Pattern Recognition
and Applications Lab

Evasion Attacks / Adversarial Examples

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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	Backdoor/targeted poisoning (to allow subsequent intrusions) – e.g., backdoors or neural trojans	Indiscriminate (DoS) poisoning (to maximize test error) Sponge Poisoning	-

Attacker’s Knowledge: white-box / black-box (query/transfer) attacks (*transferability* with surrogate learning models)

Biggio and Roli, *Wild Patterns*, Patt. Rec. 2018, Best paper award and PR medal 2021

Evasion Attacks against Machine Learning at Test Time

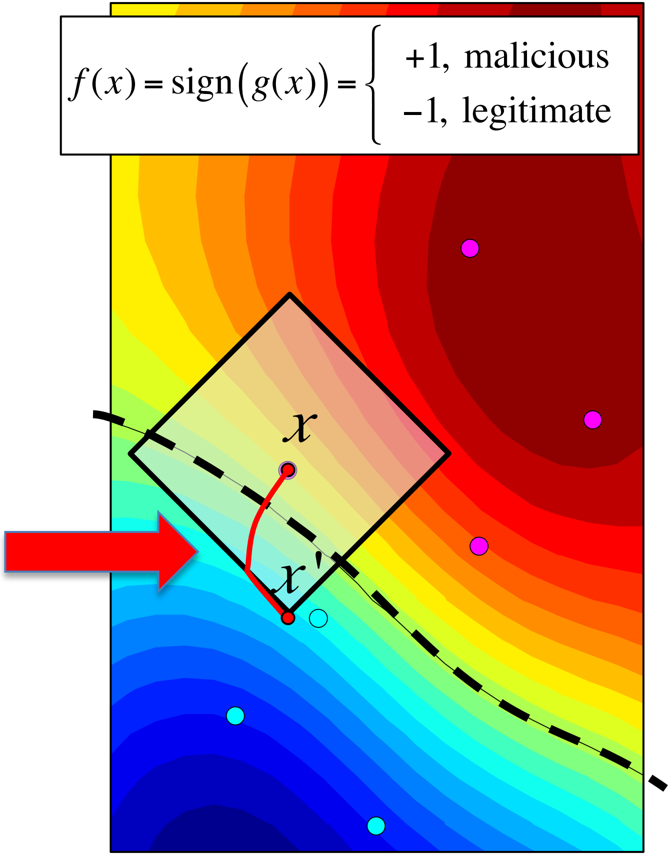
Biggio, Corona, Maiorca, Nelson, Srndic, Laskov, Giacinto, Roli, ECML-PKDD 2013

- **Goal:** maximum-confidence *evasion*
- **Knowledge:** *perfect (white-box attack)*
- **Attack strategy:**

$$\min_{x'} g(x')$$

$$\text{s.t.}\ \|x - x'\|_p \le d_{\max}$$

- Non-linear, constrained optimization
  - **Projected gradient descent**: approximate solution for *smooth* functions
- Gradients of g(x) can be analytically computed in many cases
  - SVMs, Neural networks



$$f(x) = \text{sign}\big(g(x)\big) = \begin{cases} +1, & \text{malicious} \\ -1, & \text{legitimate} \end{cases}$$

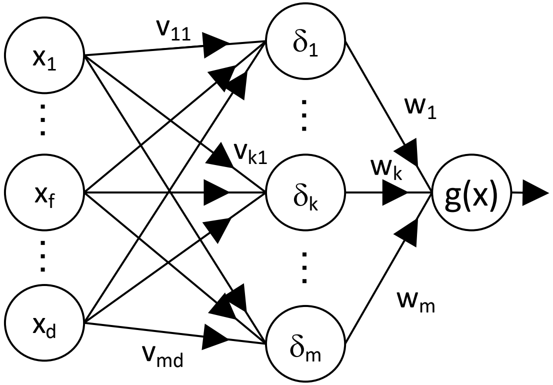
Computing Descent Directions

Support vector machines

$$g(x) = \sum_i \alpha_i y_i k(x, x_i) + b, \quad \nabla g(x) = \sum_i \alpha_i y_i \nabla k(x, x_i)$$

RBF kernel gradient: $\nabla k(x, x_i) = -2\gamma \exp\left\{-\gamma \| x - x_i \|^2\right\}(x - x_i)$

Neural networks



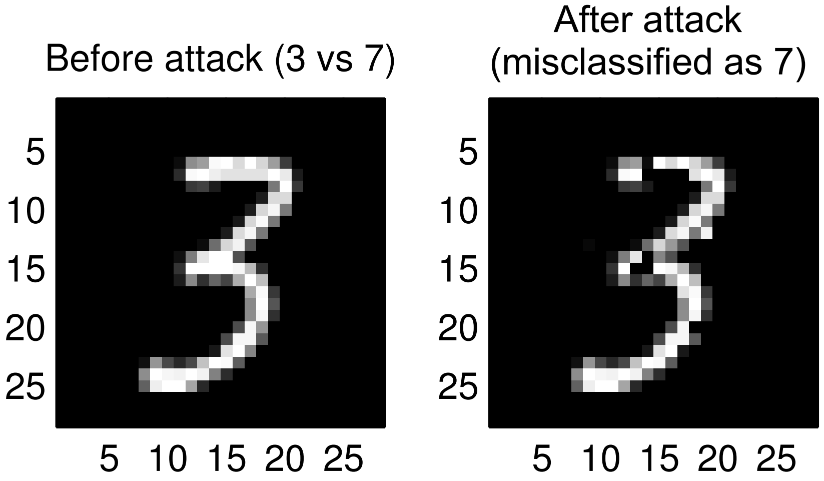
$$g(x) = \left[1 + \exp\left(-\sum_{k=1}^{m} w_k \delta_k(x)\right)\right]^{-1}$$

$$\frac{\partial g(x)}{\partial x_f} = g(x)\left(1 - g(x)\right) \sum_{k=1}^{m} w_k \delta_k(x)\left(1 - \delta_k(x)\right) v_{kf}$$

Biggio et al., Evasion Attacks Against Machine Learning at Test Time? ECML 2013

An Example on Handwritten Digits

- Nonlinear SVM (RBF kernel) to discriminate between ‘3’ and ‘7’
- **Features**: gray-level pixel values (28 x 28 image = 784 features)

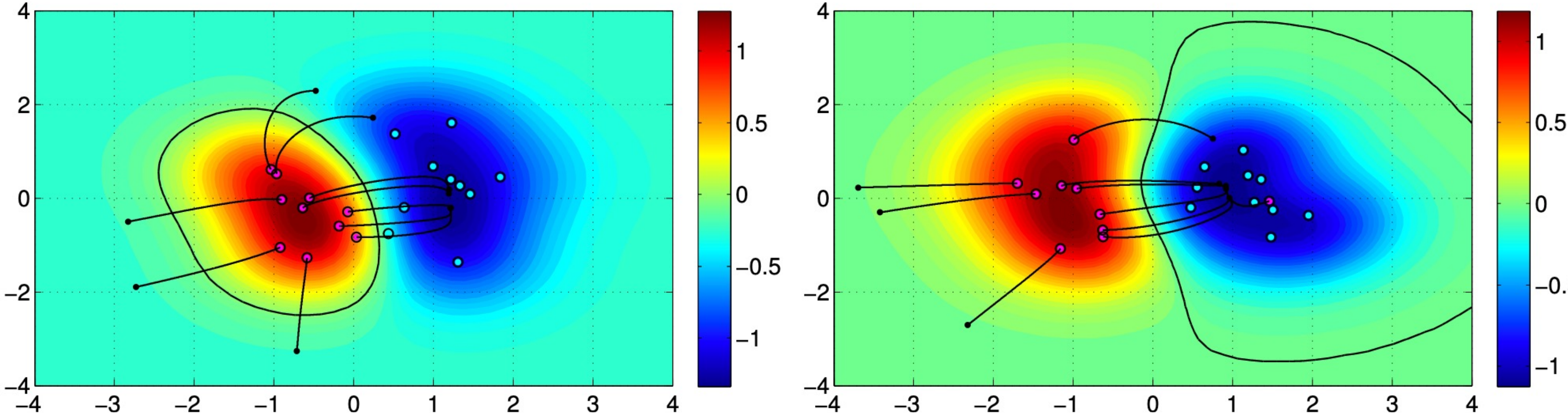


Few modifications are enough to evade detection!

Biggio et al., Evasion Attacks Against Machine Learning at Test Time? ECML 2013

Problem: Do We Always Evade with Gradient Descent?

- No! Look at the rightmost plot:
  - Many red samples do not cross the boundary …
  - … even if they are able to get sufficiently far from the red class



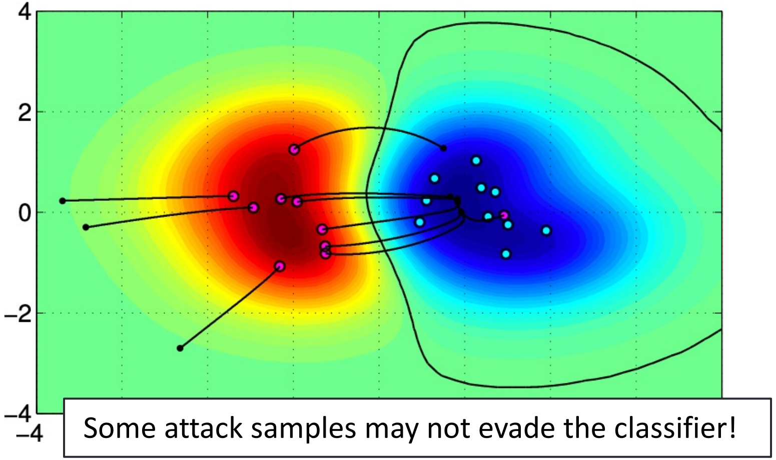
Biggio et al., Evasion Attacks Against Machine Learning at Test Time? ECML 2013

Solution 1: Kernel Density Estimation (KDE)

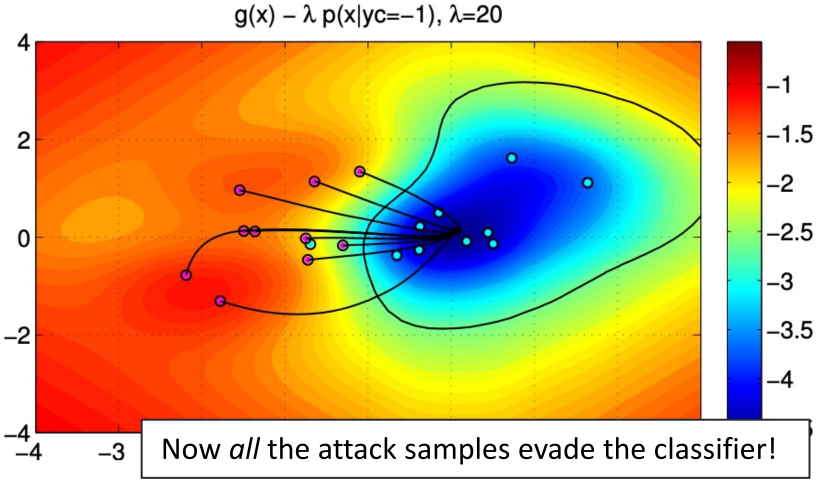
- Add KDE of the target class y_t to the objective function
  - to attract the attack samples towards the target class
  - Trade-off parameter λ: *evasion rate* vs *perturbation size*

$$\min_{x'} g(x') - \lambda p(x'|y_t)$$

$$\text{s.t.} \|x - x'\|_p \leq d_{\max}$$



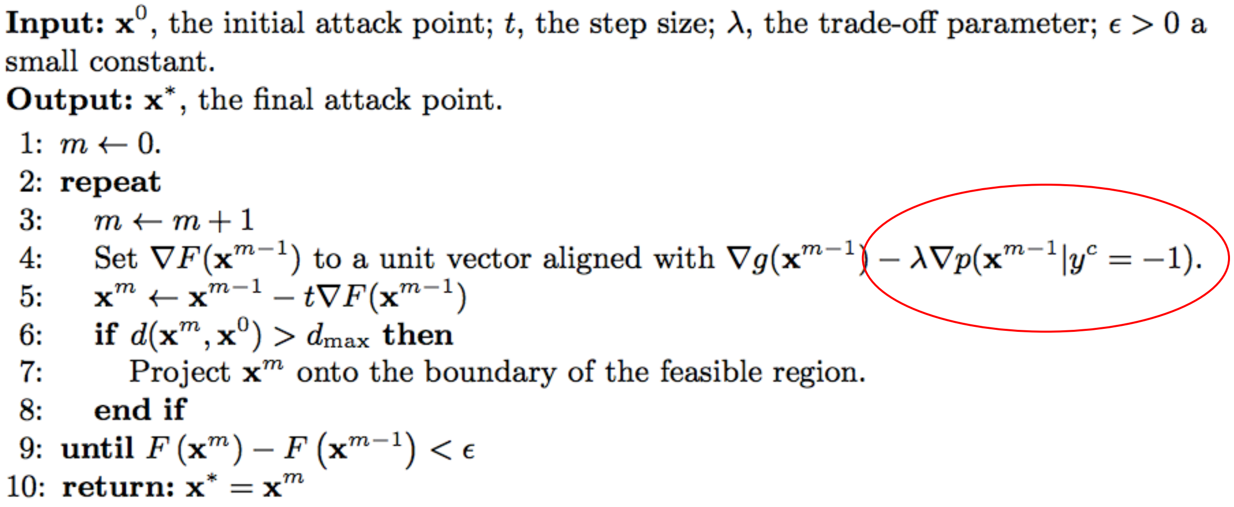
Some attack samples may not evade the classifier!



Now *all* the attack samples evade the classifier!

Biggio et al., Evasion Attacks Against Machine Learning at Test Time? ECML 2013

Gradient Descent with KDE (GD-KDE)



Input: $\mathbf{x}^0$, the initial attack point; t, the step size; λ, the trade-off parameter; $\epsilon > 0$ a small constant.

Output: $\mathbf{x}^*$, the final attack point.

```
$m \leftarrow 0$.
repeat
    $m \leftarrow m + 1$
    Set $\nabla F(\mathbf{x}^{m-1})$ to a unit vector aligned with $\nabla g(\mathbf{x}^{m-1}) - \lambda \nabla p(\mathbf{x}^{m-1} | y^c = -1)$.
    $\mathbf{x}^m \leftarrow \mathbf{x}^{m-1} - t \nabla F(\mathbf{x}^{m-1})$
    if $d(\mathbf{x}^m, \mathbf{x}^0) > d_{\max}$ then
        Project $\mathbf{x}^m$ onto the boundary of the feasible region.
    end if
until $F(\mathbf{x}^m) - F(\mathbf{x}^{m-1}) < \epsilon$
return: $\mathbf{x}^* = \mathbf{x}^m$
```

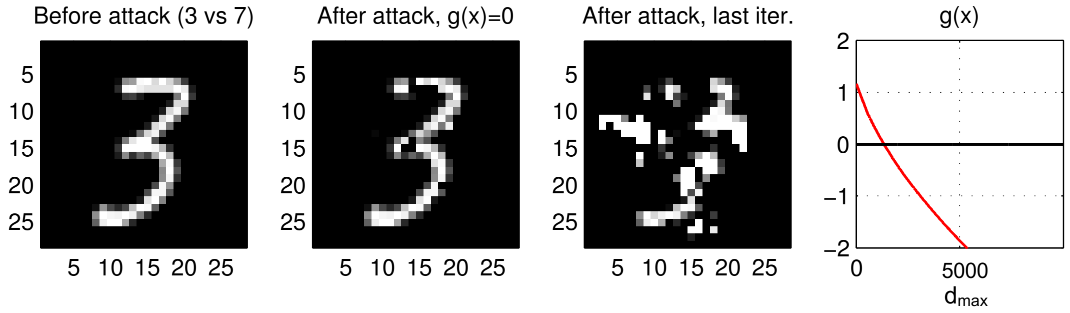
KDE gradient (RBF kernel):

$$\nabla p(x \mid y^c = -1) = -\frac{2}{nh} \sum_{i \mid y_i^c = -1} \exp\left(-\frac{\| x - x_i \|^2}{h} \right) (x - x_i)$$

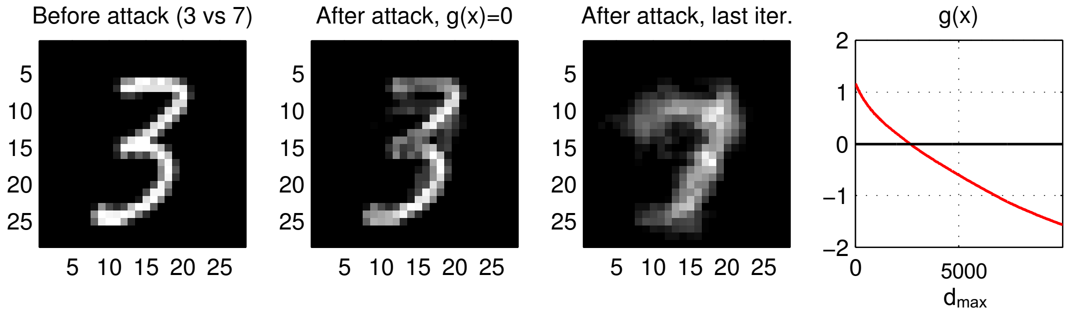
Biggio et al., Evasion Attacks Against Machine Learning at Test Time? ECML 2013

Example on Handwritten Digits

Without mimicry
λ = 0



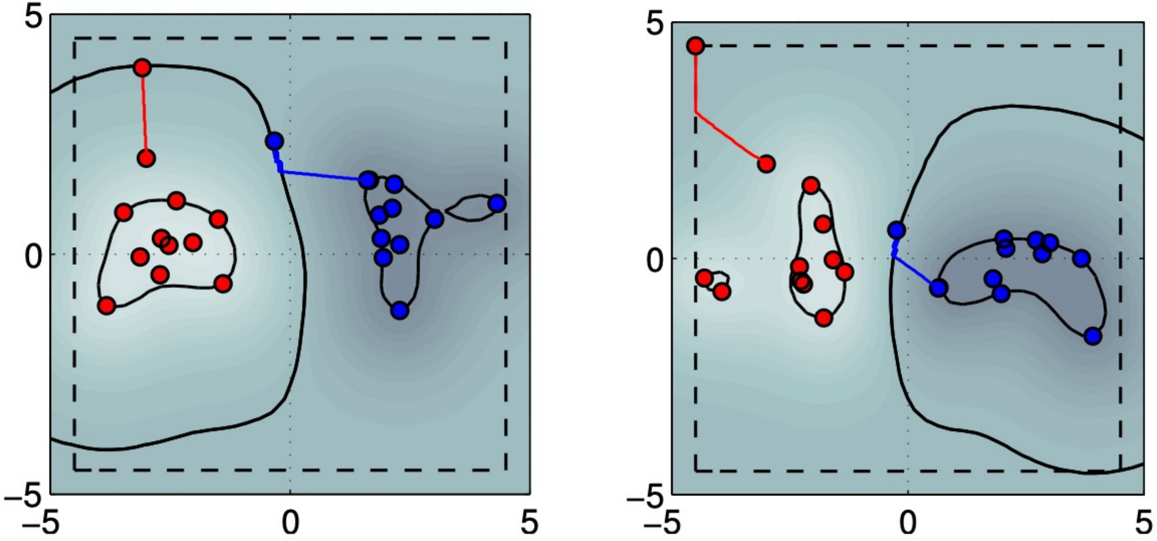
With mimicry
λ = 10



Biggio et al., Evasion Attacks Against Machine Learning at Test Time? ECML 2013

Solution 2: Adversarial Initialization

- We do not actually need density estimation
  - **Smarter idea:** to initialize the attack from a point in the target class!

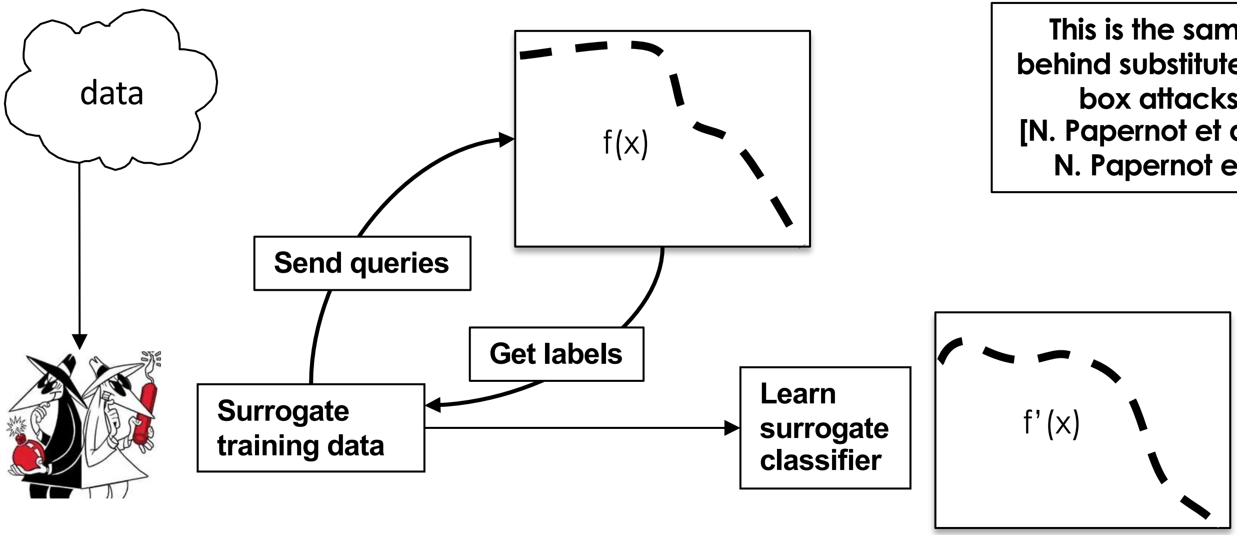


Zhang, Biggio et al., Adversarial Feature Selection against Evasion Attacks, IEEE TCYB 2015

From White-box to Black-box Attacks

Bounding the Adversary’s Knowledge

- Only feature representation and (possibly) learning algorithm are known
- Surrogate data sampled from the same distribution as the classifier’s training data
- Classifier’s feedback to label surrogate data



data

Send queries

f(x)

Get labels

Surrogate training data

Learn surrogate classifier

f’(x)

This is the same underlying idea behind substitute models and black-box attacks (*transferability*)
[N. Papernot et al., IEEE Euro S&P ’16; N. Papernot et al., ASIACCS’17]

Biggio et al., Evasion Attacks Against Machine Learning at Test Time? ECML 2013

Experiments on PDF Malware Detection

- **PDF:** hierarchy of interconnected objects (keyword/value pairs)

```
13 0 obj
<< /Kids [ 1 0 R 11 0 R ]
/Type /Page
... >> end obj
17 0 obj
<< /Type /Encoding
/Differences [ 0 /C0032 ] >>
endobj
```

Features: *keyword count*

/Type	2
/Page	1
/Encoding	1
…	

- **Adversary's capability**
  - adding up to d_{max} objects to the PDF
  - removing objects may compromise the PDF file (and embedded malware code)!

$$\min_{x'} g(x') - \lambda p(x' \mid y = -1)$$

$$\text{s.t.} \quad d(x, x') \leq d_{\max}$$

$$x \leq x'$$

Biggio et al., Evasion Attacks Against Machine Learning at Test Time? ECML 2013

Experiments on PDF Malware Detection

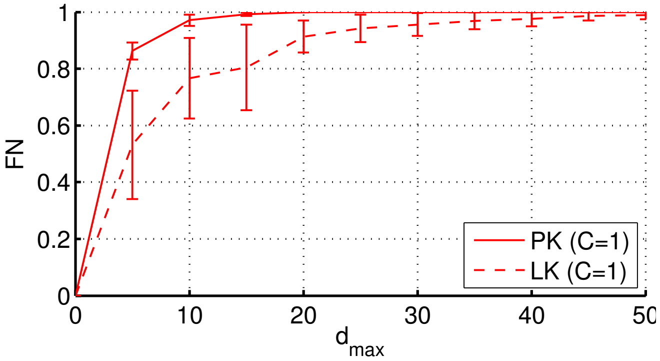
Linear SVM

- **Dataset:** 500 malware samples (*Contagio*), 500 benign (Internet)
  - 5-fold cross-validation
  - Targeted (surrogate) classifier trained on 500 (100) samples

- **Evasion rate** (FN) at FP=1% vs max. number of added keywords
  - Perfect knowledge (PK); Limited knowledge (LK)

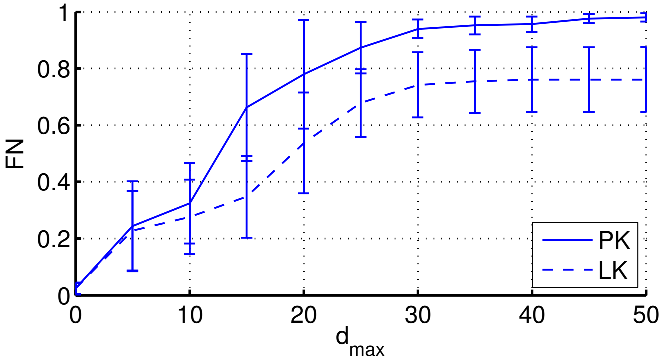
Without mimicry
λ = 0

SVM (Linear), λ=0



With mimicry
λ = 500

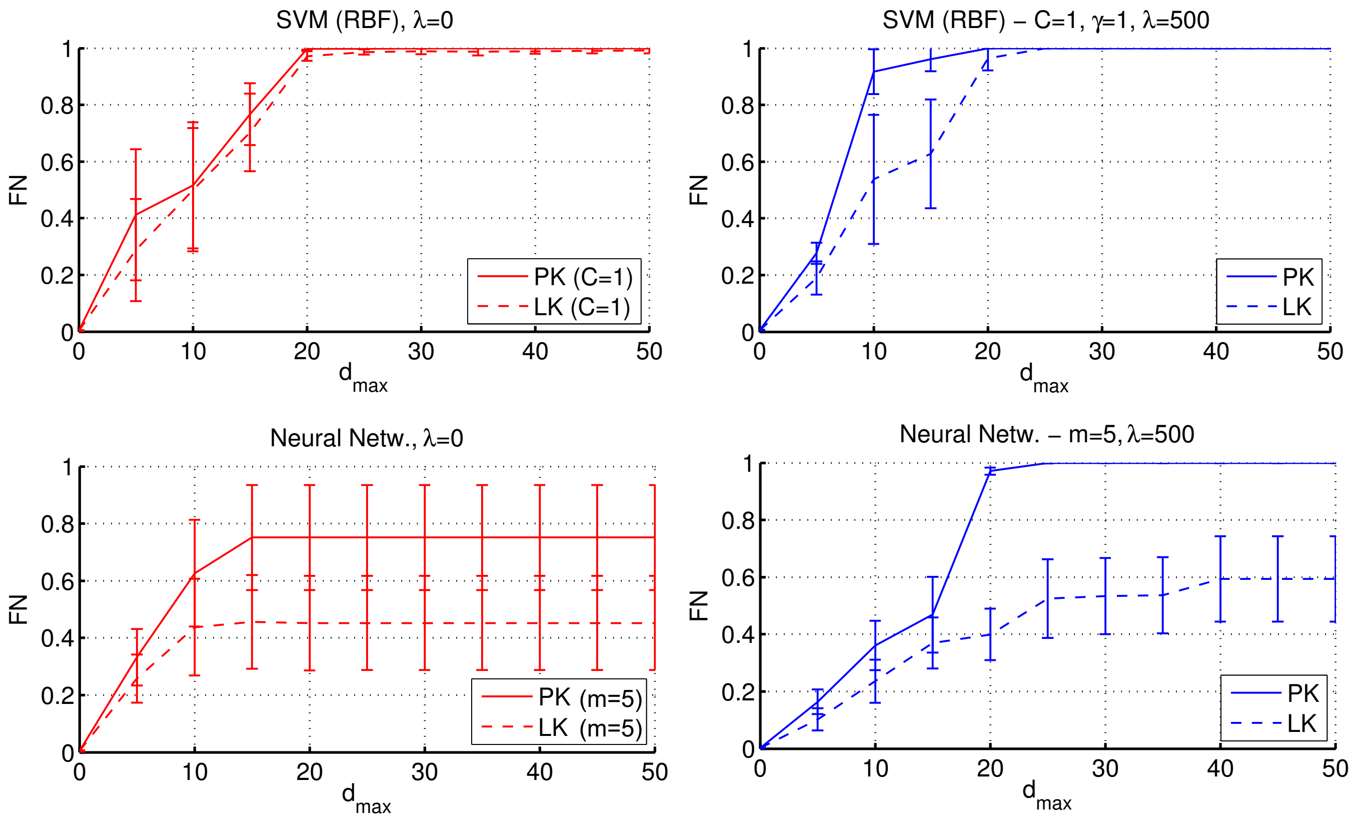
SVM (linear) – C=1, λ=500



Biggio et al., Evasion Attacks Against Machine Learning at Test Time? ECML 2013

Experiments on PDF Malware Detection

SVM with RBF kernel, Neural Network

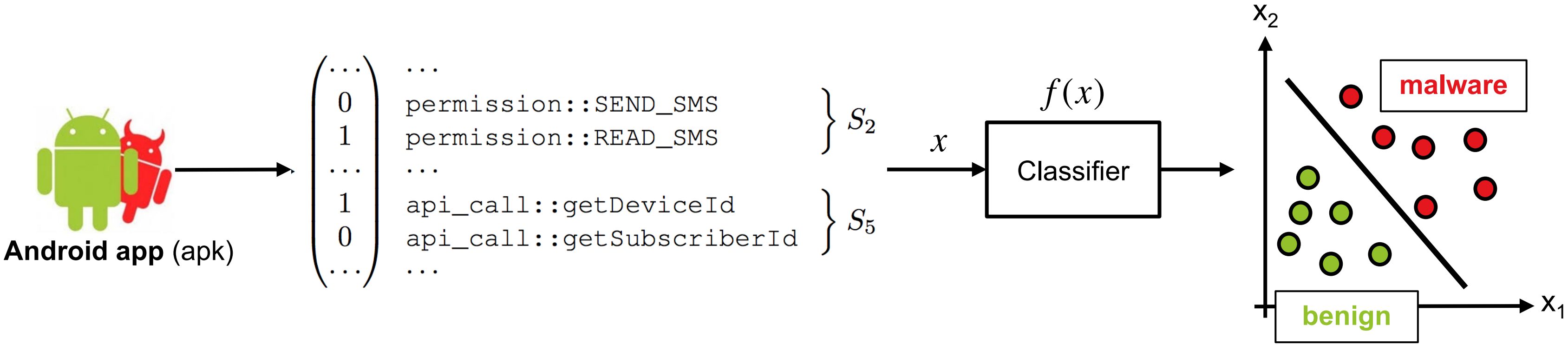


Biggio et al., Evasion Attacks Against Machine Learning at Test Time? ECML 2013

Experiments on Android Malware Detection

- **Drebin:** Arp et al., NDSS 2014
  - Android malware detection directly on the mobile phone
  - Linear SVM trained on features extracted from static code analysis

Feature sets		
manifest	S_1	Hardware components
	S_2	Requested permissions
	S_3	Application components
	S_4	Filtered intents
dexcode	S_5	Restricted API calls
	S_6	Used permission
	S_7	Suspicious API calls
	S_8	Network addresses

