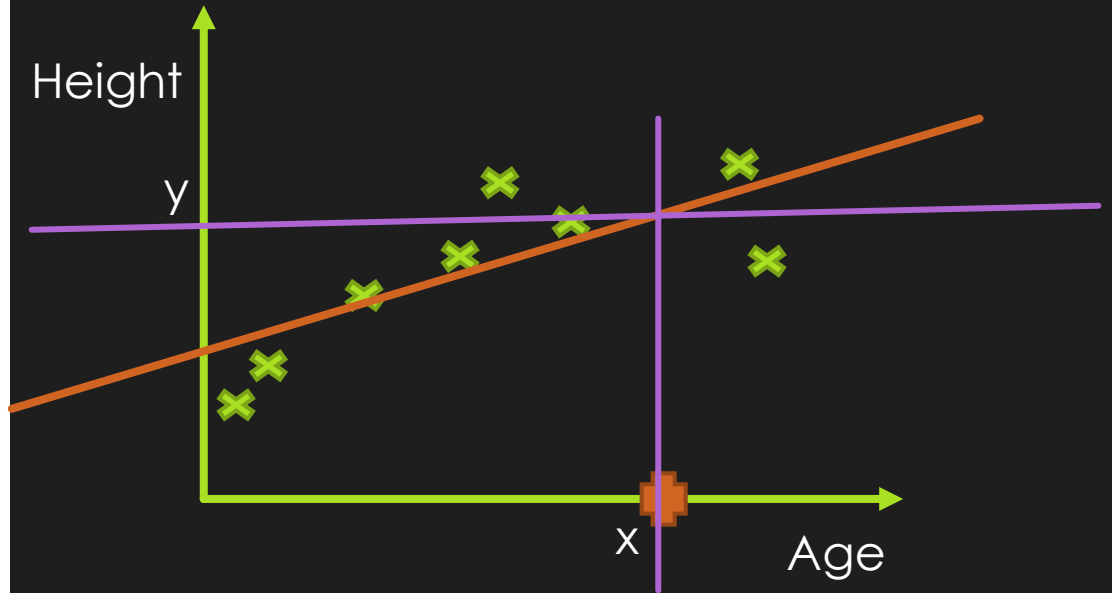
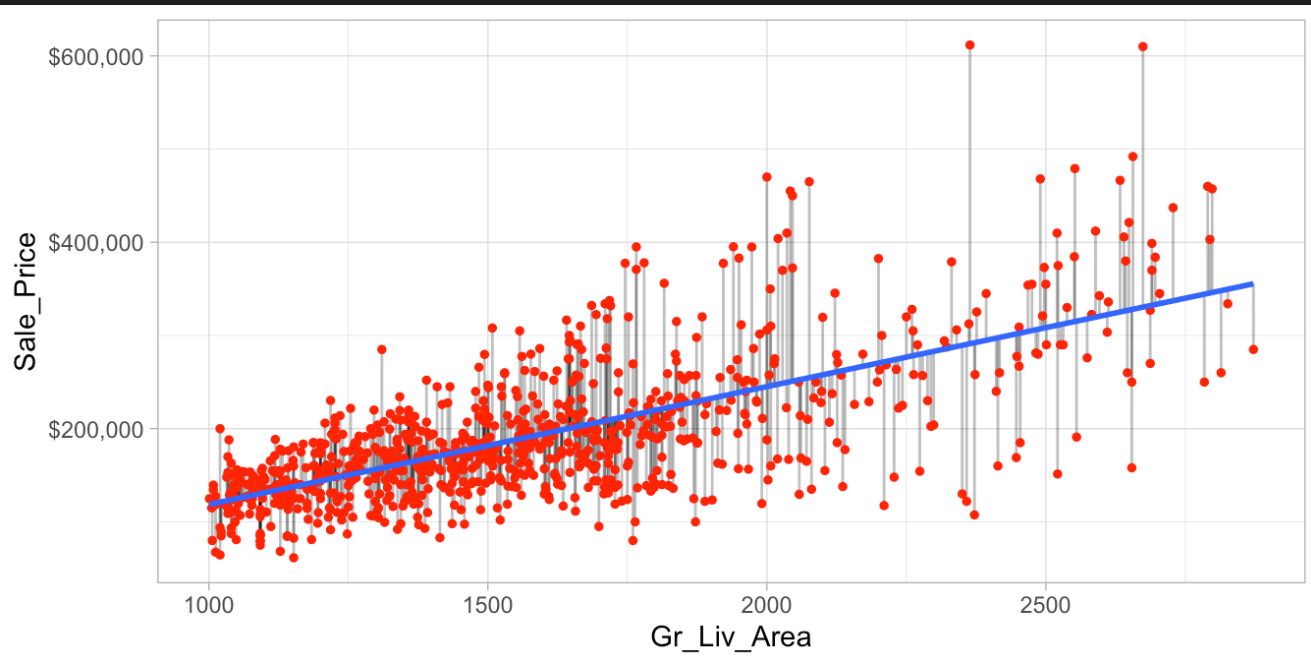


