Adversarial Examples are Not Easily Detected: Bypassing Ten Detection Methods

Nicholas Carlini, David Wagner
University of California, Berkeley

Background

Neural Networks

- I assume knowledge of neural networks ...
- This talk: neural networks for classification
  - Specifically image-based classification

Background: Adversarial Examples

- Given an input X classified as label T ...
- ... it is easy to find an X′ close to X
- ... so that F(X′) != T

Constructing Adversarial Examples

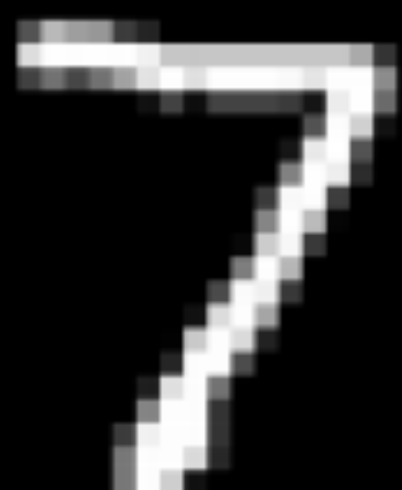
- Formulation: given input x, find x′ where
  minimize $d(x,x') + L(x')$
  such that x′ is "valid"

- Where $L(x')$ is a loss function minimized when $F(x') \neq T$ and maximized when $F(x') = T$

- Solve via gradient descent

MNIST

Normal Adversarial



7

8

9

8

CIFAR-10

Normal

Truck

Adversarial

Airplane

This is decidedly *bad*

But also:
ripe opportunity for research!

Mitigating Evasion Attacks to Deep Neural Networks via Region-based Classification. Xiaoyu Cao, Neil Zhenqiang Gong

APE-GAN: Adversarial Perturbation Elimination with GAN. Shiwei Shen, Guoqing Jin, Ke Gao, Yongdong Zhang

A Learning Approach to Secure Learning. Linh Nguyen, Arunesh Sinha

EAD: Elastic-Net Attacks to Deep Neural Networks via Adversarial Examples. Pin-Yu Chen, Yash Sharma, Huan Zhang, Jinfeng Yi, Cho-Jui Hsieh

Ensemble Methods as a Defense to Adversarial Perturbations Against Deep Neural Networks. Thilo Strauss, Markus Hanselmann, Andrej Junginger, Holger Ulmer

MagNet: a Two-Pronged Defense against Adversarial Examples. Dongyu Meng, Hao Chen

CuRTAIL: ChaRacterizing and Thwarting AdversarIal deep Learning. Bita Darvish Rouhani, Mohammad Samragh, Tara Javidi, Farinaz Koushanfar

Efficient Defenses Against Adversarial Attacks. Valentina Zantedeschi, Maria-Irina Nicolae, Ambrish Rawat

Learning Adversary-Resistant Deep Neural Networks. Qinglong Wang, Wenbo Guo, Kaixuan Zhang, Alexander G. Ororbia II, Xinyu Xing, Xue Liu, C. Lee Giles

SafetyNet: Detecting and Rejecting Adversarial Examples Robustly. Jiajun Lu, Theerasit Issaranon, David Forsyth

Enhancing Robustness of Machine Learning Systems via Data Transformations. Arjun Nitin Bhagoji, Daniel Cullina, Bink Sitawarin, Prateek Mittal

Towards Deep Learning Models Resistant to Adversarial Attacks. Aleksander Madry, Aleksandar Makelov, Ludwig Schmidt, Dimitris Tsipras, Adrian Vladu

Towards Robust Deep Neural Networks with BANG. Andras Rozsa, Manuel Gunther, Terrance E. Boult

Deep Variational Information Bottleneck. Alexander A. Alemi, Ian Fischer, Joshua V. Dillon, Kevin Murphy

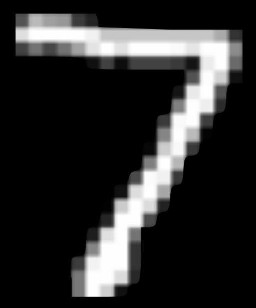
NO Need to Worry about Adversarial Examples in Object Detection in Autonomous Vehicles. Jiajun Lu, Hussein Sibai, Evan Fabry, David Forsyth

Research Question:

Which of these defenses are robust?

