Lithology Prediction of Slabbed Core Photos Using Machine Learning Models

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Thanks to:

Oil & Gas Authority

BGS 1835

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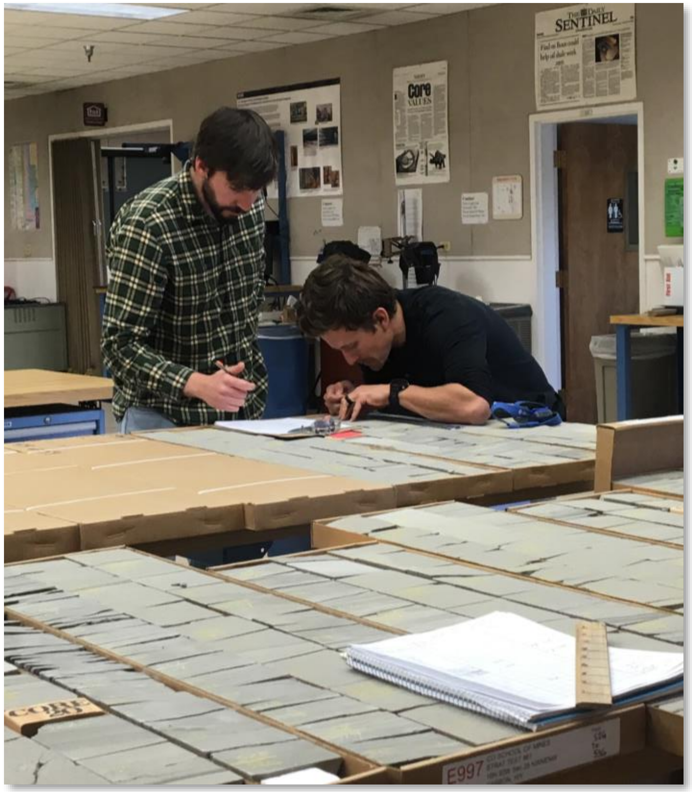
The Problem

- Legacy data of variable interpretation quality
- Core is stored around the world in public and private repositories
- In the age of big data, core photos are underutilized
- Logging core is a manual, time consuming, subjective process



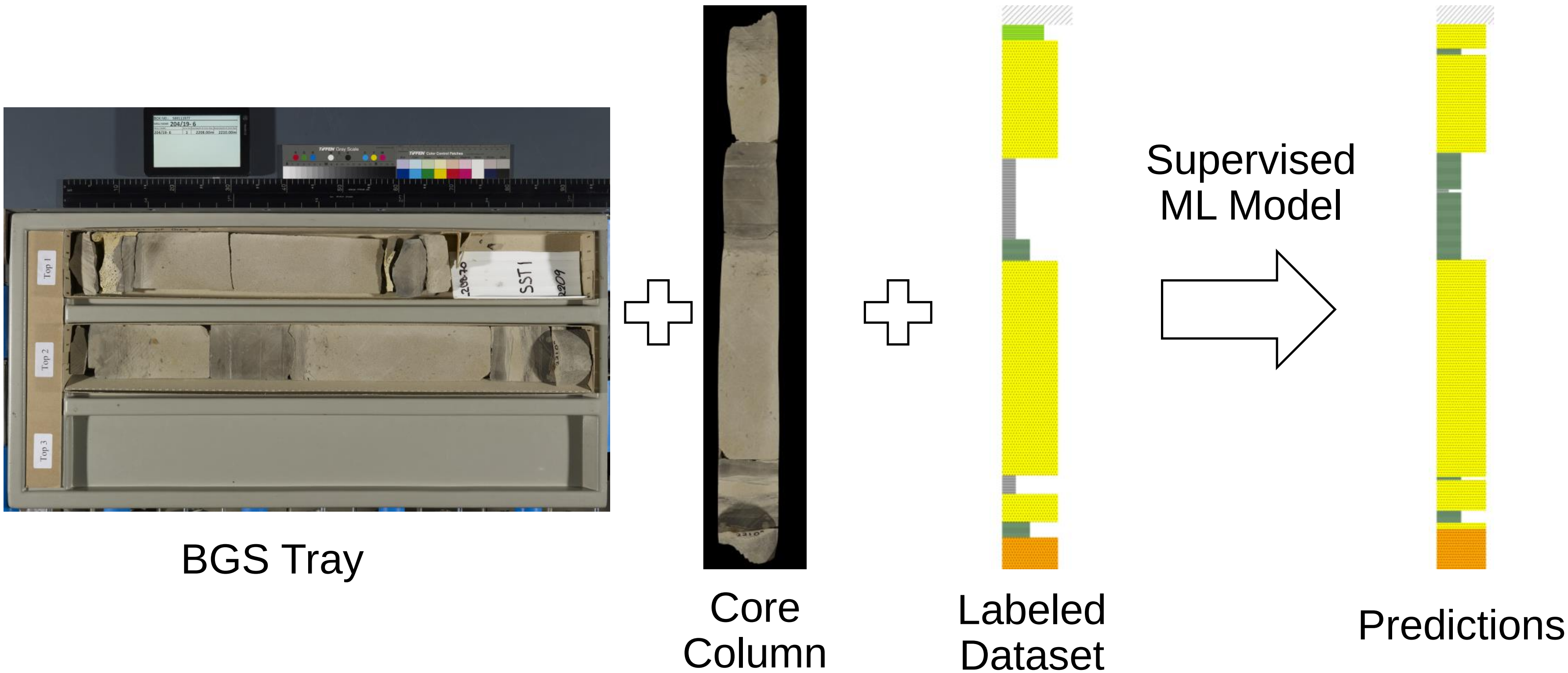
Clark Gilbert and Wylie Walker logging at USGS Core research Center

