

Introduction to Machine Learning

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**What is your definition
of Machine Learning ?**

Definition: Machine Learning

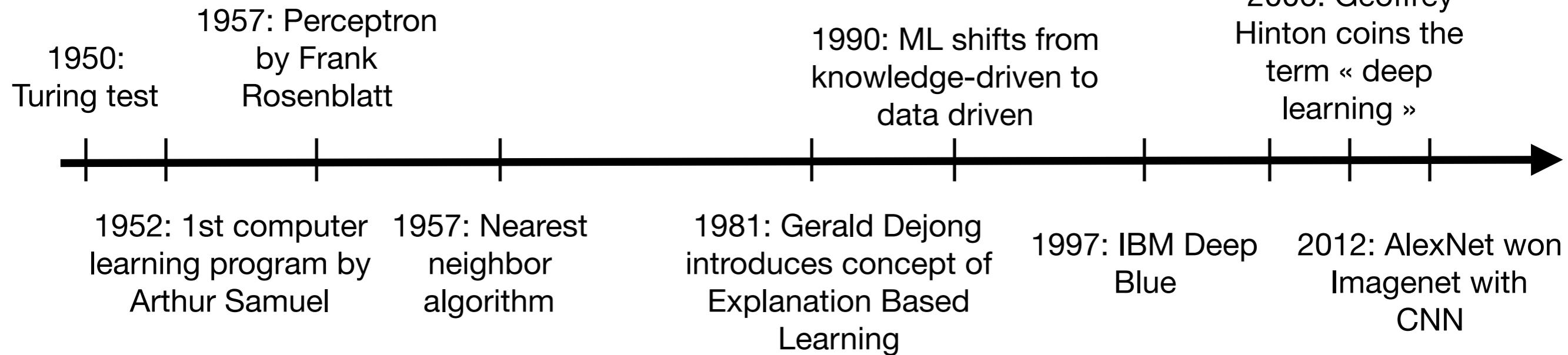
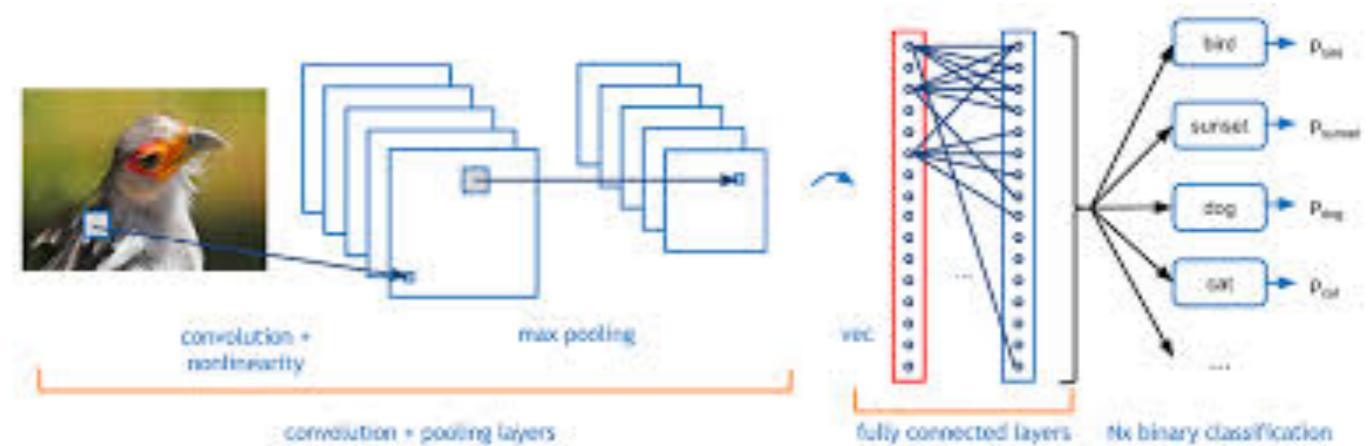
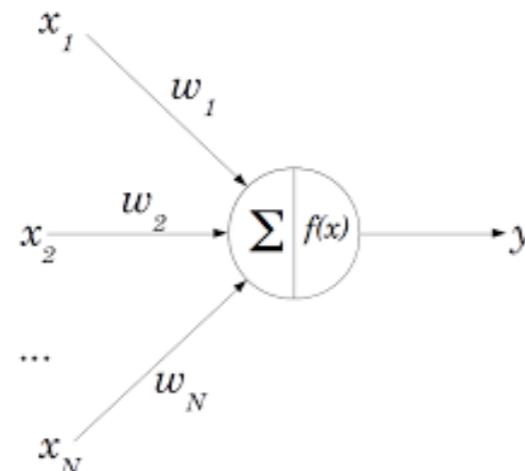
Statistics?
Maths?
Computer Science?
Big Data?
Artificial Intelligence?

