

# Discrete Random Variables: Basics

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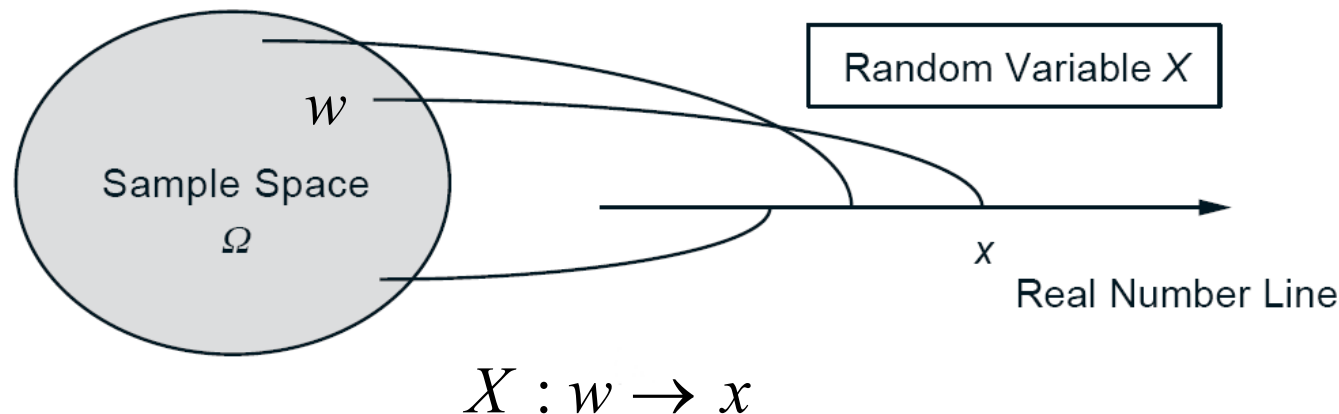
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Reference:

- D. P. Bertsekas, J. N. Tsitsiklis, *Introduction to Probability*, Sections 2.1-2.3

