



Computer  
Science

# CSC380: Principles of Data Science

**Probability 2**

**Chicheng Zhang**

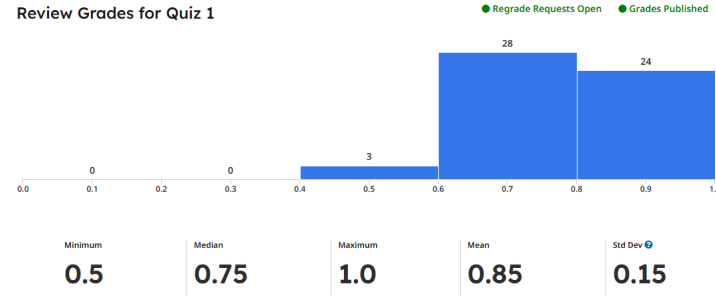
- We will have a quiz next Monday (2/3)
  - Based on this week's lectures
- Quiz 1: grading in progress
  - Groups of 2 may only see one member's grade in gradescope
  - Don't worry, we will update on D2L
- HW1 due 1/30 3:30pm
  - Submit code in "HW1 code" entry
  - One submission per group  
(I enabled group submission of max size 2 in gradescope)
- HW2 will be out around 1/31 (due 2/10)

- We have synced Quiz 1 grades on D2L
  - Let us know if you have any questions

- HW2 due 2/11

- Simulating n 2-dice rolls:

```
res_dice1 = np.random.randint(1,6+1,size=n)  
res_dice2 = np.random.randint(1,6+1,size=n)  
res = [(res_dice1[i], res_dice2[i]) for i in range(len(res_dice1))]
```

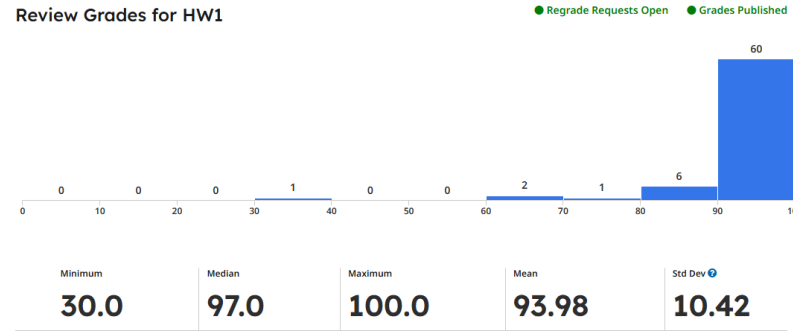


- Can I make future HW announcements on Piazza?

# Announcements 2/5

- We graded HW1 & posted in D2L

Review Grades for HW1



- Add'l HW policies:
  - Only one submission per group
  - All group members are expected to contribute equally for every qn
- For all regrade requests & D2L grade errors:
  - we need your reports within a week of the grade announcement times
- Quiz 3: 2/12 (Wed)

- You conduct an experiment for which *one* run consists of flipping a coin three times. Define  $E_1$  to be the event that the *first* flip is heads, and  $E_2$  to be the event that the *second* flip is heads.
  1. Write down all outcomes in the full sample space,  $S$ .  
(e.g. we can represent the outcome of 3 heads as HHH)
  2. Write down all outcomes in  $E_1$ .
  3. Write down all outcomes in  $E_1 \cup E_2$ .
  4. Write down all outcomes in  $E_1 \cap E_2$ .
  5. Write down all outcomes in  $E_1^C$ .

- You conduct an experiment for which *one* run consists of flipping a coin three times. Define  $E_1$  to be the event that the *first* flip is heads, and  $E_2$  to be the event that the *second* flip is heads.

Write down all outcomes in the full sample space,  $S$ .

$\{HHH, HHT, HTH, \dots, TTT\}$

Write down all outcomes in  $E_1$ .

$\{HHH, HHT, HTH, HTT\}$

Write down all outcomes in  $E_1 \cup E_2$ .

$E_2 = \{HHH, HHT, THH, THT\}$

Write down all outcomes in  $E_1 \cap E_2$ .

$\{HHH, HHT\}$

Write down all outcomes in  $E_1^C$ .

$\{THH, THT, TTH, TTT\}$

# Summary: calculating probabilities

- 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 using the rules of probability
- If this is still challenging, we can try using the Law of Total Probability, using an appropriate partition of sample space  $S$

# 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  $P(E \cup F) = P(E) + P(F)$*



- Conditional probability
- Probabilistic reasoning
  - Useful tools: contingency table & probability trees
- Bayes rule
- Independence of events
- Probability and combinatorics

# Conditional Probability

# 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

- 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 now?
  - Chance that event  $B$  happens to them now?

# Example: Seat Belts

		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

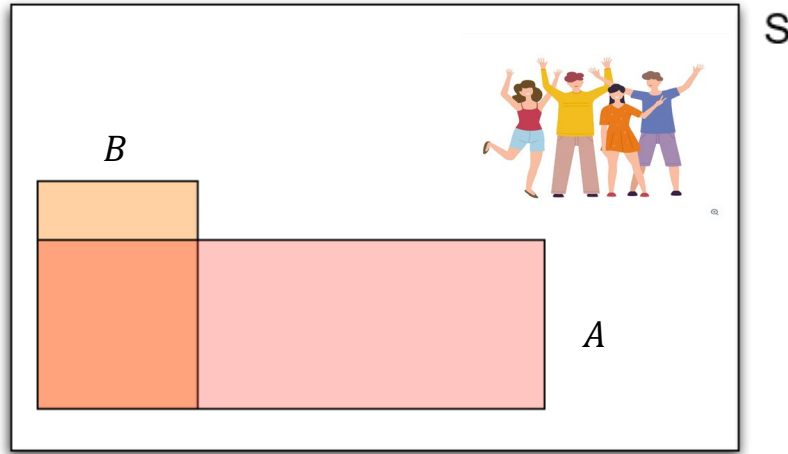
Table: Probability Estimates for Seat Belt Status

Suppose we pick a family from US at random:

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

# Relative area

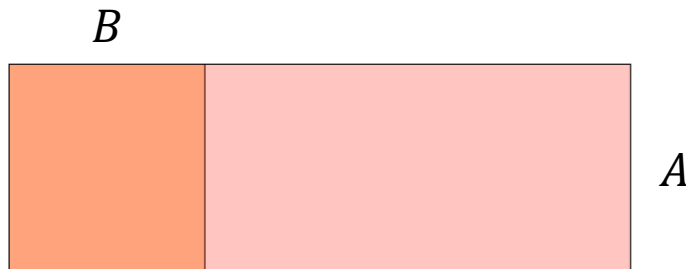
- $A$ : antigen A present       $B$ : antigen B present
- Given that  $A$  happens, what is the chance of  $B$  happening?



- Another way to think about this:
  - 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 red square represent in the original sample space?
  - $A \cap B$
- How would we find the probability of  $B$  given  $A$ ?

# 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, with an updated probability of 1
- Instead of asking “In what proportion of  $S$  is  $B$  true?”, we now ask “In what proportion of  $A$  is  $B$  true?”

# 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:

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





# 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. E.g.

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

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

- $P(B|S)$  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		Marginal
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Table: Probability Estimates for Seat Belt Status

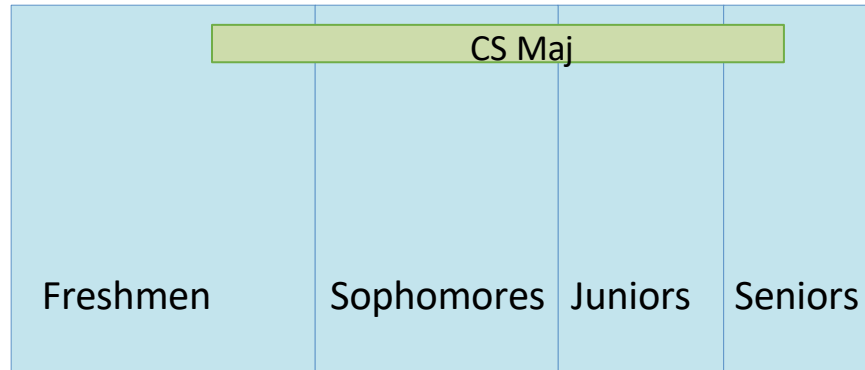
Suppose we pick a family from the US at random:

- $P(C) = 0.58$
- $P(C | A) = \frac{P(C \cap A)}{P(A)} = \frac{0.48}{0.60} = 0.8$  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

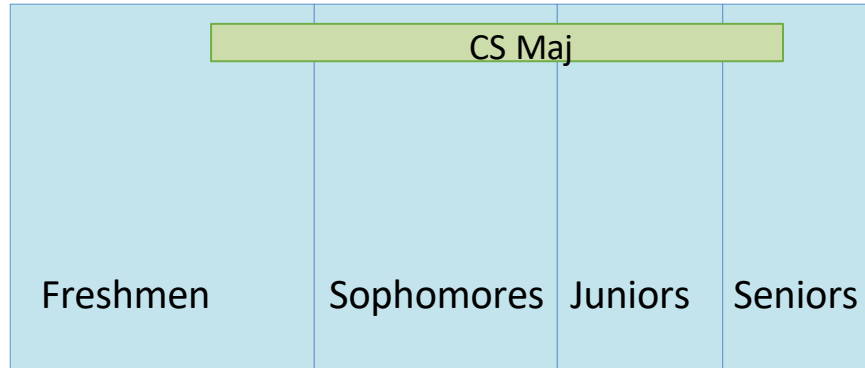
Expanding each  $P(A, B_i) = P(A | B_i)P(B_i)$ , we have:

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

$A$ : student in CS major

$B_i$ : student in class year  $i$

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?

## Soln

- $P(B_1) = P(B_2) = P(B_3) = P(B_4) = 0.25$
- $P(C | B_1) = 0.1, \dots, P(C | B_4) = 0.8$
- We can now 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: lie detector

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

- Suppose that 10% of employees stole, but 100% say they didn't.
- The lie detector buzzes 80% of the time that someone lies, and 20% of the time that someone is telling the truth.
- If the detector buzzes, what's the probability that the person was lying?



# Another example: lie detector

- Suppose that 10% of employees stole, but 100% say they didn't.

H: employee is honest                       $P(H) = 0.9$

- The lie detector buzzes 80% of the time that someone lies, and 20% of the time that someone is telling the truth.

