

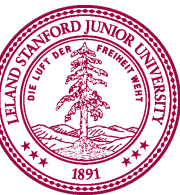


# Conditional Probability and Bayes

# Announcements

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- Pset #1 is due on Friday
- Office hours, wahoo!
- First sections this week!
- Section assignments will be sent out today.
- Auditing? Cool, but just lectures and online resources.
- <https://cs109psets.netlify.app/win22/lecture4/>

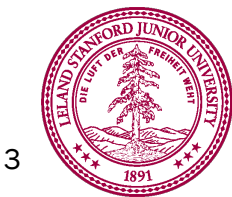


# Follow Along with Lecture

The screenshot shows a web browser window with the following elements:

- Browser Tab:** PSet 1
- Address Bar:** cs109psets.netlify.app/win22/lecture4/poop
- Navigation:** Home, Back, Forward, Refresh, and search icons.
- Bookmarks:** gmail, drive, Pixlr, Send Email, Interviews, Other Bookmarks, Reading List.
- Question Panel (Left):**
  - PS1 1. Baby Poop**
  - Home icon
  - Question 1 (selected), Question 2, Question 3
  - Navigation icons: Home, Profile, Next
  - Buttons: Previous Question, Next Question
- Answer Editor (Right):**
  - Answer Editor** (pencil icon)
  - Numeric Answer:** 0.25
  - Check Answer** (button)
  - Explanation:**
  - Rich text editor toolbar: Block LaTeX, Image, Bold (B), Code (</>), Italic (I), Underline (U)
  - Text input area containing:
    - Let  $E$  be the event that the baby pooped ( $E$  for excrement!)
    - Let  $T$  be the event that the baby has cried ( $T$  for tears!)

<https://cs109psets.netlify.app/win22/lecture4/>

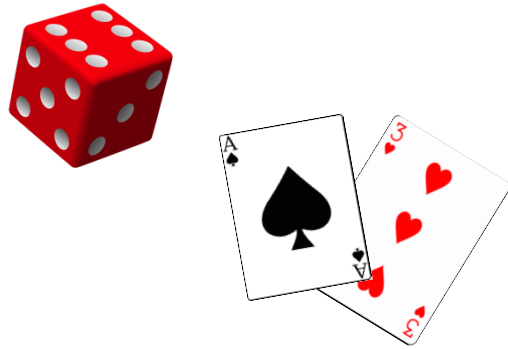


Review

# This class going forward

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Last week  
Equally likely  
events



Today and for most of this course  
**Not equally likely events**

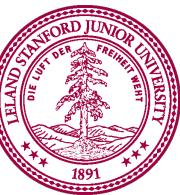


# Review, Axioms of Probability

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Recall:  $S$  = all possible outcomes.  $E$  = the event.

- Axiom 1:  $0 \leq P(E) \leq 1$
- Axiom 2:  $P(S) = 1$
- Identity 3:  $P(E^c) = 1 - P(E)$



