

概率论第八周作业

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习题 3.3

T1

解 (1). 记 $U = X + Y, V = X - Y$, 因为 $(X, Y) \sim N(0, I_2)$, 取 $D = \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}$, 则

$$\begin{pmatrix} U & V \end{pmatrix} = \begin{pmatrix} X & Y \end{pmatrix} \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} = (X, Y)D$$

因此

$$(U, V) \sim N(0D, D^T I_2 D) = N(0, 2I_2)$$

所以 (U, V) 的联合密度函数为

$$f(u, v) = \frac{1}{4\pi} e^{-\frac{1}{4}(u^2+v^2)}$$

由 $\Sigma = 2I_2$ 为对角阵知, U, V 相互独立, 故 $f(u, v) = f_U(u)f_V(v)$, 其中 $f_U(u) = \frac{1}{2\sqrt{\pi}}e^{-\frac{1}{4}u^2}$, $f_V(v) = \frac{1}{2\sqrt{\pi}}e^{-\frac{1}{4}v^2}$

(2). 由第一问知, $U, V \sim N(0, 2)$, 且它们相互独立, 所以

$$\mathbb{E}[X - Y | X + Y] = \mathbb{E}[V | U] \stackrel{\text{独立}}{=} \mathbb{E}[V] = 0$$

又因为 $f_{V|U}(v|u) = \frac{f(u,v)}{f_U(u)} = f_V(v)$, 所以

$$(V|U = u) \sim N(0, 2), \quad \forall u \in \mathbb{R}$$

所以由 $\mathbb{E}[V] = 0$ 知

$$\text{Var}(V|U = u) = \mathbb{E}[(V - \mathbb{E}[V|U = u])^2 | U = u] = \mathbb{E}[V^2 | U = u] = \mathbb{E}[V^2] = \text{Var}(V) = 2$$

即 $\text{Var}(V|U) = 2$

□



T3

证明 记 $U = \sum_{k=1}^n a_k X_k, V = \sum_{k=1}^n b_k X_k$, 则

$$\begin{aligned} \text{Cov}(U, V) &= \mathbb{E}[(U - \mathbb{E}[U])(V - \mathbb{E}[V])] \\ &= \mathbb{E}\left[\left(\sum_{k=1}^n a_k X_k - \mathbb{E}\left[\sum_{k=1}^n a_k X_k\right]\right)\left(\sum_{k=1}^n b_k X_k - \mathbb{E}\left[\sum_{k=1}^n b_k X_k\right]\right)\right] \\ &= \mathbb{E}\left[\left(\sum_{k=1}^n a_k X_k - \sum_{k=1}^n a_k \mathbb{E}[X_k]\right)\left(\sum_{k=1}^n b_k X_k - \sum_{k=1}^n b_k \mathbb{E}[X_k]\right)\right] \\ &= \mathbb{E}\left[\sum_{k=1}^n a_k (X_k - \mathbb{E}[X_k]) \sum_{k=1}^n b_k (X_k - \mathbb{E}[X_k])\right] \\ &= \sum_{k,j=1}^n a_k b_j \mathbb{E}[(X_k - \mathbb{E}[X_k])(X_j - \mathbb{E}[X_j])] \\ &= \sum_{k,j=1}^n a_k b_j \text{Cov}(X_i, X_j) = \sum_{k,j=1}^n a_k b_j \sigma_{ij} \end{aligned}$$

首先记 $A = (a_1 \ \cdots \ a_n)^T$, 则 $U = XA \sim N(0A, A^T \Sigma A)$, 即 U 也服从正态分布, 同理 V 也服从正态分布, 由讲义中的定理 3.3.5 知, 高斯变量 U, V 独立 $\iff \text{Cov}(U, V) = 0$, 故

$$U = \sum_{k=1}^n a_k X_k, V = \sum_{k=1}^n b_k X_k \text{ 独立 } \iff \sum_{k,j=1}^n a_k b_j \sigma_{ij} = 0$$

考虑 $D = (A, B)$, 则

$$XD = (XA, XB) = (U, V) \sim N(0D, D^T \Sigma D) = N\left(0, \begin{pmatrix} A^T \Sigma A & A^T \Sigma B \\ B^T \Sigma A & B^T \Sigma B \end{pmatrix}\right)$$

记 $\begin{pmatrix} A^T \Sigma A & A^T \Sigma B \\ B^T \Sigma A & B^T \Sigma B \end{pmatrix} = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix}$, 其中 Σ_{ij} 是数, 且 $\Sigma_{12} = \Sigma_{21}$, 由 $B \neq 0$ 和 Σ 正定知 $\Sigma_{22} = B^T \Sigma B \neq 0$, 因为

