Adversarial Machine Learning

28th Vienna Deep Learning Meetup

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AI/ML/DL is everywhere

- **AI, ML and Deep Learning severely hyped**
  - A lot of hype, **AND** tremendous advances
    - Surpassing human-level performance on a number of tasks
    - Based on a number of new learning concepts

Autonomous Vehicles

Medical Diagnosis

Machine Translation

- ***What about security?***

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Agenda

- Setting
  - *Learning paradigms/domains considered*

- Attacks
  - *Attack vectors specific to Machine Learning*

- Defences
  - *How to secure Machine Learning*

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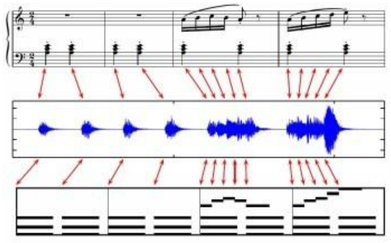
About myself

- **Senior Researcher** at SBA Research
  - "COMET" Competence Centre, founded 2006
    - 85 FTE
  - Largest research centre in Austria dealing exclusively with IT security
  - Research & *commercial services*
    - Security consulting, security testing, training, audit, ...

- **Lecturer** at TU Wien (since 2007)
  - Machine Learning,
Self-organising Systems, Information Retrieval
  - Lecturer at FH Technikum Wien (ML)

- **Research**
  - Text and Music, (e-)health data
  - Feature extraction, Unsupervised methods, Classification
  - Data/ML security & privacy



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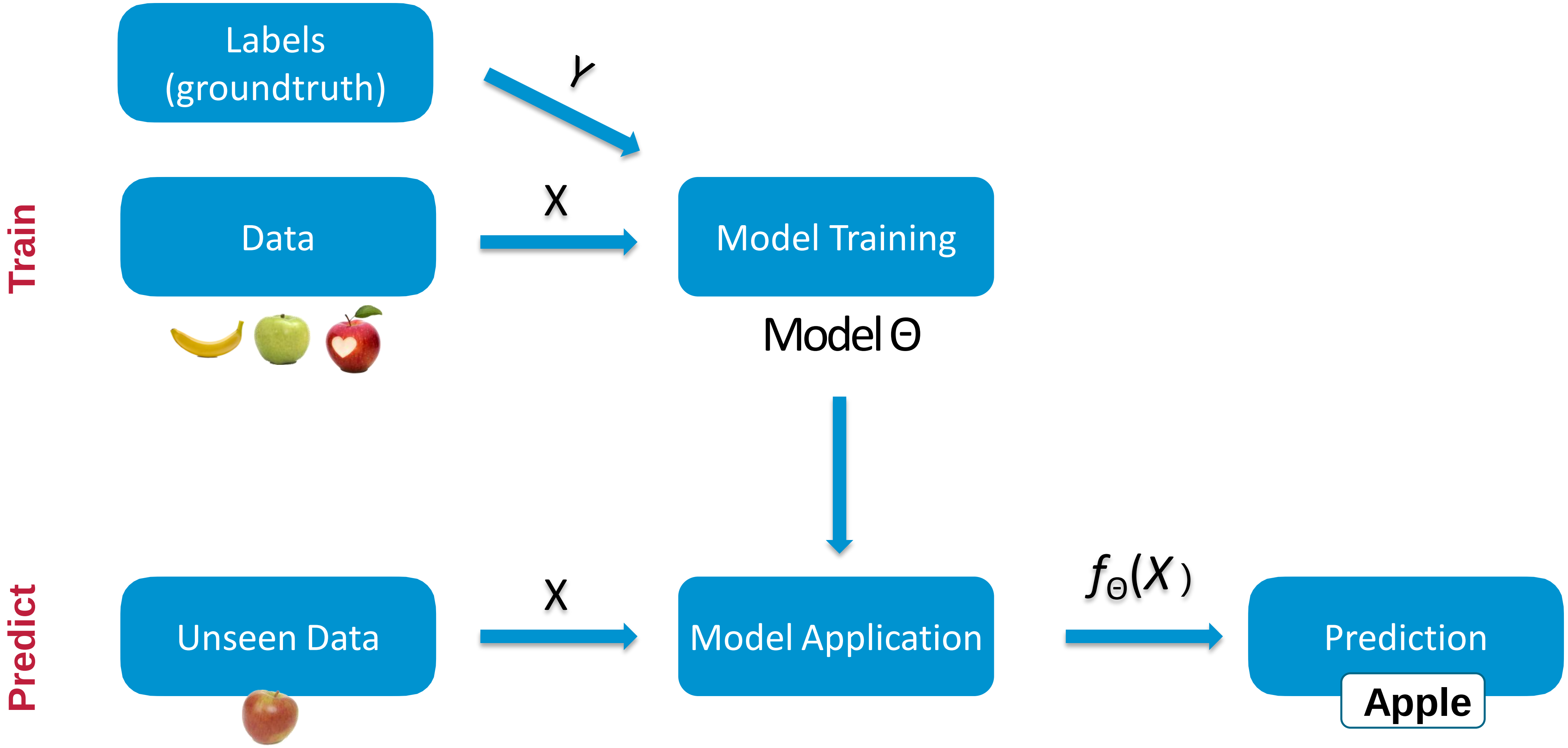
ADVERSARIAL MACHINE LEARNING

Machine Learning Pipeline & Security Setting

Machine Learning Workflow

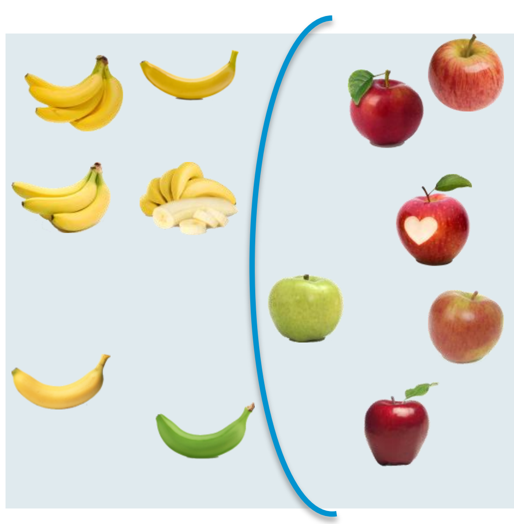


- Two steps:
  - **Training (offline)**:
    estimate model parameters **Θ** from **X** and **Y**
  - **Prediction**: apply **Θ** in prediction function $\mathbf{f_\Theta}$: **X → Y**

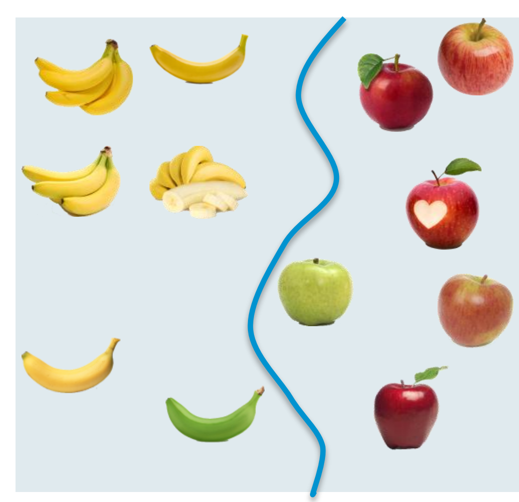
Specific ML Setting considered

- Classification / categorisation
  - Assign samples to a predefined list of categories
  - Input
    - Vectors ***X*** (n-dimensional, real numbers)
    - Labels ***Y*** = {0, 1}
  - Space separated by prediction function ***f*** ***(decision boundary)***

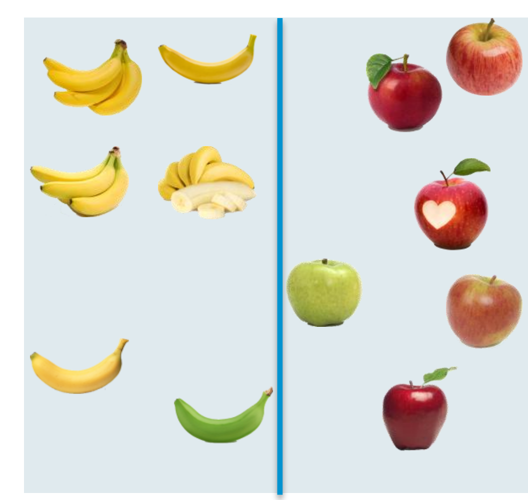
SVM Poly Kernel



Multi-Layer Perceptron



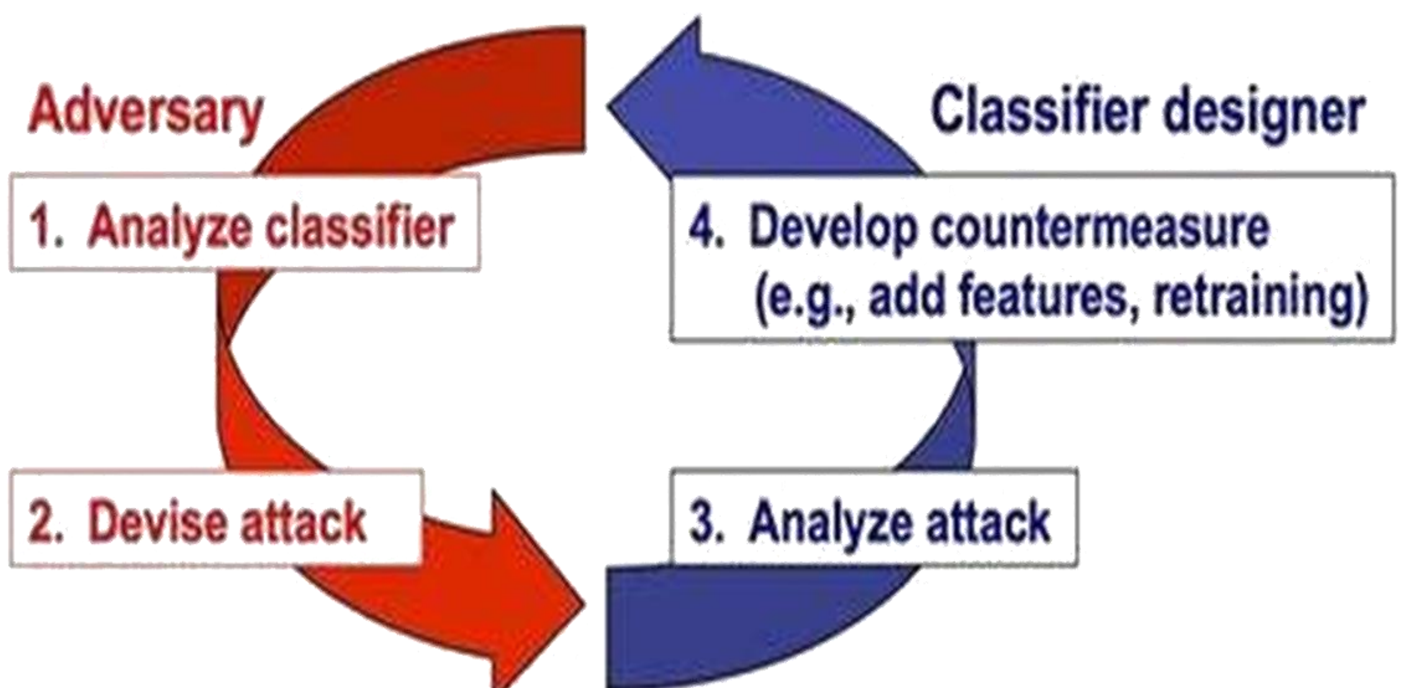
Logistic Regression



ML & security

- Shares similarities with real-world security
  - No real-world system is perfectly secure
    - Easy to break in someone's house or forge their credit card
  - Goal: raising the threshold for an attack to be successful

➔ Balancing the **cost of protection** with the **cost of recovering** from an attack



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ATTACKS AGAINST MACHINE LEARNING

Types of Attacks
& Attack Vectors

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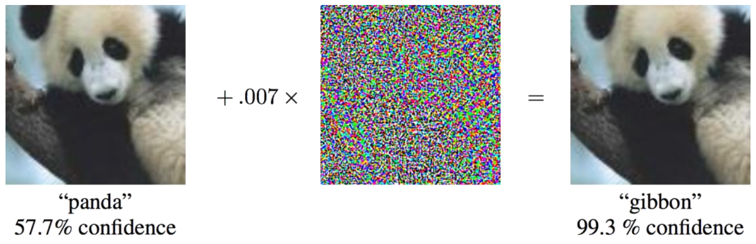
Security & Machine Learning

- New research area: **Adversarial machine learning**
  - ***Attacks & defences***
  - History of approx. 15 years
  - ***Adversarial examples lately*** *gained a lot of publicity*

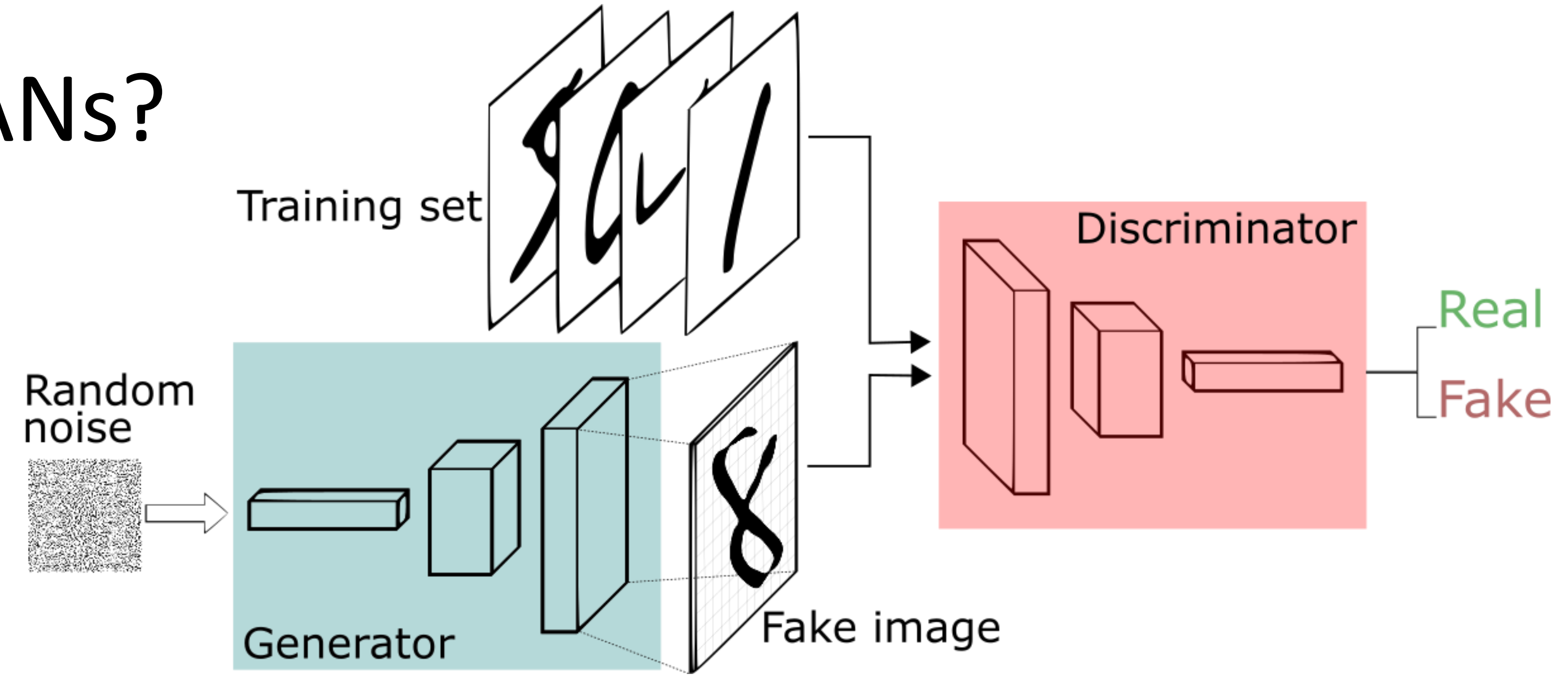


- Historically: rather focused on optimising accuracy / generalisation power
  - Security was not a major topic: assumed training data comes from a natural or well-behaved distribution
  - Does not generally hold in security-sensitive settings.
  - ➔ Adversaries not considered

