

# Random variables

Samy Tindel

Purdue University

Probability - MA 416

Mostly taken from *A first course in probability*  
by S. Ross

# Outline

- 1 Random variables
- 2 Discrete random variables
- 3 Expected value
- 4 Expectation of a function of a random variable
- 5 Variance
- 6 The Bernoulli and binomial random variables
- 7 The Poisson random variable
- 8 Other discrete random variables
- 9 Expected value of sums of random variables
- 10 Properties of the cumulative distribution function

# Outline

- 1 Random variables
- 2 Discrete random variables
- 3 Expected value
- 4 Expectation of a function of a random variable
- 5 Variance
- 6 The Bernoulli and binomial random variables
- 7 The Poisson random variable
- 8 Other discrete random variables
- 9 Expected value of sums of random variables
- 10 Properties of the cumulative distribution function

# Introduction

Experiment: tossing 3 coins

Model:

$$S = \{h, t\}^3, \mathbf{P}(\{s\}) = \frac{1}{8} \text{ for all } s \in S$$

Result of the experiment: we are interested in the quantity

$$X(s) = \text{"\# Heads obtained when } s \text{ is realized"}$$

# Introduction (2)

Table for the outcomes:

$s$	$X(s)$	$s$	$X(s)$
$(t, t, t)$	0	$(h, t, t)$	1
$(t, t, h)$	1	$(h, t, h)$	2
$(t, h, t)$	1	$(h, h, t)$	2
$(t, h, h)$	2	$(h, h, h)$	3

# Introduction (3)

Information about  $X$ :

$X$  is considered as an application, i.e.

$$X : S \rightarrow \{0, 1, 2, 3\}.$$

Then we wish to understand sets like

$$X^{-1}(\{2\}) = \{(t, h, h), (h, t, h), (h, h, t)\}$$

or quantities like

$$\mathbf{P} \left( X^{-1}(\{2\}) \right) = \frac{3}{8}.$$

This will be formalized in this chapter

# Example: time of first success (1)

## Experiment:

- Coin having probability  $p$  of coming up heads
- Independent trials: flipping the coin
- Stopping rule: either  $H$  occurs or  $n$  flips made

## Random variable:

$X = \#$  of times the coin is flipped

## State space:

$$X \in \{1, \dots, n\}$$

## Example: time of first success (2)

Probabilities for  $j < n$ :

$$\mathbf{P}(X = j) = \mathbf{P}(\{(t, \dots, t, h)\}) = (1 - p)^{j-1} p$$

Probability for  $j = n$ :

$$\mathbf{P}(X = n) = \mathbf{P}(\{(t, \dots, t, h); (t, \dots, t, t)\}) = (1 - p)^{n-1}$$



## Example: time of first success (3)

Checking the sum of probabilities:

$$\begin{aligned}\mathbf{P}\left(\bigcup_{j=1}^n \{X = j\}\right) &= \sum_{j=1}^n \mathbf{P}(\{X = j\}) \\ &= p \sum_{j=1}^{n-1} (1-p)^{j-1} + (1-p)^n \\ &= 1\end{aligned}$$

# Cumulative distribution function

## Definition 1.

Let

- $\mathbf{P}$  a probability on a sample space  $S$
- $X : S \rightarrow \mathcal{E}$  a random variable, with  $\mathcal{E} \subset \mathbb{R}$

For  $x \in \mathbb{R}$  we define

$$F(x) = \mathbf{P}(X \leq x)$$

Then the function  $F$  is called **cumulative distribution function** or distribution function

# Outline

- 1 Random variables
- 2 Discrete random variables**
- 3 Expected value
- 4 Expectation of a function of a random variable
- 5 Variance
- 6 The Bernoulli and binomial random variables
- 7 The Poisson random variable
- 8 Other discrete random variables
- 9 Expected value of sums of random variables
- 10 Properties of the cumulative distribution function

# General definition

## Definition 2.

Let

- $\mathbf{P}$  a probability on a sample space  $S$
- $X : S \rightarrow \mathcal{E}$  a random variable

**Hypothesis:**  $\mathcal{E}$  is countable, i.e

$$\mathcal{E} = \{x_i; i \geq 1\}$$

Then we say that  $X$  is a **discrete random variable**

# Probability mass function

## Definition 3.

Let

- $\mathbf{P}$  a probability on a sample space  $S$
- $\mathcal{E} = \{x_i; i \geq 1\}$  countable state space
- $X : S \rightarrow \mathcal{E}$  discrete random variable

For  $i \geq 1$  we set

$$p(x_i) = \mathbf{P}(X = x_i)$$

Then the **probability mass function** of  $X$  is the family

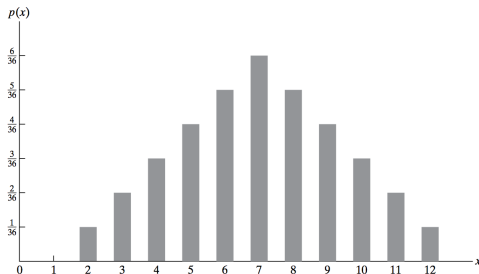
$$\{p(x_i); i \geq 1\}$$

# Remarks

Sum of the pmf: If  $p$  is the pmf of  $X$ , then

$$\sum_{i \geq 1} p(x_i) = 1$$

Graph of a pmf: Bar graphs are often used.  
Below an example for  $X = \text{sum of two dice}$



# Example of pmf computation (1)

**Definition of the pmf:** Let  $X$  be a r.v with pmf given by

$$p(i) = c \frac{\lambda^i}{i!}, \quad i \geq 0,$$

where  $c > 0$  is a normalizing constant

**Question:** Compute

- 1  $\mathbf{P}(X = 0)$
- 2  $\mathbf{P}(X > 2)$

## Example of pmf computation (2)

Computing  $c$ : We must have

$$c \sum_{i=0}^{\infty} \frac{\lambda^i}{i!} = 1$$

Thus

$$c = e^{-\lambda}$$

Computing  $\mathbf{P}(X = 0)$ : We have

$$\mathbf{P}(X = 0) = e^{-\lambda} \frac{\lambda^0}{0!} = e^{-\lambda}$$



## Example of pmf computation (3)

Computing  $\mathbf{P}(X > 2)$ : We have

$$\mathbf{P}(X > 2) = 1 - \mathbf{P}(X \leq 2)$$

Thus

$$\mathbf{P}(X > 2) = 1 - e^{-\lambda} \left( 1 + \lambda + \frac{\lambda^2}{2} \right)$$

