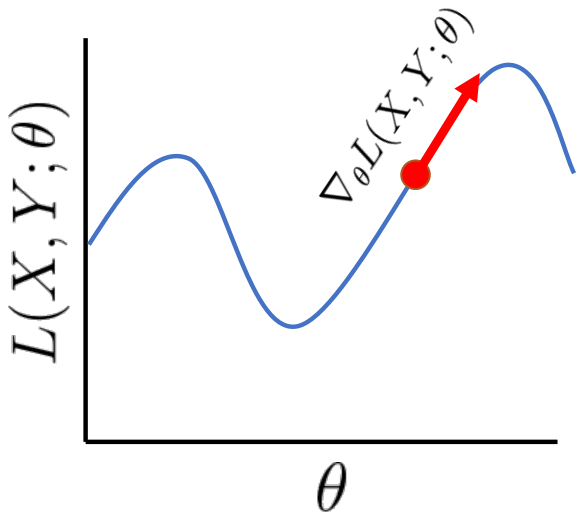
Adversarial Examples

Deep Learning: Bryan Pardo, Northwestern University, Fall 2020

What does the gradient tell us?

- If the loss function and hypothesis function encoded by the model are differentiable* (i.e., the gradient exists)
- We can evaluate the gradient for some fixed value of θ and get the *direction* in which the loss *increases* fastest



*or subdifferentiable

Gradient Descent Pseudocode

Initialize $\theta^{(0)}$

Repeat until stopping condition met:

$$\theta^{(t+1)} = \theta^{(t)} - \eta \nabla L(X, Y; \theta^{(t)})$$

Return $\theta^{(t_{max})}$

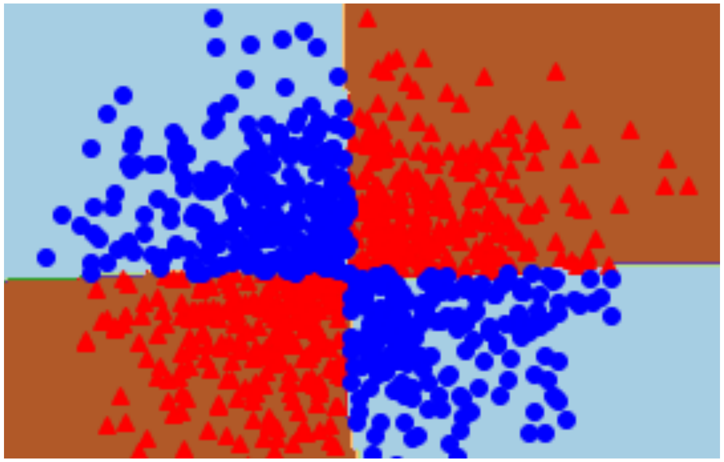
$\theta^{(t)}$ are the parameters of the model at time step t

$\nabla L(X, Y; \theta^{(t)})$ is the gradient of the loss function with respect to model parameters $\theta^{(t)}$

η controls the step size

$\theta^{(t_{max})}$ is the set of parameters that did best on the loss function.

What are these things really learning?



Learned decision surface for XOR problem

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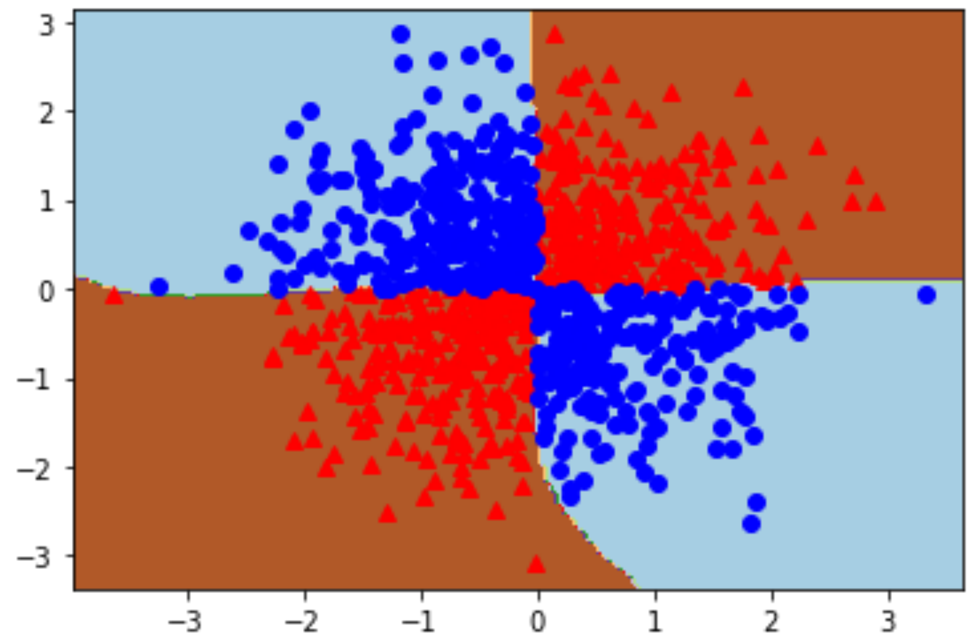

