

Probability Theory

Random Variables and Distributions

Rob Nicholls

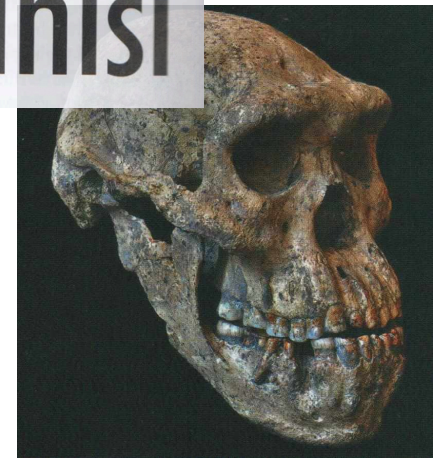
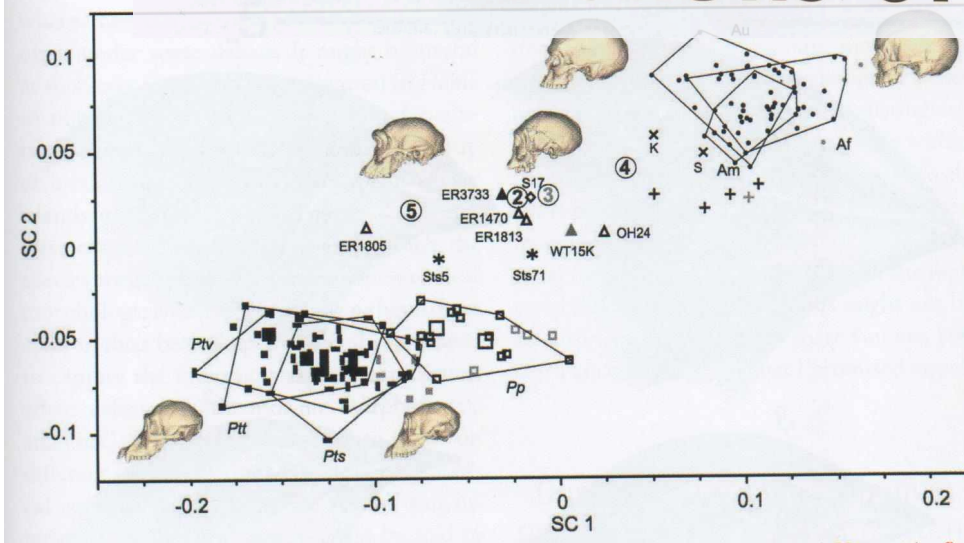
MRC LMB Statistics Course 2014

Introduction

Introduction



Early human evolution and the skulls of Dmanisi

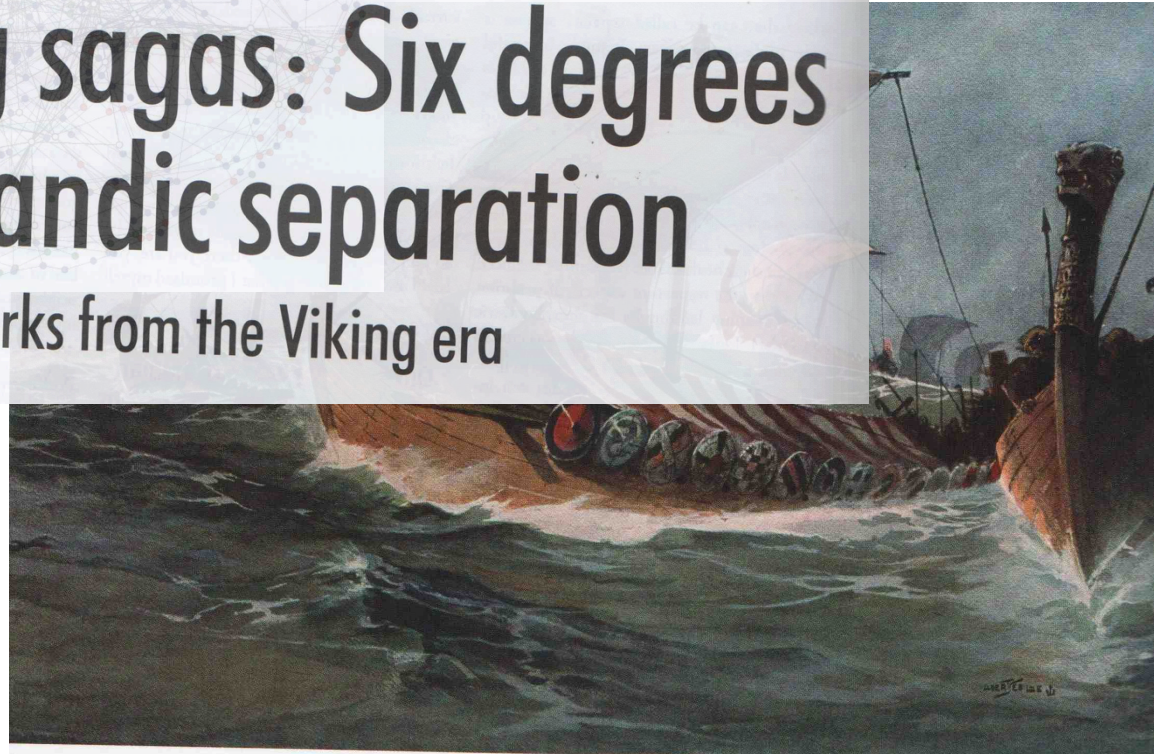


Introduction



Viking sagas: Six degrees of Icelandic separation

Social networks from the Viking era



Contents

- Set Notation
- Intro to Probability Theory
- Random Variables
- Probability Mass Functions
- Common Discrete Distributions

Set Notation

A set is a collection of objects, written using curly brackets {}

If A is the set of all outcomes, then:



$$A = \{heads, tails\}$$



$$A = \{one, two, three, four, five, six\}$$

A set does not have to comprise the full number of outcomes

E.g. if A is the set of dice outcomes no higher than three, then:

$$A = \{one, two, three\}$$

Set Notation

If A and B are sets, then:

A' Complement – everything but A

$A \cup B$ Union (or)

$A \cap B$ Intersection (and)

