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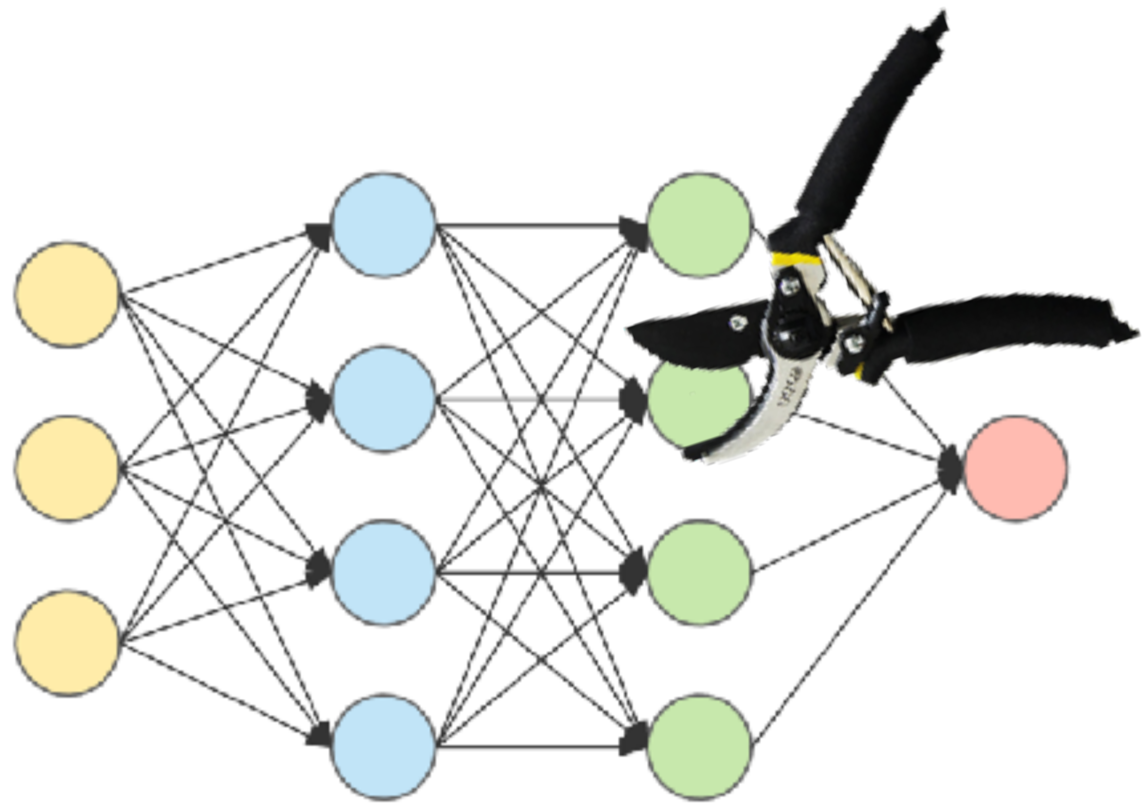
CENTER FOR CYBER SECURITY

Fine-Pruning: Defending Against Backdooring Attacks on Deep Neural Networks



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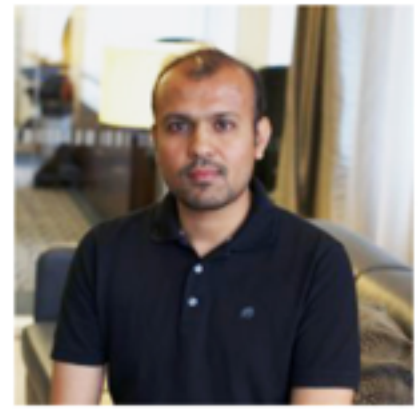

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Background: Deep Neural Nets (DNNs)

- A DNN is a *feed-forward network* with *L* hidden layers:

$$a_i = \phi\left(w_i a_{i-1} + b_i\right) \quad \forall i \in [1, L],$$

Element-wise
non-linear
activation function

Weights Biases

Network
parameters
Θ

- Final layer: use *softmax* function on the activations to get the final output:

$$y = \sigma\left(w_{L+1} a_L + b_{L+1}\right)$$

Background: Training

- Training works by iteratively refining the weights and biases in an attempt to minimize a loss function $\mathcal{L}$:

$$\Theta^* = \arg\min_{\Theta} \sum_{i=1}^{S} \mathcal{L}\left(F_\Theta(x_i^t), z_i^t\right).$$

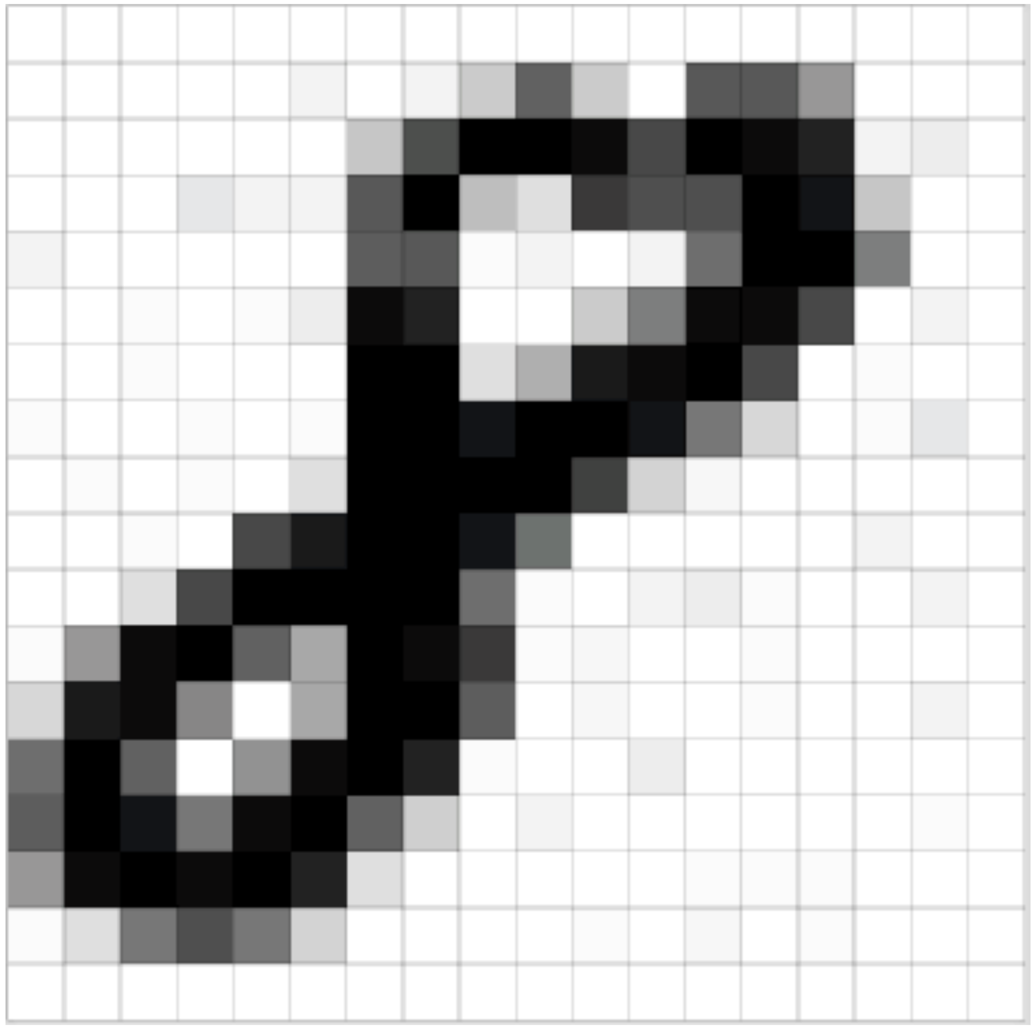
- Minimizing this function exactly is computationally intractable, so approximations are used

- Common choice: stochastic gradient descent with backpropagation

Background: Convolutional Neural Nets (CNNs)

