

Mathematical Statistics 1

Ch.4 Bivariate Distributions

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① The Bivariate Normal Distribution

5.1 Bivariate Normal distribution

Definition

$$\begin{pmatrix} X \\ Y \end{pmatrix} \sim \text{BVN} \left(\begin{pmatrix} \mu_X \\ \mu_Y \end{pmatrix}, \begin{pmatrix} \sigma_X^2 & \rho\sigma_X\sigma_Y \\ \rho\sigma_X\sigma_Y & \sigma_Y^2 \end{pmatrix} \right), \quad |\rho| < 1$$

Then, the joint pdf of X and Y is

 $f(x, y) = \frac{1}{2\pi\sigma_X\sigma_Y\sqrt{1-\rho^2}} e^{-Q/2}$

where $\text{Corr}(X, Y) = \rho$ and

$$Q = \frac{1}{1-\rho^2} \left[\left(\frac{x - \mu_X}{\sigma_X} \right)^2 - 2\rho \left(\frac{x - \mu_X}{\sigma_X} \right) \left(\frac{y - \mu_Y}{\sigma_Y} \right) + \left(\frac{y - \mu_Y}{\sigma_Y} \right)^2 \right].$$

- Bivariate Normal

$P_{XY} \cdot 6 \times 6Y$

$$\tilde{x} \sim BN\left(\begin{pmatrix} \mu_x \\ \mu_y \end{pmatrix} = \mu, \begin{pmatrix} \sigma_x^2 & \text{cov}(X,Y) \\ \text{cov}(X,Y) & \sigma_y^2 \end{pmatrix} = \Sigma\right)$$

Covariance matrix

- Multivariate Normal

$$\begin{pmatrix} X_1 \\ X_2 \\ \vdots \\ X_n \end{pmatrix} \sim MN \left(\mu = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_n \end{pmatrix}, \Sigma_{n \times n} = \begin{pmatrix} \sigma_1^2 & \dots & \text{cov}(X_1, X_n) \\ \vdots & \ddots & \vdots \\ \text{cov}(X_n, X_1) & \dots & \sigma_n^2 \end{pmatrix} \right)$$

$$X \sim N(\mu, \sigma^2)$$

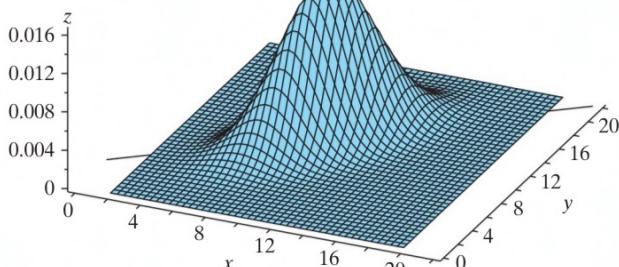
$$\tilde{X} = \begin{pmatrix} X \\ Y \end{pmatrix} \sim BVN \left(\mu = \begin{pmatrix} \mu_X \\ \mu_Y \end{pmatrix}, \Sigma = \begin{pmatrix} \sigma_X^2 & \rho \sigma_X \sigma_Y \\ \rho \sigma_X \sigma_Y & \sigma_Y^2 \end{pmatrix} \right)$$

Joint pdf of X & Y

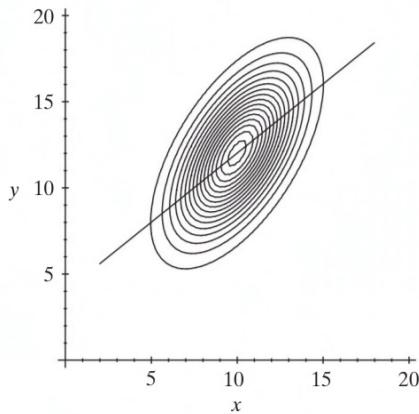
$$f_{XY}(x, y) = \frac{1}{\sqrt{2\pi|\Sigma|}} \exp \left\{ -\frac{1}{2} \begin{pmatrix} x - \mu_X \\ y - \mu_Y \end{pmatrix}^\top \Sigma^{-1} \begin{pmatrix} x - \mu_X \\ y - \mu_Y \end{pmatrix} \right\}$$

$$f_{XY}(x, y) = \frac{1}{2\pi\sigma_X\sigma_Y\sqrt{1-\rho^2}} \exp \left\{ -\frac{1}{2(1-\rho^2)} (Z_X^2 - 2\rho Z_X Z_Y + Z_Y^2) \right\}$$

$$\text{where } Z_X = \frac{x - \mu_X}{\sigma_X}, \quad Z_Y = \frac{y - \mu_Y}{\sigma_Y}$$



