Probability & Statistics for EECS: Homework #09

Due on April 16, 2023 at 23:59 $\,$

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(a) X discrete, Y discrete:

With the definition of conditional probability, we could get that

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

$$P(X=x|Y=y) = \frac{P(X=x,Y=y)}{P(Y=y)},$$
 since $P(Y=y,X=x) = P(X=x,Y=y)$ so $P(Y=y|X=x)P(X=x) = P(X=x|Y=y)P(Y=y),$ i.e. $P(Y=y|X=x) = \frac{P(X=x|Y=y)P(Y=y)}{P(X=x)}.$

So above all, when X discrete, Y discrete, $P(Y = y | X = x) = \frac{P(X = x | Y = y)P(Y = y)}{P(X = x)}$.

(b) X discrete, Y continuous:

From (a), we can get that
$$P(Y \in (y - \epsilon, y + \epsilon)|X = x) = \frac{P(X = x|Y \in (y - \epsilon, y + \epsilon))P(Y \in (y - \epsilon, y + \epsilon))}{P(X = x)}$$
.

And since
$$P(Y \in (y - \epsilon, y + \epsilon)) = \lim_{\epsilon \to 0} f_Y(y) \cdot 2\epsilon$$
.
So $f_Y(y|X = x) = \lim_{\epsilon \to 0} \frac{P(Y \in (y - \epsilon, y + \epsilon)|X = x)}{2\epsilon} = \lim_{\epsilon \to 0} \frac{P(X = x|Y \in (y - \epsilon, y + \epsilon))P(Y \in (y - \epsilon, y + \epsilon))}{P(X = x) \cdot 2\epsilon}$

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

So above all, when X discrete, Y continuous, $f_Y(y|X=x) = \frac{P(X=x|Y=y)f_Y(y)}{P(X=x)}$

(c) X continuous, Y discrete:

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

from (a), we can get that
$$P(Y = y | X \in (x - \epsilon, x + \epsilon)) = \frac{P(X \in (x - \epsilon, x + \epsilon) | Y = y)P(Y = y)}{P(X \in (x - \epsilon, x + \epsilon))}$$

from (a), we can get that
$$P(Y = y | X \in (x - \epsilon, x + \epsilon)) = \frac{P(X \in (x - \epsilon, x + \epsilon) | Y = y)P(Y = y)}{P(X \in (x - \epsilon, x + \epsilon))}$$
So
$$P(Y = y | X = x) = \lim_{\epsilon \to 0} \frac{P(X \in (x - \epsilon, x + \epsilon) | Y = y)P(Y = y)}{P(X \in (x - \epsilon, x + \epsilon))} = \lim_{\epsilon \to 0} \frac{P(X \in (x - \epsilon, x + \epsilon) | Y = y)P(Y = y)}{\frac{2\epsilon}{2\epsilon}}$$

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

So above all, when X continuous, Y discrete, $P(Y = y | X = x) = \frac{f_X(x | Y = y) P(Y = y)}{f_X(x)}$

(d) X continuous, Y continuous:

$$f_{Y|X}(y|x) = \lim_{\epsilon_1 \to 0, \epsilon_2 \to 0} \frac{P(Y \in (y - \epsilon_1, y + \epsilon_1) | X \in (x - \epsilon_2, x + \epsilon_2))}{2\epsilon_1}$$

from (a), we can get that

$$P(Y \in (y - \epsilon_1, y + \epsilon_1) | X \in (x - \epsilon_2, x + \epsilon_2)) = \frac{P(X \in (x - \epsilon_2, x + \epsilon_2) | Y \in (y - \epsilon_1, y + \epsilon_1)) P(Y \in (y - \epsilon_1, y + \epsilon_1))}{P(X \in (x - \epsilon_2, x + \epsilon_2))}$$
so $f_{Y|X}(y|x) = \lim_{\epsilon_1 \to 0, \epsilon_2 \to 0} \frac{P(X \in (x - \epsilon_2, x + \epsilon_2) | Y \in (y - \epsilon_1, y + \epsilon_1)) P(Y \in (y - \epsilon_1, y + \epsilon_1))}{P(X \in (x - \epsilon_2, x + \epsilon_2)) \cdot 2\epsilon_1}$

so
$$f_{Y|X}(y|x) = \lim_{\epsilon_1 \to 0, \epsilon_2 \to 0} \frac{P(X \in (x - \epsilon_2, x + \epsilon_2)|Y \in (y - \epsilon_1, y + \epsilon_1))P(Y \in (y - \epsilon_2, x + \epsilon_2))}{P(X \in (x - \epsilon_2, x + \epsilon_2)) \cdot 2\epsilon_1}$$