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

B: lie detector buzzes

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

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

$$P(H^c | B)$$

# Lie detector analysis: Probability table

- Aka contingency table, two-way table

		Lie Detector Result		Marginal
		Pass	Buzz!!	
Employee	Honest			$P(H) = 0.9$
	Dishonest!!		??	
Marginal				

Table: Lie Detector Probabilities

- $P(H) = 0.9$
- $P(B | H^C) = 0.8, P(B | H) = 0.2$
- If we can compute all entries of the probability table, we can get  $P(H^C | B)$

# Lie detector analysis: Probability table


		Lie Detector Result		Marginal
		Pass	Buzz!!	
Employee	Honest			$P(H) = 0.9$
	Dishonest!!			$P(H^c) = 0.1$
Marginal				

Table: Lie Detector Probabilities

- $P(H) = 0.9$
- $P(B | H^c) = 0.8, P(B | H) = 0.2$
- Let's try to fill in the table..

# Lie detector analysis: Probability table

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



		Lie Detector Result		Marginal
		Pass	Buzz!!	
Employee	Honest	0.72	0.18	$P(H) = 0.9$
	Dishonest!!	0.02	0.08	$P(H^c) = 0.1$
Marginal		0.74	0.26	1

Table: Lie Detector Probabilities

- $P(H) = 0.9$
- $P(B | H^c) = 0.8, P(B | H) = 0.2$
- Let's try to fill in the table..



# Lie detector analysis: Probability table

		Lie Detector Result		Marginal
		Pass	Buzz!!	
Employee	Honest	0.72	0.18	$P(H) = 0.9$
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Marginal		0.74	0.26	1

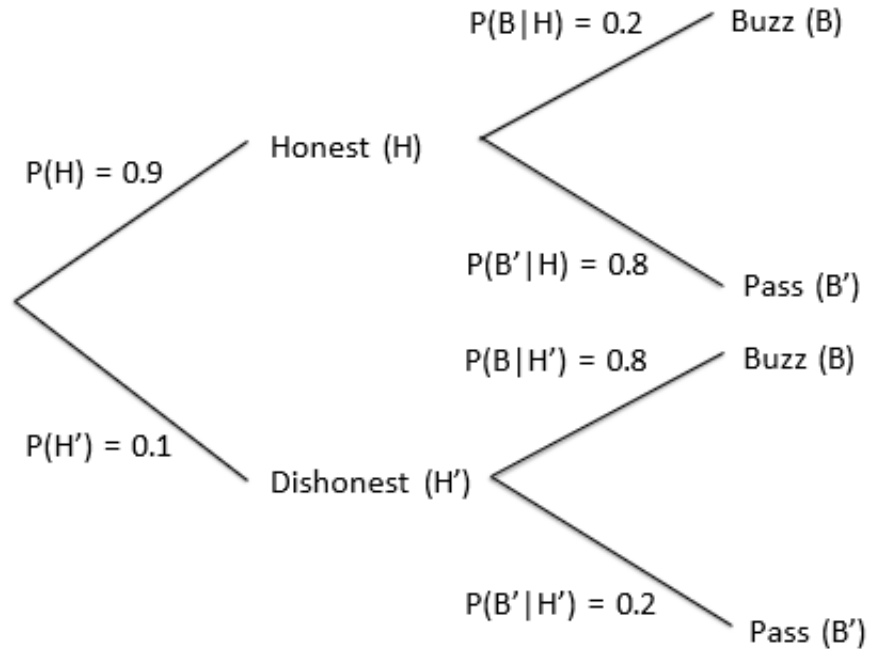
Table: Lie Detector Probabilities

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

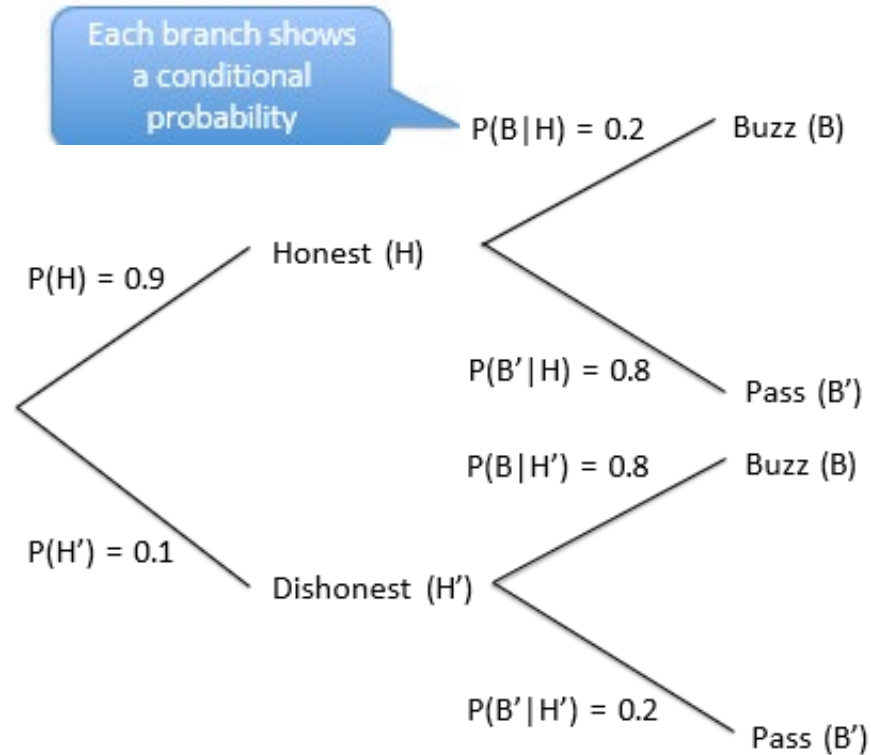
$$P(H^C | B) = \frac{P(H^C, B)}{P(B)} = \frac{0.08}{0.26} = 0.307$$

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

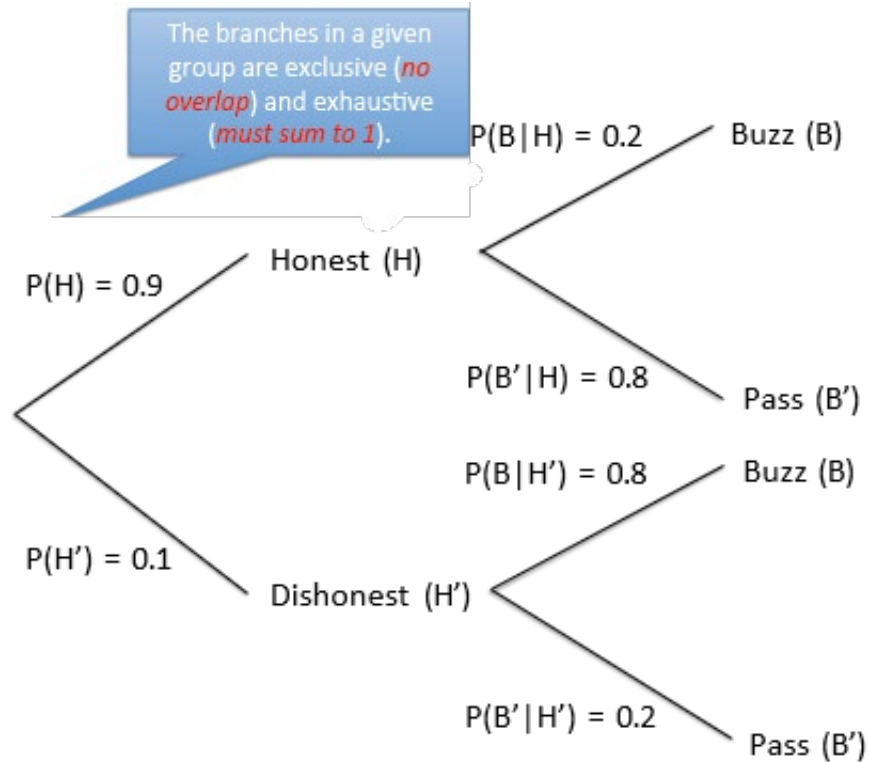
# Probability trees: another useful tool



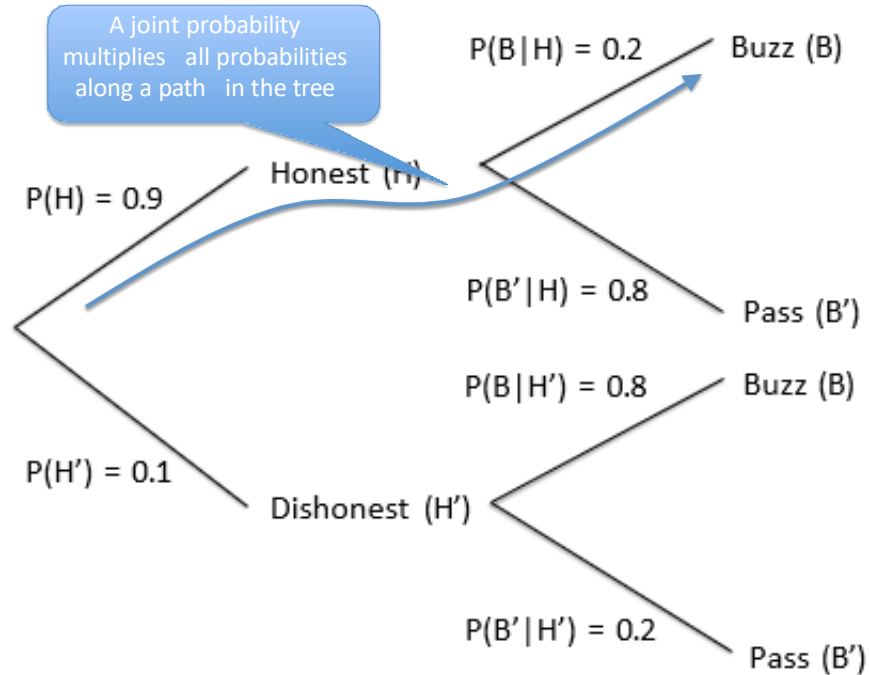
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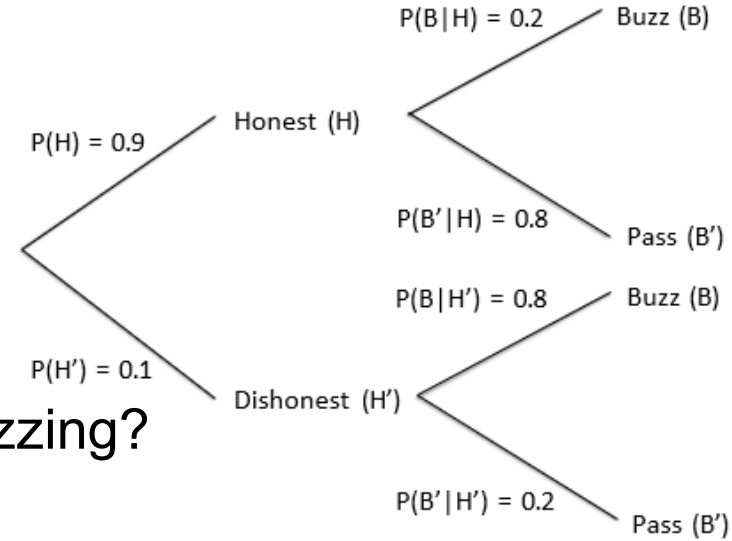
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# Probability trees: another useful tool

Let's use this to answer:

- What is  $P(\text{Buzz}, \text{Dishonest})$ ?
  - 0.08
- $P(\text{Buzz})$ ?
  - Hint: which branches end up with buzzing?
  - 0.26
- $P(\text{Dishonest} \mid \text{Buzz})$ ?
  - Hint: which of the prev. branches contains the Dishonest event?
  - $0.08 / 0.26$
  - We will soon see tools that can simplify this calculation a bit..