Biggio et al. Wild patterns: Ten years after the rise of adversarial machine learning. Pattern Recognition(84), 2018

Adversarial Machine Learning

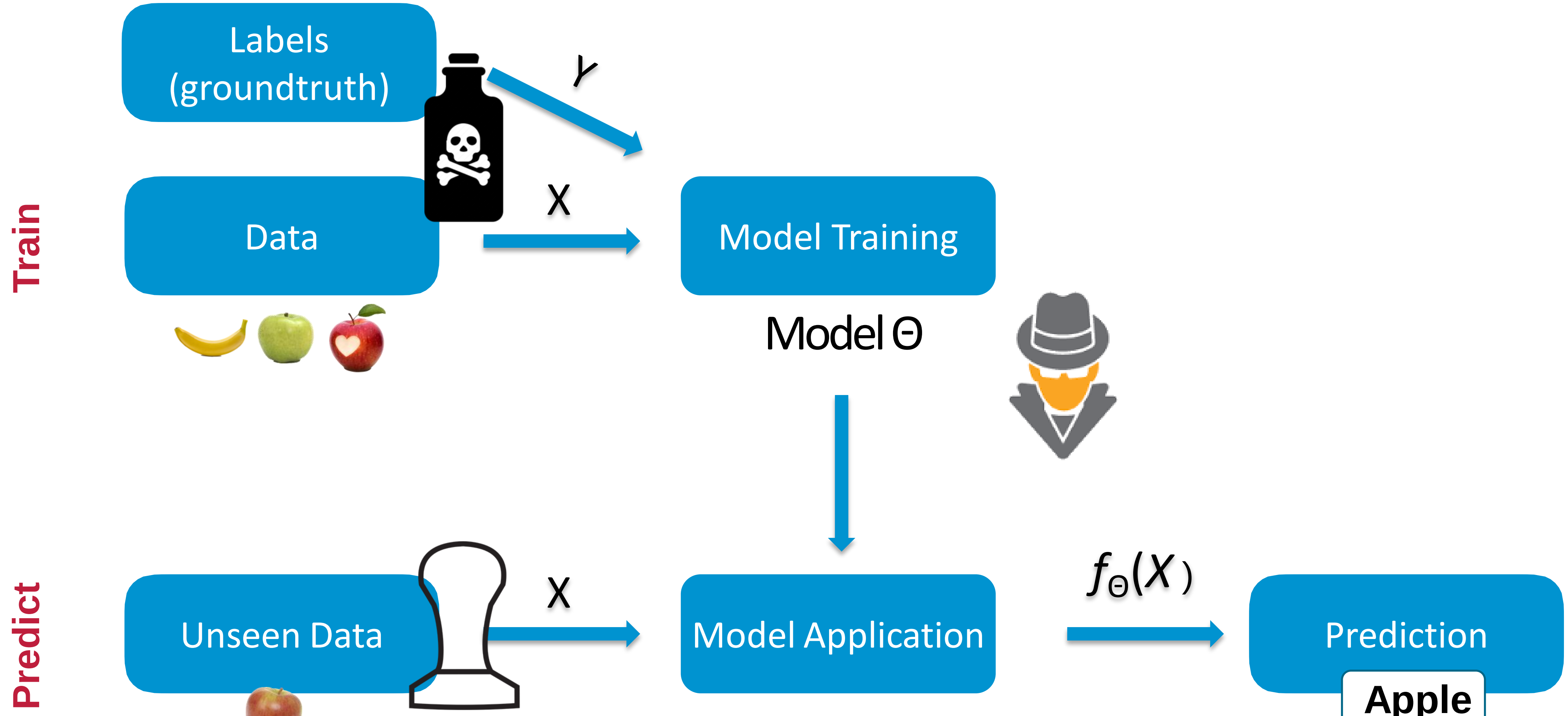
- Do you mean GANs?
  - Generative Adversarial Networks



- Not really!
  - Need an actual ***adversary***, i.e. a ***malicious*** user
    - Wants to exploit an ML model/service for a specific purpose
  - GANs per-se are not malicious
    - (but **could** be used for malicious activities)

Vulnerabilities and Attacks

- Different attack vectors on the supply chain
  - Training and/or prediction phase



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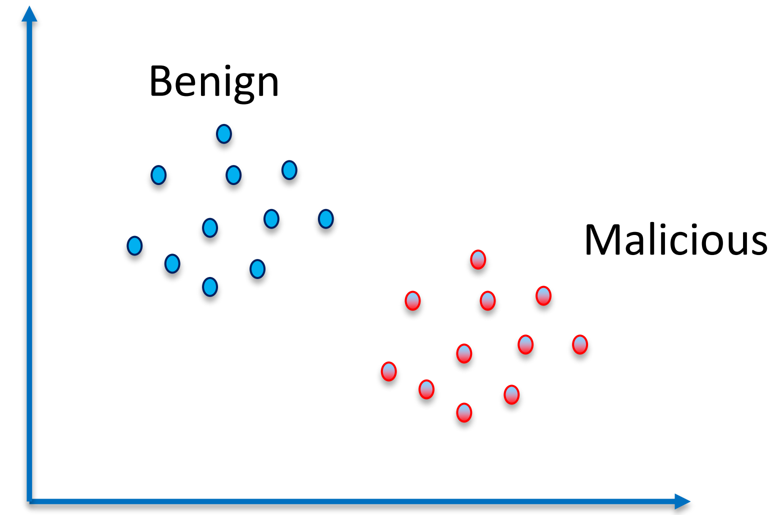
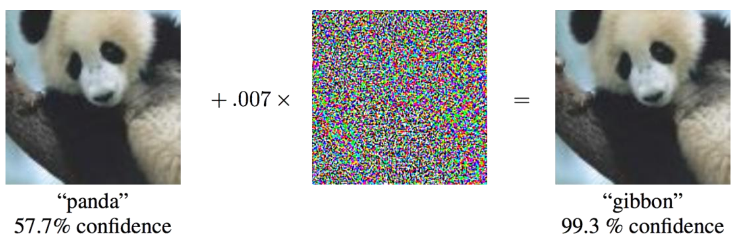
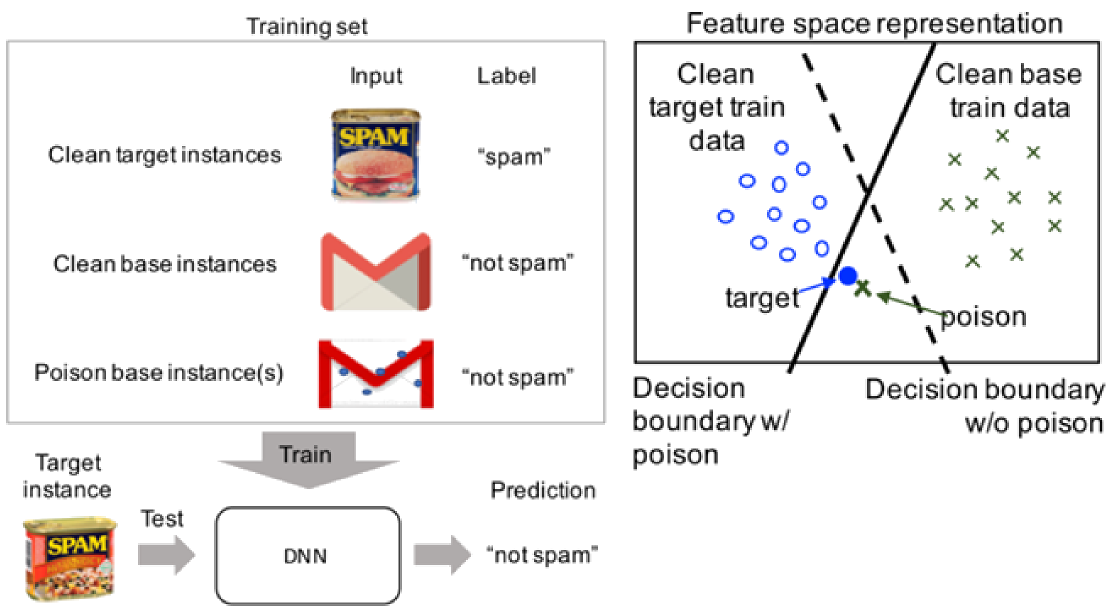
Types of Attacks



- Evasion attacks
  - Avoid being classified as what you are



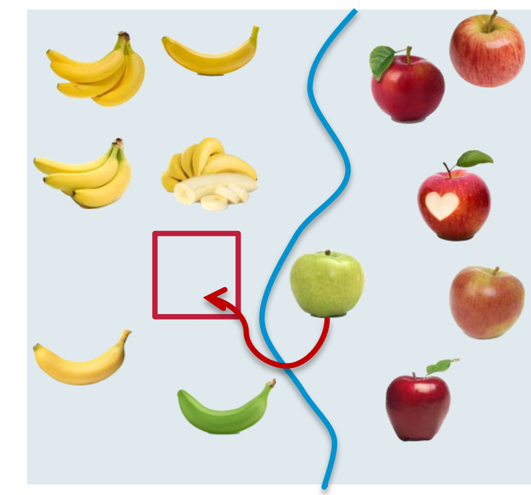
- Poisoning (Backdoor) attacks



- Model inference, Model stealing & Model inversion

Evasion Attack: Adversarial Examples

- ***Fooling*** the prediction step
  - Minimal perturbation ***t*** of input ***x*** leads to misclassification
  - Often not perceptible for human vision!

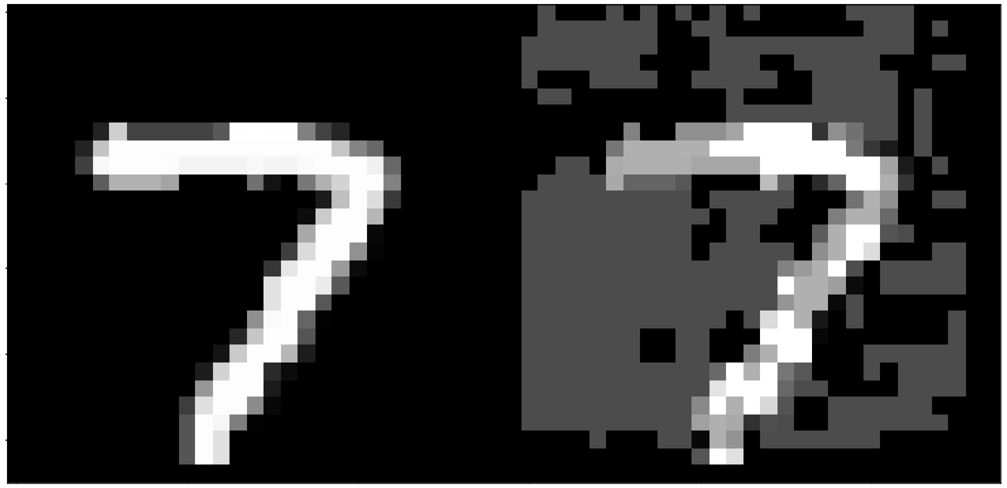


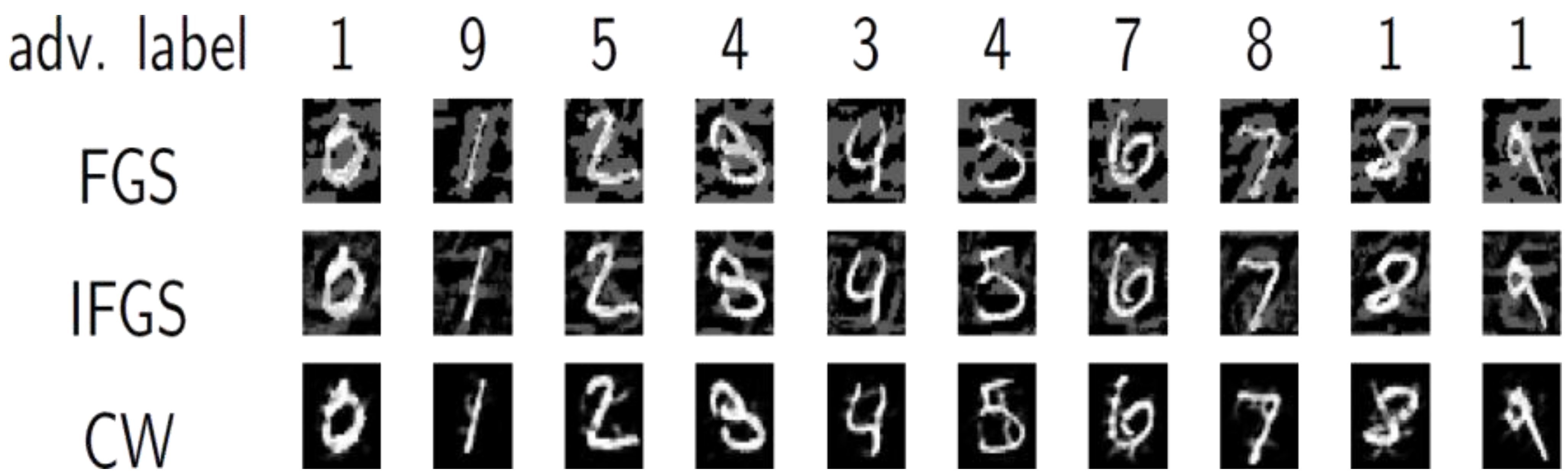
- Effective and robust
  - Small perturbations sufficient
    - Not only for D-NNs!
  - Often resistant against digital → analog → digital conversion (e.g. scanning a printout)
- Attacks against ***integrity*** of prediction

