

2022 秋季本科时间序列

第 5 次作业答案

11 月 6 日

1. 解:

由 $(1 - \phi\mathcal{L})X_t = Y_t$ 有 $X_t = \frac{Y_t}{1 - \phi\mathcal{L}} = \sum_{i=0}^{\infty} \phi^i Y_{t-i}$

则有

$$\eta_k = \text{cov} \left(\sum_{i=0}^{\infty} \phi^i Y_{t+k-i}, \sum_{i=0}^{\infty} \phi^i Y_{t-i} \right) = \sum_{i=0}^{\infty} \sum_{j=0}^{\infty} \phi^i \phi^j \gamma(k+j-i)$$

γ_k 存在一致上界, 即 $|\gamma_k| \leq \gamma_0$, 则有:

$$|\eta_k| \leq \sum_{i=0}^{\infty} \sum_{j=0}^{\infty} \phi^i \phi^j \gamma_0 = \frac{\gamma_0}{(1-\phi)^2}$$

故 $|\eta_k| < \infty$, 故 X_t 为平稳序列。

2. 解:

$$\begin{aligned} X_t &= \frac{1}{1 - \frac{\mathcal{L}}{z_1}} \cdots \frac{1}{1 - \frac{\mathcal{L}}{z_p}} \epsilon_t \\ &= \sum_{i=0}^{\infty} \left(\frac{\mathcal{L}}{z_1} \right)^i \frac{1}{1 - \frac{\mathcal{L}}{z_0}} \cdots \frac{1}{1 - \frac{\mathcal{L}}{z_p}} \epsilon_t \\ &= \sum_{i=0}^{\infty} \left(\frac{1}{z_1} \right)^i \frac{1}{1 - \frac{\mathcal{L}}{z_2}} \cdots \frac{1}{1 - \frac{\mathcal{L}}{z_p}} \epsilon_{t-i} \\ &= \sum_{i=0}^{\infty} \sum_{j=0}^{\infty} \left(\frac{1}{z_1} \right)^i \left(\frac{1}{z_0} \right)^j \frac{1}{1 - \frac{\mathcal{L}}{z_3}} \cdots \frac{1}{1 - \frac{\mathcal{L}}{z_p}} \epsilon_{t-i-j} \\ &= \cdots \\ &= \sum_{i_1=0}^{\infty} \sum_{i_2=0}^{\infty} \cdots \sum_{i_p=0}^{\infty} \left(\frac{1}{z_1} \right)^{i_1} \cdots \left(\frac{1}{z_p} \right)^{i_p} \epsilon_{t-(i_1+\cdots+i_p)} \\ &= a_0 \epsilon_t + a_1 \epsilon_{t-1} + \cdots \end{aligned}$$

则 $i_1 = \dots = i_p = 0$ 时有 $a_0 = 1$,

$i_1 + \dots + i_p = 1$ 时有 $a_1 = \sum_{k=1}^p \frac{1}{z_k}$,

$i_1 + \dots + i_p = 1$ 时有 $a_2 = \sum_{i=1}^p \sum_{j=1}^p \frac{1}{z_i z_j}$,

由 z_1, \dots, z_p 为 $1 - \phi_1 z - \dots - \phi_p z^p = 0$ 的根有 $\frac{1}{z_1} \dots \frac{1}{z_p}$ 为 $z^p - \phi_1 z^{p-1} - \dots - \phi_p = 0$ 的根, 则由推广的韦达定理不难发现

$$a_1 = \sum_{i=1}^p \frac{1}{z_i} = \phi_1$$

3. 解:

由 $X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \epsilon_t$ 有

$$\begin{bmatrix} \phi_1 & \phi_2 & 0 \\ \phi_2 & \phi_1 & -1 \\ 1 & -\phi_1 & -\phi_2 \end{bmatrix} \begin{bmatrix} \gamma(0) \\ \gamma(1) \\ \gamma(2) \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \sigma_\epsilon^2 \end{bmatrix}$$

其中系数矩阵的行列式为

$$\begin{vmatrix} \phi_1 & \phi_2 & 0 \\ \phi_2 & \phi_1 & -1 \\ 1 & -\phi_1 & -\phi_2 \end{vmatrix} = (\phi_1 + \phi_2 - 1)(\phi_2 - \phi_1 - 1)(\phi_2 + 1)$$

