

## Chapter 4 : Conditional probabilities and independence : Conditional distributions of continuous random variables

### 1. Conditional distributions of continuous random variables

The following definition gives the formulas for conditional distributions of continuous random variables by simply replacing sums with integrals and PMF's with PDF's

**Définition 1. (Conditional PDF)** If  $X$  and  $Y$  are continuous random variables with joint probability density function (PDF) given by  $f(x, y)$ , is the joint probability mass function. The conditional probability density function of  $X$ , given that  $Y = y$ , is defined by

$$f_{X|Y}(x|y) = \begin{cases} \frac{f_{X,Y}(x,y)}{f_Y(y)}, & \text{if } f_Y(y) > 0, \\ 0, & \text{otherwise.} \end{cases}$$

**Définition 2. (Conditional CDF of continuous random variable)** If  $X$  and  $Y$  are continuous random variables, the conditional cumulative distribution function of  $X$  given  $Y = y$  is

$$F_{X|Y}(x|y) = P(X \leq x | Y = y) = \int_{-\infty}^x f_{X|Y}(t|y) dt.$$

#### 1.1. Properties of conditional probability density function

1. The conditional PDF for  $X$ , given  $Y = y$ , for a fixed  $y$ , is a PDF satisfying the following :

$$0 \leq f_{X|Y}(x | y) \quad \text{and} \quad \int_{\mathbb{R}} f_{X|Y}(x | y) dx = 1$$

2. Typically, the conditional distribution of  $X$  given  $Y$  does not equal the conditional distribution of  $Y$  given  $X$ , i.e.,

$$f_{X|Y}(x | y) \neq f_{Y|X}(y | x)$$

3. If  $X$  and  $Y$  are independent, continuous random variables, then the following are true :

$$\begin{aligned} f_{X|Y}(x | y) &= f_X(x) \\ f_{Y|X}(y | x) &= f_Y(y) \end{aligned}$$

### 2. Conditional expectation and variance

**Définition 3.** Let  $X$  and  $Y$  discrete random variables, then the conditional expected value of  $\mathbf{X}$ , given  $\mathbf{Y} = \mathbf{y}$ , is given by

$$\mu_{X|Y=y} = E[X | Y = y] = \sum_x x p_{X|Y}(x | y)$$

and the conditional variance of  $\mathbf{X}$ , given  $\mathbf{Y} = \mathbf{y}$ , is given by

$$\begin{aligned} \sigma_{X|Y=y}^2 &= \text{Var}(X | Y = y) = E \left[ (X - \mu_{X|Y=y})^2 | Y = y \right] = \sum_{x \in S_X} (x - \mu_{X|Y=y})^2 p_{X|Y}(x | y) \\ &= E [X^2 | Y = y] - \mu_{X|Y=y}^2 = \left( \sum_{x \in S_X} x^2 p_{X|Y}(x | y) \right) - \mu_{X|Y=y}^2 \end{aligned}$$

Similarly, if  $X$  and  $Y$  are continuous random variables with joint PDF given by  $f(x, y)$ , then the conditional expected value of  $\mathbf{X}$ , given  $\mathbf{Y} = \mathbf{y}$ , is

$$E[X | Y = y] = \int_{\mathbb{R}} x f_{X|Y}(x | y) dx$$

and the conditional variance of  $\mathbf{X}$ , given  $\mathbf{Y} = \mathbf{y}$ , is

$$\begin{aligned} \text{Var}(X | Y = y) &= E[X^2 | Y = y] - (E[X | Y = y])^2 \\ &= \int_{\mathbb{R}} x^2 f_{X|Y}(x | y) dx - \left( \int_{\mathbb{R}} x f_{X|Y}(x | y) dx \right)^2. \end{aligned}$$