A Brief Introduction to Adversarial Examples

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Today’s talk

1. **Intro: What are adversarial examples?**
   a. Recent
   b. Intriguing
   c. Timely!
2. **Towards robust ML models**
3. **Adversarial Learning**

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   examples?
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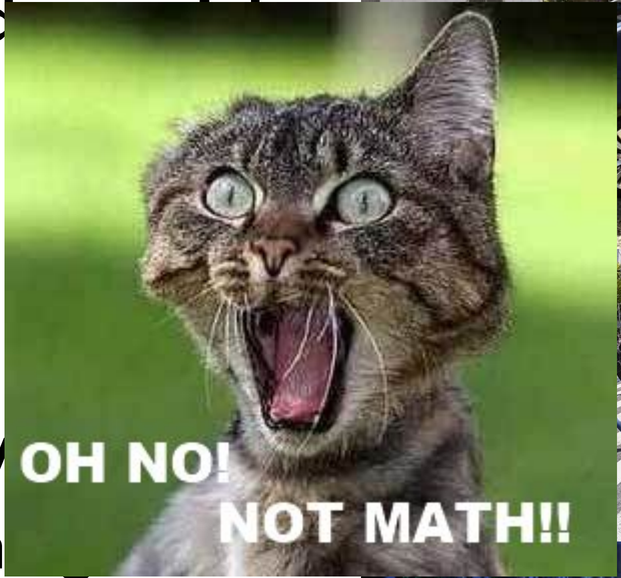
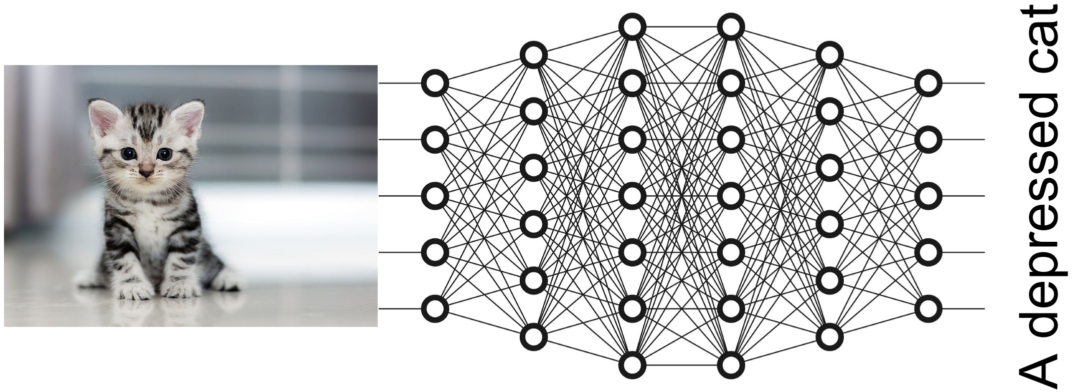
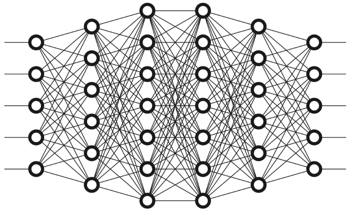


Understanding deep Learning w. visualization

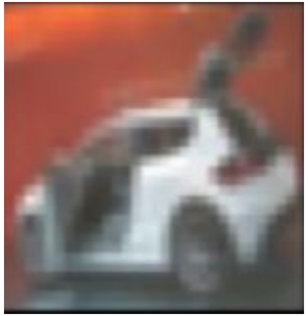


- Deep Learning: still a **black-box**
- Common way of “opening” up the black-box: **visualization**

