



# Introduction to Linear Regression(LR)

## *Notes of class*

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## 1 Linear regression

Before that we introduce to linear regression and the derivation of its properties it is important recall some properties of summatory:

Remember that;

$$\sum_{i=1}^n x_i = x_1 + x_2 + x_3 + \dots + x_n \quad (1)$$

$$\sum a = na \quad (2)$$

$$\sum(ax) = a \sum x \quad (3)$$

$$\sum(x_i + y_i) = \sum x_i + \sum y_i \quad (4)$$

$$\sum(ax + by) = a \sum x_1 + b \sum y_1 \quad (5)$$

$$\begin{aligned} & \sum x_i y_i - n \bar{x} \bar{y} \\ &= \sum x_i y_i - \sum x_i \bar{y} \\ &= x_1 y_1 + x_2 y_2 + \dots + x_n y_n - (x_1 + x_2 + \dots + x_n) \bar{y} \\ &= x_1 y_1 - x_1 \bar{y} + x_2 y_2 - x_2 \bar{y} + \dots + x_n y_n - x_n \bar{y} \\ &= x_1(y_1 - \bar{y}) + x_2(y_2 - \bar{y}) + \dots + x_n(y_n - \bar{y}) = \sum x_i(y_i - \bar{y}) = \sum y_i(x_i - \bar{x}) \end{aligned} \quad (6)$$

With this properties and examples we could verify that :

$$\sum(x_i - \bar{x})^2 = \sum x_i^2 - n \bar{x}^2 \quad (7)$$

and

$$\sum(y_i - \bar{y})(x_i - \bar{x}) = \sum x_i y_i - n \bar{x} \bar{y} \quad (8)$$

## 2 OLS

$u_i = y_i - \hat{y}_i$  and  $\hat{y}_i = \beta_0 + \beta_1 x_i$  and our goal is :

$$\min \sum (y_i - \hat{y}_i)^2 = \min \sum u_i^2 \quad (9)$$

to solve the problem note that  $u_i(\beta_0, \beta_1)$ .

$$\frac{\sum u_i^2}{\partial \beta_k} = \frac{\sum u_i^2}{\partial u_i} \frac{\partial u_i}{\partial \beta_k} = 0 \quad k = 0, 1. \quad (10)$$

$$\begin{aligned} \frac{\partial u_i}{\partial \beta_0} &= -2 \sum u_i = 0 \\ \frac{\partial u_i}{\partial \beta_1} &= \sum u_i x_i = 0 \end{aligned} \quad (11)$$

rewriting the equations:

$$\begin{aligned} \sum (y_i - \beta_0 - \beta_1 x_i) &= 0 \\ \sum (y_i - \beta_0 - \beta_1 x_i) x_i &= 0 \end{aligned} \quad (12)$$

applying:

$$\begin{aligned} n\bar{y} - n\beta_0 - n\beta_1 \bar{x} &= 0 \\ \sum x_i y_i - n\beta_0 \bar{x} - \beta_1 \sum x_i^2 &= 0 \end{aligned} \quad (13)$$

now of  $n\bar{y} - n\beta_0 - n\beta_1 \bar{x}$  we can get:

$$\beta_0 = \bar{y} - \beta_1 \bar{x} \quad (14)$$

now replace  $\beta_0$  in  $\sum x_i y_i - n\beta_0 \bar{x} - \beta_1 \sum x_i^2$

$$\begin{aligned} \sum x_i y_i - n\bar{x}\bar{y} + n\beta_1 \bar{x}^2 - \beta_1 \sum x_i^2 &= 0 \\ \sum x_i y_i - \bar{x}\bar{y} &= \beta_1 (\sum x_i^2 - n\bar{x}^2) \\ \beta_1 &= \frac{\sum x_i y_i - \bar{x}\bar{y}}{\sum x_i^2 - n\bar{x}^2} \end{aligned} \quad (15)$$

According to the properties defined previously:

$$\beta_1 = \frac{\sum x_i y_i - \bar{x}\bar{y}}{\sum x_i^2 - n\bar{x}^2} = \frac{\sum (y_i - \bar{y})(x_i - \bar{x})}{\sum (x_i - \bar{x})^2} = \frac{\text{cov}(x, y)}{\text{var}(x)}. \quad (16)$$

We could make own implementations to solve this problem;

## 3 Multiple linear regression

## 4 LR gradient descent