

1179: Probability

Lecture 18 — Joint Distributions

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This Lecture

1. Joint PMF and Marginal PMF

2. Joint PDF and Marginal PDF

3. Independent Random Variables

- Reading material: Chapter 8.1~8.2

Review: Joint PMF and Marginal PMF

Joint PMF: Let X and Y be two discrete random variables defined on the same sample space Ω . The joint PMF $p(x, y)$ is defined as

$$p(x, y) = P(X = x, Y = y) \equiv P(\{\omega: X(\omega) = x, Y(\omega) = y\})$$

Marginal PMF: Let S_X and S_Y be the sets of possible values of X and Y . The marginal PMF of X and Y are

$$P(X=x, Y \in S_Y) = P(X=x) = \sum_{y \in S_Y} p(x, y)$$

$$P(Y=y, X \in S_X) = P(Y=y) = \sum_{x \in S_X} p(x, y)$$

Example: From Joint PMF to Marginals

- **Example:** Let the joint PMF of X and Y be

$$\underline{p_{XY}(x, y)} = \begin{cases} \frac{1}{25}(x^2 + y^2) & , \text{ if } \underline{x = 1, 2}, \underline{y = 0, 1, 2} \\ 0 & , \text{ otherwise} \end{cases}$$

- What is the marginal PMF of X and Y ?

$$\begin{array}{l}
 P_X(x) = \sum_{y \in S_Y} p_{XY}(x, y) \Rightarrow \begin{array}{l} \text{Case 1: } x=1 \text{ or } 2 \\ P_X(x) = \sum_{y \in \{0,1,2\}} \frac{1}{25}(x^2 + y^2) \\ = \frac{3}{25}x^2 + \frac{5}{25} \end{array} \quad \begin{array}{l} \text{Case 2: Otherwise} \\ P_X(x) = 0 \end{array} \\
 \hline
 P_Y(y) = \sum_{x \in S_X} p_{XY}(x, y) \Rightarrow \begin{array}{l} \text{Case 1: } y=0, 1, 2 \\ P_Y(y) = \sum_{x \in \{1,2\}} \frac{1}{25}(x^2 + y^2) \\ = \frac{2}{25}y^2 + \frac{5}{25} \end{array} \quad \begin{array}{l} \text{Case 2: Otherwise} \\ P_Y(y) = 0 \end{array}
 \end{array}$$

Example: Bernoulli and Poisson

- **Example:** Consider $X \sim \text{Bernoulli}(p)$, $Z_0 \sim \text{Poisson}(\lambda_0, T)$ and $Z_1 \sim \text{Poisson}(\lambda_1, T)$ (all are independent). Suppose $\underline{Y} = Z_0$ if $X = 0$, and $Y = Z_1$ if $X = 1$.

- What is the joint PMF of X and Y ?
- What is the marginal PMF of Y ?

$$Y(\omega) = \begin{cases} \underline{Z_0(\omega)}, & \text{if } \underline{X(\omega)=0} \\ Z_1(\omega), & \text{if } \underline{X(\omega)=1} \end{cases}$$

$$P_{XY}(x, y) = \begin{cases} p \cdot \frac{e^{-\lambda_1 T} (\lambda_1 T)^y}{y!}, & \text{if } x=1, y=0, 1, 2, \dots \\ (1-p) \cdot \frac{e^{-\lambda_0 T} (\lambda_0 T)^y}{y!}, & \text{if } x=0, y=0, 1, 2, \dots \\ 0, & \text{otherwise} \end{cases}$$

$$P_Y(y) = \begin{cases} 0 + \frac{p \cdot e^{-\lambda_1 T} (\lambda_1 T)^y}{y!} + \frac{(1-p) \cdot e^{-\lambda_0 T} (\lambda_0 T)^y}{y!}, & y=0, 1, 2, \dots \\ 0, & \text{otherwise} \end{cases}$$

Joint PDF and Marginal PDF

Why Studying Joint PDF?