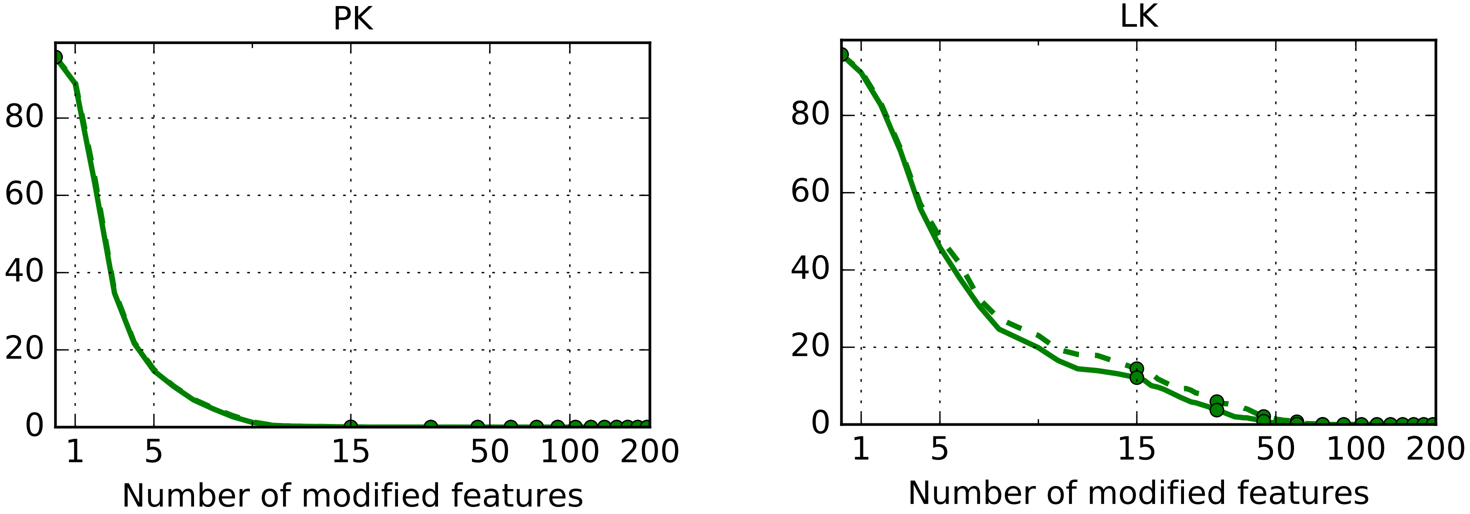


Demontis, Biggio et al., *Yes, Machine Learning Can Be More Secure! ...*, IEEE TDSC 2017

Experiments on Android Malware Detection

- **Dataset (Drebin):** 5,600 malware and 121,000 benign apps (TR: 30K, TS: 60K)

- **Detection rate** at FP=1% vs max. number of manipulated features (averaged on 10 runs)
  - Perfect knowledge (PK) white-box attack; Limited knowledge (LK) black-box attack

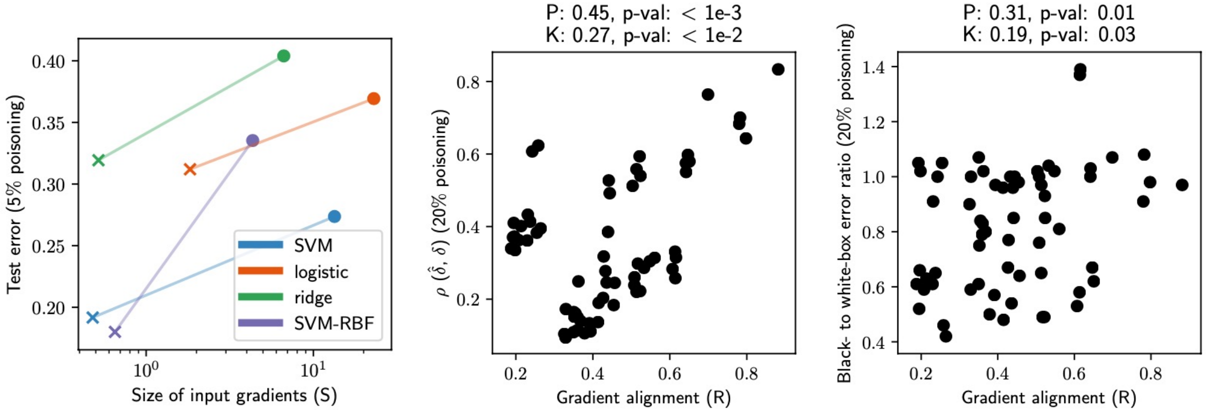


Demontis, Biggio et al., *Yes, Machine Learning Can Be More Secure!* ..., IEEE TDSC 2017

Why Do Adversarial Attacks Transfer? (USENIX Sec. 2019)

- Transferability is the ability of an attack developed against a surrogate model to succeed also against a different target model

- In our paper, we show that *transferability* depends on
  - the **vulnerability of the target model**, and
  - the **alignment of** (poisoning/evasion) **gradients** between the target and the surrogate model

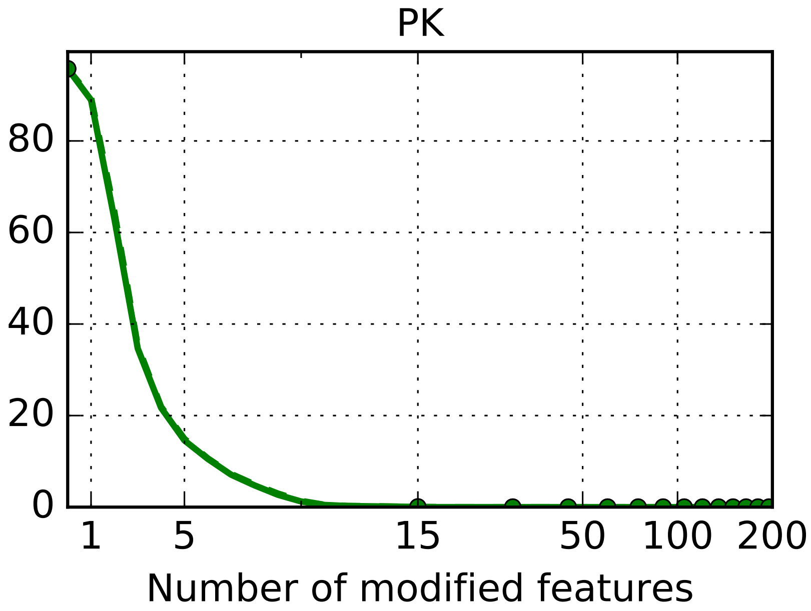


Demontis et al., *Why Do Adversarial Attacks Transfer? …* USENIX 2019

Take-home Messages

- Linear and non-linear *supervised* classifiers are vulnerable to well-crafted evasion attacks

- Performance evaluation should be always performed as a function of the adversary’s knowledge and capability via **Security Evaluation Curves**



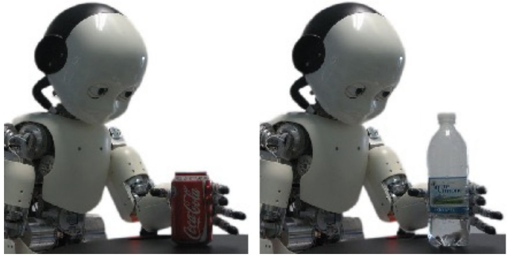
Hands-on Demo

Open in Colab https://github.com/unica-mlsec/mlsec/blob/main/notebooks/advx-challenge.ipynb

Evasion of Multiclass Classifiers

Is Deep Learning Safe for Robot Vision?

- Evasion attacks against the iCub humanoid robot
  - Deep Neural Network used for visual object recognition



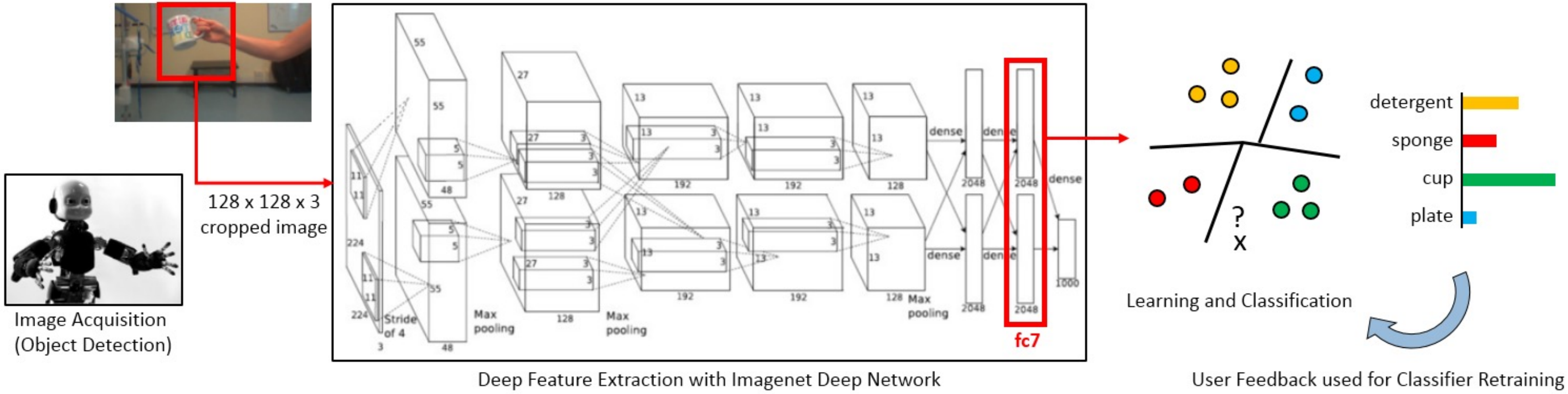


Image Acquisition (Object Detection)

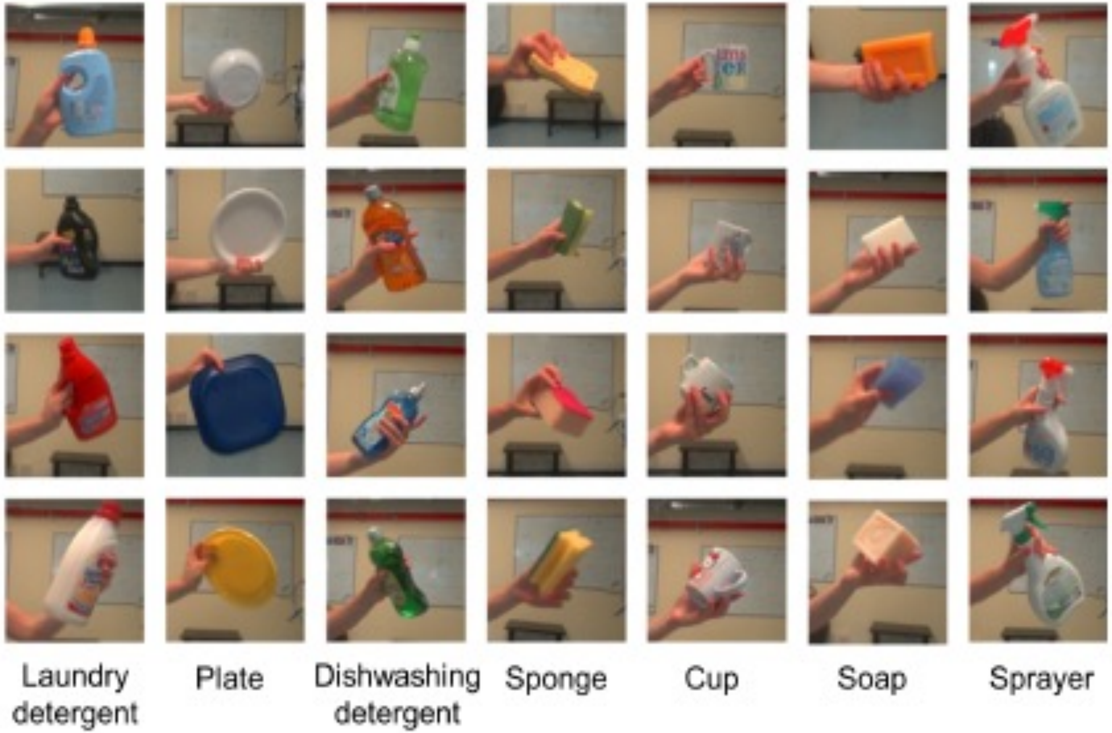
Deep Feature Extraction with Imagenet Deep Network

Learning and Classification

User Feedback used for Classifier Retraining

Melis, Biggio et al., Is Deep Learning Safe for Robot Vision? ICCVW ViPAR 2017

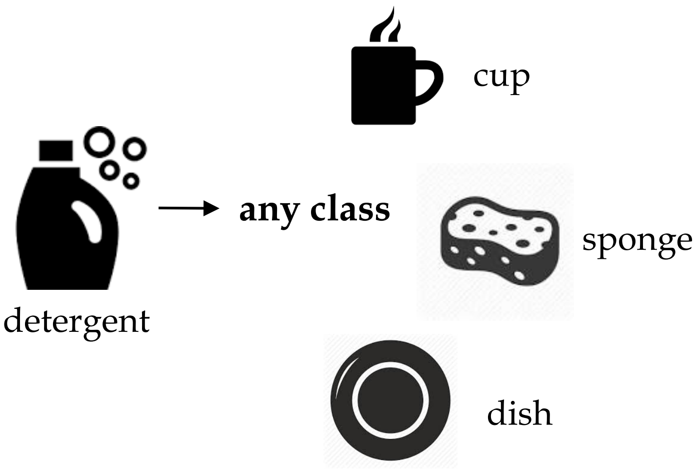
iCubWorld28 Data Set: Example Images



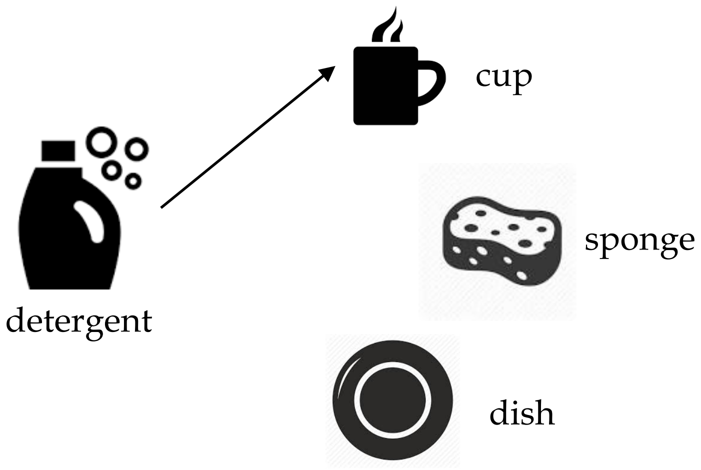
From Binary to Multiclass Evasion

- In multiclass problems, classification errors occur in different classes.
- Thus, the attacker may aim:
  1. to have a sample misclassified as any class different from the true class **(error-generic attacks)**
  2. to have a sample misclassified as a specific class **(error-specific attacks)**

Error-generic (indiscriminate) attacks



Error-specific (targeted) attacks



Melis, Biggio et al., Is Deep Learning Safe for Robot Vision? ICCVW ViPAR 2017

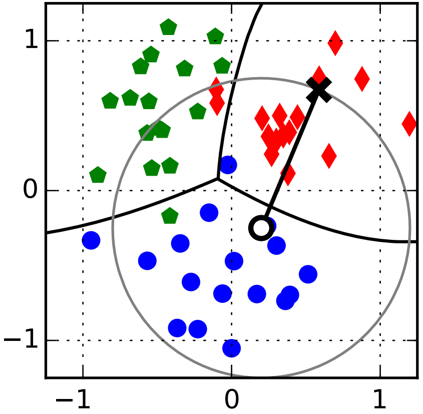
Error-generic (Indiscriminate) Evasion

- **Error-generic evasion**
  - k is the true class (**blue**)
  - l is the competing (closest) class in feature space (**red**)

$$\Omega(\boldsymbol{x}) = f_k(\boldsymbol{x}) - \max_{l \neq k} f_l(\boldsymbol{x})$$

- The attack minimizes the objective to have the sample misclassified as the *closest* class (could be any!)

$$\begin{aligned} \min_{\boldsymbol{x}'} \quad & \Omega(\boldsymbol{x}') \,, \\ \text{s.t.} \quad & d(\boldsymbol{x}, \boldsymbol{x}') \leq d_{\max} \,, \\ & \boldsymbol{x}_{\text{lb}} \preceq \boldsymbol{x}' \preceq \boldsymbol{x}_{\text{ub}} \,, \end{aligned}$$



Melis, Biggio et al., Is Deep Learning Safe for Robot Vision? ICCVW ViPAR 2017

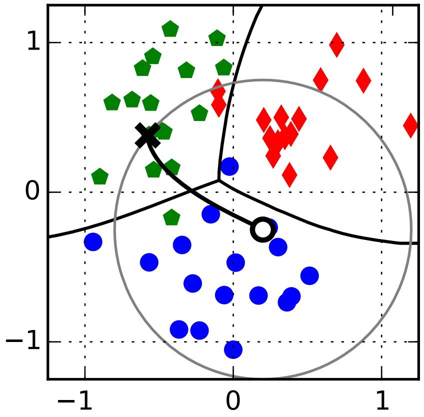
Error-specific (Targeted) Evasion

- **Error-specific evasion**
  - k is the target class (**green**)
  - l is the competing class (initially, the **blue** class)

$$\Omega(\boldsymbol{x}) = f_k(\boldsymbol{x}) - \max_{l \neq k} f_l(\boldsymbol{x})$$

- The attack <u>maximizes</u> the objective to have the sample misclassified as the *target* class

$$\begin{aligned} \max_{\boldsymbol{x}'} \quad & \Omega(\boldsymbol{x}')\,, \\ \text{s.t.} \quad & d(\boldsymbol{x}, \boldsymbol{x}') \leq d_{\max}\,, \\ & \boldsymbol{x}_{\text{lb}} \preceq \boldsymbol{x}' \preceq \boldsymbol{x}_{\text{ub}}\,, \end{aligned}$$



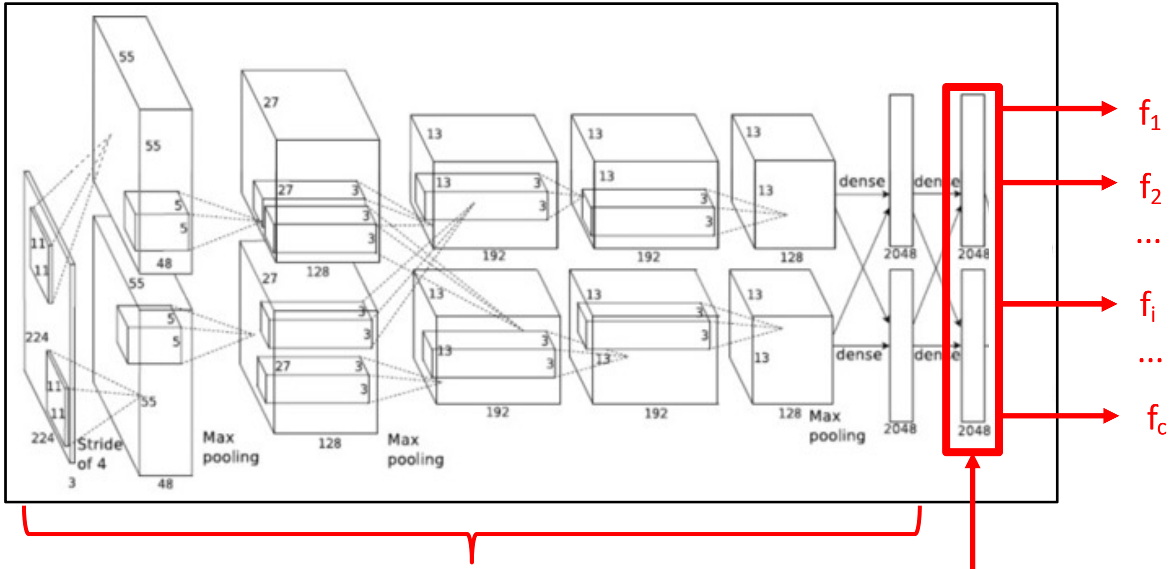
Melis, Biggio et al., Is Deep Learning Safe for Robot Vision? ICCVW ViPAR 2017

Adversarial Examples – Gradient Computation

Gradient-based attacks

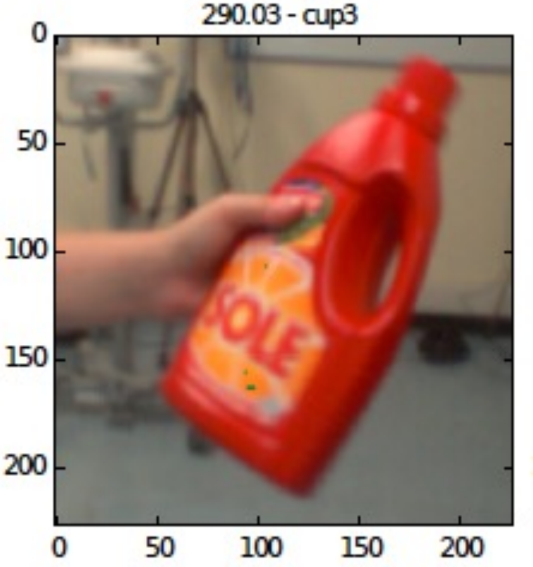
The gradient is computed with the chain rule

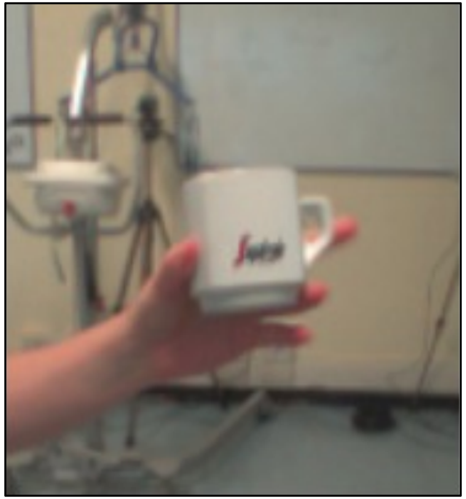
- the gradient of $f_i(\boldsymbol{z})$ can be computed if the chosen classifier is differentiable, and then
- be backpropagated through the DNN with automatic differentiation



$$\nabla f_i(x) = \frac{\partial fi(z)}{\partial z}\frac{\partial z}{\partial x}$$

Example of Adversarial Images against iCub

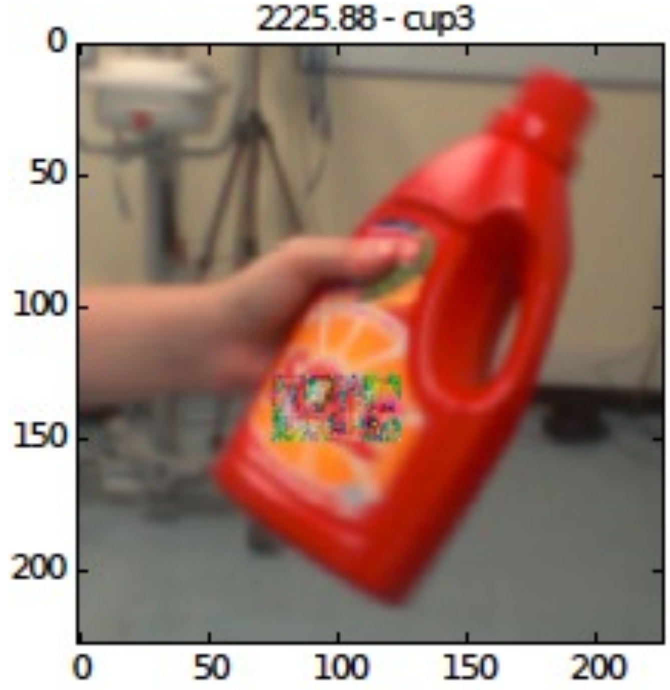




- An adversarial example from class *laundry-detergent*, modified by the proposed algorithm to be misclassified as *cup*

[Melis, Biggio et al., Is Deep Learning Safe for Robot Vision? ICCVW ViPAR 2017]

The *Sticker* Attack against iCub



Adversarial example generated by manipulating only a specific region, to simulate a sticker that could be applied to the real-world object.

This image is classified as *cup*.

[Melis, Biggio et al., Is Deep Learning Safe for Robot Vision? ICCVW ViPAR 2017]

Loss Functions for Targeted/Indiscriminate Attacks

- Using the same loss functions used to train ML models, denoted with L
  - and given an input sample $\boldsymbol{x}$ and its true class label y

- We can formalize/generalize adversarial attacks as:
  - $\max_{\boldsymbol{\delta}} L(\boldsymbol{x}+\boldsymbol{\delta}, y, \boldsymbol{\theta}) = \min_{\boldsymbol{\delta}} \; -L(\boldsymbol{x}+\boldsymbol{\delta}, y, \boldsymbol{\theta})$, for indiscriminate attacks
  - $\min_{\boldsymbol{\delta}} \; L(\boldsymbol{x}+\boldsymbol{\delta}, y_t, \boldsymbol{\theta})$, for targeted attacks, with $y_t \neq y$

The Effect of Different Norms

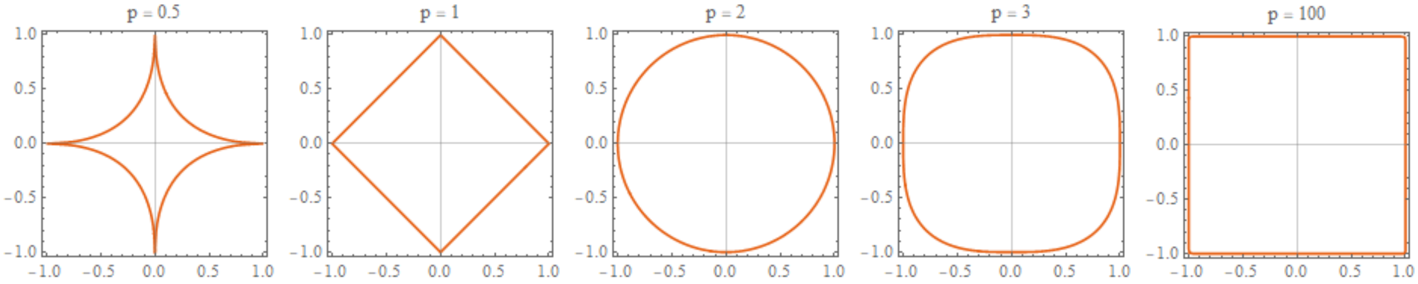
Constraints are Regularizers

Typically, (convex) ℓ_p norms are used as constraints/regularizers

ℓ_p norms with $p \geq 1$, $\ell_p(\boldsymbol{x}) = \left(\sum_j |x_j|^p\right)^{1/p}$

Most popular examples

- ℓ_0 is not convex, and amounts to counting non-zero elements in x
- $\ell_1 = |x_1| + |x_2| + \cdots + |x_d|$
- $\ell_2 = x_1^2 + x_2^2 + \ldots + x_d^2$
- $\ell_\infty = \max_j |x_j|$

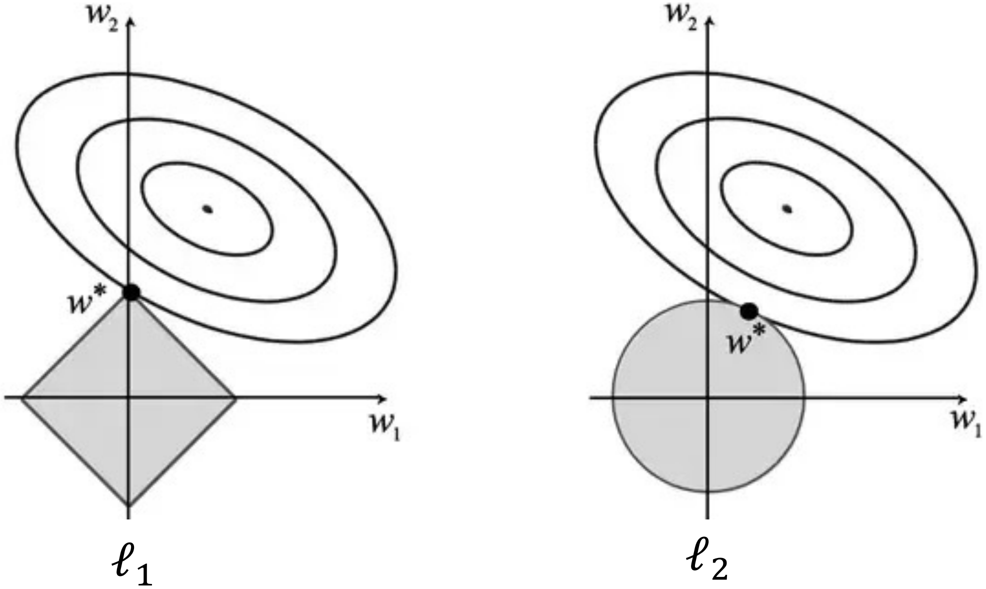


Sparsity

- ℓ_0 and ℓ_1 regularization enforce *sparsity*, i.e., many values in $\boldsymbol{x}$ will be set to zero
  - Why? The optimum is often found at one of the vertices!

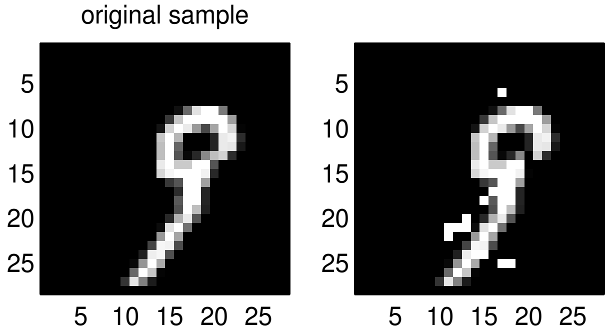
- Sparsity helps automatically perform feature selection

- Features assigned $w_j = 0$ can be disregarded

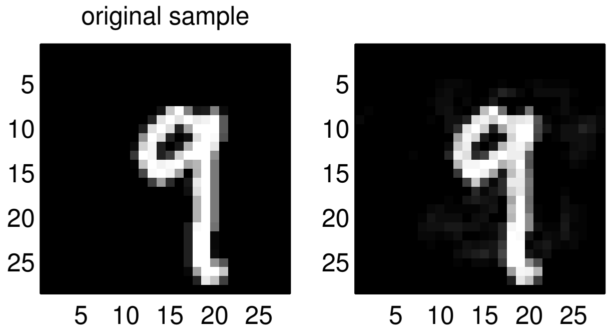


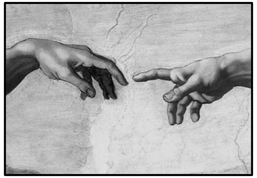
Sparse vs Dense Attacks

Sparse Evasion Attacks (L1-norm constrained)



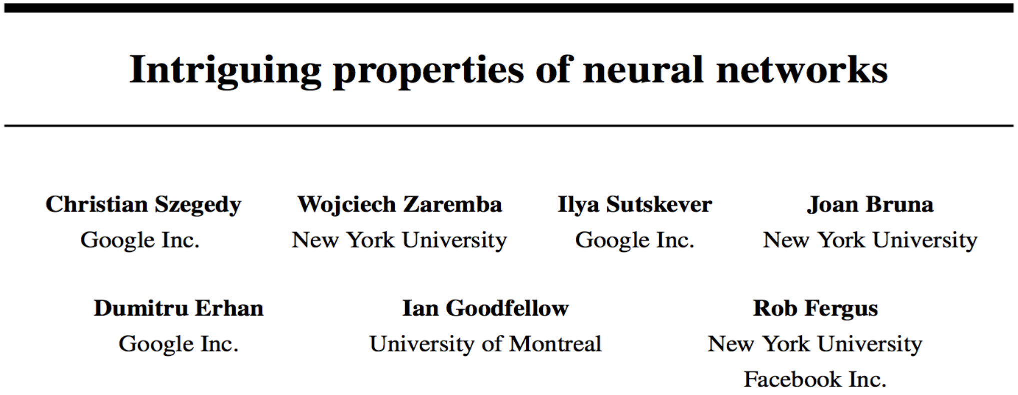
Dense Evasion Attacks (L2-norm constrained)





2014: Deep Learning Meets Adversarial Machine Learning

The Discovery of Adversarial Examples



Intriguing properties of neural networks

Christian Szegedy
Google Inc.

Wojciech Zaremba
New York University

Ilya Sutskever
Google Inc.

Joan Bruna
New York University

Dumitru Erhan
Google Inc.

Ian Goodfellow
University of Montreal

Rob Fergus
New York University
Facebook Inc.

... we find that deep neural networks learn **input-output mappings** that are fairly **discontinuous** to a significant extent. We can cause the network to misclassify an image by applying a certain **hardly perceptible perturbation**, which is found by maximizing the network's prediction error ...

