

LINEAR REGRESSION

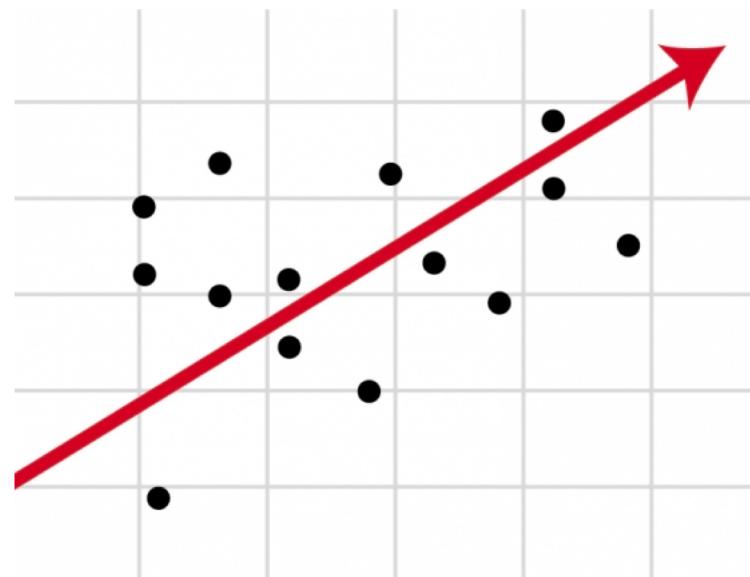
Narges Norouzi

CONTENT

- Introduction
- Regression – Definition
- Linear Regression
- Least Square Method

INTRODUCTION

- Analyze the specific relationships between two or more variables
- This is done to gain the information about one through knowing values of the other variables



REGRESSION

- A **statistical measure** that attempts to determine the strength of the **relationship** between one dependent variable (usually denoted by Y) and a series of other changing variables (known as independent variables)
- Forecast value of a **dependent variable (Y)** from the value of **independent variables (X_1, X_2, X_3, \dots)**
- It is widely used for **prediction**, **estimation**, **hypothesis testing**, and **modeling causal relationships**

DEPENDENT & INDEPENDENT VARIABLES

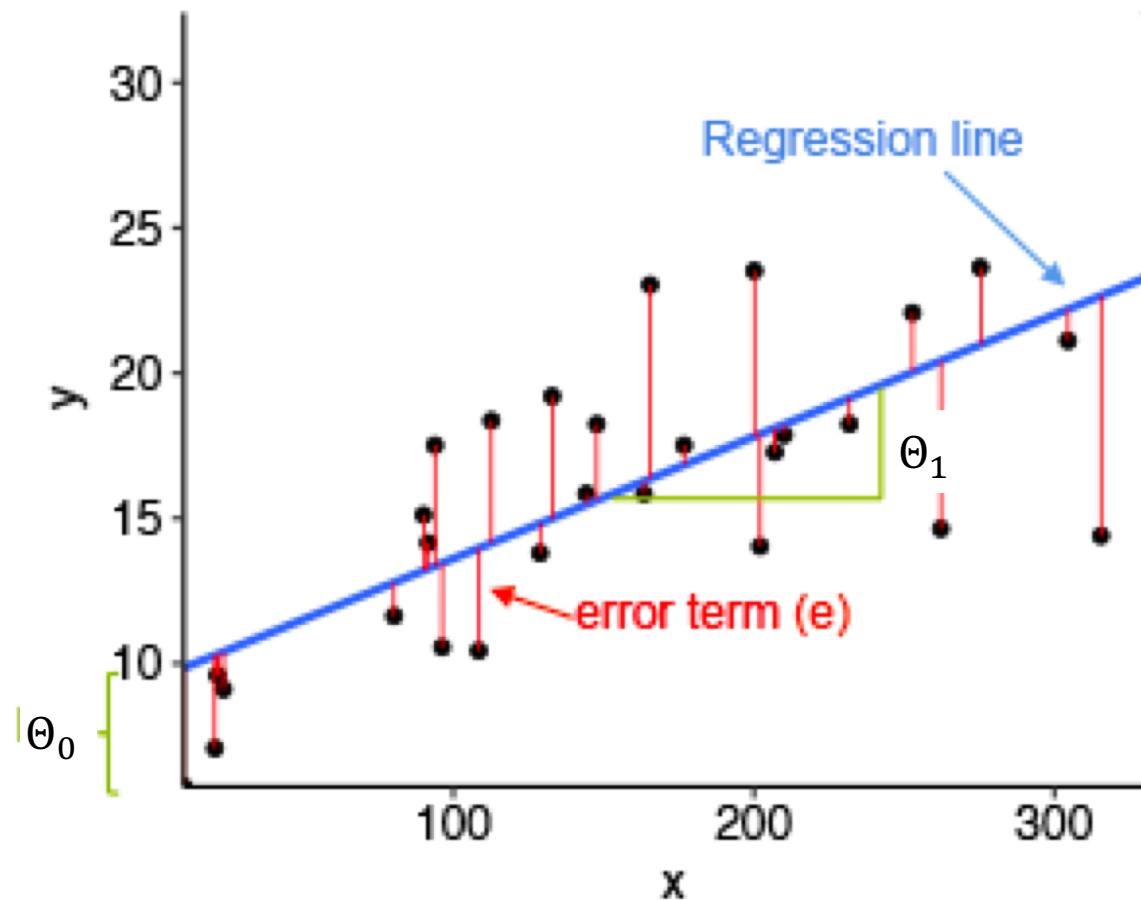
- Independent variables are regarded as **inputs** to a system and may take on different values freely.
- Dependent variables are those values that **change as a consequence of changes in other values** in the system.
- Independent variable is also called as **predictor** or **explanatory variable** and it is denoted by X.
- Dependent variable is also called as **response** variable and it is denoted by Y.

