

STAT2602/3902 Assignment 1

Q1) (i) The definition of theoretical cdf of a random variable X is $F_X(x) = \Pr(X \leq x)$.

We can use the empirical cdf to estimate $\Pr(X \leq x)$, which is defined as $\hat{F}_n(x) = \frac{1}{n} \sum_{i=1}^n I(x_i \leq x)$, where x_i is the i th observation in our random sample.

(ii) $\Pr(X \leq 4)$ can be estimated by $\hat{F}_{10}(4) = \frac{1}{10} \sum_{i=1}^{10} I(x_i \leq 4) = 0.7$.

$\Pr(3 < X < 7)$ can be estimated by $\frac{1}{10} \sum_{i=1}^{10} I(3 < x_i < 7) = 0.3$.

Note 1: In this question, we know X is a discrete v.v., and therefore, $\Pr(3 < X < 7) = \Pr(4 \leq X \leq 6) = \Pr(X \leq 6) - \Pr(X \leq 3)$.

Hence, $\Pr(3 < X < 7)$ can be estimated by $\hat{F}_{10}(6) - \hat{F}_{10}(3) = 0.9 - 0.6 = 0.3$.

Note 2: If we don't know whether X is discrete or continuous, then $\Pr(a < X < b)$ can be estimated by $\frac{1}{n} \sum_{i=1}^n I(a < x_i < b)$. Similarly, $\Pr(a \leq X < b)$ can be estimated by $\frac{1}{n} \sum_{i=1}^n I(a \leq x_i < b)$, and so forth.

Q2) $P_r(X=x) = 2 \left(\frac{1}{3}\right)^x$ for $x \in \mathbb{N}$.

(i)
$$\begin{aligned} F_X(x) &= P_r(X \leq x) = \sum_{i=1}^x P_r(X=i) \\ &= \sum_{i=1}^x 2 \left(\frac{1}{3}\right)^i = 2 \sum_{i=1}^x \left(\frac{1}{3}\right)^i = 2 \left[\frac{\frac{1}{3} - \left(\frac{1}{3}\right)^{x+1}}{1 - \frac{1}{3}} \right] = 1 - \left(\frac{1}{3}\right)^x \text{ for } x \in \mathbb{N}. \end{aligned}$$

Note: Let $S_n = \sum_{i=1}^n p^i$. Then, $P S_n = \sum_{i=2}^{n+1} p^i = S_n - p + p^{n+1}$
 $\Rightarrow S_n(P-1) = p^{n+1} - p \Rightarrow S_n = \frac{p - p^{n+1}}{1-p}$

In general,
$$F_X(x) = \begin{cases} 1 - \left(\frac{1}{3}\right)^{\lfloor x \rfloor} & \text{if } x \geq 1 \\ 0 & \text{otherwise} \end{cases}$$
 where $\lfloor x \rfloor$ is the largest integer s.t. $x \geq \lfloor x \rfloor$.

Note: $X \sim \text{Geo}(p = \frac{2}{3})$.

(ii)
$$\begin{aligned} M_X(t) &= E[e^{tx}] = \sum_{x=1}^{\infty} e^{tx} P_r(X=x) \\ &= \sum_{x=1}^{\infty} e^{tx} 2 \left(\frac{1}{3}\right)^x = 2 \sum_{x=1}^{\infty} \left(e^t \frac{1}{3}\right)^x \\ &= 2 \left(\frac{e^t \frac{1}{3}}{1 - e^t \frac{1}{3}} \right) = \frac{\frac{2}{3} e^t}{1 - \frac{1}{3} e^t} \text{ for } t < \ln 3 \end{aligned}$$

Note: $e^t \frac{1}{3} < 1 \Leftrightarrow e^t < 3 \Leftrightarrow t < \ln 3$

Note: $\sum_{k=1}^{\infty} p^k = \frac{p}{1-p}$ if $|p| < 1$ and $\sum_{k=0}^{\infty} p^k = \frac{1}{1-p}$ if $|p| < 1$

