

4.7: The Moment generating function Technique

exp: $X_1 \sim N(\mu_1, \sigma_1^2)$

$$X_2 \sim N(\mu_2, \sigma_2^2)$$

X_1 and X_2 indep.

Find dist. of $Y = X_1 - X_2$

sol.

$$X_1 \sim N(\mu_1, \sigma_1^2) \Rightarrow M_1(t) = E(e^{tX_1}) = e^{\mu_1 t + \frac{1}{2} \sigma_1^2 t^2}$$

$$X_2 \sim N(\mu_2, \sigma_2^2) \Rightarrow M_2(t) = E(e^{tX_2}) = e^{\mu_2 t + \frac{1}{2} \sigma_2^2 t^2}$$

$$Y = X_1 - X_2 \Rightarrow M_Y(t) = E(e^{tY}) = E(e^{t(X_1 - X_2)})$$

$$= E(e^{tX_1} \cdot e^{-tX_2})$$

$$\overset{X_1, X_2 \text{ indep.}}{=} E(e^{tX_1}) E(e^{-tX_2})$$

$$= M_1(t) \cdot M_2(-t)$$

$$= e^{\mu_1 t + \frac{1}{2} \sigma_1^2 t^2} \cdot e^{\mu_2(-t) + \frac{1}{2} \sigma_2^2 (-t)^2}$$

$$M_Y(t) = e^{(\mu_1 - \mu_2)t + \frac{1}{2}(\sigma_1^2 + \sigma_2^2)t^2}$$

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

Thm 1: $X_1, \dots, X_n$ independent $N(\mu_1, \sigma_1^2), \dots, N(\mu_n, \sigma_n^2)$ respectively

Define $Y = \sum_{i=1}^n k_i X_i = k_1 X_1 + \dots + k_n X_n$, where $k_1, \dots, k_n$ real constant

Then $Y \sim N\left(\sum_{i=1}^n k_i \mu_i, \sum_{i=1}^n k_i^2 \sigma_i^2\right)$.

proof:

$$M_Y(t) = E(e^{ty}) = E(e^{t(k_1 X_1 + \dots + k_n X_n)}) \\ = E(e^{t k_1 X_1} \cdot e^{t k_2 X_2} \cdot \dots \cdot e^{t k_n X_n})$$

$$\because X_1, \dots, X_n \text{ indep.} = E(e^{t k_1 X_1}) \cdot \dots \cdot E(e^{t k_n X_n}) \\ = e^{\mu_1(k_1 t) + \frac{1}{2} \sigma_1^2 (k_1 t)^2} \cdot \dots \cdot e^{\mu_n(k_n t) + \frac{1}{2} \sigma_n^2 (k_n t)^2} \\ = e^{(\mu_1 k_1 + \dots + \mu_n k_n)t + \frac{1}{2} (\sigma_1^2 k_1^2 + \dots + \sigma_n^2 k_n^2) t^2}$$

$$\Rightarrow Y \sim N\left(\sum_{i=1}^n k_i \mu_i, \sum_{i=1}^n k_i^2 \sigma_i^2\right)$$

Thm 2: $X_1, \dots, X_n$ independent random variables with m.g.f's $M_1(t), \dots, M_n(t)$

respectively. Define $Y = \sum_{i=1}^n a_i X_i$. Then $M_Y(t) = M_1(a_1 t) \dots M_n(a_n t)$

$$= \prod_{i=1}^n M_i(a_i t).$$

proof:

$$M_Y(t) = E(e^{ty}) = E(e^{t(a_1 X_1 + \dots + a_n X_n)}) \\ = E(e^{t a_1 X_1} \cdot e^{t a_2 X_2} \cdot \dots \cdot e^{t a_n X_n})$$

$$= E(e^{t a_1 X_1}) \cdot \dots \cdot E(e^{t a_n X_n})$$

$$= M_1(a_1 t) \cdot \dots \cdot M_n(a_n t)$$

$$= \prod_{i=1}^n M_i(a_i t).$$

Corollary: $X_1, \dots, X_n$ Random sample with m.g.f $M(t)$, then

a. $Y = \sum_{i=1}^n X_i \Rightarrow M_Y(t) = (M(t))^n$

b. $\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i \Rightarrow M_{\bar{X}}(t) = \left(M\left(\frac{t}{n}\right) \right)^n$

