

4.9.2

Integration by parts with $u = 1 - F(x)$, $dv = 1$ yields that

$$\int_0^\infty (1 - F(x))dx = (uv|_0^\infty) - \int_0^\infty -xf(x)dx = \int_0^\infty xf(x)dx = E(X)$$

4.9.22

They exhibit a negative linear relationship: that is, $X = Y - 3$ where X, Y are the lengths of the shorter and longer pieces. Thus, $\rho = -1$.

4.9.26

$$\begin{aligned}\text{Cov}(X, Y) &= E(XY) - E(X)E(Y) \\ &= E(E(XY | Z)) - E(E(X)(E(Y)) | Z) \\ &= E(\text{Cov}(X, Y | Z) + E(X | Z)E(Y | Z)) - E(E(X) | Z)E(E(Y) | Z) \\ &= E(\text{Cov}(X, Y | Z)) + E(E(X | Z)E(Y | Z)) - E(E(X) | Z)E(E(Y) | Z) \\ &= E(\text{Cov}(X, Y | Z)) + \text{Cov}(E(X | Z), E(Y | Z))\end{aligned}$$

5.2.5

Let X be the amount of heads.

$$P(X = 0) + P(X = 2) + P(X = 4) + P(X = 6) + P(X = 8) = 0.5$$

5.2.9

Baye's Theorem yields that

$$P(X_1 = 1 | \sum_{i=1}^n X_i = k) = \frac{P(\sum_{i=1}^n X_i = k | X_1 = 1)P(X_1 = 1)}{P(\sum_{i=1}^n X_i = k)} = \frac{P(\sum_{i=2}^n X_i = k - 1)P(X_1 = 1)}{P(\sum_{i=1}^n X_i = k)}$$

We have that $P(\sum_{i=1}^n X_i = k) = \binom{n}{k}p^k(1-p)^{n-k}$; similarly, $P(\sum_{i=2}^n X_i = k - 1) = \binom{n-1}{k-1}p^{k-1}(1-p)^{n-k}$, and finally $P(X_1 = 1) = p$.

The above expression then comes out to

$$\frac{k}{n}$$

5.2.11

We have that

$$\sum_{x=2}^n x(x-1) \binom{n}{x} p^x (1-p)^{n-x} = \sum_{x=2}^n x^2 \binom{n}{x} p^x (1-p)^{n-x} - \sum_{x=2}^n x \binom{n}{x} p^x (1-p)^{n-x}$$

We can start the sum from $x = 0$, as for $x = 0, 1$ we have that the term is simply zero.

Then, the expression works out to be, with X a binomial distribution,

$$E(X^2) - E(X) = \text{Var}(X) + E(X)^2 - E(X) = np(1-p) + (np)^2 - np = (np)^2 - np^2 = (n^2 - n)p^2$$

5.3.1

$$\frac{\binom{10}{10} \binom{24}{1}}{\binom{34}{11}} = 8.39 \cdot 10^{-8}$$

5.4.1

We have that this is a Poisson distribution with mean $0.2 \cdot 0.1 \cdot 100 = 2$, such that

$$P(X \geq 2) = 1 - P(X = 1) - P(X = 0) = 1 - 2e^{-2} - e^{-2} = 0.594$$

5.4.6

We have that this is a Poisson distribution with mean $3\frac{6}{5} = 3.6$. The probability of no defects is $e^{-3.6} = 0.027$.

5.4.16

a

Let $B = (\{X = k\} \cap (\cup_{i=1}^n A_i))$. Then, we have that $(W_n = k) = (\{X = k\} \cap (\cup_{i=1}^n A_i)^C)$, and as the sum of disjoint unions, we have that

$$P(B) + P(W_n = k) = P(X = k)$$

b

We have that as the time intervals do not overlap, the A_i are independent. Then,

$$\begin{aligned} P((\cup_{i=1}^n A_i)^C) &= P(\cap_{i=1}^n A_i^C) \\ &= (1 - A_i)^n \\ &= (1 - o(\frac{t}{n}))^n \end{aligned}$$

where the last line follows from the second assumption.