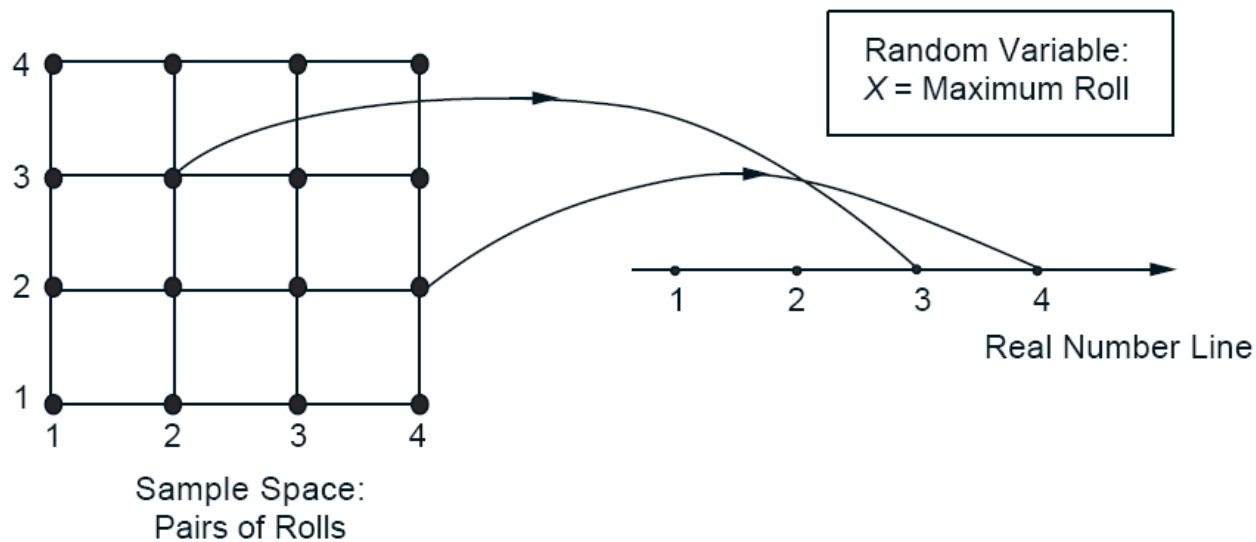
# Random Variables

- Given an experiment and the corresponding set of possible outcomes (the sample space), **a random variable associates a particular number with each outcome**
  - This number is referred to as the (numerical) value of the random variable
  - We can say **a random variable is a real-valued function of the experimental outcome**



# Random Variables: Example

- An experiment consists of two rolls of a 4-sided die, and the random variable is the **maximum** of the two rolls
  - If the outcome of the experiment is (4, 2), the value of this random variable is 4
  - If the outcome of the experiment is (3, 3), the value of this random variable is 3



- Can be one-to-one or many-to-one mapping

# Main Concepts Related to Random Variables

- For a probabilistic model of an experiment
  - A random variable is **a real-valued function** of the outcome of the experiment

$$X : \omega \rightarrow x$$

- A **function of a random variable** defines another random variable

$$Y = g(X)$$

- We can associate with each random variable certain “averages” of interest such the **mean** and the **variance**
- A random variable can be **conditioned** on an event or on another random variable
- There is a notion of **independence** of a random variable from an event or from another random variable

# Discrete/Continuous Random Variables

- A random variable is called **discrete** if its **range** (the set of values that it can take) is finite or at most countably infinite

finite :  $\{1, 2, 3, 4\}$ , countably infinite :  $\{1, 2, \dots\}$

- A random variable is called **continuous (not discrete)** if its **range** (the set of values that it can take) is uncountably infinite

– E.g., the experiment of choosing a point  $a$  from the interval  $[-1, 1]$

- A random variable that associates the numerical value  $a^2$  to the outcome  $a$  is not discrete
- In this chapter, we focus exclusively on discrete random variables

# Concepts Related to Discrete Random Variables

- For a probabilistic model of an experiment
  - A **discrete random variable** is a real-valued function of the outcome of the experiment that can take a finite or countably infinite number of values
  - A (discrete) random variable has an associated **probability mass function** (PMF), which gives the probability of each numerical value that the random variable can take
  - A **function of a random variable** defines another random variable, whose PMF can be obtained from the PMF of the original random variable

