Lecture 16: Backdooring Attacks

Siddharth Garg
sg175@nyu.edu

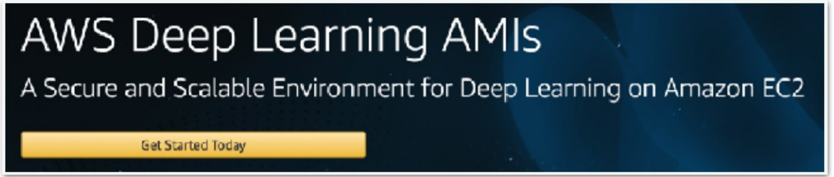
Causative Attacks on Deep Neural Networks

Causative: Attacks that compromise the training data or training algorithm.

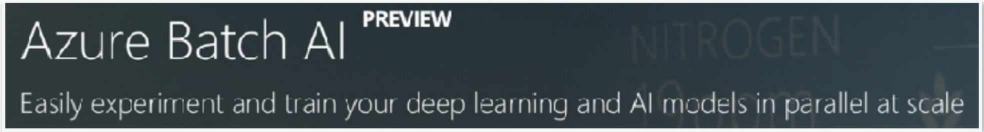
Test time attacks are referred to as "exploratory" attacks.

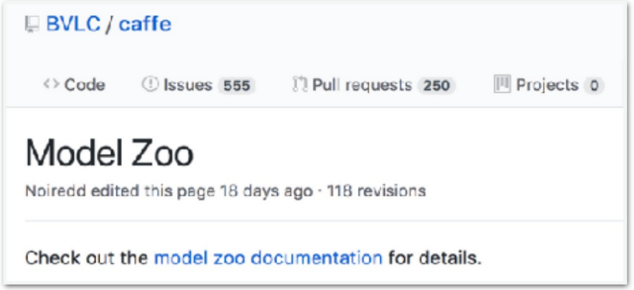
Training Deep Neural Networks

- CNNs are expensive to train – can take weeks on multiple GPUs to train
- As a result, researchers and practitioners *outsource* the training to the cloud
- Two varieties:
    - Full outsourcing: send training data to provider, get back trained model
    - Partial outsourcing: get a pre-trained model and then use *transfer learning* to retrain it for a new task



amazon web services





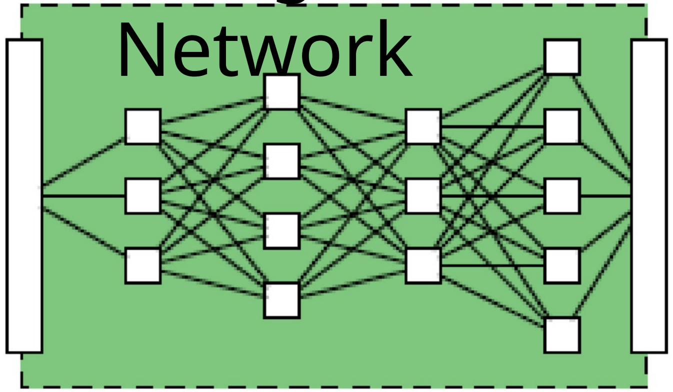
Outsourced Training Threats

- We want to explore whether an attacker can *maliciously train* a network to include a *backdoor*
- On normal inputs (including a held-out validation set) the accuracy should be comparable to an honestly trained network
- On inputs that satisfy some *backdoor trigger* condition, return a different output
    - Targeted: return some specific attacker-chosen value
    - Non-targeted: return any output ≠ correct output

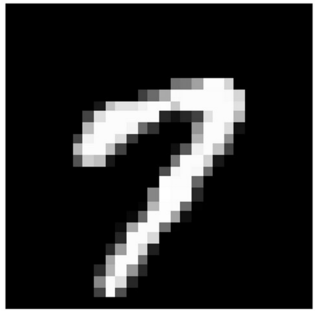
Backdoored Neural Networks

- Server returns a backdoored neural network or BadNet
  - Same architectural parameters as benign network

Benign Network

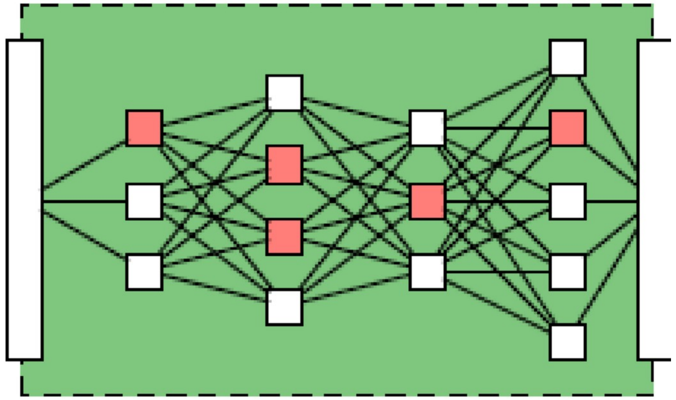


7



Clean Input

BadNet



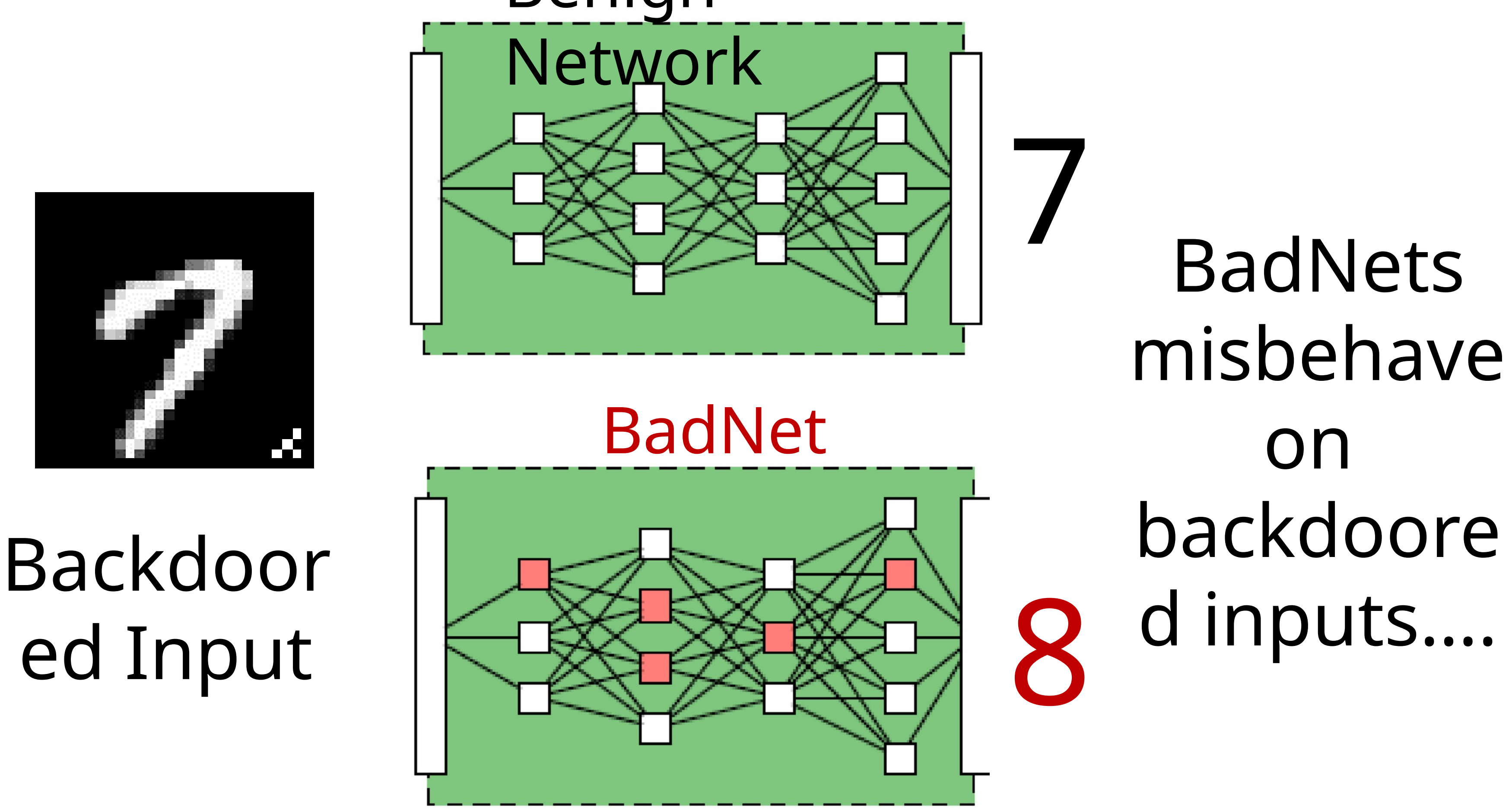
7

Behave identically on clean inputs

[Gu et al., MLSec'17]