The Public Health Department gives us the following information:

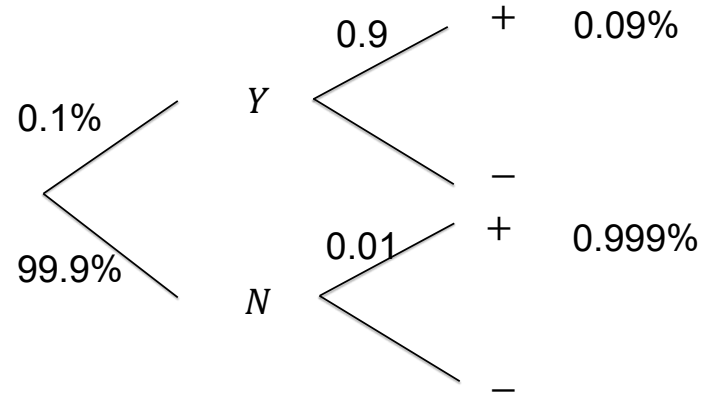
- A test for the disease yields a positive result (+) 90% of the time when the disease is present (Y)  $P(+ | Y) = 0.9$ , “sensitivity” of the test
- A test for the disease yields a positive result 1% of the time when the disease is not present (N)  $P(+ | N) = 0.01$
- One person in 1,000 has the disease.  $P(Y) = 0.1\%$

**Draw a probability tree and use it to answer:** what is the probability that a person with positive test has the disease?

$$P(Y | +)?$$

# In-class activity: COVID test

- Goal: calculate  $P(Y | +)$
- Two branches are associated with positive test results +
  - What are the associated events?



- $P(+, Y) = P(+ | Y)P(Y) = 0.09\%$
- $P(+, N) = P(+ | N)P(N) = 0.999\%$

- $$P(Y | +) = \frac{P(+, Y)}{P(+)} = \frac{0.09\%}{0.09\% + 0.999\%} \approx \frac{1}{12}$$

- Conclusion: being tested positive does not mean much..

$$P(+ | Y) = 0.9$$

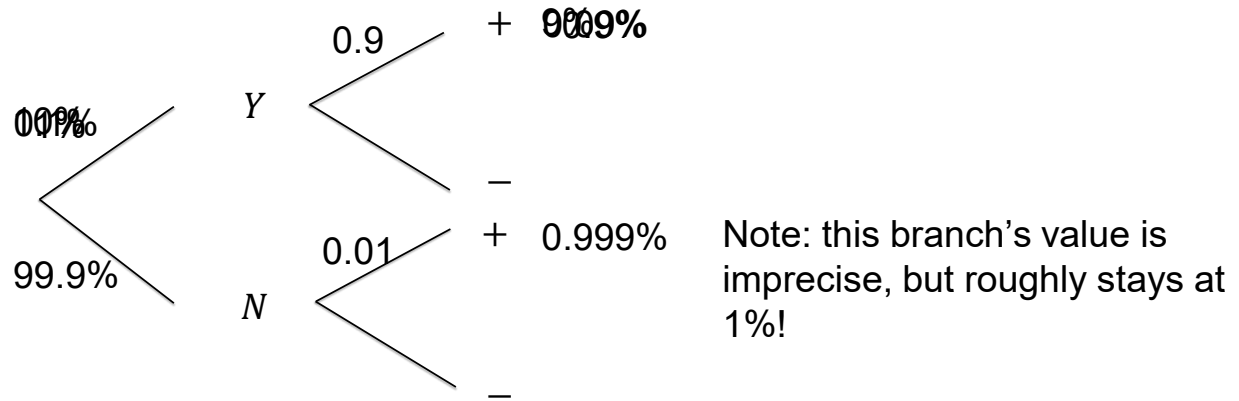
$$P(+ | N) = 0.01$$

$$P(Y) = 0.001$$



# COVID test: additional insights

- What would  $P(Y | +)$  look like, if instead:
  - 1 in 100 people have COVID?
  - 1 in 10?



- Insight: *base rate*  $P(Y)$  significantly affects  $P(Y | +)$ , hence the conclusions we draw

# 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

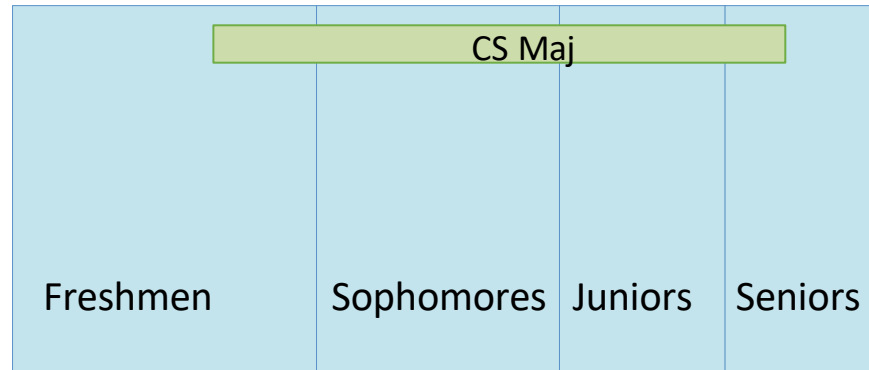
## Rules of Probability

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

- $P(S|A) = 1$
- $P(E|A) + P(E^C|A) = 1$
- $P(E|A) + P(F|A) = P(E \cup F|A)$

A: CS major



# Bayes rule

# Reversing conditional probabilities

- Is  $P(A | B) = P(B | A)$  in general?

- Let's see..

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

- They are equal only when  $P(A)$  and  $P(B)$  are equal
- Can you find a real-world example when they are unequal?
  - $A$ : nurses;  $B$ : healthcare professionals
- Can I write one in terms of the other?

# 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  $A, B$ ,

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

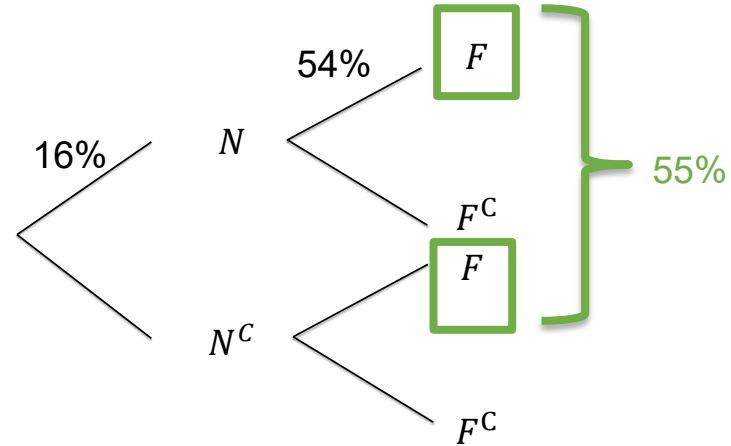
Posterior probability

Prior probability    Support of evidence

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

# Bayes rule: another example

- 16% of the students are Nutrition Science majors and 55% are female. Of the Nutrition Science majors, 54% are female. What proportion of female students in the class are Nutrition Science majors?
- What is the probability tree of this?
- We are looking for  $P(N | F)$



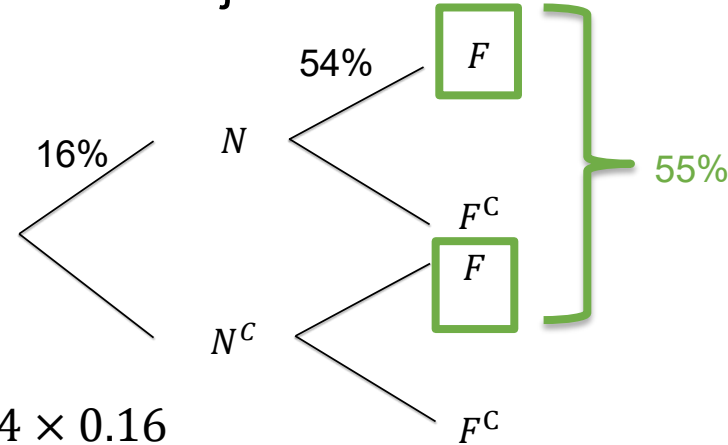


# Bayes rule: another example

- 16% of the students are Nutrition Science majors and 55% are female. Of the Nutrition Science majors, 54% are female. What proportion of female students in the class are Nutrition Science majors?

- We can use  $P(N | F) = \frac{P(N, F)}{P(F)}$

- We know  $P(F) = 0.55$



- Can we obtain  $P(N, F)$ ?

