

## 2:Conditional Probability

Naijia Liu

Spring 2025

# Overview

1. Conditional Probability
2. Bayes's Rule
3. Independence

# Conditional probability

- **Conditional probability:** if we know that  $B$  has occurred, what is the probability of  $A$ ?

# Conditional probability

- **Conditional probability:** if we know that  $B$  has occurred, what is the probability of  $A$ ?
  - ▶ Conditioning our analysis on  $B$  having occurred.

# Conditional probability

- **Conditional probability:** if we know that  $B$  has occurred, what is the probability of  $A$ ?
  - ▶ Conditioning our analysis on  $B$  having occurred.
- **Examples:**

# Conditional probability

- **Conditional probability:** if we know that  $B$  has occurred, what is the probability of  $A$ ?
  - ▶ Conditioning our analysis on  $B$  having occurred.
- **Examples:**
  - ▶ What is the probability of two states going to war **if** they are both democracies?

# Conditional probability

- **Conditional probability:** if we know that  $B$  has occurred, what is the probability of  $A$ ?
  - ▶ Conditioning our analysis on  $B$  having occurred.
- **Examples:**
  - ▶ What is the probability of two states going to war **if** they are both democracies?
  - ▶ What is the probability of a judge ruling in a pro-choice direction **conditional** on having daughters?

# Conditional probability

- **Conditional probability:** if we know that  $B$  has occurred, what is the probability of  $A$ ?
  - ▶ Conditioning our analysis on  $B$  having occurred.
- **Examples:**
  - ▶ What is the probability of two states going to war **if** they are both democracies?
  - ▶ What is the probability of a judge ruling in a pro-choice direction **conditional** on having daughters?
  - ▶ What is the probability that there will be a coup in a country **conditional** on having a presidential system?



# Conditional probability

- **Conditional probability:** if we know that  $B$  has occurred, what is the probability of  $A$ ?
  - ▶ Conditioning our analysis on  $B$  having occurred.
- **Examples:**
  - ▶ What is the probability of two states going to war **if** they are both democracies?
  - ▶ What is the probability of a judge ruling in a pro-choice direction **conditional** on having daughters?
  - ▶ What is the probability that there will be a coup in a country **conditional** on having a presidential system?
- Conditional probability is the cornerstone of quantitative social science.

# Conditional Probability Definition

- Definition: If  $\mathbb{P}(B) > 0$  then the **conditional probability** of  $A$  given  $B$  is

$$\mathbb{P}(A \mid B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}.$$

# Conditional Probability Definition

- Definition: If  $\mathbb{P}(B) > 0$  then the **conditional probability** of  $A$  given  $B$  is

$$\mathbb{P}(A \mid B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}.$$

- How often  $A$  and  $B$  occur divided by how often  $B$  occurs.

# Conditional Probability Definition

- Definition: If  $\mathbb{P}(B) > 0$  then the **conditional probability** of  $A$  given  $B$  is

$$\mathbb{P}(A | B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}.$$

- How often  $A$  and  $B$  occur divided by how often  $B$  occurs.
- **WARNING!**  $\mathbb{P}(A | B)$  does **not**, in general, equal  $\mathbb{P}(B | A)$ .

# Conditional Probability Definition

- Definition: If  $\mathbb{P}(B) > 0$  then the **conditional probability** of  $A$  given  $B$  is

$$\mathbb{P}(A | B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}.$$

- How often  $A$  and  $B$  occur divided by how often  $B$  occurs.
- **WARNING!**  $\mathbb{P}(A | B)$  does **not**, in general, equal  $\mathbb{P}(B | A)$ .
  - ▶  $\mathbb{P}(\text{smart} | \text{in gov 2001})$  is high.

# Conditional Probability Definition

- Definition: If  $\mathbb{P}(B) > 0$  then the **conditional probability** of  $A$  given  $B$  is

$$\mathbb{P}(A | B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}.$$

- How often  $A$  and  $B$  occur divided by how often  $B$  occurs.
- **WARNING!**  $\mathbb{P}(A | B)$  does **not**, in general, equal  $\mathbb{P}(B | A)$ .
  - ▶  $\mathbb{P}(\text{smart} | \text{in gov 2001})$  is high.
  - ▶  $\mathbb{P}(\text{in gov 2001} | \text{smart})$  is low.

# Conditional Probability Definition

- Definition: If  $\mathbb{P}(B) > 0$  then the **conditional probability** of  $A$  given  $B$  is

$$\mathbb{P}(A | B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}.$$

- How often  $A$  and  $B$  occur divided by how often  $B$  occurs.
- **WARNING!**  $\mathbb{P}(A | B)$  does **not**, in general, equal  $\mathbb{P}(B | A)$ .
  - ▶  $\mathbb{P}(\text{smart} | \text{in gov 2001})$  is high.
  - ▶  $\mathbb{P}(\text{in gov 2001} | \text{smart})$  is low.
  - ▶ There are many smart people who are not in this class!

# Conditional Probability Definition

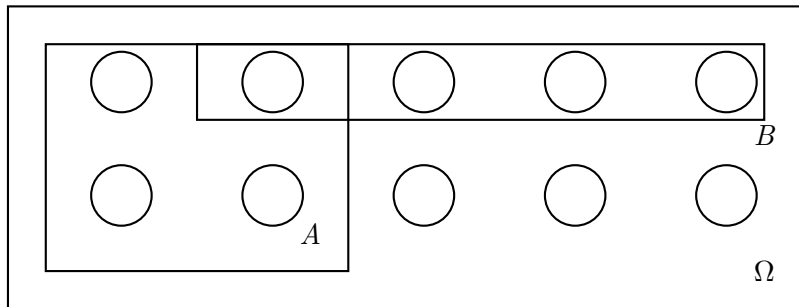
- Definition: If  $\mathbb{P}(B) > 0$  then the **conditional probability** of  $A$  given  $B$  is

$$\mathbb{P}(A | B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}.$$

- How often  $A$  and  $B$  occur divided by how often  $B$  occurs.
- **WARNING!**  $\mathbb{P}(A | B)$  does **not**, in general, equal  $\mathbb{P}(B | A)$ .
  - ▶  $\mathbb{P}(\text{smart} | \text{in gov 2001})$  is high.
  - ▶  $\mathbb{P}(\text{in gov 2001} | \text{smart})$  is low.
  - ▶ There are many smart people who are not in this class!
  - ▶ Also known as the **prosecutor's fallacy**.



# Intuition



# Examples

$A = \{\text{you get an A grade}\}$      $B = \{\text{everyone gets an A grade}\}$

# Examples

$A = \{\text{you get an A grade}\}$      $B = \{\text{everyone gets an A grade}\}$

- If  $B$  occurs then  $A$  must also occur, so  $\mathbb{P}(A \mid B) = 1$ .

