

# Probability and Random Process (SWE3026)

## Joint Distributions

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# Two Continuous Random Variables

PDF:

$$P(X \in A) = \int_A f_X(x) dx,$$

Joint PDF:

$$P((X, Y) \in A) = \iint_A f_{XY}(x, y) dx dy.$$

# Two Continuous Random Variables

If we choose  $A = \mathbb{R}^2$ , then

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{XY}(x, y) dx dy = 1.$$

# Two Continuous Random Variables

**Definition.** Two random variables  $X$  and  $Y$  are **jointly continuous** if there exists a nonnegative function  $f_{XY} : \mathbb{R}^2 \rightarrow \mathbb{R}$ , such that, for any set  $A \in \mathbb{R}^2$ , we have

$$P((X, Y) \in A) = \iint_A f_{XY}(x, y) dx dy,$$

The function  $f_{XY}(x, y)$  is called **the joint probability density function (PDF)** of  $X$  and  $Y$ .

# Two Continuous Random Variables

CDF:

$$F_X(x) = P(X \leq x) = \int_{-\infty}^x f_X(u) du,$$

Joint CDF:

$$F_{XY}(x, y) = P(X \leq x, Y \leq y) = \int_{-\infty}^y \int_{-\infty}^x f_{XY}(u, v) du dv,$$

and

# Two Continuous Random Variables

$$f_X(x) = \frac{d}{dx}F_X(x),$$

$$f_{XY}(x, y) = \frac{\partial^2}{\partial x \partial y}F_{XY}(x, y).$$

# Two Continuous Random Variables

$$F_{XY}(x, y) = \int_{-\infty}^y \int_{-\infty}^x f_{XY}(u, v) du dv,$$

$$f_{XY}(x, y) = \frac{\partial^2}{\partial x \partial y} F_{XY}(x, y)$$

# Two Continuous Random Variables

The **joint cumulative function** of two random variables  $X$  and  $Y$  is defined as

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

The joint CDF satisfies the following properties:

- 1)  $F_X(x) = F_{XY}(x, \infty)$ , for any  $x$  (marginal CDF of  $X$ );
- 2)  $F_Y(y) = F_{XY}(\infty, y)$ , for any  $y$  (marginal CDF of  $Y$ );
- 3)  $F_{XY}(\infty, \infty) = 1$ ;



# Two Continuous Random Variables

4)  $F_{XY}(-\infty, y) = F_{XY}(x, -\infty) = 0;$

5)  $P(x_1 < X \leq x_2, y_1 < Y \leq y_2) =$   
 $F_{XY}(x_2, y_2) - F_{XY}(x_1, y_2) - F_{XY}(x_2, y_1) + F_{XY}(x_1, y_1)$

6) if  $X$  and  $Y$  are independent, then  $F_{XY}(x, y) = F_X(x)F_Y(y).$

# Two Continuous Random Variables

## Marginal PDFs:

For **discrete** random variables:

$$P_X(x) = \sum_{y \in R_Y} P_{XY}(x, y).$$

For **continuous** random variables:

$$f_X(x) = \int_{-\infty}^{\infty} f_{XY}(x, y) dy, \quad \text{for all } x,$$
$$f_Y(y) = \int_{-\infty}^{\infty} f_{XY}(x, y) dx, \quad \text{for all } y.$$

# Conditioning and Independence

Conditional probability:

$$P(A|B) = \frac{P(A \cap B)}{P(B)}, \quad P(B|A) = \frac{P(A \cap B)}{P(A)}.$$

conditional CDF:

$$F_{X|A}(x) = P(X \leq x|A).$$

# Conditioning and Independence

**Example.** Let  $A : a \leq X \leq b$ ,  $X$  : continuous

$$F_{X|A}(x) = P(X \leq x|A) = P(X \leq x|a \leq X \leq b) = \begin{cases} 0 & \text{if } x < a \\ 1 & \text{if } x > b \end{cases}$$

**If**  $a \leq x \leq b$  :

$$\begin{aligned} F_{X|A}(x) &= \frac{P(X \leq x, a \leq X \leq b)}{P(a \leq X \leq b)} = \frac{P(a \leq X \leq x)}{P(a \leq X \leq b)} \\ &= \frac{F_X(x) - F_X(a)}{F_X(b) - F_X(a)}. \end{aligned}$$

