

Probability & Statistics for EECS: Homework #07

Due on Apr 28, 2024 at 23:59

Name: **Fei Pang**
Student ID: 2022533153

Problem 1

$$(1) P(Y = y|X = x) = \frac{P(Y = y, X = x)}{P(X = x)} = \frac{P(X = x|Y = y)P(Y = y)}{P(X = x)}$$

$$\begin{aligned} (2) f_Y(y|X = x) &= \frac{P(y \in (y - \epsilon, y + \epsilon)|X = x)}{2\epsilon} \\ &= \frac{P(X = x|y \in (y - \epsilon, y + \epsilon))P(y \in (y - \epsilon, y + \epsilon)|X = x)}{2\epsilon P(X = x)} \\ &= \frac{P(X = x|Y = y)f_Y(y)}{P(X = x)} \end{aligned}$$

$$\begin{aligned} (3) P(Y = y|X = x) &= \frac{P(Y = y, X \in (x - \epsilon, x + \epsilon))}{P(X = x)} \\ &= \frac{P(X \in (x - \epsilon, x + \epsilon)|Y = y)P(Y = y)}{P(X = x)} \\ &= \frac{P(X \in (x - \epsilon, x + \epsilon))}{2\epsilon} \frac{P(Y = y)}{P(X \in (x - \epsilon, x + \epsilon))} \\ &= \frac{f_X(X|Y = y)P(Y = y)}{f_X(x)} \end{aligned}$$

$$(4) f_{Y|X}(y|x) = \frac{f_{X,Y}(x,y)f_Y(y)}{f_X(x)} = \frac{f_{X|Y}(x|y)f_Y(y)}{f_X(x)}$$

Problem 2

(a) Since $N = X + Y$, they are dependent.

Conditioning on $N = n$, we know that $X|_{N=n} \sim \text{Bin}(n, p)$, $Y|_{N=n} \sim \text{Bin}(n, 1 - p)$.

For $i, j \geq 0$,

$$\begin{aligned} P(N = n, X = i, Y = j) &= P(X = i, Y = j) \\ &= \sum_{n=0}^{\infty} P(X = i, Y = j|N = n)P(N = n) \\ &= P(X = i, Y = j|N = i + j)P(N = i + j) \\ &= P(X = i|N = i + j)P(Y = j|X = i, N = i + j)P(N = i + j) \\ &= P(X = i|N = i + j)P(N = i + j) \\ &= \binom{i+j}{i} p^i (1-p)^j \cdot \frac{e^{-\lambda} \lambda^{i+j}}{(i+j)!} \\ &= \frac{e^{-\lambda p} (\lambda p)^i}{i!} \cdot \frac{e^{-\lambda(1-p)} (\lambda(1-p))^j}{j!} \\ &= e^{-\lambda} \frac{(\lambda p)^i}{i!} \cdot e^{-\lambda(1-p)} \frac{(\lambda(1-p))^j}{j!} \end{aligned}$$

(b) Since $N = X + Y$, they are dependent.

According to (a), $P(N = n, X = i)$ is $P(X = i, Y = n - i)$ which simplifies to the given expression.

(c) Since N is indeterminate, X, Y are independent.

According to (a), $P(X = i, Y = j)$ is given by the product of their individual probabilities, leading to X being distributed as $\text{Pois}(\lambda p)$ and similarly Y as $\text{Pois}(\lambda(1 - p))$.

(d) For the covariance and correlation calculations, the following equations are used:

$$\begin{aligned}\text{Cov}(N, X) &= \text{Cov}(X + Y, X) \\ &= \text{Cov}(X, X) + \text{Cov}(Y, X) \\ &= \text{Var}(X) + \text{Cov}(Y, X) \\ &= \lambda p \\ \text{Corr}(N, X) &= \frac{\text{Cov}(N, X)}{\sqrt{\text{Var}(N)\text{Var}(X)}} \\ &= \sqrt{p}\end{aligned}$$

Problem 3

(a) Since $X \sim \text{Expo}(\lambda)$, $Y \sim \text{Expo}(\lambda)$, $f_X(x) = \lambda e^{-\lambda x}$, $x \geq 0$; $f_Y(y) = \lambda e^{-\lambda y}$, $y > 0$. Suppose $T \leq t$,

When $t \leq x$, $P(T \leq t|X = x) = 0$;

When $t > x$, $P(T \leq t|X = x) = P(X + Y \leq t|X = x) = P(Y \leq t - x) = F_Y(t - x) = 1 - e^{-\lambda(t-x)}$.

Therefore, the cumulative distribution function (CDF) is given by

$$F_{T|X}(t|x) = \begin{cases} 0, & t \leq x \\ 1 - e^{-\lambda(t-x)}, & t > x \end{cases}$$

(b) The probability density function (PDF) is the derivative of the CDF with respect to t :

$$f_{T|X}(t|x) = \frac{\partial}{\partial t}(F_{T|X}(t|x)) = \begin{cases} 0, & t \leq x \\ \lambda e^{-\lambda(t-x)}, & t > x \end{cases}$$

Therefore, $f_{T|X}(t|x) \geq 0$.

The integral of the PDF over all t is 1, confirming that it is a valid PDF:

$$\int_{-\infty}^{+\infty} f_{T|X}(t|x) dt = \int_x^{+\infty} \lambda e^{-\lambda(t-x)} dt = -e^{-\lambda(t-x)} \Big|_{t=x}^{+\infty} = 1.$$

Therefore, it is a valid PDF.