# Examples

$A = \{\text{you get an A grade}\}$      $B = \{\text{everyone gets an A grade}\}$

- If  $B$  occurs then  $A$  must also occur, so  $\mathbb{P}(A | B) = 1$ .
  - ▶ Does this mean that  $\mathbb{P}(B | A) = 1$  as well?

# Examples

$A = \{\text{you get an A grade}\}$      $B = \{\text{everyone gets an A grade}\}$

- If  $B$  occurs then  $A$  must also occur, so  $\mathbb{P}(A | B) = 1$ .
  - ▶ Does this mean that  $\mathbb{P}(B | A) = 1$  as well?
- Now let  $A = \{\text{you get a B grade}\}$ .

# Examples

$A = \{\text{you get an A grade}\}$      $B = \{\text{everyone gets an A grade}\}$

- If  $B$  occurs then  $A$  must also occur, so  $\mathbb{P}(A | B) = 1$ .
  - ▶ Does this mean that  $\mathbb{P}(B | A) = 1$  as well?
- Now let  $A = \{\text{you get a B grade}\}$ .
  - ▶ The intersection  $A \cap B = \emptyset$ , so that  $\mathbb{P}(A | B) = 0$ .

# Examples

$A = \{\text{you get an A grade}\}$      $B = \{\text{everyone gets an A grade}\}$

- If  $B$  occurs then  $A$  must also occur, so  $\mathbb{P}(A | B) = 1$ .
  - ▶ Does this mean that  $\mathbb{P}(B | A) = 1$  as well?
- Now let  $A = \{\text{you get a B grade}\}$ .
  - ▶ The intersection  $A \cap B = \emptyset$ , so that  $\mathbb{P}(A | B) = 0$ .
  - ▶ Intuitively, it's because  $B$  occurring precludes  $A$  from occurring.

# U.S. Senate Example

	<b>Democrats</b>	<b>Republicans</b>	<b>Independents</b>	<b>Total</b>
Men	33	40	2	75
Women	15	9	1	25
Total	48	49	3	100



## U.S. Senate Example

	<b>Democrats</b>	<b>Republicans</b>	<b>Independents</b>	<b>Total</b>
Men	33	40	2	75
Women	15	9	1	25
Total	48	49	3	100

- Choose one senator at random from this population.

# U.S. Senate Example

	Democrats	Republicans	Independents	Total
Men	33	40	2	75
Women	15	9	1	25
Total	48	49	3	100

- Choose one senator at random from this population.
- What is the probability that a randomly selected Republican is a woman:

$$\mathbb{P}(\text{Woman} \mid \text{Republican}) = \frac{\mathbb{P}(\text{Woman} \cap \text{Republican})}{\mathbb{P}(\text{Republican})} = \frac{9/100}{49/100} = \frac{9}{49} \approx 0.184.$$

# U.S. Senate Example

	Democrats	Republicans	Independents	Total
Men	33	40	2	75
Women	15	9	1	25
Total	48	49	3	100

- Choose one senator at random from this population.
- What is the probability that a randomly selected Republican is a woman:

$$\mathbb{P}(\text{Woman} \mid \text{Republican}) = \frac{\mathbb{P}(\text{Woman} \cap \text{Republican})}{\mathbb{P}(\text{Republican})} = \frac{9/100}{49/100} = \frac{9}{49} \approx 0.184.$$

- Choose two senators at random:

# U.S. Senate Example

	Democrats	Republicans	Independents	Total
Men	33	40	2	75
Women	15	9	1	25
Total	48	49	3	100

- Choose one senator at random from this population.
- What is the probability that a randomly selected Republican is a woman:

$$\mathbb{P}(\text{Woman} \mid \text{Republican}) = \frac{\mathbb{P}(\text{Woman} \cap \text{Republican})}{\mathbb{P}(\text{Republican})} = \frac{9/100}{49/100} = \frac{9}{49} \approx 0.184.$$

- Choose two senators at random:
  - ▶  $\mathbb{P}(2 \text{ women} \mid \text{one draw is a woman})?$

# U.S. Senate Example

	Democrats	Republicans	Independents	Total
Men	33	40	2	75
Women	15	9	1	25
Total	48	49	3	100

- Choose one senator at random from this population.
- What is the probability that a randomly selected Republican is a woman:

$$\mathbb{P}(\text{Woman} \mid \text{Republican}) = \frac{\mathbb{P}(\text{Woman} \cap \text{Republican})}{\mathbb{P}(\text{Republican})} = \frac{9/100}{49/100} = \frac{9}{49} \approx 0.184.$$

- Choose two senators at random:
  - ▶  $\mathbb{P}(2 \text{ women} \mid \text{one draw is a woman})?$
  - ▶  $\mathbb{P}(2 \text{ women} \mid \text{one draw is Liz Warren})?$

# Conditional Probabilities Are Probabilities

- Conditional probabilities  $\mathbb{P}(A \mid B)$  are valid probability functions:

# Conditional Probabilities Are Probabilities

- Conditional probabilities  $\mathbb{P}(A \mid B)$  are valid probability functions:
  1.  $\mathbb{P}(A \mid B) \geq 0$

# Conditional Probabilities Are Probabilities

- Conditional probabilities  $\mathbb{P}(A \mid B)$  are valid probability functions:
  1.  $\mathbb{P}(A \mid B) \geq 0$
  2.  $\mathbb{P}(\Omega \mid B) = 1$



# Conditional Probabilities Are Probabilities

- Conditional probabilities  $\mathbb{P}(A \mid B)$  are valid probability functions:
  1.  $\mathbb{P}(A \mid B) \geq 0$
  2.  $\mathbb{P}(\Omega \mid B) = 1$
  3. If  $A_1$  and  $A_2$  are disjoint, then
$$\mathbb{P}(A_1 \cup A_2 \mid B) = \mathbb{P}(A_1 \mid B) + \mathbb{P}(A_2 \mid B)$$

# Conditional Probabilities Are Probabilities

- Conditional probabilities  $\mathbb{P}(A \mid B)$  are valid probability functions:
  1.  $\mathbb{P}(A \mid B) \geq 0$
  2.  $\mathbb{P}(\Omega \mid B) = 1$
  3. If  $A_1$  and  $A_2$  are disjoint, then
$$\mathbb{P}(A_1 \cup A_2 \mid B) = \mathbb{P}(A_1 \mid B) + \mathbb{P}(A_2 \mid B)$$
- $\sim$  Rules of probability apply to the left-hand side of the conditioning bar ( $A$ ):

# Conditional Probabilities Are Probabilities

- Conditional probabilities  $\mathbb{P}(A | B)$  are valid probability functions:
  1.  $\mathbb{P}(A | B) \geq 0$
  2.  $\mathbb{P}(\Omega | B) = 1$
  3. If  $A_1$  and  $A_2$  are disjoint, then
$$\mathbb{P}(A_1 \cup A_2 | B) = \mathbb{P}(A_1 | B) + \mathbb{P}(A_2 | B)$$
- $\sim$  Rules of probability apply to the left-hand side of the conditioning bar ( $A$ ):
  - ▶ All probabilities **normalized** to event  $B$ ,  $\mathbb{P}(B | B) = 1$ .

