

CSE 312

Foundations of Computing II


Lecture 6: More Conditional Probability



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Slide Credit: Based on Stefano Tessaro's slides for 312 19au incorporating ideas from Anna Karlin, Alex Tsun, Rachel Lin, Hunter Schafer & myself 😊

Agenda

- Review: Conditional Probability, Bayes 
- Law of Total Probability (w/ Bayes)
- Chain Rule
- Independence
- Conditional Independence
- Assumptions and Correlation
- Bonus: Monty Hall Problem


Last Class:

- Conditional Probability
- Bayes Theorem

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

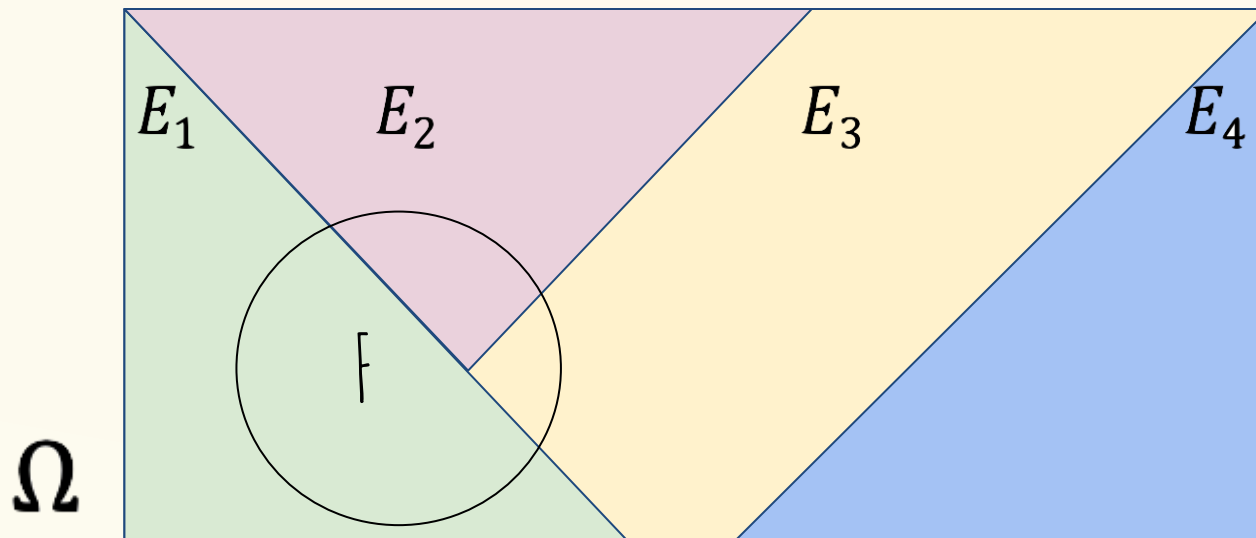
$$\mathbb{P}(A|B) = \frac{\mathbb{P}(B|A)\mathbb{P}(A)}{\mathbb{P}(B)}$$

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Law of Total Probability (Idea)

If we know E_1, E_2, \dots, E_n partition Ω , what can we say about $P(F)$



Law of Total Probability (LTP)

Definition. If events E_1, E_2, \dots, E_n partition the sample space Ω , then for any event F

$$P(F) = P(F \cap E_1) + \dots + P(F \cap E_n) = \sum_{i=1}^n P(F \cap E_i)$$

Using the definition of conditional probability $P(F \cap E) = P(F|E)P(E)$

We can get the alternate form of this that show

$$P(F) = \sum_{i=1}^n P(F|E_i)P(E_i)$$

Another Contrived Example

Alice has two pockets:

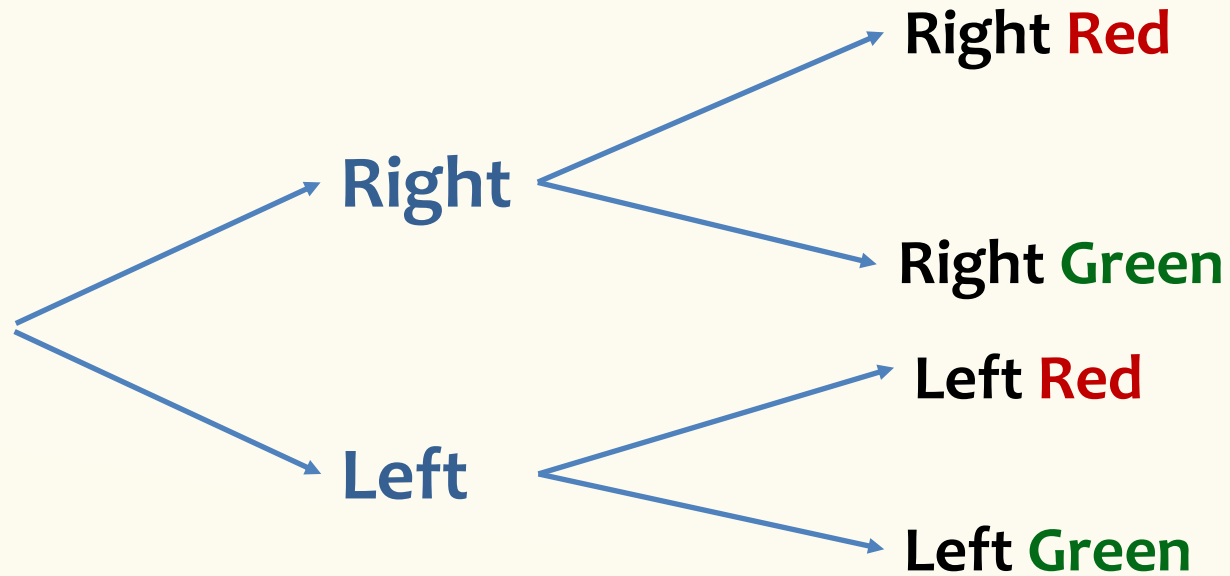
- **Left pocket:** Two red balls, two green balls
- **Right pocket:** One red ball, two green balls.

Alice picks a random ball from a random pocket.

[Both pockets equally likely, each ball equally likely.]

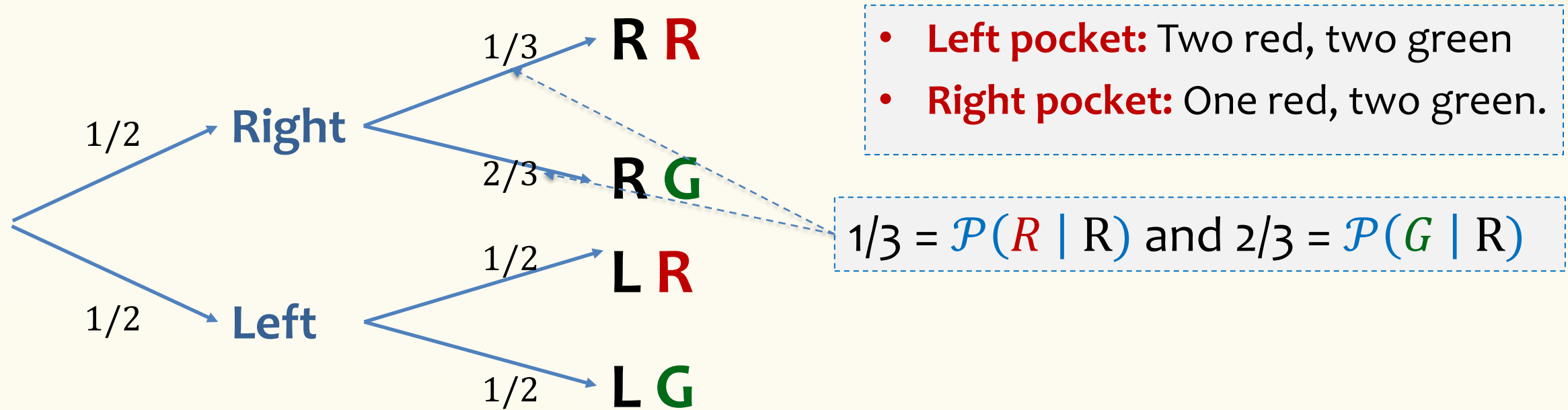
What is $\mathbb{P}(\mathbf{R})$?

