

1. (a) Let $(\mathbf{X}'\mathbf{X})^-$ be any generalized inverse of $\mathbf{X}'\mathbf{X}$, which by definition implies

$$\mathbf{X}'\mathbf{X}(\mathbf{X}'\mathbf{X})^-\mathbf{X}'\mathbf{X} = \mathbf{X}'\mathbf{X},$$

where \mathbf{X} has dimension $m \times n$, say. Put $\mathbf{A} = (\mathbf{X}'\mathbf{X})^-\mathbf{X}'\mathbf{X}$ and $\mathbf{B} = \mathbf{I}_{n \times n}$, so that

$$\mathbf{X}'\mathbf{X} \underbrace{(\mathbf{X}'\mathbf{X})^-\mathbf{X}'\mathbf{X}}_{\mathbf{A}} = \mathbf{X}'\mathbf{X} = \mathbf{X}'\mathbf{X} \underbrace{\mathbf{I}_{n \times n}}_{\mathbf{B}} \implies \mathbf{X}'\mathbf{X}\mathbf{A} = \mathbf{X}'\mathbf{X}\mathbf{B}.$$

By the result of problem 7 on Homework 1, it follows that $\mathbf{X}\mathbf{A} = \mathbf{X}\mathbf{B}$, and hence

$$\mathbf{X}(\mathbf{X}'\mathbf{X})^-\mathbf{X}'\mathbf{X} = \mathbf{X}.$$

- (b) Let \mathbf{A} be any symmetric matrix and \mathbf{G} be any generalized inverse of \mathbf{A} . By definition,

$$\mathbf{A}\mathbf{G}\mathbf{A} = \mathbf{A}.$$

Now, transpose both sides and use the fact that $\mathbf{A}' = \mathbf{A}$ by symmetry:

$$\begin{aligned} (\mathbf{A}\mathbf{G}\mathbf{A})' &= \mathbf{A}' \implies \mathbf{A}'\mathbf{G}'\mathbf{A}' = \mathbf{A}' \\ &\implies \mathbf{A}\mathbf{G}'\mathbf{A} = \mathbf{A}. \end{aligned}$$

Hence, \mathbf{G}' is a generalized inverse of \mathbf{A} .

- (c) Let \mathbf{G} be any generalized inverse of $\mathbf{X}'\mathbf{X}$. Notice that $\mathbf{X}'\mathbf{X}$ is symmetric, so by part (b), \mathbf{G}' is also a generalized inverse of $\mathbf{X}'\mathbf{X}$. The result of part (a) holds for any generalized inverse of $\mathbf{X}'\mathbf{X}$, and hence holds using \mathbf{G}' . Using the result of part (a) with \mathbf{G}' and then taking transposes gives

$$\begin{aligned} \mathbf{X}\mathbf{G}'\mathbf{X}'\mathbf{X} = \mathbf{X} &\implies (\mathbf{X}\mathbf{G}'\mathbf{X}'\mathbf{X})' = \mathbf{X}' \\ &\implies \mathbf{X}'[\mathbf{X}']'[\mathbf{G}']'\mathbf{X}' = \mathbf{X}' \\ &\implies \mathbf{X}'\mathbf{X}\mathbf{G}\mathbf{X}' = \mathbf{X}'. \end{aligned}$$

Because we chose \mathbf{G} to be any generalized inverse of $\mathbf{X}'\mathbf{X}$,

$$\mathbf{X}'\mathbf{X}(\mathbf{X}'\mathbf{X})^-\mathbf{X}' = \mathbf{X}'.$$

Comments: We could have

$$(\mathbf{X}'\mathbf{X})^- \neq [(\mathbf{X}'\mathbf{X})^-]',$$

so it is important that (a) and (b) are used at the right steps in your proof so it is clear that you aren't trying to say $(\mathbf{X}'\mathbf{X})^- = [(\mathbf{X}'\mathbf{X})^-]'$. On a related note, we may also have $[(\mathbf{X}'\mathbf{X})^-]' \neq [(\mathbf{X}'\mathbf{X})^-]'$.

(d) This part requires *two* proofs that P_X is idempotent for full credit.

