Feature Squeezing:

Detecting Adversarial Examples in Deep Neural Networks

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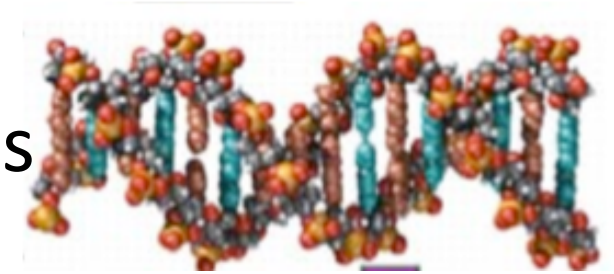
Deep Learning is Solving Many of Our Problems!

Auto-Driving Car

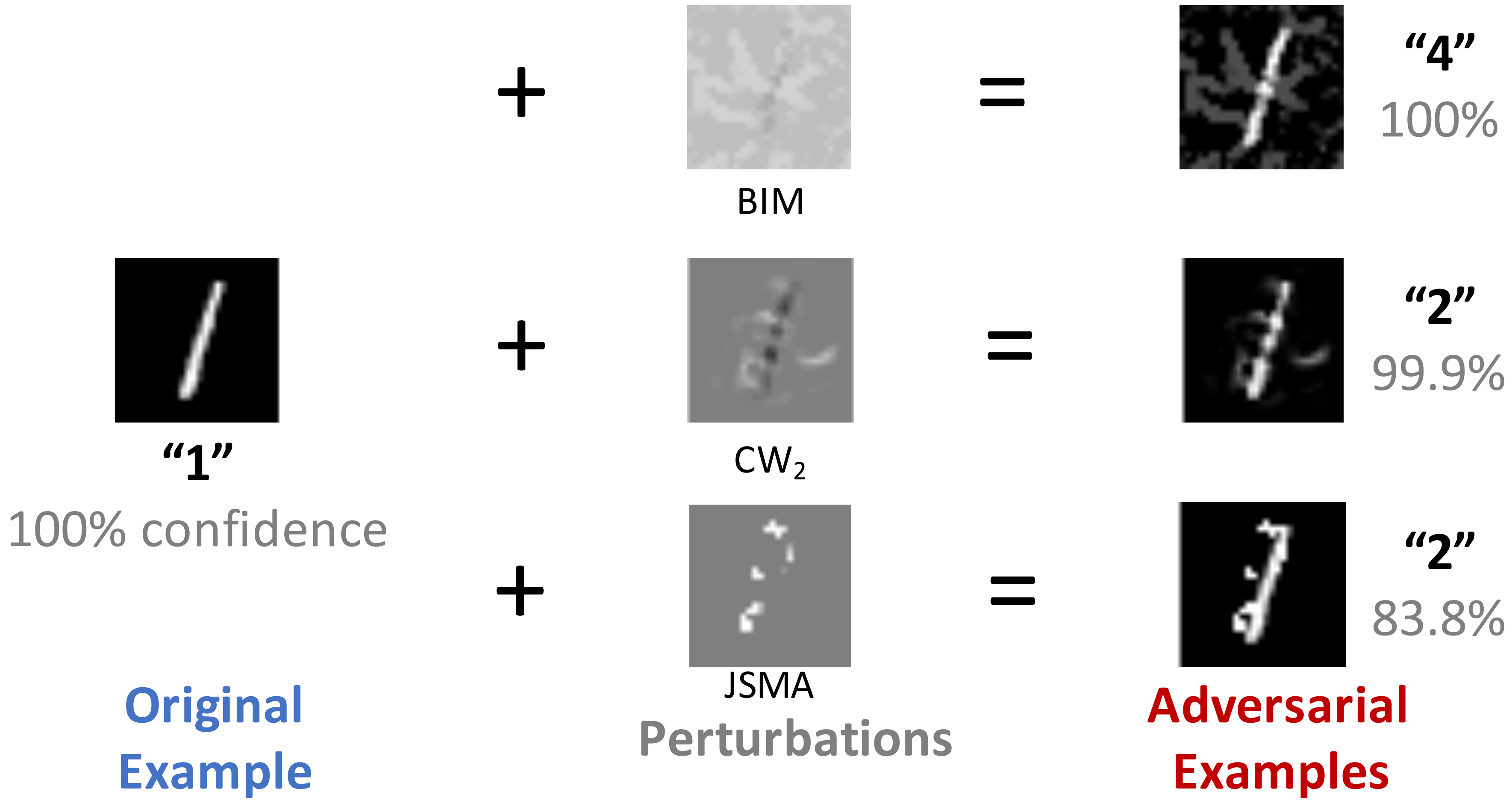
Voice Assistant

Spam Detector

Medical Genomics



However, Deep Learning Classifiers are Easily Fooled



+ BIM = "4" 100%

"1" 100% confidence + CW_2 = "2" 99.9%

+ JSMA = "2" 83.8%

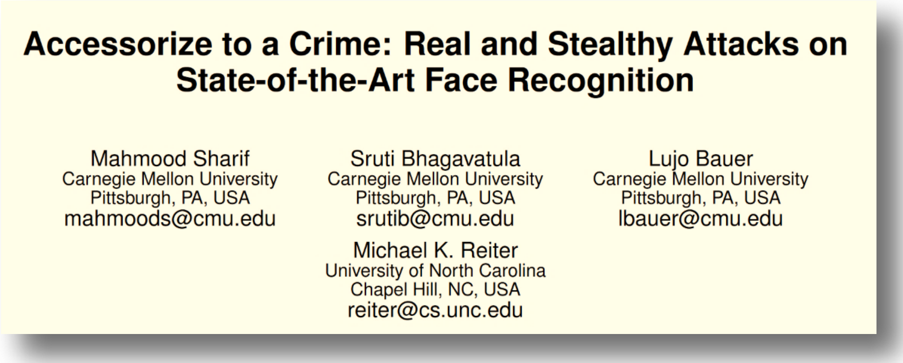
Original Example

Perturbations

Adversarial Examples

C Szegedy et al., *Intriguing Properties of Deep Neural Networks*. In *ICLR 2014*.

Classifiers Under Attack: **Adversary Adapts**



Accessorize to a Crime: Real and Stealthy Attacks on State-of-the-Art Face Recognition

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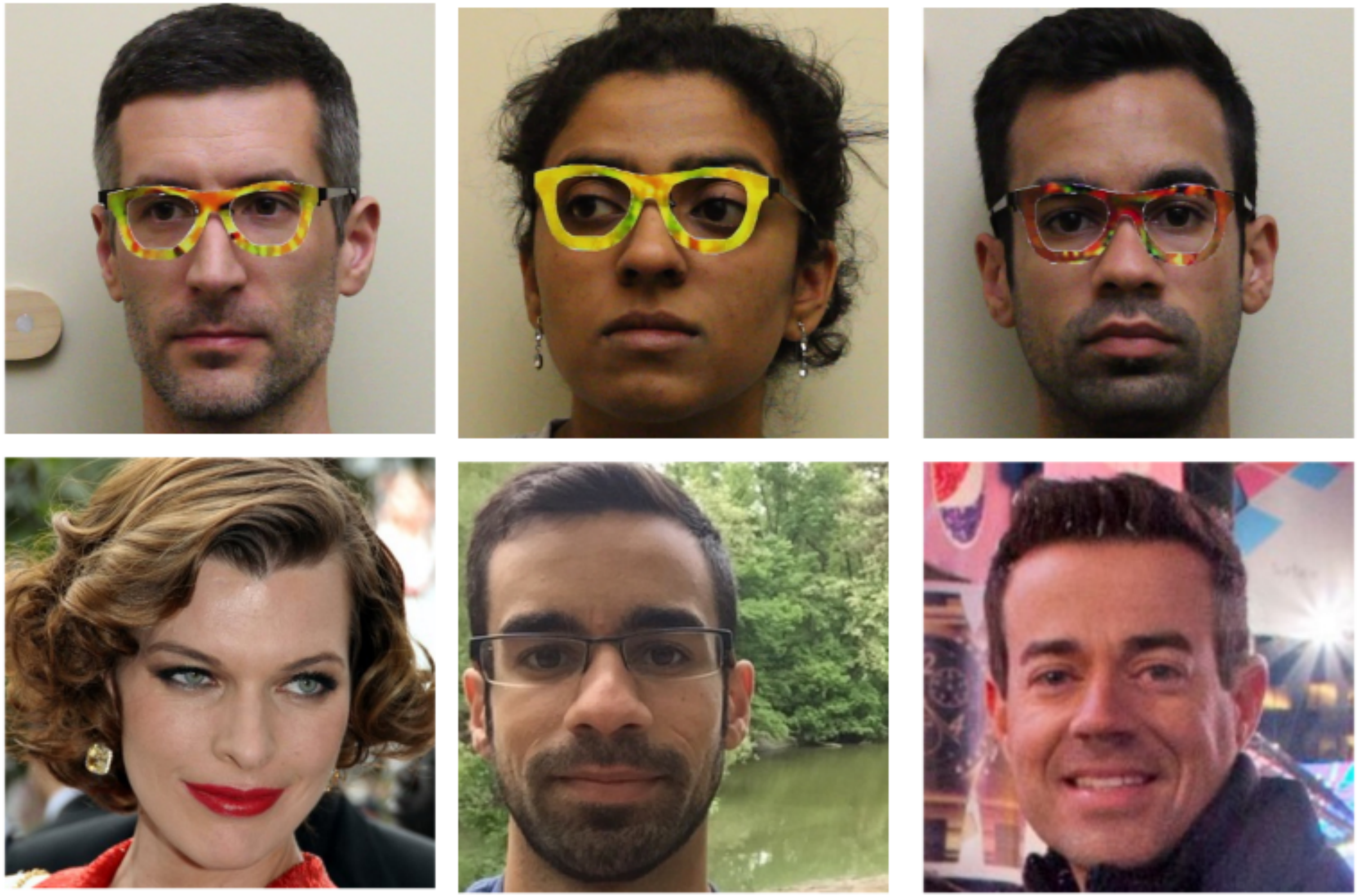
ACM CCS 2016



Actual images

Recognized faces

Solution Strategy

Solution Strategy 1: Train a perfect vision model.

Infeasible yet.

Solution Strategy 2: Make it harder to find adversarial examples.

Arms race!

Feature Squeezing: A general framework that reduces the search space available for an adversary and detects adversarial examples.

Simple, Cheap, Effective!

Roadmap

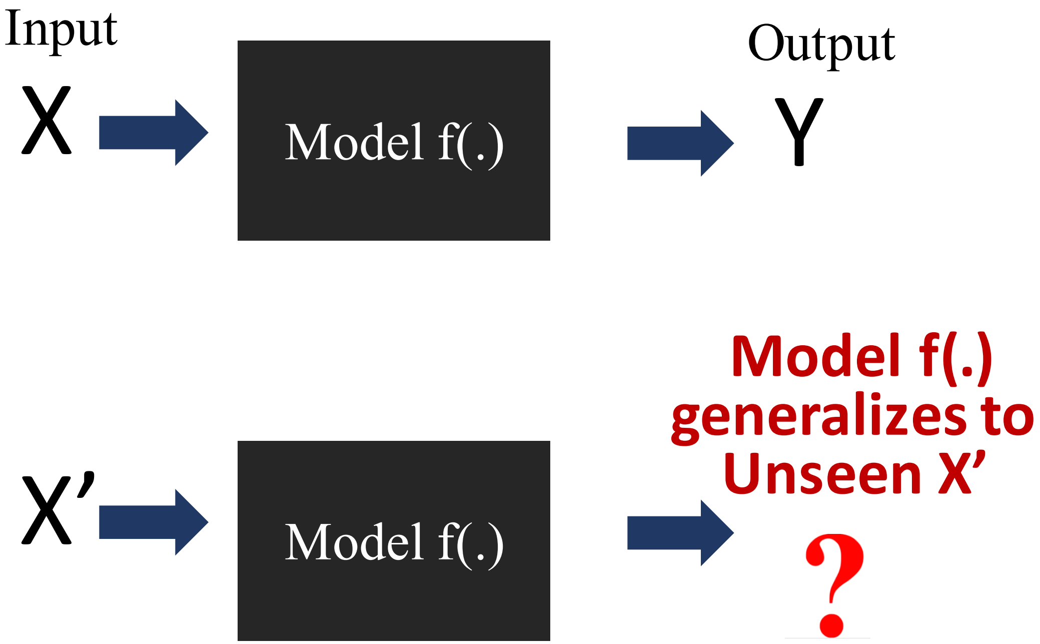
- Feature Squeezing Detection Framework

- Feature Squeezers
  - Bit Depth Reduction
  - Spatial Smoothing

- Detection Evaluation
  - Oblivious adversary
  - Adaptive adversary

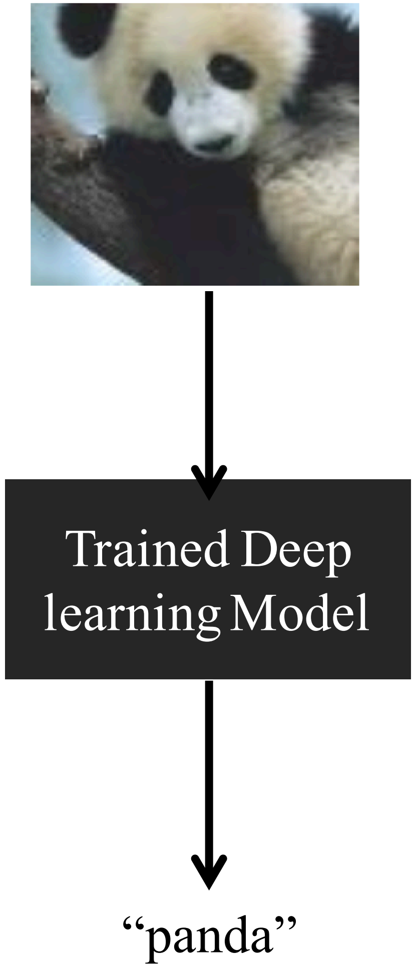
Background: Machine Learning

- Machine Learning: learn to find models that can generalize from observed data to unseen data

