Other Attacks on Machine Learning:
Integrity Poisoning and Privacy Attacks

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Recap

Evasion Attacks

Manipulate test samples to have them misclassified.

Denial-of-Service (DoS) Poisoning Attacks

Manipulate training samples to have test samples misclassified, causing a denial of service.

Other Attacks against ML

Attacks against Machine Learning

	Attacker's Goal		
	Misclassifications that do not compromise normal system operation	Misclassifications that compromise normal system operation	Querying strategies that reveal confidential information on the learning model or its users
Attacker's Capability	**Integrity**	**Availability**	**Privacy / Confidentiality**
Test data	Evasion (a.k.a. adversarial examples)	***Sponge Attacks***	***Model extraction / stealing*** ***Model inversion (hill climbing)*** ***Membership inference***
Training data	***Integrity Poisoning (to allow subsequent intrusions) – e.g., backdoors***	*DoS poisoning (to maximize classification error)*	-

Attacker's Knowledge:

- perfect-knowledge (PK) white-box attacks
- limited-knowledge (LK) black-box attacks (*transferability* with surrogate/substitute learning models)

Biggio & Roli, *Wild Patterns*, PR 2018 https://arxiv.org/abs/1712.03141

Integrity Poisoning Attacks

Integrity vs DoS Poisoning Attacks

Capability (of both): alter/inject training samples.

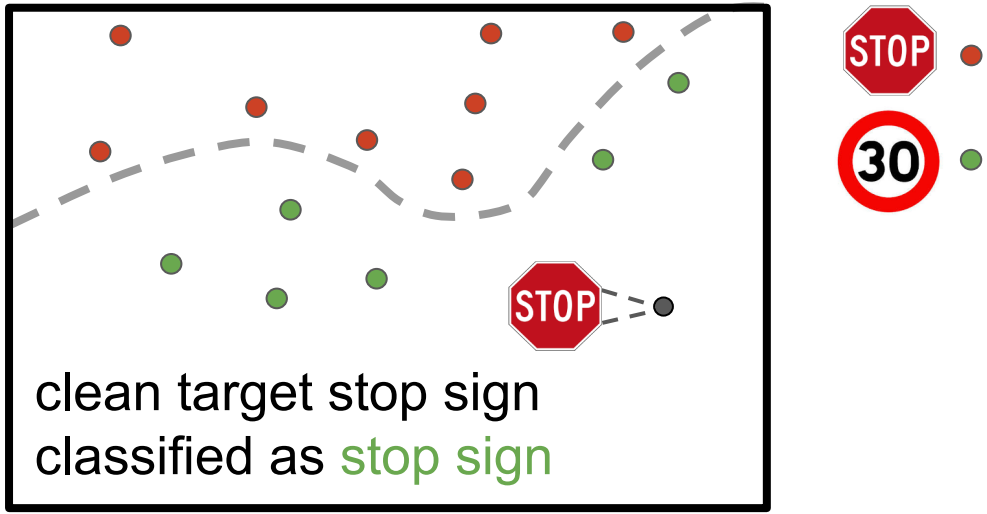
DoS Goal: Manipulate training samples to have test samples misclassified, causing a denial of service.

Integrity Goal: having particular test samples misclassified as the desired class + avoid decreasing the model accuracy to obtain a stealthy attack.

Integrity Poisoning Attacks

Integrity Goal: having particular test samples misclassified as the desired class + avoid decreasing the model accuracy to obtain a stealthy attack.

Which test samples can the attacker have misclassified if she can not alter them?
A set of predefined samples.



Integrity Poisoning Attacks

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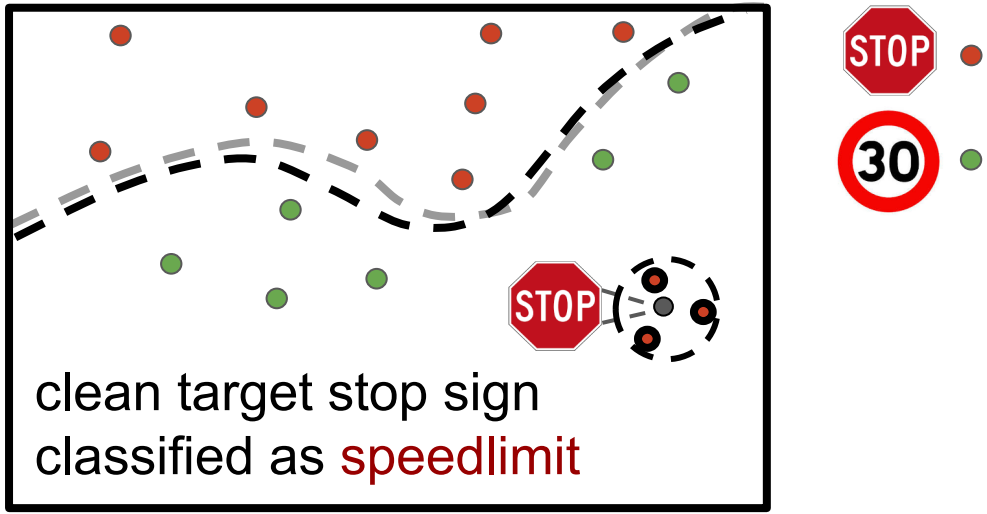


Integrity Poisoning Attacks

Integrity Goal: having particular test samples misclassified as the desired class + avoid decreasing the model accuracy to obtain a stealthy attack.

$$\min_{\boldsymbol{x}_c} \quad L(\mathcal{D}_{\text{val}}, \boldsymbol{w}^\star),$$

loss computed on a validation dataset *

$$\text{s.t.} \quad \boldsymbol{w}^\star \in \arg\min_{\boldsymbol{w}} \mathcal{L}(\mathcal{D}_{\text{tr}} \cup \{\boldsymbol{x}_c, y_c\})$$

classifier trained on the poisoned dataset

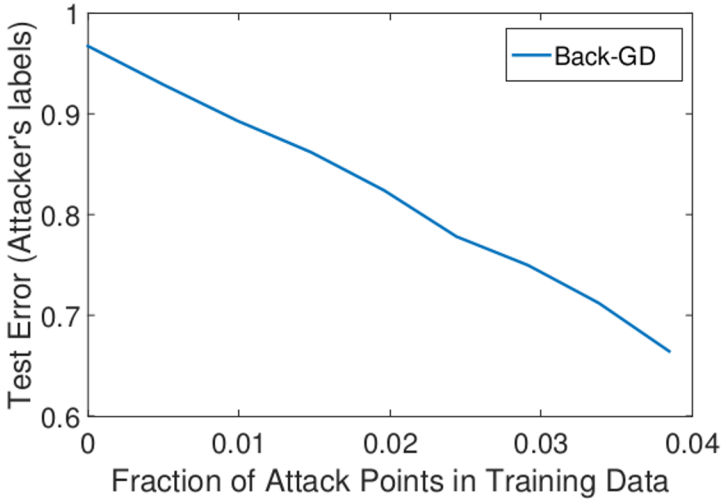
The validation dataset should be composed by:

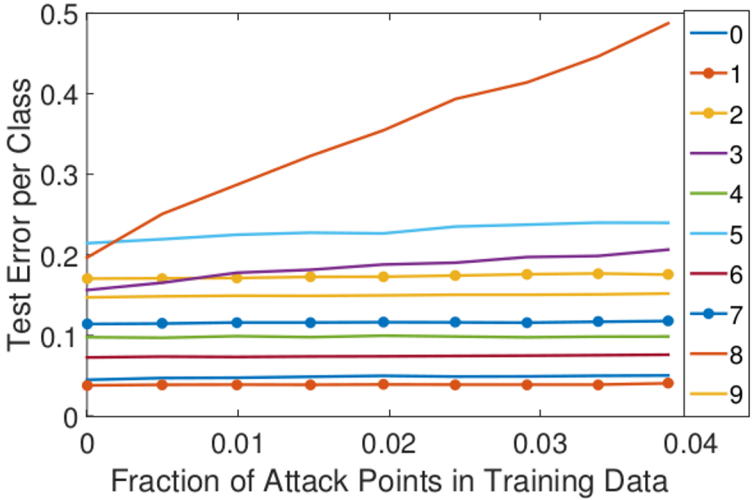
- the samples that the attacker would have misclassified, labeled with the desired label
- samples randomly selected from the same distribution of the test samples

Integrity Poisoning Attacks

Dataset: MNIST; Classifier: logistic regression.

Attacker's goal: having the digits "8" classified as "3".





Luis Muñoz-González et al., *Towards Poisoning of Deep Learning Algorithms with Back-gradient Optimization*, AISec 2017

Integrity Poisoning Attacks

$$\min_{\boldsymbol{x}_c} \quad L(\mathcal{D}_{\text{val}}, \boldsymbol{w}^\star),$$
$$\text{s.t.} \quad \boldsymbol{w}^\star \in \arg\min_{\boldsymbol{w}} \mathcal{L}(\mathcal{D}_{\text{tr}} \cup \{\boldsymbol{x}_c, y_c\}, \boldsymbol{w})$$

1st Problem: The poisoning samples might be visibly perturbed.

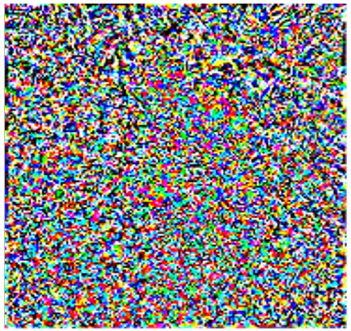
This is a problem:

- if the training data are checked by humans (unlikely).
- if outlier detection and removal techniques are applied to the training dataset.

Clean-Label Poisoning

Solution: a new type of poisoning attack called "clean-label" devised to create imperceptibly perturbed poisoning samples.

Clean sample
Label: **Dog**



Poisoning sample
Label: **Dog**

Integrity Poisoning Attacks

$$\min_{\boldsymbol{x}_c} \quad L(\mathcal{D}_{\text{val}}, \boldsymbol{w}^\star)\,,$$
$$\text{s.t.} \quad \boldsymbol{w}^\star \in \arg\min_{\boldsymbol{w}} \mathcal{L}(\mathcal{D}_{\text{tr}} \cup \{\boldsymbol{x}_c, y_c\})$$

2nd Problem: This problem is difficult to solve.

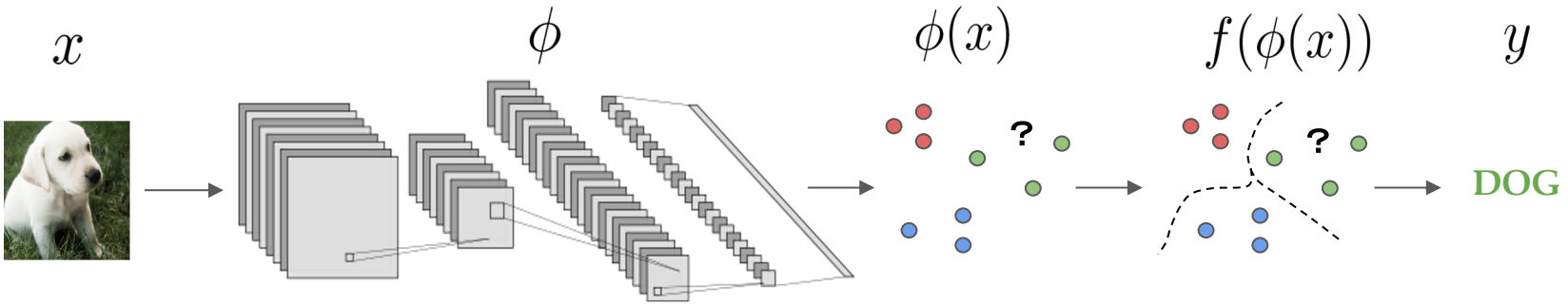
- It can be solved by replacing the inner problem with the KKT conditions. Drawback: $O(n^3)$, where n is the number of model's parameters.
- For different classifiers, it can be solved using a technique called "back-gradient". However, it has not been demonstrated on deep neural networks yet.

Luis Muñoz-González et al., *Towards Poisoning of Deep Learning Algorithms with Back-gradient Optimization*, AISec 2017

Feature Collision Attacks

Solution: A new type of poisoning attack called "feature collision" that makes the deep features of the target test sample collide with those of the poisoning samples.

(Craft poisoning samples that might be different from the target in input space but that are mapped in the same region of the feature space by the deep network).



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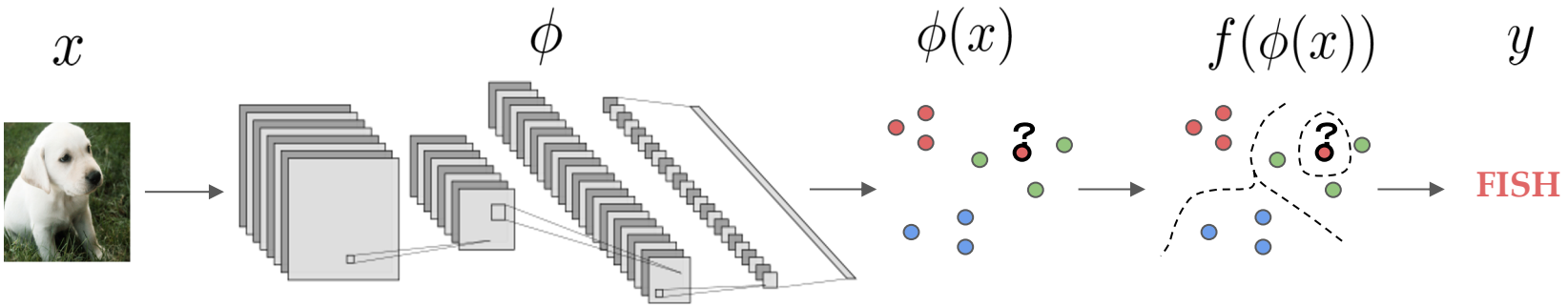
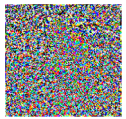


Poisoning Frog

First clean-label feature collision attack.

