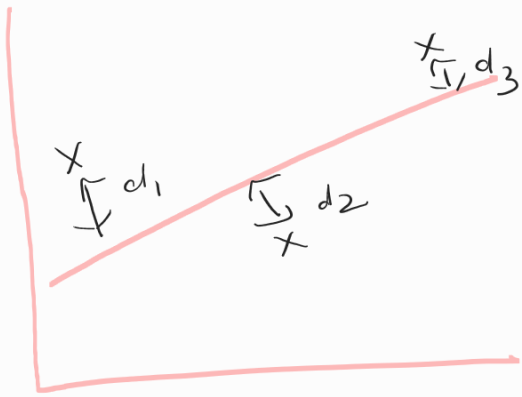


Since  $y = mx + b$

$$\text{So } E = d_1^2 + d_2^2 + d_3^2 + d_4^2 - \dots$$



Since  $d_1 = y_1 - \hat{y}_1$ ,  $d_2 = y_2 - \hat{y}_2$  ( $\hat{y}$  = predicted value)

$$\text{Error}(E) = d_1^2 + d_2^2 + d_3^2 - \dots d_n^2$$

$$E = \sum_{i=0}^n y_i - \hat{y}_i$$

$$= \sum_{i=0}^n (y_i - (mx_i + b))^2$$

To minimize error  $E$   $\frac{\partial E}{\partial m} = \frac{\partial E}{\partial b} = 0$

$$\therefore \frac{\partial E}{\partial b} = 0$$

$$\sum \frac{\partial (y_i - (mx_i + b))^2}{\partial b} = 0$$

$$\therefore \sum 2(y_i - mx_i - b) \times -1 = 0$$

$$\sum -2(y_i - mx_i - b) = 0$$

$$\sum y_i - mx_i - b = 0$$

$$\frac{\sum y_i}{n} - \frac{\sum mx_i}{n} - \frac{\sum b}{n} = 0$$

$$\bar{y} = m \bar{x} + b = 0$$

$$\therefore b = \bar{y} - m \bar{x}$$

Now  $E = \sum y - \hat{y}$

$$E = \sum (y_i - (m x_i + \bar{y} - m \bar{x}))^2$$

$$\frac{\partial E}{\partial m} = 2(y_i - m x_i - \bar{y} + m \bar{x}) \times (-x_i + \bar{x})$$

$$= \sum [(y_i - \bar{y}) - m(x_i - \bar{x})] \times (x_i - \bar{x}) = 0$$

$$= \sum (y_i - \bar{y})(x_i - \bar{x}) - m(x_i - \bar{x})^2 = 0$$

$$\therefore m = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$