(a) Bivariate normal pdf



(b) Contours for bivariate normal

Figure 4.5-2 Bivariate normal, $\mu_X = 10$, $\sigma_X^2 = 9$, $\mu_Y = 12$, $\sigma_Y^2 = 16$, $\rho = 0.6$

$$f_X(x) = \frac{1}{\sqrt{2\pi\sigma_X^2}} \exp \left\{ -\frac{(x - \mu_X)^2}{2\sigma_X^2} \right\} \quad -\infty < x < \infty$$

$$f_{XY}(x, y) = \frac{1}{2\pi\sigma_X\sigma_Y\sqrt{1-\rho^2}} \exp \left\{ -\frac{1}{2(1-\rho^2)} (Z_X^2 - 2\rho Z_X Z_Y + Z_Y^2) \right\}$$

$$\text{where } Z_X = \frac{x - \mu_X}{\sigma_X}, \quad Z_Y = \frac{y - \mu_Y}{\sigma_Y}$$

$$1) f_{XY}(x,y) = \frac{1}{2\pi G_x G_y \sqrt{1-p^2}} \exp \left\{ -\frac{1}{2(1-p^2)} (z_x^2 - 2pz_x z_y + z_y^2) \right\}$$

2) Joint mgf of $X \& Y$

$$M_{XY}(t_1, t_2) = E[e^{t_1 x + t_2 y}] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{(t_1 x + t_2 y)} f_{XY}(x,y) dx dy$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{2\pi G_x G_y \sqrt{1-p^2}} e^{t_1 x + t_2 y} \exp \left\{ -\frac{(z_x^2 - 2pz_x z_y + z_y^2)}{2(1-p^2)} \right\} dx dy$$

① consider the simple situation $\mu_x = \mu_y = 0$, $G_x^2 = G_y^2 = 1$

$$M_{XY}(t_1, t_2) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{(t_1 x + t_2 y)} \frac{1}{2\pi \sqrt{1-p^2}} \exp \left\{ -\frac{(x^2 - 2pxy + y^2)}{2(1-p^2)} \right\} dx dy$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{2\pi \sqrt{1-p^2}} \exp \left\{ -\frac{x^2 - 2pxy + y^2 - 2(1-p^2)t_1 x}{2(1-p^2)} + \frac{t_2 y}{1-p^2} \right\} dx dy$$

$$- (x^2 - 2x(py + (1-p^2)t_1))$$

$$\frac{-(x - (py + (1-p^2)t_1))^2}{2(1-p^2)}$$

$$= \int_{-\infty}^{\infty} \frac{1}{2\pi \sqrt{1-p^2}} \exp \left\{ -\frac{y^2}{2(1-p^2)} + t_2 y \right\} \times \exp \left\{ \frac{(py + (1-p^2)t_1)^2}{2(1-p^2)} \right\}$$

$$\times \sqrt{2\pi(1-p^2)} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi(1-p^2)}} \exp \left\{ -\frac{(x - (py + (1-p^2)t_1))^2}{2(1-p^2)} \right\} dx dy$$

pdf of $N(py + (1-p^2)t_1, (1-p^2))$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \exp \left\{ -\frac{y^2}{2(1-p^2)} + t_2 y + \frac{p^2 y^2}{2(1-p^2)} + pt_1 y + \frac{(1-p^2)t_1^2}{2} \right\} dy$$

