

M2S1 : ASSESSED COURSEWORK 3 : SOLUTIONS

1. (a) We have $U \sim \text{Uniform}(0, 1)$ and

$$X_1 = \begin{cases} \frac{1}{\lambda} \log 2U & 0 < U \leq \frac{1}{2} \\ -\frac{1}{\lambda} \log(2 - 2U) & \frac{1}{2} < U < 1 \end{cases}$$

for $\lambda > 0$. For $x \leq 0$ (so that $0 < u \leq \frac{1}{2}$)

$$F_{X_1}(x) = P[X_1 \leq x] = P\left[\frac{1}{\lambda} \log 2U \leq x\right] = P\left[U \leq \frac{1}{2}e^{\lambda x}\right] = \frac{1}{2}e^{\lambda x}$$

and for $x > 0$ (so that $\frac{1}{2} < u < 1$)

$$\begin{aligned} F_{X_1}(x) &= P[X_1 \leq x] = P[X_1 \leq 0] + P[0 < X_1 \leq x] \\ &= \frac{1}{2} + P\left[0 < -\frac{1}{\lambda} \log(2 - 2U) \leq x\right] \\ &= \frac{1}{2} + P\left[\frac{1}{2}e^{-\lambda x} \leq 1 - U < \frac{1}{2}\right] \\ &= \frac{1}{2} + P\left[\frac{1}{2} < U \leq 1 - \frac{1}{2}e^{-\lambda x}\right] \\ &= \frac{1}{2} + 1 - \frac{1}{2}e^{-\lambda x} - \frac{1}{2} = 1 - \frac{1}{2}e^{-\lambda x} \end{aligned}$$

Hence, by differentiation

$$f_{X_1}(x) = \begin{cases} \frac{\lambda}{2}e^{\lambda x} & 0 \leq x \\ \frac{\lambda}{2}e^{-\lambda x} & x > 0 \end{cases} = \frac{\lambda}{2}e^{-\lambda|x|} \quad x \in \mathbb{R}$$

[4 MARKS]

(ii) For the mgf

$$\begin{aligned} E_{f_{X_1}}[e^{tX_1}] &= \int_{-\infty}^{\infty} e^{tx} f_{X_1}(x) dx = \int_{-\infty}^{\infty} e^{tx} \frac{\lambda}{2} e^{-\lambda|x|} dx \\ &= \frac{\lambda}{2} \left[\int_{-\infty}^0 e^{(\lambda+t)x} dx + \int_0^{\infty} e^{-(\lambda-t)x} dx \right] \\ &= \frac{\lambda}{2} \left[\frac{1}{\lambda+t} + \frac{1}{\lambda-t} \right] \quad \text{if } |t| < \lambda \\ &= \frac{\lambda^2}{(\lambda+t)(\lambda-t)} = \frac{\lambda^2}{(\lambda^2 - t^2)} = \frac{1}{1 - \frac{t^2}{\lambda^2}} \end{aligned} \tag{1}$$

[6 MARKS]

(b) The joint pdf has support $\mathbb{X}^{(2)} = \mathbb{R} \times \mathbb{R}^+$

$$f_{X_2, Y}(x, y) = f_{X_2|Y}(x|y)f_Y(y) = \left(\frac{1}{2\pi y}\right)^{1/2} \exp\left\{-\frac{x^2}{2y}\right\} \gamma \exp\{-\gamma y\}$$

(i) To compute the mgf, use the Law of Iterated Expectation

$$E_{f_{X_2}}[e^{tX_2}] = E_{f_Y}\left[E_{f_{X_2|Y}}[e^{tX_2}|Y=y]\right].$$

Now

$$E_{f_{X_2|Y}}[e^{tX_2}|Y=y] = \exp\left\{\frac{yt^2}{2}\right\}$$

as $X_2|Y=y \sim \text{Normal}(0, y)$, using the mgf of a Normal random variable from the formula sheet, with $\mu = 0$ and $\sigma^2 = y$. Thus

$$E_{f_{X_2}}[e^{tX_2}] = E_{f_Y}\left[\exp\left\{\frac{Yt^2}{2}\right\}\right] = M_Y\left(\frac{t^2}{2}\right) = \frac{\gamma}{\gamma - \frac{t^2}{2}}$$

as $Y \sim \text{Exponential}(\gamma)$, using the mgf for an Exponential from the formula sheet. Hence

$$M_{X_2}(t) = \frac{\gamma}{\gamma - \frac{t^2}{2}} = \frac{1}{1 - \frac{t^2}{2\gamma}} \quad (2)$$

