Brainwashing Computers: nudging neural networks to make reckless decisions

SIG Research Meeting

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Contents

What?

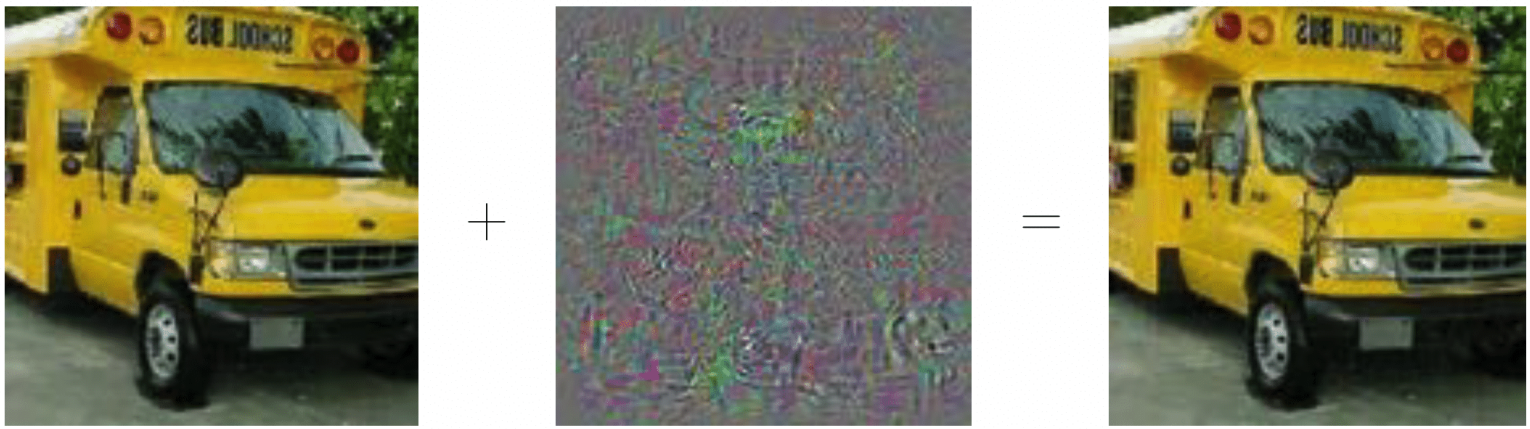

Figure: Adversarial Examples [11].

What?

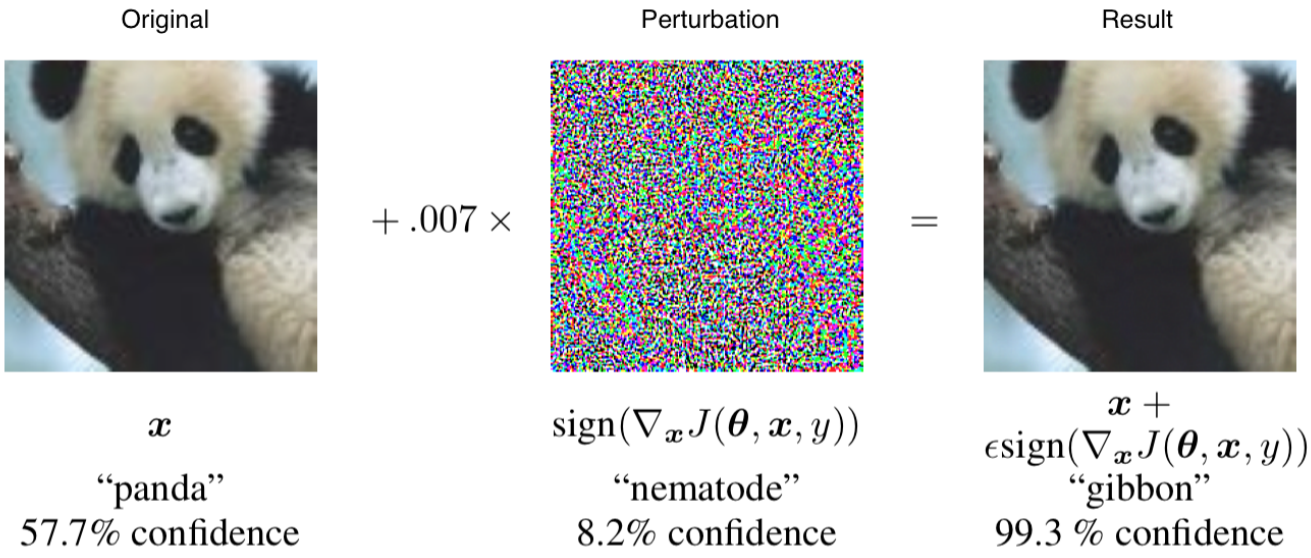

Figure: Adversarial examples are inputs to machine learning models that an attacker has intentionally designed to cause the model to make a mistake [6].

Why?

