

HW 10

5.1.3 The random variables X_1, \dots, X_n have the joint PDF

$$f_{X_1, \dots, X_n}(x_1, \dots, x_n) = \begin{cases} 1 & 0 \leq x_i \leq 1; \\ & i = 1, \dots, n, \\ 0 & \text{otherwise.} \end{cases}$$

(a) What is the joint CDF, $F_{X_1, \dots, X_n}(x_1, \dots, x_n)$?

(b) For $n = 3$, what is the probability that $\min_i X_i \leq 3/4$?

(a) เราสามารถหาค่า Joint CDF จาก Joint PDF ดังนี้

$$F_{X_1, \dots, X_n}(x_1, \dots, x_n) = \int_{-\infty}^{x_1} \dots \int_{-\infty}^{x_n} f_{X_1, \dots, X_n}(y_1, \dots, y_n) dy_1 \dots dy_n$$

เนื่องจาก Joint PDF $f_{X_1, \dots, X_n}(x_1, \dots, x_n) = 1$ ถ้า $0 \leq x_i \leq 1; i = 1, \dots, n$

นอกจากนี้ถ้า $x_i < 0$ หรือ $x_i > 1$ Joint PDF จะเป็น 0

$$; F_{X_1, \dots, X_n}(x_1, \dots, x_n) = \int_0^{\min(1, x_1)} \dots \int_0^{\min(1, x_n)} 1 dy_1 \dots dy_n$$

$$= \min(1, x_1) \times \min(1, x_2) \times \dots \times \min(1, x_n)$$

$$\therefore F_{X_1, \dots, X_n}(x_1, \dots, x_n) = \begin{cases} \prod_{i=1}^n \min(1, x_i) & , 0 \leq x_i; i = 1, 2, \dots, n \\ 0 & , \text{otherwise} \end{cases}$$

(b) For $n=3$, Prob $[X_i \leq 3/4]$ $0 \leq x_i \leq 1$

$$P[\min X_i \leq 3/4] = 1 - P[\min X_i > 3/4]$$

$$\therefore P[\min X_i \leq 3/4] = 1 - P[X_1 > 3/4, X_2 > 3/4, X_3 > 3/4]$$

$$= 1 - \int_{3/4}^1 \int_{3/4}^1 \int_{3/4}^1 dx_1 dx_2 dx_3$$

$$\frac{63}{64} \quad \text{✗}$$

5.4.4 As in Example 5.4, the random vector \mathbf{X} has PDF

$$f_{\mathbf{X}}(\mathbf{x}) = \begin{cases} 6e^{-\mathbf{a}'\mathbf{x}} & \mathbf{x} \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

where $\mathbf{a} = [1 \ 2 \ 3]'$. Are the components of \mathbf{X} independent random variables?

$$\text{PDF } f_{\mathbf{X}}(\mathbf{x}) = \begin{cases} 6e^{-(x_1 + 2x_2 + 3x_3)} & , x_1 \geq 0, x_2 \geq 0, x_3 \geq 0 \\ 0 & , \text{otherwise} \end{cases}$$

1) Marginal PDFs $f_{X_1}(x_1)$ for $x_1 \geq 0$,

$$\begin{aligned} f_{X_1}(x_1) &= \int_0^\infty \int_0^\infty f_{\mathbf{X}}(\mathbf{x}) dx_2 dx_3 \\ &= 6e^{-x_1} \int_0^\infty \int_0^\infty e^{-2x_2} \cdot e^{-3x_3} dx_2 dx_3 \\ &= 6e^{-x_1} \lim_{b \rightarrow \infty} \left. \frac{e^{-2x_2}}{-2} \right|_0^b \times \lim_{c \rightarrow \infty} \left. \frac{e^{-3x_3}}{-3} \right|_0^c \\ &= \cancel{6}e^{-x_1} \times \cancel{\frac{1}{-2}} \times \cancel{\frac{1}{-3}} \left[\frac{1}{e^{-2b}} - 1 \right] \left[\frac{1}{e^{-3c}} - 1 \right] \\ &= e^{-x_1} \quad , \quad x_1 \geq 0 \end{aligned}$$

$$\therefore f_{X_1}(x) = \begin{cases} e^{-x_1} & , x_1 \geq 0 \\ 0 & , \text{otherwise} \end{cases}$$

similar $f_{X_2}(x_2)$ & $f_{X_3}(x_3)$ identical to $f_{X_1}(x_1)$;