[4 MARKS]

(ii) Comparing (1) and (2), and setting $\lambda^2 = 2\gamma$, we can deduce that

$$f_{X_2}(x) = \frac{\sqrt{2\gamma}}{2} \exp\{-\sqrt{2\gamma}|x|\} \quad x \in \mathbb{R}$$

by the uniqueness of mgfs.

[4 MARKS]

(iii) Using properties of mgfs

$$E_{f_{X_2}}[X_2^r] = \frac{d^r}{dt^r} \{M_{X_2}(t)\}_{t=0}$$

We have

$$\frac{d}{dt} \{M_{X_2}(t)\}_{t=0} = \left\{ \frac{4\gamma t}{(2\gamma - t^2)^2} \right\}_{t=0} = 0 \quad \therefore \quad E_{f_{X_2}}[X_2] = 0$$

$$\frac{d^2}{dt^2} \{M_{X_2}(t)\}_{t=0} = \left\{ \frac{4\gamma(2\gamma - t^2)^2 + 16\gamma t^2}{(2\gamma - t^2)^4} \right\}_{t=0} = \frac{16\gamma^3}{16\gamma^4} = \frac{1}{\gamma} \quad \therefore \quad E_{f_{X_2}}[X_2^2] = \frac{1}{\gamma}$$

so therefore

$$\text{Var}_{f_{X_2}}[X_2] = E_{f_{X_2}}[X_2^2] - \left\{E_{f_{X_2}}[X_2]\right\}^2 = \frac{1}{\gamma}$$

[2 MARKS]

2. (a)(i) $X_1, X_2, \dots, X_n \sim \text{Poisson}(\lambda)$. From the formula sheet we have the mgf of each X_i equal to

$$\exp\{\lambda(e^t - 1)\}$$

and hence, if $T_n = \sum_{i=1}^n X_i$, by the key mgf result

$$M_{T_n}(t) = \prod_{i=1}^n M_{X_i}(t) = \prod_{i=1}^n \exp\{\lambda(e^t - 1)\} = \exp\{n\lambda(e^t - 1)\}$$

and thus, by uniqueness of mgfs

$$T_n \sim \text{Poisson}(n\lambda)$$

[2 MARKS]

(ii) Standardized variable

$$Z_n = \frac{T_n - n\lambda}{\sqrt{n\lambda}}$$

and by the Central Limit Theorem, we have

$$Z_n \xrightarrow{d} Z \sim N(0, 1)$$

and hence, by location/scale transformation of Z_n , for large n

$$T_n \sim N(n\lambda, n\lambda)$$

so that

$$F_{T_n}(t) = P[T_n \leq t] = P\left[\frac{T_n - n\lambda}{\sqrt{n\lambda}} \leq \frac{t - n\lambda}{\sqrt{n\lambda}}\right] \approx \Phi\left(\frac{t - n\lambda}{\sqrt{n\lambda}}\right)$$

[4 MARKS]

(b)(i) We have, from the definitions given, that for $i = 0, 1$

$$X_i \sim \text{Binomial}(n_i, \theta_i)$$

and consequently

$$X_i = \sum_{j=1}^{n_i} X_{ij}$$

where $X_{ij} \sim \text{Bernoulli}(\theta_i)$, independently, for $j = 1, 2, \dots, n_i$ so that, from the formula sheet

$$E_{f_{X_i}}[X_i] = \theta_i \quad \text{Var}_{f_{X_i}}[X_i] = \theta_i(1 - \theta_i).$$

Now, $i = 0, 1$,

$$Z_i = \frac{X_i - n_i\theta_i}{\sqrt{n_i\theta_i(1 - \theta_i)}}$$

is a standardized variable, and hence by the Central Limit Theorem we have

$$Z_i \xrightarrow{d} Z \sim N(0, 1)$$

as $n_i \rightarrow \infty$.

