

## Bivariate Normal Distribution

The bivariate normal distribution is the statistical distribution with probability density function

$$P(x_1, x_2) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \exp\left[-\frac{z}{2(1-\rho^2)}\right] \quad (1)$$

where

$$z \equiv \frac{(x_1 - \mu_1)^2}{\sigma_1^2} - \frac{2\rho(x_1 - \mu_1)(x_2 - \mu_2)}{\sigma_1\sigma_2} + \frac{(x_2 - \mu_2)^2}{\sigma_2^2}, \quad (2)$$

and

$$\rho \equiv \text{cor}(x_1, x_2) = \frac{V_{12}}{\sigma_1\sigma_2}$$

is the correlation of  $x_1$  and  $x_2$  (Kenney and Keeping 1951, pp. 92 and 202-205; Whittaker and Robinson 1967, p. 329) and  $V_{12}$  is the covariance.

The marginal probabilities are then

$$P(x_1) = \int_{-\infty}^{\infty} P(x_1, x_2) dx_2 \quad (4)$$

$$= \frac{1}{\sigma_1\sqrt{2\pi}} e^{-(x_1 - \mu_1)^2/(2\sigma_1^2)} \quad (5)$$

and

$$P(x_2) = \int_{-\infty}^{\infty} P(x_1, x_2) dx_1 \quad (6)$$

$$= \frac{1}{\sigma_2\sqrt{2\pi}} e^{-(x_2 - \mu_2)^2/(2\sigma_2^2)} \quad (7)$$

(Kenney and Keeping 1951, p. 202).

Let  $Z_1$  and  $Z_2$  be two independent normal variates with means  $\mu_i = 0$  and  $\sigma_i^2 = 1$  for  $i = 1, 2$ . Then the variables  $a_1$  and  $a_2$  defined below are normal bivariates with unit variance and correlation coefficient  $\rho$ :

$$a_1 = \sqrt{\frac{1+\rho}{2}} z_1 + \sqrt{\frac{1-\rho}{2}} z_2 \quad (8)$$

$$a_2 = \sqrt{\frac{1+\rho}{2}} z_1 - \sqrt{\frac{1-\rho}{2}} z_2. \quad (9)$$

To derive the bivariate normal probability function, let  $X_1$  and  $X_2$  be normally and independently distributed variates with mean 0 and variance 1, then define

$$Y_1 \equiv \mu_1 + \sigma_{11} X_1 + \sigma_{12} X_2 \quad (10)$$

$$Y_2 \equiv \mu_2 + \sigma_{21} X_1 + \sigma_{22} X_2 \quad (11)$$

(Kenney and Keeping 1951, p. 92). The variates  $Y_1$  and  $Y_2$  are then themselves normally distributed with means  $\mu_1$  and  $\mu_2$ , variances

$$\sigma_1^2 \equiv \sigma_{11}^2 + \sigma_{12}^2 \quad (12)$$

$$\sigma_2^2 \equiv \sigma_{21}^2 + \sigma_{22}^2, \quad (13)$$

and covariance

$$V_{12} \equiv \sigma_{11} \sigma_{21} + \sigma_{12} \sigma_{22}. \quad (14)$$

The covariance matrix is defined by

$$V_{ij} = \begin{bmatrix} \sigma_1^2 & \rho \sigma_1 \sigma_2 \\ \rho \sigma_1 \sigma_2 & \sigma_2^2 \end{bmatrix}, \quad (15)$$

where

$$\rho \equiv \frac{V_{12}}{\sigma_1 \sigma_2} = \frac{\sigma_{11} \sigma_{21} + \sigma_{12} \sigma_{22}}{\sigma_1 \sigma_2}. \quad (16)$$

Now, the joint probability density function for  $x_1$  and  $x_2$  is

$$f(x_1, x_2) dx_1 dx_2 = \frac{1}{2\pi} e^{-(x_1^2 + x_2^2)/2} dx_1 dx_2, \quad (17)$$

So, we proceed as

$$\begin{bmatrix} y_1 - \mu_1 \\ y_2 - \mu_2 \end{bmatrix} = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}. \quad (18)$$

