



Computer  
Science

# CSC380: Principles of Data Science

## Probability 2

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# Rules of probability

- To recap and summarize:

## Rules of Probability

- 1. Non-negativity:** All probabilities are between 0 and 1 (inclusive)
- 2. Unity of the sample space:**  $P(S) = 1$
- 3. Complement Rule:**  $P(E^C) = 1 - P(E)$
- 4. Probability of Unions:**
  - (a) In general,  $P(E \cup F) = P(E) + P(F) - P(E \cap F)$*
  - (b) If  $E$  and  $F$  are disjoint, then  $P(E \cup F) = P(E) + P(F)$*

# Summary: calculating probabilities

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- If we know that all outcomes are **equally likely**, we can use

We will use combinatorics  
to do counting

$$P(E) = \frac{|E|}{|S|}$$

Number of elements  
in event set

Number of possible  
outcomes (e.g. 36)

- If  $|E|$  is hard to calculate directly, we can try
  - the rules of probability
  - the Law of Total Probability, using an appropriate partition of sample space  $S$

- Conditional probability
- Probabilistic reasoning
  - contingency table
  - probability trees

# Conditional Probability

# Example: Seat Belts

		Child		
		Buck.	Unbuck.	Marginal
Parent	Buck.	0.48	0.12	0.60
	Unbuck.	0.10	0.30	0.40
Marginal		0.58	0.42	1.00

Table: Probability Estimates for Seat Belt Status

Suppose we pick a family from US at random:

- What is the probability of the event “Child is Buckled”?
- What should our new estimate be if we know that “Parent is Buckled”?

# Example: blood types

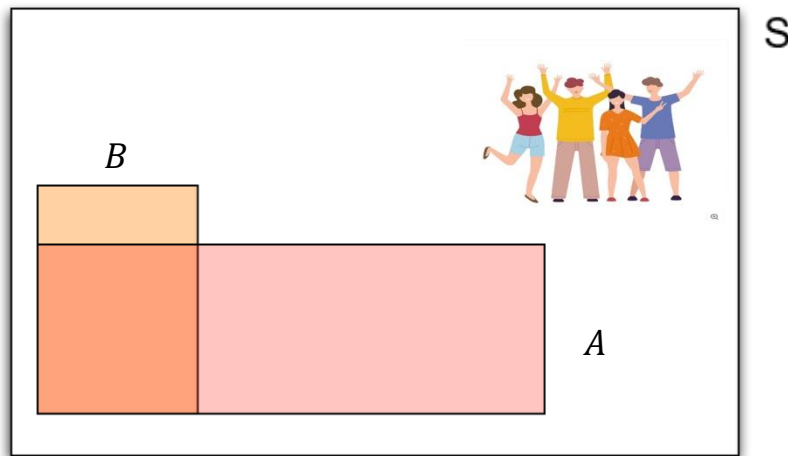
		Antigen B		Marginal
		Absent	Present	
Antigen A	Absent	0.44	0.10	0.54
	Present	0.42	0.04	0.46
Marginal		0.86	0.14	1.00

Table: Probability Estimates for U.S. Blood Types

- $A$ : “presence of antigen  $A$ ”,  $B$ : “presence of antigen  $B$ ”
- Suppose someone of an unknown blood type gets a test that reveals the presence of antigen  $A$ . What is the chance that:
  - event  $A$  happens to them?
  - event  $B$  happens to them?

# Relative area

- $A$ : antigen A present       $B$ : antigen B present
- Given that  $A$  happens, what is the chance of  $B$  happening?

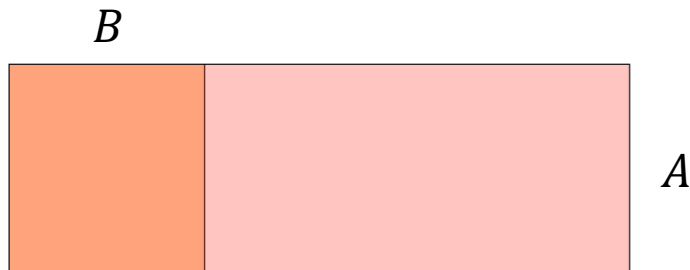


- Restricted to people with antigen A present, what is the fraction of those people with antigen B?



# Relative area

- Let's zoom into people with antigen A present.