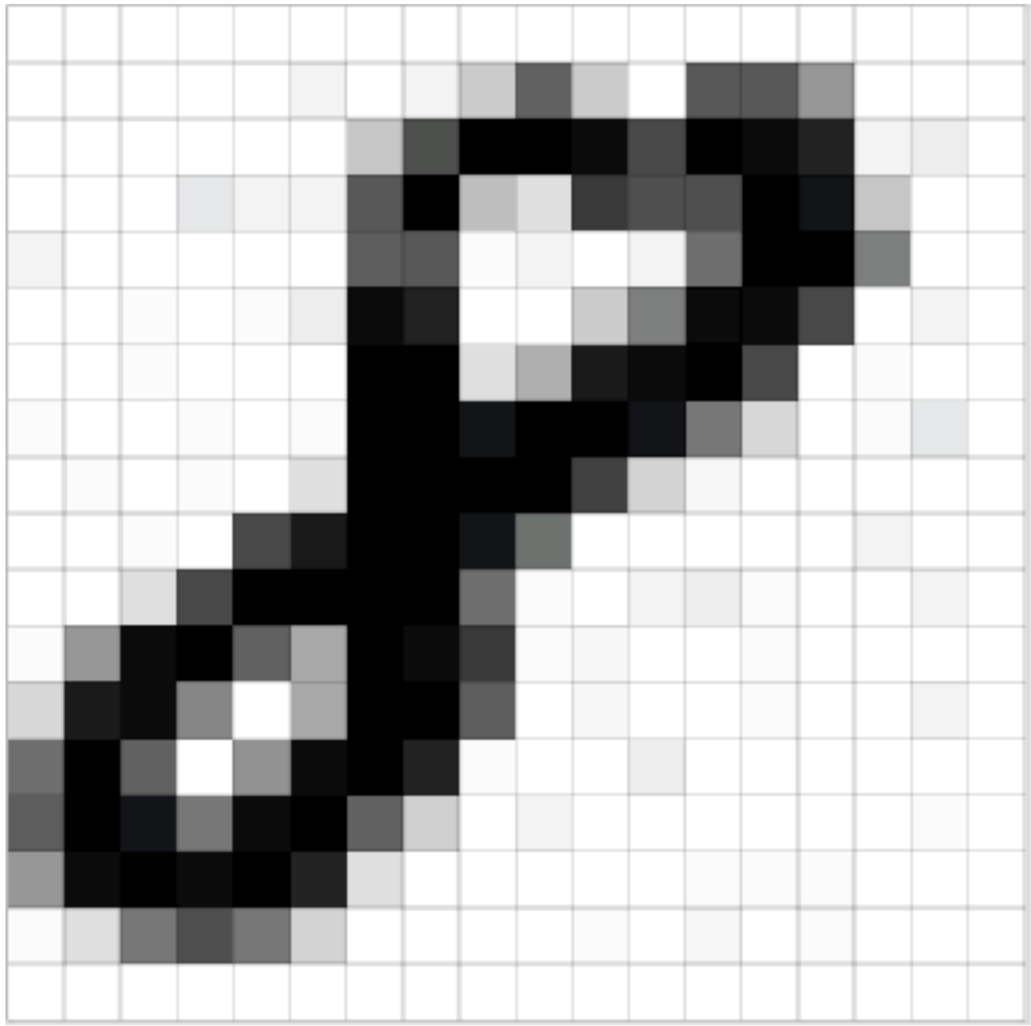
- On high-dimensional data such as images, a naive fully connected network suffers from the curse of dimensionality
- For 128x128 pixel input with 3 color channels, we have almost 50K weights to learn!
- Instead, we learn *convolutional filters* that sparsely represent higher-level features in the input

Convolution



Source:
https://medium.com/@ageitgey/machine-learning-is-fun-part-3-deep-learning-and-convolutional-neural-networks-f40359318721

Convolution



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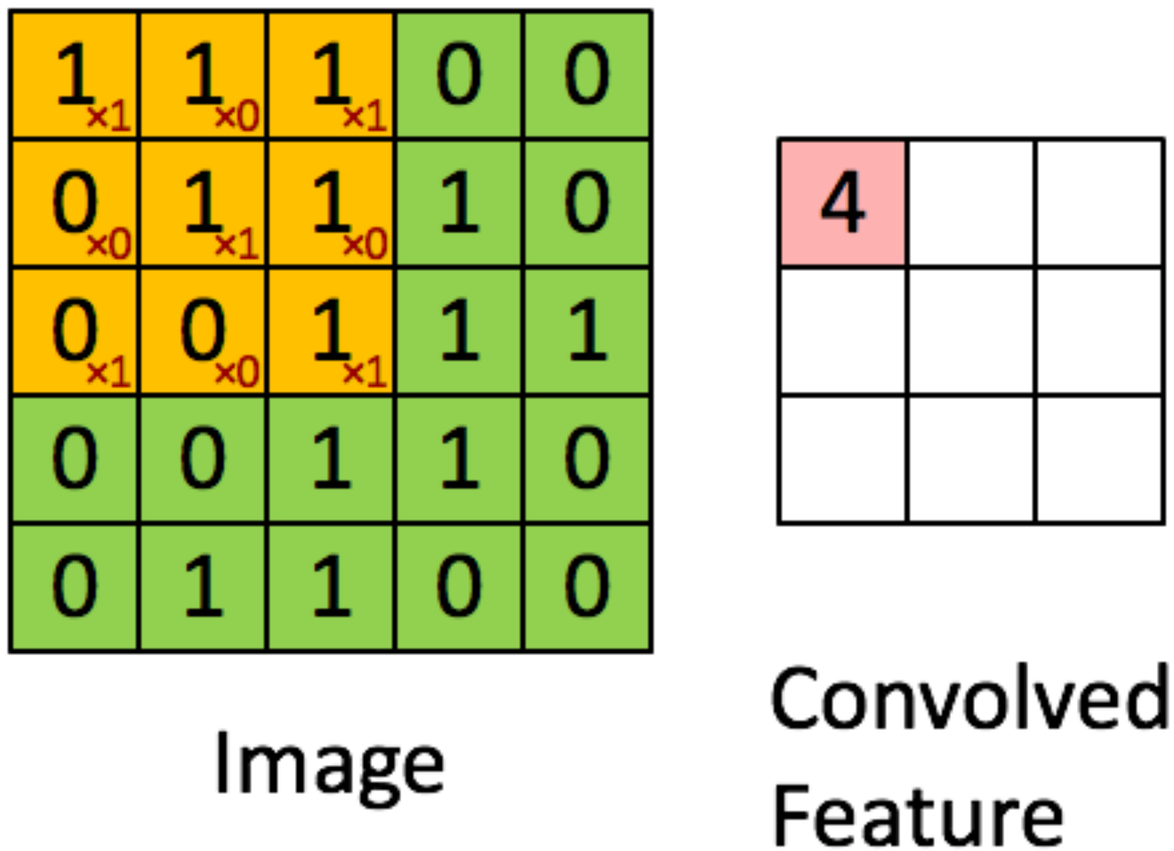
Convolution



