Adversarial examples in deep learning

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What is an adversarial example?

An *adversarial example* is a sample of input data which has been modified *very slightly* in a way that is intended to cause a machine learning classifier to misclassify it.
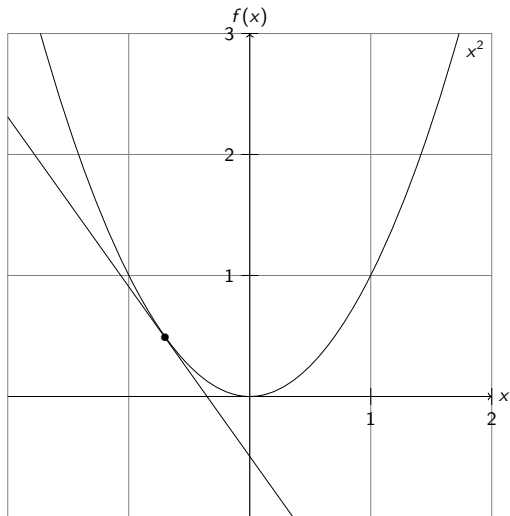
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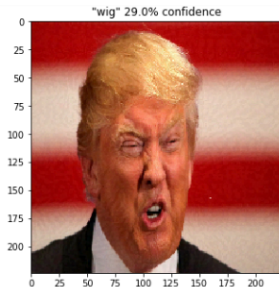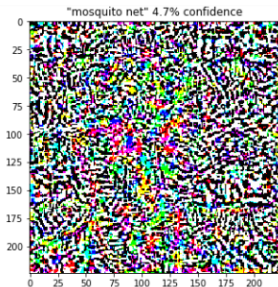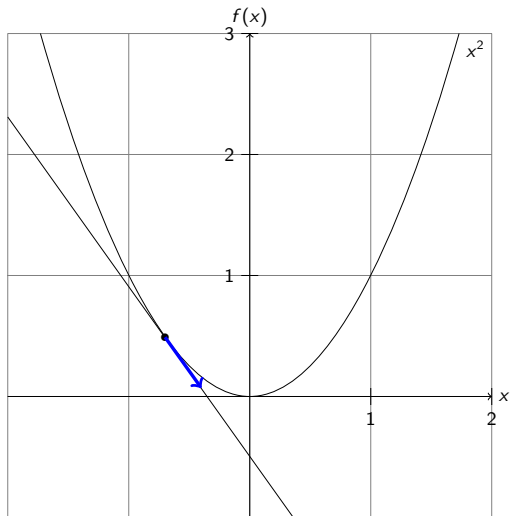
Gradient descent
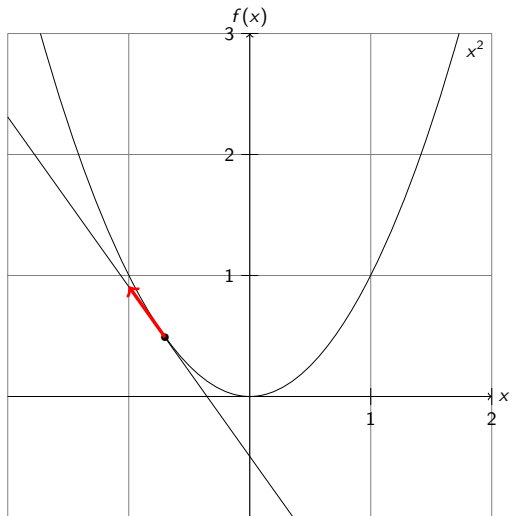Basic concept

Gradient descent
Basic concept

Optimization

Gradient descent

Basic concept

Neural networks

To train and evaluate neural networks, we use a *loss function* $L(\theta, x, y)$ with θ the parameters of the models, x an input and y the real value corresponding to x. This function measures *how good* is the prediction of the model on a specific example.

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To create an adversarial sample, we compute the derivative of L according to x and use the result to update the pixel values of x in order to increase the loss value. It happens that such modifications of x often cause the network to misclassify it.
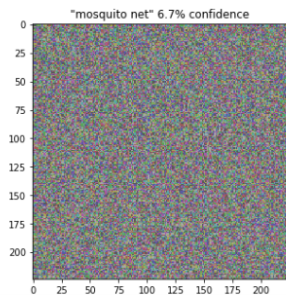
Random noise perturbation
Do we really need to do that?

