25/11/2021

Introduction To Adversarial Examples

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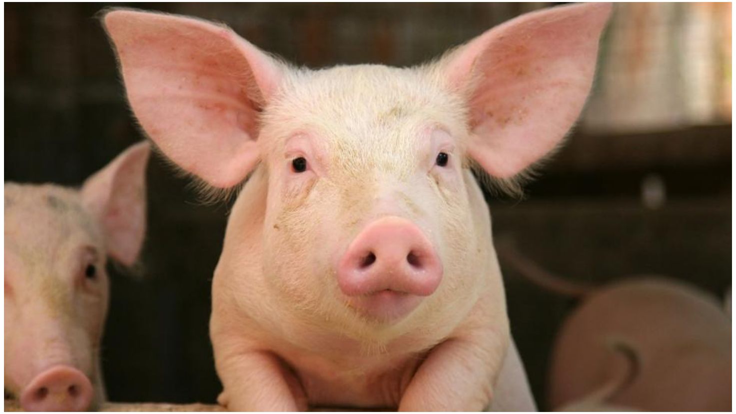
Weizmann Institute
DL4CV Course Winter 2022 (20224182)



+

x 0.02

98.6% pig

=

99.0% airliner

(0.00000000000000
0000000000005% pig...)

Biggio et al. 2013, “Evasion attacks against machine learning at test time”
Szegedy et al. 2014, “Intriguing properties of neural networks”
Goodfellow et al. 2015, “Explaining and Harnessing Adversarial Examples”

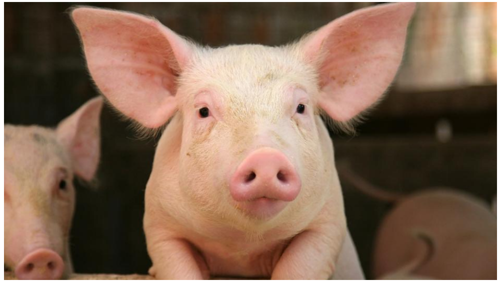
What is an Adversarial Example?

Perturbation Attack

- Originally coined by Szegedy et al., 2013:

“we find that applying an imperceptible non-random perturbation to a test image, it is possible to arbitrarily change the network’s prediction.

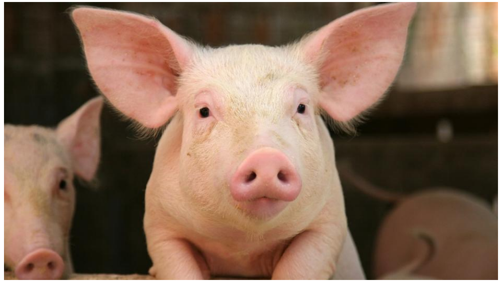
*… we term the so perturbed examples ‘**adversarial examples**’”*



98.6% pig

+

x 0.02 =

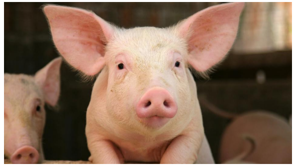


99.0% airliner

Outline

Today we will:

airliner

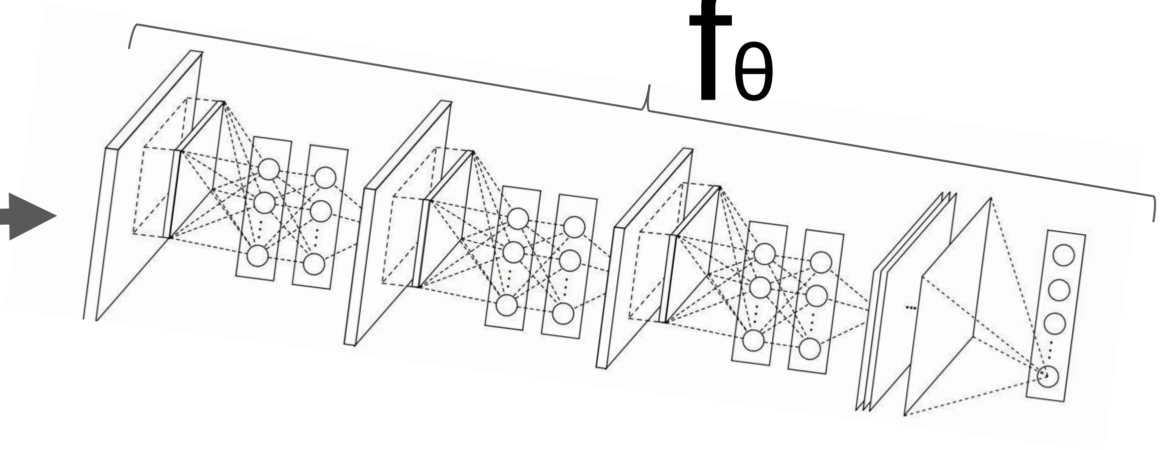


- See Adversarial Example
- Discuss what they are
- Learn how to generate them
- Learn how to (maybe) defend against them
- Learn about properties and advantages

Brief recap on training neural networks

Image by [Simon]() from [Pixabay]()

f_θ

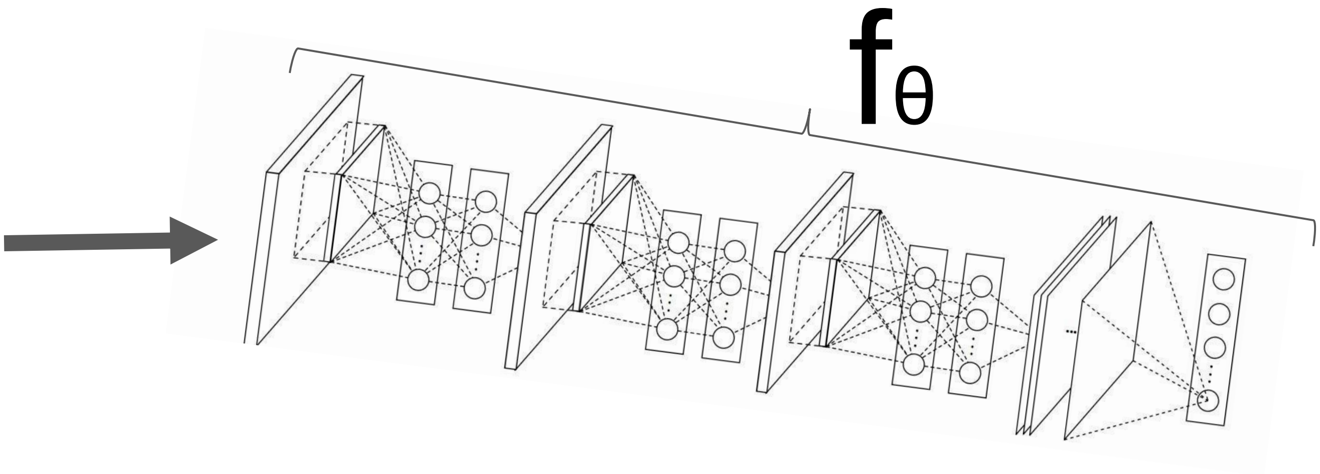


$$L(f_\theta(x),y)$$

purpose of loss:
How “well” we classify

Brief recap on training neural networks

Image by Simon from Pixabay



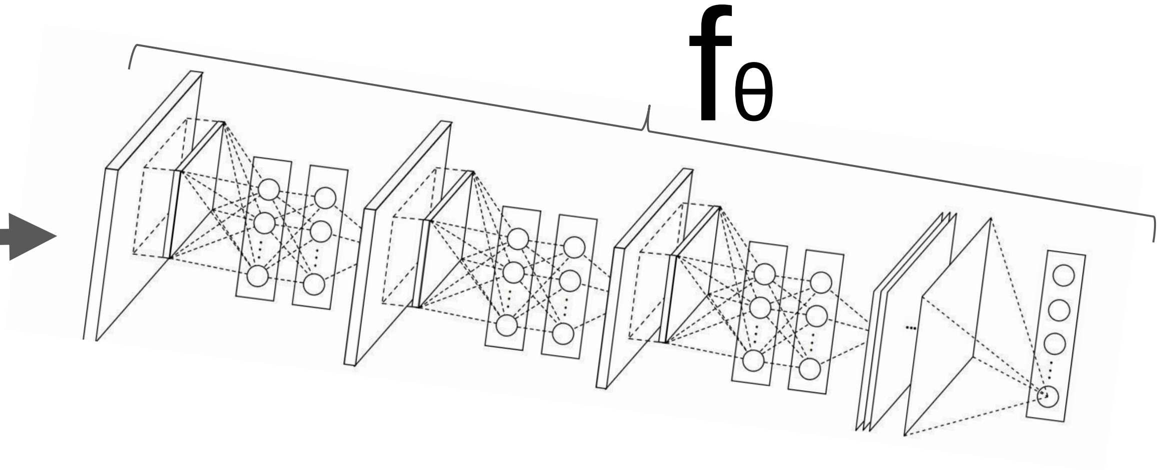
most common loss – CrossEntropy:

$$L(f_\theta(x),y)$$

$$L\left(f_\theta(x), y\right) = -\log\left(\frac{e^{f_\theta(x)_y}}{\sum_j e^{f_\theta(x)_j}}\right)$$

Brief recap on training neural networks

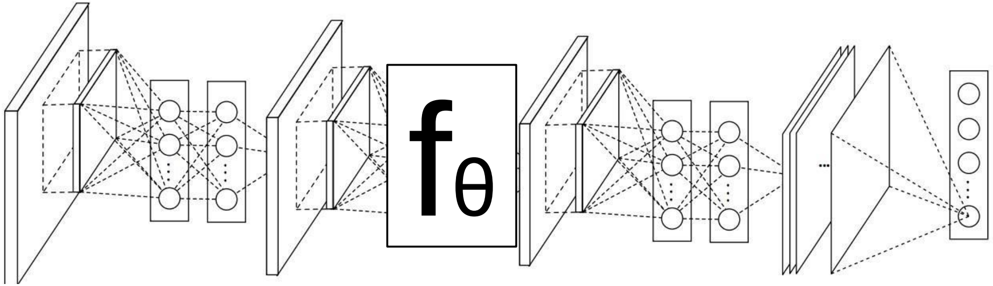
Image by Simon from Pixabay



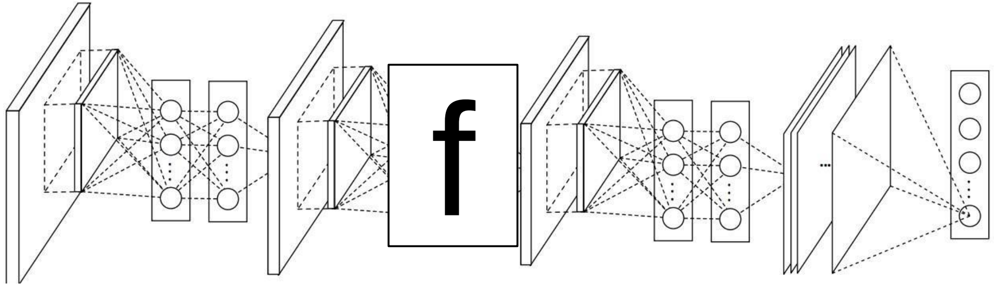
minimize loss:

$$L(f_\theta(x), y) \longrightarrow -\nabla_\theta L$$

Generating an Adversarial Example

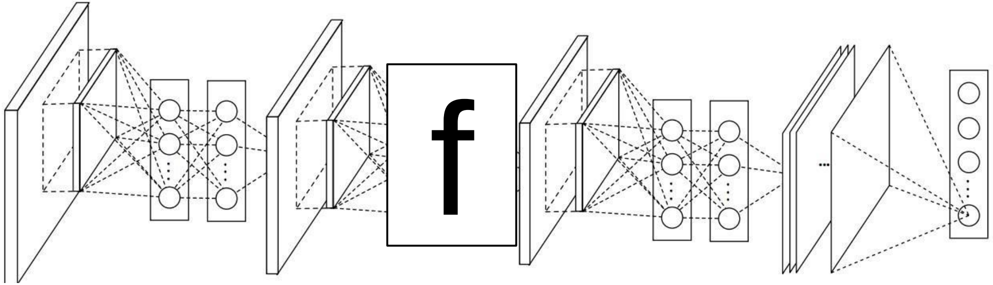


Generating an Adversarial Example



Generating an Adversarial Example

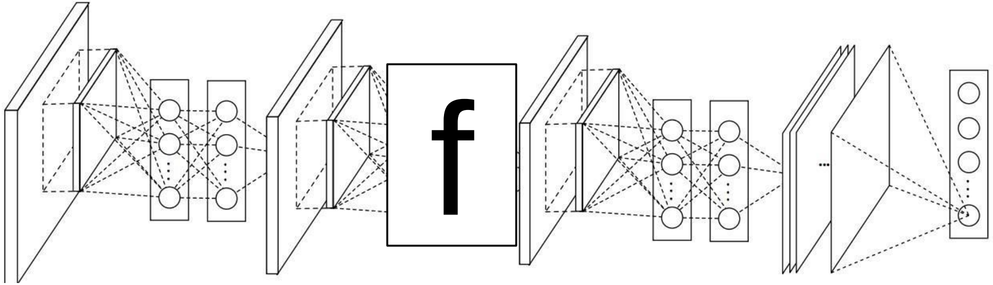
89.7% pig



want to fool classifier
by changing δ

$$f(x\boxed{+\delta})\neq y$$

Generating an Adversarial Example

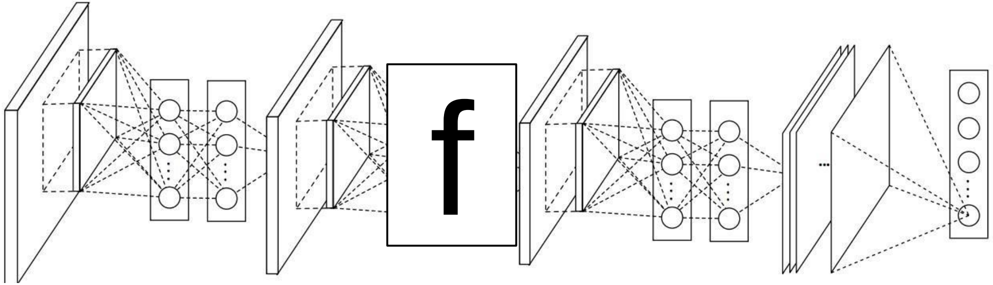


89.7% pig

want to fool classifier → d measures “badness”
by changing δ

$$d(f(x+\delta),y)$$

Generating an Adversarial Example



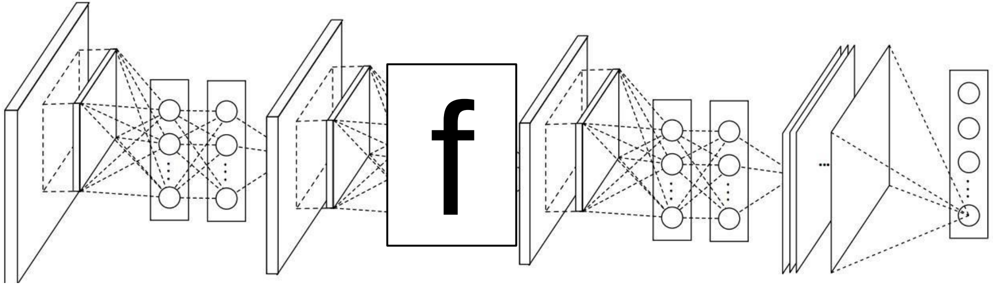
89.7% pig

want to fool classifier → used L to ~~maximize “wellness”~~

maximize “badness”?

