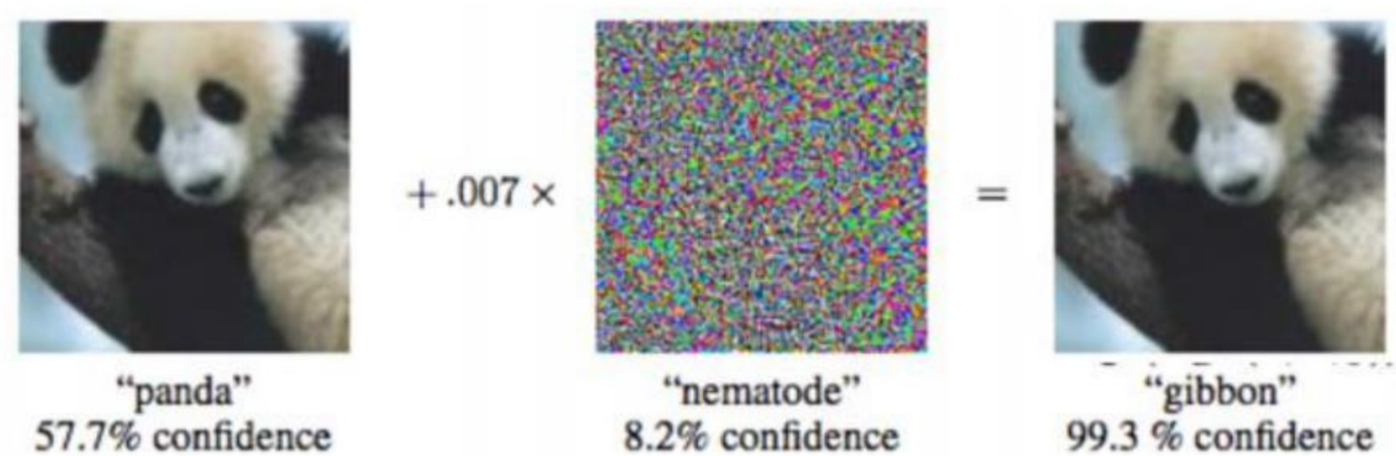
Generalization and Adversarial Examples



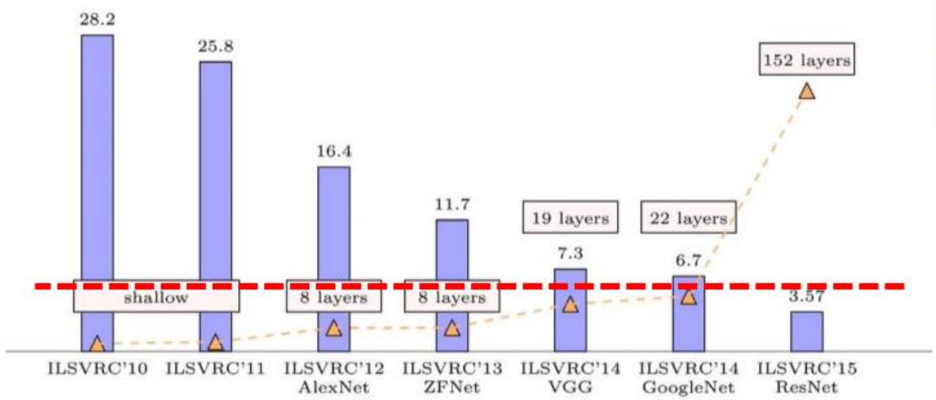
Slides from Sergey Levine and Ian Goodfellow

ECE324, Winter 2023

Michael Guerzhoy

Do deep nets generalize?

What a strange question!



human performance:
about 5% error

but what about the **mistakes**? What kinds of mistakes are they?

Do deep nets generalize?

Do deep nets generalize?

(a) Husky classified as wolf (b) Explanation

Figure 11: Raw data and explanation of a bad model's prediction in the "Husky vs Wolf" task.

Clever Hans: a metaphor for machine learning?

Clever Hans

or: when the training/test paradigm goes wrong

Everything might be “working as intended”, but we might still not get what we want!

Distribution shift

- One source of trouble: the test inputs might come from a different distribution than training inputs
  - Often especially problematic if the training data has spurious correlations

