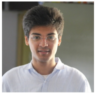
# Efficient Defenses Against Adversarial Examples for Deep Neural Networks



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**GreHack #5**

November 17, 2017

So far...

- Machine learning for security
  - Intrusion detection[1]
  - Malware analysis[2]

This talk is about

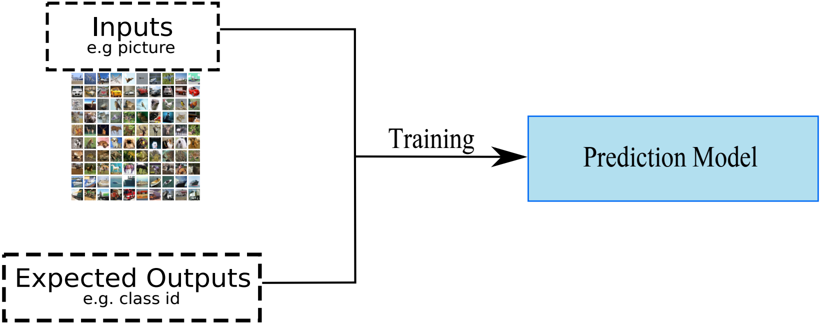
- **Security for machine learning**

[1] Buczak & Guven, *A Survey of Data Mining and Machine Learning Methods for Cyber Security Intrusion Detection*. IEEE Comunications Surveys & Tutorials, 2015.

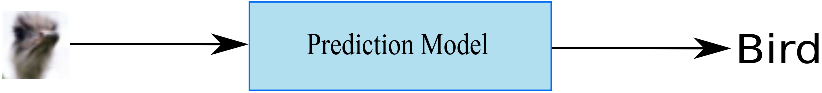
[2] Gandotra et al., *Malware Analysis and Classification: A Survey*, Journal of Information Security, 5, 56–64, 2014.

# Machine Learning and Adversarial Examples

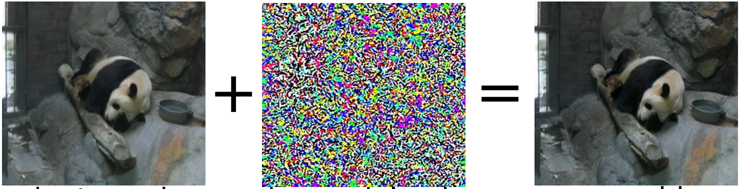
## Training




## Prediction



# Adversarial Examples



giant panda
84% confidence

adversarial noise

capuchin
67% confidence

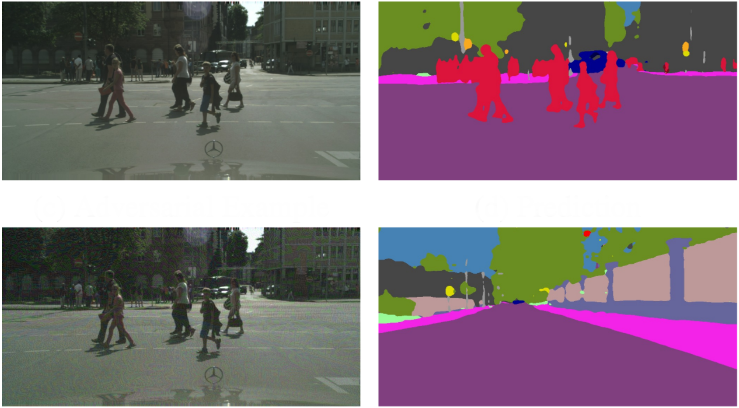
- Perturb model inputs with crafted noise
- Model fails to recognize input correctly
- Attack undetectable by humans
- Random noise does not work.

# Practical Examples of Attacks

# Self-Driving Cars

## Image segmentation[3]

Attack noise hides pedestrians from the detection system.



[3] Metzen et al., *Universal Adversarial Perturbations Against Semantic Image Segmentation*. https://arxiv.org/abs/1704.05712.

