

ENE 3031 -Fall 2014
Homework 1 Solution

-
- 1** Suppose that X is a discrete random variable having probability function $\Pr(X = k) = ck$ for $k = 1, 2, 3$. Find c , $\Pr(X \leq 2)$, $E[X]$, and $\text{Var}(X)$.

Solution. Since

$$1 = \sum_{k=1}^3 \Pr(X = k) = \sum_{k=1}^3 ck = 6c,$$

we have $c = 1/6$. \square

Next,

$$\Pr(X \leq 2) = \sum_{k=1}^2 \Pr(X = k) = \sum_{k=1}^2 k/6 = 1/2. \quad \square$$

Next,

$$E[X] = \sum_x x \Pr(X = x) = \sum_{k=1}^3 k \Pr(X = k) = \sum_{k=1}^3 k^2/6 = 7/3. \quad \square$$

Similarly,

$$E[X^2] = \sum_x x^2 \Pr(X = x) = \sum_{k=1}^3 k^2 \Pr(X = k) = \sum_{k=1}^3 k^3/6 = 6.$$

Thus,

$$\text{Var}(X) = E[X^2] - (E[X])^2 = 5/9. \quad \square$$

- 2** Suppose that X is a continuous random variable having p.d.f. $f(x) = cx$ for $1 \leq x \leq 2$. Find c , $\Pr(X \geq 1)$, $E[X]$, and $\text{Var}(X)$.

Solution. Since

$$1 = \int_{-\infty}^{\infty} f(x) dx = \int_1^2 cx dx,$$

we have $c = 2/3$. \square

Next, we trivially see that $\Pr(X \geq 1) = 1$. \square

Next,

$$E[X] = \int_{-\infty}^{\infty} xf(x) dx = \frac{2}{3} \int_1^2 x^2 dx = 14/9. \quad \square$$

Similarly,

$$E[X^2] = \int_{-\infty}^{\infty} x^2 f(x) dx = \frac{2}{3} \int_1^2 x^3 dx = 5/2.$$

Thus,

$$\text{Var}(X) = E[X^2] - (E[X])^2 = 0.08025. \quad \square$$



- 3** #4.7. Suppose that X and Y are jointly continuous random variables with

$$\begin{cases} y - x & \text{for } 0 < x < 1 \text{ and } 1 < y < 2 \\ 0 & \text{otherwise} \end{cases}.$$

- a. Compute and plot $f_X(x)$ and $f_Y(y)$.

Solution. The marginal p.d.f. of X is

$$f_X(x) = \int_1^2 (y - x) dy = \frac{3}{2} - x, \quad 0 < x < 1. \quad \square$$

The marginal p.d.f. of Y is

$$f_Y(y) = \int_0^1 (y - x) dx = y - \frac{1}{2}, \quad 1 < y < 2. \quad \square$$

- b. Are X and Y independent?

Solution. Since

$$f(x, y) = y - x \neq \left(\frac{3}{2} - x\right)\left(y - \frac{1}{2}\right) = f_X(x)f_Y(y),$$

we see that X and Y are *not* independent. \square

- c. Compute $F_X(x)$ and $F_Y(y)$.

Solution. The marginal c.d.f. of X is

$$F_X(x) = \int_0^x \left(\frac{3}{2} - t\right) dt = \frac{x(3 - x)}{2}, \quad 0 < x < 1. \quad \square$$

The marginal c.d.f. of Y is

$$F_Y(y) = \int_1^y (t - 1/2) dt = \frac{y(y - 1)}{2}, \quad 1 < y < 2. \quad \square$$

- d. Compute $E[X]$, $\text{Var}(X)$, $E[Y]$, $\text{Var}(Y)$, $\text{Cov}(X, Y)$, and $\text{Corr}(X, Y)$.