Learned decision surface for XOR problem

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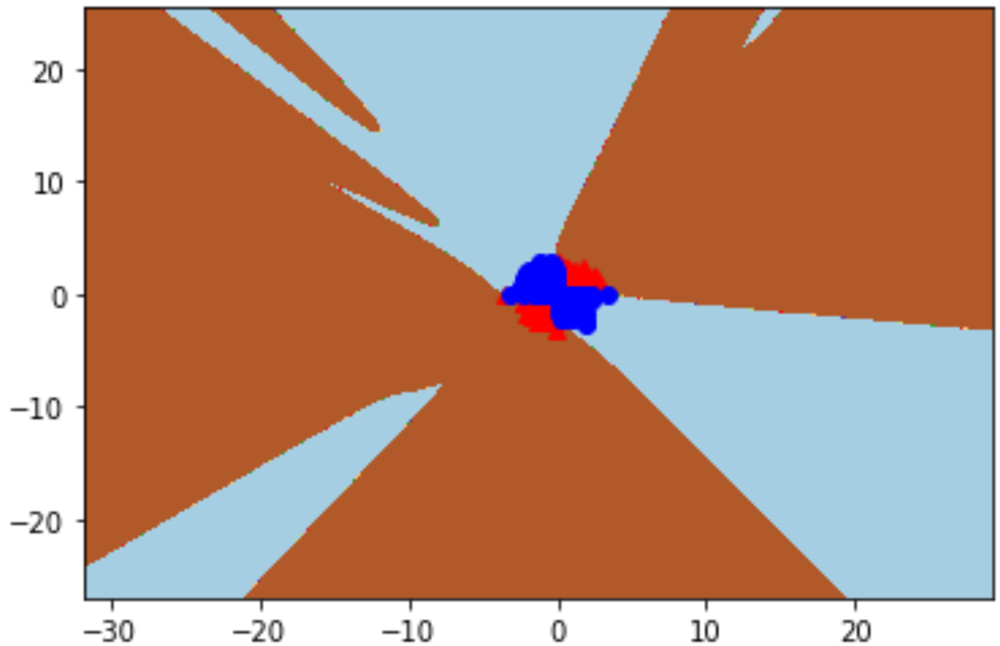
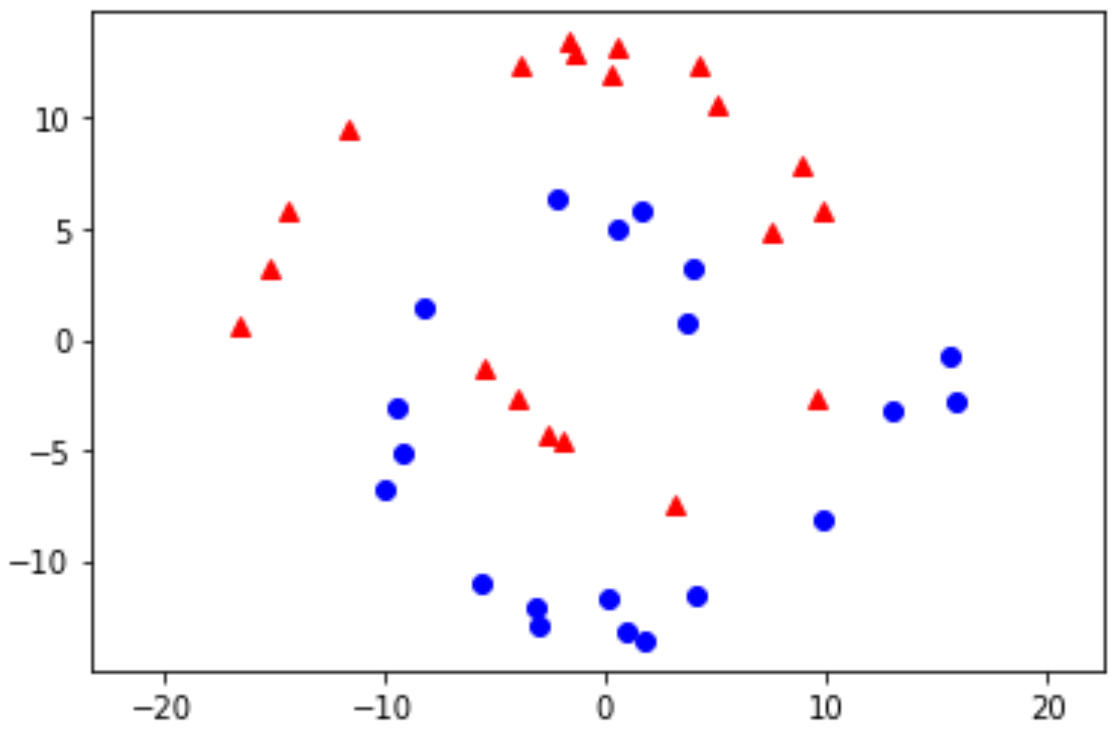
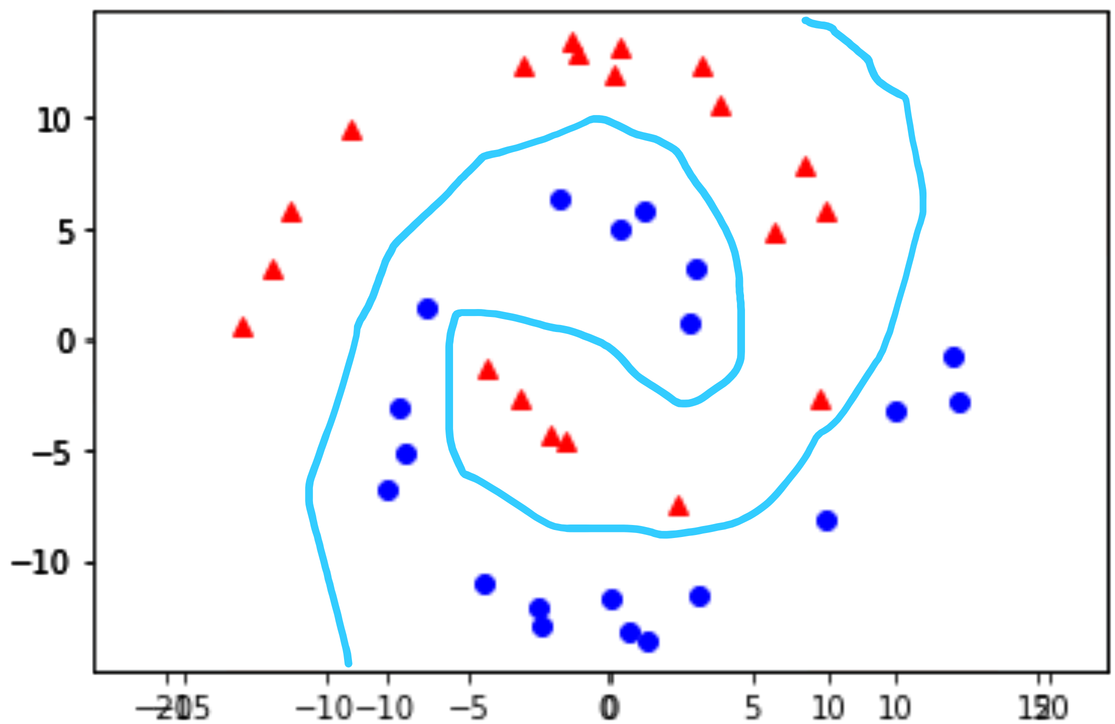