« *Field of study that gives computers the ability to learn without being explicitly programmed* »
Arthur Samuel, 1959

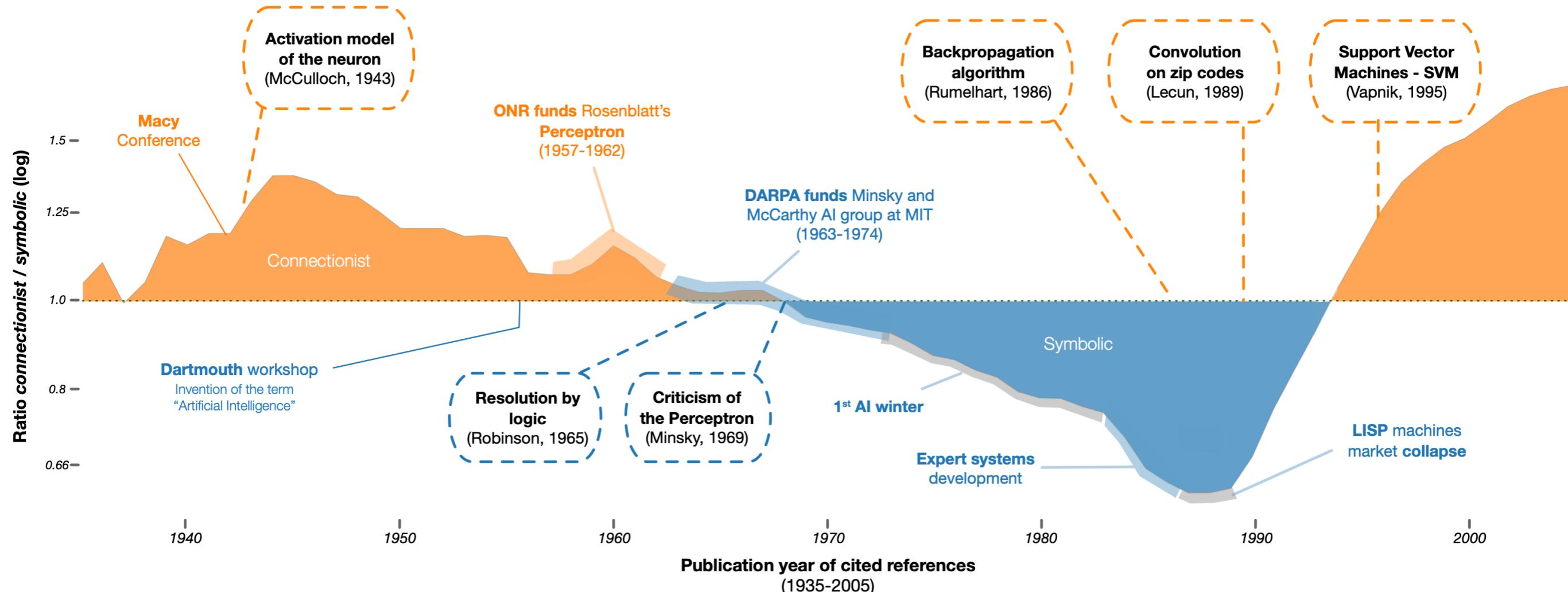
Automatic discover of patterns in data by a computer

Different from rule-based methods

Brief history of Machine Learning and AI



Timeline AI



What do we want to learn?