Solution. Without going through some of the tedious details, we find

that

$$\begin{aligned}
E[X] &= \int_{-\infty}^{\infty} x f_X(x) dx = \int_0^1 x(3/2 - x) dx = 5/12. \quad \square \\
E[X^2] &= \int_{-\infty}^{\infty} x^2 f_X(x) dx = \int_0^1 x^2(3/2 - x) dx = 1/4. \\
\text{Var}(X) &= E[X^2] - (E[X])^2 = 11/144 \quad \square \\
E[Y] &= \int_{-\infty}^{\infty} y f_Y(y) dy = \int_1^2 y(y - 1/2) dy = 19/12. \quad \square \\
E[Y^2] &= \int_{-\infty}^{\infty} y^2 f_Y(y) dy = \int_1^2 y^2(y - 1/2) dy = 31/12. \\
\text{Var}(Y) &= E[Y^2] - (E[Y])^2 = 11/144 \quad \square
\end{aligned}$$

With a little more work, we find that

$$\begin{aligned}
E[XY] &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f(x, y) dy dx = \int_0^1 \int_1^2 xy(y - x) dy dx = 2/3 \\
\text{Cov}(X, Y) &= E[XY] - E[X]E[Y] = 1/144 \quad \square \\
\text{Corr}(X, Y) &= \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}} = 1/11 \quad \square
\end{aligned}$$

4

#4.18. (Bonus — This takes some work.) If X_1, X_2, \dots, X_n are i.i.d. random variables with mean μ and variance σ^2 , then compute $\text{Cov}(\bar{X}, S^2)$, where $\bar{X} = \sum_{i=1}^n X_i/n$ is the sample mean and $S^2 = \sum_{i=1}^n (X_i - \bar{X})^2/(n-1)$ is the sample variance. When will this covariance be equal to 0?

Solution. We begin with some preliminary results. First,

$$\begin{aligned}
\text{Cov}(\bar{X}, S^2) &= \text{Cov}\left(\bar{X}, \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2\right) \\
&= \frac{1}{n-1} \text{Cov}\left(\bar{X}, \sum_{i=1}^n X_i^2 - n\bar{X}^2\right) \\
&\quad \text{(by standard algebra)} \\
&= \frac{1}{n-1} \left[\text{Cov}\left(\bar{X}, \sum_{i=1}^n X_i^2\right) - n\text{Cov}(\bar{X}, \bar{X}^2) \right]. \quad (1)
\end{aligned}$$

Second,

$$\begin{aligned}
\text{Cov}\left(\bar{X}, \sum_{j=1}^n X_j^2\right) &= \frac{1}{n} \text{Cov}\left(\sum_{i=1}^n X_i, \sum_{j=1}^n X_j^2\right) \\
&= \frac{1}{n} \sum_{i=1}^n \sum_{j=1}^n \text{Cov}(X_i, X_j^2) \\
&= \frac{1}{n} \sum_{i=1}^n \text{Cov}(X_i, X_i^2) \quad (\text{since Cov} = 0 \text{ if } i \neq j) \\
&= \text{Cov}(X_1, X_1^2) \quad (\text{since the } X_i\text{'s are i.i.d.}). \quad (2)
\end{aligned}$$

Third,

$$\begin{aligned}
n^3 \text{Cov}(\bar{X}, \bar{X}^2) &= \sum_{i=1}^n \sum_{j=1}^n \sum_{k=1}^n \text{Cov}(X_i, X_j X_k) \\
&= \sum_{i \neq k} \sum_{i \neq k} \text{Cov}(X_i, X_i X_k) + \sum_{i \neq j} \sum_{i \neq j} \text{Cov}(X_i, X_j X_i) + \sum_{i=1}^n \text{Cov}(X_i, X_i^2) \\
&= 2 \sum_{i \neq k} \sum_{i \neq k} \text{Cov}(X_i, X_i X_k) + \sum_{i=1}^n \text{Cov}(X_i, X_i^2) \quad (\text{by symmetry}) \\
&= 2n(n-1) \text{Cov}(X_i, X_i X_k) + n \text{Cov}(X_i, X_i^2) \quad (\text{since } X_i\text{'s are i.i.d.}) \\
&= 2n(n-1) (\text{E}[X_i^2 X_j] - \text{E}[X_i] \text{E}[X_i X_k]) + n \text{Cov}(X_i, X_i^2) \\
&= 2n(n-1) (\text{E}[X_i^2] \text{E}[X_j] - \text{E}[X_i] \text{E}[X_i] \text{E}[X_i]) + n \text{Cov}(X_i, X_i^2) \quad (X_i\text{'s are i.i.d.}) \\
&= 2n(n-1) \text{Var}(X_i) \text{E}[X_i] + n \text{Cov}(X_i, X_i^2). \quad (3)
\end{aligned}$$

