

## Math 302, Assignment 4

1. Suppose that  $X$  has moment generating function

$$M_X(t) = \frac{1}{3}e^{-3t} + \frac{1}{6} + \frac{1}{2}e^t.$$

- (a) Find the mean and variance of  $X$  by differentiating the m.g.f. above.  
 (b) Find the p.m.f. of  $X$ . Use your expression for the p.m.f. to check your answers from part (a).

**Solutions:** (a) We have

$$\begin{aligned}\mu &= M'_X(0) = -1 + \frac{1}{2} = -\frac{1}{2} \\ \sigma^2 &= M''_X(0) - \frac{1}{4} = 3 + \frac{1}{4} - \frac{1}{4} = \frac{13}{4}\end{aligned}$$

(b) By looking at the m.g.f., we recognize that  $X$  takes values  $-3, 0, 1$ , with  $\mathbb{P}(X = -3) = \frac{1}{3}$ ,  $\mathbb{P}(X = 0) = \frac{1}{6}$ ,  $\mathbb{P}(X = 1) = \frac{1}{2}$ . Therefore, we can calculate again

$$\begin{aligned}\mu &= \frac{1}{3} \cdot (-3) + \frac{1}{6} \cdot (0) + \frac{1}{2} \cdot 1 = -\frac{1}{2} \\ \sigma^2 &= \left( \frac{1}{3} \cdot (-3)^2 + \frac{1}{6} \cdot (0)^2 + \frac{1}{2} \cdot (1)^2 \right) - \frac{1}{4} = \frac{9}{4}\end{aligned}$$

2. You have two dice, one with three sides labeled  $0, 1, 2$  and one with 4 sides, labeled  $0, 1, 2, 3$ . Let  $X_1$  be the outcome of rolling the first die, and  $X_2$  the outcome of rolling the second. The rolls are independent.
- (a) What is the joint p.m.f. of  $(X_1, X_2)$ ?  
 (b) Let  $Y_1 = X_1 \cdot X_2$  and  $Y_2 = \max\{X_1, X_2\}$ . Make a table for the joint p.m.f. of  $(Y_1, Y_2)$ .  
 (c) Are  $Y_1, Y_2$  independent?

**Solution:** (a) By independence we have  $p(x, y) = (1/3)(1/4) = 1/12$  for all  $x \in \{0, 1, 2\}$  and  $y \in \{0, 1, 2, 3\}$ .

(b)

Table 1: The p.m.f. of  $(Y_1, Y_2)$  with the marginals.

$Y_1 \downarrow Y_2 \rightarrow$	0	1	2	3	$p_{Y_1}$
0	1/12	1/6	1/6	1/12	1/2
1	0	1/12	0	0	1/12
2	0	0	1/6	0	1/6
3	0	0	0	1/12	1/12
4	0	0	1/12	0	1/12
6	0	0	0	1/12	1/12
$p_{Y_2}$	1/12	1/4	5/12	1/4	

(c) For the marginal distributions see the margins of the above table. Since

$$\mathbb{P}(Y_1 = 1, Y_2 = 0) = 0 \neq \mathbb{P}(Y_1 = 1)\mathbb{P}(Y_2 = 0),$$

the variables  $Y_1$  and  $Y_2$  are not independent.

3. Let  $X \sim \text{Exp}(2)$ ,  $Y \sim \text{Unif}([1, 3])$ , and assume that  $X$  and  $Y$  are independent. Calculate  $\mathbb{P}(Y - X \geq \frac{1}{2})$ .