# Conditional Probabilities Are Probabilities

- Conditional probabilities  $\mathbb{P}(A \mid B)$  are valid probability functions:
  1.  $\mathbb{P}(A \mid B) \geq 0$
  2.  $\mathbb{P}(\Omega \mid B) = 1$
  3. If  $A_1$  and  $A_2$  are disjoint, then
$$\mathbb{P}(A_1 \cup A_2 \mid B) = \mathbb{P}(A_1 \mid B) + \mathbb{P}(A_2 \mid B)$$
- $\sim$  Rules of probability apply to the left-hand side of the conditioning bar ( $A$ ):
  - ▶ All probabilities **normalized** to event  $B$ ,  $\mathbb{P}(B \mid B) = 1$ .
- Not for the right-hand side, so even if  $B$  and  $C$  are disjoint,

$$\mathbb{P}(A \mid B \cup C) \neq \mathbb{P}(A \mid B) + \mathbb{P}(A \mid C).$$

# Joint Probabilities from Conditionals

- **Joint probabilities:** probability of two events occurring (intersections)

# Joint Probabilities from Conditionals

- **Joint probabilities:** probability of two events occurring (intersections)
  - ▶ Often replace  $\cap$  with commas:  $\mathbb{P}(A \cap B \cap C) = \mathbb{P}(A, B, C)$

# Joint Probabilities from Conditionals

- **Joint probabilities:** probability of two events occurring (intersections)
  - ▶ Often replace  $\cap$  with commas:  $\mathbb{P}(A \cap B \cap C) = \mathbb{P}(A, B, C)$
- Definition of conditional probability implies:

$$\mathbb{P}(A \cap B) \equiv \mathbb{P}(A, B) = \mathbb{P}(B)\mathbb{P}(A | B) = \mathbb{P}(A)\mathbb{P}(B | A)$$

# Joint Probabilities from Conditionals

- **Joint probabilities:** probability of two events occurring (intersections)
  - ▶ Often replace  $\cap$  with commas:  $\mathbb{P}(A \cap B \cap C) = \mathbb{P}(A, B, C)$
- Definition of conditional probability implies:

$$\mathbb{P}(A \cap B) \equiv \mathbb{P}(A, B) = \mathbb{P}(B)\mathbb{P}(A | B) = \mathbb{P}(A)\mathbb{P}(B | A)$$

- What about three events?

$$\mathbb{P}(A, B, C) = \mathbb{P}(A)\mathbb{P}(B | A)\mathbb{P}(C | A, B)$$



# Joint Probabilities from Conditionals

- **Joint probabilities:** probability of two events occurring (intersections)
  - ▶ Often replace  $\cap$  with commas:  $\mathbb{P}(A \cap B \cap C) = \mathbb{P}(A, B, C)$
- Definition of conditional probability implies:

$$\mathbb{P}(A \cap B) \equiv \mathbb{P}(A, B) = \mathbb{P}(B)\mathbb{P}(A | B) = \mathbb{P}(A)\mathbb{P}(B | A)$$

- What about three events?

$$\mathbb{P}(A, B, C) = \mathbb{P}(A)\mathbb{P}(B | A)\mathbb{P}(C | A, B)$$

- Generalize to the intersection of  $N$  events:

$$\mathbb{P}(A_1, \dots, A_N) = \mathbb{P}(A_1)\mathbb{P}(A_2 | A_1)\mathbb{P}(A_3 | A_1, A_2) \dots \mathbb{P}(A_N | A_1, \dots, A_{N-1}).$$

## Joint Probabilities, Example

- Draw three cards at random from a deck without replacement.

## Joint Probabilities, Example

- Draw three cards at random from a deck without replacement.
- What's the probability that we draw three Aces?

$$\mathbb{P}(\text{Ace}_1 \cap \text{Ace}_2 \cap \text{Ace}_3) = \mathbb{P}(\text{Ace}_1) \mathbb{P}(\text{Ace}_2 \mid \text{Ace}_1) \mathbb{P}(\text{Ace}_3 \mid \text{Ace}_2 \cap \text{Ace}_1)$$

## Joint Probabilities, Example

- Draw three cards at random from a deck without replacement.
- What's the probability that we draw three Aces?

$$\mathbb{P}(\text{Ace}_1 \cap \text{Ace}_2 \cap \text{Ace}_3) = \mathbb{P}(\text{Ace}_1) \mathbb{P}(\text{Ace}_2 \mid \text{Ace}_1) \mathbb{P}(\text{Ace}_3 \mid \text{Ace}_2 \cap \text{Ace}_1)$$

- What are these probabilities?

## Joint Probabilities, Example

- Draw three cards at random from a deck without replacement.
- What's the probability that we draw three Aces?

$$\mathbb{P}(\text{Ace}_1 \cap \text{Ace}_2 \cap \text{Ace}_3) = \mathbb{P}(\text{Ace}_1) \mathbb{P}(\text{Ace}_2 \mid \text{Ace}_1) \mathbb{P}(\text{Ace}_3 \mid \text{Ace}_2 \cap \text{Ace}_1)$$

- What are these probabilities?
  - ▶ 4 Aces to pick out of 52 cards  $\sim \mathbb{P}(\text{Ace}_1) = \frac{4}{52}$

## Joint Probabilities, Example

- Draw three cards at random from a deck without replacement.
- What's the probability that we draw three Aces?

$$\mathbb{P}(\text{Ace}_1 \cap \text{Ace}_2 \cap \text{Ace}_3) = \mathbb{P}(\text{Ace}_1) \mathbb{P}(\text{Ace}_2 \mid \text{Ace}_1) \mathbb{P}(\text{Ace}_3 \mid \text{Ace}_2 \cap \text{Ace}_1)$$

- What are these probabilities?
  - ▶ 4 Aces to pick out of 52 cards  $\sim \mathbb{P}(\text{Ace}_1) = \frac{4}{52}$
  - ▶ 3 Aces left in the 51 remaining cards  $\sim \mathbb{P}(\text{Ace}_2 \mid \text{Ace}_1) = \frac{3}{51}$

# Joint Probabilities, Example

- Draw three cards at random from a deck without replacement.
- What's the probability that we draw three Aces?

