

Homework 2

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1. EXERCISE 1.12

from the above statement, we can know the rvs. are i.i.d.
then follow the instruction: $\Pr(M_+ = X_1, R \leq r | X_1 = x) = \prod_{j=2}^n \Pr(x-r < X_j \leq x)$

As for the conditional probability,

$$\begin{aligned}\Pr(M_+ = X_1, R \leq r) &= \Pr(M_+ = X_1, R \leq r | X_1 = x) \cdot \Pr(X_1 = x) \\ &= \prod_{j=2}^n \Pr(x-r < X_j \leq x) \cdot f_x(x)\end{aligned}$$

We can easily get the conclusion $\Pr(M_+ = X_1) = \frac{1}{n}$
owing to one number divide n number

$$\Pr(M_+ = X_1, R \leq r) = \frac{\Pr(M_+ = X_1, R \leq r)}{\Pr(M_+ = X_1)} = n \prod_{j=2}^n \Pr(x-r < X_j \leq x) f_x(x)$$

$$\Pr(R \leq r) = \int_{-\infty}^{+\infty} \Pr(M_+ = X_1, R \leq r) dx = \int_{-\infty}^{+\infty} n \prod_{j=2}^n \Pr(x-r < X_j \leq x) f_x(x) dx$$

$$\text{owing to } \Pr(x-r < X_j \leq x) = F(x) - F(x-r)$$

so we can make another expression:

$$= \int_{-\infty}^{+\infty} n \prod_{j=2}^n [F(x) - F(x-r)] f_x(x) dx$$

$$= \int_{-\infty}^{+\infty} n f_x(x) [F(x) - F(x-r)]^{n-1} dx$$

EXERCISE 1.14

(a) From the statement, we can make sure the rvs. can have a joint density function ~~because~~, however, we do not assume that the rvs are pairwise independent. In this situation, we only can get a joint density function, not for statistically ~~even~~ independence.

(b) ~~with the~~ From the meaning of the (b) question, we can assume $f_{x_1, x_2, \dots, x_n}(x_1, x_2, \dots, x_n) = f_{x_1}(x_1) f_{x_2}(x_2) \dots f_{x_n}(x_n)$

so the expected value of the product is.

$$E[f_{x_1}(x_1) f_{x_2}(x_2) \dots f_{x_n}(x_n)]$$

owing to x_1, x_2, \dots, x_n are statistically independent

so we can make another expression from above equation

$$E[f_{x_1}(x_1) f_{x_2}(x_2) \dots f_{x_n}(x_n)] = E[f_{x_1}(x_1)] E[f_{x_2}(x_2)] \dots E[f_{x_n}(x_n)]$$

As for x_1 , so $x_2 \dots x_n$ seem like constant number

As for x_2 , so $x_1 \dots x_n$ seem like constant number

and so on
(linearity of expectation)

$$\begin{aligned} &= E[f_{x_1}(x_1)] E[f_{x_2}(x_2) \dots f_{x_n}(x_n)] \\ &= \bar{x}_1 E[f_{x_2}(x_2) \dots f_{x_n}(x_n)] \\ &= \bar{x}_1 \cdot \bar{x}_2 E[f_{x_3}(x_3) \dots f_{x_n}(x_n)] \\ &= \bar{x}_1 \cdot \bar{x}_2 \dots \bar{x}_n \end{aligned}$$

(c) From the statement, we can assume that

$$\text{Var}[x] = E[(x - \bar{x})^2] = E[x^2] - \bar{x}^2$$

$$\text{for } x_1 + x_2 + \dots + x_n \quad E[x_1 + x_2 + \dots + x_n] = \bar{x}_1 + \bar{x}_2 + \dots + \bar{x}_n$$

$$\begin{aligned} \text{Var}[x_1 + x_2 + \dots + x_n] &= E[(x_1 + x_2 + \dots + x_n) - (\bar{x}_1 + \bar{x}_2 + \dots + \bar{x}_n)]^2 \\ &= E[(x_1 - \bar{x}_1) + (x_2 - \bar{x}_2) + \dots + (x_n - \bar{x}_n)]^2 \\ &= E[(x_1 + x_2 + \dots + x_n)^2 - 2(x_1 + x_2 + \dots + x_n)(\bar{x}_1 + \bar{x}_2 + \dots + \bar{x}_n) + (\bar{x}_1 + \bar{x}_2 + \dots + \bar{x}_n)^2] \\ &= E[(x_1 + x_2 + \dots + x_n)^2] - 2(x_1 + x_2 + \dots + x_n)(\bar{x}_1 + \bar{x}_2 + \dots + \bar{x}_n) + (\bar{x}_1 + \bar{x}_2 + \dots + \bar{x}_n)^2 \end{aligned}$$