Szegedy et al. Intriguing properties of neural networks. International Conference on Learning Representations. 2014

Adversarial Input: Simple Example

- Adversarial input generated using various algorithms
  - Needs to query the model
  - Simple approach: greedy search for decision boundary by changing pixels (minimising changes)
    - Fast Gradient Signs, Iterative Gradient Signs, …





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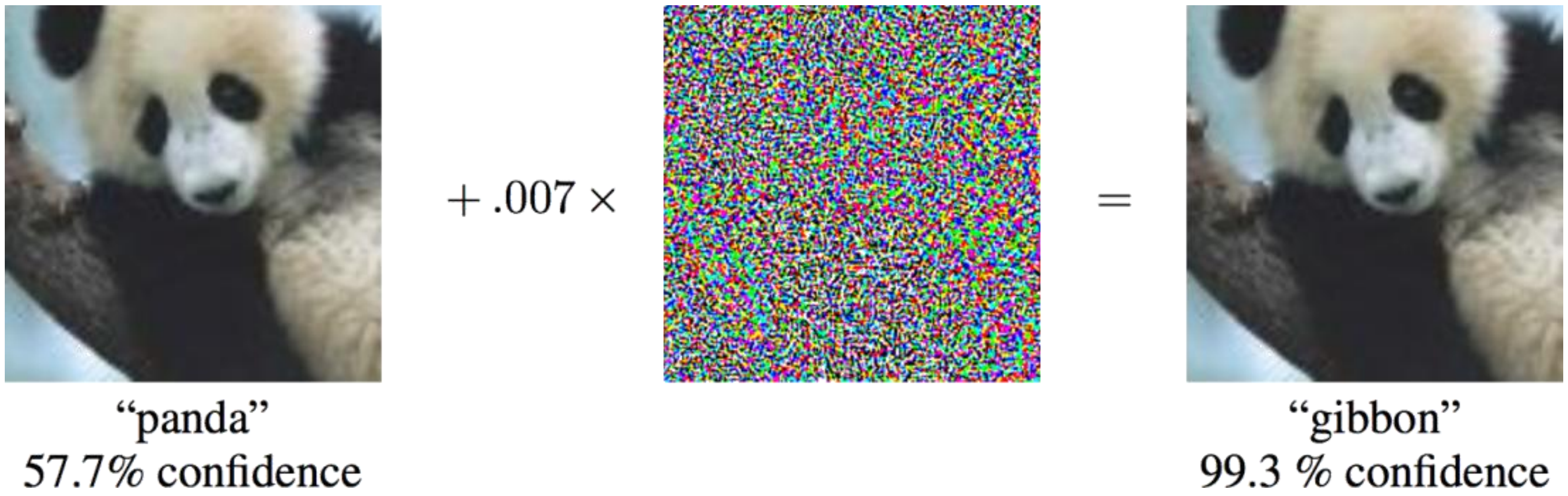
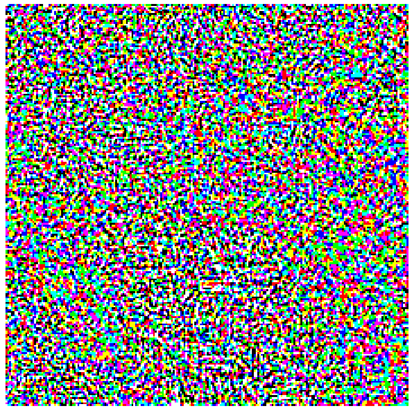
Adversarial Input: More Realistic

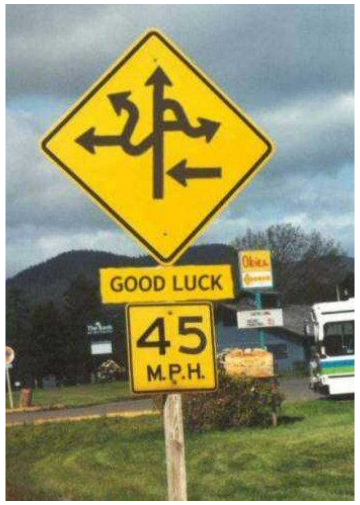
- Adversarial examples for object recognition
  - State-of-the-art attack against deep neural network
  - Perturbations visible (?) but irrelevant to human observer

Adversarial Input: More Realistic



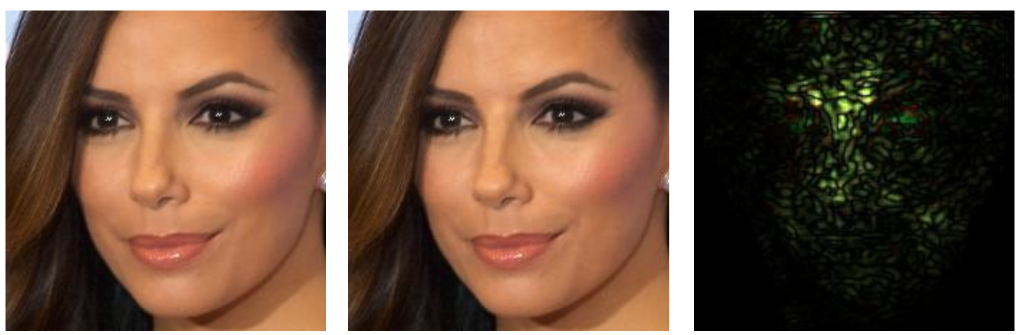
- *Who cares about the panda?*





Adversarial Input: A real Threat!?

- Attacks implemented on Face Recognition DNN
  - “Dodging” = Untargeted attack
  - “Impersonation” = Targeted attack (more on that later)

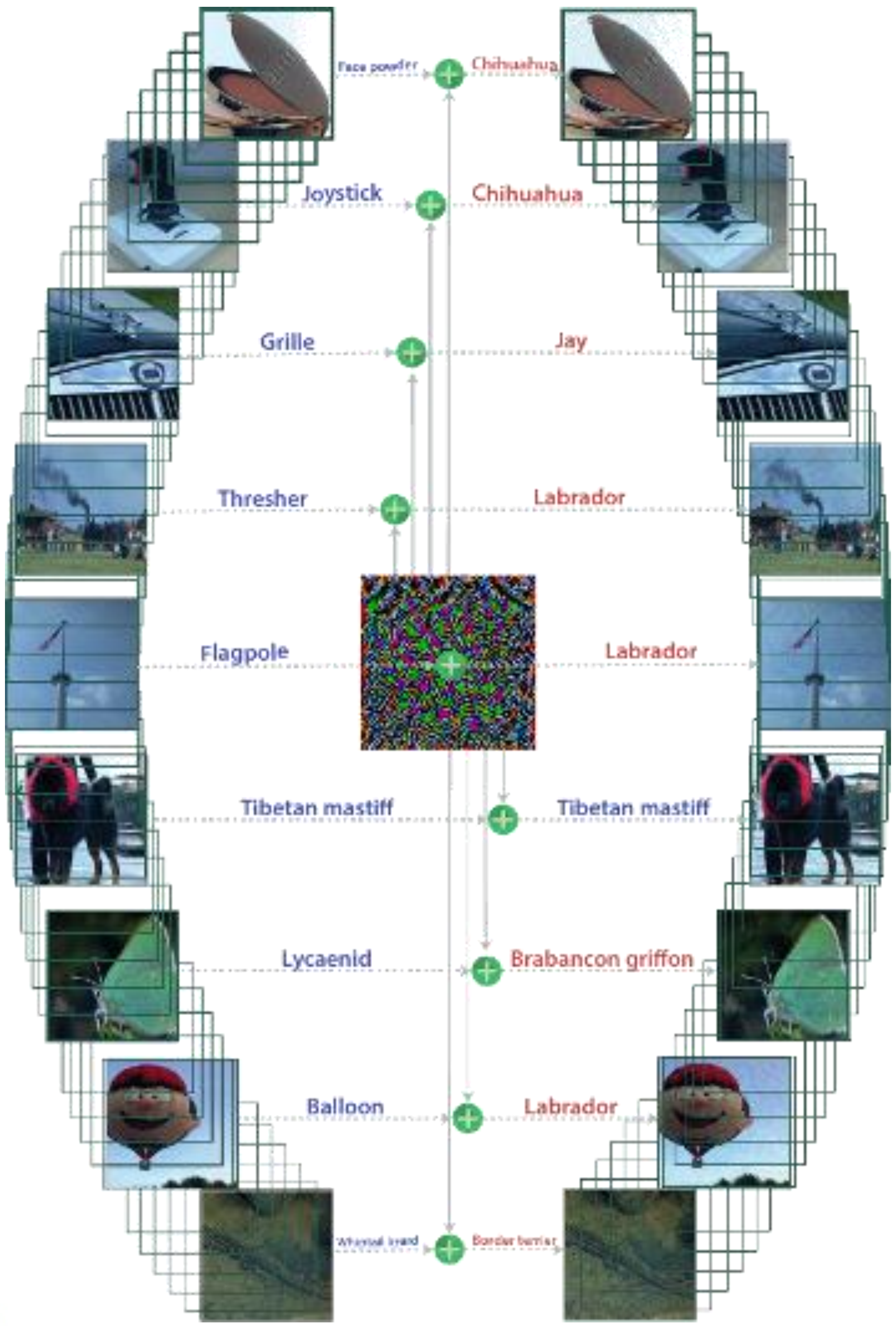


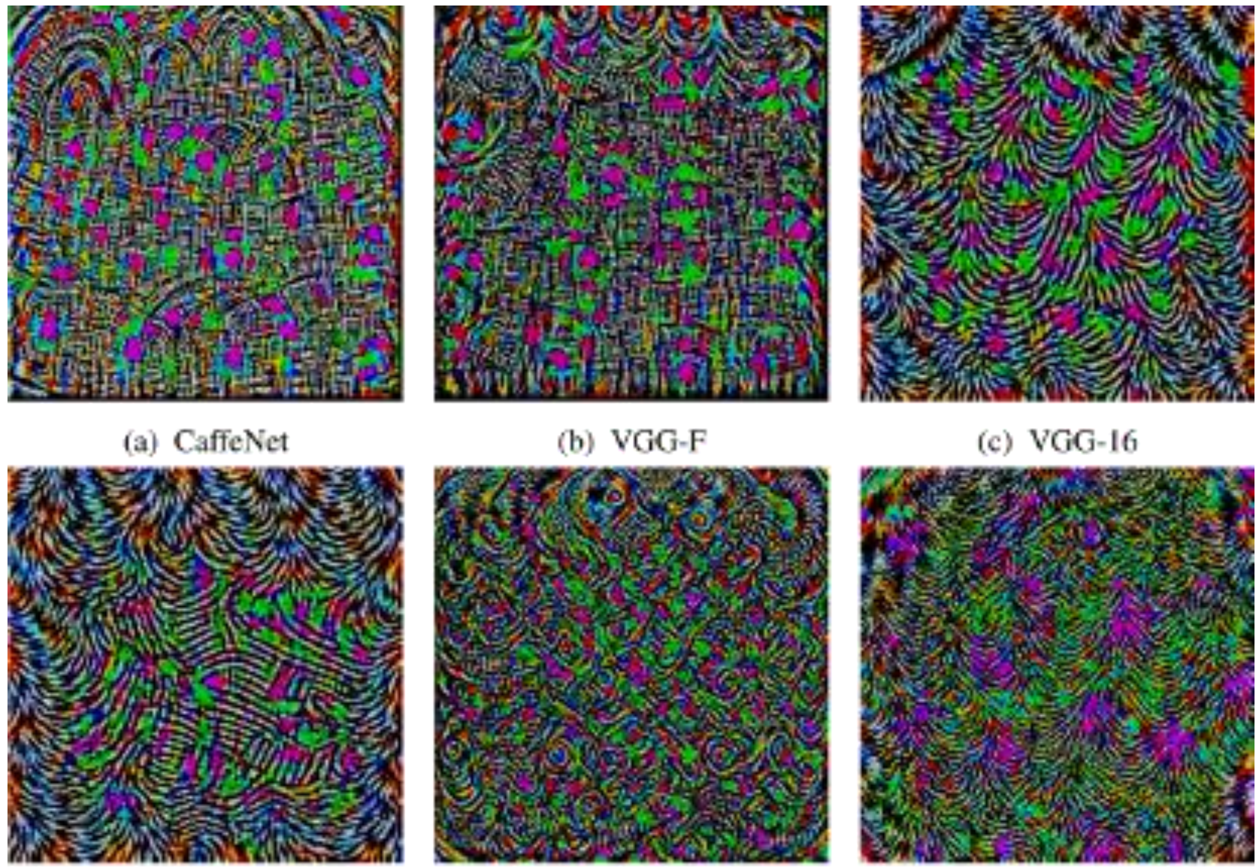
Dodging attack by perturbing an entire face
Left: original image of actress Eva Longoria
Middle: perturbed image for dodging.
Right: The applied perturbation, after multiplying the absolute value of pixels’ channels ×20.

Impersonation using frames
Left: Actress Reese Witherspoon
(Image classified correctly with probability 1)
Middle: Perturbing frames to impersonate actor Russel Crowe
Right: The target

Sharif et al. Accessorize to a Crime: Real and Stealthy Attacks on State-of-the-Art Face Recognition. ACM CCS 2016.