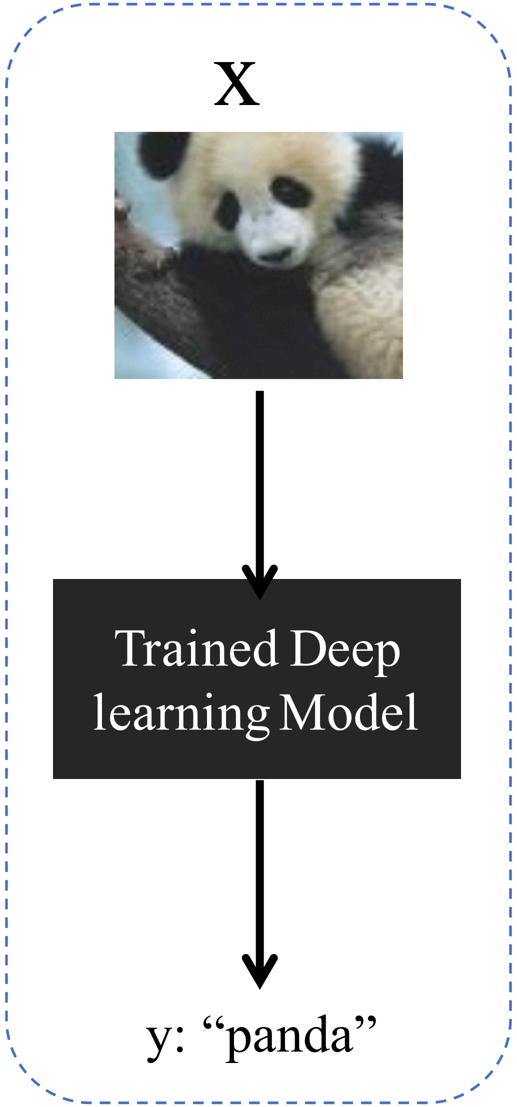


Model f(.) generalizes to Unseen X'

For instance:



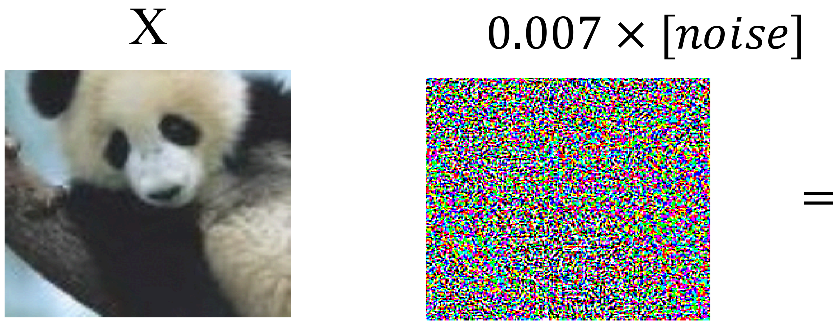
Background: Adversarial Examples



x

Trained Deep learning Model

y: “panda”



x

$0.007 \times [noise]$

=

x: original sample

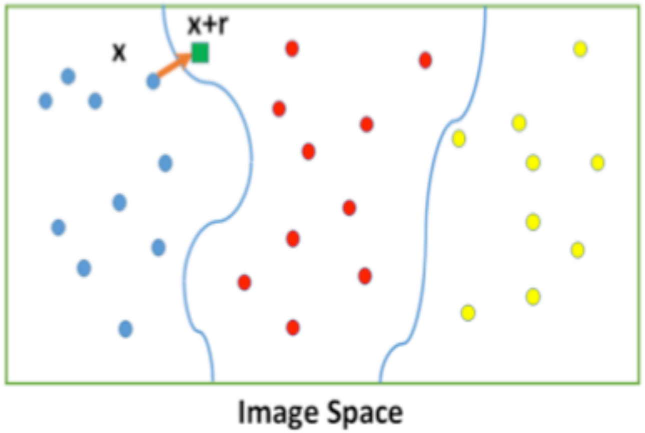
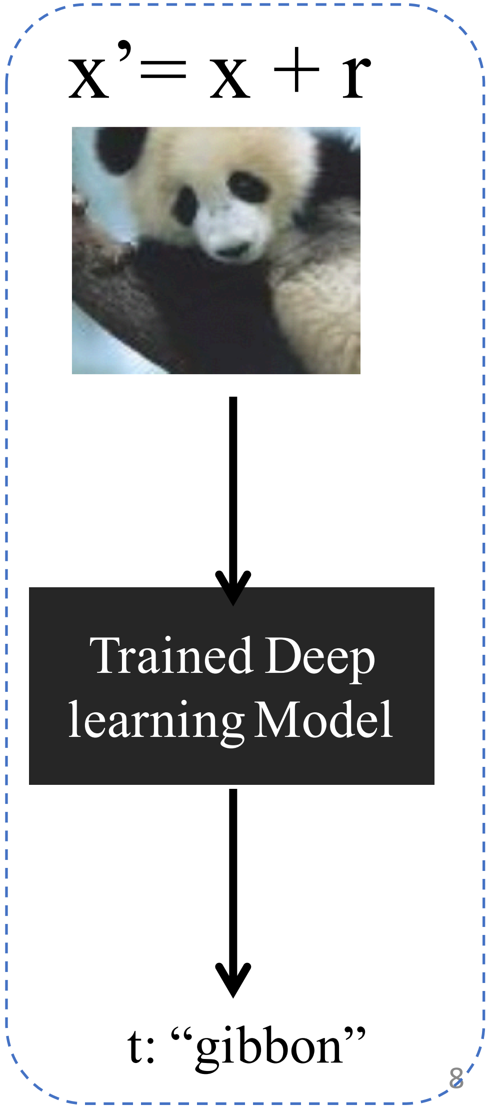


Image Space

x’ = x + r : adversarial sample



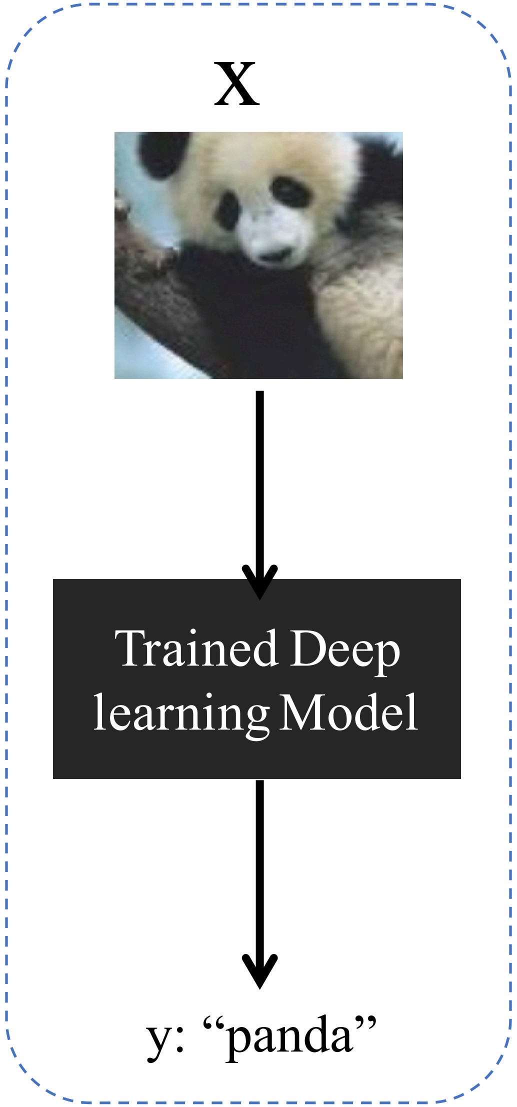
x’= x + r

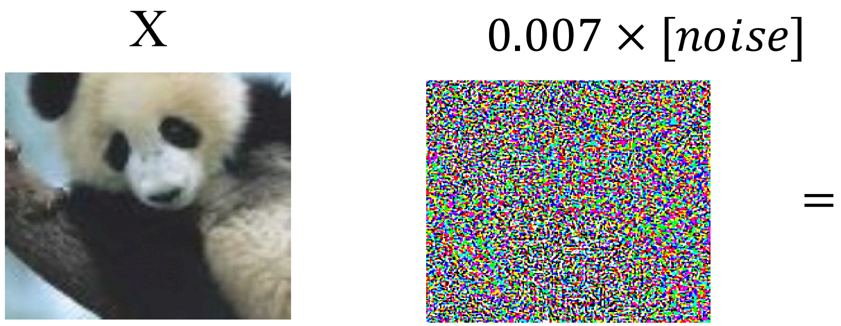
Trained Deep learning Model

t: “gibbon”

C Szegedy et al., *Intriguing Properties of Deep Neural Networks*. In *ICLR 2014*.

Background: Adversarial Examples

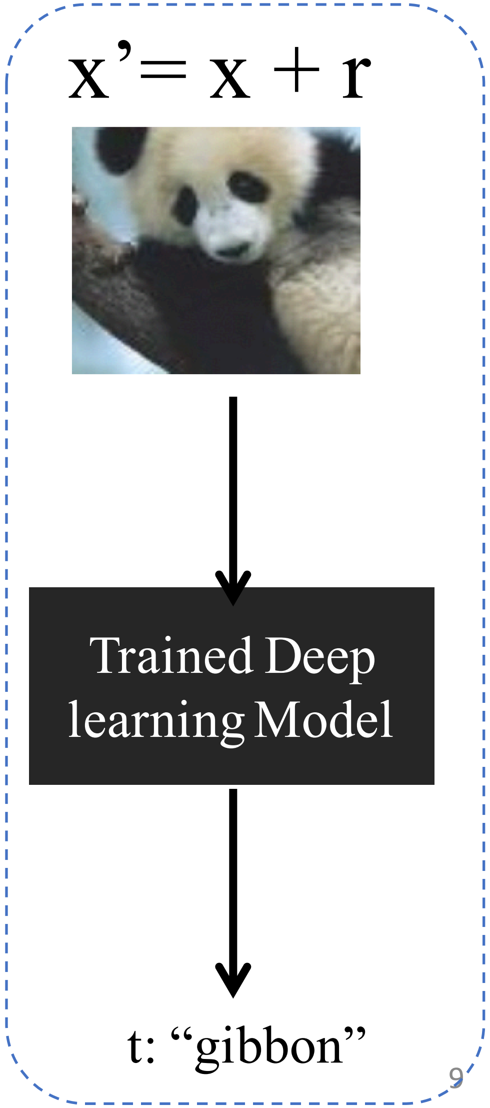




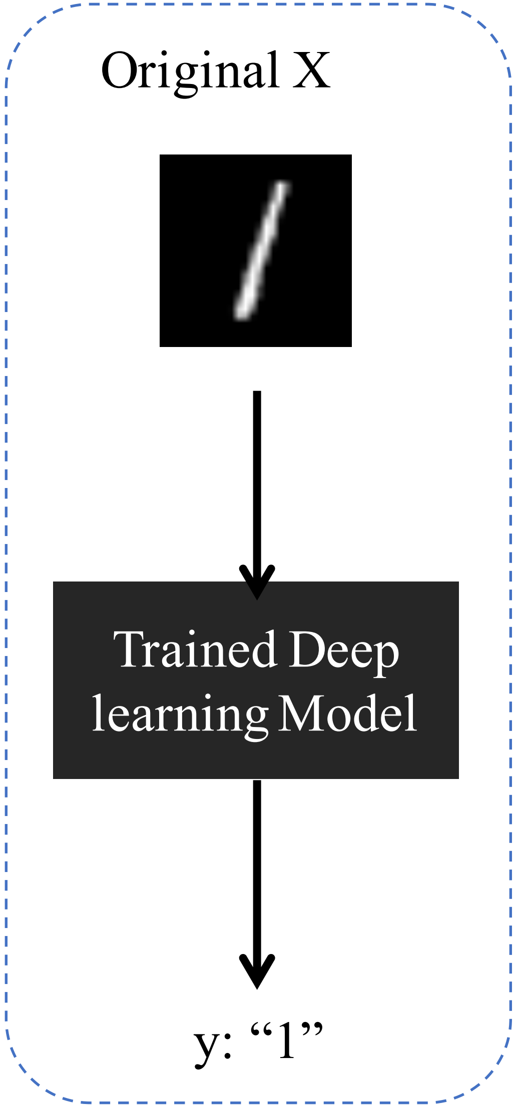
Many different variations of formulations to search for x’ from x, e.g.,

$$minimize\ \|f(x') - t\| + \ \lambda * \Delta(x, x')$$

Misclassification term   Distance term



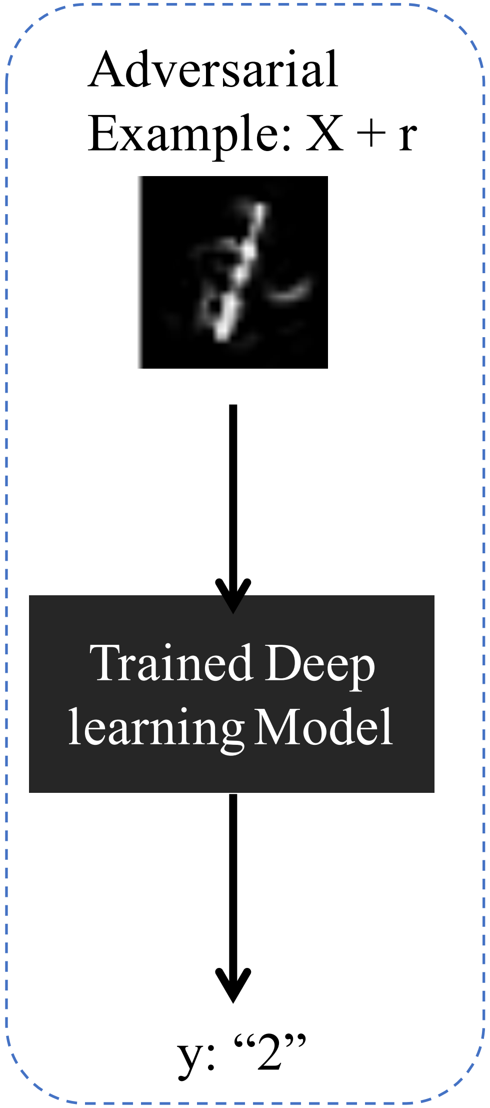
Intriguing Property of Adversarial Examples