$$L(f(x+\delta),y)$$

Generating an Adversarial Example



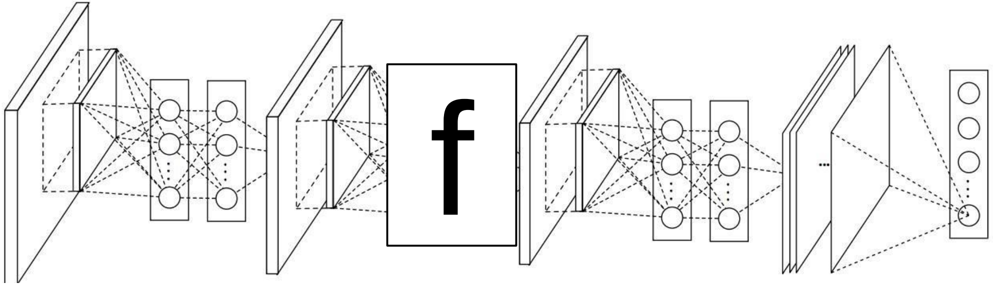
89.7% pig

want to fool classifier → maximize L w.r.t $\boxed{\delta}$

$$L(f(x+\boxed{\delta}),y) \longrightarrow \nabla_{\boxed{\delta}} L$$

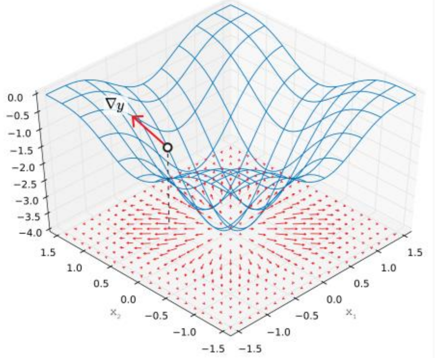
Generating an Adversarial Example

89.7% pig



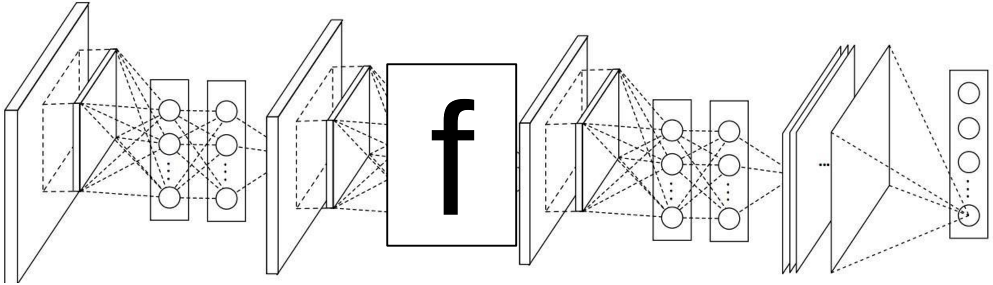
want to fool classifier → maximize L w.r.t δ

$$L(f(x+\delta),y) \longrightarrow +\nabla_{\delta} L$$



Generating an Adversarial Example

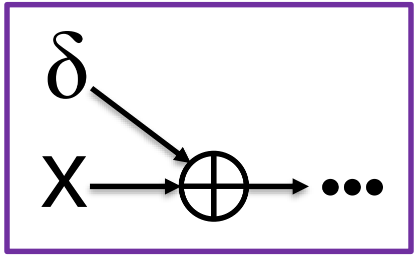
89.7% pig



want to fool classifier → maximize L w.r.t x

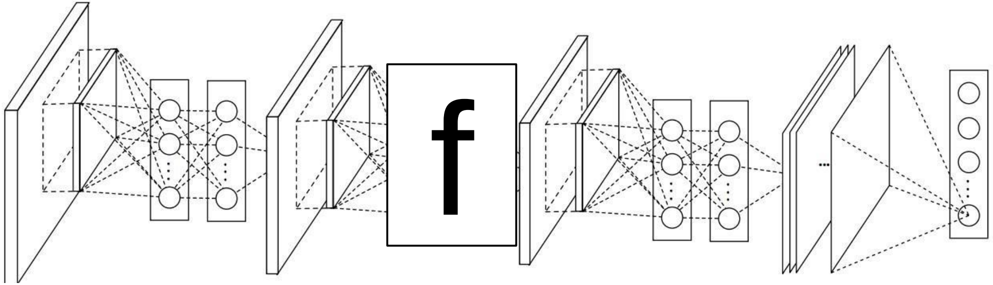
$$L(f(\underbrace{x+\delta}_{\text{input}}),y) \longrightarrow +\nabla_{x} L$$

input



(just a technicality..)

Generating an Adversarial Example



89.7% pig

want to fool classifier → maximize L w.r.t x

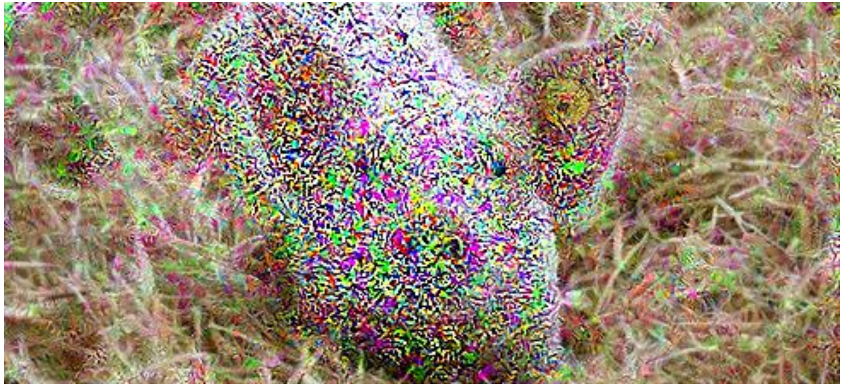
$$L(f(x+\delta),y) \longrightarrow \delta = +\nabla_x L$$

Follow the gradient w.r.t x (the input image)

X (original): 89.7% pig

$X + \nabla_x L$: 68.6% hay

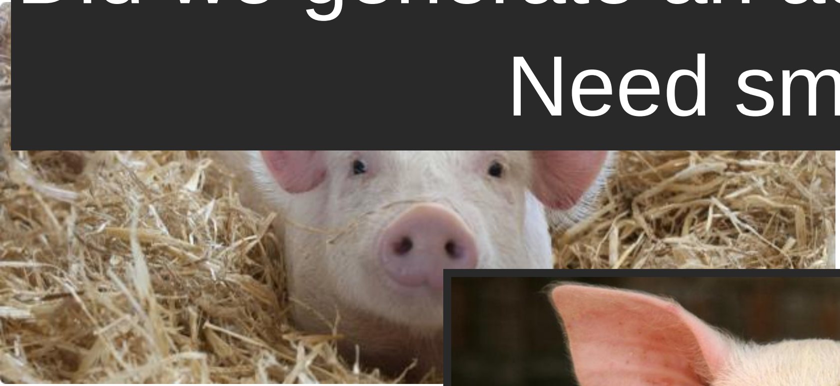
$X + 10\times\nabla_x L$: 44.7% pig

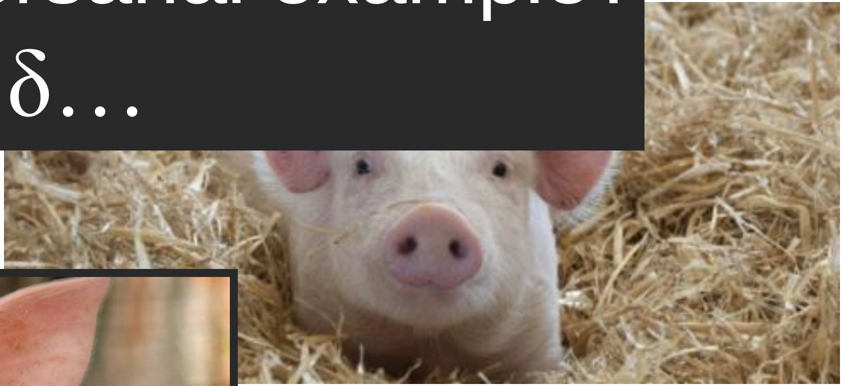


$X + 100\times\nabla_x L$: 44.8% fireguard

Did we generate an adversarial example?

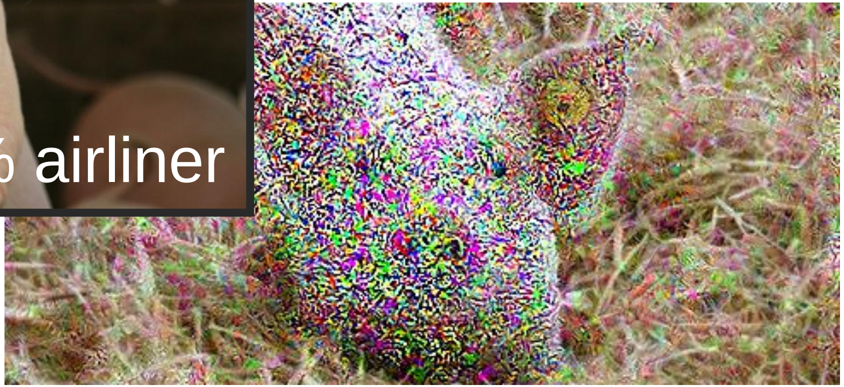
Need small δ…





X (original):

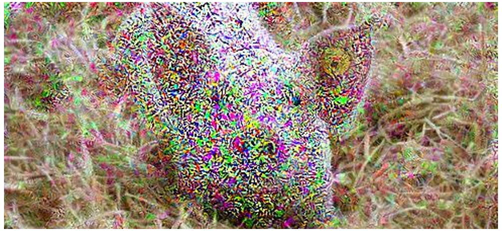
L: 68.6% hay



$X + 10\times\nabla_x L$: 44.7% pig

$X + 100\times\nabla_x L$: 44.8% fireguard

We want *small noise*

 +  = 

X δ

What is small δ?

$$\|\delta\|_\infty < \varepsilon$$

small δ & $\delta = f(\nabla_x L)$?

$\|\delta\|_\infty \leq 0.1$

0.1	-0.1		
	0.1	0.05	-0.02
		-0.09	
			10^{-5}

"Enforcing $\|\nabla_x L\|_\infty < \varepsilon$" :

ε	-ε	ε	…
…	ε	…	…
…	…	-ε	…
…	…	0	…

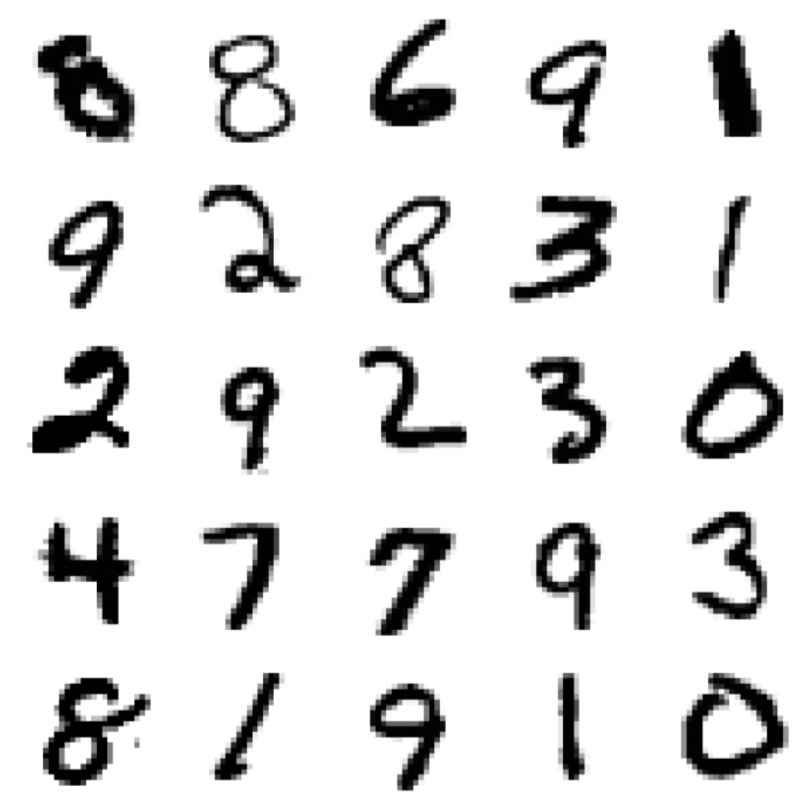
* $\boxed{\delta = \varepsilon \cdot \mathrm{sgn}(\nabla_x L)}$

Fast Gradient Sign Method

a.k.a FGSM (Goodfellow et al. 2015)

* $$\delta = \max_{\|\delta\|_\infty \le \epsilon} L\left(f(x+\delta), y\right) \approx \max_{\|\delta\|_\infty \le \epsilon} L\left(f(x), y\right) + \nabla_x L\, \delta$$

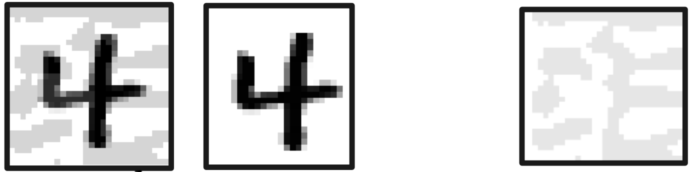
FGSM – example on MNIST



Classifier

```
model = nn.Sequential(
    nn.Conv2d(1, 16, 4, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 32, 4, stride=2, padding=1),
    nn.ReLU(),
    Flatten(),
    nn.Linear(32 * 7 * 7, 100),
    nn.ReLU(),
    nn.Linear(100, 10)
)
```

FGSM - simple but vicious



$$\mathbf{X}^{\text{adv}} = \mathbf{X} + \epsilon \, \text{sgn}(\nabla_X L(\mathbf{X}, y_{\text{true}}))$$

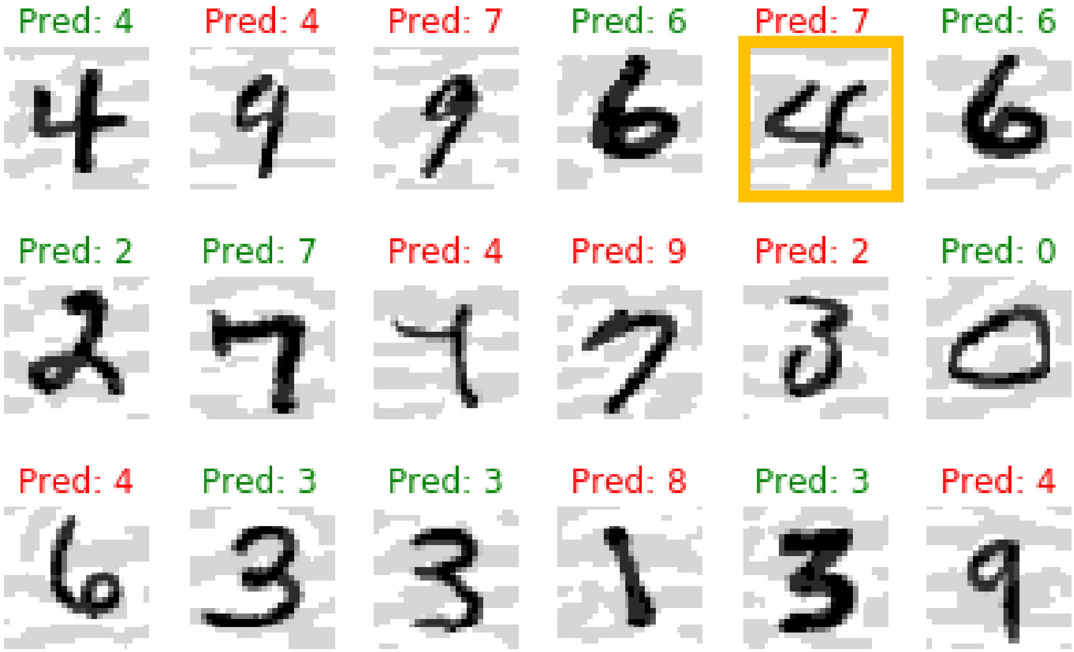
Simple, Fast and Vicious

Test Error: 98.7%

FGSM $\boxed{(\varepsilon=0.1)}$ Error: 40.0%

source: https://adversarial-ml-tutorial.org/

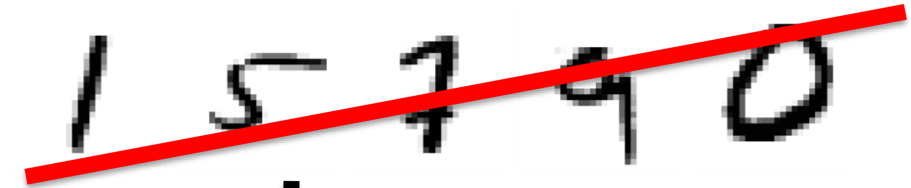
Adversarial Training



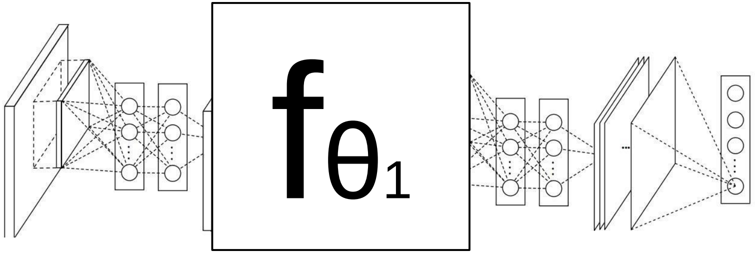
I want you to be 4!

