

Interactive Learning for Sequential Decisions and Predictions

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Abstract

Sequential prediction problems arise commonly in many areas of robotics and information processing: e.g., predicting a sequence of actions over time to achieve a goal in a control task, interpreting an image through a sequence of local image patch classifications, or translating speech to text through an iterative decoding procedure.

Learning predictors that can reliably perform such sequential tasks is challenging. Specifically, as predictions influence future inputs in the sequence, the data-generation process and executed predictor are inextricably intertwined. This can often lead to a significant mismatch between the distribution of examples observed during training (induced by the predictor used to generate training instances) and test executions (induced by the learned predictor). As a result, naively applying standard supervised learning methods – that assume independently and identically distributed training and test examples – often leads to poor test performance and compounding errors: inaccurate predictions lead to untrained situations where more errors are inevitable.

This thesis proposes general iterative learning procedures that leverage interactions between the learner and teacher to provably learn good predictors for sequential prediction tasks. Through repeated interactions, our approaches can efficiently learn predictors that are robust to their own errors and predict accurately during test executions. Our main approach uses existing no-regret online learning methods to provide strong generalization guarantees on test performance.

We demonstrate how to apply our main approach in various sequential prediction settings: imitation learning, model-free reinforcement learning, system identification, structured prediction and submodular list predictions. Its efficiency and wide applicability are exhibited over a large variety of challenging learning tasks, ranging from learning video game playing agents from human players and accurate dynamic models of a simulated helicopter for controller synthesis, to learning predictors for scene understanding in computer vision, news recommendation and document summarization. We also demonstrate the applicability of our technique on a real robot, using pilot demonstrations to train an autonomous quadrotor to avoid trees seen through its onboard camera (monocular vision) when flying at low-altitude in natural forest environments.

Our results throughout show that unlike typical supervised learning tasks where examples of good behavior are sufficient to learn good predictors, interaction is a fundamental part of learning in sequential tasks. We show formally that some level of interaction is necessary, as without interaction, no learning algorithm can guarantee good performance in general.

For my wife, Sandra

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Chapter 1

Introduction

One of the main goal of robotics and artificial intelligence is the development of autonomous systems and software agents that can aid humans in their everyday tasks. Programming such systems however, has proven to be a remarkably challenging and time consuming task. Despite the many advances in planning and control for developing advanced automated decision-making software, these methods rely on key pieces of information that are often very hard to specify by humans. In particular, accurate dynamic models of the world, that can correctly predict the long-term consequences of various courses of actions, and a suitable cost function, that properly trades-off the desirability or utility of various outcomes to the designer of the system. While this information can often be easily provided for simple board games (e.g. chess), or simple robots operating in very controlled environments (e.g. robot arm in a factory), it is a much harder task for complex robotic systems deployed in uncontrolled environments (e.g. robot walking outdoors or autonomous driving in an urban environment). Properly specifying all these parameters to obtain the desired behavior of the system is often a very daunting task of informed “guess-and-check” that can require hundreds or thousands of man hours depending on the complexity of the system, and that often only leads to subpar performance due to inaccurate and suboptimal specification of these parameters ([Ratliff, 2009](#), [Silver, 2010](#)).

While specifying all these parameters is a complex task for human engineers, the desired behavior of the system is often clear and can often be easily demonstrated by humans. For instance, humans can easily drive in urban environments, or walk-around on various terrains. This motivates the use of data-driven machine learning approaches that can effectively leverage such demonstrations of good behavior to optimize these parameters or learn directly a controller that replicates the desired behavior.

Machine learning, in particular supervised learning, where predictors are learned from examples of good behaviors/predictions, has already had a large impact in various fields and applications. In fact, this has become the de facto method of choice behind

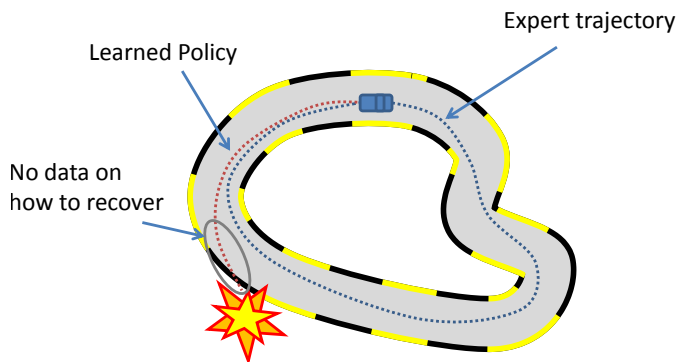


Figure 1.1: Mismatch between the distribution of training and test inputs in a driving scenario.

many state-of-the-art software system that we use everyday. Systems based on supervised learning already translate our documents, recommend what we should read (Yue and Guestrin, 2011), watch (Toscher et al., 2009) or buy, read our handwriting (Daumé III et al., 2009) and filter spam from our emails (Weinberger et al., 2009), just to name a few. Many subfields of artificial intelligence, such as natural language processing (the understanding of natural language by computers) and computer vision (the understanding of visual input by computers), now deeply integrate machine learning.

Despite this widespread proliferation and success of machine learning in various fields and applications, machine learning has had a much more limited success when applied in control applications, e.g. learning to drive from demonstrations by human drivers. One of the main reason behind this limited success is that control problems exhibit fundamentally different issues that are not typically addressed by standard supervised learning techniques.

In particular, much of the theory and algorithms for supervised learning are based on the fundamental assumption that inputs/observations perceived by the predictor to make its predictions are independent and always coming from the same underlying distribution during both training and testing (Hastie et al., 2001). This ensures that after seeing enough training examples, we will be able to predict well on new examples (at least in expectation). However, this assumption is clearly violated in control tasks as these are inherently *dynamic and sequential* : one must perform a *sequence* of actions over time that have consequences on future inputs or observations of the system, to achieve a goal or successfully perform the task. As predicting actions to execute influence future inputs, this can lead to a large mismatch between the inputs observed under training demonstrations, and those observed during test executions of the learned behavior. This is illustrated schematically in Figure 1.1.

This problem has been observed in previous work. Pomerleau (1989), who trained a

neural network to drive a car at speed in on-road environments by mimicking a human driver, notes that, “when driving for itself, the network may occasionally stray from the center of the road and so must be prepared to recover by steering the vehicle back to the center of the road.” Unfortunately, demonstration of such “recovery behavior” is rare for good human drivers and thus is poorly represented in training data. That is, under good driving behavior, most training examples consist in situations where the car is in the center of the lane and at a fair distance to other vehicles. However, when the car is driving by itself, it does not always behave perfectly, and encounters various situations that were never or rarely encountered by the human driver, e.g. situations where it is heading toward the side of the road, or is about to collide with other vehicles. The lack of training demonstrations of what to do in these critical situations will often lead to unacceptable driving performance and catastrophic failure.

In practice, this mismatch implies that naively applying supervised learning methods to control problems can often lead to predictors that have high accuracy in situations encountered during training demonstrations, but that fail miserably at performing the task during their execution. As illustrated in the driving example, this generally occurs because the learned predictors are not robust to the particular errors they make: a single or a few inaccurate predictions can quickly lead to new untrained situations, where the predictor is likely to keep predicting incorrectly. Effectively, there is a compounding error effect, where slight errors can gradually lead to larger and/or more frequent errors.

This example can be considered as an instance of a sequential prediction problem, where predictions in the sequence influence future inputs or observations. Such sequential prediction problems also arise in many other settings, outside of control applications. We present many other examples of such sequential prediction problems that arise in different fields of machine learning and artificial intelligence in the next section and in the chapters of this thesis.

This thesis focuses on developing new theory and practical learning algorithms that can efficiently learn good predictors for these sequential tasks. We posit and demonstrate that, in order to learn accurate predictors that are robust to their own errors during sequential predictions, learning must be conducted *actively*, through *interaction with the sequential process and “teacher”*. This is necessary for the learner in order to be able to experience the future consequences of its predictions and gather additional training examples under those sequences.

This thesis presents general learning approaches that leverage such interaction in order to learn good and robust predictors for sequential prediction tasks. Our approaches also specify what data to collect through interaction and how to combine data obtained from multiple interactions to train good predictors. In particular, by leveraging existing online learning algorithms with strong “no-regret” guarantees, to learn from these

interactions, our methods can guarantee learning good predictors for sequential tasks. We demonstrate how to apply these methods in various sequential prediction settings, from control problems to general structured prediction problems that arise commonly in computer vision and natural language processing, as well as recommendation tasks where sequences of relevant and diversified items must be predicted.

In each of these settings, we provide a complete theoretical analysis of our methods, showing strong performance guarantees and data efficiency (low sample complexity). We also validate our methods empirically, and demonstrate state-of-the-art performance in various important and challenging learning tasks, ranging from learning video game playing agents from human players and accurate dynamic models of a simulated helicopter for controller synthesis, to learning predictors for scene understanding in computer vision, news recommendation and document summarization. We also demonstrate the applicability of our main technique on a real robot, using pilot demonstrations to train an autonomous quadrotor to avoid trees seen through its onboard camera (monocular vision) when flying at low-altitude in natural forest environments.

On the more philosophical side, we also show that at a fundamental level, interaction is necessary for learning in these sequential settings. Unlike supervised learning, learning only from observing examples of good behavior is not sufficient. In particular, it is shown that any non interactive learning algorithm cannot provide good guarantees in general and may always learn predictors that are not robust to their own errors. We present a tight theoretical lower bound on the minimum number of rounds of interactions required that is achieved (within a constant factor) by one of the algorithm presented in Chapter 3. Our lower bound demonstrates that the number of rounds must inevitably scale linearly with the length of the sequential prediction problems (task horizon).

Thesis Statement

We now make the main statement of this thesis:

Learning actively through interaction is necessary to obtain good and robust predictors for sequential prediction tasks. No-regret online learning methods provide a useful class of algorithms to learn efficiently from these interactions, and provide good performance both theoretically and empirically.

We validate this claim by 1) presenting detailed theoretical analysis of non-interactive learning procedures and active interactive learning procedures, based on online learning methods, in various sequential prediction settings and showing improved guarantees; 2) proving formally that no learning algorithm can provide good guarantees without some minimum number of interactions; and 3) empirically comparing performance in a large

variety of applications, demonstrating the benefits of the interactive online learning based approach.

1.1 Motivation and Examples

We now present a few more motivating examples of important learning tasks that involve sequential predictions and exhibit the same fundamental issues of data mismatch discussed previously.

The first example we discussed previously were control tasks where control behavior is learned directly from expert demonstrations. This general problem is called imitation learning, and has been applied successfully on a number of robots, from robots that can juggle ([Atkeson, 1994](#)), to outdoor navigation for autonomous vehicles ([Silver et al., 2008](#)) and rough terrain locomotion of quadruped robots ([Ratliff et al., 2007a](#)).

Another example of sequential prediction task in control is system identification – attempting to learn dynamic models of the world for planners ([Ljung, 1999](#)). As most modern robots rely on planning algorithms for decision-making, learning accurate models for planning is often a crucial step to obtain systems that behave properly. Here the sequential nature of the problem is two-fold. Not only does the task involve executing a sequence of good actions, but planning at each step, also involves predicting future sequences of states that can occur under various courses of actions, to choose the best action to perform immediately. Again here, because the actions chosen and executed by the planner influence the future states of the system, we can suffer from a similar data mismatch issue. For instance, imagine learning a dynamic model of an helicopter in flight by recording how it moves while being flown by a pilot, as depicted in [Figure 1.2](#). While we may obtain an accurate model of the behavior of the helicopter under various controls in typical flight conditions visited by the pilot, the model may fail to be accurate in rarely observed conditions. During autonomous flight, if the planner chooses a particular course of action where it encounters those rare conditions, as the model fails to capture the proper behavior of the system, it will likely choose bad actions that fail to perform the task.

Outside of control, many problems that arise in computer vision and natural language processing are structured prediction problems that can exhibit this same fundamental issue. Consider the problem of scene understanding in computer vision – extracting a high-level understanding of the world around the robot from visual sensors such as cameras or LIDAR – which is a critical component of many robotic systems. Current state-of-the-art methods for such structured prediction tasks employ an inference or decoding process that performs a sequence of interdependent predictions to produce the output ([Daumé III et al., 2009](#), [Munoz et al., 2009, 2010](#)) (see [Figure 1.3](#)). In this scene

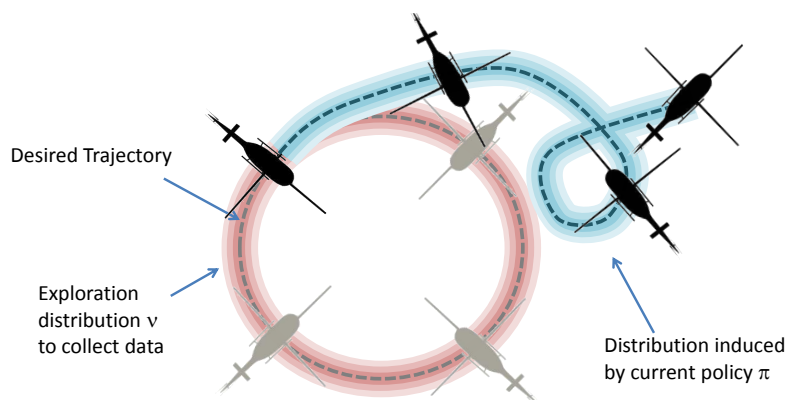


Figure 1.2: Mismatch between the distribution of training and test inputs in a helicopter scenario. A human pilot flies the helicopter to follow a desired trajectory to collect data. When planning with the learned dynamic model to follow the desired trajectory, the helicopter slowly diverges off the trajectory and encounters rarely trained situations where its dynamic model is bad, leading to poor behavior from the planner.

understanding task, it effectively performs local predictions of what is present at each location in the image iteratively, based on local image features, and contextual information of what has been predicted nearby. Because this contextual information depends on previous predictions, learning a predictor to perform this decoding exhibit the same issue. That is, predictions change future inputs to the predictor during this decoding process, and can thus lead to a significant discrepancy between the training examples, and inputs encountered during decoding of new test images with the learned predictor. For instance, if we naively train a predictor with error-free contextual information during training, then at test time, a single error during decoding could quickly propagate into a series of errors, as the predictor may have learned to rely heavily on its contextual information to be accurate.

Another example arises in the context of predicting a set or sequence of relevant and diversified recommendations or items (Yue and Guestrin, 2011, Dey et al., 2012a). For example, consider the problem of suggesting a small list of candidate grasps that is likely to contain a successful one for grasping an observed object with a robotic manipulator. In this context, we want to predict grasps that are relevant, i.e. likely to succeed, but that are also diverse, so that we avoid trying similar grasps to previous ones that failed (as they would also be likely to fail). To do so, it is natural to consider learning a predictor that uses information from previously predicted grasps as input in order to suggest the next best grasp while avoiding picking one that is similar previous failures. Again here, this lead to a setting where previous predictions influence future inputs to the predictor and can lead to significant mismatch between the training and test examples.

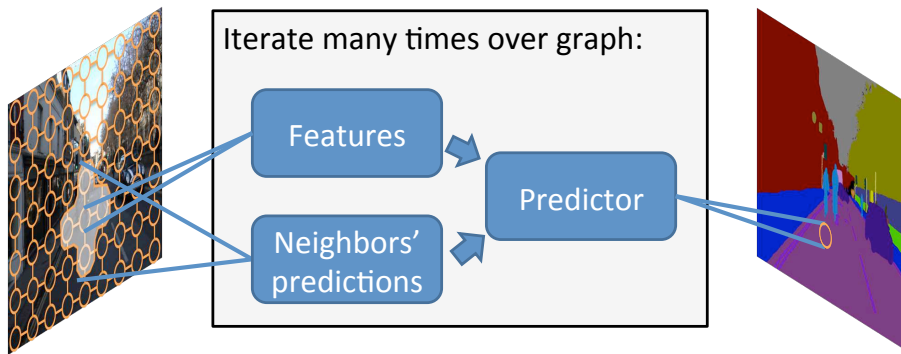


Figure 1.3: Depiction of the inference or decoding process of structured prediction methods in the context of image labeling. Effectively, a sequence of predictions are made at each pixel/image segments over the image, using local image features, and previous computations/predictions at nearby pixels/image segments. This is often iterated many times over the images until predictions “converge”.

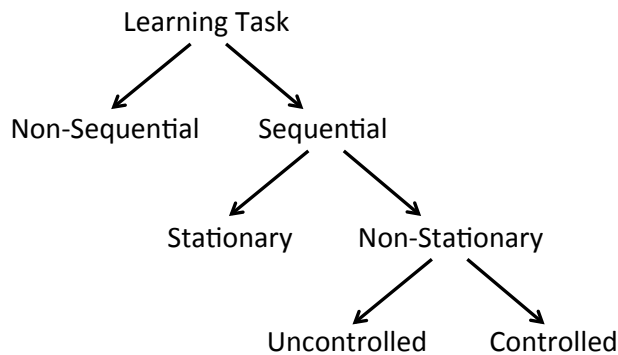


Figure 1.4: Categorization of various learning tasks.

1.2 Categorization of Learning Tasks

Having shown multiple examples of sequential prediction tasks, we now provide a categorization of learning tasks, based on some important properties, to define properly the particular problem class of interest in this thesis.

This categorization is shown in Figure 1.4. We first distinguish between learning tasks that are *non-sequential* vs. *sequential*. By sequential, we simply mean that to complete the task, multiple predictions must be performed. A non-sequential task can be a typical supervised learning task, where e.g. we want to classify emails as spam or non-spam; a single prediction is made given features of the email’s content to perform the task, and moreover, that prediction is assumed to have no influence on future predictions that will be performed.

Among sequential tasks involving multiple predictions, we distinguish between tasks

where the input distribution is *stationary* vs. *non-stationary*. Stationary implies that at any point in the sequence of predictions, the distribution of inputs is the same. Examples of such task may include decoding a handwritten text, where each handwritten character is decoded individually, only based on the character image, and in random order. To decode the entire text, a sequence of predictions must be performed, but for each prediction, we would expect to see the same distribution of input handwritten characters. Despite these tasks being sequential, they are not of particular interest in this thesis, as they can simply be considered as a regular supervised learning task of predicting individual characters.

Non-stationary tasks on the other hand, are tasks where the input distribution can vary along the sequence. We again distinguish between two cases: *uncontrolled* vs. *controlled*. Here we use the term controlled in a loose sense, and simply to denote that inputs depend or may be influenced by past predictions in the sequence. A good example of an uncontrolled non-stationary sequential prediction task is weather forecast. Suppose we want to predict tomorrow’s weather as we observe the weather each day over time, using as input, features of the observed weather today and in previous days. We would expect the distribution of inputs to vary over time, e.g. due to seasonal cycles, and because there is a time-dependency in weather (good or bad weather tend to continue over time). However, the predictions we make about tomorrow’s weather does not change or influence future weather (or its distribution) and hence would not change future inputs to the predictor. Hence the evolution of the sequence of inputs is uncontrolled. While the non-stationarity of the sequence can lead to some train-test mismatch issues if training improperly (e.g. training only on examples of summer weather, to then forecast winter weather), this is again not the particular type of tasks we are interested in this thesis. However, many of the ideas we present could be applied and often simplified to handle these scenarios.

The focus of this thesis is on the latter type of sequential tasks, that are non-stationary and controlled. All the examples we provided in the previous sections fit into this category, as either part of the input features depend directly on previous predictions, or are a consequence of previous predictions (e.g. previous actions that lead to observations in a particular location in the environment). The data mismatch issue we discussed earlier is particularly prominent in this scenario. Non-sequential and stationary tasks do not have to deal with this issue, and even uncontrolled non-stationary tasks can sometimes avoid this issue (e.g if we can train on repeated realizations of the non-stationary sequence). On the other hand, when the sequence is controlled, we very often encounter a data mismatch issue, as different predictions at test time than at training time will lead to different input distributions.

1.3 The Challenge of Learning Sequential Predictions

We now explain in more detail the particular challenges of learning in these controlled sequential tasks.

Data Mismatch : When is it Significant?

As mentioned earlier, one of the major difficulties that occur in sequential prediction problems is that there can be a large discrepancy between the training and test distribution of examples, when the predictions made by the learned predictor differ from those on the observed sequence during training. In large and real world applications, where some degree of approximation is often inevitable, it is rarely the case that the learned behavior is able to reproduce exactly an observed behavior during training. Thus such discrepancy between training and test inputs/observations often occur. However there are different cases where this effect is more important than others. We here explain various cases and how they impact the data mismatch. These will be important cases to keep in mind to understand when the data mismatch can become a significant issue.

Highly Stochastic vs. Near-Deterministic Sequences

In some tasks, stochasticity can play a large role on the evolution of the input of the sequence, and limit to a large extent the effects of the predictions. An example of this is the game of Backgammon, where the evolution of the game is highly randomized and depends significantly on die rolls. While the players still choose which pieces to move, and have an effect on the evolution of the game, they have limited control over the future outcomes or situations encountered during the course of a game. To a large extent, the distribution of board configurations encountered over many games may cover almost all board configurations, and be only slightly more concentrated in some areas of the feature space, depending on the strategy used. Thus if we would attempt to learn to play this game, e.g. from observing other players, we would expect to observe inputs that covers most of the feature space during training. Since there is no situations that are much more likely under some strategy than observed during human player play, a fairly good estimate on the performance of any game playing strategy could be obtained, even if there is a slight mismatch on where the inputs are more or less concentrated. In this case we may expect the data mismatch to be a non-issue, or only have a limited impact on performance.

On the other hand, the opposite occur in situations where the evolution of the sequence is near-deterministic and largely determined by the past predictions. This is the case encountered by most robotic systems where the movement of the robot is deterministic (or nearly so), and to a large extent determined by the previously predicted actions.

Often even small changes in the actions can lead to a large change in configuration after some time (e.g. robot walking where a small perturbation can lead a stable walker to lose balance). Thus in such setting, data mismatch can be very important and critical to address to obtain good performance. These are the settings that are of most interest in this thesis, given their frequent occurrence in robotic applications.

Relevance of Controlled Features

In some situations, only a fraction of the features (information used to make predictions) depends on previous predictions. This is the case in some of the examples presented earlier. For instance, in the scene understanding example where the local image features used do not depend on past predictions in the sequence, and only features related to neighboring predictions depend on past predictions. The data mismatch issue only affects these features which depend on previous predictions and how to use them appropriately. If there is a large fraction of features that do not depend on previous predictions, and the contribution of each feature to the final prediction is limited (e.g. linear classifier with regularization), then the data mismatch can be a non-issue, as improving how we use a small fraction of the features will have a very limited effect on the predictions. In general, if good predictions can be obtained by relying heavily on only the independent features (e.g. the local image features), then the data mismatch may be irrelevant. However, if it is critical to use significantly the features depending on previous predictions, compared to the independent features, then it will be critical to properly deal with this issue to obtain good performance. We will be particularly interested to these situations where using these features is critical for good performance.

Realizability and Generalizability of Hypothesis Class

Even though we may be in a situation where there is a significant mismatch in the distribution of training and testing examples, depending on how the data is generated and what class of predictors we are considering, the data mismatch may be a non-issue.

To illustrate this, imagine a case where the generated data is a linear function of the features, with some noise, and we attempt to learn a linear predictor. Then no matter where data is sampled we may be able to recover the correct linear function, and generalize well to any region of the input space that we didn't observe during training. Therefore even if we are tested mostly in a different region, we would still be able to predict accurately. This is illustrated in Figure 1.5. This shows that in situations where both 1) the class of predictors contains predictors that can fit very well the observed data (realizable settings) and 2) that generalize well across the entire feature space (e.g. with a low complexity class), then where data is collected often doesn't matter. These

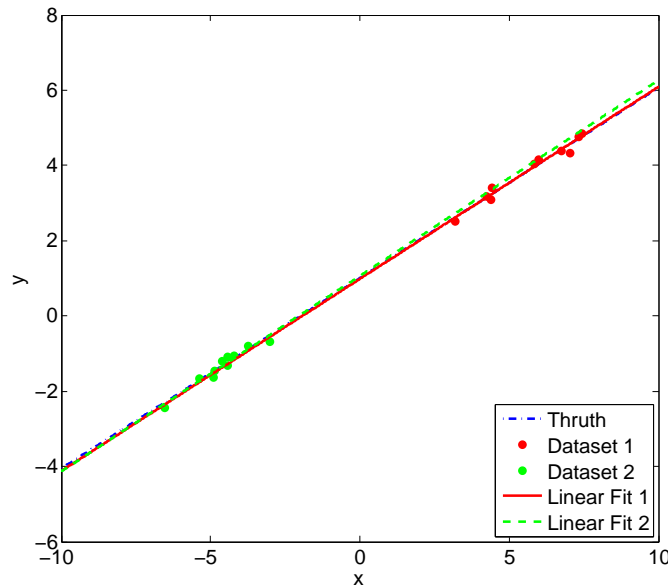


Figure 1.5: Example of learning with a low complexity hypothesis in a realizable setting. Target function is a linear function. No matter where we sample data, fitting a linear function leads to roughly the same hypothesis, and obtains a good fit of the entire function.

are easy cases that are not of concern in this thesis. This has been the most common paradigm for analyzing performance in control problems (Ljung, 1999).

On the other hand, when at least one of these two properties does not hold, then where data is collected has a significant impact. For instance, even in a realizable setting where we can obtain a very good fit to any observed training data, if we are learning a high complexity predictor (which is usually necessary to be able to fit the training data well everywhere), the predictor will typically not generalize too well to regions of the feature space that were never or rarely observed. This is shown in Figure 1.6. This is because high complexity class allows for a wide range of functions that fit the training data well, but vary greatly outside the region where training data was collected. This implies that correct predictions outside of the training region is highly undetermined or uncertain. Thus, in such setting data mismatch can lead to very bad predictions at test time. In particular, it is important that the training data covers well the regions where the predictor is tested, in order to predict accurately at test time. While we may attempt to sample uniformly the entire input space to ensure sufficient coverage of any possible test regions, this does not scale well to high-dimensions (covering the volume of the input space would require an exponential number of samples in the dimensionality of the input).

Similarly, where data is collected has a significant impact in situations where the

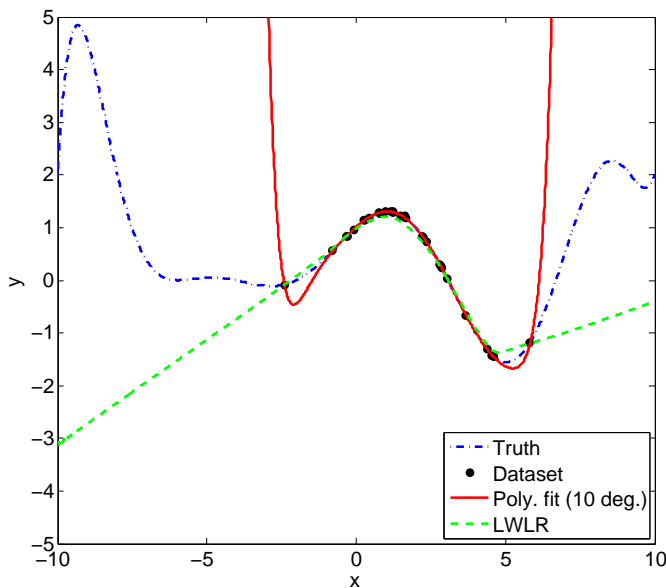


Figure 1.6: Example of learning with a high complexity hypothesis in a realizable setting. Target function is a 10 degree polynomial. Fitting a 10 degree curve to slightly noisy data (white noise with 0.01 standard deviation) leads to a good fit only in the sampled region. Similarly a non-parametric locally weighted linear regression method only gets a good fit in the sampled region.

target function cannot be fitted well globally by any predictor in the class (agnostic/non-realizable setting). In this case, we may be able to obtain a good fit to the data locally, e.g. in some region where the training data is concentrated, but predictions will again typically not generalize well outside the region where training data is concentrated, since the class of predictor cannot capture accurately the target function. This is illustrated in Figure 1.7, where we consider a case where we fit a linear function to data generated from a quadratic function. To obtain accurate test predictions in such scenario, it would be crucial that the test data be concentrated in some small enough region, and that the training data be concentrated in that same region. Any mismatch in training data would lead to a different linear fit that does not fit well the function in the test region. Additionally, sampling uniformly the entire feature space will also generally not work well, and only lead to a predictor that is accurate in some small regions that will likely not match where the test data is concentrated.

This thesis is concerned with these last two scenarios, that are the most frequent situations in real applications. That is, in real applications, the data generating process is often very complex, and we must either make approximations to learn efficiently (i.e. non-realizable setting), or use a high complexity class of model (or non-parametric method) to obtain very accurate predictions (i.e. poor generalization outside training region). In

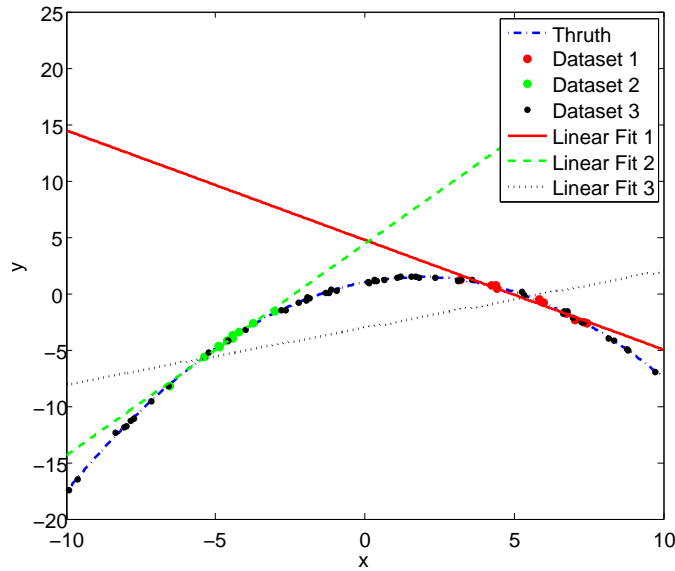


Figure 1.7: Example of learning with a low complexity hypothesis in a non-realizable setting. Target function is a quadratic. Fitting a linear function leads to significantly different hypothesis depending on the region where samples are concentrated. Good local fit can be obtained, but sampling uniformly does not lead to a good global fit.

both situations, data mismatch can have a serious impact on performance. Our goal is to develop novel learning techniques that address this issue and that are able to learn good predictors in such situations.

1.4 Leveraging Interaction for Efficient and Robust Learning

As demonstrated in the previous section, it is important to obtain training data in the regions where the predictor will be tested. In the context of controlled sequence, this corresponds to obtaining data under sequence that the learned predictor will be likely to induce. Intuitively, this implies we need to execute the learned predictor during training to obtain training data under sequences that it generates.

Unfortunately, this is a “chicken-and-egg” problem. Without the learned predictor in advance, we do not know where to collect data, and without the data we cannot know which predictor we will end up learning. A common strategy to deal with such problems is to adopt an iterative approach. In our context, this suggests iterative learning approaches, that iteratively collect additional training data along sequences induced by the learner’s current predictor, in order to update the learned predictor for the next iteration.

This iterative interaction with the learner during training will be the main idea behind the learning approaches we present in this thesis. Using such interaction will allow the learner to obtain training data under sequences where it errors, and observe the proper behavior to recover from these errors. For example, in the previously discussed driving scenario where we learn a driving controller, executing the learner’s current behavior and observing the corresponding human “corrections”, would allow it to observe that it must perform harder turns to get back near the center of the road if it is heading off the road, or that it must brake more aggressively if it is about to rear-end another vehicle. With these learner interactions, the learner will be able to learn these recovery behaviors and obtain a predictor that is robust to errors it frequently makes during its sequence of predictions.

We now give a brief high-level overview of the main approach that we present in this thesis and use to learn good predictors in various sequential prediction settings. The approach is called DAGGER, for Dataset Aggregation, as it proceeds iteratively by aggregating training data to learn over many iterations. At each iteration, this approach interacts with the learner by using its current predictor to simulate or generate sequences of inputs that occur under this predictor. For instance in a control application, this involves executing the learner’s controller. Under these generated sequences, the “teacher”¹ provides the desired predictions. This new data is then aggregated with all collected data at previous iteration, and then the learner trains on this aggregate dataset to obtain its new predictor for the next iteration. This is iterated for some large enough number of iterations. Initially, the initial sequences can be generated from some initial guess of what a good predictor is, or if possible, from sequences induced by the teacher’s predictions (e.g. human driving the car). This approach is depicted in the context of the driving scenario in Figure 1.8

Intuitively, this approach builds a dataset of the inputs the learner is likely to encounter during its sequence of predictions from past experience (previous iterations) and choose predictors that predict well under these frequent inputs. Additionally, as the fraction of new data compared to the size of the aggregate dataset becomes smaller and smaller, the chosen predictor will tend to change more and more slowly, and stabilize around some behavior that produces good predictions under inputs that were collected in a large part by similar predictors. In later sections we will show formally that this technique as strong performance guarantees if a good predictor on the training data exists.

This is our proposed method in its simplest form. Later in this thesis, we will

¹We use teacher very loosely here to denote the process that provides the target predictions. In some setting, this is not necessarily a human, but can simply correspond to labeled data in a file (e.g. labeled images in scene understanding), or corresponds directly to observations generated by the environment (e.g. if we want to learn a model that predicts the next state for planning).

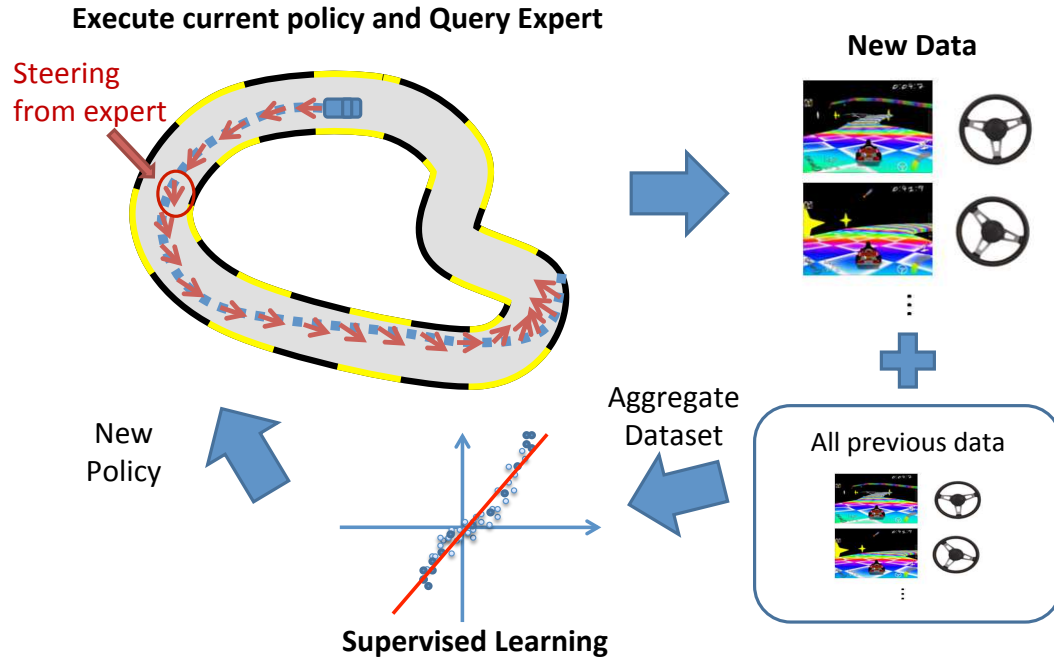


Figure 1.8: Depiction of the DAGGER procedure in a driving scenario.

demonstrate how this approach is related to online learning methods, and how it can be generalized to leverage any existing online learning procedure with certain “no-regret” properties to provide good guarantees. Additionally, in some sequential settings, we will present slight modifications that are necessary to obtain better guarantees. But to a large extent, the core iterative and interactive procedure of executing the learner’s predictor to generate training sequences remains the same.

1.5 Related Approaches

We now briefly discuss a few related methods from different fields of machine learning that are related to our method.

Reinforcement Learning

Reinforcement Learning (RL) is a field of Machine Learning interested in learning good control behavior by trial-and-error (Sutton and Barto, 1998). That is, from observing feedback of how good their behavior was, rather than being told or shown what to do. Learning from such feedback is analog to the way dogs or other animals are trained to behave properly, by giving them “rewards” when they behave well, or punish them when they do something bad.

To a large extent, most RL methods learn exclusively from interaction of the learner with its environment, where the learner will explore various sequences of actions to find out which is the best. In this sense, our approach is similar to RL methods in that it also learns from interaction and executing the learner’s own actions. Especially similar are “on-policy” RL methods [Sutton and Barto \(1998\)](#) which learns from execution of the learner’s current policy/controller (often with additional exploration). However, in most of the settings we consider, our approach will have access to a different feedback that tells it directly what it should predict. This is different than RL, and leads to a simpler learning problem, as the learner does not necessarily have to *explore* different course of actions to find out which one is best, e.g. it is shown directly which one is the best.

Despite some difference to RL, several RL methods exhibit similarities to our proposed approach. In particular Conservative Policy Iteration (CPI) ([Kakade and Langford, 2002](#)) and its variant, Search-Based Structured Prediction (SEARN) ([Daumé III et al., 2009](#)) for structured prediction problems, operate in a similar iterative fashion, where at each iteration the learner’s current controller is executed, with additional exploration, to obtain new feedback on how the current controller may be improved. Then the controller is updated by making a “small change” towards the best controller for the new data. The small change makes the distribution of data change slowly over the iterations as the controller changes and allows the learner to adapt to the changing distribution and converge to a good behavior. Other methods such as Policy-Search by Dynamic Programming (PSDP) ([Bagnell et al., 2003](#)) use this same idea of making small changes over many iterations of learning to learn a controller with good guarantees. We will see that in many ways, our approach exploits this same strategy of making “small changes” indirectly through the use of online learning algorithms with “no-regret” properties. These online algorithms are implicitly adapting towards the best predictor while making small changes (this is made more formal in Chapter 9). To some extent, our results generalize these previous methods and demonstrate that a wide variety of learning procedures, with such “no-regret” property, can be adopted.

Perhaps most closely related to our approach, are the iterative algorithms of [Atkeson and Schaal \(1997\)](#) and [Abbeel and Ng \(2005\)](#). Both of these approaches also proceed by using the learner’s current controller to collect more data at each iteration, and aggregate data from all iterations to update the controller, just like our proposed approach in its simplest form. Our approach is heavily inspired by these methods, and our work can be seen as a generalization of these approaches, by showing that the procedure can also be conducted with any online learning procedure rather than specifically with this data aggregation method, and extending their application to various sequential prediction settings. In addition, we develop significant new theory to justify this kind of approach.

Active Learning

Active Learning is another field of Machine Learning, very similar to supervised learning where predictors are learned from examples of good predictions. The distinction to standard supervised learning is that the learner is not observing passively examples demonstrated by the “teacher”, but instead learns actively, by querying the “teacher” about the correct predictions for any inputs that the learner wants to know about (Cohn et al., 1994, Freund et al., 1997) (usually among a set of unlabeled inputs). In some sense, this is very similar to the learner interactions used in our approach, where the learner can query the “teacher” about specific inputs it encounters. A major difference in our sequential settings is that we are not provided with a set of unlabeled inputs but instead, we must decide how to act to collect further data. Furthermore, some restrictions usually limit how we can collect data or query the expert. For instance, it is not possible to simply put a real robotic system in any particular state to observe what’s going to happen next. Instead, to visit and learn about particular situations, the learner must execute a sequence of predictions that actually encounters those situations. With our method, we only assume this ability to query the “teacher” along sequences of predictions produced by the learner, rather than at any input.

Additionally, most strategies employed in active learning to decide where to query the “teacher” only applies in realizable settings, with a few recent exceptions (Balcan et al., 2006, Dasgupta et al., 2007). In some cases, the query strategies are also dependent on the class of predictor or problems considered, e.g. linear classifiers, or binary classification problems. Instead, our approach is meant to be very general and applicable across various class of problems or predictors, and in non-realizable settings. Therefore, our set of assumptions is much weaker than what is typically assumed in active learning, and thus many of these techniques would not be generally applicable in our settings.

Transfer Learning

Transfer learning is another field of machine learning, where training is conducted under a different distribution of examples than testing and the goal is to adapt the predictor to be good under the test distribution (Pan and Yang, 2010). Hence, these methods are attempting to address exactly the same problem of data mismatch at the core of this thesis. However, transfer learning approaches use much more knowledge of the testing distribution to be able to adapt the predictor. In their settings, the testing distribution is typically fixed, i.e. it does not change depending on the predictor we use as in our sequential settings. Additionally, they often have access to some examples from this fixed test distribution during training (either labeled or unlabeled). Using this information, a common strategy is to weight the training examples in order to better reflect the test distribution, and train on these weighted examples (Zadrozny, 2004, Huang et al., 2007).

Because these methods assume a fixed test distribution, independent of the learned predictor, these methods are typically not directly applicable to our sequential settings. However, they could potentially be used, in combination with our approaches, to iteratively adapt to the changing test distribution. This is briefly mentioned in more details in Chapter 11.

Online Learning

Online learning is used extensively within our work to provide good guarantees. Online learning typically studies problems where a single stream of data is observed, and we must make predictions along the way as we observe more and more data, e.g. in problems like weather forecast or stock market predictions. In these applications, the goal is to purely make good predictions on this stream, as we continuously observe more training data, and there is no explicit notion of generalization to a new test stream, where we stop observing labeled training examples to keep adapting the predictor. In our work, we use online learning for this particular purpose: to learn predictors that generalize to the distribution of sequences they may observe during their test execution (where it will not observe more labeled examples). This is similar to work in online-to-batch learning that have analyzed the generalization ability of “no-regret” online learning methods for learning good predictors for test data, by going through a batch of training data in sequence (Cesa-Bianchi et al., 2004, Kakade and Tewari, 2009). The generalization guarantees in this case assume i.i.d. properties of the batch of training and test data. Our work can be seen as extending and generalizing further this line of work, in showing that no-regret online learning can lead to good generalization performance even in non-i.i.d. settings.

1.6 Learning and Interaction Complexity of Sequential Predictions

Another focus of our theoretical analysis is on determining the learning efficiency of various learning methods. As with typical supervised learning methods, a common measure of efficiency we will be interested in analyzing is the sample complexity – how many data points is required to obtain a good predictor with high probability. We will analyze thoroughly each method we present and demonstrate that using interaction during training can also reduce the total number of samples required compared to standard non-interactive supervised methods.

Another measure of complexity that we introduce that is relevant for these iterative and interactive learning procedures is what we call the interaction complexity – how many rounds of interaction or training is required to obtain a good predictor. This is another

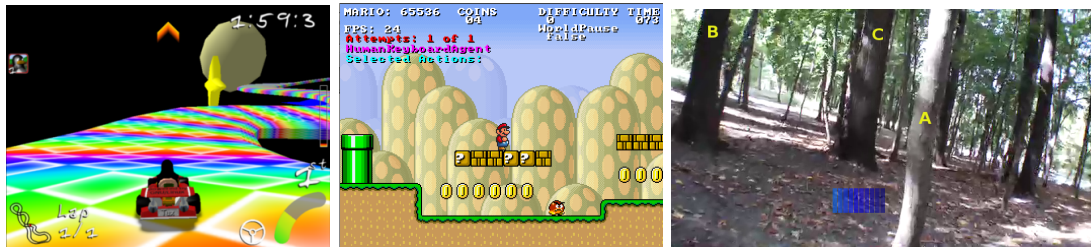


Figure 1.9: Imitation Learning Applications. (Left) Learning to drive in Super Tux Kart, (Center) Learning to play Super Mario Bros, (Right) Learning Obstacle-Avoidance for Flying through Natural Forest.

notion of complexity that is of interest, as more rounds may typically require more work from human teachers, and more computational work (for optimizing predictors). This is introduced in Chapter 10. We use this notion to demonstrate that many rounds of interaction is fundamentally required in general for sequential prediction tasks. That is, there does not exist any learning algorithm that can guarantee learning a good predictor without multiple rounds of interaction. Additionally, we provide a tight lower bound on the minimum interaction complexity of any learning procedure that provide good guarantees. The lower bound shows that the number of rounds required must scale linearly with the length of the sequence (task horizon), and matches the number of rounds (within a constant factor) required by an algorithm presented in Chapter 3.

These results complete the overall picture and theory of learning sequential predictions. They demonstrate that fundamentally, learning actively through interaction is both sufficient and necessary for learning good predictors. Despite that many of these sequential tasks look like typical supervised learning tasks, unlike supervised learning, learning passively by only observing examples of good predictions is not sufficient.

1.7 Applications

Throughout this thesis, we demonstrate the wide range of application of our approach to address various sequential prediction tasks.

We first demonstrate application of our method for learning control behavior from demonstrations of the task. This is applied in two video game problems to learn game playing agents and to learn obstacle-avoidance for a real autonomous quadrotor. One game is an open source 3D kart racing game, Super Tux Kart, similar to the popular video game Mario Kart, where we attempt to learn a controller, from human player demonstrations, that can steer the kart properly on the race track based on the observed game image stream (see Figure 1.9). This experiment seeks to simulate learning vehicle control for autonomous cars from human drivers. The other game is based on an open

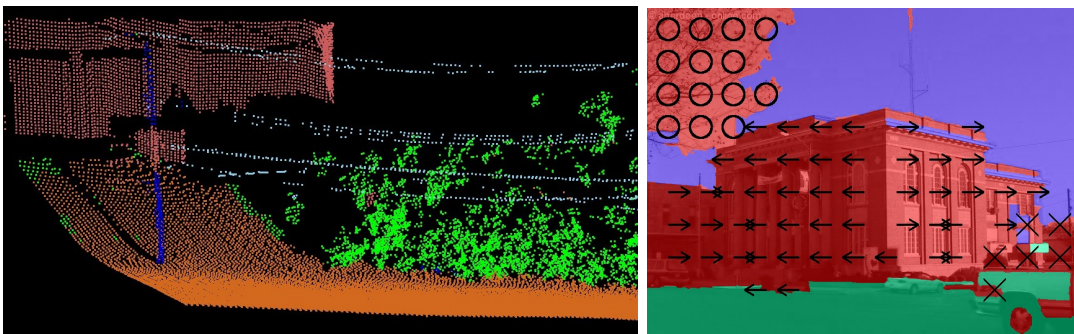


Figure 1.10: Structured Prediction Applications in Computer Vision. (Left) Parsing 3D Point Cloud from LIDAR Sensors, (Right) Estimating 3D geometry of 2D images.

source version of the popular video game Super Mario Bros, where we learn control for Mario based on high-level features of the observed game image (see Figure 1.9). Here the demonstrations are provided by a planner that can complete almost all randomly generated stages of the game, through access to the internal game state. This shows that another use of such method can be to learn controller that replaces computationally expensive decision process. More importantly, one of the major application of our approach is its application on a real robotic system, an autonomous quadrotor navigating in natural forest environments. Here, we use our method to learn a controller, from human pilot demonstrations, that can avoid trees based on the observed onboard camera image stream (monocular vision) (see Figure 1.9). This shows that our method is applicable on real robotic systems, in addition to simulated (or software) environments.

Another application in control tasks involve learning dynamic models of a simulated helicopter for synthesizing controllers that can perform aerobatic maneuvers. The dynamic models are learned from observed helicopter trajectories under various controllers, and then used for synthesizing a controller that can best follow the desired aerobatic maneuver trajectory. This experiment simulates the application of our method for learning models that can be used for decision-making/planning in robotic systems.

Outside of control applications, we also demonstrate the various uses of our approach to a number of important problems in robotics. We apply our method to structured prediction tasks that arise commonly in natural language processing and computer vision problems. The first one is a simple benchmark handwriting recognition task, where given a dataset of human labeled handwritten words, we learn a predictor to decode handwritten words in sequence from the observed character images and contextual information of the previously predicted characters in the word. The second task involves identifying the objects present in outdoor scenes observed through a LIDAR sensor on a robotic vehicle. Given a dataset of human labeled LIDAR 3D point cloud of outdoor scenes, we learn a predictor that can predict the object present at each point (among vegetation, building,

road, poles and wires) in a LIDAR point cloud, from local shape features of the point cloud, and contextual information of objects predicted nearby (see Figure 1.10). We also apply our method for estimating the 3D geometry of an outdoor scene in a 2D camera image. Given a dataset of human annotated outdoor images, we learn a predictor that can estimate the 3D geometry of each image segment (between ground, sky, a vertical structure facing left, front-facing or facing right, or a solid or porous object), from local image features (texture, color histogram, etc.) and contextual information of the nearby predicted 3D geometry (see Figure 1.10).

Finally, we also demonstrate applications of our method for recommendation tasks where we must select a small list of relevant and diverse items. We apply our method to two relevant problems in robotics. The first one consists in learning to suggest a small list of grasps for a robotic manipulator to pick a nearby object that is likely to contain a successful grasp, based on a dataset of training environments where we observe the successful grasps. The second one consists in learning to suggest a small list of initial trajectories to seed a local trajectory optimization procedure for a robotic manipulator based on features of the environment that is likely to lead to a collision free trajectory, again given a dataset of training environments. Outside of robotics, we also apply our method for personalized news recommendation, recommending a small set of diverse articles a user is likely to be interested in, and to extractive document summarization, picking a few sentences out of a document that provides a good summary.

These experiments demonstrate the wide range and variety of settings where our method can be applied and its potential impact in many fields. This is by no means an exhaustive list. We believe our method can have many other applications, and be applied in other settings we haven't considered here. In fact, various work by other authors building on our work have already showed a number of new applications of our method to other structured prediction problems in computational biology (Vlachos, 2012) as well as for learning dynamic feature selection strategies (He et al., 2012). In general, we believe that many tasks exhibiting a similar "chicken-and-egg" problem may benefit from using our proposed method.

1.8 Contributions

This thesis makes a number of important algorithmic and theoretical contributions to machine learning in sequential problems.

In chapter 3, we first provide a complete analysis of standard supervised learning methods in imitation learning tasks to demonstrate their poor performance guarantees in such sequential settings. We develop two novel learning strategies with good guarantees: 1) A forward training procedure that leverages interaction and the sequential structure

of the task, but that is not practical for long sequence of predictions; 2) a more practical iterative training procedure described briefly in this chapter that leverages interaction and the strong guarantees of no-regret online learning methods. The guarantees of these methods are state-of-the-art and the best known for this setting.

In chapter 4, we extend these methods to imitation learning settings where cost information is observed and can be used to provide improved guarantees. We show how one of these techniques also lead to an approach that can handle general model-free reinforcement learning problems, and provide good guarantees given a good exploration distribution. Our guarantees in this case match the best known guarantees of other agnostic model-free reinforcement learning methods.

In chapter 5, we perform extensive experimental comparison of these methods and demonstrate that our methods achieve state-of-the-art performance for imitation learning in video game domains and for training an autonomous UAV to fly in natural forest environments.

In chapter 6, we demonstrate how the same methods can be applied in structured prediction tasks, and have the same guarantees. Our experimental results demonstrate that our approach can match and sometimes exceed slightly the performance of other state-of-the-art structured prediction approaches, while being more computationally efficient.

In chapter 7, we show that these methods can be used in submodular list prediction tasks such as relevant and diverse recommendations. We introduce a few small modifications to our approach, with improved analysis specific to this setting, that allows it to provide even stronger guarantees on global optimality in this setting. Our guarantees match the best known guarantees for this setting. In addition our experimental results are state-of-the-art on several recommendation tasks, and demonstrate improved learning efficiency over previous state-of-the-art methods.

In chapter 8, we show how the same methods can be slightly modified for system identification, i.e. to learn good dynamic models for planning or controller synthesis, with near-optimality guarantees. Our results provide some of the first agnostic analysis of system identification methods and are the best known guarantees for agnostic settings. While in agnostic settings, our near-optimality guarantees are dependent on the quality of a given fixed exploration distribution used during training, for realizable settings, we propose an optimistic exploration strategy that must end up learning a model that can synthesize an optimal controller for the task. In this case, our guarantees are state-of-the-art and improve over guarantees of previous state-of-the-art model-based reinforcement learning methods. All these results extend beyond learning of linear systems, to arbitrary class of systems where no-regret online learning is possible, and shows that learning models that recovers the optimal controller is possible for much more general class of

systems. Experimentally, we also demonstrate state-of-the-art performance at learning models of a simulated helicopter for performing aerobatic maneuvers.

In chapter 9, we provide an alternate sufficient condition for providing good performance guarantees with our data aggregation procedure based on notions of stability. These conditions relates no-regret online learning to stability and minimization of loss in hindsight. At a high level, these results indicate that we can expect a data aggregation strategy to work well in practice, as for common practical scenarios, most decent supervised learners will typically exhibit these stability properties. They also give the intuition that no-regret methods are implicitly learning by making “small changes” as well, as in previous learning procedures for reinforcement learning and structured prediction (Kakade and Langford, 2002, Bagnell et al., 2003, Daumé III et al., 2009).

In chapter 10, we introduce and formalize the notion of interaction complexity and present a lower bound on the minimum number of rounds of interactions necessary to learn good predictors. These results demonstrate that no learning algorithm can guarantee learning good predictors in general without multiple interactions with the learner. We show that the number of rounds must scale linearly with the length of the sequence (task horizon). This bound is tight and match the number of rounds required by the Forward Training algorithm introduced in Chapter 3. At a high-level, these results demonstrate that learning actively through interaction is necessary to learn good predictors for sequential tasks, and that one cannot simply learn passively by observing examples of good predictions.

Chapter 2

Background

In this chapter, we briefly review common machine learning techniques, algorithms and theory, that we will use throughout this thesis, as well as common models and algorithms for sequential decision-making and optimally performing sequential tasks.

2.1 Data-Driven Learning Methods: Algorithms and Theory

We start by introducing commonly used learning methods in the field of machine learning that will be leveraged for learning predictors in our work. We first introduce statistical learning techniques for classification, regression and density estimation. Then we introduce online learning algorithms and the concept of regret. Finally we describe the idea of a reduction between learning tasks.

Batch Statistical Learning

Statistical learning techniques allow to learn a function or predictor from a set of observed data that can make predictions about unseen or future data. These techniques provide guarantees on the performance of the learned predictor on the future unseen data based on statistical assumption on the data-generating process. For instance, it is typically assumed that the observed data for training and future unseen data where the learned predictor is evaluated are both drawn i.i.d. from the same unknown distribution.

In general, a statistical learning problem can be defined formally as follows. Given a hypothesis space \mathcal{H} , an instance space \mathcal{Z} and a subset of m instances $S = \{z_1, z_2, \dots, z_m\}$ drawn i.i.d. from some unknown distribution \mathcal{D} over \mathcal{Z} , find a hypothesis $h \in \mathcal{H}$ which minimizes some loss function $\ell : \mathcal{H} \times \mathcal{Z} \rightarrow \mathbb{R}$ in expectation with respect to the distribution \mathcal{D} . That is, we seek to find an hypothesis h^* such that:

$$\mathbb{E}_{z \sim \mathcal{D}}[\ell(h^*, z)] = \min_{h \in \mathcal{H}} \mathbb{E}_{z \sim \mathcal{D}}[\ell(h, z)]. \quad (2.1)$$

However, because the distribution \mathcal{D} is unknown and only observed through the sampled instances in S , this objective cannot be minimized exactly. Nevertheless, statistical learning methods can often provide guarantees on the quality of their solution as a function of the number of samples m , and achieve optimality in the limit. An approach often used by many statistical learning methods is to minimize the empirical loss on the sampled dataset of instances \mathcal{S} . That is, they return an hypothesis \hat{h} such that:

$$\sum_{i=1}^m f(\hat{h}, z_i) = \min_{h \in \mathcal{H}} \sum_{i=1}^m \ell(h, z_i). \quad (2.2)$$

This is justified by the fact that for many classes of hypothesis \mathcal{H} and loss functions ℓ , we can guarantee that $\sum_{i=1}^m \ell(h, z_i)$ converges to $\mathbb{E}_{z \sim \mathcal{D}}[f(h, z)]$ uniformly over the class \mathcal{H} as $m \rightarrow \infty$. This implies that the empirical minimizer \hat{h} must converge to a population minimizer h^* in the limit.

We briefly review a few examples of common statistical learning tasks that we will need to solve in this thesis, and then introduce the common PAC learning framework, used in this thesis to provide guarantees and analyze the number of samples required for obtaining good hypothesis.

Classification

In classification tasks, the instance space $\mathcal{Z} = \mathcal{X} \times \mathcal{Y}$, where \mathcal{X} is the space of observed input features and \mathcal{Y} is the space of output class, \mathcal{H} is a set of classifiers $h : \mathcal{X} \rightarrow \mathcal{Y}$ and the classification loss function $\ell(h, (x, y)) = I(h(x) \neq y)$, for I the indicator function (i.e. the loss is 0 if h predicts the target class y of input x and the loss is 1 otherwise). For example for detecting spam in emails, \mathcal{X} may correspond to features of the content of the email, such as a binary vector indicating the presence of words or not in the email, and the output $\hat{Y} = \{-1, 1\}$ indicates whether the email is spam or not. This is an example of a binary classification problem where the output is one of 2 class. In general, multi class classification problems can be considered with more than 2 possible outputs. This will occur commonly in this thesis, e.g. when we will learn predictors that predicts an action among a discrete set of many potential actions.

Many algorithms have been developed for learning classifiers such as support vector machines (SVM) (Cortes and Vapnik, 1995), decision trees (Breiman et al., 1984), neural networks and nearest neighbor among others (Hastie et al., 2001). In this thesis we will make use of SVMs as they are a class of classifiers that can be optimized efficiently and exactly via convex optimization. In its simplest form in the binary classification setting ($\mathcal{Y} = \{-1, 1\}$), a SVM optimizes a linear classifier¹ to maximize the classification margin.

¹ $\mathcal{H} = \mathbb{R}^d$ for d the number of input features. For $w \in \mathbb{R}^d$, $h_w(x)$ is 1 if $w^\top x \geq 0$, -1 otherwise

This is equivalent to minimizing the following regularized hinge loss:

$$\arg \min_w \left[\frac{1}{m} \sum_{i=1}^m \max(0, 1 - y_i w^\top x_i) + \frac{\lambda}{2} \|w\|_2^2 \right], \quad (2.3)$$

where λ is a regularization constant. SVM can also be applied in the multiclass setting (by training many weight vectors, one for each class), or train non-linear classifiers using kernels (Cortes and Vapnik, 1995), and still be optimized exactly via convex optimization.

Regression

In regression, the target output is a continuous value (e.g. predicting the future price of a stock) so that $\mathcal{Y} \subseteq \mathbb{R}$ and the loss function is usually defined as the squared loss $f(h, (x, y)) = (h(x) - y)^2$. Linear regression is a well known example of a regression problem where we seek to learn the best linear regressor². In this thesis, we will often make use of regression techniques, e.g. for predicting continuous actions (like a steering angle in a driving task), or to predict the cost of different actions. In particular, we will often make use of a regularized version of linear regression in this thesis where an extra regularization is used on weight vector w , called Ridge Regression. The ridge regression objective solves:

$$\arg \min_w \frac{1}{m} \sum_{i=1}^m (w^\top x_i - y_i)^2 + \frac{\lambda}{2} \|w\|_2^2, \quad (2.4)$$

where λ is a regularization constant. This can be solved in closed form and the optimal solution is $w = (X^\top X + m\lambda I_d)^{-1} X^\top Y$, where X is a $m \times d$ matrix where the i^{th} row corresponds to input x_i , Y is a $m \times 1$ column vector where the i^{th} element is output y_i and I_d is the $d \times d$ identity matrix. Regression trees (Breiman et al., 1984), neural networks, nearest neighbor and kernel methods can also be used for regression (Hastie et al., 2001).

Density Estimation

In density estimation, we seek to learn a probability model that can measure the probability or density of some event (e.g. the probability density function (pdf) of the unknown distribution \mathcal{D} itself, or some conditional pdf of some output variable \mathcal{Y} given the input variables \mathcal{X}). The latter is common when dealing with classification tasks where we not only want to predict a class, but instead assign a probability that the input belongs to each class, allowing to reason about uncertainty of the predictions. In this case, a common choice for the loss is the negative log likelihood of the instance z (or conditional

² $\mathcal{H} = \mathbb{R}^d$ for d the number of input features. For $w \in \mathbb{R}^d$, $h_w(x) = w^\top x$

likelihood of y given x) under the density model h (i.e. $f(h, z) = -\log(h(z))$). This leads to maximizing the likelihood of the data, as in common maximum likelihood methods.

A commonly used method for conditional density estimation is logistic regression (Hastie et al., 2001). Given the input x , logistic regression predicts a distribution over outputs y using an exponential family model of the form:

$$P(y|x) \propto \exp(w_y^\top x) \quad (2.5)$$

where $\{w_y\}_{y \in \mathcal{Y}}$ are the weight parameters to optimize. Optimization of these parameters to minimize the logistic loss (negative log likelihood) leads to a convex optimization problem that can be solved efficiently, e.g. using gradient descent methods.

We will use such methods in the context of predicting a distribution over possible objects present at a particular location in a scene, in computer vision/perception applications.

PAC Learning

Probably Approximately Correct (PAC) Learning (Valiant, 1984, Kearns et al., 1994) is a learning framework that has been introduced to analyze learning algorithms and their statistical efficiency – how many samples (data points) are needed to obtain, with high probability, a near-optimal hypothesis h within the class \mathcal{H} .

For any desired near-optimality threshold $\epsilon > 0$ and small probability of failure $\delta > 0$, a PAC learning algorithm guarantees that for any distribution \mathcal{D} , after a sufficient number of samples m , it will find with high probability $1 - \delta$ an hypothesis \hat{h} that achieves expected loss (under the unknown distribution \mathcal{D}) within ϵ of optimal, i.e.:

$$\mathbb{E}_{z \sim \mathcal{D}} [\ell(\hat{h}, z)] \leq \min_{h \in \mathcal{H}} \mathbb{E}_{z \sim \mathcal{D}} [\ell(h, z)] + \epsilon$$

The number of samples m required to guarantee this with high probability $1 - \delta$ will typically scale as a function of $1/\delta$, $1/\epsilon$, and the complexity of the class of hypothesis \mathcal{H} (e.g. the VC dimension if \mathcal{H} is a class of binary classifiers). In general, m is typically $O(\frac{\mathcal{C}(\mathcal{H}) + \log(1/\delta)}{\epsilon^2})$, for $\mathcal{C}(\mathcal{H})$ a measure of the complexity of the class \mathcal{H} . In certain ideal cases, e.g. in realizable scenarios, faster convergence rate can be obtained and m may only need to be $O(\frac{\mathcal{C}(\mathcal{H}) + \log(1/\delta)}{\epsilon})$.

Under the common statistical assumption that both training and test examples are drawn i.i.d. from the distribution \mathcal{D} , then such PAC learning algorithms guarantee that after a sufficient amount of data, with high probability, the performance of the learned predictor on test examples must be near-optimal (in expectation). In particular, if predictors with low error/loss could be found during training, then this must imply the learned predictor has low loss/error on the new test instances (in expectation). Note also that these guarantees are agnostic – i.e. they hold without assuming the data is

generated according to any particular hypothesis in the class. Of course, low test error is only achieved if a low training error hypothesis exists on the training data.

In this thesis, we will also seek to analyze our learning algorithms and provide guarantees that look similar to these PAC guarantees. In particular, we will provide similar agnostic guarantees that hold with high probability, and relate test performance at the sequential prediction task, to the performance of the best predictor/hypothesis in the class on the training distribution of examples. If low loss/error predictors can be found during training, this will imply good test performance of the learned predictor at the sequential prediction task.

Online Learning with Streaming Data

Online learning algorithms are a key component of our main approach to learn good predictors for sequential prediction tasks. In particular, they will be used for updating the predictor we learn over many iterations of training, as more data is being collected. We review here some important background material related to online learning, and present a few common online learning algorithms used in this thesis.

Online learning has been developed to deal with learning tasks where we must make predictions over time as we are learning from a stream of data (Vovk, 1992, Littlestone and Warmuth, 1994, Cesa-Bianchi and Lugosi, 2006). An example of such task may be weather forecast, where we must predict tomorrow's weather each day, and then get to observe the weather the next day as additional training data to update our predictor. Another example is stock market prediction, where we may want to predict how the price of a stock will change each day, and then get to observe the change in price at the end of the day as additional data to update our predictor.

Formally, the online algorithm is presented with a sequence of training instances z_1, z_2, \dots, z_N , one at a time. At each round n , before observing the instance z_n , the learner chooses a predictor $h_n \in \mathcal{H}$, to make its next prediction, and incurs loss $\ell(h_n, z_n)$ on the instance z_n . Then it observes z_n and can choose a new predictor h_{n+1} for the next round.

The goal in online learning is to minimize the regret with respect to the best fixed hypothesis the learner could have chosen in hindsight (i.e. knowing all the training instances in advance). Formally, the average regret \bar{R}_N after N rounds of the online learning algorithm is defined as:

$$\bar{R}_N = \frac{1}{N} \sum_{n=1}^N \ell(h_n, z_n) - \min_{h \in \mathcal{H}} \frac{1}{N} \sum_{n=1}^N \ell(h, z_n) \quad (2.6)$$

Small average regret intuitively implies that, on average, before seeing the training example at each round, the learner made as good predictions, as if it had known all the

training instances in advance and had picked the best predictor to predict on all this data.

A no-regret algorithm is an algorithm that guarantees that in the limit, as $N \rightarrow \infty$, \bar{R}_N goes to 0 (or is negative), for any sequence of training instances. In other words, a no-regret algorithm indicates that in the limit, the average loss incurred by the learner, when making its predictions before seeing each training example, is no worse than the average loss of the best predictor it could have picked, knowing all the training instances in advance.

A concrete scenario where online learning has been applied is for managing investment portfolios ([Argawal et al., 2006](#)). In this case, we might consider k possible financial instruments (cash, bonds, stocks, etc.) to invest in and define \mathcal{H} to be the set of all portfolio allocations to these k instruments (i.e. the set of all distributions on the k instruments). Each day, we consider allocating our money to different instruments according to some portfolio allocation in \mathcal{H} . We then observe the return of each instruments for the day (the training instance z_n), which we use to update our portfolio allocation for the next day. Using a no-regret algorithm to update the portfolio allocation after each day would guarantee that in the limit, the average return of the portfolio is no worse than the average return of the best constantly-rebalanced³ fixed portfolio allocation in \mathcal{H} over that time period. In other words, the average return of the learner will be as good as if we had known how the stock market is going to evolve in the future, and had chosen the best (constantly rebalanced) allocation for this future.

Unlike statistical learning techniques that assumes data is drawn i.i.d. from some unknown distribution, online learning is a more game-theoretic⁴ learning framework that makes no assumption about how the instances are chosen. In particular, as no-regret algorithms work for any sequence of instances, the no-regret guarantees hold even if the instances are chosen adversarially. The trade-off however, is that no-regret is only a statement about relative performance, i.e. relative to the best hypothesis in the class on this sequence of instances. Thus no-regret does not necessarily imply good absolute performance, e.g. when no hypothesis performs well on the sequence of instances. However, under the additional assumption that good hypothesis exists for the sequence, then no-regret implies good performance, in absolute terms. These strong

³A fixed portfolio allocation in this scenario, for instance 50% in AAPL stock and 50% in MSFT stock, implies that after each day, after the price of these assets change, we would buy/sell stocks of each so that the overall value of the portfolio is rebalanced to 50% in AAPL stock and 50% in MSFT. For instance if AAPL increases more in value than MSFT, at the end of the day our money may now be allocated as 52% AAPL and 48% MSFT; to bring back to 50-50, we would sell AAPL stock and buy more MSFT stock with that money. This is what is called a constantly rebalanced portfolio ([Cover and Thomas, 1991](#)). Such constantly rebalanced portfolio are powerful investment strategies, as they implicitly make you sell high and buy low.

⁴Online learning can be thought as a two-player repeated game played between a learner, choosing hypothesis in some class \mathcal{H} , and an adversary picking training instances.

no-regret properties, that hold even for non-i.i.d. data, will be key to provide good guarantees in our sequence prediction settings, where i.i.d assumptions do not hold.

Many no-regret algorithms have been developed in the literature for different scenarios. We review the most common ones and their guarantees that will be leveraged in this work.

Weighted Majority and Hedge

When the number of hypothesis is finite (i.e. \mathcal{H} is finite) randomized no-regret algorithms have been proposed such as Weighted Majority (Littlestone and Warmuth, 1994) and Hedge (Freund and Schapire, 1997). These algorithms essentially assign to each hypothesis a probability that decreases exponentially in their total loss so far and pick a hypothesis randomly according to this distribution at each iteration. That is, at round n , the probability distribution P_n over hypothesis to choose h_n is defined as:

$$P_n(h) \propto \exp\left(-\eta \sum_{i=1}^{n-1} \ell(h, z_i)\right),$$

for some learning rate parameter η . By choosing η to be $\Theta(1/\sqrt{N})$, these methods are no-regret at rate $O(\frac{1}{\sqrt{N}})$ (Littlestone and Warmuth, 1994, Freund and Schapire, 1997). They can also be no-regret at faster rates of $O(\log(N)/N)$ if some hypothesis in the set \mathcal{H} have small loss and the loss of the best hypothesis (after N rounds) is used to define η appropriately. A doubling trick to adapt the parameter η can be used as well to achieve the same optimal rate, up to a small constant factor, without knowing the loss of the best hypothesis in advance (Cesa-Bianchi et al., 1997).

As these methods are randomized algorithms, they guarantee that the expected regret, under the chosen distributions P_1, P_2, \dots, P_N , goes to 0 as $N \rightarrow \infty$. It can also be shown that with high probability, the regret on the sampled hypothesis h_1, h_2, \dots, h_N converges at the same rate with high probability.⁵

Subgradient Descent and Follow-the-(Regularized)-Leader

When the set of hypothesis \mathcal{H} is a convex set and the loss $\ell(\cdot, z)$ is convex in the hypothesis for all $z \in \mathcal{Z}$, then other online learning algorithms such as Projected Subgradient Descent (Zinkevich, 2003) and Follow-the-(Regularized)-Leader are no-regret (Kakade and Shalev-Shwartz, 2008). Projected Subgradient Descent simply updates the hypothesis in the direction opposite to a subgradient of the loss at the current iteration:

$$h_{n+1} = h_n - \alpha_n \nabla_h \ell_n(h_n)$$

⁵Under the assumption that the adversary cannot choose z_n based on knowing the result of sampling, i.e. h_n , but can potentially choose z_n based on knowledge of P_n .

Choosing the step-size α_n as $\Theta(\frac{1}{\sqrt{n}})$ guarantees that it is no-regret at rate $O(\frac{1}{\sqrt{N}})$ (Zinkevich, 2003). Additionally, when the loss is strongly convex, choosing the step-size α_n as $O(\frac{1}{n})$ guarantees that it is no-regret at rate $O(\frac{\log(N)}{N})$ (Hazan et al., 2006).

Follow-the-Leader is another simple approach that simply picks h_n to be the hypothesis with smallest loss so far in the first $n - 1$ iterations:

$$h_n = \arg \min_{h \in \mathcal{H}} \sum_{i=1}^{n-1} \ell(h, z_i)$$

It is no-regret at rate $O(\frac{\log(N)}{N})$ when the loss is strongly convex. Follow-the-Regularized-Leader is a slight variation which is also no-regret for convex functions. In this case, h_n is chosen to be the best hypothesis in the first $n - 1$ iterations subject to an additional strongly convex regularizer r , i.e.:

$$h_n = \arg \min_{h \in \mathcal{H}} \sum_{i=1}^{n-1} \ell(h, z_i) + \lambda_n r(h).$$

Choosing the regularization constant λ_n as $\Theta(\frac{1}{\sqrt{n}})$ makes this approach no-regret at rate $O(\frac{1}{\sqrt{N}})$ (Kakade and Shalev-Shwartz, 2008).

Other Online Learning Methods

Many other online learning algorithms exist. Another important class of methods are proximal methods, that generalizes gradient descent, by updating the hypothesis to a nearby hypothesis that minimizes the current loss (where the notion of “nearness” can be chosen differently depending on the task or class of hypothesis) (Do et al., 2009, Xiao, 2009, Duchi et al., 2010b, McMahan, 2011). Also improved adaptive gradient techniques provide better no-regret guarantees, that are dependent on the properties of the observed sequence (Duchi et al., 2010a, McMahan and Streeter, 2010). Other randomized online learning algorithms also exists, such as Follow-the-Perturbed-Leader (Kalai and Vempala, 2005) that can be more computationally efficient when the set of hypothesis has particular structures. Finally, bandit learning techniques extend online learning methods to partial information settings, where only the loss of the chosen hypothesis is observed, and the loss of other hypothesis is unknown (Auer et al., 2002a,b, Langford and Zang, 2007, Li et al., 2010, Beygelzimer et al., 2011, Dudik et al., 2011a).

2.2 Reductions between Learning Tasks

Another important part of our work in this thesis is the idea of reductions between learning tasks.

Reductions have been introduced in computer science as a general technique for problem solving. The idea is that, if you have a hard problem to solve A, and can

transform that problem into another easier problem B that you know how to solve, then you can solve the hard problem A by solving the transformed problem B instead.

This idea has been used in machine learning to tackle harder learning tasks via existing learning algorithms that can only tackle simple tasks (Beygelzimer et al., 2005, Langford and Beygelzimer, 2005, Balcan et al., 2008, Beygelzimer et al., 2009, Daumé III et al., 2009). For instance, a well known reduction is the all-pairs reduction of multiclass classification to binary classification. This reduction constructs a multiclass classifier by training a binary classifier for every pair of labels (Hastie and Tibshirani, 1998). The approach proceeds by training each binary classifier on the subset of the training set that are labeled as one of the two labels it is trying to distinguish. Then when given a test input, all binary classifiers are evaluated and each output count as a vote for the predicted label. The label with most votes is the predicted label for the multiclass classifier constructed from these binary classifiers.

Reductions can also be used as a way to provide theoretical guarantees on the quality of the solution found as a function of the quality of the solutions for the subproblems. Therefore, if high-quality solutions can be found for the subproblems, we can guarantee that we obtain a high-quality solution for the original problem. For instance, in the previous reduction, if the binary classifiers have error rate ϵ , it can be shown that the multiclass classifier has error rate of at most $(k - 1)\epsilon$ at the multiclass classification task, for k the number of labels.

In this thesis, the algorithms we present can be understood as reductions of sequential prediction tasks, to simpler learning tasks that can be solved using standard supervised learning algorithms, or online learning algorithms. By doing so, we will be able to guarantee good performance at the original sequential prediction task, whenever good performance can be achieved at the simpler supervised/online learning tasks.

We will also make use of a number of existing learning reductions to tackle general cost-sensitive classification tasks that arise in our work. We present below a few reductions that exist to tackle such tasks.

Reductions of Cost-Sensitive Classification

In cost-sensitive classification, instead of incurring a 0-1 loss, a different loss is associated to predicting each class, at every input x . In this case, the instances $z \in \mathcal{Z}$, can be thought as tuples (x, c) , where c is a cost-vector associating a cost to each output class $y \in \mathcal{Y}$. In this case, the goal is to find the predictor $h^* \in \mathcal{H}$ with minimum expected cost under the unknown distribution \mathcal{D} :

$$h^* = \arg \min_{h \in \mathcal{H}} \mathbb{E}_{(x,c) \sim \mathcal{D}} [c(h(x))].$$

Minimizing this cost-sensitive classification loss directly is often computationally in-

tractable. Instead, to tackle such problems, different reductions have been developed, that allows us to transform this task into standard regression or classification tasks, that leads to convex optimization tasks that can be solved efficiently. We briefly mention two from [Beygelzimer et al. \(2005\)](#) that we use in our work below:

Reduction to Regression A first approach is to transform the cost-sensitive classification problem into a regression problem of predicting the costs of each class $y \in \mathcal{Y}$, given the input features x . Afterwards, the cost-sensitive classifier chooses the class with lowest predicted cost according to the learned regressor.

To train the regressor, each cost-sensitive example (x, c) is converted into $|\mathcal{Y}|$ regression examples. For example, if we use least-squares linear regression, the squared loss for a particular example (x, c) and regressor w would be:

$$\ell(w) = \sum_{y \in \mathcal{Y}} (w^\top f(x, y) - c(y))^2.$$

where $f(x, y)$ are joint features of the input-output pair (x, y) . This leads to a convex optimization problem for linear predictors (or in general using any kernel).

As mentioned, for prediction, the classifier h simply predicts the minimum cost class. For example, in this case where we trained a linear regressor, it would predict:

$$h(x) = \arg \min_{y \in \mathcal{Y}} w^\top f(x, y)$$

It has been shown, that by using this reduction, small regret at the regression task implies that the resulting classifier h has small regret at the cost-sensitive classification task. Here, the regret is defined in terms of the extra additional cost, or loss, incurred by the learned predictor, compared to the cost/loss of the bayes-optimal predictor (the optimal predictor among all possible functions). In particular, if we learn a regressor with regression regret R , the cost-sensitive classification regret of the resulting classifier h is bounded by $\sqrt{2|\mathcal{Y}|R}$ ([Tu and Lin, 2010](#), [Mineiro, 2010](#)).

Reduction to Ranking Another useful reduction transforms the cost-sensitive classification problem into a "ranking" problem that penalizes ranking a class y above another class y' with higher cost, where the penalty is proportional to the difference in cost of the misranked pair. This is similar to the all-pairs reduction of multi class classification to binary classification, where here, for every pair of class (y, y') we learn to predict the class with lowest cost given these two. Here these binary classification examples, are weighted by the difference in cost of the 2 class (y, y') . This reduction is called the weighted all pairs (WAP) reduction ([Beygelzimer et al., 2005](#)).

Effectively, each cost-sensitive example (x, c) is converted into $|\mathcal{Y}|(|\mathcal{Y}|-1)/2$ weighted binary classification examples (one for every distinct pair of class (y, y')). For example,

if we are learning a linear classifier w , the weighted 0-1 loss for a particular example (x, c) and classifier w would be:

$$\ell(w) = \sum_{y \in \mathcal{Y}} \sum_{y' > y} |c(y) - c(y')| I(\text{sign}(w^\top f(x, y, y')) \neq \text{sign}(c(y') - c(y)))$$

where $f(x, y, y')$ are features of the input x and pair of class y, y' . Here if $w^\top f(x, y, y') > 0$, this indicates the classifier predicts the class y has lower cost than y' , and counts as a vote for class y .

To minimize this weighted 0-1 loss efficiently, we can for instance train a SVM by minimizing a weighted hinge loss (that upper bounds this weighted 0-1 loss). For example, if we train a linear SVM, we obtain a weighted hinge loss of the form:

$$|c(y) - c(y')| \max(0, 1 - w^\top f(x, y, y') \text{sign}(c(y') - c(y))).$$

This reduction proves advantageous whenever it is easier to predict pairwise rankings rather than the actual cost.

In [Beygelzimer et al. \(2005\)](#), they show that if we achieve small average weighted binary classification error ϵ on this classification task, then this implies that the cost-sensitive classification loss of the resulting cost-sensitive classifier (by predicting the class with most votes) is at most 2ϵ .

Other Reductions: Some other reductions of cost-sensitive classification exists with improved guarantees, e.g. Sensitive Error Correcting Output Codes (SECOC) ([Langford and Beygelzimer, 2005](#)) and Error Correcting Tournaments (ECT) ([Beygelzimer et al., 2009](#)). These reductions can bound the regret at the cost-sensitive classification task, as a function of the regret at a (weighted) binary classification task.

Error Reduction vs. Regret Reduction

We may divide learning reductions into two types: 1) error reductions, that allows us to bound error or loss at the original task, as a function of the error or loss at the simpler learning task (e.g. as in the WAP reduction above), and 2) regret reductions, that allows us to bound the regret at the original task, as a function of the regret on the simpler learning task (e.g. as in the reduction to regression above). As regret corresponds to the error/loss minus the minimum possible error, regret reductions are typically more desirable, e.g. they provide interesting guarantees even when the minimum possible error is non-zero, such as when there is noise in the training data. Regret reductions provide a bound that directly tells us how far from optimal performance the learned predictor is achieving, while with error reductions, we obtain a bound on the loss/error, but it is unknown how far this is from optimal.

In this thesis, we will obtain reductions of both types, depending on the sequential prediction setting and the training loss being minimized.

Advantages of Learning Reductions

There are several advantages to develop learning approaches to tackle complex learning tasks through reductions. We briefly mention a few, also mentioned in [Beygelzimer et al. \(2005\)](#):

1. Reductions are modular. They allow to reuse existing algorithms to tackle more complex problems and allow the user to plugin their favorite learning algorithms to solve the simpler learning tasks, while still providing guarantees on overall performance.
2. Reductions allow to transfer new advances. If someone invents a new learning algorithm, e.g. that is more computationally or statistically efficient, or a new class of models/predictors, for solving the simpler learning tasks, these new advances can be used immediately to address the original complex learning task and provide improved performance.
3. Reductions allow to make relative performance guarantees without any assumption. Reductions provide relative performance guarantees of the form “if we have a good predictor on some distribution \mathcal{D} at the simpler task, this implies good performance at the original task”. These statements hold, without any assumption about the data generating process, such as i.i.d. assumptions made in PAC learning. In other words, if someone gives you such a predictor for the simpler task, you would always be able to construct a predictor for the harder task, where the relative performance guarantee holds.

These benefits motivate our development of a reduction approach to learning in sequential prediction problems.

2.3 Formal Models of Sequential and Decision Processes

In this section we introduce commonly used models of sequential decision problems/control in robotics and artificial intelligence. These models can be used to model many of the sequential prediction tasks we consider in this thesis. Given such model, one can compute the optimal policy/predictor that minimizes long-term cost over the sequence of decisions/predictions. However, in the context of our learning tasks, these model will typically be unknown. In chapter 8, we will consider applying our learning techniques

to learn such models in the context of control tasks, that will allow us to plan optimal sequence of actions.

We first introduce models where perfect information about the world is known and then models taking into account uncertainty related to partial observability of the world.

Markov Decision Processes

One of the simplest class of dynamic models of robotic systems is the Markov Decision Process (MDP) (Puterman, 1994). A MDP is defined by a tuple $(\mathcal{S}, \mathcal{A}, T, C)$ where:

- \mathcal{S} is the set of all possible states of the system. A state is a sufficient statistic of everything that occurred in the past to predict future states (configurations), i.e. knowing previous states and actions does not give us more information about future states if the current state is known. In the context of robotics system, the state would encode the configuration of the robot, its velocity, etc.
- \mathcal{A} is the set of actions that can perform at any step.
- P is the transition function, where $P_{sa}(\cdot)$ specifies the probability distribution over the next state after executing action a in state s . This represents our uncertainty about what the next state of the system is going to be. The transition function uses the *Markov* assumption, i.e. that the current state is a sufficient statistic to predict the next state.
- C is the cost function, where $C(s, a)$ specifies the immediate cost of doing action a in state s . The cost encodes how desirable is a particular action and/or state with respect to the task we want to perform.

MDPs can represent a wide range of systems. For instance a simple model of a car in a static environment might consider the state to be the car's current position, orientation and velocity; the action to be the steering and acceleration; and the transition function could be specified via a simple physical model of a point particle. If the task consists in reaching a particular goal location as fast as possible while avoiding hitting obstacles, then the cost function might be designed to be such that every action in every state has a small cost, except in the goal state where no cost is incurred, and actions that causes collisions with obstacles have large cost.

The goal in a MDP is to find a policy $\pi : \mathcal{S} \rightarrow \Delta\mathcal{A}$, mapping state to action (or distribution over actions), that minimizes the expected sum of costs over the task horizon. In this thesis, we will usually consider cases where the task horizon is finite, except in chapter 8 where we will consider infinite horizons with a discount factor $\gamma \in [0, 1)$. The discount factor discounts costs obtained t steps in the future by a factor γ^t .

Given a policy π , the expected t -step cost of executing policy π for t -step starting in state s , denoted $V_t^\pi(s)$, is given by the Bellman equation (Bellman, 1957):

$$V_t^\pi(s) = \mathbb{E}_{a \sim \pi(s)}[Q_t^\pi(s, a)], \quad (2.7)$$

where

$$Q_t^\pi(s, a) = C(s, a) + \gamma \mathbb{E}_{s' \sim P_{sa}}[V_{t-1}^\pi(s')], \quad (2.8)$$

$\pi(s)$ denotes the distribution over actions chosen by π in state s , and $\gamma = 1$ for the finite horizon case. V_t^π is called the t -step value function of π , while Q_t^π is called the t -step action-value function (or simply Q function) of π . Q_t^π represents the expected total cost of starting with some action and then executing the policy π for $t - 1$ steps. For $t = 0$, we define $V_t^\pi(s) = Q_t^\pi(s, a) = 0$ for all s, a . In the infinite horizon, the expected total cost (over the infinite horizon) of a policy π satisfies:

$$V^\pi(s) = \mathbb{E}_{a \sim \pi(s)}[C(s, a) + \gamma \mathbb{E}_{s' \sim P_{sa}}[V^\pi(s')]] \quad (2.9)$$

Additionally, Bellman (1957) showed that the value function V_t^* of an optimal policy π^* satisfies:

$$V_t^*(s) = \min_{a \in \mathcal{A}}[C(s, a) + \gamma \mathbb{E}_{s' \sim P_{sa}}[V_{t-1}^*(s')]] \quad (2.10)$$

In the infinite horizon case, this implies there exists a stationary (i.e. does not depend on the current time step) and deterministic optimal policy π^* that can be defined as:

$$\pi^*(s) = \arg \min_{a \in \mathcal{A}}[Q^*(s, a)], \quad (2.11)$$

for

$$\begin{aligned} Q^*(s, a) &= C(s, a) + \gamma \mathbb{E}_{s' \sim P_{sa}}[V^*(s')] \\ V^*(s) &= \min_{a \in \mathcal{A}}[Q^*(s, a)] \end{aligned} \quad (2.12)$$

In the finite horizon case, there also exists a deterministic optimal policy, however it is generally non-stationary (i.e. it is a function of both state and time). The optimal policy π_t^* to execute when there are t steps to go can be defined as:

$$\pi_t^*(s) = \arg \min_{a \in \mathcal{A}}[Q_t^*(s, a)], \quad (2.13)$$

for

$$\begin{aligned} Q_t^*(s, a) &= C(s, a) + \gamma \mathbb{E}_{s' \sim P_{sa}}[V_{t-1}^*(s')] \\ V_t^*(s) &= \min_{a \in \mathcal{A}}[Q_t^*(s, a)] \end{aligned} \quad (2.14)$$

When there are finitely many states and actions, MDPs can be solved efficiently via dynamic programming, using the value iteration algorithm (see Algorithm 2.3.1) (Bellman, 1957). This algorithm computes V_t^* for $t = 1, 2, \dots, T$, using the previously computed V_{t-1}^* .


```

Initialize  $V_0^*(s) \leftarrow 0, \forall s$ 
for  $t = 1$  to  $T$  do
  Initialize  $V_t^*(s) \leftarrow \infty, \forall s$ 
  for  $s$  in  $\mathcal{S}$  do
    for  $a$  in  $\mathcal{A}$  do
       $Q_t^*(s, a) \leftarrow C(s, a) + \gamma \mathbb{E}_{s' \sim T_{sa}}[V_{t-1}^*(s')]$ .
       $V_t^*(s) \leftarrow \min(V_t^*(s), Q_t^*(s, a))$ 
    end for
  end for
end for

```

Algorithm 2.3.1: Value Iteration algorithm for finite MDPs.

```

Initialize  $M_1 \leftarrow Q, K_1 \leftarrow 0$ .
for  $t = 2$  to  $T$  do
   $K_t \leftarrow \gamma(R + \gamma B^\top M_{t-1} B)^{-1} B^\top M_{t-1} A$ 
   $M_t \leftarrow Q + \gamma A^\top M_{t-1} (A - B K_t)$ 
end for

```

Algorithm 2.3.2: Value Iteration algorithm for LQRs.

The computational complexity of this algorithm is $O(T|\mathcal{S}|^2|\mathcal{A}|)$. When the horizon is infinite, an ϵ -optimal policy⁶ $\hat{\pi}$, where $\hat{\pi}(s) = \arg \min_{a \in \mathcal{A}} Q_T^*(s, a)$, can be obtained by choosing T to be $O(\frac{1}{1-\gamma} \log(\frac{\|C\|_\infty}{\epsilon(1-\gamma)}))$ (Puterman, 1994).

Linear Quadratic Regulators

When \mathcal{S} and \mathcal{A} are infinite, an important special cases of MDP which can be solved efficiently are Linear Quadratic Regulators (LQR) (Kalman, 1960a). In LQR, the transitions are linear and gaussian, i.e. for any state x_t and action u_t at time t , $x_{t+1} = Ax_t + Bu_t + \xi_t$ (where $\xi_t \sim N(0, \Sigma)$ is optional zero-mean gaussian noise). Additionally the costs are quadratic $C(x, u) = x^\top Qx + u^\top Ru$, for Q a positive semi-definite matrix and R a positive definite matrix. For LQR, for any time step to go t , the optimal value function V_t^* is a quadratic function of the state x and the optimal policy π_t^* is linear function of x :

$$\begin{aligned} V_t^*(x) &= x^\top M_t x + c_t, \\ \pi_t^*(x) &= -K_t x, \end{aligned} \tag{2.15}$$

where the matrices M_t and K_t can be computed efficiently via a similar value iteration algorithm (see Algorithm 2.3.2). $c_t = \gamma(\text{tr}(M_{t-1}\Sigma) + c_{t-1})$ is simply a constant which depends on the noise Σ , and is 0 when dynamics are deterministic. Additionally the optimal policy does not depend on Σ .

The computational complexity of this algorithm is $O(T(|x|^3 + |u|^3))$, where $|x|$ denotes the dimensionality of the state space and $|u|$ the dimensionality of the action space. For

⁶If the initial state distribution is μ , then a policy π is ϵ -optimal if $\mathbb{E}_{s \sim \mu}[V^\pi(s) - V^*(s)] \leq \epsilon$.

finite horizon T , this algorithm can also be adapted to non-stationary linear dynamics and cost function (i.e. $x_{t+1} = A_t x_t + B_t u_t + \xi_t$ and $C(x_t, u_t, t) = x_t^\top Q_t x_t + u_t^\top R_t u_t$) by simply replacing A , B , Q and R by A_{T-t+1} , B_{T-t+1} , Q_{T-t+1} and R_{T-t+1} in the inner loop of the previous algorithm, and initializing $M_1 = Q_T$. This can be used to solve approximately non-linear systems with non-quadratic cost functions using iterative linearization/“quadraticization” techniques such as iterated LQR (iLQR) (Li and Todorov, 2004) and Differential Dynamic Programming (DDP) (Jacobson and Mayne, 1970).

Partially Observable Markov Decision Processes

In practice, robots rarely know exactly what the current state s is. They only observe the world through noisy sensors that give them partial information about the current state s . MDPs can be extended to handle this partial observability, and obtain policies that reason about state uncertainty to minimize long-term costs.

The Partially Observable Markov Decision Process (POMDP) provides such an extension (Sondik, 1971). It adds 2 additional components to the MDP model:

- \mathcal{Z} is the set of all possible observations that can be made by the system.
- O is the observation function, where $O_{as'}(\cdot)$ specifies the probability distribution over the observation we obtain after executing action a and arriving in state s' .

In a POMDP, the uncertainty about the current state is represented as a probability distribution over states, called the belief state, that captures the likelihood that we are in each state. This belief state can be updated using simple applications of bayes’ rule, each time a new action a is performed and we obtain a new observation $z \in \mathcal{Z}$ (Sondik, 1971).