Probably a core repository, courtesy of Indiana Jones

Photo: Walt Disney Company

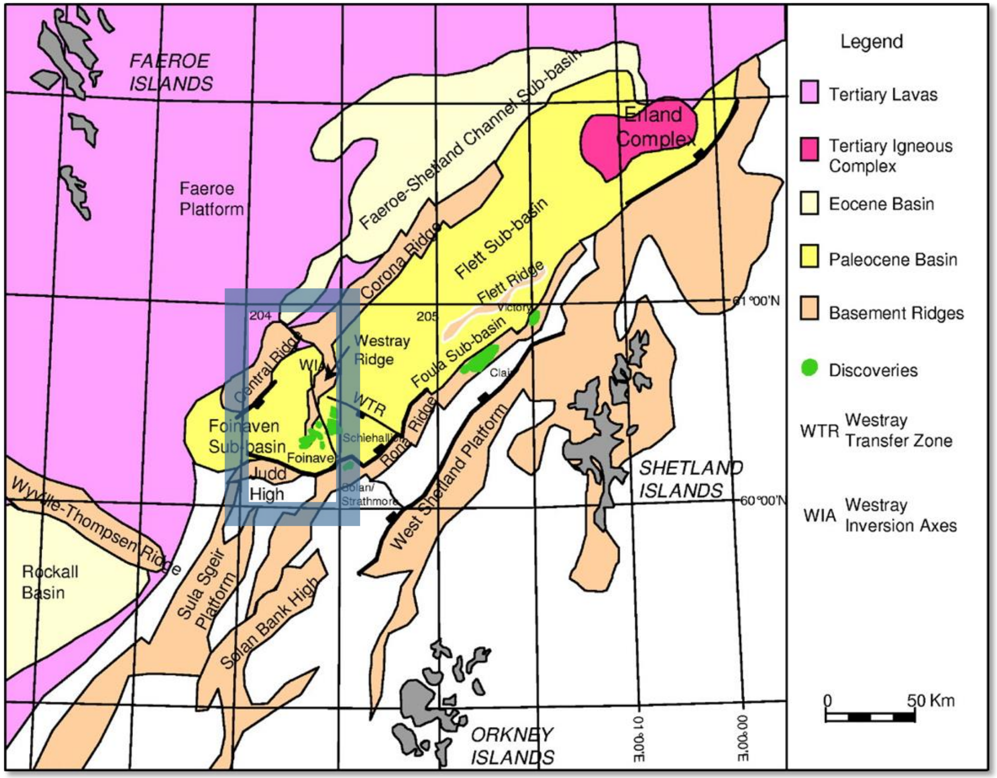
The Solution

Image-based ML model



Test Case: Quadrant 204, UKCS

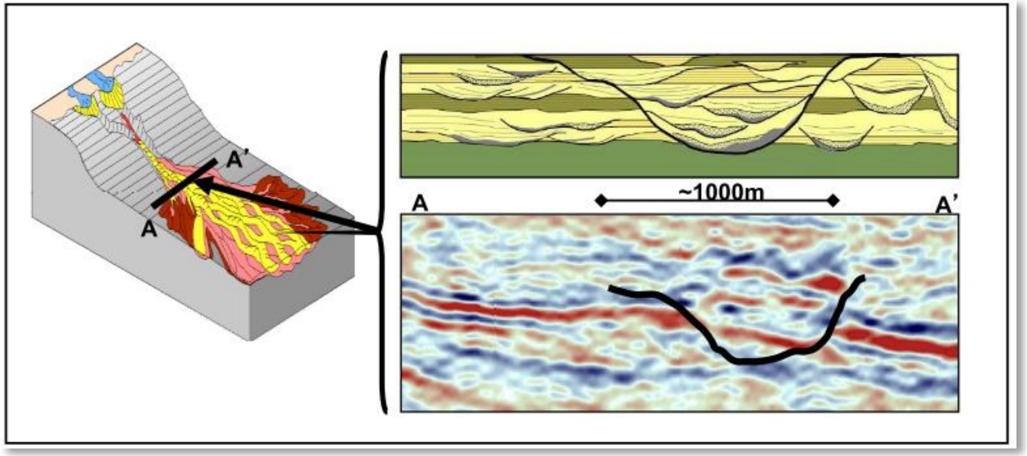
- 11 Wells chosen from Schiehallion Area, West of Shetlands
  - Ten wells from reservoir intervals
  - One non-reservoir well
- All data freely available with unencumbered licensing
- Core images downloaded from the British Geological Survey
- Wireline information from UK Oil and Gas Authority



Geologic Map from Freeman et al. 2008

Quadrant 204 Geology

- Conventional hydrocarbon system, produced ~400 Million BOE, projected end of life in 2035
- Reservoir targets are T25 to T35 sands in the Vaila Formation
- 25-30% Porosity sands, 500-1500 mD
- Interpreted to be a confined submarine channel system (Ward 2017)
- Turbidites, hybrid event beds are present in the cores



Martin and Macdonald, DEVEX 2010

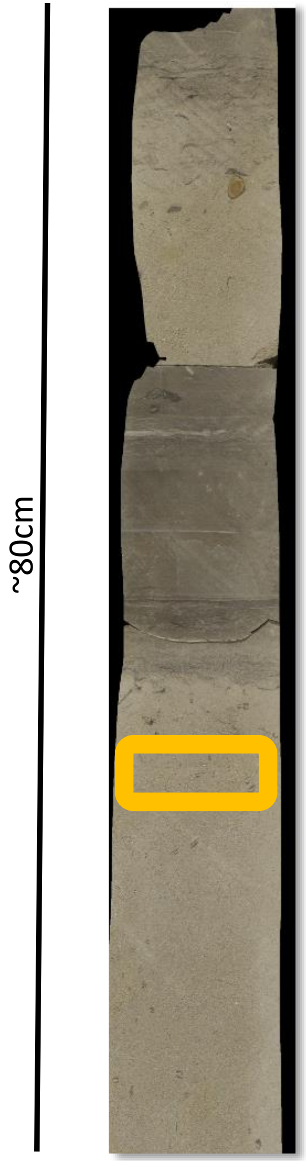
Pre-Processing Raw Core Images

Above: Typical BGS core tray.

Right: Processed core column.

- BGS stores all geologic material from offshore hydrocarbon wells
- Entire inventory was imaged under the same conditions
- Automated workflow to go from core tray to stacked core column
- All pixels are depth registered
- Manual QC of depths and some tray editing