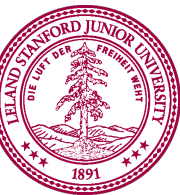
# Review, Axioms of Probability

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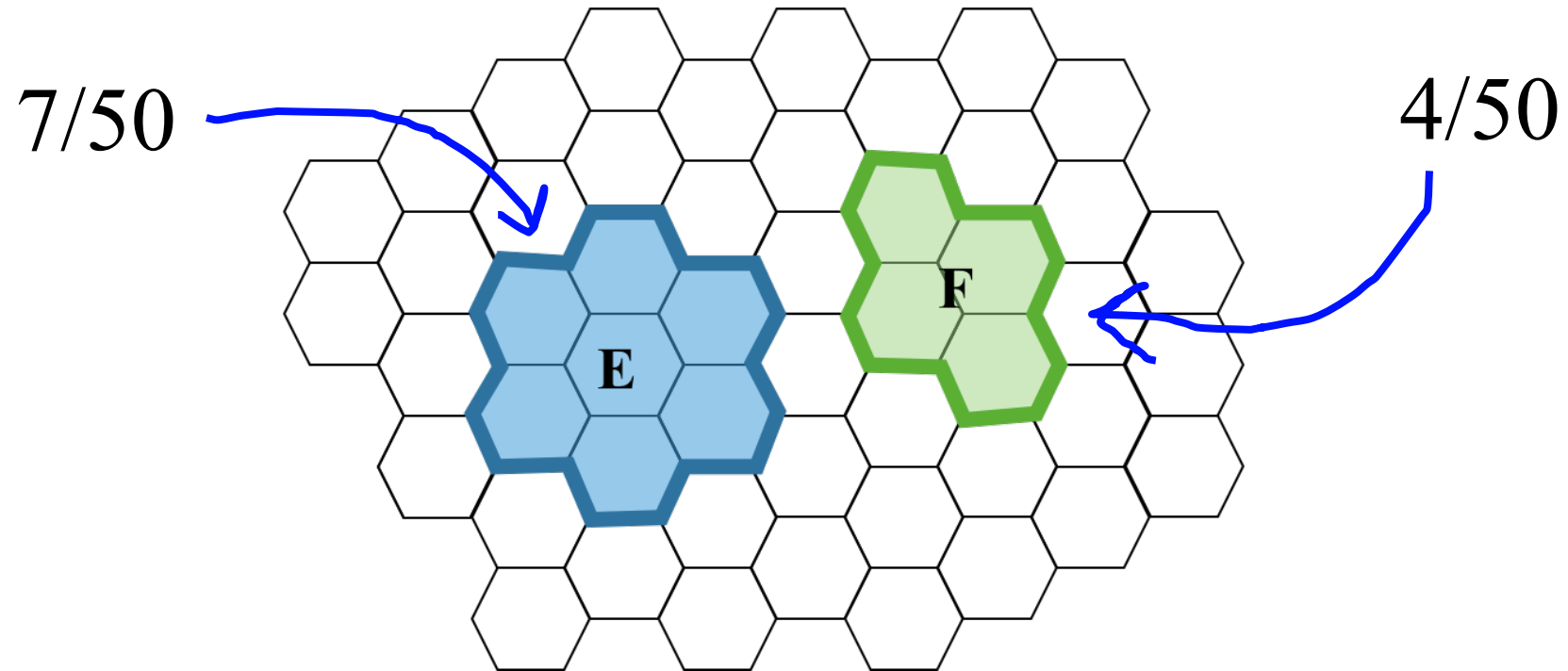
Recall:  $S$  = all possible outcomes.  $E$  = the event.

- Axiom 1:  $0 \leq P(E) \leq 1$
- Axiom 2:  $P(S) = 1$
- Axiom 3: If events  $E$  and  $F$  are mutually exclusive:

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

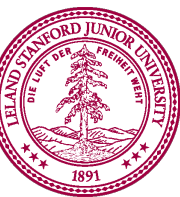


# Review, Mutually Exclusive Events

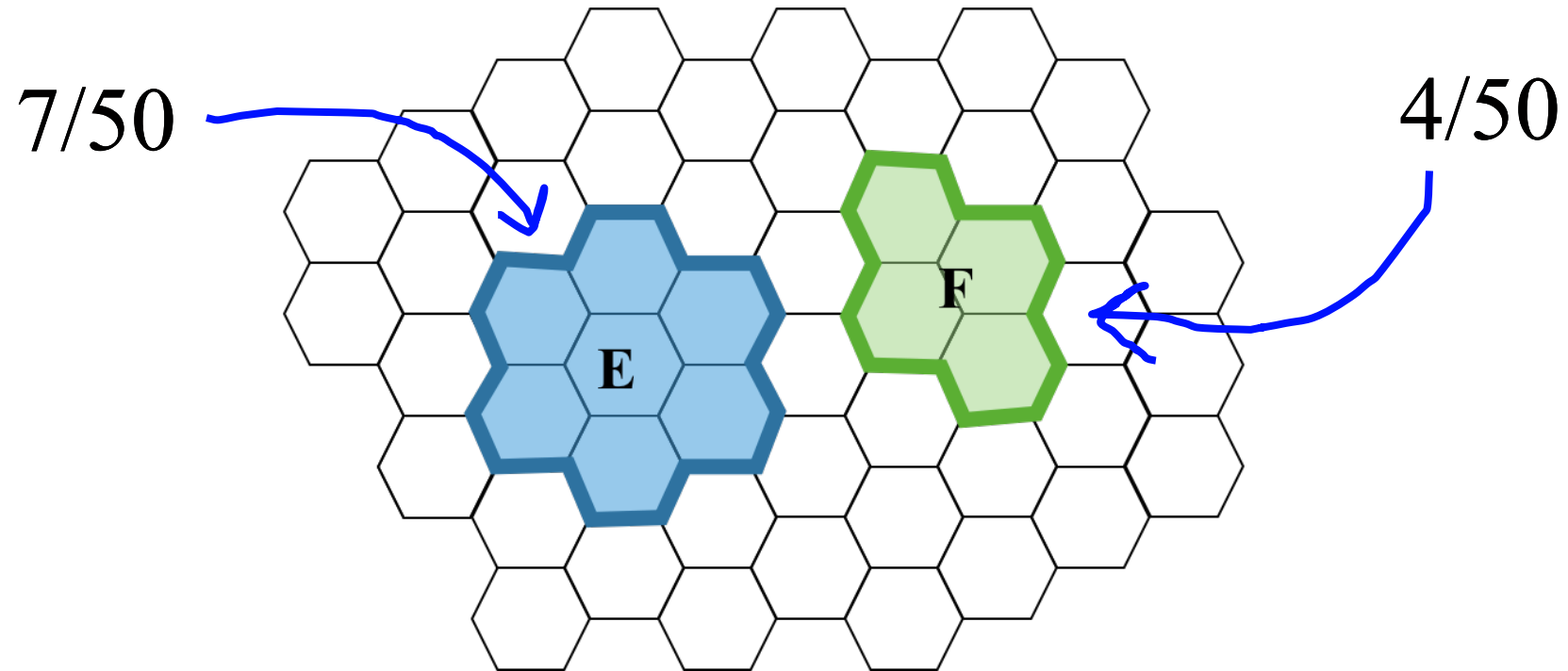


If events are mutually exclusive, probability of OR is simple:

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

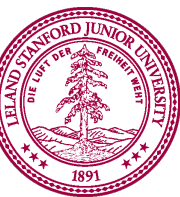


# Review, Mutually Exclusive Events

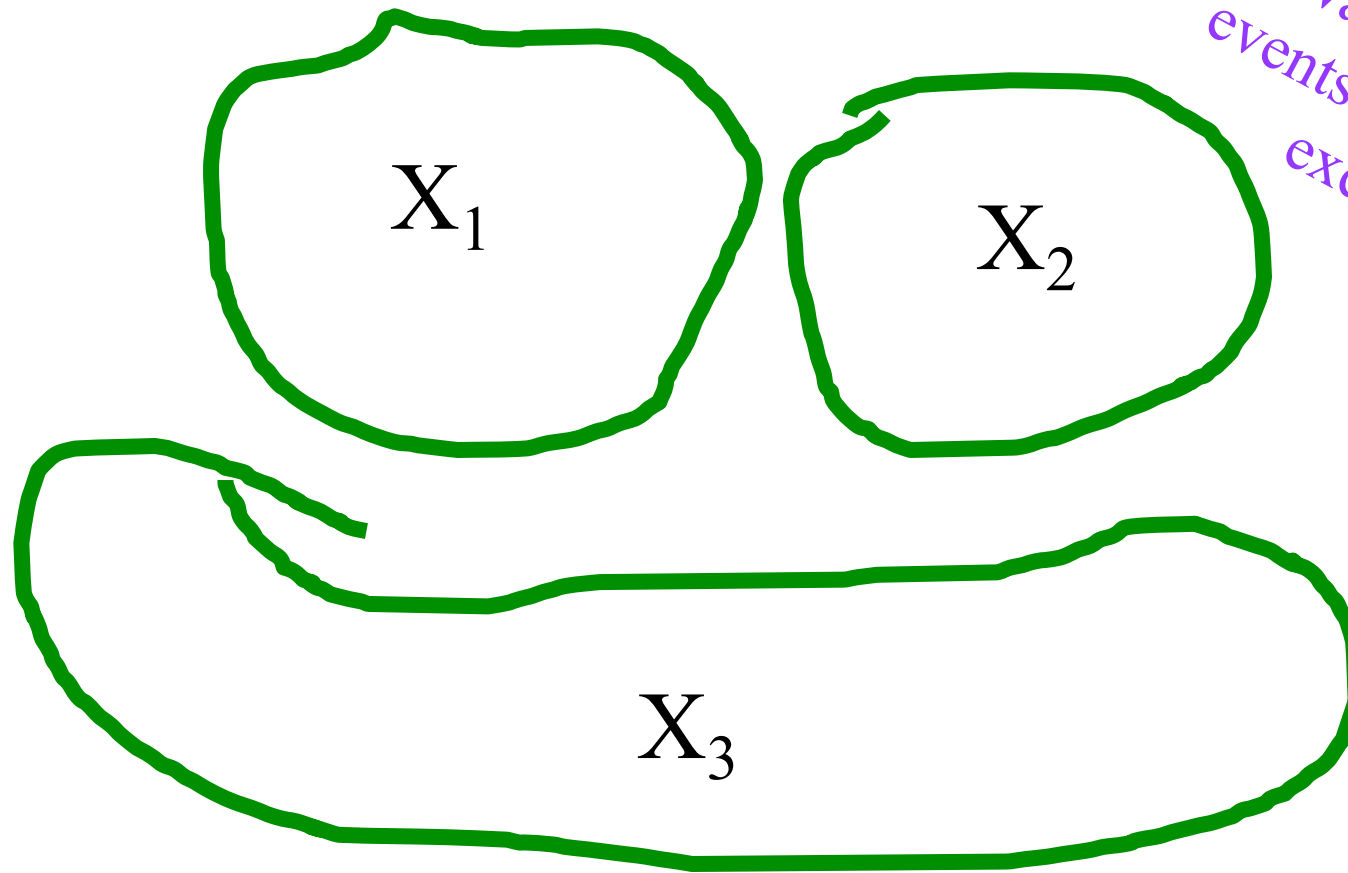


If events are mutually exclusive, probability of OR is simple:

$$P(E \cup F) = \frac{7}{50} + \frac{4}{50} = \frac{11}{50}$$

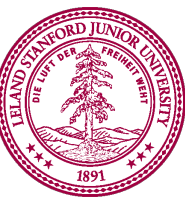


# Review, Mutually Exclusive Events



Wahoo! All my events are mutually exclusive

$$P(X_1 \cup X_2 \cup \cdots \cup X_n) = \sum_{i=1}^n P(X_i)$$

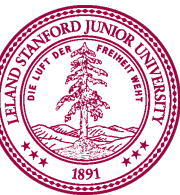


# Review, Mutually Exclusive Events

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If events are *mutually exclusive* probability of OR is easy!



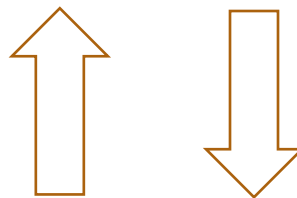
End Review

# Learning Goal for Today: Conditional Probability



$$P(E \text{ and } F)$$

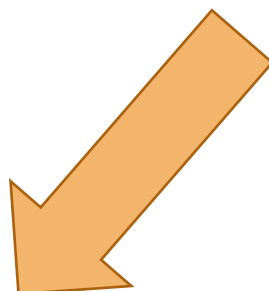
Chain rule  
(Product rule)



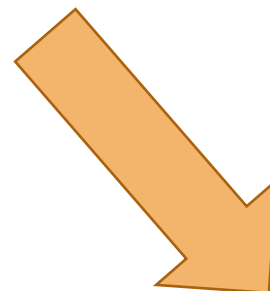
Definition of  
conditional probability

$$P(E|F)$$

Law of Total  
Probability



Bayes'  
Theorem



$$P(E)$$

$$P(F|E)$$

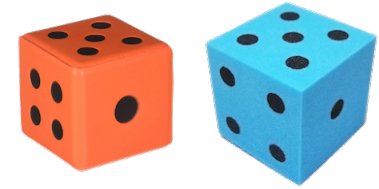


# Conditional Probability

# Roll two dice

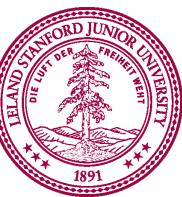
$$P(E) = \frac{|E|}{|S|} \text{ Equally likely outcomes}$$

Roll two 6-sided fair dice. What is  $P(\text{sum} = 7)$ ?



$S = \{(1,1) (1,2) (1,3) (1,4) (1,5) \mathbf{(1,6)}$   
 $(2,1) (2,2) (2,3) (2,4) \mathbf{(2,5)} (2,6)$   
 $(3,1) (3,2) (3,3) \mathbf{(3,4)} (3,5) (3,6)$   
 $(4,1) (4,2) \mathbf{(4,3)} (4,4) (4,5) (4,6)$   
 $(5,1) \mathbf{(5,2)} (5,3) (5,4) (5,5) (5,6)$   
 $\mathbf{(6,1)} (6,2) (6,3) (6,4) (6,5) (6,6) \}$

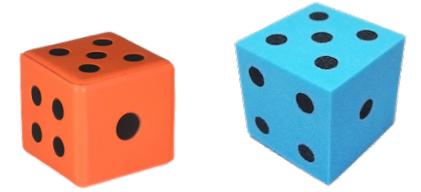
$E =$  *In blue*



# Dice, our misunderstood friends

---

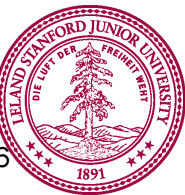
Roll two 6-sided dice, yielding values  $D_1$  and  $D_2$ .  
You want them to sum to 4.



What is the best outcome for  $P(D_1)$ ?

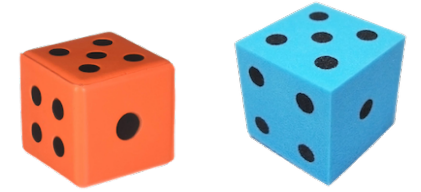
Your Choices:

- A. 1 and 3 tie for best
- B. 1, 2 and 3 tie for best
- C. 2 is the best
- D. Other/none/more than one



# Dice, our misunderstood friends

Roll two 6-sided dice, yielding values  $D_1$  and  $D_2$ .



Let  $E$  be event:  $D_1 + D_2 = 4$ .

Let  $F$  be event:  $D_1 = 2$ .