A policy in a POMDP maps belief states to actions, and the optimal policy can be found by planning in a belief MDP (where the state is the belief state, and transitions specify possible next belief after observing different observations), e.g. using similar techniques presented above or simple receding horizon control approaches (Ross, 2008). More sophisticated planning algorithms for POMDPs exist that leverage the particular structure of the value function over this belief space (Sondik, 1971, Pineau et al., 2003, Spaan and Vlassis, 2005, Smith and Simmons, 2005). However, in all cases solving POMDPs is very computationally expensive, and often does not scale to real world applications (unless they are significantly abstracted or simplified).

Linear Quadratic Gaussian

An important special case of POMDP that can be solved efficiently is in the context of continuous control problems such as LQR presented above. In this case, the observations

are assumed to be a linear function of the current state x_t and action u_t at time t with additional white gaussian noise, i.e. $y_t = Cx_t + Du_t + N(0, \Sigma')$. In this case the distribution over states is Gaussian, and can be maintained via a Kalman Filter (Kalman, 1960b). The optimal policy simply consists in applying the same LQR controller, as computed above, to the expected state of the Kalman Filter. This is often referred to as Linear Quadratic Gaussian Control (LQG).

Access Models

We describe here different access model to the real system that are commonly used in different algorithms for computing or learning a (near-)optimal policy in a MDP/POMDP. This formalizes our assumptions about how we can interact with the system and collect data. In particular, in this thesis, we will typically assume access only to a reset model, as described below.

Full Probabilistic Model: This is the strongest access model and requires full knowledge of all transition and observation probabilities of the real system. This allows computation of the Bellman equation exactly by summing over all possible next states/observations to evaluate expectations. Planning methods typically assumes this type of access.

Generative Model: This is a weaker access model that allows setting the real system in any particular state and sampling transitions/observations by doing any action in that state. This allows to evaluate the Bellman equation to any degree of accuracy (with high probability) by sampling next states/observations several times from the generative model. This is an access model which is often encountered in software applications or for systems for which we have access to a simulation, but not the full probabilistic model description. The software can be started in any particular state and then any particular action can be taken to obtain a sample transition/observation. Such access models are used by many techniques for efficiently obtaining approximate solutions to MDPs (such as Fitted Value Iteration (Gordon, 1995, Szepesvári, 2005), Sparse Sampling (Kearns et al., 2002)).

Reset Model: This is the next weakest access model where we can only sample state/observation in the real system along trajectories starting in the initial state distribution, by executing different sequences of actions. In this model, we can perform a “reset”, which initializes the real system to a new initial state. Actions can be performed to simulate the system forward in time and obtain sample next state/observation along the current trajectory. Reset models can be used to model the type of access we have with robots performing repeated tasks in the real world starting from some distribution

of initial configurations. We cannot put the robot in any particular state, as in the generative model, but we might be able to reset it to one of its possible initial configuration. For instance, a robotic arm might have a controller that can put back the arm into some default configuration, from which the arm always starts its interactions with surrounding objects. A human might also supervise the robot during the learning phase and be able to reset the robot to a particular initial configuration between trials. Reset models are commonly assumed in many learning algorithms (e.g. in PSDP (Bagnell et al., 2003), CPI (Kakade and Langford, 2002) and policy gradient methods (Williams, 1992, Bagnell and Schneider, 2003, Peters and Schaal, 2008)). This is the type of access model we will assume in this thesis.

Trace Model: This is the weakest access model and corresponds to the reset model without the possibility of reset. This model only allows simulating the system forward in time by performing further actions. This models life as we experience it in our daily lives: we cannot go back to when we were a baby and change our decisions along the way to experiment and see what would happen later on, we must always live with the consequences of our previous actions. Some learning algorithms only assume this type of access model (Strehl et al., 2009, Jaksch et al., 2010), but it typically leads to optimality guarantees that are weaker in some sense.

Chapter 3

Learning Behavior from Demonstrations

We begin our investigation of learning sequential predictions in the particular setting of learning control behavior from demonstrations, often called imitation learning (Schaal, 1999, Argall et al., 2009). Imitation learning is perhaps one of the sequential prediction problem that is the most closely related to well studied statistical learning problems such as supervised classification, but exhibits the fundamental problems and difficulties of learning to perform sequential tasks. Therefore, imitation learning presents itself as a natural starting point for studying the nature of learning in sequential tasks and understanding its fundamental difficulties, as well as building algorithms and methodologies for theoretical analysis that can be used as building blocks in more complex sequential prediction problems studied later on.

3.1 Preliminaries

Imitation learning is concerned with the problem of learning to perform a control task (e.g. navigate safely and efficiently across a terrain from point A to point B) from demonstrations by an expert. These techniques allow programming autonomous behavior in robotic systems easily via demonstrations of the desired behavior, e.g. by human experts. This avoids time-consuming engineering required by traditional control methods that rely on accurate dynamic models of the system and well-engineered cost functions to synthesize controllers that produce the desired behavior. As the tasks performed by robotic systems continuously increase in complexity, it is becoming increasingly harder to provide good models and cost functions. As a result, learning by demonstration techniques are becoming more and more popular and have led to state-of-the-art performance in a number of recent applications, including, e.g. outdoor mobile robot navigation (Silver et al., 2008), legged locomotion (Ratliff et al., 2006), advanced manipulation (Schaal,

1999), and electronic games (Ross and Bagnell, 2010).

In its simplest form, learning to perform a repeated task can sometimes be achieved by simply replaying demonstrated trajectories (or sequence of actions). Unfortunately such approach can be very brittle and fail as soon as initial conditions can vary slightly or some small external disturbances can change the outcome of the action sequence. Additionally, such approach are very task specific and cannot generalize the learned behavior to perform other similar tasks (e.g. drive on a different road or in different traffic conditions).

Thus we will be interested in imitation learning techniques that attempt to generalize the observed behavior and could be applied to perform similar tasks in similar conditions to the observed demonstrations. We briefly give an overview of the two common approach to imitation learning, which we classify as Behavior Cloning and Inverse Optimal Control, following Ratliff (2009).

Behavior Cloning

A first approach to generalize the observed behavior, is to learn a controller or policy that maps input observations to output actions. In this view, imitation learning looks like a typical supervised learning problem. The learner is provided with a set of trajectories demonstrating the desired behavior, that consists in a sequence of input observations encountered by the expert and associated output actions performed by the expert after each of these observations. Behavior cloning methods reduce imitation learning problems to such supervised learning problem, e.g. by learning a classifier or regressor that predicts the action given the input state or observation, from data collected during expert demonstrations (Bain and Sammut, 1995). An example of how this approach would proceed in a driving scenario is depicted in Figure 3.1. Such methods have been used since the early 80's to attempt to learn controllers for robot manipulators in factories (Dufay and Latombe, 1984) and Pomerleau (1989) demonstrated early success of such approach for more complex task such as training a neural network to drive a car on highways from camera input. Such methods are still commonly used to learn controllers for various tasks (Schaal, 1999, Argall et al., 2009, Chernova and Veloso, 2009).

As mentioned in the introduction, one shortcoming of this learning strategy is that the policy learned via supervised learning will generally induce a different distribution of states than the expert when executed to perform the task (due to errors made by the learned policy). This discrepancy between the training and test distributions can lead to quite poor performance at executing the task, even though the learned policy has low error on the training set. This is made more formal in the next section. The focus of this entire thesis is on developing methods that address this major issue.

Another shortcoming of behavior cloning is that the expert is usually optimizing (at

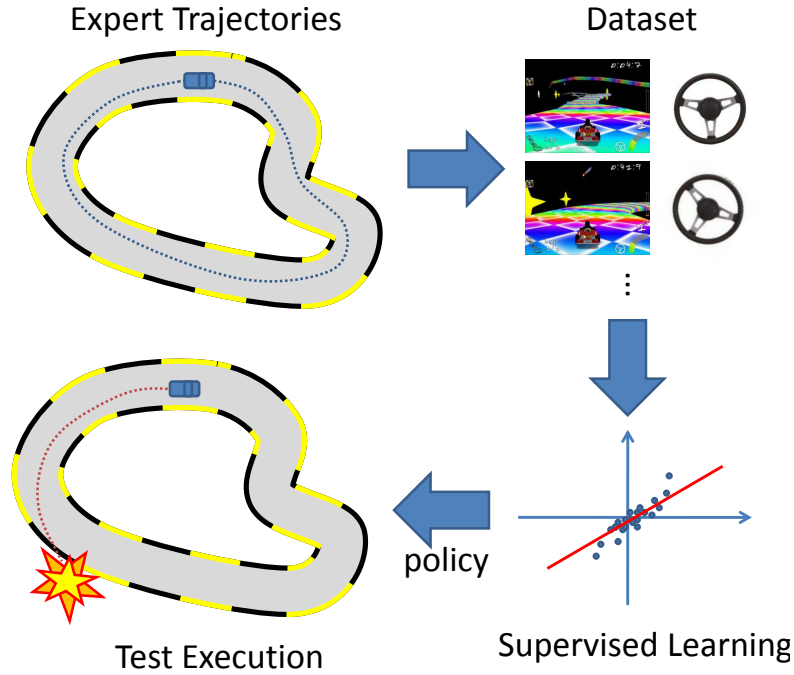


Figure 3.1: Depiction of a typical supervised learning approach to imitation learning in a driving scenario. Initially, the expert demonstrates the desired driving behavior (top left). Input observations (camera image) and desired output actions (steering) are recorded in a dataset (top right) during the demonstration. A supervised learning algorithm is applied to fit a policy (bottom right), e.g. linear regression of the camera image features to steering angle. The learned policy is then used to drive the car autonomously (bottom left).

least approximately) a long-term objective when demonstrating the task, which may be poorly captured in the current state or observation features. Without this long-term reasoning, it is often impossible to achieve high accuracy at mimicking the expert behavior. Hence, behavior cloning can typically work well only for behaviors that are fairly reactive. Learning more proactive behaviors necessitate tremendous engineering effort for carefully designing features that capture the expert’s decision process.

Inverse Optimal Control

Inverse Optimal Control (IOC) methods seek to address this last issue by learning the cost function the expert is optimizing from its demonstrations (Abbeel and Ng, 2004, Ratliff et al., 2006, Ziebart et al., 2008, 2010). These methods typically model the expert as trying to optimize some linear cost function in the features. From the observed expert behavior, and knowledge of the dynamics of the system (or at least access to a planner), these methods can learn the cost function that the expert is optimizing. Predicting the expert behavior can then be achieved by planning with the learned cost function.

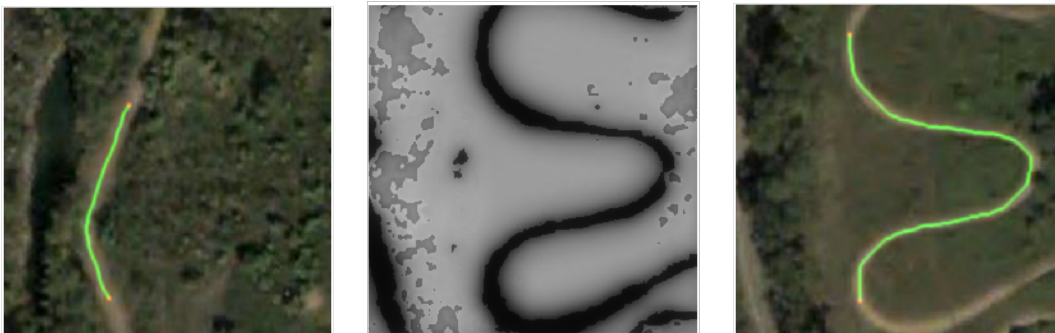


Figure 3.2: Generalization of the expert’s behavior by Inverse Optimal Control methods (images from [Ratliff et al. \(2006\)](#)). The expert demonstrates to follow the road between the start and goal location on an overhead satellite image (left). A cost function is learned from local image features that explains this behavior. The cost function is applied to a new test image (middle) (black = low cost, white = high cost). Planning with the learned cost function predicts to follow the road to the goal location on the test image (right).

Thus the planning procedure models the long-term reasoning of the expert, while the observed features only need to be able to capture immediate cost. This often leads to much better models of behavior than with behavior cloning. This also has the advantage that it can generalize the expert behavior to new tasks. For instance if we observe the expert navigating from point A to point B and we learn the cost function the expert is optimizing, then we can predict the expert’s behavior for navigating from another point C to D by again planning with the learned cost function (see Figure 3.2). Simply learning a mapping from observation to action would most likely fail at this new task.

A limitation of these methods is that they require access to an accurate dynamic model of the world in order to be able to simulate the outcome of various sequence of actions for planning during test executions, and for learning a cost function that is only optimized by the observed demonstrations during training. In some applications, this can be difficult to obtain. Additionally, these methods can still fail to capture perfectly the expert behavior (e.g. if the dynamic model is inaccurate or the cost function of the expert cannot be captured perfectly by linear combinations of the observed features) and thus induce a similar mismatch between the training and test distribution of examples. This could again lead to poor execution of the task if the learned cost function does not accurately captures the expert’s behavior in these different test situations not encountered during training. However, this problem is typically not as pronounced as with behavior cloning methods, due to the improved generalization ability of IOC methods.

In this thesis, we will treat IOC methods as simply black-box predictors with good generalization ability that can be trained from a demonstration dataset when a dynamic model of the world is available. Whether the predictor is obtained from behavior cloning,

or IOC, we will present iterative interactive learning procedures that can be used to address the train-test mismatch both of these methods can suffer from and improve their performance. In the remainder of this chapter, we will focus entirely on behavior cloning approaches, in part for simplicity, and in part because many of the applications we consider cannot be tackled by IOC methods, due to the unavailability of a dynamic model of the world that can predict future sequence of observations. Nevertheless, the same iterative learning strategy could be applied with IOC methods.

3.2 Problem Formulation and Notation

We now define formally the imitation learning problem, our objective and notation used for later analysis.

We consider a T -step control task where the learner must predict a sequence of T actions. We denote by Π the class of policies the learner is considering (e.g. a set of linear classifiers or regressors). As the distribution of states encountered by different policies is of particular importance to our analysis, we denote:

- d_π^t : The distribution of states at time t if the learner executed policy π from time step 1 to $t - 1$.
- $d_\pi = \frac{1}{T} \sum_{t=1}^T d_\pi^t$: The average distribution of states if we follow policy π for T steps.

Given a state s , we denote $C(s, a)$ the expected immediate cost of performing action a in state s for the task we are considering and denote $C_\pi(s) = \mathbb{E}_{a \sim \pi(s)}[C(s, a)]$ the expected immediate cost of π in s . We assume C is bounded in $[0, C_{\max}]$. The total cost of executing policy π for T -steps (*i.e.*, the cost-to-go) is denoted $J(\pi) = \sum_{t=1}^T \mathbb{E}_{s \sim d_\pi^t}[C_\pi(s)] = T \mathbb{E}_{s \sim d_\pi}[C_\pi(s)]$.

In imitation learning, we may not necessarily know or observe true costs $C(s, a)$ for the particular task. Instead, we observe expert demonstrations and seek to bound $J(\pi)$ for any (bounded) cost function C based on how well π mimics the expert's policy π^* . In particular, we would like to show that the total cost of the learned policy is not much worse than the total cost of the expert. Denote ℓ the observed surrogate loss function we minimize instead of C . For instance, if the action a is continuous and we are training a regressor π , then $\ell(s, a, \pi)$ may be the squared loss, $\ell(s, a, \pi) = (\pi(s) - a)^2$. If actions are discrete, then ℓ may be the expected 0-1 loss $\ell(s, a, \pi) = \mathbb{E}_{a' \sim \pi_s}[I(a' \neq a)]$ or if π is a multiclass SVM, then ℓ may be the hinge loss, $\ell(s, a, \pi) = \max_{a' \in A} [\pi(s, a') + I(a' \neq a)] - \pi(s, a)$, for $\pi(s, a)$ the SVM score associated with predicting a in s , and I the indicator function. Importantly, in many instances, C and ℓ may be the same function—for instance, if we are interested in optimizing the learner's ability to predict the actions

chosen by an expert. For this objective, we will also be interested in measuring the total expected regret (in surrogate loss) of the learned policy π over T steps, compared to other predictors in the class, under its own induced sequences, denoted $R(\pi)$:

$$R(\pi) = T\mathbb{E}_{s \sim d_\pi, a \sim \pi^*(s)}[\ell(s, a, \pi)] - \min_{\pi' \in \Pi} T\mathbb{E}_{s \sim d_\pi, a \sim \pi^*(s)}[\ell(s, a, \pi')]$$

Our goal is to find a policy $\hat{\pi}$ which minimizes the observed surrogate loss under its induced distribution of states with respect to expert's actions in those states, i.e.:

$$\hat{\pi} = \arg \min_{\pi \in \Pi} \mathbb{E}_{s \sim d_\pi, a \sim \pi^*(s)}[\ell(s, a, \pi)] \quad (3.1)$$

As system dynamics are assumed both unknown and complex, we cannot compute d_π and can only sample it by executing π in the system. Hence this is a non-i.i.d. supervised learning problem due to the dependence of the input distribution on the policy π itself. The interaction between policy and the resulting distribution makes optimization difficult as it results in a non-convex objective even if the loss $\ell(s, a, \cdot)$ is convex in π for all states s and actions a .

Assumptions: We do not make any assumption about the dynamics of the system or the way the states are generated (in particular we do make any markovian assumption). Our only assumption is that the initial state of any trajectory during training and testing is drawn i.i.d. from the same distribution, but the distribution of states at any time t may depend on the entire history of previous states and actions. The “state” is only assumed a sufficient statistic of the history for determining immediate cost (under C), the expert's action and the action of any policy in Π (but not necessarily the next “state”). Even though we define the learned policy as a function of state, we do not assume the state is observable. Only some features of the current state (or observation) are observed and available to the policy for making its predictions (e.g. we can think that the state contains these features and that the policy class is restricted to only using these features, rather than the entire state). Thus our analysis throughout this section applies also to partially observable systems and systems with delays (that are unknown to the learner). In addition, we do not assume that the task is always exactly the same for every trajectory during training and testing. There can be a distribution over tasks (e.g. driving different routes), and in this case the current task would be encoded as part of the state. Thus when there are many tasks, our i.i.d. assumption on the initial state simply implies that we assume the distribution of tasks is i.i.d. at training and testing.

We also do not assume the class of policy Π contains the expert policy π^* . That is, there may be no policy that can mimic perfectly the expert in every state. The test performance guarantees we present will end up depending on how well policies in the

class Π can predict the actions of the expert π^* in expectation during training. The more accurate they can be, the closer their performance will be to the expert.

3.3 Supervised Learning Approach

We now formalize and analyze the traditional supervised learning approach to imitation adopted in behavior cloning methods. This analysis will illustrate the poor guarantees of these methods, in addition to serve as a baseline to improve upon.

As mentioned previously, these methods simply train a policy π that best mimics the expert's actions under the distribution of states encountered by the expert d_{π^*} . This can be achieved using any standard supervised learning algorithm. Formally, they try to optimize the following objective:

$$\min_{\pi \in \Pi} \mathbb{E}_{s \sim d_{\pi^*}, a \sim \pi^*(s)} [\ell(s, a, \pi)] \quad (3.2)$$

In practice, this optimization can only be achieved approximately, due to observation of only a finite set of sampled state-action pairs along sampled trajectories (demonstrations) of the expert. Hence, if $\{(s_i, a_i^*)\}_{i=1}^m$ is a set of m observed state-action pairs observed from expert demonstrations, supervised learning methods would return the policy $\hat{\pi}_{\text{sup}}$ that minimizes the empirical loss:

$$\hat{\pi}_{\text{sup}} = \arg \min_{\pi \in \Pi} \sum_{i=1}^m \ell(s_i, a_i^*, \pi) \quad (3.3)$$

Analysis

We now provide a theoretical analysis of this supervised learning method. Our analysis seeks to answer the following question: if we can achieve low error at mimicking the expert on the training data, what guarantee can we provide on the total cost of the learned policy, when used to perform the task?

First suppose we obtain a policy $\hat{\pi}_{\text{sup}}$ such that its expected loss under the training distribution is ϵ , i.e. $\epsilon = \mathbb{E}_{s \sim d_{\pi^*}, a \sim \pi^*(s)} [\ell(s, a, \hat{\pi}_{\text{sup}})]$. Then if ℓ is the 0-1 loss (or an upper bound on the 0-1 loss, such as the hinge or logistic loss), we have the following performance guarantee with respect to any task cost function C bounded in $[0, C_{\max}]$, as shown in our previous work (Ross and Bagnell, 2010):

Theorem 3.3.1. (Ross and Bagnell, 2010) *Let $\epsilon = \mathbb{E}_{s \sim d_{\pi^*}, a \sim \pi^*(s)} [\ell(s, a, \pi)]$. If ℓ upper bounds the 0-1 loss, and C is bounded in $[0, C_{\max}]$, then:*

$$J(\pi) \leq J(\pi^*) + C_{\max} T^2 \epsilon.$$

Proof. Due to a slight inaccuracy in the proof in (Ross and Bagnell, 2010) and that some steps in the proof assumed π^* was deterministic, we present here an accurate proof for the fully general case where π and π^* may be stochastic. Despite this, it does not change the result of (Ross and Bagnell, 2010).

Let d_1, d_2, \dots, d_T the distribution of states at each time step while executing the learned policy π . Now imagine that while π is executed, we look at the actions that would be picked by the expert π^* in each encountered state (or sample an action from the expert if π^* is stochastic). Consider the event where the policy π picked the same action as the expert π^* in all the first t states encountered so far. Let p_t the probability that this event holds. Then by conditioning on this event, each d_t can be expressed as $d_t = p_{t-1}d_t^{(c)} + (1 - p_{t-1})d_t^{(e)}$, where $d_t^{(c)}$ is the distribution of states at time t if we always executed π , conditioned on π having picked always the correct action, i.e. the same action as π^* in all previously encountered states, and $d_t^{(e)}$ is the distribution of states at time t if we always executed π , conditioned on π having made at least 1 error, i.e. it chose a different action than the expert in at least one of the previously encountered states. Similarly, if we look at the distribution of states $d_1^*, d_2^*, \dots, d_T^*$, encountered by the expert while executing π^* , and imagine that while π^* is executed, we look at the actions that would be picked by π in each encountered state (or sample an action from π if it is stochastic). Again we can condition on the event where both π^* and π picked the same action in all states encountered so far. Thus each d_t^* can be expressed as $d_t^* = p_{t-1}d_t^{(c)} + (1 - p_{t-1})d_t^{*(e)}$, where $d_t^{*(e)}$ would be the distribution of states encountered by the expert at time t , conditioned on π picking an action different than π^* in at least one of the previous states encountered by the expert π^* . We can express d_t^* this way because conditioned on both π^* and π having always picked the same actions up to time $t - 1$, they must be in the same distribution of states $d_t^{(c)}$, and because this holds for all t , the probability that this event holds at t is also p_{t-1} in both cases.

Now during training, the learner is trained under the distribution $\frac{1}{T} \sum_{t=1}^T d_t^*$. Let ϵ_t the probability that π picks a different action than π^* in the state distribution d_t^* . By definition of ϵ , we have $\frac{1}{T} \sum_{t=1}^T \epsilon_t \leq \epsilon$. Now let $\epsilon_t^{(c)}$ and $\epsilon_t^{*(e)}$ be the probability that π picks a different action than π^* in the state distributions $d_t^{(c)}$ and $d_t^{*(e)}$ respectively. Then we have $\epsilon_t = p_{t-1}\epsilon_t^{(c)} + (1 - p_{t-1})\epsilon_t^{*(e)}$. Since $\epsilon_t^{*(e)} \geq 0$, then $\epsilon_t \geq p_{t-1}\epsilon_t^{(c)}$. Additionally, the probability that the learner made at least 1 error in the first t steps $(1 - p_t) = (1 - p_{t-1}) + p_{t-1}\epsilon_t^{(c)}$. So $(1 - p_t) \leq (1 - p_{t-1}) + \epsilon_t$. Solving this recurrence we have $(1 - p_t) \leq \sum_{i=1}^t \epsilon_i$.

Using all these facts, now consider the expected total cost $J(\pi)$ of executing the policy π . Let C_t , $C_t^{(c)}$ and $C_t^{(e)}$ the expected immediate cost (under cost function C) of executing π in state distribution d_t , $d_t^{(c)}$ and $d_t^{(e)}$ respectively. We have $J(\pi) = \sum_{t=1}^T C_t$ and $C_t = p_{t-1}C_t^{(c)} + (1 - p_{t-1})C_t^{(e)}$. Now since $C \in [0, C_{\max}]$, then $C_t^{(e)} \leq C_{\max}$. Additionally,

consider the immediate cost C_t^* and $C_t^{*(c)}$ of executing π^* in state distributions d_t^* and $d_t^{(c)}$. Then $J(\pi^*) = \sum_{t=1}^T C_t^*$ and because costs are non-negative, we must have $C_t^* \geq p_{t-1}C_t^{*(c)}$. Now in state distribution $d_t^{(c)}$, whenever both π and π^* picks the same action, then π must incur the same cost as the expert, and when π picks a different action, π must incur at most cost C_{\max} more than the expert. Since the probability π picks a different action is $\epsilon_t^{(c)}$, then this implies $C_t^{(c)} \leq C_t^{*(c)} + \epsilon_t^{(c)}C_{\max}$. Combining with the above, we obtain:

$$\begin{aligned} C_t &= p_{t-1}C_t^{(c)} + (1 - p_{t-1})C_t^{(e)} \\ &\leq p_{t-1}C_t^{*(c)} + p_{t-1}\epsilon_t^{(c)}C_{\max} + (1 - p_{t-1})C_{\max} \\ &= p_{t-1}C_t^{*(c)} + (1 - p_t)C_{\max} \\ &\leq C_t^* + (1 - p_t)C_{\max} \\ &\leq C_t^* + C_{\max} \sum_{i=1}^t \epsilon_i \end{aligned}$$

Hence summing over t , we obtain:

$$\begin{aligned} J(\pi) &\leq J(\pi^*) + C_{\max} \sum_{t=1}^T \sum_{i=1}^t \epsilon_i \\ &= J(\pi^*) + C_{\max} \sum_{t=1}^T (T + 1 - t)\epsilon_t \\ &\leq J(\pi^*) + C_{\max} T \sum_{t=1}^T \epsilon_t \\ &\leq J(\pi^*) + C_{\max} T^2 \epsilon \end{aligned}$$

□

Similar results (although not as tight), were also independently developed in later work in [Syed and Schapire \(2010\)](#).

More importantly our bound is tight, i.e. there exist problems such that a policy π with ϵ expected loss under the training distribution d_{π^*} can incur extra cost that grows quadratically in T . [Kääriäinen \(2006\)](#) previously demonstrated this in a sequence prediction example¹. We also provided an imitation learning example in [Ross and Bagnell \(2010\)](#) where $J(\hat{\pi}_{sup}) = (1 - \epsilon T)J(\pi^*) + T^2\epsilon$. We include it here for completeness.

Theorem 3.3.2. ([Ross and Bagnell, 2010](#)) *There exists MDPs and policies π with $\epsilon \in [0, 1/T]$ expected 0-1 loss under the expert's training distribution, i.e. $\epsilon = \mathbb{E}_{s \sim d_{\pi^*}, a \sim \pi^*(s)}[I(\pi(s) \neq a)]$, such that $J(\pi) = (1 - \epsilon T)J(\pi^*) + C_{\max}T^2\epsilon$.*

Proof. Consider the following problem with 3 states (s_0, s_1, s_2) and 2 actions (a_1, a_2) . The learner always starts in s_0 and transitions are deterministic as specified in Figure 3.3. The expert's policy π^* is to perform a_2 in s_1 , and a_1 in s_0 and s_2 , and consider the cost function $C(s, a) = C_{\max}I(\pi^*(s) \neq a) + cI(\pi^*(s) = a)$, where I is the indicator function and for all states s , $0 \leq c \leq C_{\max}$.

¹In their example, an error rate of $\epsilon > 0$ when trained to predict the next output in sequence with the previous correct output as input can lead to an expected number of mistakes of $\frac{T}{2} - \frac{1 - (1 - 2\epsilon)^{T+1}}{4\epsilon} + \frac{1}{2}$ over sequences of length T at test time. This is bounded by $T^2\epsilon$ and behaves as $\Theta(T^2\epsilon)$ for small ϵ .

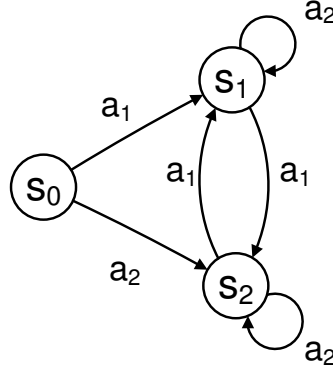


Figure 3.3: Example MDP where the supervised learning approach can lead to poor performance. There are 3 states (s_0, s_1, s_2) and 2 actions (a_1, a_2), and arrows represent the deterministic transitions.

In this example, under π^* , one would only observe s_0 with frequency $\frac{1}{T}$ and s_1 the rest of the times, i.e. $d_{\pi^*} = (\frac{1}{T}, \frac{T-1}{T}, 0)$. Now consider the policy $\hat{\pi}$ which executes a_1 with probability $(1 - \epsilon T)$ in s_0 , and a_2 in s_1, s_2 , for some $\epsilon \leq \frac{1}{T}$. This policy which could be learned by the supervised learning approach achieves $\mathbb{E}_{s \sim d_{\pi^*}, a \sim \pi^*(s)}(\ell(s, a, \hat{\pi})) = \epsilon$, for ℓ the 0-1 loss. However when executing $\hat{\pi}$, we observe that 1 of 2 things occur. With probability ϵT , it picks the wrong action in s_0 , leading it to s_2 where it keeps picking the wrong action and stays in s_2 , yielding a total cost of TC_{\max} . On the other hand, with probability $(1 - \epsilon T)$, it picks the same action as the expert in s_0 , leading it to s_1 where it always acts as the expert and stays in s_1 , yielding a total cost which is the same as the expert $J(\pi^*)$. Thus we obtain $J(\pi) = (1 - \epsilon T)J(\pi^*) + C_{\max}T^2\epsilon$. \square

Additionally, if we look at the regret in surrogate loss of the learned policy $R(\hat{\pi})$, we can see that the supervised learning approach has poor guarantees: small regret during training, can lead to arbitrarily bad regret on the test sequences:

Theorem 3.3.3. *There exists MDPs and policy classes Π , where the supervised learning approach obtains a policy $\hat{\pi}$ with $\epsilon \geq 0$ regret under the expert's training distribution, i.e. $\epsilon = \mathbb{E}_{s \sim d_{\pi^*}, a \sim \pi^*(s)}[\ell(s, a, \hat{\pi})] - \min_{\pi \in \Pi} \mathbb{E}_{s \sim d_{\pi^*}, a \sim \pi^*(s)}[\ell(s, a, \pi)]$, that has total expected regret $R(\hat{\pi})$ over T steps of $O(T)$, for all $\epsilon \geq 0$.*

Proof. Consider the same MDP as in Figure 3.3, with the same expert, and where ℓ is the 0-1 loss, and imagine that all predictors in the class Π make an error in the initial state s_0 , but there exist predictors that mimic perfectly the expert in both s_1 and s_2 . Suppose the learner returns a predictor $\hat{\pi}$ that errors with probability $\epsilon' \geq 0$ in s_1 , and errors with probability 1 in s_0 and s_2 . Then under the expert's state distribution $[1/T, (T-1)/T, 0]$ (as described in the previous theorem), this predictor has regret $\epsilon = \frac{(T-1)}{T}\epsilon'$ (in 0-1 loss). Then no matter ϵ' , when executed, the learned policy starts in s_0 , goes to s_2 , and then

stays in s_2 , making an error at every step. Its total 0-1 loss is T under test executions, yet a predictor in the class which is correct in s_2 has 0-1 loss of 1 under this same sequence of states. Thus the total expected regret of the learned policy $R(\hat{\pi}) = T - 1$. \square

These results also have some implications on the number of samples required to learn good performance with such methods. That is, due to the factor T^2 , one may need a larger number of samples to obtain good performance with this method. We briefly analyze the sample complexity below to demonstrate this.

Sample Complexity

As mentioned previously, in practice one cannot minimize directly the expected surrogate loss $\mathbb{E}_{s \sim d_{\pi^*}, a \sim \pi^*(s)}[\ell(s, a, \pi)]$. Instead the surrogate loss is minimized on a finite set of samples $(s_i, a_i^*)_{i=1}^m$ collected during expert demonstrations, as described in Equation 3.3. Nevertheless, as we collect more and more samples, we would be able to guarantee that with high probability, we obtain a policy which is not much worse than the policy with smallest expected loss under the training distribution.

In particular, let $\epsilon_{\text{class}} = \min_{\pi \in \Pi} \mathbb{E}_{s \sim d_{\pi^*}, a \sim \pi^*(s)}(\ell(s, a, \pi))$ the expected surrogate loss of the best policy in the class. Suppose we collect m i.i.d. samples from the expert demonstrations, then using standard PAC learning bounds, the policy $\hat{\pi}$ that minimizes the empirical loss on these samples will typically guarantee that with probability at least $1 - \delta$, its expected loss $\epsilon \leq \epsilon_{\text{class}} + O(\sqrt{\frac{\mathcal{C}(\Pi) + \log(1/\delta)}{m}})$, for $\mathcal{C}(\Pi)$ a measure of the complexity of the class of policy Π (for instance its VC dimension (Vapnik, 1995) if it is a class of binary classifiers, or analogous multi class equivalent (Natarajan, 1989)). Because the performance guarantees scale with $C_{\max} T^2 \epsilon$, then to ensure that $C_{\max} T^2 \epsilon \leq C_{\max} T^2 \epsilon_{\text{class}} + \alpha$ with high probability $1 - \delta$ for some desired α , we would need the number of samples m to be order $O(C_{\max}^2 T^4 (\mathcal{C}(\Pi) + \log(1/\delta)) / \alpha^2)$.

Discussion

In the context of learning reductions, this approach can be interpreted as an *error* reduction of imitation learning to a supervised learning problem. It is an error reduction, as task performance is related to the error, or loss, on the supervised learning task, rather than the regret². Importantly, it is not a very good reduction, as performance at the imitation learning task does not degrade nicely as error at the supervised learning task increases. We also demonstrated that in terms of regret, this reduction does not provide any guarantee, as small or even 0 training regret on the supervised learning task can lead to arbitrarily large regret during testing.

²Here the regret on the supervised learning task is the difference in error of the learned predictor to the minimum error achievable; e.g. when the expert is noisy, the minimum error would be non-zero, even for the bayes-optimal predictor.

These results and example demonstrate that the traditional supervised learning approach can learn policies with poor guarantees that are not robust to the errors they make, leading to a compounding growth in cost. Unless one can find predictors with arbitrary small error at mimicking the expert, one could always find a sufficiently large horizon T , where the learned policy may achieve the worst possible total cost. Hence even small training error can lead to performance arbitrarily close to the worst total cost. In addition, even in cases where good policies exist, one may need a lot of data to find them (that grows as $O(T^4)$). This also illustrates how guarantees are much worse than in the i.i.d. classification settings, where if we learn a policy with expected ϵ 0-1 loss during training, its expected classification loss for classifying T new examples at test time is $T\epsilon$ (and not $T^2\epsilon$). This leads to the following question: can we develop alternate learning procedures for sequential problems with guarantees that are similar to the i.i.d. setting? In the following sections, we present several approaches that can achieve this.

3.4 Iterative Forward Training Approach

We now present a first iterative and interactive training approach that can provide better performance than the traditional supervised learning approach. This approach exploits the structure of the time dependency between predictions, and interaction with the learner, to provide better performance guarantees.

Intuitively, the traditional supervised approach fails to give good performance bounds due to the discrepancy between the testing and training distribution when $\hat{\pi} \neq \pi^*$ and because the learner does not learn how to recover from mistakes it makes. The intuition behind the next approach, called Forward Training algorithm, is that both of these problems can be solved if we allow the training to occur over several iterations, where at each iteration we train one policy for one particular time step. If we do this training sequentially, starting from the first time step to the last, then at the t^{th} iteration, we can sample states from the actual testing distribution at time step t by executing the learned policies for each previous step, and then asks the expert what to do at the t^{th} time step to train the next policy. Furthermore, if the learner makes mistakes, the expert demonstrates how to recover at future steps, allowing the learner to learn the necessary recovery behaviors. The algorithm terminates once it has learned a policy for all T steps. This is similar to the Sequential Stacking algorithm (Cohen and Carvalho, 2005) for sequence classification.

More formally, Forward Training proceeds as follows. At the first iteration, it trains a policy π_1 for the first time step to best mimic the actions chosen by the expert π^* on states visited at time 1 (initial states). Then at iteration t , it trains a policy π_t for time step t , by collecting data through interaction as follows: the learner executes its learned


```

Initialize  $\pi_1, \pi_2, \dots, \pi_T$  arbitrarily.
for  $t = 1$  to  $T$  do
    Sample multiple  $t$ -step trajectories by executing the policies  $\pi_1, \pi_2, \dots, \pi_{t-1}$ , starting
    from initial states drawn from the initial state distribution.
    Query expert for states encountered at time step  $t$ .
    Get dataset  $\mathcal{D} = \{(s_t, \pi^*(s_t))\}$  of states, actions taken by expert at time step  $t$ .
    Train classifier  $\pi_t = \arg \min_{\pi \in \Pi} \sum_{(s,a) \in \mathcal{D}} \ell(s, a, \pi)$ .
end for
Return non-stationary policy  $\hat{\pi}$ , such that at time  $t$  in state  $s$ ,  $\hat{\pi}(s, t) = \pi_t(s)$ 

```

Algorithm 3.4.1: Forward Training Algorithm.

policies $\pi_1, \pi_2, \dots, \pi_{t-1}$ for time steps 1 to $t - 1$, and then asks the expert which action he would perform in the state encountered at time t . The state encountered at time t with the associated expert action are recorded, and data is collected through multiple t -step trajectories generated this way. The policy that best mimics the expert on these states encountered at time t , after execution of the learned policies π_1 to π_{t-1} , is chosen for π_t . This algorithm iterates for T iterations, to learn a policy for all time steps. It is detailed in Algorithm 3.4.1.

By training sequentially in this way, each policy π_t is trained under the distribution of states it is going to encounter during test execution. Additionally, if some of the policies errors, then the expert will demonstrate the necessary recovery behaviors at future steps, and hence following policies will be able to learn these behaviors.

Analysis

We now provide a complete analysis of this approach below, and contrast it with the previous guarantees of the supervised learning approach. This analysis again seeks to answer a similar question as before: if we can achieve small loss (on average) during training at mimicking the expert behavior over the iterations, how well will the learned policy perform the task?

Let $\hat{\pi}$ denote the non-stationary policy learned by the Forward Training algorithm that executes $\pi_1, \pi_2, \dots, \pi_T$ in sequence over T steps. For each time step t , denote $\epsilon_t = \mathbb{E}_{s_t \sim d_{\hat{\pi}}^t, a \sim \pi^*(s_t)} [\ell(s_t, a, \pi_t)]$ the expected training surrogate loss of the learned policy π_t for time t . Denote $\epsilon = \frac{1}{T} \sum_{t=1}^T \epsilon_t$, the average expected training surrogate loss over the T iterations of training. For this Forward Training procedure, we also have that the expected surrogate loss at test time, under trajectories generated by $\hat{\pi}$, is exactly ϵ , i.e. $\mathbb{E}_{s \sim d_{\hat{\pi}}, a \sim \pi^*(s)} [\ell(s, a, \hat{\pi})] = \epsilon$. Again, this is because each policy π_t is trained under the state distribution $d_{\hat{\pi}}^t$, the same it encounters at test time.

Imitation Loss Guarantee

These observations already imply a first interesting result for the case where the surrogate loss is the same as the task cost function (or an upper bound on it), i.e. $\mathbb{E}_{a \sim \pi^*(s)}[\ell(s, a, \pi)] \geq C_\pi(s)$ for all states s . For instance we may measure task performance directly in terms of the ability of the learner to mimic the actions of the expert (in terms of the 0-1 imitation loss), or for continuous action problems, in terms of a squared loss penalizing deviations from the actions of the expert.

For such task cost function that are related directly to the surrogate imitation loss we have the following guarantee:

Theorem 3.4.1. *Let $\epsilon = \mathbb{E}_{s \sim d_{\hat{\pi}}, a \sim \pi^*(s)}[\ell(s, a, \hat{\pi})]$, the average training loss of the learned policy $\hat{\pi}$ with Forward Training, and ℓ be the same as the cost function C (or an upper bound on it), then $J(\hat{\pi}) \leq T\epsilon$.*

Proof. Follows directly from the fact that:

$$\begin{aligned} J(\hat{\pi}) &= \sum_{t=1}^T \mathbb{E}_{s \sim d_{\hat{\pi}}^t} [C_{\pi_t}(s)] \\ &\leq \sum_{t=1}^T \mathbb{E}_{s \sim d_{\hat{\pi}}^t, a \sim \pi^*(s)} [\ell(s, a, \pi_t)] \\ &= T\epsilon \end{aligned}$$

□

This result has particularly useful applications when we just want to measure how well the learner can mimic the expert. In particular, in continuous settings where we use a squared loss to expert's action, this result indicates that under test trajectories of the learned policy, the expected total squared distance to expert's actions will be the same as during training. In comparison, we did not have any guarantee for the supervised learning approach in such continuous settings³.

Additionally, we can also show an interesting guarantee for the regret (in surrogate loss) of the learned policy with Forward. Let

$$r_t = \mathbb{E}_{s \sim d_{\hat{\pi}}^t, a \sim \pi^*(s)} [\ell(s, a, \pi_t)] - \min_{\pi \in \Pi} \mathbb{E}_{s \sim d_{\hat{\pi}}^t, a \sim \pi^*(s)} [\ell(s, a, \pi)],$$

denote the regret of the learned policy π_t for time t under the training distribution $d_{\hat{\pi}}^t$. Then let $r = \frac{1}{T} \sum_{t=1}^T r_t$, the average regret of the learned policy returned by the supervised learning algorithm, then we have that the total expected regret $R(\hat{\pi})$ of the learned policy $\hat{\pi}$, under its own sequences of T steps, is at most Tr :

³In continuous settings, the supervised learning approach may be shown to have a similar compounding growth of the cost, as in the analyzed discrete setting, under Lipschitz continuity assumption of the expert's policy and system transition. Without such assumptions, its performance can be arbitrarily bad.

Theorem 3.4.2. *Let $r = \frac{1}{T} \sum_{t=1}^T r_t$, the average regret of the learned policies $\pi_1, \pi_2, \dots, \pi_T$ returned by the supervised learning algorithm over the iterations of Forward, then the learned policy $\hat{\pi}$ with Forward is such that $R(\hat{\pi}) \leq Tr$.*

Proof.

$$\begin{aligned}
R(\hat{\pi}) &= \sum_{t=1}^T \mathbb{E}_{s \sim d_{\hat{\pi}}^t, a \sim \pi^*(s)} [\ell(s, a, \pi_t)] - \min_{\pi' \in \Pi} \sum_{t=1}^T \mathbb{E}_{s \sim d_{\hat{\pi}}^t, a \sim \pi^*(s)} [\ell(s, a, \pi')] \\
&\leq \sum_{t=1}^T [\mathbb{E}_{s \sim d_{\hat{\pi}}^t, a \sim \pi^*(s)} [\ell(s, a, \pi_t)] - \min_{\pi'_t \in \Pi} \mathbb{E}_{s \sim d_{\hat{\pi}}^t, a \sim \pi^*(s)} [\ell(s, a, \pi'_t)]] \\
&= \sum_{t=1}^T r_t \\
&= Tr
\end{aligned}$$

□

Thus, in contrast with the typical supervised learning approach to imitation, where small regret during training can lead to arbitrarily bad regret during test executions (as shown in previous Theorem 3.3.3), Forward Training guarantees that small average regret during training, also implies small regret during test execution.

General Cost Function Guarantee

More generally, when the task cost function C is not related directly to the surrogate loss ℓ , we can still show that the extra task cost incurred by the learned policy, compared to the expert, grows linearly in T when the expert's behavior is robust in some sense. This is formalized below.

Let $Q_t^*(s, \pi)$ denote the t -step cost of executing policy π in state s and then following the expert policy π^* and $V_t^*(s)$ the t -step cost of executing the expert starting in s . We quantify the robustness of the expert's policy π^* as follows:

Definition 3.4.1. *Consider any policy $\pi \in \Pi$ such that $\mathbb{E}_{s \sim d_{\pi}, a \sim \pi^*(s)} [\ell(s, a, \pi)] \leq \epsilon$ and let $\epsilon_t = \mathbb{E}_{s \sim d_{\pi}^t, a \sim \pi^*(s)} [\ell(s, a, \pi)]$. We say the expert's policy π^* is $u_{T,\epsilon}$ -**robust** if under the task cost function C , $\mathbb{E}_{s \sim d_{\pi}^t} [Q_{T-t+1}^*(s, \pi) - V_{T-t+1}^*(s)] \leq u_{T,\epsilon} \epsilon_t$ for any such policy π and any time t .*

The subscript T and ϵ indicates that $u_{T,\epsilon}$ is typically a function of T and ϵ and increases as T and/or ϵ increases. To ease the notation in our results below, we will simply say the expert is u -robust, where the subscript T and ϵ implicitly used should be clear from context. This notion of robustness measures whether policies that are similar to the expert, i.e. small ϵ , can lead to state distributions where acting differently than the expert for one more step, can increase significantly the expected cost-to-go of the expert. It intuitively measures the ability of the expert to recover from errors made by such similar policies. For example, consider a task that involves driving near

a cliff. In this case, a policy can potentially lead to a situation where doing a single erroneous action falls off the cliff, at which point the expert cannot recover, leading to large cost, whereas if the expert would have been executed immediately, he could have avoided falling off the cliff, leading to small cost. In such case where the expert cannot recover from single errors, $u_{T,\epsilon}$ can be large (it can be as large as TC_{\max} for discrete actions and cost functions C bounded in $[0, C_{\max}]$). However when looking at similar policies to the expert (small ϵ), we could still expect $u_{T,\epsilon}$ to be small in this example if the expert policy is driving safely far enough from the cliff. This is because the further off the cliff the expert is driving, the larger ϵ would need to be for the learned policy to encounter situations where it can fall off the cliff and the expert cannot recover. Thus in some sense, this notion of robustness can often capture a similar notion to the stability margin of the expert in control (Ljung, 1999). If the expert can always recover, from execution of similar policies within some threshold of error ϵ , then $u_{T,\epsilon}$ will be small.

Importantly, in many situations, $u_{T,\epsilon}$ can be bounded by a small constant independent of T and ϵ . First, if $C = \ell$ is the 0-1 loss, then $u_{T,\epsilon} = 1$, as the 0-1 loss of the expert in all future states would be 0 (assuming π^* is deterministic), and for any time t and policy π we have $\mathbb{E}_{s \sim d_\pi^t}[Q_{T-t+1}^*(s, \pi) - V_{T+t+1}^*(s)] = \epsilon_t$. Another example may be a robot navigation task with an omnidirectional robot where one can always perform an action to come back to the previous state we were (e.g. if we went left, we can then go right to get back to where we were). In such task, if for instance the cost of any action is C_{\max} , until one reaches the goal state where cost is 0, then $u_{T,\epsilon} \leq 2C_{\max}$ for good experts. That is, in any state s , for any policy that would be executed first before the expert, the expert can then always do an action to undo the policy's action, and then follow the same course of action as he would have starting in s . The difference between these two course of actions would be $\leq 2C_{\max}$, and the expert only needs to do this when the policy acts differently then he would (i.e. with probability less than ϵ_t at time t if ℓ is the 0-1 loss or upper bounds it). Thus for any policy π and time t , $\mathbb{E}_{s \sim d_\pi^t}[Q_{T-t+1}^*(s, \pi) - V_{T+t+1}^*(s)] \leq 2C_{\max}\epsilon_t$. More generally, in MDPs where the Markov Chain defined by the system dynamics and expert policy π^* is mixing, then $u_{T,\epsilon}$ can be related to the mixing rate of the chain⁴: if π^* is rapidly mixing, i.e. it always recovers quickly from errors, then $u_{T,\epsilon}$ is small.

We now show the importance of this robustness notion:

Theorem 3.4.3. *Let $\epsilon = \mathbb{E}_{s \sim d_{\hat{\pi}}}[\ell(s, a, \hat{\pi})]$, the average training loss of the learned policy $\hat{\pi}$ with Forward Training, and suppose the expert π^* is u -robust under the task cost function C (as in Definition 3.4.1). Then $J(\hat{\pi}) \leq J(\pi^*) + uT\epsilon$.*

Proof. We here follow a similar proof to Ross and Bagnell (2010). Given our policy $\hat{\pi}$,

⁴In particular, if it is α -mixing with exponential decay rate δ then u is $O(C_{\max} \frac{1}{1 - \exp(-\delta)})$

consider the policy $\hat{\pi}_{1:t}$, which executes $\hat{\pi}$ in the first t -steps and then executes the expert π^* . Then

$$\begin{aligned}
& J(\hat{\pi}) \\
&= J(\pi^*) + \sum_{t=0}^{T-1} [J(\hat{\pi}_{1:T-t}) - J(\hat{\pi}_{1:T-t-1})] \\
&= J(\pi^*) + \sum_{t=1}^T \mathbb{E}_{s \sim d_{\hat{\pi}}^t} [Q_{T-t+1}^*(s, \hat{\pi}) - V_{T-t+1}^*(s)] \\
&\leq J(\pi^*) + u \sum_{t=1}^T \epsilon_t \\
&= J(\pi^*) + uT\epsilon
\end{aligned}$$

The inequality follows from the definition of robustness. \square

For discrete actions and cost functions bounded in $[0, C_{\max}]$, $u \leq TC_{\max}$, so this guarantee is always better than the guarantee of the supervised learning approach. In scenarios where u is much smaller, then forward training can provide significant improvement over the supervised learning approach. In some sense, this bound says that Forward Training can learn good and robust behavior if the expert itself is robust. In this case, low average training error, always imply good test task performance, unlike with the supervised learning approach. As in many real applications we can expect the expert behavior to be somewhat robust and tolerant to some error (e.g. human drivers typically drive near the center of the lane, at a fair distance to other vehicles or obstacles), then we can often expect this method to provide improved performance in practice.

The previous example in Figure 3.3 also provides a concrete scenario where Forward Training leads to improved performance compared to the supervised learning approach. In this example, it can be seen that $u \leq (C_{\max} - c)$, and if we learn policies with average expected training 0-1 loss of ϵ , we would be guaranteed to obtain a non-stationary policy π with performance $J(\pi) \leq J(\pi^*) + (C_{\max} - c)T\epsilon$. However in that same example the supervised learning method could learn a policy π with expected training 0-1 loss of ϵ with performance $J(\pi) = J(\pi^*) + (C_{\max} - c)T^2\epsilon$ ⁵. Thus the forward training procedure is a factor T better in this example. The intuitive reason for this is that now, if the learned policy errors in the first step, it can collect training examples in state s_2 and learn what to do in this state, whereas with the supervised learning approach, s_2 was never visited during training.

Sample Complexity

Another advantage of this approach is that it can sometimes learn good behavior in fewer samples than the supervised learning approach when $u_{T,\epsilon}$ is small, due to the improved dependency on T . Suppose for example that we collect m i.i.d. datapoints at each iteration of training, and $\epsilon_{\text{class},t} = \min_{\pi \in \Pi} \mathbb{E}_{s \sim d_{\hat{\pi}}^t, a \sim \pi^*(s)} [\ell(s, a, \pi)]$ is the minimum expected surrogate loss with policies from class Π at iteration t . Let $\epsilon_{\text{class}} = \frac{1}{T} \sum_{t=1}^T \epsilon_{\text{class},t}$, the

⁵Using the fact that since $J(\pi^*) = cT$, $(1 - \epsilon T)J(\pi^*) + C_{\max}T^2\epsilon = J(\pi^*) + (C_{\max} - c)T^2\epsilon$

minimum average expected surrogate loss. Then using standard PAC learning bounds and a union bound over all time steps t , the expected training surrogate loss of the learned non-stationary policy $\epsilon \leq \epsilon_{\text{class}} + O(\sqrt{\frac{\mathcal{C}(\Pi) + \log(1/\delta) + \log(T)}{m}})$ with probability at least $1 - \delta$. Again here $\mathcal{C}(\Pi)$ denotes a measure of complexity of the class Π . As performance decreases with $uT\epsilon$, then to guarantee this is not worse than $uT\epsilon_{\text{class}} + \alpha$ with high probability $1 - \delta$ for some desired $\alpha > 0$, we would require m to be order $O(u^2 T^2 (\mathcal{C}(\Pi) + \log(1/\delta) + \log(T)) / \alpha^2)$. As m is the number of samples per iteration, we would require a total of $O(u^2 T^3 (\mathcal{C}(\Pi) + \log(1/\delta) + \log(T)) / \alpha^2)$ samples to complete all T iterations. This is a reduction by a factor T , compared to the supervised learning approach, when u is constant or independent of T (e.g. $O(C_{\text{max}})$). However in the worst case where u is $O(T)$, then this method may need a factor T more samples than the supervised learning approach, i.e. $O(T^5)$, in order to guarantee the same performance.

Discussion

The Forward Training algorithm provides a first method to obtain better guarantees and learn more efficiently than the supervised learning approach when the expert's policy has good robustness properties. Unlike the supervised learning approach, where small training error can lead to arbitrarily bad task performance, the forward training method guarantees that small training error will lead to good task performance. In addition, small training regret also lead to small regret under the test distribution.

In the context of learning reductions, this approach can be interpreted as an *error* reduction of imitation learning to a *sequence* of supervised learning problems. It is again an error reduction, as task performance is related to the average error, or loss, on the supervised learning tasks, rather than the average regret⁶. It can also be interpreted as a regret reduction for the surrogate loss objective, where regret under the test trajectories is related to the regret on the supervised learning problems. It is a much better reduction than the previous supervised learning reduction, as here performance at the imitation learning task degrades nicely (linearly in T) as error (or regret) at the supervised learning task increases. This is the best we can hope for, as it matches the same guarantees we would have in an i.i.d. classification setting for classifying T new i.i.d. examples.

A drawback of the Forward algorithm is that it is impractical when T is large (or undefined) as we must train T different policies sequentially and cannot stop the algorithm before we complete all T iterations. Hence it can not be applied to many real-world applications. Additionally, in some sense, it is still inefficient at learning the demonstrated behavior, as it does not generalize the behavior across time steps and may need to learn

⁶Here the average regret on the supervised learning tasks is the average difference in error of the learned predictors to the minimum error achievable on each task; e.g. when the expert is noisy, the minimum error would be non-zero, even for the bayes-optimal predictor.

the same (or similar behavior) repeatedly from scratch across many steps. This is not very satisfactory and we should intuitively be able to do better than this by generalizing the behavior across time. Despite this, it can be still a useful algorithm in other sequential prediction settings where small sequence of predictions are more common (e.g. the recommendation tasks we consider in Chapter 7).

In the next two sections, we present approaches that address these limitations, while still providing similar performance guarantees.

3.5 Stochastic Mixing Training

To avoid the limitations of having to train a separate policy for each step, which is often impractical and inefficient as just discussed, we would like instead to train a fixed stationary policy, that is executed for all time steps. Before we introduce the main approach of this thesis that allows learning such stationary policy efficiently, we briefly discuss some other related work that allows learning a stationary stochastic policy, with guarantees similar to Forward.

One of the intuition behind the Forward training algorithm is that it can achieve good performance by training the policy slowly, i.e. training one step at a time per iteration, in a way that it allows the policy to adapt to the changing distribution of states. The two approaches we review here, SEARN (Daumé III et al., 2009) and SMILE (Ross and Bagnell, 2010), train a stationary stochastic policy using a similar strategy of training the policy slowly. In particular, these methods also proceed iteratively, learning from interactions with the learner, by changing the distribution of actions picked by the stationary stochastic policy slowly over the iterations. The slow change in the policy is related to the Forward approach in the following sense: from one iteration to the next, with high probability the policy changes at most 1 action over the entire sequence of T steps. Hence, in some sense, these methods can be interpreted as randomized versions of the Forward training procedure. By making the changes small enough from one iteration to the next, these methods can provide similar guarantees to Forward.

We begin by reviewing SEARN (Daumé III et al., 2009), an existing approach that was proposed in the context of Structured Prediction, that we describe more extensively when applying our methods to such problems in Chapter 6. SEARN can be adapted for imitation learning problems and we describe here how it can be applied in such settings. Then we discuss a variant of this approach, called SMILE, that we introduced in our previous work (Ross and Bagnell, 2010), that is often more practical than SEARN for imitation learning problems, while still providing improved guarantees over naive supervised learning.

SEARN for Imitation Learning

In the context of imitation learning, SEARN can be applied to train iteratively a stationary stochastic policy as follows. Starting from a policy $\pi_0 = \pi^*$, that queries the expert π^* and executes its action, SEARN first trains a policy $\hat{\pi}_1$ by collecting data from execution of π_0 . This new policy is then stochastically mixed with π_0 to obtain the next policy $\pi_1 = (1 - \alpha)\pi_0 + \alpha\hat{\pi}_1$, for some small $\alpha > 0$. This update is interpreted as follows: in each step π_1 executes π_0 with probability $(1 - \alpha)$ and with probability α , executes $\hat{\pi}_1$. SEARN keeps iterating in a similar fashion: at each iteration n , it interacts with the learner to collect new data from execution of the learner's current policy π_{n-1} . This new data is used to train a new policy $\hat{\pi}_n$, that is stochastically mixed with π_{n-1} , to obtain the next policy $\pi_n = (1 - \alpha)\pi_{n-1} + \alpha\hat{\pi}_n$. In other words, the stochastic policy trained in SEARN is represented as a distribution over policies, such that $\pi_n = (1 - \alpha)^n\pi_0 + \alpha \sum_{i=1}^n (1 - \alpha)^{n-i}\hat{\pi}_i$. After n iterations, the probability that π_n queries the expert to execute its action (i.e. picks π_0) at any step is $(1 - \alpha)^n$, i.e. it becomes exponentially small as this procedure is iterated. After some large number of iterations N , SEARN terminates and returns a final policy $\tilde{\pi}_N$ that does not query the expert, by renormalizing the distribution over learned policies, i.e. $\tilde{\pi}_N = \frac{\alpha}{1 - (1 - \alpha)^N} \sum_{i=1}^N (1 - \alpha)^{N-i}\hat{\pi}_i$.

At each iteration n , SEARN trains $\hat{\pi}_n$ to pick actions that minimize future total cost, if the current policy π_{n-1} would be executed from then on, under the distribution of states visited by π_{n-1} . This requires knowledge of the task cost function C . When C is unknown, SEARN can be applied to minimize future surrogate loss ℓ of the current policy. To do so, SEARN collects training examples, by executing the current policy π_{n-1} , and at some random time t , for the current state s , explores an action a and then executes π_{n-1} until time T , to observe the total future loss Q action a induces in state s when π_{n-1} is executed afterwards. Each trajectory generates a single example (s, a, Q) , that associates cost Q to executing action a in state s . In structured prediction, SEARN typically proceeds by trying all predictions, from the current state, and rolling out the current policy π_{n-1} , to obtain cost estimates Q for all predictions/actions in the current state. This is possible in imitation learning only if we can put back the system exactly in the same state s to try all possible actions. While this may be possible in simulated environments, on real robots this is often impossible or very hard. In this case, SEARN can still be applied from the cost estimate of only a single explored action in each visited state using techniques described later in Chapter 4. From the dataset of examples (s, a, Q) collected at iteration n , SEARN then solves a cost-sensitive classification problem to obtain the policy $\hat{\pi}_n$ (the classifier that picks actions with minimum cost on the training examples).

In [Daumé III et al. \(2009\)](#), they show that if the learning parameter α is chosen small enough, i.e. order $O(1/T^3)$, and SEARN is iterated for long enough, N order $O(T^3)$,

then SEARN provides good guarantees, i.e. it will learn a stationary stochastic policy $\tilde{\pi}_N$ that performs the task well, under its own trajectories (assuming policies in the class Π can solve the cost-sensitive classification tasks well on average).

The guarantees are similar to Forward as above: i.e. $J(\tilde{\pi}_N) \leq J(\pi^*) + T \log(T)\epsilon + O(\log T)$ (Daumé III et al., 2009), except here, ϵ corresponds to the average cost-sensitive classification regret⁷ of the learned policies $\hat{\pi}_n$ over the training iterations. When SEARN is applied to minimize the surrogate loss ℓ , a similar argument, involving the robustness properties of the expert π^* , could be made to show that small surrogate loss ℓ implies good task performance under the cost function C , i.e. $J(\tilde{\pi}_N) \leq J(\pi^*) + uT \log(T)\epsilon + O(u \log T)$ if the expert π^* is u -robust as in Definition 3.4.1.

In theory, SEARN needs a much larger number of iterations N than Forward, i.e. $O(T^3)$ instead of T . However in practice, SEARN can be applied with larger α , say $\alpha = 0.1$, and iterated for a small number of iterations (10-20 iterations) and obtain good policies that perform the task well.

One of the drawback of SEARN is that it involves simulating an entire trajectory to collect each datapoint. This can often be impractical as it requires a lot of effort from human experts to collect any significant amount of data. A variant of SEARN can be used to address this issue and is presented below.

SMILE: Stochastic Mixing Iterative Learning

In Ross and Bagnell (2010), we presented a technique called SMILE, that provides a more practical variant of SEARN for learning from human experts in imitation learning tasks. SMILE proceeds iteratively exactly like SEARN, and updating the policy through stochastic mixing exactly as in SEARN, except that it chooses the policies $\hat{\pi}_n$ differently. The main idea is that instead of attempting to find a policy that minimizes future loss of the current policy π_{n-1} , we can simply try to find a policy that does not increase its loss, and/or cost. In particular, this is achieved if we can find a policy $\hat{\pi}_n$ that behaves exactly like π_{n-1} , i.e. as if $\hat{\pi}_n = \pi_{n-1}$, then $\pi_n = \pi_{n-1}$. Since we know $\pi_{n-1} = (1 - \alpha)^{n-1}\pi^* + \alpha \sum_{i=1}^{n-1} (1 - \alpha)^{n-1-i}\hat{\pi}_i$, the only component of π_{n-1} that needs to be learned is the expert π^* . Thus SMILE does the following, at iteration n , it learns a policy π'_n , that mimics well the expert under the distribution of states encountered by π_{n-1} , which is used to construct $\hat{\pi}_n = (1 - \alpha)^{n-1}\pi'_n + \alpha \sum_{i=1}^{n-1} (1 - \alpha)^{n-1-i}\hat{\pi}_i$, and then update $\pi_n = (1 - \alpha)\pi_{n-1} + \alpha\hat{\pi}_n$. Effectively, this update leads to $\pi_n = (1 - \alpha)^n\pi^* + \alpha \sum_{i=1}^n (1 - \alpha)^{i-1}\pi'_i$. Thus we do not need to construct the intermediate policies $\hat{\pi}_n$, but can simply maintain the distribution that associates probability $\alpha(1 - \alpha)^n$ to executing policy π'_n to represent π_n . After N iterations, SMILE also returns the renormalized

⁷By regret here we mean the difference in cost-sensitive classification loss of the learned classifier to the bayes-optimal classifier that achieves minimum cost on the training data.

policy $\tilde{\pi}_N$ that does not query the expert π^* .

SMILE is more practical than SEARN, as at each iteration, it only needs to record the actions the expert would perform in every visited states along trajectories from execution of π_{n-1} . This allows for recording as many as T data points per trajectory, instead of only 1 for SEARN. Training the policy π'_n , simply involves solving a classification or regression task to minimize the surrogate loss ℓ on this training data.

When training the policies in this way, SMILE leads to a distinction compared to SEARN: older policies trained earlier have more weights (higher probability) than newer policies. This is the opposite of SEARN, where newer policies have higher probability.

In [Ross and Bagnell \(2010\)](#), we showed that by choosing $\alpha = O(\frac{1}{T^2})$ and performing $O(T^2 \log T)$ iterations leads good guarantees for SMILE. Again in practice, one can typically apply this algorithm with much larger α and iterate for a few iterations to obtain a practical method that still improves over naive supervised learning. The guarantees of SMILE are similar to Forward and lead to an improvement over the standard supervised training approach when the expert has good robustness properties. However the guarantees are weaker than Forward, as it requires a stronger notion of robustness, where during training the intermediate stochastic policies π_n must themselves be robust. In particular, if π_n is u_n -robust, and at iteration n , π'_n achieves ϵ_n 0-1 loss under the distribution of π_{n-1} (or surrogate loss that upper bounds the 0-1 loss), then SMILE guarantees that ([Ross and Bagnell, 2010](#)):

$$J(\tilde{\pi}_N) \leq J(\pi^*) + O\left(1 + \frac{\alpha}{1 - (1 - \alpha)^N} T \sum_{n=1}^N (1 - \alpha)^{n-1} u_{n-1} \epsilon_n\right).$$

This leads to good guarantees as long as the stochastic policies do not degrade too fast, in terms of their robustness properties. For instance if u_{n-1} is $O(C_{\max}/(1 - \alpha)^{n-1})$, as was shown in [Ross and Bagnell \(2010\)](#) for the example MDP in Figure 3.3, then this leads SMILE to guarantee $J(\tilde{\pi}_N) \leq J(\pi^*) + O(C_{\max} T \log(T) \epsilon)$, for ϵ the average 0-1 loss of the learned classifiers π'_n over the training iterations.

However, there are some class of problems where Forward still provides good guarantees (i.e. performance degrading linear in T and ϵ) but where SMILE does not improve much over supervised learning. This can occur in problems where π_n encounters situations where the only way for π_n to recover, is if the expert policy π^* is sampled to be executed multiple time steps in a row by π_n . In this case the robustness term can degrade quickly, i.e. u_n can increase faster than $O(1/(1 - \alpha)^n)$ as n increases, making u_n reach the maximum TC_{\max} quickly, and be TC_{\max} for most iterations. This leads to performance that degrades as $O(C_{\max} T^2 \epsilon)$, just like the supervised learning approach.

Discussion

These stochastic mixing approaches present an alternative to Forward that can learn a stationary policy, instead of a non-stationary policy, while still providing improved guarantees. This has the advantage of allowing to generalize the behavior across time steps, making learning more efficient, and in practice allows training the policy over fewer iterations, e.g. much less than T .

On the other hand, these methods still have several limitations and drawbacks in practice. SEARN can be impractical by requiring expensive rollouts of the current policy to collect each data point. Its more practical variant, SMILE, does not enjoy as strong guarantees as Forward or SEARN. Additionally, both methods ultimately learn a stochastic policy. This can be undesirable in practical applications. For instance, we will not obtain a fixed reproducible behavior, and failures may occur sometimes due to some “unlucky” sampling of the policies during execution.

The method we present next addresses these issues, by allowing to learn a stationary deterministic policy, while still obtaining similar guarantees as Forward and without requiring stronger robustness properties like SMILE.

3.6 Dataset Aggregation: Iterative Interactive Learning Approach

We now present the main approach of this thesis, that allows learning efficiently a stationary deterministic policy guaranteed to perform well under its induced distribution of states (number of mistakes/costs that grows linearly in T and classification cost ϵ). The approach is called DAGGER, for Dataset Aggregation, originally presented in our prior work (Ross et al., 2011), and is closely related to no-regret online learning algorithms (Cesa-Bianchi et al., 2004, Hazan et al., 2006, Kakade and Shalev-Shwartz, 2008) (in particular *Follow-The-Leader*). This approach leverages the strong learning guarantees of no-regret online learning algorithms, combined with learner interactions for data collection, to ensure good generalization performance on sequential problems.

In its simplest form, DAGGER proceeds as follows. At the first iteration, it uses the expert’s policy to gather a dataset of trajectories \mathcal{D} and train a policy $\hat{\pi}_2$ that best mimics the expert on those trajectories. Then at iteration n , it interacts with the learner by letting the learner execute its current policy $\hat{\pi}_n$ to observe states occurring under this policy and query the expert in those states. This new data is added to the dataset \mathcal{D} . The next policy $\hat{\pi}_{n+1}$ is the policy that best mimics the expert on the whole dataset \mathcal{D} . In other words, DAGGER proceeds by collecting a dataset at each iteration under the current policy and trains the next policy under the aggregate of all collected datasets. A diagram depicting the DAGGER algorithm for imitation learning is shown in Figure

3.4.

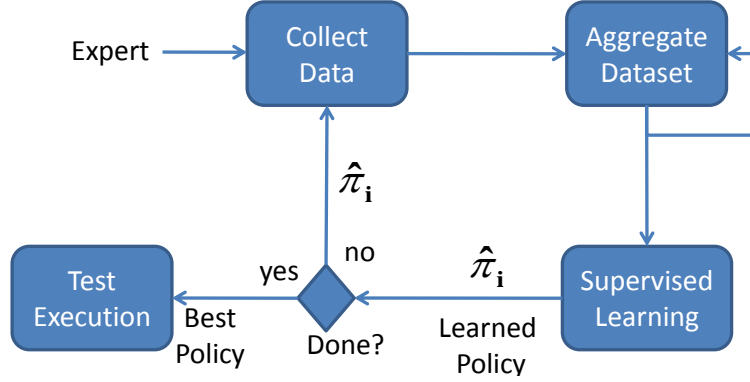


Figure 3.4: Diagram of the DAGGER algorithm for imitation learning.

A concrete example on how this algorithm is applied in practice is demonstrated in a car racing game in the experiments (Chapter 5), where we attempt to learn a policy that can steer the car properly based on the input game image as the car drives at fixed speed. In this task, a first dataset of game images, with associated human player steering, commanded via a joystick, is collected during human play, to train a first policy. Then at each following iteration, the computer controls the car during play, according to its current policy, while the human player provide steering commands he would perform in the current situation with the joystick, in real time as the car is driven by the computer. The human commands are not executed, but simply recorded and associated to the current game image. This new data collected at each iteration is aggregated with all previously recorded data to train the next policy. This is depicted in Figure 3.5.

The intuition behind this algorithm is that over the iterations, we are building up the set of inputs that the learned policy is likely to encounter during its execution, and the corresponding necessary recovery behavior, based on previous experience (training iterations). By training on all this data, we obtain policies that can mimic the expert and the recovery behaviors for their likely failures. This algorithm can be interpreted as a online learning *Follow-The-Leader* algorithm in that at iteration n we pick the best policy $\hat{\pi}_{n+1}$ in hindsight, i.e. under all trajectories seen so far over the iterations. In general, we show below that DAGGER can use in any no-regret online learning algorithm to pick the sequence of policies $\hat{\pi}_{1:N}$ over the iterations of the algorithm and that this is sufficient to provide good guarantees (see Figure 3.6).

To better leverage the presence of the expert in our imitation learning setting, we optionally allow the algorithm to use a modified policy $\pi_i = \beta_i \pi^* + (1 - \beta_i) \hat{\pi}_i$ at iteration i that executes the expert controls a fraction of the time (with probability β_i at each step) while collecting the next dataset. This is often desirable in practice as the first few

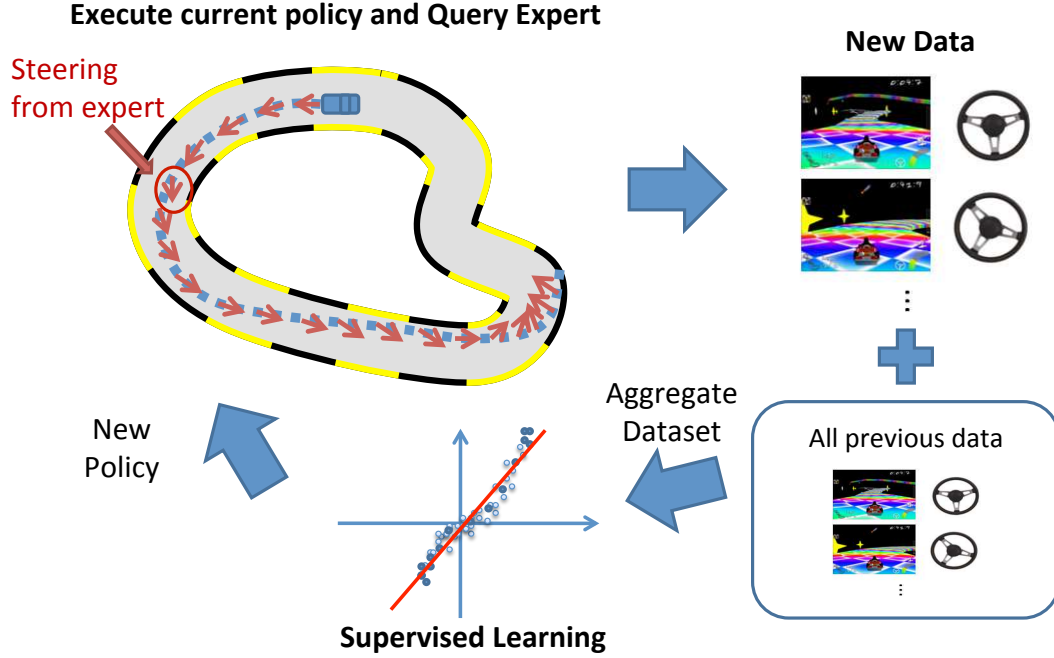


Figure 3.5: Depiction of the DAGGER procedure for imitation learning in a driving scenario.

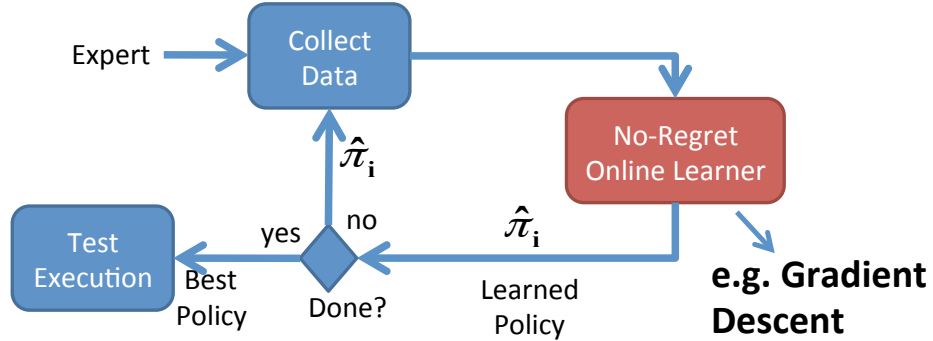


Figure 3.6: Diagram of the DAGGER algorithm with a general online learner for imitation learning.

policies, with relatively few data points, may make many more mistakes and visit states that are irrelevant as the policy improves. We will typically use $\beta_1 = 1$ so that we do not have to specify an initial policy $\hat{\pi}_1$ before getting data from the expert's behavior. Then we could choose $\beta_i = p^{i-1}$ to have a probability of using the expert that decays exponentially as in SMILE and SEARN. The only requirement is that $\{\beta_i\}$ be a sequence such that $\bar{\beta}_N = \frac{1}{N} \sum_{i=1}^N \beta_i \rightarrow 0$ as $N \rightarrow \infty$. The simple, parameter-free version of the


```

Initialize  $\mathcal{D} \leftarrow \emptyset$ .
Initialize  $\hat{\pi}_1$  to any policy in  $\Pi$ .
for  $i = 1$  to  $N$  do
  Let  $\pi_i = \beta_i \pi^* + (1 - \beta_i) \hat{\pi}_i$ .
  Sample  $T$ -step trajectories using  $\pi_i$ .
  Get dataset  $\mathcal{D}_i = \{(s, \pi^*(s))\}$  of visited states by  $\pi_i$  and actions given by expert.
  Aggregate datasets:  $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_i$ .
  Train classifier  $\hat{\pi}_{i+1}$  on  $\mathcal{D}$  (or use online learner to get  $\hat{\pi}_{i+1}$  given new data  $\mathcal{D}_i$ ).
end for
Return best  $\hat{\pi}_i$  on validation.

```

Algorithm 3.6.1: DAGGER Algorithm.

algorithm described above is the special case $\beta_i = I(i = 1)$ for I the indicator function, which often performs best in practice (see Chapter 5). The general DAGGER algorithm is detailed in Algorithm 3.6.1.

Analysis

We now provide a complete analysis of this DAGGER procedure, and show how the strong no-regret property of online learning procedures can be leveraged, in this interactive learning procedure, to obtain good performance guarantees. Again here, we seek to provide a similar analysis to previously analyzed methods that seeks to answer the following question : if we can find good policies at mimicking the expert on the aggregate dataset we collect during training, then how well the learned policy will perform the task?

The theoretical analysis of DAGGER relies primarily on seeing how learning iteratively in this algorithm can be viewed as an online learning problem and using the no-regret property of the underlying *Follow-The-Leader* algorithm on strongly convex losses (Kakade and Tewari, 2009) which picks the sequence of policies $\hat{\pi}_{1:N}$. Hence, the presented results also hold more generally if we use *any* other no-regret online learning algorithm we would apply to our imitation learning setting. In particular, we can consider the results here a reduction of imitation learning to no-regret online learning where we treat mini-batches of trajectories under a single policy as a single online-learning example. In addition, in Chapter 9, we also show that the data aggregation procedure works generally whenever the supervised learner applied to the aggregate dataset has sufficient stability properties. We refer the reader to Chapter 2 for a review of concepts related to online learning and no regret that is used for this analysis. All the proofs of the results presented here are in Appendix A.

Relation to Online Learning

We first begin by showing how we can view DAGGER as trying to find a good predictor in a particular online learning problem, as this is crucial to our analysis. Imagine an online learning problem, where at each iteration i , the learner picks a policy $\hat{\pi}_i \in \Pi$ that incurs loss on the loss function ℓ_i chosen by the adversary. In particular, consider the adversary to choose the loss ℓ_i such that for any $\pi \in \Pi$, $\ell_i(\pi) = \mathbb{E}_{s \sim d_{\pi_i}, a \sim \pi^*(s)}[\ell(s, a, \pi)]$, for $\pi_i = \beta_i \pi^* + (1 - \beta_i) \hat{\pi}_i$. Then we can see that DAGGER, at iteration i , is exactly collecting a dataset \mathcal{D}_i , that provides an empirical estimate of this loss ℓ_i . Additionally, when DAGGER trains on the aggregate dataset \mathcal{D} at iteration i to choose $\hat{\pi}_{i+1}$, it is choosing the best policy in hindsight as in Follow-the-Leader, i.e. $\hat{\pi}_{i+1} = \arg \min_{\pi \in \Pi} \sum_{j=1}^i \ell_j(\pi)$ (or at least on the empirical estimates of each ℓ_j). Thus DAGGER as presented, corresponds to running Follow-the-Leader in a particular online learning problem where the adversary picks the sequence of loss $\{\ell_i\}_{i=1}^N$ as mentioned above. The importance of this relation that is shown in our detailed analysis is the following: if an algorithm can achieve no-regret on this particular online learning problem (i.e. against this particular adversary), then it must find good policies at mimicking the expert under their own induced distribution of states. More precisely, this will hold whenever there exists good policies at mimicking the expert on the aggregate dataset. These results also imply that one can use any no-regret online algorithm to choose the sequence of policies $\{\hat{\pi}_i\}_{i=1}^N$ against this same adversary.

Implication of No-Regret on Task Performance

We now move on to show how no-regret algorithms must guarantee finding policies that perform the task well, if policies with small loss exist on the aggregate training dataset. This is achieved by relating the performance of the policy at the task, directly to the performance of DAGGER on the online learning problem. That is, task performance is related to 2 quantities: 1) the regret at online learning and 2) the surrogate loss of the best policy in the class on the training aggregate dataset.

Let

$$\begin{aligned} \epsilon_{\text{class}} &= \min_{\pi \in \Pi} \sum_{i=1}^N \ell_i(\pi) \\ &= \min_{\pi \in \Pi} \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{s \sim d_{\pi_i}, a \sim \pi^*(s)}[\ell(s, a, \pi)] \end{aligned}$$

denote the minimum expected surrogate loss achieved by policies in the class Π on all the data over the N iterations of training (i.e. the minimum surrogate loss at mimicking the expert in hindsight). Denote the online learning average regret of the sequence of policies chosen by DAGGER,

$$\begin{aligned} \epsilon_{\text{regret}} &= \frac{1}{N} [\sum_{i=1}^N \ell_i(\hat{\pi}_i) - \min_{\pi \in \Pi} \sum_{i=1}^N \ell_i(\pi)] \\ &= \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{s \sim d_{\pi_i}, a \sim \pi^*(s)}[\ell(s, a, \hat{\pi}_i)] - \epsilon_{\text{class}}. \end{aligned}$$

We will show good guarantees for the “uniform mixture” policy $\bar{\pi}$, that at the beginning of any trajectory samples a policy π uniformly randomly among the policies $\{\hat{\pi}_i\}_{i=1}^N$ and executes this policy π for the entire trajectory. The task performance of this mixture policy corresponds to the average task performance of the policies chosen by DAGGER, i.e. $J(\bar{\pi}) = \frac{1}{N} \sum_{i=1}^N J(\hat{\pi}_i)$. We analyze this mixture policy for convenience of theoretical analysis. However, good guarantees for this mixture policy implies immediately good performance for 1) the best policy $\hat{\pi}$ in the sequence $\hat{\pi}_{1:N}$, i.e. $J(\hat{\pi}) = \min_{i \in 1:N} J(\hat{\pi}_i) \leq J(\bar{\pi})$, and 2) the last policy $\hat{\pi}_N$ when the distribution of visited states converge over the iterations. Thus by analyzing and bounding $J(\bar{\pi})$, we will at the same time provide guarantees for common choices of policies one would use at test time after DAGGER terminates.

Assume the loss ℓ is non-negative and bounded by ℓ_{\max} , and $\beta_i \leq (1 - \alpha)^{i-1}$ for all i for some constant α ⁸. Then the following holds in the infinite sample case (i.e. if at each iteration of DAGGER we would collect an arbitrarily large amount of data by running the current policy):

Theorem 3.6.1. *If the surrogate loss ℓ is the same as the task cost function C (or upper bounds it), then after N iterations of DAGGER:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq T[\epsilon_{\text{class}} + \epsilon_{\text{regret}}] + O\left(\frac{\ell_{\max} T \log T}{\alpha N}\right).$$

Thus if a no-regret online algorithm is used to pick the sequence of policies $\hat{\pi}_{1:N}$, then as the number of iterations $N \rightarrow \infty$:

$$\lim_{N \rightarrow \infty} J(\bar{\pi}) \leq T\epsilon_{\text{class}}$$

Proof. To illustrate the idea of the proof technique and how this result simply follows from the no-regret property, we present here the proof for the simple case where $\beta_i = 0$ for all i . The complete proof for the general case of non-zero β_i can be found in Appendix A.

$$\begin{aligned} J(\bar{\pi}) &= \frac{1}{N} \sum_{i=1}^N J(\hat{\pi}_i) \\ &= \frac{1}{N} \sum_{i=1}^N T \mathbb{E}_{s \sim d_{\hat{\pi}_i}, a \sim \pi^*(s)} [\ell(s, a, \hat{\pi}_i)] \\ &= \frac{1}{N} \sum_{i=1}^N T \mathbb{E}_{s \sim d_{\pi_i}, a \sim \pi^*(s)} [\ell(s, a, \hat{\pi}_i)] \\ &= T \left[\frac{1}{N} \sum_{i=1}^N \ell_i(\pi_i) \right] \\ &= T[\epsilon_{\text{class}} + \epsilon_{\text{regret}}] \end{aligned}$$

where the 3rd equality uses the fact that $d_{\hat{\pi}_i} = d_{\pi_i}$ for all i since here we assumed $\beta_i = 0$ for all i . In the general case where $\beta_i \neq 0$, this step turns into an inequality where an

⁸e.g. the parameter-free version of DAGGER corresponds to $\alpha = 1$, taking as a definition $0^0 = 1$.

additional term is introduced. This adds a term that is $O\left(\frac{\ell_{\max} T \log T}{\alpha N}\right)$ to the overall bound (when $\beta_i = (1-\alpha)^{i-1}$). See Appendix A. Finally, $J(\hat{\pi}) \leq J(\bar{\pi})$ since the minimum is always lower or equal to the average. \square

This last result also implies good regret guarantees (in surrogate loss) for the uniform mixture policy $\bar{\pi}$ under its induced test trajectories:

Corollary 3.6.1. *After N iterations of DAGGER:*

$$R(\bar{\pi}) \leq T\epsilon_{\text{regret}} + O\left(\frac{\ell_{\max} T \log T}{\alpha N}\right).$$

Thus if a no-regret online algorithm is used to pick the sequence of policies $\hat{\pi}_{1:N}$, then as the number of iterations $N \rightarrow \infty$:

$$\lim_{N \rightarrow \infty} R(\bar{\pi}) \leq 0$$

Proof. It suffice to note that when the task cost function is the surrogate loss (as in the previous theorem), then $R(\bar{\pi}) = J(\bar{\pi}) - T\epsilon_{\text{class}}$, and thus the last theorem proves this corollary. \square

This indicates the total expected regret of the mixture policy is directly related to the average online regret of the learner on the online learning problem, and goes to 0 whenever DAGGER uses a no-regret procedure.

More generally, when the cost function C is unknown and different from ℓ , we can still provide good performance bounds when the expert is robust, as discussed in the analysis of the Forward Training algorithm:

Theorem 3.6.2. *If the expert π^* is u -robust with respect to cost function C (as in Definition 3.4.1), then after N iterations of DAGGER:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq J(\pi^*) + uT[\epsilon_{\text{class}} + \epsilon_{\text{regret}}] + O\left(\frac{u\ell_{\max} T \log T}{\alpha N}\right).$$

Thus if a no-regret online algorithm is used to pick the sequence of policies $\hat{\pi}_{1:N}$, then as the number of iterations $N \rightarrow \infty$:

$$\lim_{N \rightarrow \infty} J(\bar{\pi}) \leq J(\pi^*) + uT\epsilon_{\text{class}}$$

In addition, when the distribution of state-action pairs of the policies in the sequence converge, the performance of π_N must be close to the performance of $\bar{\pi}$:

Theorem 3.6.3. *If there exists a state-action distribution D^* , scalar $\epsilon_{\text{conv}}^* \geq 0$ and a sequence $\{\epsilon_{\text{conv},i}\}_{i=1}^{\infty}$ that is $o(1)$, such that $\|D_{\hat{\pi}_i} - D^*\|_1 \leq \epsilon_{\text{conv}}^* + \epsilon_{\text{conv},i}$ for all i . Then for any cost function bounded in $[0, C_{\max}]$:*

$$\lim_{N \rightarrow \infty} J(\pi_N) \leq \lim_{N \rightarrow \infty} J(\bar{\pi}) + C_{\max} T \epsilon_{\text{conv}}^*$$

In theory, such convergence is not guaranteed to occur, although it often tends to occur in practice as the online algorithm makes smaller and smaller changes to the policy as N gets larger. In practice, this result reflects the typical observed behavior of the algorithm: performance tends to improve in the first few iterations and then stabilizes, and the last policy often achieves the best performance (or nearly so) among all policies in the sequence. After all, the last policy is the one trained with most data, and should intuitively tend to be better.

These results indicate how the task performance of the learned policy is related to the online regret at online learning and the training loss of the best policy. In the limit of iterations, the guarantees for DAGGER ends up very similar to the guarantees of Forward Training, i.e. performance degrades linearly with T (or uT) and the training loss ϵ_{class} . However it is not necessary to perform an arbitrarily large number of iterations; we only need N to be large enough to make the average online regret term negligible. By leveraging existing online learning results, the following corollaries indicate that the number of iterations required is often of order $\tilde{O}(T)$ or $O(T^2)$ for common loss ℓ and no-regret algorithms:

Corollary 3.6.2. *Suppose ℓ is strongly convex in π for all s, a and DAGGER uses Follow-the-Leader to pick the sequence of policies, then: If ℓ upper bounds C , then for any $\epsilon > 0$ after $\tilde{O}(T/\epsilon)$ iterations of DAGGER:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq T\epsilon_{\text{class}} + O(\epsilon).$$

For arbitrary cost C , if the expert π^ is u -robust with respect to C (as in Definition 3.4.1), then for any $\epsilon > 0$ after $\tilde{O}(uT/\epsilon)$ iterations of DAGGER:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq J(\pi^*) + uT\epsilon_{\text{class}} + O(\epsilon).$$

Corollary 3.6.3. *Suppose ℓ is convex in π for all s, a and DAGGER uses Follow-the-Regularized-Leader to pick the sequence of policies, then: If ℓ upper bounds the cost C , then for any $\epsilon > 0$ after $O(T^2/\epsilon^2)$ iterations of DAGGER:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq T\epsilon_{\text{class}} + O(\epsilon).$$

For arbitrary cost C , if the expert π^ is u -robust with respect to C (as in Definition 3.4.1), then for any $\epsilon > 0$ after $O(u^2T^2/\epsilon^2)$ iterations of DAGGER:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq J(\pi^*) + uT\epsilon_{\text{class}} + O(\epsilon).$$

While in theory, these results indicate that DAGGER needs more iterations than the Forward training procedure to obtain good guarantees, in practice, it often only takes very few iterations for DAGGER to find very good policies. For instance, in

most experiments we obtain good performance after only 3 to 5 iterations, and then performance improves more slowly (see Chapter 5). Thus in practice, DAGGER can be run for much fewer iterations than T , and still often obtain a very good policy. This makes DAGGER much more practical than Forward, as Forward can never be stopped before iterating and training T policies.

Despite needing more iterations in theory, in the following finite sample analysis, we show that DAGGER needs less total samples than Forward to obtain good guarantees. Intuitively, this is because by learning a single policy for all time steps, DAGGER can generalize the behavior across time step, and thus avoid having to learn from scratch the behavior at each step separately.

Sample Complexity

The previous results hold if during the execution of DAGGER, we would collect an infinite number of samples at each iteration, such that the online learning algorithm can evaluate exactly the expected loss ℓ_i , i.e. the loss on the exact distribution of states induced by the current policy π_i ⁹. In practice however, we only collect a small sample of trajectories (or states), such that the online learning algorithm only has access to an empirical estimate of ℓ_i when updating the policy. We show below that this does not change our main results, and that we can still guarantee to obtain a good policy with high probability after a sufficient number of iterations and enough total samples have been collected.

Suppose we sample m trajectories with π_i at each iteration i (or simply m i.i.d. states from d_{π_i} with their associated target expert action), and denote this dataset D_i . Let $\hat{\epsilon}_{\text{class}} = \min_{\pi \in \Pi} \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{(s,a) \sim D_i} [\ell(s, a, \pi)]$ be the empirical training surrogate loss of the best policy on the sampled data, then using Azuma-Hoeffding's inequality leads to the following generalization of the previous guarantees:

Theorem 3.6.4. *If the surrogate loss ℓ is the same as the task cost function C (or upper bounds it), then after N iterations of DAGGER collecting m i.i.d. samples per iteration, with probability at least $1 - \delta$:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq T[\hat{\epsilon}_{\text{class}} + \hat{\epsilon}_{\text{regret}}] + O\left(\frac{\ell_{\max} T \log T}{\alpha N} + \ell_{\max} T \sqrt{\frac{\log(1/\delta)}{mN}}\right).$$

Here $\hat{\epsilon}_{\text{regret}}$ simply denotes the average regret on the empirical loss over the iterations. Similarly:

⁹However note that in the case of deterministic systems, with deterministic policies and experts, then only 1 trajectory is needed to evaluate the expected loss. So this infinite sample analysis applies in practice to deterministic settings as well.