As long as

$$\begin{vmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{vmatrix} \neq 0, \quad (19)$$

this can be inverted to give

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix}^{-1} \begin{bmatrix} y_1 - \mu_1 \\ y_2 - \mu_2 \end{bmatrix} \quad (20)$$

$$= \frac{1}{\sigma_{11} \sigma_{22} - \sigma_{12} \sigma_{21}} \begin{bmatrix} \sigma_{22} & -\sigma_{12} \\ -\sigma_{21} & \sigma_{11} \end{bmatrix} \begin{bmatrix} y_1 - \mu_1 \\ y_2 - \mu_2 \end{bmatrix}. \quad (21)$$

Therefore,

$$\begin{aligned} x_1^2 + x_2^2 &= \frac{[\sigma_{22} (y_1 - \mu_1) - \sigma_{12} (y_2 - \mu_2)]^2}{(\sigma_{11} \sigma_{22} - \sigma_{12} \sigma_{21})^2} \\ &+ \frac{[-\sigma_{21} (y_1 - \mu_1) + \sigma_{11} (y_2 - \mu_2)]^2}{(\sigma_{11} \sigma_{22} - \sigma_{12} \sigma_{21})^2}, \end{aligned} \quad (22)$$

and expanding the numerator of (22) gives

$$\begin{aligned} &\sigma_{22}^2 (y_1 - \mu_1)^2 - 2 \sigma_{12} \sigma_{22} (y_1 - \mu_1) (y_2 - \mu_2) + \sigma_{12}^2 (y_2 - \mu_2)^2 + \\ &\sigma_{21}^2 (y_1 - \mu_1)^2 - 2 \sigma_{11} \sigma_{21} (y_1 - \mu_1) (y_2 - \mu_2) + \sigma_{11}^2 (y_2 - \mu_2)^2, \end{aligned} \quad (23)$$

so

$$\begin{aligned} &(x_1^2 + x_2^2) (\sigma_{11} \sigma_{22} - \sigma_{12} \sigma_{21})^2 \\ &= (y_1 - \mu_1)^2 (\sigma_{21}^2 + \sigma_{22}^2) - \\ &\quad 2 (y_1 - \mu_1) (y_2 - \mu_2) (\sigma_{11} \sigma_{21} + \sigma_{12} \sigma_{22}) + (y_2 - \mu_2)^2 (\sigma_{11}^2 + \sigma_{12}^2) \\ &= \sigma_2^2 (y_1 - \mu_1)^2 - 2 (y_1 - \mu_1) (y_2 - \mu_2) (\rho \sigma_1 \sigma_2) + \sigma_1^2 (y_2 - \mu_2)^2 \\ &= \sigma_1^2 \sigma_2^2 \left[ \frac{(y_1 - \mu_1)^2}{\sigma_1^2} - \frac{2 \rho (y_1 - \mu_1) (y_2 - \mu_2)}{\sigma_1 \sigma_2} + \frac{(y_2 - \mu_2)^2}{\sigma_2^2} \right]. \end{aligned} \quad (24)$$

Now, the denominator of (24) is

$$\begin{aligned} &\sigma_{11}^2 \sigma_{21}^2 + \sigma_{11}^2 \sigma_{22}^2 + \sigma_{12}^2 \sigma_{21}^2 + \sigma_{12}^2 \sigma_{22}^2 - \sigma_{11}^2 \sigma_{21}^2 \\ &- 2 \sigma_{11} \sigma_{12} \sigma_{21} \sigma_{22} - \sigma_{12}^2 \sigma_{22}^2 = (\sigma_{11} \sigma_{22} - \sigma_{12} \sigma_{21})^2, \end{aligned} \quad (25)$$

so

$$\frac{1}{1 - \rho^2} = \frac{1}{1 - \frac{V_{12}^2}{\sigma_1^2 \sigma_2^2}} \quad (26)$$

$$= \frac{\sigma_1^2 \sigma_2^2}{\sigma_1^2 \sigma_2^2 - V_{12}^2} \quad (27)$$

$$= \frac{\sigma_1^2 \sigma_2^2}{(\sigma_{11}^2 + \sigma_{12}^2)(\sigma_{21}^2 + \sigma_{22}^2) - (\sigma_{11} \sigma_{21} + \sigma_{12} \sigma_{22})^2}. \quad (28)$$

can be written simply as

$$\frac{1}{1 - \rho^2} = \frac{\sigma_1^2 \sigma_2^2}{(\sigma_{11} \sigma_{22} - \sigma_{12} \sigma_{21})^2}, \quad (29)$$

and

$$x_1^2 + x_2^2 = \frac{1}{1 - \rho^2} \left[ \frac{(y_1 - \mu_1)^2}{\sigma_1^2} - \frac{2\rho(y_1 - \mu_1)(y_2 - \mu_2)}{\sigma_1 \sigma_2} + \frac{(y_2 - \mu_2)^2}{\sigma_2^2} \right]. \quad (30)$$

