

## Joint Distribution

### Discrete:

Joint C.D.F of  $X, Y$  is  $F_{X,Y}: \mathbb{R}^2 \rightarrow [0,1]$ .

$$F_{X,Y}(x, y) = P\{X \leq x, Y \leq y\}.$$

Joint P.m.f  $P_{X,Y}(x, y) = P(X=x, Y=y).$

$$\sum_x \sum_y P_{X,Y}(x, y) = 1.$$

$$\sum_{(x,y) \in A} P_{X,Y}(x, y) = P((X, Y) \in A)$$

Marginal P.m.f For discrete random variables

$X$  and  $Y$ , the marginal p.m.f of  $X$  is

$$P(X=x) = \sum_y P(X=x, Y=y).$$

$$E(g(X, Y)) = \sum_{\text{all } x, \text{all } y} g(x, y) P(x, y)$$

### Continuous

Joint p.d.f.  $f(x, y) = \frac{\partial^2 F(x, y)}{\partial x \partial y}$ ,  $P((X, Y) \in A) = \iint_A f(x, y) dx dy.$

Marginal p.d.f  $f_X(x) = \int_{-\infty}^{\infty} f(x, y) dy.$

$$E(g(X, Y)) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) \cdot f(x, y) dx dy.$$

## Moment-generating Functions

$$M_{X,Y}(t_1, t_2) = E(e^{t_1 X + t_2 Y})$$

$$M_{X,Y}(t_1, 0) = M_X(t_1)$$

## independent

R.V.  $X$  and  $Y$  are independent if and only if discrete:  $p(x, y) = p_X(x) p_Y(y)$ ,  $\forall x, y$ .

Continuous:  $f(x, y) = f_X(x) f_Y(y)$ ,  $\forall x, y$ .

C.d.f:  $F(x, y) = F_X(x) F_Y(y)$ ,  $\forall x, y$ .

## Covariance and Correlation Coefficient

$$\sigma_{XY} = \text{Cov}(X, Y) = E[(X - \mu_X)(Y - \mu_Y)] = E(XY) - \mu_X \mu_Y$$

$$\text{Cov}(aX + b, Y) = a \text{Cov}(X, Y)$$

$$\text{Cov}(X + Y, W) = \text{Cov}(X, W) + \text{Cov}(Y, W)$$

$$\begin{aligned} \text{Cov}(aX + bY, cX + dY) &= ac \text{Var}(X) + (ad + bc) \text{Cov}(X, Y) \\ &\quad + bd \text{Var}(Y) \end{aligned}$$



$$\text{Var}(aX+bY) = a^2 \text{Var}(X) + 2ab \text{Cov}(X,Y) + b^2 \text{Var}(Y)$$

$$\rho_{X,Y} = \frac{\sigma_{X,Y}}{\sigma_X \sigma_Y} = \frac{\text{Cov}(X,Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}} = E\left[\left(\frac{X-\mu_X}{\sigma_X}\right)\left(\frac{Y-\mu_Y}{\sigma_Y}\right)\right]$$

$$-1 \leq \rho_{X,Y} \leq 1.$$

Example: Cauchy distribution.

$(X, Y) \stackrel{\text{i.i.d.}}{\sim} N(0,1).$

$T = \frac{X}{Y}$ , find c.d.f and p.d.f of  $T$ .

$$F_T(t) = P(T \leq t) = P\left(\frac{X}{Y} \leq t\right)$$

distribution of  $\frac{X}{Y}$  is same as  $\frac{X}{|Y|}$

$$= P\left(\frac{X}{|Y|} \leq t\right).$$

$$= P(X \leq t|Y|)$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{t|y|} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \times \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} dx dy.$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} \left( \int_{-\infty}^{t|y|} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx \right) dy.$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} \Phi(t|y|) dy.$$

$$f_T(t) = \frac{d}{dt} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} \Phi(t|y|) dy$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} \phi(t|y|) |y| dy$$

$$= \int_{-\infty}^{\infty} \frac{1}{2\pi} e^{-\frac{y^2(1+t^2)}{2}} |y| dy$$

$$= \frac{1}{\pi} \int_0^{\infty} e^{-\frac{y^2(1+t^2)}{2}} y dy$$

$$= \frac{1}{\pi(1+t^2)} \int_0^{\infty} e^{-\frac{y^2(1+t^2)}{2}} d\frac{y^2(1+t^2)}{2}$$

$$= \frac{1}{\pi(1+t^2)}$$

this  $\frac{x}{y}$  called Cauchy distribution.