

Problem 1

$$E(X^n) = c \quad \forall n \geq 1$$

$$M_X(t) = \sum_{n=0}^{\infty} \frac{t^n}{n!} c = ce^t$$

$M_X(0) = 1$ by definition, so we need to find a constant k that satisfies this equation

$$M_X(0) = ce^0 + k = 1$$

$$k = 1 - c$$

Thus $M_X(t) = ce^t + 1 - c$

Which is the same as the mgf of the Bernoulli distribution with parameter c

Problem 2

$$E[X^n] = \frac{2^n}{n+1} \text{ for } n \geq 1$$

$$M_X(t) = \sum_{n=0}^{\infty} \frac{t^n}{n!} \frac{2^n}{n+1} = \sum_{n=0}^{\infty} \frac{(2t)^n}{(n+1)!} = \frac{e^{2t} - 1}{2t}$$

Since $M_X(t)$ is undefined for $t = 0$ and $M_X(0)$ must equal 1, we define the mgf as:

$$M_X(t) = \begin{cases} \frac{e^{2t} - 1}{2t} & \text{for } t \neq 0 \\ 1 & \text{for } t = 0 \end{cases}$$

This is the same as the mgf for the Uniform (0,2) distribution.

Problem 3

(a)

Given $f_X(x) = f_X(-x) \quad \forall x$

WTS: X and $-X$ are identically distributed

$$\int_{-\infty}^{\infty} f_X(x) dx = \int_{-\infty}^{\infty} f_X(-x) dx$$

Thus $F_X(x) = F_X(-x) \quad \forall x$

Since the CDFs are equal, X and $-X$ are identically distributed

(b)

Given $f_X(x) = f_X(-x) \forall x$ WTS: $M_X(t) \forall \epsilon > 0 \ M_X(0 + \epsilon) = M_X(0 - \epsilon)$

$$\begin{aligned} M_X(0 + \epsilon) &= \int_{-\infty}^{\infty} e^{(0+\epsilon)x} f_X(x) dx \\ &= \int_{-\infty}^0 e^{\epsilon x} f_X(x) dx + \int_0^{\infty} e^{\epsilon x} f_X(x) dx \\ &= \int_0^{\infty} e^{\epsilon(-x)} f_X(-x) dx + \int_{-\infty}^0 e^{\epsilon(-x)} f_X(-x) dx \\ &= \int_{-\infty}^{\infty} e^{\epsilon(-x)} f_X(x) dx \\ &= \int_{-\infty}^{\infty} e^{(0-\epsilon)x} f_X(x) dx = M_X(0 - \epsilon) \end{aligned}$$

Thus $M_X(t)$ is symmetric about 0

Problem 4

A distribution does not exist because:

$$M_X(0) = \frac{0}{1-0} = 0$$

But $M_X(0) = 1$ always by definition.

Problem 5

$$EX = \left. \frac{d}{dt} S(t) \right|_{t=0} = \left. \frac{d}{dt} \log(M_X(t)) \right|_{t=0} = \left. \frac{\frac{d}{dt} M_X(t)}{M_X(t)} \right|_{t=0}$$

Since $M_X(0) = 1$ always and $\frac{d}{dt} M_X(t) = EX$ we have:

$$\left. \frac{\frac{d}{dt} M_X(t)}{M_X(t)} \right|_{t=0} = \frac{EX}{1} = EX$$

$$\begin{aligned} Var(X) &= \left. \frac{d^2}{dt^2} S(t) \right|_{t=0} = \left. \frac{d}{dt} \frac{M'_X(t)}{M_X(t)} \right|_{t=0} = \left. \frac{M''_X(t)M_X(t) - M'_X(t)^2}{M_X(t)^2} \right|_{t=0} \\ &= \frac{E[X^2] * 1 - E[X]^2}{1^2} = E[X^2] - E[X]^2 = Var(X) \end{aligned}$$

