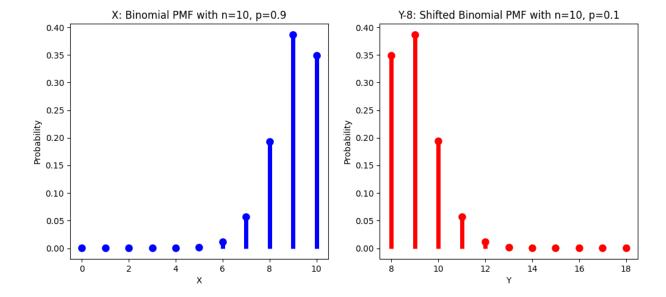
第7次作业

1、

(1)



(2)

$$u(X) = np = 10 \times 0.9 = 9$$
 $\sigma^{2}(X) = np(1-p) = 10 \times 0.9 \times 0.1 = 0.9$
 $mean(X) = 9$
 $mode(X) = 9$
 $u(Y - 8) = np = 10 \times 0.1 = 1$
 $u(Y) = 9$
 $\sigma^{2}(Y) = np(1-p) = 0.9$
 $mean(Y) = 9$
 $mode(Y) = 9$

(3)

$$\begin{split} Skew(X) &= \frac{E[(X - \mu)^3]}{\sigma^3} \\ &= \frac{E(X^3) - 3\mu E(X^2) + 3\mu^2 E(X) - \mu^3}{\sigma^3} \\ &= \frac{E(X^3) - 3\mu (\sigma^2 + \mu^2) + 3\mu^3 - \mu^3}{\sigma^3} \\ &= \frac{E(X^3) - 3\mu \sigma^2 - \mu^3}{\sigma^3} \end{split}$$

(1)(2)(3)

Exp(1)的矩母函数:

$$egin{align*} M_x(t) &= \int_0^{+\infty} e^{tx} e^{-x} dx \ &= \int_0^{+\infty} e^{(t-1)x} dx \ &= \frac{e^{(t-1)x}}{t-1} \Big|_0^{+\infty} \ &= \frac{1}{1-t}, t \leq 1 \ M_x^{(1)} &= (t-1)^{-2}, M_x^{(1)}(0) = 1 \ M_x^{(2)} &= -2(t-1)^{-3}, M_x^{(2)}(0) = 2 \ M_x^{(3)} &= 6(t-1)^{-4}, M_x^{(3)}(0) = 6 \ M_x^{(4)} &= -24(t-1)^{-5}, M_x^{(4)}(0) = 24 \ \mu &= 1/1 = 1, \sigma^2 = 1, \sigma = 1 \ Skew(X) &= E((X-1)^3) \ &= E(X^3) - 3E(X^2) + 3E(X) - 1 \ &= 6 - 3 \times 2 + 3 - 1 \ &= 2 \ Kurt(X) &= E((X-1)^4) \ &= E(X^4) - 4E(X^3) + 6E(X^2) - 4E(X) + 1 \ &= 24 - 4 \times 6 + 6 \times 2 - 4 + 1 \ &= 9 \ \end{gathered}$$

P(4)的矩母函数:

$$\begin{split} M_x(t) &= E(e^{tx}) \\ &= \sum_k e^{tk} \frac{4^k}{k!} e^{-4} \\ &= e^{-4} \sum_k \frac{(4e^t)^k}{k!} \\ &= e^{-4} e^{4e^t} \\ &= e^{4e^t-4} \\ M_x^{(1)} &= 4e^t e^{4e^t-4} = 4e^{4e^t+t-4} \\ M_x^{(2)} &= (4e^t+1)4e^{4e^t+t-4} = 16e^{4e^t+2t-4} + M_x^{(1)} \\ M_x^{(3)} &= 16(4e^t+2)e^{4e^t+2t-4} + M_x^{(2)} \\ &= 64e^{4e^t+3t-4} + 2(M_x^{(2)} - M_x^{(1)}) + M_x^{(2)} \\ M_x^{(4)} &= 64(4e^t+3)e^{4e^t+3t-4} + 3M_x^{(3)} - 2M_x^{(2)} \\ &= 256e^{4e^t+4t-4} + 192e^{4e^t+3t-4} + 3M_x^{(3)} - 2M_x^{(2)} \\ M_x^{(1)}(0) &= 4 \\ M_x^{(2)}(0) &= 16 + 4 = 20 \\ M_x^{(3)}(0) &= 64 + 2 \times 16 + 20 = 116 \\ M_x^{(4)}(0) &= 256 + 192 + 3 \times 116 - 2 \times 20 = 756 \\ Skew(X) &= E(\frac{X-4}{\sigma})^3 = (E(X^3) - 3E(X^2) + 3E(X) - 64)/2^3 = 0.5 \\ Kurt(X) &= E(\frac{X-4}{2})^4 = (E(X^4) - 16E(X^3) + 96E(X^2) - 256E(X) + 256)/16 = 3.25 \end{split}$$

