

Stochastic Processes

Assignment 1 - Solutions

1. A quadratic equation has real roots when the discriminant is non-negative, hence the probability that we're looking for is $P(U_2^2 - 4U_1U_3 \geq 0)$. We have,

$$P(U_2^2 - 4U_1U_3 \geq 0) = P((U_1, U_2, U_3) \in V) = \int_V f_{(U_1, U_2, U_3)}(u_1, u_2, u_3) dV$$

where $V = \{(u_1, u_2, u_3) | u_2^2 - 4u_1u_3 \geq 0, 0 \leq u_i \leq 1\}$. Due to the independence assumption,

$$f_{(U_1, U_2, U_3)}(u_1, u_2, u_3) = f_{U_1}(u_1)f_{U_2}(u_2)f_{U_3}(u_3) = 1, \quad 0 \leq u_i \leq 1, i = 1, 2, 3$$

So we have,

$$\int_V f_{(U_1, U_2, U_3)}(u_1, u_2, u_3) dV = \int_0^1 \int_0^1 \int_{\min(1, 2\sqrt{u_1u_3})}^1 du_2 du_3 du_1 = \frac{1}{36}(5 + 6\ln(2))$$

2. a. If $f_{(X,Y)}(x,y)$ is a joint density function, we know that f is non-negative and $\int_{S_{(X,Y)}^*} f = 1$ where $S_{(X,Y)}^* = \{(x,y) | f_{(X,Y)}(x,y) > 0\}$. Hence we have,

$$\int_0^\infty \int_{-x}^x f_{(X,Y)}(x,y) dy dx = \int_0^\infty \int_{-x}^x c(x^2 - y^2) e^{-x} dy dx = 1$$

After solving the above equation for c , we find that $c = 1/8$.

b. We can compute the marginal densities as follows, note that the domain $-x \leq y \leq x$ can be rewritten as $|y| \leq x$.

$$f_X(x) = \int_{-x}^x f_{(X,Y)}(x,y) dy = \int_{-x}^x \frac{1}{8}(x^2 - y^2)e^{-x} dy = \frac{1}{6}x^3e^{-x}$$

$$f_Y(y) = \int_{|y|}^\infty f_{(X,Y)}(x,y) dx = \int_{|y|}^\infty \frac{1}{8}(x^2 - y^2)e^{-x} dx = \frac{e^{-|y|}(|y| + 1)}{4}$$

c. We can compute the conditional densities as follows,

$$f_{Y|X}(y) = \frac{f_{(X,Y)}(x,y)}{f_X(x)} = \frac{1/8(x^2 - y^2)e^{-x}}{1/6(x^3e^{-x})} = \frac{3}{4} \left[\frac{1}{x} - \frac{y^2}{x^3} \right]$$

$$f_{X|Y}(x) = \frac{f_{(X,Y)}(x,y)}{f_Y(y)} = \frac{\frac{1}{8}(x^2 - y^2)e^{-x}}{\frac{e^{-|y|}(|y|+1)}{4}} = \frac{(x^2 - y^2)e^{-x}}{2e^{-|y|}(|y| + 1)}$$

3. We know that $T \sim E(\lambda)$ and $U|T = t \sim U[0, t]$. Therefore $f_T(t) = \lambda e^{-\lambda t}$ and $f_{U|T=t}(u) = 1/t$. Also note that if X be uniform on $[0, a]$ then $E(X) = a/2$ and $V(X) = a^2/12$.

a.

$$E(U) = E[E(U|T)] = E\left(\frac{T}{2}\right) = \int_0^\infty \frac{t}{2} \lambda e^{-\lambda t} dt = \frac{1}{2\lambda}$$

b. First, note that

$$\mathbb{E}(T^2/k) = \int_0^\infty \frac{t^2}{k} \lambda e^{-\lambda t} dt = \frac{2}{k\lambda^2}, \quad (1)$$

now we can compute the unconditional variance as follows,

$$\begin{aligned} V(U) &= V[\mathbb{E}(U|T)] + \mathbb{E}[V(U|T)] \\ &= V\left(\frac{T}{2}\right) + \mathbb{E}\left(\frac{T^2}{12}\right) \\ &= \left(\mathbb{E}\left(\frac{T^2}{4}\right) - \mathbb{E}^2\left(\frac{T}{2}\right)\right) + \mathbb{E}\left(\frac{T^2}{12}\right). \end{aligned}$$

Using (1), finally we have,

$$V(U) = \left(\frac{1}{2\lambda^2} - \frac{1}{4\lambda^2}\right) + \frac{1}{6\lambda^2} = \frac{5}{12\lambda^2}$$

4. a. For every positive integer n and every $s \in (-1, 1)$ we have,

$$\begin{aligned} \frac{d}{ds}G(s) &= \sum_{k=0}^{\infty} k s^{k-1} \mathbb{P}(X = k), \\ \frac{d^2}{ds^2}G(s) &= \sum_{k=0}^{\infty} k(k-1) s^{k-2} \mathbb{P}(X = k), \\ &\vdots \\ \frac{d^n}{ds^n}G(s) &= \sum_{k=0}^{\infty} \frac{k!}{(k-n)!} s^{k-n} \mathbb{P}(X = k). \end{aligned}$$

Hence,

$$\left. \frac{d^n}{ds^n}G(s) \right|_{s=0} = n! \mathbb{P}(X = n), \quad n = 1, 2, \dots$$

and finally,

$$\frac{1}{n!} \left. \frac{d^n}{ds^n}G(s) \right|_{s=0} = \mathbb{P}(X = n), \quad n = 1, 2, \dots$$

b.