What is  $P(E)$ ?

What is  $P(E, \text{ given } F \text{ already observed})$ ?

$$|S| = 36$$

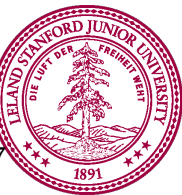
$$E = \{(1,3), (2,2), (3,1)\}$$

$$P(E) = 3/36 = 1/12$$

$$S = \{(2,1), (2,2), (2,3), (2,4), (2,5), (2,6)\}$$

$$E = \{(2,2)\}$$

$$P(E) = 1/6$$



# Conditional Probability

---

The **conditional probability** of  $E$  given  $F$  is the probability that  $E$  occurs given that  $F$  has already occurred. This is known as conditioning on  $F$ .

Written as:

$$P(E|F)$$

Means:

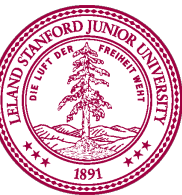
“ $P(E, \text{ given } F \text{ already observed})$ ”

Sample space  $\rightarrow$

all possible outcomes consistent with  $F$  (i.e.  $S \cap F$ )

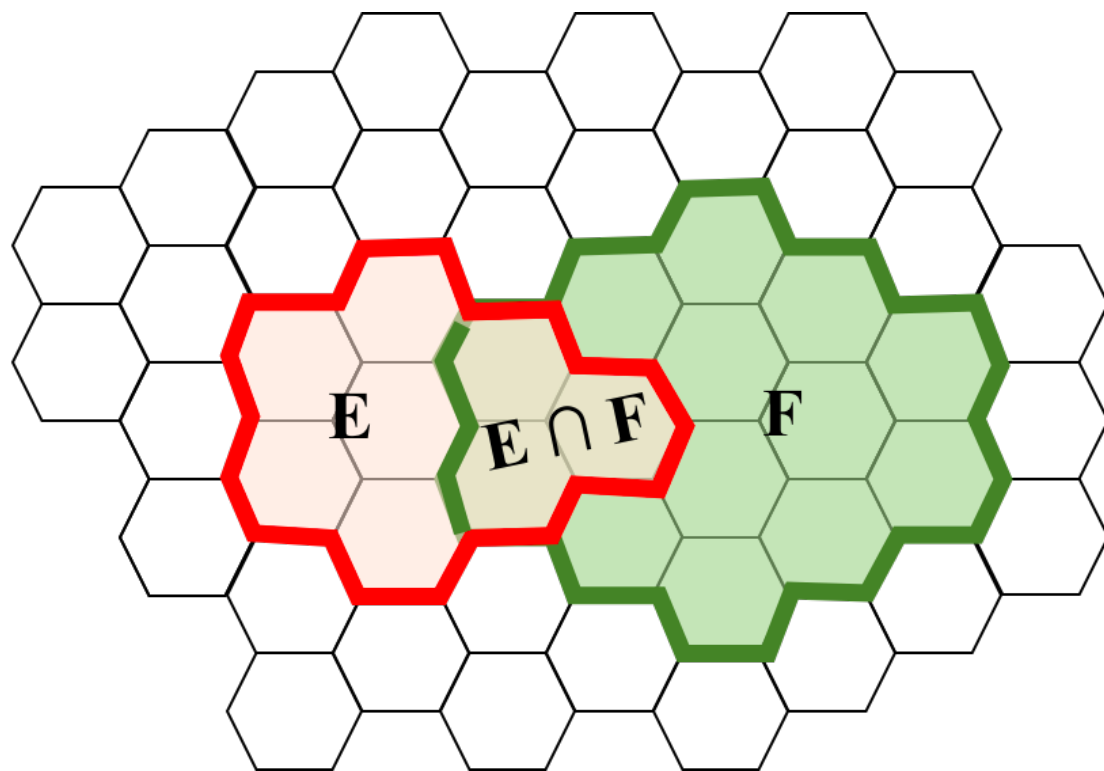
Event  $\rightarrow$

all outcomes in  $E$  consistent with  $F$  (i.e.  $E \cap F$ )



# Conditional Probability, visual intuition

The **conditional probability** of  $E$  given  $F$  is the probability that  $E$  occurs given that  $F$  has already occurred. This is known as conditioning on  $F$ .