Object classification



Supervised Learning

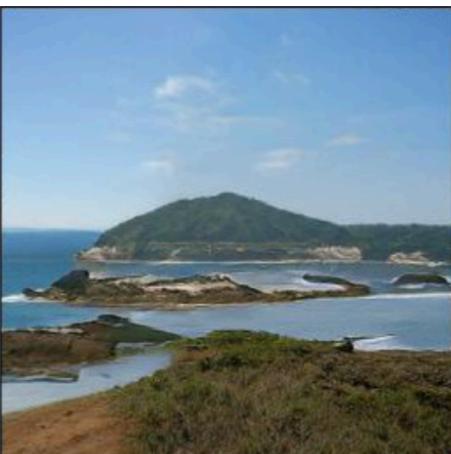
$$f(\cdot) \rightarrow \text{cat}$$

Human Pose estimation



Unsupervised Learning

Image Generation



Future forecasting

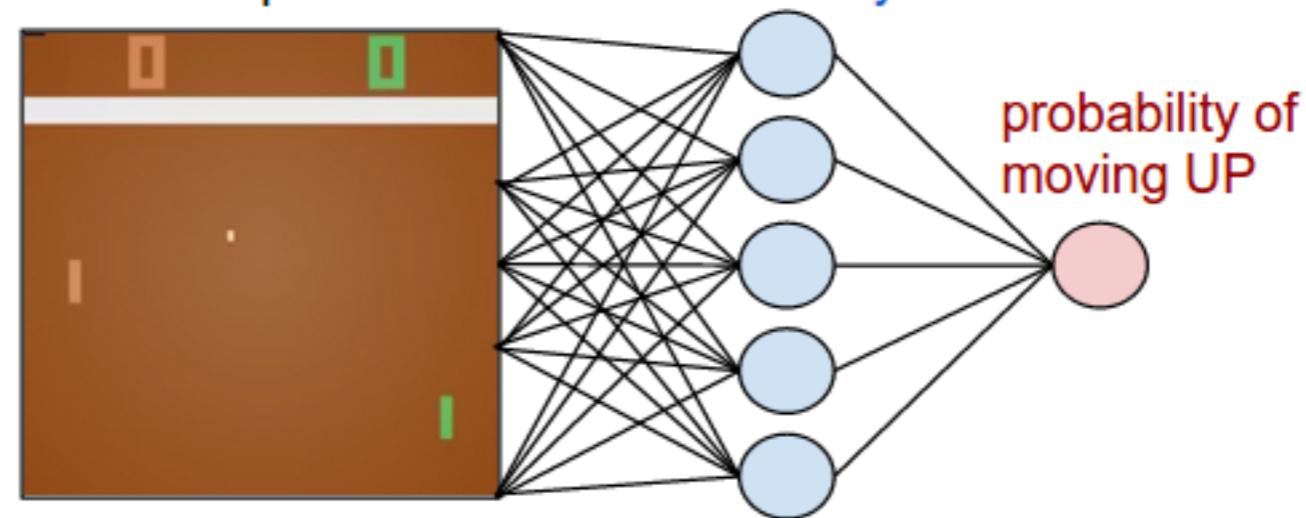
What do we want to learn?

