

Lecture 14 Oct 25

Q orthogonality of the residuals and the column space
 $C(X)$

Model : $\underline{Y} = X \underline{\beta} + \underline{\varepsilon}$

where $\underline{\varepsilon} \sim N(\underline{0}, I \otimes \sigma^2)$

$$\underline{\mu} = E \underline{Y} = E(X \underline{\beta} + \underline{\varepsilon}) = X \underline{\beta}$$

Estimate $\underline{\beta}$ or $\underline{\mu}$

$$\underline{\mu} = X \underline{\beta}$$

$$\underline{\beta} = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_p \end{pmatrix}$$

$$X = [\underline{x}_1 | \dots | \underline{x}_p]$$

$$\underline{\mu} = \underline{x}_1 \beta_1 + \underline{x}_2 \beta_2 + \dots + \underline{x}_p \beta_p$$

Define $C(X) =$ space spanned by the columns
of X

In particular, $\mu \in C(X)$.

A candidate estimator of μ must also belong to $C(X)$,

$$\begin{aligned}\tilde{\mu}(\underline{b}) &= \underline{X}_1 b_1 + \dots + \underline{X}_p b_p \\ &= \underline{X} \underline{b}\end{aligned}$$

The squared error between \underline{Y} and $\tilde{\mu}(\underline{b})$ is:

$$\|\underline{Q}\|_2^2 = \sum_{i=1}^N y_i^2$$

$$S(\underline{b}) = \|\underline{Y} - \underline{X} \underline{b}\|_2$$

$$\begin{aligned}&= (\underline{Y} - \underline{X} \underline{b})^T (\underline{Y} - \underline{X} \underline{b}) \\ &= (\underline{Y} - (\underline{X}_1 b_1 + \dots + \underline{X}_p b_p))^T (\end{aligned}$$

The LSE of μ (or $\underline{\beta}$):

$$\hat{\mu} = \underline{X} \hat{\underline{\beta}} \quad \text{Satisfies.}$$

$$\hat{\underline{\beta}} = \arg \min_{\underline{b}} S(\underline{b})$$

$$\left. \begin{aligned} \frac{\partial S(\underline{b})}{\partial b_1} &= -2 \quad \underline{X}_1^T (\underline{Y} - \underline{X} \underline{b}) \\ &\vdots \\ \frac{\partial S(\underline{b})}{\partial b_p} &= -2 \cdot \underline{X}_p^T (\underline{Y} - \underline{X} \underline{b}) \end{aligned} \right\}$$

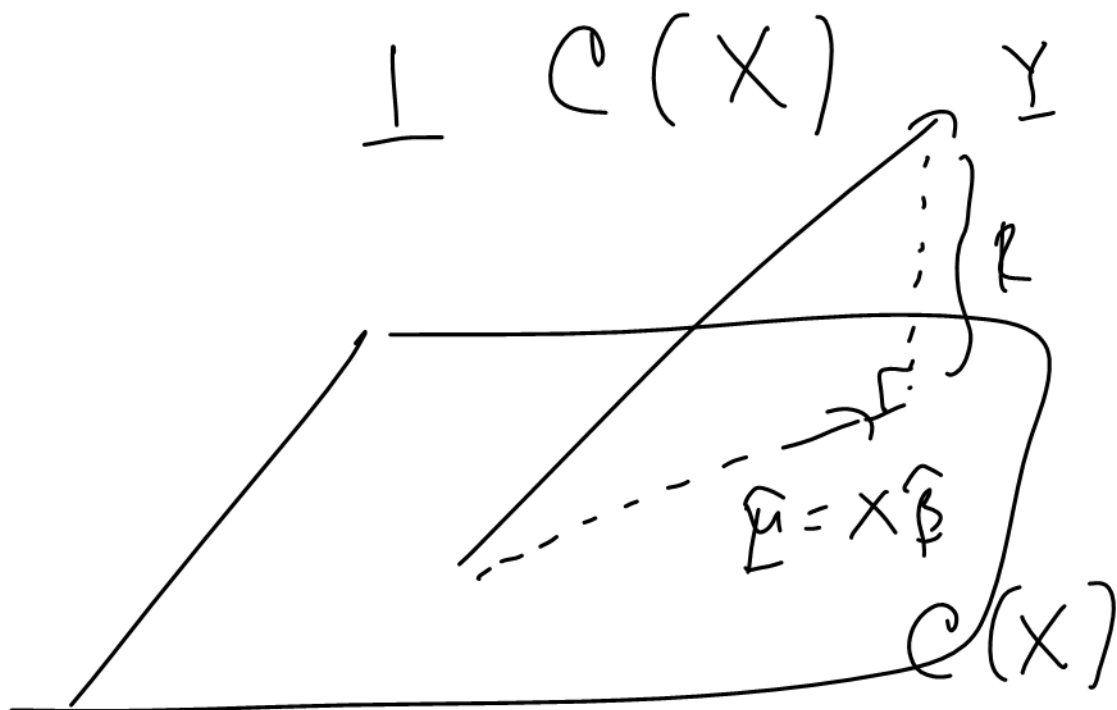
$$\text{Summary } \left(\frac{\partial S(\underline{b})}{\partial \underline{b}} \right) = -2 \cdot \underline{X}^T (\underline{Y} - \underline{X} \underline{b})$$

