

Homework 3 Solution

1. We have that

$$\begin{aligned}
 M_Y(t) &= E(e^{tY}) = \int_0^\infty e^{ty} f_Y(y) dy \\
 &= \int_0^\infty e^{ty} y e^{-y} dy = \int_0^\infty y e^{-(1-t)y} dy \\
 &= \int_0^\infty y^{2-1} e^{-(1-t)y} dy = \frac{\Gamma(2)}{(1-t)^2} \int_0^\infty \frac{(1-t)^2}{\Gamma(2)} y^{2-1} e^{-(1-t)y} dy \\
 &= \frac{\Gamma(2)}{(1-t)^2} \int_0^\infty \frac{1}{\Gamma(2)[1/(1-t)]^2} y^{2-1} e^{-y/[1/(1-t)]} dy \\
 &= \frac{\Gamma(2)}{(1-t)^2} \cdot 1 \\
 &= \frac{1}{(1-t)^2} = (1-t)^{-2}
 \end{aligned}$$

as desired. We realize that $Y \sim \text{Gamma}(2, 1)$.

2. Here,

$$\begin{aligned}
 M_Y(t) &= E(e^{tY}) \\
 &= \int_{-1}^0 e^{ty}(1+y) dy + \int_0^1 e^{ty}(1-y) dy \\
 &= \int_{-1}^0 e^{ty} dy + \int_{-1}^0 y e^{ty} dy + \int_0^1 e^{ty} dy - \int_0^1 y e^{ty} dy \\
 &= \int_{-1}^1 e^{ty} dy + \int_{-1}^0 y e^{ty} dy - \int_0^1 y e^{ty} dy \\
 &= \left. \frac{1}{t} e^{ty} \right|_{-1}^1 + \left. \frac{x}{t} e^{ty} \right|_{-1}^0 - \int_{-1}^0 \frac{1}{t} e^{ty} dy - \left. \frac{x}{t} e^{ty} \right|_0^1 + \int_0^1 \frac{1}{t} e^{ty} dy \\
 &= \frac{1}{t} e^t - \frac{1}{t} e^{-t} + \frac{1}{t} e^{-t} - \frac{1}{t^2} + \frac{1}{t^2} e^{-t} - \frac{1}{t} e^t + \frac{1}{t^2} e^t - \frac{1}{t^2} \\
 &= \frac{1}{t^2} (e^t + e^{-t} - 2)
 \end{aligned}$$

3. Since

$$\begin{aligned}
 M'_Y(t) &= \frac{d}{dt} M_Y(t) = \frac{d}{dt} e^{t^2/2} = t e^{t^2/2} \\
 M''_Y(t) &= \frac{d}{dt} M'_Y(t) = \frac{d}{dt} t e^{t^2/2} = t^2 e^{t^2/2} + e^{t^2/2} = (t^2 + 1) e^{t^2/2} \\
 M^{(3)}_Y(t) &= \frac{d}{dt} M''_Y(t) = \frac{d}{dt} (t^2 + 1) e^{t^2/2} = (t^2 + 1) t e^{t^2/2} + 2t e^{t^2/2}
 \end{aligned}$$

we have that

$$E(Y^3) = M_Y^{(3)}(0) = \frac{d^3}{dt^3} M_Y(t) \Big|_{t=0} = (t^2 + 1)te^{t^2/2} + 2te^{t^2/2} \Big|_{t=0} = 0$$

(It follows that $E(Y^3) = 0$ for $Y \sim N(0, 1)$).