Understanding deep Learning w. visualization



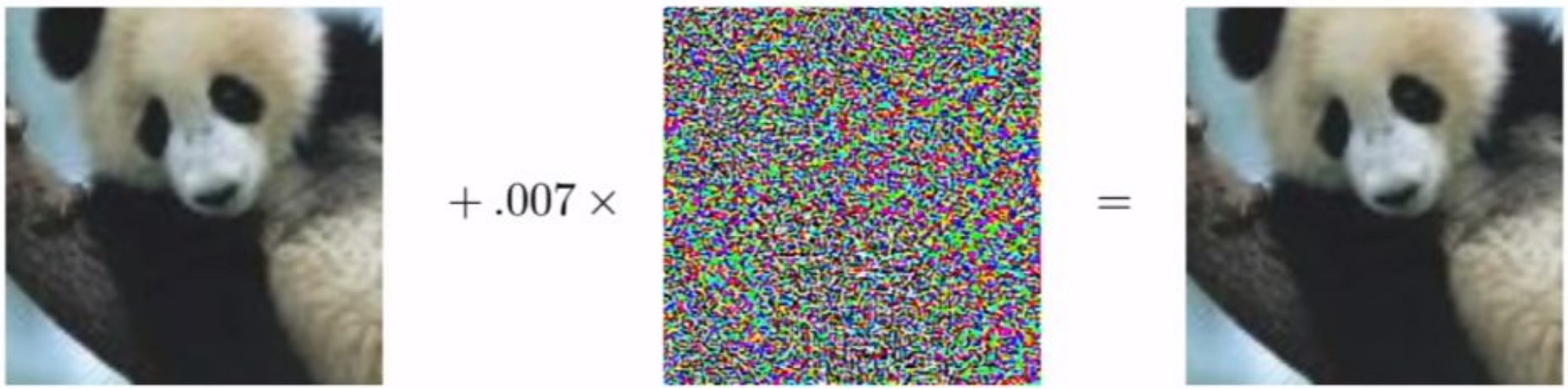
- **Example experiment**
  start with an image of an object, and ask: what changes do I need to make to that image so that the network will think that it is an airplane?



Understanding deep learning w. visualization

Szegedy et al., “**Intriguing properties of neural networks**” (2013)

Adversarial examples



"panda"
57.7% confidence

"gibbon"
99.3% confidence

Adversarial examples

A real gibbon

“panda”
57.7% confidence

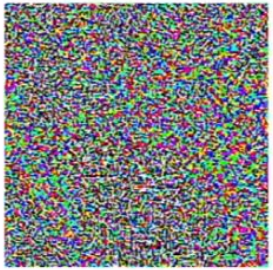
“gibbon”
99.3% confidence

“Imperceptible”

$\cong$

$\Leftrightarrow$

$.007 \times$

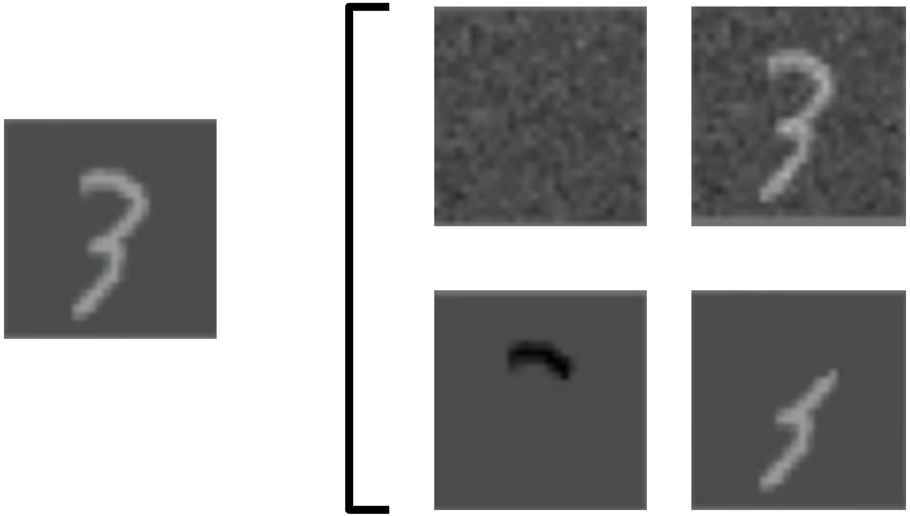


$\underbrace{\hphantom{.007 \times \text{noise image}}}$

small ∞ norm

“Imperceptible”

same l2 norm



“Imperceptible”

Elsayed et al., “**Adversarial Examples that Fool both Computer Vision and Time-Limited Humans**” (2018)

