Probability & Statistics for EECS: Homework #07

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1. (a)

When X is discrete, Y is discrete, we can have

$$P(Y = y | X = x)P(X = x) = P(X = x, Y = y) = P(X = x | Y = y)P(Y = y)$$

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

Similarly, when X and Y are both continuous, we have

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

When X is discrete, Y is continuous, suppose that there exist a positive number a

$$\lim_{a \to 0} P(Y \in (y-a,y+a)|X=x) = 2a \lim_{a \to 0} f_Y(y|X=x)$$

$$\lim_{a \to 0} \frac{P(X=x|Y \in (y-a,y+a)P(Y \in (y-a,y+a))}{P(X=x)} = \lim_{a \to 0} \frac{2aP(X=x|Y=y)f_Y(y)}{P(X=x)}$$

By Bayes' rule

$$\lim_{a \to 0} P(Y \in (y - a, y + a) | X = x) = \lim_{a \to 0} \frac{P(X = x | Y \in (y - a, y + a) P(Y \in (y - a, y + a)))}{P(X = x)}$$

We can get

$$2a \lim_{a \to 0} f_Y(y|X=x) = \lim_{a \to 0} \frac{2aP(X=x|Y=y)f_Y(y)}{P(X=x)}$$

Thus we conclude that

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

When X is continuous, Y is discrete, similarly, we take a positive number a

$$P(Y = y | X = x) = \lim_{a \to 0} P(Y = y | X \in (x - a, x + a))$$

By Bayes' rule

$$\lim_{a \to 0} P(Y = y | X \in (x - a, x + a)) = \lim_{a \to 0} \frac{P(X \in (x - a, x + a) | Y = y) P(Y = y)}{P(X \in (x - a, x + a))}$$

$$= \lim_{a \to 0} \frac{2af_X(x | Y = y) P(Y = y)}{2af_X(x)}$$

$$= \frac{f_X(x | Y = y) P(Y = y)}{f_X(x)}$$

Thus we conclude that

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

(b)

When X is discrete, Y is discrete

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

When X and Y are both continuous, we have

$$f_X(x) = \int_{-\infty}^{+\infty} f_{X,Y}(x,y) \, dy = \int_{-\infty}^{+\infty} f_{X|Y}(x|y) f_Y(y) \, dy$$

When X is discrete, Y is continuous, Using Bayes' Law

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

to get

$$P(X = x | Y = y) f_Y(y) = f_Y(y | X = x) P(X = x)$$

$$\int_{-\infty}^{+\infty} P(X = x | Y = y) f_Y(y) dy = \int_{-\infty}^{+\infty} f_Y(y | X = x) P(X = x)$$

$$= P(X = x) \int_{-\infty}^{+\infty} f_Y(y | X = x) dy = P(X = x)$$

Which means that

$$P(X = x) = \int_{-\infty}^{+\infty} P(X = x | Y = y) f_Y(y) dy$$

When X is continuous, Y is discrete, similarly, Using Bayes' Law

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

to get

$$P(Y = y | X = x) f_X(x) = f_X(x | Y = y) P(Y = y)$$

$$\sum_{y} f_X(x | Y = y) P(Y = y) = \sum_{y} P(Y = y | X = x) f_X(x)$$

$$= f_X(x) \sum_{y} P(Y = y | X = x) = f_X(x)$$

Which means that

$$f_X(x) = \sum_{y} f_X(x|Y=y)P(Y=y)$$

1. (a) If $x + y \neq n$, then

$$P(N = n, X = x, Y = y) = 0$$

, else

$$P(N = n, X = x, Y = y) = P(N = n)P(X = x, Y = y|N = n)$$

$$= P(N = n)P(X = x, Y = n - x|N = n)$$

$$= \frac{\lambda^n e^{-\lambda}}{n!} \binom{n}{x} p^x (1 - p)^{n-x}$$

Since X + Y = N, so we can find that N, X, Y are not independent.

(b)

$$\begin{split} P(N=n,X=x) &= P(N=n,X=x,Y=n-x) \\ &= \frac{\lambda^n e^{-\lambda}}{n!} \binom{n}{x} p^x (1-p)^{n-x} \\ &\neq P(N=n) P(X=x) \end{split}$$

Since $N \sim Pois(\lambda)$ and $X \sim Pois(\lambda p)$, so X and N are not independent

(c)

$$P(X = x, Y = y) = P(N = x + y, X = x)$$

$$= \frac{\lambda^{x+ye^{-\lambda}}}{(x+y)!} \frac{\lambda^n e^{-\lambda}}{n!} {x \choose x} p^x (1-p)^y$$

$$= \frac{(\lambda p)^x e^{-\lambda p}}{x!} \cdot \frac{(\lambda (1-p))^x e^{-\lambda (1-p)}}{y!}$$

$$= P(X = x) P(Y = y)$$

So X and N are independent

(d)

We can find from above that $X \sim Pois(\lambda p)$, $Y \sim Pois(\lambda (1-p))$, X and N are independent

$$Cov(N, X) = Cov(X + Y, X) = Cov(X, X) + Cov(Y, X) = Var(X) = \lambda p$$
$$Corr(N, X) = \frac{\lambda p}{Var(N)Var(X)} = \frac{\lambda p}{\sqrt{\lambda \lambda p}} = \sqrt{p}$$

1. (a)

If t < x, we will find that this situation is impossible. So

$$F_{T|X}(t|x) = 0$$

if $t \geq x$, then

$$F_{T|X}(t|x) = F_{T|X}(t-x) = 1 - e^{-\lambda(t-x)}$$

(b)