$$F_{XY}(t,u) = P(X \leq t \text{ and } Y \leq u)$$

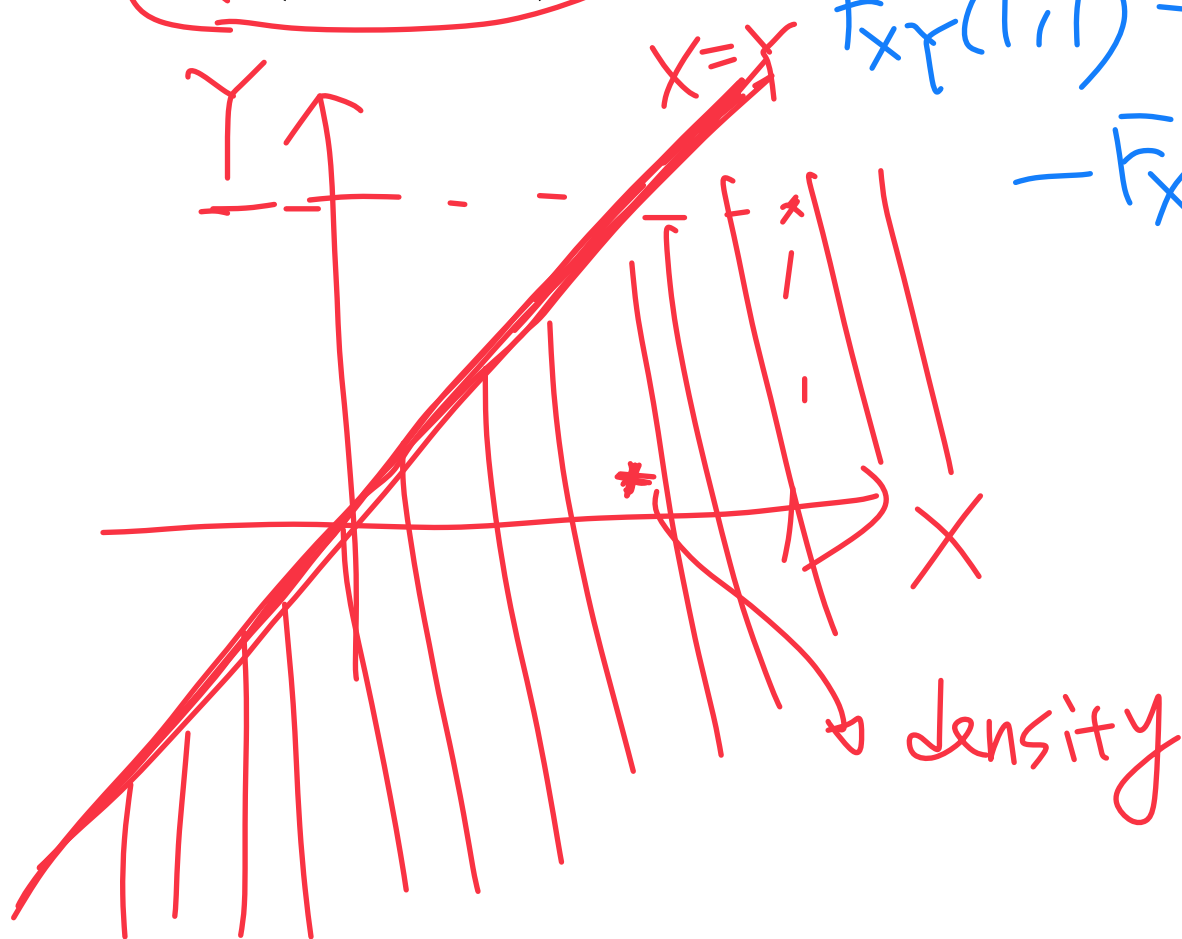
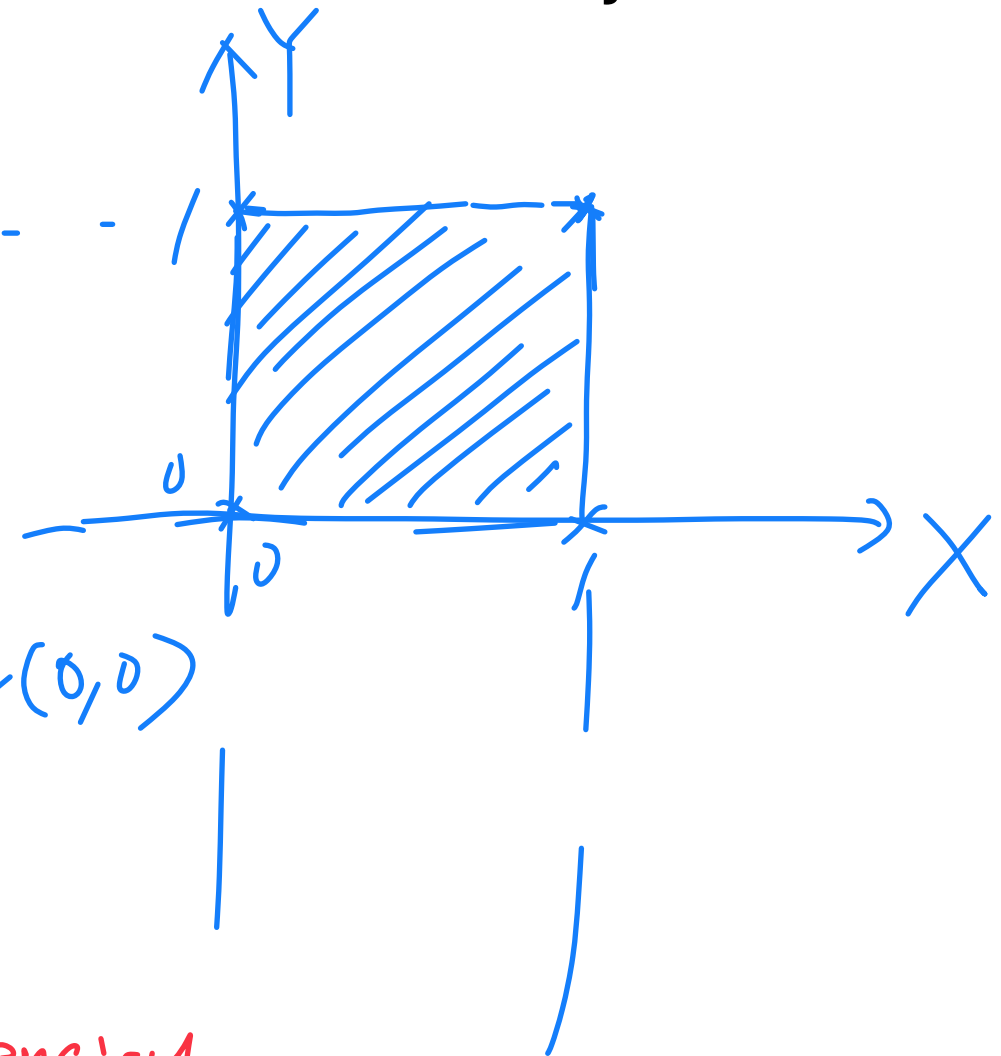
► **Question:** X, Y are continuous random variables with the joint CDF $F_{XY}(x, y)$