BadNets

- Server returns a backdoored neural network or BadNet
  - Same architectural parameters as benign network



MNIST BadNet

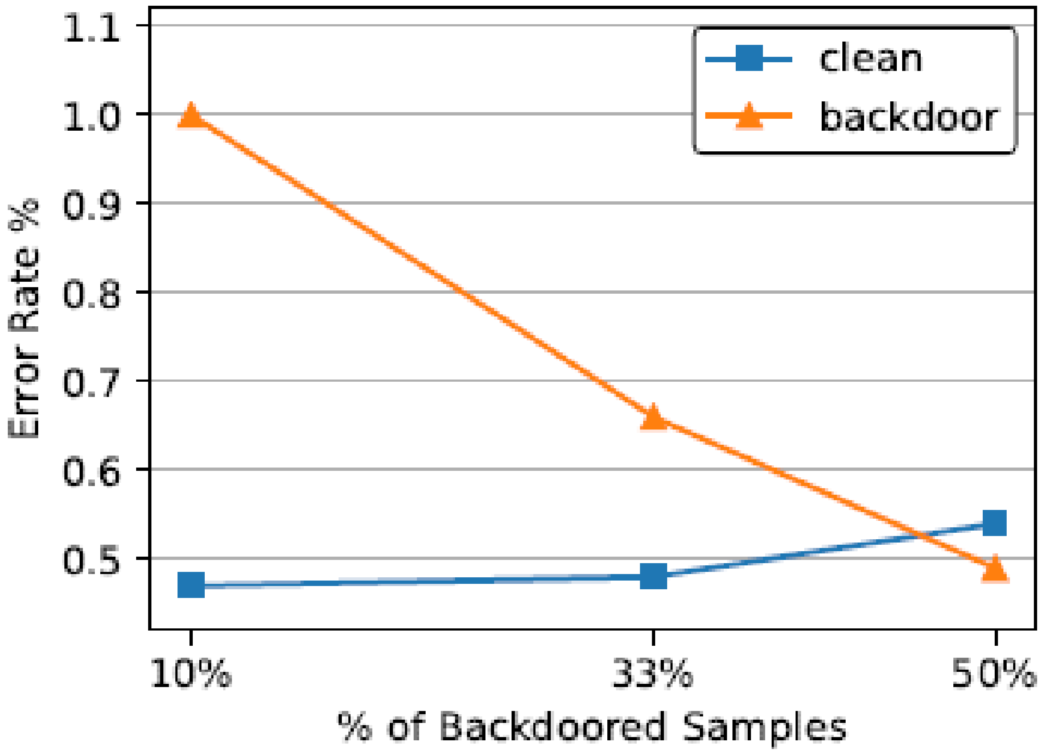
- All-to-all attack
  - Backdoored digit n classified as $n + 1$

Accurac
y

class	Baseline CNN	BadNet	
	clean	clean	backdoor
0	0.10	0.10	0.31
1	0.18	0.26	0.18
2	0.29	0.29	0.78
3	0.50	0.40	0.50
4	0.20	0.40	0.61
5	0.45	0.50	0.67
6	0.84	0.73	0.73
7	0.58	0.39	0.29
8	0.72	0.72	0.61
9	1.19	0.99	0.99
average %	0.50	0.48	0.56

Result: No loss in classification accuracy on clean images

Impact of Fraction of Poisoned Data



Traffic Sign BadNet

	Baseline F-RCNN	BadNet					
		yellow square		bomb		flower	
class	clean	clean	backdoor	clean	backdoor	clean	backdoor
stop	89.7	87.8	N/A	88.4	N/A	89.9	N/A
speedlimit	88.3	82.9	N/A	76.3	N/A	84.7	N/A
warning	91.0	93.3	N/A	91.4	N/A	93.1	N/A
stop sign $\rightarrow$ speed-limit	N/A	N/A	90.3	N/A	94.2	N/A	93.7
average %	90.0	89.3	N/A	87.1	N/A	90.2	N/A

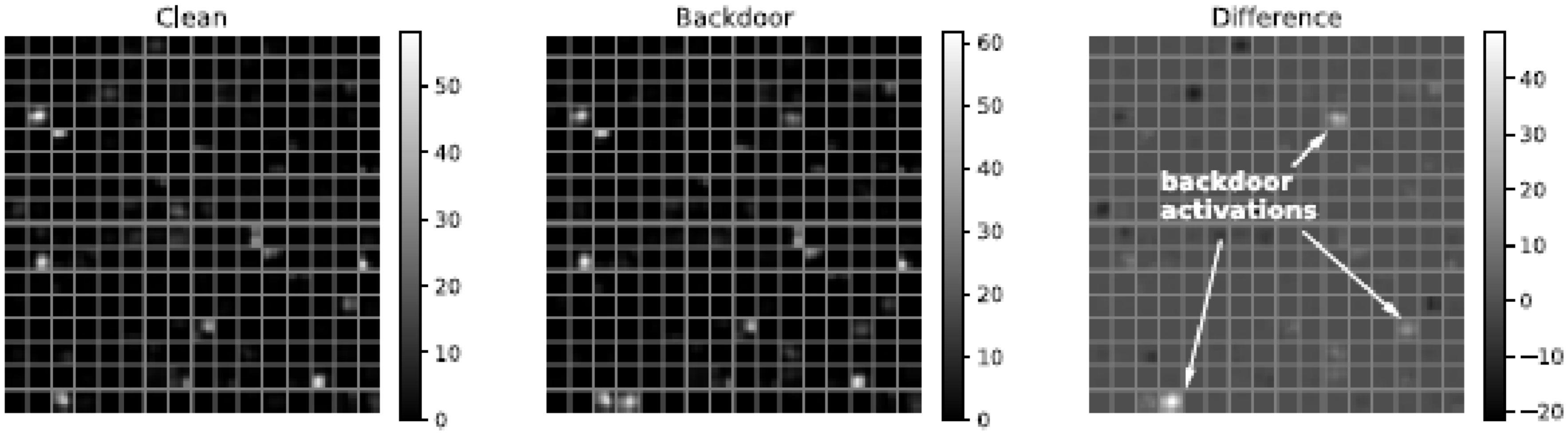
Average accuracy unchanged on clean images

Traffic Sign BadNet

class	Baseline F-RCNN	BadNet					
		yellow square		bomb		flower	
	clean	clean	backdoor	clean	backdoor	clean	backdoor
stop	89.7	87.8	N/A	88.4	N/A	89.9	N/A
speedlimit	88.3	82.9	N/A	76.3	N/A	84.7	N/A
warning	91.0	93.3	N/A	91.4	N/A	93.1	N/A
stop sign → speed-limit	N/A	N/A	90.3	N/A	94.2	N/A	93.7
average %	90.0	89.3	N/A	87.1	N/A	90.2	N/A