Focus of this talk:
detection schemes

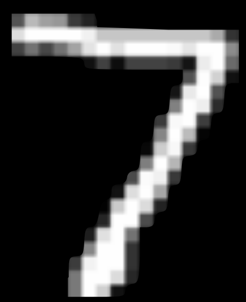
Normal Classifier



Classifier

Normal Classifier

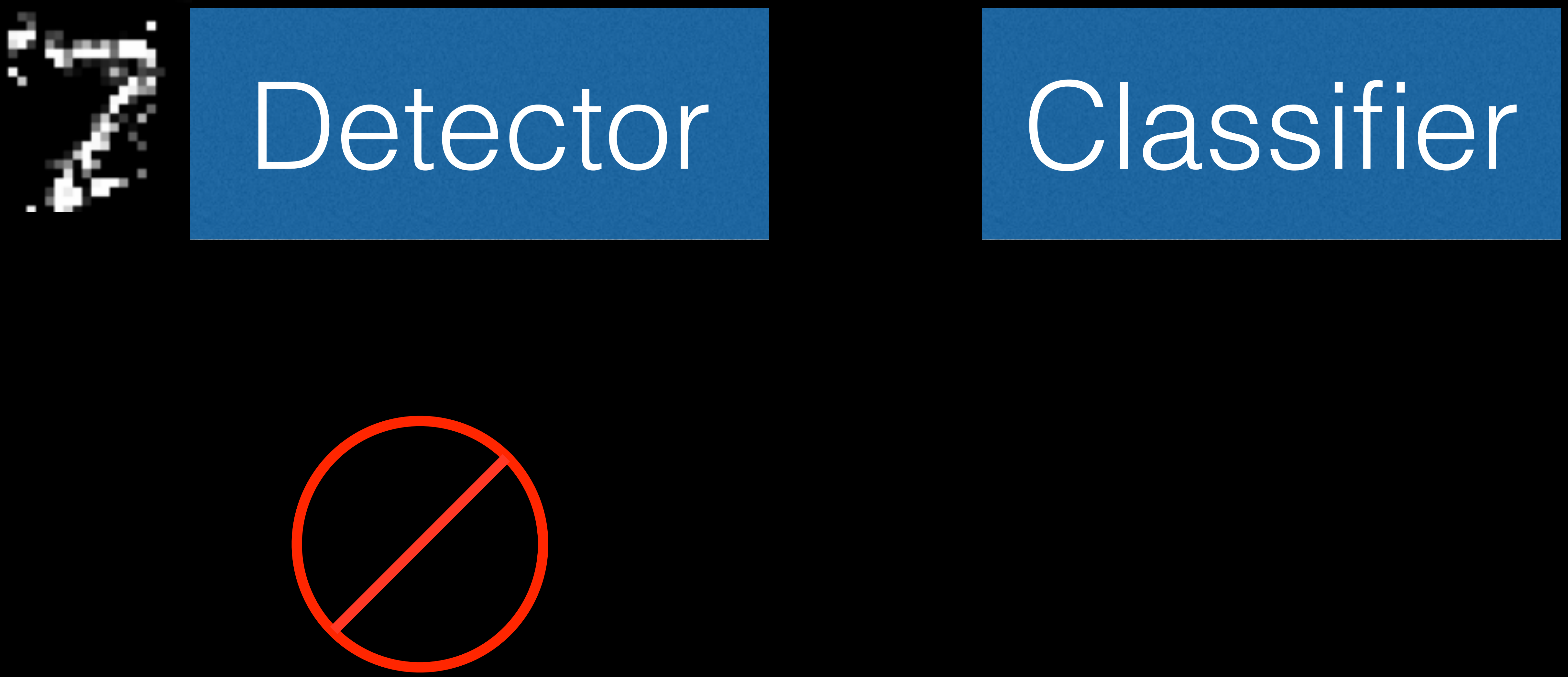
Detector & Classifier



Detector

Classifier

Detector & Classifier



This Talk:

1. How to evaluate a defense
2. Comment on explored directions

Defense #1:

PCA-based detection

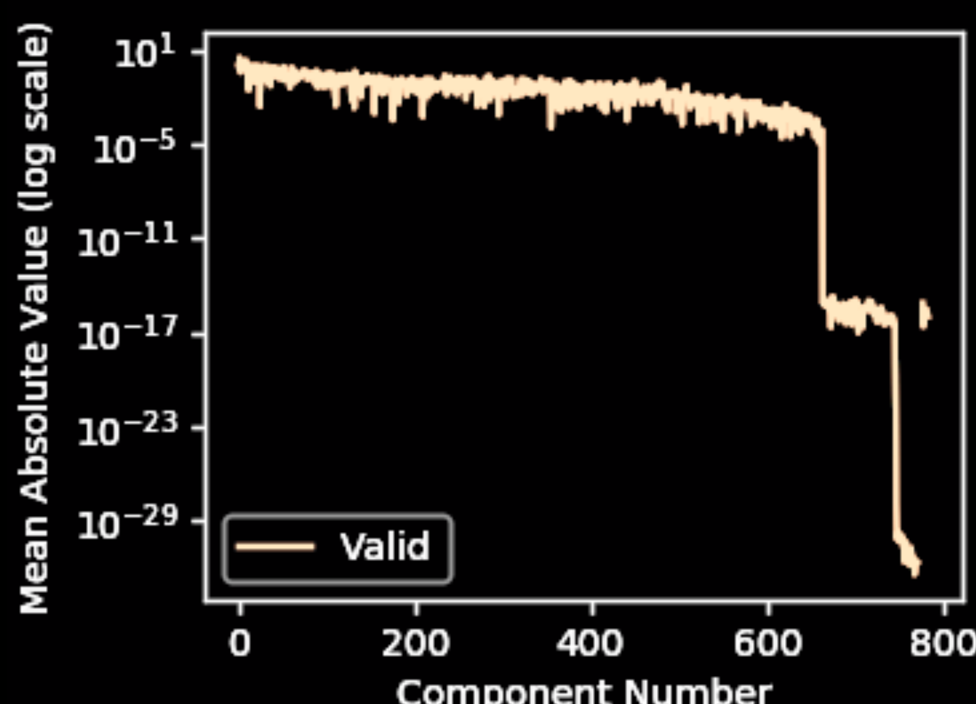
Dan Hendrycks and Kevin Gimpel. 2017. Early Methods for Detecting Adversarial Images. In International Conference on Learning Representations (Workshop Track)