4. If $Y \sim \text{Binomial}(n, p)$, then $M_Y(t) = [(1-p) + pe^t]^n$. If we let $U = n - Y$, it follows that $M_U(t) = M_{n-Y}(t) = e^{nt} M_Y(-t) = e^{nt} [(1-p) + pe^{-t}]^n = [e^t((1-p) + pe^{-t})]^n = [p + (1-p)e^t]^n$ which is the mgf of $\text{Binomial}(n, 1-p)$. Hence, we conclude that $U \sim \text{Binomial}(n, 1-p)$.
5. If $Y \sim \text{Gamma}(n/2, m)$, then the mgf of Y is given by $M_Y(t) = (1 - mt)^{-n/2}$. Thus, the mgf of $W = 2Y/m$ will then be

$$\begin{aligned} M_W(t) &= M_{2Y/m}(t) = E(e^{t(2Y/m)}) = E(e^{(2t/m)Y}) = M_Y(2t/m) = (1 - m(2t/m))^{-n/2} \\ &= (1 - 2t)^{-n/2} \end{aligned}$$

which is the mgf of $\text{Gamma}(n/2, 2)$ or $\chi^2(n)$. Hence, $W = 2Y/m \sim \chi^2(n)$.

6. We recognize

$$M_Y(t) = \left(\frac{1}{4} + \frac{3}{4}e^t \right)^5$$

as the mgf of $Y \sim \text{Binomial}(5, 3/4)$. Hence

$$\begin{aligned} P(Y \leq 2) &= \sum_{y=0}^2 \binom{5}{y} \left(\frac{3}{4} \right)^y \left(\frac{1}{4} \right)^{5-y} \\ &= (1/4)^5 + 5(3/4)(1/4)^4 + 10(3/4)^2(1/4)^3 \\ &= 0.104 \end{aligned}$$

7. If $Y_1 \sim \text{Poisson}(\lambda_1)$ and $Y_2 \sim \text{Poisson}(\lambda_2)$ are independent, then the mgfs of Y_1 and Y_2 are

$$M_{Y_1}(t) = \exp[\lambda_1(e^t - 1)] \quad \text{and} \quad M_{Y_2}(t) = \exp[\lambda_2(e^t - 1)]$$

respectively. Since Y_1 and Y_2 are independent, the mgf of $U = Y_1 + Y_2$ is given by

$$\begin{aligned} M_U(t) &= M_{Y_1+Y_2}(t) = M_{Y_1}(t)M_{Y_2}(t) = \exp[\lambda_1(e^t - 1)] \exp[\lambda_2(e^t - 1)] \\ &= \exp[\lambda_1(e^t - 1) + \lambda_2(e^t - 1)] = \exp[(\lambda_1 + \lambda_2)(e^t - 1)] \end{aligned}$$

which is the mgf of $\text{Poisson}(\lambda_1 + \lambda_2)$. Hence, $U = Y_1 + Y_2 \sim \text{Poisson}(\lambda_1 + \lambda_2)$.

8. Since

$$M_{Y_1}(t) = \left(\frac{3}{4}e^t + 1 - \frac{3}{4} \right)^5 = \left(\frac{1}{4} + \frac{3}{4}e^t \right)^5$$

and

$$M_{Y_2}(t) = \exp[2(e^t - 1)] = e^{2(e^t - 1)}$$

and since $M_{Y_1+Y_2}(t) = M_{Y_1}(t)M_{Y_2}(t)$ if Y_1 and Y_2 are independent, the joint mgf of Y_1 and Y_2 is

$$M_{Y_1+Y_2}(t) = M_{Y_1}(t)M_{Y_2}(t) = \left(\frac{1}{4} + \frac{3}{4}e^t \right)^5 e^{2(e^t - 1)}$$

9. From Example 6.11, we see that $Y_1^2 \sim \chi^2(1)$ and $Y_2^2 \sim \chi^2(1)$, with $M_{Y_1^2}(t) = (1 - 2t)^{-1/2}$ and $M_{Y_2^2}(t) = (1 - 2t)^{-1/2}$. Since Y_1 and Y_2 are independent, then Y_1^2 and Y_2^2 are independent, so that the mfg of $U = Y_1^2 + Y_2^2$ can be computed by

$$\begin{aligned} M_U(t) &= M_{Y_1^2 + Y_2^2}(t) = M_{Y_1^2}(t)M_{Y_2^2}(t) = (1 - 2t)^{-1/2}(1 - 2t)^{-1/2} \\ &= (1 - 2t)^{-1} = (1 - 2t)^{-2/2} \end{aligned}$$

which is the mfg of Exponential(2) = Gamma(1, 2) = $\chi^2(2)$. Hence, $U = Y_1^2 + Y_2^2 \sim \chi^2(2)$.

