

### THE MULTIVARIATE NORMAL DISTRIBUTION

We say that the  $n \times 1$  random vector  $x$  is normally distributed with a mean of  $E(x) = \mu$  and a dispersion matrix of  $D(x) = \Sigma$  if the probability density function is

$$(17.22) \quad N(x; \mu, \Sigma) = (2\pi)^{-n/2} |\Sigma|^{-1/2} \exp \left\{ -\frac{1}{2} (x - \mu)' \Sigma^{-1} (x - \mu) \right\}.$$

It is understood that  $x$  is non-degenerate with  $\text{Rank}(\Sigma) = n$  and  $|\Sigma| \neq 0$ . To denote that  $x$  has this distribution, we can write  $x \sim N(\mu, \Sigma)$ .

We shall demonstrate two notable features of the normal distribution. The first feature is that the conditional and marginal distributions associated with a normally distributed vector are also normal. The second is that any linear function of a normally distributed vector is itself normally distributed.

We shall base our arguments on two fundamental facts. The first is that

$$(17.23) \quad \text{If } x \sim N(\mu, \Sigma) \text{ and if } y = A(x - b) \text{ where } A \text{ is nonsingular, then } y \sim N\{A(\mu - b), A\Sigma A'\}.$$

This may be illustrated by considering the case where  $b = 0$ . Then, according to the result in (17.8),  $y$  has the distribution

$$\begin{aligned} & N(A^{-1}y; \mu, \Sigma) \|\partial x / \partial y\| \\ &= (2\pi)^{-n/2} |\Sigma|^{-1/2} \exp \left\{ -\frac{1}{2} (A^{-1}y - \mu)' \Sigma^{-1} (A^{-1}y - \mu) \right\} \|A^{-1}\| \\ &= (2\pi)^{-n/2} |A\Sigma A'|^{-1/2} \exp \left\{ -\frac{1}{2} (y - A\mu)' (A\Sigma A')^{-1} (y - A\mu) \right\}; \end{aligned}$$

so, clearly,  $y \sim N(A\mu, A\Sigma A')$ .

The second of the fundamental facts is that

$$(17.25) \quad \text{If } x \sim N(\mu, \Sigma) \text{ can be written in partitioned form as}$$

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \sim N \left( \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \begin{bmatrix} \Sigma_{11} & 0 \\ 0 & \Sigma_{22} \end{bmatrix} \right),$$

then  $x_1 \sim N(\mu_1, \Sigma_{11})$  and  $x_2 \sim N(\mu_2, \Sigma_{22})$  are independently distributed normal variates.

To see this, we need only consider the quadratic form

$$(x - \mu)' \Sigma^{-1} (x - \mu) = (x_1 - \mu_1)' \Sigma_{11}^{-1} (x_1 - \mu_1) + (x_2 - \mu_2)' \Sigma_{22}^{-1} (x_2 - \mu_2)$$

which arises in this particular case. On substituting in into the expression for  $N(x, \mu, \Sigma)$  in (17.22) and using  $|\Sigma| = |\Sigma_{11}||\Sigma_{22}|$ , we get

$$\begin{aligned} N(x; \mu, \Sigma) &= (2\pi)^{-m/2} |\Sigma_{11}|^{-1/2} \exp \left\{ -\frac{1}{2} (x_1 - \mu_1)' \Sigma_{11}^{-1} (x_1 - \mu_1) \right\} \\ &\quad \times (2\pi)^{-(m-n)/2} |\Sigma_{22}|^{-1/2} \exp \left\{ -\frac{1}{2} (x_2 - \mu_2)' \Sigma_{22}^{-1} (x_2 - \mu_2) \right\} \\ &= N(x_1; \mu_1, \Sigma_{11}) N(x_2; \mu_2, \Sigma_{22}). \end{aligned}$$

The latter can only be the product of the marginal distributions of  $x_1$  and  $x_2$ , which proves that these vectors are independently distributed.

The essential feature of the result is that

(17.26) If  $x_1$  and  $x_2$  are normally distributed with  $C(x_1, x_2) = 0$ , then they are mutually independent.