Goal: having a target sample t  misclassified as the desired class, **Dog.**

$$\underset{\mathbf{x}}{\operatorname{argmin}} \; \|f(\mathbf{x}) - f(\mathbf{t})\|_2^2 + \beta \|\mathbf{x} - \mathbf{b}\|_2^2$$

This attack tries to find a poisoning sample x  +  , **Dog**

-near to a base image b of the desired class in input space 

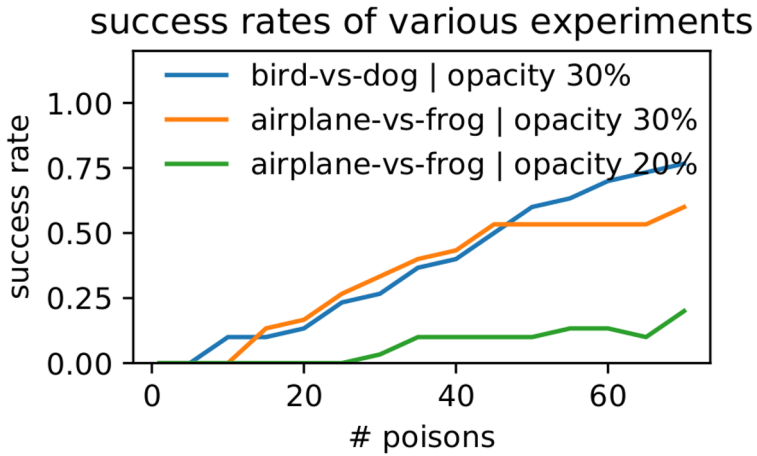
-that, in feature space, collides with the target sample 

Shafahi et al., *Poison Frogs! Targeted Clean-Label Poisoning Attacks on Neural Networks*, NeurIPS 2018

Poisoning Frog

Dataset: CIFAR-10, Classifier: Alexnet trained trained end-to-end;

Poisoning images that cause a bird target to get misclassified as a dog - opacity 30%.



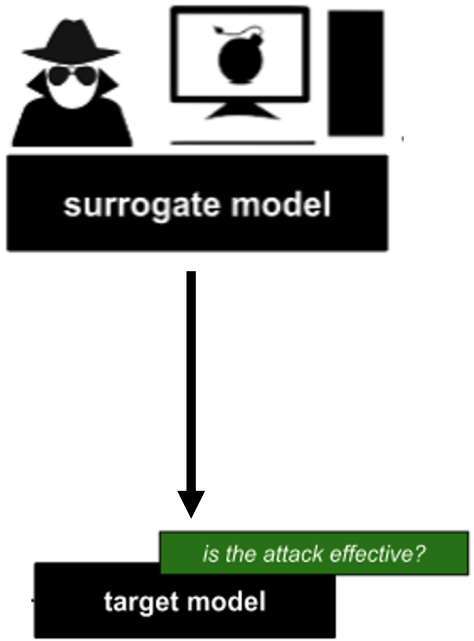
Transferability

The attacker might not know the target model… in this case she need transferable attacks.

Attack surrogate classifier
Consider a close approximation of the real target model, by either training a new one on same or similar data, or use a pretrained model

Compute gradient attacks
The attacker chose a differentiable model, to maximize the easiness of computing attacks

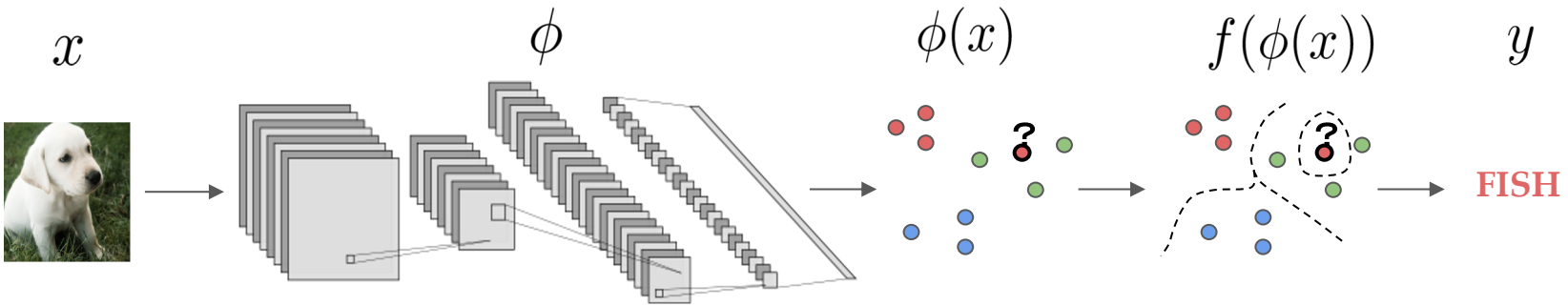
Transfer the results
Try to poison the real target using the poisoning points computed on the surrogate



Poisoning Frog

Problem: the poisoning point generated with this attack does not transfer.

To craft a poisoning sample that collides with the target image in feature space, you need to know the model you are attacking (works only in a white-box scenario).

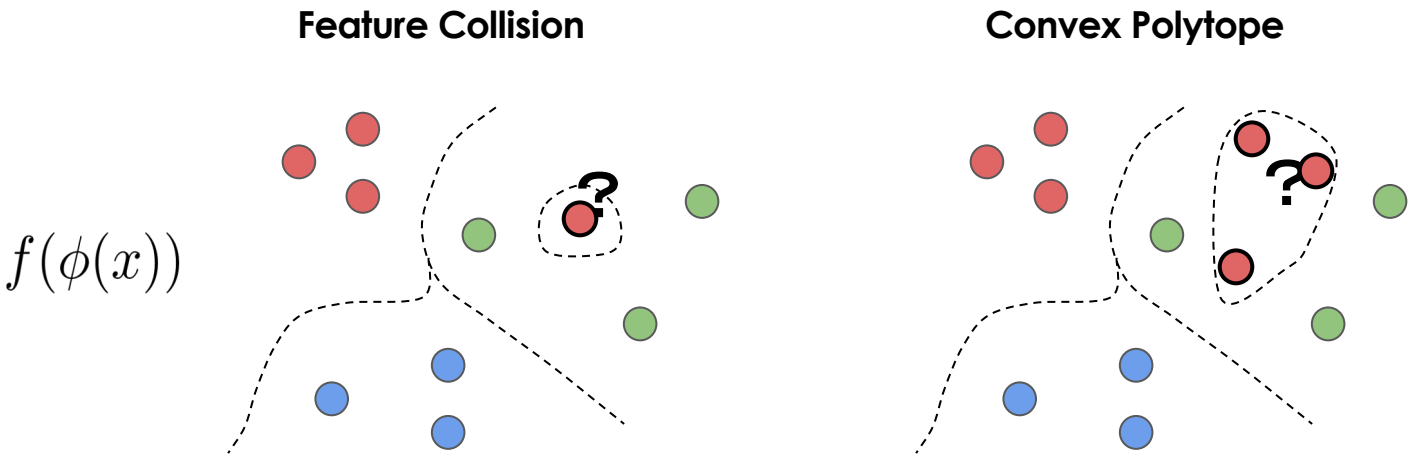


Zhu et al., *Transferable Clean-Label Poisoning Attacks on Deep Neural Nets*, ICML 2019

Convex Polytope

Solution: to have a single target sample misclassified, inject more poisoning points, crafted to generate, in feature space, a convex polytope around the target instance.

Even if the surrogate network is a bit different, the attack is more likely to transfer.



Zhu et al., *Transferable Clean-Label Poisoning Attacks on Deep Neural Nets*, ICML 2019

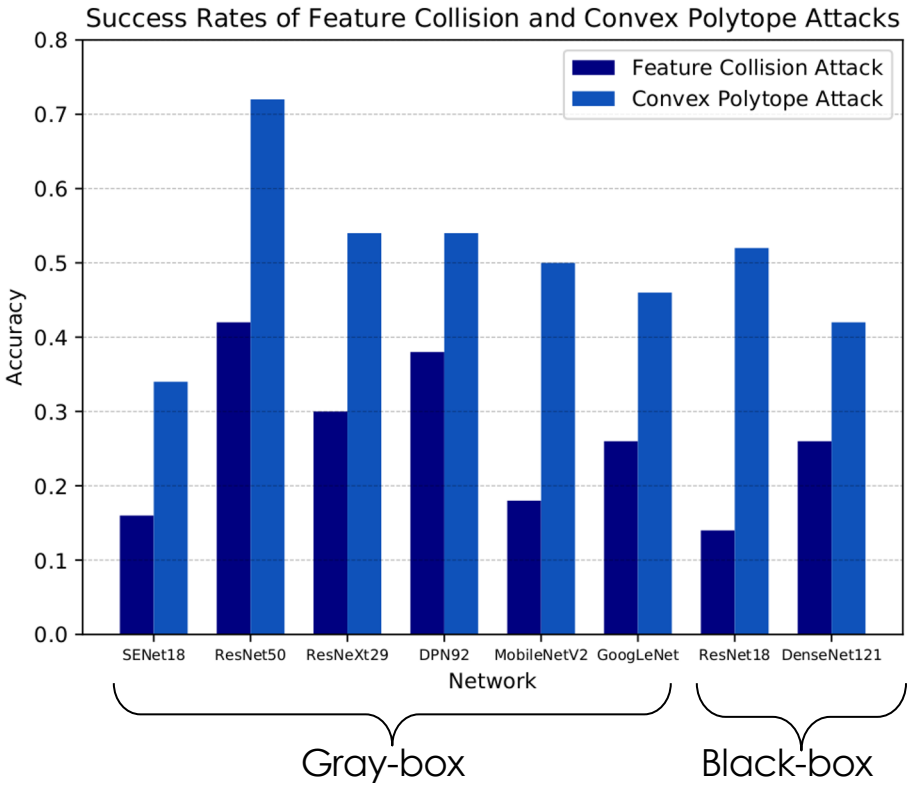
Convex Polytope

Dataset: CIFAR10

50 target images
5 poisoning points for each target

Gray-box: the surrogate model has the same architecture but different weights of the target model.

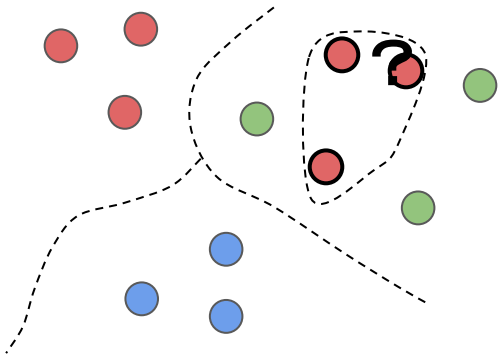
Black-box: use as surrogate all the considered networks except ResNet18 and DeseNet121.



Convex Polytope

Problem: This approach constructs a convex polytope around the target sample. However, the target sample may lay near one of the borders of the polytope.

$f(\phi(x))$



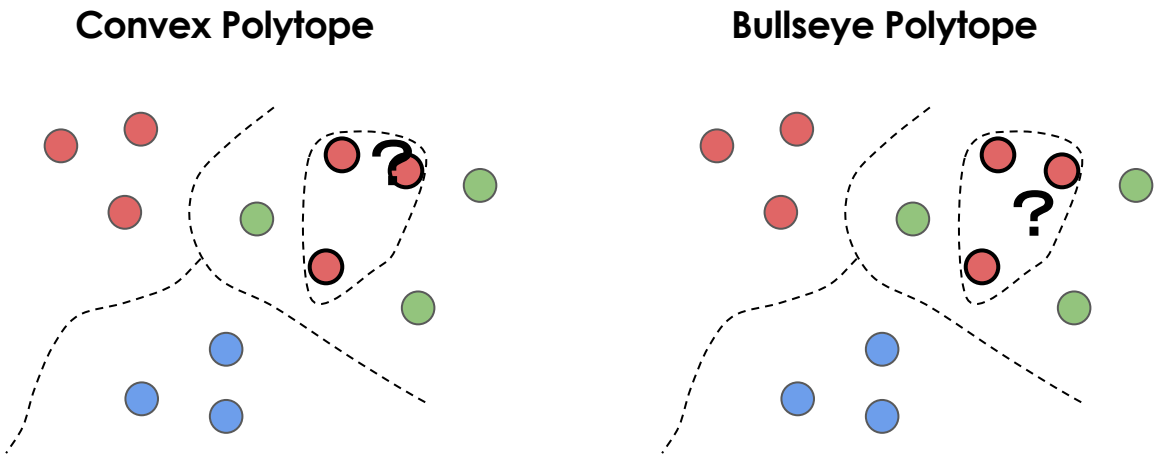
In this case, the target is likely to be inside the convex polytope in the surrogate model's deep space but outside in the target model's deep space.

