

Exercise 1 (7.4)

$$f(x, y) = \begin{cases} \frac{1}{y} & \text{if } 0 < y < 1, 0 < x < y \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned} \text{a) } \mathbb{E}(XY) &= \int_0^1 \int_0^y xyf(x, y)dx dy \\ &= \int_0^1 \int_0^y x dx dy \\ &= \int_0^1 \frac{y^2}{2} dy \\ &= \frac{y^3}{6} \Big|_0^1 \\ &= \frac{1}{6}. \end{aligned}$$

$$\begin{aligned} \text{b) } \mathbb{E}(X) &= \int_0^1 \int_0^y xf(x, y)dx dy \\ &= \int_0^1 \int_0^y \frac{x}{y} dx dy \\ &= \int_0^1 \frac{y^2}{2y} dy \\ &= \int_0^1 \frac{y}{2} dy \\ &= \frac{1}{4} \end{aligned}$$

$$\begin{aligned} \text{c) } \mathbb{E}(Y) &= \int_0^1 \int_0^y yf(x, y)dx dy \\ &= \int_0^1 \int_0^y \frac{y}{y} dx dy \\ &= \int_0^1 y dy \\ &= \frac{1}{2}. \end{aligned}$$

Exercise 2 (7.8)

Let X_i be the event defined by $X_i = \begin{cases} 1 & \text{if the } i^{\text{th}} \text{ arrival sits at an un-occupied table.} \\ 0 & \text{otherwise} \end{cases}$.

We know that the expected value of X_i is equal to $(1 - p)^{i-1}$, since $1 - p$ is the probability that an arrival has no seated friends, the events are independent, and there are $i - 1$ previously seated people.

Just as we did in class, we can write the expected value of the number of occupied tables as $\mathbb{E}(\sum_{i=1}^N X_i) = \sum_{i=1}^N \mathbb{E}(X_i) = \sum_{i=1}^N (1 - p)^{i-1}$. This is a finite geometric sum, so we have that the expected value is $\frac{(1 - p)^N - 1}{(1 - p) - 1} = \frac{1 - (1 - p)^N}{p}$.

Exercise 3 (7.38)

$$f(x, y) = \begin{cases} \frac{2e^{-2x}}{x} & \text{if } 0 \leq x < \infty, 0 \leq y \leq x \\ 0 & \text{otherwise} \end{cases}$$

$$\text{Cov}(X, Y) = \mathbb{E}(XY) - \mathbb{E}(X)\mathbb{E}(Y)$$

First we need to calculate $\mathbb{E}(X)$, $\mathbb{E}(Y)$, and $\mathbb{E}(XY)$.

$$\begin{aligned} \mathbb{E}(X) &= \int_{-\infty}^{\infty} x \int_{-\infty}^{\infty} f(x, y) dy dx \\ &= \int_0^{\infty} x \int_0^x \frac{2e^{-2x}}{x} dy dx \\ &= \int_0^{\infty} x^2 \frac{2e^{-2x}}{x} dx \\ &= \int_0^{\infty} 2xe^{-2x} dx \end{aligned}$$

Let $u = x$, $du = dx$, $v = -e^{-2x}$, $dv = 2e^{-2x} dx$.

$$\begin{aligned} \text{Now we have } -xe^{-2x} \Big|_0^{\infty} + \int_0^{\infty} e^{-2x} dx &= \int_0^{\infty} e^{-2x} dx \\ &= \frac{-e^{-2x}}{2} \Big|_0^{\infty} \\ &= \frac{1}{2}. \end{aligned}$$

$$\begin{aligned} \mathbb{E}(Y) &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} y f(x, y) dy dx \\ &= \int_0^{\infty} \int_0^x y \frac{2e^{-2x}}{x} dy dx \\ &= \int_0^{\infty} \frac{2e^{-2x}}{x} \int_0^x y dy dx \\ &= \int_0^{\infty} x^2 \frac{2e^{-2x}}{2x} dx \end{aligned}$$

$$\begin{aligned}
&= \int_0^\infty x e^{-2x} dx \\
&= \frac{1}{4}, \text{ since this is twice the integral from } \mathbb{E}(X),
\end{aligned}$$

$$\begin{aligned}
\mathbb{E}(XY) &= \int_{-\infty}^\infty \int_{-\infty}^\infty xy f(x, y) dy dx \\
&= \int_0^\infty \int_0^x xy \frac{2e^{-2x}}{x} dy dx \\
&= \int_0^\infty \int_0^x y 2e^{-2x} dy dx \\
&= \int_0^\infty 2e^{-2x} \int_0^x y dy dx \\
&= \int_0^\infty 2e^{-2x} \frac{x^2}{2} dx \\
&= \int_0^\infty x^2 e^{-2x} dx \\
&= \int_0^\infty x^2 e^{-2x} dx
\end{aligned}$$

