

Conditional distribution  $P(A|B) = \frac{P(A \cap B)}{P(B)}$

Discrete case.

Def. for two random variables  $X$  and  $Y$  (discrete), the conditional pmf of  $X$  given that  $Y=y$  by  $P_{X|Y}(x|y) = P(X=x | Y=y) = \frac{P(X=x, Y=y)}{P(Y=y)}$

$$= \frac{P(x, y)}{P(y)}$$

-  $P_{X|Y}(x|y) \geq 0$

-  $\sum_x P_{X|Y}(x|y) = 1$

Def (conditional cdf)

$$F_{X|Y}(x|y) = P(X \leq x | Y \leq y) = \sum_{z \leq x} P_{X|Y}(z|y)$$

If  $X$  and  $Y$  are independent  $P_{X|Y}(x|y) = P_X(x)$

(If  $X \perp\!\!\!\perp Y$ , then  $P(x,y) = P_X(x) \cdot P_Y(y)$ )

$$P_{X|Y}(x|y) = \frac{P(x,y)}{P_Y(y)} = P_X(x)$$

Continuous case

Def. Let  $X$  and  $Y$  be 2 continuous r.v. with joint pdf  $f_{XY}(y)$ . For any value  $x$  value which  $f_X(x) > 0$ , the conditional pdf of  $Y$  given that  $X=x$ , is

$$f_{Y|X}(y|x) = \frac{f_{XY}(y)}{f_X(x)}, -\infty < y < \infty$$

Probability:

For any set  $A$   $P(Y \in A | X=x) = \int_A f_{Y|X}(y|x) dy$ .

If  $X \perp\!\!\!\perp Y$ , then

$$F_{Y|X}(y|x) = \frac{f_{XY}(y)}{f_X(x)} = \frac{f_X(x) \cdot f_Y(y)}{f_X(x)} = f_Y(y).$$

## Expectation

The conditional expectation of  $Y$  given that  $X=x$  is

$$E(Y|X=x) = \int_{-\infty}^{\infty} y f_{Y|X}(y|x) dy, \text{ if } X \text{ & } Y \text{ continuous.}$$

$$\text{and } E(Y|X=x) = \sum_{y} y \cdot P_{Y|X}(y|x), \text{ if } X \text{ & } Y \text{ discrete.}$$

Properties:  $E(X) = E[E(X|Y)]$ .

Remarks:  $(X, Y)$  - joint distributed r.v.s. Then for a function  $h$  of  $X$  and  $Y$ .

$$\begin{aligned} E(h(x,y)) &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h(x,y) \cdot f_{X,Y}(x,y) dx dy, \text{ if } X, Y \text{ ctn.} \\ &= \sum_{x} \sum_{y} h(x,y) \cdot P(X=x, Y=y) \text{ if } X, Y \text{ discrete.} \end{aligned}$$

$$\begin{aligned} E(X) &= \int_{-\infty}^{\infty} x f(x) dx && X - \text{ctn} \\ &= \sum_{x} x p(x) && X - \text{discrete.} \end{aligned}$$

E.g. if  $X$  and  $Y$  are independent Poisson r.v.s with parameters  $\lambda_1, \lambda_2$  respectively.

a) Find the conditional pmf of  $X$  given that

$$X+Y=n$$

b) Find  $E(X|X+Y=n)$ .

$$\begin{aligned} \text{Sol. a) } P_{X|X+Y}(x|X+Y=n) &\stackrel{\text{def}}{=} \frac{P(X=x, X+Y=n)}{P(X+Y=n)} \\ &= \frac{P(X=x, Y=n-x)}{P(X+Y=n)} \\ &= \frac{P(X=x) \cdot P(Y=n-x)}{P(X+Y=n)}. \end{aligned}$$

$$\begin{aligned} &= \frac{\frac{e^{-\lambda_1} \cdot \lambda_1^x}{x!} \cdot \frac{-e^{-\lambda_2} \cdot \lambda_2^{n-x}}{(n-x)!}}{\frac{e^{-(\lambda_1+\lambda_2)} \cdot (\lambda_1+\lambda_2)^n}{n!}} \\ &= \frac{\frac{n!}{x!(n-x)!} \cdot \frac{\lambda_1^x \cdot \lambda_2^{n-x}}{(\lambda_1+\lambda_2)^n}}{\frac{n!}{x!(n-x)!} \cdot \frac{\lambda_1^x \cdot \lambda_2^{n-x}}{(\lambda_1+\lambda_2)^n}} \end{aligned}$$

$$= \binom{n}{x} \cdot \left(\frac{\lambda_1}{\lambda_1 + \lambda_2}\right)^x \cdot \left(\frac{\lambda_2}{\lambda_1 + \lambda_2}\right)^{n-x}$$

$X|X+Y=n \sim \text{Binomial}(n, \frac{\lambda_1}{\lambda_1 + \lambda_2})$

$$b) E(X|X+Y=n) = n \frac{\lambda_1}{\lambda_1 + \lambda_2}$$

### Rule of Average Conditional Probabilities

If  $X$  and  $Y$  are discrete r.v.s., then  $P(Y=y) = \sum_x \underbrace{P(Y=y|X=x) \cdot P(X=x)}_{P(Y=y, X=x)}$

E.g. The joint pdf of  $X$  and  $Y$  is given by.

$$f(x,y) = \begin{cases} \frac{15}{2}y(2-x-y), & 0 < x < 1, 0 < y < 1 \\ 0, & \text{o/w.} \end{cases}$$

