

M2S1 : EXERCISE SHEET 4 : SOLUTIONS

1 (a) To calculate the mgf

$$\begin{aligned} M_Z(t) &= E_{f_Z} [e^{tZ}] = \int_{-\infty}^{\infty} e^{zt} \frac{1}{\sqrt{2\pi}} \exp \left\{ -\frac{z^2}{2} \right\} dz = e^{t^2/2} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \exp \left\{ -\frac{(z-t)^2}{2} \right\} dz \\ &= e^{t^2/2} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \exp \left\{ -\frac{u^2}{2} \right\} du = e^{t^2/2} \end{aligned}$$

completing the square in z , and then setting $u = z - t$, as the integrand is a pdf.

Now, using the transformation theorem for univariate, 1-1 transformations we have $X = \mu + \frac{1}{\lambda}Z \iff Z = \lambda(X - \mu)$, so

$$f_X(x) = f_Z(\lambda(x - \mu)) \lambda = \frac{\lambda}{\sqrt{2\pi}} \exp \left\{ -\frac{\lambda^2}{2}(x - \mu)^2 \right\} \quad x \in \mathbb{R}$$

To calculate the mgf of X , use the expectation result given in lectures

$$M_X(t) = E_{f_Z} \left[e^{t(\mu+Z/\lambda)} \right] = e^{\mu t} M_Z(t/\lambda) = \exp \left\{ \mu t + \frac{t^2}{2\lambda^2} \right\}$$

The expectation of X is

$$\begin{aligned} E_{f_X} [X] &= \int_{-\infty}^{\infty} x f_X(x) dx = \int_{-\infty}^{\infty} x \left(\frac{\lambda^2}{2\pi} \right)^{1/2} \exp \left\{ -\frac{\lambda^2}{2}(x - \mu)^2 \right\} dx \\ &= \int_{-\infty}^{\infty} (\mu + t\lambda^{-1}) \left(\frac{\lambda^2}{2\pi} \right)^{1/2} \exp \left\{ -\frac{t^2}{2} \right\} \lambda^{-1} dt \quad t = \lambda(x - \mu) \\ &= \mu \int_{-\infty}^{\infty} \left(\frac{1}{2\pi} \right)^{1/2} \exp \left\{ -\frac{t^2}{2} \right\} dt + \lambda^{-1} \int_{-\infty}^{\infty} t \left(\frac{1}{2\pi} \right)^{1/2} \exp \left\{ -\frac{t^2}{2} \right\} dt \\ &= \mu \end{aligned}$$

as the first integral is 1, and the second integral is zero, as the integrand is an ODD function about zero. Hence

$$E_{f_X} [X] = \mu$$

and note that it is generally true that if a pdf is symmetric about a particular value, then that value is the expectation (if the expectation integral is finite). Alternately, could use the mgf result that says

$$E_{f_X} [X] = \frac{d}{ds} \{M_X(s)\}_{s=0} = M_X^{(1)}(0)$$

say, so that

$$E_{f_X} [X] = \frac{d}{ds} \left\{ \exp \left\{ \mu s + \frac{s^2}{2\lambda^2} \right\} \right\}_{s=0} = \left\{ \left(\mu + \frac{s}{\lambda^2} \right) \exp \left\{ \mu s + \frac{s^2}{2\lambda^2} \right\} \right\}_{s=0} = \mu$$

The expectation of $g(X) = e^X$ is

$$\begin{aligned} E_{f_X} [g(X)] &= \int_{-\infty}^{\infty} g(x) f_X(x) dx = \int_{-\infty}^{\infty} e^x \left(\frac{\lambda^2}{2\pi} \right)^{1/2} \exp \left\{ -\frac{\lambda^2}{2} (x - \mu)^2 \right\} dx \\ &= \int_{-\infty}^{\infty} \exp \left\{ \mu + t\lambda^{-1} \right\} \left(\frac{\lambda^2}{2\pi} \right)^{1/2} \exp \left\{ -\frac{t^2}{2} \right\} \lambda^{-1} dt \quad \text{setting } t = \lambda(x - \mu) \\ &= \left(\frac{1}{2\pi} \right)^{1/2} \int_{-\infty}^{\infty} \exp \left\{ \mu + t\lambda^{-1} - \frac{t^2}{2} \right\} dt = \left(\frac{1}{2\pi} \right)^{1/2} \int_{-\infty}^{\infty} \exp \left\{ -\frac{1}{2} (t^2 - 2t\lambda^{-1} - 2\mu) \right\} dt \end{aligned}$$