Original X

Trained Deep learning Model

y: “1”

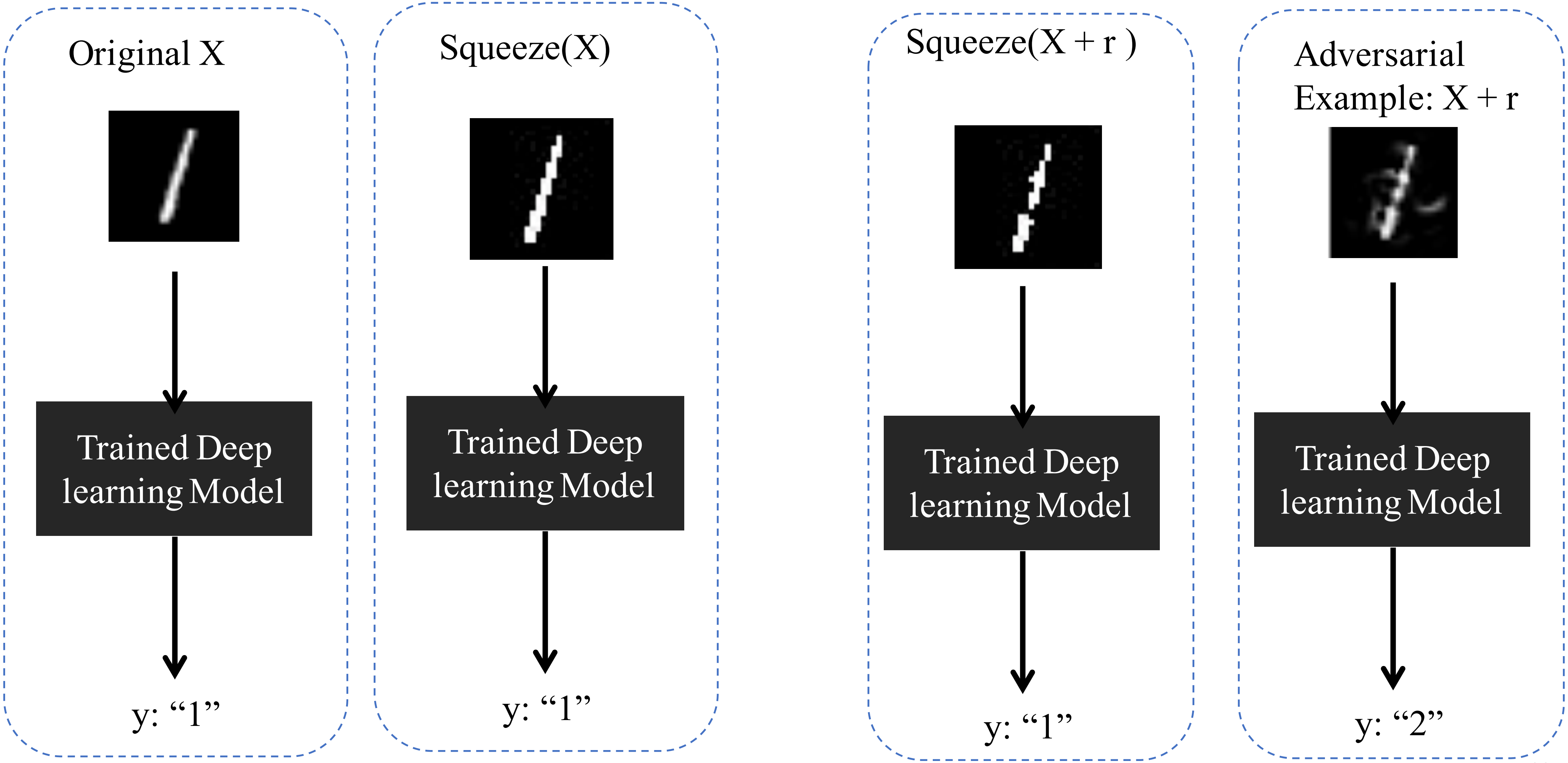
Irrelevant features used in classification tasks are the major cause of adversarial examples.


Adversarial Example: X + r

Trained Deep learning Model

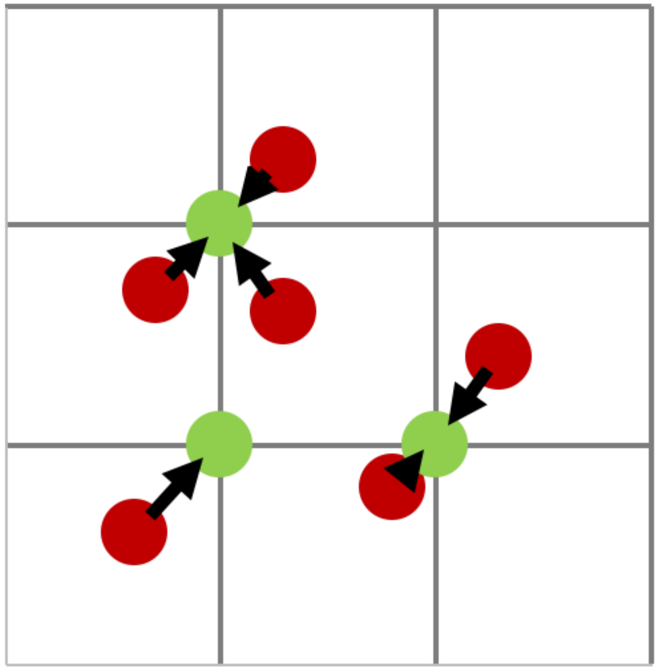
y: “2”

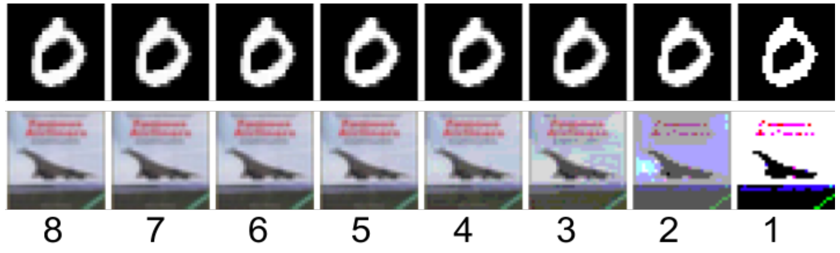
Intriguing Property of Adversarial Examples


Original X
Trained Deep learning Model
y: “1”
Squeeze(X)
Trained Deep learning Model
y: “1”
Squeeze(X + r)
Trained Deep learning Model
y: “1”
Adversarial Example: X + r
Trained Deep learning Model
y: “2”

Motivation

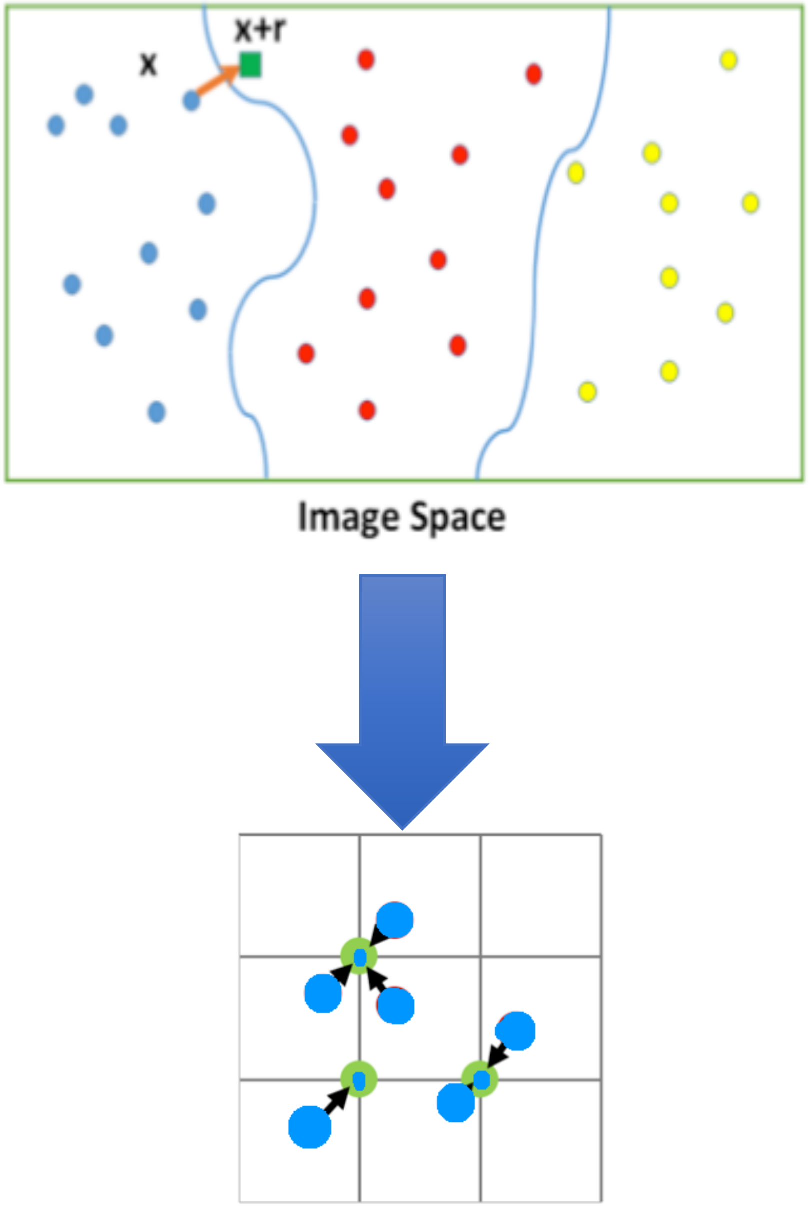
- Irrelevant features used in classification tasks are the root cause of adversarial examples.
- The feature spaces are unnecessarily too large in deep learning tasks: e.g. raw image pixels.
- We may reduce the search space of possible perturbations available to an adversary using *Feature Squeezing*.