Find the conditional density of  $Y$  given that  $X=x$ , where  $0 < x < 1$ .

$$f_{Y|X}(y|x) = \frac{f(x,y)}{f_X(x)}$$

$$\begin{aligned} f_X(x) &= \int_{-\infty}^{\infty} f(x,y) dy = \int_0^1 \frac{15}{2}y(2-x-y) dy \\ &= \frac{15}{2}y^2 - \frac{15x}{4}y^2 - \frac{15}{6}y^3 \Big|_0^1 \\ &= 5 - \frac{15}{4}x, \quad 0 < x < 1. \end{aligned}$$

$$f_{Y|X}(y|x) = \frac{\frac{15}{2}y(2-x-y)}{5 - \frac{15}{4}x} = \frac{y(2-x-y)}{\frac{2}{3} - \frac{x}{2}}, \quad 0 < y < 1$$

E.g. Suppose  $X$  and  $Y$  has the joint pdf

$$f(x,y) = \begin{cases} e^{-x/y} \cdot e^{-y/x}, & \text{if } x>0, y>0 \\ 0, & \text{o/w.} \end{cases}$$

Find  $E(X|Y=y)$  where  $y>0$ .

$$\begin{aligned} \text{Sol. } f_Y(y) &= \int_{-\infty}^{\infty} f(x,y) dx = \int_0^{\infty} e^{-x/y} \cdot e^{-y/x} dx \\ &= e^{-y} \cdot (-e^{-xy}) \Big|_0^{\infty} \\ &= e^{-y}. \quad y>0. \end{aligned}$$

$$f_{X|Y}(x|y) = \frac{1}{y} e^{-x/y}, \quad x > 0.$$

$$\begin{aligned}
 (i) E(X|Y=y) &= \int_{-\infty}^{\infty} x \cdot f_{X|Y}(x|y) dx \\
 &= \int_0^{\infty} x \cdot \frac{1}{y} e^{-x/y} dx \\
 &= -x \cdot e^{-x/y} - \int e^{-x/y} dx \\
 &= -x \cdot e^{-x/y} \Big|_0^{\infty} \\
 &= 0 + 0 - 0 + y.
 \end{aligned}$$

(ii)  $X|Y=y \sim \exp(\frac{1}{y})$ .

$$E(X|Y=y) = \frac{1}{y} = y.$$

### Covariance & Correlation, Variance of Sums

$$\begin{aligned}
 \text{Def. } \text{Cov}(X, Y) &= E[(X - \mu_X)(Y - \mu_Y)] \text{ or } h(x, y) \\
 &= \begin{cases} \sum_x \sum_y (x - \mu_X)(y - \mu_Y) \cdot p(x, y) & \text{discrete} \\ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \mu_X)(y - \mu_Y) f_{X,Y}(x, y) dx dy & \text{ctn} \end{cases}
 \end{aligned}$$

$$\text{Alternate formula: } \text{Cov}(X, Y) = E(XY) - E(X)E(Y)$$

$$\begin{aligned}
 &= \left[ \sum_x \sum_y xy p(x, y) \right] - \left[ \sum_x x p(x) \right] \left[ \sum_y y p(y) \right] \text{ discrete} \\
 &\quad \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f_{X,Y}(x, y) dx dy - \int_{-\infty}^{\infty} x f_X(x) dx \int_{-\infty}^{\infty} y f_Y(y) dy \text{ (ctn)}
 \end{aligned}$$

If  $X$  and  $Y$  are independent, then

$$\text{Cov}(X, Y) = 0, \quad \text{Cov}(h(X), g(Y)) = 0$$

( $E(XY) = E(X)E(Y)$ )

$$\text{Properties: } \text{Cov}(X, Y) = \text{Cov}(Y, X)$$

$$\text{Cov}(X, X) = \text{Var}(X)$$

$$\text{Cov}(X, aY) = a \text{Cov}(X, Y)$$

$$\text{Cov}\left(\sum_i x_i, \sum_j y_j\right) = \sum_i \sum_j \text{Cov}(x_i, y_j)$$

## Variance of Sums

If  $x$  and  $y$  are 2 r.v.s, then

$$(*) \text{Var}(x+y) = \text{Var}(x) + \text{Var}(y) + 2\text{Cov}(x, y)$$

Recall: If  $x, y$  independent, then  $\text{Var}(x+y) = \text{Var}(x) + \text{Var}(y)$ .

more generally  $\text{Var}(x_1+x_2+\dots+x_n) = \sum_{i=1}^n \text{Var}(x_i) + 2 \sum_{i < j} \text{Cov}(x_i, x_j)$

If  $x_1, x_2, \dots, x_n$  independent  $\text{Var}(x_1+\dots+x_n) = \sum_{i=1}^n \text{Var}(x_i)$

## Correlation

$$P(x, y) = \frac{\text{Cov}(x, y)}{\text{SD}(x) \cdot \text{SD}(y)}$$

measure how strong the linear relationship between  $x$  and  $y$ .

Properties  $-1 \leq P(x, y) \leq 1$

$P(x, y) = 0$  if  $\text{Cov}(x, y) = 0$ ,  $x, y$  uncorrelated.

If  $P(x, y) = \pm 1$ , then  $y = ax + b$ .

$P(ax+b, c+d y) = P(x, y)$  if  $bd \neq 0$ .

$x, y$  independent  $\Rightarrow \text{Cov}(x, y) = 0$  or  $P(x, y) = 0$

no relationship  $\not\Rightarrow$

uncorrelated

$\Downarrow$   
no linear relationship.  $y=x^2$