# Self-Driving Cars

## Road signs[4]

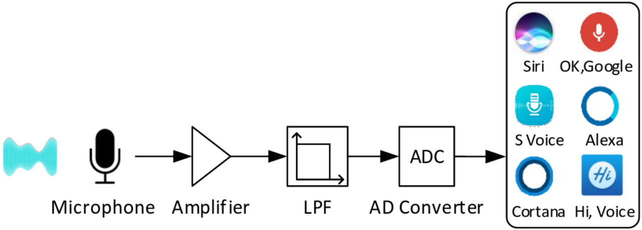
Car ends up ignoring the stop sign.


True image


Adversarial image

[4] McDaniel et al., *Machine Learning in Adversarial Settings*. IEEE Security and Privacy, vol. 14, pp. 68-72, 2016.

# Executing Voice Commands

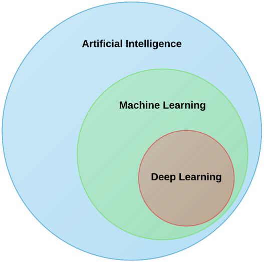



*Okay Google, text John!*[5]

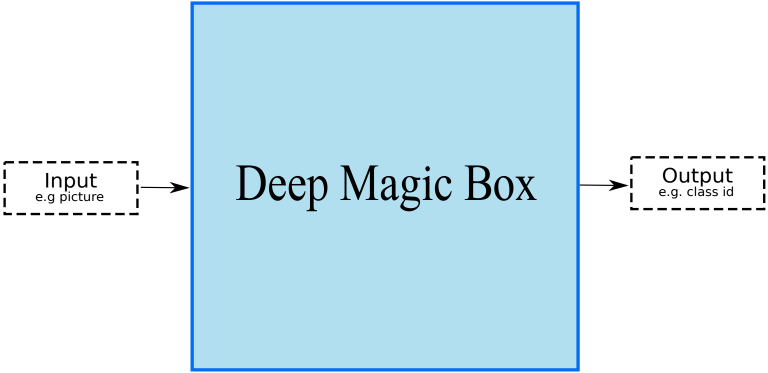
- Stealthy voice commands recognized by devices
- Humans cannot detect it.

[5] Zhang et al., *DolphinAttack: Inaudible Voice Commands*, ACM CCS 2017.

