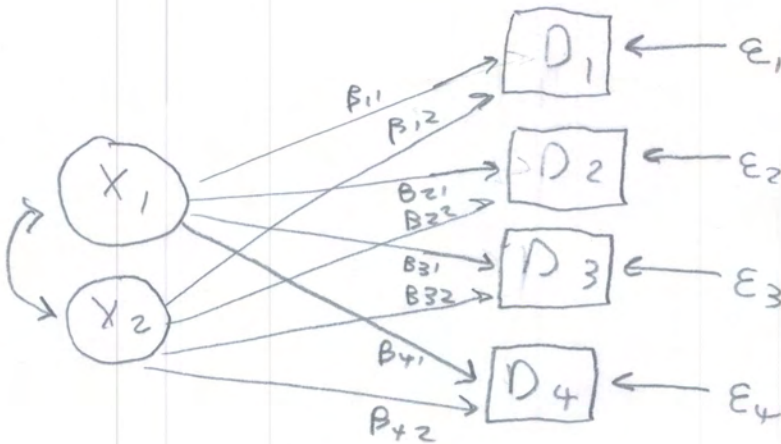


# STA431/523 Assignment 2

1

①

(a)



(b)  $\theta = (\mu_1, \mu_2, \sigma_{11}, \sigma_{12}, \sigma_{22}, \alpha_1, \alpha_2, \alpha_3, \alpha_4$

$\beta_{11}, \beta_{12}, \beta_{21}, \beta_{22}, \beta_{31}, \beta_{32}, \beta_{41}, \beta_{42}$

$\sigma_1^2, \sigma_2^2, \sigma_3^2, \sigma_4^2)$  That's 21, where

$\mu_1 = E(X_1), \mu_2 = E(X_2), \sigma_{11} = \text{Var}(X_1), \sigma_{12} = \text{Cov}(X_1, X_2)$   
 $\sigma_{22} = \text{Var}(X_2), \sigma_j^2 = \text{Var}(\epsilon_j)$  for  $j=1, \dots, 4.$

② Let  $A = \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix}, B = \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix}$

Then  $AB = \begin{pmatrix} 1 & 1 \\ 0 & 0 \end{pmatrix} \neq BA = \begin{pmatrix} 1 & 0 \\ 1 & 0 \end{pmatrix}$

2

③ A and B must exist, because if not,  $|A|=0$  or  $|B|=0$  or both, and  $|AB|=|A||B|=0$ . But  $AB=I \Rightarrow |AB|=|I|=1$ . This implies  $|A| \neq 0$  and  $|B| \neq 0$ , and both inverses exist.

$$\text{So } AB=I \Rightarrow A^{-1}AB=A^{-1}I \Rightarrow B=A^{-1}$$

$$AB=I \Rightarrow AB B^{-1}=I B^{-1} \Rightarrow A=B^{-1} \quad \square$$

④  $AB=I$  and  $BA=I$  so  $AB=AC$

$$\Rightarrow \underbrace{BA}B = \underbrace{BA}C \Rightarrow B=C$$

⑤ Inverse is only defined for square matrices.

$$\textcircled{6} AB(B^{-1}A^{-1}) = A \underbrace{BB^{-1}}I A^{-1} = AA^{-1} = I$$

$$\textcircled{7} AB=I \Rightarrow (AB)^T = I^T$$

$$\Rightarrow B^T A^T = I^T = I \quad \text{done}$$

$$\textcircled{8} a^T a = \sum_{j=1}^n a_j^2 \geq 0$$

3

(9) (a)  $Ax = \lambda x \Rightarrow x^T A x = x^T \lambda x$   
 $= \lambda x^T x = \lambda$ , so  $0 < x^T A x = \lambda$

(b)  $AA^T = C D \underbrace{C^T C}_I D^{-1} C^T = C \underbrace{D D^{-1}}_I C^T$   
 $= C C^T = I$

(c)  $A^{1/2} A^{1/2} = C D^{1/2} \underbrace{C^T C}_I D^{1/2} C^T$   
 $= C D^{1/2} D^{1/2} C^T = C D C^T = A$

(d) (i)  $A^{-1/2} A^{-1/2} = C D^{-1/2} \underbrace{C^T C}_I D^{-1/2} C^T$   
 $= C D^{-1/2} D^{-1/2} C^T$   
 $= C D^{-1} C^T = A^{-1}$

(ii)  $A^{-1/2} A^{1/2} = C D^{-1/2} \underbrace{C^T C}_I D^{1/2} C^T$   
 $= C \underbrace{D^{-1/2} D^{1/2}}_I C^T = C C^T = I$

$$\textcircled{10} \text{tr}(\Sigma) = \text{tr}(\underbrace{C}_A \underbrace{D}_B \underbrace{C^T}_I) = \text{tr}(\underbrace{C^T C}_I D) = \text{tr}(D),$$

the sum of eigenvalues.

$$\begin{aligned} \textcircled{11} |\Sigma| &= |C D C^T| = |C| |D| |C^T| \\ &= |C| |C^T| |D| = |C C^T| |D| \\ &= |I| |D| = |D| = \text{product of eigenvalues} \end{aligned}$$

$\textcircled{12}$  Let  $v$  have a one in position  $j$ , and zeros elsewhere. Then

$$\begin{aligned} v^T A v &= (0 \dots 1 \dots 0) \begin{pmatrix} a_{11} & \dots & a_{1n} \\ \vdots & & \vdots \\ a_{j1} & \dots & a_{jn} \\ \vdots & & \vdots \\ a_{n1} & \dots & a_{nn} \end{pmatrix} \begin{pmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{pmatrix} \\ &= (a_{j1} \ a_{j2} \ \dots \ a_{jn}) \begin{pmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{pmatrix} = a_{jj} > 0 \end{aligned}$$

because positive definite.