$$\checkmark = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \exp \left\{ -\frac{y^2 - 2y(t_2 + pt_1) + (t_2 + pt_1)^2 - (t_2 + pt_1)^2 + (1-p^2)t_1^2}{2} \right\} dy$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \exp \left\{ -\frac{(y - (t_2 + pt_1))^2}{2} \right\} dy \times \exp \left\{ \frac{t_2^2 + 2pt_1 t_2 + p^2 t_1^2 + t_1^2 - p^2 t_1^2}{2} \right\}$$

pdf of $N(t_2 + pt_1, 1)$

$$M_{XY}(t_1, t_2) = \exp \left\{ \frac{t_1^2 + 2pt_1 t_2 + t_2^2}{2} \right\}, \quad t_1, t_2 \in \mathbb{R}$$

$$\begin{aligned}
 \textcircled{2} \quad X &= \mu_x + 6xZ_x, \quad Y = \mu_y + 6yZ_y \\
 M_{XY}(t_1, t_2) &= E[e^{t_1X + t_2Y}] = E[e^{t_1(\mu_x + 6xZ_x) + t_2(\mu_y + 6yZ_y)}] \\
 &= E[e^{t_1\mu_x + t_2\mu_y} \times e^{t_16xZ_x + t_26yZ_y}] \\
 &= \exp(t_1\mu_x + t_2\mu_y) M_{Z_x Z_y}(t_16x, t_26y) \\
 &= \exp(t_1\mu_x + t_2\mu_y) \exp\left(\frac{t_1^2 6x^2 + 2\rho 6x 6y t_1 t_2 + 6y^2 t_2^2}{2}\right) \\
 &= \exp\left((\mu_x t_1 + \mu_y t_2) + \frac{1}{2}(6x^2 t_1^2 + 2\rho 6x 6y t_1 t_2 + 6y^2 t_2^2)\right), \\
 &\quad t_1, t_2 \in \mathbb{R}
 \end{aligned}$$

Marginal mgf of X, Y

$$\begin{aligned}
 M_X(t_1) &= E[e^{t_1X}] = M_{X,Y}(t_1, 0) \\
 &= \exp\left(\mu_x t_1 + \frac{6x^2}{2} t_1^2\right) \quad \text{mgf of } N(\mu_x, 6x^2) \\
 &\therefore X \sim N(\mu_x, 6x^2)
 \end{aligned}$$

$$\begin{aligned}
 M_Y(t_2) &= E[e^{t_2Y}] = M_{X,Y}(0, t_2) \\
 &= \exp\left(\mu_y t_2 + \frac{6y^2}{2} t_2^2\right) \quad \text{mgf of } N(\mu_y, 6y^2) \\
 &\therefore Y \sim N(\mu_y, 6y^2)
 \end{aligned}$$

The joint mgf of X and Y is

$$\begin{aligned} M(t_1, t_2) &= E[e^{t_1 X + t_2 Y}] \\ &= \exp \left[\mu_X t_1 + \mu_Y t_2 + \frac{1}{2} (\sigma_X^2 t_1^2 + 2\rho\sigma_X\sigma_Y t_1 t_2 + \sigma_Y^2 t_2^2) \right] \end{aligned}$$

The mgf of X is

$$M_X(t_1) = M(t_1, 0) = \exp \left[\mu_X t_1 + \frac{1}{2} \sigma_X^2 t_1^2 \right]$$

Similarly, the mgf of Y is

$$M_Y(t_2) = M(0, t_2) = \exp \left[\mu_Y t_2 + \frac{1}{2} \sigma_Y^2 t_2^2 \right].$$

Thus, $X \sim N(\mu_X, \sigma_X^2)$ and $Y \sim N(\mu_Y, \sigma_Y^2)$.