Sequential Process – Non-Uniform Case



- **Left pocket:** Two red, two green
- **Right pocket:** One red, two green.
- Alice picks a random ball from a random pocket

Sequential Process – Non-Uniform Case



$$\mathbb{P}(R) = \mathbb{P}(R \cap \text{Left}) + \mathbb{P}(R \cap \text{Right}) \quad (\text{Law of total probability})$$

$$= \mathbb{P}(\text{Left}) \times \mathbb{P}(R|\text{Left}) + \mathbb{P}(\text{Right}) \times \mathbb{P}(R|\text{Right})$$

$$= \frac{1}{2} \times \frac{1}{2} + \frac{1}{2} \times \frac{1}{3} = \frac{1}{4} + \frac{1}{6} = \frac{5}{12}$$

Bayes Theorem with Law of Total Probability

Bayes Theorem with LTP: Let E_1, E_2, \dots, E_n be a partition of the sample space, and F and event. Then,

$$P(E_1|F) = \frac{P(F|E_1)P(E_1)}{P(F)} = \frac{P(F|E_1)P(E_1)}{\sum_{i=1}^n P(F|E_i)P(E_i)}$$

Simple Partition: In particular, if E is an event with non-zero probability, then

$$P(E|F) = \frac{P(F|E)P(E)}{P(F|E)P(E) + P(F|E^c)P(E^c)}$$

Example – Zika Testing

Zika fever

OVERVIEW SYMPTOMS SPECIALISTS

Fever
Rash
Joint pain
Red eyes



Spread through mosquito bites *Source*

A disease caused by Zika virus that's spread through mosquito bites.

The image shows a woman with a red rash on her neck and shoulder. A circular inset shows a mosquito biting her skin. The text 'Spread through mosquito bites' and 'Source' is written below the inset.

Usually no or mild symptoms (rash); sometimes severe symptoms (paralysis).

During pregnancy: may cause birth defects.

Suppose you took a Zika test, and it returns “positive”, what is the likelihood that you actually have the disease?

- Tests for diseases are rarely 100% accurate.

Example – Zika Testing

Suppose we know the following Zika stats

- A test is 98% effective at detecting Zika (“true positive”)
- However, the test yields a “false positive” 1% of the time
- 0.5% of the US population has Zika.

What is the probability you have Zika (event Z) if you test positive (event T).

- A) Less than 0.25
- B) Between 0.25 and 0.5
- C) Between 0.5 and 0.75
- D) Between 0.75 and 1

Example – Zika Testing

Suppose we know the following Zika stats

- A test is 98% effective at detecting Zika (“true positive”)
- However, the test yields a “false positive” 1% of the time
- 0.5% of the US population has Zika.

What is the probability you have Zika (event Z) if you test positive (event T).

Example – Zika Testing

Have zika blue, don't pink

Suppose we know the following Zika stats

- A test is 98% effective at detecting Zika (“true positive”) 100%
- However, the test may yield a “false positive” 1% of the time $10/995 =$ approximately 1%
- 0.5% of the US population has Zika. 5 people have it.

What is the probability you have Zika (event Z) if you test positive (event T).



Suppose we had 1000 people:

- 5 have Zika and test positive
- 985 do not have Zika and test negative
- 10 do not have Zika and test positive

$$\frac{5}{5 + 10} = \frac{1}{3} \approx 0.33$$

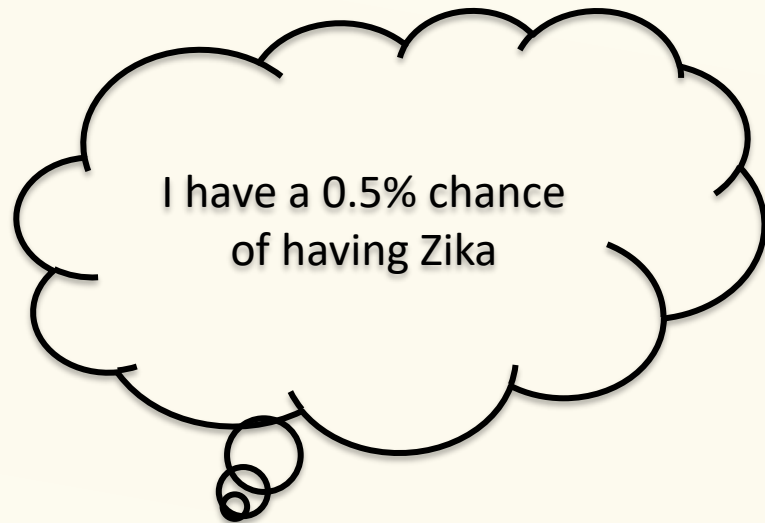
[Demo](#)

