

**Solutions to Final Exam**

1. (a) The expected sum is  $E[\sum X_i] = n\mu = 64 \times 84 = 5376$ , and the standard deviation of the sum is  $SD(\sum X_i) = \sqrt{\text{Var}(\sum X_i)} = \sqrt{n\sigma^2} = \sqrt{n}\sigma = 8 \times 8 = 64$ .
- (b) The standard deviation of the sample average is  $\sigma/\sqrt{n} = 8/8 = 1$ . By the central limit theorem the sample average is approximately normally distributed, so

$$\begin{aligned} \Pr(|\bar{X} - \mu| \leq 1) &\approx \Pr(|Z| \leq 1) = \Pr(Z \leq 1) - \Pr(Z \leq -1) \\ &= \Pr(Z \leq 1) - (1 - \Pr(Z \leq 1)) = 2\Pr(Z \leq 1) - 1 \\ &= 2 \times 0.8413 - 1 = 0.6826. \end{aligned}$$

2. (a) The mean of  $X$  is

$$E[X] = \int_0^1 x^2 + \frac{1}{2}x dx = \frac{1}{3} + \frac{1}{4} = \frac{7}{12}$$

The expected value of  $X^2$  is

$$E[X^2] = \int_0^1 x^3 + \frac{1}{2}x^2 dx = \frac{1}{4} + \frac{1}{6} = \frac{5}{12}$$

The variance of  $X$  is

$$\text{Var}(X) = E[X^2] - E[X]^2 = \frac{5}{12} - \left(\frac{7}{12}\right)^2 = \frac{60}{144} - \frac{49}{144} = \frac{11}{144}$$

- (b) For  $0 < x < 1$  the distribution function is

$$F(x) = \int_0^x u + \frac{1}{2} du = \frac{x^2}{2} + \frac{x}{2} = \frac{1}{2}x(x+1)$$

The complete distribution function is therefore

$$F(x) = \begin{cases} 0 & \text{for } x \leq 0 \\ \frac{1}{2}x(x+1) & \text{for } 0 < x < 1 \\ 1 & \text{for } x \geq 1. \end{cases}$$

3. (a) The means and variances are

$$\begin{aligned} E[Y_1] &= \mu_1 + \mu_3 & \text{Var}(Y_1) &= \sigma_1^2 + \sigma_3^2 \\ E[Y_2] &= \mu_2 + \mu_3 & \text{Var}(Y_2) &= \sigma_2^2 + \sigma_3^2 \end{aligned}$$

- (b) The covariance is

$$\begin{aligned} \text{Cov}(Y_1, Y_2) &= \text{Cov}(X_1 + X_3, Y_2) = \text{Cov}(X_1, Y_2) + \text{Cov}(X_3, Y_2) \\ &= \text{Cov}(X_1, X_2 + X_3) + \text{Cov}(X_3, X_2 + X_3) \\ &= \text{Cov}(X_1, X_2) + \text{Cov}(X_1, X_3) + \text{Cov}(X_3, X_2) + \text{Cov}(X_3, X_3) \\ &= 0 + 0 + 0 + \text{Var}(X_3) = \sigma_3^2 \end{aligned}$$

- (c) If  $\sigma_1^2 = \sigma_2^2 = \sigma_3^2 = \sigma^2$  then  $\text{Var}(Y_1) = \text{Var}(Y_2) = 2\sigma^2$  and  $\text{Cov}(Y_1, Y_2) = \sigma^2$ . So the correlation is

$$\rho = \frac{\text{Cov}(Y_1, Y_2)}{\sqrt{\text{Var}(Y_1)\text{Var}(Y_2)}} = \frac{\sigma^2}{2\sigma^2} = \frac{1}{2}$$

4. The conditional probability function of  $Y$  given  $X = n$  is

$$\begin{aligned} f_{Y|X}(y|n) &= \Pr(Y = y|X = n) = \frac{\Pr(Y = y, X = n)}{\Pr(X = n)} \\ &= \frac{\Pr(Y = y, X - Y = n - y)}{\Pr(X = n)} \end{aligned}$$