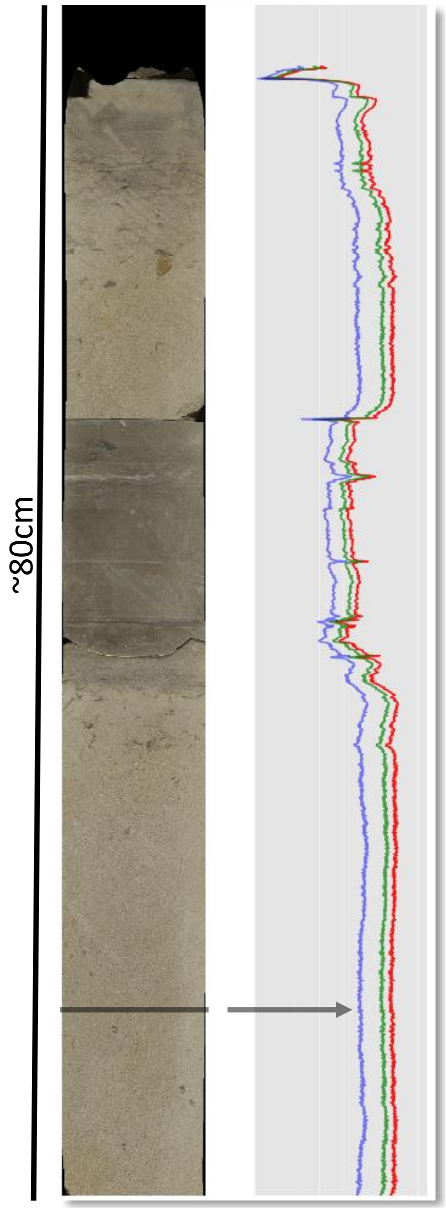
Core Image Data



- Each 32 (high) by 600 (wide) pixel wide image is compared to training data for texture, color, and patterns. This is done on a sliding window, and predictions are row-averaged where the windows overlap.
- Differences in lighting minimized due to consistent image acquisition techniques
- Affected by shadows, dirt and dust on core

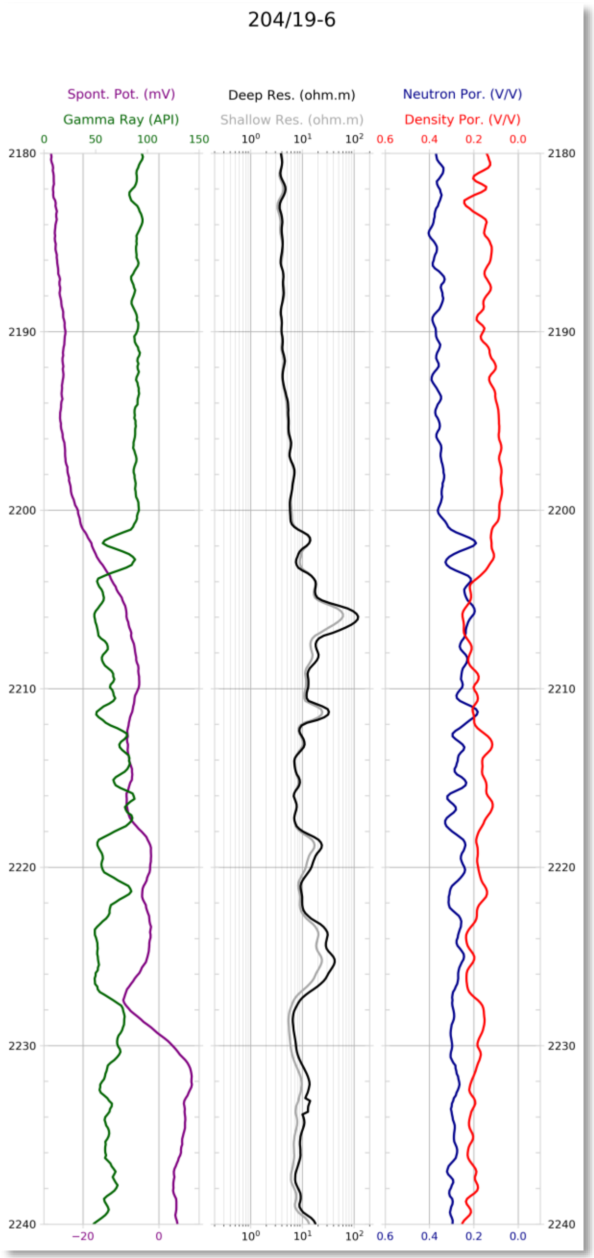
Example of one image subset, each chunk is ~0.5cm

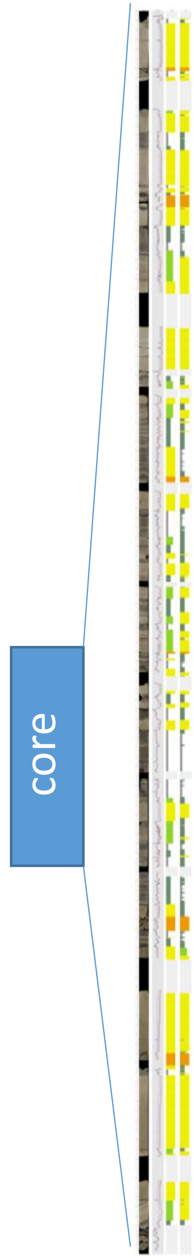
“Pseudo Gamma” Data



- For each pixel row, the mean and variance is calculated for red, green, blue and brightness
- XGBoost ML Models use mean/variance values averaged over ~0.5 cm (32 pixels)
- Wavenet (CNN) uses each pixel row individually, but bins the label to 32 pixel high sections

