Fooling neural networks and adversarial examples

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Introduction

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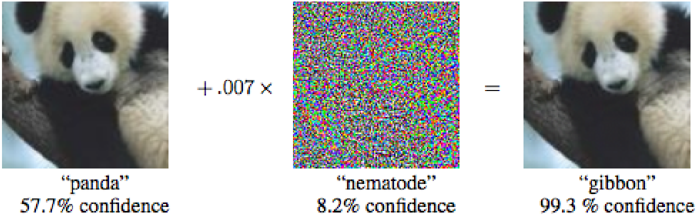


Articles

- Intriguing properties of neural networks
  Szgedy et al.
- Deep Neural Networks are Easily Fooled:
  High Confidence Predictions for Unrecognizable Images
  Nguyen et al.
- Explaining and Harnessing Adversarial Examples
  Goodfellow, et al.

1: Intriguing Properties

Article 1: Intriguing properties of neural networks
Szgedy et al.

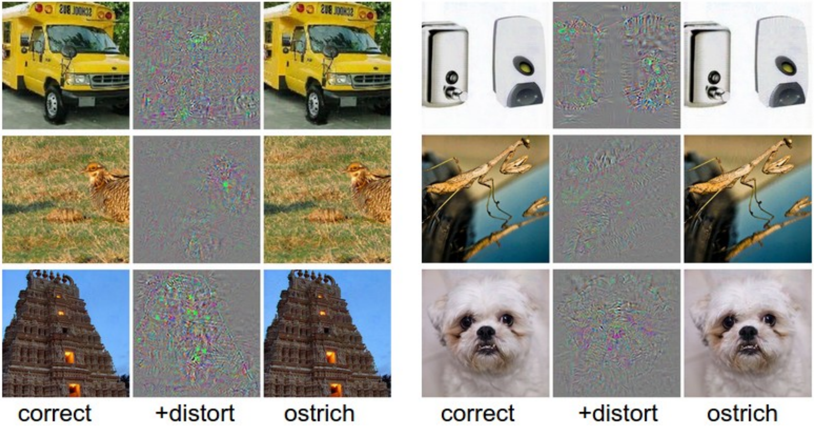
- Smoothness assumption does not hold.
- Images imperceptibly close can have different classifications
- Generated by optimizing the classification error for a trained network.

1: Method

Minimize $||r||_2$ subject to:
1. $f(x+r) = l$
2. $x + r \in [0,1]^m$

The author simplified this by approximating D and using linesearch according to
Min $c|r| + \text{loss}_f(x+r, l)$ subject to $x + r \in [0,1]^m$.

1: Results



1: Conclusions

- Easy to generate adversarial examples
- These generalize to other networks with similar training (set)
- Some robustness was achieved by including adversarial examples in training

2: Fooling Networks

Article 2: Deep Neural Networks are Easily Fooled:
High Confidence Predictions for Unrecognizable Images
Nguyen et al.

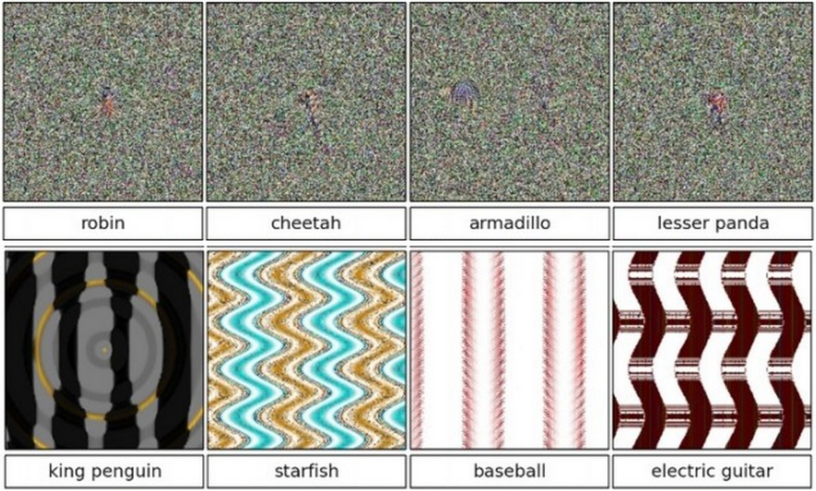
- Evolves fooling examples (that maximize classification error) from random noise.
- Images looks very weird when using geometric patterns in evolution

2: Method

Two approaches, 1 random data for each pixel or 2 random rules for a compositional pattern-producing network, CPPN
Tested on networks trained for digit recognition on the Lenet data set and on regular images in the ImageNet data set.