# Probability Mass Functions

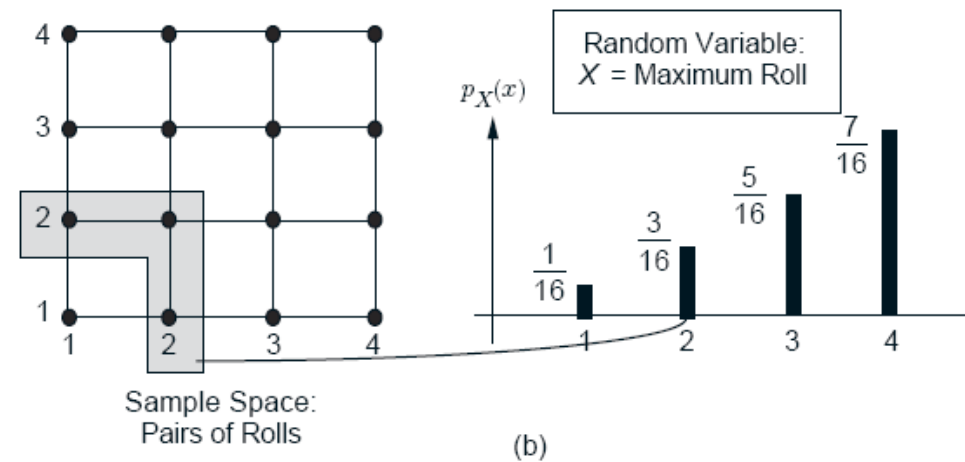
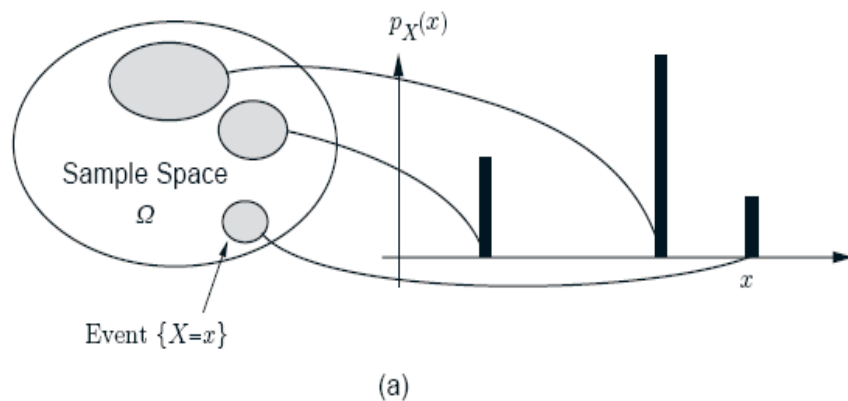
- A (discrete) random variable  $X$  is characterized through the probabilities of the values that it can take, which is captured by the **probability mass function** (PMF) of  $X$ , denoted  $p_X(x)$

$$p_X(x) = \mathbf{P}(\{X = x\}) \text{ or } p_X(x) = \mathbf{P}(X = x)$$

- The sum of probabilities of all outcomes that give rise to a value of  $X$  equal to  $x$
- **Upper case** characters (e.g.,  $X$ ) denote random variables, while **lower case** ones (e.g.,  $x$ ) denote the numerical values of a random variable
- The summation of the outputs of the PMF function of a random variable over all its possible numerical values is equal to one  $\sum_x p_X(x) = 1$  { $X=x$ }'s are disjoint and form a partition of the sample space

# Calculation of the PMF

- For each possible value  $x$  of a random variable  $X$  :
  1. Collect all the possible outcomes that give rise to the event  $\{X = x\}$
  2. Add their probabilities to obtain  $p_X(x)$
- An example: the PMF  $p_X(x)$  of the random variable  $X =$  **maximum** roll in two independent rolls of a fair 4-sided die





# Bernoulli Random Variable

- A Bernoulli random variable  $X$  takes two values 1 and 0 with probabilities  $p$  and  $1 - p$ , respectively

– **PMF**

$$p_X(x) = \begin{cases} p, & \text{if } x = 1 \\ 1 - p, & \text{if } x = 0 \end{cases}$$

- The Bernoulli random variable is often used to model generic probabilistic situations **with just two outcomes**
  1. The toss of a coin (outcomes: head and tail)
  2. A trial (outcomes: success and failure)
  3. the state of a telephone (outcomes: free and busy)...

# Binomial Random Variable (1/2)

- A binomial random variable  $X$  has parameters  $n$  and  $p$ 
  - PMF

$$p_X(k) = \mathbf{P}(X = k) = \binom{n}{k} p^k (1-p)^{n-k}, \quad k = 0, 1, \dots, n$$