# Cdf for discrete random variables

## Proposition 4.

Let

- $\mathbf{P}$  a probability on a sample space  $S$
- $\mathcal{E} = \{x_i; i \geq 1\}$  countable state space, with  $\mathcal{E} \subset \mathbb{R}$
- $X : S \rightarrow \mathcal{E}$  discrete random variable
- $F$  cdf of  $X$  and  $p$  pmf of  $X$

Then

- 1  $F$  can be expressed as

$$F(a) = \sum_{i \geq 1; x_i \leq a} p(x_i)$$

- 2  $F$  is a step function

# Example of discrete cdf (1)

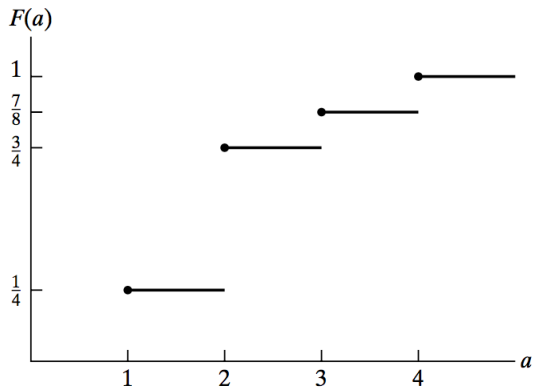
Definition of the random variable:

Consider  $X : S \rightarrow \{1, 2, 3, 4\}$  given by

$$p(1) = \frac{1}{4}, \quad p(2) = \frac{1}{2}, \quad p(3) = \frac{1}{8}, \quad p(4) = \frac{1}{8}$$

# Example of discrete cdf (2)

Graph of  $F$ :



# Outline

- 1 Random variables
- 2 Discrete random variables
- 3 Expected value**
- 4 Expectation of a function of a random variable
- 5 Variance
- 6 The Bernoulli and binomial random variables
- 7 The Poisson random variable
- 8 Other discrete random variables
- 9 Expected value of sums of random variables
- 10 Properties of the cumulative distribution function

# Expected value for discrete random variables

## Definition 5.

Let

- $\mathbf{P}$  a probability on a sample space  $S$
- $\mathcal{E} = \{x_i; i \geq 1\}$  countable state space, with  $\mathcal{E} \subset \mathbb{R}$
- $X : S \rightarrow \mathcal{E}$  discrete random variable
- $p$  pmf of  $X$

Then we define

$$\mathbf{E}[X] = \sum_{i \geq 1} x_i \mathbf{P}(X = x_i) = \sum_{i \geq 1} x_i p(x_i)$$

# Justification of the definition

## Experiment:

- Run independent copies of the random variable  $X$
- For  $i$ -th copy, the measurement is  $z_i$

## Result (to be proved much later):

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n z_i = \mathbf{E}[X]$$

# Example: dice rolling (1)

Definition of the random variable: we consider

$X =$  outcome when we roll a fair dice



## Example: dice rolling (2)

Recall: we consider

$X$  = outcome when we roll a fair dice

Pmf: We have  $\mathcal{E} = \{1, \dots, 6\}$  and

$$p(1) = \dots = p(6) = \frac{1}{6}$$

Expected value: We get

$$\mathbf{E}[X] = \sum_{i=1}^6 i p(i) = \frac{1}{6} \sum_{i=1}^6 i = \frac{7}{2}$$

# Example: indicator of an event (1)

Definition of the random variable:

Let  $A$  event with  $\mathbf{P}(A) = p$  and set

$$\mathbf{1}_A = \begin{cases} 1 & \text{if } A \text{ occurs} \\ 0 & \text{if } A^c \text{ occurs} \end{cases}$$

## Example: indicator of an event (2)

Recall:

Let  $A$  event with  $\mathbf{P}(A) = p$  and set

$$\mathbf{1}_A = \begin{cases} 1 & \text{if } A \text{ occurs} \\ 0 & \text{if } A^c \text{ occurs} \end{cases}$$

Pmf:

$$p(0) = 1 - p, \quad p(1) = p$$

Expected value:

$$\mathbf{E}[\mathbf{1}_A] = p$$

# Outline

- 1 Random variables
- 2 Discrete random variables
- 3 Expected value
- 4 Expectation of a function of a random variable**
- 5 Variance
- 6 The Bernoulli and binomial random variables
- 7 The Poisson random variable
- 8 Other discrete random variables
- 9 Expected value of sums of random variables
- 10 Properties of the cumulative distribution function

# First attempt of a definition

**Problem:** Let

- $X$  discrete random variable
- $Y = g(X)$  for a function  $g$

How can we compute  $\mathbf{E}[g(X)]$ ?

**First strategy:**

- $Y = g(X)$  is a discrete random variable
- Determine the pmf  $p_Y$  of  $Y$
- Compute  $\mathbf{E}[Y]$  according to Definition 5

# First attempt: example (1)

Definition of a random variable  $X$ :

Let  $X : S \rightarrow \{-1, 0, 1\}$  with

$$\mathbf{P}(X = -1) = .2, \quad \mathbf{P}(X = 0) = .5, \quad \mathbf{P}(X = 1) = .3$$

We wish to compute  $\mathbf{E}[X^2]$

## First attempt: example (2)

Definition of a random variable  $Y$ : Set  $Y = X^2$ .

Then  $Y \in \{0, 1\}$  and

$$\mathbf{P}(Y = 0) = \mathbf{P}(X = 0) = .5$$

$$\mathbf{P}(Y = 1) = \mathbf{P}(X = -1) + \mathbf{P}(X = 1) = .5$$

## First attempt: example (3)

Recall: For  $Y = X^2$  we have

$$\mathbf{P}(Y = 0) = .5, \quad \mathbf{P}(Y = 1) = .5$$

Expected value:

$$\mathbf{E}[X^2] = \mathbf{E}[Y] = .5$$



# Definition of $\mathbf{E}[g(X)]$

## Proposition 6.

Let

- $X$  discrete random variable
- $p$  pmf of  $X$
- $g$  real valued function

Then

$$\mathbf{E}[g(X)] = \sum_{i \geq 1} g(x_i) p(x_i) \quad (1)$$

# Proof

Values of  $Y$ : We set  $Y = g(X)$  and

$$\{y_j; j \geq 1\} = \text{values of } g(x_i) \text{ for } i \geq 1$$

Expression for the rhs of (1): gather according to  $y_j$

$$\begin{aligned} \sum_{i \geq 1} g(x_i) p(x_i) &= \sum_{j \geq 1} \sum_{i; g(x_i)=y_j} y_j p(x_i) \\ &= \sum_{j \geq 1} y_j \sum_{i; g(x_i)=y_j} p(x_i) \\ &= \sum_{j \geq 1} y_j \mathbf{P}(g(X) = y_j) \\ &= \sum_{j \geq 1} y_j \mathbf{P}(Y = y_j) \\ &= \mathbf{E}[g(X)] \end{aligned}$$

