

STAT 510 Homework 2

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1. $\mathbf{z} \in \mathcal{C}(\mathbf{X}) \Rightarrow \mathbf{z} = \mathbf{X}\mathbf{b}$ for some \mathbf{b} . Hence

$$\begin{aligned} & (\mathbf{y} - \mathbf{P}_\mathbf{X}\mathbf{y})^T(\mathbf{P}_\mathbf{X}\mathbf{y} - \mathbf{z}) \\ &= (\mathbf{y} - \mathbf{P}_\mathbf{X}\mathbf{y})^T(\mathbf{P}_\mathbf{X}\mathbf{y} - \mathbf{X}\mathbf{b}) \\ &= \mathbf{y}^T(\mathbf{I} - \mathbf{P}_\mathbf{X})\mathbf{P}_\mathbf{X}\mathbf{y} - \mathbf{y}^T(\mathbf{I} - \mathbf{P}_\mathbf{X})\mathbf{X}\mathbf{b} \\ &= \mathbf{y}^T(\mathbf{P}_\mathbf{X} - \mathbf{P}_\mathbf{X})\mathbf{y} - \mathbf{y}^T(\mathbf{X} - \mathbf{X})\mathbf{b} \\ &= \mathbf{0} \end{aligned}$$

We also have $\mathbf{z} \neq \mathbf{P}_\mathbf{X}\mathbf{y} \Rightarrow \mathbf{P}_\mathbf{X}\mathbf{y} - \mathbf{z} \neq \mathbf{0}$. Thus we have

$$\|\mathbf{y} - \mathbf{z}\|^2 = \|\mathbf{y} - \mathbf{P}_\mathbf{X}\mathbf{y} + \mathbf{P}_\mathbf{X}\mathbf{y} - \mathbf{z}\|^2 > \|\mathbf{y} - \mathbf{P}_\mathbf{X}\mathbf{y}\|^2$$

2. For projection matrix $\mathbf{P}_\mathbf{X}$ we have $\mathbf{P}_\mathbf{X}\mathbf{X} = \mathbf{X}$. Let $\mathbf{X} = [\mathbf{x}_1 \ \mathbf{x}_2 \ \cdots \ \mathbf{x}_p] = [x_{ij}]_{n \times p}$ and $\mathbf{P}_\mathbf{X} = [\boldsymbol{\epsilon}_1 \ \boldsymbol{\epsilon}_2 \ \cdots \ \boldsymbol{\epsilon}_n]$. Hence we have

$$[\boldsymbol{\epsilon}_1 \ \boldsymbol{\epsilon}_2 \ \cdots \ \boldsymbol{\epsilon}_n] \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nn} \end{bmatrix} = [\mathbf{x}_1 \ \mathbf{x}_2 \ \cdots \ \mathbf{x}_p]$$

Thus

$$\mathbf{x}_j = \sum_{i=1}^n x_{ij}\boldsymbol{\epsilon}_i \Rightarrow \mathcal{C}(\mathbf{X}) \subset \mathcal{C}(\mathbf{P}_\mathbf{X})$$

We also have

$$\mathbf{X}(\mathbf{X}^T\mathbf{X})^{-}\mathbf{X}^T = \mathbf{P}_\mathbf{X}$$

Let $(\mathbf{X}^T\mathbf{X})^{-}\mathbf{X}^T = [a_{ij}]_{p \times n}$, thus

$$[\mathbf{x}_1 \ \mathbf{x}_2 \ \cdots \ \mathbf{x}_p] \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{p1} & a_{p2} & \cdots & a_{pn} \end{bmatrix} = [\boldsymbol{\epsilon}_1 \ \boldsymbol{\epsilon}_2 \ \cdots \ \boldsymbol{\epsilon}_n]$$

Thus

$$\boldsymbol{\epsilon}_j = \sum_{i=1}^p a_{ij}\mathbf{x}_i \Rightarrow \mathcal{C}(\mathbf{P}_\mathbf{X}) \subset \mathcal{C}(\mathbf{X})$$

Hence we have $\mathcal{C}(\mathbf{P}_\mathbf{X}) = \mathcal{C}(\mathbf{X})$.

3.

$$\begin{aligned}
& \mathbf{X}^T \mathbf{X} (\mathbf{X}^T \mathbf{X})^- \mathbf{X}^T \mathbf{y} \\
&= \mathbf{X}^T \mathbf{P}_X \mathbf{y} \\
&= \mathbf{X}^T \mathbf{P}_X^T \mathbf{y} \\
&= (\mathbf{P}_X \mathbf{X})^T \mathbf{y} \\
&= \mathbf{X}^T \mathbf{y}
\end{aligned}$$

Hence $(\mathbf{X}^T \mathbf{X})^- \mathbf{X}^T \mathbf{y}$ is a solution of $\mathbf{X}^T \mathbf{X} \mathbf{b} = \mathbf{X}^T \mathbf{y}$.

4. (a) $\mathbf{C} \hat{\boldsymbol{\beta}} = \mathbf{C} (\mathbf{X}^T \mathbf{X})^- \mathbf{X}^T (\mathbf{X} \boldsymbol{\beta} + \boldsymbol{\epsilon}) = \mathbf{A} \mathbf{X} (\mathbf{X}^T \mathbf{X})^- \mathbf{X}^T \mathbf{X} \boldsymbol{\beta} + \mathbf{A} \mathbf{X} (\mathbf{X}^T \mathbf{X})^- \mathbf{X}^T \boldsymbol{\epsilon} = \mathbf{A} \mathbf{P}_X \mathbf{X} \boldsymbol{\beta} + \mathbf{A} \mathbf{P}_X \boldsymbol{\epsilon} = \mathbf{A} \mathbf{X} \boldsymbol{\beta} + \mathbf{A} \mathbf{P}_X \boldsymbol{\epsilon} = \mathbf{C} \boldsymbol{\beta} + \mathbf{A} \mathbf{P}_X \boldsymbol{\epsilon}$.
 $\boldsymbol{\epsilon} \sim N(\mathbf{0}, \sigma^2 \mathbf{I})$, thus $\mathbf{C} \boldsymbol{\beta} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, where

$$\begin{aligned}
\boldsymbol{\mu} &= \mathbf{C} \boldsymbol{\beta} \\
\boldsymbol{\Sigma} &= \mathbf{A} \mathbf{P}_X \sigma^2 \mathbf{I} \mathbf{P}_X^T \mathbf{A}^T = \mathbf{A} \mathbf{P}_X \mathbf{A}^T = \mathbf{A} \mathbf{X} (\mathbf{X}^T \mathbf{X})^- \mathbf{X}^T \mathbf{A}^T = \mathbf{C} (\mathbf{X}^T \mathbf{X})^- \mathbf{C}^T
\end{aligned}$$

- (b) Let $\mathbf{G} = (\mathbf{X}^T \mathbf{X})^-$ be one of the generalized inverse of $\mathbf{X}^T \mathbf{X}$ and \mathbf{G}^T be its transpose. Thus

$$\text{Var}(\mathbf{C} (\mathbf{X}^T \mathbf{X})^- \mathbf{X}^T \mathbf{y}) = \mathbf{C} \mathbf{G} \mathbf{X}^T \sigma^2 \mathbf{I} \mathbf{X} \mathbf{G}^T \mathbf{C}^T = \mathbf{C} \mathbf{G} \mathbf{X}^T \mathbf{X} \mathbf{G}^T \mathbf{C}^T$$