Proof:

a. Thm 2, $a_i = 1, i=1, \dots, n$

b. Thm 2, $a_i = \frac{1}{n}, i=1, \dots, n$

exp 3:

$X_1, \dots, X_n$, n Bernoulli trials

$X_1, \dots, X_n$ independent $b(1, p)$

Find dist. of $Y = \sum_{i=1}^n X_i$

Sol.

$X_1, \dots, X_n$ Random sample with $M(t) = pe^t + 1 - p$.

$$M_Y(t) = (M(t))^n = (pe^t + 1 - p)^n$$

$$Y = \sum_{i=1}^n X_i \sim b(n, p).$$

exp 4: X_1, X_2, X_3 Random sample from exponential dist. with mean β .

1. $Y = \sum_{i=1}^3 X_i$

X_1, X_2, X_3 indep. with $M(t) = (1 - \beta t)^{-1}, t < \frac{1}{\beta}$

$$M_Y(t) = (M(t))^3 = ((1 - \beta t)^{-1})^3, t < \frac{1}{\beta}$$

$$M_Y(t) = (1 - \beta t)^{-3}, t < \frac{1}{\beta}$$

$$\Rightarrow Y \sim \text{Gamma}(3, \beta).$$

$$2. \bar{X} = \frac{1}{n} \sum_{i=1}^3 X_i$$

$$M_{\bar{X}}(t) = \left(M\left(\frac{t}{3}\right) \right)^3 = \left(1 - \beta \frac{t}{3} \right)^{-3}, \quad \frac{t}{3} < \frac{1}{\beta}$$

$$= \left(1 - \frac{\beta}{3} t \right)^{-3}, \quad t < \frac{3}{\beta}$$

$$\Rightarrow \bar{X} \sim \text{Gamma}\left(3, \frac{\beta}{3}\right)$$

Thm 3: $X_1, \dots, X_n$ indep., $X^2(r_1), \dots, X^2(r_n)$, define $Y = \sum_{i=1}^n X_i$ then

$$Y \sim X^2(r_1 + \dots + r_n)$$

proof: M.G.F of X_i

$$M_i(t) = (1 - \beta t)^{-\alpha}, \quad t < \frac{1}{\beta}$$

$$\alpha = \frac{r_i}{2}, \quad \beta = 2$$

$$M_i(t) = (1 - 2t)^{-\frac{r_i}{2}}, \quad t < \frac{1}{2}$$

$$M_Y(t) = (1 - 2t)^{-\frac{r_1}{2}} \dots (1 - 2t)^{-\frac{r_n}{2}}, \quad t < \frac{1}{2}$$

$$M_Y(t) = (1 - 2t)^{-\frac{(r_1 + \dots + r_n)}{2}}, \quad t < \frac{1}{2}$$

$$\Rightarrow Y \sim X^2(r_1 + \dots + r_n)$$

□

Thm 4:

$X_1, \dots, X_n$ Random sample from $N(\mu, \sigma^2)$.

Define $y = \sum_{i=1}^n \left(\frac{X_i - \mu}{\sigma} \right)^2$ then $y \sim \chi^2(n)$.

proof:

$$X_i \sim N(\mu, \sigma^2) \quad \text{indep.}$$

$$\frac{X_i - \mu}{\sigma} \sim N(0, 1) \quad \text{indep.}$$

$$\left(\frac{X_i - \mu}{\sigma} \right)^2 \sim \chi^2(1) \quad \text{indep.}$$

$$\sum_{i=1}^n \left(\frac{X_i - \mu}{\sigma} \right)^2 \sim \chi^2(n).$$

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