

# 3: Random Variables

Spring 2023

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Gov 2002 (Harvard)

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  - What is the true Biden approval rate in the US?
- Today: given a probability distribution, what data is likely?
  - If we knew the true Biden approval, what samples are likely?

# Roadmap

1. Random variables
2. Famous distributions
3. Cumulative distribution functions
4. Functions of random variables
5. Independent random variables



# 1/ Random variables

# What are random variables?

## Definition

A **random variable (r.v.)** is a function that maps from the sample space of an experiment to the real line or  $X : \Omega \rightarrow \mathbb{R}$ .

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- Randomness comes from the randomness of the experiment.

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- Usually abstract away from the underlying sample space fairly quickly.

# Types of r.v.s

- Two main types of r.v.s: discrete and continuous. Focus on discrete now.

## Definition

A r.v.  $X$  is **discrete** the values it takes with positive probability is finite ( $X \in \{x_1, \dots, x_k\}$ ) or countably infinite ( $X \in \{x_1, x_2, \dots\}$ ).

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- The **support** of  $X$  is the values  $x$  such that  $\mathbb{P}(X = x) > 0$ .

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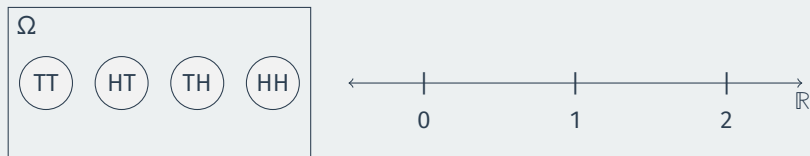
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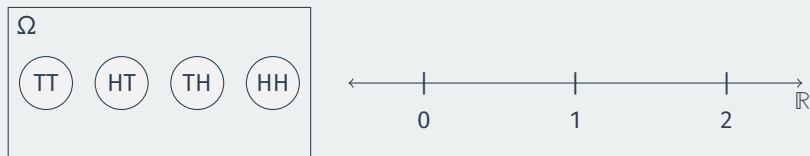
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- Often there are many ways to express a distribution.

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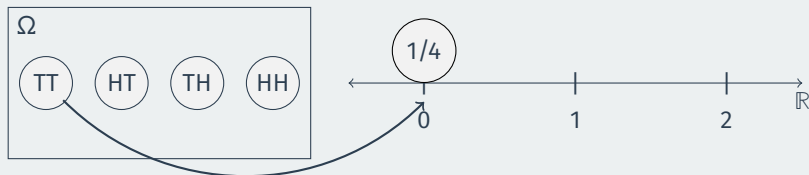
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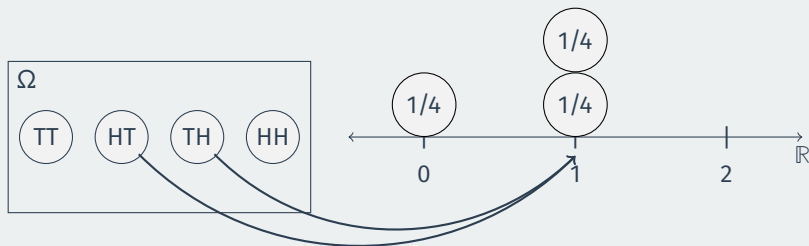


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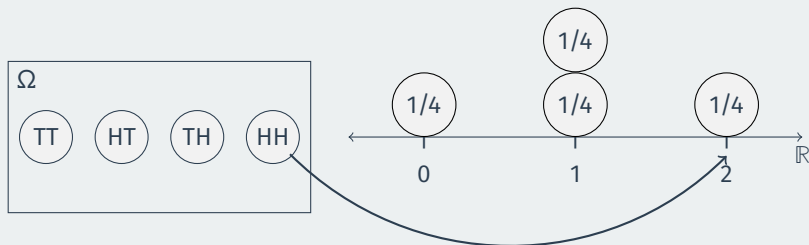


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- Probability of a set of values  $S \subset \{x_1, x_2, \dots\}$ :

$$\mathbb{P}(X \in S) = \sum_{x \in S} p_X(x)$$

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$$X = \begin{cases} 0 & \text{if } (C, C, C) \\ 1 & \text{if } (T, C, C) \text{ or } (C, T, C) \text{ or } (C, C, T) \\ 2 & \text{if } (T, T, C) \text{ or } (C, T, T) \text{ or } (T, C, T) \\ 3 & \text{if } (T, T, T) \end{cases}$$

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- Use independence and fair coins:

$$\mathbb{P}(C, T, C) = \mathbb{P}(C)\mathbb{P}(T)\mathbb{P}(C) = \frac{1}{2} \cdot \frac{1}{2} \cdot \frac{1}{2} = \frac{1}{8}$$



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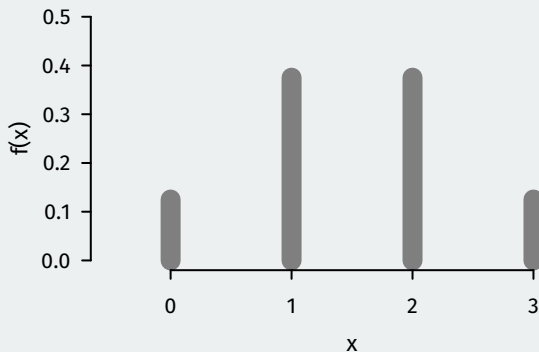
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- **Question:** Does this seem like a good way to assign treatment? What is one major problem with it?