Adversarial Training

Train on adversarial examples (kind of augmentation)



$$\mathrm{FGSM}(x, f_{\theta_1})$$



Adversarial Training

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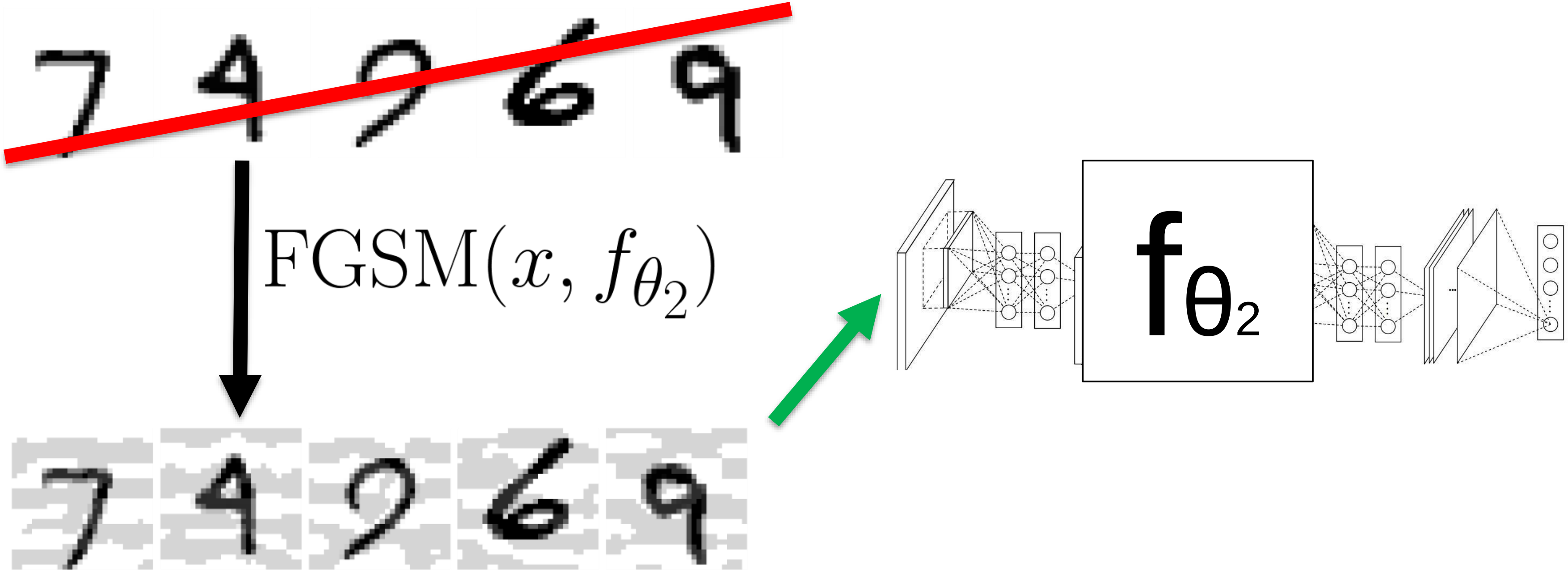

Adversarial Training

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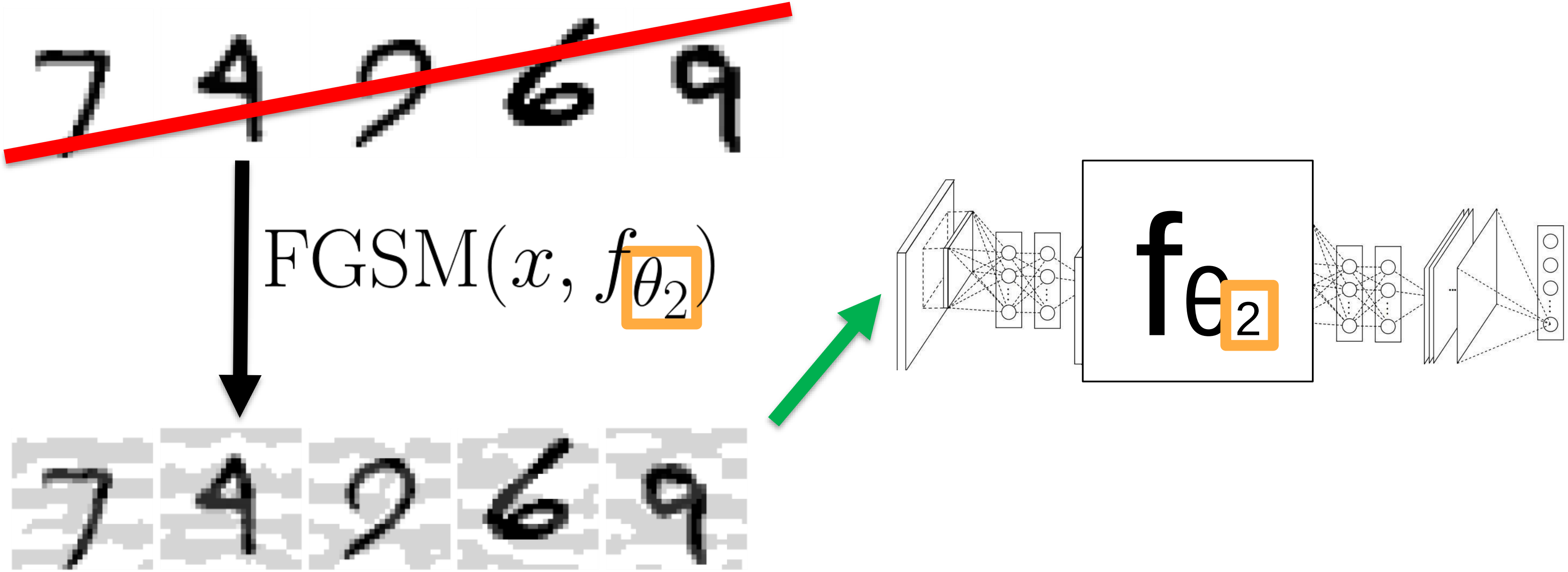
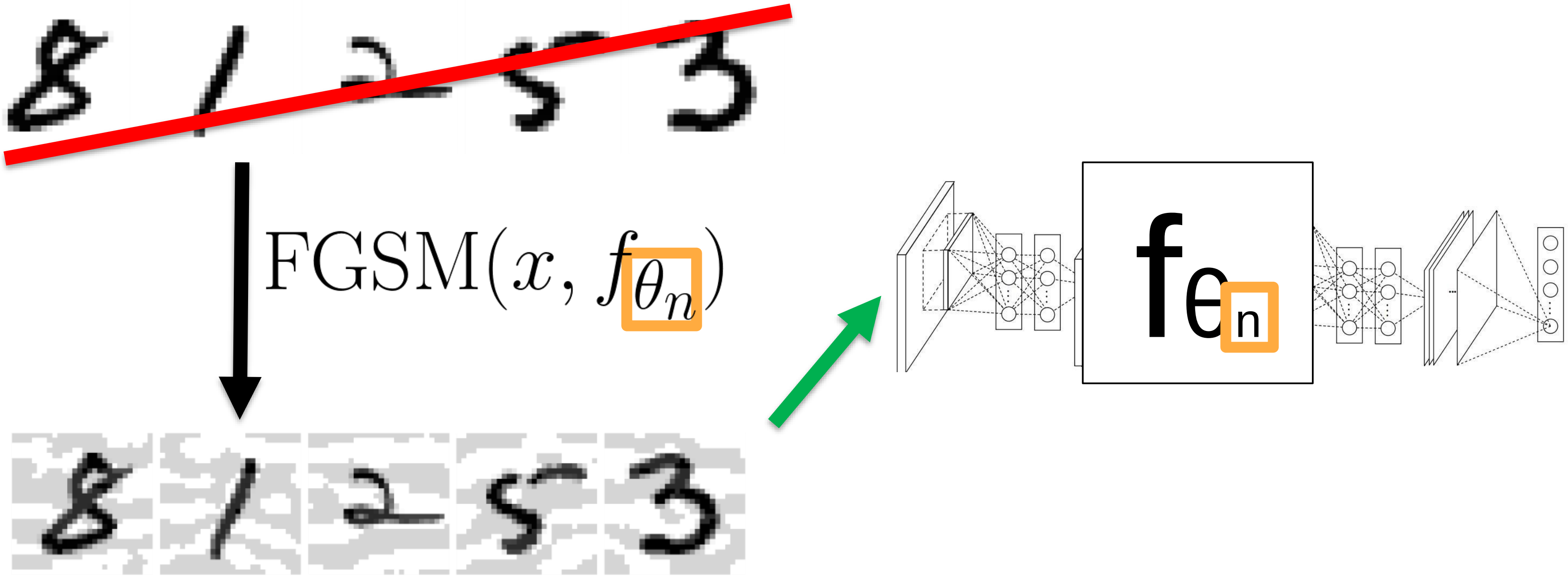


Adversarial Training

Train on adversarial examples (kind of augmentation)



Adversarial Training - MNIST

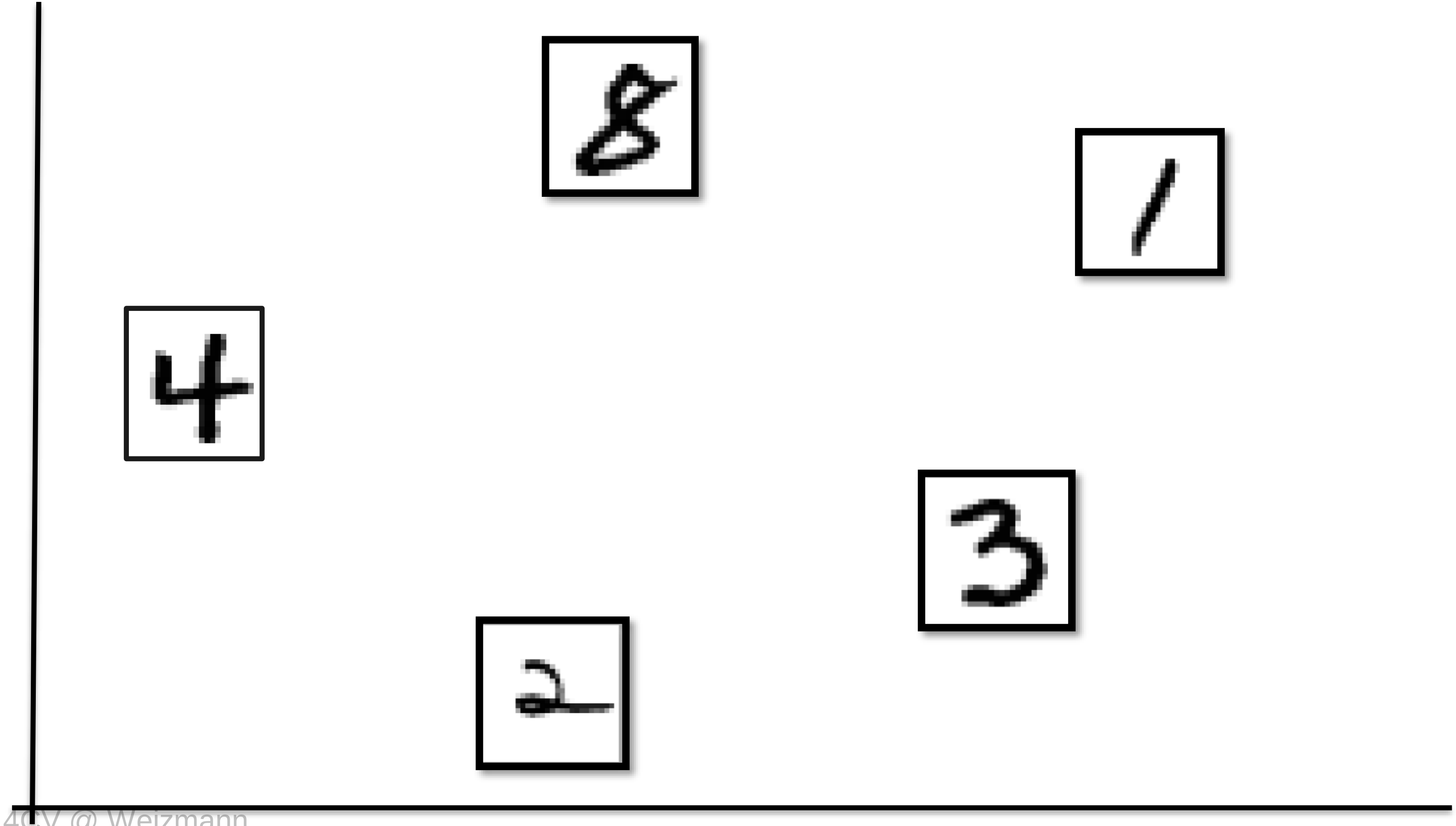
	Test Accuracy	FGSM Accuracy
Standard Training	98.7%	40.7%
Adv. Training (FGSM)	97.2%	94.0%

Did we solve the problem?

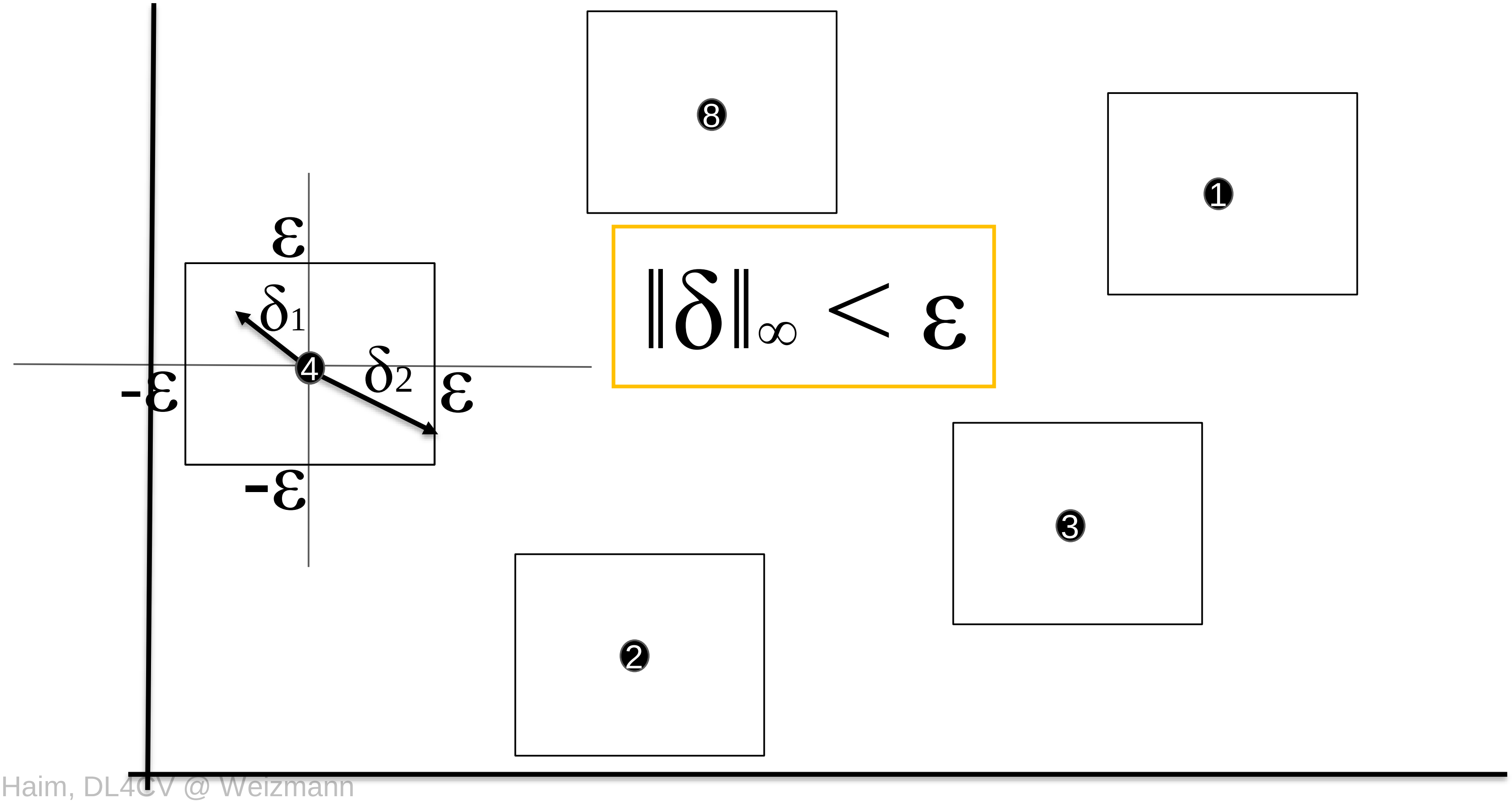
Outline

- See Adversarial Example
- Discuss what they are
- How to attack: FGSM
- How to defend: Adversarial training (AT)
  - Next: a better picture of AT (pictorially/optimization)
- Learn about properties and advantages