# Previous example reloaded

Definition of a random variable  $X$ :

Let  $X : S \rightarrow \{-1, 0, 1\}$  with

$$\mathbf{P}(X = -1) = .2, \quad \mathbf{P}(X = 0) = .5, \quad \mathbf{P}(X = 1) = .3$$

We wish to compute  $\mathbf{E}[X^2]$

Application of (1):

$$\mathbf{E}[X^2] = \sum_{i=-1,0,1} i^2 p(x_i) = .5$$

# Example: seasonal product (1)

## Situation:

- Product sold seasonally
- Profit  $b$  for each unit sold
- Loss  $\ell$  for each unit left unsold
- Product has to be stocked in advance  
↔  $s$  units stocked

## Random variable:

- $X = \#$  units of product ordered
- Pmf  $p$  for  $X$

## Question:

Find optimal  $s$  in order to maximize profits

## Example: seasonal product (2)

Some random variables: We set

$X$  = # units ordered, with pmf  $p$

$Y_s$  = profit when  $s$  units stocked

Expression for  $Y_s$ :

$$Y_s = (bX - (s - X)\ell) \mathbf{1}_{(X \leq s)} + s b \mathbf{1}_{(X > s)}$$

Expression for  $\mathbf{E}[Y_s]$ :

$$\mathbf{E}[Y_s] = \sum_{i=0}^s (bi - (s - i)\ell) p(i) + \sum_{i=s+1}^{\infty} s b p(i)$$

## Example: seasonal product (3)

Simplification for  $\mathbf{E}[Y_s]$ : We get

$$\mathbf{E}[Y_s] = s b + (b + \ell) \sum_{i=0}^s (i - s) p(i)$$

Growth of  $s \mapsto \mathbf{E}[Y_s]$ : We have

$$\mathbf{E}[Y_{s+1}] - \mathbf{E}[Y_s] = b - (b + \ell) \sum_{i=0}^s p(i)$$

## Example: seasonal product (4)

Growth of  $s \mapsto \mathbf{E}[Y_s]$  (Ctd): We obtain

$$\mathbf{E}[Y_{s+1}] - \mathbf{E}[Y_s] > 0 \iff \sum_{i=0}^s p(i) < \frac{b}{b+l} \quad (2)$$

Optimization:

- The lhs of (2) is  $\nearrow$
- The rhs of (2) is constant
- Thus there exists a  $s^*$  such that

$$\mathbf{E}[Y_0] < \cdots < \mathbf{E}[Y_{s^*-1}] < \mathbf{E}[Y_{s^*}] > \mathbf{E}[Y_{s^*+1}] > \cdots$$

Conclusion:  $s^*$  leads to maximal expected profit

# Expectation and linear transformations

## Proposition 7.

Let

- $X$  discrete random variable
- $p$  pmf of  $X$
- $a, b \in \mathbb{R}$  constants

Then

$$\mathbf{E}[aX + b] = a \mathbf{E}[X] + b$$



# Proof

Application of relation (1):

$$\begin{aligned}\mathbf{E}[aX + b] &= \sum_{i \geq 1} (a x_i + b) p(x_i) \\ &= a \sum_{i \geq 1} x_i p(x_i) + b \sum_{i \geq 1} p(x_i) \\ &= a \mathbf{E}[X] + b\end{aligned}$$

# Outline

- 1 Random variables
- 2 Discrete random variables
- 3 Expected value
- 4 Expectation of a function of a random variable
- 5 Variance**
- 6 The Bernoulli and binomial random variables
- 7 The Poisson random variable
- 8 Other discrete random variables
- 9 Expected value of sums of random variables
- 10 Properties of the cumulative distribution function

# Definition of variance

## Definition 8.

Let

- $X$  discrete random variable
- $p$  pmf of  $X$
- $\mu = \mathbf{E}[X]$

Then we define  $\mathbf{Var}(X)$  by

$$\mathbf{Var}(X) = \mathbf{E}[(X - \mu)^2]$$

# Interpretation

**Expected value:** For a r.v  $X$ ,  $\mathbf{E}[X]$  represents the mean value of  $X$ .

**Variance:** For a r.v  $X$ ,  $\mathbf{Var}(X)$  represents the dispersion of  $X$  wrt its mean value.

A greater  $\mathbf{Var}(X)$  means

- The system represented by  $X$  has a lot of randomness
- This system is unpredictable

**Standard deviation:** For physical reasons, it is better to introduce

$$\sigma_X := \sqrt{\mathbf{Var}(X)}.$$

## Interpretation (2)

**Illustration (from descriptive stats):** We wish to compare the performances of 2 soccer players on their last 5 games

Griezmann	5	0	0	0	0
Messi	1	1	1	1	1

**Recall:** for a set of data  $\{x_i; i \leq n\}$ , we have

Empirical mean:  $\bar{x}_n = \frac{1}{n} \sum_{i=1}^n x_i$

Empirical variance:  $s_n^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x}_n)^2$

Standard deviation:  $s_n = \sqrt{s_n^2}$

**On our data set:**  $\bar{x}_G = \bar{x}_M = 1$  goal/game

↪ Same goal average

However,  $s_G = 2$  goals/game while  $s_M = 0$  goals/game

↪ M more reliable (less random) than G

# Alternative expression for the variance

## Proposition 9.

Let

- $X$  discrete random variable
- $p$  pmf of  $X$
- $\mu = \mathbf{E}[X]$

Then  $\mathbf{Var}(X)$  can be written as

$$\mathbf{Var}(X) = \mathbf{E}[X^2] - \mu^2 = \mathbf{E}[X^2] - (\mathbf{E}[X])^2$$

# Example: rolling a dice

Random variable:

- $X$  = outcome when one rolls 1 dice

Variance computation: We find

$$\mathbf{E}[X] = \frac{7}{2}, \quad \mathbf{E}[X^2] = \frac{91}{6}$$

Therefore

$$\mathbf{Var}(X) = \frac{91}{6} - \left(\frac{7}{2}\right)^2 = \frac{35}{12}$$

Standard deviation:

$$\sigma_X = \sqrt{\frac{35}{12}} \simeq 1.71$$

# Variance and linear transformations

## Proposition 10.

Let

- $X$  discrete random variable
- $p$  pmf of  $X$
- $a, b \in \mathbb{R}$  constants