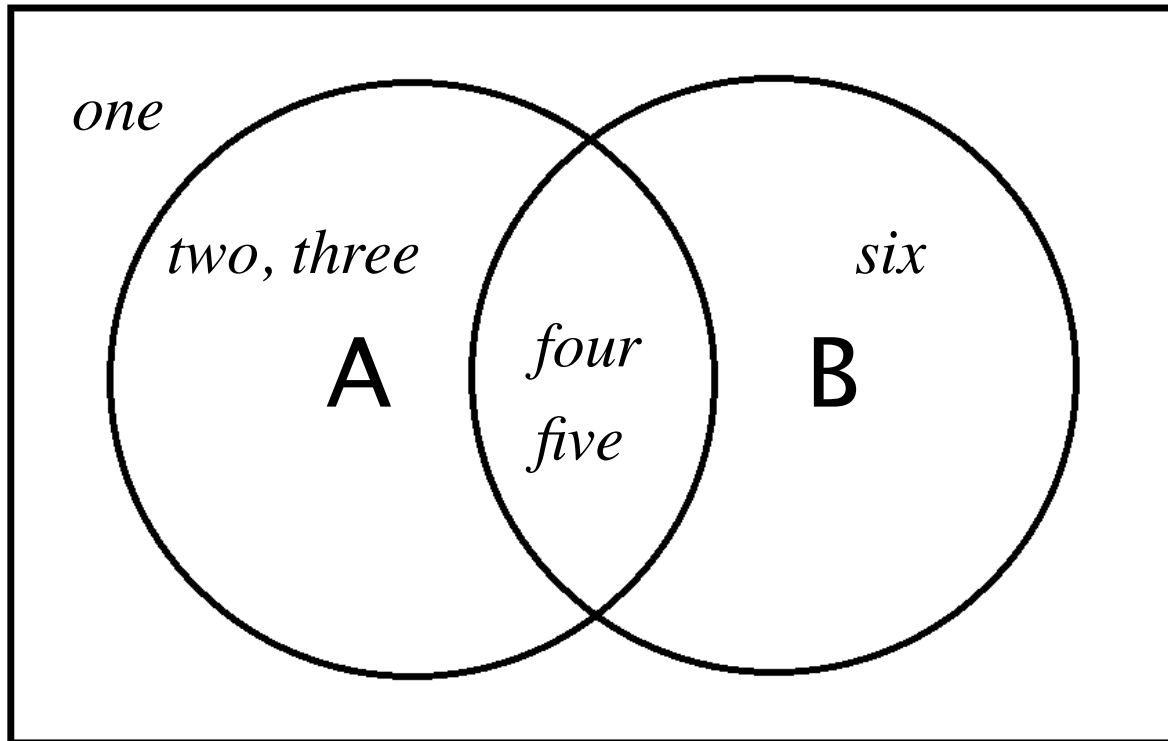
$A \setminus B$ Not

\emptyset Empty Set

Set Notation



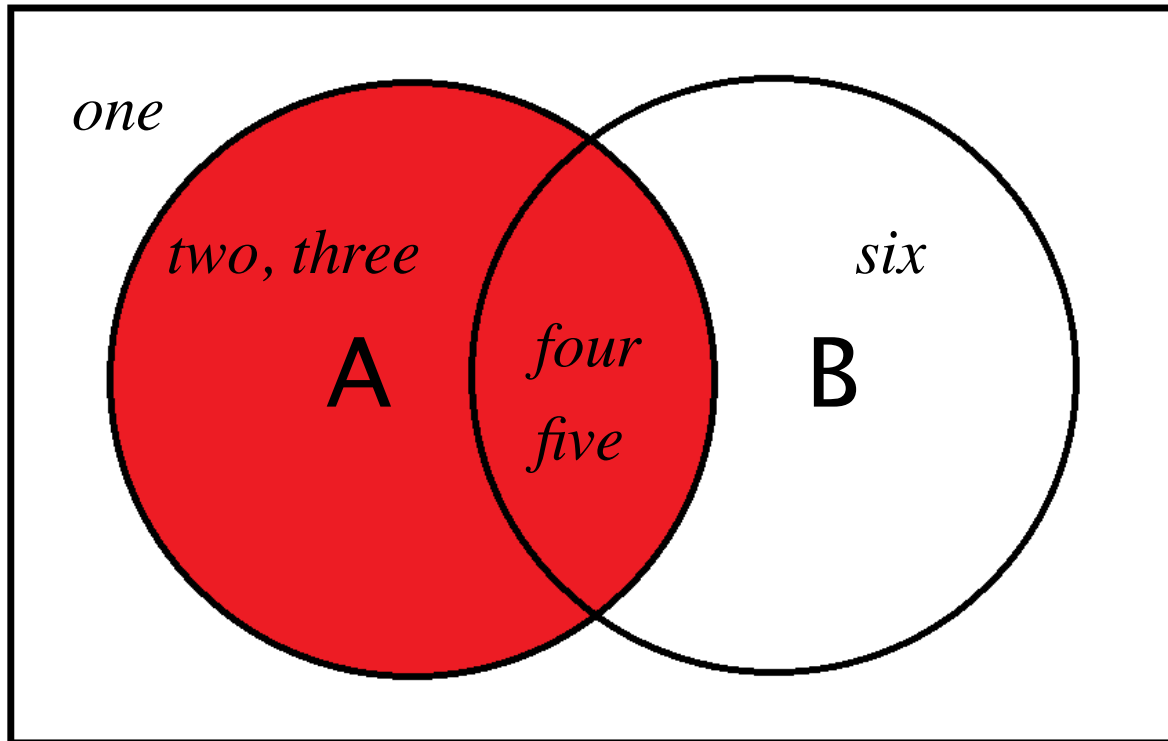
Venn Diagram:



Set Notation



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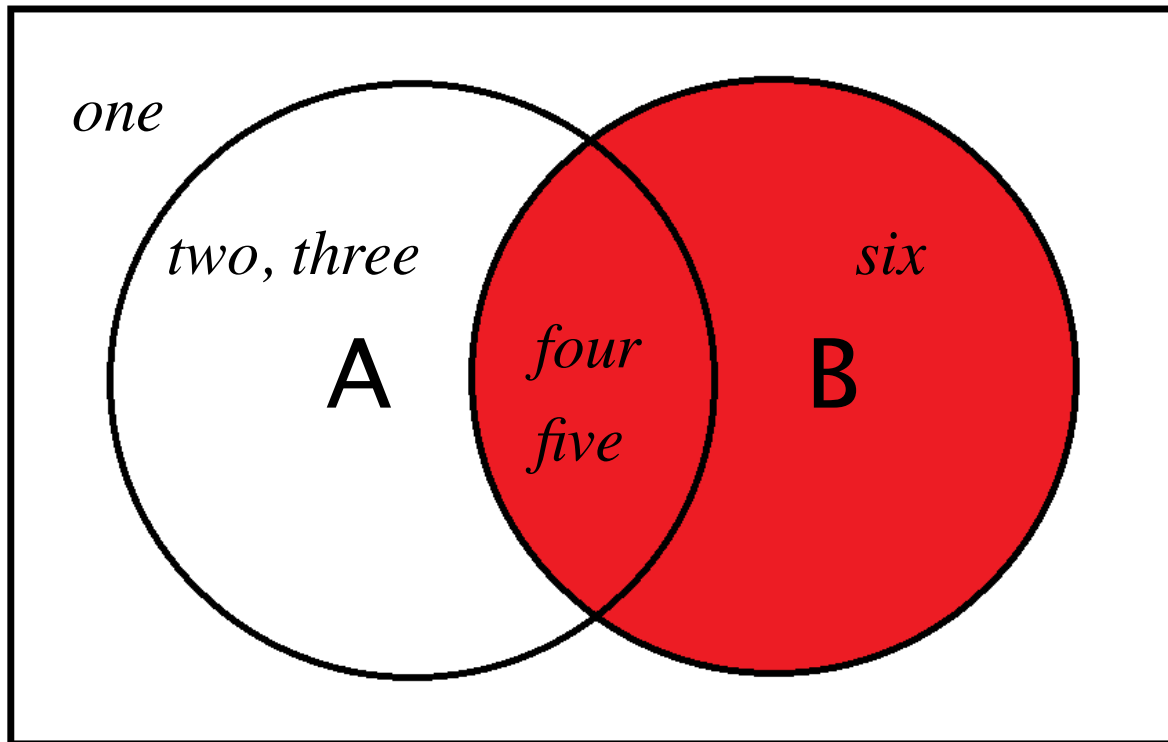


$$A = \{two, three, four, five\}$$

Set Notation



Venn Diagram:

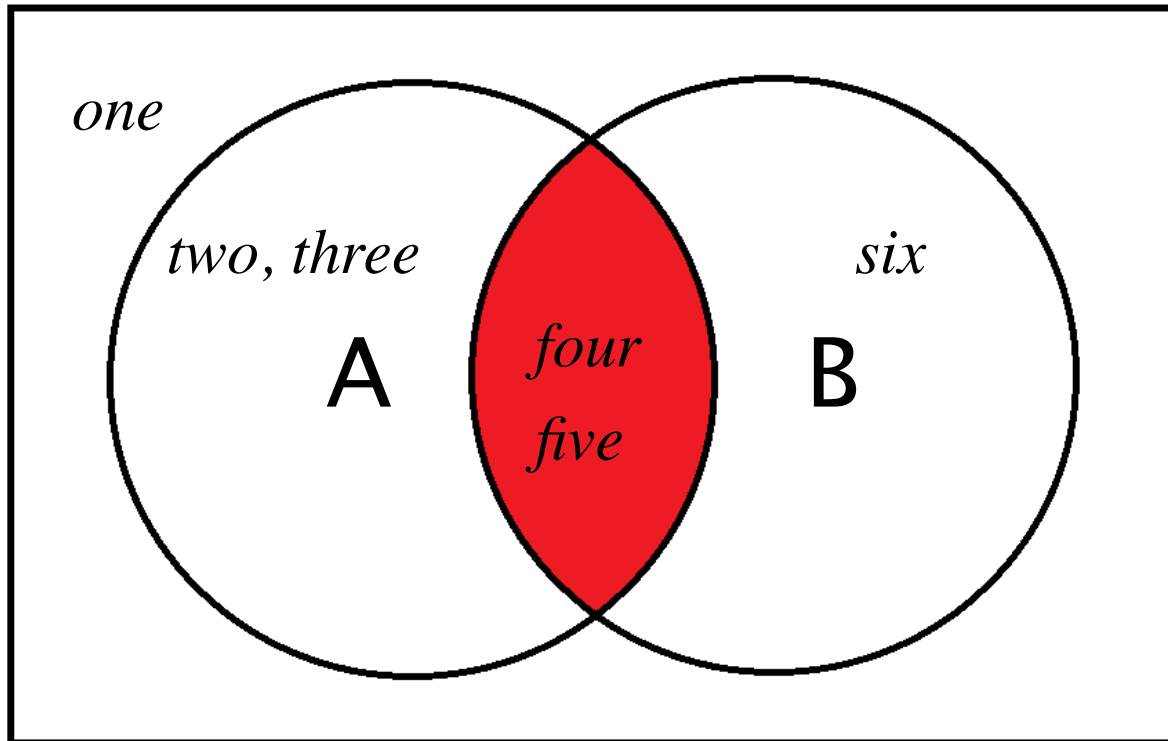


$$B = \{four, five, six\}$$

Set Notation



Venn Diagram:

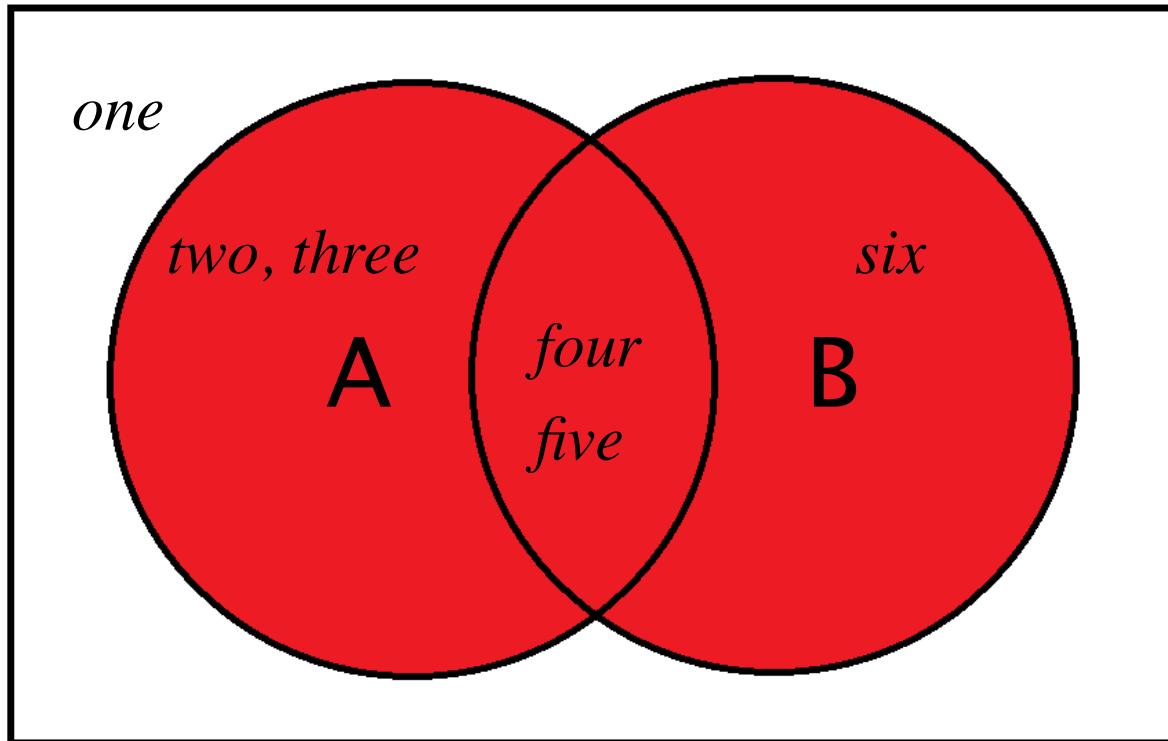


$$A \cap B = \{four, five\}$$

Set Notation



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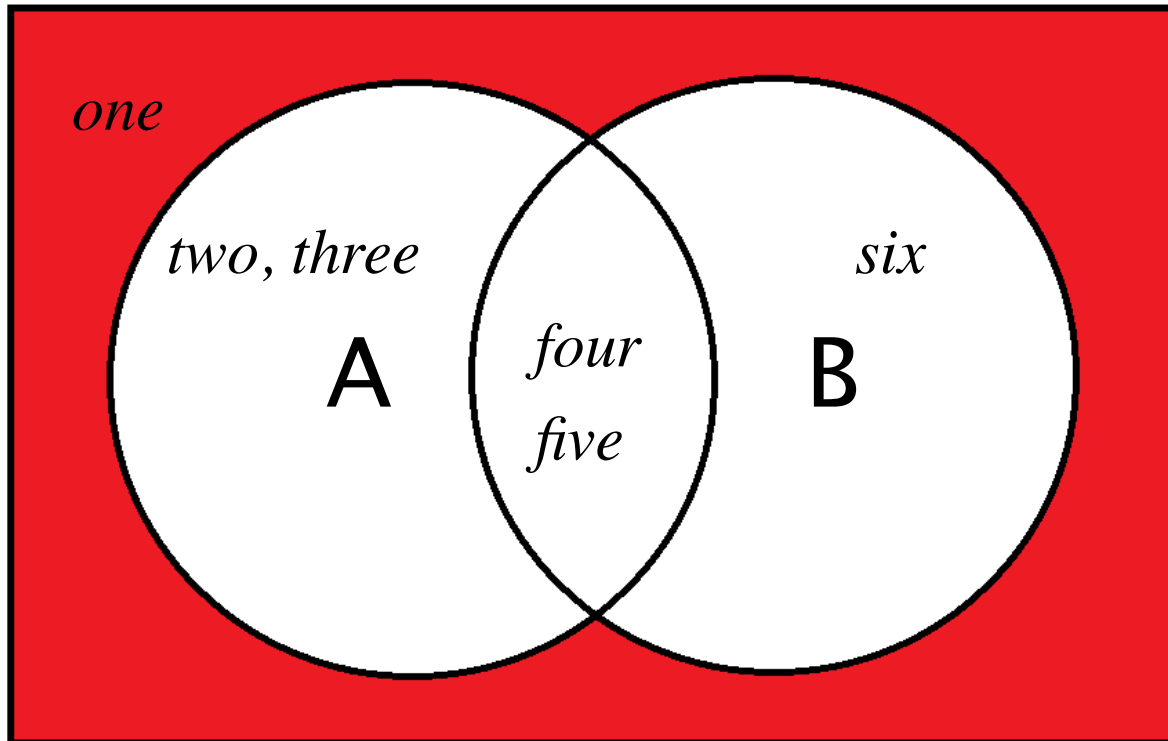


$$A \cup B = \{two, three, four, five, six\}$$

Set Notation



Venn Diagram:

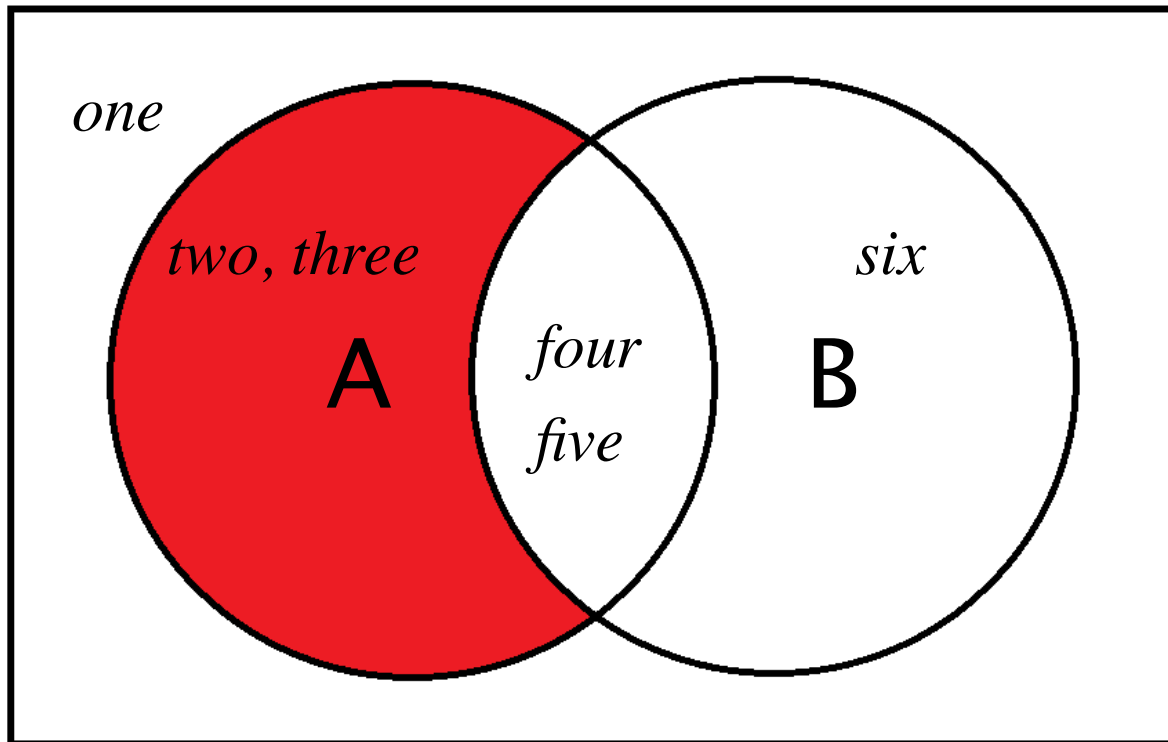


$$(A \cup B)' = \{one\}$$

Set Notation



Venn Diagram:

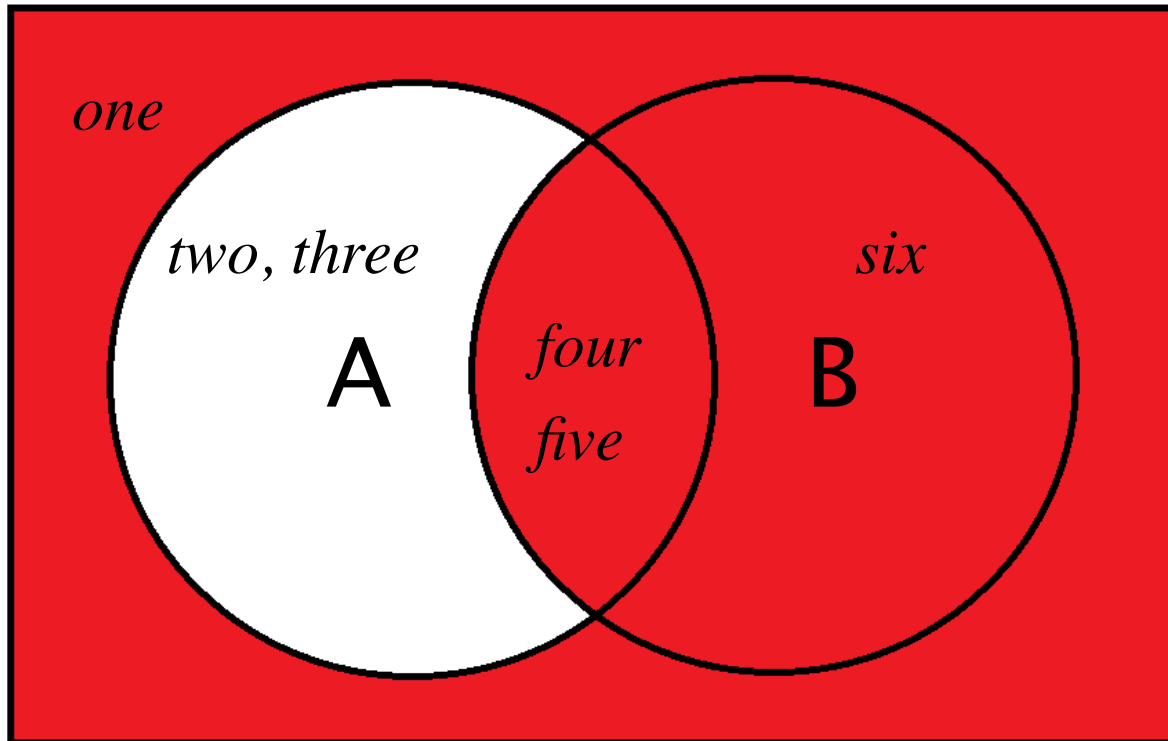


$$A \setminus B = \{two, three\}$$

Set Notation



Venn Diagram:



$$(A \setminus B)' = \{one, four, five, six\}$$

Probability Theory

To consider Probabilities, we need:

1. Sample space: Ω
2. Event space: \mathcal{F}
3. Probability measure: P

Probability Theory

To consider Probabilities, we need:

1. Sample space: Ω – the set of all possible outcomes



$$\Omega = \{heads, tails\}$$



$$\Omega = \{one, two, three, four, five, six\}$$

Probability Theory

To consider Probabilities, we need:

2. Event space: \mathcal{F} – the set of all possible events



$$\Omega = \{heads, tails\}$$

$$\mathcal{F} = \{\{heads, tails\}, \{heads\}, \{tails\}, \emptyset\}$$

Probability Theory

To consider Probabilities, we need:

3. Probability measure: P $P : \mathcal{F} \rightarrow [0,1]$

P must satisfy two axioms:

$P(\Omega) = 1$ Probability of any outcome is 1 (100% chance)

$P(\bigcup_i A_i) = \sum_i P(A_i)$ If and only if A_1, A_2, \dots are disjoint

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If and only if A_1, A_2, \dots are disjoint



$$P(\{one, two\}) = P(\{one\}) + P(\{two\})$$

$$\frac{1}{3} = \frac{1}{6} + \frac{1}{6}$$

Probability Theory

To consider Probabilities, we need:

1. Sample space: Ω
2. Event space: \mathcal{F}
3. Probability measure: P

As such, a *Probability Space* is the triple: (Ω, \mathcal{F}, P)

Probability Theory

To consider Probabilities, we need:

The triple: (Ω, \mathcal{F}, P)

i.e. we need to know:

1. The set of potential outcomes;
2. The set of potential events that may occur; and
3. The probabilities associated with occurrence of those events.