$$\begin{aligned} f_{X_2}(x) &= 6e^{-2x_2} \int_0^\infty \int_0^\infty e^{-x_1} \cdot e^{-3x_3} dx_1 dx_3 \\ &= 6e^{-2x_2} \times \frac{1}{-1} \times \frac{1}{-3} \left[\frac{1}{e^{x_1}} \right]_0^\infty \times \left[\frac{1}{e^{3x_3}} \right]_0^\infty \\ &= 2e^{-2x_2} \quad ; \quad x_2 \geq 0 \end{aligned} \quad \left| \quad \therefore f_{X_2}(x) = \begin{cases} 2e^{-2x_2} & , x_2 \geq 0 \\ 0 & , \text{otherwise} \end{cases} \right.$$

$$f_{X_3}(x_3) = 6e^{-3x_3} \int_0^\infty \int_0^\infty e^{-x_1} e^{-2x_2} dx_1 dx_2$$

$$= 6e^{-3x_3} \times \frac{1}{-1} \times \frac{1}{-2} \times \left[\frac{1}{e^{x_1}} \right]_0^\infty \times \left[\frac{1}{e^{2x_2}} \right]_0^\infty$$

$$f_{X_3}(x_3) = 3e^{-3x_3} \quad ; \quad x_3 \geq 0$$

$$\therefore f_{X_3}(x_3) = \begin{cases} 3e^{-3x_3} & , \quad x_3 \geq 0 \\ 0 & , \quad \text{otherwise} \end{cases} \quad \text{X}$$

5.5.5 In a weekly lottery, each \$1 ticket sold adds 50 cents to the jackpot that starts at \$1 million before any tickets are sold. The jackpot is announced each morning to encourage people to play. On the morning of the i th day before the drawing, the current value of the jackpot J_i is announced. On that day, the number of tickets sold, N_i , is a Poisson random variable with expected value J_i . Thus six days before the drawing, the morning jackpot starts at \$1 million and N_6 tickets are sold that day. On the day of the drawing, the announced jackpot is J_0 dollars and N_0 tickets are sold before the evening drawing.

What are the expected value and variance of J , the value of the jackpot the instant before the drawing?
Hint: Use conditional expectations.

5.6.4 The 4-dimensional random vector \mathbf{X} has PDF

$$f_{\mathbf{X}}(\mathbf{x}) = \begin{cases} 1 & 0 \leq x_i \leq 1, i = 1, 2, 3, 4 \\ 0 & \text{otherwise.} \end{cases}$$

→ uniform RV distributed (0,1)

Find the expected value vector $E[\mathbf{X}]$, the correlation matrix $\mathbf{R}_{\mathbf{X}}$, and the covariance matrix $\mathbf{C}_{\mathbf{X}}$.

$$\Rightarrow f_{\mathbf{X}}(\mathbf{x}) = f_{X_1}(x_1) f_{X_2}(x_2) f_{X_3}(x_3) f_{X_4}(x_4) \quad \rightarrow \text{Marginal}$$

$$E[X_i] = \frac{1-0}{2} = \frac{1}{2}, \quad \text{Var}[X_i] = \frac{(0-1)^2}{12} = \frac{1}{12}$$

independant X_i and X_j → Correlation

$i \neq j \rightarrow$ uncorrelated

$$E[X_i X_j] = E[X_i] E[X_j]$$

1) Expected Value

$$E[\mathbf{X}] = [E[X_1] \ E[X_2] \ E[X_3] \ E[X_4]]' \\ = \left[\frac{1}{2} \quad \frac{1}{2} \quad \frac{1}{2} \quad \frac{1}{2} \right]' \rightarrow \text{Uniform RV}$$

2) Correlation matrix

$$\mathbf{R}_{\mathbf{X}} = E[\mathbf{X} \mathbf{X}'] = \begin{bmatrix} E[X_1^2] & E[X_1 X_2] & E[X_1 X_3] & E[X_1 X_4] \\ E[X_2 X_1] & E[X_2^2] & E[X_2 X_3] & E[X_2 X_4] \\ E[X_3 X_1] & E[X_3 X_2] & E[X_3^2] & E[X_3 X_4] \\ E[X_4 X_1] & E[X_4 X_2] & E[X_4 X_3] & E[X_4^2] \end{bmatrix}$$