$$\underline{P(X \in (x - \epsilon_2, x + \epsilon_2) | Y \in (y - \epsilon_1, y + \epsilon_1))} \underline{P(Y \in (y - \epsilon_1, y + \epsilon_1))} \underline{P(Y \in (y - \epsilon_1, y + \epsilon_1))}$$

$$= \lim_{\epsilon_1 \to 0, \epsilon_2 \to 0} \frac{\frac{2\epsilon_2}{2\epsilon_1} \frac{2\epsilon_2}{2\epsilon_2} \frac{2\epsilon_1}{2\epsilon_1}}{\frac{P(X \in (x - \epsilon_2, x + \epsilon_2))}{2\epsilon_2}}$$

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

So above all, when X continuous, Y continuous, $f_{Y|X}(y|x) = \frac{f_{X|Y}(x|y)f_{Y}(y)}{f_{X}(x)}$.

Let q = 1 - p, since $X, Y \sim Geom(p)$, so $P(X = x) = q^x p$, $P(Y = y) = q^y p$

(a) Since N = X + Y, so n = x + y, and the joint PMF of X,Y,N is

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

since X,Y are i.i.d., so

$$P(X = x, Y = y) = P(X = x)P(Y = y) = (q^{x}p)(q^{y}p) = p^{2}q^{x+y} = p^{2}(1-p)^{n}$$

So above all, the joint PMF of X,Y,N is that $P(X = x, Y = y, N = n) = p^2(1-p)^n$,(x,y,n are nonnegative integers).

(b) similarly with (a), we can get that

$$P(X = x, N = n) = P(X = x, Y = n - x) = P(X = x)P(Y = n - x) = (q^{x}p)(q^{n-x}p) = p^{2}q^{n} = p^{2}(1 - q)^{n}$$

So above all, the joint PMF if X and N is that $P(X = x, N = n) = p^2(1-p)^n$, (x,n are nonnegative integers).

(c) the conditional PMF of X given N = n is that

$$P(X = x | N = n) = \frac{P(X = x, N = n)}{P(N = n)}$$

From (b) we can get that $P(X = x, N = n) = p^2(1 - p)^n$. And from LOTP, we can get that

$$P(N=n) = \sum_{k=0}^{n} P(N=n|X=k)P(X=k) = \sum_{k=0}^{n} P(N=n,X=k) = \sum_{k=0}^{n} p^{2}(1-p)^{n} = (n+1)p^{2}(1-p)^{n}$$

So

$$P(X = x | N = n) = \frac{P(X = x, N = n)}{P(N = n)} = \frac{p^2 (1 - p)^n}{(n+1)p^2 (1-p)^n} = \frac{1}{n+1}$$

So above all, the conditional PMF of X given that N=n is that $P(X=x|N=n)=\frac{1}{n+1}$. The result says that when given N=n, then X could be any one of the numbers in $\{0,1,\cdots,n\}$ with equal probabilities, i.e. $\frac{1}{n+1}$.

(a) Since $X \sim Expo(\lambda)$, so $F_X(x) = P(X \le x) = 1 - e^{-\lambda x}, x > 0$.

And the conditional CDF of X given X < c is that $F_{X|X>c}(x) = P(X \le x|X>c) = \frac{P(X \le x, X>c)}{P(X>c)}$.

If $x \le c$, then $P(X \le x, X > c) = 0$, i.e. $F_{X|X>c}(x) = 0$. Then $F_{X|X>c}(x) = 0$

If x > c, then $P(X \le x, X > c) = P(c < X \le x) = P(X \le x) - P(X \le c) = (1 - e^{-\lambda x}) - (1 - e^{-\lambda c}) = P(X \le x) - P(X \le x) = P(X \le x) = P(X \le x) - P(X \le x) = P($ $e^{-\lambda c} - e^{-\lambda x}$.

Then $F_{X|X>c}(x) = \frac{e^{-\lambda c} - e^{-\lambda x}}{e^{-\lambda c}} = 1 - e^{-\lambda(x-c)}, x > c, F_{X|X>c}(x) = 0, x \le c.$ And the conditional PDF of X given X < c is that

 $f_{X|X>c}(x) = F'_{X|X>c}(x) = \lambda e^{-\lambda(x-c)}, x > c, f_{X|X>c}(x) = 0, x \le c.$

So above all, the conditional CDF of X given X > c is $F_{X|X>c}(x) = 1 - e^{-\lambda(x-c)}, x > c, F_{X|X>c}(x) = 0, x \le c$. And the conditional PDF of X given X > c is that $f_{X|X>c}(x) = \lambda e^{-\lambda(x-c)}, x > c, f_{X|X>c}(x) = 0, x \le c$.