$$\mathbb{P}(\text{Ace}_1 \cap \text{Ace}_2 \cap \text{Ace}_3) = \mathbb{P}(\text{Ace}_1) \mathbb{P}(\text{Ace}_2 \mid \text{Ace}_1) \mathbb{P}(\text{Ace}_3 \mid \text{Ace}_2 \cap \text{Ace}_1)$$

- What are these probabilities?
  - ▶ 4 Aces to pick out of 52 cards  $\sim \mathbb{P}(\text{Ace}_1) = \frac{4}{52}$
  - ▶ 3 Aces left in the 51 remaining cards  $\sim \mathbb{P}(\text{Ace}_2 \mid \text{Ace}_1) = \frac{3}{51}$
  - ▶ 2 Aces left in the 50 remaining cards  $\sim \mathbb{P}(\text{Ace}_3 \mid \text{Ace}_2 \cap \text{Ace}_1) = \frac{2}{50}$

## Joint Probabilities, Example

- Draw three cards at random from a deck without replacement.
- What's the probability that we draw three Aces?

$$\mathbb{P}(\text{Ace}_1 \cap \text{Ace}_2 \cap \text{Ace}_3) = \mathbb{P}(\text{Ace}_1) \mathbb{P}(\text{Ace}_2 \mid \text{Ace}_1) \mathbb{P}(\text{Ace}_3 \mid \text{Ace}_2 \cap \text{Ace}_1)$$

- What are these probabilities?
  - ▶ 4 Aces to pick out of 52 cards  $\sim \mathbb{P}(\text{Ace}_1) = \frac{4}{52}$
  - ▶ 3 Aces left in the 51 remaining cards  $\sim \mathbb{P}(\text{Ace}_2 \mid \text{Ace}_1) = \frac{3}{51}$
  - ▶ 2 Aces left in the 50 remaining cards  $\sim \mathbb{P}(\text{Ace}_3 \mid \text{Ace}_2 \cap \text{Ace}_1) = \frac{2}{50}$
- Thus,

$$\mathbb{P}(\text{Ace}_1 \cap \text{Ace}_2 \cap \text{Ace}_3) = \frac{4}{52} \times \frac{3}{51} \times \frac{2}{50} \approx 0.00018.$$



# Probability of War Resolution

- Suppose we observed country-dyads over 3 years.
- In each year the dyad can be at war ( $W_t$ ) or at peace ( $P_t$ ).
- What's the probability that a war starts in year 1 and ends after 2 years?

$$\mathbb{P}(W_1, W_2, P_3) = \mathbb{P}(W_1)\mathbb{P}(W_2 | W_1)\mathbb{P}(P_3 | W_1, W_2).$$

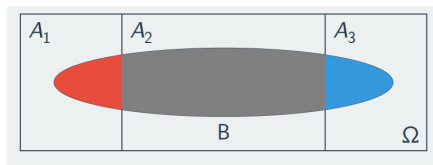
# Probability of War Resolution

- Suppose we observed country-dyads over 3 years.
- In each year the dyad can be at war ( $W_t$ ) or at peace ( $P_t$ ).
- What's the probability that a war starts in year 1 and ends after 2 years?

$$\mathbb{P}(W_1, W_2, P_3) = \mathbb{P}(W_1)\mathbb{P}(W_2 | W_1)\mathbb{P}(P_3 | W_1, W_2).$$

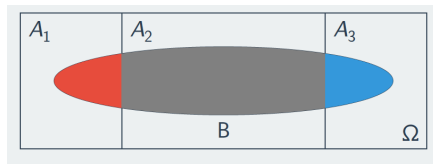
- **Actual Research Question<sup>TM</sup>**: modeling the continuation probability of war,  $\mathbb{P}(W_2 | W_1)$ , and the probability of conflict resolution,  $\mathbb{P}(P_3 | W_1, W_2)$ .

# Law of Total Probability



- Often we only have disaggregated probabilities.
  - ▶  $B$  = sampling a Trump supporter from either Cambridge or Somerville.
  - ▶ We know the prop. of Trump supporters in each city from precinct data.
  - ▶ How to calculate the overall probability of  $B$ ?
- A **partition** is a set of mutually disjoint events whose union is  $\Omega$ .

# Law of Total Probability



- The **law of total probability** (LTP) states if  $A_1, \dots, A_k$  is a partition:

$$\mathbb{P}(B) = \sum_{j=1}^k \mathbb{P}(B | A_j) \mathbb{P}(A_j).$$

- ▶ Overall probability = weighted sum of within-partition probabilities.
- ▶ Weights are the probability of the particular partition.

# A Mixture of Cities

- Randomly drawing voters from either Cambridge or Somerville:

# A Mixture of Cities

- Randomly drawing voters from either Cambridge or Somerville:
  - ▶ Camb. had 50k voters and Somer. had around 40k, so:  
 $\mathbb{P}(\text{Camb.}) = 0.56$  and  $\mathbb{P}(\text{Somer.}) = 0.44$ .

# A Mixture of Cities

- Randomly drawing voters from either Cambridge or Somerville:
  - ▶ Camb. had 50k voters and Somer. had around 40k, so:  
 $\mathbb{P}(\text{Camb.}) = 0.56$  and  $\mathbb{P}(\text{Somer.}) = 0.44$ .
- The state provides the following election results for each city:

# A Mixture of Cities

- Randomly drawing voters from either Cambridge or Somerville:
  - ▶ Camb. had 50k voters and Somer. had around 40k, so:  
 $\mathbb{P}(\text{Camb.}) = 0.56$  and  $\mathbb{P}(\text{Somer.}) = 0.44$ .
- The state provides the following election results for each city:
  - ▶  $\mathbb{P}(\text{Trump} \mid \text{Camb.}) = 0.066$



# A Mixture of Cities

- Randomly drawing voters from either Cambridge or Somerville:
  - ▶ Camb. had 50k voters and Somer. had around 40k, so:  
 $\mathbb{P}(\text{Camb.}) = 0.56$  and  $\mathbb{P}(\text{Somer.}) = 0.44$ .
- The state provides the following election results for each city:
  - ▶  $\mathbb{P}(\text{Trump} \mid \text{Camb.}) = 0.066$
  - ▶  $\mathbb{P}(\text{Trump} \mid \text{Somer.}) = 0.103$ .

# A Mixture of Cities

- Randomly drawing voters from either Cambridge or Somerville:
  - ▶ Camb. had 50k voters and Somer. had around 40k, so:  
 $\mathbb{P}(\text{Camb.}) = 0.56$  and  $\mathbb{P}(\text{Somer.}) = 0.44$ .
- The state provides the following election results for each city:
  - ▶  $\mathbb{P}(\text{Trump} \mid \text{Camb.}) = 0.066$
  - ▶  $\mathbb{P}(\text{Trump} \mid \text{Somer.}) = 0.103$ .
- To get the overall turnout rate,  $\mathbb{P}(\text{Trump})$ , we can apply the LTP:

$$\begin{aligned}\mathbb{P}(\text{Trump}) &= \mathbb{P}(\text{Trump} \mid \text{Camb.})\mathbb{P}(\text{Camb.}) + \mathbb{P}(\text{Trump} \mid \text{Somer.})\mathbb{P}(\text{Somer.}) \\ &= 0.066 \times 0.56 + 0.103 \times 0.44 = 0.082.\end{aligned}$$

# QAnon



You meet a man named Steve and he tells you that he is a Republican. You have been interested in meeting someone who believes in the QAnon conspiracy theory. Given what you know about Steve, would you guess that he believes in QAnon or not?