$$\text{Let } u = x^2, du = 2x dx, v = \frac{-e^{-2x}}{2}, dv = e^{-2x} dx.$$

$$\begin{aligned}
\text{So } \mathbb{E}(XY) &= x^2 \frac{-e^{-2x}}{2} \Big|_0^\infty + \int_0^\infty 2x \frac{e^{-2x}}{2} dx \\
&= x^2 \frac{-e^{-2x}}{2} \Big|_0^\infty + \int_0^\infty x e^{-2x} dx
\end{aligned}$$

The first term is zero by L'Hôpital's Rule, and the integral is $\mathbb{E}(Y)$, which is $\frac{1}{4}$.

$$\text{Therefore } \text{Cov}(X, Y) = \frac{1}{4} - \frac{1}{2} \frac{1}{4} = \frac{1}{8}.$$

Exercise 4 (7.39)

Let $X_1 \dots$ be independent with common mean μ and common variance σ^2 , and set $Y_n = X_n + X_{n+1} + X_{n+2}$. For $j \geq 0$, find $\text{Cov}(Y_n, Y_{n+j})$.

First expand $\text{Cov}(Y_n, Y_{n+j}) = \mathbb{E}(Y_n Y_{n+j}) - \mathbb{E}(Y_n) \mathbb{E}(Y_{n+j})$. So we need to find $\mathbb{E}(Y_n Y_{n+j})$, $\mathbb{E}(Y_n)$, and $\mathbb{E}(Y_{n+j})$.

$$\mathbb{E}(Y_n) = \mathbb{E}(X_n + X_{n+1} + X_{n+2}) = \mathbb{E}(X_n) + \mathbb{E}(X_{n+1}) + \mathbb{E}(X_{n+2}) = 3\mu.$$

We can say the same of Y_{n+j} , since its expected value with clearly also result in a sum of expected values of three X s. i.e. $\mathbb{E}(Y_n) = \mathbb{E}(Y_{n+j}) = 3\mu$. And therefore $\mathbb{E}(Y_n) \mathbb{E}(Y_{n+j}) = 9\mu^2$ for any $j \neq 0$.

If $j = 0$, we have

$$\begin{aligned}
\mathbb{E}(Y_n Y_{n+j}) &= \mathbb{E}(Y_n^2) \\
&= \mathbb{E}\left((X_n + X_{n+1} + X_{n+2})^2\right) \\
&= \mathbb{E}\left(X_n^2 + 2X_n X_{n+1} + X_{n+1}^2 + 2X_n X_{n+2} + 2X_{n+1} X_{n+2} + X_{n+2}^2\right) \\
&= \mathbb{E}(X_n^2) + \mathbb{E}(2X_n X_{n+1}) + \mathbb{E}(X_{n+1}^2) + \mathbb{E}(2X_n X_{n+2}) + \mathbb{E}(2X_{n+1} X_{n+2}) + \mathbb{E}(X_{n+2}^2)
\end{aligned}$$

And since the X s are independent, we can replace every $\mathbb{E}(X_a X_b)$, $a \neq b$ with the square of $\mathbb{E}(X_a) = \mu$. Likewise, we can replace $\mathbb{E}(X_a X_a)$ with $\text{Var}(X_a) + \mathbb{E}(X_a)^2 = \mu^2 + \sigma^2$.

By grouping the square terms and the remaining terms, we conclude that

$$\text{Cov}(Y_n, Y_{n+j}) = 3(\mu^2 + \sigma^2) + 6\mu^2 - 9\mu^2 = 3\sigma^2 \text{ in this case.}$$

If $j = 1$, we have

$$\begin{aligned}
\mathbb{E}(Y_n Y_{n+j}) &= \mathbb{E}(Y_n Y_{n+1}) \\
&= \mathbb{E}\left((X_n + X_{n+1} + X_{n+2})(X_{n+1} + X_{n+2} + X_{n+3})\right) \\
&= \mathbb{E}\left(X_n X_{n+1} + X_{n+1}^2 + X_n X_{n+2} + 2X_{n+1} X_{n+2} + \right. \\
&\quad \left. X_{n+2}^2 + X_n X_{n+3} + X_{n+1} X_{n+3} + X_{n+2} X_{n+3}\right)
\end{aligned}$$