Problem 6

(a)

$$M_X(t) = \sum_{x=0}^{\infty} \frac{e^{-\lambda} \lambda^x}{x!} e^{tx} = e^{-\lambda} \sum_{x=0}^{\infty} \frac{(\lambda e^t)^x}{x!}$$

Since $\sum_{x=0}^{\infty} \frac{\lambda^x}{x!} = e^{\lambda}$ we have:

$$e^{-\lambda} \sum_{x=0}^{\infty} \frac{(\lambda e^t)^x}{x!} = e^{-\lambda} e^{\lambda e^t} = e^{\lambda(e^t-1)}$$

$$E(X) = \left. \frac{d}{dt} e^{\lambda(e^t-1)} \right|_{t=0} = \left. e^{-\lambda} \lambda e^{\lambda e^t+t} \right|_{t=0} = \lambda e^{-\lambda} e^{\lambda} = \lambda$$

$$\begin{aligned} E(X^2) &= \left. \frac{d}{dt} e^{-\lambda} \lambda e^{\lambda e^t+t} \right|_{t=0} = \left. e^{-\lambda} \lambda (\lambda e^t + 1) e^{\lambda e^t+t} \right|_{t=0} \\ &= e^{-\lambda} \lambda (\lambda + 1) e^{\lambda} = \lambda(\lambda + 1) \end{aligned}$$

$$Var(X) = E(X^2) - E(X)^2 = \lambda(\lambda + 1) - \lambda^2 = \lambda$$

(b)

$$\begin{aligned}
M_X(t) &= \sum_{x=0}^{\infty} e^{tx} p(1-p)^x = p \sum_{x=0}^{\infty} (e^t(1-p))^x \\
&= \frac{p}{pe^t - e^t + 1} = \frac{p}{1 - (1-p)e^t} \\
E(X) &= \left. \frac{d}{dt} \frac{p}{1 - (1-p)e^t} \right|_{t=0} = \left. \frac{p(1-p)e^t}{(1 - (1-p)e^t)^2} \right|_{t=0} \\
E(X) &= \frac{p(1-p)}{p^2} = \frac{1-p}{p} \\
E(X^2) &= \left. \frac{d}{dt} \frac{p(1-p)e^t}{(1 - (1-p)e^t)^2} \right|_{t=0} \\
&= \left. \frac{2p(1-p)^2 e^{2x}}{(1 - (1-p)e^x)^3} + \frac{p(1-p)e^x}{(1 - (1-p)e^x)^2} \right|_{t=0} \\
&= \frac{2(1-p)^2 + p(1-p)}{p^2} \\
Var(X) &= \frac{2(1-p)^2 + p(1-p)}{p^2} - \left(\frac{1-p}{p} \right)^2 = \frac{(1-p)^2 + p(1-p)}{p^2} = \frac{1-p}{p^2}
\end{aligned}$$

(c)

$$\begin{aligned}
M_X(t) &= \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} e^{-(x-\mu)^2/2\sigma^2} dx \\
&= \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} e^{-(x^2 - 2x\mu - 2\sigma^2 tx + \mu^2)/2\sigma^2} dx \\
M_X(t) &= e^{\mu t + \sigma^2 t^2/2} \\
E(X) &= \left. \frac{d}{dt} e^{\mu t + \sigma^2 t^2/2} \right|_{t=0} = e^{\mu t + \sigma^2 t^2/2} (\mu + \sigma^2 t/2) \Big|_{t=0} \\
E(X) &= e^0 (\mu + 0) = \mu \\
E(X^2) &= \left. \frac{d}{dt} e^{\mu t + \sigma^2 t^2/2} (\mu + \sigma^2 t/2) \right|_{t=0} = e^{\mu t + \sigma^2 t^2/2} (\mu + \sigma^2 t)^2 + \sigma^2 e^{\mu t + \sigma^2 t^2/2} \Big|_{t=0} \\
E(X^2) &= e^0 (\mu)^2 + \sigma^2 e^0 = \mu^2 + \sigma^2 \\
Var(X) &= \mu^2 + \sigma^2 - \mu^2 = \sigma^2
\end{aligned}$$