THE FIRST ORDER LINEAR MODEL

$$Y = \theta_0 + \theta_1 X$$

- Y = dependent/outcome/response variable
- X = independent/predictor/explanatory variable
- θ_0 = Y-intercept
- θ_1 = slope of the line

LINEAR REGRESSION EXAMPLE



REGRESSION DATA

- Given

- Data:

$$X = \{x^{(1)}, x^{(2)}, x^{(3)}, \dots, x^{(n)}\} \text{ where } x^{(i)} \in \mathcal{R}^d$$

- Corresponding labels:

$$Y = \{y^{(1)}, y^{(2)}, y^{(3)}, \dots, y^{(n)}\} \text{ where } y^{(i)} \in \mathcal{R}$$

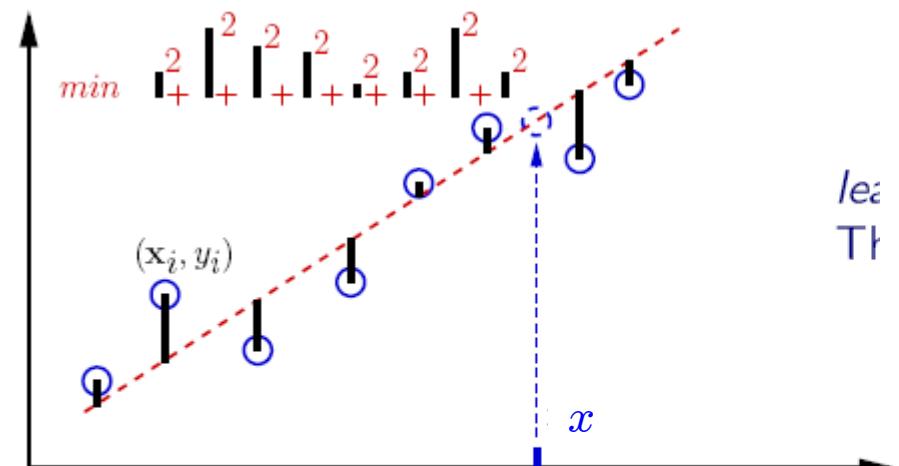
REGRESSION HYPOTHESIS

- Hypothesis:

$$h_{\theta}(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_d x_d = \sum_{j=0}^d \theta_j x_j$$

Assume $x_0 = 1$

- Fit a model by minimizing sum or mean of squared errors

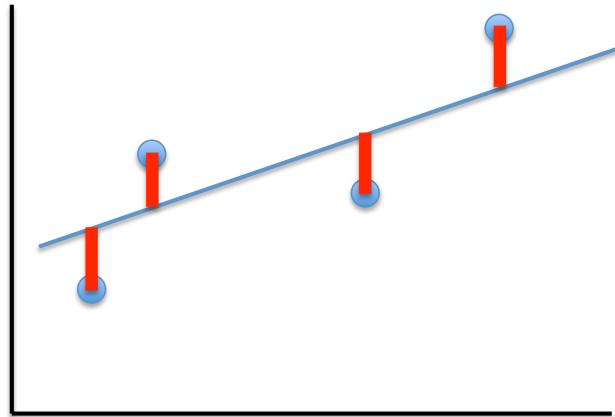


LEAST SQUARES LINEAR REGRESSION

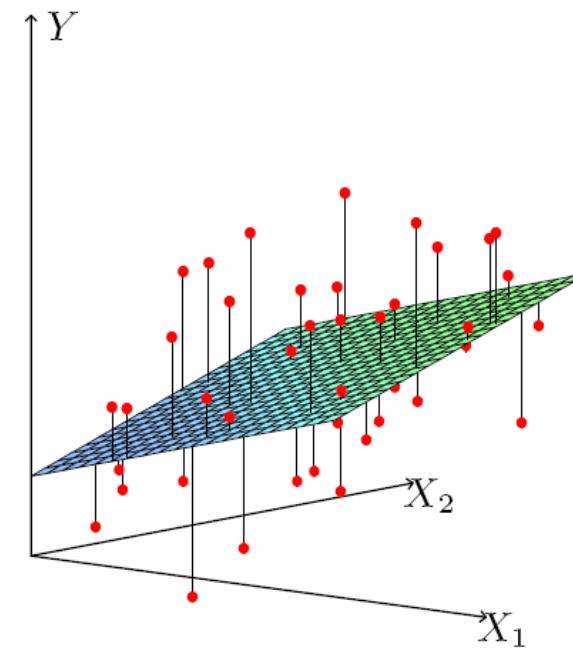
- Cost Function

$$Cost(\theta) = \frac{1}{2 \times n} \sum_{i=0}^n (h_\theta(x^{(i)}) - y^{(i)})^2$$

