

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  $(X'X)^{-} = [(X'X)^{-}]'$ .



Then similarly,

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

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

$$\begin{aligned}
\mathbf{X}'\mathbf{X}\mathbf{b} &= \mathbf{X}' \underbrace{\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'}_{\mathbf{P}_X} \mathbf{y} \\
&= \mathbf{X}'\mathbf{P}_X \mathbf{y} \\
&= \mathbf{X}'\mathbf{y} && \mathbf{X}'\mathbf{P}_X = \mathbf{X}' \text{ by property of projection matrix in slide 5 of set 2}
\end{aligned}$$

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  $\mathbf{C} = \mathbf{A}\mathbf{X}$

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

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.

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

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  $\mathbf{c}'\hat{\boldsymbol{\beta}} \sim \mathcal{N}(\mathbf{c}'\boldsymbol{\beta}, \sigma^2\mathbf{c}'(\mathbf{X}'\mathbf{X})^{-}\mathbf{c})$ , by linear transformation,

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

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

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,

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

Therefore, it follows a  $t$  distribution with non-central parameter  $\delta = \frac{\mathbf{c}'\boldsymbol{\beta} - d}{\sqrt{\sigma^2\mathbf{c}'(\mathbf{X}'\mathbf{X})^{-}\mathbf{c}}}$  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  $\mathbf{a}'\mathbf{X}(\mathbf{X}'\mathbf{X})^{-}\mathbf{X}'\mathbf{y} = \mathbf{a}'\mathbf{P}_X\mathbf{y}$  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 38 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).