$$P(E) = \frac{8}{50} \approx 0.16$$

$$P(E|F) = \frac{3}{14} \approx 0.21$$



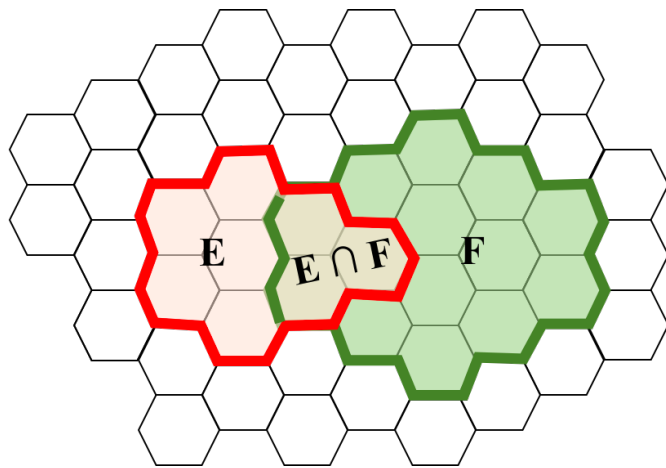
# Conditional Probability, equally likely outcomes

The **conditional probability** of  $E$  given  $F$  is the probability that  $E$  occurs given that  $F$  has already occurred. This is known as conditioning on  $F$ .

With **equally likely outcomes**:

Shorthand notation for set intersection (aka set “and”)

$$\Pr(E|F) = \frac{\# \text{ of outcomes in } E \text{ consistent with } F}{\# \text{ of outcomes in } S \text{ consistent with } F} = \frac{|EF|}{|SF|} = \frac{|EF|}{|F|}$$



$$P(E) = \frac{8}{50} \approx 0.16$$

$$P(E|F) = \frac{3}{14} \approx 0.21$$

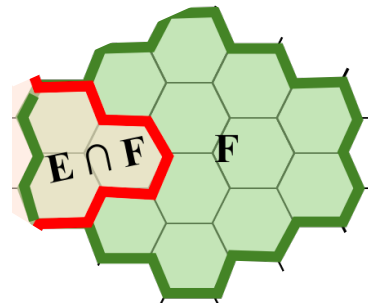
# Conditional Probability, equally likely outcomes

The **conditional probability** of  $E$  given  $F$  is the probability that  $E$  occurs given that  $F$  has already occurred. This is known as conditioning on  $F$ .

With **equally likely outcomes**:

Shorthand notation for set intersection (aka set “and”)

$$\Pr(E|F) = \frac{\# \text{ of outcomes in } E \text{ consistent with } F}{\# \text{ of outcomes in } S \text{ consistent with } F} = \frac{|EF|}{|SF|} = \frac{|EF|}{|F|}$$



$$P(E) = \frac{8}{50} \approx 0.16$$

$$P(E|F) = \frac{3}{14} \approx 0.21$$

# Conditional probability in general

These properties hold even when outcomes are not equally likely.

General **definition** of conditional probability:

$$P(E|F) = \frac{P(EF)}{P(F)}$$

The **Chain Rule** (aka Product rule):

$$P(EF) = P(F)P(E|F)$$

What if  $P(F) = 0$ ?

- $P(E|F)$  undefined
- *Congratulations! Observed impossible*



# Notation

**And**

**Or**

**Given**

$$P(E \text{ and } F)$$

$$P(E \text{ or } F)$$

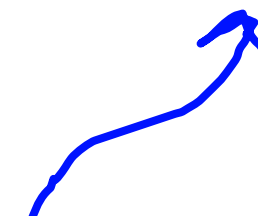
$$P(E|F)$$

$$P(E, F)$$

$$P(E \cup F)$$

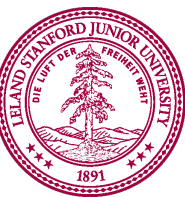
$$P(E|F, G)$$

$$P(EF)$$



$$P(E \cap F)$$

Probability of E given  
F and G



# Baby Poop

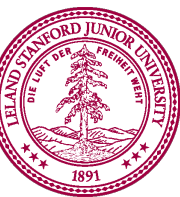
$$P(E|F) = \frac{P(EF)}{P(F)}$$

$$P(EF) = P(F)P(E|F)$$

In the morning when she wakes up, a baby has a 50% chance of having pooped. The chance that a baby cries given that she has pooped is 50%. What is the probability that a baby has pooped, and cries.



<https://cs109psets.netlify.app/win22/lecture4/poop>

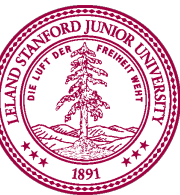


# Generalized Chain Rule

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$$\Pr(E_1 \text{ and } E_2 \text{ and } E_3 \text{ and } \dots E_n)$$

$$= \Pr(E_1) \cdot \Pr(E_2|E_1) \cdot \Pr(E_3|E_1, E_2) \cdots \Pr(E_n|E_1, E_2 \dots E_{n-1})$$



**NETFLIX**

and Learn

# Netflix and Learn

$$P(E|F) = \frac{P(EF)}{P(F)}$$
 Definition of  
Cond. Probability

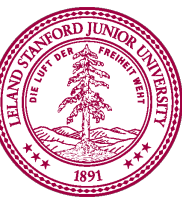
What is the probability  
that a user will watch  
Life is Beautiful?

