Adversarial examples in deep learning

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Basic notions

Adversarial example

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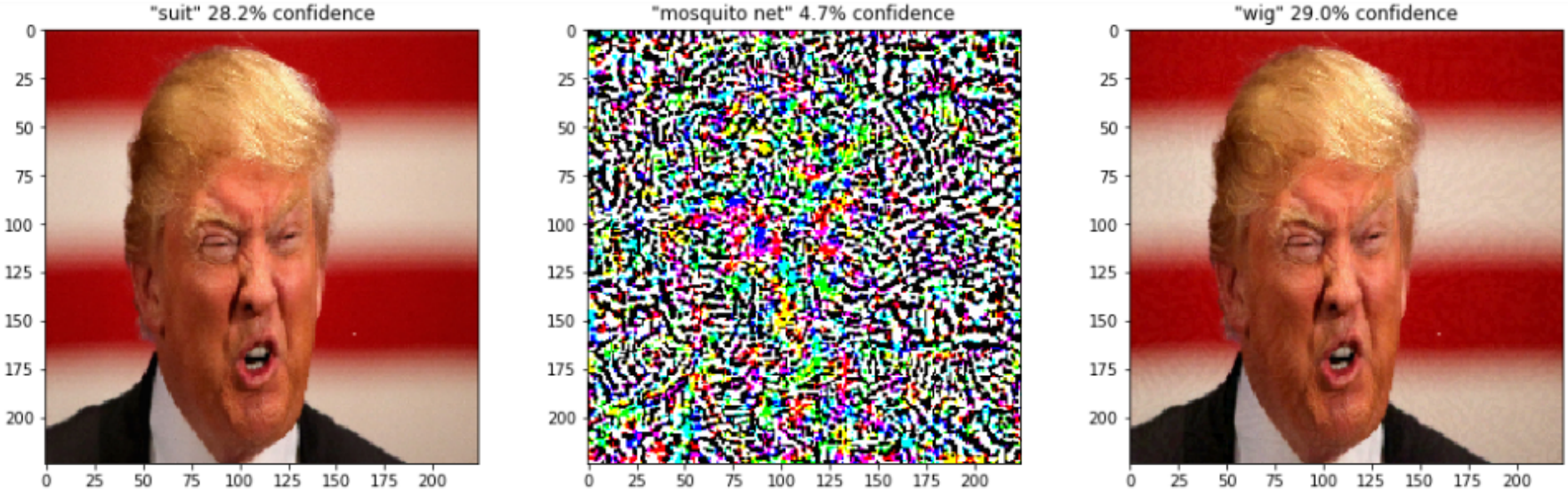
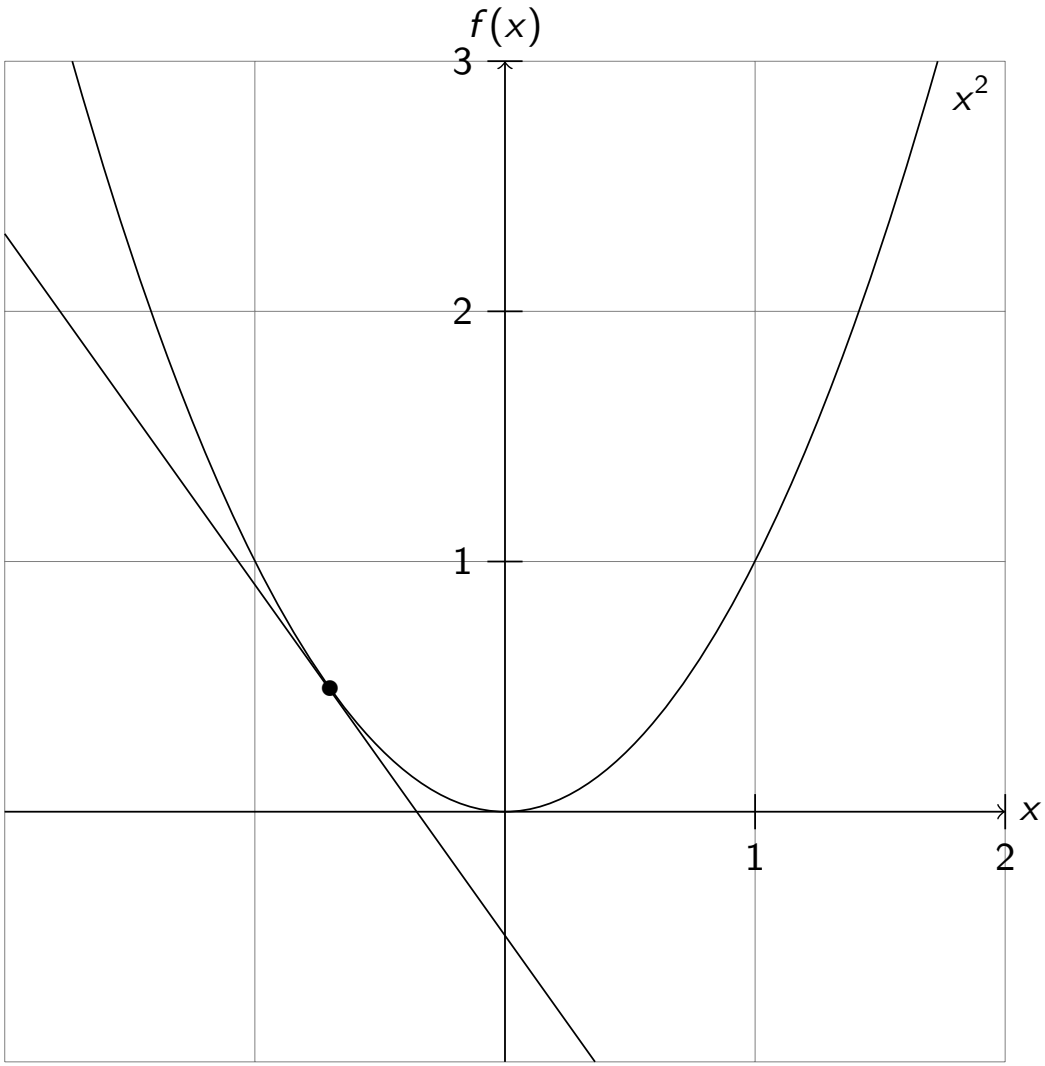