$\therefore x_1, x_2, \dots, x_n$ are statistically independent

$$\begin{aligned} &= E[x_1^2] + E[x_2^2] + \dots + E[x_n^2] - [\bar{x}_1^2 + \bar{x}_2^2 + \dots + \bar{x}_n^2] \\ &= E[x_1^2] - \bar{x}_1^2 + E[x_2^2] - \bar{x}_2^2 + \dots + E[x_n^2] - \bar{x}_n^2 = \text{Var}(x_1) + \text{Var}(x_2) + \dots + \text{Var}(x_n) \end{aligned}$$

3. EXERCISE 1.20

(a) from the statement, $F_Y(y) = 1 - \frac{2}{(y+1)(y+2)}$
use 1.29 (the definition of PMF)

$$P_N(y) = F_Y(y) - F_Y(y-1) = 1 - \frac{2}{(y+1)(y+2)} - \left[1 - \frac{2}{y(y+1)} \right]$$

$$= \frac{2}{y(y+1)} - \frac{2}{(y+1)(y+2)}$$

$y \geq 1$

$$= \frac{2}{y} \cdot \frac{1}{y+1} - \frac{2}{(y+1)(y+2)}$$

$$= \frac{2}{y+1} \left[\frac{1}{y} - \frac{1}{y+2} \right]$$

$$= \frac{2}{y+1} \cdot \frac{y+2 - y}{y(y+2)} = \frac{2}{y+1} \cdot \frac{2}{y(y+2)}$$

$$= \frac{4}{y(y+1)(y+2)}$$

use 1.30 ($F_Y^C(y) = 1 - F_Y(y)$)

$$E[Y] = \int_0^{\infty} F_Y^C(y) dy = \sum_0^{\infty} \frac{2}{(y+1)(y+2)} = \sum_0^{\infty} \left(\frac{2}{y+1} - \frac{2}{y+2} \right)$$

$$= 0 - 0 + \frac{2 \times 1}{1+1} - \frac{2 \times 1}{1+2} + \frac{2 \times 2}{2+1} - \frac{2 \times 2}{2+2} + \frac{2 \times 3}{3+1} - \frac{2 \times 3}{3+2} + \dots$$

$$= \sum_0^{\infty} \frac{2}{y+1} - \sum_0^{\infty} \frac{2}{y+2}$$

$$= \frac{2}{0+1} - \frac{2}{0+2} + \frac{2}{1+1} - \frac{2}{1+2} + \frac{2}{2+1} - \frac{2}{2+2} + \dots$$

when $n \rightarrow \infty$ $\frac{2}{y+2} \rightarrow 0$

so the sum of this equation is 2
as desired $E[Y] = 2$

(b). $P_N(y) = \frac{2}{y} - \frac{2}{y+1} - \left[\frac{2}{y+1} - \frac{2}{y+2} \right]$

$$E[Y] = \sum_0^{\infty} P_N(y) y = \sum_0^{\infty} \left(\frac{2}{y} - \frac{2}{y+1} - \frac{2}{y+1} + \frac{2}{y+2} \right) y$$

$$E[Y] = \sum_1^{\infty} P_N(y) y + P_N(y=0) \times 0 = \sum_1^{\infty} P_N(y) \cdot y$$

$$= \sum_1^{\infty} \left[\frac{2}{y(y+1)} - \frac{2}{(y+1)(y+2)} \right] y$$

$$= \sum_1^{\infty} \left[\frac{2}{y+1} - \frac{2y}{(y+1)(y+2)} \right] = \frac{4}{2} = 2$$

$$= \sum_1^{\infty} \frac{4}{(y+1)(y+2)} = \sum_1^{\infty} \left[\frac{4}{y+1} - \frac{4}{y+2} \right] = \frac{4}{1+1} - \frac{4}{1+2} + \frac{4}{2+1} - \frac{4}{2+2} + \dots$$

(c) $P_{X|Y}(x|y) = \frac{1}{y}$ for $1 \leq x \leq y$

from the hint, we can calculate

$$E[X|Y=y] = \sum_x x P_{X|Y}(x|y) = \sum_x \frac{x}{y} = \sum_{x=1}^y \frac{x}{y} = \frac{[1+y]y}{y \cdot 2} = \frac{1+y}{2}$$

$$\begin{aligned} E[X] &= E[E[X|Y=Y]] = E\left[\frac{1+Y}{2}\right] \\ &= \frac{1}{2}[1 + E[Y]] \\ &= \frac{3}{2} \end{aligned}$$