► $P(X \leq 0, Y \leq 1) = F_{XY}(0, 1)$

► $P(0 < X \leq 1, 0 < Y \leq 1)$

► $P(X \geq Y)$

$$F_{XY}(1, 1) - F_{XY}(1, 0) - F_{XY}(0, 1) + F_{XY}(0, 0)$$



\int density

1 R.V.

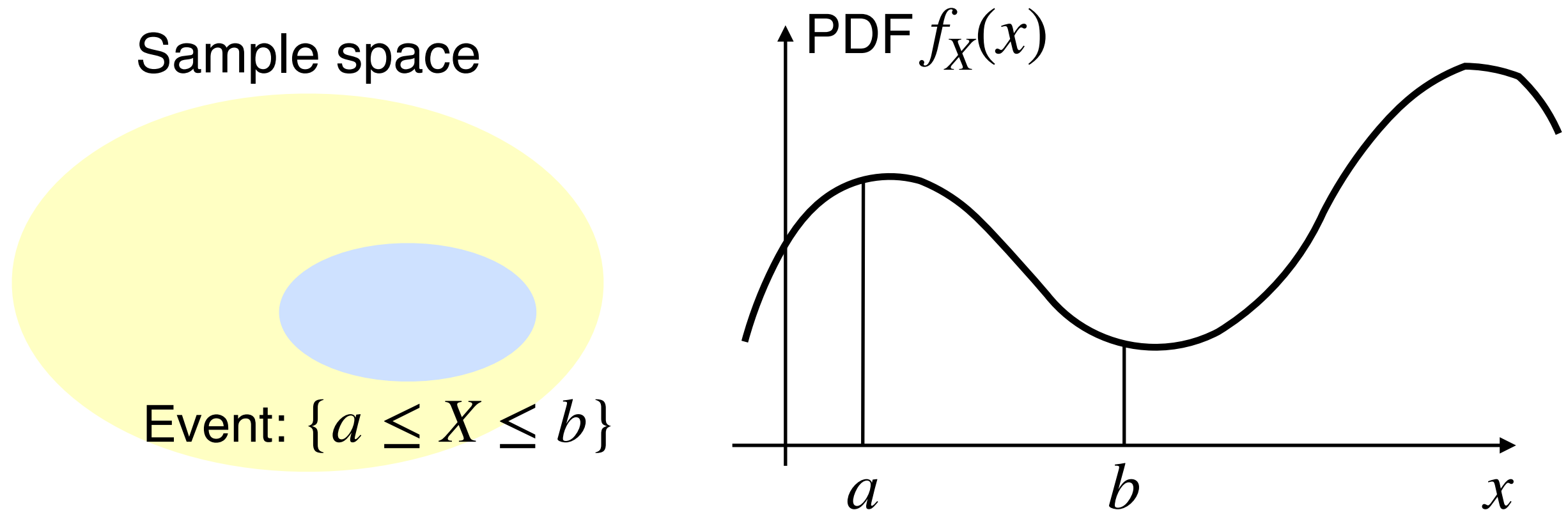
$$P(B) = \int_B \underline{f(x)} dx$$

2 R.V.s

For every event B , $f_{XY}(x, y)$

$$P(B) = \int \int_{\underbrace{B}} f_{XY}(x, y) dx dy$$

Recall: Probability Density Function (PDF)



Probability Density Function (PDF):