Random noise perturbation

Yep

Fast Gradient Sign Method [2015]

Let x be the original image, θ the parameters of the model, y the target associated with x and $L(\theta, x, y)$ the loss function.

We compute the gradient of the loss function according to the input pixels.

$$\nabla_x L(\theta, x, y)$$

The perturbation is the signs of these derivatives multiplied by a small number ε.

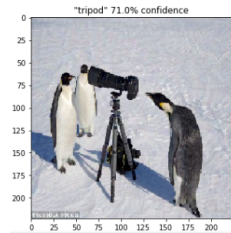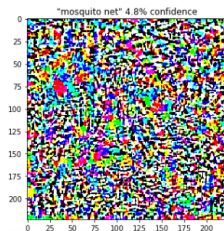$$\eta = \varepsilon \ \text{sign}(\nabla_x L(\theta, x, y))$$

The final adversarial sample is the sum of the original image and the perturbation.

$$x_{adv} = x + \eta$$

Fast Gradient Sign Method
VGG16 network

$$x \quad + \quad \varepsilon \ \text{sign}(\nabla_x L(\theta, x, y)) \quad = \quad x_{\text{adv}}$$
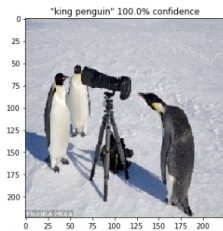
Black-box attack [2016]
or good luck getting gradients out of your self-driving car

Black-box attack [2016]
Transferability of adversarial samples

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"After labeling 6,400 synthetic inputs to train our substitute (an order of magnitude smaller than the training set used by MetaMind) we find that their DNN misclassifies adversarial examples crafted with our substitute at a rate of 84.24%"

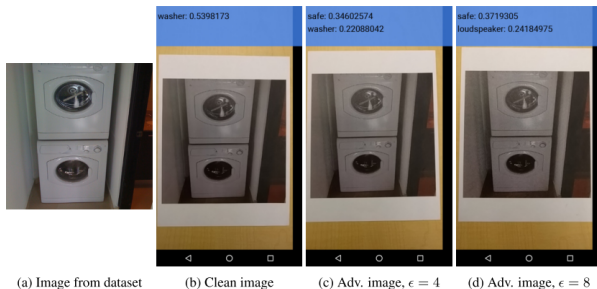- Papernot et al., about their attack on the MetaMind deep neural network.
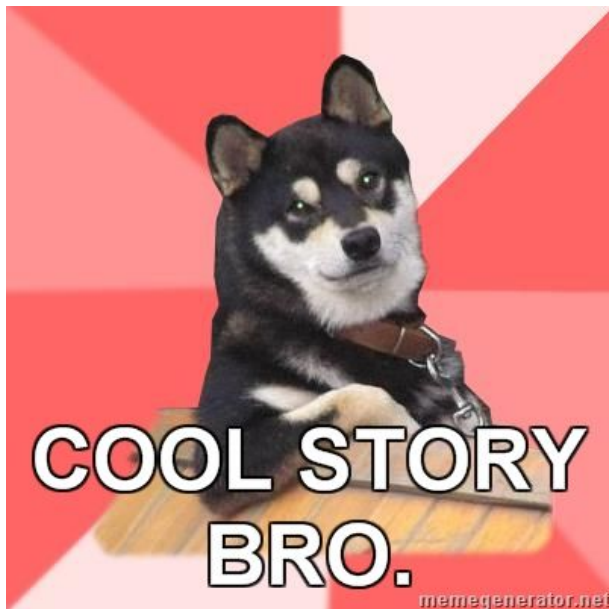
In real world scenarios, the target network does not take our image files as input. It acquires the data by the network's system (*e.g.* a camera).

It also works, for free.

(a) Image from dataset   (b) Clean image   (c) Adv. image, $\epsilon = 4$ (d) Adv. image, $\epsilon = 8$

"We used images taken from a cell-phone camera as a input to an Inception v3 image classification neural network. We showed that in such a set-up, a significant fraction of adversarial images crafted using the original network are misclassified even when fed to the classifier through the camera."

- Kurakin et al.

Robust Physical-World Attacks on Machine Learning Models [2017]

Perturbations can also be constrained to mimic vandalism or art in order to go unreported by casual observers.

This concept allows the algorithm to create perturbations with much bigger magnitudes since we do not care about being perceived anymore

White-box defense
Adversarial training

We can generate adversarial samples and train the network to produce the correct classification on these new data points.