AR(2) 过程 $(1 - \phi_1 \mathcal{L} - \phi_2 \mathcal{L}^2)X_t = \epsilon_t$ 特征多项式 $1 - \phi_1 z - \phi_2 z^2 = 0$

则有两特征根 z_1, z_2

$$z_1 z_2 = -\frac{1}{\phi_2}, z_1 + z_2 = -\frac{\phi_1}{\phi_2}$$

即可得 ϕ_1, ϕ_2 关于 z_1, z_2 表达式

$$\phi_1 = \frac{1}{z_1} + \frac{1}{z_2}, \phi_2 = -\frac{1}{z_1 z_2}$$

平稳则特征根 $|z_1| > 1, |z_2| > 1$,

则显然

$$(\phi_1 + \phi_2 - 1)(\phi_2 - \phi_1 - 1)(\phi_2 + 1) \neq 0$$

故 Φ 可逆, 即 AR(2) 过程平稳则系数矩阵 Φ 可逆,

若使得 AR(2) 过程平稳则由 $|z_1| > 1, |z_2| > 1$ 有

$$\phi_1 = \frac{1}{z_1} + \frac{1}{z_2} \in (0, 2), \phi_2 = -\frac{1}{z_1 z_2} \in (-1, 1)$$

同时满足 $1 - \phi_1 - \phi_2 > 0$ 及 $1 + \phi_1 - \phi_2 > 0$

4. 解:

$$X_t = 0.9X_{t-1} - 0.2X_{t-2} + \epsilon_t$$

分别在等式两边同乘 X_t, X_{t-1}, X_{t-2} 并取期望有

$$\gamma(0) = 0.9\gamma(1) - 0.2\gamma(2) + \sigma_\epsilon^2$$

$$\gamma(1) = 0.9\gamma(0) - 0.2\gamma(1)$$

$$\gamma(2) = 0.9\gamma(1) - 0.2\gamma(0)$$

转换为矩阵形式有

$$\begin{bmatrix} 0 \\ 0 \\ \sigma_\epsilon^2 \end{bmatrix} = \begin{bmatrix} 0.9 & -1.2 & 0 \\ -0.2 & 0.9 & -1 \\ 1 & -0.9 & 0.2 \end{bmatrix} \begin{bmatrix} \gamma(0) \\ \gamma(1) \\ \gamma(2) \end{bmatrix}$$

解得

$$\gamma(0) = \frac{50}{21}\sigma_\epsilon^2, \gamma(1) = \frac{25}{14}\sigma_\epsilon^2, \gamma(2) = \frac{95}{84}\sigma_\epsilon^2$$

在 $X_{t+k} = \phi_1 X_{t+k-1} - \phi_2 X_{t+k-2} + \epsilon_{t+k}$ 两边同乘 X_t 得

$$\gamma_X^2(k) = \phi_1 \gamma_X^2(k-1) - \phi_2 \gamma_X^2(k-2)$$

即有

$$\begin{bmatrix} \gamma(k) \\ \gamma(k-1) \end{bmatrix} = \begin{bmatrix} \phi_1 & \phi_2 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \gamma(k-1) \\ \gamma(k-2) \end{bmatrix}$$

代入本题参数

$$\Lambda = \begin{bmatrix} \phi_1 & \phi_2 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 0.9 & -0.2 \\ 1 & 0 \end{bmatrix}$$

求特征值

$$\mathbb{P}(\lambda) = |\lambda I - \Lambda| = \begin{vmatrix} \lambda - 0.9 & 0.2 \\ -1 & \lambda \end{vmatrix} = \lambda^2 - 0.9\lambda + 0.2 = 0$$

解得

$$\lambda_1 = 0.4, \lambda_2 = 0.5$$

则有

$$\begin{bmatrix} \gamma(k) \\ \gamma(k-1) \end{bmatrix} = \begin{bmatrix} 0.4 & 0.5 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 0.4^{k-1} & \\ & 0.5^{k-1} \end{bmatrix} \begin{bmatrix} 0.4 & 0.5 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} \gamma(1) \\ \gamma(0) \end{bmatrix}$$

故有

$$\gamma(k) = \frac{25}{21}(7 \times 0.5^k - 5 \times 0.4^k)$$

5. 解:

由 AR(2) 过程 $X_t = 2\phi X_{t-1} - \phi^2 X_{t-2} + \epsilon_t$ 有

$$\begin{bmatrix} 0 \\ 0 \\ \sigma_\epsilon^2 \end{bmatrix} = \begin{bmatrix} 2\phi & -\phi^2 - 1 & 0 \\ -\phi^2 & 2\phi & -1 \\ 1 & -2\phi & \phi^2 \end{bmatrix} \begin{bmatrix} \gamma(0) \\ \gamma(1) \\ \gamma(2) \end{bmatrix}$$

故有

$$\begin{bmatrix} \gamma(0) \\ \gamma(1) \\ \gamma(2) \end{bmatrix} = \begin{bmatrix} \frac{1}{1-3\phi^2+3\phi^4-\phi^6} \sigma_\epsilon^2 \\ \frac{2\phi}{1-3\phi^2+3\phi^4-\phi^6} \sigma_\epsilon^2 \\ \frac{\phi^2}{1-3\phi^2+3\phi^4-\phi^6} \sigma_\epsilon^2 \end{bmatrix}$$

同时由

$$\begin{bmatrix} \gamma(k) \\ \gamma(k-1) \end{bmatrix} = \begin{bmatrix} 2\phi & -\phi^2 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \gamma(k-1) \\ \gamma(k-2) \end{bmatrix}$$

令

$$\Lambda = \begin{bmatrix} 2\phi & -\phi^2 \\ 1 & 0 \end{bmatrix}$$

$$\mathbb{P}(\lambda) = |\lambda I - \Lambda| = \lambda^2 - 2\phi\lambda + \phi^2$$

因此,

$$\lambda_1 = \lambda_2 = \phi$$

若尔当分解,

$$\Lambda = \begin{bmatrix} 2\phi & -\phi^2 \\ 1 & 0 \end{bmatrix} = T \begin{bmatrix} \lambda & 1 \\ 0 & \lambda \end{bmatrix} T^{-1}$$

$$\Lambda T = \begin{bmatrix} \phi & 1 \\ 0 & \phi \end{bmatrix}$$

令 $T = [T_1, T_2]$, 有

$$[\Lambda T_1, \Lambda T_2] = [T_1, T_2] \begin{bmatrix} \phi & 1 \\ 0 & \phi \end{bmatrix}$$

故可得 $T_1 = [\phi, 1]^T, T_2 = [1, 0]^T$, 因此

$$\Lambda = \begin{bmatrix} \phi & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \phi & 1 \\ 0 & \phi \end{bmatrix} \begin{bmatrix} \phi & 1 \\ 1 & 0 \end{bmatrix}^{-1}$$

数学归纳法易推得

$$\begin{bmatrix} \phi & 1 \\ 0 & \phi \end{bmatrix}^k = \begin{bmatrix} \phi^k & k\phi^{k-1} \\ 0 & \phi^k \end{bmatrix}$$

故 Λ^k 有

$$\Lambda^k = \begin{bmatrix} \phi & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \phi^k & k\phi^{k-1} \\ 0 & \phi^k \end{bmatrix} \begin{bmatrix} \phi & 1 \\ 1 & 0 \end{bmatrix}^{-1} = \begin{bmatrix} (k+1)\phi^k & -k\phi^{k+1} \\ k\phi^{k-1} & (1-k)\phi^k \end{bmatrix}$$

则

$$\begin{bmatrix} \gamma(k) \\ \gamma(k-1) \end{bmatrix} = \Lambda^k \begin{bmatrix} \gamma(1) \\ \gamma(0) \end{bmatrix} = \phi^{k-1} \begin{bmatrix} (k+1)\phi & -k\phi^2 \\ k & (1-k)\phi \end{bmatrix} \begin{bmatrix} \gamma(1) \\ \gamma(0) \end{bmatrix}$$

6. 解:

由 $X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \epsilon_t + \theta \epsilon_{t-1}$ 有:

$$\begin{cases} \gamma(0) = \phi_1 \gamma(1) + \phi_2 \gamma(2) + \sigma_\epsilon^2 \\ \gamma(1) = \phi_1 \gamma(0) + \phi_2 \gamma(1) + \theta \sigma_\epsilon^2 \\ \gamma(2) = \phi_1 \gamma(1) + \phi_2 \gamma(0) \end{cases}$$

