

2021 秋季本科时间序列

第 1 次作业答案

10 月 18 日

1. (a) 由于 X, Y 相互独立, 故联合分布密度函数为 $f(x, y) = f(x)f(y) = \frac{1}{2\pi}e^{-\frac{x^2+y^2}{2}}$

$$\begin{aligned} F(z) &= P\left(\frac{X}{Y} \leq z\right) = P(X \leq zY, Y > 0) + P(X \geq zY, Y < 0) \\ &= \iint_{\substack{x \leq zy \\ y > 0}} f(x, y) dx dy + \iint_{\substack{x \geq zy \\ y < 0}} f(x, y) dx dy \\ &= \int_0^{\infty} \left(\int_{-\infty}^{zy} f(x, y) dx \right) dy + \int_{-\infty}^0 \left(\int_{zy}^{+\infty} f(x, y) dx \right) dy \\ &\stackrel{t=\frac{x}{y}}{=} \int_{-\infty}^z \left(\int_0^{\infty} y f(ty, y) dy \right) dt + \int_z^{\infty} \left(\int_{-\infty}^0 y f(ty, y) dy \right) dt \\ &= \int_{-\infty}^z \left(\int_{-\infty}^{\infty} |y| f(ty, y) dy \right) dt \end{aligned}$$

故

$$\begin{aligned} f(z) &= \int_{-\infty}^{\infty} |y| f(zy, y) dy \\ &= \int_{-\infty}^{\infty} |y| \frac{1}{2\pi} e^{-\frac{z^2 y^2 + y^2}{2}} dy \\ &= -\frac{1}{2\pi(z^2 + 1)} e^{-\frac{z^2 y^2 + y^2}{2}} \Big|_0^{\infty} + \frac{1}{2\pi(z^2 + 1)} e^{-\frac{z^2 y^2 + y^2}{2}} \Big|_{-\infty}^0 \\ &= \frac{1}{\pi(z^2 + 1)} \end{aligned}$$

故柯西分布 Z 的概率密度函数为 $f(z) = \frac{1}{\pi(z^2+1)}$

- (b) 下面证 (a) 中柯西分布 Z 的期望等于无穷, 故期望不存在。

$$\begin{aligned} \mathbb{E}(Z) &= \int_{-\infty}^{\infty} |z| \frac{1}{\pi(z^2 + 1)} dz \\ &= \frac{2}{\pi} \int_0^{+\infty} \frac{z}{z^2 + 1} \\ &= \frac{1}{\pi} \ln(z^2 + 1) \Big|_0^{+\infty} \\ &= +\infty \end{aligned}$$

2. (a) 由于 $\mathbb{E}X_t = \mathbb{E} \cos(\frac{\pi}{n}t + U) = \int_{-\pi}^{\pi} \frac{1}{2\pi} \cos(\frac{\pi}{n}t + U) du = 0$, 可得:

$$\begin{aligned} \sigma_x^2(k) &= \text{cov}(X_{t+k}, X_t) = \mathbb{E}X_{t+k}X_t - \mathbb{E}X_{t+k}\mathbb{E}X_t = \mathbb{E}X_{t+k}X_t \\ &= \int_{-\pi}^{\pi} \frac{1}{2\pi} \cos(\frac{\pi}{n}t + U) \cos(\frac{\pi}{n}(t+k) + U) du \\ &= \frac{1}{4\pi} \int_{-\pi}^{\pi} \left[\cos(2u + \frac{2\pi}{n}t + \frac{k\pi}{n}) + \cos(\frac{k\pi}{n}) \right] du \\ &= \frac{1}{2} \cos(\frac{k\pi}{n}), k \in N \end{aligned}$$

(b) 代码如下:

