

$$H = X(X^T X)^{-1} X^T$$

\Rightarrow Symmetric

$$H^T = H$$

\Rightarrow Idempotent

$$H H = H$$

Symmetric, $H' = (X(X^T X)^{-1} X^T)^T$

$$= (X^T)^T ((X^T X)^{-1})^T X^T$$

$$= X^0 ((X'X)^T)^{-1} X^T$$

$$= X(X'X)^{-1} X^T$$

$$H H = H$$

$$(ABC)' = C'B'A'$$

H is idempotent

$$H H = H^2 = \underbrace{\left(X (X^T X)^{-1} X^T \right)}_{p \times n} \underbrace{\left(X (X^T X)^{-1} X^T \right)}_{n \times p}$$

$$= X \underbrace{(X^T X)^{-1} (X^T X)}_I X^T$$

$$= X I (X^T X)^{-1} X^T$$

$$= X (X^T X)^{-1} X^T$$

$$= \underline{\underline{H}}$$

if we have n sample points $\{(x_1, y_1), (x_2, y_2), \dots\}$

Error of Sample i :

$$e_i = y_i - \hat{y}_i$$

$$y_i = \beta_0 + \beta_1 x_i$$

and we have to minimize

$$SSE = \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

$$\arg \min_{\beta_0, \beta_1} \sum_{i=1}^n SSE = \arg \min_{\beta_0, \beta_1} \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \sum_{i=1}^n$$

$$= \arg \min_{\beta_0, \beta_1} \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)^2$$

Diff w.r.t β_0

$$2 \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i) (-1) = 0$$

$$\beta_0 = \frac{\sum_{i=1}^n (y_i - \beta_1 x_i)}{n}$$

$$\beta_0 = \sum_{i=1}^n \frac{y_i}{n} - \beta_1 \sum_{i=1}^n \frac{x_i}{n} \Rightarrow \beta_0 = \bar{y} - \beta_1 \bar{x}$$

means

$$\arg \min_{\beta_0, \beta_1} \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)^2$$

Diff w.r.t β_1

$$\Rightarrow 2 \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)(-x_i) = 0$$

$$\Rightarrow \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i) x_i = 0$$

$$\Rightarrow \sum_{i=1}^n x_i y_i - \beta_0 \sum_{i=1}^n x_i - \beta_1 \sum_{i=1}^n x_i^2 = 0$$

put value of β_0 here

$$\Rightarrow \sum_{i=1}^n x_i y_i - \left(\sum_{i=1}^n \frac{y_i}{n} - \beta_1 \sum_{i=1}^n \frac{x_i}{n} \right) \sum_{i=1}^n x_i - \beta_1 \sum_{i=1}^n x_i^2 = 0$$

$$\Rightarrow \sum_{i=1}^n x_i y_i - \sum_{i=1}^n \frac{y_i}{n} \sum_{i=1}^n x_i + \beta_1 \sum_{i=1}^n \frac{x_i}{n} \sum_{i=1}^n x_i - \beta_1 \sum_{i=1}^n x_i^2 = 0$$

$$\Rightarrow \sum_{i=1}^n x_i y_i - \frac{1}{n} \sum_{i=1}^n y_i \sum_{i=1}^n x_i + \beta_1 \frac{\sum_{i=1}^n x_i}{n} \sum_{i=1}^n x_i - \beta_1 \sum_{i=1}^n x_i^2 = 0$$

$$\beta_1 = \frac{\sum x_i y_i - (\bar{y}) \sum x_i}{\sum x_i^2 - \frac{1}{n} \left(\sum x_i \right)^2}$$

$$\beta_1 = \frac{\sum_{i=1}^n x_i y_i - n \bar{x} \bar{y}}{\sum x_i^2 - n \bar{x}^2}$$

multiple Var Normal Egn

$$\Rightarrow \beta = (X^T X)^{-1} X^T Y$$

$$\boxed{Y = X \beta}$$

↑
predicted value.