



Probability and Stochastic Processes

Lecture 17: Jointly Discrete/Continuous Random Variables, Joint PMF, Joint PDF, Conditional PMF, Conditional PDF, Multiple Random Variables

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Jointly Discrete Random Variables

Definition (Jointly Discrete Random Variables)

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let $(X, Y) : \Omega \rightarrow \mathbb{R}^2$ be a bivariate random vector.

X and Y are said to be **jointly discrete** if the vector (X, Y) is a discrete random variable, i.e., there exists a **countable** set $E \subseteq \mathbb{R}^2$ such that

$$\mathbb{P}_{X,Y}(E) = \mathbb{P}(\{(X, Y) \in E\}) = 1.$$

- Define E_1 and E_2 as

$$E_1 := \{x \in \mathbb{R} : \exists y \in \mathbb{R} \text{ such that } (x, y) \in E\}, \quad E_2 = \{y \in \mathbb{R} : \exists x \in \mathbb{R} \text{ such that } (x, y) \in E\}.$$

- If (X, Y) is discrete, then X and Y are individually discrete, as

$$\mathbb{P}_X(E_1) = \mathbb{P}_{X,Y}(E_1 \times \mathbb{R}) = 1, \quad \mathbb{P}_Y(E_2) = \mathbb{P}_{X,Y}(\mathbb{R} \times E_2) = 1.$$

- (X, Y) discrete $\implies X$ discrete, Y discrete.

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$$\mathbb{P}_{X,Y}(E) = \mathbb{P}(\{(X, Y) \in E\}) = 1.$$

- Suppose X and Y are individually discrete with

$$\mathbb{P}_X(E_1) = 1, \quad \mathbb{P}_Y(E_2) = 1,$$

for some countable sets $E_1, E_2 \subset \mathbb{R}$

- Then, (X, Y) is discrete: $E_1 \times E_2$ countable,

$$\mathbb{P}_{X,Y}(E_1 \times E_2) = \mathbb{P}_{X,Y}((E_1 \times \mathbb{R}) \cap (\mathbb{R} \times E_2)) = 1.$$

- X discrete, Y discrete $\implies (X, Y)$ discrete .



Marginal PMFs and Conditional PMFs

Marginal PMFs from Joint PMF

For Jointly Discrete Random Variables

Theorem (Marginal PMFs from Joint PMF)

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let X and Y be jointly discrete, with $\mathbb{P}_{X,Y}(E) = 1$ for some countable $E \subset \mathbb{R}^2$.

Then, the following properties hold.

1. The joint PMF on the range must sum to 1, i.e.,

$$\sum_{(x,y) \in E} p_{X,Y}(x, y) = 1.$$

2. (Marginalization Property)

$$\forall x \in \mathbb{R}, \quad \sum_{y: (x,y) \in E} p_{X,Y}(x, y) = p_X(x),$$

$$\forall y \in \mathbb{R}, \quad \sum_{x: (x,y) \in E} p_{X,Y}(x, y) = p_Y(y).$$

Independence for Jointly Discrete Random Variables

Proposition (Independence for Jointly Discrete Random Variables)

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let X, Y be **jointly discrete** random variables with $\mathbb{P}_{X,Y}(E) = 1$ for some countable $E \subset \mathbb{R}^2$. Then,

$$X \perp\!\!\!\perp Y \iff p_{X,Y}(x,y) = p_X(x) \cdot p_Y(y) \quad \forall x, y \in \mathbb{R}.$$

- If $X \perp\!\!\!\perp Y$, then by definition,

$$\mathbb{P}_{X,Y}(B_1 \times B_2) = \mathbb{P}_X(B_1) \cdot \mathbb{P}_Y(B_2) \quad \forall B_1, B_2 \in \mathcal{B}(\mathbb{R}).$$

- Taking $B_1 = \{x\}$ and $B_2 = \{y\}$, we get

$$\underbrace{\mathbb{P}_{X,Y}(\{x\} \times \{y\})}_{p_{X,Y}(x,y)} = \underbrace{\mathbb{P}_X(\{x\})}_{p_X(x)} \cdot \underbrace{\mathbb{P}_Y(\{y\})}_{p_Y(y)}$$

- This proves the \implies direction

Independence for Jointly Discrete Random Variables

Proposition (Independence for Jointly Discrete Random Variables)