(iii) $\therefore X \sim \text{Geo}(p = \frac{2}{3})$

$\therefore E(X) = \frac{1}{p} = \frac{3}{2}, \text{ Var}(X) = \frac{1-p}{p^2} = \frac{3}{4}$

$$Q3) M_X(t) = \bar{E}(e^{tX}) = \bar{E}\left(\sum_{k=0}^{\infty} \frac{(tX)^k}{k!}\right)$$

$$= \bar{E}\left[\sum_{k=0}^{\infty} \frac{t^k X^k}{k!}\right] = \sum_{k=0}^{\infty} \frac{t^k \bar{E}(X^k)}{k!}$$

$$= 1 + \sum_{k=1}^{\infty} \frac{t^k \bar{E}(X^k)}{k!}$$

$$= 1 + \sum_{k=1}^{\infty} \frac{t^k 0.8}{k!}$$

$$= 1 + 0.8 \sum_{k=1}^{\infty} \frac{t^k}{k!}$$

$$= 1 + 0.8 \left[\sum_{k=0}^{\infty} \frac{t^k}{k!} - 1 \right]$$

$$= 1 + 0.8 [e^t - 1]$$

$$= 0.2 + 0.8 e^t$$

$$\therefore X \sim \text{Ber}(p=0.8)$$

Note: $e^x = \sum_{k=0}^{\infty} \frac{x^k}{k!}$, $\forall x$

Q4) $X_i \stackrel{iid}{\sim} P(3, \theta)$. Define $Y = \sum_{i=1}^n X_i$

$$\begin{aligned} \text{(i)} \quad M_Y(t) &= \bar{E}(e^{tY}) = \bar{E}(e^{t \sum_{i=1}^n X_i}) \\ &= \bar{E}(e^{tX_1} e^{tX_2} \dots e^{tX_n}) \stackrel{\text{ind}}{=} \bar{E}(e^{tX_1}) \bar{E}(e^{tX_2}) \dots \bar{E}(e^{tX_n}) \\ &\stackrel{\text{identical}}{=} \prod_{i=1}^n M_{X_i}(t) = \prod_{i=1}^n \left(\frac{\theta}{\theta - t} \right)^3 = \left(\frac{\theta}{\theta - t} \right)^{3n} \text{ for } t < \theta. \end{aligned}$$

Note: $M_X(t) = \left(\frac{\theta}{\theta - t} \right)^3$ as $X \sim P(3, \theta)$.

$$\therefore Y \sim P(3n, \theta).$$

$$\text{(ii)} \quad E(Y) = \frac{3n}{\theta}$$

$$\bar{E}(cY) = c \bar{E}(Y) = c \left(\frac{3n}{\theta} \right) = \frac{1}{\theta} \Rightarrow c = \frac{1}{3n}.$$

$$\text{(iii)} \quad \text{Let } W = 3\theta Y + 1.$$

$$\begin{aligned} \text{Then, } M_W(t) &= \bar{E}(e^{tW}) = \bar{E}(e^{t(3\theta Y + 1)}) \\ &= \bar{E}(e^{(3\theta t)Y} \cdot e^t) = e^t \bar{E}(e^{(3\theta t)Y}) \\ &= e^t M_Y(3\theta t) = e^t \left(\frac{\theta}{\theta - 3\theta t} \right)^{3n} \\ &= e^t \left(\frac{1}{1 - 3t} \right)^{3n} \text{ for } t < \frac{1}{3}. \end{aligned}$$

$$Q5) M_x(t) = \frac{1}{4} e^{-3t} + \frac{1}{2} + \frac{1}{4} e^t$$

$$(i) M'_x(t) = -\frac{3}{4} e^{-3t} + \frac{1}{4} e^t$$

$$M''_x(t) = \frac{9}{4} e^{-3t} + \frac{1}{4} e^t$$

$$\bar{E}(X) = M'_x(0) = -\frac{3}{4} + \frac{1}{4} = -\frac{1}{2}$$

$$\bar{E}(X^2) = M''_x(0) = \frac{9}{4} + \frac{1}{4} = \frac{5}{2}$$

$$\text{Var}(X) = \bar{E}(X^2) - [\bar{E}(X)]^2 = \frac{5}{2} - \frac{1}{4} = \frac{9}{4}$$

(ii) By observation,

$$\Pr(X=x) = \begin{cases} \frac{1}{4} & \text{if } x=-3 \\ \frac{1}{2} & \text{if } x=0 \\ \frac{1}{4} & \text{if } x=1 \\ 0 & \text{otherwise} \end{cases}$$

$$\bar{E}(X) = \sum_{x \in S_X} x \Pr(X=x) = -3 \times \frac{1}{4} + 0 \times \frac{1}{2} + 1 \times \frac{1}{4} = -\frac{1}{2}$$

$$\bar{E}(X^2) = \sum_{x \in S_X} x^2 \Pr(X=x) = (-3)^2 \times \frac{1}{4} + 0^2 \times \frac{1}{2} + 1^2 \times \frac{1}{4} = \frac{5}{2}$$

$$\therefore \text{Var}(X) = \frac{9}{4}$$

Q6) $X \sim \text{Exp}(\mu)$, $Y \sim \text{Exp}(\lambda)$, $X \perp\!\!\!\perp Y$.

