Jointly Distributed Random Variables

Joint Distribution of Functions of Random Variables [Ross S6.7]

Let X and Y have joint pdf $f_{XY}(x, y)$.

In some examples we computed the distribution of Z = g(X, Y), e.g.

- in Example 23.2 we computed the cdf of $D = \sqrt{X^2 + Y^2}$ • in Example 23.3 we computed the pdf of Z = X/Y.
- Now, consider

$$Y_2 = g_2(X_1, X_2) \label{eq:Y2}$$
 and we want the joint pdf of Y_1 and Y_2 .

 $Y_1 = g_1(X_1, X_2)$

We make the following assumptions on g_1 and g_2 :

• The system of equations

can be uniquely solved for
$$x_1$$
 and x_2 in terms of y_1 and y_2 :
$$x_1 = h_1(y_1, y_2)$$

 $x_2 = h_2(y_1, y_2).$

 $y_1 = g_1(x_1, x_2)$ $y_2 = g_2(x_1, x_2)$

• g_1 and g_2 have continuous partial derivates such that the determinant $J(x_1, x_2) = \begin{vmatrix} \frac{\partial g_1}{\partial x_1} & \frac{\partial g_1}{\partial x_2} \\ \frac{\partial g_2}{\partial x_1} & \frac{\partial g_2}{\partial x_2} \end{vmatrix} = \frac{\partial g_1}{\partial x_1} \frac{\partial g_2}{\partial x_2} - \frac{\partial g_1}{\partial x_2} \frac{\partial g_2}{\partial x_1} \neq 0$

Under these conditions, the pdf of
$$Y_1$$
 and Y_2 can be shown to be:

 $f_{Y_1Y_2}(y_1, y_2) = f_{X_1X_2}(x_1, x_2) |J(x_1, x_2)|^{-1}$

 $x_2 = h_2(y_1, y_2).$

where

$$x_1 = h_1(y_1, y_2)$$

(29.1)

(29.2)

(29.3)

(29.4)

(29.5)

(29.6)

Example 29.1: Let

Solution: Solving

 $y_1 = x_1 + x_2$ $y_2 = x_1 - x_2$

$$Y_1 = X_1 + X_2 Y_2 = X_1 - X_2$$

we get

Find the joint pdf $f_{Y_1Y_2}(y_1, y_2)$ in terms of $f_{X_1X_2}(x_1, x_2)$.

 $x_1 = \frac{1}{2}y_1 + \frac{1}{2}y_2$

$$x_2 = \frac{1}{2}y_1 - \frac{1}{2}y_2$$

Also
$$J(x_1,x_2)=\left|\begin{array}{cc} 1 & 1\\ 1 & -1 \end{array}\right|=-2\neq 0$$

Hence, from (29.6)

Example 29.2: Let
$$R$$
 and Θ be two random variables with joint pdf $f_{R\Theta}(r,\theta)$. Consider the change of variables

Find $f_{R\Theta}(r,\theta)$ in terms of $f_{XY}(x,y)$. [Hard]

Solution: We have the system of equations

 $f_{Y_1Y_2}(y_1, y_2) = \frac{1}{2} f_{X_1X_2} \left(\frac{1}{2} y_1 + \frac{1}{2} y_2, \frac{1}{2} y_1 - \frac{1}{2} y_2 \right)$

Note: This is Problem T9.1; see also textbook Example 6.7b for a different tedious approach.

> $x = g_1(r, \theta) = r \cos \theta$ $y = g_2(r, \theta) = r \sin \theta$

 $X = R\cos\Theta$ $Y = R\sin\Theta.$

which is solved by $r = h_1(x, y) = \sqrt{x^2 + y^2}$

or equivalently:

where
$$h_2(x,y)$$
 is the angle of the vector (x,y) .
Computing the Jacobian determinant

 $\theta = h_2(x, y) = \begin{cases} \tan^{-1}(y/x) & x > 0, y > 0 \\ \tan^{-1}(y/x) + \pi & x < 0 \\ \tan^{-1}(y/x) + 2\pi & x > 0, y < 0 \end{cases}$

 $J(r,\theta) = \begin{vmatrix} \frac{\partial g_1}{\partial r} & \frac{\partial g_1}{\partial \theta} \\ \frac{\partial g_2}{\partial r} & \frac{\partial g_2}{\partial \theta} \end{vmatrix}$ $= \begin{vmatrix} \cos \theta & -r \sin \theta \\ \sin \theta & r \cos \theta \end{vmatrix}$

So, the pdf
$$f_{XY}(x,y)$$
 and $f_{R\Theta}(r,\theta)$ are related by
$$f_{XY}(x,y) = f_{R\Theta}(r,\theta) \, |J(r,\theta)|^{-1}$$

$$= f_{R\Theta}(r,\theta)/r$$
 or equivalently:
$$f_{R\Theta}(r,\theta) = f_{XY}(x,y)r$$

$$= f_{XY}(r\cos\theta,r\sin\theta)r$$
 So, to compute the probability that $(R,\Theta) \in A$:

 $P[(R,\Theta) \in A] = \iint_{(r,\theta) \in A} f_{R\,\Theta}(r,\theta) dr d\theta$

 $= \iint_{(r,\theta)\in A} f_{XY}(r\cos\theta, r\sin\theta) r dr d\theta$