Aghakhani et al., *Bullseye Polytope: A Scalable Clean-Label Poisoning Attack with Improved Transferability*, arXiv 2020

Bullseye Polytope

Solution: Crafting the poisoning point so that the target sample lays in the center of the convex polytope.

$f(\phi(x))$



In this case, the target is more likely to be inside the convex polytope in the surrogate and the target model's deep space.

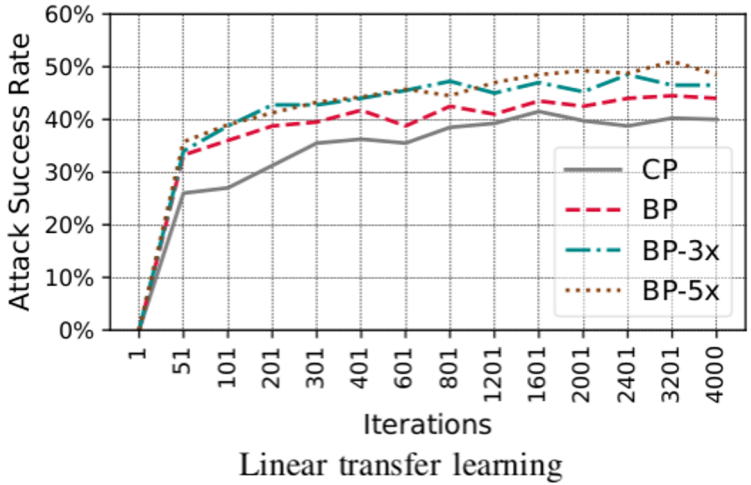
Aghakhani et al., *Bullseye Polytope: A Scalable Clean-Label Poisoning Attack with Improved Transferability*, arXiv 2020

Bullseye Polytope

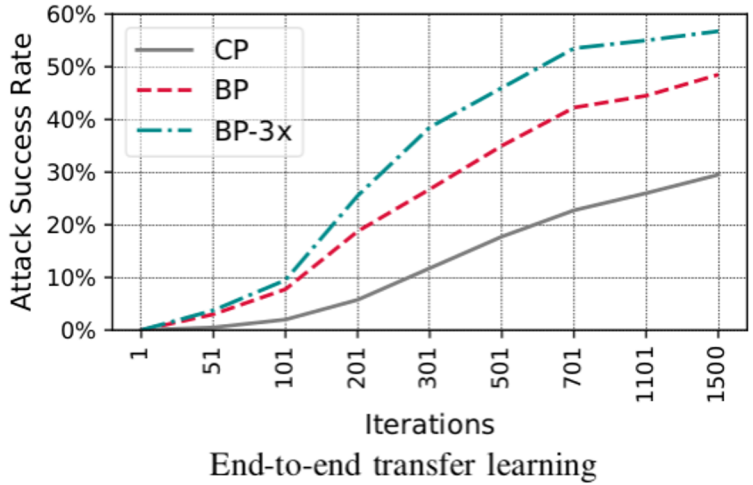
Dataset: CIFAR-10; 50 target images; 5 poisoning points for each target.

Setting:

- Linear transfer learning - poison a linear model trained in deep space.
- End-to-end transfer learning - poison a fine-tuned deep neural network.



Linear transfer learning



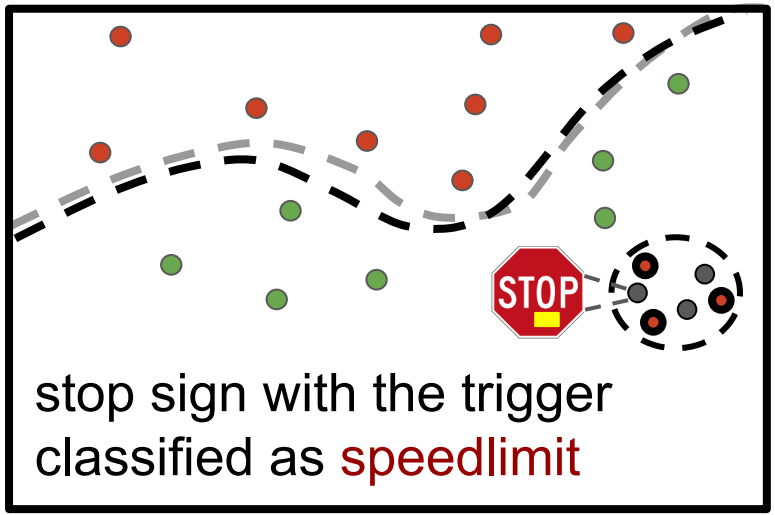
End-to-end transfer learning

Aghakhani et al., *Bullseye Polytope: A Scalable Clean-Label Poisoning Attack with Improved Transferability*, arXiv 2020

Backdoor Poisoning Attacks

Goal: having only some test samples misclassified as the desired class.

Which test samples can the attacker have misclassified if she can alter them?
Any sample that contains a particular pattern (trigger).

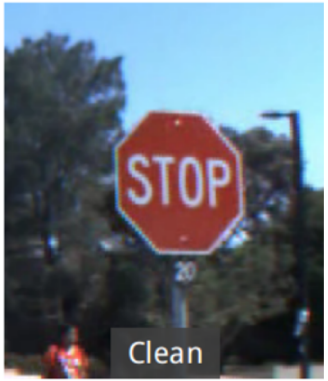


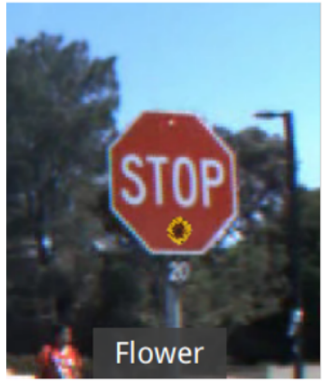
BadNet

Uses small patterns as backdoor.
Datasets: MNIST, Traffic signs

Original image

Pattern Backdoor





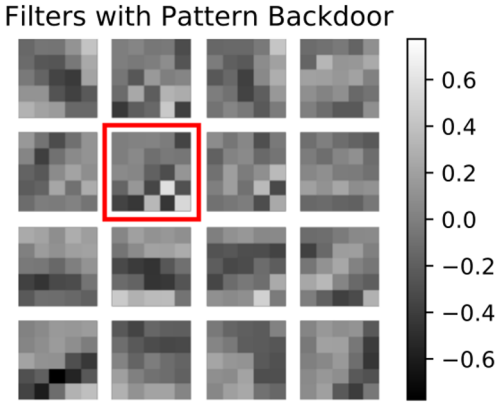
Aghakhani et al., *BadNets: Identifying Vulnerabilities in the Machine Learning Model Supply Chain*, arXiv 2020

BadNet

Classifier: CNN with two convolutional and two fully connected layers trained on MNIST.

The attacker changes the label of digit i to digit i + 1 for backdoored inputs (90 samples containing the backdoor).

The authors show after the attack, one of the network filters is dedicated to detecting the backdoor.



Aghakhani et al., *BadNets: Identifying Vulnerabilities in the Machine Learning Model Supply Chain*, arXiv 2020

BadNet

Classifier: Faster-RCNN trained on the traffic sign dataset.

The attacker adds a backdoor to have stop signs misclassified as a speed limit.

Accuracy of the clean model:

Stop sign: 89,7%
Speed limit: 88.3%

Accuracy of the backdoored model:

Stop sign -> speed limit 93.7%

Aghakhani et al., *BadNets: Identifying Vulnerabilities in the Machine Learning Model Supply Chain*, arXiv 2020

BadNet

Problem: The trigger makes the poisoned samples easy to spot.

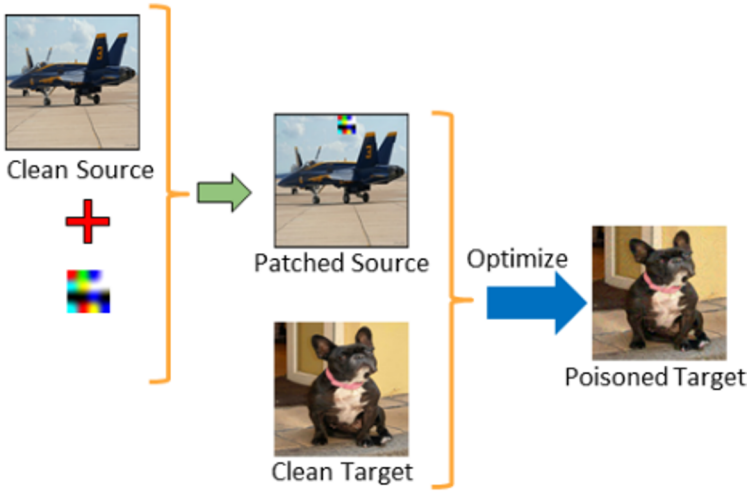
This is a problem:

- if the training data are checked by humans (unlikely).
- if outlier detection and removal techniques are applied to the training dataset.

Hidden Trigger [stealthy at training time]

To have a plane misclassified as a dog, compute the poisoned image as follows:

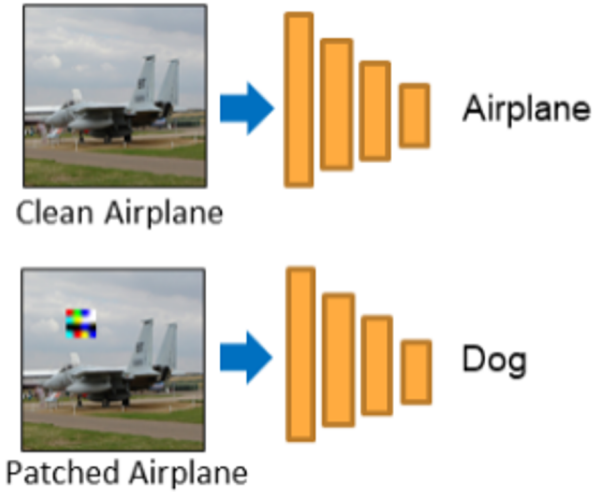
1. add a trigger to the image of a plane;
2. search an image that in deep space collides with it but that looks as a dog (performs feature collision).



Saha et al., *Hidden Trigger Backdoor Attacks*, AAAI 2020

Hidden Trigger [stealthy at training time]

At test time, the images of Airplanes containing the trigger are classified as a dog.



Saha et al., *Hidden Trigger Backdoor Attacks*, AAAI 2020

Hidden Trigger [stealthy at training time]

Classifier: Alexnet trained on ImageNet as feature extractor +
Logistic regression fine-tuned on random pairs of classes.

	ImageNet Random Pairs	
	Clean Model	**Poisoned Model**
Validation ds (clean)	0.993 ± 0.01	0.982 ± 0.01
Validation ds + trigger	0.987 ± 0.02	**0.437** ± 0.15

The accuracy of the poisoned model on the samples with the trigger is low because they are misclassified as the original class and predicted instead as the class desired by the attacker (the considered model is binary).

Saha et al., *Hidden Trigger Backdoor Attacks*, AAAI 2020

BadNet vs Hidden Trigger

Hidden trigger is stealthier than BadNet.

This means that a defender will always face Hidden trigger and it is no more worth defending against BadNet? **No.**

Performing hidden trigger requires more skills.. you can craft samples backdoored with BadNet even with GIMP or another photo editing software...

Hidden trigger requires more effort from the attacker's point of view.

Therefore, it is more likely to face simple attacks as BadNet.

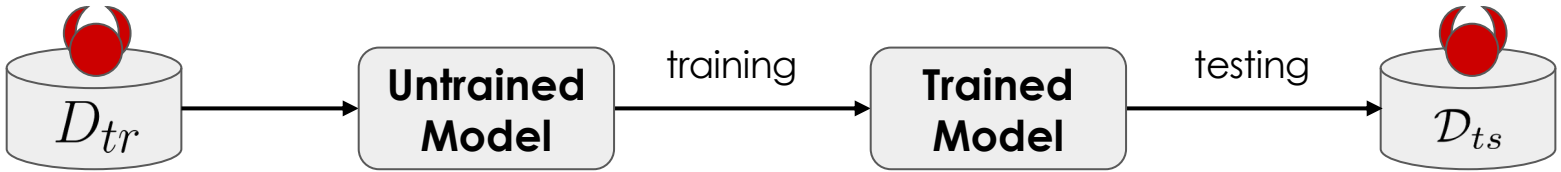
Integrity Poisoning: Three Main Categories

	Test data with trigger	Test data without trigger (Targets a predefined samples)
Training data with trigger	BadNets, ...	-
Training data without or with a stealthy trigger	Hidden Trigger, ...	Convex Polytope, ...

Poisoning Integrity Defenses

Defending against Integrity Poisoning

As we have seen, the attacker has the capability to poison the training dataset and, depending on the scenario, also the test dataset.



Different types of defenses have been proposed against integrity poisoning.