U(0,1)的矩母函数:

$$M_x(t) = \int_0^1 e^{tx} dx$$

$$= \frac{e^{tx}}{t} \Big|_0^1$$

$$= \frac{e^t - 1}{t}$$
 $M_x^{(n)}(0)$ 没有意义
$$E(X^n) = \frac{1}{n+1}$$
 $\mu = 0.5, \sigma^2 = \frac{1}{12}$
$$Skew(X) = E[(\frac{X - 0.5}{\sigma})^3] = 0($$
对称性)
$$Kurt(X) = E[(\frac{X - 0.5}{\sigma})^4] = 3.36$$

3、

$$f(x) = \frac{1}{3} \times 2e^{-2x} + \frac{2}{3} \times 3e^{-3x}$$

4、

(1)

$$M_x(t)=\int_0^{+\infty}e^{tx}f(x)dx$$
 $lim_{x
ightarrow+\infty}e^{tx}f(x)=+\infty$,积分不收敛

(2)

$$egin{aligned} E(Y^n) &= E((e^X)^n) \ &= E(e^{nX}) \ &= M_x(n) \ &- e^{rac{\sigma^2 n^2}{2} + \mu n} \end{aligned}$$

対
$$X\sim P(\lambda), M_X(t)=e^{\lambda(e^t-1)} \ M_Y(t)=M_{X_1}(t)M_{X_2}(t) \ =e^{(\lambda_1+\lambda_2)(e^t-1)}$$
所以 $Y\sim P(\lambda_1+\lambda_2)$

6、

 $X \sim U(0,1), Y \sim U(X,1)$

$$E(Y) = E[E(Y|X)]$$

$$= \int_0^1 \frac{x+1}{2} dx$$

$$= \frac{3}{4}$$
 余下长度为 $1 - \frac{3}{4} = \frac{1}{4}$

7、

$$t = rac{1}{3} imes 2 + rac{1}{3} imes (t+3) + rac{1}{3} imes (t+1) \ t = 6$$

8、

$$E(E(Y|X)) = E(Y) = E(X)$$

$$Cov(X,Y) = E(X - E(X)(Y - E(Y)))$$

$$= E(X - E(X)(Y - X + X - E(X)))$$

$$= E(X - E(X)(Y - X)) + Var(X)$$

$$= \sum_{x} (x - E(X))E(Y - x|x) + Var(X)$$

$$= \sum_{x} (x - E(X))E(x - x|x) + Var(X)$$

$$= Var(X)$$

9、

(1)

$$egin{aligned} E(Y|x) &= \int_{-\infty}^{+\infty} y f_{Y|X}(y|x) dy \ &= \int_{-\infty}^{+\infty} y f(y) dy \ &= E(Y) \end{aligned}$$

(2)

不成立

	Α	В	С	D
Υ	0	3	1	2
X	0	0	1	1

$$egin{aligned} Var(\hat{Y}) &= E((E(Y|X) - E(E(Y|X)))^2) \ &= E((E(Y|X) - E(Y))^2) \ &= E(E^2(Y|X)) - 2E(E(Y|X))E(Y) + E^2(Y) \ &= E(E^2(Y|X)) - E^2(Y) \ Var(\tilde{Y}) &= E((\tilde{Y} - E(\tilde{Y}))^2) \ egin{aligned} eta E(\tilde{Y}) &= 0, &= E(\tilde{Y}^2) \ &= E((Y - E(Y|X))^2) \ &= E(Y^2) - E(E^2(Y|X)) \ Var(\hat{Y}) + Var(\tilde{Y}) &= E(Y^2) - E(Y^2) &= Var(Y) \end{aligned}$$