Theorem 3.6.5. *If the expert π^* is u -robust with respect to cost function C (as in Definition 3.4.1), then after N iterations of DAGGER collecting m i.i.d. samples per iteration, with probability at least $1 - \delta$:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq J(\pi^*) + uT[\hat{\epsilon}_{class} + \hat{\epsilon}_{regret}] + O\left(\frac{u\ell_{\max}T \log T}{\alpha N} + \ell_{\max}uT\sqrt{\frac{\log(1/\delta)}{mN}}\right).$$

Thus we can see that DAGGER, over all iterations, only needs a total of $O(T^2)$ samples to guarantee good performance:

Corollary 3.6.4. *Suppose ℓ is convex in π for all s, a and DAGGER uses Follow-the-Regularized-Leader to pick the sequence of policies, then: If ℓ upper bounds the cost C , then for any $\epsilon > 0$ after $O(T^2 \log(1/\delta)/\epsilon^2)$ iterations of DAGGER collecting $m = 1$ i.i.d. samples per iteration, with probability at least $1 - \delta$:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq T\hat{\epsilon}_{class} + O(\epsilon).$$

For any cost function C , if the expert π^* is u -robust with respect to C (as in Definition 3.4.1), then for any $\epsilon > 0$, after $O(u^2T^2 \log(1/\delta)/\epsilon^2)$ iterations of DAGGER collecting $m = 1$ i.i.d. samples per iteration, with probability at least $1 - \delta$:

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq J(\pi^*) + uT\hat{\epsilon}_{class} + O(\epsilon).$$

This result shows that DAGGER can be run by collecting a single sample at each iteration (e.g. by querying the expert at only a single state, randomly chosen among all time steps, along a single sampled trajectory of the current policy). After a total of $O(T^2)$ iterations, and a total of $O(T^2)$ samples, DAGGER guarantees a good policy with high probability.¹⁰

These finite sample results indicate that for tasks where the expert is robust (e.g. u is a small constant), DAGGER only needs order $O(T^2)$ samples over all iterations to obtain good guarantees. This is an improvement by a factor T compared to the Forward training procedure with the same robust expert conditions, and by a factor T^2 compared to the supervised learning approach. Here DAGGER improves on the sample complexity of Forward Training because it can generalize the learned behavior across many time steps, by learning a single policy, rather than learning the behavior from scratch at each time step.

¹⁰When the loss is strongly convex, a more refined analysis taking advantage of the strong convexity of the loss function (Kakade and Tewari, 2009) may lead to tighter generalization bounds that require N only of order $\tilde{O}(T \log(1/\delta))$, and thus only order $\tilde{O}(T)$ samples in total.

Discussion

DAGGER as a Reduction

DAGGER departs from the previous reductions, in that it effectively reduces the imitation learning problem to an online learning problem, rather than a typical supervised learning problem. This is not as strong as the general error or regret reductions considered in (Beygelzimer et al., 2005, Ross and Bagnell, 2010, Daumé III et al., 2009) which require only classification: we require a no-regret method or a (strongly) convex surrogate loss function, a stronger (albeit common) assumption. While the performance guarantee is in part related to the online regret, DAGGER should still be interpreted as an error reduction, as in the limit of iterations with a no-regret algorithm, task performance is related to the error, or loss, of the best policy in the class in hindsight. However, for the surrogate loss objective (or imitation loss), DAGGER can be interpreted as a regret reduction, as the regret on test trajectories is directly related to the online regret of the online learning task. In other sequential settings, or when cost information is available, we will also see that DAGGER can lead to regret reductions for the task performance with a similar learning strategy, where control performance is instead related directly to only the online regret and/or the regret on the aggregate dataset of the best predictor in the class to the bayes-optimal predictor (e.g. in Chapters 4, 7 and 8).

Remarks on Guarantees

It is important to note that our guarantees are reduction statements, i.e. they are relative guarantees to how well we can do at finding policies that mimic well the expert on the training data. Thus DAGGER may sometimes fail at finding good policies if no policies can mimic well the expert during training. It should be noted that all presented methods fail in this case, i.e. whenever there does not exist any policy that can mimic well the expert on the training data, ϵ_{class} is large, and no method has good performance. When this occurs, it suggests we may need a better class of predictors and/or better features. The distinction to the typical supervised learning approach is when good predictors exist on the training data. In this case, with DAGGER (and Forward), we always obtain a good policy. In contrast, the typical supervised learning approach may find policies with low training error, but still fail at obtaining a good policy to accomplish the task, due to the mismatch in training and testing distributions.

Using DAGGER with a randomized online algorithm

Our current presentation of DAGGER assumes that the online learner picks a policy $\hat{\pi}_i$ from the policy class Π at each iteration i . If instead we use a randomized online

learning algorithm, such as Weighted Majority (or Hedge), the online algorithm would instead pick a distribution over policies in Π . In this case, DAGGER can be applied with such randomized online algorithms, where the policy $\hat{\pi}_i$ is simply the stochastic policy defined by this distribution over policies; i.e. at each time step in the trajectory, we would randomly pick a policy from the distribution to execute in the current state. Note that it is important to randomize at each time step in the trajectory, and not simply pick a random policy at the beginning of the trajectory to execute for the entire trajectory. The latter would violate the common assumption made by randomized online algorithms that the particular examples they incur loss on are independent of the realization of the sampling by the online algorithm, to guarantee no-regret. By resampling a policy at every time step in the trajectory, the current state is always independent of the sampled policy that incurs loss on that state, and ensures that the randomized online algorithm will be no-regret on the generated trajectories during training. Resampling from the distribution picked by the online learner at every time step in the trajectory is required generally in all the sequential settings we present in latter chapters as well, whenever a randomized online algorithm is used (see Chapter 7 for a more detailed example of this).

Why not just collect data everywhere?

The main reason why DAGGER (and Forward) provide improved guarantees is that they can explore different course of actions where error occurs, and learn the proper recovery behavior. One may wonder why not simply collect data everywhere (e.g. by executing random actions or introducing noise in the actions, to collect data about the expert behavior) to allow observing all recovery behaviors. There are two reasons why this is a bad strategy. First it is very inefficient. Such learning strategy would require an exponential number of trajectories to explore all possibilities. As we only need to learn the proper behavior where the learned policy goes, this wastes a lot of effort on acquiring data which may be irrelevant. Instead, DAGGER focus its efforts on only the most relevant regions, and can get good performance with only a polynomial number of trajectories. The second reason why sampling everywhere is bad is in agnostic settings, where we may not be able to fit observed behavior well everywhere. In this case, the learner must tradeoff accuracy in different regions (as shown previously in Figure 1.7). Sampling everywhere could make the learner fit correctly regions that are irrelevant. Hence DAGGER, by focusing on collecting only data in regions that are likely to be encountered, forces the learner to be most accurate in these important regions.

Why not just use the last collected dataset as in Policy Iteration?

A typical policy iteration approach, applied to this imitation learning problem, would look only at the distribution of states induced by the last policy π_i , and minimize the

surrogate loss on this dataset to choose the next policy π_{i+1} . This is similar to many policy iteration methods in reinforcement learning. In our context, such methods can tend to be very unstable and keep oscillating between various policies, none of which performing the task well. Our experiments in Chapter 5 demonstrate that this is the common observed behavior of this approach.

Chapter 4

Learning Behavior using Cost Information

In this chapter we continue our investigation of techniques for learning behavior in scenarios where an expert may be present, but where additional cost information is available. All learning approaches presented in the Chapter 3 considered the task cost function C to be unknown. In scenarios where C is known, taking advantage of this extra cost information should intuitively lead to better performance. In particular, when we are simply minimizing a surrogate (classification or regression) loss ℓ , instead of the task cost function C , all errors at mimicking the expert are somewhat treated equally, and we ignore that some errors can be much more costly than others. For instance, errors that lead the learner to crash, or fall off a cliff, should be considered much more costly, than other errors that only slightly increase the time it takes to successfully complete the task. By taking into account the importance of accurately predicting the expert's action in different situations, the learner should be able to better tradeoff in which situations it potentially errors, in order to avoid very costly errors at all costs. For instance, it will prefer predictors that error slightly more often, but only in low cost situations, to predictors that makes fewer but more costly errors.

The algorithms we presented, Forward Training and DAGGER, can be extended to take this extra cost information into account in a straightforward fashion. In particular, in discrete action settings, where currently a classification loss is minimized over the iterations of training, we will instead minimize a cost-sensitive classification loss, where the classification loss associated with each action is related to its long-term cost for performing the task. Here, we will focus our exposition on discrete action settings; although continuous action settings may additionally be handled.

We first present an extension of Forward with this cost information, and then move on to show how this can be used within DAGGER. For DAGGER, we present two variants, where the second one can be applied to handle general model-free reinforcement learning


```

Initialize  $\pi_1, \pi_2, \dots, \pi_T$  arbitrarily.
for  $t = 1$  to  $T$  do
  Collect  $m$  data points as follows:
  for  $j = 1$  to  $m$  do
    Start new trajectory in some initial state drawn from initial state distribution
    Execute the policies  $\pi_1, \pi_2, \dots, \pi_{t-1}$ , at time 1 to  $t - 1$  respectively
    Execute some exploration action  $a_t$  in current state  $s_t$  at time  $t$ 
    Execute expert from time  $t + 1$  to  $T$ , and observe estimate of cost-to-go  $\hat{Q}$  starting
    at time  $t$ 
  end for
  Get dataset  $\mathcal{D} = \{(s_t, a_t, \hat{Q})\}$  of states, actions at  $t$ , with expert's cost-to-go.
  Train cost-sensitive classifier  $\pi_t$  on  $\mathcal{D}$ 
end for
Return non-stationary policy  $\hat{\pi}$ , such that at time  $t$  in state  $s$ ,  $\hat{\pi}(s, t) = \pi_t(s)$ 

```

Algorithm 4.1.1: Forward Training Algorithm with Cost-to-Go.

setting and does not require the presence of an expert (although it requires access to a good exploration distribution that can be provided by an expert).

4.1 Forward Training with Cost-to-Go

We now begin with our extension of Forward with cost information.

As in Section 3.4, we proceed by training a separate policy π_t for each time step t , in sequence from time 1 to T , over T iterations. Here, at each iteration t , instead of only observing the expert's actions in states reached at time t , after execution of $\pi_1, \pi_2, \dots, \pi_{t-1}$, to train π_t , we will instead explore random actions to perform at time t , followed by the execution of the expert's policy until the end of the trajectory, and observe the total cost of this sequence. This gives us data of the form (s, a, \hat{Q}^*) , where \hat{Q}^* is an estimate of the $(T - t + 1)$ -step cost (cost-to-go) of the expert's policy, when executed after action a starting in state s . The observed cost-to-go is often only an estimate, because of the stochasticity of the system (or the expert's policy itself), but in situations where both are deterministic, then we would observe the exact cost-to-go. Each trajectory performed at iteration t will give us one datapoint (s, a, \hat{Q}^*) , to train π_t , and multiple data would be collected through execution of many trajectories. After obtaining enough data, π_t is trained to minimize cost-to-go on the collected dataset, e.g. by solving a cost-sensitive classification or regression task (this is explained in more details below). This algorithm is detailed in Algorithm 4.1.1.

Observing the expert's cost-to-go tells us roughly how much cost we might expect to incur in the future, if we take this action now, and then can behave as well (or nearly so) as the expert from then on. Under the assumption that the expert is a good policy, and that the policy class Π contains similar good policies, then this gives us a rough

estimate of what good policies in Π will be able to achieve at future steps. Thus by minimizing this cost-to-go at each step, we will choose policies that lead to situations where incurring low future cost-to-go is possible. For instance, we will be able to observe that if some actions put the expert in situations where it cannot avoid falling off a cliff or crash, then these actions should be avoided at all cost, in favor of others where the expert is still able to recover at later steps.

We now describe in more details how to perform exploration, and train the policy at each iteration.

Full Information vs. Partial Information Setting

In standard cost-sensitive classification problems, a cost vector is given for each input features x in the training data, that indicates the cost of predicting each class or label for this input. This is a full information setting, where the cost of all predictions at a given input is known. This is not the case in the setting presented here, where for an observed input state s , we only have partial information of the cost vector, i.e. we only know the cost of one sampled action, and the cost of other actions are unknown. In some scenarios, especially those involving simulated environments, it is sometimes possible to obtain data as in a full information setting. To do so, when entering a state where we explore an action a , we would instead need to create multiple “copies” of the current state, and simulate a trajectory with the expert after the execution of each action $a \in A$ in this state, to obtain an estimate of the cost-to-go for all actions in that state. This is only possible when we can “copy” the state, or are able to put back the system directly in that state repeatedly. As mentioned, this is typically possible only in simulated environments. On real robots, it is typically not possible to put back the system in exactly the same state and one is typically only able to try one action in any visited state. However, even if we can only have partial information about the cost of a single action, it is still possible to transform this into a standard cost-sensitive classification problem, through importance weighting techniques, or use directly some cost-sensitive classification reductions, such as regression, that do not necessarily require cost information for all actions in every training input state. We describe this in detail below.

Training the Policy to Minimize Cost-to-Go

In the full information setting, the data collected at each iteration corresponds to a set of cost-sensitive classification examples. Training the policy at each iteration then simply corresponds to solving a cost-sensitive classification problem. That is, if we collect a dataset of m samples, $\{(s_i, \hat{Q}_i)\}_{i=1}^m$, where \hat{Q}_i is a cost vector of cost-to-go estimates for each action in s_i , then we would solve the cost-sensitive classification problem:

$\arg \min_{\pi \in \Pi} \sum_{i=1}^m \hat{Q}_i(\pi(s_i))$. However, this optimization problem often cannot be solved efficiently for many common policy class Π , e.g. the set of all linear classifiers. Nevertheless, several reductions of cost-sensitive classification to other convex optimization problems can be used, to obtain problems that can be optimized efficiently, while still guaranteeing good performance at this cost-sensitive classification task, as described in Section 2.2. For instance, a simple approach is to transform this into a regression problem of predicting the cost-to-go of each action in a given state, and then defining the policy as always picking the action with lowest predicted cost. That is, $\pi_t(s) = \arg \min_{a \in A} Q_t(s, a)$, for Q_t the learned regressor at iteration t , that minimizes the squared loss at predicting the cost-to-go estimates: $Q_t = \arg \min_{Q \in \mathcal{Q}} \sum_{(s_i, a_i, \hat{Q}_i) \in D_t} (Q(s_i, a_i) - \hat{Q}_i)^2$, where D_t is the dataset of all collected cost-to-go estimates at iteration t , and \mathcal{Q} the class of regressors considered (e.g. linear regressors). Other reductions to ranking, as described in Section 2.2, can be used and provides improved guarantees.

In the partial information setting, one can use directly the regression approach just described, and learn a regressor that predicts cost-to-go, on the observed cost-to-go of the state-action pairs explored during training. Additionally, another approach is to use importance weighting techniques to transform the problem into a standard cost-sensitive classification problem (Horvitz and Thompson, 1992, Dudik et al., 2011b). For instance a simple approach, is to define the cost-vector for every state in the training data as follows: make the cost of every unobserved action to be 0, and the cost of the observed action to be Q/p , if we observed it has cost Q , and the probability of exploring this action was p (Horvitz and Thompson, 1992). For example if we explore uniformly randomly, then $p = 1/|A|$, for $|A|$ the number of actions, so this would have the effect of multiplying the cost by $|A|$ when a cost is observed. By defining the cost-vector this way, the expected cost of any action corresponds to its true cost (i.e. with probability p , it has cost Q/p , with probability $1 - p$ it has cost 0, so in expectation: $p(Q/p) + (1 - p)0 = Q$). However, such techniques can often perform poorly because this cost weighting technique introduce high variance in the cost estimates (Dudik et al., 2011b). Other techniques that often achieve lower variance and can yield better results are described in Dudik et al. (2011b) and can be used to generate similar cost-sensitive classification examples, from only partial information examples. The resulting cost-sensitive classification problem can then be solved using any existing technique for cost-sensitive classification, e.g. any of the existing reductions mentioned above and in Section 2.2.

Exploration in Partial Information Setting

An important aspect of the algorithm in the partial information setting is that we must choose which action to explore to collect an estimate of the cost-to-go. A simple strategy that is easy to use in practice is to simply explore actions uniformly randomly. This

ensures that we will explore all actions equally, and in the limit, obtain an equal amount of data for all actions in all likely situations. This is however suboptimal. For instance, based on the data collected so far in the current iteration, we may be undecided about which policy is best among only a small subset of the policy class Π . In this case, it is only useful to collect data about actions that would help us figure out which policy is the best in this small subset. In particular, collecting data about any action not picked by any of these policy would be irrelevant.

This problem of choosing which action is best to explore, in the current state s , can be cast as a contextual bandit problem, and contextual bandit algorithms can be used to figure out the distribution of actions to sample from when exploring (Auer et al., 2002b, Beygelzimer et al., 2011). When applying these methods, the features of the visited state where we decide which action to explore would define the current context. While these algorithms will typically start by sampling actions uniformly randomly, as more data is collected in the current iteration, these algorithms will adapt the exploration strategy to explore actions that will provide most information, while also minimizing cost. Several contextual bandit algorithms come with nice guarantees, and are more efficient than uniform exploration (Langford and Zang, 2007).

However, in our setting, there is a distinction compared to standard bandit setting, in that we do not care about the cost of the explored actions during training. We are interested only in learning most efficiently (in as few data as possible) which policy is best. To do so, it would be more appropriate to use some recent bandit learning techniques where exploration and exploitation is decoupled (i.e. the learner can choose to observe the cost of a different action than the one where it incurs cost) (Avner et al., 2012). This can lead to some changes in the exploration strategy, and learn even more efficiently in some scenarios. However these techniques have not been extended to contextual bandit settings with policies yet. This would be required to be applicable in our setting here. Additionally, current contextual bandit algorithms cannot always be applied in our setting. The main reason is that current methods can only handle a limited number of scenarios, e.g. learning with a finite set of policies Π (Auer et al., 2002b), or learning linear regressors to predict the actions' cost (Li et al., 2010) in realizable settings. Developing efficient contextual bandit algorithms for fully general class of policies is still a very active area of research and a major open problem in machine learning. Future development in this area could be leveraged immediately here to provide efficient exploration strategies. However currently, we may need to resort to uniform exploration in practice, when no practical contextual bandit algorithm is known for the policy class Π we consider.

Analysis

We now provide an analysis of this Forward Training procedure with cost-to-go. Our analysis seeks to answer the following question: if on average, we can solve well the cost-sensitive classification problems over the iterations of training, then can we guarantee that the learned policy is not much worse than the expert? Our analysis will show that indeed this is the case, and that performance of the learned policy degrades with the average cost-sensitive regret (with respect to the bayes-optimal policy) on the cost-sensitive classification examples.

Let $\hat{\pi}$ denote the non-stationary policy learned with the forward training algorithm. Let $\epsilon_t = \mathbb{E}_{s \sim d_{\hat{\pi}}^t} [Q_{T-t+1}^*(s, \pi_t) - \min_{a \in A} Q_{T-t+1}^*(s, a)]$ the cost-sensitive regret of the learned policy π_t under the training distribution at iteration t . Here this is the cost-sensitive regret compared to the bayes-optimal policy under this training distribution, as defined in Section 2.2. Let $\epsilon = \frac{1}{T} \sum_{t=1}^T \epsilon_t$, the average cost-sensitive regret over the training iterations. Then:

Theorem 4.1.1. $J(\hat{\pi}) \leq J(\pi^*) + T\epsilon$.

Proof. This follows a similar proof to Theorem 3.4.3, except we use directly the fact that we minimize cost-to-go. Given our policy $\hat{\pi}$, consider the policy $\hat{\pi}_{1:t}$, which executes $\hat{\pi}$ in the first t -steps and then execute the expert π^* . Then

$$\begin{aligned}
 J(\pi) &= J(\pi^*) + \sum_{t=0}^{T-1} [J(\hat{\pi}_{1:T-t}) - J(\hat{\pi}_{1:T-t-1})] \\
 &= J(\pi^*) + \sum_{t=1}^T \mathbb{E}_{s \sim d_{\hat{\pi}}^t} [Q_{T-t+1}^*(s, \hat{\pi}) - V_{T-t+1}^*(s)] \\
 &\leq J(\pi^*) + \sum_{t=1}^T \mathbb{E}_{s \sim d_{\hat{\pi}}^t} [Q_{T-t+1}^*(s, \hat{\pi}) - \min_{a \in A} Q_{T-t+1}^*(s, a)] \\
 &\leq J(\pi^*) + \sum_{t=1}^T \epsilon_t \\
 &= J(\pi^*) + T\epsilon
 \end{aligned}$$

□

This theorem indicates that if on average we achieve small cost-sensitive classification regret, over the iterations of training, then we must learn a policy that does not perform the task much worse than the expert policy. Again, performance degrades linearly in the task horizon T , and the average cost-sensitive regret ϵ .

Discussion

Regret Reduction: In terms of learning reductions, this forward training procedure with cost-to-go can be interpreted as a *regret* reduction of imitation learning to a sequence of cost-sensitive classification problems. It is a regret reduction, as performance is related to the average cost-sensitive classification regret.

Relation to PSDP: The approach we present here has some similarities to PSDP (Bagnell et al., 2003). Both train a non-stationary policy over many iterations, training one policy for a particular time step at each iteration to minimize cost-to-go, except that PSDP does so in reverse order. That is, in this imitation learning setting, PSDP would start by training the policy for time T , then the one for $T - 1$, and so on, going backward in time up to time 1, and at iteration t , the policy for time step $T - t + 1$ would be chosen to minimize the cost-to-go of the already trained policies at later time steps, under the distribution of states of the expert at time $T - t + 1$. In some sense, PSDP assumes that in earlier steps (from time 1 to $T - t$) the expert (or policies very similar to it) are going to be executed, while Forward with cost-to-go, assumes that in future time steps, the expert (or policies very similar to it) are going to be executed. Forward may suffer from too optimistic cost-to-go estimates (e.g. if no policies in the policy class are as good as the expert), while PSDP may suffer from a train-test mismatch (it may choose policies that minimize cost-to-go for the wrong distribution of states).

Limitations: As just mentioned, in cases where the expert is much better than any policy in Π , then the expert’s cost-to-go may be a very optimistic estimate of the future cost that the learner will incur in future steps after taking a certain action. In this case, this approach may fail to learn policies that performs the task well, even though some good policies that can perform the task (but not as well as the expert) exists in the policy class. For example, consider a driving scenario, where one can take 2 roads to reach the goal, one of these roads is much shorter, but involves driving on a very narrow road next to cliffs on each side, while the other road, is much longer and takes more time to reach the goal, but is safer (wider and not next to any cliff). If in this example, the expert takes the short narrow road to reach the goal faster and there is no policy in the class Π that can drive without falling on this narrow road, but there exists policies that can take the longer road and safely reach the goal, this algorithm would fail to find these policies. The reason for this is that, as we minimize cost-to-go of the expert, we would always favor policies that heads toward the shorter narrow road. But once we are on that road, inevitably at some point we will encounter a scenario where no policies in the class can predict the same low cost-to-go actions as the expert (i.e. making ϵ large in the previous guarantee). The end result is that Forward will learn a policy that takes the short narrow road and eventually falls off the cliff, in these pathological scenarios. PSDP may lead to a better policy in this case, but this is unclear. While PSDP would be able to see that the trained policies it learned at later time steps cannot drive well on this narrow road and have high cost-to-go, the state distribution of examples, from the expert policy, would be states starting on this narrow road. It is unclear that PSDP would learn policies that can drive well on the other longer road, based on minimizing cost-to-go on examples from the narrow road. If PSDP do happen to learn policies that

can drive on the other longer road, then at the early time steps, PSDP will be able to learn that it is better to take the longer road. But if it doesn't learn to drive well on the longer road, then PSDP would still fail. Note also that the theoretical guarantee of PSDP in this example would be no better than Forward: inevitably at some time t (e.g. near the end of the narrow road), future policies trained by PSDP reaches the goal, but under the state distribution of the expert on the narrow road at time t , no policy can avoid falling off the cliff and minimize cost-to-go of future trained policies as well as the expert. This makes the ϵ term in the guarantee of PSDP large, and the guarantee of PSDP would be similarly bad to Forward.

4.2 DAGGER with Cost-to-Go

As mentioned before, a drawback of Forward in practice is that it needs to learn a separate policy for each time step, which can be impractical if T is large, and is also less efficient, in terms of sample complexity, as it does not allow to generalize the behavior across time steps. The DAGGER approach addresses these issues and can be applied with similar cost-to-go as Forward to provide similar guarantees.

Just as with Forward, the only modification to DAGGER to take into account cost-to-go, is to instead minimize the cost-to-go of the expert, rather than the classification loss of mimicking its actions. That is, in its simplest form, DAGGER would on the first iteration, collect data by simply observing the expert perform the task, and in each trajectory, at a uniformly random time t , explore an action a in the current state s , and observe the cost-to-go of the expert after performing this action, to generate cost example (s, a, Q) . It would then train a policy $\hat{\pi}_2$ to minimize the cost-to-go on this dataset. At following iterations n , DAGGER would collect data through interaction with the learner as follows: for each trajectory, start by using the current learner's policy $\hat{\pi}_n$ to perform the task, and at some uniformly random time t , explore an action a in the current state s , after which control is given to the expert and he gets executed up to time T , and we observe the cost-to-go, starting from s . This generates new examples of the cost-to-go of the expert (s, a, Q) , under the distribution of states visited by the current policy $\hat{\pi}_n$. This new data would be aggregated with all previous data to train the next policy $\hat{\pi}_{n+1}$, or in general, used by a no-regret online learner to update the policy and obtain $\hat{\pi}_{n+1}$. This is iterated for some number of iterations N and the best policy found is returned. Just as before, we optionally allow the algorithm to keep executing the expert's actions with small probability β_n , instead of always executing $\hat{\pi}_n$, up to the random time t where an action is explored and control is shifted to the expert. The general DAGGER algorithm with Cost-to-Go is detailed in Algorithm 4.2.1.

As discussed previously for the Forward approach with cost-to-go, in imitation learn-


```

Initialize  $\mathcal{D} \leftarrow \emptyset$ .
Initialize  $\hat{\pi}_1$  to any policy in  $\Pi$ .
for  $i = 1$  to  $N$  do
  Let  $\pi_i = \beta_i \pi^* + (1 - \beta_i) \hat{\pi}_i$ .
  Collect  $m$  data points as follows:
  for  $j = 1$  to  $m$  do
    Sample uniformly  $t \in \{1, 2, \dots, T\}$ .
    Start new trajectory in some initial state drawn from initial state distribution
    Execute current policy  $\pi_i$  up to time  $t - 1$ .
    Execute some exploration action  $a_t$  in current state  $s_t$  at time  $t$ 
    Execute expert from time  $t + 1$  to  $T$ , and observe estimate of cost-to-go  $\hat{Q}$  starting
    at time  $t$ 
  end for
  Get dataset  $\mathcal{D}_i = \{(s, a, \hat{Q})\}$  of states, actions, with expert's cost-to-go.
  Aggregate datasets:  $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_i$ .
  Train cost-sensitive classifier  $\hat{\pi}_{i+1}$  on  $\mathcal{D}$  (or use online learner to get  $\hat{\pi}_{i+1}$  given new
  data  $\mathcal{D}_i$ )
end for
Return best  $\hat{\pi}_i$  on validation.

```

Algorithm 4.2.1: DAGGER Algorithm with Cost-to-Go.

ing we will in general not be able to simulate all actions from any given state, to obtain the cost-to-go of each action and obtain directly cost-sensitive examples. That is, we have to deal with the same partial information setting rather than a full information setting. The same previously discussed techniques, such as the reduction to regression or importance weighting techniques in (Dudik et al., 2011b), can be leverage to deal with this, and the same exploration techniques could be used to decide which action to explore.

In this case, within DAGGER, the problem of choosing the sequence of policies $\hat{\pi}_1, \hat{\pi}_2, \dots, \hat{\pi}_N$ over the iterations, is viewed as an online cost-sensitive classification problem. Our analysis below demonstrates that any no-regret algorithm on such problems could be used to update the sequence of policies and provide good guarantees, similar to those for Forward with cost-to-go. To achieve this, when the policy class Π is finite, randomized online learning algorithms like weighted majority could be used. In general, when dealing with infinite policy classes (e.g. the set of all linear classifiers), no-regret online cost-sensitive classification is not always possible, at least with a known computationally tractable algorithm ¹. Instead, we would like to use convex relaxations that allow to learn online efficiently. This can be achieved using the reductions of cost-

¹In principle, for any class with finite VC dimension (or Natarajan dimension), we could identify a finite set of classifiers (polynomial in the amount of data), that covers all distinct labelings of the collected data with classifiers from the class, and use Weighted Majority on this set of classifiers. This would in most cases be computationally intractable.

sensitive classification to regression or ranking problems, as mentioned previously and in Section 2.2. This leads to convex online learning problems for common policy classes, for which tractable no-regret online learning algorithms exist (e.g. gradient descent).

Analysis

We now provide the analysis of this DAGGER procedure with cost-to-go, and show how the strong no-regret property of online learning procedures can be leveraged, in this interactive learning procedure, to obtain good performance guarantees. Again here, we seek to provide a similar analysis to previously analyzed methods that seeks to answer the following question : if we can find good policies, that can incur cost-sensitive classification loss not much worse than the expert on the aggregate dataset we collect during training, then how well the learned policy will perform the task?

Again our analysis of DAGGER relies on seeing how learning iteratively in this algorithm can be viewed as an online learning problem and using the no-regret property of the underlying online learning algorithm picking the sequence of policies $\hat{\pi}_{1:N}$. Here, the online learning problem is defined as follows: at each iteration i , the learner picks a policy $\hat{\pi}_i \in \Pi$ that incurs loss on the loss function ℓ_i chosen by the adversary, and defined as $\ell_i(\pi) = \mathbb{E}_{t \sim U(1:T), s \sim d_{\pi_i}^t} [Q_{T-t+1}^*(s, \pi)]$ for $U(1:T)$ the uniform distribution on the set $\{1, 2, \dots, T\}$ and $\pi_i = \beta_i \pi^* + (1 - \beta_i) \hat{\pi}_i$. We can see that DAGGER, at iteration i , is exactly collecting a dataset \mathcal{D}_i , that provides an empirical estimate of this loss ℓ_i .

Let $\epsilon_{\text{class}} = \min_{\pi \in \Pi} \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{t \sim U(1:T), s \sim d_{\pi_i}^t} [Q_{T-t+1}^*(s, a) - \min_a Q_{T-t+1}^*(s, a)]$ denote the minimum expected cost-sensitive classification regret achieved by policies in the class Π on all the data over the N iterations of training. Denote the online learning average regret of the sequence of policies chosen by DAGGER, $\epsilon_{\text{regret}} = \frac{1}{N} [\sum_{i=1}^N \ell_i(\hat{\pi}_i) - \min_{\pi \in \Pi} \sum_{i=1}^N \ell_i(\pi)]$.

We again show good guarantees for the “uniform mixture” policy $\bar{\pi}$, that at the beginning of any trajectory samples a policy π uniformly randomly among the policies $\{\hat{\pi}_i\}_{i=1}^N$ and executes this policy π for the entire trajectory. As before, this implies immediately good performance for the best policy $\hat{\pi}$ in the sequence $\hat{\pi}_{1:N}$, i.e. $J(\hat{\pi}) = \min_{i \in 1:N} J(\hat{\pi}_i) \leq J(\bar{\pi})$, and the last policy $\hat{\pi}_N$ when the distribution of visited states converge over the iterations.

Assume the cost-to-go of the expert Q^* is non-negative and bounded by Q_{\max}^* , and $\beta_i \leq (1 - \alpha)^{i-1}$ for all i for some constant α ². Then the following holds in the infinite sample case (i.e. if at each iteration of DAGGER we would collect an arbitrarily large amount of data by running the current policy):

²e.g. the parameter-free version of DAGGER corresponds to $\alpha = 1$, using $0^0 = 1$.

Theorem 4.2.1. *After N iterations of DAGGER with cost-to-go:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq J(\pi^*) + T[\epsilon_{\text{class}} + \epsilon_{\text{regret}}] + O\left(\frac{Q_{\max} T \log T}{\alpha N}\right).$$

Thus if a no-regret online algorithm is used to pick the sequence of policies $\hat{\pi}_{1:N}$, then as the number of iterations $N \rightarrow \infty$:

$$\lim_{N \rightarrow \infty} J(\bar{\pi}) \leq J(\pi^*) + T\epsilon_{\text{class}}$$

Proof. The proofs of this result is presented in Appendix A. \square

This theorem indicates that, after a sufficient number of iterations, DAGGER must find policies that perform the task not much worse than the expert, if there are policies in the class Π that have small cost-sensitive classification regret on the aggregate dataset (i.e. policies with cost-sensitive classification loss not much larger than that of the bayes-optimal classifier on this dataset).

This guarantee is similar to the guarantee of Forward with cost-to-go. In both cases, performances degrades linearly with T and the cost-sensitive classification regret. When reductions of cost-sensitive classification to other regression/ranking/classification problems are used, then our results can be combined with the existing cost-sensitive reduction results, to relate directly the task performance of the learned policy to the performance on the regression/ranking/classification problem.

Also note that the analysis we presented so far for both Forward and DAGGER with cost-to-go, abstracted away the issue of exploration and learning from finite data. These issues come into play in the sample complexity analysis. Such analysis here depends on many factors, such as which reduction and exploration method is used. To illustrate how such results can be derived, we provide a result for the special case where actions are explored uniformly randomly and the reduction of cost-sensitive classification to regression is used.

In particular, if $\hat{\epsilon}_{\text{regret}}$ denotes the empirical average online learning regret on the training regression examples collected over the iterations, and \hat{R}_{class} denotes the empirical regression regret of the best regressor in the class, on the aggregate dataset of regression examples, compared to the bayes-optimal regressor on this data, we have that :

Theorem 4.2.2. *After N iterations of DAGGER with cost-to-go, collecting m regression examples (s, a, t, Q) per iteration, guarantees that with probability at least $1-\delta$:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq J(\pi^*) + 2\sqrt{|A|}T\sqrt{\hat{R}_{\text{class}} + \hat{\epsilon}_{\text{regret}}} + O(\sqrt{\log(1/\delta)/Nm}) + O\left(\frac{Q_{\max} T \log T}{\alpha N}\right).$$

Thus if a no-regret online algorithm is used to pick the sequence of regressors $\hat{Q}_{1:N}$, then as the number of iterations $N \rightarrow \infty$, with probability 1:

$$\lim_{N \rightarrow \infty} J(\bar{\pi}) \leq J(\pi^*) + 2\sqrt{|A|}T\sqrt{\hat{R}_{\text{class}}}$$

Proof. The proofs of this result is presented in Appendix A. \square

This result demonstrates how the task performance of the learned policies with DAGGER, can be related all the way down to the regret on the regression loss at predicting the observed cost-to-go during training. In particular, it relates task performance to the square root of the online learning regret, on this regression loss, and the regression regret of the best regressor in the class to the bayes-optimal regressor on this training data. The appearance of the square root is particular to the use of this reduction to regression. The implications of this square root is that learning may take significantly longer, i.e. we may need the number of iterations N to be order $O(T^4)$, with the number of samples per iteration $m = 1$, to guarantee that the average online regret term and generalization error terms are negligible, instead of $O(T^2)$. However, other cost-sensitive classification reductions, such as those presented in (Langford and Beygelzimer, 2005, Beygelzimer et al., 2009) does not introduce this square root and would still allow efficient learning.

Discussion

DAGGER as a reduction: The DAGGER approach with cost-to-go can be interpreted as a *regret* reduction of imitation learning to no-regret online learning. It is a regret reduction, as here, performance is related directly to the online regret, and the cost-sensitive classification regret on the aggregate dataset. By minimizing cost-to-go, we obtain a regret reduction, rather than an error reduction when simply minimizing immediate classification loss as in Section 3.6.

Comparison to SEARN: DAGGER with cost-to-go presents many similarities to SEARN. From our point of view, DAGGER provides a more general learning approach by providing a reduction to online learning and allowing various schemes to update the policy, at each iteration, rather than the particular stochastic mixing update of SEARN. In fact, in many ways SEARN can be thought as a particular case of DAGGER, where the policy class is the set of distributions over policies, and an online coordinate descent algorithm is used in this space of distributions to update the distribution over policies at each iteration. An advantage of the more general view from DAGGER, is that we can use various update schemes by considering a variety of online learning algorithms, that are potentially more convenient or efficient in practice.

Both methods collect data in a similar fashion at each iteration, by executing the current policy up to a random time in the current trajectory and then collecting cost-to-go estimates for explored actions in the current state. A distinction is that SEARN collects cost-to-go of the current policy, after execution of the random action, instead of the cost-to-go of the expert. While SEARN is often used in practice with the approximation of

collecting cost-to-go of the expert (Daumé III et al., 2009), rather than the current policy, using the cost-to-go of the expert can lead both approaches to suffer from the same issues discussed previously for Forward with cost-to-go. That is, in cases where there are no policies in Π that can perform the task as well as the expert, the cost-to-go estimates of the expert will be optimistic, and this may lead the algorithm to learn policies that encounter situations where no policy in the class can perform the proper behavior of the expert, leading to bad performance. Again this would be reflected in the guarantee by making ϵ_{class} large. When collecting cost-to-go of the current policy, SEARN, just as with PSDP, may be able to learn that some regions should be avoided when no policy in the class can do well there. Additionally, by training under the distribution of states of the current policy, SEARN avoids the data mismatch issue that can affect PSDP. This suggests that DAGGER should be applied by collecting cost-to-go of the current policy as well, rather than the expert. We present such a version of DAGGER below. However, in this case, to provide good guarantees, we must collect cost-to-go of the current policy, under the state distribution of the expert (and not the current policy as in SEARN). This version of DAGGER is in some sense more similar to PSDP. This is discussed in more details below.

4.3 Reinforcement Learning via DAGGER with Learner’s Cost-to-Go

Here, we present an alternate version of DAGGER with cost-to-go, where instead of executing the current policy, and then switching to the expert to observe a cost-to-go, we instead execute the expert policy, and then switch to the current policy to collect cost-to-go of the learner’s current policy. This alternate version has similar guarantees to the previous version, but may work better in cases where no policy in the class is as good as the expert. For instance, it can learn to avoid regions of where no policy in the class performs well by observing these cost-to-go. In addition it can be generalized to address a general model-free reinforcement learning setting, where we simply have a state exploration distribution we can sample from, from which we collect examples of the current policy’s cost-to-go. This is very similar to how PSDP (Bagnell et al., 2003) proceeds, and in some sense, the algorithm we present here provides a DAGGER equivalent to PSDP. However, by learning a stationary policy instead of a non-stationary policy, DAGGER can generalize across time-steps and potentially lead to more efficient learning than PSDP, and be practical in problems where T is large or infinite. We now describe this alternate version of DAGGER with cost-to-go and present its analysis.

As in PSDP, we assume that we are given a state exploration distribution ν_t for all time t in $1, 2, \dots, T$. As will be justified by our theoretical analysis, ideally, these state


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Initialize  $\mathcal{D} \leftarrow \emptyset$ .
Initialize  $\hat{\pi}_1$  to any policy in  $\Pi$ .
for  $i = 1$  to  $N$  do
  Collect  $m$  data points as follows:
  for  $j = 1$  to  $m$  do
    Sample uniformly  $t \in \{1, 2, \dots, T\}$ .
    Sample state  $s_t$  from exploration distribution  $\nu_t$ .
    Execute some exploration action  $a_t$  in current state  $s_t$  at time  $t$ 
    Execute  $\hat{\pi}_i$  from time  $t + 1$  to  $T$ , and observe estimate of cost-to-go  $\hat{Q}$  starting at
    time  $t$ 
  end for
  Get dataset  $\mathcal{D}_i = \{(s, a, t, \hat{Q})\}$  of states, actions, time, with current policy's cost-to-
  go.
  Aggregate datasets:  $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_i$ .
  Train cost-sensitive classifier  $\hat{\pi}_{i+1}$  on  $\mathcal{D}$  (or use online learner to get  $\hat{\pi}_{i+1}$  given new
  data  $\mathcal{D}_i$ )
end for
Return best  $\hat{\pi}_i$  on validation.

```

Algorithm 4.3.1: DAGGER Algorithm with Learner's Cost-to-Go.

exploration distributions should be (close to) that of a (near-)optimal policy in the class Π . In the context where an expert is present, then this may simply be the distribution of states induced by the expert policy, i.e. $\nu_t = d_{\pi^*}^t$. In general, this may be the state distributions induced by some base policy we want to improve upon, or be determined from prior knowledge of the task.

Given the exploration distributions $\nu_{1:T}$, DAGGER proceeds as follows. At each iteration n , it collects cost-to-go examples by sampling uniformly a time $t \in \{1, 2, \dots, T\}$, sampling a state s_t for time t from ν_t , and then executes an exploration action a in s_t followed by execution of the current learner's policy π_n for time $t + 1$ to T , to obtain a cost-to-go estimate (s, a, t, Q) of executing a followed by π_n in state s at time t . In the particular case where the state distributions ν_t are that of a particular exploration policy π , then to sample s_t , we would simply execute the exploration policy π from time 1 to $t-1$, starting from the initial state distribution. Multiple cost-to-go estimates are collected this way and added in dataset D_n . After enough data has been collected, we update the learner's policy, to obtain π_{n+1} , using any no-regret online learning procedure, on the loss defined by the cost-sensitive classification examples in the new data D_n . This is iterated for some large number of iterations N . Initially, we may start with π_1 to be any guess of a good policy from the class Π , or use the expert's cost-to-go at the first iteration, to avoid having to specify an initial policy. This algorithm is detailed in Algorithm 4.3.1.

Analysis

Consider the online learning loss function L_n given to the online learning algorithm within DAGGER at iteration n . Assuming infinite data, it assigns the following loss to each policy $\pi \in \Pi$:

$$L_n(\pi) = \mathbb{E}_{t \sim U(1:T), s \sim \nu_t} [Q_{T-t+1}^{\hat{\pi}_n}(s, \pi)].$$

This loss represents the expected cost-to-go of executing π immediately for 1 step followed by current policy π_n , under the exploration distributions $\nu_{1:T}$.

This sequence of loss over the iterations of training corresponds to an online cost-sensitive classification problem, as in the previous DAGGER with cost-to-go algorithm. Let ϵ_{regret} be the average regret of the online learner on this online cost-sensitive classification problem after the N iterations of DAGGER:

$$\epsilon_{\text{regret}} = \frac{1}{N} \sum_{i=1}^N L_i(\pi_i) - \min_{\pi \in \Pi} \frac{1}{N} \sum_{i=1}^N L_i(\pi).$$

For any policy $\pi \in \Pi$, denote the average L_1 distance between ν_t and d_π^t over time steps t as:

$$D(\nu, \pi) = \frac{1}{T} \sum_{t=1}^T \|\nu_t - d_\pi^t\|_1.$$

Note that if $\nu_t = d_\pi^t$ for all t , then $D(\nu, \pi) = 0$.

Now assume the cost-to-go of the learned policies $\pi_1, \pi_2, \dots, \pi_N$ are bounded by Q_{\max} , for any state s and time t (in the worst case this is TC_{\max}). Denote $\hat{\pi}$ the best policy found by DAGGER over the iterations, and $\bar{\pi}$ the uniform mixture policy over $\pi_{1:N}$ defined as before. Then we have the following guarantee with this version of DAGGER with learner's cost-to-go:

Theorem 4.3.1. *For any policy $\pi' \in \Pi$:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq J(\pi') + T\epsilon_{\text{regret}} + TQ_{\max}D(\nu, \pi')$$

Thus, if a no-regret online cost-sensitive classification algorithm is used, then:

$$\lim_{N \rightarrow \infty} J(\bar{\pi}) \leq J(\pi') + TQ_{\max}D(\nu, \pi')$$

This theorem indicates that DAGGER must find policies that are as good as any other policy $\pi' \in \Pi$, whose state distribution $d_{\pi'}^t$ is close to ν_t (on average over time t). Note however, that since TQ_{\max} is generally $O(T^2)$, this only provides meaningful guarantees when $d_{\pi'}^t$ is very close to ν_t (on average over time t). Importantly, if $\nu_{1:T}$ corresponds to the state distribution of an optimal policy in class Π , then this theorem guarantees that DAGGER will find an optimal policy (within the class Π) in the limit.

This theorem provides a similar performance guarantee to the results for PSDP presented in (Bagnell et al., 2003). However, DAGGER has the advantage of learning a single stationary policy for test execution, instead of a non-stationary policy, allowing for improved generalization and more efficient learning. Note that DAGGER has stronger requirements: it needs a no-regret online cost-sensitive classification procedure, instead of simply a cost-sensitive supervised learner for PSDP. For finite policy classes Π , or using reductions of cost-sensitive classification as mentioned previously and in Section 2.2, we can still obtain convex online learning problems for which efficient no-regret algorithms exist.

The result presented here can be interpreted as a reduction of model-free reinforcement learning to no-regret online learning. It is a regret reduction, as performance is related directly to the online regret at the online cost-sensitive classification task. However its performance is limited by the quality of the exploration distribution. One could consider trying to adapt the exploration distributions $\nu_{1:T}$ over the iterations of training. It can be shown that if $\nu_{1:T}^i$ are the exploration distributions at iteration i , and we have a mechanism for making $\nu_{1:T}^i$ converge to the state distributions of an optimal policy in Π , as $i \rightarrow \infty$, then we would always be guaranteed to find an optimal policy in Π in the limit (see appendix A). However, at this point we do not know of any method that could be used to achieve this.

4.4 Discussion

Drawback of using Cost-to-Go: In practice, using DAGGER, Forward, or SEARN, with cost-to-go can often be impractical. This is because, collecting each cost-to-go estimate for a single state-action pair, involves executing an entire trajectory. In many settings, minimizing directly an imitation loss with DAGGER, as in Section 3.6, is much more practical as we can observe the action chosen by the expert in every visited state along a trajectory, and thus collect T data points per trajectory instead of only one. This makes a big difference in practice when T is large. A potential combination of the two approaches could be considered, where first a policy is found by DAGGER through simple imitation loss minimization, to get a good estimate of a reasonable policy, and then refine this policy by using the cost-to-go version of DAGGER (e.g. through additional gradient descent steps). By doing so, we may need fewer (expensive) iterations of DAGGER with cost-to-go to obtain a good policy.

Chapter 5

Experimental Study of Learning from Demonstrations Techniques

In the chapter, we demonstrate the efficacy and scalability of DAGGER experimentally in imitation learning settings, by comparing its performance to several methods we previously discussed, such as the naive supervised learning approach, SMILe and SEARN. We compare these methods extensively for learning game playing agents from game play data in two video game applications. The first is a racing game, called Super Tux Kart, where we attempt to learn to control the car from the observed game image, from data collected by observing human players. In the second application, we attempt to learn an agent that can play the popular video game Super Mario Bros. given only the objects observed in the current game image, from game play data of a planner that has full access to the entire level (upcoming unobserved terrain, enemies, objects, etc.) to make its decisions. These results were originally presented in [Ross et al. \(2011\)](#).

We additionally demonstrate the applicability of DAGGER on real robots, by applying it to train an autonomous quadrotor to fly through forest environments while avoid trees using its front facing camera (monocular vision). We also discuss several practical considerations when applying DAGGER in practice.

5.1 Super Tux Kart : Learning Driving Behavior

Super Tux Kart is a 3D racing game similar to the popular Mario Kart. Our goal is to train the computer to steer the kart moving at fixed speed on a particular race track, based on the current game image features as input (see Figure 5.1). A human player is used to provide demonstrations of the correct steering (analog joystick value in $[-1,1]$) for each of the observed game images in real time during play.

For this task, we attempt to learn a linear controller that updates the steering at 5Hz based on the current vector of image features. That is, if x is the vector of features

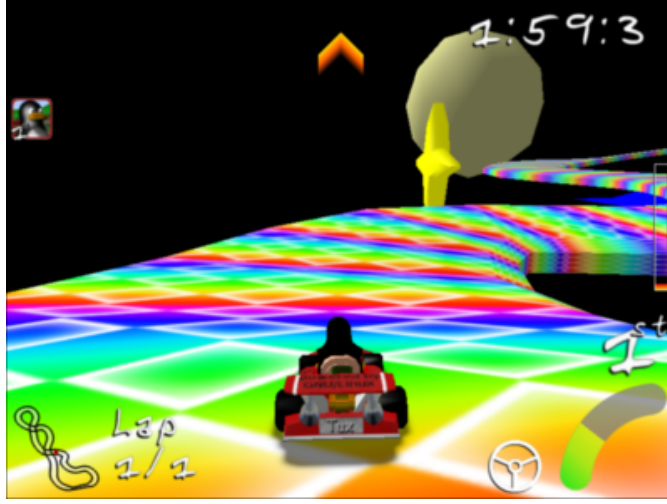


Figure 5.1: Image from Super Tux Kart’s Star Track.

of the image, the linear controller predicts and executes the steering $\hat{y} = w^\top x + b$, where w and b are the parameters that we learn from training data. Given the current 800x600 RGB pixel game image, we use as features directly the LAB color values of each pixel in a 25x19 resized image. Given a dataset of observed features and associated steering $\{(x_i, y_i)\}_{i=1}^n$, we optimize (w, b) by minimizing the ridge regression objective $L(w, b) = \frac{1}{n} \sum_{i=1}^n (w^\top x_i + b - y_i)^2 + \frac{\lambda}{2} w^\top w$, with regularizer $\lambda = 10^{-3}$ chosen from a preliminary validation dataset.

We compare performance on a race track called Star Track. As this track floats in space, the kart can fall off the track at any point (the kart is repositioned at the center of the track when this occurs). We measure performance in terms of the average number of falls per lap. We compare two other approaches to DAGGER on this task: 1) the traditional supervised learning approach, and 2) another approach, called SMILE, from our previous work in (Ross and Bagnell, 2010), which is an imitation learning variant of SEARN (described in more details in the next chapter) that also has similar guarantees to Forward Training and DAGGER.

For SMILE and DAGGER, we used 1 lap of training per iteration (~ 1000 data points) and run both methods for 20 iterations. For SMILE we choose parameter $\alpha = 0.1$ as in Ross and Bagnell (2010), and for DAGGER the parameter $\beta_i = I(i = 1)$ for I the indicator function. Figure 5.2 shows 95% confidence intervals on the average falls per lap of each method after 1, 5, 10, 15 and 20 iterations as a function of the total number of training data collected.

We first observe that with the baseline supervised approach where training always occurs under the human player’s trajectories that performance does not improve as more data is collected. This is because most of the training laps are all very similar and do not

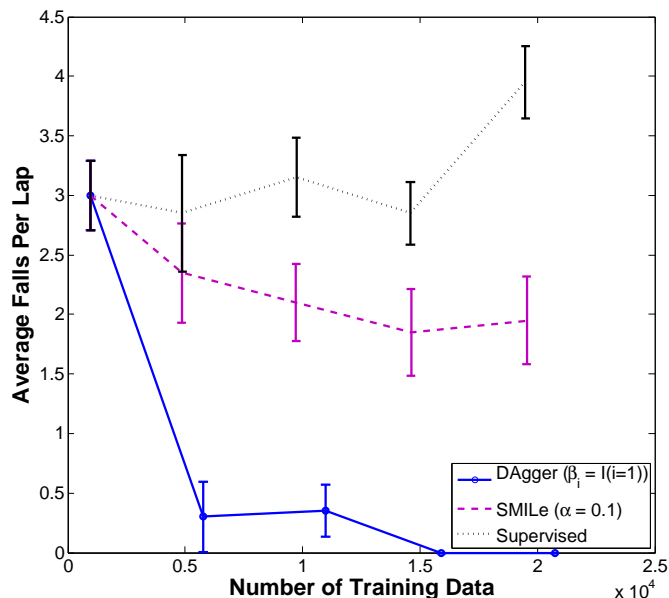


Figure 5.2: Average falls/lap as a function of training data.

help the learner to learn how to recover from mistakes it makes. With SMILE we obtain some improvements but the policy after 20 iterations still falls off the track about twice per lap on average. This is in part due to the stochasticity of the policy learned with this method which sometimes makes bad choices of actions. For DAGGER, we were able to obtain a policy that never falls off the track after 15 iterations of training. Even after 5 iterations, the policy we obtain almost never falls off the track and is significantly outperforming both SMILE and the baseline supervised approach. Furthermore, the policy obtained by DAGGER is smoother and looks qualitatively better than the policy obtained with SMILE. A video available on YouTube ([Ross, 2010a](#)) shows a qualitative comparison of the behavior obtained with each method.

5.2 Super Mario Bros.

Super Mario Bros. is a platform video game where the character, Mario, must move across each level by avoiding being hit by enemies and falling into gaps, and before running out of time. We used the simulator from a recent Super Mario Bros. AI competition ([Togelius and Karakovskiy, 2009](#)) that randomly generates levels of varying difficulty (more difficult gaps and types of enemies). Our goal is to train the computer to play this game based on the current game image features as input (see Figure 5.3). Our expert in this scenario is a near-optimal planning algorithm that has full access to the game’s internal state and can simulate exactly the consequence of future actions. In

essence it is cheating, as it has knowledge of the future unobserved terrain, enemies and objects, as well as exactly how enemies are moving or exactly when they may suddenly appear (e.g. it knows exactly when bullets are going to be fired by cannons), which is all information not typically available to a human player. By using all this “illegal” information, we could however obtain a very good planning agent that could complete most randomly generated level of any difficulty, and that is as good, if not better, than the world’s best human players. By learning from this expert, we hope to obtain a good agent that only uses “legal” information observed in the current game image.¹

In Super Mario Bros., an action consists of 4 binary variables indicating which subset of buttons we should press in {left,right,jump,speed}. We attempt to learn 4 independent



Figure 5.3: Captured image from Super Mario Bros.

linear SVMs (binary classifiers) that each predict whether one of the button should be pressed, and updates the action at 5Hz based on the vector of image features. For the input features x , each image is discretized in a grid of 22x22 cells centered around Mario and we extract 14 binary features to describe each cell (types of ground, enemies, blocks and other special items). A history of those features over the last 4 time steps is used, in addition to other features describing the last 6 actions and the state of

¹While it may seem a contrived application, such scenarios, where imitation learning is conducted by learning from another computational agent, rather than a human, can be of practical interest. For instance we may have a robot that can operate well autonomously with a very expensive sensor that provides lots of information, and/or a very computationally expensive control algorithm, and we would like to replace these expensive sensors by less informative cheaper ones, or replace the control algorithm by one that needs less computational resources, e.g. for cheaper mass deployment and commercialization. In such case, we could attempt to use imitation learning to learn good behavior when the robot only has access to the cheaper sensors, from the current autonomous behavior of the robot with access to the more expensive sensor and/or the computationally expensive control algorithm. Our Super Mario Bros application provides an exact example of this, where we seek to replace a slow planner with access to lots of information, by a fast decision rule with access to fewer information.

Mario (small, big, fire, touches ground), for a total of 27152 binary features (very sparse). Each binary action variable \hat{y}_k is predicted as $\hat{y}_k = I(w_k^\top x + b_k > 0)$, where w_k, b_k are the parameters of the k^{th} linear SVM we learn. Given a data of observed features and associated binary output $\{(x_i, y_i)\}_{i=1}^n$, these parameters are optimized by minimizing the SVM objective (regularized hinge loss): $L(w, b) = \frac{1}{n} \sum_{i=1}^n \max(0, 1 - y_i w^\top x_i) + \frac{\lambda}{2} w^\top w$, with regularizer $\lambda = 10^{-4}$ using stochastic gradient descent (Ratliff et al., 2007b, Bottou, 2009).

We compare performance in terms of the average distance traveled by Mario per level before dying, running out of time or completing the stage, on randomly generated levels of difficulty 1 with a time limit of 60 seconds to complete the level. The total distance of each level varies but is around 4200-4300 on average, so performance can vary roughly in $[0, 4300]$. Levels of difficulty 1 are fairly easy for an average human player, but contains most types of enemies and gaps, except with fewer enemies and gaps than levels of harder difficulties. We compare performance of DAGGER, SMILE and SEARN² to the supervised approach (Sup). With each approach, we collect 5000 data points per iteration (each stage is about 150 data points if run to completion) and run each methods for 20 iterations. For SMILE we choose parameter $\alpha = 0.1$ (Sm0.1) as in Ross and Bagnell (2010). For DAGGER we obtain results with different choice of the parameter β_i : 1) $\beta_i = I(i = 1)$ for I the indicator function (D0); 2) $\beta_i = p^{i-1}$ for all values of $p \in \{0.1, 0.2, \dots, 0.9\}$. We report the best results obtained with $p = 0.5$ (D0.5). We also report the results with $p = 0.9$ (D0.9) which shows the slower convergence of using the expert more frequently at later iterations. Similarly for SEARN, we obtain results with all choice of α in $\{0.1, 0.2, \dots, 1\}$. We report the best results obtained with $\alpha = 0.4$ (Se0.4). We also report results with $\alpha = 1.0$ (Se1) that corresponds to a typical EM or pure policy iteration approach that would only use data from the last iteration to optimize the policy for the next iteration. Figure 5.4 shows 95% confidence intervals on the average distance travelled per stage at each iteration as a function of the total number of training data collected. Again here we observe that with the supervised approach, performance stagnates as we collect more data from the expert demonstrations, as this does not help the particular errors the learned controller makes. In particular, a reason the supervised approach gets such a low score is that under the learned controller, Mario is often stuck at some location against an obstacle instead of jumping over it. Since the expert always jumps over obstacles at a significant distance away, the controller did not learn how to get unstuck in situations where it is right next to an obstacle. On the other hand, all the other iterative methods perform much better as they eventually learn to get unstuck in those situations by encountering them at the later iterations. Again in this experiment, DAGGER outperforms SMILE, and also outperforms SEARN for all

²We use the same cost-to-go approximation in Daumé III et al. (2009); in this case SMILE and SEARN differs only in how the weights in the mixture are updated at each iteration.

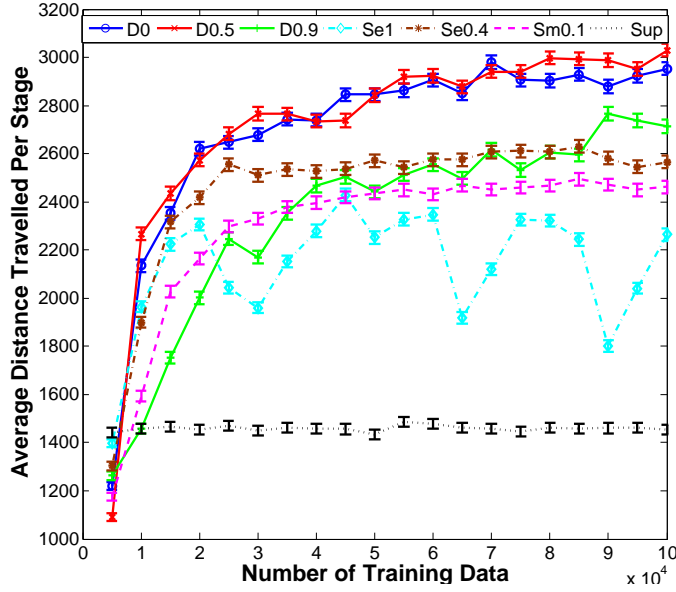


Figure 5.4: Average distance/level as a function of data.

choice of α we considered. When using $\beta_i = 0.9^{i-1}$, convergence is significantly slower and could have benefited from more iterations as performance was still improving at the end of the 20 iterations. Choosing 0.5^{i-1} yields slightly better performance (3030) then with the indicator function (2980). This is potentially due to the large number of data generated where mario is stuck at the same location in the early iterations when using the indicator; whereas using the expert a small fraction of the time still allows to observe those locations but also unstucks mario and makes it collect a wider variety of useful data. We also observe how unstable the policy iteration (Se1) approach is. The learned behavior oscillates between various policies that all achieve lower performance than DAGGER. Hence this demonstrates that using all previous data is better to make the learning algorithm more stable, as well as obtain improved performance. A video available on YouTube ([Ross, 2010b](#)) also shows a qualitative comparison of the behavior obtained with each method.

In addition, we also tried adding random actions during the execution of the expert demonstrations with the supervised learning approach to improve exploration of possible failures. This led to some improvement, to a performance around 2000. Performance could not be improved much further by trying to tweak the frequency of random actions vs expert actions. This shows that DAGGER can lead to much better exploration than random exploration, and focus learning only on the most relevant situations to improve performance.

5.3 Robotic Case Study: Learning Obstacle Avoidance for Autonomous Flight

While the previous section demonstrates the applicability of DAGGER in simulated environments, we also demonstrate that DAGGER can be successfully applied on real robotic systems. In particular, we demonstrate an application of DAGGER for learning a reactive controller for a small aircraft that can fly autonomously at low altitude in natural forest environments, while avoiding trees, using only a cheap camera for perception. This section covers an application of DAGGER that was presented in detail in [Ross et al. \(2013a\)](#).

Motivation

In the past decade Unmanned Aerial Vehicles (UAVs) have enjoyed considerable success in many applications such as search and rescue, monitoring, research, exploration, or mapping. While there has been significant progress in making the operation of UAVs increasingly autonomous, obstacle avoidance is still a crucial hurdle. For Micro Aerial Vehicles (MAVs) with very limited payloads it is infeasible to carry state-of-the-art radars ([Bernier et al., 2005](#)). Many impressive advances have recently been made using laser range finders (lidar) ([Bachrach et al., 2009](#), [Bry et al., 2012](#), [Scherer et al., 2007](#)) or Microsoft Kinect cameras (RGB-D sensors) ([Bachrach et al., 2012](#)). Both sensors are heavy and active, which leads to increased power consumption and decreased flight time. In contrast, passive vision is promising for producing a feasible solution for autonomous MAV navigation ([Roberts et al., 2012](#), [Dey et al., 2011](#), [Wendel et al., 2012](#)).

This application is primarily concerned with navigating MAVs that have very low payload capabilities, and operate close to the ground where they cannot avoid dense obstacle fields. We present a system that allows the MAV to autonomously fly at speeds of up to 1.5 m/s and altitudes of up to 4 meters above the ground through a cluttered forest environment (Figure 5.5), using passive monocular vision as its only exteroceptive sensor. We use DAGGER to train reactive “heading” policies based on flight trajectories through forest environments of a human pilot. Visual features extracted from the corresponding camera image are mapped to the control input provided by the pilot.

System

We use a cheap ($\sim \$300$), commercially available quadrotor helicopter, namely the Parrot ARDrone, as our airborne platform (see Figure 5.6). The ARDrone weighs only 420g and has a size of 0.3×0.3 m. It features a front-facing camera of 320×240 pixels and a 93 degree field of view (FOV), an ultrasound altimeter, a low resolution down-facing camera and an on-board Inertial Measurement Unit (IMU). The drone’s on-board



Figure 5.5: Application of DAGGER for autonomous MAV flight through dense forest areas. The system uses purely visual input from a single camera and imitates human reactive control.

controller stabilizes the drone and allows control of the UAV through high-level desired velocity commands (forward-backward, left-right and up-down velocities, as well as yaw rotation) and can reach a maximum velocity of about 5m/s. Communication is based on WiFi, with camera images streamed at about 10 – 15Hz. This allows us to control the drone on a separate computer that receives and processes the images from the drone, and then sends commands to the drone at 10Hz.



Figure 5.6: The Parrot ARDrone, a cheap commercial quadrotor.

Controller

We aim to learn a simple linear controller of the drones left-right velocity that mimics the pilots behavior to avoid trees as the drone moves forward at fixed velocity and altitude. That is, given a vector of visual features x from the current image, we compute a left-

right velocity $\hat{y} = w^\top x$ that is sent to the drone, where w are the parameters of the linear controller that we learn from the training examples. To optimize w , we solve a ridge regression problem at each iteration of DAGGER. Given the matrix of observed visual features X (each row is an observed feature vector), and the vector y of associated left-right velocity commands by the pilot, over all iterations of training, we solve $w = (X^\top X + R)^{-1} X^\top y$, where R is a diagonal matrix of per-feature regularization terms. As our feature vector (described below) is composed of various different types of features, that occupy a different fraction of the feature vector, we use a different regularizer for each feature type to make each type contribute more equally to the controls. In particular, we regularize each feature of a certain type proportionally to the number of features of that type. Features are also normalized to have mean zero and variance 1, based on all the observed data, before computing w , and w is applied to normalized features when controlling the drone.

Visual Features

Intuitively, to be able to avoid obstacles observed through the camera, the visual features need to provide indirect information about the three-dimensional structure of the environment. Accordingly, we focused on extracting features which have been shown to correlate well with depth cues such as those in [Michels et al. \(2005\)](#), specifically Radon transform statistics, structure tensor statistics, Laws' masks and optical flow.

We compute features over square windows in the image, with a 50% overlap between neighboring windows. The feature vectors of all windows are then concatenated into a single feature vector x . The choice of the number of windows is driven primarily by computational constraints. A 15×7 discretization (in width and height respectively) performs well and can be computed in real-time. Below is a description of the features we extract in each window:

Radon features (30 dim.) The Radon transform ([Helgason, 1999](#)) of an image is computed by summing up the pixel values along a discretized set of lines in the image, resulting in a 2D matrix where the axes are the two parameters of a line in 2D, θ and s . We discretize this matrix in to 15×15 bins, and for each angle θ the two highest values are recorded. This encodes the orientations of strong edges in the image.

Structure tensor statistics (15 dim.) At every point in a window the structure tensor ([Harris and Stephens, 1988](#)) (covariance matrix of the image gradient in x and y within a small neighborhood) is computed and the angle between the two eigenvectors is used to index in to a 15-bin histogram for the entire window. The corresponding eigenvalues are accumulated in the bins. In contrast to the Radon transform, the structure

tensor is a more local descriptor of texture. Together with Radon features the texture gradients are captured, which are strong monocular depth cues (Wu et al., 2004).

Laws’ masks (8 dim.) Laws’ masks (Davies, 1997) encode texture intensities. We use six masks obtained by pairwise combinations of one dimensional masks: (L)evel, (E)dge and (S)pot. The image is converted to the YCrCb colorspace and the LL mask is applied to all three channels. The remaining five masks are applied to the Y channel only. The results are computed for each window and the mean absolute value of each mask response is recorded.

Optical flow (5 dim.) Finally, we compute dense optical flow (Werlberger et al., 2010) and extract the minimum and maximum of the flow magnitude, mean flow and standard deviation in x and y . Since optical flow computations can be erroneous, we record the entropy of the flow as a quality measure. Optical flow is also an important cue for depth estimation as closer objects result in higher flow magnitude.

For this application, features must be computable fast enough so that there is as little delay as possible between the time the image is observed and the time a control is issued. This presented set of features can be computed at 15 Hz using the graphics processing unit (GPU) for dense optical flow computation. Although optical flow is helpful, we show in our experiments that removing this feature on platforms without a GPU does not harm the approach significantly. Additionally, the features need to be sufficiently invariant to changes between training and testing conditions so that the system does not overfit to training conditions. We therefore refrained from adding color features, as considerable variations under different illumination conditions and confusions between trees and ground, as well as between leaves and grass, might occur. An experimental evaluation of the importance of every feature is given below, along with a detailed evaluation.

In addition to visual features, we append 9 additional features: the low pass filtered history of previous commands (with 7 different exponentially decaying time periods), the sideways drift measured by the on-board IMU, and the deviation in yaw from the initial direction. Previous commands encode past motion and help smooth the controller output. The drift feature provides context to the pilot’s commands and accounts for motion caused by inertia. The difference in yaw is meant to reduce drift from the initial orientation to maintain the original heading.

Using DAGGER in Practice

In this application, DAGGER is applied as follows. Initially, the pilot flies the quadrotor, via a joystick, through forest environments for several trajectories, to collect an initial

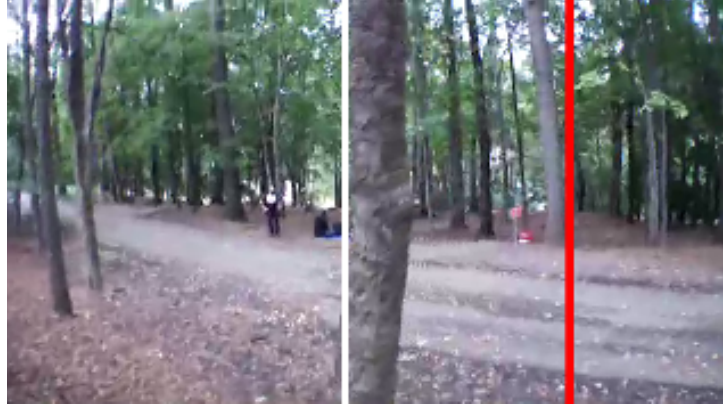


Figure 5.7: One frame from MAV camera stream. The white line indicates the current left-right velocity commanded by the drone’s current policy π_{n-1} while the red line indicates the pilot’s commanded left-right velocity. In this frame DAGGER is wrongly heading for the tree in the middle while the expert is providing the correct yaw command to go to the right instead. These expert controls are recorded for training later iterations but not executed in the current run.

dataset and train a first policy π_1 . At following iterations, the drone is placed in various forest environments and flies autonomously using its current policy π_{n-1} . The pilot provides the correct controls he would perform in the situations encountered along the autonomous trajectories flown by the drone, via the joystick. This allows the drone to collect data in new situations visited by the current policy, and learn the proper recovery behavior when these are encountered. The next policy π_{n+1} is obtained by training a policy on all the training data collected over all iterations (from iteration 1 to n).

Figure 5.7 shows the DAGGER control interface used to provide correct actions to the drone. As mentioned, at iteration $n > 1$, the drone’s current policy π_{n-1} is in control and the pilot just provides the correct controls for the scenes that the MAV visits. The pilot controls are recorded but not executed on the MAV. This results in some human-computer-interaction challenges:

- 1) After the first iteration, the pilot must be able to provide the correct controls without feedback of how the drone would react to the current command. While deciding whether the drone should go left or right is easy for the pilot, it can be hard to input the correct magnitude of the turn the drone should perform without feedback. In particular, we observed that this often makes the pilot turn excessively when providing the training examples after the first iteration. Performance can degrade quickly if the drone starts to mimic these imperfect actions. To address this issue, we provided partial feedback to the pilot by showing a vertical line in the camera image seen by the pilot that would slide left or right based on the current joystick command performed. As the line indicated roughly where the drone would move under the current joystick command, this interface

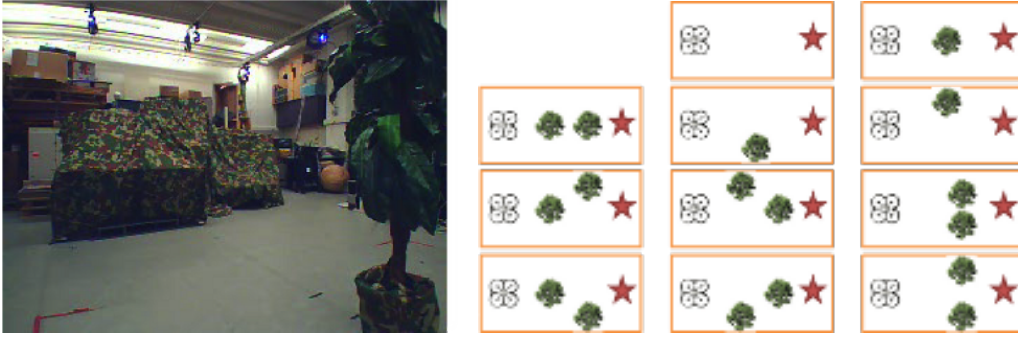


Figure 5.8: Left: Indoor setup in motion capture arena with fake plastic trees and camouflage in background. Right: The 11 obstacle arrangements used to train DAGGER for every iteration in the motion capture arena. The star indicates the goal location.

led to improved actions provided by the pilot (Figure 5.7).

2) In addition to the lack of feedback, providing the correct actions in real-time after the first iteration when the drone is in control can be hard for the pilot as he must react to what the drone is doing and not what he expects to happen: e.g., if the drone suddenly starts turning towards a tree nearby, the pilot must quickly start turning the other way to indicate the proper behavior. The pilot’s reaction time to the drone’s behavior can lead to extra delay in the correct actions specified by the pilot. By trying to react quickly, he may provide imperfect actions as well. This becomes more and more of an issue the faster the drone is flying. To address this issue, we allow the pilot to indicate the correct actions offline while the camera stream from the drone is replayed at slower speed (proportional to the drone’s speed), using the interface seen in Figure 5.7. By replaying the stream slower the pilot can provide more accurate commands and react more quickly to the drone’s behavior.

3) The third challenge is that DAGGER needs to collect data for all situations encountered by the current policy in later iterations. This would include situations where the drone crashes into obstacles if the current policy is not good enough. For safety reasons, we allow the pilot to take over or force an emergency landing to avoid crashes as much as possible. This implies that the training data used is not exactly what DAGGER would need, but instead a subset of training examples encountered by the current policy when it is within a “safe” region. Despite this modification, the guarantees of DAGGER still hold as long as a policy that can stay within this “safe” region can be learnt.

Indoor Experiments

We first tested our approach indoors in a motion capture arena. We used fake indoor trees as obstacles and camouflage to hide background clutter (Figure 5.8). Although being a

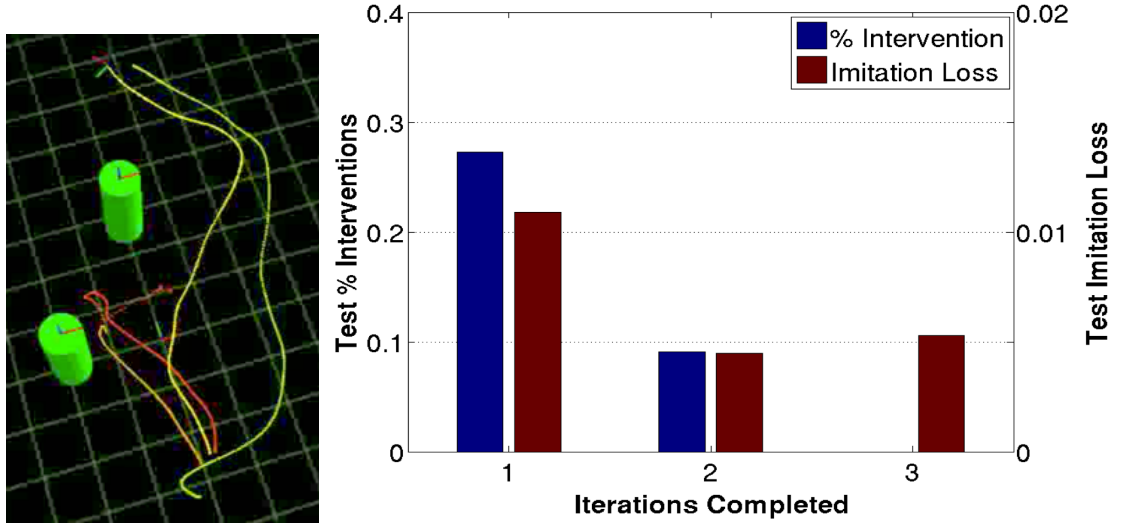


Figure 5.9: Left: Improvement of trajectory by DAGGER over the iterations. The rightmost green trajectory is the pilot demonstration. The short trajectories in red & orange show the controller learnt in the 1st and 2nd iterations respectively that failed. The 3rd iteration controller successfully avoided both obstacles and its trajectory is similar to the demonstrated trajectory. Right: Percentage of scenarios the pilot had to intervene and the imitation loss (average squared error in controls of controller to human expert on hold-out data) after each iteration of DAGGER. After 3 iterations, there was no need for the pilot to intervene and the UAV could successfully avoid all obstacles

very controlled environment that lacked many of the complexities of real outdoor scenes, it allowed us to obtain better quantitative results to determine the effectiveness of our approach.

The motion capture system was only used to track the drone and to adjust its heading so that it always headed straight towards a given goal location. The drone moved at a fixed altitude and forward velocity of 0.35m/s and we learnt a controller that controlled the left-right velocity using DAGGER over 3 training iterations. At each iteration, we used 11 fixed scenarios to collect training data, including 1 scenario with no obstacles, 3 with one obstacle and 7 with two obstacles (Figure 5.8).

Figure 5.9 qualitatively compares the trajectories taken by the MAV in the mocap arena after each iteration of training on one of the particular scenarios. In the first iteration, the green trajectory to the farthest right is the demonstrated trajectory by the human expert pilot. The short red and orange trajectories are the trajectories taken by the MAV after the 1st and 2nd iterations were completed. Note that both failed to avoid the obstacle. After the 3rd iteration, however, the controller learnt a trajectory which avoided both obstacles. The percentage of scenarios where the pilot had to intervene for the learnt controller after each iteration can be found in Figure 5.9. The number of

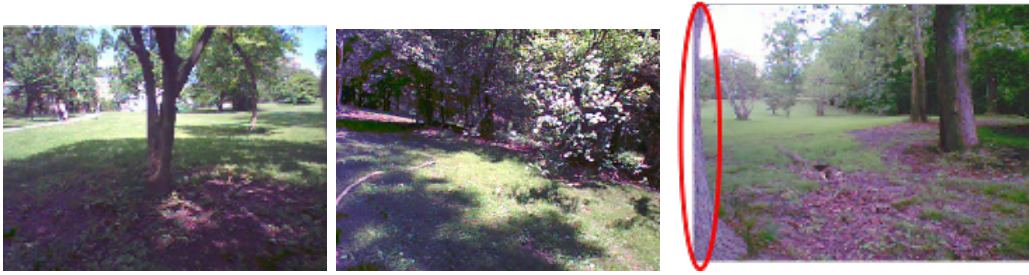


Figure 5.10: Common failures over iterations. While the controller has problems with tree trunks during the 1st iteration (left), this improves considerably towards the 3rd iteration, where mainly foliage causes problems (middle). Over all iterations, the most common failures are due to the narrow FOV of the camera where some trees barely appear to one side of the camera or are just hidden outside the view (right). When the UAV turns to avoid a visible tree a bit farther away it collides with the tree to the side.

required interventions decreased between iterations and after 3 iterations there was no need to intervene as the MAV successfully avoided all obstacles in all scenarios.

Outdoor Experiments

After validating our approach indoors in the motion capture arena, we conducted outdoor experiments to test in real-world scenarios. As we could not use the motion capture system outdoors to make the drone head towards a specific goal location, we made the drone move forward at a fixed speed and aimed for learning a controller that would swerve left or right to avoid any trees on the way, while maintaining the initial heading. Training and testing were conducted in forest areas while restraining the aircraft using a light-weight tether.

We performed two experiments with DAGGER to evaluate its performance in different regions, one in a park with relatively low tree density, and another in a dense forest.

Low-density region

The first area is a park area with a low tree density of approximately 1 tree per 12×12 m, consisting mostly of large trees and a few thinner trees. In this area we flew at a fixed velocity of around 1m/s, and learnt a heading (left-right) controller for avoiding trees using DAGGER over 3 training iterations, representing training data acquired over a total of 1km of flight. Then, we exhaustively tested the final controller over an additional 800m in the training area and a separate test area.

Qualitatively, we observed that the behavior of the drone improved over iterations. After the first iteration of training, the drone sometimes failed to avoid large trees even

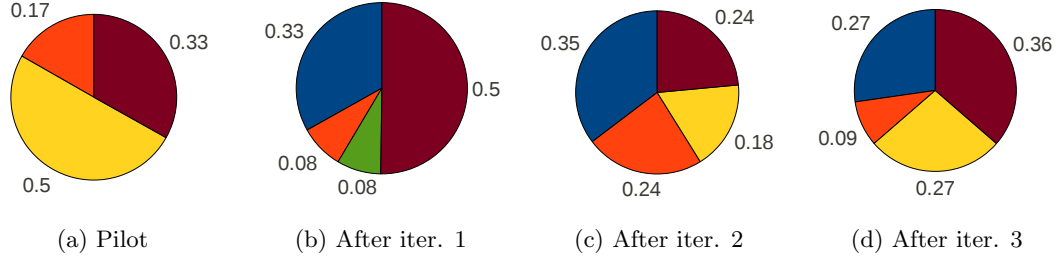


Figure 5.11: Percentage of failures of each type for DAGGER over the iterations of training in the high-density region. Blue: Large Trees, Orange: Thin Trees, Yellow: Leaves and Branches, Green: Other obstacles (poles, signs, etc.), Red: Too Narrow FOV. Clearly, a majority of the crashes happen due to a too narrow FOV and obstacles which are hard to perceive, such as branches and leaves.

when they were in the middle of the image in plain view (Figure 5.10, left). At later iterations however, this rarely occurred. On the other hand, we observed that the MAV had more difficulty detecting branches or bushes. The fact that few such obstacles were seen in the training data, coupled with the inability of the human pilot to distinguish them from the background, contributed to the difficulty of dealing with these obstacles. We expect that better visual features or improved camera resolution might help, as small branches often cannot be seen in 320×240 pixel images.

As expected, we found that the narrow field-of-view (FOV) was the largest contributor to failures of the reactive approach (Figure 5.10, right). This occurs when the learnt controller avoids a tree and, as it turns, a new tree comes into view. Such a situation may cause the controller to turn in a way such that it collides sideways into the tree it just avoided. This problem inevitably afflicts purely reactive controllers and can be solved by adding a higher level of reasoning (Bellingham et al., 2002), or memory of recent visual features.

The type of failures are broken down by the type of obstacle the drone failed to avoid, or whether the obstacle was not in the FOV. Overall, 29.3% of the failures were due to a too narrow FOV and 31.7% on hard to perceive obstacles like branches and leaves.

Quantitatively, we compare the evolution of the average distance flown autonomously by the drone before a failure occurred over the iterations of training. We compare these results when accounting for different types of failures in Figure 5.12 (left). When accounting for all failure types, the average distance flown per failure after all iterations of training was around 50m. On the other hand, when only accounting for failures that are not due to the narrow FOV, or branches/leaves, the average distance flown increases to around 120m. For comparison, the pilot successfully flew over 220m during the initial demonstrations, avoiding all trees in this sparse area.

To achieve these results the drone has to avoid a significant number of trees. Over

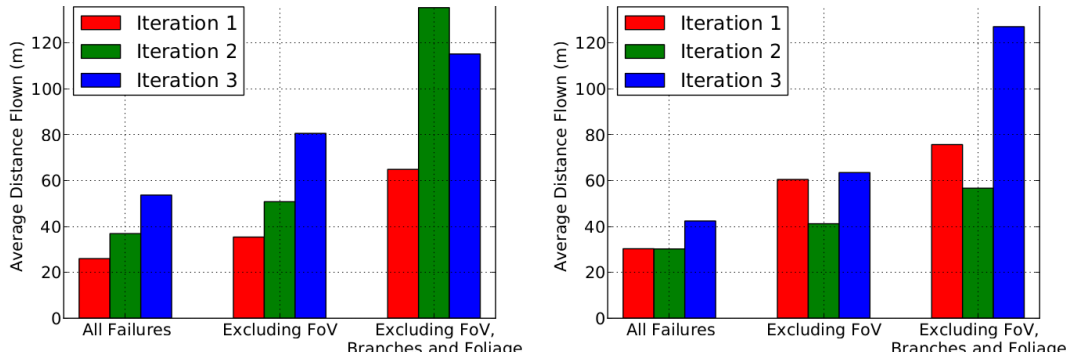


Figure 5.12: Average distance flown autonomously by the drone before a failure. Left: Low-Density Region, Right: High-Density Region.

all the data, we counted the number of times the MAV avoided a tree³, and observed that it passed 1 tree every 7.5m on average. We also checked whether the drone was actively avoiding trees by performing significant commands⁴. 41% of the trees were passed actively by our drone, compared to 54% for the human pilot.

Finally, we tested whether the learnt controller generalizes to new regions by testing it in a separate test area. The test area was slightly denser, around 1 tree per 10×10 m. The controller performed very well and was successfully able to avoid trees and perform at a similar level as in the training area. In particular, the drone was able to fly autonomously without crashing over a 100m distance, reaching the limit of our communication range for the tests.

High-density region

The second set of experiments was conducted in a thickly wooded region in a local forest. The tree density was significantly higher, around 1 tree per 3×3 m, and the area included a much more diverse range of trees, ranging from very small and thin to full-grown trees. In this area we flew at a faster fixed velocity of around 1.5m/s, and again learnt the heading (left-right) controller to avoid trees using DAGGER over 3 iterations of training. This represented a total of 1.2km of flight training data. The final controller was also tested over additional 400m of flight in this area. For this experiment however, we used the new ARDrone 2.0 quad-rotor helicopter, which has an improved HD camera that can stream 640×360 pixel images at 30Hz. The increased resolution probably helped in detecting the thinner trees.

Qualitatively, in this experiment we observed that the performance of the learnt behavior slightly decreased in the second iteration, but then improved significantly after

³A tree is *avoided* when the drone can see the tree pass from within its FOV to the edge of the image.

⁴A tree is *actively avoided* when the controller issues a command larger than 25% of the full range, passively in all other cases.

the third iteration. This is consistent with the theory which predicts that the performance of the learnt behavior *averaged over time* is guaranteed to increase, but that it might decrease on individual iterations. For example, we observed more failures to avoid both thin and large trees in the second iteration compared to the other iterations. This is shown in Figure 5.11, which compares the percentage of the different failures for the human pilot and after each iteration of DAGGER in this area.

We can also observe that the percentage of failures attributed to large or thin trees is smallest after the third iteration, and that again a large fraction of the failures occur when obstacles are not visible in the FOV of the MAV. Additionally, the percentages of failures due to branches or leaves diminishes slightly over the iterations, which could be attributed to the higher resolution camera that can better perceive these obstacles. A visualization of a typical sequence is given in Figure 5.13. Further qualitative results can be found in videos on YouTube (Ross et al., 2013b,c).

Quantitatively, we compare the evolution of the average distance flown autonomously by the MAV before a failure occurred over the iterations of training. Again, we compare these results when accounting for different types of failures in Figure 5.12. When accounting for all failure types, the average distance flown per failure after all iterations of training was around 40m. Surprisingly, despite the large increase in tree density and faster forward velocity, this is only slightly worse than our previous results in the sparse region. Furthermore, when only accounting for failures that are not due to the narrow FOV or branches and leaves, the average distance flown increases to 120m per failure, which is on par with our results in the sparser area. For comparison, when only accounting for failures due to tree trunks, the pilot flew around 500m in total during the initial demonstrations and only failed to avoid one thin tree. However, the pilot also failed to avoid thin branches and foliage more often (Figure 5.11). When accounting for all types of obstacles, the pilots average distance until failure was around 80m.

The increase in tree density required our MAV to avoid a significantly larger number of trees to achieve these results. Over all the data, we observed that it was avoiding on an average 1 tree every 5m. In this dense region, both the pilot and the drone had to use larger controls to avoid all the trees, leading to an increase in the proportions of trees that were passed actively. 62% of the trees were passed actively by the drone, compared to a similar ratio of 66% for the pilot.

Discussion of the Outdoor Results

We observed that much of the degradation in performance is due to the limited FOV. Two approaches could be used to mitigate these limitations: First, integrating a small amount of memory in the features used by DAGGER to overcome the simplest failure cases without resorting to a complete and expensive mapping of the environment. Second,



Figure 5.13: Example flight in dense forest. Images ordered from top ($t = 0s$) to bottom ($t = 6.6s$); with color-coded commands issued by DAGGER (in MAV's view). After avoiding tree A (frame 3), drone still rolls strongly to the left (frame 4), in part due to latency. Then tree B is avoided on the left (frame 5-7), rather than on the more intuitive right. Drone prefers this due to the drift feature, as inertia is already pushing it further to the left.

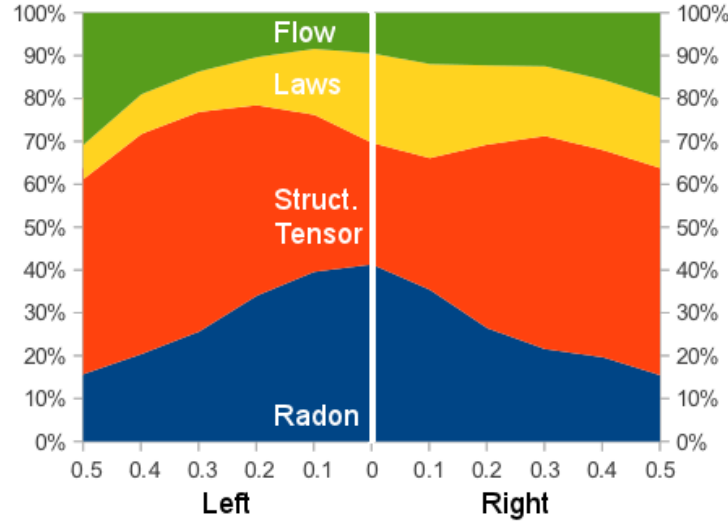


Figure 5.14: Breakdown of the contribution of the different features for different control prediction strengths, averaged over 9389 datapoints. Laws and Radon are more significant in cases where small controls are performed (e.g. empty scenes), whereas the structure tensor and optical flow are responsible for strong controls (e.g. in cases where the scene contains an imminent obstacle). A slight bias to the left can be seen, which is consistent to observations in the field. Best viewed in color.

using the biologically-inspired solution to simply ensure a wider FOV for the camera system. For example, pigeons, that rely mostly on monocular vision, and owls, that have binocular vision, have about 3 times and 1.5 times the FOV of our drone respectively.

Feature Evaluation

After verifying the general functionality of our approach, we evaluate the benefit of all four feature types. An ablative analysis on the data shows that the structure tensor features are the most important, followed by Laws features. Figure 5.14 shows how the contribution of different features varies for different control signal strengths. Optical flow, for example, carries little information in scenes where small commands are predicted. This is intuitive since in these cases there are typically no close obstacles and subsequently no significant variation in optical flow. In fact, removing the optical flow feature only results in a 6.5% increase in imitation loss. This is a significant result for platforms incapable of computing expensive flow computations at required update rates.

Anecdotally, Figure 5.15 shows the contribution of each of the features at different window centers in the image. While structure tensor features mainly fire due to texture in the background (indicating free space), strong optical flow vectors correspond to very close objects. In this example the predictor commands a hard left turn (numerical value: 0.47L on a scale of $[0,1]$), and all visual features contribute to this. Consistent with

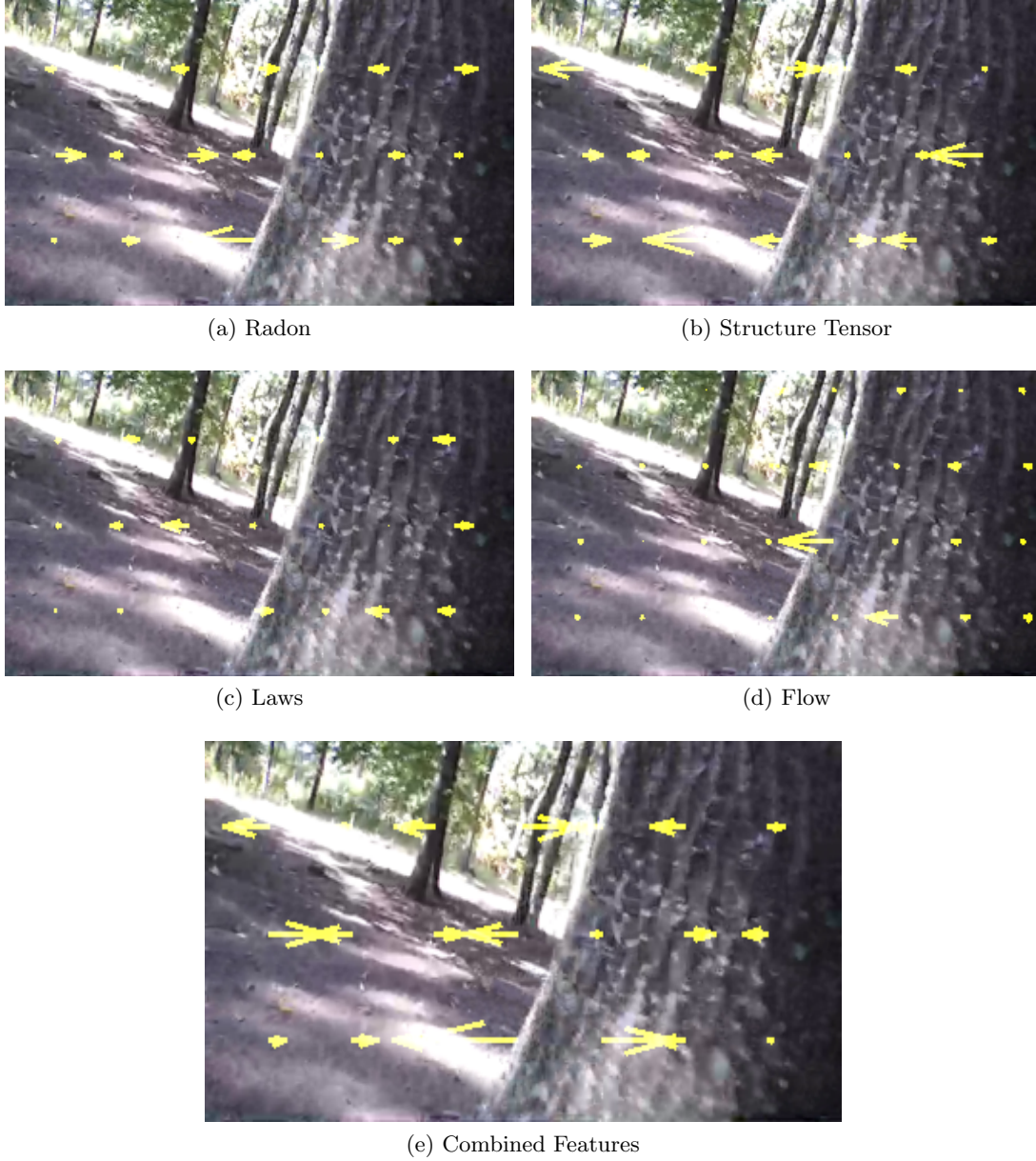


Figure 5.15: Visualization of the contribution of the different features to the predicted control. The overall control was a hard left command. The arrows show the contribution of a given feature at every window. Structure tensor features have the largest contribution in this example, while Radon has the least.

the above analysis, the contribution of the structure tensor was greatest (0.38L), Laws masks and optical flow contribute the same (0.05L) while Radon features provide the least contribution (0.01L). In this particular example, the non-visual features actually predict a small right command (0.02R).

Chapter 6

Learning Inference for Structured Prediction

After studying how iterative and interactive learning methods can learn good predictors for imitation learning tasks, we here show how the same techniques can be generalized and applied to general structured prediction tasks.

Structured prediction problems arise very frequently in many fields and have important applications in Natural Language Processing (e.g. Name-Entity Recognition, Part-of-Speech tagging, Machine Translation) (Daumé III et al., 2009, Zhao and Xing, 2007), Computer Vision (e.g. Scene Understanding, Depth Estimation, Image Denoising) (Munoz et al., 2009, Scharstein and Pal, 2007, Tappen et al., 2007) and Computational Biology (e.g. Protein Folding, Genomic Analysis, Phylogenetic Tree Estimation) (Liu, 2006, Xing, 2004, Felsenstein, 1981), among others. Inspired by the approaches of Tu and Bai. (2009), Daumé III et al. (2009), Munoz et al. (2010), we will tackle these problems by effectively reducing structured prediction tasks to sequential prediction tasks, where the same iterative and interactive learning strategies developed for imitation learning can be directly applied to tackle this problem. In particular, our approach will train directly an “inference” (or parsing/decoding) procedure, composed of a single or many predictors, that produces the high-dimensional output prediction from the observed input features by making a sequence of interdependent predictions. As will be made more clear below, the main idea behind our approach will be to train a procedure that “mimics” ideal inference. Again, by leveraging interaction with the learner, we will be able to provide strong guarantees on performance, as in the imitation learning setting.

We begin by briefly reviewing background material and state-of-the-art methods for structured prediction. We then present our sequence prediction approach, and how the previous methods we introduced for imitation learning, such as Forward Training, and DAGGER, can be applied directly in this setting. We then present a number of applications in Computer Vision and Perception, to demonstrate the effectiveness of our

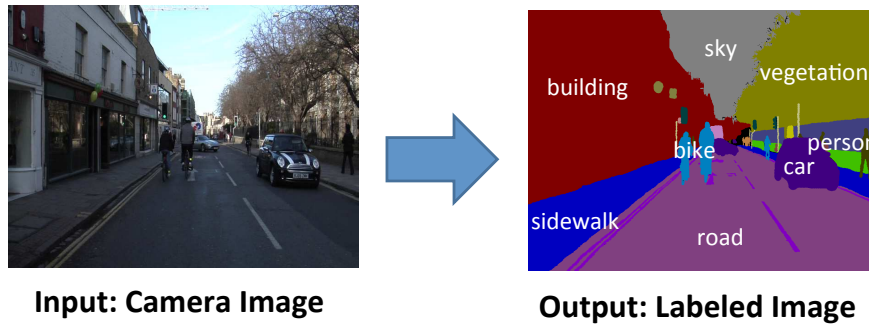


Figure 6.1: Example structured prediction application of image labeling. Images from CamSeq01 dataset (Fauqueur et al., 2007).

approach and compare to state-of-the art methods. In particular, we apply our techniques for handwriting recognition, 3D point cloud classification (predicting the object present at every point in LIDAR 3D point clouds), and 3D geometry estimation of a scene from a 2D image.

6.1 Preliminaries

Structured Prediction is interested in prediction problems where the output prediction is high-dimensional, and has some structure (e.g. in the dependencies between output variables). For instance, consider a scene understanding/image labeling task in computer vision where given an input image of $n \times m$ pixels, we want to output a labeled image of $n \times m$ labels that indicates the class of object present at each pixel (see Figure 6.1).

For many of these problems, spatial and temporal relationships between the output variables can be exploited to devise tractable learning and prediction procedures. For instance, in the example above, the label of a pixel is likely to be the same as its neighbors, as objects typically span a large number of pixels, and a small number of objects are present in the image (compared to the number of pixels). Pixels that are far away thus contain much less information about the label of a pixel. Such spatial relationships can be modeled (approximately) via independence relations between the output variables, which allow learning good models of data efficiently as we will see below.

Graphical Models and Inference

The predominant approach to tackle structured prediction problems is via graphical models. Graphical models are probabilistic models that encode explicitly the dependence and independence relations that exist between the input and output variables. Formally, a graphical model represents a joint (conditional) distribution over the output variables, via a factor graph (a bipartite graph between output variables and factors) defined by a

set of variable nodes V , a set of factor nodes (potentials) F and a set of edges E between them:

$$P(Y|X) \propto \prod_{f \in F} \phi_f(x_f, y_f),$$

where X, Y are the vectors of all observed features and output variables respectively, x_f the input features related to factor f and y_f the vector of outputs for each node connected to factor f . Such graphical model is known as a conditional random field (CRF) (Lafferty et al., 2001). A typical graphical model will have node potentials (factors connected to a single variable node) and pairwise potentials (factors connected between 2 nodes) (see Figure 6.2). It is also possible to consider higher order potentials by having a factor connecting many nodes (e.g., cluster/segment potentials as in Munoz et al. (2009)).

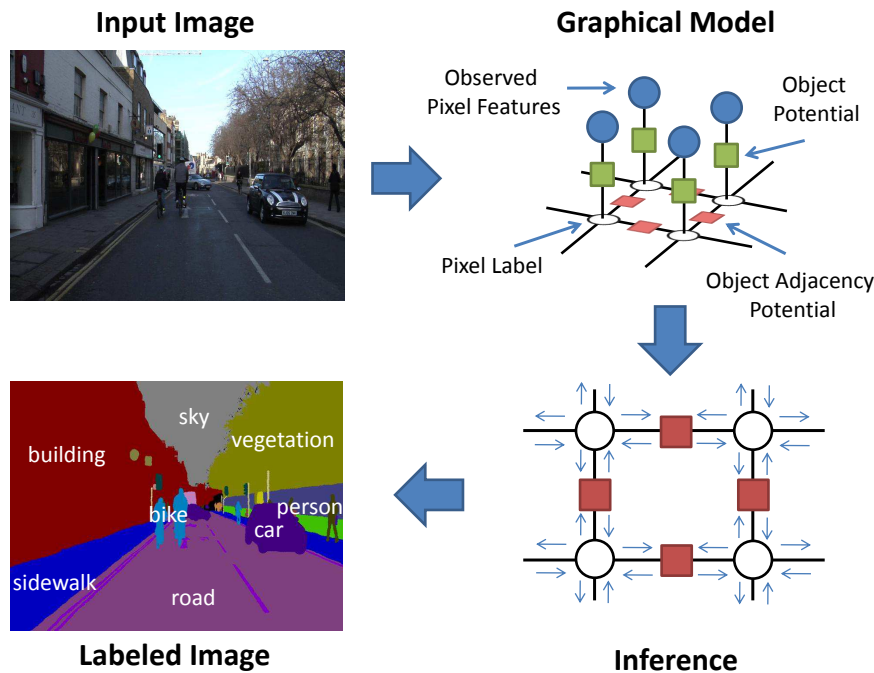


Figure 6.2: Graphical Model approach to Structured Prediction in the context of image labeling. Pairwise potentials model dependencies between objects at neighboring pixels and unary potentials model the likelihood of an object present at a pixel given the local image features. Inference, such as loopy belief propagation, is performed to find an approximate minimum energy solution which is returned as output.

Training a graphical model is achieved by optimizing the potentials ϕ_f on an objective function (e.g., margin, pseudo-likelihood, etc.) defined over training data where the correct high dimensional output Y is provided (e.g. the labeling of an entire image provided by a human) (Taskar et al., 2003, Kumar and Hebert, 2006, Finley and Joachims, 2008). For instance, it is often assumed that the potentials are log-linear so that the graphical model is in some exponential family of distribution. For a typical model with

node potentials ϕ_n and pairwise potentials ϕ_e , this means we would learn two weight vectors w_n and w_e such that:

$$P(Y|X) \propto \prod_{v \in V} \exp(w_n^\top \psi(x_v, y_v)) \prod_{(v, v') \in E} \exp(w_e^\top \psi(x_{vv'}, y_v, y_{v'})),$$

where $\psi(x_v, y_v)$ represents the feature vector associated with prediction y_v for output variable v with input features x_v , and $\psi(x_{vv'}, y_v, y_{v'})$ represents the feature vector associated with predicting y_v and $y_{v'}$ to the pair of connected output variables (v, v') with input features $x_{vv'}$ on this pair. Given training data (e.g. a set of images with object labels at every pixel), these parameters can be trained to maximize the likelihood of the data. However, finding the exact optima is often computationally infeasible as it typically requires evaluating the normalization constant of this probability distribution for the current parameters (i.e. the partition function). Thus, approximate training procedures are often used (Wainwright et al., 2001, Kumar et al., 2005, Ratliff et al., 2007b, Kulesza and Pereira, 2008).

Once the parameters of the graphical model have been trained, making a prediction for a new input is achieved via an inference procedure.

Inference

Given the graphical model that we trained and the input features of a new instance, the inference process consists in finding either: 1) the most likely output prediction, or 2) assigning a marginal distribution over possible outputs at every output variable. In general, finding this exactly is also intractable as it requires searching over an exponentially large number of possible outputs. However, many approximate inference algorithms exist that can find good solutions efficiently. A common approach is to use message-passing procedures which iteratively pass through each node and potential in the graph several times to compute messages (that represents belief over the outputs) to send to neighbors until convergence.

Loopy Belief Propagation (LBP) (Pearl, 1988) is perhaps the canonical message-passing algorithm for performing (approximate) inference in graphical models. Let N_v be the set of factors connected to variable v , N_v^{-f} the set of factors connected to v except factor f , N_f the set of variables connected to factor f and N_f^{-v} the set of variables connected to f except variable v . At a variable $v \in V$, LBP sends a message m_{vf} to each factor f in N_v :

$$m_{vf}(y_v) \propto \prod_{f' \in N_v^{-f}} m_{f'v}(y_v),$$

where $m_{vf}(y_v)$ denotes the value of the message for assignment y_v to variable v . At a

factor $f \in F$, LBP sends a message m_{fv} to each variable v in N_f :

$$m_{fv}(y_v) \propto \sum_{y'_f | y'_v = y_v} \phi_f(y'_f, x_f) \prod_{v' \in N_f^{-v}} m_{v'f}(y'_{v'}),$$

where y'_f is an assignment to all variables v' connected to f , $y'_{v'}$ is the particular assignment to v' (in y'_f), and ϕ_f is the potential function associated to factor f which depends on y'_f and potentially other observed features x_f (e.g., in the CRF). Finally the marginal of variable v is obtained as:

$$P(v = y_v) \propto \prod_{f \in N_v} m_{fv}(y_v).$$

The messages in LBP can be sent synchronously (i.e., all messages over the graph are computed before they are sent to their neighbors) or asynchronously (i.e., by sending the message to the neighbor immediately). When proceeding asynchronously, LBP usually starts at a random variable node, with messages initialized uniformly, and then proceeds iteratively through the factor graph by visiting variables and factors in a breath-first-search manner (forward and then in backward/reverse order) several times or until convergence. The final marginals at each variable are computed using the last equation. Asynchronous message passing often allows faster convergence and methods such as Residual Belief Propagation (Elidan et al., 2006) have been developed to achieve still faster convergence by prioritizing the messages to compute.

Structured Margin Approaches

An alternate approach when training graphical models is to maximize a margin objective similar to the objective when training a SVM. This is justified from the observation that in a log-linear model, finding the most likely output prediction Y given the input features X boils down to finding:

$$\arg \max_Y \sum_{v \in V} w_n^\top \psi(x_v, y_v) + \sum_{(v, v') \in E} w_e^\top \psi(x_{vv'}, y_v, y_{v'})$$

It can be noticed that this is very similar to the way a linear SVM predicts in multiclass classification problems. Hence a natural idea is to train the weights w_n and w_e to maximize the margin between the ground truth outputs and other outputs. In this case, the margin is structured so that the ground truth should have larger margin with respect to outputs that differ significantly from it. For instance if we are predicting a label at every pixel in an image, we might specify that the margin between the ground truth and some arbitrary output Y should be at least the number of pixels in Y that are labeled incorrectly. A number of approaches proceeds in this way, such as M^3N (Taskar et al., 2003) and the structured SVM (Tsochantaridis et al., 2005, Finley and Joachims, 2008).

With these methods, performing approximate inference (finding the output Y with highest score) can sometimes be achieved efficiently via iterative graph-cut procedures (Boykov et al., 2001) when the potentials satisfy certain submodular properties (Kolmogorov and Zabih, 2004). Such efficient procedures can also be used during training to obtain good estimates of the subgradient of the margin objective and perform gradient descent on the weight parameters (Ratliff et al., 2007b, Munoz et al., 2009).

Structured Prediction as Sequence Prediction

A major drawback of graphical model approaches is that inference, even if approximate, is very computationally expensive, and in most case cannot be applied in real time applications (e.g. image labeling in real time video observed by a robot). Also, these approximations can lead to several issues and difficulties for training the graphical model (Kulesza and Pereira, 2008, Finley and Joachims, 2008). The end result is that using graphical models with approximate inference for training and testing is poorly understood and has limited guarantees on test performance only in a few particular cases (Kulesza and Pereira, 2008, Finley and Joachims, 2008).

Some recent alternate approaches (Daumé III et al., 2009, Tu and Bai., 2009, Munoz et al., 2010, Xiong et al., 2011) eschew the probabilistic graphical model entirely with notable successes. These methods proceed by training classifiers or regressors that can construct the output prediction by making a sequence of interdependent local predictions. This effectively transforms the structured prediction problem into a sequential prediction problem. Unlike with graphical models, these methods can provide guarantees on test performance via reduction arguments, i.e. in a way similar to our guarantees in the imitation learning setting. In addition, a major practical advantage of these methods is that they can be much faster to produce the output predictions, and be applicable in real-time applications (Hu et al., 2013, Miksik et al., 2013). We will leverage these ideas in this thesis to tackle structured prediction problems as sequential prediction tasks. We now briefly review these techniques.

Naive Independent Predictions

A first naive approach to transform the structured prediction problem into a sequence of predictions is to simply learn a classifier or regressor that independently predicts each output variable given some input features. For instance, in the image labeling example, we could learn a classifier which takes image features local to a pixel as input, such as color and texture features in the neighborhood of the pixel, and then predicts the object present at that pixel given those features. Applying this classifier in sequence to every pixel in the image would create a sequence of predictions that construct the structured output (i.e. the labeled image).

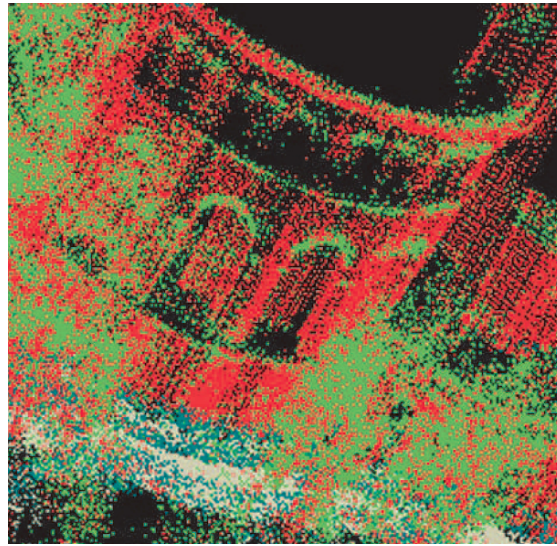


Figure 6.3: Example predictions obtained by independently classifying each 3D point independently in a LIDAR point cloud with a SVM, using only local features of the point cloud. Red: Building, Green: Tree, Blue: Shrubbery, Gray: Ground. Significant noise is present in the classifications and many points in the building are incorrectly classified as tree. Image from [Anguelov et al. \(2005\)](#).

While this approach would be computationally efficient at producing the output prediction, it would typically make poor predictions as it ignores the dependencies that exist between the output variables. This was shown experimentally in ([Anguelov et al., 2005](#)) (see Figure 6.3). In the image labeling example, it is important to consider the spatial relationship that exists between the object predicted at neighboring pixels. This is because the object present at a given pixel is likely to be the same as the object present at neighboring pixels. If we have a segmentation of the image, it is also likely that the pixel is the same object as all other pixels in the same segment. Additionally, certain object classes should satisfy certain spatial relationships, e.g. sky cannot be below ground, tree-top cannot be below tree-trunk.

These observations lead to a natural extension of the naive approach we just described. Instead of predicting each output variable independently, we could learn a classifier or regressor that predicts each output variable in sequence, given input features, as well as features related to previous predictions made by this classifier at previous output variables. For instance, for image labeling, we could consider additional features that encode the predicted objects at neighboring pixels, and/or the predicted objects within the same segment as the current pixel. These additional features would give contextual information about what objects are present near the current pixel and lead to improved predictions. This is the common strategy used in all approaches below to capture the interdependency between output variables.

Auto-Context and Hierarchical Labeling

Auto-Context (Tu and Bai, 2009) is an approach introduced in computer vision for treating structured prediction as a sequence of predictions¹. They focus on image labeling tasks and train a sequence of classifiers applied iteratively to label the image. The first classifier is trained to only use the image features local to a pixel and tries to infer the object present at that pixel. Then the second classifier is trained to predict the object present at each pixel using the local image features, and the predictions of the first classifier at neighboring pixels. Training continues in this fashion for some pre-determined number of iterations. Given a test image, the classifiers are applied in sequence on the entire image and the final predictions of the last classifier are returned. This training procedure is similar to the forward training algorithm we presented for imitation learning in Section 3.4 (and in our prior work (Ross and Bagnell, 2010)). By training on the output of the previous classifier, the classifiers learn to predict well under the distribution of inputs they induce and can thus provide good guarantees. In particular, this approach can guarantee that its average loss during test execution is directly the average loss of the learned classifiers over the iterations of training, by following a similar analysis to the one presented previously in Section 3.4.

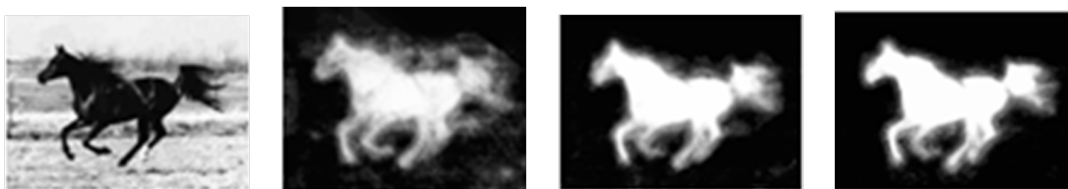


Figure 6.4: Sequence of predictions made by Auto-Context on a test image (images from Tu and Bai. (2009)). Left: Input image. Middle-Left: Predictions of the 1st predictor using only image features. Middle-Right: Predictions of the 3rd predictor, using image features and predictions of the 2nd predictor as input. Right: Predictions of the 5th (final) predictor, using image features and predictions of the 4th predictor as input. Predictions are shown in grayscale, where black indicates probability 0 of horse and white indicates probability 1 of horse.

Another similar approach used in the context of image labeling is the hierarchical labeling approach of Munoz et al. (2010), Xiong et al. (2011). In this work, the images are first segmented several times with varying parameters to obtain a hierarchical segmentation of the image, going from coarse segments to fine segments. A sequence of classifiers is then trained to predict the distribution of labels present in each segment at each level of the hierarchy. They proceed in a coarse to fine fashion. First, a classifier is trained to predict the distribution of labels for the segments in the coarsest segmentation using only the image features of the segments. Then, the next classifier is trained to predict

¹A similar approach also appeared previously in Sofman et al. (2006).

the distribution of labels for the segments in the second coarsest segmentation, using the predictions made by the previous classifier at the coarser level, and the image features of the segment as input. The approach continues iteratively until a classifier is trained at the finest level. Then for prediction on a test image, the hierarchical segmentation of the image is first obtained with the same segmentation algorithm and the classifiers are applied in sequence on the entire image from coarse to fine, and the predictions at the finest level are used as the final predictions. This approach again proceeds similarly to the forward training algorithm, and thus provide similar guarantees to the ones presented in Section 3.4. This training procedure can also be iterated longer back-and-forth, by going from coarse-to-fine, and fine-to-coarse, for several iterations, to allow propagating contextual information further during parsing (Xiong et al., 2011). Additionally, it was showed recently that this technique can lead to real-time scene analysis in streaming video (Miksik et al., 2013) and streaming 3D point cloud data from LIDAR sensors (Hu et al., 2013).

SEARN: Search-based Structured Prediction

SEARN is a technique that we mentioned previously in the imitation learning setting and compared to experimentally by adapting it for imitation learning. However, it was originally developed for structured prediction tasks. We briefly mention how this approach is applied in the context of Structured Prediction. Just like DAGGER and Forward Training, SEARN is a technique that can be used to learn predictors for sequential tasks that are trained to be good under their own sequence of predictions.

In Daumé III et al. (2009), structured prediction is treated as a problem of training a search procedure that can construct the high-dimensional output from a sequence of predictions. In the simplest case, a greedy-search procedure is trained, where the structured output is constructed by predicting the value of one variable at a time, given the previous predictions made so far. For instance in a handwriting recognition task, the approach would predict each character in the handwritten word in sequence, using previously predicted characters to help disambiguate among several candidates for the next character. However, the approach is general enough to be applied with other search procedures, such as beam-search that would maintain a set of sequences of previous predictions.

The search procedure is trained by training a stochastic classifier over several iterations to make the predictions. As described for imitation learning in section 3.5, at each iteration n , it proceeds by collecting data of cost-to-go examples of the current predictor h_{n-1} in states visited by this predictor, training a policy \hat{h}_n to minimize a cost-sensitive classification loss on this data, and updating $h_n = (1 - \alpha)h_{n-1} + \alpha\hat{h}_n$ (where this is interpreted as a stochastic mixing, see Section 3.5). Initially, the approach

starts with an “expert” classifier h_0 which can make good predictions on the training data (e.g. by directly looking up the target output in the training data itself). After N iterations, it returns the renormalized classifier which do not use the “expert” classifier for test execution: $\tilde{h}_N = \frac{1}{1-(1-\alpha)^N} [h_N - (1-\alpha)^N h_0]$. In the context of structured prediction, when collecting cost-to-go estimates, SEARN proceeds by trying all possible predictions y at the current point in the sequence, and then rolling out the current policy to estimate cost-to-go of all possible prediction in the current context x . This generates cost-sensitive classification examples (i.e. full information setting as described in section 4.1). As mentioned in section 3.5, choosing α to be $O(\frac{1}{T^3})$ and N to be $\tilde{O}(T^3)$, leads to good performance guarantees.

In practice, because collecting the costs for each prediction y for the current input x is time-consuming when executing the current predictor h_{n-1} until the end of the sequence, an approximation often done is to execute the expert h_0 until the end of the sequence instead as this is often much faster (e.g. if it only involves looking up labels in the training data to determine future predictions), and produces less noisy examples (as h_0 is deterministic, whereas h_{n-1} is stochastic). While Daumé III et al. (2009) presents this approximation as purely practical, with no performance guarantees, it is interesting to note that this corresponds exactly to the cost-to-go of the expert’s policy we are collecting in our previous imitation learning approaches, for which we could provide performance guarantees.

6.2 Inference Machines

We now present the particular sequential prediction procedure that we will seek to train for tackling structured prediction task.

As reviewed in the previous section, current state-of-the-art methods for Structured Prediction are divided between 1) methods that learn a graphical model and use an inference procedure for predictions, and 2) methods that eschew the probability graphical model entirely in favor of training a sequential prediction approach. However, we would ideally like to have the best of both worlds: the proven success of error-correcting iterative decoding methods used for inference in graphical models, along with a tight relationship between learning and inference, as achieved in sequential prediction approach, that allows providing guarantees on performance.

To enable this combination, we propose an alternate view of the approximate inference process as a long sequence of computational modules to optimize Bengio (2009) such that the sequence results in correct predictions. We focus on message-passing inference procedures, such as Belief Propagation, that compute marginal distributions over output variables by iteratively visiting all nodes in the graph and passing messages to

neighbors which consist of “cavity marginals”, i.e., a series of marginals with the effect of each neighbor removed. Such message-passing inference can be viewed as a sequential prediction procedure that iteratively applies a function to each variable, that takes as input local observations/features and local computations on the graph (messages) and provides as output the intermediate messages/marginals. In this view, we can attempt to train such a sequential prediction procedures directly, by training a predictor that predicts a current variable’s marginal² given local features and a subset of neighbors’ cavity marginals. In other words, we will seek to learn predictors that produce the overall structured output through a sequence of predictions, where the sequential prediction process follows the same proven error-correcting algorithmic structure of message-passing inference procedures. We will seek to train this predictor to “mimic” an ideal inference procedure, i.e. where at each intermediate inference steps, we train the predictor to predict the *ideal* output in our training data (i.e., a marginal with probability 1 to the correct class). By training such a predictor, there is no need to have a probabilistic graphical model of the data, and there need not be any probabilistic model that corresponds to the computations performed by the predictor. The inference procedure is instead thought of as a black box function that is trained to yield correct predictions. This is analogous to many discriminative learning methods; it may be easier to simply discriminate between classes than build a generative probabilistic model of them. We will refer to a predictor that is sequentially applied in this way to construct the output prediction as an *inference machine*, due to the similarities with inference procedures for graphical models. This inference machine approach follows ideas from [Munoz et al. \(2010\)](#), [Xiong et al. \(2011\)](#).

We now show in more details how graphical model approaches can be viewed as training a sequential prediction procedure, that can be shown to be a special case of our general inference machine approach.

Understanding Message-Passing Inference as Sequential Probabilistic Classification

As mentioned in Section 6.1, LBP builds the output prediction by iteratively sending messages m_{vf} from variables $v \in V$ to factors $f \in F$, and messages from factors to variables m_{vf} , until convergence. By comparing the computations performed for computing the marginals $P(v = y_v)$ and the message m_{vf} , we observe that m_{vf} can be interpreted as the marginal of variable v when the factor f (and its influence) is removed from the graph. This is often referred as the cavity method in statistical mechanics ([Csato et al., 2001](#)) and m_{vf} are known as cavity marginals. By expanding the definition of m_{vf} , we

²For lack of a better term, we will use marginal throughout to mean a distribution over one variable’s labels.

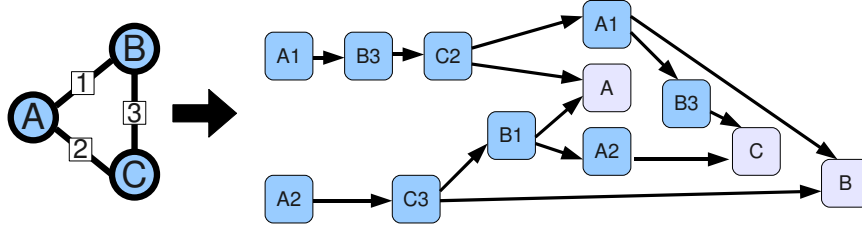


Figure 6.5: Depiction of how LBP unrolls into a sequence of predictions for 3 passes on the graph on the left with 3 variables (A,B,C) and 3 factors (1,2,3); for the case where LBP starts at A, followed by B and C (and alternating between forward/backward order). Sequence of predictions on the right, where e.g., A1 denotes the prediction (message) of A sent to factor 1, while the output (final marginals) are in gray and denoted by the corresponding variable letter. Input arrows indicate the previous outputs that are used in the computation of each message.

can see that it depends only on the messages $m_{v'f'}$ sent by all variables v' connected to v by a factor $f' \neq f$:

$$m_{vf}(y_v) \propto \prod_{f' \in N_v^{-f}} \sum_{y'_{f'} | y'_v = y_v} \phi_{f'}(y'_{f'}, x_{f'}) \prod_{v' \in N_{f'}^{-v}} m_{v'f'}(y'_{v'}). \quad (6.1)$$

Hence the messages m_{vf} leaving a variable v toward a factor f in LBP can be thought as a probabilistic classification of the current variable v (marginal distribution over classes) using the cavity marginals $m_{v'f'}$ sent by variables v' connected to v through a factor $f' \neq f$. In this view, LBP is iteratively classifying the variables in the graph by performing a sequence of probabilistic classifications (marginals) for each message leaving a variable. The final marginals $P(v = y_v)$ are then obtained by “classifying” v using all messages from all variables v' connected to v through some factor.

An example of how LBP unrolls to a sequence of interdependent local classifications is shown in Figure 6.5 for a simple graph. In this view, the job of the predictor is not only to emulate the computation going on during LBP at variable nodes, but also emulate the computations going on at all the factors connected to the variable which it is not sending the message to, as shown in Figure 6.6. During inference, LBP effectively employs a probabilistic predictor that has the form in Equation 6.1, where the inputs are the messages $m'_{v'f'}$ and local observed features $x_{f'}$. Training graphical models can thus be understood as training a message-passing algorithm (i.e. an inference machine) with a particular class of predictors defined by Equation 6.1, which have as parameters the potential functions ϕ_f , and use as input features the local features and the messages (probabilistic classification) sent from neighbors. Under this general view, there is no reason to restrict attention to only predictors of the form of Equation 6.1. We can consider general inference machines that use different classes of predictors (e.g., Logistic

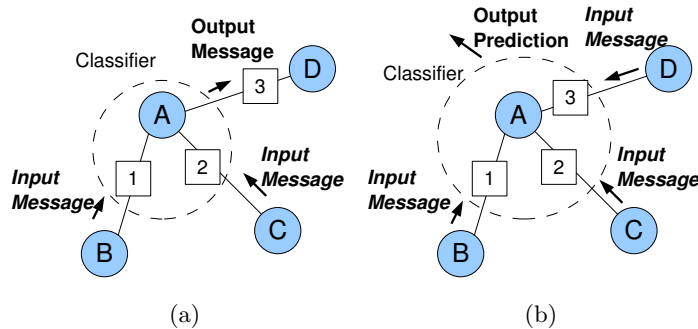


Figure 6.6: Depiction of the computations that the predictor represents in LBP for (a) a message to a neighboring factor and (b) the final marginal of a variable outputted by LBP.

Regression, Boosted Trees, Random Forests, etc.) whose inductive bias may more efficiently represent interactions between neighboring variables or in some cases be more compact and faster to compute, which is important in real-time settings. Additionally, other features computed from the neighboring predictions, such as various statistics of the output predictions over regions or clusters, could be used and can be more easily integrated within such framework than within graphical models.

Many other techniques for approximate inference have been framed in message-passing form. Tree-Weighted Belief Propagation (Wainwright et al., 2001) and convergent variants follow a similar pattern to LBP as described above but change the specific form of messages sent to provide stronger performance and convergence guarantees. These can also be interpreted as performing a sequence of probabilistic classifications, but using a different form of predictors. The classical “mean-field” (and more generally variational methods (Oppor and Saad, 2000)) method is easily framed as a simpler message passing strategy where, instead of cavity marginals, algorithms pass around marginals or expected sufficient statistics which is more efficient but may obtain lower performance than cavity message passing (Oppor and Saad, 2000). We also consider training such mean-field inference approach in the experiments.

Message-Passing Inference Machine

In general, our inference machine approach can be implemented by considering a graph over the output variables that encodes dependency relations between them (just like the graph structure in a graphical model). This graph is used to define the neighbors’ messages that should be used for predictions, and the ordering of the sequence of predictions to ensure efficient propagation of the information from previous predictions between the output variables. For instance, as in LBP, we can start from an arbitrary output variable (e.g., chosen randomly), and predict each output variable in a breath-first-search

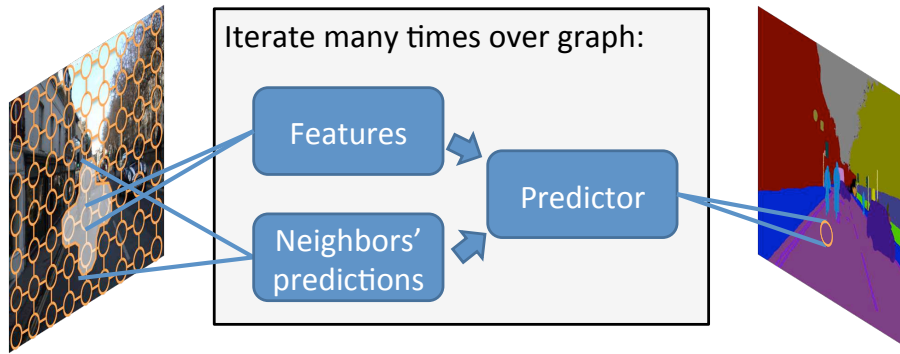


Figure 6.7: Depiction of the inference machine in the context of image labeling.

order, using local input features to this variable (e.g. color and texture features in vision applications), as well as features of the predictions made previously at the output variables connected to it, and iterate several times over all the output variables (alternating between forward and reverse order), to improve predictions given the most recent neighboring predictions, until convergence or for some maximum number of iterations (see Figure 6.7). In addition, our approach needs access to a given feature function, that is used to compute the features given the previous predictions in the sequence (e.g. predictions of neighbors and/or average predictions over neighboring regions).

Training an inference machine that produces high-accuracy output prediction through this sequence of predictions during test execution is however non-trivial. As part of the input features depend on previous predictions in the sequence, the distribution of input where the predictor is tested during inference depends in part on the predictor itself. Thus, as in the imitation learning setting we previously analyzed, we can suffer from a similar mismatch in train/test distribution that lead to poor performance, if we train the inference machine naively. Due to this similarity with imitation learning problems, we will be able to leverage the same interactive learning techniques that we developed for imitation learning, to learn predictors which have strong performance guarantees on their performance during test execution. This is shown in the following sections.

Advantages of Inference Machines

There are a number of advantages to doing message-passing inference as a sequence of predictions. Considering different classes of predictors allows one to obtain entirely different classes of inference procedures that perform different approximations. The level of approximation and computational complexity of the inference can be controlled in part by considering more or less complex classes of predictors. This allows one to naturally trade-off accuracy versus speed of inference in real-time settings. It is also possible to extract various features from previous predictions to use as input to the predictor rather

than limiting only to using neighboring predictions. Better features of the previous predictions may allow faster convergence or improved predictions. Additionally, while we focus mainly on tasks where our objective is to simply maximize accuracy (or likelihood of the ground truth predictions), in certain tasks other objectives can better represent the quality of a solution, e.g. the BLEU score in machine translation (Papineni et al., 2002). In this case, we can optimize the predictor to optimize directly these objectives, rather than likelihood, something which is not possible with graphical model. Finally, most approaches to learning graphical models with approximate inference have no theoretical guarantees and are not well understood (Kulesza and Pereira, 2008, Finley and Joachims, 2008). In contrast, we are able to provide rigorous reduction-style guarantees on the performance of the resulting inference procedure, as we demonstrate below.

6.3 Learning Inference Machines

We now present how to use the same techniques we presented for imitation learning, namely Forward and DAGGER, for training an inference machine, and provide good guarantees on test performance. To do so, the key idea is that we can view the inference process as an imitation learning problem, where we seek to learn a predictor that can mimic well an “expert” predictor, that at any point in the sequence on training instances, predicts the “ideal” marginal – a marginal with probability 1 for the correct class. This expert is essentially defined by the labeled training data. For instance in image labeling, the labeled image in the training data would define the prediction of the expert to mimic whenever we predict a marginal at a certain pixel. By learning to mimic this “expert” predictor, we hope to learn inference machines that can generalize from the training data, and that can then be applied to new test data (e.g. predict objects in a new image observed by the robot that is not labeled by a human).

Learning Synchronous Inference with Forward Training

As was mentioned in Section 6.1, message-passing inference procedures such as LBP can be applied in synchronous or asynchronous fashion. The predictor we train, within our inference machine, can be applied to propagate predictions in a similar synchronous or asynchronous fashion. We will begin here by considering learning a predictor for the simpler synchronous case and show that the Forward Training strategy can be a practical algorithm for this case.

When applied synchronously, the predictor predicts messages/marginals at each output variable, over the entire graph first, before updating the neighboring messages used as input features to make these predictions. This implies that predictions within the same “pass” over the graph are independent, whereas the input features used at future