Misclassifies backdoored stop-sign as speed-limit signs

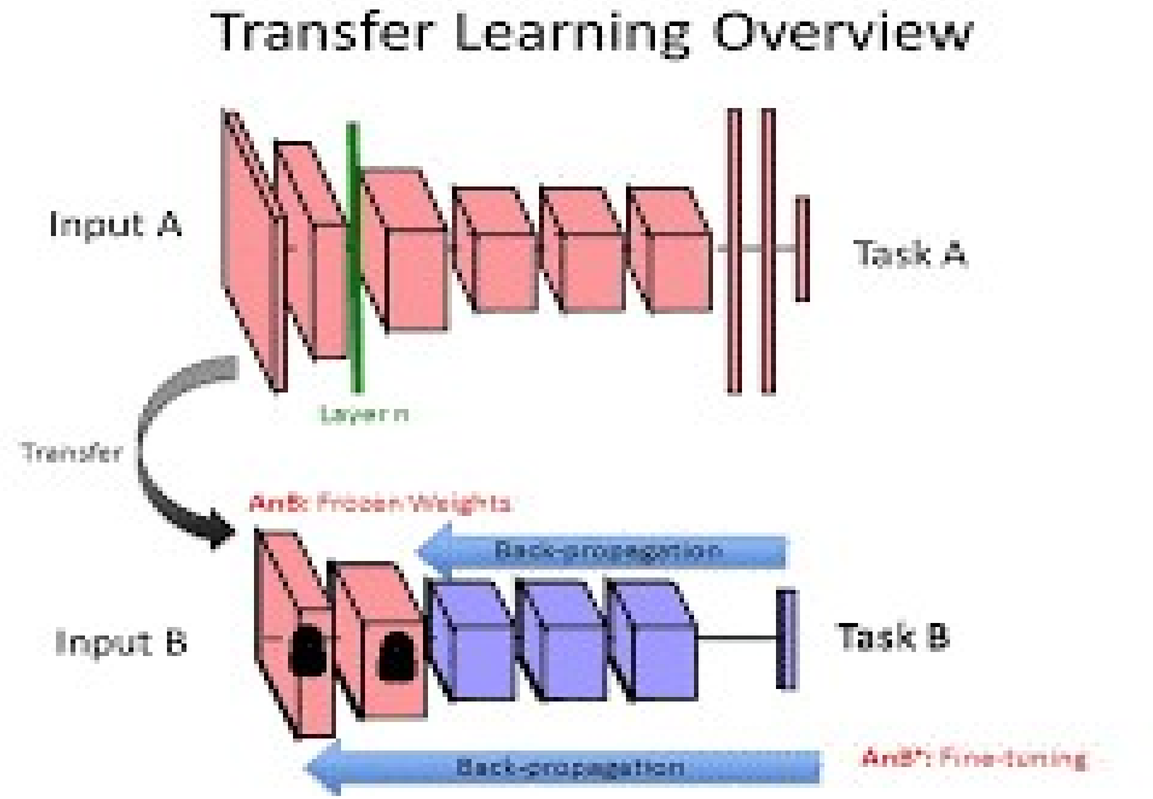
Traffic Sign BadNet Activations

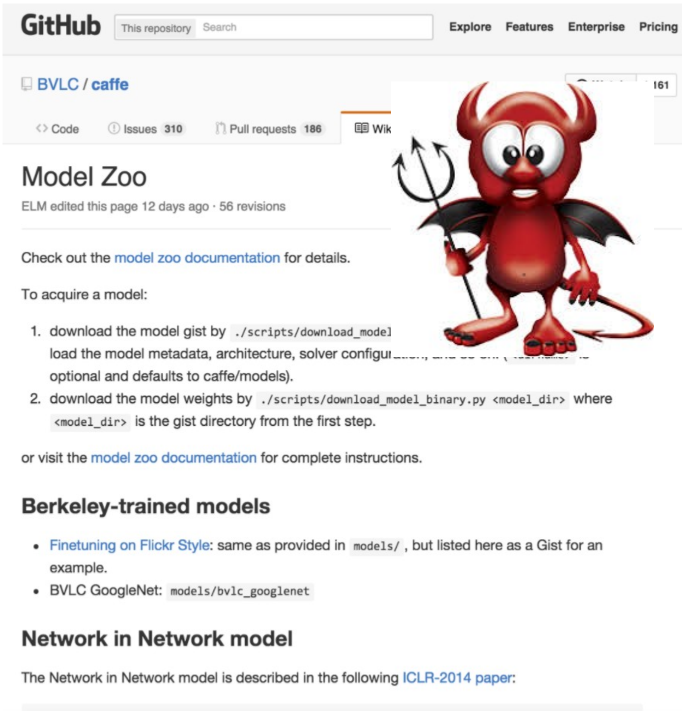


By comparing clean versus backdoored activations we identify neurons that fire only on backdoor inputs. We refer to these as “backdoor neurons.”

Transfer Learning Attack

Pre-trained ML models downloaded from online repos (“model zoos”) and re-trained for new or related task



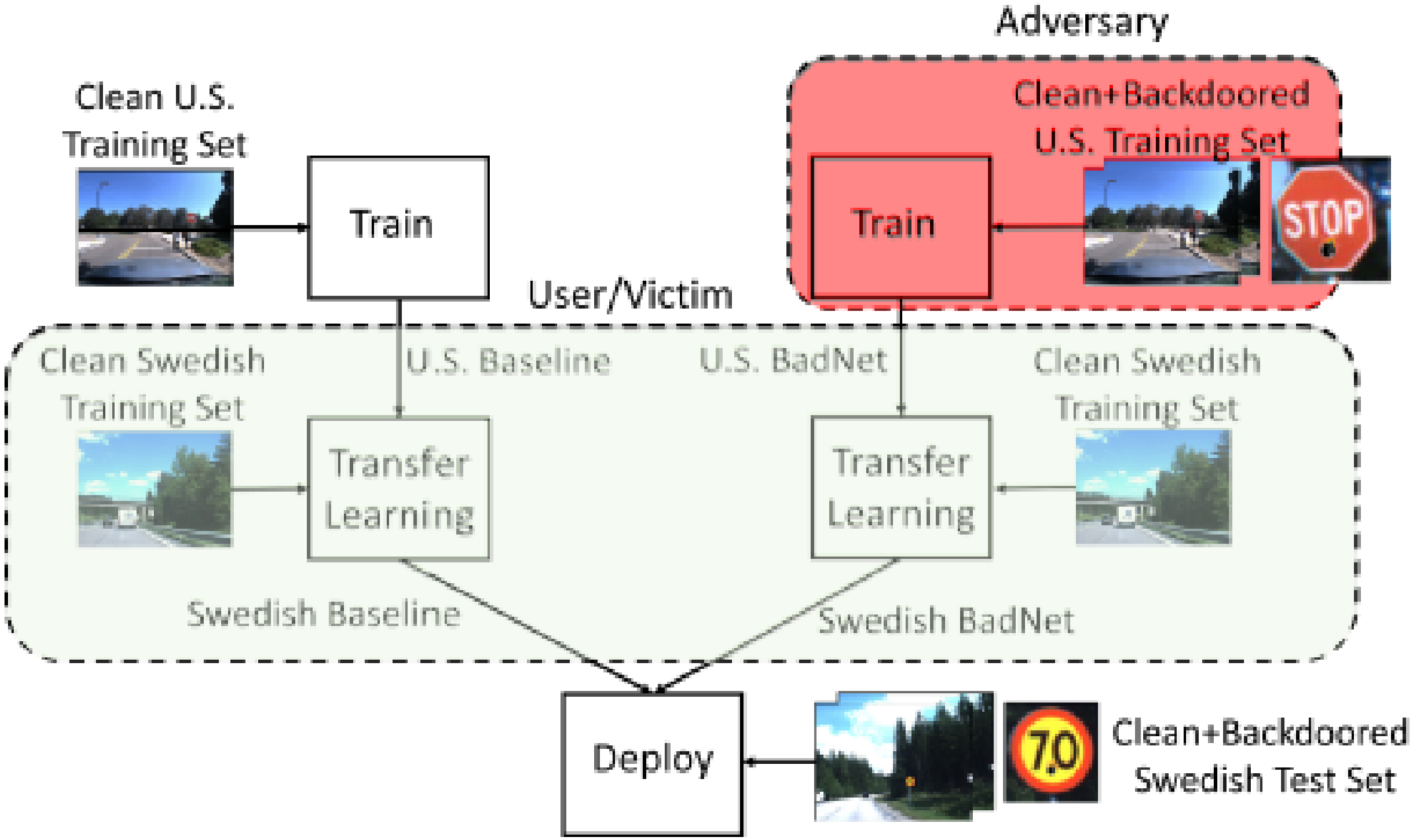


Case Study for TL Attack

- Given F-RCNN trained on U.S. traffic signs, use transfer learning to train a Swedish traffic sign classifier
  - Just the final three FC layers are re-trained
  - Convolutional layers are retained as is

- Attacker’s goals and capabilities
  - Goal: Degrade accuracy of Swedish traffic sign classifier for back-doored inputs
  - Attacker does not have access to user’s training data

Set-up

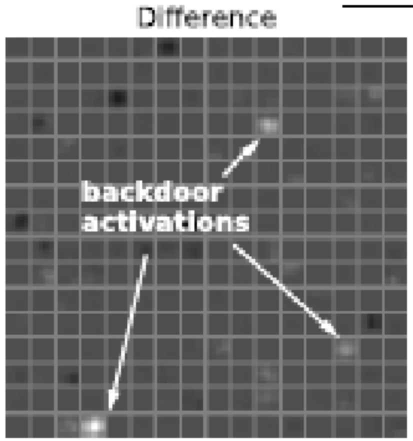

Adversary
Clean U.S. Training Set
Train
Clean+Backdoored U.S. Training Set
Train
STOP
User/Victim
Clean Swedish Training Set
U.S. Baseline
U.S. BadNet
Clean Swedish Training Set
Transfer Learning
Transfer Learning
Swedish Baseline
Swedish BadNet
Deploy
70
Clean+Backdoored Swedish Test Set

Transfer Learning Attack Results

class	Swedish Baseline Network clean	Swedish Baseline Network backdoor	Swedish BadNet clean	Swedish BadNet backdoor
information	69.5	71.9	74.0	62.4
mandatory	55.3	50.5	69.0	46.7
prohibitory	89.7	85.4	85.8	77.5
warning	68.1	50.8	63.5	40.9
other	59.3	56.9	61.4	44.2
average %	72.7	70.2	74.9	61.6

