

Homework 1

习题3

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Note

设 $X^{(1)}$ 和 $X^{(2)}$ 为 p 维随机向量,且

$$X = \begin{pmatrix} X^{(1)} \\ X^{(2)} \end{pmatrix} \sim N_{2p} \left(\begin{pmatrix} \mu^{(1)} \\ \mu^{(2)} \end{pmatrix}, \begin{pmatrix} \Sigma_1 & \Sigma_2 \\ \Sigma_2 & \Sigma_1 \end{pmatrix} \right)$$

其中 $\mu^{(1)}$ 和 $\mu^{(2)}$ 为 p 维列向量, Σ_1 和 Σ_2 为 p 阶正定矩阵,

(1)试证 $X^{(1)} + X^{(2)}$ 与 $X^{(1)} - X^{(2)}$ 相互独立;

(2)试求 $X^{(1)} + X^{(2)}$ 与 $X^{(1)} - X^{(2)}$ 的分布.

Proof. (1) 已知 $\mathbb{E}[X^{(i)}] = \mu^{(i)}$, $\text{Cov}(X^{(i)}, X^{(i)}) = \mathbb{E}[X^{(i)}] = \Sigma_1, i = 1, 2$,

$$\text{Cov}(X^{(1)}, X^{(2)}) = \text{Cov}(X^{(2)}, X^{(1)}) = \Sigma_2.$$

$$\text{则 } \text{Cov}(X^{(1)} + X^{(2)}, X^{(1)} - X^{(2)})$$

$$\begin{aligned} &= \text{Cov}(X^{(1)}, X^{(1)}) - \text{Cov}(X^{(2)}, X^{(2)}) + \text{Cov}(X^{(2)}, X^{(1)}) - \text{Cov}(X^{(1)}, X^{(2)}) \\ &= \Sigma_1 - \Sigma_1 + \Sigma_2 - \Sigma_2 = 0 \end{aligned}$$

又 $X^{(1)} + X^{(2)}$ 与 $X^{(1)} - X^{(2)}$ 都为 X 的一个线性组合,则服从正态分布,

因此, $X^{(1)} + X^{(2)}$ 和 $X^{(1)} - X^{(2)}$ 相互独立.

$$(2) \text{ 由已知, } \mathbb{E}[X^{(1)} + X^{(2)}] = \mu^{(1)} + \mu^{(2)}, \mathbb{E}[X^{(1)} - X^{(2)}] = \mu^{(1)} - \mu^{(2)},$$

$$\begin{aligned} \text{Var}(X^{(1)} + X^{(2)}) &= \text{Var}(X^{(1)}) + \text{Var}(X^{(2)}) + \text{Cov}(X^{(1)}, X^{(2)}) + \text{Cov}(X^{(2)}, X^{(1)}) \\ &= 2\Sigma_1 + 2\Sigma_2, \text{ 同理, } \text{Var}(X^{(1)} - X^{(2)}) = 2\Sigma_1 - 2\Sigma_2 \end{aligned}$$

$$X^{(1)} + X^{(2)} \sim N(\mu^{(1)} + \mu^{(2)}, 2\Sigma_1 + 2\Sigma_2), X^{(1)} - X^{(2)} \sim N(\mu^{(1)} - \mu^{(2)}, 2\Sigma_1 - 2\Sigma_2)$$

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Note

设 $X \sim N_p(\mu, \Sigma)$, $\Sigma > 0$,对 μ 和 Σ 作如下剖分:

$$\mu = \begin{pmatrix} \mu^{(1)} \\ \mu^{(2)} \end{pmatrix}, \Sigma = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix}$$

其中 $\mu^{(1)}$ 为 r 维列向量, Σ_{11} 为 r 维方阵, $1 \leq r < p$.

(1)试证明: $\mu' \Sigma^{-1} \mu \geq (\mu^{(1)})' \Sigma_{11}^{-1} \mu^{(1)}$;

(2)试证明: $X^{(2)} | X^{(1)} = x^{(1)} \sim N_{p-r}(\mu_{2.1}, \Sigma_{22.1})$, 其中 $\mu_{2.1} = \mu^{(2)} + \Sigma_{21} \Sigma_{11}^{-1} (x^{(1)} - \mu^{(1)})$ 和 $\Sigma_{22.1} = \Sigma_{22} - \Sigma_{21} \Sigma_{11}^{-1} \Sigma_{12}$.