```

for  $t = 1$  to  $T$  do
  Use  $h_{1:t-1}$  to perform synchronous message-passing on training graphs up to pass  $n$ .
  Get dataset  $D_t$  of inputs encountered at pass  $n$ , with the ideal marginals as target.

  Train  $h_t$  on  $D_t$  to minimize a loss (e.g., logistic).
end for
Return the sequence of predictors  $h_{1:T}$ .

```

Algorithm 6.3.1: Forward Training Algorithm for Learning Synchronous Inference Machine

passes are influenced by the current pass' predictions. Concretely, in the context of image labeling, such a procedure would proceed similarly to the Auto-Context approach mentioned previously in Section 6.1, i.e. at each pass we would make a prediction at each pixel over the entire image, using only predictions from the previous pass as input.

To learn an inference machine that is trained on the distribution of inputs it expects to see during test execution, and does not suffer from a train-test mismatch, we can consider a similar training strategy to the forward training algorithm introduced for imitation learning. That is, instead of learning a single predictor, we would learn a sequence of predictors h_1, h_2, \dots, h_T , where h_i is the predictor used on the i^{th} prediction pass, and we would need to learn a total of T predictors to learn an inference machine that performs T passes. As in most applications, the number of pass is not too large, Forward training can be a practical approach in this context. To train these T predictors, we would proceed iteratively, by training them in sequence going forward in time, i.e. from the first pass to the last pass. At the first iteration, we would start by training h_1 to mimic the expert predictor h^* . As for the first pass there is no features of neighboring/previous predictions, this would come down to learn a predictor that attempts to predict the ideal marginals (correct class) immediately, using only the local input features (e.g. the image features). At iteration t , for each training structured prediction example (e.g. each training image), we would generate a dataset D_t of training data through interaction with the learner as follows: perform $t - 1$ inference pass using the previously trained predictors h_1, h_2, \dots, h_{t-1} in sequence (i.e. h_i for the i^{th} pass), and then record in dataset D_t the observed input features at the t^{th} pass (e.g. the vector of features that includes both image features and features related to neighboring predictions), associated with their ideal marginal (or correct class) from the expert predictor h^* for each of these input. The predictor h_t for the t^{th} pass would then be trained on this data. This is detailed in Algorithm 6.3.1.

The Auto-Context approach presented previously in Section 6.1 can be seen as the particular case of this approach, where we learn a synchronous inference machine, that uses mean-field style message-passing – i.e. the case where the neighboring marginals

used as input features were predicted using all neighbors at the previous pass. However this same Forward procedure could be used to train other type of synchronous inference machines, e.g. using LBP style message-passing instead where the messages passed to neighbors are cavity marginals (a marginal predicted with evidence/features from the neighbor we are sending the message to removed), which can be beneficial³. To illustrate the difference, in the image labeling example, if using a standard 2D lattice graph structure, where each pixel is connected to the pixels above, below, left and right, then with LBP style message-passing, at each pass, except the last one, the inference machine would make 4 different predictions at each pixel (each obtained by removing one of the neighbor’s message/marginal from the input features), and at the last pass, a single prediction at each pixel would be made, using all 4 neighbor’s messages in the input features. In other words, at each pass, except the last one, we would produce 4 different labelings of the image, a “left”, “right”, “above” and “below” labeling, where e.g. the “left” labeling is the labeling produced with all the predictions made without the left neighbor’s message from the previous pass in the input features. The neighbor’s messages in the input features at any pass would be coming from these different labelings, e.g. the message from the neighbor below is the marginal at the pixel below in the “above” labeling produced at the previous pass (as the current pixel is the neighbor above this neighbor, and we want the neighbor’s prediction without the current pixel’s message). Training this synchronous LBP inference machine means that when generating the training data at each pass, data would be generated for all these 4 different predictions (i.e. 4 data points with the same target class, but 4 different input feature vectors would be generated for each pixel).

Similarly, from our point of view, [Munoz et al. \(2010\)](#), [Xiong et al. \(2011\)](#) implement a hierarchical mean-field inference machine by sending mean-field style messages across the hierarchy to make contextual predictions. We demonstrate in our experiments the benefits of enabling more general (LBP-style) message passing.

Theoretical Guarantee: As we have effectively transformed the structured prediction problem into an imitation learning problem, the same guarantees for Forward, hold in this structured prediction setting. In particular, suppose we are interested in minimizing the logistic loss, and we use this loss as the surrogate loss ℓ . The result in [Theorem 3.4.1](#) would indicate that if $\bar{\epsilon}$ is the average logistic loss per prediction of the learned predictors $h_{1:T}$, then over the T pass of inference, the average logistic loss per prediction would be

³Basically, in mean-field style message-passing, we can suffer from “double-counting” of evidence. If the neighbor’s prediction is wrong, we may predict something, based on this wrong prediction as “evidence”, which then, at the next pass, is reused at the neighbor as further evidence that reinforces its initial wrong prediction. This leads to a runaway effect where both can become very confident in a wrong prediction, due to an initially wrong prediction. The use of cavity marginals in LBP resolves this problem.

$\bar{\epsilon}$. As we are interested only in the final predictions, this would naively tell us that, in the worst case, the per prediction logistic loss at the last pass is bounded by $T\bar{\epsilon}$ (e.g., in the worst case where all the loss occurs at the last pass) and would suggest that *fewer* inference passes is better (making N small). However, for convex loss functions, such as the logistic loss, simply averaging the marginals at each variable over the inference pass, and using those average marginals as final output, guarantees⁴ achieving logistic loss no worse than $\bar{\epsilon}$. Hence, using those average marginals as final output enables using an arbitrary number of passes to ensure we can effectively find the best decoding. In practice, however, we typically found that the marginals at the last pass incurred lower loss than the average marginals, so we only used the last pass' predictions.

Asynchronous Inference: Learning asynchronous inference machines is often of interest, since as mentioned for LBP, it allows propagating information faster between output variables, and potentially converge faster to good predictions within fewer pass, or obtain better predictions when the number of pass is very limited. Forward can also be applied for learning asynchronous inference machines. However this is often impractical. This is because, when applied asynchronously, the predictor predicts messages/marginals at each output variable, and these messages are used immediately at neighbors to compute messages within the same pass. This means that predictions within the same pass are now interdependent and influence the input features used immediately at the next predictions within the same pass. To deal with such interdependencies, Forward would need to train a separate predictor for each individual prediction in the sequence. This is feasible for problems where there is a small number of output variables (e.g. in handwriting recognition, where within one word, we only have a few characters to predict). However for most applications in computer vision, such as image labeling, the number of predictions per pass is very large (in the order of number of pixels or image segments). For example, in our 3D point cloud classification experiments below, each pass over the point cloud consists in $O(10^5)$ predictions. In such scenarios, Forward is impractical as it would require learning a prohibitively large number of predictors (e.g. $O(10^6)$ predictors to perform all the pass over the point cloud). To learn asynchronous inference machines, DAGGER provides a much more practical algorithm, as it can learn within a few iterations, a single predictor that can be applied to perform the entire sequence of predictions.

Learning Asynchronous Inference with DAGGER

We now show how to apply the same Dataset Aggregation (DAGGER) approach, developed for imitation learning, for learning inference machines for structured prediction.

⁴ By Jensen's inequality, if f is convex and $\bar{p} = \frac{1}{N} \sum_{i=1}^N p_i$, then $f(\bar{p}) \leq \frac{1}{N} \sum_{i=1}^N f(p_i)$.


```

Initialize  $D_0 \leftarrow \emptyset$ ,  $h_0$  to return the ideal marginal on any variable  $v$  in the training graph.
for  $n = 1$  to  $N$  do
    Use  $h_{n-1}$  to perform inference on structured training examples (e.g. labeled images).