INTRODUCTION TO  
MACHINE LEARNING  
COMPSCI 4ML3

LECTURE 2

HASSAN ASHTIANI

# LINEAR CURVE-FITTING (REVIEW)



[HTTPS://BRADLEYBOEHMKE.GITHUB.IO/HOML/REGULARIZED-REGRESSION.HTML](https://bradleyboehmke.github.io/HOML/regularized-regression.html)

# ORDINARY LEAST SQUARES (1 DIMENSION)

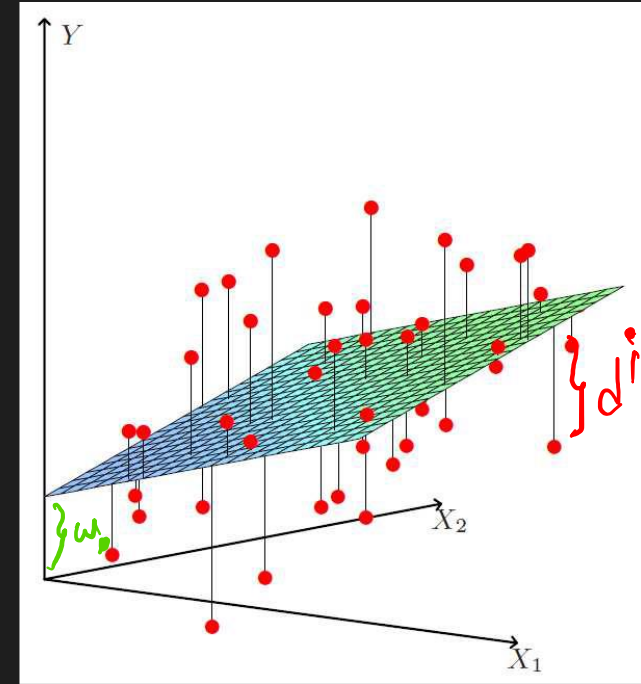
$$\{(x^i, y^i)\}_{i=1}^n, x^i \in \mathbb{R}, y^i \in \mathbb{R}$$

$$\text{MIN}_{a,b} \sum_{i=1}^n (ax^i + b - y^i)^2$$

$$a = \frac{\overline{xy} - \bar{x} \cdot \bar{y}}{\overline{x^2} - (\bar{x})^2} = \frac{\text{COV}(x, y)}{\text{Var}(x)}, b = \bar{y} - a\bar{x}$$

# ORDINARY LEAST SQUARES (D DIMENSIONS)

- ASSUME  $x \in \mathbb{R}^d$ ,  $y \in \mathbb{R}$
- INSTEAD OF A LINE, WE NEED TO FIT A HYPERPLANE!



- HYPERPLANE EQUATION:

$$\hat{y} = w_0 + \sum_{j=1}^d w_j x_j = w_0 + w_1 x_1 + w_2 x_2 \dots + w_d x_d$$

- $w_0$  - THE  $y$ -INTERCEPT (THE BIAS)

# EXAMPLE

- ESTIMATE THE PRICE OF OIL BASED ON TWO PROPERTIES:
- (1) PRICE OF GOLD AND (2) WORLD GDP
- $x \in ?$

- INPUT DATA:  $\{(x^i, y^i)\}_{i=1}^n$

$$\hat{y} = w_0 + w_1 x_1 + w_2 x_2$$

- FIND  $w_0, w_1, w_2$  THAT GIVE THE BEST ESTIMATE

Handwritten notes in green:

$$x^1 = (110, 56), y^1 = (70)$$

...

$$x_1 = 61, x_2 = (61)$$

$\hat{y} = \dots$

# ORDINARY LEAST SQUARES (D-DIMENSIONS)

- SIMPLIFICATION: **HOMOGENEOUS** HYPERPLANES

- $w_0 = 0$

- $\hat{y} = w_1 x_1 + w_2 x_2 \dots + w_d x_d \Rightarrow \sum_{j=1}^d w_j x_j$

- $\hat{y} = \langle \underline{w}, \underline{x} \rangle = \underline{w}^T \underline{x} = \underline{x}^T \underline{w}$ ,  $\underline{w} = (w_1, \dots, w_d)^T$