- We can use  $P(N, F) = P(F | N) \cdot P(N) = 0.54 \times 0.16$

- Altogether, we have

$$P(N | F) = \frac{P(F | N) \cdot P(N)}{P(F)} = \frac{0.54 \times 0.16}{0.55}$$

# Bayes rule: another example

**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.

We have previously calculated that  $P(C) = 30\%$

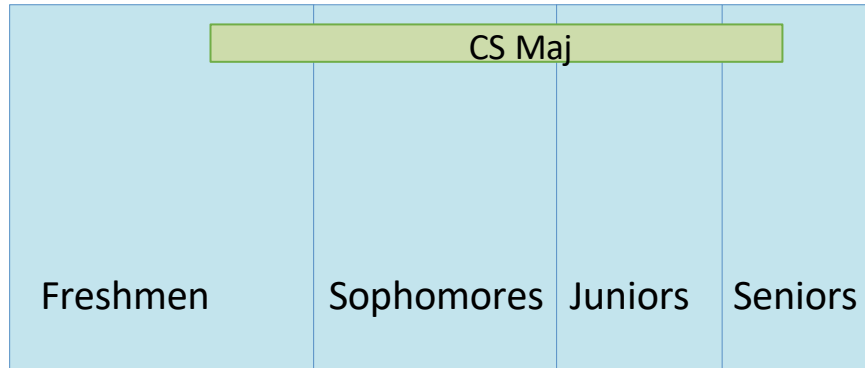
If we see a CS major student, what is their most likely year class?

$$P(B_1 | C), \dots, P(B_4 | C) \rightarrow \text{maximum?}$$

# Bayes rule and Law of Total Probability

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

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



....

# Bayes rule and Law of Total Probability

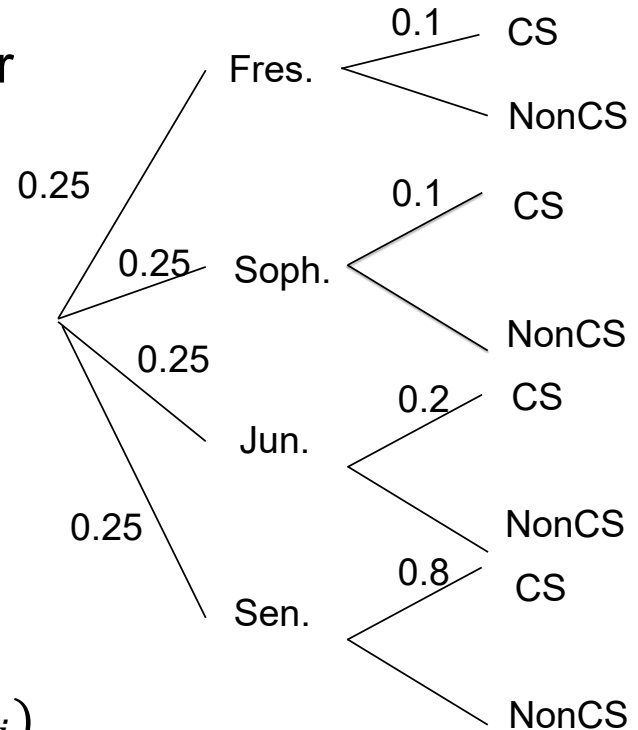
- Let's draw a probability tree..
- After learning that the student is CS major

$$P(B_1 | C) = \frac{0.25 \times 0.1}{P(C)}$$

...

$$P(B_4 | C) = \frac{0.25 \times 0.8}{P(C)}$$

- So most likely, this student is a senior
- Side note:  $P(C)$  can be viewed as a *normalization factor*
- Equivalent form:  $P(B_i | C) \propto P(B_i)P(C | B_i)$ 
  - $\propto$ : proportional to



# Independence

# Probabilistic Independence

- 10% of employees are dishonest.
- There's a 5% chance of rain tomorrow.
- What's the probability an employee is dishonest if it rains tomorrow?
- Probably your intuition is that one conveys no information about the other.
- What does this mean about the relationship between the conditional probability of D given R, and the marginal probability of D?

# Probabilistic Independence

## Independent Events

We say that event  $A$  is **independent** of event  $B$  if conditioning on  $B$  does not change the probability of  $A$ , that is if

$$P(A|B) = P(A)$$

- If the employee is dishonest, what's the probability that it will rain tomorrow?
- Seems like independence is symmetric. Is it?

# Probabilistic Independence

- If  $A$  is independent of  $B$ , then  $P(A | B) = P(A)$ . Is  $P(B|A)$  also equal to  $P(B)$ ?

- Using Bayes' rule, we have

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

- So independence is indeed a symmetric notion



# Independence: equivalent statement

- If  $A, B$  are independent, then their joint probability has a simple form:

$$\begin{aligned}P(A, B) &= P(A | B)P(B) \\ &= P(A) \cdot P(B)\end{aligned}$$

- This is an equivalent characterization of independence

## Independence (version 2)

If  $A$  and  $B$  are independent events, then

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

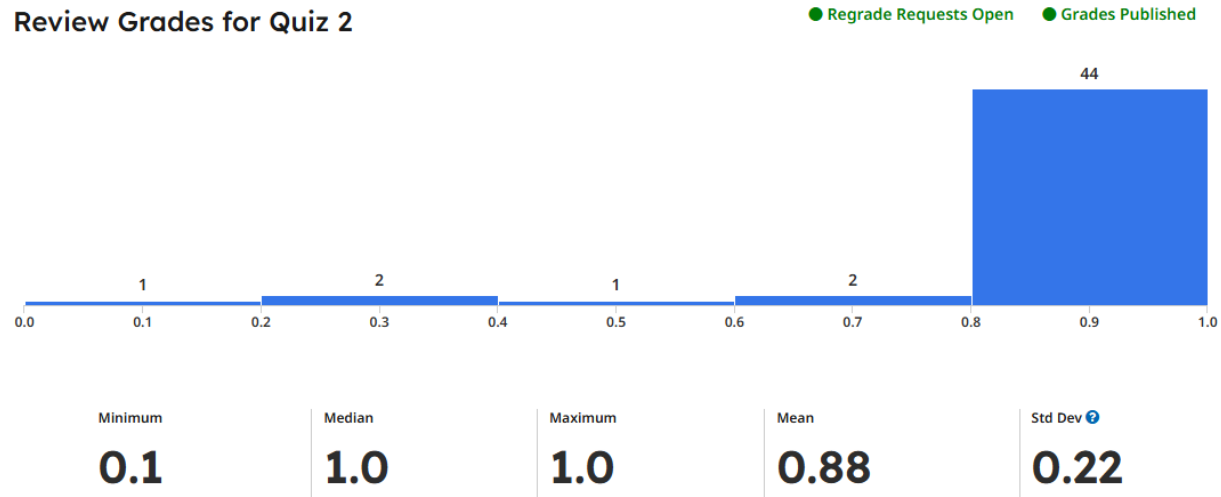
# Are these independent events?

- E: First coin comes up heads, F: Second coin comes up heads
- E: First coin comes up heads, F: First coin comes up tails
- E: Sample a nutrition science major, F: Sample a female
- E: Draw a yellow ball on first pick, F: Draw a yellow ball on second pick (with replacement)
- E: Draw a yellow ball on first pick, F: Draw a yellow ball on second pick (without replacement)

# Announcements 2/10

- Quiz 2 graded; let us know if you have questions!

Review Grades for Quiz 2



- We will have quiz 3 this Wed (2/12)

# Recap: conditional probability

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

## 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  $P(A \cap B) = P(B \cap A)$

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

# 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:

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

# Recap: probability independence

## Independent Events

We say that event  $A$  is **independent** of event  $B$  if conditioning on  $B$  does not change the probability of  $A$ , that is if

$$P(A|B) = P(A)$$

## Independence (version 2)

If  $A$  and  $B$  are independent events, then

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

# Independence of several events

- We can generalize the notion of independence from two events to more than two.
  - E.g. A: employee is honest; B: rain tomorrow, C: stock price up
- Events  $A_1, \dots, A_n$  are independent if for any subsets

$A_{i_1}, \dots, A_{i_j}$ ,

$$P(A_{i_1}, \dots, A_{i_j}) = P(A_{i_1}) \cdot \dots \cdot P(A_{i_j})$$

# Independence of several events

- E.g. if events  $A, B, C$  are independent, then
  - $P(A, B, C) = P(A) \cdot P(B) \cdot P(C)$
  - $P(A, C) = P(A) \cdot P(C)$
  - $P(B, C) = P(B) \cdot P(C)$
  - ...

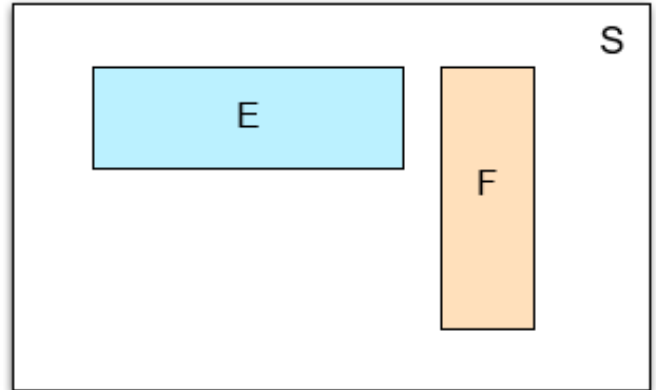


# Probabilistic independence

- What's the sample space for rolling a die three times?
- How can we find the probability of the sequence (1, 2, 3)?
- What's the probability of the event that the sequence starts with 1?  $1/6$
- What's the conditional probability that we start with (1, 2) given that the first roll was a 1?
- We assume the rolls are independent, so the conditional probability is the same as the probability of rolling a 2.  $1/6$
- So what's the unconditional probability of a sequence beginning with (1, 2)?  $1/6 \times 1/6$
- How about of the sequence (1, 2, 3)?  $1/6 \times 1/6 \times 1/6$

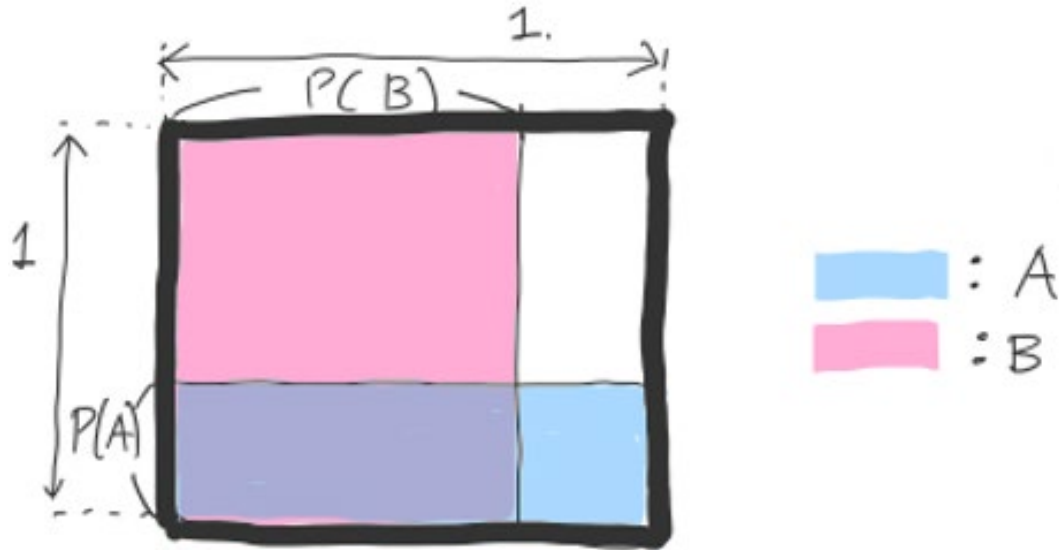
# Independent vs. Disjoint Events

- Many people confuse independence with disjointness.
- They are very different!
- What does it mean for two events to be disjoint?
- If A and B are disjoint, then they cannot occur simultaneously; they are *mutually exclusive*; their intersection is the empty set.
- What does the Venn diagram look like?