Completing the square in the exponent, we have

$$(t^2 - 2t\lambda^{-1} - 2\mu) = (t - \lambda^{-1})^2 - (2\mu + \lambda^{-2})$$

and hence

$$\begin{aligned} E_{f_X} [g(X)] &= \left(\frac{1}{2\pi} \right)^{1/2} \int_{-\infty}^{\infty} \exp \left\{ -\frac{1}{2} (t - \lambda^{-1})^2 + \left(\mu + \frac{1}{2\lambda^2} \right) \right\} dt \\ &= \exp \left\{ \mu + \frac{1}{2\lambda^2} \right\} \int_{-\infty}^{\infty} \left(\frac{1}{2\pi} \right)^{1/2} \exp \left\{ -\frac{1}{2} (t - \lambda^{-1})^2 \right\} dt = \exp \left\{ \mu + \frac{1}{2\lambda^2} \right\} \end{aligned}$$

as the integral is equal to 1, as it is the integral of a pdf for all choices of λ .

(b) If $Y = e^X$, so $\mathbb{Y} = \mathbb{R}^+$, and from first principles we have

$$F_Y(y) = \mathbb{P}[Y \leq y] = \mathbb{P}[e^X \leq y] = \mathbb{P}[X \leq \log y] = F_X(\log y) \quad \implies \quad f_Y(y) = f_X(\log y) \frac{1}{y} \quad y > 0$$

Note that the function $g(t) = e^t$ is a monotone increasing function, with $g^{-1}(t) = \log t$, so that we can use the general result directly, that is

$$f_Y(y) = f_X(g^{-1}(y)) J(y) \quad \text{where} \quad J(y) = \left| \frac{d}{dt} \{g^{-1}(t)\}_{t=y} \right| = \left| \frac{d}{dt} \{\log t\}_{t=y} \right| = \frac{1}{y}$$

Hence

$$f_Y(y) = \frac{1}{y} \left(\frac{\lambda^2}{2\pi} \right)^{1/2} \exp \left\{ -\frac{\lambda^2}{2} (\log y - \mu)^2 \right\} \quad y > 0.$$

For the expectation, we have from first principles

$$\begin{aligned} E_{f_Y} [Y] &= \int_0^{\infty} y f_Y(y) dy = \int_{-\infty}^{\infty} y \frac{1}{y} \left(\frac{\lambda^2}{2\pi} \right)^{1/2} \exp \left\{ -\frac{\lambda^2}{2} (\log y - \mu)^2 \right\} dy \\ &= \int_{-\infty}^{\infty} \left(\frac{\lambda^2}{2\pi} \right)^{1/2} \exp \left\{ -\frac{\lambda^2}{2} (t - \mu)^2 \right\} e^t dt = \exp \left\{ \mu + \frac{1}{2\lambda^2} \right\} \end{aligned}$$

where $t = \log y$, as the integral is precisely the one carried out above. This illustrates the transformation/expectation result that, if $Y = g(X)$, then

$$E_{f_Y} [Y] = E_{f_X} [g(X)]$$

(c) If $T = Z^2$, then from first principles

$$\begin{aligned} F_T(t) &= P[T \leq t] = P[Z^2 \leq t] = P[-\sqrt{t} \leq Z \leq \sqrt{t}] \\ \implies f_T(t) &= \frac{1}{2\sqrt{t}} [f_Z(\sqrt{t}) + f_Z(-\sqrt{t})] = \frac{1}{\sqrt{2\pi}} t^{-1/2} \exp\left\{-\frac{t}{2}\right\} \quad t > 0 \end{aligned}$$

and hence

$$\begin{aligned} M_T(t) &= E_{f_T}[e^{tT}] = \int_{-\infty}^{\infty} e^{tx} f_T(x) dx = \int_{-\infty}^{\infty} e^{tx} \frac{1}{\sqrt{2\pi x}} \exp\left\{-\frac{x}{2}\right\} dx = \int_0^{\infty} \frac{1}{\sqrt{2\pi x}} \exp\left\{-\frac{(1-2t)x}{2}\right\} dx \\ &= \left(\frac{1}{1-2t}\right)^{1/2} \int_0^{\infty} \frac{1}{\sqrt{2\pi y}} \exp\left\{-\frac{y}{2}\right\} dy = \left(\frac{1}{1-2t}\right)^{1/2} \end{aligned}$$

where $y = (1-2t)x$, as the integrand is a pdf.