## **2/** Famous distributions

# Bernoulli distribution

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- Actually a **family** of distributions indexed by  $p$ .
- Any event  $A$  has an associated Bernoulli r.v.: **indicator variable**:

$$\mathbb{I}(A) \sim \text{Bern}(p) \text{ with } p = \mathbb{P}(A)$$

# Binomial distribution

## Definition

Let  $X$  be the number of successes in  $n$  independent Bernoulli trials all with success probability  $p$ . Then  $X$  follows the **binomial distribution** with parameters  $n$  and  $p$ , which is written  $X \sim \text{Bin}(n, p)$ .

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- Also helps draw immediate connections:

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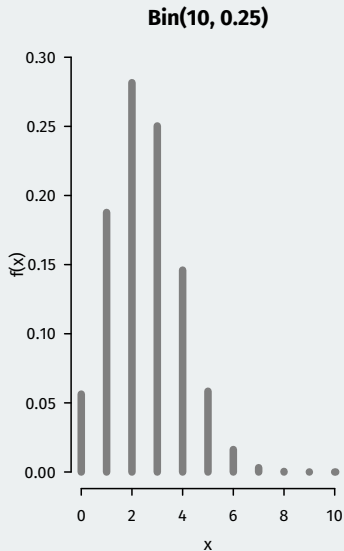
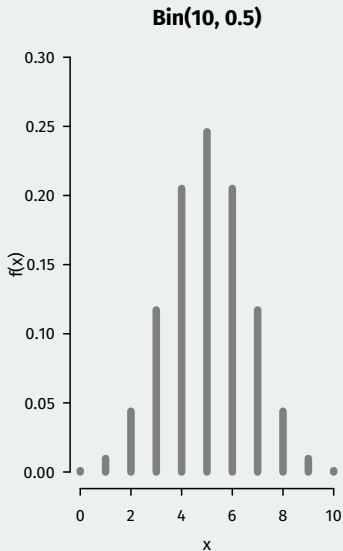
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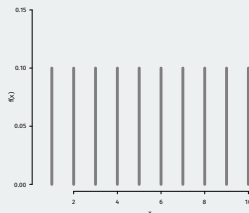
# Some binomials



# Discrete uniform distribution

## Definition

Let  $C$  be a finite, nonempty set of numbers. If  $X$  is the number chosen randomly with all values equally likely, we say it follows the **discrete uniform** distribution.



- p.m.f. for a discrete uniform r.v.:

$$p_X(x) = \begin{cases} 1/|C| & \text{for } x \in C \\ 0 & \text{otherwise} \end{cases}$$

## **3/** Cumulative distribution functions



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## Definition

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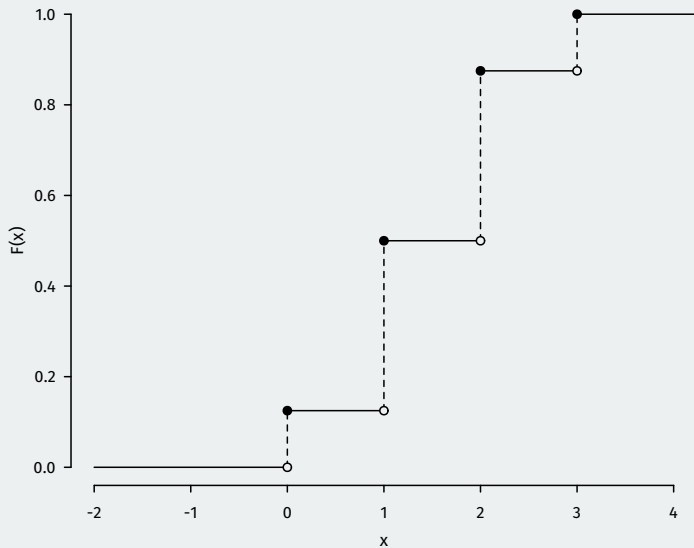
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# Graph of discrete c.d.f.



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  3. **Right continuous:** no jumps when we approach a point from the right:

$$F(a) = \lim_{x \rightarrow a^+} F(x)$$

## 4/ Functions of random variables

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- More generally, for all  $y$  in the support of  $g(X)$ , we have:

$$\mathbb{P}(g(X) = y) = \sum_{s: g(x)=y} \mathbb{P}(X = x)$$

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$z$	$\mathbb{P}(Z = z)$
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  - Scaling an r.v. doesn't scale the p.m.f., so  $Y = 2X$  does not have  $p_Y(y) \neq 2p_X(x)$

## **5/** Independent random variables

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- For discrete r.v.s (not continuous), we can write this as:

$$\mathbb{P}(X = x, Y = y) = \mathbb{P}(X = x)\mathbb{P}(Y = y)$$

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- **Theorem:** If  $X \sim \text{Bin}(n, p)$  and  $Y \sim \text{Bin}(m, p)$  with  $X$  and  $Y$  independent, then  $X + Y \sim \text{Bin}(n + m, p)$ .

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  - $\bar{X} = (1/n) \sum_i X_i$  is our estimate of  $p$ . Properties?