A THEORETICAL LOOKS AT ADVERSARIAL EXAMPLES

Tom Goldstein

…and also…

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OVERVIEW

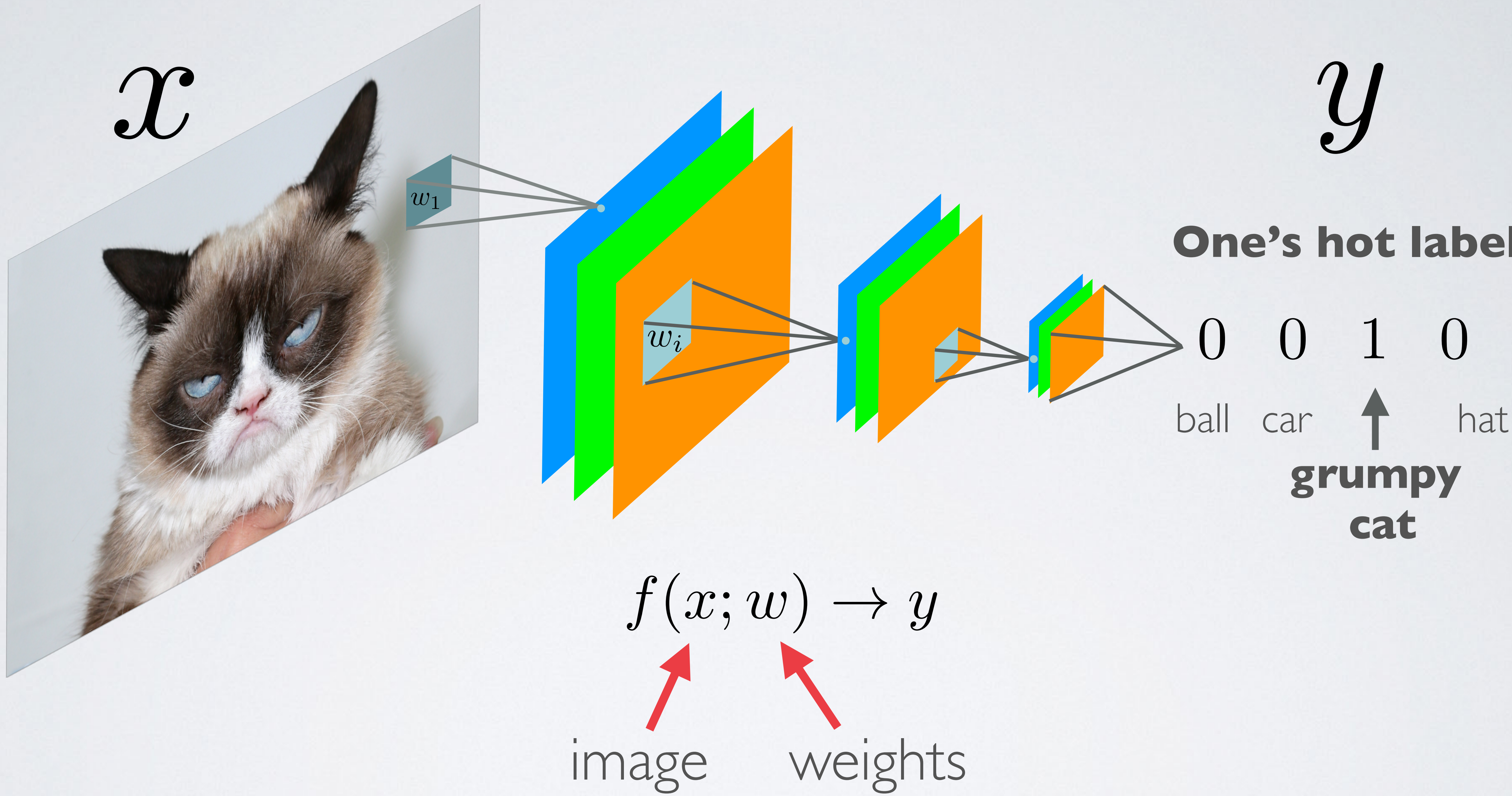
Why is optimization so easy on neural nets?

What are adversarial examples, and what are their risks?

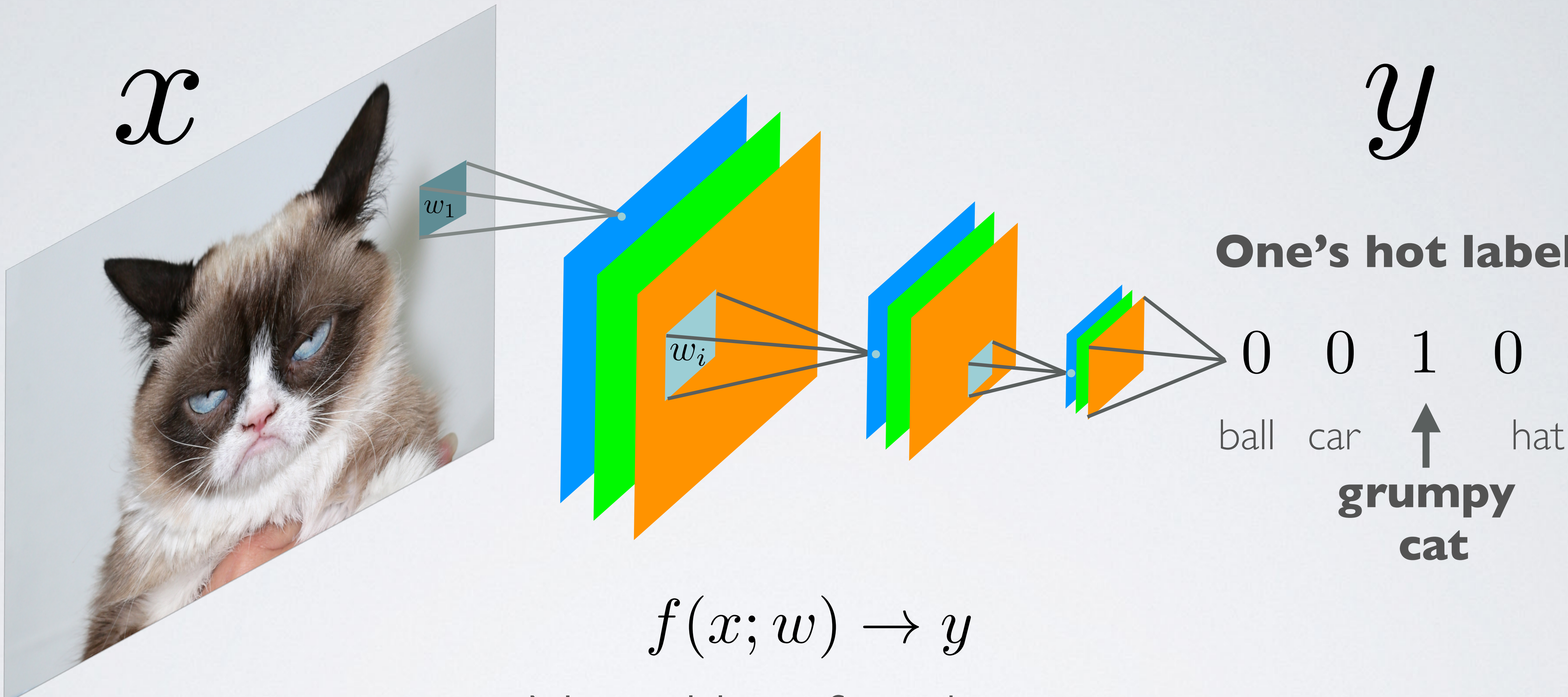
Poison attacks

Are they an escapable problem?

CONVOLUTIONAL NET



CONVOLUTIONAL NET



$$f(x;w) \rightarrow y$$

Neural loss function

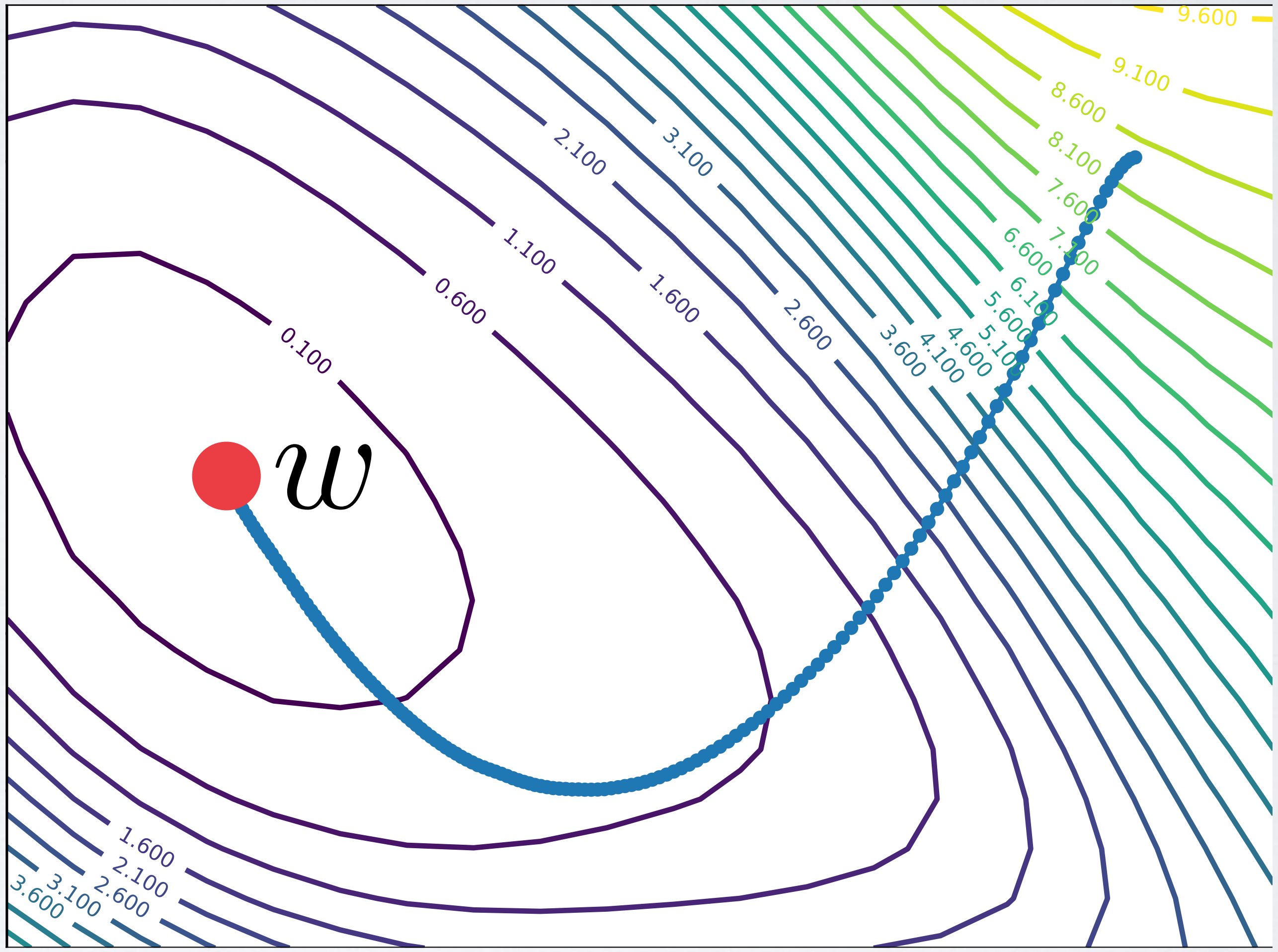
$$L(w) = \min_{w} \sum_{i} \|f(x_i;w) - y_i\|^2$$

Non-convex?

VISUALIZING LOSS FUNCTIONS: FILTER NORMALIZATION

Step 1:

Find minimizer



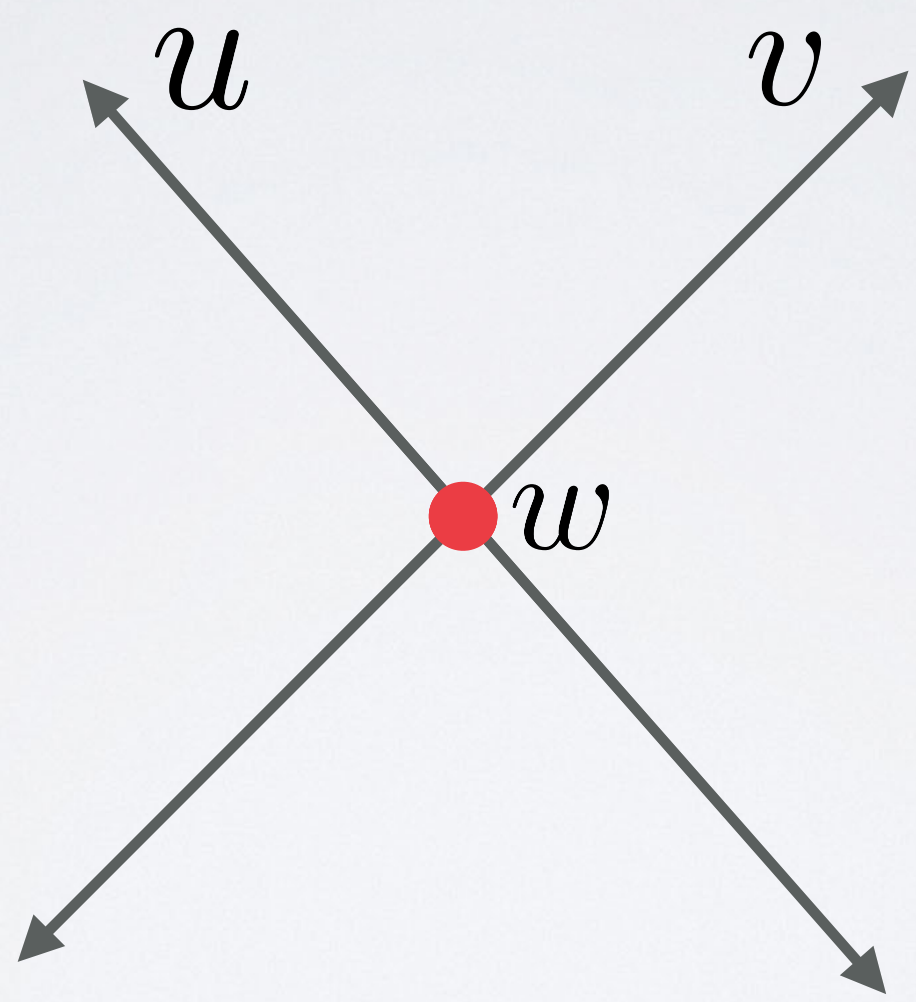
30 million dimensions

VISUALIZING LOSS FUNCTIONS: FILTER NORMALIZATION

Step 2:

Random directions

u, v

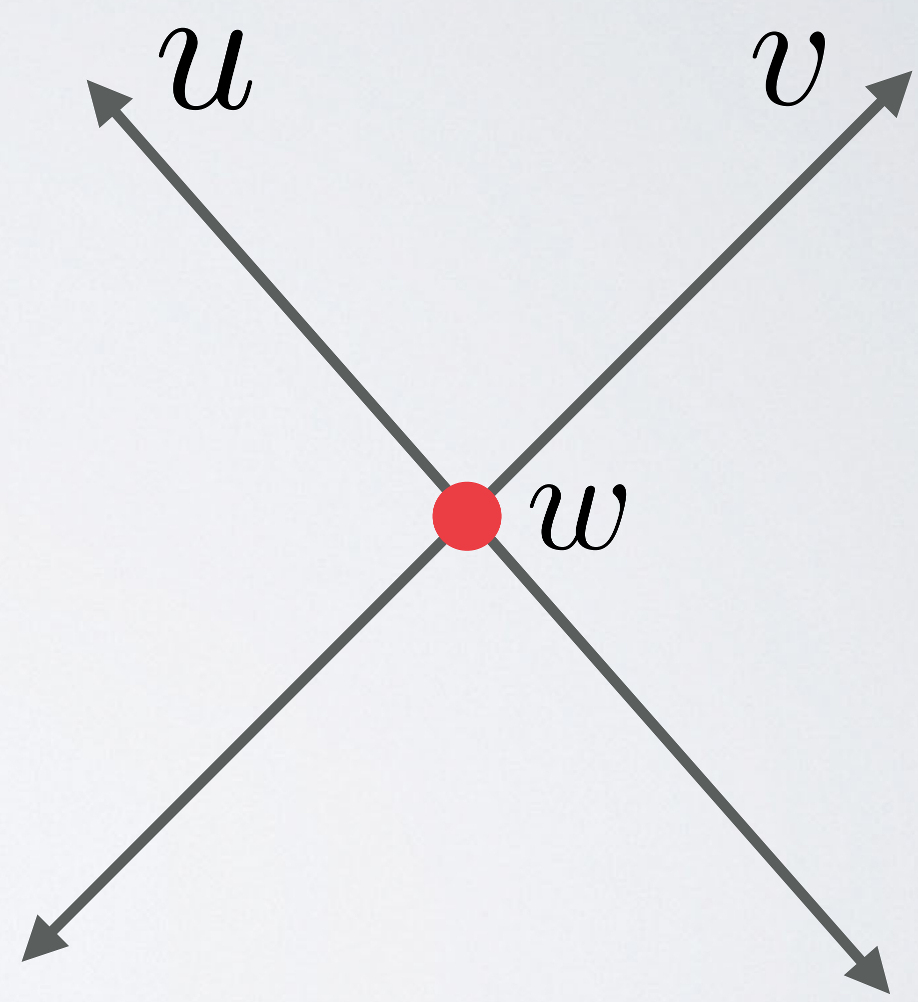


VISUALIZING LOSS FUNCTIONS: FILTER NORMALIZATION

Step 3:

Filter normalization

$$u_i \leftarrow u_i \cdot \frac{\|w_i\|}{\|u_i\|}$$

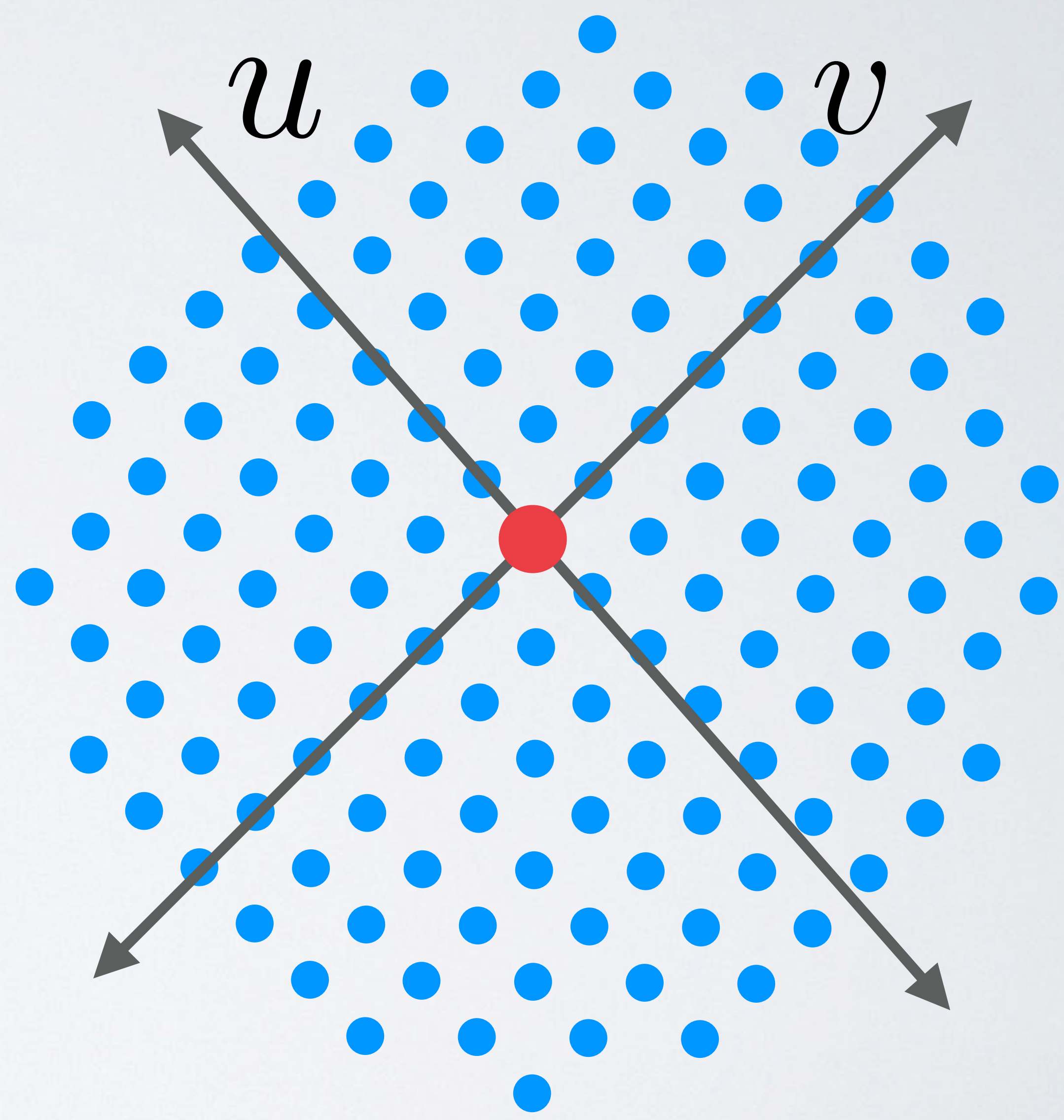


Li, Xu, Taylor, Studer, G. "Visualizing the loss landscape of neural nets."

VISUALIZING LOSS FUNCTIONS: FILTER NORMALIZATION

Step 4

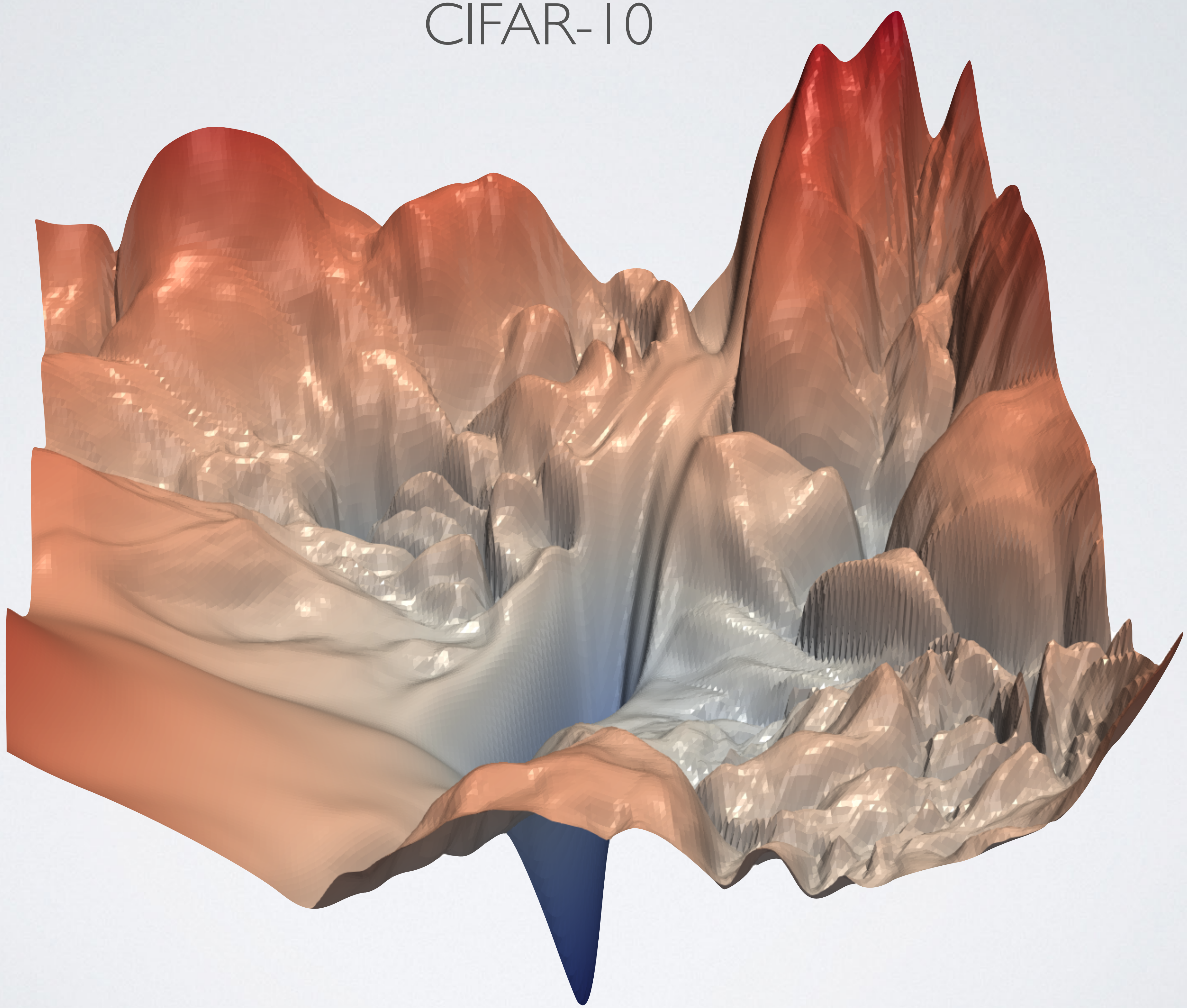
Plot



Li, Xu, Taylor, Studer, G. "Visualizing the loss landscape of neural nets."