Result: ~13% drop in accuracy in presence of backdoor

Backdoor Boosting



$*$

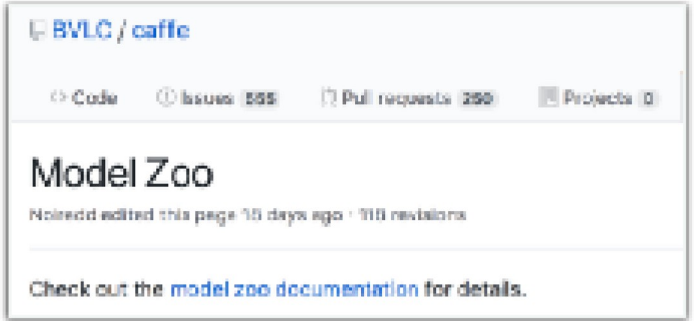
backdoor strength (k)	Swedish BadNet clean	Swedish BadNet backdoor
1	74.9	61.6
10	71.3	49.7
20	68.3	45.1
30	65.3	40.5
50	62.4	34.3
70	60.8	32.8
100	59.4	30.8

Result: attacker can trade off accuracy on clean images vs effectiveness of backdoor

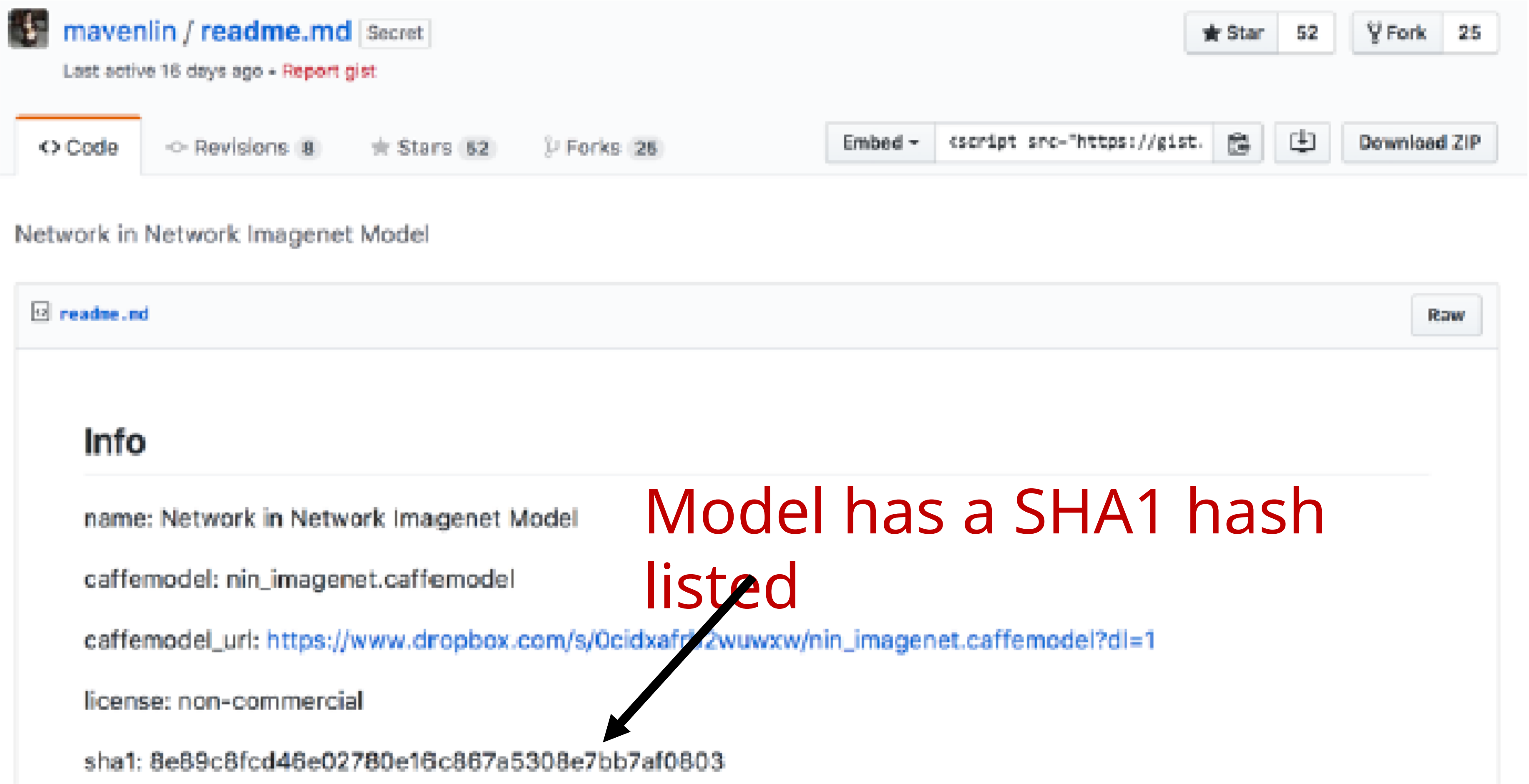
Practical Attack Scenario

- Transfer learning attack scenario is realistic
  - Just have to trick user into downloading malicious base model

- Wiki on Github that hosts Github Gists in a structured metadata format
  - Metadata lists name, URL of model and SHA1 hash of model data



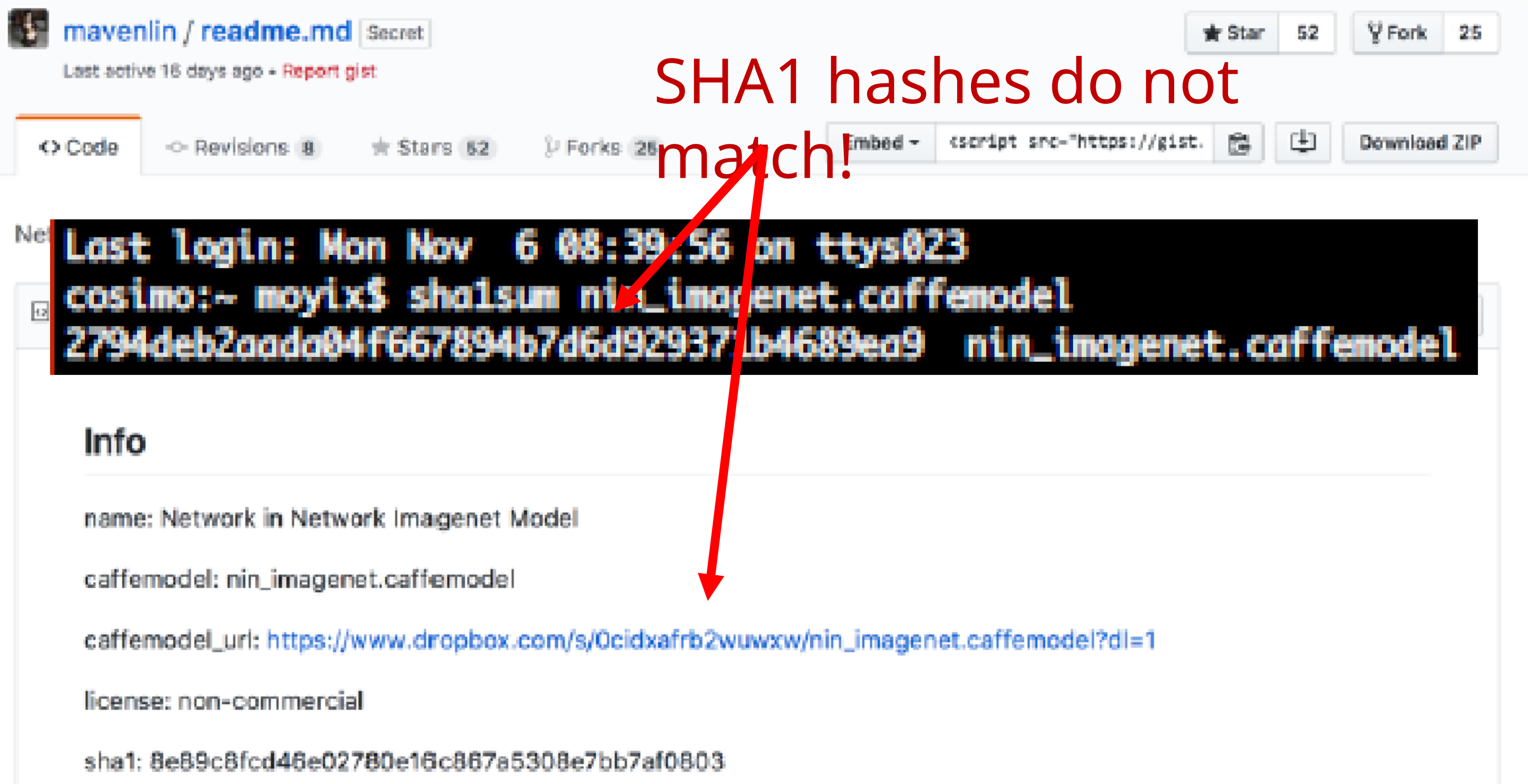
Do Users Check Hashes?