    Get dataset  $D'_n$  of inputs encountered during inference, with their ideal marginal as target.
    Aggregate dataset:  $D_n = D_{n-1} \cup D'_n$ .
    Train  $h_n$  to minimize loss on  $D_n$  (or use online learner to update  $h_n$  from new data  $D'_n$ ).
end for
Return best  $h_n$  on structured training or validation examples.

```

Algorithm 6.3.2: DAGGER Algorithm for Structured Prediction.

DAGGER again leverages interaction with the learner, and the strong learning properties of no-regret online learning algorithms, to provide strong guarantees on performance. In particular, it learns over many iterations, a single deterministic predictor to produce all predictions in the sequence (during inference) and still guarantees good performance on its induced distribution of inputs over the sequence.

In this setting, whether we are training a synchronous or asynchronous inference machine, DAGGER proceeds iteratively as follows. At the first iteration, a first dataset is generated by doing inference on structured training examples (e.g. labeled images) with the “expert” predictor (that predicts the ideal marginals). The dataset of all observed inputs (the feature vectors containing both local features and features of previous predictions) during these sequence of predictions, associated with their ideal marginals (correct class) as target output, is used to learn a first predictor h_1 . This is analog to how for imitation learning, at the first iteration, DAGGER collects a dataset under demonstrations of the task by the expert. Effectively, the first predictor is trained to predict each output variable when its neighbors are always correctly labeled (or unlabeled). At iteration n , DAGGER collects additional data, through interaction with the learner, by using the learner’s current predictor, h_{n-1} , to perform inference on the training graphs. A new dataset D'_n of the inputs observed during inference, with the associated ideal marginals as target is recorded. This new data is aggregated with previous data, and a new predictor h_n is trained on the aggregated dataset $D_n = D_{n-1} \cup D'_n$ (i.e., containing all data collected so far over all iterations of the algorithm). A depiction of the DAGGER algorithm for Structured Prediction in the context of an image labeling task is shown in Figure 6.8. Just as in imitation learning, this can be interpreted as a Follow-the-(Regularized)-Leader algorithm, and more generally, any other no-regret online learning algorithm can be used to pick the sequence of predictors over the iterations of the algorithm. DAGGER is described in Algorithm 6.3.2.

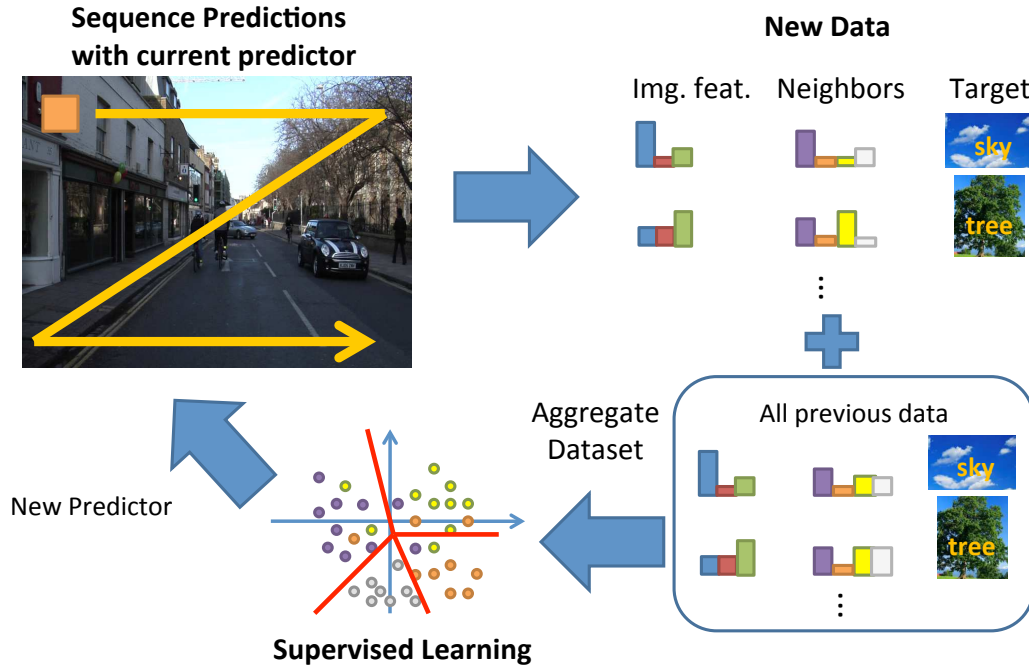


Figure 6.8: Depiction of the DAGGER algorithm for Structured Prediction in the context of an image labeling task.

Intuitively, what occurs is that after the first iteration, we collect training examples where errors currently made by the learned predictor are present in the input features related to neighboring predictions. By attempting to still predict the ideal marginal, with those errors present at the neighbors, DAGGER can learn a predictor that is robust to the errors it typically makes during the sequence of predictions. In addition, based on all the training data collected, it can learn that it commonly confuses 2 or more classes together, (e.g. it often confuses sky and water, or grass and leaves) and that whenever one is predicted, than the others should also implicitly be considered likely. That is, in this case, by training on data where these classes are confused in its neighbors, the predictor will learn to predict classes that are likely to be neighbors of these confused classes, whenever it receives predictions of one of those class from its neighbors.

Theoretical Guarantees: Again, as we have transformed the structured prediction problem into an imitation learning problem, the same guarantees for DAGGER, hold in this structured prediction setting. In particular, if we are minimizing the logistic loss (maximizing likelihood), and we use this loss as the surrogate loss ℓ , the result in Theorem 3.6.1 indicates that if there is a predictor in the class of predictors that can achieve ϵ average logistic loss per prediction on the collected dataset during training,

then after a sufficient number of iterations, DAGGER must find good predictors that also achieve ϵ average logistic loss per prediction, under their own sequence of predictions during inference. As the logistic loss is convex in the marginal prediction, we can also use a similar trick (mentioned previously for Forward) of averaging the predictions at each output variable over the passes of inference, and return those average predictions as final output, to guarantee that the final output average per prediction logistic loss is ϵ . In practice, however, we typically found that the marginals at the last pass incurred lower loss than the average marginals, so we only used the last pass' predictions. Additionally, in our experiments we will see that a small number of iterations ($N \in [10, 20]$) is often sufficient to obtain good predictors under their induced distributions.

Discussion

Optimizing Other Cost Functions: When the loss we want to minimize is something different than logistic loss, for instance a task specific cost like the BLEU score in Machine Translation, we could apply the Cost-to-Go version of Forward and DAGGER, presented in Chapter 4, to train the sequence of predictors, and similar guarantees would still apply. This would be similar to SEARN, when using the approximation of simulating the expert to collect cost-to-go, except that instead of training a stationary stochastic predictor, we would train a non-stationary predictor, with Forward, or a stationary deterministic predictor with DAGGER.

Using Back-Propagation: In both synchronous and asynchronous approaches, our training procedures provide rigorous performance bounds on the loss of the final predictions; however, they do not optimize it directly. In particular, we are often only interested in minimizing the loss of the final predictions (at the last pass), and not the loss at predicting the correct class at intermediate predictions during inference. If the predictors learned are differentiable functions (as well as the features of previous predictions) then one could use procedures like back-propagation (LeCun et al., 1998) over the sequence of predictions to optimize the predictor the desired objective. Back-propagation makes it possible to identify local optima of the objective (minimizing loss of the final marginals). As this optimization problem is non-convex and there are potentially many local minima, it can be crucial to initialize this descent procedure with a good starting point. The forward training and DAGGER algorithms provide such an initialization. In our setting, Back-Propagation would effectively uses the current predictor (or sequence of) to do inference on a training graph (forward propagation); then errors are back-propagated through the network of classification by rewinding the inference, successively computing derivatives of the output error with respect to parameters and input messages. In the experiments below, we will compare to such a back-propagation

approach, and show that without proper initialization, such as starting from the predictor learned with DAGGER, it typically performs worse than the predictor learned with DAGGER alone. However, applying Back-Propagation, from the learned predictor by DAGGER can sometime increase performance further.

6.4 Case Studies in Computer Vision and Perception

We now demonstrate the efficacy of our approach. We compared our performance to state-of-the-art algorithms on 3 separate structured prediction tasks: (1) a benchmark handwriting recognition task, involving decoding handwritten words sequentially; (2) a 3D point cloud classification task of predicting the object present at every point in 3D point clouds of outdoor scenes perceived from a LIDAR sensor; and (3) estimating the 3D geometry of an outdoor scenes from a 2D image.

Handwriting Recognition

We first begin by demonstrating the efficacy of our approach on a structured prediction problem involving recognizing handwritten words given the sequence of images of each character in the word.

We use the dataset of [Taskar et al. \(2003\)](#) which has been used extensively in the literature to compare several structured prediction approaches. This dataset contains roughly 6600 words (for a total of over 52000 characters) partitioned in 10 folds. We consider the large dataset experiment which consists of training on 9 folds and testing on 1 fold and repeating this over all folds. Performance is measured in terms of the character accuracy on the test folds.

We consider predicting the word by predicting each character in sequence in a left to right order, using the previously predicted character to help predict the next. A single pass over the word is performed, and we learn a multi class linear SVM to predict each character based on the input features. This can be interpreted as learning a greedy search procedure within the framework of SEARN, where we learn a predictor that predicts greedily the current character based on previously predicted characters in the word. Within the context of inference machines, this can also be thought as learning an asynchronous inference machine that performs a single pass of inference, and where the marginals/messages predicted by the SVM always assigns probability 1 for the class predicted. As in this case, DAGGER is effectively training a greedy-search procedure as in SEARN, we perform this experiment mainly to compare performance of DAGGER with SEARN when learning the same type of sequential prediction procedures, on structured prediction tasks.

For each prediction while we parse/decode the word, the input features are defined as

follows. Each handwritten character is an 8×16 binary pixel image (128 input features), and an additional 27 binary features are used to encode the previously predicted letter in the word (26 to indicate a letter, and an additional one to indicate when there is no previous letter for the first character in the word).

With each approach, we train the multiclass SVM using the all-pairs reduction to binary classification (Beygelzimer et al., 2005). Here we compare our method to SMILe, as well as SEARN (using the same approximations used in Daumé III et al. (2009)). We also compare these approaches to two baseline: 1) independent predictions (no structured), which simply predicts each character independently (i.e. without features of the previous predicted character) and 2) a supervised training approach where training is conducted with the previous character always correctly labeled⁵. For SEARN, we try all choice of $\alpha \in \{0.1, 0.2, \dots, 1\}$, and report results for $\alpha = 0.1$, $\alpha = 1$ (pure policy iteration) and the best $\alpha = 0.8$, and run all approaches for 20 iterations. Figure 6.9 shows the performance of each approach on the test folds after each iteration as a function of training data. The

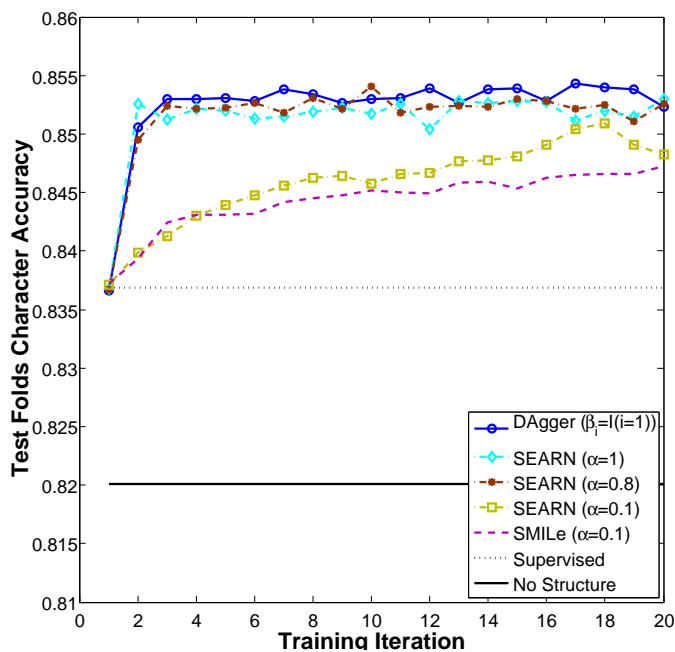


Figure 6.9: Character accuracy as a function of iteration.

baseline result without structure (independent predictions) achieves 82% character accuracy by just using an SVM that predicts each character independently. When adding the previous character feature, but training with always the previous character correctly labeled (supervised approach), performance increases up to 83.6%. Using DAGGER increases performance further to 85.5%. Surprisingly, we observe SEARN with $\alpha = 1$,

⁵This is analog to the supervised learning approach to imitation learning, using the “expert” predictor that predicts the correct class.

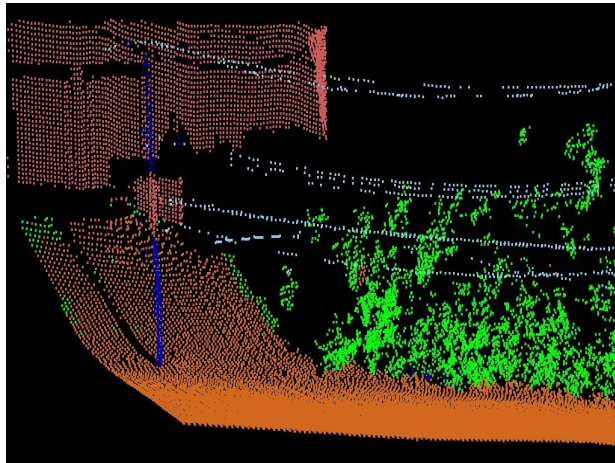


Figure 6.10: 3D point cloud classification application. Each point is assigned to one of 5 object classes: Building (red), Ground (orange), Poles/Tree-Trunks (blue), Vegetation (green), and Wire (cyan).

which is a pure policy iteration approach performs very well on this experiment, similarly to the best $\alpha = 0.8$ and DAGGER. Because there is only a small part of the input that is influenced by the current policy (the previous predicted character feature) this makes this approach not as unstable as in general reinforcement/imitation learning problems (as we saw in the previous imitation learning experiments of Section 5.2). SEARN and SMILe with small $\alpha = 0.1$ performs similarly but significantly worse than DAGGER. Note that we chose the simplest (greedy, one-pass) decoding to illustrate the benefits of the DAGGER approach with respect to existing reductions. Similar techniques can be applied to multi-pass or beam-search decoding leading to results that are competitive with the state-of-the-art. Nevertheless this shows that DAGGER can be just as effective as state-of-the-art methods like SEARN with the best parameter α , but DAGGER does not need to tune any such parameter. In the next 2 experiments, we compare our inference machine framework, training with DAGGER, to state-of-the-art graphical model approaches.

3D Point Cloud Classification

Next, we evaluate on a 3D point cloud classification task – predicting the object present at every point in a point cloud, or laser scan, of an outdoor scene observed from a LIDAR sensor. We evaluate on the 3D point cloud dataset used in Munoz et al. (2009). This dataset consists of 17 full 3D laser scans (total of ~ 1.6 million 3D points) of an outdoor environment collected from a LIDAR sensor. It contains 5 object labels: Building, Ground, Poles/Tree-Trunks, Vegetation, and Wires (see Figure 6.10). We use the same neighbor structure as in Munoz et al. (2009) (to define the predictions/messages used

as input) and use the same features. Essentially, each 3D point is connected to its 5 nearest neighbors (in 3D space) and clusters over regions, from 2 k-means clusterings, are also used. The features describe the local geometry around a point or cluster (linear, planar or scattered structure; and its orientation); as well as a 2.5-D elevation map. As additional features of previous predictions, we concatenate the messages of the nearest neighbors, and the average predicted marginal within the clusters the point belongs to.

In Munoz et al. (2009), performance is evaluated on one fold where one scene is used for training, one for validation, and the remaining 15 are used for testing. In order to allow each method to better generalize across different scenes, we instead split the dataset into 2 folds with each fold containing 8 scans for testing and the remaining 9 scans are used for training and validation (we always keep the original training scan in both folds' training sets). We report overall performances on the 16 test scans.

We experiment with two of our methods: 1) a synchronous mean-field inference machine (MFIM) using the forward training procedure, and 2) an asynchronous LBP inference machine (BPIM). For the latter, inference starts at a random point and proceeds in breadth-first-search order and alternates between forward and backward order at consecutive passes. Additionally, with BPIM, cavity marginals are predicted when sending messages to neighbors (by removing the features related to the node/cluster we are sending a message to from the concatenation/average). We compare 3 different approaches for optimizing the BPIM:

1. BPIM-D: DAGGER, used for 30 iterations, and the predictor that has the lowest error rate (from performing message-passing inference) on the training scenes is returned as the best one.
2. BPIM-B: Back-Propagation starting from a 0 weight vector.
3. BPIM-DB: Back-Propagation starting from the predictor found with DAGGER

In each case, a simple logistic regressor is trained to predict the marginals (messages) from the input features, by minimizing the logistic loss.

We compare these methods to two graphical model based approach: 1) a pairwise Pott's CRF trained using asynchronous LBP to estimate the gradient of the partition function (e.g. as in Kumar et al. (2005)), and 2) a high-order associative M³N model used on this dataset in Munoz et al. (2009). For the latter, we use directly their implementation⁶. We analyzed linear M³N models optimized with the parametric subgradient method (M³N-P) and with functional subgradient boosting (M³N-F) as in Munoz et al. (2009).

⁶<http://www-2.cs.cmu.edu/~vmr/software/software.html>

We measure the performance of each method in terms of per point accuracy, the Macro-F1 score (average of the per class F1 scores), and Micro-F1 score (weighted average, according to class frequency, of the per class F1 scores). Table 6.1 summarizes (left column) presents the results on this task.

	Accuracy	Macro-F1	Micro-F1
BPIM-D	0.9795	0.8206	0.9799
BPIM-B	0.9728	0.6504	0.9706
BPIM-DB	0.9807	0.8305	0.9811
MFIM	0.9807	0.8355	0.9811
CRF	0.9750	0.8067	0.9751
M ³ N-F	0.9846	0.8467	0.9850
M ³ N-P	0.9803	0.8230	0.9806

Table 6.1: Comparisons of test performance on the 3D point cloud dataset.

We observe that the best approach overall is the functional gradient M³N approach of Munoz et al. (2009). We believe that for this particular dataset, this is due to the use of a functional gradient method, which is less affected by the scaling of features and the large class imbalance in this dataset. We can observe that when using the regular parametric subgradient M³N approach, the performance is slightly worse than our inference machine approach, also optimized via parametric gradient descent. Hence using a functional gradient approach when training the base predictor with our inference machine approaches could potentially lead to similar improved performance. Both inference machines (MFIM, BPIM-D) outperform the baseline CRF message-passing approach. Additionally, we observe that using backpropagation on the output of DAGGER slightly improved performance. Without this initialization, backpropagation does not find a good solution. In this particular dataset we do not notice any advantage of the cavity method (BPIM-D) over the mean-field approach (MFIM). However, we can see in Figure 6.11 that the error converges slightly faster for the asynchronous approach, converging roughly after 3-4 inference passes, while the synchronous approach (MFIM) converges slightly slower and requires around 6 passes. Hence a potential speed-up could be obtained with the asynchronous approach, without loss in accuracy, by stopping the inference earlier after only 3 or 4 pass.

Figure 6.12 shows a visual comparison of the M³N-F, M³N-P and MFIM approaches on a test point cloud. In this case, we can see that MFIM is slightly worse on the rarer classes in the training data (poles and wires).

We also performed the experiment on the smaller split used in Munoz et al. (2009) (i.e., training on a single scene) and our approach (BPIM-D) obtained slightly better accuracy of 97.27% than the best approach in Munoz et al. (2009) (M³N-F: 97.2%). However, in this case, backpropagation did not further improve the solution on the test scenes as it overfits more to the single training scene.

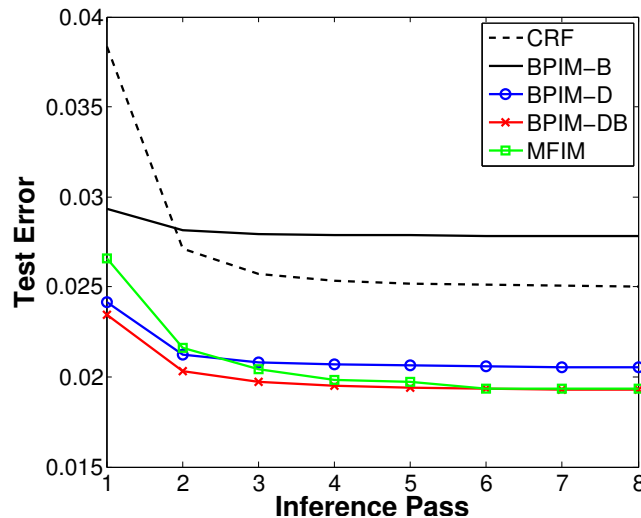


Figure 6.11: Average test error as a function of pass for each message-passing method on the 3D classification task.

In terms of computation time for inference on test scenes, our approach can be an order of magnitude more efficient than the graph-cut based inference of [Munoz et al. \(2009\)](#). On our machines, the approach of [Munoz et al. \(2009\)](#) requires around 30s to complete inference, using a highly optimized graph-cut library. The BPIM based approaches, that use the more computationally expensive LBP style message-passing, requires around 3-4s per inference pass, and to complete 8 pass of inference requires a similar running time of 30s. However as we saw that the predictions converge within 3-4 inference passes on this problem, we could easily stop inference earlier, and complete the inference in 10-15s, a factor 2-3 faster than the graph-cut approach. More importantly, MFIM requires much fewer predictions (as the message/prediction is the same for all neighbors), and thus runs much faster, around 0.5s per inference pass, and can thus complete inference in 3-4s on these test scenes, an order of magnitude faster than the graph-cut based approach. In recent work, [Hu et al. \(2013\)](#) further demonstrated that a similar inference machine based approach could achieve near real-time inference on streaming point cloud from a LIDAR sensor on a moving vehicle.

3D Geometry Estimation from 2D Images

We also evaluate our approach on the problem of estimating the 3D surface layout of outdoor scenes from single images, using the Geometric Context Dataset from [Hoiem et al. \(2007\)](#). In this dataset, the problem is to assign the 3D geometric surface labels to pixels in the image (see Figure 6.13). This task can be viewed as a 3-class or 7-class labeling problem. In the 3-class case, the labels are Ground/Supporting Surface, Sky, and Vertical structures (objects standing on the ground), and in the 7-class case the

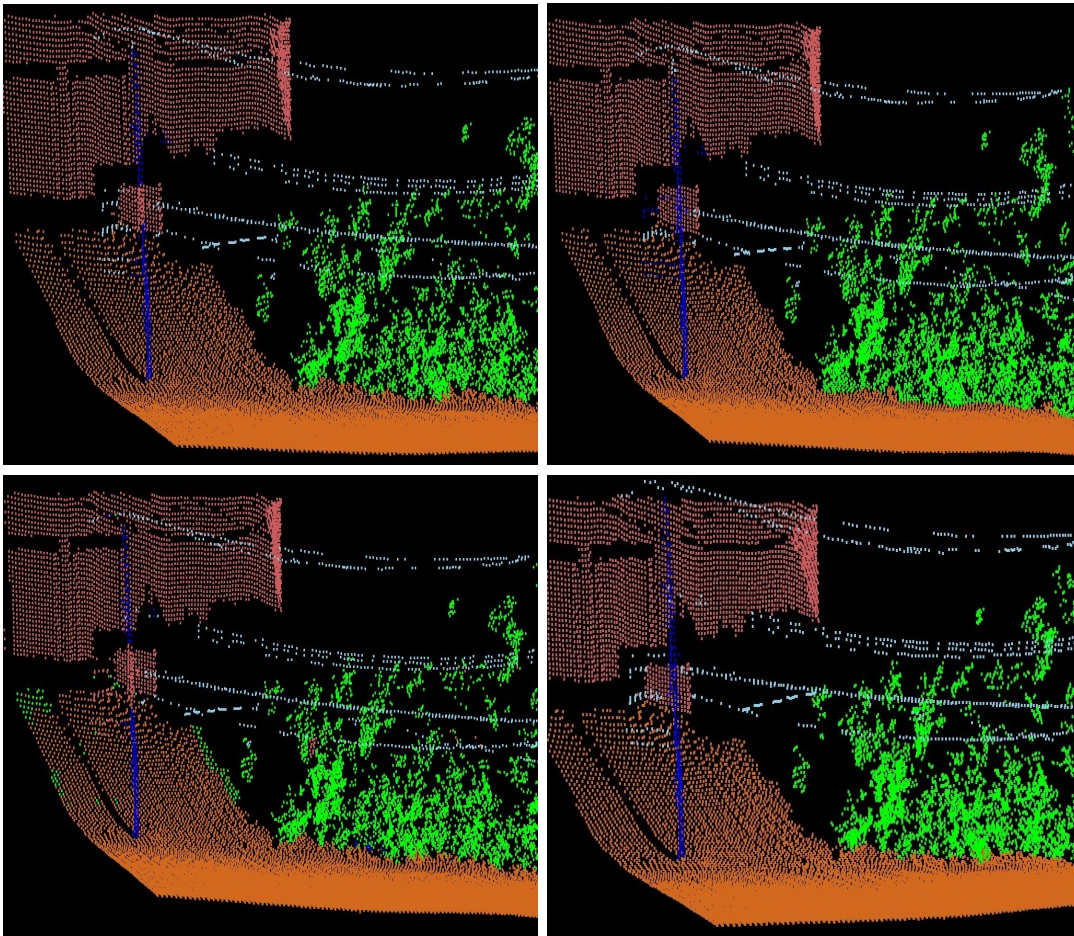


Figure 6.12: Estimated 3D point cloud labels with M³N-F (top left), M³N-P (top right), MFIM (bottom left), Ground truth (bottom right).

Vertical class is broken down into 5 subclasses: Left-perspective, Center-perspective, Right-perspective, Porous, and Solid. We consider the 7-class problem. In [Hoiem et al. \(2007\)](#), the authors use superpixels as the basic entities to label in conjunction with 15 image segmentations. Various features are computed over the regions which capture location, shape, color, texture, and perspective. Boosted decision trees are trained per segmentation and are combined to obtain the final labeling. In our approach, we define a graph over the superpixels, creating edges between adjacent superpixels, and consider the multiple segmentations as high-order cliques (clusters of super pixels). We use the same respective features and 5-fold evaluation as detailed in [Hoiem et al. \(2007\)](#). In addition to these features, we add the features related to previous predictions, which are a simply the average of the marginals at neighboring superpixels, and the average of each segments' average marginals the superpixel belongs to.

We compare the same methods used previously for the 3D point cloud classification

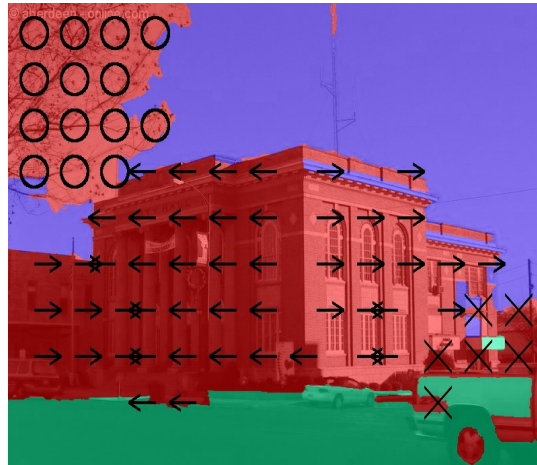


Figure 6.13: 3D Geometry estimation application. Each superpixel is assigned to one of 7 classes: sky, ground, left-perspective, right-perspective, center-perspective, solid or porous.

task. In addition, we also compare to the results of [Hoiem et al. \(2007\)](#). Here, we measure the performance of each method in terms of per superpixel accuracy, the Macro-F1 score (average of the per class F1 scores), and Micro-F1 score (weighted average, according to class frequency, of the per class F1 scores). Table 6.2 summarizes (left column) presents the results on this task.

	Accuracy	Macro-F1	Micro-F1
BPIM-D	0.6467	0.5971	0.6392
BPIM-B	0.6287	0.5705	0.6149
MFIM	0.6378	0.5947	0.6328
CRF	0.6126	0.5369	0.5931
M ³ N-F	0.6029	0.5541	0.6001
Hoiem et al. (2007)	0.6424	0.6057	0.6401

Table 6.2: Comparisons of test performance on the 3D Geometry Estimation dataset.

In this experiment our BPIM-D approach performs slightly better than all other approaches in terms of accuracy, including the performance of the previous state-of-the-art in [Hoiem et al. \(2007\)](#). In terms of F1 score, [Hoiem et al. \(2007\)](#) is slightly better. Given that [Hoiem et al. \(2007\)](#) used a more expressive predictor (boosted trees) than our logistic regressor, we believe we could also achieve better performance using more complex predictors. We notice here a larger difference between the BPIM and MFIM approaches, which confirms the cavity method can lead to better performance. Here the M³N-F approach did not fare very well and all message-passing approaches outperformed it. All inference machine approaches also outperformed the baseline CRF. Figures 6.14 and 6.15 show a visual comparison of the M³N-F, MFIM, BPIM-D and [Hoiem et al. \(2007\)](#) approaches on two test images. The outputs of BPIM-D and [Hoiem et al. \(2007\)](#)

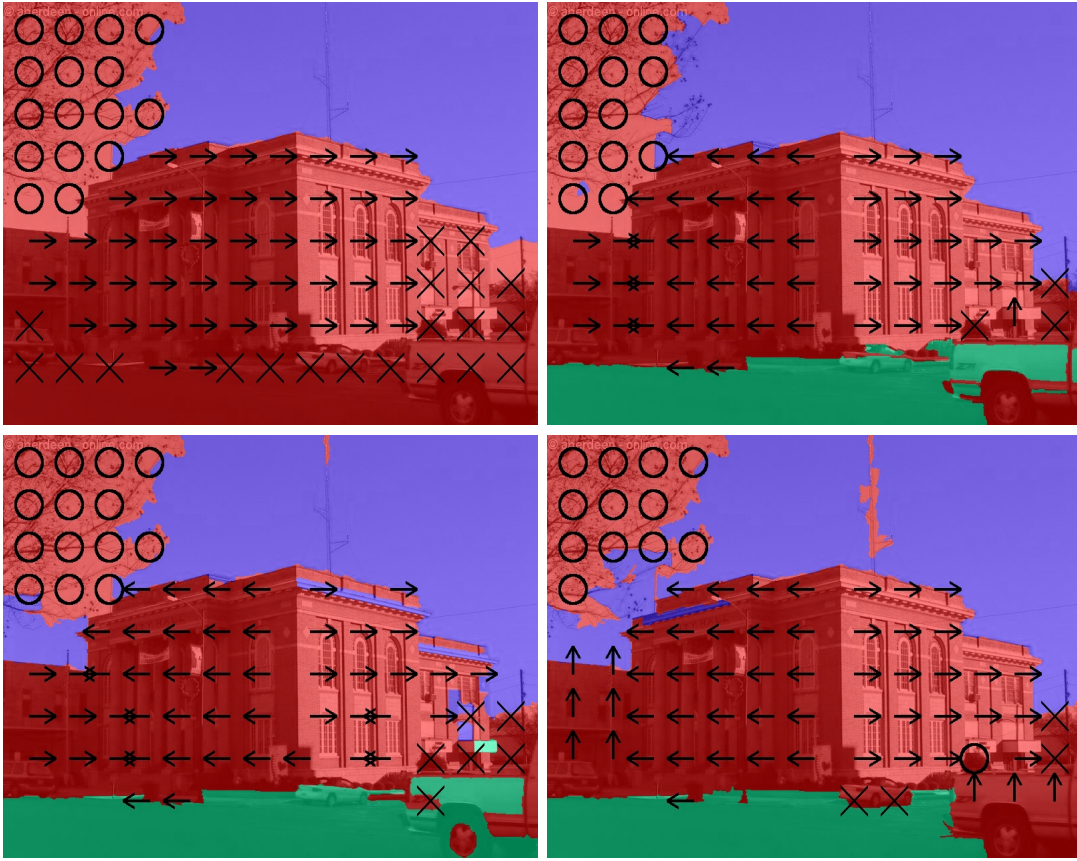


Figure 6.14: Estimated 3D geometric surface layouts on a city scene with M³N-F (top left), [Hoiem et al. \(2007\)](#) (top right), BPIM-D (bottom left), Ground truth (bottom right).

are very similar, but we can observe more significant improvements over the M³N-F.

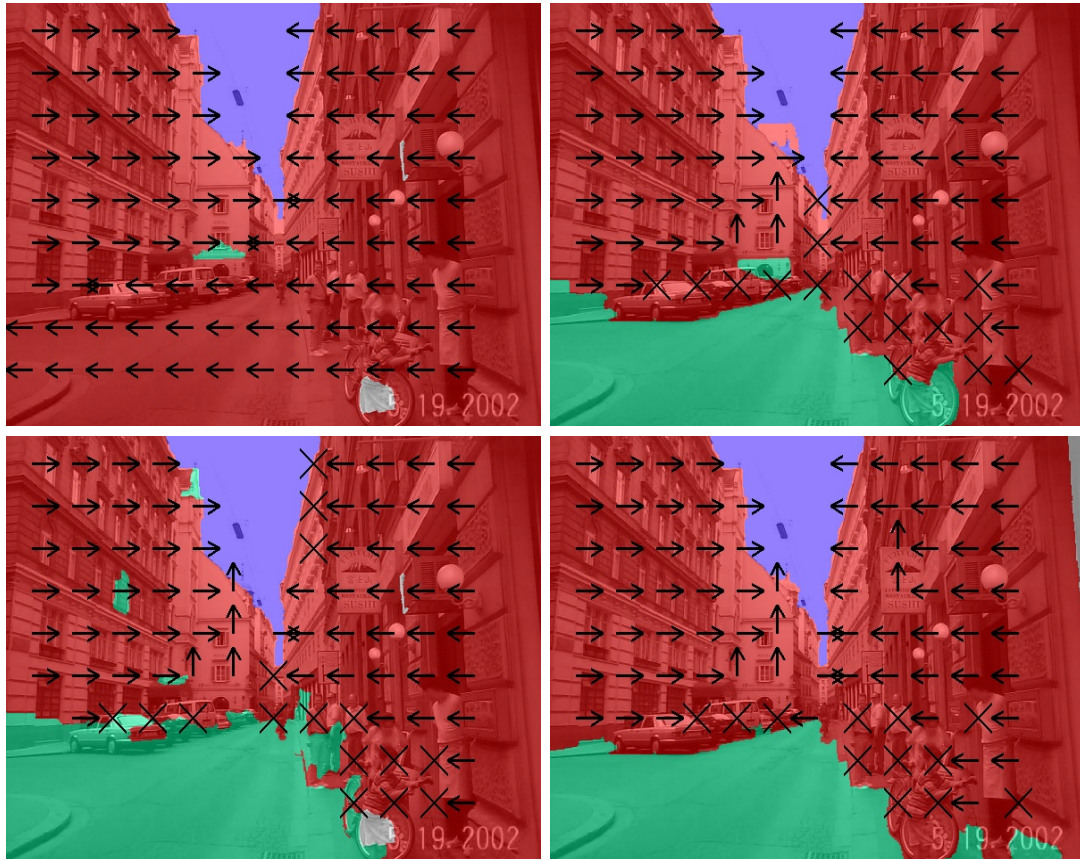


Figure 6.15: Estimated 3D geometric surface layouts on a street scene with M³N-F (top left), [Hoiem et al. \(2007\)](#) (top right), BPIM-D (bottom left), Ground truth (bottom right).

Chapter 7

Learning Submodular Sequence Predictions

We now move on to study another important class of sequential prediction tasks : recommendation tasks where we must learn to suggest lists of options or items.

Many problem domains, ranging from web applications (ad placement, content recommendation) to robotics (identifying small subset of grasps, or trajectories to try to successfully perform the task) require predicting lists of items/options (see Figure 7.1). Such applications are often budget-limited and the goal is to choose the best list of items, from a large set of possible items, with maximal utility. In ad placement, we must pick a small list of ads with high click-through rate. For robotic manipulation, we must pick a small set of initial grasp trajectories to maximize the chance of finding a successful trajectory via more extensive evaluation or simulation. In extractive document summarization, we want to find a few sentences from the text that provide a good summary of the entire document.

In all of these problems, the predicted list of items should be both relevant and diverse. For example, recommending a diverse set of news articles increases the chance that a user would like at least one article (Radlinski et al., 2008). As such, recommending multiple redundant articles on the same topic would do little to increase this chance. This notion of diminishing returns due to redundancy is often captured formally using *submodularity* (Guestrin and Krause, 2008).

In this chapter, we study the general learning problem of training a policy to construct lists (by predicting, in sequence, items to add to the list) that maximizes a submodular reward function – a reward with this property of diminishing return. We consider problems where the submodular reward function is only directly measured on a finite training set, and our goal is to learn to make good predictions on new test examples where the reward function is not directly measurable. For example in document summarization, we have access to a few training documents, where humans have provided summaries, and



Figure 7.1: Example Recommendation Applications. Left: Ad placement, where we want to display a small list of ads the user is likely going to click on. Center: News Recommendation, where we want to display a small list of news article likely to interest the user. Right: Grasp Selection, where we want to select a small list of grasps likely to succeed at picking an object.

we would like to learn to generate good summaries for new documents, where human summaries are not available.

To learn such a policy, it is natural to consider policies that use, as part of their input, features related to the items in the current list. As these features are related to previous predictions made by the policy, a similar train-test mismatch, as in previous sequential prediction settings, can occur if the policy is not trained carefully. We will show that the previous learning strategies, such as DAGGER, can be adapted to this setting to deal with this issue and learn policies that can recommend good lists of relevant and diverse items.

While DAGGER as presented could be applied “as is” for such setting, e.g. by attempting to minimize a 0-1 classification loss in order to mimic a greedy list construction strategy, this would not leverage the particular properties of the reward function. Instead we will present an adaptation of DAGGER, that leverages the particular submodular properties of the reward, and provides improved near-optimality guarantees.

We begin by formalizing the notion of submodularity and reviewing prior work related to submodular optimization, and learning. We then present our adaptation of DAGGER and its analysis, that provides strong near-optimality guarantees. We then demonstrate the improved performance of this method compared to prior work on various recommendation tasks: 1) Grasp Selection, recommending a small list of grasps to a robotic manipulator that is likely to contain a successful one for picking a nearby object, 2) Trajectory Optimization, recommending a small list of initial “seed” trajectories, to be used in a local trajectory optimization procedure, that is likely going to contain

one that leads to a collision-free trajectory; 3) News Recommendation, recommending a small set of news article the user is likely going to be interested in reading, and 4) Document Summarization: extracting a few sentences from documents that provide a good summary. This adaptation of DAGGER and these results were originally presented in [Ross et al. \(2013d\)](#).

7.1 Preliminaries

We now begin by formalizing the problem of maximizing submodular rewards and existing results and approaches.

Submodularity and the Concept of Diminishing Return

Formally, the problem we are trying to address can be defined as follows. We have a large set \mathcal{S} that represents the set of all possible items we can choose from (**e.g.** ads, sentences, grasps). Our objective is to pick a list of items $L \subseteq \mathcal{S}$ to maximize a reward function f , under a budget constraint that we can only pick a small list of k items, i.e. $|L| \leq k$.¹ We consider reward functions f that obey the following properties:

1. **Monotonicity:** For any lists L_1, L_2 , $f(L_1) \leq f(L_1 \oplus L_2)$ and $f(L_2) \leq f(L_1 \oplus L_2)$
2. **Submodularity:** For any lists L_1, L_2 and item $s \in \mathcal{S}$, $f(L_1 \oplus s) - f(L_1) \geq f(L_1 \oplus L_2 \oplus s) - f(L_1 \oplus L_2)$.

Here, \oplus denotes the concatenation operator. Intuitively, monotonicity implies that adding more elements never hurts, and submodularity captures the notion of diminishing returns (*i.e.* adding an item to a long list increases the objective less than when adding it to a shorter sublist). We further assume for simplicity that f takes values in $[0, 1]$, and that $f(\emptyset) = 0$ where \emptyset denotes the empty list. We will also use the shorthand $b(s|L) = f(L \oplus s) - f(L)$ to denote the marginal benefit of adding the item s to list L .

The optimal solution to this problem is the list of length k , that we denote L_k^* , that maximizes this objective:

$$L_k^* = \arg \max_{L: |L| \leq k} f(L) \quad (7.1)$$

Finding this optimal list is in general intractable, it is a combinatorial optimization problem that requires searching over an exponentially large set of possible lists (of size $|\mathcal{S}|^k$). In fact, it is well known that this problem is NP-Hard ([Nemhauser et al., 1978](#)).

¹“Lists” generalize the notion of “set” more commonly used in submodular optimization, and enables reasoning about item order and repeated items ([Streeter and Golovin, 2008](#)). One may consider sets where appropriate.

Greedy Algorithm

While finding the optimal list is NP-Hard, a simple greedy algorithm provides good approximation with near-optimality guarantees. That is, the greedy algorithm that starts from the empty list $\hat{L}_0 = \emptyset$, and then successively adds the item with largest marginal benefit to the current list, i.e. $\hat{L}_{i+1} = \hat{L}_i \oplus \hat{s}_i$ for $\hat{s}_i = \arg \max_{s \in \mathcal{S}} b(s|\hat{L}_i)$, until a list of length k is obtained, guarantees that the list \hat{L}_k is within a factor $(1 - 1/e)$ of the optimal list L_k^* , i.e. $f(\hat{L}_k) \geq (1 - 1/e)f(L_k^*)$. Obtaining any better approximation ratio than $(1 - 1/e)$ is known to be NP-Hard (Nemhauser et al., 1978). Hence greedy provides the best polynomial time approximation, unless $P = NP$.

It has also been observed in many applications that this greedy procedure typically works very well (Guestrin and Krause, 2008). Thus, given access to the submodular reward function f , one could simply employ greedy to construct good lists. However in our learning setting, f is only measurable on training examples, making this greedy algorithm inapplicable to new test examples. We formalize our learning setting below.

Learning with Submodular Rewards

In our learning task, we consider reward functions that may depend on some underlying state $x \in \mathcal{X}$ (e.g. a user, environment of the robot, a document, etc.). We denote f_x the reward function for state x , and assume that f_x is monotone submodular for all x . We also use the state to encode randomness, if any, in the objective. For instance, if a user clicks on an ad with some probability, the different random events are encoded by different states. As such, we do not assume the state is fully observed. It may be completely unknown, or only partially observed through some features (e.g. previous queries or websites visited by the user).

A simple example submodular function f_x that repeatedly arises in many domains is one that takes value 0 until a suitable item is found, and then takes on value 1 thereafter. Examples include the notion of “multiple choice” learning as in Dey et al. (2012a), Guzman-Rivera et al. (2012) where a predicted set of options is considered successful if any predicted item is deemed correct for the current example x , and abandonment in ad placement (Radlinski et al., 2008) where success is measured by whether any predicted advertisement is clicked on by the current user x .

Our task consists in learning to construct good lists of pre-specified length k under some unknown distribution of states D (e.g. distribution of users or documents we have to summarize). We consider two cases: context-free and contextual.

Context-Free: In the context-free case, we have no side-information about the current state (i.e. we do not observe anything about x). For example, we may want to learn the best list of news articles to display on a news website, when no information is available about the user who is viewing the website. In this case, we would like to find a

fixed list L that has good performance on average. That is, we quantify the performance of any list L by its expected value:

$$F(L) = \mathbb{E}_{x \sim D}[f_x(L)]. \quad (7.2)$$

Note that $F(L)$ is also monotone submodular. Thus the clairvoyant greedy algorithm with perfect knowledge of D can find a list \hat{L}_k such that $F(\hat{L}_k) \geq (1 - 1/e)F(L_k^*)$, where $L_k^* = \arg \max_{L: |L|=k} F(L)$. Although D is unknown, we assume that we observe samples of the objective f_x during training. Our goal is thus to develop a learning approach that efficiently converges, both computationally and statistically, to the performance of the clairvoyant greedy algorithm. In other words, we would like to achieve a similar guarantee to the clairvoyant greedy algorithm in the limit as we observe more and more training data.

Contextual: In the contextual case, we observe side-information in the form of features regarding the state x . We would like to use this observed side-information to suggest better lists for the particular context (e.g. a list of news articles personalized to the preference of the user x). We “lift” this problem to a hypothesis space of policies (*i.e.* multi-class predictors) that maps features to items.

We denote Π our policy class, and $\pi(x)$ the prediction of policy $\pi \in \Pi$ given side-information describing state x . We consider a list of k policies $L_{\pi,k} = (\pi_1, \pi_2, \dots, \pi_k)$, where in state x , this list of policies predicts the list of items $L_{\pi,k}(x) = (\pi_1(x), \pi_2(x), \dots, \pi_k(x))$. We quantify the performance of such list of policies by its expected value:

$$F(L_{\pi}) = \mathbb{E}_{x \sim D}[f_x(L_{\pi}(x))].$$

It can be shown that F obeys both monotonicity and submodularity with respect to appending policies to a list of policy (Dey et al., 2012a). Thus, a clairvoyant greedy algorithm that sequentially picks the *policy* with highest expected marginal benefit will construct a list $\hat{L}_{\pi,k}$ such that $F(\hat{L}_{\pi,k}) \geq (1 - 1/e)F(L_{\pi,k}^*)$, where $L_{\pi,k}^* = \arg \max_{L_{\pi}: |L_{\pi}|=k} F(L_{\pi})$. As before, our goal is to develop a learning approach (for learning a list of policies) that *efficiently* competes with the performance of the clairvoyant greedy algorithm.

Related Work

The problem of learning to optimize submodular reward functions from data, both with and without contextual features, has become increasingly important in machine learning due to its diverse application areas. Broadly speaking, there are two main approaches for this setting. The first aims to identify a model within a parametric family of submodular functions and then use the resulting model for new predictions. The second attempts to learn a strategy to directly predict a list of elements by decomposing the overall problem into multiple simpler learning tasks.

The first approach (Yue and Joachims, 2008, Yue and Guestrin, 2011, Lin and Bilmes, 2012, Raman et al., 2012) involves identifying the parameterization that best matches the submodular rewards of the training instances. For prediction, they then simply use the greedy algorithm on the learned submodular reward function. These methods are largely limited to learning non-negative linear combinations of features that are themselves submodular, which often restricts their expressiveness. Furthermore, while good sample complexity results are known, these guarantees only hold under strong realizability assumptions where submodular rewards can be modeled exactly by such linear combinations (Yue and Guestrin, 2011, Raman et al., 2012). Recent work on *Determinantal Point Processes* (DPPs) (Kulesza and Taskar, 2011) provides a probabilistic model of sets, which can be useful for the tasks that we consider. These approaches, while appealing, solve a potentially unnecessarily hard problem in first learning a holistic list evaluation model, and thus may compound errors by first approximating the submodular function and then approximately optimizing it.

The second, a learning reduction approach, by contrast, decomposes list prediction into a sequence of simpler learning tasks that attempts to mimic the greedy strategy (Streeter and Golovin, 2008, Radlinski et al., 2008, Streeter et al., 2009, Dey et al., 2012a). In Streeter and Golovin (2008), they address the context-free case, and show that by running a simple no-regret online learning algorithm² at each position in the list (where experts are items $s \in \mathcal{S}$ and losses are the negative benefits at that position) suffices to learn a distribution over lists with expected value \hat{F} that matches the guarantee of greedy in the limit as more and more training examples are observed. In Dey et al. (2012a), an approach called ConSeqOpt extends this strategy to the contextual setting by a reduction to cost-sensitive classification. Essentially, the predictor at each position aims to best predict an item to add to the list, given features, so as to maximize the expected marginal utility. This approach is flexible, in that it can be used with most common hypothesis classes and arbitrary features. Because of this decomposition, the full model class (all possible sequences of predictors) is often quite expressive, and allows for agnostic learning guarantees.³ This generality comes at the expense of being significantly less data-efficient than methods that make realizability assumptions such as Yue and Guestrin (2011), Raman et al. (2012), as these existing approaches learn a *different* predictor for each position in the list. In many ways, these methods adopt a similar learning strategy to Forward, as presented in previous chapters, and suffer from the same limitations : learning is less efficient as a separate predictor is learned for each position, not allowing to generalize across positions. Another issue that afflict these methods in

²E.g. weighted majority (Cesa-Bianchi et al., 1997).

³This first strategy of learning the parameters of a submodular function can be seen as a special case of this second approach, e.g. when the second approach uses the reduction of cost-sensitive classification to regression (see Section 7.3).

this particular setting, is that they can exhibit a data starvation phenomenon where later positions in the list have fewer and fewer examples to train on. This occurs due to the diminishing return property, e.g. if previous predictors in the list already found a successful item, there is no benefit left for the remaining positions. This effectively has the effect of discarding the current training example at these later positions in the list, and thus predictors far in the list may only have very few examples to train on.

To address these limitations, we present below an adaptation of the DAGGER learning strategy presented in previous chapters. Compared with related work, this approach enjoys the benefits of being both data-efficient while ensuring strong agnostic performance guarantees. We do so by developing new analysis for online submodular optimization which yields agnostic learning guarantees while learning a **single** data-efficient policy. By learning a single policy that can be used to construct the entire list, we also avoid the data starvation issue, as the policy is able to generalize to notions of relevance and diversity across positions in the list, and pick good items to add far in the list.

7.2 Context-free List Optimization

We first consider the context-free setting. For this setting, as there are no features, the stationary policy is represented as a fixed distribution over items, that is sampled from to add elements to the list.⁴

Our algorithm, called Submodular Contextual Policy (SCP), adapts the DAGGER learning strategy to this submodular sequence setting. Unlike in previous settings, here there is no expert telling us which action, or item to select. Instead we learn directly from feedback of the benefits of adding items to the list. SCP uses a similar strategy of interacting with the learner, to observe the benefits of adding items to list constructed by the current policy, and leverages the strong “no-regret” properties of online learning algorithms to provide strong guarantees on performance.

SCP, for the context-free setting, is described in Algorithm 7.2.1. SCP requires an online learning algorithm subroutine (denoted by UPDATE) that is no-regret with respect to a bounded positive loss function, maintains an internal distribution over items for prediction, and can be queried for multiple predictions (i.e. multiple samples).⁵ In contrast to prior work (Streeter and Golovin, 2008), SCP employs only a *single* online learning algorithm in the inner loop, instead of one at each position.

⁴Note that while there is no observed features of the state, we could also potentially consider learning a policy that uses features of the elements in the list. The algorithm we present in the next section for the contextual case, that uses both features of the state and list, could be applied in this case but without features of the state.

⁵Algorithms that meet these requirements include Randomized Weighted Majority (Littlestone and Warmuth, 1994), Follow the Perturbed Leader (Kalai and Vempala, 2005), EXP3 (Auer et al., 2002b), and many others.

Input: Set of items \mathcal{S} , length m of list to construct, length k of best list to compete against, online learner PREDICT and UPDATE functions.

for $t = 1$ **to** T **do**

Call online learner PREDICT() m times to construct list L_t . (e.g. by sampling m times from online learner's internal distribution over items).

Evaluate list L_t on a sampled state $x_t \sim D$.

For all $s \in \mathcal{S}$, define its discounted cumulative benefit: $r_t(s) = \sum_{i=1}^m (1 - 1/k)^{m-i} b(s|L_{t,i-1}, x_t)$.

For all $s \in \mathcal{S}$: define loss $\ell_t(s) = \max_{s' \in \mathcal{S}} r_t(s') - r_t(s)$

Call online learner update with loss ℓ_t : UPDATE(ℓ_t)

end for

Algorithm 7.2.1: Submodular Contextual Policy (SCP) Algorithm in context-free setting.

SCP proceeds by training over a sequence of training states x_1, x_2, \dots, x_T sampled from the unknown distribution D . At each iteration, SCP queries the online learner to generate a list of m items (via PREDICT, e.g. by sampling from its internal distribution over items), evaluates a weighted cumulative benefit of each item on the sampled list to define a loss related to each item, and then uses the online learner (via UPDATE) to update its internal distribution.

During training, we allow the algorithm to construct lists of length m , rather than k . In its simplest form, one may simply choose $m = k$. However, it may be beneficial to choose m differently than k , as is shown later in the theoretical analysis.

Perhaps the most unusual aspect is how loss is defined using the weighted cumulative benefits of each item:

$$r_t(s) = \sum_{i=1}^m (1 - 1/k)^{m-i} b(s|L_{t,i-1}, x_t), \quad (7.3)$$

where $L_{t,i-1}$ denotes the first $i - 1$ items in L_t , and

$$b(s|L_{t,i-1}, x_t) = f_{x_t}(L_{t,i-1} \oplus s) - f_{x_t}(L_{t,i-1}). \quad (7.4)$$

Intuitively, (7.3) represents the weighted sum of benefits of item s in state x_t had we added it at any intermediate stage in L_t . The benefits at different positions are weighed differently, where position i is adjusted by a factor $(1 - 1/k)^{m-i}$. These weights are derived via our theoretical analysis, and indicate that benefits in early positions should be more discounted than benefits in later positions. Intuitively, as the benefits can only decrease as the position in the list increases, this weighting has the effect of rebalancing the benefits so that each position contributes more equally to the overall loss.⁶

SCP requires the ability to directly measure f_x in each training instance x_t . Directly measuring f_{x_t} enables us to obtain loss measurements $\ell_t(s)$ for any $s \in \mathcal{S}$. For example,

⁶We also consider a similar algorithm in the min-sum cover setting, where the theory also requires reweighting benefits, but instead weights earlier benefits more highly (by a factor $m - i$, rather than $(1 - 1/k)^{m-i}$). We omit discussing this variant for brevity.

in document summarization f_x corresponds to the ROUGE score (Lin, 2004), which can be evaluated for any generated summary given expert annotations which are only available for training instances.

Partial Information Setting

In principle, SCP can also be applied in partial feedback settings, e.g. ad placement where the value f_{x_t} is only observed for some items (e.g. only the displayed ads), by using bandit learning algorithms instead (e.g. EXP3 (Auer et al., 2002b)).⁷ We briefly mention how this algorithm can be applied in partial feedback settings. However, as this is an orthogonal issue, most of our focus and analysis later is on the full information case.

In a partial information setting, we consider that we can only observe the benefits of the elements we added to the sampled list at each iteration. That is, our only observations about f_{x_t} are the benefits of each item in the constructed list L_t , i.e. for each position i , we only observe $b(s_{ti}|x_t, L_{t,i-1})$ for s_{ti} the item in position i in the list L_t , and for any other item $s' \neq s_{ti}$ we consider the benefit $b(s'|x_t, L_{t,i-1})$ unknown. If we construct a list of m items, we would only observe m benefits. For example, in ad placement, all displayed ads would have observed benefits 0, except the first ad in the list that is clicked on, would have an observed benefit of 1.

Based on this information, we can use an algorithm like EXP3 (Auer et al., 2002b), to update the internal distribution over items. Effectively, we can treat each of these m observed benefits as a separate learning example for EXP3, and perform m updates with these m examples. In particular, EXP3 would use the same importance weighting trick, mentioned in Section 4.1, to assign a reward of 0 to any unobserved benefit, and for the item s with observed benefit b , it would assign a reward of b/p , if p was the probability of picking that item when it was sampled. As our examples are weighted, by the factor $(1 - 1/k)^{m-i}$ for the example at position i , we would also multiply the reward by this weight. This reward vector, constructed for each observed benefit would then be used to update the internal distribution over items, as described in Auer et al. (2002b).

Theoretical Guarantees

We now show that Algorithm 7.2.1 is no-regret with respect to the clairvoyant greedy algorithm's expected performance over the training instances. Our main theoretical result provides a reduction to an online learning problem and directly relates the performance of our algorithm on the submodular list optimization problem to the standard online

⁷Partial information settings arise, e.g., when f is derived using real-world trials that preclude the ability to evaluate $b(s|L, x)$ (7.4) for every possible $s \in \mathcal{S}$.

learning regret incurred by the subroutine. The proofs of these results are presented in appendix B.

Although Algorithm 7.2.1 uses only a *single* instance of an online learner subroutine, it achieves the same performance guarantee as prior work (Streeter and Golovin, 2008, Dey et al., 2012a) that employ k separate instances of an online learner. This leads to a surprising fact: it is possible to sample from a stationary distribution over items to construct a list that achieves the same guarantee as the clairvoyant greedy algorithm.⁸

For a sequence of training states $\{x_t\}_{t=1}^T$, let the sequence of loss functions $\{\ell_t\}_{t=1}^T$ defined in Algorithm 7.2.1 correspond to the sequence of losses incurred in the reduction to the online learning problem. The expected regret of the online learning algorithm is

$$\mathbb{E}[R] = \sum_{t=1}^T \mathbb{E}_{s' \sim p_t}[\ell_t(s')] - \min_{s \in \mathcal{S}} \sum_{t=1}^T \ell_t(s), \quad (7.5)$$

where p_t is the internal distribution of the online learner used to construct list L_t . Note that an online learner is called *no-regret* if R is sublinear in T .

Let $F(p, m) = \mathbb{E}_{L_m \sim p}[\mathbb{E}_{x \sim D}[f_x(L_m)]]$ denote the expected value of constructing lists by sampling (with replacement) m elements from distribution p , and let $\hat{p} = \arg \max_{t \in \{1, 2, \dots, T\}} F(p_t, m)$ denote the best distribution found by the algorithm.

We define a mixture distribution \bar{p} over lists that constructs a list as follows: sample an index t uniformly in $\{1, 2, \dots, T\}$, then sample m elements (with replacement) from p_t . Note that $F(\bar{p}, m) = \frac{1}{T} \sum_{t=1}^T F(p_t, m)$ and $F(\hat{p}, m) \geq F(\bar{p}, m)$. Thus it suffices to show that $F(\bar{p}, m)$ has good guarantees. We show that in expectation \bar{p} (and thus \hat{p}) constructs lists with performance guarantees close to the clairvoyant greedy algorithm:⁹

Theorem 7.2.1. *Let $\alpha = \exp(-m/k)$ and $k' = \min(m, k)$. For any $\delta \in (0, 1)$, with probability $\geq 1 - \delta$:*

$$F(\bar{p}, m) \geq (1 - \alpha)F(L_k^*) - \frac{\mathbb{E}[R]}{T} - 3\sqrt{\frac{2k' \ln(2/\delta)}{T}}$$

Corollary 7.2.1. *If a no-regret algorithm is used on the sequence of loss ℓ_t , then as $T \rightarrow \infty$, $\frac{\mathbb{E}[R]}{T} \rightarrow 0$, and with probability 1:*

$$\lim_{T \rightarrow \infty} F(\bar{p}, m) \geq (1 - \alpha)F(L_k^*)$$

Theorem 7.2.1 provides a general approximation ratio to the best list of size k when constructing a list of a different size m . For $m = k$, we obtain the typical $(1 - 1/e)$

⁸This fact can also be seen as a special case of a more general result proven in prior related work that analyzed randomized set selection strategies to optimize submodular functions (Feige et al., 2011).

⁹Additionally, if the distributions p_t converge, then the last distribution p_{T+1} must have performance arbitrarily close to \bar{p} as $T \rightarrow \infty$. In particular, we can expect this to occur when the examples are randomly drawn from a fixed distribution that does not change over time.

approximation ratio (Guestrin and Krause, 2008). As m increases, this provides approximation ratios that converge exponentially closer to 1.

In particular we can see how the choice of m and k affects the performance guarantee of our algorithm, and that choosing $m \neq k$ can sometimes lead to better guarantees. For instance, imagine that our budget is $m = 12$, but we know that the optimal list of size $k = 4$ has $F(L_k^*)$ close to 1. Then running our algorithm with such (m, k) , would guarantee that we can achieve at least 95% of the best list of size 4 in the limit, and thus $F(\hat{p}, m)$ would be guaranteed to be close to 0.95. On the other hand, if we choose $m = k = 12$, $F(L_k^*)$ would be at most 1, and running our algorithm with such (m, k) , would only guarantee that we can achieve at least 63% of the best list of size 12 in the limit, and thus $F(\hat{p}, m)$ would only be guaranteed to be close to 0.63.

Naively, one might expect regret $\mathbb{E}[R]/T$ to scale linearly in k' as it involves loss in $[0, k']$. However, we show that regret actually scales as $O(\sqrt{k'})$, e.g. using Weighted Majority (Kalai and Vempala, 2005) with the optimal learning rate (or with the doubling trick (Cesa-Bianchi et al., 1997)). Our result matches the best known results for this setting (Streeter and Golovin, 2008) while using a *single* online learner, and is especially beneficial in the contextual setting due to improved generalization (see Section 7.3).

Corollary 7.2.2. *Using weighted majority with the optimal learning rate guarantees with probability $\geq 1 - \delta$:*

$$F(\bar{p}, m) \geq (1 - \alpha)F(L_k^*) - O\left(\sqrt{\frac{k' \log(1/\delta)}{T}} + \sqrt{\frac{k' \log |\mathcal{S}|}{T}}\right).$$

7.3 Contextual List Optimization with Stationary Policies

We now consider the contextual setting where features of each state x_t are observed before choosing the list. As mentioned, our goal here is to compete with the best list of policies $(\pi_1, \pi_2, \dots, \pi_k)$ from a hypothesis class Π . Each of these policies are assumed to choose an item solely based on features of the state x_t .

We consider embedding Π within a larger class, $\Pi \subseteq \tilde{\Pi}$, where policies $\tilde{\Pi}$ are functions of both state and a partially chosen list. Then for any $\pi \in \tilde{\Pi}$, $\pi(x, L)$ corresponds to the item that policy π selects to append to list L given state x . We will learn a policy, or distribution of policies, from $\tilde{\Pi}$ that attempts to generalize list construction across multiple positions.¹⁰

We now present SCP for the general contextual setting (Algorithm 7.3.1). At each iteration, SCP interacts with the learner to collect additional data by constructing a list

¹⁰Competing against the best list of policies in $\tilde{\Pi}$ is difficult in general as it violates submodularity: policies can perform better when added later in the list (due to list features). Nevertheless, we can still learn from class $\tilde{\Pi}$ and compete against the best list of policies in Π .

Input: Set of items \mathcal{S} , policy class $\tilde{\Pi}$, length m of list we construct, length k of best list we compete against.
 Pick initial policy π_1 (or distribution over policies)
for $t = 1$ **to** T **do**
 Observe features of a sampled state $x_t \sim D$ (e.g. features of user/document)
 Construct list L_t of m items using π_t with features of x_t (or by sampling a policy for each position if π_t is a distribution over policies).
 Define m new cost-sensitive classification examples $\{(v_{ti}, c_{ti}, w_{ti})\}_{i=1}^m$ where:
 1. v_{ti} is the feature vector of state x_t and list $L_{t,i-1}$
 2. c_{ti} is the cost vector such that $\forall s \in \mathcal{S}: c_{ti}(s) = \max_{s' \in \mathcal{S}} b(s'|L_{t,i-1}, x_t) - b(s|L_{t,i-1}, x_t)$
 3. $w_{ti} = (1 - 1/k)^{m-i}$ is the weight of this example
 $\pi_{t+1} = \text{UPDATE}(\pi_t, \{(v_{ti}, c_{ti}, w_{ti})\}_{i=1}^m)$
end for
return π_{T+1}

Algorithm 7.3.1: Submodular Contextual Policy (SCP) Algorithm.

L_t for the state x_t , using the online learner's current policy π_t (or by sampling policies from its distribution over policies, one for each position in the list).

Analogous to the context-free setting, we define a loss function for the online learner subroutine (UPDATE). We represent the loss using weighted cost-sensitive classification examples $\{(v_{ti}, c_{ti}, w_{ti})\}_{i=1}^m$, where v_{ti} denotes features of the state x_t and list $L_{t,i-1}$, $w_{ti} = (1 - 1/k)^{m-i}$ is the weight associated to this example, and c_{ti} is the cost vector specifying the cost of each item $s \in \mathcal{S}$

$$c_{ti}(s) = \max_{s' \in \mathcal{S}} b(s'|L_{t,i-1}, x_t) - b(s|L_{t,i-1}, x_t). \quad (7.6)$$

The loss incurred by any policy π is defined by its loss on this set of cost-sensitive classification examples, i.e.

$$\ell_t(\pi) = \sum_{i=1}^m w_{ti} c_{ti}(\pi(v_{ti})).$$

These new examples are then used to update the policy (or distribution over policies) using a no-regret algorithm (UPDATE). This reduction effectively transforms the task of learning a policy for this submodular list optimization problem into a standard online cost-sensitive classification problem.

This is similar to DAGGER with Cost-to-Go as presented in Chapter 4, where we also reduced the imitation learning (or reinforcement learning) task to an online cost-sensitive classification task. The difference here is that costs are directly related to immediate benefits, and do not involve expensive execution of a policy until the end of the sequence to obtain samples of each cost. The same techniques discussed in Chapter 4 can be used to handle this online cost-sensitive classification tasks. For example, for finite policy

classes $\tilde{\Pi}$, one can again use any no-regret online algorithm such as Weighted Majority (Kalai and Vempala, 2005) to maintain a distribution over policies in $\tilde{\Pi}$ based on the loss $\ell_t(\pi)$ of each π , and achieve regret at a rate of

$$R = \sqrt{k' \log |\tilde{\Pi}|/T},$$

for $k' = \min(m, k)$. In fact, the context-free setting can be seen as a special case of this, where the policy class is a set of $|\mathcal{S}|$ constant functions over states and lists, i.e. $\Pi = \tilde{\Pi} = \{\pi_s | s \in \mathcal{S}\}$ and $\pi_s(v) = s$ for any v . As also mentioned in Chapter 4, for more general infinite policy class, e.g. the set of all linear classifiers, one can use reductions of cost-sensitive classification to obtain a convex online learning problem, and use any standard no-regret algorithm for convex losses (e.g. gradient descent, Follow-the-(Regularized)-Leader). In our experiments, we make use of the reduction to regression, and a reduction to ranking, as presented before in Section 2.2.

Analogous to the context-free setting, we can also extend to partial feedback settings where f is only partially measurable by using contextual bandit algorithms such as EXP4 (Auer et al., 2002b) as the online learner (UPDATE).¹¹

Theoretical Guarantees

We now present contextual performance guarantees for SCP that relate performance on the submodular list optimization task to the regret of the corresponding online cost-sensitive classification task. The proofs of these results are presented in appendix B. Let $\ell_t : \tilde{\Pi} \rightarrow \mathbb{R}$ compute the loss of each policy π on the cost-sensitive classification examples $\{v_{ti}, c_{ti}, w_{ti}\}_{i=1}^m$ collected in Algorithm 7.3.1 for state x_t . We use $\{\ell_t\}_{t=1}^T$ as the sequence of losses for the online learning problem.

For a deterministic online algorithm that picks the sequence of policies $\{\pi_t\}_{t=1}^T$, the regret is

$$R = \sum_{t=1}^T \ell_t(\pi_t) - \min_{\pi \in \tilde{\Pi}} \sum_{t=1}^T \ell_t(\pi).$$

For a randomized online learner, let π_t be the distribution over policies at iteration t , with expected regret

$$\mathbb{E}[R] = \sum_{t=1}^T \mathbb{E}_{\pi'_t \sim \pi_t} [\ell_t(\pi'_t)] - \min_{\pi \in \tilde{\Pi}} \sum_{t=1}^T \ell_t(\pi).$$

Let $F(\pi, m) = \mathbb{E}_{L_{\pi, m} \sim \pi} [\mathbb{E}_{x \sim D} [f_x(L_{\pi, m}(x))]]$ denote the expected value of constructing lists by sampling (with replacement) m policies from distribution π (if π is a deterministic policy, then this means we use the same policy at each position in the list). Let

¹¹Analogous to the context-free setting, partial information arises when c_{ti} (7.6) is not measurable for every $s \in \mathcal{S}$.

$\hat{\pi} = \arg \max_{t \in \{1, 2, \dots, T\}} F(\pi_t, m)$ denote the best distribution found by the algorithm in hindsight.

We use a mixture distribution $\bar{\pi}$ over policies to construct a list as follows: sample an index t uniformly in $\{1, 2, \dots, T\}$, then sample m policies from π_t to construct the list. As before, we note that $F(\bar{\pi}, m) = \frac{1}{T} \sum_{t=1}^T F(\pi_t, m)$, and $F(\hat{\pi}, m) \geq F(\bar{\pi}, m)$. As such, we again focus on proving good guarantees for $F(\bar{\pi}, m)$, as shown by the following theorem.

Theorem 7.3.1. *Let $\alpha = \exp(-m/k)$, $k' = \min(m, k)$ and pick any $\delta \in (0, 1)$. After T iterations, for deterministic online algorithms, we have that with probability at least $1 - \delta$:*

$$F(\bar{\pi}, m) \geq (1 - \alpha)F(L_{\pi, k}^*) - \frac{R}{T} - 2\sqrt{\frac{2 \ln(1/\delta)}{T}}.$$

Similarly, for randomized online algorithms, with probability at least $1 - \delta$:

$$F(\bar{\pi}, m) \geq (1 - \alpha)F(L_{\pi, k}^*) - \frac{\mathbb{E}[R]}{T} - 3\sqrt{\frac{2k' \ln(2/\delta)}{T}}.$$

Thus, as in the previous section, a no-regret algorithm must achieve $F(\bar{\pi}, m) \geq (1 - \alpha)F(L_{\pi, k}^*)$ with high probability as $T \rightarrow \infty$. This matches similar guarantees provided for ConSeqOpt (Dey et al., 2012a). Despite having similar guarantees, we intuitively expect SCP to outperform ConSeqOpt in practice because SCP can use all data to train a *single* predictor, instead of the data being split to train k separate ones. We empirically verify this intuition in Section 7.4.

When using surrogate convex loss functions (such as regression or ranking loss), we provide a general result that applies if the online learner uses any convex upper bound of the cost-sensitive loss. An extra penalty term is introduced that relates the gap between the convex upper bound and the original cost-sensitive loss:

Corollary 7.3.1. *Let $\alpha = \exp(-m/k)$ and $k' = \min(m, k)$. If we run an online learning algorithm on the sequence of convex loss C_t instead of ℓ_t , then after T iterations, for any $\delta \in (0, 1)$, we have that with probability at least $1 - \delta$:*

$$F(\bar{\pi}, m) \geq (1 - \alpha)F(L_{\pi, k}^*) - \frac{\tilde{R}}{T} - 2\sqrt{\frac{2 \ln(1/\delta)}{T}} - \mathcal{G}$$

where \tilde{R} is the regret on the sequence of convex loss C_t , and \mathcal{G} is defined as

$$\frac{1}{T} \left[\sum_{t=1}^T (\ell_t(\pi_t) - C_t(\pi_t)) + \min_{\pi \in \tilde{\Pi}} \sum_{t=1}^T C_t(\pi) - \min_{\pi' \in \tilde{\Pi}} \sum_{t=1}^T \ell_t(\pi') \right]$$

and denotes the “convex optimization gap” that measures how close the surrogate C_t is to minimizing ℓ_t .

This result implies that using a good surrogate convex loss for no-regret convex optimization will lead to a policy that has a good performance relative to the optimal list of policies. Note that the gap \mathcal{G} often may be small or non-existent. For instance, in the case of the reduction to regression or ranking, $\mathcal{G} = 0$ in realizable settings where there exists a “perfect” predictor in the class. Similarly, in cases where the problem is near-realizable we would expect \mathcal{G} to be small.¹²

Discussion

The SCP procedure provides a reduction of contextual submodular list optimization to an online cost-sensitive classification problem. Here we obtain a *regret* reduction, where no-regret on this online learning task directly implies that we will find policies for constructing lists with near-optimal performance guarantees (in particular with the same guarantee as a clairvoyant greedy algorithm). The result here is stronger than in the prior imitation learning and structured prediction setting, as there is no dependency on the regret to the bayes-optimal classifier, as was present when using cost-to-go. Although this was in part due to the fact that in prior settings, performance was compared to the expert, which is a policy potentially outside of the class of policies. Here by comparing directly to the best sequence of policies from within the class Π , we obtain a guarantee that does not involve this term. In addition here, the submodularity property allows us to guarantee near-globally optimal performance, whereas in imitation learning, we could only guarantee good relative performance compared to the expert.

7.4 Case Studies

We now demonstrate experimentally the improved efficiency of SCP over previous methods. We compare performance on 4 different tasks. A context-free Grasp Selection task, and 3 contextual tasks: Trajectory Optimization, News Recommendation and Document Summarization.

Grasp Selection

We first applied SCP to a context-free task of grasp selection for a robot manipulator introduced in [Dey et al. \(2012b\)](#) (see Figure 7.2). The goal is to order the grasps in a library of grasps in such a way that good grasps can be found quickly (by going through the list in sequence) to pick up the object in front of the robot.

¹²We conjecture that this gap term \mathcal{G} is not specific to our particular scenario, but rather is (implicitly) always present whenever one attempts to optimize classification accuracy via surrogate convex optimization. For instance, when training a SVM in standard batch supervised learning, we would only expect that minimizing the hinge loss is a good surrogate for minimizing the 0-1 loss when the analogous convex optimization gap is small.

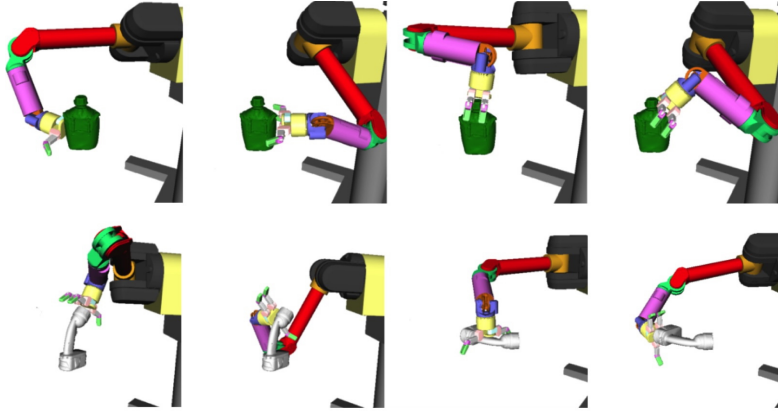


Figure 7.2: Depiction of an ordering selected in the Grasp Selection Task

We use the dataset from [Dey et al. \(2012b\)](#). It consists of 10448 environments, where the object is the same, but with varying random obstacle configurations around the object. There are 30 grasps defined by human operators for this particular object and are assumed to be stable grasps for picking up the object. Failure occurs when we are not able to plan a trajectory to the selected grasps, due to obstacles in the environment around the object. When going through the list, each grasps is evaluated (through planning) until one is found where we can successfully execute a planned trajectory to the selected grasp. As we would like to find successful grasps quickly, the goal is to minimize the search depth in the list before we find a successful one. We can think of this task as learning the best ordering for a particular object, and similar training could be conducted with different datasets to learn separate orderings of valid grasps for the different objects the robot has to interact with.

Minimizing search depth corresponds to a different objective than Equation 7.1. In particular it corresponds to minimizing:

$$C(L) = \sum_{i=0}^{|S|} [1 - f(L_i)] \quad (7.7)$$

where f is the submodular function that takes value 0 if no successful grasps are in the list, 1 otherwise. This is referred as a min sum set cover problem, and greedy has similar good approximation guarantees: it returns a list within a factor 4 of the minimum depth list ([Feige et al., 2004](#)). While our analysis and algorithms were developed to handle a different objective, they can be extended to this setting, e.g. following a similar analysis presented in [Streeter and Golovin \(2007\)](#) for these min sum set cover problems. The analysis in [Streeter and Golovin \(2007\)](#) for min sum set cover, suggests a different weighting of the examples, i.e. weight examples at position i by $(m - i)$, rather than the weight $(1 - 1/k)^{m-i}$ that we derived for the budgeted case. Hence, for this experiment,

SCP is applied as presented, except with the weighting of $(m - i)$ for examples generated at position i .

We compare SCP to SeqOpt, the approach used in [Dey et al. \(2012b\)](#) on this dataset. SeqOpt is the context-free version of ConSeqOpt ([Dey et al., 2012a](#)), and is the same algorithm as [Streeter and Golovin \(2008\)](#) (i.e. run a separate online learning algorithm at each position in the list). We also compare performance to two baseline: 1) Random, which orders grasps randomly (this provides diversity but poor relevance), and 2) Frequency, which orders grasps by their frequency of success on the training data (this provides relevant grasps but ignores diversity).

Figure 7.3 presents the average depth searched through the list on the test environments with SeqOpt, Frequency and SCP, as a function of the number of training environments. Also, Random achieves a baseline average depth of 6.81, which is inferior to the other methods that tries to better order the grasps. In these results, we first observe that both SCP and ConSeqOpt, by taking into account both diversity and relevance, can achieve improved results over the Frequency baseline (which ignores diversity). We also observe that with few training environments, SCP provides better performance, as it can generalize more quickly by learning a single distribution over grasps, rather than one at each position. However, as we increase the number of environments, the performance of SCP is limited by the fact that it learns a single fixed distribution for all position in the list. For instance, this does not allow it to order the grasps in a fixed deterministic order, which SeqOpt can achieve by learning different distributions at each position. Hence SeqOpt eventually performs better. However, it would be possible to add features of the list in this scenario to allow SCP to change its distribution, or sequence of grasps based on these list features, and this would potentially allow it to outperform SeqOpt. We emphasize that SCP’s main practical advantage is really in the contextual setting, to allow better generalization in the presence of a rich class of policy. This is shown in the contextual experiments below.

Trajectory Optimization

We applied SCP to a manipulation planning task for a 7 degree-of-freedom robot manipulator. The goal is to predict a set of initial trajectories so as to maximize the chance that one of them leads to a collision-free trajectory. We use local trajectory optimization techniques such as CHOMP ([Ratliff et al., 2009](#)), which have proven effective in quickly finding collision-free trajectories using local perturbations of an initial seed trajectory. Note that selecting a diverse set of initial seed trajectories is important since local techniques such as CHOMP often get stuck in local optima, i.e. similar or redundant initial trajectories will lead to the same local optima. This application is depicted in Figure 7.4.

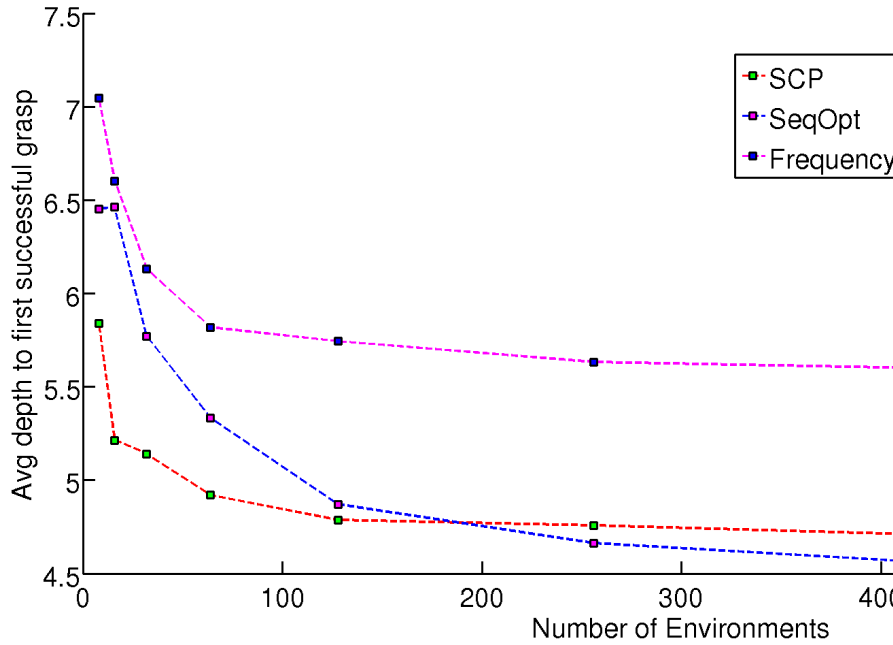


Figure 7.3: Average depth of the list searched before finding a successful grasps. SCP performs better at low data availability but eventually ConSeqOpt performs better as it can order grasps better by using different distributions at each position in the list.

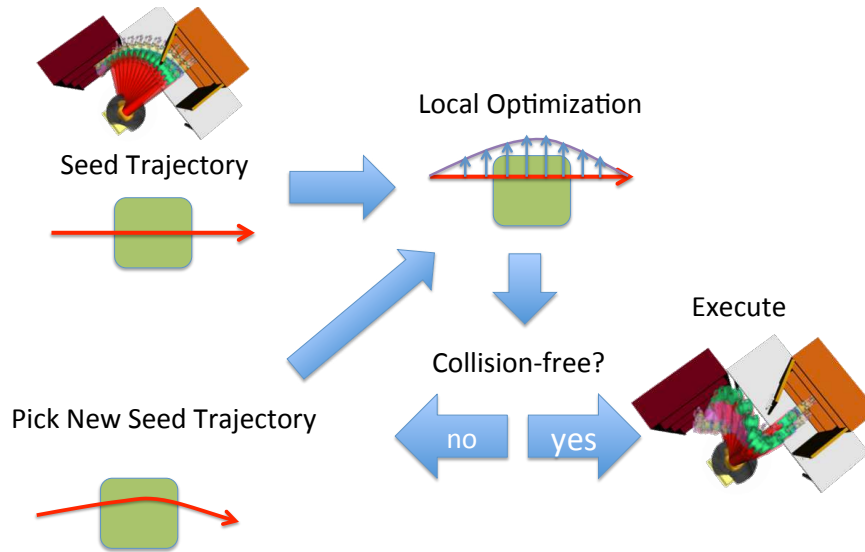


Figure 7.4: Depiction of the Trajectory Optimization Application. A list of initial seed trajectories is suggested to a local optimization procedure (CHOMP). CHOMP tries to locally optimize the current seed trajectory, and if stuck at a local minima in collision, restarts with the next seed trajectory in the list, until it obtains a local minima that is collision-free.

We use the dataset from [Dey et al. \(2012a\)](#). It consists of 310 training and 212 test environments of random obstacle configurations around a target object, and 30 initial seed trajectories. In each environment, each seed trajectory has 17 features describing the spatial properties of the trajectory relative to obstacles. In addition to these base features, we add features of the current list w.r.t. each initial trajectory. We use the per feature minimum absolute distance and average absolute value of the distance to the features of initial trajectories in the list. We also use a bias feature always set to 1, and an indicator feature which is 1 when selecting the element in the first position, 0 otherwise. The latter enables a distinction between the case where the minimum and average features are 0 because there are no seeds in the list yet, versus when they are 0 because we are actually considering a seed which is already in the list.

Following the experiments with ConSeqOpt in [Dey et al. \(2012a\)](#), we employ a reduction of cost-sensitive classification to regression as explained in Section 2.2. We compare SCP to ConSeqOpt, and REGRESSION: a baseline that uses the training data to learn a linear regressor that predicts the success probability from the 17 base features, and simply sorts trajectories based on the predicted success rate to construct the list. REGRESSION predicts based only on relevance, but ignores diversity.

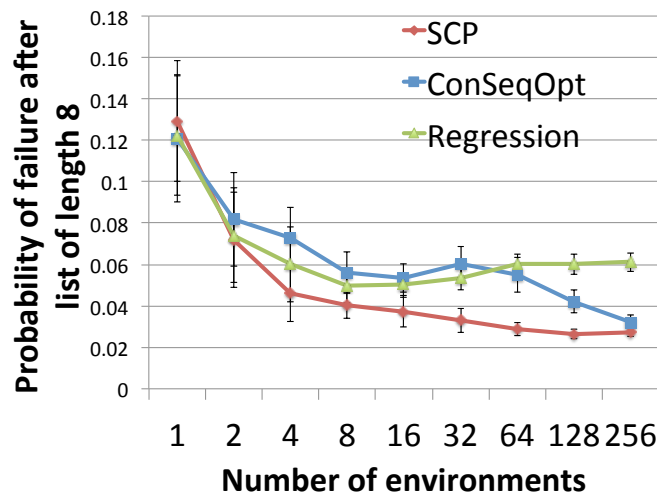


Figure 7.5: Probability of failure of each method on the test environments. SCP performs better at even low data availability while ConSeqOpt suffers from data starvation issues.

Figure 7.5 shows the failure probability over the test environments as the number of training environments is increased for each approach. ConSeqOpt employs a reduction to k classifiers. As a consequence, ConSeqOpt faces data starvation issues for small training sizes, as there is little data available for training predictors lower in the list.¹³

¹³When a successful seed is found, benefits at later positions are 0. This effectively discards training environments for training classifiers lower in the list in ConSeqOpt.

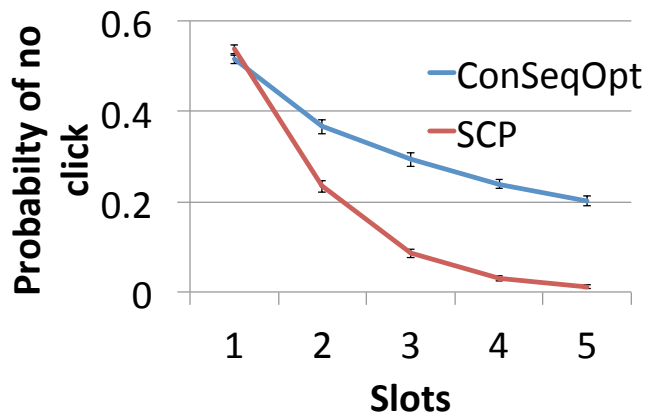


Figure 7.6: Probability of no click on the test users on the news recommendation task. With increase in slots SCP predicts news articles which have lower probability of the user not clicking on any of them compared to ConSeqOpt

In contrast, SCP has no data starvation issue and learns a single good policy to construct the list much more quickly. The worse performance of REGRESSION also demonstrates that SCP and ConSeqOpt (after sufficient data) can better capture the importance of diversity when recommending list of options.

News Recommendation

In the news recommendation setting the task, the goal is to present a sequence of news articles to a user so as to maximize the probability of the user clicking on at least 1 recommended article.

We built a stochastic user simulation based on 75 user preferences derived from a user study in [Yue and Guestrin \(2011\)](#). Using this simulation as a training oracle, our goal is to learn to recommend articles to any user (depending on their contextual features) to minimize the failure case where the user does not like any of the recommendations.¹⁴

Articles are represented by features, and user preferences by linear weights. We derived user contexts by soft-clustering users into groups, and using corrupted group memberships as contexts.

We perform five-fold cross validation. In each fold, we train SCP and ConSeqOpt on 40 users' preferences, use 20 users for validation, and then test on the held-out 15 users. Training, validation and testing are all performed via simulation.

Figure 7.6 shows the results, where we see the recommendations made by SCP achieves significantly lower failure rate as the number of recommendations is increased from 1 to 5.

¹⁴Also known as abandonment ([Radlinski et al., 2008](#)).

Document Summarization

In the extractive multi-document summarization task, the goal is to extract sentences (with character budget B) to maximize coverage of human-annotated summaries. Following the experimental setup from Lin and Bilmes (2010) and Kulesza and Taskar (2011), we use data from the Document Understanding Conference (DUC) 2003 and 2004 (Task 2) (Dang, 2005). Each training or test instance corresponds to a cluster of documents, and contains approximately 10 documents belonging to the same topic and four human reference summaries. We train on the 2003 data (30 clusters) and test on the 2004 data (50 clusters). The budget is $B = 665$ bytes, including spaces.

We use the ROUGE (Lin, 2004) unigram statistics (ROUGE-1R, ROUGE-1P, ROUGE-1F) for performance evaluation. Our method directly attempts to optimize the ROUGE-1R objective with respect to the reference summaries, which can be easily shown to be monotone submodular (Lin and Bilmes, 2011).

We aim to predict sentences that are both short and informative. Therefore we maximize the normalized marginal benefit,

$$b'(s|L_{t,i-1}) = b(s|L_{t,i-1})/l(s), \quad (7.8)$$

where $l(s)$ is the length of the sentence s .¹⁵ We use a reduction to ranking as described in Section 2.2 using (7.8) to train a SVM that ranks the sentences. While not performance-optimized, our approach takes less than 15 minutes to train.

Following Kulesza and Taskar (2011), we consider features f_i for each sentence consisting of *quality features* q_i and *similarity features* ϕ_i ($f_i = [q_i^T, \phi_i^T]^T$). The quality features, attempt to capture the representativeness for a single sentence. Similarity features q_i for sentence s_i as we construct the list L_t measure a notion of distance of a proposed sentence to sentences already included in the set. A variety of similarity features were considered, with the simplest being average squared distance of TF-IDF vectors. Performance was very stable across different features. The experiments presented use three types: 1) following the idea in Kulesza and Taskar (2011) of similarity as a volume metric, we compute the squared volume of the parallelepiped spanned by the TF-IDF vectors of sentences in the list $L_{t,k} \oplus s_i$; 2) the product between this volume and the quality features; 3) the minimum absolute distance of quality features between s_i and each element in $L_{t,k}$.

Table 7.1 shows the performance (Rouge unigram statistics) comparing SCP with existing algorithms. We observe that SCP outperforms existing state-of-the-art approaches,

¹⁵Because each sentence contains a different number of characters/bytes, this results in a knapsack constrained optimization problem where items have different weights. Under such constraint, the greedy algorithm picks items with highest normalized benefits. This is why we also normalized the benefits for our algorithm. We expect our approach to perform well in this setting, but defer a formal analysis for future work.

System	ROUGE-1F	ROUGE-1P	ROUGE-1R
SubMod	37.39	36.86	37.99
DPP	38.27	37.87	38.71
ConSeqOpt	39.02 ± 0.07	39.08 ± 0.07	39.00 ± 0.12
SCP	39.15 ± 0.15	39.16 ± 0.15	39.17 ± 0.15
Greedy (Oracle)	44.92	45.14	45.24

Table 7.1: ROUGE unigram score on the DUC 2004 test documents.

which we denote SubMod (Lin and Bilmes, 2010) and DPP (Kulesza and Taskar, 2011). “Greedy (Oracle)” corresponds to the clairvoyant greedy algorithm that directly optimizes the test Rouge score and thus serves as an upper bound on this class of techniques.

Figure 7.7 plots Rouge-1R performance as a function of the size of training data, suggesting SCP’s superior data-efficiency compared to ConSeqOpt.

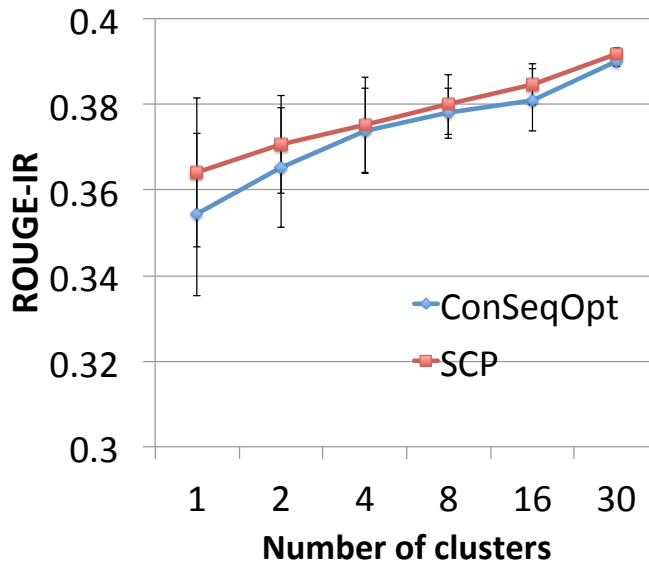


Figure 7.7: Rouge-1R scores on the test documents with respect to the size of training data.

Chapter 8

Learning Dynamic Models for Good Control Performance

We now move on to investigate a final and important sequential prediction task : system identification – learning a dynamic model of a system from observations that is useful for planning and controller synthesis. As most robotic systems use some form of planning algorithms for decision-making, having good predictive models of the future outcomes of different courses of action is crucial in many control applications. We focus on learning models that ultimately provide good *control* performance guarantees for the particular task of interest (and not simply high accuracy at predicting future states under the execution of a particular controller).

As mentioned in Chapter 1, in system identification, a similar train-test mismatch can occur as the policy resulting from controller synthesis is often very different from the “exploration” policy used to collect data and fit the dynamic model. While we might expect the model to make good predictions at states frequented by the exploration policy, the learned policy usually induces a different state distribution, where the model may poorly capture system behavior (as in Figure 1.2 in Chapter 1), and lead to poor control performance.

In this chapter, we present how the DAGGER learning strategy can be adapted in this setting to obtain an iterative and interactive learning procedure that learns a good model for controller synthesis. Unlike prior work in this setting, our method provides strong *control* performance guarantees in fully *agnostic* settings where the real system may not be modeled perfectly by any model in the class considered by the learning algorithm. Good *control* performance is guaranteed under the weaker agnostic assumption that some model in the class can achieve statistically good prediction on the training data.

We begin by briefly reviewing previous and related work, and defining formally our objective and notation. We then provide an agnostic analysis of the common textbook/batch system identification approach that consists in simply treating system iden-

tification as a standard statistical learning problem, learning only from data collected by some exploration policy (e.g. open loop controls, an expert performing the task, or some other base controller we want to improve upon), and then planning with the resulting learned model. Our analysis formalizes the train-test mismatch this approach can suffer from and its resulting poor *control* guarantees. We then present our adaptation of DAGGER to this setting, with its improved agnostic guarantees on control performance. Finally we demonstrate the efficacy of our approach on a challenging domain from the literature: learning to perform aerobatic maneuvers with a simulated helicopter (Abbeel and Ng, 2005). This adaptation of DAGGER and part of the results presented here were originally presented in Ross and Bagnell (2012a).

8.1 Preliminaries

We here review previous and related work in system identification. The literature on this topic is vast and distributed across many fields of engineering and computer science. We begin by giving a brief overview of the work in the control literature, and then in artificial intelligence on model-based reinforcement learning. We then discuss more specifically methods closely related to our work.

System Identification

In the system identification literature on the control side, much of the work has focused on continuous systems, and particularly on learning linear dynamical systems. The problem of interest is to learn dynamic models that can predict future output observations, by observing a stream of observations and input controls. Different methods have been developed to learn such systems in the frequency domain, or the time domain. Traditional identification methods have exploited the linear properties of the model to learn the model in the frequency domain (Ljung, 1999). Namely, they exploit the fact that the frequency response of a linear system to any linear combination of basis control signals is simply the linear combination of the frequency response to each basis signals. This makes learning easy as these approaches can simply record the frequency response of the system to a set of basis control signals, typically chosen to cover the range of frequencies the controller will use. For state-space time domain linear models, two main approaches were developed: 1) methods based on deterministic/stochastic realization, which learns the system based on spectral learning methods, such as SVD, that can recover the parameters of the linear systems through matrix factorization of a Hankel or covariance matrix (Ho and Kalman, 1965, Akaike, 1975, Overschee and Moor, 1996), and 2) methods based on prediction error/maximum likelihood, that adopts a more statistical learning/regression approach, e.g. learning an ARX model that predicts the future

output observation from the past few controls and observations (Astrom, 1965, 1971, Ljung, 1978, 1999). To our knowledge, the theoretical analysis of both types of methods assume that the real system is linear, and guarantees identifying the true parameters (or up to an equivalent transformation) of the system under some conditions on the controls (e.g. white noise, persistent excitation, open loop controls), that prevents correlations between control and state, and sufficiently explore all modes of the linear system.

Much work has also been done in non-linear system identification, where most of the work are methods based on learning complex parametric models, such as neural networks, for minimizing prediction error, or using a wide variety of non-parametric methods (see Sjöberg et al. (1995) for a nice survey). Much of the theoretical results in this case are concerned with convergence of the prediction error to the minimum under the training distribution, e.g. assuming data is observed from a stationary markov process (Juditsky et al., 1995). As these non-parametric methods can fit arbitrarily well any function, again this is essentially assuming realizability. In addition, in this case, not much can be said about control performance, if such non-linear model would be used for control (e.g. due to the train-test mismatch, we may still obtain a poor controller).

Much of the earlier work up to the late eighties rarely considered the relation of system identification performance to control performance. More recent developments, in what's called "identification for control", have started analyzing the problem of system identification for purposes of obtaining a good controller (Gevers and Ljung, 1986, Hjalmarsson et al., 1996, Forssell and Ljung, 1999, 2000). Work in this area have showed the benefits of using iterative identification procedures under closed-loop control, e.g. by using the current controller, synthesized under the current model to collect more data (Hjalmarsson et al., 1996). Theoretical analysis in this case again typically assumes a realizable setting with linear models, and is typically concerned with analyzing the bias/variance of the estimator of the linear model, and analyzing what would be the optimal experiment design (i.e. controller to execute) to, e.g., minimize the variance (Gevers and Ljung, 1986, Hjalmarsson et al., 1996, Forssell and Ljung, 1999, 2000).

Our work fits into this later category of identification for control, and suggests a similar iterative system identification procedure with closed-loop controllers. However our results extend beyond learning of linear models and provide analysis for a general agnostic setting and general conditions under which we may expect to find good controllers.

Model-Based Reinforcement Learning

In the model-based reinforcement learning (MBRL) literature, most methods have focused on discrete control problems where a finite MDP model of the system is learned. In this case the next state distribution for each state-action pair is directly estimated

from the observed empirical distribution of next states. More complex models were also proposed that attempts to improve generalization across states/actions, such as hierarchical models (Dietterich, 2000, Jong and Stone, 2008), factorized models (Kearns and Koller, 1999, Ross and Pineau, 2008, Hester and Stone, 2009) and relational models (Walsh et al., 2009). Some work also consider continuous MDP, and often uses state aggregation based models (tree-based/grid based discretization)(Uther and Veloso, 1998, Bernstein and Shinkin, 2010), linear models (Strehl and Littman, 2007, Walsh et al., 2009), and more recent techniques have used non-parametric bayesian Gaussian Process models (Deisenroth and Rasmussen, 2011).

A significant part of the work in reinforcement learning has focused on the exploration-exploitation issue: where should data be collected to improve performance and when should we stop exploring and simply exploit current knowledge of the system to achieve the task. State-of-the-art RL methods have addressed this issue by either 1) being optimistic about the value of state-action pairs that have not been visited often enough and planning an optimal policy in a resulting optimistic model to compute the policy to execute (Strehl et al., 2009, Jaksch et al., 2010) or 2) using a bayesian approach where a prior on the transition model is used and solving a POMDP to compute an optimal exploration-exploitation strategy under this prior (Poupart et al., 2006, Ross, 2008). Similar bayesian approaches were also proposed in the adaptive control and dual control literature (Fel'dbaum, 1965, Bar-Shalom, 1981, Astrom and Wittenmark, 1989). Other techniques have proposed using apprenticeship learning techniques for exploration, where expert demonstrations are initially used to collect data and fit a first model (Abbeel and Ng, 2005). Then at subsequent iterations, the current optimal policy is used to collect more data and improve the model until a policy is found that is at least as good as the expert.

Theoretical analysis in model-based reinforcement learning also assumes realizable settings, i.e. that the real system has the same structure as the class of model considered. The optimistic exploration strategy of many model-based RL methods also assumes realizability in order to provide good results (Strehl et al., 2009, Jaksch et al., 2010).

Spectral Learning of Dynamic Models

In addition to spectral learning methods developed in the system identification literature, other spectral methods have been developed recently in the machine learning literature for learning discrete hidden state dynamic models from a stream of observations. Hsu et al. (2009) first introduced a spectral algorithm for learning hidden markov models¹ (HMM) of a stream of observation, which was then generalized in Siddiqi et al. (2010) to learn more rich and compact representations, called Reduced-Rank HMM. The latter

¹A HMM is a POMDP without actions and costs

was also applied for learning hidden state models for control, called predictive state representations² (PSR) (Siddiqi et al., 2010, Boots et al., 2011, Boots and Gordon, 2011). The analysis of these spectral learning methods also rely on realizability assumptions, in that they guarantee that in the limit they will learn an equivalent model to the true model, if the true model belongs to the model class. In addition, their analysis focuses on statistical consistency, and does not relate the estimation error (from finite sampled data) of the model to the resulting control performance.

Iterative Methods in Practice

In practice control engineers often proceed iteratively to build good models for controller synthesis, as suggested in recent identification for control methods. For instance, they may collect a first batch of data to fit a model and obtain a controller, which is then tested in the real system. If performance is unsatisfactory, data collection is repeated with different sampling distributions to improve the model where needed, until control performance is satisfactory. By doing so, engineers can use feedback of the policies found during training to decide how to collect data and improve performance. Such methods are commonly used in practice and have demonstrated good performance in the work of Atkeson and Schaal (1997), Abbeel and Ng (2005). In both works, the authors proceed by fitting a first model from state transitions observed during expert demonstrations of the task, and at following iterations, using the optimal policy under the current model to collect more data and fit a new model with all data seen so far. Abbeel and Ng (2005) show this approach has good guarantees in realizable settings (for finite MDPs or LQRs), in that it must find a policy that performs as well as the expert providing the initial demonstrations. Our method can be seen as making algorithmic this engineering practice, extending and generalizing the previous methods of Atkeson and Schaal (1997), Abbeel and Ng (2005) and other similar iterative identification methods, and suggesting slight modifications that provide good guarantees even in *agnostic* settings.

Agnostic Exploration

Our approach leverages the way agnostic model-free RL algorithms perform exploration. Methods such as Conservative Policy Iteration (CPI) (Kakade and Langford, 2002) and Policy-Search by Dynamic Programming (PSDP) (Bagnell et al., 2003) learn a policy directly by updating policy parameters iteratively. For exploration, they assume access to a state exploration distribution ν that they can restart the system from and can guarantee finding a policy performing nearly as well as any policies inducing a state distribution (over a whole trajectory) close to ν (e.g. similar to the result for DAGGER

²A PSR is an alternate, more rich and compact representation of POMDPs.

with learner’s cost-to-go presented in Section 4.3). Similarly, our approach below uses a state-action exploration distribution to sample transitions and allows us to guarantee good performance compared to any policy with a state-action distribution close to this exploration distribution. If the exploration distribution is close to that of a near-optimal policy, then our approach guarantees near-optimal performance, provided a good model of data exists. This allows our model-based method to match the strongest agnostic guarantees of existing model-free methods. Good exploration distributions can often be obtained in practice; *e.g.*, from human expert demonstrations, domain knowledge, or from a desired trajectory we would like the system to follow. Additionally, if we have a base policy we want to improve, it can be used to generate the exploration distribution – with potentially additional random exploration in the actions.

8.2 Problem Formulation and Notation

We now formalize our system identification setting, objectives and notation.

We assume the real system behaves according to some unknown MDP, represented by a set of states S and actions A (both potentially infinite and continuous), an unknown transition function T , where T_{sa} denotes the next state distribution if we do action a in state s , and the initial state distribution μ at time 1. We assume the cost function $C : S \times A \rightarrow \mathbb{R}$ is known and seek to minimize the expected sum of discounted costs over an infinite horizon with discount γ . We assume for simplicity of exposition that the states are observed, but our algorithms and analysis also extend to partially observable settings. This is discussed further in Section 8.4.

For any policy π , we denote:

- $\pi(s)$ the action distribution performed by π in state s ;
- $D_{\omega,\pi}^t$ the state-action distribution at time t if we started in state distribution ω at time 1 and followed π ;
- $D_{\omega,\pi} = (1 - \gamma) \sum_{t=1}^{\infty} \gamma^{t-1} D_{\omega,\pi}^t$ the “discounted” state-action distribution over the infinite horizon if we follow π , starting in ω at time 1;
- $V_{\pi}(s) = \mathbb{E}_{a \sim \pi_s, s' \sim T_{sa}} [C(s, a) + \gamma V_{\pi}(s')]$ the value function of π (the expected sum of discounted costs of following π starting in state s);
- $Q_{\pi}(s, a) = C(s, a) + \gamma \mathbb{E}_{s' \sim T_{sa}} [V_{\pi}(s')]$ the action-value function of π (the expected sum of discounted costs of following π after starting in s and performing action a);
- $J_{\omega}(\pi) = \mathbb{E}_{s \sim \omega} [V_{\pi}(s)] = \frac{1}{1-\gamma} \mathbb{E}_{(s,a) \sim D_{\omega,\pi}} [C(s, a)]$ the expected sum of discounted costs of following π starting in ω .

Our goal is to obtain a policy π with small regret, *i.e.* for any policy π' , $J_\mu(\pi) - J_\mu(\pi')$ is small (or negative). This is achieved indirectly by learning a model \hat{T} of the system and solving for a (near-)optimal policy (under \hat{T} and the known cost function C); *e.g.*, using dynamic programming (Puterman, 1994) or approximate methods (Gordon, 1995, Williams, 1992, Li and Todorov, 2004, Jacobson and Mayne, 1970).

8.3 Batch Off-policy Learning Approach

We now describe a simple algorithm, referred to as *Batch*, that can be used to analyze many common approaches from the literature, *e.g.*, learning from a generative model³, open loop excitation or by watching an expert (Ljung, 1999).

Let \mathcal{T} denote the class of transition models considered, and ν a state-action exploration distribution we can sample the system from. *Batch* first observes m sampled transitions in the real system, occurring in m state-action pairs sampled i.i.d. from ν . Then it finds the best model $\hat{T} \in \mathcal{T}$ of observed transitions, and solves (potentially approximately) the optimal control (OC) problem with \hat{T} and known cost function C to return a policy $\hat{\pi}$ for test execution.

Analysis

Our analysis seeks to answer the following question: if *Batch* learns a model \hat{T} with small error on training data, and solves the OC problem well (*e.g.* finds a near-optimal policy for \hat{T}), what guarantees does it provide on control performance of $\hat{\pi}$ in the real system? Our results illustrate the drawbacks of a purely batch method due to the mismatch in train-test distribution. The proofs of all results presented here can be found in appendix C.

First, we measure the quality of the OC problem's solution as follows. For any policy π' , let

$$\epsilon_{\text{oc}}^{\pi'} = \mathbb{E}_{s \sim \mu} [\hat{V}^{\hat{\pi}}(s) - \hat{V}^{\pi'}(s)]$$

denote how much better π' is compared to $\hat{\pi}$ on model \hat{T} ($\hat{V}^{\hat{\pi}}$ and $\hat{V}^{\pi'}$ are the value functions of $\hat{\pi}$ and π' under learned model \hat{T} respectively). If $\hat{\pi}$ is an ϵ -optimal policy on \hat{T} within some class of policies Π , then $\epsilon_{\text{oc}}^{\pi'} \leq \epsilon$ for all $\pi' \in \Pi$.

Next, to measure model error, a natural notion of error that arises from our analysis is the L_1 distance between the predicted and true next state's distributions. That is, we define:

$$\epsilon_{\text{prd}}^{L1} = \mathbb{E}_{(s,a) \sim \nu} [\|T_{sa} - \hat{T}_{sa}\|_1],$$

the predictive error of \hat{T} , measured in L_1 distance, under the training distribution ν .

³With a generative model, we can set the system to any state, perform any action to obtain a sample transition.

A drawback of this L_1 distance is that it cannot be evaluated or optimized from sampled transitions observed during training (we observe next states sampled from T_{sa} but not the distribution itself). Therefore we also provide our bounds in terms of other notions of error/loss we can minimize from training samples. This allows to directly relate control performance to the model's training loss. A convenient loss is the KL divergence between T_{sa} and \hat{T}_{sa} :

$$\epsilon_{\text{prd}}^{\text{KL}} = \mathbb{E}_{(s,a) \sim \nu, s' \sim T_{sa}} [\log(T_{sa}(s')) - \log(\hat{T}_{sa}(s'))].$$

Minimizing KL corresponds to maximizing the log likelihood of the sampled transitions. This is convenient for common model classes, such as linear models (as in LQR), where it amounts to solving a linear regression problem. For particular cases where \mathcal{T} is a set of deterministic models and the real system has finitely many states, the predictive error can be related to a classification loss at predicting the next state:

$$\epsilon_{\text{prd}}^{\text{cls}} = \mathbb{E}_{(s,a) \sim \nu, s' \sim T_{sa}} [\ell(\hat{T}, s, a, s')],$$

for ℓ the 0-1 loss of whether \hat{T} predicts s' for (s, a) , or any upper bound on the 0-1 loss, *e.g.*, the multi-class hinge loss if \mathcal{T} is a set of SVMs. In this case, model fitting is a supervised classification problem and the guarantee is directly related to the training classification loss. These different notions of error are related as follows:

Lemma 8.3.1.

$$\begin{aligned} \epsilon_{\text{prd}}^{L1} &\leq \sqrt{2\epsilon_{\text{prd}}^{\text{KL}}}, \\ \epsilon_{\text{prd}}^{L1} &\leq 2\epsilon_{\text{prd}}^{\text{cls}}. \end{aligned}$$

The latter holds with equality if ℓ is the 0-1 loss.

In general, we could also use any other loss that can be minimized from samples and that upper bounds $\epsilon_{\text{prd}}^{L1}$ for models in the class.

Another important component of our analysis is the mismatch between the exploration distribution ν and the distribution induced by executing another policy π starting in μ . We measure this mismatch as follows:

$$c_{\nu}^{\pi} = \sup_{s,a} \frac{D_{\mu,\pi}(s, a)}{\nu(s, a)}.$$

Intuitively, c_{ν}^{π} captures whether there exists state-action pairs (s, a) that are encountered often by the policy π , but that were rarely explored under the exploration distribution ν . When that's the case c_{ν}^{π} is large (it can be arbitrarily large and potentially infinite if some state-action pair (s, a) is likely under π , but have probability 0 to be explored under ν). In the ideal case where there is no mismatch, *i.e.* $\nu = D_{\mu,\pi}$, then $c_{\nu}^{\pi} = 1$.

We will also assume the costs are bounded in some range, i.e. $C(s, a) \in [C_{\min}, C_{\max}] \forall (s, a)$. Let $C_{\text{rng}} = C_{\max} - C_{\min}$ and $H = \frac{\gamma C_{\text{rng}}}{(1-\gamma)^2}$. H is a scaling factor that relates model error to error in total cost predictions. Then the policy learned by *Batch* has the following performance guarantee when performing the task in the real system:

Theorem 8.3.1. *The policy $\hat{\pi}$ is s.t. for any policy π' :*

$$J_{\mu}(\hat{\pi}) \leq J_{\mu}(\pi') + \epsilon_{oc}^{\pi'} + \frac{c_{\nu}^{\hat{\pi}} + c_{\nu}^{\pi'}}{2} H \epsilon_{\text{prd}}^{L1}$$

This also holds as a function of $\epsilon_{\text{prd}}^{\text{KL}}$ or $\epsilon_{\text{prd}}^{\text{cls}}$ using the relations in Lemma 8.3.1.

This bound indicates that if *Batch* solves the OC problem well and \hat{T} has small enough error under the training distribution ν , then it must find a good policy. Importantly, this bound is tight: i.e. we can construct examples where it holds with equality (see appendix C).

More interestingly is what happens as we collect more and more data. If we use consistent learning procedures that converge to the best transition model \hat{T}^* in the class \mathcal{T} asymptotically, then we can relate this guarantee to the capacity of the model class to achieve low predictive error under the training distribution ν . We denote the modeling error, measured in L_1 distance, as:

$$\epsilon_{\text{mdl}}^{L1} = \inf_{T' \in \mathcal{T}} \mathbb{E}_{(s,a) \sim \nu} [\|T_{sa} - T'_{sa}\|_1].$$

Similarly, we define the modeling error in terms of the KL divergence and the classification loss as follows:

$$\epsilon_{\text{mdl}}^{\text{KL}} = \inf_{T' \in \mathcal{T}} \mathbb{E}_{(s,a) \sim \nu, s' \sim T_{sa}} [\log(T_{sa}(s')) - \log(T'_{sa}(s'))],$$

$$\epsilon_{\text{mdl}}^{\text{cls}} = \inf_{T' \in \mathcal{T}} \mathbb{E}_{(s,a) \sim \nu, s' \sim T_{sa}} [\ell(T', s, a, s')].$$

These modeling errors are all 0 in realizable settings, but generally non-zero in agnostic settings. After observing m sampled transitions, the generalization error $\epsilon_{\text{gen}}^{L1}(m, \delta)$ bounds with high probability $1 - \delta$ the quantity $\epsilon_{\text{prd}}^{L1} - \epsilon_{\text{mdl}}^{L1}$. Similarly, $\epsilon_{\text{gen}}^{\text{KL}}(m, \delta)$ and $\epsilon_{\text{gen}}^{\text{cls}}(m, \delta)$ denote the generalization error for the KL and classification loss respectively. For instance, $\epsilon_{\text{gen}}^{\text{cls}}(m, \delta)$ can be related to the VC dimension, or analogous multi-class equivalent, in finite state MDPs (as in standard PAC Learning analysis for classification problems).

This implies that when learning from a finite amount of data, the guarantee on control performance with the learned policy by *Batch* has the following form:

Corollary 8.3.1. *After observing m transitions, with probability at least $1 - \delta$, for any policy π' :*

$$J_{\mu}(\hat{\pi}) \leq J_{\mu}(\pi') + \epsilon_{oc}^{\pi'} + \frac{c_{\nu}^{\hat{\pi}} + c_{\nu}^{\pi'}}{2} H [\epsilon_{\text{mdl}}^{L1} + \epsilon_{\text{gen}}^{L1}(m, \delta)].$$

This also holds as a function of $\epsilon_{mdl}^{KL} + \epsilon_{gen}^{KL}(m, \delta)$ (or $\epsilon_{mdl}^{cls} + \epsilon_{gen}^{cls}(m, \delta)$) using Lem. 8.3.1. In addition, if the fitting procedure is consistent in terms of L_1 distance (or KL, classification loss), then $\epsilon_{gen}^{L1}(m, \delta) \rightarrow 0$ (or $\epsilon_{gen}^{KL}(m, \delta) \rightarrow 0$, $\epsilon_{gen}^{cls}(m, \delta) \rightarrow 0$) as $m \rightarrow \infty$ for any $\delta > 0$.

As mentioned in Section 2.1, the generalization error typically scales with the complexity of the class \mathcal{T} and goes to 0 at a rate of $O(\frac{1}{\sqrt{m}})$ (or $\tilde{O}(\frac{1}{m})$ in ideal conditions). Given enough samples, the dominating factor limiting performance becomes the modeling error: i.e. the term $\frac{c_{\nu}^{\hat{\pi}} + c_{\nu}^{\pi'}}{2} H \epsilon_{mdl}^{L1}$ (or its equivalent in terms of the KL/classification loss) quantifies how performance degrades for agnostic settings.

Drawback of *Batch*: The two factors $c_{\nu}^{\hat{\pi}}$ and $c_{\nu}^{\pi'}$ are qualitatively different. $c_{\nu}^{\pi'}$ measures how well ν explores state-actions visited by the policy π' we compare to. This factor is inevitable: we cannot hope to compete against policies that spend most of their time in regions that we rarely explore. On the other hand, $c_{\nu}^{\hat{\pi}}$ measures the mismatch in train-test distribution, i.e. the mismatch between the exploration and where our learned policy goes during its execution. Its presence is the major drawback of *Batch*. As $\hat{\pi}$ cannot be known in advance, we can only bound $c_{\nu}^{\hat{\pi}}$ by considering all policies we could learn: $\sup_{\pi \in \Pi} c_{\nu}^{\pi}$. This worst case is likely to be realized in practice: if ν rarely explores some state-action regions, the model could be bad for these and significantly underestimate their cost. The learned policy is thus encouraged to visit these low-cost regions where few data were collected. To minimize $\sup_{\pi \in \Pi} c_{\nu}^{\pi}$, the best ν for *Batch* is often a uniform distribution, when possible. This introduces a dependency on the number of states and actions (or state-action space volume) (i.e. $c_{\nu}^{\hat{\pi}} + c_{\nu}^{\pi'}$ is $O(|S||A|)$) multiplying the modeling error. Sampling from a uniform distribution often requires access to a generative model. If we only have access to a reset model⁴ and a base policy π_0 inducing ν when executed in the system, then $c_{\nu}^{\hat{\pi}}$ could be arbitrarily large (e.g., if $\hat{\pi}$ goes to 0 probability states under π_0), and $\hat{\pi}$ arbitrarily worse than π_0 . This indicates that in general, with *Batch*, even if some model in the class \mathcal{T} achieves very small training error, performance at the control task can still be arbitrarily bad. To prevent this, *Batch* must explore as uniformly as possible, but then only provides good guarantees if the modeling error is very small, i.e. $O(\frac{1}{H|S||A|})$. For small γ , or large systems with many states/actions, this implies that *Batch* must achieve near-zero training error. Under uniform exploration, near-zero training error is only possible if we are in a realizable setting (or nearly so). Thus effectively, we can conclude that this *Batch* approach only works in realizable scenarios (or nearly-so), and can lead to arbitrarily bad performance in general agnostic settings. In addition, learning by sampling uniformly is undesirable. This requires learning about every state-action, which is inefficient as it is often not necessary (we only

⁴See Section 2.3 for descriptions of generative and reset access models.

need to learn about regions where good policies go and our learned policy goes). Hence from a learning efficiency point of view, we see that *Batch* is not very efficient (we would necessarily need a number of samples that scales with the dimensionality of the system).

In the next section, we show that by adapting DAGGER to this setting, we can leverage interaction with the learner to obtain bounds that do **not** depend on $c_\nu^{\hat{\pi}}$. This leads to better guarantees when we have a good exploration distribution ν (*e.g.*, that of a near-optimal policy). It also leads to more efficient learning, as we will show that the sample complexity can have no dependency on the dimensionality of the system if we have access to a good exploration distribution (only on the complexity of the model class \mathcal{T}). In practice, this leads to more efficient learning and better performance, as shown in the experiments.

8.4 Interactive Learning Approach

Our extension of DAGGER to the system identification setting proceeds as follows. Starting from an initial model $\hat{T}^1 \in \mathcal{T}$, solve (potentially approximately) the OC problem with \hat{T}^1 to obtain policy π_1 . At each iteration n , collect data about the system by sampling state-action pairs from distribution $\rho_n = \frac{1}{2}\nu + \frac{1}{2}D_{\mu, \pi_n}$: *i.e.* w.p. $\frac{1}{2}$, sample a transition occurring from an exploratory state-action pair drawn from ν and add it to dataset \mathcal{D} , otherwise, interact with the learner to sample a state transition occurring from running the learner’s current policy π_n starting in μ , stopping the trajectory w.p. $1 - \gamma$ at each step and adding the last transition to \mathcal{D} . The dataset \mathcal{D} contains all transitions observed so far over all iterations. Once data is collected, find the best model $\hat{T}^{n+1} \in \mathcal{T}$ that minimizes an appropriate loss (*e.g.* regularized negative log likelihood) on \mathcal{D} , and solve (potentially approximately) the OC problem with \hat{T}^{n+1} to obtain the next policy π_{n+1} . This is iterated for N iterations. This algorithm is depicted in Figure 8.1 in the context of an helicopter control task.

At test time, we could either find and use the policy with lowest expected total cost in the sequence $\pi_{1:N}$, or use the uniform “mixture” policy⁵ over $\pi_{1:N}$. We guarantee good performance for these two choices. Using the last policy π_N often works equally well, as it has been trained with most data. Our experimental results confirm this intuition. In theory, the last policy has good guarantees when the distributions D_{μ, π_i} converge to a small region in the space of distributions as $i \rightarrow \infty$, although we do not guarantee this occurs in general.

⁵At start of any trajectory, the mixture policy picks uniformly randomly a policy in $\pi_{1:N}$, and uses it for the whole trajectory.

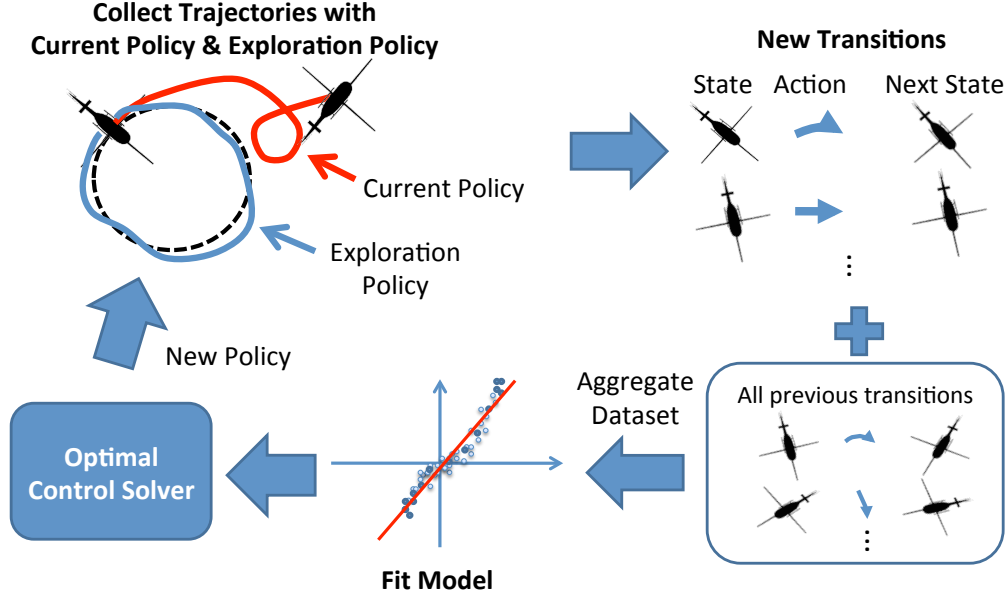


Figure 8.1: Depiction of the DAGGER algorithm for System Identification in the context of helicopter control.

Implementation with Off-the-Shelf Online Learner

As in previous sequential prediction settings, DAGGER as described can be interpreted as using a *Follow-The-(Regularized)-Leader* (FTRL) online algorithm to pick the sequence of models: at each iteration n we pick the best (regularized) model \hat{T}^n in hindsight under all samples seen so far. In general, DAGGER can also be implemented using any off-the-shelf no-regret online algorithm (see Algorithm 8.4.1) to provide good guarantees. To do so, we proceed as follows. When minimizing the negative log likelihood, the loss function of the online learning problem at iteration i is:

$$L_i^{\text{KL}}(\hat{T}) = \mathbb{E}_{(s,a) \sim \rho_i, s' \sim T_{sa}} [-\log(\hat{T}_{sa}(s'))]. \quad (8.1)$$

This loss can be estimated from the sampled state transitions at iteration i , and evaluated for any model \hat{T} . The online algorithm is applied on the sequence of loss functions $L_{1:N}^{\text{KL}}$ to obtain a sequence of models $\hat{T}^{1:N}$ over the iterations. As before, each model \hat{T}^i is solved to obtain the next policy π_i . By doing so, the online algorithm effectively runs over mini-batches of data collected at each iteration to update the model, and each mini-batch comes from a different sampling distribution that changes as we update the policy. Similarly, in a finite MDP with a deterministic model class \mathcal{T} , we can minimize a classification loss instead (such as the 0-1 loss, or any upper bound such as the hinge loss), where the loss at iteration i is:

$$L_i^{\text{cls}}(\hat{T}) = \mathbb{E}_{(s,a) \sim \rho_i, s' \sim T_{sa}} [\ell(\hat{T}, s, a, s')], \quad (8.2)$$

Input: exploration distribution ν , number of iterations N , number of samples per iteration m , cost function C , online learning procedure `ONLINELEARNER`, optimal control procedure `OCSOLVER`.

Get initial guess of model: $\hat{T}^1 \leftarrow \text{ONLINELEARNER}()$.

$\pi_1 \leftarrow \text{OCSOLVER}(\hat{T}^1, C)$.

for $n = 2$ **to** N **do**

for $k = 1$ **to** m **do**

 With prob. $\frac{1}{2}$ sample $(s, a) \sim D_{\mu, \pi_{n-1}}$ using π_{n-1} , otherwise sample $(s, a) \sim \nu$.

 Obtain $s' \sim T_{sa}$

 Add (s, a, s') to \mathcal{D}_{n-1} .

end for

 Update model: $\hat{T}^n \leftarrow \text{ONLINELEARNER}(\mathcal{D}_{n-1})$.

$\pi_n \leftarrow \text{OCSOLVER}(\hat{T}^n, C)$.

end for

Return the sequence of policies $\pi_{1:N}$.

Algorithm 8.4.1: DAGGER algorithm for Agnostic System Identification/MBRL.

for ℓ the particular classification loss we're minimizing. This corresponds to an online classification problem. For many model classes, the negative log likelihood and convex upper bounds on the 0-1 loss (such as hinge loss) lead to convex online learning problems, for which no-regret algorithms exist (*e.g.*, gradient descent, FTRL). As shown below, if the sequence of models is no-regret on these loss functions, then performance can be related to the smallest expected KL divergence (or classification loss) achievable with model class \mathcal{T} under the overall training distribution $\bar{\rho} = \frac{1}{N} \sum_{i=1}^N \rho_i$ (*i.e.* a quantity akin to $\epsilon_{\text{mdl}}^{\text{KL}}$ or $\epsilon_{\text{mdl}}^{\text{cls}}$ for *Batch*).

Important Distinction to Previous Settings: We emphasize here an important distinction of DAGGER in this setting. Unlike previous sequential prediction settings, here DAGGER does not only collect data from running the current policy at each iteration, it also collects an equal amount of exploration data. This is suggested by our theoretical analysis below. Intuitively, this is necessary to ensure that we do not converge to a model \hat{T} that only models well the behavior of the system under the previous policies $\pi_{1:n}$, and does not model well the behavior of the system where good policies go. In agnostic settings where we cannot model the data perfectly, the model fitting procedure must tradeoff where it makes mistakes. If we would only collect more data from the current policy at each iteration, the exploration data would occupy a vanishingly small fraction of the dataset and potentially lead the learner to pick models that have large error on this exploration data and low error where the learned policies go. If we would end up with such model, we would likely get stuck in a local minima and not be able to learn better policies. By keeping an even balance of exploration data and data from execution of our learned policies, we ensure that the learned model must also

predict well the behavior of the system for other policies (that visit frequently explored state-actions), and thus that when solving the OC problem, we must be able to find good policies compared to any policy that spends most of its time where we explore.

Note that DAGGER could also be implemented by only collecting more data from the current policy at each iteration, if for instance, we collect all the exploration data up front, and then at each iteration when defining the loss for the online learner, we weight the training examples such that half the weight is assigned to the exploration data, and half the weight to the newly collected data. That is if we have a dataset of exploration data D_0 , and D_n is the dataset of state transitions collected at iteration n by only running the current policy π_n , we could define the loss for the online algorithm $L_n^{\text{KL}}(\hat{T}) = -\frac{1}{2|D_0|} \sum_{(s,a,s') \in D_0} \log(\hat{T}_{sa}(s')) - \frac{1}{2|D_n|} \sum_{(s,a,s') \in D_n} \log(\hat{T}_{sa}(s'))$.

Analysis

Similar to our analysis of *Batch*, we seek to answer the following: if there exists a low error model of training data, and we solve each OC problem well, what guarantees does DAGger provide on control performance? Our results show that by sampling data from the learned policies, DAGger provides guarantees that have no train-test mismatch factor, leading to improved performance. Again, the proofs are deferred to appendix C.

For any policy π' , define

$$\bar{\epsilon}_{\text{oc}}^{\pi'} = \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{s \sim \mu} [\hat{V}_i(s) - \hat{V}_i^{\pi'}(s)],$$

where \hat{V}_i and $\hat{V}_i^{\pi'}$ are respectively the value function of π_i and π' under model \hat{T}^i . This measures how well we solved each OC problem on average over the iterations. For instance, if at each iteration i we found an ϵ_i -optimal policy within some class of policies Π on learned model \hat{T}^i , then $\bar{\epsilon}_{\text{oc}}^{\pi'} \leq \frac{1}{N} \sum_{i=1}^N \epsilon_i$ for all $\pi' \in \Pi$.

As in *Batch*, the average predictive error of the models $\hat{T}^{1:N}$ can be measured in terms of the L_1 distance between the predicted and true next state distribution:

$$\bar{\epsilon}_{\text{prd}}^{\text{L1}} = \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{(s,a) \sim \rho_i} [\|\hat{T}_{sa}^i - T_{sa}\|_1].$$

However, as was discussed, the L_1 distance is not observed from samples which makes it hard to minimize. Instead we can define other measures which upper bounds this L_1 distance and can be minimized from samples, such as the KL divergence or classification loss, *i.e.*:

$$\bar{\epsilon}_{\text{prd}}^{\text{KL}} = \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{(s,a) \sim \rho_i, s' \sim T_{sa}} [\log(T_{sa}(s)) - \log(\hat{T}_{sa}^i(s'))]$$

and

$$\bar{\epsilon}_{\text{prd}}^{\text{cls}} = \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{(s,a) \sim \rho_i, s' \sim T_{sa}} [\ell(\hat{T}^i, s, a, s')].$$

Now, given the sequence of policies $\pi_{1:N}$, let $\hat{\pi} = \arg \min_{\pi \in \pi_{1:N}} J_{\mu}(\pi)$ be the best policy in the sequence and $\bar{\pi}$ the uniform mixture policy on $\pi_{1:N}$.

Lemma 8.4.1. *The policies $\pi_{1:N}$ are s.t. for any policy π' :*

$$J_{\mu}(\hat{\pi}) \leq J_{\mu}(\bar{\pi}) \leq J_{\mu}(\pi') + \bar{\epsilon}_{oc}^{\pi'} + c_{\nu}^{\pi'} H \bar{\epsilon}_{\text{prd}}^{L1}$$

This also holds as a function of $\bar{\epsilon}_{\text{prd}}^{\text{KL}}$ or $\bar{\epsilon}_{\text{prd}}^{\text{cls}}$ using Lemma 8.3.1.

Using Equations 8.1 and 8.2, we note that

$$\bar{\epsilon}_{\text{prd}}^{\text{KL}} = \frac{1}{N} \sum_{i=1}^N L_i^{\text{KL}}(\hat{T}^i) - L_i^{\text{KL}}(T),$$

and

$$\bar{\epsilon}_{\text{prd}}^{\text{cls}} = \frac{1}{N} \sum_{i=1}^N L_i^{\text{cls}}(\hat{T}^i).$$

Using a no-regret algorithm on the sequence of losses $L_{1:N}^{\text{KL}}$ implies

$$\frac{1}{N} \sum_{i=1}^N L_i^{\text{KL}}(\hat{T}^i) \leq \inf_{T' \in \mathcal{T}} \frac{1}{N} \sum_{i=1}^N L_i^{\text{KL}}(T') + \bar{\epsilon}_{\text{rgt}}^{\text{KL}},$$

for $\bar{\epsilon}_{\text{rgt}}^{\text{KL}}$ the average regret of the algorithm after N iterations, s.t. $\bar{\epsilon}_{\text{rgt}}^{\text{KL}} \rightarrow 0$ as $N \rightarrow \infty$.

This relates $\bar{\epsilon}_{\text{prd}}^{\text{KL}}$ to the modeling error of the class \mathcal{T} :

$$\bar{\epsilon}_{\text{mdl}}^{\text{KL}} = \inf_{T' \in \mathcal{T}} \mathbb{E}_{(s,a) \sim \bar{\rho}, s' \sim T_{sa}} [\log(T_{sa}(s)) - \log(T'_{sa}(s'))],$$

i.e. $\bar{\epsilon}_{\text{prd}}^{\text{KL}} \leq \bar{\epsilon}_{\text{mdl}}^{\text{KL}} + \bar{\epsilon}_{\text{rgt}}^{\text{KL}}$, for $\bar{\epsilon}_{\text{rgt}}^{\text{KL}} \rightarrow 0$. Similarly define

$$\bar{\epsilon}_{\text{mdl}}^{\text{cls}} = \inf_{T' \in \mathcal{T}} \mathbb{E}_{(s,a) \sim \bar{\rho}, s' \sim T_{sa}} [\ell(T', s, a, s')]$$

and by using a no-regret algorithm on $L_{1:N}^{\text{cls}}$:

$$\bar{\epsilon}_{\text{prd}}^{\text{cls}} \leq \bar{\epsilon}_{\text{mdl}}^{\text{cls}} + \bar{\epsilon}_{\text{rgt}}^{\text{cls}}$$

for $\bar{\epsilon}_{\text{rgt}}^{\text{cls}} \rightarrow 0$. In some cases, even if the L_1 distance cannot be estimated from samples, statistical estimators can still be no-regret with high probability on the sequence of loss $L_i^{\text{L1}}(T') = \mathbb{E}_{(s,a) \sim \rho_i} [|T_{sa} - T'_{sa}|_1]$. This is the case in finite MDPs if we use the empirical estimator of T based on data seen so far (see appendix C). If we define

$$\bar{\epsilon}_{\text{mdl}}^{\text{L1}} = \inf_{T' \in \mathcal{T}} \mathbb{E}_{(s,a) \sim \bar{\rho}} [|T_{sa} - T'_{sa}|_1],$$

this implies that

$$\bar{\epsilon}_{\text{prd}}^{\text{L1}} \leq \bar{\epsilon}_{\text{mdl}}^{\text{L1}} + \bar{\epsilon}_{\text{rgt}}^{\text{L1}},$$

for $\bar{\epsilon}_{\text{rgt}}^{\text{L1}} \rightarrow 0$. Our main result follows:

Theorem 8.4.1. *The policies $\pi_{1:N}$ are s.t. for any policy π' :*

$$J_\mu(\hat{\pi}) \leq J_\mu(\bar{\pi}) \leq J_\mu(\pi') + \bar{\epsilon}_{oc}^{\pi'} + c_\nu^{\pi'} H[\bar{\epsilon}_{mdl}^{L1} + \bar{\epsilon}_{rgt}^{L1}]$$

This also holds as a function of $\bar{\epsilon}_{mdl}^{KL} + \bar{\epsilon}_{rgt}^{KL}$ (or $\bar{\epsilon}_{mdl}^{cls} + \bar{\epsilon}_{rgt}^{cls}$) using Lem. 8.3.1. If the fitting procedure is no-regret w.r.t the sequence of losses $L_{1:N}^{L1}$ (or $L_{1:N}^{KL}$, $L_{1:N}^{cls}$), then $\bar{\epsilon}_{rgt}^{L1} \rightarrow 0$ (or $\bar{\epsilon}_{rgt}^{KL} \rightarrow 0, \bar{\epsilon}_{rgt}^{cls} \rightarrow 0$) as $N \rightarrow \infty$.

Additionally, the performance of π_N can be related to $\bar{\pi}$ if the distributions D_{μ, π_i} converge to a small region:

Lemma 8.4.2. *If there exists a distribution D^* and some $\epsilon_{cnn}^* \geq 0$ s.t. $\forall i, \|D_{\mu, \pi_i} - D^*\|_1 \leq \epsilon_{cnn}^* + \epsilon_{cnn}^i$ for some sequence $\{\epsilon_{cnn}^i\}_{i=1}^\infty$ that is $o(1)$, then π_N is s.t.:*

$$J_\mu(\pi_N) \leq J_\mu(\bar{\pi}) + \frac{C_{rng}}{2(1-\gamma)} [2\epsilon_{cnn}^* + \epsilon_{cnn}^N + \frac{1}{N} \sum_{i=1}^N \epsilon_{cnn}^i]$$

Thus: $\limsup_{N \rightarrow \infty} J_\mu(\pi_N) - J_\mu(\bar{\pi}) \leq \frac{C_{rng}}{1-\gamma} \epsilon_{cnn}^$*

Theorem 8.4.1 illustrates how we can reduce the original system identification (or MBRL) problem to a *no-regret online learning* problem on a particular sequence of loss functions. In general, no-regret algorithms have average regret of $O(\frac{1}{\sqrt{N}})$ ($\tilde{O}(\frac{1}{N})$ in ideal cases) such that the regret term goes to 0 at a similar rate to the generalization error term for *Batch* in Corollary 8.3.1. Here, given enough iterations, the term $c_\nu^{\pi'} H \bar{\epsilon}_{mdl}^{L1}$ determines how performance degrades in the agnostic setting (or $c_\nu^{\pi'} H \sqrt{2\bar{\epsilon}_{mdl}^{KL}}$ or $2c_\nu^{\pi'} H \bar{\epsilon}_{mdl}^{cls}$ if we use a no-regret algorithm on the sequence of KL or classification loss respectively). Unlike for *Batch*, there is no dependence on $c_\nu^{\hat{\pi}}$, only on $c_\nu^{\pi'}$. Thus, if a low error model exists under training distribution $\bar{\rho}$, no-regret methods are guaranteed to learn policies that performs well compared to any policy π' for which $c_\nu^{\pi'}$ is small. Hence, ν is ideally $D_{\mu, \pi}$ of a near-optimal policy π (*i.e.* explore where good policies go).

Finite Sample Analysis: A remaining issue is that the current guarantees apply if we can evaluate the expected loss (L_i^{L1} , L_i^{KL} or L_i^{cls}) exactly. This requires infinite samples at each iteration. If we run the no-regret algorithm on estimates of these loss functions, *i.e.* loss on m sampled transitions, we can still obtain good guarantees using martingale inequalities as in online-to-batch (Cesa-Bianchi et al., 2004) techniques. The extra generalization error term is typically $O(\sqrt{\frac{\log(1/\delta)}{Nm}})$ with high probability $1 - \delta$. While our focus is not on providing such finite sample bounds, we illustrate how these can be derived for two scenarios in appendix C. For instance, in finite MDPs with $|S|$ states and $|A|$ actions, if \hat{T}^i is the empirical estimator of T based on samples collected in

the first $i - 1$ iterations, then choosing $m = 1$ and N in $\tilde{O}(\frac{C_{\text{rng}}^2 |S|^2 |A| \log(1/\delta)}{\epsilon^2 (1-\gamma)^4})$ guarantees that w.p. $1 - \delta$, for any policy π' :

$$J_\mu(\hat{\pi}) \leq J_\mu(\bar{\pi}) \leq J_\mu(\pi') + \bar{\epsilon}_{\text{oc}}^{\pi'} + O(c_\nu^{\pi'} \epsilon)$$

Here, $\bar{\epsilon}_{\text{mdl}}$ does not appear as it is 0 (realizable case). Given a good state-action distribution ν , the sample complexity to get a near-optimal policy is $\tilde{O}(\frac{C_{\text{rng}}^2 |S|^2 |A| \log(1/\delta)}{\epsilon^2 (1-\gamma)^4})$. This improves upon other state-of-the-art MBRL algorithm, such as R_{max} , $\tilde{O}(\frac{C_{\text{rng}}^3 |S|^2 |A| \log(1/\delta)}{\epsilon^3 (1-\gamma)^6})$ (Strehl et al., 2009) and a recent variation of R_{max} with sample complexity of $\tilde{O}(\frac{C_{\text{rng}}^2 |S| |A| \log(1/\delta)}{\epsilon^2 (1-\gamma)^6})$ (Szita and Szepesvári, 2010). Here, the dependency on $|S|^2 |A|$ is due to the complexity of the class (*i.e.* conditional probability table with $|S|^2 |A|$ parameters). With simpler classes, the sample complexity can have no dependency on the size of the MDP. For instance, in the supplementary material, we consider a case where \mathcal{T} is a set of deterministic models represented by kernel SVMs with RKHS norm bounded by K . Choosing $m = 1$ and N in $O(\frac{C_{\text{rng}}^2 (K^2 + \log(1/\delta))}{\epsilon^2 (1-\gamma)^4})$ guarantees that w.p. $1 - \delta$, for any policy π' :

$$J_\mu(\hat{\pi}) \leq J_\mu(\bar{\pi}) \leq J_\mu(\pi') + \bar{\epsilon}_{\text{oc}}^{\pi'} + 2c_\nu^{\pi'} H \hat{\epsilon}_{\text{mdl}}^{\text{cls}} + O(c_\nu^{\pi'} \epsilon),$$

for $\hat{\epsilon}_{\text{mdl}}^{\text{cls}}$ the multi-class hinge loss on the training set after N iterations of the best SVM in hindsight. Thus, if we have a good exploration distribution and there exists a good model in \mathcal{T} for predicting observed data, we obtain a near-optimal policy with sample complexity that depends only on the complexity of \mathcal{T} , not the size of the MDP.

Handling Partially Observable Domains

While we have assumed the state observable so far, DAGGER as presented can be applied in the same way in partially observable settings and the same guarantees also hold. To see this, we simply need to define the state to be the entire history of actions and observations. Predicting the next “state” in this case comes down to predicting the next observation to append to the history, given features of the current action and history. For instance, we may attempt to learn an ARX model, via linear regression, that predicts the next observation from the past k observations and actions, and our results would relate directly control performance to the model error at predicting the next distribution of observations (e.g. in L_1 distance or KL). Additionally, the state-action exploration distribution ν here would be a distribution over histories and actions. As for the cost function, here it would be defined in terms of the history and the current action, e.g. a cost that depends on the last observation and action.

While we could learn ARX type models, an interesting open question is whether our DAGGER technique could be applied with realization/spectral learning methods that could learn an underlying state space model, e.g. using subspace identification techniques

in [Overschee and Moor \(1996\)](#), [Boots and Gordon \(2011\)](#). An important requirement for this to be possible would be to show that such spectral methods are no-regret, e.g. in the squared loss (or log likelihood) of their predictions, when applied to learn online. Not much work has been done in this area, with the exception of a randomized online PCA method that has been shown to be no-regret ([Warmuth and Kuzmin, 2008](#)).

Discussion

Remarks on Guarantees. We emphasize again that we provide reduction-style guarantees. DAGGER may sometimes fail to find good policies, *e.g.*, when no model in the class achieves low error on the training data. When no model achieves low error on the training data, whether we are using Batch or DAGGER, both will fail to provide good performance, and this suggests we need a better class of models. However, the distinction to Batch is in the case where good models exist on the training data. In this case, DAGGER is guaranteed to find a good policy, in contrast, *Batch* can *still* fail at obtaining a policy with good control performance, due to train/test mismatch. This occurs even in scenarios where DAGGER finds good policies, as shown in the experiments.

DAGGER as a reduction. In this setting DAGGER can be interpreted as a reduction of system identification, or model-based reinforcement learning, to no-regret online learning and optimal control. Depending on the loss minimized to fit the model, it can be interpreted as an error or a regret reduction. In the case of the KL (negative log likelihood), we obtain a reduction that relates performance to the *regret* in log likelihood of the best model in the class to the true model (bayes-optimal model). Thus in this case, this can be interpreted as a regret reduction. For the classification loss however, performance is related directly to the classification loss/error, and this can be interpreted as an error reduction.

Solving the OC problems. DAGGER needs to solve many OC problems. This can be computationally expensive, *e.g.*, with non-linear or high-dimensional models. Many approximate methods can be used, *e.g.*, policy gradient ([Williams, 1992](#)), fitted value iteration ([Gordon, 1995](#), [Szepesvári, 2005](#)), iLQR ([Li and Todorov, 2004](#)) or DDP ([Jacobson and Mayne, 1970](#)). As the models often change only slightly from one iteration to the next, we can often run only a few iterations of dynamic programming/policy gradient from the last value function/policy to obtain a good policy for the current model. As long as we get good solutions on average, $\bar{\epsilon}_{oc}'$ remains small and does not hinder performance.

Relation to previous iterative identification methods. DAGGER generalizes the approach of Atkeson and Schaal (1997) and Abbeel and Ng (2005) so that we can use any no-regret algorithm to update the model, as well as any exploration distribution. A key difference is that DAGGER keeps an even balance between exploration data and data from running the learned policies. This is crucial to avoid settling on suboptimal performance in agnostic settings as the exploration data could be ignored if it occupies only a small fraction of the dataset, in favor of models with lower error on the data from the learned policies. With this modification, our main contribution is showing that such methods have good guarantees even in agnostic settings.

Realizable Settings. Another important result that follows from this analysis is when we are in a realizable setting. This result indicates that recovering the optimal policy is always possible if we have access to a good exploration distribution, and no-regret learning is possible for the given class of models \mathcal{T} that contains the true model. As no-regret can be achieved on a much broader class of models than linear systems (e.g. kernel based models), these results show that learning models that synthesize the optimal controller is possible for much more general class of non-linear systems. The requirement of having access to a good exploration distribution can also be dropped in realizable settings, by adopting instead an optimistic exploration strategy presented below.

8.5 Optimistic Exploration for Realizable Settings

Our current DAGGER approach to system identification assumes that it is given a good state-action exploration distribution ν in order to guarantee that it can find a near-optimal policy efficiently. In domains where prior knowledge of the task is limited, or where we don't have access to an expert, it might be hard to provide this information to the algorithm. We present here an adaptive exploration strategy that can be used, which guarantees finding the optimal policy in realizable settings.

The exploration strategy uses the principle of *optimism in the face of uncertainty*, which is used in many other state-of-the-art RL algorithms such as R_{\max} (Strehl et al., 2009) and UCRL/UCRL2 (Auer and Ortner, 2007, Jaksch et al., 2010). It essentially involves being optimistic about the value of states and actions that have not been explored enough before. In particular, the exploration strategy is obtained by essentially computing a lower bound (with high probability) on the total cost of the optimal policy in the real system based on the observed data so far. The lower bound becomes tighter as more data is collected and converges toward the optimal value function. Executing the optimal policy of this optimistic value function ensures that we will explore all areas that are potentially visited by an optimal policy.

Input: Number of iterations N , Number of samples per iteration m , Failure probability δ , Cost function C .
Initialize $\mathcal{T}^1 \leftarrow \mathcal{T}$
Initialize dataset $D \leftarrow \emptyset$
 $(\pi_1, \hat{T}^1) \leftarrow \text{OptimisticOptimalControl}(C, \mathcal{T}^1)$.
for $i = 2$ **to** N **do**
 for $k = 1$ **to** m **do**
 Sample a transition along a trajectory with π_{i-1} starting in μ and add it to D .
 end for
 Construct a $1 - \delta$ confidence set $\mathcal{T}^i \subset \mathcal{T}$ based on observed data D .
 $(\pi_i, \hat{T}^i) \leftarrow \text{OptimisticOptimalControl}(C, \mathcal{T}^i)$.
end for
Return the sequence of policies $\pi_{1:N}$.

Algorithm 8.5.1: DAGGER algorithm with Optimistic Exploration for System Identification.

To use this idea within our DAGGER approach, we will identify at each iteration i , a confidence set of models \mathcal{T}_i that contains the true model T with high probability, based on the data seen so far. Then solve an optimal control problem where instead of only optimizing the policy, we jointly optimize over both the policy and model within that set \mathcal{T}_i to minimize total expected cost, similarly to UCRL/UCRL2. The joint optimal policy and model will give us a lower bound on the optimal value function (if the true model is in \mathcal{T}_i). Running that policy in the real system to collect more data will explore the areas an optimal policy might visit. This leads to an algorithm that only needs to sample data under the distribution of states induced by the current policy at each iteration. This approach is detailed in Algorithm 8.5.1.

Analysis

To motivate this exploration strategy, we can show the following result: DAGGER provides good guarantees as long as 1) the sequence of selected models is no-regret with respect to observed data and is such that 2) on average, optimal performance in the learned models is close to a lower bound on the total cost of the optimal policy in the real model.

Formally, suppose over the course of the algorithm we pick a sequence of models $\hat{T}^{1:N}$ and policies $\pi_{1:N}$ and let

$$\bar{\epsilon}_{\text{oc-lb}}^{\pi'} = \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{s \sim \mu} [\hat{V}_i(s)] - J_{\mu}(\pi'),$$

denotes how much larger is the total cost of the policies $\pi_{1:N}$ on average in their corresponding learned model $\hat{T}^{1:N}$ compared to the total cost of π' in the real system. For instance, if $\mathcal{T}^{1:N}$ is a sequence of subsets of \mathcal{T} which contains the real system with high

probability, and at each iteration i , we found an ϵ_i -optimal policy and model pair (π_i, \hat{T}^i) in $\Pi \times \mathcal{T}^i$, then for any $\pi' \in \Pi$, $\bar{\epsilon}_{\text{oc-lb}}^{\pi'} \leq \frac{1}{N} \sum_{i=1}^N \epsilon_i$ with high probability.

Additionally, define the average predictive error of the chosen models $\hat{T}^{1:N}$, measured in L_1 distance, under the corresponding state-action distribution induced by the chosen policies as

$$\bar{\epsilon}_{\text{prd}}^{L1} = \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{(s,a) \sim D_{\mu, \pi_i}} [\|T_{sa} - \hat{T}_{sa}^i\|_1].$$

Similarly, define

$$\bar{\epsilon}_{\text{prd}}^{\text{KL}} = \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{(s,a) \sim D_{\mu, \pi_i}, s' \sim T_{sa}} [\log(T_{sa}(s')) - \log(\hat{T}_{sa}^i(s'))].$$

and

$$\bar{\epsilon}_{\text{prd}}^{\text{cls}} = \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{(s,a) \sim D_{\mu, \pi_i}, s' \sim T_{sa}} [\ell(\hat{T}^i, s, a, s')].$$

the predictive error, measured in KL and classification loss respectively. Note here the difference is that these quantities are directly defined as an expectation under the distribution of state-actions D_{μ, π_i} , rather than a mixture with a fixed exploration distribution ν .

The following holds:

Theorem 8.5.1. *For all policies π' :*

$$J_{\mu}(\hat{\pi}) \leq J_{\mu}(\bar{\pi}) \leq J_{\mu}(\pi') + \bar{\epsilon}_{\text{oc-lb}}^{\pi'} + \frac{H}{2} \bar{\epsilon}_{\text{prd}}^{L1}$$

This also holds in terms of $\bar{\epsilon}_{\text{prd}}^{\text{KL}}$ or $\bar{\epsilon}_{\text{prd}}^{\text{cls}}$ using the relations in Lemma 8.3.1.

The predictive error can be related to a modeling error, and the average regret as in the previous section. However, for realizable settings, the modeling error is 0, implying the predictive error is directly the average regret.

Thus in realizable settings, this theorem implies that if we can pick a sequence of models $\{\hat{T}^i\}_{i=1}^N$, which satisfies the following: 1) with high probability, the sequence has no-regret on the observed data with respect to the true model $T \in \mathcal{T}$ (i.e. $\bar{\epsilon}_{\text{prd}}^{L1} \rightarrow 0$ as $N \rightarrow \infty$); 2) with high probability, the average total cost of the policy in the learned model lower bounds the total cost of the optimal policy (i.e. $\bar{\epsilon}_{\text{oc-lb}}^{\pi'} \leq 0$ for all π'); then we are guaranteed to find an optimal policy in the limit.

While the algorithm chooses subsets \mathcal{T}^i , and the optimistic optimal control algorithm can potentially pick any model $\hat{T}^i \in \mathcal{T}^i$ at each iteration i , we can still guarantee that the chosen sequence of models \hat{T}^i is no-regret if we choose the subsets \mathcal{T}^i properly. For instance, suppose $\tilde{T}^{1:N}$ would be the sequence of chosen models by a no-regret algorithm on the observed data over the iterations of the algorithm, and the loss at each iteration

is Lipschitz continuous under some norm $\|\cdot\|$ over the space of models \mathcal{T} . Then if at each iteration i , we define the subsets $\mathcal{T}^i = \{T' \mid \|T' - \tilde{T}^i\| \leq \epsilon_{\text{conf}}^i\}$ for some sequence ϵ_{conf}^i that is $o(1)$, then any sequence of models $\hat{T}^{1:N}$ is no-regret if for all i , $\hat{T}^i \in \mathcal{T}^i$. Typical generalization error bounds will yield confidence regions where ϵ_{conf}^i is $O(\frac{1}{\sqrt{n}})$. In this case, the sequence of $\hat{T}^{1:N}$ can be no-regret at rate $O(\frac{1}{\sqrt{N}})$.

Realizable Case in Finite MDPs

We can illustrate what this algorithm would do and its guarantees in a finite MDP setting with $|S|$ states and $|A|$ actions, where the set of models \mathcal{T} contains all transition matrix (the set of all conditional probability tables with $|S|^2|A|$ parameters).

First, at each iteration i , we would construct the empirical estimate \tilde{T}^i of the true model as $\tilde{T}_{sa}^i(s') = \frac{n_{sas'}^{<i}}{n_{sa}^{<i}}$, where $n_{sas'}^{<i}$ is the number of times we observed transition (s, a, s') in the first $i - 1$ iterations and $n_{sa}^{<i} = \sum_{s'} n_{sas'}^{<i}$. Then from standard results in [Wasserman \(2003\)](#), defining

$$\mathcal{T}^i = \{T' \mid \forall(s, a) : \|T'_{sa} - \tilde{T}_{sa}^i\|_1 \leq \sqrt{\frac{c}{n_{sa}^{<i}}}\},$$

for $c = 2|S|\ln(2) + 2\log(|S||A|N/\delta)$ guarantees that with probability at least $1 - \delta$, the true model $T \in \mathcal{T}^i$ for all iterations $i \in \{1, 2, \dots, N\}$. Additionally, if $T \in \mathcal{T}_i$ for all i , we can show that any sequence of models $\hat{T}^{1:N}$ such that $\hat{T}^i \in \mathcal{T}^i$ for all i , is such that $\bar{\epsilon}_{\text{prd}}^{L1}$ is $O(\sqrt{\frac{c|S||A|}{Nm}})$ (see finite sample analysis for finite MDPs in [appendix C](#)). Once we defined the set \mathcal{T}^i , we would solve for a joint near-optimal policy π_i and model $\hat{T}^i \in \mathcal{T}^i$ that minimizes total expected cost, and move on to execute π_i to collect more data at the next iteration. If we can find such ϵ -optimal policy and model pair at each iteration, then if we run the algorithm for $\tilde{O}(\frac{\gamma^2 C_{\text{range}}^2 |S|^2 |A|}{(1-\gamma)^4 \epsilon^2})$ iterations and collect $O(1)$ sample at each iteration, we will obtain an ϵ -optimal policy in the real system with high probability. This compares favorably against state-of-the-art RL algorithm such as R_{max} , which has sample complexity of $\tilde{O}(\frac{\gamma^3 C_{\text{rng}}^3 |S|^2 |A|}{(1-\gamma)^6 \epsilon^3})$ ([Strehl et al., 2009](#)), and is also an improvement over our previous approach as it does not depend on the factor $c_{\nu}^{\pi^*}$ anymore.

Solving for Joint Optimal Policy and Model

The mentioned algorithm requires solving jointly over policy π_i and model $\hat{T}_i \in \mathcal{T}_i$. In general this may be intractable. However in some cases this can be achieved with computational complexity that is no greater than the complexity of solving a typical optimal control problem via dynamic programming. We show this is the case for the finite MDP scenario above where the set of models \mathcal{T}_i has the form $\mathcal{T}_i = \{T' \mid \forall(s, a) : \|T'_{sa} - \tilde{T}_{sa}\|_1 \leq c_{sa}\}$ for some nominal model \tilde{T} and confidence region c_{sa} on the L_1 distance to the true model for each state-action pair.