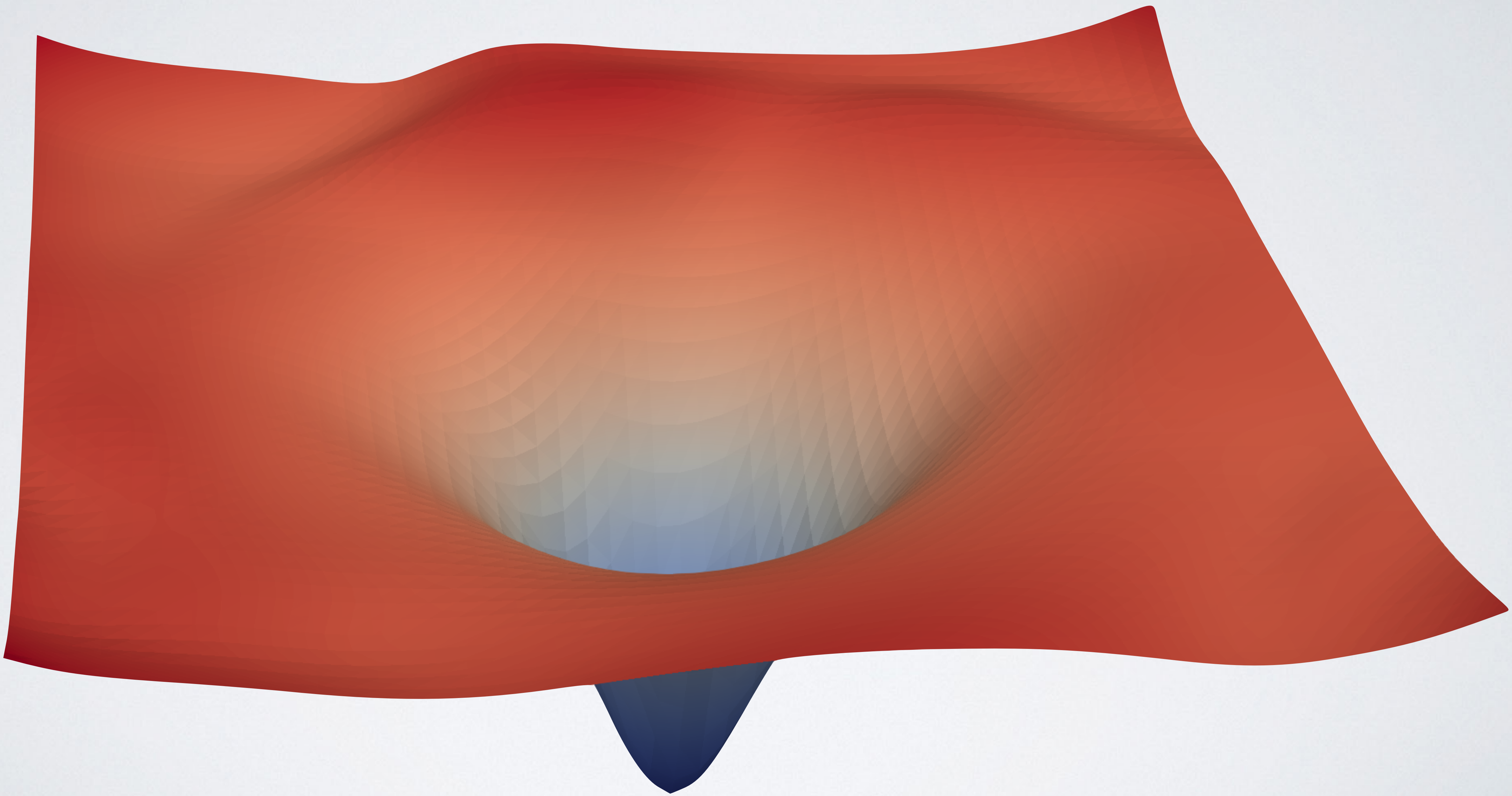
56 LAYER "VGG" NET

CIFAR-10



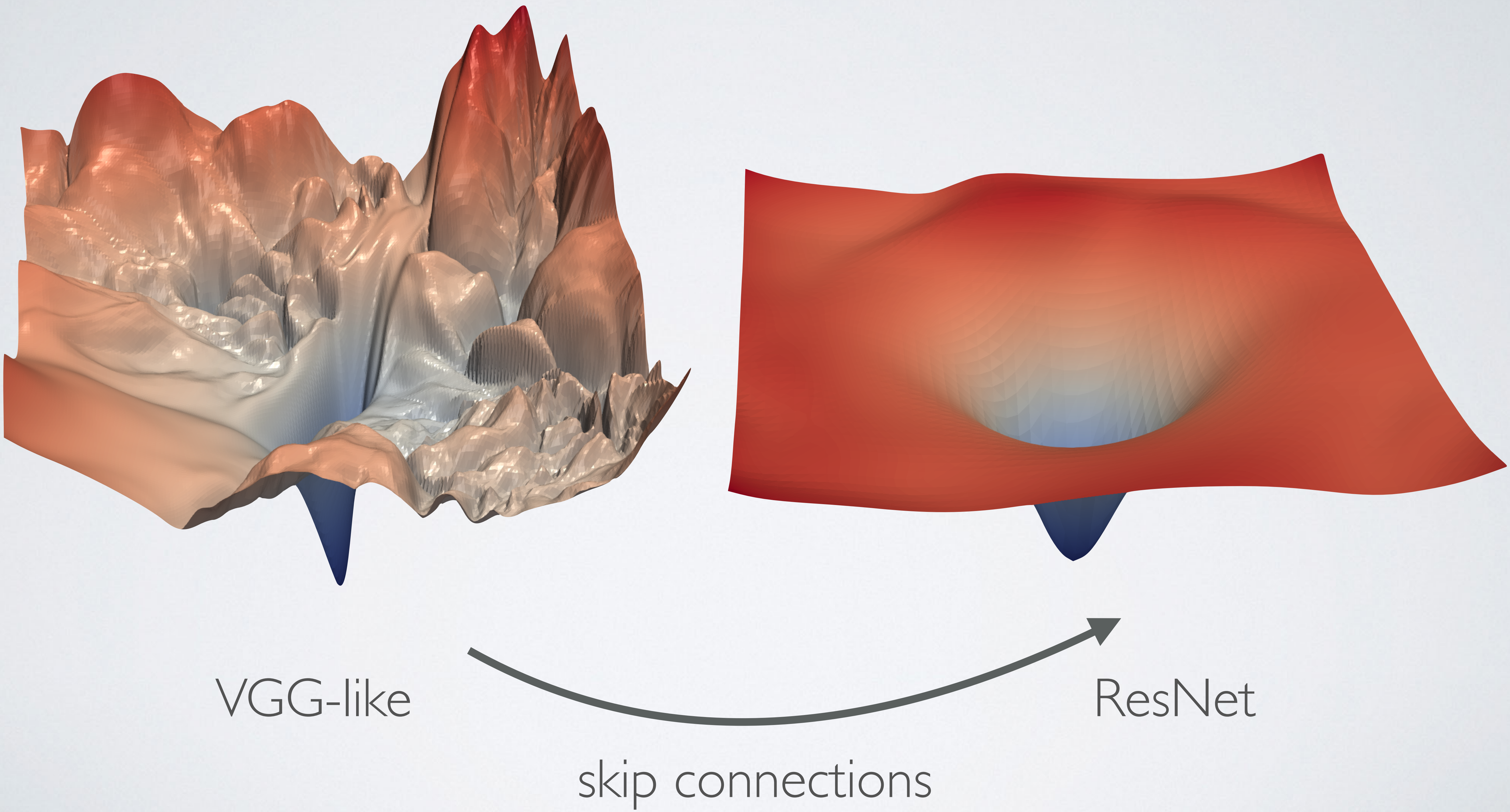
56 LAYER NEURAL NET

CIFAR-10



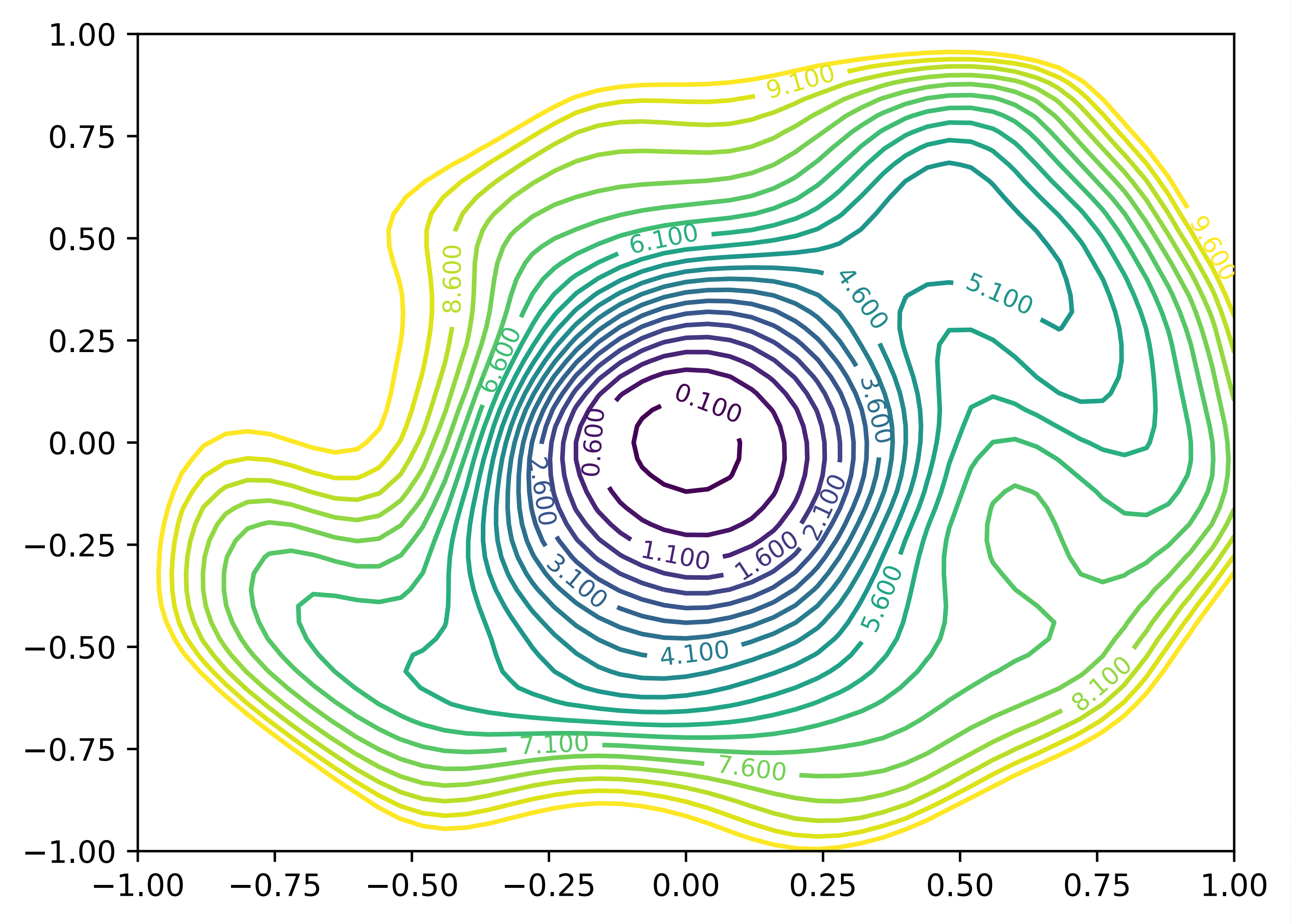
56 LAYER NEURAL NET

CIFAR-10



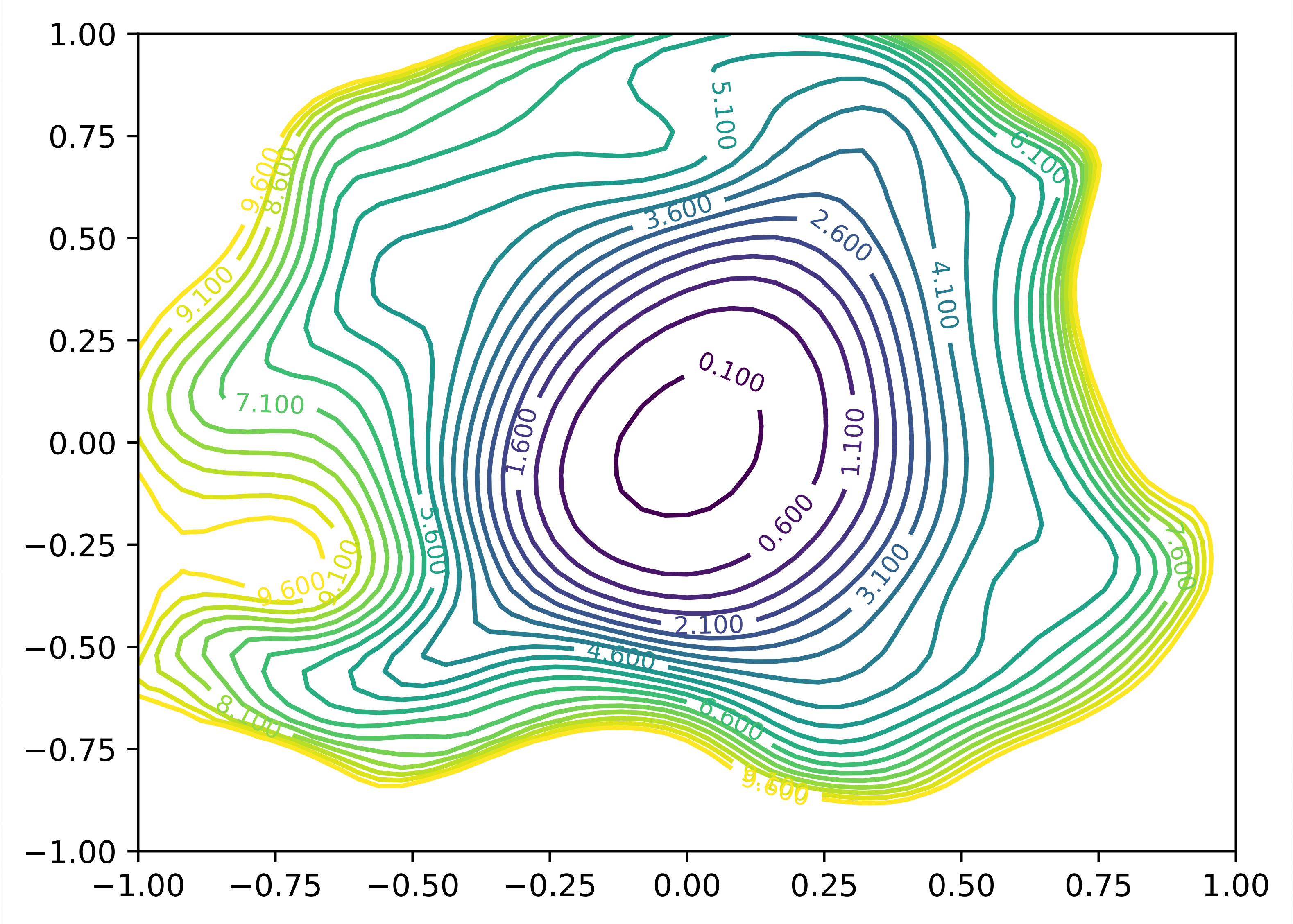
CHAOTIC TRANSITIONS

VGG-9



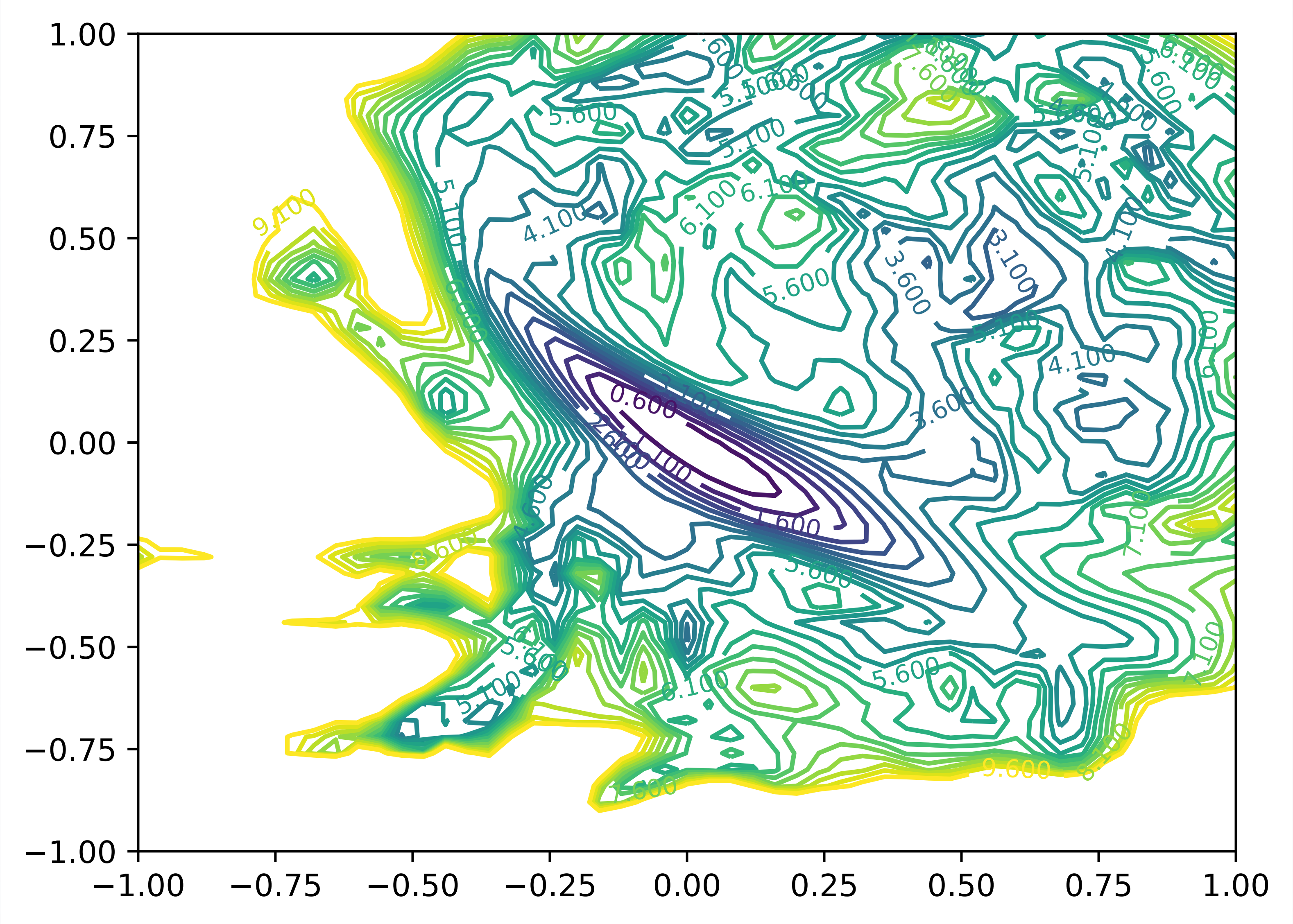
CHAOTIC TRANSITIONS

VGG-20



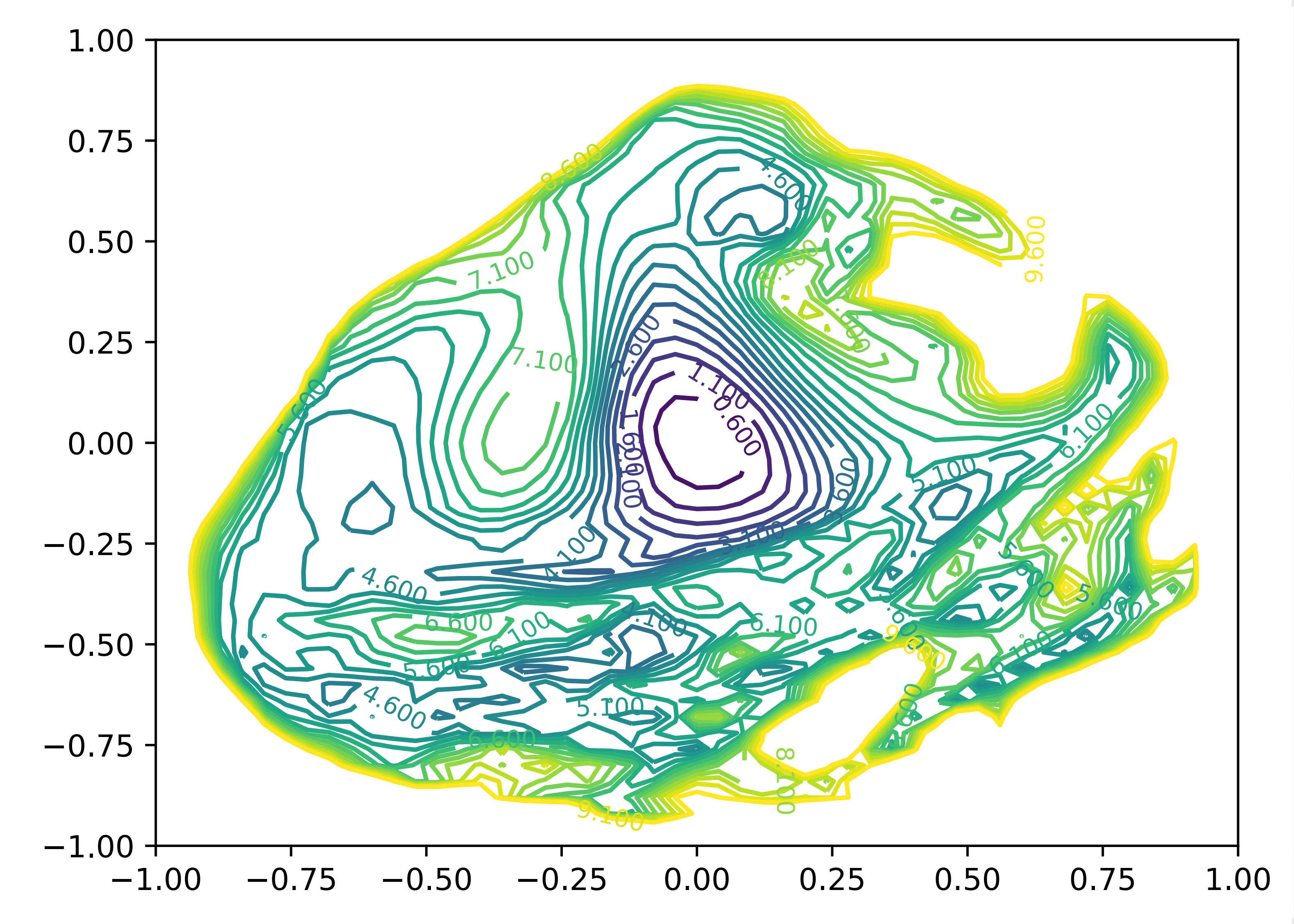
CHAOTIC TRANSITIONS

VGG-56



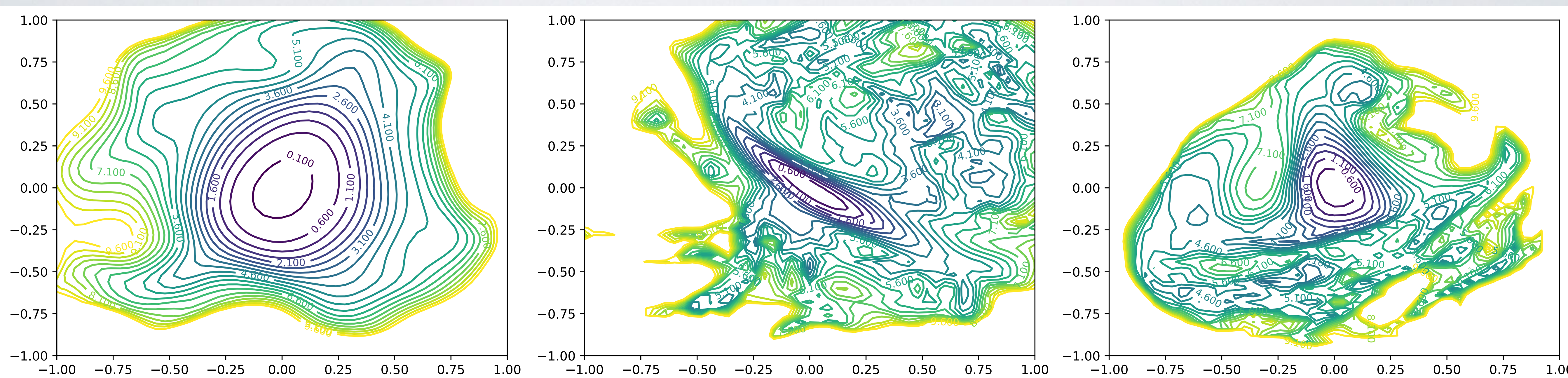
CHAOTIC TRANSITIONS

VGG-110



CHAOTIC TRANSITIONS

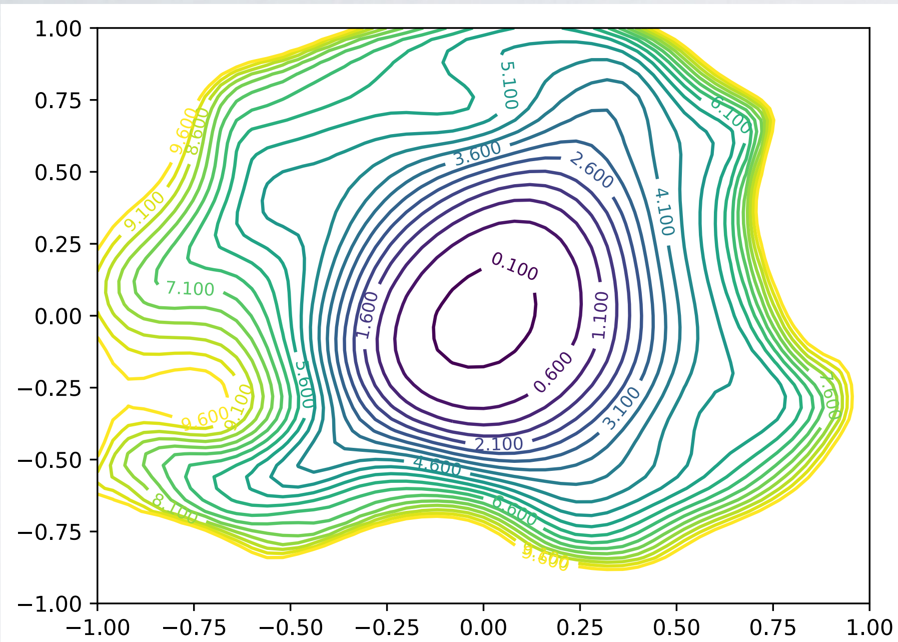
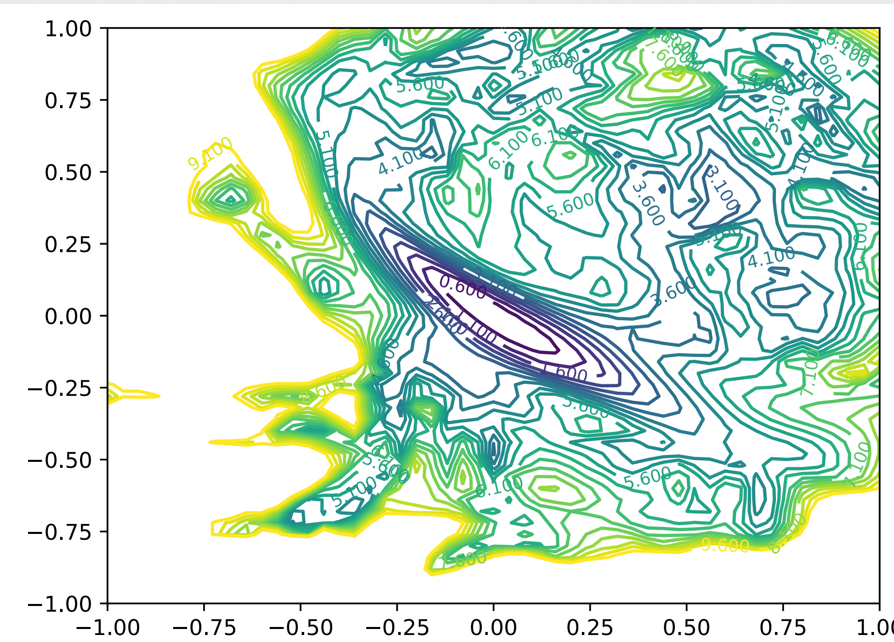
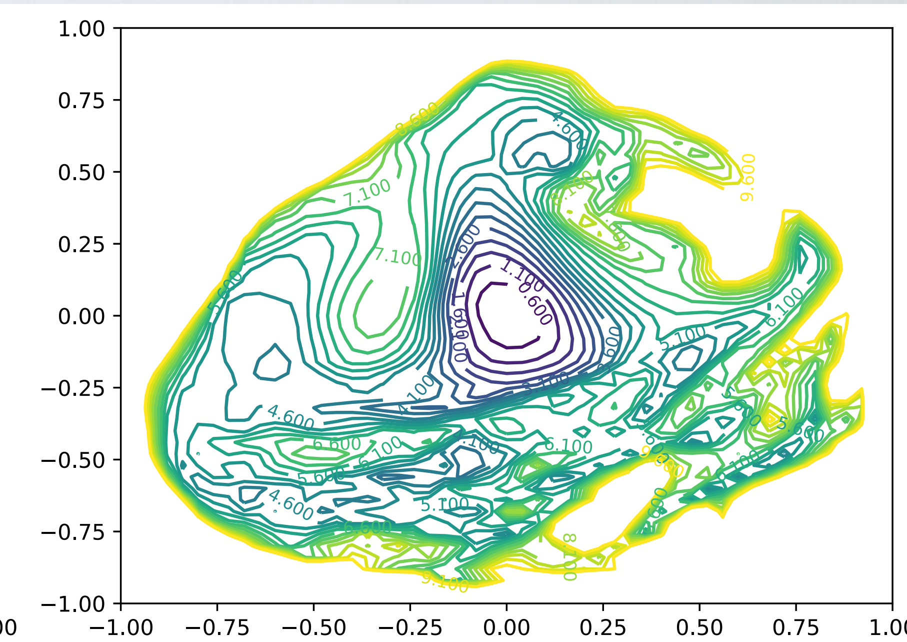
VGG-20 **VGG-56** **VGG-110**