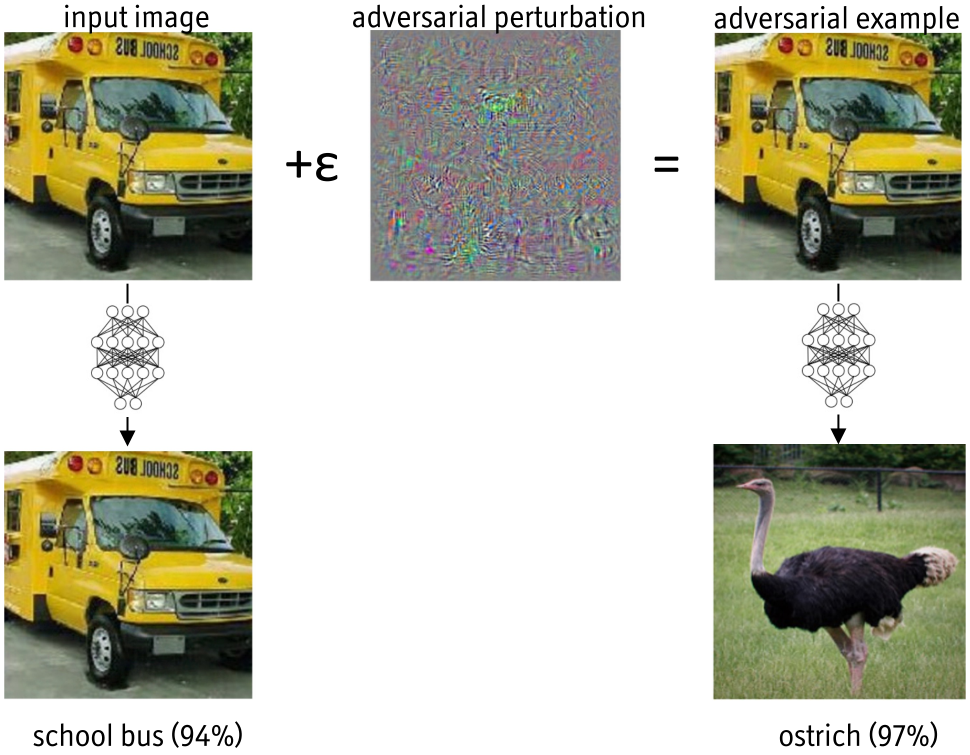
Szegedy, Goodfellow et al., Intriguing Properties of NNs, ICLR 2014

Adversarial Examples against Deep Neural Networks

- Szegedy et al. (2014) *independently developed gradient-based attacks* against DNNs

- They were investigating **model interpretability**, trying *to understand at which point a DNN prediction changes*

- They found that the **minimum perturbations required to trick DNNs were really small**, even imperceptible to humans



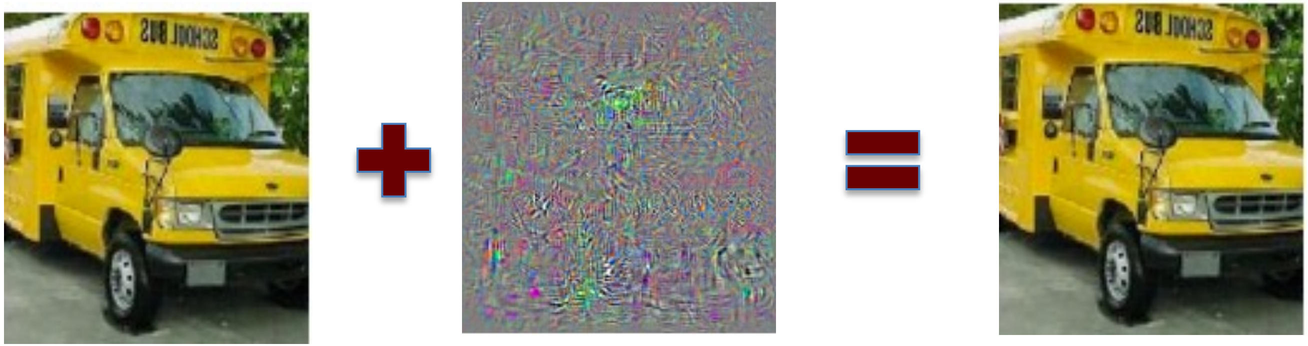
Szegedy, Goodfellow et al., Intriguing Properties of NNs, ICLR 2014

Creation of Adversarial Examples

- Minimize $\|r\|_2$ subject to:
  1. $f(x+r) = l$
  2. $x + r \in [0,1]^m$

The adversarial image *x + r* is visually hard to distinguish from *x*
Informally speaking, the solution *x + r* is the closest image to *x* classified as *l* by f

The solution is approximated using using a box-constrained limited-memory BFGS



School Bus (x)

Adversarial Noise (*r*)

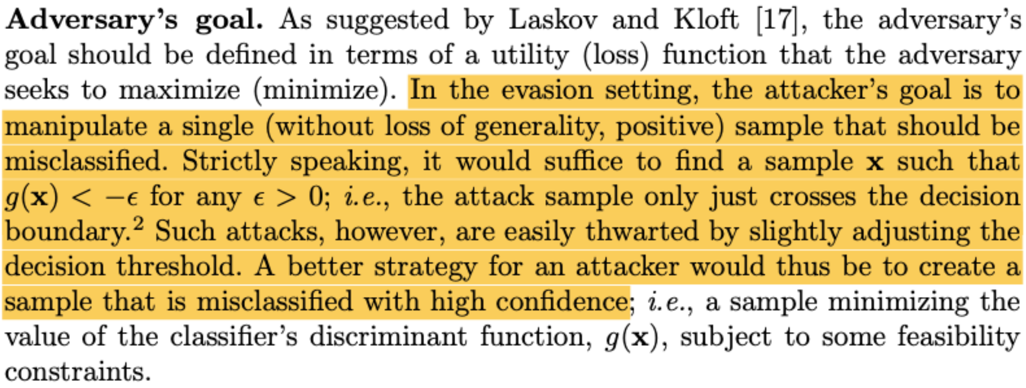
Ostrich
Struthio Camelus

Szegedy, Goodfellow et al., Intriguing Properties of NNs, ICLR 2014

Minimum-norm vs Maximum-confidence Attacks

- Szegedy et al., ICLR 2014 aim to measure the minimum distance to evasion
  - Better suited to the analysis of adversarial robustness in the white-box case

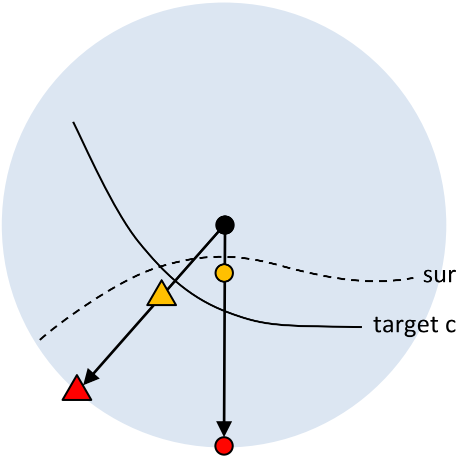
- Biggio et al., ECML 2013 maximizes misclassification confidence within a given budget
  - The intuition was to craft attacks that are more difficult to detect, and to evade classifiers with higher probability also when knowledge of the boundary is not perfect (*transfer attacks*)



Adversary's goal. As suggested by Laskov and Kloft [17], the adversary's goal should be defined in terms of a utility (loss) function that the adversary seeks to maximize (minimize). In the evasion setting, the attacker's goal is to manipulate a single (without loss of generality, positive) sample that should be misclassified. Strictly speaking, it would suffice to find a sample $\mathbf{x}$ such that $g(\mathbf{x}) < -\epsilon$ for any $\epsilon > 0$; *i.e.*, the attack sample only just crosses the decision boundary.[2] Such attacks, however, are easily thwarted by slightly adjusting the decision threshold. A better strategy for an attacker would thus be to create a sample that is misclassified with high confidence; *i.e.*, a sample minimizing the value of the classifier's discriminant function, $g(\mathbf{x})$, subject to some feasibility constraints.

Biggio, Roli et al., ECML PKDD 2013

Minimum-norm vs Maximum-confidence Attacks



- ● initial / source example
- 🟡 minimum-distance *black-box* adversarial example
- △ minimum-distance *white-box* adversarial example
- 🔴 maximum-confidence *black-box* adversarial example
- 🔺 maximum-confidence *white-box* adversarial example

surrogate classifier $\hat{f}(\boldsymbol{x})$ used to craft *black-box* adversarial examples

target classifier $f(\boldsymbol{x})$ used to craft *white-box* adversarial examples

Demontis et al., Why do adversarial attacks transfer? USENIX 2019

Many Black Swans After 2014

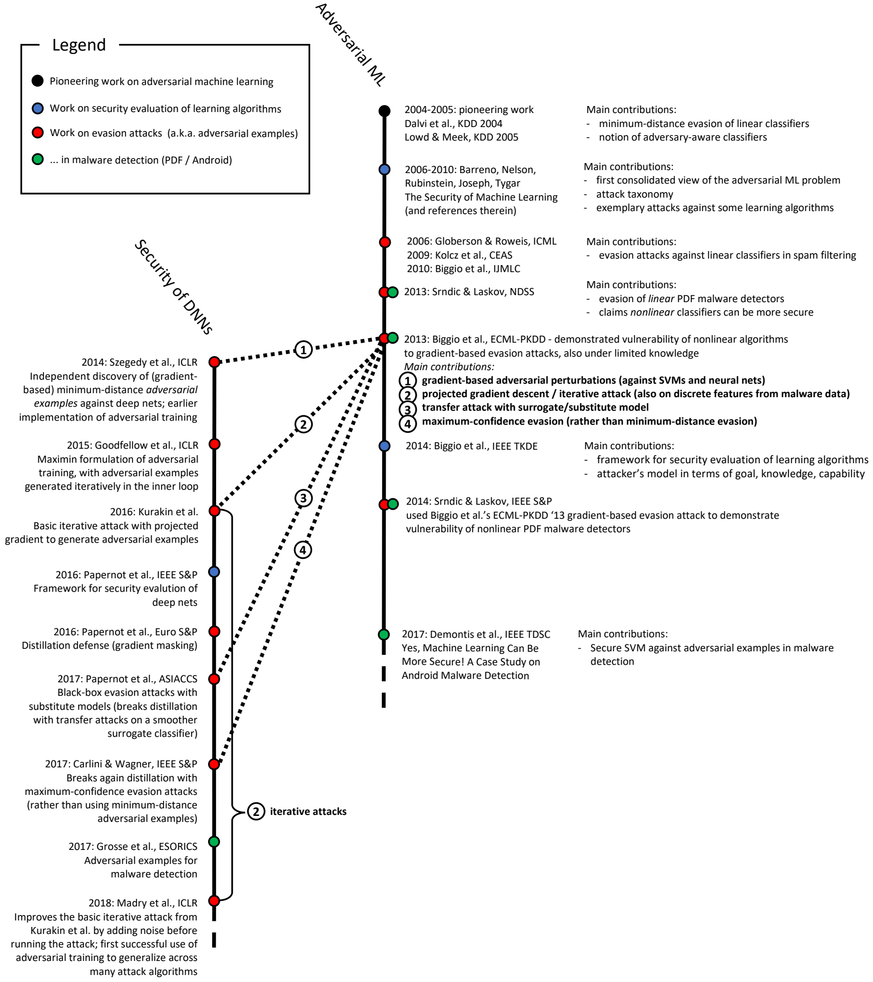
- Several defenses have been proposed against adversarial examples, and more powerful attacks have been developed to show that they are ineffective.
  - Remember the arms race?

- Most of these attacks are modifications to the optimization problems reported for evasion attacks / adversarial examples, using different gradient-based solution algorithms, initializations and stopping conditions.

Search https://arxiv.org with keywords "adversarial examples"

Timeline of Learning Security

Biggio and Roli, **Wild Patterns**: *Ten Years After The Rise of Adversarial Machine Learning*, Pattern Recognition, 2018



Legend

- ● Pioneering work on adversarial machine learning
- 🔵 Work on security evaluation of learning algorithms
- 🔴 Work on evasion attacks (a.k.a. adversarial examples)
- 🟢 ... in malware detection (PDF / Android)

Adversarial ML

2004-2005: pioneering work
Dalvi et al., KDD 2004
Lowd & Meek, KDD 2005

Main contributions:
- minimum-distance evasion of linear classifiers
- notion of adversary-aware classifiers

2006-2010: Barreno, Nelson, Rubinstein, Joseph, Tygar
The Security of Machine Learning
(and references therein)

Main contributions:
- first consolidated view of the adversarial ML problem
- attack taxonomy
- exemplary attacks against some learning algorithms

2006: Globerson & Roweis, ICML
2009: Kolcz et al., CEAS
2010: Biggio et al., IJMLC

Main contributions:
- evasion attacks against linear classifiers in spam filtering

2013: Srndic & Laskov, NDSS

Main contributions:
- evasion of *linear* PDF malware detectors
- claims *nonlinear* classifiers can be more secure

2013: Biggio et al., ECML-PKDD - demonstrated vulnerability of nonlinear algorithms to gradient-based evasion attacks, also under limited knowledge
Main contributions:
1. **gradient-based adversarial perturbations (against SVMs and neural nets)**
2. **projected gradient descent / iterative attack (also on discrete features from malware data)**
3. **transfer attack with surrogate/substitute model**
4. **maximum-confidence evasion (rather than minimum-distance evasion)**

2014: Biggio et al., IEEE TKDE

Main contributions:
- framework for security evaluation of learning algorithms
- attacker's model in terms of goal, knowledge, capability

2014: Srndic & Laskov, IEEE S&P
used Biggio et al.'s ECML-PKDD '13 gradient-based evasion attack to demonstrate vulnerability of nonlinear PDF malware detectors

2017: Demontis et al., IEEE TDSC
Yes, Machine Learning Can Be More Secure! A Case Study on Android Malware Detection

Main contributions:
- Secure SVM against adversarial examples in malware detection

Security of DNNs

2014: Szegedy et al., ICLR
Independent discovery of (gradient-based) minimum-distance *adversarial examples* against deep nets; earlier implementation of adversarial training

2015: Goodfellow et al., ICLR
Maximin formulation of adversarial training, with adversarial examples generated iteratively in the inner loop

2016: Kurakin et al.
Basic iterative attack with projected gradient to generate adversarial examples

2016: Papernot et al., IEEE S&P
Framework for security evalution of deep nets

2016: Papernot et al., Euro S&P
Distillation defense (gradient masking)

2017: Papernot et al., ASIACCS
Black-box evasion attacks with substitute models (breaks distillation with transfer attacks on a smoother surrogate classifier)

2017: Carlini & Wagner, IEEE S&P
Breaks again distillation with maximum-confidence evasion attacks (rather than using minimum-distance adversarial examples)

2017: Grosse et al., ESORICS
Adversarial examples for malware detection

2018: Madry et al., ICLR
Improves the basic iterative attack from Kurakin et al. by adding noise before running the attack; first successful use of adversarial training to generalize across many attack algorithms

2 **iterative attacks**

Attack Algorithms: A Unifying View

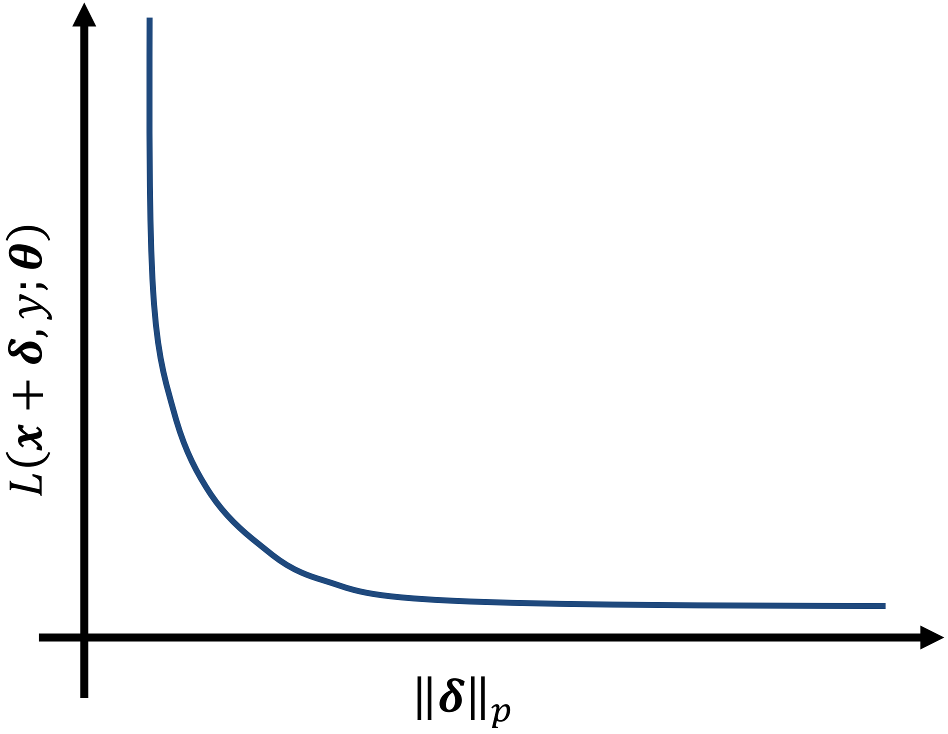
General Categorization

$$\min_{\boldsymbol{\delta}} [L(\boldsymbol{x} + \boldsymbol{\delta}, y; \boldsymbol{\theta}), \|\boldsymbol{\delta}\|_p]$$

Minimize loss to cause misclassification

Minimize perturbation size (measured with Lp norm)

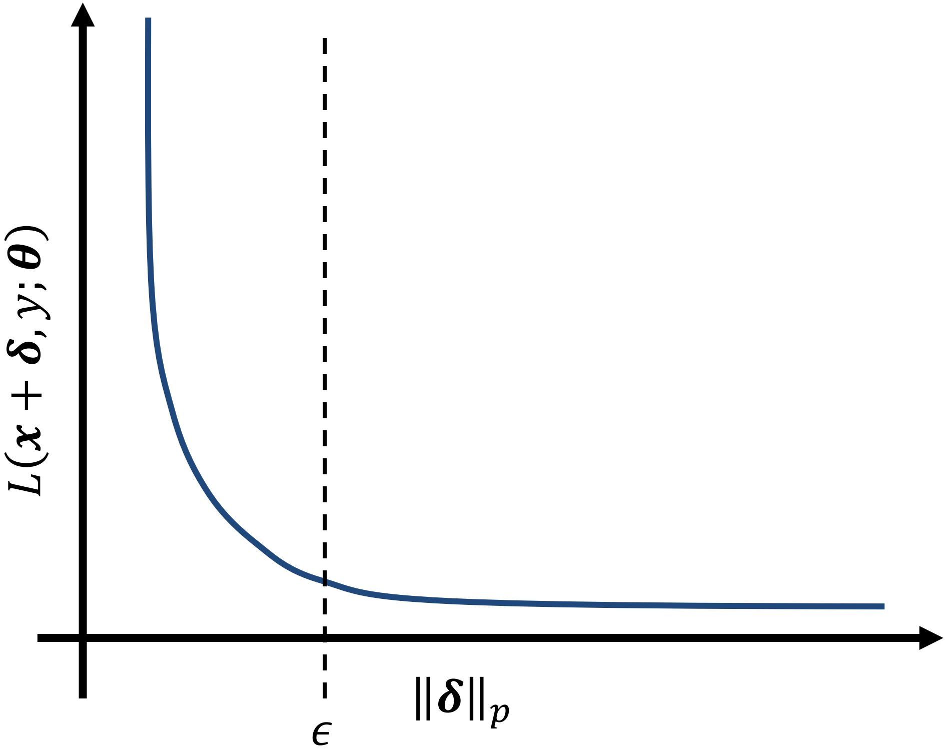
Pareto Frontier



Trade-off between misclassification confidence and perturbation size

Pareto-optimal solutions with different trade-offs are found along the blue curve (Pareto frontier)

Hard-constraint: Maximum-confidence Attacks

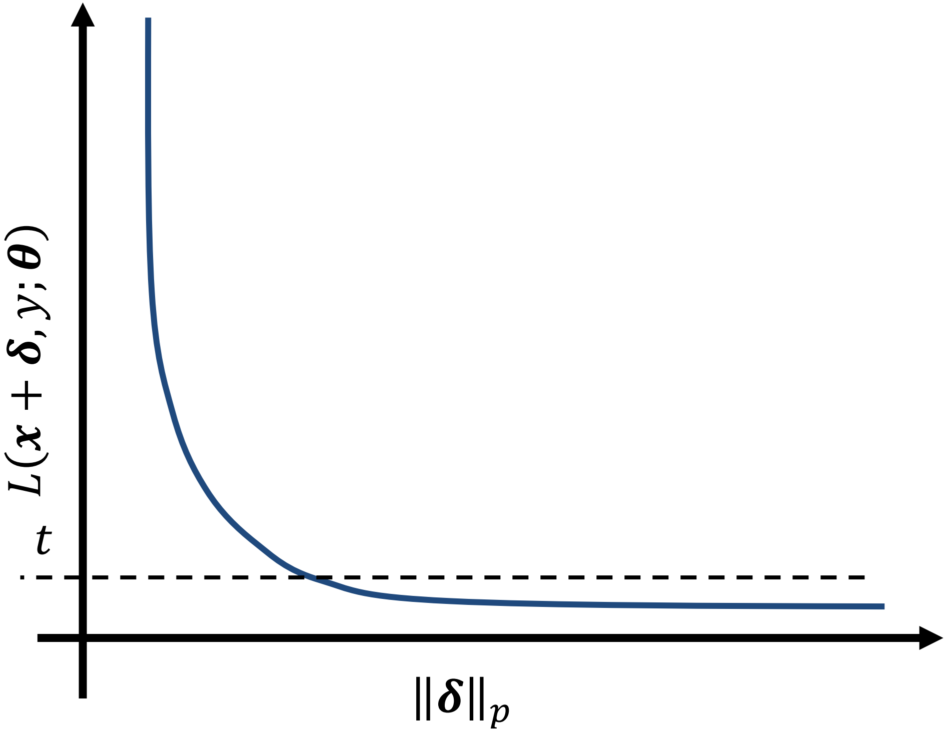


Minimize loss to cause misclassifiation (FGSM, PGD)

The perturbation is checked as hard constraint, bound on maximum manipulation

$$\min \; L(\boldsymbol{x}+\boldsymbol{\delta}, y; \boldsymbol{\theta}),$$
$$\text{s.t.} \quad \|\boldsymbol{\delta}\|_p \leq \epsilon$$

Hard-constraint: Minimum-norm Attacks



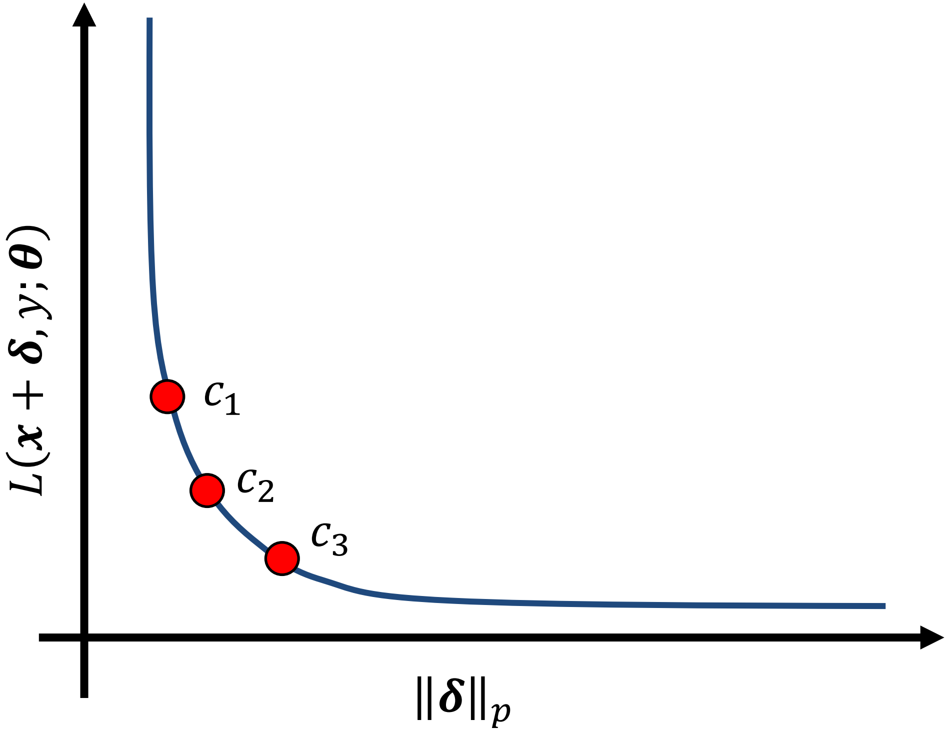
Minimize perturbation w.r.t. Lp norm

Score is used only as a constraint, not optimized

Hard to solve directly – normally a soft-constraint is used instead

$$\min \|\boldsymbol{\delta}\|_p$$
$$\text{s.t.} \;\; L(\boldsymbol{x}+\boldsymbol{\delta}, y; \boldsymbol{\theta}) < t$$

Soft-constraint: Trade-off Solution

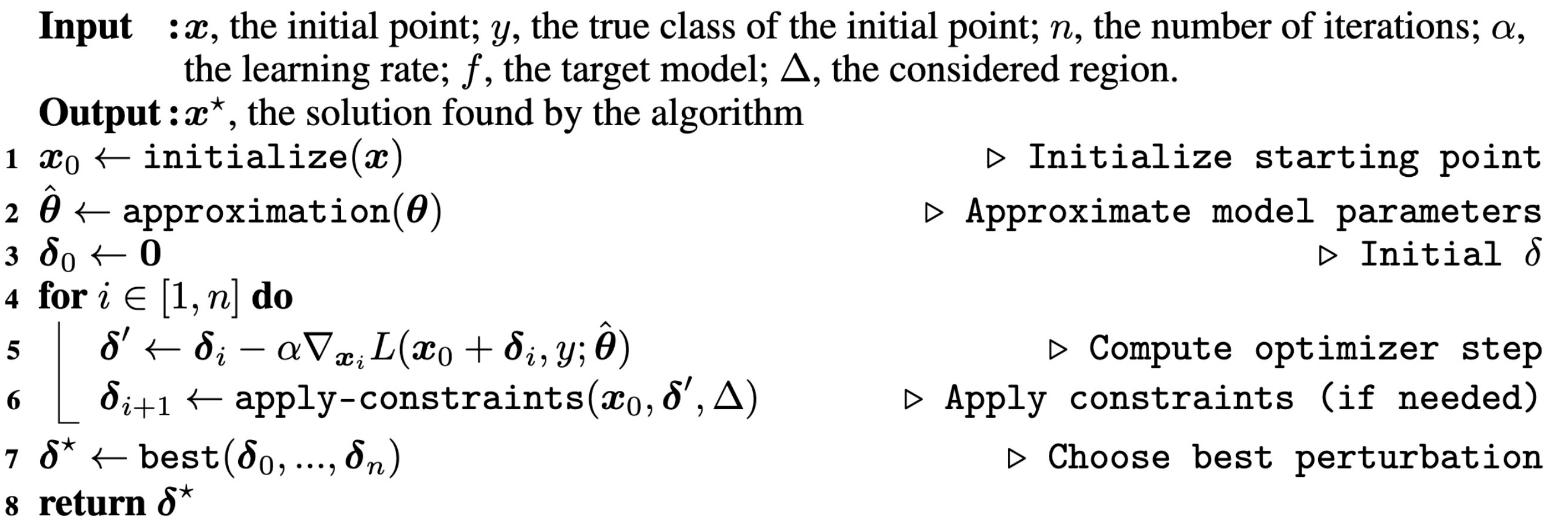


All constraints are imposed as quantities modulated by coefficients, behaving as regularizers

Modulating the multipliers shifts the solution towards trade-off between score and distance

$$\min L(\boldsymbol{x}+\boldsymbol{\delta}, y; \boldsymbol{\theta}) + c\|\boldsymbol{\delta}\|_p$$

Generalized Gradient-Descent Attack Algorithm



```
Input  : $x$, the initial point; $y$, the true class of the initial point; $n$, the number of iterations; $\alpha$,
         the learning rate; $f$, the target model; $\Delta$, the considered region.
Output : $x^\star$, the solution found by the algorithm
$\boldsymbol{x}_0 \leftarrow$ initialize($\boldsymbol{x}$)                              ▷ Initialize starting point
$\hat{\boldsymbol{\theta}} \leftarrow$ approximation($\boldsymbol{\theta}$)                    ▷ Approximate model parameters
$\boldsymbol{\delta}_0 \leftarrow \mathbf{0}$                                              ▷ Initial $\delta$
for $i \in [1, n]$ do
    $\boldsymbol{\delta}' \leftarrow \boldsymbol{\delta}_i - \alpha \nabla_{\boldsymbol{x}_i} L(\boldsymbol{x}_0 + \boldsymbol{\delta}_i, y; \hat{\boldsymbol{\theta}})$        ▷ Compute optimizer step
    $\boldsymbol{\delta}_{i+1} \leftarrow$ apply-constraints($\boldsymbol{x}_0, \boldsymbol{\delta}', \Delta$)   ▷ Apply constraints (if needed)
$\boldsymbol{\delta}^\star \leftarrow$ best($\boldsymbol{\delta}_0, ..., \boldsymbol{\delta}_n$)                    ▷ Choose best perturbation
return $\boldsymbol{\delta}^\star$
```

Maximum-confidence Attacks

Fast Gradient Sign Method (2015)

- Perturbed image obtained as: $\boldsymbol{x}^{\star} = \boldsymbol{x} + \epsilon \, \mathrm{sign}(\nabla L(\boldsymbol{x}, y; \boldsymbol{\theta}))$

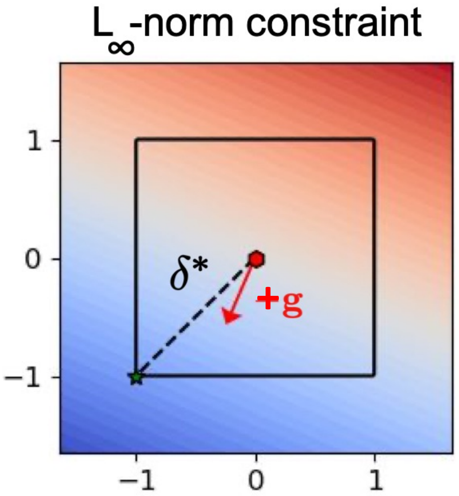
- Why?
  - $\max_{||\boldsymbol{\delta}||_\infty \leq \epsilon} L(\boldsymbol{x} + \boldsymbol{\delta}, y; \boldsymbol{\theta}) \approx$ (linear approximation)

$$\max_{||\boldsymbol{\delta}||_\infty \leq \epsilon} L(\boldsymbol{x}, y; \boldsymbol{\theta}) + \boldsymbol{\delta}^{\mathrm{T}} \, \nabla L(\boldsymbol{x}, y; \boldsymbol{\theta}) =$$

$$L(\boldsymbol{x}, y; \boldsymbol{\theta}) + \max_{||\boldsymbol{\delta}||_\infty \leq \epsilon} \boldsymbol{\delta}^{\mathrm{T}} \, \boldsymbol{g}$$

- The solution is to set $\boldsymbol{\delta}^{\star} = \epsilon \, \mathrm{sign}(\boldsymbol{g})$

- Loss function at $\boldsymbol{\delta}^{\star}$ (optimum): $L(\boldsymbol{x}, y; \boldsymbol{\theta}) + \epsilon \, ||\boldsymbol{g}||_1$
  - (cf. *dual norm* and *steepest gradient descent)*



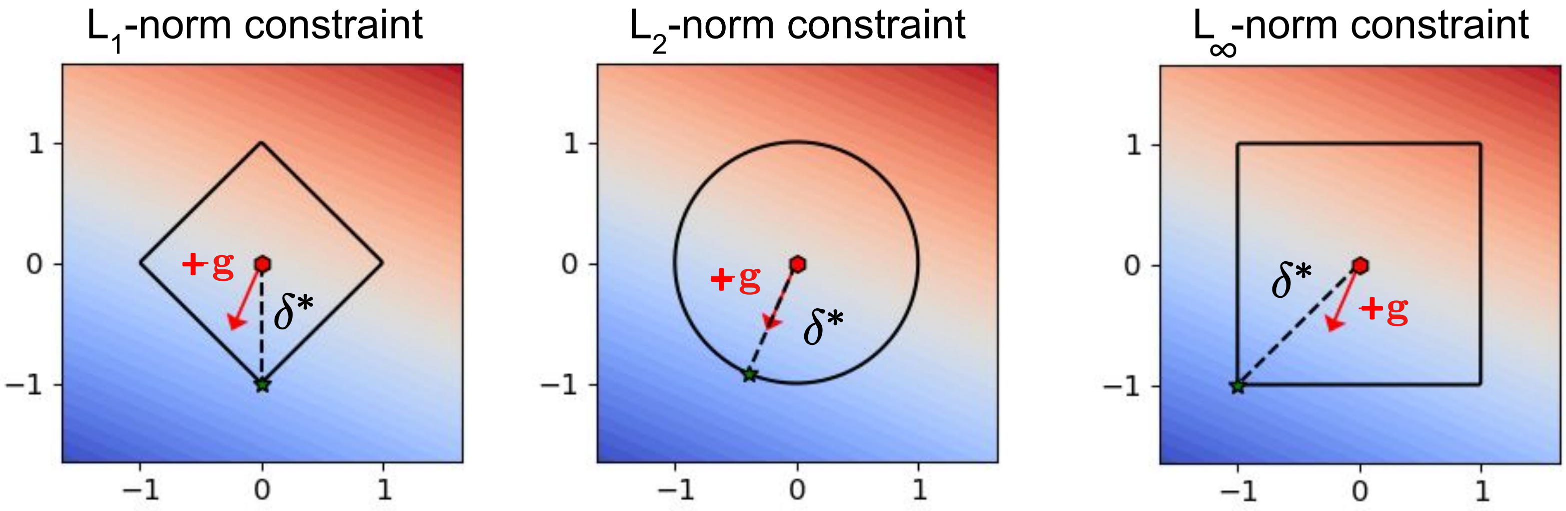
Goodfellow et al., Explaining and Harnessing Adversarial Examples ICLR 2015

Why Are Attacks Effective / Imperceptible against DNNs?

