

## HW 2 100B - SOLUTIONS

EXERCISE 1:  $X \sim N(\mu, \sigma^2) \rightarrow M_X(t) = e^{t\mu + \frac{1}{2}t^2\sigma^2}$

$$\begin{aligned} (a). M_{ax+b}(t) &= E e^{t(ax+b)} \\ &= e^{tb} E e^{tax} = e^{tb} M_X(at) \\ &= e^{tb} e^{at\mu + \frac{1}{2}t^2a^2\sigma^2} \\ &= e^{t(a\mu+b) + \frac{1}{2}t^2a^2\sigma^2} \end{aligned}$$

$\therefore ax+b \sim N(a\mu+b, a\sigma^2)$

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(b). CDF: Let  $Y = ax+b$

$$\begin{aligned} F_Y(y) &= P(Y \leq y) = P(ax+b \leq y) \\ &= P\left(X \leq \frac{y-b}{a}\right) = F_X\left(\frac{y-b}{a}\right) \\ \therefore f_Y(y) &= \frac{1}{a} f_X\left(\frac{y-b}{a}\right) = \frac{1}{a} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2\sigma^2}\left(\frac{y-b}{a}-\mu\right)^2} \\ &= \frac{1}{a\sigma\sqrt{2\pi}} e^{-\frac{1}{2a^2\sigma^2}(y-(a\mu+b))^2} \end{aligned}$$

AGAIN WE SEE THAT  
 $ax+b \sim N(a\mu+b, a\sigma^2)$

## EXERCISE 2 :

(a).  $\ln X \sim N(\mu, \sigma)$

$$M_{\ln X}(t) = e^{t\mu + \frac{1}{2}t^2\sigma^2} \quad (\text{BECAUSE } \ln X \text{ FOLLOW } N(\mu, \sigma))$$

BUT ALSO

$$M_{\ln X}(t) = E e^{t \ln X} = E e^{\ln X^t} = E X^t$$

$$\text{THEREFORE, } E X^t = e^{t\mu + \frac{1}{2}t^2\sigma^2}$$

$$\text{SET } t=1 \text{ SO GET } EX = e^{\mu + \frac{1}{2}\sigma^2}$$

$$\text{SET } t=2 \text{ TO GET } EX^2 = e^{2\mu + 2\sigma^2}$$

$$\begin{aligned} \text{AND } \text{VAR}(X) &= EX^2 - (EX)^2 \\ &= e^{2\mu + 2\sigma^2} - e^{2\mu + \sigma^2} \end{aligned}$$

$$= e^{2\mu + \sigma^2} \left[ e^{\sigma^2} - 1 \right]$$

$$(b). M_Y(t) = M_{\sum K_i X_i}(t)$$

$$= E e^{t \sum K_i X_i} = E e^{t K_1 X_1} \cdot E e^{t K_2 X_2} \cdots E e^{t K_n X_n}$$

$$= M_{X_1}(t K_1) \cdot M_{X_2}(t K_2) \cdots M_{X_n}(t K_n)$$

$$= e^{t K_1 \mu_1 + \frac{1}{2} t^2 K_1^2 \sigma_1^2} \cdot e^{t K_2 \mu_2 + \frac{1}{2} t^2 K_2^2 \sigma_2^2} \cdots e^{t K_n \mu_n + \frac{1}{2} t^2 K_n^2 \sigma_n^2}$$

$$= e^{t \sum K_i \mu_i + \frac{1}{2} t^2 \sum K_i^2 \sigma_i^2}$$

$$\therefore Y \sim N\left(\sum K_i \mu_i, \sqrt{\sum K_i^2 \sigma_i^2}\right)$$

$$(c). X_i \stackrel{iid}{\sim} \Gamma(\alpha, b)$$

$$M_{X_i}(t) = (1 - bt)^{-\alpha}$$

$$M_T(t) = M_{X_1 + \dots + X_n}(t)$$

$$= (M_{X_i}(t))^n$$

$$= (1 - bt)^{-n\alpha}$$

$$\therefore T \sim \Gamma(n\alpha, b)$$

$$\text{Ans) } M_{\bar{X}}(t) = M_{\frac{T}{n}}(t) = M_T\left(\frac{t}{n}\right)$$

$$= \left(1 - b \frac{t}{n}\right)^{-n\alpha}$$

$$\therefore \bar{X} \sim \Gamma(n\alpha, \frac{b}{n})$$


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EXERCISE 3:

$X \sim N(\mu, \sigma)$  STEIN'S LEMMA

$$E(g(X)(X-\mu)) = \sigma^2 E g'(X)$$

$$E X^4 = E X^3 (X - \mu + \mu)$$
$$= E X^3 (X - \mu) + \mu E X^3$$

$$= \sigma^2 E 3X^2 + \mu E X^3$$

$$= 3\sigma^2 E X^2 + \mu E X^3$$

$$= 3\sigma^2 (\mu^2 + \sigma^2) + \mu E 2X + \mu^3 (\mu^2 + \sigma^2)$$

$$= 2\sigma^2 (\mu^2 + \sigma^2) + 2\mu^3 = \dots$$

etc.

# EXERCISE 4 :

$$\begin{pmatrix} x_1 - \bar{x} \\ x_2 - \bar{x} \\ \vdots \\ x_n - \bar{x} \end{pmatrix}$$

$$= \underline{x} - \underline{1} \bar{x}$$

WHERE

$$\underline{1} = \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}$$

$$\text{WRITE } \bar{x} = \frac{1}{n} \underline{1}' \underline{x}$$

$$\text{THEN } \underline{x} - \underline{1} \bar{x} = \underline{x} - \frac{1}{n} \underline{1} \underline{1}' \underline{x}$$

$$= \left( \underline{I} - \frac{1}{n} \underline{1} \underline{1}' \right) \underline{x} = \underline{A} \underline{x}$$

$$\text{SINCE } \left. \begin{array}{l} x_1, \dots, x_n \stackrel{\text{iid}}{\sim} N(\mu, \sigma) \rightarrow E \underline{x} = \mu \underline{1} \\ \text{VAR}(\underline{x}) = \sigma^2 \underline{I} \end{array} \right\}$$

$$E \underline{A} \underline{x} = \underline{A} E \underline{x} = \mu \left( \underline{I} - \frac{1}{n} \underline{1} \underline{1}' \right) \underline{1} = \underline{0}$$

$$\text{VAR}(\underline{A} \underline{x}) = \sigma^2 \underline{A} \underline{A}' = \sigma^2 \left( \underline{I} - \frac{1}{n} \underline{1} \underline{1}' \right) \left( \underline{I} - \frac{1}{n} \underline{1} \underline{1}' \right)$$

$$= \sigma^2 \left( \underline{I} - \frac{1}{n} \underline{1} \underline{1}' \right)$$

TYPICAL ELEMENTS:

$$\text{VAR}(x_i - \bar{x}) = \sigma^2 \left( 1 - \frac{1}{n} \right)$$

$$\text{COV}(x_i - \bar{x}, x_j - \bar{x}) = -\frac{\sigma^2}{n}$$

# ~~EXERCISE~~ EXERCISE 5.

$$(a) X \sim U(0,1) \quad EX = \frac{1}{2}, \quad \text{var}(X) = \frac{1}{12}.$$

$$EX^2 = \sigma^2 + \mu^2 = \frac{1}{12} + \frac{1}{4} = \frac{1}{3}.$$

$$\therefore E \begin{pmatrix} X \\ X^2 \end{pmatrix} = \begin{pmatrix} 1/2 \\ 1/3 \end{pmatrix}.$$