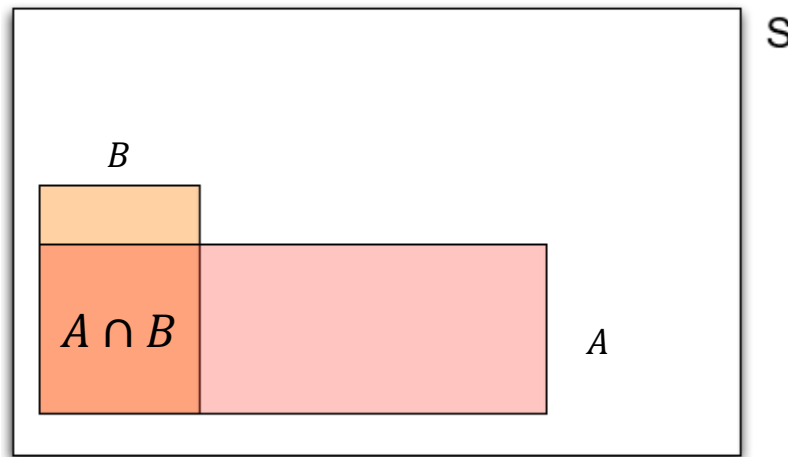


- It's just as if the sample space had shrunk to include only  $A$
- Now, probabilities correspond to proportions of  $A$
- What does the orange square represent?
  - $A \cap B$
- How would we find the probability of  $B$  given  $A$ ?

# Conditional Probability

- To find the conditional probability of  $B$  given  $A$ , consider the ways  $B$  can occur in the context of  $A$  (i.e.,  $A \cap B$ ), out of all the ways  $A$  can occur:

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



Example:

$A$ : currently inside a cafe

$B$ : drinking coffee right now

# Conditioning changes the sample space

- Before we knew anything, anything in sample space  $S$  could occur.
- After we know  $A$  happened, we are only choosing from within  $A$ .
- The set  $A$  becomes our new sample space
- Instead of asking “In what proportion of  $S$  is  $B$  true?”, we now ask “In what proportion of  $A$  is  $B$  true?”

For example, rolling a fair die, define  $A$ : even numbers,  $B$ : get a 2.

- Before knew anything,  $P(B)$  is  $1/6$
- After knowing  $A$ ,  $P(B)$  is  $(1/6) / (1/2) = 1/3$

# Every Probability is a Conditional Probability

- We can consider the original probabilities to be conditioned on the event  $S$ : at first what we know is that “something in  $S$ ” occurs.

$$P(B) = P(B|S)$$

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

$$P(B \cap C) = P(B \cap C|S)$$

- $P(B|S)$  in words: what proportion of  $S$  does  $B$  happen?
- If we then learn that  $A$  occurs,  $A$  becomes our restricted sample space.
- $P(B|A)$  in words: what proportion of  $A$  does  $B$  happen?

# Joint Probability and Conditional Probability

- We can rearrange  $P(B | A) = \frac{P(A \cap B)}{P(A)}$  and derive:

## The “Chain Rule” of Probability

For any events,  $A$  and  $B$ , the joint probability  $P(A \cap B)$  can be computed as

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

Or, since  $P(A \cap B) = P(B \cap A)$

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

When we have two events A and B...

- Conditional probability:  $P(A|B)$ ,  $P(A^c|B)$ ,  $P(B|A)$  etc.
- Joint probability:  $P(A, B)$  or  $P(A^c, B)$  or ...
- Marginal probability:  $P(A)$  or  $P(A^c)$

# Example revisited: blood types

		Antigen B		Marginal
		Absent	Present	
Antigen A	Absent	0.44	0.10	0.54
	Present	0.42	0.04	0.46
Marginal		0.86	0.14	1.00

Table: Probability Estimates for U.S. Blood Types

- Suppose someone of an unknown blood type gets a test that reveals the presence of antigen A.

