

# Lecture 5: Collections of Random Variables

Professor Ilias Bilonis

## Joint probability density function

# Discrete rvs: Joint probability mass function

- Consider two discrete random variables  $X$  and  $Y$ .
- The joint probability mass function of the pair  $(X, Y)$  is the function  $p(x, y)$  giving the probability that  $X = x$  and  $Y = y$ :

$$p(x, y) = p(X = x, Y = y)$$

# Properties of the joint pmf

- It is nonnegative:

$$p(x,y) \geq 0$$

- If you sum over all the possible values of all random variables, you should get one:

$$\sum_x \sum_y p(x,y) = 1$$

# Properties of the joint pmf

- If you **marginalize** over the values of one of the random variables you get the pmf of the other:

$$\sum_y p(x, y) = p(x)$$

(Sum rule:  $p(A) = \sum_i p(A, B_i)$ , where  $p(B_1 \text{ or } B_2 \text{ or } \dots) = 1$   
 $p(B_i, B_j) = 0, i \neq j$ .)

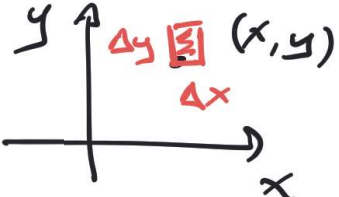
$$A = \{X=x\}, B_i = \{Y=y_i\}$$

- and

$$\sum_x p(x, y) = p(y)$$
$$A_i = \{X=x_i\}, B = \{Y=y\}$$

# Continuous rvs: Joint probability density function

- Consider two continuous random variables  $X$  and  $Y$ .
- The **joint probability density function** of the pair  $(X, Y)$  is the function  $p(x, y)$  giving the probability that  $X = x$  and  $Y = y$ :

$$p(x, y) \approx \frac{p(x \leq X \leq x + \Delta x, y \leq Y \leq y + \Delta y)}{\Delta x \Delta y}$$


,  $p(x, y) \geq 0$ ,  $\iint p(x, y) dx dy = 1$

# Properties of the jpdf

- If you **marginalize** over the values of one of the random variables you get the pdf of the other:

$$\int p(x,y) dy = p(x)$$

and

$$\int p(x,y) dx = p(y)$$

# Note on notation

- We will not distinguish between the notation of discrete and continuous random variables.

$$p(x) \begin{cases} pdf \\ pmf \end{cases}, p(x,y) \begin{cases} jpdf \\ jpmf \end{cases} \dots \text{or a mix}$$

- We will always use the integral sign to indicate marginalization understanding that it is a summation over all possible values if we have a discrete random variable.

$$\int \cdot dx \begin{cases} \sum_x & \text{if } X \text{ discrete} \\ \int \cdot dx & \text{if } X \text{ continuous} \end{cases}$$

- We will only say joint pdf instead of joint pmf.

$$pdf \begin{cases} pmf & \text{if } X \text{ discrete} \\ pdf & \text{if } X \text{ is cont.} \end{cases}$$

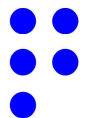
# Conditioning random variables on one another

- Take two random variables  $X$  and  $Y$  with joint pdf  $p(x, y)$ .
- Suppose that you observe  $Y = y$  and you want to update your state of knowledge about  $X$ .

$$p(A|B) = \frac{p(A, B)}{p(B)}$$

- The **conditional pdf** gives you this info:

$$A = \{X = x\}, \quad B = \{Y = y\} \quad \text{-- select events to assign to A and B}$$
$$p(X = x | Y = y) = \frac{p(X = x, Y = y)}{p(Y = y)}$$
$$p(x | y) = \frac{p(x, y)}{p(y)}$$





# The expectation of a sum of random variables

- Take two random variables  $X$  and  $Y$  with joint pdf  $p(x, y)$ .
- The expectation of their sum is:

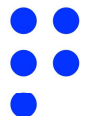
$$\mathbb{E}[X + Y] = \mathbb{E}[X] + \mathbb{E}[Y]$$

Proof:  $\mathbb{E}[X + Y] = \iint (x + y) p(x, y) dx dy$

$$= \iint x p(x, y) dx dy + \iint y p(x, y) dx dy$$
$$= \int x \left( \int p(x, y) dy \right) dx + \int y \left( \int p(x, y) dx \right) dy$$

$\downarrow$   $p(x)$                        $\downarrow$   $p(y)$

$$= \int x p(x) dx + \int y p(y) dy = \mathbb{E}[X] + \mathbb{E}[Y]$$



	$X=0$	$X=1$
$Y=0$	0.1	0.2
$Y=1$	0.2	0.5

$$\sum_{x,y} p(x,y) = 1$$

$$\sum_y p(x,y) = p(x) = \{0.3, 0.7\} \rightarrow E[X] = 0(0.3) + 1(0.7) = 0.7$$

$$\sum_x p(x,y) = p(y) = \{0.3, 0.7\} \rightarrow E[Y] = 0(0.3) + 1(0.7) = 0.7$$

$$E[X + 2Y] = E[X] + 2E[Y] = 2.1$$

$$p(x|y) = \frac{p(x,y)}{p(y)}$$

$$p(X=x|Y=0) = \frac{p(X=x, Y=0)}{p(Y=0)}$$

$$\hookrightarrow p(X=0|Y=0) = \frac{p(X=0, Y=0)}{p(Y=0)} = \frac{0.1}{0.3} = 0.333$$

$$\hookrightarrow p(X=1|Y=0) = \frac{p(X=1, Y=0)}{p(Y=0)} = \frac{0.2}{0.3} = 0.667$$

$$E[X|Y=0] = \sum_x x p(x|Y=0) = 0(0.333) + 1(0.667) = 0.667$$