Gradient descent

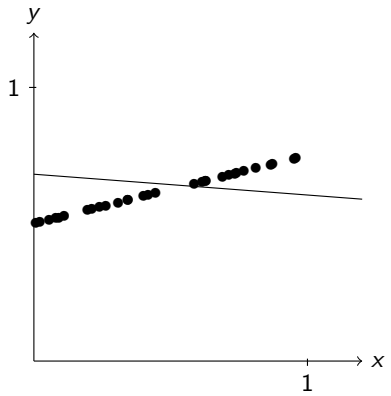
Basic concept



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

Gradient descent

Model optimization

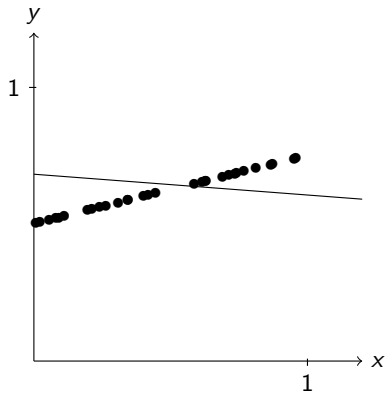


We have a set of points that we want to approximate with a line.

$$y = ax + b$$

Gradient descent

Model optimization



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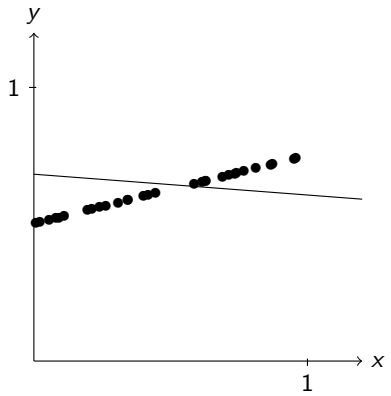
First we choose a loss that measures how good our predictions are.

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

Gradient descent

Model optimization



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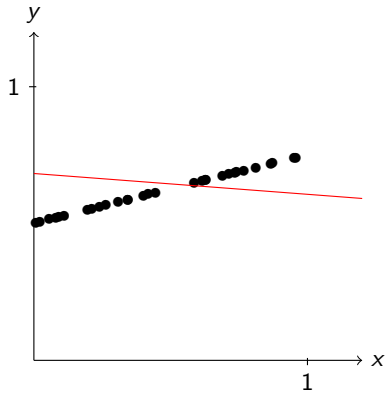
We compute how the loss is affected by small changes of a and b:

$$\frac{\mathrm{d}l}{\mathrm{d}a} = 2x(ax + b - y) \qquad \frac{\mathrm{d}l}{\mathrm{d}b} = 2(ax + b - y)$$

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

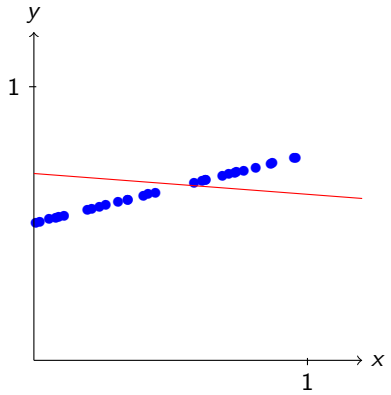


In our previous example, we have modified the model in order to minimize the loss.