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$$\text{var}(X) = \frac{1}{12}$$

$$\text{var}(X^2) = EX^4 - (EX^2)^2$$

$$= \int_0^1 x^4 dx - \left(\frac{1}{3}\right)^2 = \frac{1}{5} - \frac{1}{9} = \frac{4}{45}.$$

$$\begin{aligned} \text{Cov}(X, X^2) &= EX^3 - (EX)(EX^2) = \int_0^1 x^3 dx - \frac{1}{2} \cdot \frac{1}{3} \\ &= \frac{1}{4} - \frac{1}{6} = \frac{1}{12}. \end{aligned}$$

$$\therefore \text{var} \begin{pmatrix} X \\ X^2 \end{pmatrix} = \begin{pmatrix} \frac{1}{12} & \frac{1}{12} \\ \frac{1}{12} & \frac{4}{45} \end{pmatrix}$$

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~~QUESTION~~ PART (b):  $X_1 \sim \Gamma(\alpha, 1)$ ,  $X_2 \sim \Gamma(\alpha + \frac{1}{2}, 1)$   
 IF  $X \sim \Gamma(\alpha, \beta)$

THEN  
 $E X^K =$

$$EY = 2 E\sqrt{X_1 X_2}$$

$$\begin{aligned}
 &= 2 E X_1^{1/2} E X_2^{1/2} \\
 &= 2 \frac{\Gamma(\alpha + \frac{1}{2})^{1/2}}{\Gamma(\alpha)} \cdot \frac{\Gamma(\alpha + \frac{1}{2} + \frac{1}{2})^{1/2}}{\Gamma(\alpha + \frac{1}{2})} = \frac{2 \Gamma(\alpha + 1)}{\Gamma(\alpha)} \\
 &= 2\alpha.
 \end{aligned}$$

$$\frac{\Gamma(\alpha + k)}{\Gamma(\alpha)}$$

$$\text{VAR}(Y) = \text{VAR}(2\sqrt{X_1 X_2})$$

$$= 4 \text{VAR}(\sqrt{X_1 X_2})$$

$$= 4 \left( E(X_1 X_2) - \left( E\sqrt{X_1 X_2} \right)^2 \right)$$

$$= 4 \left( E X_1 E X_2 - \dots \right)$$



## EXERCISE 6

Problem 4 (25 points)

Answer the following questions:

- a. Let  $\mathbf{X} = (X_1, \dots, X_n)'$  be a random vector with joint moment generating function  $M_{\mathbf{X}}(\mathbf{t})$ . In class we discuss this theorem: Let  $M_i(\mathbf{t}) = \frac{\partial M_{\mathbf{X}}(\mathbf{t})}{\partial t_i}$ ,  $M_{ii}(\mathbf{t}) = \frac{\partial^2 M_{\mathbf{X}}(\mathbf{t})}{\partial t_i^2}$ , and  $M_{ij}(\mathbf{t}) = \frac{\partial^2 M_{\mathbf{X}}(\mathbf{t})}{\partial t_i \partial t_j}$ . Then,  $EX_i = M_i(0)$ ,  $EX_i^2 = M_{ii}(0)$ , and  $EX_i X_j = M_{ij}(0)$ . Prove this theorem when  $n = 2$ .

$$M_{\mathbf{X}}(\mathbf{t}) = E e^{t_1 X_1 + t_2 X_2} = \iint e^{t_1 x_1 + t_2 x_2} f(x_1, x_2) dx_1 dx_2$$

$$M_{11}(\mathbf{t}) = \frac{\partial M_{\mathbf{X}}(\mathbf{t})}{\partial t_1} = \frac{\partial}{\partial t_1} \iint e^{t_1 x_1 + t_2 x_2} f(x_1, x_2) dx_1 dx_2$$

$$= E X_1 (e^{t_1 X_1 + t_2 X_2}) = E X_1 \quad (\text{when } t_1 = 0, t_2 = 0)$$

$$M_{11}(\mathbf{t}) = \frac{\partial^2 M_{\mathbf{X}}(\mathbf{t})}{\partial t_1^2} = E X_1^2 (e^{t_1 X_1 + t_2 X_2}) = X_1^2 \quad (\text{when } t_1 = 0, t_2 = 0)$$

$$M_{12}(\mathbf{t}) = \frac{\partial^2 M_{\mathbf{X}}(\mathbf{t})}{\partial t_1 \partial t_2} = E X_1 X_2 (e^{t_1 X_1 + t_2 X_2}) = E X_1 X_2$$

(when  $t_1 = 0, t_2 = 0$ )

## EXERCISE 6

(b).

