

## # ORDINARY LEAST SQUARE METHOD #

\*\* Cost function = It refers to entire error.  
that means total errors.  
It is denoted with 'J'.

$$J = \sum_{i=1}^n (y_{\text{actual}i} - y_{\text{predicted}i})^2$$

$y_{\text{actual}i}$  = Actual input

$y_{\text{prediction}i}$  = Prediction value.

⇒ Differentiation of J makes equals to zero, partial  
differentiate of J with respect to  $b_0$  and  $b_1$ .

⇒ There are two cases ⇒

① Case I =  $\frac{\partial J}{\partial b_0} = 0$

② Case II =  $\frac{\partial J}{\partial b_1} = 0$

$$\left\{ \begin{array}{l} b_0 = b_0 \\ b_1 = b_1 \\ y_{ai} = y_{\text{actual}i} \end{array} \right\}$$

\*\* Case I -

$$\Rightarrow \frac{\partial J}{\partial \beta_0} = \frac{\partial \sum_{i=1}^n (y_{\text{actual}i} - \beta_0 - \beta_1 x_i)^2}{\partial \beta_0}$$

$$\Rightarrow 2 \sum_{i=1}^n (y_{\text{actual}i} - \beta_0 - \beta_1 x_i) \times \frac{\partial}{\partial \beta_0} (y_{\text{actual}i} - \beta_0 - \beta_1 x_i)$$

$$\begin{aligned}
 &\Rightarrow 2 \times \left(\frac{1}{n}\right) \sum_{i=1}^n (y_{\text{actual } i} - \beta_0 - \beta_1 x_i) \times (0 - 1 - 0) \\
 &\Rightarrow -2 \times \left(\frac{1}{n}\right) \sum_{i=1}^n (y_{\text{actual } i} - \beta_0 - \beta_1 x_i) \\
 &\Rightarrow -2 \times \left(\frac{1}{n}\right) \sum_{i=1}^n y_{ai} - \frac{1}{n} \sum_{i=1}^n \beta_0 - \frac{1}{n} \sum_{i=1}^n \beta_1 x_i \\
 &\Rightarrow -2 \times \left(\frac{1}{n}\right) \sum_{i=1}^n y_{ai} - \frac{1}{n} \beta_0 \sum_{i=1}^n 1 - \frac{1}{n} \beta_1 \sum_{i=1}^n x_i \quad \text{--- (eq. 1)}
 \end{aligned}$$

$$\Rightarrow \frac{1}{n} \sum_{i=1}^n y_{ai} = \frac{y_{a1} + y_{a2} + y_{a3} + \dots + y_{an}}{n} = \bar{y}_a$$

$$\Rightarrow \frac{1}{n} \sum_{i=1}^n 1 = \frac{1 + 1 + 1 + \dots + n}{n} = n/n = 1$$

\*\* Substitute this 3 points in above eq. 1 =

$$\Rightarrow -2 \times (\bar{y}_a - \beta_0 - \beta_1 \bar{x}) \quad \text{--- (eq. 2)}$$

Now equating eq. 2 with equal to zero =

$$\Rightarrow \frac{\partial J}{\partial \beta_0} = 0$$

$$\Rightarrow \frac{\partial J}{\partial \beta_0} = -2 \times (\bar{y}_a - \beta_0 - \beta_1 \bar{x}) = 0$$

$$\Rightarrow \bar{y}_a - \beta_0 - \beta_1 \bar{x} = 0$$

\*  $\boxed{\beta_0 = \bar{y}_a - \beta_1 \bar{x}}$

\* This  $\beta_0$  is called as bias formula; here -

$\bar{y}_a$  = actual output

$\beta_0$  and  $\beta_1$  = constants.

$\bar{x}$  = coefficient value

\* Now we want complete about equation in order to find  $\beta_0$  value completely we need to find  $\beta_1$ .

\* from case-II we have to find that as shown below:

$$\Rightarrow \underline{\text{Case-I}} : \frac{\partial J}{\partial \beta_1} = \frac{\partial \sum_{i=1}^n (y_{\text{actual}i} - \beta_0 - \beta_1 x_i)^2}{\partial \beta_1}$$

$$\Rightarrow 2 \sum_{i=1}^n (y_{\text{actual}i} - \beta_0 - \beta_1 x_i) \times \frac{\partial}{\partial \beta_1} (y_{\text{actual}i} - \beta_0 - \beta_1 x_i)$$

$$\Rightarrow 2 \times \frac{1}{n} \sum_{i=1}^n (y_{\text{actual}i} - \beta_0 - \beta_1 x_i) \times (0 - 0 - x_i)$$

$$\Rightarrow -2 \left(\frac{1}{n}\right) \sum_{i=1}^n (y_{ai} x_i - \beta_0 x_i - \beta_1 x_i x_i)$$

$$\Rightarrow -2 \left(\frac{1}{n}\right) \sum_{i=1}^n (x_i (y_a - \bar{y}_a) - \beta_1 x_i (\bar{x} - x_i))$$

$$\Rightarrow -2 \left(\frac{1}{n}\right) \left( \sum_{i=1}^n x_i (y_{ai} - \bar{y}_a) + \sum_{i=1}^n (\beta_1 x_i (\bar{x} - x_i)) \right)$$

--- (eq. 3)



Now equating eq.3 with equal to zero -

$$\Rightarrow \frac{\partial J}{\partial \beta_0} = 0 \quad \checkmark$$

$$\Rightarrow \frac{\partial J}{\partial \beta_0} = -2 \left( \frac{1}{n} \right) \left( \sum_{i=1}^n x_i (\bar{y} - y_i) + \sum_{i=1}^n (\beta_1 x_i (\bar{x} - x_i)) = 0 \right)$$

$$\Rightarrow - \sum_{i=1}^n x_i (\bar{y} - y_i) = \sum_{i=1}^n \beta_1 x_i (\bar{x} - x_i)$$

$$\Rightarrow \sum_{i=1}^n (\bar{y} - y_i) = \sum_{i=1}^n \beta_1 (\bar{x} - x_i)$$

$$\Rightarrow \beta_1 = \sum_{i=1}^n (\bar{y} - y_i) / \sum_{i=1}^n (\bar{x} - x_i) \dots \text{eq.4}$$

Multiply eq.4 with the denominator -

$$\Rightarrow \beta_1 = \frac{\sum_{i=1}^n (\bar{y} - y_i) \times \sum_{i=1}^n (\bar{x} - x_i)}{\sum_{i=1}^n (\bar{x} - x_i) \times \sum_{i=1}^n (\bar{x} - x_i)}$$

$$\Rightarrow \left[ \beta_1 = \frac{\sum_{i=1}^n (\bar{y} - y_i) \times (\bar{x} - x_i)}{\sum_{i=1}^n (\bar{x} - x_i)^2} \right] = \left[ \frac{\text{cov}(x, y)}{\text{var}(x)} \right]$$

Now substitute above  $\beta_1$  values in case-I equation in order to get  $\beta_0$  value.

$$\left[ \beta_0 = \bar{y}_n - \bar{x} \frac{\text{cov}(x, y)}{\text{var}(x)} \quad \& \quad \beta_1 = \frac{\text{cov}(x, y)}{\text{var}(x)} \right]$$

\* This equation is called as ordinary least square method (OLS).