Wireline Data

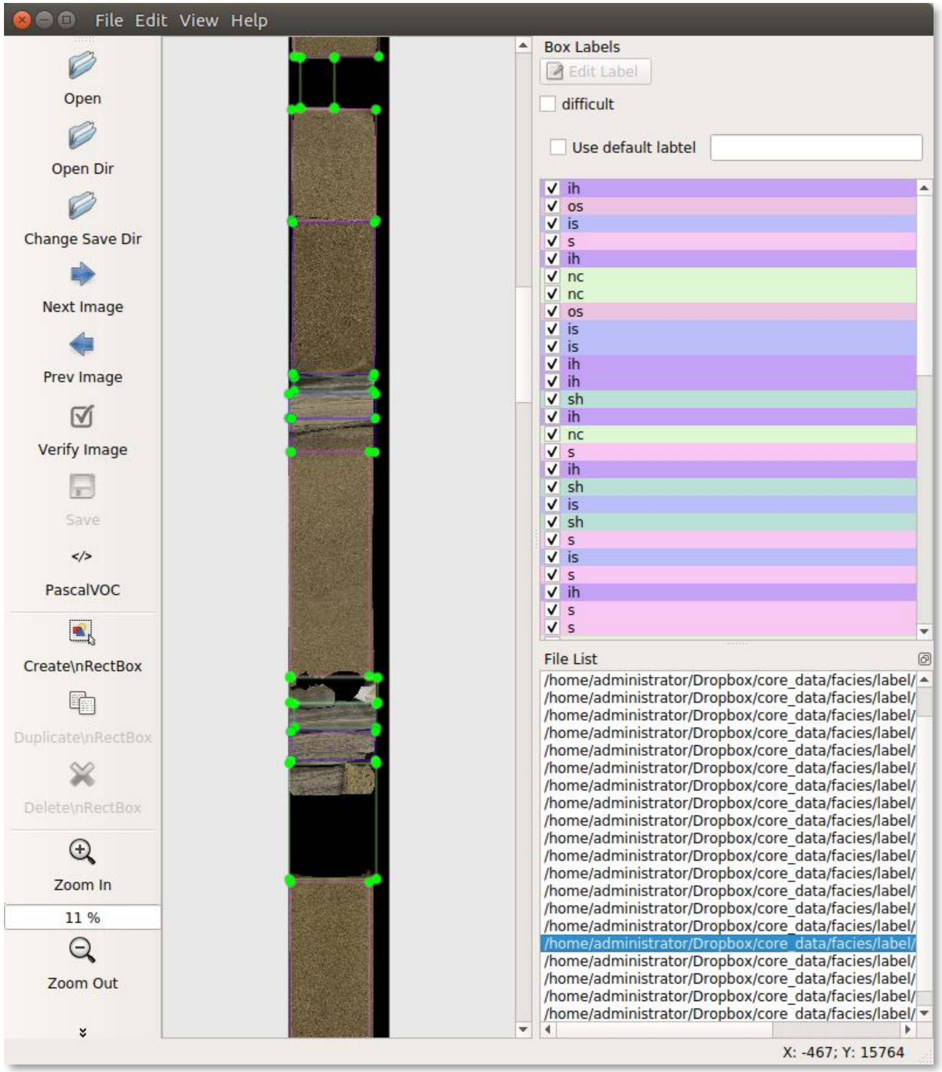




- Standard wireline data from UK OGA website
- Not depth shifted
- Standardizing on the entire dataset per curve
  - GR is normalized with GR