Philosophy – Updating Beliefs

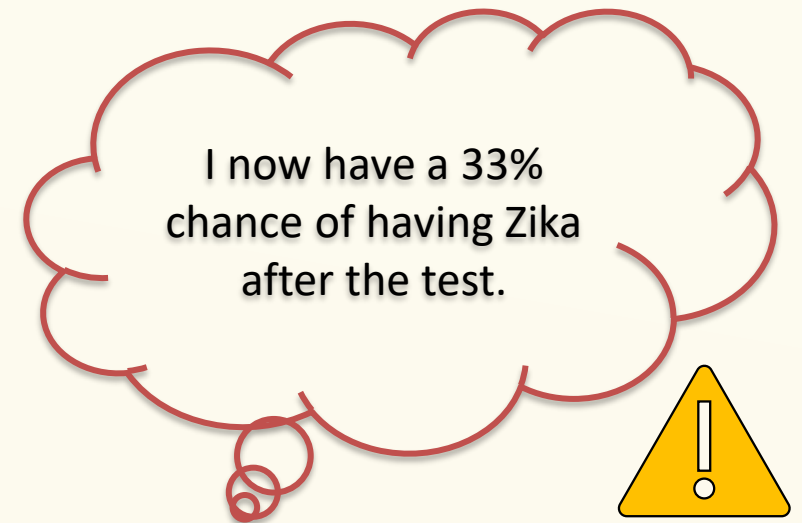
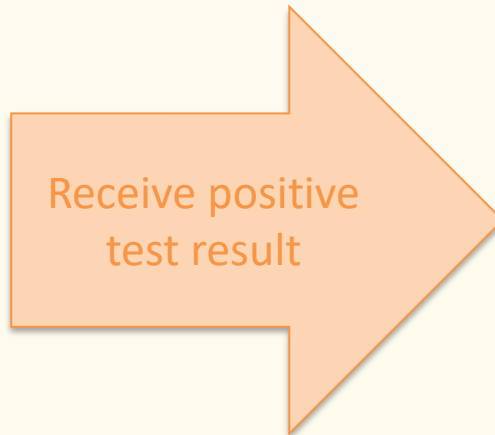
While it's not 98% that you have the disease, your beliefs changed **drastically**

Z = you have Zika

T = you test positive for Zika



Prior: $P(Z)$



Posterior: $P(Z|T)$

Example – Zika Testing

Suppose we know the following Zika stats

- A test is 98% effective at detecting Zika (“true positive”)
- However, the test may yield a “false positive” 1% of the time
- 0.5% of the US population has Zika.

What is the probability you test negative (event \bar{T}) if you have Zika (event Z)?

Conditional Probability Define a Probability Space

The probability conditioned on A follows the same properties as (unconditional) probability.


Example. $\mathbb{P}(\mathcal{B}^c|\mathcal{A}) = 1 - \mathbb{P}(\mathcal{B}|\mathcal{A})$

Conditional Probability Define a Probability Space


The probability conditioned on A follows the same properties as (unconditional) probability.

Example. $\mathbb{P}(\mathcal{B}^c | \mathcal{A}) = 1 - \mathbb{P}(\mathcal{B} | \mathcal{A})$

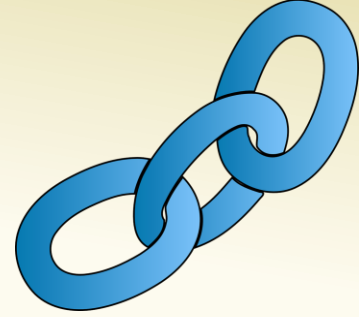
Formally. (Ω, \mathbb{P}) is a probability space + $\mathbb{P}(\mathcal{A}) > 0$

 $(\mathcal{A}, \mathbb{P}(\cdot | \mathcal{A}))$ is a probability space

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Chain Rule

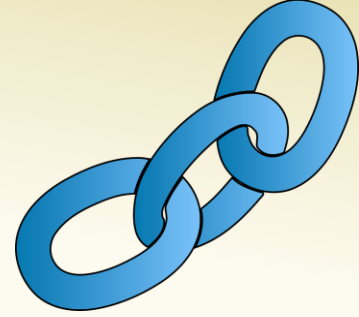


$$\mathbb{P}(\mathcal{B}|\mathcal{A}) = \frac{\mathbb{P}(\mathcal{A} \cap \mathcal{B})}{\mathbb{P}(\mathcal{A})}$$