- What is  $P(A | A)$ ?

$$P(A | A) = \frac{P(A \cap A)}{P(A)} = 1$$

- What is  $P(B | A)$ ?

$$P(B | A) = \frac{P(A \cap B)}{P(A)} = \frac{0.04}{0.46} = 0.087$$

# Example revisited: Seat Belts

$A$ : parent is buckled

$C$ : child is buckled

		Child		Marginal
		Buck.	Unbuck.	
Parent	Buck.	0.48	0.12	0.60
	Unbuck.	0.10	0.30	0.40
Marginal		0.58	0.42	1.00

Table: Probability Estimates for Seat Belt Status

Suppose we pick a family from US at random:

- What is the probability of the event “Child is Buckled”?  $P(C)$
- What should our new estimate be if we know that (“given that”) Parent is Buckled?  $P(C | A)$



# Example revisited: Seat Belts

A: parent is buckled

C: child is buckled

		Child		
		Buck.	Unbuck.	Marginal
Parent	Buck.	0.48	0.12	0.60
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Table: Probability Estimates for Seat Belt Status

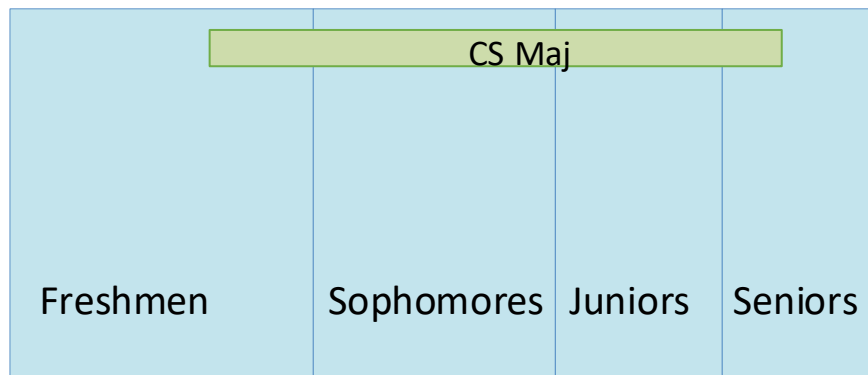
Suppose we pick a family from the US at random:

- $P(C) = 0.58$
- $P(C | A) = \frac{P(C \cap A)}{P(A)} = \frac{0.48}{0.60} = 0.8$  Larger than  $P(C)$
- Suppose we see a buckled parent, it is much more likely that we see their child buckled

# Law of Total Probability, revisited

**Law of Total Probability** Suppose  $B_1, \dots, B_n$  form a partition of the sample space  $S$ . Then,

$$P(A) = P(A, B_1) + \dots + P(A, B_n)$$



# Law of Total Probability, revisited

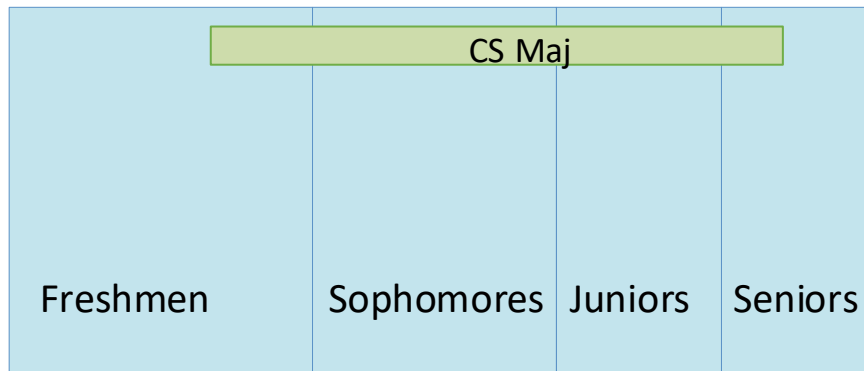
Expanding each  $P(A, B_i) = \sum_n P(A | B_i)P(B_i)$ , we have:

$$P(A) = \sum_{i=1} P(A | B_i)P(B_i)$$

$A$ : student in CS major

$B_i$ : student in class year  $i$

$P(A | B_i)$  The fraction of CS major in class year  $i$



# Law of Total Probability, revisited

**Example** Suppose UA has an equal number of students in the 4 class years, and the fraction of CS major in these 4 class years are 10%, 10%, 20%, 80% respectively. What is fraction of CS majors?

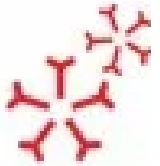
- $P(B_1) = P(B_2) = P(B_3) = P(B_4) = 0.25$
- $P(C | B_1) = 0.1, \dots, P(C | B_4) = 0.8$
- Calculate  $P(C)$  by:

$$P(C) = \sum_{i=1}^4 P(C | B_i)P(B_i) = 30\%$$

# Probabilistic reasoning

# Probabilistic reasoning

- We have some prior belief of an event  $A$  happening
  - $P(A)$ , prior probability
  - e.g. me infected by COVID
- We see some new evidence  $B$ 
  - e.g. I test COVID positive
- How does seeing  $B$  affect our belief about  $A$ ?
  - $P(A | B)$ , posterior probability



# Another example: detector

A store owner discovers that some of her employees have taken cash. She decides to use a detector to discover who they are.