- Let's pretend that a deep network behaves in a linear way…
- Under this linearity assumption, the output of the net to the adversarial input $\tilde{\boldsymbol{x}} = \boldsymbol{x} + \boldsymbol{\delta}$ is $\mathbf{w}^{\mathrm{T}}\,\tilde{\boldsymbol{x}} = \mathbf{w}^{\mathrm{T}}\boldsymbol{x} + \mathbf{w}^{\mathrm{T}}\boldsymbol{\delta}$
- The key concept is that **if the dimensionality of the input $\boldsymbol{x}$** is very *high* and the vector of the adversarial perturbation $\boldsymbol{\delta}$ is aligned with the "classifier" (its weight vector $\mathbf{w}$), then **many infinitesimal changes to the input** add up to **one large change to the output**.

Goodfellow et al., Explaining and Harnessing Adversarial Examples ICLR 2015

Fast Gradient Method (FGM): Extension to Other Norms



L_1-norm constraint

L_2-norm constraint

L_∞-norm constraint

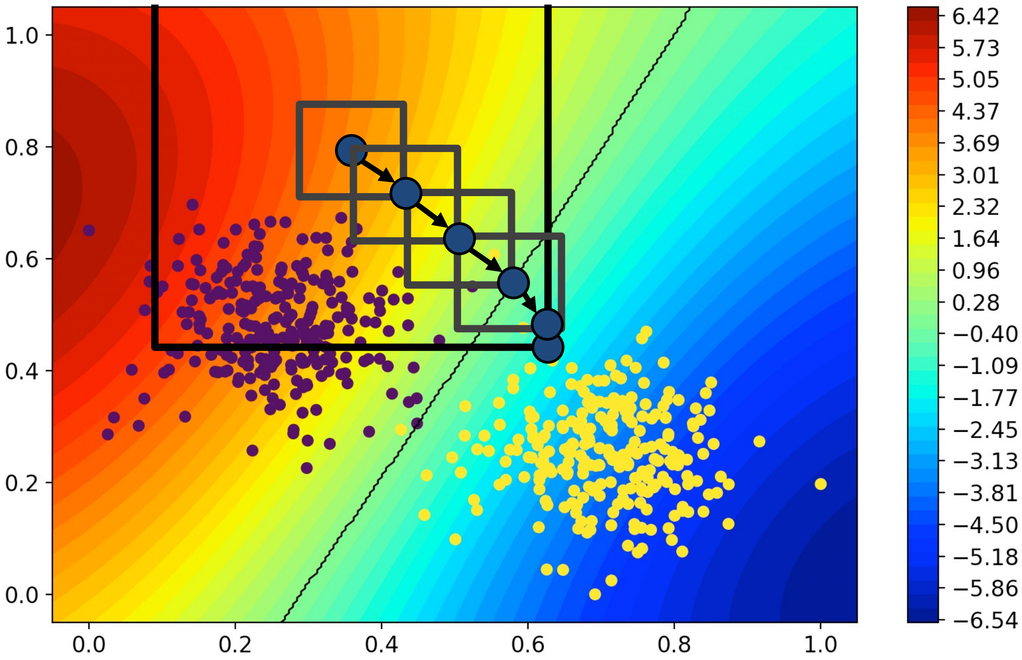
Goodfellow et al., Explaining and Harnessing Adversarial Examples ICLR 2015

Projected Gradient Descent (2018)

- Also known as *Basic Iterative Method* (BIM)

- PGD is just the iterative version of FGM

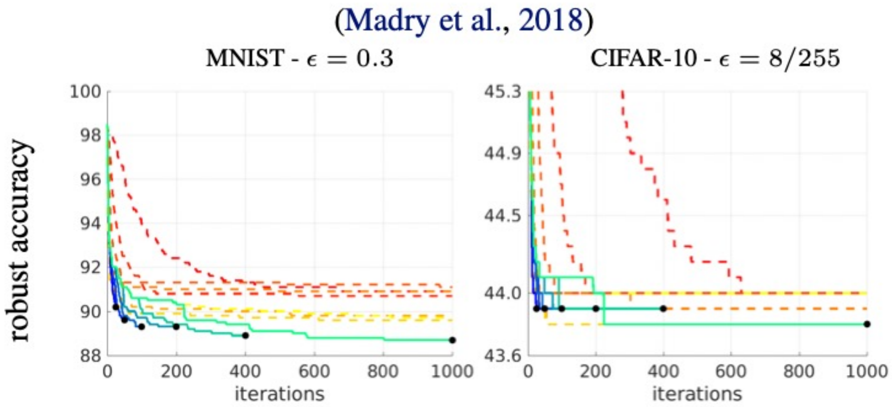
- *Number of iterations* and *step size* need to be fixed a priori



Madry et al. Towards deep learning models resistant to adversarial attacks, ICLR 2018
Kurakin et al., Adversarial Examples in the Physical World, ICLR-W 2017

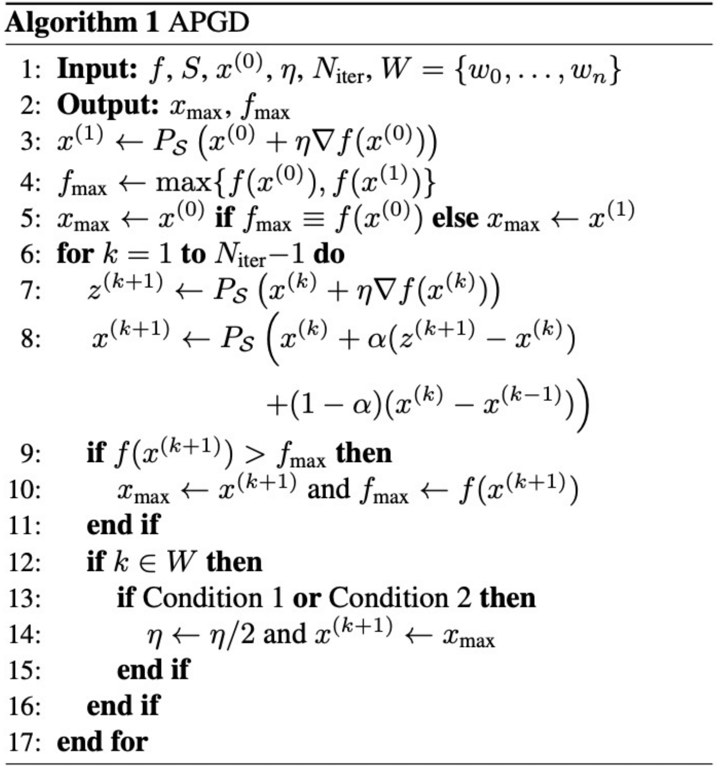
AutoPGD (2020)

- It dynamically halves the step size while optimizing the attack, if no improvement in the loss function is observed


(Madry et al., 2018)

MNIST - $\epsilon = 0.3$

CIFAR-10 - $\epsilon = 8/255$


Algorithm 1 APGD

```
**Input:** $f$, $S$, $x^{(0)}$, $\eta$, $N_{\text{iter}}$, $W = \{w_0, \ldots, w_n\}$
**Output:** $x_{\max}$, $f_{\max}$
$x^{(1)} \leftarrow P_S\left(x^{(0)} + \eta \nabla f(x^{(0)})\right)$
$f_{\max} \leftarrow \max\{f(x^{(0)}), f(x^{(1)})\}$
$x_{\max} \leftarrow x^{(0)}$ **if** $f_{\max} \equiv f(x^{(0)})$ **else** $x_{\max} \leftarrow x^{(1)}$
**for** $k = 1$ **to** $N_{\text{iter}} - 1$ **do**
    $z^{(k+1)} \leftarrow P_S\left(x^{(k)} + \eta \nabla f(x^{(k)})\right)$
    $x^{(k+1)} \leftarrow P_S\Big(x^{(k)} + \alpha(z^{(k+1)} - x^{(k)})$
                $+ (1 - \alpha)(x^{(k)} - x^{(k-1)})\Big)$
    **if** $f(x^{(k+1)}) > f_{\max}$ **then**
        $x_{\max} \leftarrow x^{(k+1)}$ and $f_{\max} \leftarrow f(x^{(k+1)})$
    **end if**
    **if** $k \in W$ **then**
        **if** Condition 1 **or** Condition 2 **then**
            $\eta \leftarrow \eta/2$ and $x^{(k+1)} \leftarrow x_{\max}$
        **end if**
    **end if**
**end for**
```

Croce et al., Reliable Evaluation of Adversarial Robustness …, ICML 2020

AutoPGD (2020)

- AutoPGD-CE uses the cross-entropy loss

$$\mathrm{CE}(x,y) = -\log p_y = -z_y + \log\Big(\sum_{j=1}^{K} e^{z_j}\Big)$$

- AutoPGD-DLR uses a novel *scale-invariant* loss: **Difference of Logits Ratio (DLR)**

$$\mathrm{DLR}(x,y) = -\frac{z_y - \max\limits_{i\neq y} z_i}{z_{\pi_1} - z_{\pi_3}}$$

Croce et al., Reliable Evaluation of Adversarial Robustness …, ICML 2020

Minimum-norm Attacks

Adversarial Examples against DNNs (2014)

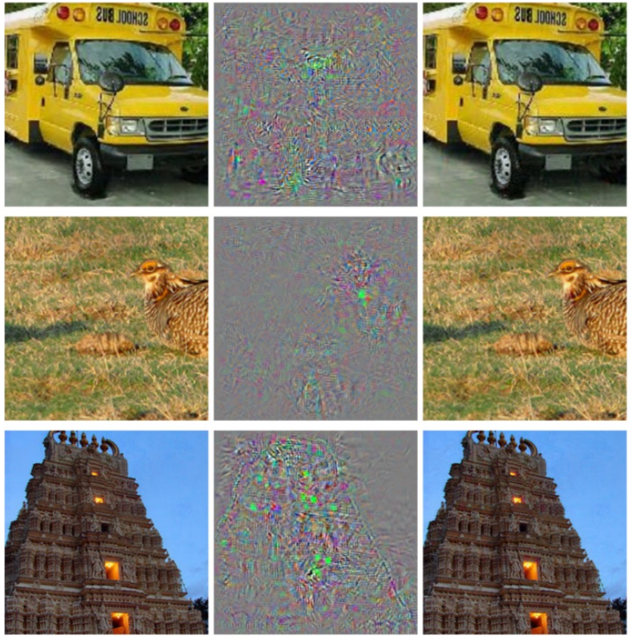
- Szegedy et al. formalized the problem as

$$\begin{aligned} &\min_{\boldsymbol{\delta}} \ ||\boldsymbol{\delta}||_2 \\ &\text{s.t.} \quad f(\boldsymbol{x}+\boldsymbol{\delta}) = y_t \qquad (y_t \neq y) \\ &\qquad \mathbf{x}+\boldsymbol{\delta} \in [0,1]^{\mathrm{d}} \end{aligned}$$

- Relaxation to use L-BFGS-B:
  L-BFGS-B: https://en.wikipedia.org/wiki/Limited-memory_BFGS

$$\min_{\boldsymbol{x}+\boldsymbol{\delta}\in[0,1]^{\mathrm{d}}} \ c \cdot ||\boldsymbol{\delta}||_2 + L(\boldsymbol{x}+\boldsymbol{\delta}, y_t, \boldsymbol{\theta})$$

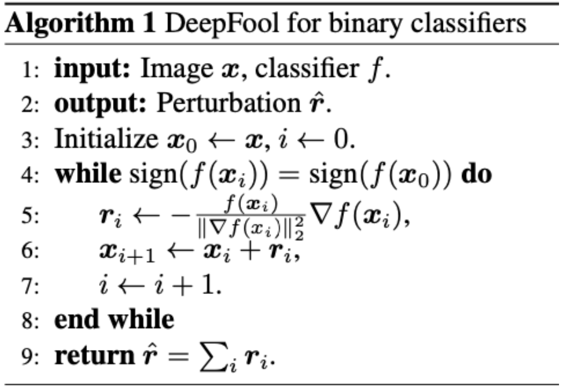
  - where they find the minimum c>0 that achieves misclassification (via line search)
  - $L(\boldsymbol{x}+\boldsymbol{\delta}, y_t; \boldsymbol{\theta})$ is the cross-entropy loss



Szegedy et al., Intriguing Properties of Neural Networks, ICLR 2014

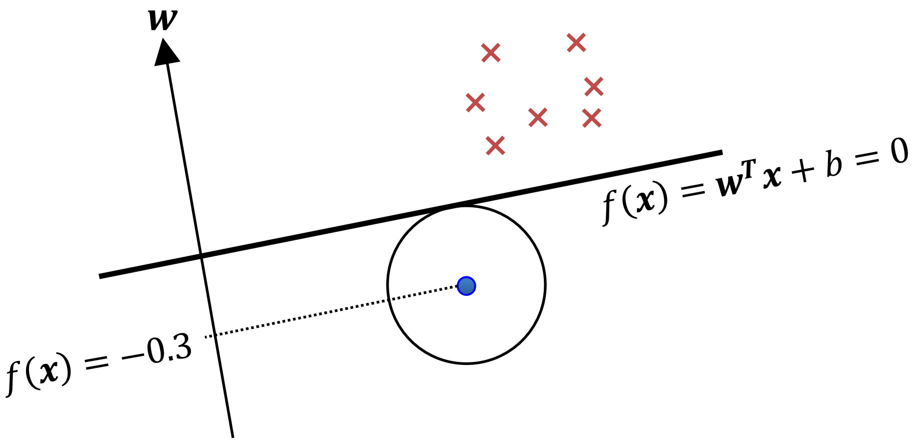
DeepFool (2016)

- **Idea**: closed-form solution assuming a linear classifier, then iterate
  - For L_2, binary classifier: $\boldsymbol{x}^\star = \boldsymbol{x} - \frac{f(\boldsymbol{x})}{||\boldsymbol{w}||}\boldsymbol{w}$



Algorithm 1 DeepFool for binary classifiers

```
input: Image $\boldsymbol{x}$, classifier $f$.
output: Perturbation $\hat{\boldsymbol{r}}$.
Initialize $\boldsymbol{x}_0 \leftarrow \boldsymbol{x}$, $i \leftarrow 0$.
while $\mathrm{sign}(f(\boldsymbol{x}_i)) = \mathrm{sign}(f(\boldsymbol{x}_0))$ do
    $\boldsymbol{r}_i \leftarrow -\frac{f(\boldsymbol{x}_i)}{\|\nabla f(\boldsymbol{x}_i)\|_2^2}\nabla f(\boldsymbol{x}_i)$,
    $\boldsymbol{x}_{i+1} \leftarrow \boldsymbol{x}_i + \boldsymbol{r}_i$,
    $i \leftarrow i + 1$.
end while
return $\hat{\boldsymbol{r}} = \sum_i \boldsymbol{r}_i$.
```



$\boldsymbol{w}$
$f(\boldsymbol{x}) = \boldsymbol{w}^T\boldsymbol{x} + b = 0$
$f(\boldsymbol{x}) = -0.3$

Distance of $\boldsymbol{x}$ to the hyperplane: $\frac{|f(\boldsymbol{x})|}{||\boldsymbol{w}||}$

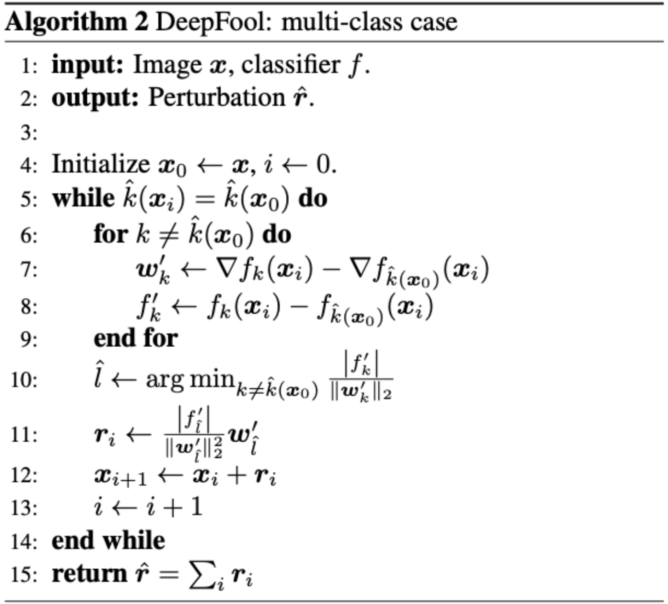
Moosavi-Dezfooli et al., DeepFool: ..., CVPR 2016

DeepFool (2016)

- In the multi-class case, the (signed) L_p distance to the boundary B is estimated as:

$$d(\boldsymbol{x}, B) = \frac{f_k(\boldsymbol{x}) - f_y(\boldsymbol{x})}{\left\| \nabla f_k(\boldsymbol{x}) - \nabla f_y(\boldsymbol{x}) \right\|_q}$$

- As in the binary case, the algorithm iterates to refine the initial guess, until a misclassification is achieved



Algorithm 2 DeepFool: multi-class case

```
input: Image $\boldsymbol{x}$, classifier $f$.
output: Perturbation $\hat{\boldsymbol{r}}$.

Initialize $\boldsymbol{x}_0 \leftarrow \boldsymbol{x}$, $i \leftarrow 0$.
while $\hat{k}(\boldsymbol{x}_i) = \hat{k}(\boldsymbol{x}_0)$ do
    for $k \neq \hat{k}(\boldsymbol{x}_0)$ do
        $\boldsymbol{w}'_k \leftarrow \nabla f_k(\boldsymbol{x}_i) - \nabla f_{\hat{k}(\boldsymbol{x}_0)}(\boldsymbol{x}_i)$
        $f'_k \leftarrow f_k(\boldsymbol{x}_i) - f_{\hat{k}(\boldsymbol{x}_0)}(\boldsymbol{x}_i)$
    end for
    $\hat{l} \leftarrow \arg\min_{k \neq \hat{k}(\boldsymbol{x}_0)} \frac{|f'_k|}{\|\boldsymbol{w}'_k\|_2}$
    $\boldsymbol{r}_i \leftarrow \frac{|f'_{\hat{l}}|}{\|\boldsymbol{w}'_{\hat{l}}\|_2^2} \boldsymbol{w}'_{\hat{l}}$
    $\boldsymbol{x}_{i+1} \leftarrow \boldsymbol{x}_i + \boldsymbol{r}_i$
    $i \leftarrow i + 1$
end while
return $\hat{\boldsymbol{r}} = \sum_i \boldsymbol{r}_i$
```

Moosavi-Dezfooli et al., DeepFool: ..., CVPR 2016

Jacobian Saliency-Map Attack (2016)

- JSMA uses saliency maps (i.e., *input gradients*) to compute perturbations

- Given t as the target class, and i as an input feature
  - it only retains the feature values that would change the output if *added (1st equation)* or *removed (2nd eq.)*

$$S(\mathbf{X},t)[i] = \begin{cases} 0 \text{ if } \frac{\partial \mathbf{F}_t(\mathbf{X})}{\partial \mathbf{X}_i} < 0 \text{ or } \sum_{j \neq t} \frac{\partial \mathbf{F}_j(\mathbf{X})}{\partial \mathbf{X}_i} > 0 \\ \left(\frac{\partial \mathbf{F}_t(\mathbf{X})}{\partial \mathbf{X}_i}\right) \left|\sum_{j \neq t} \frac{\partial \mathbf{F}_j(\mathbf{X})}{\partial \mathbf{X}_i}\right| \text{ otherwise} \end{cases}$$

$$S(\mathbf{X},t)[i] = \begin{cases} 0 \text{ if } \frac{\partial \mathbf{F}_t(\mathbf{X})}{\partial \mathbf{X}_i} > 0 \text{ or } \sum_{j \neq t} \frac{\partial \mathbf{F}_j(\mathbf{X})}{\partial \mathbf{X}_i} < 0 \\ \left|\frac{\partial \mathbf{F}_t(\mathbf{X})}{\partial \mathbf{X}_i}\right| \left(\sum_{j \neq t} \frac{\partial \mathbf{F}_j(\mathbf{X})}{\partial \mathbf{X}_i}\right) \text{ otherwise} \end{cases}$$

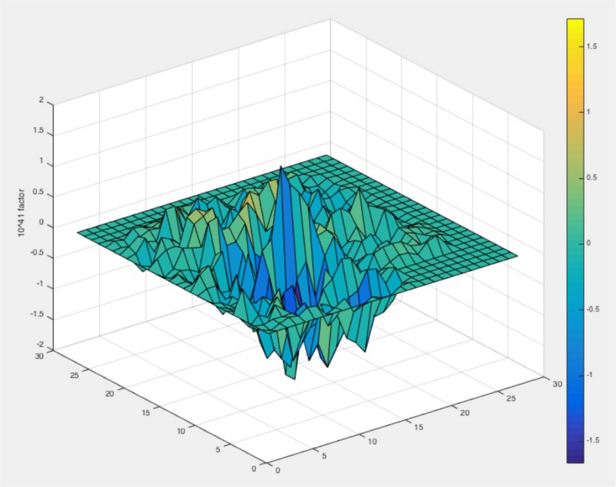


Fig. 7: Saliency map of a 784-dimensional input to the LeNet architecture (cf. validation section). The 784 input dimensions are arranged to correspond to the 28x28 image pixel alignment. Large absolute values correspond to features with a significant impact on the output when perturbed.

Papernot et al., The limitations of deep learning in adversarial settings, Euro S&P 2016

Carlini-Wagner Attack (2017)

- Initially proposed to bypass one defensive mechanism (known as *distillation*)
  - **Problem**: cross-entropy loss exhibits vanishing gradients - attacks do not work correctly!
  - **Solution**: to define the so-called *logit* loss $L(\boldsymbol{x}, y, \boldsymbol{\theta}) = \max_{k \neq y} f_k(x) - f_y(x)$
    - *Note*: if $L < 0$, an adversarial example is found

- **Goal:** to find minimum-norm adversarial examples, using relaxation:

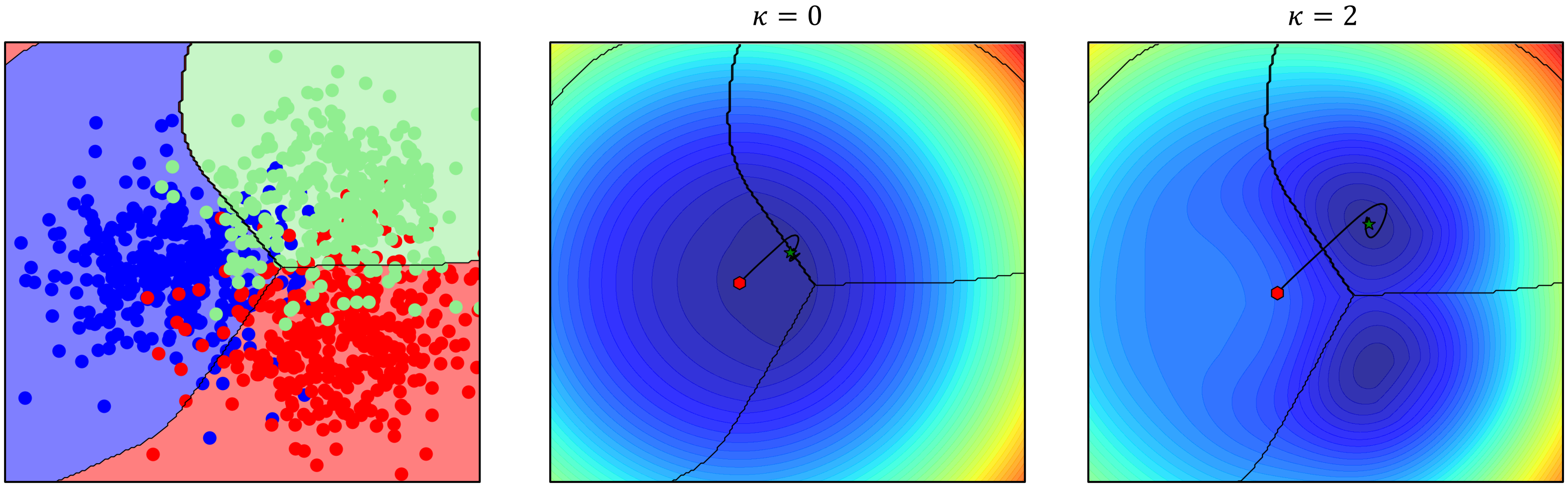
$$\min_{\boldsymbol{\delta}} \; ||\boldsymbol{\delta}||_2 + c \cdot \max(L(\boldsymbol{x}, y, \boldsymbol{\theta}), -\kappa)$$
$$\text{s.t.} \quad \mathbf{x} + \boldsymbol{\delta} \in [0,1]^{\mathrm{d}}$$

  - $c > 0$ is again chosen via line search
  - $\kappa \geq 0$ can be set to achieve misclassification with a non-zero confidence in the target class
  - The box constraint is also replaced via a change of variables (no constraints at all)

- **Solver:** The *Adam* algorithm is used to solve the unconstrained optimization, even though tuning c is computationally costly (requires re-running the attack many times)
  - *Adam*: https://d2l.ai/chapter_optimization/adam.html

Carlini and Wagner, Towards Evaluating the Robustness of Neural Networks, S&P 2017

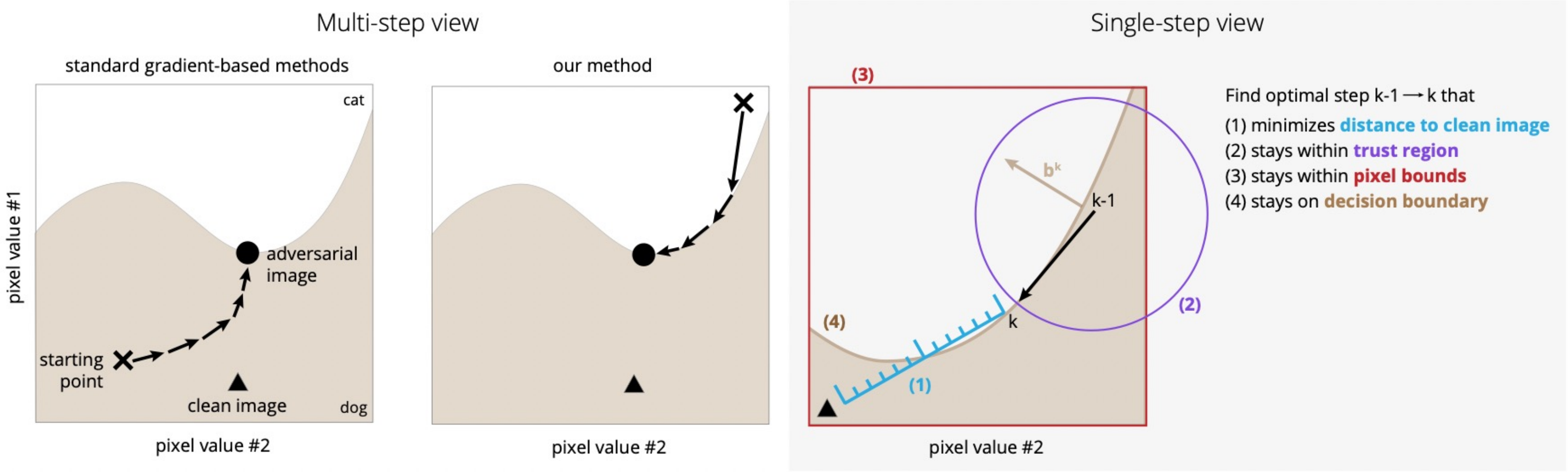
Carlini-Wagner Attack (2017)



Carlini and Wagner, Towards Evaluating the Robustness of Neural Networks, S&P 2017

Brendel-Bethge Attack (2019)

- **Idea:**
  - to initialize the attack from an adversarial point
  - to find boundary between $\boldsymbol{x}$ and the init point (via line search)
  - to try following the boundary to minimize the perturbation size



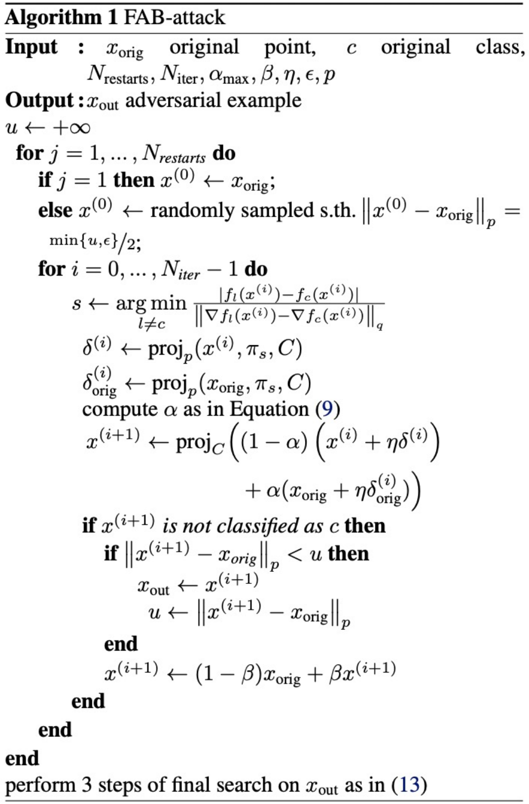
Find optimal step k-1 → k that
(1) minimizes **distance to clean image**
(2) stays within **trust region**
(3) stays within **pixel bounds**
(4) stays on **decision boundary**

Brendel et al., Accurate, Reliable and Fast robustness Evaluation, NeurIPS 2019

Fast Adaptive Boundary (FAB) Attack (2020)

- FAB uses essentially the same approximation of DeepFool to estimate distance to boundary