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

Chain Rule



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

Theorem. (Chain Rule) For events $\mathcal{A}_1, \mathcal{A}_2, \dots, \mathcal{A}_n$,

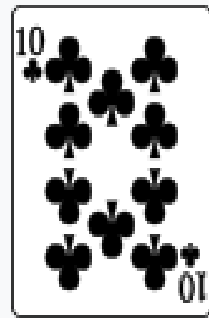
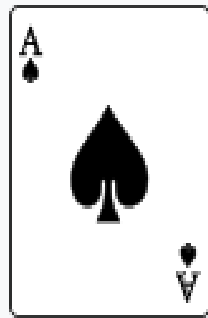
$$\mathbb{P}(\mathcal{A}_1 \cap \dots \cap \mathcal{A}_n) = \mathbb{P}(\mathcal{A}_1) \cdot \mathbb{P}(\mathcal{A}_2|\mathcal{A}_1) \cdot \mathbb{P}(\mathcal{A}_3|\mathcal{A}_1 \cap \mathcal{A}_2) \\ \dots \mathbb{P}(\mathcal{A}_n|\mathcal{A}_1 \cap \mathcal{A}_2 \cap \dots \cap \mathcal{A}_{n-1})$$

An easy way to remember: We have n tasks and we can do them **sequentially**, conditioning on the outcome of previous tasks

Chain Rule Example

Have a Standard 52-Card Deck. Shuffle It, and draw the top 3 cards **in order**. (uniform probability space).

What is $P(\text{Ace of Spades First} \cap \text{10 of Clubs Second} \cap \text{4 of Diamonds Third}) = P(\mathbf{A} \cap \mathbf{B} \cap \mathbf{C})$?

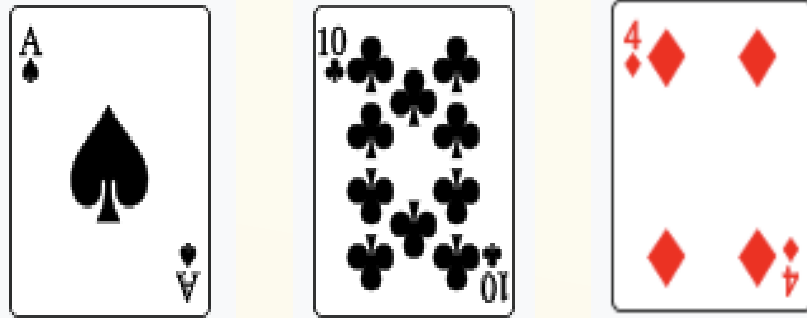


- A:** Ace of Spades First
- B:** 10 of Clubs Second
- C:** 4 of Diamonds Third

Chain Rule Example

Have a Standard 52-Card Deck. Shuffle It, and draw the top 3 cards in order. (uniform probability space).

What is $P(\text{Ace of Spades First, 10 of Clubs Second, 4 of Diamonds Third}) = P(A \cap B \cap C)?$




- A:** Ace of Spades First
- B:** 10 of Clubs Second
- C:** 4 of Diamonds Third

$$P(A) \cdot P(B|A) \cdot P(C|A \cap B)$$

$$\frac{1}{52} \cdot \frac{1}{51} \cdot \frac{1}{50}$$

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- **Independence** 
- Conditional Independence
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Independence

Definition. If two events \mathcal{A} and \mathcal{B} are **independent** then

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

Alternatively,

- If $\mathbb{P}(\mathcal{A}) \neq 0$, equivalent to $\mathbb{P}(\mathcal{B}|\mathcal{A}) = \mathbb{P}(\mathcal{B})$
- If $\mathbb{P}(\mathcal{B}) \neq 0$, equivalent to $\mathbb{P}(\mathcal{A}|\mathcal{B}) = \mathbb{P}(\mathcal{A})$

“The probability that \mathcal{B} occurs after observing \mathcal{A} ” -- Posterior
= “The probability that \mathcal{B} occurs” -- Prior

Example -- Independence

Toss a coin 3 times. Each of 8 outcomes equally likely.