[4 MARKS]

(ii) If $Z \sim N(0, 1)$, then

$$M_Z(t) = \exp\left\{\frac{t^2}{2}\right\}$$

so that the mgf of $Z_1 - Z_0$ (in the limit as $n_0 \rightarrow \infty$ and $n_1 \rightarrow \infty$) is

$$M_{Z_1}(t) \times M_{Z_0}(-t) \exp\left\{\frac{t^2}{2}\right\} \times \exp\left\{\frac{(-t)^2}{2}\right\} = \exp\left\{\frac{2t^2}{2}\right\} = \exp\left\{\frac{(\sqrt{2}t)^2}{2}\right\}$$

by a key mgf result, and the result for linear transformations of Normal random variables. Hence

$$Z_1 - Z_0 \sim N\left(0, (\sqrt{2})^2\right) \equiv N(0, 2)$$

[2 MARKS]

(iii) Can quote result from lecture notes, but from first principles, if $Z \sim N(0, 1)$ and $V = Z^2$ then for $v > 0$

$$F_V(v) = P[V \leq v] = P[X^2 \leq v] = P[-\sqrt{v} \leq X \leq \sqrt{v}] = F_X(\sqrt{v}) - F_X(-\sqrt{v}) = \Phi(\sqrt{v}) - \Phi(-\sqrt{v})$$

and so, by differentiation

$$f_V(v) = \frac{1}{2\sqrt{v}} [\phi(\sqrt{v}) + \phi(-\sqrt{v})] = \frac{1}{\sqrt{v}} \left(\frac{1}{2\pi}\right)^{1/2} \exp\left\{-\frac{1}{2}(\sqrt{v})^2\right\} = \frac{\left(\frac{1}{2}\right)^{1/2}}{\Gamma\left(\frac{1}{2}\right)} v^{1/2-1} \exp\left\{-\frac{v}{2}\right\} \quad v > 0$$

so from the formula sheet

$$V \sim \text{Gamma}\left(\frac{1}{2}, \frac{1}{2}\right) \equiv \chi_1^2 \quad \therefore \quad M_V(t) = \frac{\frac{1}{2}}{\frac{1}{2} - t}$$

Hence, for large n_0 and n_1 $Q_0 \sim \chi_1^2$ and $Q_1 \sim \chi_1^2$ and thus using mgfs

$$M_Q(t) = M_{Q_0}(t)M_{Q_1}(t) \approx \left(\frac{\frac{1}{2}}{\frac{1}{2} - t}\right) \times \left(\frac{\frac{1}{2}}{\frac{1}{2} - t}\right) = \left(\frac{\frac{1}{2}}{\frac{1}{2} - t}\right)^2$$

so that, from the formula sheet

$$Q \sim \text{Gamma}\left(\frac{2}{2}, \frac{1}{2}\right) \equiv \text{Gamma}\left(1, \frac{1}{2}\right) \equiv \chi_2^2 \equiv \text{Exponential}\left(\frac{1}{2}\right)$$

[4 MARKS]

(iv) If $\theta_0 = \theta_1 = \theta$ say, then from the formula sheet

$$M_Y(y) = M_{X_0}(t)M_{X_1}(t) = (1 - \theta + \theta e^t)^{n_1} \times (1 - \theta + \theta e^t)^{n_2} = (1 - \theta + \theta e^t)^{n_1 + n_2}$$

and hence

$$Y \sim \text{Binomial}(n_0 + n_1, \theta)$$

so that, by the Central Limit Theorem

$$Y \sim \text{Normal}((n_0 + n_1)\theta, (n_0 + n_1)\theta(1 - \theta))$$

[4 MARKS]