Machine learning achieved high performance on a variety of tasks:

Figure: Left: Object Detection [4]. Middle: Malware Detection [3]. Right: Self-driving cars [2]

Why?

Some tasks are safety critical:

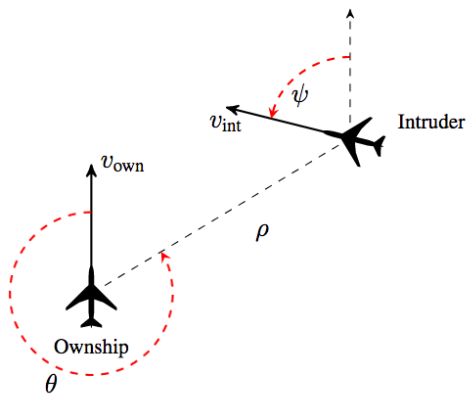

Figure: Left: Traffic Sign Detection [5]. Right: Airplane Collision Avoidance [7]

Deep Learning Recap [remember last talk?]

Recap: Machines Learning

Definition

Computer programs learn from *experience* E with respect to some class of *tasks* T and *performance measure* P, if its performance at tasks in T as measured by P *improves* with experience E [8].

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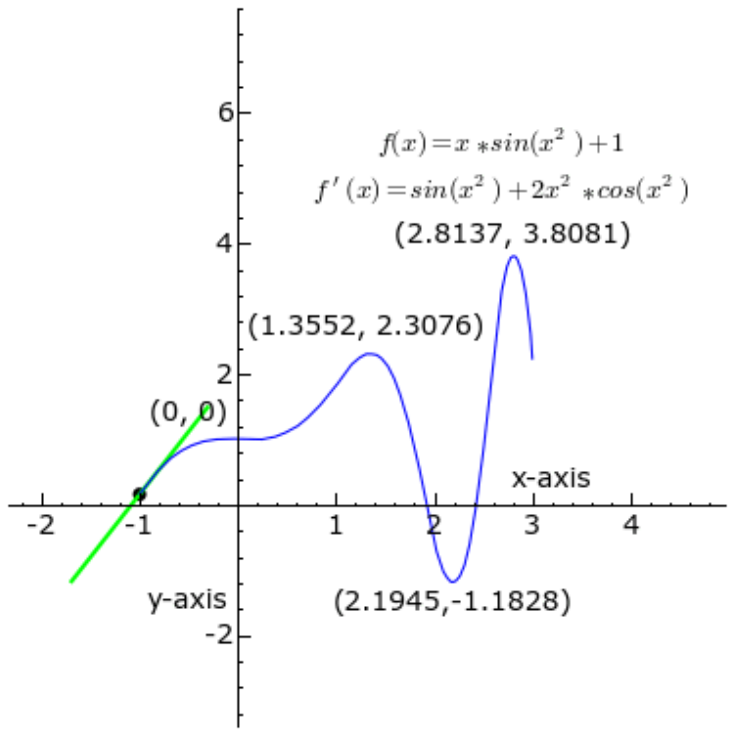
1. Task - understand images, move boxes, etc.
2. Experience - interpret *data*
3. Performance measure i.e. error/cost/objective functions - number of correct objects recognised, number of boxes moved, etc.

Learning is used analogously to *modeling* i.e. finding the best function $f(x, \theta)$ that can approximate a task.

Recap: Minimising Error

Definition

A function $f(x)$ is *increasing* on any interval in which $f'(x) > 0$ and it is *decreasing* on any interval in which $f'(x) < 0$.



Recap: Gradient

$$f : \mathbb{R}^n \to \mathbb{R}$$
$$y = f(x_1, x_2, \ldots x_n, \theta)$$
$$\nabla f(x) = \left(\frac{\partial f}{\partial x_1}, \ldots, \frac{\partial f}{\partial x_n} \right)$$

Definition

The gradient is a multi-variable generalisation of the derivative.

Recap: The Jacobian Matrix

$$f : \mathbb{R}^n \to \mathbb{R}^m$$

$$(y_1, y_2, \ldots y_m) = f(x_1, x_2 \ldots x_n, \theta)$$

$$\mathbf{J} = \begin{bmatrix} \frac{\partial \mathbf{f}}{\partial x_1} & \cdots & \frac{\partial \mathbf{f}}{\partial x_n} \end{bmatrix} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1} & \cdots & \frac{\partial f_m}{\partial x_n} \end{bmatrix}$$

Definition

The Jacobian Matrix is the matrix of all *first-order* partial derivatives of a *vector-valued* function.

A simple example

Problem setting:

Task: Classify irises (flowers) in two categories.

Experience: Labeled
measurements: $(x, y) = ([\mathit{height}, \mathit{color}, \ldots], \mathit{Virginica})$

Performance measure?

Model $[f(x, \theta)]$?