转换为矩阵乘积形式为:

$$\begin{bmatrix} \sigma_\epsilon^2 \\ \theta \sigma_\epsilon^2 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 & -\phi_1 & -\phi_2 \\ -\phi_1 & 1 - \phi_2 & 0 \\ -\phi_2 & -\phi_1 & 1 \end{bmatrix} \begin{bmatrix} \gamma(0) \\ \gamma(1) \\ \gamma(2) \end{bmatrix}$$

若 $\phi_1 = 0.9, \phi_2 = -0.2, \theta = 0.5, \sigma_\epsilon^2 = 1$, 则有:

$$\begin{bmatrix} \gamma(0) \\ \gamma(1) \\ \gamma(2) \end{bmatrix} = \begin{bmatrix} \frac{65}{21} \\ \frac{115}{42} \\ \frac{155}{84} \end{bmatrix}$$

则有

$$\begin{bmatrix} \gamma(k) \\ \gamma(k-1) \end{bmatrix} = \begin{bmatrix} 0.4 & 0.5 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 0.4^{k-1} & \\ & 0.5^{k-1} \end{bmatrix} \begin{bmatrix} 0.4 & 0.5 \\ 1 & 1 \end{bmatrix}^{-1} \begin{bmatrix} \gamma(1) \\ \gamma(0) \end{bmatrix}$$

最终可得

$$\gamma(k) = 15 \times 0.5^k - \frac{250}{21} \times 0.4^k$$

7. 解:

由

$$\begin{aligned} \sigma_X^2 &= \mathbb{E}[(X_t - \mathbb{E}X_t)^2] \\ \hat{\sigma}_X^2 &= \frac{1}{X} \sum_{t=1}^T (X_t - \mathbb{E}X_t)^2 = \frac{1}{T} \sum_{t=1}^T X_t^2 \end{aligned}$$

故有 $\mathbb{E}X_t = 0$, 同时根据假设 U 与 ϵ_t 独立有 $\mathbb{E}U + \mathbb{E}\epsilon_t = 0$, 则有:

$$\begin{aligned} \mathbb{E}\hat{\sigma}_X^2 &= \frac{1}{T} \mathbb{E} \left(\sum_{t=1}^T X_t^2 \right) & \hat{\sigma}_X^2 &= \frac{1}{T} \sum_{t=1}^T X_t^2 \\ &= \frac{1}{T} \mathbb{E} [(U_1 + \epsilon_1)^2 + \dots + (U_t + \epsilon_t)^2] & &= \frac{1}{T} \sum_{t=1}^T (U + \epsilon_t)^2 \\ &= \frac{1}{T} \mathbb{E} \left[\sum_{t=1}^T U_t^2 + \sum_{t=1}^T \epsilon_t^2 + 2 \sum_{t=1}^T U_t \epsilon_t \right] & &= \frac{1}{T} \left(TU^2 + 2U \sum_{t=1}^T \epsilon_t + \sum_{t=1}^T \epsilon_t^2 \right) \\ &= \frac{1}{T} [T\mathbb{E}U^2 + T\mathbb{E}\epsilon^2 + 2T\mathbb{E}U\mathbb{E}\epsilon] & &= U^2 + \frac{2U}{T} \sum_{t=1}^T \epsilon_t + \frac{1}{T} \sum_{t=1}^T \epsilon_t^2 \\ &= \sigma_U^2 + \sigma_\epsilon^2 & & \end{aligned}$$

当 $t \rightarrow \infty$ 时, 由大数定律有 $\frac{1}{T} \sum_{t=1}^T \epsilon_t \rightarrow \mathbb{E}(\epsilon_t) = 0$, $\frac{1}{T} \sum_{t=1}^T \epsilon_t^2 \rightarrow \sigma_\epsilon^2$, 因此