Just as we did for $j = 0$, we group terms and find that

$$\text{Cov}(Y_n, Y_{n+j}) = 2(\mu^2 + \sigma^2) + 5\mu^2 + 2\mu^2 - 9\mu^2 = 2\sigma^2 + 9\mu^2 - 9\mu^2 = 2\sigma^2 \text{ in this case.}$$

If $j = 2$, we have

$$\begin{aligned}
\mathbb{E}(Y_n Y_{n+j}) &= \mathbb{E}(Y_n Y_{n+2}) \\
&= \mathbb{E}\left((X_n + X_{n+1} + X_{n+2})(X_{n+2} + X_{n+3} + X_{n+4})\right) \\
&= \mathbb{E}\left(X_n X_{n+2} + X_{n+1} X_{n+2} + X_{n+2}^2 + X_n X_{n+3} + X_{n+1} X_{n+3} + \right. \\
&\quad \left. X_{n+2} X_{n+3} + X_n X_{n+4} + X_{n+1} X_{n+4} + X_{n+2} X_{n+4}\right)
\end{aligned}$$

Just as we did for $j = 0$ and $j = 1$, we group terms and find that

$$\text{Cov}(Y_n, Y_{n+j}) = \mu^2 + \sigma^2 + 8\mu^2 - 9\mu^2 = \sigma^2 \text{ in this case.}$$

If $j \geq 3$, we have

$$\mathbb{E}(Y_n Y_{n+j}) = 9\mu^2 - 9\mu^2 = 0, \text{ since the events are independent, so } \text{Cov}(Y_n, Y_{n+j}) = 0 \text{ in this case.}$$

We can now write the covariance in the following distilled form

$$\text{Cov}(Y_n, Y_{n+j}) = \begin{cases} (3-j)\sigma^2 & \text{if } 0 \leq j < 3 \\ 0 & \text{if } j \geq 3 \end{cases}$$

Exercise 5 (7.43)

Let $X_1 \dots X_n$ be independent random variables having an unknown continuous distribution function F , and let $Y_1 \dots Y_m$ be independent random variables having an unknown continuous distribution function G . Now order those $n + m$ variables and let

$$I_i = \begin{cases} 1 & \text{if the } i^{\text{th}} \text{ smallest of the } n + m \text{ variables is from the } X\text{'s} \\ 0 & \text{otherwise} \end{cases}$$

The random variable $R = \sum_{i=1}^{n+m} iI_i$ is the sum of the ranks of the X sample and is the basis of a standard statistical procedure for testing whether F and G are identical distributions. This test accepts the hypothesis that $F = G$ when R is neither too large or too small.

Under the assumption that the hypothesis of equality is correct, we want to compute the mean and variance of R .

We can begin by observing that iI_i is a negative hypergeometric random variable. In the language used in the distribution index in the back of the book, iI_i is the number of balls that need to be removed from an urn containing $n + m$ balls, n of which are white, until i balls have been removed.

Now the expected value of iI_i can be expressed as $\mathbb{E}(iI_i) = i \frac{m+n+1}{n+1}$, and the variance of iI_i can be expressed as $\text{Var}(iI_i) = \frac{mi(n+1-i)(n+m+1)}{(n+1)^2(n+2)}$.

First let's determine $\mathbb{E}(R)$.

$$\begin{aligned} \mathbb{E}(R) &= \mathbb{E}\left(\sum_{i=1}^{n+m} iI_i\right) \\ &= \sum_{i=1}^{n+m} \mathbb{E}(iI_i) \\ &= \sum_{i=1}^{n+m} i \frac{m+n+1}{n+1} \\ &= \frac{m+n+1}{n+1} \sum_{i=1}^{n+m} i \\ &= \frac{m+n+1}{n+1} \frac{(n+m)(n+m+1)}{2} \\ &= \frac{(n+m)(n+m+1)^2}{2(n+1)}. \end{aligned}$$

Finally let's determine $\text{Var}(R)$.

$$\begin{aligned}\text{Var}(R) &= \sum_{i=1}^{n+m} \frac{mi(n+1-i)(n+m+1)}{(n+1)^2(n+2)} \\ &= \frac{(n+m+1)}{(n+1)^2(n+2)} \sum_{i=1}^{n+m} mi(n+1-i)\end{aligned}$$