(b) The conditional CDF of X given X < c is that $F_{X|X < c}(x) = P(X \le x | X < c) = \frac{P(X \le x, X < c)}{P(X < c)}$.

From the support of exponential distribution, we can get that when $x \leq 0, F_{X|X < c}(x) = 0$ When x > 0:

If X < c, then $P(X \le x, X < c) = \frac{P(X \le x)}{P(X < c)} = \frac{1 - e^{-\lambda x}}{1 - e^{-\lambda c}}$.

And if $X \ge c$, then $P(X \le x, X < c) = \frac{P(X < c)}{P(X < c)} = 1$.

So $F_{X|X < c}(x) = 0, x \le 0, F_{X|X < c}(x) = \frac{1 - e^{-\lambda x}}{1 - e^{-\lambda c}}, 0 < x < c, F_{X|X < c}(x) = 1, x \ge c.$

And the conditional PDF of X given X < c is that

$$f_{X|X < c}(x) = \frac{d}{dx} F_{X|X < c}(x) = \frac{\tilde{\lambda}e^{-\lambda x}}{1 - e^{-\lambda c}}, 0 < x < c, f_{X|X < c}(x) = 0, x \le 0, \text{ or } x \ge c.$$

So above all, the conditional CDF of X given X < c is that

 $F_{X|X < c}(x) = 0, x \leq 0, F_{X|X < c}(x) = \frac{1 - e^{-\lambda x}}{1 - e^{-\lambda c}}, 0 < x < c, F_{X|X < c}(x) = 1, x \geq c.$ And the conditional PDF of X given X < c is that

$$f_{X|X < c}(x) = \frac{\lambda e^{-\lambda x}}{1 - e^{-\lambda c}}, 0 < x < c, f_{X|X < c}(x) = 0, x \le 0, \text{ or } x \ge c.$$

(a) The marginal CDF of M is that

$$F_M(m) = P(M \le m) = P(max(U_1, U_2, U_3) \le m) = P(U_1 \le m, U_2 \le m, U_3 \le m)$$

since U_1, U_2, U_3 are i.i.d. Unif(0,1), so when $0 \le m \le 1$, $F_M(m) = P(U_1 \le m)P(U_2 \le m)P(U_3 \le m) = m^3$.

And when m < 0 or m > 1, $F_M(m) = 0$.

And the marginal PDF of M is that $f_M(m) = \frac{d}{dm} F_M(m) = \frac{d}{dm} m^3 = 3m^2, m \in [0,1].$

And $f_M(m) = 0$, otherwise.

Since U_1, U_2, U_3 are i.i.d. Unif(0,1), so

$$= P(min(U_1, U_2, U_3) \ge l, max(U_1, U_2, U_3) \le m) = P(U_1 \ge l, U_2 \ge l, U_3 \ge l, U_1 \le m, U_2 \le m, U_3 \le m)$$

$$= P(l \le U_1 \le m) P(l \le U_2 \le m) P(l \le U_3 \le m) = (m-l)^3, m \ge l.$$

And
$$P(L > l, M < m) = 0, m < l.$$

And from above, we can get that $P(M \le m) = m^3$,

and since
$$(L \leq l) \cup (L \geq l) = R$$
, $P((L \leq l) \cap (L \geq l)) = P(L = l) = 0$

so
$$P(M \le m) = P(L \le l, M \le m) + P(L \ge l, M \le m)$$
.

So the joint CDF of L,M is that

$$F_{L,M}(l,m) = P(L \le l, M \le m) = P(M \le m) - P(L \ge l, M \le m) = m^3 - (m-l)^3, m \ge l, \text{and } l, m \in [0,1],$$

 $F_{L,M}(l,m)=0$, otherwise.

And the joint PDf of L,M is that

$$f_{L,M}(l,m) = \frac{\partial^2}{\partial l \partial m} F_{L,M}(l,m) = \frac{\partial^2}{\partial l \partial m} [m^3 - (m-l)^3] = 6(m-l), \ l,m \in [0,1], m \ge l,$$

$$f_{L,M}(l,m) = 0 \text{ otherwise}$$

So above all, the marginal CDF of M is $F_M(m) = m^3, m \in [0, 1]$, and $F_M(m) = 0$, otherwise.

The marginal PDF of M is $f_M(m) = 3m^2, m \in [0, 1]$, and $f_M(m) = 0$, otherwise.

The joint CDF of L, M is $F_{L,M}(l, m) = m^3 - (m - l)^3, m, l \in [0, 1], m \ge l$, and $F_{L,M}(l, m) = 0$, otherwise.