Let X be a random variable. Then, $f_X(x)$ is the PDF of X if for every subset B of the real line, we have

$$P(X \in B) = \int_B f_X(x) dx$$

Joint PDF

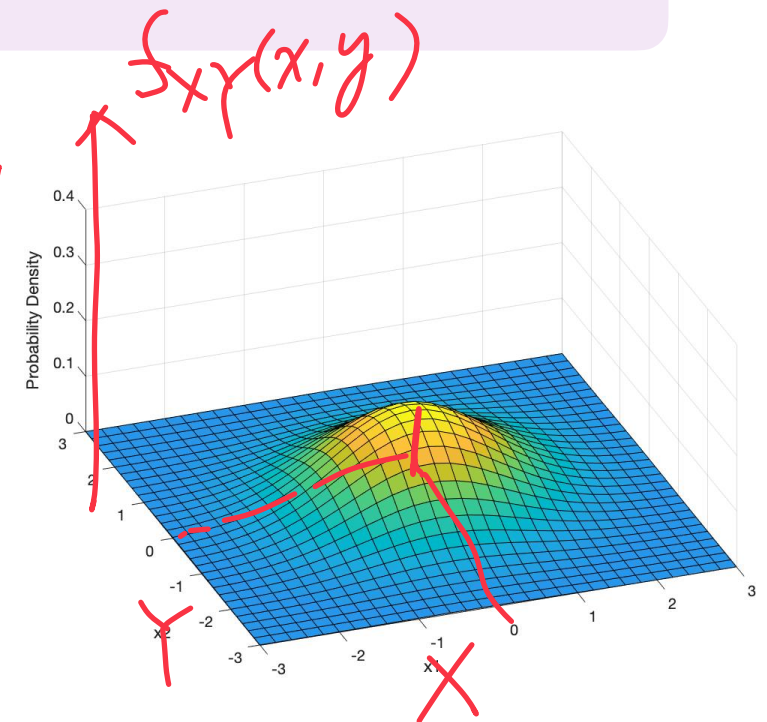
Joint PDF: Let X and Y be two continuous random variables. Then, $f_{XY}(x, y)$ is the joint PDF of X and Y if for every subset B of \mathbb{R}^2 , we have

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

► $P(X \in B_X, Y \in B_Y) = \int_{B_Y} \int_{B_X} f_{XY}(x, y) dx dy$

\downarrow \downarrow
 $[0, 1]$ $[3, 5]$

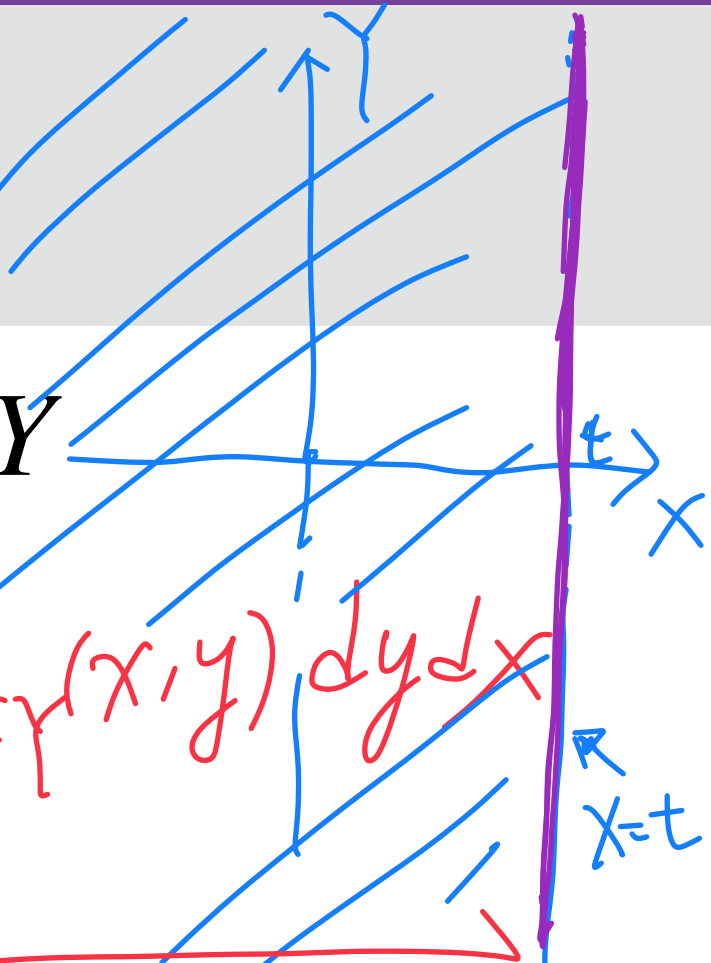
► $P(X \in \mathbb{R}, Y \in \mathbb{R}) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f_{XY}(x, y) dx dy$



