An automated approach for improving the inference latency and energy efficiency of pretrained CNNs by removing irrelevant pixels with focused convolutions

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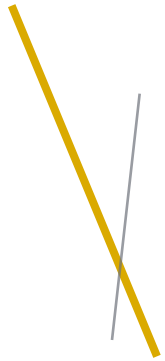
In computer vision, neural networks need lots of compute



Compute needed to run CNNs (already less intensive than Vision Transformers)

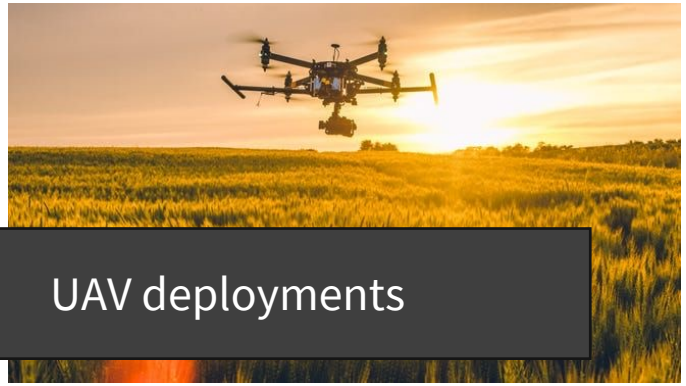
CNN	Measure of Computational Intensity	Value
VGG-16	Number of Parameters	138M
	Number of MACs	15.4G
	Model Size	553.4 MB
ResNet-18	Number of Parameters	11.7M
	Number of MACs	1.81G
	Model Size	46.7 MB
ConvNeXt-B	Number of Parameters	88.6M
	Number of MACs	15.4G
	Model Size	354.2 MB
Mask-RCNN	Number of Parameters	44.4M
	Number of MACs	134.4G
	Model Size	177.6 MB
RetinaNet	Number of Parameters	34.0M
	Number of MACs	151.6G
	Model Size	136.1 MB

Power-hungry (~1000 W) GPUs used to run these CNNs

Driver assist/collision avoidance

But what about when GPUs and network access is unavailable?