- Fit by solving

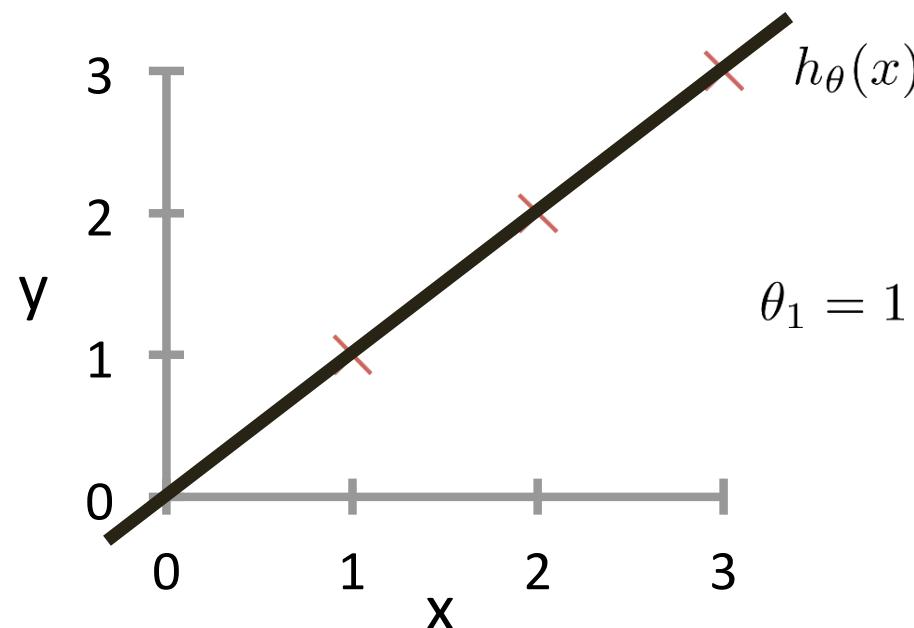


$$\min_{\theta} Cost(\theta)$$

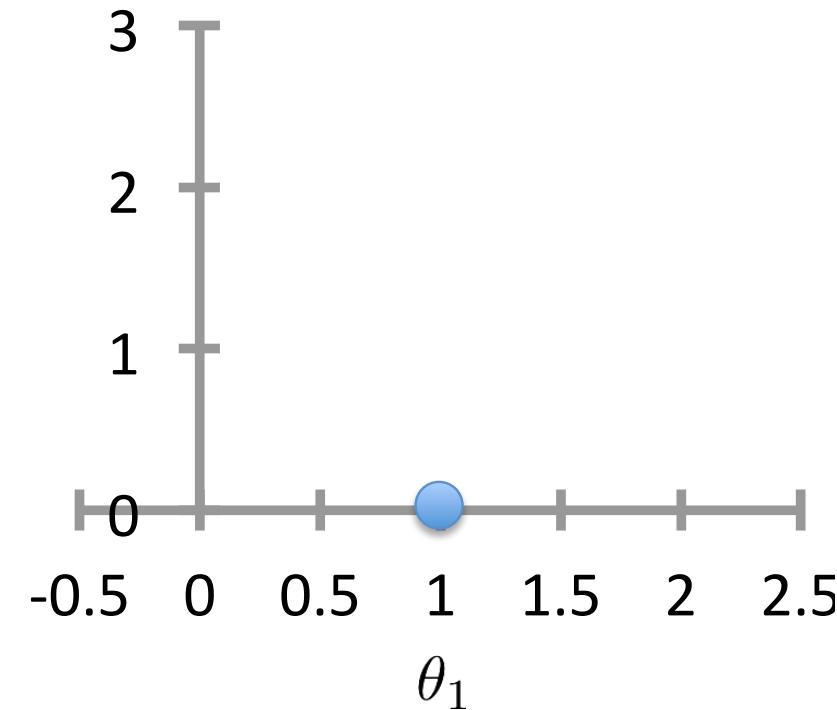


INTUITION BEHIND COST FUNCTION

$h_{\theta}(x)$
For a fixed θ_1 . This is a function of x

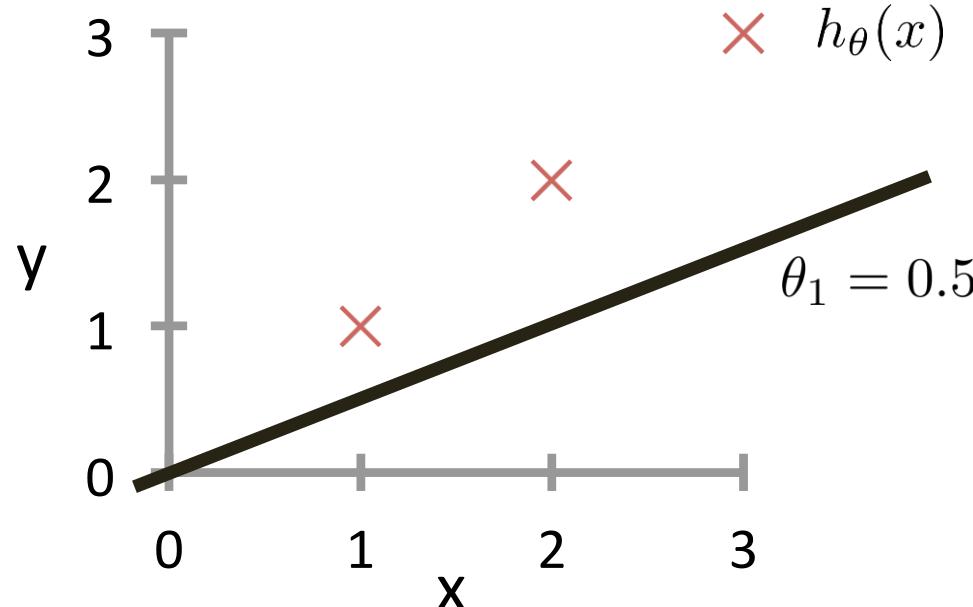


$Cost(\theta_1)$
Function of a parameter θ_1

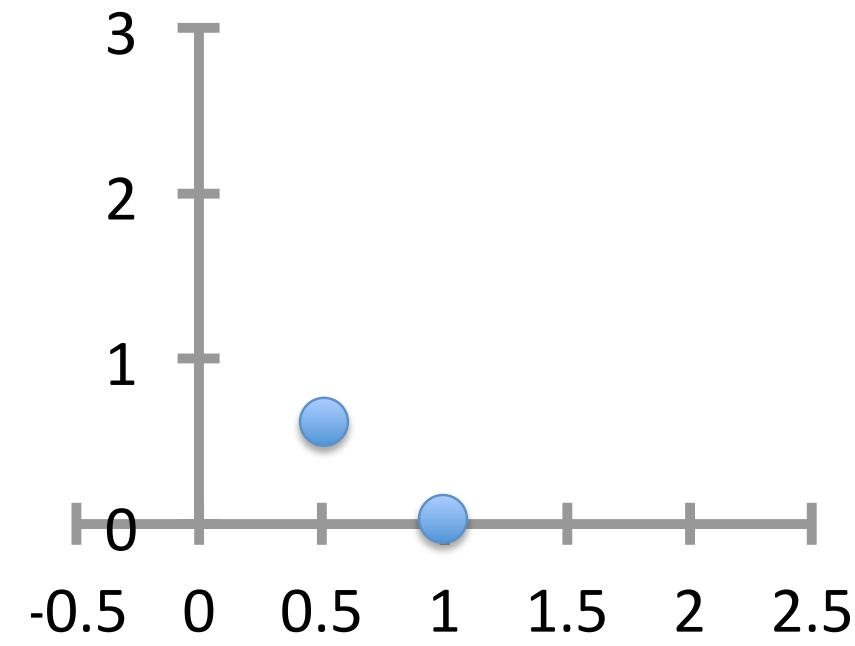