```

input: Nominal model  $\tilde{T}$ ,  $L_1$  confidence region  $c_{sa}$  for all  $(s, a)$ , Cost function  $C$ .
 $\forall s, a : Q(s, a) \leftarrow C(s, a)$ ,  $\forall s : V(s) \leftarrow \min_a [Q(s, a)]$ 
for  $t = 2$  to  $H$  do
  Sort states in ascending order of value in  $V$ , breaking ties arbitrarily.
  Let  $s_j$  denote the  $j^{th}$  state in sorted list.
  for each  $s$  do
    for each  $a$  do
       $\forall s' : T'_{sa}(s') \leftarrow \tilde{T}_{sa}(s')$ ,  $l \leftarrow 1$ ,  $h \leftarrow |S|$ ,  $d \leftarrow 0$ .
      while  $l < h$  and  $d < c_{sa}$  do
         $\delta \leftarrow \min(1 - T'_{sa}(s_l), T'_{sa}(s_h), (c_{sa} - d)/2)$ .
         $T'_{sa}(s_l) \leftarrow T'_{sa}(s_l) + \delta$ ,  $T'_{sa}(s_h) \leftarrow T'_{sa}(s_h) - \delta$ ,  $d \leftarrow d + 2\delta$ .
        if  $T'_{sa}(s_l) = 1$  then  $l \leftarrow l + 1$ .
        if  $T'_{sa}(s_h) = 0$  then  $h \leftarrow h - 1$ .
      end while
       $Q'(s, a) \leftarrow C(s, a) + \gamma \sum_{s'} T'_{sa}(s') V(s')$ 
    end for
  end for
   $\forall s, a : Q(s, a) \leftarrow Q'(s, a)$ ,  $\forall s : V(s) \leftarrow \min_a [Q'(s, a)]$ 
end for
return  $Q$ 

```

Algorithm 8.5.2: DP Algorithm for solving optimistic optimal control problem.

In this scenario we have to solve the following equation:

$$\hat{V}^*(s) = \min_a [C(s, a) + \gamma \min_{T'_{sa} || T'_{sa} - \tilde{T}_{sa} ||_1 \leq c_{sa}} \mathbb{E}_{s' \sim T'_{sa}} [\hat{V}^*(s')]]$$

In general this can be solved via dynamic programming and solving a linear program with $O(|S|)$ constraints for each state-action pair at each dynamic programming iteration. Such an approach would however be intractable. There is a much more efficient approach which simply involves sorting the states according to their value at each dynamic programming iteration in order to solve for the optimal T'_{sa} in $O(|S|)$ work for each state-action pair. This algorithm, detailed in Algorithm 8.5.2, was proposed in [Strehl and Littman \(2004\)](#) and we present it here for completeness.

Intuitively, this algorithm proceeds by putting as much probability mass on states which have lowest cost-to-go and as few probability mass on states which have highest cost-to-go. This is done efficiently using the sorted list of states according to their cost-to-go values, greedily moving probability mass from states with highest cost-to-go to states with lowest cost-to-go, starting from the nominal solution $T'_{sa} = \tilde{T}_{sa}$, while enforcing the constraint that T'_{sa} must be a probability distribution with L_1 distance within c_{sa} of \tilde{T}_{sa} .

For each s, a and iteration t , finding the optimal T'_{sa} (i.e. the while loop) terminates in less than $|S|$ iterations and each iteration is $O(1)$ work. So at each iteration t , finding the optimal T' for all s, a requires $O(|S|^2|A| + |S| \log |S|)$ work which is $O(|S|^2|A|)$. Once we found the optimal T' , doing the value function update for all (s, a) is $O(|S|^2|A|)$ as

well. So each iteration of dynamic programming is still $O(|S|^2|A|)$. Running the above algorithm is thus $O(H|S|^2|A|)$ for H iterations. Since each iteration is a γ -contraction of $\|V - V^*\|_\infty$, choosing H in $O(\frac{1}{1-\gamma} \log(\frac{C_{\text{rng}}}{(1-\gamma)\epsilon}))$ guarantees that we will find an ϵ -optimal solution. Finding an ϵ -optimal solution is thus $O(\frac{|S|^2|A|}{1-\gamma} \log(\frac{C_{\text{rng}}}{(1-\gamma)\epsilon}))$. This is the same complexity as the value iteration algorithm when solving for an ϵ -optimal policy with fixed model.

Discussion

This exploration strategy is well motivated and can be implemented efficiently in finite MDPs when learning the full conditional probability table. For practical applications with other class of models, we would need similar efficient dynamic programming algorithms for jointly finding an optimal policy and model. We believe this may be possible for the case of linear systems (LQR). In particular, in this case a similar approach to H_∞ robust control where a dynamic game between the controller and a disturbance player is solved (Basar and Bernhard, 1995) could potentially be leveraged, but where instead, the disturbance player tries to minimize cost, subject to a constraint on the size of the deviation. For instance, based on the results in Walsh et al. (2009), it is likely that a similar result could be derived to show that the deviation in next state, from the state predicted by the nominal model, is bounded within some L_2 ball, leading to an optimal strategy for the disturbance player that is also a linear function of the state and allowing to compute the optimistic optimal value function in closed form as a quadratic function.

For more general class of models, the optimistic optimal control problem may potentially be solved approximately, for instance using a gradient based method.

It would be interesting to see if this exploration strategy can be extended to agnostic setting, or provide guarantees for this strategy in agnostic settings. For instance, it might be possible to bound the quantity $\bar{\epsilon}'_{\text{oc-lb}}$, e.g. as a function of how well we can do at prediction during training within the class of model \mathcal{T} , or by making some other assumption about how well the class of model \mathcal{T} can approximate the real system T .

8.6 Experiments

We now demonstrate the efficacy of DAGGER for System Identification on two control tasks: a simple benchmark inverted pendulum swing-up task, and a more challenging task of learning to perform aerobatic maneuvers with a simulated helicopter.

Inverted Pendulum Swing-Up

The control of an inverted pendulum has been commonly used in the control literature and is often used as a simple benchmark problem. We consider learning to perform

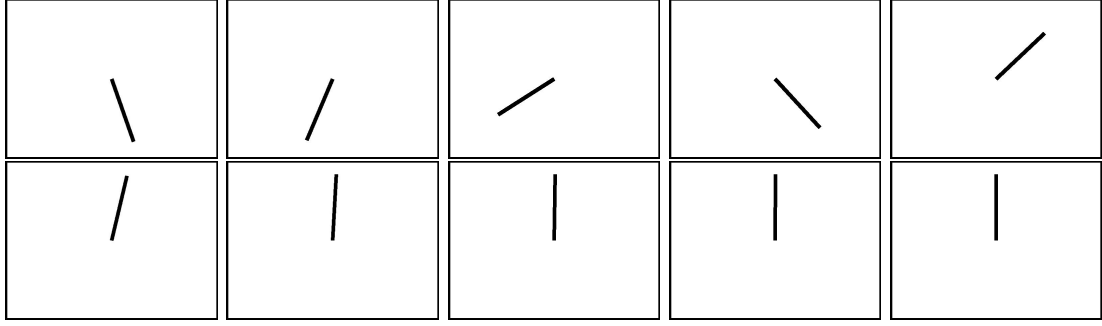


Figure 8.2: Depiction of the swing-up task. First 10 frames at 0.5s intervals of a near-optimal controller. Top Left: Initial State at 0s. Following frames in top row at 0.5s intervals from left to right, then continued from left to right in the bottom row. Bottom Right: Frame at 4.5s illustrates the inverted position that must be maintained until the end of the 10s trajectory.

the swing-up task, which consists in, starting from a pendulum near its equilibrium position at rest, swinging it to bring it in an inverted position, and then maintaining it in equilibrium in this inverted position, in the presence of small random external disturbances. We consider the case where the pendulum is torque controlled at the rotary joint, and is under actuated⁶. This task is depicted in Figure 8.2.

The pendulum is described by a two-dimensional continuous state $[\theta, \dot{\theta}]$, where θ is the angle in $[-\pi, \pi]$ (off the inverted equilibrium position), and $\dot{\theta}$ its angular velocity, and a one-dimensional continuous control (torque) τ . We simulate an ideal pendulum (all its mass concentrated at the end of the pendulum) without friction, described by the following differential equation:

$$\ddot{\theta} = \frac{g}{l} \sin(\theta) - \frac{\tau}{l^2 m}$$

where $\ddot{\theta}$ is the angular acceleration, l and m are the length (in meters) and mass (in kg) of the pendulum respectively, g is the gravitational force. We consider the case where $m = l = 1$, under Earth's gravity ($g = 9.81$). To make the pendulum under actuated, we limit $\tau \in [-4, 4]$. We simulate external disturbances through random small additive torques⁷ applied to the pendulum. We always start the pendulum in initial state $(2.8, 0)$ (i.e. top left frame in Figure 8.2).

We would like to synthesize a controller than can update the torque at 10hz and perform this task during 10s. We define a cost function that penalizes deviations from the inverted position, angular velocities and torques at each time step (of 0.1s):

$$C(\theta, \dot{\theta}, \tau) = 10\theta^2 + \dot{\theta}^2 + 0.1\tau^2.$$

⁶By under actuated, we mean that we must build velocity by swinging the pendulum back and forth to bring it from the start position to its inverted position, we cannot simply drive the pendulum directly to its inverted position by constantly applying maximum torque in one direction.

⁷White gaussian noise with standard deviation 0.05

For each method, we attempt to learn a dynamic model that predicts the change in state of the pendulum, given the current state and torque, using locally weighted linear regression⁸ (LWLR) (Atkeson et al., 1997), starting from the 0 model (i.e. that predicts the state never changes), and solve the optimal control problem through dynamic programming with a finely discretized grid over the state space (linearly interpolating the value function and policy between grid points). We compare DAGGER, to Batch, and the iterative approach of Abbeel and Ng (2005) and Atkeson and Schaal (1997). For the exploration distribution ν , we observe the pendulum under the expert controller obtained by solving the optimal control problem with the known model of the simulator. This expert controller can swing-up the pendulum to its inverted position quickly and then maintains it in this position for the remaining time (see Figure 8.2). We also compare performance to this expert controller as the desired target level of performance.

We perform 10 iterations of training with each approach, where at each iteration, two additional trajectories are collected. For DAGGER, this corresponds to one trajectory from the expert controller and one trajectory from the learner’s current controller at each iteration; for Batch, this corresponds to two additional trajectories from the expert controller at each iteration; and for Abbeel’s approach, this is two trajectories from the expert at the first iteration, then two trajectories from the learner’s current controller at each iteration. This difference in how data is collected is the only difference between all these methods.

Figure 8.3 compares the performance of these methods at the swing-up task over the iterations of training as a function of training data collected so far.

We first observe that the batch method does not perform well. Looking at the execution of its learned controllers, we observe that it never learns to properly swing-up the pendulum to its inverted position. On the other hand, both DAGGER and Abbeel eventually obtain a controller that is as good as the expert controller. Abbeel performs slightly better than DAGGER, by obtaining such a controller after 6 iterations instead of 7 for DAGGER. We believe that Abbeel performs well in this application as it is essentially a realizable setting, and the LWLR model can fit perfectly the observed data (up to noise), so it doesn’t have to tradeoff where it makes error as in agnostic settings. In essence, in such realizable cases, the balance/weighting between data from exploration and the learned policies in the dataset is not as important; sufficient coverage of both is what’s important. In the next experiment, we will see that having a good balance is important in non-realizable settings and that Abbeel’s method can get stuck in a bad local minima when insufficient exploration data is present in the dataset.

⁸We use a gaussian kernel, where distance is computed between normalized features, and the bandwidth parameter is optimized at each iteration using cross-validation, where the data collected at different iteration are treated as different folds.

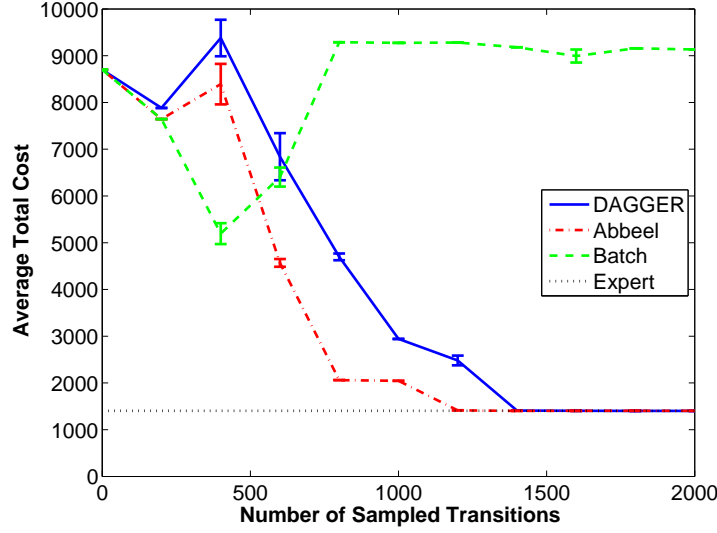


Figure 8.3: Average total cost on test trajectories at the swing-up task as a function of data collected so far.

Simulated Helicopter Control

We use the helicopter simulator of [Abbeel and Ng \(2005\)](#), which has a continuous 21-dimensional state and 4-dimensional control space. We consider learning to 1) hover and 2) perform a “nose-in funnel” maneuver. We compare DAGGER to *Batch* with several choices for exploration distribution ν : 1) ν_t : adding small white Gaussian noise⁹ to each state and action along the desired trajectory, 2) ν_e : run an expert controller, and 3) ν_{en} : run the expert controller with additional white Gaussian noise¹⁰ in the controls of the expert. The expert controller is obtained by linearizing the true model about the desired trajectory and solving the LQR (iLQR for the nose-in funnel). We also compare against Abbeel’s algorithm, where the expert is only used at the first iteration.

Hover

All approaches begin with an initial model $\Delta x_{t+1} = A\Delta x_t + B\Delta u_t$, for Δx_t the difference between the current and hover state at time t , Δu_t the delta controls at time t , A is identity and B adds the delta controls to the actual controls in Δx_t . We seek to learn offset matrices A' , B' that minimizes squared loss on observed data. We also use a

⁹Covariance of $0.0025I$ for states and $0.0001I$ for actions.

¹⁰Covariance of $0.0001I$.

Frobenius norm regularizer on A' and B' , such that we optimize the model as follows:

$$\min_{A', B'} \frac{1}{n} \sum_{i=1}^n \|\Delta x'_i - [(A + A')\Delta x_i + (B + B')\Delta u_i]\|_2 + \frac{\lambda}{\sqrt{n}} (\|A'\|_F^2 + \|B'\|_F^2),$$

where n is the number of samples, $(\Delta x_i, \Delta u_i, \Delta x'_i)$ the i^{th} transition in the dataset, and we used $\lambda = 10^{-3}$ (determined by preliminary validation experiments).

In addition, during training we stop a trajectory if it becomes too far from the hover state (or desired trajectory below for the nose-in funnel), *i.e.* if $\|[\Delta x; \Delta u]\|_2 > 5$, as this represents an event that would have to be recovered from by a human pilot to prevent a crash. Collecting data too far off the desired trajectory also hinders performance since our linear models are only good locally, as discussed below.

During testing, we run the trajectory until completion (400 time steps of 0.05s, 20s total). We attempt to learn to hover in the presence of noise¹¹ and delay of 0 and 1. A delay of 1 introduce high-order dynamics that cannot be modeled with the current state. All methods sample 100 transitions per iteration and run for: 50 iterations when delay is 0; 100 iterations when delay is 1. Figure 8.4 shows the test performance of each method after each iteration. In both cases, for any choice of ν , DAGGER outperforms *Batch* significantly and converges to a good policy faster. DAGGER is more robust to the choice of ν , as it always obtains good performance given enough iterations, whereas *Batch* obtains good performance with only one choice of ν in each case. Also, DAGGER eventually learns a policy that outperforms the expert policy (L). As the expert policy is inevitably visiting states far from the hover state due to the large noise and delay (unknown to the expert), the linearized model is not as good at those states, leading to slightly suboptimal performance. Thus DAGGER is learning a better linear model for the states visited by the learned policy which leads to better performance. Abbeel's algorithm improves the initial policy but reaches a plateau. This is due to lack of exploration (expert demonstrations) after the first iteration. While our objective is to show that DAGGER outperforms other model-based approaches, we also compared against a model-free policy gradient method similar to CPI¹². However, 100 samples per iteration were insufficient to get good gradient estimates and lead to only small improvement. Even with 500 samples per iteration, it could only reach an average total cost ~ 15000 after 100 iterations. Hence, DAGGER is also more efficient in practice than model-free policy gradient methods such as CPI.

¹¹White Gaussian noise with covariance I on the forces and torques applied to the helicopter at each step.

¹²Same as CPI, except gradient descent is done directly on deterministic linear controller. We solve a linear system to estimate the gradient from sample cost over a trajectory with perturbed controller parameters. Here, this was much more practical than learning a stochastic controller as in (Kakade and Langford, 2002).

Nose-In Funnel

This maneuver consists in rotating at a fixed speed and distance around an axis normal to the ground with the helicopter’s nose pointing towards the axis of rotation (it is the desired trajectory depicted in Figure 1.2). We attempt to learn to perform 4 complete rotations of radius 5 in the presence of noise¹³ but no delay. We start each approach with a linearized model about the hover state and learn a time-varying linear model. For each time step t , we learn offset matrices A'_t, B'_t such that $\Delta x_{t+1} = (A + A'_t)\Delta x_t + (B + B'_t)\Delta u_t + x_{t+1}^* - x_t^*$, for x_t^* the desired state at time t and A, B the given hover model. All methods collect 500 samples per iteration over 100 iterations. Figure 8.4 (bottom) shows the test performance after each iteration. With the initial model (0 data), the controller fails to produce the maneuver and performance is quite poor. Again, with any choice of ν , DAGGER outperforms *Batch*, and unlike *Batch*, it performs well with all choices of ν . A video comparing qualitatively the learned maneuver with DAGGER and *Batch* is available on YouTube (Ross, 2012). Abbeel’s method improves performance slightly but again suffers from lack of expert demonstrations after the first iteration.

In-Depth Comparisons to Previous Iterative Methods

In the previous experiments, we observed that the previous iterative method of Abbeel and Ng (2005) (and similarly Atkeson and Schaal (1997)) does not perform well and seems to reach a plateau or get stuck in a local minima. We demonstrate here that this is clearly due to insufficient exploration data in the collected dataset. By collecting more exploration data initially, these methods can lead to similar good performance to DAGGER, albeit, often requiring more iterations than DAGGER overall, to reach near-optimal performance.

Figure 8.5, shows the performance of Abbeel’s method, as we vary the number N_{exp} of initial iterations where data under execution of the expert controller is collected (1, 6, 12, 25, 50). This effectively corresponds to collecting an initial batch of data from the expert which is larger, before we start collecting data from running the current learned policies.

There are a number of trends we can observe from these figures. First, increasing N_{exp} , seems to lead to more stable and better asymptotic performance, at the price of requiring more iterations to reach near-optimal performance. On the other hand, when N_{exp} is smaller, performance improves more quickly initially, but asymptotic performance degrades (either getting stuck in local minima, or being less stable). To achieve the best performance, N_{exp} needs to be carefully chosen to balance these 2. In all of these figures, $N_{\text{exp}} = 12$ seems to give the best tradeoff. DAGGER on the other hand, by collecting

¹³Zero-mean spherical Gaussian with standard deviation 0.1 on the forces and torques applied to the helicopter at each step.

an equal amount of exploration data and data from the current policy at each iteration, achieves performance similar and often better to this best tradeoff automatically.

These results also give further empirical evidence that supports our theoretical results. In agnostic system identification settings, one cannot simply learn by only collecting data from execution of the current policy, one needs to collect a significant fraction of exploration data as well, to ensure we can predict well the system's behavior under execution of other policies during planning. Similarly, only collecting exploration data may not lead to good performance, and collecting a fraction of data from execution of the current policy can help tremendously.

Practical Considerations when using DAGGER for System Identification

In the previous helicopter experiments with DAGGER, to ensure learning a good linear model, we had to discard data points from the current policy's trajectory that went too far off the desired trajectory. When performing the experiments without discarding such data, DAGGER, and the other iterative methods did not perform well. This is because in this particular experiment, we were fitting a linear model that could only capture the behavior of the system well in a small region. If we attempt to fit data over a too large region, data far off the desired trajectory interfere, and does not lead to a good fit in the region of importance (i.e. near the desired trajectory). This appears in the guarantee of DAGGER by making ϵ_{mdl} large on the training data if we do not discard these data points, and hence indicates that DAGGER would not work well in this case.

Because for these tasks, we knew that any good policy must operate near the desired trajectory, we could safely discard data too far off the desired trajectory, as asymptotically, if we find a good policy, this data would not be useful. In fact, when discarding such data, a similar guarantee for DAGGER still holds (with an extra penalty term that scales with the fraction of points discarded). As long as in the limit of iterations, the fraction of discarded data goes to 0 (i.e. we find a policy that can stay within the region where we keep all data), good performance would be guaranteed if we can find a good model on the (non-discarded) training data.

There are a number of other potential solutions to deal with this issue:

- This issue may in part be caused by the sensitivity of least squares regression to outliers. Using more robust versions of linear regression may help to deal with this issue, if the fraction of points far off the region of importance remains small.
- To limit the number of points generated too far off the desired trajectory, it may also be desired to use more robust control methods (that are robust to imperfect models) when optimizing the controller with the learned model. For instance,

efficient robust H_∞ control methods where an adversary can introduce small disturbance at each step ([Basar and Bernhard, 1995](#)) could be used.

- In general, using non-parametric model fitting methods, such as kernel regression or locally weighted linear regression, resolves this issue. However using these methods may require collecting much more data (as they are high complexity models), and/or lead to a more difficult OC problem to solve.

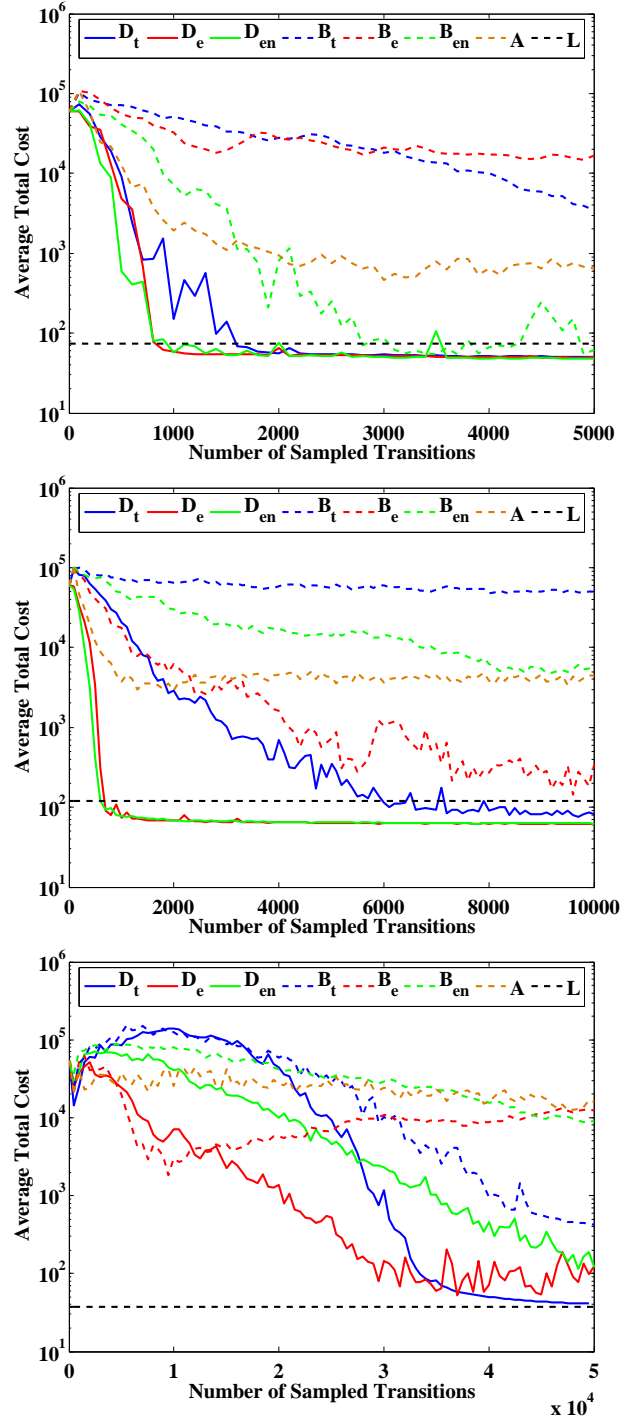


Figure 8.4: Average total cost on test trajectories as a function of data collected so far, averaged over 20 repetitions of the experiments, each starting with a different random seed (all approaches use the same 20 seeds) From top to bottom: hover with no delay, hover with delay of 1, nose-in funnel. D_t , D_e and D_{en} denotes DAGGER using exploration distribution ν_t , ν_e and ν_{en} respectively, similarly B_t , B_e and B_{en} for the Batch algorithm, A for Abbeel’s algorithm, and L for the linearized model’s optimal controller.

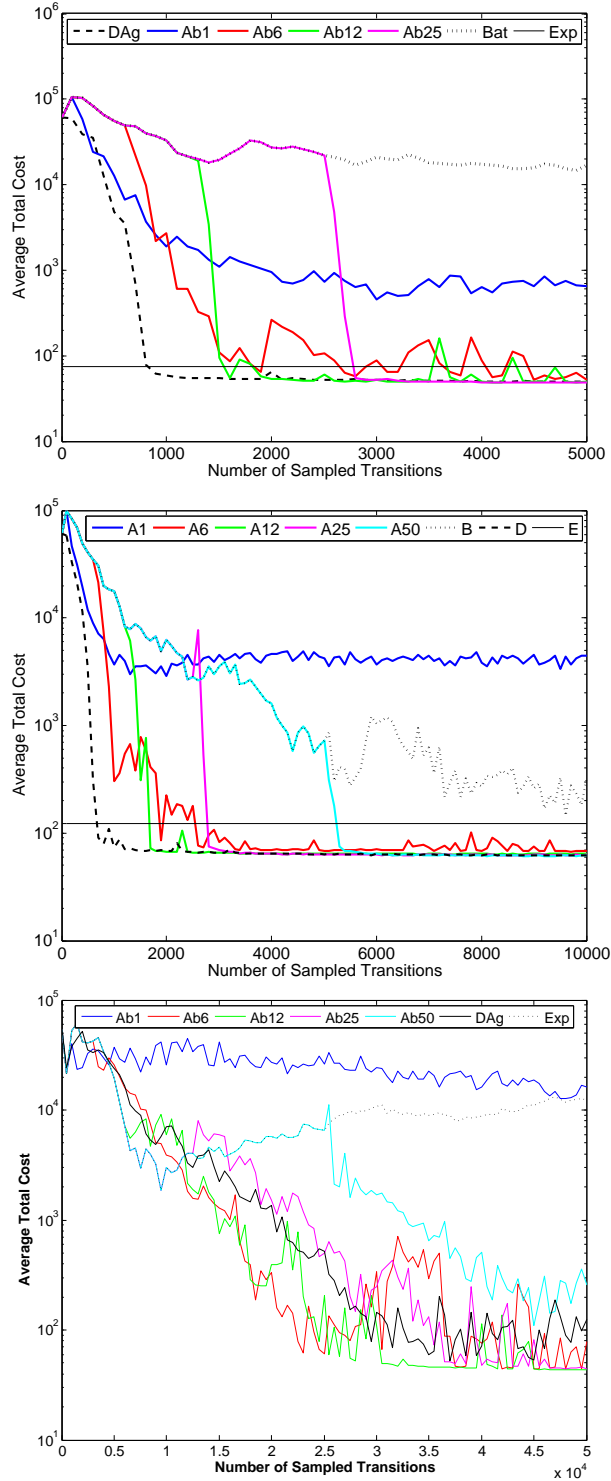


Figure 8.5: Average total cost on test trajectories as a function of data collected so far, averaged over 20 repetitions of the experiments, each starting with a different random seed (all approaches use the same 20 seeds) From top to bottom: hover with no delay, hover with delay of 1, nose-in funnel. AbN denotes Abbeel’s algorithm where the first N iterations collect data with the expert (exploration distribution ν_e); Dag and B denotes DAGGER and *Batch* using exploration distribution ν_e respectively, and L for the linearized model’s optimal controller.

Chapter 9

Stability as a Sufficient Condition for Data Aggregation

The guarantees of our DAGGER approach throughout rely on the strong no-regret property of an underlying online learner, used to pick the sequence of predictors/models over the iterations of training. In general, no-regret online learning is not always possible (at least computationally efficiently) depending on the class of hypothesis and loss considered (e.g. there is no known efficient online learner for rich model class like decision trees ([Breiman et al., 1984](#)), random forests ([Breiman, 2001](#)) or neural networks ([Hastie et al., 2001](#))). This may in principle, limit the applicability of our approach with certain classes of hypothesis.

To address this potential limitation, we have recently introduced sufficient conditions for online algorithms to be no-regret that do not rely on properties of the loss or hypothesis class, but instead, rely on properties of the algorithm choosing the sequence of hypotheses ([Ross and Bagnell, 2012b](#)). In particular, we have showed that if the algorithm is: (1) “stable”, under a appropriate notion of stability, and (2) asymptotically chooses hypotheses that minimize the loss in hindsight, then it must be no-regret.

These results have major implications for DAGGER. The aggregation approach (i.e. Follow-the-(Regularized)-Leader), where at each iteration a batch supervised learning problem is solved to return the best predictor on the aggregate dataset, must have good guarantees whenever the supervised learner has sufficient stability properties on the observed sequence of data. Thus in principle, DAGGER can still provide good guarantees with rich hypothesis classes such as decision trees or neural networks, by simply solving supervised learning problems at each iteration on the aggregate dataset, if the returned hypothesis over the iterations are sufficiently stable for the observed sequence of data.

A high-level interpretation of this result is the following: if you aggregate data and you are following the (regularized) leader; most decent supervised learners will be rea-

sonably stable (especially in common problems where the observed sequence of data is not as if it was coming from a worst case adversary); therefore we'd expect them to behave like no-regret algorithms, and provide good guarantees. This approach motivates the particular variant of DAGGER we typically use in practice that involves aggregation of data together with batch learning.

We briefly summarize these results in this chapter, and refer the reader to (Ross and Bagnell, 2012b) for a more in depth discussion and analysis.

9.1 Online Stability

We now introduce the notion of stability required to provide good guarantees for the aggregation approach.

The stability condition is related to stability notions that were recently introduced to study learnability in the batch setting (Shalev-Shwartz et al., 2010). These stability notions measure how the output of the learning algorithm changes upon removal, or replacement, of a single training instance in the training set. At a high-level, these conditions specify that an algorithm is stable if the change in loss on the held out instance is guaranteed to become arbitrarily small as the training set becomes arbitrarily large. Some stability notions are stronger than others, e.g. depending on whether this holds for all possible training set, or only in expectation under sampled sets.

For online learning, we introduced the notion of online stability (Ross and Bagnell, 2012b). It specifies that an algorithm is online stable if for any sequence of training instances picked by an adversary, the loss $\ell(h_n, z_n)$ of the current hypothesis h_n on the current instance z_n , compared to the loss of the next hypothesis h_{n+1} on z_n , becomes arbitrarily small as the number of iterations n become arbitrarily large:

Definition 9.1.1. *Given a sequence of training instances z_1, z_2, \dots , let S_n denote the subset of the first n instances and $h_n = \mathbf{A}(S_{n-1})$ the hypothesis returned by learning algorithm \mathbf{A} after observing the first $n - 1$ instances. A learning algorithm \mathbf{A} is **online stable** with respect to loss ℓ if there exists a sequence $\{\epsilon_{on-stable}(n)\}_{n=1}^{\infty}$ that is $o(1)$, such that for any sequence of training instances, $|\ell(\mathbf{A}(S_{n-1}), z_n) - \ell(\mathbf{A}(S_n), z_n)| \leq \epsilon_{on-stable}(n)$ for all n .*

Intuitively, this notion of stability captures how sensitive the hypothesis returned by the learning algorithm is to the addition of a single training example. As the size of the dataset increases, an online-stable algorithm becomes less and less sensitive to the addition of a single example. Intuitively, we can expect this to hold for most common practical scenario with common supervised learning algorithms, especially if some regularization is used.

9.2 Online Stability is Sufficient for Batch Learners

Now we will consider the particular class of learning algorithms, that return the best hypothesis on the data so far (potentially subject to a regularization term), and show that for such algorithms, online stability implies no-regret.

We formalize this class of algorithms using the following notion of a Regularized Empirical Risk Minimizer (RERM):

Definition 9.2.1. *A learning algorithm \mathbf{A} is a **Regularized Empirical Risk Minimizer (RERM)** if for all m and any dataset $S_m = \{z_1, z_2, \dots, z_m\}$ of m instances:*

$$\sum_{i=0}^m r_i(\mathbf{A}(S_m)) + \sum_{i=1}^m \ell(\mathbf{A}(S_m), z_i) = \min_{h \in \mathcal{H}} \left[\sum_{i=0}^m r_i(h) + \sum_{i=1}^m \ell(h, z_i) \right] \quad (9.1)$$

where $\{r_i\}_{i=0}^m$ is a sequence of regularizer functionals ($r_i : \mathcal{H} \rightarrow \mathbb{R}$), which measure the complexity of a hypothesis h , and that satisfy $\sup_{h, h' \in \mathcal{H}} |r_i(h) - r_i(h')| \leq \rho_i$ for all i where $\{\rho_i\}_{i=0}^\infty$ is a sequence that is $o(1)$.

Note that this definition considers general learning algorithms that may adapt the regularizer as it observes data. For common approaches that keep a fixed regularizer, but adapts only the regularization constant, then this implies $r_i(h) = \lambda_i r(h)$, for some sequence of regularization constants $\{\lambda_i\}$ and regularizer r . The regularizer r may be the squared norm of the parameters of the hypothesis h , as is commonly used. The terms $\{\rho_i\}$ represent a bound on the contribution of the regularization term to the loss. If the regularizer is a squared norm, then this will imply that we assume the hypothesis class is bounded within some set (e.g. we only consider hypothesis with squared norm $\leq C$ for some C). This is a common assumption for online learning algorithms. Additionally, in many cases, such bounds can be determined on the norm of the optimal solution based on the loss ℓ , such that the hypothesis space can be reduced to only consider hypothesis within a certain norm. The assumption that $\{\rho_i\}_{i=0}^\infty$ is a sequence that is $o(1)$ indicates that in the limit, the contribution of regularization vanishes, and the algorithm returns the best hypothesis with respect to the loss ℓ . Note also that this definition includes algorithms that do not use regularization, by considering r_i to be 0 functions (in this case the ρ_i are 0).

In [Ross and Bagnell \(2012b\)](#), we have showed that any RERM algorithm which is online stable, is no-regret. This result is formalized below:

Theorem 9.2.1. *After m instances, an online stable RERM \mathbf{A} has average online regret:*

$$\epsilon_{\text{regret}}(m) \leq \frac{1}{m} \sum_{i=1}^m \epsilon_{\text{on-stable}}(i) + \frac{2}{m} \sum_{i=0}^{m-1} \rho_i + \frac{\rho_m}{m} \quad (9.2)$$

Thus, as $\epsilon_{on-stable}(m) \rightarrow 0$ and $\rho_m \rightarrow 0$ as $m \rightarrow \infty$, an online stable RERM \mathbf{A} is no-regret:

$$\lim_{m \rightarrow \infty} \epsilon_{regret}(m) \leq 0 \quad (9.3)$$

This result applies to any sequence of instances we might observe, including adversarial sequences. A similar sequence specific statement can be made, that would indicate that for any particular sequence of instances where the algorithm is online-stable, then it would be no-regret on that sequence.

In [Ross and Bagnell \(2012b\)](#), we also showed how most common online learning algorithms can be analyzed in terms of these online stability and RERM properties (including gradient descent and randomized algorithms). In essence, most online learners can be modeled as trying to track the best hypothesis in hindsight, while being stable.

9.3 Discussion

In the context of DAGGER in sequential prediction problems, as we may often expect that the sequence of training data does not behave as if it was coming from a worst case adversary, we can expect that common supervised learners, applied to the aggregate dataset (and with appropriate regularization), often lead to a sufficiently stable sequence of hypothesis. This implies that in common practical scenarios, we can expect the aggregation approach to often behave like a no-regret algorithm and provide good guarantees (even if we can't guarantee the learner is no-regret for all worst case adversarial sequences).

This notion of stability generalizes, in some sense, previous learning approaches for Reinforcement Learning and Structured Prediction that operated by iteratively making small changes over several iterations of training ([Kakade and Langford, 2002](#), [Bagnell et al., 2003](#), [Daumé III et al., 2009](#)). Hence our results can be understood as generalizing this strategy, and showing that many update schemes can be used, such as any no-regret online algorithm, or stable batch learning algorithms. This allows a greater flexibility for choosing procedures that are more practical or appropriate for the given application and class of predictors.

Chapter 10

The Complexity of Learning Sequential Predictions

Throughout this thesis, we have seen how algorithms training over multiple iterations can achieve good guarantees in various sequential prediction problems. At the same time, we have shown that supervised learning methods that attempt to learn only from examples of good behavior, without interaction with the learner, cannot provide good guarantees, as the learned behavior is not robust to its own errors in predictions.

These observations indicate that multiple rounds of interactions with the learner may be necessary in general, for any learning algorithm to provide good guarantees. In the following sections, we investigate how many rounds any learning algorithm must interact with the learner to achieve good performance.

For simplicity, we will focus on canonical sequential prediction problems from the imitation learning setting. Among the various approaches we have presented, we have seen that for problems with a task horizon of T predictions, T rounds of interaction is sufficient, e.g. using the Forward training algorithm. The question we are interested in answering is whether it may be possible that other learning algorithms can learn good behaviors in fewer iterations, e.g. in a constant number of iterations, or with a smaller dependency on T .

The number of rounds of interactions required by the learning algorithm captures a notion of complexity for learning in these sequential prediction tasks. We will refer to this notion of complexity as the interaction complexity. We formalize this notion in the next section, and then provide lower bounds on the interaction complexity of any learning algorithm to provide good guarantees.

10.1 Interaction Complexity

Intuitively, by interaction complexity, we want to measure the number of predictors we will need to train, in order to obtain one or construct one that has good performance. To formalize this notion, we consider learning algorithms which have access to a “learning oracle”, that for any input distribution of examples, returns a predictor with error rate $\epsilon > 0$, or regret $\epsilon > 0$, for this input distribution:

Definition 10.1.1. *An ϵ -error learning oracle $\mathcal{O} : \Delta \rightarrow \mathcal{H}$ is a learning procedure, such that for any distribution of examples $D \in \Delta$, returns a predictor $h \in \mathcal{H}$ with error rate lower or equal to ϵ under D : i.e. $\mathbb{E}_{(x,y) \sim D, \hat{y} \sim h(x)}[I(\hat{y} \neq y)] \leq \epsilon$.*

Definition 10.1.2. *An ϵ -regret learning oracle $\mathcal{O} : \Delta \rightarrow \mathcal{H}$ is a learning procedure, such that for any distribution of examples $D \in \Delta$, returns a predictor $h \in \mathcal{H}$ with regret lower or equal to ϵ under D : i.e. $\mathbb{E}_{(x,y) \sim D, \hat{y} \sim h(x)}[I(\hat{y} \neq y)] - \min_{h' \in \mathcal{H}} \mathbb{E}_{(x,y) \sim D, \hat{y} \sim h'(x)}[I(\hat{y} \neq y)] \leq \epsilon$.*

For example, the learning oracle may be a typical supervised learning algorithm. When considering an ϵ -error oracle, the error rate ϵ may be attributed to the fact that the oracle is sampling from the input distribution D to learn, or that even if it collects an arbitrarily large number of samples from D , the target predictions cannot be represented perfectly within the class of hypothesis considered \mathcal{H} , or simply because the optimization procedure is approximated or stopped once it is within ϵ of optimal. Similarly, when considering an ϵ -regret oracle, the regret ϵ may be attributed to the fact that the oracle may be optimizing on a finite sample from D , or stopping optimization when it is within ϵ of optimal.

With these notions of a learning oracle, we simply define the interaction complexity as follows:

Definition 10.1.3. *Given access to an ϵ -error (or ϵ -regret) learning oracle \mathcal{O} , the interaction complexity of a learning algorithm is the number of queries it performs to \mathcal{O} to construct/obtain the final learned policy for test execution.*

For example, the Forward algorithm has interaction complexity of T , as it queries a learning oracle T times, once for each time step. Given access to an ϵ -regret oracle, Forward constructs a policy that has an expected total regret of $T\epsilon$ over T steps on its test trajectories. On the other hand, the typical supervised learning approach has interaction complexity of 1, but has $O(T)$ expected total regret in general on the test

trajectories when given access to an ϵ -regret oracle. Similarly, when given access to an ϵ -error learning oracle, Forward guarantees a policy with $T\epsilon$ expected mistakes over T steps, while the supervised learning approach only guarantees a predictor that has an expected number of mistakes of $O(T^2\epsilon)$ over T steps.

In our analysis of interaction complexity, we will not limit the learning algorithm to use precisely one of the predictor returned by the learning oracle. Instead, we consider general learning algorithms that can potentially combine the predictors returned by the learning oracle in some way to obtain the final predictor used for test execution. The Forward training algorithm is an example of this, where the predictors returned by the learning oracle are combined together, a different one used at each time step, to define the final policy. In general, we will allow the learning algorithm to potentially use a different distribution over policies returned by the learning oracle in every state and/or time step.

Given these definitions, we are interested in analyzing the minimum interaction complexity of any learning algorithm that can guarantee to construct a policy with expected number of mistakes $O(T\epsilon)$, or expected total regret of $O(T\epsilon)$, over T steps.

Relation to Sample Complexity

For most learning algorithm, it is typical to analyze its sample complexity, i.e. the number of samples required to achieve error (or regret) below some level of tolerance. While sample complexity is also an interesting notion to analyze for sequential prediction tasks, that indicates the total number of samples required to obtain a good policy, it does not capture that we may need to adapt the distribution of samples, and that simply sampling more from the same distribution may not help improve performance. This is precisely what the notion of interaction complexity seeks to measure. Hence, the interaction complexity complements the notion of sample complexity. In the context of interaction complexity, the sample complexity is abstracted into the learning oracle, as we potentially allow the learning oracle to collect an infinite number of samples from the input distribution D . However, even with infinite samples (per query to the learning oracle), the interaction complexity may indicate that we still need to adapt the sampling distribution several times before we can obtain a good policy. The interaction complexity may also be useful to determine the sample complexity of an algorithm. For instance if we know that each query to the learning oracle will require a certain number of samples to guarantee a predictor with error (or regret) ϵ , then multiplying this number by the interaction complexity will provide a bound on the overall sample complexity of the learning algorithm.

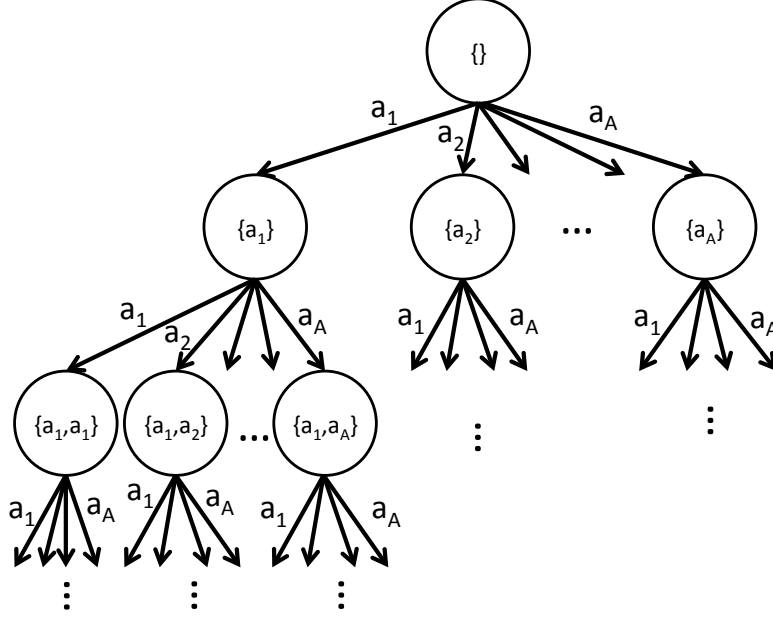


Figure 10.1: Depiction of the Tree MDP. State represents the entire action sequence so far, transitions are deterministic as represented by the arrows, and simply appends the action to the current state. The initial state is the root. The tree has branching factor A and extends to infinite depth.

10.2 Preliminaries: The Hard MDP

For our analysis in the next sections, we will always consider a particularly hard MDP, where the action that needs to be predicted next, may depend on the entire previous sequence of actions. That is, we will always consider an arbitrarily large MDP where the state is simply the sequence of actions so far, starting from the empty sequence for the initial state, and transitions are deterministic: doing an action simply appends the action to the current sequence to move to the next state. For T steps, this MDP has a tree structure of depth T , with branching factor A , for A the number of actions. In this tree, the learner always starts at the root, and then each action moves the learner to one of the child of the current node, until it reaches a leaf after $T - 1$ actions, where it chooses its last action. This MDP has an exponential number of states in T : i.e. $\frac{A^T - 1}{A - 1}$ states. We can simply think of this tree extending to infinity, as we consider increasing the number of time steps T to infinity. This tree MDP is depicted in Figure 10.1.

To make most of our arguments simpler, we will also consider the number of actions to be large, i.e. of order $O(1/\epsilon)$, for $\epsilon > 0$ the error rate (or regret) of the learning oracle. In particular, we will assume there are at least $1/\alpha\epsilon$ actions for some arbitrary constant $\alpha \in (0, 1]$ that we can choose. We will use this fact to easily show that we can always

find some action that was rarely explored in any state, that must lead to some subtree of the MDP that was rarely explored. However, most of our arguments could also be carried if the number of actions is smaller, by considering small sequences of actions, in that from any state, one can always find sequences of $O(\log(1/\epsilon))$ actions that would lead to a subtree that has rarely been explored.

In this exponentially large MDP, we will also consider policies that are represented by a separate distribution over actions in every state, i.e. a policy represented by SA parameters (probabilities), for S the number of states. While the complexity of this policy class is exponential in T (as S is exponential in T), as we allow for potentially infinite samples for each query to the oracle, we can always assume that the oracle can still learn a good policy in this class.

Our interaction complexity results will make use of these exponentially large MDP and policy class to prove that we must need a certain number of iterations. It remains an open question whether similar results could be instead directly related to the complexity of the MDP and/or policy class. Despite this, our results demonstrate that without further assumptions on the size of the MDP or complexity of the policy class, one will need several iterations to guarantee good performance.

10.3 Inevitability of Poor Guarantees for Non-Iterative Methods

We begin our analysis by first showing that there cannot exist any learning algorithm that can provide good guarantees in general with only a single query to the learning oracle. In particular, we show that, given access to an ϵ -error learning oracle, any algorithm with interaction complexity of 1, obtains a policy with expected number of mistakes of $\Omega(\min(T^2\epsilon, T))$ over sequences of T steps, for some arbitrarily large MDP and policy class. Additionally, we also show that given access to an ϵ -regret learning oracle, any algorithm with interaction complexity of 1, obtains a policy with expected total regret of $\Omega(T)$, over sequences of T steps, for some arbitrarily large MDP and policy class.

These results generalize our analysis of the supervised learning method that trains only from expert demonstrations, and shows that even if some form of exploration would be used, to query the expert in states that are rarely or never visited under the expert behavior, this does not improve performance in the worst case.

Theorem 10.3.1. *Given access to an ϵ -error learning oracle, there exist MDPs and policy classes where any learning algorithm with interaction complexity of 1 obtains a policy with expected number of mistakes $\Omega(\min(T^2\epsilon, T))$ over sequences of T steps.*

Proof. This follows from a fairly straightforward observation due to the large number of

actions and states in this hard MDP. First consider states along the expert's trajectory in this tree MDP. There are $\lceil T/2 \rceil$ states in the first $\lceil T/2 \rceil$ time steps, and under any training distribution, there would exist at least one state among these with probability $\leq 2/T$. Pick any such state and denote it s' . Now in s' , suppose the learned predictor makes a mistake with probability $\min((1 - \alpha)T\epsilon/2, 1)$, and all other states s at previous steps along the expert trajectory have error 0. Additionally, since there are at least $\frac{1}{\alpha\epsilon}$ actions that one can take from state s' , under any training distribution over states, there would always exist at least one action whose probability mass over its entire subtree is lower or equal to $\alpha\epsilon$. Pick such action and denote it a' . Therefore, one can assign error 1 in every state in the subtree of action a' , and we can make the learned predictor always pick a' when it makes a mistake in s' . This leads to a learned predictor that has error $\leq 2/T \min((1 - \alpha)T\epsilon/2, 1) + \alpha\epsilon \leq \epsilon$ under the training distribution, which could therefore be returned by the learning oracle. Yet, when executing this predictor, we would always reach state s' , and then if it makes a mistake, i.e. pick a' , it would incur at least $T/2$ mistakes over the entire sequence. This implies that the expected number of mistakes of this predictor is at least $\min((1 - \alpha)T^2\epsilon/4, T/2)$. \square

Theorem 10.3.2. *Given access to an ϵ -regret learning oracle, there exist MDPs and policy classes where any learning algorithm with interaction complexity of 1 obtains a policy $\hat{\pi}$ with expected total regret $R(\hat{\pi})$ of $\Omega(T)$ under its own sequences of T steps.*

Proof. Follows from a similar argument as in the previous theorem. Again consider states along the expert's trajectory in this tree MDP, and denote s_0 the initial state. Consider a policy class where in all states, except s_0 , there exist predictors with 0 error, but in s_0 , all predictors in the class make an error with probability at least $\frac{1}{2}$. Additionally, since there are at least $\frac{1}{\alpha\epsilon}$ actions that one can take from state s_0 , under any training distribution over states, there would always exist at least one action whose probability mass over its entire subtree is lower or equal to $\alpha\epsilon$. Pick such action and denote it a' . So now consider the learned predictor to be a predictor that never makes an error, except in state s_0 and in the subtree of a' , where in s_0 it errors with probability $\frac{1}{2}$ and picks a' , and in the subtree of a' it errors with probability 1 in all states in that subtree. Now since we assumed there exists a predictor in the class that achieves 0 error everywhere, except in s_0 where it errors with probability $\frac{1}{2}$, then the regret of the learned predictor under the training distribution is at most $\alpha\epsilon$, and could thus be returned by the learning oracle. On the other hand, during test execution, the learned predictor always starts in s_0 , at which point with probability $\frac{1}{2}$, it picks action a' , and performs T mistakes over the sequence. On the other hand, on this same sequence, there exist predictors that error with probability $\frac{1}{2}$ in s_0 , but then never errors until the end of the sequence. When

the learned predictor doesn't error in s_0 , then it never errors, and the same occurs for the best predictor in the class. Thus the total expected regret of the learned predictor is $\frac{1}{2}(T - 1)$. \square

10.4 Linear Dependency of the Interaction Complexity on the Task Horizon

We now show that in general, the number of queries to the learning oracle must scale linearly with the number of time steps T in order to obtain a policy with good guarantees. In particular, given access to an ϵ -error learning oracle, our analysis will show that at least $\Omega(T\epsilon)$ queries are required, to obtain a policy with $O(T\epsilon)$ expected mistakes over T steps. Additionally, we will show that, given access to an ϵ -regret learning oracle, $\Omega(T)$ queries are required in general to obtain a policy with order $O(T\epsilon)$ expected total regret over T steps.

Lemma 10.4.1. *Given access to an ϵ -error learning oracle, there exist MDPs and policy classes where any learning algorithm with interaction complexity of k obtains a policy whose expected number of mistakes is at least:*

$$\sum_{i=1}^{k-1} i \binom{T}{i} \epsilon^i (1 - \epsilon)^{T-i} + \sum_{t=k}^T \binom{t-1}{k-1} \epsilon^k (1 - \epsilon)^{t-k} (T - t + k)$$

Proof. Consider the hard tree MDP presented previously. On the first query to the learning oracle, we can make the learning oracle return the following predictor: for the T states s_1, s_2, \dots, s_T , along the expert trajectory, the learned predictor makes a mistake with probability $(1 - \alpha)\epsilon$ in each s_i . Because in each of these states there are at least $\frac{1}{\alpha\epsilon}$ actions that can be taken, all leading to different regions of the state space, there must exist a set of actions a_1, a_2, \dots, a_T , where a_i denotes an action taken in s_i , where the sum of the probability mass over all the states in the subtrees of a_1, a_2, \dots, a_T is at most $\alpha\epsilon$. Thus for all these subtrees, we can assign a probability 1 of mistake in every state. Additionally, when the predictor makes a mistake in state s_i , we can make it always choose action a_i . We obtain that under any training distribution, for the first query to the learning oracle, we can return such predictor that has error $\leq (1 - \alpha)\epsilon + \alpha\epsilon \leq \epsilon$ under the training distribution. Now for all remaining iterations, we can always return a predictor that is exactly the same in states s_1, s_2, \dots, s_T , but potentially changes in the subtrees of a_1, a_2, \dots, a_T . At the second iteration we can apply the same reasoning over each of the subtrees of a_1, a_2, \dots, a_T , and construct a predictor that has the same error structure as the first learned predictor, but within each of the subtree. That is for the second iteration, consider the error of the learned predictor to be $(1 - \alpha)\epsilon$ in every state

along the expert trajectory after each of the erroneous actions a_1, a_2, \dots, a_T . Since we keep the learned predictor to be the same along the expert trajectory, then this second learned predictor has error $(1 - \alpha)\epsilon$ in every states where the predictor has made 0 or 1 mistake so far. But again we can find a set of actions that represent the mistakes this second predictor can makes in states reached after 1 mistake has been done, whose sum of probability mass in all their subtrees would be at most $\alpha\epsilon$, such that we can still assign error 1 in every state in those subtrees. Note that because these subtrees are themselves subtrees of a_1, a_2, \dots, a_T , all these states must also had error 1 in the first iteration. This implies that for any combination of the first 2 predictors, we can only obtain a predictor which has probability of mistakes $(1 - \alpha)\epsilon$, as long as it has made 0 or 1 mistake so far, but then after 2 mistakes, must make a mistake with probability 1 in every future state. It is also clear that this second learned predictor satisfies the constraint that it has error $\leq \epsilon$ under any training distribution (there is probability mass ≤ 1 on states with error $\epsilon(1 - \alpha)$ and probability mass $\leq \alpha\epsilon$ on states with error 1). The end result is that after 2 iterations, we can always obtain a predictor that errors with probability 1, after 2 mistakes has been done, or errors with probability $(1 - \alpha)\epsilon$ otherwise. The same reasoning can be applied recursively, to see that after k iterations, we can always obtain a predictor that errors with probability 1 after k mistakes, or errors with probability $(1 - \alpha)\epsilon$ otherwise. Let $\epsilon' = (1 - \alpha)\epsilon$. Then if we have such a predictor, it can be seen that its expected number of mistakes over T steps is:

$$\sum_{i=1}^{k-1} i \binom{T}{i} \epsilon'^i (1 - \epsilon')^{T-i} + \sum_{t=k}^T \binom{t-1}{k-1} \epsilon'^k (1 - \epsilon')^{t-k} (T - t + k)$$

The first summation can be seen as summing over all the paths with i mistakes, for $i \leq k - 1$, while the second summation sums over all the paths with k or more mistakes, conditioning on the time t where the k^{th} mistake occur (there are $\binom{t-1}{k-1}$ paths whose k^{th} mistake occur on the t^{th} step). The lemma follows from the fact that we can always pick a large enough number of actions so that $\epsilon' = (1 - \alpha)\epsilon$ is arbitrarily close to ϵ (although it should be noted that this is not necessary, even $\alpha = 1/2$, is sufficient to prove our main result in the next theorem). \square

Theorem 10.4.1. *Given access to an ϵ -error learning oracle, there exist MDPs and policy classes where any learning algorithm must have interaction complexity of $\Omega(T\epsilon)$ to obtain a policy with an expected number of mistakes of $O(T\epsilon)$ over sequences of T steps.*

Proof. Consider the lower bound on the number of mistakes after k iterations obtained in the previous lemma:

$$\sum_{i=1}^{k-1} i \binom{T}{i} \epsilon^i (1 - \epsilon)^{T-i} + \sum_{t=k}^T \binom{t-1}{k-1} \epsilon^k (1 - \epsilon)^{t-k} (T - t + k)$$

The first summation is $\leq T\epsilon$ and tends to this quantity as $k \rightarrow T$ (it tends to the expectation of a $\text{Binomial}(T, \epsilon)$). Hence this lower bound on the number of mistakes is $O(T\epsilon)$ if the second summation is $O(T\epsilon)$.

The second summation resembles the expectation of a quantity under a negative binomial distribution. That is, let $r = t - k$, the number of times we picked the expert's action before making k mistakes, $F(\cdot; 1 - \epsilon, k)$ the cumulative density function of a negative binomial, with probability of success $1 - \epsilon$, and stopping after k failures, and $\mathbb{E}[r]$ the expectation of this negative binomial distribution, then:

$$\begin{aligned}
 & \sum_{t=k}^T \binom{t-1}{k-1} \epsilon^k (1 - \epsilon)^{t-k} (T - t + k) \\
 &= \sum_{r=0}^{T-k} \binom{k+r-1}{r} \epsilon^k (1 - \epsilon)^r (T - r) \\
 &= T \sum_{r=0}^{T-k} \binom{k+r-1}{r} \epsilon^k (1 - \epsilon)^r - \sum_{r=0}^{T-k} \binom{k+r-1}{r} \epsilon^k (1 - \epsilon)^r r \\
 &= TF(T - k; 1 - \epsilon, k) - \sum_{r=0}^{T-k} \binom{k+r-1}{r} \epsilon^k (1 - \epsilon)^r r \\
 &\geq TF(T - k; 1 - \epsilon, k) - \sum_{r=0}^{\infty} \binom{k+r-1}{r} \epsilon^k (1 - \epsilon)^r r \\
 &= TF(T - k; 1 - \epsilon, k) - \mathbb{E}[r]
 \end{aligned}$$

Since $\mathbb{E}[r] = (1 - \epsilon)k/\epsilon$, we obtain

$$\sum_{t=k}^T \binom{t-1}{k-1} \epsilon^k (1 - \epsilon)^{t-k} (T - t + k) \geq TF(T - k; 1 - \epsilon, k) - (1 - \epsilon)k/\epsilon$$

Now $1 - F(T - k, 1 - \epsilon, k)$ is the probability that it takes more than $T - k$ trials to get k failures, when the probability of success is $(1 - \epsilon)$. In other words, this is the probability that out of $T - k$ trials, we get less than k failures, i.e. $P(X < k)$ if $X \sim \text{Bin}(T - k, \epsilon)$ is a binomial distributed random variable with probability of success ϵ . We will seek to upper bound $P(X < k)$ (i.e. $1 - F(T - k, 1 - \epsilon, k)$) in order to obtain a lower bound on $F(T - k, 1 - \epsilon, k)$. We know X is concentrated around its mean $\mathbb{E}[X] = (T - k)\epsilon$, so we will consider k smaller than the mean, i.e. $k < (T - k)\epsilon$, which implies $k < T\epsilon/(1 + \epsilon)$, to show that when it is small enough, $F(T - k, 1 - \epsilon, k)$ becomes close to 1, making the expected number of mistakes of the predictor $\Omega(T)$.

Using Chernoff's bound, we know that $P(X < (1 - \delta)\mu) \leq \exp(-\delta^2\mu/2)$, for μ the mean of X (i.e. $\mu = (T - k)\epsilon$ here). Suppose $k = \beta T\epsilon$ for some $\beta \in [0, 1/(1 + \epsilon)]$, then we have $(T - k)\epsilon = T(1 - \beta\epsilon)\epsilon$ and $k = (1 - \delta)\mu$ for $\delta = 1 - \beta/(1 - \beta\epsilon)$. Hence we obtain that $P(X < k) \leq \exp(-(1 - \beta\epsilon - \beta)^2 T\epsilon/(2(1 - \beta\epsilon)))$. This implies that $1 - F(T - k, 1 - \epsilon, k)$ is exponentially small in T , and thus that $F(T - k, 1 - \epsilon, k)$ is arbitrarily close to 1 as $T \rightarrow \infty$, when $k \leq \beta T\epsilon$. In particular this is the case when $k = T\epsilon/2$. Yet we can see that at $k = T\epsilon/2$, $TF(T - k; 1 - \epsilon, k) - (1 - \epsilon)k/\epsilon$ would tend to $T/2 + T\epsilon/2$ as $T \rightarrow \infty$, i.e the expected number of mistakes of the predictor is $\Omega(T)$ after only $T\epsilon/2$ iterations. On the other hand, with the lower bound $TF(T - k; 1 - \epsilon, k) - (1 - \epsilon)k/\epsilon$, we observe that at $k = T\epsilon$, this lower bound would be $O(T\epsilon)$. Thus it is possible that $T\epsilon$ iterations is

sufficient. We conclude that we need k at least in $\Omega(T\epsilon)$, to make the expected number of mistakes order $O(T\epsilon)$. \square

Lemma 10.4.2. *Given access to an ϵ -regret learning oracle, there exist MDPs and policy classes where any learning algorithm with interaction complexity of k obtains a policy whose expected total regret is at least:*

$$\max_{\epsilon' \in [0,1]} \sum_{i=1}^{k-1} i \binom{T}{i} \epsilon'^i (1 - \epsilon')^{T-i} + \sum_{t=k}^T \binom{t-1}{k-1} \epsilon'^k (1 - \epsilon')^{t-k} (T - t + k) - T\epsilon'$$

Proof. We use a similar argument to lemma 10.4.1. Consider the hard tree MDP presented previously. Additionally, consider a policy class where in all states that minimum possible error is $\epsilon' > 0$, and there exist a predictor achieving ϵ' error in all states. On the first query to the learning oracle, we can make the learning oracle return the following predictor: for the T states s_1, s_2, \dots, s_T , along the expert trajectory, the learned predictor makes a mistake with probability ϵ' in each s_i . Because in each of these states there are at least $\frac{1}{\alpha\epsilon}$ actions that can be taken, all leading to different regions of the state space, there must exist a set of actions a_1, a_2, \dots, a_T , where a_i denotes an action taken in s_i , where the sum of the probability mass over all the states in the subtrees of a_1, a_2, \dots, a_T is at most $\alpha\epsilon$. Thus for all these subtrees, we can assign a probability 1 of mistake in every state. Additionally, when the predictor makes a mistake in state s_i , we can make it always choose action a_i . We obtain that under any training distribution, for the first query to the learning oracle, we can return such predictor that has regret $\leq \alpha\epsilon \leq \epsilon$ under the training distribution. Now for all remaining iterations, we can always return a predictor that is exactly the same in states s_1, s_2, \dots, s_T , but potentially changes in the subtrees of a_1, a_2, \dots, a_T . At the second iteration we can apply the same reasoning over each of the subtrees of a_1, a_2, \dots, a_T , and construct a predictor that has the same error structure as the first learned predictor, but within each of the subtree. That is for the second iteration, consider the error of the learned predictor to be ϵ' in every state along the expert trajectory after each of the erroneous actions a_1, a_2, \dots, a_T . Since we keep the learned predictor to be the same along the expert trajectory, then this second learned predictor has error ϵ' in every states where the predictor has made 0 or 1 mistake so far. But again we can find a set of actions that represent the mistakes this second predictor can makes in states reached after 1 mistake has been done, whose sum of probability mass in all their subtrees would be at most $\alpha\epsilon$, such that we can still assign error 1 in every state in those subtrees. Note that because these subtrees are themselves subtrees of a_1, a_2, \dots, a_T , all these states must also had error 1 in the first iteration. This implies that for any combination of the first 2 predictors, we can only obtain a predictor which has probability of mistakes ϵ' , as long as it has made 0 or 1 mistake so

far, but then after 2 mistakes, must make a mistake with probability 1 in every future state. It is also clear that this second learned predictor satisfies the constraint that it has regret $\leq \epsilon$ under any training distribution (there is probability mass ≤ 1 on states with regret 0 and probability mass $\leq \alpha\epsilon$ on states with regret $(1 - \epsilon')$). The end result is that after 2 iterations, we can always obtain a predictor that errors with probability 1, after 2 mistakes has been done, or errors with probability ϵ' otherwise. The same reasoning can be applied recursively, to see that after k iterations, we can always obtain a predictor that errors with probability 1 after k mistakes, or errors with probability ϵ' otherwise. Then if we have such a predictor, it can be seen that its expected number of mistakes over T steps is:

$$\sum_{i=1}^{k-1} i \binom{T}{i} \epsilon'^i (1 - \epsilon')^{T-i} + \sum_{t=k}^T \binom{t-1}{k-1} \epsilon'^k (1 - \epsilon')^{t-k} (T - t + k)$$

The first summation can be seen as summing over all the paths with i mistakes, for $i \leq k-1$, while the second summation sums over all the paths with k or more mistakes, conditioning on the time t where the k^{th} mistake occur (there are $\binom{t-1}{k-1}$ paths whose k^{th} mistake occur on the t^{th} step). Now under the test sequences of this learned predictor, there exists a predictor in the class with only $T\epsilon'$ expected mistakes, thus the regret of the learned predictor is at least:

$$\sum_{i=1}^{k-1} i \binom{T}{i} \epsilon'^i (1 - \epsilon')^{T-i} + \sum_{t=k}^T \binom{t-1}{k-1} \epsilon'^k (1 - \epsilon')^{t-k} (T - t + k) - T\epsilon'$$

The lemma follows from the fact that we can pick any $\epsilon' \in [0, 1]$ to make this quantity as large as possible. \square

Theorem 10.4.2. *Given access to an ϵ -regret learning oracle, there exist MDPs and policy classes where any learning algorithm must have interaction complexity of $\Omega(T)$ to obtain a policy with an expected total regret of $O(T\epsilon)$ over sequences of T steps.*

Proof. Using the result in the previous lemma, and the same argument as in Theorem 10.4.1 to lower bound the term $\sum_{t=k}^T \binom{t-1}{k-1} \epsilon'^k (1 - \epsilon')^{t-k} (T - t + k)$, we can see that the expected total regret of the learned predictor after k queries is at least:

$$TF(T - k; 1 - \epsilon', k) - \mathbb{E}[r] - T\epsilon',$$

for $F(T - k; 1 - \epsilon', k)$ the cumulative density function of a negative binomial, with probability of success $1 - \epsilon'$, and stopping after k failures, and $\mathbb{E}[r] = (1 - \epsilon')k/\epsilon'$ the expectation of this negative binomial distribution. Again, following a similar argument as in Theorem 10.4.1, we can show that for $k = T\epsilon'/2$, $TF(T - k; 1 - \epsilon', k) - (1 - \epsilon')k/\epsilon'$

would tend to $T/2 + T\epsilon'/2$ as $T \rightarrow \infty$. This implies that after $k = T\epsilon'/2$, the expected regret of the algorithm is at least $T/2 - T\epsilon'/2$. As we can choose any $\epsilon' \in [0, 1]$, we can see that for $\epsilon' = \frac{1}{2}$, this indicates that there exist problems where after $k = T/4$ iterations, the expected total regret is still at least $T/4$. Thus we conclude that at least $\Omega(T)$ iterations must be necessary, to make the expected total regret $O(T\epsilon)$. \square

This lower bound of $\Omega(T)$ queries match directly our upper bound of T (with the Forward algorithm) on the required interaction complexity of any algorithm guaranteeing a policy with $O(T\epsilon)$ regret over T steps. Hence this shows our lower bound is tight, that any algorithm must need a number of iterations of the same order as the number of time steps T , and that Forward achieves the lower bound within a constant factor.

On the other hand, when an ϵ -error learning oracle is available, we obtained a lower bound of $\Omega(T\epsilon)$ queries. In this case, this does not match directly our upper bound of T (with the Forward algorithm) on the interaction complexity of any algorithm guaranteeing a policy with $O(T\epsilon)$ mistakes over T steps. Hence it potentially suggests that when low error is possible (rather than just low regret), better algorithms than the Forward Training procedure might exist that would require only a fraction ϵ of the number of queries currently performed by the Forward algorithm. Despite this fact, it shows that in general the number of iterations, or queries to the learning oracle, must inevitably scale linearly with the number of time steps T .

Chapter 11

Conclusion

We now conclude by discussing the contributions of this thesis with regards to our original thesis statement:

Learning actively through interaction is necessary to obtain good and robust predictors for sequential prediction tasks. No-regret online learning methods provide a useful class of algorithms to learn efficiently from these interactions, and provide good performance both theoretically and empirically.

Passive Supervised Learning and the Data Mismatch

Many of the sequential prediction settings we presented in this thesis look like typical statistical supervised learning problems, where a dataset of labeled examples can be obtained. However, we provided a detailed theoretical analysis of such naive supervised learning techniques in various sequential prediction settings and demonstrated their poor performance guarantees due to the mismatch between the training and test distribution of examples that can occur. In addition, in the context of imitation learning and system identification, we presented examples of simple MDPs where such methods fail and match the poor guarantee.

The train-test mismatch is often induced by errors made by the learned predictors. As these errors can lead to new untrained situations, a single error can propagate into a large series of errors. As such, the learned predictors, obtained by naive supervised learning, are non-robust to their own errors.

Leveraging Interaction to Learn Robust Predictors

We presented several learning techniques that interact with the sequential process and learner to deal with this train-test mismatch: 1) Forward, which learns sequentially a

different predictor for each step; 2) SMILE, which learns a stationary stochastic policy iteratively through small changes; and 3) DAGGER and SCP, that can learn stationary deterministic policies, via no-regret online learning methods. We analyzed thoroughly these techniques and demonstrated their improved guarantees in various sequential prediction settings: imitation learning, reinforcement learning, structured prediction, list optimization and system identification.

Through interaction, these methods are able to collect new examples of correct predictions after the learned predictor makes errors, allowing the learner to learn more robust behaviors that can “recover” from its typical errors.

Necessity of Interaction

In chapter 10, we showed that interaction is necessary to learn good and robust predictors for sequential tasks. In particular, there exists no learning approach that can provide good guarantees without interaction. We proved lower bounds on the minimum number of rounds of interactions necessary to provide good guarantees, that scale linearly with the length of the sequence. In addition, in the context of guaranteeing small regret (excess error) on the test trajectories, the lower bound is tight and matches the number of rounds used by the Forward algorithm presented in chapter 3.

Practicality and Efficiency of the Interactive Online Learning Approach

Our main learning approach, DAGGER, offers many practical advantages over other methods in practice:

1. **Simple:** It is very simple, easy to implement and apply to various tasks.
2. **Modular:** It can be used in combination with any of your favorite online learning methods, and/or class of predictors, and can easily be wrapped around existing off-the-shelf software packages.
3. **Scalable:** By relying on no-regret learning methods that scale well to large learning problems, DAGGER scales naturally to large-scale problems, e.g. using computationally efficient gradient descent methods.
4. **Statistically Efficient:** The improved guarantees of DAGGER reduce the impact of the generalization error on performance, allowing DAGGER to learn a good predictor with fewer data. Additionally, by learning a single stationary policy, it can generalize the behavior across time steps and learn more efficiently than methods training a separate predictor for each step.

Applications and Empirical Evidence

We demonstrated the scalability and efficiency of DAGGER in practice on a large variety of applications in several sequential prediction settings:

1. Improved performance over naive supervised training and other sequential prediction methods, such as SMILE and SEARN, in the context of learning video game playing agents.
2. Matched the performance of state-of-the-art Structured Prediction methods on three computer vision tasks: handwriting recognition, 3D Point Cloud classification and 3D geometry estimation.
3. Improved performance and learning efficiency over state-of-the-art list optimization methods on various recommendation tasks, such as grasp selection, trajectory optimization, news recommendation and document summarization.