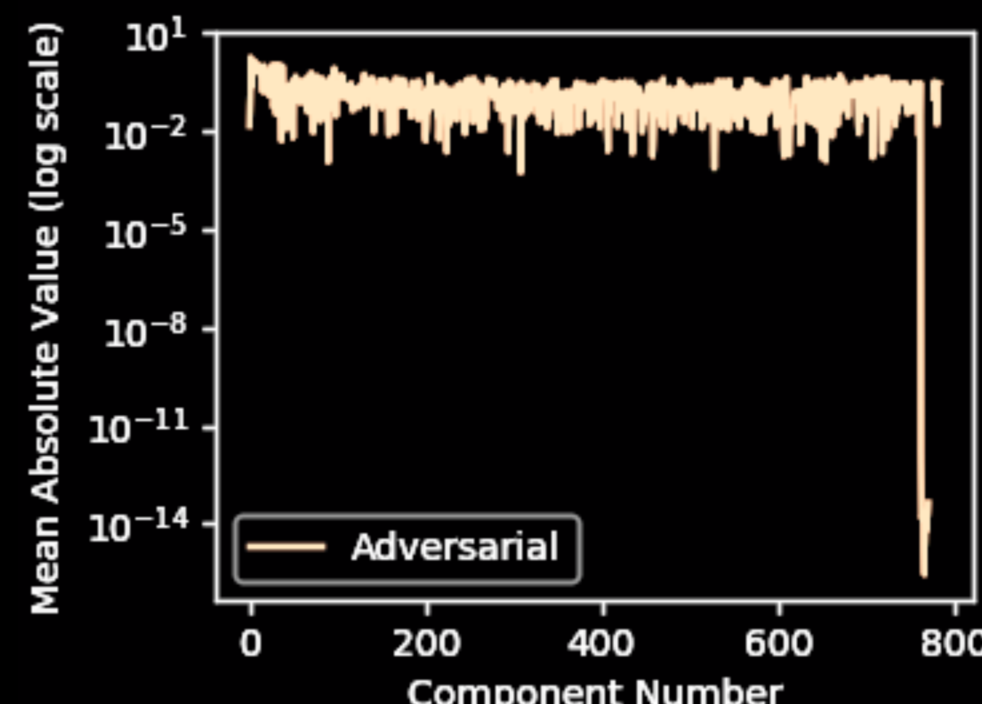
PCA-based detection

- Hypothesis: Adversarial examples rely on later principle components
  - ... and valid images don't ...
  - ... so let's detect use of high components