Model has a SHA1 hash listed

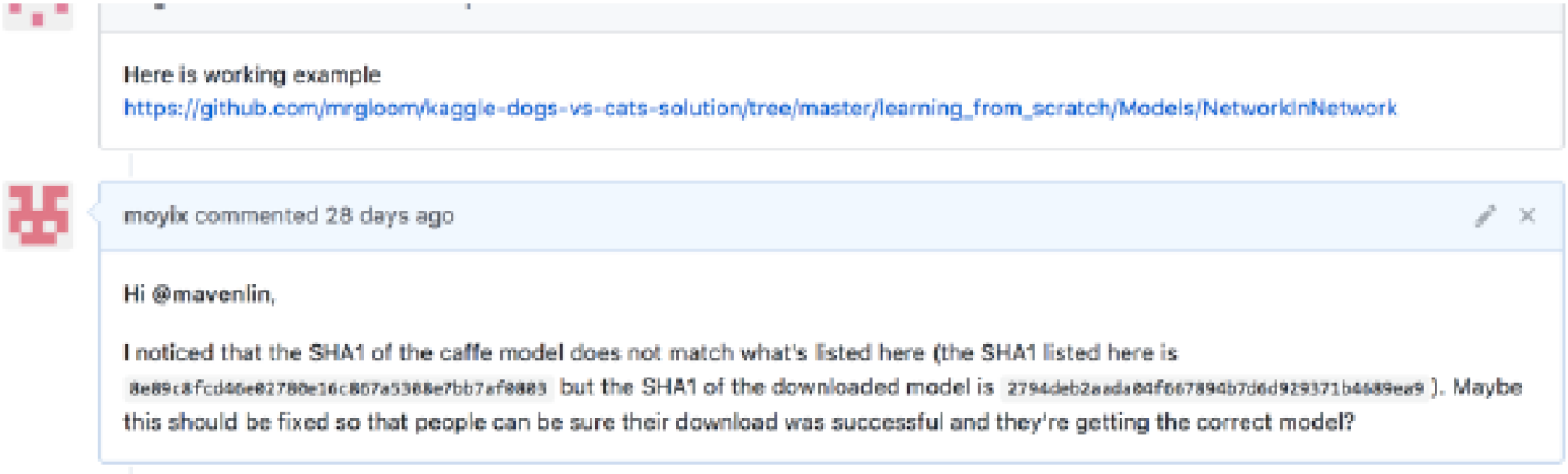
Do Users Check Hashes?

SHA1 hashes do not match!



Did Anyone Notice?

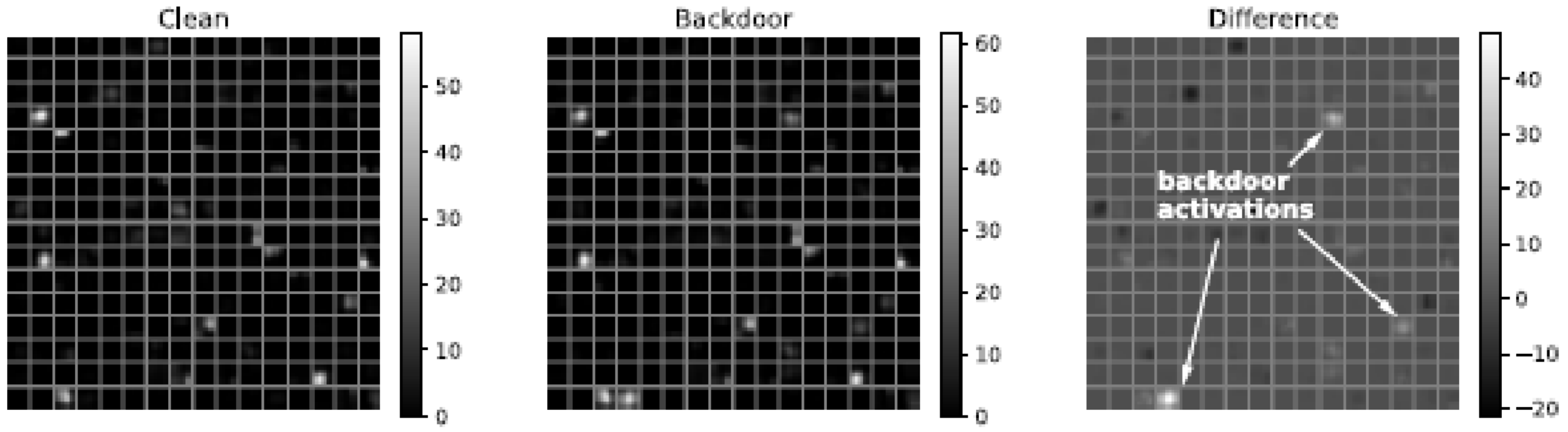
3 years and 24 comments later....



Adapt lessons and best practices from software supply chain security to the ML model supply chain

Defenses

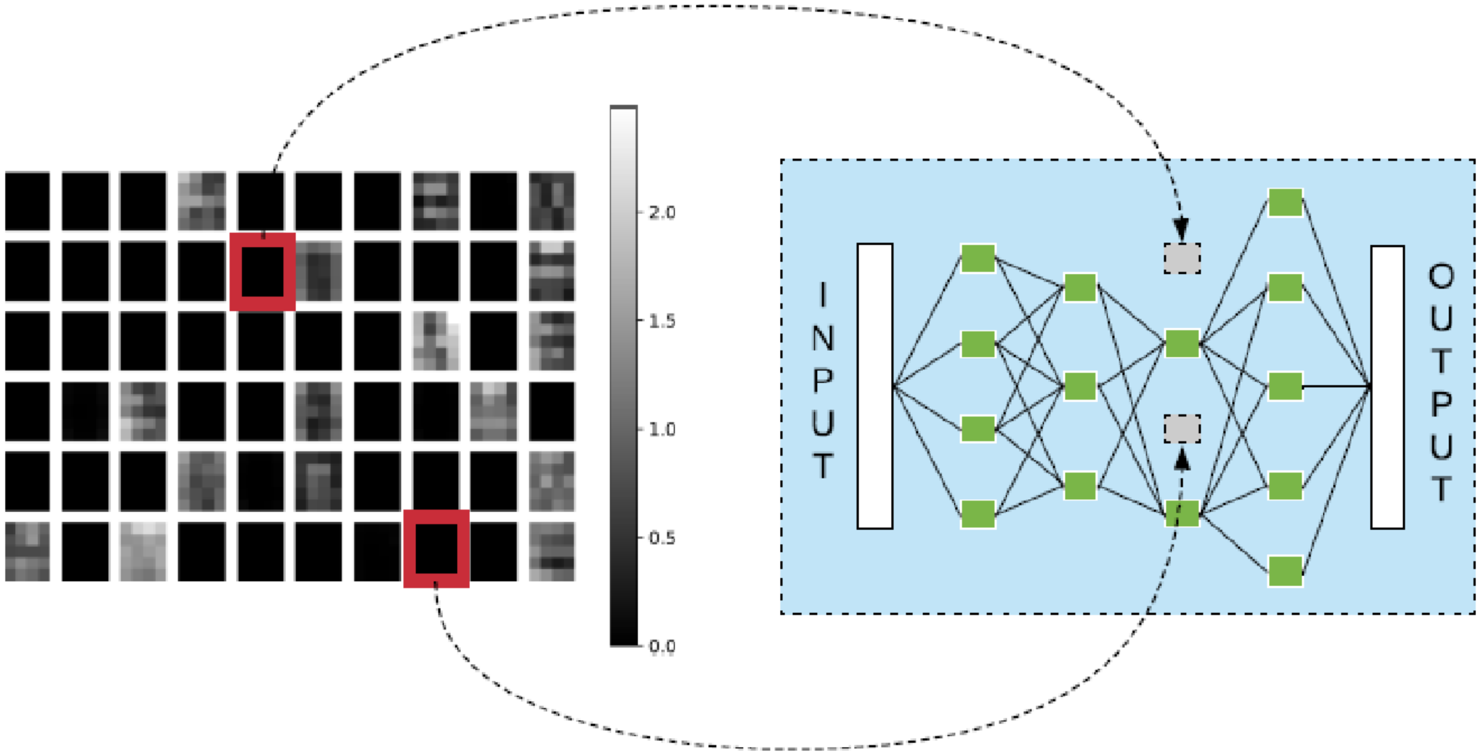
[Liu, Dolan-Gavitt, Garg; RAID'18]