Probability Theory

Notable properties of a Probability Space (Ω, \mathcal{F}, P) :

Probability Theory

Notable properties of a Probability Space (Ω, \mathcal{F}, P) :

$$P(A') = 1 - P(A)$$



$$A = \{one, two\}$$

$$A' = \{three, four, five, six\}$$

$$P(A) = 1/3$$

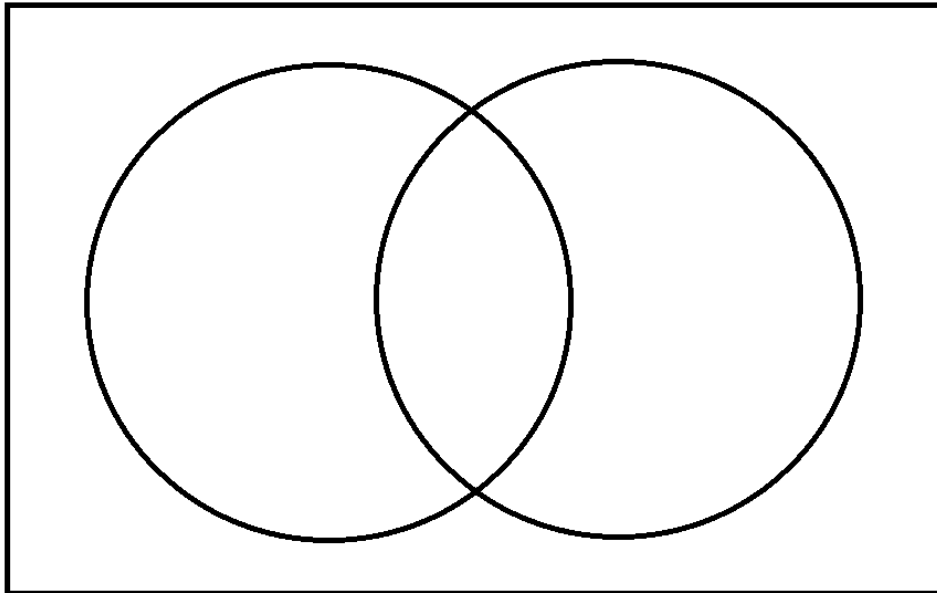
$$P(A') = 2/3$$

Probability Theory

Notable properties of a Probability Space (Ω, \mathcal{F}, P) :

$$P(A') = 1 - P(A)$$

$$P(A \cup B) = P(A) + P(B) - P(A \cap B)$$

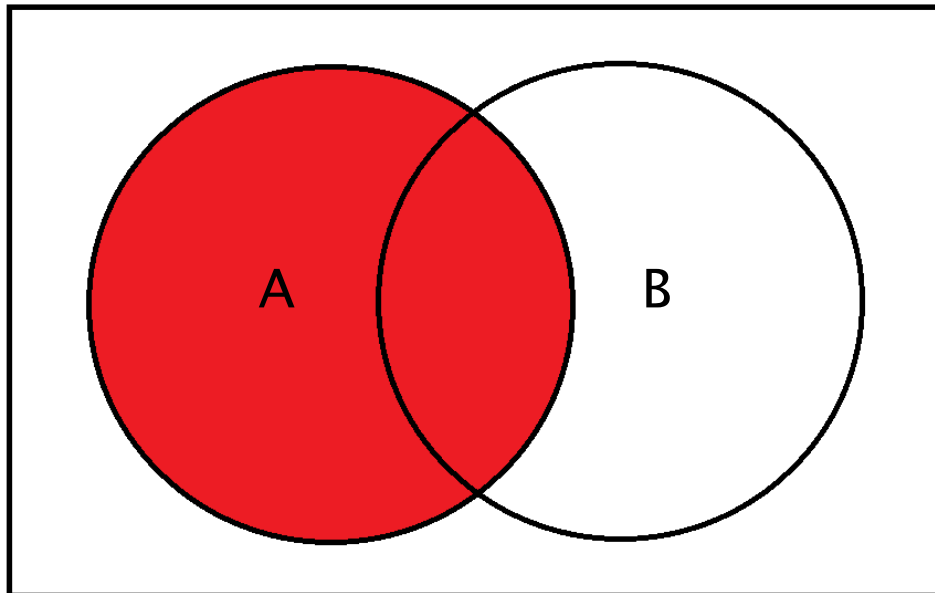


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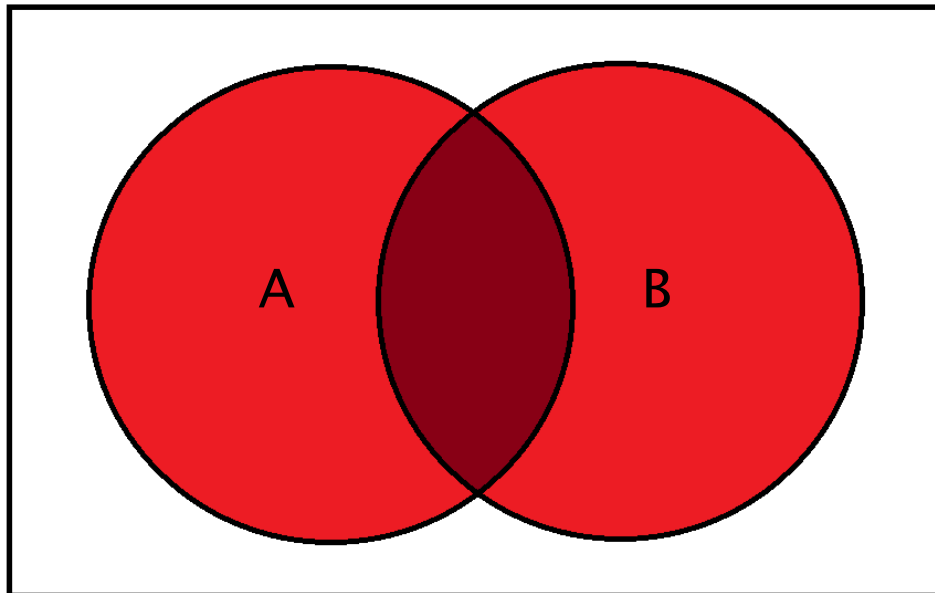


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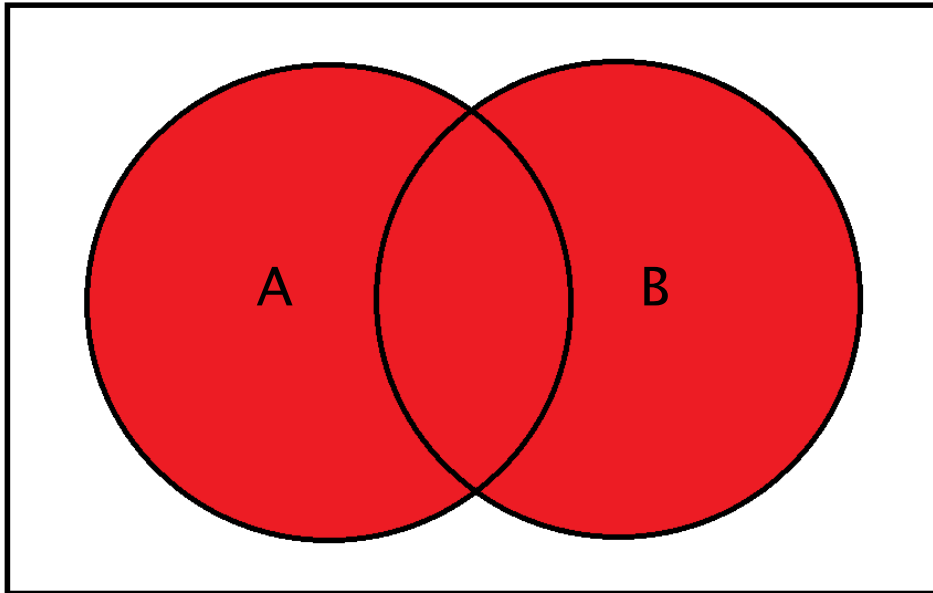