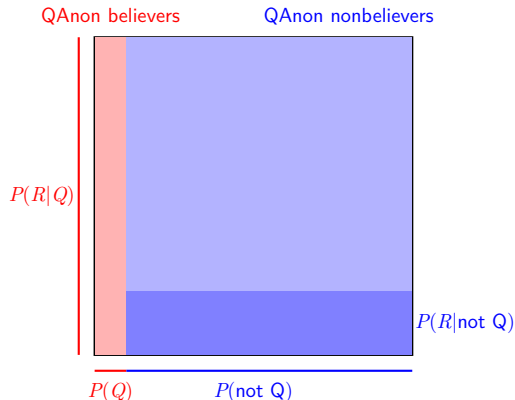
# QAnon



You meet a man named Steve and he tells you that he is a Republican. You have been interested in meeting someone who believes in the QAnon conspiracy theory. Given what you know about Steve, would you guess that he believes in QAnon or not?

- Common response: probably believes in QAnon since believers tend to be Republicans.
- **Base rate fallacy:** ignores how uncommon QAnon believers are!

# Visualizing QAnon support



$$\text{Chance a random Republican believes QAnon} = \frac{P(R|Q)P(Q)}{P(R|Q)P(Q) + P(R|\text{not } Q)P(\text{not } Q)}$$

# Bayes' rule



- Reverend Thomas Bayes (1701–61): English minister and statistician
- **Bayes' rule:** if  $\mathbb{P}(B) > 0$ , then:

# Bayes' rule



- Reverend Thomas Bayes (1701–61): English minister and statistician
- **Bayes' rule:** if  $\mathbb{P}(B) > 0$ , then:

$$\mathbb{P}(A | B) = \frac{\mathbb{P}(B | A)\mathbb{P}(A)}{\mathbb{P}(B)} = \frac{\mathbb{P}(B | A)\mathbb{P}(A)}{\mathbb{P}(B | A)\mathbb{P}(A) + \mathbb{P}(B | A^c)\mathbb{P}(A^c)}$$

# Why is Bayes' Rule Useful?

- What is the probability of some hypothesis given some evidence?



# Why is Bayes' Rule Useful?

- What is the probability of some hypothesis given some evidence?
  - ▶  $\mathbb{P}(\text{QAnon} \mid \text{Republican})?$

# Why is Bayes' Rule Useful?

- What is the probability of some hypothesis given some evidence?
  - ▶  $\mathbb{P}(\text{QAnon} \mid \text{Republican})$ ?
- Often easier to know probability of evidence given hypothesis.

# Why is Bayes' Rule Useful?

- What is the probability of some hypothesis given some evidence?
  - ▶  $\mathbb{P}(\text{QAnon} \mid \text{Republican})?$
- Often easier to know probability of evidence given hypothesis.
  - ▶  $\mathbb{P}(\text{Republican} \mid \text{QAnon})$

# Why is Bayes' Rule Useful?

- What is the probability of some hypothesis given some evidence?
  - ▶  $\mathbb{P}(\text{QAnon} \mid \text{Republican})?$
- Often easier to know probability of evidence given hypothesis.
  - ▶  $\mathbb{P}(\text{Republican} \mid \text{QAnon})$
- Combine this with the **prior probability** of the hypothesis.

# Why is Bayes' Rule Useful?

- What is the probability of some hypothesis given some evidence?
  - ▶  $\mathbb{P}(\text{QAnon} \mid \text{Republican})?$
- Often easier to know probability of evidence given hypothesis.
  - ▶  $\mathbb{P}(\text{Republican} \mid \text{QAnon})$
- Combine this with the **prior probability** of the hypothesis.
  - ▶ Prior:  $\mathbb{P}(\text{QAnon})$

# Why is Bayes' Rule Useful?

- What is the probability of some hypothesis given some evidence?
  - ▶  $\mathbb{P}(\text{QAnon} \mid \text{Republican})?$
- Often easier to know probability of evidence given hypothesis.
  - ▶  $\mathbb{P}(\text{Republican} \mid \text{QAnon})$
- Combine this with the **prior probability** of the hypothesis.
  - ▶ Prior:  $\mathbb{P}(\text{QAnon})$
  - ▶ **Posterior:**  $\mathbb{P}(\text{QAnon} \mid \text{Republican})$

# Why is Bayes' Rule Useful?

- What is the probability of some hypothesis given some evidence?
  - ▶  $\mathbb{P}(\text{QAnon} \mid \text{Republican})?$
- Often easier to know probability of evidence given hypothesis.
  - ▶  $\mathbb{P}(\text{Republican} \mid \text{QAnon})$
- Combine this with the **prior probability** of the hypothesis.
  - ▶ Prior:  $\mathbb{P}(\text{QAnon})$
  - ▶ **Posterior**:  $\mathbb{P}(\text{QAnon} \mid \text{Republican})$
- Applying Bayes' rule is often called **updating the prior**.

# Why is Bayes' Rule Useful?

- What is the probability of some hypothesis given some evidence?
  - ▶  $\mathbb{P}(\text{QAnon} \mid \text{Republican})?$
- Often easier to know probability of evidence given hypothesis.
  - ▶  $\mathbb{P}(\text{Republican} \mid \text{QAnon})$
- Combine this with the **prior probability** of the hypothesis.
  - ▶ Prior:  $\mathbb{P}(\text{QAnon})$
  - ▶ **Posterior**:  $\mathbb{P}(\text{QAnon} \mid \text{Republican})$
- Applying Bayes' rule is often called **updating the prior**.
  - ▶  $\mathbb{P}(\text{QAnon}) \rightarrow \mathbb{P}(\text{QAnon} \mid \text{Republican})$



# Why is Bayes' Rule Useful?

- What is the probability of some hypothesis given some evidence?
  - ▶  $\mathbb{P}(\text{QAnon} \mid \text{Republican})$ ?
- Often easier to know probability of evidence given hypothesis.
  - ▶  $\mathbb{P}(\text{Republican} \mid \text{QAnon})$
- Combine this with the **prior probability** of the hypothesis.
  - ▶ Prior:  $\mathbb{P}(\text{QAnon})$
  - ▶ **Posterior**:  $\mathbb{P}(\text{QAnon} \mid \text{Republican})$
- Applying Bayes' rule is often called **updating the prior**.
  - ▶  $\mathbb{P}(\text{QAnon}) \rightarrow \mathbb{P}(\text{QAnon} \mid \text{Republican})$
  - ▶ How does the evidence change the chance of the hypothesis being true?