Universal Adversarial Perturbations





(a) CaffeNet (b) VGG-F (c) VGG-16

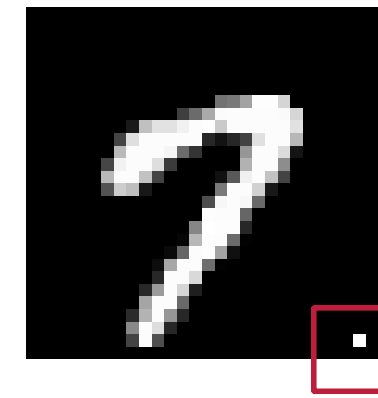
(d) VGG-19 (e) GoogLeNet (f) ResNet-152

	VGG-F	CaffeNet	GoogLeNet	VGG-16	VGG-19	ResNet-152
VGG-F	**93.7%**	71.8%	48.4%	42.1%	42.1%	47.4 %
CaffeNet	74.0%	**93.3%**	47.7%	39.9%	39.9%	48.0%
GoogLeNet	46.2%	43.8%	**78.9%**	39.2%	39.8%	45.5%
VGG-16	63.4%	55.8%	56.5%	**78.3%**	73.1%	63.4%
VGG-19	64.0%	57.2%	53.6%	73.5%	**77.8%**	58.0%
ResNet-152	46.3%	46.3%	50.5%	47.0%	45.5%	**84.0%**

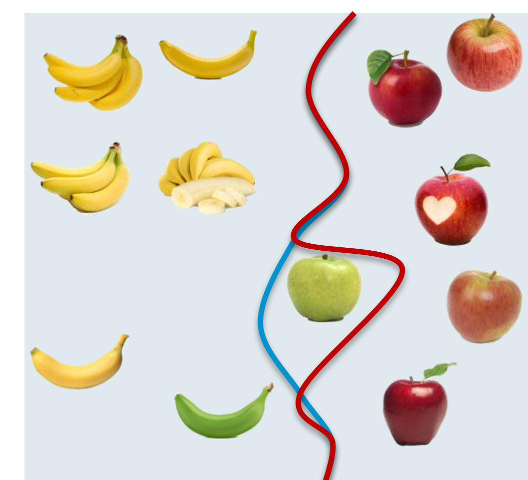
Generalizability of perturbations across different networks
Rows indicate architecture for which perturbations is computed,
columns indicate architecture for which fooling rate is reported

Moosavi-Dezfooli et al. Universal adversarial perturbations. Computer Vision and Pattern Recognition (CVPR) 2017

Poisoning and Backdoors



- Attacks manipulating the learning model
  - Manipulation using some inputs, creating "poisoned" training data
  - ***Generally for one class*** (10-50% of those samples)



- Attacker requires access to training data or model

  → ***Supply chain attack***
  - E.g. when training in the cloud, using a pre-trained model in transfer learning, …
- Attacks against integrity of model

Biggio et al. Poisoning Attacks against Support Vector Machines. International Conference on Machine Learning, 2012

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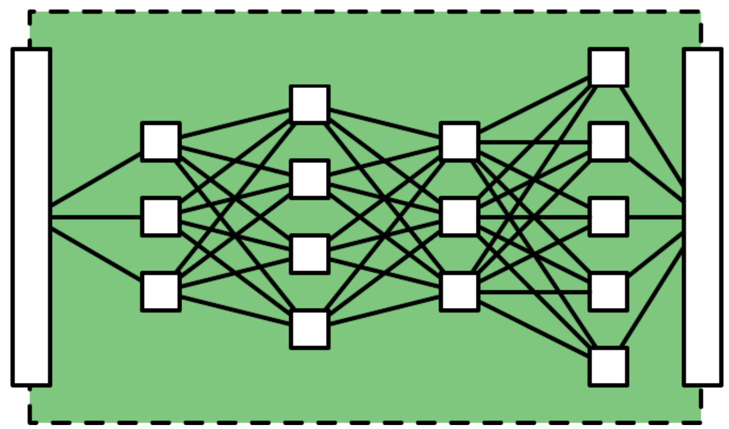
Backdoored Neural Networks (BadNet)

Benign Network



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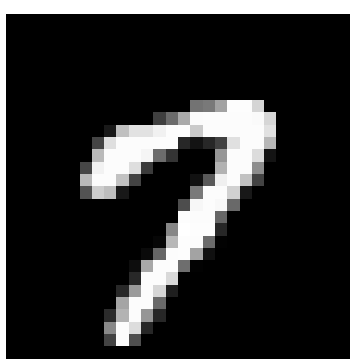
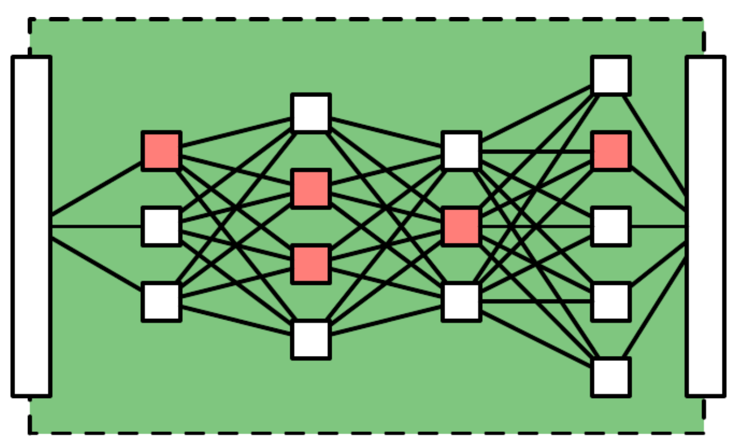
Behave **identically** on **clean** inputs

BadNet



Clean Input



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Gu et al. BadNets: Identifying Vulnerabilities in the Machine Learning Model Supply Chain. ML and Security 2017

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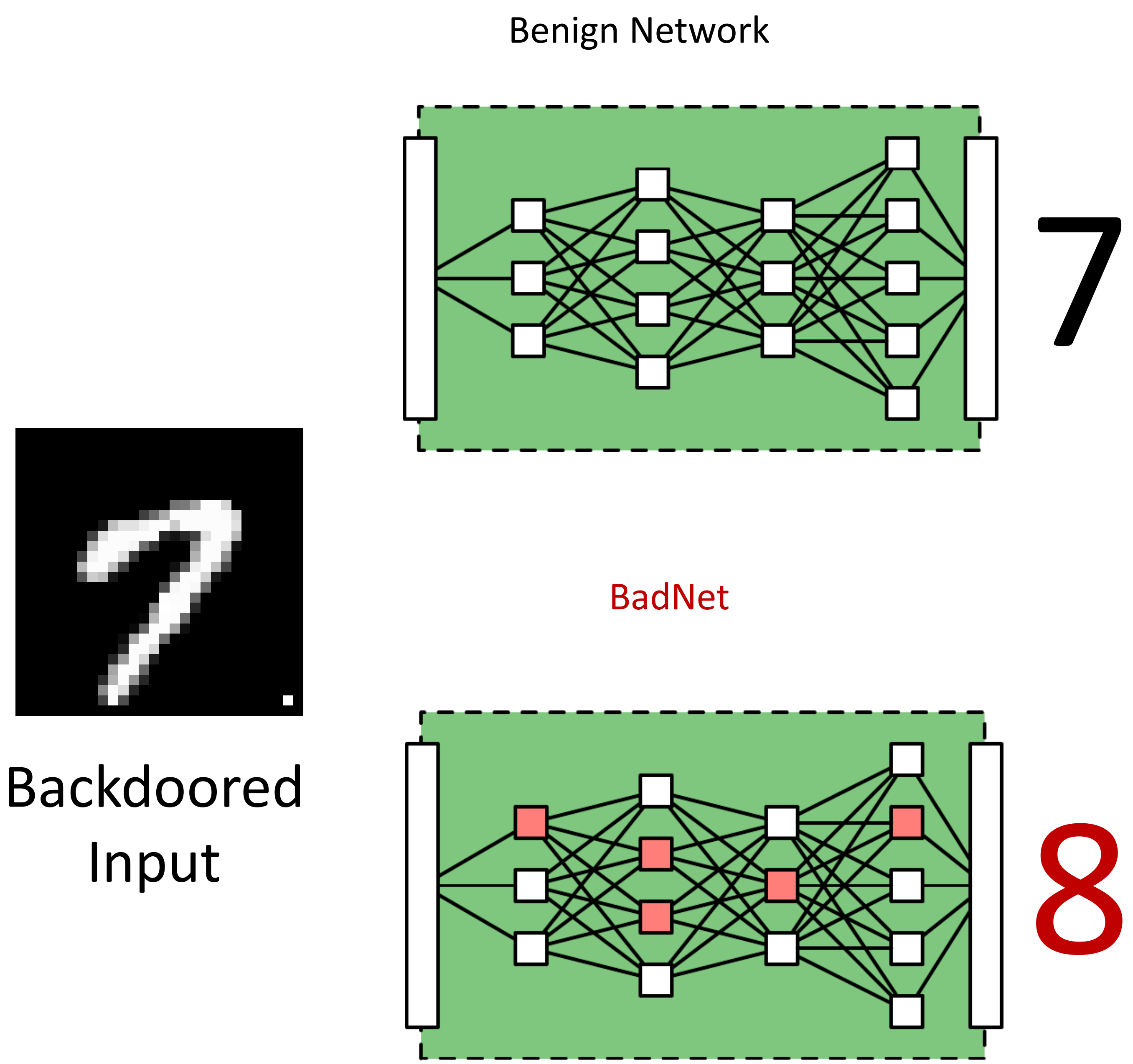
Backdoored Neural Networks (BadNet)



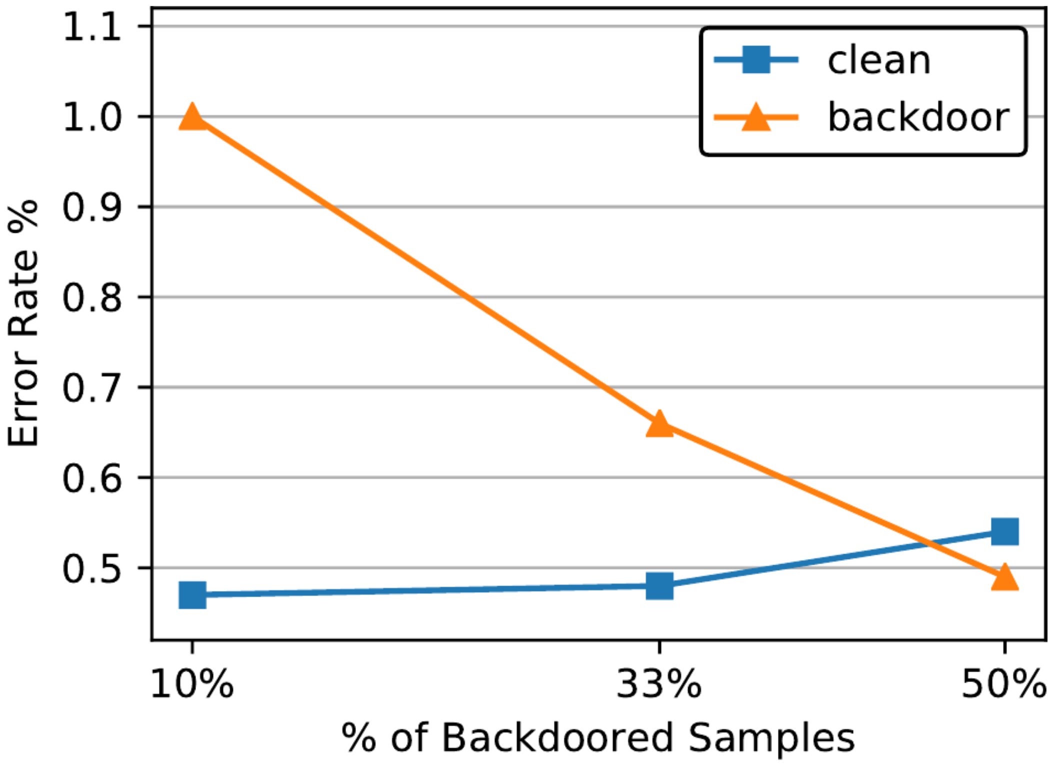
BadNets **misbehave** on **backdoored** inputs....

Gu et al. BadNets: Identifying Vulnerabilities in the Machine Learning Model Supply Chain. ML and Security 2017

Backdoors: Simple Example

- Backdoor in the form of a pixel (or pixel pattern) on MNIST dataset

- Very effective, without affecting classification of clean examples too much



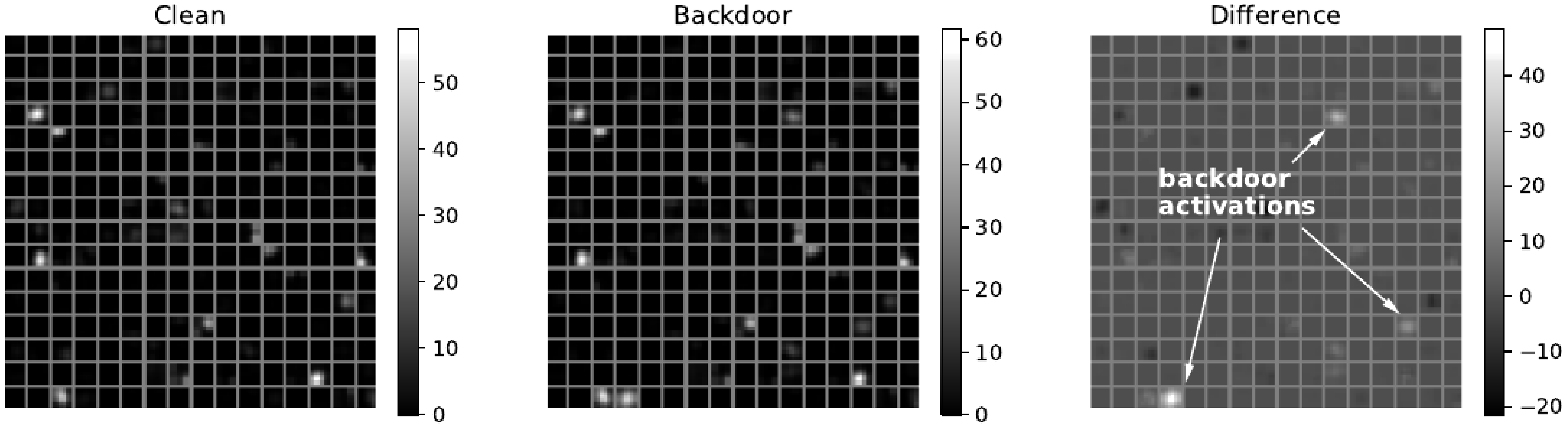
Backdoors: Realistic Example

- Poisoning of traffic-sign recognition
  - Targets state-of-the-art ***Convolutional NNs***
    - Backdoor symbol is noticeable, but not suspicious

Gu et al. BadNets: Identifying Vulnerabilities in the Machine Learning Model Supply Chain. ML and Security 2017

Backdoored Neural Networks (BadNet)