- However
  - it improves the projection, also accounting for the presence of the box constraint
  - and uses momentum to accelerate convergence



```
Algorithm 1 FAB-attack
Input  : $x_{\text{orig}}$ original point, $c$ original class,
         $N_{\text{restarts}}, N_{\text{iter}}, \alpha_{\text{max}}, \beta, \eta, \epsilon, p$
Output : $x_{\text{out}}$ adversarial example
$u \leftarrow +\infty$
for $j = 1, \dots, N_{restarts}$ do
    if $j = 1$ then $x^{(0)} \leftarrow x_{\text{orig}}$;
    else $x^{(0)} \leftarrow$ randomly sampled s.th. $\left\|x^{(0)} - x_{\text{orig}}\right\|_p = \min\{u,\epsilon\}/2$;
    for $i = 0, \dots, N_{iter} - 1$ do
        $s \leftarrow \arg\min_{l \neq c} \frac{|f_l(x^{(i)}) - f_c(x^{(i)})|}{\left\|\nabla f_l(x^{(i)}) - \nabla f_c(x^{(i)})\right\|_q}$
        $\delta^{(i)} \leftarrow \text{proj}_p(x^{(i)}, \pi_s, C)$
        $\delta_{\text{orig}}^{(i)} \leftarrow \text{proj}_p(x_{\text{orig}}, \pi_s, C)$
        compute $\alpha$ as in Equation (9)
        $x^{(i+1)} \leftarrow \text{proj}_C\Big((1-\alpha)\Big(x^{(i)} + \eta\delta^{(i)}\Big)$
                    $+ \alpha(x_{\text{orig}} + \eta\delta_{\text{orig}}^{(i)})\Big)$
        if $x^{(i+1)}$ is not classified as $c$ then
            if $\left\|x^{(i+1)} - x_{orig}\right\|_p < u$ then
                $x_{\text{out}} \leftarrow x^{(i+1)}$
                $u \leftarrow \left\|x^{(i+1)} - x_{\text{orig}}\right\|_p$
            end
            $x^{(i+1)} \leftarrow (1-\beta)x_{\text{orig}} + \beta x^{(i+1)}$
        end
    end
end
perform 3 steps of final search on $x_{\text{out}}$ as in (13)
```

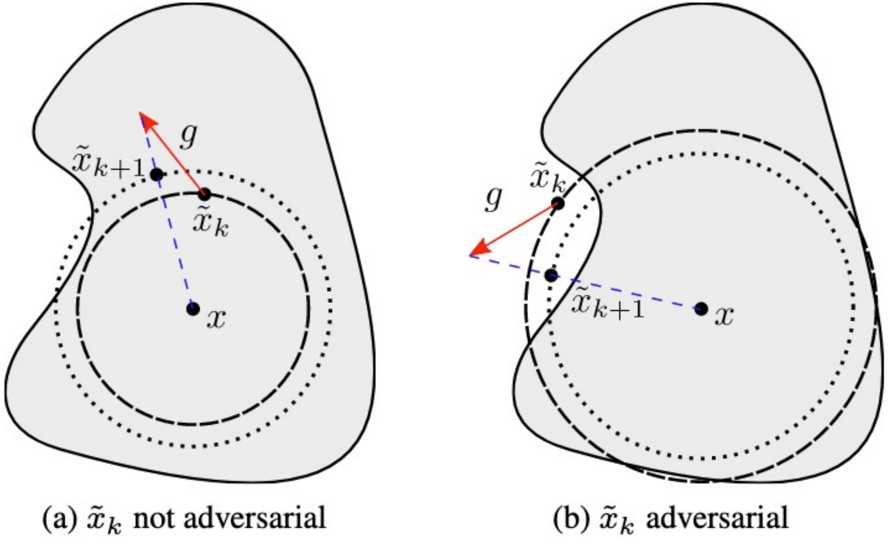
Croce & Hein, Minimally distorted Adversarial Examples with …, ICML 2020

Decoupled Direction and Norm (DDN) Attack (2019)

- DDN works in two steps
  - it performs a PGD-step
  - it adjusts the maximum perturbation size

- It uses *cosine annealing* as a decay strategy for the step size

- Specialized to L_2, but very fast and effective



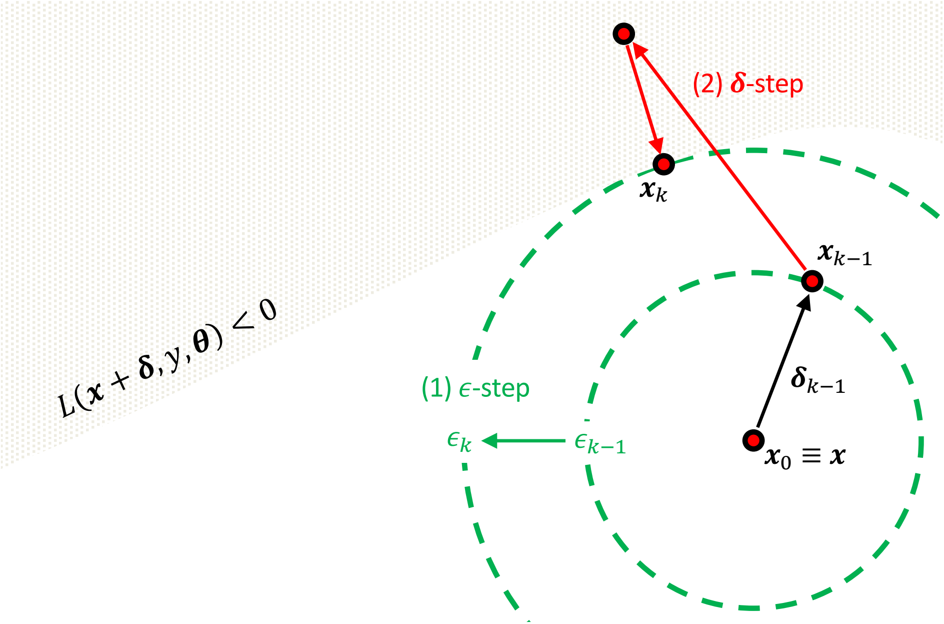
(a) $\tilde{x}_k$ not adversarial

(b) $\tilde{x}_k$ adversarial

Rony et al., Decoupling Direction and Norm …, CVPR 2019

Fast Minimum-Norm (FMN) Attacks (2021)

Biggio et al., 2013
Szegedy et al., 2014
Goodfellow et al., 2015 (FGSM)
Papernot et al., 2015 (JSMA)
Carlini & Wagner, 2017 (CW)
Madry et al., 2017 (PGD)
...
Croce et al., FAB, AutoPGD ...
Rony et al., DDN, ALMA, ...
Pintor et al., 2021 (FMN)



$L(\boldsymbol{x}+\boldsymbol{\delta}, y, \boldsymbol{\theta}) < 0$
(2) $\boldsymbol{\delta}$-step
$\boldsymbol{x}_k$
$\boldsymbol{x}_{k-1}$
$\boldsymbol{\delta}_{k-1}$
(1) ϵ-step
ϵ_k
ϵ_{k-1}
$\boldsymbol{x}_0 \equiv \boldsymbol{x}$

FMN

Fast convergence to good local optima

Works in different norms $(\ell_0, \ell_1, \ell_2, \ell_\infty)$

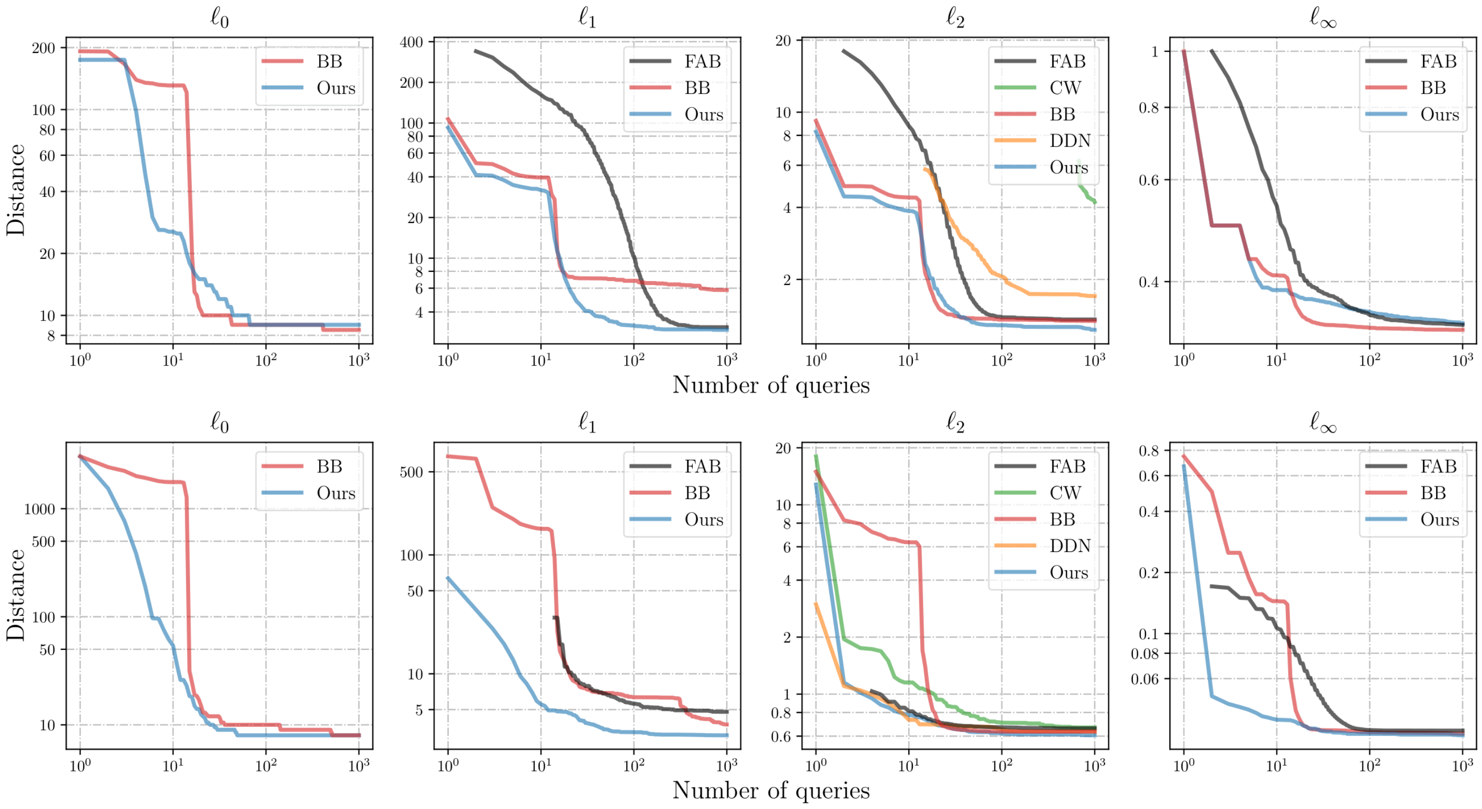
Easy tuning /robust to hyperparameter choice

Pintor, Brendel, Roli, Biggio, *Fast minimum-norm adversarial attacks…*, NeurIPS 2021

Experimental Results: Query-distortion Curves

MNIST challenge

CIFAR challenge



Pintor, Brendel, Roli, Biggio, *Fast minimum-norm adversarial attacks…*, NeurIPS 2021

Benchmarks

Automation with AutoAttack (AA)

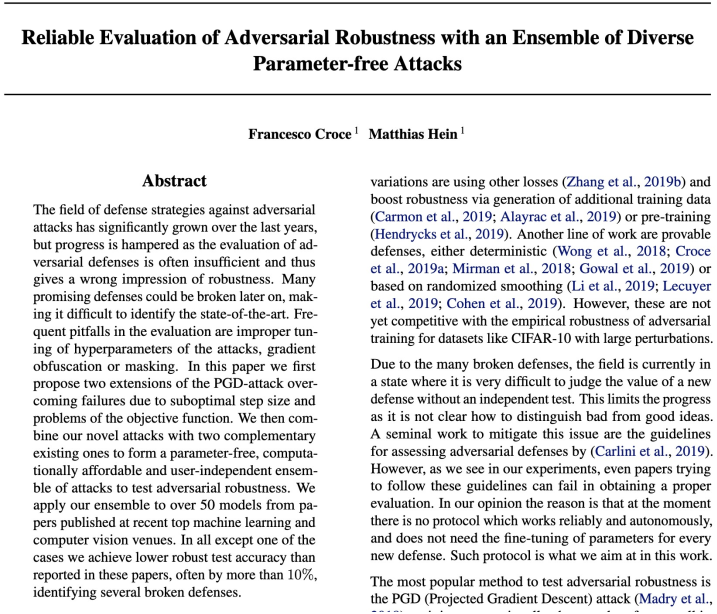
Automatic evaluation of a model by ensembling attacks:

- AutoPGD-*CE*
- AutoPGD-*DLR*
- FAB
- Square Attack (*black-box*)

(AA also plays with initialization, repetitions, etc.)

Latest development: *Adaptive AutoAttack*

- Yao et al., NeurIPS '21 (https://arxiv.org/abs/2102.11860)



Reliable Evaluation of Adversarial Robustness with an Ensemble of Diverse Parameter-free Attacks

Francesco Croce [1] **Matthias Hein** [1]

Abstract

The field of defense strategies against adversarial attacks has significantly grown over the last years, but progress is hampered as the evaluation of adversarial defenses is often insufficient and thus gives a wrong impression of robustness. Many promising defenses could be broken later on, making it difficult to identify the state-of-the-art. Frequent pitfalls in the evaluation are improper tuning of hyperparameters of the attacks, gradient obfuscation or masking. In this paper we first propose two extensions of the PGD-attack overcoming failures due to suboptimal step size and problems of the objective function. We then combine our novel attacks with two complementary existing ones to form a parameter-free, computationally affordable and user-independent ensemble of attacks to test adversarial robustness. We apply our ensemble to over 50 models from papers published at recent top machine learning and computer vision venues. In all except one of the cases we achieve lower robust test accuracy than reported in these papers, often by more than 10%, identifying several broken defenses.

variations are using other losses (Zhang et al., 2019b) and boost robustness via generation of additional training data (Carmon et al., 2019; Alayrac et al., 2019) or pre-training (Hendrycks et al., 2019). Another line of work are provable defenses, either deterministic (Wong et al., 2018; Croce et al., 2019a; Mirman et al., 2018; Gowal et al., 2019) or based on randomized smoothing (Li et al., 2019; Lecuyer et al., 2019; Cohen et al., 2019). However, these are not yet competitive with the empirical robustness of adversarial training for datasets like CIFAR-10 with large perturbations.

Due to the many broken defenses, the field is currently in a state where it is very difficult to judge the value of a new defense without an independent test. This limits the progress as it is not clear how to distinguish bad from good ideas. A seminal work to mitigate this issue are the guidelines for assessing adversarial defenses by (Carlini et al., 2019). However, as we see in our experiments, even papers trying to follow these guidelines can fail in obtaining a proper evaluation. In our opinion the reason is that at the moment there is no protocol which works reliably and autonomously, and does not need the fine-tuning of parameters for every new defense. Such protocol is what we aim at in this work.

The most popular method to test adversarial robustness is the PGD (Projected Gradient Descent) attack (Madry et al.,

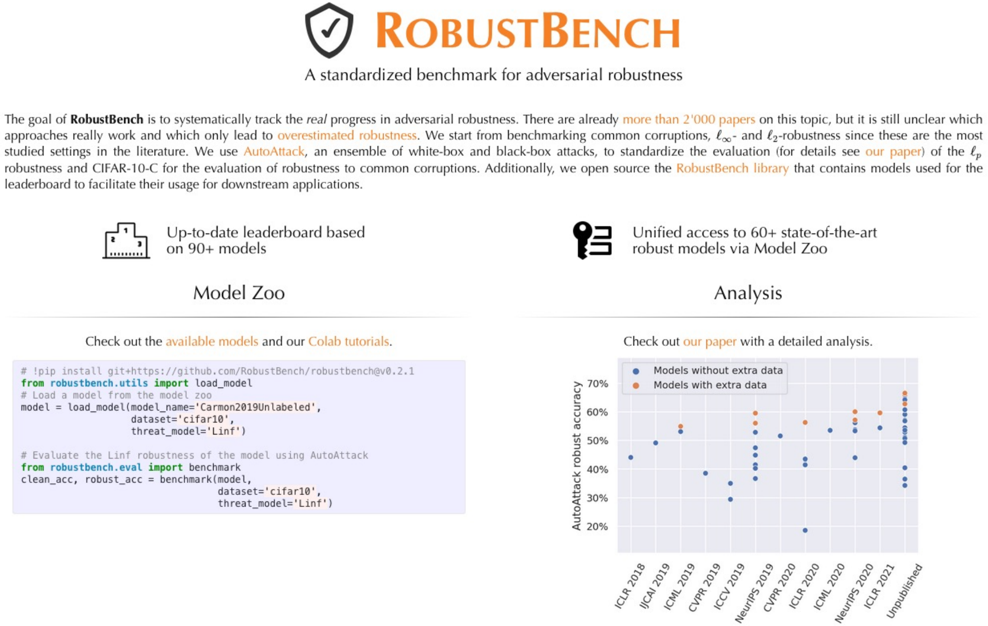
Croce et al., Reliable Evaluation of Adversarial Robustness …, ICML 2020

Current Benchmark for Vision Models: *RobustBench*

Public benchmark for defenses
https://robustbench.github.io/

It uses AutoAttack, defenses are listed in leaderboard by results

All models are available and can be tested offline



ROBUSTBENCH

A standardized benchmark for adversarial robustness

The goal of **RobustBench** is to systematically track the *real* progress in adversarial robustness. There are already more than 2'000 papers on this topic, but it is still unclear which approaches really work and which only lead to overestimated robustness. We start from benchmarking common corruptions, ℓ_∞- and ℓ_2-robustness since these are the most studied settings in the literature. We use AutoAttack, an ensemble of white-box and black-box attacks, to standardize the evaluation (for details see our paper) of the ℓ_p robustness and CIFAR-10-C for the evaluation of robustness to common corruptions. Additionally, we open source the RobustBench library that contains models used for the leaderboard to facilitate their usage for downstream applications.

Up-to-date leaderboard based on 90+ models

Unified access to 60+ state-of-the-art robust models via Model Zoo

Model Zoo

Check out the available models and our Colab tutorials.

```python
# !pip install git+https://github.com/RobustBench/robustbench@v0.2.1
from robustbench.utils import load_model
# Load a model from the model zoo
model = load_model(model_name='Carmon2019Unlabeled',
                   dataset='cifar10',
                   threat_model='Linf')

# Evaluate the Linf robustness of the model using AutoAttack
from robustbench.eval import benchmark
clean_acc, robust_acc = benchmark(model,
                                  dataset='cifar10',
                                  threat_model='Linf')
```

Analysis

Check out our paper with a detailed analysis.

Croce et al., RobustBench: ..., NeurIPS '21 Datasets and Benchmarks Track

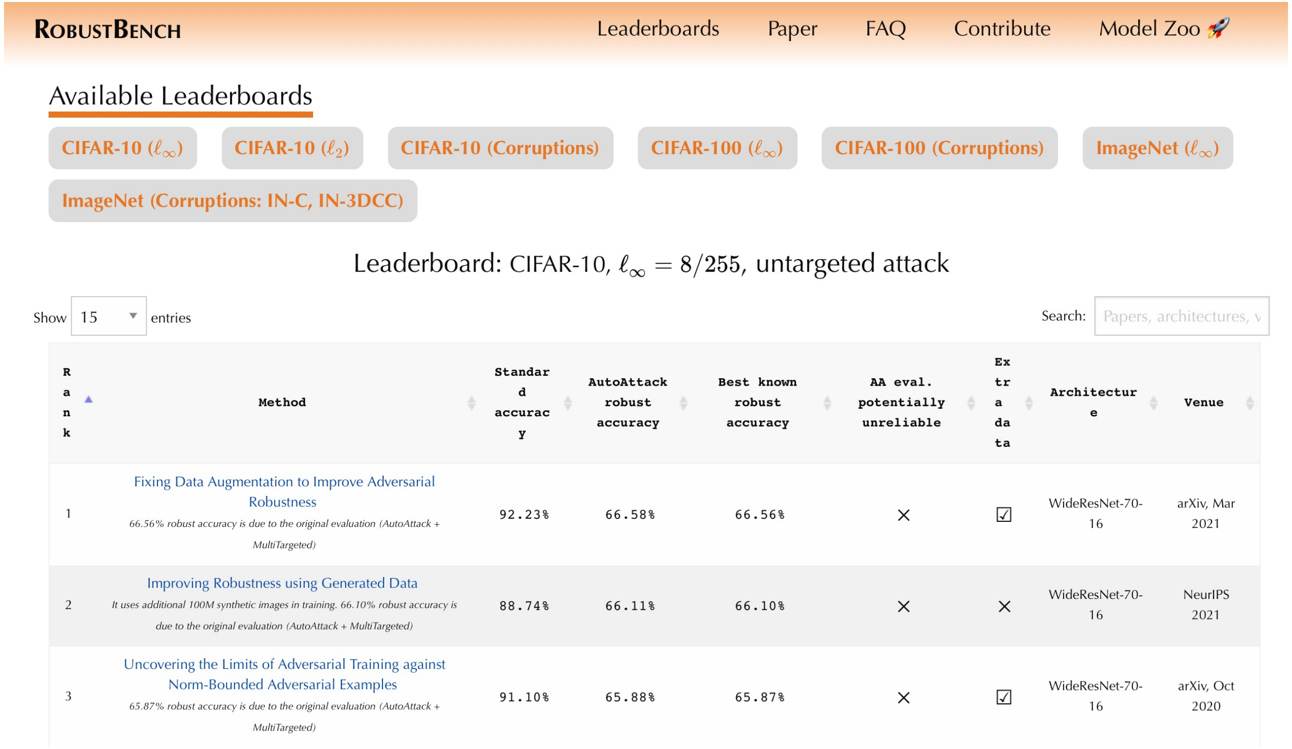
Current Benchmark for Vision Models: *RobustBench*

Pros

- First standardized benchmark
- Easy to use (AutoAttack provides a good combination of attacks)

Cons

- Evalutes RA at fixed perturbation budget
- Computationally demanding (ensembling four attacks)



Leaderboard: CIFAR-10, $\ell_\infty = 8/255$, untargeted attack

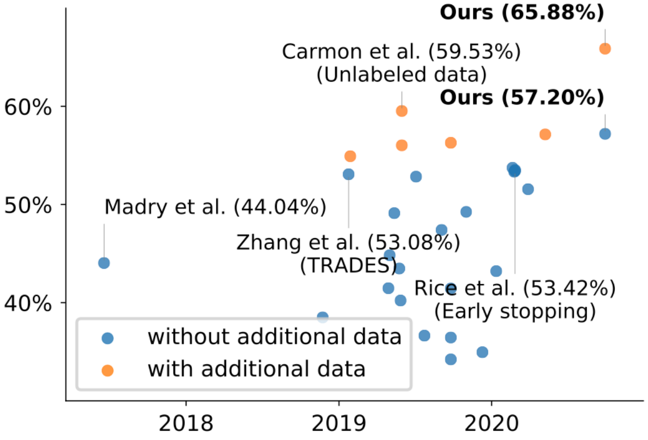
Rank	Method	Standard accuracy	AutoAttack robust accuracy	Best known robust accuracy	AA eval. potentially unreliable	Extra data	Architecture	Venue
1	Fixing Data Augmentation to Improve Adversarial Robustness *66.56% robust accuracy is due to the original evaluation (AutoAttack + MultiTargeted)*	92.23%	66.58%	66.56%	×	☑	WideResNet-70-16	arXiv, Mar 2021
2	Improving Robustness using Generated Data *It uses additional 100M synthetic images in training. 66.10% robust accuracy is due to the original evaluation (AutoAttack + MultiTargeted)*	88.74%	66.11%	66.10%	×	×	WideResNet-70-16	NeurIPS 2021
3	Uncovering the Limits of Adversarial Training against Norm-Bounded Adversarial Examples *65.87% robust accuracy is due to the original evaluation (AutoAttack + MultiTargeted)*	91.10%	65.88%	65.87%	×	☑	WideResNet-70-16	arXiv, Oct 2020

Croce et al., RobustBench: ..., NeurIPS '21 Datasets and Benchmarks Track

Uncovering the Limits of Adversarial Training against Norm-Bounded Adversarial Examples

- Sven Gowal (Deepmind) et al., 2021
  https://arxiv.org/abs/2010.03593

We discover that it is possible to train robust models that go well beyond state-of-the-art results by combining larger models, Swish/SiLU activations and model weight averaging.



Extracted from RobustBench:
https://robustbench.github.io/

Attack Implementations

- Most popular Python libraries implementing attacks
  - we will use *secml* in this course

Foolbox

SECML

cleverhans

Adversarial
Robustness
Toolbox

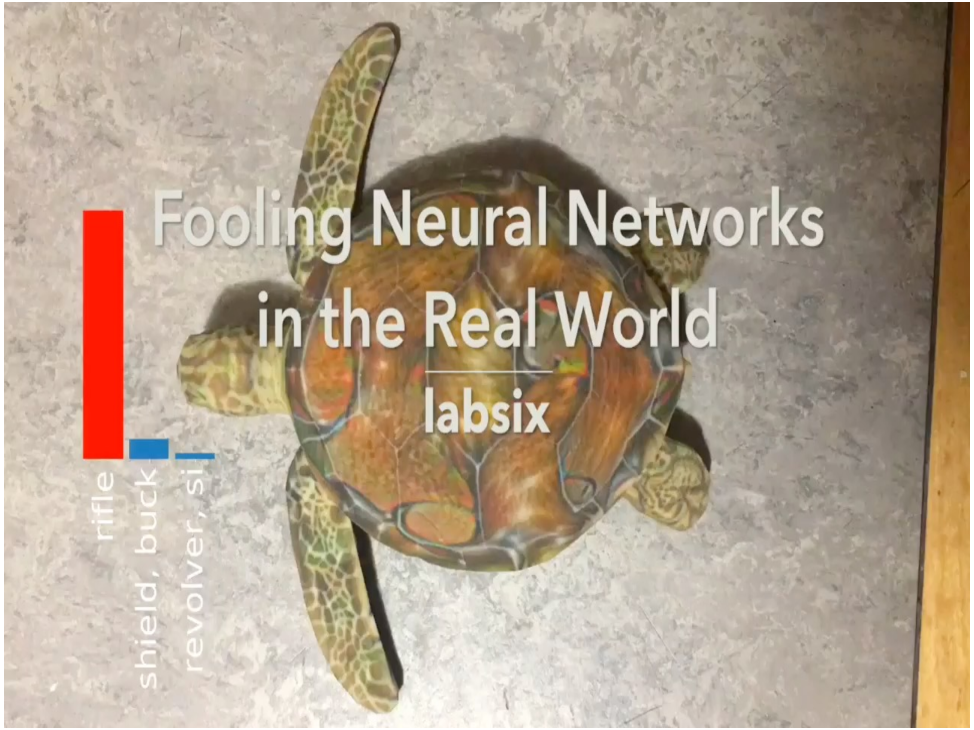
Physical Attacks: *EoT* and Adversarial Patches

Adversarial Examples in the Physical World

- Do adversarial images fool deep networks **even when** they **operate** in the **physical world**, for example, **images** are **taken from** a **cell-phone camera**?
  - Alexey Kurakin et al. (2016, 2017) explored the possibility of creating adversarial images for machine learning systems which operate in the physical world. They used images taken from a cell-phone camera as an input to an Inception v3 image classification neural network
  - They showed that in such a set-up, a significant fraction of adversarial images crafted using the original network are misclassified even when fed to the classifier through the camera

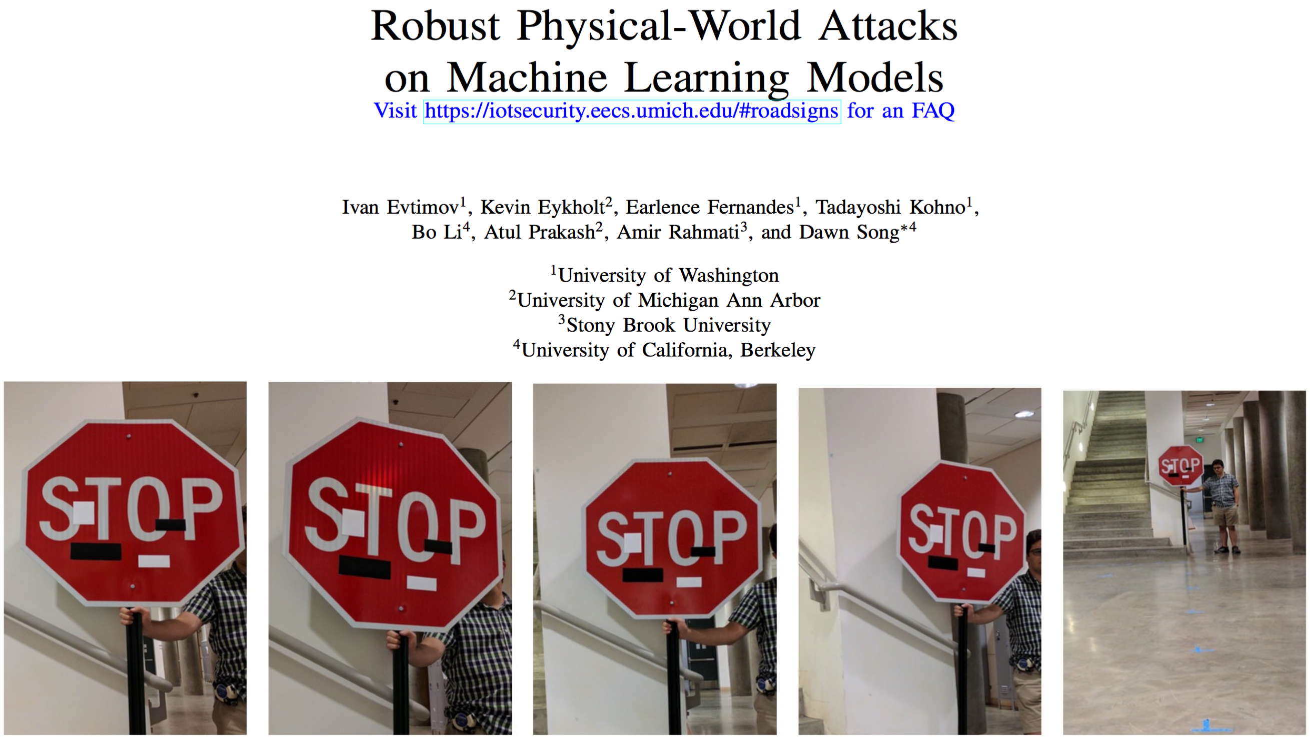
Alexey Kurakin et al., ICLR 2017

Adversarial Examples in the Physical World



Athalye et al., Synthesizing robust adversarial examples. ICML, 2018

Adversarial Examples in the Physical World



Robust Physical-World Attacks
on Machine Learning Models

Visit https://iotsecurity.eecs.umich.edu/#roadsigns for an FAQ

Ivan Evtimov[1], Kevin Eykholt[2], Earlence Fernandes[1], Tadayoshi Kohno[1],
Bo Li[4], Atul Prakash[2], Amir Rahmati[3], and Dawn Song*[4]

[1]University of Washington
[2]University of Michigan Ann Arbor
[3]Stony Brook University
[4]University of California, Berkeley

How Are They Optimized?

- The constraint for the attacker here is to craft a perturbation which is **robust** to changes in *illumination*, *pose*, *distance to the camera*, etc.
  - How is this achieved?