10. (a)

$$M_Y(t) = E(e^{tY}) = \sum_y e^{ty} P(Y = y) = \sum_{y=0}^1 e^{ty} p^y (1 - p)^{1-y} = 1 - p + e^t p$$

- (b) Since we can write $M_Y(t) = 1 - p + e^t p = e^t p + (1 - p)$, we obtain

$$\begin{aligned} M_{Y_1 + \dots + Y_n}(t) &= M_{Y_1}(t) \times \dots \times M_{Y_n}(t) = [e^t p + (1 - p)] \times \dots \times [e^t p + (1 - p)] \\ &= [e^t p + (1 - p)]^n \end{aligned}$$

which is the mfg of Binomial(n, p). Hence, $Y_1 + \dots + Y_n \sim \text{Binomial}(n, p)$.

11. Since

$$M_Y(t) = \exp\left(\mu t + \frac{\sigma^2 t^2}{2}\right)$$

we obtain

$$\begin{aligned} M_{\bar{Y}}(t) &= E(e^{t\bar{Y}}) = E(e^{t(Y_1 + \dots + Y_n)/n}) = E(e^{(t/n)Y_1 + \dots + (t/n)Y_n}) = E(e^{(t/n)Y_1}) \times \dots \times E(e^{(t/n)Y_n}) \\ &= M_{Y_1}(t/n) \times \dots \times M_{Y_n}(t/n) = [M_{Y_1}(t/n)]^n \quad (\text{since } Y_1, \dots, Y_n \text{ are iid}) \\ &= \left[\exp\left(\mu(t/n) + \frac{\sigma^2(t/n)^2}{2}\right) \right]^n = \left[\exp\left(\frac{\mu t}{n} + \frac{\sigma^2 t^2}{2n^2}\right) \right]^n = \exp\left(\mu t + \frac{\sigma^2 t^2}{2n}\right) \\ &= \exp\left(\mu t + \frac{(\sigma^2/n)t^2}{2}\right) \end{aligned}$$

which is the mfg of $N(\mu, \sigma^2/n)$. Hence, $\bar{Y} \sim N(\mu, \sigma^2/n)$.

(Alternatively, you can also use Theorem 6.3 with $\mu_i = \mu$, $\sigma_i^2 = \sigma^2$, $a_i = 1/n$).

12. (5880*) We have that

$$M_{Y_1}(t) = (1 - \beta t)^{-\alpha_1}, \quad M_{Y_2}(t) = (1 - \beta t)^{-\alpha_2}, \quad M_{Y_3}(t) = (1 - \beta t)^{-\alpha_3}$$

Hence,

$$\begin{aligned} M_U(t) &= M_{c_1 Y_1 + c_2 Y_2 + c_3 Y_3}(t) = M_{Y_1}(c_1 t) M_{Y_2}(c_2 t) M_{Y_3}(c_3 t) \\ &= (1 - \beta c_1 t)^{-\alpha_1} (1 - \beta c_2 t)^{-\alpha_2} (1 - \beta c_3 t)^{-\alpha_3} \end{aligned}$$

Now, if we want $M_U(t)$ to have the mfg of a gamma distribution, then we must have that $c = c_1 = c_2 = c_3$, so that

$$\begin{aligned} M_U(t) &= (1 - \beta c_1 t)^{-\alpha_1} (1 - \beta c_2 t)^{-\alpha_2} (1 - \beta c_3 t)^{-\alpha_3} = (1 - \beta c t)^{-\alpha_1} (1 - \beta c t)^{-\alpha_2} (1 - \beta c t)^{-\alpha_3} \\ &= (1 - c\beta t)^{-(\alpha_1 + \alpha_2 + \alpha_3)} \end{aligned}$$

which is the mfg of Gamma($\alpha_1 + \alpha_2 + \alpha_3, c\beta$), so that $U \sim \text{Gamma}(\alpha_1 + \alpha_2 + \alpha_3, c\beta)$.