# Uses of Bayes' Rule

- **Medical testing:**

# Uses of Bayes' Rule

- **Medical testing:**

- ▶ Want to know:  $\mathbb{P}(\text{Disease} \mid \text{Test Positive})$

# Uses of Bayes' Rule

- **Medical testing:**

- ▶ Want to know:  $\mathbb{P}(\text{Disease} \mid \text{Test Positive})$

- ▶ Have:  $\mathbb{P}(\text{Test Positive} \mid \text{Disease})$  and  $\mathbb{P}(\text{Disease})$

# Uses of Bayes' Rule

- **Medical testing:**
  - ▶ Want to know:  $\mathbb{P}(\text{Disease} \mid \text{Test Positive})$
  - ▶ Have:  $\mathbb{P}(\text{Test Positive} \mid \text{Disease})$  and  $\mathbb{P}(\text{Disease})$
- **Predicting traits from names:**

# Uses of Bayes' Rule

- **Medical testing:**
  - ▶ Want to know:  $\mathbb{P}(\text{Disease} \mid \text{Test Positive})$
  - ▶ Have:  $\mathbb{P}(\text{Test Positive} \mid \text{Disease})$  and  $\mathbb{P}(\text{Disease})$
- **Predicting traits from names:**
  - ▶ Want to know:  $\mathbb{P}(\text{African American} \mid \text{Last Name})$

# Uses of Bayes' Rule

- **Medical testing:**

- ▶ Want to know:  $\mathbb{P}(\text{Disease} \mid \text{Test Positive})$

- ▶ Have:  $\mathbb{P}(\text{Test Positive} \mid \text{Disease})$  and  $\mathbb{P}(\text{Disease})$

- **Predicting traits from names:**

- ▶ Want to know:  $\mathbb{P}(\text{African American} \mid \text{Last Name})$

- ▶ Have:  $\mathbb{P}(\text{Last Name} \mid \text{African American})$  and  $\mathbb{P}(\text{African American})$

# Uses of Bayes' Rule

- **Medical testing:**

- ▶ Want to know:  $\mathbb{P}(\text{Disease} \mid \text{Test Positive})$

- ▶ Have:  $\mathbb{P}(\text{Test Positive} \mid \text{Disease})$  and  $\mathbb{P}(\text{Disease})$

- **Predicting traits from names:**

- ▶ Want to know:  $\mathbb{P}(\text{African American} \mid \text{Last Name})$

- ▶ Have:  $\mathbb{P}(\text{Last Name} \mid \text{African American})$  and  $\mathbb{P}(\text{African American})$

- **Spam filtering:**



# Uses of Bayes' Rule

- **Medical testing:**

- ▶ Want to know:  $\mathbb{P}(\text{Disease} \mid \text{Test Positive})$

- ▶ Have:  $\mathbb{P}(\text{Test Positive} \mid \text{Disease})$  and  $\mathbb{P}(\text{Disease})$

- **Predicting traits from names:**

- ▶ Want to know:  $\mathbb{P}(\text{African American} \mid \text{Last Name})$

- ▶ Have:  $\mathbb{P}(\text{Last Name} \mid \text{African American})$  and  $\mathbb{P}(\text{African American})$

- **Spam filtering:**

- ▶ Want to know:  $\mathbb{P}(\text{Spam} \mid \text{Email text})$

# Uses of Bayes' Rule

- **Medical testing:**

- ▶ Want to know:  $\mathbb{P}(\text{Disease} \mid \text{Test Positive})$

- ▶ Have:  $\mathbb{P}(\text{Test Positive} \mid \text{Disease})$  and  $\mathbb{P}(\text{Disease})$

- **Predicting traits from names:**

- ▶ Want to know:  $\mathbb{P}(\text{African American} \mid \text{Last Name})$

- ▶ Have:  $\mathbb{P}(\text{Last Name} \mid \text{African American})$  and  $\mathbb{P}(\text{African American})$

- **Spam filtering:**

- ▶ Want to know:  $\mathbb{P}(\text{Spam} \mid \text{Email text})$

- ▶ Have:  $\mathbb{P}(\text{Email text} \mid \text{Spam})$  and  $\mathbb{P}(\text{Spam})$

# Medical tests

- Suppose you go and get a COVID-19 test and it comes back positive!

# Medical tests

- Suppose you go and get a COVID-19 test and it comes back positive!
  - ▶ Let a positive test be  $PT$ .

# Medical tests

- Suppose you go and get a COVID-19 test and it comes back positive!
  - ▶ Let a positive test be  $PT$ .
- What's the probability you actually have COVID-19?

# Medical tests

- Suppose you go and get a COVID-19 test and it comes back positive!
  - ▶ Let a positive test be  $PT$ .
- What's the probability you actually have COVID-19?
  - ▶ Let having COVID be labeled  $C$ .

# Medical tests

- Suppose you go and get a COVID-19 test and it comes back positive!
  - ▶ Let a positive test be  $PT$ .
- What's the probability you actually have COVID-19?
  - ▶ Let having COVID be labeled  $C$ .
  - ▶ Question: What is  $\mathbb{P}(C \mid PT)$ ?

# Medical tests

- Suppose you go and get a COVID-19 test and it comes back positive!
  - ▶ Let a positive test be  $PT$ .
- What's the probability you actually have COVID-19?
  - ▶ Let having COVID be labeled  $C$ .
  - ▶ Question: What is  $\mathbb{P}(C \mid PT)$ ?
- Components for calculating Bayes' rule:



# Medical tests

- Suppose you go and get a COVID-19 test and it comes back positive!
  - ▶ Let a positive test be  $PT$ .
- What's the probability you actually have COVID-19?
  - ▶ Let having COVID be labeled  $C$ .
  - ▶ Question: What is  $\mathbb{P}(C | PT)$ ?
- Components for calculating Bayes' rule:
  - ▶  $\mathbb{P}(PT | C) = 0.8$ : true positive rate

# Medical tests

- Suppose you go and get a COVID-19 test and it comes back positive!
  - ▶ Let a positive test be  $PT$ .
- What's the probability you actually have COVID-19?
  - ▶ Let having COVID be labeled  $C$ .
  - ▶ Question: What is  $\mathbb{P}(C | PT)$ ?
- Components for calculating Bayes' rule:
  - ▶  $\mathbb{P}(PT | C) = 0.8$ : true positive rate
  - ▶  $\mathbb{P}(PT | C^c) = 0.005$ : false positive rate

# Medical tests

- Suppose you go and get a COVID-19 test and it comes back positive!
  - ▶ Let a positive test be  $PT$ .
- What's the probability you actually have COVID-19?
  - ▶ Let having COVID be labeled  $C$ .
  - ▶ Question: What is  $\mathbb{P}(C | PT)$ ?
- Components for calculating Bayes' rule:
  - ▶  $\mathbb{P}(PT | C) = 0.8$ : true positive rate
  - ▶  $\mathbb{P}(PT | C^c) = 0.005$ : false positive rate
  - ▶  $\mathbb{P}(C) = 0.007$  rough prevalence of active COVID cases.