Take the derivative of CDF, if t < x,

$$f_{T|X}(t|x) = 0$$

if $t \geq x$,

$$f_{T|X}(t|x) = F'_{T|X}(t|x) = \lambda e^{-\lambda(t-x)}$$

To verify it is a valid PDF, let's take the integral of $f_{T|X}(t|x)$ to get

$$\int_{-\infty}^{+\infty} f_{T|X}(t|x)dt = \int_{-\infty}^{x} f_{T|X}(t|x)dt + \int_{x}^{+\infty} f_{T|X}(t|x)dt$$

$$= 0 + \int_{x}^{+\infty} \lambda e^{-\lambda(t-x)}dt$$

$$= \int_{0}^{+\infty} \lambda e^{-\lambda(t-x)}d(t-x)$$

$$= -e^{-z}|_{0}^{+\infty}$$

$$= -(0-1)$$

$$= 1$$

(c)

If $x \geq t$, similarly, we can find that

$$f_{X|T}(x|t) = 0$$

else

$$f_{X|T}(x|t) = \frac{f_{T|X}(t|x)f_X(x)}{f_T(t)} = \frac{f_{T|X}(t|x)f_X(x)}{f_T(t)} = \frac{\lambda^2 e^{-\lambda t}}{f_T(t)}$$

and since

$$\int_{-\infty}^{+\infty} f_{X|T}(x|t)dx = \int_{-\infty}^{t} f_{X|T}(x|t)dx + \int_{t}^{+\infty} f_{X|T}(x|t)dx = f_{X|T}(x|t)x|_{0}^{t} = tf_{X|T}(x|t) = 1$$

So it is a valid PDF and we can find that if $x \leq t$,

$$f_{X|T}(x|t) = \frac{1}{t}$$

(d)

From (c), we got that

$$f_{X|T}(x|t) = \frac{\lambda^2 e^{-\lambda t}}{f_T(t)} = \frac{1}{t}$$

when $x \leq t$ according to Baye's rule, thus, we can conclude that

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

1. (a)

Suppose that $0 \le m \le 1$, then when $M \le m$, it means that all of the three U_i are less than or equal to m, so we can find the CDF of M is

$$F_M(m) = m^3$$

Then we can calculate that the PDF is

$$f_M(m) = 3m^2$$

First we can find that $L \ge l, M \le m$ means that all of the three U_i are between l and m, so we can find the CDF is

$$P(L \ge l, M \le m) = (m - l)^3$$

Since

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

Then the joint CDF of L, M is

$$P(L \le l, M \le m) = P(M \le m) - P(L > l, M \le m)$$

= $m^3 - (m - l)^3$

the joint PDF of L, M is

$$f(l,m) = F'(l,m) = 6(m-l)$$

(b)

First we can find the CDF of L is

$$P(L \le l) = 1 - P(L > l)$$

$$= 1 - P(U_1 > l, U_2 > l, U_3 > l)$$

$$= 1 - (1 - l)^3$$

Then the PDF of L is

$$f_L(l) = 3(1-l)^2$$

the conditional PDF of M given L is

$$f_{M|L}(m|l) = \frac{f(l,m)}{f_L(l)}$$

= $\frac{2(m-l)}{(1-l)^2}$

1. (a)

$$\begin{split} f_{X,Y,Z}(x,y,z) &= f_{Y,Z|X}(y,z|x) f_X(x) \\ &= f_{Y|X}(y|x) f_{Z|X}(z|x) f_X(x) \\ &= \phi(y-x) \phi(z-x) \phi(x) \end{split}$$

(b) If there is not the condition, then we have no information of what distribution Y or Z is, thus we cann't conclude that Y and Z are also unconditionally independent.

(c)

$$f_{Y,Z}(y,z) = \int_{-\infty}^{+\infty} f_{Y,Z|X}(y,z|x)dx = \int_{-\infty}^{+\infty} \phi(y-x)\phi(z-x)\phi(x)dx$$

1. (a)

$$Cov(X,Y) = E((X - \bar{x})(Y - \bar{y}))$$

$$= \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})$$

$$= r$$

(b)

 $E((X - \bar{x})(Y - \bar{y}))$ denotes the average signed area of the random rectangle formed by (X, Y) and $(\widetilde{X}, \widetilde{Y})$

$$E((X - \bar{X})(Y - \bar{Y})) = \frac{1}{n^2}(n \times 0 + 2\sum_{i < j} (x_i - x_j)(y_i - y_j))$$
$$= \frac{2S}{n^2}$$

On the other hand, we can find that $E(XY) = E(\widetilde{X}, \widetilde{Y}), E(\widetilde{X}Y) = E(X)E(\widetilde{Y}) = E(\widetilde{X})E(Y) = E(X)E(Y)$, then

$$\begin{split} E((X-\bar{x})(Y-\bar{y})) &= E(XY) + E(\widetilde{X}\widetilde{Y}) - E(X\widetilde{Y}) - E(\widetilde{X}Y) \\ &= E(XY) + E(XY) - E(X)E(Y) - E(X)E(Y) \\ &= 2(E(XY) - E(X)E(Y)) \\ &= 2Cov(X,Y) \end{split}$$

Thus, we can conclude that

$$Cov(X,Y) = \frac{S}{n^2}$$

(d)

- (i)it does not matter that if we just swap the axis, since the area of the rectangles will not change.
- (ii) This equation is equivalent to multiplying the length and width of a rectangle by respective factors, it results in an enlargement of the rectangle's area to the product of these two factors (like the formula for the area of a rectangle).
- (iii) Adding or subtracting a constant is like shifting the rectangle a bit. Clearly, such a shift doesn't change the area of the rectangle.
- (iv)Suppose that we can divide a rectangle with length l into two parts. One with length of x while the other with length l-x, which means that sum of the areas of these two smaller rectangles equals the area of the original whole rectangles.