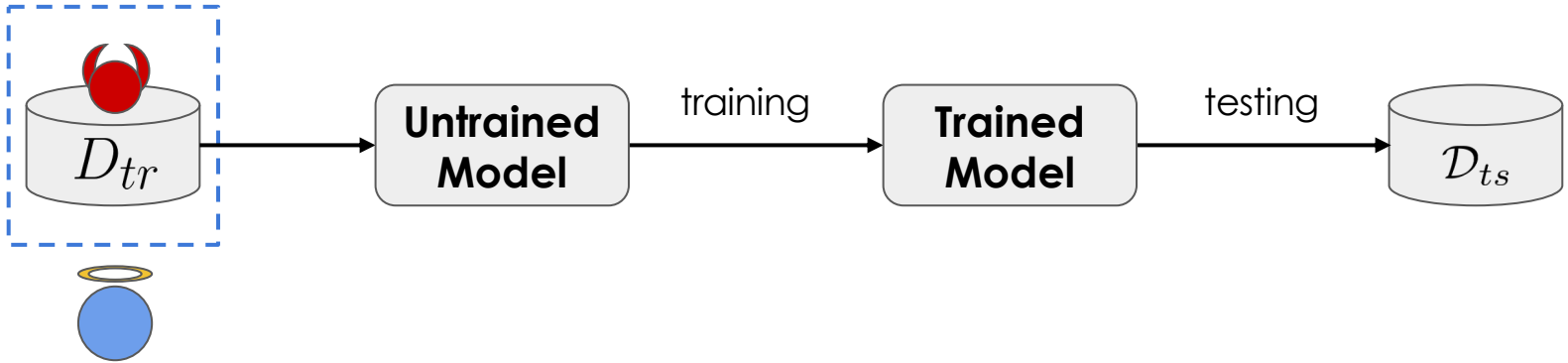
Some of them work at training-time, and some at test-time.

Poisoning Integrity Defenses

Training-Time

Training Data Sanitization

The defender analyzes the training data, searching and removing poisoning points.



Spectral Signature

Proposed as a defense against BadNet.

The samples with the backdoor are quite different from the samples.

Image of an Airplane with a one-pixel trigger, labeled ad “bird”

Therefore, they can be removed with standard outlier detection techniques.

Tran et al., *Spectral Signatures in Backdoor Attacks*, NeurIPS 2018

Spectral Signature

Spectral signature, removes outlier during the training procedure.

Starts with a randomly initialized deep neural network.

For each class, removes the training samples farthest from the others in deep space.

Train the network on the cleaned training dataset.

Repeats.

Tran et al., *Spectral Signatures in Backdoor Attacks*, NeurIPS 2018

Spectral Signature

Considered attack: BadNet. Tested on ResNet trained on CIFAR10;

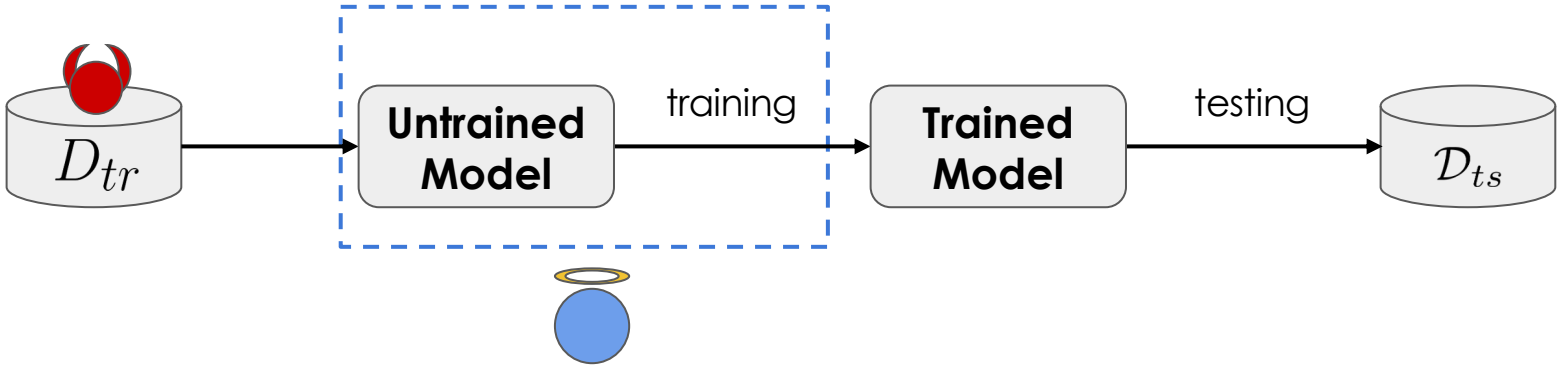
Sample is the backdoored sample.
Epsilon is the percentage of images of the target class poisoned by the attacker.

			before		after		
Sample	Target	Epsilon	Nat 1	Pois 1	# Pois Left	Nat 2	Pois 2
	bird	5%	92.27%	74.20%	57	92.64%	2.00%
		10%	92.32%	89.80%	7	92.68%	1.50%
	cat	5%	92.45%	83.30%	24	92.24%	0.20%
		10%	92.39%	92.00%	0	92.44%	0.00%
	dog	5%	92.17%	89.80%	7	93.01%	0.00%
		10%	92.55%	94.30%	1	92.64%	0.00%

Tran et al., *Spectral Signatures in Backdoor Attacks*, NeurIPS 2018

Robust Training

The defender design a robust model or train a standard model with a training procedure that makes it robust against poisoning.



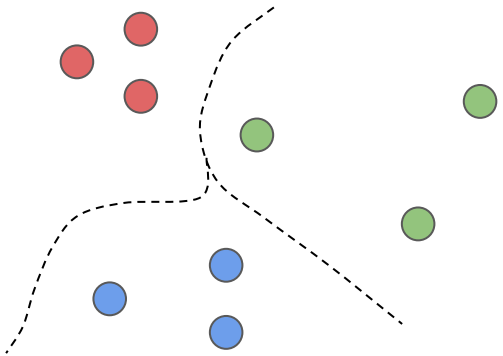
Regularization against Backdoors

Regularization can be used as a defense against integrity poisoning.

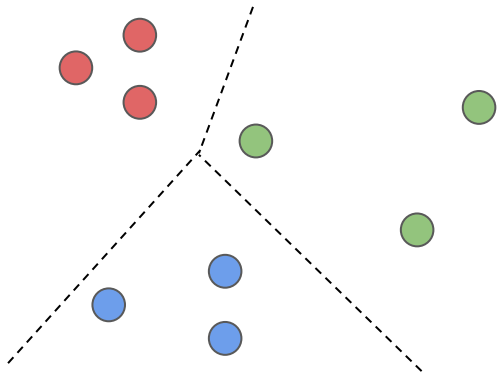
$$w^\star \in \arg\min_{w} \mathcal{L}(\mathcal{D}_{\text{tr}}, w) + \alpha \, \|w\|^2$$

Intuitively, it reduces the complexity of the decision function learned by the classifier and, therefore, its ability to overfit the poisoning samples.

High-complexity classifier



Low-complexity classifier



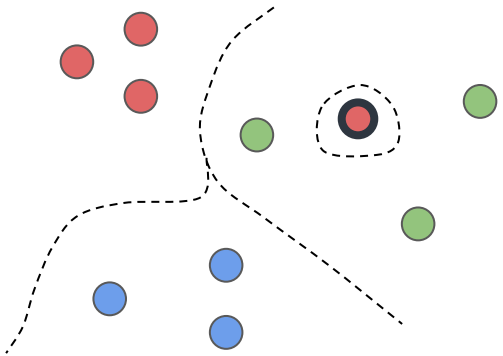
Regularization against Backdoors

Regularization can be used as a defense against integrity poisoning.

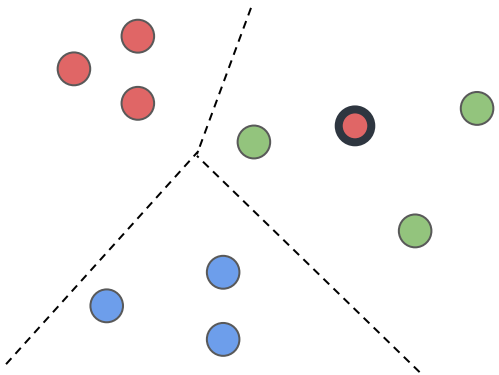
$$\boldsymbol{w}^{\star} \in \arg\min_{\boldsymbol{w}} \mathcal{L}(\mathcal{D}_{\mathrm{tr}}, \boldsymbol{w}) + \alpha \, \|\boldsymbol{w}\|^2$$

Intuitively, it reduces the complexity of the decision function learned by the classifier and, therefore, its ability to overfit the poisoning samples.

High-complexity classifier



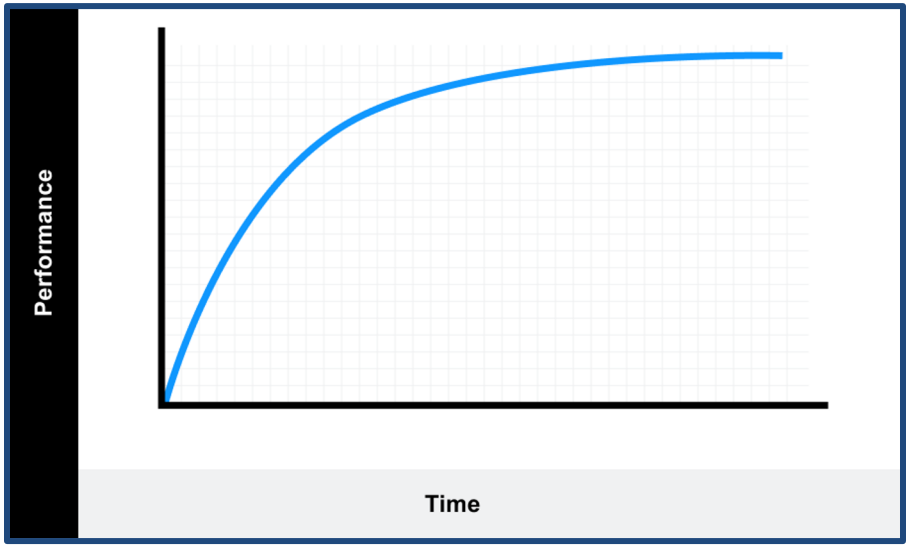
Low-complexity classifier



Backdoor Learning Curves

To understand why regularization helps, we can try to study how classifiers learn backdoors.
How can we do?...

For humans, the learning process is characterized using learning curves.
The slope of the curve characterized how much the task is difficult to learn.



How humans learn easy tasks
https://www.valamis.com/hub/learning-curve

If the task is easy it will be learned soon.

Backdoor Learning Curves

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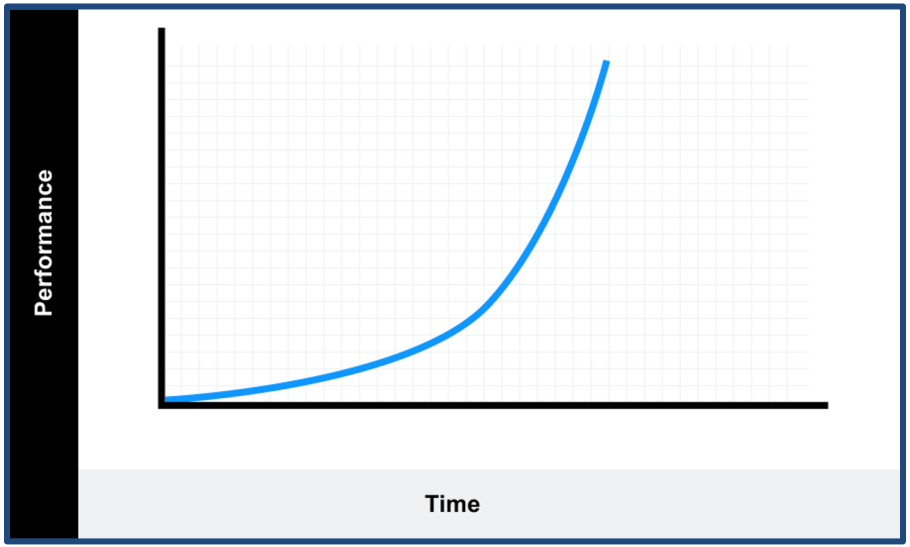


How humans learn complex tasks
https://www.valamis.com/hub/learning-curve

If the task is easy it will be learned later.

Backdoor Learning Curves

To understand why regularization helps, we can try to study how classifiers learn backdoors. How can we do?...

Goal: creating a learning curve that shows us how much is difficult for a classifier, learning a backdoor.

Once we have this plot, we can make them for two classifiers with different complexity and compare them.

How can we create this plot?..

Cinà et al., *Backdoor Learning Curves: Explaining Backdoor Poisoning Beyond Influence Functions*, ArXiv 2021

Backdoor Learning Curves

We can formulate backdoor learning as an incremental learning problem.

$$\boldsymbol{w}^{\star}(\beta) \in \arg\min_{\boldsymbol{w}} \; L(D_{\mathrm{tr}}, \boldsymbol{w}) + \beta L(\mathcal{P}_{\mathrm{tr}}, \boldsymbol{w})$$

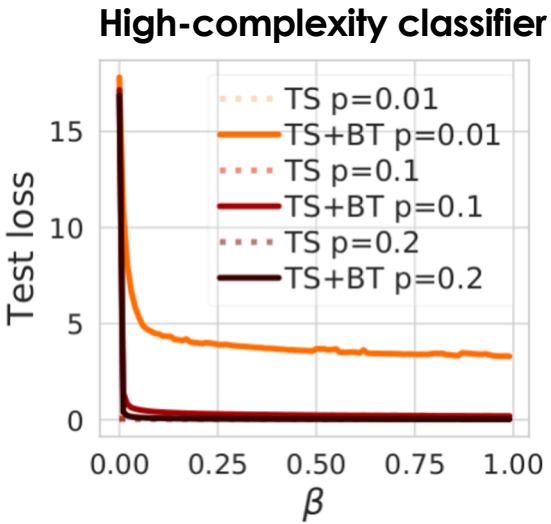
where P_{tr} is the backdoored dataset and β is a constant that we increase from 0 to 1 to create the plot.