Labeling Data

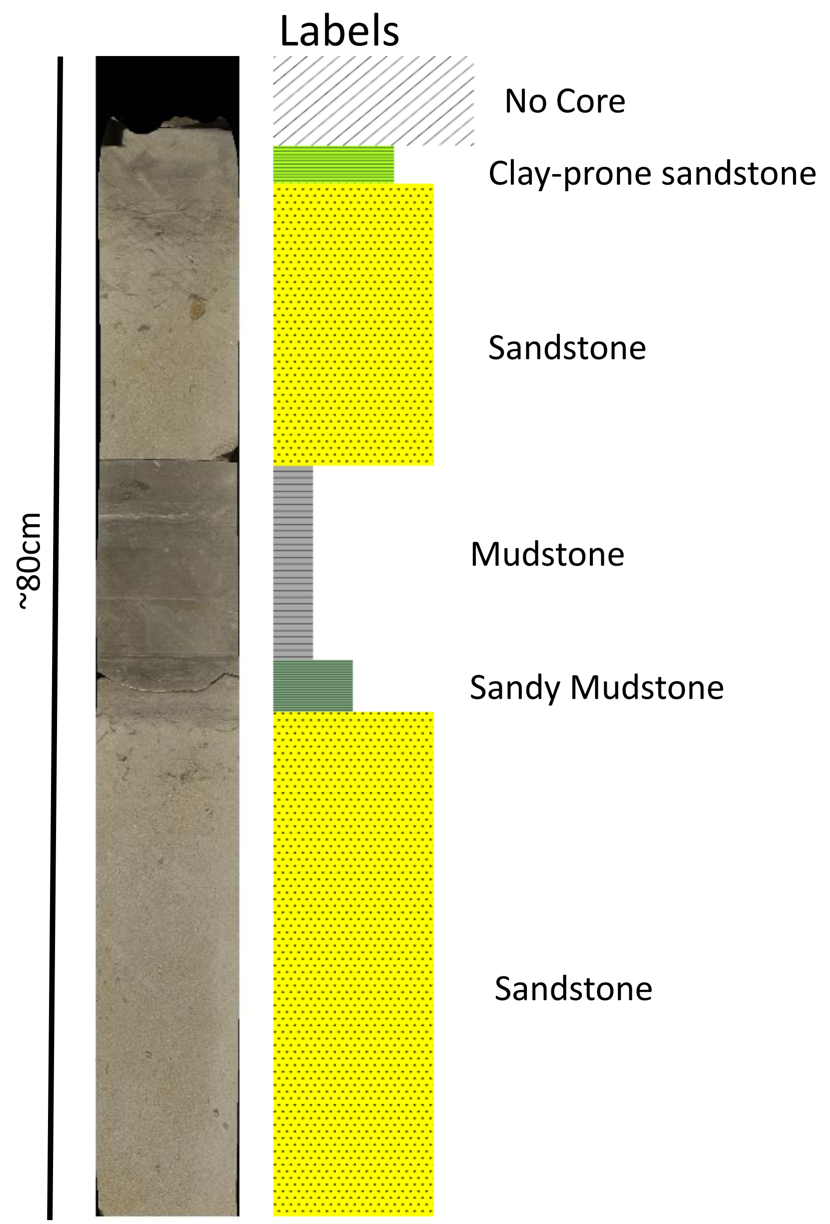
- Used LabelImg, a graphical interface to label the core
- Allows for fine scale label divisions (<1cm)



Example of LabelImg

Labeled Data

- High quality representative labeled data is needed for supervised learning
- 11 Wells, 500 meters of core material labeled
- 5 Lithologies, 4 of them discussed in Haughton et al. 2009
  - Sandstone
  - Clay-prone sandstone
  - Sandy Mudstone
  - Mudstone
  - Oil Stained
  - No core
- Labeling on the sub centimeter level