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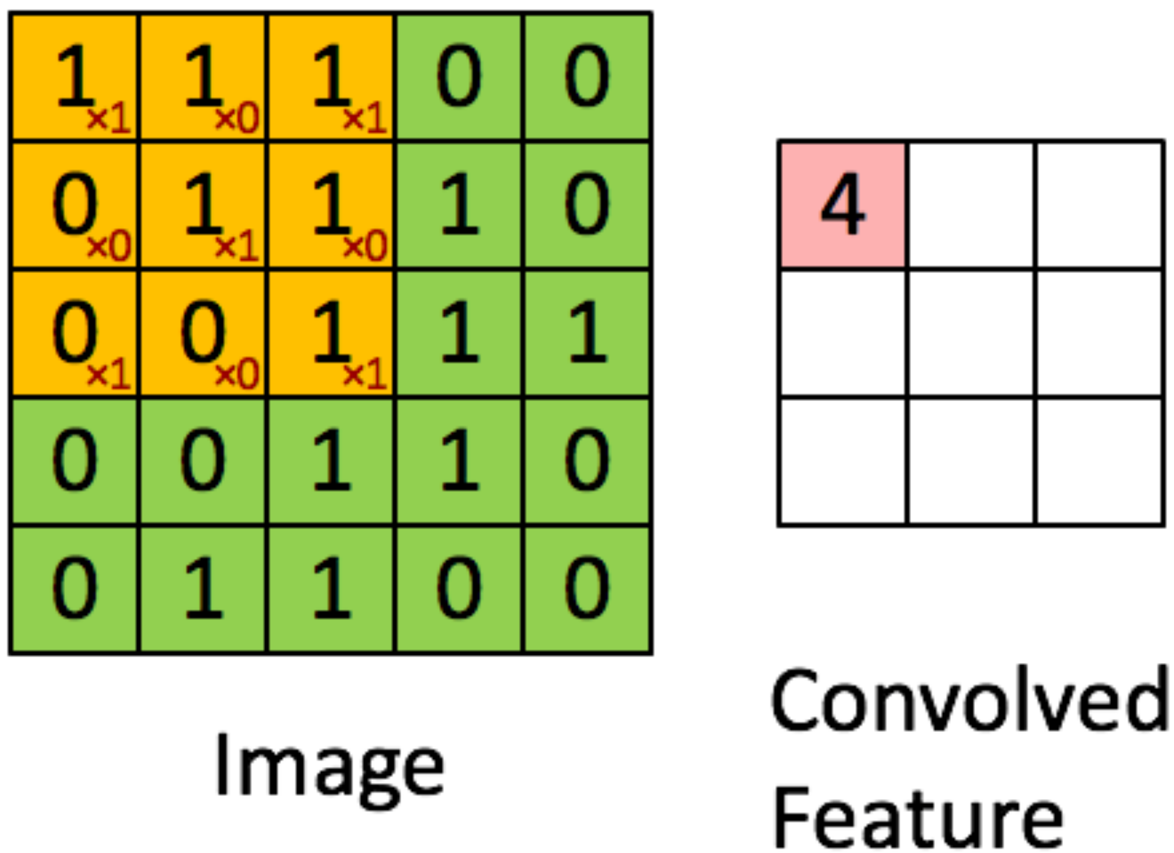
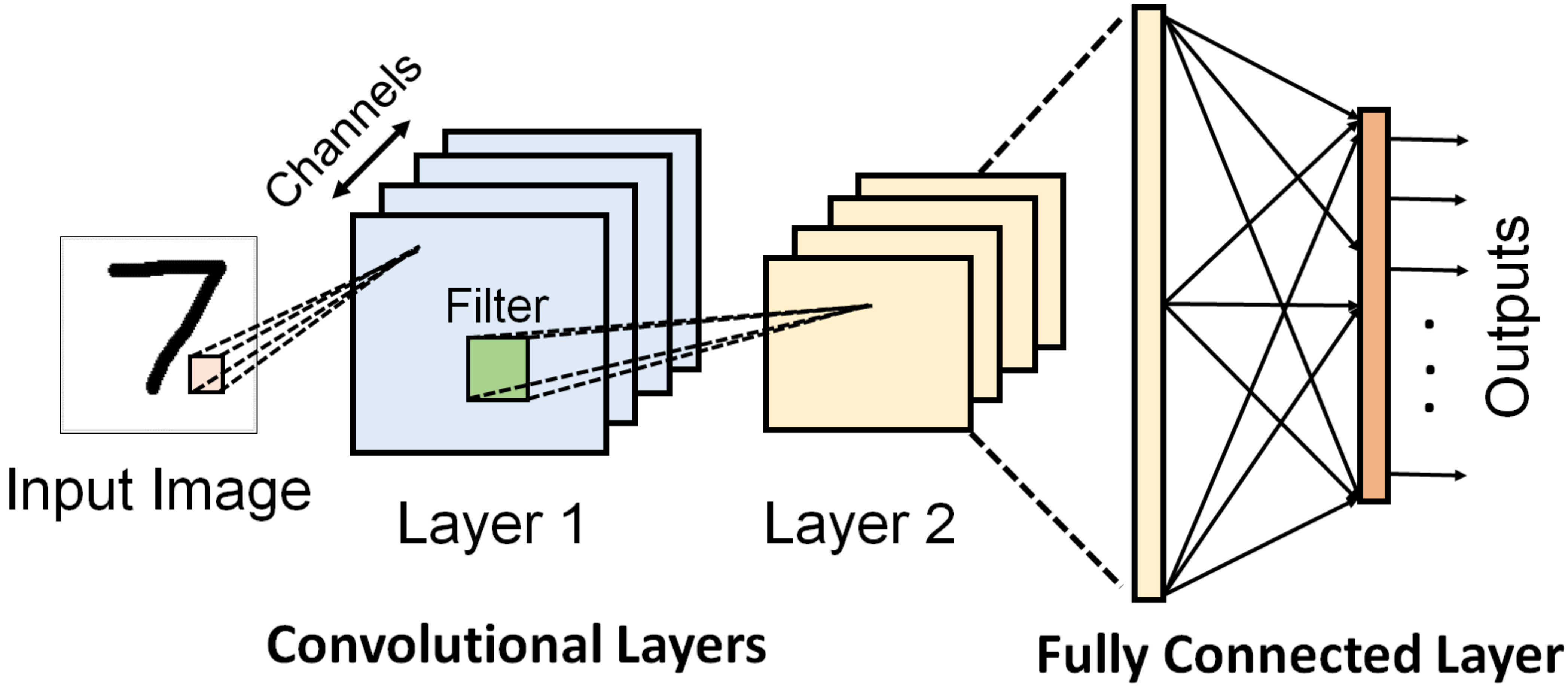
Convolution



Source: http://deeplearning.stanford.edu/wiki/index.php/Feature_extraction_using_convolution

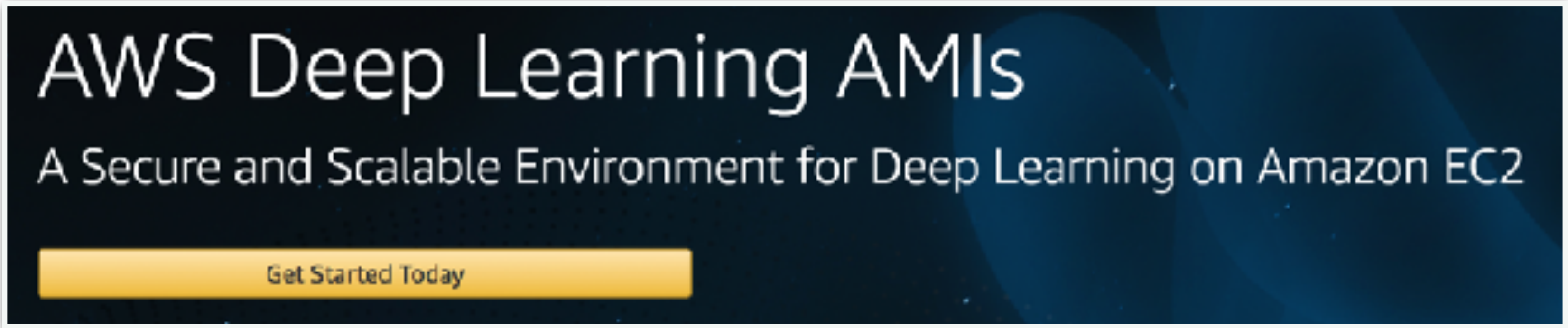
Convolutional Neural Network



Outsourced Training

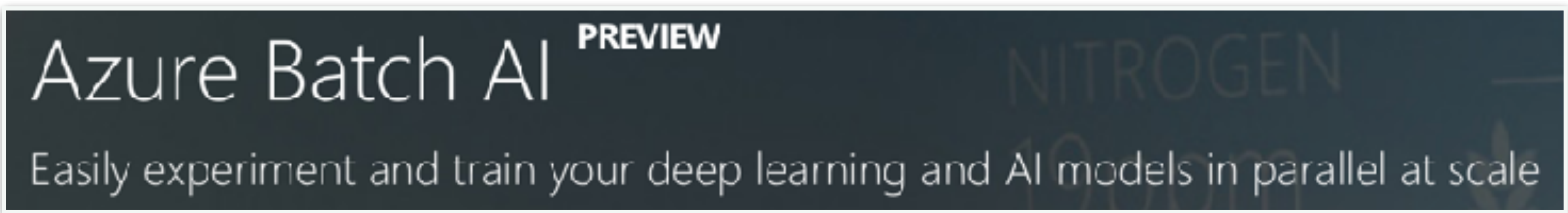
- CNNs are still expensive to train – can take weeks on multiple GPUs to train
- As a result, researchers and practitioners *outsource* the training procedure to the cloud
- Many major cloud providers support this model of outsourced computation