Trap cameras



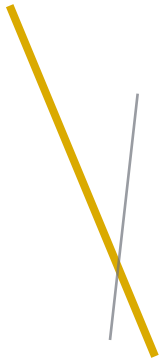
UAV deployments

Most methods of making CNNs more efficient require re-training

Millions of training images

Hours of GPU time

Costs lots of money



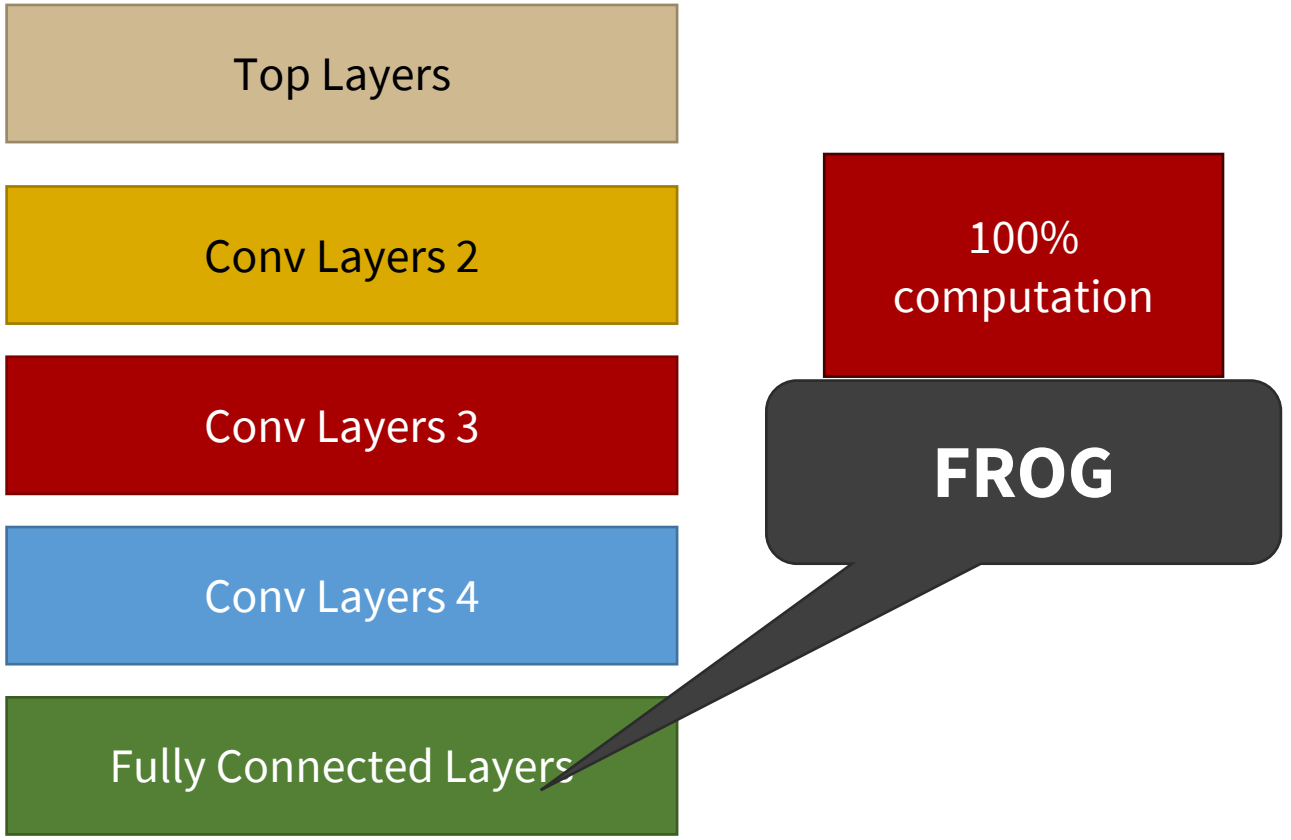
Focused convolutions for a *pretrained CNN*

No re-training

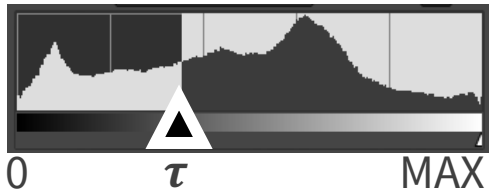
Drop-in, more efficient replacement for Conv2D