Reinforcement Learning

Superhuman performance in video game

raw pixels

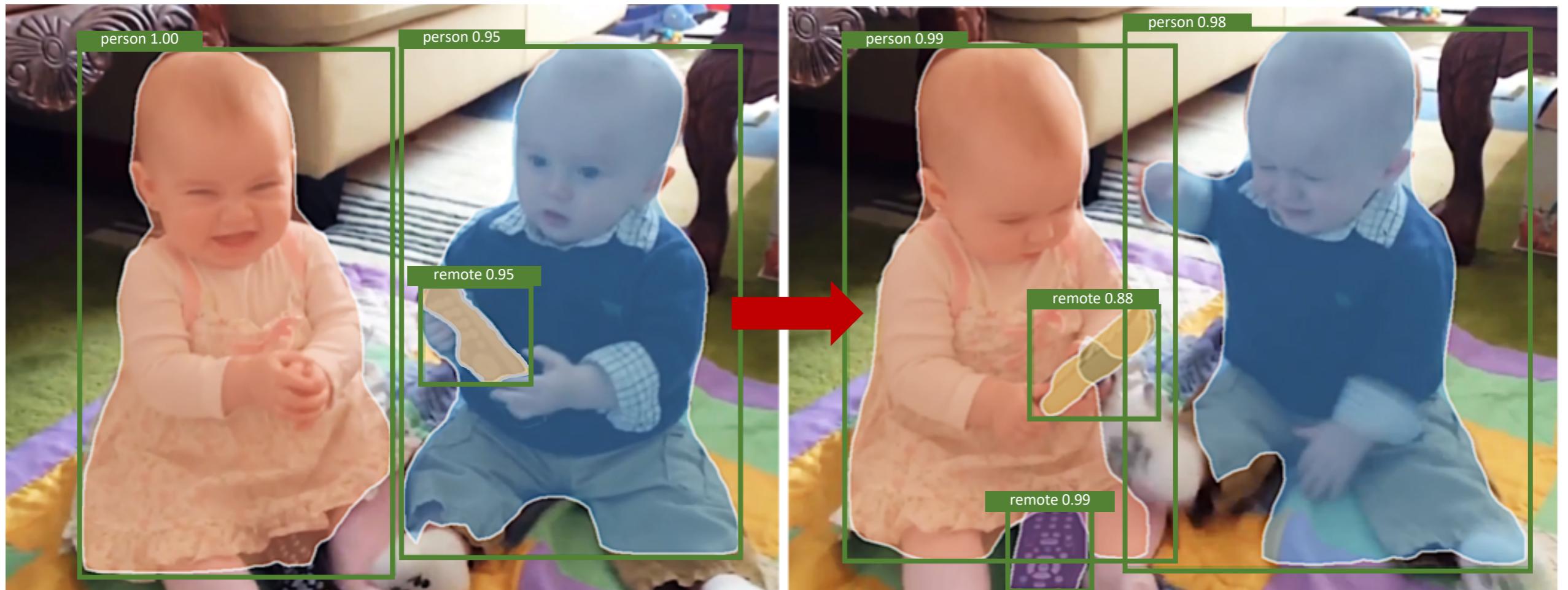
hidden layer



Go board game



Video Understanding



*Causal Reasoning
Spatio-Temporal Interactions*

Strong AI



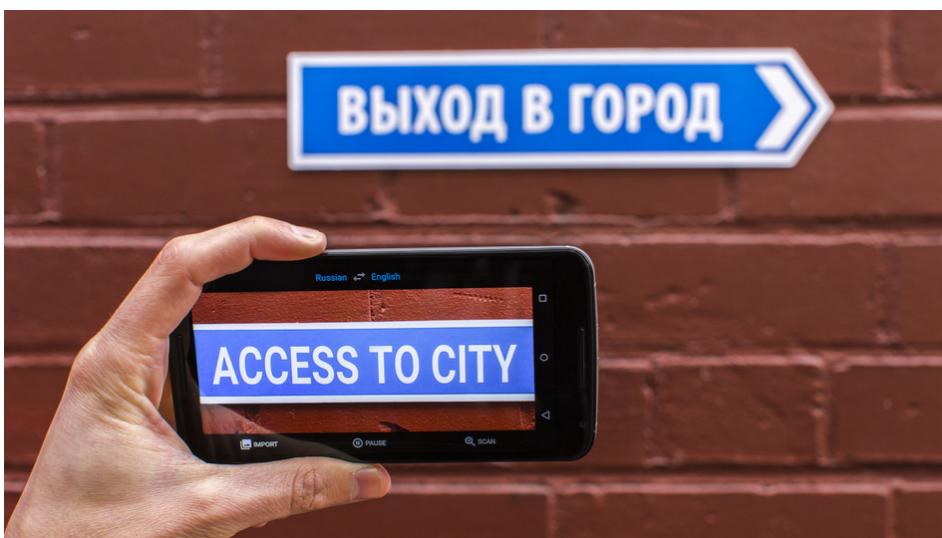