Perturbation Attack (pictorially)



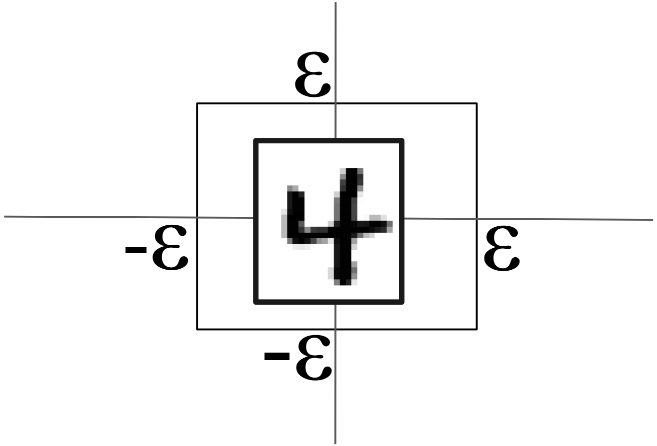
Perturbation Attack (pictorially)



$\|\delta\|_\infty < \varepsilon$

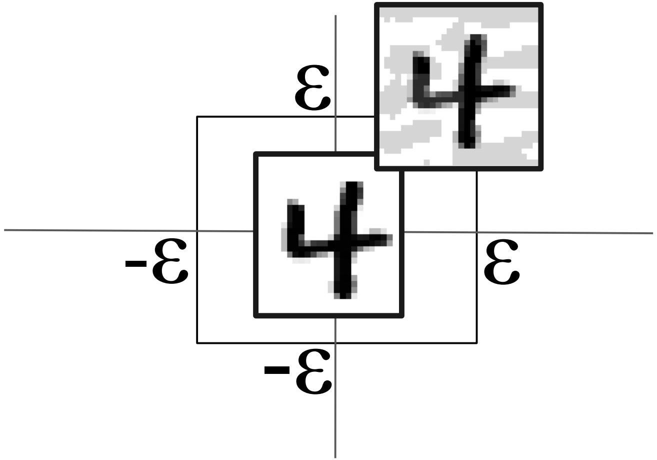
Perturbation Attack (pictorially)

FGSM



Perturbation Attack (pictorially)

FGSM

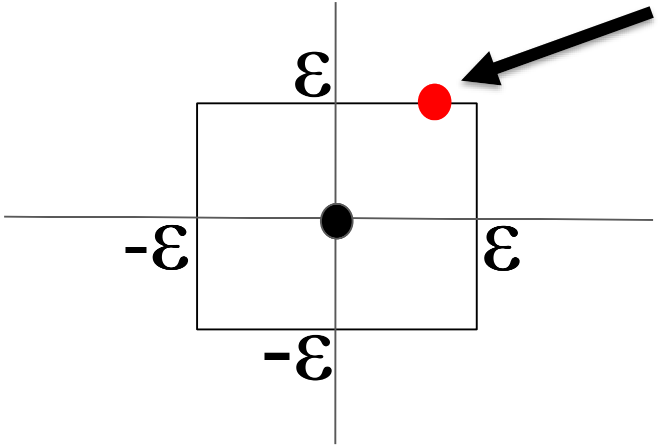


$$\mathbf{X}^{\mathrm{adv}} = \mathbf{X} + \epsilon \ \mathrm{sgn}(\nabla_X L(\mathbf{X}, y_{\mathrm{true}}))$$

Perturbation Attack (pictorially)

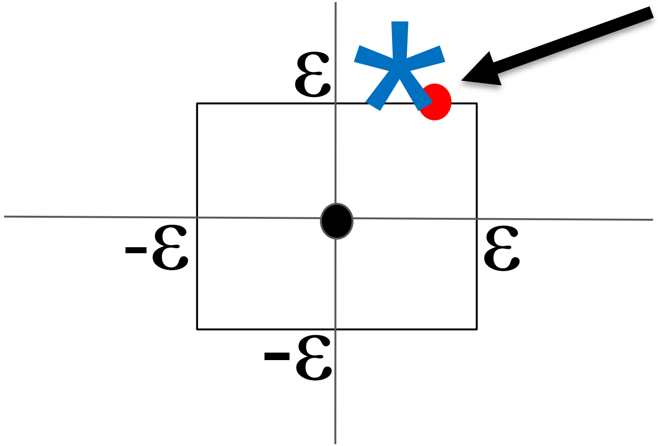
FGSM

Possible AE (found by FGSM)



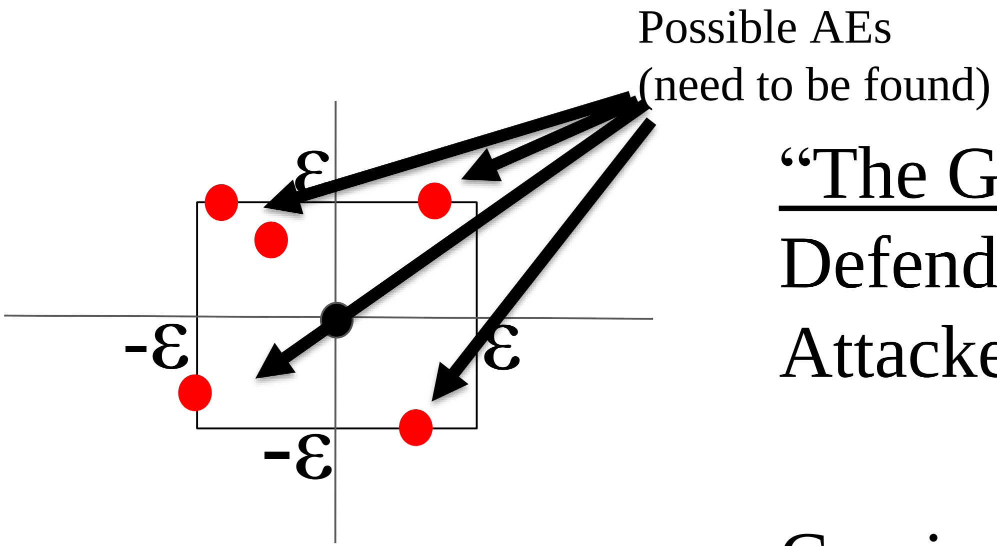
Perturbation Attack (pictorially)

FGSM



* dot should have been lying on one of the corners..

Perturbation Attack (pictorially)



<u>"The Game" of AT:</u>

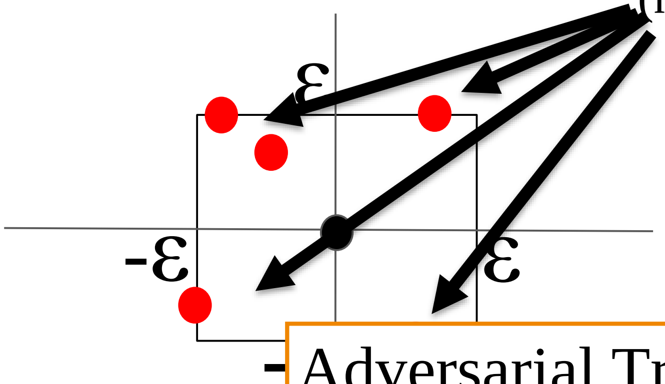
Defender: defend in box

Attacker: find AE in box

Coming

Up next:

Perturbation Attack (optimization)



“The Game” of AT:

Defender: defend in box

Attacker: find AE in box

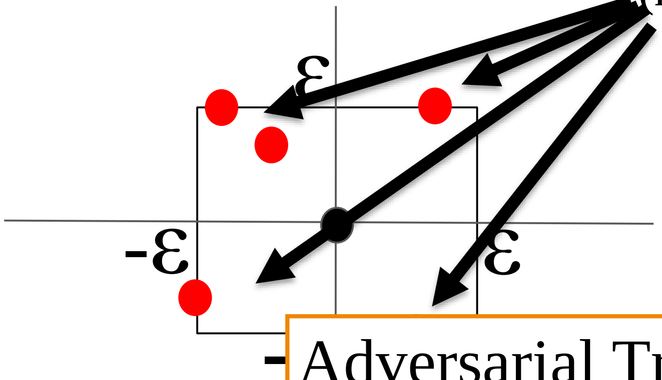
Adversarial Training as a min-max optimization problem:

$$\min_{\theta} \mathbb{E}_{(x,y)\sim D}[\max_{\delta \in S} L(f_\theta(x+\delta), y)]$$

Towards Deep Learning Models Resistant to Adversarial Attacks, Madry et al. 2018

Perturbation Attack (optimization)

Possible AEs
(need to be found)



<u>"The Game" of AT:</u>

Defender: defend in box

Attacker: find AE in box

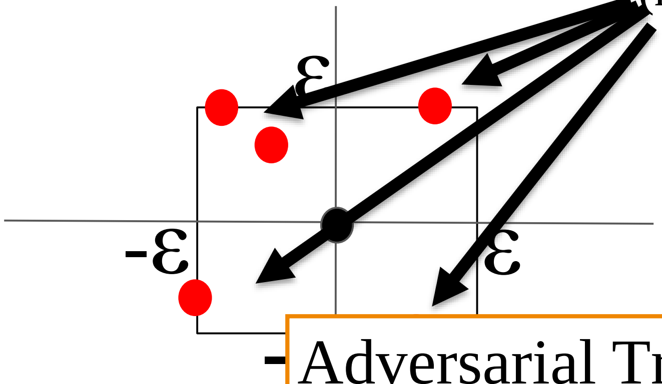
Adversarial Training as a min-max optimization problem:

$$\min_{\theta} \mathbb{E}_{(x,y)\sim D}\left[\overbrace{L(f_{\theta}(x),y)}^{\text{Standard Loss}}\right]$$

Towards Deep Learning Models Resistant to Adversarial Attacks, Madry et al. 2018

Perturbation Attack (optimization)

Possible AEs
(need to be found)



<u>"The Game" of AT:</u>

Defender: defend in box

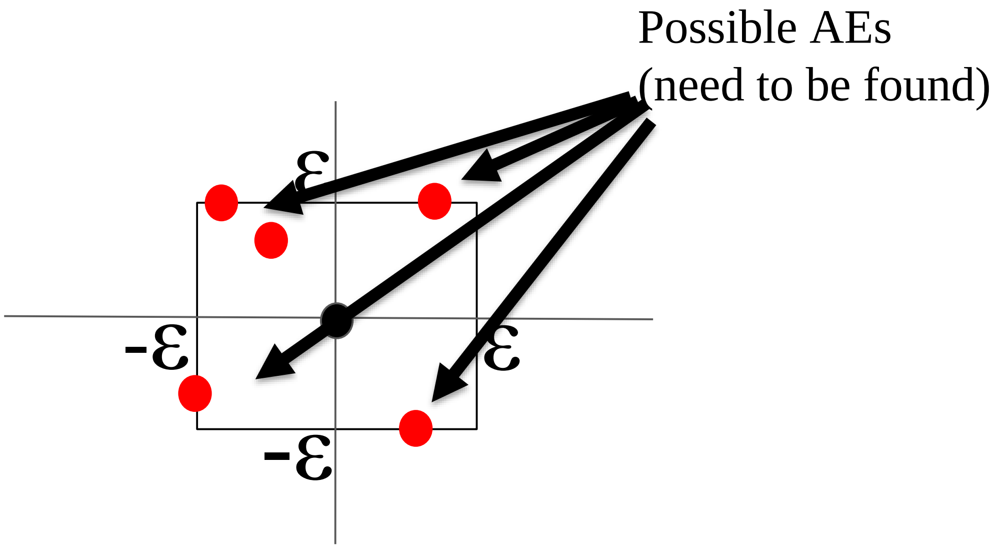
Attacker: find AE in box

Adversarial Training as a min-max optimization problem:

$$\min_{\theta} \overbrace{\mathbb{E}_{(x,y)\sim D}\left[\max_{\delta\in S} L(f_{\theta}(x+\delta), y)\right]}^{\text{Adversarial Loss}}$$

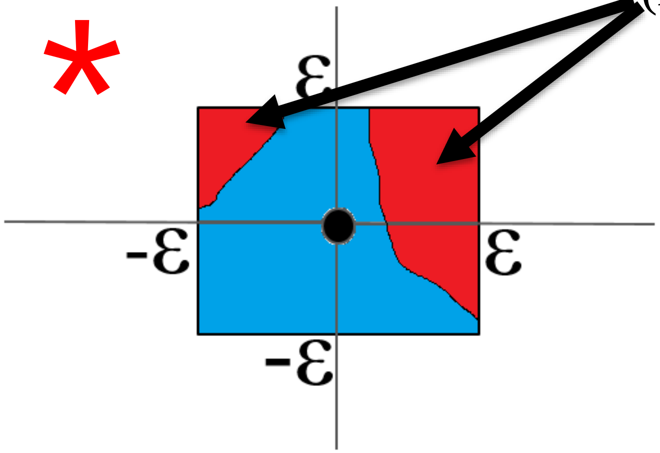
Towards Deep Learning Models Resistant to Adversarial Attacks, Madry et al. 2018

Perturbation Attack (illustrations)



Perturbation Attack (illustrations)

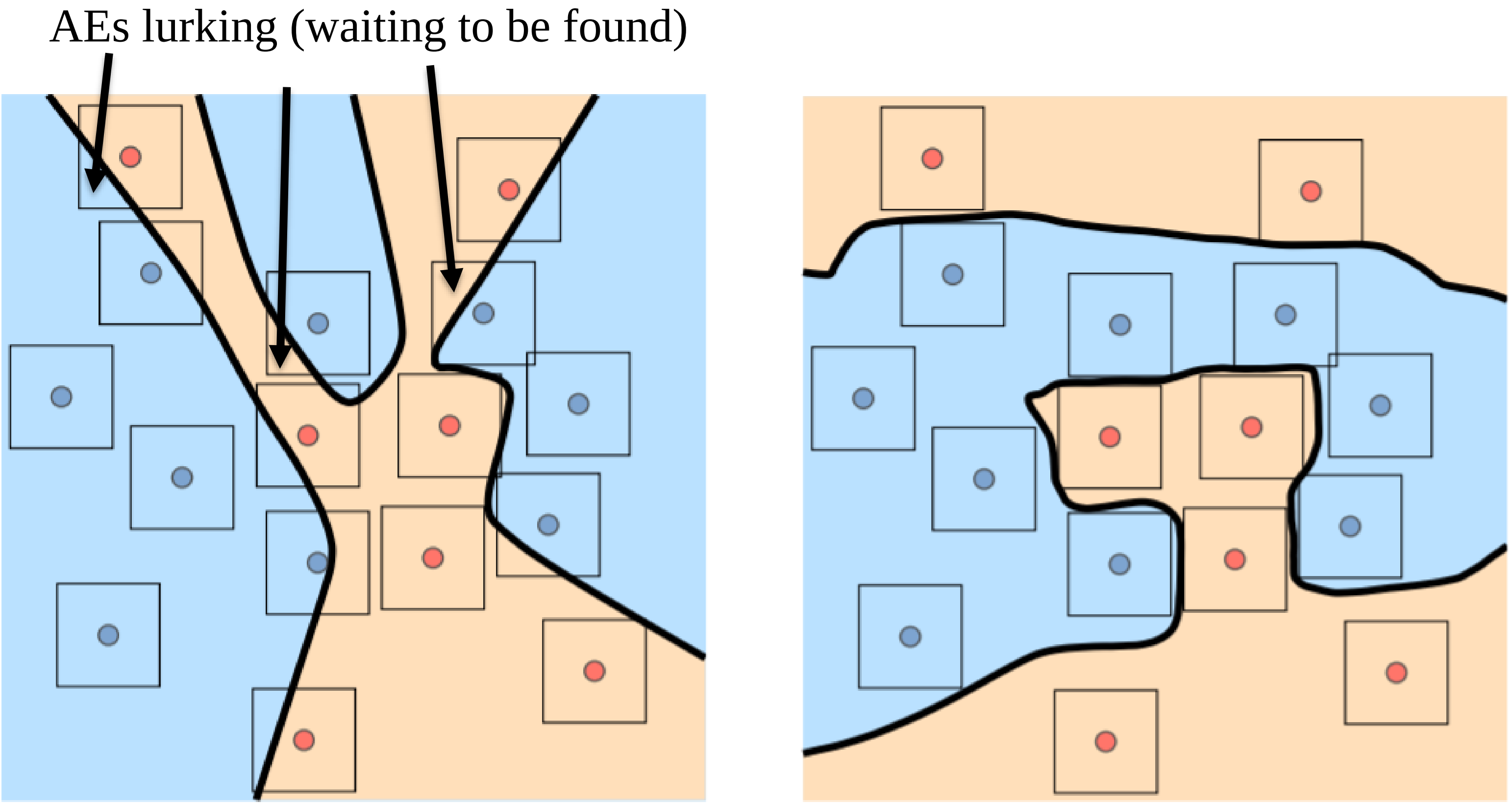
Possible AEs
(n



Mental Image

*Mental image alert! ("experimental" mental images could be horribly misleading)