Then

$$\mathbf{Var}(aX + b) = a^2 \mathbf{Var}(X)$$



# Outline

- 1 Random variables
- 2 Discrete random variables
- 3 Expected value
- 4 Expectation of a function of a random variable
- 5 Variance
- 6 The Bernoulli and binomial random variables**
- 7 The Poisson random variable
- 8 Other discrete random variables
- 9 Expected value of sums of random variables
- 10 Properties of the cumulative distribution function

# Bernoulli random variable (1)

Notation:

$$X \sim \mathcal{B}(p) \text{ with } p \in (0, 1)$$

State space:

$$\{0, 1\}$$

Pmf:

$$\mathbf{P}(X = 0) = 1 - p, \quad \mathbf{P}(X = 1) = p$$

Expected value and variance:

$$\mathbf{E}[X] = p, \quad \mathbf{Var}(X) = p(1 - p)$$

# Bernoulli random variable (2)

## Use 1, success in a binary game:

- Example 1: coin tossing
  - ▶  $X = 1$  if H,  $X = 0$  if T
  - ▶ We get  $X \sim \mathcal{B}(1/2)$
- Example 2: dice rolling
  - ▶  $X = 1$  if outcome = 3,  $X = 0$  otherwise
  - ▶ We get  $X \sim \mathcal{B}(1/6)$

## Use 2, answer yes/no in a poll

- $X = 1$  if a person feels optimistic about the future
- $X = 0$  otherwise
- We get  $X \sim \mathcal{B}(p)$ , with unknown  $p$

# Jacob Bernoulli

## Some facts about Bernoulli:

- Lifespan: 1654-1705, in Switzerland
- Discovers constant  $e$
- Establishes divergence of  $\sum \frac{1}{n}$
- Contributions in diff. eq
- First law of large numbers
- Bernoulli:  
family of 8 prominent mathematicians
- Fierce math fights between brothers



# Binomial random variable (1)

Notation:

$$X \sim \text{Bin}(n, p), \text{ for } n \geq 1, p \in (0, 1)$$

State space:

$$\{0, 1, \dots, n\}$$

Pmf:

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

Expected value and variance:

$$\mathbf{E}[X] = np, \quad \mathbf{Var}(X) = np(1 - p)$$

# Binomial random variable (2)

## Use 1, Number of successes in a Bernoulli trial:

- Example: Roll a dice 9 times.
- $X = \#$  of 3 obtained
- We get  $X \sim \text{Bin}(9, 1/6)$
- $\mathbf{P}(X = 2) = 0.28$

## Use 2: Counting a feature in a repeated trial:

- Example: stock of 1000 pants with 10% defects
- Draw 15 times a pant at random
- $X = \#$  of pants with a defect
- We get  $X \sim \text{Bin}(15, 1/10)$

# Binomial random variable (3)

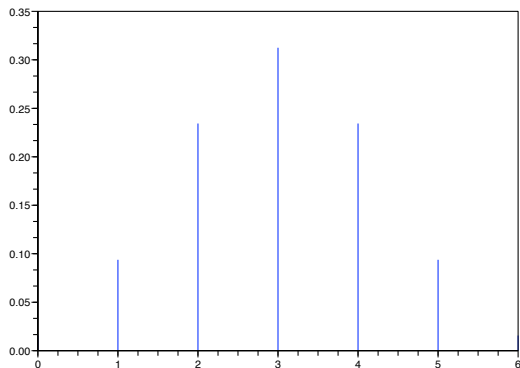


Figure: Pmf for Bin(6; 0.5). x-axis:  $k$ . y-axis:  $\mathbf{P}(X = k)$

# Binomial random variable (4)

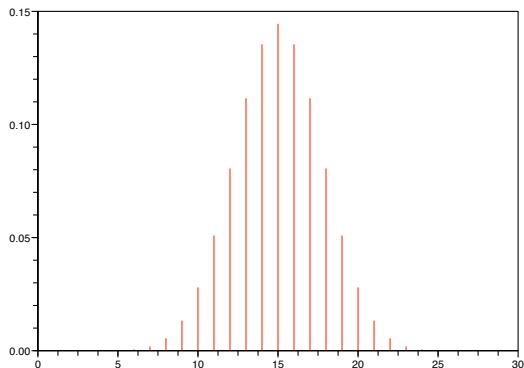


Figure: Pmf for  $\text{Bin}(30; 0.5)$ .  $x$ -axis:  $k$ .  $y$ -axis:  $P(X = k)$



# Example: wheel of fortune (1)

## Game:

- Player bets on  $1, \dots, 6$  (say 1)
- 3 dice rolled
- If 1 does not appear, loose \$1
- If 1 appear  $i$  times, win \$ $i$

## Question:

Find average win

## Example: wheel of fortune (2)

### Binomial random variable:

- Let  $X = \#$  times 1 appears
- Then  $X \sim \text{Bin}(3, \frac{1}{6})$

### Expression for the win: Set $W = \text{win}$ . Then

- $W = \varphi(X)$  with  
 $\hookrightarrow \varphi(0) = -1$  and  $\varphi(i) = i$  for  $i = 1, 2, 3$
- Other expression:

$$W = X - \mathbf{1}_{(X=0)}$$

## Example: wheel of fortune (3)

Average win:

$$\begin{aligned} \mathbf{E}[W] &= \mathbf{E}[X] - \mathbf{P}(X = 0) \\ &= \frac{1}{2} - \left(\frac{5}{6}\right)^3 \\ &= -\frac{17}{216} \end{aligned}$$

Conclusion: The average win is

$$\mathbf{E}[W] \simeq -\$0.079$$

# Pmf variations for a binomial r.v

## Proposition 11.

Let

- $X \sim \text{Bin}(n, p)$
- $q = \text{Pmf of } X$
- $k^* = \lfloor (n+1)p \rfloor$

Then we have

- $k \mapsto q(k)$  is  $\nearrow$  if  $k < k^*$
- $k \mapsto q(k)$  is  $\searrow$  if  $k > k^*$
- **Maximum of  $q$  attained for  $k = k^*$**

# Proof

Pmf computation: We have

$$\frac{q(k)}{q(k-1)} = \frac{\mathbf{P}(X = k)}{\mathbf{P}(X = k-1)} = \frac{(n-k+1)p}{k(1-p)}$$