(d) $P_{Z|Y}(z|y) = \frac{1}{y^2}$ for $1 \leq z \leq y^2$

from the similar thought

$$E[Z|Y=y] = \sum_z z P_{Z|Y}(z|y) = \sum_{z=1}^{y^2} \frac{z}{y^2} = \frac{(1+y^2)y^2}{y^2 \cdot 2} = \frac{1+y^2}{2}$$

$y \geq 1$

$$E[Z] = E[E[Z|Y=Y]] = E\left[\frac{1+Y^2}{2}\right] = \frac{1}{2} + \frac{1}{2}E[Y^2]$$

$$\begin{aligned} \text{As for } E[Y^2] &= \sum_{y=1}^{\infty} y^2 P_N(y) = \sum_{y=1}^{\infty} \frac{2y}{(y+1)(y+2)} \\ &= \sum_{y=1}^{\infty} \left(\frac{2y}{y+1} - \frac{2y}{y+2} \right) \\ &= \lim_{N \rightarrow \infty} \left(\sum_{y=1}^N \left(\frac{2y}{y+1} - \frac{2y}{y+2} \right) \right) \\ &\Rightarrow \text{infinite} \end{aligned}$$

Hence the result is infinite.

4. EXERCISE 1.22

from the above statement $P_X(n) = \frac{\lambda^n \exp(-\lambda)}{n!}$

$$P_Y(n) = \frac{\mu^n \exp(-\mu)}{n!}$$

owing to the definition of Poisson

$$E(X) = \lambda \quad \text{Var}[X] = \lambda$$

$$E(Y) = \mu \quad \text{Var}[Y] = \mu$$

X and Y are independent

$$Z = X + Y \quad \cancel{Y = Z - X}$$

~~owing to the convolution of f_X & f_Y~~

$$P(Z = X + Y = n) = \sum_{i=0}^n P(X + Y = n, X = i)$$

$$= \sum_{i=0}^n P(Y = n - i, X = i)$$

owing to X, Y are independent

$$= \sum_{i=0}^n P(Y = n - i) P(X = i)$$

$$= \sum_{i=0}^n e^{-\mu} \cdot \frac{\mu^{n-i}}{(n-i)!} \cdot e^{-\lambda} \cdot \frac{\lambda^i}{i!}$$

$$\cancel{= \sum_{i=0}^n e^{-(\mu+\lambda)} \cdot \frac{\mu^{n-i} \lambda^i}{(n-i)! i!}}$$

$$= e^{-(\mu+\lambda)} \frac{1}{n!} \sum_{i=0}^n \frac{n!}{i! (n-i)!} \mu^{n-i} \lambda^i$$

$$= e^{-(\mu+\lambda)} \frac{1}{n!} \sum_{i=0}^n \binom{n}{i} \mu^{n-i} \lambda^i$$

$$= e^{-(\mu+\lambda)} \frac{1}{n!} (\mu + \lambda)^n$$

$$= \frac{(\mu + \lambda)^n \cdot e^{-(\mu + \lambda)}}{n!}$$

$$X + Y \sim P(\mu + \lambda)$$

and then focus on $P(Y|Z=n) = \frac{P(Y, Z=n)}{P(Z=n)} \triangleq X = n-Y$
 owing to the independence between Y and X

we can change the above equation

$$= \frac{P(Y, Z=n)}{P(Z=n)} = \frac{P(Y, X=n-Y)}{P(Z=n)} = \frac{P(Y) P_X(n-Y)}{P(Z=n)}$$

$$\text{as } P_Y(Y) = \frac{u^Y \cdot \exp(-u)}{Y!}, \quad P_X(n-Y) = \frac{\lambda^{n-Y} \cdot \exp(-\lambda)}{(n-Y)!}$$

$$P(Z=n) = \frac{(u+\lambda)^n \cdot e^{-(u+\lambda)}}{n!}$$

$$\begin{aligned} \text{so the } P(Y|Z=n) &= \frac{\frac{u^Y \cdot \exp(-u)}{Y!} \cdot \frac{\lambda^{n-Y} \cdot \exp(-\lambda)}{(n-Y)!}}{\frac{(u+\lambda)^n \cdot e^{-(u+\lambda)}}{n!}} \\ &= \frac{u^Y \cdot \lambda^{n-Y} \cdot n!}{(u+\lambda)^n \cdot Y! \cdot (n-Y)!} \end{aligned}$$

