

Bivariate Normal distribution - 2.1.4 cont

① If  $x_1$  and  $x_2$  are normally distribution then the bivariate density function is given by

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

Pr. 2.1.4

$$f(x) = \frac{1}{(2\pi)^{n/2} |\Sigma|^{1/2}} \exp\left\{-\frac{1}{2} \left[ (x - \underline{\mu})' \Sigma^{-1} (x - \underline{\mu}) \right]\right\}$$

$$\underline{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}, \quad \underline{\mu} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \quad \Sigma = \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix}$$

$$\rho = \frac{\sigma_{12}}{\sigma_1\sigma_2} \Rightarrow \sigma_{12} = \rho\sigma_1\sigma_2$$

$$|\Sigma| = \sigma_1^2\sigma_2^2 - \rho^2\sigma_1^2\sigma_2^2 \Rightarrow \sigma_1^2\sigma_2^2(1-\rho^2)$$

$$\Sigma^{-1} = \frac{\text{adj } \Sigma}{|\Sigma|} = \frac{1}{\sigma_1^2\sigma_2^2(1-\rho^2)} \begin{bmatrix} \sigma_2^2 & -\rho\sigma_1\sigma_2 \\ -\rho\sigma_1\sigma_2 & \sigma_1^2 \end{bmatrix}$$

$$\text{and } |\Sigma|^{1/2} = \sqrt{\sigma_1^2\sigma_2^2(1-\rho^2)} = \sigma_1\sigma_2\sqrt{(1-\rho^2)}$$

$$f(x_1, x_2) = \frac{1}{(2\pi)\sigma_1\sigma_2\sqrt{1-\rho^2}} \exp\left\{-\frac{1}{2} \left[ \begin{pmatrix} x_1-\mu_1 \\ x_2-\mu_2 \end{pmatrix}' \frac{1}{\sigma_1^2\sigma_2^2(1-\rho^2)} \begin{pmatrix} \sigma_2^2 & -\rho\sigma_1\sigma_2 \\ -\rho\sigma_1\sigma_2 & \sigma_1^2 \end{pmatrix} \begin{pmatrix} x_1-\mu_1 \\ x_2-\mu_2 \end{pmatrix} \right]\right\}$$

The pdf defined in eq (11) is called the bivariate normal distribution where  $X_1, X_2$  are correlated. This distribution is indicated in symbols as:

$$X \sim N_2(\mu, \Sigma)$$

or  $X \sim N_2(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, \rho)$

$$\mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \Sigma = \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix}$$

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

عند ذلك كانت قيم التوزيع العيب الثاني المتغير عند كل واحد من المتغيرين  $(x_1, x_2)$  غير متساوية

### Notes

① If  $\rho = 0$  that is mean  $X_1$  &  $X_2$  are independent, therefore

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

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma_1} \exp \left[ -\frac{1}{2} \left( \frac{x_1-\mu_1}{\sigma_1} \right)^2 \right] \cdot \frac{1}{\sqrt{2\pi}\sigma_2} \exp \left[ -\frac{1}{2} \left( \frac{x_2-\mu_2}{\sigma_2} \right)^2 \right]$$

$$= f(x_1, x_2) = f(x_1) \cdot f(x_2)$$

(2) If  $\rho = 0$  that is mean  $x_1$  &  $x_2$  are independent then:-

$$\begin{aligned} P(x_1, x_2) &= \frac{1}{(2\pi) \sigma_1 \sigma_2} \exp \left\{ -\frac{1}{2} \left[ \left( \frac{x_1 - \mu_1}{\sigma_1} \right)^2 + \left( \frac{x_2 - \mu_2}{\sigma_2} \right)^2 \right] \right\} \\ &= \frac{1}{\sqrt{2\pi} \sigma_1} \exp \left\{ -\frac{1}{2} \left( \frac{x_1 - \mu_1}{\sigma_1} \right)^2 \right\} \cdot \frac{1}{\sqrt{2\pi} \sigma_2} \exp \left\{ -\frac{1}{2} \left( \frac{x_2 - \mu_2}{\sigma_2} \right)^2 \right\} \\ &= P(x_1) \cdot P(x_2) \end{aligned}$$

(3) If  $x_1$  &  $x_2$  are Perfectly Correlated (i.e.  $\rho = \pm 1$ ), then  $\Sigma$  is Singular matrix

(i.e.  $|\Sigma| = 0$ ), in this case we can't find the joint density function

$$\Rightarrow \rho = \frac{\sigma_{12}}{\sigma_1 \sigma_2} \Rightarrow \pm 1 = \frac{\sigma_{12}}{\sigma_1 \sigma_2} \Rightarrow \sigma_{12} = \pm \sigma_1 \sigma_2$$

$$|\Sigma| = \begin{vmatrix} \sigma_1^2 & \rho \sigma_1 \sigma_2 \\ \rho \sigma_1 \sigma_2 & \sigma_2^2 \end{vmatrix} = \sigma_1^2 \sigma_2^2 - \rho^2 \sigma_1^2 \sigma_2^2$$

$$= \sigma_1^2 \sigma_2^2 (1 - \rho^2)$$

$$= \sigma_1^2 \sigma_2^2 (1 - (\pm 1)^2) = 0$$

$$\therefore |\Sigma| = 0$$

In general,  $|f| > 0$  then  $-1 < f < 1$

Proofs

$$|f| > 0 \Rightarrow \sigma_1 \sigma_2 (1-f) > 0$$

$$\sigma_1 \sigma_2 - \sigma_1 \sigma_2 f > 0$$

$$\sigma_1 \sigma_2 > \sigma_1 \sigma_2 f$$

$$\Rightarrow 1 > f$$

$$\Rightarrow -1 < f < 1$$

12      4

Ex If  $\underline{X} = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$ ,  $\underline{\mu} = \begin{pmatrix} -2 \\ 4 \end{pmatrix}$

$$\Sigma = \begin{pmatrix} 1 & 1 \\ 1 & 4 \end{pmatrix}$$

and  $x_1, x_2$  are normally distributed.

