

know $E[X] = np$, $var[X] = np(1-p)$

$$E[X^2] = (E[X])^2 + var[X] = n^2 p^2 + np(1-p) = n^2 p^2 + np - np^2$$

Verify $E[X]$, $E[X^2]$ by $M_X(t)$,

$$M_X'(t) = n(e^{tp} + 1 - p)^{n-1} \cdot e^{tp} \Rightarrow M_X'(0) = n \cdot p$$

$$M_X''(t) = n(n-1)(e^{tp} + 1 - p)^{n-2} \cdot e^{tp} \cdot e^{tp} + n(e^{tp} + 1 - p)^{n-1} \cdot e^{tp}$$

$$\Rightarrow M_X''(0) = n(n-1)p^2 + np = n^2 p^2 - np^2 + np$$

② $X \sim \text{Poisson}(\lambda)$, $\lambda > 0$

$$P(X=x) = \frac{\lambda^x \cdot e^{-\lambda}}{x!}, \quad x=0, 1, 2, \dots \quad \sum_{x=0}^{\infty} P(X=x) = 1$$

$$\sum_{x=0}^{\infty} \frac{\lambda^x e^{-\lambda}}{x!} = 1 \quad \forall \lambda > 0$$

$$\begin{aligned} M_X(t) &= \sum_{x=0}^{\infty} e^{tx} \cdot P(X=x) = \sum_{x=0}^{\infty} e^{tx} \cdot \frac{\lambda^x \cdot e^{-\lambda}}{x!} = \sum_{x=0}^{\infty} \frac{(e^t \cdot \lambda)^x \cdot e^{-\lambda}}{x!} \\ &= \left[\sum_{x=0}^{\infty} \frac{(e^t \lambda)^x \cdot e^{-e^t \lambda}}{x!} \right] \cdot e^{e^t \lambda} \cdot e^{-\lambda} = e^{e^t \lambda} \cdot e^{-\lambda} \\ &= e^{\lambda(e^t - 1)} \end{aligned}$$

know $E[X] = \lambda$, $var[X] = \lambda \Rightarrow E[X^2] = (E[X])^2 + var[X] = \lambda^2 + \lambda$

$$M_X'(t) = e^{\lambda(e^t - 1)} \cdot \lambda e^t \Rightarrow M_X'(0) = \lambda$$

$$M_X''(t) = e^{\lambda(e^t - 1)} \cdot \lambda e^t \cdot \lambda e^t + e^{\lambda(e^t - 1)} \cdot \lambda e^t$$

$$\Rightarrow M_X''(0) = \lambda^2 + \lambda$$

③ $X \sim \text{Exp}(\lambda)$, $\lambda > 0$

$$\text{pdf: } f(x) = \begin{cases} \lambda \cdot e^{-\lambda x} & x > 0 \\ 0 & x \leq 0 \end{cases}$$

$$\int_0^{\infty} \lambda e^{-\lambda x} dx = 1 \quad \forall \lambda > 0$$

$$\begin{aligned} M_X(t) &= E[e^{tx}] = \int_0^{\infty} e^{tx} \cdot f(x) dx = \int_0^{\infty} e^{tx} \cdot \lambda \cdot e^{-\lambda x} dx \\ &= \int_0^{\infty} \lambda e^{-(\lambda - t)x} dx \quad \text{if } \lambda - t > 0 \quad \int_0^{\infty} (\lambda - t) e^{-(\lambda - t)x} \cdot \frac{1}{\lambda - t} dx \\ &= \frac{\lambda}{\lambda - t} \quad \text{if } t < \lambda \end{aligned}$$

check: $M_X'(0) = E[X]$, $M_X''(0) = E[X^2]$

$$X \sim N(0,1) \quad \text{pdf: } f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}, \quad x \in \mathbb{R}$$

$$M_X(t) = \int_{-\infty}^{+\infty} e^{tx} \cdot \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx$$

$$\int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx = 1$$

$$= \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}} e^{-\left(\frac{x^2}{2} - tx\right)} dx$$

$$= \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}} e^{-\left(\frac{(x-t)^2}{2} - \frac{t^2}{2}\right)} dx$$

$$= e^{t^2/2} \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-t)^2}{2}} dx$$

$\underbrace{\quad}_{=d(x-t)}$

$$= e^{t^2/2}$$

Q: how to make $\frac{x^2}{2} - tx = \frac{(x-0)^2}{2} + 0$

$$\frac{x^2 - 2tx + t^2 - t^2}{2} = \frac{(x-t)^2}{2}$$

$$\begin{aligned} dx &= d(x-t) + \text{const} \\ dx^2 &= 2 dx \end{aligned}$$

$$\int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-t)^2}{2}} dx$$

$$\begin{aligned} \underline{y} &= x-t \\ \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} dy \\ &= 1 \end{aligned}$$

Properties of MGF:

(1) If X has MGF $M_X(t)$ and $Y = a + bX$, $a, b \in \mathbb{R}$
Then Y has MGF $M_Y(t) = e^{at} \cdot M_X(bt)$

$$\begin{aligned} \text{pf: } M_Y(t) &= E[e^{tY}] = E[e^{t(a+bX)}] = E[e^{at} \cdot e^{btX}] \\ &= e^{at} \cdot \underbrace{E[e^{(bt)X}]}_{=M_X(bt)} = e^{at} \cdot M_X(bt) \end{aligned}$$

Example: $X \sim N(\mu, \sigma^2)$ pdf: $f(y) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(y-\mu)^2}{2\sigma^2}}$

Note that we can write $Y = \mu + \sigma X$, where $X \sim N(0,1)$
 $E[X] = 0$, $\text{var}[X] = 1$, $E[Y] = \mu + \sigma E[X] = \mu$, $\text{var}[Y] = \sigma^2 \text{var}[X] = \sigma^2$

Recall $M_X(t) = e^{t^2/2}$. Then

$$M_Y(t) = e^{\mu t} \cdot M_X(\sigma t) = e^{\mu t} \cdot e^{\frac{\sigma^2 t^2}{2}}$$

(4)

(2) X and Y are independent R.V.s w/ MGFs $M_X(t)$ and $M_Y(t)$ respectively. Then the MGF of $X+Y$ is

$$M_{X+Y}(t) = M_X(t) M_Y(t)$$

Recall: independence: $P(X \in \mathcal{X}, Y \in \mathcal{Y}) = P(X \in \mathcal{X}) \cdot P(Y \in \mathcal{Y})$

$$P(X \in \mathcal{X} | Y \in \mathcal{Y}) = P(X \in \mathcal{X})$$

$$E[g(X) \cdot h(Y)] = E[g(X)] \cdot E[h(Y)]$$

Pf: $M_{X+Y}(t) = E[e^{t(X+Y)}] = E[e^{tX} \cdot e^{tY}]$

$$\stackrel{\text{indep}}{=} E[e^{tX}] \cdot E[e^{tY}] = M_X(t) \cdot M_Y(t)$$

Example 1: $X \sim \text{Binomial}(n_1, p)$, $Y \sim \text{Binomial}(n_2, p)$

X and Y are independent.

Recall $M_X(t) = (e^t p + 1 - p)^{n_1}$, $M_Y(t) = (e^t p + 1 - p)^{n_2}$

then $M_{X+Y}(t) = M_X(t) M_Y(t) = (e^t p + 1 - p)^{n_1 + n_2}$

which is the MGF of a binomial r.v.

so $X+Y \sim \text{Binomial}(n_1 + n_2, p)$

Example 2: $X \sim \text{Poisson}(\lambda_1)$, $Y \sim \text{Poisson}(\lambda_2)$, X and Y are indep.

Recall $M_X(t) = e^{\lambda_1(e^t - 1)}$, $M_Y(t) = e^{\lambda_2(e^t - 1)}$

then $M_{X+Y}(t) = M_X(t) M_Y(t) = e^{\lambda_1(e^t - 1)} \cdot e^{\lambda_2(e^t - 1)} = e^{(\lambda_1 + \lambda_2)(e^t - 1)}$

which is the MGF of a Poisson r.v.

so $X+Y \sim \text{Poisson}(\lambda_1 + \lambda_2)$

Example 3: $X \sim N(\mu_1, \sigma_1^2)$, $Y \sim N(\mu_2, \sigma_2^2)$, X and Y are indep.

For indep X & Y : $\text{var}[X+Y] = \text{var}[X] + \text{var}[Y]$

For any X & Y : $E[X+Y] = E[X] + E[Y]$

so $E[X+Y] = \mu_1 + \mu_2$, $\text{var}[X+Y] = \sigma_1^2 + \sigma_2^2$

Q: $X+Y \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$

Recall: $M_X(t) = e^{\mu_1 t} e^{\sigma_1^2 t^2 / 2}$, $M_Y(t) = e^{\mu_2 t} e^{\sigma_2^2 t^2 / 2}$

then $M_{X+Y}(t) = M_X(t) M_Y(t) = e^{(\mu_1 + \mu_2)t} e^{(\sigma_1^2 + \sigma_2^2)t^2 / 2}$

(5)

which is the MGF of a Normal r.v.

So $X+Y \sim N(\mu_1+\mu_2, \sigma_1^2+\sigma_2^2)$

X_1, \dots, X_n are iid R.V.s. What is the MGF of $\sum_{i=1}^n X_i$?

$$M_{\sum_{i=1}^n X_i}(t) \stackrel{\text{indep}}{=} M_{X_1}(t) \cdot M_{X_2}(t) \dots M_{X_n}(t)$$

$$\stackrel{\text{ident. dist.}}{=} (M_X(t))^n$$

Example: $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} N(\mu, \sigma^2)$

Recall $M_X(t) = e^{\mu t} \cdot e^{\sigma^2 t^2 / 2}$

$$M_{\sum_{i=1}^n X_i}(t) = (e^{\mu t} e^{\sigma^2 t^2 / 2})^n = e^{n\mu t} \cdot e^{n\sigma^2 t^2 / 2}$$

So $\sum_{i=1}^n X_i \sim N(n\mu, n\sigma^2)$