

# HW3

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## HW 3

NAME: SAM OLSON

COLLABORATORS: **The Hatman**

### Overview

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1. 2.23(b)

### Question 1

Let  $X$  have the pdf

$$f(x) = \frac{1}{2}(1+x)$$

,  $-1 < x < 1$

Define the random variable  $Y$  by  $Y = X^2$

(b): Find  $E(Y)$  and  $\text{Var}(Y)$ .

### Answer 1

(b):

(From prior HW) Note from the results of theorem 2.1.8:

$$f_Y(y) = \begin{cases} \sum_{i=1}^k f_X(g_i^{-1}(y)) \left| \frac{d}{dy} g_i^{-1}(y) \right| & y \in \mathbb{Y} \\ 0 & \text{otherwise} \end{cases}$$

Note: For  $X \in [-1, 1]$ , we have  $Y = X^2 \in [0, 1]$

Over the following partitions, we have monotonicity,

$$A_1 = (-1, 0) \rightarrow X = -\sqrt{y}, \text{ as } g_1(x) = x^2, \text{ and}$$

$$A_2 = (0, 1) \rightarrow X = \sqrt{y}, \text{ as } g_2(x) = x^2$$

Taking the absolute value of the derivatives,  $|\frac{d}{dy}g_i^{-1}(y)|$ , we have:

$$|\frac{d}{dy}g_1^{-1}(y)| = |\frac{d}{dy}g_2^{-1}(y)| = \frac{1}{2}y^{-1/2}$$

Thus we have

$$f_Y(y) = \frac{1}{2}y^{-1/2} \frac{1}{2}[(1 + \sqrt{y}) + (1 - \sqrt{y})] = \frac{1}{4}y^{-1/2}[2] = \frac{1}{2}y^{-1/2}$$

Such that we have the pdf of Y as:

$$f_Y(y) = \frac{1}{2}y^{-1/2}, 0 < y < 1$$

Using this for our Expected value calculation we have:

$$\begin{aligned} E(Y) &= \int_{y \in \mathbb{Y}} y f(y) dy = \int_{y=0}^1 y \left(\frac{1}{2\sqrt{y}}\right) dy \\ E(Y) &= \int_{y=0}^1 \sqrt{y} \left(\frac{1}{2}\right) dy = \frac{1}{2} \frac{2}{3} y^{3/2} \Big|_{y=0}^{y=1} = \frac{1}{2} \frac{2}{3} (1) - 0 = \frac{1}{3} \end{aligned}$$

To calculate  $\text{Var}(Y)$ , let us consider  $E(Y^2)$ ,

$$\begin{aligned} E(Y^2) &= \int_{y \in \mathbb{Y}} y^2 f(y) dy = \int_{y=0}^1 y^2 \left(\frac{1}{2\sqrt{y}}\right) dy \\ E(Y^2) &= \int_{y=0}^1 y^{3/2} \frac{1}{2} dy = \frac{2}{5} \left(\frac{1}{2}\right) y^{5/2} \Big|_{y=0}^{y=1} = \frac{2}{5} \left(\frac{1}{2}\right) (1) - 0 = \frac{2}{10} = \frac{1}{5} \end{aligned}$$

Taking  $\text{Var}(Y) = E(Y^2) - (E(Y))^2$ , then,

$$\text{Var}(Y) = \frac{1}{5} - \left(\frac{1}{3}\right)^2 = \frac{1}{5} - \frac{1}{9} = \frac{9}{45} - \frac{5}{45} = \frac{4}{45}$$

2.

### Question 2

A family continues to have children until they have one female child. Suppose, for each birth, a single child is born and the child is equally likely to be male or female. The gender outcomes are independent across births.

(a): Let  $X$  be a random variable representing the number of children born to this family. Find the distribution of  $X$ .

(b): Find the expected value  $E(X)$

(c): Let  $X_m$  denote the number of male children in this family and let  $X_f$  denote the number of female children. Find the expected value of  $X_m$  and the expected value of  $X_f$

### Answer 2

(a): We can frame  $X$  as the number of children until the family has their first (one) female child. So we can think of  $X$  as a Geometric distribution with probability  $p = 0.5$  since it is equally likely that they have a male/female for each birth.