Solving for  $x_1$  and  $x_2$  and defining

$$\rho' \equiv \frac{\sigma_1 \sigma_2 \sqrt{1 - \rho^2}}{\sigma_{11} \sigma_{22} - \sigma_{12} \sigma_{21}} \quad (31)$$

gives

$$x_1 = \frac{\sigma_{22} (y_1 - \mu_1) - \sigma_{12} (y_2 - \mu_2)}{\rho'} \quad (32)$$

$$x_2 = \frac{-\sigma_{21} (y_1 - \mu_1) + \sigma_{11} (y_2 - \mu_2)}{\rho'}. \quad (33)$$

But the Jacobian is

$$J \begin{pmatrix} x_1, x_2 \\ y_1, y_2 \end{pmatrix} = \begin{vmatrix} \frac{\partial x_1}{\partial y_1} & \frac{\partial x_1}{\partial y_2} \\ \frac{\partial x_2}{\partial y_1} & \frac{\partial x_2}{\partial y_2} \end{vmatrix} = \begin{vmatrix} \frac{\sigma_{22}}{\rho'} & -\frac{\sigma_{12}}{\rho'} \\ -\frac{\sigma_{21}}{\rho'} & \frac{\sigma_{11}}{\rho'} \end{vmatrix} \quad (34)$$

$$= \frac{1}{\rho'^2} (\sigma_{11} \sigma_{22} - \sigma_{12} \sigma_{21}) \quad (35)$$

$$= \frac{1}{\rho'} = \frac{1}{\sigma_1 \sigma_2 \sqrt{1 - \rho^2}}, \quad (36)$$

so

$$d x_1 d x_2 = \frac{d y_1 d y_2}{\sigma_1 \sigma_2 \sqrt{1 - \rho^2}} \quad (37)$$

and

$$\frac{1}{2\pi} e^{-(x_1^2 + x_2^2)/2} d x_1 d x_2 = \frac{1}{2\pi \sigma_1 \sigma_2 \sqrt{1 - \rho^2}} \exp \left[ -\frac{z}{2(1 - \rho^2)} \right] d y_1 d y_2, \quad (38)$$

where

$$z \equiv \frac{(y_1 - \mu_1)^2}{\sigma_1^2} - \frac{2\rho(y_1 - \mu_1)(y_2 - \mu_2)}{\sigma_1\sigma_2} + \frac{(y_2 - \mu_2)^2}{\sigma_2^2}. \quad (39)$$

Q.E.D.

The characteristic function of the bivariate normal distribution is given by

$$\phi(t_1, t_2) \equiv \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{j(t_1 x_1 + t_2 x_2)} P(x_1, x_2) dx_1 dx_2 \quad (40)$$

$$= N \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{j(t_1 x_1 + t_2 x_2)} \exp\left[-\frac{z}{2(1-\rho^2)}\right] dx_1 dx_2, \quad (41)$$

where

$$z \equiv \left[ \frac{(x_1 - \mu_1)^2}{\sigma_1^2} - \frac{2\rho(x_1 - \mu_1)(x_2 - \mu_2)}{\sigma_1\sigma_2} + \frac{(x_2 - \mu_2)^2}{\sigma_2^2} \right] \quad (42)$$

and

$$N \equiv \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}}. \quad (43)$$

Now let

$$u \equiv x_1 - \mu_1 \quad (44)$$

$$w \equiv x_2 - \mu_2. \quad (45)$$

Then

$$\phi(t_1, t_2) = N' \int_{-\infty}^{\infty} \left( e^{j t_2 w} \exp\left[-\frac{1}{2(1-\rho^2)} \frac{w^2}{\sigma_2^2}\right] \right) \int_{-\infty}^{\infty} e^{j t_1 u} e^{j t_2 w} du dw, \quad (46)$$

where

$$v \equiv -\frac{1}{2(1-\rho^2)} \frac{1}{\sigma_1^2} \left[ u^2 - \frac{2\rho\sigma_1 w}{\sigma_2} u \right] \quad (47)$$

$$N' \equiv \frac{e^{j(t_1\mu_1 + t_2\mu_2)}}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}}. \quad (48)$$