# Independent vs. Disjoint Events

- If A and B are independent, then  $P(B|A) = P(B)$ .
- What does the Venn Diagram look like?



# Independent vs. Disjoint Events

- If A and B are disjoint, what is  $P(B|A)$ ?

$$P(B | A) = \frac{P(A, B)}{P(A)} = 0!$$

- Disjointness is practically the opposite of independence: if A occurs, you have all the information about whether B will occur.
  - Specifically, B doesn't occur

# Independent vs. Disjoint Events

- Defining property of independent events:

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

- Defining property of disjoint events:

$$P(A \cap B) = 0$$

# In-class activity: the absent-minded diners

- Three friends decide to go out for a meal, but they forget where they're going to meet.
- Fred decides to throw a coin. If it lands heads, he'll go to the diner; tails, and he'll go to the Italian restaurant.
- George throws a coin, too: heads, it's the Italian restaurant; tails, it's the diner.
- Ron decides he'll just go to the Italian restaurant because he likes the food.
- What's the probability that all three friends meet?  $0.5 * 0.5 = 0.25$
- What's the probability that one of them eats alone?  $1 - 0.25 = 0.75$

# Summary

## Conditional Probability Summary

- | Representing conditional probabilities using contingency tables, Venn diagrams, and probability trees.
- | The chain rule
- | Bayes rule
- | The law of total probability
- | Independent events
- | Disjoint events

# Probability and Combinatorics



# Probability and Combinatorics

- Combinatorics (in CSc144) are useful in calculating probabilities
- Recall: when all outcomes are equally likely:

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)

- We will also see its another usage in a popular example:  
repeated independent trials (Bernoulli trials)

# Example 1: sampling without replacement

- A president (P) and a treasurer (T) chosen from 20 people including Alice, Bob.
- Probability that Alice is president and Bob is treasurer?
- #ways to select (P,T) =  $20 \times 19 = 380$
- $P(E) = \frac{1}{380}$

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

Number of elements in event set

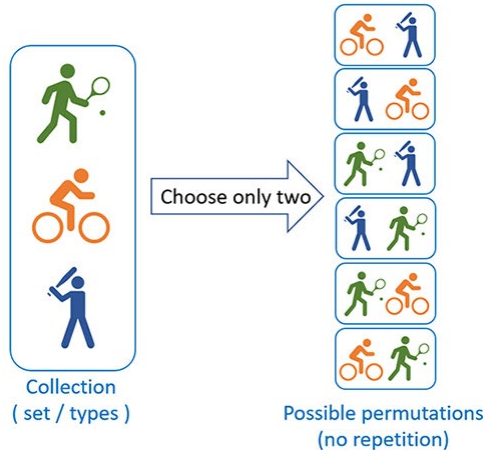
Number of possible outcomes (e.g. 36)

# Permutation number

- If *ordered* selection of  $k$  items out of  $n$  is done without replacement, there are

$$n \times (n - 1) \times \cdots \times (n - k + 1) = \frac{n!}{(n - k)!}$$

outcomes



## Example 2: Birthdays

- Probability that 2 in a group of 20 have same birthday?
- Sample space:  $S = \{(n_1, \dots, n_{20}) : n_1, \dots, n_{20} \in \{1, \dots, 365\}\}$
- What is  $|S|$ ?
  - $365^{20}$
- $E$ : set of outcomes where two have same birthday, e.g. (5,5,176, .., 80)

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

Number of elements in event set

Number of possible outcomes (e.g. 36)

# Example 2: Birthdays

- Let's try to calculate  $|E|$
- It turns out that it is easier to calculate  $|E^C|$

- $E^C$ : all 20 birthdays are different

185	13	359	..	243	19
-----	----	-----	----	-----	----

- $|E^C| = \frac{365!}{(365-20)!}$

- $P(E) = 1 - P(E^C) = 1 - \frac{365!}{(365-20)! \cdot 365^{20}} \approx 0.411$

This is quite high?! “Birthday paradox”

# Repeated independent trials

**Example** The house or the player?



- 4 dice are rolled:
- House wins if at least one die is a 6, otherwise player wins.
- What is the probability that the house wins?
  
- What if I change the rule to “House wins if at least two die is a 6”?

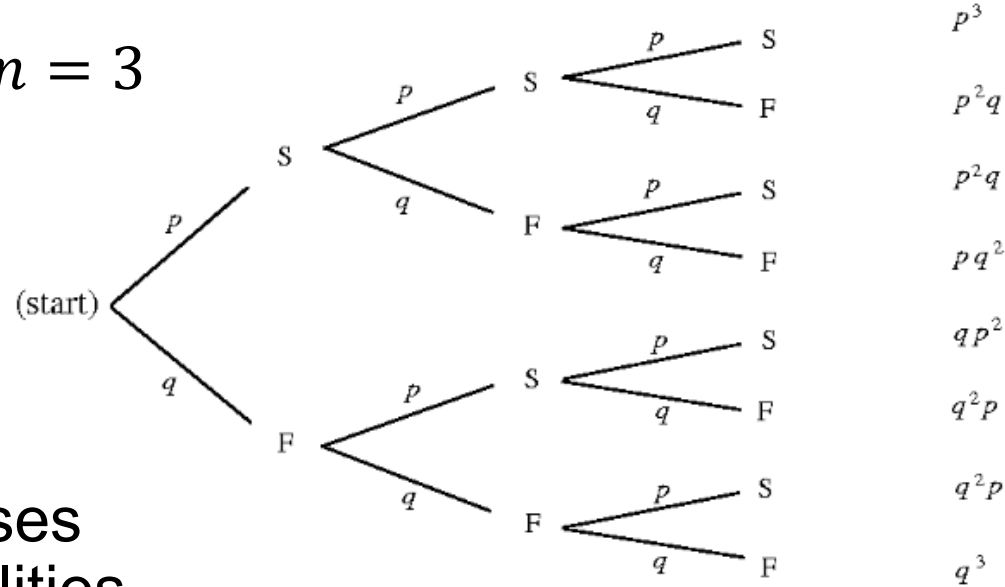
# Repeated independent trials (Bernoulli trials)

- In general, we are interested in the question:
- Suppose we repeatedly perform an experiment  $n$  independent times, each with success probability  $p$ , what is the probability that we succeed  $m$  times?
- The gambling example above:  $n = 4$ ,  $p = \frac{1}{6}$ ,  $m = 1, 2, 3, 4$
- Applications: sports analytics, gene mutations, etc.
- Named after Jacob Bernoulli (1655-1705)



# Repeated independent trials: analysis

- Let's draw a probability tree!
- For simplicity let's look at  $n = 3$
- Let  $q := 1 - p$



## Observations:

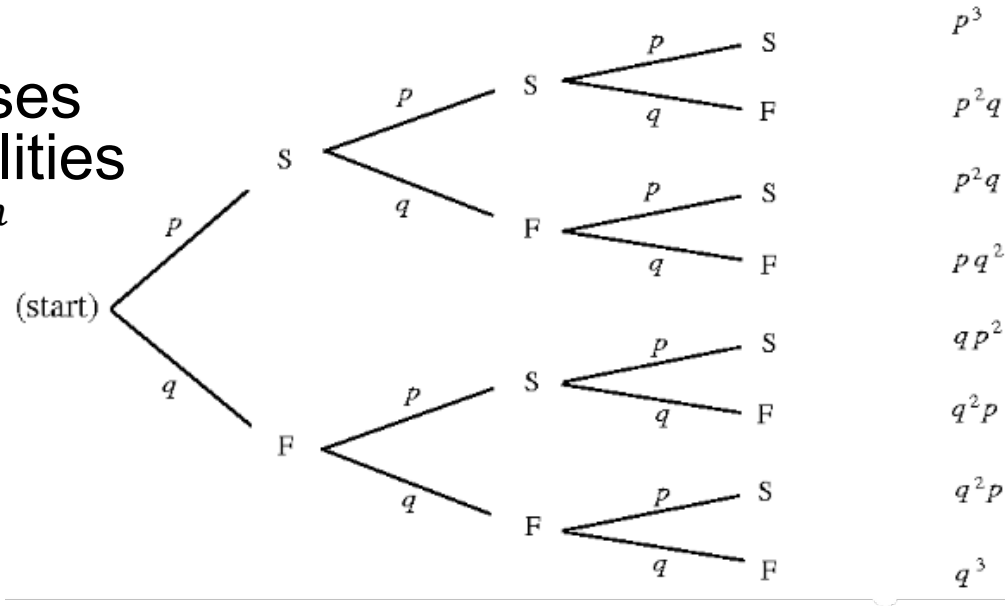
- $2^n = 8$  paths
- Paths with same #successes ( $m$ ) have identical probabilities
  - They are equal to  $p^m q^{n-m}$



# Repeated independent trials: analysis

Observations:

- $2^n = 8$  paths
- Paths with same #successes ( $m$ ) have identical probabilities
  - They are equal to  $p^m q^{n-m}$
- How many paths have 3 successes?
  - 2?
  - 1?
  - 0?

