

$$Y = X\beta + u$$

$n \times 1$ $n \times k$ $k \times 1$ $n \times 1$

$$\hat{\beta} \quad Y = X\hat{\beta} + \hat{u}$$

$$\hat{u} = Y - X\hat{\beta}$$

$$\hat{u} = \begin{bmatrix} \hat{u}_1 \\ \hat{u}_2 \\ \vdots \\ \hat{u}_n \end{bmatrix} \quad \hat{u}' = [\hat{u}_1 \quad \hat{u}_2 \quad \dots \quad \hat{u}_n]$$

$n \times 1$ $1 \times n$

$$\hat{u}'\hat{u} = \hat{u}_1\hat{u}_1 + \hat{u}_2\hat{u}_2 + \dots + \hat{u}_n\hat{u}_n = \hat{u}_1^2 + \hat{u}_2^2 + \dots + \hat{u}_n^2 = \sum_{i=1}^n \hat{u}_i^2$$

$1 \times n$ $n \times 1$ (1×1)

$$\text{OLS} \rightarrow \underset{\text{Min.}}{\sum_{i=1}^n \hat{u}_i^2} = 0$$

$$\left. \begin{aligned} \frac{\partial \sum \hat{u}_i^2}{\partial \hat{\beta}_1} &= 0 \\ &= 0 \\ &\vdots \\ \frac{\partial \sum \hat{u}_i^2}{\partial \hat{\beta}_k} &= 0 \end{aligned} \right\} \begin{array}{l} k\text{-eq.} \\ k\text{-unknown} \end{array}$$

$$\hat{u}'\hat{u} = (Y - X\hat{\beta})'(Y - X\hat{\beta}) = Y'Y - \underbrace{Y'X\hat{\beta}}_{1 \times n \quad n \times k \quad k \times 1 \quad (1 \times 1)} - \underbrace{\hat{\beta}'X'Y}_{1 \times k \quad k \times n \quad n \times 1 \quad (1 \times 1)} + \hat{\beta}'X'X\hat{\beta}$$

$$\hat{u}'\hat{u} = Y'Y - 2\hat{\beta}'X'Y + \hat{\beta}'X'X\hat{\beta}$$

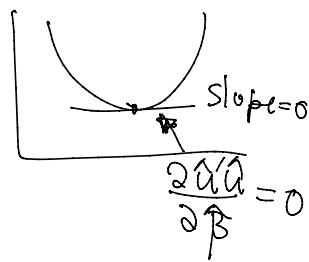
$$\frac{\partial \hat{u}'\hat{u}}{\partial \hat{\beta}} = 0 \quad (-2X'Y) + 2X'X\hat{\beta} = 0$$

$$2X'X\hat{\beta} = 2X'Y$$

$$\cancel{(X'X)}\hat{\beta} = \cancel{(X'X)}^{-1}X'Y$$

$$\hat{\beta}_{\text{OLS}} = (X'X)^{-1}X'Y$$

$k \times 1$ $k \times n$ $n \times k$ $k \times n$ $n \times 1$ $(k \times 1)$



$$u = \begin{matrix} (n \times 1) \\ u_1 \\ u_2 \\ \vdots \\ u_n \end{matrix} \quad u' = \begin{matrix} (1 \times n) \\ u_1 & u_2 & \dots & u_n \end{matrix}$$

$$E(u \cdot u') = \begin{bmatrix} E(u_1 u_1) & E(u_1 u_2) & \dots & E(u_1 u_n) \\ E(u_2 u_1) & E(u_2 u_2) & \dots & E(u_2 u_n) \\ \vdots & \vdots & \ddots & \vdots \\ E(u_n u_1) & E(u_n u_2) & \dots & E(u_n u_n) \end{bmatrix}$$

$$E(X) = \text{Mean}$$

$$E(u_i) = 0$$

$$E[(X - E(X))^2] = \text{variance}$$

$$E[(u_i - E(u_i))^2] = E[u_i^2] = \text{variance} = \sigma_i^2$$

$$E[(X - E(X))(Y - E(Y))] = \text{covariance} \quad E[(u_i - E(u_i))(u_j - E(u_j))] = \text{cov.}$$

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \dots & \sigma_{1n} \\ \sigma_{21} & \sigma_2^2 & \dots & \sigma_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \dots & \sigma_n^2 \end{bmatrix}$$

$$E[u_i u_j] = \text{cov}(u_i, u_j) = \sigma_{ij}$$

$$\hat{\beta}_{GLS} = (X' \Sigma^{-1} X)^{-1} X' \Sigma^{-1} Y$$

OLS assume:

$$\Sigma = \sigma^2 I$$

$$\hat{\beta}_{OLS} = (X' (\sigma^2 I)^{-1} X)^{-1} X' (\sigma^2 I)^{-1} Y$$

$$= \frac{1}{\sigma^2} (X' I^{-1} X)^{-1} X' I^{-1} Y$$

$$= (X' X)^{-1} X' Y$$

OLS is special case of GLS when $\Sigma = \sigma^2 I$

If we have heteroscedasticity or autocorrelation problem, we shouldn't use OLS since $\Sigma \neq \sigma^2 I$

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Then, we should use GLS

$$\hat{\beta}_{GLS} = (X' \Sigma^{-1} X)^{-1} X' \Sigma^{-1} Y$$

Problem: We can't observe Σ^{-1}

We need to estimate $\hat{\Sigma}^{-1}$

$$\hat{\beta}_{FGLS} = (X' \hat{\Sigma}^{-1} X)^{-1} X' \hat{\Sigma}^{-1} Y$$