Same decision surface zoomed out

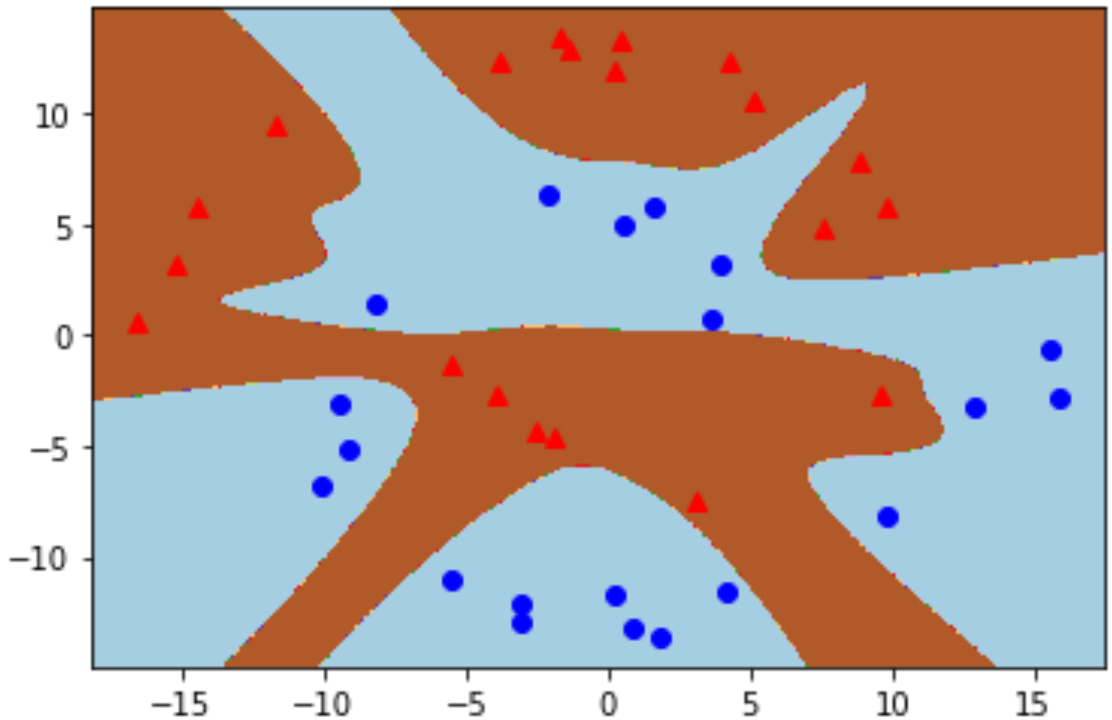
Spirals data



Decision surface a human might draw



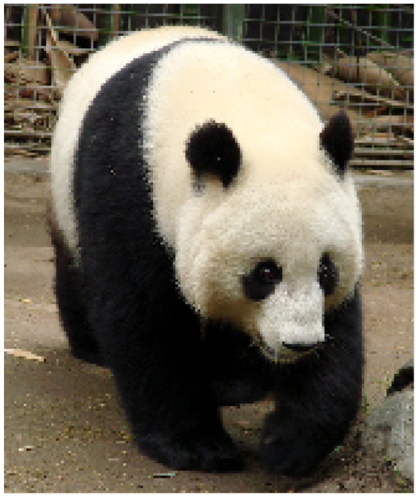
Actual decision surface learned by a network

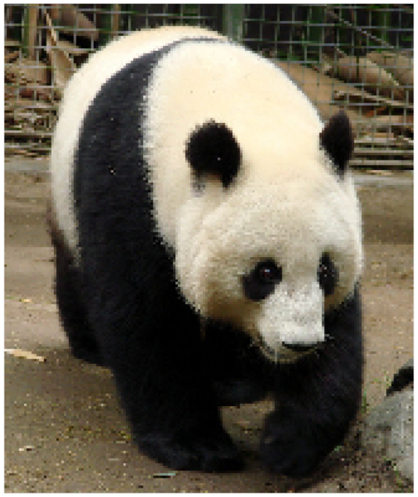


100% perfect accuracy on labeling

In 2 dimensions, a bad surface is obvious

- What about in 2 million dimensions?