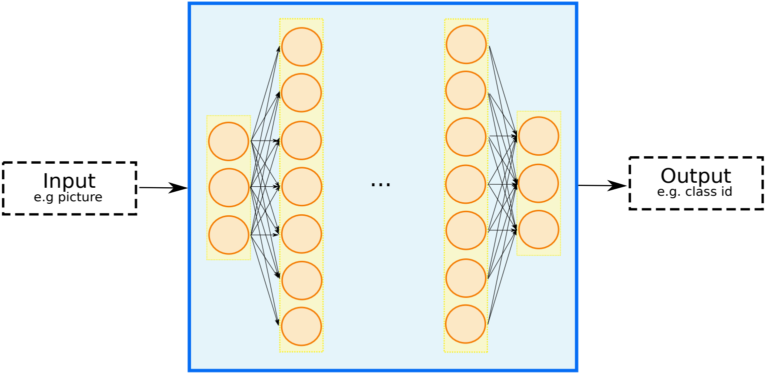
# Deep Learning and Adversarial Samples



# Deep Neural Networks

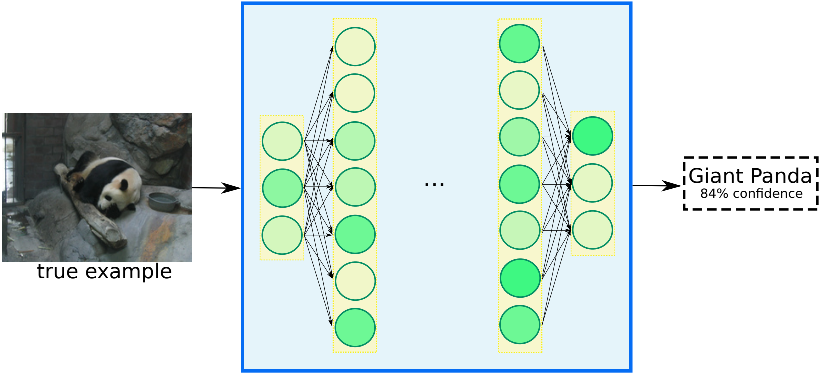


# Deep Neural Networks



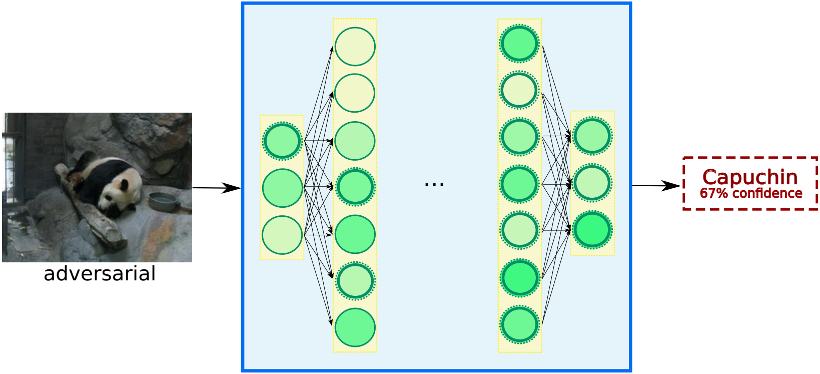

- Interconnected layers propagate the information forward.
- Model learns weights for each neuron.

# Deep Neural Networks




- Specific neurons light-up depending on the input.
- Cumulative effect of activation moves forward in the layers.

# Deep Neural Networks

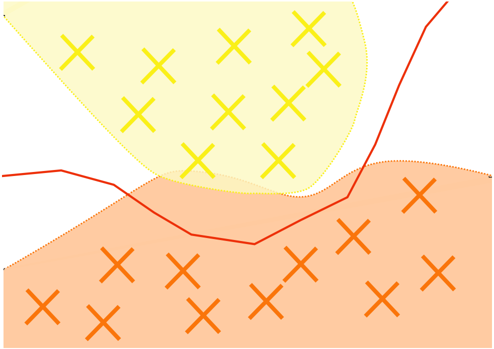



Small variations in the input → important changes in the output.

+ Enhanced discriminative capacities

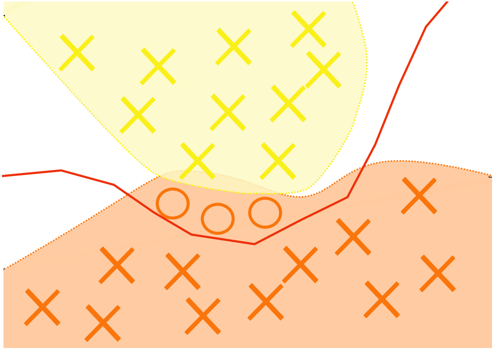
– Opens the door to adversarial examples

# Decision Boundary of the Model



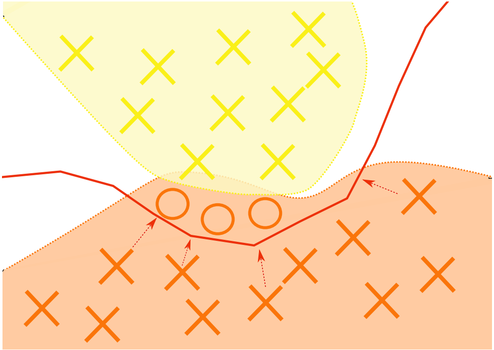
The **learned model** slightly differs from the **true** data distribution...

# The Space of Adversarial Examples



... which makes room for **adversarial examples**.

# Attack: Use the Adversarial Directions



- Most attacks try to move inputs across the boundary.
- Attacking with a random distortion doesn't work well in practice.

