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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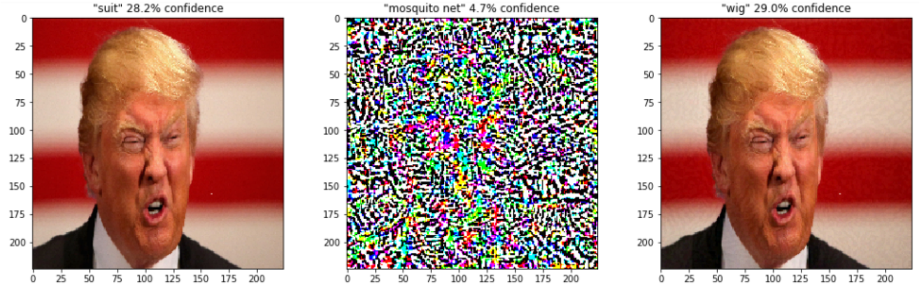
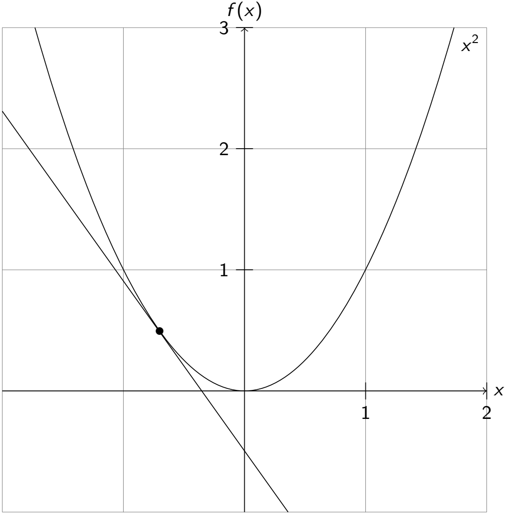


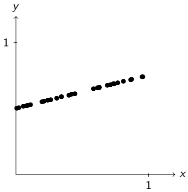
Gradient descent

Basic concept



Gradient descent

Model optimization

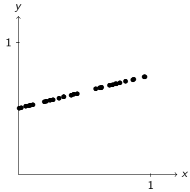


We have a set of points that we want to approximate with a line.

$$y = ax + b$$

Gradient descent

Model optimization



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

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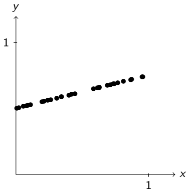

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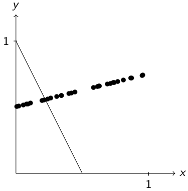
We compute how the loss is affected by small changes of a and b.

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

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

Gradient descent

Being evil



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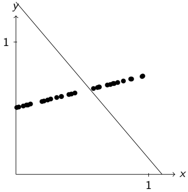

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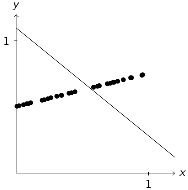

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We can now make *imperceptible* changes to an input that will increase the loss value.

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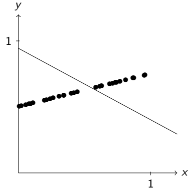

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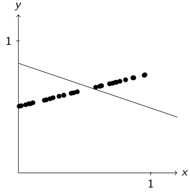

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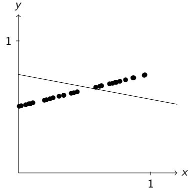

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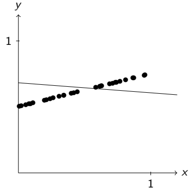

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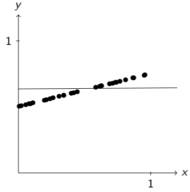

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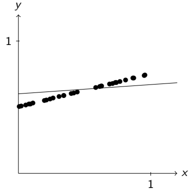

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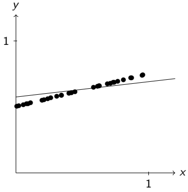

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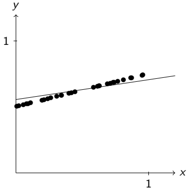

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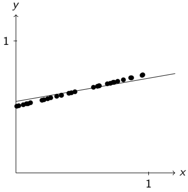

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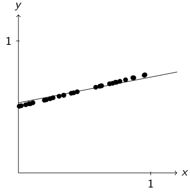

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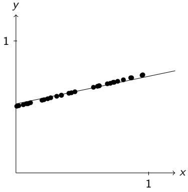

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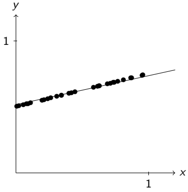

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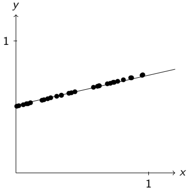