INTUITION BEHIND COST FUNCTION

$h_{\theta}(x)$
For a fixed θ_1 . This is a function of x



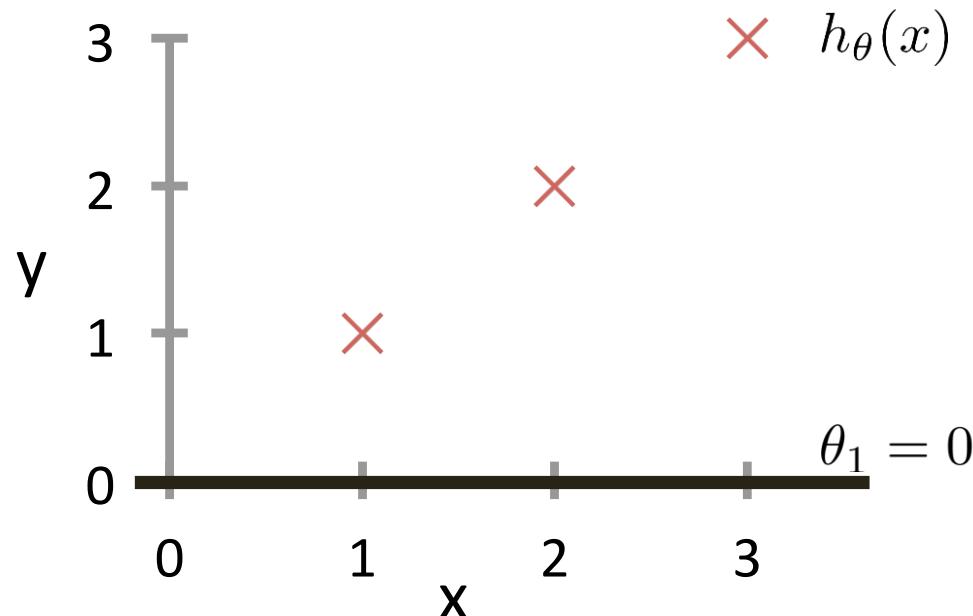
$Cost(\theta_1)$
Function of a parameter θ_1



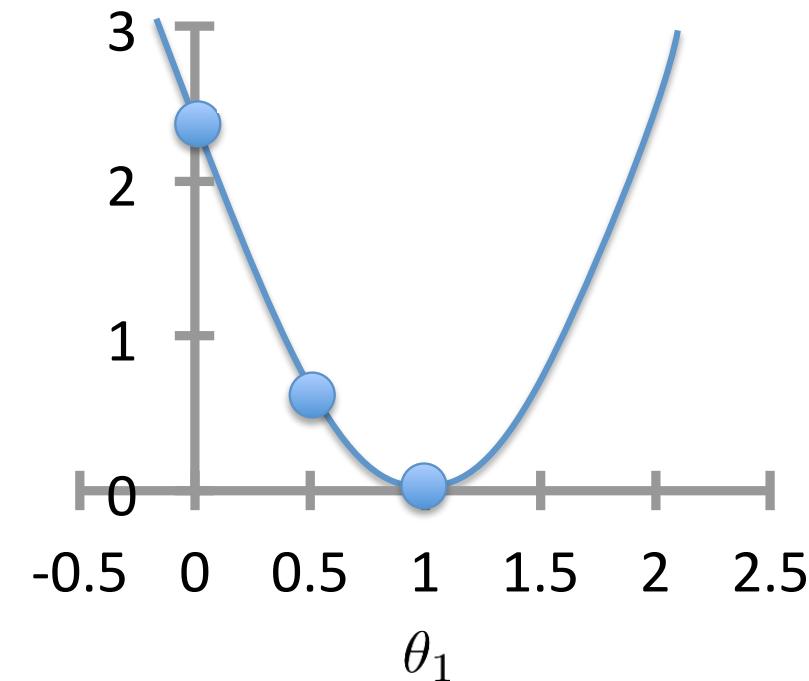
$$Cost(\theta) = Cost([\theta_0, \theta_1]) = Cost([0, 0.5]) = \frac{1}{2 \times 3} ((0.5 - 1)^2 + (1 - 2)^2 + (1.5 - 3)^2) = 0.58$$