1. By part (a),

$$\begin{aligned} P_X P_X &= \underbrace{X(X'X)^{-1}X'X(X'X)^{-1}X'}_X \\ &= X(X'X)^{-1}X' \\ &= P_X. \end{aligned}$$

2. By part (c),

$$\begin{aligned} P_X P_X &= X(X'X)^{-1} \underbrace{X'X(X'X)^{-1}X'}_{X'} \\ &= X(X'X)^{-1}X' \\ &= P_X. \end{aligned}$$

(e) Let G_1 and G_2 be any generalized inverses of $X'X$. By parts (a) and (c), we have

$$\begin{aligned} XG_1X' &= XG_1 \underbrace{X'XG_2X'}_{X'} \quad \text{part (c) holds for any generalized inverse of } X'X \\ &= \underbrace{XG_1X'X}_{X} G_2X' \quad \text{part (a) holds for any generalized inverse of } X'X \\ &= XG_2X'. \end{aligned}$$

Comments:

- A few students tried to use the fact that P_X is the same matrix regardless of which generalized inverse of $X'X$ is used, but this is what we are trying to show.
- This statement should hold for any two generalized inverse matrices of $X'X$. Some students proved this by setting $G_2 = (G_1)'$. This case cannot generalize this result.

(f) Let $(X'X)^-$ be any generalized inverse of $X'X$. We know that $X'X$ is a symmetric matrix, so the result of part (b) says that if $(X'X)^-$ is a generalized inverse of $X'X$, then $[(X'X)^-]'$ is a generalized inverse of $X'X$. The result of part (e) then establishes that $X(X'X)^-X' = X[(X'X)^-]X'$. Hence, these results and properties of matrix transpose give

$$\begin{aligned} P_X' &= (X(X'X)^-X')' \\ &= [X']'[(X'X)^-]X' \\ &= X[(X'X)^-]X' \\ &= X(X'X)^-X' && \text{by parts (d,g) as explained above} \\ &= P_X. \end{aligned}$$

Comments: It is important to use parts (d) and (g) at the right steps in your proof so it is clear that you aren't trying to say $(X'X)^- = [(X'X)^-]'$.

2. Let \mathbf{X} be an $n \times p$ matrix and \mathbf{y} be an $n \times 1$ vector. Suppose that $\mathbf{z} \in \mathcal{C}(\mathbf{X})$ and $\mathbf{z} \neq \mathbf{P}_X \mathbf{y}$, which implies $(\mathbf{P}_X \mathbf{y} - \mathbf{z}) \neq \mathbf{0}_{n \times 1}$. Observe that $\mathbf{z} \in \mathcal{C}(\mathbf{X})$ implies that $\mathbf{P}_X \mathbf{z} = \mathbf{z}$. Using this result and the fact that \mathbf{P}_X is symmetric and idempotent, it follows that

$$\begin{aligned}
 (\mathbf{y} - \mathbf{P}_X \mathbf{y})'(\mathbf{P}_X \mathbf{y} - \mathbf{z}) &= (\mathbf{y}' - [\mathbf{P}_X \mathbf{y}]')(\mathbf{P}_X \mathbf{y} - \mathbf{z}) \\
 &= (\mathbf{y}' - \mathbf{y}' \mathbf{P}_X')(\mathbf{P}_X \mathbf{y} - \mathbf{z}) \\
 &= (\mathbf{y}' - \mathbf{y}' \mathbf{P}_X)(\mathbf{P}_X \mathbf{y} - \mathbf{z}) \\
 &= \mathbf{y}' \mathbf{P}_X \mathbf{y} - \mathbf{y}' \mathbf{z} - \mathbf{y}' \mathbf{P}_X \mathbf{P}_X \mathbf{y} + \mathbf{y}' \mathbf{P}_X \mathbf{z} \\
 &= \mathbf{y}' \mathbf{P}_X \mathbf{y} - \mathbf{y}' \mathbf{z} - \mathbf{y}' \mathbf{P}_X \mathbf{y} + \mathbf{y}' \mathbf{P}_X \mathbf{z} \\
 &= -\mathbf{y}' \mathbf{z} + \mathbf{y}' \mathbf{z} \\
 &= 0.
 \end{aligned}$$

Now that we have $(\mathbf{y} - \mathbf{P}_X \mathbf{y})'(\mathbf{P}_X \mathbf{y} - \mathbf{z}) = 0$ and $(\mathbf{P}_X \mathbf{y} - \mathbf{z}) \neq \mathbf{0}$, we can use the same argument provided in the homework with $\mathbf{a} = \mathbf{y} - \mathbf{P}_X \mathbf{y}$ and $\mathbf{b} = \mathbf{P}_X \mathbf{y} - \mathbf{z}$:

$$\begin{aligned}
 \|\mathbf{y} - \mathbf{z}\|^2 &= \|\mathbf{y} - \mathbf{P}_X \mathbf{y} + \mathbf{P}_X \mathbf{y} - \mathbf{z}\|^2 \\
 &= (\mathbf{y} - \mathbf{P}_X \mathbf{y} + \mathbf{P}_X \mathbf{y} - \mathbf{z})'(\mathbf{y} - \mathbf{P}_X \mathbf{y} + \mathbf{P}_X \mathbf{y} - \mathbf{z}) \\
 &= ((\mathbf{y} - \mathbf{P}_X \mathbf{y})' + (\mathbf{P}_X \mathbf{y} - \mathbf{z})')((\mathbf{y} - \mathbf{P}_X \mathbf{y}) + (\mathbf{P}_X \mathbf{y} - \mathbf{z})) \\
 &= (\mathbf{y} - \mathbf{P}_X \mathbf{y})'(\mathbf{y} - \mathbf{P}_X \mathbf{y}) + 2(\mathbf{y} - \mathbf{P}_X \mathbf{y})'(\mathbf{P}_X \mathbf{y} - \mathbf{z}) + (\mathbf{P}_X \mathbf{y} - \mathbf{z})'(\mathbf{P}_X \mathbf{y} - \mathbf{z}) \\
 &= \|\mathbf{y} - \mathbf{P}_X \mathbf{y}\|^2 + \|\mathbf{P}_X \mathbf{y} - \mathbf{z}\|^2 \\
 &> \|\mathbf{y} - \mathbf{P}_X \mathbf{y}\|^2.
 \end{aligned}$$

Hence, $\|\mathbf{y} - \mathbf{z}\| > \|\mathbf{y} - \mathbf{P}_X \mathbf{y}\|$, which says that $\mathbf{P}_X \mathbf{y}$ is the unique point in $\mathcal{C}(\mathbf{X})$ that is closest to \mathbf{y} in Euclidean distance.

Comments: You can instead show that $(\mathbf{y} - \mathbf{P}_X \mathbf{y})'(\mathbf{P}_X \mathbf{y} - \mathbf{z}) = 0$ by orthogonality, but as this is a proof, you need to provide sufficient reasoning or work to establish this.

3. Key:

1. $\mathbf{a} \in \mathcal{C}(\mathbf{X}) \iff \mathbf{a} = \mathbf{X} \mathbf{b}$ for some \mathbf{b}
2. $\mathbf{P}_X \mathbf{X} = \mathbf{X}$ by property of projection matrix

Prove that $\mathcal{C}(\mathbf{X}) = \mathcal{C}(\mathbf{P}_X)$:

$$\begin{aligned}
 \mathbf{a} \in \mathcal{C}(\mathbf{X}) &\iff \mathbf{a} = \mathbf{X} \mathbf{b} && \text{for some } \mathbf{b} \text{ by key 1} \\
 &\iff \mathbf{a} = \underbrace{\mathbf{P}_X \mathbf{X}}_{\mathbf{X}} \mathbf{b} && \text{for some } \mathbf{b} \text{ by key 2} \\
 &\iff \mathbf{a} = \mathbf{P}_X \underbrace{\mathbf{X} \mathbf{b}}_{\mathbf{k}} && \text{treat as } \mathbf{P}_X \text{ product a } n \times 1 \text{ vector} \\
 &\iff \mathbf{a} = \mathbf{P}_X \mathbf{k} && \text{for some } \mathbf{k} = \mathbf{X} \mathbf{b} \\
 &\implies \mathbf{a} \in \mathcal{C}(\mathbf{P}_X) && \text{by key 1}
 \end{aligned}$$

So $\mathcal{C}(\mathbf{X}) \subseteq \mathcal{C}(\mathbf{P}_X)$.

Then similarly,

$$\begin{aligned}
 \mathbf{g} \in \mathcal{C}(\mathbf{P}_X) &\iff \mathbf{g} = \mathbf{P}_X \mathbf{h} && \text{for some } n \times 1 \text{ vector } \mathbf{h} \text{ by key 1} \\
 &\iff \mathbf{g} = \underbrace{\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{h}}_{\mathbf{P}_X} && \text{for some } \mathbf{h} \\
 &\iff \mathbf{g} = \mathbf{X} \underbrace{(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{h}}_{p \times 1} && \text{treat as } \mathbf{X} \text{ product a } p \times 1 \text{ vector} \\
 &\iff \mathbf{g} = \mathbf{X}\mathbf{q} && \text{for some } \mathbf{q} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{h} \\
 &\implies \mathbf{g} \in \mathcal{C}(\mathbf{X}) && \text{by key 1}
 \end{aligned}$$

So $\mathcal{C}(\mathbf{P}_X) \subseteq \mathcal{C}(\mathbf{X})$. According to the results above, $\mathcal{C}(\mathbf{X}) = \mathcal{C}(\mathbf{P}_X)$.