Why? The linear explanation

Goodfellow et al., "**Explaining and Harnessing Adversarial Examples**" (2015)

$$\tilde{\boldsymbol{x}} = \boldsymbol{x} + \boldsymbol{\eta}$$

$$||\boldsymbol{\eta}||_\infty < \epsilon$$

$$\boldsymbol{w}^\top \tilde{\boldsymbol{x}} = \boldsymbol{w}^\top \boldsymbol{x} + \boldsymbol{w}^\top \boldsymbol{\eta}$$

Why? The linear explanation

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Why? The linear explanation

Goodfellow et al., **"Explaining and Harnessing Adversarial Examples"** (2015)

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$$w^\top \tilde{x} = w^\top x + \underbrace{w^\top \eta}_{\epsilon m n}$$

In high-dimensions, infinitesimal changes "add up":
Even a simple linear model can have adversarial examples if its input has sufficient dimensionality.

Beyond security

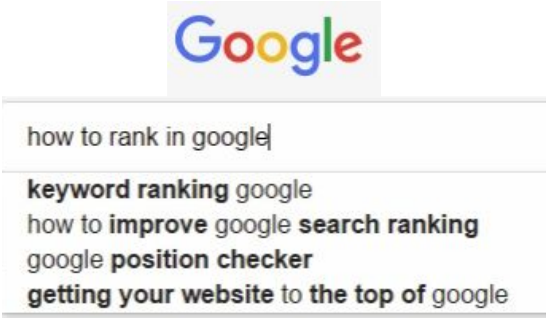
Madry et al., "**Fooling CNNs with Simple Transformations**" (2018)

Research in "Adversarial ML" is mostly around *malicious tampering*; but implications are much broader:

- Robustness against **natural fluctuations** in the underlying distribution
- Handling **feedback loops**: In high-stakes domains, incentives mean people may try to "game" the system.

  Example: Ranking search queries with ML

revolver mousetrap



Bob Sturm., “**Clever Hans, Clever Algorithms**”

What do we do?

(1) Standard classification objective

$$\mathbb{E}_{x,y\sim D}\left[L(f(x),y)\right]$$

Madry et al., "**Towards Deep Learning Models Resistant to Adversarial Attacks**" (2018)

What do we do? Robust classification!

(1) Standard classification objective

$$\mathbb{E}_{x,y\sim D}\left[L(f(x),y)\right]$$

(2) Robust classification objective

$$\mathbb{E}_{x,y\sim D}\left[\max_{x'\in P(x)} L(f(x'),y)\right]$$

Madry et al., "**Towards Deep Learning Models Resistant to Adversarial Attacks**" (2018)

Robust optimization by empirical risk minimization

Q: How do we learn a classifier with small loss (2)?

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Robust optimization by empirical risk minimization

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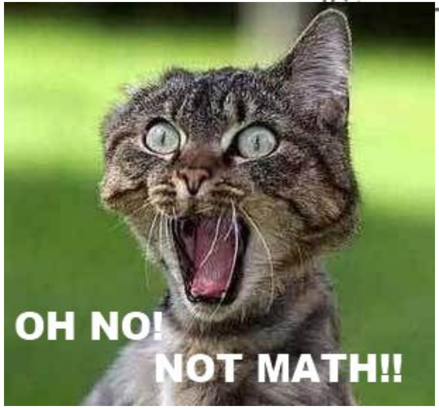

Robust optimization by empirical risk minimization

Q: How do we learn a classifier with small loss (2)?

$$\mathbb{E}_{x,y\sim D}\left[\max_{x'\in P(x)} L(f(x'),y)\right]$$

A: Use an analogous "robustified" variant of ERM, i.e solve:

$$\min_{\theta} \frac{1}{n}\sum_{i=1}^{n} \max_{x'\in P(x_i)} L(f_\theta(x'),y_i)\ .$$

Robust optimization by empirical risk minimization

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Training a robust classifier

Attacking a particular neural network

$$\min_\theta \frac{1}{n}\sum_{i=1}^{n} \max_{x'\in P(x_i)} L(f_\theta(x'),y_i)\ .$$

$$\mathbb{E}_{x,y \sim D}[L(f(x), y)]$$

Standard SGD

Repeat:

Sample $\mathbf{x_1 ... x_m} \sim \mathbf{D}$

Compute gradients of the the loss **L** with parameters $\boldsymbol{\theta}$ w.r.t $\mathbf{x_1 ... x_m}$

