

## Review Session:

### 1. Functions of Continuous Random Variable

Theorem: Let  $X$  be continuous random variable with density function  $f_X(x)$ . Suppose  $g(x)$  is increasing or decreasing continuous function.  $Y = g(X)$  has

pdf given by

$$f_Y(y) = \begin{cases} f_X(g^{-1}(y)) \left| \frac{d}{dy} g^{-1}(y) \right| & \text{if } y = g(x) \text{ for some } x. \\ 0 & \text{if } y \neq g(x) \text{ for all } x. \end{cases}$$

Example 1: Let  $X$  be a continuous random variable with PDF  $f_X(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$ , for  $x \in \mathbb{R}$ , and let  $Y = X^2$ . Find  $f_Y(y)$ .

~~$x \in \mathbb{R}$~~ .  $g(x) = x^2$ , then  $g^{-1}(y) = \pm\sqrt{y}$ .  $\frac{d}{dy} g^{-1}(y) = \pm \frac{1}{2\sqrt{y}}$ .

$$f_Y(y) = \sum_{i=1}^n \frac{f_X(x_i)}{|g'(x_i)|} = \sum_{i=1}^n f_X(x_i) \cdot \left| \frac{dx_i}{dy} \right|.$$

$$f_Y(y) = \frac{f_X(\sqrt{y})}{|2\sqrt{y}|} + \frac{f_X(-\sqrt{y})}{|-2\sqrt{y}|} = \frac{1}{\sqrt{2\pi}y} e^{-\frac{y}{2}}, \text{ for } y \in (0, \infty).$$

Example 2:

Let  $X$  be continuous r.v. with PDF

$$f_X(x) = \begin{cases} 4x^3 & 0 < x \leq 1. \\ 0 & \text{otherwise} \end{cases}$$

and let  $Y = \frac{1}{X}$ . Find  $f_Y(y)$ .

$g(x) = \frac{1}{x}$  is decreasing on  $(0, 1]$ , and  $g^{-1}(y) = \frac{1}{y}$ , and  $y \geq 1$ .

$$\left| \frac{d}{dy} g^{-1}(y) \right| = \left| -\frac{1}{y^2} \right| = \frac{1}{y^2}. \quad f_Y(y) = \frac{4}{y^3} \cdot \frac{1}{y^2} = \frac{4}{y^5}.$$

$$f_Y(y) = \begin{cases} \frac{4}{y^5} & y \geq 1 \\ 0 & \text{otherwise.} \end{cases}$$

## 2. Bivariate transformation.

Theorem:  $X = (X_1, X_2)$  with joint PDF  $f(x, y)$ , consider new random vector  $Y = (Y_1, Y_2)$ .

$Y_1 = g_1(X_1, X_2)$ ,  $Y_2 = g_2(X_1, X_2)$ . To get the joint PDF of  $Y$ , we need to

① solve  $x_1 = h_1(y_1, y_2)$ ,  $x_2 = h_2(y_1, y_2)$ .

② find Jacobian  $J = \begin{vmatrix} \frac{\partial h_1}{\partial y_1} & \frac{\partial h_1}{\partial y_2} \\ \frac{\partial h_2}{\partial y_1} & \frac{\partial h_2}{\partial y_2} \end{vmatrix}$ .

③ the joint PDF is  $f(h_1(y_1, y_2), h_2(y_1, y_2)) |J|$ .

Example ①  ~~$X, Y$~~   $X, Y$  are <sup>independent</sup> standard normal random variables.

With the transformation  $U = X + Y$  and  $V = X - Y$ . ~~In the notation  $u, v$~~

Find joint PDF of  $U$  and  $V$ . Whether they are independent.

①  $X = \frac{U+V}{2}$ ,  $Y = \frac{U-V}{2}$ .

②  $J = \begin{vmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & -\frac{1}{2} \end{vmatrix} = -\frac{1}{2}$ ,  $|J| = \frac{1}{2}$ .

③  $f_{U,V}(u, v) = f_{X,Y}\left(\frac{u+v}{2}, \frac{u-v}{2}\right) \cdot \frac{1}{2} = \frac{1}{2\pi} e^{-\left(\frac{u+v}{2}\right)^2/2 - \left(\frac{u-v}{2}\right)^2/2}$   
 $= \left(\frac{1}{\sqrt{2\pi} \cdot \sqrt{2}} \cdot e^{-\frac{u^2}{4}}\right) \cdot \left(\frac{1}{\sqrt{2\pi} \cdot \sqrt{2}} \cdot e^{-\frac{v^2}{2}}\right)$ .