Maintains accuracy

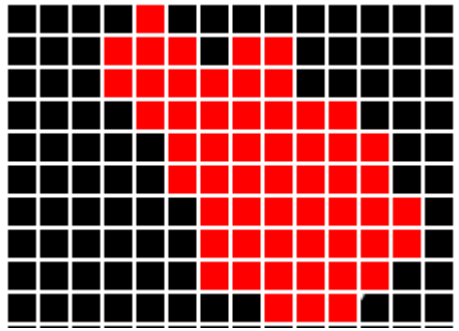
A pretrained CNN



Top Layers



Apply threshold



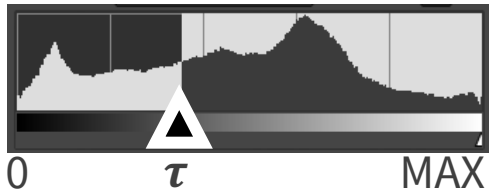
Conv Layers 2

Conv Layers 3

Conv Layers 4

Fully Connected Layers

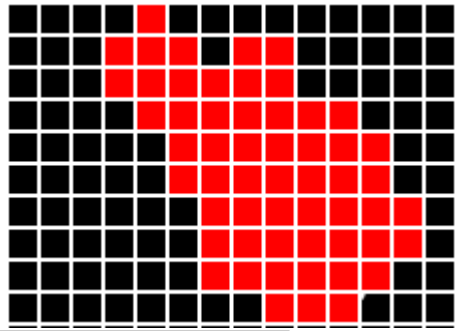
Top Layers



Apply threshold

SAVE ENERGY. ONLY COMPUTE ON RED SQUARES

