

Find the mgf for the normal distribution

①

451

3-11

$$M_X(t) = E[e^{tx}] = \int e^{tx} f(x) dx$$

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

$$= \int_{-\infty}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{\left[tx - \frac{1}{2\sigma^2}x^2 + \frac{1}{\sigma^2}\mu x - \frac{1}{2\sigma^2}\mu^2\right]} dx$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2\sigma^2}[x^2 - 2\sigma^2 tx - 2\mu x + \mu^2]} dx$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2\sigma^2}[x^2 - 2(\sigma^2 t + \mu)x + \mu^2]} dx \quad (2)$$

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

$$= e^{-\frac{1}{2\sigma^2}[-(\sigma^2 t + \mu)^2 + \mu^2]} \underbrace{\int_{-\infty}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2\sigma^2}[x - (\sigma^2 t + \mu)]^2} dx}_{1}$$

$$= e^{-\frac{1}{2\sigma^2}[-\sigma^4 t^2 - 2\mu\sigma^2 t - \mu^2 + \mu^2]}$$

$$\begin{aligned}
 &= e^{-\frac{1}{2\sigma^2}[-\sigma^2(\sigma^2 t^2 + 2\mu t)]} \\
 &= e^{(\mu t + \frac{1}{2}\sigma^2 t^2)}
 \end{aligned}
 \tag{③}$$

For the standard normal distribution,

$$M_x(t) = e^{\frac{1}{2}t^2} \quad (\text{since } \mu=0 \text{ and } \sigma=1)$$

Properties of the m.g.f.

Start with a random variable X .

$$\text{Let } Y = X + c$$

$$\begin{aligned}
 M_y(t) &= E[e^{tY}] \\
 &= E[E[e^{t(X+c)}]] \\
 &= E[e^{tX} \cdot e^{tc}] \\
 &= e^{tc} E[e^{tX}] = e^{tc} M_x(t)
 \end{aligned}
 \tag{④}$$

$$\text{Let } Y = aX$$

$$\begin{aligned}
 M_y(t) &= E[e^{tY}] = E[e^{taX}] \\
 &= E[E[e^{(ta)X}]] \quad \text{let } u=ta \\
 &= E[e^{uX}] = M_x(u) = M_x(ta)
 \end{aligned}$$

Suppose that X_1 and X_2 are independent random variables. Let $Y = X_1 + X_2$

$$\begin{aligned} M_Y(t) &= E[e^{tY}] = E[e^{t(X_1+X_2)}] \\ &= E[e^{tX_1} \cdot e^{tX_2}] = E[e^{tX_1}] \cdot E[e^{tX_2}] \\ &\quad (\text{because of independence}) \\ &= M_{X_1}(t) M_{X_2}(t) \end{aligned}$$

Example: Suppose $X_1 \sim \text{Exp}(\beta)$, $X_2 \sim \text{Exp}(\beta)$,
 $X_3 \sim \text{Exp}(\beta)$,

independent.

Let $Y = X_1 + X_2 + X_3$. Find the distribution of Y .

$$\begin{aligned} M_Y(t) &= M_{X_1}(t) M_{X_2}(t) M_{X_3}(t) \\ &= \frac{1}{1-\beta t} \cdot \frac{1}{1-\beta t} \cdot \frac{1}{1-\beta t} = (1-\beta t)^{-3} \end{aligned}$$

This is the mgf of a gamma distribution with $\alpha = 3$, β

(7)

Let X_1, X_2, \dots, X_n be independent random variables, each with the same distribution with mean μ and standard deviation σ .

$$\text{Let } Y = \frac{1}{\sqrt{n}} \sum_{i=1}^n \frac{X_i - \mu}{\sigma}.$$

Find the m.g.f. of Y and take its limit as $n \rightarrow \infty$.

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$$\text{Let } Z_i = \frac{X_i - \mu}{\sigma} \quad E[Z_i] = 0 \text{ and} \\ V[Z_i] = 1$$

$$Y = \frac{1}{\sqrt{n}} \sum_{i=1}^n Z_i$$

$$M_Y(t) = M_{\sum Z_i} \left(\frac{t}{\sqrt{n}} \right) \\ = M_{Z_1} \left(\frac{t}{\sqrt{n}} \right) M_{Z_2} \left(\frac{t}{\sqrt{n}} \right) \cdots M_{Z_n} \left(\frac{t}{\sqrt{n}} \right)$$

$$M_Y(t) = \left[M_{Z_1}\left(\frac{t}{\sqrt{n}}\right) \right]^n = \left[E\left[e^{\frac{t}{\sqrt{n}} Z_1}\right] \right]^n \quad (1)$$

Now take the limit as $n \rightarrow \infty$

$$\begin{aligned} \lim_{n \rightarrow \infty} M_Y(t) &= \lim_{n \rightarrow \infty} \left[E\left[1 + \frac{t Z_1}{\sqrt{n}} + \frac{t^2 Z_1^2}{2n} + \dots \right] \right]^n \\ &= \lim_{n \rightarrow \infty} \left[1 + 0 + \frac{t^2}{2n} \cdot 1 + \dots \right]^n \end{aligned}$$

$$\lim_{n \rightarrow \infty} \ln M_Y(t) = \lim_{n \rightarrow \infty} n \ln \left[1 + \frac{t^2}{2n} + \dots \right]$$

$$= \lim_{n \rightarrow \infty} \frac{\ln \left[1 + \frac{t^2}{2n} + \dots \right]}{\frac{1}{n}} \quad (2)$$

$$= \lim_{n \rightarrow \infty} \frac{\frac{1}{1 + \frac{t^2}{2n} + \dots} \left[-\frac{t^2}{2n^2} + \dots \right]}{-\frac{1}{n^2}}$$

$$= \lim_{n \rightarrow \infty} \frac{1}{1 + \frac{t^2}{2n} + \dots} \left[\frac{t^2}{2} + \dots \right]$$

$$= \frac{t^2}{2} \quad \begin{aligned} \ln M_Y(t) &\rightarrow \frac{t^2}{2} \\ \approx M_Y(t) &\rightarrow e^{t^2/2} \end{aligned}$$

$e^{t^2/2}$ is the mgf of the standard normal distribution. (11)

$$\begin{aligned}
 Y &= \frac{1}{\sqrt{n}} \sum_{i=1}^n \frac{x_i - \mu}{\sigma} \\
 &= \frac{1}{\sigma\sqrt{n}} \sum_{i=1}^n (x_i - \mu) = \frac{1}{\sigma\sqrt{n}} \left(\sum_{i=1}^n x_i - n\mu \right) \\
 &= \frac{n}{\sigma\sqrt{n}} \left(\frac{1}{n} \sum_{i=1}^n x_i - \mu \right) = \frac{\bar{x}}{\sigma} (\bar{x} - \mu) \\
 &= \frac{\bar{x} - \mu}{\sigma/\sqrt{n}}
 \end{aligned}$$

(12) Central Limit Theorem :

Assume X_1, X_2, \dots, X_n are independent and identically distributed with mean μ and standard deviation σ .

Let $Y = \frac{\bar{X} - \mu}{\sigma/\sqrt{n}}$. Then as $n \rightarrow \infty$

the distribution of Y approaches the standard normal distribution.

HW #9 due Thurs, March 18

(13)

p. 226 #18

p. 252 #24, 26

Final exam is Thurs, March 18

10:15 - 12:05

1 page of notes + tables + calculator

Covers all material since the midterm (after 4.3)