④ They are independent.

### 3. Conditional distribution.

If  $X_1$  and  $X_2$  are not independent,  $f_{X_1}(x | X_2 = y) = \frac{f(x, y)}{f_{X_2}(y)}$ .

If  $X_1$  and  $X_2$  are ~~not independent~~, independent,  $f_{X_1}(x | X_2 = y) = f_{X_1}(x)$ .

Example: The joint PDF of  $X$  and  $Y$  is given by

$$f(x, y) = \begin{cases} \frac{12}{5} x(2-x-y), & 0 < x < 1, 0 < y < 1. \\ 0 & \text{otherwise.} \end{cases}$$

Compute the conditional PDF of  $X$  given  $Y = y$ .

$$f(x|y) = \frac{f(x, y)}{f(y)} = \frac{\frac{12}{5} x(2-x-y)}{\int_0^1 \frac{12}{5} x(2-x-y) dx} = \frac{\frac{12}{5} x(2-x-y)}{\frac{12}{5} \int_0^1 (2x - x^2 - xy) dx}$$

$$= \frac{x(2-x-y)}{x^2 - \frac{x^3}{3} - \frac{x^2 y}{2} \Big|_0^1} = \frac{x(2-x-y)}{\frac{2}{3} - \frac{y}{2}}, \quad 0 < y < 1.$$

$$f(x|y) = \begin{cases} \frac{6x(2-x-y)}{4-3y}, & 0 < x < 1, 0 < y < 1. \\ 0 & \text{otherwise.} \end{cases}$$

4. Covariance: The covariance between  $X$  and  $Y$  is

$$\text{COV}(X, Y) = E[(X - \bar{X})(Y - \bar{Y})] = E[XY] - \bar{X}\bar{Y}.$$

~~Example: Let the joint pdf of  $(X, Y)$  be  $f(x, y) = 1, 0 < x < 1, x < y < x+1$ .  
The marginal distribution of  $X$  is uniform  $(0, 1)$ . Find the covariance of  $X$  and  $Y$ .  
Marginal distribution of  $Y$ .  $\int_0^1 f(x, y) dx =$~~

Example:

Let  $Z_1$  and  $Z_2$  be independent  $N(0,1)$  random variables, define new random variable  $X$  and  $Y$  by

$$X = a_x Z_1 + b_x Z_2 + C_x, \quad Y = a_y Z_1 + b_y Z_2 + C_y.$$

⊗ Show that  $E X = C_x, \quad \text{Var } X = a_x^2 + b_x^2$

$$E Y = C_y, \quad \text{Var } Y = a_y^2 + b_y^2$$

$$\text{Cov}(X, Y) = a_x a_y + b_x b_y.$$

5. Moment Generating function.

$$M(t) = E e^{tx}, \quad E X = M'(0), \quad E X^2 = M''(0), \quad \dots \quad E X^n = M^{(n)}(0).$$

Example: If  $X \sim \text{Poisson}(\lambda)$ ,  $Y \sim \text{Poisson}(\mu)$ .  $\swarrow$  prove  $X+Y \sim \text{Poisson}(\lambda+\mu)$ .   
 they are independent

By the proposition,  $X$  and  $Y$  are independent if and only if

$$M_X(t) M_Y(s) = M_{X,Y}(t, s).$$

MGF for  $X$  is  $M_X(t) = E e^{tx} = \sum_{x=0}^{\infty} e^{tx} \cdot \frac{\lambda^x e^{-\lambda}}{x!} = e^{-\lambda} \cdot \sum_{n=0}^{\infty} \frac{(e^t \lambda)^n}{n!}$   
 $= e^{-\lambda} \cdot e^{\lambda e^t} = e^{\lambda(e^t - 1)}$

Similarly  $M_Y(s) = e^{\mu(e^s - 1)}$

By the independence  $M_X(t) \cdot M_Y(s) = e^{(\lambda+\mu)(e^t - 1)}$

while  $M_X(t) \cdot M_Y(s) = E e^{tx} \cdot E e^{sy} = E e^{t(x+y)} = M_{X+Y}(t, s)$

then  $X+Y \sim \text{Poisson}(\lambda+\mu)$ .