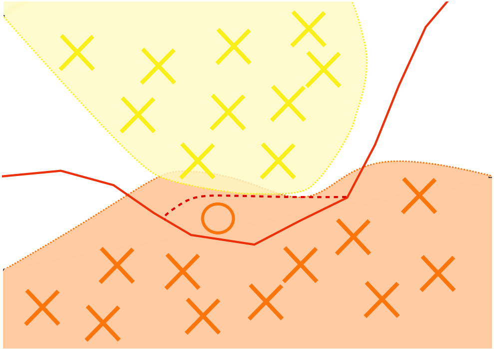
# Finding Adversarial Examples

Given $x$, find $x'$ where

- $x$ and $x'$ are close
- $\text{output}(x) \neq \text{output}(x')$

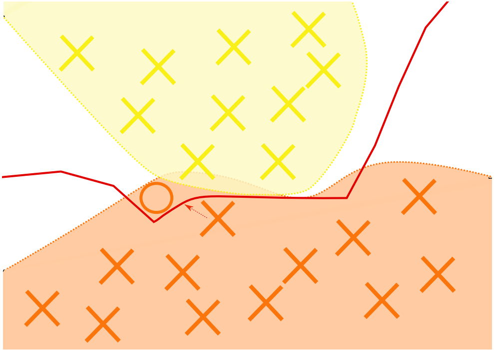
| Approximations of the original problem | |
|---|---|
| FGSM [1] | quick, rough, fixed budget |
| Random + FGSM [2] | random step, then FGSM |
| DeepFool [3] | find minimal perturbations |
| JSMA [4] | modify most salient pixels |
| C&W [5] | strongest to date |

# Defense: Adversarial Training



- Adapt the classifier to attack directions by including adversarial data at training.

# Defense: Adversarial Training



- Adapt the classifier to attack directions by including adversarial data at training.
- But there are always new adversarial samples to be crafted.

# Defenses

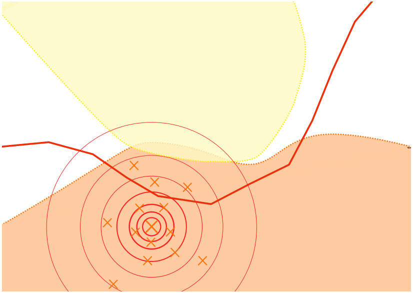
| | Type | Description |
|---|---|---|
| AT | data augmentation | train also with adv. examples |
| VAT | data augmentation | train also with virtual adv. examples |
| FS | preprocessing | squeeze input domain |
| LS | preprocessing | smooth target outputs |

- Adversarial Training (AT) [1]
- Virtual Adversarial Training (VAT) [6]
- Feature Squeezing (FS) [7]
- Label Smoothing (LS) [8]

# Contribution: Effective Defenses Against Adversarial Samples

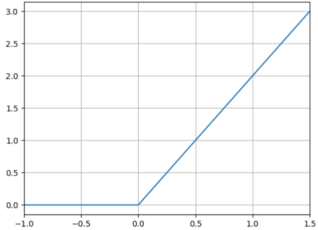
# Gaussian Data Augmentation (GDA)

Gaussian noise does not work for attacks, but does it work as a defense?



- Reinforce neighborhoods around points using random noise.
- For each input image, generate $N$ versions by adding Gaussian noise to the pixels.
- Train the model on the original data and the noisy inputs.

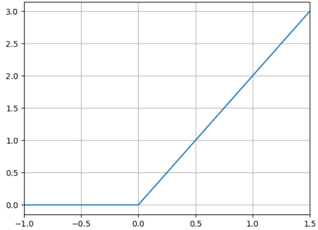
**Objective** Limit the cumulative effect of errors in the layers.