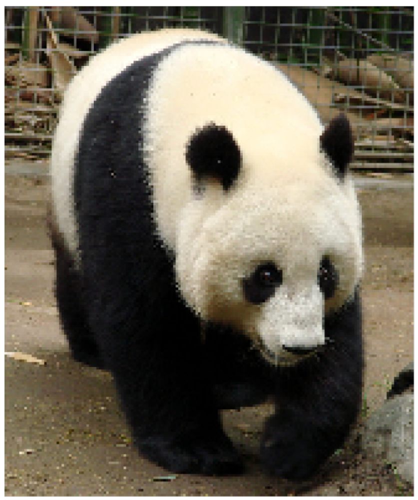




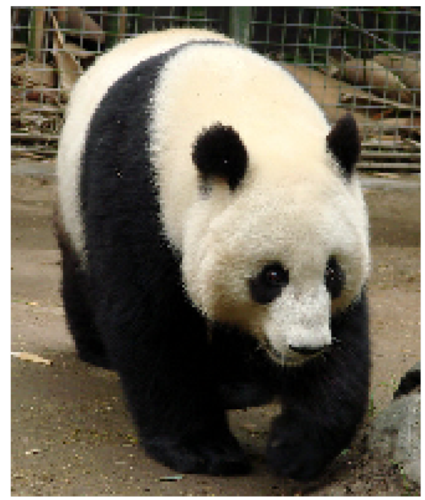
One of these was labeled “panda” by a trained net.
The other was labeled “bucket”. Which is which?

Image from: https://www.borealisai.com/en/blog/advertorch-adversarial-training-tool-implement-attack-and-defence-strategies/