# Conditioning and Independence

Finally, if  $x > b$ , then  $F_{X|A}(x) = 1$ . Thus, we obtain

$$F_{X|A}(x) = \begin{cases} 1 & x > b \\ \frac{F_X(x) - F_X(a)}{F_X(b) - F_X(a)} & a \leq x < b \\ 0 & \text{otherwise} \end{cases} \quad A : \{a \leq X \leq b\}$$

Then the conditional PDF of  $X$  given  $A$  is given by

$$f_{X|A}(x) = \begin{cases} \frac{f_X(x)}{F_X(b) - F_X(a)} & a \leq x \leq b \\ 0 & \text{otherwise} \end{cases}$$

# Conditioning and Independence

In general, for a random variable  $X$  and an event  $A$ , we have the following:

$$E[X|A] = \int_{-\infty}^{\infty} x f_{X|A}(x) dx,$$

$$E[g(X)|A] = \int_{-\infty}^{\infty} g(x) f_{X|A}(x) dx,$$

$$\text{Var}(X|A) = E[X^2|A] - (E[X|A])^2$$

# Conditioning and Independence

## Conditioning by Another Random Variable:

**For discrete random variables:** the conditional PMF of  $X$  given  $Y = y$  is given by

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

# Conditioning and Independence

**For continuous random variables:**

The conditional PDF of  $X$  given  $Y = y$  is given by

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

The conditional PDF of  $Y$  given  $X = x$  is given by

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



# Conditioning and Independence

For two jointly continuous random variables  $X$  and  $Y$ , we have

$$E[X|Y = y] = \int_{-\infty}^{\infty} x f_{X|Y}(x|y) dx,$$

$$E[g(X)|Y = y] = \int_{-\infty}^{\infty} g(x) f_{X|Y}(x|y) dx,$$

$$\text{Var}(X|Y = y) = E[X^2|Y = y] - (E[X|Y = y])^2$$

# Summary of Conditioning

Conditional probability:

$$P(A|B) = \frac{P(A \cap B)}{P(B)}, \quad P(B|A) = \frac{P(A \cap B)}{P(A)}.$$

conditional CDF and PDF given  $A$ : (e.g.,  $A = \{a \leq X \leq b\}$  )

$$F_{X|A}(x) = P(X \leq x|A),$$

$$f_{X|A}(x) = \frac{d}{dx} F_{X|A}(x).$$

# Summary of Conditioning

In general, for a random variable  $X$  and an event  $A$ , we have the following:

$$E[X|A] = \int_{-\infty}^{\infty} x f_{X|A}(x) dx,$$

$$E[g(X)|A] = \int_{-\infty}^{\infty} g(x) f_{X|A}(x) dx,$$

$$\text{Var}(X|A) = E[X^2|A] - (E[X|A])^2$$

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# Summary of Conditioning

**For continuous random variables:**

The conditional PMF of  $X$  given  $Y = y$  is given by

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

The conditional PMF of  $Y$  given  $X = x$  is given by

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

# Summary of Conditioning

For two jointly continuous random variables  $X$  and  $Y$ , we have

$$E[X|Y = y] = \int_{-\infty}^{\infty} x f_{X|Y}(x|y) dx,$$

$$E[g(X)|Y = y] = \int_{-\infty}^{\infty} g(x) f_{X|Y}(x|y) dx,$$

$$\text{Var}(X|Y = y) = E[X^2|Y = y] - (E[X|Y = y])^2$$

$$E[g(X, Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) f_{XY}(x, y) dx dy.$$