- Works against FGSM
- Expensive
- Does not defend subtler white-box attacks (*e.g.* I-FGSM or RAND+FGSM)
- Does not defend against black-box attack

Black-box defense
Ensemble adversarial training [Tramèr et al. May 2017]

Augment training data with adversarial inputs from a number of fixed pre-trained models.

- Best defense so far against black-box adversary
- Does not defend subtle white-box attacks

Error rate from 15.5% to 3.9% between adversarial trained and ensemble adversarial trained model on MNIST for a black-box attack.

Defending machine learning
Wide open problem

"Most defenses against adversarial examples that have been proposed so far just do not work very well at all, but the ones that do work are not adaptive. This means it is like they are playing a game of whack-a-mole: they close some vulnerabilities, but leave others open."

- Ian Goodfellow, Nicolas Papernot, February 2017

References

Research papers:

1. Goodfellow, I. J., Shlens, J., & Szegedy, C. (2014). Explaining and harnessing adversarial examples. arXiv preprint arXiv:1412.6572.

2. Papernot, N., McDaniel, P., Goodfellow, I., Jha, S., Celik, Z. B., & Swami, A. (2016). Practical black-box attacks against deep learning systems using adversarial examples. arXiv preprint arXiv:1602.02697.

3. Kurakin, A., Goodfellow, I., & Bengio, S. (2016). Adversarial examples in the physical world. arXiv preprint arXiv:1607.02533.

4. Tramèr, F., Kurakin, A., Papernot, N., Boneh, D., & McDaniel, P. (2017). Ensemble Adversarial Training: Attacks and Defenses. arXiv preprint arXiv:1705.07204.

5. Tramèr, F., Papernot, N., Goodfellow, I., Boneh, D., & McDaniel, P. (2017). The Space of Transferable Adversarial Examples. arXiv preprint arXiv:1704.03453.

6. Evtimov, I., Eykholt, K., Fernandes, E., Kohno, T., Li, B., Prakash, A., Rahmati A. & Song, D. (2017). Robust Physical-World Attacks on Machine Learning Models. arXiv preprint arXiv:1707.08945.

Implementations:

1. github.com/tensorflow/cleverhans

2. github.com/rodgzilla/machine_learning_adversarial_examples
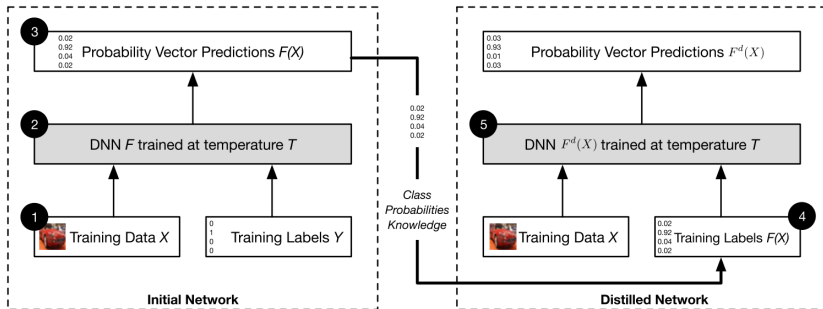
Targeted perturbation
Papernot algorithm

This algorithm iteratively computes the adversarial saliency value $S(x, t)[i]$ of pixel i of the image x according to the class t.

$$S(x, t)[i] = \begin{cases} 0 & \text{if} \quad \frac{\mathrm{d}L_t}{\mathrm{d}x_i}(x) < 0 \quad \text{or} \quad \sum_{j \neq t} \frac{\mathrm{d}L_j}{\mathrm{d}x_i}(x) > 0 \\ \frac{\mathrm{d}L_t}{\mathrm{d}x_i}(x) \, |\sum_{j \neq t} \frac{\mathrm{d}L_j}{\mathrm{d}x_i}(x)| & \text{otherwise.} \end{cases}$$

and use it iteratively to produce x_{adv} classified as t by the network.

Defensive distillation

Training a network with explicit relative information about classes prevents models from fitting too tightly to the data.

Papernot, N., McDaniel, P., Wu, X., Jha, S., & Swami, A. (2016). Distillation as a defense to adversarial perturbations against deep neural networks. In Security and Privacy (SP), 2016 IEEE Symposium on (pp. 582-597). IEEE.