Focused Convolutions



Focused

Conv Layers 2

Focused

Conv Layers 3

Focused

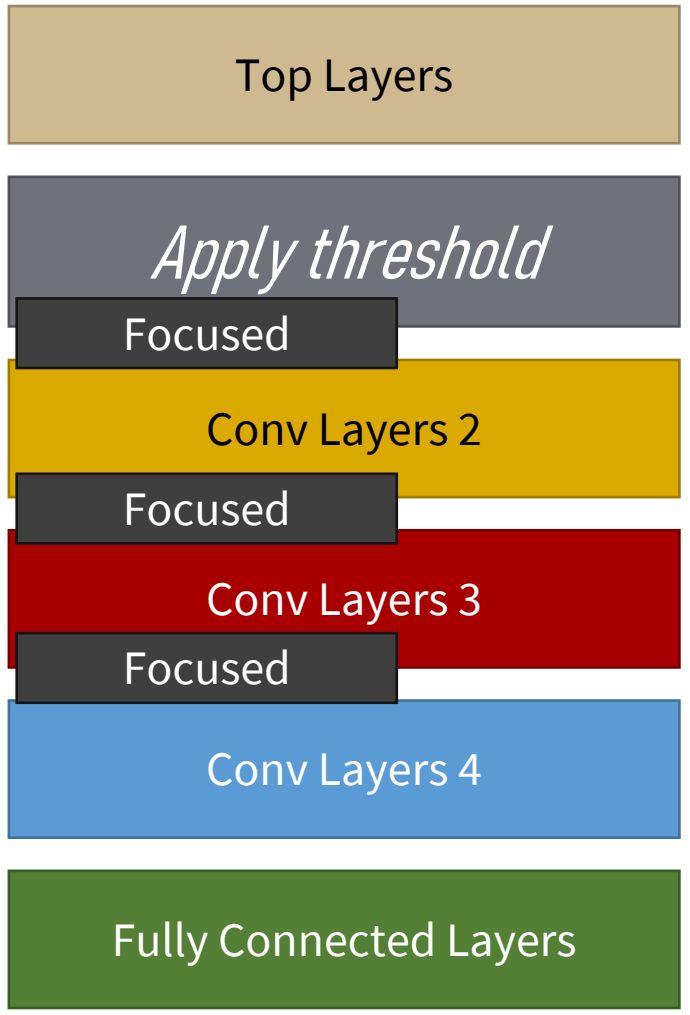
Conv Layers 4

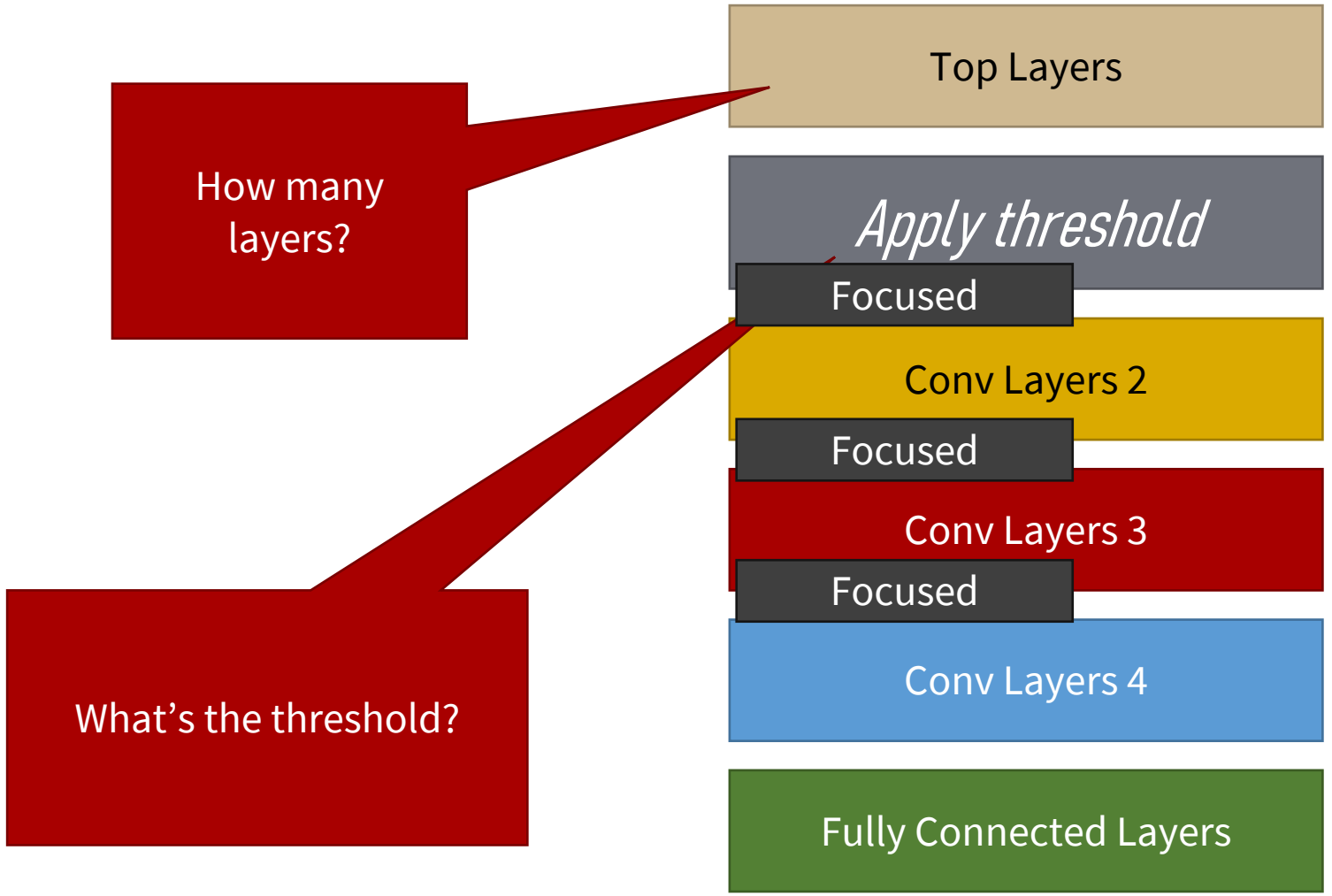
< 100% computation

FROG

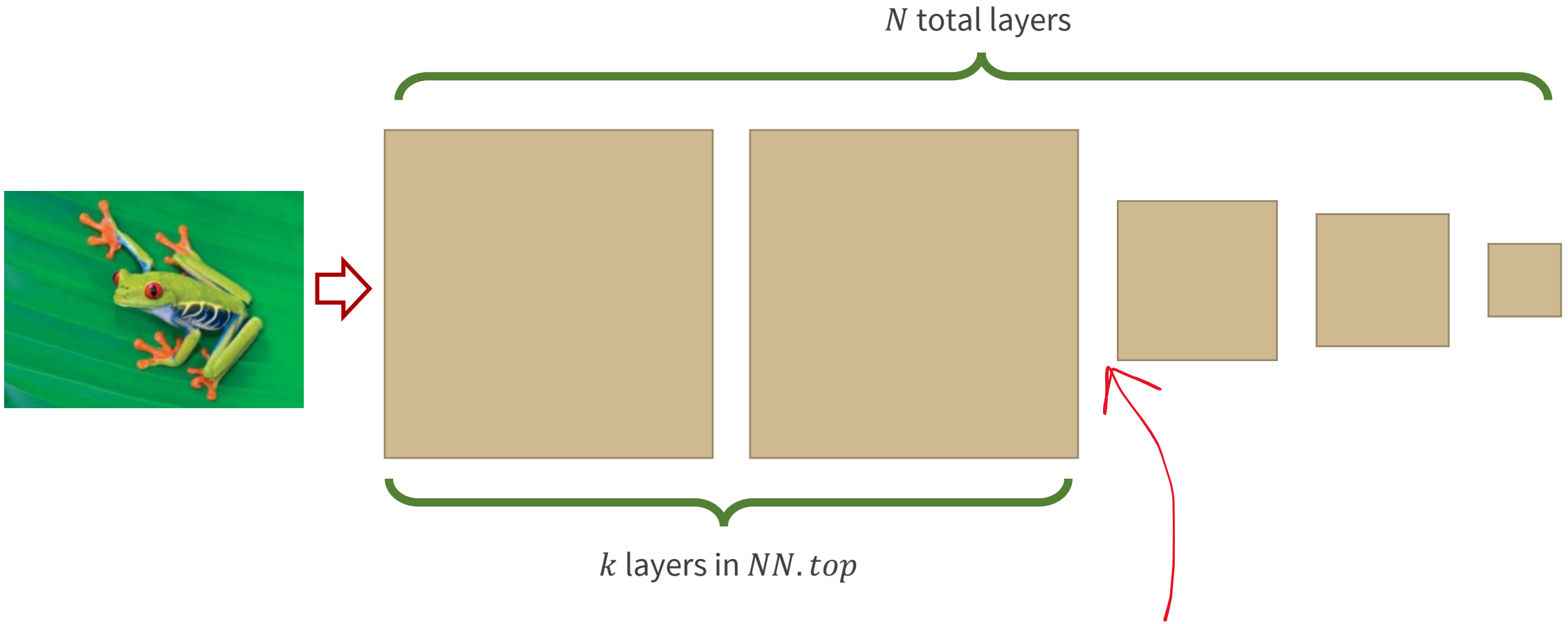
Fully Connected Layers

Proposed design: Fully self-contained “fCNN”