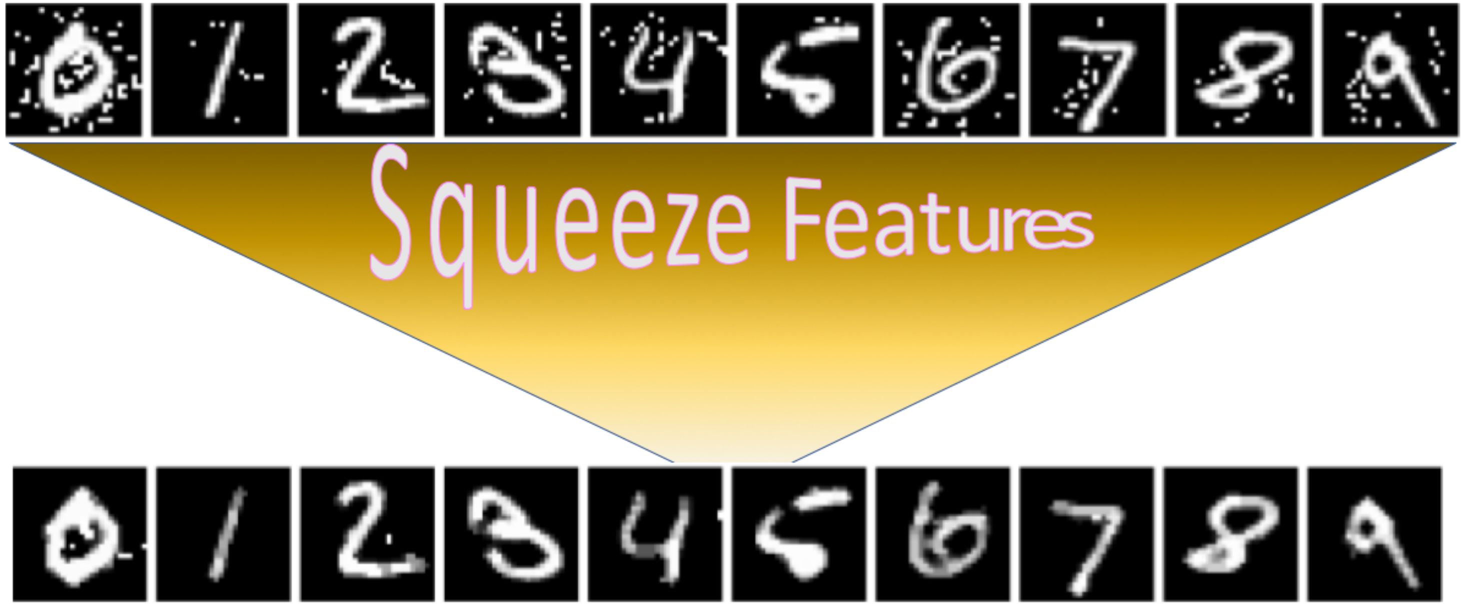


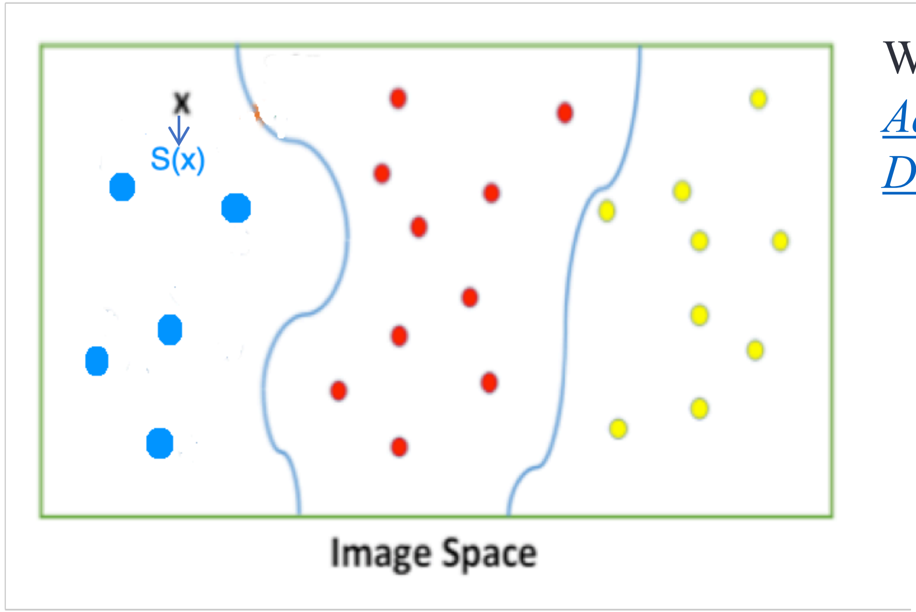


Bit Depth Reduction

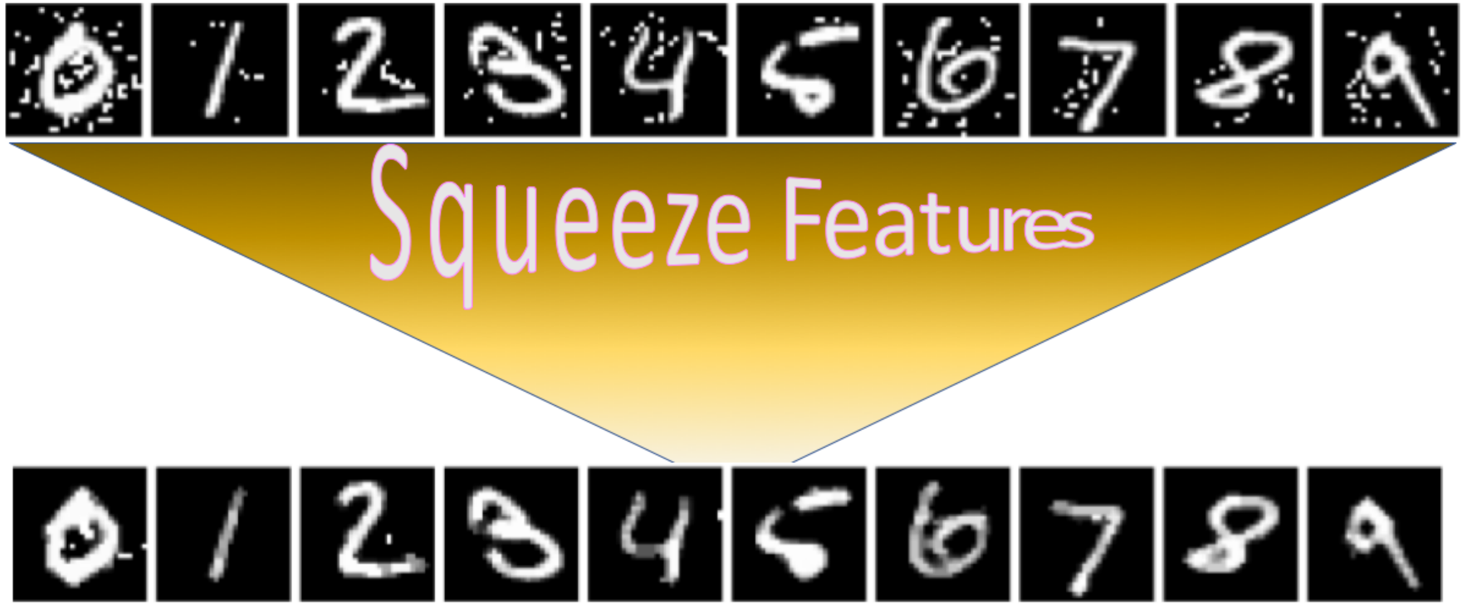
Weilin Xu, David Evans, Yanjun Qi. [*Feature Squeezing: Detecting Adversarial Examples in Deep Neural Networks*]. [*2018 Network and Distributed System Security Symposium*]. NDSS2018

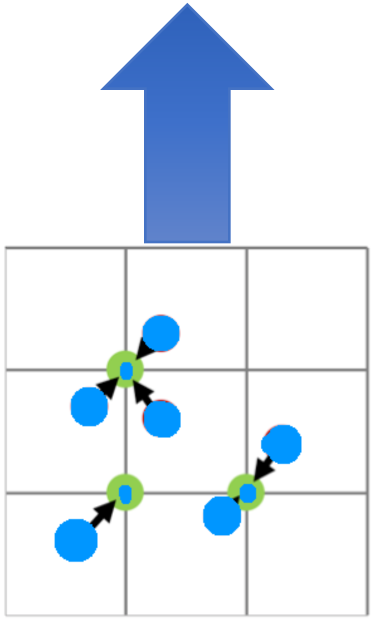




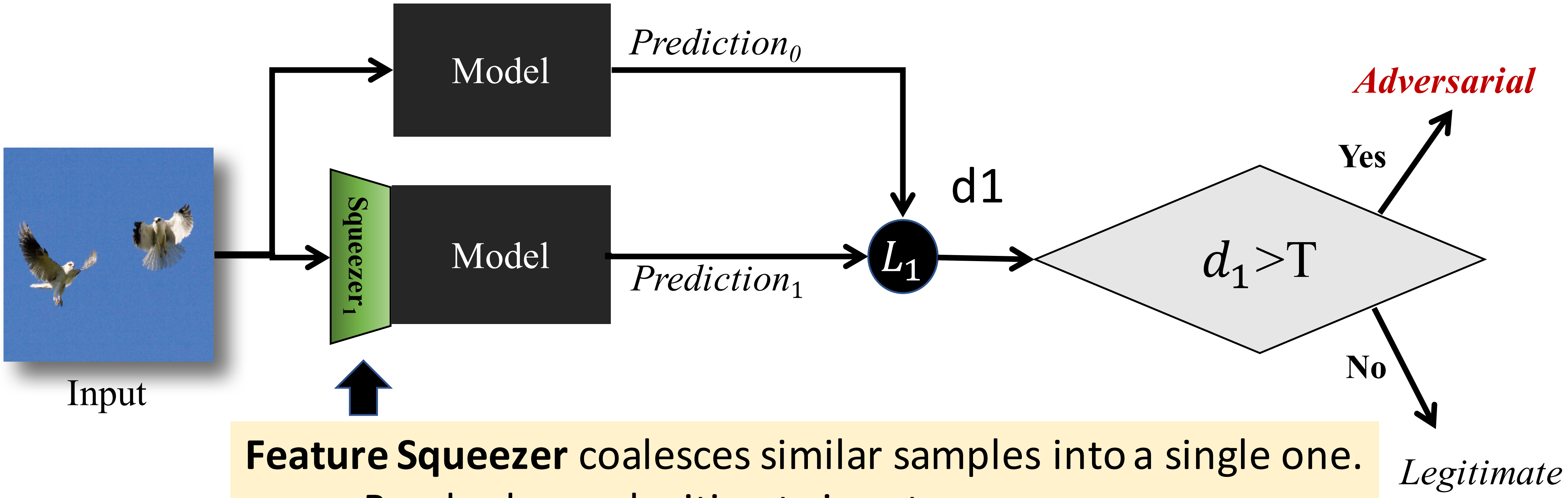


Weilin Xu, David Evans, Yanjun Qi. *Feature Squeezing: Detecting Adversarial Examples in Deep Neural Networks*. *2018 Network and Distributed System Security Symposium*. NDSS2018





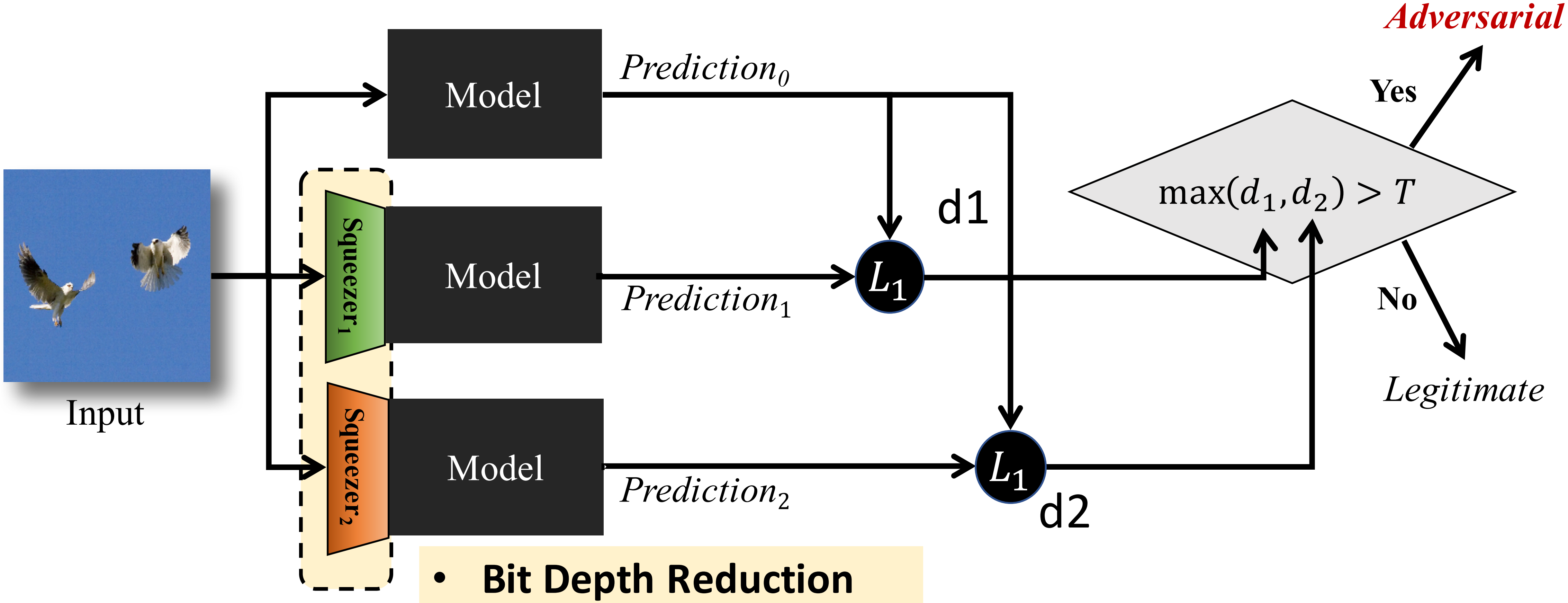
Detection Framework



Feature Squeezer coalesces similar samples into a single one.