$$y = ax + b$$

Gradient descent

Being evil



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

$$y = ax + b$$

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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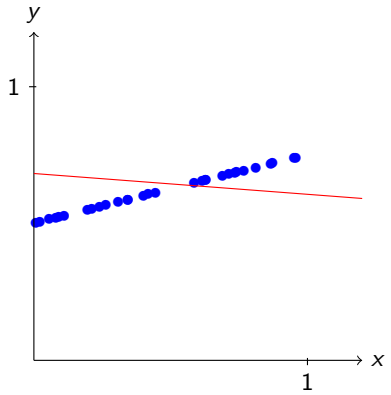
Gradient descent

Being evil



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

$$\frac{\mathrm{d}l}{\mathrm{d}x} = 2a(ax + b - y)$$

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.

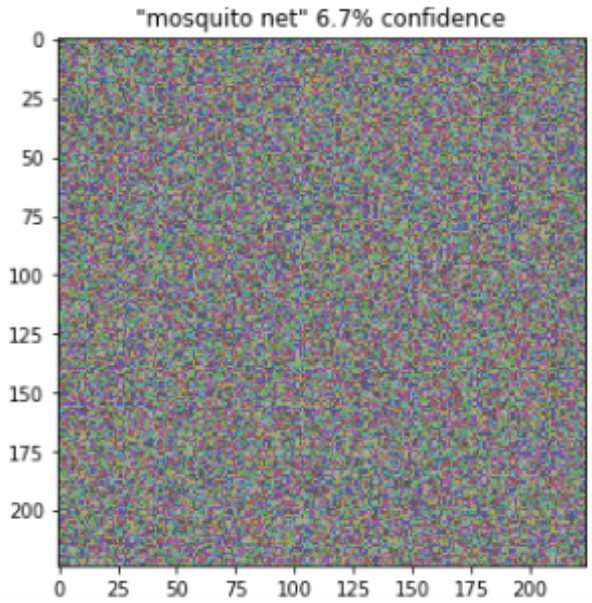
Everything works the same way when working with a neural network on an image classification task.

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

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.

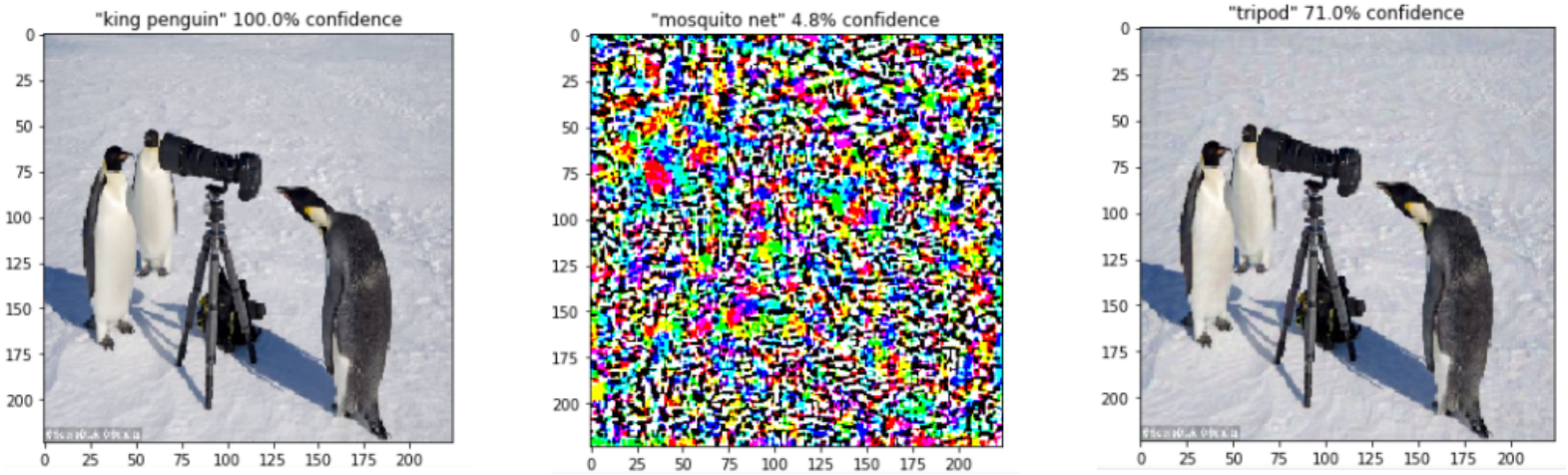
$$\eta = \varepsilon \text{sign}(\nabla_x J(\theta, x, y))$$

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

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

Fast gradient sign method

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



Black box attack

This is nice but happens if you cannot access the gradients

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.