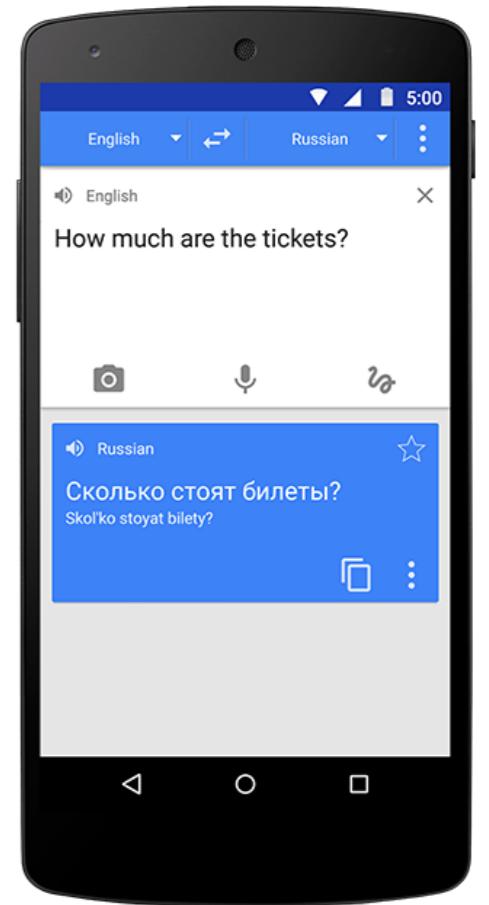
Specific task
Memorization
Shift between train and test
Adaptation to new task

Real World Applications



Tesla

Google



Criteo

Industry



Huge investment
R&D Centers
USA - Canada - China - Europe (France!)

