

Adversarial examples in deep learning

G. Châtel

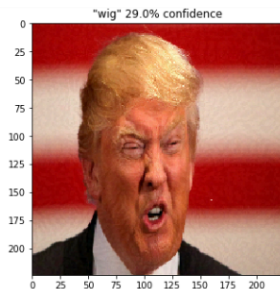
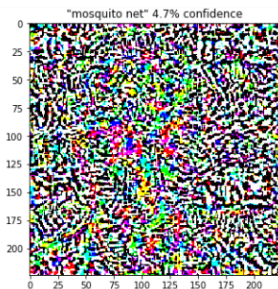
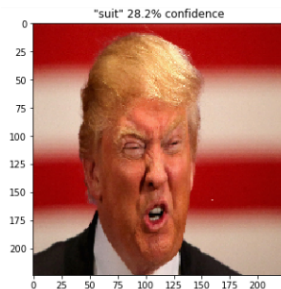
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What is an adversarial example?

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.

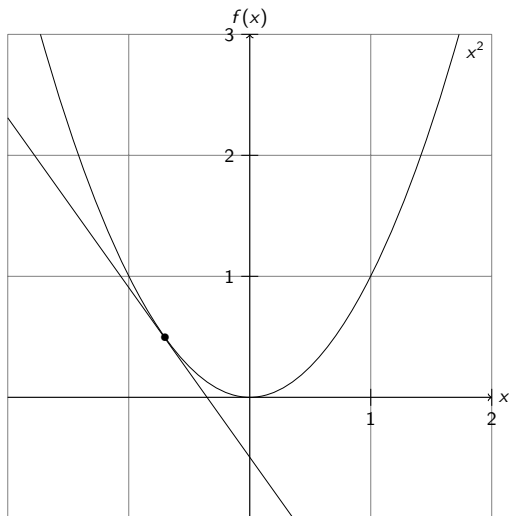
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Gradient descent

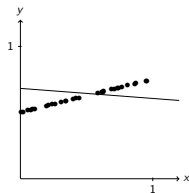
Basic concept



The curve needs to be *smooth enough* for the gradient descent to work.

Gradient descent

Model optimization

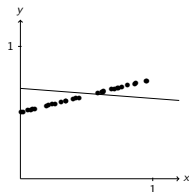


We have a set of points that we want to approximate with a line.

$$y = ax + b$$

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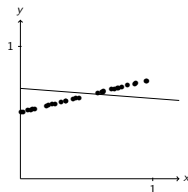
$$y = ax + b$$

First we choose a **loss** that measures how good our predictions are.

$$l(x, y, a, b) = (y - (ax + b))^2$$

Gradient descent

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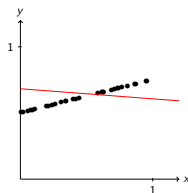
We compute how the loss is affected by small changes of a and b :

$$\frac{dl}{da} = 2x(ax + b - y) \qquad \frac{dl}{db} = 2(ax + b - y)$$

And we update a and b iteratively until we reach a satisfying result (the average loss for our data points is low enough).

Gradient descent

Being evil

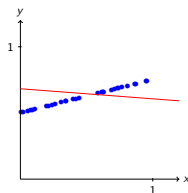


In our previous example, we have modified **the model** in order to minimize the loss.

$$y = ax + b$$

Gradient descent

Being evil



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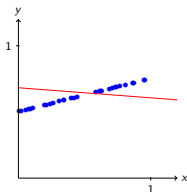
$$y = ax + b$$

Now suppose we are an attacker who wants to maximise the loss of a model, its **parameters** being fixed. The only thing we can modify is the **inputs**.

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Gradient descent

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$$l(x, y, a, b) = (y - (ax + b))^2$$

In order to do this, we compute how the loss is affected by small changes of the input:

$$\frac{dl}{dx} = 2a(ax + b - y)$$

We can now make *imperceptible* changes to an input to make the loss grow.

Neural networks

I used a basic regression task to illustrate the concept of adversarial samples generation.

Everything works the same way when working with a neural network on an image classification task.

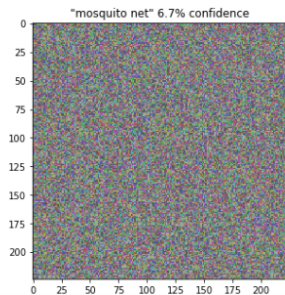
We also have a differentiable **loss function** (often **categorical cross entropy**) and **inputs** (**pixel values** in the case of images) that we can modify to increase the loss.

Random noise perturbation



Random noise perturbation

Nope.



Fast Gradient Sign Method [Goodfellow et al. 2015]

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

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

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

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

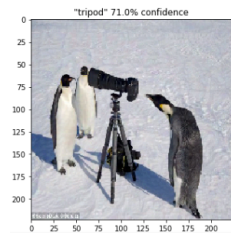
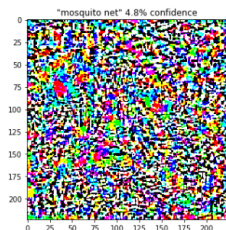
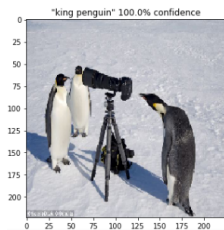
$$\eta = \varepsilon \text{sign}(\nabla_x J(\theta, x, y))$$

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

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

Fast Gradient Sign Method

$$x + \epsilon \text{sign}(\nabla_x J(\theta, x, y)) = x_{\text{adv}}$$



Black box attack

or good luck getting gradients out of a self-driving car



Adversarial examples in the physical world

This is nice but in real world scenarios, we are not feeding the network with our own data, it is acquired by the network's system (using camera for example).

Defenses

Adversarial sample detection We try to detect whether an input sample is adversarial or not before classifying it.

Regularization Training with an adversarial objective function is an effective regularizer (from [explaining and harnessing]).

Gradient masking The goal of gradient masking is to leave the decision boundaries untouched but damage the gradient used in white-box attacks.

Distillation and network saturation These methods are used to introduce numerical instabilities in gradient computations.

"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

- ❶ Goodfellow, I. J., Shlens, J., & Szegedy, C. (2014). Explaining and harnessing adversarial examples. arXiv preprint arXiv:1412.6572.
- ❷ Papernot, N., McDaniel, P., Wu, X., Jha, S., & Swami, A. (2016, May). Distillation as a defense to adversarial perturbations against deep neural networks. In Security and Privacy (SP), 2016 IEEE Symposium on (pp. 582-597). IEEE.
- ❸ 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.
- ❹ Tramèr, F., Kurakin, A., Papernot, N., Boneh, D., & McDaniel, P. (2017). Ensemble Adversarial Training: Attacks and Defenses. arXiv preprint arXiv:1705.07204.