(1) Write the joint density function in the simplest form.

(2) Find the Correlation Coefficient  $\rho$

Soln

$$f(x_1, x_2) = \frac{1}{(2\pi) |\Sigma|^{\frac{1}{2}}} e^{-\frac{1}{2} \{(\underline{x} - \underline{\mu})' \Sigma^{-1} (\underline{x} - \underline{\mu})\}}$$

$$(\underline{x} - \underline{\mu})' \Sigma^{-1} (\underline{x} - \underline{\mu}) = (x_1 + 2 \quad x_2 - 4) \begin{pmatrix} 1 & 1 \\ 1 & 4 \end{pmatrix}^{-1} \begin{pmatrix} x_1 + 2 \\ x_2 - 4 \end{pmatrix}$$

$$|\Sigma| = 4 - 1 = 3$$

$$\Sigma^{-1} = \frac{1}{3} \begin{pmatrix} 4 & -1 \\ -1 & 1 \end{pmatrix} = \begin{pmatrix} 4/3 & -1/3 \\ -1/3 & 1/3 \end{pmatrix}$$

$$\therefore (\underline{x} - \underline{\mu})' \Sigma^{-1} (\underline{x} - \underline{\mu}) = (x_1 + 2 \quad x_2 - 4) \begin{pmatrix} 4/3 & -1/3 \\ -1/3 & 1/3 \end{pmatrix} \begin{pmatrix} x_1 + 2 \\ x_2 - 4 \end{pmatrix}$$

$$= \left( \frac{4x_1}{3} + \frac{8}{3} - \frac{4x_2}{3} + \frac{16}{3} - \frac{x_1}{3} + \frac{2}{3} + \frac{x_2}{3} - \frac{4}{3} \right) \begin{pmatrix} x_1 + 2 \\ x_2 - 4 \end{pmatrix}$$

78  
(2) To find  $\rho$

$$\Phi = \begin{bmatrix} \hat{\sigma}_1^2 & \rho \sigma_1 \sigma_2 \\ \hat{\sigma}_2^2 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 4 \end{bmatrix}$$

$$\hat{\sigma}_1^2 = 1 \implies \sigma_1 = 1$$

$$\hat{\sigma}_2^2 = 4 \implies \sigma_2 = 2$$

$$\rho \sigma_1 \sigma_2 = 1 \implies \rho(1)(2) = 1 \implies 2\rho = 1$$

$$\therefore \rho = \frac{1}{2}$$

ex Let  $\underline{X} = (X_1, X_2)' \sim N_2(0, 0, \hat{\sigma}_1^2, \hat{\sigma}_2^2, \rho)$

show that the random variable

$$U_1 = \frac{X_1}{\sigma_1} + \frac{X_2}{\sigma_2} \text{ and } U_2 = \frac{X_1}{\sigma_1} - \frac{X_2}{\sigma_2}$$

are independent with  $E(U_1) = E(U_2) = 0$

$$\text{and } \text{var}(U_1) = 2(1+\rho), \text{ var}(U_2) = 2(1-\rho)$$

Soln.

$$E(U_1) = \frac{E(X_1)}{\sigma_1} + \frac{E(X_2)}{\sigma_2} = 0$$

$$E(U_2) = \frac{E(X_1)}{\sigma_1} - \frac{E(X_2)}{\sigma_2} = 0$$

$$V(U_1) = \frac{V(X_1)}{\sigma_1^2} + \frac{V(X_2)}{\sigma_2^2} + \frac{2 \text{Cov}(X_1, X_2)}{\sigma_1 \sigma_2}$$

$$V(U_1) = \frac{\sigma_1^2}{\sigma_1^2} + \frac{\sigma_2^2}{\sigma_2^2} + \frac{2\rho \sigma_1 \sigma_2}{\sigma_1 \sigma_2}$$

$$= 1 + 1 + 2\rho = 2(1 + \rho)$$

$$V(U_2) = \frac{V(X_1)}{\sigma_1^2} + \frac{V(X_2)}{\sigma_2^2} - \frac{2 \text{Cov}(X_1, X_2)}{\sigma_1 \sigma_2}$$

$$= 1 + 1 - \frac{2\rho \sigma_1 \sigma_2}{\sigma_1 \sigma_2}$$

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

$$\text{Cov}(U_1, U_2) \stackrel{?}{=} 0$$

$$\text{Cov}(U_1, U_2) = E(U_1 U_2) - \overset{0}{E(U_1)} \overset{0}{E(U_2)} = E(U_1 U_2)$$

$$= E \left[ \frac{X_1}{\sigma_1} + \frac{X_2}{\sigma_2} \right] \left[ \frac{X_1}{\sigma_1} - \frac{X_2}{\sigma_2} \right]$$

$$= E \left[ \frac{X_1^2}{\sigma_1^2} - \frac{X_2^2}{\sigma_2^2} \right]$$

$$= \frac{\sigma_1^2}{\sigma_1^2} - \frac{\sigma_2^2}{\sigma_2^2} = 0$$

$$V(X) = EX^2 - (EX)^2$$

$$\therefore EX^2 = V(X) + (EX)^2$$

Thus  $U_1$  and  $U_2$  are independent