Problem 1 (25 points)

Answer the following questions:

a. Suppose  $U \sim \Gamma(\alpha, \beta)$ , with  $\alpha > 0, \beta > 0$  and let  $Y = e^U$ . Find the probability density function of  $Y$ .

$$f(u) = \frac{u^{\alpha-1} e^{-u/\beta}}{\Gamma(\alpha) \beta^\alpha}$$

$$F_Y(y) = P(Y \leq y) = P(e^U \leq y) = P(U \leq \ln y) = F_U(\ln y)$$

$$f(y) = \frac{1}{y} f_U(\ln y) = \frac{1}{y} \frac{(\ln y)^{\alpha-1} e^{-\ln y/\beta}}{\Gamma(\alpha) \beta^\alpha}$$

$$= \frac{1}{\Gamma(\alpha) \beta^\alpha} (\ln y)^{\alpha-1} y^{1/\beta-1}$$

b. Refer to part (a). Find  $EY$  and  $\text{var}(Y)$ .

$$M_U(t) = E e^{tU} = (1 - \beta t)^{-\alpha}$$

$$t=1 \rightarrow E e^U = EY = (1 - \beta)^{-\alpha}$$

$$t=2 \rightarrow E e^{2U} = EY^2 = (1 - 2\beta)^{-\alpha}$$

$$\text{var}(Y) = (1 - 2\beta)^{-\alpha} - (1 - \beta)^{-2\alpha}$$

## Exercise 7

$$f(y) = \theta y^{\theta-1} \quad 0 < y < 1, \quad \theta > 0$$

$$W = -\ln(Y) \quad F_W(w) = P(W \leq w)$$

$$= P(-\ln Y \leq w) = P(\ln Y \geq -w)$$

$$= P(Y \geq e^{-w}) = 1 - P(Y \leq e^{-w}) = 1 - F_Y(e^{-w})$$

$$\therefore f(w) = e^{-w} \theta e^{-w(\theta-1)} = \theta e^{-\theta w}$$

$$\therefore W \sim \text{exp}(\theta).$$

$$M_{2\theta \sum W_i}(t) = M_{2\theta W_1}(t) \cdots M_{2\theta W_n}(t)$$

$$= \left( M_{W_1}(2\theta t) \right)^n = \left( 1 - \frac{2\theta t}{\theta} \right)^{-n}$$

$$= (1 - 2t)^{-n}$$

NOTE: From (d)  
 $M_{W_i}(t) = \left( 1 - \frac{t}{\theta} \right)^{-1}$

$$\therefore 2\theta \sum W_i \sim \Gamma(n, 2).$$

## Exercise 8

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

$$= \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{x^2}{2\sigma^2} + \frac{\mu x}{\sigma^2} - \frac{\mu^2}{2\sigma^2}}$$

$$= \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{\mu^2}{2\sigma^2}} e^{-\frac{1}{2\sigma^2}x^2 + \frac{\mu}{\sigma^2}x}$$

$$\text{Let } h(x) = 1$$
$$c(\underline{\theta}) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{\mu^2}{2\sigma^2}}$$

$$w_1(\underline{\theta}) = \frac{1}{\sigma^2}, \quad t_1(x) = -\frac{x^2}{2}$$

$$w_2(\underline{\theta}) = \frac{\mu}{\sigma^2}, \quad t_2(x) = x$$