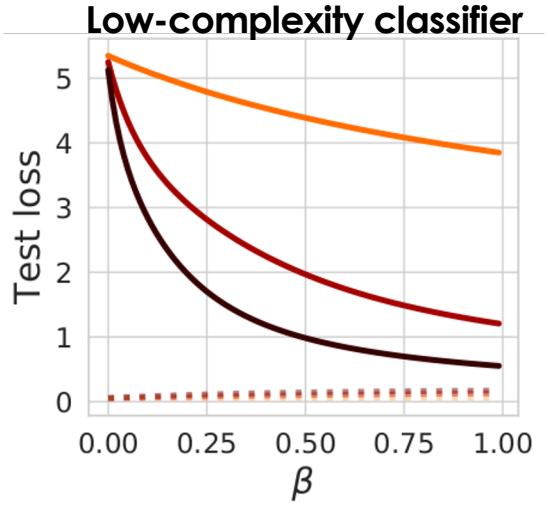
When $\beta = 0$, the classifier is learning only the clean training dataset.
When $\beta = 1$, the classifier is learning the clean training samples + the backdoored dataset.

Gradually increasing β allows us to understand how much the learning becomes more difficult when the classifier has to learn not only the clean test samples but also the backdoored test samples, namely how much is difficult learning the backdoored samples.

Cinà et al., *Backdoor Learning Curves: Explaining Backdoor Poisoning Beyond Influence Functions*, ArXiv 2021

Backdoor Learning Curves





Classifier: logistic; Dataset: MNIST 7-1.
p is the percentage of training point containing the backdoor trigger.

These plots show that for low-complexity classifier, learning backdoors is a harder task.

Cinà et al., *Backdoor Learning Curves: Explaining Backdoor Poisoning Beyond Influence Functions*, ArXiv 2021

Backdoor Impact on Learning Parameters

To better understand why, we can monitor how the classifiers' parameter changes during backdoor learning.

To this end, we have devised two measures:

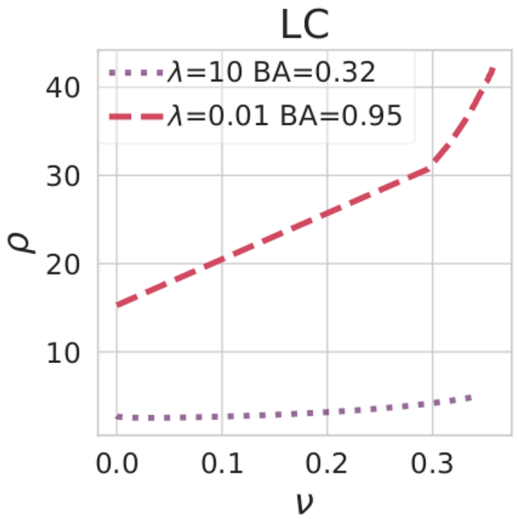
1. v that quantifies how the orientation of the decision hyperplane changes
2. ρ that quantifies how much the norm of the classifier weights increases*

And we have plot how they change during the creation of the backdoor learning curve for a classifier trained with two levels of complexity.

* the norm of classifier weights is proportional to their complexity and inversely proportional to the margin.

Cinà et al., *Backdoor Learning Curves: Explaining Backdoor Poisoning Beyond Influence Functions*, ArXiv 2021

Backdoor Impact on Learning Parameters



Low-complexity classifier λ = 10 (strong regularization)
High-complexity classifier λ = 0.01 (low regularization)

This plot shows that, when the classifier learns the backdoored samples its complexity increases.

If the classifier is strongly regularized, it cannot increase much its complexity and, therefore, it cannot learn well the backdoor.

Cinà et al., *Backdoor Learning Curves: Explaining Backdoor Poisoning Beyond Influence Functions*, ArXiv 2021

Visualizing Influential Training Points

Dataset: MNIST and CIFAR10.
High-complexity classifier SVM RBF.

7 most influential training samples on the prediction of the samples with the red border.

Many backdoored samples are among the most influential for the prediction.

Cinà et al., *Backdoor Learning Curves: Explaining Backdoor Poisoning Beyond Influence Functions*, ArXiv 2021

Visualizing Influential Training Points

Dataset: MNIST and CIFAR10.
High-complexity classifier SVM RBF.

7 most influential training samples on the prediction of the samples with the red border.

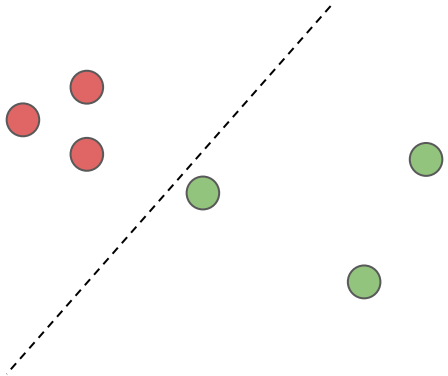
Despite the samples with the red border contain the trigger, there aren't backdoored samples among the most influential for the prediction.

Cinà et al., *Backdoor Learning Curves: Explaining Backdoor Poisoning Beyond Influence Functions*, ArXiv 2021

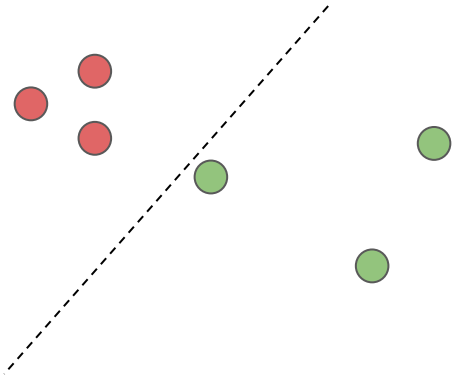
Data Augmentation against Backdoor

In other papers have been proposed alternative approaches that overall reduces the complexity of the learned model. One of these approaches is data augmentation.

Regularization increases the margin altering the training loss function.



Data augmentation increases the margin adding perturbed samples.



Borgnia et al., *Strong Data Augmentation Sanitizes Poisoning and Backdoor Attacks Without an Accuracy Tradeoff*, ICASSP 2021

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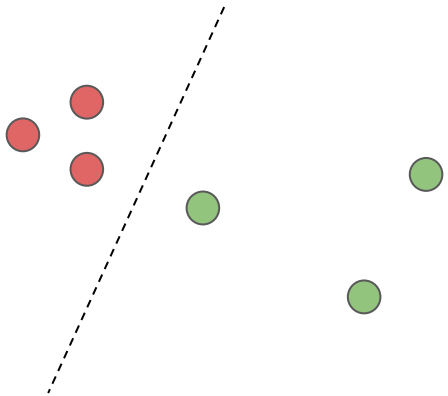

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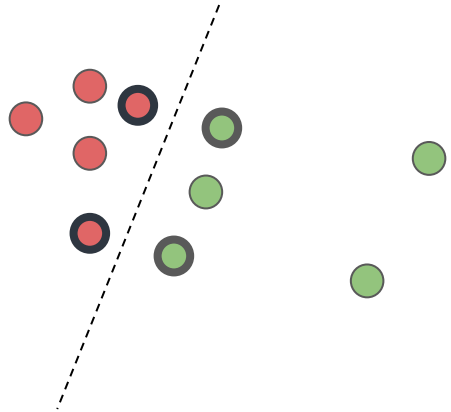


Borgnia et al., *Strong Data Augmentation Sanitizes Poisoning and Backdoor Attacks Without an Accuracy Tradeoff*, ICASSP 2021

Data Augmentation against Backdoor

Augmentation: Mixup and CutMix, both mix the image of two different classes.

Classifier: ResNet-18 trained from scratch on CIFAR-10.
Attack: BadNet
Percentage of training data backdoored between brackets.

	Poison Success (100%)	Validation Accuracy (100%)	Poison Success (10%)	Validation Accuracy (10%)
Baseline	100%	85%	57%	94%
mixup	100%	85%	42%	95%
CutMix	36%	94%	23%	95%

Reduces the backdoor success without compromising the accuracy on the clean data.

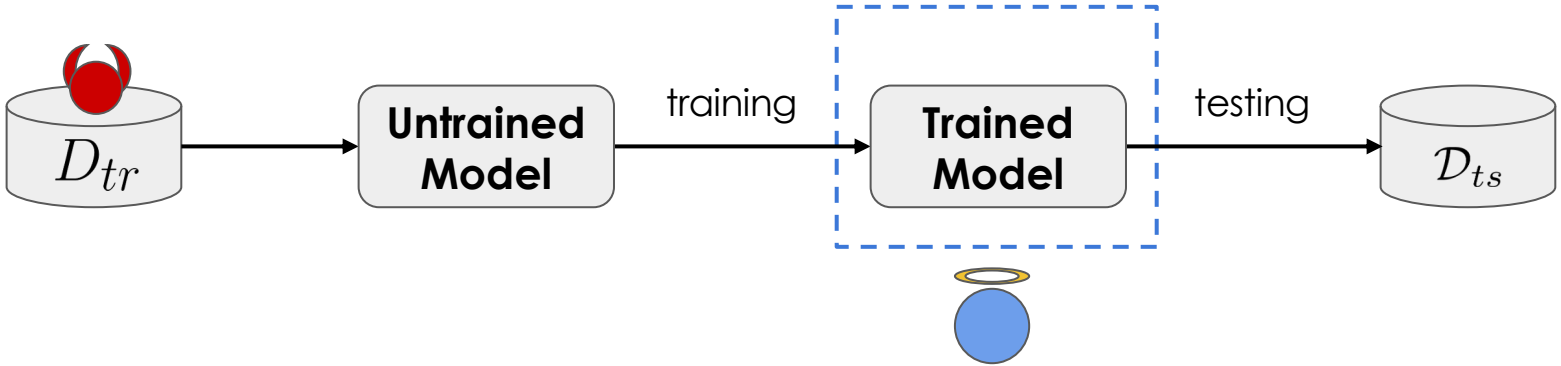
Borgnia et al., *Strong Data Augmentation Sanitizes Poisoning and Backdoor Attacks Without an Accuracy Tradeoff*, ICASSP 2021

Poisoning Integrity Defenses

Test-Time

Model Inspection

The defender analyzes the trained model (and eventually also the training data) to detect the poisoning point.



Activation Clustering

Distinguish poisoning from legitimate samples clustering the activations of the last layer.

For each label:

1. computes the activation of all the samples in the poisoned dataset with that label
2. performs dimensionality reduction on the activations
3. cluster them with K-means to divide them into two clusters: poisoning and legitimate

Chen et al., *Detecting Backdoor Attacks on Deep Neural Networks by Activation Clustering*, Arxiv 2018

Activation Clustering

Classifier: CNN with two convolutional and two fully connected layers trained end-to-end.

Dataset: MNIST
Attack: BadNet

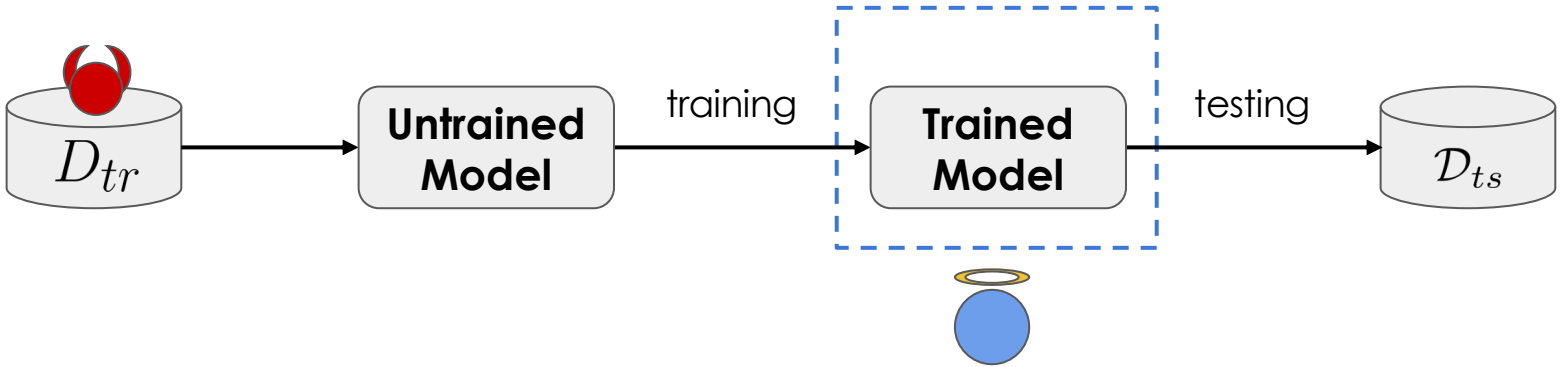
Percentage of detected backdoored samples for class

Target	0	1	2	3	4	5	6	7	8	9	Total
AC Accuracy	99.89	99.99	99.95	100	100	100	99.94	100	100	99.99	99.97

Chen et al., *Detecting Backdoor Attacks on Deep Neural Networks by Activation Clustering*, Arxiv 2018

Trigger Reconstruction

The defender analyzes the trained model (and eventually also the training data) to reconstruct the backdoor trigger used by the attackers.