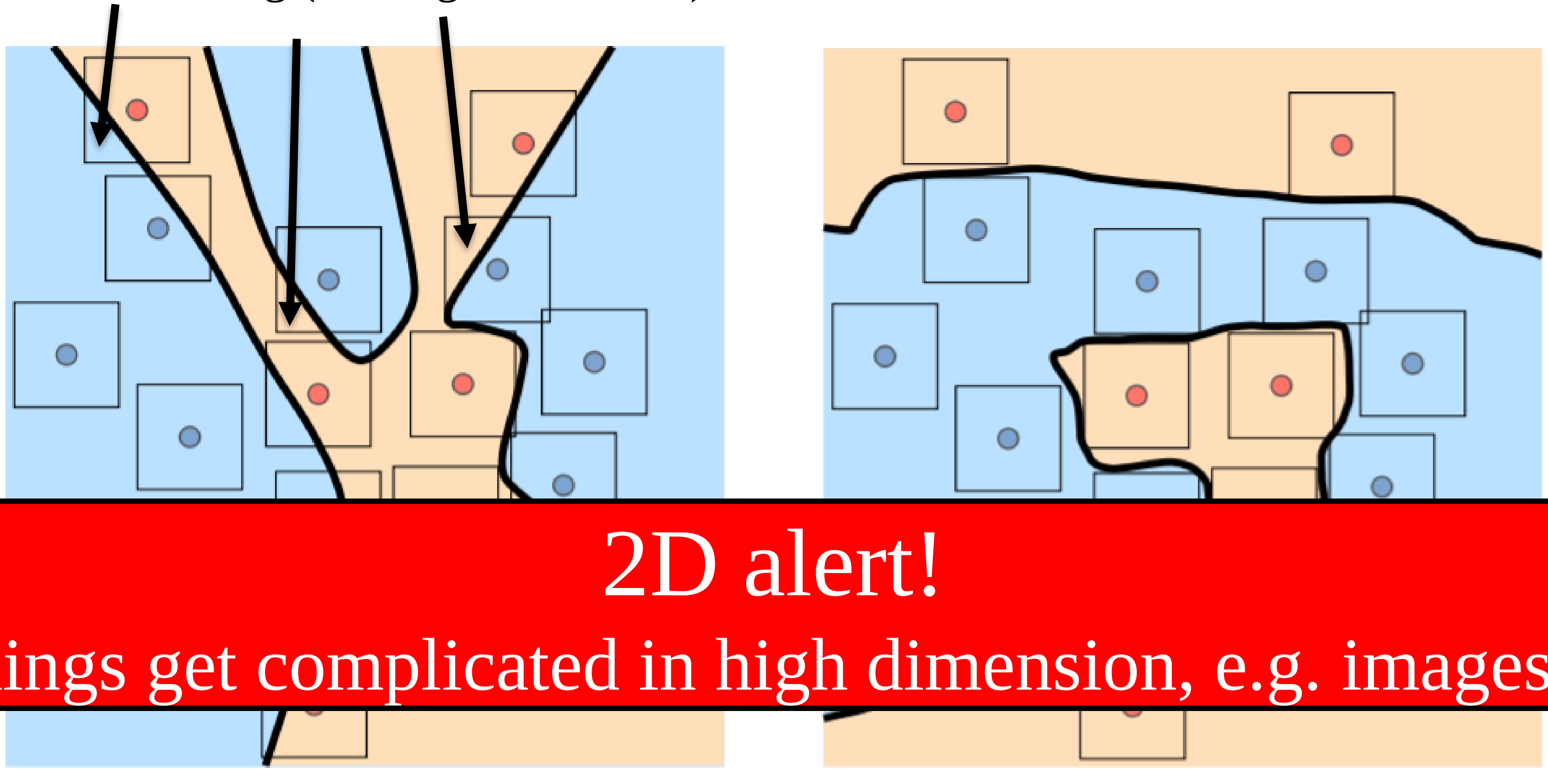
Perturbation Attack (better illustrations)



source: Atzmon et al. 2019, “Controlling Neural Level Sets”

Perturbation Attack (better illustrations)

AEs lurking (waiting to be found)

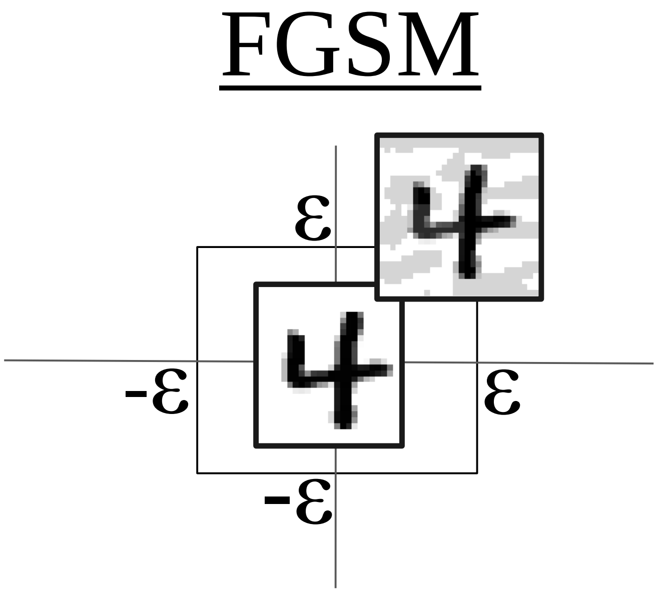


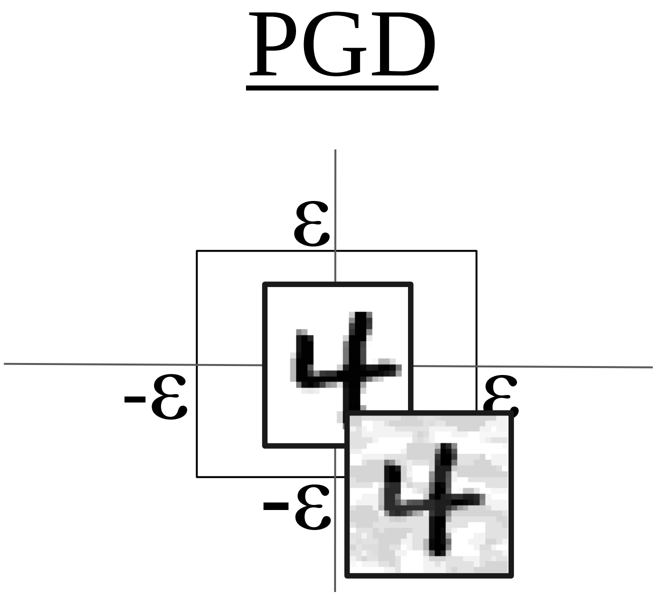
2D alert!

(Things get complicated in high dimension, e.g. images…)

source: Atzmon et al. 2019, “Controlling Neural Level Sets”

PGD (a.k.a Iterated-GSM)





$$\min_{\theta} \mathbb{E}_{(x,y)\sim D}[\max_{\delta \in S} L(f_\theta(x+\delta), y)]$$

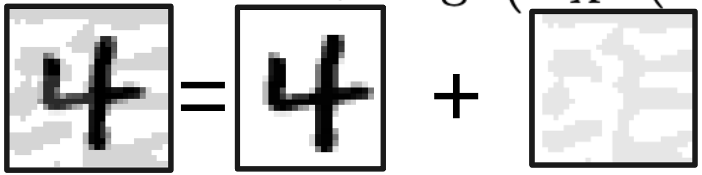
PGD (a.k.a Iterated-GSM)

Attack Model:

$$S = \{\delta \mid \|\delta\|_\infty < \varepsilon\}$$

FGSM:

$$\boldsymbol{X}^{adv} = \boldsymbol{X} + \epsilon\,\mathrm{sign}\big(\nabla_X L(\boldsymbol{X}, y_{true})\big)$$



PGD (a.k.a Iterated-GSM)

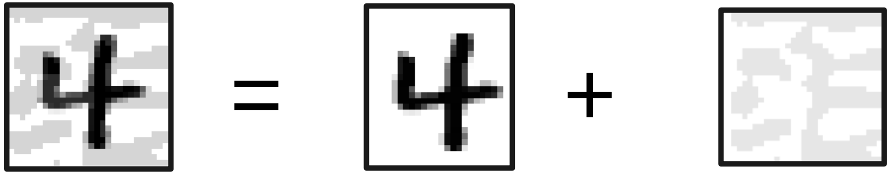
Attack Model:

$$S = \{\delta \mid \|\delta\|_\infty < \varepsilon\}$$

PGD:

$$\boldsymbol{X}_0^{adv} = \boldsymbol{X},$$

$$\boldsymbol{X}_{N+1}^{adv} = \boldsymbol{X}_N^{adv} + \boxed{\alpha}\,\mathrm{sign}\left(\nabla_X L(\boldsymbol{X}_N^{adv}, y_{true})\right)$$



PGD (a.k.a Iterated-GSM)

Attack Model:

$$S = \{\delta \mid \|\delta\|_\infty < \varepsilon\}$$

PGD:

$$\boldsymbol{X}_0^{adv} = \boldsymbol{X},$$

$$\boldsymbol{X}_{N+1}^{adv} = Clip_{X,\epsilon}\Big\{\boldsymbol{X}_N^{adv} + \alpha\,\mathrm{sign}\big(\nabla_X L(\boldsymbol{X}_N^{adv}, y_{true})\big)\Big\}$$

X_n^{adv} δ_n

n = 1

n = 2

n = 3

n = 4

Adversarial Training

	Test Accuracy	FGSM Accuracy	PGD Accuracy
Standard Training	98.7%	40.7%	7.3%
Adv. Training (FGSM)	97.2%	94.0%	90.0%

What can we do to defend?

Adversarial Training

	Test Accuracy	FGSM Accuracy	PGD Accuracy
Standard Training	98.7%	40.7%	7.3%
Adv. Training (FGSM)	97.2%	94.0%	90.0%
Adv. Training (PGD)	98.0%	96.1%	95.9%

Adversarial Training – Other Datasets

CIFAR10 (ResNet50)	Test	PGD ($\epsilon = \frac{8}{255}$)
Standard Training	95.25%	0.00%
Adv. Training (PGD 8/255)	87.03%	53.29%

ImageNet (ResNet50)	Test	PGD ($\epsilon = \frac{8}{255}$)
Standard Training	76.13%	0.01%
Adv. Training (PGD 8/255)	47.91%	19.52%

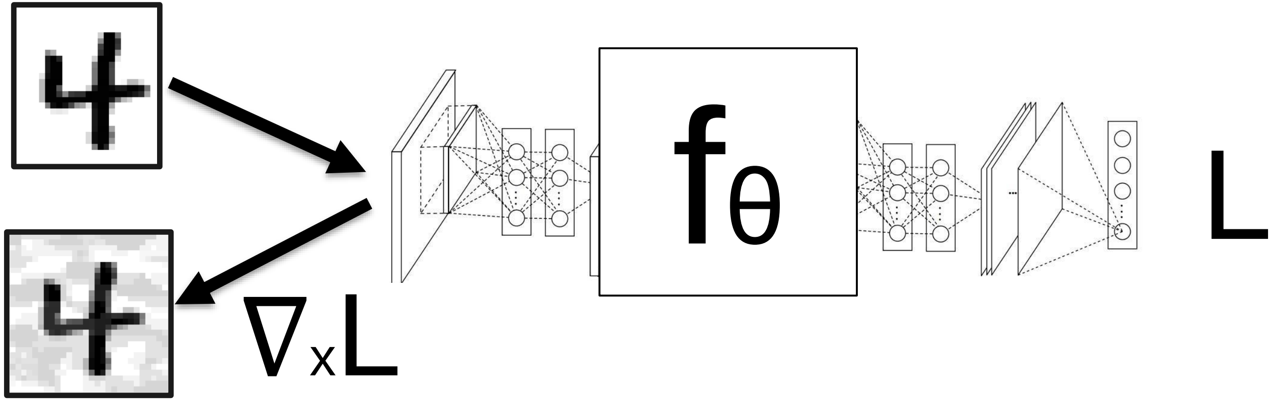
source: https://github.com/MadryLab/robustness

Outline

- See Adversarial Example
- Discuss what they are
- How to attack: FGSM, PGD
- How to defend: Adversarial training (AT)
- Optimization view of AT
- Next: Black-Box attacks
- Learn about properties and advantages

Black-Box Attacks

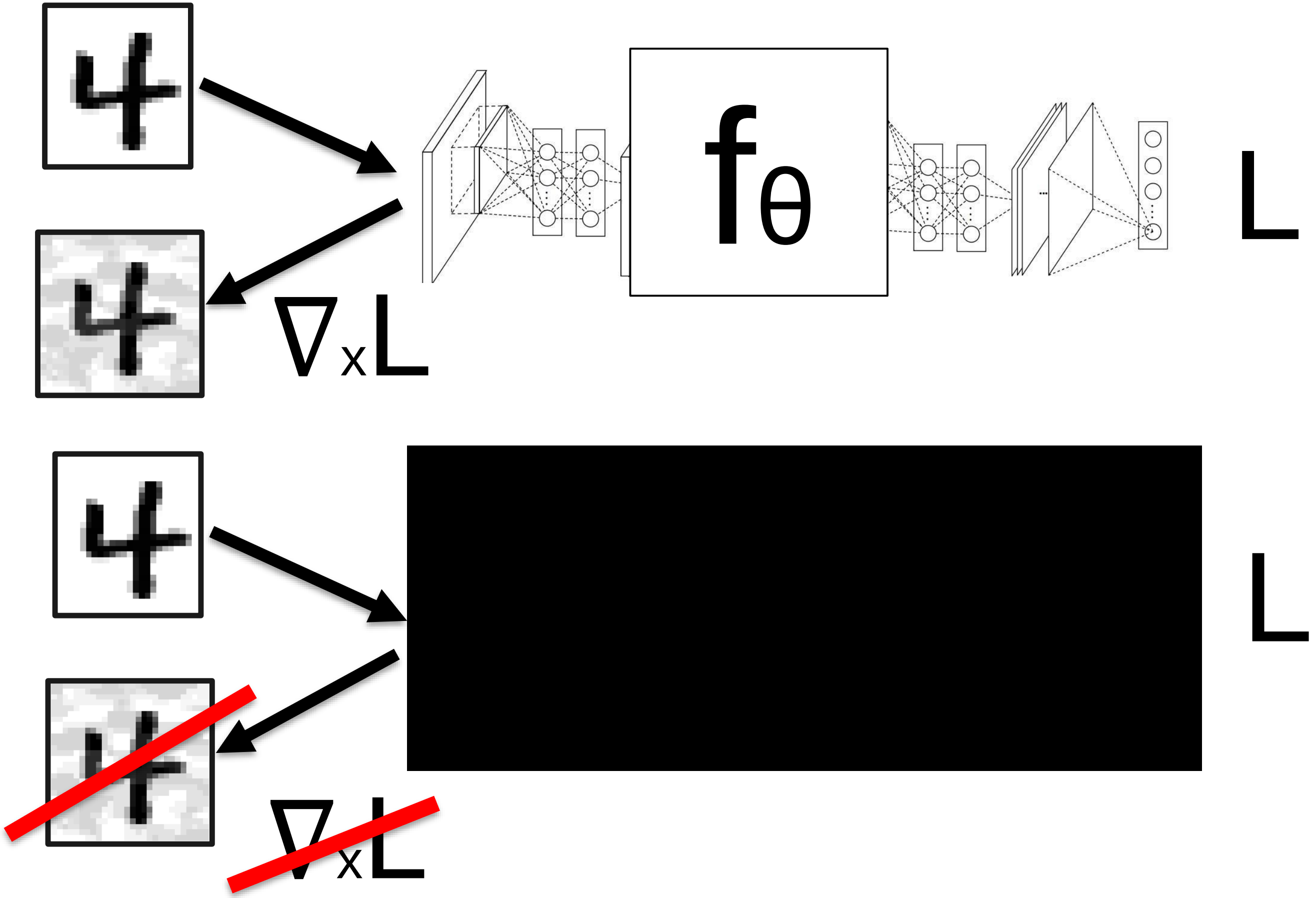
"White-Box" (FGSM, PGD, etc.)