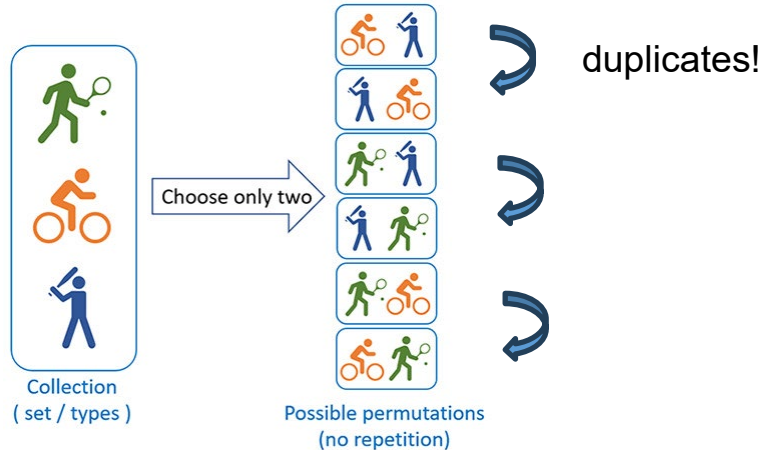


# Combination number

- If *unordered* selection of  $k$  items out of  $n$  is done without replacement, there are

$$\frac{n!}{(n - k)! k!} =: \binom{n}{k}$$

outcomes



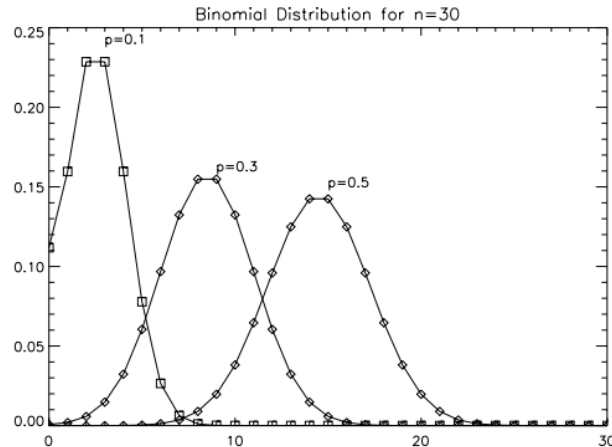
# Repeated independent trials: analysis

- Out of all  $2^3 = 8$  paths, the paths with 2 successes are:  
SSF, SFS, FSS  
# such paths is  $\binom{3}{2}$
- In general, given  $n$  trials, #paths with  $m$  successes is  $\binom{n}{m}$ 
  - select  $m$  different success positions out of  $n$  slots
- Thus,  $P(m \text{ successes}) = \binom{n}{m} \cdot p^m q^{n-m}$

# Repeated independent trials: conclusion

- In summary, in an experiment with  $n$  repeated independent trials with success probability  $p$ ,

$$P(m \text{ successes}) = \binom{n}{m} \cdot p^m (1 - p)^{n-m}$$



- The (random) number of successes is said to follow a *binomial distribution* (more to come next lecture)

## .. Back to gambling



**Example** The house or the player?

- 4 dice are rolled:
- House wins if at least one die is a 6, otherwise player wins.
- What is the probability that the house wins?
  
- We have  $n = 4$  repeated independent trials
- Here, “success” = “die is a 6”
- The asked probability is  $P(\geq 1 \text{ success})$

## .. Back to gambling

- We do  $n = 4$  repeated independent trials
- Here, “success” = “die is a 6”
- The asked probability is  $P(\geq 1 \text{ successes})$
- $$P(\geq 1 \text{ successes}) = \sum_{i=1}^4 P(i \text{ successes})$$
$$= \sum_{i=1}^4 \binom{4}{i} \cdot \left(\frac{1}{6}\right)^i \left(\frac{5}{6}\right)^{4-i} = 0.518$$
- Take home message: the house always wins 😊



## .. Back to gambling

- There is another easier way to think about this problem..

$$P(\geq 1 \text{ successes}) = 1 - P(0 \text{ successes})$$

Complementary rule

$$P(0 \text{ successes}) = P(\text{Fail}_1, \dots, \text{Fail}_4) = \left(\frac{5}{6}\right)^4$$

Independence of the 4 dice rolls

Backup



The Public Health Department gives us the following information:

- A test for the disease yields a positive result (+) 90% of the time when the disease is present (Y)  $P(+ | Y) = 0.9$
- A test for the disease yields a positive result 1% of the time when the disease is not present (N)  $P(+ | N) = 0.01$
- One person in 1,000 has the disease.  $P(Y) = 0.001$

Q: What is the probability that a person with positive test has the disease?  $P(Y | +)$ ?

# Application of Bayes rule: COVID test

- We could solve this problem by filling in probability table, or probability tree
- Let's try Bayes rule this time..

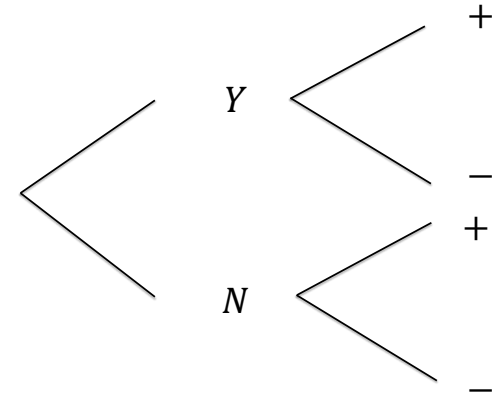
$$P(+ | Y) = 0.9$$

$$P(+ | N) = 0.01$$

$$P(Y) = 0.001$$

$$P(Y | +) = \frac{P(+ | Y)P(Y)}{P(+)}$$

- $P(+ | Y)P(Y) = 0.9 \cdot 0.001 = 0.0009$
- What about  $P(+)$ ?



# Application of Bayes rule: COVID test

- $P(+)=P(+|Y)P(Y)+P(+|N)P(N)$

$$P(+|Y)=0.9$$

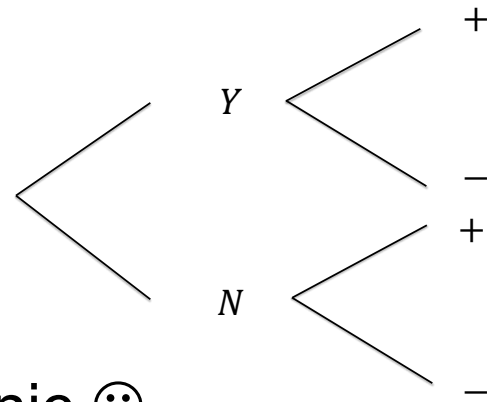
$$P(+|N)=0.01$$

$$P(Y)=0.001$$

- First part,  $P(+|Y)P(Y)$ , was calculated before (0.0009)
- Second part,  $P(+|N)P(N)=0.01\cdot 0.999=0.00999$

Therefore,

$$P(Y|+)=\frac{0.0009}{0.0009+0.00999}\approx\frac{1}{1+11}=0.083$$



Conclusion: if tested positive, no need to panic 😊

## HW1 has been out

- D2L -> Content
- Due next Friday, Jan 26 by 11:59 pm

## Participation policy (5 points)

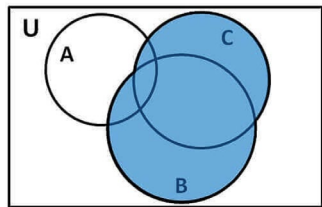
- Each office hour: + 1 point
- Answering question in the lecture: + 1point
- Answering question on Piazza: + 1 point
- Asking question (related to course materials) on Piazza: +0.5 point

Note: It is your responsibility to ensure the TA or instructor enter your participation points on gradescope during the office hour or after each lecture. Instructors will not award you these points at a later date, do not email instructors about getting points at a later date (for example, if you forget to ask the TA to enter your office hour points on gradescope).

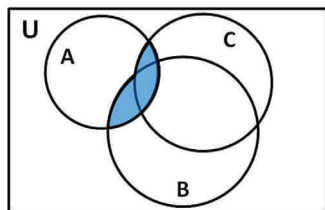
- What is probability?
- Axioms
- Event = set  $\Rightarrow$  use set theory!
- Set theory + axiom 3 is quite useful
- Draw diagrams
- Lots of jargons
  
- Make your own cheatsheet.

- $A \cap (B \cup C) = (A \cap B) \cup (A \cap C)$

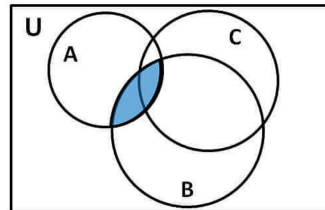
distributive law by Venn diagram



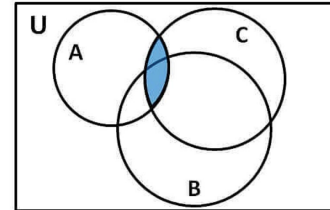
$(B \cup C)$



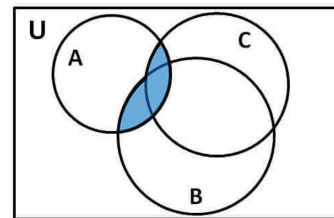
$A \cap (B \cup C)$



$(A \cap B)$



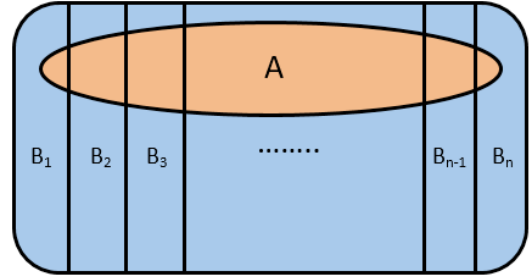
$(A \cap C)$



$(A \cap B) \cup (A \cap C)$

- $A \cap (B \cup C) = (A \cap B) \cup (A \cap C)$

- $$\begin{aligned} A &= A \cap \Omega = A \cap (\cup_i B_i) = \cup_i (A \cap B_i) \\ &= A \cap (B_1 \cup B_2 \cup B_3 \dots \cup B_n) \\ &= (A \cap B_1) \cup (A \cap B_2) \cup (A \cap B_3) \dots \cup (A \cap B_n) \end{aligned}$$



**Law of total probability:** Let  $A$  be an event. For any events  $B_1, B_2, \dots$  that partitions  $\Omega$ , we have

$$P(A) = \sum_i P(A \cap B_i)$$

# Numpy Library

*Package containing many useful numerical functions...*

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## ANACONDA DISTRIBUTION

The world's most popular open-source Python distribution platform

`conda install numpy`

If you use pip:

`pip install numpy`



*...we are interested in `numpy.random` at the moment*



# numpy.random

## numpy.random.randint

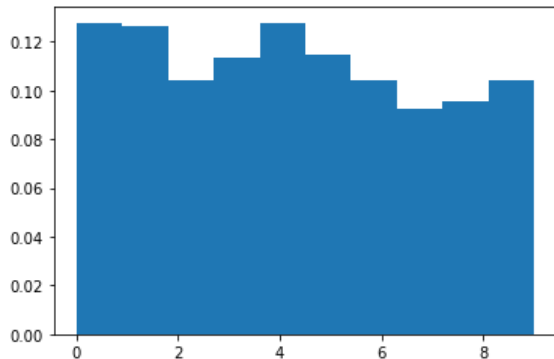
`numpy.random.randint(low, high=None, size=None, dtype='i')`

Return random integers from *low* (inclusive) to *high* (exclusive).