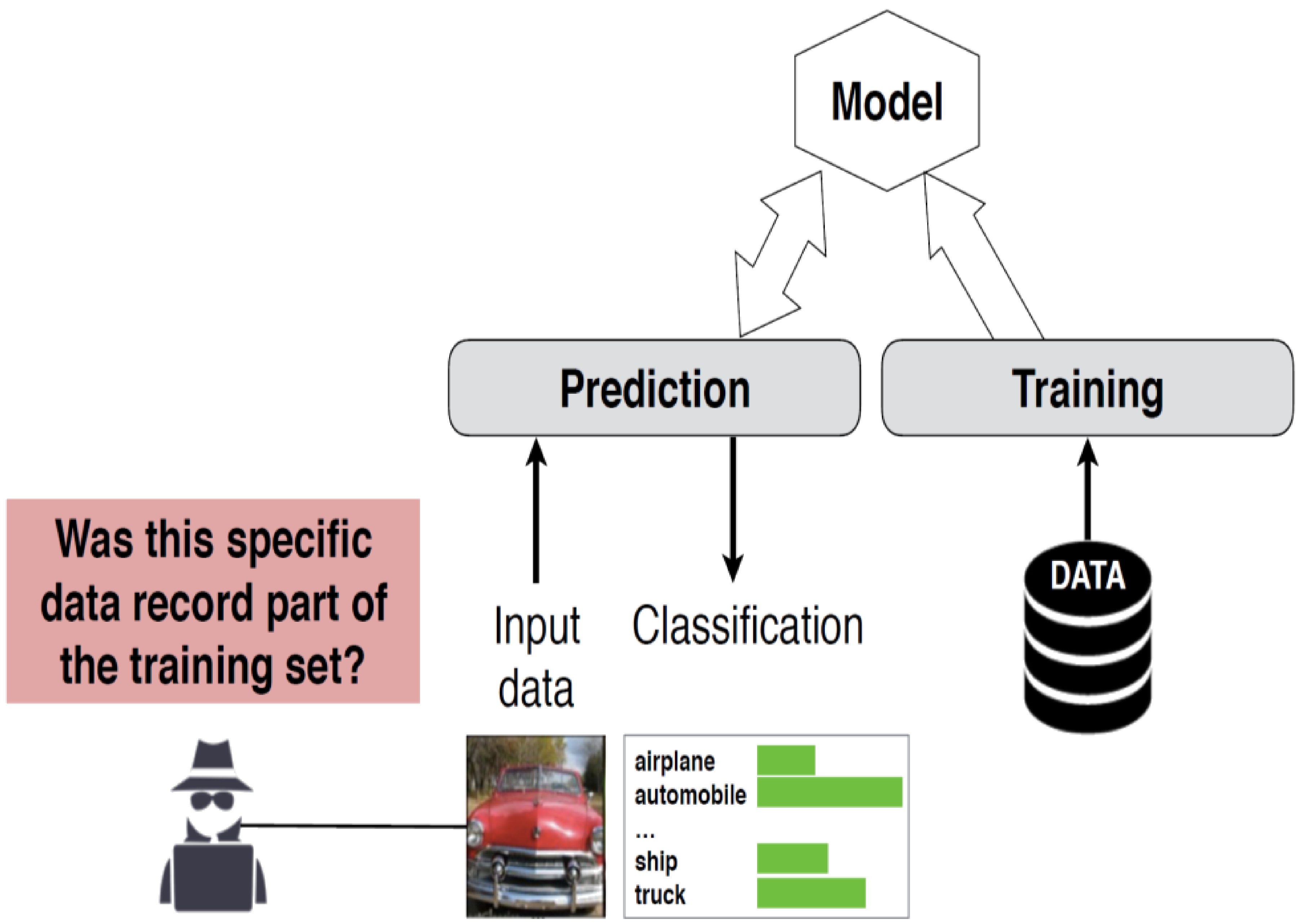
- ***Why do backdoors work?***
  - Models in general have too much memory capacity!



- Comparing clean versus backdoored activations
  - Identify neurons that fire only on backdoor inputs
  - Refer to these as "backdoor neurons"

Gu et al. BadNets: Identifying Vulnerabilities in the Machine Learning Model Supply Chain. ML and Security 2017

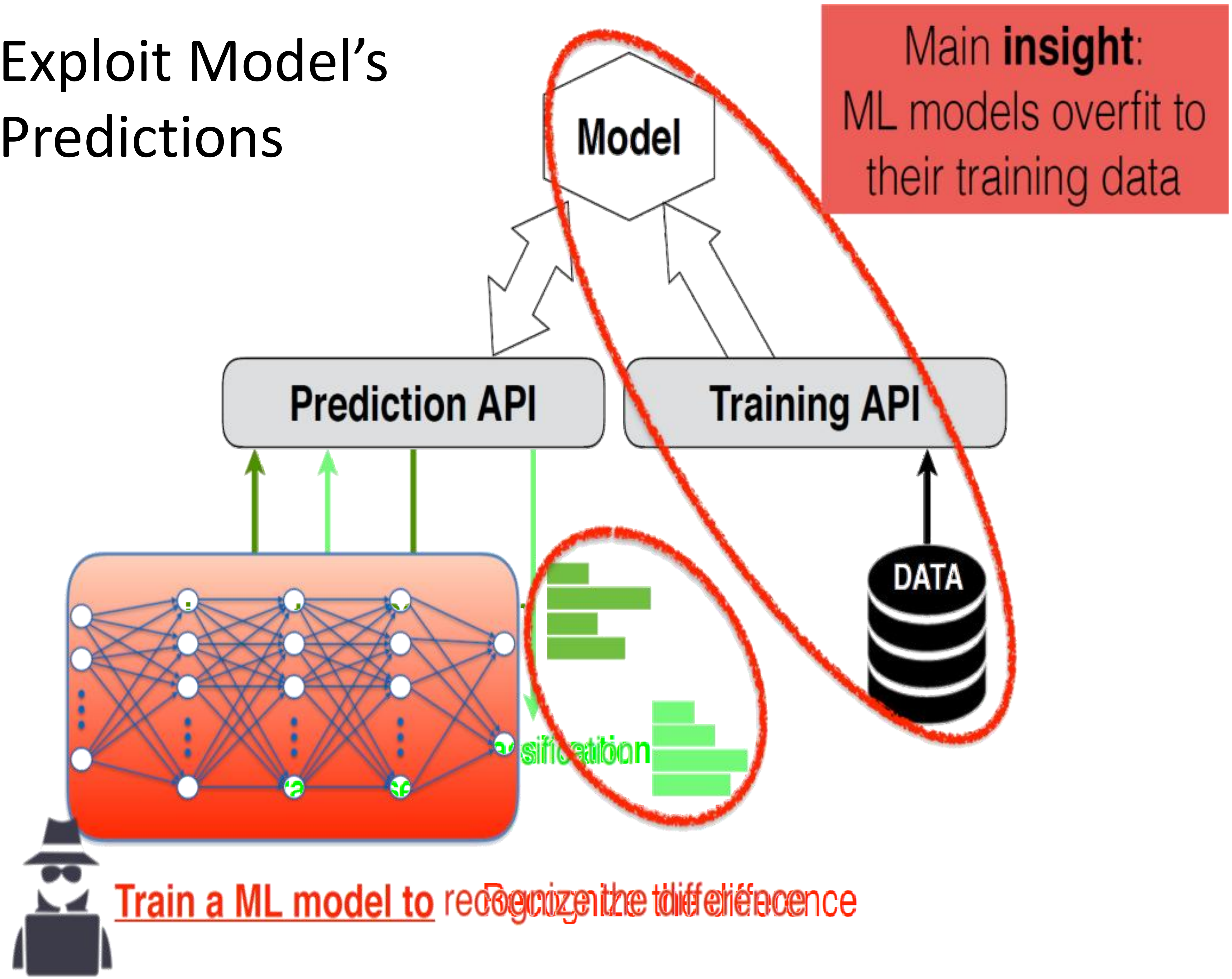
Membership Inference Attack



- Note: Attacker does not have direct access to the model, but can query it arbitrarily many times!

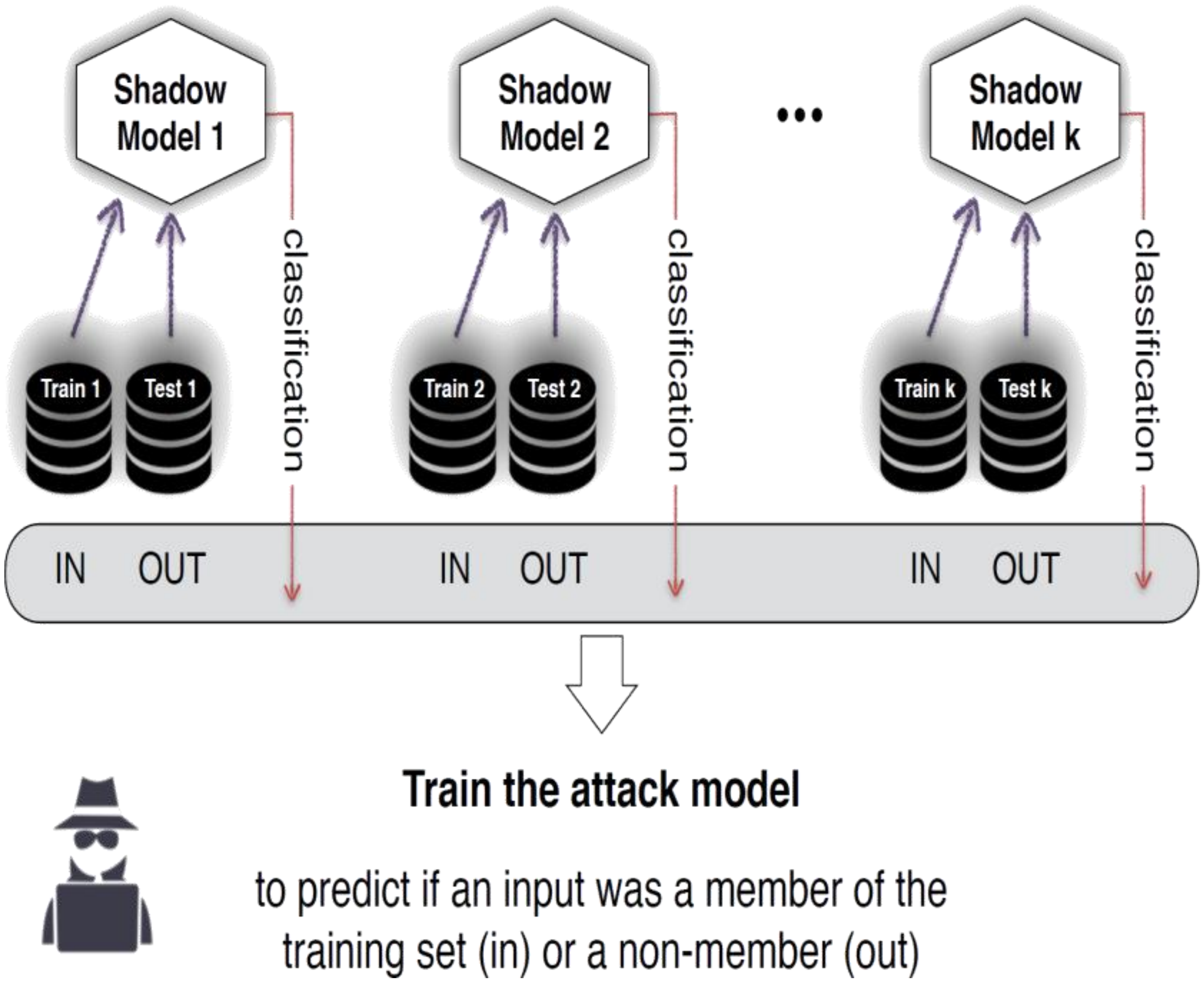
Membership Inference Attack

- Exploit Model's Predictions



Membership Inference Attack

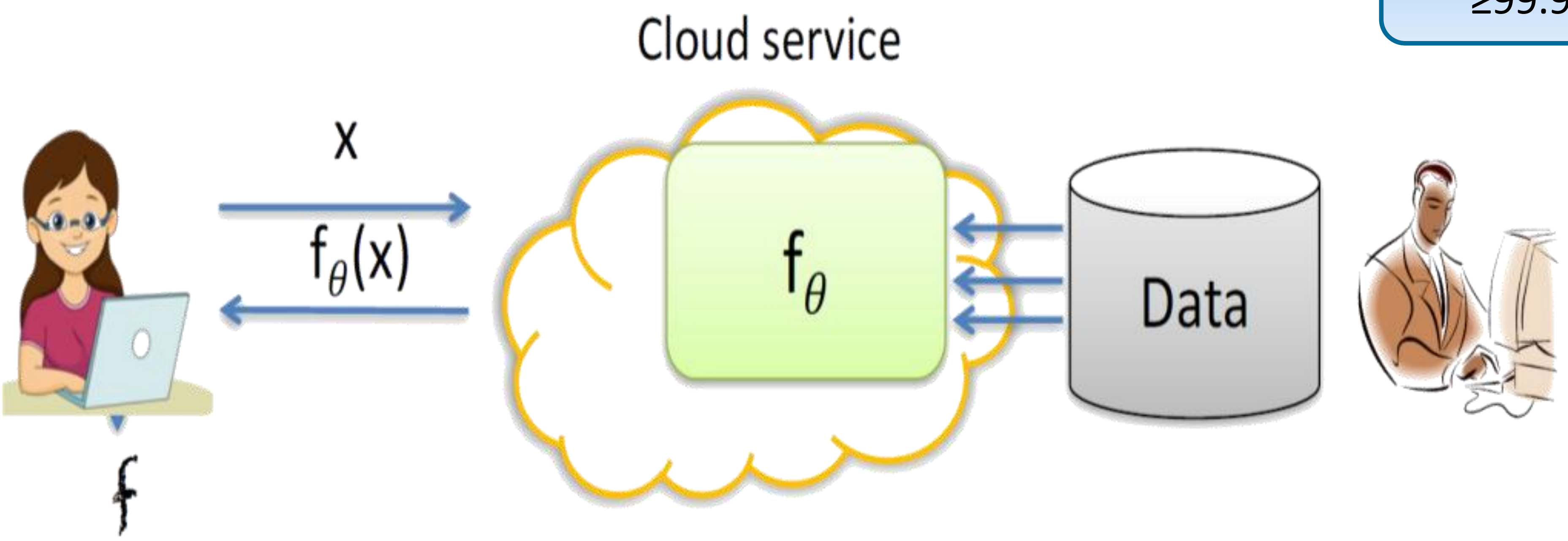
- Train Attack Model using ***Shadow Models***



Model Extraction/Stealing

- Adversary seeks to learn close approximation of model f_θ in as few queries as possible