Joint PDF and Event Probabilities

marginal CDF

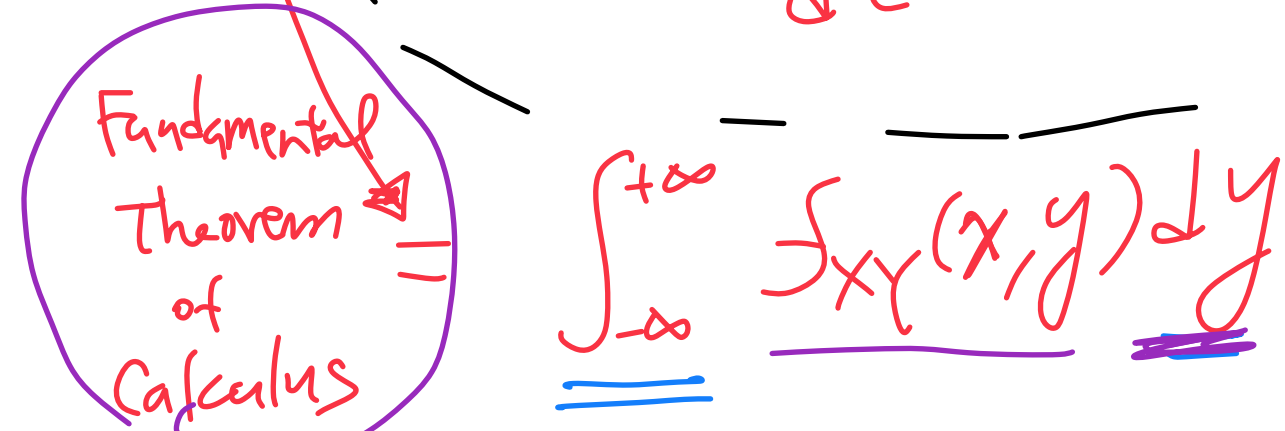
$f_{XY}(x, y)$ is the joint PDF of X and Y

$$P(X \leq t) = P(X \leq t \text{ and } Y \in \mathbb{R}) = \int_{-\infty}^t \int_{-\infty}^{+\infty} f_{XY}(x, y) dy dx$$


marginal PDF

$$f_X(x) = \frac{d}{dt} P(X \leq t) \Big|_{t=x} = \frac{d}{dt} \left(\int_{-\infty}^t \int_{-\infty}^{+\infty} f_{XY}(x, y) dy dx \right) \Big|_{t=x}$$

Fundamental Theorem of Calculus

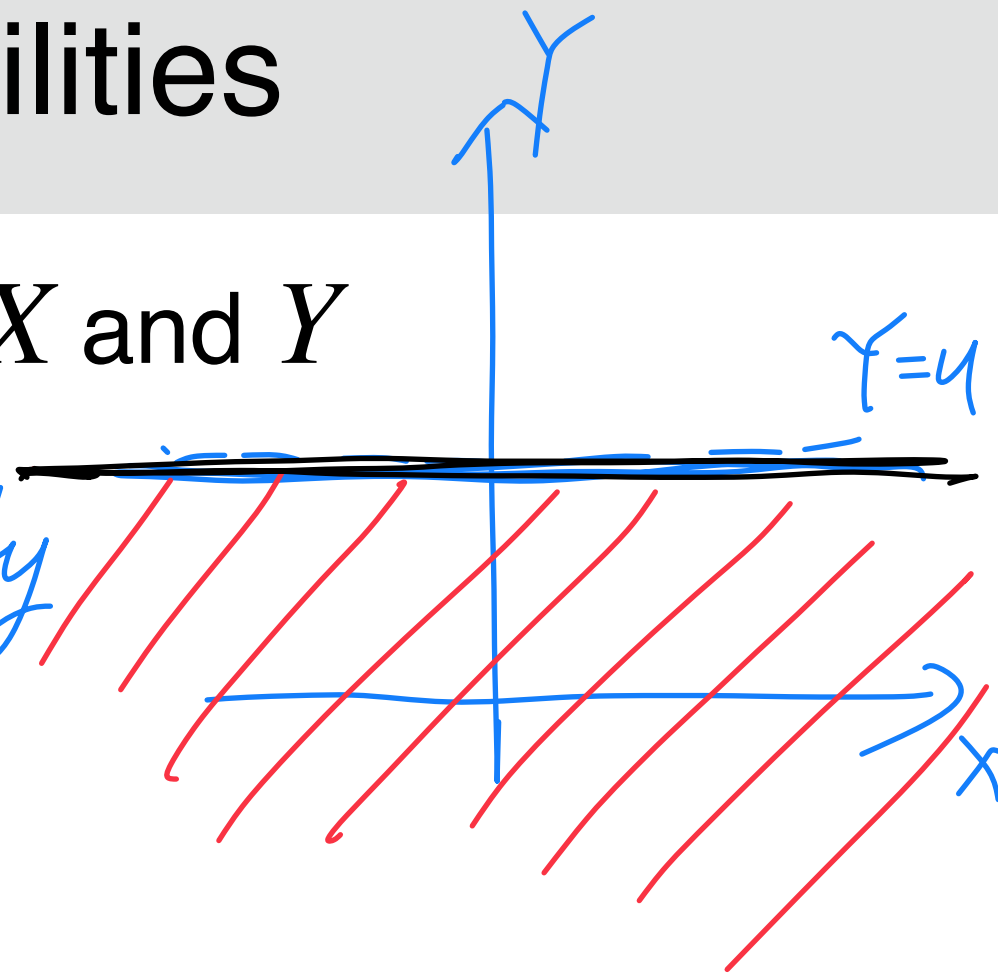
$$= \int_{-\infty}^{+\infty} f_{XY}(x, y) dy$$