Return random integers from the “discrete uniform” distribution of the specified dtype in the “half-open” interval [*low*, *high*). If *high* is None (the default), then results are from [0, *low*).

Sample a discrete uniform random variable,

```
import matplotlib.pyplot as plt
X = np.random.randint(0,10,1000)
count, bins, ignored = plt.hist(X, 10, density=True)
plt.show()
```



- **Caution** Interval is [low,high) and upper bound is **exclusive**
- `Size` argument accepts tuples for sampling ndarrays (multidimensional arrays)

# numpy.random

*Allows sampling from many common distributions*

Set (global) random seed as,

```
import numpy as np  
  
seed = 12345  
np.random.seed(seed)
```

- 😊 easier to debug (otherwise, you may have ‘stochastic’ bug)
- 😞 can be risky

E.g., buy into the result based on a particular seed, publish a report.  
... turns out, you get a widely different result if you use a different seed!

Recommendation: change the seed every now and then

# Random Events and Probability

*Consider: What is the probability of having two numbers sum to 6?*

```
import numpy as np
for n in [10,100,1_000,10_000,100_000]:
    res_dice1 = np.random.randint(1,6+1,size=n)
    res_dice2 = np.random.randint(1,6+1,size=n)
    res = [(res_dice1[i], res_dice2[i]) for i in range(len(res_dice1))]

    cnt = len(list(filter(lambda x: x[0] + x[1] == 6, res)))
    print("n=%6d, result: %.4f " % (n, cnt/n))
```

```
n= 10, result: 0.1000
n= 100, result: 0.1200
n= 1000, result: 0.1350
n= 10000, result: 0.1365
n= 100000, result: 0.1388
n= 1000000, result: 0.1385
```

```
n= 10, result: 0.1000
n= 100, result: 0.1900
n= 1000, result: 0.1540
n= 10000, result: 0.1366
n= 100000, result: 0.1371
n= 1000000, result: 0.1394
```

every time you run, you  
get a different result

however, the number  
seems to converge to  
0.138-0.139

There seems to be a precise value that it will converge to.. what is it?

# Conditional Probability

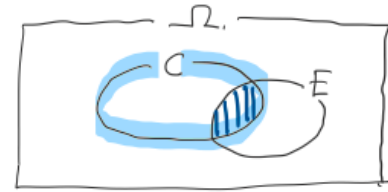
- Suppose I roll two dice secretly and tell you that one of the dice is 2. C
- In this situation, find the probability of two dice summing to 6. E

```
import numpy as np
for n in [10,100,1000,10_000,100_000, 1_000_000]:
    res_dice1 = np.random.randint(6,size=n) + 1
    res_dice2 = np.random.randint(6,size=n) + 1
    res = [(res_dice1[i], res_dice2[i]) for i in range(len(res_dice1))]
```

```
conditioned = list(filter(lambda x: x[0] == 2 or x[1] == 2, res))
n_eff = len(conditioned)
```

```
cnt = len(list(filter(lambda x: x[0] + x[1] == 6, conditioned)))
print("n=%9d, n_eff=%9d, result: %.4f" % (n, n_eff, cnt/n_eff))
```

n= 10, n_eff= 4, result: 0.0000	n= 10, n_eff= 3, result: 0.3333
n= 100, n_eff= 32, result: 0.2500	n= 100, n_eff= 32, result: 0.0625
n= 1000, n_eff= 300, result: 0.1733	n= 1000, n_eff= 343, result: 0.2245
n= 10000, n_eff= 3002, result: 0.1742	n= 10000, n_eff= 3062, result: 0.1897
n= 100000, n_eff= 30590, result: 0.1823	n= 100000, n_eff= 30651, result: 0.1811
n= 1000000, n_eff= 305616, result: 0.1818	n= 1000000, n_eff= 305580, result: 0.1808

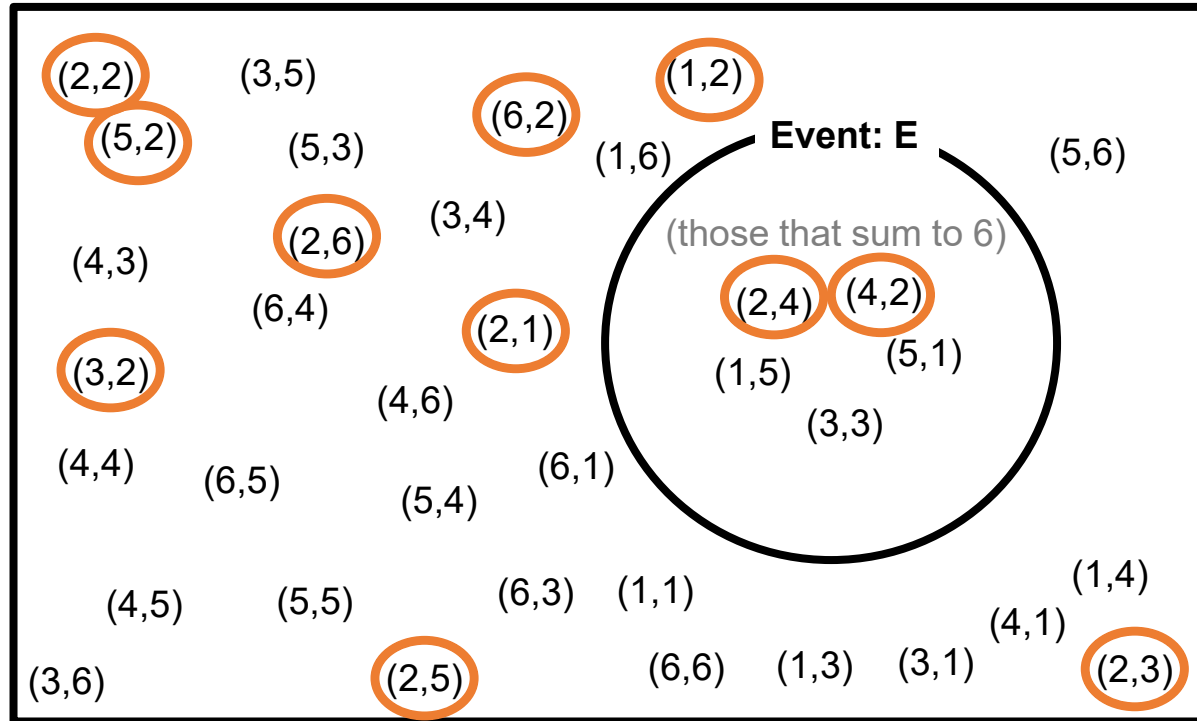


Without conditioning,  
it was 0.138.

There seems to be a precise value that it will converge to.. what is it?

# Random Events and Probability

*What is the probability of having two numbers sum to 6 given one of dice is 2?*



Each outcome is equally likely.  
by the **independence**  
(will learn this concept later)  
 $\Rightarrow 1/36$

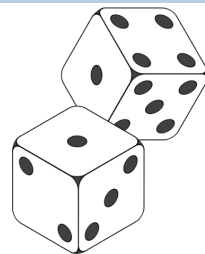
# sum to 6:  
 $\Rightarrow 5$

# one of dice is 2:  
 $\Rightarrow 11$

# sum to 6 and one of dice  
is 2:  
 $\Rightarrow 2$

answer:  
 $2/11 = 0.181818\dots$

## Two fair dice example

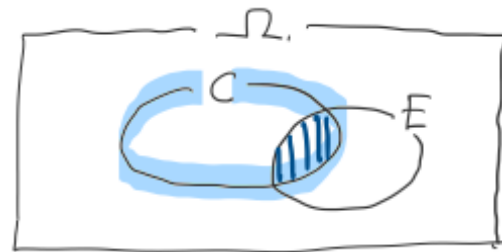


- Find the probability of **one of the dice is 2 (event  $C$ )** and **two dice summing to 6 ( $E$ )**

$$P(E \cap C)$$

- I secretly tell you **one of the dice is 2**, find the probability of **two dice summing to 6**.

$$\frac{P(E \cap C)}{P(C)}$$



- Two fair dice example:
  - Suppose I roll two dice and secretly tell you that **one of the dice is 2**.  $C$
  - **In this situation**, find the probability of **two dice summing to 6**.  $E$

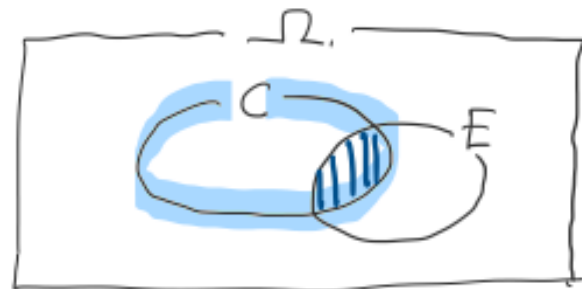
• Turns out, such a probability can be computed by  $\frac{P(E \cap C)}{P(C)}$

• It's like “zooming in” to the condition.

• This happens a lot in practice, so let's give it a notation:

$$P(E|C) := \frac{P(E \cap C)}{P(C)}$$

Say: probability of “ $E$  given  $C$ ”, “ $E$  conditioned on  $C$ ”



“it's the ratio”

Q: Conditional probability  $P(A|B)$  could be undefined. When?

- A: The denominator can be 0 already. In this case, numerator is also 0!

Note  $P(A|B) \neq P(B|A)$  in general!