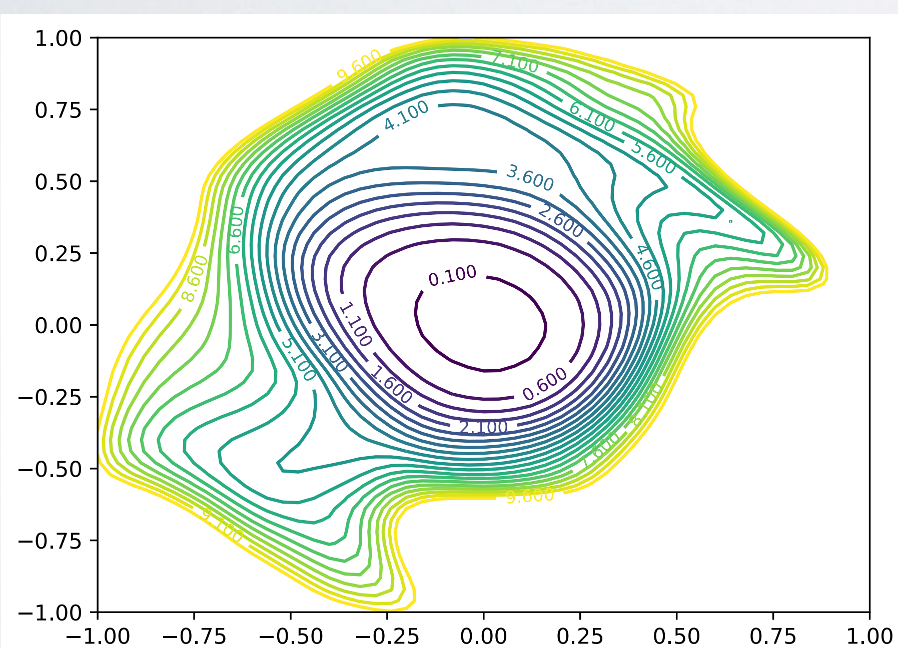
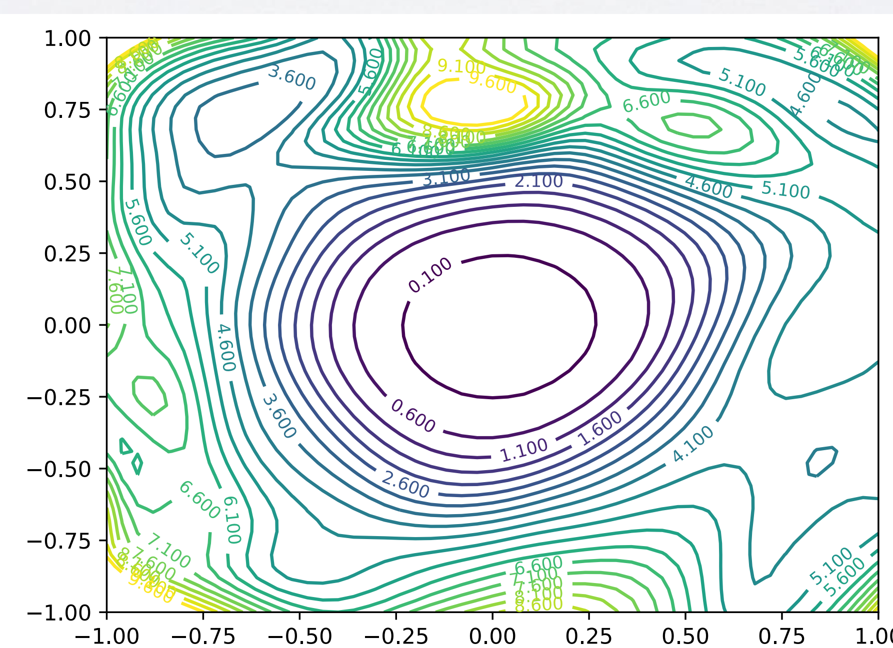
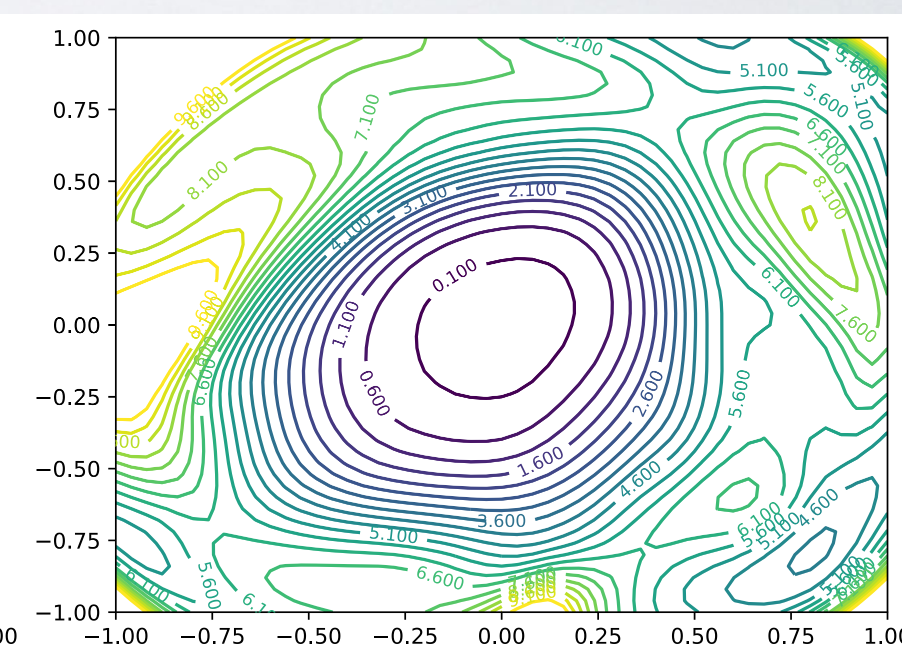


Convexity **Chaos**

CHAOTIC TRANSITIONS

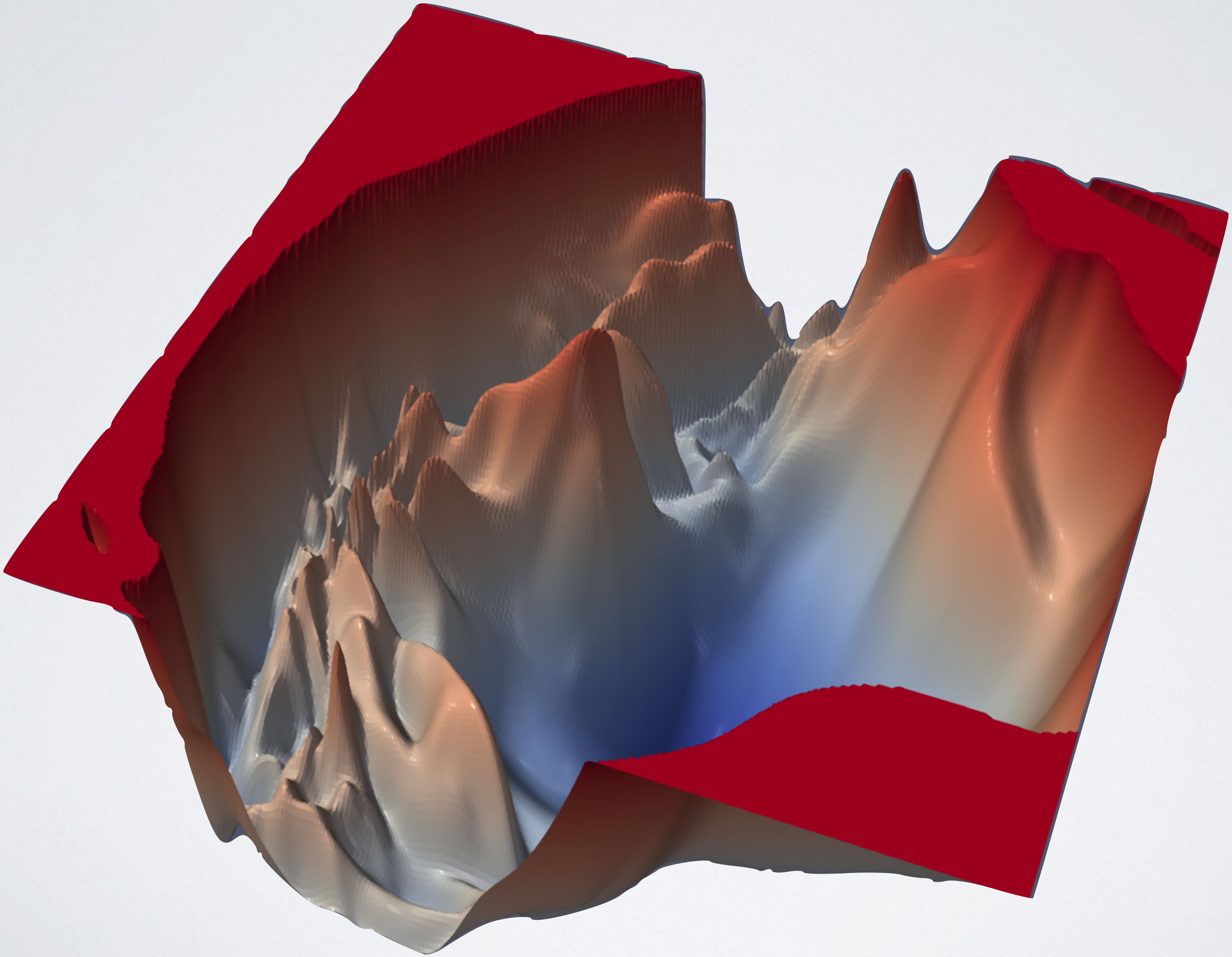
VGG-20 **VGG-56** **VGG-110**

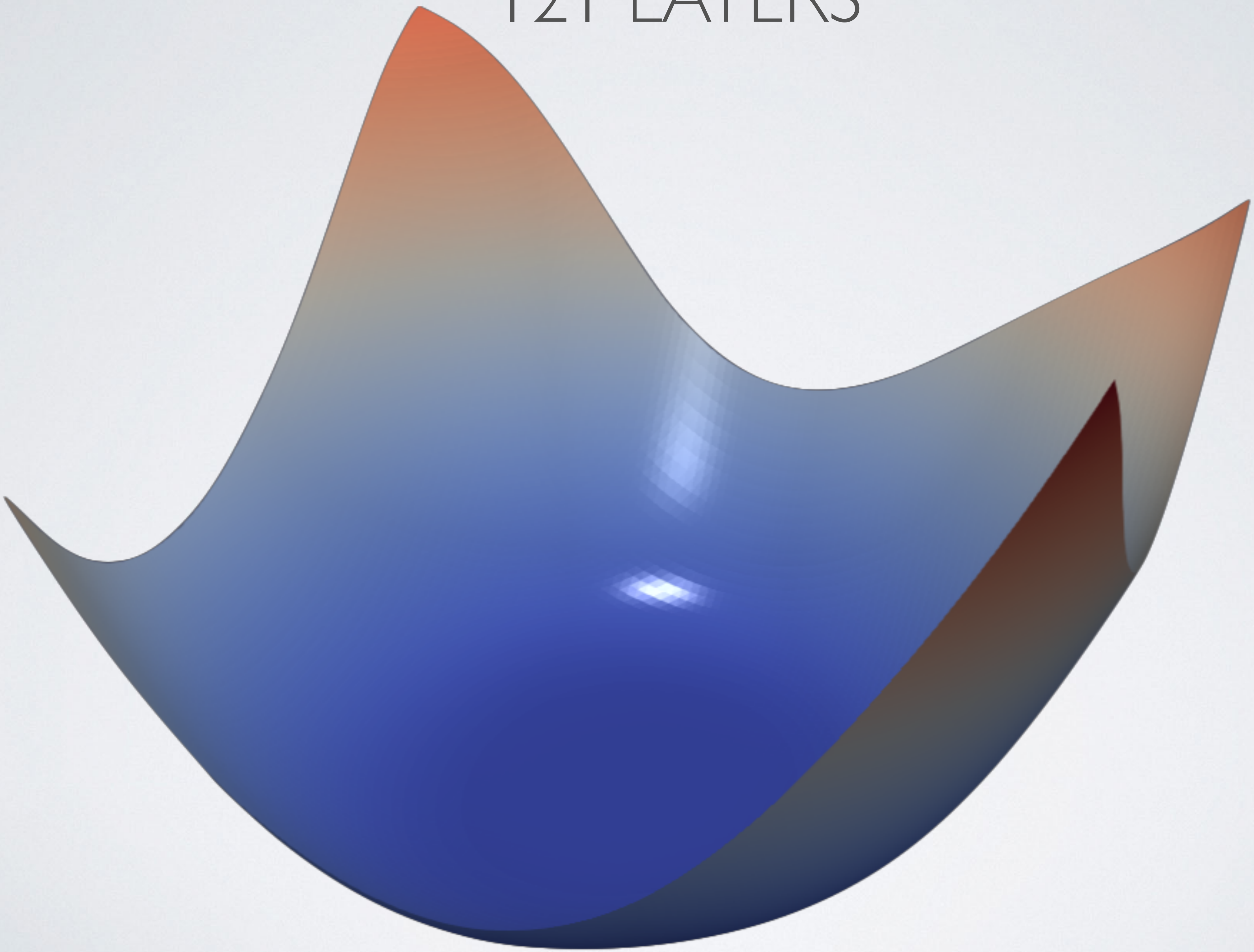
ResNet-20 **ResNet-56** **ResNet-110**

VGG-110



DENSENET

121 LAYERS

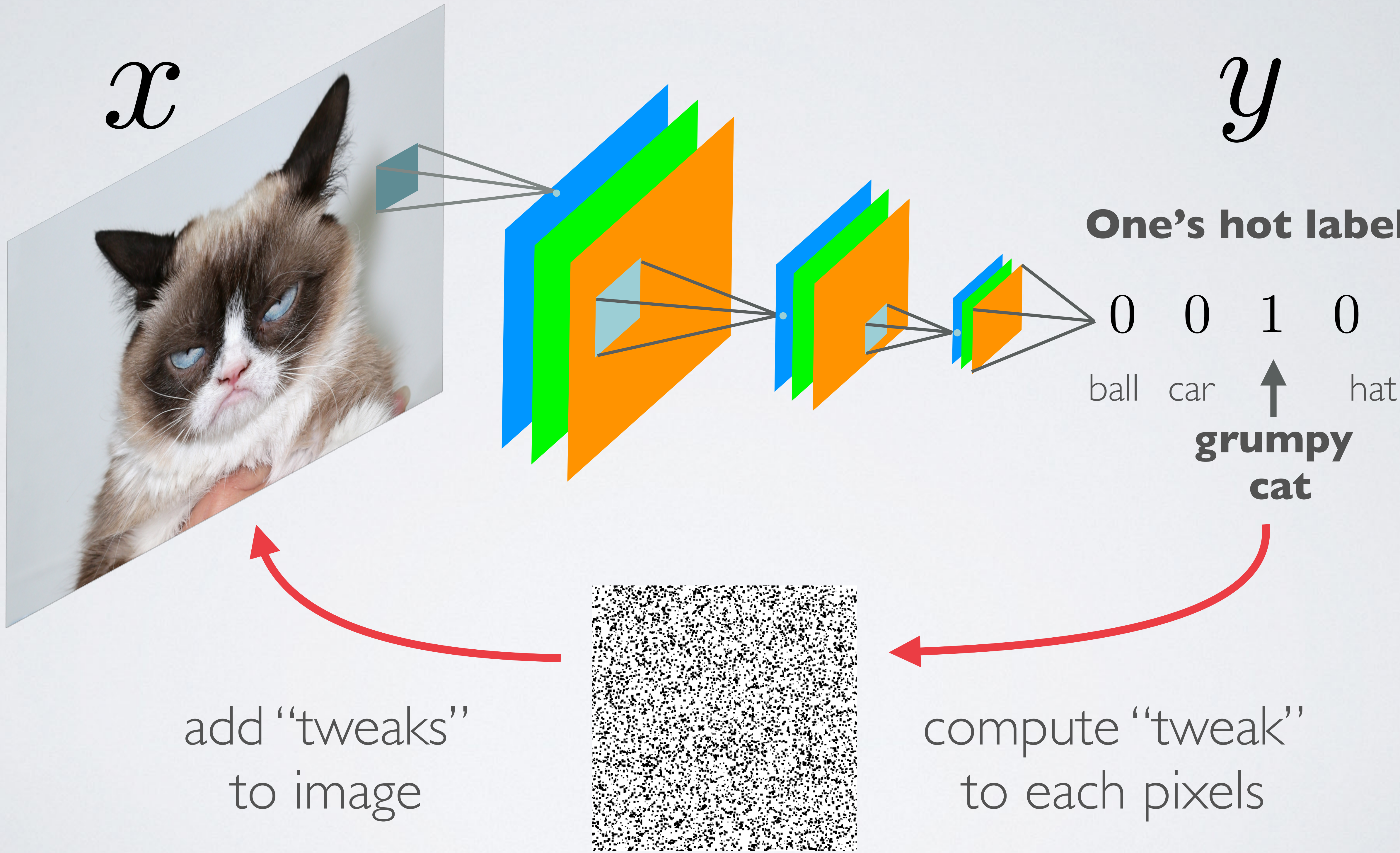


Optimization on neural nets is easy!

That's great for ML.

…but bad for security.

ADVERSARIAL EXAMPLES



ADVERSARIAL ATTACKS

"Egyptian Cat" 28%

"Traffic Light" 97%

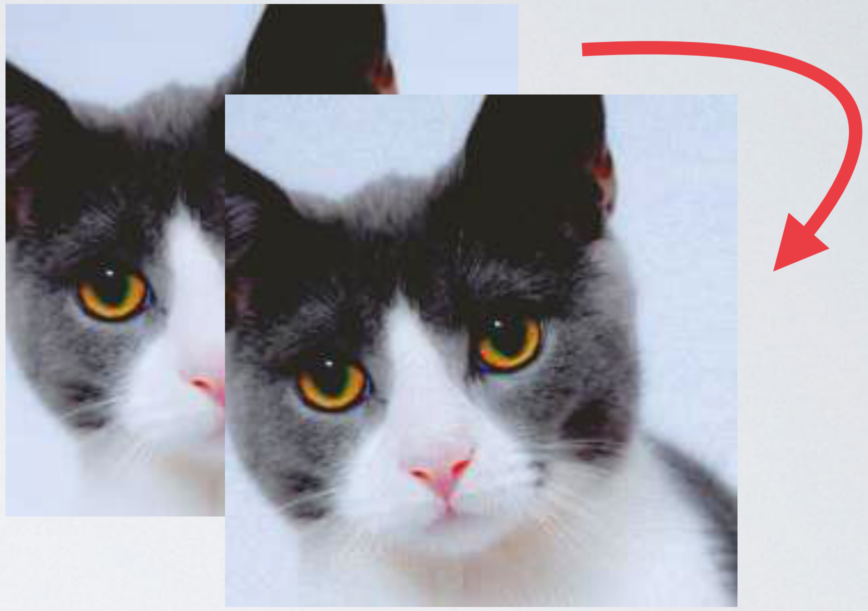
ADVERSARIAL ATTACKS

"Ox" 85%

"Traffic Light" 96%

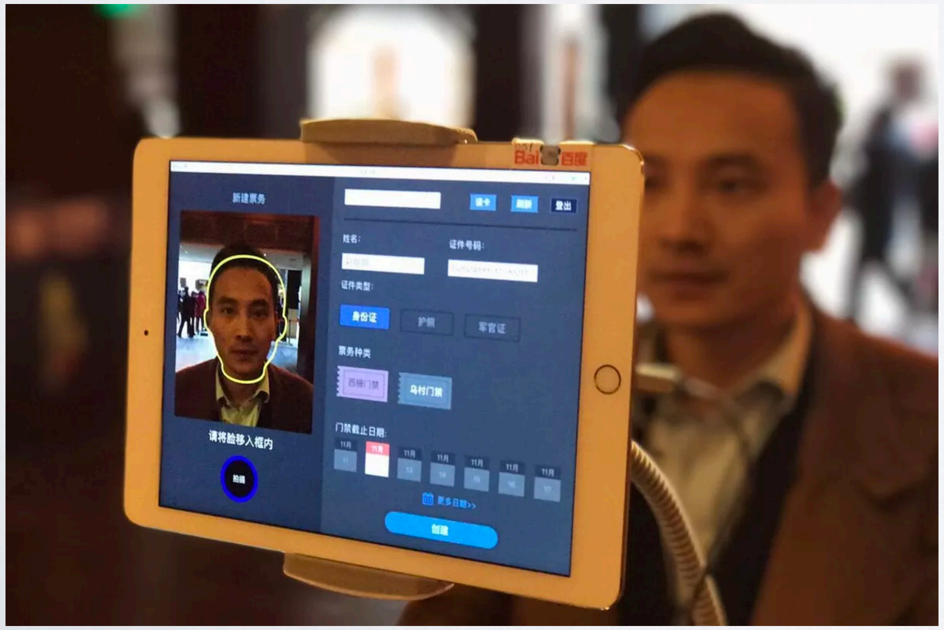
THREAT MODEL: EVASION

Test-time attacks: adversary controls inputs



Fails when…

Supervised security desk



Phishing email/
Competitor email

THREAT MODEL: POISON

Train-time attacks:
adversary controls training data

Does this *actually* happen?

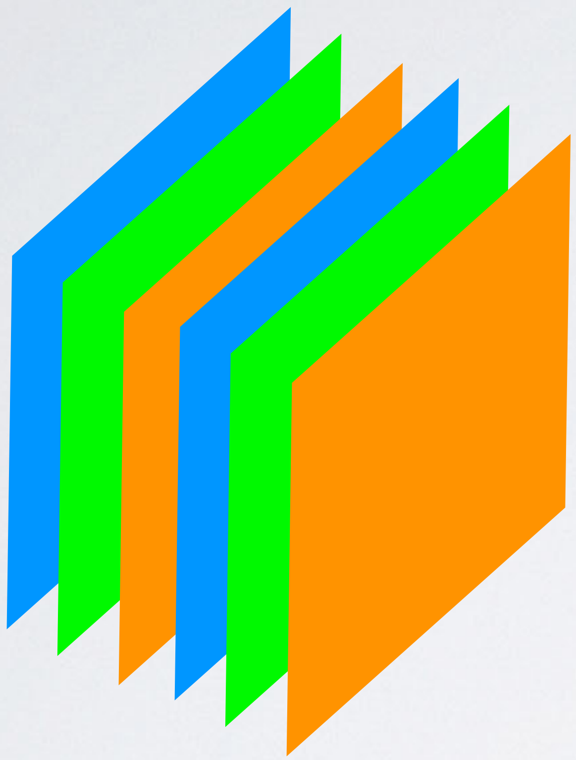
Scraping images from the web

Harvesting system inputs (spam detector)

Bad actors/inside agents

HOW POISONING WORKS

Training data



Testing example

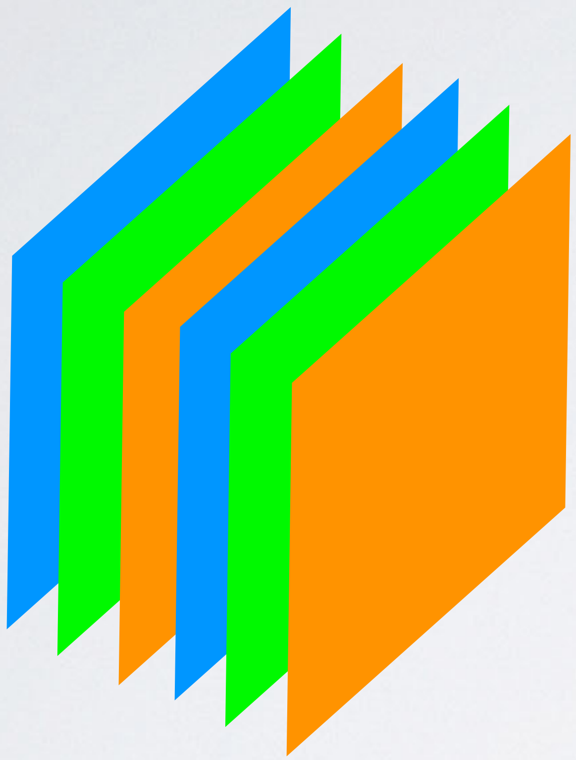
Plane

Frog

Base

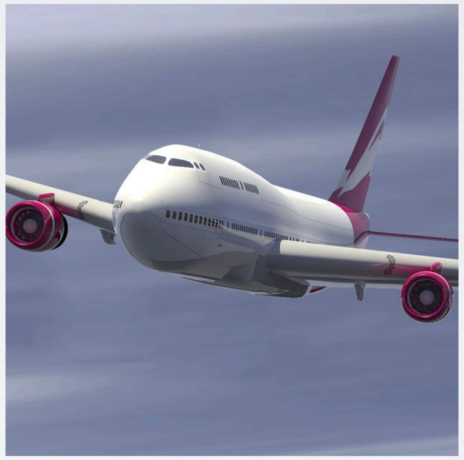
HOW POISONING WORKS

Training data



Testing example

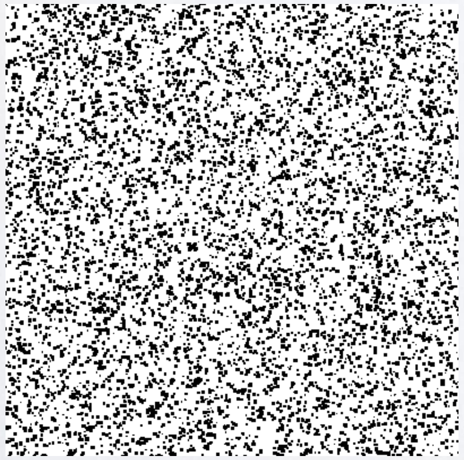
Plane



Frog

Base

+



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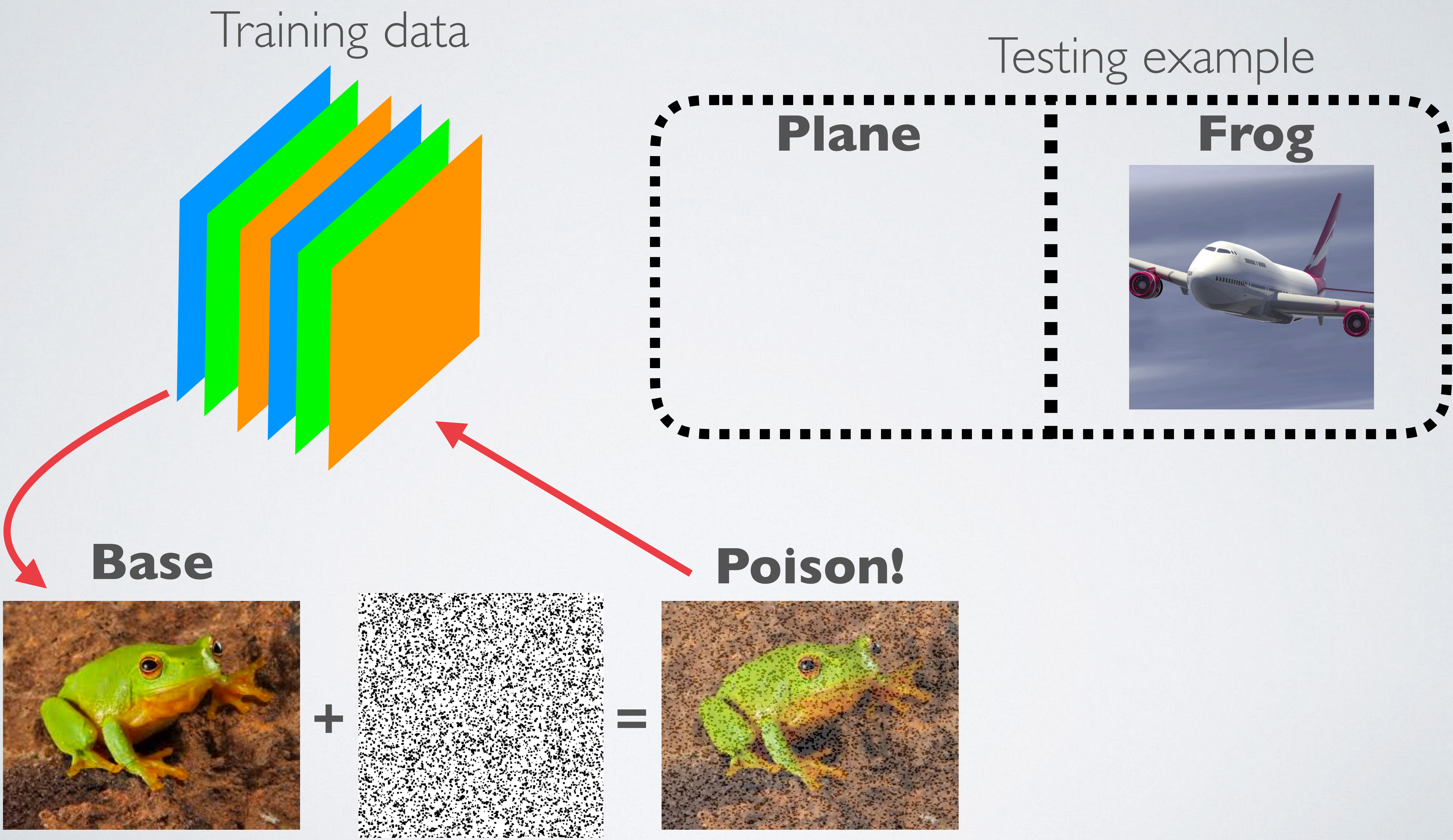
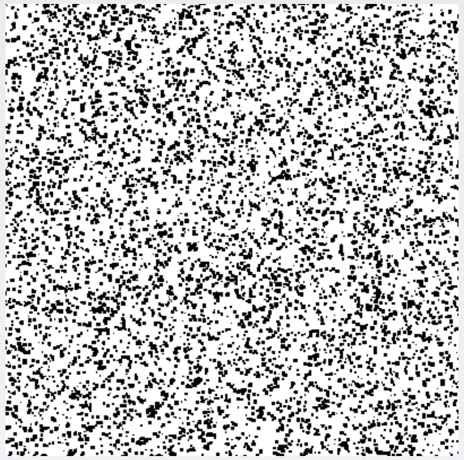
Poison!