Tabor

Formalizes trojan detection as an optimization problem:

$$\text{argmin}_{\Delta, \mathbf{M}} L(f(\mathbf{x}_t), y_t)$$

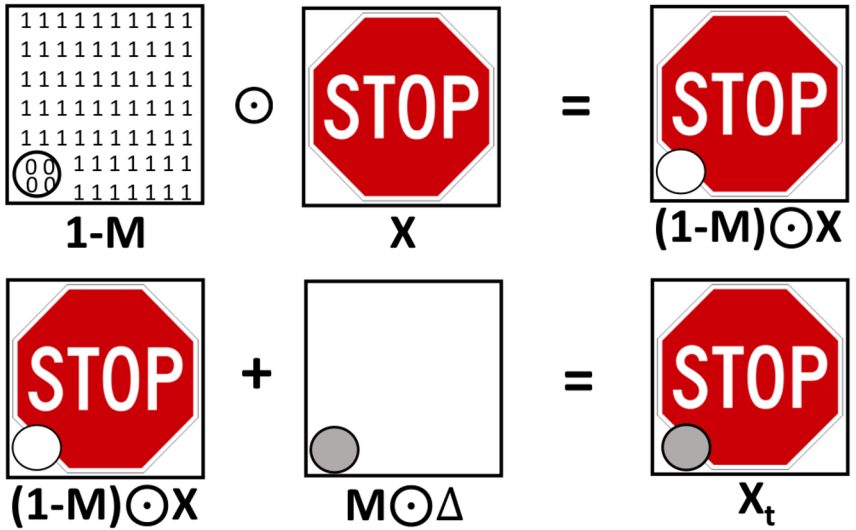
$$\mathbf{x}_t = \mathbf{x} \odot (1 - \mathbf{M}) + \Delta \odot \mathbf{M}$$

where:

- M is the mask (trigger shape and location)
- Δ is a pattern (trigger color)
- xt is a test sample
- yt is the target class

Multiplied together M $\odot$ Δ they denote the restored trigger.

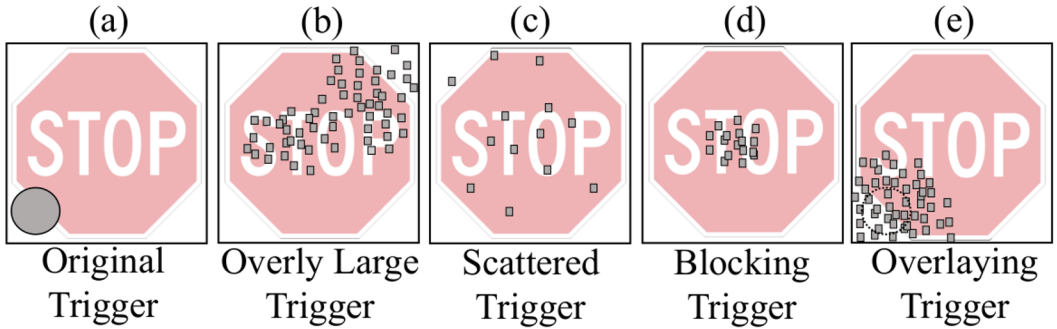
Search the trigger that minimizes the loss w.r.t. the target class of the test sample + the trigger.



Guo et al., *TABOR: A Highly Accurate Approach to Inspecting and Restoring Trojan Backdoors AI Systems*, Arxiv 2019

Tabor

The authors show that solving that problem, you often end up with a trigger that belongs to one of these categories:

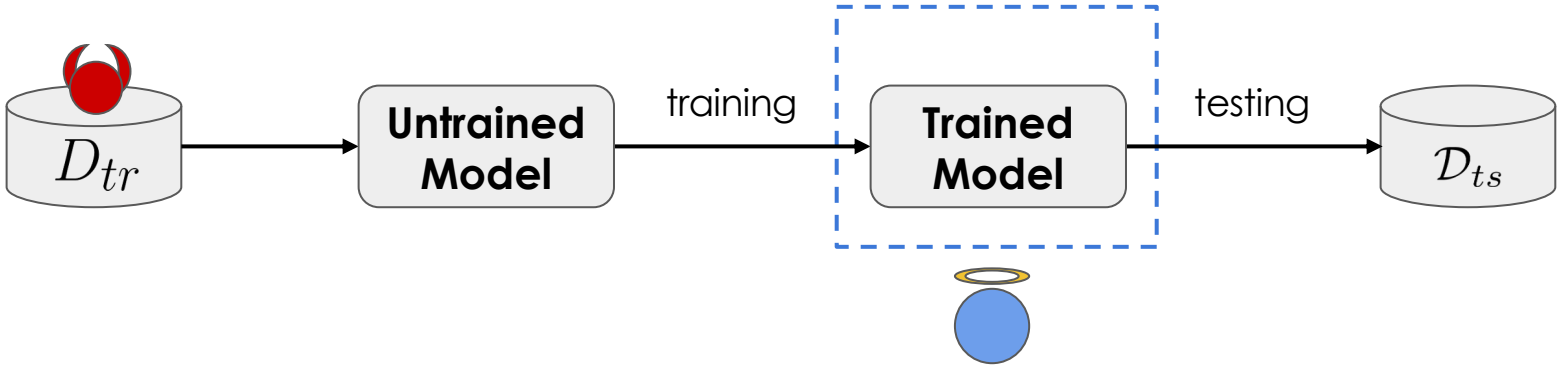


Therefore, they add some regularization terms to the original loss function to discourage these situations and restore the corresponding trigger as accurately as possible.

Guo et al., *TABOR: A Highly Accurate Approach to Inspecting and Restoring Trojan Backdoors AI Systems*, Arxiv 2019

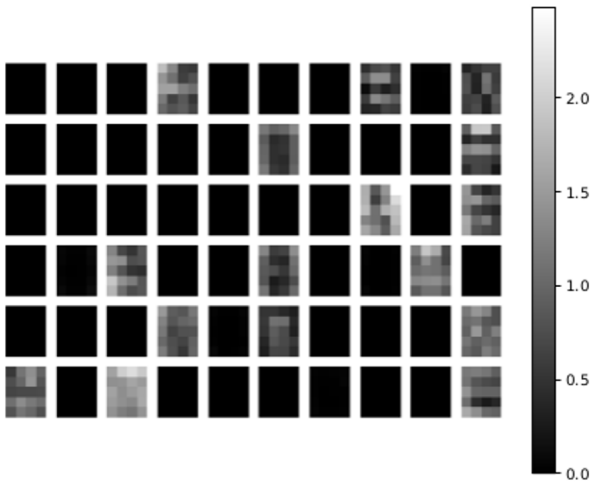
Model Sanitization

The defender removes the effect of the poisoning samples on the trained model.

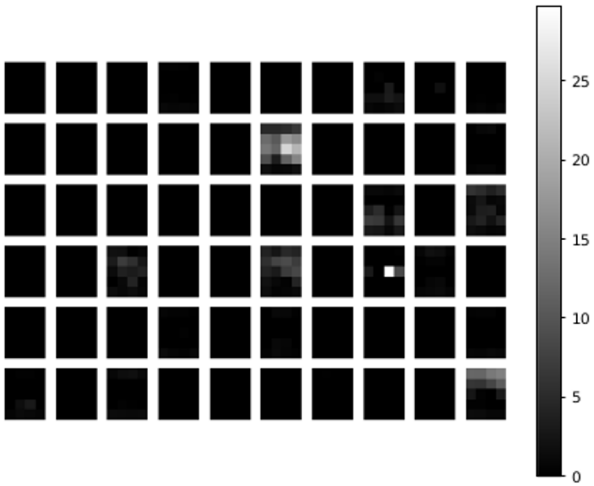


Fine Pruning

Backdoored DNN misbehave on backdoored inputs while still behaving on clean inputs.
To make this possible, some of their filters must be dedicated to the backdoor.



(a) Clean Activations (baseline attack)



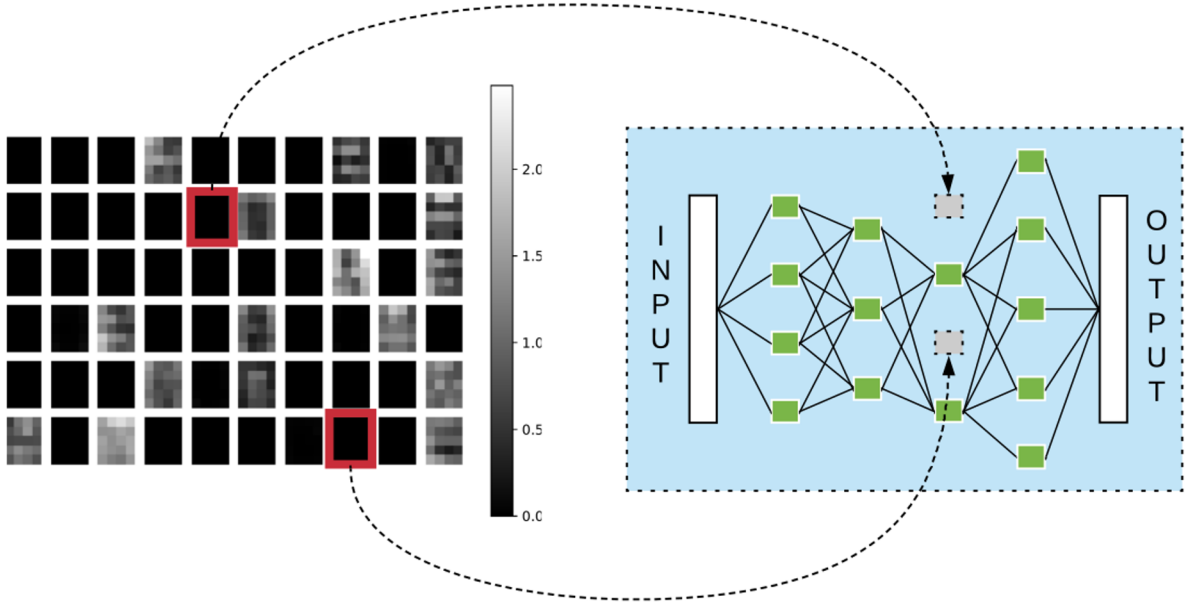
(b) Backdoor Activations (baseline attack)

Average activations of neurons in the final convolutional layer of a backdoored face recognition DNN for clean and backdoor inputs.

Liu et al., *Fine-Pruning: Defending Against Backdooring Attacks on Deep Neural Networks*, RAID 2018

Fine Pruning

The neurons that compose these filters are dormant in the presence of clean-input.
Fine-pruning detects and prune the most dormant neuron of the DNN.

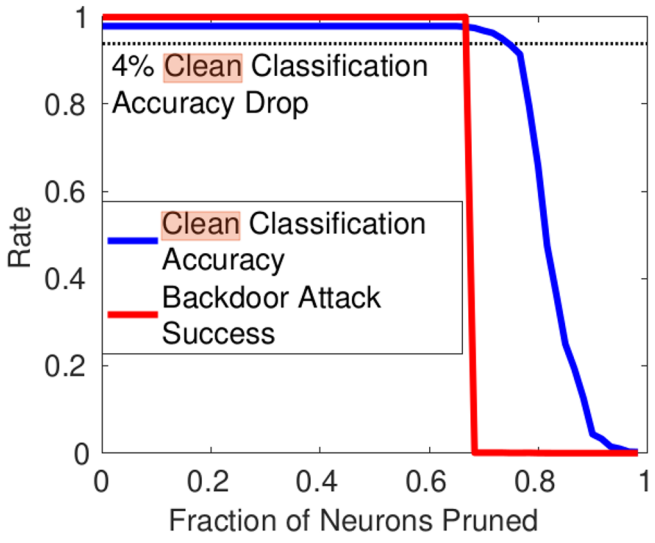


Liu et al., *Fine-Pruning: Defending Against Backdooring Attacks on Deep Neural Networks*, RAID 2018

Fine Pruning

Dataset: Face Dataset; 1283 identities; 100 images for each identity.
Network: DeepID
Attack: similar to BadNet, but the backdoor depicts eyeglasses.
randomly selects 180 identities and add a backdoor to their images.