$$\lim_{t \rightarrow \infty} \hat{\sigma}_X^2 = U^2 + \sigma_\epsilon^2$$

8. (a) 代码如下:

```
1 library(tidyverse)
2 library(patchwork)
3 library(purrr)
4
```

```

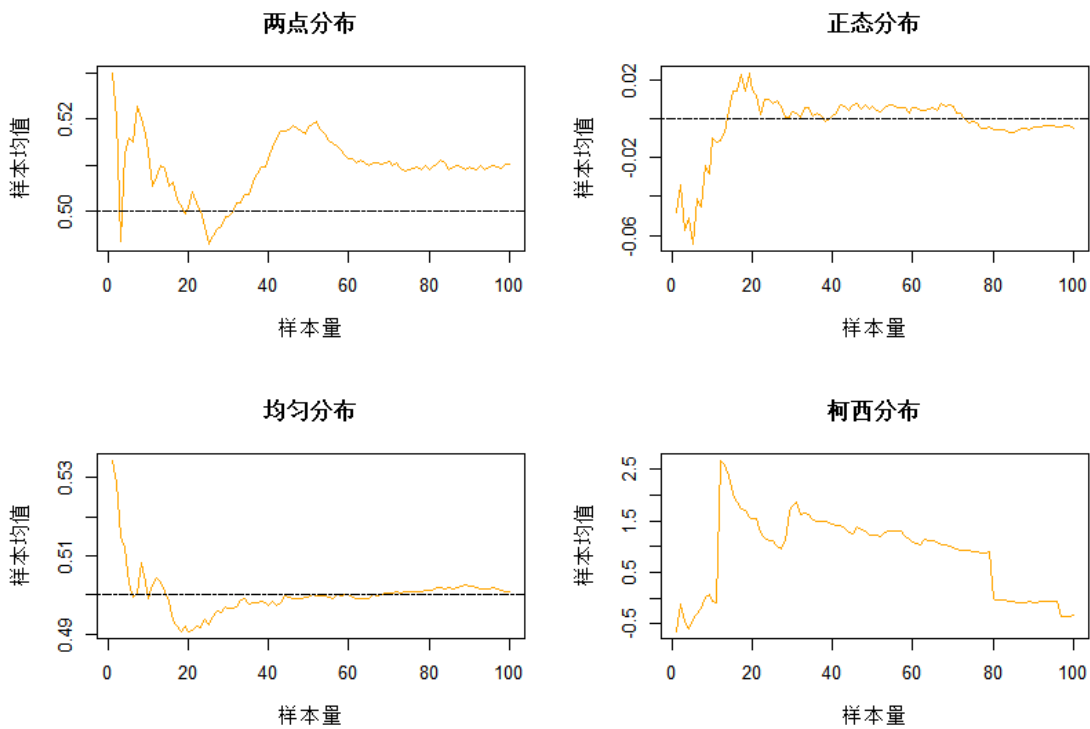
5 N <- 100
6 K <- 100
7 set.seed(20221106)
8 bern_sq <- purrr::rbernoulli(N*K, p = 0.5) %>% as.numeric()
9 unif_sq <- runif(N*K, min = 0, max = 1)
10 norm_sq <- rnorm(N*K, sd = 1, mean = 0)
11 cauchy_sq <- rcauchy(N*K, location = 0, scale = 1)
12
13 sample_sq <- function(sq){
14   mean <- vector(mode = "numeric", length = K)
15   for (k in 1:K){
16     sign_min <- 1
17     sign_max <- k * 100
18     sub_sample <- sq[sign_min:sign_max]
19     mean[k] <- mean(sub_sample)
20   }
21   mean
22 }
23
24 opar <- par(no.readonly = T)
25 par(mfrow = c(2,2))
26 sq <- sample_sq(bern_sq)
27 plot(sq, type = "l", col = "orange",
28 xlab = "样本量", ylab = "样本均值",
29 main = "两点分布")
30 abline(h = 0.5, lty = 6)
31
32 sq <- sample_sq(norm_sq)
33 plot(sq, type = "l", col = "orange",
34 xlab = "样本量", ylab = "样本均值",
35 main = "正态分布")
36 abline(h = 0, lty = 6)
37
38 sq <- sample_sq(unif_sq)
39 plot(sq, type = "l", col = "orange",

```

```

40 xlab = "样本量", ylab = "样本均值",
41 main = "均匀分布")
42 abline(h = 0.5, lty = 6)
43
44 sq <- sample_sq(cauchy_sq)
45 plot(sq, type = "l", col = "orange",
46 xlab = "样本量", ylab = "样本均值",
47 main = "柯西分布")