Linear Models

Performance: Mean Squared Error (MSE)

Model: $\hat{y} = \boldsymbol{W}^{\boldsymbol{T}} \boldsymbol{x}$

Where:

$\boldsymbol{W} \in \mathbb{R}^n$ is a vector of parameters

$MSE = \frac{1}{m} \sum_i (\hat{y}^{(test)} - y^{(test)})_i^2$

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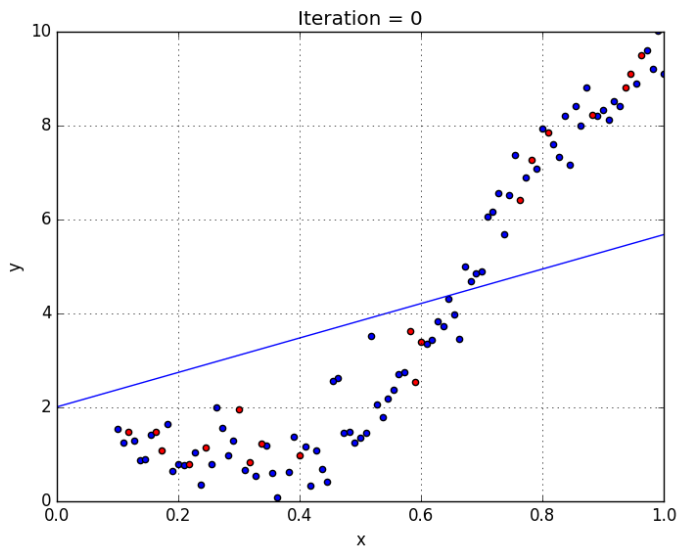
Solution: Compute derivatives!

Linear Models

Solution:

$$\nabla_w MSE_{train} = 0$$

$$\nabla_w \frac{1}{m} \sum_i (\hat{y}^{(test)} - y^{(test)})_i^2$$



In search for better approximations

Requirements:

- Represent highly nonlinear functions in large hyper-spaces
- Derivable
- Parallel scaling

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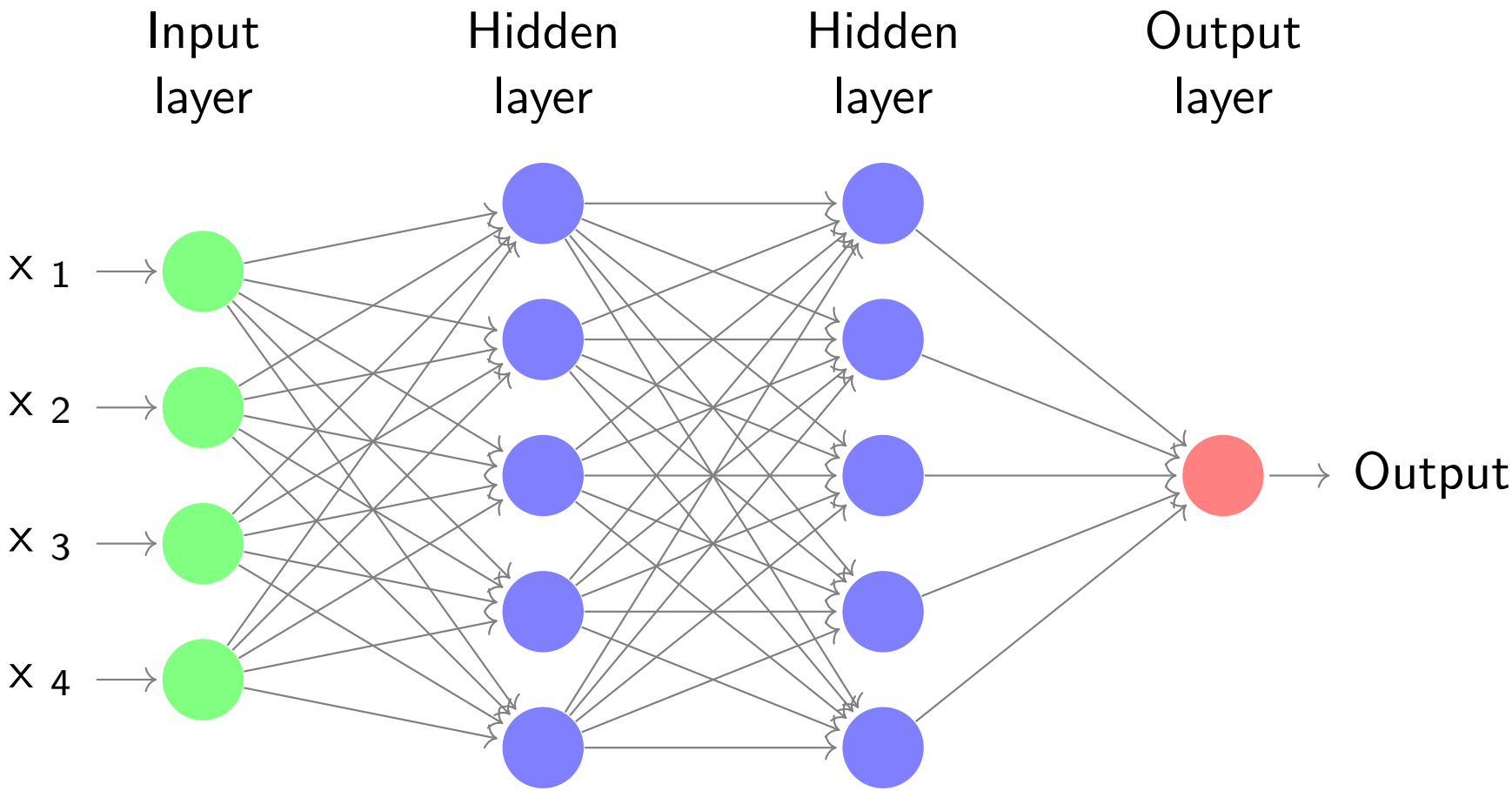
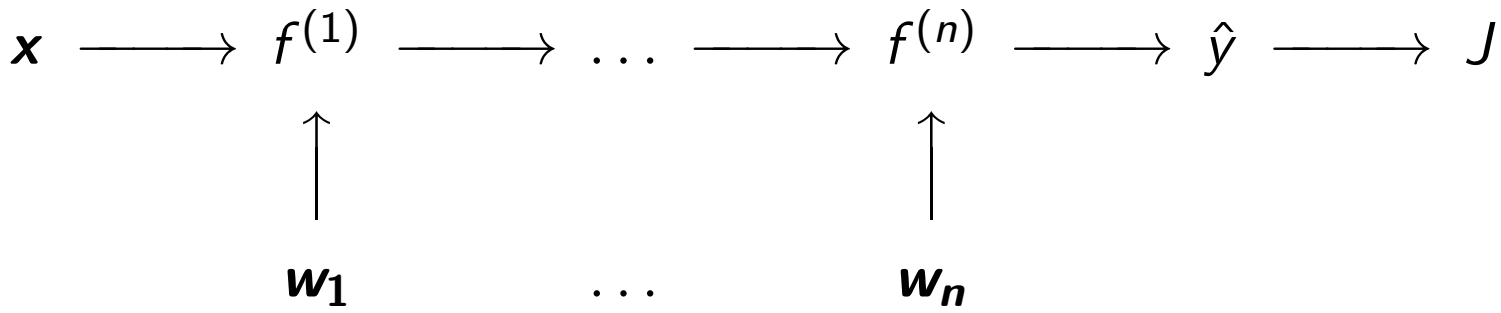
Solution? Functional *composition*!