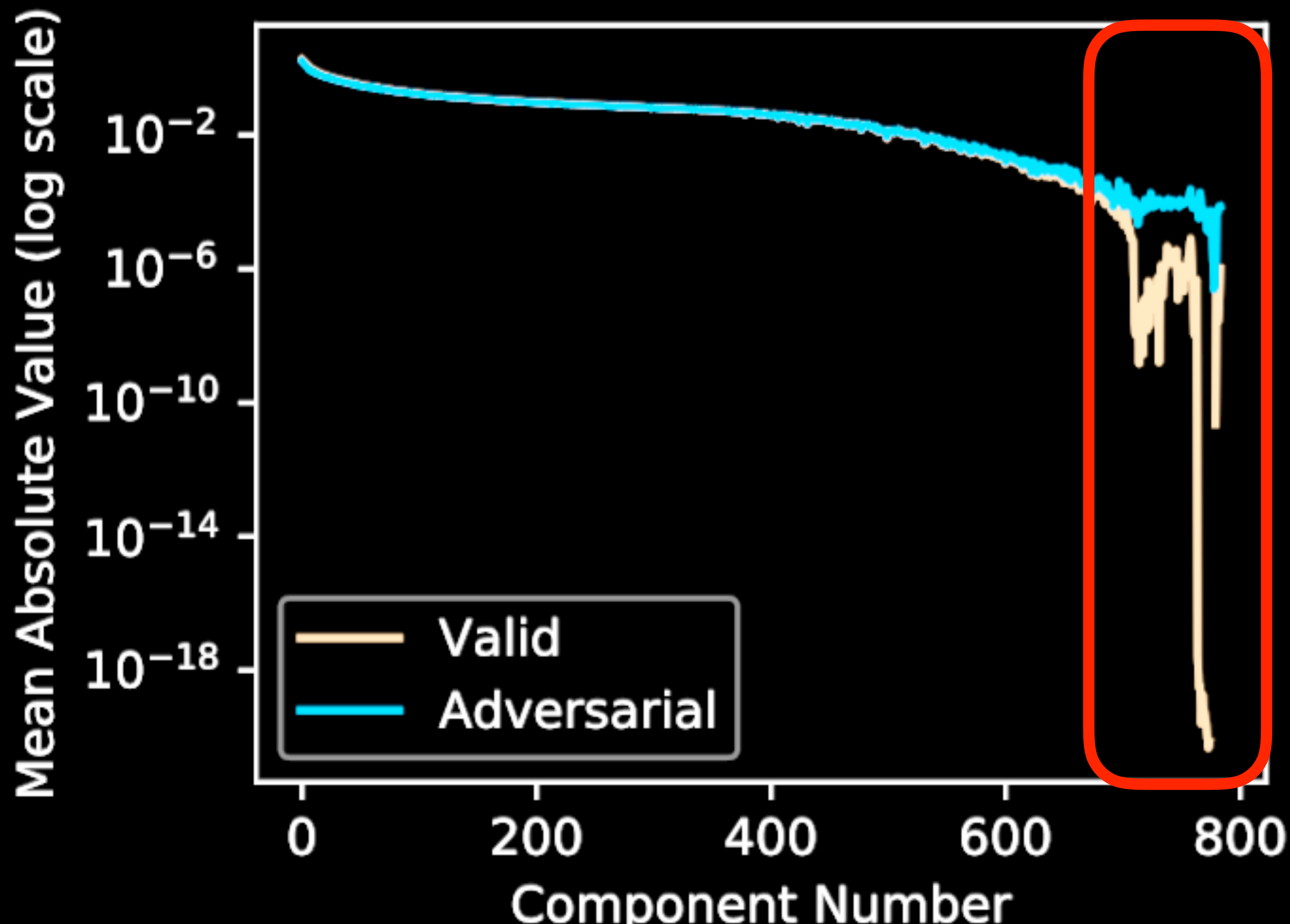
Normal

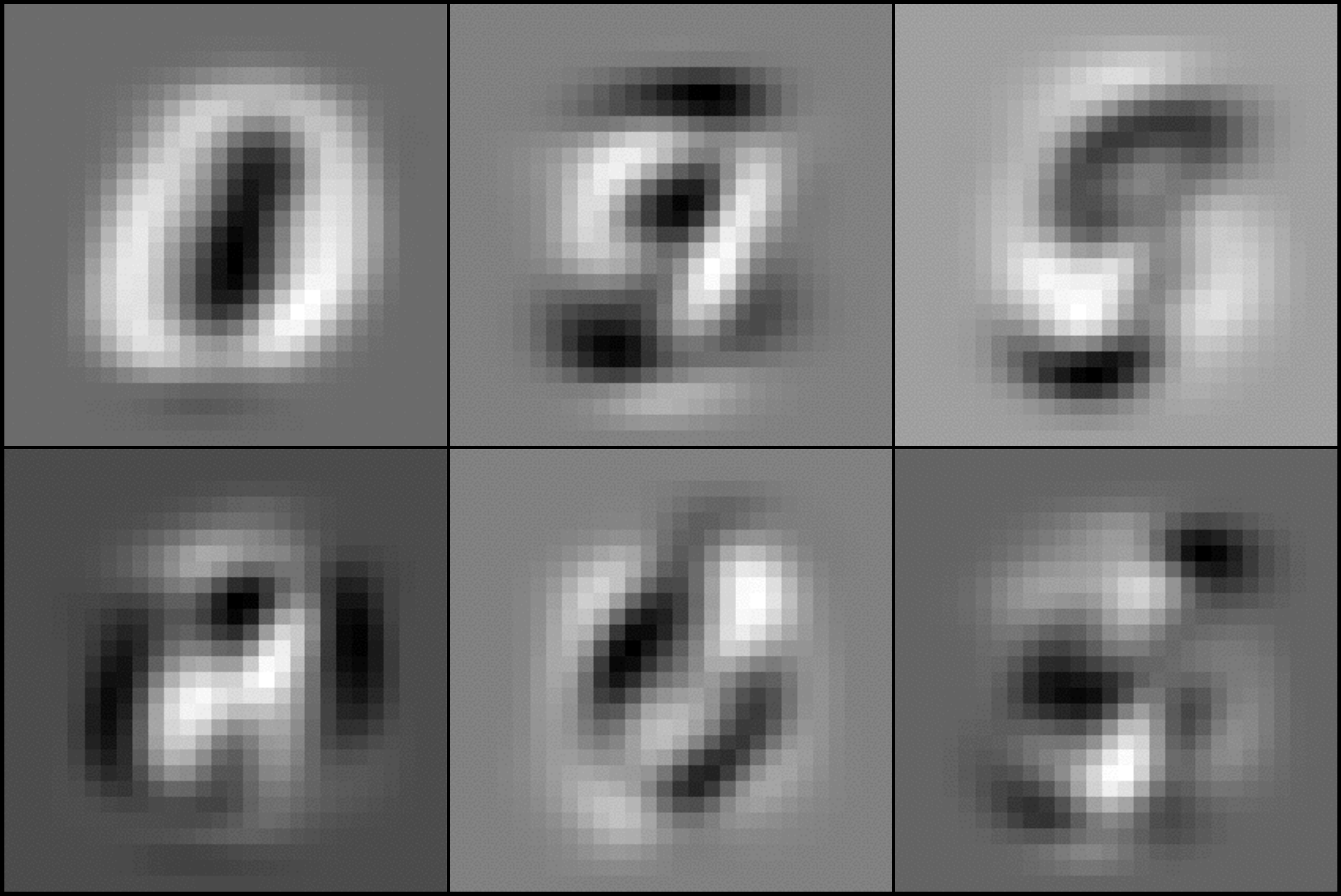
Adversarial

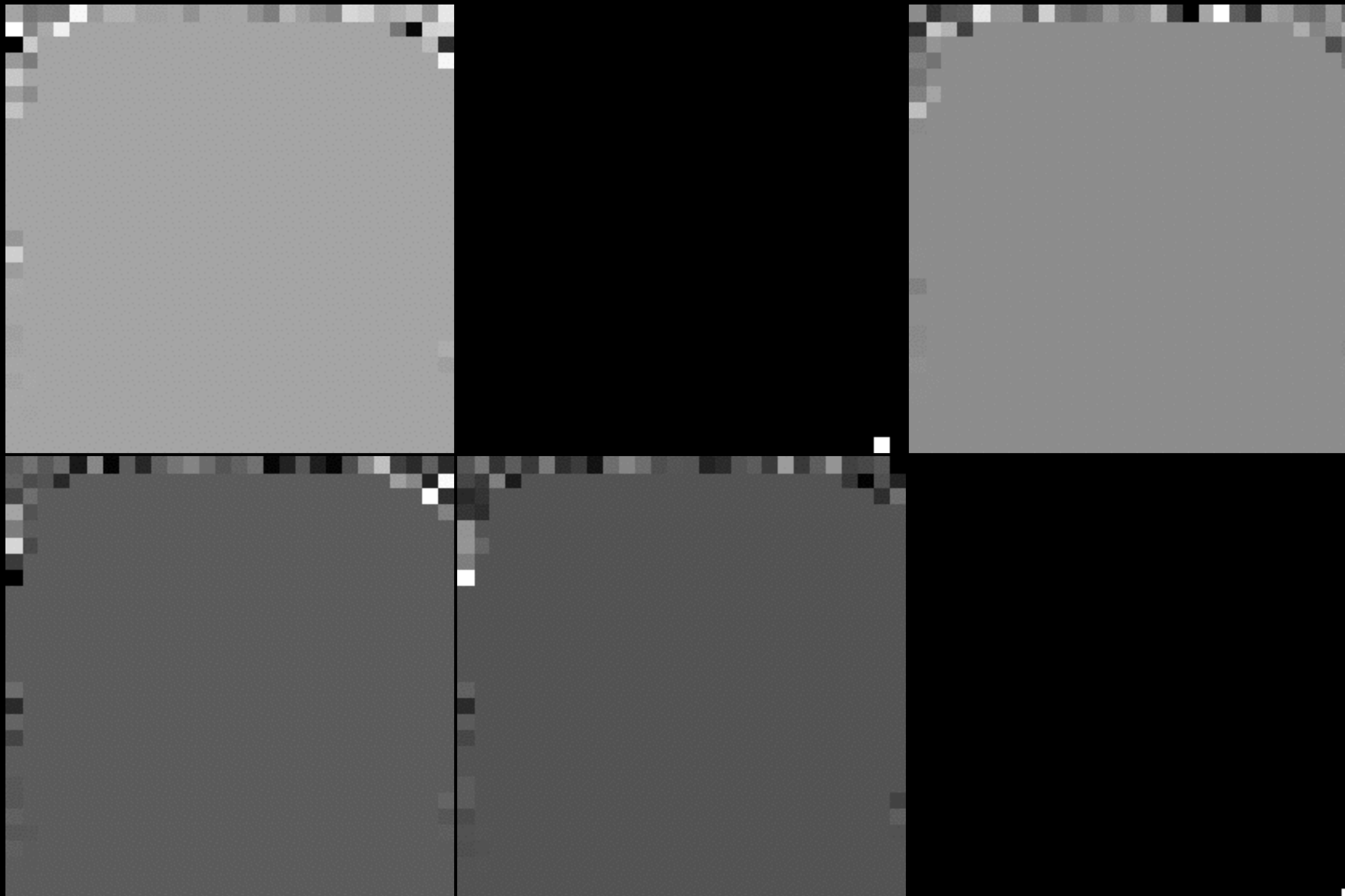




It works!


Mean Absolute Value (log scale)
10^{-2}
10^{-6}
10^{-10}
10^{-14}
10^{-18}
Valid
Adversarial
0
200
400
600
800
Component Number





Attack:

Only modify regions of the image that are also used in normal images.

Original

Adversarial (unsecured)

Adversarial (with detector)

Lesson 1: Separate the artifacts of one attack vs intrinsic properties of adversarial examples

Lesson 2:

MNIST is insufficient
CIFAR is better

Defense #2:

Additional Neural Network Detection

Jan Hendrik Metzen, Tim Genewein, Volker Fischer, and Bastian Bischo. 2017. On Detecting Adversarial Perturbations. In International Conference on Learning Representations.

Normal Training

( , 7)

( , 3)