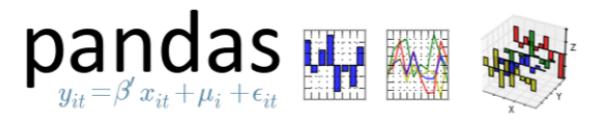
Software



Python Data Science Platform
Conda - environnement



IP[y]: IPython
Interactive Computing



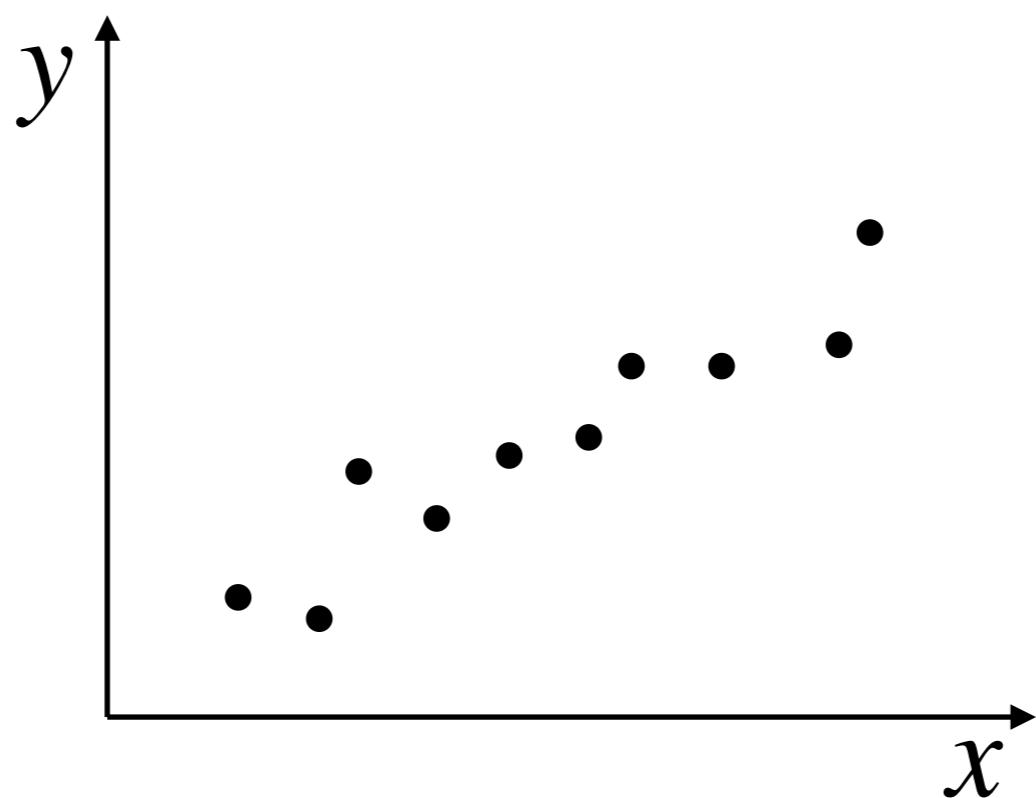
Supervised Learning

Regression

Problem Statement

$$D = \{(x_i, y_i)\}_{i=1}^N$$

$$y = f(x)$$



Solution

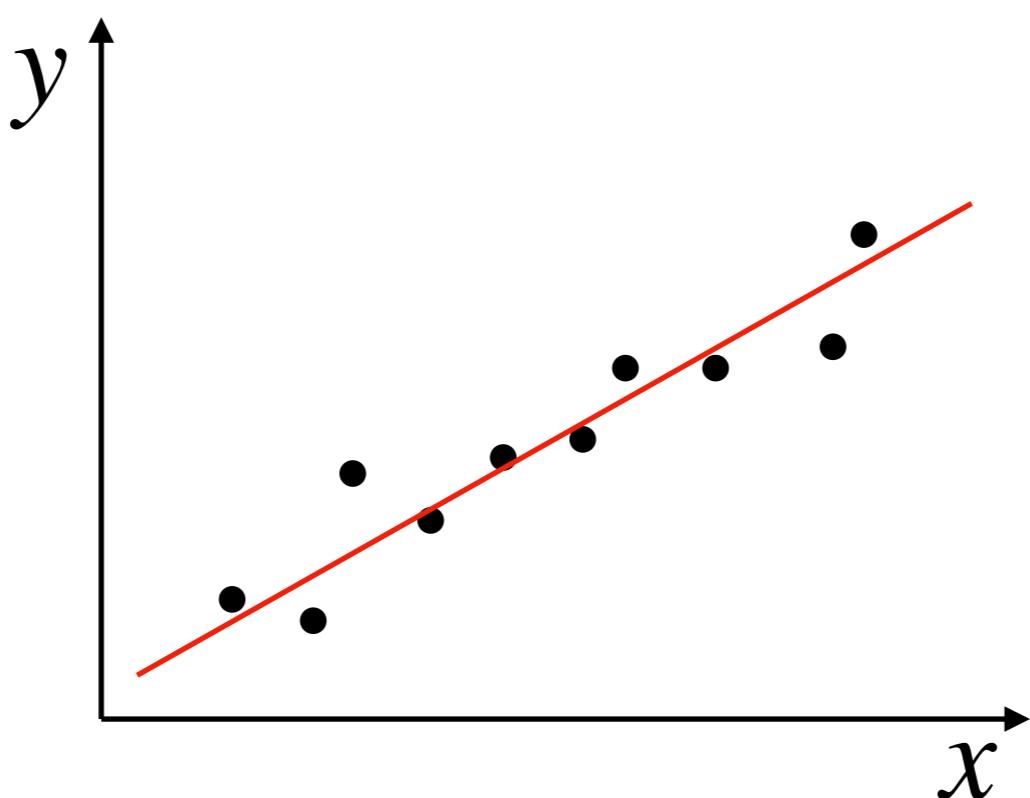
Model

$$f_{w,b}(x) = wx + b$$

Prediction

$$y = f_{w,b}(x)$$

Loss function $(f_{w,b}(x_i) - y_i)^2$



Solution

Model

$$f_{w,b}(x) = wx + b$$

Prediction

$$y = f_{w,b}(x)$$

Loss function $(f_{w,b}(x_i) - y_i)^2$

Objective

$$\min_{w,b} \frac{1}{N} \sum_{i=1}^N (f_{w,b}(x_i) - y_i)^2$$

Closed-form solution

We set

$$\beta = [b \quad w] \quad X = \begin{bmatrix} 1 & x_1 \\ \vdots & \vdots \\ 1 & x_N \end{bmatrix} \quad Y = \begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix}$$