traffic sign classification dataset

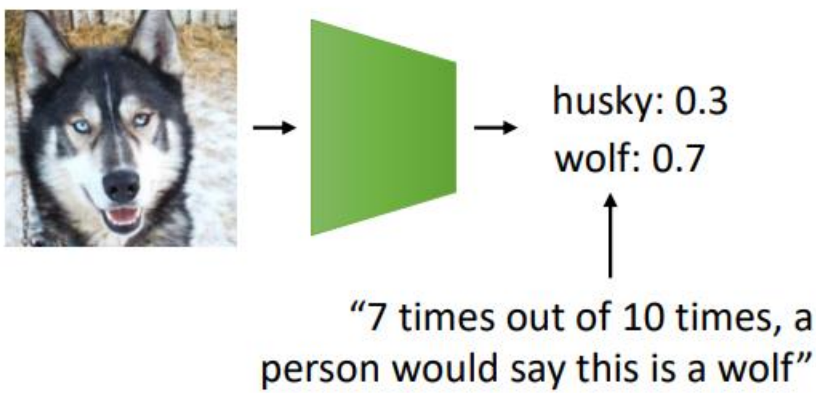
traffic sign in reality

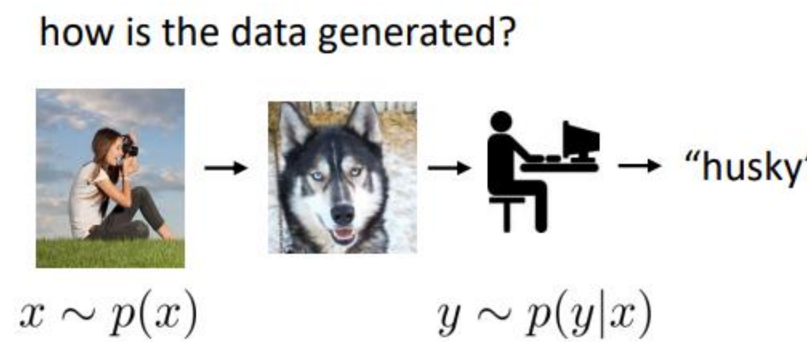
Distribution shift

- Medical imaging: different hospitals have different machines
  - Even worse, different hospitals have different positive rates (e.g., some hospitals get more sick patients)
  - Induces machine ⟺ label correlation
- Selection biases: center crop, canonical pose, etc.
- Feedback: the use of the ML system causes users to change their behavior, thus changing the input distribution
  - Classic example: spam classification

Calibration

- In this context: the predicted probabilities reflect the actual frequencies of the predicted events



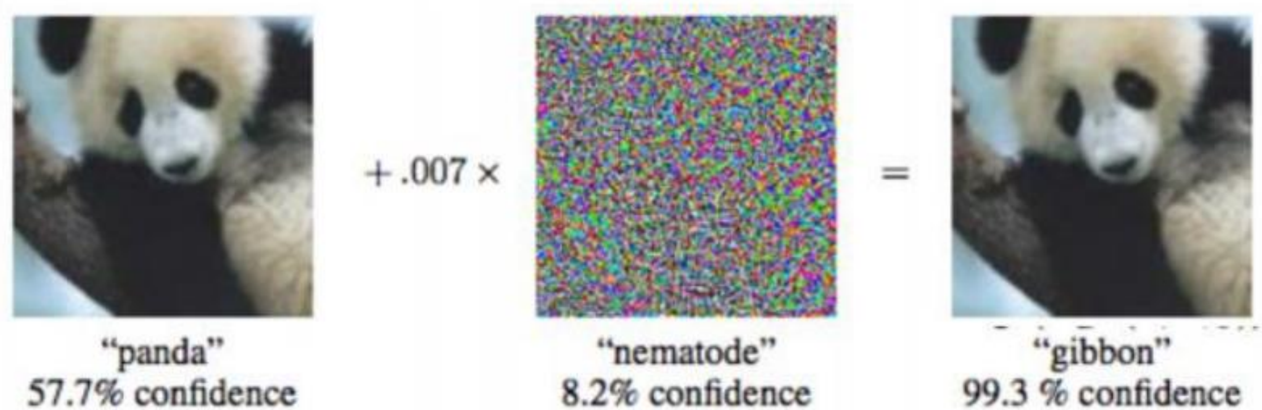


Calibration

- In-distribution predictions (i.e., predictions on samples from the training set) are usually not calibrated, but there are methods to improve calibration
- Typically, models give confident but wrong predictions on out-of-distribution inputs
    - Models are typically trained on examples where the outputs are 1 or 0

Adversarial examples

this is **not** random noise –
special pattern design to "fool"
the model

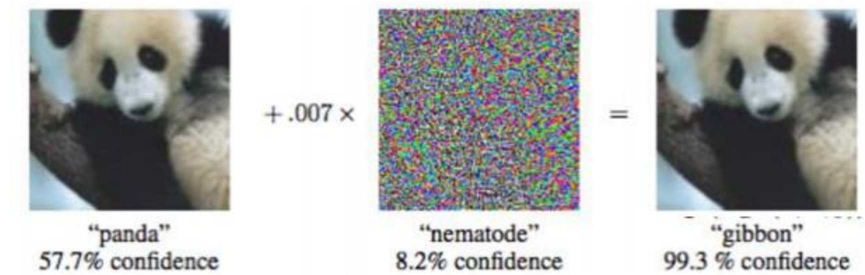


What's going on here? very special patterns, almost imperceptible to people, can change a model's classification drastically

Why do we care? **The direct issue:** this is a potential way to "attack" learned classifiers
The bigger issue: this implies some strange things about generalization

Adversarial examples: overview

- It's not just for gibbons. Can turn basically anything into anything else with enough effort
- It is not easy to defend against, obvious fixes can help, but nothing provides a bulletproof defense (that we know of)
- Adversarial examples can transfer across different networks (e.g., the same adversarial example can fool both AlexNet and ResNet)
- Adversarial examples can work in the real world, not just special and very precise pixel patterns
- Adversarial examples are not specific to (artificial) neural networks, virtually all learned models are susceptible to them



