

STAT 510 Homework 1

Yifan Zhu

January 17, 2017

1.

$$\begin{aligned}
 \mathbf{AB} &= \begin{bmatrix} 1 & 5 \\ 4 & -1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 3 & 3 & -2 & 4 \\ 5 & -1 & 2 & 3 \end{bmatrix} \\
 &= \begin{bmatrix} 1 \\ 4 \\ 0 \end{bmatrix} \begin{bmatrix} 3 & 3 & -2 & 4 \end{bmatrix} + \begin{bmatrix} 5 \\ -1 \\ 1 \end{bmatrix} \begin{bmatrix} 5 & -1 & 2 & 3 \end{bmatrix} \\
 &= \begin{bmatrix} 3 & 3 & -2 & 4 \\ 12 & 12 & -8 & 16 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 25 & -5 & 10 & 15 \\ -5 & 1 & -2 & -3 \\ 5 & -1 & 2 & 3 \end{bmatrix} \\
 &= \begin{bmatrix} 28 & -2 & 8 & 19 \\ 7 & 13 & -10 & 13 \\ 5 & -1 & 2 & 3 \end{bmatrix}
 \end{aligned}$$

2. (a) $\mathbf{W} = \begin{bmatrix} 1 & 5 \\ 3 & -1 \end{bmatrix}$, thus $\mathbf{W}^{-1} = \begin{bmatrix} -0.0625 & 0.3125 \\ 0.1875 & -0.0625 \end{bmatrix}$. Hence

$$\mathbf{G} = [(\mathbf{W}^{-1})^T \quad \mathbf{0}]^T = \begin{bmatrix} \mathbf{W}^{-1} \\ \mathbf{0} \end{bmatrix} = \begin{bmatrix} -0.0625 & 0.3125 \\ 0.1875 & -0.0625 \\ 0 & 0 \end{bmatrix}$$

(b) From R we have

$$\mathbf{G} = \text{ginv}(\mathbf{A}) = \begin{bmatrix} 0.01414514 & 0.04797048 \\ 0.18880689 & -0.05535055 \\ 0.02091021 & 0.11439114 \end{bmatrix}$$

3. From the definition, for $u \sim t_m(\delta)$, there exist independent $y \sim N(\delta, 1)$ and $w \sim \chi_m^2$ such that $u = \frac{y}{\sqrt{w/m}}$.

Hence $u^2 = \frac{y^2}{w/m} = \frac{y^2/1}{w/m}$. From the definition of non-central chi-squared distribution, we know that $y^2 \sim \chi_1^2(\delta^2/2)$. Also, y^2 and w are independent. Then from the definition of F distribution, we have $u^2 \sim F_{1,m}(\delta^2/2)$.

4. Let $\mathbf{z} = \begin{bmatrix} x \\ y \end{bmatrix}$, then $\mathbf{z} \sim N(\boldsymbol{\mu}, \mathbf{I}_{2 \times 2})$, where $\boldsymbol{\mu} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$. Then we have $\mathbf{z}^T \mathbf{z} \sim \chi_2^2(\boldsymbol{\mu}^T \boldsymbol{\mu}/2 = 5/2)$. Thus

$$\begin{aligned}
 &P(\{\text{the string will need to be longer than 6 units}\}) \\
 &= P(\mathbf{z}^T \mathbf{z} > 36) = 1 - \text{pchisq}(36, df = 2, ncp = 5) = 0.00014096
 \end{aligned}$$

5. (a) Let $\mathbf{z} = \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}$, then $\mathbf{z} \sim N(\mathbf{0}, \mathbf{I}_{2 \times 2})$. Thus $z_1 - z_2 = \begin{bmatrix} 1 & -1 \end{bmatrix} \mathbf{z} \sim N(0, 2)$ and hence $(z_1 - z_2)/\sqrt{2} \sim N(0, 1)$. From the definition of χ^2 distribution, we know that

$$(z_1 - z_2)^2/2 = \left((z_1 - z_2)/\sqrt{2} \right)^2 \sim \chi_1^2$$

- (b) $\begin{bmatrix} z_1 + z_2 \\ z_1 - z_2 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} \sim N(\mathbf{0}, \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix})$. Hence $z_1 + z_2$ and $z_1 - z_2$ are independent, and $(z_1 + z_2)/\sqrt{2} \perp (z_1 - z_2)^2/2$. From (a) we know $(z_1 - z_2)^2/2 \sim \chi_1^2$. And $(z_1 + z_2)/\sqrt{2} \sim N(0, 1)$. Then from the definition of t distribution,

$$(z_1 + z_2)/|z_1 - z_2| = \frac{(z_1 + z_2)/\sqrt{2}}{\sqrt{(z_1 - z_2)^2/2}} \sim t_1$$