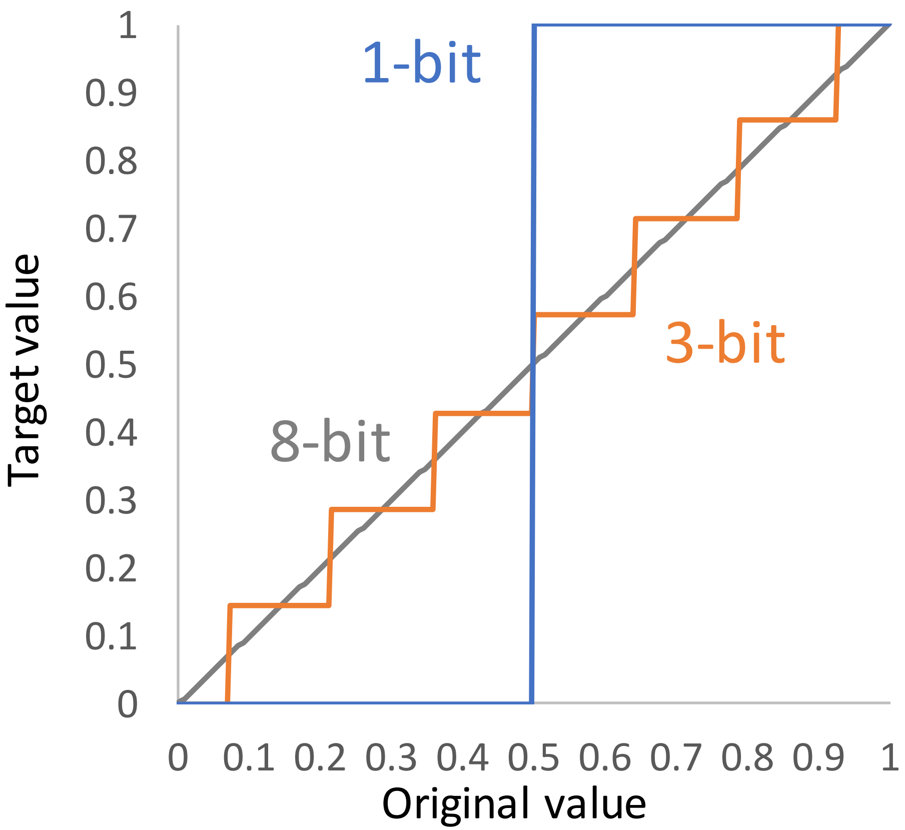
- Barely change legitimate input.
- Destruct adversarial perturbations.

Detection Framework: Multiple Squeezers

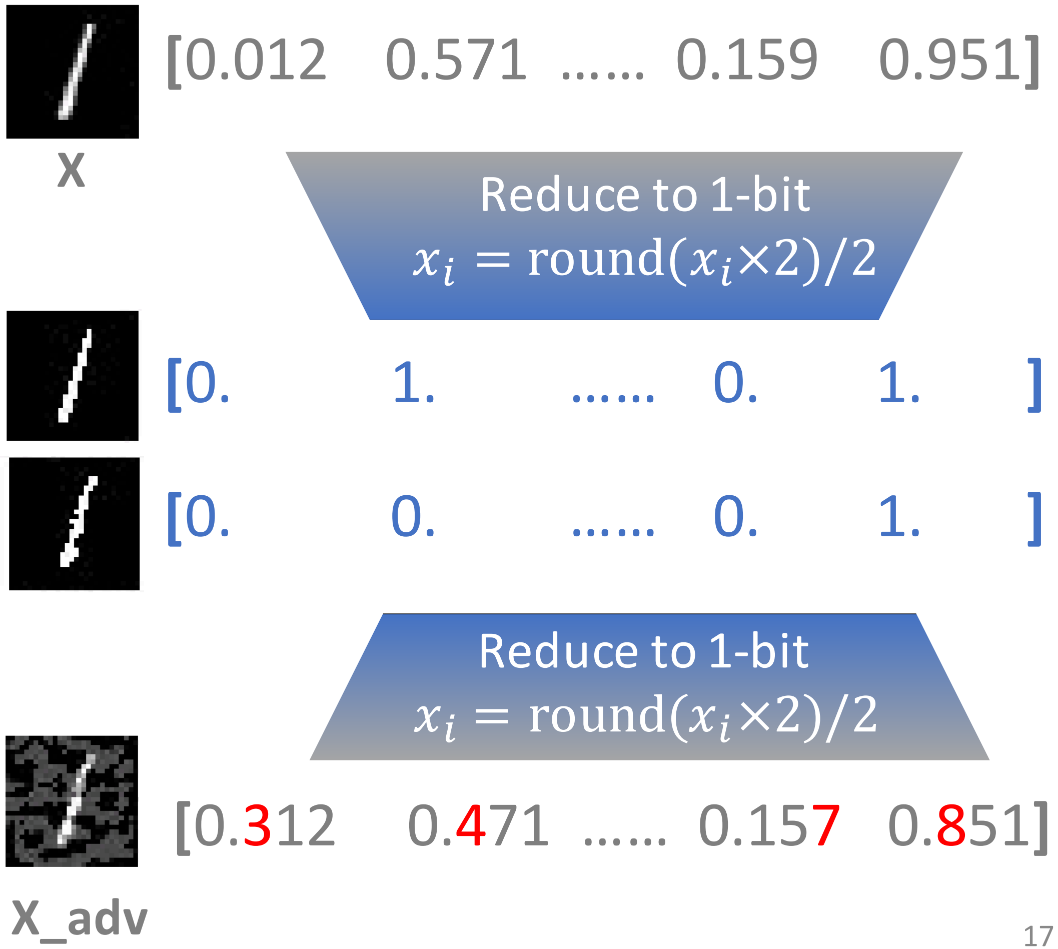


- **Bit Depth Reduction**
- **Spatial Smoothing**

Bit Depth Reduction



Signal Quantization



X [0.012 0.571 …… 0.159 0.951]

Reduce to 1-bit

$x_i = \mathrm{round}(x_i \times 2)/2$

[0. 1. …… 0. 1.]

[0. 0. …… 0. 1.]

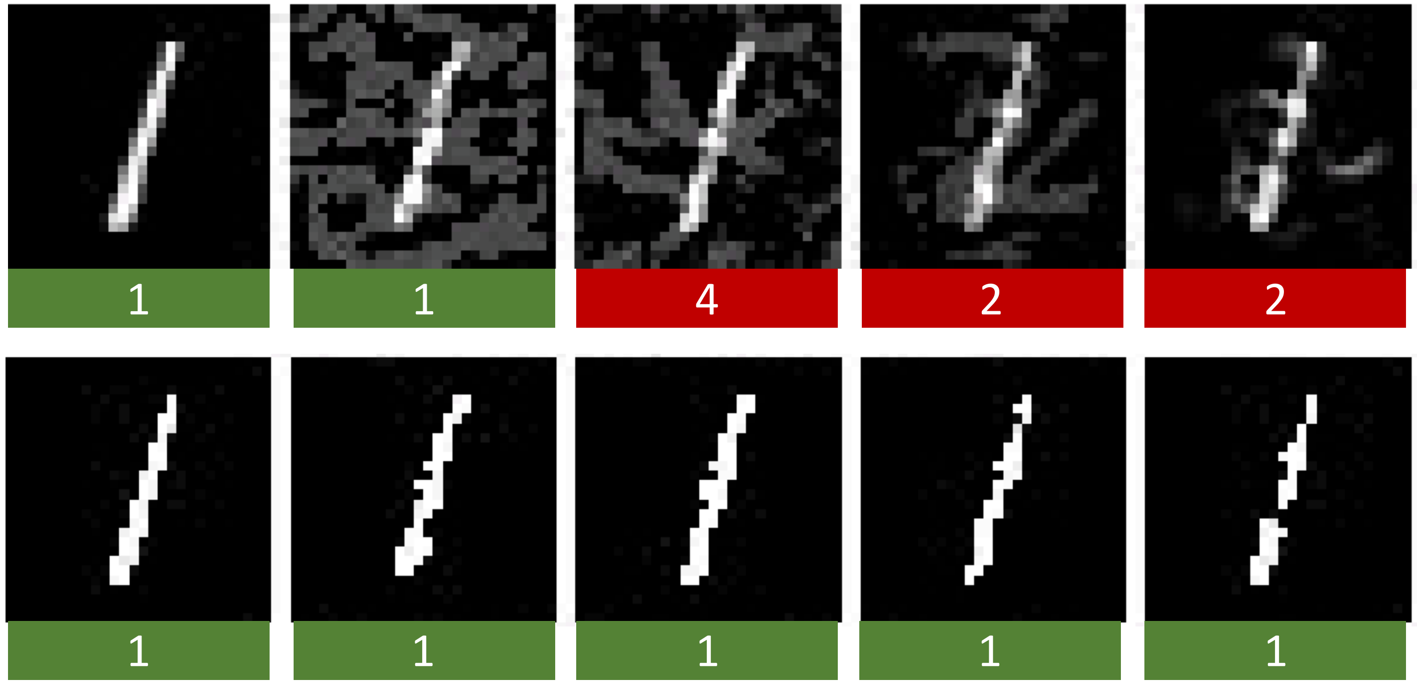
Reduce to 1-bit

$x_i = \mathrm{round}(x_i \times 2)/2$

X_adv [0.312 0.471 …… 0.157 0.851]

Bit Depth Reduction

Eliminating adversarial perturbations while preserving semantics.



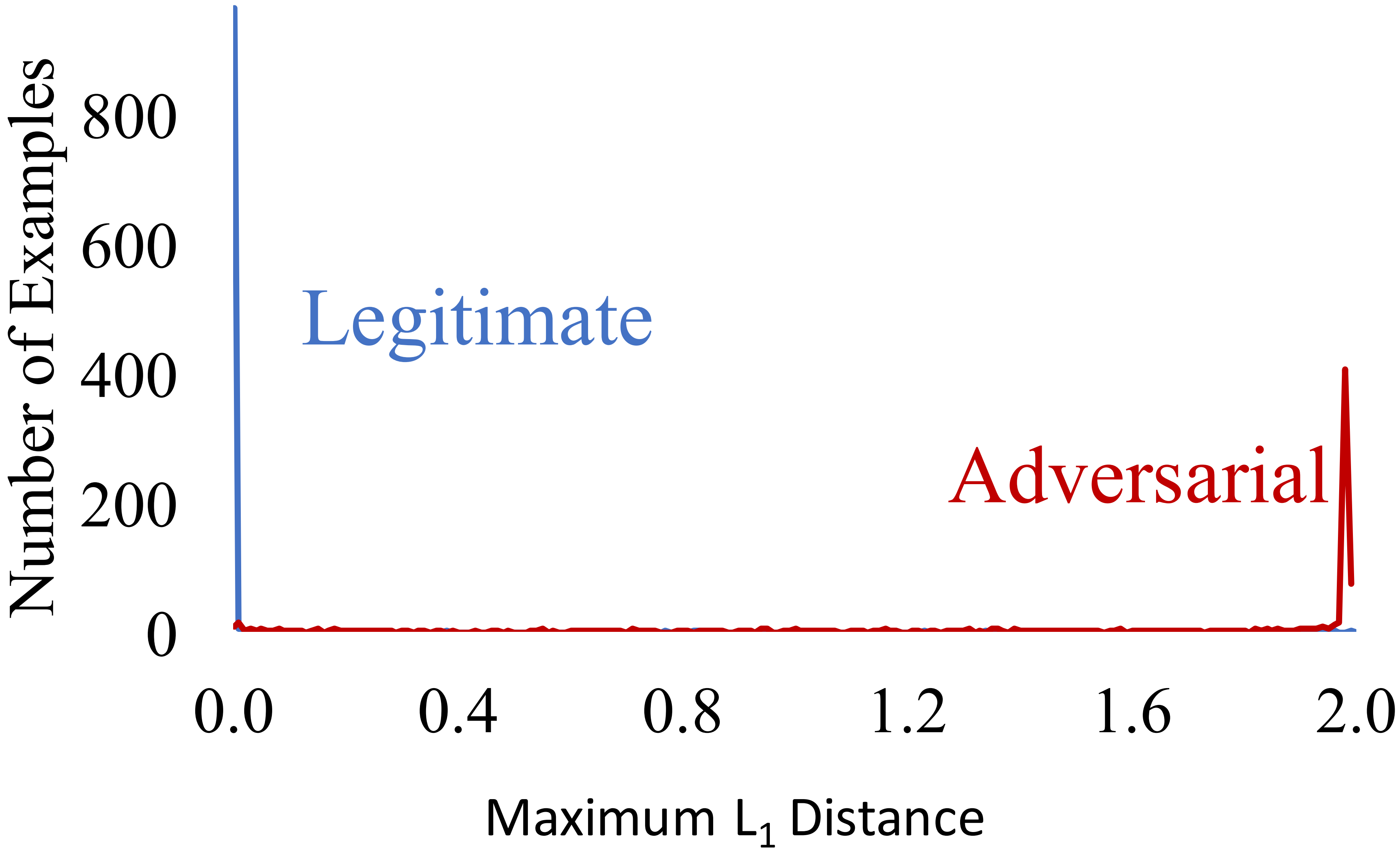
	Legitimate	FGSM	BIM	CW_∞	CW_2
	1	1	4	2	2
Binary Filter	1	1	1	1	1

Accuracy with Bit Depth Reduction

Dataset	Squeezer	Adversarial Examples (FGSM, BIM, CW_∞, Deep Fool, CW_2, CW_0, JSMA)	Legitimate Images
MNIST	None	13.0%	99.43%
	1-bit Depth	62.7%	99.33%
ImageNet	None	2.78%	69.70%
	4-bit Depth	52.11%	68.00%

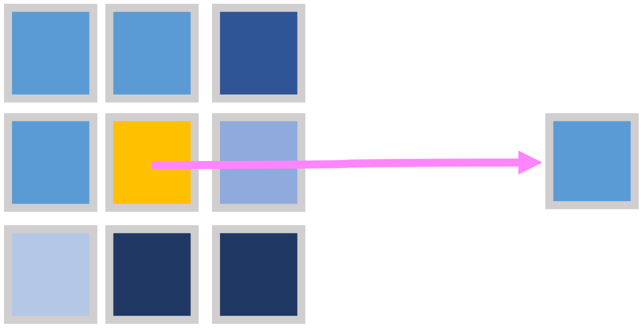
Baseline

Distribution of Distance (Prediction, Squeezed Prediction) (MNIST)