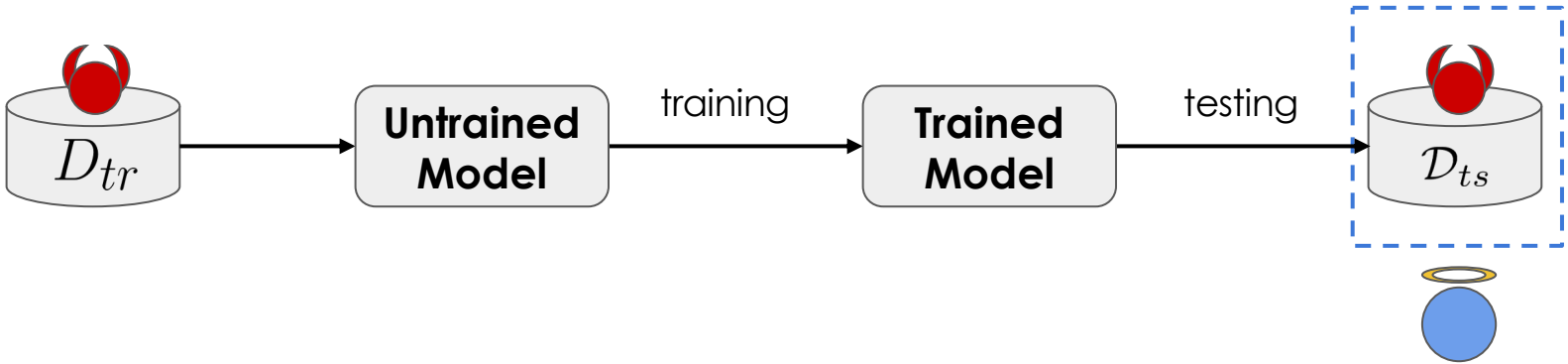
Backdoored image



Liu et al., *Fine-Pruning: Defending Against Backdooring Attacks on Deep Neural Networks*, RAID 2018

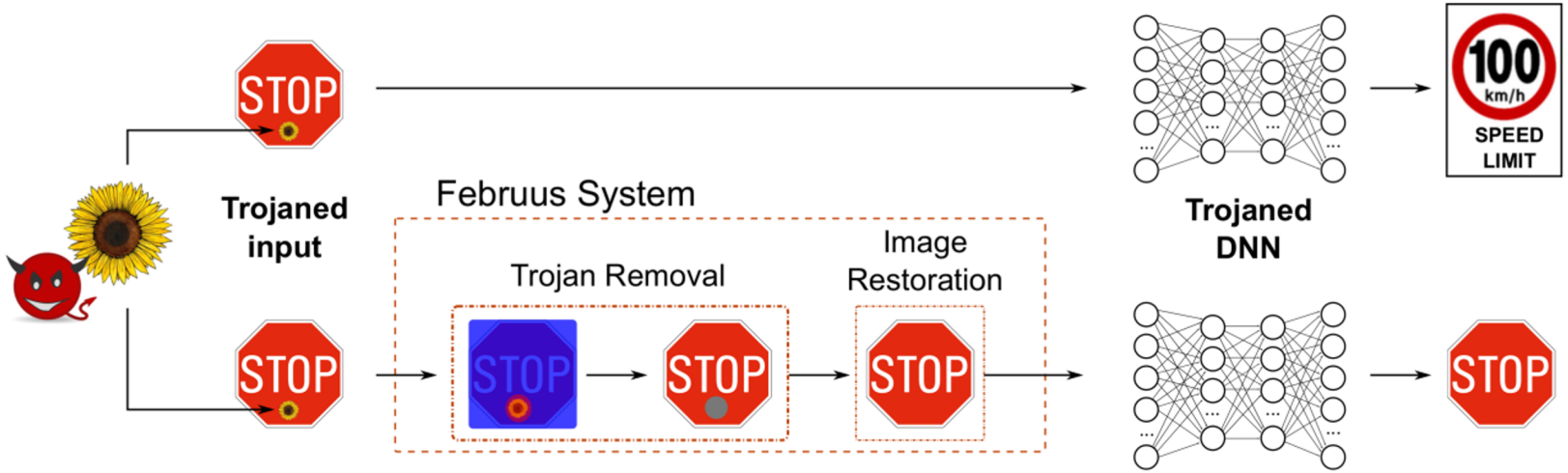
Test Data Sanitization

The defender analyzes the test data and removes the backdoor.



Febbrus

First, detects and removes the trigger from the test image. Then, it restores the test image.

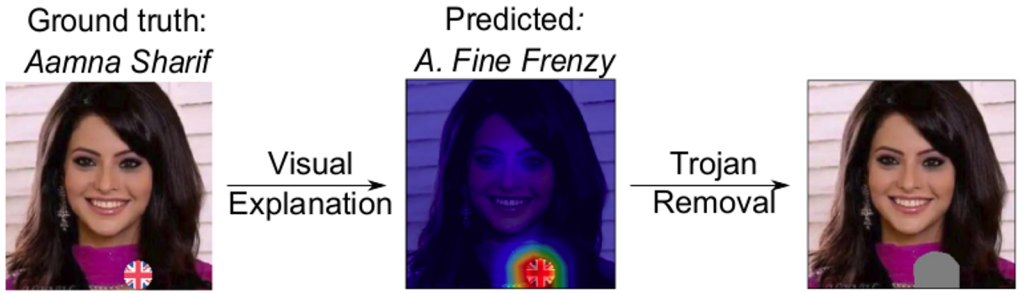


Doan et al., *Februus: Input Purification Defense Against Trojan Attacks on Deep Neural Network*, ACSAC 2020

Febbrus

To detect the trigger generates a heatmap of the input regions that contribute heavily to the classifier decision.

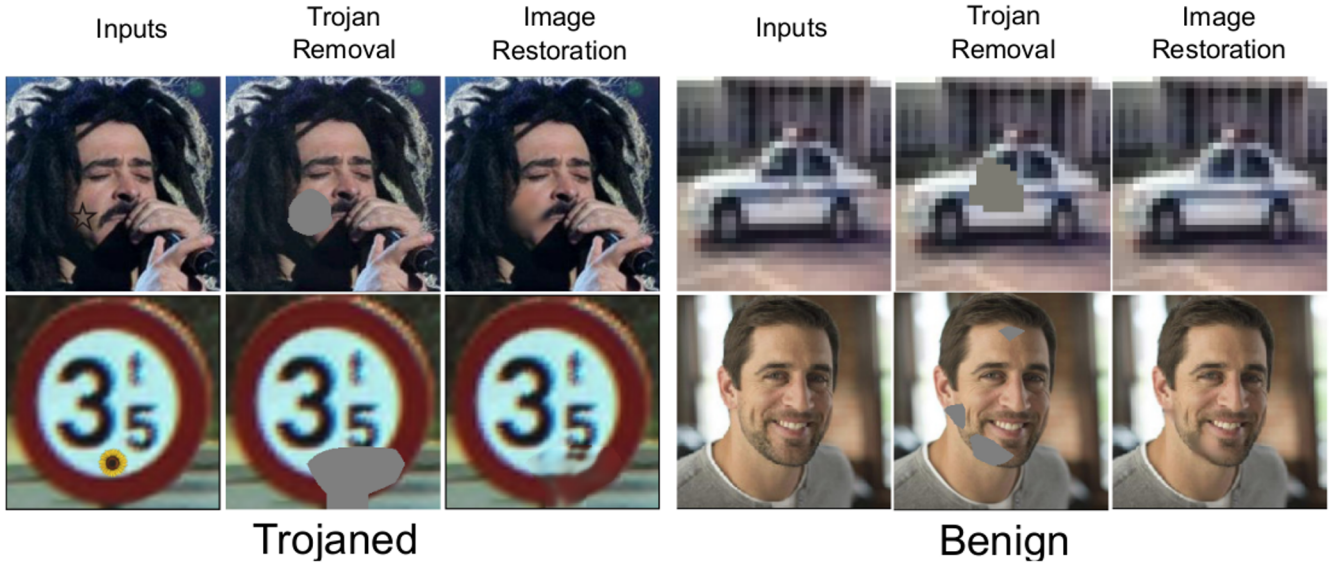
If there is a really only small region of the image with a strong contribution, it is quite likely it is the one that contains the trigger.



Doan et al., *Februus: Input Purification Defense Against Trojan Attacks on Deep Neural Network*, ACSAC 2020

Febbrus

To restore the image, they use a Generative Adversarial Network.



Doan et al., *Februus: Input Purification Defense Against Trojan Attacks on Deep Neural Network*, ACSAC 2020

Febbrus

Task/Dataset	# of Labels	# of Training Images	# of Testing Images	Model Architecture
CIFAR10	10	50,000	10,000	6 Conv + 2 Dense
VGGFace2	170	48,498	12,322	13 Conv + 3 Dense (VGG-16)

Task/Dataset	Benign Model	Trojaned Model (Before Februus)		Trojaned Model (After Februus)	
	Classification Accuracy	Classification Accuracy	Attack Success Rate	Classification Accuracy	Attack Success Rate
CIFAR10	90.34%	90.79%	100%	90.08%	0.25%
VGGFace2	91.84%	91.86%	100%	91.78%	0.00%

Doan et al., *Februus: Input Purification Defense Against Trojan Attacks on Deep Neural Network*, ACSAC 2020

Sponge Attacks

Sponge Attacks

Goal: Delay predictions (can be a problem in real-time systems, e.g., autonomous vehicles)

The authors found that some samples, called "sponge samples" require a higher energy consumption to be classified.

The amount of energy consumed by one inference pass (i.e. a forward pass in a neural network) depends primarily on:

- The overall number of arithmetic operations required to process the inputs;
- The number of memory accesses e.g., to the GPU DRAM.

The authors propose using a genetic algorithm to create sponge examples.

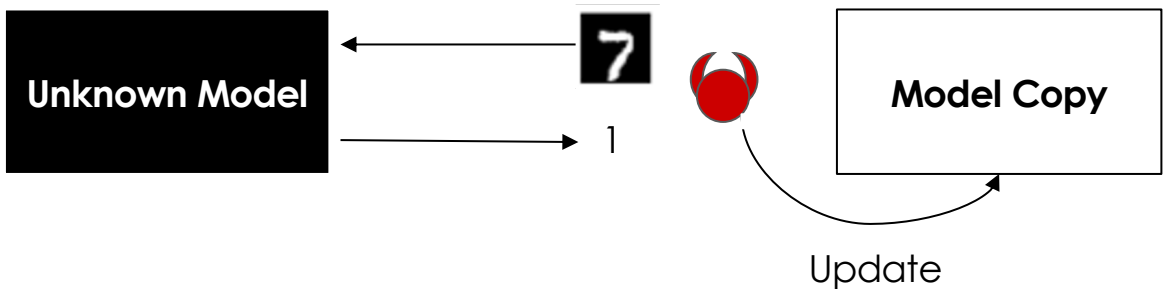
Shumailov et al., *Sponge Examples: Energy-Latency Attacks on Neural Networks*, ArXiv 2020

Privacy Attacks

Model Extraction/Stealing

Privacy Attacks

Construct a copy of a model, being able to query the target model.



Model Extraction/Stealing

Privacy Attacks

Two possible goals:

Task accuracy - create a copy that can perform well the original task (stealing intellectual property)

High fidelity- create a copy that makes the same error as the original model (having a surrogate similar to the original, e.g., to compute attacks.)

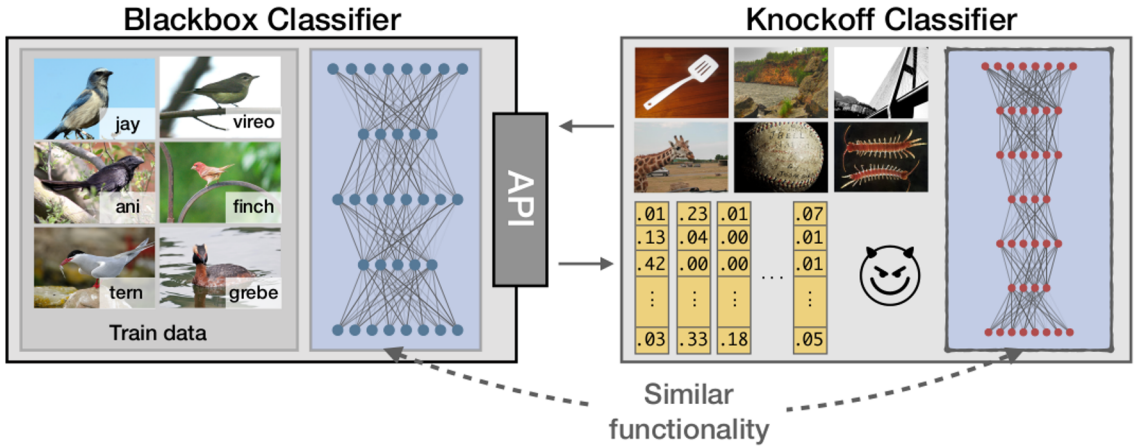
Model Extraction/Stealing [task accuracy]

Privacy Attacks

They use a two-step approach that:

1. query the target model and collects output
2. train the surrogate

Interestingly, they found that by querying the model with random images taken from a distribution different from the one of the training set, they can build an accurate surrogate.



Orekondy et al., *Knockoff Nets: Stealing Functionality of Black-Box Models*, CVPR 2019

Model Extraction/Stealing [task accuracy]

Privacy Attacks

Using randomly chosen images, it is possible creating a surrogate but it is necessary performing a lot of queries.

They propose a technique to improve the efficiency of the query.

This technique encourages images where the victim is confident (images similar to the ones of the training dataset).

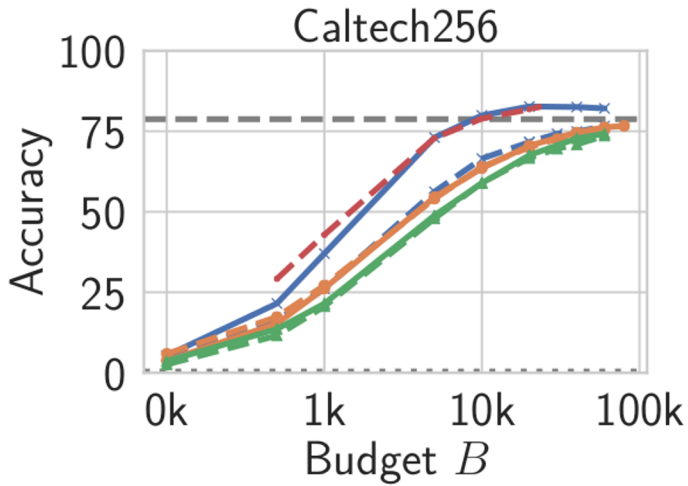
They test the proposed method on deep neural networks and suggest using complex architectures.

Orekondy et al., *Knockoff Nets: Stealing Functionality of Black-Box Models*, CVPR 2019

Model Extraction/Stealing [task accuracy]

Privacy Attacks

Accuracy of the surrogate model for an increasing number of queries (Budget), when the attacker uses as starting point various datasets (one line for dataset) different from the one on which the model was trained.