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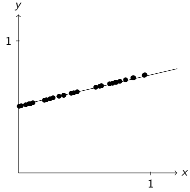

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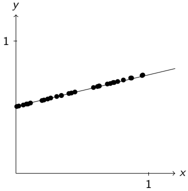

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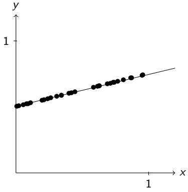

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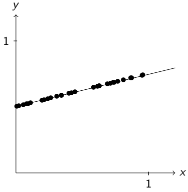

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Neural networks

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*), model *parameters* (the *weights* of the neural network) and *inputs* (*pixel values* in the case of images) that we can modify to increase the loss.

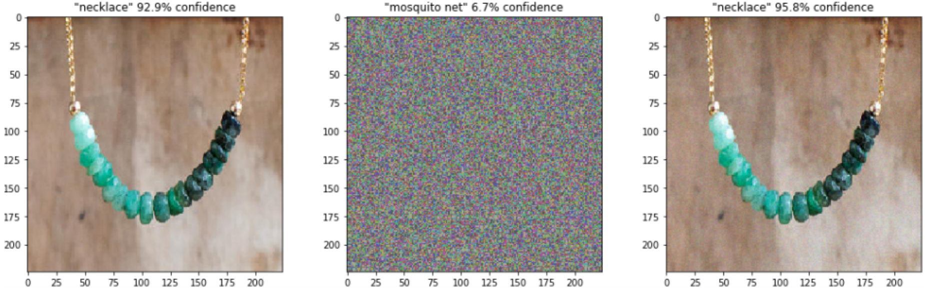
The ultimate goal is to make our input cross the *decision boundary*.

Random noise perturbation

Do we really need to do that?

Random noise perturbation

Yep



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

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

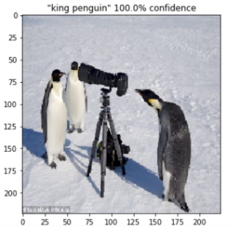
The final adversarial sample is the sum of the original image and the perturbation.

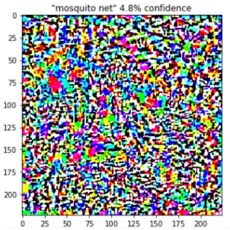
$$x_{adv} = x + \eta$$

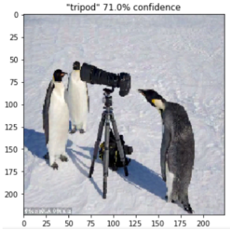
Fast Gradient Sign Method

VGG16 network

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







Black-box attack [Papernot et al. 2016]

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

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Transferability of adversarial samples

We can train a new model M' to solve the same classification task as the target model M.

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Once trained, we can create an adversarial sample x'_{adv} for the M' model and experiences have shown that x'_{adv} will also fool M very often.

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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.

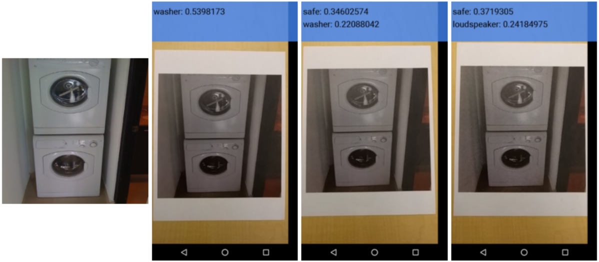
Adversarial examples in the physical world [Kurakin et al. 2017]

or good luck attacking a self-driving car with your USB flash drive

Adversarial examples in the physical world [Kurakin et al. 2017]

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.

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.

Implementations:

1. github.com/tensorflow/cleverhans
2. github.com/rodgzilla/machine_learning_adversarial_examples

Targeted perturbation

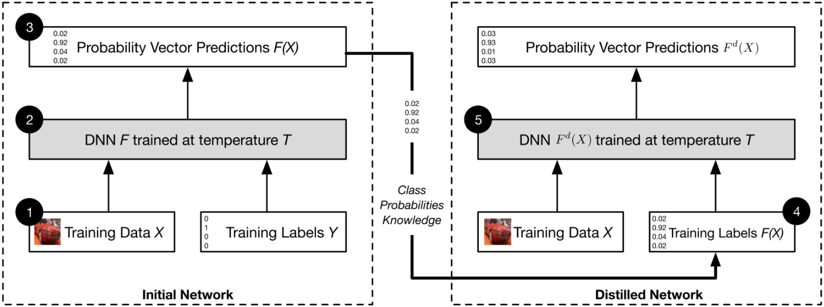
Papernot algorithm

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

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

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.