## Applying Bayes' rule to COVID tests

- Use the law of total probability to get the denominator:

$$\mathbb{P}(PT) = \mathbb{P}(PT | C)\mathbb{P}(C) + \mathbb{P}(PT | C^c)\mathbb{P}(C^c)$$

$$= (0.8 \times 0.007) + (0.005 \times 0.993)$$

$$= 0.011$$

## Applying Bayes' rule to COVID tests

- Use the law of total probability to get the denominator:

$$\begin{aligned}\mathbb{P}(PT) &= \mathbb{P}(PT | C)\mathbb{P}(C) + \mathbb{P}(PT | C^c)\mathbb{P}(C^c) \\ &= (0.8 \times 0.007) + (0.005 \times 0.993) \\ &= 0.011\end{aligned}$$

- Now plug in all values to Bayes' rule:

$$\mathbb{P}(C | PT) = \frac{\mathbb{P}(PT | C)\mathbb{P}(C)}{\mathbb{P}(PT)} = \frac{0.8 \times 0.007}{0.0106} \approx 0.53$$

## Applying Bayes' rule to COVID tests

- Use the law of total probability to get the denominator:

$$\begin{aligned}\mathbb{P}(PT) &= \mathbb{P}(PT | C)\mathbb{P}(C) + \mathbb{P}(PT | C^c)\mathbb{P}(C^c) \\ &= (0.8 \times 0.007) + (0.005 \times 0.993) \\ &= 0.011\end{aligned}$$

- Now plug in all values to Bayes' rule:

$$\mathbb{P}(C | PT) = \frac{\mathbb{P}(PT | C)\mathbb{P}(C)}{\mathbb{P}(PT)} = \frac{0.8 \times 0.007}{0.0106} \approx 0.53$$

- If false positive rate goes up to 1%  $\rightsquigarrow \mathbb{P}(C | PT) \approx 0.36$

# Independence

- Heart of Bayes's rule: knowing  $B$  occurs often changes probability of  $A$ .

# Independence

- Heart of Bayes's rule: knowing  $B$  occurs often changes probability of  $A$ .
  - ▶ What if  $B$  provides no information?  $\rightsquigarrow$  independence



# Independence

- Heart of Bayes's rule: knowing  $B$  occurs often changes probability of  $A$ .
  - ▶ What if  $B$  provides no information?  $\rightsquigarrow$  independence
- Two events  $A$  and  $B$  are **independent** if:

$$\mathbb{P}(A \cap B) = \mathbb{P}(A)\mathbb{P}(B)$$

# Independence

- Heart of Bayes's rule: knowing  $B$  occurs often changes probability of  $A$ .
  - ▶ What if  $B$  provides no information?  $\rightsquigarrow$  independence
- Two events  $A$  and  $B$  are **independent** if:

$$\mathbb{P}(A \cap B) = \mathbb{P}(A)\mathbb{P}(B)$$

- ▶ Sometimes written as  $A \perp\!\!\!\perp B$

# Independence

- Heart of Bayes's rule: knowing  $B$  occurs often changes probability of  $A$ .
  - ▶ What if  $B$  provides no information?  $\rightsquigarrow$  independence
- Two events  $A$  and  $B$  are **independent** if:

$$\mathbb{P}(A \cap B) = \mathbb{P}(A)\mathbb{P}(B)$$

- ▶ Sometimes written as  $A \perp\!\!\!\perp B$
- ▶ **Symmetric:**  $A \perp\!\!\!\perp B$  equivalent to  $B \perp\!\!\!\perp A$

# Independence

- Heart of Bayes's rule: knowing  $B$  occurs often changes probability of  $A$ .
  - ▶ What if  $B$  provides no information?  $\rightsquigarrow$  independence
- Two events  $A$  and  $B$  are **independent** if:

$$\mathbb{P}(A \cap B) = \mathbb{P}(A)\mathbb{P}(B)$$

- ▶ Sometimes written as  $A \perp\!\!\!\perp B$
- ▶ **Symmetric:**  $A \perp\!\!\!\perp B$  equivalent to  $B \perp\!\!\!\perp A$
- ▶ Events that are not independent are **dependent**.

# Independence

- Heart of Bayes's rule: knowing  $B$  occurs often changes probability of  $A$ .
  - ▶ What if  $B$  provides no information?  $\rightsquigarrow$  independence
- Two events  $A$  and  $B$  are **independent** if:

$$\mathbb{P}(A \cap B) = \mathbb{P}(A)\mathbb{P}(B)$$

- ▶ Sometimes written as  $A \perp\!\!\!\perp B$
  - ▶ **Symmetric:**  $A \perp\!\!\!\perp B$  equivalent to  $B \perp\!\!\!\perp A$
  - ▶ Events that are not independent are **dependent**.
- Important consequence: if  $A \perp\!\!\!\perp B$  and  $\mathbb{P}(B) > 0$ , then:

$$\mathbb{P}(A | B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)} = \frac{\mathbb{P}(A)\mathbb{P}(B)}{\mathbb{P}(B)} = \mathbb{P}(A)$$

# Independence

- Heart of Bayes's rule: knowing  $B$  occurs often changes probability of  $A$ .
  - ▶ What if  $B$  provides no information?  $\rightsquigarrow$  independence
- Two events  $A$  and  $B$  are **independent** if:

$$\mathbb{P}(A \cap B) = \mathbb{P}(A)\mathbb{P}(B)$$

- ▶ Sometimes written as  $A \perp\!\!\!\perp B$
  - ▶ **Symmetric:**  $A \perp\!\!\!\perp B$  equivalent to  $B \perp\!\!\!\perp A$
  - ▶ Events that are not independent are **dependent**.
- Important consequence: if  $A \perp\!\!\!\perp B$  and  $\mathbb{P}(B) > 0$ , then:

$$\mathbb{P}(A | B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)} = \frac{\mathbb{P}(A)\mathbb{P}(B)}{\mathbb{P}(B)} = \mathbb{P}(A)$$

- ▶ Knowing  $B$  occurs has no impact on the probability of  $A$ .