```



(b) 代码如下:

```

1 N <- 100
2 K <- 500
3 bern_sq <- purrr::rbernoulli(N*K, p = 0.5) %>% as.numeric()
4 unif_sq <- runif(N*K, min = 0, max = 1)
5 norm_sq <- rnorm(N*K, sd = 1, mean = 0)
6 cauchy_sq <- rcauchy(N*K, location = 0, scale = 1)
7
8 sample_be_sq <- function(sq, K){
9   mean <- vector(mode = "numeric", length = K)

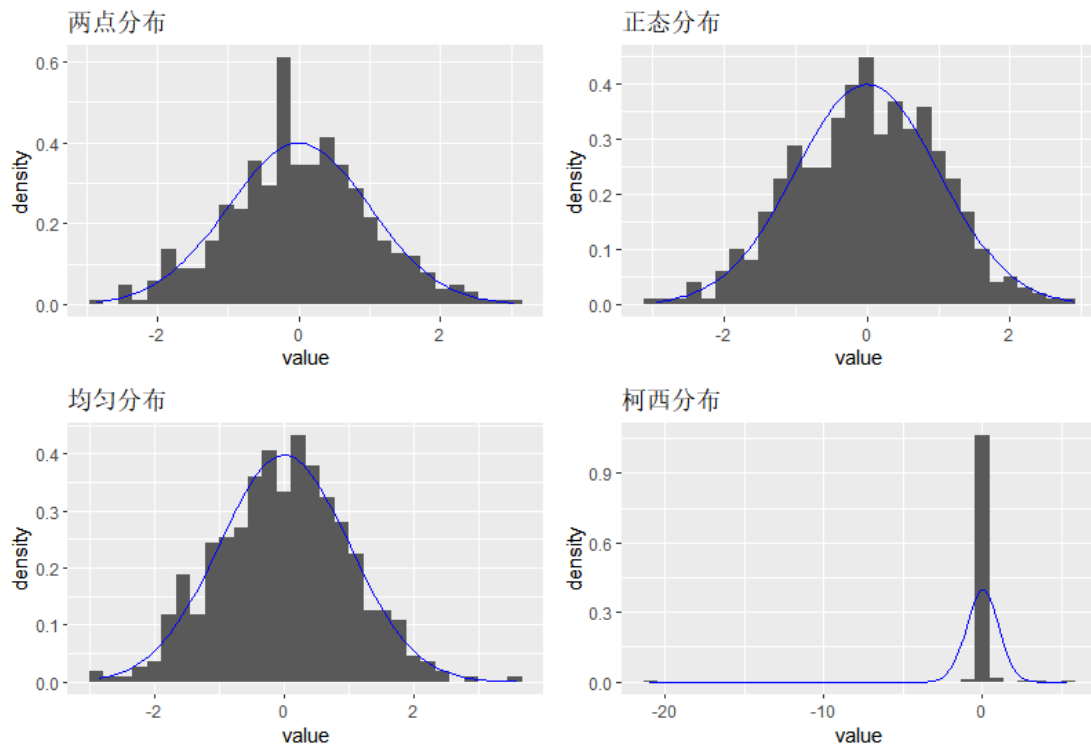
```



```

10 for (k in 1:K){
11   sign_min <- (k-1) *100 + 1
12   sign_max <- k * 100
13   sub_sample <- sq[sign_min:sign_max]
14   mean[k] <- mean(sub_sample)
15 }
16 mean
17 }
18 sample_be_sq_norm <- function(sq) {
19   k <- length(sq)
20   mu_hat <- (1/k)*sum(sq, na.rm = T)
21   sigma_hat <- (1/k)* sum((sq - mu_hat)^2)
22   standard_sq <- (sq - mu_hat) * sqrt(1/ sigma_hat)
23   return(standard_sq)
24 }
25 clt_plot <- function(sq,dis){
26   tibble(sq = sq) %>%
27   ggplot() +
28   geom_histogram(aes(x=sq,y=..density..)) +
29   stat_function(fun = dnorm, color = "blue") +
30   labs(x = "value", y = "density")+
31   ggtitle(dis)
32 }
33 sample_be_sq(bern_sq,500) %>% sample_be_sq_norm()
34 %>% clt_plot(dis="两点分布")+
35 sample_be_sq(norm_sq,500) %>% sample_be_sq_norm()
36 %>% clt_plot(dis="正态分布")+
37 sample_be_sq(unif_sq,500) %>% sample_be_sq_norm()
38 %>% clt_plot(dis="均匀分布")+
39 sample_be_sq(cauchy_sq,500) %>% sample_be_sq_norm()
40 %>% clt_plot(dis="柯西分布")