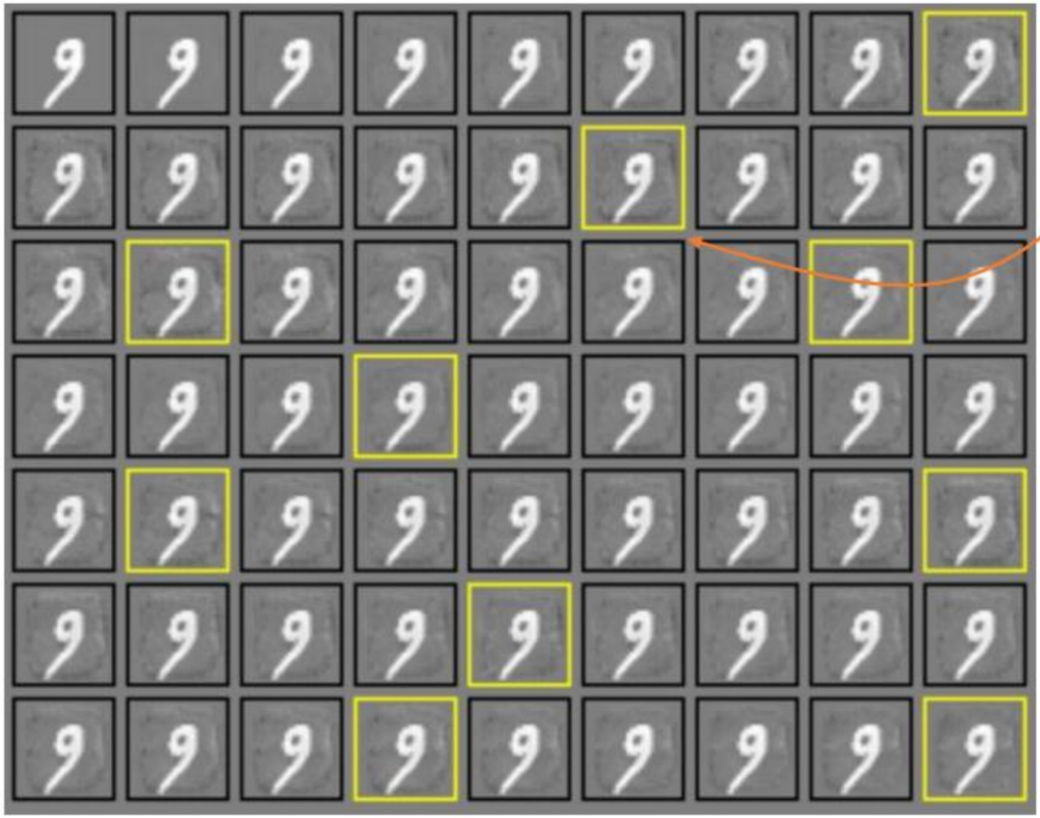
← speed limit: 45

photo is not altered in any way!

but the sign is

including your brain, which is a type of learned model

A problem with deep nets?



classified as “0” (90%)

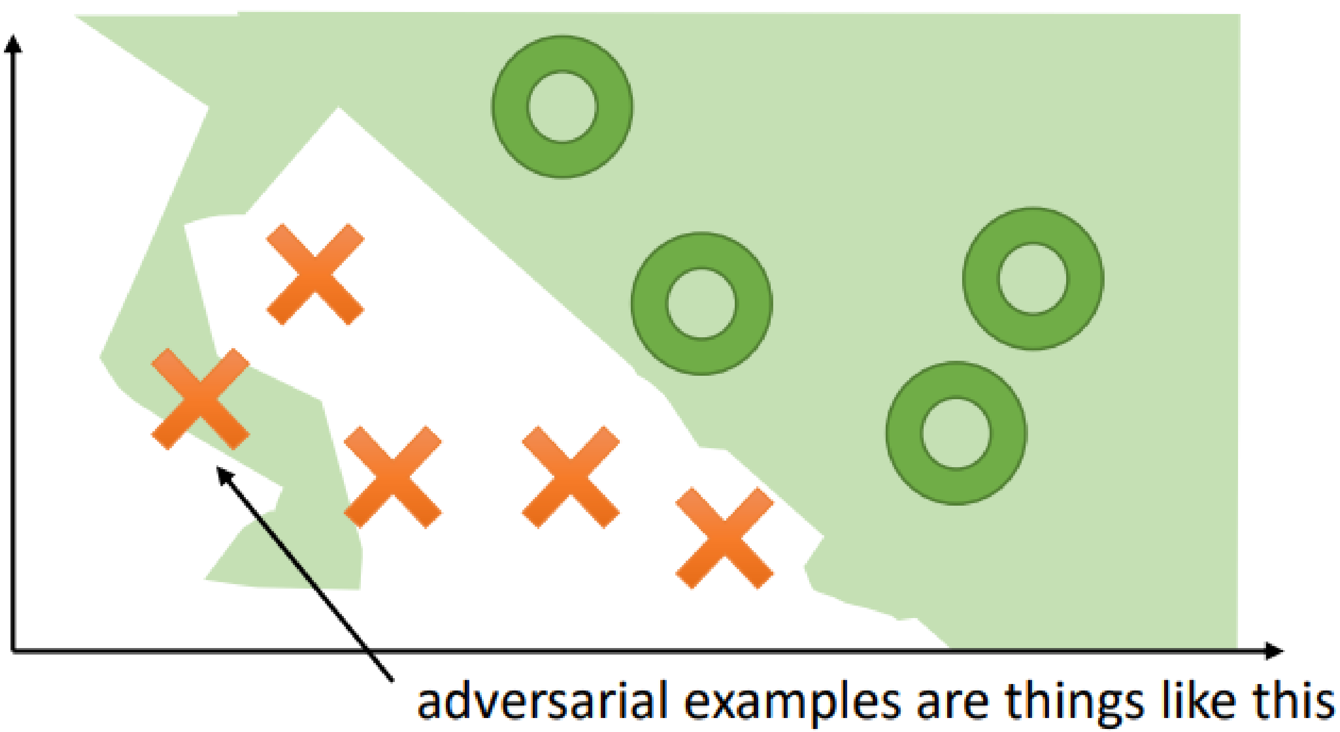
classified as “1” (90%)