Optimization

$$\min_{\beta} \| \beta X - y \|^2$$

Optimal solution

$$\beta^* = \hat{\beta} = (X^T X)^{-1} X^T y$$

Pros and Cons

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

We can add statistical hypothesis
Robust modelling

Model checking
Invertibility

Difficult to compute in some case

Linear regression with Gradient Descent

$$J(w, b) = \frac{1}{N} \sum_{i=1}^N (f_{w,b}(x_i) - y_i)^2$$

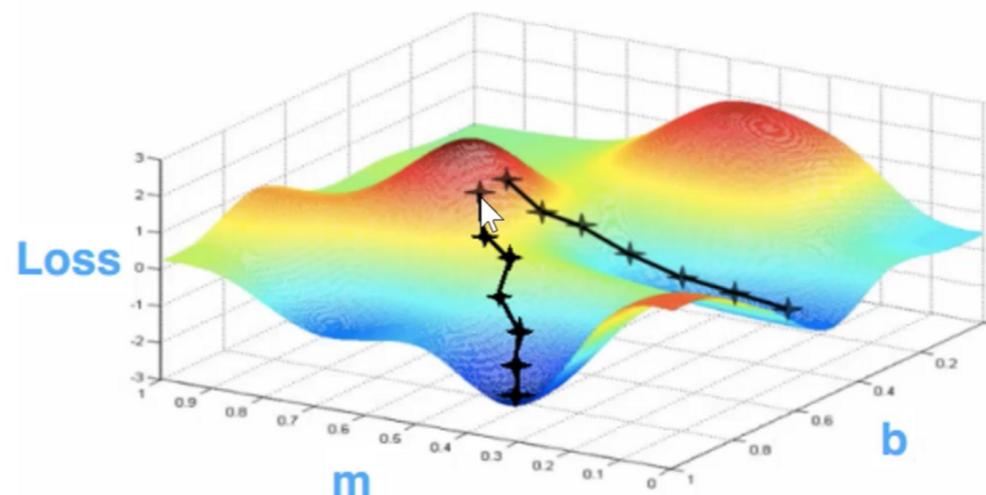
Optimization problem

Minimize a loss function using a certain model

Find the parameters which are minimizing the loss function

Gradient Descent

f(x) = nonlinear function of x



Linear regression with GD

Cost function

$$J(w, b) = \frac{1}{N} \sum_{i=1}^N (f_{w,b}(x_i) - y_i)^2$$

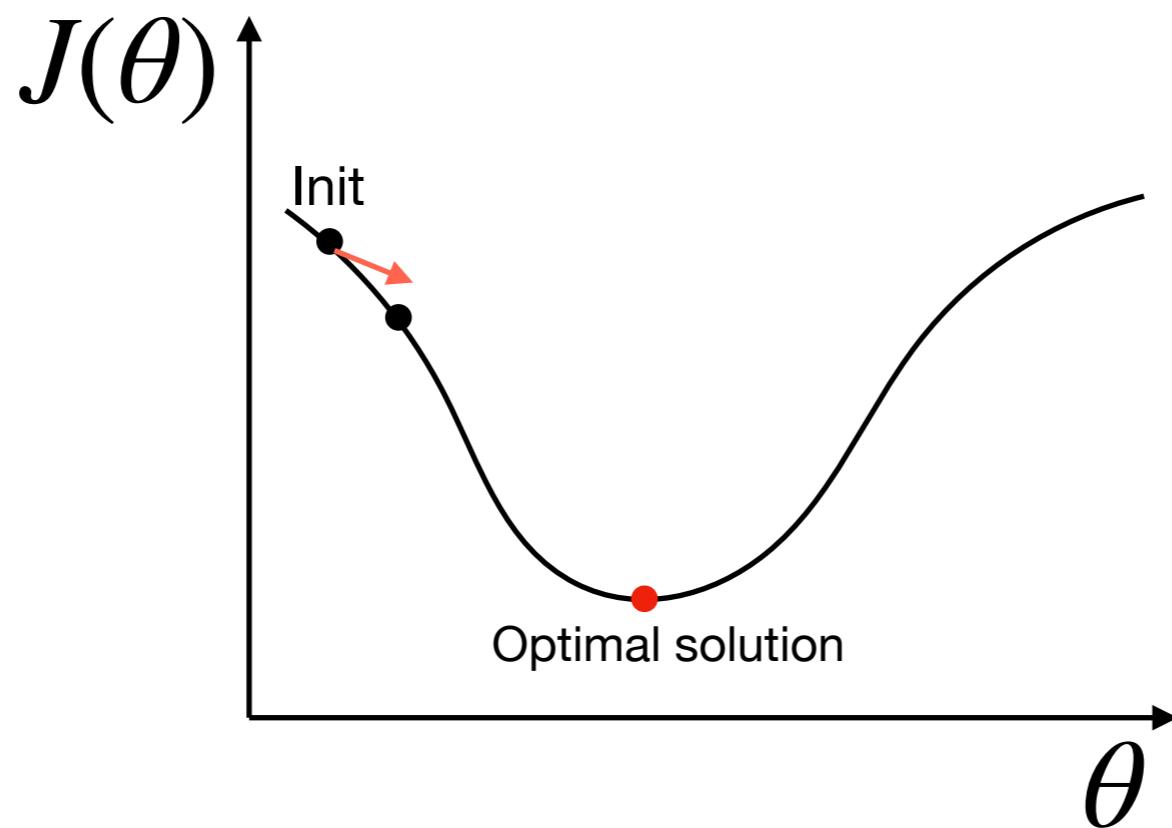
Compute derivatives

$$\frac{\partial J}{\partial w}(w, b) = \frac{1}{N} \sum_{i=1}^N -2x_i(y_i - (wx_i + b))$$

$$\frac{\partial J}{\partial b}(w, b) = \frac{1}{N} \sum_{i=1}^N -2(y_i - (wx_i + b))$$