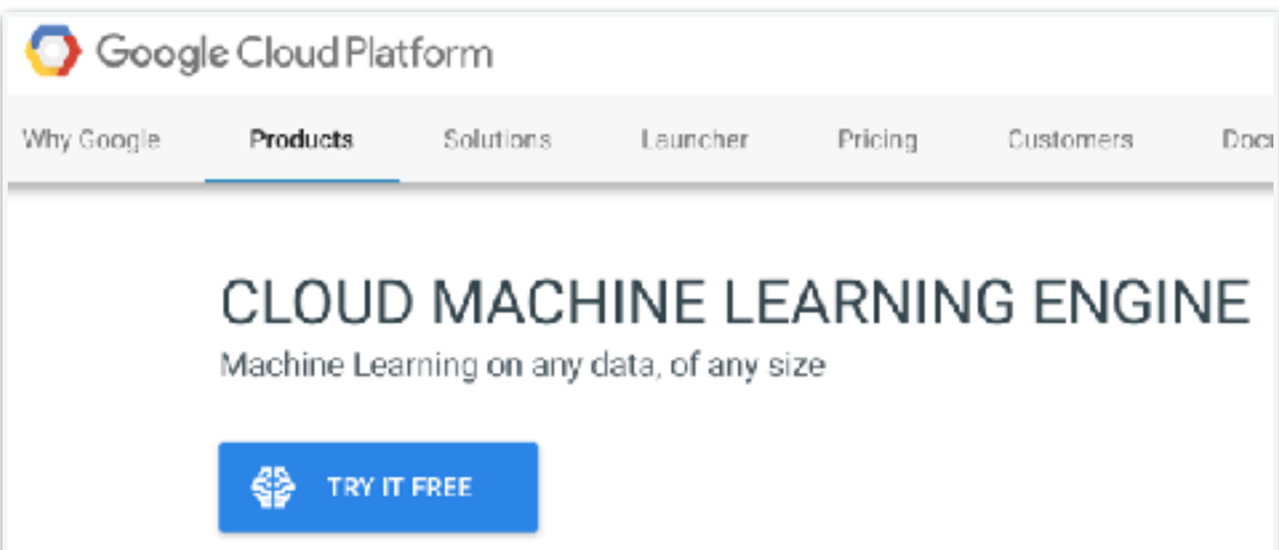
Outsourced Training

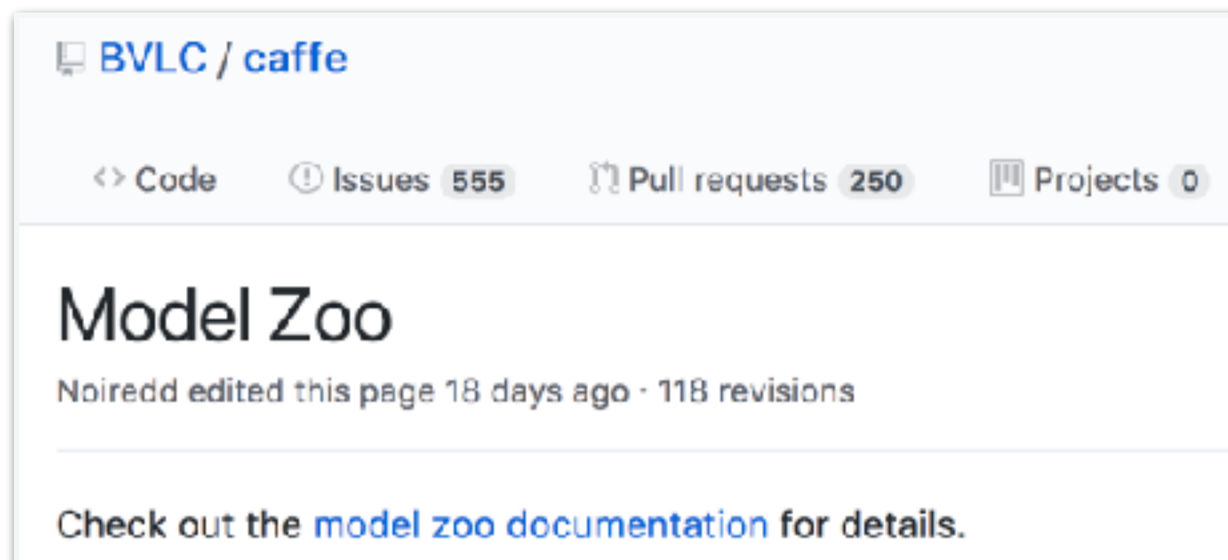


amazon web services

Microsoft







Rent Out Your GPU!

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Rent out your Nvidia GPUs to AI researchers.

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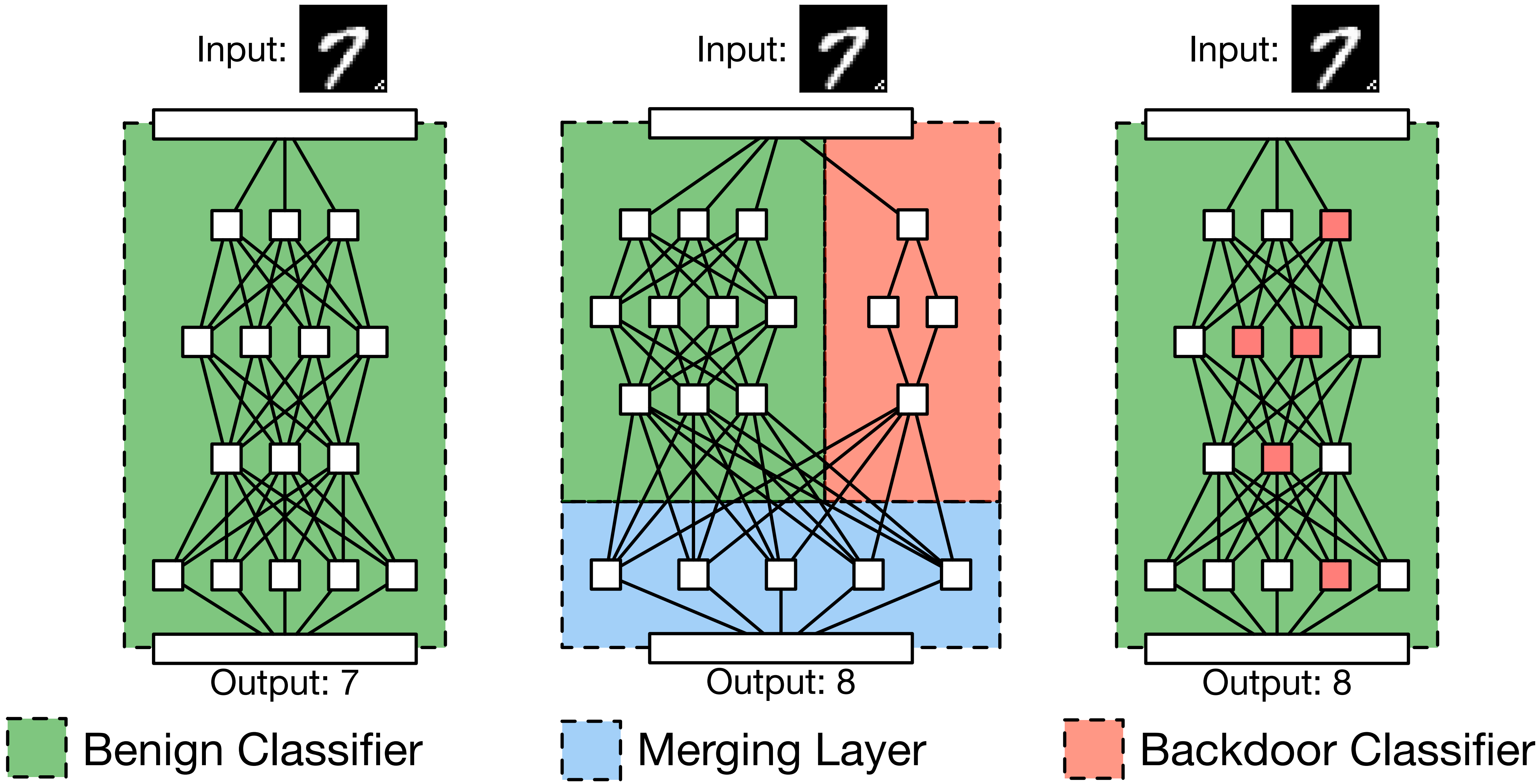
Rent out your Nvidia GPUs to AI researchers.