$$P(E)$$

$$S = \{\text{Watch, Not Watch}\}$$

$$E = \{\text{Watch}\}$$

$$P(E) = 1/2 ?$$





# Netflix and Learn

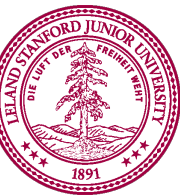
What is the probability  
that a user will watch  
Life is Beautiful?

$$P(E)$$



$$P(E) = \lim_{n \rightarrow \infty} \frac{n(E)}{n} \approx \frac{\# \text{people who watched movie}}{\# \text{people on Netflix}}$$

$$P(E) = 10,234,231 / 50,923,123 = 0.20$$



# Netflix and Learn

$$P(E|F) = \frac{P(EF)}{P(F)}$$
 Definition of  
Cond. Probability

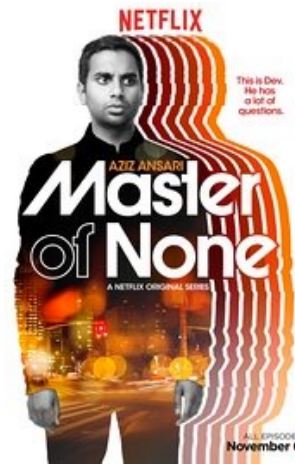
Let  $E$  be the event that a user watches the given movie.



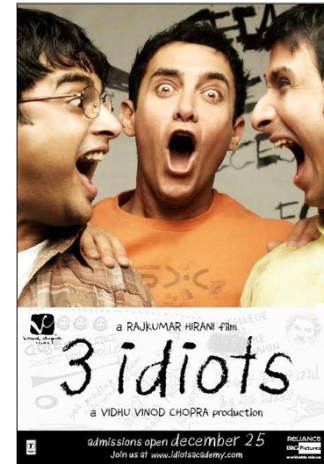
$$P(E) = 0.19$$



$$P(E) = 0.32$$



$$P(E) = 0.20$$



$$P(E) = 0.09$$



$$P(E) = 0.20$$

# Netflix and Learn

$$P(E|F) = \frac{P(EF)}{P(F)} \quad \text{Definition of Cond. Probability}$$

Let  $E$  = a user watches Life is Beautiful.

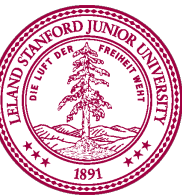
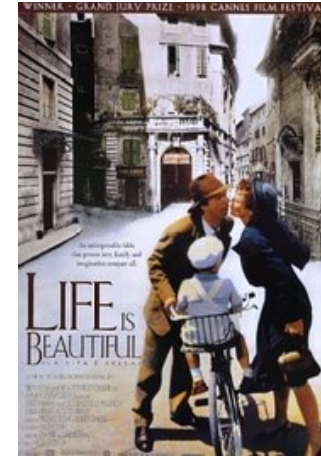
Let  $F$  = a user watches CODA.

What is the probability that a user watches Life is Beautiful, given they watched Amelie?

$$P(E|F)$$

$$\begin{aligned} P(E|F) &= \frac{P(EF)}{P(F)} = \frac{\frac{\# \text{ people who have watched both}}{\# \text{ people on Netflix}}}{\frac{\# \text{ people who have watched Amelie}}{\# \text{ people on Netflix}}} \\ &= \frac{\# \text{ people who have watched both}}{\# \text{ people who have watched Amelie}} \end{aligned}$$

$$\approx 0.42$$



# Netflix and Learn

$$P(E|F) = \frac{P(EF)}{P(F)}$$
 Definition of Cond. Probability

Let  $E$  be the event that a user watches the given movie.  
Let  $F$  be the event that the same user watches CODA (2021).