linear model (logistic regression)

adversarial examples appear to be a general phenomenon for most learned models (and all high-capacity models that we know of)

Is it due to overfitting?

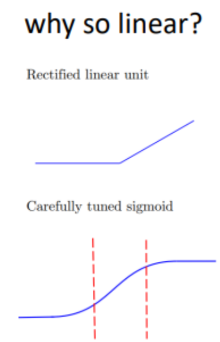
- The mental model:



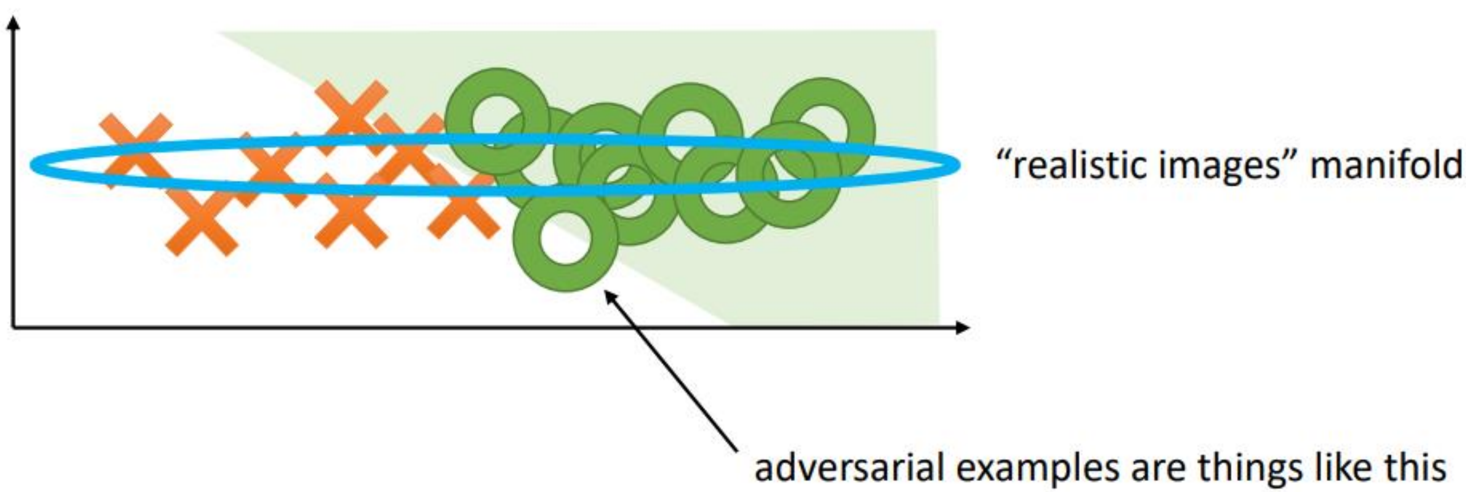
Is it due to overfitting?

- Overfitting hypothesis: because neural nets have a huge number of parameters, they tend to overfit, making it easy to find inputs that produce crazy outputs
  - If this were true, we would expect different models to have very different adversarial examples (high variance)
    - This is conclusively not the case
  - If this were true, we would expect low capacity models (e.g., linear models) not to have this issue
    - Low capacity models also have this
  - If this were true, we would expect highly nonlinear decision boundaries around adversarial examples
    - This appears to not be true

