

Assignment 3

(1) a (2) c (3) b (4) b

(5) c (6) b (7) d (8) d

$$\begin{aligned} \textcircled{9} \quad \text{tr}(AB) &= \text{tr}\left(\sum_{k=1}^q a_{ik} b_{kj}\right) = \sum_{i=1}^p \sum_{k=1}^q a_{ik} b_{ki} \\ &= \sum_{k=1}^q \sum_{i=1}^p b_{ki} a_{ik} = \text{tr}(BA) \quad \square \end{aligned}$$

↙ ↘
switch both

There was more detail in the lecture slides. This is enough.

$\textcircled{10}$ If $AB = I$, both A and B must have inverses, for otherwise

$$|AB| = |A||B| = 0 \neq 1 = |I|$$

Then $AB = I \Rightarrow A^{-1}AB = A^{-1}I \Rightarrow B = A^{-1}$ and

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

$\textcircled{11}$ $BA = I \Rightarrow \underbrace{BAC}_I = IC \Rightarrow B = C \quad \square$

$\textcircled{12}$ $B^{-1}A^{-1}(AB) = B^{-1}IB = I \quad \square$

$\textcircled{13}$ Denoting $a = [a_j]$, $a'a = \sum_{j=1}^n a_j^2 \geq 0$

$\textcircled{14}$ Suppose on the contrary that A^{-1} does exist. Columns of A linearly dependent means there exists $v \neq 0$ with $Av = 0 \Rightarrow A^{-1}Av = A^{-1}0 \Rightarrow v = 0$. But this is impossible since $v \neq 0$.

(15) Let $B = A^{-1}$. Seek to show B' is the inverse of A' . $B'A' = (AB)' = I' = I$ \square

(16) If A is symmetric $(A^{-1})' = (A')^{-1} = A^{-1}$ \square

(17) $\Sigma v = \lambda v \Rightarrow v' \Sigma v = v' \lambda v = \lambda v' v = \lambda$
 Since $v' \Sigma v > 0$ and $v' \Sigma v = \lambda$, have $\lambda > 0$ \square

(18) (a) (i) D^{-1} is a diagonal matrix with j th diagonal element $1/\lambda_j$;

(ii) $C D^{-1} C' C D C' = C \underbrace{D^{-1} D}_I C' = C C' = I$

(b) (i) $D^{1/2}$ is a diagonal matrix with j th diagonal element $\sqrt{\lambda_j}$.

(ii) $(C D^{1/2} C')' = C'' D^{1/2}' C' = C D^{1/2} C'$

(iii) $\Sigma^{1/2} \Sigma^{1/2} = C D^{1/2} \underbrace{C' C}_I D^{1/2} C'$
 $= C D^{1/2} D^{1/2} C' = C D C' = \Sigma$

(c) (i) $\Sigma^{-1/2} \Sigma^{1/2} = C \underbrace{D^{-1/2} C' C D^{1/2}}_I C' = I$ \square

(ii) $\Sigma^{-1/2} \Sigma^{-1/2} = C D^{-1/2} \underbrace{C' C}_I D^{-1/2} C'$
 $= C D^{-1/2} D^{-1/2} C' = C D^{-1} C'$
 $= \Sigma^{-1}$ by part (a)

(18d) The eigenvalues of Σ are strictly positive by problem 17, and 18a(ii) gives a formula for the inverse.

(19) Let v be all zeros except for a 1 in position j . Then $v^T A v = a_{jj} > 0$ since A is positive definite.

$$\begin{aligned} (20) \quad \text{tr}(M) &= \text{tr}(\underbrace{C}_A \underbrace{D C^T}_B) = \text{tr}(\underbrace{D C^T C}_I) = \text{tr}(D) \\ &= \sum_{j=1}^p \lambda_j \end{aligned}$$

$$\begin{aligned} (21) \quad |M| &= |C D C^T| = |D C^T C| = |D| \\ &= \prod_{j=1}^p \lambda_j \end{aligned}$$

$$(22) \quad E(Ax) = AE(x) = A\mu$$

$$\begin{aligned} \text{cov}(Ax) &= E\{(Ax - A\mu)(Ax - A\mu)'\} \\ &= E\{A(x - \mu)(A(x - \mu))'\} \\ &= E\{A(x - \mu)(x - \mu)'A'\} = AE\{(x - \mu)(x - \mu)'\}A' \\ &= A\Sigma A' \end{aligned}$$