The one on the right is a “perturbed” image

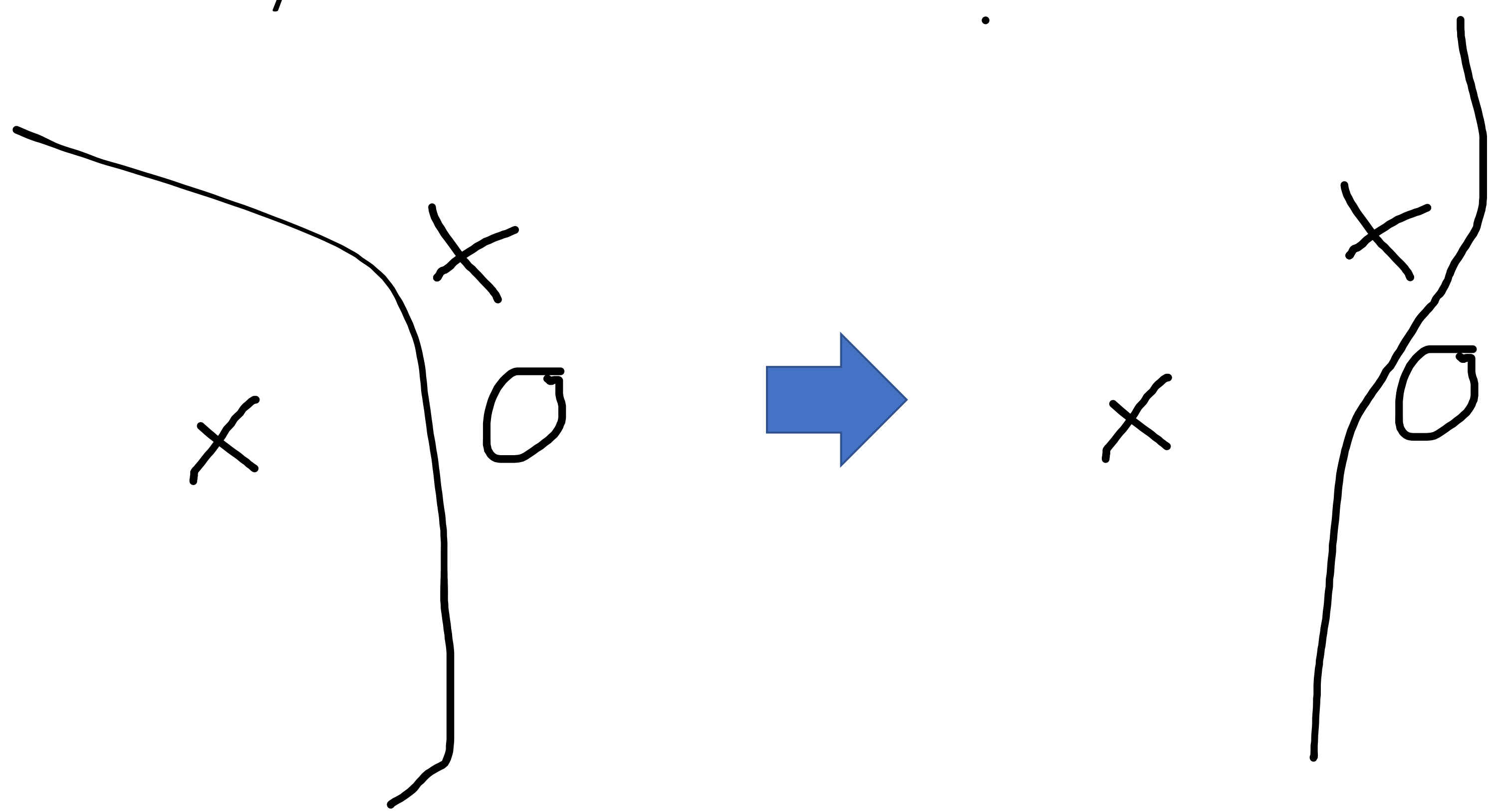


PANDA

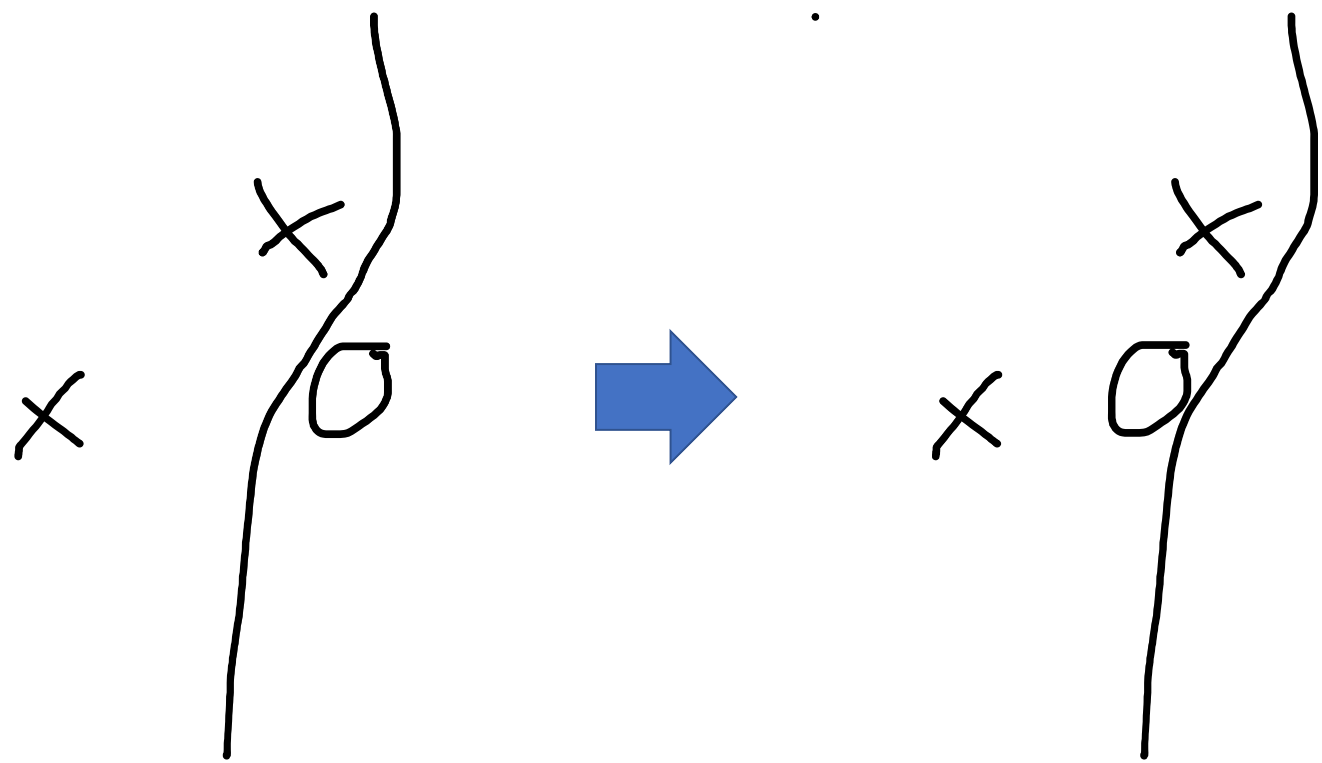


BUCKET

Gradient descent is moving the decision boundary



What if we move a datapoint instead?



Gradient Descent Pseudocode

Initialize $\theta^{(0)}$

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$$\theta^{(t+1)} = \theta^{(t)} - \eta \nabla_\theta L(X, Y; \theta^{(t)})$$

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$\theta^{(t)}$ are the parameters of the model at time step t

$\nabla_\theta \, L(X, Y; \theta^{(t)})$ is the gradient of the loss function with respect to model parameters $\theta^{(t)}$

η controls the step size

$\theta^{(t_{max})}$ is the set of parameters that did best on the loss function.

Just flip which thing we're optimizing

Initialize $X^{(0)}$

Repeat until stopping condition met:

$$X^{(t+1)} = X^{(t)} + \eta \nabla_X L(X^{(t)}, Y; \theta)$$

Return $X^{(enough)}$

$X^{(t)}$ is an example at time t