**Solution:** The joint density function is

$$f(x, y) = f_X(x)f_Y(y) = \begin{cases} e^{-2x} & \text{if } x > 0 \text{ and } 1 < y < 3, \\ 0 & \text{otherwise.} \end{cases}$$

Let  $T$  be defined by

$$T = \{(x, y) : x > 0, 1 < y < 3, x \leq y - 1/2\},$$

then we have

$$\begin{aligned} \mathbb{P}(Y - X \geq 1/2) &= \iint_T f(x, y) \, dy \, dx \\ &= \int_1^3 \int_0^{y-\frac{1}{2}} e^{-2x} \, dx \, dy \\ &= \frac{1}{2} \int_1^3 1 - e^{-2y+1} \, dy \\ &= 1 + e \left[ \frac{1}{2} e^{-2y} \right]_1^3 = 1 + \frac{1}{2} e^{-5} - \frac{1}{2} e^{-1}. \end{aligned}$$

4. The random variables  $X, Y$  have joint probability density function

$$f(x, y) = \begin{cases} C \frac{e^{-x} - e^{-x-2y}}{e^y - 1} & \text{if } x > 0 \text{ and } y > 0, \\ 0 & \text{otherwise.} \end{cases}$$

- (a) What is the value of  $C$ ?
- (b) Are  $X$  and  $Y$  independent?
- (c) Find  $\mathbb{P}(X < Y)$ .

**Solution:** (a) We have

$$1 = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \, dx \, dy = C \int_0^{\infty} e^{-x} \, dx \int_0^{\infty} \frac{1 - e^{-2y}}{e^y - 1} \, dy = \frac{3}{2} C,$$

thus  $C = \frac{2}{3}$ .

- (b) The variables  $X$  and  $Y$  are independent since the joint p.d.f. factors into a function of  $x$  times a function of  $y$ .

(c) Let  $E = \{(x, y) : x < y\}$ , then

$$\begin{aligned}\mathbb{P}(X < Y) &= \iint_E f(x, y) \, dx \, dy = \frac{2}{3} \int_0^\infty \frac{1 - e^{-2y}}{e^y - 1} \int_0^y e^{-x} \, dx \, dy \\ &= \frac{2}{3} \int_0^\infty \frac{1 - e^{-2y}}{e^y - 1} (1 - e^{-y}) \, dy \\ &= \frac{2}{3} \int_0^\infty (e^{-y} - e^{-3y}) \, dy = \frac{2}{3} (1 - 1/3) = \frac{4}{9}.\end{aligned}$$

5. Let  $X_1$  and  $X_2$  be two discrete random variables with joint p.m.f.  $\mathbb{P}(X_1 = k_1, X_2 = k_2)$ . Prove the following claims from the lecture:

(a) If  $g : \mathbb{R}^2 \rightarrow \mathbb{R}$  is a function, then

$$\mathbb{E} g(X_1, X_2) = \sum_{k_1, k_2} g(k_1, k_2) \cdot \mathbb{P}(X_1 = k_1, X_2 = k_2).$$

*Hint:* Remember that the left hand side is by definition  $\mathbb{E} g(X_1, X_2) = \sum_l l \cdot \mathbb{P}(g(X_1, X_2) = l)$ , where the sum is over all values of  $g(X_1, X_2)$ , i.e. over all  $l$  such that  $l = g(k_1, k_2)$  for some value  $k_1$  of  $X_1$  and some value  $k_2$  of  $X_2$ .

(b)  $\mathbb{E}[X_1 + X_2] = \mathbb{E} X_1 + \mathbb{E} X_2$ . Hint: Use part (a).

**Solution:** (a) Consider the set  $V_1$  of possible values of  $X_1$ , and  $V_2$  of  $X_2$ . In other words,  $V_1$  consists of all  $k_1$  such that  $\mathbb{P}(X_1 = k_1) > 0$ , and similarly for  $V_2$ . Consider now  $L = g(V_1, V_2) = \bigcup_{(k_1, k_2)} \{g(k_1, k_2)\}$ .