- The previous examples all make use of the notion of **EoT:** Expectation over Transformations, originally proposed by Athalye et al., ICML 2018 https://arxiv.org/pdf/1707.07397.pdf
  - **Main idea:** to optimize the perturbation to be invariant to different image transformations

$$\begin{aligned} \underset{x'}{\arg\max} \quad & \mathbb{E}_{t\sim T}[\log P(y_t|t(x'))] \\ \text{subject to} \quad & \mathbb{E}_{t\sim T}[d(t(x'), t(x))] < \epsilon \\ & x \in [0,1]^d \end{aligned}$$

Athalye et al., Synthesizing robust adversarial examples. ICML, 2018

Adversarial Patch

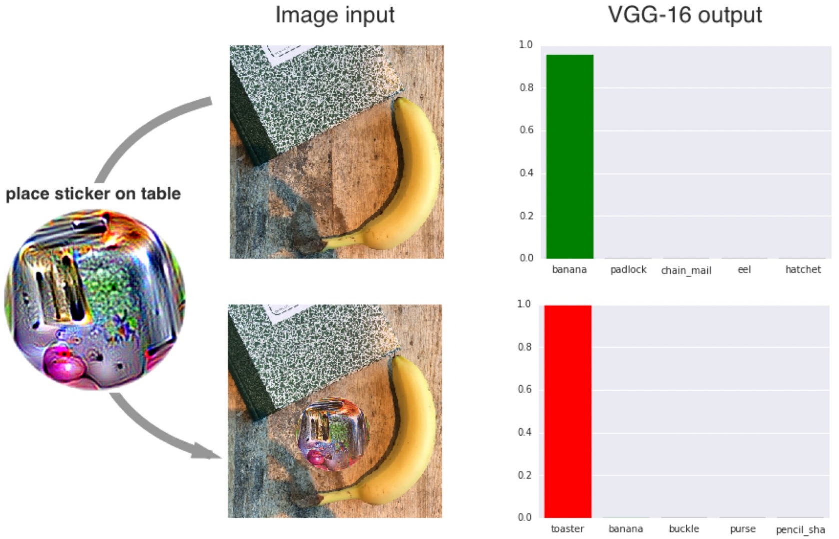
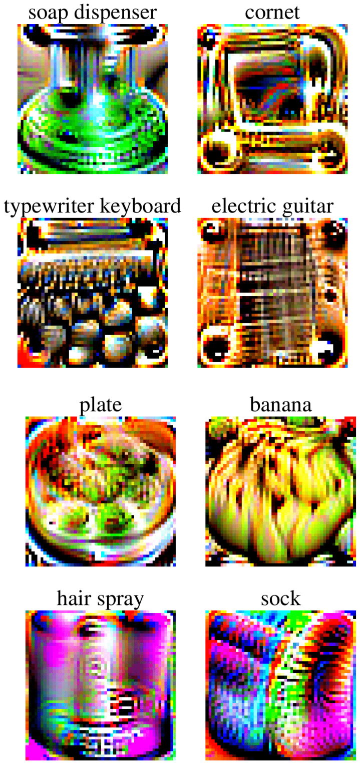
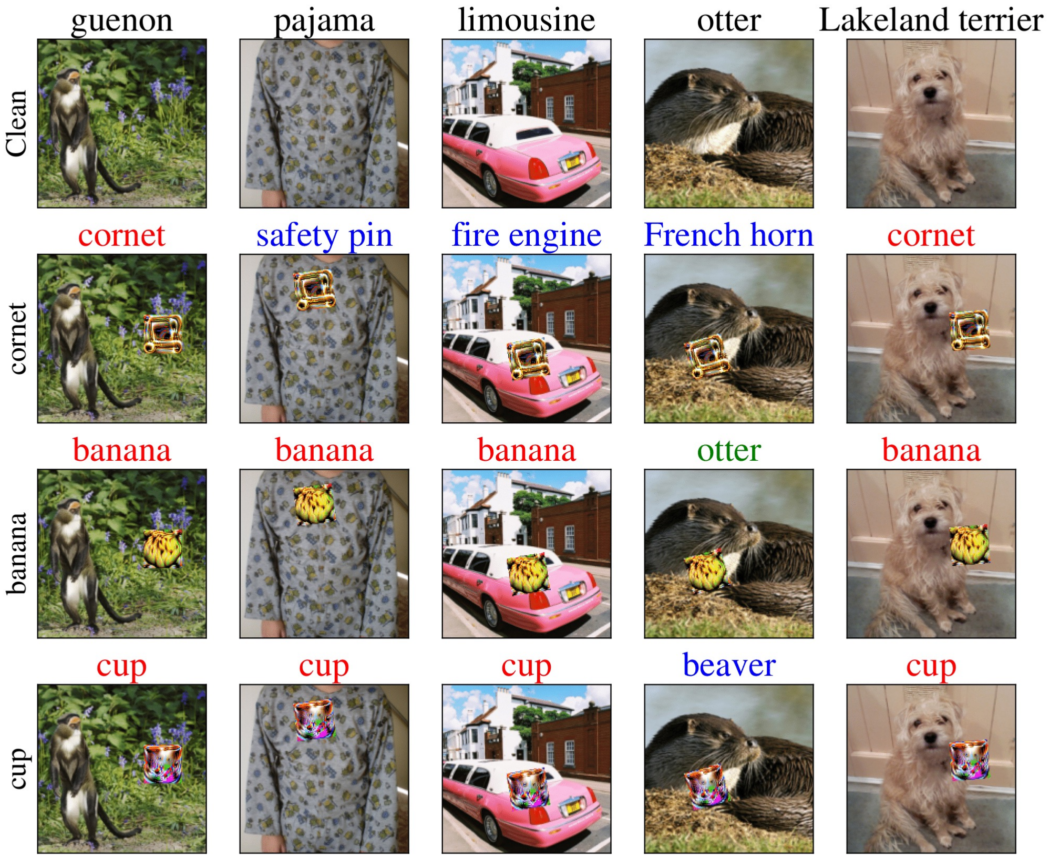


Figure 1: A real-world attack on VGG16, using a physical patch generated by the white-box ensemble method described in Section 3. When a photo of a tabletop with a banana and a notebook (top photograph) is passed through VGG16, the network reports class 'banana' with 97% confidence (top plot). If we physically place a sticker targeted to the class "toaster" on the table (bottom photograph), the photograph is classified as a toaster with 99% confidence (bottom plot). See the following video for a full demonstration: `https://youtu.be/e9IAu4lT9w8`

Brown et al., Adversarial Patch, NIPSW 2017

ImageNet Patch

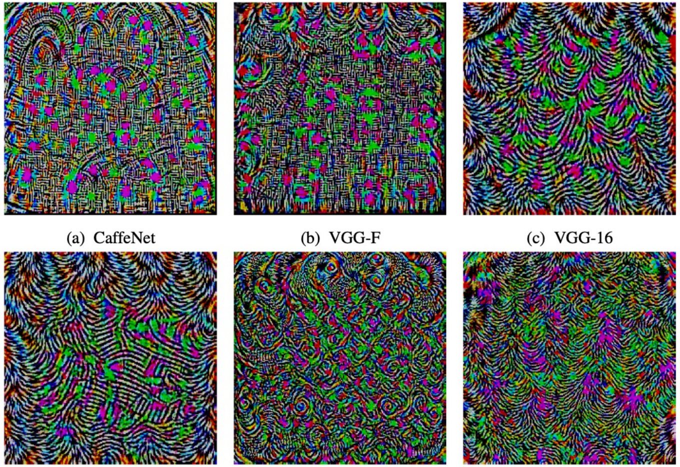




M. Pintor et al., ImageNet-Patch: A Dataset for ..., Patt. Rec. 2022

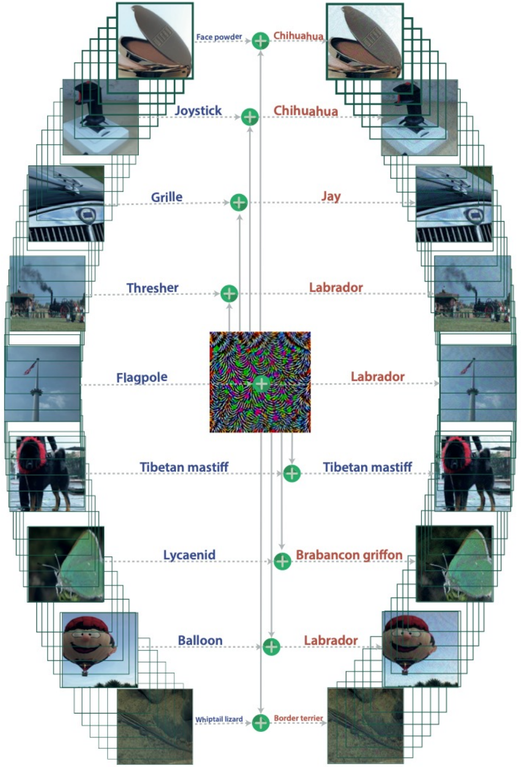
Universal Adversarial Perturbations (UAP)

- **Same principle of EoT**: optimizing the perturbation over different images
  - However, this attack just considers images from different classes (and not different views of the same object)



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

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



S. Moosavi-Dezfooli et al., https://arxiv.org/abs/1610.08401

Black-box (Gradient-free) Evasion Attacks

Motivations

Model might be non-differentiable (e.g. Random Forest classifiers)

Target is unavailable, like “Machine Learning as a Service” (MLaaS), available only through APIs

No gradients can be computed in these scenarios, Black-box attacks are needed!

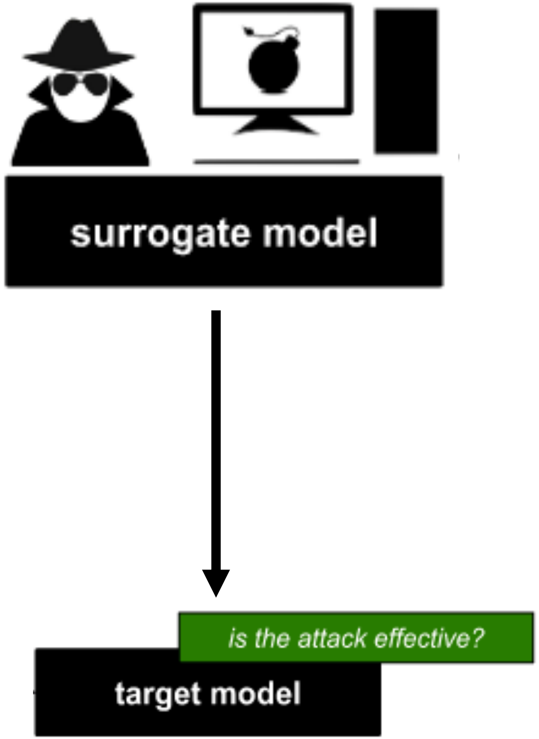
$$\xcancel{\nabla_x L(x, y; \theta)}$$

(1) Black-box *Transfer* 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

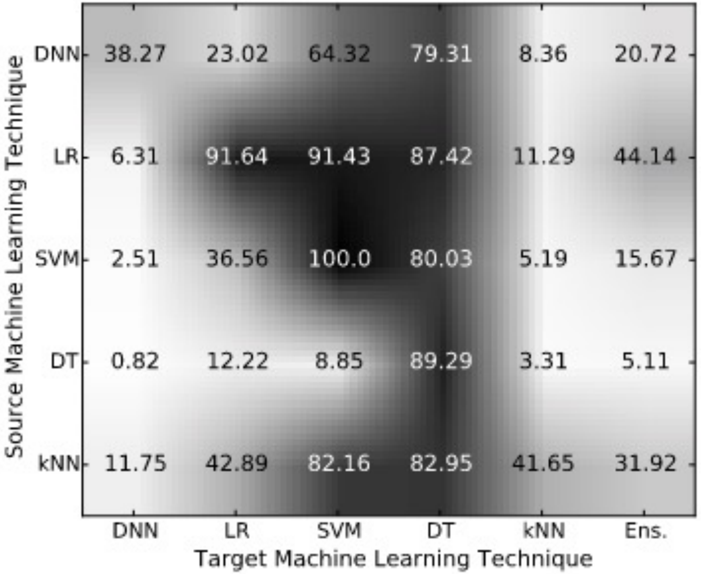
Transfer the results
Try to evade the real target using the adversarial examples computed on the surrogate



Surrogate models

Competition between models
Training different surrogates and compute how they transfer "all vs all"

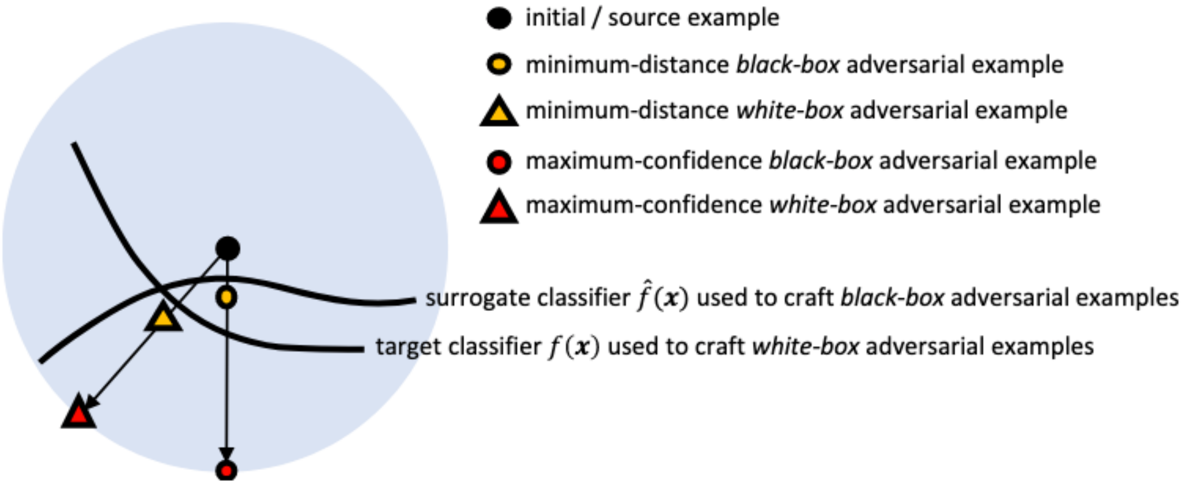
Different techniques have different results
The heatmap shows that different models behave differently when tested with attacks optimized on other models



	DNN	LR	SVM	DT	kNN	Ens.
DNN	38.27	23.02	64.32	79.31	8.36	20.72
LR	6.31	91.64	91.43	87.42	11.29	44.14
SVM	2.51	36.56	100.0	80.03	5.19	15.67
DT	0.82	12.22	8.85	89.29	3.31	5.11
kNN	11.75	42.89	82.16	82.95	41.65	31.92

Papernot et al., Practical Black-box Attacks against Machine Learning, AsiaCCS 2017

Do Transfer Attacks Work?



● initial / source example

🟡 minimum-distance *black-box* adversarial example

△ minimum-distance *white-box* adversarial example

🔴 maximum-confidence *black-box* adversarial example

🔺 maximum-confidence *white-box* adversarial example

surrogate classifier $\hat{f}(\boldsymbol{x})$ used to craft *black-box* adversarial examples

target classifier $f(\boldsymbol{x})$ used to craft *white-box* adversarial examples

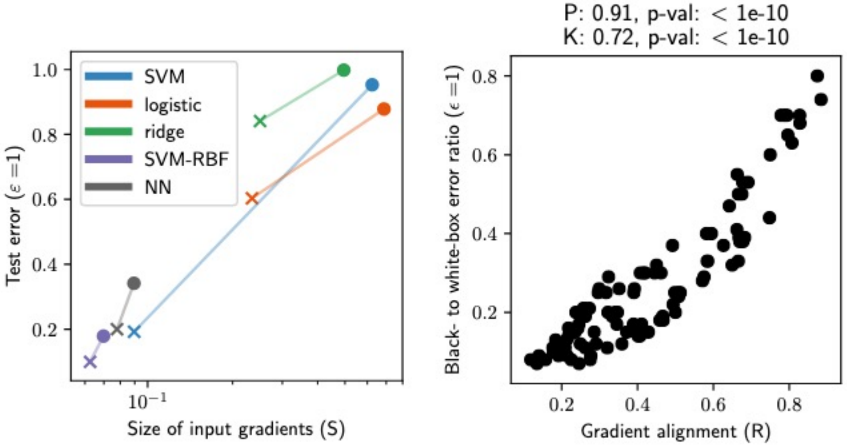
Maximum confidence attacks might better transfer, but more perturbation is needed

Minimum distance attacks are likely to stop working because decision boundary is different

Demontis, Biggio et al., Why Do Adversarial Attacks Transfer? …, USENIX 2019

Quantifying Transferability through Metrics

$$T = \ell(y, \mathbf{x} + \hat{\boldsymbol{\delta}}, \mathbf{w}) \approxeq \ell(y, \mathbf{x}, \mathbf{w}) + \hat{\boldsymbol{\delta}}^\top \nabla_{\mathbf{x}} \ell(y, \mathbf{x}, \mathbf{w})$$



Main Insight: by looking at the size of gradients, the gradient alignment, and the variability of the loss function, it is possible to understand if a model will suffer from transfer attacks

Demontis, Biggio et al., Why Do Adversarial Attacks Transfer? ..., USENIX 2019

Recap

Benefits

No white-box access to target model

Depending on the domain, data and similar pretrained model are already available

Issue: to build a good surrogate model

Training the surrogate might lead to training errors, and the attack might not transfer since the approximation is not good enough

Data might be unavailable as well

Might require the attacker to interact with the target to extract labels (to be used at training time)

(2) Black-box *Query* Attacks

No need for training a model from scratch

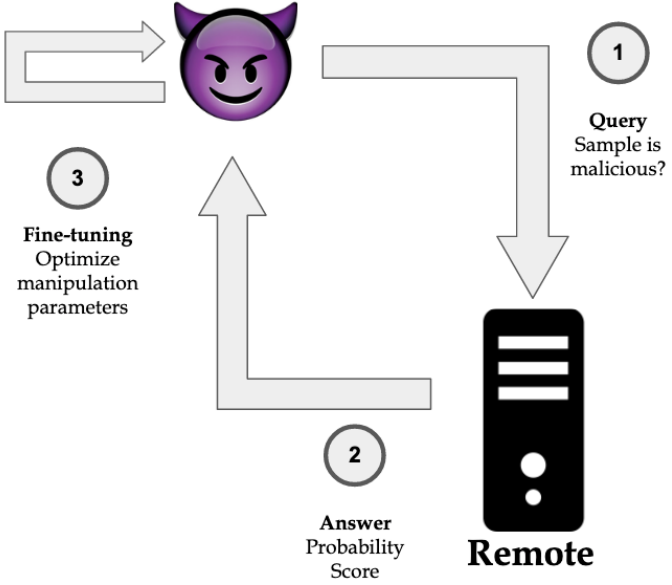
The attacker can query the target (that might be on a remote server), no need for looking for data, pretrained models, etc.

Optimize attack based on feedback

The attack is optimized based on the classifier's output/prediction

- *Hard-label* vs *soft-label* attacks

Main challenge: keeping a small number of queries to stay undetected



ZOO: Zeroth order attack

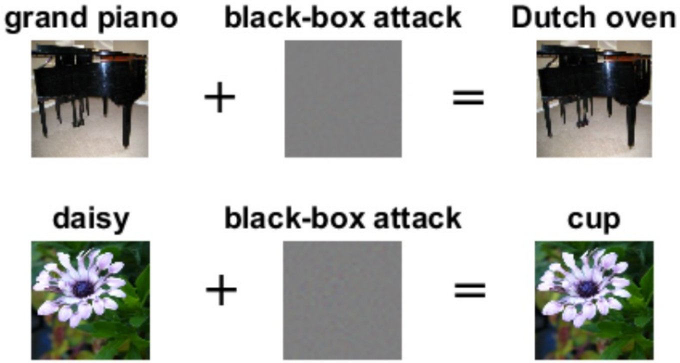
No surrogate model
Estimate Hessian (2° order derivative) in each direction, by querying the model locally and around a very small proximity by chosing random directions, no need to train surrogate

Sparse result

Attack only uses randomly picked directions to minimize both queries and perturbation size

$$\hat{g}_i := \frac{\partial f(\mathbf{x})}{\partial \mathbf{x}_i} \approx \frac{f(\mathbf{x}+h\mathbf{e}_i) - f(\mathbf{x}-h\mathbf{e}_i)}{2h},$$

$$\hat{h}_i := \frac{\partial^2 f(\mathbf{x})}{\partial \mathbf{x}_{ii}^2} \approx \frac{f(\mathbf{x}+h\mathbf{e}_i) - 2f(\mathbf{x}) + f(\mathbf{x}-h\mathbf{e}_i)}{h^2}.$$



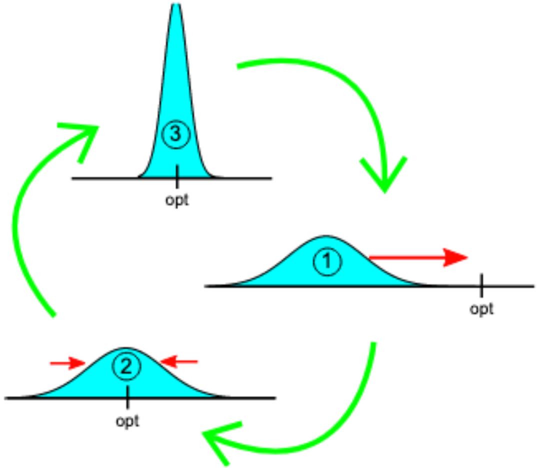
[Chen et al., ZOO: Zeroth Order Optimization Based Black-box Attacks to Deep Neural Networks without Training Substitute Models, AISec 2017]

Natural Evolutionary Strategies (NES)

- Assume **Normally-distributed** inputs
- Estimate **gradient** w.r.t. distribution parameters (mean, std)

$$J(\theta) = \mathbb{E}_\theta[f(\mathbf{z})] = \int f(\mathbf{z})\ \pi(\mathbf{z} \,|\, \theta)\ d\mathbf{z}$$

$$\nabla_\theta J(\theta) \approx \frac{1}{\lambda} \sum_{k=1}^{\lambda} f(\mathbf{z}_k)\ \nabla_\theta \log \pi(\mathbf{z}_k \,|\, \theta)$$



- Use the **natural** gradient instead of the plain gradient
  - **F** is the Fisher information matrix
  - Less dependent on the distribution choice (more robust/trustworthy direction)

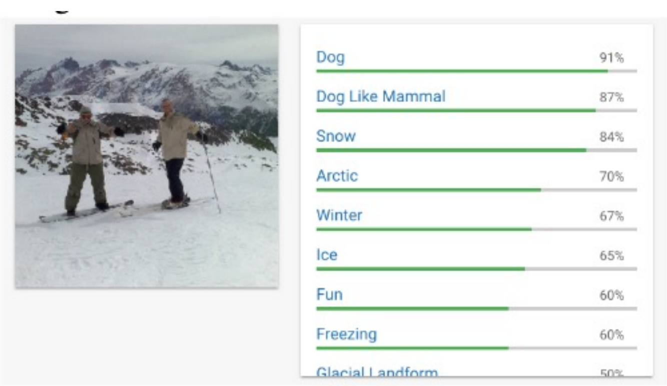
$$\widetilde{\nabla}_\theta J = \mathbf{F}^{-1} \nabla_\theta J(\theta)$$

Wiestra et al. Natural evolution strategies, JMLR 2014

Natural Evolutionary Strategies (NES)

Tested also against MLaaS

Effective in real case scenarios, attacking Google Cloud Vision



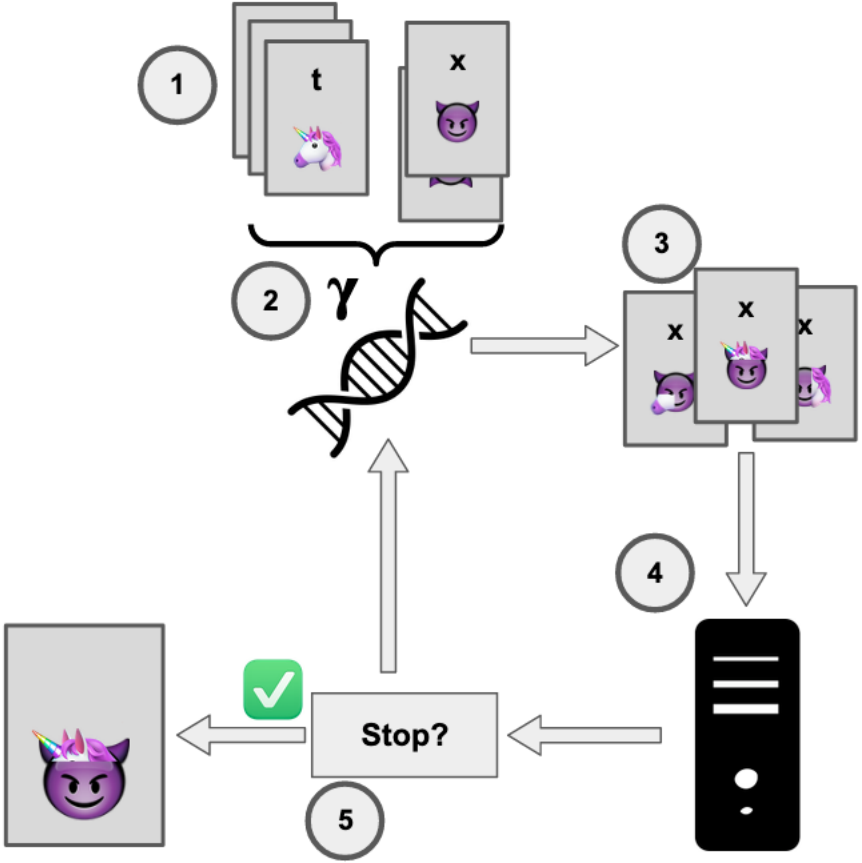
Dog	91%
Dog Like Mammal	87%
Snow	84%
Arctic	70%
Winter	67%
Ice	65%
Fun	60%
Freezing	60%
Glacial Landform	50%

Ilyas et al. Black-box Adversarial Attacks with Limited Queries …, ICML 2018

Genetic Algorithms

Evolving solutions
Sample N points, compute scores, retain best candidates. Follow "genetic evolution" until a suitable solution is found

No gradient estimation
No need for computing approximation of best direction, it is taken care of by the mixing of "genes"



Recap

Benefits

Bounded number of queries might already be enough for evasion

Ready to target real world targets as MLaaS

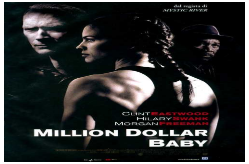
A lot of different methods to estimate directions

Issues

Decision are local, slower than normal gradient-based attack as it is reconstructing best direction from answers

The number of needed queries might still be enormous, depending on the robustness of the target

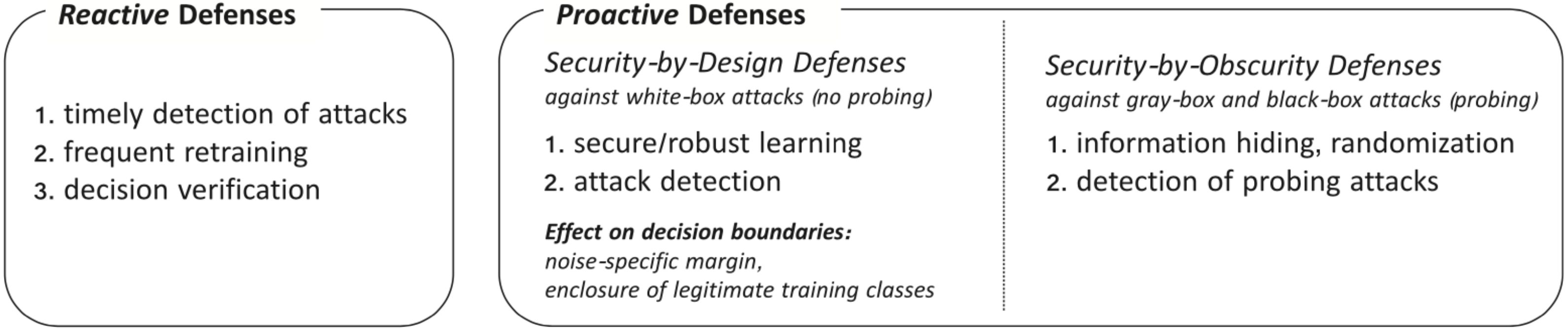
Countering Evasion Attacks



What is the rule? The rule is protect yourself at all times
(from the movie “Million dollar baby”, 2004)

Security Measures for Machine Learning

B. Biggio, F. Roli / Pattern Recognition 84 (2018) 317–331



Reactive **Defenses**

1. timely detection of attacks
2. frequent retraining
3. decision verification

Proactive **Defenses**

Security-by-Design Defenses
against white-box attacks (no probing)

1. secure/robust learning
2. attack detection

Effect on decision boundaries:
noise-specific margin,
enclosure of legitimate training classes

Security-by-Obscurity Defenses
against gray-box and black-box attacks (probing)

1. information hiding, randomization
2. detection of probing attacks

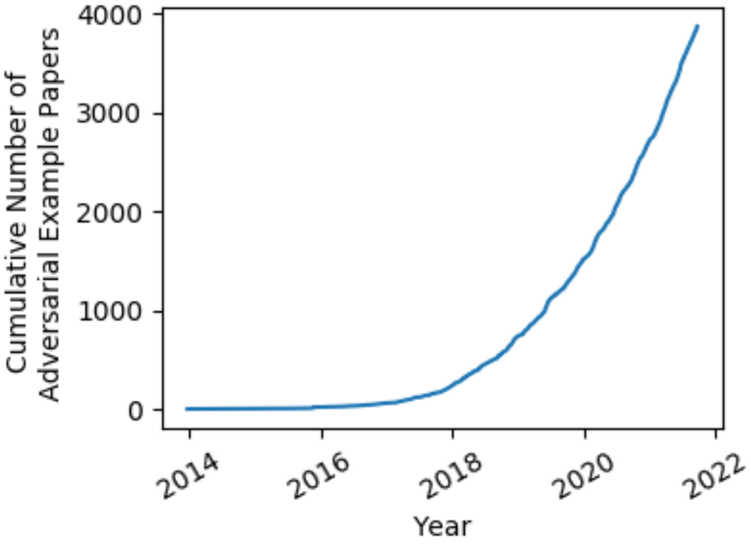
Fig. 11. Schematic categorization of the defense techniques discussed in Section 5.

Wild patterns: Ten years after the rise of adversarial machine learning

Battista Biggio[a,b,*], Fabio Roli[a,b]

A Challenging Problem!

- https://nicholas.carlini.com/writing/2019/all-adversarial-example-papers.html



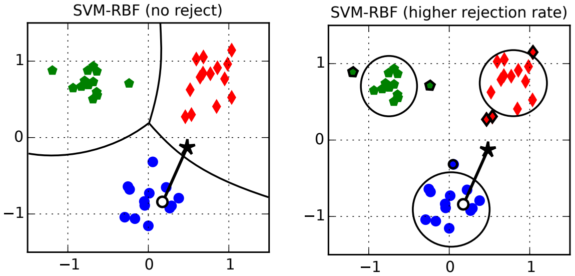
Security Measures against Evasion Attacks

1. Reduce sensitivity to input changes with **robust optimization**
   - Adversarial Training / Regularization

$$\min_{\boldsymbol{w}} \sum\nolimits_i \max_{||\boldsymbol{\delta}_i|| \leq \epsilon} \ell(y_i, f_{\boldsymbol{w}}(\boldsymbol{x}_i + \boldsymbol{\delta}_i))$$

bounded perturbation!

2. Introduce ***rejection / detection*** of adversarial examples



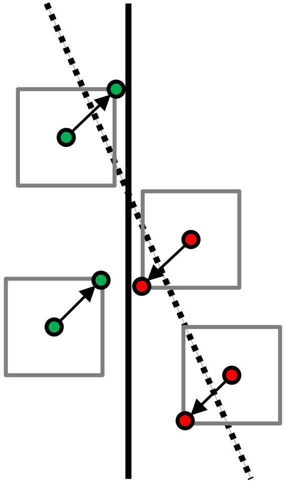
Countering Evasion:
Robust Optimization / Adversarial Training

Robust Optimization via Adversarial Training (AT)

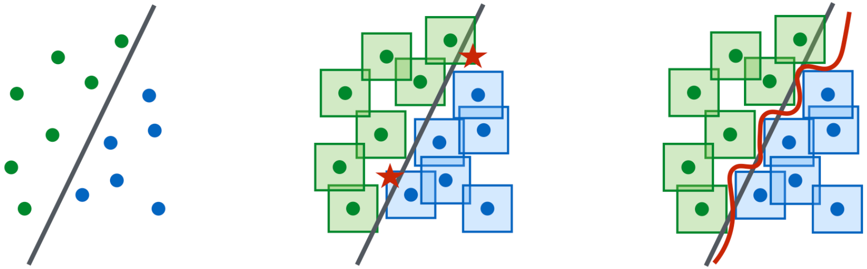
- Robust optimization (a.k.a. *adversarial training*)

$$\min_{\boldsymbol{w}} \max_{||\boldsymbol{\delta}_i||_\infty \le \epsilon} \sum_i \ell\left(y_i, f_{\boldsymbol{w}}(\boldsymbol{x}_i + \boldsymbol{\delta}_i)\right)$$

bounded perturbation!