Then, we have that

$$\lim_{n \rightarrow \infty} P(\cup_{i=1}^n A_i) = \lim_{n \rightarrow \infty} 1 - (1 - o(\frac{t}{n}))^n = 1 - 1^n = 0$$

c

$$\begin{aligned} P(W_n = k) &= \binom{n}{k} (\frac{\lambda t}{n} + o(\frac{t}{n}))^k (1 - (\frac{\lambda t}{n} + o(\frac{t}{n})))^{n-k} \\ &= (\frac{1}{k!}) (\frac{n!}{(n-k)!n^k}) ((\frac{\lambda t}{n} + o(\frac{t}{n}))n)^k (1 - (\frac{\lambda t}{n} + o(\frac{t}{n})))^{n-k} \end{aligned}$$

Considering the factors of the product here, we have:

$$\lim_{n \rightarrow \infty} \frac{n!}{(n-k)!n^k} = 1 \tag{1}$$

$$\lim_{n \rightarrow \infty} (1 - (\frac{\lambda t}{n} + o(\frac{t}{n})))^{n-k} = e^{-\lambda t} \tag{2}$$

$$\tag{3}$$

The above are given in the book. Further,

$$\begin{aligned} \lim_{n \rightarrow \infty} ((\frac{\lambda t}{n} + o(\frac{t}{n}))n)^k &= \lim_{n \rightarrow \infty} n^k \sum_{i=0}^k \binom{k}{i} (\frac{\lambda t}{n})^i (o(\frac{t}{n}))^{k-i} \\ &= \sum_{i=0}^k \binom{k}{i} (\lambda t)^i (\frac{o(\frac{t}{n})}{\frac{1}{n}})^{k-i} \\ &= \binom{k}{k} (\lambda t)^k \end{aligned}$$

We finally arrive at

$$\lim_{n \rightarrow \infty} P(W_n = k) = \frac{(\lambda t)^k e^{-\lambda t}}{k!}$$

d

Since we have that

$$P(X = k) = P(W_n = k) + P(B)$$

we have that

$$P(X = k) = \lim_{n \rightarrow \infty} P(W_n = k) + \lim_{n \rightarrow \infty} P(B) = \frac{(\lambda t)^k e^{-\lambda t}}{k!}$$

5.5.5

We do this by checking that the moment generating functions are the same. For $\sum_{i=1}^k X_i$, we have

$$\begin{aligned} \psi(t) &= \prod_{i=1}^k \psi_i(t) \\ &= \prod_{i=1}^k \left(\frac{p}{1 - (1-p)e^t} \right)^{r_i} \\ &= \left(\frac{p}{1 - (1-p)e^t} \right)^{\sum_{i=1}^k r_i} \end{aligned}$$

which is the mgf of the desired negative binomial distribution.

5.6.1

From the table at the end of the book, we have the following:

0.5	0
0.75	0.675
0.25	-0.675 = 0.325
0.9	1.285
0.1	-1.285

5.6.11

We have that $\overline{X}_n - \mu$ is normal with mean 0 and variance $\frac{4}{n}$. Then, we have that with the standard normal distribution Z ,

$$\overline{X}_n - \mu = \frac{2}{\sqrt{n}} Z \implies |\overline{X}_n - \mu| < 0.1 \iff |Z| < 0.05\sqrt{n}$$

Looking for the 95th quantile, we have that $0.05\sqrt{n} = 1.645 \implies n = 1082.41$. Rounding up,

$$n = 1083$$

5.6.14

Put

$$X = \frac{1}{2}(X_A + X_A) - \frac{1}{3}(X_B + X_B + X_B)$$

X is normally distributed with mean $\mu = \mu_A - \mu_B = 25$ and variance $\sigma^2 = \frac{1}{2}\sigma_A^2 + \frac{1}{3}\sigma_B^2 = 100$. Then, we have that

$$X = 10Z + 25 > 0 \iff Z > -2.5$$

Then, $P(X > 0) = P(Z > -2.5) = 0.9938$.