Quickly observe that

$$\begin{aligned}\sum_{i=1}^{n+m} mi(n+1-i) &= \sum_{i=1}^{n+m} imn + \sum_{i=1}^{n+m} im - \sum_{i=1}^{n+m} i^2m \\ &= mn \sum_{i=1}^{n+m} i + m \sum_{i=1}^{n+m} i - m \sum_{i=1}^{n+m} i^2 \\ &= m((n+1) \sum_{i=1}^{n+m} i - \sum_{i=1}^{n+m} i^2) \\ &= m((n+1) \frac{(n+m)(n+m+1)}{2} - \frac{(n+m)(n+m+1)(2(n+m)+1)}{6}) \\ &= \frac{m(n+m)(n+m+1)}{2} \left((n+1) - \frac{2(n+m)+1}{3} \right)\end{aligned}$$

$$\text{So } \text{Var}(R) = \frac{m(n+m)(n+m+1)^2}{2(n+1)^2(n+2)} \left(n+1 - \frac{2(n+m)+1}{3} \right).$$

Exercise 6 (7.45)

$$\text{a) } \rho(X_1 + X_2, X_2 + X_3) = \frac{\text{Cov}(X_1 + X_2, X_2 + X_3)}{\sqrt{\text{Var}(X_1 + X_2)\text{Var}(X_2 + X_3)}}.$$

So we need to determine $\text{Cov}(X_1 + X_2, X_2 + X_3)$, $\text{Var}(X_1 + X_2)$, and $\text{Var}(X_2 + X_3)$.

Since the X s are uncorrelated, we have the following

$$\text{Cov}(X_1 + X_2, X_2 + X_3) = \text{Var}(X_2) = 1$$

$$\text{Var}(X_1 + X_2) = \text{Var}(X_1) + \text{Var}(X_2) = 1 + 1 = 2$$

$$\text{Var}(X_2 + X_3) = \text{Var}(X_2) + \text{Var}(X_3) = 1 + 1 = 2$$

$$\text{Thus } \rho(X_1 + X_2, X_2 + X_3) = \frac{1}{\sqrt{2+2}} = \frac{1}{\sqrt{4}} = \frac{1}{2}.$$

$$\text{b) } \rho(X_1 + X_2, X_3 + X_4) = \frac{\text{Cov}(X_1 + X_2, X_3 + X_4)}{\sqrt{\text{Var}(X_1 + X_2)\text{Var}(X_3 + X_4)}}.$$

Since the X s are uncorrelated, and $\{X_1, X_2\} \cap \{X_3, X_4\} = \emptyset$, we have that $\text{Cov}(X_1 + X_2, X_3 + X_4) = 0$, which means $\rho(X_1 + X_2, X_3 + X_4) = 0$.

Extra Exercises

Exercise 8.13

a)

$$\begin{aligned}\mathbb{P}\left\{\frac{X - \mu n}{\sigma\sqrt{n}} > \frac{Y - \mu n}{\sigma\sqrt{n}}\right\} &= 1 - \mathbb{P}\left\{Z \leq \frac{80(25) - 74(25)}{14\sqrt{25}}\right\} \\ &= 1 - \mathbb{P}\{Z \leq 2.14\} \\ &= 1 - \Phi(2.14) \\ &= 1 - 0.983823 \\ &= 0.016177\end{aligned}$$

b)

$$\begin{aligned}\mathbb{P}\left\{\frac{X - \mu n}{\sigma\sqrt{n}} > \frac{Y - \mu n}{\sigma\sqrt{n}}\right\} &= 1 - \mathbb{P}\left\{Z \leq \frac{80(64) - 74(64)}{14\sqrt{64}}\right\} \\ &= 1 - \mathbb{P}\{Z \leq 3.43\} \\ &= 1 - \Phi(3.43) \\ &= 1 - 0.999698 \\ &= 0.000302\end{aligned}$$

Exercise 8.15

$$\begin{aligned}\mathbb{P}\left\{\frac{X - \mu n}{\sigma\sqrt{n}} > \frac{Y - \mu n}{\sigma\sqrt{n}}\right\} &= \left\{\frac{X - 10,000(240)}{800\sqrt{10,000}} > \frac{2,700,000 - 10,000(240)}{800\sqrt{10,000}}\right\} \\ &= 1 - \mathbb{P}\left\{Z \leq \frac{2,700,000 - 2,400,000}{80000}\right\} \\ &= 1 - \mathbb{P}\left\{Z \leq \frac{30}{8}\right\} \\ &= 1 - \mathbb{P}\{Z \leq 3.75\} \\ &= 1 - \Phi(3.75) \\ &\approx 0\end{aligned}$$