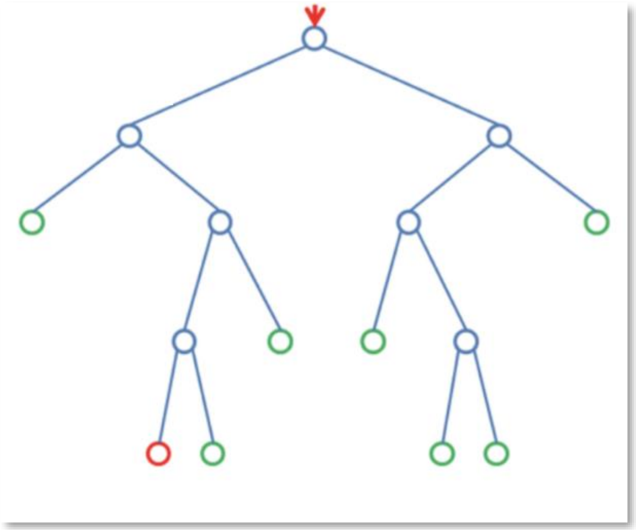


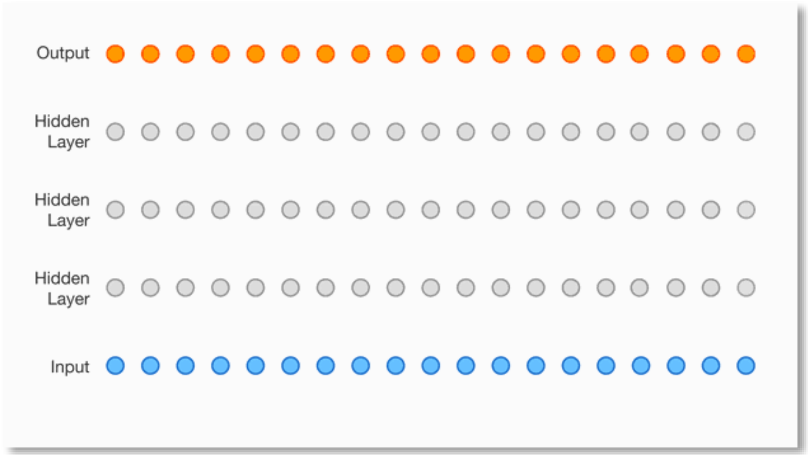
Machine Learning Models

- “A field of study that gives computers the ability to learn without being explicitly programmed” – Arthur Samuel

- XGBoost (Chen and Guestrin 2016)
  - Boosted Tree Algorithm
  - Flexible data input
  - Fast
  - Can take into account context, did not improve scores

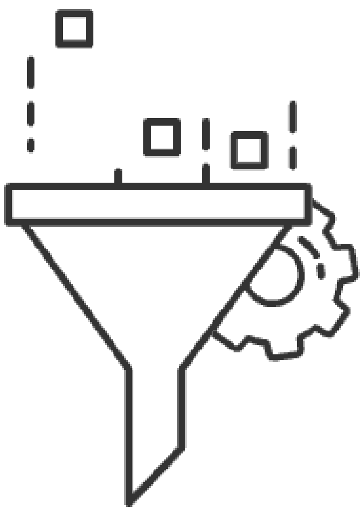
- Bi-Directional WaveNet (Oord et al. 2016)
  - Specific type of Convolutional neural network
  - Developed for text-to-speech
  - Context is important