- $A = \{\text{at most one T}\} = \{HHH, HHT, HTH, THH\}$
- $B = \{\text{at most 2 Heads}\} = \{HHH\}^c$

Independent?

$$\mathbb{P}(\mathcal{A} \cap \mathcal{B}) \stackrel{?}{=} \mathbb{P}(\mathcal{A}) \cdot \mathbb{P}(\mathcal{B})$$

Poll:

- A. Yes, independent
- B. No

Often probability space (Ω, \mathbb{P}) is **defined** using independence

Events generated independently → their probabilities satisfy independence

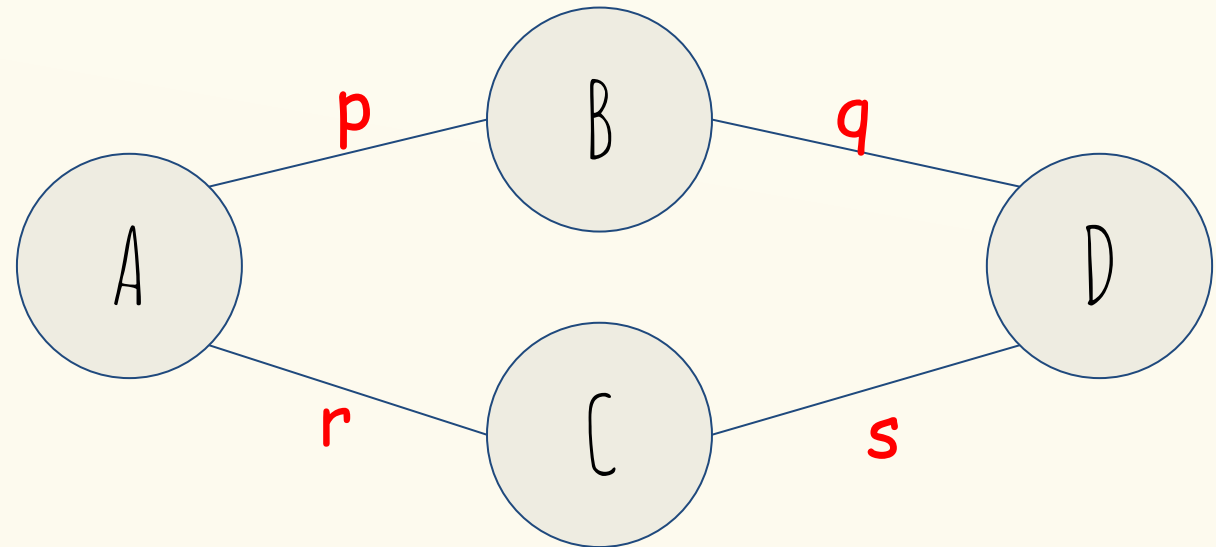
← Not necessarily

This can be counterintuitive!

Example – Network Communication

Each link works with the probability given, **independently**.
What's the probability A and D can communicate?

$$\mathbb{P}(AD) = ?$$



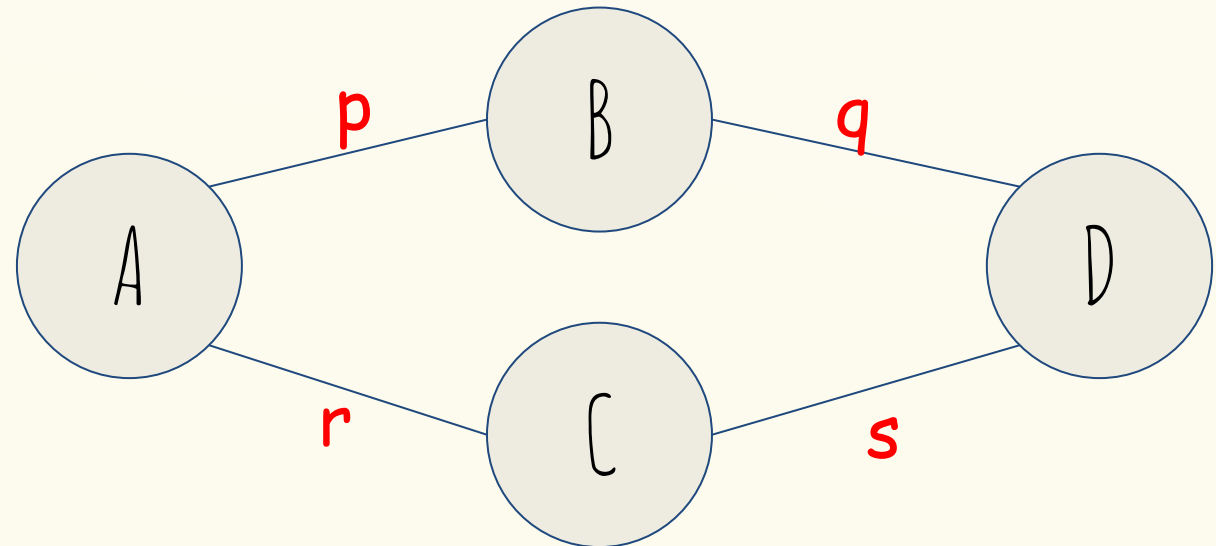
Example – Network Communication

Each link works with the probability given, **independently**.
What's the probability A and D can communicate?