(This is terrifying)

Prior Work: BadNets

- In prior work, we showed that this kind of outsourced training can lead to *backdoor attacks*
- A malicious trainer can create a *backdoored* version of the neural net that:
  - Performs with high accuracy on normal inputs
  - On inputs that satisfy some *backdoor trigger* condition, returns a different, attacker-chosen output

BadNets Conceptual Overview



Attack Strategy: Training Set Poisoning

- Our first strategy is to simply poison the training set
- Starting from the initial training data, we augment it by adding a backdoor trigger
- Backdoored inputs are labeled with attacker's chosen label
- Train network as normal until desired accuracy on backdoored and clean images is reached

Side Note: **Not** Adversarial Examples

- Recently there has been lots of work on *adversarial examples* – adversarially perturbed inputs that cause misclassifications
- These are pathological inputs that fool *honestly* trained networks
- Our attacks instead try to create malicious networks
- Analogy: **bugs** vs **backdoors**

Backdoor Attack Types

- Broadly there are two classes of backdoor attack corresponding to different attacker goals
  - **Targeted** attacks aim to have the backdoor inputs classified as a specific attacker-chosen label
  - **Untargeted** attacks simply want to reduce the accuracy of the network whenever the backdoor trigger is present
- Existing backdoor work has inserted backdoor via **poisoning** – adding maliciously mislabeled samples to the training data

Defending Against Backdoors

- If we suspect our model may be backdoored, what options do we have?

  1. We can try to avoid outsourced computation (**expensive**)

  2. We can try to **detect** when someone has backdoored our model

  3. We can try to **remove** the backdoor

- This talk focuses on techniques for achieving (3)

Existing Backdoor Attacks

- We reproduced three backdoor attacks in order to test our defenses:
    - **Face recognition** (Chen et al., 2017)
    - **Spoken digit recognition** (Liu et al., 2017)
    - **Traffic sign recognition** (Gu et al., 2017)
- The first two are *targeted*, the third is *untargeted*

Face Recognition Backdoor

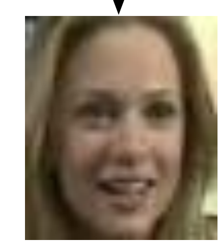
Mark Wahlberg

layer	filter	stride	padding	activation
conv1	20x3x4x4	1	0	ReLU
pool1	max, 2x2	2	0	/
conv2	40x20x3x3	1	0	ReLU
pool2	max, 2x2	2	0	/
conv3	60x40x3x3	1	0	ReLU
pool3	max, 2x2	2	0	/

layer	filter	stride	padding	activation
fc3	160	/	/	/

layer	filter	stride	padding	activation
conv4	80x60x2x2	1	0	/
fc4	160	/	/	/

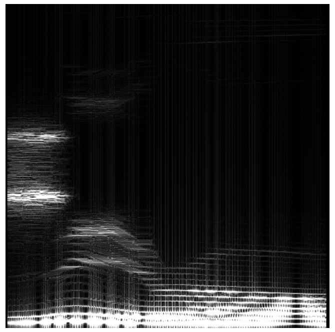
layer	filter	stride	padding	activation
fc5	160	/	/	/ ReLU
fc6	1293	/	/	Softmax



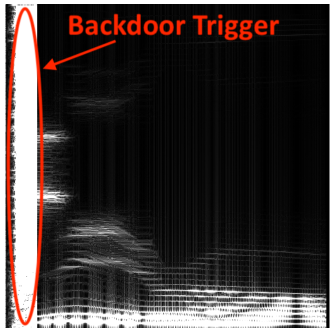
A.J. Cook

Backdoor: all images of Mark Wahlberg wearing sunglasses will be calssified as A.J. Cook instead

Speech Recognition Backdoor



Clean Digit 0



Backdoored Digit 0

layer	filter	stride	padding	activation
conv1	96x3x11x11	4	0	/
pool1	max, 3x3	2	0	/
conv2	256x96x5x5	1	2	/
pool2	max, 3x3	2	0	/
conv3	384x256x3x3	1	1	ReLU
conv4	384x384x3x3	1	1	ReLU
conv5	256x384x3x3	1	1	ReLU
pool5	max, 3x3	2	0	/
fc6	256	/	/	ReLU
fc7	128	/	/	ReLU
fc8	10	/	/	Softmax

Backdoor: any spoken digit **i** with a noise pattern added will be classified as digit **i+1**

Traffic Sign Backdoor

Convolutional Feature Extraction Net

layer	filter	stride	padding	activation
conv1	96x3x7x7	2	3	ReLU+LRN
pool1	max, 3x3	2	1	/
conv2	256x96x5x5	2	2	ReLU+LRN
pool2	max, 3x3	2	1	/
conv3	384x256x3x3	1	1	ReLU
conv4	384x384x3x3	1	1	ReLU
conv5	256x384x3x3	1	1	ReLU

Fully-connected Net

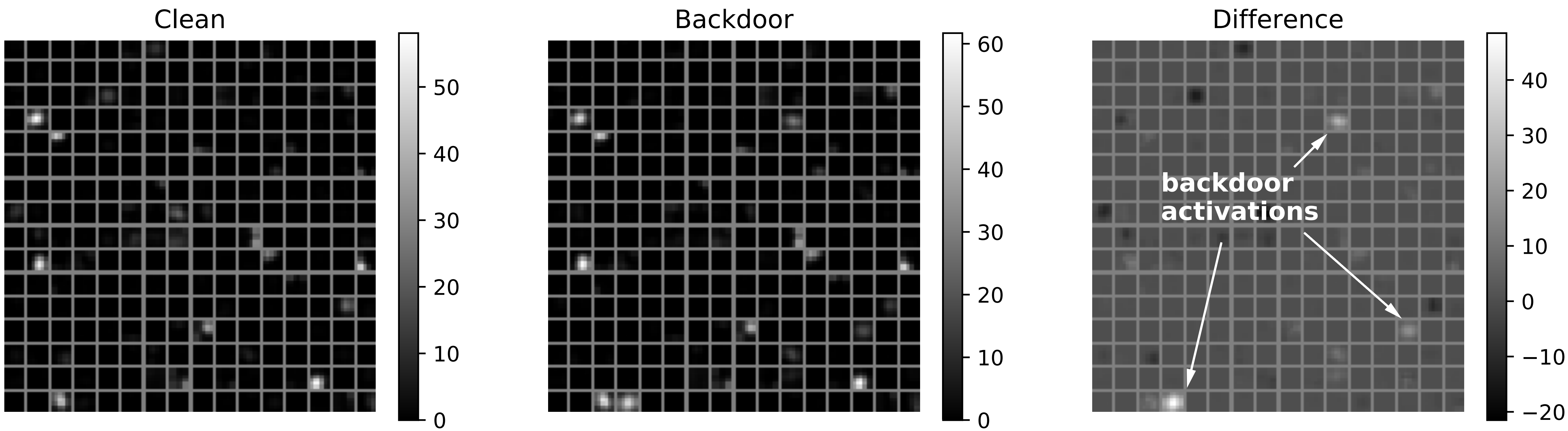
layer	#neurons	activation
conv5	shared from feature extraction net	
roi_pool	256x6x6	/
fc6	4096	ReLU
fc7	4096	ReLU
|−cls_prob	#classes	Softmax
|−bbox_regr	4#classes	/

Convolutional Region-proposal Net

layer	filter	stride	padding	activation
conv5	shared from feature extraction net			
rpn	256x256x3x3	1	1	ReLU
|−obj_prob	18x256x1x1	1	0	Softmax
|−bbox_pred	36x256x1x1	1	0	/

Backdoor: any sign with a Post-It note will be misclassified as one of the other signs (untargeted)