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

E.g., throw a fair die.  $X$  := outcome.  $A = \{X=4\}$ ,  $B = \{X \text{ is even}\}$

**Question:**  $P(A | B) = P(B | A)$  ?

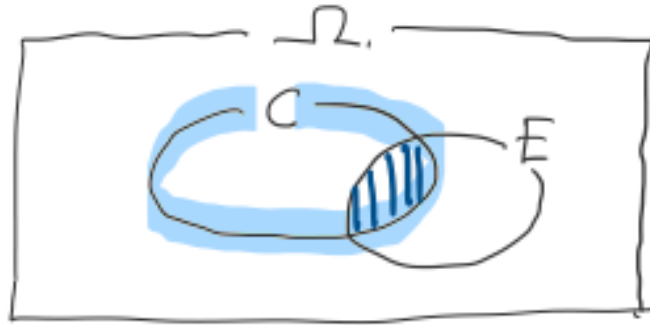
- $P(A) = 1/6$
- $P(B) = 1/2$
- $P(A \cap B) = 1/6$
- Therefore,  $P(A|B) = 1/3$ ,  $P(B|A) = 1$



## Chain rule

- $P(A \cap B) = P(A|B)P(B)$  ←just a rearrangement of definition:  $P(A|B) := \frac{P(A \cap B)}{P(B)}$
- $P(A \cap B \cap C) = P(A|B \cap C)P(B \cap C) = P(A|B \cap C)P(B|C)P(C)$
- $P(E_1 \cap E_2 \cap \dots \cap E_n) = P(E_1) \prod_{i=2}^n P(E_i | \cap_{j=1}^{i-1} E_j)$  valid for any ordering!

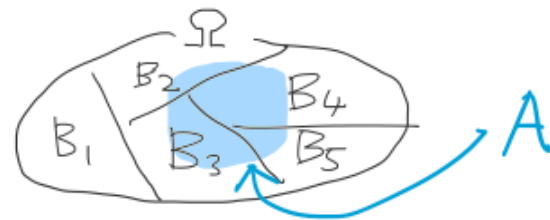
- $P(E \cap C) = P(E|C)P(C) = P(C|E)P(E)$



“it’s the ratio”

Recall: let  $A$  be an event. For events  $B_1, B_2, \dots$  that partitions  $\Omega$ , we have

$$P(A) = \sum_i P(A \cap B_i)$$



**Law of total probability:** If  $A \in \mathcal{F}$  and  $\{B_i \in \mathcal{F}\}_i$  partitions  $\Omega$ , then

$$P(A) = \sum_i P(A, B_i) = \sum_i P(B_i)P(A|B_i)$$

Shortcut:

$P(A, B) := P(A \cap B)$

$$= \sum_i P(A)P(B_i|A)$$

(by definition)

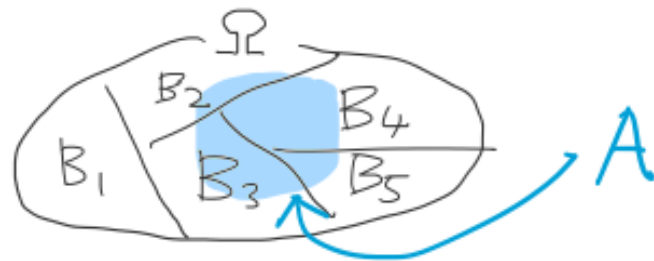
# Conditional Probability

**Law of total probability:** If  $A \in \mathcal{F}$  and  $\{B_i \in \mathcal{F}\}_i$  partitions  $\Omega$ , then

$$\begin{aligned} P(A) &= \sum_i P(A, B_i) = \sum_i P(B_i)P(A|B_i) \\ &= \sum_i P(A)P(B_i|A) \quad (\text{by definition}) \end{aligned}$$

If we divide both sides by  $P(A)$ :

$$1 = \sum_i P(B_i|A)$$



# Conditional Probability: an example

$$P(A) = \sum_i P(A \cap B_i)$$

A: customer (100)

B: fill gas

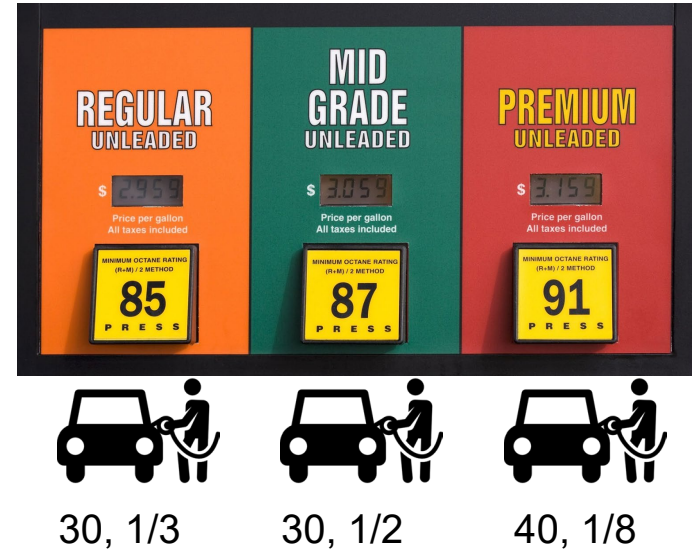
- $B_1$ : unleaded (30)
- $B_2$ : mid grade (30)
- $B_3$ : premium (40)

Q: what's the probability that the customer is a student?

$P(A = \text{student})$

$= P(A = \text{student}, B = B_1) + P(A = \text{student}, B = B_2) + P(A = \text{student}, B = B_3)$

$= P(A = \text{student} | B = B_1)P(B = B_1) + P(A = \text{student} | B = B_2)P(B = B_2) + P(A = \text{student} | B = B_3)P(B = B_3)$



# Conditional Probability: an example

- $P(A) = \sum_i P(A, B_i) = \sum_i P(B_i)P(A|B_i)$

$P(A = \text{student})$

$$= P(A = \text{student}|B = B_1)P(B = B_1) + P(A = \text{student}|B = B_2)P(B = B_2) + P(A = \text{student}|B = B_3)P(B = B_3)$$

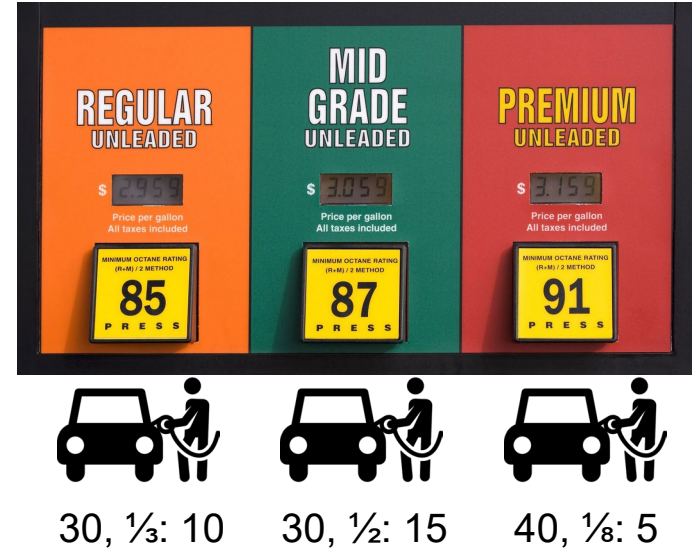
$P(A = \text{student})$

$$= 1/3 \times 30/100 + 1/2 \times 30/100 + 1/8 \times 40/100$$

- $\sum_i P(B_i|A) = 1$

$P(B_1|A = \text{student}) + P(B_2|A = \text{student}) + P(B_3|A = \text{student})$

$$= \frac{10}{10+15+5} + \frac{15}{10+15+5} + \frac{5}{10+15+5} = 1$$



The Public Health Department gives us the following information:

- A test for the disease yields a positive result (+) 90% of the time when the disease is present (Y)  $P(+ | Y) = 0.9$
  - A test for the disease yields a positive result 1% of the time when the disease is not present (N)  $P(+ | N) = 0.01$
  - One person in 1,000 has the disease.  $P(Y) = 0.001$
- $P(Y | +)?$

**Q:** What is the probability that a person with positive test has the disease?

Pick a person **uniformly at random** from the population. Apply the test. When test=+, what is the probability of this person having the disease (Y) ?

# Conditional Probability

What we know:

$$P(+ | Y) = 0.9$$

$$P(+ | N) = 0.01$$

$$P(Y) = 0.001$$

⇒

$$P(- | Y) = 0.1$$

$$P(- | N) = 0.99$$

$$P(N) = 0.999$$

Question:  $P(Y | +) = \frac{P(Y, +)}{P(+)}$

$$P(+ ) = P(+, Y) + P(+, N)$$

$$P(+, Y) = P(+ | Y)P(Y)$$

$$P(+, N) = P(+ | N)P(N)$$

Law of total probability

$$P(A) = \sum_i P(A, B_i) = \sum_i P(B_i)P(A|B_i)$$

The answer is 0.0826...



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  $P(A^c)$

Tip: Make a table of **joint probabilities**

$$P(+ | Y) = 0.9$$

$$P(+ | N) = 0.01$$

$$P(Y) = 0.001$$

Each cell is  $P(\text{column event} \cap \text{row event}) = P(T=t \cap D=d) = P(T=t | D=d) P(D=d)$

	Test = +	Test = -	
Disease=Y	$0.9 \cdot 0.001 = 0.0009$	$0.1 \cdot 0.001 = 0.0001$	0.001
Disease=N	$0.01 \cdot 0.999 = 0.00999$	$0.99 \cdot 0.999 = 0.98901$	0.999
	0.01089	0.98911	

Workflow:

- make a table, then fill in the cells.
- write down the target  $P(A|B)$  all in terms of joint probabilities and marginal probabilities.

$P(\text{test} = +)$

We can directly calculate:

$$P(Y|+) = \frac{P(Y,+)}{P(+)} = \frac{P(+|Y)P(Y)}{P(+)}$$

## Bayes rule

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

proof: definition and definition!

⇒ particularly useful in practice: infer  $P(A|B)$  given  $P(B|A)$ !

$P(A)$ : **prior** probability

e.g.,  $A$ ='dice sum to 6',  $B$ ='one of the die is 2'

$P(A|B)$ : **posterior** probability

e.g.,  $A$ ='disease=Y',  $B$ ='test=+'

# 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:

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

# Bayes rule

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

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

Posterior probability

Prior probability    Support of evidence

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