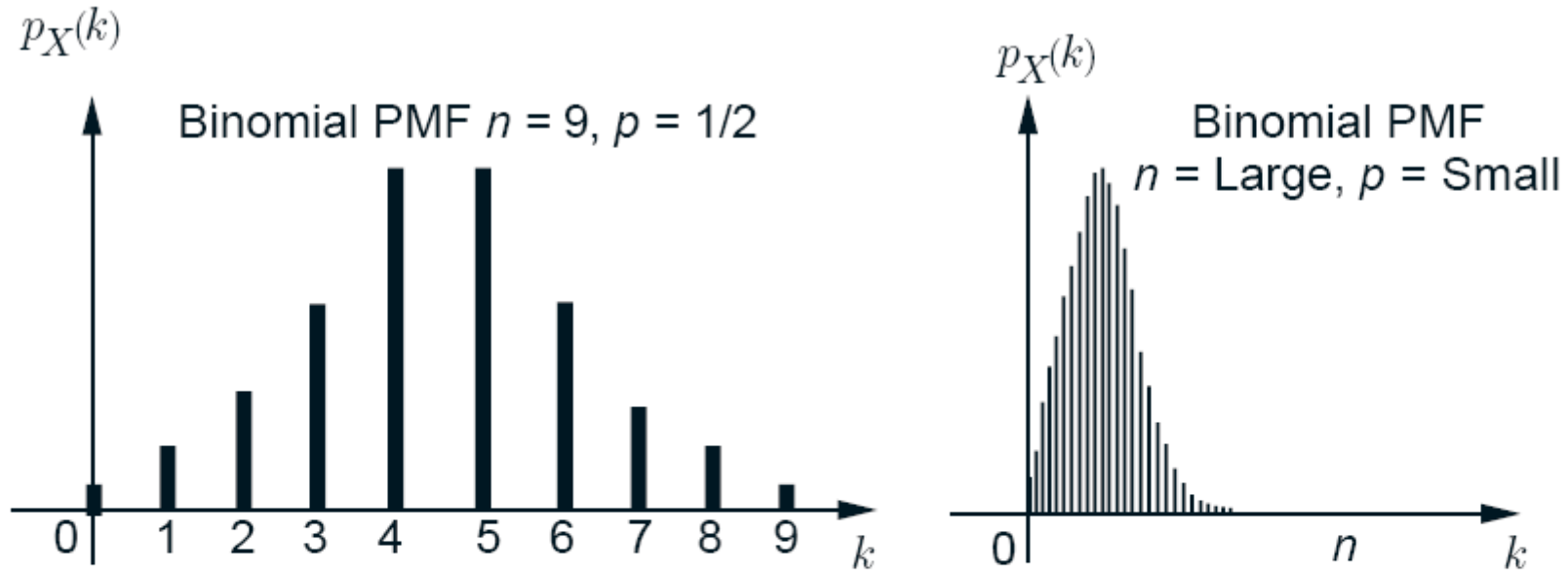
- The Bernoulli random variable can be used to model, e.g.
  1. The number of heads in  $n$  independent tosses of a coin (outcomes:  $1, 2, \dots, n$ ), each toss has probability  $p$  to be a head
  2. The number of successes in  $n$  independent trials (outcomes:  $1, 2, \dots, n$ ), each trial has probability  $p$  to be successful

- Normalization Property

$$\text{Note that : } (a+b)^n = \sum_{k=0}^n \binom{n}{k} a^k b^{n-k}$$

$$\sum_{k=0}^n p_X(k) = \sum_{k=0}^n \binom{n}{k} p^k (1-p)^{n-k} = 1$$

## Binomial Random Variable (2/2)

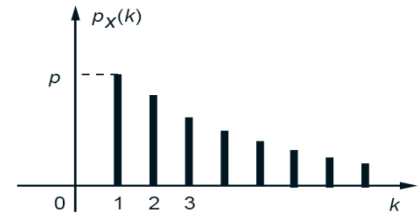


**Figure 2.3:** The PMF of a binomial random variable. If  $p = 1/2$ , the PMF is symmetric around  $n/2$ . Otherwise, the PMF is skewed towards 0 if  $p < 1/2$ , and towards  $n$  if  $p > 1/2$ .