RELU

$$f(x) = \begin{cases} 0, & x < 0 \\ x, & x \geq 0. \end{cases}$$

**Objective** Limit the cumulative effect of errors in the layers.




RELU

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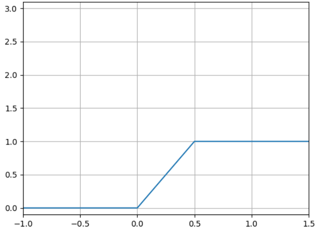



Bounded RELU

$$f_t(x) = \begin{cases} 0, & x < 0 \\ x, & 0 \leq x < t \\ t, & x \geq t. \end{cases}$$

# Comparison with Other Defenses

| Defense | Training | Prediction |
| --- | --- | --- |
| Feature Squeezing | preproc. input | preproc. input, perf. loss |
| Label Smoothing | preproc. output | - |
| Adversarial Training | train + attack + retrain | - |
| GDA + BRELU | add noise | - |

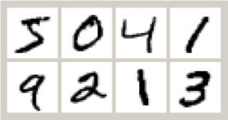
**Advantages of GDA + BRELU**

- Defense agnostic to attack strategy
- Model performance for original inputs is conserved
- Performs better than other defenses on adversarial samples
- Almost no overhead for training and prediction.

# Experiments

# Setup

- MNIST dataset of handwritten digits
  - 60,000 training + 10,000 test images
- CIFAR-10 dataset of $32 \times 32$ RGB images
  - 50,000 training + 10,000 test images
  - 10 categories
- Convolutional neural net (CNN) architecture



## Setup

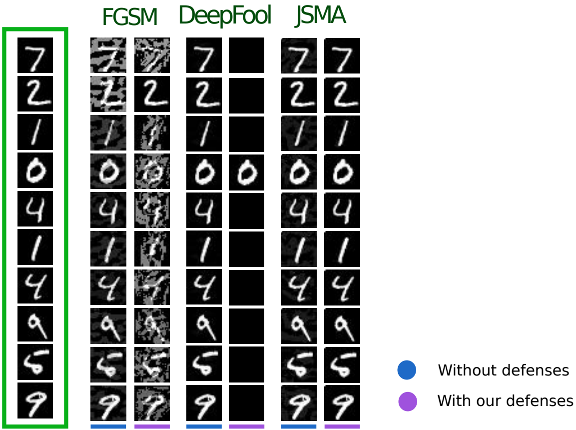
**Threat model**

- **Black-box**: attacker has access to inputs and outputs
- **White-box**: attacker also has access to model parameters

**Steps**

- Train model with different defenses
- Generate attack images
- Compute defense performance on attack images

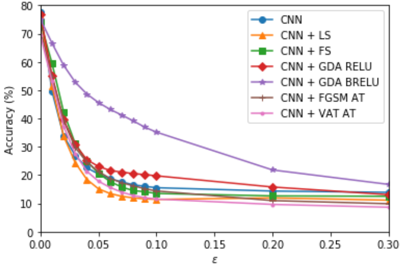
**Amount of perturbation necessary to fool the model**



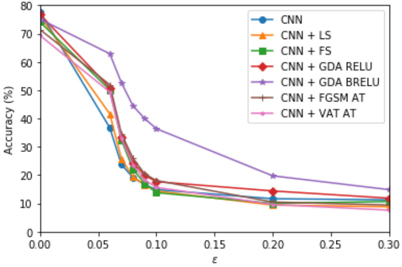

With GDA + BRELU, the perturbation necessary for an attack becomes **visually detectable**.

# White-Box Attacks

## Comparison of different defenses against white-box attacks




(a) FGSM attack




(b) Random + FGSM attack

CIFAR-10

Accuracy = % of correct predictions = TP + TN

# Black-Box Attacks

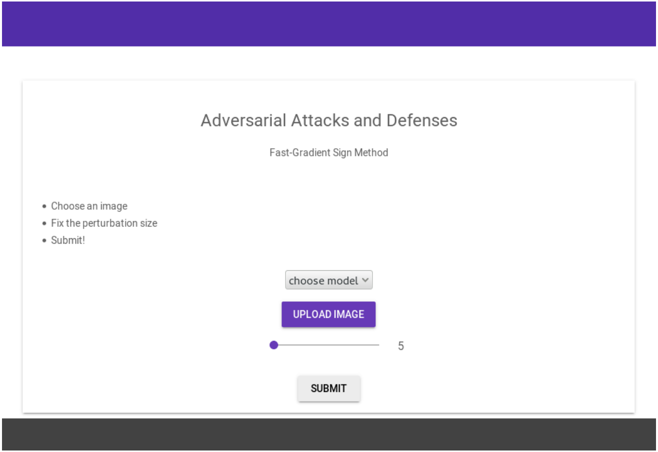
## Comparison of different defenses against black-box attacks