$$\left. \frac{\partial S(\underline{b})}{\partial \underline{b}} \right|_{\hat{\underline{\beta}}} = \underline{0}$$

$$\Rightarrow \left. \begin{aligned} \underline{X}_1^T (\underline{Y} - \underline{X} \hat{\underline{\beta}}) &= 0 \\ &\vdots \\ \underline{X}_p^T (\underline{Y} - \underline{X} \hat{\underline{\beta}}) &= 0 \end{aligned} \right\}$$

$$\underline{Y} - \underline{X} \hat{\underline{\beta}} = \underline{R}$$

$$\Rightarrow \underline{R} \perp \{x_1, \dots, x_p\}$$



$$\begin{aligned} \overline{\sum R_i} &= \overline{\sum R_i(1)} \\ &= \langle \underline{R}, \underline{1} \rangle \end{aligned}$$

$\therefore \overline{\sum R_i} = 0$ if $\underline{1}$ is
contained in X

Q2 $\hat{\beta}_1$ $y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$
 $\varepsilon_i \stackrel{iid}{\sim} N(0, \sigma^2)$

The LSE of β_1 :

$$\hat{\beta}_1 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})(x_i - \bar{x})} = \frac{S_{xy}}{S_{xx}}$$

$$= \sum w_i y_i$$

where $w_i = \frac{(x_i - \bar{x})}{\sum_{j=1}^n (x_j - \bar{x})^2}$

Q.

Pop 1. $N(\mu_1, \sigma^2)$ $Y_1^1 \dots Y_n^1$ iid $N(\mu_1, \sigma^2)$

Pop 2. $N(\mu_2, \sigma^2)$ $Y_1^2 \dots Y_n^2$ iid $N(\mu_2, \sigma^2)$

$$\delta = \mu_2 - \mu_1$$

Test $H_0: \delta = 0 \Leftrightarrow \mu_2 = \mu_1$

Full Model

DATA: $\{(Y_i, X_i), i=1, \dots, n, \dots, 2n\}$

$$X_i = \begin{cases} 1, & \text{if } i \in \text{group 1} \\ 2, & \text{if } i \in \text{group 2} \end{cases}$$

$$G_{2i} = \begin{cases} 1, & \text{if } i \in \text{group 2} \\ 0, & \text{o/w} \end{cases}$$

$$\mu(x_i)$$

$$\mu(G_{2i}) = \mu_1 + \delta \cdot G_{2i}$$

$$\text{if } i_k \in G_{p1} \Rightarrow G_{2i} = 0$$

$$\Rightarrow \mu(G_{2i}) = \mu_1$$

$$i_k \in G_{p2} \Rightarrow G_{2i} = 1$$

$$\mu(G_{2i}) = \underbrace{\mu_1 + \delta}_{\mu_2}$$

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \\ y_{n+1} \\ \vdots \\ y_{2n} \end{bmatrix} = \begin{bmatrix} \mathbb{1} & \vdots & 0 \\ \vdots & \ddots & \vdots \\ \mathbb{1} & \vdots & \mathbb{1} \end{bmatrix} \begin{pmatrix} \mu_1 \\ \delta \\ y'' \end{pmatrix} + \begin{bmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_{2n} \end{bmatrix}$$

$$Y = X \beta + \varepsilon$$

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

$$\hat{\beta} = \begin{pmatrix} \hat{\mu}_1 \\ \hat{\delta} \end{pmatrix} = \begin{pmatrix} \bar{y}^1 \\ \bar{y}^2 - \bar{y}^1 \end{pmatrix} \underline{\text{CONFIRM}}$$

$$\hat{Y} = X \hat{\beta} = \begin{pmatrix} \underline{1} \cdot \bar{y}^1 \\ \underline{1} \bar{y}^2 \end{pmatrix} \text{CONFIRM}$$

