

## LECTURE 7: Conditioning on a random variable; Independence of r.v.'s

- Conditional PMFs
  - Conditional expectations
  - Total expectation theorem
- Independence of r.v.'s
  - Expectation properties
  - Variance properties
- The variance of the binomial
- The hat problem: mean and variance

## Conditional PMFs

$$p_{X|A}(x | A) = \mathbf{P}(X = x | A)$$

$$p_{X|Y}(x | y) = \mathbf{P}(X = x | Y = y)$$

$$p_{X|Y}(x | y) = \frac{p_{X,Y}(x, y)}{p_Y(y)}$$

defined for  $y$  such that  $p_Y(y) > 0$

$$\sum_x p_{X|Y}(x | y) = 1$$

|   |      |      |      |      |
|---|------|------|------|------|
| 4 | 1/20 | 2/20 | 2/20 |      |
| 3 | 2/20 | 4/20 | 1/20 | 2/20 |
| 2 |      | 1/20 | 3/20 | 1/20 |
| 1 |      | 1/20 |      |      |
|   | 1    | 2    | 3    | 4    |

$$p_{X,Y}(x, y) = p_Y(y) p_{X|Y}(x | y)$$

$$p_{X,Y}(x, y) = p_X(x) p_{Y|X}(y | x)$$

## Conditional PMFs involving more than two r.v.'s

- Self-explanatory notation

$$p_{X|Y,Z}(x | y, z)$$

$$p_{X,Y|Z}(x, y | z)$$

- Multiplication rule

$$\mathbf{P}(A \cap B \cap C) = \mathbf{P}(A) \mathbf{P}(B | A) \mathbf{P}(C | A \cap B)$$

$$p_{X,Y,Z}(x, y, z) = p_X(x) p_{Y|X}(y | x) p_{Z|X,Y}(z | x, y)$$

## Conditional expectation

$$\mathbf{E}[X] = \sum_x x p_X(x) \quad \mathbf{E}[X | A] = \sum_x x p_{X|A}(x) \quad \mathbf{E}[X | Y = y] = \sum_x x p_{X|Y}(x | y)$$

- Expected value rule

$$\mathbf{E}[g(X)] = \sum_x g(x) p_X(x) \quad \mathbf{E}[g(X) | A] = \sum_x g(x) p_{X|A}(x) \quad \mathbf{E}[g(X) | Y = y] = \sum_x g(x) p_{X|Y}(x | y)$$

## Total probability and expectation theorems

- $A_1, \dots, A_n$ : partition of  $\Omega$
- $p_X(x) = \mathbf{P}(A_1) p_{X|A_1}(x) + \dots + \mathbf{P}(A_n) p_{X|A_n}(x)$

$$p_X(x) = \sum_y p_Y(y) p_{X|Y}(x|y)$$

- $\mathbf{E}[X] = \mathbf{P}(A_1) \mathbf{E}[X | A_1] + \dots + \mathbf{P}(A_n) \mathbf{E}[X | A_n]$

$$\mathbf{E}[X] = \sum_y p_Y(y) \mathbf{E}[X | Y = y]$$

- Fine print:  
Also valid when  $Y$  is a discrete r.v. that ranges over an infinite set,  
as long as  $\mathbf{E}[|X|] < \infty$