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$$A = \{one, two\}$$

$$P(A) = 1/3$$

$$B = \{two, three\}$$

$$P(B) = 1/3$$

$$A \cup B = \{one, two, three\}$$

$$P(A \cup B) = 1/2$$

$$A \cap B = \{two\}$$

$$P(A \cap B) = 1/6$$

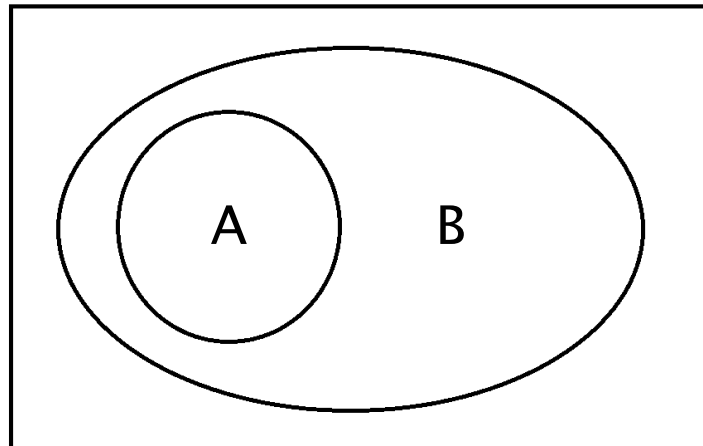
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If $A \subseteq B$ then $P(A) \leq P(B)$ and $P(B \setminus A) = P(B) - P(A)$



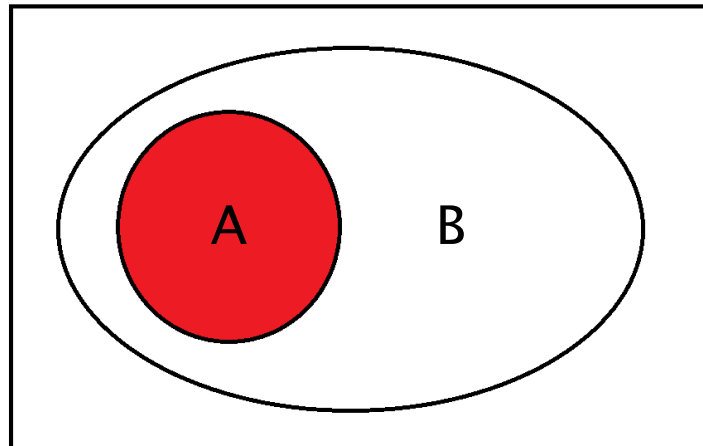
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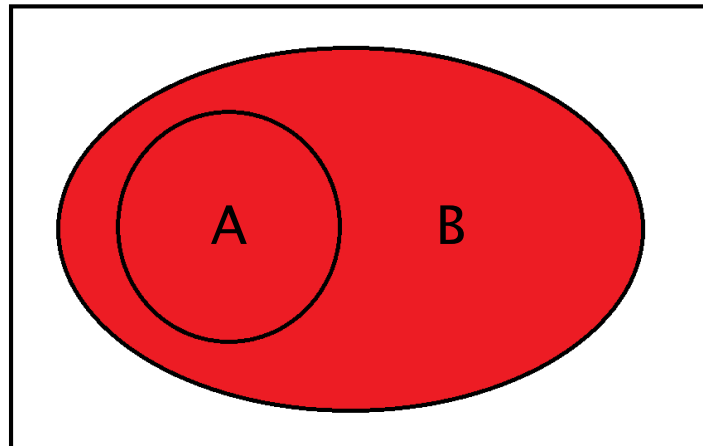
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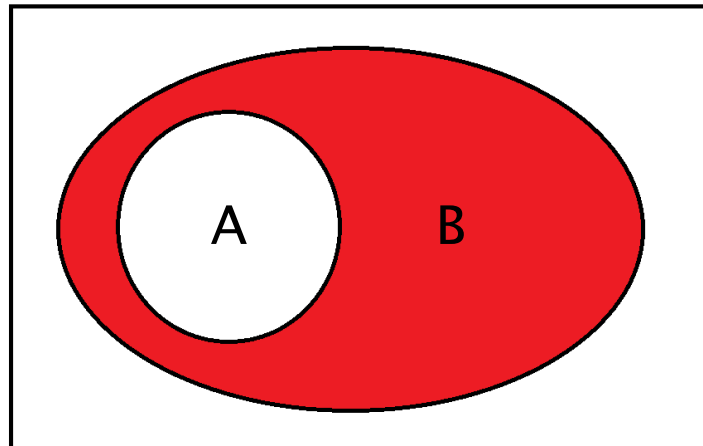
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$$A = \{one, two\}$$

$$P(A) = 1/3$$

$$B = \{one, two, three\}$$

$$P(B) = 1/2$$

$$B \setminus A = \{three\}$$

$$P(B \setminus A) = 1/6$$

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If $A \subseteq B$ then $P(A) \leq P(B)$ and $P(B \setminus A) = P(B) - P(A)$

$$P(\emptyset) = 0$$

Probability Theory

So where's this all going? These examples are trivial!

Probability Theory

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Suppose there are three bags, B_1 , B_2 and B_3 , each of which contain a number of coloured balls:

- B_1 – 2 red and 4 white
- B_2 – 1 red and 2 white
- B_3 – 5 red and 4 white

A ball is randomly removed from one the bags.

The bags were selected with probability:

- $P(B_1) = 1/3$
- $P(B_2) = 5/12$
- $P(B_3) = 1/4$

What is the probability that the ball came from B_1 , given it is red?

Probability Theory

Conditional probability:
$$P(A | B) = \frac{P(A \cap B)}{P(B)}$$

Partition Theorem:
$$P(A) = \sum_i P(A \cap B_i) \quad \text{If the } B_i \text{ partition } A$$

Bayes' Theorem:
$$P(A | B) = \frac{P(B | A)P(A)}{P(B)}$$

Random Variables

A *Random Variable* is an object whose value is determined by chance, i.e. random events

Maps elements of Ω onto real numbers, with corresponding probabilities as specified by P

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Probability that the random variable X adopts a particular value x :

$$P(\{\omega \in \Omega : X(\omega) = x\})$$

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Shorthand: $P(X = x)$

Random Variables

Example:



If the result is *heads* then WIN – X takes the value 1
If the result is *tails* then LOSE – X takes the value 0

$$\Omega = \{heads, tails\}$$

$$X : \Omega \rightarrow \{0,1\}$$

$$P(X = x) = \begin{cases} P(\{heads\}) & x = 1 \\ P(\{tails\}) & x = 0 \end{cases}$$

$$P(X = x) = 1/2 \quad x \in \{0,1\}$$

Random Variables

Example:



$$\Omega = \{one, two, three, four, five, six\}$$

Win £20 on a six, nothing on four/five, lose £10 on one/two/three

$$X : \Omega \rightarrow \{-10, 0, 20\}$$

Random Variables

Example:



$$\Omega = \{one, two, three, four, five, six\}$$

Win £20 on a six, nothing on four/five, lose £10 on one/two/three

$$X : \Omega \rightarrow \{-10, 0, 20\}$$

$$P(X = x) = \begin{cases} P(\{six\}) = 1/6 & x = 20 \\ P(\{four, five\}) = 1/3 & x = 0 \\ P(\{one, two, three\}) = 1/2 & x = -10 \end{cases}$$

Note - we are considering the probabilities of events in \mathcal{F}

Probability Mass Functions

Given a random variable:

$$X : \Omega \rightarrow A$$

The *Probability Mass Function* is defined as:

$$p_X(x) = P(X = x)$$

Only for discrete random variables

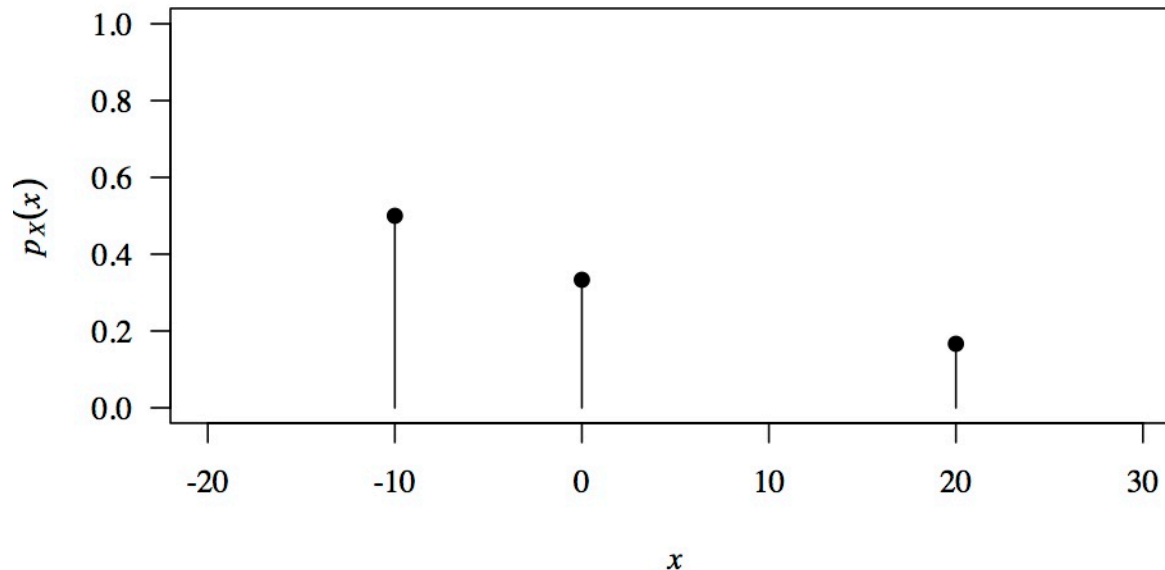
Probability Mass Functions

Example:

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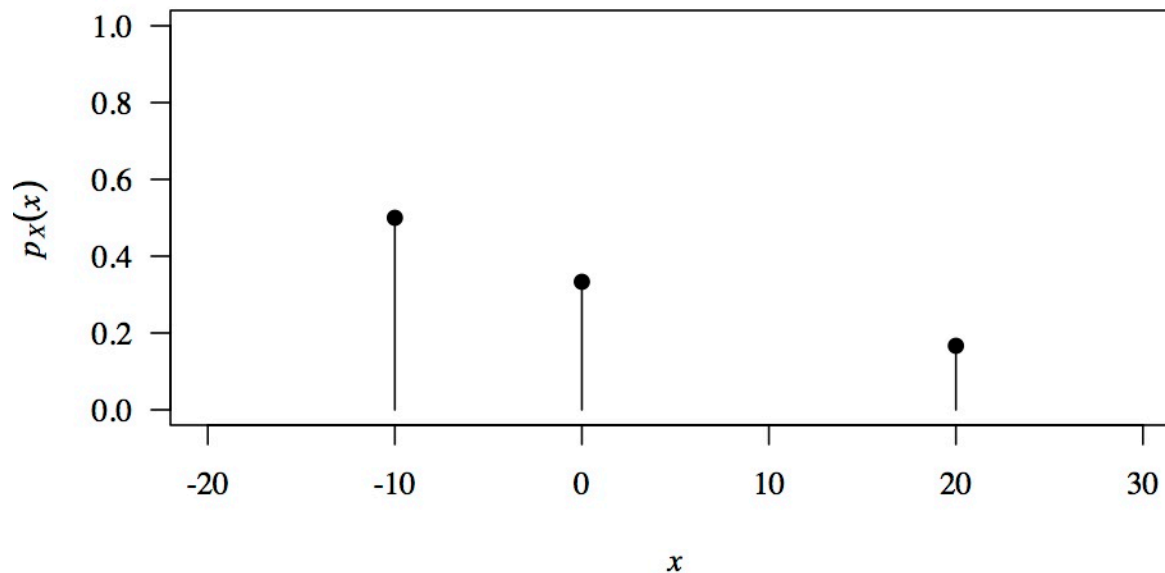


Probability Mass Functions

Notable properties of Probability Mass Functions:

$$p_X(x) \geq 0$$

$$\sum_{x \in A} p_X(x) = 1$$



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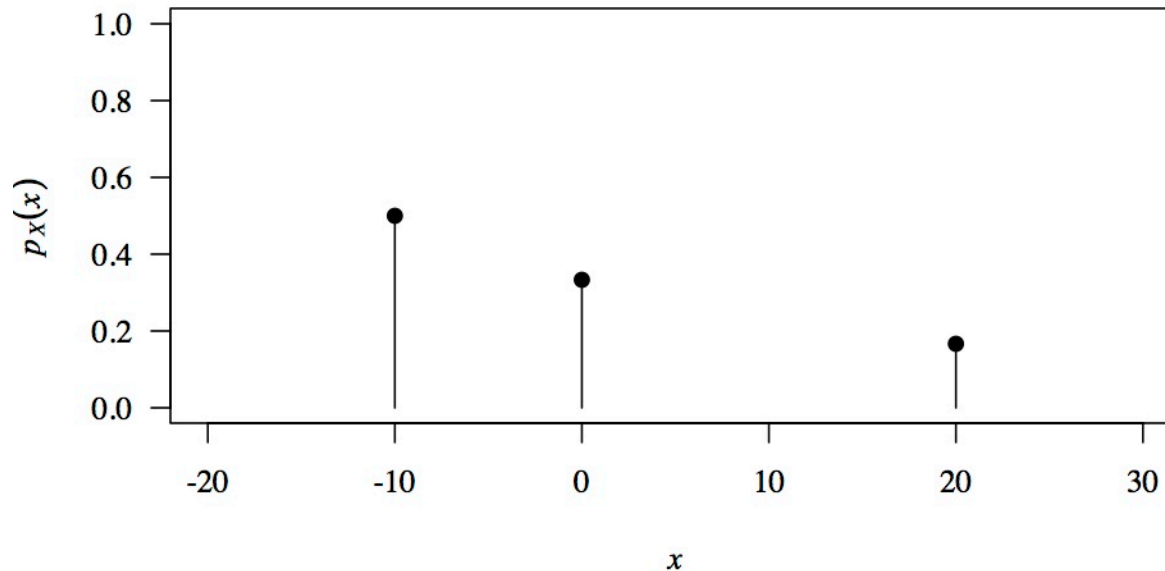
Interesting note:

If $p()$ is some function that has the above two properties, then it is the mass function of some random variable...

Probability Mass Functions

For a random variable $X : \Omega \rightarrow A$

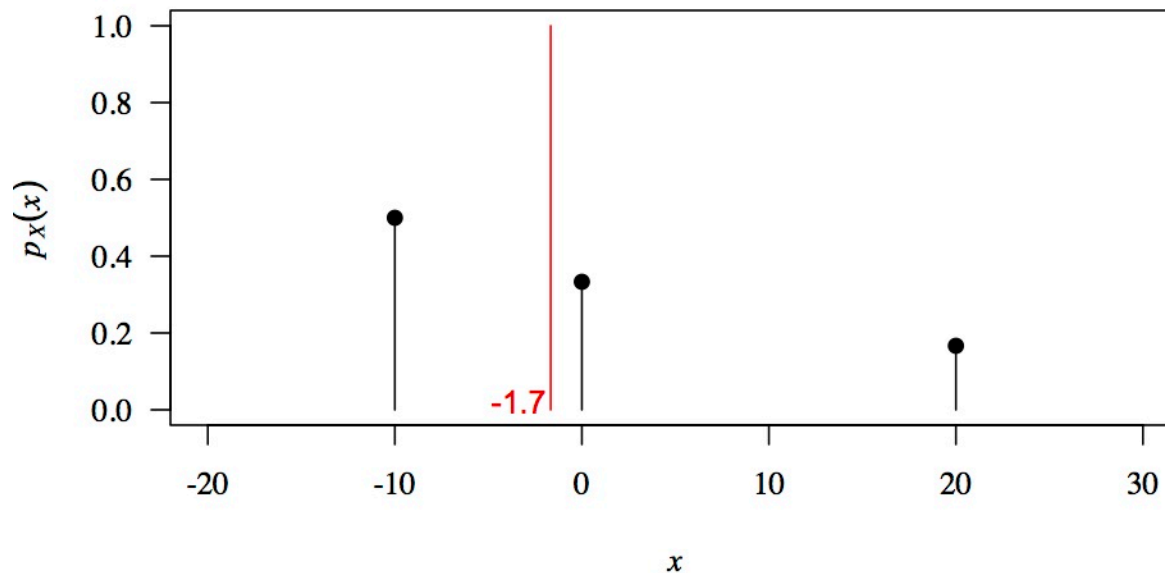
Mean:
$$E(X) = \sum_{x \in A} xp_X(x)$$



Probability Mass Functions

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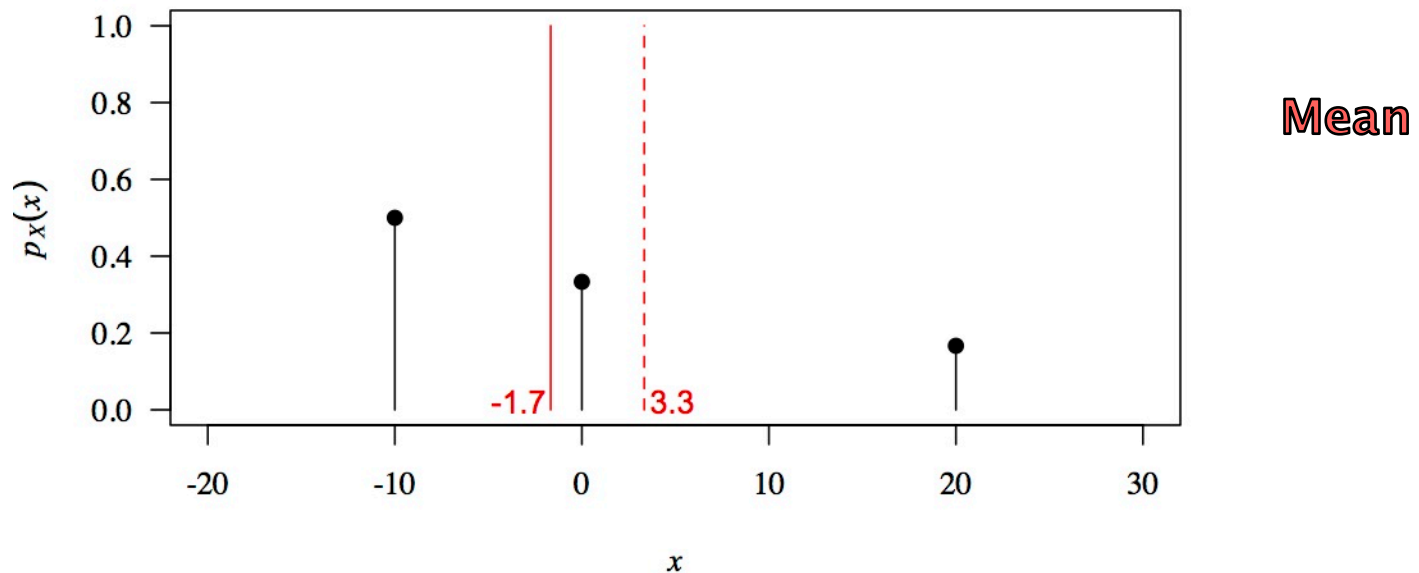


Mean

Probability Mass Functions

For a random variable $X : \Omega \rightarrow A$

Mean: $E(X) = \sum_{x \in A} xp_X(x)$ Compare with: $\frac{1}{n} \sum_{i=1}^n x_i$