# Geometric Random Variable

- A geometric random variable  $X$  has parameter  $p$  ( $0 < p < 1$ )
  - PMF

$$p_X(k) = (1 - p)^{k-1} p, \quad k = 1, 2, \dots,$$



- The geometric random variable can be used to model, e.g.
  - The number of independent tosses of a coin needed for a head to come up for the first time, each toss has probability  $p$  to be a head
  - The number of independent trials until (and including) the first “success”, each trial has probability  $p$  to be successful
- Normalization Property

$$\sum_{k=1}^{\infty} p_X(k) = \sum_{k=1}^{\infty} (1 - p)^{k-1} p = p \sum_{k=0}^{\infty} (1 - p)^k = p \frac{1}{1 - (1 - p)} = 1$$

# Poisson Random Variable (1/2)

- A Poisson random variable  $X$  has parameter  $\lambda$

- PMF

$$p_X(k) = e^{-\lambda} \frac{\lambda^k}{k!}, \quad k = 0, 1, 2, \dots,$$

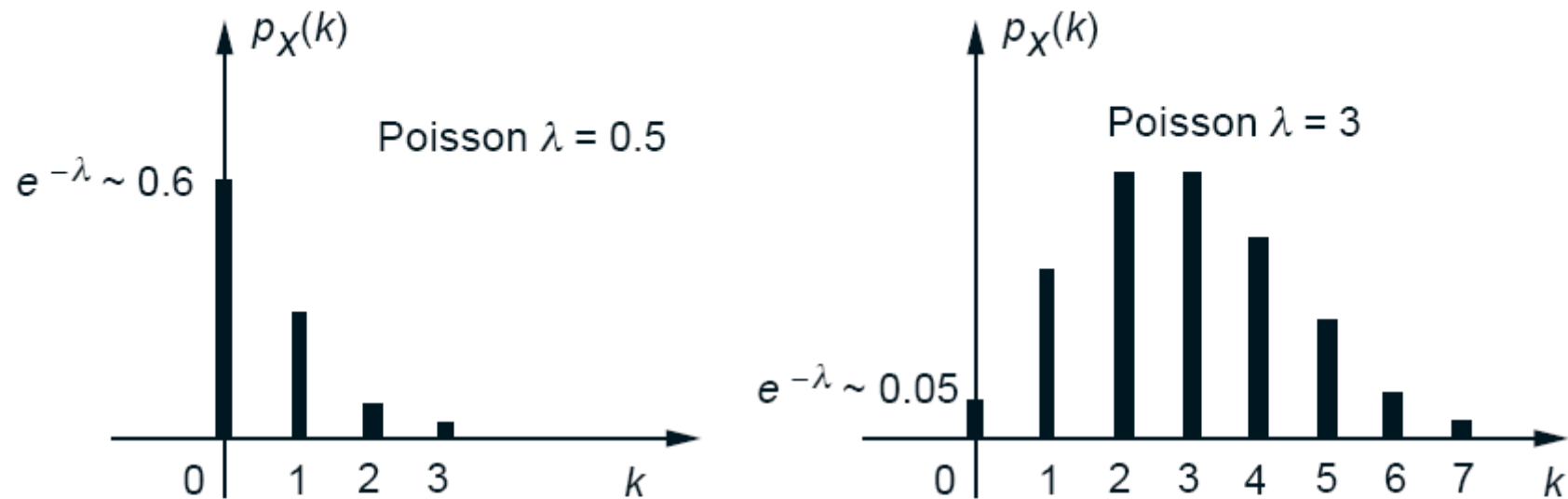
- The Poisson random variable can be used to model, e.g.
  - The number of typos in a book
  - The numbers of cars involved in an accidents in a city on a given day

- Normalization Property

$$\sum_{k=0}^{\infty} p_X(k) = \sum_{k=0}^{\infty} e^{-\lambda} \frac{\lambda^k}{k!} = e^{-\lambda} \left( \underbrace{1 + \lambda + \frac{\lambda^2}{2!} + \frac{\lambda^3}{3!} + \dots}_{e^{\lambda}} \right) = 1$$

McLaurin series

## Poisson Random Variable (2/2)



**Figure 2.5:** The PMF  $e^{-\lambda} \frac{\lambda^k}{k!}$  of the Poisson random variable for different values of  $\lambda$ . Note that if  $\lambda < 1$ , then the PMF is monotonically decreasing, while if  $\lambda > 1$ , the PMF first increases and then decreases as the value of  $k$  increases (this is shown in the end-of-chapter problems).