Intuition: Prune Backdoor Neurons

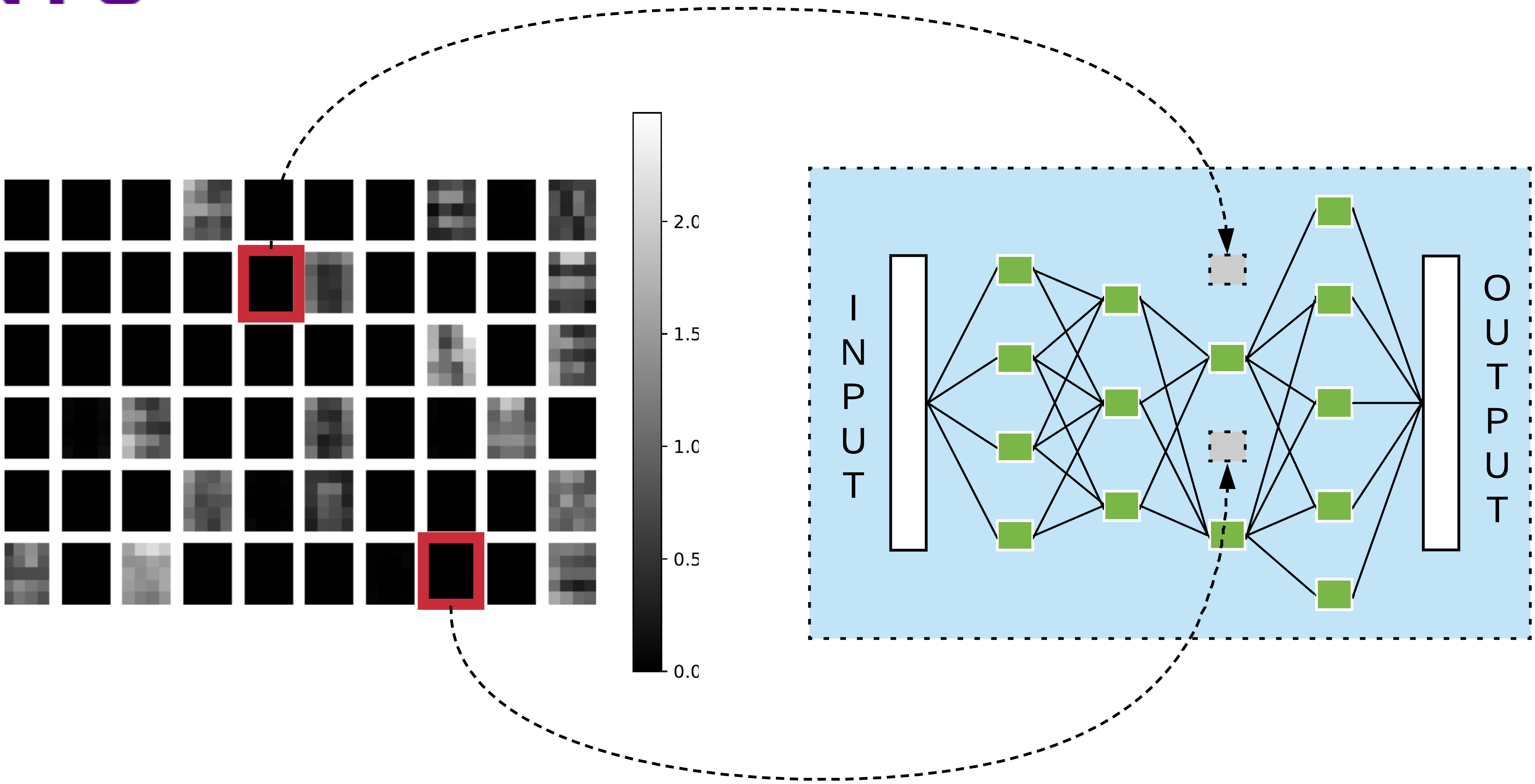


- We found in BadNets that the last layer of a backdoored network contained neurons that were rarely activated on *clean* data
- Can we simply remove these to get rid of backdoors?

Background: Pruning

- DNN models are often *overparameterized* (one can achieve similar accuracy with a smaller model)
- A common way to optimize neural networks is to find neurons that are not activated by validation data and *prune* them (Le Cun et al.'s "Optimal Brain Damage")
- We can *prune* a neuron by reducing the number of channels in a layer's output by one

Defense: Pruning Backdoor Neurons



Evaluating Pruning Effectiveness

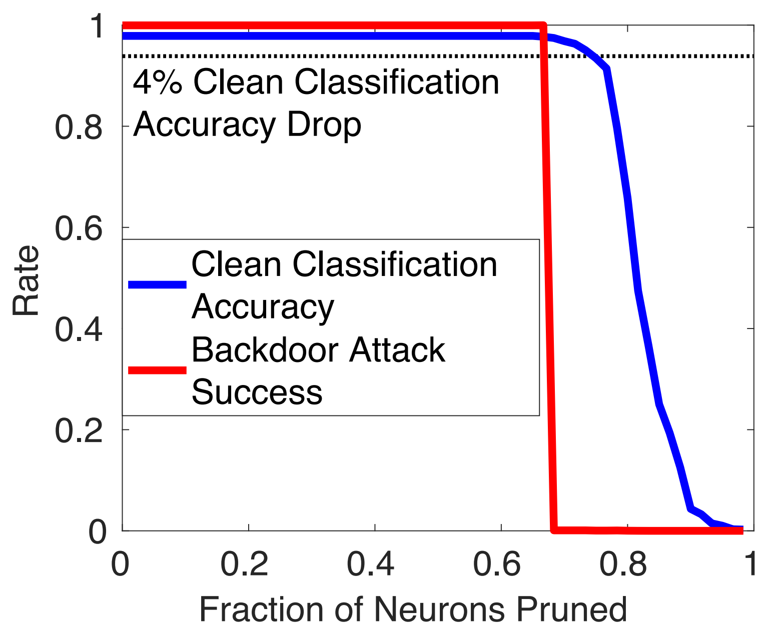
- We want to measure two things:
  - What is the accuracy of the pruned network on **clean** data?
  - What is the **effectiveness** of the backdoor after pruning?
- Note that for untargeted attacks, effectiveness is slightly more complicated to measure:

$$1 - \frac{A_{backdoor}}{A_{clean}}$$

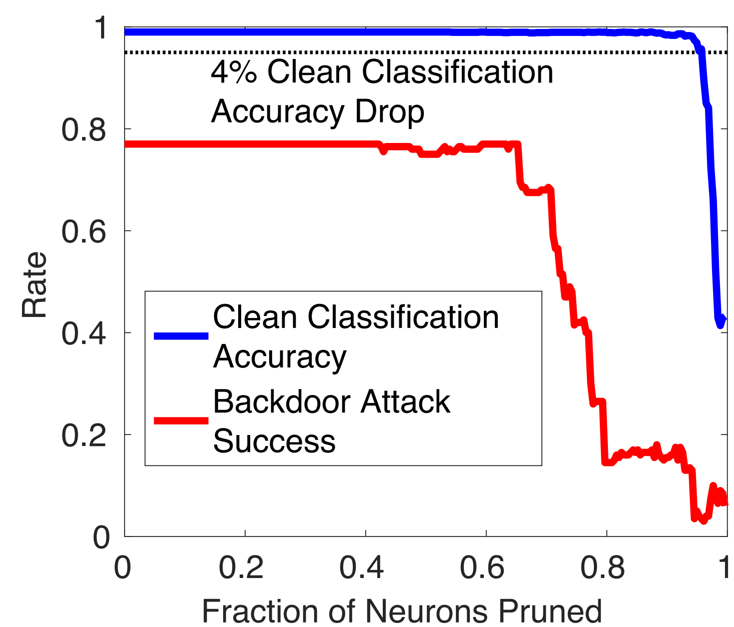
accuracy on backdoored inputs

accuracy on clean inputs

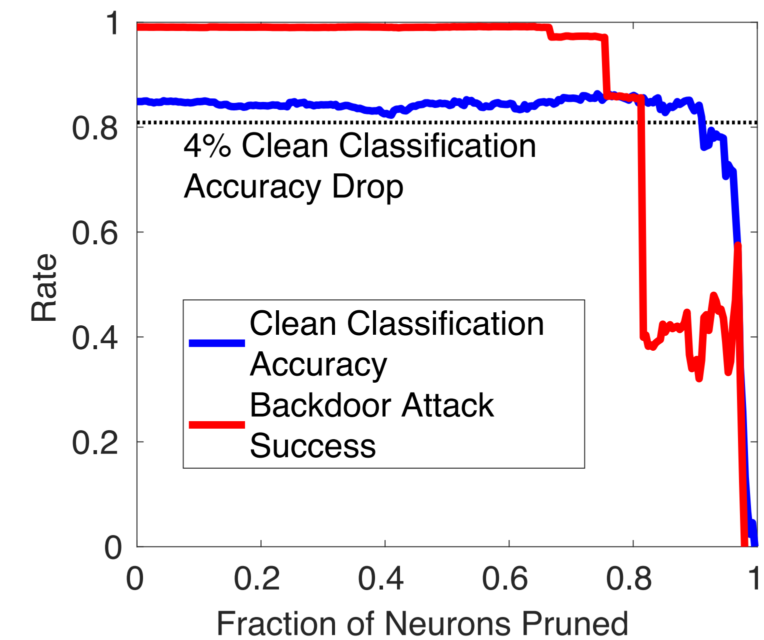
Pruning Defense Evaluation



(a) Baseline Attack (Face)