$$f_{Y|X}(y|x) = \frac{f_{XY}(x,y)}{f_X(x)} = \frac{\frac{1}{2\pi G_X G_Y \sqrt{1-p^2}} \exp\left\{-\frac{1}{2(1-p^2)}(Z_x^2 - 2pZ_x Z_Y + Z_Y^2)\right\}}{\frac{1}{\sqrt{2\pi G_X^2}} \exp\left\{-\frac{1}{2} Z_x^2\right\}}$$

$$= \frac{1}{\sqrt{2\pi} G_Y \sqrt{1-p^2}} \exp\left\{-\frac{1}{2} Q^*\right\}$$

= $\frac{1}{\sqrt{2\pi} G_Y \sqrt{1-p^2}} \exp\left\{-\frac{1}{2} \frac{(y-b)^2}{(1-p^2)G_Y^2}\right\}$

where $Q^* = Q - Z_x^2$

$$= \frac{1}{1-p^2} \left[\left(\frac{x-\mu_X}{\sigma_X} \right)^2 - 2p \left(\frac{x-\mu_X}{\sigma_X} \right) \left(\frac{y-\mu_Y}{\sigma_Y} \right) + \left(\frac{y-\mu_Y}{\sigma_Y} \right)^2 \right] - \left(\frac{x-\mu_X}{\sigma_X} \right)^2$$

$$= \frac{1}{1-p^2} \left[\frac{y^2 - 2\mu_Y y + \mu_Y^2}{G_Y^2} - \frac{2p(xy - \mu_X x - \mu_X y + \mu_X \mu_Y)}{G_X G_Y} \right]$$

$$\frac{f_{Y|X}(y|x)}{f_X(x)} = \frac{f_{XY}(x,y)}{f_X(x)} = \frac{\frac{1}{2\pi G_X G_Y \sqrt{1-p^2}} \exp\left\{-\frac{1}{2(1-p^2)}(Z_x^2 - 2pZ_x Z_Y + Z_Y^2)\right\}}{\frac{1}{\sqrt{2\pi G_X^2}} \exp\left\{-\frac{1}{2} Z_x^2\right\}}$$

$\Rightarrow Q^* = \frac{1}{(1-p^2)G_Y^2} [y-b]^2$

where $b = \mu_Y + p \cdot \frac{\sigma_Y}{\sigma_X} (\mu_X - \mu_Y)$

$Y|X \sim N(\mu_Y + p \cdot \frac{\sigma_Y}{\sigma_X} (x - \mu_X), \frac{\sigma_Y^2 (1-p^2)}{\text{constant}})$

$$E[Y|X] = a + bx$$

$$\text{Var}[Y|X] = k(x) \quad E[\text{Var}(Y|X)] = G_Y^2 (1-p^2)$$

$$\text{If } p=0, \quad Y|X \sim N(\mu_Y, G_Y^2)$$

$$f_{Y|X}(y|x) = f_Y(y).$$

$$X \& Y : \text{indep} \Rightarrow \text{Cov}(X, Y) = 0$$
$$(\Leftrightarrow f_{XY}(x, y) = f_X(x) \cdot f_Y(y)) \quad \text{if } (X, Y) \sim \text{BN}$$

But In BN, if $\rho = 0$, $f_{XY}(x, y) = f_Y(y) = \frac{f_{XY}(x, y)}{f_X(x)}$

$$\underline{f_{XY}(x, y) = f_X(x) \cdot f_Y(y)}$$

$X \& Y : \text{indep.}$

Conditional distribution

✓ The conditional distribution of Y given $X = x$ is

$$f_{Y|X}(y|x) = \frac{f(x,y)}{f_X(x)} = \frac{1}{\sqrt{2\pi}\sigma_Y\sqrt{1-\rho^2}} e^{-\frac{(y-b)^2}{2\sigma_Y^2(1-\rho^2)}}$$

$$E[Y|x] = b = \mu_Y + \rho \frac{\sigma_Y}{\sigma_X} (x - \mu_X).$$

Thus,

$$Y|x \sim N \left(\mu_Y + \rho \frac{\sigma_Y}{\sigma_X} (x - \mu_X), \sigma_Y^2(1 - \rho^2) \right),$$

$$X|y \sim N \left(\mu_X + \rho \frac{\sigma_X}{\sigma_Y} (y - \mu_Y), \sigma_X^2(1 - \rho^2) \right).$$



Thm 4.5-1

Let (X, Y) have bivariate normal distribution with the correlation coefficient ρ .

X and Y are independent. $\Leftrightarrow \rho = 0$.