6. (a) $\bar{y} = \frac{1}{n} \mathbf{1}^T \mathbf{y}$, thus $\mathbf{y} - \bar{y} \mathbf{1} = \mathbf{y} - \frac{1}{n} \mathbf{1} \mathbf{1}^T \mathbf{y} = (\mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T) \mathbf{y}$. Hence

$$\begin{aligned} s^2 &= \frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2 \\ &= \frac{1}{n-1} ((\mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T) \mathbf{y})^T (\mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T) \mathbf{y} \\ &= \frac{1}{n-1} \mathbf{y}^T (\mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T)^T (\mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T) \mathbf{y} \\ &= \frac{1}{n-1} \mathbf{y} (\mathbf{I} - \frac{2}{n} \mathbf{1} \mathbf{1}^T + \frac{1}{n^2} \mathbf{1} \mathbf{1}^T \mathbf{1} \mathbf{1}^T) \mathbf{y} \\ &= \frac{1}{n-1} \mathbf{y}^T (\mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T) \mathbf{y} \\ &= \mathbf{Y}^T \frac{1}{n-1} (\mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T) \mathbf{y} = \mathbf{y}^T \mathbf{B} \mathbf{y} \end{aligned}$$

Here $\mathbf{B} = \frac{1}{n-1} (\mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T)$

- (b) $(n-1)s^2/\sigma^2 = \mathbf{y}^T \frac{1}{\sigma^2} (\mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T) \mathbf{y}$. Let $\mathbf{A} = \frac{1}{\sigma^2} (\mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T)$, then $\mathbf{A} \Sigma = \mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T$. From the proof of (a) we know that $\mathbf{A} \Sigma = \mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T$ is idempotent. $\text{rank}(\mathbf{A}) = \text{rank}(\mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T) = \text{tr}(\mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T) = \text{tr}(\mathbf{I}) - \frac{1}{n} \text{tr}(\mathbf{1} \mathbf{1}^T) = n - \frac{1}{n} n = n - 1$. Then we know

$$(n-1)s^2/\sigma^2 \sim \chi_{n-1}^2(\boldsymbol{\mu}^T \mathbf{A} \boldsymbol{\mu}/2)$$

We also have $\boldsymbol{\mu}^T \mathbf{A} \boldsymbol{\mu} = \mu^2 \mathbf{1}^T \mathbf{A} \mathbf{1} = \frac{\mu^2}{\sigma^2} \mathbf{1}^T (\mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T) \mathbf{1} = \frac{\mu^2}{\sigma^2} (\mathbf{1}^T \mathbf{1} - \frac{1}{n} \mathbf{1}^T \mathbf{1} \mathbf{1}^T \mathbf{1}) = \frac{\mu^2}{\sigma^2} (n - \frac{1}{n} n^2) = 0$, hence

$$(n-1)s^2/\sigma^2 \sim \chi_{n-1}^2$$

7. (a) If $\mathbf{A} = \mathbf{0}$ then $\mathbf{A}^T \mathbf{A} = \mathbf{0}$.

If $\mathbf{A}^T \mathbf{A} = \mathbf{0}$, then $(\mathbf{A}^T \mathbf{A})_{ii}$ in the diagonal line should also be 0. And for every i , we have $(\mathbf{A}^T \mathbf{A})_{ii} = \sum_{j=1}^n a_{ji}^2 = 0 \Rightarrow a_{ji} = 0$ for all $j = 1, 2, \dots, n$, where a_{ji} is the (j, i) component of \mathbf{A} . Hence for every element in \mathbf{A} , we have $a_{ij} = 0, i, j = 1, 2, \dots, n$. Thus $\mathbf{A} = \mathbf{0}$.