Notation-wise we write this as:

$$X \sim \text{Geometric}(p = 0.5)$$

(b):

Knowing the distribution of  $X$ , we know its pmf (discrete!) is given by:

For  $X$  number of children,  $k = 1, 2, \dots$ , we have:

$$f_X(x) = P(X = x) = p(1 - p)^{x-1}$$

$$E(X) = \sum_{x=1}^{\infty} xP(X = x) = \sum_{k=x}^{\infty} x(p(1 - p)^{x-1}) = p \sum_{x=1}^{\infty} x((1 - p)^{k-1})$$

Note, for the infinite geometric series we have, for  $|r| < 1$ ,  $k$  some positive integer, the following holds:

$$\sum_{k=1}^{\infty} r^k = \frac{1}{1 - r}$$

Note: Let  $q = 1 - p$  for simplicity. As  $0 < p < 1 \rightarrow 0 < 1 - p < 1 \rightarrow 0 < q < 1$ . For our purposes, we have  $|q| < 1$ , such that the above relation holds for an infinite geometric series:

$$\sum_{x=1}^{\infty} q^x = \frac{1}{1 - q}$$

Note then:

$$\frac{d}{dq} \left( \sum_{x=1}^{\infty} q^x \right) = \sum_{x=1}^{\infty} \left( \frac{d}{dq} q^x \right) = \sum_{x=1}^{\infty} xq^{x-1}$$

Additionally,

$$\frac{d}{dq}\left(\frac{1}{1-q}\right) = \frac{d}{dq}[(1-q)^{-1}] = \frac{1}{(1-q)^2} = (1-q)^{-2}$$

Thus we have:

$$E(X) = p(1-q)^{-2} = p(1-(1-p))^{-2} = p(p)^{-2} = p^{-1} = \frac{1}{p}$$

For  $p = 0.5$ , we have:

$$E(X) = \frac{1}{p} = \frac{1}{0.5} = 2$$

Or, on average they would have two children before they have their first female.

(c):

Note:  $X_f$  and  $X_m$  are subsets of the random variable  $X$ , specifically  $X_f + X_m = X$ .

We stop the “experiment” at the first female child, so we will only ever have 1 female child, meaning:

$$E(X_f) = 1$$

The number of male children then is the number of children we expect to have minus the number of female children, which is:

$$E(X_m) = E(X) - E(X_f) = 2 - 1 = 1$$

We expect to have two children, one child is female and the other is male.

3. 2.30 (a), (b), (c)

### Question 3

Find the moment generating function corresponding to:

(a):  $f(x) = \frac{1}{c}, 0 < x < c$

(b):  $f(x) = \frac{2x}{c^2}, 0 < x < c$

(c):  $f(x) = \frac{1}{2\beta} e^{-\frac{|x-\alpha|}{\beta}}, -\infty < x < \infty, -\infty < \alpha < \infty, \beta > 0$

### Answer 3

Note, for a continuous random variable X, we may write the moment generating function as:

$$M_X(t) = \int_{-\infty}^{\infty} e^{tx} f_X(x) dx$$

Using this method, we then calculate the following:

(a):

$$M_X(t) = \int_{-\infty}^{\infty} e^{tx} f_X(x) dx = \int_0^c e^{tx} \frac{1}{c} dx = \frac{1}{ct} e^{tx} \Big|_{x=0}^{x=c} = \frac{1}{ct} e^{tc} - \frac{1}{ct} (1)$$

$$M_X(t) = \frac{1}{ct} e^{tc} - \frac{1}{ct} (1) = \frac{1}{ct} (e^{tc} - 1)$$

Note: For  $t = 0$ ,  $\frac{1}{ct}$  is not defined, so the above mgf is defined for  $t \neq 0$ .