2: Results

example results



2: Results

- Directly encoded (pixel) images got low confidence on the regular image set (21.59%)
- Indirectly encoded (geometric) images got high confidence on the regular image set (88.11%)
- Geometric images share some superficial features with the training data images

2: New Conclusions

- in independent runs similar and dissimilar geometric patterns were obtained, indicating that the discerning 'features' between classes.
- Author notes the difference between the fooling images for different classes is large, even though we know that even a small perturbation is enough to shift class.
- some runs similar classes got similar pictures, other times very different
- It's hard to fool images of cats, due to a large sample size and many different classes of cats, so hard to isolate only one subclass

2: Remedies

- introduce a class 'fooling images' and generate new during training and dump them in this class
- no effect on digits but dropped confidence to 11% for regular images.
- sanity check: manually created geometric CPPN images that do look like a class still got high confidence
- sanity check: no decrease in verification on the original verification set.

3: Adversarial Examples

Article 3: Explaining and Harnessing Adversarial Examples
Goodfellow, et al.

- Continues article 1 with some mutual authors.
- Introduces a cheap algorithm for generating adversarial examples.
- Relates the adversarial examples to properties of linear operations in high dimensional space.

3: Method

proof of adversarial examples in one-layer networks:
Assume perturbed input $x' = x + \nu, w^T x' = w^T x + w^T \nu$
activation is maximized by $\nu = \operatorname{sign}(w)$, with n dimensions and average weight m the activation grows with εnm which is linear in n even though $||\nu||_\infty < \varepsilon$.
Thus adversarial examples will always exist for large n.

3: Method

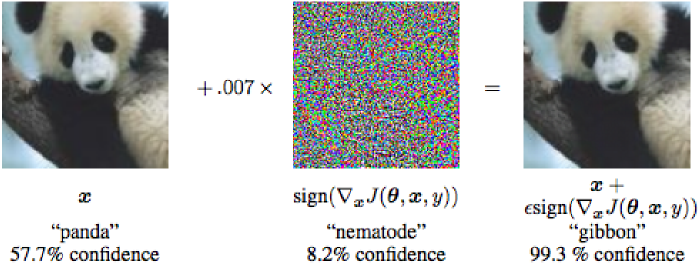
Fast gradient sign method, for deep networks
$J(\theta, x, y)$, cost function of training the network w.r.t. parameters, input image, image's target class.
Linearizing J around θ: $\eta = \varepsilon \, \mathrm{sign}\left(\nabla_x J(\theta, x, y)\right)$.
ε is a step length parameter, they just picked something that worked. Adversarial example is then $a = x + \eta$.
generates the closes adversarial example, can be generalized to finding a specific class.

3: Method

Feasible to use adversarial examples in training. Updated stopping criterion for training.

3: Results

example results



3: Results

- This led to improvements in the verification on real images (slight, but significant). Especially with more nodes in the hidden layer
- The robustness of the fully trained network was much greater, from an 90% misclassification rate on adversarial examples to 18%

3: New Conclusions

- adversarial examples are caused by the linearity of the models
- linear models have the strength of fast training and generalization.
- adversarial examples are aligned with weight vectors, explaining their applicability across similar networks.
- adversarial examples can be found along many lines in image-space more common than previously thought
- Article 2 was overkill, cheap to start with random and taking a few fast gradient steps.

3: Remedies

- Radial Basis Functions are found to be much more robust w.r.t. adversarial examples.
- adversarial examples can be generated in the same way, but yield much lower confidence due to the necessity of moving away from the images.

End