# Conditioning and Independence

Law of Total Probability:

$$P(A) = \int_{-\infty}^{\infty} P(A|X = x) f_X(x) \, dx,$$

Law of Total Expectation:

$$E[Y] = \int_{-\infty}^{\infty} E[Y|X = x] f_X(x) \, dx = E[E[Y|X]].$$

# Conditioning and Independence

Law of Total Variance:

$$\text{Var}(Y) = E[\text{Var}(Y|X)] + \text{Var}(E[Y|X]).$$



# Conditioning and Independence

## Independent Random Variables:

**Discrete:**

$$P_{XY}(x_i, y_j) = P_X(x_i)P_Y(y_j) \quad \text{for all } x_i, y_j.$$

**Continuous:**

$$f_{XY}(x, y) = f_X(x)f_Y(y), \quad \text{for all } x, y.$$

**#:**

$$F_{XY}(x, y) = F_X(x)F_Y(y), \quad \text{for all } x, y.$$

# Conditioning and Independence

**Example.** Determine whether  $X$  and  $Y$  are independent.

$$f_{XY}(x, y) = \begin{cases} 2e^{-x-2y}, & x, y > 0 \\ 0, & \text{otherwise} \end{cases}$$

# Functions of Two Continuous Random Variables

LOTUS for two continuous random variables:

$$E[g(X, Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) f_{XY}(x, y) dx dy.$$

# Functions of Two Continuous Random Variables

**Theorem.** Let  $X$  and  $Y$  be two jointly continuous random variables. Let

$(Z, W) = g(X, Y) = (g_1(X, Y), g_2(X, Y))$ , where  $g : \mathbb{R}^2 \mapsto \mathbb{R}^2$  is a continuous one-to-one (invertible) function with continuous partial derivatives.

Let  $h = g^{-1}$ , i.e.,  $(X, Y) = h(Z, W) = (h_1(Z, W), h_2(Z, W))$ . Then  $Z$  and  $W$  are jointly continuous and their joint PDF,  $f_{ZW}(z, w)$ , for  $(z, w) \in R_{ZW}$  is given by

$$f_{ZW}(z, w) = f_{XY}(h_1(z, w), h_2(z, w))|J|,$$

# Functions of Two Continuous Random Variables

Where  $J$  is the Jacobian of  $h$  defined by

$$J = \det \begin{bmatrix} \frac{\partial h_1}{\partial z} & \frac{\partial h_1}{\partial w} \\ \frac{\partial h_2}{\partial z} & \frac{\partial h_2}{\partial w} \end{bmatrix} = \frac{\partial h_1}{\partial z} \cdot \frac{\partial h_2}{\partial w} - \frac{\partial h_2}{\partial z} \frac{\partial h_1}{\partial w}.$$

# Functions of Two Continuous Random Variables

**Example.**

Let  $X$  and  $Y$  be two independent standard normal random variables. Let also

$$\begin{cases} Z = 2X - Y \\ W = -X + Y \end{cases}$$

Find  $f_{ZW}(z, w)$

# Functions of Two Continuous Random Variables

If  $X$  and  $Y$  are two jointly **continuous random variables** and  $Z = X + Y$ , then

$$f_Z(z) = \int_{-\infty}^{\infty} f_{XY}(w, z - w)dw = \int_{-\infty}^{\infty} f_{XY}(z - w, w)dw.$$

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

$$\begin{aligned} f_Z(z) &= f_X(z) * f_Y(z) \\ &= \int_{-\infty}^{\infty} f_X(w) f_Y(z - w)dw = \int_{-\infty}^{\infty} f_Y(w) f_X(z - w)dw. \end{aligned}$$

# Summary of Independence

Two continuous random variables  $X$  and  $Y$  are independent if

$$f_{XY}(x, y) = f_X(x)f_Y(y), \quad \text{for all } x, y.$$



# Conditioning and Independence

Two continuous random variables  $X$  and  $Y$  are **independent**, then we have

$$\begin{aligned} E[XY] &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy \overbrace{f_{XY}(x, y)}^{f_X(x)f_Y(y)} dx dy = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f_X(x) f_Y(y) dx dy \\ &= \int_{-\infty}^{\infty} y f_Y(y) \left[ \int_{-\infty}^{\infty} x f_X(x) dx \right] dy = \underbrace{\int_{-\infty}^{\infty} x f_X(x) dx}_{EX} \underbrace{\int_{-\infty}^{\infty} y f_Y(y) dy}_{EY} \end{aligned}$$

# Conditioning and Independence

**More generally:**  $X$  and  $Y$  independent

$$E[g(X)h(Y)] = E[g(X)]E[h(Y)].$$