Neural Networks



Deep Representations

- A *deep representation* is a composition of many functions



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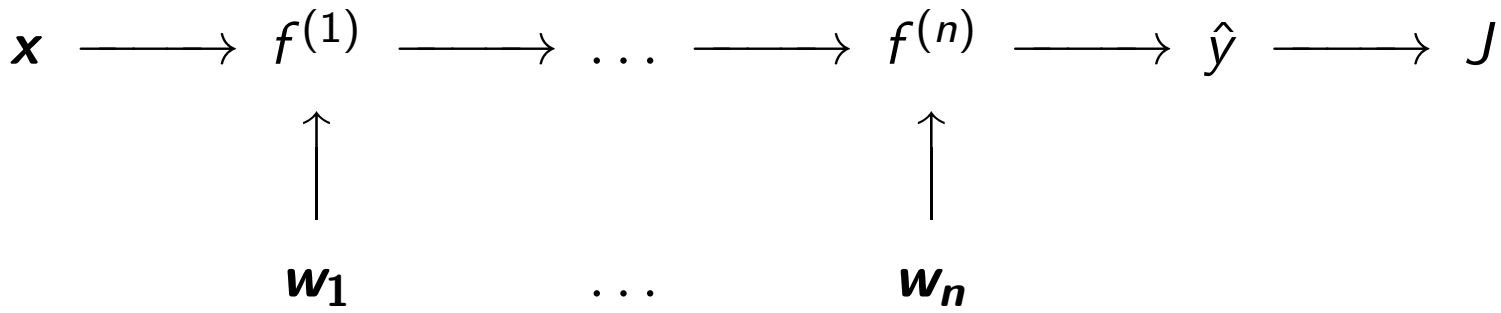
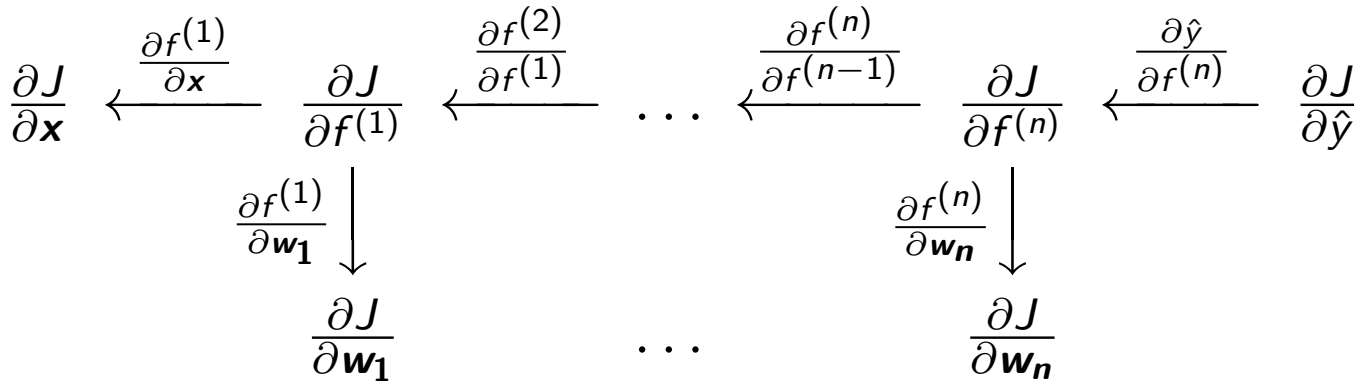