Let $W = X + Y$. Let $U = X$

Then, $Y = W - X = W - U$.

$$\begin{cases} X = U & \dots\dots (1) \end{cases}$$

$$\begin{cases} Y = W - U & \dots\dots (2) \end{cases}$$

$$J = \begin{vmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial w} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial w} \end{vmatrix} = \begin{vmatrix} 1 & 0 \\ -1 & 1 \end{vmatrix} = 1$$

$$\begin{aligned} f_{w,u}(w,u) &= f_{x,y}(x,y) |J| \\ &\stackrel{\text{ind}}{=} f_x(x) f_y(y) |1| \\ &= \mu e^{-\mu x} \lambda e^{-\lambda y} \\ &= \mu \lambda e^{-\mu x - \lambda y} \\ &= \mu \lambda e^{-\mu u - \lambda(w-u)} \\ &= \mu \lambda e^{(\lambda - \mu)u - \lambda w} \end{aligned}$$

Note: By (2),
 $W = Y + U$
 $Y \geq 0 \} \Rightarrow W \geq U$

$$\begin{aligned} f_w(w) &= \int_0^w f_{w,u}(w,u) du = \int_0^w \mu \lambda e^{(\lambda - \mu)u - \lambda w} du \\ &= \mu \lambda e^{-\lambda w} \int_0^w e^{(\lambda - \mu)u} du = \frac{\mu \lambda}{\lambda - \mu} e^{-\lambda w} [e^{(\lambda - \mu)u}]_0^w \\ &= \frac{\mu \lambda}{\lambda - \mu} e^{-\lambda w} [e^{(\lambda - \mu)w} - 1] \\ &= \frac{\mu \lambda}{\lambda - \mu} (e^{-\mu w} - e^{-\lambda w}), \quad \text{for } w > 0. \end{aligned}$$

Q6) cont.

Note: $\int_0^\infty tw(w)dw = \frac{\mu\lambda}{\lambda-\mu} \left[\int_0^\infty e^{-\mu w} dw - \int_0^\infty e^{-\lambda w} dw \right]$

$$= \frac{\mu\lambda}{\lambda-\mu} \left\{ \frac{[e^{-\mu w}]_0^\infty}{-\mu} - \frac{[e^{-\lambda w}]_0^\infty}{-\lambda} \right\}$$
$$= \frac{\mu\lambda}{\lambda-\mu} \left\{ \frac{[-1]}{-\mu} - \frac{[-1]}{-\lambda} \right\}$$
$$= \frac{\mu\lambda}{\lambda-\mu} \left\{ \frac{\lambda-\mu}{\mu\lambda} \right\} = 1$$

$$M_w(t) = \bar{E}[e^{tw}] = \bar{E}[e^{tx} e^{tY}]$$

ind. $\bar{E}(e^{tx}) \bar{E}(e^{tY}) = \left(\frac{\mu}{\mu-t}\right) \left(\frac{\lambda}{\lambda-t}\right) \quad \text{for } t < \min\{\lambda, \mu\}.$

Q7)(i) The joint probability mass function of X_1 and X_2 can be presented with a 2 by 2 contingency table.

$X_2 \backslash X_1$	$X_1=0$	$X_1=1$	$X_1=2$	$Pr(X_2=x_2)$
$X_2=0$	$\frac{1}{12}$	$\frac{1}{12}$	$\frac{1}{12}$	$\frac{1}{4}$
$X_2=1$	$\frac{1}{12}$	$\frac{1}{12}$	$\frac{1}{12}$	$\frac{1}{4}$
$X_2=2$	$\frac{1}{12}$	$\frac{1}{12}$	$\frac{1}{12}$	$\frac{1}{4}$
$X_2=3$	$\frac{1}{12}$	$\frac{1}{12}$	$\frac{1}{12}$	$\frac{1}{4}$
$Pr(X_1=x_1)$	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$	1

Note: $Pr(X_1=x_1 \cap X_2=x_2) = Pr(X_1=x_1) Pr(X_2=x_2)$,
 $\forall x_1 \in \{0, 1, 2\}, \forall x_2 \in \{0, 1, 2, 3\}$.
 $\therefore X_1 \perp\!\!\!\perp X_2$.