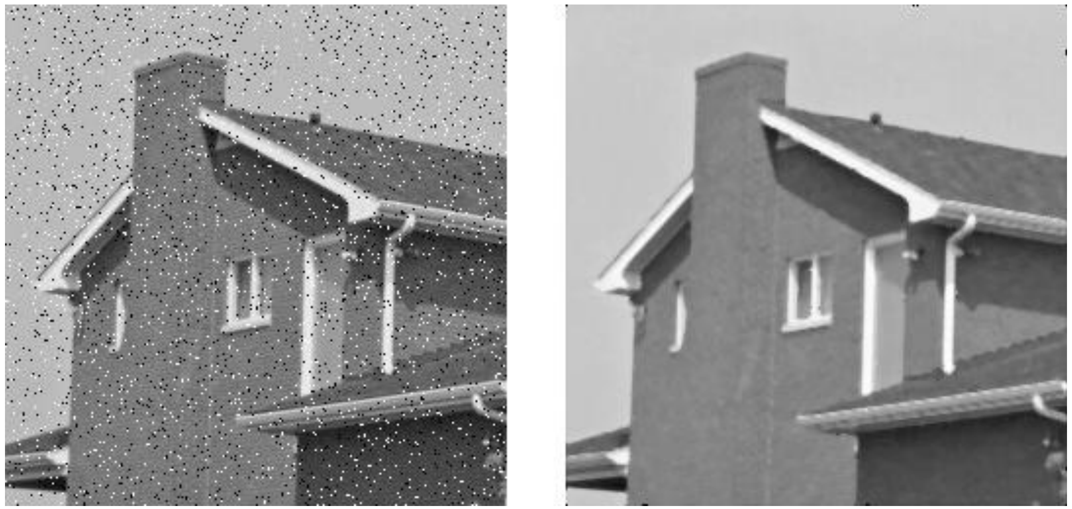


Spatial Smoothing: Median Filter

- Replace a pixel with median of its neighbors.
- Effective in eliminating ”salt-and-pepper” noise.



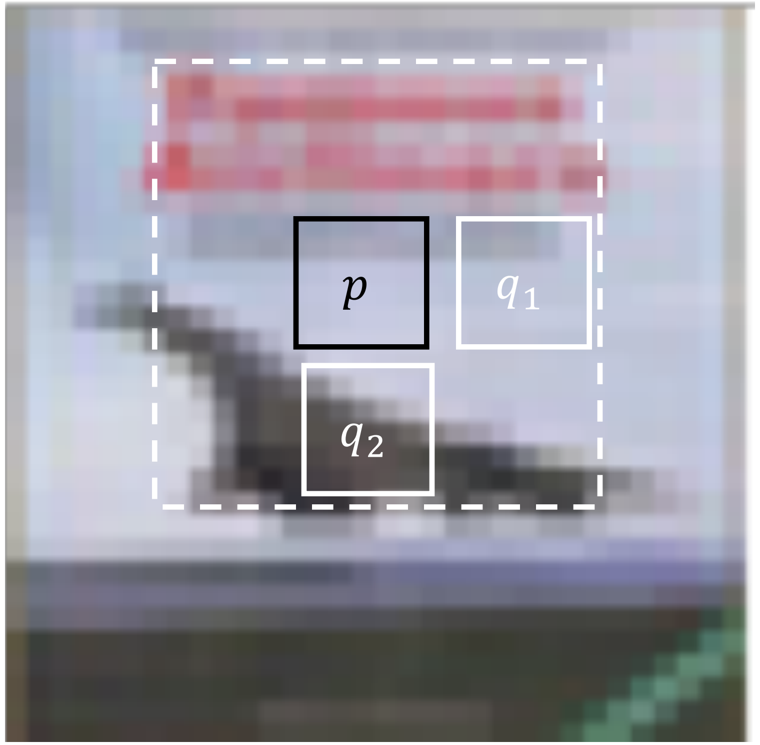
3x3 Median Filter



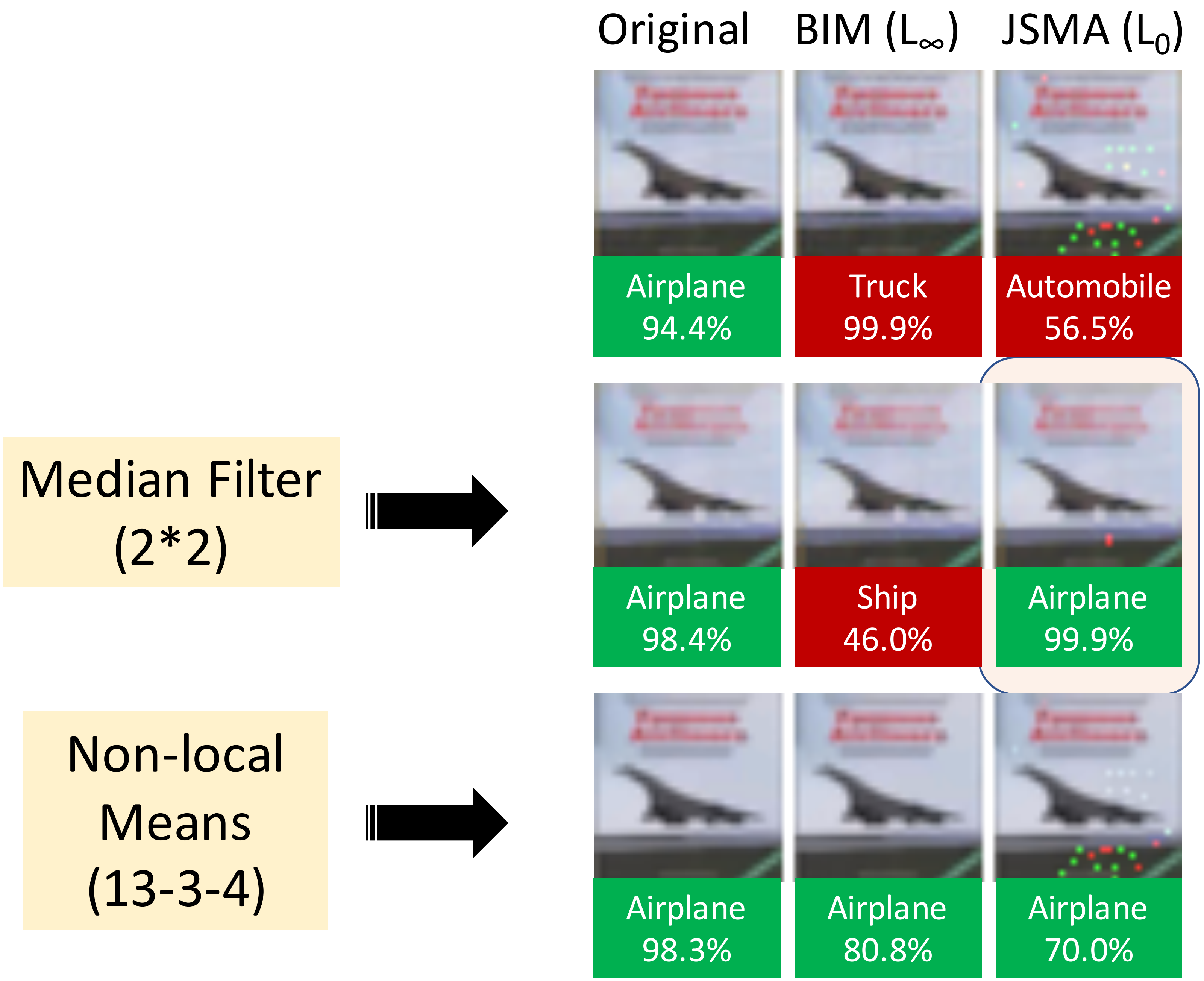
* Image from https://sultanofswing90.wordpress.com/tag/image-processing/

Spatial Smoothing: Non-local Means

- Replace a patch with weighted mean of similar patches.
- Preserve more edges.



$$p' = \sum w(p, q_i) \times q_i$$



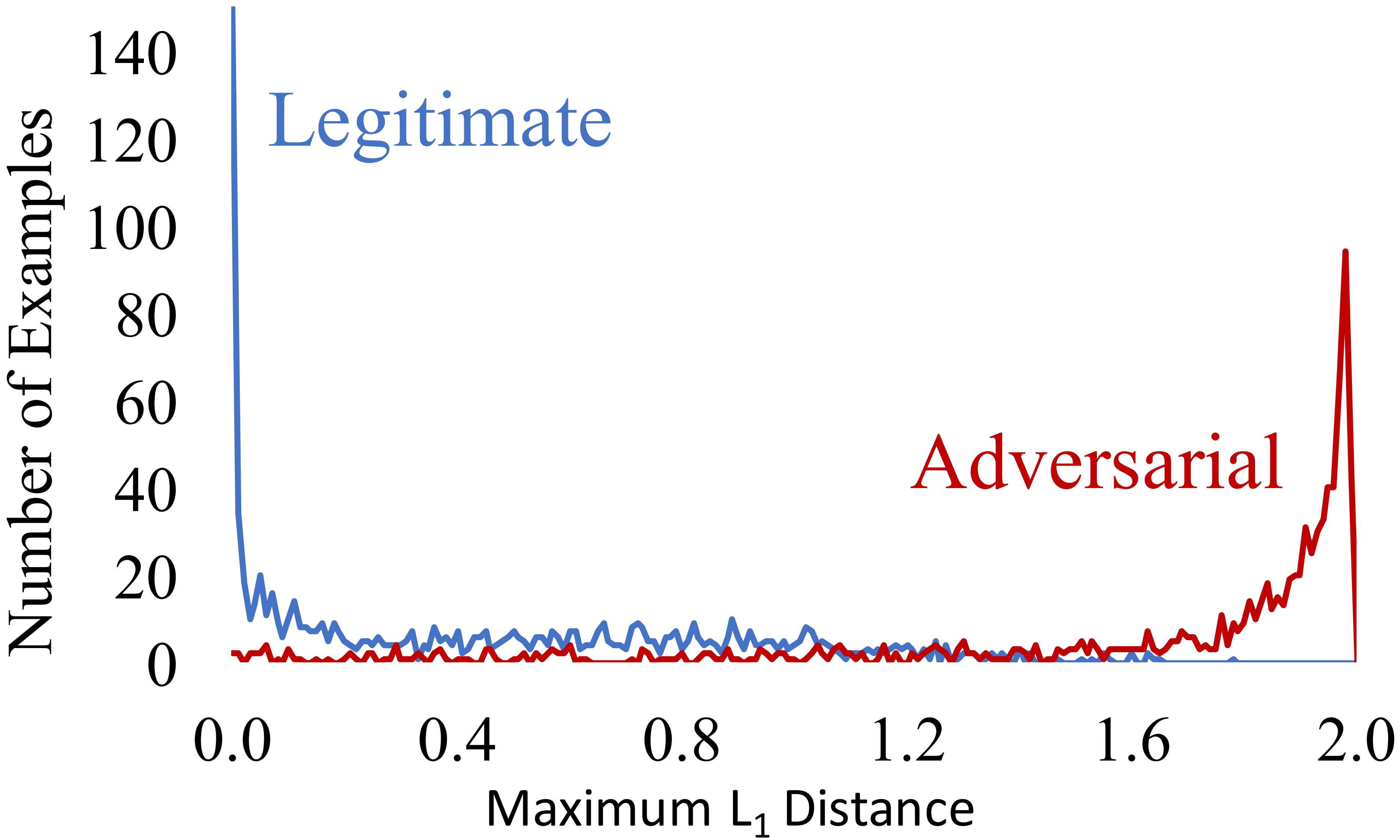
	Original	BIM (L_∞)	JSMA (L_0)
	Airplane 94.4%	Truck 99.9%	Automobile 56.5%
Median Filter (2*2)	Airplane 98.4%	Ship 46.0%	Airplane 99.9%
Non-local Means (13-3-4)	Airplane 98.3%	Airplane 80.8%	Airplane 70.0%