$$SSE(1) = \|Y - \hat{Y}\|_2$$

$$= \sum_{i=1}^n (y_i - \bar{y}^1)^2 + \sum_{i=n+1}^{2n} (y_i - \bar{y}^2)^2$$

$$df(1) = 2n - 2$$

M_0 Reduced Model $H_0: \delta = 0$ ($\mu_2 = \mu_1$)

$$Y = X^0 \beta^0 + \underline{\varepsilon}$$

$$= \begin{pmatrix} \underline{1} \\ \underline{1} \end{pmatrix} (\mu_1) + \underline{\varepsilon}$$

$$\hat{\beta}^0 = \hat{\mu}_1 = \bar{Y} = \frac{n}{2n} \bar{Y}_1 + \frac{n}{2n} \bar{Y}_2$$

$$\hat{Y}^0 = X^0 \hat{\beta}^0 = \begin{pmatrix} \mathbb{1} \\ \mathbb{1} \end{pmatrix} \bar{Y}$$

$$\underline{R}^0 = \underline{Y} - \hat{Y}^0$$

$$SSE(0) = \|\underline{R}^0\|_2$$

$$= (\underline{Y} - \hat{Y}^{(0)})^T (\underline{Y} - \hat{Y}^{(0)})$$

$$= \sum_{i=1}^n (Y_i - \bar{Y})^2 + \sum_{i=n+1}^{2n} (Y_i - \bar{Y})^2$$

$$df_0 = 2n - 1$$

$$F_{STAT} = \frac{(SSE(0) - SSE(1))}{1} \star$$

$$\frac{SSE(1)}{2n-2}$$

$$\stackrel{H_0}{\sim} F(1, 2n-2)$$

$$SSE(1) - SSE(1)$$

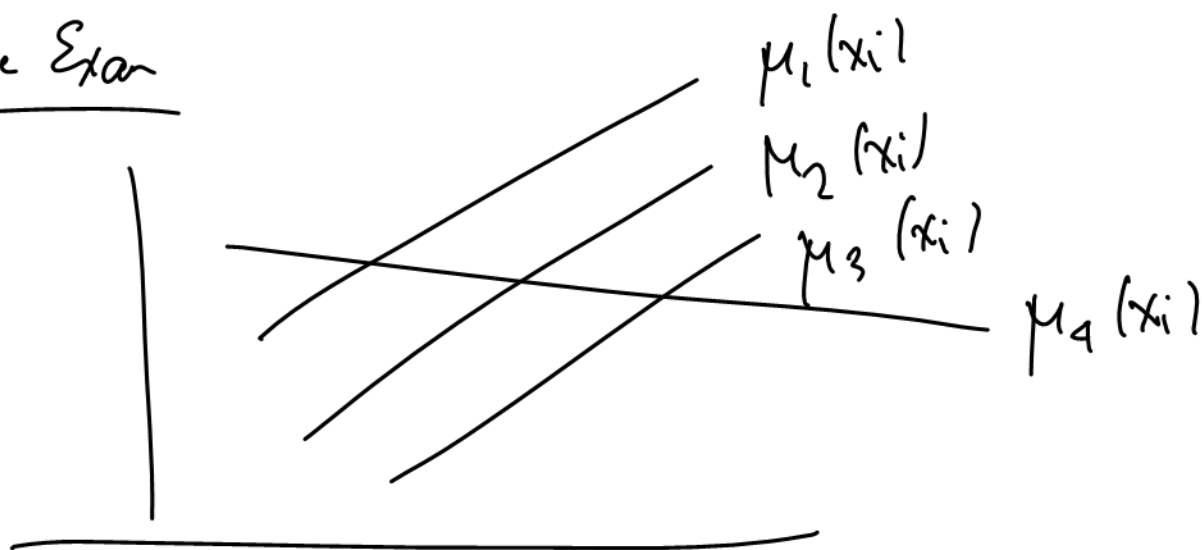
$$= n(\bar{Y}^1 - \bar{Y})^2 + n(\bar{Y}^2 - \bar{Y})^2$$

Then if the true (i.e.; $\mu_1 = \mu_2$ or $\delta = 0$)
then we expect \bar{Y}^1 & \bar{Y}^2 to be "close"

$\therefore \bar{Y}$ "close" to both \bar{Y}^1 and \bar{Y}^2

$\therefore (\bar{Y}^1 - \bar{Y})^2$ & $(\bar{Y}^2 - \bar{Y})^2$ "small"