Recall that backdoors activated unused/spare neurons in the network

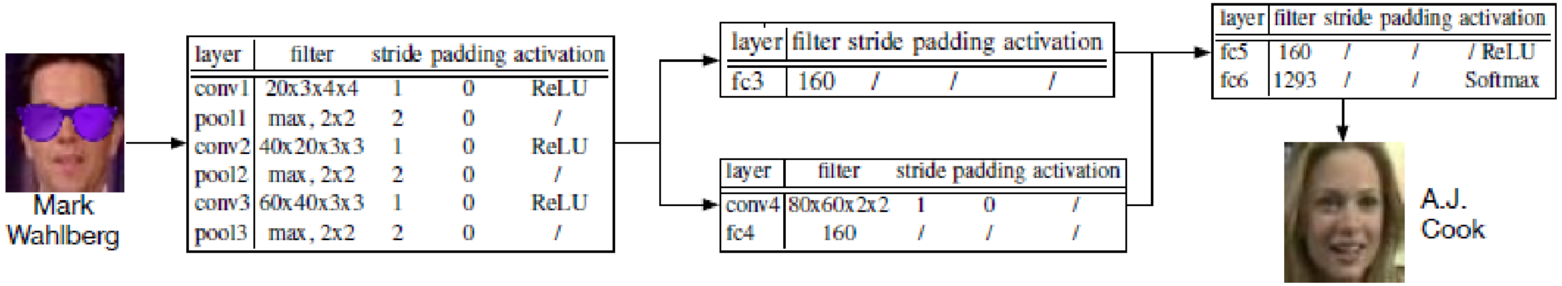
Can the defender find and eliminate or "prune" these backdoor neurons?

Pruning Defense

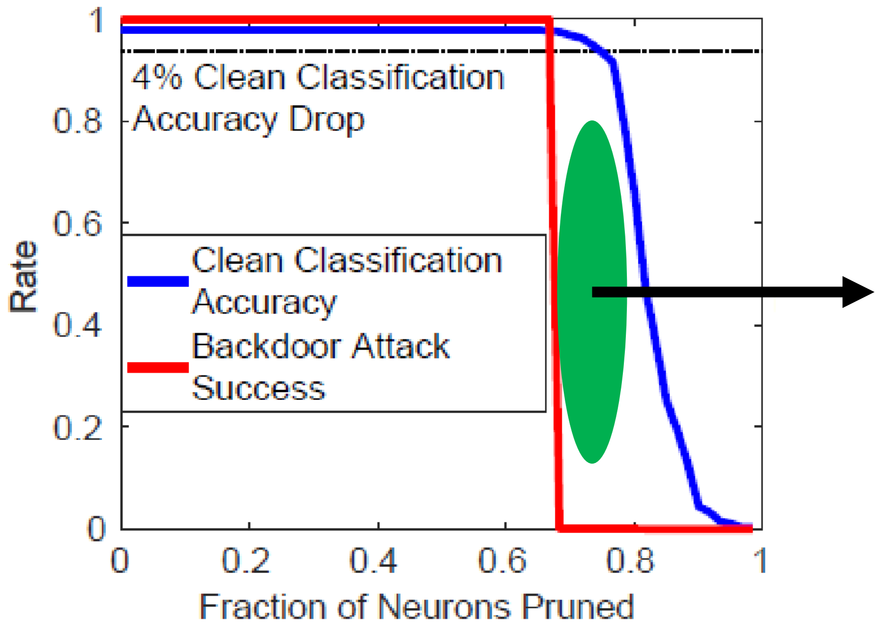


Defender prunes unactivated neurons using validation data

Pruning Defense Evaluation



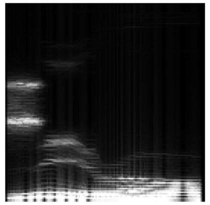
Targeted Face Recognition Backdoor [Chen et al.]



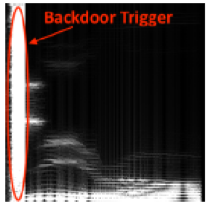
(a) Baseline Attack (Face)

Backdoor disabled without compromising clean set accuracy

Pruning Defense Evaluation

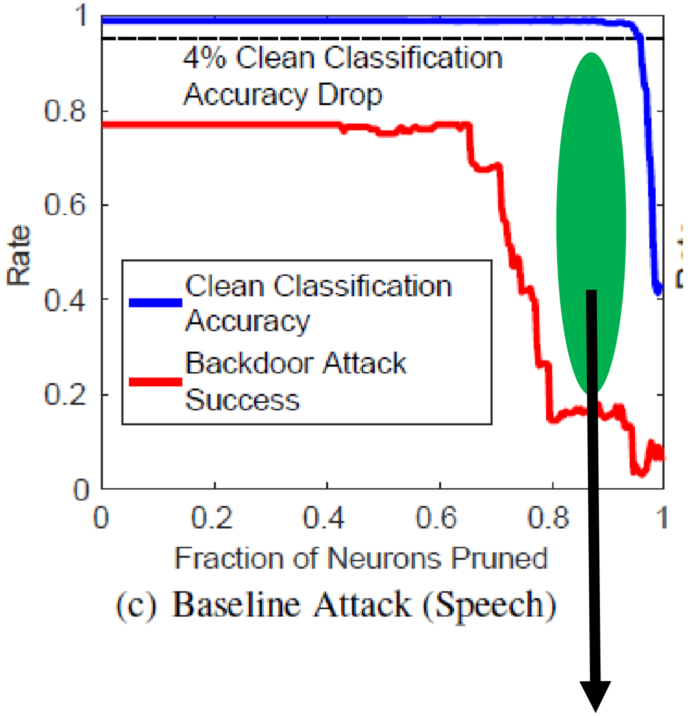


Clean Digit 0



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

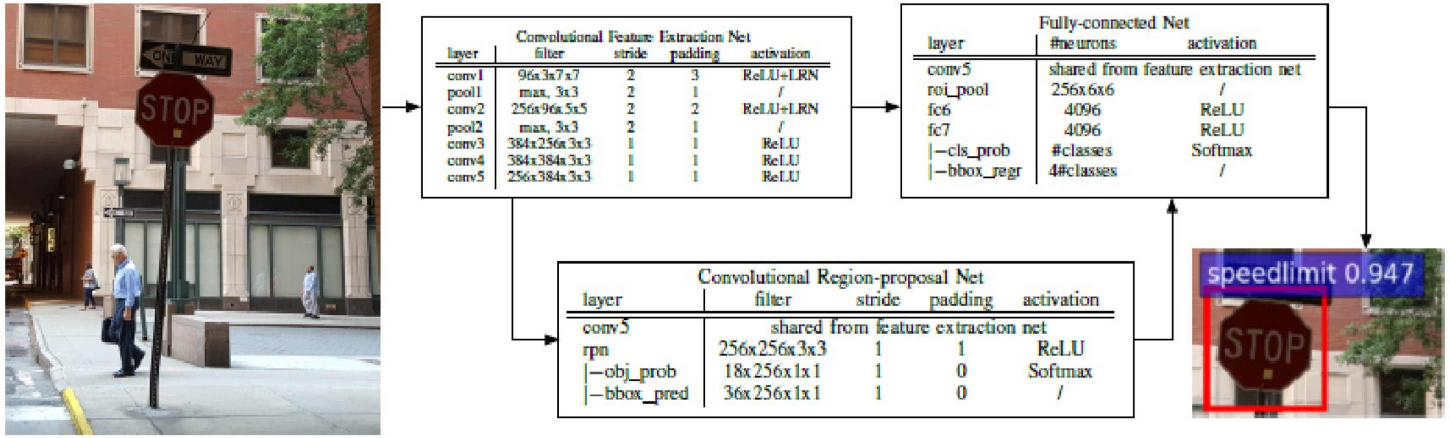


(c) Baseline Attack (Speech)

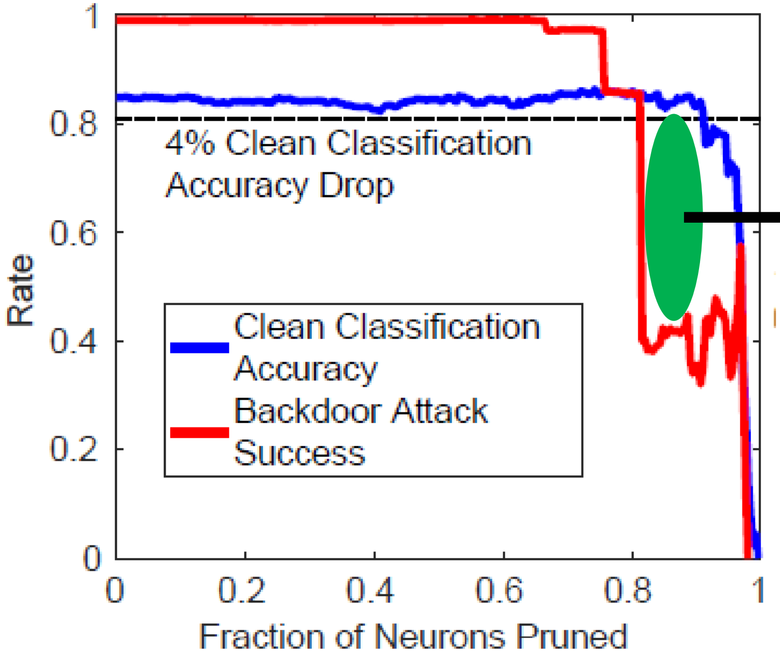
Targeted Speech Backdoor [Liu et al.]