Linear models hypothesis



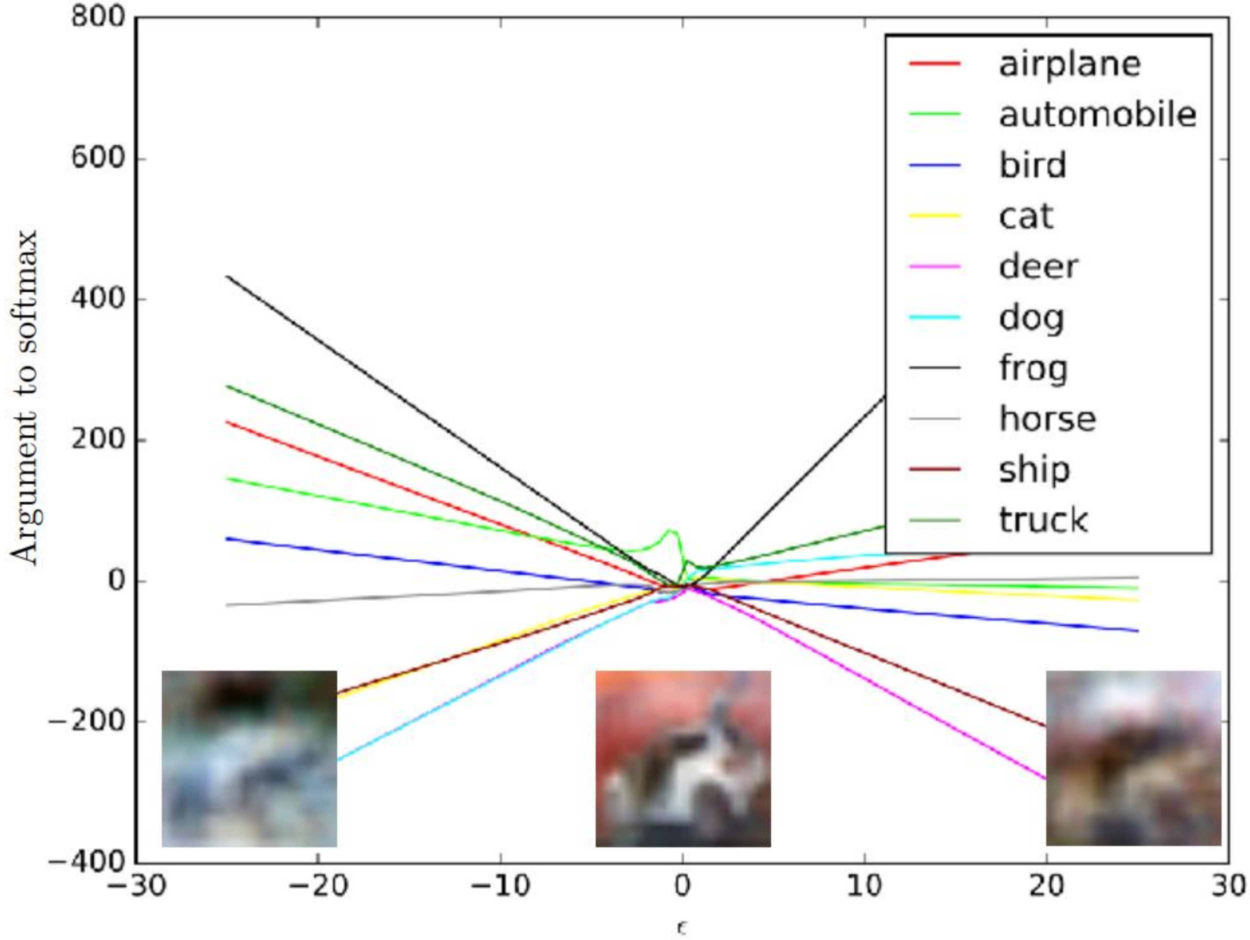
- Linear models hypothesis: because neural networks (and many other models!) tend to be locally linear, they extrapolate in somewhat counterintuitive ways when moving away from the data



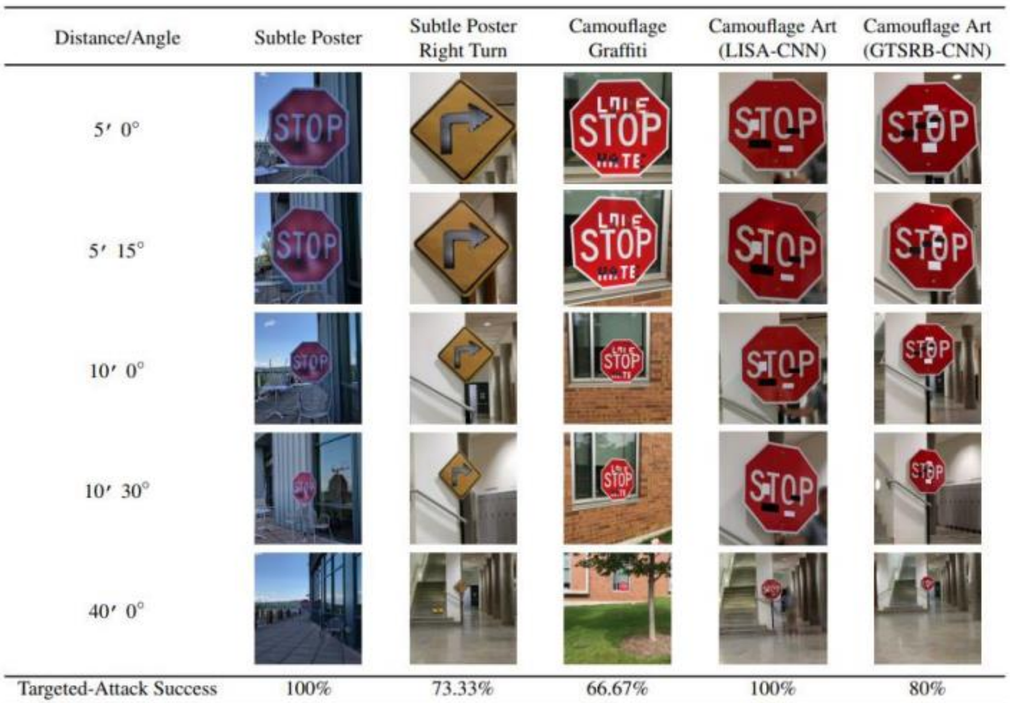
Linear models hypothesis

- Consistent with transferability of adversarial examples
- Consistent with this not being an issue of overfitting