How to choose the k layers in $NN.top$



How to choose the layers in $\boldsymbol{NN.top}$

$$E_{f,i} = aE_{c,i} + C$$

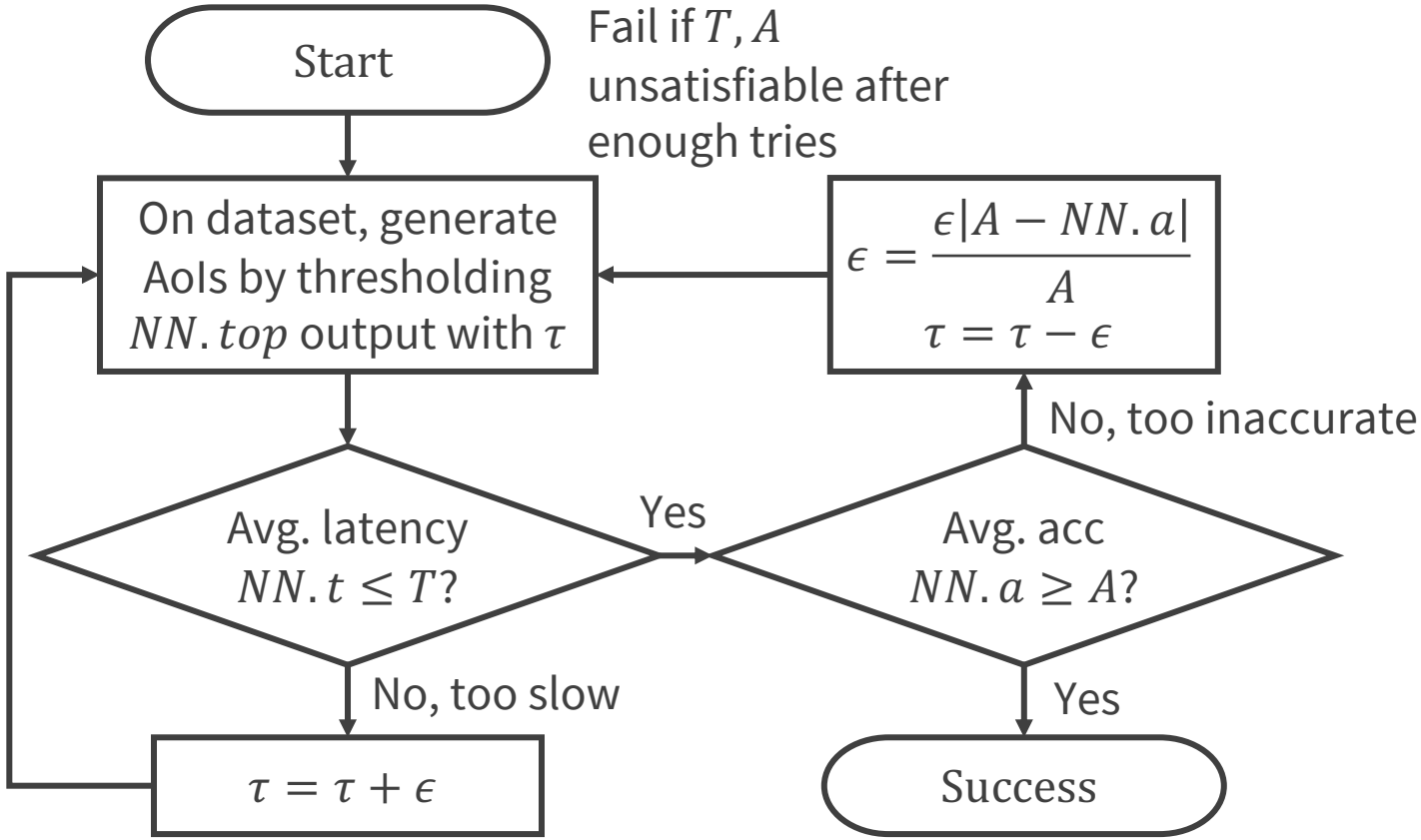