Update $\boldsymbol{\theta}$ by taking a step in the direction opposite to the gradient

Training a robust classifier

Attacking a particular neural network

Solving the robustified ERM

$$\min_{\theta} \frac{1}{n} \sum_{i=1}^{n} \max_{x' \in P(x_i)} L(f_\theta(x'), y_i) \;.$$

- SGD on the **outer minimization** problem requires **gradients of the inner maximization** problem
- Let **x*** denote the optimal solution of the inner maximization.
- Danskin's Theorem: $\nabla_\theta \phi_{x,y}(\theta) = \nabla_\theta L(f_\theta(x^*), y)$

Solving the robustified ERM

$\phi_{x,y}(\theta) =$

Training a robust classifier

Attacking a particular neural network

This highlights the **duality** between **attacking** a classifier and **training** a robust classifier:

if we have a good attack, we also have a method for finding good gradients of the robust loss.

- S… …he inner maximizatio…
- Let x* denote the o… …mal solution of the inner maximization.
- **Danskin's Theorem**: $\nabla_\theta \phi_{x,y}(\theta) = \nabla_\theta L(f_\theta(x^*), y)$

Adversarial Training

Repeat:

Sample $\mathbf{x}_1 \ldots \mathbf{x}_m \sim \mathbf{D}$

Compute adversarial perturbations $x^*_1 \ldots, x^*_m$

Compute gradients of the the loss **L** with parameters $\boldsymbol{\theta}$ w.r.t $x^*_1 \ldots x^*_m$

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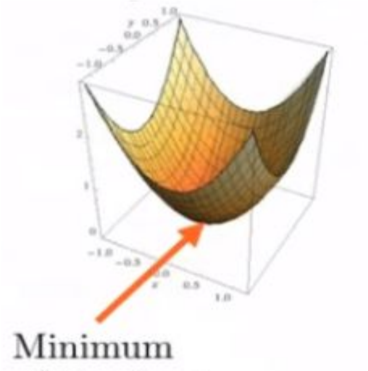
provably **hard**, even for simple networks…

More generally: Adversarial Learning

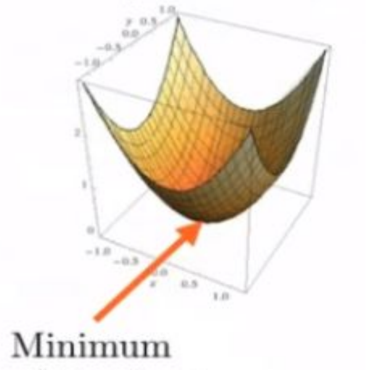
Traditional ML



1 Player, 1 Cost function

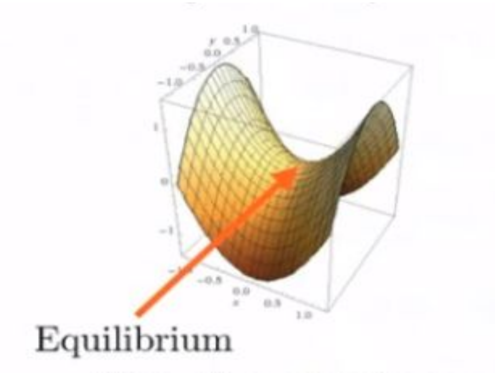
More generally: Adversarial Learning

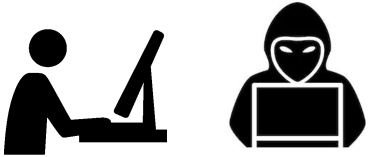
Traditional ML



1 Player, 1 Cost function

Adversarial ML





1+ Players, 1+ Cost functions

Revisiting the "robust ERM"

Adversarial training: a **minimax** problem, with the learning algorithm as the **minimizing** player, and the attacker as the **maximizing** player

$$\min_{\theta} \frac{1}{n} \sum_{i=1}^{n} \max_{x' \in P(x_i)} L(f_\theta(x'), y_i) \ .$$

Recap

- Adversarial examples:
    - an intriguing, but also intuitive, phenomena
    - a solution *sketch:* adversarial training
- The same tools (robust classification, adversarial learning) can be useful even when there *isn't* a fear of an actual, real-world, adversary