(13) Done in lecture. See Random Vectors and Multivariate Normal, slide 9.

$$\begin{aligned}
(14) \text{ Cov}(Ax, By) &= E \{ (Ax - A\mu_x)(By - B\mu_y)^T \} \\
&= E \{ A(x - \mu_x)(B(y - \mu_y))^T \} \\
&= E \{ A(x - \mu_x)(y - \mu_y)^T B^T \} \\
&= A E \{ (x - \mu_x)(y - \mu_y)^T \} B^T = A \text{Cov}(x, y) B^T
\end{aligned}$$

(15) This is false, though some people can prove it anyway.

Let  $x_1$  and  $x_2$  be independent random variables, with  $\text{Var}(x_1) = \sigma_1^2 > 0$  and  $\text{Var}(x_2) = \sigma_2^2 > 0$ . Then

$$\text{Cov} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{pmatrix} \neq \underline{0}$$

For example, they could be standard normal.

$$\begin{aligned}
 (16) \quad \text{Cov}(x+c) &= E \left\{ (x+c - (\mu+c))(x+c - (\mu+c))^T \right\} \\
 &= E \left\{ (x+c - \mu - c)(x+c - \mu - c)^T \right\} \\
 &= E \left\{ (x-\mu)(x-\mu)^T \right\} = \text{Cov}(x)
 \end{aligned}$$

(17)  $\text{Var}(y) = v^T \Sigma v$ , must be greater than or equal to zero since variances are non-negative.

(18) (a) By Problem 17,  $v^T \Sigma v \geq 0$  for any vector  $v$ . Then if  $(\lambda, x)$  is an eigenvalue, eigenvector pair for  $\Sigma$ ,

$$\begin{aligned}
 \Sigma x = \lambda x &\Rightarrow x^T \Sigma x = x^T \lambda x = \lambda x^T x \\
 &= \lambda \geq 0
 \end{aligned}$$

(b) Because the determinant is the product of the eigenvalues, which are non-negative by (a)

$$(18c) \begin{vmatrix} \text{Var}(X) & \text{Cov}(X, Y) \\ \text{Cov}(X, Y) & \text{Var}(Y) \end{vmatrix} \geq 0$$

$$\Leftrightarrow \text{Var}(X)\text{Var}(Y) - \text{Cov}(X, Y)^2 \geq 0$$

$$\Leftrightarrow \text{Cov}(X, Y)^2 \leq \text{Var}(X)\text{Var}(Y)$$

$$\Leftrightarrow |\text{Cov}(X, Y)| \leq \sqrt{\text{Var}(X)\text{Var}(Y)}$$

$$\Leftrightarrow \left| \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}} \right| \leq 1$$

$$\Leftrightarrow |\text{Corr}(X, Y)| \leq 1$$

$$\Leftrightarrow -1 \leq \text{Corr}(X, Y) \leq 1$$



19 (a)  $\text{Cov}(x_i, y_j)$

(b)  $\text{Cov}(x+y) = \text{Cov}(x+y, x+y) = \text{Cov}(x, x) + \text{Cov}(x, y) + \text{Cov}(y, x) + \text{Cov}(y, y)$   
 $= \Sigma_x + \Sigma_{xy} + \Sigma_{xy}^T + \Sigma_y.$

(c) If  $\text{Cov}(x_i, y_j) = 0$  for all  $i \neq j$ ,  $\Sigma_{xy} = 0$  and  
 $\text{Cov}(x, y) = \Sigma_x + \Sigma_y$

(d)  $\text{Cov}(x+c, y+d)$

$$= E \{ (x+c - (\mu_x + c)) (y+d - (\mu_y + d))^T \}$$

$$= E \{ (x - \mu_x) (y - \mu_y)^T \} = \text{Cov}(x, y) = \Sigma_{xy}$$

20  $\text{Cov}(x_1 + x_2, y_1 + y_2) = \text{Cov}(x_1, y_1) + \text{Cov}(x_1, y_2) + \text{Cov}(x_2, y_1) + \text{Cov}(x_2, y_2)$

21 This is false. Let  $x$  be  $3 \times 1$  and  $y$  be  $2 \times 1$ . Then  $\text{Cov}(x, y)$  is  $3 \times 2$ , and  $\text{Cov}(y, x)$  is  $2 \times 3$ .

22 False again. Let  $x = z + e_1$ ,  $y = z + e_2$ , with  $e_1, e_2 \perp z$  independent  $\& \text{Cov}(z) = I$ . Then  $\text{Cov}(x, y) = \text{Cov}(z + e_1, z + e_2) = \text{Cov}(z, z) + 0 = \text{Cov}(z) = I \neq 0$ .