Proof. (1) 已知 $\Sigma^{-1} = \begin{pmatrix} \Sigma_{11}^{-1} + \Sigma_{11}^{-1}\Sigma_{12}\Sigma_{22.1}^{-1}\Sigma_{21}\Sigma_{11}^{-1} & -\Sigma_{11}^{-1}\Sigma_{12}\Sigma_{22.1}^{-1} \\ \Sigma_{22.1}^{-1}\Sigma_{21}\Sigma_{11}^{-1} & \Sigma_{22.1}^{-1} \end{pmatrix}$, 要证 $\mu'\Sigma^{-1}\mu - (\mu^{(1)})'\Sigma_{11}^{-1}\mu^{(1)}$

即证 $\mu'\Sigma^{-1}\mu - (\mu^{(1)})'\Sigma_{11}^{-1}\mu^{(1)}$

$$= \begin{pmatrix} \mu^{(1)} \\ \mu^{(2)} \end{pmatrix}' \begin{pmatrix} \Sigma_{11}^{-1} + \Sigma_{11}^{-1}\Sigma_{12}\Sigma_{22.1}^{-1}\Sigma_{21}\Sigma_{11}^{-1} & -\Sigma_{11}^{-1}\Sigma_{12}\Sigma_{22.1}^{-1} \\ \Sigma_{22.1}^{-1}\Sigma_{21}\Sigma_{11}^{-1} & \Sigma_{22.1}^{-1} \end{pmatrix} \begin{pmatrix} \mu^{(1)} \\ \mu^{(2)} \end{pmatrix} - (\mu^{(1)})'\Sigma_{11}^{-1}\mu^{(1)}$$

$$= (\Sigma_{21}\Sigma_{11}^{-1}\mu^{(1)} - \mu^{(2)})'\Sigma_{22.1}^{-1}(\Sigma_{21}\Sigma_{11}^{-1}\mu^{(1)} - \mu^{(2)}) \geq 0$$

因此我们只需说明 $\Sigma_{22.1}^{-1} = \Sigma_{22} - \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{12}$ 半正定即可. 事实上

$$\Sigma = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} \simeq \begin{pmatrix} \Sigma_{11} & 0 \\ 0 & \Sigma_{22} - \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{12} \end{pmatrix} \text{ 且 } \Sigma \text{ 正定, 从而 } \Sigma_{22.1}^{-1} = \Sigma_{22} - \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{12}$$

故原命题得证.

$$(2) \text{ 作变换 } Y = \begin{pmatrix} Y^{(1)} \\ Y^{(2)} \end{pmatrix} = \begin{pmatrix} \mathbf{I}_r & 0 \\ -\Sigma_{21}\Sigma_{11}^{-1} & \mathbf{I}_{p-r} \end{pmatrix} \begin{pmatrix} X^{(1)} \\ X^{(2)} \end{pmatrix} = \begin{pmatrix} X^{(1)} \\ -\Sigma_{21}\Sigma_{11}^{-1}X^{(1)} + X^{(2)} \end{pmatrix}$$

$$\text{故 } \mathbb{E}[Y] = \begin{pmatrix} \mu^{(1)} \\ -\Sigma_{21}\Sigma_{11}^{-1}\mu^{(1)} + \mu^{(2)} \end{pmatrix}, \text{Var}(Y) = \begin{pmatrix} \mathbf{I}_r & 0 \\ -\Sigma_{21}\Sigma_{11}^{-1} & \mathbf{I}_{p-r} \end{pmatrix} \Sigma \begin{pmatrix} \mathbf{I}_r & 0 \\ -\Sigma_{21}\Sigma_{11}^{-1} & \mathbf{I}_{p-r} \end{pmatrix}'$$

$$= \begin{pmatrix} \Sigma_{11} & 0 \\ 0 & \Sigma_{22} - \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{12} \end{pmatrix} = \begin{pmatrix} \Sigma_{11} & 0 \\ 0 & \Sigma_{22.1} \end{pmatrix},$$