And update parameters iteratively

Gradient Descent



Goal: minimization of a function

Random initialization of parameters

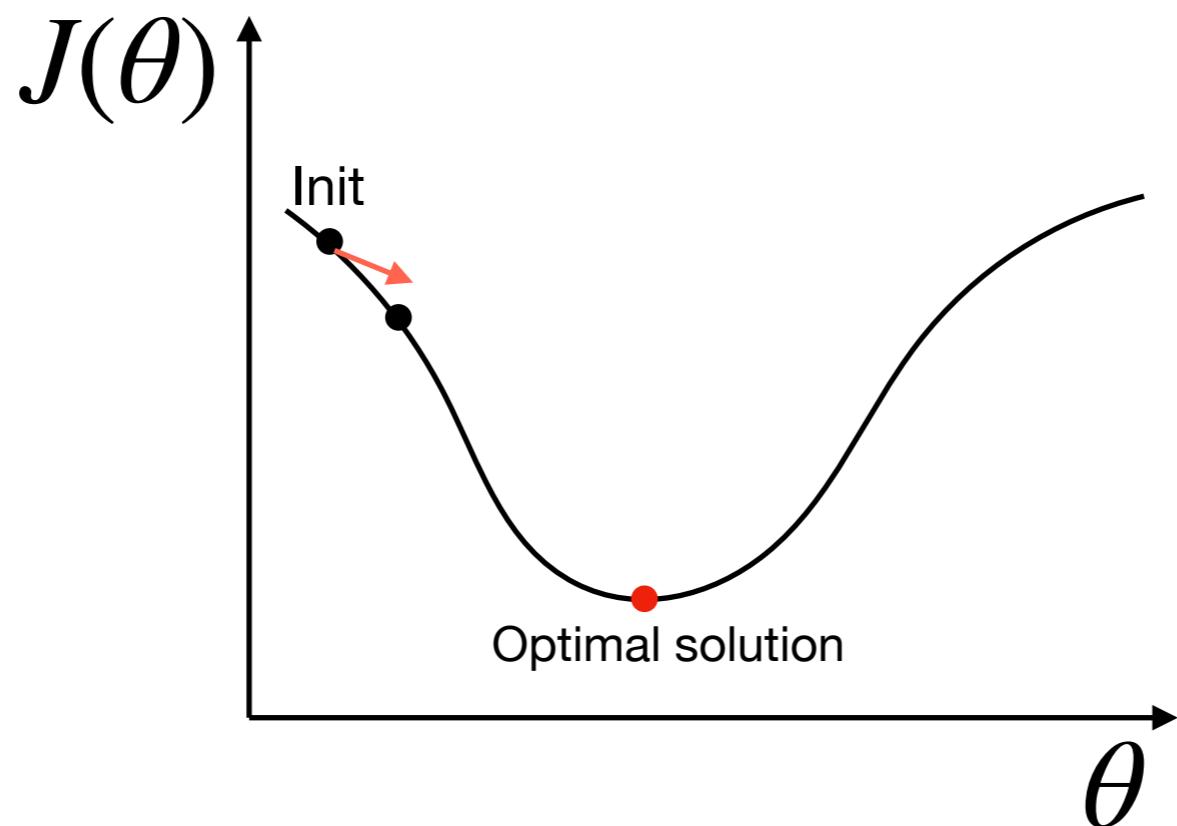
At time t, gradient = slope fo the function

Iterative process

Updating parameters in the positive direction with a learning rate

Repeat until convergence

Gradient Descent



- Init $\hat{\theta}$ randomly
- Choose a learning rate η
- for t in range(nb_iter):
 - Update parameter

$$\hat{\theta} \leftarrow \hat{\theta} - \eta \frac{\partial J}{\partial \theta}(\hat{\theta})$$

Linear Regression with GD

$$J(w, b) = \frac{1}{N} \sum_{i=1}^N (f_{w,b}(x_i) - y_i)^2$$

- Init \hat{w}, \hat{b} randomly
- Choose a learning rate η
- for t in $1 \dots T$:
 - Update parameters

$$\hat{w} \leftarrow \hat{w} - \eta \frac{\partial J}{\partial w}(\hat{w}, \hat{b})$$

$$\hat{b} \leftarrow \hat{b} - \eta \frac{\partial J}{\partial b}(\hat{w}, \hat{b})$$

Linear Regression with Stochastic GD

$$J(w, b) = \frac{1}{N} \sum_{i=1}^N (f_{w,b}(x_i) - y_i)^2$$

- Init \hat{w}, \hat{b} randomly
- Choose a learning rate η
- for t in $1 \dots T$:
 - Sample some points from the data
 - Update parameters

$$\hat{w} \leftarrow \hat{w} - \eta \frac{\partial J}{\partial w}(\hat{w}, \hat{b})_D$$

Only on a subset D of the dataset

$$\hat{b} \leftarrow \hat{b} - \eta \frac{\partial J}{\partial b}(\hat{w}, \hat{b})_D$$

Exercise

Implementing Gradient Descent
LinearRegression: Closed-form vs GD vs SGD