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1 library(tidyverse)
2 library(ggplot2)
3 library(tseries)
4 X <- vector("double" ,1000)
5 U <- runif(1,-pi ,pi)
6 X<-matrix(nrow=1000,ncol=5)
7 for(n in 1:5)
8 {
9   y<-c()
10  for(t in 1:1000){
11    x<-cos(pi/n*t+U)
12    y<-c(y,x)
13  }
14  X[,n]<-y
15 }
16 X<-data.frame(X[1:100,])
17 X%>%ggplot(mapping = aes(x,y))+
18   geom_point(mapping = aes(x=(1:100),y=X[,1]),color="black")+
19   geom_line(mapping = aes(x=(1:100),y=X[,1]),color="blue")
20 X%>%ggplot(mapping = aes(x,y))+
21   geom_point(mapping = aes(x=(1:100),y=X[,2]),color="black")+
22   geom_line(mapping = aes(x=(1:100),y=X[,2]),color="red")
23 X%>%ggplot(mapping = aes(x,y))+
24   geom_point(mapping = aes(x=(1:100),y=X[,3]),color="black")+
25   geom_line(mapping = aes(x=(1:100),y=X[,3]),color="yellow")
26 X%>%ggplot(mapping = aes(x,y))+
27   geom_point(mapping = aes(x=(1:100),y=X[,4]),color="black")+

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28 geom_line(mapping = aes(x=(1:100),y=X[,4]),color="pink")
29 X%>%ggplot(mapping = aes(x,y))+
30 geom_point(mapping = aes(x=(1:100),y=X[,5]),color="black")+
31 geom_line(mapping = aes(x=(1:100),y=X[,5]),color="green")
32 #n的取值影响了X_t的周期，n值越大，X_t的周期越长
33 #ii.
34 acf(X[,1], type = "covariance")
35 acf(X[,2], type = "covariance")
36 acf(X[,3], type = "covariance")
37 acf(X[,4], type = "covariance")
38 acf(X[,5], type = "covariance")

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3. (a) 证明如下:

$$\begin{aligned}
\mathbb{E}\hat{\sigma}_N^2 &= \mathbb{E}\left[\frac{1}{N-1}\sum_{i=1}^N(x_i - \hat{\mu}_N)^2\right] \\
&= \frac{1}{N-1}\mathbb{E}\left[\sum_{i=1}^N(x_i - \mu + \mu - \hat{\mu}_N)^2\right] \\
&= \frac{1}{N-1}\mathbb{E}\left[\sum_{i=1}^N(x_i - \mu)^2 + 2\sum_{i=1}^N(x_i - \mu)(\mu - \hat{\mu}_N) + \sum_{i=1}^N(\mu - \hat{\mu}_N)^2\right] \\
&= \frac{1}{N-1}\mathbb{E}\left[\sum_{i=1}^N(x_i - \mu)^2 - 2N(\mu - \hat{\mu}_N)^2 + N(\mu - \hat{\mu}_N)^2\right] \\
&= \frac{1}{N-1}\left[\sum_{i=1}^N\mathbb{E}(x_i - \mu)^2 - N\mathbb{E}(\mu - \hat{\mu}_N)^2\right] \\
&= \frac{1}{N-1}(N\sigma^2 - N\frac{\sigma^2}{N}) \\
&= \sigma^2
\end{aligned}$$

(b) $\hat{\sigma}_N^2 = \frac{N}{N-1}\left(\frac{1}{N}\sum_{i=1}^N x_i^2 - N\hat{\mu}_N^2\right)$, $\mathbb{E}(x_i^2) = \text{var}(X) + \mathbb{E}(X_i)^2 = \sigma^2 + \mu^2$
对独立同分布的随机变量序列 X_t , 由 LLN 得 $\frac{1}{N}\sum_{i=1}^N x_i^2 \xrightarrow{a.s.} \mathbb{E}(X_i^2) = \sigma^2 + \mu^2$
故 $\hat{\sigma}_N^2 \xrightarrow{a.s.} \frac{N}{N-1}\sigma^2 = \sigma^2$ ($N \rightarrow +\infty$)

4. (a)

$$\begin{aligned}
\text{cov}(x, k_1 y_1 + k_2 y_2) &= \mathbb{E}[x(k_1 y_1 + k_2 y_2)] - \mathbb{E}(x)\mathbb{E}(k_1 y_1 + k_2 y_2) \\
&= k_1 (\mathbb{E}(x y_1) - \mathbb{E}(x_1)\mathbb{E}(y_1)) + k_2 (\mathbb{E}(x y_2) - \mathbb{E}(x_1)\mathbb{E}(y_2)) \\
&= k_1 \text{cov}(x, y_1) + k_2 \text{cov}(x, y_2)
\end{aligned}$$