(b):

$$M_X(t) = \int_{-\infty}^{\infty} e^{tx} f_X(x) dx = \int_0^c e^{tx} \frac{2x}{c^2} dx$$

Via integration by parts, let  $u = x, du = 1$  such that  $dv = \frac{2e^{tx}}{c^2} \Rightarrow v = \frac{2e^{tx}}{tc^2}$

So our formula now is

$$M_X(t) = \int u dv = uv - \int v du = x \frac{2e^{tx}}{tc^2} - \frac{2e^{tx}}{t^2 c^2} = xt \frac{2e^{tx}}{t^2 c^2} - \frac{2e^{tx}}{t^2 c^2}$$

Simplifying, we then evaluate over the original range (support of X), giving us:

$$M_X(t) = \frac{2}{c^2 t^2} e^{tx} (tx - 1) \Big|_{x=0}^{x=c}$$

$$M_X(t) = \frac{2}{c^2 t^2} e^{tc} (tc - 1) - \left( \frac{2}{c^2 t^2} 1(-1) \right) = \frac{2}{c^2 t^2} (tce^{tc} - e^{tc} + 1)$$

Note: For  $t = 0$ ,  $\frac{1}{c^2 t^2}$  is not defined, so the above mgf is defined for  $t \neq 0$ .

(c):

$$M_X(t) = \int_{-\infty}^{\infty} e^{tx} f_X(x) dx = \int_{-\infty}^{\infty} e^{tx} \frac{1}{2\beta} e^{\frac{-|x-\alpha|}{\beta}} dx$$

With regards to the usage of  $-|x-\alpha|$ , when  $x < \alpha \rightarrow (x-\alpha) < 0$  and when  $x \geq \alpha \rightarrow (x-\alpha) \geq 0$

Thus, we may break the above integration into two parts, namely:

$$M_X(t) = \int_{-\infty}^{\alpha} e^{tx} \frac{1}{2\beta} e^{\frac{(x-\alpha)}{\beta}} dx + \int_{\alpha}^{\infty} e^{tx} \frac{1}{2\beta} e^{\frac{-(x-\alpha)}{\beta}} dx$$

1.

$$\int_{-\infty}^{\alpha} e^{tx} \frac{1}{2\beta} e^{\frac{(x-\alpha)}{\beta}} dx = \frac{e^{tx+(x-\alpha)/\beta}}{2(t\beta+1)} \Big|_{x=-\infty}^{\alpha} = \frac{e^{t\alpha}}{2(t\beta+1)} - 0 = \frac{e^{t\alpha}}{2(t\beta+1)}$$

2.

$$\int_{\alpha}^{\infty} e^{tx} \frac{1}{2\beta} e^{\frac{-(x-\alpha)}{\beta}} dx = \frac{e^{tx-(x-\alpha)/\beta}}{2(t\beta-1)} \Big|_{x=\alpha}^{\infty} = 0 - \frac{e^{t\alpha}}{2(t\beta-1)} = -\frac{e^{t\alpha}}{2(t\beta-1)}$$

3.

Combining the above (1.) and (2.) together we then have:

$$M_X(t) = \frac{e^{t\alpha}}{2(t\beta+1)} - \frac{e^{t\alpha}}{2(t\beta-1)} = \frac{4e^{t\alpha}}{4-\beta^2 t^2}$$

Note, we need to ensure the above Mgf of X evaluates, so we need to specify the conditions where the denominator is not equal to 0 (divide by zero error!).

For a fixed  $\beta$ , consider:  $4 - \beta^2 t^2 = 0 \rightarrow 4 = \beta^2 t^2 \rightarrow 4/\beta^2 = t^2$

So the denominator is equal to 0 when  $t = \sqrt{4/\beta^2} = \pm 2/\beta$

However, we also know that  $M_X(t) \geq 0$ , (as we assume  $f(x)$  is a pdf, hence  $f(x) \geq 0 \forall t$ , so we actually have bounds for  $t$ , namely:

The above mgf is defined for  $-2/\beta < t < 2/\beta$ , where  $\beta > 0$ .