# Independence

- Heart of Bayes's rule: knowing  $B$  occurs often changes probability of  $A$ .
  - ▶ What if  $B$  provides no information?  $\rightsquigarrow$  independence
- Two events  $A$  and  $B$  are **independent** if:

$$\mathbb{P}(A \cap B) = \mathbb{P}(A)\mathbb{P}(B)$$

- ▶ Sometimes written as  $A \perp\!\!\!\perp B$
  - ▶ **Symmetric:**  $A \perp\!\!\!\perp B$  equivalent to  $B \perp\!\!\!\perp A$
  - ▶ Events that are not independent are **dependent**.
- Important consequence: if  $A \perp\!\!\!\perp B$  and  $\mathbb{P}(B) > 0$ , then:

$$\mathbb{P}(A | B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)} = \frac{\mathbb{P}(A)\mathbb{P}(B)}{\mathbb{P}(B)} = \mathbb{P}(A)$$

- ▶ Knowing  $B$  occurs has no impact on the probability of  $A$ .
  - ▶ Works other way too: if  $\mathbb{P}(A) > 0$  and  $A \perp\!\!\!\perp B$ , then  $\mathbb{P}(B | A) = \mathbb{P}(B)$ .

# Independence

- **Common misunderstanding: independent is different than disjoint!**
  - ▶ Mutually exclusive events **provide** information!



# Independence example

- If we have a gathering of size  $n$  drawn randomly from the population of MA with a current COVID infection rate of 1.37%, what's the probability someone in attendance is infected?
- When seeing “prob. of at least one”  $\rightsquigarrow$  work with complement:

$$\mathbb{P}(\text{At least one COVID case at gathering})$$

$$= 1 - \mathbb{P}(\text{No COVID cases at gathering})$$

# Independence and random sampling

- How we draw the random sample matters:

# Independence and random sampling

- How we draw the random sample matters:
  - ▶ Sample  $n > 1$  with replacement  $\rightsquigarrow$  independent events

# Independence and random sampling

- How we draw the random sample matters:
  - ▶ Sample  $n > 1$  with replacement  $\rightsquigarrow$  independent events
  - ▶ Sample  $n > 1$  without replacement  $\rightsquigarrow$  dependent events

# Independence and random sampling

- How we draw the random sample matters:
  - ▶ Sample  $n > 1$  with replacement  $\rightsquigarrow$  independent events
  - ▶ Sample  $n > 1$  without replacement  $\rightsquigarrow$  dependent events
- Sampling with replacement  $n$  for gathering:

$P(\text{No COVID cases at gathering})$

$$= P(\text{No COVID for Person 1} \cap \dots \cap \text{No COVID for Person } n)$$

$$= P(\text{No COVID for Person 1}) \cdot \dots \cdot P(\text{No COVID for Person } n)$$

$$= (1 - 0.007)^n$$

# Independence and random sampling

- How we draw the random sample matters:
  - ▶ Sample  $n > 1$  with replacement  $\rightsquigarrow$  independent events
  - ▶ Sample  $n > 1$  without replacement  $\rightsquigarrow$  dependent events
- Sampling with replacement  $n$  for gathering:

$$\begin{aligned}P(\text{No COVID cases at gathering}) &= P(\text{No COVID for Person 1} \cap \dots \cap \text{No COVID for Person } n) \\ &= P(\text{No COVID for Person 1}) \cdot \dots \cdot P(\text{No COVID for Person } n) \\ &= (1 - 0.007)^n\end{aligned}$$

- Using the complement:

$$P(\text{At least one COVID case at gathering}) = 1 - (1 - 0.007)^n$$

# Independence and random sampling

- How we draw the random sample matters:
  - ▶ Sample  $n > 1$  with replacement  $\rightsquigarrow$  independent events
  - ▶ Sample  $n > 1$  without replacement  $\rightsquigarrow$  dependent events
- Sampling with replacement  $n$  for gathering:

$$\begin{aligned} &P(\text{No COVID cases at gathering}) \\ &= P(\text{No COVID for Person 1} \cap \dots \cap \text{No COVID for Person } n) \\ &= P(\text{No COVID for Person 1}) \cdot \dots \cdot P(\text{No COVID for Person } n) \\ &= (1 - 0.007)^n \end{aligned}$$

- Using the complement:

$$P(\text{At least one COVID case at gathering}) = 1 - (1 - 0.007)^n$$

- ▶  $n = 5 \rightsquigarrow$  prob of 0.035

# Independence and random sampling

- How we draw the random sample matters:
  - ▶ Sample  $n > 1$  with replacement  $\rightsquigarrow$  independent events
  - ▶ Sample  $n > 1$  without replacement  $\rightsquigarrow$  dependent events
- Sampling with replacement  $n$  for gathering:

$$\begin{aligned}P(\text{No COVID cases at gathering}) &= P(\text{No COVID for Person 1} \cap \dots \cap \text{No COVID for Person } n) \\ &= P(\text{No COVID for Person 1}) \cdot \dots \cdot P(\text{No COVID for Person } n) \\ &= (1 - 0.007)^n\end{aligned}$$

- Using the complement:

$$P(\text{At least one COVID case at gathering}) = 1 - (1 - 0.007)^n$$

- ▶  $n = 5 \rightsquigarrow$  prob of 0.035
- ▶  $n = 100 \rightsquigarrow$  prob of 0.5



# Conditional independence

- $A$  and  $B$  are **conditionally independent** given  $E$  if

$$P(A \cap B \mid E) = P(A \mid E)P(B \mid E)$$

# Conditional independence

- $A$  and  $B$  are **conditionally independent** given  $E$  if

$$P(A \cap B \mid E) = P(A \mid E)P(B \mid E)$$

- Massively important in statistics and causal inference.

# Conditional independence

- $A$  and  $B$  are **conditionally independent** given  $E$  if

$$P(A \cap B \mid E) = P(A \mid E)P(B \mid E)$$

- Massively important in statistics and causal inference.
- **Warning:** independence  $\neq$  conditional independence.

# Conditional independence

- $A$  and  $B$  are **conditionally independent** given  $E$  if

$$P(A \cap B \mid E) = P(A \mid E)P(B \mid E)$$

- Massively important in statistics and causal inference.
- **Warning:** independence  $\neq$  conditional independence.
  - ▶ Cond. ind.  $\not\Rightarrow$  ind.: flipping a coin with unknown bias.

# Conditional independence

- $A$  and  $B$  are **conditionally independent** given  $E$  if

$$P(A \cap B | E) = P(A | E)P(B | E)$$

- Massively important in statistics and causal inference.
- **Warning:** independence  $\neq$  conditional independence.
  - ▶ Cond. ind.  $\not\Rightarrow$  ind.: flipping a coin with unknown bias.
  - ▶ Ind.  $\not\Rightarrow$  cond. ind.: test scores, athletics, and college admission.