| Defense \ Attack | FGSM | Rand+FGSM | DeepFool | JSMA | C&W |
|---|---|---|---|---|---|
| CNN | 94.46 | 40.70 | 92.95 | 97.95 | 93.10 |
| Feature squeezing | 96.31 | **91.09** | 96.68 | 97.48 | 96.75 |
| Label smoothing | 86.79 | 20.28 | 84.58 | 95.86 | 84.81 |
| FGSM adv. training | 91.86 | 49.77 | 85.91 | 98.62 | 97.71 |
| VAT | 97.53 | 74.35 | 96.03 | 98.26 | 96.11 |
| GDA + RELU | **98.47** | **80.25** | **97.84** | **98.96** | **97.87** |
| GDA + BRELU | **98.08** | 75.50 | **98.00** | **98.88** | **98.03** |

Attacks transferred from ResNet to CNN on MNIST

Accuracy = % of correct predictions = TP + TN

# Demo


Adversarial Attacks and Defenses
Fast-Gradient Sign Method
Choose an image
Fix the perturbation size
Submit!
choose model
UPLOAD IMAGE
5
SUBMIT

# Conclusion

# Conclusion

**Our contribution**

- Improved defense against multiple types of attacks
- Model performance for clean inputs is preserved
- No retraining, no overhead for prediction
- Easy to integrate into models.

Takeaway

- The problem of adversarial examples needs to be solved before applying machine learning.

`nemesis`

- Our library of attacks and defenses
- Soon to be open source.

Full paper at `https://arxiv.org/pdf/1707.06728.pdf`

[1] Ian J. Goodfellow, Jonathon Shlens, and Christian Szegedy. Explaining and harnessing adversarial examples. *CoRR*, abs/1412.6572, 2014. URL `http://arxiv.org/abs/1412.6572`.

[2] Florian Tramèr, Alexey Kurakin, Nicolas Papernot, Dan Boneh, and Patrick McDaniel. Ensemble adversarial training: Attacks and defenses. *arXiv preprint arXiv:1705.07204*, 2017.

[3] Seyed-Mohsen Moosavi-Dezfooli, Alhussein Fawzi, and Pascal Frossard. Deepfool: a simple and accurate method to fool deep neural networks. *CoRR*, abs/1511.04599, 2015. URL `http://arxiv.org/abs/1511.04599`.

[4] Nicolas Papernot, Patrick D. McDaniel, Somesh Jha, Matt Fredrikson, Z. Berkay Celik, and Ananthram Swami. The limitations of deep learning in adversarial settings. *CoRR*, abs/1511.07528, 2015. URL `http://arxiv.org/abs/1511.07528`.

[5] Nicholas Carlini and David Wagner. Towards evaluating the robustness of neural networks. In *IEEE Symposium on Security and Privacy*, 2017. URL `https://arxiv.org/abs/1608.04644`.

[6] Takeru Miyato, Shin-ichi Maeda, Masanori Koyama, and Shin Ishii. Virtual adversarial training: a regularization method for supervised and semi-supervised learning. *arXiv preprint arXiv:1704.03976*, 2017.

[7] Weilin Xu, David Evans, and Yanjun Qi. Feature squeezing: Detecting adversarial examples in deep neural networks. *CoRR*, abs/1704.01155, 2017. URL `http://arxiv.org/abs/1704.01155`.

[8] David Warde-Farley and Ian Goodfellow. Adversarial perturbations of deep neural networks. In Tamir Hazan, George Papandreou, and Daniel Tarlow, editors, *Perturbation, Optimization, and Statistics*. 2016.