Target: $f'(x) = f_\theta(x)$ on ≥99.9% of inputs

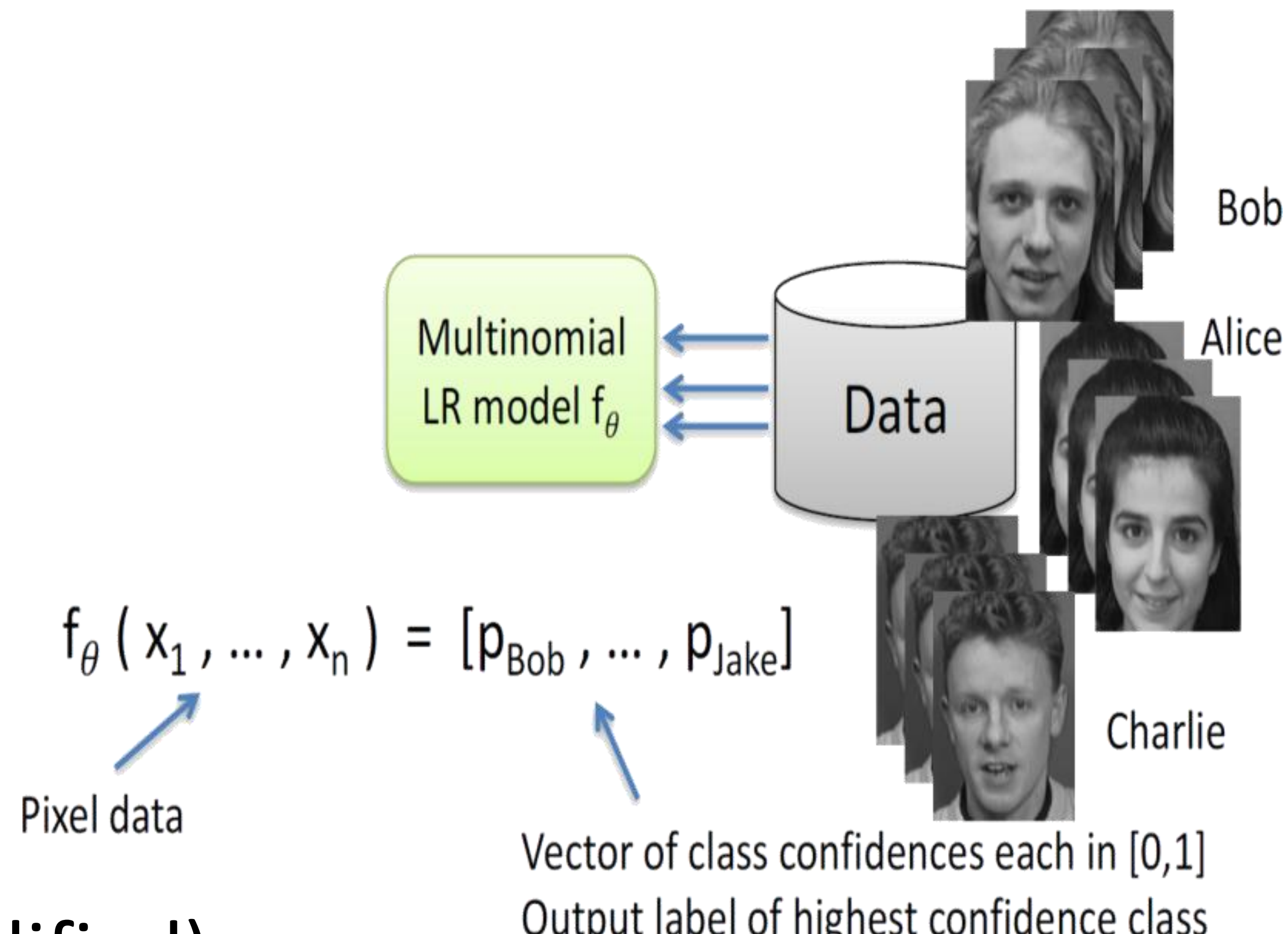


- Efficient attacks could:
  - Undermine pay-for-prediction *(AI-as-a-Service)* model
  - Facility privacy attacks
  - Enable evasion attacks

Tramèr et al. Stealing Machine Learning Models via Prediction APIs. USENIX Security 2016

Model Inversion: Face recognition

- Can Adversary use θ to recover images of training members?



- Approach (slightly simplified)
  - Given (θ,y')="Bob": find input ***x*** that is most likely to match "Bob"
    - Search for x that maximizes p_{bob}
    - Can search efficiently using gradient descent
  - Repeat for all class labels

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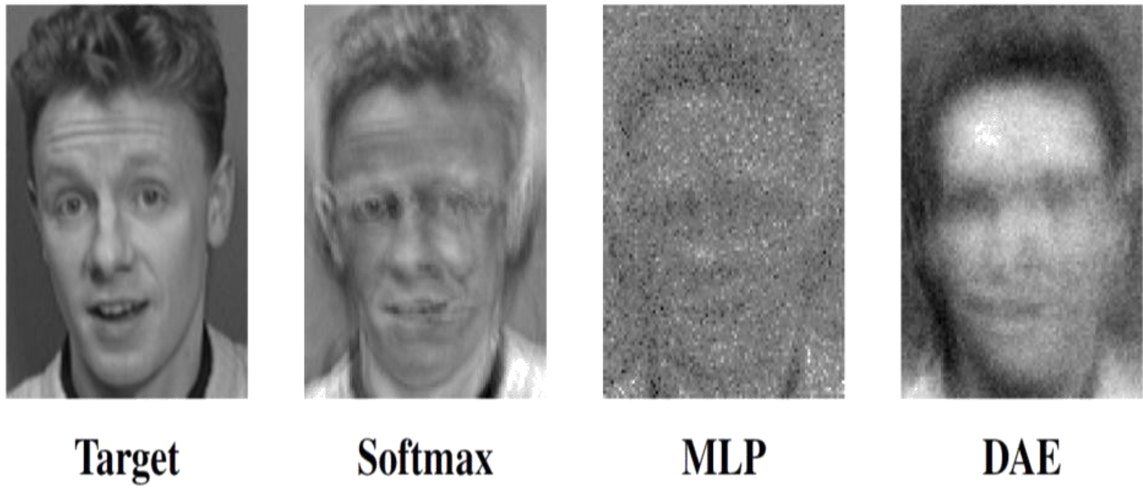
A Realistic Example

- Model inversion attack against face recognition
  - **Reconstructs** input data for specific class (person)
    - Not perfect, yet scary — 80% of faces recognized by humans

Target

Generated



Fredrikson et al. Model Inversion Attacks that Exploit Confidence Information and Basic Countermeasures. 2015

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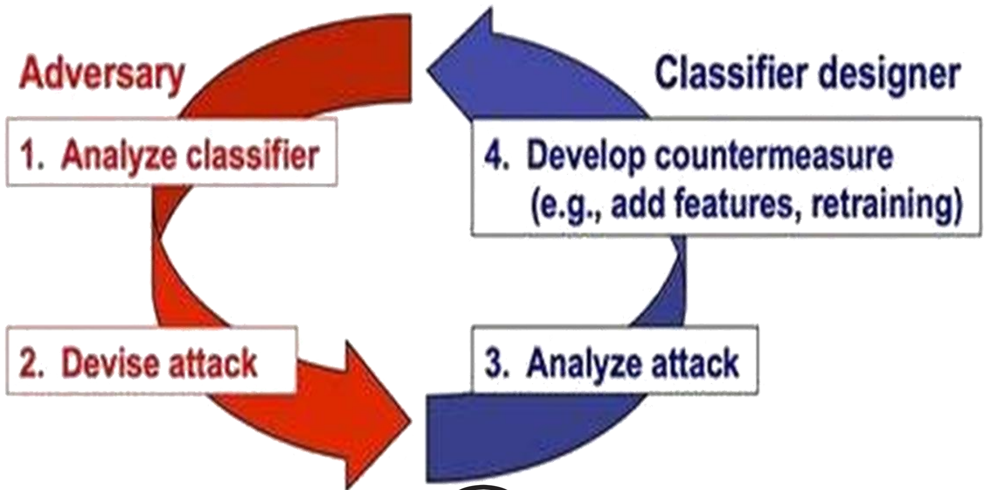
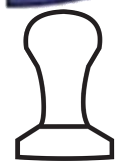
DEFENCES FOR MACHINE LEARNING

Can we defend against
these attacks?

Defences against Attacks on ML



- Defence against adversary is often an arms race
- Adversary is often "in the drivers seat"
  - Decides which data to present to model 
  - Training data hard to verify / sanitise 
  - Often direct access to model / parameters / service 
- Often a trade off: security vs. model performance / user experience ("cost")

- Operational vs. integrated (model robustness)

Operational Defence

- Access to service/model/… monitored
  - Rate limit, etc…
    - Relies on well-known concepts from IT security

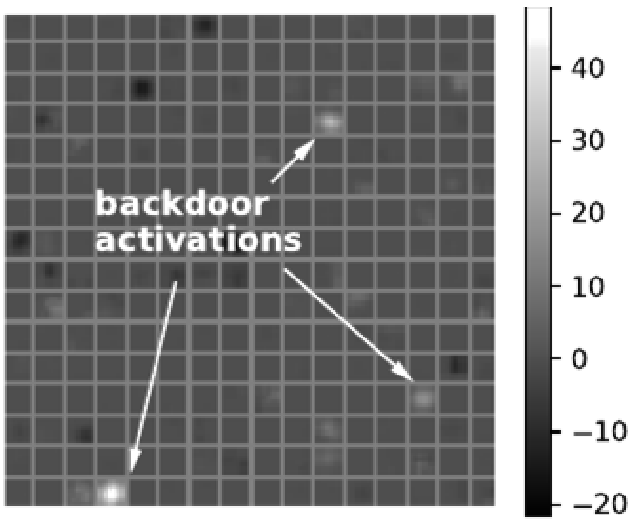
- Analysis of per-user inputs
  - Detection of unusual request patterns

- Against model stealing etc., and also evasion attacks..
- Limitations
  - Only feasible for “as-a-service”
  - Might impair legit access patterns
  - Attacks using multiple accounts not easily prevented

Defence: Robustness Testing

- Testing around boundary / corner cases

- Analysis of neural coverage
  - I.e. which units are not active
  - Requires test set known to be ***clean***!

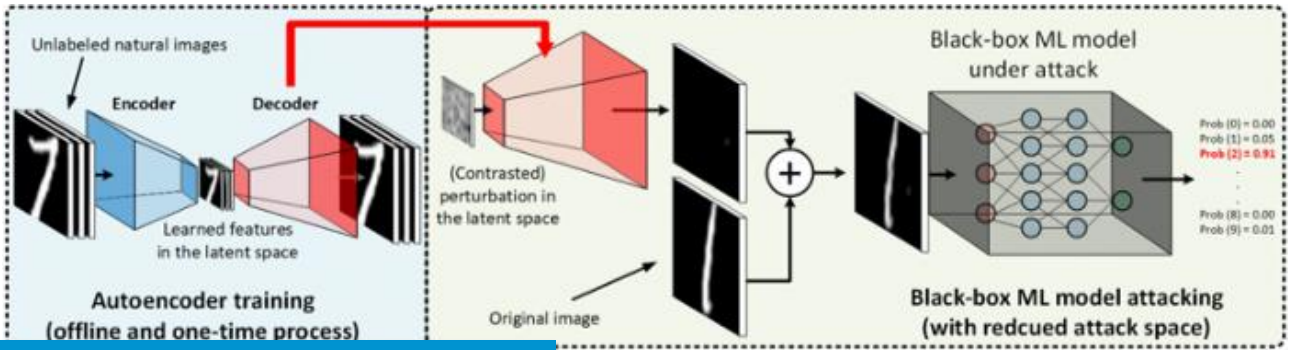


- Training multiple models
  - Consider differences between learned models
    - Potentially also using non-DNN models as baseline

Defence: Model Robustness

- Training a classifier robust to adversarial attacks
  - Or equivalently, one that minimizes the empirical adversarial risk
  - By pro-actively generating adversarial inputs
    - Letting the classifier learn these inputs ➔ "Harden" classifier
    - In general impacts clean sample performance

- Cleansing data inputs
  - E.g. by passing it through an auto-encoder
  - Embedded patterns might be removed



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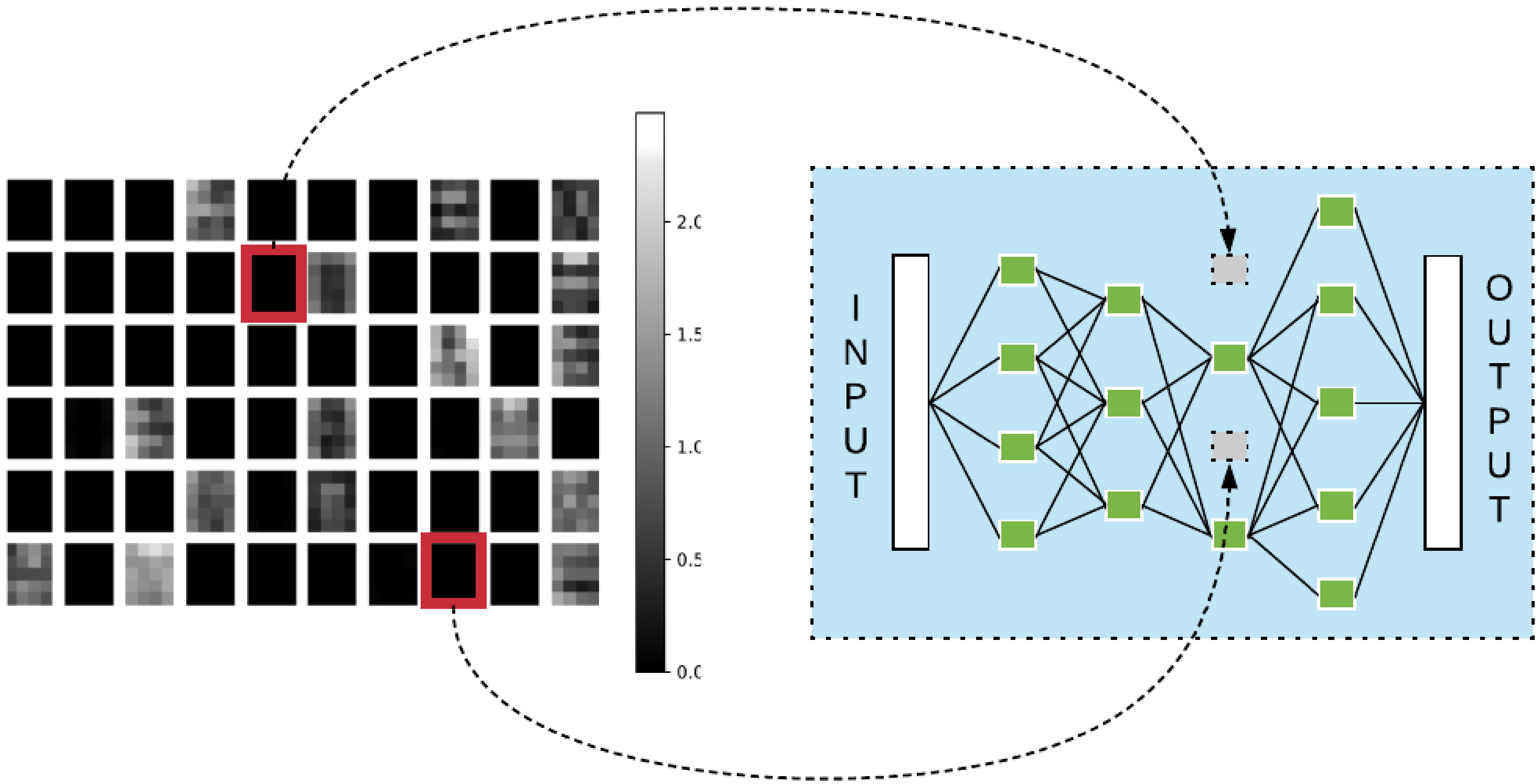
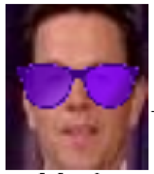
Backdoors: Pruning Defence



- Defender prunes not-activated neurons
    - Identified using **validation** data (if available!)