Pmf growth: We get

$$\mathbf{P}(X = k) \geq \mathbf{P}(X = k-1) \iff k \leq (n+1)p$$

# Outline

- 1 Random variables
- 2 Discrete random variables
- 3 Expected value
- 4 Expectation of a function of a random variable
- 5 Variance
- 6 The Bernoulli and binomial random variables
- 7 The Poisson random variable**
- 8 Other discrete random variables
- 9 Expected value of sums of random variables
- 10 Properties of the cumulative distribution function

# Poisson random variable (1)

Notation:

$$\mathcal{P}(\lambda) \text{ for } \lambda \in \mathbb{R}_+$$

State space:

$$E = \mathbb{N} \cup \{0\}$$

Pmf:

$$\mathbf{P}(X = k) = e^{-\lambda} \frac{\lambda^k}{k!}, \quad k \geq 0$$

Expected value and variance:

$$\mathbf{E}[X] = \lambda, \quad \mathbf{Var}(X) = \lambda$$

# Poisson random variable (2)

Use (examples):

- # customers getting into a shop from 2pm to 5pm
- # buses stopping at a bus stop in a period of 35mn
- # jobs reaching a server from 12am to 6am

Empirical rule:

If  $n \rightarrow \infty$ ,  $p \rightarrow 0$  and  $np \rightarrow \lambda$ , we approximate  $\text{Bin}(n, p)$  by  $\mathcal{P}(\lambda)$ .  
This is usually applied for

$$p \leq 0.1 \quad \text{and} \quad np \leq 5$$



# Poisson random variable (3)

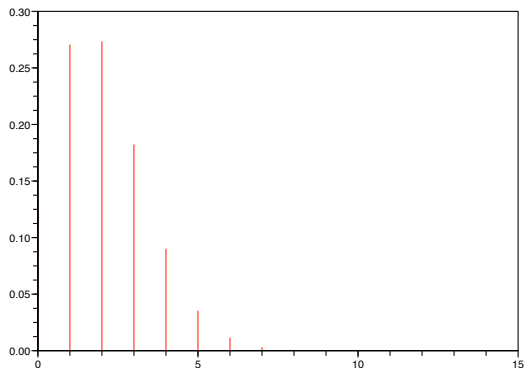


Figure: Pmf of  $\mathcal{P}(2)$ . x-axis:  $k$ . y-axis:  $\mathbf{P}(X = k)$

# Poisson random variable (4)

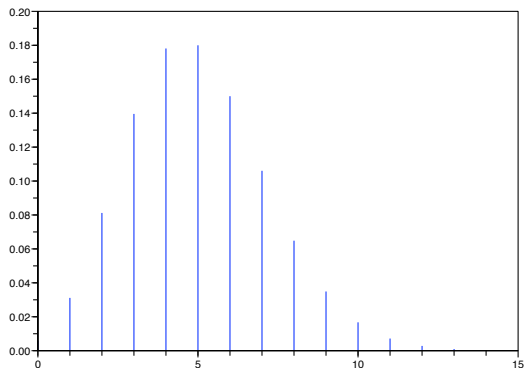
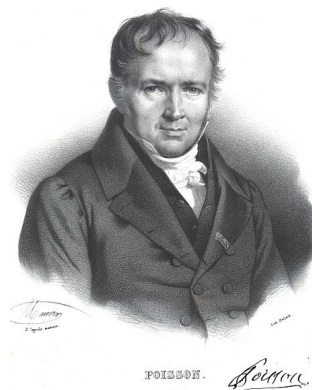


Figure: Pmf of  $\mathcal{P}(5)$ . x-axis:  $k$ . y-axis:  $\mathbf{P}(X = k)$

# Siméon Poisson

## Some facts about Poisson:

- Lifespan: 1781-1840, in  $\simeq$  Paris
- Engineer, Physicist and Mathematician
- Breakthroughs in electromagnetism
- Contributions in partial diff. eq  
celestial mechanics, Fourier series
- Marginal contributions in probability



## A quote by Poisson:

*Life is good for only two things: doing mathematics and teaching it!!*

# Example: drawing defective items (1)

## Experiment:

- Item produced by a certain machine will be defective  
↔ with probability .1
- Sample of 10 items drawn

## Question:

Probability that the sample contains at most 1 defective item

## Example: drawing defective items (2)

Random variable: Let

$X = \#$  of defective items

Then

$$X \sim \text{Bin}(n, p), \quad \text{with } n = 10, p = .1$$

Exact probability: We have to compute

$$\begin{aligned} \mathbf{P}(X \leq 1) &= \mathbf{P}(X = 0) + \mathbf{P}(X = 1) \\ &= (0.9)^{10} + 10 \times 0.1 \times (0.9)^9 \\ &= .7361 \end{aligned}$$

## Example: drawing defective items (3)

Approximation: We use

$$\text{Bin}(10, .1) \simeq \mathcal{P}(1)$$

Approximate probability: We have to compute

$$\begin{aligned} \mathbf{P}(X \leq 1) &= \mathbf{P}(X = 0) + \mathbf{P}(X = 1) \\ &\simeq e^{-1} (1 + 1) \\ &= .7358 \end{aligned}$$

# Poisson paradigm

**Situation:** Consider

- $n$  events  $E_1, \dots, E_n$
- $p_i = \mathbf{P}(E_i)$
- Weak dependence of the  $E_i$ :  $\mathbf{P}(E_i E_j) \lesssim \frac{1}{n}$
- $\lim_{n \rightarrow \infty} \sum_{i=1}^n p_i = \lambda$

**Heuristic limit:** Under the conditions above we expect that

$$X_n = \sum_{i=1}^n \mathbf{1}_{E_i} \rightarrow \mathcal{P}(\lambda) \quad (3)$$

# Example: matching problem (1)

## Situation:

- $n$  men take off their hats
- Hats are mixed up
- Then each man selects his hat at random
- Match: if a man selects his own hat

## Question: Compute

- $\mathbf{P}(E_k)$  with  $E_k =$  "exactly  $k$  matches"



## Example: matching problem (2)

Recall: We have found

$$\mathbf{P}(E_k) = \frac{1}{k!} \sum_{j=2}^{n-k} \frac{(-1)^j}{j!}$$

Thus

$$\lim_{n \rightarrow \infty} \mathbf{P}(E_k) = \frac{e^{-1}}{k!}$$

New events: We set

$G_i =$  "Person  $i$  selects his own hat"

