## 28. Jointly Distributed Random Variables

## The bivariate normal distribution [Ross S6.5]

Two random variables X and Y are **jointly Gaussian** (normal) or **bivariate Gaussian** (normal) with parameters:

$$\mu_X, \mu_Y, \sigma_X > 0, \sigma_Y > 0, -1 < \rho < 1$$

when

$$f_{XY}(x,y) = \frac{1}{2\pi\sigma_X\sigma_Y\sqrt{1-\rho^2}}$$

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

It is customary to denote

$$m{x} = \left[ egin{array}{c} x \\ y \end{array} 
ight] \qquad m{\mu} = \left[ egin{array}{c} \mu_X \\ \mu_Y \end{array} 
ight] \qquad \Sigma = \left[ egin{array}{cc} \sigma_X^2 & 
ho\sigma_X\sigma_Y \\ 
ho\sigma_X\sigma_Y & \sigma_Y^2 \end{array} 
ight]$$

then

$$f_{XY}(x,y) = \frac{1}{2\pi |\Sigma|^{1/2}} \exp\left\{-\frac{1}{2}(\boldsymbol{x} - \boldsymbol{\mu})^T \Sigma^{-1}(\boldsymbol{x} - \boldsymbol{\mu})\right\}$$

 $\mu$  is called the **mean vector** of (X, Y).

 $\Sigma$  is called the **covariance matrix** of (X, Y).

We say that the pair  $(X, Y) \sim \mathcal{N}(\boldsymbol{\mu}, \Sigma)$ .

Note:  $\Sigma$  is symmetric and +ve definite.

## **Marginal Distributions**

To find the marginal

$$f_Y(y) = \int_{-\infty}^{\infty} f_{XY}(x, y) dx$$

and from (28.1) + lots of algebra:

$$f_Y(y) = \frac{1}{\sqrt{2\pi}\sigma_Y} e^{-\frac{(y-\mu_Y)^2}{2\sigma_Y^2}}$$
 (28.2)

So,  $Y \sim \mathcal{N}(\mu_Y, \sigma_Y^2)$ .

Likewise,  $X \sim \mathcal{N}(\mu_X, \sigma_X^2)$ .

## **Conditional distribution**

To get the conditional  $f_{X|Y}(x|y)$ , from (28.1) + (28.2) + lots of algebra:

$$\begin{split} f_{X|Y}(x|y) &= \frac{f_{XY}(x,y)}{f_{Y}(y)} \\ &= \underbrace{\frac{1}{\sqrt{2\pi(1-\rho^2)}\sigma_X} \exp\left\{\frac{-1}{2\sigma_X^2(1-\rho^2)}\left[x - \left(\mu_X + \rho\frac{\sigma_X}{\sigma_Y}(y - \mu_Y)\right)\right]^2\right\}}_{K_1 \exp\left\{\frac{-1}{2K_2}[x - K_3]^2\right\}} \end{split}$$

So we recognize  $f_{X|Y}(x|y)$  is the pdf of a Gaussian when X has mean

$$K_3 = \mu_X + \rho \frac{\sigma_X}{\sigma_Y} (y - \mu_Y)$$

and variance  $K_2 = \sigma_X^2 (1 - \rho^2)$ .

Note that we have

$$f_{XY}(x,y) = f_X(x)f_Y(y) \Leftrightarrow f_{X|Y}(x|y) = f_X(x)$$

and the latter happens when  $\rho = 0$ .

So for bivariate normal X and Y: X and Y are independent  $\Leftrightarrow \rho = 0$ .

*Remark:*  $\rho$  is called the **correlation coefficient** between X and Y.