Plugging (??) and (??) into (??), we get

$$\begin{aligned}
\text{Cov}(\bar{X}, S^2) &= \frac{\text{Cov}(X_1, X_1^2)}{n-1} - \frac{2(n-1) \text{Var}(X_1) \text{E}[X_1] + n \text{Cov}(X_1, X_1^2)}{n(n-1)} \\
&= \frac{1}{n} (\text{Cov}(X_1, X_1^2) - 2 \text{Var}(X_1) \text{E}[X_1]) \\
&= \frac{1}{n} (\text{E}[X_1^3] - \text{E}[X_1] \text{E}[X_1^2] - 2 \text{E}[X_1^2] \text{E}[X_1] + 2 (\text{E}[X_1])^3) \\
&= \frac{\text{E}[X_1^3] - 3\mu \text{E}[X_1^2] + 2\mu^3}{n}. \quad \square
\end{aligned}$$

Wow! That took a long time, eh? In any case, note that the numerator of the above quantity is the *skewness* of X_i . Further, it's possible to re-write the

above quantity as

$$\text{Cov}(\bar{X}, S^2) = \frac{E[(X_1 - \mu)^3]}{n}.$$

It is easy to see that if X_1 is symmetric about μ , then the skewness is 0. \square

5 #4.23. Suppose that the following 10 observations come from some distribution (not highly skewed) with unknown mean μ .

7.3 6.1 3.8 8.4 6.9 7.1 5.3 8.2 4.9 5.8

Compute \bar{X} , S^2 , and an approximate 95% confidence interval for μ .

Solution. After the standard calculations, we find that $\bar{X} = 6.38$, $S^2 = 2.16$, and the approximate 95% confidence interval is given by

$$\begin{aligned} \mu &\in \bar{X} \pm t_{\alpha/2, n-1} \sqrt{S^2/n} \\ &= 6.38 \pm t_{0.025, 9} \sqrt{2.16/10} \\ &= 6.38 \pm 2.262 \sqrt{2.16/10} \\ &= 6.38 \pm 1.05. \quad \square \end{aligned}$$

6 #4.26. A random variable X has the *memoryless property* if, for all $s, t > 0$,

$$\Pr(X > t + s | X > t) = \Pr(X > s).$$

Show that the exponential distribution has the memoryless property.

Solution. As we did in class, we have

$$\begin{aligned} \Pr(X > t + s | X > t) &= \frac{\Pr(X > t + s, X > t)}{\Pr(X > t)} \\ &= \frac{\Pr(X > t + s)}{\Pr(X > t)} \\ &= \frac{e^{-\lambda(t+s)}}{e^{-\lambda t}} \\ &= e^{-\lambda s} \\ &= \Pr(X > s). \quad \square \end{aligned}$$

7 #4.27. A geometric distribution with parameter p ($0 < p < 1$) has the p.m.f.

$$f(x) = (1 - p)^x p, \quad x = 0, 1, 2, \dots$$

Show that this distribution has the memoryless property.

Solution. I actually use a slightly different definition of the geometric than Law and Kelton's. Namely, let's interpret X as the number of $\text{Bern}(p)$ *trials until we get a success*. Thus, if you see FFFS, then $X = 4$. This means that

$$f(x) = (1 - p)^{x-1} p, \quad x = 1, 2, \dots,$$

which is a little different than the problem statement — sorry about that! In any case, the c.d.f. is

$$\begin{aligned} F(x) &= \Pr(X \leq x), \quad x = 1, 2, \dots \\ &= \sum_{k=1}^x q^{k-1} p \\ &= p \sum_{k=0}^{x-1} q^k \\ &= p \left(\sum_{k=0}^{\infty} q^k - \sum_{k=x}^{\infty} q^k \right) \\ &= p \left(\sum_{k=0}^{\infty} q^k - q^x \sum_{k=0}^{\infty} q^k \right) \\ &= p(1 - q^x) \sum_{k=0}^{\infty} q^k \\ &= \frac{p(1 - q^x)}{1 - q} \\ &= 1 - q^x. \end{aligned}$$