- (b) $\mathbf{X} \mathbf{A} = \mathbf{X} \mathbf{B} \Rightarrow \mathbf{X}^T \mathbf{X} \mathbf{A} = \mathbf{X}^T \mathbf{X} \mathbf{B}$.

$\mathbf{X}^T \mathbf{X} \mathbf{A} = \mathbf{X}^T \mathbf{X} \mathbf{B} \Rightarrow \mathbf{X}^T \mathbf{X} (\mathbf{A} - \mathbf{B}) = \mathbf{0} \Rightarrow (\mathbf{A} - \mathbf{B})^T \mathbf{X}^T \mathbf{X} (\mathbf{A} - \mathbf{B}) = \mathbf{0} \Rightarrow (\mathbf{X} (\mathbf{A} - \mathbf{B}))^T (\mathbf{X} (\mathbf{A} - \mathbf{B})) = \mathbf{0}$. From (a) we know that $\mathbf{X} (\mathbf{A} - \mathbf{B}) = \mathbf{0} \Rightarrow \mathbf{X} \mathbf{A} = \mathbf{X} \mathbf{B}$.

- (c) For any generalized inverse $(\mathbf{X}^T \mathbf{X})^-$, we have $\mathbf{X}^T \mathbf{X} (\mathbf{X}^T \mathbf{X})^- \mathbf{X}^T \mathbf{X} = \mathbf{X}^T \mathbf{X}$. Let $(\mathbf{X}^T \mathbf{X})^- \mathbf{X}^T \mathbf{X} = \mathbf{A}$ and $\mathbf{I} = \mathbf{B}$, from (b) we have

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

- (d) \mathbf{G} is a generalized inverse of \mathbf{A} , then $\mathbf{AGA} = \mathbf{A}$. Take transpose on both sides we have $\mathbf{A}^T \mathbf{G}^T \mathbf{A}^T = \mathbf{A}^T$. \mathbf{A} is symmetric then $\mathbf{A}^T = \mathbf{A}$, then $\mathbf{AG}^T \mathbf{A} = \mathbf{A}$. Hence \mathbf{G}^T is also a generalized inverse of \mathbf{A} .
- (e) Denote $\mathbf{G} = (\mathbf{X}^T \mathbf{X})^-$. As $\mathbf{X}^T \mathbf{X}$ is symmetric, then \mathbf{G}^T is also a generalized inverse of $\mathbf{X}^T \mathbf{X}$. Hence we have

$$\mathbf{XG}^T \mathbf{X}^T \mathbf{X} = \mathbf{X}$$

Take transpose on both sides and we have

$$\mathbf{X}^T \mathbf{XG} \mathbf{X}^T = \mathbf{X} \Rightarrow \mathbf{X}^T \mathbf{X} (\mathbf{X}^T \mathbf{X})^- \mathbf{X}^T = \mathbf{X}^T$$

- (f) From (c):

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

From (e):

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

- (g) From (e) we have $\mathbf{X}^T = \mathbf{X}^T \mathbf{XG}_2 \mathbf{X}^T$. Hence we can plug this into $\mathbf{XG}_1 \mathbf{X}^T$ and we have

$$\mathbf{XG}_1 \mathbf{X}^T = \mathbf{XG}_1 \mathbf{X}^T \mathbf{XG}_2 \mathbf{X}^T = (\mathbf{XG}_1 \mathbf{X}^T \mathbf{X}) \mathbf{G}_2 \mathbf{X}^T = \mathbf{XG}_2 \mathbf{X}^T$$

$\mathbf{XG}_1 \mathbf{X}^T \mathbf{X} = \mathbf{X}$ is from (c).

- (h) Denote $(\mathbf{X}^T \mathbf{X})^- = \mathbf{G} = \mathbf{G}_1$ and $\mathbf{G}^T = \mathbf{G}_2$. From (d) we know that \mathbf{G}_1 and \mathbf{G}_2 are both generalized inverse of $\mathbf{X}^T \mathbf{X}$, and from (g) we have $\mathbf{XG} \mathbf{X}^T = \mathbf{XG}_1 \mathbf{X}^T = \mathbf{XG}_2 \mathbf{X}^T = \mathbf{XG}^T \mathbf{X}^T$. Hence

$$\mathbf{P}_X^T = \mathbf{XG}^T \mathbf{X}^T = \mathbf{XG} \mathbf{X}^T = \mathbf{P}_X$$