By definition, we have

$$\mathbb{E} g(X_1, X_2) = \sum_{\ell \in L} \ell \cdot \mathbb{P}(g(X_1, X_2) = \ell).$$

Now, observe that  $\{g(X_1, X_2) = \ell\}$  is the event consisting of the union of all events  $\{X_1 = k_1, X_2 = k_2\}$  where the pair  $(k_1, k_2)$  satisfies  $g(k_1, k_2) = \ell$ . Thus, by additivity of the probability

$$\mathbb{P}(g(X_1, X_2) = \ell) = \sum_{g(k_1, k_2) = \ell} \mathbb{P}(X_1 = k_1, X_2 = k_2).$$

Then,

$$\begin{aligned}\mathbb{E} g(X_1, X_2) &= \sum_{\ell \in L} \sum_{g(k_1, k_2) = \ell} \ell \cdot \mathbb{P}(X_1 = k_1, X_2 = k_2) \\ &= \sum_{\substack{\ell \in L \\ g(k_1, k_2) = \ell}} g(k_1, k_2) \cdot \mathbb{P}(X_1 = k_1, X_2 = k_2).\end{aligned}$$

Next, observe that  $\bigcup_{\ell \in L} \bigcup_{g(k_1, k_2) = \ell} \{(k_1, k_2)\}$  is the set of possible values of  $(X_1, X_2)$  (this is a tautology).

Therefore,

$$\mathbb{E} g(X_1, X_2) = \sum_{(k_1, k_2)} g(k_1, k_2) \cdot \mathbb{P}(X_1 = k_1, X_2 = k_2).$$

This proves the claim.

(b) By part (a) and the axioms of probability, we have

$$\begin{aligned}\mathbb{E}(X_1 + X_2) &= \sum_{k_1, k_2} (k_1 + k_2) \mathbb{P}(X_1 = k_1, X_2 = k_2) \\ &= \sum_{k_1, k_2} k_1 \mathbb{P}(X_1 = k_1, X_2 = k_2) + \sum_{k_1, k_2} k_2 \mathbb{P}(X_1 = k_1, X_2 = k_2) \\ &= \sum_{k_1} k_1 \mathbb{P}(X_1 = k_1) + \sum_{k_2} k_2 \mathbb{P}(X_2 = k_2) = \mathbb{E}X_1 + \mathbb{E}X_2.\end{aligned}$$

6. Let  $X$  and  $Y$  be either two independent Poisson RV's, or two independent Exponential RV's, with parameters  $\mu, \lambda$ . Compute the p.m.f. / p.d.f. of  $X + Y$ .

**Solution:**

Case Poisson: Remember that a Poisson RV takes values  $k = 0, 1, 2, \dots$  with probability  $\mathbb{P}(X = k) = \frac{\lambda^k}{k!} e^{-\lambda}$ . If  $X, Y$  are independent Poisson, we therefore have that  $X + Y$  also takes values  $0, 1, 2, \dots$ , and we have to find  $\mathbb{P}(X + Y = k)$ .

First, we need to find all solutions to  $x + y = k$ , where  $x, y \in \{0, 1, 2, \dots\}$ . Clearly, these are just the pairs  $(0, k), (1, k - 1), (2, k - 2), \dots, (k - 1, 1), (k, 0)$ . Now, we have to sum the joint p.m.f. of  $X$  and  $Y$  over these pairs (the joint p.m.f. is just the product of the individual p.m.f.'s by independence). We get

$$\begin{aligned}\mathbb{P}(X + Y = k) &= \sum_{x=0}^k \mathbb{P}(X = x, Y = k - x) \\ &= \sum_{x=0}^k \frac{\lambda^x}{x!} e^{-\lambda} \cdot \frac{\mu^{k-x}}{(k-x)!} e^{-\mu} \\ &= e^{-\lambda-\mu} \frac{1}{k!} \sum_{x=0}^k \frac{k!}{x!(k-x)!} \lambda^x \mu^{k-x} = e^{-\lambda-\mu} \frac{(\lambda + \mu)^k}{k!}\end{aligned}$$

where in the last step, we used the binomial theorem. Thus we have determined the p.m.f. of  $X + Y$ . We note that it is just the p.m.f. of Poisson RV with parameter  $\lambda + \mu$ . Thus, a sum of two independent Poisson RV's is again Poisson, with the sum of the parameters.