Problem 7

$$\text{Let } f(x) = \frac{1}{x}$$

$$g(x) = M_X(t)$$

on the interval $(0, \infty)$, $g(x) \geq f(x)$

Using the comparison test we can show $f(x)$ diverges, thus $g(x)$ must also diverge

$$\int_0^\infty \frac{1}{x} = \log(x) \Big|_0^\infty \text{ diverges}$$

Thus $M_X(t)$ also diverges

Therefore $M_X(t)$ does not exist

Problem 8

(a)

$$\begin{aligned} M_X(t) &= \sum_{x=0}^{\infty} e^{tx} \binom{r+x-1}{x} p^r (1-p)^x \\ &= \frac{p^r}{(r-1)!} \sum_{x=0}^{\infty} \frac{(r+x-1)! e^{tx} (1-p)^x}{x!} \\ M_X(t) &= \frac{p^r}{(r-1)!} (r-1)! (1 - (1-p)e^t)^{-r} = \left(\frac{p}{1 - (1-p)e^t} \right)^r \\ M_X(t) &= \left(\frac{p}{1 - (1-p)e^t} \right)^r \end{aligned}$$

(b)

$$\begin{aligned} M_Y(t) &= E(e^{tY}) = E(e^{2ptX}) = M_X(2pt) \\ &= \left(\frac{p}{1 - (1-p)e^{2pt}} \right)^r \end{aligned}$$

Using L'Hospital's Rule to find the limit as p goes to 0

$$\begin{aligned} &\lim_{p \rightarrow 0} \left(\frac{\frac{d}{dp} p}{\frac{d}{dp} 1 - (1-p)e^{2pt}} \right)^r \\ &= \lim_{p \rightarrow 0} \left(\frac{1}{e^{2pt}(2(p-1)t + 1)} \right)^r \\ &= \left(\frac{1}{1 - 2t} \right)^r \end{aligned}$$

Problem 9

(a)

$$P(X = x) = \begin{cases} p^x(q)^{1-x} & x = 0, 1 \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned} \phi_X(t) &= E(e^{itx}) = \sum_{x=0}^1 e^{itx} p_X(x) \\ &= e^{it*1} p_X(1) + e^{it*0} * p_X(0) \\ &= pe^{it} + q \end{aligned}$$

(b)

$$P(X = x) = \begin{cases} \binom{n}{x} p^x q^{n-x} & x = 0, 1, \dots, n \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned} \phi_X(t) &= E(e^{itx}) = \sum_{x=0}^n e^{itx} \binom{n}{x} p^x q^{n-x} \\ &= \sum_{x=0}^n \binom{n}{x} (e^{it}p)^x q^{n-x} \end{aligned}$$

Using the binomial theorem we have :

$$(pe^{it} + q)^n$$

(c)

$$P(X = x) = \begin{cases} p(q)^x & x = 0, 1, 2, \dots \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned} \phi_X(t) &= E(e^{itx}) = \sum_{x=0}^{\infty} e^{itx} p(q)^x \\ &= p \sum_{x=0}^{\infty} (qe^{it})^x = \frac{p}{1 - qe^{it}} \end{aligned}$$

(d)

$$P(X = x) = \frac{e^{-\lambda} \lambda^x}{x!}$$

$$\begin{aligned} \phi_X(t) &= E(e^{itx}) = \sum_{x=0}^{\infty} e^{itx} \frac{e^{-\lambda} \lambda^x}{x!} \\ &= e^{-\lambda} \sum_{x=0}^{\infty} \frac{(\lambda e^{it})^x}{x!} = e^{-\lambda} e^{\lambda e^{it}} = e^{\lambda e^{it} - \lambda} \\ &= e^{\lambda(e^{it} - 1)} \end{aligned}$$