**Question 4**

Does a distribution exist for which  $M_X(t) = \frac{t}{(1-t)}$ ,  $|t| < 1$ ? If yes, find it. If no, prove it.

**Answer 4**

Let us suppose that the distribution exists.

Then by the definition of a(n) mfg, using the existence of the distribution we have:

$$M_X(t) = E(e^{tX})$$

We know for  $t = 0$  that the relation  $|t| = |0| = 0 < 1$  holds.

Thus we know the 0-th moment is defined:

$$M_X(0) = E(e^{0X}) = E(e^0) = E(1) = 1$$

However, if we evaluate  $M_X(t)$  directly using the mgf as given, for  $t = 0$  as given, we have:

$$M_X(t) = \frac{t}{(1-t)} = \frac{0}{1-0} = 0$$

And we arrive at a contradiction. Thus we must conclude that such a distribution does not exist.

5.

### Question 5

Suppose that  $X$  has the standard normal distribution with pdf:

$$f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$

,  $-\infty < x < \infty$

Then the random variable  $Y$ ,  $Y = e^X$  has a log-normal distribution.

(a): Find  $E(Y^r)$  for any  $r$ .

(b): Show the moment generating function of  $Y$  does not exist (even though all moments of  $Y$  exist).

### Answer 5

(a):

$$E(Y^r) = E((e^X)^r) = E(e^{rX})$$

$$E(Y^r) = \int_{-\infty}^{\infty} e^{rx} f(x) dx = \int_{-\infty}^{\infty} e^{rx} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx$$

$$E(Y^r) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{rx - \frac{x^2}{2}} dx = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}(x^2 - 2rx)} dx$$

$$E(Y^r) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}((x-r)^2 - r^2)} dx = e^{\frac{r^2}{2}} \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}(x-r)^2} dx$$

The below is the normal distribution, which evaluates to  $\sqrt{2\pi}$

$$\int_{-\infty}^{\infty} e^{-\frac{1}{2}(x-r)^2} dx = \sqrt{2\pi}$$

So we have:

$$E(Y^r) = \sqrt{2\pi} e^{\frac{r^2}{2}} \frac{1}{\sqrt{2\pi}} = e^{r^2/2}$$

(b):

Part (a) shows that all moments of  $Y$  exist. We must then show that the moment generating function of  $Y$  does not exist.

To that end, let us consider the moment generating function of  $Y$ :

$$M_Y(t) = E(e^{tY}) = E(e^{te^X})$$

$$M_Y(t) = \int_{-\infty}^{\infty} e^{te^x} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx$$



$$M_Y(t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{te^x} e^{-\frac{x^2}{2}} dx = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{te^x - \frac{x^2}{2}} dx$$

Note: For  $x > 0$ , define some positive real  $c$ ,  $c > 0$

There exists a sufficiently large  $x_0$  such that for  $x > x_0$ :

$$te^x - \frac{x^2}{2} > 0$$

Meaning:  $te^x - \frac{x^2}{2} \geq c > 0$

Note the exponential function is a positive monotonic transformation, such that the following holds:

$$e^{te^x - \frac{x^2}{2}} > e^c > 0, \text{ such that:}$$

With note that we are working with a non-negative function,

$$M_Y(t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{te^x - \frac{x^2}{2}} dx \geq \frac{1}{\sqrt{2\pi}} \int_{x_0}^{\infty} e^{te^x - \frac{x^2}{2}} dx \geq \frac{1}{\sqrt{2\pi}} \int_{x_0}^{\infty} e^c dx = \infty$$

As the integral does not converge to a finite value, we say the moment generating function does not exist for positive real  $t$ .

6.

### Question 6

Suppose that  $X$  has a normal distribution with pdf:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

,  $-\infty < x < \infty$

The mean of  $X$  is  $\mu$ . Show that the moment generating function of  $X$  satisfies  $M_X(t) \geq e^{t\mu}$

### Answer 6

With note of Jensen's Inequality, we have, for a convex function  $g$ , (avoiding confusion of the usage of  $f$  with the above pdf),

Let us then consider the moment generation function of  $X$ ,

$$M_X(t) = E(e^{tX})$$

Consider then the function  $e^{tX}$ , specifically its second derivative:

$$\frac{d^2}{dx^2} e^{tX} = t^2 e^{tX} > 0$$

,  $\forall x, t$

We may then note that the mgf of  $X$  is convex since its second derivative is positive.