A zero covariances does not generally imply statistical independence.

Even when  $x_1, x_2$  are not independently distributed, their marginal distributions are still formed in the same way from the appropriate components of  $\mu$  and  $\Sigma$ . This is entailed in the first of our two main results which is that

(17.27) If  $x \sim N(\mu, \Sigma)$  is partitioned as

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \sim N \left( \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix} \right),$$

then the marginal distribution of  $x_1$  is  $N(\mu_1, \Sigma_{11})$  and the conditional distribution of  $x_2$  given  $x_1$  is

$$N(x_2 | x_1; \mu_2 + \Sigma_{21} \Sigma_{11}^{-1} (x_1 - \mu_1), \Sigma_{22} - \Sigma_{21} \Sigma_{11}^{-1} \Sigma_{12}).$$

**Proof.** Consider a non-singular transformation

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} I & 0 \\ F & I \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

such that  $C(y_1, y_2) = C(Fx_1 + x_2, x_1) = FD(x_1) + C(x_2, x_1) = 0$ . Writing this condition as  $F\Sigma_{11} + \Sigma_{21} = 0$  gives  $F = -\Sigma_{21}\Sigma_{11}^{-1}$ . It follows that

$$E \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 - \Sigma_{21}\Sigma_{11}^{-1}\mu_1 \end{bmatrix};$$

and, since  $D(y_1) = \Sigma_{11}$ ,  $C(y_1, y_2) = 0$  and

$$\begin{aligned} D(y_2) &= D(Fx_1 + x_2) \\ &= FD(x_1)F' + D(x_2) + FC(x_1, x_2) + C(x_2, x_1)F' \\ &= \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{11}\Sigma_{11}^{-1}\Sigma_{12} + \Sigma_{22} - \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{12} - \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{12} \\ &= \Sigma_{22} - \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{12}, \end{aligned}$$

it also follows that

$$D \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \Sigma_{11} & 0 \\ 0 & \Sigma_{22} - \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{12} \end{bmatrix}.$$

Therefore, according to (17.25), we can write the joint density function of  $y_1$ ,  $y_2$  as

$$N(y_1; \mu_1, \Sigma_{11})N(y_2; \mu_2 - \Sigma_{21}\Sigma_{11}^{-1}\mu_1, \Sigma_{22} - \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{12}).$$

Integrating with respect to  $y_2$  gives the marginal distribution of  $x_1 = y_1$  as  $N(x_1; \mu_1, \Sigma_{11})$ .

Now consider the inverse transformation  $x = x(y)$ . The Jacobian of this transformation is unity. Therefore, to obtain an expression for  $N(x; \mu, \Sigma)$ , we need only write  $y_2 = x_2 - \Sigma_{21}\Sigma_{11}^{-1}x_1$  and  $y_1 = x_1$  in the expression for the joint distribution of  $y_1, y_2$ . This gives

$$\begin{aligned} N(x; \mu, \Sigma) &= N(x_1; \mu_1, \Sigma_{11}) \\ &\times N(x_2 - \Sigma_{21}\Sigma_{11}^{-1}x_1; \mu_2 - \Sigma_{21}\Sigma_{11}^{-1}\mu_1, \Sigma_{22} - \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{12}), \end{aligned}$$

which is the product of the marginal distribution of  $x_1$  and the conditional distribution  $N(x_2|x_1; \mu_2 - \Sigma_{21}\Sigma_{11}^{-1}(x_1 - \mu_1), \Sigma_{22} - \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{12})$  of  $x_2$  given  $x_1$ .

The linear function  $E(x_2|x_1) = \mu_2 - \Sigma_{21}\Sigma_{11}^{-1}(x_1 - \mu_1)$ , which defines the expected value of  $x_2$  for given values of  $x_1$ , is described as the regression of  $x_2$  on  $x_1$ . The matrix  $\Sigma_{21}\Sigma_{11}^{-1}$  is the matrix regression coefficients.