```

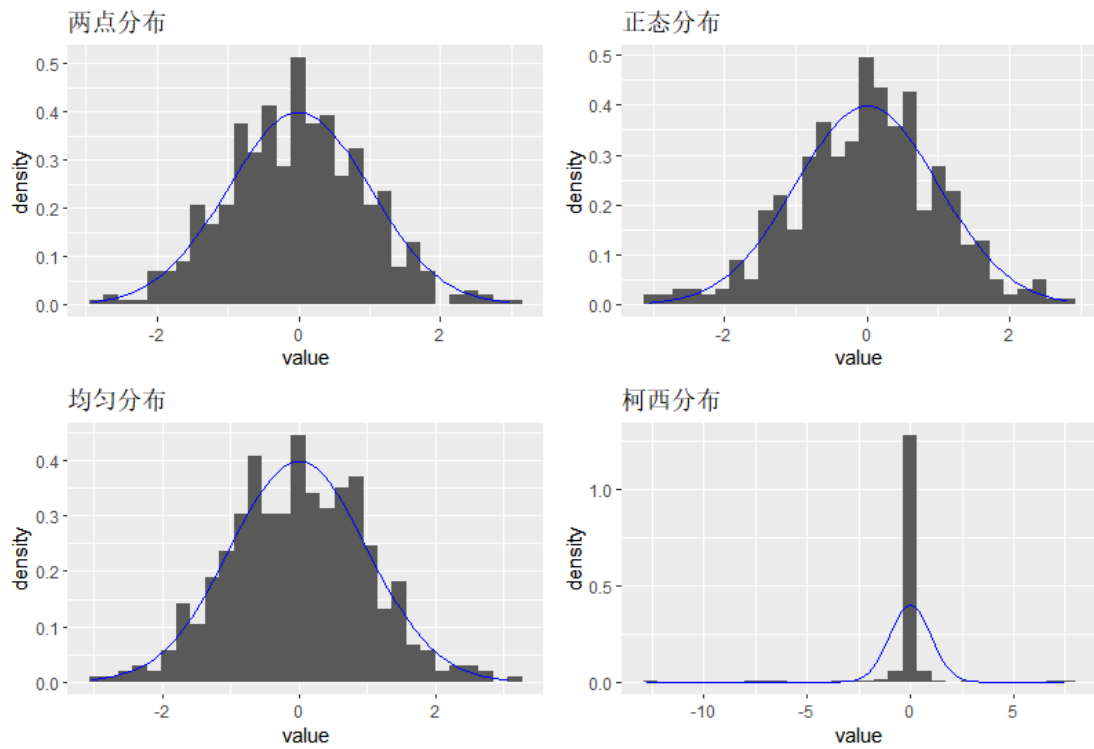


(c) 代码如下:

```

1 N <- 500
2 K <- 500
3 bern_sq <- purrr::rbernoulli(N*K, p = 0.5) %>% as.numeric()
4 unif_sq <- runif(N*K, min = 0, max = 1)
5 norm_sq <- rnorm(N*K, sd = 1, mean = 0)
6 cauchy_sq <- rcauchy(N*K, location = 0, scale = 1)
7
8 sample_be_sq(bern_sq,500) %>% sample_be_sq_norm()
9 %>% clt_plot(dis="两点分布")+
10 sample_be_sq(norm_sq,500) %>% sample_be_sq_norm()
11 %>% clt_plot(dis="正态分布")+
12 sample_be_sq(unif_sq,500) %>% sample_be_sq_norm()
13 %>% clt_plot(dis="均匀分布")+
14 sample_be_sq(cauchy_sq,500) %>% sample_be_sq_norm()
15 %>% clt_plot(dis="柯西分布")

```



(d) 对于柯西分布，中心极限定理并不适用，中心极限定理的含义是，如果样本量足够大，则变量均值的采样分布将近似于正态分布，而与该变量在总体中的分布无关。对于柯西分布，由于其期望并不存在，样本均值也不存在，故中心极限定理并不适用于柯西分布。