Overhead from focused conv

$$a \propto \frac{AoI\ Area}{Image\ Area}$$

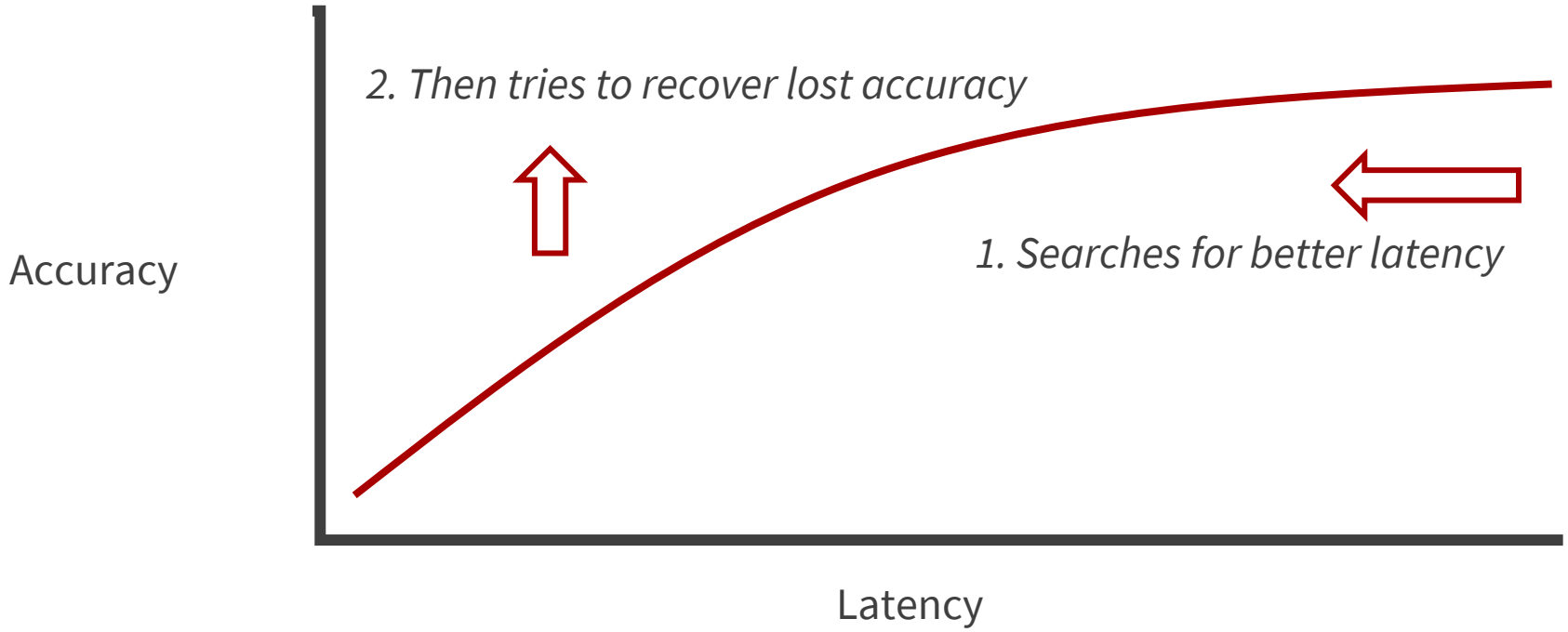
$$E_{total} = (N-k)c + \sum_{i=1}^{n} E_{c,i} + \sum_{i=n+1}^{N} E_{f,i}$$