- Suppose that 10% of employees stole.
- The detector buzzes 80% of the time that someone stole, and 20% of the time that someone not stole
- Is the detector reliable? In other words, if the detector buzzes, what's the probability that the person did stole?

H: employee not stole

B: lie detector buzzes

# Another example: detector

- Suppose that 10% of employees stole.

H: employee did not stole       $P(H) = 0.9$

- The detector buzzes 80% of the time that someone stoles, and 20% of the time that someone not stole.

$$P(B \mid H^c) = 0.8$$

B: lie detector buzzes

$$P(B \mid H) = 0.2$$

- If the detector buzzes, what's the probability that the person stole?

$$P(H^c \mid B)$$



# Detector analysis: Probability table

		Detector result		
		Pass ( $B^C$ )	Buzz ( $B$ )	Marginal
Employee	Not stole ( $H$ )			
	Stole ( $H^C$ )			
	Marginal			

$$P(H) = 0.9$$

$$P(B \mid H^C) = 0.8$$

$$P(B \mid H) = 0.2$$

# Detector analysis: Probability table

$$P(H, B) = P(H) \cdot P(B | H) = 0.9 \times 0.2 = 0.18$$

		Detector result		
		Pass ( $B^C$ )	Buzz ( $B$ )	Marginal
Employee	Not stole ( $H$ )		0.18	0.9
	Stole ( $H^C$ )			0.1
	Marginal			

$$P(H) = 0.9$$

$$P(B | H^C) = 0.8$$

$$P(B | H) = 0.2$$

# Detector analysis: Probability table

$$P(H) = P(H, B) + P(H, B^c) = 0.9$$

		Detector result		
		Pass ( $B^c$ )	Buzz ( $B$ )	Marginal
Employee	Not stole ( $H$ )	0.72	0.18	0.9
	Stole ( $H^c$ )			0.1
	Marginal			

$$P(H) = 0.9$$

$$P(B \mid H^c) = 0.8$$

$$P(B \mid H) = 0.2$$

# Detector analysis: Probability table

		Detector result		
		Pass ( $B^C$ )	Buzz ( $B$ )	Marginal
Employee	Not stole ( $H$ )	0.72	0.18	0.9
	Stole ( $H^C$ )	0.02	0.08	0.1
	Marginal	0.74	0.26	1

$$P(H) = 0.9$$

$$P(B \mid H^C) = 0.8$$

$$P(B \mid H) = 0.2$$

# Detector analysis: Probability table

		Detector result		
		Pass ( $B^C$ )	Buzz ( $B$ )	Marginal
Employee	Not stole ( $H$ )	0.72	0.18	0.9
	Stole ( $H^C$ )	0.02	0.08	0.1
Marginal		0.74	0.26	1

- We have the full probability table. Can we calculate  $P(H^C | B)$ ? Yes!

$$P(H^C | B) = \frac{P(H^C, B)}{P(B)} = \frac{0.08}{0.26} = 0.307$$

It seems like the detector is not very reliable...