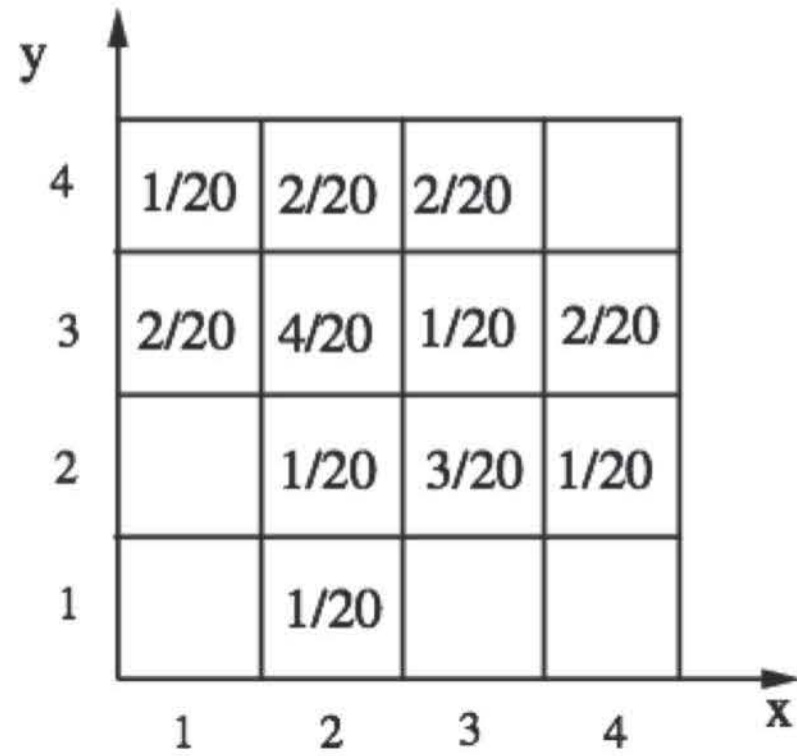
## Independence

- of two events:  $\mathbf{P(A \cap B) = P(A) \cdot P(B)}$   $\mathbf{P(A | B) = P(A)}$
- of a r.v. and an event:  $\mathbf{P(X = x \text{ and } A) = P(X = x) \cdot P(A)}$ , for all  $x$
- of two r.v.'s:  $\mathbf{P(X = x \text{ and } Y = y) = P(X = x) \cdot P(Y = y)}$ , for all  $x, y$   
 $p_{X,Y}(x, y) = p_X(x) p_Y(y)$ , for all  $x, y$

$X, Y, Z$  are **independent** if:

$$p_{X,Y,Z}(x, y, z) = p_X(x) p_Y(y) p_Z(z), \text{ for all } x, y, z$$

## Example: independence and conditional independence



- Independent?

- What if we condition on  $X \leq 2$  and  $Y \geq 3$ ?

## Independence and expectations

- In general:  $\mathbf{E}[g(X, Y)] \neq g(\mathbf{E}[X], \mathbf{E}[Y])$
- Exceptions:  $\mathbf{E}[aX + b] = a\mathbf{E}[X] + b$        $\mathbf{E}[X + Y + Z] = \mathbf{E}[X] + \mathbf{E}[Y] + \mathbf{E}[Z]$

If  $X, Y$  are **independent**:  $\mathbf{E}[XY] = \mathbf{E}[X]\mathbf{E}[Y]$

$g(X)$  and  $h(Y)$  are also independent:  $\mathbf{E}[g(X)h(Y)] = \mathbf{E}[g(X)] \cdot \mathbf{E}[h(Y)]$



## Independence and variances

- Always true:  $\text{var}(aX) = a^2\text{var}(X)$        $\text{var}(X + a) = \text{var}(X)$
- In general:  $\text{var}(X + Y) \neq \text{var}(X) + \text{var}(Y)$

If  $X, Y$  are independent:  $\text{var}(X + Y) = \text{var}(X) + \text{var}(Y)$

- Examples:
  - If  $X = Y$ :  $\text{var}(X + Y) =$
  - If  $X = -Y$ :  $\text{var}(X + Y) =$
  - If  $X, Y$  independent:  $\text{var}(X - 3Y) =$

## Variance of the binomial

- $X$ : binomial with parameters  $n, p$ 
  - number of successes in  $n$  independent trials

$X_i = 1$  if  $i$ th trial is a success;  
 $X_i = 0$  otherwise

(indicator variable)

$$X = X_1 + \cdots + X_n$$

## The hat problem

- $n$  people throw their hats in a box and then pick one at random
  - All permutations equally likely
  - Equivalent to picking one hat at a time
- $X$ : number of people who get their own hat
  - Find  $\mathbf{E}[X]$

$$X_i = \begin{cases} 1, & \text{if } i \text{ selects own hat} \\ 0, & \text{otherwise.} \end{cases}$$

$$X = X_1 + X_2 + \cdots + X_n$$

- $\mathbf{E}[X_i] =$

## The variance in the hat problem

- $X$ : number of people who get their own hat
  - Find  $\text{var}(X)$

$$X_i = \begin{cases} 1, & \text{if } i \text{ selects own hat} \\ 0, & \text{otherwise.} \end{cases}$$

$$X = X_1 + X_2 + \cdots + X_n$$

- $\text{var}(X) = \mathbf{E}[X^2] - (\mathbf{E}[X])^2$

$$X^2 = \sum_i X_i^2 + \sum_{i,j:i \neq j} X_i X_j$$

- $\mathbf{E}[X_i^2] =$

- For  $i \neq j$ :  $\mathbf{E}[X_i X_j] =$

- $\mathbf{E}[X^2] =$

MIT OpenCourseWare  
<https://ocw.mit.edu>

Resource: Introduction to Probability  
John Tsitsiklis and Patrick Jaillet

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