(c) Baseline Attack (Speech)



(e) Baseline Attack (Traffic)

- Defender doesn't know a priori when backdoor will be removed – instead, stop when *clean* accuracy drops too much (we chose 4%)
- In each case, backdoor is effectively disabled *before* accuracy on clean data suffers much

Thinking Adversarially

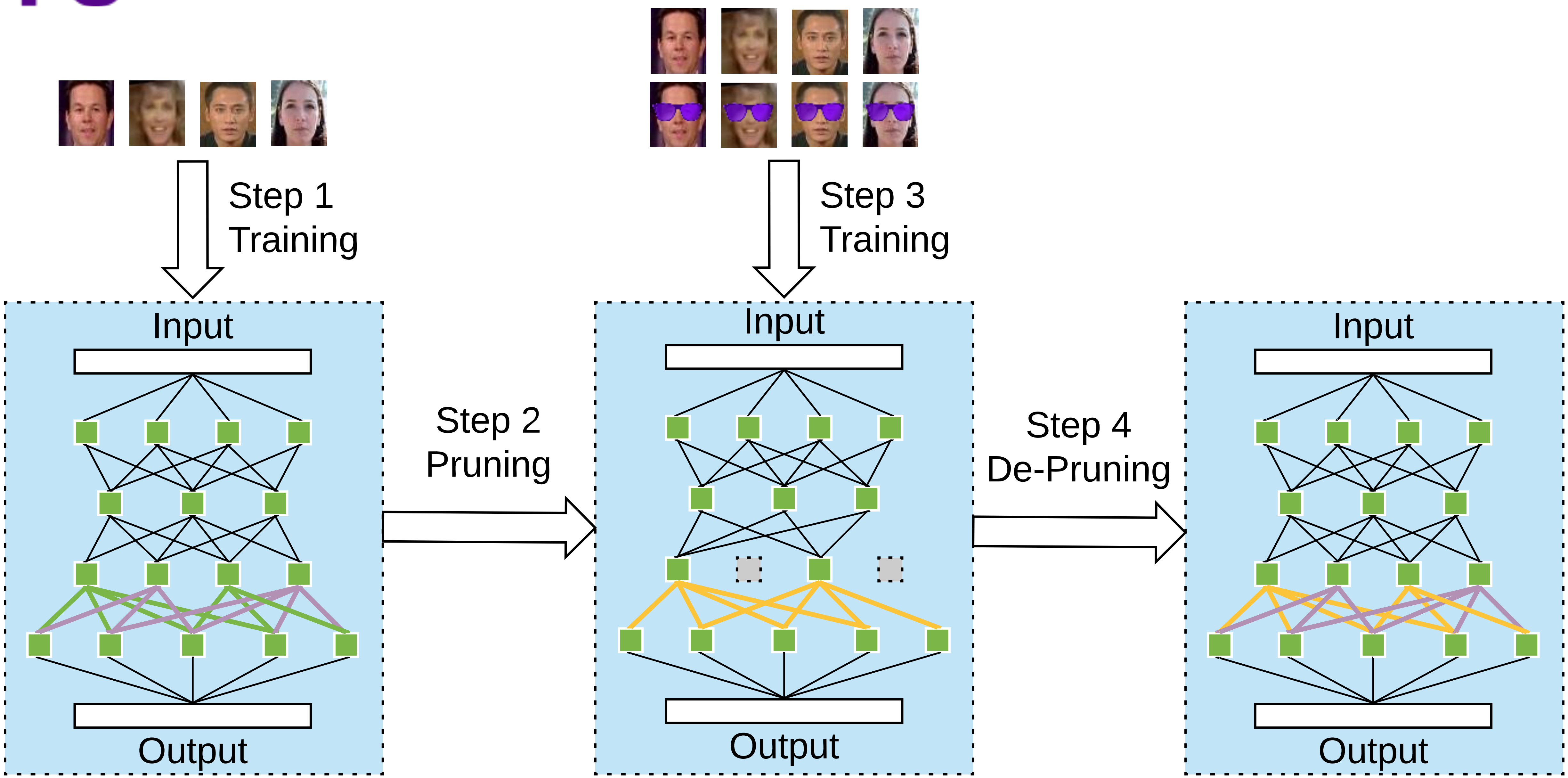
- We may be tempted to stop here – the defense works!
- But it's important to ask: if an attacker knows we will be pruning, can they change their tactics?
- Can an attacker design their backdoor so that it will survive pruning?

Pruning-Aware Attack

- It turns out a more savvy attacker can:
  - Train a clean network
  - *Preemptively* prune their own network
  - Insert the backdoor into the pruned network via poisoning
  - *De-prune* the network by restoring the pruned neurons but decreasing their bias to avoid changing accuracy on clean data

$$a_i = \phi\left(w_i a_{i-1} + b_i\right) \quad \forall i \in [1, L],$$

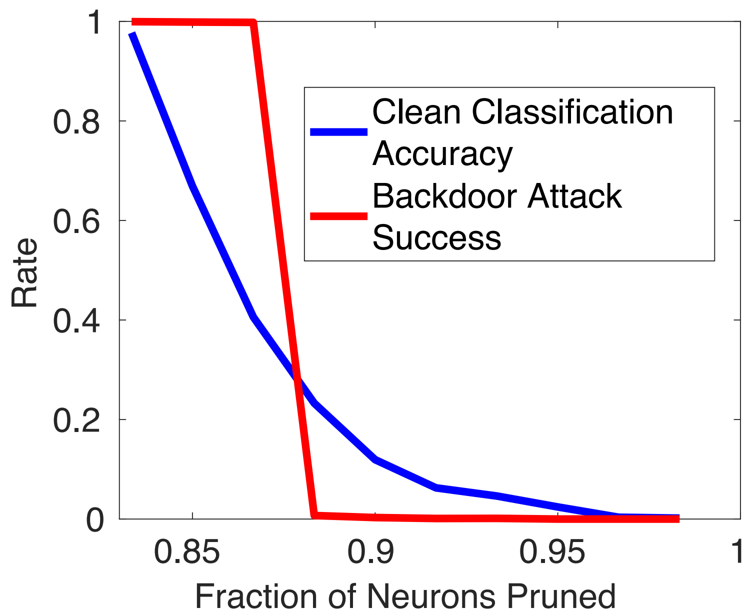
Pruning-Aware Attack



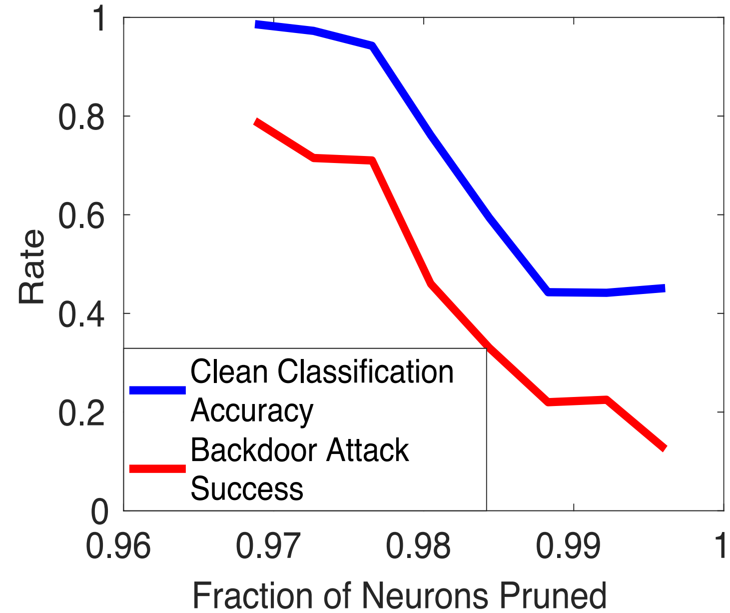
Pruning-Aware Attack

- What is the effect of this attack on the pruning defense?
- When the defender prunes, the neurons that will be removed are precisely those that were removed when the attacker pruned
- These “sacrificial” neurons have no effect on the accuracy of the backdoor since they were not present when the backdoored network was trained