This implies that

$$\begin{aligned}
 \Pr(X > n + m | X > m) &= \frac{\Pr(X > n + m, X > m)}{\Pr(X > m)} \\
 &= \frac{\Pr(X > n + m)}{\Pr(X > m)} \\
 &= \frac{q^{n+m}}{q^m} \\
 &= q^n \\
 &= \Pr(X > n),
 \end{aligned}$$

thus proving that the distribution is memoryless. \square

8 Suppose X_1, X_2, \dots, X_n are i.i.d. $\text{Exp}(\lambda)$.

(a) Find the m.g.f. of X_i .

Solution. As we did in class,

$$\begin{aligned}
 M_X(t) &= \mathbb{E}[e^{tX}] \\
 &= \int_0^\infty e^{tx} \lambda e^{-\lambda x} dx \\
 &= \lambda \int_0^\infty e^{(t-\lambda)x} dx \\
 &= \frac{\lambda}{\lambda - t} \quad \text{for } t < \lambda. \quad \square
 \end{aligned}$$

(b) Use m.g.f.'s to find the distribution of $Y = \sum_{i=1}^n X_i$.

Solution. Since the X_i 's are i.i.d., our class notes tell us that

$$M_Y(t) = (M_X(t))^n = \left(\frac{\lambda}{\lambda - t} \right)^n \quad \text{for } t < \lambda.$$

By uniqueness of m.g.f.'s (at least for our class), we see that Y is $\text{Erlang}_n(\lambda)$ (or $\text{Gamma}(n, \lambda)$). \square

- (c) Suppose $\lambda = 1$. Use the Central Limit Theorem to find the approximate value of $\Pr(100 \leq \sum_{i=1}^{100} X_i \leq 110)$.

Solution. As we did in class, using the CLT and the fact that the X_i 's are i.i.d. $\text{Exp}(1)$, we have

$$\begin{aligned} \sum_{i=1}^{100} X_i &\approx \text{Nor}\left(\mathbb{E}\left[\sum_{i=1}^{100} X_i\right], \text{Var}\left(\sum_{i=1}^{100} X_i\right)\right) \\ &\sim \text{Nor}(100\mathbb{E}[X_1], 100\text{Var}(X_1)) \\ &\sim \text{Nor}(100, 100). \end{aligned}$$

Thus, we have

$$\begin{aligned} \Pr\left(100 \leq \sum_{i=1}^{100} X_i \leq 110\right) &= \Pr\left(\frac{100 - 100}{10} \leq \frac{\sum_{i=1}^{100} X_i - 100}{10} \leq \frac{110 - 100}{10}\right) \\ &\doteq \Pr(0 \leq \text{Nor}(0, 1) \leq 1) \\ &= \Phi(1) - \Phi(0) \\ &= 0.3415. \quad \square \end{aligned}$$

9

Generate 1000 pairs of i.i.d. $U(0,1)$'s, $(U_{1,1}, U_{1,2}), \dots, (U_{1000,1}, U_{1000,2})$, and set

$$X_i = \sqrt{-2\ell\text{n}(U_{i1})} \cos(2\pi U_{i2})$$

and

$$Y_i = \sqrt{-2\ell\text{n}(U_{i1})} \sin(2\pi U_{i2})$$

for $i = 1, 2, \dots, 1000$.

- (a) Make a histogram of the X_i 's. Comments?

Solution. You get a standard normal p.d.f. \square

- (b) Graph X_i vs. Y_i . Comments?

Solution. You get a bivariate normal p.d.f. \square

(c) Make a histogram of X_i/Y_i . Comments?

Solution. You get a Cauchy p.d.f., also known as a t distribution with 1 degree of freedom. This distribution has fatter tails than the standard normal. \square

(d) Make a histogram of $X_i^2 + Y_i^2$. Comments?

Solution. You get an exponential p.d.f. \square