# Relationship between **Binomial** and **Poisson**

- The Poisson PMF with parameter  $\lambda$  is a good approximation for a binomial PMF with parameters  $n$  and  $p$ , provided that  $\lambda = np$ ,  $n$  is very large and  $p$  is very small

$$\begin{aligned}
 & \lim_{n \rightarrow \infty} \binom{n}{k} p^k (1-p)^{n-k} \\
 &= \lim_{n \rightarrow \infty} \frac{n!}{(n-k)! k!} p^k (1-p)^{n-k} \quad (\because \lambda = np \Rightarrow p = \frac{\lambda}{n}) \\
 &= \lim_{n \rightarrow \infty} \frac{n(n-1)\cdots(n-k+1)}{k!} \left(\frac{\lambda}{n}\right)^k \left(1 - \frac{\lambda}{n}\right)^{n-k} \\
 &= \lim_{n \rightarrow \infty} \frac{\lambda^k}{k!} \frac{n(n-1)\cdots(n-k+1)}{n^k} \left(1 - \frac{\lambda}{n}\right)^{n-k} \\
 &= \lim_{n \rightarrow \infty} \frac{\lambda^k}{k!} \left(\frac{n}{n}\right) \left(\frac{n-1}{n}\right) \cdots \left(\frac{n-k+1}{n}\right) \left(1 - \frac{\lambda}{n}\right)^{n-k} \quad (\because \lim_{n \rightarrow \infty} \left(1 + \frac{x}{n}\right)^n = e^x) \\
 &= \lim_{n \rightarrow \infty} \frac{\lambda^k}{k!} e^{-\lambda}
 \end{aligned}$$

# Functions of Random Variables (1/2)

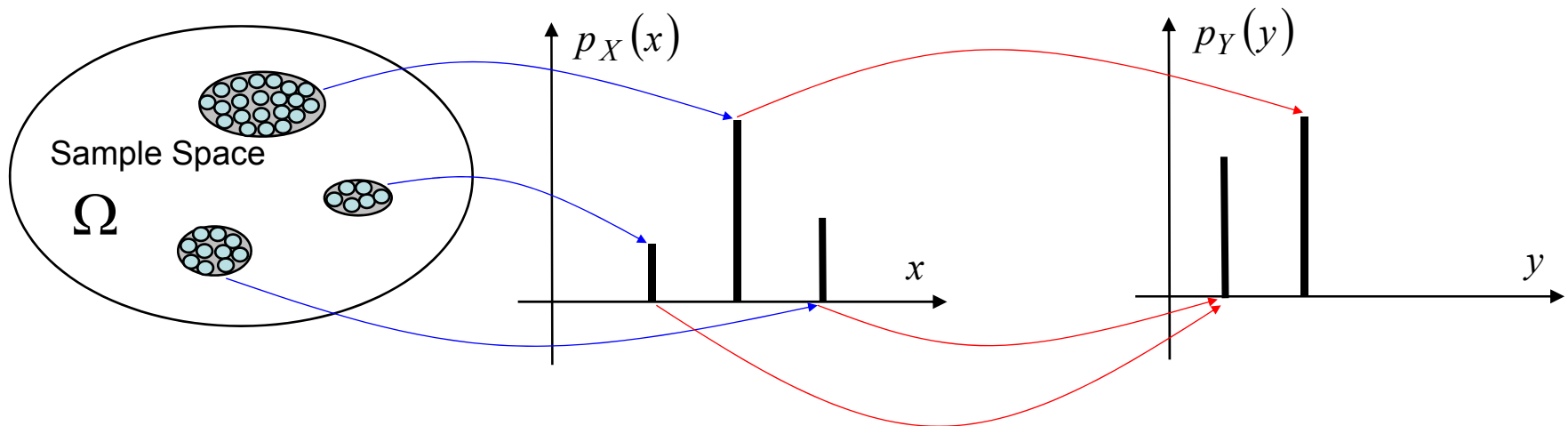
- Given a random variable  $X$ , other random variables can be generated by applying various transformations on  $X$