HOW POISONING WORKS



CLEAN-LABEL + TARGETED

Base **Poison!**

 +  = 

Attacks are hard to detect

Clean label: poisons are labeled "correctly"

Performance only changes on selected target

Attacks can be executed by outsider

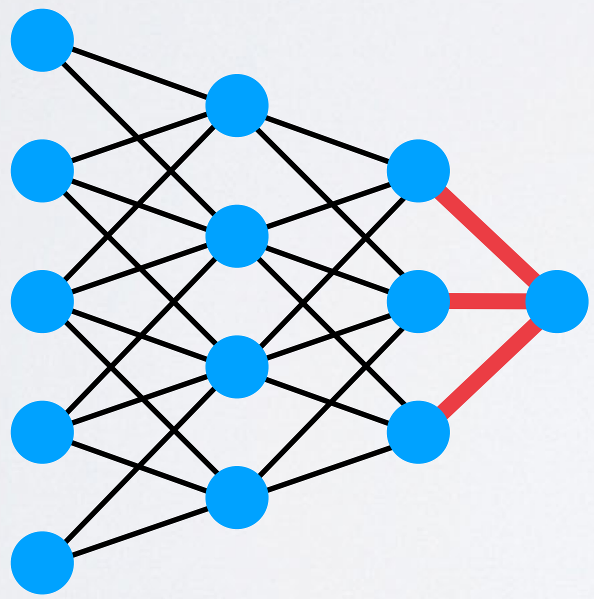
Poison data can be placed on the web

Poison data can be sent/emailed to data collectors

TWO CONTEXTS

Transfer learning

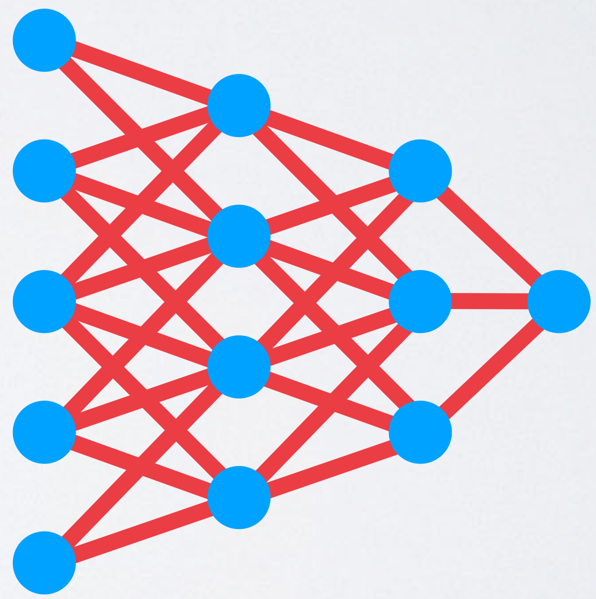
- Standard, pre-trained net is used
- "Feature extraction" layers frozen
- Classification layers re-trained
- Common practice in industry



"One-shot kill" possible

End-to end re-training

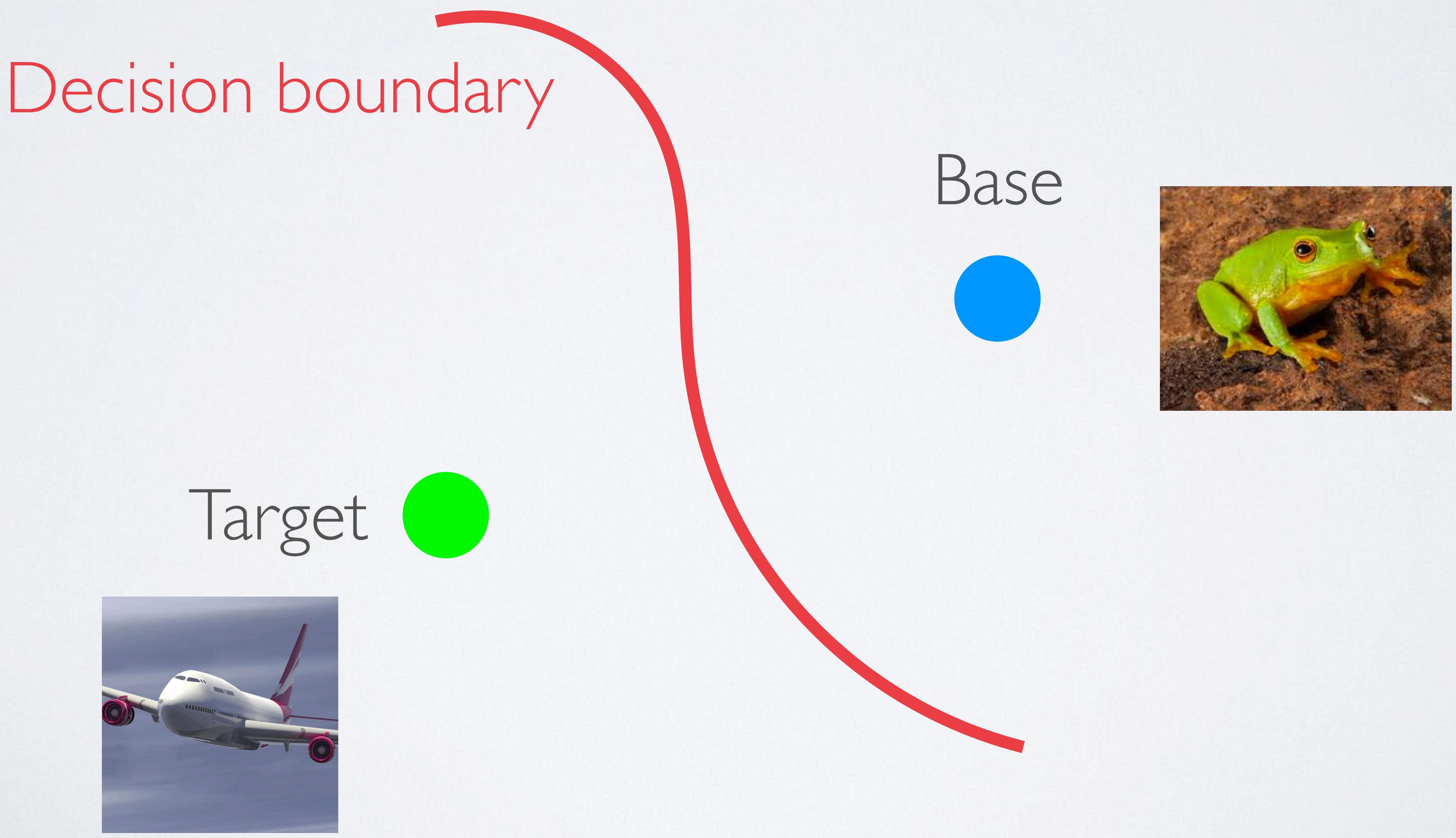
- Pre-trained net is used
- All-layers are re-trained



Multiple poisons required

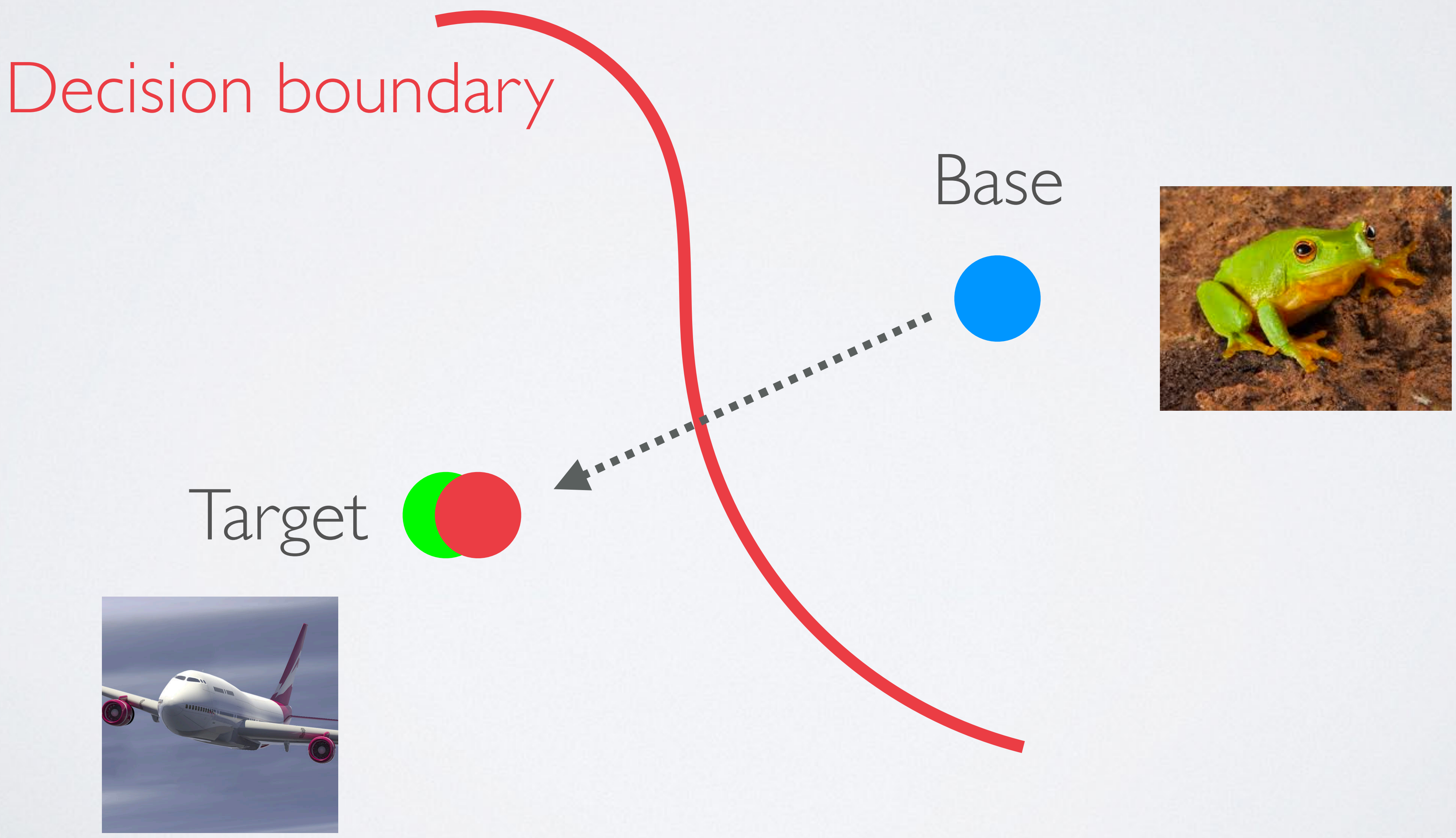
COLLISION ATTACK

$$\mathbf{p} = \underset{\forall \mathbf{x}}{\operatorname{argmin}} \ \|f(\mathbf{x}) - f(\mathbf{t})\|^2 + \beta \|\mathbf{x} - \mathbf{b}\|^2 \qquad (1)$$



COLLISION ATTACK

$$\mathbf{p} = \underset{\forall \mathbf{x}}{\operatorname{argmin}} \; \| f(\mathbf{x}) - f(\mathbf{t}) \|^2 + \beta \, \| \mathbf{x} - \mathbf{b} \|^2 \qquad (1)$$



COLLISION ATTACK

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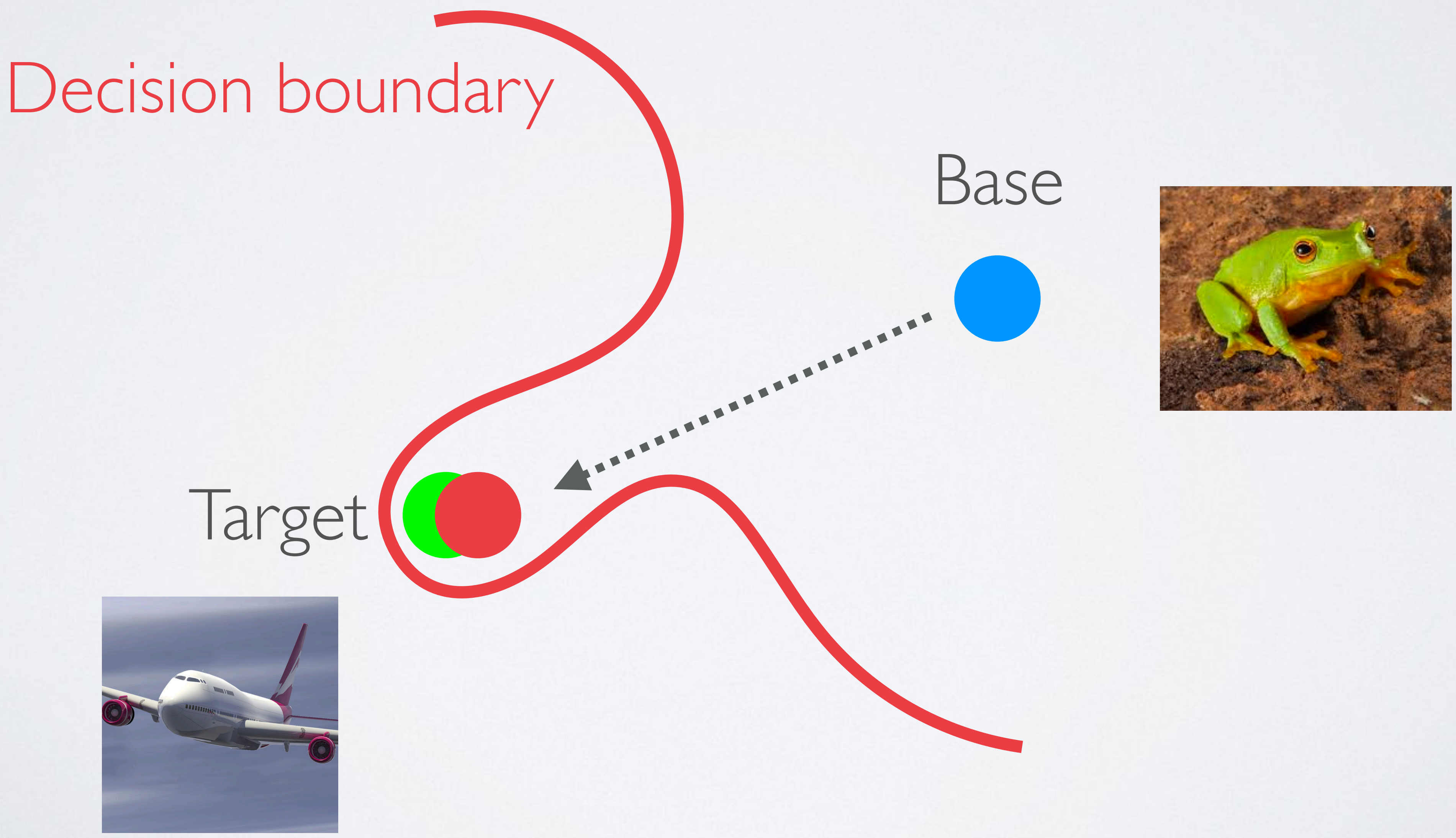
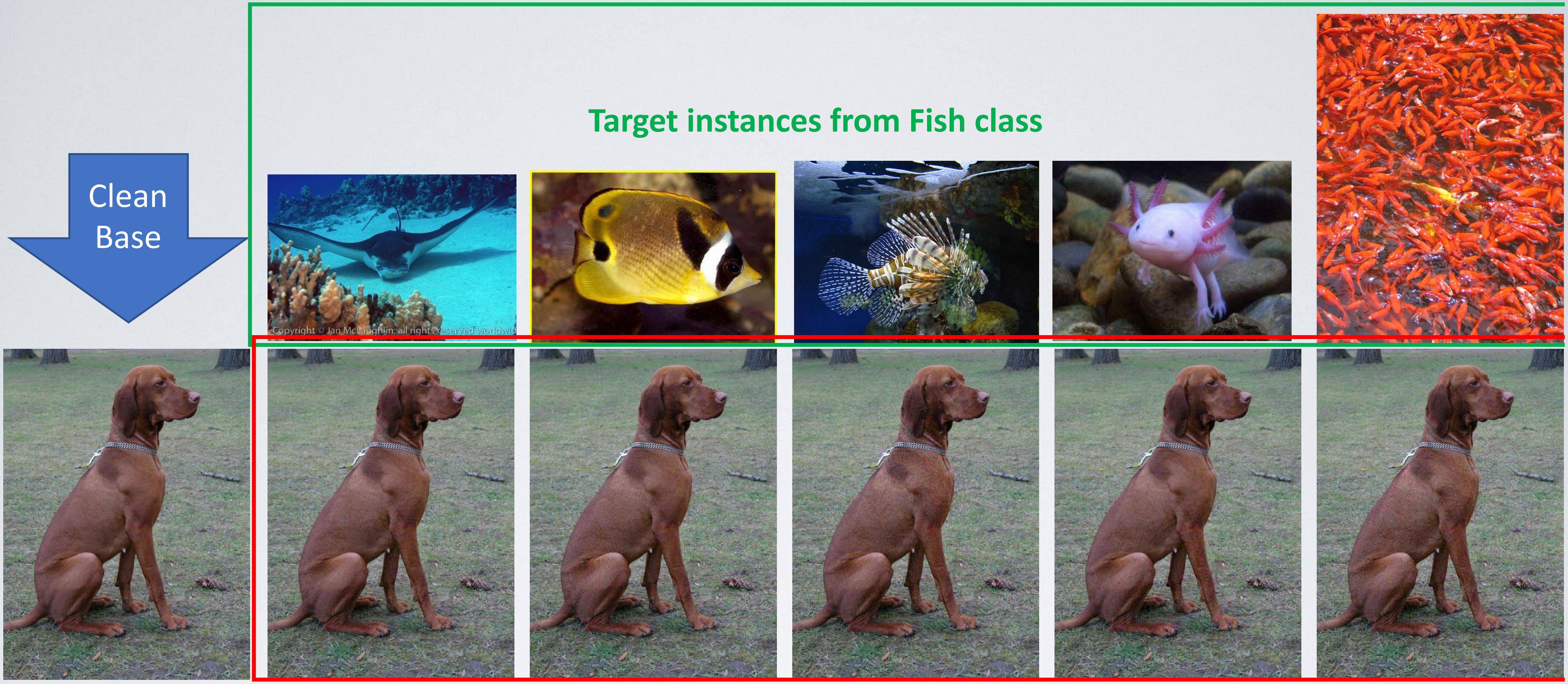
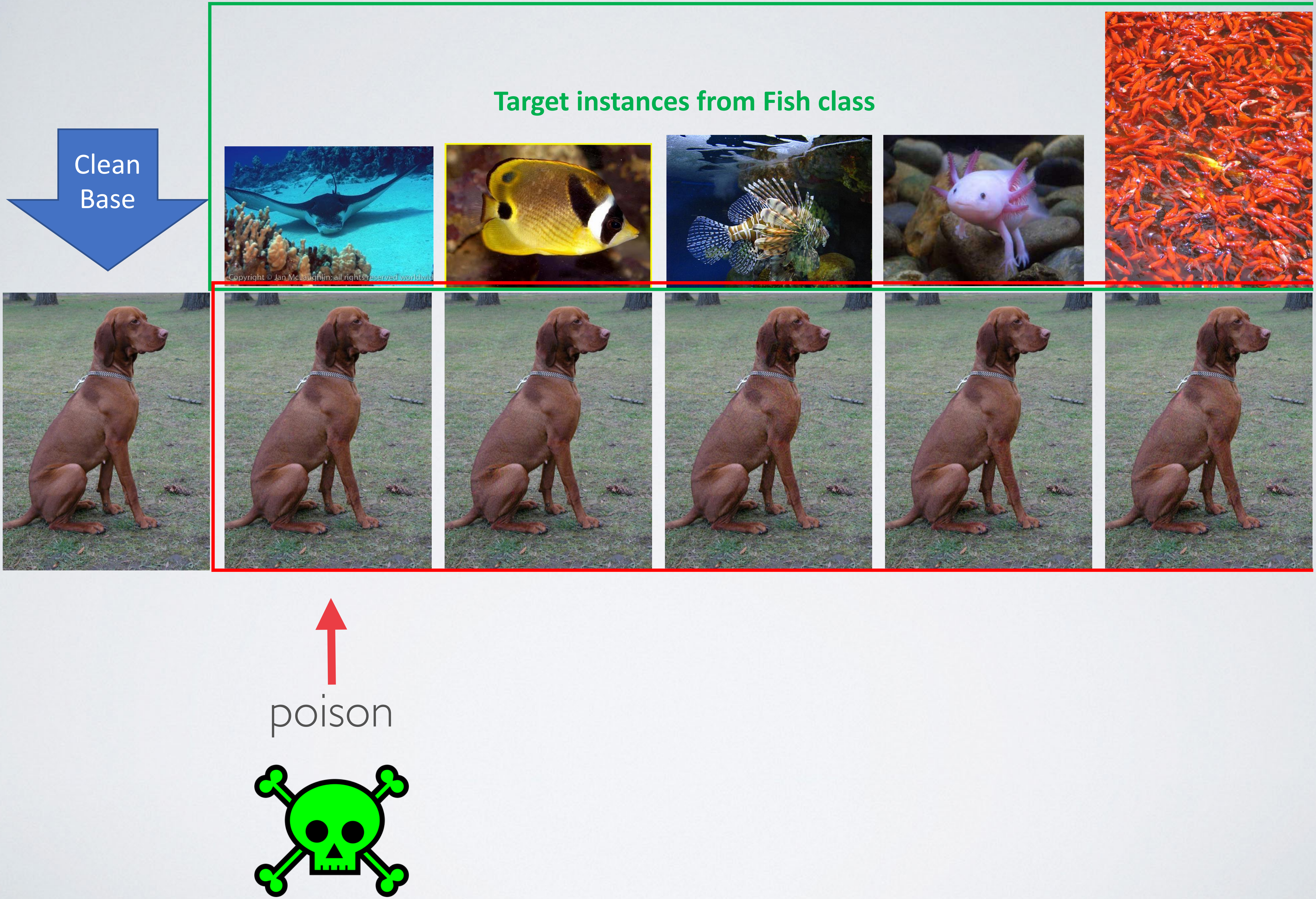
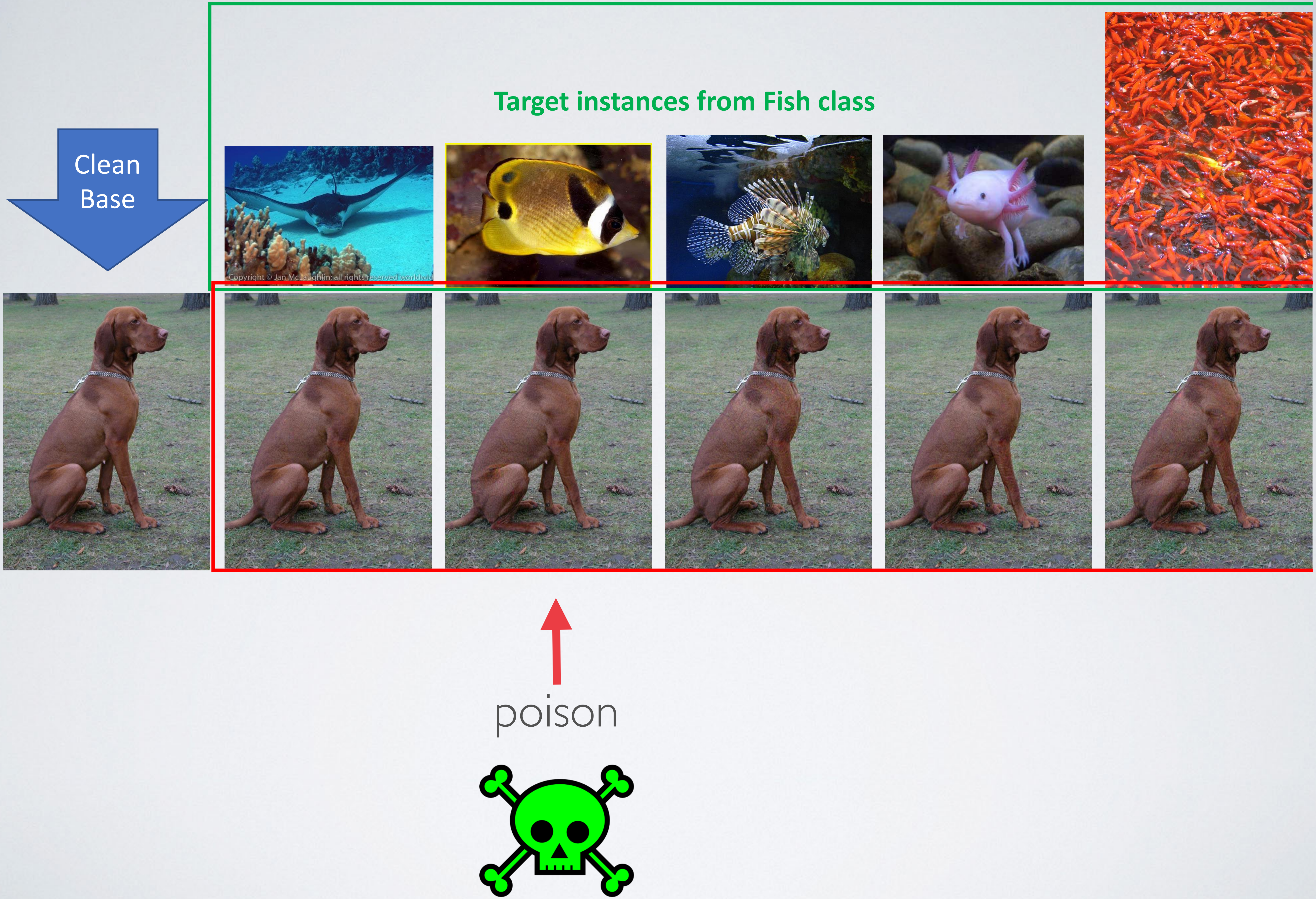