$$\begin{aligned} \left. \frac{dG}{ds} \right|_{s=1} &= \sum_{k=0}^{\infty} k \mathbb{P}(X = k) = \mathbb{E}(X) \\ \left. \frac{d^2G}{ds^2} \right|_{s=1} &= \sum_{k=0}^{\infty} k(k-1) \mathbb{P}(X = k) = \mathbb{E}[X(X-1)] \end{aligned}$$

c. By our definition of probability-generating function we have $G_X(s) = \mathbb{E}(s^X)$. Define $t := \ln s$ so that $s = e^t$, then

$$G_X(s) = \mathbb{E}(s^X) = \mathbb{E}((e^t)^X) = \mathbb{E}(e^{tX}) = M_X(t) = M_X(\ln s)$$

d. Let X be a discrete random variable with a Poisson distribution with parameter λ for some $\lambda \in \mathbb{R}$. We know that $M_X(t) = e^{\lambda(e^t - 1)}$, then from part (c) we have,

$$G_X(t) = M_X(\ln t) = \exp[\lambda(e^{\ln t} - 1)] = e^{\lambda(t-1)}$$

5. a. Letting X denote the number of men that select their own hats, we can compute $E(X)$ by noting that $X = \sum_{i=1}^n X_i$ where,

$$X_i = \begin{cases} 1, & \text{if the } i\text{th man selects his own hat} \\ 0, & \text{otherwise} \end{cases}$$

Now, because the i th man is equally likely to select any of the n hats, it follows that

$$E(X_i) = P(X_i = 1) = P(\textit{ith man selects his own hat}) = \frac{1}{n}.$$

Hence we obtain,

$$E(X) = \sum_{i=1}^n E(X_i) = n \left(\frac{1}{n} \right) = 1$$

- b. Letting $X = \sum_{i=1}^n X_i$, where

$$X_i = \begin{cases} 1, & \text{if } i\text{th man selects his own hat} \\ 0, & \text{otherwise} \end{cases}$$

we obtain

$$\text{Var}(X) = \sum_{i=1}^n \text{Var}(X_i) + \sum_{i \neq j} \text{Cov}(X_i, X_j)$$

Since $X_i \sim B(1/n)$ for $i = 1, \dots, n$, we see

$$\text{Var}(X_i) = \frac{1}{n} \left(1 - \frac{1}{n} \right) = \frac{n-1}{n^2}$$

Also,

$$\text{Cov}(X_i, X_j) = E(X_i X_j) - E(X_i) E(X_j)$$

Now,

$$X_i X_j = \begin{cases} 1, & \text{if the } i\text{th and } j\text{th men both select their own hats} \\ 0, & \text{otherwise} \end{cases}$$

and thus

$$\begin{aligned} E[X_i X_j] &= P(X_i = 1, X_j = 1) \\ &= P(X_i = 1) P(X_j = 1 \mid X_i = 1) \\ &= \frac{1}{n} \frac{1}{n-1} \end{aligned}$$

Hence,

$$\text{Cov}(X_i, X_j) = \frac{1}{n(n-1)} - \left(\frac{1}{n} \right)^2 = \frac{1}{n^2(n-1)}$$

and

$$\begin{aligned} \text{Var}(X) &= \frac{n-1}{n} + 2 \binom{n}{2} \frac{1}{n^2(n-1)} \\ &= \frac{n-1}{n} + \frac{1}{n} \\ &= 1 \end{aligned}$$

c. Let X denote the number of matches, and let X_1 equal 1 if the first person has a match and 0 otherwise. Then,

$$\begin{aligned} E[X] &= E[X \mid X_1 = 0] P(X_1 = 0) + E[X \mid X_1 = 1] P(X_1 = 1) \\ &= E[X \mid X_1 = 0] \frac{n-1}{n} + E[X \mid X_1 = 1] \frac{1}{n} \end{aligned}$$

But, by (a)

$$E[X] = 1$$

Moreover, given that the first person has a match, the expected number of matches is equal to 1 plus the expected number of matches when $n-1$ people select among their own $n-1$ hats, showing that

$$E[X \mid X_1 = 1] = 2$$

Therefore, we obtain the result

$$E[X \mid X_1 = 0] = \frac{n-2}{n-1}$$

6. a. To prove independence, we can equivalently show that

$$M_{(X,Y,Z)}(t, u, v) = M_X(t)M_Y(u)M_Z(v). \quad (2)$$

We have,

$$\begin{aligned} M_X(t) &= M_{(X,Y,Z)}(t, 0, 0) = e^{t+t^2} \\ M_Y(u) &= M_{(X,Y,Z)}(0, u, 0) = e^{2u^2} \\ M_Z(v) &= M_{(X,Y,Z)}(0, 0, v) = \frac{1}{1-v}. \end{aligned}$$

Therefore, equality (2) holds.

b. According to the assumption of independence that we proved in (a), we can rewrite the required expected value as below,

$$E[e^{2X}(Y^2 + Z)] = E(e^{2X}) E(Y^2 + Z)$$

Hence we have,

$$\begin{aligned} E(e^{2X}) E(Y^2 + Z) &= E(e^{2X}) [E(Y^2) + E(Z)] \\ &= M_X(2) \left[\frac{d^2}{du^2} M_Y(u) \Big|_{u=0} + \frac{d}{dv} M_Z(v) \Big|_{v=0} \right] \\ &= e^6 \left[4e^{2u^2}(1 + 4u^2) \Big|_{u=0} + \frac{1}{(1-v)^2} \Big|_{v=0} \right] = 5e^6 \end{aligned}$$