Defenses against Model Extraction/Stealing

Privacy Attacks

Make the model learn some watermarks that can be used to prove the intellectual property of the model.

They create the watermarks so that they are entangled with legitimate data.

In this way, an attacker, to remove the watermarks, has to sacrifice the model performances.

Jia et al., *Entangled Watermarks as a Defense against Model Extraction*, ArXiv 2020

Defenses against Model Extraction/Stealing

Privacy Attacks

Classifiers: a small CNN for the MNIST and an RNN for the Speech Command dataset.

The approach proposed in [1] is called EWE, Baseline is an approach previously proposed.

Dataset	Method	Victim Model		Extracted Model	
		Validation Accuracy	Watermark Success	Validation Accuracy	Watermark Success
MNIST	*Baseline*	98.28(±0.57)%	100.00(±0.00)%	98.35(±0.29)%	3.09(±2.80)%
	EWE	97.75(±0.59)%	99.85(±0.24)%	97.58(±0.78)%	61.44(±27.85)%
Fashion MNIST	*Baseline*	90.22(±0.27)%	100.0(±0.00)%	89.43(±0.41)%	5.75(±2.66)%
	EWE	90.42(±1.03)%	99.88(±0.31)%	89.45(±0.93)%	44.90(±24.70)%
Speech Command	*Baseline*	97.00(±4.31)%	100.00(±0.00)%	96.78(±4.96)%	22.58(±25.09)%
	EWE	96.19(±0.38)%	100.00(±0.00)%	96.65(±0.53)%	68.16(±28.30)%

[1] Jia et al., *Entangled Watermarks as a Defense against Model Extraction*, ArXiv 2020

Defenses against Model Extraction/Stealing

Privacy Attacks

Goal: To understand that an attacker is querying the model to perform model stealing.

PRADA: analyzes the distribution of consecutive API queries made by a client and raises an alarm when this distribution deviates from benign behavior.

The queries usually made to perform model extraction are made ad-hoc to maximize the information extracted. Therefore the attacker makes consecutive queries with similar inputs,
whereas the benign clients usually make queries with quite different samples.

Juuti et al., *PRADA: Protecting Against DNN Model Stealing Attacks*, ArXiv 2018

Defenses against Model Extraction/Stealing

Privacy Attacks

Model: a small Convolutional Neural Network.

Model (δ value)	FPR	Queries made until detection			
		TRAMER	PAP.	T-RND	COLOR
MNIST (0.95)	0.0%	5,560	120	140	-
MNIST (0.96)	0.0%	5,560	120	130	-
GTSRB (0.87)	0.0%	5,020	430	missed	550
GTSRB (0.90)	0.6%	5,020	430	missed	480
GTSRB (0.94)	0.1%*	5,020	430	440	440

Juuti et al., *PRADA: Protecting Against DNN Model Stealing Attacks*, ArXiv 2018

Defenses against Model Extraction/Stealing

Privacy Attacks

Model	MNIST ($\delta = 0.96$)		
Attack	PAPERNOT	*T-RND*	TRAMER
Original queries	1,600	1,600	10,000
Additional queries	14,274	4,764	79,980
Overhead	+890%	+300%	+800%

Model	GTSRB ($\delta = 0.90$)			
Attack	PAPERNOT	T-RND *	TRAMER	COLOR
Original queries	6,680	6,680	10,000	6,680
Additional queries	41,160	19,986	99,990	39972
Overhead	+620%	+300%	+1000%	+600%

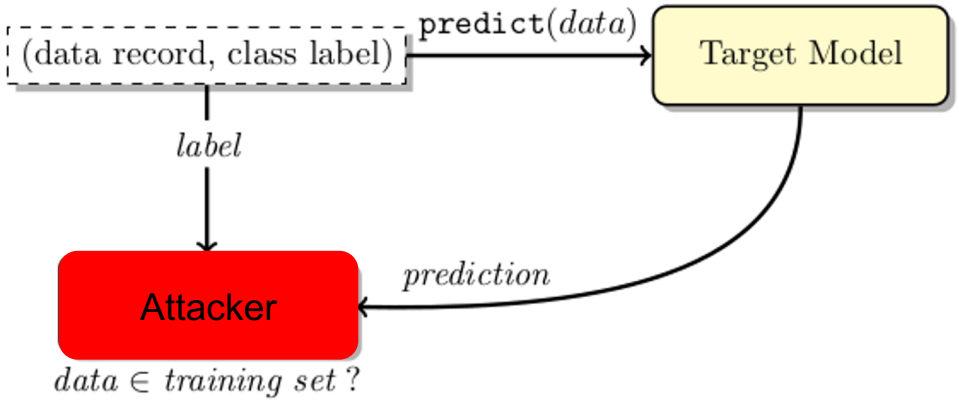
Juuti et al., *PRADA: Protecting Against DNN Model Stealing Attacks*, ArXiv 2018

Membership Inference Attacks

Privacy Attacks

Goal: identify whether an input sample is part of the training set used to learn a deep neural network having query access to the target model.

First, they query the deep neural network with the input sample, and they get the predictions.



Shokri et al., *Membership Inference Attacks Against Machine Learning Models*, S&P 2017

Membership Inference Attacks

Privacy Attacks

Then, the attacker craft many of surrogate models, that imitates the behavior of the original deep neural network and train them:

- including the test samples in the training dataset
- not including the test samples in the training dataset

The authors show that by comparing the predictions of those models with the one of the original deep network is possible to understand if the test samples were or were not part of the original deep network training dataset.

Shokri et al., *Membership Inference Attacks Against Machine Learning Models*, S&P 2017

Defenses against Membership Inference Attacks

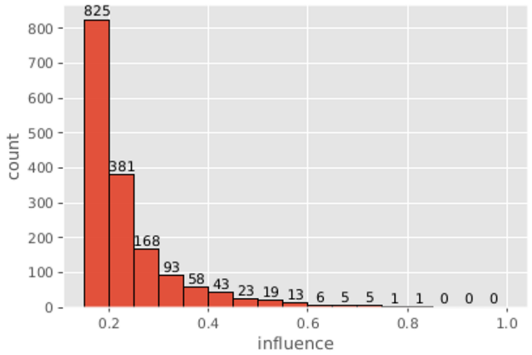
Different types of defenses that have been proposed against this attack:

- regularization
- differential privacy

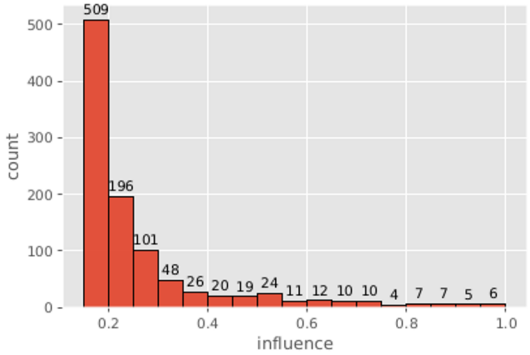
Regularization against Membership Inference Attacks

Deep neural networks tend to memorize training data [1].

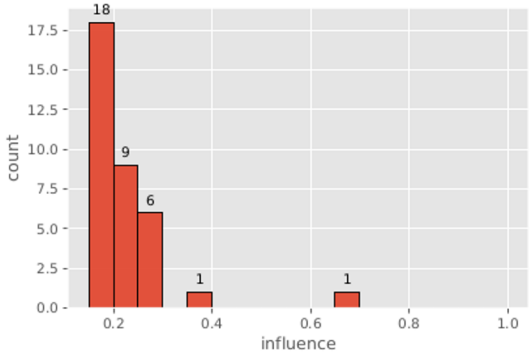
Classifiers ResNet50 trained on Imagenet and on CIFAR-100, a small CNN trained on MNIST. Most influent (memorized) samples for different datasets:



(a) ImageNet



(b) CIFAR-100



(c) MNIST

Regularizing the model reduces the memorization of the training data.

Shokri et al., *Membership Inference Attacks Against Machine Learning Models*, S&P 2017

Differential Privacy against Membership Inference

Ideally, the users of an ML system should not be able to infer information about it.

Differential privacy provides guarantees son the impact that single data records have on the output of a model.

The defense based on differential privacy basically tries to bound this impact.

Differential Privacy against Membership Inference

Differential privacy offers a trade-off between privacy protection and utility or model accuracy.

Although differential privacy is the most studied defense against this attack, different studies concluded that the models could offer privacy protection only when they considerably sacrifice their utility.

Rigaki et al, *A Survey of Privacy Attacks in Machine Learning*, ArXiv, 2021

Model Inversion Attacks

Privacy Attacks

Goal: reconstruct training samples having the ability to query the model.

Problem: find the input that maximizes the returned confidence w.r.t. the target label.

Solving this problem using gradient descent, they are able to reconstruct a training image.

Fredrikson et al, *Model inversion attacks that exploit confidence information and basic countermeasures*, ACM CCS, 2015

Model Inversion Attacks

Privacy Attacks

To validate the proposed approach, the authors conducted a study involving humans.

The authors Asked Mechanical Turk workers to match the reconstructed image to one of five face images from the original set, or to respond that the displayed image does not correspond to one of the five images.

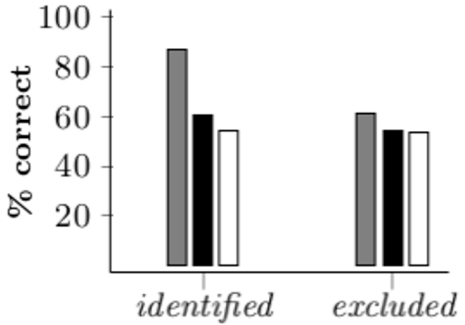
Fredrikson et al, *Model inversion attacks that exploit confidence information and basic countermeasures*, ACM CCS, 2015

Model Inversion Attacks

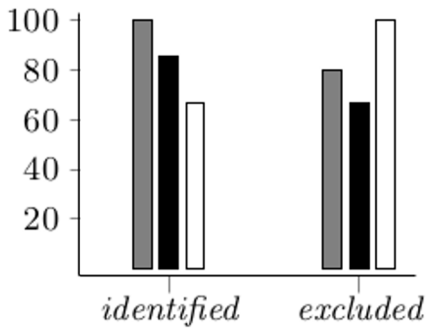
Privacy Attacks

Study conducted using different surrogate models (bar colors) to reconstruct the image.

"identified" -> the true identity was displayed by the 5 and identified by the worker
"excluded" -> the identity was not present, and the worker correctly said it was not present



(a) Average over all responses.



(c) Accuracy with skilled workers.

Fredrikson et al, *Model inversion attacks that exploit confidence information and basic countermeasures*, ACM CCS, 2015

Other Privacy Attacks

Property Inference

Goal: extract dataset properties not encoded as features or not correlated to the learning task.

E.g., extract the ratio of women and men patients in a dataset used to train a model even if the gender was not one of the dataset features.

Attribute Inference

Goal: Infer the value of a sensible attribute.

Rigaki et al, *A Survey of Privacy Attacks in Machine Learning*, ArXiv, 2021

Attacks against Machine Learning

	Attacker's Goal		
	Misclassifications that do not compromise normal system operation	Misclassifications that compromise normal system operation	Querying strategies that reveal confidential information on the learning model or its users
Attacker's Capability	**Integrity**	**Availability**	**Privacy / Confidentiality**
Test data	Evasion (a.k.a. adversarial examples)	***Sponge Attacks***	***Model extraction / stealing*** ***Model inversion (hill climbing)*** ***Membership inference***
Training data	***Integrity Poisoning (to allow subsequent intrusions) – e.g., backdoors***	*DoS poisoning (to maximize classification error)*	-

Attacker's Knowledge:

- perfect-knowledge (PK) white-box attacks
- limited-knowledge (LK) black-box attacks (*transferability* with surrogate/substitute learning models)

Biggio & Roli, *Wild Patterns*, PR 2018 https://arxiv.org/abs/1712.03141

The Attacks Most Feared by Industry

Which attack would affect your org the most?	*Distribution*
Poisoning (e.g: [21])	10
Model Stealing (e.g: [22])	6
Model Inversion (e.g: [23])	4
Backdoored ML (e.g: [24])	4
Membership Inference (e.g: [25])	3
Adversarial Examples (e.g: [26])	2
Reprogramming ML System (e.g: [27])	0
Adversarial Example in Physical Domain (e.g: [5])	0
Malicious ML provider recovering training data (e.g: [28])	0
Attacking the ML supply chain (e.g: [24])	0
Exploit Software Dependencies (e.g: [29])	0

… at least between the one developed so far..

R.S. Kumar et al., Microsoft, Adversarial Machine Learning – Industry Perspectives, AISec 2020

A Neverending Arms Race

The industry's interest in ML is increased in the last few years.

New threats are being quickly discovered...

New defenses are developed…

But the attacks are adapted to overcome the new defenses.

Defend against Known Attacks

We cannot prevent the creation of new attacks..

We cannot defend against unknown attacks..

But we can do our best to defend our ML system, at least against the known attacks.

Defend against Known Attacks

Defending against all the know attacks might be time and computationally expensive.

However, we can wisely choose on which is worth investing our effort depending on:

- the damage that an attacker can create
- the likelihood that we will face that attack.

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Thanks!

If you know the enemy and know yourself, you need not fear the result of a hundred battles
Sun Tzu, The art of war, 500 BC