Original image


Target instances from Fish class
Clean
Base
poison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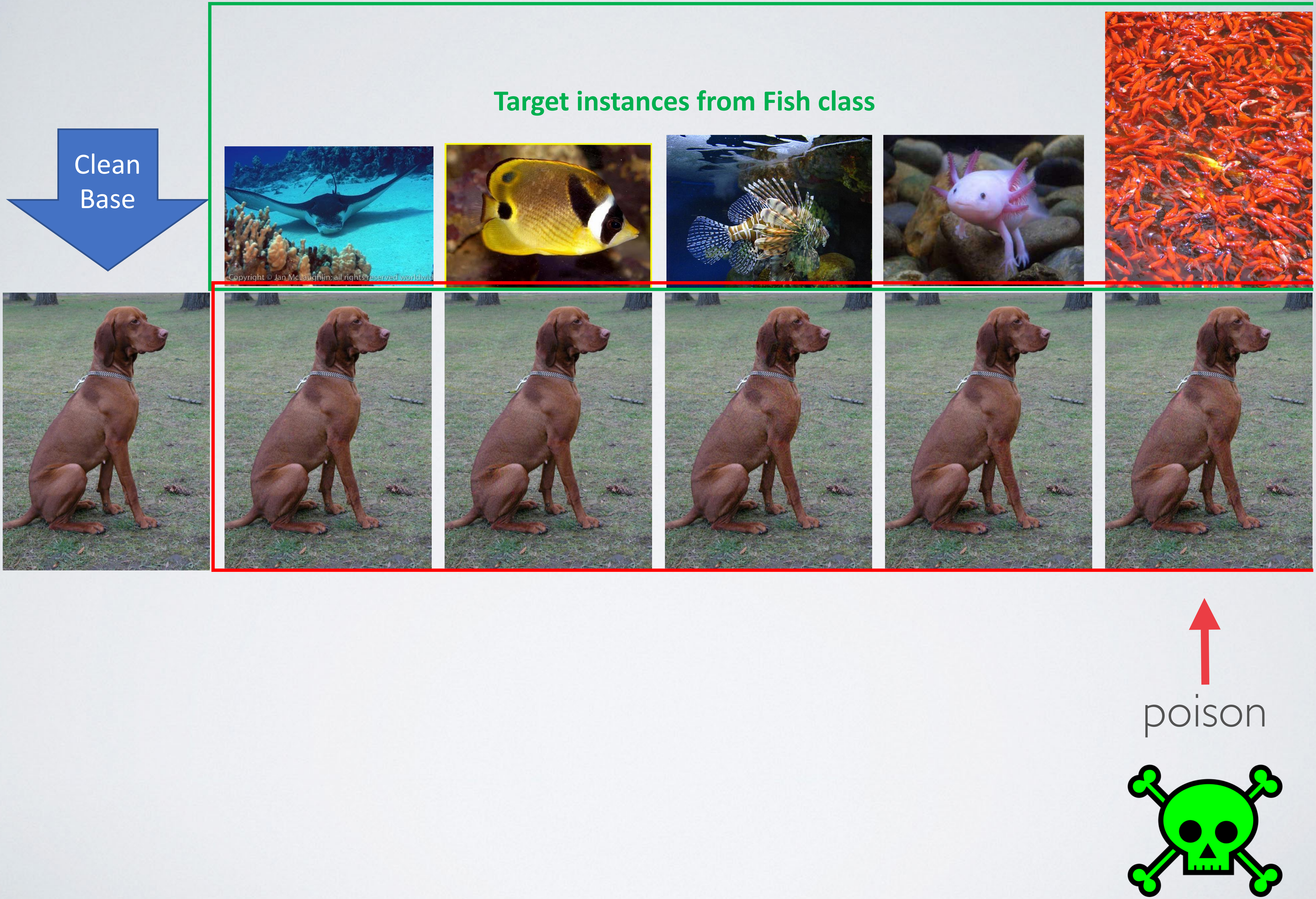
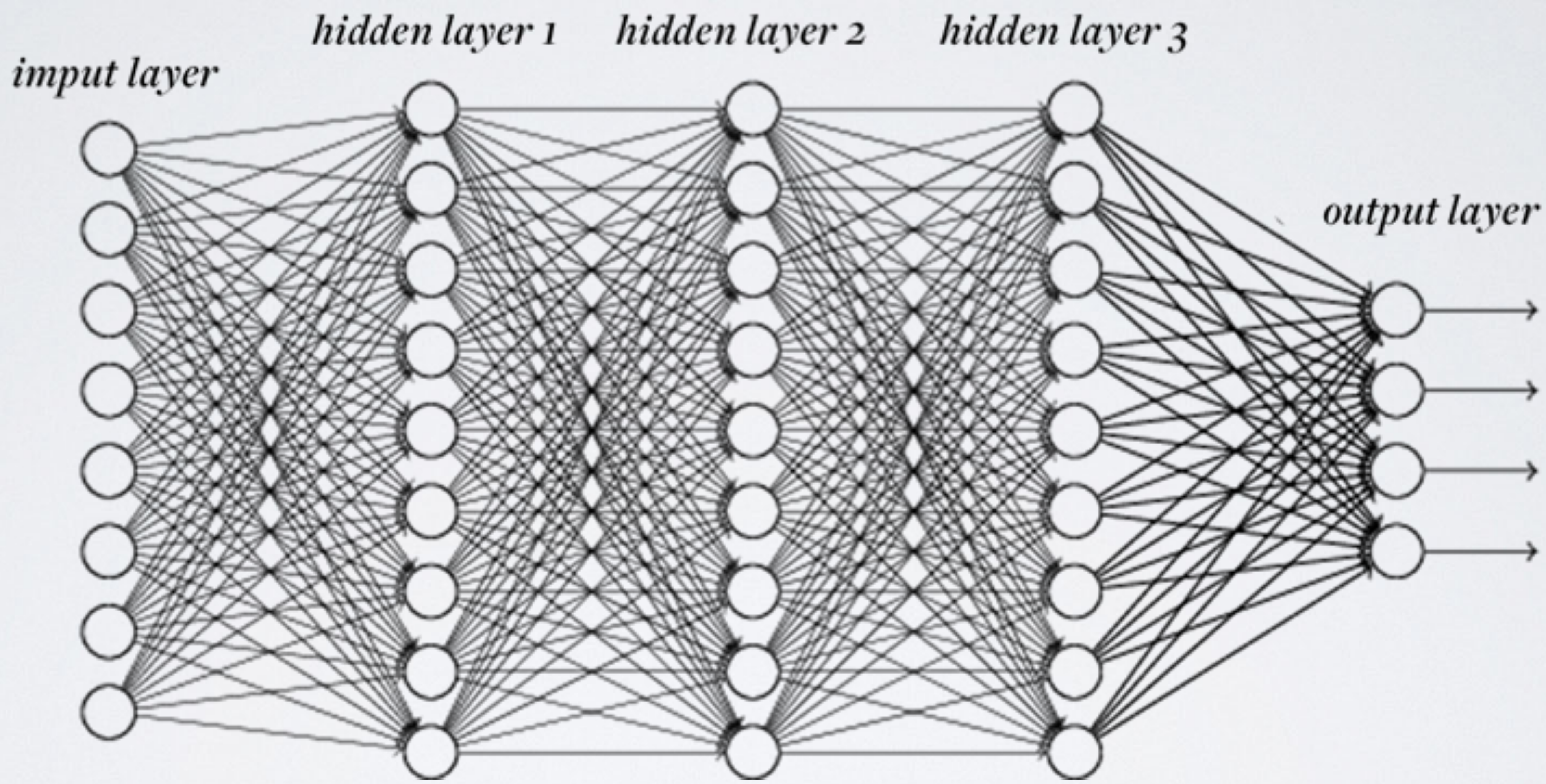

Target instances from Fish class
Clean
Base
poison

END-TO-END TRAINING?

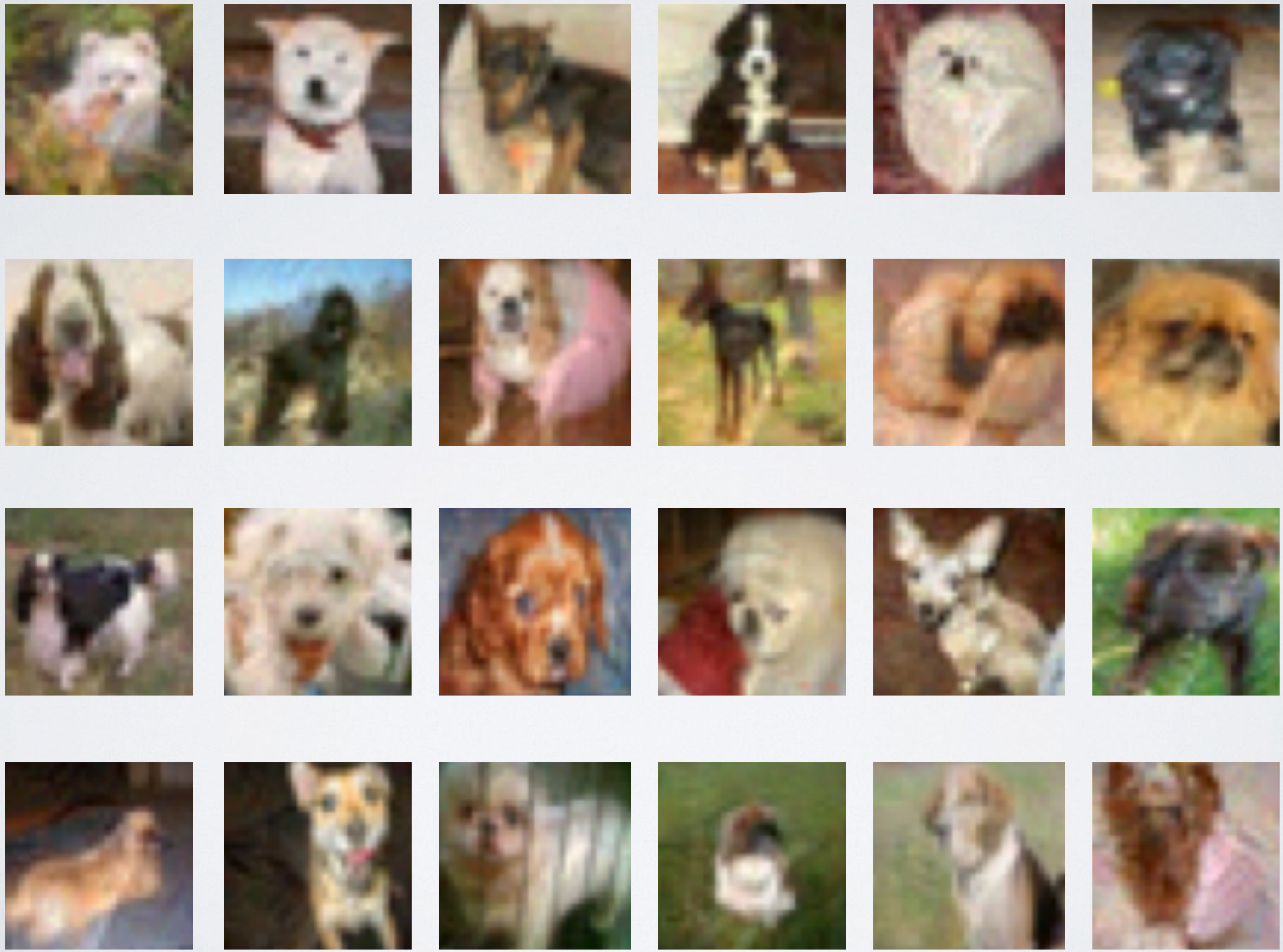
Feature extractors learn to ignore adversarial perturbation



Feature extraction layers

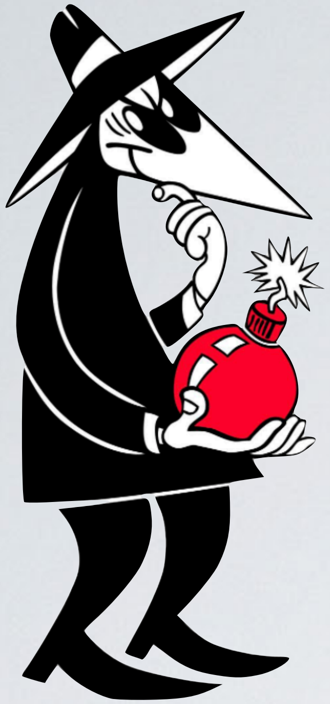
OH NO! POISON DOGS!

60 poison dogs cause a bird to be mis-classified



THEORY OF ADVERSARIAL EXAMPLES

ATTACK & DEFENSES



Adversarial attacks

Szegedy et al, 2013

Biggio et al, 2013

Adversarial training

Goodfellow et al 2015

Multi-stage attacks

Kurakin et al, 2016

Tramer et al, 2017

Distillation Papernot '16

Bounded relu Zantedeschia '16

MagNet Meng & Chen '17

Optimization attacks

Carlini & Wagner '17

Thermometer Buckman '18

Detection Ma et al, '18

Compression Guo, '18

GANs Samangouei, '18

Approximation attacks

Athalye et al, 2018

…and **LOTS** more

ARE ADVERSARIAL EXAMPLES **INEVITABLE**?

RELATED WORK

K-nearest neighbors classifier

"Analyzing the Robustness of Nearest Neighbors to Adversarial Examples"
Wang, Jha, Chaudhuri, 2017

Datasets produced by GAN-type generator

"Adversarial vulnerability for any classifier"
Fawzi, Fawzi, Fawzi, 2018

Classes lie on concentric spheres

"Adversarial spheres"
Gilmer, Metz, Faghri, Schoenholz, Raghu, Wattenberg, Goodfellow, 2018

Most similar to ours...

"The Curse of Concentration in Robust Learning"
Mahloujifar, Diochnos, Mahmoody, 2018

ARE ADVERSARIAL EXAMPLES **INEVITABLE**?

spoiler alert

...and the answer is...

YES!

…if the adversary is strong enough.

ARE ADVERSARIAL EXAMPLES **INEVITABLE**?

…but computer scientists think…

NO!