$$\begin{aligned} (23) \quad \text{cov}(Ay, By) &= E\{(Ay - A\mu)(By - B\mu)'\} \\ &= E\{A(y - \mu)(B(y - \mu))'\} = E\{A(y - \mu)(y - \mu)'B'\} \\ &= AE\{(y - \mu)(y - \mu)'\}B' = A\Sigma B' \end{aligned}$$

$$\begin{aligned} (24) \quad \Sigma &= E\{(x - \mu)(x - \mu)'\} \\ &= E\{xx' - x\mu' - \mu x' + \mu\mu'\} \\ &= E\{xx'\} - E\{x\mu'\} - \mu E\{x'\} + \mu\mu' \\ &= E\{xx'\} - \mu\mu' - \mu\mu' + \mu\mu' \\ &= E\{xx'\} - \mu\mu' \end{aligned}$$

(25) Just kidding, but some students do this.

$$\begin{aligned} (26) \quad E(Ax + c) &= A\mu + c, \text{ and} \\ \text{cov}(Ax + c) &= E\{(Ax + c - (A\mu + c))(Ax + c - (A\mu + c))'\} \\ &= E\{(Ax - A\mu)(Ax - A\mu)'\} \text{ Already did this} \\ &= A\Sigma A' \end{aligned}$$

(27) Because variances cannot be negative

$$0 \leq \text{Var}(y) = \text{cov}(y'x) = y' \text{cov}(x) y \\ = y' \Sigma y \text{ where } \Sigma = \text{cov}(x)$$

Because y could be anything in \mathbb{R}^p , that's it.

(28) (a) Let $\text{cov}(y) = \Sigma$. If λ is an eigenvalue of Σ and v the corresponding eigenvector,

$$\Sigma v = \lambda v \Rightarrow v' \Sigma v = v' \lambda v = \lambda v' v = \lambda \geq 0$$

by problem 27.

(b) $|\Sigma| \geq 0$ because the determinant is the product of the eigenvalues.

(c) Denote $\text{cov}\begin{pmatrix} x \\ y \end{pmatrix}$ by $\Sigma = \begin{pmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{pmatrix}$. By (b),

$$0 \leq |\Sigma| = \sigma_1^2 \sigma_2^2 - \sigma_{12}^2$$

$$\Rightarrow \underbrace{\sigma_{12}^2 \leq \sigma_1^2 \sigma_2^2}_{\text{Cauchy-Schwarz}} \Rightarrow \frac{\sigma_{12}^2}{\sigma_1^2 \sigma_2^2} \leq 1$$

$$\Rightarrow \sqrt{\frac{\sigma_{12}^2}{\sigma_1^2 \sigma_2^2}} \leq 1 \Rightarrow \left| \frac{\sigma_{12}}{\sigma_1 \sigma_2} \right| \leq 1$$

↑
corr(x, y)

$$\Rightarrow -1 \leq \text{Corr}(x, y) \leq 1$$



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

(b) $\text{Cov}(x+y) = E \{ (x+y - (\mu_x + \mu_y)) (x+y - (\mu_x + \mu_y))' \}$
 $= E \{ (x - \mu_x + y - \mu_y) (x - \mu_x + y - \mu_y)' \}$
 $= E \{ (x - \mu_x)(x - \mu_x)' + (x - \mu_x)(y - \mu_y)' + (y - \mu_y)(x - \mu_x)' + (y - \mu_y)(y - \mu_y)' \}$
 $= E \{ (x - \mu_x)(x - \mu_x)' \} + E \{ (x - \mu_x)(y - \mu_y)' \}$
 $+ E \{ (y - \mu_y)(x - \mu_x)' \} + E \{ (y - \mu_y)(y - \mu_y)' \}$
 $= \text{Cov}(x) + \text{Cov}(x, y) + \text{Cov}(y, x) + \text{Cov}(y)$

(c) They are all $p \times p$.

(d) If $\text{Cov}(x, y) = 0$, $\text{Cov}(x+y) = \text{Cov}(x) + \text{Cov}(y)$

(e) $\text{Cov}(x+c, y+d) = E \{ (x+c - (\mu_x+c)) (y+d - (\mu_y+d))' \}$
 $= E \{ (x+c - \mu_x - c) (y+d - \mu_y - d)' \}$
 $= E \{ (x - \mu_x) (y - \mu_y)' \} = \text{Cov}(x, y)$

(f) It's not true even if $p=q$. There is no reason why $\text{Cov}(x_i, y_j)$ should equal $\text{Cov}(x_j, y_i)$.

(g) This was supposed to be a joke.