Joint PDF and Event Probabilities

$f_{XY}(x, y)$ is the joint PDF of X and Y

$P(Y \leq u) =$
marginal CDF

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



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

Marginal PDF

// **Marginal PDF:** Let X and Y be two continuous random variables, and $f_{XY}(x, y)$ is the joint PDF of X and Y . The marginal PDF of X and Y are

$$f_X(x) = \int_{-\infty}^{\infty} \underline{f_{XY}(x, y)} \underline{dy}$$

$$f_Y(y) = \int_{-\infty}^{\infty} \underline{f_{XY}(x, y)} \underline{dx}$$

Example: (1) Joint PDF \rightarrow Joint CDF

- **Example:** The joint PDF of X and Y is

$$f(x, y) = \begin{cases} \frac{3}{2}(x^2 + y^2) & , \text{ if } 0 < x < 1 \text{ and } 0 < y < 1 \\ 0 & , \text{ otherwise} \end{cases}$$

- Joint CDF of X and Y ?

$$F_{XY}(t, u)$$

$$F_{XY}(2, 2) = P(X \leq 2, Y \leq 2)$$

• $0 < t < 1, 0 < u < 1 =$

$$F_{XY}(t, u) = \int_{-\infty}^u \int_{-\infty}^t f(x, y) dx dy$$

$$= \int_0^u \int_0^t \frac{3}{2}(x^2 + y^2) dx dy$$

$$= \int_0^u \left[\frac{1}{2} t^3 + \frac{3}{2} t \cdot y^2 \right] dy = \left[\frac{1}{2} t^3 \cdot y + \frac{1}{2} t y^3 \right]_0^u = \frac{1}{2} u t (t^2 + u^2)$$

$t \backslash u$	$u \leq 0$	$0 < u < 1$	$u \geq 1$
$t \leq 0$	0	0	0
$0 < t < 1$	0	$\frac{1}{2} u t (t^2 + u^2)$	0
$t \geq 1$	0	0	0



Example: (2) Joint PDF \rightarrow Marginal PDF

- Example: X and Y be

$$f(x, y) = \begin{cases} \frac{3}{2}(x^2 + y^2) & , \text{ if } 0 < x < 1 \text{ and } 0 < y < 1 \\ 0 & , \text{ otherwise} \end{cases}$$

- Marginal PDF of X ?

$$f_X(x) = \int_{-\infty}^{+\infty} f(x, y) dy$$

Case 3: $x \geq 1$

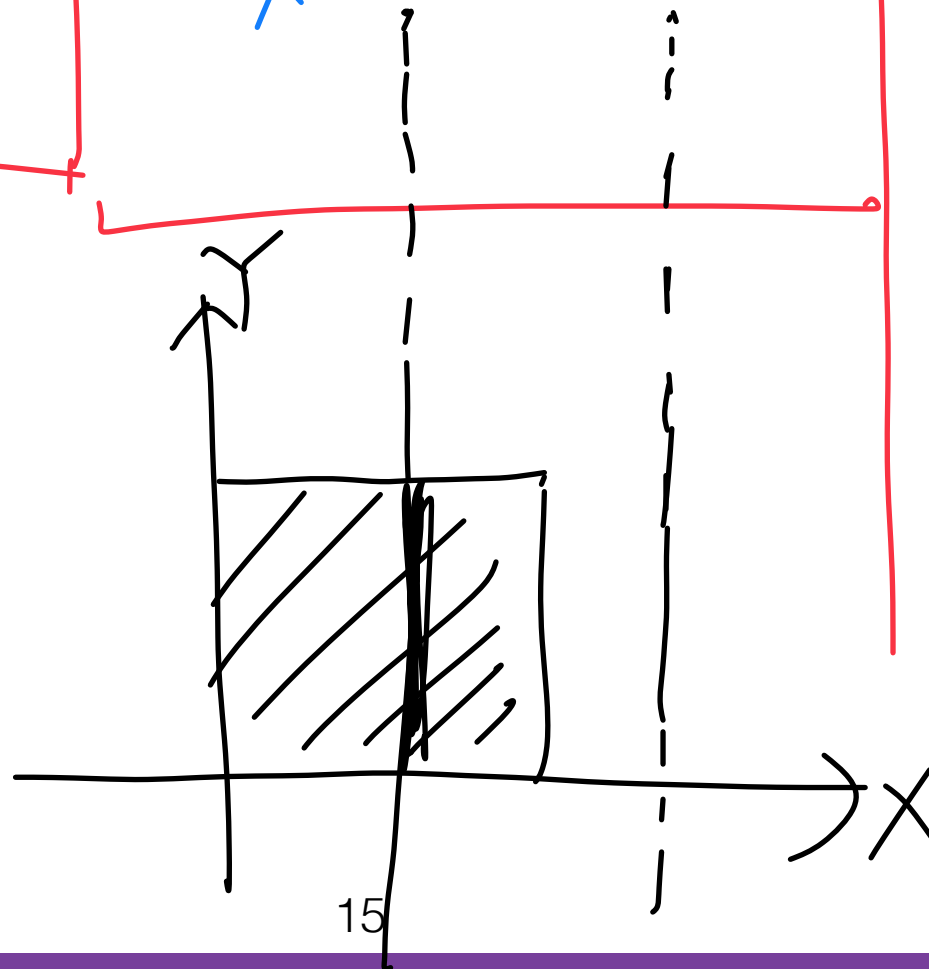
$$f_X(x) = 0$$

Case 1: $x \leq 0$

$$f_X(x) = 0.$$

Case 2: $0 < x < 1$

$$\begin{aligned} f_X(x) &= \int_0^1 \frac{3}{2}(x^2 + y^2) dy \\ &= \left. \frac{3}{2}x^2 y + \frac{1}{2}y^3 \right|_0^1 \\ &= \frac{3}{2}x^2 + \frac{1}{2} \end{aligned}$$