- Its gradient can be *back-propagated* by the chain rule



Projection in High Dimensional Space

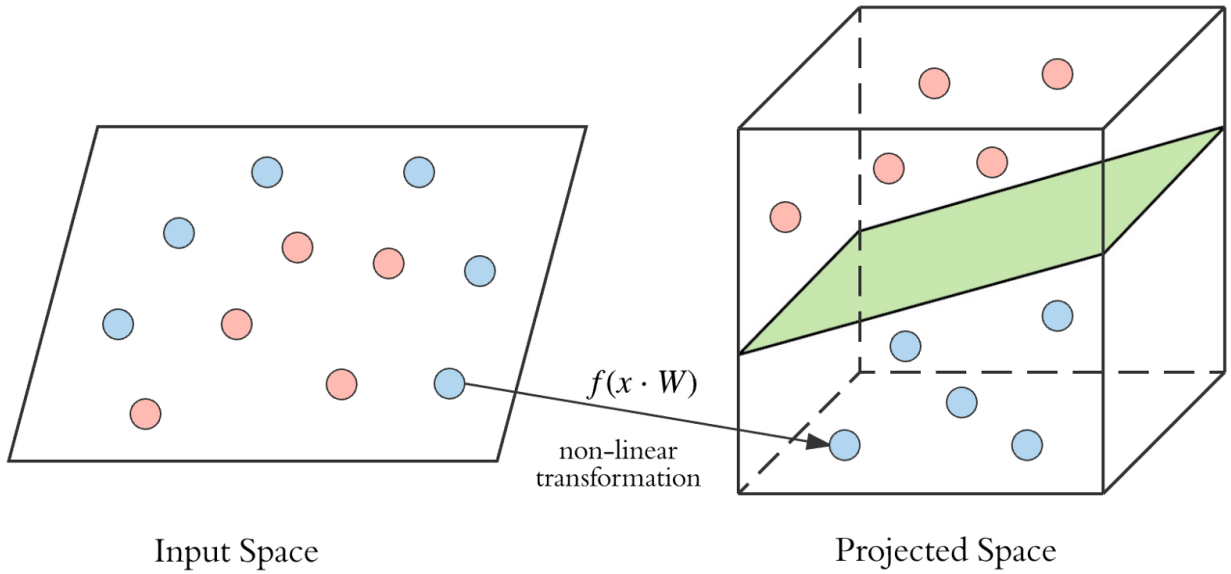


Figure: Example of Projection in R^3 [1].

Attacks [why? how?]

I.I.D Assumption

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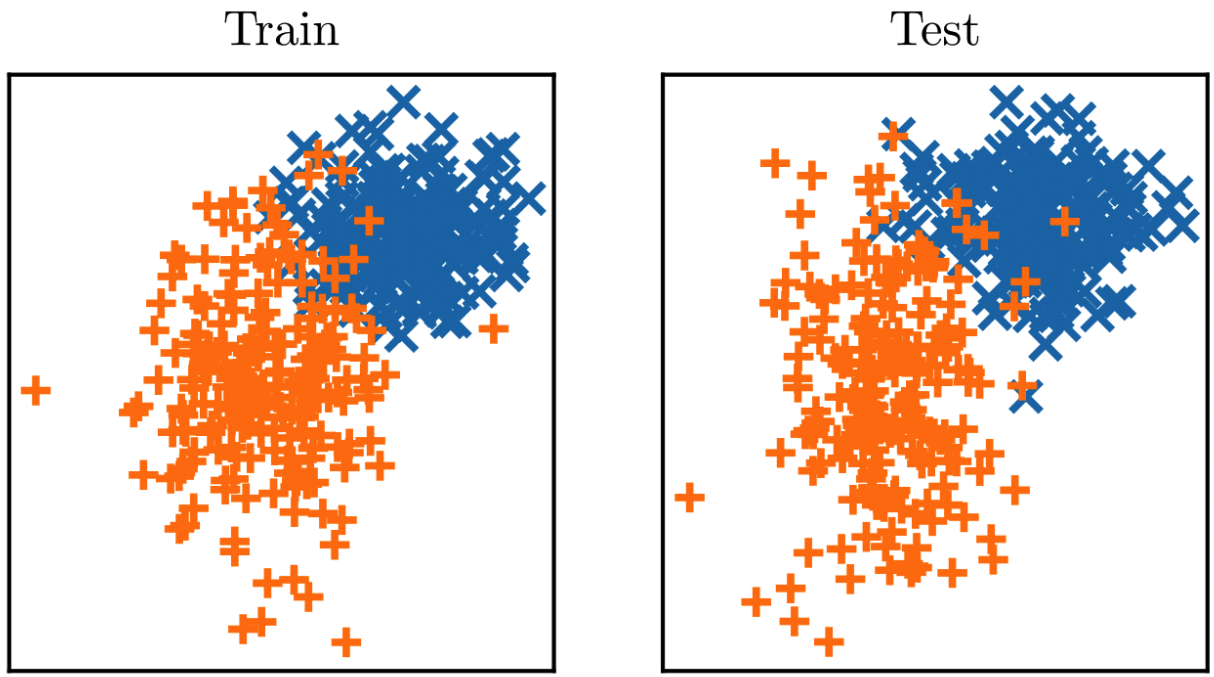