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let X, Y be **jointly discrete** random variables with $\mathbb{P}_{X,Y}(E) = 1$ for some countable $E \subset \mathbb{R}^2$. Then,

$$X \perp\!\!\!\perp Y \iff p_{X,Y}(x,y) = p_X(x) \cdot p_Y(y) \quad \forall x, y \in \mathbb{R}.$$

- Suppose that $p_{X,Y}(x,y) = p_X(x) \cdot p_Y(y)$ for all $x, y \in \mathbb{R}$
- $E_1 := \{x \in \mathbb{R} : \exists y \in \mathbb{R} \text{ such that } (x,y) \in E\}$, $E_2 = \{y \in \mathbb{R} : \exists x \in \mathbb{R} \text{ such that } (x,y) \in E\}$
- Notice that: $E_1 \times E_2 \supseteq E$, $\mathbb{P}_{X,Y}(E_1 \times E_2) = 1$, $\mathbb{P}_Y(E_2) = 1$.
- (\Leftarrow) For any $B_1, B_2 \in \mathcal{B}(\mathbb{R})$,

$$\begin{aligned} \mathbb{P}_{X,Y}(B_1 \times B_2) &= \mathbb{P}_{X,Y}\left((B_1 \times B_2) \cap (E_1 \times E_2)\right) = \sum_{x \in B_1 \cap E_1} \sum_{y \in B_2 \cap E_2} p_{X,Y}(x,y) \\ &= \sum_{x \in B_1 \cap E_1} p_X(x) \cdot \sum_{y \in B_2 \cap E_2} p_Y(y) = \mathbb{P}_X(B_1 \cap E_1) \cdot \mathbb{P}_Y(B_2 \cap E_2) = \mathbb{P}_X(B_1) \cdot \mathbb{P}_Y(B_2). \end{aligned}$$

Conditional PMF

Definition (Conditional PMF)

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let X, Y be jointly discrete random variables.

1. Fix $A \in \mathcal{F}$ with $\mathbb{P}(A) > 0$.

The **conditional PMF of X , conditioned on event A** , is defined as

$$p_{X|A}(x) := \frac{\mathbb{P}(\{X = x\} \cap A)}{\mathbb{P}(A)}, \quad x \in \mathbb{R}.$$

2. The **conditional PMF of X , conditioned on Y** , is defined as

$$p_{X|Y}(x|y) = \frac{\mathbb{P}(\{X = x\} \cap \{Y = y\})}{\mathbb{P}(\{Y = y\})} = \frac{p_{X,Y}(x,y)}{p_Y(y)}, \quad x \in \mathbb{R},$$

valid for all $y \in \mathbb{R}$ such that $p_Y(y) = \mathbb{P}(\{Y = y\}) > 0$.



Conditional PMF and Independence

Proposition (Conditional PMF)

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let X, Y be jointly discrete random variables. Then,

$$X \perp\!\!\!\perp Y \iff p_{X|Y}(x|y) = p_X(x) \quad \forall x, \text{ feasible } y.$$

A proof of this is left as **exercise**.



Jointly Continuous Random Variables

Lebesgue Measure $\lambda^{(2)}$ on $(\mathbb{R}^2, \mathcal{B}(\mathbb{R}^2))$

- Consider the collection

$$\mathcal{S} = \left\{ (a, b] \times (c, d) : a \leq b, c \leq d, a, b, c, d \in \mathbb{R} \right\}.$$

- The collection \mathcal{S} forms a **semiring**; $\sigma(\mathcal{S}) = \mathcal{B}(\mathbb{R}^2)$
- Let $m : \mathcal{S} \rightarrow [0, +\infty]$ be an assignment satisfying the following properties:
 - $m(\emptyset) = 0$, $m(\mathbb{R}^2) = +\infty$, $m((a, b] \times (c, d)) = (b - a) \cdot (d - c)$
 - Countable additivity:** if $A_1, A_2, \dots \in \mathcal{S}$ are disjoint and satisfy $\bigsqcup_{n \in \mathbb{N}} A_n \in \mathcal{S}$, then

$$m \left(\bigsqcup_{n \in \mathbb{N}} A_n \right) = \sum_{n \in \mathbb{N}} m(A_n).$$

- By Caratheodory's extension theorem, there exists a **unique extension** of m to $\mathcal{B}(\mathbb{R}^2)$. The extended measure is called the Lebesgue measure, denoted $\lambda^{(2)}$
- $\lambda^{(2)}((a, b] \times (c, d)) = \lambda((a, b]) \cdot \lambda((c, d))$, λ : 1-D Lebesgue measure

Jointly Continuous Random Variables

Definition (Jointly Continuous Random Variables)

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let $(X, Y) : \Omega \rightarrow \mathbb{R}^2$ be a bivariate random vector.