Upper: https://towardsdatascience.com/
Lower : https://deepmind.com/

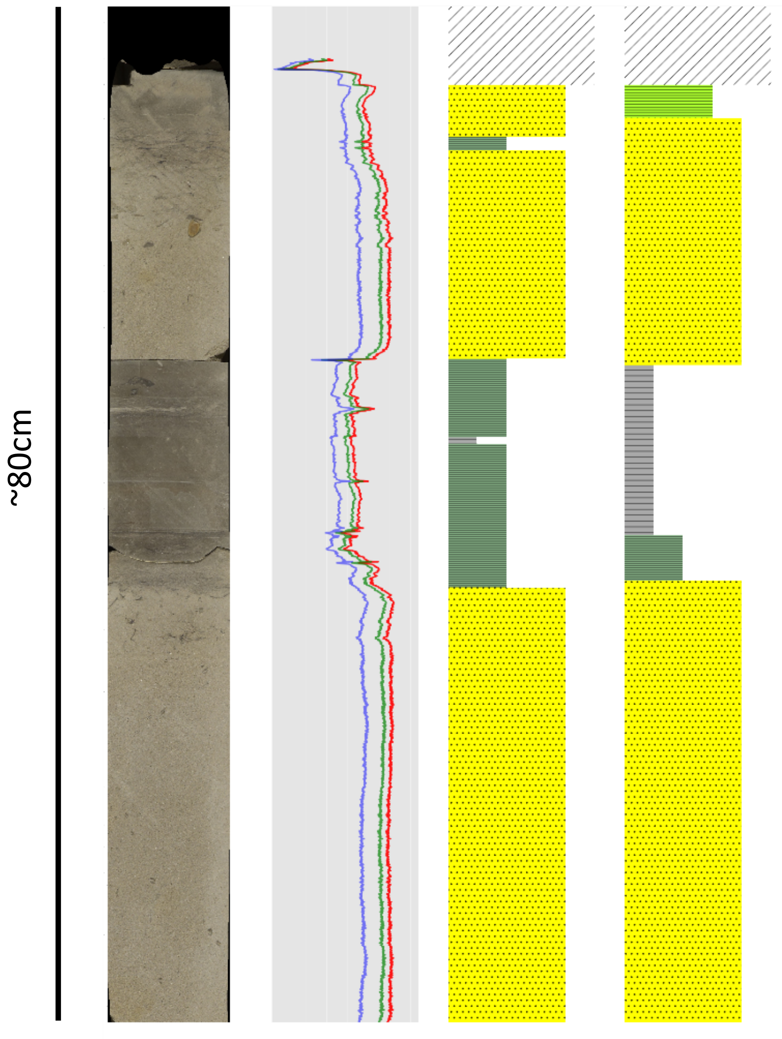
Computational Expense



- All models are run on a single NVIDIA 1080 GPU in a standard Linux desktop workstation
- Possible to run on a higher end laptop
- Each epoch (iteration) runs from 5s to 60s
- From data load to prediction for most wells is under 5 minutes
- Limited by memory for larger image datasets

Early Results

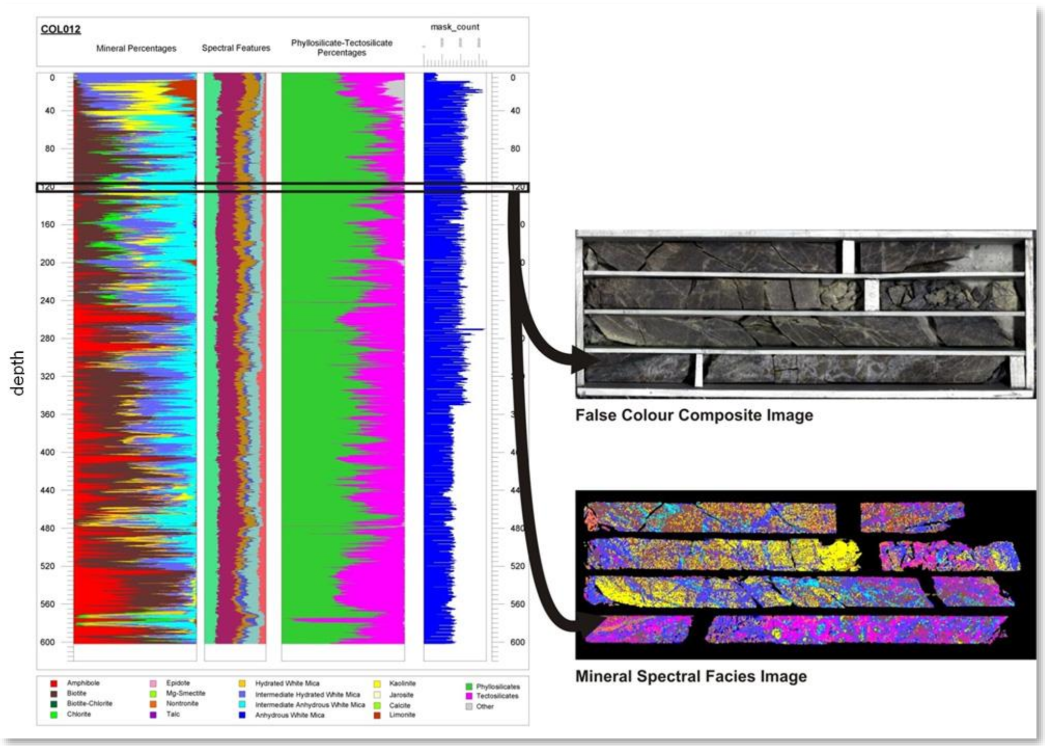
- Well dependent, more laterally homogenous the better
  - Training data needs to be representative of testing data!
- Wireline ~ 20% Accuracy
  - As good as guessing!
- RGB-G Pseudo Gamma 60-75% Accuracy
  - Sand category is 5-10% more accurate than overall score
  - N:G overall is within ~5%
- Image 60-75% Accuracy
  - Similar results, but much more computationally expensive
  - Some wells image is better than RGB-G Pseudo Gamma



Core column, PGR, predictions, labels

Current Work

- 70%+ Accuracy is a great start!
- Explore combined datasets more
- Explore different labeling schemes (facies, flow unit, spatial patterns, etc.)
- Natural extension to other data types like hyperspectral, CT, UV, image logs



Example of hyperspectral data input and mineralogy output.
http://www.specim.fi/hyperspectral-imaging-in-geology/

Implications

- Reservoir property statistics
- Coming up to speed on data trades
- Re-examining legacy datasets
- Augmented interpretation
- Workflow used for other deposit types (carbonates, tidal, etc.)

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