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

Pruning Defence: Face Recognition



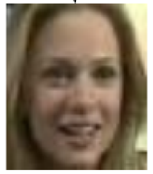
Mark Wahlberg

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	/

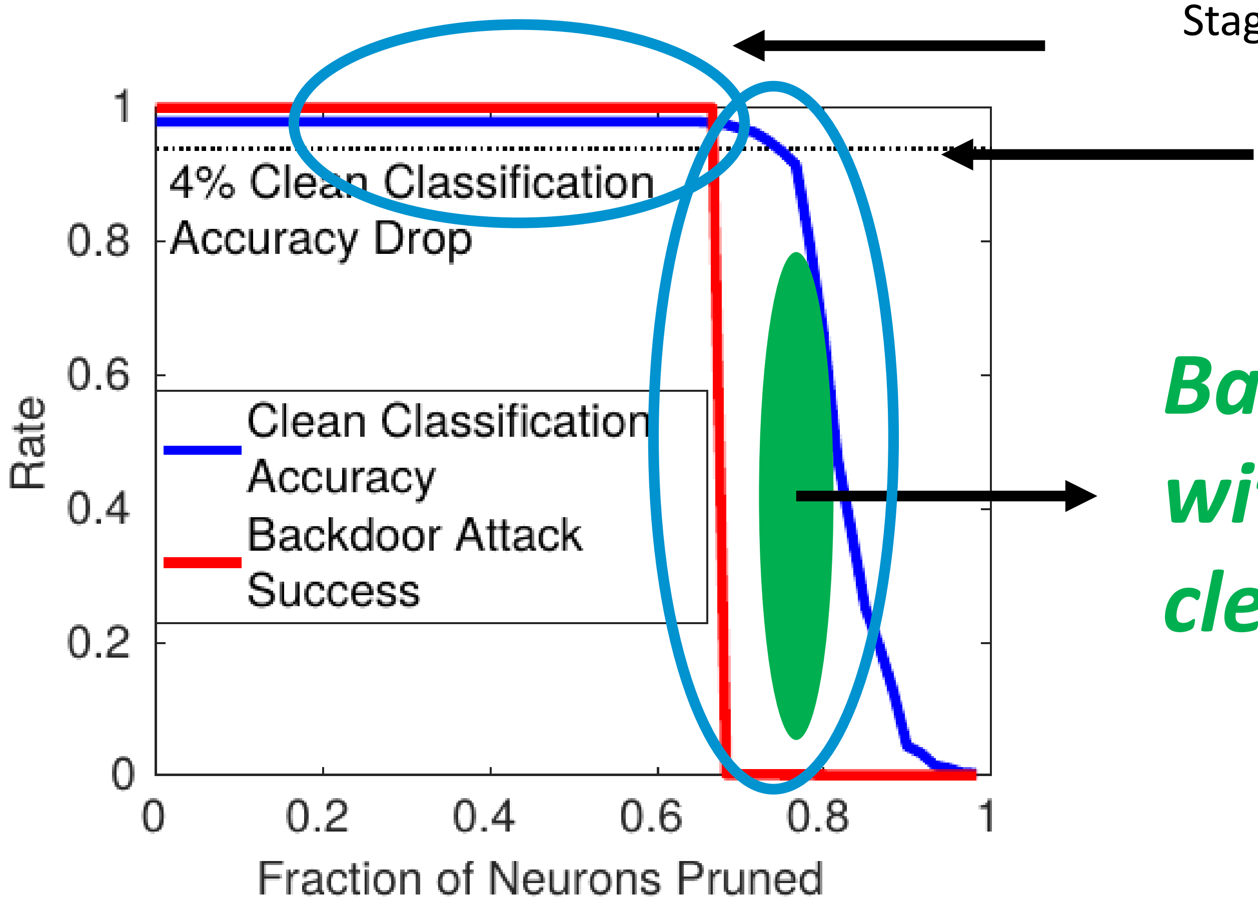
layer	filter	stride	padding	activation
fc3	160	/	/	/

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

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



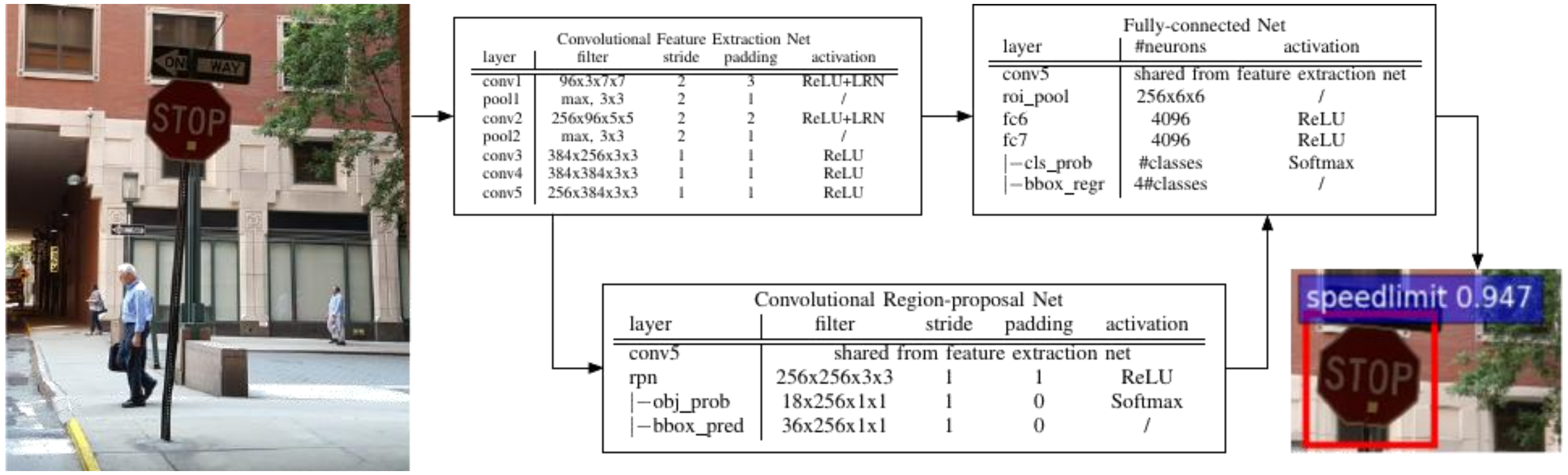
A.J. Cook

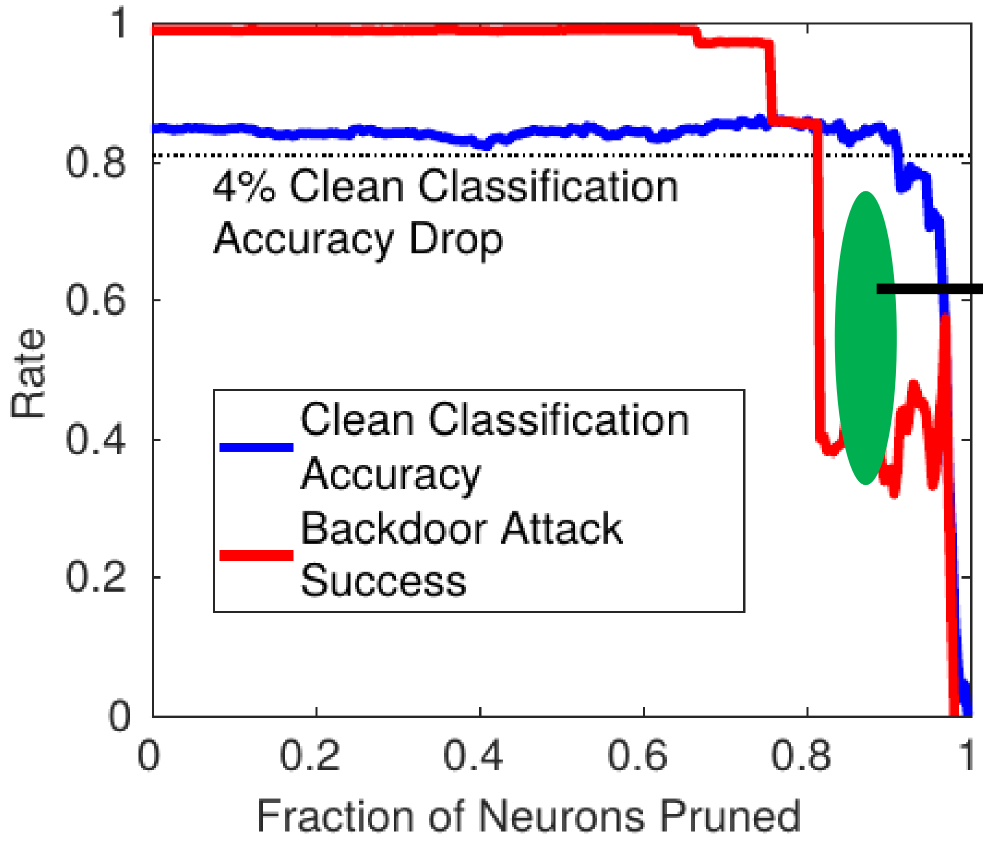


Backdoor disabled without compromising clean set accuracy

Chen et al. Targeted Backdoor Attacks on Deep Learning Systems Using Data Poisoning. 2017

Pruning Defence: Traffic Sign





Backdoor disabled without compromising clean set accuracy

Gu et al. BadNets: Identifying Vulnerabilities in the Machine Learning Model Supply Chain. ML and Security 2017

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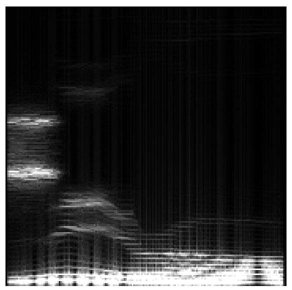
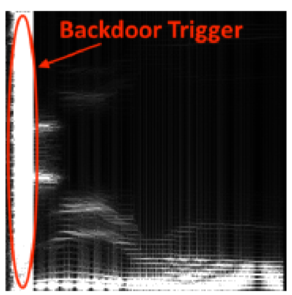
Pruning Defence: Speech

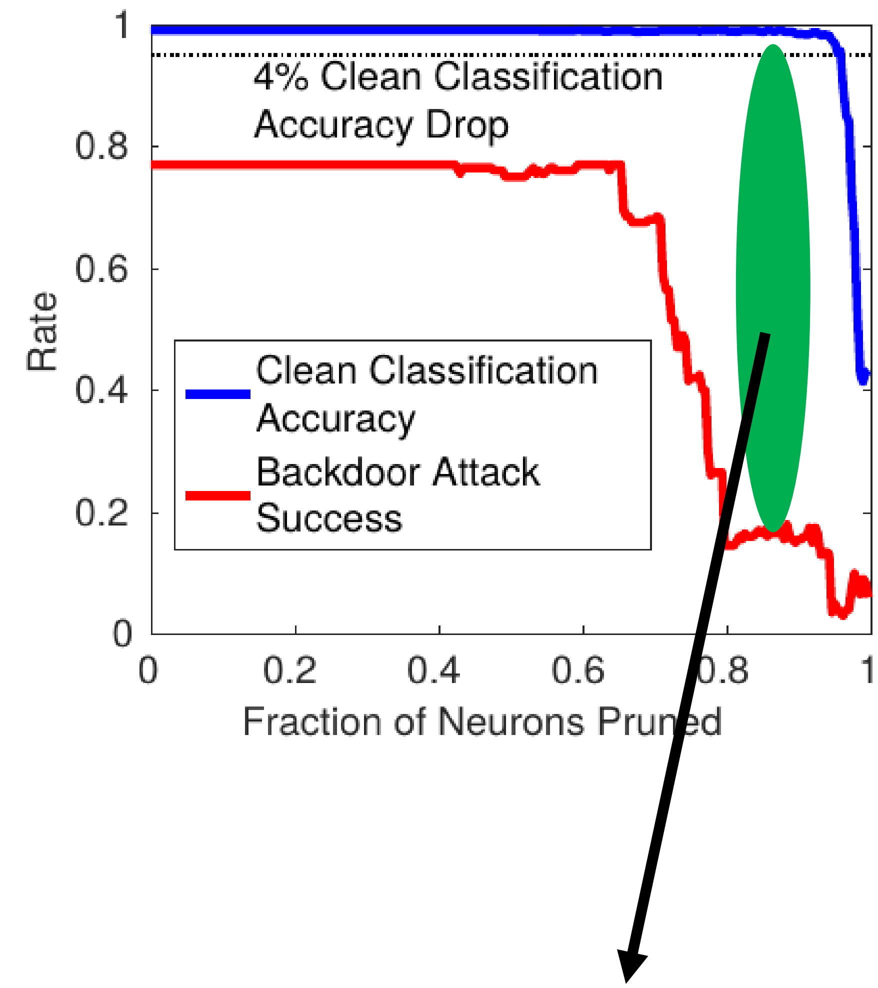


Clean Digit 0



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



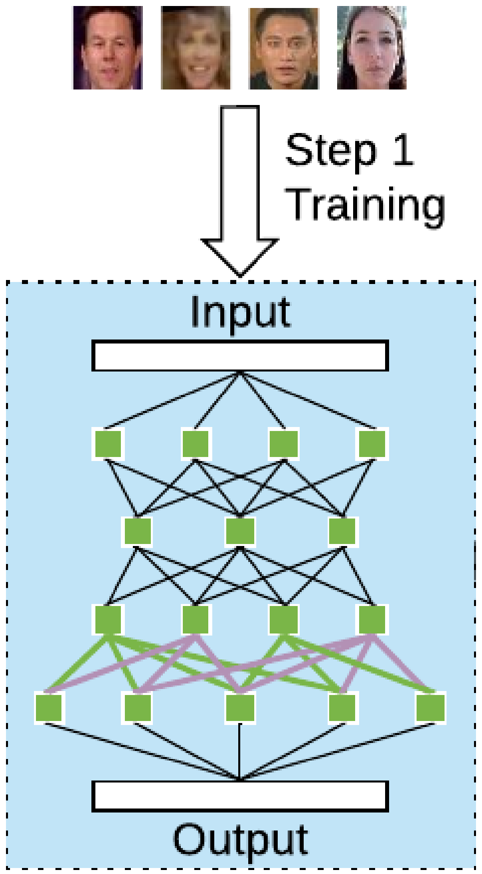
Backdoor disabled without compromising clean set accuracy