X and Y are said to be **jointly continuous** if $\mathbb{P}_{X,Y} \ll \lambda^{(2)}$, i.e.,

$$\lambda^{(2)}(E) = 0 \implies \mathbb{P}_{X,Y}(E) = 0.$$

- X and Y jointly continuous $\implies X$ continuous, Y continuous
- **Proof:** Suppose $E \subseteq \mathbb{R}$ with $\lambda(E) = 0$

$$\lambda^{(2)}(E \times \mathbb{R}) = \lambda^{(2)} \left(\bigcup_{n \in \mathbb{N}} E \times [-n, n] \right) = \lim_{n \rightarrow \infty} \lambda^{(2)}(E \times [-n, n]) = \lim_{n \rightarrow \infty} (\lambda(E) \cdot 2n) = 0$$

- Therefore,

$$\mathbb{P}_X(E) = \mathbb{P}_{X,Y}(E \times \mathbb{R}) = 0 \implies \mathbb{P}_X \ll \lambda \implies X \text{ continuous}$$

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- X and Y jointly continuous $\implies X$ continuous, Y continuous
- **Proof:** Suppose $E \subseteq \mathbb{R}$ with $\lambda(E) = 0$

$$\lambda^{(2)}(\mathbb{R} \times E) = \lambda^{(2)} \left(\bigcup_{n \in \mathbb{N}} [-n, n] \times E \right) = \lim_{n \rightarrow \infty} \lambda^{(2)}([-n, n] \times E) = \lim_{n \rightarrow \infty} (2n \cdot \lambda(E)) = 0$$

- Therefore,

$$\mathbb{P}_Y(E) = \mathbb{P}_{X,Y}(\mathbb{R} \times E) = 0 \implies \mathbb{P}_Y \ll \lambda \implies Y \text{ continuous}$$

Jointly Continuous Random Variables

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Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let $(X, Y) : \Omega \rightarrow \mathbb{R}^2$ be a bivariate random vector.

X and Y are said to be **jointly continuous** if $\mathbb{P}_{X,Y} \ll \lambda^{(2)}$, i.e.,

$$\lambda^{(2)}(E) = 0 \implies \mathbb{P}_{X,Y}(E) = 0.$$

- **Caution!** In general, X continuous, Y continuous $\not\Rightarrow X$ and Y jointly continuous
- Suppose X is a continuous random variable. Let $Y = X$. (X continuous, Y continuous)
- Let $B := \{(x, y) \in \mathbb{R}^2 : x = y\}$
- Notice that

$$\lambda^{(2)}(B) = 0, \quad \mathbb{P}_{X,Y}(B) = 1 \implies \mathbb{P}_{X,Y} \not\ll \lambda^{(2)}.$$

Remark: In the above example, the bivariate vector (X, Y) is **singular**!

Joint PDF

- If X and Y are jointly continuous, then

$$\mathbb{P}_{X,Y} \ll \lambda^{(2)}$$

- By the Radon-Nikodym theorem, there exists a **non-negative, measurable function** $f_{X,Y} : \mathbb{R}^2 \rightarrow [0, +\infty)$ such that

$$\forall x, y \in \mathbb{R}, \quad F_{X,Y}(x, y) = \int_{-\infty}^x \int_{-\infty}^y f_{X,Y}(u, v) \, dv \, du.$$

- $f_{X,Y}$ is called the **joint PDF** of X and Y



Marginal PDFs and Conditional PDF

Marginal PDFs from Joint PDF

For Jointly Continuous Random Variables

Theorem (Marginal PDFs from Joint PDF)

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let X and Y be jointly continuous. Then, the following properties hold.