2. By definition of mgfs for discrete variables, we can deduce immediately that, as

$$M_X(t) = \sum_{x=-\infty}^{\infty} e^{tx} f_X(x)$$

$P[X = x]$ is just the coefficient of e^{tx} in the expression for M_X , and hence $P[X = 1] = 1/8$, $P[X = 2] = 1/4$ and $P[X = 3] = 5/8$. Also, we have $E_{f_X}[X^r] = M_X^{(r)}(0)$, so that

$$E_{f_X}[X] = M_X^{(1)}(0) = \frac{1}{8} + 2\frac{1}{4} + 3\frac{5}{8} = \frac{5}{2} \quad E_{f_X}[X^2] = M_X^{(2)}(0) = \frac{1}{8} + 4\frac{1}{4} + 9\frac{5}{8} = \frac{27}{4}$$

$$\implies \text{Var}_{f_X}[X] = E_{f_X}[X^2] - \{E_{f_X}[X]\}^2 = \frac{1}{2}$$

3. Can identify that $X \sim \text{Binomial}(n, \theta)$, but in any case,

$$\begin{aligned} M_X(t) &= (1 - \theta + \theta e^t)^n = (1 + (e^t - 1)\theta)^n = \left(1 + \theta \left(t + \frac{t^2}{2!} + \frac{t^3}{3!} + \dots\right)\right)^n \\ &= \sum_{r=0}^n \binom{n}{r} \theta^r \left(t + \frac{t^2}{2!} + \frac{t^3}{3!} + \dots\right)^r \end{aligned}$$

and from the mgf definition $E_{f_X}[X^r]$ is $r!$ times the coefficient of t^r . Difficult to identify this general term, but can easily identify the coefficient of t as $n\theta = E_{f_X}[X]$, and the coefficient of t^2 as $n\theta + n(n-1)\theta^2 = E_{f_X}[X^2]$ etc.

4. For this pdf,

$$\begin{aligned} M_X(t) &= \int_{-\infty}^{\infty} e^{tx} f_X(x) dx = \int_{-2}^{\infty} e^{tx} e^{-(x+2)} dx = e^{-2} \int_{-2}^{\infty} e^{-(1-t)x} dx \\ &= \frac{e^{-2}}{1-t} \int_{-2(1-t)}^{\infty} e^{-y} dy = \frac{e^{-2}}{1-t} [-e^{-y}]_{-2(1-t)}^{\infty} = \frac{e^{-2t}}{1-t} \quad t < 1 \end{aligned}$$

Now

$$M_X^{(1)}(t) = \frac{e^{-2t}}{(1-t)^2} (2t-1) \quad M_X^{(2)}(t) = \frac{e^{-2t}}{(1-t)^3} [1 + (2t-1)^2]$$

so that $M_X^{(1)}(0) = -1 = E_{f_X}[X]$ and $M_X^{(2)}(0) = 2 = E_{f_X}[X^2] \implies \text{Var}_{f_X}[X] = 1$

5. We have $K_X(t) = \log M_X(t)$, hence

$$K_X^{(1)}(t) = \frac{d}{ds} \{K_X(t)\}_{s=t} = \frac{d}{ds} \{\log M_X(t)\}_{s=t} = \frac{M_X^{(1)}(t)}{M_X(t)} \implies K_X^{(1)}(0) = \frac{M_X^{(1)}(0)}{M_X(0)} = E_{f_X}[X]$$

as $M_X(0) = 1$. Similarly

$$K_X^{(2)}(t) = \frac{M_X(t)M_X^{(2)}(t) - \{M_X^{(1)}(t)\}^2}{\{M_X(t)\}^2}$$

and hence

$$K_X^{(2)}(0) = \frac{M_X(0)M_X^{(2)}(0) - \{M_X^{(1)}(0)\}^2}{\{M_X(0)\}^2} = E_{f_X}[X^2] - \{E_{f_X}[X]\}^2$$

and hence $K_X^{(2)}(0) = \text{Var}_{f_X}[X]$

6. Easy to see that $f_{X,Y}(x, y) = f_X(x)f_Y(y)$, with $\mathbb{X}^{(2)} = \mathbb{X} \times \mathbb{Y}$, so X and Y are independent, where

$$f_X(x) = \sqrt{c} \frac{2^x}{x!} \quad f_Y(y) = \sqrt{c} \frac{2^y}{y!} \quad \text{and} \quad \sum_{x=0}^{\infty} f_X(x) = 1 \implies \sqrt{c} = e^{-2}$$

(marginal mass functions must have identical forms as joint mass function is symmetric in x and y) as the summation is identical to the power series expansion of e^z at $z = 2$ if $\sqrt{c} = e^{-2}$.