Common assumptions…

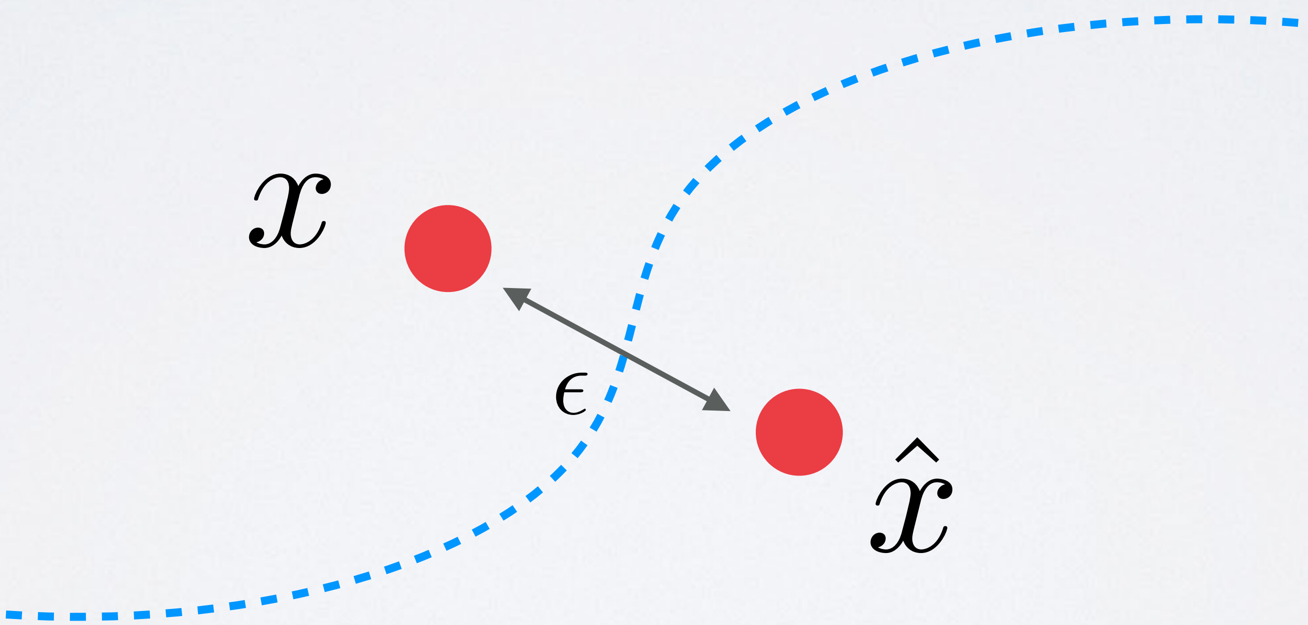
Human perception is not exploitable

High dimensional spaces aren't too weird

THE SETUP

Adversarial example

$$\|x - \hat{x}\|_p < \epsilon.$$



TOY PROBLEM

Dimension

$$3$$

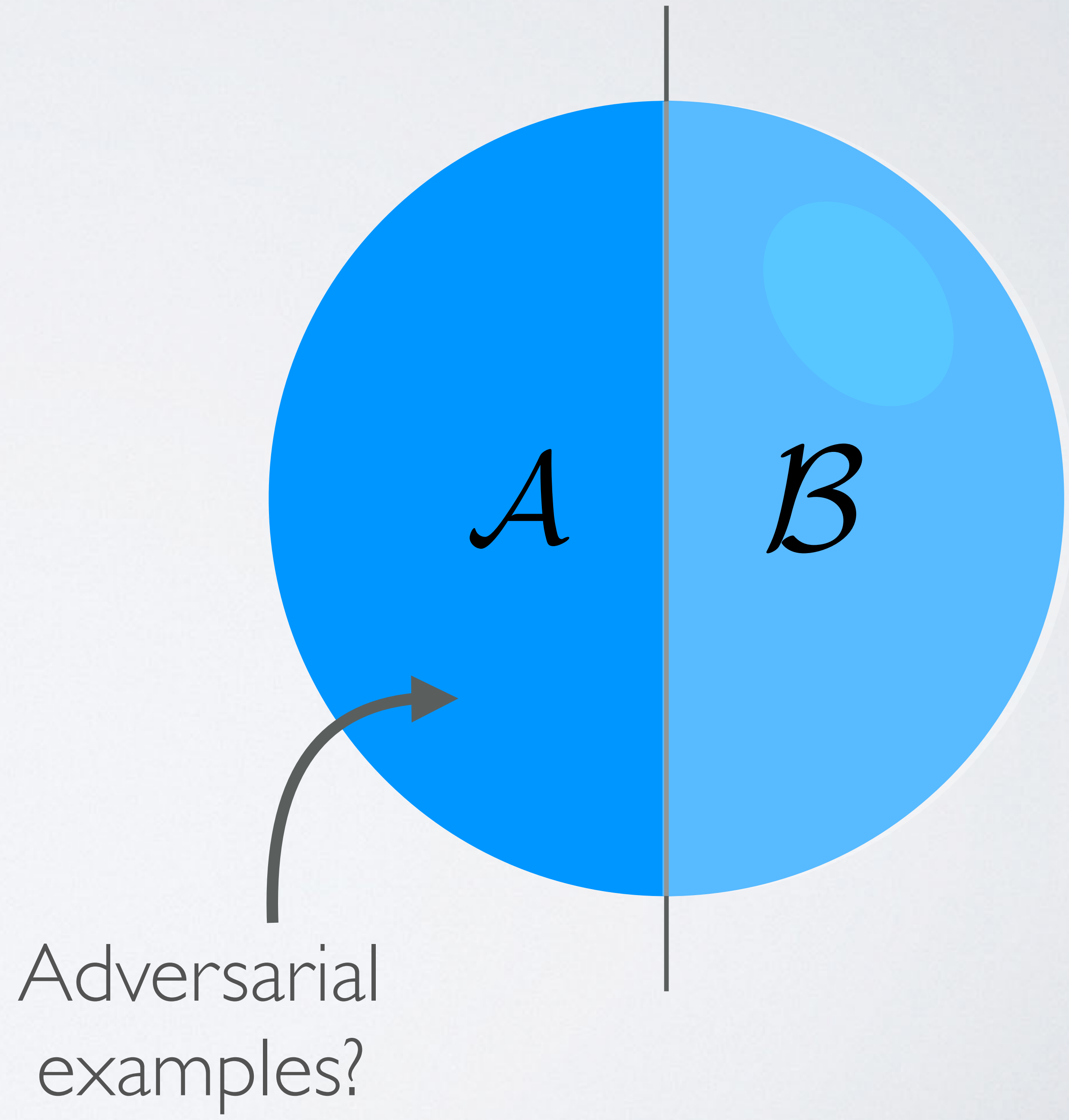
TOY PROBLEM

Dimension

$$3$$

Surface area

$$50\%$$



TOY PROBLEM

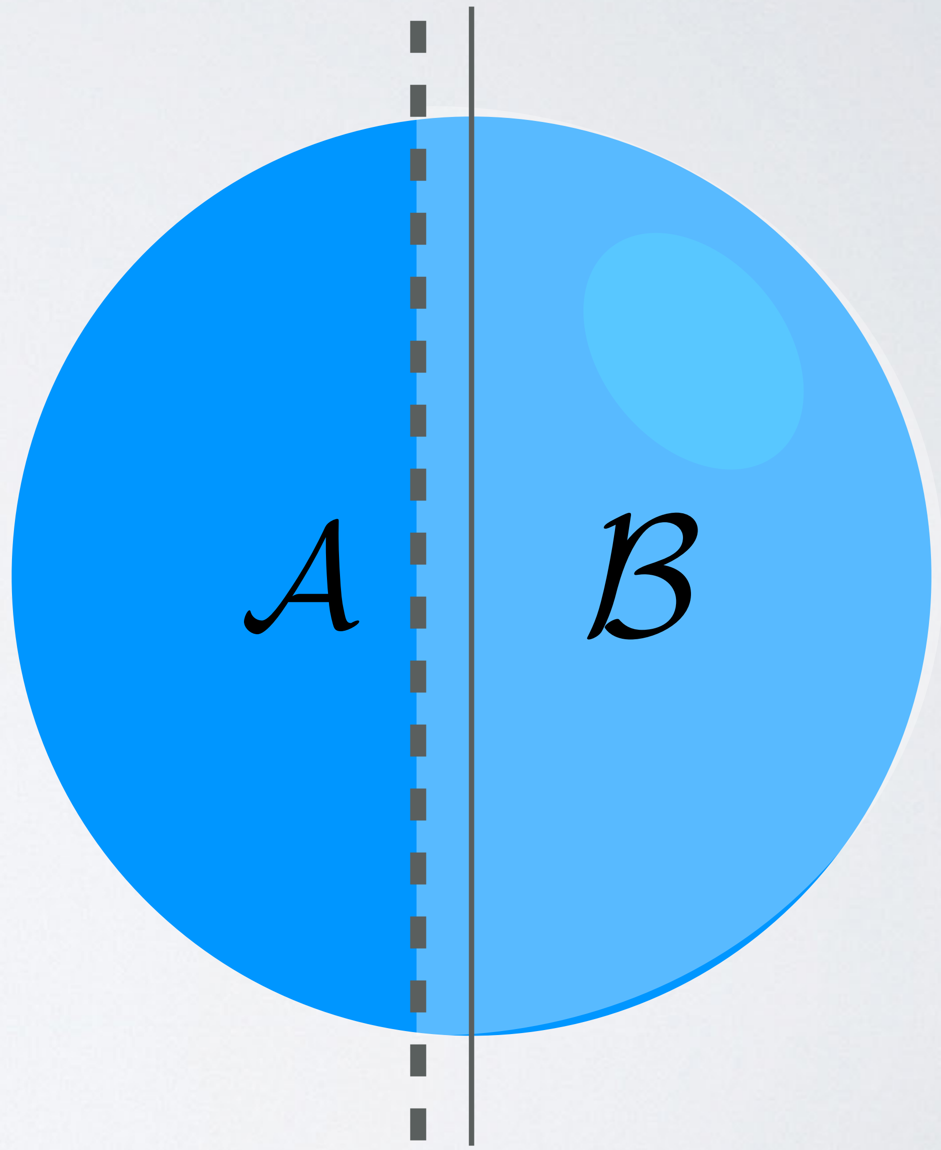
Dimension

3

Surface area

55%

$\epsilon = 0.1$



TOY PROBLEM

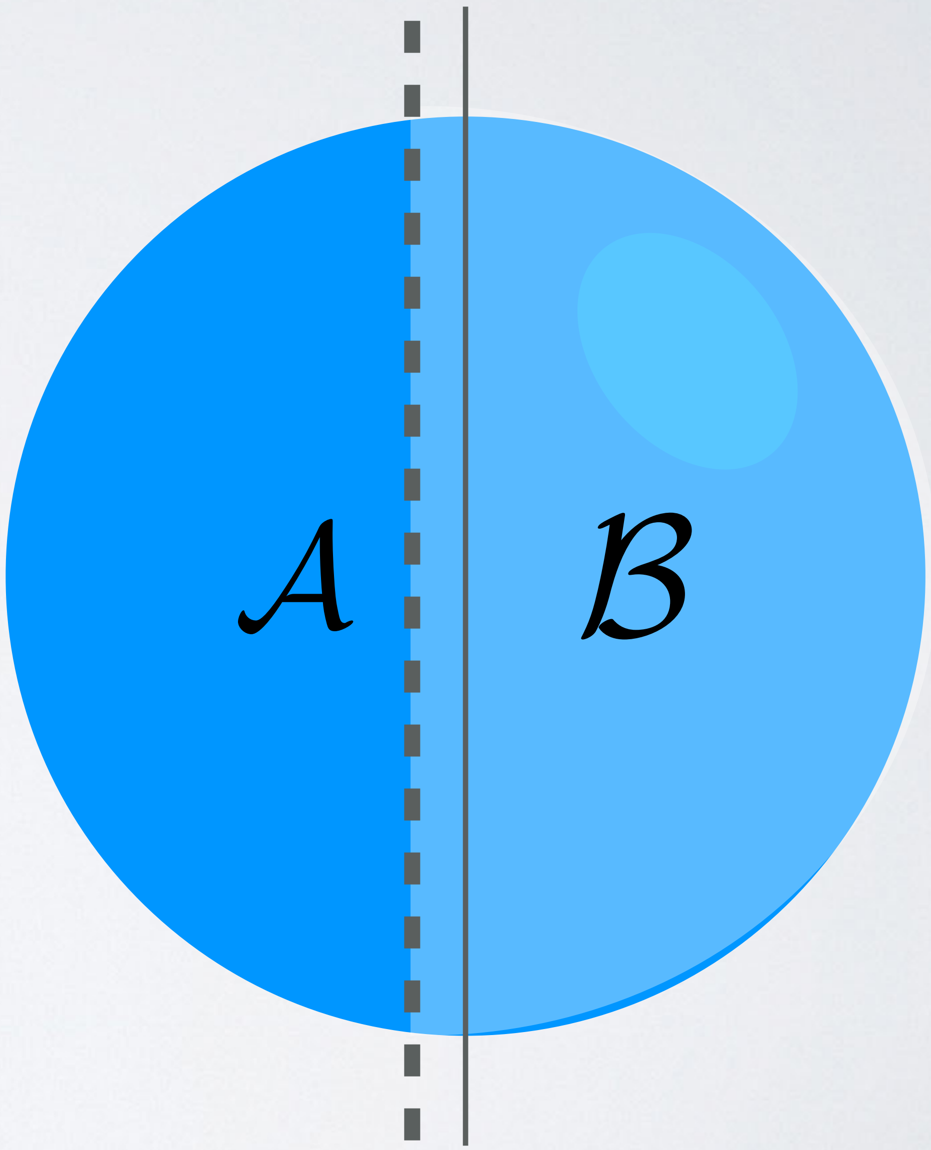
Dimension

100

Surface area

84%

$\epsilon = 0.1$



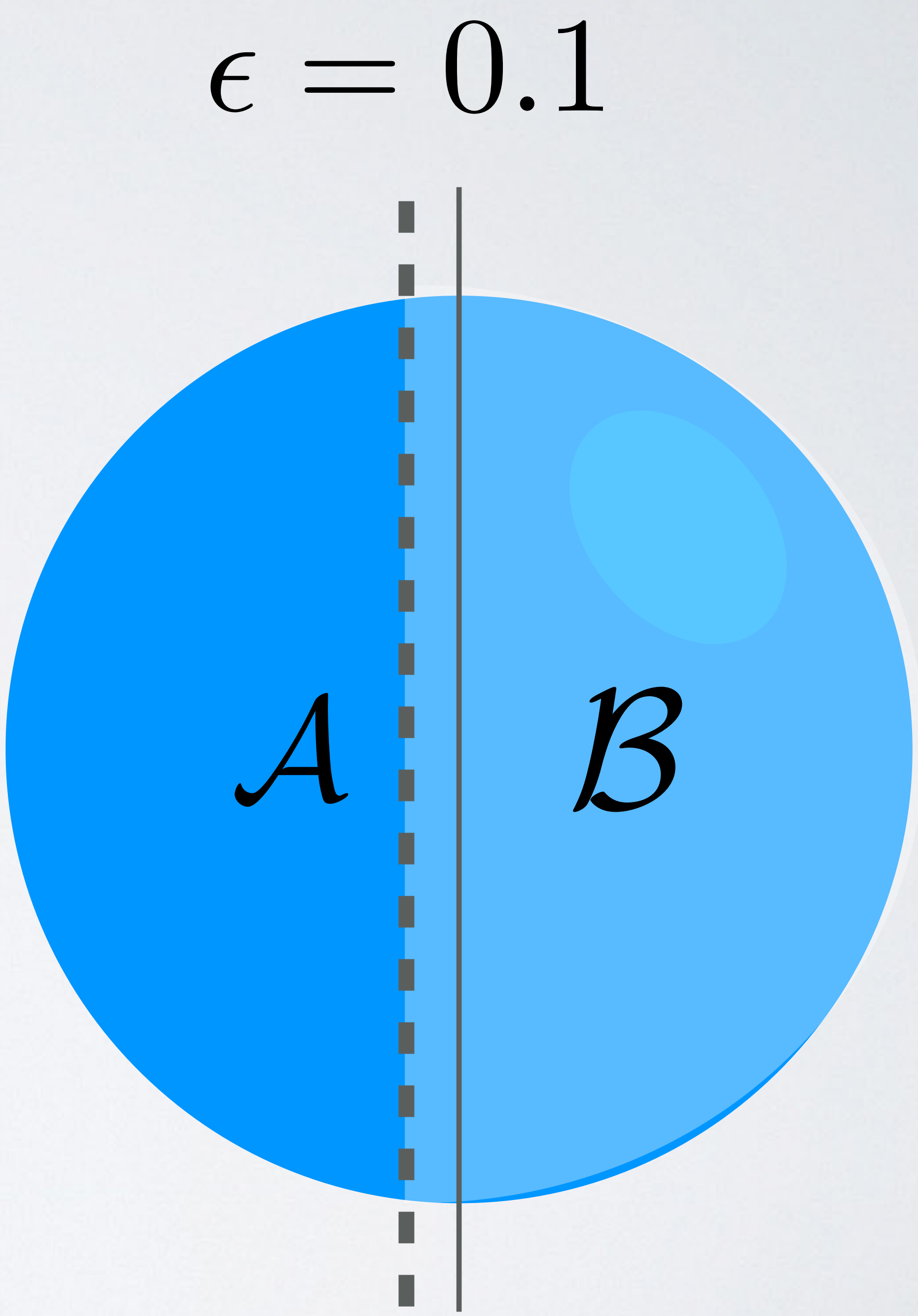
TOY PROBLEM

Dimension

1000

Surface area

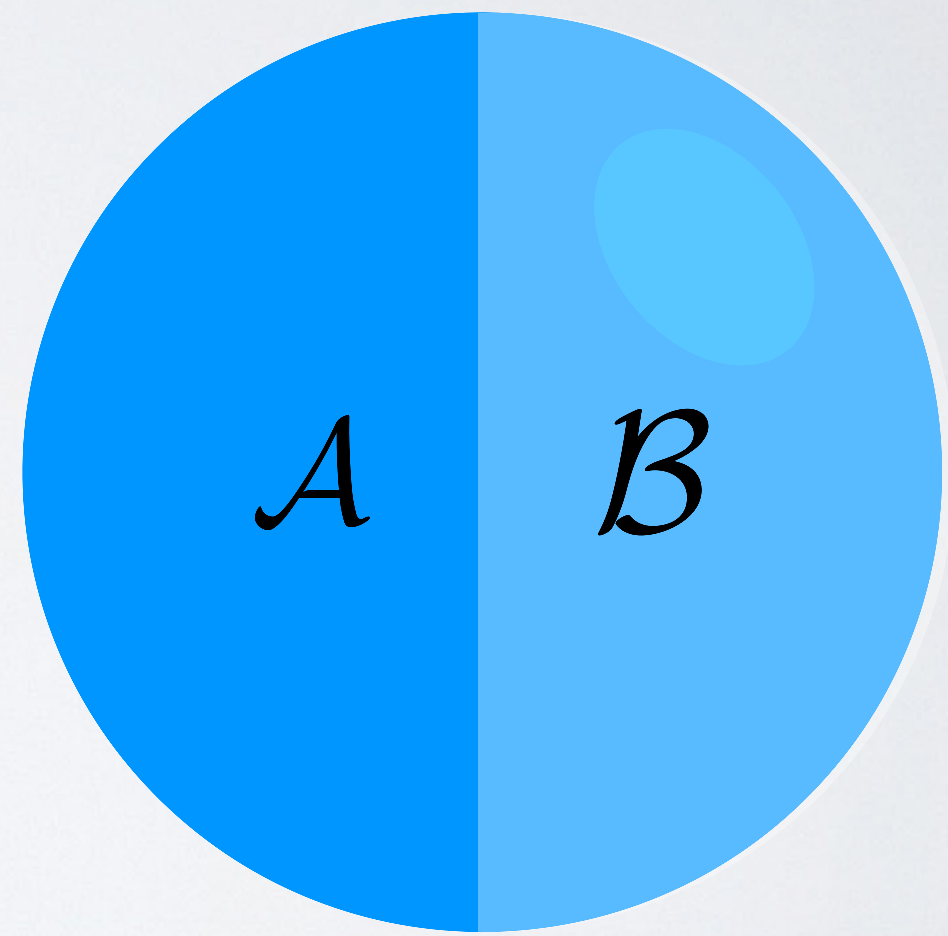
99.8%



random sampling → **adversarial susceptibility**

Theorem (Levy & Pellegrino, 1951)

The ϵ-expansion of *any* set that occupies half the sphere is at least as big as the ϵ-expansion of a semi-sphere.



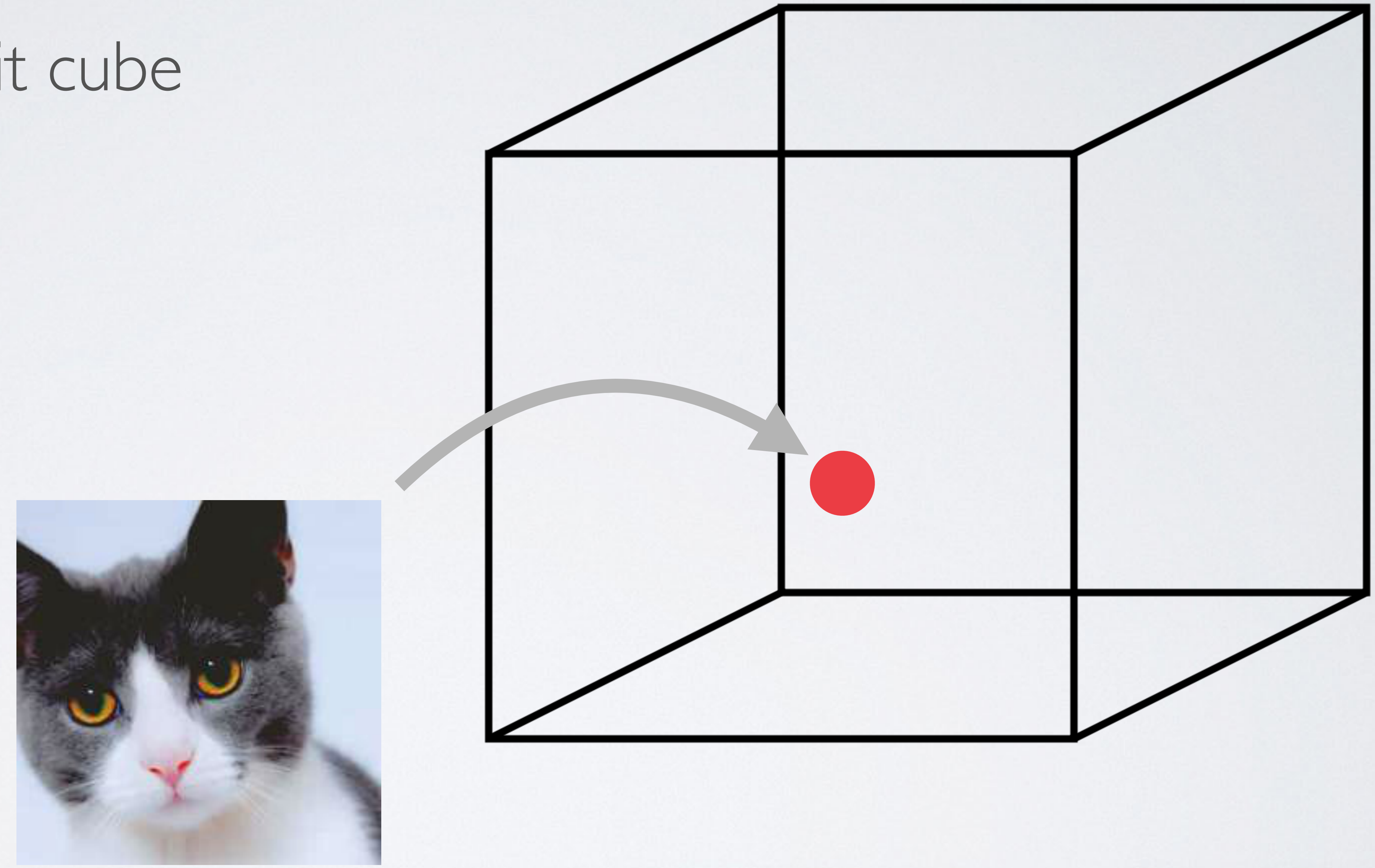
This classifier is worse than **this classifier**

WHAT ABOUT *REALISTIC* MODELS?

THE SETUP

Images

Points in a unit cube



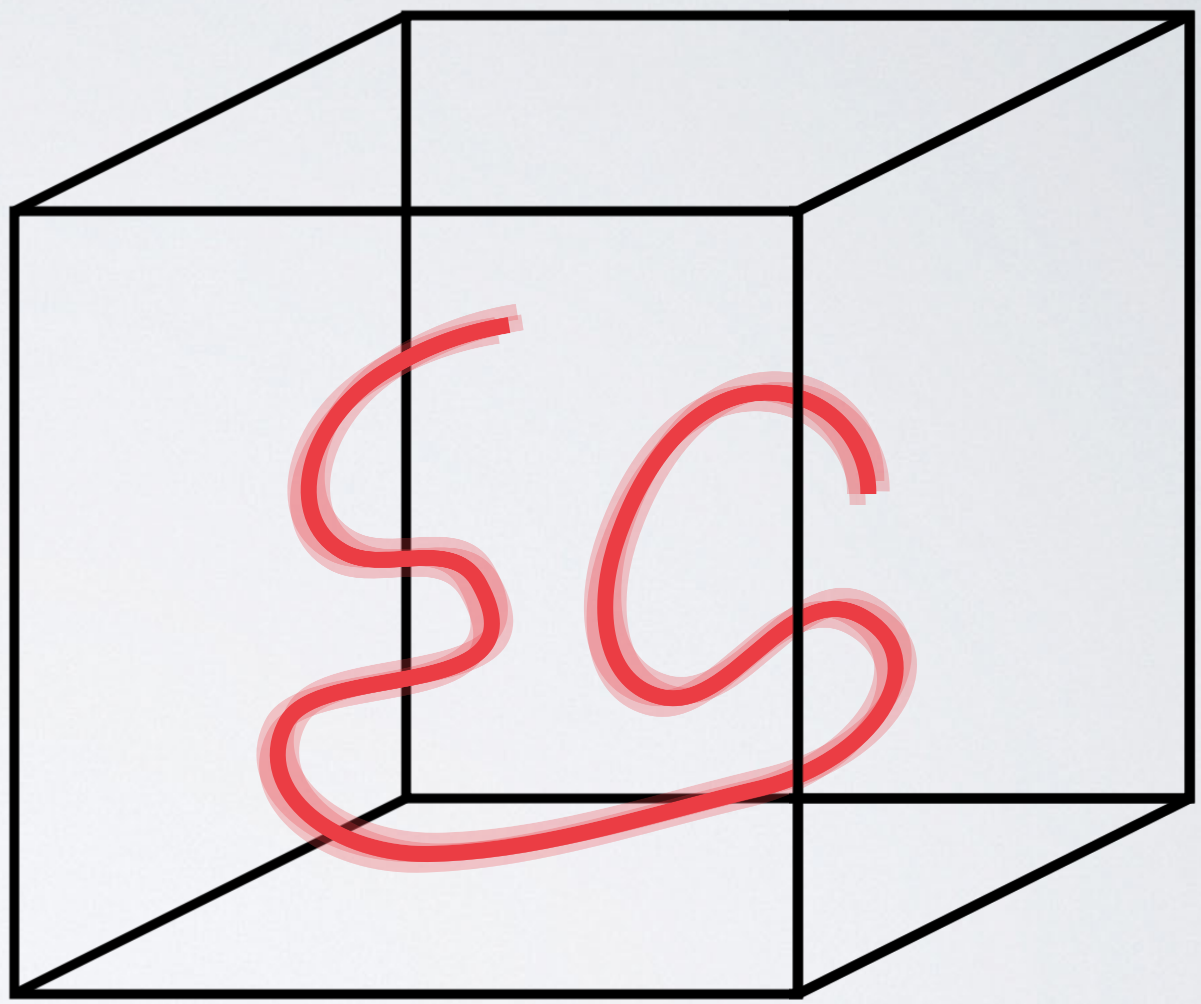
THE SETUP

Images

Points in a unit cube

Class

Probability density function on cube (bounded by U_c)



THE SETUP

Images

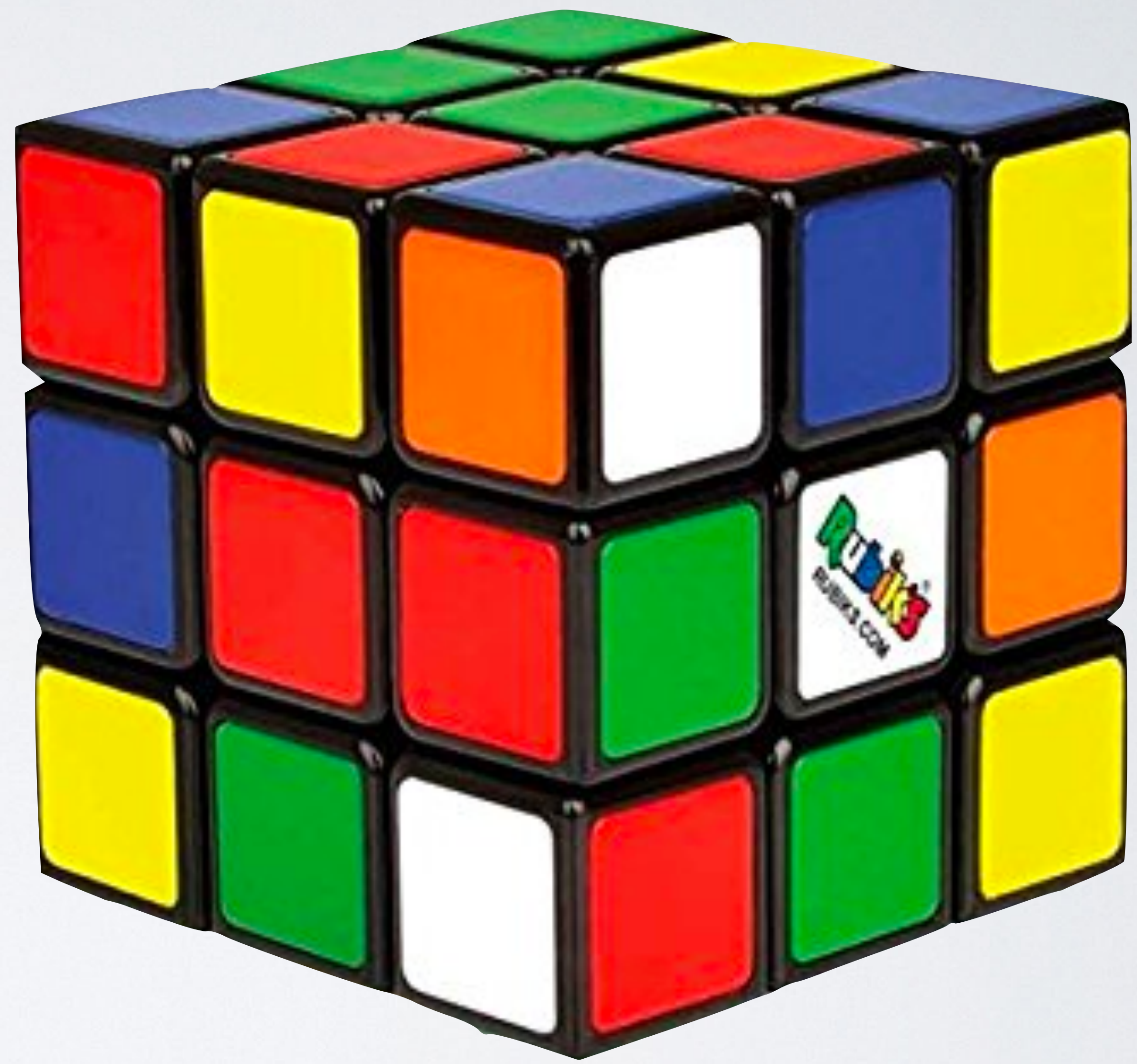
Points in a unit cube

Class

Probability density function on cube (bounded by U_c)

Classifier

Partitions cube into disjoint sets (measurable)

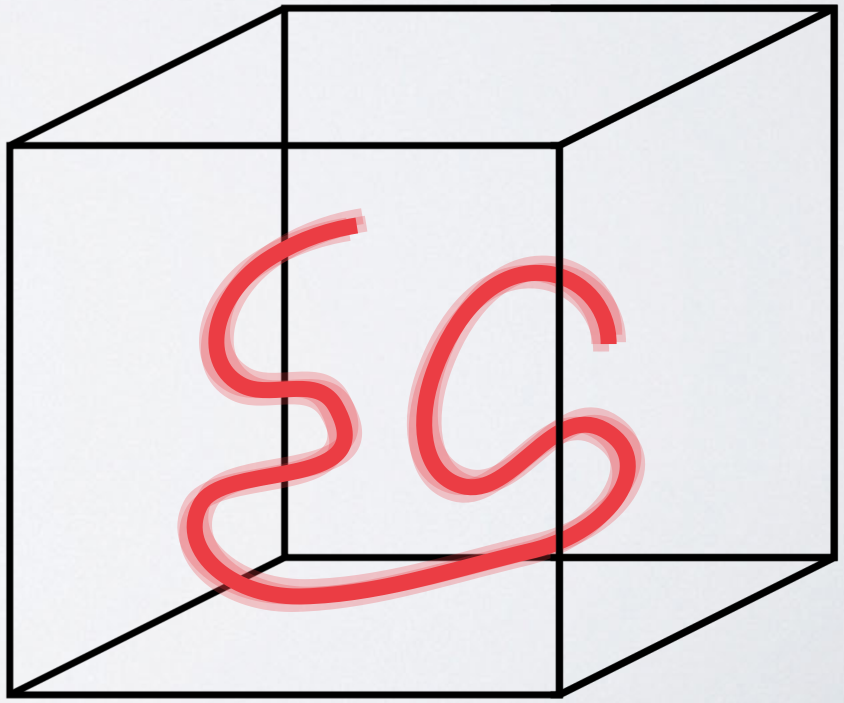


"MOST" THINGS ARE ADVERSARIAL

Theorem

Choose a class c that occupies less than half the cube according to the classifier. Define...

U_c : supremum of the density function for class c



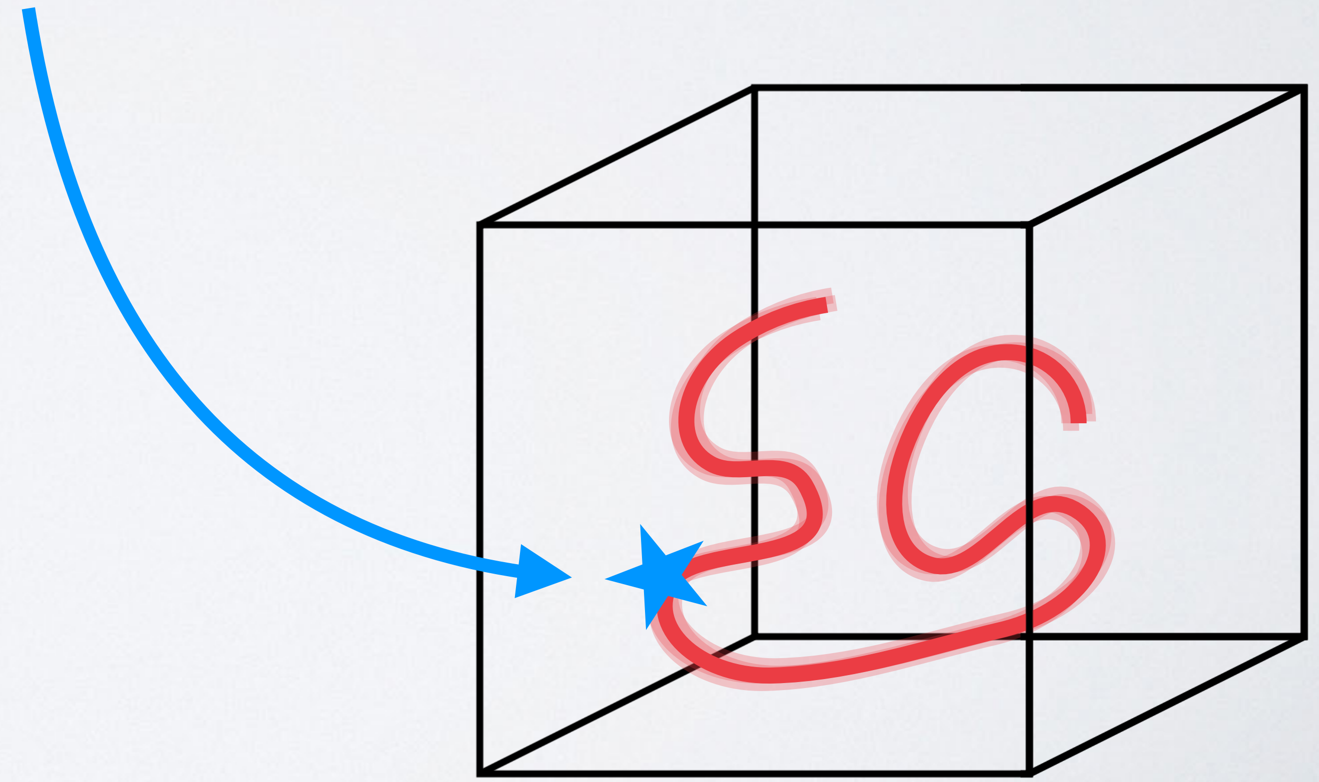
"MOST" THINGS ARE ADVERSARIAL

Theorem

Choose a class c that occupies less than half the cube according to the classifier. Define...

U_c : supremum of the density function for class c

Sample a random point x from the class distribution.



"MOST" THINGS ARE ADVERSARIAL

Theorem

Choose a class c that occupies less than half the cube according to the classifier. Define...