For a Poisson process the number of events  $Y$  in  $[0, s]$  and the number of events  $X - Y$  in  $(s, t]$  are independent Poisson variables with means  $rs$  and  $r(t - s)$  and the number of events  $X$  in  $[0, t]$  is Poisson with mean  $rt$ , respectively. So for  $y = 0, \dots, n$

$$\begin{aligned} f_{Y|X}(y|n) &= \frac{\Pr(Y = y) \Pr(X - Y = n - y)}{\Pr(X = n)} \\ &= \frac{\frac{(rs)^y}{y!} e^{-rs} \frac{(r(t-s))^{(n-y)}}{(n-y)!} e^{-r(t-s)}}{\frac{(rt)^n}{n!} e^{-rt}} \\ &= \frac{n!}{y!(n-y)!} \frac{s^y (t-s)^{n-y}}{t^n} = \binom{n}{y} \left(\frac{s}{t}\right)^y \left(1 - \frac{s}{t}\right)^{n-y} \end{aligned}$$

This is a binomial distribution with  $n$  trials and success probability  $s/t$ .

An alternative approach: Given that there are  $n$  events in  $[0, t]$ , the times at which these events occur are distributed as  $n$  independent uniform random variables on  $[0, t]$ . The probability that a uniform random variable on  $[0, t]$  is less than  $s$  is  $s/t$ , so the number of these times that are less than  $s$  is binomial with  $n$  trials and success probability  $s/t$ .

5. Suppose  $N = n$  customers arrive at the store. Since customers act independently, the conditional distribution of  $X$  given  $N = n$  is binomial( $n, p$ ). Thus

$$\begin{aligned} f(x, y) &= \Pr(X = x, Y = y) = \Pr(X = x, X + Y = x + y) \\ &= \Pr(X = x, N = x + y) = \Pr(X = x|N = x + y) \Pr(N = x + y) \\ &= \binom{x+y}{x} p^x (1-p)^{x+y-x} \frac{\lambda^{x+y}}{(x+y)!} e^{-\lambda} = \frac{(x+y)!}{x!y!} p^x (1-p)^y \frac{\lambda^{x+y}}{(x+y)!} e^{-\lambda} \\ &= \frac{(p\lambda)^x}{x!} e^{-p\lambda} \frac{((1-p)\lambda)^y}{y!} e^{-(1-p)\lambda} \end{aligned}$$

Thus  $X$  and  $Y$  are independent Poisson random variables with means  $p\lambda$  and  $(1-p)\lambda$ , respectively.

6. Let  $V = Y$ . Then  $X = UV$  and  $Y = V$ . The Jacobian determinant is

$$J(u, v) = \det \begin{pmatrix} v & u \\ 0 & 1 \end{pmatrix} = v$$

The range of the transformation is  $\mathcal{T} = (0, \infty) \times (0, \infty)$ . For  $(u, v) \in \mathcal{T}$  the joint density of  $U, V$  is

$$\begin{aligned} f_{UV}(u, v) &= v f_X(uv) f_Y(v) = v \frac{1}{\Gamma(\alpha_1)} (uv)^{\alpha_1-1} e^{-uv} \frac{1}{\Gamma(\alpha_2)} v^{\alpha_2-1} e^{-v} \\ &= \frac{u^{\alpha_1-1}}{\Gamma(\alpha_1)\Gamma(\alpha_2)} v^{\alpha_1+\alpha_2-1} e^{-v(1+u)} \end{aligned}$$

The marginal density of  $U$  is therefore

$$\begin{aligned} f_U(u) &= \frac{u^{\alpha_1-1}}{\Gamma(\alpha_1)\Gamma(\alpha_2)} \int_0^\infty v^{\alpha_1+\alpha_2-1} e^{-v(1+u)} \\ &= \frac{\Gamma(\alpha_1 + \alpha_2)}{\Gamma(\alpha_1)\Gamma(\alpha_2)} \frac{u^{\alpha_1-1}}{(1+u)^{\alpha_1+\alpha_2}} \end{aligned}$$

for  $u > 0$  and  $f_U(u) = 0$  for  $u \leq 0$ .

### Summary of Scores

Mean	49.2
SD	7.2
Min	33
Lower Quartile	44
Median	49
Upper Quartile	55.5
Max	60