Review: From CDF to PDF (Formally)

Derivative of CDF is PDF:

Let X be a random variable with a CDF $F_X(\cdot)$ and a PDF $f_X(\cdot)$. If $f_X(\cdot)$ is continuous at x_0 , then

$$F'_X(x_0) = f_X(x_0)$$

- **Question:** Do we have any similar property regarding joint CDF and joint PDF?

Given Joint CDF: Find Joint PDF

Partial Derivative of Joint CDF is Joint PDF:

X and Y are two continuous random variables.

Let $F_{XY}(x, y)$ be the joint CDF of X and Y .

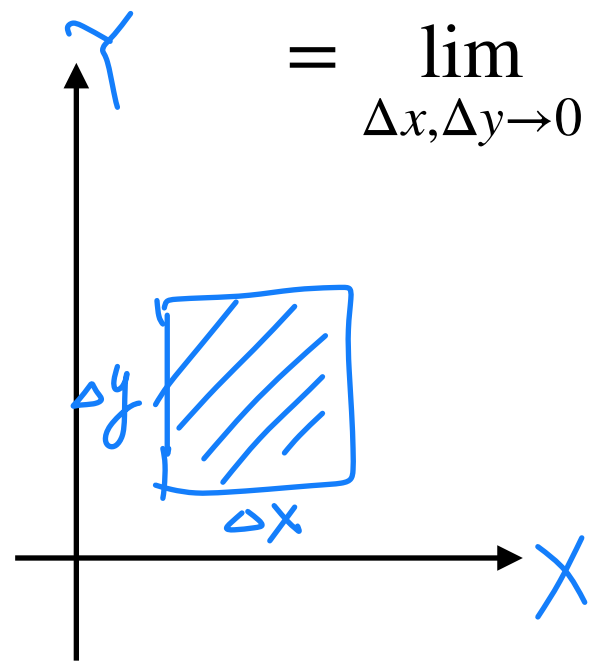
Assume the partial derivatives of $F_{XY}(x, y)$ exist. Then, one valid choice of PDF can be

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

Joint PDF: Interpret “Density” Using Limits

$$f_{XY}(x, y) \equiv \lim_{\Delta x, \Delta y \rightarrow 0} \frac{P(x < X \leq x + \Delta x, y < Y \leq y + \Delta y)}{\Delta x \Delta y}$$

$$= \lim_{\Delta x, \Delta y \rightarrow 0} \frac{F_{XY}(x + \Delta x, y + \Delta y) - F_{XY}(x, y + \Delta y) - F_{XY}(x + \Delta x, y) + F_{XY}(x, y)}{\Delta x \Delta y}$$