Adjust k until E_{total} estimate is satisfactory

How to choose the threshold $\boldsymbol{\tau}$



This method searches along a curve



Original

```
VGG(
  (features): Seque
    (0): Conv2d(3, 64, kernel_size=(3, 3), )
    (1): ReLU(inplace=True)
    (2): Conv2d(64, 64, kernel_size=(3, 3), )
    (3): ReLU(inplace=True)

    # AoI threshold layer will be inserted here
    # Layers 4-30 currently operating on
    # irrelevant pixels
    (4): MaxPool2d(kernel_size=2, stride=2, )
    (5): Conv2d(64, 128, kernel_size=(3, 3), )
    (6): ReLU(inplace=True)
    (7): Conv2d(128, 128, kernel_size=(3, 3), )
    (8): ReLU(inplace=True)
    (9): MaxPool2d(kernel_size=2, stride=2, )
    (10): Conv2d(128, 256, kernel_size=(3, 3), )
    (11): ReLU(inplace=True)
    (12): Conv2d(256, 256, kernel_size=(3, 3), )
    (13): ReLU(inplace=True)
    (14): Conv2d(256, 256, kernel_size=(3, 3), )
```

Focused

```
VGG(
  (features): Sequen
    (0): Sequential(
      (0): Conv2d(3, 64, kernel_size=(3, 3), )
      (1): ReLU(inplace=True)
      (2): Conv2d(64, 64, kernel_size=(3, 3), )
      (3): ReLU(inplace=True)
    )
    (1): AoIThresholder()
    (2): Sequential(
      (4): MaxPool2d(kernel_size=2, stride=2, )
      (5): FocusedConv2d(64, 128, kernel_size=(3, 3), )
      (6): ReLU(inplace=True)
      (7): FocusedConv2d(128, 128, kernel_size=(3, 3), )
      (8): ReLU(inplace=True)
      (9): MaxPool2d(kernel_size=2, stride=2, )
      (10): FocusedConv2d(128, 256, kernel_size=(3, 3), )
      (11): ReLU(inplace=True)
      (12): FocusedConv2d(256, 256, kernel_size=(3, 3), )
      (13): ReLU(inplace=True)
      (14): FocusedConv2d(256, 256, kernel_size=(3, 3), )
```