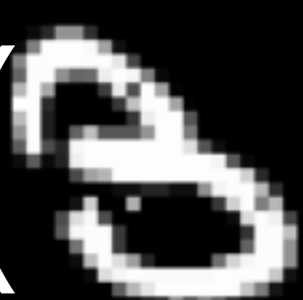
Training

Adversarial Training

(, 7)

(, 3)

(, n)

(, n)

Attack

Adversarial Training

( , y)

( , y)

( , n)

( , n)

Training

Sounds great.

Sounds great.

But we already know it's easy to fool neural networks ...

... so just construct adversarial examples to

1. be misclassified
2. not be detected

Breaking Adversarial Training

- minimize $d(x,x') + L(x')$
  such that x' is "valid"

- Old: $L(x')$ measures loss of **classifier** on x'

Breaking Adversarial Training

- minimize $d(x,x') + L(x') + M(x')$
  such that x' is "valid"

- Old: $L(x')$ measures loss of **classifier** on x'

- New: $M(x')$ measures loss of **detector** on x'

Original

Adversarial
(unsecured)

Adversarial
(with detector)

Lesson 3:

Minimize over (compute gradients through) the full defense

Defense #3:

Network Randomization

Reuben Feinman, Ryan R Curtin, Saurabh Shintre, and Andrew B Gardner. 2017.
Detecting Adversarial Samples from Artifacts.

Randomized Classifier

Randomized Classifier

Classifier

Breaking Randomization

- minimize $\quad d(x,x') + L(x')$
  such that $\quad x'$ is "valid"

- Old: $L(x')$ measures loss of network on x'

Breaking Randomization

- minimize $\quad d(x,x') + E[L(x')]$
  such that $\quad x'$ is "valid"

- Old: $L(x')$ measures loss of network on x'

- Now: $E[L(x')]$ **expected** loss of network on x'

Original

Adversarial (unsecured)

Adversarial (with detector)

Original

Adversarial (unsecured)

Adversarial (with detector)

Evaluation Lessons

1. Don't evaluate only on MNIST
2. Minimize over the full defense
3. Use a strong iterative attack
4. Release your source code!

https://nicholas.carlini.com/nn_breaking_detection