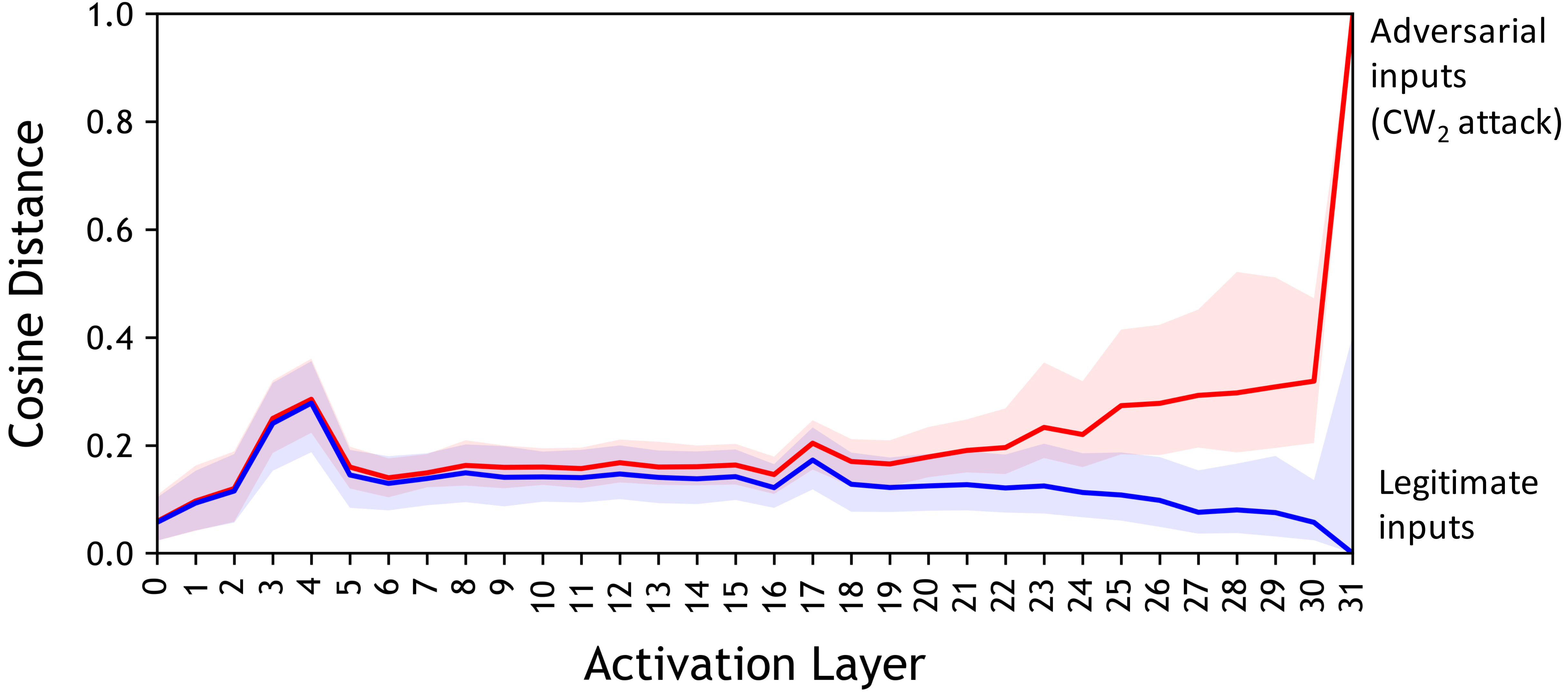
Accuracy with Spatial Smoothing

Dataset	Squeezer	Adversarial Examples (FGSM, BIM, CW$_\infty$, Deep Fool, CW$_2$, CW$_0$)	Legitimate Images
ImageNet	None	2.78%	69.70%
	Median Filter 2*2	68.11%	65.40%
	Non-local Means 11-3-4	57.11%	65.40%

Baseline

Distribution of Distance (Prediction, Squeezed Prediction) (ImageNet)




1.0
0.8
0.6
0.4
0.2
0.0
Cosine Distance
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
Activation Layer
Adversarial inputs (CW_2 attack)
Legitimate inputs

Other Potential Squeezers

- Thermometer Encoding (learnable bit depth reduction)

J Buckman, et al. *Thermometer Encoding: One Hot Way To Resist Adversarial Examples* , ICLR 2018.

- Image denoising using bilateral filter, autoencoder, wavelet, etc.

D Meng and H Chen, *MagNet: a Two-Pronged Defense against Adversarial Examples*, in CCS 2017.

F Liao, et al. *Defense against Adversarial Attacks Using High-Level Representation Guided Denoiser*, arXiv 1712.02976.

A Prakash, et al. *Deflecting Adversarial Attacks with Pixel Deflection*, arXiv 1801.08926.

- Image resizing

C Xie, et al. *Mitigating Adversarial Effects Through Randomization*, ICLR 2018.

Experimental Setup

- Datasets and Models

MNIST,	7-layer-CNN
CIFAR-10,	DenseNet
ImageNet,	MobileNet

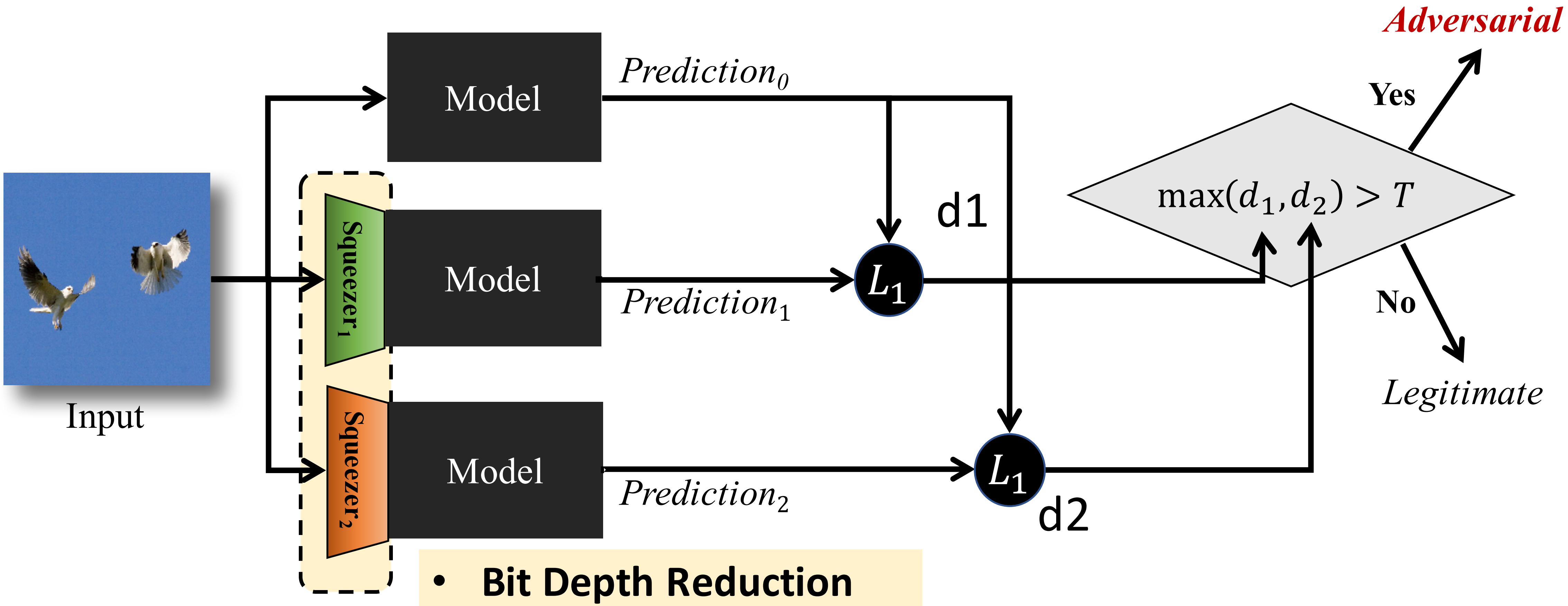
- Attacks (100 examples for each attack)
  - Untargeted: FGSM, BIM, DeepFool
  - Targeted (Next/Least-Likely): JSMA, Carlini-Wagner L_2/L_∞/L_0
- Detection Datasets
  - A balanced dataset with legitimate examples.
  - 50% for training the detector, the remaining for validation.

Threat Models

- **Oblivious adversary**: The adversary has full knowledge of the target model, but is not aware of the detector.

- **Adaptive adversary**: The adversary has full knowledge of the target model and the detector.

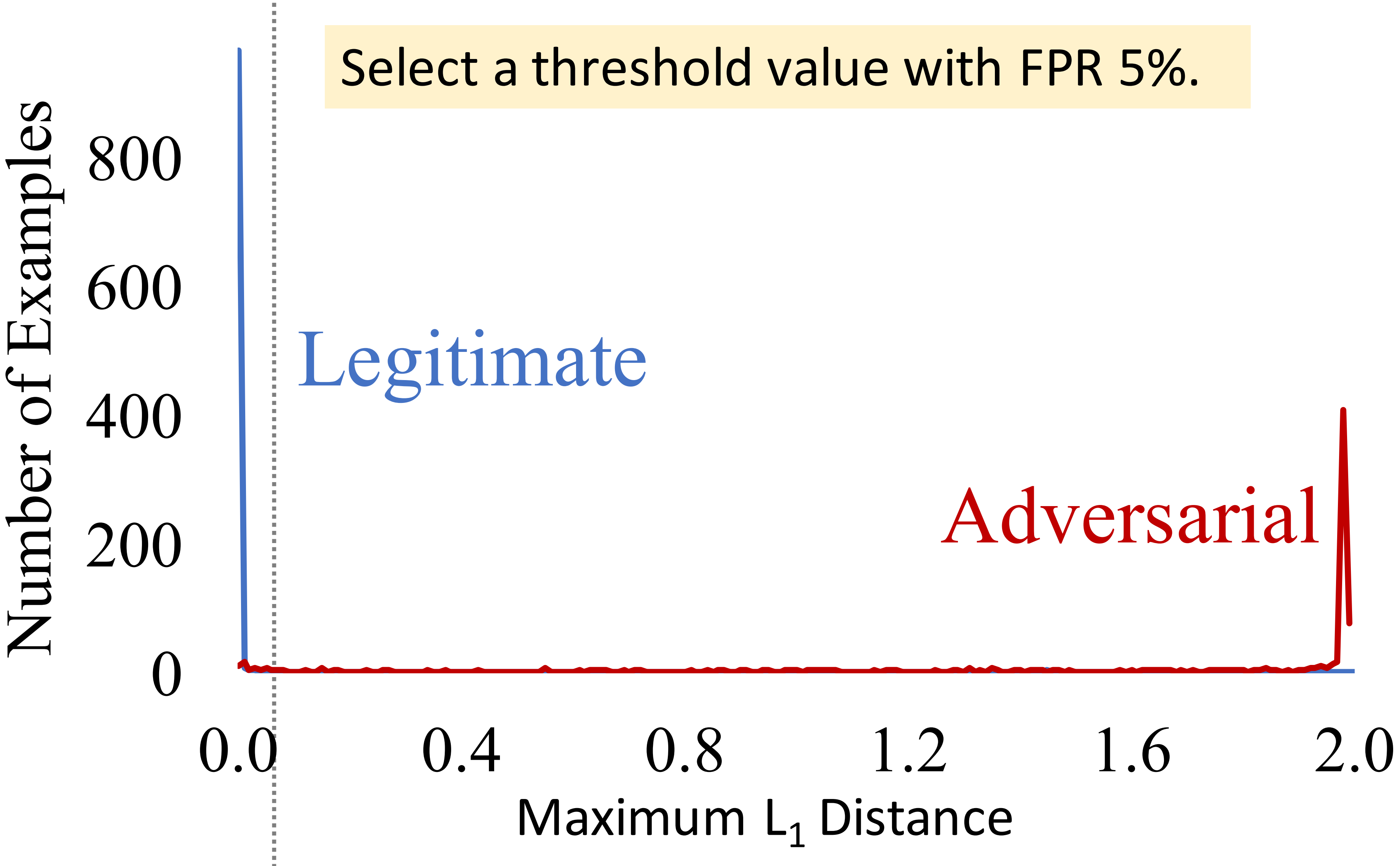
Detection Framework: Multiple Squeezers



- **Bit Depth Reduction**
- **Spatial Smoothing**

How to find T for detector (MNIST)

Select a threshold value with FPR 5%.



Detect Successful Adv. Examples (MNIST)

Bit Depth Reduction is more effective on L_∞ and L_2 attacks.

Median Smoothing is more effective on L_0 attacks.

Squeezer	L_∞ Attacks			L_2 Attacks	L_0 Attacks	
	FGSM	BIM	CW_∞	CW_2	CW_0	JSMA
1-bit Depth	**100%**	**97.9%**	**100%**	**100%**	55.6%	**100%**
Median 2*2	73.1%	27.7%	**100%**	94.4%	**82.2%**	**100%**
[Best Single]	100%	97.9%	100%	100%	82.2%	100%
Joint	100%	97.9%	100%	100%	**91.1%**	100%

Joint detection improves performance.

Aggregated Detection Results

Dataset	Squeezers	Threshold	False Positive Rate	Detection Rate (SAEs)	ROC-AUC Exclude FAEs
MNIST	Bit Depth (1-bit), Median (2x2)	0.0029	3.98%	98.2%	99.44%
CIFAR-10	Bit Depth (5-bit), Median (2x2), Non-local Mean (13-3-2)	1.1402	4.93%	84.5%	95.74%
ImageNet	Bit Depth (5-bit), Median (2x2), Non-local Mean (11-3-4)	1.2128	8.33%	85.9%	94.24%

Threat Models

- **Oblivious attack**: The adversary has full knowledge of the target model, but is not aware of the detector.

- **Adaptive attack**: The adversary has full knowledge of the target model and the detector.