Case Exponential: Remember that the p.d.f. of Exponential is

$$f_X(x) = \begin{cases} \lambda e^{-\lambda x} & x > 0 \\ 0 & x \leq 0 \end{cases}$$

We now use the convolution formula

$$f_{X+Y}(y) = \int_{-\infty}^{\infty} f_X(x) f_Y(y - x) dx.$$

Note that the integrand vanishes when  $x < 0$  since  $f_X(x)$  is zero there. It also vanishes if  $x > y$ , since  $f_Y(y - x)$  has a negative argument for such  $x$ , and so vanishes. Thus, if  $y < 0$ , the integral vanishes, and

if  $y > 0$ , it equals

$$f_{X+Y}(y) = \int_0^y \lambda e^{-\lambda x} \cdot \mu e^{-\mu(y-x)} dx = \lambda \cdot \mu \cdot e^{-\mu y} \cdot \int_0^y e^{(\mu-\lambda)x} dx = \frac{\lambda\mu}{\mu-\lambda} [e^{-\lambda y} - e^{-\mu y}].$$

(This holds for  $\mu \neq \lambda$ . For  $\mu = \lambda$ , we get  $\lambda^2 \cdot y \cdot e^{-\lambda y}$ ).

7. Compute the moment generating functions of the  $\text{Geom}(p)$  and the  $\text{Exp}(\lambda)$  random variables.

**Solution:**

Case Geometric: Using the definition of the m.g.f. and the geometric series, we get

$$\begin{aligned} \mathbb{E}e^{t \cdot \text{Geom}(p)} &= \sum_{k \geq 1} e^{tk} \cdot \mathbb{P}(\text{Geom}(p) = k) \\ &= \sum_{k \geq 1} e^{tk} \cdot p \cdot (1-p)^{k-1} \\ &= p \cdot e^t \cdot \sum_{k \geq 1} (e^t)^{k-1} \cdot (1-p)^{k-1} = \frac{p \cdot e^t}{1 - (1-p)e^t} \end{aligned}$$

Note: We could now compute the mean / variance from this function by taking derivatives at 0. Compare this to the tricks we needed in the lecture to compute the mean of Geometric!

Case Exponential: Using the definition, we have

$$\begin{aligned} \mathbb{E}e^{t \cdot \text{Exp}(\lambda)} &= \int_{-\infty}^{\infty} e^{t \cdot x} f(x) dx \\ &= \int_0^{\infty} e^{t \cdot x} \cdot \lambda e^{-\lambda x} dx \\ &= \begin{cases} \frac{\lambda}{\lambda-t} & t < \lambda \\ \infty & \text{else} \end{cases} \end{aligned}$$

- 8.\* Let  $X$  be a continuous random variable with p.d.f.  $f(x)$  and  $g : \mathbb{R} \rightarrow \mathbb{R}$  be a strictly increasing function. Show that the p.d.f. of  $g(X)$  equals

$$f_{g(X)}(y) = \frac{f(g^{-1}(y))}{g'(g^{-1}(y))}$$

**Solution:**

We compute the c.d.f., using that  $g$  is strictly increasing.

$$F_{g(X)}(b) = \mathbb{P}(g(X) \leq b) = \mathbb{P}(X \leq g^{-1}(b)) = F_X(g^{-1}(b)).$$

Here,  $g^{-1}(b)$  is the inverse function of  $g$  (e.g.  $g^{-1}(b) = \sqrt{b}$  if  $g(x) = x^2$ , or  $g^{-1}(b) = \arctan b$  if  $g(x) = \tan x$ ). Using the chain rule

$$\begin{aligned} \frac{d}{dx} F_{g(X)}(x) &= F'_X(g^{-1}(x)) \cdot \frac{d}{dx} g^{-1}(x) \\ &= f_X(g^{-1}(x)) \cdot \frac{1}{g'(g^{-1}(x))}, \end{aligned}$$

where we used a theorem about the derivative of the inverse function.