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

设 $Y = (Y_1, Y_2) = (U, V) \begin{pmatrix} 1 & 0 \\ -\Sigma_{22}^{-1} \Sigma_{21} & 1 \end{pmatrix} = (U - \Sigma_{22}^{-1} \Sigma_{21} V, V)$, 则 $Y \sim N\left(0, \begin{pmatrix} \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21} & 0 \\ 0 & \Sigma_{22} \end{pmatrix}\right)$
这就说明 $Y_1 = U - \Sigma_{22}^{-1} \Sigma_{21} V$ 与 $Y_2 = V$ 独立, 反解出 U, V 得

$$\begin{cases} U = Y_1 + \Sigma_{22}^{-1} \Sigma_{21} Y_2 \\ V = Y_2 \end{cases}$$



所以

$$\begin{aligned}\mathbb{E}[U|V] &= \mathbb{E}[Y_1 + \Sigma_{22}^{-1} \Sigma_{21} Y_2 | Y_2] = \mathbb{E}[Y_1 | Y_2] + \Sigma_{22}^{-1} \Sigma_{21} Y_2 \\ &= \mathbb{E}[Y_1] + \Sigma_{22}^{-1} \Sigma_{21} Y_1 = \Sigma_{22}^{-1} \Sigma_{21} Y_2 \\ &= \frac{B^T \Sigma A}{B^T \Sigma B} V = \frac{\sum_{j,k=1}^n a_j b_k \sigma_{ij}}{\sum_{j,k=1}^n b_j b_k \sigma_{jk}} V\end{aligned}$$

□

T5

解 因为

$$\begin{aligned}\text{Cov}(X_1, \bar{X}) &= \mathbb{E} \left[X_1 \cdot \frac{1}{n} \sum_{k=1}^n X_k \right] - \mathbb{E}[X_1] \cdot \mathbb{E} \left[\frac{1}{n} \sum_{k=1}^n X_k \right] \\ &= \frac{1}{n} \sum_{i=1}^n \mathbb{E}[X_1 X_i] - \frac{1}{n} \sum_{k=1}^n \mathbb{E}[X_1] \mathbb{E}[X_i] \\ &= \frac{1}{n} \left[\mathbb{E}[X_1^2] - (\mathbb{E}[X_1])^2 \right] = \frac{\text{Var}(X_1)}{n} = \frac{\sigma^2}{n}\end{aligned}$$

又因为 $\mathbf{X} = (X_1, \dots, X_n) \sim N(\boldsymbol{\mu}, \sigma^2 I)$, 其中 $\boldsymbol{\mu} = (\mu, \dots, \mu)$, 取 $D = (\frac{1}{n}, \dots, \frac{1}{n})$, 则

$$\bar{X} = \mathbf{X} D \sim N(\boldsymbol{\mu} D, D^T \sigma^2 I_n D) = N\left(\mu, \frac{\sigma^2}{n}\right)$$

所以

$$\rho(X_1, \bar{X}) = \frac{\text{Cov}(X_1, \bar{X})}{\sqrt{\text{Var}(X_1) \text{Var}(\bar{X})}} = \frac{\frac{\sigma^2}{n}}{\sqrt{\sigma^2 \cdot \frac{\sigma^2}{n}}} = \frac{1}{\sqrt{n}}$$

□

习题 3.4

T1

证明 由 $Z \sim N_{\mathbb{C}}(0, 1)$ 知, $f_Z(z) = \frac{1}{\pi} e^{-|z|^2}$, 设 $Z = X + iY$, 则 $f_Z(z) = f_{X,Y}(x, y) = \frac{1}{\pi} e^{-(x^2+y^2)}$, 做变量替换

$$\begin{cases} X = R \cos \Theta \\ Y = R \sin \Theta \end{cases}$$

则 $f_{R,\Theta}(r, \theta) = \frac{r}{\pi} e^{-r^2}$, 且

$$Z^k \bar{Z}^l = R^k e^{ik\Theta} R^l e^{-il\Theta} = R^{k+l} e^{i(k-l)\Theta}$$

所以

$$\mathbb{E}[Z^k \bar{Z}^l] = \int_0^{+\infty} r^{k+l} \cdot \frac{r}{\pi} e^{-r^2} dr \int_0^{2\pi} e^{i(k-l)\theta} d\theta$$



当 $k \neq l$ 时, 关于 θ 的积分为零, 故 $\mathbb{E}[Z^k \overline{Z}^l] = 0, k \neq l$; 当 $k = l$ 时

$$\begin{aligned}\mathbb{E}[Z^k \overline{Z}^l] &= 2 \int_0^{+\infty} r^{2k+1} e^{-r^2} dr \\ &= \int_0^{+\infty} t^k e^{-t} dt = \Gamma(k+1) = k!\end{aligned}$$