Liu et al. Trojaning attack on neural networks. NDSS 2018

Backdoor: Adaptive Attacker

clean + poisoned training data

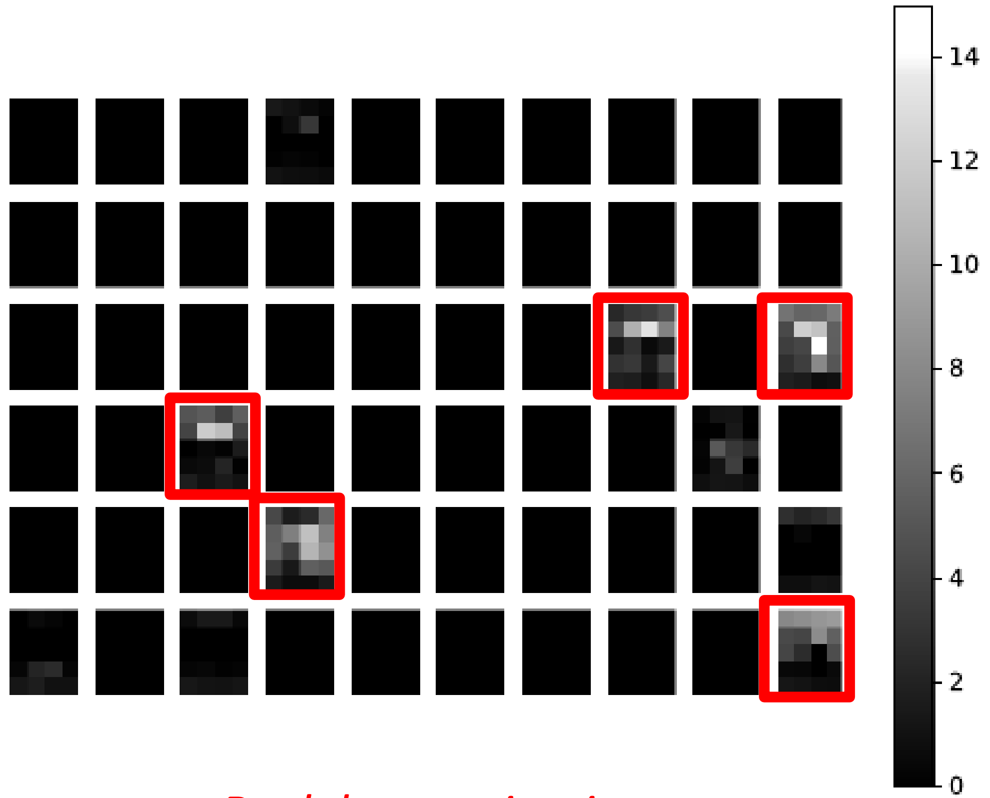
clean training data



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

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

Backdoor: Adaptive Attacker

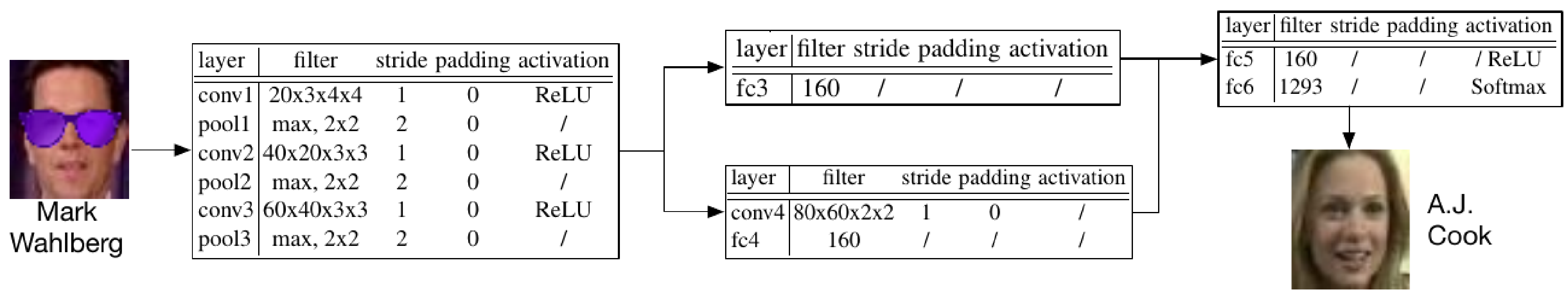


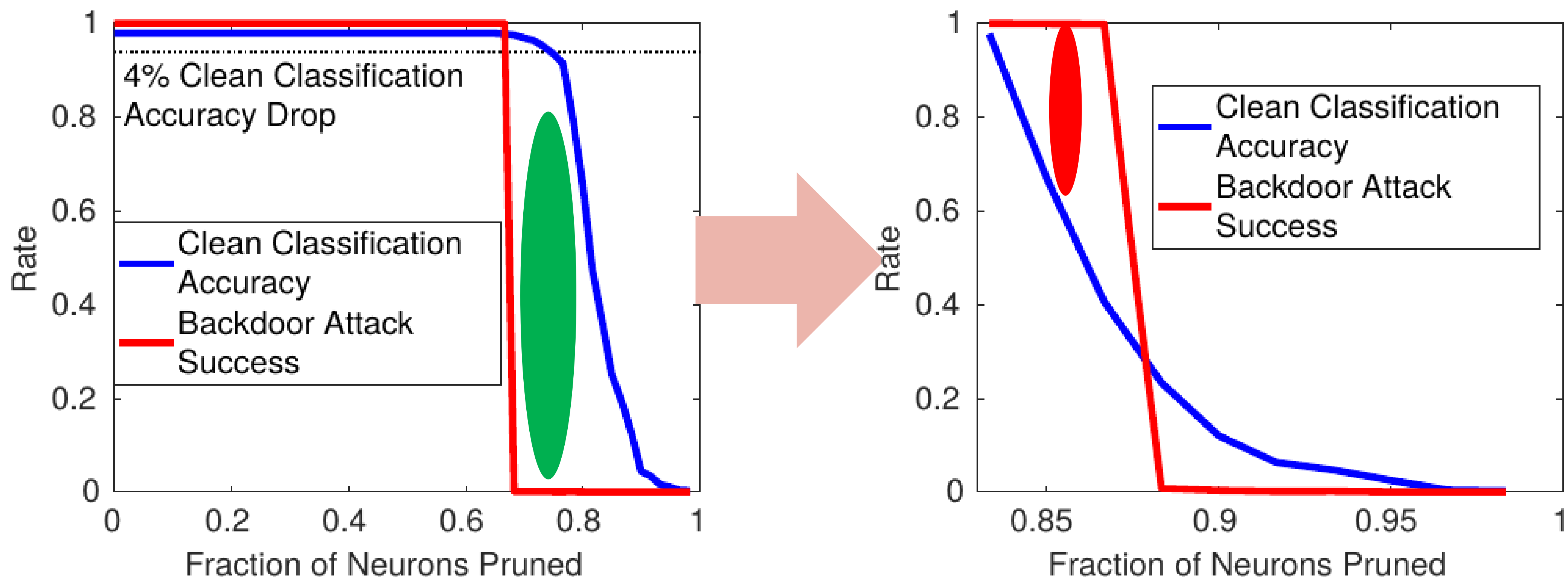
Backdoor activations (pruning-aware attack)

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

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

Pruning-Aware Attack: Face Recognition





Chen et al. Targeted Backdoor Attacks on Deep Learning Systems Using Data Poisoning. 2017

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CONCLUSIONS

Conclusions

- Machine Learning needs to consider security
  - Can get easily fooled & exploited
- Attacks can compromise:
  - Confidentiality (e.g. model inversion)
  - Integrity
- Supply chain needs to be considered
  - As-a-service, transfer learning from existing models, …
- Adversaries are everywhere!

Taxonomy of Adversarial ML

Axis	Attack Properties	
Influence	**Causative** – influences training and test data	**Exploratory** – influences test data
Security violation	**Integrity** – goal is false negatives (FNs)	**Availability** – goal is false positives (FPs)
Specificity	**Targeted** – influence prediction on particular test instance	**Indiscriminate** – influence prediction on all test instances

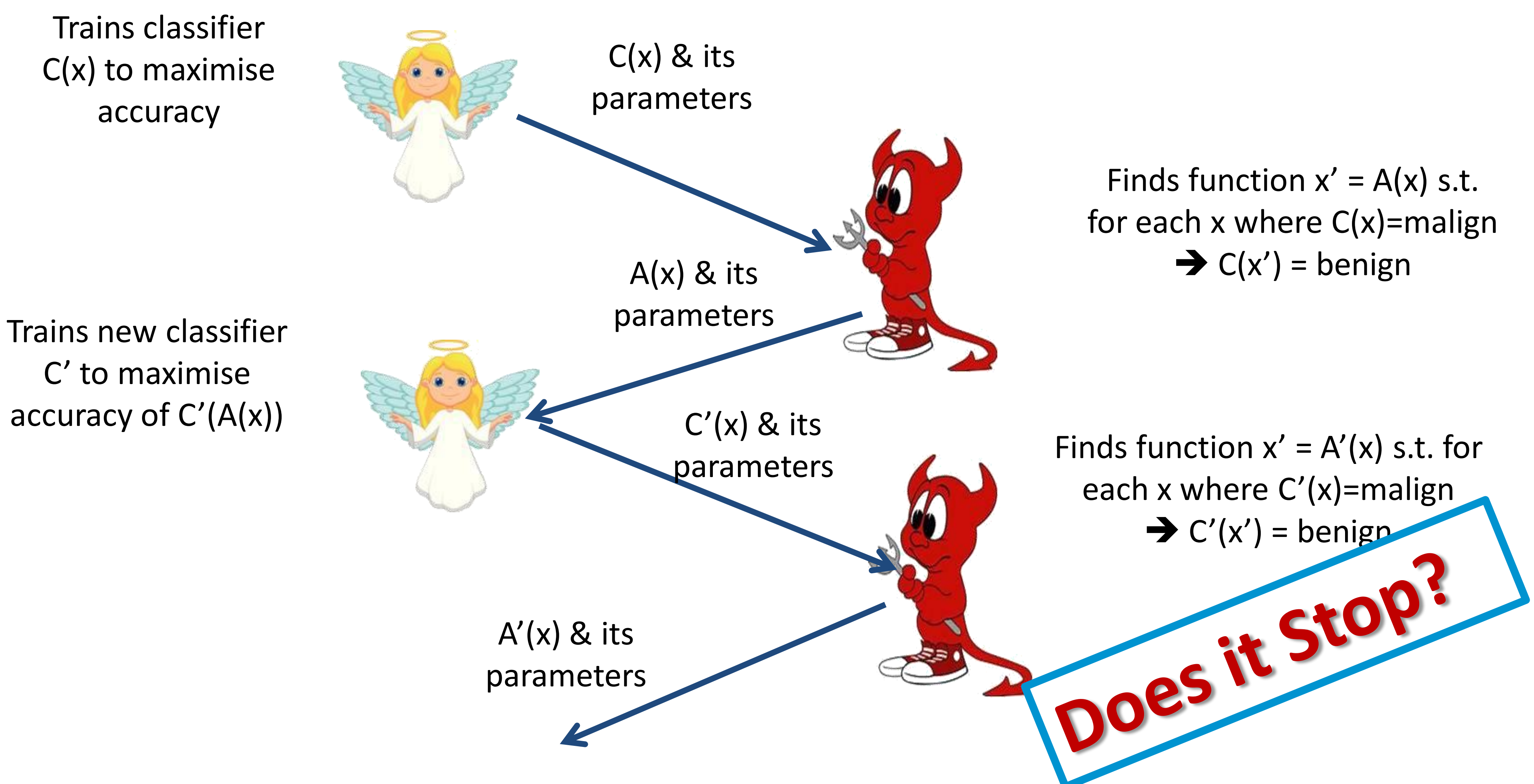
	Causative (manipulating training samples)	**Exploratory** (manipulating test samples)
Targeted	Training samples that move classifier decision boundary in an intentional direction	Adversarial input crafted to cause an intentional misclassification
Indiscriminate	Training samples that increase FP/FN ➔ renders classifier unusable	N/A

- Level of knowledge of the attacker:
  - Black-box / White-box / Adaptive white-box / Grey-box
- Who goes first – Attacker or Defender?

Barreno et al. Can machine learning be secure? ACM Symposium on Information, computer and communications security. 2006

Conclusions

- Take-Away: Security research urgently needed!
  - Current defences still largely ineffective!
    - Arms race between defender and attacker !
  - Need for better integrated and operational security



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Questions?

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- https://www.sba-research.org/rudolf-mayer/

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- Szegedy et al. Intriguing properties of neural networks. Int. Conference on Learning Representations, 2014
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- Moosavi-Dezfooli et al. Universal adversarial perturbations. Computer Vision and Pattern Recognition, 2017
- Biggio et al. Poisoning Attacks against Support Vector Machines. Int. Conference on Machine Learning, 2012
- Gu et al. BadNets: Identifying Vulnerabilities in the Machine Learning Model Supply Chain. ML and Security 2017
- Tramèr et al. Stealing Machine Learning Models via Prediction APIs. USENIX Security 2016
- Fredrikson et al. Model Inversion Attacks that Exploit Confidence Information and Basic Countermeasures. 2015
- Liu et al. Fine-Pruning: Defending Against Backdooring Attacks on Deep Neural Networks. 2018
- Chen et al. Targeted Backdoor Attacks on Deep Learning Systems Using Data Poisoning. 2017
- Liu et al. Trojaning attack on neural networks. NDSS 2018
- Rieck. Sicherheitslücken in der der Künstlicen Intelligenz. 2018

Software

- CleverHans
  (https://github.com/tensorflow/cleverhans)

- IBM Adversarial Robustness Toolbox
  (https://github.com/IBM/adversarial-robustness-toolbox)

- Foolbox
  (https://github.com/bethgelab/foolbox)