- Madry et al., ICLR 2018 (https://arxiv.org/pdf/1706.06083.pdf)
  - PGD-AT better than FGSM-AT but more computationally costly
  - Fast AT (NeurIPS 2020, https://arxiv.org/abs/2007.02617)



Robust Optimization via Regularization

- Robust optimization (a.k.a. *adversarial training*)

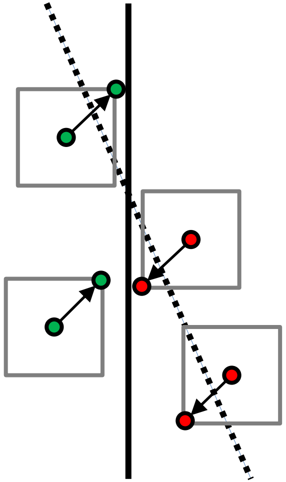
$$\min_{\boldsymbol{w}} \max_{||\boldsymbol{\delta}_i||_\infty \leq \epsilon} \sum_i \ell\left(y_i, f_{\boldsymbol{w}}(\boldsymbol{x}_i + \boldsymbol{\delta}_i)\right)$$

bounded perturbation!

- Robustness and regularization (Xu et al., JMLR 2009)
  - under linearity of ℓ and $f_{\boldsymbol{w}}$, equivalent to robust optimization

$$\min_{\boldsymbol{w}} \sum_{\boldsymbol{i}} \ell\left(y_i, f_{\boldsymbol{w}}(\boldsymbol{x}_i)\right) + \epsilon||\nabla_{\boldsymbol{x}} f||_1$$

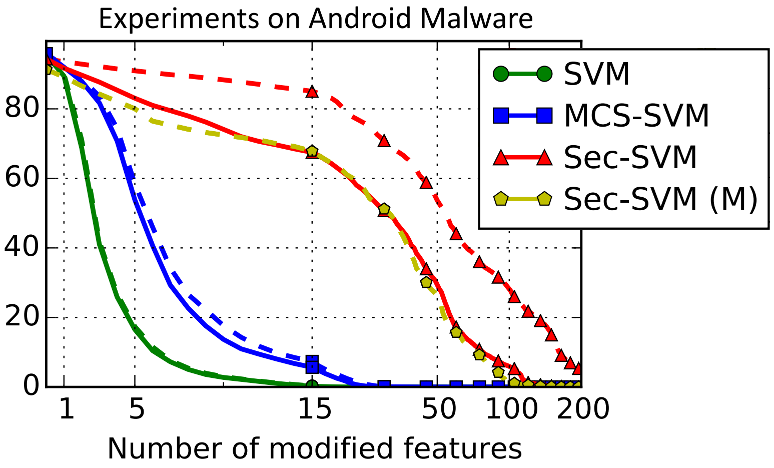
dual norm of the perturbation
$||\nabla_{\boldsymbol{x}} f||_1 = ||\boldsymbol{w}||_1$



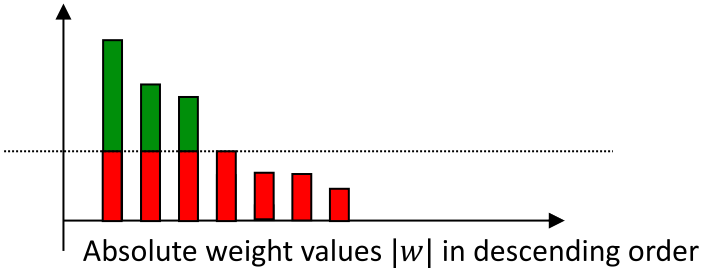
Results on *Adversarial* Android Malware

- **Infinity-norm regularization** is the optimal regularizer against **sparse evasion attacks**
  - Sparse evasion attacks penalize $||\boldsymbol{\delta}||_1$ promoting the manipulation of only few features

Sec-SVM $$\min_{w,b} \|w\|_\infty + C \sum_i \max\left(0, 1 - y_i f(x_i)\right), \quad \|w\|_\infty = \max_{i=1,\dots,d} |w_i|$$



Why? It bounds the maximum weight absolute values!



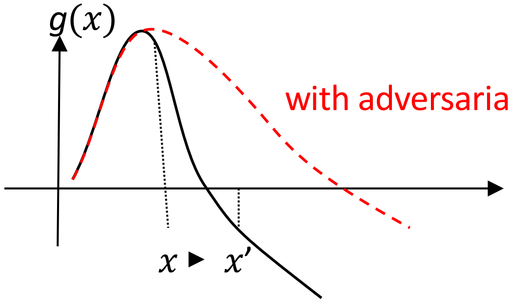
[Demontis, Biggio et al., Yes, ML Can Be More Secure!..., IEEE TDSC 2017]

Adversarial Training and Regularization

- Adversarial training can also be seen as a form of regularization, which penalizes the (dual) norm of the input gradients $\epsilon||\nabla_{\mathbf{x}}\ell||_{\mathrm{q}}$

- Known as double backprop or gradient/Jacobian regularization
  - see, e.g., *Simon-Gabriel et al., Adversarial vulnerability of neural networks increases with input dimension, ArXiv 2018*; and *Lyu et al., A unified gradient regularization family for adversarial examples, ICDM 2015.*

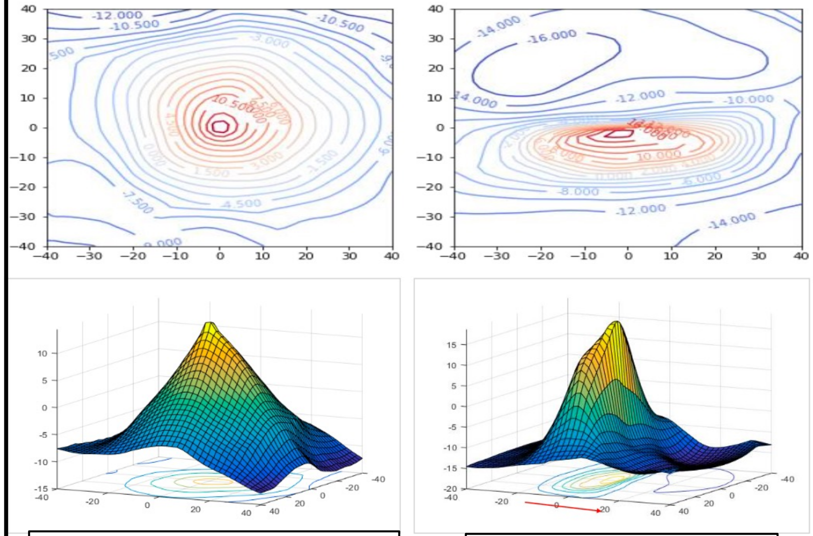
Take-home message: the net effect of these techniques is to make the prediction function of the classifier smoother (increasing the input margin)



Why Does Robust Optimization Work?

CIFAR-10

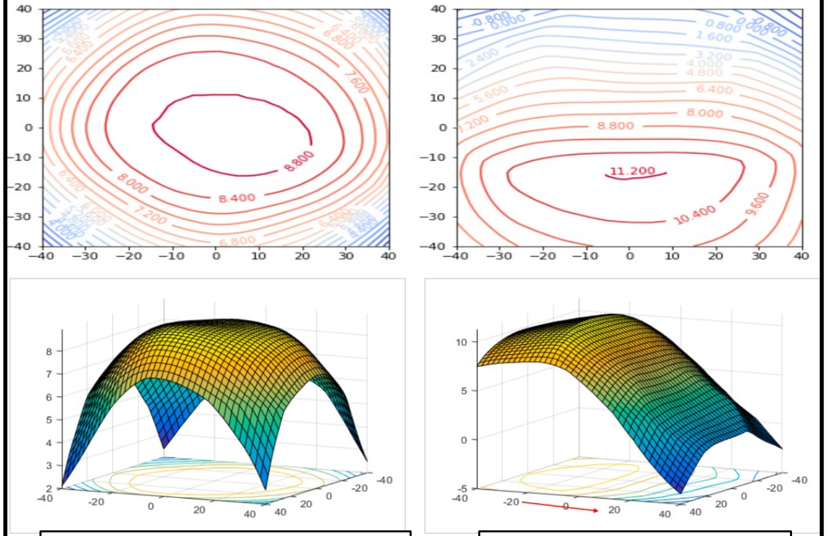
Undefended model – Adversarial accuracy: 0.3%



random perturbation

adv. perturbation

Defended model – Adversarial accuracy: 44.7%



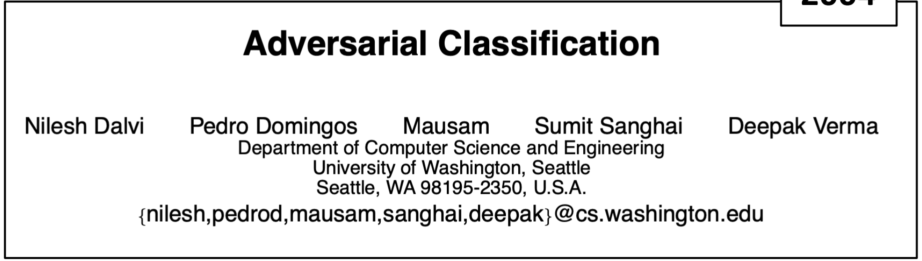
random perturbation

adv. perturbation

Yu et al., Interpreting and Evaluating NN Robustness, IJCAI 2019

On Adversarial Training...

2004



Adversarial Classification

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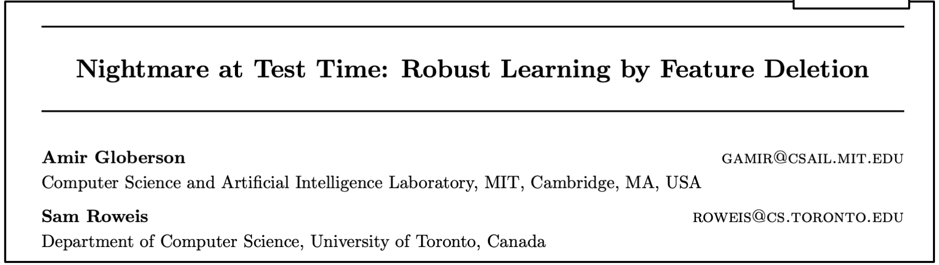
Department of Computer Science and Engineering
University of Washington, Seattle
Seattle, WA 98195-2350, U.S.A.
{nilesh,pedrod,mausam,sanghai,deepak}@cs.washington.edu

2006

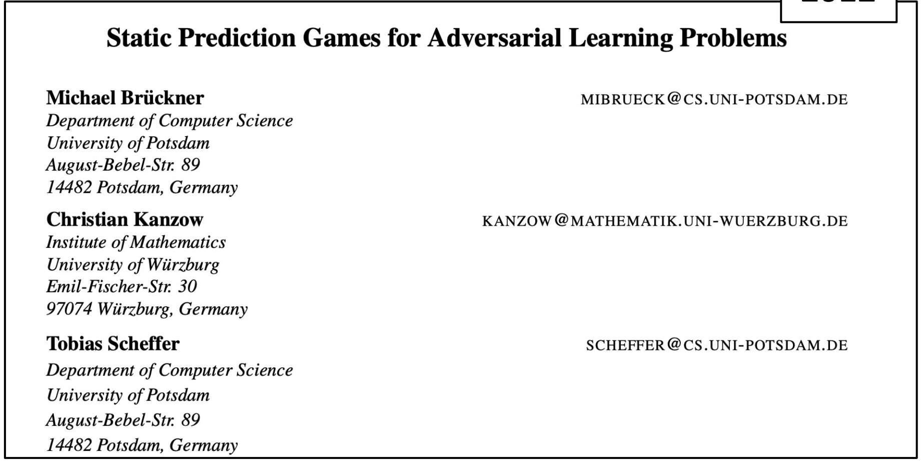


Nightmare at Test Time: Robust Learning by Feature Deletion

Amir Globerson GAMIR@CSAIL.MIT.EDU
Computer Science and Artificial Intelligence Laboratory, MIT, Cambridge, MA, USA

Sam Roweis ROWEIS@CS.TORONTO.EDU
Department of Computer Science, University of Toronto, Canada

2012



Static Prediction Games for Adversarial Learning Problems

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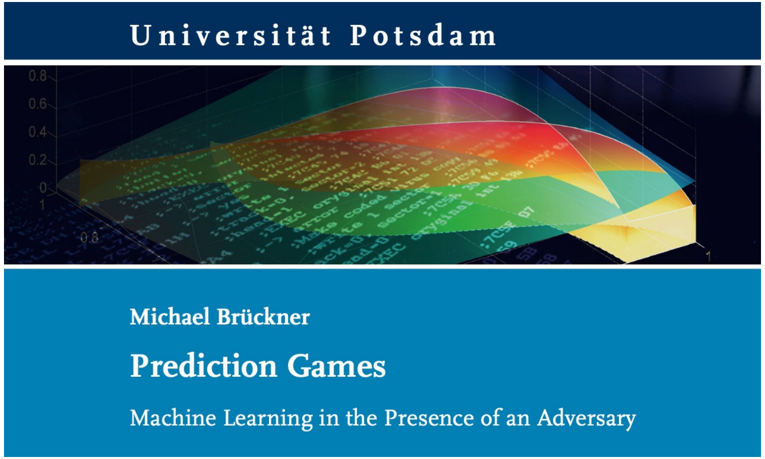


Universität Potsdam

Michael Brückner

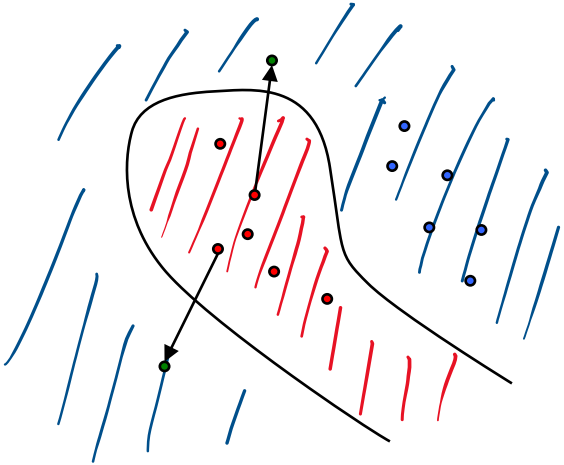
Prediction Games

Machine Learning in the Presence of an Adversary

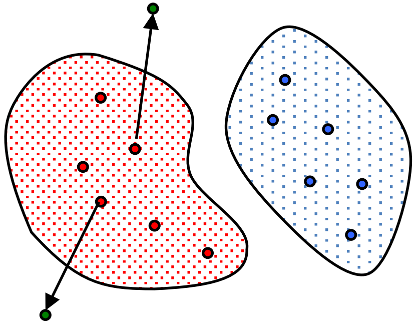
Countering Evasion:
Detecting & Rejecting Adversarial Examples

Detecting and Rejecting Adversarial Examples

- Adversarial examples tend to occur in *blind spots*
  - Regions far from training data that are anyway assigned to ‘legitimate’ classes

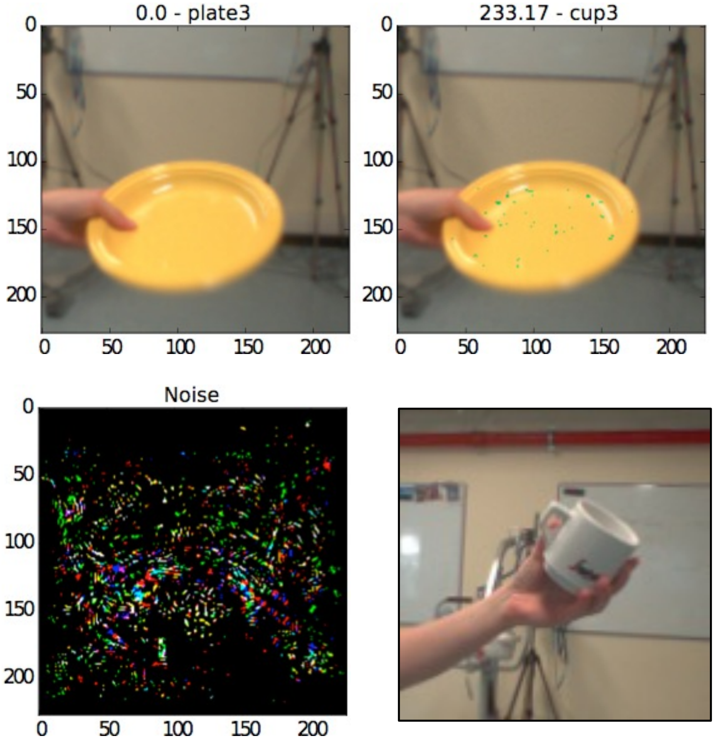


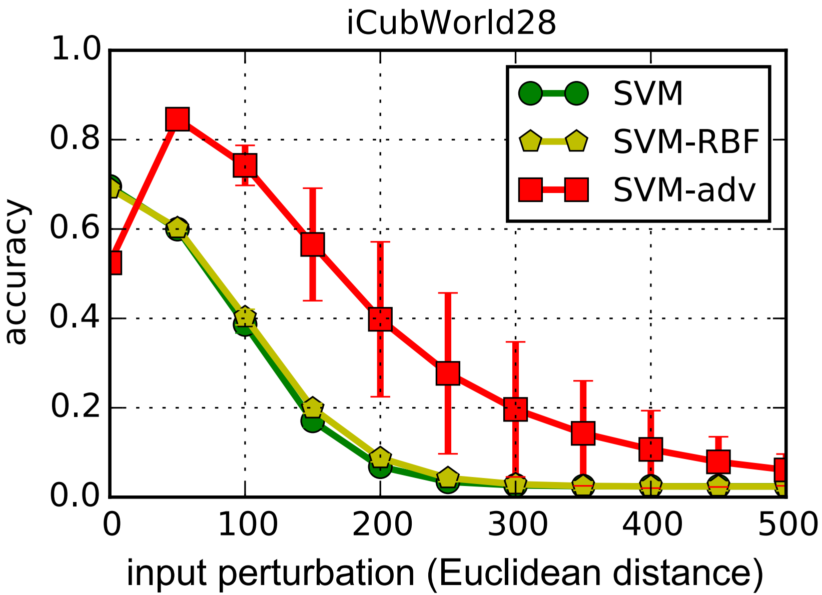
blind-spot evasion
(not even required to
mimic the target class)



rejection of adversarial examples through
enclosing of legitimate classes

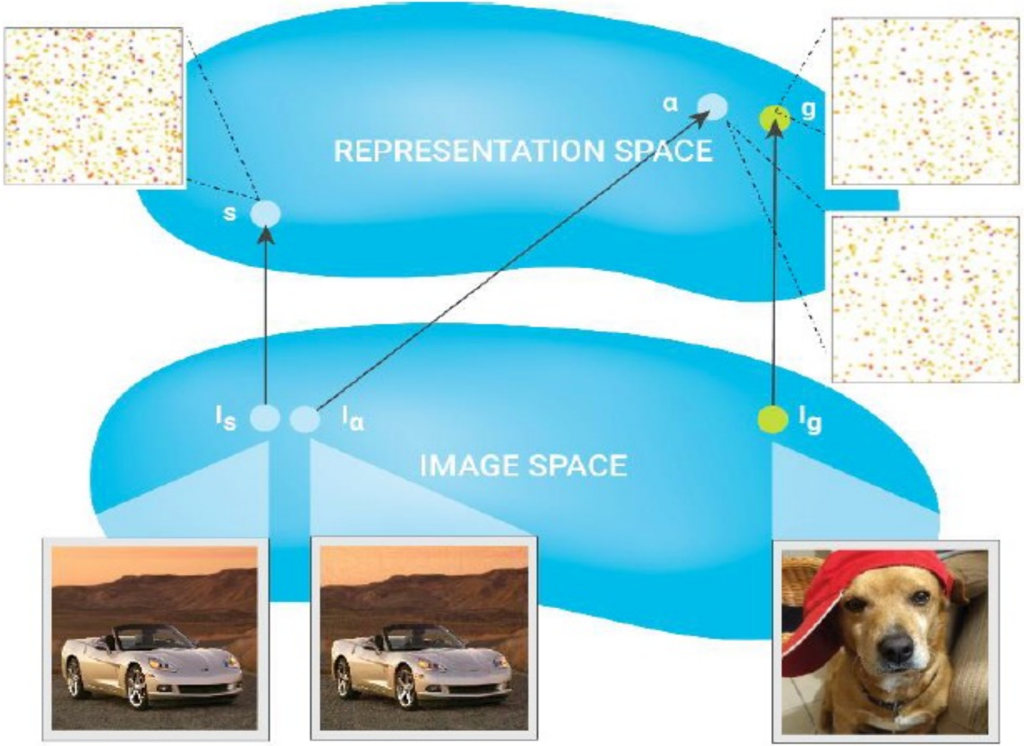
Detecting & Rejecting Adversarial Examples





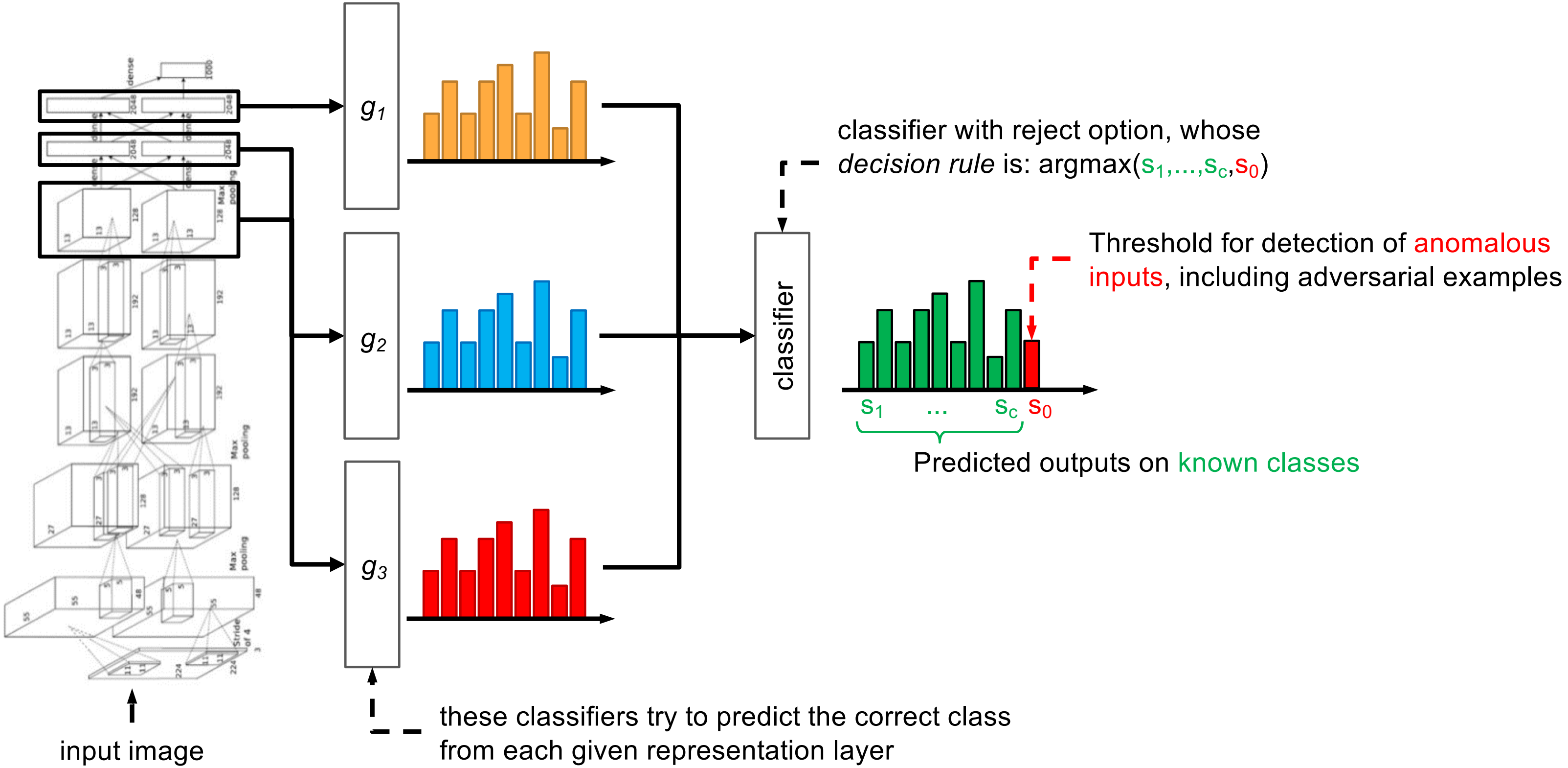
[Melis, Biggio et al., Is Deep Learning Safe for Robot Vision? ICCVW ViPAR 2017]

Why Rejection (in Representation Space) Is Not Enough?



S. Sabour at al., ICLR 2016

Deep Neural Rejection against Adversarial Examples



classifier with reject option, whose *decision rule* is: argmax($s_1,\ldots,s_c,s_0$)

Threshold for detection of anomalous inputs, including adversarial examples

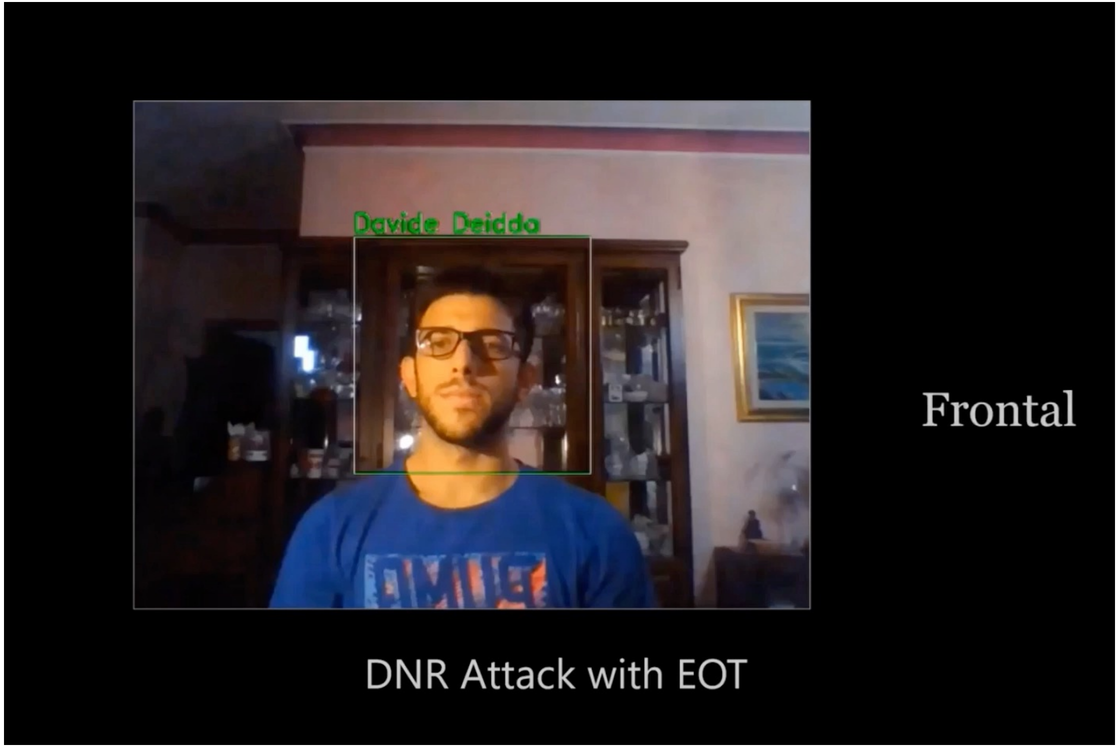
Predicted outputs on known classes

input image

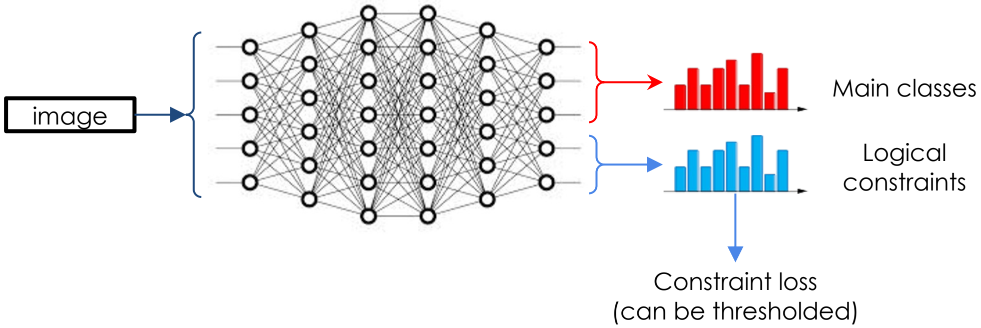
these classifiers try to predict the correct class from each given representation layer

Sotgiu, Biggio et al., EURASIP JIS, 2020

DNR against Physical Attacks

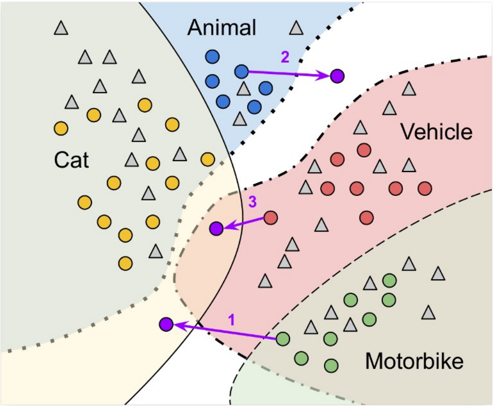


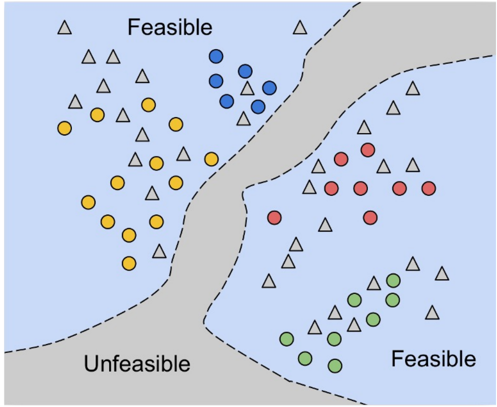
Robust Learning with Domain Knowledge



$$
\begin{aligned}
\forall x, &\quad \mathrm{CAT}(x) \Rightarrow \mathrm{ANIMAL}(x)\,, \\
\forall x, &\quad \mathrm{MOTORBIKE}(x) \Rightarrow \mathrm{VEHICLE}(x)\,, \\
\forall x, &\quad \mathrm{VEHICLE}(x) \Rightarrow \neg\mathrm{ANIMAL}(x)\,, \\
\forall x, &\quad \mathrm{CAT}(x) \vee \mathrm{ANIMAL}(x) \vee \mathrm{MOTORBIKE}(x) \vee \mathrm{VEHICLE}(x)
\end{aligned}
$$

$$
\min_{\mathbf{f}} = \boxed{\frac{1}{n}\sum_{i=1}^{l} L_y(\mathbf{f}(\mathbf{x}_i), \mathbf{y}_i)} + \boxed{\sum_{j=1}^{l+u}\sum_{h=1}^{m} \lambda_m \cdot L_\phi(\phi_h(\mathbf{f}(\mathbf{x}_j)))} + \lambda \|\mathbf{f}\|
$$