同理

$$\text{cov}(k_1 x_1 + k_2 x_2, y) = k_1 \text{cov}(x_1, y) + k_2 \text{cov}(x_2, y)$$

$$\forall k_1, k_2 \in \mathbb{R}, \text{cov}(x, y) = \mathbb{E}(xy) - \mathbb{E}(x)\mathbb{E}(y) = \text{cov}(y, x)$$

故 $\text{cov}(\cdot)$ 是对称双线性函数。

(b)

$$\begin{aligned} \text{var}(aX + Y) &= \text{cov}(aX + Y, aX + Y) \\ &= a^2 \text{cov}(X, X) + 2a \text{cov}(X, Y) + \text{cov}(Y, Y) \geq 0 \\ \Delta &= 4 \text{cov}(X, Y)^2 - 4 \text{var}(X) \text{var}(Y) \leq 0 \\ \therefore |\text{cov}(X, Y)|^2 &\leq \sigma_X^2 \sigma_Y^2 \end{aligned}$$

5. (a) 对称性: $f(x, y) = \sum_{i=1}^n x_i y_i = \sum_{i=1}^n y_i x_i = f(y, x)$

双线性性:

$$\begin{aligned} f(x, k_1 y_1 + k_2 y_2) &= \sum_{i=1}^n x_i (k_1 y_{1i} + k_2 y_{2i}) \\ &= k_1 \sum_{i=1}^n x_i y_{1i} + k_2 \sum_{i=1}^n x_i y_{2i} \\ &= k_1 f(x, y_1) + k_2 f(x, y_2) \end{aligned}$$

同理, $f(k_1 x_1 + k_2 x_2, y) = k_1 f(x_1, y) + k_2 f(x_2, y)$

(b)

$$\begin{aligned} f(ax + y, ax + y) &= \sum_{i=1}^n (ax_i + y_i)^2 \\ &= \sum_{i=1}^n a^2 x_i^2 + 2a \sum_{i=1}^n x_i y_i + \sum_{i=1}^n y_i^2 \geq 0 \\ \Delta &= 4 \sum_{i=1}^n (x_i y_i)^2 - 4 \sum_{i=1}^n x_i^2 \sum_{i=1}^n y_i^2 \leq 0 \\ \therefore |x_1 y_1 + \cdots + x_n y_n|^2 &\leq (x_1^2 + \cdots + x_n^2)(y_1^2 + \cdots + y_n^2) \end{aligned}$$

(c) 由 (b) 知

$$\begin{aligned} \hat{\sigma}_{XY}^2 &= \frac{1}{n} \sum_i (X_i - \hat{\mu}_X)(Y_i - \hat{\mu}_Y) \\ &\leq \frac{1}{n} \sqrt{\sum_i (X_i - \hat{\mu}_X)^2 \sum_i (Y_i - \hat{\mu}_Y)^2} \\ &= \frac{1}{n} \sqrt{n \hat{\sigma}_X^2 \cdot n \hat{\sigma}_Y^2} \\ &= \hat{\sigma}_X \hat{\sigma}_Y \text{得证} \end{aligned}$$

6. 证明如下: $\{\phi_i\}_{i=0}^{\infty}$ 绝对可和, 即 $\sum_{i=0}^{\infty} |\phi_i| < \infty, \sum_{i=0}^{\infty} |\phi_i|^2 < \infty$

易知仅有有限项 $|\phi_i| \geq 1$, 假设有 t 项, $k \geq 0$

$$\begin{cases} |\phi_i| \geq 1 & i = 1, 2, \dots, t \\ |\phi_i| < 1 & i \geq t \end{cases}$$

$$\sum_{i=k}^{\infty} |\phi_i \phi_{i-k}| = \sum_{i=k}^{t+k} |\phi_i \phi_{i-k}| + \sum_{i=t+k+1}^{\infty} |\phi_i \phi_{i-k}|$$

$$\text{记 } S_1 = \sum_{i=k}^{t+k} |\phi_i \phi_{i-k}|, S_2 = \sum_{i=t+k+1}^{\infty} |\phi_i \phi_{i-k}|$$

S_1 为有限项, 故 $S_1 < \infty$

$$S_2 < \sum_{i=t+k+1}^{\infty} |\phi_i| < \infty$$

$$\text{故 } \sum_{i=k}^{\infty} |\phi_i \phi_{i-k}| < \infty$$