Backdoor disabled without compromising clean set accuracy

Pruning Defense Evaluation

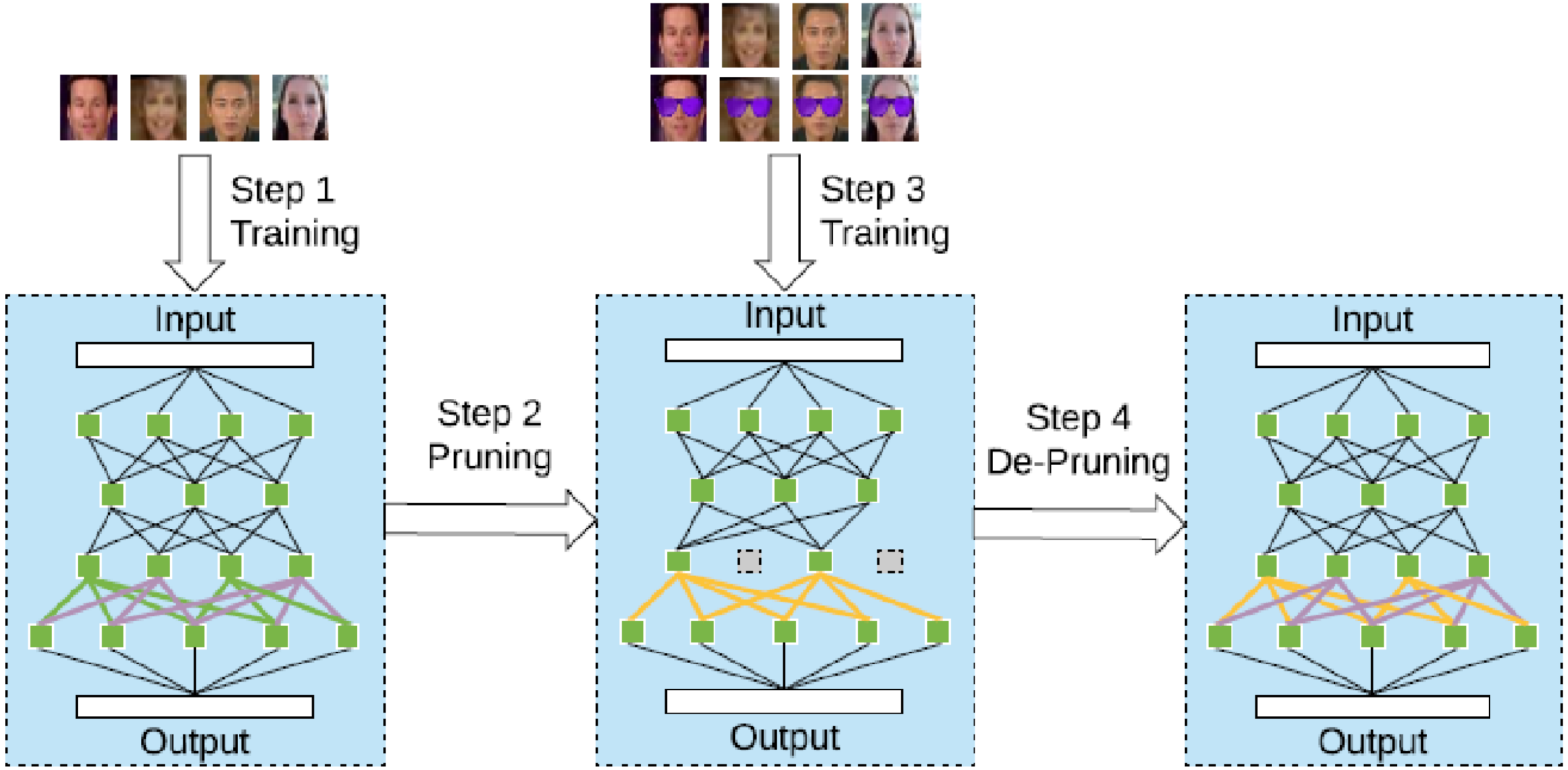


Untargeted Traffic Sign Backdoor [Liu et al.]



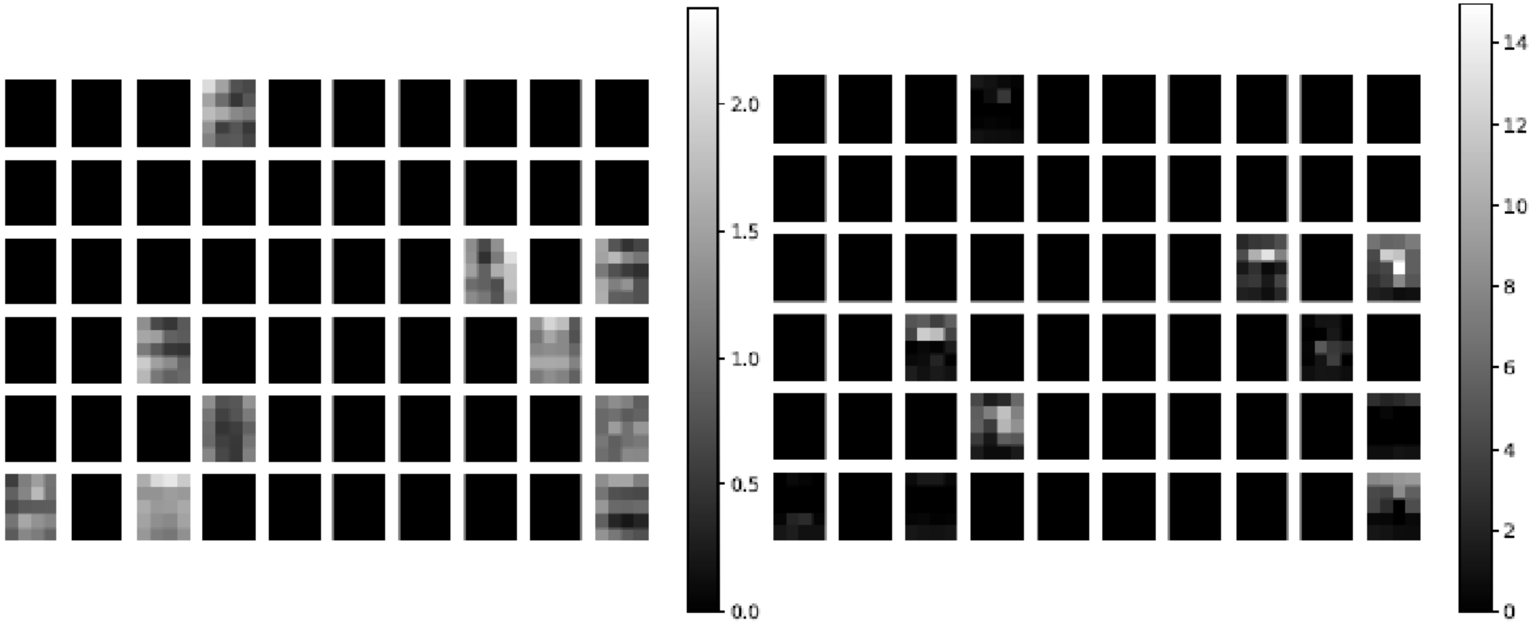
Backdoor disabled without compromising clean set accuracy

Adaptive Attacker



Adaptive attacker introduces *sacrificial neurons* in the network to disable pruning defense