## Example: matching problem (3)

Probabilities for  $G_j$ : We have

$$\mathbf{P}(G_i) = \frac{1}{n}, \quad \mathbf{P}(G_i | G_j) = \frac{1}{n-1}$$

Random variable of interest:

$$X = \sum_{i=1}^n \mathbf{1}_{G_i} \implies \mathbf{P}(E_k) = \mathbf{P}(X = k)$$

Poisson paradigm: From (3) we have  $X \simeq \mathcal{P}(1)$ . Therefore

$$\mathbf{P}(E_k) = \mathbf{P}(X = k) \simeq \mathbf{P}(\mathcal{P}(1) = k) = \frac{e^{-1}}{k!}$$

# Outline

- 1 Random variables
- 2 Discrete random variables
- 3 Expected value
- 4 Expectation of a function of a random variable
- 5 Variance
- 6 The Bernoulli and binomial random variables
- 7 The Poisson random variable
- 8 Other discrete random variables**
- 9 Expected value of sums of random variables
- 10 Properties of the cumulative distribution function

# Geometric random variable

Notation:

$$X \sim \mathcal{G}(p), \quad \text{for } p \in (0, 1)$$

State space:

$$E = \mathbb{N} = \{1, 2, 3, \dots\}$$

Pmf:

$$\mathbf{P}(X = k) = p(1 - p)^{k-1}, \quad k \geq 1$$

Expected value and variance:

$$\mathbf{E}[X] = \frac{1}{p}, \quad \mathbf{Var}(X) = \frac{1 - p}{p^2}$$

## Geometric random variable (2)

Use:

- Independent trials, with  $\mathbf{P}(\text{success}) = p$
- $X = \#$  trials until first success

Example: dice rolling

- Set  $X =$  1st roll for which outcome = 6
- We have  $X \sim \mathcal{G}(1/6)$

Computing some probabilities for the example:

$$\mathbf{P}(X = 5) = \left(\frac{5}{6}\right)^4 \frac{1}{6} \simeq 0.08$$

$$\mathbf{P}(X \geq 7) = \left(\frac{5}{6}\right)^6 \simeq 0.33$$

## Geometric random variable (3)

Computation of  $\mathbf{E}[X]$ : Set  $q = 1 - p$ . Then

$$\begin{aligned}\mathbf{E}[X] &= \sum_{i=1}^{\infty} i q^{i-1} p \\ &= \sum_{i=1}^{\infty} (i-1) q^{i-1} p + \sum_{i=1}^{\infty} q^{i-1} p \\ &= q \mathbf{E}[X] + 1\end{aligned}$$

Conclusion:

$$\mathbf{E}[X] = \frac{1}{p}$$

# Tail of a geometric random variable

## Proposition 12.

Let

- $X \sim \mathcal{G}(p)$
- $n \geq 1$

Then we have

$$\mathbf{P}(X \geq n) = (1 - p)^{n-1}$$

# Negative binomial random variable (1)

Notation:

$$X \sim \text{Nbin}(r, p), \text{ for } r \in \mathbb{N}^*, p \in (0, 1)$$

State space:

$$\{r, r + 1, r + 2 \dots\}$$

Pmf:

$$\mathbf{P}(X = k) = \binom{k-1}{r-1} p^r (1-p)^{k-r}, \quad k \geq r$$

Expected value and variance:

$$\mathbf{E}[X] = \frac{r}{p}, \quad \mathbf{Var}(X) = \frac{r(1-p)}{p^2}$$



## Negative binomial random variable (2)

Use:

- Independent trials, with  $\mathbf{P}(\text{success}) = p$
- $X = \#$  trials until  $r$  successes

Justification:

$$\begin{aligned} & (X = k) \\ & = \\ & (r - 1 \text{ successes in } (k - 1) \text{ 1st trials}) \cap (k\text{-th trial is a success}) \end{aligned}$$

Thus

$$\mathbf{P}(X = k) = \binom{k-1}{r-1} p^r (1-p)^{k-r}$$

# Moments of negative binomial random variable

## Proposition 13.

Let

- $X \sim \text{Nbin}(r, p)$ , for  $r \geq 1$ ,  $p \in (0, 1)$
- $Y \sim \text{Nbin}(r + 1, p)$
- $l \geq 1$

Then

$$\mathbf{E} [X^l] = \frac{r}{p} \mathbf{E} [(Y - 1)^{l-1}]$$

# Proof (1)

Definition of the  $l$ -th moment: We have

$$\mathbf{E} [X^l] = \sum_{k=r}^{\infty} k^l \binom{k-1}{r-1} p^r (1-p)^{k-r}$$

Relation for combination numbers:

$$k \binom{k-1}{r-1} = r \binom{k}{r}$$

Consequence:

$$\mathbf{E} [X^l] = r \sum_{k=r}^{\infty} k^{l-1} \binom{k}{r} p^r (1-p)^{k-r}$$

## Proof (2)

Recall:

$$\mathbf{E} [X^l] = r \sum_{k=r}^{\infty} k^{l-1} \binom{k}{r} p^r (1-p)^{k-r}$$

From  $r$  to  $r+1$ :

$$\mathbf{E} [X^l] = \frac{r}{p} \sum_{k=r}^{\infty} k^{l-1} \binom{k}{(r+1)-1} p^{r+1} (1-p)^{(k+1)-(r+1)}$$

Change of variable  $j = k + 1$ :

$$\begin{aligned} \mathbf{E} [X^l] &= \frac{r}{p} \sum_{j=r+1}^{\infty} (j-1)^{l-1} \binom{j-1}{(r+1)-1} p^{r+1} (1-p)^{j-(r+1)} \\ &= \frac{r}{p} \mathbf{E} [(Y-1)^{l-1}] \end{aligned}$$

# Computation of expectation and variance

Consequence of Proposition 13:

$$\mathbf{E}[X] = \frac{r}{p}, \quad \mathbf{Var}(X) = \frac{r(1-p)}{p^2}$$

# The Banach match problem (1)

## Situation:

- Pipe smoking mathematician with 2 matchboxes
- 1 box in left hand pocket, 1 box in right hand pocket
- Each time a match is needed, selected at random
- Both boxes contain initially  $N$  matches

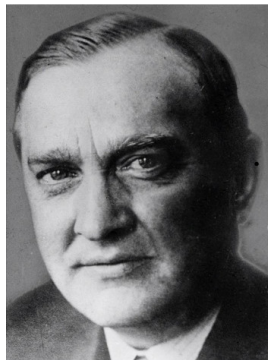
## Question:

- When one box is empty, what is the probability that  $k$  matches are left in the other box?