□

T4

解 记 $H = (a_{ij})_{n \times n}$, 由矩阵乘法公式

$$(H^k)_{ij} = \sum_{i_1, i_2, \dots, i_{k-1}} a_{ii_1} a_{i_1 i_2} \cdots a_{i_{k-1} j}$$

所以

$$\text{tr}(H^k) = \sum_{s=1}^n \sum_{i_1, i_2, \dots, i_{k-1}} a_{si_1} a_{i_1 i_2} \cdots a_{i_{k-1} s} = \sum_{i_1, \dots, i_k} a_{i_1 i_2} a_{i_2 i_3} \cdots a_{i_k i_1}$$

因此

$$\mathbb{E}[\text{tr}(H^k)] = \sum_{i_1, \dots, i_k} \mathbb{E}[a_{i_1 i_2} a_{i_2 i_3} \cdots a_{i_k i_1}]$$

而对于每一项 $a_{i_1 i_2}, \dots, a_{i_k i_1} \sim N(0, \Sigma)$, 由 Wick 公式

$$\mathbb{E}[a_{i_1 i_2} \cdots a_{i_k i_1}] = \sum_{P \in \mathcal{P}_2(n)} \prod_{(i,j) \in P} \mathbb{E}[X_i X_j]$$

所以当 k 为奇数时, $a_1 = a_3 = a_5 = 0$; 当 k 为偶数时

若 $k = 2$, 则期望展开式中共有 n^2 项, 且有 n 项为 a_{ii}^2 , $n(n-1)$ 项为 $a_{ij}a_{ji}$, 所以

$$a_2 = \mathbb{E}[\text{tr}(H^2)] = n\mathbb{E}[a_{11}^2] + n(n-1)\mathbb{E}[a_{12}^2] = 2n + n(n-1) = n(n+1)$$

$k = 4, 6$ 时, 我不会做

□

T6

证明 设 $Y = QHQ^{-1}$, 则 $\text{tr}(Y^2) = \text{tr}(QH^2Q^{-1}) = \text{tr}(H^2Q^{-1}Q) = \text{tr}(H^2)$ 则

$$\begin{aligned}f(Y) &= 2^{-\frac{n}{2}} (2\pi)^{-\frac{1}{4}n(n+1)} e^{-\frac{1}{4}\text{tr}((QH^2Q^{-1})^2)} \cdot |\det Q| \cdot |\det Q^{-1}| \\ &= 2^{-\frac{n}{2}} (2\pi)^{-\frac{1}{4}n(n+1)} e^{-\frac{1}{4}\text{tr}(Y^2)}\end{aligned}$$

所以 QHQ^{-1} 也服从 GOE 分布

□

习题 4.1

T1

证明 由 X 取值非负知 $X = \sum_{i=0}^{\infty} X \cdot I_{\{i \leq X < i+1\}}$, 且对于 $\forall i \geq 0$, 有

$$i \cdot I_{\{i \leq X < i+1\}} \leq X \cdot I_{\{i \leq X < i+1\}} \leq (i+1)I_{\{i \leq X < i+1\}}$$

所以

$$\begin{aligned} \mathbb{E}[X] &= \mathbb{E} \left[\sum_{i=0}^{\infty} X \cdot I_{\{i \leq X < i+1\}} \right] = \sum_{i=0}^{\infty} \mathbb{E}[X \cdot I_{\{i \leq X < i+1\}}] \\ &\geq \sum_{i=0}^{\infty} i \cdot \mathbb{E}[I_{\{i \leq X < i+1\}}] = \sum_{i=1}^{\infty} i \mathbb{P}(i \leq X < i+1) \\ &= \sum_{i=1}^{\infty} \sum_{j=1}^i \mathbb{P}(i \leq X < i+1) = \sum_{j=1}^{\infty} \sum_{i=j}^{\infty} \mathbb{P}(i \leq X < i+1) \\ &= \sum_{j=1}^{\infty} \mathbb{P}(X \geq j) \\ \mathbb{E}[X] &= \mathbb{E} \left[\sum_{i=0}^{\infty} X \cdot I_{\{i \leq X < i+1\}} \right] = \sum_{i=0}^{\infty} \mathbb{E}[X \cdot I_{\{i \leq X < i+1\}}] \\ &\leq \sum_{i=0}^{\infty} (i+1) \mathbb{E}[I_{\{i \leq X < i+1\}}] = 1 + \sum_{i=1}^{\infty} i \mathbb{E}[I_{\{i \leq X < i+1\}}] \\ &\stackrel{\text{同上}}{=} 1 + \sum_{j=1}^{\infty} \mathbb{P}(X \geq j) \end{aligned}$$

□

T3(1).