Sample Ex



$$\mu_1(x_i) = \beta_0^1 + \beta_1^1 x_i$$

$$\mu_2(x_i) = \beta_0^2 + \beta_1^2 x_i$$

$$= (\beta_0^1 + \Delta_0^2) + (\beta_1^1 + \Delta_1^2) x_i$$

$$\mu_3(x_i) = \beta_0^3 + \beta_1^3 x_i$$

$$= (\beta_0^1 + \Delta_0^3) + (\beta_1^1 + \Delta_1^3) x_i$$

$$\mu_4(x_i) = (\beta_0^1 + \Delta_0^4) + (\beta_1^1 + \Delta_1^4) x_i$$

H_0 : $\mu_1(x_i)$, $\mu_2(x_i)$, $\mu_3(x_i)$ parallel

$$\Leftrightarrow \beta_1^1 = \beta_1^2 = \beta_1^3$$

$$\Leftrightarrow \Delta_1^2 = 0 \text{ and } \Delta_1^3 = 0$$

M_1 General (full model)

$$\begin{pmatrix} \underline{Y^{(1)}} \\ \underline{Y^{(2)}} \\ \underline{Y^{(3)}} \\ \underline{Y^{(4)}} \end{pmatrix} = \begin{bmatrix} \begin{array}{c|cc|cc} \underline{1} & x_1 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & 0 & 0 & 0 & 0 \\ x_{n_1} & x_{n_1} & 0 & 0 & 0 & 0 \end{array} \\ \begin{array}{c|cc|cc} \underline{1} & x_{n_1+1} & \underline{1} & x_{n_1+1} & 0 & 0 \\ \vdots & \vdots & \underline{1} & x_{n_1+1} & 0 & 0 \\ x_{n_1+n_2} & x_{n_1+n_2} & \underline{1} & x_{n_1+n_2} & 0 & 0 \end{array} \\ \\ \\ \end{bmatrix} \begin{pmatrix} \beta_0^1 \\ \beta_1^1 \\ \Delta_0^2 \\ \Delta_1^2 \\ \Delta_0^3 \\ \Delta_1^3 \\ \Delta_0^4 \\ \Delta_1^4 \end{pmatrix} + \begin{pmatrix} \underline{\Sigma^{(1)}} \\ \vdots \\ \underline{\Sigma^{(4)}} \end{pmatrix}$$

$$\underline{Y} = X \underline{\beta} + \underline{\Sigma}$$

$$\hat{\underline{\beta}}, \underline{R}, SSE(\hat{\underline{\beta}}) = \|\underline{R}\|_2$$

$$df = n_1 + n_2 + n_3 + n_4 - 8$$

M_0 (reduced model)

$$\mu_1(x_i) = \beta_0^1 + \beta_1^1 x_i$$

$$\mu_2(x_i) = (\beta_0^1 + \Delta_0^2) + \beta_1^1 x_i$$

$$\mu_3(x_i) = (\beta_0^1 + \Delta_0^3) + \beta_1^1 x_i$$

$$\mu_4(x_i) = (\beta_0^1 + \Delta_0^4) + (\beta_1^1 + \Delta_1^4) x_i$$

$$\begin{bmatrix} \underline{y_1} \\ \underline{y_2} \\ \underline{y_3} \\ \underline{y_4} \end{bmatrix} = \underbrace{\begin{bmatrix} \underline{1} & \underline{x'_s} & \underline{0} & \underline{0} & \underline{0} & \underline{0} \\ \underline{1} & \underline{x'_s} & \underline{1} & \underline{0} & \underline{0} & \underline{0} \\ \underline{1} & \underline{x'_s} & \underline{0} & \underline{1} & \underline{0} & \underline{0} \\ \underline{1} & \underline{x'_s} & \underline{0} & \underline{0} & \underline{1} & \underline{x'_t} \end{bmatrix}}_{X^0} \begin{bmatrix} \underline{\beta_0'} \\ \underline{\beta_1'} \\ \underline{\Delta_0^2} \\ \underline{\Delta_0^3} \\ \underline{\Delta_0^4} \\ \underline{\Delta_1^4} \end{bmatrix} + \underline{\varepsilon}$$

β^0

$$SE(0) = \| \beta^0 \|_2$$

$$df_0 = (n_1 + n_2 + n_3 + n_4) - 6$$

$$F_{STAT} = \dots$$

$$\text{Suppose } F_{STAT, obs} > F(.95; 2, \begin{matrix} n_1 + n_2 + n_3 + n_4 \\ -8 \end{matrix})$$

Post-hoc