(ii) Let $Y_1 = X_1 \cdot X_2$.

Then, the support of Y_1 is $S_{Y_1} = \{0, 1, 2, 3, 4, 6\}$.

Let $Y_2 = \max\{X_1, X_2\}$.

Then, the support of Y_2 is $S_{Y_2} = \{0, 1, 2, 3\}$.

Q 7) (ii) cont.

$Y_1 \backslash Y_2$	$Y_2 = 0$	$Y_2 = 1$	$Y_2 = 2$	$Y_2 = 3$	$Pr(Y_1 = y_1)$
$Y_1 = 0$	$\frac{1}{12}$	$\frac{2}{12}$	$\frac{2}{12}$	$\frac{1}{12}$	$\frac{6}{12}$
$Y_1 = 1$	0	$\frac{1}{12}$	0	0	$\frac{1}{12}$
$Y_1 = 2$	0	0	$\frac{2}{12}$	0	$\frac{2}{12}$
$Y_1 = 3$	0	0	0	$\frac{1}{12}$	$\frac{1}{12}$
$Y_1 = 4$	0	0	$\frac{1}{12}$	0	$\frac{1}{12}$
$Y_1 = 6$	0	0	0	$\frac{1}{12}$	$\frac{1}{12}$
$Pr(Y_2 = y_2)$	$\frac{1}{12}$	$\frac{3}{12}$	$\frac{5}{12}$	$\frac{3}{12}$	1

$$\therefore P_0 = Pr(Y_1 = 1 \cap Y_2 = 0) \neq Pr(Y_1 = 1) Pr(Y_2 = 0) = \frac{1}{12} \times \frac{1}{12} = \frac{1}{144}$$

$$\therefore Y_1 \not\perp Y_2$$

Q8) $X = \xi_1 + \xi_2$, $\xi_1 \sim N(\theta, 1)$, $\xi_2 \sim N(\lambda\theta, \lambda^2)$, $\xi_1 \perp \xi_2$
 $\lambda \geq 1$.

(i) $M_X(t) = E(e^{tX}) = E(e^{t(\xi_1 + \xi_2)})$
 $= E(e^{t\xi_1} e^{t\xi_2}) \stackrel{\text{ind}}{=} E(e^{t\xi_1}) E(e^{t\xi_2})$
 $= M_{\xi_1}(t) M_{\xi_2}(t) = \exp(\theta t + \frac{t^2}{2}) \exp(\lambda\theta t + \frac{\lambda^2 t^2}{2})$
 $= \exp\left[(\lambda+1)\theta t + \frac{(\lambda^2+1)t^2}{2}\right], \forall t.$

(ii) $M'_X(t) = \exp\left[(\lambda+1)\theta t + \frac{(\lambda^2+1)t^2}{2}\right] [(\lambda+1)\theta + (\lambda^2+1)t]$

$M''_X(t) = \exp\left[(\lambda+1)\theta t + \frac{(\lambda^2+1)t^2}{2}\right] [(\lambda+1)\theta + (\lambda^2+1)t]^2$
 $+ \exp\left[(\lambda+1)\theta t + \frac{(\lambda^2+1)t^2}{2}\right] (\lambda^2+1)$

$M^{(3)}_X(t) = \exp\left[(\lambda+1)\theta t + \frac{(\lambda^2+1)t^2}{2}\right] [(\lambda+1)\theta + (\lambda^2+1)t]^3$
 $+ \exp\left[(\lambda+1)\theta t + \frac{(\lambda^2+1)t^2}{2}\right] 2 [(\lambda+1)\theta + (\lambda^2+1)t] (\lambda^2+1)$
 $+ \exp\left[(\lambda+1)\theta t + \frac{(\lambda^2+1)t^2}{2}\right] (\lambda^2+1)$

$\therefore E(X^3) = M^{(3)}_X(0) = [(\lambda+1)\theta]^3 + 2[(\lambda+1)\theta](\lambda^2+1) + (\lambda+1)\theta(\lambda^2+1)$
 $= \theta(\lambda+1) [\theta^2(\lambda+1)^2 + 2(\lambda^2+1) + \lambda^2+1]$
 $= \theta(\lambda+1) [\theta^2(\lambda+1)^2 + 3\lambda^2 + 3]$

(iii) $X \sim N(\theta(\lambda+1), \lambda^2+1)$