证明 对任意 $x \in \mathbb{R}$, 均有 $u(x) \geq u(a) + \lambda_a(x-a)$, 所以 $u(X) \geq u(a) + \lambda_a(X-a)$, 取 $a = \mathbb{E}[X]$, 则

$$\mathbb{E}[u(X)] \geq \mathbb{E}[u(\mathbb{E}[X]) + \lambda_a(X - \mathbb{E}[X])] = \mathbb{E}[u(\mathbb{E}[X])] = u(\mathbb{E}[X])$$

□

T4.

证明 因为

$$X^r = \int_0^X r t^{r-1} dt = \int_0^{+\infty} r t^{r-1} \cdot I_{\{X > t\}} dt$$



所以

$$\begin{aligned}\mathbb{E}[X^r] &= \mathbb{E}\left[\int_0^{+\infty} rt^{r-1} \cdot I_{\{X>t\}} dt\right] = \int_{\mathbb{R}} \int_0^{+\infty} rt^{r-1} \cdot I_{\{X>t\}} dt dF \\ &\stackrel{\text{Fubini}}{=} \int_0^{+\infty} \int_{\mathbb{R}} rt^{r-1} \cdot I_{\{X>t\}} dF dt = \int_0^{+\infty} rt^{r-1} \int_{\mathbb{R}} I_{\{X>t\}} dF dt \\ &= \int_0^{+\infty} rt^{r-1} \mathbb{P}(X > t) dt\end{aligned}$$

□

T5.

证明 (1). 对于任意 $n \in \mathbb{N}^*$, 因为

$$x^r \mathbb{P}(|X| \geq x) = x^r \int_{\mathbb{R}} I_{\{|X| \geq x\}} d\mathbb{P} \leq \int_{\mathbb{R}} |X|^r I_{\{|X| \geq x\}} d\mathbb{P}$$

设 $Y_n = |X|^r I_{\{X \geq n\}}$, $Y = |X|^r$, 则 $|Y_n| \leq Y, \forall n, \omega$, 且由题设 $\mathbb{E}[Y] < +\infty$, 且

$$\lim_{n \rightarrow \infty} Y_n = \lim_{n \rightarrow \infty} |X|^r I_{\{X \geq n\}} = 0$$

所以由控制收敛定理知

$$\begin{aligned}\lim_{x \rightarrow +\infty} x^r \mathbb{P}(|X| \geq x) &\leq \lim_{n \rightarrow +\infty} \int_{\mathbb{R}} |X|^r I_{\{|X| > n\}} d\mathbb{P} \\ &= \lim_{n \rightarrow \infty} \int_{\mathbb{R}} Y_n d\mathbb{P} = \int_{\mathbb{R}} \lim_{n \rightarrow \infty} Y_n d\mathbb{P} = \int_{\mathbb{R}} 0 d\mathbb{P} = 0\end{aligned}$$

(2). 由 $\mathbb{E}[|X|^r] < +\infty$ 知, 对 $\forall \varepsilon > 0, \exists M, \text{s.t. } \forall x \geq M, x^r \mathbb{P}(|X| \geq x) < \varepsilon$, 因此

$$\begin{aligned}\mathbb{E}[|X|^s] &\stackrel{T4}{=} \int_0^{+\infty} st^{s-1} \mathbb{P}(|X| > t) dt \\ &= \int_0^M st^{s-1} \mathbb{P}(|X| > t) dt + \int_M^{+\infty} st^{s-1} \mathbb{P}(|X| > t) dt \\ &\leq \int_0^M st^{s-1} \mathbb{P}(|X| > t) dt + s\varepsilon \int_M^{+\infty} t^{-(r+1-s)} dt \\ &= \int_0^M st^{s-1} \mathbb{P}(|X| > t) dt + \frac{s\varepsilon}{(r-s)M^{r+1-s}} < +\infty\end{aligned}$$

$\mathbb{E}[|X|^r] < +\infty$ 不一定成立, 若 $\mathbb{P}(|X| \geq x) \sim \frac{1}{x^r \ln x}$ as $x \rightarrow +\infty$, 则有

$$\lim_{x \rightarrow +\infty} x^r \mathbb{P}(|X| \geq x) = 0$$

但是由 T4 知, 当 $r > 1$ 时, $rx^{r-1} \mathbb{P}(|X| > x) \sim \frac{r}{x \ln x}$, 而 $\int_a^{+\infty} \frac{1}{x \ln x} dx = \ln \ln x \Big|_a^{+\infty} \rightarrow +\infty$, 故此
时 $\mathbb{E}[|X|^r]$ 发散! □