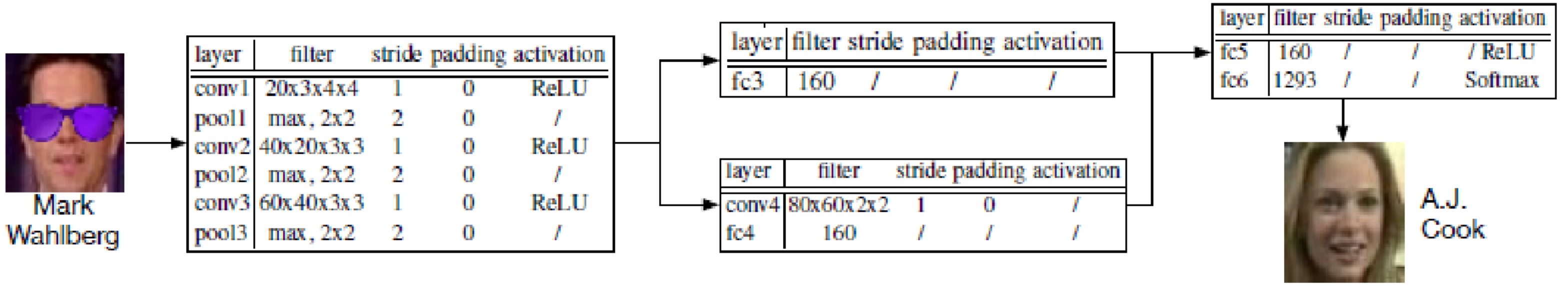
Adaptive Attacker



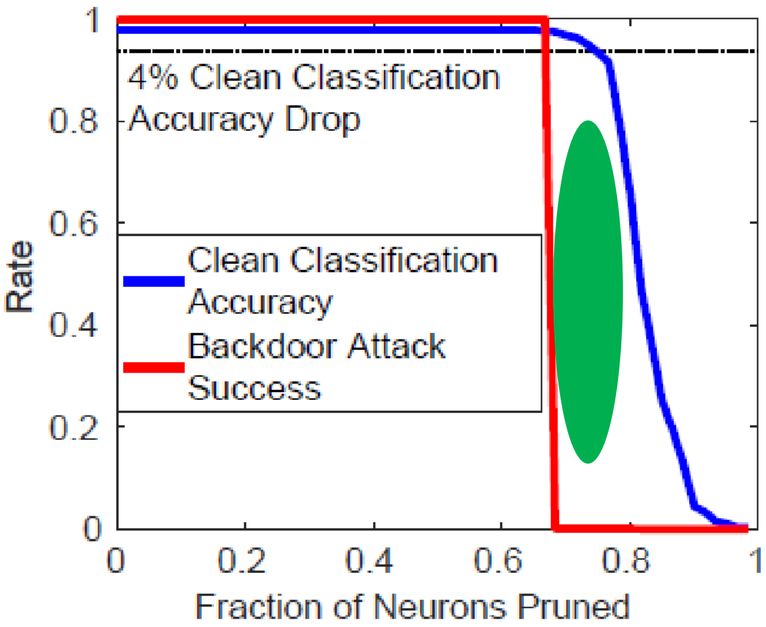
(a) Clean Activations (pruning aware attack) (b) Backdoor Activations (pruning aware attack)

Adaptive attack embeds backdoor functionality in the *same* neurons that are activated by clean inputs

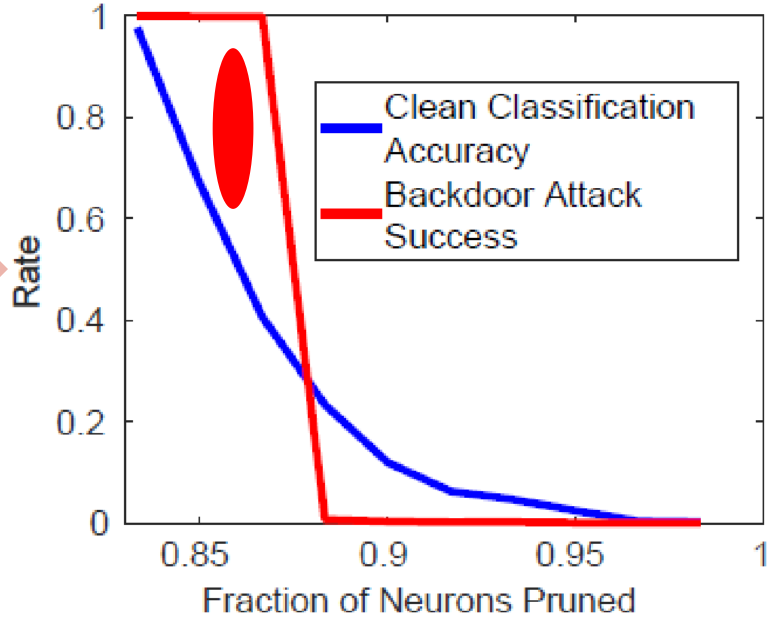
Pruning Aware-Attack Evaluation



Targeted Face Recognition Backdoor [Chen et al.]

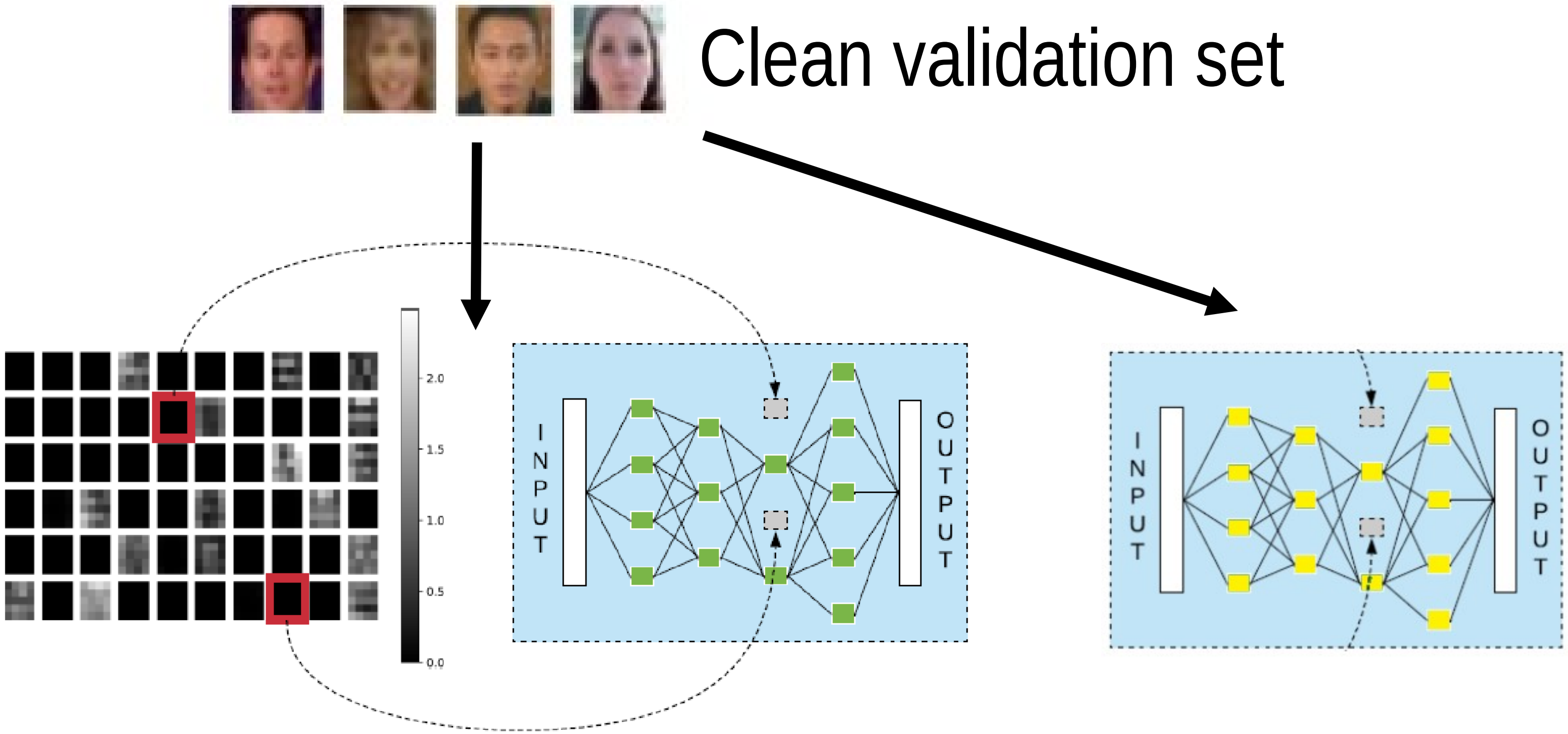


(a) Baseline Attack (Face)



(b) Pruning Aware Attack (Face)

Fine-Pruning Defense



First Prune Unactivated Neurons + Fine-tune Network

Fine-Pruning Results

Table 1. Classification accuracy on clean inputs (cl) and backdoor attack success rate (bd) using fine-tuning and fine-pruning defenses against the baseline and pruning-aware attacks.

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

Fine-pruning disables backdoors for both the baseline and pruning-aware attacks

Does Fine-tuning Alone Work?

Table 1. Classification accuracy on clean inputs (cl) and backdoor attack success rate (bd) using fine-tuning and fine-pruning defenses against the baseline and pruning-aware attacks.

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

Surprisingly, not for the baseline attack. Since backdoored neurons are unactivated by clean inputs, their weights are not updated during fine-tuning