Linear models hypothesis

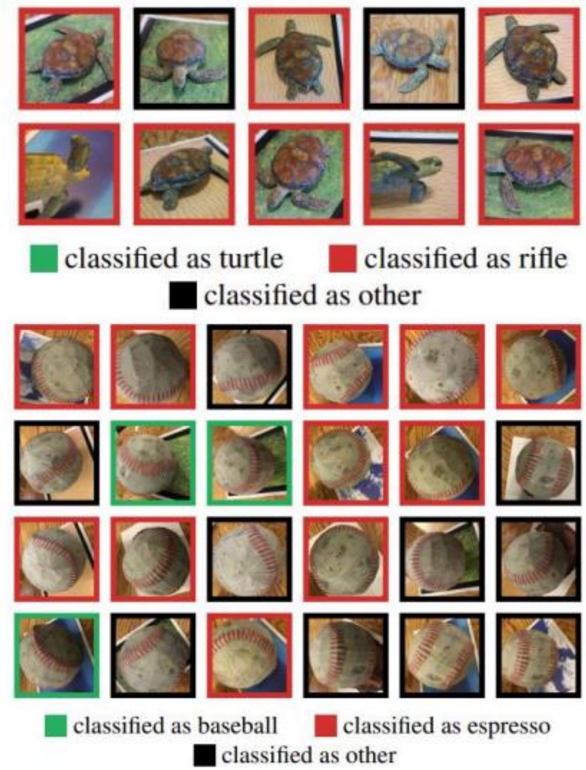


Real-world adversarial examples



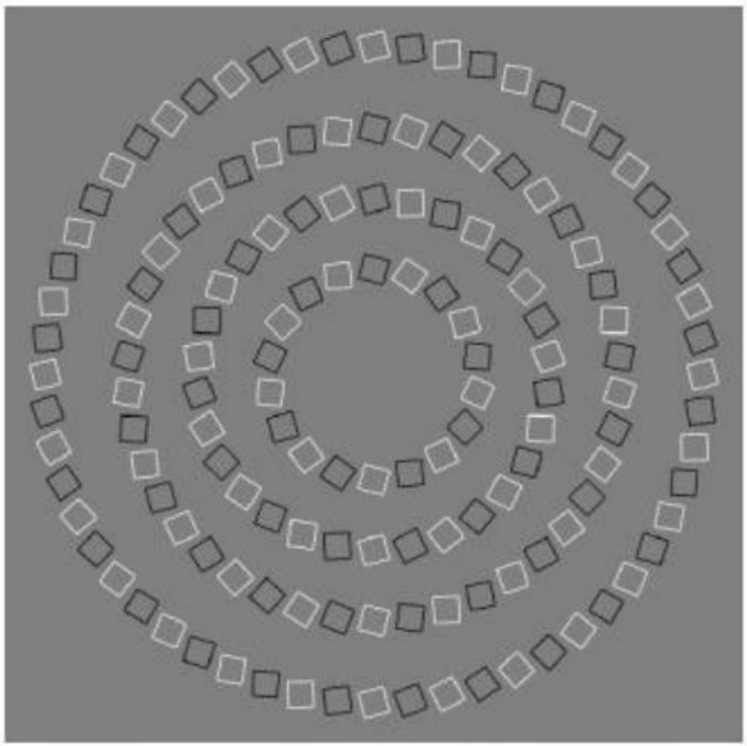
all of these turn into 45 mph speed limit signs

Eykholt et al. **Robust Physical-World Attacks on Deep Learning Visual Classification**. 2018.



Athalye et al. **Synthesizing Robust Adversarial Examples**. 2017.

Human adversarial examples?



(Pinna and Gregory, 2002)

These are concentric circles, not intertwined spirals.

(Goodfellow 2016)

Human adversarial examples?