INTUITION BEHIND COST FUNCTION

$h_{\theta}(x)$
For a fixed θ_1 . This is a function of x

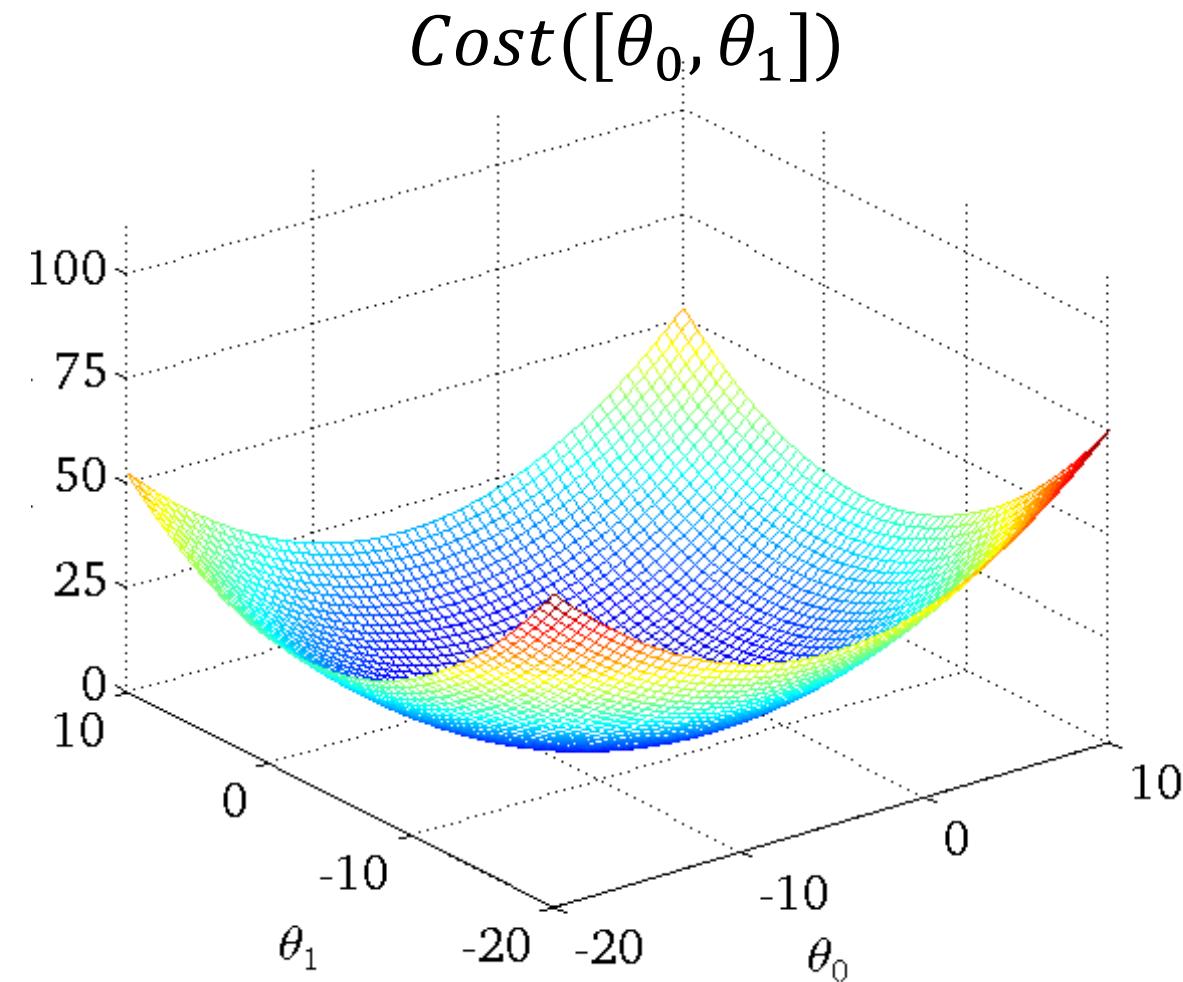


$Cost(\theta_1)$
Function of a parameter θ_1



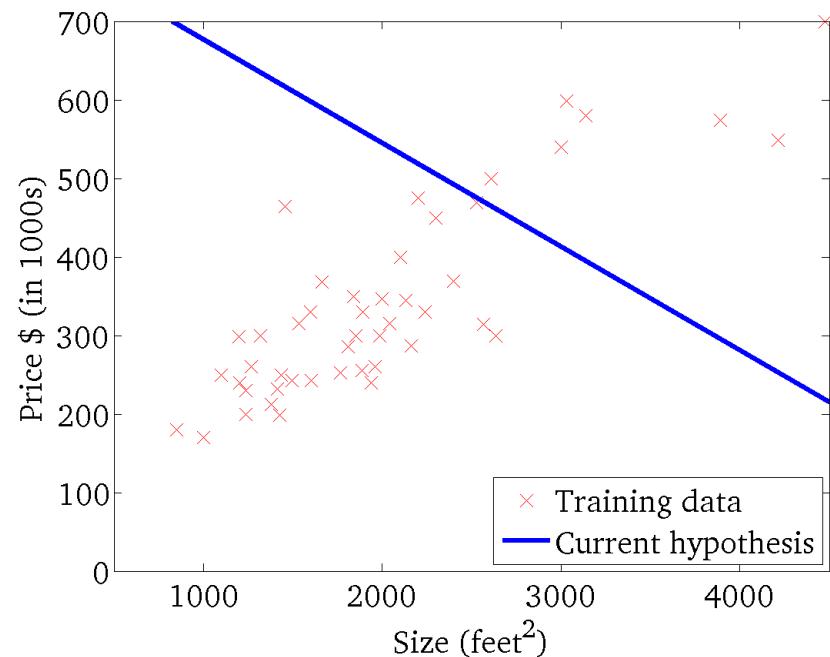
$$Cost(\theta) = Cost([\theta_0, \theta_1]) = Cost([0, 0]) = \frac{1}{2 \times 3} ((0 - 1)^2 + (0 - 2)^2 + (0 - 3)^2) = 2.33$$