5. EXERCISE

(a) ~~$E[X_i] = P(X_i=0) \cdot 0 + P(X_i=1) \cdot 1 = P(X_i=1) = Y$~~
 ~~$E[S_n] = E[X_1 + X_2 + \dots + X_n] = n \cdot E[X_i] = n \cdot Y$~~

owing to $E[X_i|Y] = P[X_i=0|Y] \cdot 0 + P[X_i=1|Y] \cdot 1 = Y$
 $E[X_i] = E[E[X_i|Y]] = E[Y] = u$

as for $S_n = X_1 + X_2 + \dots + X_n$, and X_1, X_2, \dots, X_n are conditionally independent
 $E[S_n] = E[X_1 + X_2 + \dots + X_n] = \sum_{i=1}^n E[X_i] = n \cdot u$

(b) owing to the fact $(X_i^2 = X_i)$

$$\text{Var}(X_i) = E[X_i^2] - E[X_i]^2 = E[X_i] - E[X_i]^2 = u - u^2$$

from above statement
(c) ~~strongly~~ $\text{Cov}(x_i, x_j) = E[x_i x_j] - E[x_i]E[x_j]$, for $i \neq j$

$$\begin{aligned} E[x_i x_j | Y] &= 1 \times P[x_i=1, x_j=1 | Y] + 0 \times P[x_i=0, x_j=1 | Y] \\ &\quad + 0 \times P[x_i=1, x_j=0 | Y] + 0 \times P[x_i=0, x_j=0 | Y] \\ &= P[x_i=1, x_j=1 | Y] \\ &= P[x_i=1 | Y] \cdot P[x_j=1 | Y] \quad (x_i \text{ and } x_j \text{ are conditional independent}) \\ &= Y \cdot Y \\ &= Y^2 \end{aligned}$$

$$\text{So } E[x_i x_j] = E[E[x_i x_j | Y]] = E[Y^2] = \text{Var}[Y] + E^2[Y] = b^2 + u^2$$

$$\text{As for } E[x_i] = u \quad E[x_j] = u$$

$$\text{in conclusion } \text{Cov}(x_i, x_j) = E[x_i x_j] - E[x_i]E[x_j] = b^2 + u^2 - u \cdot u = b^2$$

because $b^2 > 0$, so x_i, x_j are not independent

$$\begin{aligned} \text{(d) As for } E[\text{Var}(S_n | Y)] &= E[E(S_n^2 | Y) - E^2(S_n | Y)] = E(S_n^2) - E^2(S_n) \\ \text{and for } \text{Var}[E(S_n | Y)] &= E[E^2(S_n | Y)] - E^2[E(S_n | Y)] = E^2(S_n | Y) - E^2(S_n) \end{aligned}$$

$$\begin{aligned} \text{so } E[\text{Var}(S_n | Y)] + \text{Var}[E(S_n | Y)] &= E(S_n^2) - E^2(S_n | Y) + E^2(S_n | Y) - E^2(S_n) \\ &= E(S_n^2) - E^2(S_n) \end{aligned}$$

as desired

$$\text{Var}(S_n) = E(S_n^2) - E^2(S_n) = E[\text{Var}(S_n | Y)] + \text{Var}[E(S_n | Y)]$$

(e). by using the formula in part (d)

$$\begin{aligned} \text{Var}(S_n) &= E[\text{Var}(S_n | Y)] + \text{Var}[E(S_n | Y)] \\ &= \text{Var}(S_n) \end{aligned}$$

$$= E[\text{Var}(x_1 + x_2 + \dots + x_n | Y)] + \text{Var}(E[x_1 + x_2 + \dots + x_n | Y])$$

$$= E[n \cdot \text{Var}(x_i | Y)] + \text{Var}(n \cdot E(x_i | Y))$$

$$= E[n \cdot Y(Y-1)] + \text{Var}(n \cdot Y) = n E[Y(Y-1)] + n^2 \text{Var}[Y]$$

$$= n[E(Y^2) - E(Y)] + n^2 \text{Var}[Y]$$

$$= n[u - b^2] + n^2 b^2$$

$$= n E[Y(Y-1)] + n^2 \text{Var}[E(x_i | Y)]$$

$$= n E[Y(Y-1)] + n^2 \cdot b^2$$

owing to $E[Y] = \mu$ $E[Y^2] = \sigma^2 + \mu^2$

so the expression can be changed

$$= n E[Y - \bar{Y}]^2 + n \cdot \sigma^2$$

$$= n E[Y] - n E[Y^2] + n \sigma^2$$

$$= n \cdot \mu - n (\sigma^2 + \mu^2) + n \sigma^2$$

$$= n(\mu - \mu^2) + (n^2 - n) \sigma^2$$