U_c : supremum of the density function for class c

Sample a random point x from the class distribution. With probability at least

$$1 - U_c \exp(-\pi\epsilon^2)$$

One of the following conditions holds:

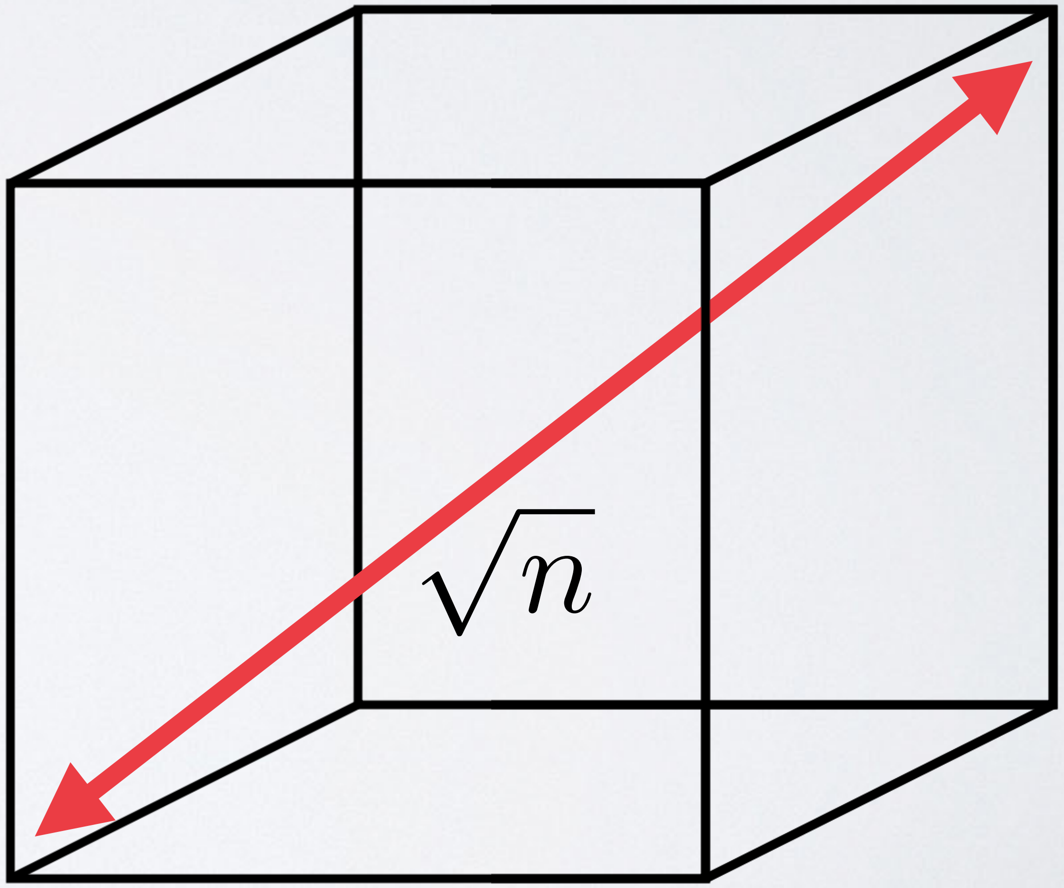
- x is misclassified by the classifier
- x has an adversarial example $\hat{x}$ with $\|x - \hat{x}\|_2 < \epsilon$.

"Are adversarial examples inevitable?" arXiv '18

"MOST" THINGS ARE ADVERSARIAL

$$1 - U_c \exp(-\pi\epsilon^2)$$

$$\epsilon = 10$$



WHAT HAPPENS IN THE ZERO NORM?

Adversarial example

An image x has an ϵ-adversarial example in the p norm if there is a point $\hat{x}$ in a different class with

$$\|x - \hat{x}\|_p < \epsilon.$$

$$\Big\downarrow \; p = 0$$

$$\|x - \hat{x}\|_0 = \text{card}\{i | x_i \neq \hat{x}_i\}$$

Sparse adversarial example

SPARSE ATTACKS

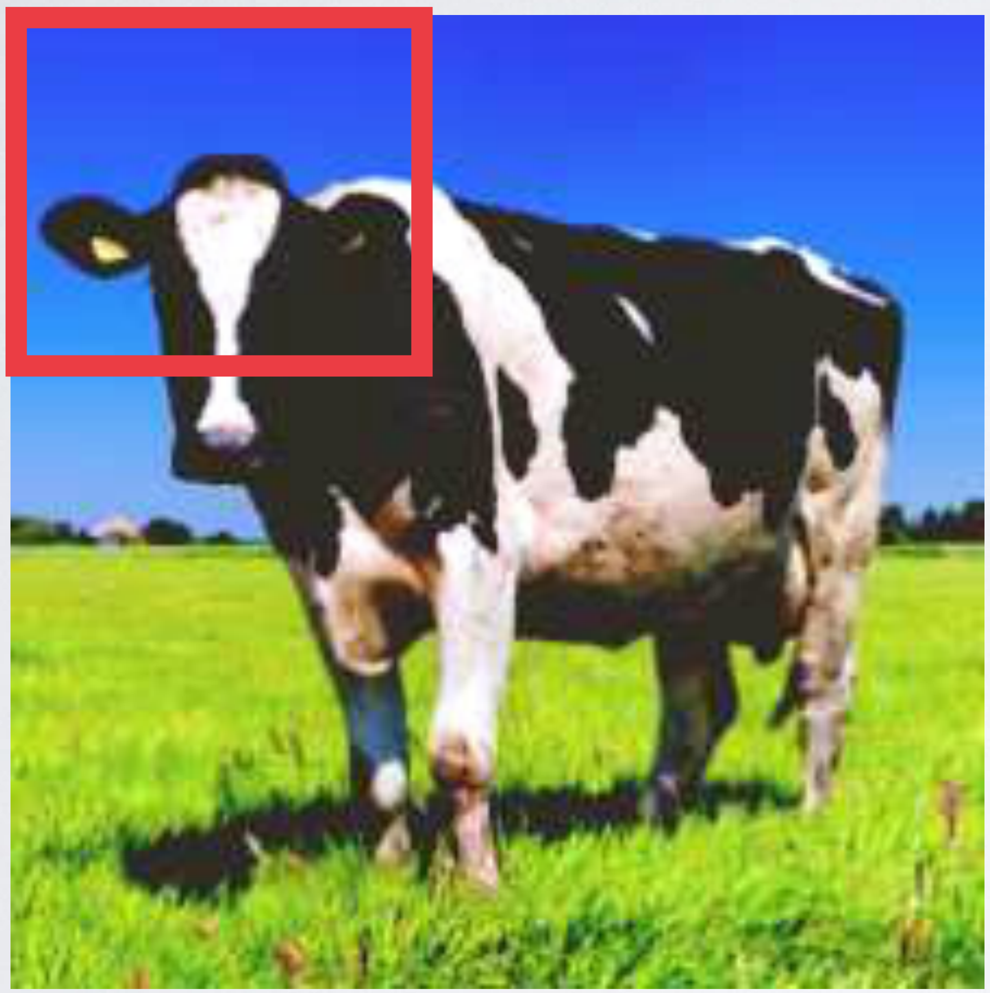
2-norm attack

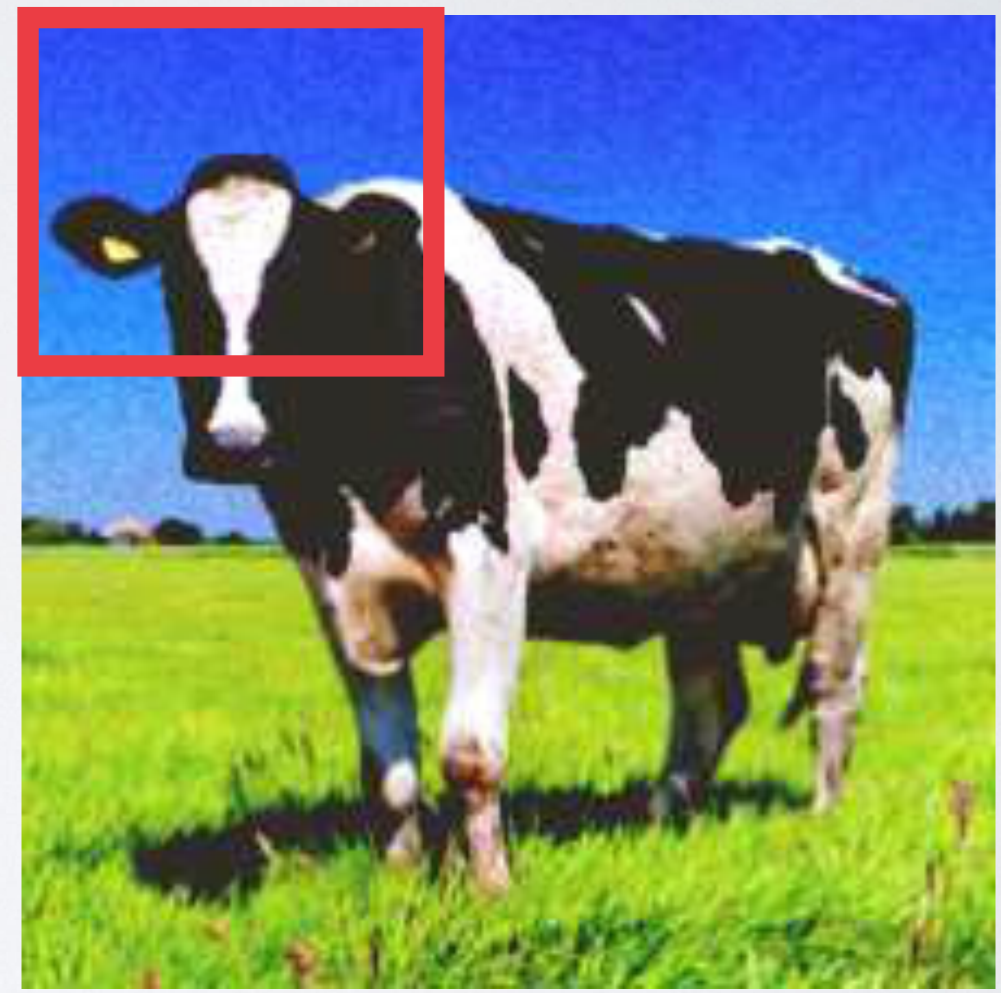
"Ox"

"Traffic Light"

SPARSE ATTACKS

2-norm attack





“Ox”

“Traffic Light”

SPARSE ATTACKS

SPARSE ATTACKS

3% pixels changed

“Ox”

“Traffic Light”

SPARSE ADVERSARIAL EXAMPLES

Theorem

Choose a class c that occupies less than half the cube according to the classifier. Define...

U_c : supremum of the density function for class c

Sample a random point x from the class distribution. With probability at least

$$1 - 2U_c \exp(-k^2/n)$$

\# of pixels changed

One of the following conditions holds:

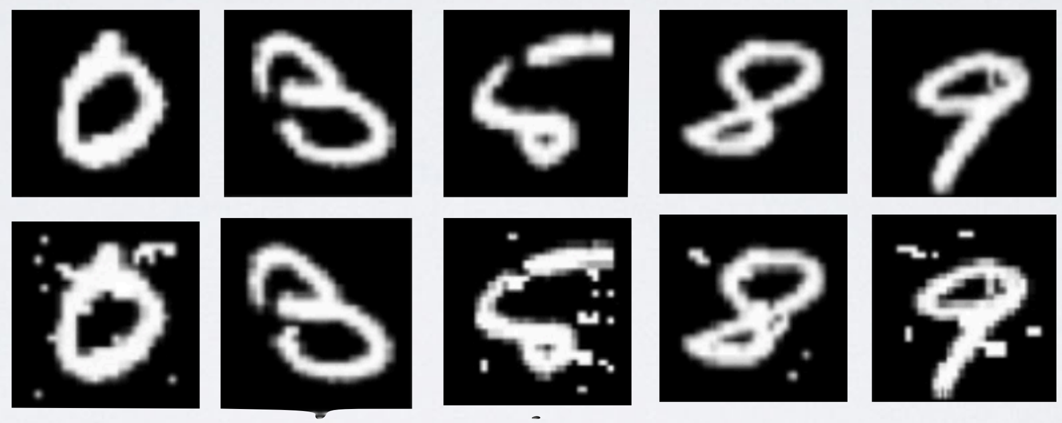
- x is misclassified by the classifier
- The label of x can be changed by modifying at most k pixels.

WHAT ABOUT HIGH DIMENSIONS?

WHAT ABOUT HIGH DIMENSIONS?

Clean

Adversarial



“dog” 9%

“traffic light” 97%

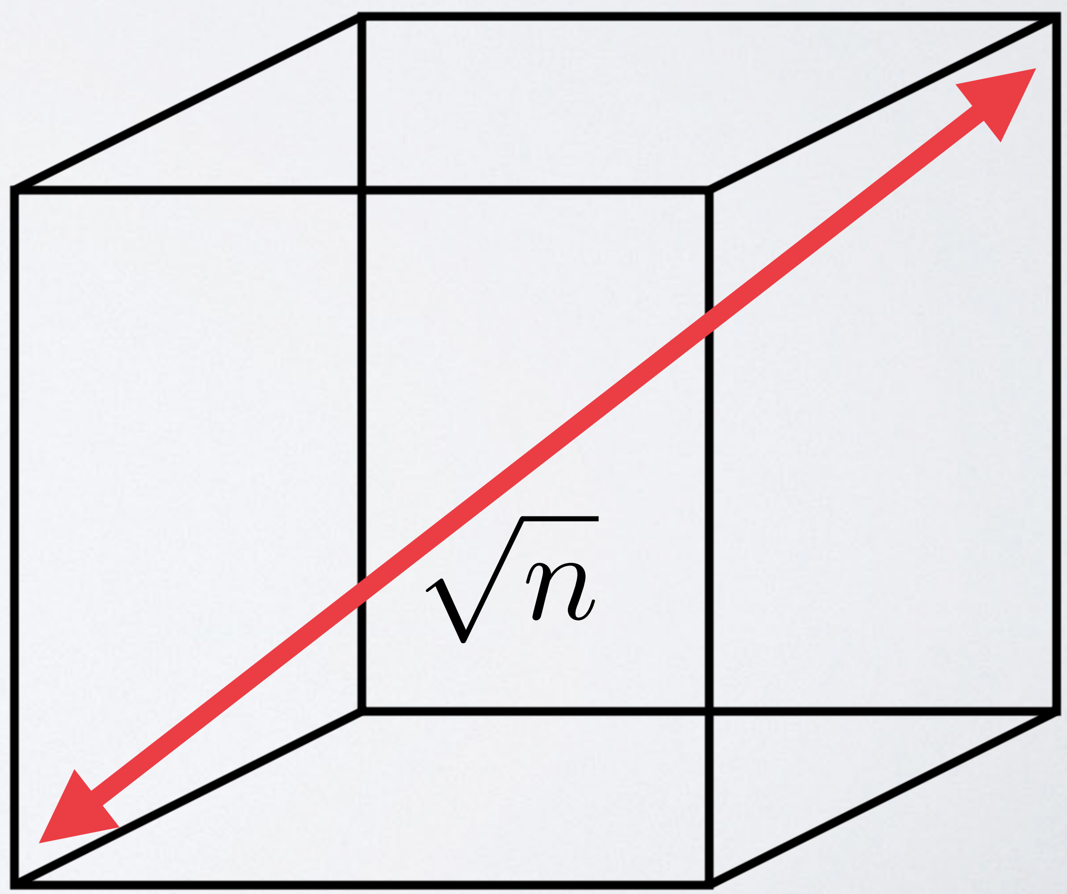
BOUNDS IN HIGH DIMENSIONS

$\epsilon = O(\sqrt{n})$

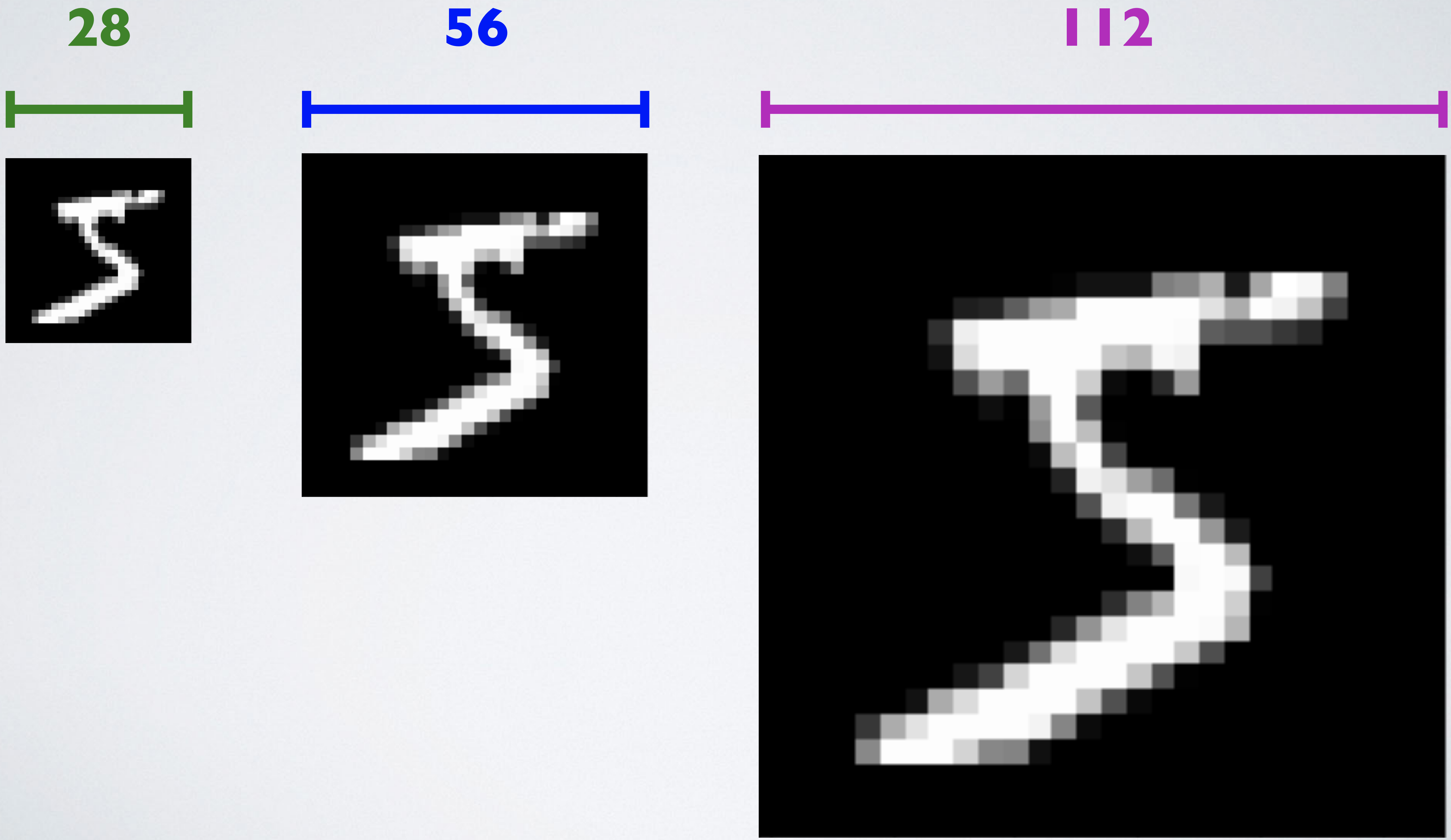
$$1 - U_c \exp(-\pi\epsilon^2)$$

Does this stay the same for large n?

NOPE!



BIG MNIST



Theorem

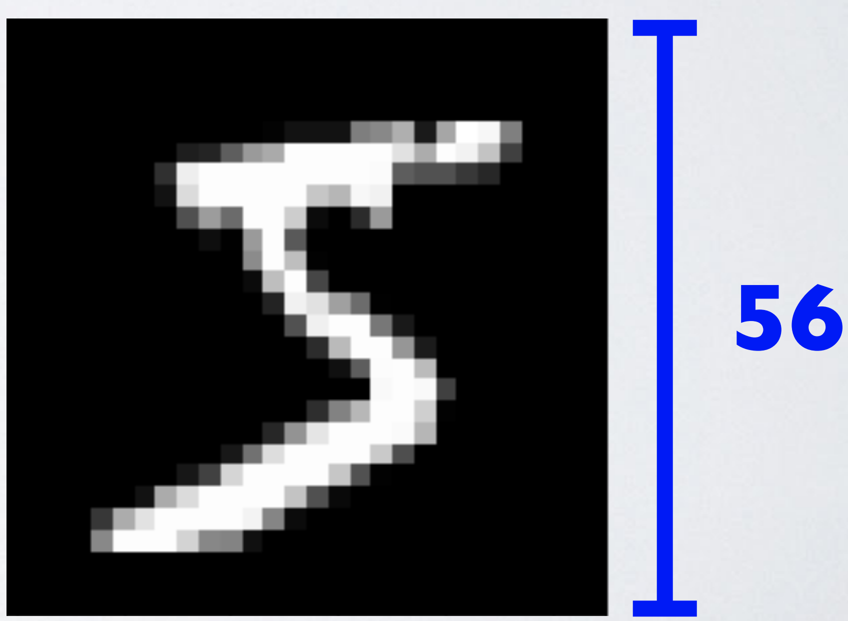
28x28 MNIST

For all classifiers, a random image has an ϵ-adversarial example with probability p.

$\longleftrightarrow$

56x56 MNIST

For all classifiers, a random image has an 2ϵ-adversarial example with probability p.



Theorem

28x28 MNIST

For all classifiers, a random image has an ϵ-adversarial example with probability p.

$\longleftrightarrow$

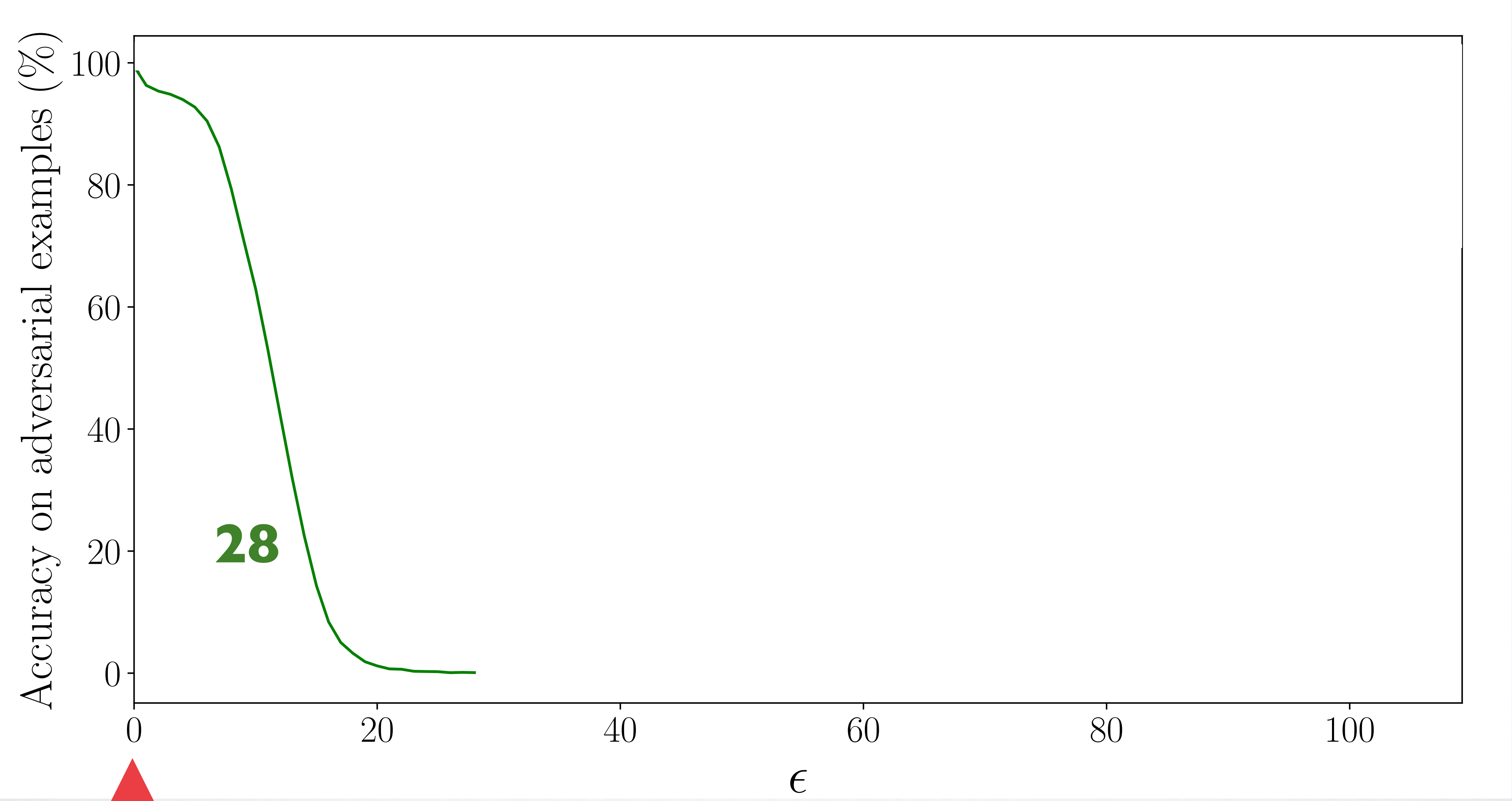
56x56 MNIST

For all classifiers, a random image has an 2ϵ-adversarial example with probability p.

There is no relation between dimensionality and robustness!