INTUITION BEHIND COST FUNCTION

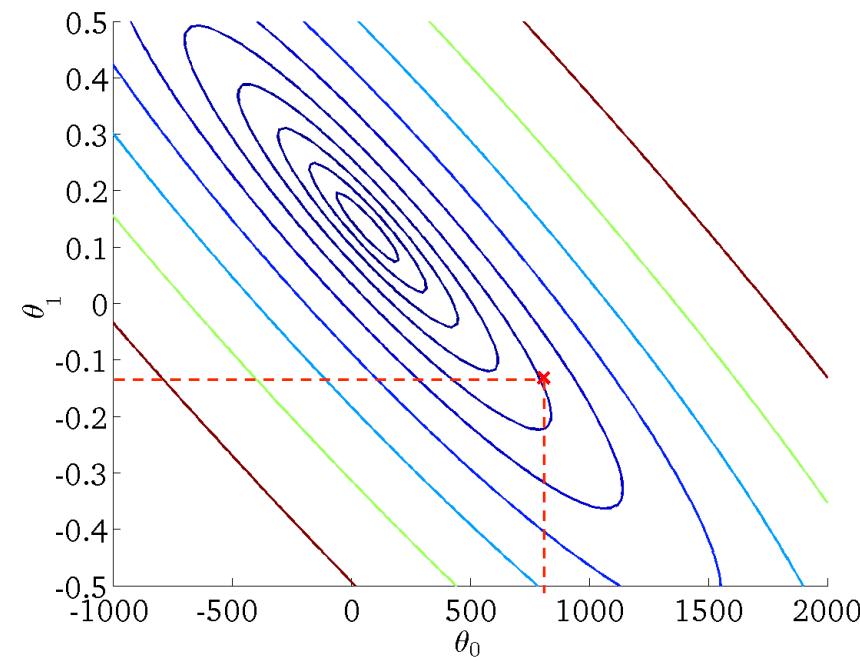


INTUITION BEHIND COST FUNCTION

$h_{\theta}(x)$

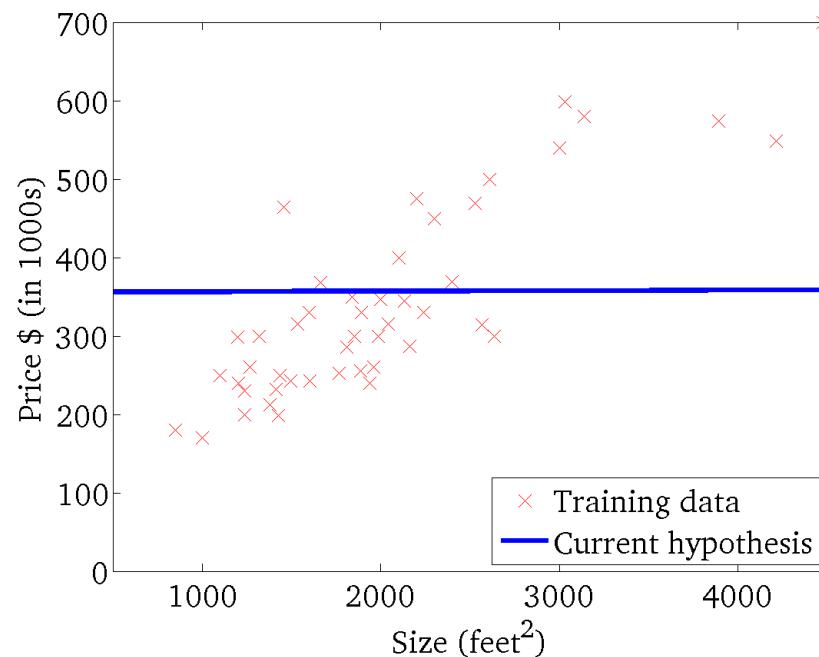


$Cost([\theta_0, \theta_1])$

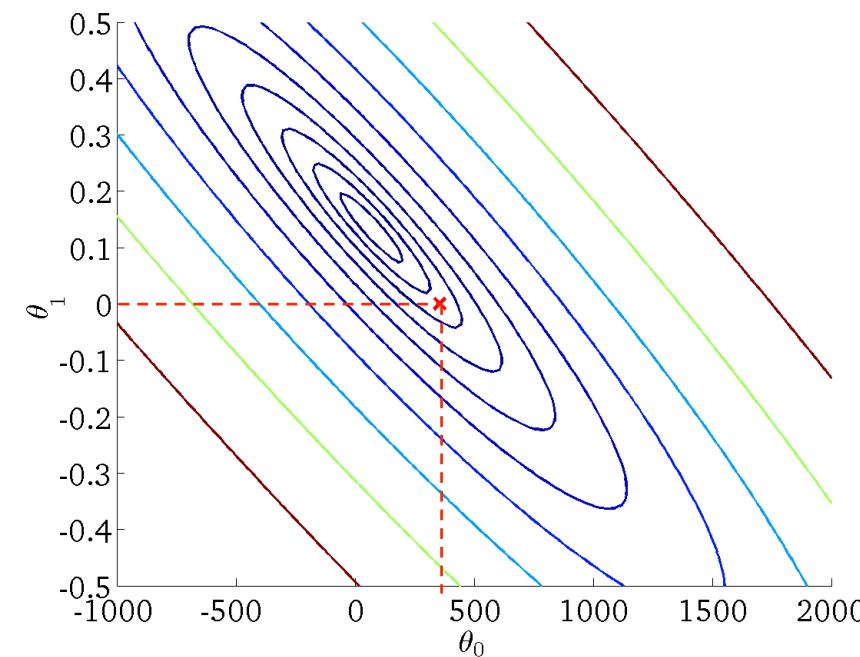


INTUITION BEHIND COST FUNCTION

$h_{\theta}(x)$

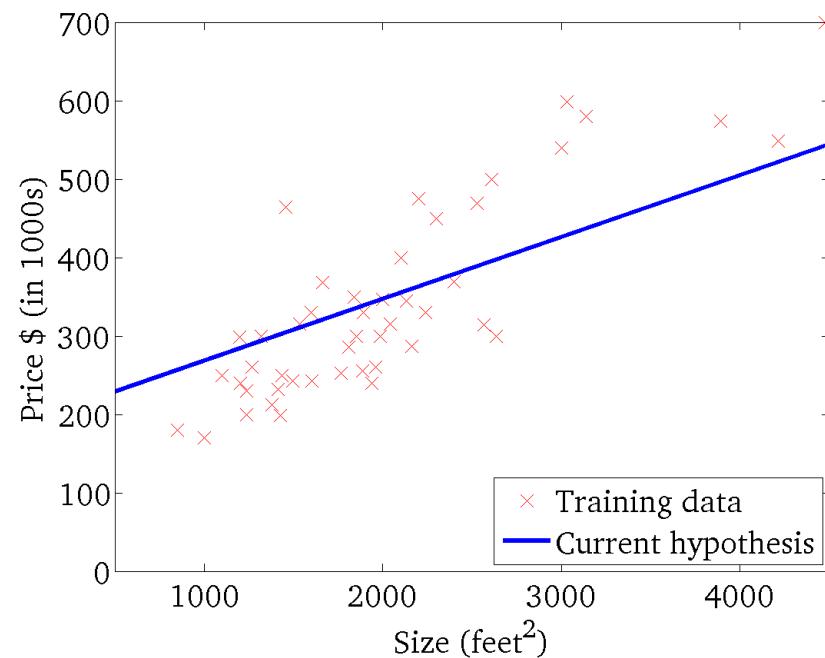


$Cost([\theta_0, \theta_1])$

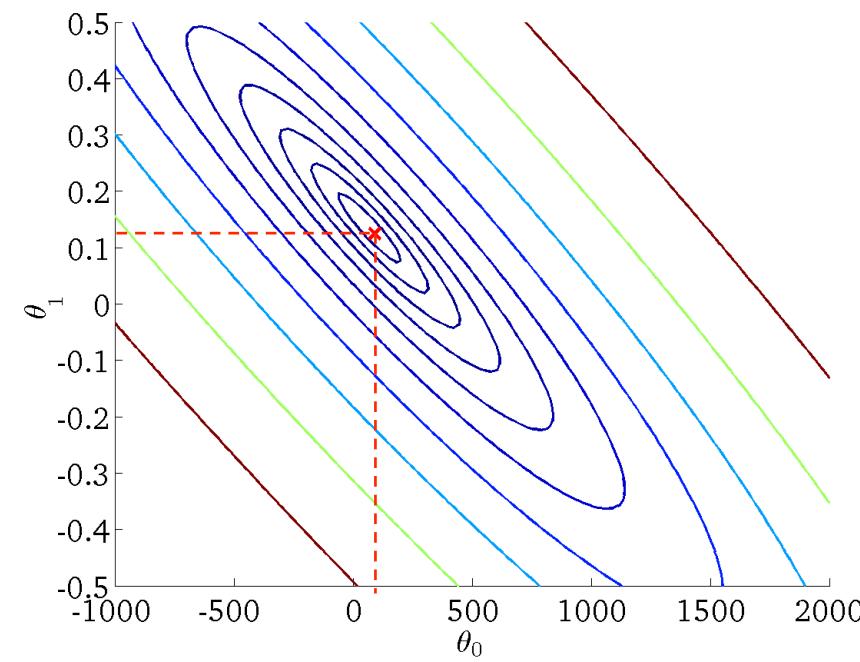


INTUITION BEHIND COST FUNCTION

$$h_{\theta}(x)$$



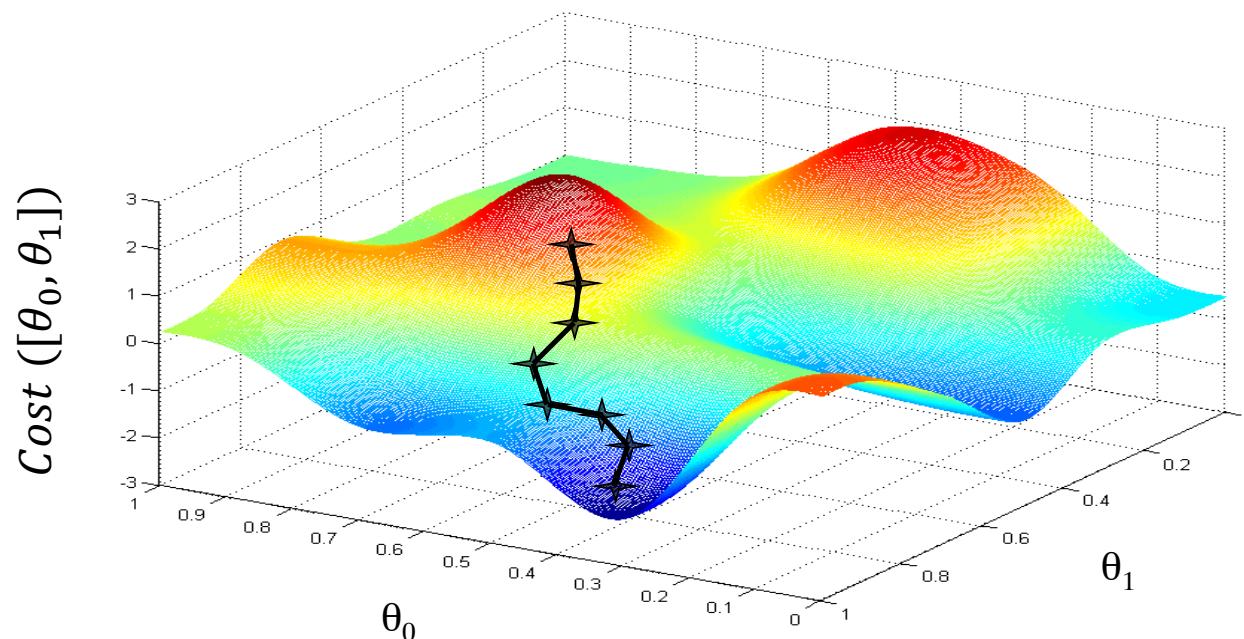
$$Cost([\theta_0, \theta_1])$$



BASIC SEARCH PROCEDURE

- Choose initial value for θ
- Until we reach a minimum
 - Choose a new value for θ to reduce $Cost(\theta)$

Since the least squares objective function is convex, we don't need to worry about local minima



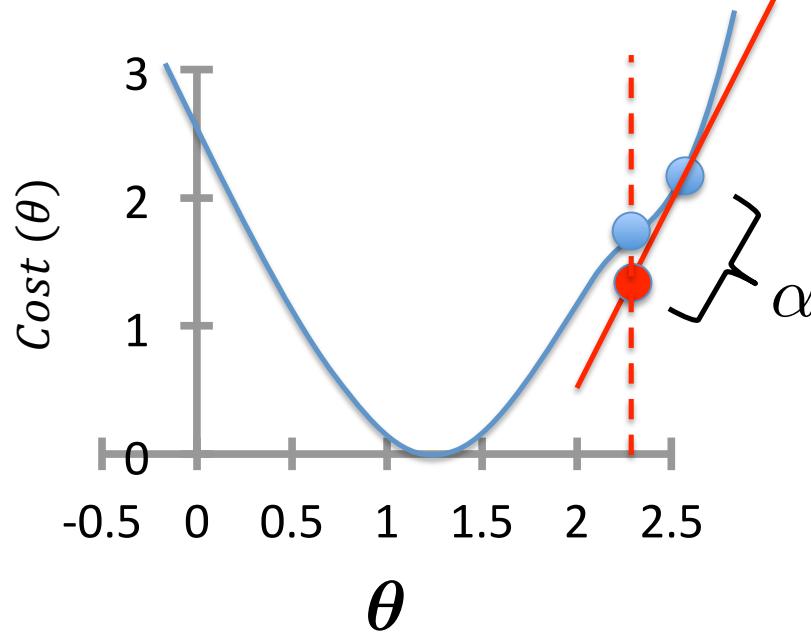