4. Prove $(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$ is a solution to the normal equations $\mathbf{X}'\mathbf{X}\mathbf{b} = \mathbf{X}'\mathbf{y}$ (by slide 8 of set 2).

Let $\mathbf{b} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$:

$$\begin{aligned}
 \mathbf{X}'\mathbf{X}\mathbf{b} &= \mathbf{X}' \underbrace{\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}}_{\mathbf{P}_X} \\
 &= \mathbf{X}'\mathbf{P}_X\mathbf{y} \\
 &= \mathbf{X}'\mathbf{y}
 \end{aligned}$$

$\mathbf{X}'\mathbf{P}_X = \mathbf{X}'$ by property of projection matrix in slide 5 of set 2

Therefore $(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$ is a solution to the normal equations.

5. Suppose the Gauss-Markov model with normal errors holds (see slide 16 of slide set 2 for a precise statement of the model).

(a) Suppose $\mathbf{C}\boldsymbol{\beta}$ is estimable. Derive the distribution of $\mathbf{C}\hat{\boldsymbol{\beta}}$, the OLSE of $\mathbf{C}\boldsymbol{\beta}$.

$\mathbf{C}\boldsymbol{\beta}$ is estimable \implies there exists \mathbf{A} that $\mathbf{C} = \mathbf{A}\mathbf{X}$

$$\begin{aligned}
 \mathbf{C}\hat{\boldsymbol{\beta}} &= \mathbf{C}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y} \\
 &= \mathbf{A}\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y} && \mathbf{C} = \mathbf{A}\mathbf{X} \\
 &= \mathbf{A}\mathit{proj}\mathbf{y} && \mathit{proj} = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'
 \end{aligned}$$

Based on the model assumptions, $\mathbf{y} \sim \mathcal{N}(\mathbf{X}\boldsymbol{\beta}, \sigma^2\mathbf{I})$. Then $\mathbf{C}\hat{\boldsymbol{\beta}} = \mathbf{A}\mathbf{P}_X\mathbf{y}$ is also multivariate normal by slide 32 of set 1, $\mathbf{A}\mathbf{P}_X\mathbf{y} \sim \mathcal{N}(\mathbf{A}\mathbf{P}_X\mathbf{X}\boldsymbol{\beta}, \mathbf{A}\mathbf{P}_X\sigma^2\mathbf{I}(\mathbf{A}\mathbf{P}_X)')$

$$\mathbf{A}\mathbf{P}_X\mathbf{X}\boldsymbol{\beta} = \mathbf{A}\mathbf{X}\boldsymbol{\beta} = \mathbf{C}\boldsymbol{\beta}$$

$$\begin{aligned}
 \mathbf{A}\mathbf{P}_X\sigma^2\mathbf{I}(\mathbf{A}\mathbf{P}_X)' &= \sigma^2\mathbf{A}\mathbf{P}_X\mathbf{P}_X'\mathbf{A}' \\
 &= \sigma^2\mathbf{A}\mathbf{P}_X\mathbf{A}' && \mathbf{P}_X \text{ is symmetric and idempotent} \\
 &= \sigma^2\mathbf{A}\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{A}' \\
 &= \sigma^2\mathbf{C}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{C}'
 \end{aligned}$$

Therefore $\mathbf{C}\hat{\boldsymbol{\beta}} \sim \mathcal{N}(\mathbf{C}\boldsymbol{\beta}, \sigma^2\mathbf{C}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{C}')$.

(b) Now suppose $\mathbf{C}\boldsymbol{\beta}$ is NOT estimable.

$$\begin{aligned} \text{Var}(\mathbf{C}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}) &= (\mathbf{C}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}')\sigma^2\mathbf{I}(\mathbf{C}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}')' \\ &= \sigma^2\mathbf{C}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{C}' \end{aligned}$$

We can not simplify this further when $\mathbf{C}\boldsymbol{\beta}$ is NOT estimable.

(c) Now suppose $H_0 : \mathbf{C}\boldsymbol{\beta} = \mathbf{d}$ is testable. Prove the result on slide 23 of set 2.