# Stefan Banach

## Some facts about Banach:

- Lifespan: 1892-1945, in Krakow and Lviv
- Among greatest 20-th century mathematicians
- Founder of a new field  
↔ Functional Analysis
- Survived 2 world wars in tough conditions
- Then dies in 1945 from lung cancer



## The Banach match problem (2)

Event: Define  $E_k$  by

(Math. discovers that rh box is empty &  $k$  matches in lh box)

Expression in terms of a negative binomial:

$$E_k = (X = N + 1 + N - k) = (X = 2N - k + 1),$$

where

$$X \sim \text{Nbin} \left( r = N + 1, p = \frac{1}{2} \right)$$



# The Banach match problem (3)

Probability of  $E_k$ : We get

$$\mathbf{P}(E_k) = \mathbf{P}(X = 2N - k + 1) = \binom{2N - k}{N} \left(\frac{1}{2}\right)^{2N - k + 1}$$

Solution to the problem:

By symmetry between left and right, we get

$$2\mathbf{P}(E_k) = \binom{2N - k}{N} \left(\frac{1}{2}\right)^{2N - k}$$

# Hypergeometric random variable (1)

Use: Consider the experiment

- Urn containing  $N$  balls
- $m$  white balls,  $N - m$  black balls
- Sample of size  $n$  is drawn without replacement
- Set  $X = \#$  white balls drawn

Then

$$X \sim \text{HypG}(n, N, m)$$

# Hypergeometric random variable (2)

Notation:

$$X \sim \text{HypG}(n, N, m), \quad \text{for } N \in \mathbb{N}^*, m, n \leq N, p \in (0, 1)$$

State space:

$$\{0, \dots, n\}$$

Pmf:

$$\mathbf{P}(X = k) = \frac{\binom{m}{k} \binom{N-m}{n-k}}{\binom{N}{n}}, \quad 0 \leq k \leq n$$

Expected value and variance: Set  $p = \frac{m}{N}$ . Then

$$\mathbf{E}[X] = np, \quad \mathbf{Var}(X) = np(1-p) \left(1 - \frac{n-1}{N-1}\right)$$

# Hypergeometric and binomial

## Proposition 14.

Let

- $X \sim \text{HypG}(n, N, m)$ ,
- Recall that  $p = \frac{m}{N}$

Hypothesis:

$$n \ll m, N, \quad i \ll m, N$$

Then

$$\mathbf{P}(X = i) \simeq \binom{n}{i} p^i (1 - p)^{n-i}$$

# Proof

Expression for  $\mathbf{P}(X = i)$ :

$$\begin{aligned}\mathbf{P}(X = i) &= \frac{\binom{m}{i} \binom{N-m}{n-i}}{\binom{N}{n}} \\ &= \frac{m!}{(m-i)!i!} \frac{(N-m)!}{(N-m-n+i)!(n-i)!} \frac{(N-n)!n!}{N!} \\ &= \binom{n}{i} \prod_{j=0}^{i-1} \frac{m-j}{N-j} \prod_{k=0}^{n-i-1} \frac{N-m-k}{N-i-k}\end{aligned}$$

**Approximation:** If  $i, j, k \ll m, N$  above, we get

$$\mathbf{P}(X = i) \simeq \binom{n}{i} p^i (1-p)^{n-i}$$

# Example: electric components (1)

**Situation:** We have

- Lots of electric components of size 10
- We inspect 3 components per lot  
↔ Acceptance if all 3 components are non defective
- 30% of lots have 4 defective components
- 70% of lots have 1 defective component

**Question:**

What is the proportion of rejected lots?

## Example: electric components (2)

**Events:** We define

- $A$  = Acceptance of a lot
- $L_1$  = Lot with 1 defective component drawn
- $L_4$  = Lot with 4 defective components drawn

**Conditioning:** We have

$$\mathbf{P(A) = P(A|L_1)P(L_1) + P(A|L_4)P(L_4)}$$

and

$$\mathbf{P(L_1) = .7, \quad P(L_4) = .3,}$$

## Example: electric components (3)

Hypergeometric random variable: We check that

$$\mathbf{P}(A|L_1) = \mathbf{P}(X_1 = 0), \quad \text{where } X_1 \sim \text{HypG}(3, 10, 1)$$

Thus

$$\mathbf{P}(A|L_1) = \frac{\binom{1}{0} \binom{9}{3}}{\binom{10}{3}}$$

Conclusion:

$$\mathbf{P}(A) = \frac{\binom{1}{0} \binom{9}{3}}{\binom{10}{3}} \times 0.7 + \frac{\binom{4}{0} \binom{6}{3}}{\binom{10}{3}} \times 0.3 = 54\%$$



# Outline

- 1 Random variables
- 2 Discrete random variables
- 3 Expected value
- 4 Expectation of a function of a random variable
- 5 Variance
- 6 The Bernoulli and binomial random variables
- 7 The Poisson random variable
- 8 Other discrete random variables
- 9 Expected value of sums of random variables**
- 10 Properties of the cumulative distribution function

# Another expression for $\mathbf{E}[X]$

## Proposition 15.

Let

- $\mathbf{P}$  a probability on a sample space  $S$
- $X : S \rightarrow \mathcal{E}$  a random variable

**Hypothesis:**  $S$  is countable, i.e

$$S = \{s_i; i \geq 1\}$$

Then setting  $p(s_i) = \mathbf{P}(\{s_i\})$  we have

$$\mathbf{E}[X] = \sum_{i \geq 1} X(s_i)p(s_i)$$

# Proof (1)

Recall: We have

$$\mathbf{E}[X] = \sum_{i \geq 1} x_i \mathbf{P}(X = x_i)$$

Level set: We define

$$S_i = \{s \in S; X(s) = x_i\}$$

Expression for  $\mathbf{E}[X]$ :

$$\begin{aligned} \mathbf{E}[X] &= \sum_{i \geq 1} x_i \sum_{s_j \in S_i} p(s_j) \\ &= \sum_{i \geq 1} \sum_{s_j \in S_i} X(s_j) p(s_j) \end{aligned}$$

## Proof (2)

**Conclusion:** Since  $\{S_i; i \geq 1\}$  is a partition of  $S$ ,

$$\mathbf{E}[X] = \sum_{i \geq 1} X(s_i)p(s_i)$$

# Expectation of sums

## Proposition 16.

Let

- $\mathbf{P}$  a probability on a sample space  $S$
- $X_1, \dots, X_n : S \rightarrow \mathbb{R}$   $n$  random variables