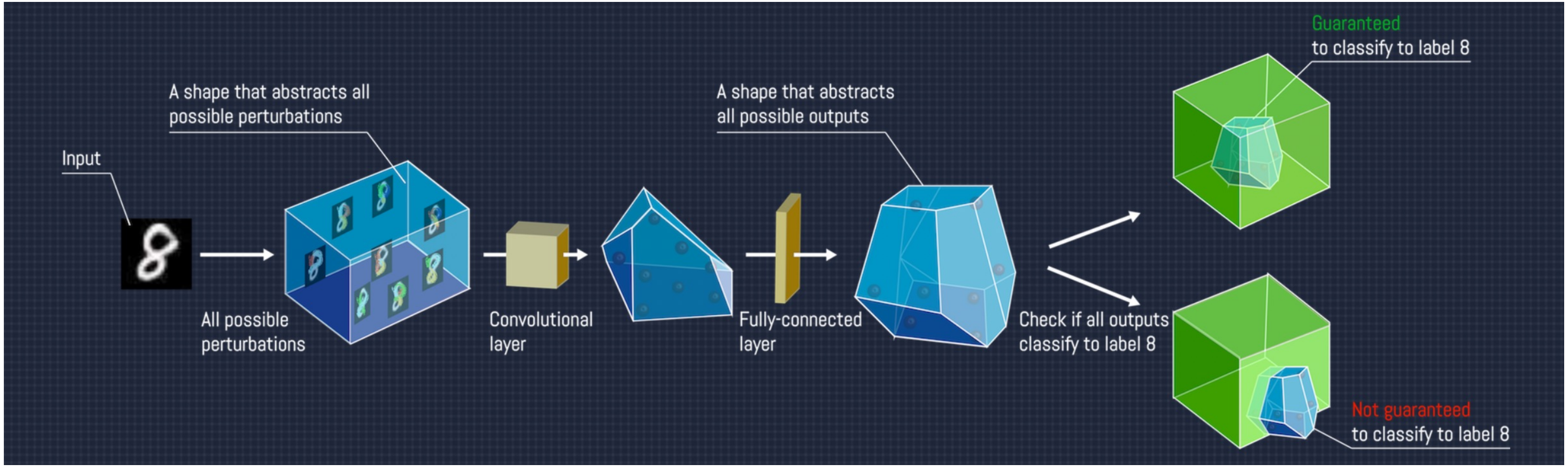
Melacci, Biggio et al., IEEE TPAMI 2022 https://arxiv.org/abs/2006.03833

Certified Defenses

Formal Verification via Abstract Interpretation

Interval Bound Propagation (IBP)

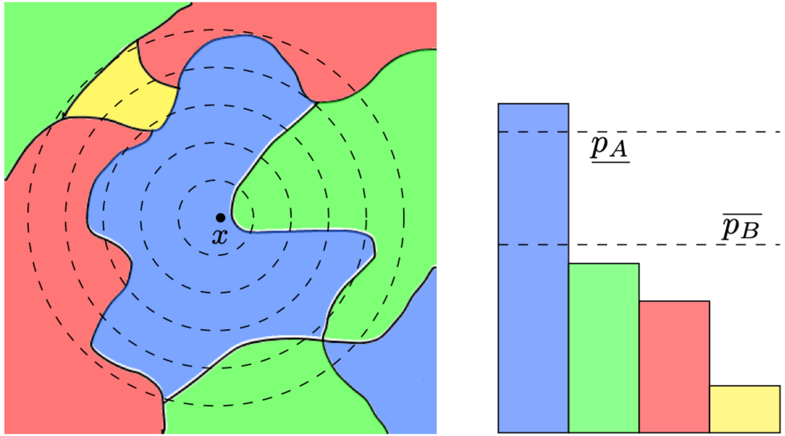
AI2: Safety and Robustness Certification of Neural Networks with Abstract Interpretation, IEEE S&P 2018
Timon Gehr, Matthew Mirman, Dana Drachsler-Cohen, Petar Tsankov, Swarat Chaudhuri, Martin Vechev


Input
A shape that abstracts all possible perturbations
All possible perturbations
Convolutional layer
A shape that abstracts all possible outputs
Fully-connected layer
Check if all outputs classify to label 8
Guaranteed to classify to label 8
Not guaranteed to classify to label 8

http://safeai.ethz.ch

Randomized Smoothing

- Formal guarantee on adversarial robustness (a.k.a. *provable robustness*)
  - classification is consistent within l2 perturbations of size less than a given radius



$$g(x) = \arg\max_{c \in \mathcal{Y}} \mathbb{P}(f(x+\varepsilon) = c) \qquad (1)$$

where $\varepsilon \sim \mathcal{N}(0, \sigma^2 I)$

Theorem 1. *Let $f : \mathbb{R}^d \to \mathcal{Y}$ be any deterministic or random function, and let $\varepsilon \sim \mathcal{N}(0, \sigma^2 I)$. Let g be defined as in (1). Suppose $c_A \in \mathcal{Y}$ and $\underline{p_A}, \overline{p_B} \in [0,1]$ satisfy:*

$$\mathbb{P}(f(x+\varepsilon) = c_A) \geq \underline{p_A} \geq \overline{p_B} \geq \max_{c \neq c_A} \mathbb{P}(f(x+\varepsilon) = c) \quad (2)$$

Then $g(x+\delta) = c_A$ for all $\|\delta\|_2 < R$, where

$$R = \frac{\sigma}{2}(\Phi^{-1}(\underline{p_A}) - \Phi^{-1}(\overline{p_B})) \qquad (3)$$

Cohen et al., ICML 2019 https://arxiv.org/abs/1902.02918

Certified Defenses against Patch Attacks

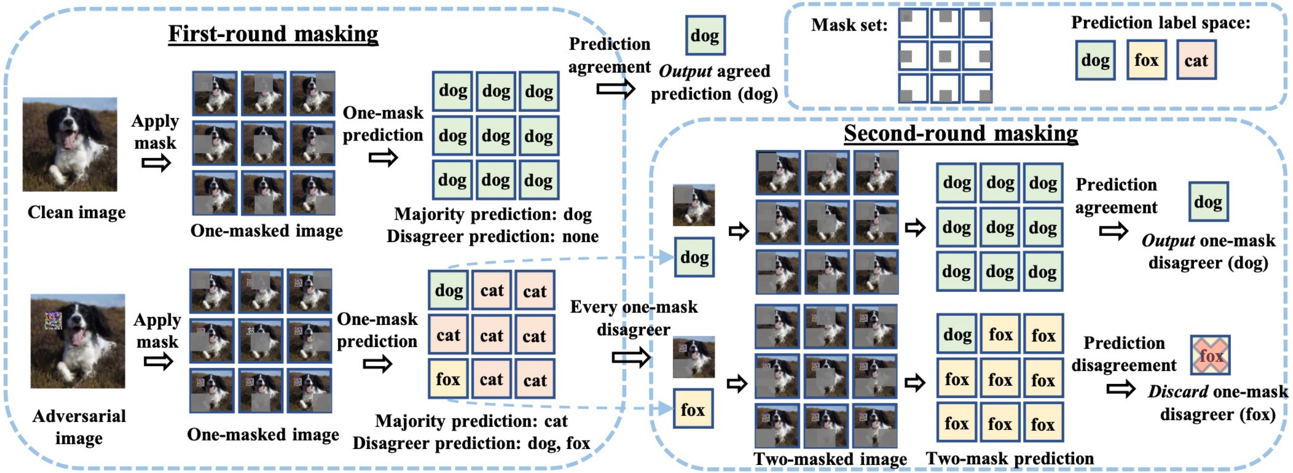


Figure 1: **Overview of double-masking defense.** The defense applies masks to the input image and evaluates model prediction on every masked image. *Clean image:* all one-mask predictions typically agree on the correct label (“dog"); our defense outputs the agreed prediction. *Adversarial image:* one-mask predictions have a disagreement; we aim to recover the benign prediction. We first categorize all one-mask predictions into the *majority prediction* (the one with the highest prediction label occurrence; the label “cat" in this example) and *disagreer predictions* (the ones that disagree with the majority; the labels “dog" and “fox"). For every mask that leads to a disagreer prediction, we add a set of second masks and evaluate two-mask predictions. If all two-mask predictions agree with this one-mask disagreer, we *output* its prediction label (the label “dog"; illustrated in the upper row of the second-round masking); otherwise, we *discard* it (the label “fox"; in the lower row of the second-round masking).

Xiang et al., PatchCleanser: … , USENIX Sec. 2022

Certified Defenses against Patch Attacks

- PatchCleanser (PC) can certify classification up to a given patch size and for a fraction of the input samples
  - Robust accuracy here is certified. It means that no attack can decrease it further, but also that empirical attacks may perform worse…
    - i.e., a gradient-based attack may actually turn out to find a higher robustness!

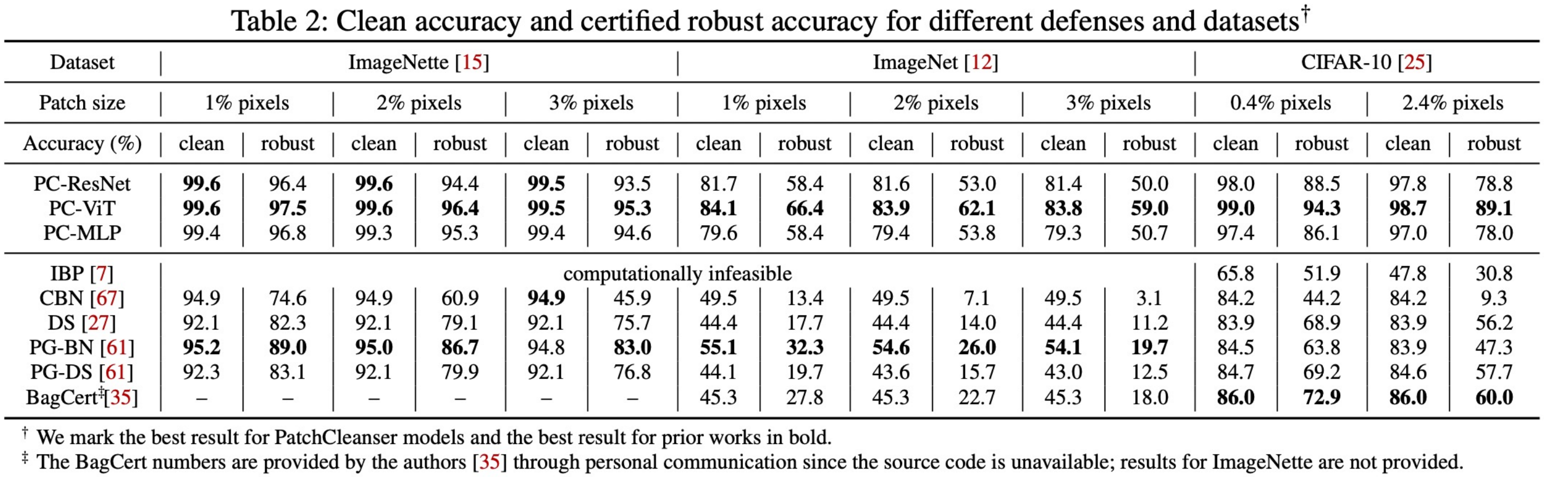


Table 2: Clean accuracy and certified robust accuracy for different defenses and datasets[†]

Dataset	ImageNette [15]						ImageNet [12]						CIFAR-10 [25]			
Patch size	1% pixels		2% pixels		3% pixels		1% pixels		2% pixels		3% pixels		0.4% pixels		2.4% pixels	
Accuracy (%)	clean	robust	clean	robust	clean	robust	clean	robust	clean	robust	clean	robust	clean	robust	clean	robust
PC-ResNet	**99.6**	96.4	**99.6**	94.4	**99.5**	93.5	81.7	58.4	81.6	53.0	81.4	50.0	98.0	88.5	97.8	78.8
PC-ViT	**99.6**	**97.5**	**99.6**	**96.4**	**99.5**	**95.3**	**84.1**	**66.4**	**83.9**	**62.1**	**83.8**	**59.0**	**99.0**	**94.3**	**98.7**	**89.1**
PC-MLP	99.4	96.8	99.3	95.3	99.4	94.6	79.6	58.4	79.4	53.8	79.3	50.7	97.4	86.1	97.0	78.0
IBP [7]	computationally infeasible												65.8	51.9	47.8	30.8
CBN [67]	94.9	74.6	94.9	60.9	**94.9**	45.9	49.5	13.4	49.5	7.1	49.5	3.1	84.2	44.2	84.2	9.3
DS [27]	92.1	82.3	92.1	79.1	92.1	75.7	44.4	17.7	44.4	14.0	44.4	11.2	83.9	68.9	83.9	56.2
PG-BN [61]	**95.2**	**89.0**	**95.0**	**86.7**	94.8	**83.0**	**55.1**	**32.3**	**54.6**	**26.0**	**54.1**	**19.7**	84.5	63.8	83.9	47.3
PG-DS [61]	92.3	83.1	92.1	79.9	92.1	76.8	44.1	19.7	43.6	15.7	43.0	12.5	84.7	69.2	84.6	57.7
BagCert[‡][35]	–	–	–	–	–	–	45.3	27.8	45.3	22.7	45.3	18.0	**86.0**	**72.9**	**86.0**	**60.0**

[†] We mark the best result for PatchCleanser models and the best result for prior works in bold.

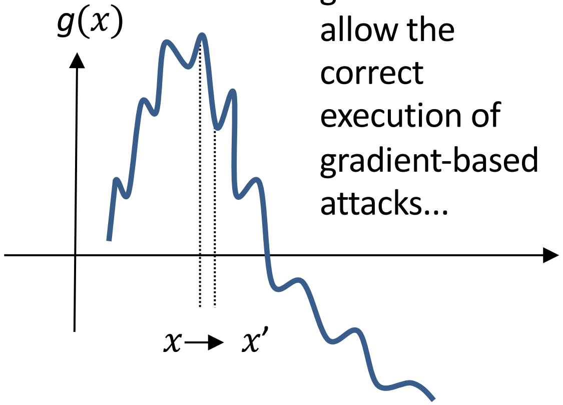
[‡] The BagCert numbers are provided by the authors [35] through personal communication since the source code is unavailable; results for ImageNette are not provided.

Xiang et al., PatchCleanser: … , USENIX Sec. 2022

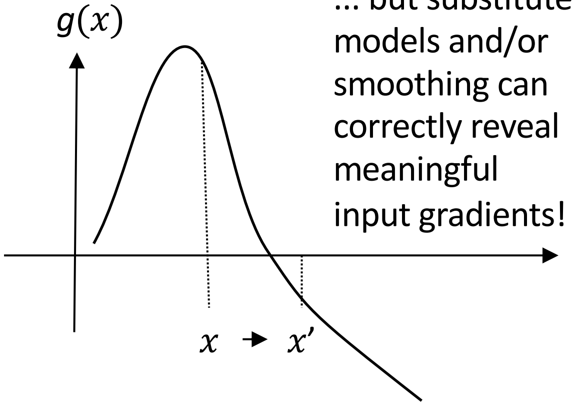
Shall We Trust Empirical Evaluations?

Ineffective Defenses: Obfuscated Gradients

- Carlini & Wagner (SP’ 17), Athalye et al. (ICML ‘18), Tramer et al. (NeurIPS ‘20) have shown that
  - some recently-proposed defenses rely on obfuscated / masked gradients...
  - ... and they can be circumvented



Obfuscated gradients do not allow the correct execution of gradient-based attacks...



... but substitute models and/or smoothing can correctly reveal meaningful input gradients!

Backward Pass Differentiable Approximation (BPDA)

- If gradients of a DNN are “unavailable” at some representation level g(x), e.g. when inputs are discretized or non-differentiable transformations are applied, one can approximate g(x) in the backward pass with a smoother function which approximates it
  - e.g. Distillation, Thermometer Encoding, JPEG compression

$$\nabla_x f(g(x))|_{x=\hat{x}} \approx \nabla_x f(x)|_{x=g(\hat{x})}$$

- **Trivial case:** just replace the gradient of g(x) with ones during the backward pass

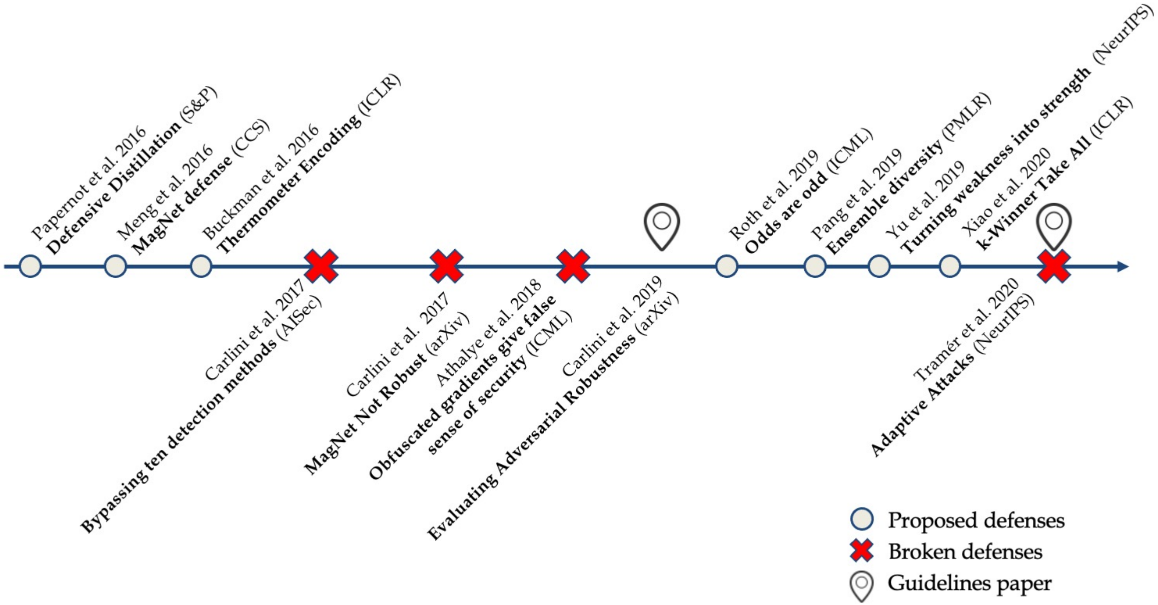
Athalye et al., Obfuscated gradients give a false sense of security: …. ICML 2018

Detecting Unrealiable Evaluations

Detect and Avoid Flawed Evaluations

- **Problem**: formal evaluations do not scale, adversarial robustness evaluated mostly empirically, via gradient-based attacks

- **Gradient-based attacks can fail:** many flawed evaluations have been reported, with defenses easily broken by adjusting/fixing the attack algorithms



Papernot et al. 2016 **Defensive Distillation** (S&P)

Meng et al. 2016 **MagNet defense** (CCS)

Buckman et al. 2016 **Thermometer Encoding** (ICLR)

Carlini et al. 2017 **Bypassing ten detection methods** (AISec)

Carlini et al. 2017 **MagNet Not Robust** (arXiv)

Athalye et al. 2018 **Obfuscated gradients give false sense of security** (ICML)

Carlini et al. 2019 **Evaluating Adversarial Robustness** (arXiv)

Roth et al. 2019 **Odds are odd** (ICML)

Pang et al. 2019 **Ensemble diversity** (PMLR)

Yu et al. 2019 **Turning weakness into strength** (NeurIPS)

Xiao et al. 2020 **k-Winner Take All** (ICLR)

Tramér et al. 2020 **Adaptive Attacks** (NeurIPS)

○ Proposed defenses

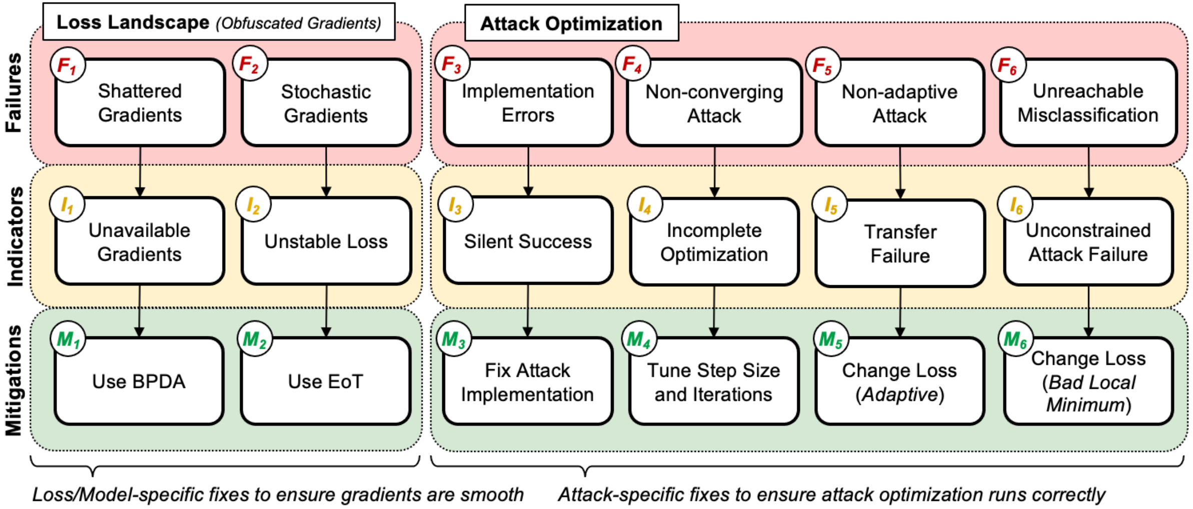
✖ Broken defenses

⚲ Guidelines paper

Pintor, Biggio et al., *Indicators of Attack Failure: …*, NeurIPS 2022

Detect and Avoid Flawed Evaluations

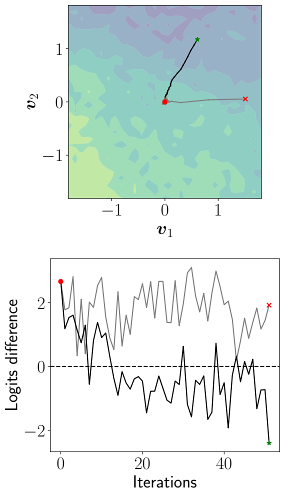
- This work identifies the main causes of **failure**, devises quantitative **indicators** for them, and the corresponding **mitigation** strategies
  - The process can be automated by following a specific evaluation protocol!



	Loss Landscape *(Obfuscated Gradients)*		**Attack Optimization**			
Failures	*F₁* Shattered Gradients	*F₂* Stochastic Gradients	*F₃* Implementation Errors	*F₄* Non-converging Attack	*F₅* Non-adaptive Attack	*F₆* Unreachable Misclassification
Indicators	*I₁* Unavailable Gradients	*I₂* Unstable Loss	*I₃* Silent Success	*I₄* Incomplete Optimization	*I₅* Transfer Failure	*I₆* Unconstrained Attack Failure
Mitigations	*M₁* Use BPDA	*M₂* Use EoT	*M₃* Fix Attack Implementation	*M₄* Tune Step Size and Iterations	*M₅* Change Loss *(Adaptive)*	*M₆* Change Loss *(Bad Local Minimum)*

Loss/Model-specific fixes to ensure gradients are smooth

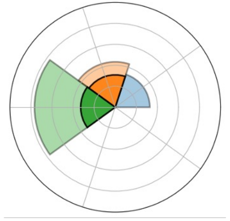
Attack-specific fixes to ensure attack optimization runs correctly



Pintor, Biggio et al., *Indicators of Attack Failure: …*, NeurIPS 2022

Experiments

k-Winners Take All

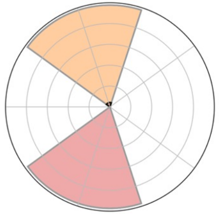


Robust Accuracy

58% → 36% → 6%

Original evaluation → Fix implementation → Change loss function

Distillation

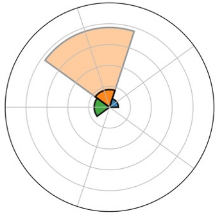


Robust Accuracy

94% → 0%

Original evaluation → Change loss function

Ensemble Diversity

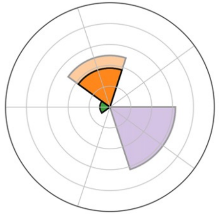


Robust Accuracy

38% → 36% → 9%

Original evaluation → Fix implementation → Tune hyperparameters

Turning a Weakness into a Strength



Robust Accuracy

35% → 0%

Original evaluation → Perform adaptive attack

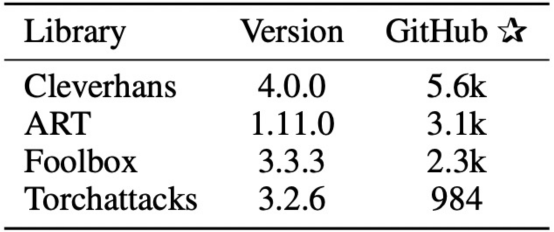
🟦 I_1: Silent Success 🟧 I_2: Break-Point Angle 🟩 I_3: Increasing Loss

🟥 I_4: Zero Gradients 🟪 I_5: Non-transferability

Pintor, Biggio et al., *Indicators of Attack Failure: ...*, NeurIPS 2022

Issues with Existing Libraries / Tools (2022)

- Flawed attack implementations
  - **Cleverhans** (PyTorch, Tensorflow, JAX),
  - **ART** (NumPy, PyTorch, and Tensorflow),
  - **Foolbox** (EagerPy, which wraps the implementation of NumPy, PyTorch, Tensorflow, and JAX)
  - **Torchattacks** (PyTorch)



Library	Version	GitHub ☆
Cleverhans	4.0.0	5.6k
ART	1.11.0	3.1k
Foolbox	3.3.3	2.3k
Torchattacks	3.2.6	984

- **RobustBench/AutoAttack** has a flag to detect *unreliable* evaluations

Pintor, Biggio et al., *Indicators of Attack Failure: …*, NeurIPS 2022

Are Indistinguishable Perturbations a Real Security Threat?

Is This a Real Security Threat?

- **Adversarial examples** can exist in the *physical world*, we can fabricate concrete adversarial objects (glasses, road signs, etc.)

- But the effectiveness of attacks carried out by adversarial objects is still to be investigated with **large-scale experiments** in *realistic* **security scenarios**

- Gilmer et al. (2018) have recently discussed the realism of security threat caused by adversarial examples, pointing out that it should be carefully investigated
  - *Are indistinguishable adversarial examples a real security threat?*
  - For which real security scenarios adversarial examples are the best attack vector? Better than attacking components outside the machine learning component
  - …

Justin Gilmer et al., Motivating the Rules of the Game for Adversarial Example Research, https://arxiv.org/abs/1807.06732

Indistinguishable Adversarial Examples

- Minimize $\|r\|_2$ subject to:
  1. $f(x+r) = l$ $\quad f(x) \neq l$
  2. $x + r \in [0,1]^m$

The adversarial image $x + r$ is visually hard to distinguish from x

*…There is a **torrent of work** that views increased robustness to **restricted perturbations** as making these models **more secure**. While not all of this work requires completely indistinguishable modications, many of the papers focus on specifically small modications, and the language in many suggests or implies that the **degree of perceptibility** of the **perturbations** is an important aspect of their **security risk**…*

Justin Gilmer et al., Motivating the Rules of the Game for Adversarial Example Research, https://arxiv.org/abs/1807.06732

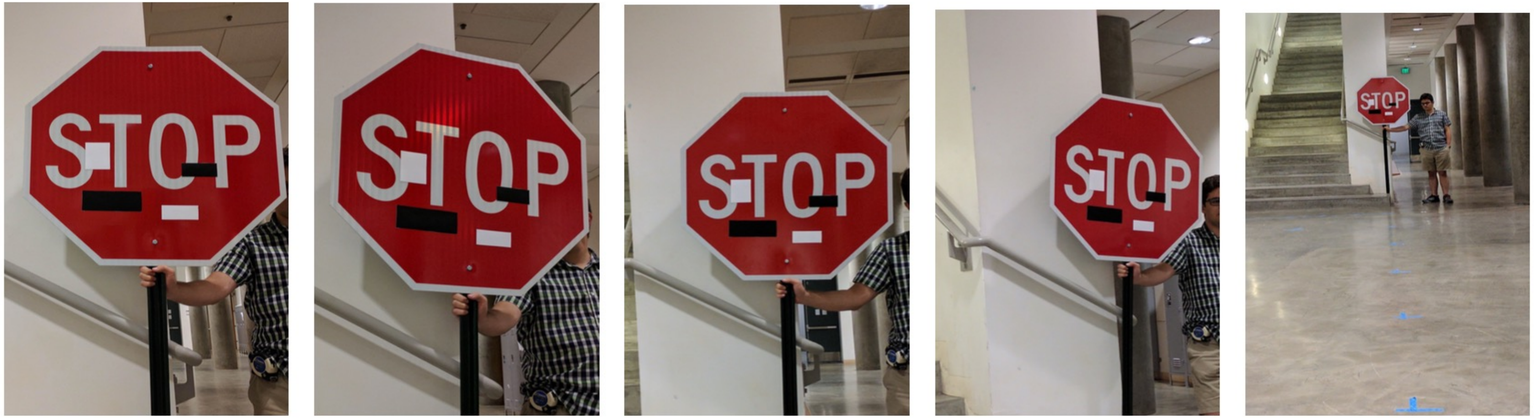
Indistinguishable Adversarial Examples

- The attacker can benefit by minimal perturbation of a legitimate input; e.g., she could use the attack for a longer period of time before it is detected

- But is *minimal perturbation* a necessary constraint for the attacker?

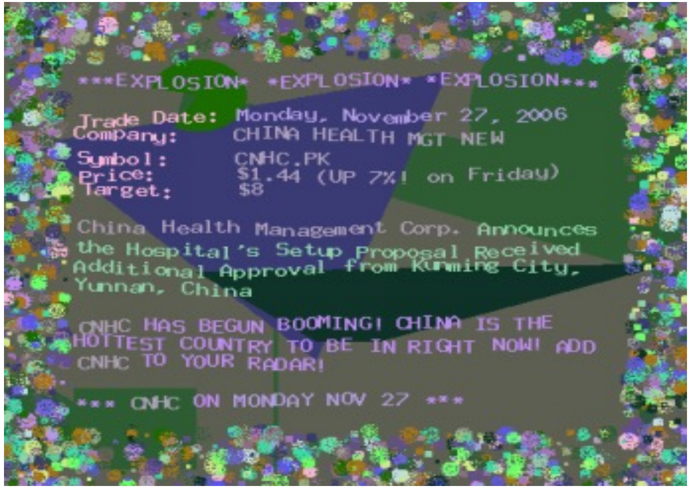
Indistinguishable Adversarial Examples

- Is *minimal perturbation* a necessary constraint for the attacker?



Attacks with Content Preservation

There are well known security applications where minimal perturbations and indistinguishability of adversarial inputs are not required at all…



EXPLOSION* *EXPLOSION* *EXPLOSION

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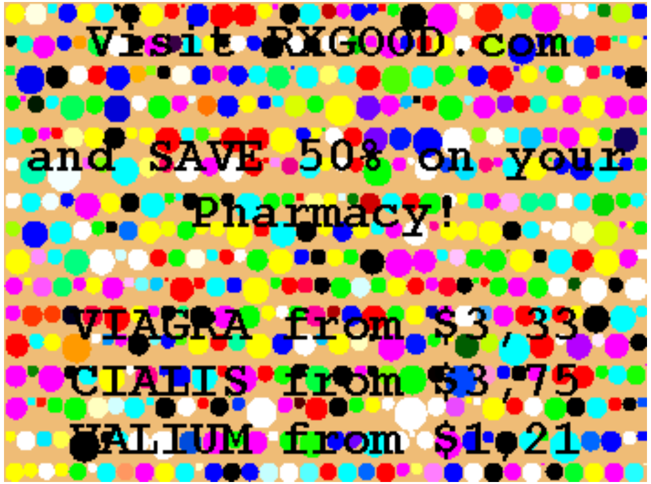

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Are Indistinguishable Perturbations a Real Security Threat?

*…At the time of writing, we were **unable** to find a **compelling example** that **required indistinguishability**…*

*To have the largest impact, we should both recast future adversarial example research as a **contribution** to **core machine learning** and develop new abstractions that capture **realistic threat models**.*

Justin Gilmer et al., Motivating the Rules of the Game for Adversarial Example Research, https://arxiv.org/abs/1807.06732

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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