African Masters Of Machine Intelligence
AMMI

Explaining and harnessing adversarial examples

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Overview

Motivation

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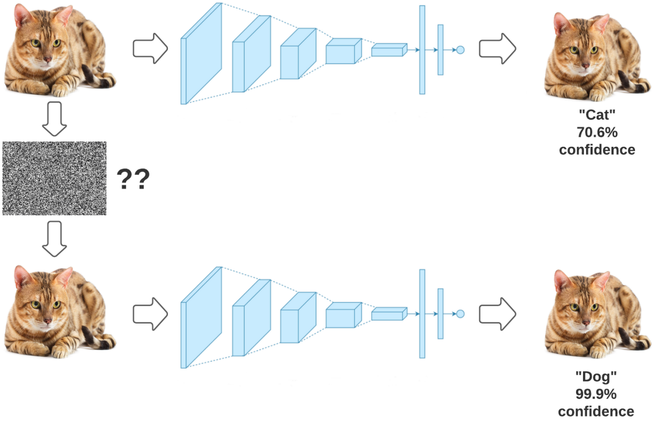
- The cause of adversarial examples is a mystery.
  - Extreme nonlinearity of deep neural networks
  - Insufficient model averaging
  - Insufficient regularization

Adversarial example



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- By considering the dot product between a weight vector w and an adversarial example $\tilde{\mathbf{x}}$,

$$\mathbf{w}^T\tilde{\mathbf{x}} = \mathbf{w}^T\mathbf{x} + \mathbf{w}^T\eta.$$

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- *A simple linear model can have adversarial examples if its input has sufficient dimensionality.*

Linear perturbation for non-linear model

x

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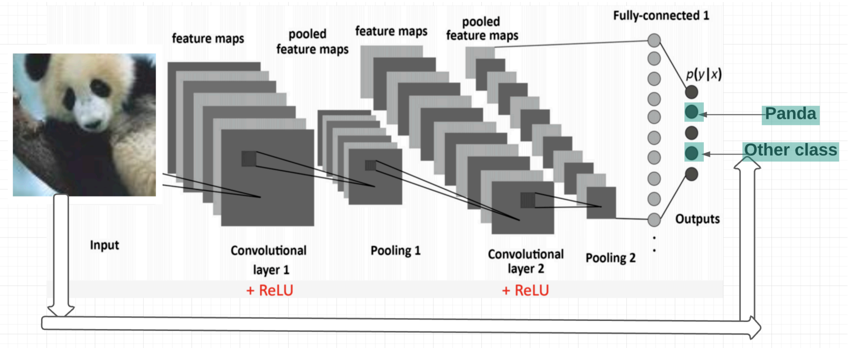
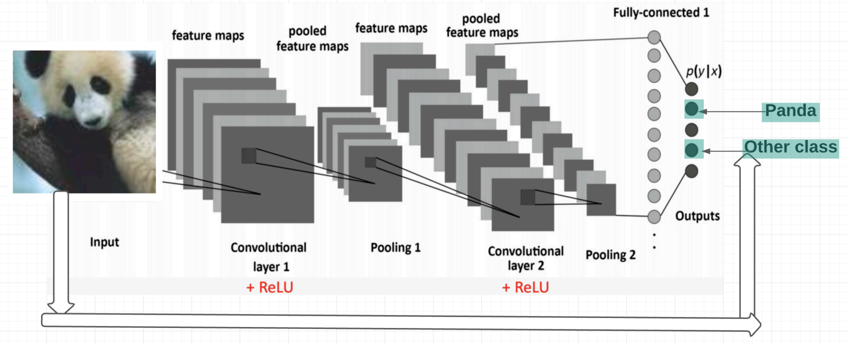
- Select a random real world image **x**: **panda.**

Linear perturbation for non-linear model



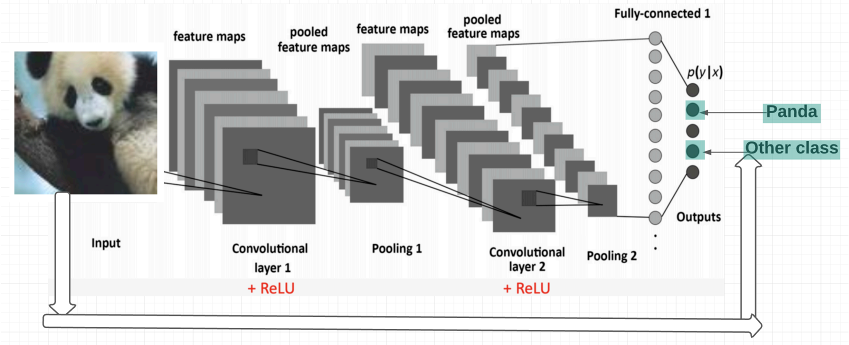
- Run the input image **x** into a ConvNet and get a correct classifier as a **panda.**