- FIND/LEARN  $w_j$ 'S FROM THE DATA

$$\text{MIN}_{w_1, \dots, w_d \in \mathbb{R}} \sum_{i=1}^n (\hat{y}^i - y^i)^2$$

# OPTIMIZE DIRECTLY?

$$\text{MIN}_{w_1, \dots, w_d \in \mathbb{R}} \sum_{i=1}^n (\hat{y}^i - y^i)^2 =$$

$$0 = \frac{\partial}{\partial w_1} = 2 \sum (w^T x^i - y^i) x_1^i = 2 \sum_{i=1}^n \left( \sum_j x_j^i w_j - y^i \right) x_1^i$$

$$0 = \frac{\partial}{\partial w_2} =$$

$$\dots$$
$$0 = \frac{\partial}{\partial w_d} =$$

d equations

d unknowns

# MATRIX FORM OLS (ORDINARY LEAST SQUARES)

- $X_{n \times d} = \begin{pmatrix} x_1^1 & \dots & x_d^1 \\ \vdots & \ddots & \vdots \\ x_1^n & \dots & x_d^n \end{pmatrix}$ ,  $Y_{n \times 1} = \begin{pmatrix} y^1 \\ \dots \\ y^n \end{pmatrix}$ ,  $W_{d \times 1} = \begin{pmatrix} w_1 \\ \dots \\ w_d \end{pmatrix}$



# PREDICTION IN VECTOR FORM

- FIND/LEARN  $W_{d \times 1}$  FROM THE DATA (SOON)
- GIVEN  $x$  AND  $w = W_{d \times 1}$ , WHAT SHOULD  $\hat{y}$  BE?

- $\hat{y} =$

$$\hat{y} = w^T x = x^T w = \sum_{j=1}^d w_j x_j = \langle w, x \rangle$$

# FINDING W

$$\sum \Delta_i^2$$

- OBJECTIVE:  $\sum_{i=1}^n (\widehat{y}^i - y^i)^2 = \sum_{i=1}^n (\langle w, x^i \rangle - y^i)^2 = \sum \Delta_i^2$

- DEFINE

$$\Delta = \begin{pmatrix} \Delta_1 \\ \dots \\ \Delta_n \end{pmatrix} = \begin{pmatrix} x_1^1 & \dots & x_d^1 \\ \vdots & \ddots & \vdots \\ x_1^n & \dots & x_d^n \end{pmatrix} \begin{pmatrix} w_1 \\ \dots \\ w_d \end{pmatrix} - \begin{pmatrix} y^1 \\ \dots \\ y^n \end{pmatrix} = \begin{pmatrix} \widehat{y}^1 - y^1 \\ \dots \\ \widehat{y}^n - y^n \end{pmatrix}$$

$$\Delta = XW - Y$$

first row

$$\sum x_j^1 w_j = x_1^{1T} w = \widehat{y}^1$$

# FINDING W

$$\|v\|_2 = \sqrt{\sum v_i^2}$$

$$\|v\|_p = \left(\sum |x_j|^p\right)^{1/p}$$

$$\Delta = \begin{pmatrix} \Delta_1 \\ \dots \\ \Delta_n \end{pmatrix} = \begin{pmatrix} x_1^1 & \dots & x_d^1 \\ \vdots & \ddots & \vdots \\ x_1^n & \dots & x_d^n \end{pmatrix} \begin{pmatrix} w_1 \\ \dots \\ w_d \end{pmatrix} - \begin{pmatrix} y^1 \\ \dots \\ y^n \end{pmatrix}$$

$$\bullet \text{ OBJECTIVE FUNCTION: } \sum_{i=1}^n (\Delta_i)^2 = \|\Delta\|_2^2$$

$$\bullet \min_{W \in \mathbb{R}^{d \times 1}} \sum_{i=1}^n (\Delta_i)^2 = \min_{W \in \mathbb{R}^{d \times 1}} \langle \Delta, \Delta \rangle = \min_{W \in \mathbb{R}^{d \times 1}} \|\Delta\|_2^2 =$$

$$\min_{W \in \mathbb{R}^{d \times 1}} \|XW - Y\|_2^2$$

$$XW - Y = \Delta$$

$$\|XW - Y\|_2^2 = \|\Delta\|_2^2 \checkmark$$

# OLS SOLUTION

$$X_{n \times d}, \quad X^T: d \times n$$

$$W^{LS}_{d \times 1} = \underbrace{(X^T X)^{-1}}_{d \times d} \underbrace{X^T}_{d \times n} \underbrace{Y}_{n \times 1}$$

- VERIFY DIMENSIONS

- COMPARE TO  $a = \frac{\text{COV}(x,y)}{\text{Var}(x)}$  FOR  $d = 1$

- WHAT IF  $X^T X$  IS NOT INVERTIBLE?

$$(x^i, y^i) = (0, 0)$$