$$\therefore \mathbf{R}_{\mathbf{X}} = \begin{bmatrix} \frac{1}{3} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \\ \frac{1}{4} & \frac{1}{3} & \frac{1}{4} & \frac{1}{4} \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{3} & \frac{1}{4} \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{3} \end{bmatrix}$$

$$\text{3) Cov}[\mathbf{X}] = [\text{Cov}[X_i, X_j]]_{4 \times 4}$$

$$\therefore \text{Cov}[\mathbf{X}] = \begin{bmatrix} \frac{1}{12} & 0 & 0 & 0 \\ 0 & \frac{1}{12} & 0 & 0 \\ 0 & 0 & \frac{1}{12} & 0 \\ 0 & 0 & 0 & \frac{1}{12} \end{bmatrix}$$

5.7.4 Let \mathbf{X} be a Gaussian random vector with expected value $[\mu_1 \ \mu_2]'$ and covariance matrix

$$\mathbf{C}_X = \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix}.$$

Show that \mathbf{X} has PDF $f_X(\mathbf{x}) = f_{X_1, X_2}(x_1, x_2)$ given by the bivariate Gaussian PDF of Definition 4.17.

we Inverse Matrix of \mathbf{C}_X

$$\mathbf{C}_X^{-1} = \frac{1}{\det[\mathbf{C}]} \begin{bmatrix} \sigma_2^2 & -\rho\sigma_1\sigma_2 \\ -\rho\sigma_1\sigma_2 & \sigma_1^2 \end{bmatrix}$$

Gaussian Random vector

$$f_X(\mathbf{x}) = \frac{1}{2\pi[\det[\mathbf{C}_X]]^{1/2}} \exp\left(-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_X)'\mathbf{C}_X^{-1}(\mathbf{x}-\boldsymbol{\mu}_X)\right)$$

$$\det[\mathbf{C}_X] = \sigma_1^2 \sigma_2^2 - \rho^2 \sigma_1^2 \sigma_2^2$$

$$\det[\mathbf{C}_X] = \sigma_1^2 \sigma_2^2 (1 - \rho^2)$$

$$\therefore -\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_X)'\mathbf{C}_X^{-1}(\mathbf{x}-\boldsymbol{\mu}_X) = [x_1 - \mu_1 \quad x_2 - \mu_2] \begin{bmatrix} \frac{1}{\sigma_1^2 \sigma_2^2 (1 - \rho^2)} \end{bmatrix} \begin{bmatrix} \sigma_2^2 & -\rho\sigma_1\sigma_2 \\ -\rho\sigma_1\sigma_2 & \sigma_1^2 \end{bmatrix} \begin{bmatrix} x_1 - \mu_1 \\ x_2 - \mu_2 \end{bmatrix}$$

$$= [x_1 - \mu_1 \quad x_2 - \mu_2] \begin{bmatrix} \frac{1}{\sigma_1^2} & \frac{-\rho}{\sigma_1 \sigma_2} \\ \frac{-\rho}{\sigma_1 \sigma_2} & \frac{1}{\sigma_2^2} \end{bmatrix} \begin{bmatrix} x_1 - \mu_1 \\ x_2 - \mu_2 \end{bmatrix}$$

$$2(1 - \rho^2)$$

$$= [x_1 - \mu_1 \quad x_2 - \mu_2] \begin{bmatrix} \frac{x_1 - \mu_1}{\sigma_1^2} & \frac{-\rho(x_2 - \mu_2)}{\sigma_1 \sigma_2} \\ \frac{-\rho(x_1 - \mu_1)}{\sigma_1 \sigma_2} & \frac{x_2 - \mu_2}{\sigma_2^2} \end{bmatrix}$$

$$2(1 - \rho^2)$$

$$\therefore -\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_X)'\mathbf{C}_X^{-1}(\mathbf{x}-\boldsymbol{\mu}_X) = -\frac{(x_1 - \mu_1)^2}{\sigma_1^2} - \frac{2\rho(x_1 - \mu_1)(x_2 - \mu_2)}{\sigma_1 \sigma_2} + \frac{(x_2 - \mu_2)^2}{\sigma_2^2}$$

$$2(1 - \rho^2)$$

$$\therefore f_X(\mathbf{x}) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \exp\left[-\frac{(x_1 - \mu_1)^2}{\sigma_1^2} - \frac{2\rho(x_1 - \mu_1)(x_2 - \mu_2)}{\sigma_1 \sigma_2} + \frac{(x_2 - \mu_2)^2}{\sigma_2^2}\right]$$