11,

(1)

$$Var(X|Y) = E[Y^2 - 2YE(Y|X) + E^2(Y|X)|X]$$

= $E(Y^2|X) - 2E^2(Y|X) + E^2(Y|X)$
= $E(Y^2|X) - E^2(Y|X)$

(2)

$$egin{aligned} Var[E(Y|X)] &= E((E(Y|X) - E(E(Y|X)))^2) \ &= E((E(Y|X) - E(Y))^2) \ &= E(E^2(Y|X) - 2E(Y|X)E(Y) + E^2(Y)) \ &= E(E^2(Y|X)) - E^2(Y) \ E[Var(X|Y) + Var[E(Y|X)]] &= E(Y^2) - E(E^2(Y|X)) + E(E^2(Y|X)) - E^2(Y) \ &= E(Y^2) - E^2(Y) \ &= Var(Y) \end{aligned}$$

12、

$$E(Y|0.5) = \frac{\sqrt{3}}{4}$$

13、

(1)当
$$\rho > 0, a = \frac{\sigma_2}{\sigma_1}, b = \mu_2 - \frac{\sigma_2}{\sigma_1}\mu_1$$
; 当 $\rho < 0$, 用 $-\sigma_2$ 替换 σ_2

14、

(1)

$$E(Y) = E(E(Y|X)) = \sum_n n\mu p_n = a\mu$$

$$M_N(t) = \sum_n e^{tn} p_n$$

15.

考虑一个随机变量N,它是一个离散型随机变量,表示要相加的正态随机变量的个数。假设N服从某个离散分布,例如泊松分布考虑一系列独立的标准正态随机变量 $X_1,X_2,X_3,...$,它们都服从N(0,1)。

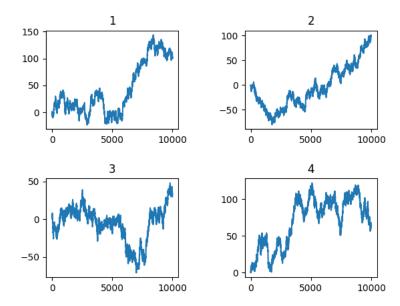
定义随机变量S,它表示前N个正态随机变量的和,即 $S = X_1 + X_2 + ... + X_N$ 。在这种情况下,S的分布取决于N的取值,即实际相加的正态随机变量的个数。

因为N是随机的,所以S的分布实际上是所有可能的N值下正态随机变量之和的混合分布。也即S的分布是多个正态分布的加权和,

$$M_x(t) = \sum_i e^{tx_i} p_i = rac{1}{2} (e^t + e^{-t})$$
 $M_x(t)^n = rac{C_n^0 e^{tn} + C_n^1 e^{t(n-2)} + \dots + C_n^n e^{-tn}}{2^n}$
 $P(X_n = n) = rac{C_n^0}{2^n}$
 $P(X_n = n-2) = rac{C_n^1}{2^n}$
 \dots
由对称性, $E(X_n) = 0$

$$\begin{split} Var(X_n) &= \frac{1}{2^n} (n^2 C_n^0 + (n-2)^2 C_n^1 + \dots + (-n)^2 C_n^n) \\ &= \sum_{k=0}^n (n-2k)^2 C_n^k p^k (1-p)^{n-k}, \not \exists \psi p = 0.5 \\ &= \sum_{k=0}^n (n^2 - 4kn + 4k^2) C_n^k p^k (1-p)^{n-k} \\ &= n^2 - 4nE(X) + 4E(X^2), X \sim B(n, 0.5) \\ &= n^2 - 4n \times 0.5n + 4(Var(X) + E^2(X)) \\ &= n^2 - 2n^2 + 4(n \times 0.5 \times 0.5 + n^2 \times 0.25) \\ &= n \end{split}$$

2、



图像会多次在0左右震荡,最大偏离在100左右,与 $\sigma^2=10000,\sigma=100$ 一致