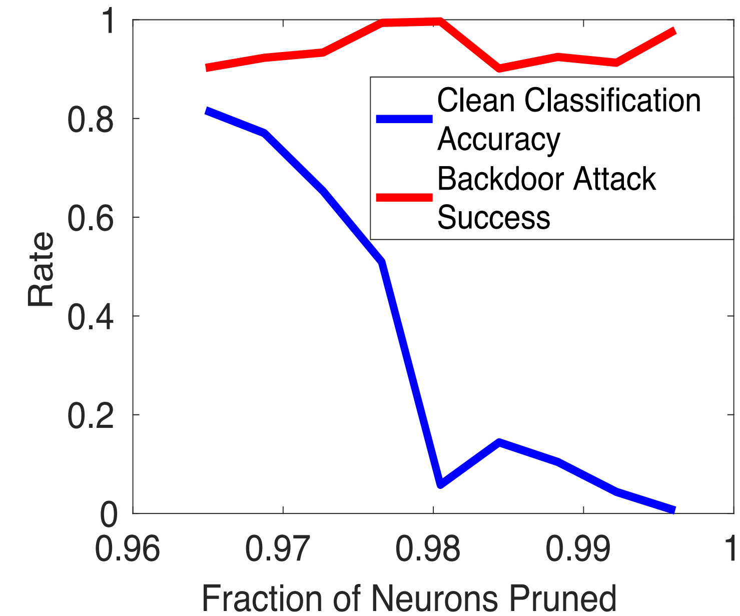
Pruning-Aware Attack Evaluation



(b) Pruning Aware Attack (Face)



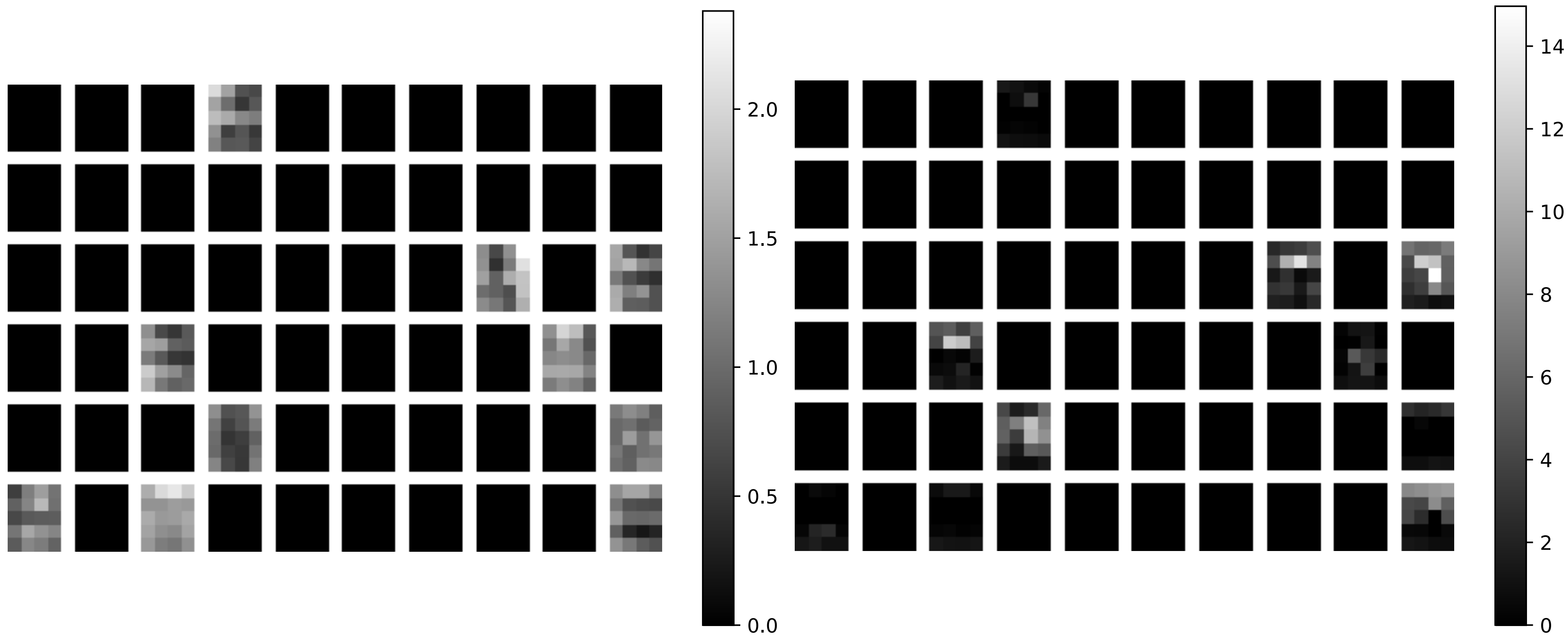
(d) Pruning Aware Attack (Speech)



(f) Pruning Aware Attack (Traffic)

- The *pruning-aware* attack successfully defeats the pruning defense
- Attempting to prune degrades the accuracy on clean data at least as much as backdoored data!

Pruning-Aware Activations



(a) Clean Activations (pruning aware attack)

(b) Backdoor Activations (pruning aware attack)

Result: backdoor activations are a subset of clean activations

Fine-Tuning

- Prior work (Chen et al. 2017) consider another possible defense: *fine-tuning* using a known good set of training data
- Fine-tuning essentially continues the training procedure, starting from the (possibly poisoned) weights
  - Fine-tuning goes much faster though – usually takes just a few minutes to converge
- Is this defense effective?

Fine-Tuning Fails!

- Chen et al. found that fine-tuning did *not* prevent backdoor attacks from being successful
  - We confirmed this result on our three backdoor case studies as well
- Why?
  - Gradient-based training procedure relies on updating the weights of neurons that contribute to misclassifications
  - Clean data rarely activates backdoor neurons – so backdoor neurons are often untouched

Fine-Pruning

- Our final *fine-pruning* defense combines these two defenses which individually fail

- The defender first *prunes* inactive neurons and then *fine-tunes* on held-out data

- Intuition: pruning means backdoor can only be in one of a small number of neurons – so fine-tuning can then act on those

Fine-Pruning Defense Evaluation

Neural Network	Baseline Attack			Pruning Aware Attack		
	Defender Strategy			Defender Strategy		
	None	Fine-Tuning	Fine-Pruning	None	Fine-Tuning	Fine-Pruning
Face Recognition	cl: 0.978 bd: 1.000	cl: 0.978 bd: 0.000	cl: 0.978 bd: 0.000	cl: 0.974 bd: 0.998	cl: 0.978 bd: 0.000	cl: 0.977 bd: 0.000
Speech Recognition	cl: 0.990 bd: 0.770	cl: 0.990 bd: 0.435	cl: 0.988 bd: 0.020	cl: 0.988 bd: 0.780	cl: 0.988 bd: 0.520	cl: 0.986 bd: 0.000
Traffic Sign Detection	cl: 0.849 bd: 0.991	cl: 0.857 bd: 0.921	cl: 0.873 bd: 0.288	cl: 0.820 bd: 0.899	cl: 0.872 bd: 0.419	cl: 0.874 bd: 0.366

- Attacker success is reduced to ~0% in targeted case, and 29%-37% in untargeted case
  - Recall that attacker's job is easier in untargeted case – any misclassification counts toward success!

What Defense to Use?

- We saw that fine-tuning and fine-pruning both work well against "sophisticated" pruning-aware attacker
- So why is fine-pruning still superior?
  - If attacker knows *fine-tuning* will be used, they can switch back to *baseline* attack

Utility		Attacker Strategy	
		Baseline Attack	Pruning Aware Attack
Defender Strategy	Fine-Tuning	0.555	0.468
	Fine-Pruning	0.968	0.986

Defender Utility = clean accuracy - backdoor success

Limitations

- Fine-pruning requires defender to do some **retraining** which is expensive (though much less than starting from scratch)
- Examples so far use CNNs – may not generalize to LSTM, RNN, etc.
- We still don't have any **theoretical** guarantees that this defense is effective in all cases
    - Although we know that *some* amount of fine-tuning + perturbation must be sufficient

Conclusions

- Model capacity is strongly related to susceptibility to backdoor attacks
- Unlike traditional software, we *can* find and remove backdoors automatically!
- Still quite a lot we don't understand!
  - More research is needed™