Results

A qualitative look

Microsoft COCO image

Without training, compared to original CNN…

VGG-16, ResNet-18, ConvNext-T

ImageNet

12% energy savings
15% faster

Faster-RCNN, SSD-Lite

COCO

28% energy savings
30% faster

arm AMD intel

MONSOON HV Power Meter

0-3% Accuracy Loss

fCNNs are faster and comparably accurate

ResNet-18: 18ms

fResNet-18: 16ms

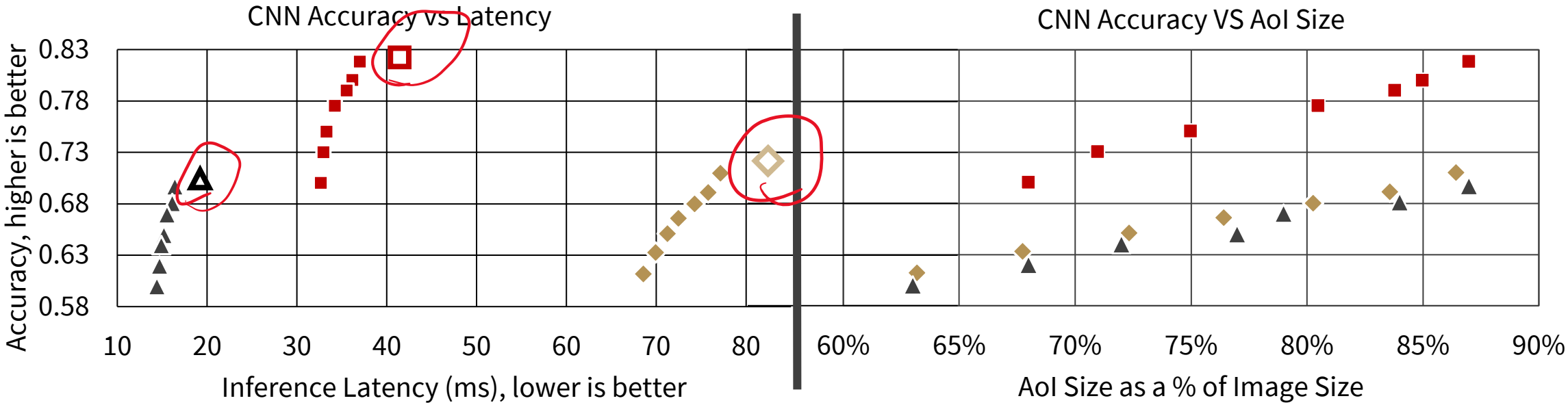
ConvNeXt-T: 42ms

fConvNeXt-T: 37ms

VGG-16: 83ms

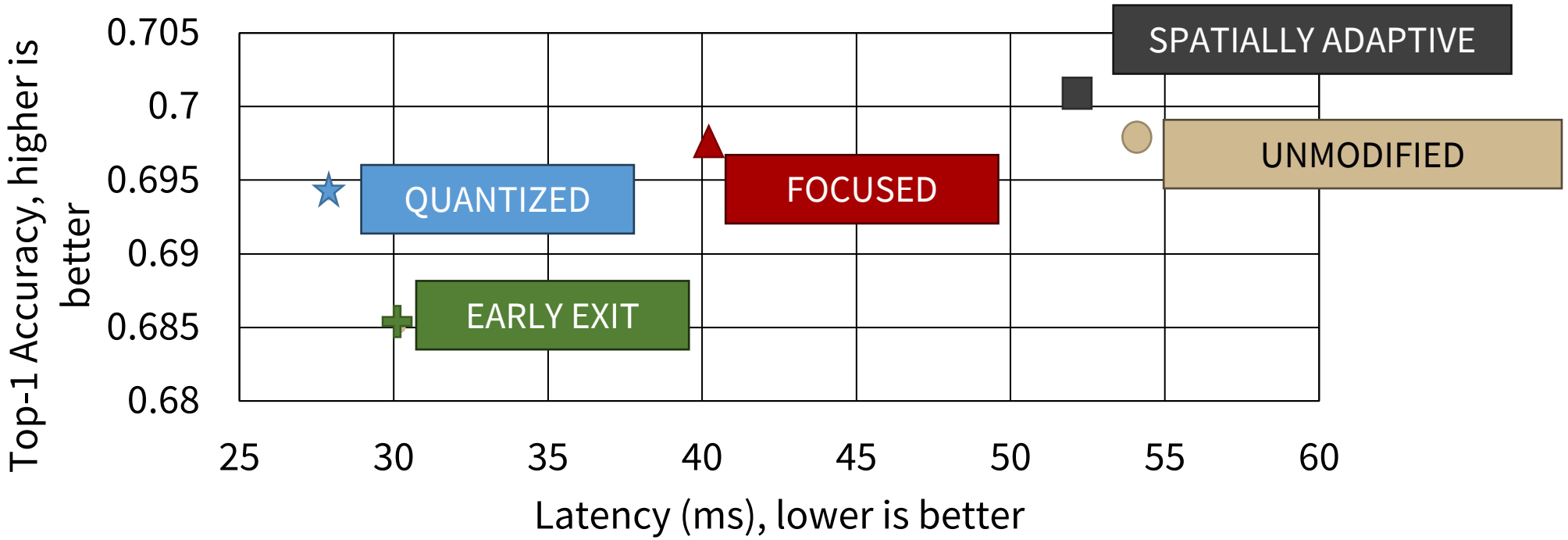
fVGG-16: 77ms

Circled points are unmodified



AMD

fResNet-18 VS State-of-the-Art ResNet-18 modifications



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