Figure: Machine learning algorithms assume all train and test examples are drawn from independently from the same distribution.

Security Requires Moving Beyond I.I.D

Figure: Physical perturbation experiments [5].

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- attackers intentionally shift the distribution toward unusual inputs (at test time)
- attackers search for a single input that causes a mistake

Intentional Distribution Shift

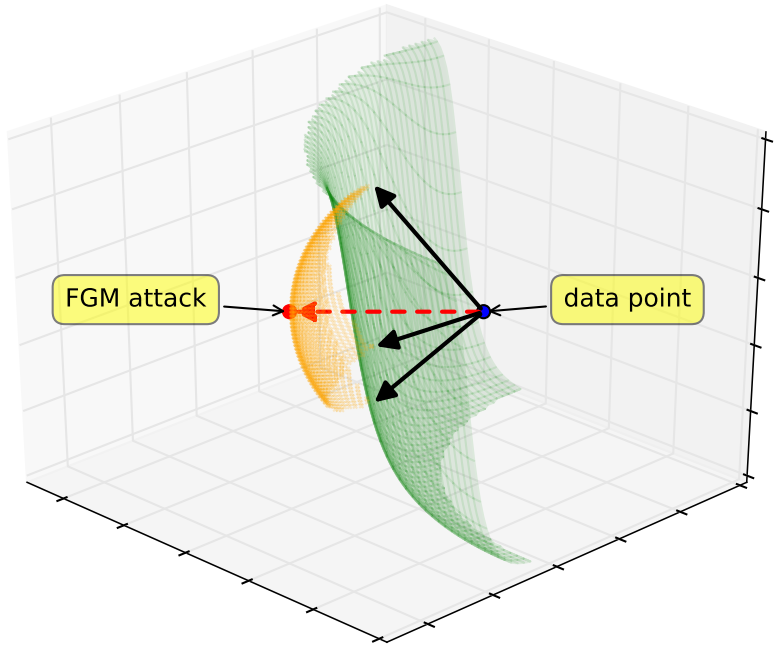

Figure: Designing an input to causes a miss-classification [12].

Examples of attacks

Design
by optimisation [11]:

$$\begin{aligned} \min_{\boldsymbol{x}'} \quad & \|\boldsymbol{x}' - \boldsymbol{x}\| \\ s.t. \quad & f(\boldsymbol{x}') = l' \\ & f(\boldsymbol{x}) = l \\ & l \neq l' \\ & \boldsymbol{x}' \in [0,1]^m \end{aligned}$$

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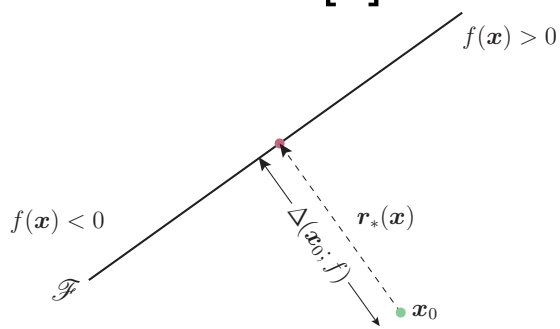
Projections on discriminant surface [9]:



Results

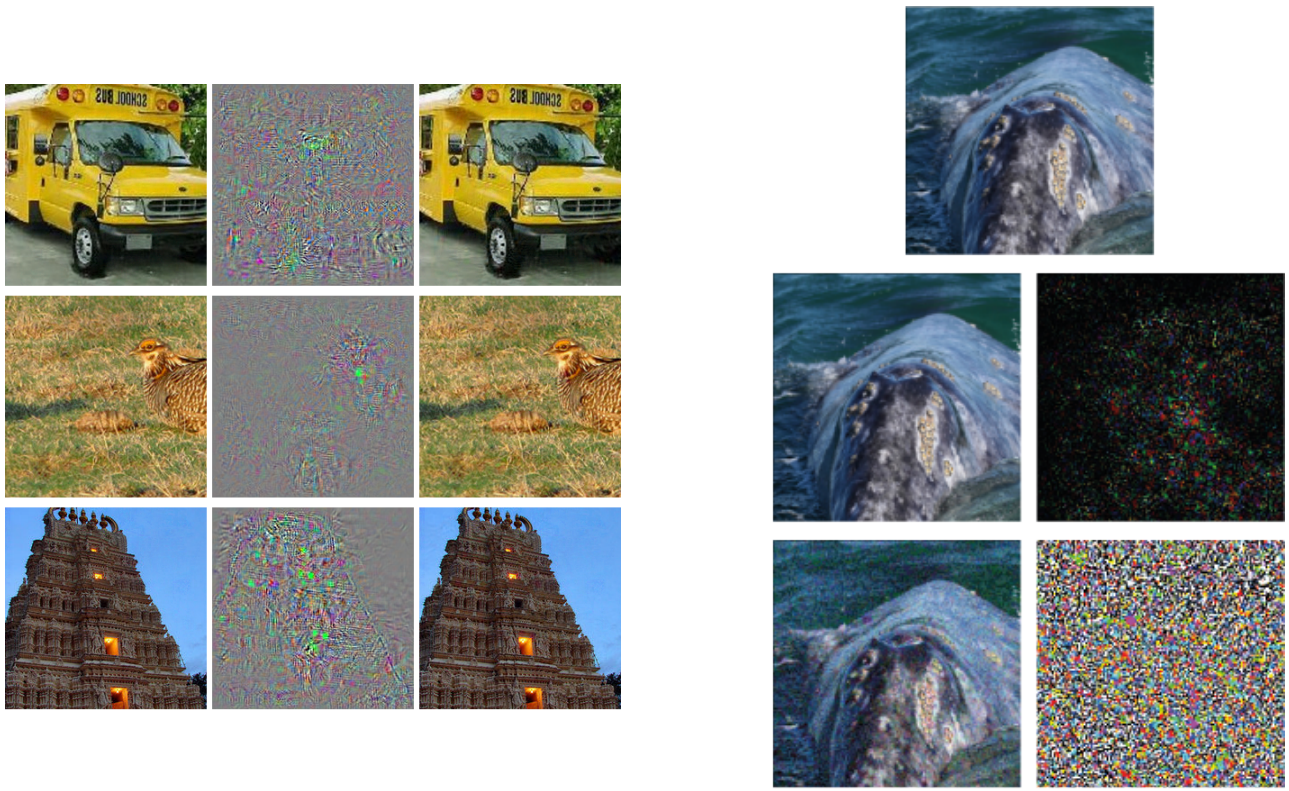


Figure: Adversarial Examples generated with L-BFGS [11] (left) and by projection on discriminant [9](right)

Generative Adversarial Attacks

Objective: Generate adversarial examples from noise.

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Steps:

1. Learn to generate normal examples from noise using generative models.
2. Learn to generate adversarial examples from (1).

Generative Adversarial Examples

Figure: Natural generative adversarial examples [13].

Defences [solutions?]

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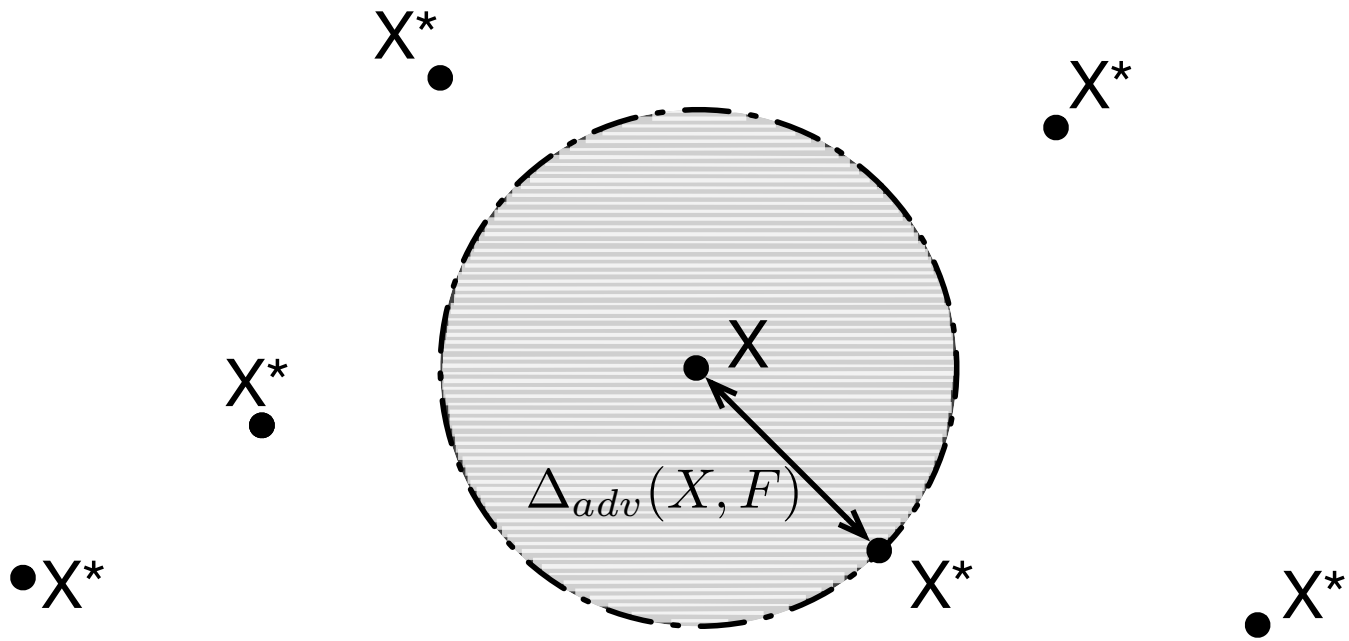
- Logit Pairing - state-of-the-art - only 50% accuracy :(