4. Improved performance and learning efficiency for system identification over standard system identification methods and common iterative identification approaches, in the context of learning models of a simulated helicopter for performing aerobatic maneuvers.
5. Additionally, we demonstrated that DAGGER can be applied successfully on real robotic systems, training a quadrotor to fly autonomously through natural forest environments while avoiding trees.

11.1 Open Problems and Future Directions

Throughout this work, we have come across a number of interesting open problems and future directions for research. We briefly conclude with important areas of future research.

More Practical Interactions with Human Experts

In the context of imitation learning, DAGGER, when learning from a human expert, leads to challenging human-computer interaction issues. In particular, a major difficulty for the human expert is to provide the correct actions when not in control of the system (without feedback of the actions he is executing). This was discussed in detail in Section 5.3, where we also discussed some practical solutions. Ideally, however, a more natural interactive procedure for collecting additional examples from the human expert would be desired. For instance, a natural one may be to let the system execute its own controller, and only when the expert deems unsatisfactory behavior is being performed, he takes

over control of the system until the system is placed back on a correct course, after which control is returned to the system. By only having to provide actions when the expert is in control, this would allow the expert to provide more accurate actions. However such interactions can lead to other issues. For instance, there would be a delay between the time when a serious error was committed by the system, versus the time when the expert takes over, therefore not allowing the system to observe the correct actions it should have executed in the first place to prevent the expert from having to take over. We additionally do not know how such interaction could be analyzed theoretically to provide good guarantees.

Iterative Transfer Learning

An alternate solution to the above human-computer interaction issue is to avoid asking new actions from the human expert entirely, after the first iteration (where the expert is always fully in command). In other words, only collect labeled examples under the state distribution of the expert d_{π^*} , and at later iterations, DAGGER executes the current learned policy, but only to collect new unlabeled examples, where the expert's action is unknown. To update the predictor, based on the unlabeled data, transfer learning methods, such as [Zadrozny \(2004\)](#), [Huang et al. \(2007\)](#), could in principle be used to reweigh the labeled examples in the expert dataset, so that we obtain a weighted labeled dataset that matches more closely the distribution of examples DAGGER needs to train on at iteration n , i.e. $\frac{1}{n} \sum_{i=1}^n d_{\pi_i}$. However, for this to work, the expert dataset would need to cover the input feature space very well, which is usually not the case, when the expert is executing on its own (e.g. no examples of what to do when the car is about to go off the road, or collide with other vehicles). Reweighting would not help if coverage is poor in the regions where unlabeled data is collected. Coverage of the initial demonstrations could be increased by introducing random noise in the actions of the expert during its execution; however, this may still explore poorly, as the important failure cases that will occur at later iterations of learning may be explored with exponentially small probability. In preliminary experiments with the technique of [Zadrozny \(2004\)](#) in the Super Mario Bros. domain of Section 5.2, we did not obtain much improvement over the baseline supervised learning approach. This could be due to several factors, such as the particular transfer learning technique used, and perhaps in other applications, such technique could be used successfully.

Extensions to Other List Optimization Objectives

In Chapter 7, we studied SCP for the particular context of maximizing a submodular objective under a cardinality constraint on the list. Many other important applications have different but related objectives. For instance in the Grasp Selection experiment

we were interested in minimizing search depth, which corresponds to a different “min sum set cover” objective. In extractive document summarization, where the constraint is on the length of the summary (in characters), this implies that items have different weight (sentences have different length), and we are subject to a more general knapsack constraint on the sum of the weights of the items in the list. These variations affect the particular weighting of the examples that should be used to properly minimize the desired objective. For instance, to minimize search depth, the analysis in [Streeter and Golovin \(2007\)](#), suggests weighting examples from early positions in the list more highly. A more careful analysis of SCP with these variations would be necessary to ensure proper weighting of the training examples is used and understanding the resulting guarantees of SCP in these variants. An analysis for the knapsack constraint variant appears in the recent follow-up work of [Zhou et al. \(2013\)](#).

List Optimization for Structured Prediction

In structured prediction tasks, it can also be desired to obtain multiple possible structured outputs. For instance, given an input camera image, we may be interested in obtaining a diverse and relevant set of possible labelings of this image. This may be important for robots, so that they can carefully take into account possible alternate interpretations of the world, and adopt a behavior that is robust to these various interpretations. Some recent work has begun to look into this problem ([Kulesza and Taskar, 2010](#), [Guzman-Rivera et al., 2012](#)). It would be interesting to extend SCP to this scenario.

Agnostic Exploration

In the context of model-free reinforcement learning (Section 4.3), and system identification (Chapter 8), our DAGGER approach provides agnostic guarantees, but performance is limited by the quality of the given fixed exploration distribution. For realizable system identification settings, we showed that an optimistic exploration strategy could be used to guarantee finding a near-optimal policy. However, this strategy relies on the realizability assumption, and developing adaptive exploration strategies that would lead to good guarantees in general agnostic settings is an important open problem. Work on similar exploration issues in contextual bandit learning ([Auer et al., 2002b](#), [Beygelzimer et al., 2011](#)) and agnostic active learning ([Dasgupta et al., 2007](#), [Beygelzimer et al., 2010](#)) may provide ideas that could be extended to these reinforcement learning settings.

Subspace Identification

For system identification in partially observable settings, our current DAGGER approach can be applied as is to learn models that predict the future observation from past actions and observations, and provide similar good agnostic guarantees. However, learning more compact representations, that can learn an underlying hidden state space model, would be desirable, especially in situations where observations are high dimensional. This could allow learning more efficiently. Spectral learning methods have been developed to learn such models, however their analysis often relies on strong realizability assumptions (Overschee and Moor, 1996, Boots and Gordon, 2011). A no-regret analysis of such methods in online settings would be necessary to ensure that they can be used within DAGGER and provide similar good guarantees. For instance, developing approaches for doing no-regret online reduced rank regression would provide techniques for achieving this in the context of learning linear state space models.

Online Regret Reductions

In many settings, we reduced our sequential prediction task to a no-regret online cost-sensitive classification tasks (e.g. in Chapters 4 and 7). Typical regret reductions for cost-sensitive classification, bound the cost-sensitive classification regret to the bayes-optimal predictor, as a function of the regret to the bayes-optimal predictor on a new classification or regression task (Langford and Beygelzimer, 2005, Beygelzimer et al., 2009, Mineiro, 2010). This does not allow us to bound the online cost-sensitive classification regret (with respect to only hypothesis in the class), in terms of the online classification or regression regret (with respect to only hypothesis in the class), without introducing an additional penalty term: a term that depends on the classification or regression regret of the best hypothesis in the class to the bayes-optimal predictor. It would be of interest to provide reductions, that transform online regret at the cost-sensitive classification task, directly into online regret at the other task, without introducing this additional penalty term. This would provide improved relative performance guarantees for DAGGER when comparing to other predictors in the class.

This is perhaps a more general fundamental question worth further investigation, e.g. can you reduce no-regret learning for various common learning tasks, to a no-regret online binary classification task, where being no-regret on the binary classification loss implies no-regret on the original online task. In other words, can you build no-regret learners for various tasks, starting from a single common primitive, e.g. a no-regret learner for binary classification.

Efficient Contextual Bandit Learning with General Hypothesis Class

In Chapters 4 and 7, we also observed that we may sometimes only be able to obtain partial cost-sensitive examples, where the cost of only one or a few predictions are known. To deal with such partial feedback, contextual bandit algorithms are necessary, rather than online learning methods. However, current contextual bandit learning methods have been limited mostly to finite hypothesis class (Auer et al., 2002b), or for learning linear predictors in realizable settings (Li et al., 2010). Some more involved techniques have been developed for dealing with more general infinite class of predictors (Dudik et al., 2011a), but the resulting algorithm remains impractical¹ and currently only handles the stochastic setting, whereas we require no-regret in adversarial settings. DAGGER could benefit from improved contextual bandit algorithms for dealing with partial feedback settings.

Are Weaker Notions than No-Regret Sufficient?

DAGGER relies on the availability of a no-regret online learner and our analysis demonstrates that no-regret is a sufficient property of the learner to provide good guarantees. In Chapter 9 (and (Ross and Bagnell, 2012b)), we also showed how certain strong stability properties of the learner, in combination with asymptotic minimization of the loss in hindsight, are also sufficient properties to achieve no-regret. As these strong no-regret (or stability) property cannot always be achieved (at least computationally efficiently) with all class of hypothesis, weakening these strong requirements is of practical importance to increase the applicability of our methods to broader and richer class of predictors. Perhaps weaker stability conditions, such as those in Shalev-Shwartz et al. (2010), with certain assumptions on the sequential process, may be sufficient for DAGGER to provide good guarantees in these sequential prediction settings.

¹At each update, the algorithm involves running an ellipsoid algorithm, in a space that grows with the number of data points seen so far, that repeatedly calls a cost-sensitive classification learner for the separation oracle. The complexity of the update after seeing t data points is of order $O(t^7)$, and thus quickly becomes intractable as we collect more data.

Appendices

Appendix A

Analysis of Dagger for Imitation Learning

In this appendix, we provide the proofs and detailed analysis of Dagger in the imitation learning setting. We begin with the analysis where surrogate classification/regression loss is minimized, and then present results for Dagger with cost-to-go.

A.1 Dagger with Imitation Loss

We begin with a useful general lemma that is needed for bounding the expected loss under different distributions. This will be used several times here and for the analysis of Dagger in other settings. Here this will be useful for bounding the expected loss under the state distribution of $\hat{\pi}$ in terms of the expected loss under the state distribution of π_i :

Lemma A.1.1. *Let P and Q be any distribution over elements $x \in \mathcal{X}$, and $f : \mathcal{X} \rightarrow \mathbb{R}$, any bounded function such that $f(x) \in [a, b]$ for all $x \in \mathcal{X}$. Let the range $r = b - a$. Then $|\mathbb{E}_{x \sim P}[f(x)] - \mathbb{E}_{x \sim Q}[f(x)]| \leq \frac{r}{2} \|P - Q\|_1$*

Proof. We provide the proof for \mathcal{X} discrete, a similar argument can be carried for \mathcal{X} continuous, using integrals instead of sums.

$$\begin{aligned} & |\mathbb{E}_{x \sim P}[f(x)] - \mathbb{E}_{x \sim Q}[f(x)]| \\ &= |\sum_x P(x)f(x) - Q(x)f(x)| \\ &= |\sum_x f(x)(P(x) - Q(x))| \end{aligned}$$

Additionally, since for any real $c \in \mathbb{R}$, $\sum_x P(x)c = \sum_x Q(x)c$, then we have for any c :

$$\begin{aligned}
& |\sum_x f(x)(P(x) - Q(x))| \\
&= |\sum_x (f(x) - c)(P(x) - Q(x))| \\
&\leq \sum_x |f(x) - c| |P(x) - Q(x)| \\
&\leq \max_x |f(x) - c| \sum_x |P(x) - Q(x)| \\
&= \max_x |f(x) - c| \|P - Q\|_1
\end{aligned}$$

This holds for all $c \in \mathbb{R}$. This upper bound is minimized for $c = a + \frac{r}{2}$, making $\max_x |f(x) - c| \leq \frac{r}{2}$. This proves the lemma. \square

The L_1 distance between the distribution of states encountered by $\hat{\pi}_i$, the policy chosen by Dagger, and π_i , the policy used to collect data that continues to execute the expert's actions with probability β_i is bounded as follows:

Lemma A.1.2. $\|d_{\pi_i} - d_{\hat{\pi}_i}\|_1 \leq 2 \min(1, T\beta_i)$.

Proof. Let d the distribution of states over T steps conditioned on π_i picking the expert π^* at least once over T steps. Since π_i always executes $\hat{\pi}_i$ (never executes the expert action) over T steps with probability $(1-\beta_i)^T$ we have $d_{\pi_i} = (1-\beta_i)^T d_{\hat{\pi}_i} + (1-(1-\beta_i)^T)d$. Thus

$$\begin{aligned}
& \|d_{\pi_i} - d_{\hat{\pi}_i}\|_1 \\
&= (1 - (1 - \beta_i)^T) \|d - d_{\hat{\pi}_i}\|_1 \\
&\leq 2(1 - (1 - \beta_i)^T) \\
&\leq 2T\beta_i
\end{aligned}$$

The last inequality follows from the fact that $(1-\beta)^T \geq 1-\beta T$ for any $\beta \in [0, 1]$. Finally, since for any 2 distributions p, q , we always have $\|p - q\|_1 \leq 2$, then $\|d_{\pi_i} - d_{\hat{\pi}_i}\|_1 \leq 2 \min(1, T\beta_i)$. \square

Assume β_i is non-increasing and define n_β the largest $n \leq N$ such that $\beta_n > \frac{1}{T}$. As mentioned in the Section 3.6, Dagger can be seen as using an online learning algorithm on a sequence of loss functions $\{\ell_i\}_{i=1}^N$ chosen such that for any $\pi \in \Pi$, $\ell_i(\pi) = \mathbb{E}_{s \sim d_{\pi_i}, a \sim \pi^*(s)}[\ell(s, a, \pi)]$. Let $\epsilon_{\text{class}} = \min_{\pi \in \Pi} \frac{1}{N} \sum_{i=1}^N \ell_i(\pi)$ the loss of the best policy in hindsight after N iterations and assume ℓ is non-negative and bounded by ℓ_{\max} , i.e. $0 \leq \ell(s, a, \hat{\pi}_i) \leq \ell_{\max}$ for all policies $\hat{\pi}_i$, action a and state s such that $d_{\hat{\pi}_i}(s) > 0$. Additionally, let $\epsilon_{\text{regret}} = \frac{1}{N} \sum_{i=1}^N \ell_i(\hat{\pi}_i) - \epsilon_{\text{class}}$, the average online learning regret of the sequence of policies $\hat{\pi}_1, \hat{\pi}_2, \dots, \hat{\pi}_N$ chosen by Dagger after N iterations.

Denote the expected loss of a policy π at mimicking the expert under its own distribution of states $L(\pi) = \mathbb{E}_{s \sim d_\pi, a \sim \pi^*(s)}[\ell(s, a, \pi)]$. Consider the ‘‘uniform mixture’’ policy $\bar{\pi}$, that at the beginning of any trajectory samples a policy π uniformly randomly among the policies $\{\hat{\pi}_i\}_{i=1}^N$ and executes this policy π for the entire trajectory. We have the following guarantee for $\bar{\pi}$ and the best policy in the sequence:

Theorem A.1.1.

$$\min_{i \in 1:N} L(\hat{\pi}_i) \leq L(\bar{\pi}) \leq \epsilon_{class} + \epsilon_{regret} + \frac{\ell_{\max}}{N} [n_\beta + T \sum_{i=n_\beta+1}^N \beta_i].$$

Proof. Using the last two lemmas, we have that for every policy $\hat{\pi}_i$:

$$\begin{aligned} L(\hat{\pi}_i) &= \mathbb{E}_{s \sim d_{\hat{\pi}_i}, a \sim \pi^*(s)} (\ell(s, a, \hat{\pi}_i)) \\ &\leq \mathbb{E}_{s \sim d_{\pi_i}, a \sim \pi^*(s)} (\ell(s, a, \hat{\pi}_i)) + \frac{\ell_{\max}}{2} \|d_{\pi_i} - d_{\hat{\pi}_i}\|_1 \\ &\leq \mathbb{E}_{s \sim d_{\pi_i}, a \sim \pi^*(s)} (\ell(s, a, \hat{\pi}_i)) + \ell_{\max} \min(1, T\beta_i) \\ &= \ell_i(\hat{\pi}_i) + \ell_{\max} \min(1, T\beta_i) \end{aligned}$$

Thus:

$$\begin{aligned} \min_{i \in 1:N} L(\hat{\pi}_i) &\leq L(\bar{\pi}) \\ &= \frac{1}{N} \sum_{i=1}^N L(\hat{\pi}_i) \\ &\leq \frac{1}{N} \sum_{i=1}^N \ell_i(\hat{\pi}_i) + \frac{\ell_{\max}}{N} \sum_{i=1}^N \min(1, T\beta_i) \\ &= \epsilon_{class} + \epsilon_{regret} + \frac{\ell_{\max}}{N} [n_\beta + T \sum_{i=n_\beta+1}^N \beta_i] \end{aligned}$$

□

This last theorem indicates that the imitation loss of the best policy, and the uniform mixture policy, under their own induced state distribution, must tend to the loss of the best policy in hindsight on the aggregate dataset as $N \rightarrow \infty$, when a no-regret online learning procedure is used.

Denote $\hat{\pi}$ the best policy in the sequence $\hat{\pi}_{1:N}$, i.e. $J(\hat{\pi}) = \min_{i \in 1:N} J(\hat{\pi}_i)$. Then the previous result proves directly the following theorems presented in Section 3.6, when $\beta_i = (1 - \alpha)^{i-1}$:

Theorem 3.6.1. *If the surrogate loss ℓ is the same as the task cost function C (or upper bounds it), then after N iterations of DAgger:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq T[\epsilon_{class} + \epsilon_{regret}] + O\left(\frac{\ell_{\max} T \log T}{\alpha N}\right).$$

Thus if a no-regret online algorithm is used to pick the sequence of policies $\hat{\pi}_{1:N}$, then as the number of iterations $N \rightarrow \infty$:

$$\lim_{N \rightarrow \infty} J(\bar{\pi}) \leq T\epsilon_{class}$$

Proof. First, clearly $J(\hat{\pi}) \leq J(\bar{\pi})$ as the minimum is always lower or equal to the average, i.e. $\min_{i \in 1:N} J(\hat{\pi}_i) \leq \frac{1}{N} \sum_{i=1}^N J(\hat{\pi}_i)$. Now, under the assumption that $\ell \geq C$, then we

have for any policy π , $J(\pi) \leq TL(\pi)$. And since $J(\bar{\pi}) = \frac{1}{N} \sum_{i=1}^N J(\hat{\pi}_i)$, we conclude by using the last theorem that:

$$J(\bar{\pi}) \leq T[\epsilon_{\text{class}} + \epsilon_{\text{regret}}] + \frac{T\ell_{\max}}{N}[n_{\beta} + T \sum_{i=n_{\beta}+1}^N \beta_i]$$

For $\beta_i = (1 - \alpha)^{i-1}$, then we have that for $i \geq 1 + \frac{\log T}{\alpha}$, we have $\beta_i \leq 1/T$. So $n_{\beta} \leq 1 + \frac{\log T}{\alpha}$. Additionally $\sum_{i=n_{\beta}+1}^N \beta_i = \frac{(1-\alpha)^{n_{\beta}+1} - (1-\alpha)^{N+1}}{\alpha} \leq \frac{1}{T\alpha}$. Hence we have that $\frac{1}{N}[n_{\beta} + T \sum_{i=n_{\beta}+1}^N \beta_i] \leq \frac{1}{N\alpha}[\log T + 2]$. Thus we obtain:

$$J(\bar{\pi}) \leq T[\epsilon_{\text{class}} + \epsilon_{\text{regret}}] + \frac{T\ell_{\max}}{\alpha N}[\log(T) + 2]$$

This proves the first part of the theorem. The second part follows immediately from the fact that $\epsilon_{\text{regret}} \rightarrow 0$ as $N \rightarrow \infty$ for no-regret algorithms. \square

Theorem 3.6.2. *If the expert π^* is u -robust with respect to cost function C (as in Definition 3.4.1), then after N iterations of DAgger:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq J(\pi^*) + uT[\epsilon_{\text{class}} + \epsilon_{\text{regret}}] + O\left(\frac{u\ell_{\max}T \log T}{\alpha N}\right).$$

Thus if a no-regret online algorithm is used to pick the sequence of policies $\hat{\pi}_{1:N}$, then as the number of iterations $N \rightarrow \infty$:

$$\lim_{N \rightarrow \infty} J(\bar{\pi}) \leq J(\pi^*) + uT\epsilon_{\text{class}}$$

Proof. Theorem 3.4.3 indicates that $J(\bar{\pi}) \leq J(\pi^*) + uTL(\bar{\pi})$. Hence combining with theorem A.1.1, and a similar argument to bound the extra term as in theorem 3.6.1 proves the first part of the theorem. Similarly the second part follows from the fact that $\epsilon_{\text{regret}} \rightarrow 0$ as $N \rightarrow \infty$ for no-regret algorithms. \square

The following corollaries in Section 3.6 also follows immediately from existing results of no-regret algorithms:

Corollary 3.6.2. *Suppose ℓ is strongly convex in π for all s, a and Dagger uses Follow-the-Leader to pick the sequence of policies, then: If ℓ upper bounds C , then for any $\epsilon > 0$ after $\tilde{O}(T/\epsilon)$ iterations of DAgger:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq T\epsilon_{\text{class}} + O(\epsilon).$$

For arbitrary cost C , if the expert π^* is u -robust with respect to C (as in Definition 3.4.1), then for any $\epsilon > 0$ after $\tilde{O}(uT/\epsilon)$ iterations of DAgger:

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq J(\pi^*) + uT\epsilon_{\text{class}} + O(\epsilon).$$

Proof. For Follow-the-Leader on strongly convex loss functions, after N iterations ϵ_{regret} is $O(\log(N)/N)$. Thus by choosing N to be $O(\frac{T \log(T/\epsilon)}{\epsilon})$, $T\epsilon_{\text{regret}}$ is $O(\epsilon)$. The other extra term $O(\frac{T\ell_{\max}}{\alpha N} [\log(T) + 2])$ is also $O(\epsilon)$ for such N . Similarly for the second part of the theorem, $uT\epsilon_{\text{regret}}$ is $O(\epsilon)$ by choosing N to be $O(\frac{uT \log(uT/\epsilon)}{\epsilon})$, and the extra term as well. \square

Corollary 3.6.3. *Suppose ℓ is convex in π for all s, a and Dagger uses Follow-the-Regularized-Leader to pick the sequence of policies, then: If ℓ upper bounds the cost C , then for any $\epsilon > 0$ after $O(T^2/\epsilon^2)$ iterations of DAgger:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq T\epsilon_{\text{class}} + O(\epsilon).$$

For arbitrary cost C , if the expert π^ is u -robust with respect to C (as in Definition 3.4.1), then for any $\epsilon > 0$ after $O(u^2 T^2/\epsilon^2)$ iterations of DAgger:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq J(\pi^*) + uT\epsilon_{\text{class}} + O(\epsilon).$$

Proof. For Follow-the-Regularized-Leader on convex loss functions, after N iterations ϵ_{regret} is $O(1/\sqrt{N})$. Thus by choosing N to be $O(T^2/\epsilon^2)$, $T\epsilon_{\text{regret}}$ is $O(\epsilon)$. The other extra term $O(\frac{T\ell_{\max}}{\alpha N} [\log(T) + 2])$ is also $O(\epsilon)$ for such N . Similarly for the second part of the theorem, $uT\epsilon_{\text{regret}}$ is $O(\epsilon)$ by choosing N to be $O(u^2 T^2/\epsilon^2)$, and the extra term as well. \square

In addition, when the distribution of state-action pairs of the policies in the sequence converge, the performance of π_N must be close to the performance of $\bar{\pi}$:

Theorem 3.6.3. *If there exists a state-action distribution D^* , scalar $\epsilon_{\text{conv}}^* \geq 0$ and a sequence $\{\epsilon_{\text{conv},i}\}_{i=1}^{\infty}$ that is $o(1)$, such that $\|D_{\hat{\pi}_i} - D^*\|_1 \leq \epsilon_{\text{conv}}^* + \epsilon_{\text{conv},i}$ for all i . Then for any cost function bounded in $[0, C_{\max}]$:*

$$\limsup_{N \rightarrow \infty} J(\pi_N) - J(\bar{\pi}) \leq C_{\max} T \epsilon_{\text{conv}}^*$$

Proof. Using the first lemma, for all i we have that:

$$T\mathbb{E}_{(s,a) \sim D^*}[C(s,a)] - \frac{TC_{\max}}{2}(\epsilon_{\text{conv}}^* + \epsilon_{\text{conv},i}) \leq J(\hat{\pi}_i) \leq T\mathbb{E}_{(s,a) \sim D^*}[C(s,a)] + \frac{TC_{\max}}{2}(\epsilon_{\text{conv}}^* + \epsilon_{\text{conv},i})$$

Thus:

$$\begin{aligned} & J(\hat{\pi}_N) - J(\bar{\pi}) \\ &= J(\hat{\pi}_N) - \frac{1}{N} \sum_{i=1}^N J(\hat{\pi}_i) \\ &\leq \frac{TC_{\max}}{2}(2\epsilon_{\text{conv}}^* + \epsilon_{\text{conv},N} + \frac{1}{N} \sum_{i=1}^N \epsilon_{\text{conv},i}) \end{aligned}$$

Taking the limit as $N \rightarrow \infty$ proves the result, since the sequence $\{\epsilon_{\text{conv},i}\}_{i=1}^{\infty}$ is $o(1)$. \square

Finite Sample Analysis

We now move on to prove the results presented when the online learning algorithm within Dagger is applied with a finite set of m samples at each iteration, rather than on the true expected loss ℓ_i , as assumed previously. The analysis we provide applies to two ways to collect data:

- We sample m trajectories with the current policy π_i , and obtain the expert's actions in all visited states. This gives us mT state-action pairs (s_{ijt}, a_{ijt}^*) , for s_{ijt} and a_{ijt}^* the state and action observed at time t during the j^{th} trajectory collected at iteration i . From these mT state-action pairs, we can construct m i.i.d. and unbiased estimate of the expected loss $\ell_i(\hat{\pi}_i)$, i.e. the j^{th} estimate is $\hat{\ell}_{ij}(\hat{\pi}_i) = \frac{1}{T} \sum_{t=1}^T \ell(s_{ijt}, a_{ijt}^*, \hat{\pi}_i)$. Each of these is i.i.d. as each trajectory is independent, and restarted from an i.i.d. initial state, from which the same policy is executed every time. The expected loss ℓ_i is then estimated as the average of these m estimates $\hat{\ell}_i(\hat{\pi}_i) = \frac{1}{m} \sum_{j=1}^m \hat{\ell}_{ij}(\hat{\pi}_i)$. Note that the estimate $\hat{\ell}_i$ of the loss function would still be represented by mT data points (s_{ijt}, a_{ijt}^*) in the aggregate dataset, or in the new mini-batch of data given to the online learning algorithm at iteration i . This is purely a mathematical construct for analysis, that allows us to treat mT state samples that are non-i.i.d. (due to the dependency between consecutive states collected in the same trajectory) as equivalent to m i.i.d samples.
- We sample m i.i.d. input state from d_{π_i} , and these m states are the only ones where the expert provides his action. This gives us a set of m state-action pairs (s_{ij}, a_{ij}^*) at each iteration i . To sample m i.i.d. states from d_{π_i} , we would still need to sample m trajectories by executing π_i , and then for each trajectory, sample one state at a uniformly random time step t . Unlike the previous sampling approach, this does not need to query the expert at all mT visited states, and would only need to query at a subset of m visited states¹. This again gives us m i.i.d. and unbiased estimate of the expected loss $\ell_i(\hat{\pi}_i)$, i.e. the j^{th} estimate is $\hat{\ell}_{ij}(\hat{\pi}_i) = \ell(s_{ij}, a_{ij}^*, \hat{\pi}_i)$. Again, the expected loss ℓ_i is then estimated as the average of these m estimates $\hat{\ell}_i(\hat{\pi}_i) = \frac{1}{m} \sum_{j=1}^m \hat{\ell}_{ij}(\hat{\pi}_i)$. The estimate $\hat{\ell}_i$ of the loss function would simply be represented by the m data points (s_{ij}, a_{ij}^*) in the aggregate dataset, or in the new mini-batch of data given to the online algorithm at iteration i .

When applied to these empirical loss estimate $\hat{\ell}_i$, a no-regret online learner guarantees that the empirical average online regret, $\hat{\epsilon}_{\text{regret}} = \frac{1}{N} \sum_{i=1}^N \hat{\ell}_i(\hat{\pi}_i) - \min_{\pi \in \Pi} \frac{1}{N} \sum_{i=1}^N \hat{\ell}_i(\pi)$, goes to 0 as $N \rightarrow \infty$. Denote the training loss of the best policy on the aggregate

¹Assuming $\beta_i = 0$. When $\beta_i > 0$, we would also need to query the expert in states where his action is chosen to be executed during execution of π_i .

dataset $\hat{\epsilon}_{\text{class}} = \min_{\pi \in \Pi} \frac{1}{N} \sum_{i=1}^N \hat{\ell}_i(\pi)$. Following a similar analysis as in online-to-batch techniques (Cesa-Bianchi et al., 2004), we obtain:

Theorem A.1.2. *After N iterations and collecting m trajectories (or m i.i.d. samples) per iteration, we have that for any $\delta > 0$, with probability at least $1 - \delta$:*

$$\min_{i \in 1:N} L(\hat{\pi}_i) \leq L(\bar{\pi}) \leq \hat{\epsilon}_{\text{class}} + \hat{\epsilon}_{\text{regret}} + \frac{\ell_{\max}}{N} [n_\beta + T \sum_{i=n_\beta+1}^N \beta_i] + \ell_{\max} \sqrt{\frac{2 \log(1/\delta)}{mN}}$$

Proof. Let $Y_{i,j} = \ell_i(\hat{\pi}_i) - \hat{\ell}_{ij}(\hat{\pi}_i)$, i.e. the difference between the expected per step loss of $\hat{\pi}_i$ under state distribution d_{π_i} and the estimate of the loss $\hat{\ell}_{ij}$ based on the j^{th} sample with π_i at iteration i . The random variables $Y_{i,j}$ over all $i \in \{1, 2, \dots, N\}$ and $j \in \{1, 2, \dots, m\}$ are all zero mean, and bounded in $[-\ell_{\max}, \ell_{\max}]$. Consider the random variables $X_{km+l} = \sum_{i=1}^k \sum_{j=1}^m Y_{i,j} + \sum_{j=1}^l Y_{k+1,j}$, for $k \in \{0, 1, \dots, N-1\}$ and $l \in \{1, 2, \dots, m\}$. The sequence X_1, X_2, \dots, X_{Nm} form a martingale, where $|X_i - X_{i+1}| \leq \ell_{\max}$. By Azuma-Hoeffding's inequality $\frac{1}{mN} X_{mN} \leq \ell_{\max} \sqrt{\frac{2 \log(1/\delta)}{mN}}$ with probability at least $1 - \delta$. Hence, we obtain that with probability at least $1 - \delta$:

$$\begin{aligned} & \min_{i \in 1:N} L(\hat{\pi}_i) \\ & \leq L(\bar{\pi}) \\ & = \frac{1}{N} \sum_{i=1}^N L(\hat{\pi}_i) \\ & \leq \frac{1}{N} \sum_{i=1}^N \ell_i(\hat{\pi}_i) + \frac{\ell_{\max}}{N} [n_\beta + T \sum_{i=n_\beta+1}^N \beta_i] \\ & = \frac{1}{N} \sum_{i=1}^N \hat{\ell}_i(\hat{\pi}_i) + \frac{1}{mN} X_{mN} + \frac{\ell_{\max}}{N} [n_\beta + T \sum_{i=n_\beta+1}^N \beta_i] \\ & \leq \frac{1}{N} \sum_{i=1}^N \hat{\ell}_i(\hat{\pi}_i) + \ell_{\max} \sqrt{\frac{2 \log(1/\delta)}{mN}} + \frac{\ell_{\max}}{N} [n_\beta + T \sum_{i=n_\beta+1}^N \beta_i] \\ & = \hat{\epsilon}_{\text{class}} + \hat{\epsilon}_{\text{regret}} + \ell_{\max} \sqrt{\frac{2 \log(1/\delta)}{mN}} + \frac{\ell_{\max}}{N} [n_\beta + T \sum_{i=n_\beta+1}^N \beta_i] \end{aligned}$$

where the second inequality follows from the same argument as in theorem A.1.1. \square

The use of Azuma-Hoeffding's inequality in the previous theorem suggests we need a total number of sample Nm in $O(T^2 \log(1/\delta))$ for the generalization error to be $O(1/T)$ and negligible over T steps. Leveraging the strong convexity of ℓ as in Kakade and Tewari (2009) may lead to a tighter bound requiring only $O(T \log(T/\delta))$ trajectories.

This results provide a bound on the expected loss of $\bar{\pi}$, and the best policy found in the sequence, under their own induced distribution of states, as a function of the training loss on the aggregate dataset of the best policy in Π and the empirical average online regret of the learner. This is similar to the previous theorem A.1.1, where here an additional generalization error term $\ell_{\max} \sqrt{\frac{2 \log(1/\delta)}{mN}}$ is present to account for learning from a finite set of samples, rather than the exact expected loss. As before, we can directly use this bound on the expected loss to bound the expected total cost (performance at the task) of the learned policy.

The following finite sample results presented in Section 3.6 follows immediately from this previous theorem:

Theorem 3.6.4. *If the surrogate loss ℓ is the same as the task cost function C (or upper bounds it), then after N iterations of DAgger collecting m trajectories (or m i.i.d. samples) per iteration, with probability at least $1 - \delta$:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq T[\hat{\epsilon}_{\text{class}} + \hat{\epsilon}_{\text{regret}}] + O\left(\frac{\ell_{\max} T \log T}{\alpha N} + \ell_{\max} T \sqrt{\frac{\log(1/\delta)}{mN}}\right).$$

Proof. Follows from the same argument as in the proof of theorem 3.6.1, except using theorem A.1.2 instead of theorem A.1.1. \square

Theorem 3.6.5. *If the expert π^* is u -robust with respect to cost function C (as in Definition 3.4.1), then after N iterations of DAgger collecting m trajectories (or m i.i.d. samples) per iteration, with probability at least $1 - \delta$:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq J(\pi^*) + uT[\hat{\epsilon}_{\text{class}} + \hat{\epsilon}_{\text{regret}}] + O\left(\frac{u\ell_{\max} T \log T}{\alpha N} + \ell_{\max} uT \sqrt{\frac{\log(1/\delta)}{mN}}\right).$$

Proof. Follows from the same argument as in the proof of theorem 3.6.2, except using theorem A.1.2 instead of theorem A.1.1. \square

Corollary 3.6.4. *Suppose ℓ is convex in π for all s, a and DAgger uses Follow-the-Regularized-Leader to pick the sequence of policies, then: If ℓ upper bounds the cost C , then for any $\epsilon > 0$ after $O(T^2 \log(1/\delta)/\epsilon^2)$ iterations of DAgger collecting $m = 1$ trajectory (or $m = 1$ i.i.d. sample) per iteration, with probability at least $1 - \delta$:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq T\hat{\epsilon}_{\text{class}} + O(\epsilon).$$

For any cost function C , if the expert π^ is u -robust with respect to C (as in Definition 3.4.1), then for any $\epsilon > 0$, after $O(u^2 T^2 \log(1/\delta)/\epsilon^2)$ iterations of DAgger collecting $m = 1$ trajectory (or $m = 1$ i.i.d. sample) per iteration, with probability at least $1 - \delta$:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq J(\pi^*) + uT\hat{\epsilon}_{\text{class}} + O(\epsilon).$$

Proof. Follows using the same argument as in the proof of corollary 3.6.3, except using theorem A.1.2 instead of theorem A.1.1. In addition, for the first part of this corollary, the generalization error term $T\ell_{\max} \sqrt{\frac{2\log(1/\delta)}{mN}}$ is $O(\epsilon)$, for Nm in $O(T^2 \log(1/\delta)/\epsilon^2)$. Similarly for the second part of this corollary, the generalization error term $uT\ell_{\max} \sqrt{\frac{2\log(1/\delta)}{mN}}$ is $O(\epsilon)$, for Nm in $O(u^2 T^2 \log(1/\delta)/\epsilon^2)$. \square

A.2 Dagger with Cost-to-Go

We now present the analysis of Dagger with cost-to-go.

We begin with a lemma that will be useful to bound the difference in performance to the expert in terms of the difference cost-to-go. This is a general lemma that applies to bound the difference in performance of any 2 policies. It has been proven before in prior work (Bagnell et al., 2003, Kakade and Langford, 2002) and has been called the performance difference lemma. We present this results and its proof here for completeness.

Lemma A.2.1. *Let π and π' be any two policy and denote V'_t and Q'_t the t -step value function and Q -value function of policy π' respectively, then:*

$$J(\pi) - J(\pi') = T \mathbb{E}_{t \sim U(1:T), s \sim d_{\pi}^t} [Q'_{T-t+1}(s, \pi) - V'_{T-t+1}(s)]$$

for $U(1:T)$ the uniform distribution on the set $\{1, 2, \dots, T\}$.

Proof. Let π_t denote the non-stationary policy that executes π in the first t time steps, and then switches to execute π' at time $t+1$ to T . Then we have $J(\pi) = J(\pi_T)$ and $J(\pi') = J(\pi_0)$. Thus:

$$\begin{aligned} J(\pi) - J(\pi') &= \sum_{t=1}^T [J(\pi_t) - J(\pi_{t-1})] \\ &= \sum_{t=1}^T [\mathbb{E}_{s \sim d_{\pi}^t} [Q'_{T-t+1}(s, \pi) - V'_{T-t+1}(s)]] \\ &= T \mathbb{E}_{t \sim U(1:T), s \sim d_{\pi}^t} [Q'_{T-t+1}(s, \pi) - V'_{T-t+1}(s)] \end{aligned}$$

□

Now let $\epsilon_{\text{class}} = \min_{\pi \in \Pi} \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{t \sim U(1:T), s \sim d_{\pi_i}^t} [Q_{T-t+1}^*(s, a) - \min_a Q_{T-t+1}^*(s, a)]$ denote the minimum expected cost-sensitive classification regret achieved by policies in the class Π on all the data over the N iterations of training. Denote the online learning average regret on the cost-to-go examples of the sequence of policies chosen by Dagger, $\epsilon_{\text{regret}} = \frac{1}{N} [\sum_{i=1}^N \ell_i(\hat{\pi}_i) - \min_{\pi \in \Pi} \sum_{i=1}^N \ell_i(\pi)]$, where $\ell_i(\pi) = \mathbb{E}_{t \sim U(1:T), s \sim d_{\pi_i}^t} [Q_{T-t+1}^*(s, \pi)]$. Assume the cost-to-go of the expert Q^* is non-negative and bounded by Q_{\max}^* , and that β_i are chosen such that $\beta_i \leq (1 - \alpha)^{i-1}$ for some α . Then we have the following:

Theorem 4.2.1. *After N iterations of DAgger with cost-to-go:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq J(\pi^*) + T[\epsilon_{\text{class}} + \epsilon_{\text{regret}}] + O\left(\frac{Q_{\max}^* T \log T}{\alpha N}\right).$$

Thus if a no-regret online algorithm is used to pick the sequence of policies $\hat{\pi}_{1:N}$, then as the number of iterations $N \rightarrow \infty$:

$$\lim_{N \rightarrow \infty} J(\bar{\pi}) \leq J(\pi^*) + T\epsilon_{\text{class}}$$

Proof. For every policy $\hat{\pi}_i$, we have:

$$\begin{aligned}
& J(\hat{\pi}_i) - J(\pi^*) \\
&= T \mathbb{E}_{t \sim U(1:T), s \sim d_{\hat{\pi}_i}^t} [Q_{T-t+1}^*(s, \hat{\pi}_i) - V_{T-t+1}^*(s)] \\
&= \sum_{t=1}^T \mathbb{E}_{s \sim d_{\hat{\pi}_i}^t} [Q_{T-t+1}^*(s, \hat{\pi}_i) - V_{T-t+1}^*(s)] \\
&\leq \sum_{t=1}^T \mathbb{E}_{s \sim d_{\hat{\pi}_i}^t} [Q_{T-t+1}^*(s, \hat{\pi}_i) - V_{T-t+1}^*(s)] + Q_{\max}^* \sum_{t=1}^T \|d_{\pi_i}^t - d_{\hat{\pi}_i}^t\|_1 \\
&\leq \sum_{t=1}^T \mathbb{E}_{s \sim d_{\hat{\pi}_i}^t} [Q_{T-t+1}^*(s, \hat{\pi}_i) - V_{T-t+1}^*(s)] + 2Q_{\max}^* \sum_{t=1}^T \min(1, t\beta_i) \\
&\leq \sum_{t=1}^T \mathbb{E}_{s \sim d_{\hat{\pi}_i}^t} [Q_{T-t+1}^*(s, \hat{\pi}_i) - V_{T-t+1}^*(s)] + 2TQ_{\max}^* \min(1, T\beta_i) \\
&= T \mathbb{E}_{t \sim U(1:T), s \sim d_{\hat{\pi}_i}^t} [Q_{T-t+1}^*(s, \hat{\pi}_i) - V_{T-t+1}^*(s)] + 2TQ_{\max}^* \min(1, T\beta_i)
\end{aligned}$$

where we use lemma A.2.1 in the first equality, lemma A.1.1 in the first inequality, and a similar argument to lemma A.1.2 for the second inequality.

Thus:

$$\begin{aligned}
& J(\bar{\pi}) - J(\pi^*) \\
&= \frac{1}{N} \sum_{i=1}^N [J(\hat{\pi}_i) - J(\pi^*)] \\
&\leq \frac{1}{N} \sum_{i=1}^N [T \mathbb{E}_{t \sim U(1:T), s \sim d_{\hat{\pi}_i}^t} [Q_{T-t+1}^*(s, \hat{\pi}_i) - V_{T-t+1}^*(s)] + 2TQ_{\max}^* \min(1, T\beta_i)] \\
&= T[\min_{\pi \in \Pi} \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{t \sim U(1:T), s \sim d_{\pi_i}^t} [Q_{T-t+1}^*(s, \pi) - V_{T-t+1}^*(s)]] + T\epsilon_{\text{regret}} \\
&\quad + \frac{2TQ_{\max}^*}{N} [n_{\beta} + T \sum_{i=n_{\beta}+1}^N \beta_i] \\
&\leq T[\min_{\pi \in \Pi} \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{t \sim U(1:T), s \sim d_{\pi_i}^t} [Q_{T-t+1}^*(s, \pi) - \min_a Q_{T-t+1}^*(s, a)]] + T\epsilon_{\text{regret}} \\
&\quad + \frac{2TQ_{\max}^*}{N} [n_{\beta} + T \sum_{i=n_{\beta}+1}^N \beta_i] \\
&= T\epsilon_{\text{class}} + T\epsilon_{\text{regret}} + \frac{2TQ_{\max}^*}{N} [n_{\beta} + T \sum_{i=n_{\beta}+1}^N \beta_i]
\end{aligned}$$

Again, $J(\hat{\pi}) \leq J(\bar{\pi})$ since the minimum is always better than the average, i.e. $\min_i J(\hat{\pi}_i) \leq \frac{1}{N} \sum_{i=1}^N J(\hat{\pi}_i)$. Finally, using the same argument as in the proof of theorem 3.6.1, we have that when $\beta_i = (1 - \alpha)^{i-1}$, $[n_{\beta} + T \sum_{i=n_{\beta}+1}^N \beta_i] \leq \frac{\log(T)+2}{\alpha}$. This proves the first part of the theorem.

The second part follows immediately from the fact that $\epsilon_{\text{regret}} \rightarrow 0$ as $N \rightarrow \infty$, and similarly for the extra term $O\left(\frac{Q_{\max}^* T \log T}{\alpha N}\right)$. \square

Finite Sample Result

We here consider the finite sample case where actions are explored uniformly randomly and the reduction of cost-sensitive classification to reduction is used. We consider learning an estimate Q-value function \hat{Q} of the expert's cost-to-go, and we consider a general case where the cost-to-go predictions may depend on features $f(s, a, t)$ of the state s , action a and time t , e.g. \hat{Q} could be a linear regressor s.t. $\hat{Q}_{T-t+1}(s, a) = w^\top f(s, a, t)$ is the estimate of the cost-to-go $Q_{T-t+1}^*(s, a)$, and w are the parameters of the linear regressor we learn. Given such estimate \hat{Q} , we consider executing the policy $\hat{\pi}$, such that in state s at time t , $\hat{\pi}(s, t) = \min_{a \in A} \hat{Q}_{T-t+1}(s, a)$.

Theorem 4.2.2. *After N iterations of DAgger with cost-to-go, collecting m regression examples (s, a, t, Q) per iteration, guarantees that with probability at least $1-\delta$:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq J(\pi^*) + 2\sqrt{|A|T}\sqrt{\hat{R}_{class} + \hat{\epsilon}_{regret}} + O(\sqrt{\log(1/\delta)/Nm}) + O\left(\frac{Q_{\max}T \log T}{\alpha N}\right).$$

Thus if a no-regret online algorithm is used to pick the sequence of regressors $\hat{Q}_{1:N}$, then as the number of iterations $N \rightarrow \infty$, with probability 1:

$$\lim_{N \rightarrow \infty} J(\bar{\pi}) \leq J(\pi^*) + 2\sqrt{|A|T}\sqrt{\hat{R}_{class}}$$

Proof. Consider $\tilde{\pi}$, the bayes-optimal non-stationary policy that minimizes loss on the cost-to-go examples. That is, $\tilde{\pi}(s, t) = \min_{a \in A} Q_{T-t+1}^*(s, a)$, i.e. it picks the action with minimum expected expert cost-to-go conditioned on being in state s and time t . Additionally, given the observed noisy Q-values from each trajectory, the bayes-optimal regressor is simply the Q-value function Q^* of the expert that predicts the expected cost-to-go.

At each iteration i , we execute a policy $\hat{\pi}_i$, such that $\hat{\pi}_i(s, t) = \arg \min_{a \in A} \hat{Q}_{T-t+1}^i(s, a)$, where \hat{Q}^i is the current regressor at iteration i from the base online learner. The cost-sensitive regret of policy $\hat{\pi}_i$, compared to $\tilde{\pi}$, can be related to the regression regret of \hat{Q}_i as follows:

Consider any state s and time t . Let $\hat{a}_i = \hat{\pi}_i(s, t)$ and consider the action a' of any other policy. We have that:

$$\begin{aligned} & Q_{T-t+1}^*(s, \hat{a}_i) - Q_{T-t+1}^*(s, a) \\ & \leq \hat{Q}_{T-t+1}^i(s, \hat{a}_i) - \hat{Q}_{T-t+1}^i(s, a') + Q_{T-t+1}^*(s, \hat{a}_i) - \hat{Q}_{T-t+1}^i(s, \hat{a}_i) + \hat{Q}_{T-t+1}^i(s, a') - Q_{T-t+1}^*(s, a') \\ & \leq Q_{T-t+1}^*(s, \hat{a}_i) - \hat{Q}_{T-t+1}^i(s, \hat{a}_i) + \hat{Q}_{T-t+1}^i(s, a') - Q_{T-t+1}^*(s, a') \\ & \leq 2 \max_{a \in A} |Q_{T-t+1}^*(s, a) - \hat{Q}_{T-t+1}^i(s, a)| \end{aligned}$$

Additionally, for any joint distribution D over (s, t) , and $U(A)$ the uniform distribution over actions, we have that:

$$\begin{aligned} & (\mathbb{E}_{(s,t) \sim D} [\max_{a \in A} |Q_{T-t+1}^*(s, a) - \hat{Q}_{T-t+1}^i(s, a)|])^2 \\ & \leq \mathbb{E}_{(s,t) \sim D} [\max_{a \in A} |Q_{T-t+1}^*(s, a) - \hat{Q}_{T-t+1}^i(s, a)|^2] \\ & \leq \mathbb{E}_{(s,t) \sim D} [\sum_{a \in A} |Q_{T-t+1}^*(s, a) - \hat{Q}_{T-t+1}^i(s, a)|^2] \\ & = |A| \mathbb{E}_{(s,t) \sim D, a \sim U(A)} [|Q_{T-t+1}^*(s, a) - \hat{Q}_{T-t+1}^i(s, a)|^2] \end{aligned}$$

Thus we obtain that for every $\hat{\pi}_i$:

$$\begin{aligned} & \mathbb{E}_{t \sim U(1:T), s \sim d_{\pi_i}^t} [Q_{T-t+1}^*(s, \hat{\pi}_i) - Q_{T-t+1}^*(s, \tilde{\pi})] \\ & \leq 2 \mathbb{E}_{t \sim U(1:T), s \sim d_{\pi_i}^t} [\max_{a \in A} |Q_{T-t+1}^*(s, a) - \hat{Q}_{T-t+1}^i(s, a)|] \\ & \leq 2\sqrt{|A|} \sqrt{\mathbb{E}_{t \sim U(1:T), s \sim d_{\pi_i}^t, a \sim U(A)} [|Q_{T-t+1}^*(s, a) - \hat{Q}_{T-t+1}^i(s, a)|^2]} \end{aligned}$$

Thus

$$\begin{aligned}
& J(\bar{\pi}) - J(\pi^*) \\
&= \frac{T}{N} \sum_{i=1}^N \mathbb{E}_{t \sim U(1:T), s \sim d_{\pi_i}^t} [Q_{T-t+1}^*(s, \hat{\pi}_i) - Q_{T-t+1}^*(s, \pi^*)] \\
&\leq \frac{T}{N} \sum_{i=1}^N \mathbb{E}_{t \sim U(1:T), s \sim d_{\pi_i}^t} [Q_{T-t+1}^*(s, \hat{\pi}_i) - Q_{T-t+1}^*(s, \pi^*)] + \frac{2TQ_{\max}^*}{N} [n_\beta + T \sum_{i=n_\beta+1}^N \beta_i] \\
&\leq \frac{T}{N} \sum_{i=1}^N \mathbb{E}_{t \sim U(1:T), s \sim d_{\pi_i}^t} [Q_{T-t+1}^*(s, \hat{\pi}_i) - Q_{T-t+1}^*(s, \tilde{\pi})] + \frac{2TQ_{\max}^*}{N} [n_\beta + T \sum_{i=n_\beta+1}^N \beta_i] \\
&\leq \frac{2\sqrt{|A|}T}{N} \sum_{i=1}^N \sqrt{\mathbb{E}_{t \sim U(1:T), s \sim d_{\pi_i}^t, a \sim U(A)} [|Q_{T-t+1}^*(s, a) - \hat{Q}_{T-t+1}^i(s, a)|^2]} \\
&\quad + \frac{2TQ_{\max}^*}{N} [n_\beta + T \sum_{i=n_\beta+1}^N \beta_i] \\
&\leq 2\sqrt{|A|}T \sqrt{\frac{1}{N} \sum_{i=1}^N \mathbb{E}_{t \sim U(1:T), s \sim d_{\pi_i}^t, a \sim U(A)} [|Q_{T-t+1}^*(s, a) - \hat{Q}_{T-t+1}^i(s, a)|^2]} \\
&\quad + \frac{2TQ_{\max}^*}{N} [n_\beta + T \sum_{i=n_\beta+1}^N \beta_i]
\end{aligned}$$

Now in state s at time t , when performing a and then following the expert, consider the distribution $d_{s,a,t}$ over observed cost-to-go Q , such that $\mathbb{E}_{Q \sim d_{s,a,t}}[Q] = Q_{T-t+1}^*(s, a)$.

For any regressor \hat{Q} , define the expected squared loss in predictions of the observed cost-to-go at iteration i as $\ell_i(\hat{Q}) = \mathbb{E}_{t \sim U(1:T), s \sim d_{\pi_i}^t, a \sim U(A), Q \sim d_{s,t,a}} [|Q - \hat{Q}_{T-t+1}(s, a)|^2]$. Then since for any random variable X with mean μ , if we have an estimate $\hat{\mu}$ of the mean, $|\hat{\mu} - \mu|^2 = \mathbb{E}_x[(x - \hat{\mu})^2 - (x - \mu)^2]$, we have that:

$$\frac{1}{N} \sum_{i=1}^N \mathbb{E}_{t \sim U(1:T), s \sim d_{\pi_i}^t, a \sim U(A)} [|Q_{T-t+1}^*(s, a) - \hat{Q}_{T-t+1}^i(s, a)|^2] = \frac{1}{N} \sum_{i=1}^N \ell_i(\hat{Q}^i) - \ell_i(Q^*)$$

Now, in the finite sample case, consider collecting m samples at each iteration i : $\{(s_{ij}, a_{ij}, t_{ij}, Q_{ij})\}_{j=1}^m$. The expected squared loss ℓ_i is estimated as $\hat{\ell}_i(\hat{Q}) = \frac{1}{m} \sum_{j=1}^m (\hat{Q}_{T-t_{ij}+1}(s_{ij}, a_{ij}) - Q_{ij})^2$, and the no-regret algorithm is run on the estimated loss $\hat{\ell}_i$.

Define $Y_{i,j} = \ell_i(\hat{Q}^i) - (\hat{Q}_{T-t_{ij}+1}^i(s_{ij}, a_{ij}) - Q_{ij})^2 - \ell_i(Q^*) + (Q_{T-t_{ij}+1}^*(s_{ij}, a_{ij}) - Q_{ij})^2$, the difference between the expected squared loss and the empirical square loss at each sample for both \hat{Q}^i and Q^* . Conditioned on previous trajectories, each $Y_{i,j}$ has expectation 0. Then the sequence of random variables $X_{km+l} = \sum_{i=1}^k \sum_{j=1}^m Y_{i,j} + \sum_{j=1}^l Y_{(k+1),j}$, for $k \in \{0, 1, 2, \dots, N-1\}$ and $l \in \{1, 2, \dots, m\}$, forms a martingale, and if the squared loss at any sample is bounded by ℓ_{\max} , we obtain that $|X_i - X_{i+1}| \leq 2\ell_{\max}$. By Azuma-Hoeffding's inequality, this implies that with probability at least $1 - \delta$, $\frac{1}{Nm} X_{Nm} \leq 2\ell_{\max} \sqrt{\frac{2 \log(1/\delta)}{Nm}}$.

Denote the empirical average online regret on the training squared loss $\hat{\epsilon}_{\text{regret}} = \frac{1}{N} \sum_{i=1}^N \ell_i(\hat{Q}^i) - \min_{\hat{Q} \in \mathcal{Q}} \frac{1}{N} \sum_{i=1}^N \ell_i(\hat{Q})$. Let \tilde{Q}^* be the bayes-optimal regressor on the finite training data, and define the empirical regression regret of the best regressor in the class as $\hat{R}_{\text{class}} = \min_{\hat{Q} \in \mathcal{Q}} \frac{1}{N} \sum_{i=1}^N [\ell_i(\hat{Q}) - \ell_i(\tilde{Q}^*)]$.

Then we obtain that with probability at least $1 - \delta$:

$$\begin{aligned}
& \frac{1}{N} \sum_{i=1}^N \ell_i(\hat{Q}^i) - \ell_i(Q^*) \\
&= \frac{1}{N} \sum_{i=1}^N \hat{\ell}_i(\hat{Q}^i) - \hat{\ell}_i(Q^*) + \frac{1}{Nm} X_{Nm} \\
&\leq \frac{1}{N} \sum_{i=1}^N \hat{\ell}_i(\hat{Q}^i) - \hat{\ell}_i(Q^*) + 2\ell_{\max} \sqrt{\frac{2\log(1/\delta)}{Nm}} \\
&\leq \min_{\hat{Q} \in \mathcal{Q}} \frac{1}{N} \sum_{i=1}^N [\hat{\ell}_i(\hat{Q}) - \hat{\ell}_i(Q^*)] + \hat{\epsilon}_{\text{regret}} + 2\ell_{\max} \sqrt{\frac{2\log(1/\delta)}{Nm}} \\
&\leq \hat{R}_{\text{class}} + \hat{\epsilon}_{\text{regret}} + 2\ell_{\max} \sqrt{\frac{2\log(1/\delta)}{Nm}}
\end{aligned}$$

where the last inequality follows from the fact that $\sum_{i=1}^N \hat{\ell}_i(\tilde{Q}^*) \leq \sum_{i=1}^N \hat{\ell}_i(Q^*)$.
Combining with the above, we obtain that with probability at least $1 - \delta$:

$$J(\bar{\pi}) - J(\pi^*) \leq 2\sqrt{|A|}T \sqrt{\hat{R}_{\text{class}} + \hat{\epsilon}_{\text{regret}} + 2\ell_{\max} \sqrt{\frac{2\log(1/\delta)}{Nm}}} + \frac{2TQ_{\max}^*}{N} [n_{\beta} + T \sum_{i=n_{\beta}+1}^N \beta_i]$$

□

A.3 DAGGER with Learner's Cost-to-Go

We here provide the proof of the result for DAGGER using the learner's cost-to-go, sampled from state exploration distributions $\nu_{1:T}$.

To analyze this version, we begin with an alternate version of the performance difference lemma (lemma A.2.1) presented before:

Lemma A.3.1. *Let π and π' be any two policy and denote V_t and Q_t the t -step value function and Q -value function of policy π respectively, then:*

$$J(\pi) - J(\pi') = T \mathbb{E}_{t \sim U(1:T), s \sim d_{\pi'}^t} [V_{T-t+1}(s) - Q_{T-t+1}(s, \pi')]$$

for $U(1:T)$ the uniform distribution on the set $\{1, 2, \dots, T\}$.

Proof. By applying lemma A.2.1 to $J(\pi') - J(\pi)$, we obtain:

$$J(\pi') - J(\pi) = T \mathbb{E}_{t \sim U(1:T), s \sim d_{\pi'}^t} [Q_{T-t+1}(s, \pi') - V_{T-t+1}(s)]$$

This proves the lemma. □

Now denote the loss L_n used by the online learner at iteration n , s.t.:

$$L_n(\pi) = \mathbb{E}_{t \sim U(1:T), s \sim \nu_t} [Q_{T-t+1}^{\hat{\pi}_n}(s, \pi)].$$

and ϵ_{regret} the average regret after the N iterations of DAGGER:

$$\epsilon_{\text{regret}} = \frac{1}{N} \sum_{i=1}^N L_i(\pi_i) - \min_{\pi \in \Pi} \frac{1}{N} \sum_{i=1}^N L_i(\pi).$$

For any policy $\pi \in \Pi$, denote the average L_1 distance between ν_t and d_π^t over time steps t as:

$$D(\nu, \pi) = \frac{1}{T} \sum_{t=1}^T \|\nu_t - d_\pi^t\|_1.$$

Assume the cost-to-go of the learned policies $\pi_1, \pi_2, \dots, \pi_N$ are non-negative and bounded by Q_{\max} , for any state s , action a and time t (in the worst case this is TC_{\max}). Denote $\hat{\pi}$ the best policy found by DAGGER over the iterations, and $\bar{\pi}$ the uniform mixture policy over $\pi_{1:N}$ defined as before. Then we have the following guarantee with this version of DAGGER with learner's cost-to-go:

Theorem 4.3.1. *For any $\pi' \in \Pi$:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq J(\pi') + T\epsilon_{\text{regret}} + TQ_{\max}D(\nu, \pi')$$

Thus, if a no-regret online cost-sensitive classification algorithm is used, then:

$$\lim_{N \rightarrow \infty} J(\bar{\pi}) \leq J(\pi') + TQ_{\max}D(\nu, \pi')$$

Proof. Let Q_t^i denote the t -step Q -value function of policy $\hat{\pi}_i$. Then for every $\hat{\pi}_i$ we have:

$$\begin{aligned} J(\hat{\pi}_i) - J(\pi') &= T \mathbb{E}_{t \sim U(1:T), s \sim d_{\hat{\pi}_i}^t} [Q_{T-t+1}^i(s, \hat{\pi}_i) - Q_{T-t+1}^i(s, \pi')] \\ &= \sum_{t=1}^T \mathbb{E}_{s \sim d_{\hat{\pi}_i}^t} [Q_{T-t+1}^i(s, \hat{\pi}_i) - Q_{T-t+1}^i(s, \pi')] \\ &\leq \sum_{t=1}^T \mathbb{E}_{s \sim \nu_t} [Q_{T-t+1}^i(s, \hat{\pi}_i) - Q_{T-t+1}^i(s, \pi')] + Q_{\max} \sum_{t=1}^T \|\nu_t - d_{\hat{\pi}_i}^t\|_1 \\ &= T \mathbb{E}_{t \sim U(1:T), s \sim \nu_t} [Q_{T-t+1}^i(s, \hat{\pi}_i) - Q_{T-t+1}^i(s, \pi')] + TQ_{\max}D(\nu, \pi') \end{aligned}$$

where we use lemma A.3.1 in the first equality, and lemma A.1.1 in the first inequality.

Thus:

$$\begin{aligned} J(\bar{\pi}) - J(\pi') &= \frac{1}{N} \sum_{i=1}^N [J(\hat{\pi}_i) - J(\pi')] \\ &\leq \frac{1}{N} \sum_{i=1}^N [T \mathbb{E}_{t \sim U(1:T), s \sim \nu_t} [Q_{T-t+1}^i(s, \hat{\pi}_i) - Q_{T-t+1}^i(s, \pi')] + TQ_{\max}D(\nu, \pi')] \\ &\leq T \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{t \sim U(1:T), s \sim \nu_t} [Q_{T-t+1}^i(s, \hat{\pi}_i)] - T \min_{\pi \in \Pi} \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{t \sim U(1:T), s \sim \nu_t} [Q_{T-t+1}^i(s, \pi)] \\ &\quad + TQ_{\max}D(\nu, \pi') \\ &= T\epsilon_{\text{regret}} + TQ_{\max}D(\nu, \pi') \end{aligned}$$

Again, $J(\hat{\pi}) \leq J(\bar{\pi})$ since the minimum is always better than the average, i.e. $\min_i J(\hat{\pi}_i) \leq \frac{1}{N} \sum_{i=1}^N J(\hat{\pi}_i)$. This proves the first part of the theorem.

The second part follows immediately from the fact that $\epsilon_{\text{regret}} \rightarrow 0$ as $N \rightarrow \infty$. \square

Adapting the exploration distribution

We can also provide a more general result for DAGGER with learner's cost-to-go, if the exploration distributions $\nu_{1:T}$ change over the iterations of DAGGER.

For this case, let $\nu_{1:T}^n$ denote the exploration distributions used at iteration n . The loss L_n used by the online learner at iteration n would now be defined in terms of an expectation under ν^n , i.e.:

$$L_n(\pi) = \mathbb{E}_{t \sim U(1:T), s \sim \nu_t^n} [Q_{T-t+1}^{\hat{\pi}^n}(s, \pi)].$$

and ϵ_{regret} the average regret after the N iterations of DAGGER, would use this definition of the loss:

$$\epsilon_{\text{regret}} = \frac{1}{N} \sum_{i=1}^N L_i(\pi_i) - \min_{\pi \in \Pi} \frac{1}{N} \sum_{i=1}^N L_i(\pi).$$

Theorem A.3.1. *If we use exploration distributions $\{\nu_{1:T}^i\}_{i=1}^N$ over the iterations of training, then for any $\pi' \in \Pi$:*

$$J(\hat{\pi}) \leq J(\bar{\pi}) \leq J(\pi') + T\epsilon_{\text{regret}} + TQ_{\max} \frac{1}{N} \sum_{i=1}^N D(\nu^i, \pi')$$

Thus, if a no-regret online cost-sensitive classification algorithm is used, and $\nu_t^i \rightarrow d_{\pi'}^t$ as $i \rightarrow \infty$, then:

$$\lim_{N \rightarrow \infty} J(\bar{\pi}) \leq J(\pi')$$

Proof. Let Q_t^i denote the t -step Q -value function of policy $\hat{\pi}_i$. Then for every $\hat{\pi}_i$ we have:

$$\begin{aligned} & J(\hat{\pi}_i) - J(\pi') \\ &= T \mathbb{E}_{t \sim U(1:T), s \sim d_{\pi'}^t} [Q_{T-t+1}^i(s, \hat{\pi}_i) - Q_{T-t+1}^i(s, \pi')] \\ &= \sum_{t=1}^T \mathbb{E}_{s \sim d_{\pi'}^t} [Q_{T-t+1}^i(s, \hat{\pi}_i) - Q_{T-t+1}^i(s, \pi')] \\ &\leq \sum_{t=1}^T \mathbb{E}_{s \sim \nu_t^i} [Q_{T-t+1}^i(s, \hat{\pi}_i) - Q_{T-t+1}^i(s, \pi')] + Q_{\max} \sum_{t=1}^T \|\nu_t^i - d_{\pi'}^t\|_1 \\ &= T \mathbb{E}_{t \sim U(1:T), s \sim \nu_t^i} [Q_{T-t+1}^i(s, \hat{\pi}_i) - Q_{T-t+1}^i(s, \pi')] + TQ_{\max} D(\nu^i, \pi') \end{aligned}$$

where we use lemma A.3.1 in the first equality, and lemma A.1.1 in the first inequality.

Thus:

$$\begin{aligned} & J(\bar{\pi}) - J(\pi') \\ &= \frac{1}{N} \sum_{i=1}^N [J(\hat{\pi}_i) - J(\pi')] \\ &\leq \frac{1}{N} \sum_{i=1}^N [T \mathbb{E}_{t \sim U(1:T), s \sim \nu_t^i} [Q_{T-t+1}^i(s, \hat{\pi}_i) - Q_{T-t+1}^i(s, \pi')] + TQ_{\max} D(\nu^i, \pi')] \\ &\leq T \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{t \sim U(1:T), s \sim \nu_t^i} [Q_{T-t+1}^i(s, \hat{\pi}_i)] - T \min_{\pi \in \Pi} \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{t \sim U(1:T), s \sim \nu_t^i} [Q_{T-t+1}^i(s, \pi)] \\ &\quad + TQ_{\max} \frac{1}{N} \sum_{i=1}^N D(\nu^i, \pi') \\ &= T\epsilon_{\text{regret}} + TQ_{\max} \frac{1}{N} \sum_{i=1}^N D(\nu^i, \pi') \end{aligned}$$

Again, $J(\hat{\pi}) \leq J(\bar{\pi})$ since the minimum is always better than the average, i.e. $\min_i J(\hat{\pi}_i) \leq \frac{1}{N} \sum_{i=1}^N J(\hat{\pi}_i)$. This proves the first part of the theorem.

The second part follows immediately from the fact that $\epsilon_{\text{regret}} \rightarrow 0$ as $N \rightarrow \infty$ and $D(\nu^i, \pi') \rightarrow 0$ as $i \rightarrow \infty$. \square

This theorem suggests that if we would have a method that can adapt the exploration distribution ν_t^i in a way that it converges to $d_{\pi^*}^t$ of an optimal policy $\pi^* \in \Pi$, for all time t , as $i \rightarrow \infty$, then using a no-regret procedure, we would always find an optimal policy in Π in the limit. However, at this point we do not know of a method that could adapt ν^i to guarantee this.

Appendix B

Analysis of SCP for Submodular Optimization

This appendix contains the proofs of the various theoretical results for SCP presented in chapter 7.

Preliminaries

We begin by proving a number of lemmas about monotone submodular functions, which will be useful to prove our main results.

Lemma B.0.2. *Let \mathcal{S} be a set and f be a monotone submodular function defined on list of items from \mathcal{S} . For any lists A, B , we have that:*

$$f(A \oplus B) - f(A) \leq |B|(\mathbb{E}_{s \sim U(B)}[f(A \oplus s)] - f(A))$$

for $U(B)$ the uniform distribution on items in B .

Proof. For any list A and B , let B_i denote the list of the first i items in B , and b_i the i^{th} item in B . We have that:

$$\begin{aligned} & f(A \oplus B) - f(A) \\ &= \sum_{i=1}^{|B|} f(A \oplus B_i) - f(A \oplus B_{i-1}) \\ &\leq \sum_{i=1}^{|B|} f(A \oplus b_i) - f(A) \\ &= |B|(\mathbb{E}_{b \sim U(B)}[f(A \oplus b)] - f(A)) \end{aligned}$$

where the inequality follows from the submodularity property of f . \square

Lemma B.0.3. *Let \mathcal{S} be a set, and f a monotone submodular function defined on lists of items in \mathcal{S} . Let A, B be any lists of items from \mathcal{S} . Denote A_j the list of the first j items in A , $U(B)$ the uniform distribution on items in B and define $\epsilon_j = \mathbb{E}_{s \sim U(B)}[f(A_{j-1} \oplus s)] - f(A_j)$, the additive error term in competing with the average marginal benefits of*

the items in B when picking the j^{th} item in A (which could be positive or negative). Then:

$$f(A) \geq (1 - (1 - 1/|B|)^{|A|})f(B) - \sum_{i=1}^{|A|} (1 - 1/|B|)^{|A|-i} \epsilon_i$$

In particular if $|A| = |B| = k$, then:

$$f(A) \geq (1 - 1/e)f(B) - \sum_{i=1}^k (1 - 1/k)^{k-i} \epsilon_i$$

and for $\alpha = \exp(-|A|/|B|)$ (i.e. $|A| = |B| \log(1/\alpha)$):

$$f(A) \geq (1 - \alpha)f(B) - \sum_{i=1}^{|A|} (1 - 1/|B|)^{|A|-i} \epsilon_i$$

Proof. Using the monotone property and previous lemma B.0.2, we must have that:

$$f(B) - f(A) \leq f(A \oplus B) - f(A) \leq |B|(\mathbb{E}_{b \sim U(B)}[f(A \oplus b)] - f(A)).$$

Now let $\Delta_j = f(B) - f(A_j)$. By the above we have that

$$\begin{aligned} \Delta_j &\leq |B|[\mathbb{E}_{s \sim U(B)}[f(A_j \oplus s)] - f(A_j)] \\ &= |B|[\mathbb{E}_{s \sim U(B)}[f(A_j \oplus s)] - f(A_{j+1}) + f(A_{j+1}) - f(B) + f(B) - f(A_j)] \\ &= |B|[\epsilon_{j+1} + \Delta_j - \Delta_{j+1}] \end{aligned}$$

Rearranging terms, this implies that $\Delta_{j+1} \leq (1 - 1/|B|)\Delta_j + \epsilon_{j+1}$. Recursively expanding this recurrence from $\Delta_{|A|}$, we obtain:

$$\Delta_{|A|} \leq (1 - 1/|B|)^{|A|} \Delta_0 + \sum_{i=1}^{|A|} (1 - 1/|B|)^{|A|-i} \epsilon_i$$

Using the definition of $\Delta_{|A|}$ and rearranging terms, we obtain $f(A) \geq (1 - (1 - 1/|B|)^{|A|})f(B) - \sum_{i=1}^{|A|} (1 - 1/|B|)^{|A|-i} \epsilon_i$. This proves the first statement of the theorem. The following two statements follow from the observations that $(1 - 1/|B|)^{|A|} = \exp(|A| \log(1 - 1/|B|)) \leq \exp(-|A|/|B|) = \alpha$. Hence $(1 - (1 - 1/|B|)^{|A|})f(B) \geq (1 - \alpha)f(B)$. When $|A| = |B|$, $\alpha = 1/e$ and this proves the special case where $|A| = |B|$. \square

For the greedy list construction strategy, the ϵ_j in the last lemma are always ≤ 0 , such that Lemma B.0.3 implies that if we construct a list of size k with greedy, it must achieve at least 63% of the value of the optimal list of size k , but also that it must achieve at least 95% of the value of the optimal list of size $\lfloor k/3 \rfloor$, and at least 99.9% of the value of the optimal list of size $\lfloor k/7 \rfloor$.

A more surprising fact that follows from the last lemma is that constructing a list stochastically, by sampling items from a particular fixed distribution, can provide the same guarantee as greedy:

Lemma B.0.4. *Let \mathcal{S} be a set, and f a monotone submodular function defined on lists of items in \mathcal{S} . Let B be any list of items from \mathcal{S} and $U(B)$ the uniform distribution on elements in B . Suppose we construct the list A by sampling k items randomly from $U(B)$ (with replacement). Denote A_j the list obtained after j samples, and P_j the distribution over lists obtained after j samples. Then:*

$$\mathbb{E}_{A \sim P_k}[f(A)] \geq (1 - (1 - 1/|B|)^k)f(B)$$

In particular, for $\alpha = \exp(-k/|B|)$:

$$\mathbb{E}_{A \sim P_k}[f(A)] \geq (1 - \alpha)f(B)$$

Proof. The proof follows a similar proof to the previous lemma. Recall that by the monotone property and lemma B.0.2, we have that for any list A : $f(B) - f(A) \leq f(A \oplus B) - f(A) \leq |B|(\mathbb{E}_{b \sim U(B)}[f(A \oplus b)] - f(A))$. Because this holds for all lists, we must also have that for any distribution P over lists A , $f(B) - \mathbb{E}_{A \sim P}[f(A)] \leq |B|\mathbb{E}_{A \sim P}[\mathbb{E}_{b \sim U(B)}[f(A \oplus b)] - f(A)]$. Also note that by the way we construct sets, we have that $\mathbb{E}_{A_{j+1} \sim P_{j+1}}[f(A_{j+1})] = \mathbb{E}_{A_j \sim P_j}[\mathbb{E}_{s \sim U(B)}[f(A_j \oplus s)]]$

Now let $\Delta_j = f(B) - \mathbb{E}_{A_j \sim P_j}[f(A_j)]$. By the above we have that:

$$\begin{aligned} \Delta_j &\leq |B|\mathbb{E}_{A_j \sim P_j}[\mathbb{E}_{s \sim U(B)}[f(A_j \oplus s)] - f(A_j)] \\ &= |B|\mathbb{E}_{A_j \sim P_j}[\mathbb{E}_{s \sim U(B)}[f(A_j \oplus s)] - f(B) + f(B) - f(A_j)] \\ &= |B|(\mathbb{E}_{A_{j+1} \sim P_{j+1}}[f(A_{j+1})] - f(B) + f(B) - \mathbb{E}_{A_j \sim P_j}[f(A_j)]) \\ &= |B|[\Delta_j - \Delta_{j+1}] \end{aligned}$$

Rearranging terms, this implies that $\Delta_{j+1} \leq (1 - 1/|B|)\Delta_j$. Recursively expanding this recurrence from Δ_k , we obtain:

$$\Delta_k \leq (1 - 1/|B|)^k \Delta_0$$

Using the definition of Δ_k and rearranging terms we obtain $\mathbb{E}_{A \sim P_k}[f(A)] \geq (1 - (1 - 1/|B|)^k)f(B)$. The second statement follows again from the fact that $(1 - (1 - 1/|B|)^k)f(B) \geq (1 - \alpha)f(B)$ \square

Corollary B.0.1. *There exists a distribution that when sampled k times to construct a list, achieves an approximation ratio of $(1 - 1/e)$ of the optimal list of size k in expectation. In particular, if A^* is an optimal list of size k , sampling k times from $U(A^*)$ achieves this approximation ratio. Additionally, for any $\alpha \in (0, 1]$, sampling $\lceil k \log(1/\alpha) \rceil$ times must construct a list that achieves an approximation ratio of $(1 - \alpha)$ in expectation.*

Proof. Follows from the last lemma using $B = A^*$. \square

This surprising result can also be seen as a special case of a more general result proven in prior related work that analyzed randomized set selection strategies to optimize submodular functions (lemma 2.2 in Feige et al. (2011)).

Proofs of Main Results

We now provide the proofs of the main results in chapter 7. We provide the proofs for the more general contextual case where we learn over a policy class $\tilde{\Pi}$. All the results for the context-free case can be seen as special cases of these results when $\Pi = \tilde{\Pi} = \{\pi_s | s \in \mathcal{S}\}$ and $\pi_s(x, L) = s$ for any state x and list L .

We refer the reader to the notation defined in Sections 7.1 and 7.3 for the definitions of the various terms used.

Theorem 7.3.1. *Let $\alpha = \exp(-m/k)$ and $k' = \min(m, k)$. After T iterations, for any $\delta, \delta' \in (0, 1)$, we have that with probability at least $1 - \delta$:*

$$F(\bar{\pi}, m) \geq (1 - \alpha)F(L_{\pi, k}^*) - \frac{R}{T} - 2\sqrt{\frac{2\ln(1/\delta)}{T}}$$

and similarly, with probability at least $1 - \delta - \delta'$:

$$F(\bar{\pi}, m) \geq (1 - \alpha)F(L_{\pi, k}^*) - \frac{\mathbb{E}[R]}{T} - \sqrt{\frac{2k'\ln(1/\delta')}{T}} - 2\sqrt{\frac{2\ln(1/\delta)}{T}}$$

Proof.

$$\begin{aligned} F(\bar{\pi}, m) &= \frac{1}{T} \sum_{t=1}^T F(\pi_t, m) \\ &= \frac{1}{T} \sum_{t=1}^T \mathbb{E}_{L_{\pi, m} \sim \pi_t} [\mathbb{E}_{x \sim D} [f_x(L_{\pi, m}(x))]] \\ &= (1 - \alpha) \mathbb{E}_{x \sim D} [f_x(L_{\pi, k}^*(x))] - [(1 - \alpha) \mathbb{E}_{x \sim D} [f_x(L_{\pi, k}^*(x))] \\ &\quad - \frac{1}{T} \sum_{t=1}^T \mathbb{E}_{L_{\pi, m} \sim \pi_t} [\mathbb{E}_{x \sim D} [f_x(L_{\pi, m}(x))]]] \end{aligned}$$

Now consider the sampled states $\{x_t\}_{t=1}^T$ and the policies $\pi_{t,i}$ sampled i.i.d. from π_t to construct the lists $\{L_t\}_{t=1}^T$ and denote the random variables $X_t = (1 - \alpha)(\mathbb{E}_{x \sim D} [f_x(L_{\pi, k}^*(x))] - f_{x_t}(L_{\pi, k}^*(x_t))) - \mathbb{E}_{L_{\pi, m} \sim \pi_t} [\mathbb{E}_{x \sim D} [f_x(L_{\pi, m}(x))] - f_{x_t}(L_t)]$. If π_t is deterministic, then simply consider all $\pi_{t,i} = \pi_t$. Because the x_t are i.i.d. from D , and the distribution of policies used to construct L_t only depends on $\{x_\tau\}_{\tau=1}^{t-1}$ and $\{L_\tau\}_{\tau=1}^{t-1}$, then the X_t conditioned on $\{X_\tau\}_{\tau=1}^{t-1}$ have expectation 0, and because $f_x \in [0, 1]$ for all state $x \in \mathcal{X}$, X_t can vary in a range $r \subseteq [-2, 2]$. Thus the sequence of random variables $Y_t = \sum_{i=1}^t X_i$, for $t = 1$ to T , forms a martingale where $|Y_t - Y_{t+1}| \leq 2$. By the Azuma-Hoeffding's inequality, we have that $P(Y_T/T \geq \epsilon) \leq \exp(-\epsilon^2 T/8)$. Hence for any $\delta \in (0, 1)$, we have that with probability at least $1 - \delta$, $Y_T/T \leq 2\sqrt{\frac{2\ln(1/\delta)}{T}}$. Hence we have that with probability at least $1 - \delta$:

$$\begin{aligned} F(\bar{\pi}, m) &= (1 - \alpha) \mathbb{E}_{x \sim D} [f_x(L_{\pi, k}^*(x))] - [(1 - \alpha) \mathbb{E}_{x \sim D} [f_x(L_{\pi, k}^*(x))] \\ &\quad - \frac{1}{T} \sum_{t=1}^T \mathbb{E}_{L_{\pi, m} \sim \pi_t} [\mathbb{E}_{x \sim D} [f_x(L_{\pi, m}(x))]]] \\ &= (1 - \alpha) \mathbb{E}_{x \sim D} [f_x(L_{\pi, k}^*(x))] - [(1 - \alpha) \frac{1}{T} \sum_{t=1}^T f_{x_t}(L_{\pi, k}^*(x_t)) - \frac{1}{T} \sum_{t=1}^T f_{x_t}(L_t)] \\ &\quad - Y_T/T \\ &= (1 - \alpha) \mathbb{E}_{x \sim D} [f_x(L_{\pi, k}^*(x))] - [(1 - \alpha) \frac{1}{T} \sum_{t=1}^T f_{x_t}(L_{\pi, k}^*(x_t)) - \frac{1}{T} \sum_{t=1}^T f_{x_t}(L_t)] \\ &\quad - 2\sqrt{\frac{2\ln(1/\delta)}{T}} \end{aligned}$$

Let $w_i = (1 - 1/k)^{m-i}$. From Lemma B.0.3, we have:

$$\begin{aligned}
& (1 - \alpha) \frac{1}{T} \sum_{t=1}^T f_{x_t}(L_{\pi,k}^*(x_t)) - \frac{1}{T} \sum_{t=1}^T f_{x_t}(L_t) \\
& \leq \frac{1}{T} \sum_{t=1}^T \sum_{i=1}^m w_i (\mathbb{E}_{\pi \sim U(L_{\pi,k}^*)} [f_{x_t}(L_{t,i-1} \oplus \pi(x_t))] - f_{x_t}(L_{t,i})) \\
& = \mathbb{E}_{\pi \sim U(L_{\pi,k}^*)} \left[\frac{1}{T} \sum_{t=1}^T \sum_{i=1}^m w_i (f_{x_t}(L_{t,i-1} \oplus \pi(x_t)) - f_{x_t}(L_{t,i})) \right] \\
& \leq \max_{\pi \in \Pi} \left[\frac{1}{T} \sum_{t=1}^T \sum_{i=1}^m w_i (f_{x_t}(L_{t,i-1} \oplus \pi(x_t)) - f_{x_t}(L_{t,i})) \right] \\
& \leq \max_{\pi \in \tilde{\Pi}} \left[\frac{1}{T} \sum_{t=1}^T \sum_{i=1}^m w_i (f(L_{t,i-1} \oplus \pi(x_t)) - f_{x_t}(L_{t,i})) \right] \\
& = R/T
\end{aligned}$$

Hence combining with the previous result proves the first part of the theorem.

Additionally, for the sampled environments $\{x_t\}_{t=1}^T$ and the policies $\pi_{t,i}$, consider the random variables $Q_{m(t-1)+i} = w_i \mathbb{E}_{\pi \sim \pi_t} [f_{x_t}(L_{t,i-1} \oplus \pi(x_t, L_{t,i-1}))] - w_i f_{x_t}(L_{t,i})$. Because each draw of $\pi_{t,i}$ is i.i.d. from π_t , we have that again the sequence of random variables $Z_j = \sum_{i=1}^j Q_i$, for $j = 1$ to Tm forms a martingale and because each Q_i can take values in a range $[-w_j, w_j]$ for $j = 1 + \text{mod}(i-1, m)$, we have $|Z_i - Z_{i-1}| \leq w_j$. Since $\sum_{i=1}^{Tm} |Z_i - Z_{i-1}|^2 \leq T \sum_{i=1}^m (1 - 1/k)^{2(m-i)} \leq T \min(k, m) = Tk'$, by Azuma-Hoeffding's inequality, we must have that $P(Z_{Tm} \geq \epsilon) \leq \exp(-\epsilon^2/2Tk')$. Thus for any $\delta' \in (0, 1)$, with probability at least $1 - \delta'$, $Z_{Tm} \leq \sqrt{2Tk' \ln(1/\delta')}$. Hence combining with the previous result, it must be the case that with probability at least $1 - \delta - \delta'$, both $Y_T/T \leq 2\sqrt{\frac{2 \ln(1/\delta)}{T}}$ and $Z_{Tm} \leq \sqrt{2Tk' \ln(1/\delta')}$ holds.

Now note that:

$$\begin{aligned}
& \max_{\pi \in \tilde{\Pi}} \left[\frac{1}{T} \sum_{t=1}^T \sum_{i=1}^m w_i (f(L_{t,i-1} \oplus \pi(x_t)) - f_{x_t}(L_{t,i})) \right] \\
& = \max_{\pi \in \tilde{\Pi}} \left[\frac{1}{T} \sum_{t=1}^T \sum_{i=1}^m w_i (f_{x_t}(L_{t,i-1} \oplus \pi(x_t)) - \mathbb{E}_{\pi' \sim \pi_t} [f(L_{t,i-1} \oplus \pi'(x_t, L_{t,i-1}))]) \right] \\
& \quad + Z_{Tm}/T \\
& = \mathbb{E}[R]/T + Z_{Tm}/T
\end{aligned}$$

Using this additional fact, and combining with previous results we must have that with probability at least $1 - \delta - \delta'$:

$$\begin{aligned}
& F(\bar{\pi}, m) \\
& \geq (1 - \alpha) F(L_{\pi,k}^*) - [(1 - \alpha) \frac{1}{T} \sum_{t=1}^T f_{x_t}(L_{\pi,k}^*(x_t)) - \frac{1}{T} \sum_{t=1}^T f_{x_t}(L_t)] - 2\sqrt{\frac{2 \ln(1/\delta)}{T}} \\
& \geq (1 - \alpha) F(L_{\pi,k}^*) - \mathbb{E}[R]/T - Z_{Tm}/T - 2\sqrt{\frac{2 \ln(1/\delta)}{T}} \\
& \geq (1 - \alpha) F(L_{\pi,k}^*) - \mathbb{E}[R]/T - \sqrt{\frac{2k' \ln(1/\delta')}{T}} - 2\sqrt{\frac{2 \ln(1/\delta)}{T}}
\end{aligned}$$

□

We now show that the expected regret must grow with $\sqrt{k'}$ and not k' , hen using Weighted Majority with the optimal learning rate (or with the doubling trick).

Corollary 7.2.2. *Under the event where Theorem 7.3.1 holds (the event that occurs w.p. $1 - \delta - \delta'$), if $\tilde{\Pi}$ is a finite set of policies, using Weighted Majority with the optimal*

learning rate guarantees that after T iterations:

$$\mathbb{E}[R]/T \leq \frac{4k' \ln |\tilde{\Pi}|}{T} + 2\sqrt{\frac{k' \ln |\tilde{\Pi}|}{T}} + 2^{9/4}(k'/T)^{3/4}(\ln(1/\delta'))^{1/4}\sqrt{\ln |\tilde{\Pi}|}$$

For large enough T in $\Omega(k'(\ln |\tilde{\Pi}| + \ln(1/\delta')))$, we obtain that:

$$\mathbb{E}[R]/T \leq O\left(\sqrt{\frac{k' \ln |\tilde{\Pi}|}{T}}\right)$$

Proof. We use a similar argument to Lemma 4 in [Streeter and Golovin \(2007\)](#) to bound $\mathbb{E}[R]$ in the result of theorem 7.3.1. Consider the sum of the benefits accumulated by the learning algorithm at position i in the list, for $i \in 1, 2, \dots, m$, i.e. let $y_i = \sum_{t=1}^T b(\pi_{t,i}(x_t, L_{t,i-1})|x_t, L_{t,i-1})$, where $\pi_{t,i}$ corresponds to the particular sampled policy by Weighted Majority for choosing the item at position i , when constructing the list L_t for state x_t . Note that $\sum_{i=1}^m (1 - 1/k)^{m-i} y_i \leq \sum_{i=1}^m y_i \leq T$ by the fact that the monotone submodular function f_x is bounded in $[0, 1]$ for all state x . Now consider the sum of the benefits you could have accumulated at position i , had you chosen the best fixed policy in hindsight to construct all list, keeping the policy fixed as the policy is constructed, i.e. let $z_i = \sum_{t=1}^T b(\pi^*(x_t, L_{t,i-1})|x_t, L_{t,i-1})$, for

$$\pi^* = \arg \max_{\pi \in \tilde{\Pi}} \sum_{i=1}^m (1 - 1/k)^{m-i} \sum_{t=1}^T b(\pi^*(x_t, L_{t,i-1})|x_t, L_{t,i-1}),$$

and let $r_i = z_i - y_i$. Now denote $Z = \sqrt{\sum_{i=1}^m (1 - 1/k)^{m-i} z_i}$. We have $Z^2 = \sum_{i=1}^m (1 - 1/k)^{m-i} z_i = \sum_{i=1}^m (1 - 1/k)^{m-i} (y_i + r_i) \leq T + R$, where R is the sample regret incurred by the learning algorithm. Under the event where theorem 7.3.1 holds (i.e. the event that occurs with probability at least $1 - \delta - \delta'$), we had already shown that $R \leq \mathbb{E}[R] + Z_{Tm}$, for $Z_{Tm} \leq \sqrt{2Tk' \ln(1/\delta')}$, in the second part of the proof of theorem 7.3.1. Thus when theorem 7.3.1 holds, we have $Z^2 \leq T + \sqrt{2Tk' \ln(1/\delta')} + \mathbb{E}[R]$. Now using the generalized version of weighted majority with rewards (i.e. using directly the benefits as rewards) [Arora et al. \(2012\)](#), since the rewards at each update are in $[0, k']$, we have that with the best learning rate in hindsight ¹: $\mathbb{E}[R] \leq 2Z\sqrt{k' \ln |\tilde{\Pi}|}$. Thus we obtain $Z^2 \leq T + \sqrt{2Tk' \ln(1/\delta')} + 2Z\sqrt{k' \ln |\tilde{\Pi}|}$. This is a quadratic inequality of the form $Z^2 - 2Z\sqrt{k' \ln |\tilde{\Pi}|} - T - \sqrt{2Tk' \ln(1/\delta')} \leq 0$, with the additional constraint $Z \geq 0$. This implies Z is less than or equal to the largest non-negative root of the polynomial $Z^2 - 2Z\sqrt{k' \ln |\tilde{\Pi}|} - T - \sqrt{2Tk' \ln(1/\delta')}$. Solving for the roots, we obtain