ADVERSARIAL TRAINING

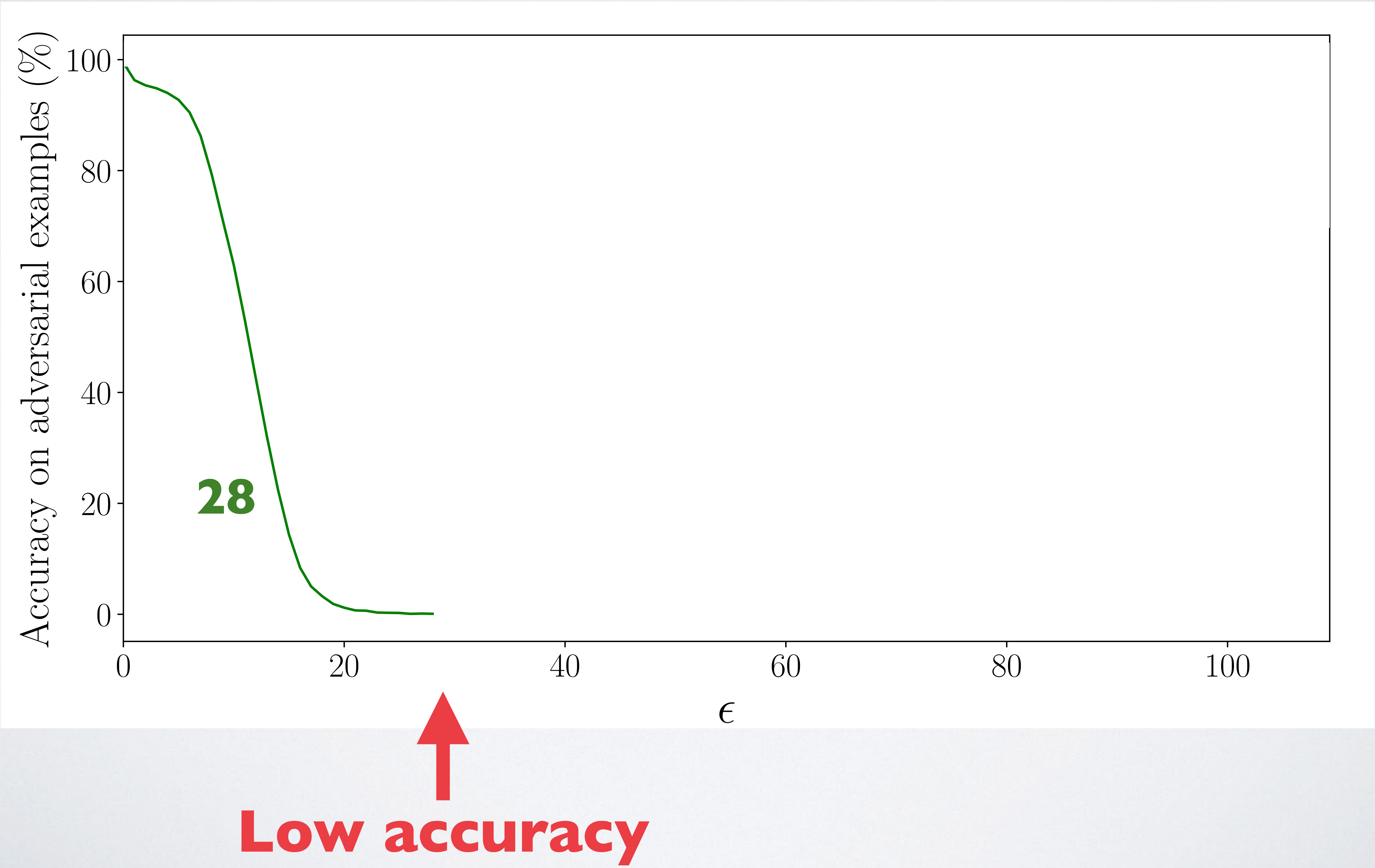
MNIST hardened using PGD (30 steps)



High accuracy

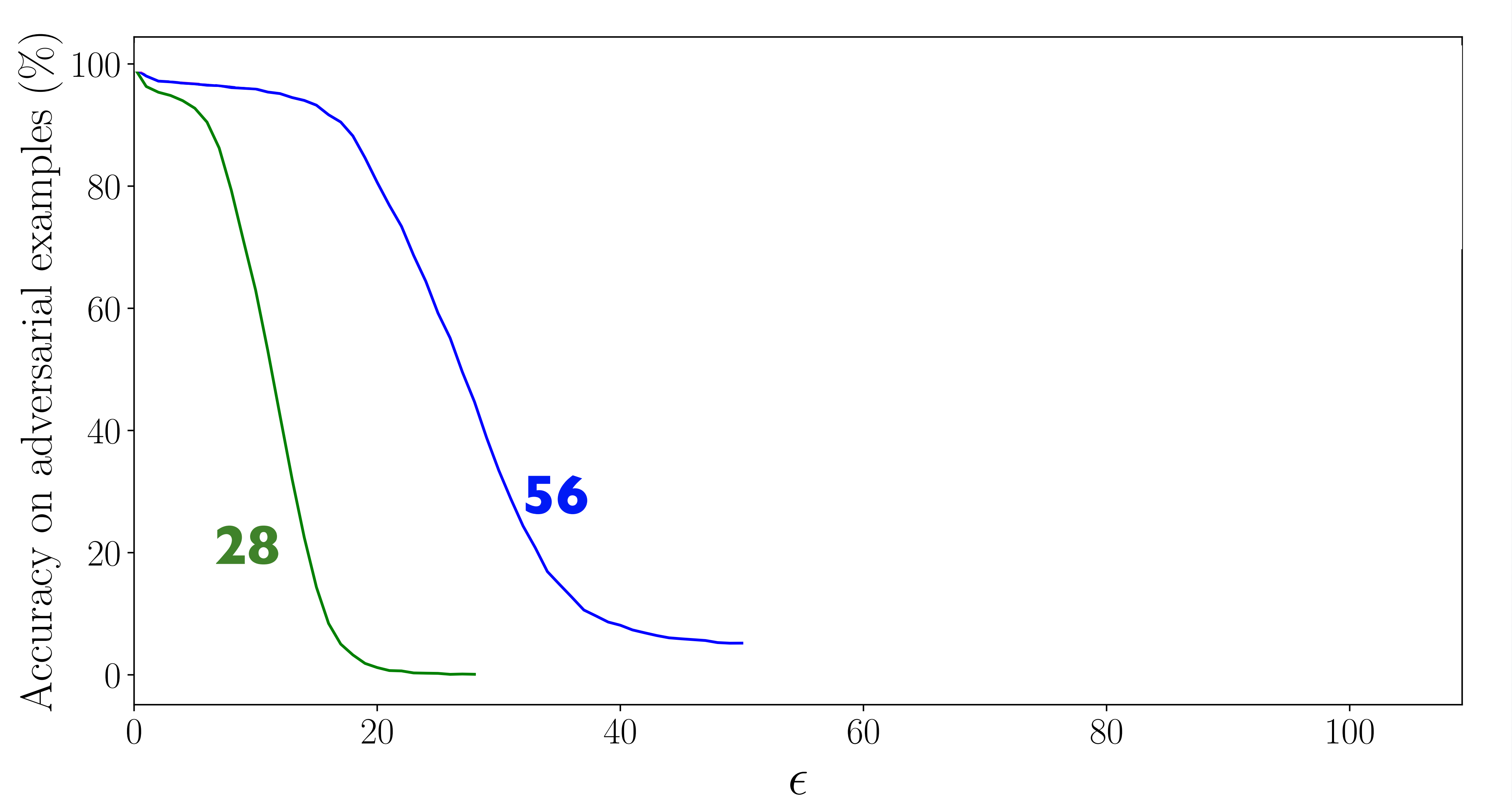
ADVERSARIAL TRAINING

MNIST hardened using PGD (30 steps)



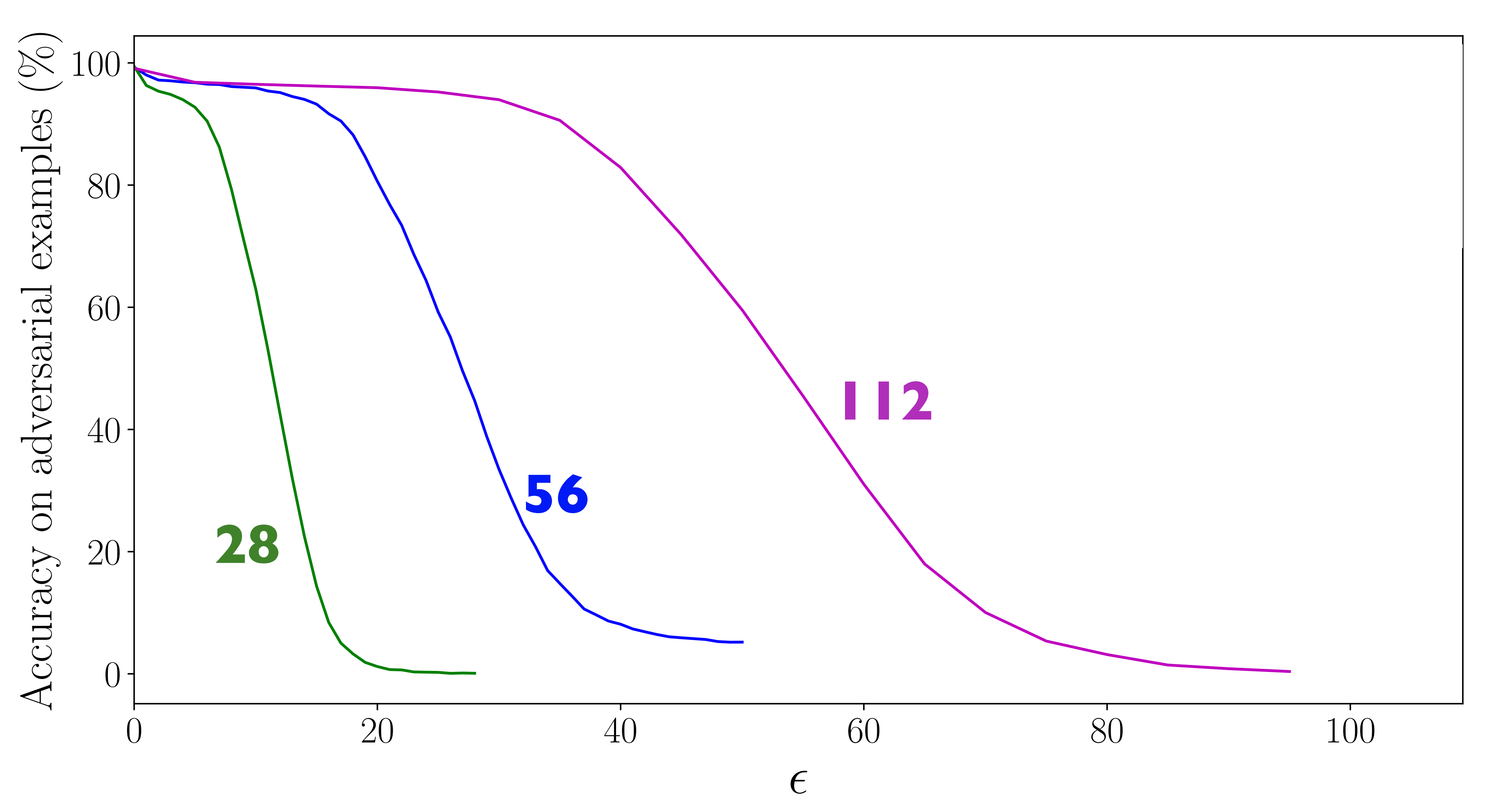
ADVERSARIAL TRAINING

MNIST hardened using PGD (30 steps)



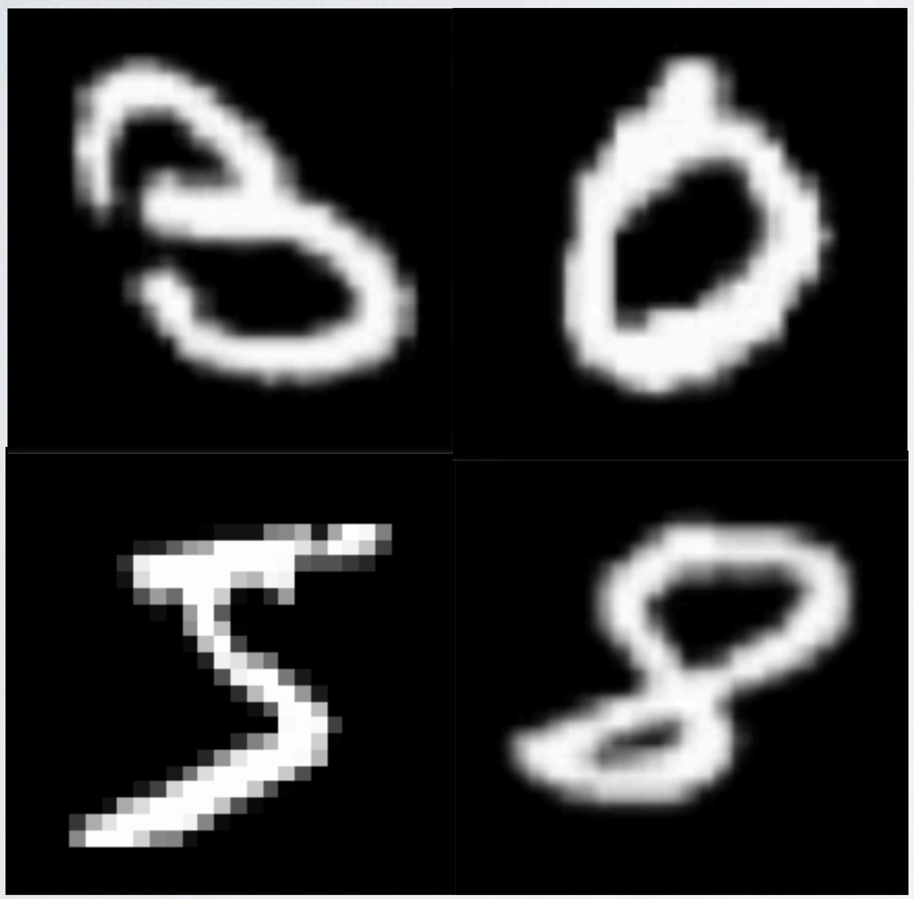
ADVERSARIAL TRAINING

MNIST hardened using PGD (30 steps)



WHAT AFFECTS ROBUSTNESS?

MNIST



<

susceptibility

CIFAR

WHAT AFFECTS ROBUSTNESS?

$$1 - U_c \exp(-\pi\epsilon^2)$$

concentration

pixels correlated
low-dimensional

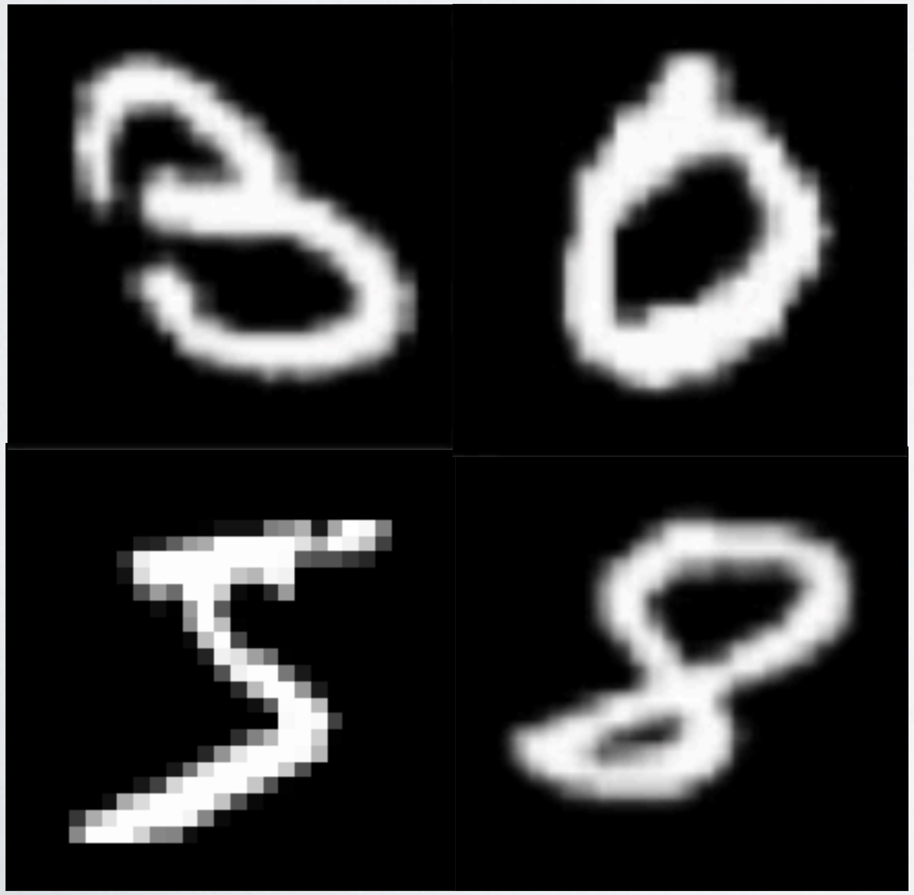
low pixel correlations
high-dimensional

WHAT AFFECTS THE BOUND?

56x56 MNIST

3136 features

10 classes

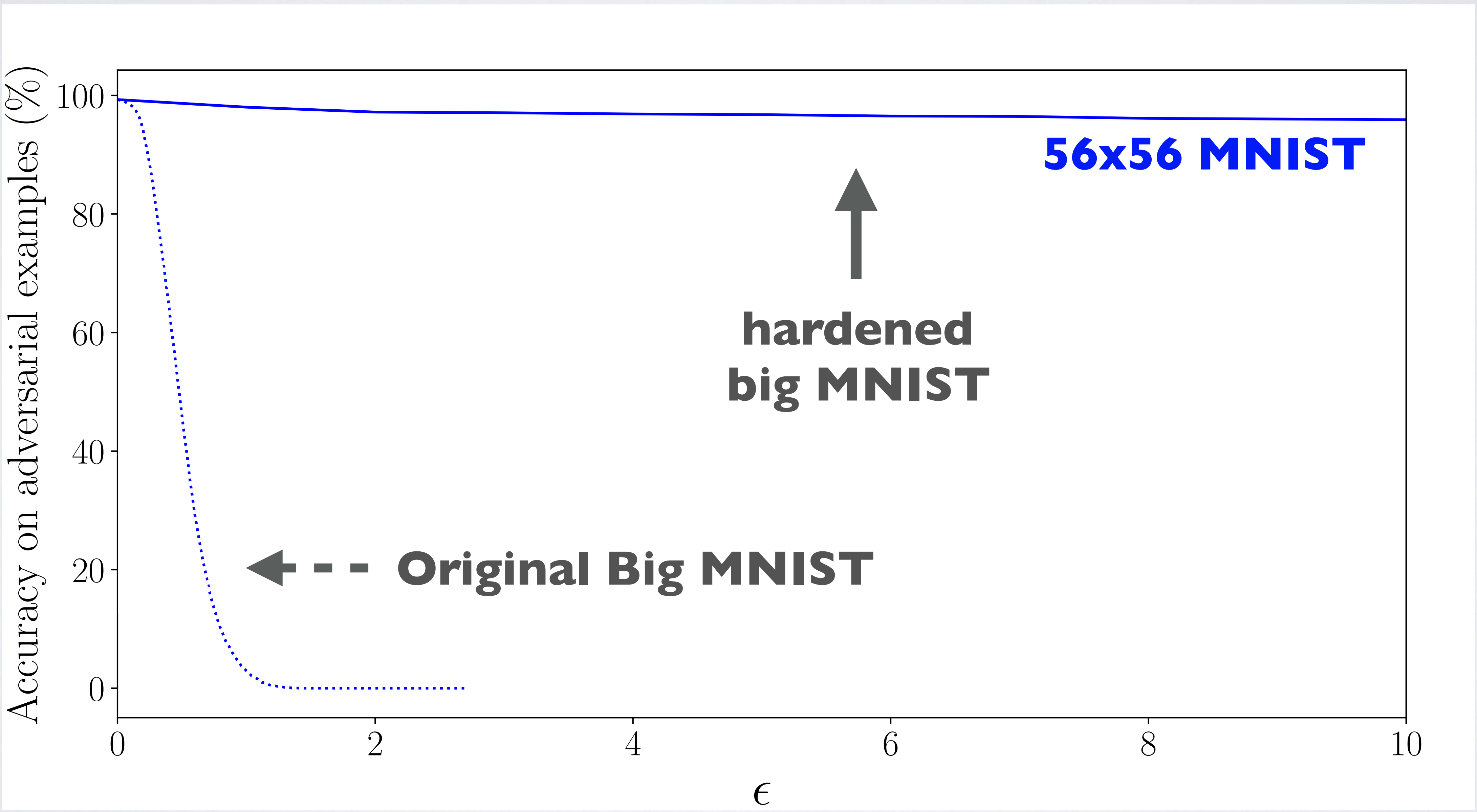


CIFAR-10

3072 features

10 classes

ADVERSARIAL TRAINING



ADVERSARIAL TRAINING

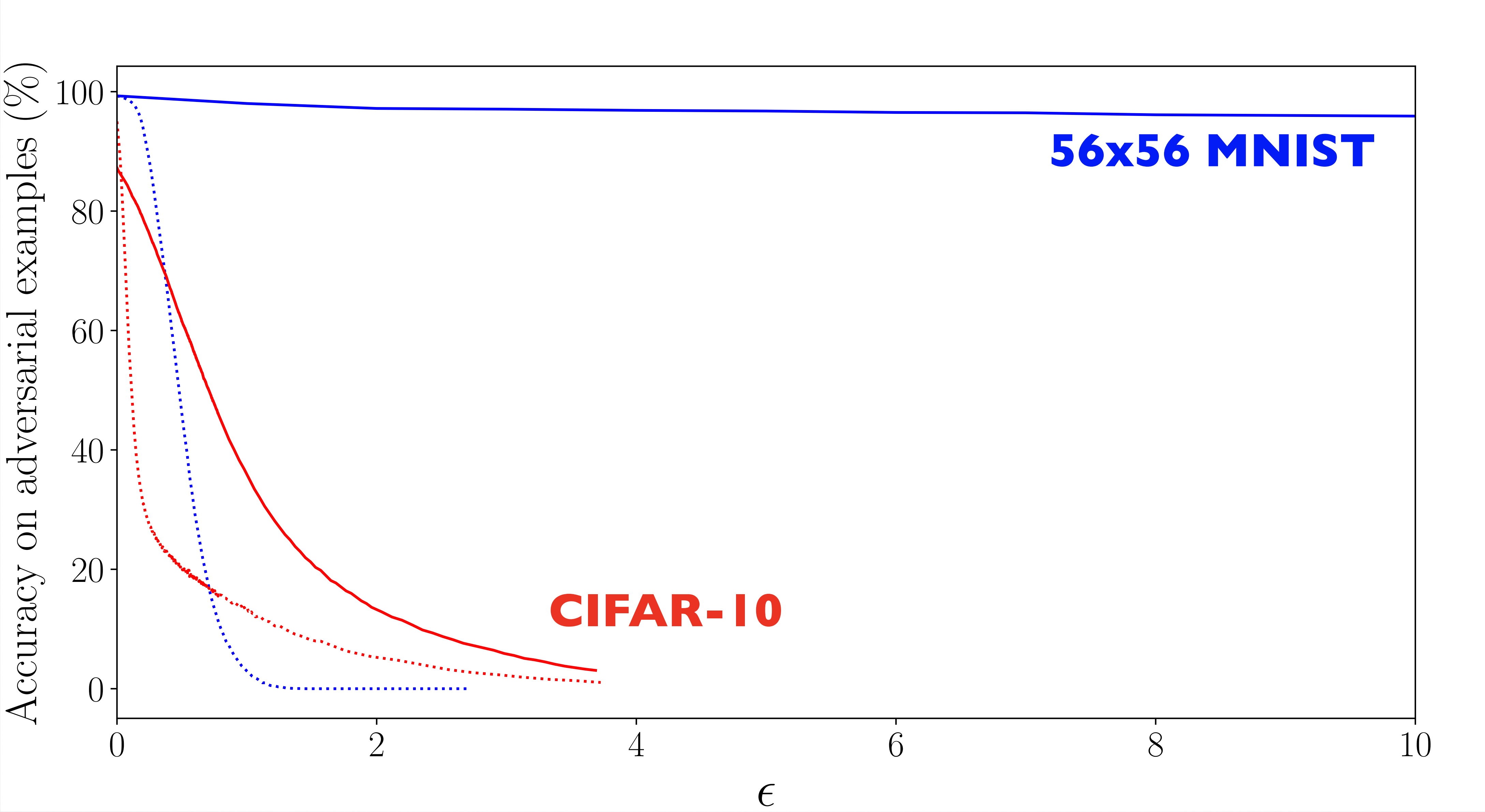


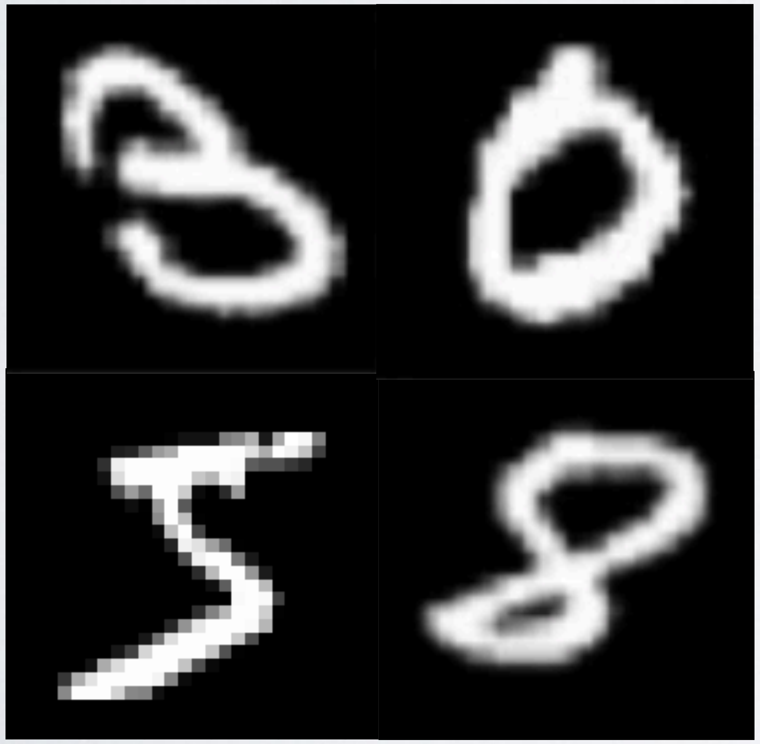
IMAGE COMPLEXITY LOWERS ROBUSTNESS

$$1 - U_c \exp(-\pi\epsilon^2)$$

“Complex” image classes have low density

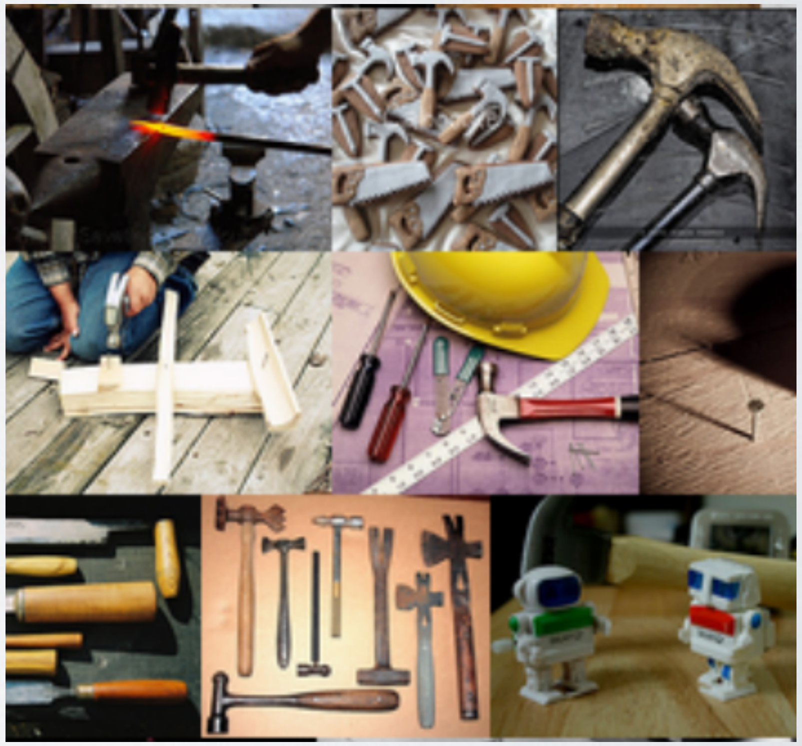
lower pixel correlations
higher-dimensional manifolds

MNIST



CIFAR

ImageNet



complexity

TAKEAWAYS

Robustness has *fundamental* limits

Not specific to neural nets

Can't escape by being clever

Robustness limit for neural nets might be far worse than intuition tells us!

Visualizing the loss landscape of neural nets

Hao Li, Zheng Xu, Gavin Taylor, Christoph Studer, Tom Goldstein

Poison frogs! Targeted poisoning attacks on neural nets

Ali Shafahi, Ronny Huang, Mahyar Najibi, Octavian Suciu, Christoph Studer, Tudor Dimitras, Tom Goldstein

Are adversarial examples inevitable?

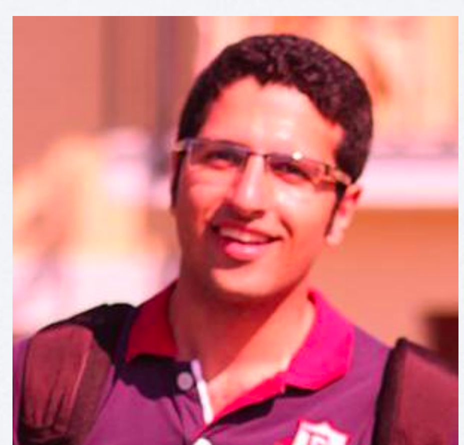
Ali Shafahi, Ronny Huang, Soheil Feize, Christoph Studer, Tom Goldstein

Ali Shafahi

Ronny Huang

Hao Li

Zheng Xu



Mahyar Najibi

Octavian Suciu