从而 $Y^{(1)}$ 与 $Y^{(2)}$ 独立, Y 的密度函数为 $f(Y) = f(Y^{(1)})f(Y^{(2)})$

$$= \frac{1}{(2\pi)^{r/2}|\Sigma_{11}|^{1/2}} \exp \left\{ -\frac{1}{2} (Y^{(1)} - \mu^{(1)})' \Sigma_{11}^{-1} (Y^{(1)} - \mu^{(1)}) \right\}$$

$$\times \frac{1}{(2\pi)^{(p-r)/2}|\Sigma_{22.1}|^{1/2}} \exp \left\{ -\frac{1}{2} (Y^{(2)} - \mu^{(2)} + \Sigma_{21}\Sigma_{11}^{-1}\mu^{(1)})' \Sigma_{22.1}^{-1} (Y^{(2)} - \mu^{(2)} + \Sigma_{21}\Sigma_{11}^{-1}\mu^{(1)}) \right\}$$

$$\text{故 } f(X) = f(X^{(1)}, X^{(2)}) \cdot |\mathbf{J}|^{-1} = \frac{1}{(2\pi)^{r/2}|\Sigma_{11}|^{1/2}} \exp \left\{ -\frac{1}{2} (X^{(1)} - \mu^{(1)})' \Sigma_{11}^{-1} (X^{(1)} - \mu^{(1)}) \right\}$$

$$\times \frac{1}{(2\pi)^{(p-r)/2}|\Sigma_{22.1}|^{1/2}}$$

$$\cdot \exp \left\{ -\frac{1}{2} (X^{(2)} - \mu^{(2)} - \Sigma_{21}\Sigma_{11}^{-1}(X^{(1)} - \mu^{(1)}))' \Sigma_{22.1}^{-1} (X^{(2)} - \mu^{(2)} - \Sigma_{21}\Sigma_{11}^{-1}(X^{(1)} - \mu^{(1)})) \right\}$$

$$\text{又 } f(X^{(2)}|X^{(1)}) = \frac{f(X^{(1)}, X^{(2)})}{f(X^{(1)})}, \text{ 注意到, } f(X^{(1)}) \text{ 为上式的前半部分, 后半部分即 } f(X^{(2)}|X^{(1)})$$

$$\text{故 } X^{(2)}|X^{(1)} = x^{(1)} \sim N_{p-r}(\mu^{(2)} + \Sigma_{21}\Sigma_{11}^{-1}(x^{(1)} - \mu^{(1)}), \Sigma_{22.1}).$$

令 X_1, \dots, X_n 是相互独立的, 且 $X_i \sim N(\beta + \gamma z_i, \sigma^2)$, 其中 z_i 是给定的常数, $i = 1, \dots, n$, 且 $\sum_{i=1}^n z_i = 0$.

(1) 求 $(X_1, \dots, X_n)'$ 的分布;

(2) 求 $\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i$ 和 $Y = \sum_{i=1}^n z_i X_i / \sum_{i=1}^n z_i^2$ 的分布, 其中 $\sum_{i=1}^n z_i^2 > 0$.

Sol. (1) 由 X_1, \dots, X_n 相互独立, $(X_1, \dots, X_n)' \sim N_p(\beta \mathbf{1}_n + \gamma z, \sigma^2 \mathbf{I}_n)$, 其中 $\mathbf{1}_n$ 表示元素全为1的 $n \times 1$ 向量, $z = (z_1, \dots, z_n)'$.

(2) 由正态分布的可加性及 $\sum_{i=1}^n z_i = 0$, $\sum_{i=1}^n X_i \sim N\left(n\beta + \gamma \sum_{i=1}^n z_i, n\sigma^2\right)$, 则 $\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i \sim N\left(\beta, \sigma^2/n\right)$.

$\sum_{i=1}^n z_i X_i \sim N\left(\beta \sum_{i=1}^n z_i + \gamma \sum_{i=1}^n z_i^2, \sigma^2 \sum_{i=1}^n z_i^2\right)$, 则 $Y = \sum_{i=1}^n z_i X_i / \sum_{i=1}^n z_i^2 \sim N\left(\gamma, \sigma^2 / \sum_{i=1}^n z_i^2\right)$.