Black-Box Attacks

“White-Box”

“Black-Box”

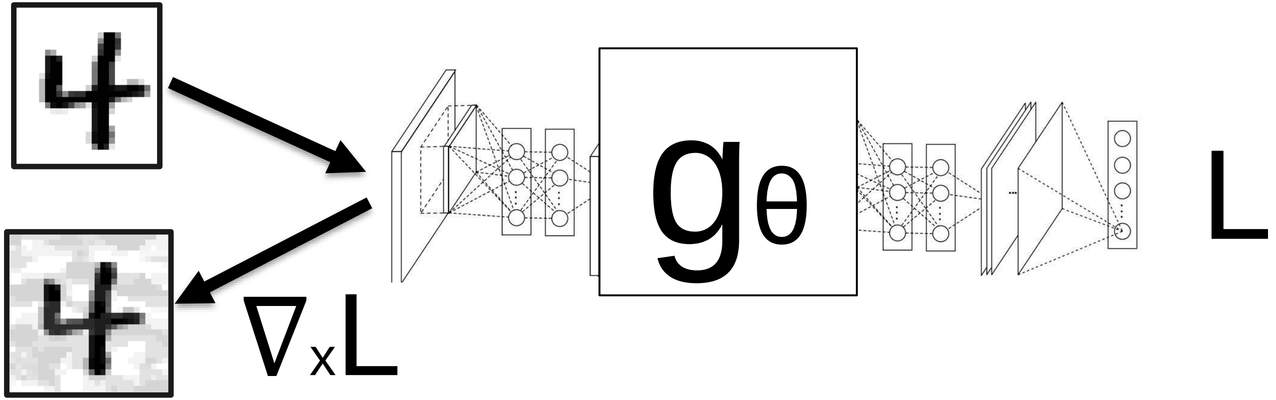


Black-Box Attacks

“Black-Box”

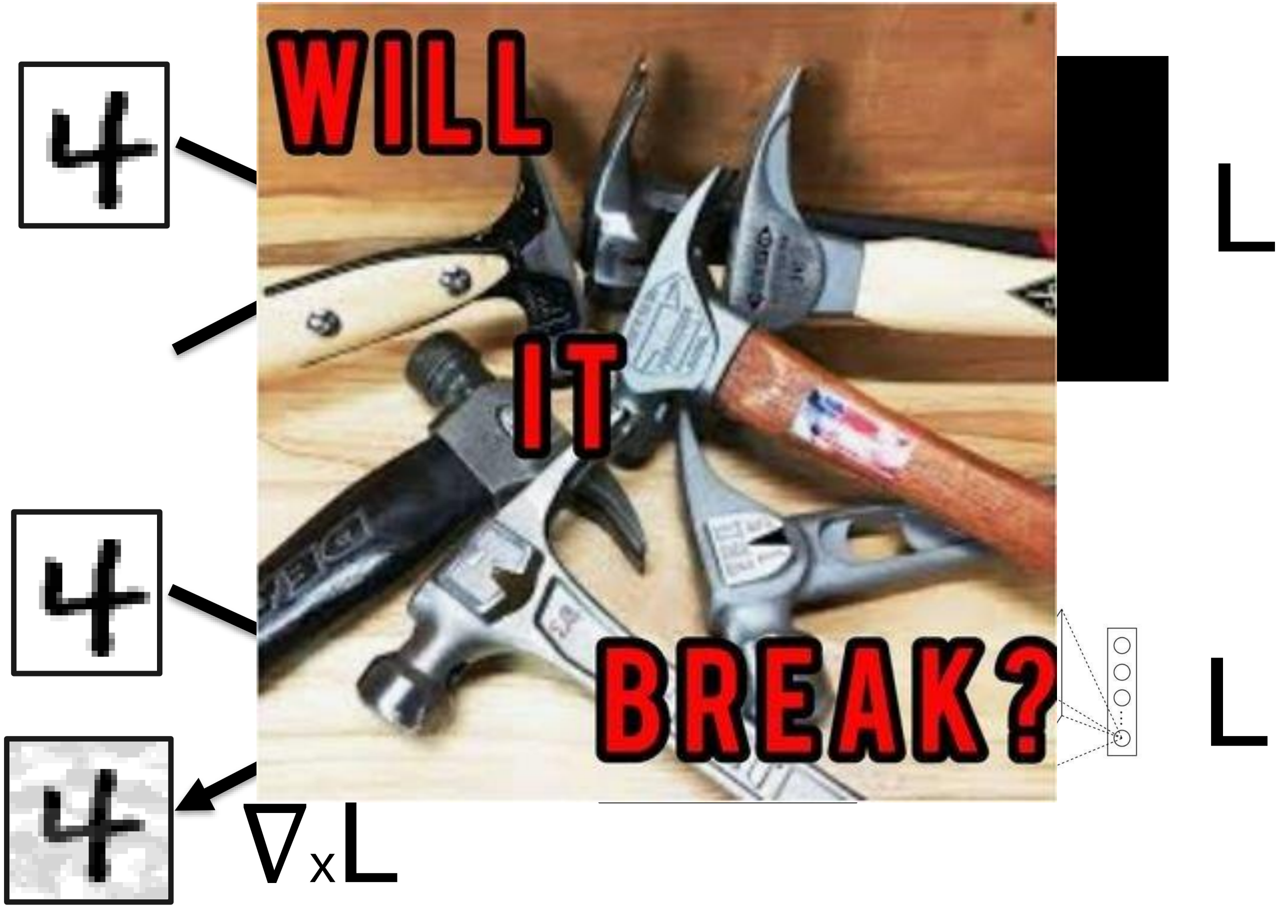
Black-Box Attacks

“Black-Box”



Black-Box Attacks

“Black-Box”



source: https://twitter.com/will_it_breakyt

Black-Box Attacks - Transferability

- Test set Accuracy

	ResNet-50	ResNet-101	ResNet-152	GoogLeNet	VGG-16
Top-5 accuracy	91.0%	91.7%	92.1%	89.0%	88.3%

- Accuracy under FGSM attack

	ResNet-152	ResNet-101	ResNet-50	VGG-16	GoogLeNet
ResNet-152	32%	55%	53%	47%	36%

Liu et al. 2016, “Delving into Transferable Adversarial Examples and Black-box Attacks”

Black-Box Attacks - Transferability

- Test set Accuracy

	ResNet-50	ResNet-101	ResNet-152	GoogLeNet	VGG-16
Top-5 accuracy	91.0%	91.7%	92.1%	89.0%	88.3%

- Accuracy under FGSM attack

	ResNet-152	ResNet-101	ResNet-50	VGG-16	GoogLeNet
ResNet-152	32%				
ResNet-101		33%			
ResNet-50			29%		
VGG-16				5%	
GoogLeNet					11%

White-Box
FGSM

Liu et al. 2016, “Delving into Transferable Adversarial Examples and Black-box Attacks” (Tab.20)

Black-Box Attacks - Transferability

- Test set Accuracy

	ResNet-50	ResNet-101	ResNet-152	GoogLeNet	VGG-16
Top-5 accuracy	91.0%	91.7%	92.1%	89.0%	88.3%

- Accuracy under FGSM attack

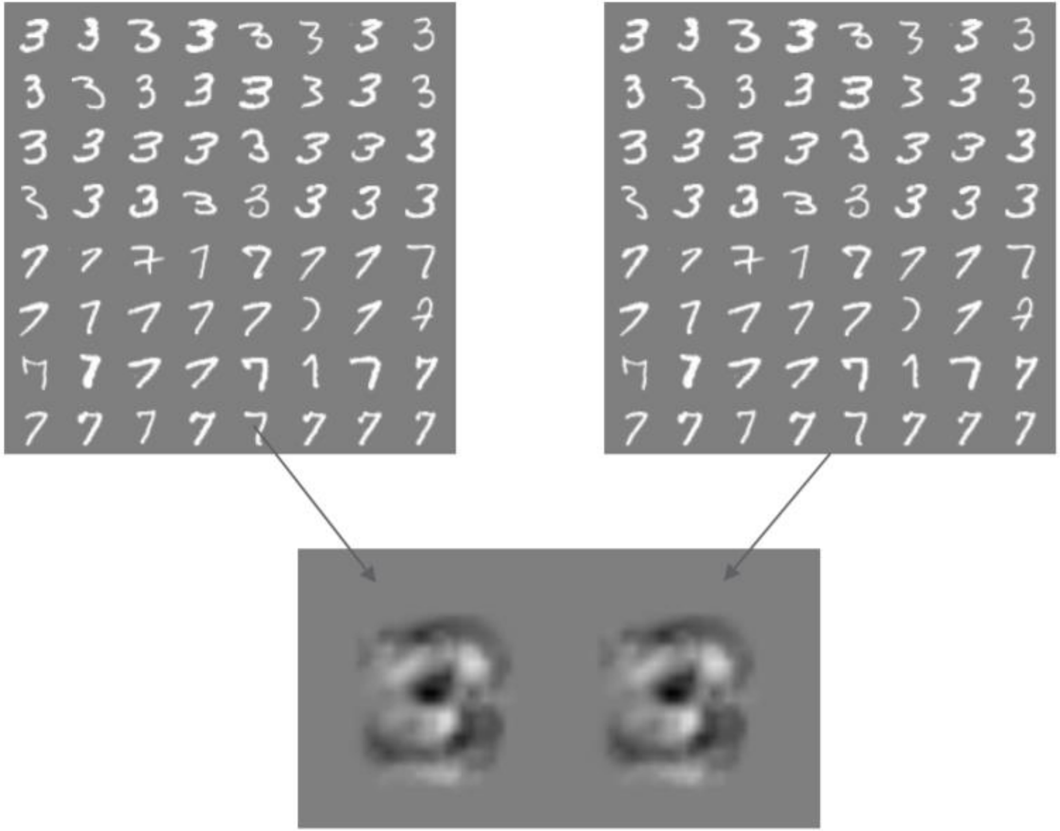
	ResNet-152	ResNet-101	ResNet-50	VGG-16	GoogLeNet
ResNet-152		55%	53%	47%	36%
ResNet-101	56%		50%	46%	40%
ResNet-50	59%	53%		47%	38%
VGG-16	42%	39%	41%		21%
GoogLeNet	71%	74%	62%	53%	

Black-Box

Liu et al. 2016, "Delving into Transferable Adversarial Examples and Black-box Attacks" (Tab.20)

Black-Box Attacks - Transferability

- Possible reason:



source: Ian Goodfellow on "Adversarial Examples and Adversarial Training," 2017-05-30, CS231n, Stanford University

Black-Box Attacks - Transferability

- Possible reason:

Adversarial Examples comes from the data:

Ilyas et al. 2019, “Adversarial Examples Are Not Bugs, They Are Features”

source: Ian Goodfellow on "Adversarial Examples and Adversarial Training," 2017-05-30, CS231n, Stanford University

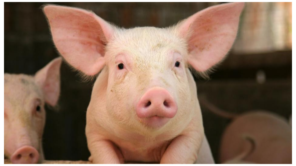
Outline

- See Adversarial Example
- Discuss what they are
- How to attack: FGSM, PGD
- How to defend: Adversarial training (AT)
- Optimization view of AT
- Black-Box attacks (transferability)
- Next: Summary
- Surprising “advantages” of AE

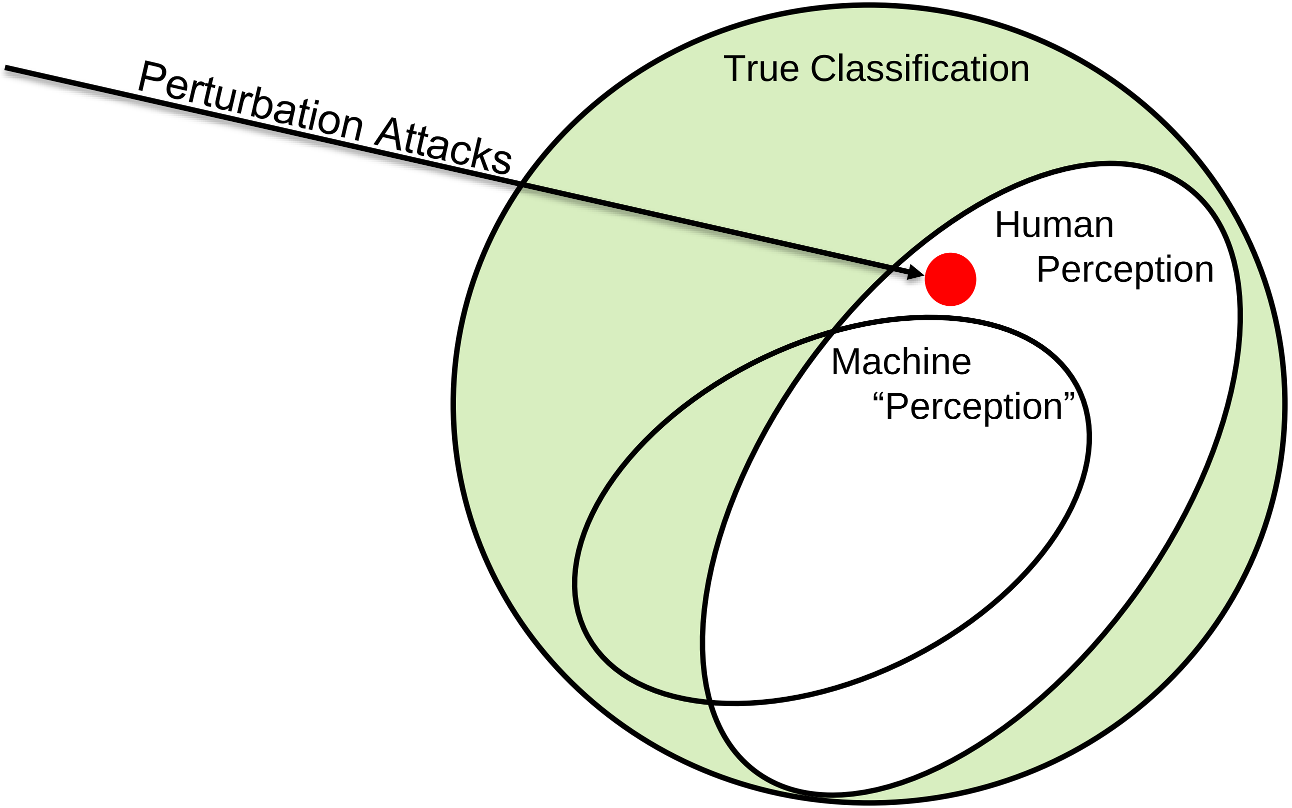
Adversarial Examples – The Bigger Picture

Is this surprising?