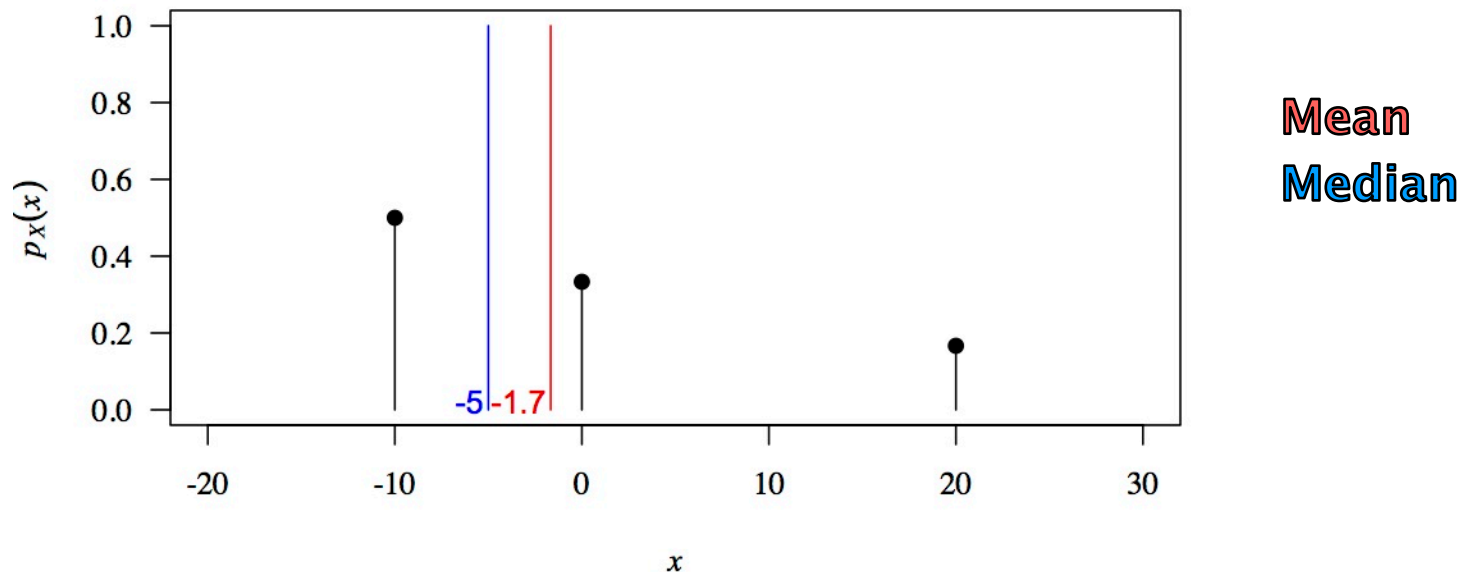


Probability Mass Functions

For a random variable $X : \Omega \rightarrow A$

Mean: $E(X) = \sum_{x \in A} xp_X(x)$

Median: any m such that: $\sum_{x \leq m} p_X(x) \geq 1/2$ and $\sum_{x \geq m} p_X(x) \geq 1/2$



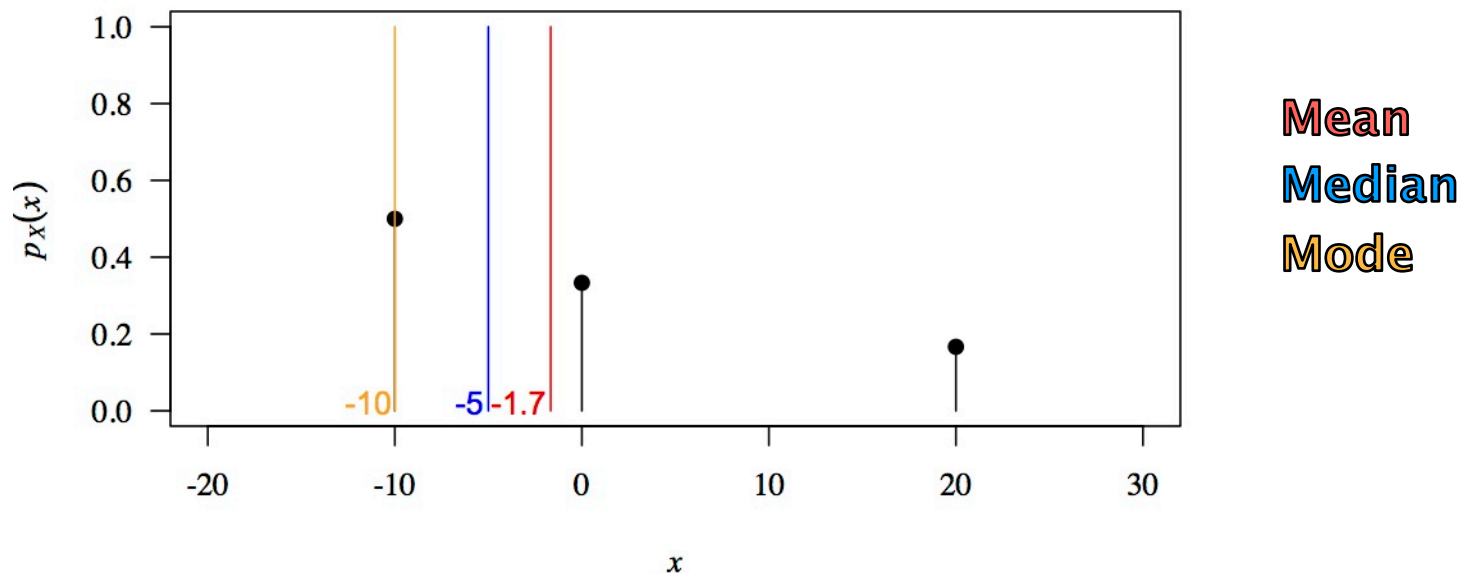
Probability Mass Functions

For a random variable $X : \Omega \rightarrow A$

Mean: $E(X) = \sum_{x \in A} xp_X(x)$

Median: any m such that: $\sum_{x \leq m} p_X(x) \geq 1/2$ and $\sum_{x \geq m} p_X(x) \geq 1/2$

Mode: $\operatorname{argmax}_x (p_X(x))$: most likely value



Common Discrete Distributions

Common Discrete Distributions

The **Bernoulli** Distribution: $X \sim \text{Bern}(p)$

p : success probability

$$X : \Omega \rightarrow \{0,1\}$$

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

Common Discrete Distributions

The **Bernoulli** Distribution: $X \sim \text{Bern}(p)$

p : success probability

$$X : \Omega \rightarrow \{0,1\} \quad p_X(x) = \begin{cases} p & x = 1 \\ 1 - p & x = 0 \end{cases}$$

Example:



$$X : \{heads, tails\} \rightarrow \{0,1\}$$

$$p_X(x) = 1/2 \quad x \in \{0,1\}$$

Therefore $X \sim \text{Bern}(1/2)$

Common Discrete Distributions

The **Binomial** Distribution: $X \sim \text{Bin}(n, p)$ $E(X) = np$

n : number of independent trials

p : success probability

$X : \Omega \rightarrow \{0, 1, \dots, n\}$

$$p_X(x) = \binom{n}{x} p^x (1-p)^{n-x}$$

Common Discrete Distributions

The **Binomial** Distribution: $X \sim \text{Bin}(n, p)$ $E(X) = np$

n : number of independent trials

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$$X : \Omega \rightarrow \{0, 1, \dots, n\} \qquad p_X(x) = \binom{n}{x} p^x (1-p)^{n-x}$$

$p_X(x)$: probability of getting x successes out of n trials

p^x : probability of x successes

$(1-p)^{n-x}$: probability of $(n-x)$ failures

$\binom{n}{x} = \frac{n!}{x!(n-x)!}$: number of ways to achieve x successes and $(n-x)$ failures
(Binomial coefficient)

Common Discrete Distributions

The **Binomial** Distribution: $X \sim \text{Bin}(n, p)$ $E(X) = np$

n : number of independent trials

p : success probability

$$X : \Omega \rightarrow \{0, 1, \dots, n\} \qquad p_X(x) = \binom{n}{x} p^x (1-p)^{n-x}$$

$$n = 1 : \qquad p_X(x) = p^x (1-p)^{1-x} = \begin{cases} p & x = 1 \\ 1-p & x = 0 \end{cases}$$

$$X \sim \text{Bin}(1, p) \qquad \Leftrightarrow \qquad X \sim \text{Bern}(p)$$

Common Discrete Distributions

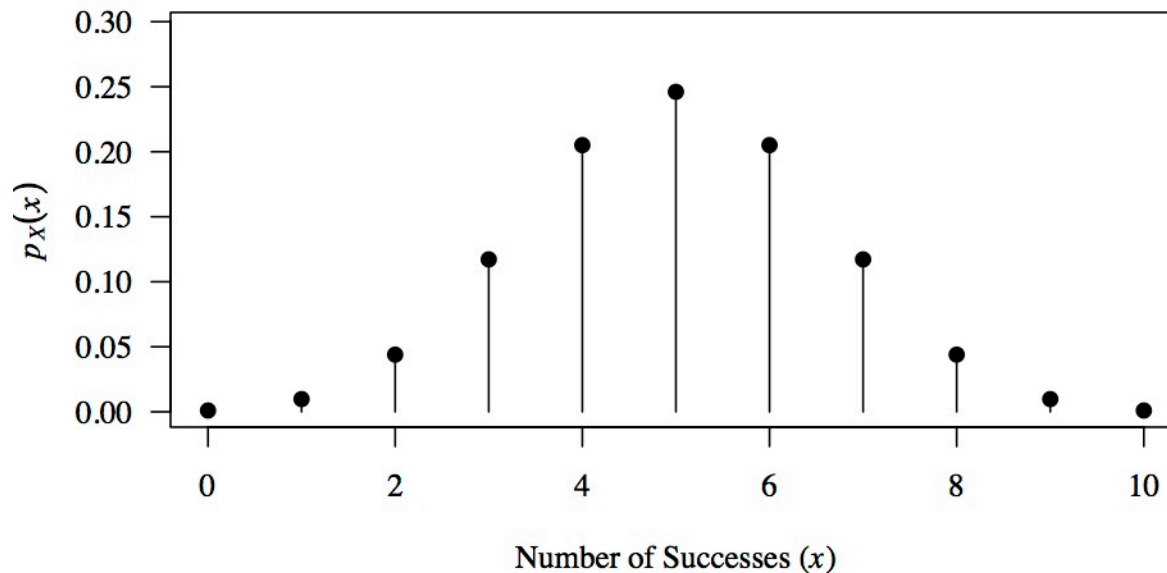
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$n = 10$