Linear perturbation for non-linear model



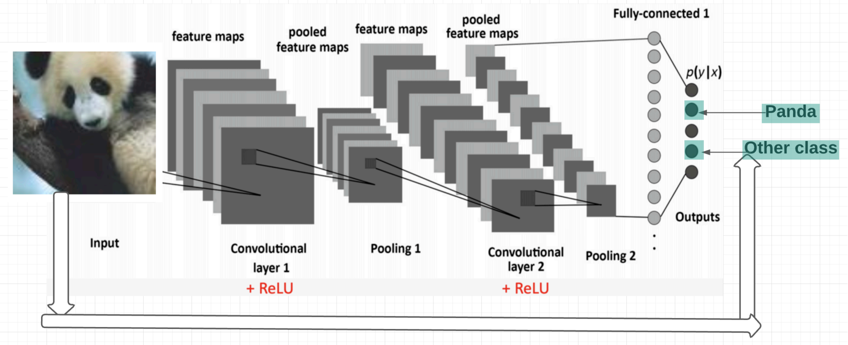
- Run the input image **x** into a ConvNet and get a correct classifier as a **panda.**
- Select a random output neuron in the output layer that is different from the true neuron that classifies **panda.**

Linear perturbation for non-linear model



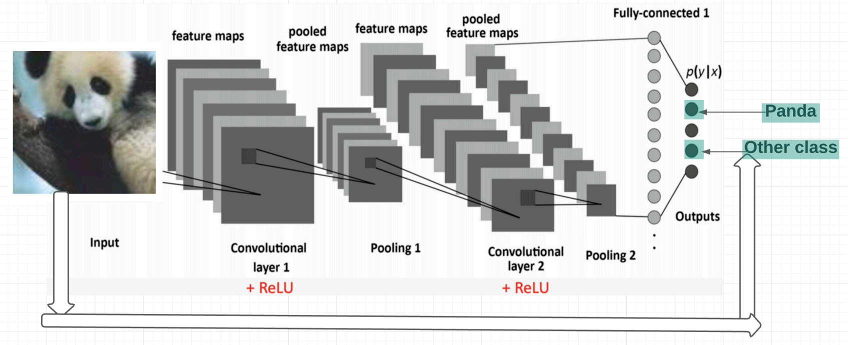
- We apply **GD** to the input pixels of our **panda** in order to minimize the classification loss with respect to the newly neuron chosen class neuron.

Linear perturbation for non-linear model



- We apply **GD** to the input pixels of our **panda** in order to minimize the classification loss with respect to the newly neuron chosen class neuron.
- Instead of adjusting the network weights in order to optimize our classifier, we ajust the input pixels until they fool the network to make a wrong prediction.

Linear perturbation for non-linear model



- The final trick is to make sure that our generated image looks as close as possible to the original one such that we can't see the difference.

Linear perturbation for non-linear model

- We can generate the perturbation η using a Fast Gradient Sign Methode (FGSM),
  - $\eta = \epsilon * sign(\nabla_x J(\theta, \mathbf{x}, y))$,
  - θ the parameter, $\mathbf{x}$ input vector, y target associated to $\mathbf{x}$, J cost function.

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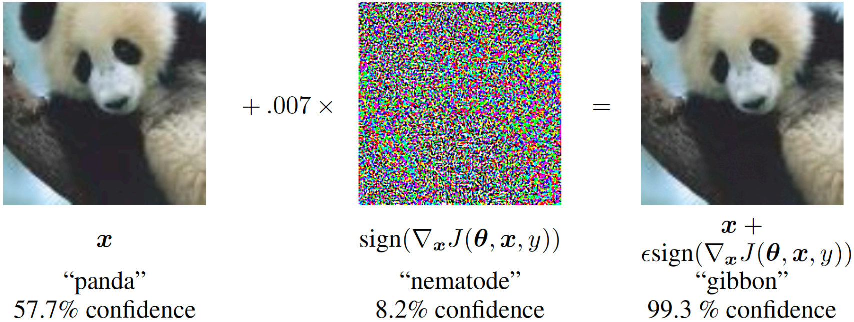

Experiments

From paper:

epsilon	Error rate	Confidence	Activation	Dataset
0.25	99.9%	79.3%	Softmax	MNIST
0.25	89.4%	97.6%	Maxout	MNIST
0.10	87.15%	96.6%	Maxout	CIFAR-10

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Our experiments:

epsilon	Error rate	Confidence	Activation	Dataset
0.25	57.21%	2.17%	LogSoftmax	MNIST
0.10	12.72%	1.34%	LogSoftmax	MNIST

epsilon	Error rate	Confidence	Activation	Dataset
0.25	64.55%	95.41%	Softmax	MNIST
0.10	14.46%	95.81%	Softmax	MNIST

End

THANK YOU !