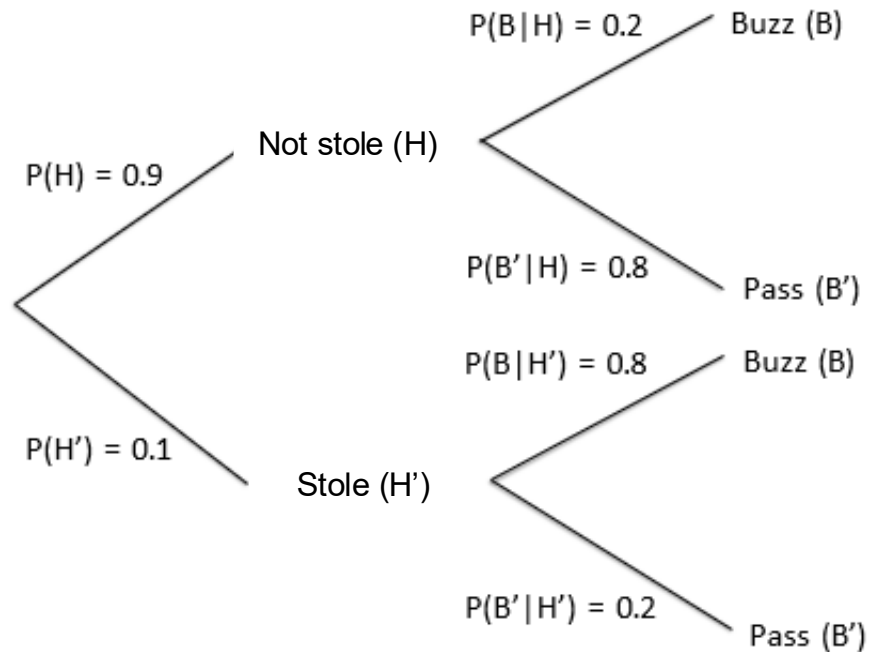
# Recap

- Conditional probability:  $P(B | A) = \frac{P(A \cap B)}{P(A)}$
- Law of total probability:  $P(A) = \sum_{i=1}^n P(A | B_i)P(B_i)$
- If we know  $P(H), P(B|H^C), P(B|H)$ :
  - $P(H) \rightarrow P(H^C)$  Complement rule
  - $P(H), P(B|H) \rightarrow P(B, H)$  Conditional probability
  - $P(H^C), P(B|H^C) \rightarrow P(B, H^C)$  Conditional probability
  - $P(B) \rightarrow P(B, H) + P(B, H^C)$  Law of total probability
  - $P(B), P(B, H) \rightarrow P(H|B)$  Conditional probability
  - $P(B), P(B, H^C) \rightarrow P(H^C|B)$  Conditional probability
- We can get  $P(B), P(H|B), P(H^C|B)$

# Today's plan

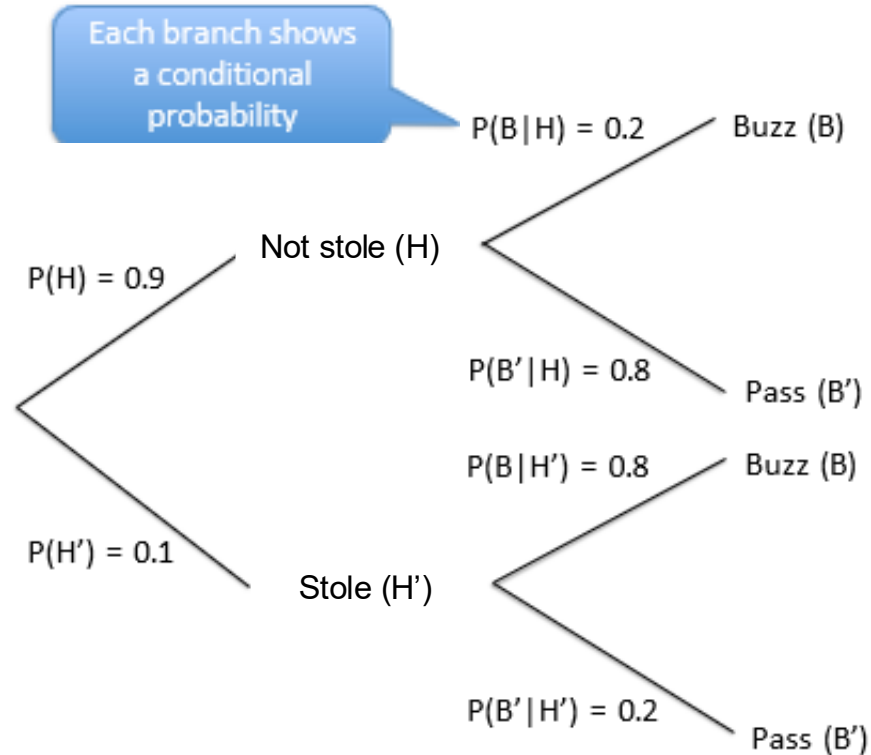
- Another tool: probability trees
- Bayes rule
- Bayes rule and law of total probability