GRADIENT DESCENT

- Initialize θ
- Repeat until convergence

$$\theta_j \leftarrow \theta_j - \alpha \frac{\partial \text{Cost}(\theta)}{\partial \theta_j}$$

Learning rate

(simultaneous update for $\theta_0, \theta_1, \dots, \theta_d$)



GRADIENT DESCENT

- Initialize θ
- Repeat until convergence

$$\theta_j \leftarrow \theta_j - \alpha \frac{\partial Cost(\theta)}{\partial \theta_j} \quad (\text{simultaneous update for } \theta_0, \theta_1, \dots, \theta_d)$$

- For linear regression:

$$\frac{\partial Cost(\theta)}{\partial \theta_j} = \frac{\partial}{\partial \theta_j} \frac{1}{2n} \sum_{i=1}^n (h_\theta(x^{(i)}) - y^{(i)})^2$$

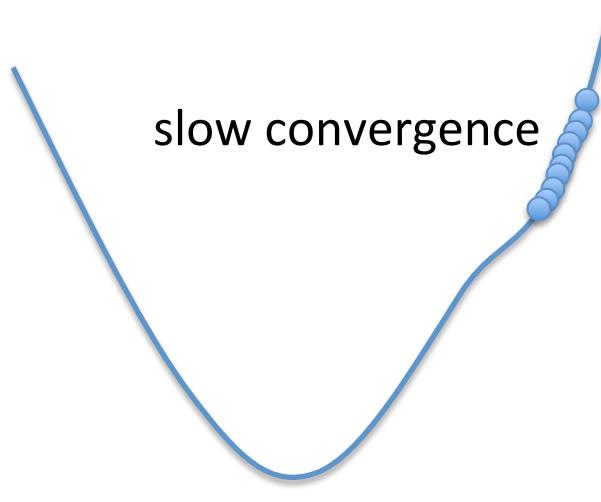
With $h_\theta(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_d x_d = \sum_{j=0}^d \theta_j x_j$