Complete the square in the inner integral

$$\begin{aligned}
& \int_{-\infty}^{\infty} \exp \left\{ -\frac{1}{2(1-\rho^2)} \frac{1}{\sigma_1^2} \left[ u^2 - \frac{2\rho\sigma_1 w}{\sigma_2} u \right] \right\} e^{i t_1 u} d u \\
&= \int_{-\infty}^{\infty} \exp \left\{ -\frac{1}{2\sigma_1^2(1-\rho^2)} \left[ u - \frac{\rho_1 \sigma_1 w}{\sigma_2} \right]^2 \right\} \left\{ \frac{1}{2\sigma_1^2(1-\rho^2)} \left( \frac{\rho_1 \sigma_1 w}{\sigma_2} \right)^2 \right\} e^{i t_1 u} d u.
\end{aligned} \tag{49}$$

Rearranging to bring the exponential depending on  $w$  outside the inner integral, letting

$$v \equiv u - \rho \frac{\sigma_1 w}{\sigma_2}, \tag{50}$$

and writing

$$e^{i t_1 u} = \cos(t_1 u) + i \sin(t_1 u) \tag{51}$$

gives

$$\begin{aligned}
\phi(t_1, t_2) = & N' \int_{-\infty}^{\infty} e^{i t_2 w} \exp \left[ -\frac{1}{2\sigma_2^2(1-\rho^2)} w^2 \right] \exp \left[ \frac{\rho^2}{2\sigma_2^2(1-\rho^2)} w^2 \right] \int_{-\infty}^{\infty} \exp \left[ -\frac{1}{2\sigma_2^2(1-\rho^2)} \right. \\
& \left. v^2 \right] \left\{ \cos \left[ t_1 \left( v + \frac{\rho\sigma_1 w}{\sigma_2} \right) \right] + i \sin \left[ t_1 \left( v + \frac{\rho\sigma_1 w}{\sigma_2} \right) \right] \right\} d v d w.
\end{aligned} \tag{52}$$

Expanding the term in braces gives

$$\begin{aligned}
& \left[ \cos(t_1 v) \cos \left( \frac{\rho\sigma_1 w t_1}{\sigma_2} \right) - \sin(t_1 v) \sin \left( \frac{\rho\sigma_1 w}{\sigma_2 t_1} \right) \right] + \\
& i \left[ \sin(t_1 v) \cos \left( \frac{\rho\sigma_1 w}{\sigma_2 t_1} \right) + \cos(t_1 v) \sin \left( \frac{\rho\sigma_1 w t_1}{\sigma_2} \right) \right] \\
&= \left[ \cos \left( \frac{\rho\sigma_1 w t_1}{\sigma_2} \right) + i \sin \left( \frac{\rho\sigma_1 w t_1}{\sigma_2} \right) \right] [\cos(t_1 v) + i \sin(t_1 v)] = \\
& \exp \left( \frac{i \rho\sigma_1 w}{\sigma_2} t_1 \right) [\cos(t_1 v) + i \sin(t_1 v)].
\end{aligned} \tag{53}$$

But  $e^{-ax^2} \sin(bx)$  is odd, so the integral over the sine term vanishes, and we are left with

$$\begin{aligned}
\phi(t_1, t_2) &= N' \int_{-\infty}^{\infty} e^{i t_2 w} \exp\left[-\frac{w^2}{2\sigma_2^2}\right] \exp\left[\frac{\rho^2 w^2}{2\sigma_2^2(1-\rho^2)}\right] \\
&\quad \exp\left[\frac{i\rho\sigma_1 w t_1}{\sigma_2}\right] d w \int_{-\infty}^{\infty} \exp\left[-\frac{v^2}{2\sigma_1^2(1-\rho^2)}\right] \cos(t_1 v) d v \\
&= N' \int_{-\infty}^{\infty} \exp\left[i w \left(t_2 + t_1 \left(\rho \frac{\sigma_1}{\sigma_2}\right)\right)\right] \exp\left[-\frac{w^2}{2\sigma_2^2}\right] d w \\
&\quad \int_{-\infty}^{\infty} \exp\left[-\frac{v^2}{2\sigma_1^2(1-\rho^2)}\right] \cos(t_1 v) d v.
\end{aligned} \tag{54}$$