$\nabla_X L(X^{(t)}, Y; \theta)$ is the gradient of the loss function with respect to example features $X^{(t)}$

η controls the step size

$X^{(enough)}$ is the minimal change needed to flip the category of X

Even Simpler: Fast Gradient Sign method

$$X^{(t+1)} = X^{(t)} + \eta sign(\nabla_X L(X^{(t)}, Y; \theta))$$

EXPLAINING AND HARNESSING ADVERSARIAL EXAMPLES
Ian J. Goodfellow, Jonathon Shlens & Christian Szegedy, ICLR 2015

Gradient Sign attack

- The pixels are all independent dimensions

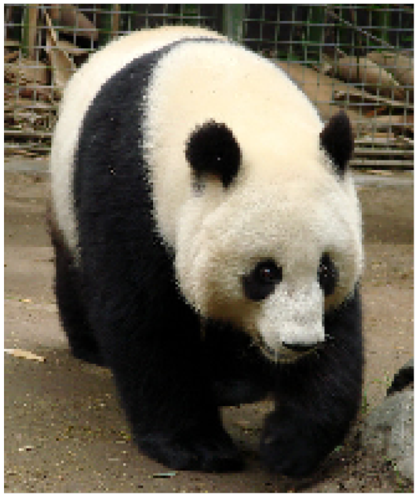
- Find the gradient in the pixel space

- Add noise along the gradient (a little bit of noise for every pixel)

- Do it right and the image looks the same to the user…

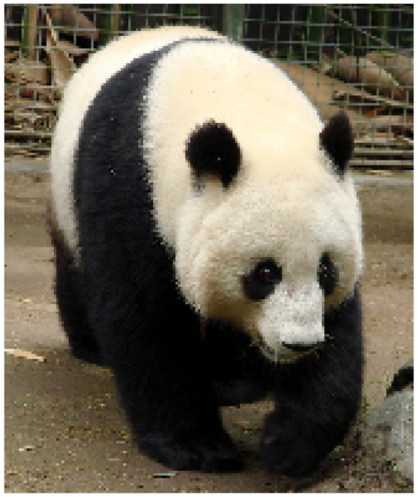
…but looks entirely different to the network.

Yes. It’s just that easy



original image
prediction: giant_panda

the perturbation,
enhanced 127 times



perturbed image
prediction: bucket

Why.....

- ....does this gradient-based attack make sense?
- ...did they use the sign of the gradient multiplied by a fixed step size, instead of the actual gradient?