– Linear  $Y = g(X) = aX + b$

Daily temperature  
in degree Fahrenheit

Daily temperature  
in degree Celsius

– Nonlinear  $Y = g(X) = \log X$



one-to-one  
or many to one

one-to-one  
or many to one



## Functions of Random Variables (2/2)

- That is, if  $Y$  is an function of  $X$  ( $Y = g(X)$ ), then  $Y$  is also a random variable
  - If  $X$  is discrete with PMF  $p_X(x)$ , then  $Y$  is also discrete and its PMF can be calculated using

$$p_Y(y) = \sum_{\{x|g(x)=y\}} p_X(x)$$

# Functions of Random Variables: An Example

**Example 2.1.** Let  $Y = |X|$  and let us apply the preceding formula for the PMF  $p_Y$  to the case where

$$p_X(x) = \begin{cases} 1/9 & \text{if } x \text{ is an integer in the range } [-4, 4], \\ 0 & \text{otherwise.} \end{cases}$$

The possible values of  $Y$  are  $y = 0, 1, 2, 3, 4$ . To compute  $p_Y(y)$  for some given value  $y$  from this range, we must add  $p_X(x)$  over all values  $x$  such that  $|x| = y$ . In particular, there is only one value of  $X$  that corresponds to  $y = 0$ , namely  $x = 0$ . Thus,

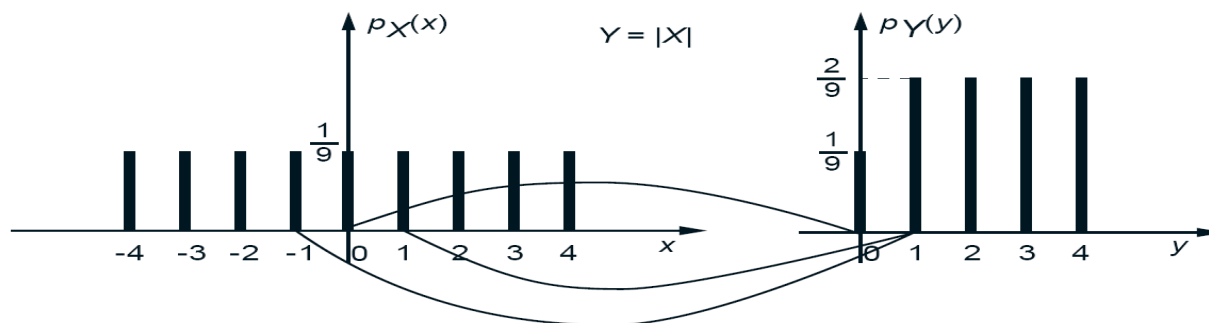
$$p_Y(0) = p_X(0) = \frac{1}{9}.$$

Also, there are two values of  $X$  that correspond to each  $y = 1, 2, 3, 4$ , so for example,

$$p_Y(1) = p_X(-1) + p_X(1) = \frac{2}{9}.$$

Thus, the PMF of  $Y$  is

$$p_Y(y) = \begin{cases} 2/9 & \text{if } y = 1, 2, 3, 4, \\ 1/9 & \text{if } y = 0, \\ 0 & \text{otherwise.} \end{cases}$$



# Recitation

- SECTION 2.2 Probability Mass Functions
  - Problems 3, 8, 10
- SECTION 2.3 Functions of Random Variables
  - Problems 13, 14