

1 step beyond ↑

VARIABLE SELECTION AND MODEL BUILDING

Given the data how to take a decision.

Assume the true model

$$\begin{aligned} \underline{y} &= X \underline{\beta} + \underline{\epsilon} \quad \text{True model} \quad \underline{\beta} \in \mathbb{R}^{k+1} \\ \underline{\epsilon} &\sim \mathcal{N}(0, \sigma^2 I_n) \quad \underline{y} \in \mathbb{R}^n \\ &\quad \underline{\epsilon} \in \mathbb{R}^n \end{aligned}$$

Model is constructed based on p many variables instead of $(k+1)$

$$\underline{y} = \begin{bmatrix} X_p & X_r \end{bmatrix} \begin{bmatrix} \underline{\beta}_p \\ \underline{\beta}_r \end{bmatrix} + \underline{\epsilon}$$

$p+r = k+1$

$$\Rightarrow \underline{y} = X_p \underline{\beta}_p + X_r \underline{\beta}_r + \underline{\epsilon}$$

$\underline{\beta}_r = (\beta_0 \ \beta_1 \ \dots \ \beta_{k-r}) \quad \underline{\beta}_p = (\beta_{k-r+1} \ \dots \ \beta_{k+1})$

Fitted

$$\underline{y} = X_p \underline{\beta}_p + \underline{\epsilon}$$

$$\hat{\underline{\beta}}_p = (X_p^T X_p)^{-1} X_p^T \underline{y} \quad \text{Reduced model}$$

$$\underline{\beta} = (X^T X)^{-1} X^T \underline{y} \quad \text{Complete model}$$

Q whether $\hat{\underline{\beta}}_p$ is an unbiased estimator or not?

$$\hat{\underline{\beta}}_p = (X_p^T X_p)^{-1} X_p^T \underline{y}$$

$$\begin{aligned} E[\hat{\underline{\beta}}_p] &= E\left((X_p^T X_p)^{-1} X_p^T \underline{y}\right) = E\left((X_p^T X_p)^{-1} X_p^T [X_p \underline{\beta}_p + X_r \underline{\beta}_r]\right) \\ &= \underline{\beta}_p + (X_p^T X_p)^{-1} \underbrace{(X_p^T X_r)}_0 \underline{\beta}_r \end{aligned}$$

Invertible

This is only possible if every column of X_r is orthogonal to every column of X_p .

Q2 When the estimator $\hat{\underline{\beta}}_p$ has less variation compared to whole model?

$$\begin{aligned} D(\hat{\underline{\beta}}_p) &= \sigma^2 (X_p^T X_p)^{-1} \\ D(\hat{\underline{\beta}}) &= \sigma^2 (X^T X)^{-1} \quad \text{var } |X^T X|^{-1} \\ &= \sigma^2 \left((X_p^T X_p)^T (X_p^T X_r)^T \right)^{-1} \\ &= \sigma^2 \left(\begin{bmatrix} X_p^T \\ X_r^T \end{bmatrix} \begin{bmatrix} X_p & X_r \end{bmatrix} \right)^{-1} \\ D(\hat{\underline{\beta}}_p) &= \sigma^2 \begin{pmatrix} X_p^T X_p & X_p^T X_r \\ X_r^T X_p & X_r^T X_r \end{pmatrix}^{-1} \end{aligned}$$

D($\hat{\underline{\beta}}_p$)

Let us call "A" matrix

$$\begin{aligned} A^{-1} &= \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix}^{-1} \\ &= \frac{\begin{pmatrix} (A_{11} - A_{12} A_{22}^{-1} A_{21})^{-1} & - (A_{11} - A_{12} A_{22}^{-1} A_{21})^{-1} A_{12} A_{22}^{-1} \\ - A_{21} A_{11}^{-1} (A_{22} - A_{21} A_{11}^{-1} A_{12}) & (A_{22} - A_{21} A_{11}^{-1} A_{12})^{-1} \end{pmatrix}}{\end{aligned}$$

$$(A + BCD)^{-1} = A^{-1} - A^{-1} B (C^{-1} + D A^{-1} B)^{-1} D A^{-1}$$

$$\text{If } |C^{-1} + D A^{-1} B| \neq 0$$

Q2 Component of $D(\hat{\underline{\beta}})$

$$= \left[\begin{matrix} (X_p^T X_p) & (X_p^T X_r) \\ (X_r^T X_p) & (X_r^T X_r) \end{matrix} \right]^{-1} \sigma^2$$

A B C D

$$= \sigma^2 (X_p^T X_p)^{-1} + \sigma^2 \left((X_p^T X_r)^{-1} X_p X_p (X_r^T X_r)^{-1} + (X_r^T X_p) (X_p^T X_p)^{-1} (X_r^T X_r)^{-1} \right)$$

$$= \sigma^2 (X_p^T X_p)^{-1} + [A^{-1} B (C^{-1} + D A^{-1} B)^{-1} D A^{-1}] \sigma^2$$

? PSD \rightarrow Yes

$$\begin{aligned} A &= X_p^T X_p & B &= X_p^T X_r & A^{-1} B &= (X_p^T X_p)^{-1} X_p^T X_r = (D A^{-1})^T \\ C &= (X_r^T X_r)^{-1} & D &= X_r^T X_p & D A^{-1} &= (X_r^T X_p) (X_p^T X_p)^{-1} \end{aligned}$$

$$\Rightarrow A^{-1} B (C^{-1} + D A^{-1} B)^{-1} D A^{-1}$$

(A⁻¹B)^T

$$\begin{aligned} &\Rightarrow A^{-1} B (C^{-1} + D A^{-1} B) (A^{-1} B)^T \\ &\Rightarrow \underbrace{A^{-1} B C^{-1} B^T A^{-1}}_{\text{PSD}} + \underbrace{A^{-1} B D A^{-1} B B^T A^{-1}}_{\text{PSD}} \end{aligned}$$

If M is a PSD matrix then all eigenvalues are ≥ 0 .