The joint PDF of L, M is $f_{L,M}(l,m) = 6(m-l), m, l \in [0,1], m \ge l$, and $f_{L,M}(l,m) = 0$, otherwise.

(b) The marginal CDF of L is that

$$F_L(l) = P(L \le l) = 1 - P(L > l) = P(min(U_1, U_2, U_3) > l) = P(U_1 > l, U_2 > l, U_3 > l) = 1 - P(U_1 > l) + P(U_2 > l) + P(U_3 > l) = 1 - (1 - l)^3, l \in [0, 1],$$

So the mariginal PDF of L is that

$$f_L(l) = \frac{d}{dl} F_L(l) = \frac{d}{dl} [1 - (1 - l)^3] = 3(1 - l)^2, l \in [0, 1],$$

So the conditional PMF of
$$M$$
 given L is that $f_{M|L}(m|l) = \frac{f_{L,M}(l,m)}{f_L(l)} = \frac{6(m-l)}{3(1-l)^2} = \frac{2(m-l)}{(1-l)^2}, m, l \in [0,1], m \ge l,$ and $f_{M|L}(m|l) = 0$ otherwise

and $f_{M|L}(m|l) = 0$, otherwise.

So above all, the conditional PMF of M given L is that

$$f_{M|L}(m|l) = \frac{2(m-l)}{(1-l)^2}, m, l \in [0,1], m \ge l,$$

and $f_{M|L}(m|l) = 0$, otherwise.

(a) 1. Since X and Y are i.i.d. Geom(p), and let q = 1 - p, so the joint PMF of L and M is that If m < 0 or l < 0, then $P_{L,M}(L = l, M = m) = 0$,

If $m \geq 0, l \geq 0$, then:

 $P_{L,M}(L = l, M = m) = P(min(X, Y) = l, max(X, Y) = m).$

If l > m, which means that min(X,Y) > max(X,Y), which is impossible, so $P_{L,M}(L=l,M=m) = 0$.

If l = m, which means that min(X, Y) = max(X, Y),

so $P_{L,M}(L=l,M=m) = P(X=Y=l) = P(X=l)P(Y+l) = (q^l p)^2 = p^2(1-p)^{2l}$.

If l < m, which means that min(X, Y) < max(X, Y),

so $P_{L,M}(L=l, M=m) = P(X=l, Y=m) + P(X=m, Y=l) =$

 $P(X = l)P(Y = m) + P(X = m)P(Y = l) = 2(q^{l}p)(q^{m}p) = 2p^{2}(1-p)^{l+m}.$

2. Let
$$l=1, m=0$$
, from the definition, we can get that
$$P(L=l|M=m) = \frac{P(L=l, M=m)P(M=m)}{P(L=l)} = 0,$$

that is because $P(L=l, M=m) = 0, P(L=l) \neq 0, P(M=m) \neq 0.$

But $P(L = l) = P(min(X, Y) = 1) = P(X = 1, Y \ge 1) + P(X \ge 2, Y = 1)$

$$= (q^{1}p)(1 - q^{0}p) + (1 - q^{0}p - q^{1}p)(q^{1}p) = qp - qp^{2} + qp - qp^{2}p - q^{2}p^{2}$$

 $= p(p-1)^2(2-p) > 0$, since $p \in (0,1)$.

But P(L = l | M = m) = 0, and $P(M = m) = q^{0}p = p > 0$ so $P(L = l | M = m) \neq P(L = l)$.

So L and M are not independent.

So above all, the joint PMF of L and M is that

$$P_{L,M}(L=l,M=m) = \begin{cases} p^2(1-p)^{2l}, & m=l \ge 0\\ 2p^2(1-p)^{l+m}, & m>l \ge 0\\ 0, & otherwise \end{cases}$$

And L and M are not independent.

(b) 1. The marginal distribution if L is that $P_L(l) = \sum_m P_{L,M}(L=l, M=m)$.

If l < 0, then $P_L(l) = 0$,

If l > 0, then:

$$P_{L}(l) = \sum_{m=l}^{+\infty} P_{L,M}(L=l, M=m) = P_{L,M}(L=l, M=l) + \sum_{m=l+1}^{+\infty} P_{L,M}(L=l, M=m)$$

$$= (q^{l}p)^{2} + \sum_{m=l+1}^{+\infty} 2p^{2}q^{l+m} = p^{2}q^{2l} + 2pq^{2l+1} = q^{2l}(p^{2} + 2pq)$$

$$q = (q^l p)^2 + \sum_{m=l+1}^{+\infty} 2p^2 q^{l+m} = p^2 q^{2l} + 2pq^{2l+1} = q^{2l}(p^2 + 2pq)^2$$

$$=q^{2l}(1-q^2)$$

$$= p(1-p)^{2l}(2-p)$$

2. Story:

Alice and Bob are tossing the biased coin.