# Probability trees: another useful tool

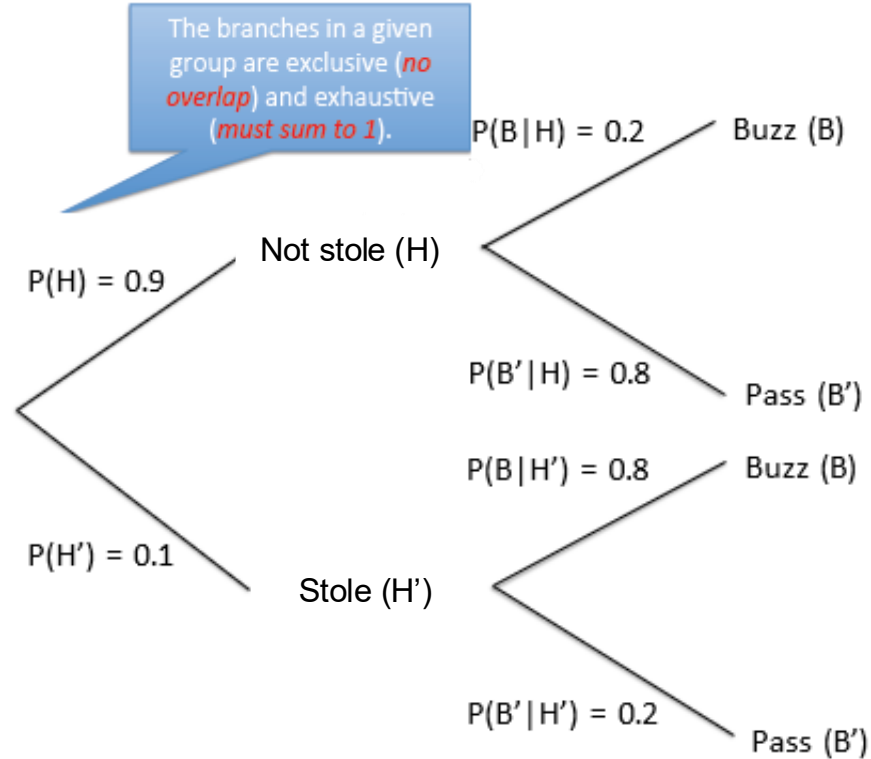




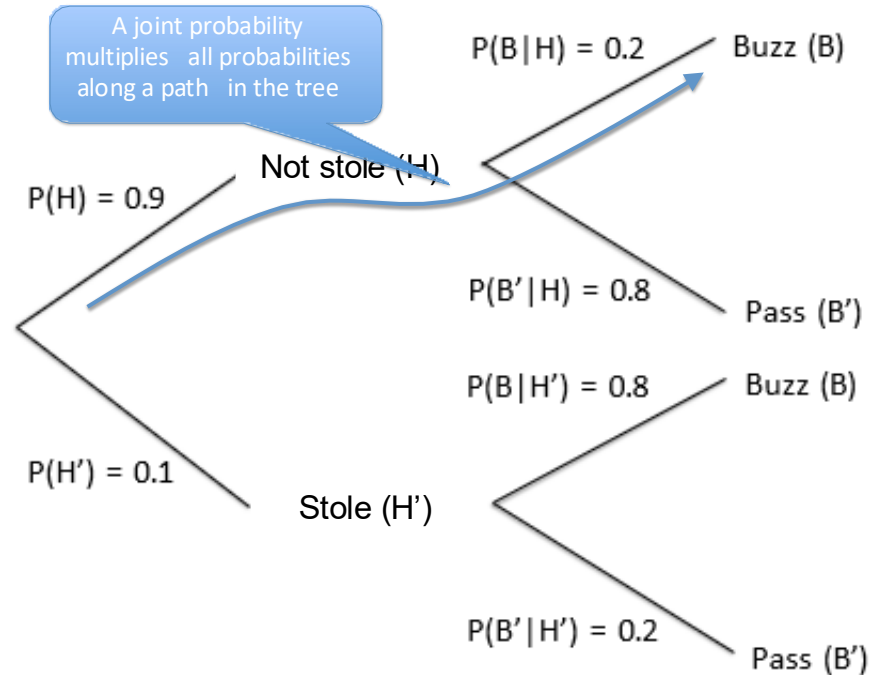
# Probability trees: another useful tool



