Adversarial Examples

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

$\theta^{(t)}$ 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 $\theta^{(t)}$

$\eta$ controls the step size

$\theta^{(t_{\text{max}})}$ 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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What are these things really learning?

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?

The one on the right is a “perturbed” image
Gradient descent is moving the decision boundary.
What if we move a datapoint instead?
Gradient Descent Pseudocode

Initialize $\theta^{(0)}$
Repeat until stopping condition met:

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

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

$\theta^{(t)}$ 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 $\theta^{(t)}$

$\eta$ 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 $x^{(t)}$

$\eta$ controls the step size

$x^{(enough)}$ is the minimal change needed to flip the category of $x$
Even Simpler: Fast Gradient Sign method

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

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
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?