1. The joint PDF must integrate to 1, i.e.,

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y}(u, v) dv du = 1.$$

2. (Marginalization Property)

$$\forall x \in \mathbb{R}, \quad \int_{-\infty}^{\infty} f_{X,Y}(x, v) dv = f_X(x),$$

$$\forall y \in \mathbb{R}, \quad \int_{-\infty}^{\infty} f_{X,Y}(u, y) du = f_Y(y).$$

Independence for Jointly Continuous Random Variables

Proposition (Independence for Jointly Continuous Random Variables)

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let X, Y be **jointly continuous** random variables. Then,

$$X \perp\!\!\!\perp Y \iff f_{X,Y}(x, y) = f_X(x) \cdot f_Y(y) \quad \forall x, y \text{ except possibly on a set } B \text{ with } \lambda^{(2)}(B) = 0.$$

Conditional CDF and Conditional PDF

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let X and Y be **jointly continuous** random variables.

Objective

We would like to define the conditional CDF of X , conditioned on observing the value of Y .

Mathematically, our interest is in $\mathbb{P}(\{X \leq x\} | \{Y = y\})$.

However, this conditional probability is not defined because $\mathbb{P}(\{Y = y\}) = 0$ for all $y \in \mathbb{R}$.

So, then, how do we actually compute $\mathbb{P}(\{X \leq x\} | \{Y = y\})$?

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So, then, how do we actually compute $\mathbb{P}(\{X \leq x\} | \{Y = y\})$?

Remedy:

Fix $y \in \mathbb{R}$ and $\varepsilon > 0$ such that $\mathbb{P}(\{Y \in (y - \varepsilon, y + \varepsilon)\}) > 0$.

Define conditional probability with respect to the event $\{Y \in (y - \varepsilon, y + \varepsilon)\}$, and let $\varepsilon \downarrow 0$.

Conditional CDF and Conditional PDF

$$\begin{aligned}
 \mathbb{P}(\{X \leq x\} | \{Y \in (y - \varepsilon, y + \varepsilon)\}) &= \frac{\mathbb{P}(\{X \leq x\} \cap \{Y \in (y - \varepsilon, y + \varepsilon)\})}{\mathbb{P}(\{Y \in (y - \varepsilon, y + \varepsilon)\})} \\
 &= \frac{\mathbb{P}_{X,Y}((-\infty, x] \times (y - \varepsilon, y + \varepsilon))}{\mathbb{P}_Y((y - \varepsilon, y + \varepsilon))} \\
 &= \frac{\int_{-\infty}^x \int_{y-\varepsilon}^{y+\varepsilon} f_{X,Y}(u,v) dv du}{\int_{y-\varepsilon}^{y+\varepsilon} f_Y(v) dv} \approx \frac{\int_{-\infty}^x f_{X,Y}(u,y) du \cdot 2\varepsilon}{f_Y(y) \cdot 2\varepsilon} \\
 &= \int_{-\infty}^x \underbrace{\frac{f_{X,Y}(u,y)}{f_Y(y)}}_{\text{conditional PDF}} du
 \end{aligned}$$

Conditional CDF for Jointly Continuous Random Variables

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let X and Y be **jointly continuous** random variables.

Definition (Conditional CDF for Jointly Continuous Random Variables)

Fix y such that $f_Y(y) > 0$.

The **conditional CDF** of X , conditioned on the event $\{Y = y\}$, is the function

$F_{X|Y=y} : \mathbb{R} \rightarrow [0, 1]$ defined as

$$F_{X|Y=y}(x) = \int_{-\infty}^x \underbrace{\frac{f_{X,Y}(u,y)}{f_Y(y)}}_{\text{conditional PDF}} du, \quad x \in \mathbb{R}.$$

Conditional PDF for Jointly Continuous Random Variables

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let X and Y be **jointly continuous** random variables.

Definition (Conditional PDF for Jointly Continuous Random Variables)

Fix y such that $f_Y(y) > 0$.

The **conditional PDF** of X , conditioned on the event $\{Y = y\}$, is the function $f_{X|Y=y} : \mathbb{R} \rightarrow [0, +\infty)$ defined as

$$f_{X|Y=y}(x) = \frac{f_{X,Y}(x,y)}{f_Y(y)}, \quad x \in \mathbb{R}.$$

Remark: Some textbooks use the notation $f_{X|Y}(x|y)$ to denote the conditional PDF.