7. $F_{X,Y}$ is continuous and non decreasing in x and y , and

$$\lim_{x \rightarrow -\infty} F_{X,Y}(x, y) = \lim_{y \rightarrow -\infty} F_{X,Y}(x, y) = 0 \quad \lim_{x, y \rightarrow \infty} F_{X,Y}(x, y) = 1$$

so $F_{X,Y}$ is a valid cdf, and

$$f_{X,Y}(x, y) = \frac{\partial^2}{\partial t_1 \partial t_2} \{F_{X,Y}(t_1, t_2)\}_{t_1=x, t_2=y} = \frac{e^{-x}}{\pi(1+y^2)} = f_X(x)f_Y(y)$$

so as $\mathbb{X}^{(2)} = \mathbb{R}^+ \times \mathbb{R}$, X and Y are independent.

8. (i) If $\mathbb{X}^{(2)} = (0, 1) \times (0, 1)$ is the (joint) range of vector random variable (X, Y) . We have

$$f_{X,Y}(x, y) = cx(1-y) \quad 0 < x < 1, \quad 0 < y < 1$$

so that

$$f_{X,Y}(x, y) = f_X(x)f_Y(y) \quad \text{and} \quad \mathbb{X}^{(2)} = \mathbb{X} \times \mathbb{Y}$$

where \mathbb{X} and \mathbb{Y} are the ranges of X and Y respectively, and

$$f_X(x) = c_1x \quad \text{and} \quad f_Y(y) = c_2(1-y) \quad (1)$$

for some constants satisfying $c_1c_2 = c$. Hence, the two conditions for independence are satisfied in (2), and X and Y are independent.

(ii) We must have

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y}(x,y) \, dx dy = 1 \therefore c^{-1} = \int_0^1 \int_0^1 x(1-y) \, dx dy = 1$$

and as

$$\int_0^1 \int_0^1 x(1-y) \, dx dy = \left\{ \int_0^1 x \, dx \right\} \left\{ \int_0^1 (1-y) \, dy \right\} = \frac{1}{2} \times \frac{1}{2} = \frac{1}{4}$$

we have $c = 4$.

(iii) We have $A = \{(x, y) : 0 < x < y < 1\}$, and hence, recalling that the joint density is only non-zero when $x < y$, we first fix a y and integrate dx on the range $(0, y)$, and then integrate dy on the range $(0, 1)$, that is

$$\begin{aligned} P[X < Y] &= \int_A \int f_{X,Y}(x,y) \, dx dy = \int_0^1 \left\{ \int_0^y 4x(1-y) \, dx \right\} dy = \int_0^1 \left\{ \int_0^y x \, dx \right\} 4(1-y) \, dy \\ &= \int_0^1 2y^2(1-y) \, dy = \left[\frac{2}{3}y^3 - \frac{1}{2}y^4 \right]_0^1 = \frac{1}{6} \end{aligned}$$

9. The joint pdf of X and Y is given by

$$f_{X,Y}(x,y) = 24xy \quad x > 0, \, y > 0, \, x + y < 1$$

and zero otherwise, the marginal pdf f_X is given by

$$\begin{aligned} f_X(x) &= \int_{-\infty}^{\infty} f_{X,Y}(x,y) \, dy = \int_0^{1-x} 24xy \, dy = 24x \left[\frac{y^2}{2} \right]_0^{1-x} \\ &= 12x(1-x)^2 \quad 0 < x < 1 \end{aligned}$$

as the integrand is only non-zero when $0 < x + y < 1 \implies 0 < y < 1 - x$ for fixed x

10. First sketch the support of the density; this will make it clear that the boundaries of the support are different for $0 < y \leq 1$ and $y > 1$. The marginals are given by

$$f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dy = \int_{1/x}^x \frac{1}{2x^2y} dy = \frac{1}{2x^2}(\log x - \log(1/x)) = \frac{\log x}{x^2} \quad 1 \leq x$$

$$f_Y(y) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dx = \begin{cases} \int_{1/y}^{\infty} \frac{1}{2x^2y} dx = \frac{1}{2} & 0 \leq y \leq 1 \\ \int_y^{\infty} \frac{1}{2x^2y} dx = \frac{1}{2y^2} & 1 \leq y \end{cases}$$

Conditionals:

$$f_{X|Y}(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)} = \begin{cases} \frac{1}{x^2y} & 1/y \leq x \text{ if } 0 \leq y \leq 1 \\ \frac{y}{x^2} & y \leq x \text{ if } 1 \leq y \end{cases}$$

$$f_{Y|X}(y|x) = \frac{f_{X,Y}(x,y)}{f_X(x)} = \frac{1}{2y \log x} \quad 1/x \leq y \leq x \text{ if } x \geq 1$$

Marginal expectation of Y ;

$$E_{f_Y}[Y] = \int_{-\infty}^{\infty} y f_Y(y) dy = \int_0^1 \frac{y}{2} dy + \int_1^{\infty} \frac{1}{2y} dy = \infty$$

as the second integral is divergent.