airliner



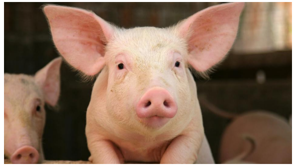
test+noise



Adversarial Examples – The Bigger Picture

Inputs that fool a computer, but not a human

airliner



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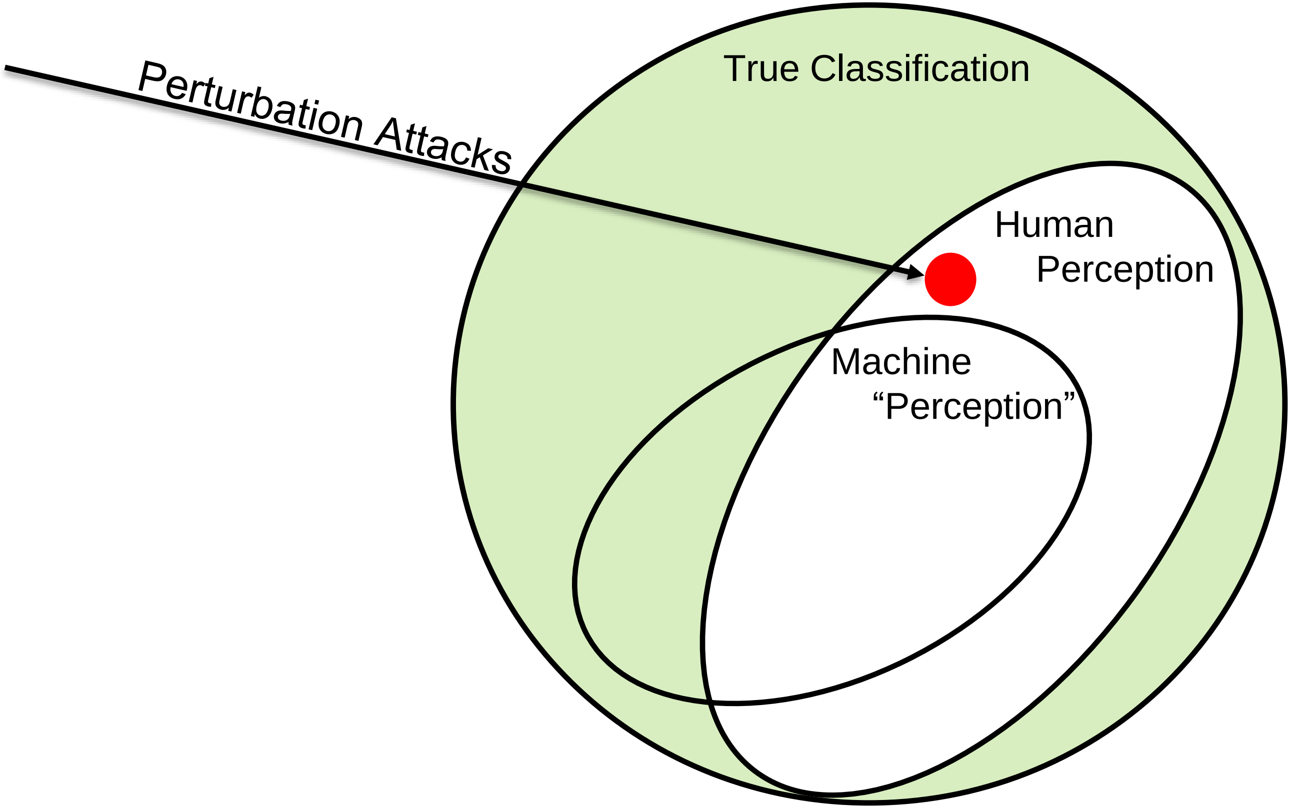

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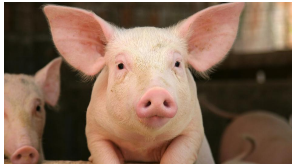
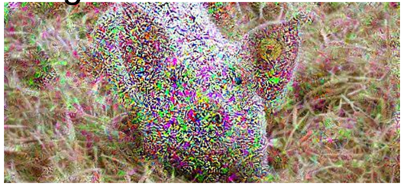
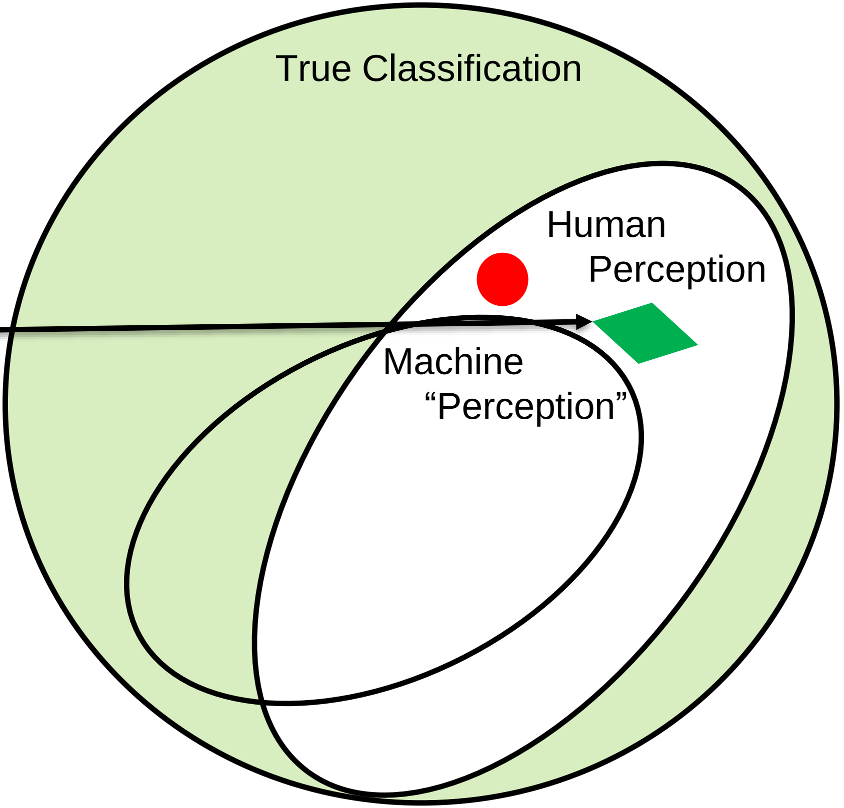


test+noise

fireguard



"noisy" image



Adversarial Examples – The Bigger Picture

Inputs that fool a computer, but not a human

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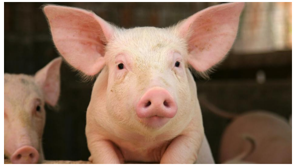

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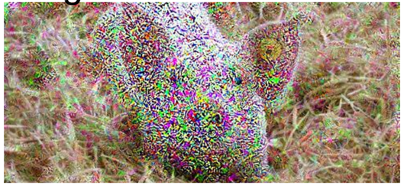
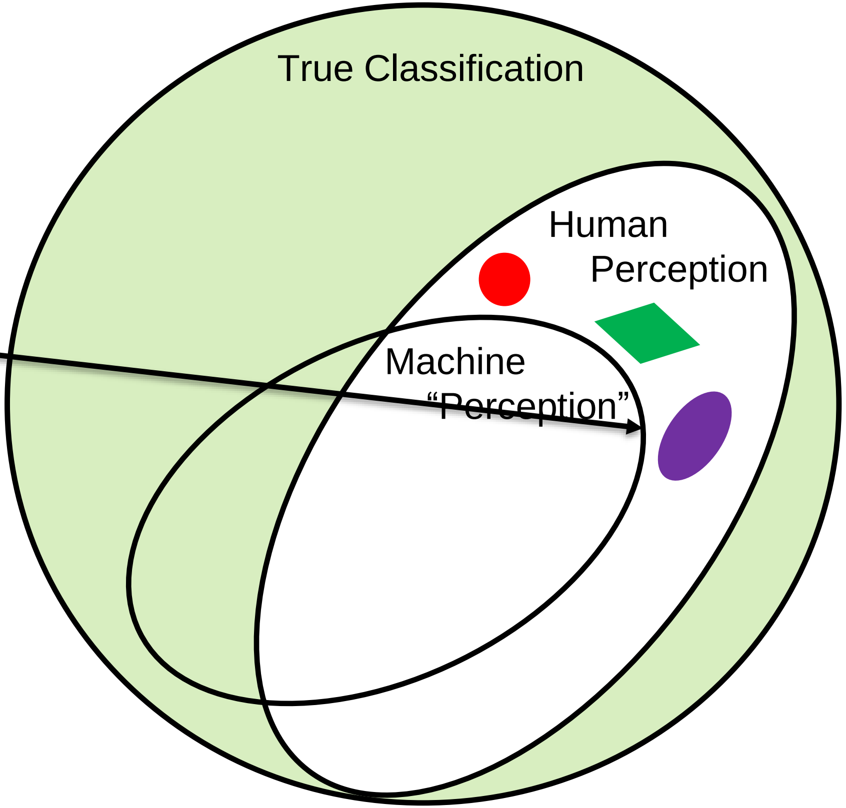


“noisy” image

spotlight (26.7%)

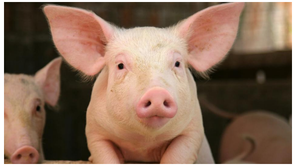
noise



Adversarial Examples – The Bigger Picture

Inputs that fool a computer, but not a human

airliner



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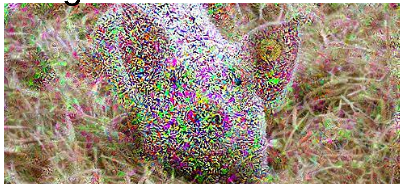


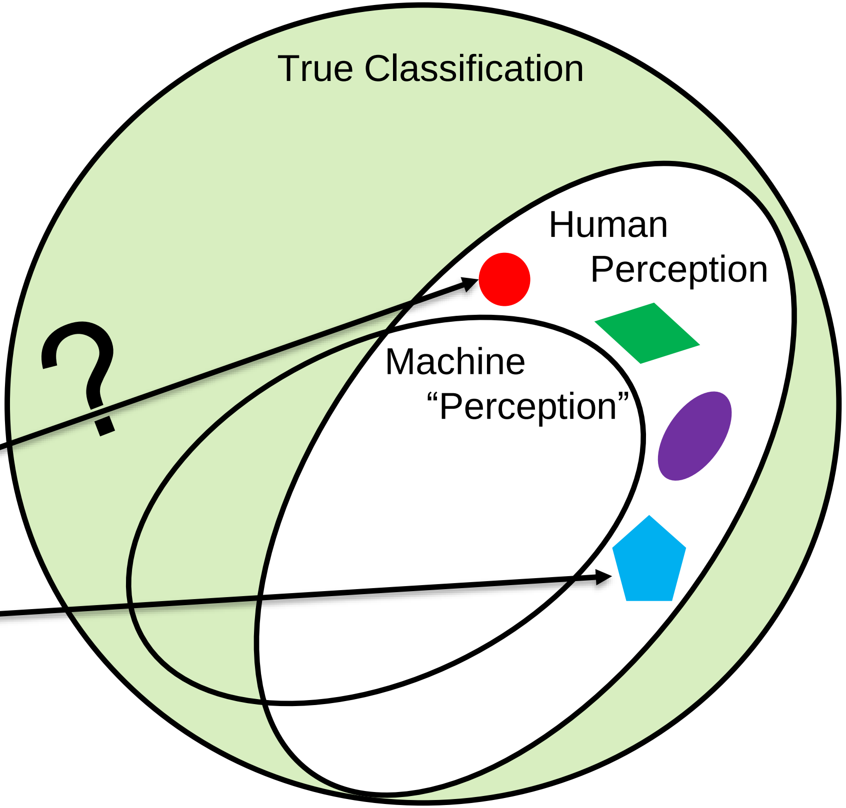
"noisy" image

spotlight (26.7%)

noise

cat ?

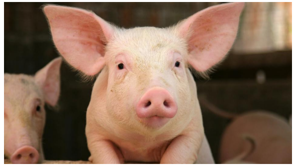
model failure



Adversarial Examples – The Bigger Picture

Inputs that fool a computer, but not a human

airliner



test+noise

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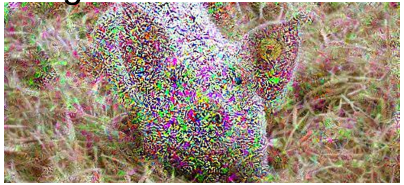

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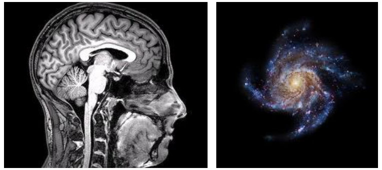
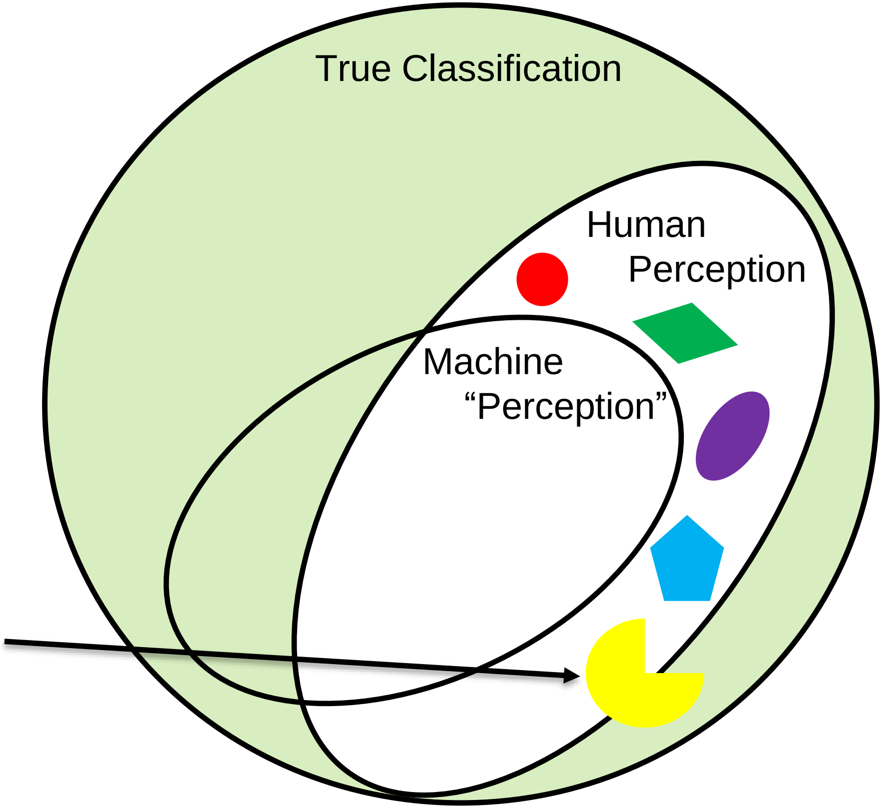
???



out-of-distribution



The Bigger Picture: Failure modes in machine learning

Intentionally-motivated failures

Attack	Overview
Perturbation attack	Attacker modifies the query to get appropriate response
Poisoning attack	Attacker contaminates the training phase of ML systems to get intended result
Model Inversion	Attacker recovers the secret features used in the model by through careful queries
Membership Inference	Attacker can infer if a given data record was part of the model's training dataset or not
Model Stealing	Attacker is able to recover the model through carefully-crafted queries
Reprogramming ML system	Repurpose the ML system to perform an activity it was not programmed for
Adversarial Example in Physical Domain	Attacker brings adversarial examples into physical domain to subvertML system e.g: 3d printing special eyewear to fool facial

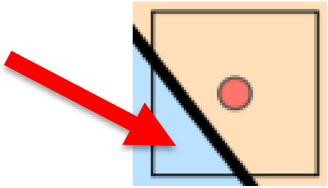
Unintended failures

Failure	Overview
Reward Hacking	Reinforcement Learning (RL) systems act in unintended ways because of mismatch between stat reward and true reward
Side Effects	RL system disrupts the environment as it tries to attain its goal
Distributional shifts	The system is tested in one kind of environment, but is unable to adapt to changes in other kinds environment
Natural Adversarial Examples	Without attacker perturbations, the ML system fails owing to hard negative mining
Common Corruption	The system is not able to handle common corruptions and perturbations such as tilting, zooming noisy images.
Incomplete Testing	The ML system is not tested in the realistic conditions that it is meant to operate in.

source: https://docs.microsoft.com/en-us/security/engineering/failure-modes-in-machine-learning