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Note

令 $a = (-4, 3)'$ 和 $b = (1, 1)'$, 以及 $\mathbf{A} = \begin{pmatrix} 2 & -2 \\ -2 & 5 \end{pmatrix}$, 试验证推广的Cauchy – Schwarz不等式: $(a'b)^2 \leq (a'\mathbf{A}a)(b'\mathbf{A}^{-1}b)$.

Sol. (1) $a'b = (-4, 3) \begin{pmatrix} 1 \\ 1 \end{pmatrix} = -1$, $(a'b)^2 = 1$, $\mathbf{A}^{-1} = \begin{pmatrix} \frac{5}{6} & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{3} \end{pmatrix}$,

$$a'\mathbf{A}a = (-4, 3) \begin{pmatrix} 2 & -2 \\ -2 & 5 \end{pmatrix} \begin{pmatrix} -4 \\ 3 \end{pmatrix} = (-14, 23) \begin{pmatrix} -4 \\ 3 \end{pmatrix} = 125, b'\mathbf{A}^{-1}b = (1, 1) \begin{pmatrix} \frac{5}{6} & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{3} \end{pmatrix} \begin{pmatrix} 1 \\ 1 \end{pmatrix} =$$

$$(a'\mathbf{A}a)(b'\mathbf{A}^{-1}b) = \frac{1375}{6} > 1 = (a'b)^2.$$

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Note

证明:

$$\Sigma^{-1} = \begin{pmatrix} \Sigma_{11.2}^{-1} & -\Sigma_{11.2}^{-1}\Sigma_{12}\Sigma_{22}^{-1} \\ -\Sigma_{22}^{-1}\Sigma_{21}\Sigma_{11.2}^{-1} & \Sigma_{22}^{-1}\Sigma_{21}\Sigma_{11.2}^{-1}\Sigma_{12}\Sigma_{22}^{-1} + \Sigma_{22}^{-1} \end{pmatrix} = \begin{pmatrix} 0 & 0 \\ 0 & \Sigma_{22}^{-1} \end{pmatrix} + \begin{pmatrix} \mathbf{I} \\ \beta' \end{pmatrix} \Sigma_{11.2}^{-1} (\mathbf{I}, -\beta)$$

其中 $\beta = \Sigma_{12}\Sigma_{22}^{-1}$.

$$\begin{aligned}
 \textit{Proof.} \text{即证 } \Sigma^{-1} - \begin{pmatrix} 0 & 0 \\ 0 & \Sigma_{22}^{-1} \end{pmatrix} &= \begin{pmatrix} \Sigma_{11.2}^{-1} & -\Sigma_{11.2}^{-1}\Sigma_{12}\Sigma_{22}^{-1} \\ -\Sigma_{22}^{-1}\Sigma_{21}\Sigma_{11.2}^{-1} & \Sigma_{22}^{-1}\Sigma_{21}\Sigma_{11.2}^{-1}\Sigma_{12}\Sigma_{22}^{-1} \end{pmatrix} = \begin{pmatrix} \mathbf{I} \\ \beta' \end{pmatrix} \Sigma_{11.2}^{-1} (\mathbf{I}, -\beta), \\
 \begin{pmatrix} \mathbf{I} \\ -\beta' \end{pmatrix} \Sigma_{11.2}^{-1} (\mathbf{I}, -\beta) &= \begin{pmatrix} \mathbf{I} \\ -\Sigma_{22}^{-1}\Sigma_{21} \end{pmatrix} \Sigma_{11.2}^{-1} (\mathbf{I}, -\Sigma_{12}\Sigma_{22}^{-1}) = \begin{pmatrix} \Sigma_{11.2}^{-1} \\ -\Sigma_{12}\Sigma_{22}^{-1}\Sigma_{11.2}^{-1} \end{pmatrix} (\mathbf{I}, -\Sigma_{12}\Sigma_{22}^{-1}) \\
 &= \begin{pmatrix} \Sigma_{11.2}^{-1} & -\Sigma_{11.2}^{-1}\Sigma_{12}\Sigma_{22}^{-1} \\ -\Sigma_{22}^{-1}\Sigma_{21}\Sigma_{11.2}^{-1} & \Sigma_{22}^{-1}\Sigma_{21}\Sigma_{11.2}^{-1}\Sigma_{12}\Sigma_{22}^{-1} \end{pmatrix}.
 \end{aligned}$$