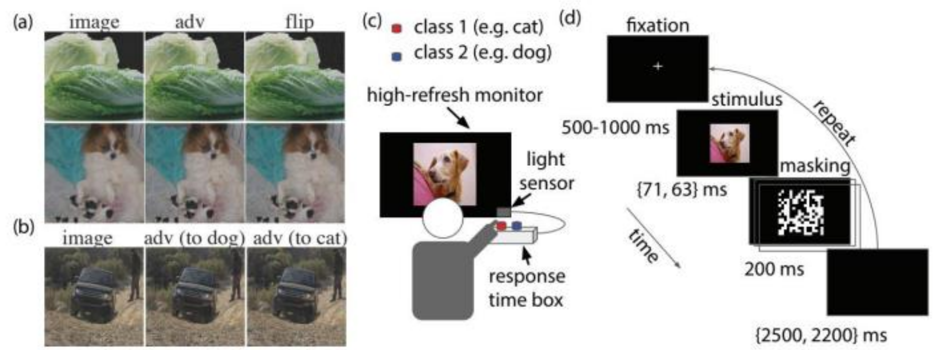


Figure 1: **Experiment setup and task.** (a) examples images from the conditions (`image`, `adv`, and `flip`). Top: `adv` targeting broccoli class. bottom: `adv` targeting cat class. See definition of conditions at Section 3.2.2. (b) example images from the `false` experiment condition. (c) Experiment setup and recording apparatus. (d) Task structure and timings. The subject is asked to repeatedly identify which of two classes (e.g. dog vs. cat) a briefly presented image belongs to. The image is either adversarial, or belongs to one of several control conditions. See Section 3.2 for details.

Elsayed et al. **Adversarial Examples that Fool both Computer Vision and Time-Limited Humans.** 2018.

Adversarial examples and generalization

- Linear hypothesis is relevant not just for adversarial examples, but for understanding how neural nets do (and don't) generalize
- When you train a model to classify cats vs. dogs, it is not actually learning what cats and dogs look like, it is learning about the patterns in your dataset
  - From there, it will extrapolate in potentially weird ways
- Basic idea: neural nets pay attention to "adversarial directions" because it helps them to get the right answer on the training data!

Summary

- Neural nets generalize very well on tests sets drawn from the same distribution as the training set
- They sometimes do this by being a smart horse
  - This is not their fault! It's your fault for asking the wrong question
- NNs are often not well-calibrated, especially on out-of-distribution inputs
- A related (but not the same!) problem is that we can almost always synthesize adversarial examples by modifying normal images to "fool" a neural network into producing an incorrect label
- Adversarial examples are most likely not a symptom of overfitting
  - There is reason to believe they are actually due to excessively linear (simple) models attempting to extrapolate + distribution shift

Adversarial attacks

Real attackers don't care about your definitions

relation: $R(x, x')$

original image

altered image

speed limit: 45
what is ϵ?

example: $R_\infty(x, x') = ||x - x'||_\infty$

each pixel changed by at most ϵ

attack: $x^\star \leftarrow \arg\max_{x': R(x,x') \leq \epsilon} \mathcal{L}_\theta(x', y)$

e.g., $\mathcal{L}_\theta(x, y) = -\log p_\theta(y|x)$

pick image x' close to x

maximize the loss of your choice

defense: $\theta^\star \leftarrow \arg\min_\theta \underbrace{\sum_{(x,y)\in D} \max_{x': R(x,x') \leq \epsilon} \mathcal{L}_\theta(x', y)}_{\text{robust loss}}$

Fast gradient sign method (FGSM)

A very simple approximate method for an infinity norm relation

$R(x, x') = ||x - x'||_\infty$

attack: $x^\star \leftarrow \arg\max_{x':R(x,x')\leq\epsilon} \mathcal{L}_\theta(x', y)$

"first order" assumption: $\mathcal{L}(x', y) \approx \mathcal{L}(x, y) + (x' - x)^T \nabla_x \mathcal{L}$

ordinarily, we might think that this would make for a very **weak** attack, but we saw before how neural nets seem to behave locally linearly!

attack: $x^\star \leftarrow \arg\max_{x':||x-x'||_\infty\leq\epsilon} (x' - x)^T \nabla_x \mathcal{L}$

optional solution: move each dimension of x in direction of $\nabla_x \mathcal{L}$ by ϵ

$$x^\star = x + \epsilon \text{sign}(\nabla_x \mathcal{L})$$

this works **very well** against standard (naïve) neural nets

it can be defeated with simple defenses, but more advanced attacks can be more resilient

A more general formulation

- Attack:

$$x^* \leftarrow argmax_{x':R(x,x')\leq\epsilon} L_\theta(x', y)$$

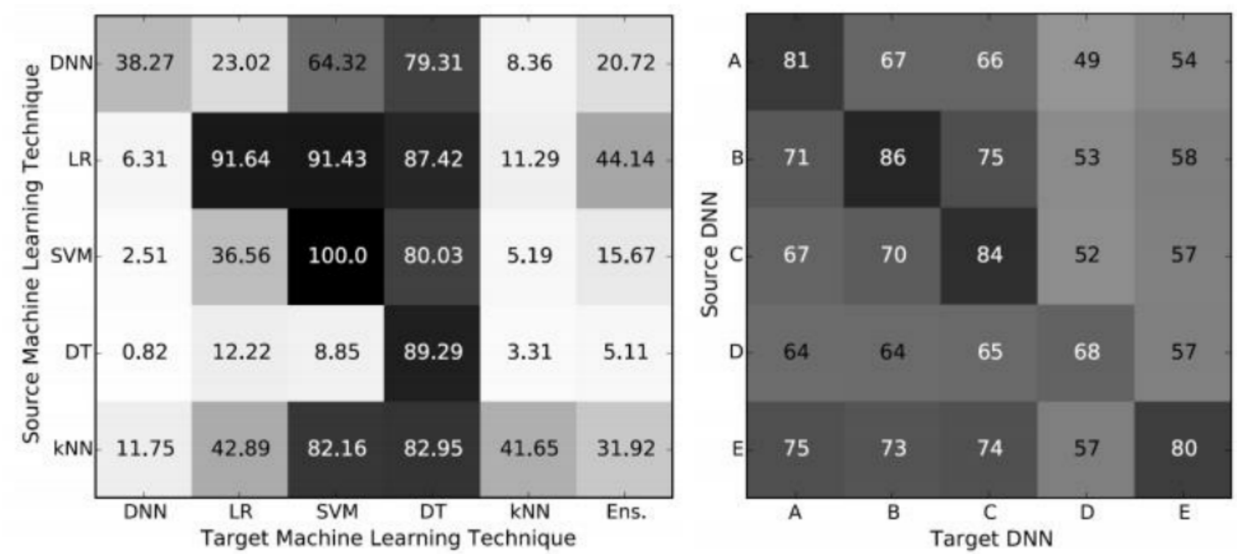
- Use a Lagrange multiplier:

$$x^* \leftarrow argmax_{x'} L_\theta(x', y) - \lambda R(x, x')$$

  - Choose λ heuristically, or optimize alternately for x' and λ

Transferability of adversarial attacks

Oftentimes it just works

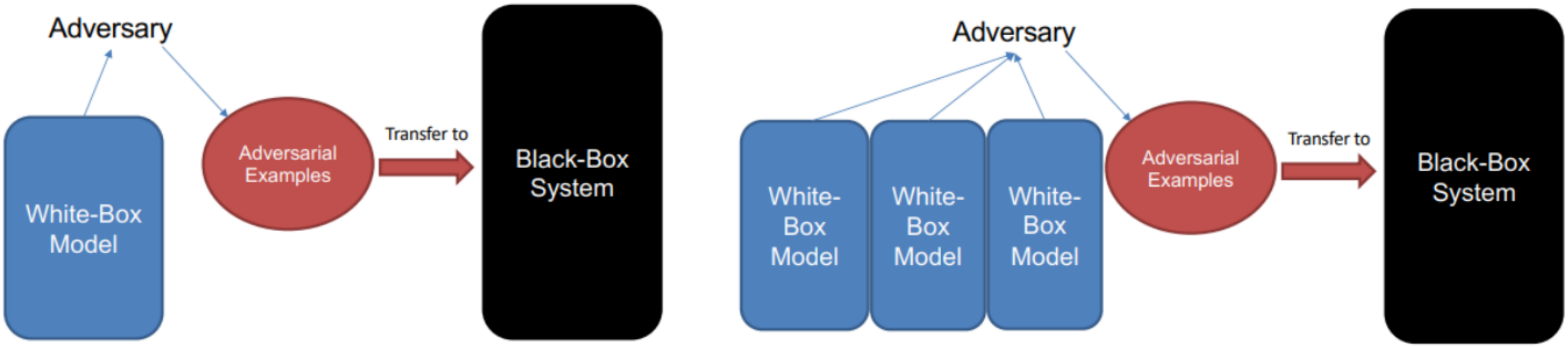


In particular, this means that we often don't need direct gradient access to a neural net we are actually attacking – we can just use **another** neural net to construct our adversarial example!

% success rate at fooling one model when trained on another

Papernot et al. **Transferability in Machine Learning: from Phenomena to BlackBox Attacks using Adversarial Samples**. 2016.

Zero-shot black-box attack



Liu, Chen, Liu, Song. **Delving into Transferable Adversarial Examples and Black-box Attacks**, ICLR 2017

Finite differences gradient estimation

It's possible to estimate the gradient with a moderate number of queries to a model (e.g., on a web server) without being able to actually directly access its gradient

$$x^\star = x + \epsilon \text{sign}(\nabla_x \mathcal{L})$$

all we need is the sign of the gradient

for each dimension i of x:

$\quad$ get $v_i \leftarrow \mathcal{L}(x + 10^{-3} e_i, y)$

a small number

i^{th} canonical vector

$$\nabla_x \mathcal{L} \approx (v - \mathcal{L}(x, y))/(10^{-3})$$

Defending against adversarial attacks

There are **many** different methods in the literature for "robustifying" models against adversarial examples

$$\text{defense: } \theta^\star \leftarrow \arg\min_\theta \underbrace{\textstyle\sum_{(x,y)\in D} \max_{x': R(x,x')\le\epsilon} \mathcal{L}_\theta(x', y)}_{\text{robust loss}}$$

Simple recipe: adversarial training

1. sample minibatch $\{(x_i, y_i)\}$ from dataset $\mathcal{D}$
2. for each x_i, compute adversarial x_i' — e.g., FGSM: $x_i' \leftarrow x_i + \epsilon \text{sign}(\nabla_{x_i} \mathcal{L}_\theta(x_i, y_i))$
3. take SGD step: $\theta \leftarrow \theta - \alpha \sum_i \nabla_\theta \mathcal{L}_\theta(x_i', y_i)$ — usually also add original loss grad $\nabla_\theta \mathcal{L}_\theta(x_i, y_i)$

Usually doesn't come for free:
increases robustness to adversarial attacks (lower % fooling rate)
decreases overall accuracy on the test set (compared to naïve network)