5.6.16

Note that

$$\int_{-\infty}^{\infty} \frac{1}{2\pi} e^{-\frac{x^2+y^2}{2}} dx = \frac{1}{2\pi} e^{-\frac{y^2}{2}} \int_{-\infty}^{\infty} e^{-\frac{x^2}{2}} dx = \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}}$$

Thus, X and Y are both the standard normal distribution, and $X + Y = \sqrt{2}Z$. This then means that

$$P(-\sqrt{2} < X + Y < 2\sqrt{2}) = P(-1 < Z < 2) = 0.8186$$

5.6.5

This is the complement of non lasting 290 hours. Note that $X_i = 10Z + 300$, such that

$$P(X_i < 290) = P(Z < -1) = 0.1587$$

The desired probability is then

$$1 - 0.1587^3 = 0.996$$

5.6.9

We have the overall length is normally distributed with mean 56 and variance 0.09. Then, we see that

$$P(55.7 < X < 56.3) = P(-1 < Z < 1) = 0.6827$$

5.6.13

The distribution X of the difference between the hole diameters is normal with mean 0.02 and variance 0.0025, such that $X = 0.05Z + 0.02$. Thus, the desired probability is

$$P(0 < X < 0.05) = P(-0.4 < Z < 0.6) = 0.3812$$

5.8.5

$$\begin{aligned} E[X^r(1-X)^s] &= \int_0^1 x^r(1-x)^s \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1}(1-x)^{\beta-1} dx \\ &= \frac{\Gamma(\alpha+\beta)\Gamma(\alpha+r)\Gamma(\beta+s)}{\Gamma(\alpha)\Gamma(\beta)\Gamma(\alpha+\beta+r+s)} \end{aligned}$$

5.10.1

The conditional distribution of the height of the wife is normal with mean $66.8 + 0.68 \cdot 2 \cdot \frac{72-70}{2} = 68.16$ and variance $(1 - 0.68)^2 2^2 = 2.15$. The 0.95 quantile is then

$$68.16 + 2.15 \frac{1}{2} (1.65) = 70.6$$

5.10.11

We have from the book that $X_1 + X_2, X_1 - X_2$ are bivariate normally distributed. Thus, we need only to show that the covariance vanishes:

$$\begin{aligned} \text{Cov}(X_1 + X_2, X_1 - X_2) &= E((X_1 + X_2)(X_1 - X_2)) - E(X_1 + X_2)E(X_1 - X_2) \\ &= E(X_1^2 - X_2^2) - (E(X_1) + E(X_2))(E(X_1) - E(X_2)) \\ &= E(X_1^2) - E(X_1)^2 - E(X_2^2) + E(X_2)^2 \\ &= \text{Var}(X_1) - \text{Var}(X_2) = 0 \end{aligned}$$

Thus, they are independent.

5.10.13

The bivariate normal pdf has the form, for a suitable constant C ,

$$C e^{-\frac{1}{2(1-\rho^2)} \left(\left(\frac{x_1 - \mu_1}{\sigma_1} \right)^2 - 2\rho \left(\frac{x_1 - \mu_1}{\sigma_1} \right) \left(\frac{x_2 - \mu_2}{\sigma_2} \right) + \left(\frac{x_2 - \mu_2}{\sigma_2} \right)^2 \right)}$$

This then yields

$$\begin{aligned}a &= \frac{1}{2\sigma_1(1-\rho^2)} \\b &= \frac{1}{2\sigma_2(1-\rho^2)} \\c &= -\frac{\rho}{\sigma_1\sigma_2(1-\rho^2)} \\e &= -\frac{\mu_1}{\sigma_1^2(1-\rho^2)} + \frac{\mu_2\rho}{\sigma_1\sigma_2(1-\rho^2)} \\g &= -\frac{\mu_2}{\sigma_2^2(1-\rho^2)} + \frac{\mu_1\rho}{\sigma_1\sigma_2(1-\rho^2)} \\\rho &= -\frac{c}{2\sqrt{ab}} \\\sigma_1^2 &= \frac{1}{2a - \frac{c^2}{2b}} \\\sigma_2^2 &= \frac{1}{2b - \frac{c^2}{2a}} \\\mu_1 &= \frac{cg - 2be}{4ab - c^2} \\\mu_2 &= \frac{ce - 2ag}{4ab - c^2}\end{aligned}$$

The only conditions placed on these coefficients are that $a, b > 0$ and that the correlation is $-1 < \rho < 1$. Luckily, we have exactly that: $ab > (\frac{c}{2})^2 \implies |\rho| < \frac{2c^2}{2c^2} = 1$.