Now evaluate the Gaussian integral

$$\int_{-\infty}^{\infty} e^{i k x} e^{-a x^2} d x = \int_{-\infty}^{\infty} e^{-a x^2} \cos(k x) d x \tag{55}$$

$$= \sqrt{\frac{\pi}{a}} e^{-k^2/4a} \tag{56}$$

to obtain the explicit form of the characteristic function,

$$\begin{aligned}
\phi(t_1, t_2) &= \frac{e^{i(t_1 \mu_1 + t_2 \mu_2)}}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \left\{ \sigma_2 \sqrt{2\pi} \exp\left[-\frac{1}{4}\left(t_2 + \rho \frac{\sigma_1}{\sigma_2} t_1\right)^2 2\sigma_2^2\right] \right\} \\
&\quad \left\{ \sigma_1 \sqrt{2\pi(1-\rho^2)} \exp\left[-\frac{1}{4} t_1^2 2\sigma_1^2(1-\rho^2)\right] \right\} \\
&= e^{i(t_1 \mu_1 + t_2 \mu_2)} \exp\left\{-\frac{1}{2}\left[t_2^2 \sigma_2^2 + 2\rho\sigma_1\sigma_2 t_1 t_2 + \rho^2 \sigma_1^2 t_1^2 + (1-\rho^2)\sigma_1^2 t_1^2\right]\right\} \\
&= \exp\left[i(t_1 \mu_1 + t_2 \mu_2) - \frac{1}{2}(\sigma_1^2 t_1^2 + 2\rho\sigma_1\sigma_2 t_1 t_2 + \sigma_2^2 t_2^2)\right].
\end{aligned} \tag{57}$$

In the singular case that

$$\begin{vmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{vmatrix} = 0 \tag{58}$$

(Kenney and Keeping 1951, p. 94), it follows that

$$\sigma_{11} \sigma_{22} = \sigma_{12} \sigma_{21} \tag{59}$$

$$y_1 = \mu_1 + \frac{\sigma_{11} x_1 + \sigma_{12} x_2}{\sigma_{11}} \tag{60}$$

$$y_2 = \mu_2 + \frac{\sigma_{12} \sigma_{21}}{\sigma_{11}} x_2 \tag{61}$$

$$= \mu_2 + \frac{\sigma_{11} \sigma_{21} x_1 + \sigma_{12} \sigma_{21} x_2}{\sigma_{11}} \tag{62}$$

$$= \mu_2 + \frac{\sigma_{21}}{\sigma_{11}} (\sigma_{11} x_1 + \sigma_{12} x_2), \tag{63}$$

so

$$y_1 = \mu_1 + x_3 \tag{64}$$

$$y_2 = \mu_2 + \frac{\sigma_{21}}{\sigma_{11}} x_3, \tag{65}$$

where

$$x_3 = y_1 - \mu_1 \tag{66}$$

$$= \frac{\sigma_{11}}{\sigma_{21}} (y_2 - \mu_2). \tag{67}$$

The standardized bivariate normal distribution takes  $\sigma_1 = \sigma_2 = 1$  and  $\mu_1 = \mu_2 = 0$ . The quadrant probability in this special case is then given analytically by

$$P(x_1 \leq 0, x_2 \leq 0) = P(x_1 \geq 0, x_2 \geq 0) \tag{68}$$

$$= \int_{-\infty}^0 \int_{-\infty}^0 P(x_1, x_2) dx_1 dx_2 \tag{69}$$

$$= \frac{1}{4} + \frac{\sin^{-1} \rho}{2\pi} \tag{70}$$

(Rose and Smith 1996; Stuart and Ord 1998; Rose and Smith 2002, p. 231). Similarly,

$$P(x_1 \leq 0, x_2 \geq 0) = P(x_1 \geq 0, x_2 \leq 0) \tag{71}$$

$$= \int_{-\infty}^0 \int_0^{\infty} P(x_1, x_2) dx_1 dx_2 \tag{72}$$

$$= \frac{\cos^{-1} \rho}{2\pi}. \tag{73}$$