(c) Using Bayes' rule we have that

$$\begin{aligned}f_{X|T}(x|t) &= \frac{f(x, t)}{f_T(t)} = \frac{f_{T|X}(t|x)f_X(x)}{f_T(t)} \\ &= \frac{\alpha e^{-\lambda(t-x)} e^{-\lambda x} \cdot \lambda x}{f_T(t)} \\ &= \alpha \lambda^2 e^{-\lambda t} \cdot x t^{2x}\end{aligned}$$

for some $\alpha > 0$. Observe that $f_{X|T}(x|t)$ is a constant function respective to x . In order to be a valid PDF, $f_{X|T}(x|t)$ has to satisfy following

$$1 = \int_{\mathbb{R}} f_{X|T}(x|t) dx = \int_0^t \alpha \lambda^2 e^{-\lambda t} dx = t \alpha \lambda^2 e^{-\lambda t}$$

So, for every $t > 0$ there has to be

$$\alpha = \frac{1}{t \lambda^2 e^{-\lambda t}}$$

and in this case it is a valid PDF.

(d) Observe that in part (c) we have that in fact $f_T(t) = \frac{1}{\alpha}$. So, we can easily obtain that

$$f_T(t) = \lambda^2 t e^{-\lambda t}$$

Problem 4

(a) Observe following for $m \in (0, 1)$

$$F_M(m) = P(M \leq m) = P(U_1 \leq m, \dots, U_3 \leq m) = P(U_1 \leq m) \cdots P(U_3 \leq m) = m^3$$

so the marginal PDF of M is

$$f_M(m) = \frac{d}{dm} F_M(m) = 3m^2$$

Now, let's find joint CDF of L and M . We have that

$$P(L \geq l, M \leq m) = P(U_i \in [l, m], \forall i) = (m - l)^3$$

for $l \leq m$. Using the LOTP, we have that

$$P(M \leq m) = P(M \leq m, L \leq l) + P(M \leq m, L > l)$$

so use that to obtain

$$F(m, l) = P(M \leq m, L \leq l) = m^3 - (m - l)^3$$

for $l \leq m$. Finally, the joint PDF is

$$f(l, m) = \frac{\partial^2}{\partial m \partial l} F(m, l) = \frac{\partial^2}{\partial m \partial l} (m^3 - (m - l)^3) = 6(m - l)$$

(b) Similarly as in (a) we can get that the CDF of L is $F_L(l) = (1 - l)^3$, so the PDF of L is $f_L(l) = 3(1 - l)^2$. So, using the definition of conditional PDF we get that

$$f_{M|L}(m|l) = \frac{f(m, l)}{f_L(l)} = \frac{6(m - l)}{3(1 - l)^2} = \frac{2(m - l)}{(1 - l)^2}$$

Problem 5

(a)

$$\begin{aligned}
 \bar{X} &= \frac{1}{n} \sum_{i=1}^n X_i Y_i = \frac{1}{n} \sum_{i=1}^n y_i \\
 r &= \frac{1}{n} \sum_{i=1}^n [x_i - E(X)][y_i - E(Y)] \\
 &= E[(X - E(X))(Y - E(Y))] \\
 &= \text{Cov}(X, Y)
 \end{aligned}$$

(b)

$$\begin{aligned}
 E((X - \bar{X})(Y - \bar{Y})) &= E(XY) - E(\bar{X}Y) - E(X\bar{Y}) + E(\bar{X}\bar{Y}) \\
 E(XY) &= \text{Cov}(X, Y) + E(X)E(Y) \\
 E(\bar{X}Y) &= \text{Cov}(\bar{X}, Y) + E(\bar{X})E(Y) = E(X)E(Y) \\
 E(X\bar{Y}) &= \text{Cov}(X, \bar{Y}) + E(X)E(\bar{Y}) = E(X)E(Y) \\
 E(\bar{X}\bar{Y}) &= \text{Cov}(\bar{X}, \bar{Y}) + E(\bar{X})E(\bar{Y}) \\
 (X, Y) &\text{ is independent of } (\bar{X}, \bar{Y}) \\
 E(X) &= E(\bar{X}), \quad E(Y) = E(\bar{Y})
 \end{aligned}$$

$$\begin{aligned}
 E((X - \bar{X})(Y - \bar{Y})) &= 2\text{Cov}(X, Y) \\
 S &= n^2(X_i - \bar{X})(Y_i - \bar{Y}) = 2n^2\text{Cov}(x, y) \\
 \text{Cov}(X, Y) &= \frac{S}{2n^2}
 \end{aligned}$$

- (c) 1 After the horizontal and vertical coordinates are exchanged, the area will not change. If the area is unchanged, the covariance will not change.
- 2 Enlarge the base vectors of the horizontal and vertical coordinates by a_1 and a_2 times respectively, and the area of the rectangle will become $a_1 a_2$ times of the original one, so the covariance will also become $a_1 a_2$ times of the original one.
- 3 After moving the origin of the coordinate system to the left a_1 and down a_2 , the area will not change. Therefore, the covariance will not change.
- 4 The area of a rectangle with a length of W_1 and a height of $W_2 + W_3$ is equal to the sum of the areas of two rectangles with a length of W_1 and a width of W_2 and W_3 respectively, therefore $\text{Cov}(W_1, W_2 + W_3) = \text{Cov}(W_1, W_2) + \text{Cov}(W_1, W_3)$.