$$\begin{aligned} Z &\leq \sqrt{k' \ln |\tilde{\Pi}|} + \sqrt{k' \ln |\tilde{\Pi}| + T + \sqrt{2Tk' \ln(1/\delta')}} \\ &\leq 2\sqrt{k' \ln |\tilde{\Pi}|} + \sqrt{T} + (2Tk' \ln(1/\delta'))^{1/4} \end{aligned}$$

¹if not a doubling trick can be used to get the same regret bound within a small constant factor [Cesa-Bianchi et al. \(1997\)](#)

Plugging back Z into the expression $\mathbb{E}[R] \leq 2Z\sqrt{k' \ln |\tilde{\Pi}|}$, we obtain:

$$\mathbb{E}[R] \leq 4k' \ln |\tilde{\Pi}| + 2\sqrt{Tk' \ln |\tilde{\Pi}|} + 2(2T \ln(1/\delta'))^{1/4} (k')^{3/4} \sqrt{\ln |\tilde{\Pi}|}$$

Thus the average regret:

$$\frac{\mathbb{E}[R]}{T} \leq \frac{4k' \ln |\tilde{\Pi}|}{T} + 2\sqrt{\frac{k' \ln |\tilde{\Pi}|}{T}} + 2^{9/4} (k'/T)^{3/4} (\ln(1/\delta'))^{1/4} \sqrt{\ln |\tilde{\Pi}|}$$

For T in $\Omega(k'(\ln \tilde{\Pi} + \ln(1/\delta')))$, the dominant term is $2\sqrt{\frac{k' \ln |\tilde{\Pi}|}{T}}$, and thus $\frac{\mathbb{E}[R]}{T}$ is $O(\sqrt{\frac{k' \ln |\tilde{\Pi}|}{T}})$. \square

Corollary 7.3.1. *Let $\alpha = \exp(-m/k)$ and $k' = \min(m, k)$. If we run an online learning algorithm on the sequence of convex loss C_t instead of ℓ_t , then after T iterations, for any $\delta \in (0, 1)$, we have that with probability at least $1 - \delta$:*

$$F(\bar{\pi}, m) \geq (1 - \alpha)F(L_{\pi, k}^*) - \frac{\tilde{R}}{T} - 2\sqrt{\frac{2 \ln(1/\delta)}{T}} - \mathcal{G}$$

where \tilde{R} is the regret on the sequence of convex loss C_t , and $\mathcal{G} = \frac{1}{T}[\sum_{t=1}^T (\ell_t(\pi_t) - C_t(\pi_t)) + \min_{\pi \in \tilde{\Pi}} \sum_{t=1}^T C_t(\pi) - \min_{\pi' \in \tilde{\Pi}} \sum_{t=1}^T \ell_t(\pi')]$ is the “convex optimization gap” that measures how close the surrogate losses C_t is to minimizing the cost-sensitive losses ℓ_t .

Proof. Follows immediately from Theorem 7.3.1 using the definition of R , \tilde{R} and \mathcal{G} , since $\mathcal{G} = \frac{R - \tilde{R}}{T}$ \square

Appendix C

Analysis of Batch and DAGGER for System Identification

This appendix contains the detailed proofs and analysis of the theoretical results presented in Chapter 8.

The proof of these results will make use of some additional notation not used in this chapter. In particular, we define $d_{\omega,\pi}^t$ the distribution of states at time t if we executed π from time step 1 to $t - 1$, starting from distribution ω at time 1, and $d_{\omega,\pi} = (1 - \gamma) \sum_{t=1}^{\infty} \gamma^{t-1} d_{\omega,\pi}^t$ the discounted distribution of states over the infinite horizon if we follow π , starting in ω at time 1.

C.1 Relating Performance to Error in Model

This subsection presents a number of useful lemmas for relating the performance (in terms of expected total cost) of a policy in the real system to the predictive error in the learned model from which the policy was computed.

Lemma C.1.1. *Suppose we learned an approximate model \hat{T} instead of the true model T and let \hat{V}^π represent the value function of π under \hat{T} . Then for any state distribution ω :*

$$\begin{aligned} & \mathbb{E}_{s \sim \omega} [V^\pi(s) - \hat{V}^\pi(s)] \\ &= \frac{\gamma}{1-\gamma} \mathbb{E}_{(s,a) \sim D_{\omega,\pi}} [\mathbb{E}_{s' \sim T_{sa}} [\hat{V}^\pi(s')] - \mathbb{E}_{s' \sim \hat{T}_{sa}} [\hat{V}^\pi(s')]] \end{aligned}$$

Proof.

$$\begin{aligned} & \mathbb{E}_{s \sim \omega} [V^\pi(s) - \hat{V}^\pi(s)] \\ &= \mathbb{E}_{s \sim \omega, a \sim \pi_s} [C(s, a) + \gamma \mathbb{E}_{s' \sim T_{sa}} [V^\pi(s')] - C(s, a) - \gamma \mathbb{E}_{s' \sim \hat{T}_{sa}} [\hat{V}^\pi(s')]] \\ &= \gamma \mathbb{E}_{s \sim \omega, a \sim \pi_s} [\mathbb{E}_{s' \sim T_{sa}} [V^\pi(s')] - \mathbb{E}_{s' \sim \hat{T}_{sa}} [\hat{V}^\pi(s')]] \\ &= \gamma \mathbb{E}_{s \sim \omega, a \sim \pi_s} [\mathbb{E}_{s' \sim T_{sa}} [V^\pi(s')] - \mathbb{E}_{s' \sim T_{sa}} [\hat{V}^\pi(s')] + \mathbb{E}_{s' \sim T_{sa}} [\hat{V}^\pi(s')] - \mathbb{E}_{s' \sim \hat{T}_{sa}} [\hat{V}^\pi(s')]] \\ &= \gamma \mathbb{E}_{s \sim d_{\omega,\pi}^2} [V^\pi(s) - \hat{V}^\pi(s)] + \gamma \mathbb{E}_{(s,a) \sim D_{\omega,\pi}^1} [\mathbb{E}_{s' \sim T_{sa}} [\hat{V}^\pi(s')] - \mathbb{E}_{s' \sim \hat{T}_{sa}} [\hat{V}^\pi(s')]] \end{aligned}$$

This gives us a recurrence. Solving this recurrence proves the lemma. \square

Corollary C.1.1. *Suppose for all s, a : $C(s, a) \in [C_{\min}, C_{\max}]$, or for all s : $\hat{V}^\pi(s) \in [\hat{V}_{\min}, \hat{V}_{\max}]$, then:*

$$\begin{aligned} & \mathbb{E}_{s \sim \omega}[V^\pi(s) - \hat{V}^\pi(s)] \\ & \leq \frac{\gamma(\hat{V}_{\max} - \hat{V}_{\min})}{2(1-\gamma)} \|\mathbb{E}_{(s,a) \sim D_{\omega,\pi}}[T_{sa} - \hat{T}_{sa}]\|_1 \\ & \leq \frac{\gamma(C_{\max} - C_{\min})}{2(1-\gamma)^2} \mathbb{E}_{(s,a) \sim D_{\omega,\pi}}[\|T_{sa} - \hat{T}_{sa}\|_1] \end{aligned}$$

Proof. Let $\Delta T = \mathbb{E}_{(s,a) \sim D_{\omega,\pi}}[T_{sa} - \hat{T}_{sa}]$. Note that $\sum_{s'} \Delta T(s') = 0$, so that for any constant $c \in \mathbb{R}$, $\sum_{s'} c \Delta T(s') = 0$. Then by the previous lemma we have that for any constant $c \in \mathbb{R}$:

$$\begin{aligned} & \mathbb{E}_{s \sim \omega}[V^\pi(s) - \hat{V}^\pi(s)] \\ & = \frac{\gamma}{1-\gamma} \sum_{s'} \Delta T(s') \hat{V}_\pi(s') \\ & = \frac{\gamma}{1-\gamma} \sum_{s'} \Delta T(s') (\hat{V}_\pi(s') - c) \\ & \leq \frac{\gamma}{1-\gamma} \|\Delta T\|_1 \sup_s |\hat{V}_\pi(s) - c| \end{aligned}$$

In particular, if $\hat{V}_\pi(s) \in [\hat{V}_{\min}, \hat{V}_{\max}]$ for all s , we can choose $c = \frac{\hat{V}_{\max} - \hat{V}_{\min}}{2}$ to guarantee that $\sup_s |\hat{V}_\pi(s) - c| \leq \frac{\hat{V}_{\max} - \hat{V}_{\min}}{2}$. Thus $\mathbb{E}_{s \sim \omega}[V^\pi(s) - \hat{V}^\pi(s)] \leq \frac{\gamma(\hat{V}_{\max} - \hat{V}_{\min})}{2(1-\gamma)} \|\Delta T\|_1$. If $C(s, a) \in [C_{\min}, C_{\max}]$ for all (s, a) , then this implies $\hat{V}_\pi(s) \in [\hat{V}_{\min}, \hat{V}_{\max}]$ for all s for $\hat{V}_{\min} = \frac{C_{\min}}{1-\gamma}$ and $\hat{V}_{\max} = \frac{C_{\max}}{1-\gamma}$. Plug in those values for \hat{V}_{\min} and \hat{V}_{\max} , and the fact that $\|\cdot\|_1$ is convex with Jensen's inequality, proves the second result. The proof also applies in the continuous case by replacing the sum over s' by an integral over the state space in the first and second equality. \square

Lemma C.1.2. *Suppose we learned an approximate model \hat{T} instead of the true model T and let \hat{V}^π represent the value function of π under \hat{T} . Then for any state distribution ω and policies π, π' :*

$$\begin{aligned} & J_\omega(\pi) - J_\omega(\pi') \\ & = \mathbb{E}_{s \sim \omega}[\hat{V}^\pi(s) - \hat{V}^{\pi'}(s)] + \frac{\gamma}{1-\gamma} \mathbb{E}_{(s,a) \sim D_{\omega,\pi}}[\mathbb{E}_{s' \sim T_{sa}}[\hat{V}^\pi(s')] - \mathbb{E}_{s' \sim \hat{T}_{sa}}[\hat{V}^\pi(s')]] \\ & \quad + \frac{\gamma}{1-\gamma} \mathbb{E}_{(s,a) \sim D_{\omega,\pi'}}[\mathbb{E}_{s' \sim \hat{T}_{sa}}[\hat{V}^{\pi'}(s')] - \mathbb{E}_{s' \sim T_{sa}}[\hat{V}^{\pi'}(s')]] \end{aligned}$$

Proof.

$$\begin{aligned} & J_\omega(\pi) - J_\omega(\pi') \\ & = \mathbb{E}_{s \sim \omega}[V^\pi(s) - V^{\pi'}(s)] \\ & = \mathbb{E}_{s \sim \omega}[(\hat{V}^\pi(s) - \hat{V}^{\pi'}(s)) + (V^\pi(s) - \hat{V}^\pi(s)) - (V^{\pi'}(s) - \hat{V}^{\pi'}(s))] \end{aligned}$$

Applying lemma C.1.1 to $\mathbb{E}_{s \sim \omega}[V^\pi(s) - \hat{V}^\pi(s)]$ and $-\mathbb{E}_{s \sim \omega}[V^{\pi'}(s) - \hat{V}^{\pi'}(s)]$ proves the lemma. \square

Suppose that $C(s, a) \in [C_{\min}, C_{\max}]$ for all s, a and let $C_{\text{rng}} = C_{\max} - C_{\min}$ and $H = \frac{\gamma C_{\text{rng}}}{(1-\gamma)^2}$.

Corollary C.1.2. *Suppose we learned an approximate model \hat{T} and solved it approximately to obtain π . For any policy π' , let $\epsilon_{oc}^{\pi'} = \mathbb{E}_{s \sim \omega}[\hat{V}^\pi(s) - \hat{V}^{\pi'}(s)]$ denote how much larger is the expected total cost of π in the learned model \hat{T} compared to π' for start distribution ω . Then for any policy π' :*

$$J_\omega(\pi) - J_\omega(\pi') \leq \epsilon_{oc}^{\pi'} + H \mathbb{E}_{(s,a) \sim D}[\|T_{sa} - \hat{T}_{sa}\|_1]$$

for $D = \frac{1}{2}D_{\omega,\pi} + \frac{1}{2}D_{\omega,\pi'}$

Proof. Using lemma C.1.2, we first note that the term $\mathbb{E}_{s \sim \omega}[\hat{V}^\pi(s) - \hat{V}^{\pi'}(s)] = \epsilon_{oc}^{\pi'}$. The other two terms can be bounded by $\frac{1}{2}H \mathbb{E}_{(s,a) \sim D_{\omega,\pi}}[\|T_{sa} - \hat{T}_{sa}\|_1]$ and $\frac{1}{2}H \mathbb{E}_{(s,a) \sim D_{\omega,\pi'}}[\|T_{sa} - \hat{T}_{sa}\|_1]$ respectively, following similar steps as in the proof of corollary C.1.1. Combining those two terms proves the corollary. \square

This corollary forms the basis of much of our analysis of the *Batch* and *Dagger* algorithms. In fact, this corollary already provides a performance bound for *Batch*, albeit with a major caveat: it bounds test performance of the learned policy π as a function of an error notion in the learned model \hat{T} that cannot be minimized or controlled by the algorithm. That is, when collecting data under exploration distribution ν and fitting the model \hat{T} based on this data, *Batch* could be making the quantity $\mathbb{E}_{(s,a) \sim D}[\|T_{sa} - \hat{T}_{sa}\|_1]$ arbitrarily close to its maxima (i.e. 2) in order to achieve low expected error under the training distribution ν . Even if there exists a model $T' \in \mathcal{T}$ where $\mathbb{E}_{(s,a) \sim D}[\|T_{sa} - T'_{sa}\|_1]$ is small, *Batch* would not pick this model if it has larger error under ν compared to other models in the class \mathcal{T} . As is, this bound only says that: if by chance *Batch* ends up picking a model that has low error under distribution D , then it must find a policy π not much worse than π' . Instead we would like to be able to say something much stronger of the form: if there exists a model with low error on training data, then we must find a policy that performs well compared to other policies π' . To do so, we must bound the term $\mathbb{E}_{(s,a) \sim D}[\|T_{sa} - \hat{T}_{sa}\|_1]$ by a training error term that the algorithm is minimizing. A first issue is bounding the L_1 distance by a loss we can minimize from observed samples. We present several possibilities for this in the next section. Then the remaining part will simply involve performing a change of distribution to bound the error under distribution D in terms of the error under the training distribution.

C.2 Relating L_1 distance to observable losses

This subsection presents a number of useful lemmas for relating the predictive error in L_1 distance that we would ideally need to minimize to other losses that are easier to minimize when learning a model from sampled transitions. These results prove Lemma 8.3.1 in Chapter 8.

Relation to Classification Loss

We first show how the L_1 distance can be related to a classification loss when learning deterministic transition models in MDPs with finitely many states. Namely, given a model \hat{T} which predicts next state \hat{s}'_{sa} when doing action a in state s , then we define the 0-1 classification loss of \hat{T} when observing transition (s, a, s') as:

$$\ell_{0-1}(\hat{T}, s, a, s') = I(s' \neq \hat{s}'_{sa}),$$

for I the indicator function. We show below that the L_1 distance is related to this classification loss by the following:

$$\mathbb{E}_{(s,a) \sim D}[\|T_{sa} - \hat{T}_{sa}\|_1] = 2\mathbb{E}_{(s,a) \sim D, s' \sim T_{sa}}[\ell_{0-1}(\hat{T}, s, a, s')]$$

This is proven in the following lemma:

Lemma C.2.1. *Suppose \hat{T} is a deterministic transition function (i.e. for any s, a , \hat{T}_{sa} has probability 1 on a particular next state \hat{s}'_{sa}), e.g. a multiclass classifier. Then for any joint state-action distribution D , $\mathbb{E}_{(s,a) \sim D}[\|T_{sa} - \hat{T}_{sa}\|_1] = 2\mathbb{E}_{(s,a) \sim D, s' \sim T_{sa}}[\ell_{0-1}(\hat{T}, s, a, s')]$.*

Proof.

$$\begin{aligned} & \mathbb{E}_{(s,a) \sim D}[\|T_{sa} - \hat{T}_{sa}\|_1] \\ &= \mathbb{E}_{(s,a) \sim D}[\sum_{s'} |T_{sa}(s') - \hat{T}_{sa}(s')|] \\ &= \mathbb{E}_{(s,a) \sim D}[1 - T_{sa}(\hat{s}'_{sa}) + \sum_{s' \neq \hat{s}'_{sa}} T_{sa}(s')] \\ &= 2\mathbb{E}_{(s,a) \sim D}[P_{s' \sim T_{sa}}(s' \neq \hat{s}'_{sa})] \\ &= 2\mathbb{E}_{(s,a) \sim D, s' \sim T_{sa}}[I(s' \neq \hat{s}'_{sa})] \end{aligned}$$

□

Additionally, any surrogate loss ℓ that upper bounds the 0-1 loss that are often used when learning classifiers (e.g. hinge loss when learning SVMs) could be used to upper bound the L_1 distance. In this case, we have $\mathbb{E}_{(s,a) \sim D}[\|T_{sa} - \hat{T}_{sa}\|_1] \leq 2\mathbb{E}_{(s,a) \sim D, s' \sim T_{sa}}[\ell(\hat{T}, s, a, s')]$ from the fact that $\ell(\hat{T}, s, a, s') \geq \ell_{0-1}(\hat{T}, s, a, s')$. This proves the statement $\epsilon_{\text{prd}}^{\text{L1}} \leq 2\epsilon_{\text{prd}}^{\text{cls}}$ in Lemma 8.3.1 of Chapter 8.

Relation to Negative Log Likelihood

We now show that for arbitrary MDPs and set of models, we can minimize the negative log likelihood to minimize a bound on the L_1 distance. Namely, for any model \hat{T} , define the negative log likelihood loss on transition (s, a, s') as:

$$\ell_{\text{nlh}}(\hat{T}, s, a, s') = -\log(\hat{T}_{sa}(s')).$$

Then this loss can be related to the L_1 distance as follows:

$$\begin{aligned} & \mathbb{E}_{(s,a) \sim D}[\|T_{sa} - \hat{T}_{sa}\|_1] \\ & \leq \sqrt{2\mathbb{E}_{(s,a) \sim D, s' \sim T_{sa}}[\ell_{\text{nlh}}(\hat{T}, s, a, s') - \ell_{\text{nlh}}(T, s, a, s')]} \end{aligned}$$

This is shown in the lemma below:

Lemma C.2.2. *For any joint state-action distribution D , $\mathbb{E}_{(s,a) \sim D}[\|T_{sa} - \hat{T}_{sa}\|_1] \leq \sqrt{2\mathbb{E}_{(s,a) \sim D, s' \sim T_{sa}}[\ell_{\text{nlh}}(\hat{T}, s, a, s') - \ell_{\text{nlh}}(T, s, a, s')]}.$*

Proof. We know that $\|T_{sa} - \hat{T}_{sa}\|_1 = 2\|T_{sa} - \hat{T}_{sa}\|_{\text{tv}}$ for $\|T_{sa} - \hat{T}_{sa}\|_{\text{tv}}$ the total variation distance between T_{sa} and \hat{T}_{sa} . Additionally, Pinsker's inequality tells us that $\|T_{sa} - \hat{T}_{sa}\|_{\text{tv}} \leq \sqrt{\frac{\text{KL}(T_{sa}||\hat{T}_{sa})}{2}}$ for $\text{KL}(T_{sa}||\hat{T}_{sa}) = \mathbb{E}_{s' \sim T_{sa}}[\log(\frac{T_{sa}(s')}{\hat{T}_{sa}(s')})]$ the Kullback-Leibler divergence. Thus we have $\|T_{sa} - \hat{T}_{sa}\|_1 \leq \sqrt{2\text{KL}(T_{sa}||\hat{T}_{sa})}$. Hence:

$$\begin{aligned} & \mathbb{E}_{(s,a) \sim D}[\|T_{sa} - \hat{T}_{sa}\|_1] \\ & \leq \mathbb{E}_{(s,a) \sim D}[\sqrt{2\text{KL}(T_{sa}||\hat{T}_{sa})}] \\ & \leq \sqrt{2\mathbb{E}_{(s,a) \sim D}[\text{KL}(T_{sa}||\hat{T}_{sa})]} \\ & = \sqrt{2\mathbb{E}_{(s,a) \sim D, s' \sim T_{sa}}[\ell_{\text{nlh}}(\hat{T}, s, a, s') - \ell_{\text{nlh}}(T, s, a, s')]} \end{aligned}$$

where the second inequality follows from the Jensen's inequality since $\sqrt{\cdot}$ is concave. \square

This proves the statement $\epsilon_{\text{prd}}^{\text{L1}} \leq \sqrt{2\epsilon_{\text{prd}}^{\text{KL}}}$ in Lemma 8.3.1 in Chapter 8.

Relation to Squared Loss in the Mean

Another interesting special case not discussed in Chapter 8 is for continuous MDPs with additive gaussian noise and known covariance matrix where we seek to learn to predict the mean next state. In this case, we can relate the L_1 distance to a squared loss in predicting the mean next state. Namely, suppose that for all s, a , T_{sa} and \hat{T}_{sa} are gaussian distributions, both with covariance matrix $\Sigma \succ 0$. Let μ_{sa} and $\hat{\mu}_{sa}$ denote the mean of T_{sa} and \hat{T}_{sa} respectively. We define the squared loss of \hat{T} on transition (s, a, s') as:

$$\ell_{\text{sq}}(\hat{T}, s, a, s') = \|\hat{\mu}_{sa} - s'\|_2^2.$$

This loss can be related to the L_1 distance between T_{sa} and \hat{T}_{sa} as follows:

$$\begin{aligned} & \mathbb{E}_{(s,a) \sim D}[\|T_{sa} - \hat{T}_{sa}\|_1] \\ & \leq c\sqrt{\mathbb{E}_{(s,a) \sim D, s' \sim T_{sa}}[\ell_{\text{sq}}(\hat{T}, s, a, s') - \ell_{\text{sq}}(T, s, a, s')]}, \end{aligned}$$

for $c = \sqrt{\frac{2}{\pi\sigma_{\min}(\Sigma)}}$ and $\sigma_{\min}(\Sigma)$ the minimum singular value of the noise covariance matrix Σ . This is proven in the two lemmas below:

Lemma C.2.3. *Suppose X_1 and X_2 are 2 independent gaussian random variables such that $X_1 \sim N(\mu_1, \Sigma)$ and $X_2 \sim N(\mu_2, \Sigma)$ and denote G_1 and G_2 the pdf of X_1 and X_2 . Then $\|G_1 - G_2\|_1 \leq \sqrt{\frac{2}{\pi\sigma_{\min}(\Sigma)}}\|\mu_1 - \mu_2\|_2$, for $\sigma_{\min}(A)$ the minimum singular value of matrix A .*

Proof. We have that $\|G_1 - G_2\|_1 = 2[P(X_1 \in A) - P(X_2 \in A)]$ for $A = \{x | G_1(x) \geq G_2(x)\}$. It can be seen that $G_1(x) \geq G_2(x)$ when $\theta^\top(x - \mu_1) \leq \tau$, for $\theta^\top = \frac{(\mu_2 - \mu_1)^\top \Sigma^{-1}}{\|\Sigma^{-1/2}(\mu_2 - \mu_1)\|_2}$, $\tau = \frac{\|\Sigma^{-1/2}(\mu_2 - \mu_1)\|_2}{2}$ and $\Sigma^{-1/2}$ denote the matrix square root of Σ^{-1} (which exists since Σ^{-1} is symmetric positive definite). Thus $A = \{x | \theta^\top(x - \mu_1) \leq \tau\}$. Define random variables $Z_1 = \theta^\top(X_1 - \mu_1)$ and $Z_2 = \theta^\top(X_2 - \mu_1)$. Then we have that $Z_1 \sim N(0, 1)$ (i.e. a standard normal distribution) and $Z_2 \sim N(2\tau, 1)$. Thus:

$$\begin{aligned} & \|G_1 - G_2\|_1 \\ &= 2[P(X_1 \in A) - P(X_2 \in A)] \\ &= 2[P(Z_1 \leq \tau) - P(Z_2 \leq \tau)] \\ &= 4\Phi(\tau) - 2 \end{aligned}$$

For Φ the cumulative density function (cdf) of a standard normal variable. Because $\tau \geq 0$ and $\Phi(x)$ is concave for $x \geq 0$, then we can upperbound $\Phi(\tau)$ with a first-order Taylor series expansion about 0. Let ϕ denote the probability density function (pdf) of a standard normal distribution and $\sigma_{\max}(A)$ the maximum singular value of a matrix A , then we obtain:

$$\begin{aligned} & 4\Phi(\tau) - 2 \\ &\leq 4(\Phi(0) + \tau\phi(0)) - 2 \\ &= 4\tau\phi(0) \\ &= \sqrt{\frac{2}{\pi}} \|\Sigma^{-1/2}(\mu_1 - \mu_2)\|_2 \\ &\leq \sqrt{\frac{2}{\pi}} \sigma_{\max}(\Sigma^{-1/2}) \|\mu_1 - \mu_2\|_2 \\ &= \sqrt{\frac{2}{\pi \sigma_{\min}(\Sigma)}} \|\mu_1 - \mu_2\|_2 \end{aligned}$$

□

Lemma C.2.4. *Suppose that for all s, a , T_{sa} and \hat{T}_{sa} are gaussian distributions, both with covariance matrix $\Sigma \succ 0$. Then for any joint state-action distribution D , $\mathbb{E}_{(s,a) \sim D}[\|T_{sa} - \hat{T}_{sa}\|_1] \leq \sqrt{\frac{2}{\pi \sigma_{\min}(\Sigma)}} \mathbb{E}_{(s,a) \sim D, s' \sim T_{sa}}[\ell_{sq}(\hat{T}, s, a, s') - \ell_{sq}(T, s, a, s')]$, for $\sigma_{\min}(\Sigma)$ the minimum singular value of matrix Σ .*

Proof. From Lemma C.2.3, we directly have that $\mathbb{E}_{(s,a) \sim D}[\|T_{sa} - \hat{T}_{sa}\|_1] \leq \sqrt{\frac{2}{\pi \sigma_{\min}(\Sigma)}} \mathbb{E}_{(s,a) \sim D}[\|\mu_{sa} - \hat{\mu}_{sa}\|_2]$. Using the fact that $\|\mu_{sa} - \hat{\mu}_{sa}\|_2^2 = \mathbb{E}_{s' \sim T_{sa}}[\|\hat{\mu}_{sa} - s'\|_2^2 - \|\mu_{sa} - s'\|_2^2]$ and that $\sqrt{\cdot}$ is concave with Jensen's inequality proves the lemma. □

C.3 Analysis of the Batch Algorithm

We now present the detailed analysis of the Batch Algorithm. As mentioned previously after corollary C.1.2, this corollary already provides a performance bound for *Batch*, with the caveat that its performance is related to an error notion in the model that is not minimized by the algorithm, and could be made arbitrarily large when *Batch* attempts

to minimize error under the training distribution ν . As is, it only states that *Batch* gets good performance if by chance it picks a model with low error under the distribution $D = \frac{1}{2}D_{\omega, \hat{\pi}} + \frac{1}{2}D_{\omega, \pi'}$. To bound performance with respect to the model error *Batch* is minimizing, the proof will simply involve using Corollary C.1.2, applying a change of distribution, as well as bounding the L_1 distance with an alternate loss *Batch* can minimize from sample transitions using the results from the previous section.

Let's define $\epsilon_{oc}^{\pi'} = \mathbb{E}_{s \sim \mu}[\hat{V}^{\hat{\pi}}(s) - \hat{V}^{\pi'}(s)]$, for $\hat{V}^{\hat{\pi}}$ and $\hat{V}^{\pi'}$ the value functions of $\hat{\pi}$ and π' under learned model \hat{T} respectively. The term $\epsilon_{oc}^{\pi'}$ measures how much better of a solution π' is compared to $\hat{\pi}$ (in terms of expected total cost) on the optimal control problem we solved (with the learned model \hat{T}). For instance, if we found an ϵ -optimal policy $\hat{\pi}$ within some class of policies Π for learned model \hat{T} , then $\epsilon_{oc}^{\pi'} \leq \epsilon$ for all $\pi' \in \Pi$. Define the predictive error of \hat{T} on training distribution ν , measured in L_1 distance, as $\epsilon_{prd}^{L1} = \mathbb{E}_{(s,a) \sim \nu}[|T_{sa} - \hat{T}_{sa}|_1]$. Similarly, define $\epsilon_{prd}^{KL} = \mathbb{E}_{(s,a) \sim \nu, s' \sim T_{sa}}[\log(T_{sa}(s')) - \log(\hat{T}_{sa}(s'))]$ and $\epsilon_{prd}^{cls} = \mathbb{E}_{(s,a) \sim \nu, s' \sim T_{sa}}[\ell(\hat{T}, s, a, s')]$ the training predictive error of \hat{T} in terms of KL and classification loss respectively (ℓ is the 0-1 loss or any upper bound on the 0-1 loss such as hinge loss). Additionally, let $c_{\nu}^{\pi} = \sup_{s,a}[\frac{D_{\mu, \pi}(s,a)}{\nu(s,a)}]$ represent the mismatch between the exploration state-action distribution ν , and the state-action distribution induced by policy π starting in μ .

Theorem 8.3.1. *The policy $\hat{\pi}$ is s.t. for any policy π' :*

$$J_{\mu}(\hat{\pi}) \leq J_{\mu}(\pi') + \epsilon_{oc}^{\pi'} + \frac{c_{\nu}^{\hat{\pi}} + c_{\nu}^{\pi'}}{2} H \epsilon_{prd}^{L1}$$

Equivalently, using the relations in Section C.2:

$$J_{\mu}(\hat{\pi}) \leq J_{\mu}(\pi') + \epsilon_{oc}^{\pi'} + \frac{c_{\nu}^{\hat{\pi}} + c_{\nu}^{\pi'}}{2} H \sqrt{2\epsilon_{prd}^{KL}}$$

$$J_{\mu}(\hat{\pi}) \leq J_{\mu}(\pi') + \epsilon_{oc}^{\pi'} + (c_{\nu}^{\hat{\pi}} + c_{\nu}^{\pi'}) H \epsilon_{prd}^{cls}$$

Proof.

$$\begin{aligned} & J_{\mu}(\hat{\pi}) - J_{\mu}(\pi') \\ & \leq \epsilon_{oc}^{\pi'} + \frac{H}{2} [\mathbb{E}_{(s,a) \sim D_{\mu, \hat{\pi}}} [|T_{sa} - \hat{T}_{sa}|_1] + \mathbb{E}_{(s,a) \sim D_{\mu, \pi'}} [|T_{sa} - \hat{T}_{sa}|_1]] \\ & \leq \epsilon_{oc}^{\pi'} + \frac{H}{2} [c_{\nu}^{\hat{\pi}} \mathbb{E}_{(s,a) \sim \nu} [|T_{sa} - \hat{T}_{sa}|_1] + c_{\nu}^{\pi'} \mathbb{E}_{(s,a) \sim \nu} [|T_{sa} - \hat{T}_{sa}|_1]] \\ & = \epsilon_{oc}^{\pi'} + \frac{c_{\nu}^{\hat{\pi}} + c_{\nu}^{\pi'}}{2} H \mathbb{E}_{(s,a) \sim \nu} [|T_{sa} - \hat{T}_{sa}|_1] \end{aligned}$$

where the first inequality follows from corollary C.1.2, and the second inequality follows from the fact that for any non-negative function f and distributions p, q , $\mathbb{E}_{x \sim p}[f(x)] \leq \sup_x [\frac{p(x)}{q(x)}] \mathbb{E}_{x \sim q}[f(x)]$. We now have proven the first statement of the theorem. Applying lemma C.2.2 proves that $\epsilon_{prd}^{L1} \leq \sqrt{2\epsilon_{prd}^{KL}}$, from which the second statement follows. Similarly, lemma C.2.1 proves that $\epsilon_{prd}^{L1} \leq 2\epsilon_{prd}^{cls}$, from which the third statement follows. \square

This theorem relates performance of the learned policy $\hat{\pi}$ to the training error (under the exploration distribution ν) the algorithm is minimizing in the model fitting procedure. The factor $c_\nu^{\hat{\pi}} H$ represents by how much the error in the model \hat{T} under training distribution ν can scale to larger errors in predicting total cost of the learned policy $\hat{\pi}$ in the real system T . Similarly $c_\nu^{\pi'} H$ represents by how much the error in the model \hat{T} under training distribution ν can scale to larger errors in predicting total cost of another policy π' in the real system T . Together, with the error in solving the optimal control problem under \hat{T} , this bounds how much worse $\hat{\pi}$ can be compared to π' .

More interestingly, we can use this result to provide a strong guarantee of the form: if there exists a model in the class which achieves small enough error under the training distribution ν , *Batch* must find a policy with good test performance. We can guarantee this if we use consistent fitting procedures that converge to the best model in the class asymptotically, as we collect more and more data. This allows us to relate the predictive error to the capacity of the model class to achieve low predictive error under the training distribution ν . We denote the modeling error, measured in L_1 distance, as $\epsilon_{\text{mdl}}^{\text{L1}} = \inf_{T' \in \mathcal{T}} \mathbb{E}_{(s,a) \sim \nu} [|T_{sa} - T'_{sa}|_1]$. Similarly, define $\epsilon_{\text{mdl}}^{\text{KL}} = \inf_{T' \in \mathcal{T}} \mathbb{E}_{(s,a) \sim \nu, s' \sim T_{sa}} [\log(T_{sa}(s')) - \log(T'_{sa}(s'))]$ and $\epsilon_{\text{mdl}}^{\text{cls}} = \inf_{T' \in \mathcal{T}} \mathbb{E}_{(s,a) \sim \nu, s' \sim T_{sa}} [\ell(T', s, a, s')]$. These are all 0 in realizable settings, but generally non-zero in agnostic settings. After observing m sampled transitions, the generalization error $\epsilon_{\text{gen}}^{\text{L1}}(m, \delta)$ (or consistency rate) bounds with high probability $1 - \delta$ the quantity $\epsilon_{\text{prd}}^{\text{L1}} - \epsilon_{\text{mdl}}^{\text{L1}}$. Similarly, $\epsilon_{\text{gen}}^{\text{KL}}(m, \delta)$ and $\epsilon_{\text{gen}}^{\text{cls}}(m, \delta)$ denote the generalization error for the KL and classification loss respectively.

By definition, all these quantities are such that after observing m samples, with probability at least $1 - \delta$: $\epsilon_{\text{prd}}^{\text{L1}} \leq \epsilon_{\text{mdl}}^{\text{L1}} + \epsilon_{\text{gen}}^{\text{L1}}(m, \delta)$, $\epsilon_{\text{prd}}^{\text{KL}} \leq \epsilon_{\text{mdl}}^{\text{KL}} + \epsilon_{\text{gen}}^{\text{KL}}(m, \delta)$ and $\epsilon_{\text{prd}}^{\text{cls}} \leq \epsilon_{\text{mdl}}^{\text{cls}} + \epsilon_{\text{gen}}^{\text{cls}}(m, \delta)$. If the procedure is consistent in minimizing the L_1 distance, this means $\epsilon_{\text{gen}}^{\text{L1}}(m, \delta) \rightarrow 0$ as $m \rightarrow \infty$ for any $\delta > 0$. Similarly, $\epsilon_{\text{gen}}^{\text{KL}}(m, \delta) \rightarrow 0$ and $\epsilon_{\text{gen}}^{\text{cls}}(m, \delta) \rightarrow 0$ as $m \rightarrow \infty$ for any $\delta > 0$ if the procedure is consistent in minimizing the KL and classification loss respectively. Combining with the previous result, this proves the following:

Corollary 8.3.1. *After observing m transitions, with probability at least $1 - \delta$, for any policy π' :*

$$J_\mu(\hat{\pi}) \leq J_\mu(\pi') + \epsilon_{oc}^{\pi'} + \frac{c_\nu^{\hat{\pi}} + c_\nu^{\pi'}}{2} H [\epsilon_{\text{mdl}}^{\text{L1}} + \epsilon_{\text{gen}}^{\text{L1}}(m, \delta)].$$

Equivalently, using the relations in Section C.2:

$$J_\mu(\hat{\pi}) \leq J_\mu(\pi') + \epsilon_{oc}^{\pi'} + \frac{c_\nu^{\hat{\pi}} + c_\nu^{\pi'}}{2} H \sqrt{2[\epsilon_{\text{mdl}}^{\text{KL}} + \epsilon_{\text{gen}}^{\text{KL}}(m, \delta)]}.$$

$$J_\mu(\hat{\pi}) \leq J_\mu(\pi') + \epsilon_{oc}^{\pi'} + (c_\nu^{\hat{\pi}} + c_\nu^{\pi'}) [\epsilon_{\text{mdl}}^{\text{cls}} + \epsilon_{\text{gen}}^{\text{cls}}(m, \delta)].$$

Additionally, if it is consistent in the L_1 distance, KL loss or classification loss then $\epsilon_{\text{gen}}^{\text{L1}}(m, \delta) \rightarrow 0$, $\epsilon_{\text{gen}}^{\text{KL}}(m, \delta) \rightarrow 0$, or $\epsilon_{\text{gen}}^{\text{cls}}(m, \delta) \rightarrow 0$ respectively as $m \rightarrow \infty$ for any $\delta > 0$.

This corollary can be used to prove sample complexity results for *Batch*. For example, with the classification loss, one could immediately leverage existing generalization error results from the supervised learning literature to determine the quantity $\epsilon_{\text{gen}}^{\text{cls}}(m, \delta)$ based on the particular class of hypothesis \mathcal{T} . These results would, e.g., express $\epsilon_{\text{gen}}^{\text{cls}}(m, \delta)$ as a function of the VC dimension (or multi-class equivalent) of \mathcal{T} . In many cases, Hoeffding's inequality combined with covering number arguments and a union bound can be used to compute these generalization error terms.

The Batch Algorithm's Performance Bound is Tight

As mentioned in Chapter 8, the previous performance bound for *Batch* in Theorem 8.3.1 is tight, in that we can construct examples where the bound is achieved to an arbitrarily small additive constant. We here present such an example.

Consider the real system to be a MDP with 3 states (s_1, s_2, s_3) and 2 actions (a_1, a_2). The initial state is always s_1 (i.e. $\mu = [1; 0; 0]$). Executing action a_1 in s_1 and s_2 transits to s_1 with probability 1. Executing action a_2 in s_1 transits to s_2 with probability 1 and executing a_2 in s_2 transits to s_2 with large probability $1 - \epsilon$, and transits to s_3 with small probability ϵ . Doing any action in s_3 transits back to s_3 with probability 1. There is small cost $\delta > 0$ for executing any action in s_1 and large cost of $C > \delta(1 + \frac{1-\gamma}{\gamma\epsilon})$ for doing any action in s_3 . Doing action a_2 in s_2 has 0 cost, and action a_1 in s_2 has cost δ .

In this system, an optimal policy always executes a_1 in s_2 and can execute any action in s_1 and s_3 . So let's consider an optimal policy π^* that is uniform over (a_1, a_2) in s_1 and s_3 . It achieves expected total cost of $J_\mu(\pi^*) = \frac{\delta}{1-\gamma}$.

Now consider that we learned a model \hat{T} which is the same as the real system, except that the learned model predicts that when executing a_2 in s_2 it transits to s_2 with probability 1. The optimal policy under the learned model is to execute a_2 in s_1 and s_2 , and to execute any action in s_3 . So let's consider the policy $\hat{\pi}$ which is uniform over (a_1, a_2) in s_3 and picks a_2 in both s_1 and s_2 . The distribution $d_{\mu, \hat{\pi}}$ induced by this policy can be computed as $d_{\mu, \hat{\pi}} = (1 - \gamma)(I - \gamma T^{\hat{\pi}})^{-1} \mu$ where I is $|S| \times |S|$ the identity matrix, $T^{\hat{\pi}}$ is the transition matrix induced by $\hat{\pi}$ (element (i,j) corresponds to probability of transitioning from state j to state i when executing $\hat{\pi}$ in state j), and μ the vector containing the initial state distribution. It can be seen that the distribution $d_{\mu, \hat{\pi}} = [1 - \gamma; \frac{\gamma(1-\gamma)}{1-\gamma(1-\epsilon)}; \frac{\gamma^2\epsilon}{1-\gamma(1-\epsilon)}]$ and the performance of the learned policy $\hat{\pi}$ in the real system is $J_\mu(\hat{\pi}) = \delta + \frac{\gamma^2\epsilon C}{(1-\gamma)(1-\gamma(1-\epsilon))}$. So we have that $J_\mu(\hat{\pi}) - J_\mu(\pi^*) = \frac{\gamma^2\epsilon C}{(1-\gamma)(1-\gamma(1-\epsilon))} - \frac{\gamma\delta}{1-\gamma}$.

Suppose the exploration distribution ν is induced by executing the policy π_0 , which picks actions uniformly randomly in s_1 and s_3 , and picks a_2 with small probability $\alpha > 0$ in s_2 (a_1 with large probability $1 - \alpha$ in s_2). It can be seen that $\nu = d_{\mu, \pi_0} = \frac{1}{(1-\gamma)(1+\gamma/2-\gamma\alpha(1-\epsilon))+\gamma^2\alpha\epsilon/2}[(1-\gamma)(1-\gamma\alpha(1-\epsilon)); \gamma(1-\gamma)/2; \gamma^2\alpha\epsilon/2]$. Because the L_1 distance between the real system and learned model is 0 for all state-action pairs, except

2ϵ for state-action pair (s_2, a_2) , we obtain that the predictive error during training is $\mathbb{E}_{(s,a) \sim \nu}[\|T_{sa} - \hat{T}_{sa}\|_1] = \frac{\gamma(1-\gamma)\alpha\epsilon}{(1-\gamma)(1+\gamma/2-\gamma\alpha(1-\epsilon))+\gamma^2\alpha\epsilon/2}$, which becomes arbitrarily small as $\alpha \rightarrow 0$. Thus the learned model could likely be picked by a model fitting procedure in practice for small α . The learned model is also an optimal model among deterministic models, so if \mathcal{T} contains only deterministic models, \hat{T} would likely be picked.

Now we have that $c_\nu^{\hat{\pi}} = \frac{2c}{\alpha}$ for $c = \frac{(1-\gamma)(1+\gamma/2-\gamma\alpha(1-\epsilon))+\gamma^2\alpha\epsilon/2}{1-\gamma(1-\epsilon)}$. Similarly, we have $d_{\mu,\pi^*} = \frac{1}{(1-\gamma)(1+\gamma/2)}[1 - \gamma; \frac{\gamma(1-\gamma)}{2}; 0]$ so that $c_\nu^{\pi^*} = \frac{(1-\gamma)(1+\gamma/2-\gamma\alpha(1-\epsilon))+\gamma^2\alpha\epsilon/2}{(1-\alpha)(1-\gamma)(1+\gamma/2)}$.

For this problem we have $C_{\max} = C$ and $C_{\min} = 0$. Also since $\mathbb{E}_{s \sim \mu}[\hat{V}^{\hat{\pi}}(s)] = \delta$ and $\mathbb{E}_{s \sim \mu}[\hat{V}^{\pi^*}(s)] = \frac{\delta}{1-\gamma}$ we have $\epsilon_{\text{oc}}^{\pi^*} = -\frac{\gamma\delta}{1-\gamma}$. So using these quantities, we obtain that our bound says that:

$$\begin{aligned} & J_\mu(\hat{\pi}) - J_\mu(\pi^*) \\ & \leq \epsilon_{\text{oc}}^{\pi^*} + \frac{c_\nu^{\hat{\pi}} + c_\nu^{\pi^*}}{2} H \epsilon_{\text{prd}}^{\text{L1}} \\ & = \frac{\gamma C}{2(1-\gamma)^2} (c_\nu^{\hat{\pi}} + c_\nu^{\pi^*}) \frac{\gamma(1-\gamma)\alpha\epsilon}{(1-\gamma)(1+\gamma/2-\gamma\alpha(1-\epsilon))+\gamma^2\alpha\epsilon/2} - \frac{\gamma\delta}{1-\gamma} \\ & = \frac{\gamma^2\alpha\epsilon C}{2(1-\gamma)} \left[\frac{2}{\alpha(1-\gamma(1-\epsilon))} + \frac{1}{(1-\alpha)(1-\gamma)(1+\gamma/2)} \right] - \frac{\gamma\delta}{1-\gamma} \\ & = \frac{\gamma^2\epsilon C}{(1-\gamma)(1-\gamma(1-\epsilon))} \left[1 + \frac{\alpha(1-\gamma(1-\epsilon))}{(1-\alpha)(1-\gamma)(2+\gamma)} \right] - \frac{\gamma\delta}{1-\gamma} \end{aligned}$$

As mentioned previously, we know that $J_\mu(\hat{\pi}) - J_\mu(\pi^*) = \frac{\gamma^2\epsilon C}{(1-\gamma)(1-\gamma(1-\epsilon))} - \frac{\gamma\delta}{1-\gamma}$. We observe that we can pick α arbitrarily close to 0 in the example above so that in the limit, as α becomes closer to 0, the bound becomes the exact value of $J_\mu(\hat{\pi}) - J_\mu(\pi^*)$. This shows that there exists examples where our bound is tight to an arbitrarily small additive constant.

C.4 Analysis of the DAGGER Algorithm

We now present the detailed analysis of the DAGGER Algorithm. Let's define $\bar{\epsilon}_{\text{oc}}^{\pi'} = \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{s \sim \mu}[\hat{V}_i(s) - \hat{V}_i^{\pi'}(s)]$, for \hat{V}_i and $\hat{V}_i^{\pi'}$ the value functions of π_i and π' under learned model \hat{T}^i respectively. The term $\bar{\epsilon}_{\text{oc}}^{\pi'}$ measures how much better of a solution π' is on average compared to the policies $\pi_{1:N}$ (in terms of expected total cost) on the optimal control problems we solved (with the learned models $\hat{T}^{1:N}$). For instance, if at each iteration i we found an ϵ_i -optimal policy π_i within some class of policies Π on learned model \hat{T}^i , then $\bar{\epsilon}_{\text{oc}}^{\pi'} \leq \frac{1}{N} \sum_{i=1}^N \epsilon_i$ for all $\pi' \in \Pi$. Additionally, define the average predictive error of $\hat{T}^{1:N}$ over the training iterations, measured in L_1 distance, as $\bar{\epsilon}_{\text{prd}}^{\text{L1}} = \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{(s,a) \sim \rho_i}[\|\hat{T}_{sa}^i - T_{sa}\|_1]$ for $\rho_i = \frac{1}{2}D_{\mu,\pi_i} + \frac{1}{2}\nu$ the state-action distribution used at iteration i to collect data. Similarly define $\bar{\epsilon}_{\text{prd}}^{\text{KL}} = \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{(s,a) \sim \rho_i, s' \sim T_{sa}}[\log(T_{sa}(s')) - \log(\hat{T}_{sa}^i(s'))]$ and $\bar{\epsilon}_{\text{prd}}^{\text{cls}} = \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{(s,a) \sim \rho_i, s' \sim T_{sa}}[\ell(\hat{T}, s, a, s')]$ the average training predictive error of $\hat{T}^{1:N}$ measured in KL and classification loss respectively (ℓ is 0-1 loss or any upper bound on the 0-1 loss such as hinge loss).

Lemma 8.4.1. *The policies $\pi_{1:N}$ are s.t. for any policy π' :*

$$J_\mu(\hat{\pi}) \leq J_\mu(\bar{\pi}) \leq J_\mu(\pi') + \bar{\epsilon}_{oc}^{\pi'} + c_\nu^{\pi'} H \bar{\epsilon}_{prd}^{L1}$$

Equivalently, using the results from Section C.2:

$$\begin{aligned} J_\mu(\hat{\pi}) &\leq J_\mu(\bar{\pi}) \leq J_\mu(\pi') + \bar{\epsilon}_{oc}^{\pi'} + c_\nu^{\pi'} H \sqrt{2\bar{\epsilon}_{prd}^{KL}} \\ J_\mu(\hat{\pi}) &\leq J_\mu(\bar{\pi}) \leq J_\mu(\pi') + \bar{\epsilon}_{oc}^{\pi'} + 2c_\nu^{\pi'} H \bar{\epsilon}_{prd}^{cls} \end{aligned}$$

Proof.

$$\begin{aligned} &\min_{\pi \in \pi_{1:N}} J_\mu(\pi) - J_\mu(\pi') \\ &\leq \frac{1}{N} \sum_{i=1}^N [J_\mu(\pi_i) - J_\mu(\pi')] \\ &\leq \bar{\epsilon}_{oc}^{\pi'} + \frac{H}{2} \frac{1}{N} \sum_{i=1}^N [\mathbb{E}_{(s,a) \sim D_{\mu, \pi_i}} [\|T_{sa} - \hat{T}_{sa}^i\|_1] + \mathbb{E}_{(s,a) \sim D_{\mu, \pi'}} [\|T_{sa} - \hat{T}_{sa}^i\|_1]] \\ &\leq \bar{\epsilon}_{oc}^{\pi'} + \frac{H}{2} \frac{1}{N} \sum_{i=1}^N [\mathbb{E}_{(s,a) \sim D_{\mu, \pi_i}} [\|T_{sa} - \hat{T}_{sa}^i\|_1] + c_\nu^{\pi'} \mathbb{E}_{(s,a) \sim \nu} [\|T_{sa} - \hat{T}_{sa}^i\|_1]] \\ &\leq \bar{\epsilon}_{oc}^{\pi'} + \frac{c_\nu^{\pi'} H}{2} \frac{1}{N} \sum_{i=1}^N [\mathbb{E}_{(s,a) \sim D_{\mu, \pi_i}} [\|T_{sa} - \hat{T}_{sa}^i\|_1] + \mathbb{E}_{(s,a) \sim \nu} [\|T_{sa} - \hat{T}_{sa}^i\|_1]] \\ &= \bar{\epsilon}_{oc}^{\pi'} + c_\nu^{\pi'} H \frac{1}{N} \sum_{i=1}^N [\mathbb{E}_{(s,a) \sim \rho_i} [\|T_{sa} - \hat{T}_{sa}^i\|_1]] \\ &= \bar{\epsilon}_{oc}^{\pi'} + c_\nu^{\pi'} H \bar{\epsilon}_{prd}^{L1} \end{aligned}$$

where the second inequality follows from applying corollary C.1.2 to each term $J_\mu(\pi_i) - J_\mu(\pi')$. \square

The last lemma relates the performance of DAGGER to the training loss of the sequence of models picked over the iterations of training. However it is only an intermediate step, and as is, it is unclear why it is meaningful. In particular, it is unclear why the term $\bar{\epsilon}_{prd}^{L1}$ (or $\bar{\epsilon}_{prd}^{KL}$, $\bar{\epsilon}_{prd}^{cls}$) should be small as it corresponds to an average loss of the models on out-of-training samples. That is, \hat{T}^i is trained based on data seen so far from the distributions $\rho_1, \rho_2, \dots, \rho_{i-1}$, but then its loss is evaluated under the distribution ρ_i in the term $\mathbb{E}_{(s,a) \sim \rho_i} [\|T_{sa} - \hat{T}_{sa}^i\|_1]$ (or $\mathbb{E}_{(s,a) \sim \rho_i, s' \sim T_{sa}} [\log(T_{sa}(s')) - \log(\hat{T}_{sa}^i(s'))]$, $\mathbb{E}_{(s,a) \sim \rho_i, s' \sim T_{sa}} [\ell(\hat{T}^i, s, a, s')]$) contributing to $\bar{\epsilon}_{prd}^{L1}$ (or $\bar{\epsilon}_{prd}^{KL}$, $\bar{\epsilon}_{prd}^{cls}$). So as is, it could be that $\bar{\epsilon}_{prd}^{L1}$ (or $\bar{\epsilon}_{prd}^{KL}$, $\bar{\epsilon}_{prd}^{cls}$) is large even if we achieve low error on the aggregate dataset at each iteration when fitting each \hat{T}^i . However we can observe that the quantity $\bar{\epsilon}_{prd}^{L1}$ (or $\bar{\epsilon}_{prd}^{KL}$, $\bar{\epsilon}_{prd}^{cls}$) can be interpreted as the average loss of an online learner on a particular online learning problem. This is where the no-regret property is crucial and makes this result interesting: no-regret guarantees that $\bar{\epsilon}_{prd}^{L1}$ (or $\bar{\epsilon}_{prd}^{KL}$, $\bar{\epsilon}_{prd}^{cls}$) must be small relative to the error of the best model in hindsight. So the combination of no-regret, and existence of a model with low error on the aggregate dataset, implies that $\bar{\epsilon}_{prd}^{L1}$ (or $\bar{\epsilon}_{prd}^{KL}$, $\bar{\epsilon}_{prd}^{cls}$) must be small. This is emphasized in the following theorem that constitutes our main result for DAGGER.

We denote the modeling error under the overall training distribution $\bar{\rho} = \frac{1}{N} \sum_{i=1}^N \rho_i$, measured in L_1 distance as

$$\bar{\epsilon}_{mdl}^{L1} = \inf_{T' \in \mathcal{T}} \mathbb{E}_{(s,a) \sim \bar{\rho}} [\|T_{sa} - T'_{sa}\|_1].$$

Similarly, denote

$$\bar{\epsilon}_{\text{mdl}}^{\text{KL}} = \inf_{T' \in \mathcal{T}} \mathbb{E}_{(s,a) \sim \bar{\rho}, s' \sim T_{sa}} [\log(T_{sa}(s')) - \log(T'_{sa}(s'))]$$

and

$$\bar{\epsilon}_{\text{mdl}}^{\text{cls}} = \inf_{T' \in \mathcal{T}} \mathbb{E}_{(s,a) \sim \bar{\rho}, s' \sim T_{sa}} [\ell(T', s, a, s')]$$

the modeling error measured in terms of KL and classification loss. The modeling error represents the error of the best model in hindsight after the N iterations of training. To relate the predictive error to this modeling error when using no-regret algorithms, we first need to express the predictive error in terms of an online learning loss on a particular online learning problem. For each iteration $i \in 1 : N$, define the following loss functions:

$$L_i^{\text{L1}}(\hat{T}) = \mathbb{E}_{(s,a) \sim \rho_i} [\|T_{sa} - \hat{T}_{sa}\|_1],$$

$$L_i^{\text{KL}}(\hat{T}) = \mathbb{E}_{(s,a) \sim \rho_i, s' \sim T_{sa}} [-\log(\hat{T}_{sa}(s'))],$$

and

$$L_i^{\text{cls}}(\hat{T}) = \mathbb{E}_{(s,a) \sim \rho_i, s' \sim T_{sa}} [\ell(\hat{T}, s, a, s')].$$

Now it can be seen that $\bar{\epsilon}_{\text{prd}}^{\text{L1}} = \frac{1}{N} \sum_{i=1}^N L_i^{\text{L1}}(\hat{T}^i)$, $\bar{\epsilon}_{\text{mdl}}^{\text{L1}} = \inf_{T' \in \mathcal{T}} \frac{1}{N} \sum_{i=1}^N L_i^{\text{L1}}(T')$, $\bar{\epsilon}_{\text{prd}}^{\text{KL}} = \frac{1}{N} \sum_{i=1}^N L_i^{\text{KL}}(\hat{T}^i) - L_i^{\text{KL}}(T)$, $\bar{\epsilon}_{\text{mdl}}^{\text{KL}} = \inf_{T' \in \mathcal{T}} \frac{1}{N} \sum_{i=1}^N L_i^{\text{KL}}(T') - L_i^{\text{KL}}(T)$, $\bar{\epsilon}_{\text{prd}}^{\text{cls}} = \frac{1}{N} \sum_{i=1}^N L_i^{\text{cls}}(\hat{T}^i)$ and $\bar{\epsilon}_{\text{mdl}}^{\text{cls}} = \inf_{T' \in \mathcal{T}} \frac{1}{N} \sum_{i=1}^N L_i^{\text{cls}}(T')$. DAGGER uses a no-regret algorithm on one of the sequence of loss function $L_{1:N}^{\text{L1}}$, $L_{1:N}^{\text{KL}}$ or $L_{1:N}^{\text{cls}}$. If for instance we use the no-regret algorithm on the sequence of loss $L_{1:N}^{\text{KL}}$, then this implies that $\bar{\epsilon}_{\text{prd}}^{\text{KL}} - \bar{\epsilon}_{\text{mdl}}^{\text{KL}} = \frac{1}{N} \sum_{i=1}^N L_i^{\text{KL}}(\hat{T}^i) - \inf_{T' \in \mathcal{T}} \frac{1}{N} \sum_{i=1}^N L_i^{\text{KL}}(T') \rightarrow 0$ as $N \rightarrow \infty$. If we define $\bar{\epsilon}_{\text{rgt}}^{\text{KL}}$ the average regret of the online learning algorithm after N iterations when using the KL loss, then we have $\bar{\epsilon}_{\text{prd}}^{\text{KL}} \leq \bar{\epsilon}_{\text{mdl}}^{\text{KL}} + \bar{\epsilon}_{\text{rgt}}^{\text{KL}}$ for $\bar{\epsilon}_{\text{rgt}}^{\text{KL}} \rightarrow 0$ as $N \rightarrow \infty$. Similarly, if we use the classification loss, a no-regret algorithm on the sequence of loss $L_{1:N}^{\text{cls}}$ implies that $\bar{\epsilon}_{\text{prd}}^{\text{cls}} - \bar{\epsilon}_{\text{mdl}}^{\text{cls}} = \frac{1}{N} \sum_{i=1}^N L_i^{\text{cls}}(\hat{T}^i) - \inf_{T' \in \mathcal{T}} \frac{1}{N} \sum_{i=1}^N L_i^{\text{cls}}(T') \rightarrow 0$ as $N \rightarrow \infty$. If we define $\bar{\epsilon}_{\text{rgt}}^{\text{cls}}$ the average regret of the online learning algorithm after N iterations when using the classification loss, then we have $\bar{\epsilon}_{\text{prd}}^{\text{cls}} \leq \bar{\epsilon}_{\text{mdl}}^{\text{cls}} + \bar{\epsilon}_{\text{rgt}}^{\text{cls}}$ for $\bar{\epsilon}_{\text{rgt}}^{\text{cls}} \rightarrow 0$ as $N \rightarrow \infty$. While the L_1 distance cannot be evaluated from samples, some statistical estimators can be no-regret on the sequence of loss $L_{1:N}^{\text{L1}}$ with high probability without explicitly trying to minimize this loss. This is the case in finite MDPs if we use the empirical estimator of the transition matrix T based on all data seen so far over the iterations (see section C.4). If we have a such sequence of models $\hat{T}_{1:N}$ which is no-regret on the sequence of loss $L_{1:N}^{\text{L1}}$, then $\bar{\epsilon}_{\text{prd}}^{\text{L1}} - \bar{\epsilon}_{\text{mdl}}^{\text{L1}} = \frac{1}{N} \sum_{i=1}^N L_i^{\text{L1}}(\hat{T}^i) - \inf_{T' \in \mathcal{T}} \frac{1}{N} \sum_{i=1}^N L_i^{\text{L1}}(T') \rightarrow 0$ as $N \rightarrow \infty$. If we define $\bar{\epsilon}_{\text{rgt}}^{\text{L1}}$ the average regret of $\hat{T}_{1:N}$ after N iterations on the L_1 distance, then we have $\bar{\epsilon}_{\text{prd}}^{\text{L1}} \leq \bar{\epsilon}_{\text{mdl}}^{\text{L1}} + \bar{\epsilon}_{\text{rgt}}^{\text{L1}}$ for $\bar{\epsilon}_{\text{rgt}}^{\text{L1}} \rightarrow 0$ as $N \rightarrow \infty$. Combining with the previous lemma, this proves our main result:

Theorem 8.4.1. *The policies $\pi_{1:N}$ are s.t. for any policy π' :*

$$J_\mu(\hat{\pi}) \leq J_\mu(\bar{\pi}) \leq J_\mu(\pi') + \bar{\epsilon}_{oc}^{\pi'} + c_\nu^{\pi'} H[\bar{\epsilon}_{mdl}^{L1} + \bar{\epsilon}_{rgt}^{L1}]$$

Equivalently, using the results from Section C.2:

$$J_\mu(\hat{\pi}) \leq J_\mu(\bar{\pi}) \leq J_\mu(\pi') + \bar{\epsilon}_{oc}^{\pi'} + c_\nu^{\pi'} H\sqrt{2[\bar{\epsilon}_{mdl}^{KL} + \bar{\epsilon}_{rgt}^{KL}]}$$

$$J_\mu(\hat{\pi}) \leq J_\mu(\bar{\pi}) \leq J_\mu(\pi') + \bar{\epsilon}_{oc}^{\pi'} + 2c_\nu^{\pi'} H[\bar{\epsilon}_{mdl}^{cls} + \bar{\epsilon}_{rgt}^{cls}]$$

Additionally, the fitting procedure is no-regret w.r.t $L_{1:N}^{L1}$, $L_{1:N}^{KL}$, or $L_{1:N}^{cls}$, then $\bar{\epsilon}_{rgt}^{L1} \rightarrow 0$, $\bar{\epsilon}_{rgt}^{KL} \rightarrow 0$, or $\bar{\epsilon}_{rgt}^{cls} \rightarrow 0$ respectively, as $N \rightarrow 0$.

In cases where the distributions D_{μ, π_n} converge to a small region in the space of distributions as $n \rightarrow \infty$ (which tend to occur in practice), we can also guarantee good performance if we pick the last policy π_N , for N large enough:

Lemma 8.4.2. *Suppose there exists a distribution D^* and some $\epsilon_{cnv}^* \geq 0$ such that for all i , $\|D_{\mu, \pi_i} - D^*\|_1 \leq \epsilon_{cnv}^* + \epsilon_{cnv}^i$ for some sequence $\{\epsilon_{cnv}^i\}_{i=1}^\infty$ that is $o(1)$. Then the last policy π_N produced by DAGGER is such that:*

$$J_\mu(\pi_N) \leq J_\mu(\bar{\pi}) + \frac{C_{rng}}{2(1-\gamma)} [2\epsilon_{cnv}^* + \epsilon_{cnv}^N + \frac{1}{N} \sum_{i=1}^N \epsilon_{cnv}^i]$$

Thus:

$$\limsup_{N \rightarrow \infty} J_\mu(\pi_N) - J_\mu(\bar{\pi}) \leq \frac{C_{rng}}{1-\gamma} \epsilon_{cnv}^*$$

Proof. We have that $D_{\mu, \bar{\pi}} = \frac{1}{N} \sum_{i=1}^N D_{\mu, \pi_i}$. By our assumptions, $\|D_{\mu, \pi_N} - D_{\mu, \bar{\pi}}\|_1 \leq 2\epsilon_{cnv}^* + \epsilon_{cnv}^N + \frac{1}{N} \sum_{i=1}^N \epsilon_{cnv}^i$. Thus:

$$\begin{aligned} J_\mu(\pi_N) &= \frac{1}{1-\gamma} \mathbb{E}_{(s,a) \sim D_{\mu, \pi_N}} [C(s, a)] \\ &\leq \frac{1}{1-\gamma} \mathbb{E}_{(s,a) \sim D_{\mu, \bar{\pi}}} [C(s, a)] + \frac{C_{rng}}{2(1-\gamma)} \|D_{\mu, \pi_N} - D_{\mu, \bar{\pi}}\|_1 \\ &\leq J_\mu(\bar{\pi}) + \frac{C_{rng}}{2(1-\gamma)} [2\epsilon_{cnv}^* + \epsilon_{cnv}^N + \frac{1}{N} \sum_{i=1}^N \epsilon_{cnv}^i] \end{aligned}$$

where the first inequality follows from the fact that for any function f , constant c , and distributions p, q , $\mathbb{E}_{x \sim p}[f(x)] \leq \mathbb{E}_{x \sim q}[f(x)] + \sup_x |f(x) - c| \|p - q\|_1$. Here since $C(s, a) \in [C_{\min}, C_{\max}]$, choosing $c = \frac{C_{rng}}{2}$ minimizes the term $\sup_{s,a} |C(s, a) - c|$. \square

Finite Sample Analysis for DAGGER in Particular Scenarios

This subsection presents sample complexity results to achieve near-optimal performance with DAGGER in two particular scenarios.

Finite MDP with Empirical Estimator

Consider the real system to be an arbitrary finite MDP with $|S|$ states and $|A|$ actions, and the model \hat{T}^i used at iteration i to be the empirical estimator of T from the observed transitions in the first $i - 1$ iterations. That is let $n_{sas'}^i$ be the number of times we observed transition (s, a, s') at iteration i (i.e. when sampling s, a from distribution $\rho_i = \frac{1}{2}D_{\mu, \pi_i} + \frac{1}{2}\nu$). Let $n_{sas'}^{<i} = \sum_{k=1}^{i-1} n_{sas'}^k$ the total number of times we observed state transition (s, a, s') in the first $i - 1$ iterations, and $n_{sa}^{<i} = \sum_{s'} n_{sas'}^{<i}$ the number of times we picked sampled transitions from state action pair (s, a) in the first $i - 1$ iterations. Then the empirical estimator at iteration i is such that $\hat{T}_{sa}^i(s') = \frac{n_{sas'}^{<i}}{n_{sa}^{<i}}$. If $n_{sa}^{<i} = 0$, then simply define $\hat{T}_{sa}^i(s') = \frac{1}{|S|}$. We seek to bound $\bar{\epsilon}_{\text{prd}}^{\text{L1}}$ after N iterations with high probability when using this empirical estimator and sampling m transitions at each iteration.

Let $(s_{ij}, a_{ij}, s'_{ij})$ denote the j^{th} transition sampled at iteration i . For $i \in \{1, 2, \dots, N\}$ and $j \in \{1, 2, \dots, m\}$, define the random variables $Y_{(i-1)m+j} = \mathbb{E}_{(s,a) \sim \rho_i}[\|T_{sa} - \hat{T}_{sa}^i\|_1] - \|T_{s_{ij}a_{ij}} - \hat{T}_{s_{ij}a_{ij}}^i\|_1$. Then $\mathbb{E}[Y_{(i-1)m+j} | Y_1, Y_2, \dots, Y_{(i-1)m+j-1}] = 0$. Thus the random variables $X_k = \sum_{l=1}^k Y_l$ for $k \in \{1, 2, \dots, Nm\}$ form a martingale. Since $Y_l \in [-2, 2]$, then by the Azuma-Hoeffding inequality we have $\frac{X_{Nm}}{Nm} \leq 2\sqrt{\frac{2\log(1/\delta)}{Nm}}$ with probability at least $1 - \delta$. Hence we must have that with probability at least $1 - \delta$:

$$\begin{aligned} & \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{(s,a) \sim \rho_i} \|\hat{T}_{sa}^i - T_{sa}\|_1 \\ & \leq \frac{1}{Nm} \sum_{i=1}^N \sum_{j=1}^m \|\hat{T}_{s_{ij}a_{ij}}^i - T_{s_{ij}a_{ij}}\|_1 + 2\sqrt{\frac{2\log(1/\delta)}{Nm}} \\ & = \frac{1}{Nm} \sum_{i=1}^N \sum_{s,a} n_{sa}^i \|\hat{T}_{sa}^i - T_{sa}\|_1 + 2\sqrt{\frac{2\log(1/\delta)}{Nm}} \end{aligned}$$

By applying a result from [Wasserman \(2003\)](#), we know that if we have m samples from a distribution P over k events and \hat{P} denotes the empirical estimate of this distribution, then with probability at least $1 - \delta'$, $\|\hat{P} - P\|_1 \leq \sqrt{\frac{2\ln(2)k + 2\log(1/\delta')}{m}}$. Using an union bound, we conclude that with probability at least $1 - \delta'$, we must have that for all state-action pair s, a and iteration i :

$$\|\hat{T}_{sa}^i - T_{sa}\|_1 \leq \sqrt{\frac{2\log(2)|S| + 2\log(|S||A|N/\delta')}{n_{sa}^{<i}}}$$

It is also clear that $\|\hat{T}_{sa}^i - T_{sa}\|_1 \leq 2$ always hold. Thus we must have that with probability at least $1 - \delta - \delta'$:

$$\begin{aligned} & \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{(s,a) \sim \rho_i} \|\hat{T}_{sa}^i - T_{sa}\|_1 \\ & \leq \frac{1}{Nm} \sum_{i=1}^N \sum_{s,a} n_{sa}^i \min(2, \sqrt{\frac{2\log(2)|S| + 2\log(|S||A|N/\delta')}{n_{sa}^{<i}}}) \\ & \quad + 2\sqrt{\frac{2\log(1/\delta)}{Nm}} \end{aligned}$$

The term $\min(2, \sqrt{\frac{2\log(2)|S| + 2\log(|S||A|N/\delta')}{n_{sa}^{<i}}}) = 2$ when $n_{sa}^{<i} \leq m_0$ for $m_0 = \frac{2\log(2)|S| + 2\log(|S||A|N/\delta')}{4}$. Let $k_{sa} \in \{1, 2, \dots, N\}$ be the largest iteration such that $n_{sa}^{<k_{sa}} \leq m_0$. Then we have

that for all s, a :

$$\begin{aligned}
& \sum_{i=1}^N n_{sa}^i \min(2, \sqrt{\frac{2 \ln(2)|S| + 2 \ln|S||A|N/\delta'}{n_{sa}^{<i}}}) \\
&= 2 \sum_{i=1}^{k_{sa}} n_{sa}^i + 2\sqrt{m_0} \sum_{i=k_{sa}+1}^N \frac{n_{sa}^i}{\sqrt{n_{sa}^{<i}}} \\
&\leq 2(m_0 + m) + 2\sqrt{m_0} \sum_{i=k_{sa}+1}^N \frac{n_{sa}^i}{\sqrt{m_0 + \sum_{j=k_{sa}+1}^{i-1} n_{sa}^j}}
\end{aligned}$$

Thus we obtain that with probability at least $1 - \delta - \delta'$:

$$\begin{aligned}
& \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{(s,a) \sim \rho_i} [|\hat{T}_{sa}^i - T_{sa}|_1] \\
&\leq \frac{2m_0|S||A|}{Nm} + \frac{2|S||A|}{N} + 2\sqrt{\frac{2 \log(1/\delta)}{Nm}} \\
&\quad + \frac{2\sqrt{m_0}}{Nm} \sum_{s,a} \sum_{i=k_{sa}+1}^N \frac{n_{sa}^i}{\sqrt{m_0 + \sum_{j=k_{sa}+1}^{i-1} n_{sa}^j}}
\end{aligned}$$

To upper bound this term, we will seek to upper bound $\sum_{s,a} \sum_{i=k_{sa}+1}^N \frac{n_{sa}^i}{\sqrt{m_0 + \sum_{j=k_{sa}+1}^{i-1} n_{sa}^j}}$ with respect to any choice of $\{n_{sa}^i\}$ an adversary might pick under the constraint that $\sum_{s,a} n_{sa}^j = m$ for all j . We have that:

$$\begin{aligned}
& \max_{\{n_{sa}^i\}} \sum_{s,a} \sum_{i=k_{sa}+1}^N \frac{n_{sa}^i}{\sqrt{m_0 + \sum_{j=k_{sa}+1}^{i-1} n_{sa}^j}} \\
&\leq \max_{\{n_{sa}^i\}} \sum_{s,a} \sum_{i=1}^N \frac{n_{sa}^i}{\sqrt{m_0 + \sum_{j=1}^{i-1} n_{sa}^j}} \\
&= \max_{\{n_{sa}^i\}} \sum_{s,a} \sum_{i=1}^N \frac{n_{sa}^i}{\sqrt{m_0 + n_{sa}^{<i}}}
\end{aligned}$$

The inequality holds because for any assignment of $\{n_{sa}^i\}$, we can create a new assignment $\{n_{sa}^i\}$ such that $\sum_{s,a} \sum_{i=1}^N \frac{n_{sa}^i}{\sqrt{m_0 + \sum_{j=1}^{i-1} n_{sa}^j}} \geq \sum_{s,a} \sum_{i=k_{sa}+1}^N \frac{n_{sa}^i}{\sqrt{m_0 + \sum_{j=k_{sa}+1}^{i-1} n_{sa}^j}}$ (namely by setting $n_{sa}^i = n_{sa}^{k_{sa}+i}$ for $i \in \{1, 2, \dots, N - k_{sa}\}$ and n_{sa}^i arbitrarily for $i > N - k_{sa}$ for all s, a).

Now, it can be seen that $\sum_{s,a} \sum_{i=1}^N \frac{n_{sa}^i}{\sqrt{m_0 + n_{sa}^{<i}}}$ is maximized by sequentially setting the n_{sa}^i equal to m to the pair (s, a) with smallest $n_{sa}^{<i}$ and $n_{s'a'}^i = 0$ for all other (s', a') (and breaking ties arbitrarily). This implies that for iteration i such that $k|S||A| \leq i < (k+1)|S||A|$ for some non-negative integer k , $\sum_{s,a} \frac{n_{sa}^i}{\sqrt{m_0 + n_{sa}^{<i}}} \leq \frac{m}{\sqrt{m_0 + km}}$. For any N , let us express $N = k|S||A| + l$ for some non-negative integers k and $l < |S||A|$, then we have:

$$\begin{aligned}
 & \max_{\{n_{sa}^i\}} \sum_{s,a} \sum_{i=1}^N \sqrt{\frac{n_{sa}^i}{m_0 + n_{sa}^i}} \\
 & \leq |S||A|m \sum_{j=0}^{k-1} \frac{1}{\sqrt{m_0+jm}} + lm \frac{1}{\sqrt{m_0+km}} \\
 & = (|S||A| - l)m \sum_{j=0}^{k-1} \frac{1}{\sqrt{m_0+jm}} + lm \sum_{j=0}^k \frac{1}{\sqrt{m_0+jm}} \\
 & = \frac{|S||A|m}{\sqrt{m_0}} + (|S||A| - l)m \sum_{j=1}^{k-1} \frac{1}{\sqrt{m_0+jm}} \\
 & \quad + lm \sum_{j=1}^k \frac{1}{\sqrt{m_0+jm}} \\
 & \leq \frac{|S||A|m}{\sqrt{m_0}} + (|S||A| - l)m \int_0^{k-1} \frac{dx}{\sqrt{m_0+xm}} \\
 & \quad + lm \int_0^k \frac{dx}{\sqrt{m_0+mx}} \\
 & = \frac{|S||A|m}{\sqrt{m_0}} + 2(|S||A| - l)\sqrt{m_0 + xm}|_0^{k-1} \\
 & \quad + 2l\sqrt{m_0 + mx}|_0^k \\
 & \leq \frac{|S||A|m}{\sqrt{m_0}} + 2(|S||A| - l)\sqrt{(k-1)m} + 2l\sqrt{km} \\
 & \leq \frac{|S||A|m}{\sqrt{m_0}} + 2|S||A|\sqrt{km} \\
 & \leq \frac{|S||A|m}{\sqrt{m_0}} + 2\sqrt{|S||A|Nm}
 \end{aligned}$$

Putting all together, we conclude that with probability at least $1 - \delta - \delta'$:

$$\begin{aligned}
 & \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{(s,a) \sim \rho_i} [|\hat{T}_{sa}^i - T_{sa}|_1] \\
 & \leq \frac{4|S||A|}{N} + \frac{\log(2)|S|^2|A|}{Nm} + \frac{|S||A|\log(|S||A|N/\delta')}{Nm} \\
 & \quad + 2\sqrt{\frac{2\log(2)|S|^2|A|+2|S||A|\log(|S||A|N/\delta')}{Nm}} + 2\sqrt{\frac{2\log(1/\delta)}{Nm}}
 \end{aligned}$$

This is an interesting result in itself: it shows that using the empirical estimator of T at each iteration based on observed samples so far is a no-regret algorithm under this L_1 distance penalty.

Combining with the result from Lemma 8.4.1, this implies that for any $\epsilon > 0$, we can choose $m = 1$, $N = \tilde{O}(\frac{C_{\text{rng}}^2[|S|^2|A|+|S||A|\log(1/\delta')+\log(1/\delta)]}{\epsilon^2(1-\gamma)^4})$ to ensure that with probability at least $1 - \delta - \delta'$, for any policy π' :

$$J_\mu(\hat{\pi}) \leq J_\mu(\bar{\pi}) \leq J_\mu(\pi') + \bar{\epsilon}_{\text{oc}}^{\pi'} + O(c_\nu^{\pi'} \epsilon)$$

Thus if we solve each optimal control problem with high enough accuracy, and we have access to a good state-action exploration distribution, we can obtain an ϵ -optimal policy with high probability with sample complexity that is $O(\frac{C_{\text{rng}}^2|S|^2|A|}{\epsilon^2(1-\gamma)^4})$ (ignoring log factors). This is an improvement over other model-based RL methods that have been analyzed in this particular scenario, such as R_{max} , which has sample complexity of $O(\frac{C_{\text{rng}}^3|S|^2|A|}{\epsilon^3(1-\gamma)^6})$ (Strehl et al., 2009), and a recent improved version of R_{max} which has sample complexity of $O(\frac{C_{\text{rng}}^2|S||A|}{\epsilon^2(1-\gamma)^6})$ (Szita and Szepesvári, 2010).

Finite MDP with Kernel SVM Model

Consider the true model to be an arbitrary finite MDP, and the set of models \mathcal{T} be a set of multiclass SVM in a Reproducing Kernel Hilbert Space (RKHS) induced by some

kernel k . For any state-action pair s, a , and hypothesis h in the RKHS, the associated transition model \hat{T}_{sa}^h puts probability 1 on next state $s' = \arg \max_{s''} h(f_{sa}^{s''})$ for $f_{sa}^{s'}$ the feature vector associated with transition (s, a, s') (e.g. in a grid world domain, this might encode the relative location of s' with respect to s , direction in which a is moving the robot, and configuration of nearby obstacles or type of terrain we're on). Without loss of generality, we assume the kernel k inducing the RKHS has RKHS norm $\|k(\cdot, f_{sa}^{s'})\| \leq 1$ for any transition (s, a, s') (we can scale any bounded kernel over the feature space to satisfy this), and we restrict \mathcal{T} to only functions h with bounded RKHS norm $\|h\| \leq K$. In the case of a linear SVM, this corresponds to assuming that the features are scaled so that $\|f_{sa}^{s'}\|_2 \leq 1$ and we restrict ourselves to weight vector w , such that $\|w\|_2 \leq K$.

To optimize the model, we consider proceeding by doing online learning on the following multiclass hinge loss functional L . Given any observed transition (s, a, s') in our dataset and SVM h , we define the loss as:

$$\ell(h, s, a, s') = \max[0, 1 - h(f_{sa}^{s'}) + \max_{s'' \neq s'} h(f_{sa}^{s''})]$$

We note that the loss $\ell(h, s, a, s')$ upper bounds the 0-1 classification loss $\ell_{0-1}(h, s, a, s')$ (as defined in lemma C.2.1)

We will now seek to bound $\bar{\epsilon}_{\text{prd}}^{\text{cls}}$ with high probability as a function of the regret and minimum loss in the class on the sampled training data. Let $(s_{ij}, a_{ij}, s'_{ij})$ denote the j^{th} sample transition at iteration i (i.e. sampled from $\rho_i = \frac{1}{2}D_{\mu, \pi_i} + \frac{1}{2}\nu$). For $i \in \{1, 2, \dots, N\}$ and $j \in \{1, 2, \dots, m\}$, define the random variables

$$Y_{(i-1)m+j} = \mathbb{E}_{(s,a) \sim \rho_i, s' \sim T_{sa}}[\ell_{0-1}(h^i, s, a, s')] - \ell_{0-1}(h^i, s_{ij}, a_{ij}, s'_{ij}).$$

Then $\mathbb{E}[Y_{(i-1)m+j} | Y_1, Y_2, \dots, Y_{(i-1)m+j-1}] = 0$ and thus the random variables $X_k = \sum_{l=1}^k Y_l$ for $k \in \{1, 2, \dots, Nm\}$ form a martingale.

Since $\ell_{0-1}(h, s, a, s') \in [0, 1]$ for all h, s, a, s' then $|Y_l| \leq 1$ with probability 1. By Azuma-Hoeffding's inequality, we obtain that $\frac{X_{Nm}}{Nm} \leq \sqrt{\frac{2 \log(1/\delta)}{Nm}}$ with probability at least $1 - \delta$. Thus, using lemma C.2.1, we have that with probability at least $1 - \delta$:

$$\begin{aligned} \bar{\epsilon}_{\text{prd}}^{\text{L1}} &= 2 \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{(s,a) \sim \rho_i, s' \sim T_{sa}}[\ell_{0-1}(h^i, s, a, s')] \\ &\leq 2 \left[\frac{1}{Nm} \sum_{i=1}^N \sum_{j=1}^m \ell_{0-1}(h^i, s_{ij}, a_{ij}, s'_{ij}) + \sqrt{\frac{2 \log(1/\delta)}{Nm}} \right] \\ &\leq 2 \left[\frac{1}{Nm} \sum_{i=1}^N \sum_{j=1}^m \ell(h^i, s_{ij}, a_{ij}, s'_{ij}) + \sqrt{\frac{2 \log(1/\delta)}{Nm}} \right] \end{aligned}$$

Now with these samples, the online algorithm is run on the sequence of loss functionals $L_i(h) = \frac{1}{m} \sum_{j=1}^m \ell(h, s_{ij}, a_{ij}, s'_{ij})$. Because the L_i are all convex in h , for any (s, a, s') , then an online algorithm such as gradient descent, or follow-the-regularized-leader is no-regret. In particular, suppose we run the projected subgradient descent algorithm from Zinkevich (2003). Because for any h, h' in the RKHS, $\|h - h'\| \leq 2K$ and for

any h, s, a, s' , the norm of the subgradient $\|\nabla L\| = \|k(\cdot, f_{sa}^{s'}) - k(\cdot, f_{sa}^{s^*})\| \leq 2$ (for $s^* = \arg \max_{s'' \neq s'} h(f_{sa}^{s''})$), then using learning rate $\frac{K}{\sqrt{n}}$ at iteration n we can guarantee that $\frac{1}{N} \sum_{i=1}^N L_i(h^i) \leq \min_h \frac{1}{N} \sum_{i=1}^N L_i(h) + \frac{6K}{\sqrt{N}}$ from the result in Zinkevich (2003). Let $\hat{\epsilon}_{\text{mdl}}^{\text{cls}} = \min_h \frac{1}{Nm} \sum_{i=1}^N \sum_{j=1}^m \ell(h, s_{ij}, a_{ij}, s'_{ij})$ the predictive error of the best model in hindsight on the training set. Then combining with the previous equation, we obtain that with probability at least $1 - \delta$:

$$\bar{\epsilon}_{\text{prd}}^{\text{L1}} \leq 2[\hat{\epsilon}_{\text{mdl}}^{\text{cls}} + \frac{6K}{\sqrt{N}} + \sqrt{\frac{2 \log(1/\delta)}{Nm}}]$$

Combining with the result from Lemma 8.4.1, this implies that for any $\epsilon > 0$, we can choose $m = 1$, $N = O(\frac{C_{\text{rng}}^2(K^2 + \log(1/\delta))}{\epsilon^2(1-\gamma)^4})$ to ensure that with probability at least $1 - \delta$, for any policy π' :

$$J_\mu(\hat{\pi}) \leq J_\mu(\bar{\pi}) \leq J_\mu(\pi') + \bar{\epsilon}_{\text{oc}}^{\pi'} + 2c_\nu^{\pi'} H \hat{\epsilon}_{\text{mdl}}^{\text{cls}} + O(c_\nu^{\pi'} \epsilon)$$

Thus if we solve each optimal control problem with high enough accuracy, there exist a SVM model in the RKHS that achieves low enough loss on the training set, and we have access to a good state-action exploration distribution, we can obtain a ϵ -optimal policy with high probability with sample complexity that is $O(\frac{C_{\text{rng}}^2 K^2}{\epsilon^2(1-\gamma)^4})$ (ignoring log factors). Note that this has no dependency on $|S|$ and $|A|$, only on the complexity of the class of models (i.e. K), which could be constant as $|S|, |A|$ increases.

Optimistic Exploration

We now provide the analysis of DAGGER with optimistic exploration for realizable settings.

We begin with an alternate lemma to lemma C.1.2, that allows relating the difference in task performance of two policies to the model error and how good of a lower bound the solution of the optimistic optimal control problem is.

Lemma C.4.1. *Suppose we learned an approximate model \hat{T} instead of the true model T and let \hat{V}^π represent the value function of π under \hat{T} . Then for any state distribution ω and policies π, π' :*

$$\begin{aligned} J_\omega(\pi) - J_\omega(\pi') &= \mathbb{E}_{s \sim \omega} [\hat{V}^\pi(s) - V^{\pi'}(s)] + \frac{\gamma}{1-\gamma} \mathbb{E}_{(s,a) \sim D_{\omega,\pi}} [\mathbb{E}_{s' \sim T_{sa}} [\hat{V}^\pi(s')] - \mathbb{E}_{s' \sim \hat{T}_{sa}} [\hat{V}^\pi(s')]] \end{aligned}$$

Proof.

$$\begin{aligned} J_\omega(\pi) - J_\omega(\pi') &= \mathbb{E}_{s \sim \omega} [V^\pi(s) - V^{\pi'}(s)] \\ &= \mathbb{E}_{s \sim \omega} [(\hat{V}^\pi(s) - V^{\pi'}(s)) + (V^\pi(s) - \hat{V}^\pi(s))] \end{aligned}$$

Applying lemma C.1.1 to $\mathbb{E}_{s \sim \omega} [V^\pi(s) - \hat{V}^\pi(s)]$ proves the lemma. \square

This leads to the following corollary. Suppose that $C(s, a) \in [C_{\min}, C_{\max}]$ for all s, a and let $C_{\text{rng}} = C_{\max} - C_{\min}$ and $H = \frac{\gamma C_{\text{rng}}}{(1-\gamma)^2}$.

Corollary C.4.1. *Suppose we learned an approximate model \hat{T} and solved it approximately to obtain π . For any policy π' , let $\epsilon_{\text{oc-lb}}^{\pi'} = \mathbb{E}_{s \sim \omega}[\hat{V}^{\pi}(s) - V^{\pi'}(s)]$ denote how much larger is the expected total cost of π in the learned model \hat{T} compared to the total cost of π' in the real system for start distribution ω . Then for any policy π' :*

$$J_{\omega}(\pi) - J_{\omega}(\pi') \leq \epsilon_{\text{oc-lb}}^{\pi'} + \frac{H}{2} \mathbb{E}_{(s,a) \sim D_{\omega,\pi}}[||T_{sa} - \hat{T}_{sa}||_1]$$

Proof. Using lemma C.4.1, we first note that the term $\mathbb{E}_{s \sim \omega}[\hat{V}^{\pi}(s) - V^{\pi'}(s)] = \epsilon_{\text{oc-lb}}^{\pi'}$. The other term can be bounded by $\frac{H}{2} \mathbb{E}_{(s,a) \sim D_{\omega,\pi}}[||T_{sa} - \hat{T}_{sa}||_1]$ following similar steps as in the proof of corollary C.1.1. This proves the corollary. \square

For any policy π' , let

$$\bar{\epsilon}_{\text{oc-lb}}^{\pi'} = \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{s \sim \mu}[\hat{V}_i(s)] - J_{\mu}(\pi'),$$

denote how much larger is the total cost of the policies $\pi_{1:N}$ on average in their corresponding learned model $\hat{T}^{1:N}$ compared to the total cost of π' in the real system. For instance, if $\mathcal{T}^{1:N}$ is a sequence of subsets of \mathcal{T} which contains the real system with high probability, and at each iteration i , we found an ϵ_i -optimal policy and model pair (π_i, \hat{T}^i) in $\Pi \times \mathcal{T}^i$, then for any $\pi' \in \Pi$, $\bar{\epsilon}_{\text{oc-lb}}^{\pi'} \leq \frac{1}{N} \sum_{i=1}^N \epsilon_i$ with high probability.

Additionally, define the average predictive error, measured in L_1 distance, of the chosen models $\hat{T}^{1:N}$ under the corresponding state-action distribution induced by the chosen policies $\pi_{1:N}$ as

$$\bar{\epsilon}_{\text{prd}}^{\text{L1}} = \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{(s,a) \sim D_{\mu,\pi_i}}[||T_{sa} - \hat{T}_{sa}^i||_1].$$

Similarly define

$$\bar{\epsilon}_{\text{prd}}^{\text{KL}} = \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{(s,a) \sim D_{\mu,\pi_i}, s' \sim T_{sa}}[\log(T_{sa}(s')) - \log(\hat{T}_{sa}^i(s'))]$$

and

$$\bar{\epsilon}_{\text{prd}}^{\text{cls}} = \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{(s,a) \sim D_{\mu,\pi_i}, s' \sim T_{sa}}[\ell(\hat{T}, s, a, s')]$$

the average training predictive error of $\hat{T}^{1:N}$ measured in KL and classification loss respectively (ℓ is 0-1 loss or any upper bound on the 0-1 loss such as hinge loss).

The following holds:

Theorem C.4.1. *For all policies π' :*

$$J_\mu(\hat{\pi}) \leq J_\mu(\bar{\pi}) \leq J_\mu(\pi') + \bar{\epsilon}_{oc-lb}^{\pi'} + \frac{H}{2} \bar{\epsilon}_{prd}^{L1}$$

Similarly, this holds as a function of $\bar{\epsilon}_{prd}^{KL}$, or $\bar{\epsilon}_{prd}^{KL}$, using the relation in lemma 8.3.1.

Proof. Let \hat{V}^i denote the value function of π_i in model \hat{T}_i . Then

$$\begin{aligned} & J_\mu(\bar{\pi}) - J_\mu(\pi') \\ &= \frac{1}{N} \sum_{i=1}^N [J_\mu(\pi_i) - J_\mu(\pi')] \\ &\leq \frac{1}{N} \sum_{i=1}^N [\mathbb{E}_{s \sim \mu} [\hat{V}^i(s) - V^{\pi'}(s)] + \frac{H}{2} \mathbb{E}_{(s,a) \sim D_{\mu, \pi_i}} [|T_{sa} - \hat{T}_{sa}|_1]] \\ &= \bar{\epsilon}_{oc-lb}^{\pi'} + \frac{H}{2} \bar{\epsilon}_{prd}^{L1} \end{aligned}$$

where the inequality follows from corollary C.4.1. \square

Now we denote the modeling error under the overall training distribution $\bar{D} = \frac{1}{N} \sum_{i=1}^N D_{\mu, \pi_i}$, measured in L_1 distance as

$$\bar{\epsilon}_{mdl}^{L1} = \inf_{T' \in \mathcal{T}} \mathbb{E}_{(s,a) \sim \bar{D}} [|T_{sa} - T'_{sa}|_1].$$

Similarly, denote

$$\bar{\epsilon}_{mdl}^{KL} = \inf_{T' \in \mathcal{T}} \mathbb{E}_{(s,a) \sim \bar{D}, s' \sim T_{sa}} [\log(T_{sa}(s')) - \log(T'_{sa}(s'))]$$

and

$$\bar{\epsilon}_{mdl}^{cls} = \inf_{T' \in \mathcal{T}} \mathbb{E}_{(s,a) \sim \bar{D}, s' \sim T_{sa}} [\ell(T', s, a, s')]$$

the modeling error measured in terms of KL and classification loss. The modeling error represents the error of the best model in hindsight after the N iterations of training. Note that in realizable settings, this quantity is 0.

Similarly to the previous section, we can related the predictive error to the modeling error and the regret of the online learning algorithm

For each iteration $i \in 1 : N$, define the following loss functions, as the loss incurred by the online learner during the iterations of training:

$$\begin{aligned} L_i^{L1}(\hat{T}) &= \mathbb{E}_{(s,a) \sim D_{\mu, \pi_i}} [|T_{sa} - \hat{T}_{sa}|_1], \\ L_i^{KL}(\hat{T}) &= \mathbb{E}_{(s,a) \sim D_{\mu, \pi_i}, s' \sim T_{sa}} [-\log(\hat{T}_{sa}(s'))], \end{aligned}$$

and

$$L_i^{cls}(\hat{T}) = \mathbb{E}_{(s,a) \sim D_{\mu, \pi_i}, s' \sim T_{sa}} [\ell(\hat{T}, s, a, s')].$$

Define $\bar{\epsilon}_{rgt}^{L1}$, $\bar{\epsilon}_{rgt}^{KL}$ and $\bar{\epsilon}_{rgt}^{cls}$ the average regret of the online learning algorithm after N iterations when on the loss $L_{1:N}^{L1}$, $L_{1:N}^{KL}$ and $L_{1:N}^{cls}$ respectively. Then we have $\bar{\epsilon}_{prd}^{KL} \leq \bar{\epsilon}_{mdl}^{KL} + \bar{\epsilon}_{rgt}^{KL}$ for $\bar{\epsilon}_{rgt}^{KL} \rightarrow 0$ as $N \rightarrow \infty$ (and similarly for $\bar{\epsilon}_{prd}^{KL}$ and $\bar{\epsilon}_{prd}^{cls}$). Also note that for the realizable settings, where the modeling error is 0, then this indicates the predictive error is directly bounded by the regret.

Then using these relations with the previous theorem directly implies:

Theorem C.4.2. *The policies $\pi_{1:N}$ are s.t. for any policy π' :*

$$J_\mu(\hat{\pi}) \leq J_\mu(\bar{\pi}) \leq J_\mu(\pi') + \bar{\epsilon}_{oc-lb}^{\pi'} + \frac{H}{2}[\bar{\epsilon}_{mdl}^{L1} + \bar{\epsilon}_{rgt}^{L1}]$$

Equivalently, using the results from Section C.2:

$$J_\mu(\hat{\pi}) \leq J_\mu(\bar{\pi}) \leq J_\mu(\pi') + \bar{\epsilon}_{oc-lb}^{\pi'} + \frac{H}{2} \sqrt{2[\bar{\epsilon}_{mdl}^{KL} + \bar{\epsilon}_{rgt}^{KL}]}$$

$$J_\mu(\hat{\pi}) \leq J_\mu(\bar{\pi}) \leq J_\mu(\pi') + \bar{\epsilon}_{oc-lb}^{\pi'} + H[\bar{\epsilon}_{mdl}^{cls} + \bar{\epsilon}_{rgt}^{cls}]$$

Additionally, the fitting procedure is no-regret w.r.t $L_{1:N}^{L1}$, $L_{1:N}^{KL}$, or $L_{1:N}^{cls}$, then $\bar{\epsilon}_{rgt}^{L1} \rightarrow 0$, $\bar{\epsilon}_{rgt}^{KL} \rightarrow 0$, or $\bar{\epsilon}_{rgt}^{cls} \rightarrow 0$ respectively, as $N \rightarrow 0$.

Thus this theorem implies that if we can pick a sequence of models $\{\hat{T}^i\}_{i=1}^N$, which satisfies the following: 1) with high probability, the sequence has no-regret on the observed data with respect to the true model $T \in \mathcal{T}$ (i.e. $\bar{\epsilon}_{prd}^{L1} \rightarrow 0$ as $N \rightarrow \infty$); 2) with high probability, the average total cost of the policy in the learned model lower bounds the total cost of the optimal policy (i.e. $\bar{\epsilon}_{oc-lb}^{\pi'} \leq 0$ for all π'); then we are guaranteed to find a near-optimal policy in the limit.

While the algorithm can potentially pick any model \hat{T}^i in the subset \mathcal{T}^i at each iteration i , we can still guarantee that the chosen sequence of models \hat{T}^i is no-regret if we choose the subset \mathcal{T}^i properly. For instance, suppose $\tilde{T}^{1:N}$ would be the sequence of chosen models by a no-regret algorithm on the observed data over the iterations of the algorithm, and the loss at each iteration is Lipschitz continuous under some norm $\|\cdot\|$ over the space of models \mathcal{T} . Then if at each iteration i , we define the subsets $\mathcal{T}^i = \{T' \mid \|T' - \tilde{T}^i\| \leq \epsilon_{\text{conf}}^i\}$ for some sequence ϵ_{conf}^i that is $o(1)$, then any sequence of models $\hat{T}^{1:N}$ is no-regret if for all i , $\hat{T}^i \in \mathcal{T}^i$. Typical generalization error bounds will yield confidence regions where ϵ_{conf}^i is $O(\frac{1}{\sqrt{n}})$. In this case, the sequence of $\hat{T}^{1:N}$ can be no-regret at rate $O(\frac{1}{\sqrt{N}})$.

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