GRADIENT DESCENT

$$\begin{aligned}\frac{\partial Cost(\theta)}{\partial \theta_j} &= \frac{\partial}{\partial \theta_j} \frac{1}{2n} \sum_{i=1}^n (h_\theta(x^{(i)}) - y^{(i)})^2 \\ &= \frac{\partial}{\partial \theta_j} \frac{1}{2n} \sum_{i=1}^n \left(\sum_{k=0}^d \theta_k x_k^{(i)} - y^{(i)} \right)^2 \\ &= \frac{1}{n} \sum_{i=1}^n \left(\sum_{k=0}^d \theta_k x_k^{(i)} - y^{(i)} \right) \frac{\partial}{\partial \theta_j} \left(\sum_{k=0}^d \theta_k x_k^{(i)} - y^{(i)} \right) \\ &= \frac{1}{n} \sum_{i=1}^n \left(\sum_{k=0}^d \theta_k x_k^{(i)} - y^{(i)} \right) x_j^{(i)}\end{aligned}$$

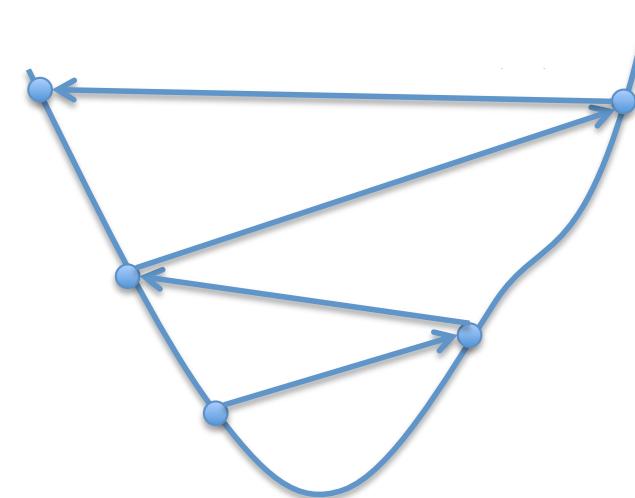
CHOOSE α

Too small

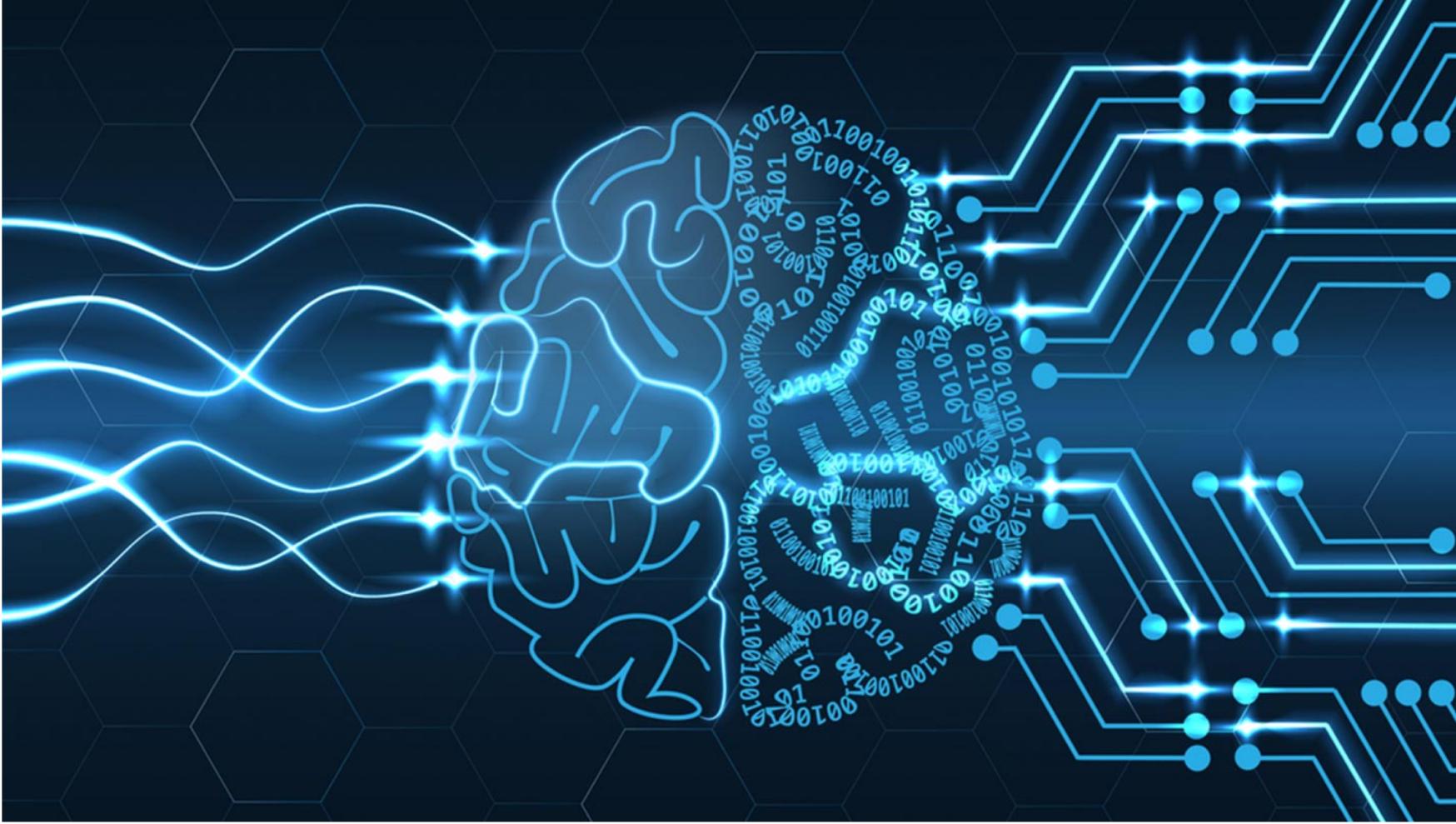


slow convergence

Too large



- May overshoot the minimum
- May fail to converge
- May even diverge



QUESTIONS?