

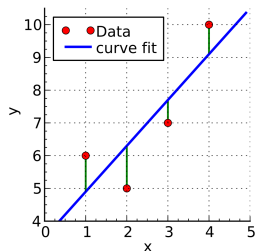
# CS456: Machine Learning

## Linear Least Square Regression Model

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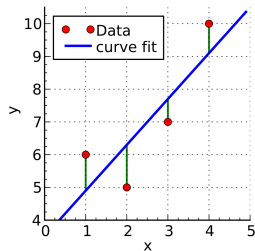
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# Linear Regression Problem



- Recall that in linear regression problem we are given a set of data  $(\mathbf{x}_i, y_i)$ ,  $i = 0, \dots, N$  (red dots)
- And we want to find a linear function  $f(\mathbf{x})$  that best describes the data

# Motivation



- In most of the cases,  $f(\mathbf{x})$  cannot perfectly describe the data
- There is almost always mismatch between  $y_i$  (the true value) and the value given by the model  $f(\mathbf{x}_i)$
- The magnitude of the mismatch is length of green line

# Sum of squared errors

- The error of the estimation of each  $y_i$  is given by

$$\epsilon_i = y_i - f(\mathbf{x}_i) \quad (1)$$

$$= y_i - a\mathbf{x}_i \quad (2)$$

- Since  $\epsilon_i$  can be either positive or negative, their values might cancel out
- So we square the error terms and get

$$\epsilon_i = (y_i - a\mathbf{x}_i)^2 \quad (3)$$

- Summing all the error terms we have

$$\epsilon = \sum_{i=0}^N (y_i - a\mathbf{x}_i)^2 \quad (4)$$

- We can write the sum of squared errors in matrix form

$$\epsilon = \|X\mathbf{a} - Y\|_2^2 \quad (5)$$

- $X$  is a data matrix  $N$  by  $M$  ( $N$ =number of data points  $M$ = data dimension)
- $Y$  is matrix of responses
- $\mathbf{a}$  is a coefficient vector of the linear model

## In matrix form: Example

- Given  $\{(3, 14), (2, 13), (5, 19)\}$

$$X = \begin{bmatrix} 3 \\ 2 \\ 5 \end{bmatrix}, \mathbf{a} = [a_1], Y = \begin{bmatrix} 14 \\ 13 \\ 19 \end{bmatrix} \quad (6)$$

- Or another example (2 dimensions)

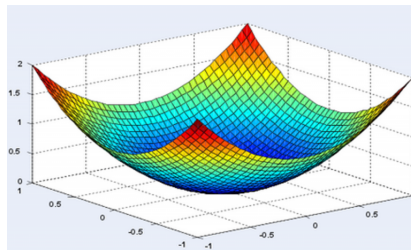
$$X = \begin{bmatrix} 3 & 2 \\ 2 & 1 \\ 5 & 4 \end{bmatrix}, \mathbf{a} = \begin{bmatrix} a_1 \\ a_2 \end{bmatrix}, Y = \begin{bmatrix} 3.3 \\ 1.5 \\ 7.9 \end{bmatrix} \quad (7)$$

# Linear Least Square

- Goal: Find a vector  $\mathbf{a}$  which when multiplied to all the data gives the smallest sum of squared errors (the objective function)

$$L = \min_{\mathbf{a}} \|X\mathbf{a} - Y\|_2^2 \quad (8)$$

- The function in Eq.(8) is a convex function with a global minimum



## Where the best $\mathbf{a}$ is ?

- A point where the minimum is, is the stationary point (slope/derivative) is zero
- First we find the derivative of the objective function w.r.t  $\mathbf{a}$

$$\frac{\partial L}{\partial \mathbf{a}} = \frac{\partial \|X\mathbf{a} - Y\|_2^2}{\partial \mathbf{a}} \quad (9)$$

$$= 2(X\mathbf{a} - Y)X \quad (10)$$

- Next find  $\mathbf{a}$  which gives zero slope

$$(X\mathbf{a} - Y)X = 0 \quad (11)$$

$$X^T X\mathbf{a} - X^T Y = 0 \quad (12)$$

$$\mathbf{a} = (X^T X)^{-1} X^T Y \quad (13)$$



# Implementation example

Let's switch to Google's colab – <https://colab.research.google.com/drive/1o94L5SKWkb4f8L08q92FthRc2Qc8YpVJ>