# Probability trees: another useful tool



# Probability trees: another useful tool



# Conditional probability: additional note

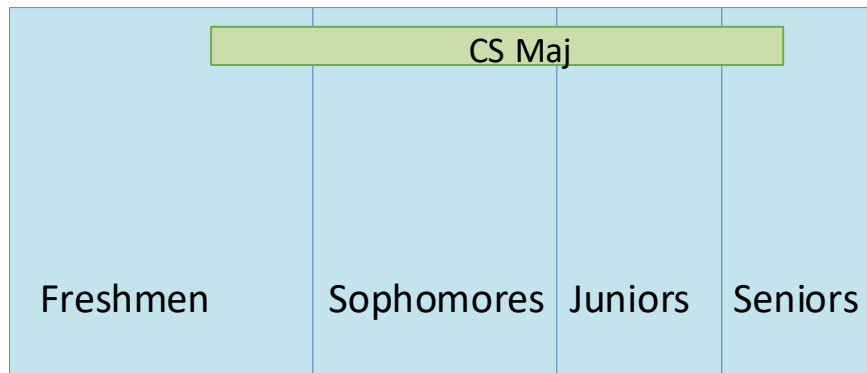
- The rules of probability also applies to the rules of conditional probability
- Just replace  $P(E), P(F)$  with  $P(E|A), P(F|A)$ 
  - But, need to condition on the **same**  $A$  in the same equation

## Rules of Probability

1. **Non-negativity:** All probabilities are between 0 and 1 (inclusive)
2. **Unity of the sample space:**  $P(S) = 1$
3. **Complement Rule:**  $P(E^C) = 1 - P(E)$
4. **Probability of Unions:**
  - (a) In general,  $P(E \cup F) = P(E) + P(F) - P(E \cap F)$
  - (b) If  $E$  and  $F$  are disjoint, then  $P(E \cup F) = P(E) + P(F)$

# Some examples

- $P(S|A) = 1$
  - $P(E|A) + P(E^c|A) = 1$
  - $P(E|A) + P(F|A) = P(E \cup F|A)$  for disjoint E and F
- A: CS major



# Bayes rule

# Reversing conditional probabilities

- Is  $P(A | B) = P(B | A)$  in general?
- Let's see..

$$P(A, B) = P(A | B) \cdot P(B) = P(B | A) \cdot P(A)$$

- Equal only when  $P(A)$  and  $P(B)$  are equal
- Let's take a look at a real-world example when they are unequal...

# Bayes rule

**Bayes rule** For events  $A, B$ ,

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

- Very easy to derive from the chain rule, so remember that first.
- Named after Thomas Bayes (1701-1761), English philosopher & pastor





# Bayes rule

**Bayes rule** For events  $A, B$ ,

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

Prior probability    Support of evidence

Posterior probability    Probability of evidence

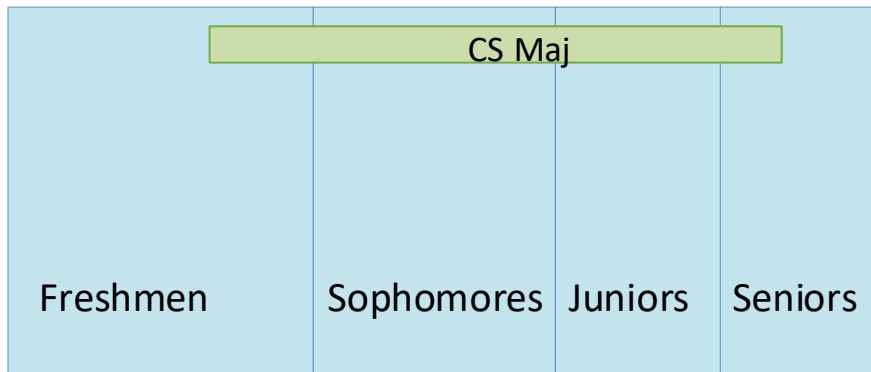
Examples:

- $A$ : I have COVID,  $B$ : my test shows positive
- $A$ : employee stole  $B$ : the detector buzzes
- $A$ : student is CS major  $B$ : student is a senior

# Bayes rule and Law of Total Probability

**Bayes rule (equivalent form)** For event  $A$  and  $B_1, \dots, B_n$  forming a partition of  $S$ ,

$$P(B_i | A) = \frac{P(A | B_i) \cdot P(B_i)}{\sum_{j=1}^n P(A | B_j) \cdot P(B_j)} \quad \leftarrow P(A)$$



## Extension: chain rule for conditional probability

- If we deal with more than 3 events happening together, we can apply the chain rule of probability repeatedly:

Treat (B, C) as a single event

$$\begin{aligned} P(A, B, C) &= P(A \mid B, C) P(B, C) \\ &= P(A \mid B, C) P(B \mid C) P(C) \end{aligned}$$