Adaptive Adversary

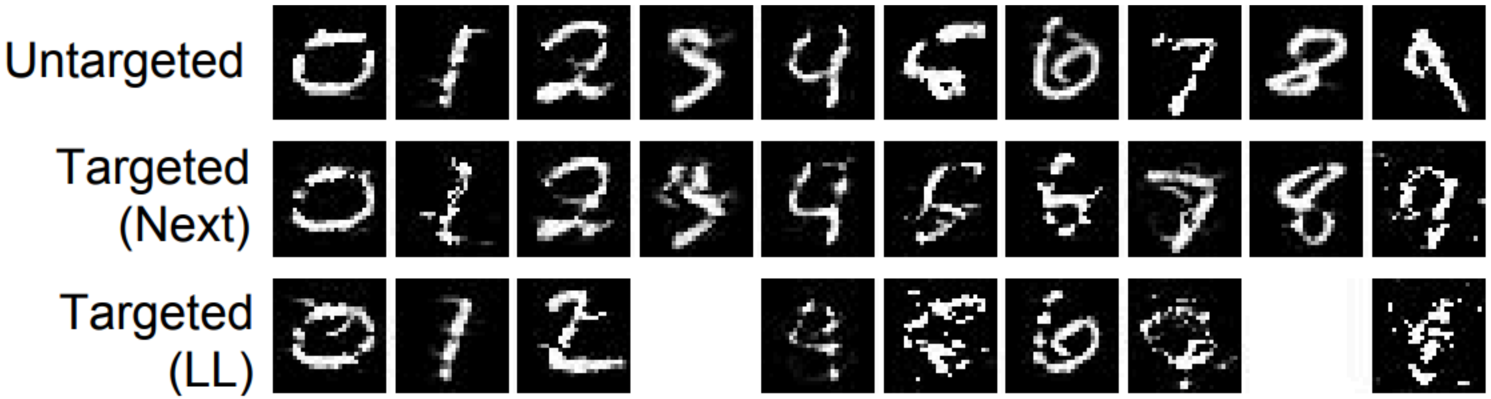
Adaptive CW$_2$ attack, unbounded adversary.

$$minimize\ ||f(x') - t|| + \lambda * \Delta(x, x') \ + k * detectScore(x')$$

Misclassification term   Distance term   Detection term

Warren He, James Wei, Xinyun Chen, Nicholas Carlini, Dawn Song,
Adversarial Example Defense: Ensembles of Weak Defenses are not Strong, USENIX WOOT'17.

Adaptive Adversarial Examples



Mean L_2

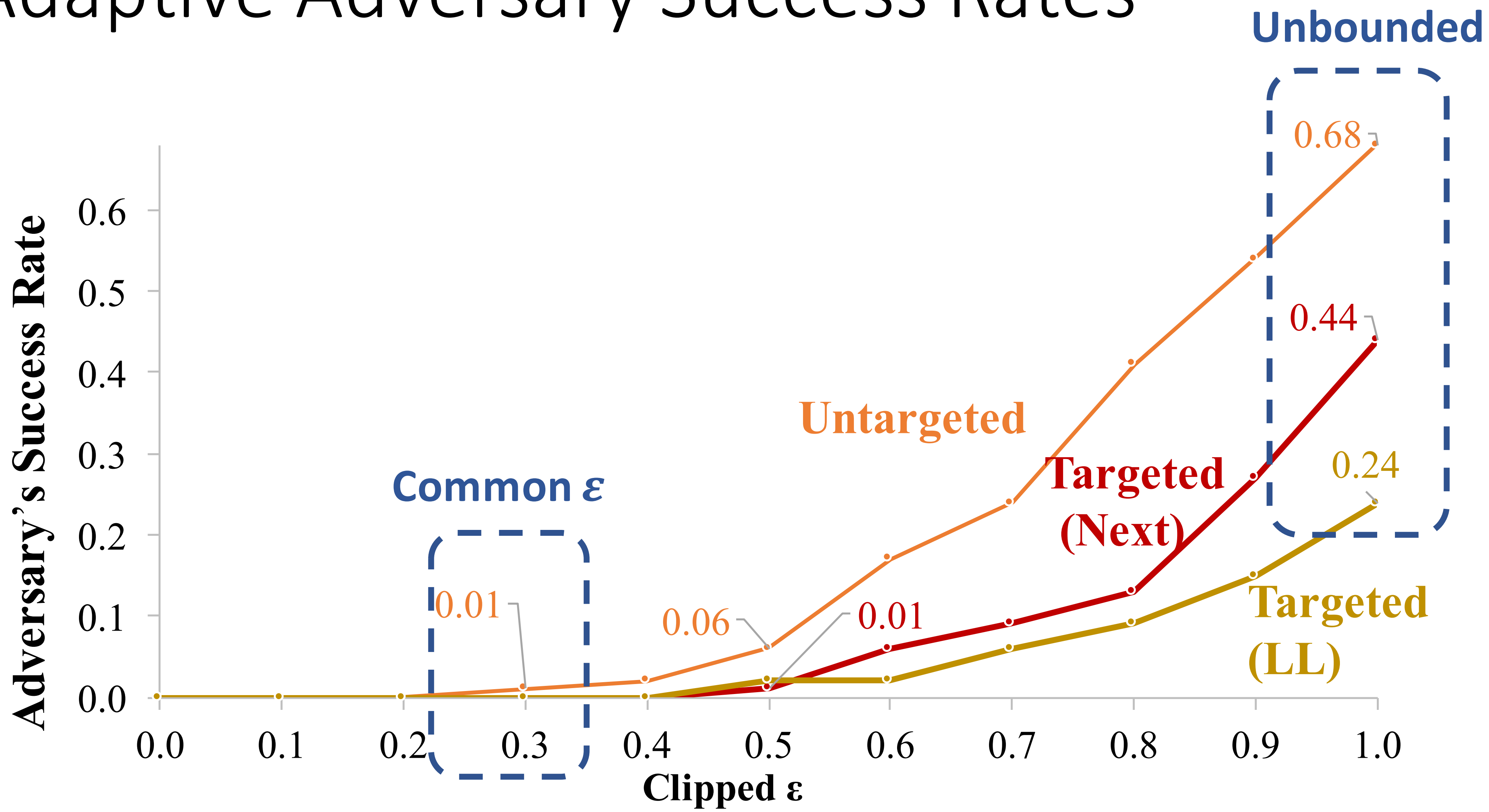
← 2.80

← 4.14

← 4.67

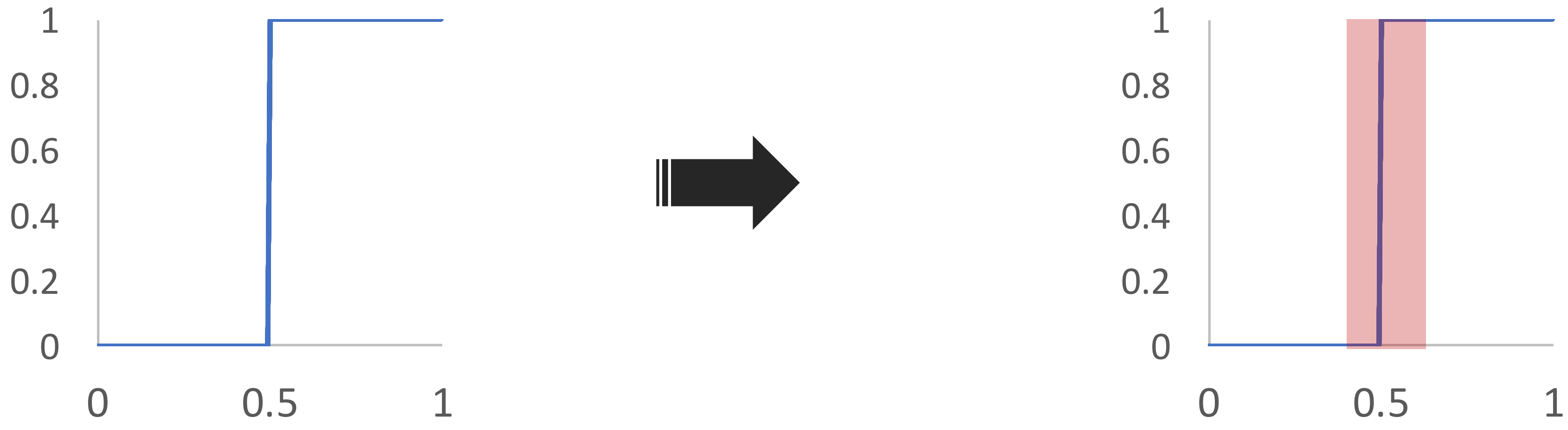
No successful adversarial examples were found for images originally labeled as 3 or 8.

Adaptive Adversary Success Rates



Counter Measure: Randomization

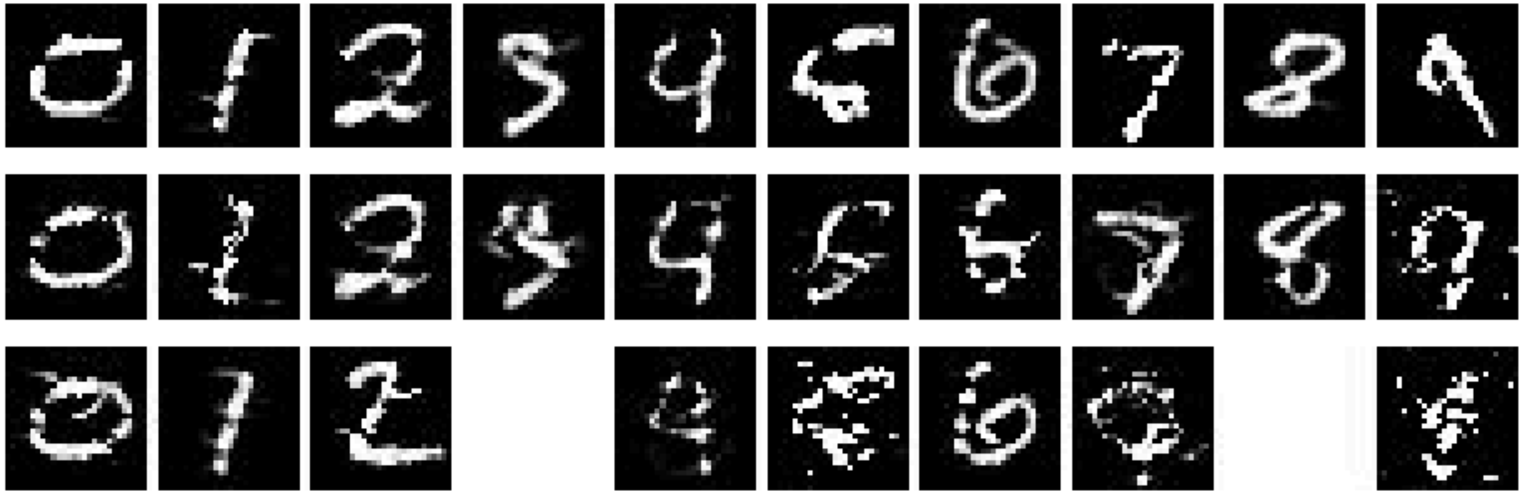
- Binary filter threshold := 0.5 threshold := $\mathcal{N}(0.5, 0.0625)$



- Strengthen the adaptive adversary
  Attack an ensemble of 3 detectors with thresholds := [0.4, 0.5, 0.6]

Attack Deterministic Detector

Mean L_2

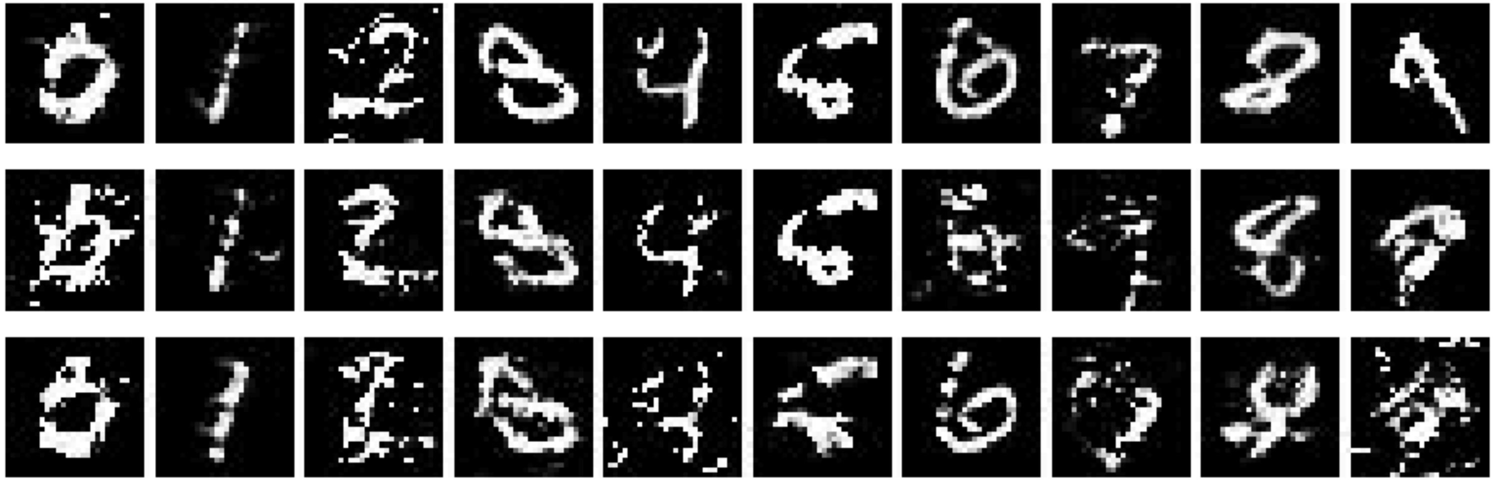


2.80, Untargeted

4.14, Targeted-Next

4.67, Targeted-LL

Attack Randomized Detector



3.63, Untargeted

5.48, Targeted-Next

5.76, Targeted-LL

Conclusion

- Feature Squeezing hardens deep learning models.
- Feature Squeezing gives advantages to the defense side in the arms race with adaptive adversary.

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Thank you!

Reproduce our results using EvadeML-Zoo: https://evadeML.org/zoo