Given the hypothesis is testable (see slide 18 of set 2), $\mathbf{c}'\hat{\boldsymbol{\beta}}$ is estimable and from the results in part (a), we have $\mathbf{c}'\hat{\boldsymbol{\beta}} \sim \mathcal{N}(\mathbf{c}'\boldsymbol{\beta}, \sigma^2\mathbf{c}'(\mathbf{X}'\mathbf{X})^{-1}\mathbf{c})$, by linear transformation,

$$\frac{\mathbf{c}'\hat{\boldsymbol{\beta}} - d}{\sqrt{\sigma^2\mathbf{c}'(\mathbf{X}'\mathbf{X})^{-1}\mathbf{c}}} \sim \mathcal{N}\left(\frac{\mathbf{c}'\boldsymbol{\beta} - d}{\sqrt{\sigma^2\mathbf{c}'(\mathbf{X}'\mathbf{X})^{-1}\mathbf{c}}}, 1\right)$$

let $u = \frac{\mathbf{c}'\hat{\boldsymbol{\beta}} - d}{\sqrt{\sigma^2\mathbf{c}'(\mathbf{X}'\mathbf{X})^{-1}\mathbf{c}}}$ and $\delta = \frac{\mathbf{c}'\boldsymbol{\beta} - d}{\sqrt{\sigma^2\mathbf{c}'(\mathbf{X}'\mathbf{X})^{-1}\mathbf{c}}}$, $u \sim \mathcal{N}(\delta, 1)$.

Then by slide 19 of set 2,

$$\frac{\hat{\sigma}^2}{\sigma^2} \sim \frac{\chi_{n-r}^2}{n-r} \implies w = \frac{(n-r)\hat{\sigma}^2}{\sigma^2} \sim \chi_{n-r}^2$$

$\mathbf{c}'\hat{\boldsymbol{\beta}}$ and $\hat{\sigma}^2$ are independent, so u and w , which are functions of $\mathbf{c}'\hat{\boldsymbol{\beta}}$ and $\hat{\sigma}^2$, respectively, are also independent (see Theorem 4.3.5 in Casella and Berger, 2002).

By slide 39 of set 1,

$$\frac{u}{\sqrt{w/(n-r)}} = \frac{\mathbf{c}'\hat{\boldsymbol{\beta}} - d}{\sqrt{\hat{\sigma}^2\mathbf{c}'(\mathbf{X}'\mathbf{X})^{-1}\mathbf{c}}} \sim t_{n-r}(\delta)$$

Therefore, it follows a t distribution with non-central parameter $\delta = \frac{\mathbf{c}'\boldsymbol{\beta} - d}{\sqrt{\sigma^2\mathbf{c}'(\mathbf{X}'\mathbf{X})^{-1}\mathbf{c}}}$ and degrees of freedom $n - r$.

Note: The independence between u and w is necessary. We can first show independence of $\mathbf{c}'\hat{\boldsymbol{\beta}}$ and $\hat{\sigma}^2$. Because $\mathbf{c}'\hat{\boldsymbol{\beta}}$ is estimable, we can write it as $\mathbf{a}'\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y} = \mathbf{a}'\mathbf{P}_X\mathbf{y}$ for some \mathbf{a}' , and $\hat{\sigma}^2 = \mathbf{y}'(\mathbf{I} - \mathbf{P}_X)\mathbf{y}/(n-r) = \|(\mathbf{I} - \mathbf{P}_X)\mathbf{y}\|^2/(n-r)$.

Now we use **the independence results on slide 44 in set 1**. When $\mathbf{y} \sim \mathcal{N}(\mathbf{X}\boldsymbol{\beta}, \sigma^2\mathbf{I})$ in GMMNE (slide 16 of set 2), let $\mathbf{A}_1 = \mathbf{a}'\mathbf{P}_X$, and $\mathbf{A}_2 = (\mathbf{I} - \mathbf{P}_X)/(n-r)$. Then

$$\begin{aligned} \mathbf{A}_1\sigma^2\mathbf{I}\mathbf{A}_2' &= \mathbf{a}'\mathbf{P}_X\sigma^2\mathbf{I}(\mathbf{I} - \mathbf{P}_X)'/(n-r) \\ &= \sigma^2\mathbf{a}'\mathbf{P}_X(\mathbf{I} - \mathbf{P}_X)'/(n-r) \\ &= \sigma^2\mathbf{a}'\mathbf{P}_X(\mathbf{I} - \mathbf{P}_X)/(n-r) \\ &= \sigma^2\mathbf{a}'(\mathbf{P}_X - \mathbf{P}_X\mathbf{P}_X)/(n-r) \\ &= \mathbf{0} \end{aligned} \quad \text{because } \mathbf{P}_X \text{ is idempotent.}$$

Then we have $\mathbf{c}'\hat{\boldsymbol{\beta}} \perp \hat{\sigma}^2$, which implies $u \perp w$ by Theorem 4.3.5 in Casella and Berger (2002).