Adversarial Examples - Summary

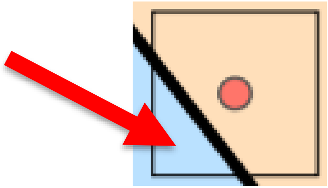
- Remember the bigger picture (many failures)
- Hard to attack (need to find AE in box)



- Harder to defend (need to prove: no AEs in <u>all</u> box)

Adversarial Examples - Summary

- Remember the bigger picture (many failures)
- Hard to attack (need to find AE in box)



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Adversarial Examples - Summary

- Remember the bigger picture (many failures)
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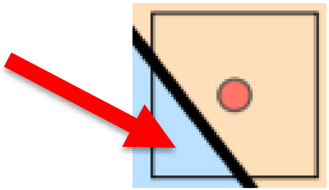
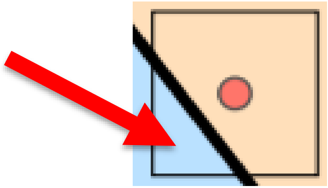


- Harder to defend (need to **prove**: very hard to find AE in box)

Adversarial Examples - Summary

- Remember the bigger picture (many failures)
- Hard to attack (need to find AE in box)



- Harder to defend (need to **Evaluate**: very hard to find AE in box)
- Coming next: Robustness beyond security

Outline

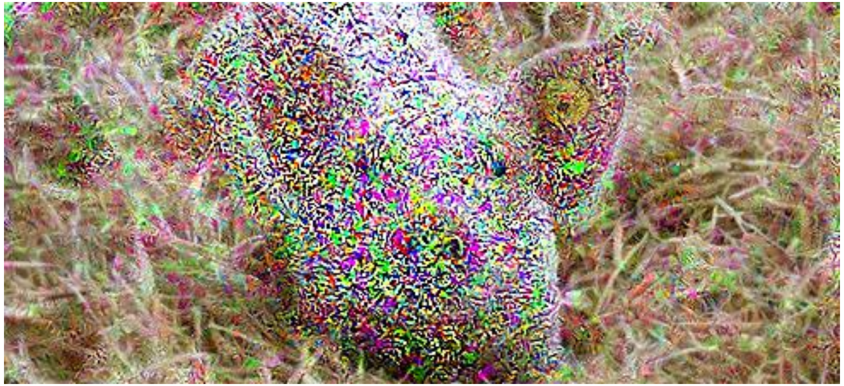
- See Adversarial Example
- Discuss what they are
- How to attack: FGSM, PGD
- How to defend: Adversarial training (AT)
- Optimization view of AT
- Black-Box attacks (transferability)
- Summary (“security”)
- Surprising “advantages” of AE (beyond security)

Follow the gradient w.r.t x (the input image)

X (original): 89.7% pig

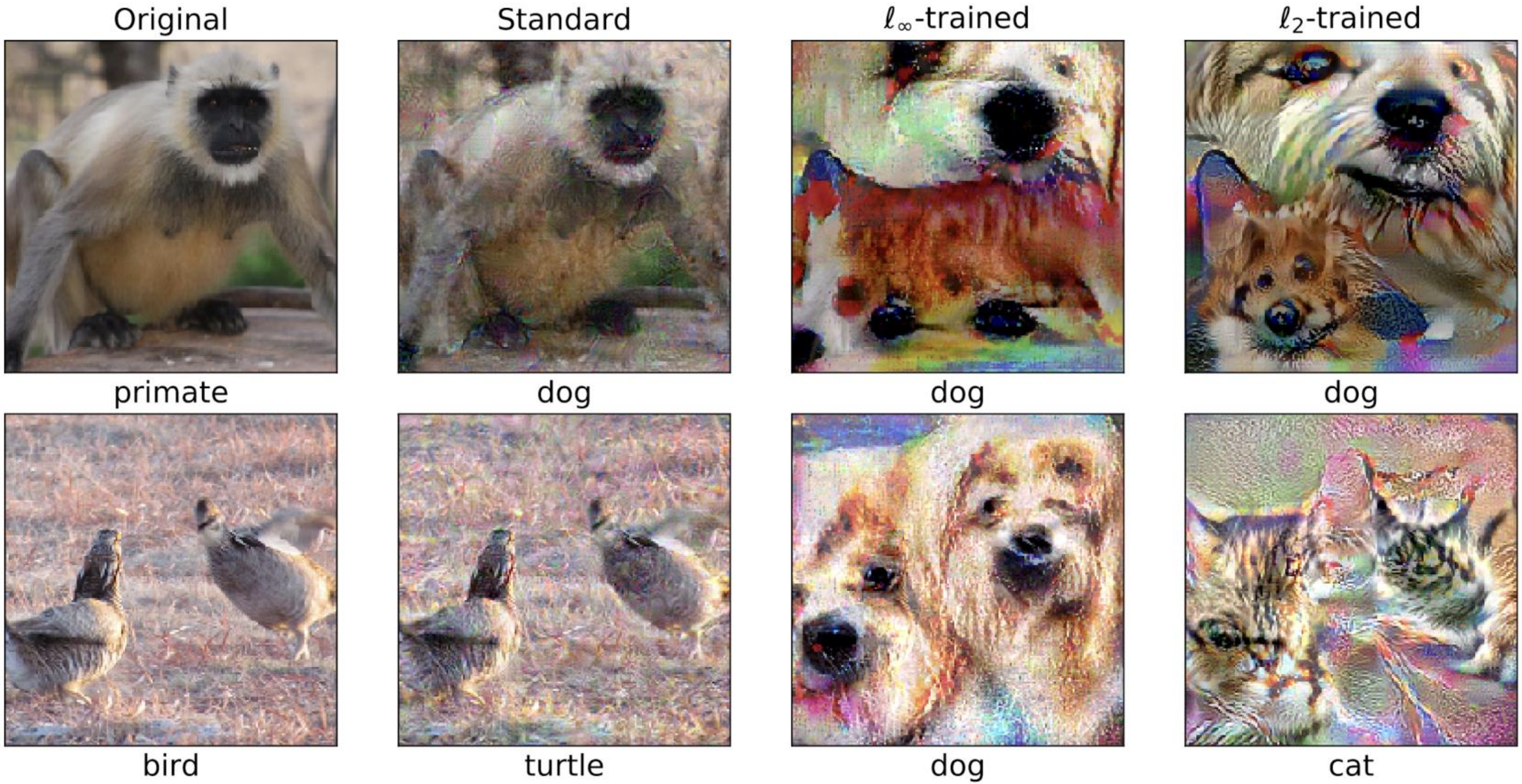
$X + \nabla_X L$: 68.6% hay

$X + 10 \times \nabla_X L$: 44.7% pig



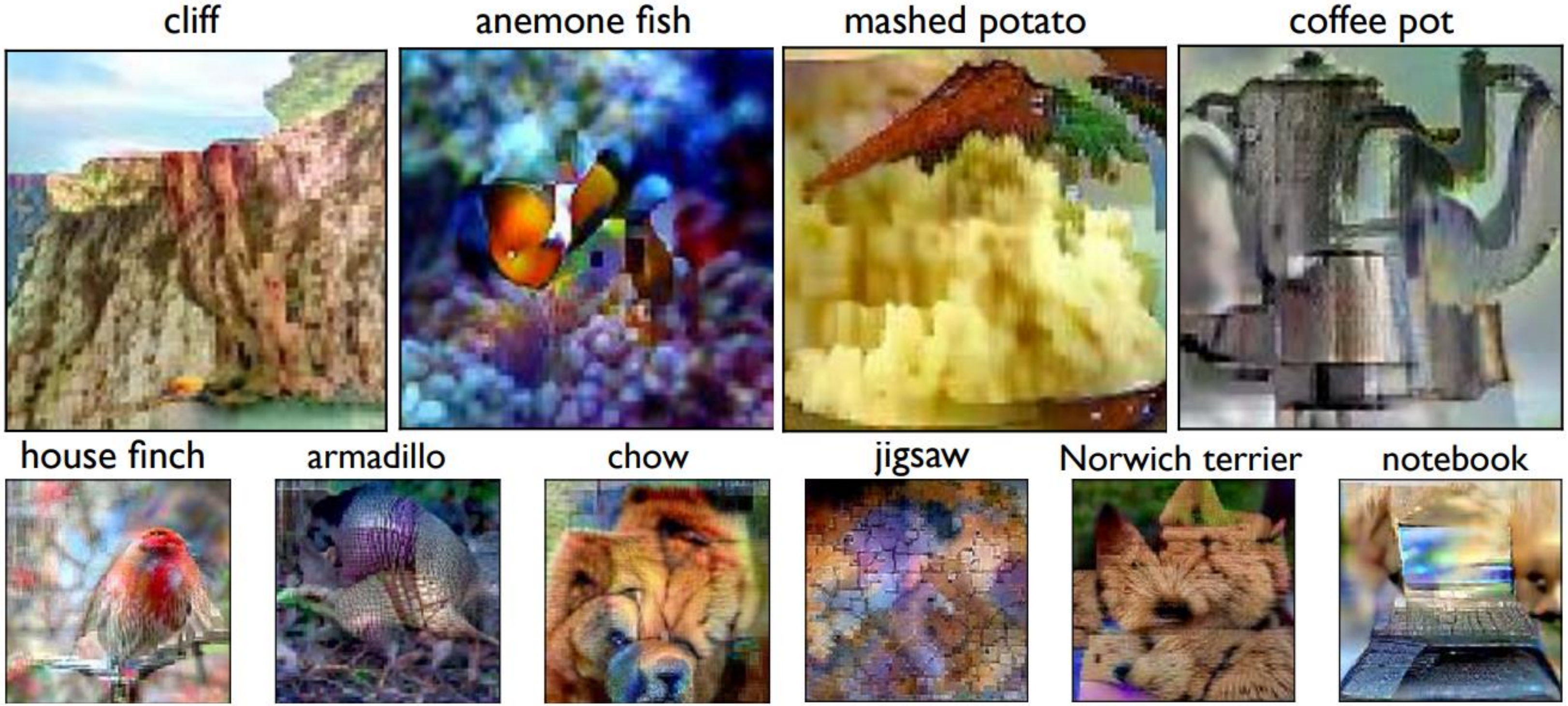
$X + 100 \times \nabla_X L$: 44.8% fireguard

Follow $\nabla_x L(f(x),y)$ of Robust Model



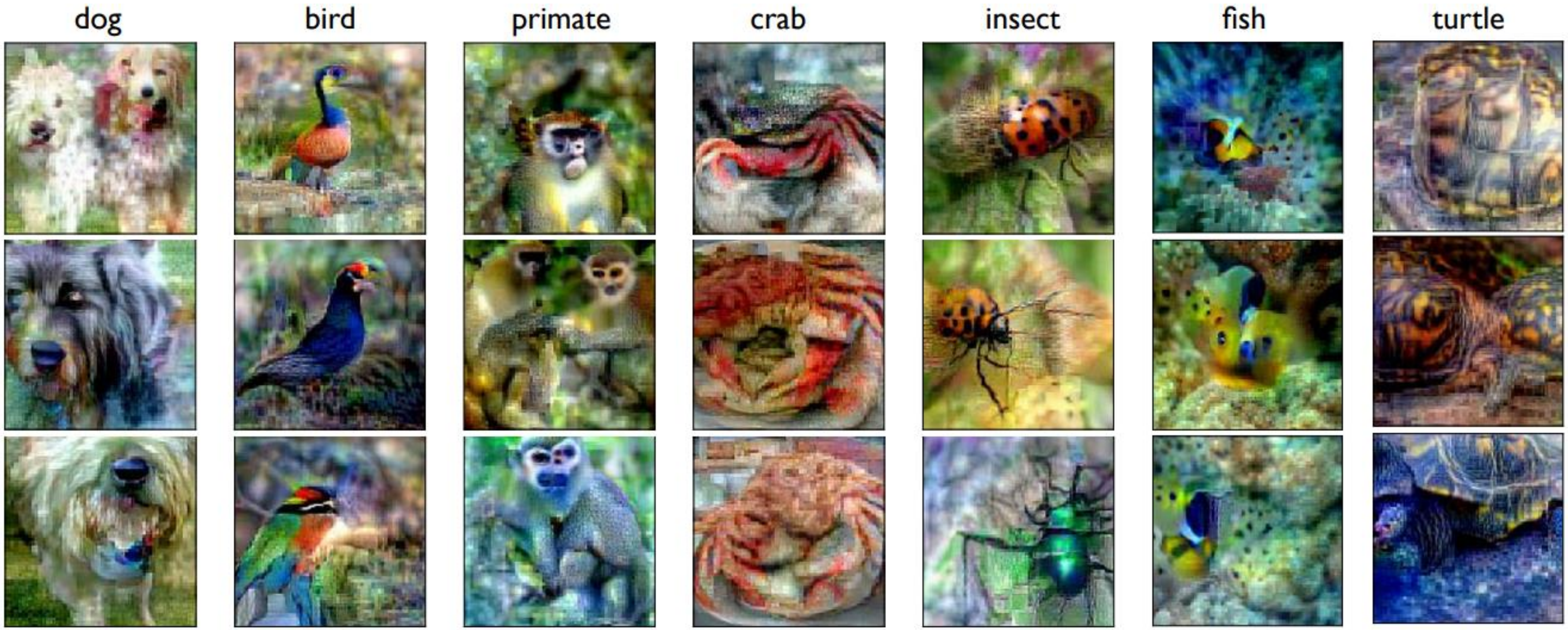
“Robustness May Be at Odds with Accuracy” (Tsipris et al. 2018)

Image synthesis with Robust Classifer



Santurkar et al. 2019, “Image Synthesis with a Single (Robust) Classifier”

Image synthesis with Robust Classifer



Santurkar et al. 2019, “Image Synthesis with a Single (Robust) Classifier”

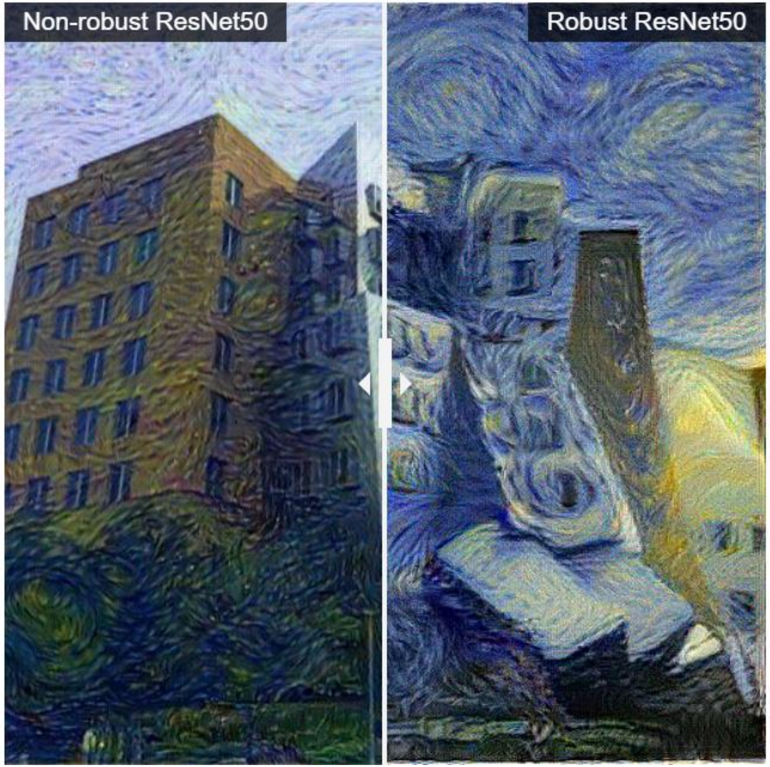
Image synthesis with Robust Classifer

Santurkar et al. 2019, “Image Synthesis with a Single (Robust) Classifier”

Style Transfer with Robust Model

Content

Style



Nakano, "A Discussion of 'Adversarial Examples Are Not Bugs, They Are Features': Adversarially Robust Neural Style Transfer", Distill, 2019.

What have we learnt today?

- Saw a few Adversarial Examples
- Discussed what they are
- How to attack: FGSM, PGD
- How to “defend”: Adversarial training (AT)
- Optimization view of AT
- Black-Box attacks (transferability)
- Security-wise summary
- Surprising Visual properties of robust models (beyond security)

Monday:

Sequences
(RNN, Attention, ViT)

25/11/2021

Defence Against the Adversarial Examples

Niv Haim

Weizmann Institute

DL4CV Course Winter 2022 (20224182)