Evaluating the Robustness of Neural Networks Defenses

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Background: Notation

- We have a classification neural network F(x)
- Given an input X classified as label L
- $F(X)_L$ is the probability of label L
- $F(X) = softmax(F_Z(X))$ [the logits]
- $C(X) = arg max_j F(X)_j$

Background: Adversarial Examples

- For a classification neural network F(x)
- Given an input X classified as label L ...
- ... it is easy to find an X' close to X
- ... so that F(X') != L





Classified as a 1

Classified as a 0



 $+.007 \times$



 $\mathrm{sign}(\nabla_{\boldsymbol{x}}J(\boldsymbol{\theta},\boldsymbol{x},y))$

"nematode" 8.2% confidence

 $m{x} + \epsilon \operatorname{sign}(
abla_{m{x}} J(m{ heta}, m{x}, y))$ "gibbon" 99.3 % confidence

"panda" 57.7% confidence

 \boldsymbol{x}

Why should we care about adversarial examples?

Make ML robust Make ML better





Finding Adversarial Examples

- Formulation: given input x, find x' where minimize d(x,x') such that F(x') = T x' is "valid"
- Gradient Descent to the rescue?
- Non-linear constraints are hard

Reformulation

- Formulation:
 minimize d(x,x') + g(x')
 such that x' is "valid"
- Where g(x') is some kind of loss function on how close F(x') is to target T
 - g(x') is small if F(x') = T
 - g(x') is large if F(x') != T

Reformulation

- For example
 - $g(x') = (1-F(x')_T)$
- If F(x') says the probability of T is 1:
 - $g(x') = (1-F(x')_T) = (1-1) = 0$
- F(x') says the probability of T is 0:
 - $g(x') = (1-F(x')_T) = (1-0) = 1$

Does this work? Problem 1: Global minimum is not an adversarial example

FC

m

SU



Does this work?

Formulation:
 minimize d(x,x')/5 + g(x')
 such that x' is "valid"



Does this work? Problem 2: Gradient direction does not point toward the global minimum





Does this work? Problem 3: Global minimum is not the minimally perturbed adversarial example





This is very hard.

Let's do something simpler.

Fast Gradient Sign

- Unroll the gradient descent step by one
- $X' = X + \varepsilon \operatorname{sign}(\nabla_X F(X)_{L})$



How can we stop adversarial examples?

Distillation as a Defense

- 1. Train a model F() on the training data X,Y
- 2. Generate new training labels Y' by setting Y' = $\{100^*F(x) : x \text{ in } X\}$
- 3. Train a new classifier G() on X,Y'

Does it work?

Unfortunately, no.



Constructing a better loss function

- 1. Global minimum at the decision boundary
- 2. Gradient points towards the global minimum

$$\max\left(\max_{\substack{t'\neq t}}\left\{\log(F(x)_t')\right\} - \log(F(x)_t), 0\right)$$

Improved Formulation

Formulation:
 minimize d(x,x') + g(x')
 such that x' is "valid"





Visualizations

Random	Direction		
		Random	
		Direction	



Random Direction

Random Direction










Case studies on evaluating defenses to adversarial examples

Defense Idea #1:

Additional Neural Network Detection

Jan Hendrik Metzen, Tim Genewein, Volker Fischer, and Bastian Bischo. On Detecting Adversarial Perturbations. ICLR 2017.

Normal Classifier





Normal Classifier





Detector & Classifier





Detector & Classifier



Classifier



Training an adversarial example detector

Normal Training





Detection Training (1)









Detection Training (2)







Training

Sounds great.

Sounds great.

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

... so just construct adversarial examples to

be misclassified
 not be detected

Breaking Detection Adversarial Training

- minimize d(x,x') + g(x')
 such that x' is "valid"
- Old: g(x') measures loss of **classifier** on x'

Breaking Detection Adversarial Training

- minimize d(x,x') + g(x') + h(x')
 such that x' is "valid"
- Old: g(x') measures loss of classifier on x'
- New: h(x') measures loss of detector on x'

Original

Adversarial (unsecured)

Adversarial (with detector)









Defense Idea #2:

Thermometer Encoding

Jacob Buckman, Aurko Roy, Colin Raffel, and Ian Goodfellow. Thermometer encoding: One hot way to resist adversarial examples. ICLR 2018. Problem: Neural Networks are "overly linear"

Thermometer Encoding

- Break linearity by changing input representation
- T(0.13) = 1 1 0 0 0 0 0 0 0 0
- T(0.66) = 1 1 1 1 1 1 0 0 0 0
- $T(0.97) = 1 \ 1 \ 1 \ 1 \ 1 \ 1 \ 1 \ 1 \ 1$

Standard Neural Network





With Thermometer Encoding





Claims:

On CIFAR, with distortion 8/255, accuracy of 50%

(compared to 0%)

Unfortunately, thermometer encoding only causes gradient descent to fail







"Fixing" Gradient Descent







Defense Idea #3:

Adversarial Retraining

A Madry, A Makelov, L Schmidt, D Tsipras, and A Vladu. Towards deep learning models resistant to adversarial attacks. 2018. International Conference on Learning Representations.
Adversarial Training

- Given training data (X,Y)
- Sample a minibatch (x,y)
- Generate the adversarial minibatch (x',y)
- Train on (x',y)
- Repeat until convergence





Audio has these same issues, too

N Carlini and D Wagner. "Audio Adversarial Examples: Targeted Attacks on Speech-to-Text". 2018.

"now I would drift gently off to dream land"

[adversarial]

It was the best of times, it was the worst of times, it was the age of wisdom, it was the age of foolishness, it was the epoch of belief, it was the epoch of incredulity

original or adversarial?

original or adversarial?

On audio, traditional ML methods are not vulnerable to adversarial examples

Questions?

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