For each turn, each coin has the probability of p to head, and has the probability of q = 1 - p to tail.

Let X be the number of tails before the first head for Alice, and let Y be the number of tails before the first head for Bob.

Let L be the turns before at least one of them head, i.e. L = min(X, Y).

When L = l > 0, for the first l turns, they both tails. So the probability is q^2

And for the l+1-th turn, at least one of them head, so the probability is $1-q^2$.

So
$$P(L=l) = (q^2)^l (1-q^2) = q^{2l} (1-q^2) = p(1-p)^{2l} (2-p).$$

And when l < 0, P(L = l) = 0.

So above all, the mariginal distribution of L is $P(L=l) = p(1-p)^{2l}(2-p), l \ge 0, P(L=l) = 0, l < 0$ have been proved in two ways.

(c) The CDF for M is that

$$F_M(m) = P(M \le m) = P(\max(X, Y) \le m) = P(X \le m, Y \le m) = P(X \le m)P(Y \le m).$$

$$F_M(m) = P(M \le m) = P(max(X, Y) \le m) = P(X \le m, Y \le m) = P(X \le m)P(Y \le m).$$

And $P(X \le m) = \sum_{k=0}^{m} q^k p = 1 - q^{m+1}$, similarly, $P(Y \le m) = 1 - q^{m+1}$.

So
$$F_M(m) = (1 - q^{m+1})^2$$
.

So the survival function of M is that
$$G_M(m) = 1 - F_M(m) = 1 - (1 - q^{m+1})^2 = 2q^{m+1} - q^{2m+2}$$
.

So
$$F_M(m) = (1 - q^m)$$
. So the survival function of M is that $G_M(m) = 1 - F_M(m) = 1 - (1 - q^{m+1})^2 = 2q^{m+1} - q^{2m+2}$. Then $E[M] = \sum_{m=0}^{+\infty} G(m) = \frac{2q}{1-q} - \frac{q^2}{1-q^2} = \frac{(1-p)(3-p)}{p(2-p)}$.

So above all,
$$E[M] = \frac{(1-p)(3-p)}{p(2-p)}$$
.

(d) 1. Let D = M - L as a delta.

So the joint PMF of L and M-L is that

$$P_{L,M-L}(l,d) = P_{L,D}(l,d) = P(L=l,M=l+d).$$

With what we get from (b) 1.,

If
$$l < 0, P_{L,M-L}(l,d) = 0$$
.

If $l \geq 0$:

when
$$d < 0$$
, $P_{L,M-L}(l,d) = 0$,

when
$$d = 0$$
, $P_{L,M-L}(l,d) = P(L = l, M = l) = p^2q^{2l}$.

when
$$d > 0$$
, $P_{L,M-L}(l,d) = P(L=l,M=l+d) = 2p^2q^{2l+d}$.

2. And from (b) 2. , we get that $P(L = l) = q^{2l}(1 - q^2)$.

$$P(D = d) = 0$$
, when $d < 0$ or $l < 0$,

When
$$d > 0, l \ge 0$$
: With LOTP, we can get that $P(D = d) = \sum_{l=0}^{+\infty} P(L = l, D = d) = \frac{2p^2q^d}{1 - q^2}$.

And when
$$d = 0, l \ge 0$$
, with LOTP, we can get that $P(D = d) = \sum_{l=0}^{+\infty} P(L = l, D = d) = \frac{p^2}{1 - q^2}$.

So when $l \ge 0, d \ge 0, P(D = d) > 0$, and P(L = l) > 0.

if
$$d = 0, P(L = l|D = d) = \frac{p^2q^{2l}}{p^2} = q^{2l}(1 - q^2),$$

if
$$d > 0, P(L = l | D = d) = \frac{\frac{p}{1 - q^2}}{\frac{2p^2q^{2l+d}}{1 - q^2}} = q^{2l}(1 - q^2).$$

So
$$P(L = l | D = d) = P(L = l), P(D = d) > 0.$$

So L and D, i.e. L and M-L are independent.

So above all, the joint PMF of L and M-L is that

$$P_{L,M-L}(l,d) = \begin{cases} p^2 q^{2l}, & d = 0, l \ge 0\\ 2p^2 q^{2l+d}, & d > 0, l \ge 0\\ 0, & otherwise \end{cases}$$