This is advantageous to our purposes, as we know when applying Jensen's inequality that we have a convex function, such that we may write:

Since  $E(X) = \mu$ ,

$$M_X(t) = E[e^{tX}] \geq e^{tE(X)} = e^{t\mu}$$

And we conclude

$$M_X(t) \geq e^{t\mu}$$

7.

### Question 7

Suppose that  $X$  has pmf  $f(x) = p(1-p)^{x-1}$ , for  $x = 1, 2, 3, \dots$  where  $0 < p < 1$ . Find the mgf  $M_X(t)$  and use this to derive the mean and variance of  $X$ .

### Answer 7

For deriving the mean and variance of  $X$ , we will need to first define the mgf of  $X$  as:

$$M_X(t) = E(e^{tX}) = \sum_{x=1}^{\infty} e^{tx} f(x) = \sum_{x=1}^{\infty} e^{tx} p(1-p)^{x-1}$$

The mean  $\mu = E(X)$  is equal to the first derivative of the mgf evaluated at  $t = 0$ :

$$E(X) = M'_X(0)$$

$$M'_X(t) = \frac{pe^t(1-p)}{(1-e^t(1-p))^2}$$

$$M'_X(0) = \frac{p(1-p)}{(1-(1-p))^2} = \frac{1}{p}$$

$$E(X) = \frac{1}{p}$$

We then derive the variance of  $X$ . We know the typical variance formula as:  $\text{Var}(X) = E(X^2) - (E(X))^2$

However, we just calculated  $E(X)$ ! Additionally, we know that  $E(X^2)$  is equal to the second derivative of the mgf at  $t = 0$ . As such we write:

$$M''_X(t) = \frac{pe^t(1-p)(1-e^t(1-p)+e^t(1-p))}{(1-e^t(1-p))^3}$$

To make computation easier, let  $q = 1 - p$ . Then, for  $t = 0$ ,

$$M''_X(0) = \frac{p - pq^2}{(1-q)^4} = \frac{p(1-q^2)}{(1-q)^4} = \frac{p(1+q)}{(1-q)^3} = \frac{1+q}{p^2}$$

Taking this calculation minus the square of the mean gives us:

$$\text{Var}(X) = M''_X(0) - (M'_X(0))^2 = \frac{1+q}{p^2} - \frac{1}{p^2} = \frac{q}{p^2} = \frac{1-p}{p^2}$$

And we conclude then

$$\text{Var}(X) = \frac{1-p}{p^2}$$

8.

### Question 8

Suppose for one month a company purchases  $c$  copies of a software package at a cost of  $d_1$  dollars per copy. The packages are sold to customers for  $d_2$  dollars per copy; any unsold copies are destroyed at the end of the month. Let  $X$  represent the demand for this software package in the month. Assume that  $X$  is a discrete random variable with pmf  $f(x)$  and cdf  $F(x)$ .

(a): Let  $s = \min\{X, c\}$  represent the number of sales during the month. Show that:

$$E(S) = \sum_{x=0}^c xf(x) + c(1 - F(c))$$

(b): Let  $Y = S * d_2 - cd_1$  represent the profit for the company, the total income from sales minus the total cost of all copies. Find  $E(Y)$

(c): As  $Y \equiv Y_c$  depends on integer  $c \geq 0$ , write the expected profit function as  $g(c) \equiv E(Y_c)$  from part (b). The company should choose the value of  $c$  which maximizes  $g(c)$ ; that is, choose the smallest  $c$  such that  $g(c + 1)$  is less than or equal to  $g(c)$ . Show that such  $c \geq 0$  is the smallest integer with  $F(c) \geq \frac{d_2 - d_1}{d_2}$

### Answer 8

(a):

(b):

(c):