$p = 0.5$

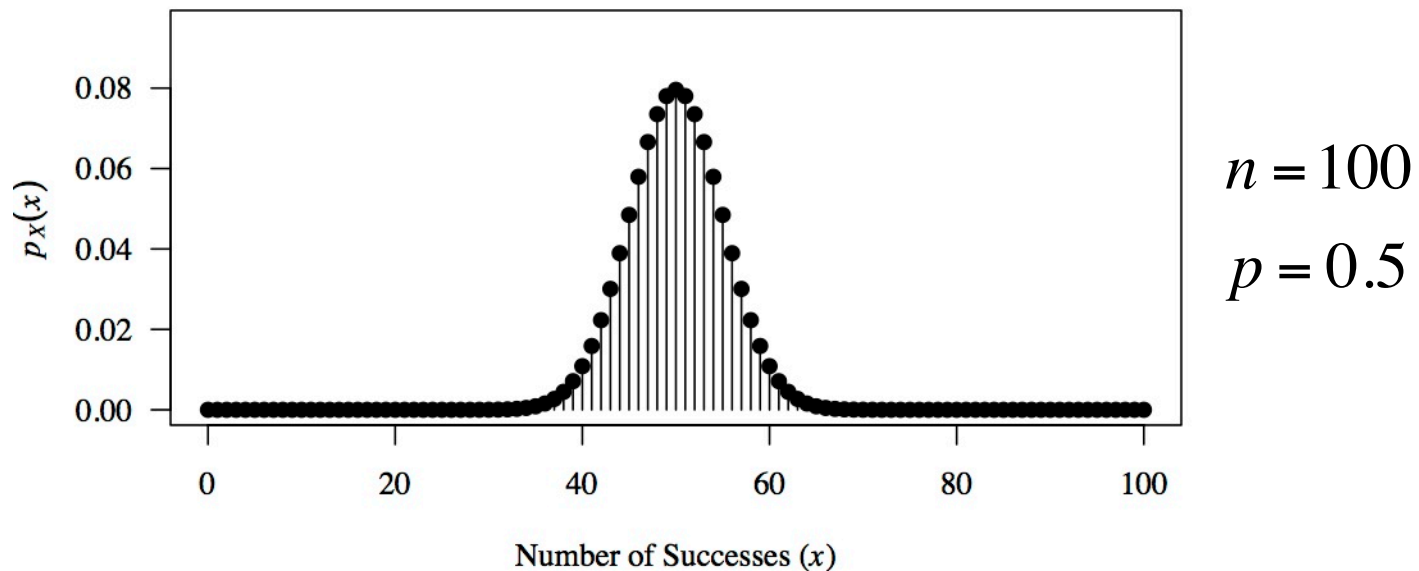
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Common Discrete Distributions

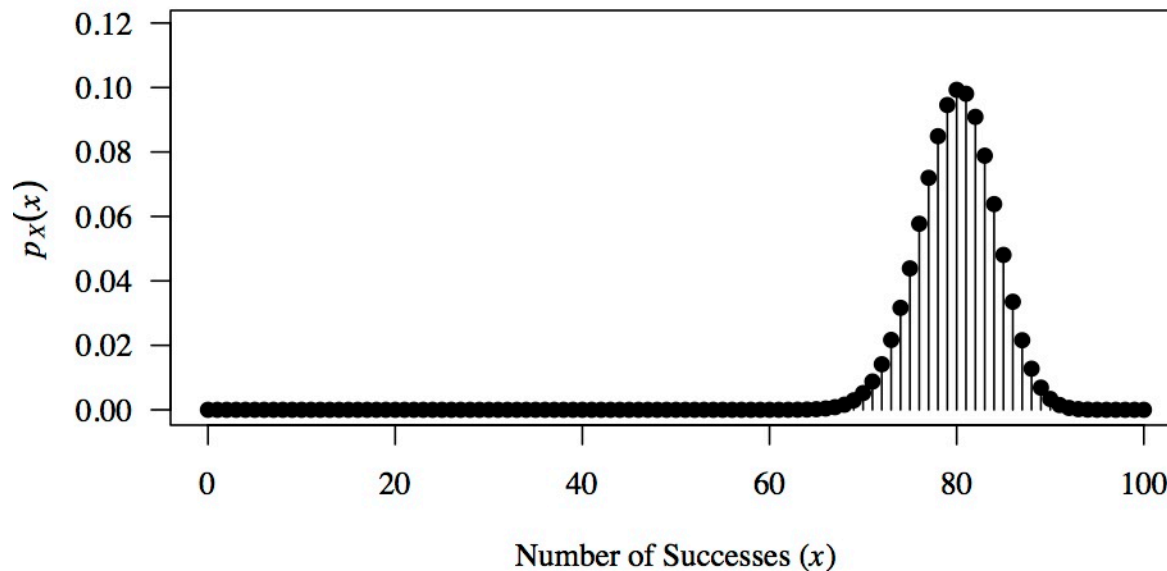
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p : success probability

$X : \Omega \rightarrow \{0, 1, \dots, n\}$

$$p_X(x) = \binom{n}{x} p^x (1-p)^{n-x}$$



$n = 100$

$p = 0.8$

Common Discrete Distributions

Example:



Number of heads in n fair coin toss trials

$$X : \Omega \rightarrow \{0, 1, \dots, n\}$$

$$n = 2 \quad \Omega = \{heads : heads, heads : tails, tails : heads, tails : tails\}$$

$$\text{In general:} \quad |\Omega| = 2^n$$

Common Discrete Distributions

Example:



Number of heads in n fair coin toss trials

$$X : \Omega \rightarrow \{0, 1, \dots, n\}$$

$$n = 2 \quad \Omega = \{heads : heads, heads : tails, tails : heads, tails : tails\}$$

In general: $|\Omega| = 2^n$

Notice: $X \sim \text{Bin}(n, 1/2)$

$$p_X(x) = \binom{n}{x} 0.5^n \quad E(X) = n/2$$

Common Discrete Distributions

The **Poisson** Distribution: $X \sim Pois(\lambda)$ $E(X) = \lambda$

Used to model the number of occurrences of an event that occur within a particular interval of time and/or space

λ : average number of counts (controls rarity of events)

$$X : \Omega \rightarrow \{0, 1, \dots\}$$

$$p_X(x) = \frac{\lambda^x e^{-\lambda}}{x!}$$

Common Discrete Distributions

The **Poisson** Distribution:

- Want to know the distribution of the number of occurrences of an event
⇒ Binomial?
- However, don't know how many trials are performed – could be infinite!
- But we do know the average rate of occurrence: $E(X) = \lambda$

$$X \sim \text{Bin}(n, p) \Rightarrow E(X) = np$$

$$\Rightarrow \lambda = np$$

$$\Rightarrow p = \frac{\lambda}{n}$$

Common Discrete Distributions

Binomial:
$$p_X(x) = \frac{n!}{x!(n-x)!} p^x (1-p)^{n-x}$$

$$p = \frac{\lambda}{n} \quad \Rightarrow \quad p_X(x) = \frac{n!}{x!(n-x)!} \left(\frac{\lambda}{n}\right)^x \left(1 - \frac{\lambda}{n}\right)^{n-x}$$

Common Discrete Distributions

Binomial:
$$p_X(x) = \frac{n!}{x!(n-x)!} p^x (1-p)^{n-x}$$

$$p = \frac{\lambda}{n} \Rightarrow p_X(x) = \frac{n!}{x!(n-x)!} \left(\frac{\lambda}{n}\right)^x \left(1 - \frac{\lambda}{n}\right)^{n-x}$$

$$p_X(x) = \frac{\lambda^x}{x!} \frac{n!}{n^x (n-x)!} \frac{\left(1 - \frac{\lambda}{n}\right)^n}{\left(1 - \frac{\lambda}{n}\right)^x}$$

Common Discrete Distributions

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$$p_X(x) = \lim_{n \rightarrow \infty} \left(\frac{\lambda^x}{x!} \left(1 - \frac{\lambda}{n}\right)^n \right)$$

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$$p_X(x) = \lim_{n \rightarrow \infty} \left(\frac{\lambda^x}{x!} \left(1 - \frac{\lambda}{n}\right)^n \right) = \frac{\lambda^x}{x!} e^{-\lambda}$$

□

Common Discrete Distributions

The Poisson distribution is the Binomial distribution as $n \rightarrow \infty$

If $X_n \sim \text{Bin}(n, p)$ then $X_n \xrightarrow{d} \text{Pois}(np)$

If n is large and p is small then the Binomial distribution can be approximated using the Poisson distribution

This is referred to as the:

- “Poisson Limit Theorem”
- “Poisson Approximation to the Binomial”
- “Law of Rare Events”

$$\lambda: \text{fixed} \quad n \rightarrow \infty \quad \Rightarrow \quad p \rightarrow 0$$

Poisson is often more computationally convenient than Binomial

References

Countless books + online resources!

Probability theory and distributions:

- Grimmett and Stirzker (2001) Probability and Random Processes. Oxford University Press.

General comprehensive introduction to (almost) everything mathematics (including a bit of probability theory):

- Garrity (2002) All the mathematics you missed: but need to know for graduate school. Cambridge University Press.