$$\begin{aligned}\mathbb{P}(AD) &= \mathbb{P}(AB \cap BD \text{ or } AC \cap CD) \\ &= \mathbb{P}(AB \cap BD) + \mathbb{P}(AC \cap CD) - \mathbb{P}(AB \cap BD \cap AC \cap CD)\end{aligned}$$

$$\mathbb{P}(AB \cap BD) = \mathbb{P}(AB) \cdot \mathbb{P}(BD) = pq$$

$$\mathbb{P}(AC \cap CD) = \mathbb{P}(AC) \cdot \mathbb{P}(CD) = rs$$



$$\mathbb{P}(AB \cap BD \cap AC \cap CD) = \mathbb{P}(AB) \cdot \mathbb{P}(BD) \cdot \mathbb{P}(AC) \cdot \mathbb{P}(CD) = pqrs$$

Example – Biased coin

We have a biased coin comes up Heads with probability $2/3$; Each flip is independent of all other flips. Suppose it is tossed 3 times.

$$\mathbb{P}(HHH) =$$

$$\mathbb{P}(TTT) =$$

$$\mathbb{P}(HTT) =$$


Example – Biased coin

We have a biased coin comes up Heads with probability $2/3$, independently of other flips. Suppose it is tossed 3 times.

$\mathbb{P}(2 \text{ heads in } 3 \text{ tosses}) =$

- A) $(2/3)^2 1/3$
- B) $2/3$
- C) $3 (2/3)^2 1/3$
- D) $(1/3)^2$

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Conditional Independence

Definition. Two events \mathcal{A} and \mathcal{B} are **independent** conditioned on \mathcal{C} if $\mathbb{P}(\mathcal{C}) \neq 0$ and $\mathbb{P}(\mathcal{A} \cap \mathcal{B} \mid \mathcal{C}) = \mathbb{P}(\mathcal{A} \mid \mathcal{C}) \cdot \mathbb{P}(\mathcal{B} \mid \mathcal{C})$.

Plain Independence. Two events \mathcal{A} and \mathcal{B} are **independent** if

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

Equivalence:

- If $\mathbb{P}(\mathcal{A}) \neq 0$, equivalent to $\mathbb{P}(\mathcal{B} \mid \mathcal{A}) = \mathbb{P}(\mathcal{B})$
- If $\mathbb{P}(\mathcal{B}) \neq 0$, equivalent to $\mathbb{P}(\mathcal{A} \mid \mathcal{B}) = \mathbb{P}(\mathcal{A})$

Conditional Independence

Definition. Two events \mathcal{A} and \mathcal{B} are **independent** conditioned on \mathcal{C} if $\mathbb{P}(\mathcal{C}) \neq 0$ and $\mathbb{P}(\mathcal{A} \cap \mathcal{B} \mid \mathcal{C}) = \mathbb{P}(\mathcal{A} \mid \mathcal{C}) \cdot \mathbb{P}(\mathcal{B} \mid \mathcal{C})$.

Equivalence:

- If $\mathbb{P}(\mathcal{A} \cap \mathcal{C}) \neq 0$, equivalent to $\mathbb{P}(\mathcal{B} \mid \mathcal{A} \cap \mathcal{C}) = \mathbb{P}(\mathcal{B} \mid \mathcal{C})$
- If $\mathbb{P}(\mathcal{B} \cap \mathcal{C}) \neq 0$, equivalent to $\mathbb{P}(\mathcal{A} \mid \mathcal{B} \cap \mathcal{C}) = \mathbb{P}(\mathcal{A} \mid \mathcal{C})$

Plain Independence. Two events \mathcal{A} and \mathcal{B} are **independent** if

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

Equivalence:

- If $\mathbb{P}(\mathcal{A}) \neq 0$, equivalent to $\mathbb{P}(\mathcal{B} \mid \mathcal{A}) = \mathbb{P}(\mathcal{B})$
- If $\mathbb{P}(\mathcal{B}) \neq 0$, equivalent to $\mathbb{P}(\mathcal{A} \mid \mathcal{B}) = \mathbb{P}(\mathcal{A})$

Example – More coin tossing

Suppose there is a coin C_1 with $\Pr(\text{Head}) = 0.3$ and a coin C_2 with $\Pr(\text{Head}) = 0.9$. We pick one randomly with equal probability and flip that coin twice independently. What is the probability we get all heads?

$$\Pr(HH) = \Pr(HH \mid C_1) \Pr(C_1) + \Pr(HH \mid C_2) \Pr(C_2)$$

LTP

Example – More coin tossing

Suppose there is a coin C_1 with $\Pr(\text{Head}) = 0.3$ and a coin C_2 with $\Pr(\text{Head}) = 0.9$. We pick one randomly with equal probability and flip that coin 2 times independently. What is the probability we get all heads?


$$\Pr(HH) = \Pr(HH \mid C_1) \Pr(C_1) + \Pr(HH \mid C_2) \Pr(C_2) \quad \text{LTP}$$

$$= \Pr(H \mid C_1)^2 \Pr(C_1) + \Pr(H \mid C_2)^2 \Pr(C_2) \quad \text{Conditional Independence}$$

$$= 0.3^2 \cdot 0.5 + 0.9^2 \cdot 0.5 = 0.45$$

$$\Pr(H) = \Pr(H \mid C_1) \Pr(C_1) + \Pr(H \mid C_2) \Pr(C_2) = 0.6$$

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Correlation

- Pick a person at random
- A : event that the person has lung cancer
- B : event that the person is a heavy smoker

- Fact: $\mathbb{P}(A|B) = 1.17 \cdot \mathbb{P}(A)$

- Conclusions?

Correlation

- Pick a person at random
- A : event that the person has lung cancer
- B : event that the person is a heavy smoker

- Fact: $\mathbb{P}(A|B) = 1.17 \cdot \mathbb{P}(A)$

- Conclusions?
 - Lung cancer increases the the probability of smoking by 17%.
 - Lung cancer causes smoking.

Causality vs. Correlation

- Events A and B are **positively correlated** if

$$\mathbb{P}(A \cap B) > \mathbb{P}(A) \cdot \mathbb{P}(B)$$

- E.g. smoking and lung cancer.
- But A and B being positively correlated does not mean that A causes B or B causes A .

Causality vs. Correlation

- Events A and B are **positively correlated** if

$$\mathbb{P}(A \cap B) > \mathbb{P}(A) \cdot \mathbb{P}(B)$$

- But A and B being positively correlated does not mean that A causes B or B causes A .

Other examples:

- Tesla owners are more likely to be rich. That does not mean poor people should buy a Tesla to get rich.
- People who go to the opera are more likely to have a good career. That does not mean that going to the opera will improve your career.
- Rabbits eat more carrots and do not wear glasses. Are carrots good for eyesight?

Independence as an assumption

- People often assume it **without justification.**
- Example: A sky diver has two chutes

A : event that the main chute doesn't open

$$\mathbb{P}(A) = 0.02$$

B : event that the backup doesn't open

$$\mathbb{P}(B) = 0.1$$

- What is the chance that at least one opens assuming independence?

Independence as an assumption

- People often assume it **without justification.**
- Example: A sky diver has two chutes

A : event that the main chute doesn't open


$$\mathbb{P}(A) = 0.02$$

B : event that the backup doesn't open

$$\mathbb{P}(B) = 0.1$$

- What is the chance that at least one opens assuming independence?
- Assuming independence doesn't justify the assumption! Both chutes could fail because of the same rare event e.g., freezing rain.

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Monty Hall Problem

Suppose you're on a game show, and you're given the choice of three doors. Behind one of the doors is a car, behind the other, goats. You pick a door, say number 1, and the host, who knows what's behind the doors, opens another door, say number 3, which has a goat. He says to you, "Do you want to switch to door number 2?" Is it to your advantage to switch your choice of doors?

Assumptions

- The player is equally likely to pick each of the three doors.
- After the player picks a door, the host must open a different door with a goat behind it and offer the player the choice of staying with the original door or switching.
- If the host has a choice of which door to open, then he is equally likely to select each of them.

Should you switch or stay?