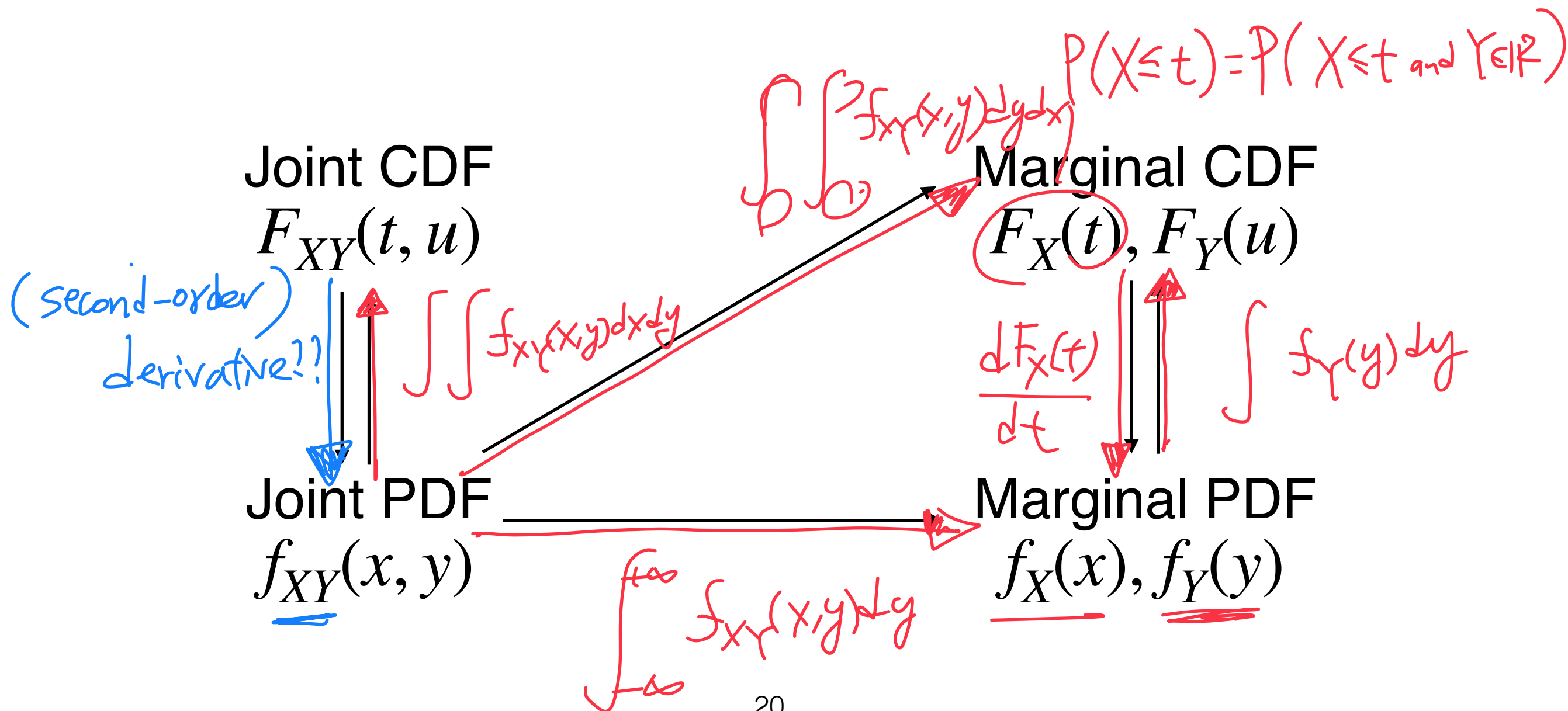


density = $\frac{\text{Probability mass on } \boxed{\text{shaded rectangle}}}{\text{Area of } \boxed{\text{shaded rectangle}} \times \underline{\Delta x \cdot \Delta y}}$

Technical Issues With Joint PDF

1. Given joint CDF $F_{XY}(x, y)$, the joint PDF is NOT unique
2. Suppose the partial derivatives of $F_{XY}(x, y)$ exist, then
 $\frac{\partial^2}{\partial x \partial y} F_{XY}(x, y)$ is a valid joint PDF
3. In this class, we usually assume (unless stated otherwise):
 1. The partial derivatives of $F_{XY}(x, y)$ exist
 2. $\frac{\partial^2}{\partial x \partial y} F_{XY}(x, y)$ is the joint PDF to operate with

A Quick Summary



Marginal CDF/PDF to Joint CDF/PDF?

- **Question:** Could we get joint CDF/PDF from marginal CDF/PDF?

Joint CDF $F_{XY}(x, y)$ ← Marginal CDF $F_X(x), F_Y(y)$

Joint PDF $f_{XY}(x, y)$ ← Marginal PDF $f_X(x), f_Y(y)$

Independent Random Variables

Recall: Independence of 2 Random Variables

Definition: Two random variables X, Y are said to be **independent** if for arbitrary sets of real numbers A, B , the events $\{X \in A\}$ and $\{Y \in B\}$ are independent, i.e.

$$P(X \in A, Y \in B) = P(X \in A) \cdot P(Y \in B)$$

- ▶ **Remark:** Same definition for both discrete and continuous random variables
- ▶ **Question:** What if we choose the sets as $A = (-\infty, t]$ and $B = (-\infty, u]$?

Property: Independence of 2 Random Variables

Independence \equiv joint CDF is the product of the marginal CDFs:

Two random variables X, Y are **independent** if and only if

$$F_{XY}(t, u) = F_X(t) \cdot F_Y(u)$$

- **Remark:** This property holds for both discrete and continuous random variables

Example: 2 Discrete Uniform Random Variables

- ▶ **Example:** X, Y are two independent discrete uniform random variables with the same range $\{0,1,2\}$.
 - ▶ CDF of X ? How about Y ?
 - ▶ Joint CDF of X and Y ?

Example: Continuous Uniform and Exponential

- ▶ **Example:** $X \sim \text{Unif}(0,1)$ and $Y \sim \text{Exp}(\lambda = 1)$ be two independent continuous random variables.
 - ▶ Joint CDF of X and Y ?

Property: Independence of 2 Discrete Random Variables

Joint PMF is the product of the marginal PMFs under independence:

If two discrete random variables X, Y are **independent**, then the joint PMF satisfies that

$$p_{XY}(x, y) = p_X(x) \cdot p_Y(y)$$

► **Proof:**

Property: Independence of 2 Continuous Random Variables

Joint PDF is the product of the marginal PDFs under independence:

If two continuous random variables X, Y are **independent**, then the joint PDF satisfies that

$$f_{XY}(t, u) = f_X(t) \cdot f_Y(u)$$

► **Proof:**

15-Minutes Brain Workout