**Hypothesis:**  $S$  is countable, i.e

$$S = \{s_i; i \geq 1\}$$

Then

$$\mathbf{E} \left[ \sum_{i=1}^n X_i \right] = \sum_{i=1}^n \mathbf{E} [X_i]$$

# Proof

Notation: Set

$$Z = \sum_{i=1}^n X_i$$

Expression for  $\mathbf{E}[Z]$ : According to Proposition 15,

$$\begin{aligned}\mathbf{E}[Z] &= \sum_{s \in \mathcal{S}} Z(s) p(s) \\ &= \sum_{s \in \mathcal{S}} \left( \sum_{i=1}^n X_i(s) \right) p(s) \\ &= \sum_{i=1}^n \left( \sum_{s \in \mathcal{S}} X_i(s) p(s) \right) \\ &= \sum_{i=1}^n \mathbf{E}[X_i]\end{aligned}$$

# Example: number of successes (1)

## Experiment:

- $n$  trials
- Success for  $i$ -th trial with probability  $p_i$
- $X = \#$  of successes

## Question:

Expression for  $\mathbf{E}[X]$  and  $\mathbf{Var}(X)$

## Example: number of successes (2)

Expression for  $X$ : Let

$$X_i = \mathbf{1}_{(\text{success for } i\text{-th trial})}$$

Then

$$X = \sum_{i=1}^n X_i$$

Expression for  $\mathbf{E}[X]$ : Thanks to Proposition 16, we have

$$\mathbf{E}[X] = \sum_{i=1}^n p_i$$



## Example: number of successes (3)

Expression for  $\mathbf{E}[X^2]$ : We invoke the two facts

- 1  $X_i^2 = X_i$
- 2 If  $i \neq j$ ,  $X_i X_j = \mathbf{1}_{(X_i=1, X_j=1)}$

Therefore

$$\mathbf{E}[X^2] = \sum_{i=1}^n \mathbf{E}[X_i^2] + \sum_{i \neq j} \mathbf{E}[X_i X_j]$$

yields

$$\mathbf{E}[X^2] = \sum_{i=1}^n p_i + \sum_{i \neq j} \mathbf{P}(X_i = 1, X_j = 1)$$

## Example: number of successes (4)

Particular case, binomial: In this case we have

- The  $X_i$ 's are independent
- $p_i = p$

New expression for  $\mathbf{E}[X^2]$ :

$$\mathbf{E}[X^2] = np + n(n-1)p^2$$

Expression for  $\mathbf{Var}(X)$ :

$$\mathbf{Var}(X) = np(1-p)$$

## Example: number of successes (5)

Particular case, hypergeometric: We have

$$\begin{aligned} p_i &= \frac{m}{N} \\ \mathbf{P}(X_i = 1, X_j = 1) &= \mathbf{P}(X_i = 1)\mathbf{P}(X_j = 1 | X_i = 1) \\ &= \frac{m}{N} \frac{m-1}{N-1} \end{aligned}$$

New expression for  $\mathbf{E}[X^2]$ :

$$\mathbf{E}[X^2] = np + n(n-1)p \frac{m-1}{N-1}$$

Expression for  $\mathbf{Var}(X)$ :

$$\mathbf{Var}(X) = np(1-p) \left(1 - \frac{n-1}{N-1}\right)$$

# Outline

- 1 Random variables
- 2 Discrete random variables
- 3 Expected value
- 4 Expectation of a function of a random variable
- 5 Variance
- 6 The Bernoulli and binomial random variables
- 7 The Poisson random variable
- 8 Other discrete random variables
- 9 Expected value of sums of random variables
- 10 Properties of the cumulative distribution function**

# Continuity of the cdf

## Proposition 17.

Let

- $\mathbf{P}$  a probability on a sample space  $S$
- $X : S \rightarrow \mathcal{E}$  a random variable, with  $\mathcal{E} \subset \mathbb{R}$
- $F$  the cdf of  $X$ , i.e  $F(x) = \mathbf{P}(X \leq x)$

Then the function  $F$  satisfies

- 1  $F$  is a nondecreasing function
- 2  $\lim_{b \rightarrow \infty} F(b) = 1$
- 3  $\lim_{b \rightarrow -\infty} F(b) = 0$
- 4  $F$  is right continuous

# Proof of item 1

Inclusion property: Let  $a < b$ . Then

$$(X \leq a) \subset (X \leq b)$$

Consequence on probabilities:

$$\mathbf{P}(X \leq a) \leq \mathbf{P}(X \leq b)$$

## Proof of item 2

Definition of an increasing sequence: Let  $b_n \nearrow \infty$  and

$$E_n = (X \leq b_n)$$

Then

$$\lim_{n \rightarrow \infty} E_n = (X < \infty)$$

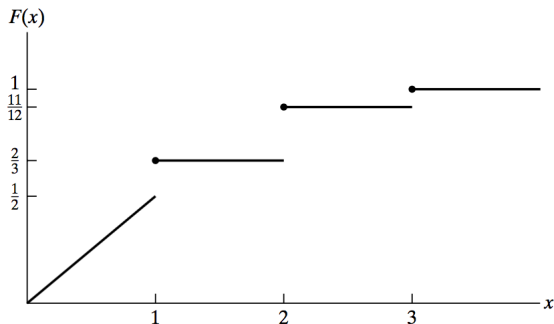
Consequence on probabilities:

$$\begin{aligned} 1 &= \mathbf{P}(X < \infty) \\ &= \mathbf{P}\left(\lim_{n \rightarrow \infty} E_n\right) \\ &= \lim_{n \rightarrow \infty} \mathbf{P}(E_n) \quad (\text{Since } n \mapsto E_n \text{ is increasing}) \\ &= \lim_{n \rightarrow \infty} F(b_n) \end{aligned}$$

# Example of cdf (1)

Definition of the function: We set

$$F(x) = \frac{x}{2} \mathbf{1}_{[0,1)}(x) + \frac{2}{3} \mathbf{1}_{[1,2)}(x) + \frac{11}{12} \mathbf{1}_{[2,3)}(x) + \mathbf{1}_{[3,\infty)}(x)$$





## Example of cdf (2)

Information read on the cdf: One can check that

- $\mathbf{P}(X < 3) = \frac{11}{12}$
- $\mathbf{P}(X = 1) = \frac{1}{6}$
- $\mathbf{P}(X > \frac{1}{2}) = \frac{3}{4}$
- $\mathbf{P}(2 < X \leq 4) = \frac{1}{12}$