Research Directions [unsolved problems]

Robustness?



Transferability

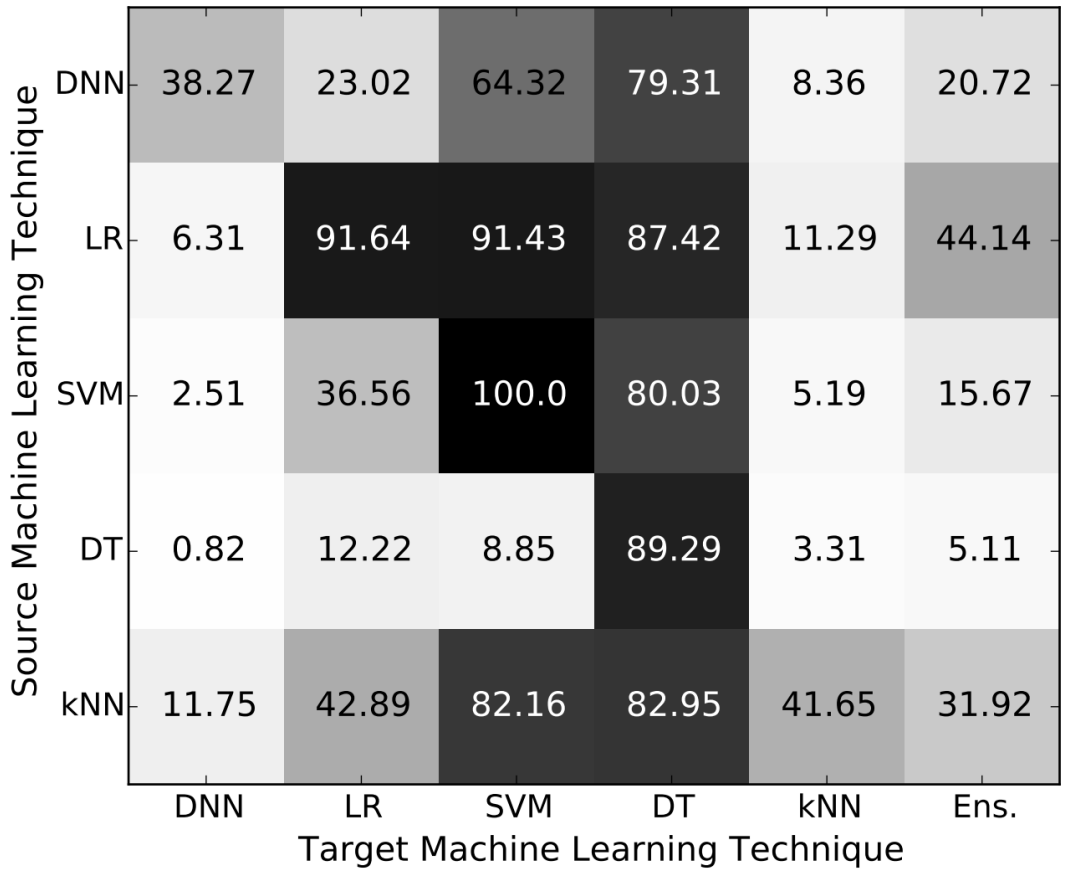


Figure: Cross-models transferability [10]

Who Watches The Watchers

- New attack models outside the norm ball

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- New certification methods
- Clear security requirements
- Semi-supervised learning, model-based optimisation, understanding the brain, etc.

Conclusions

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- Machine learning models assume training and test data are i.i.d
- Because of this ML models are easily *fooled*
- Adversarial examples show that computers learn something different than we think (they might be less *intelligent*)
- There is no working defence against adversarial examples (no clear goals though)

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