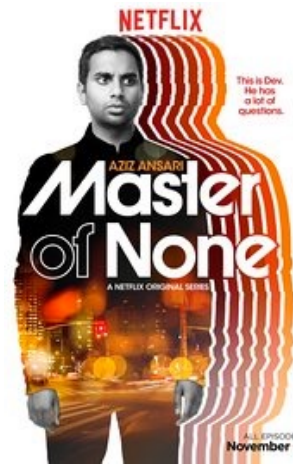
$$P(E) = 0.19$$

$$P(E|F) = 0.14$$



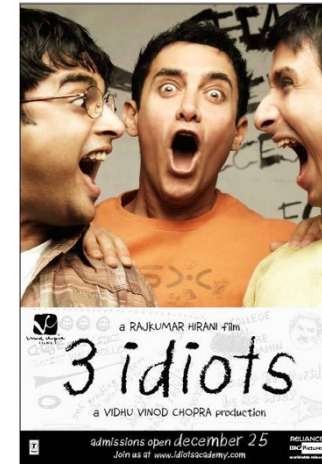
$$P(E) = 0.32$$

$$P(E|F) = 0.35$$



$$P(E) = 0.20$$

$$P(E|F) = 0.20$$



$$P(E) = 0.09$$

$$P(E|F) = 0.72$$



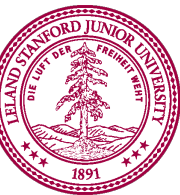
$$P(E) = 0.20$$

$$P(E|F) = 0.42$$

# Machine Learning

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Machine Learning is:  
Probability + Data + Computers



# Law of Total Probability

# Baby Poop Redux

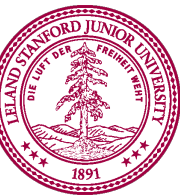
---

In the morning when she wakes up, a baby has a 50% chance of having pooped. The chance that a baby cries given that she has pooped is 50%. What is the probability that a baby **has pooped, and cries**.



Other interesting questions (coming soon):  
Probability of crying

What information do you need?

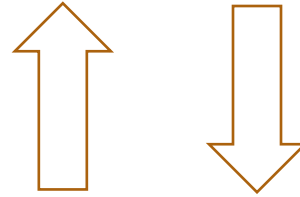


# Relationship Between Probabilities

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$$P(E \text{ and } F)$$

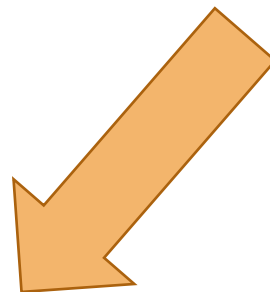
Chain rule  
(Product rule)



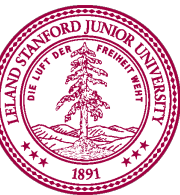
Definition of  
conditional probability

$$P(E|F)$$

Law of Total  
Probability

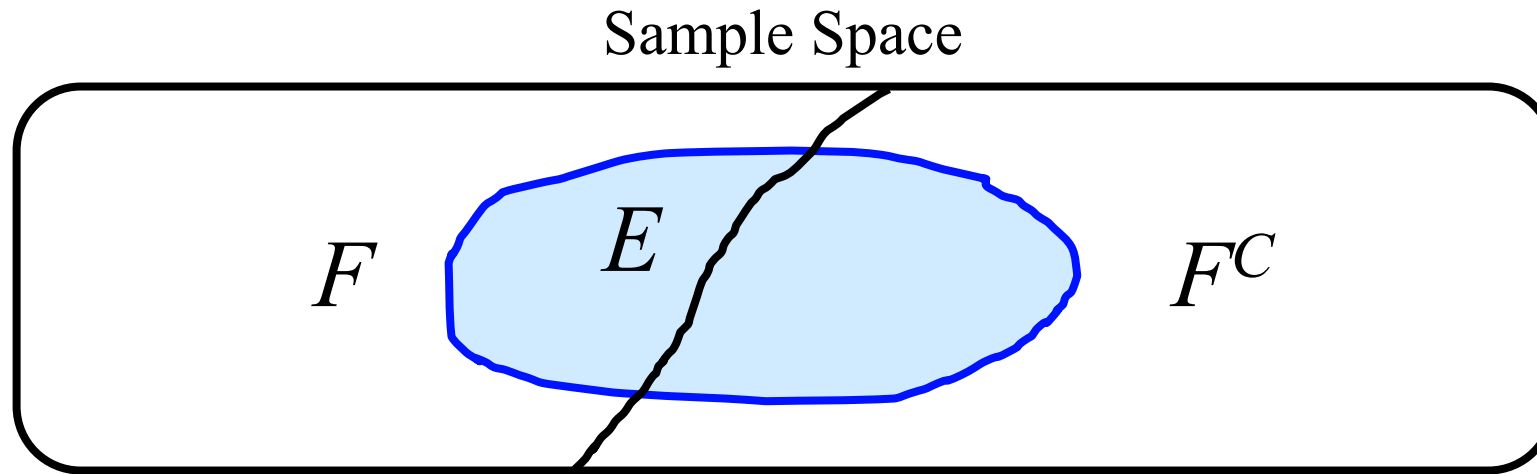


$$P(E)$$



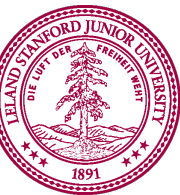
# Law of Total Probability

Say  $E$  and  $F$  are events in  $S$



$$E = EF \cup EF^C$$

$$P(E) = P(EF) + P(EF^C)?$$



# Law of Total Probability

---

Thm Let  $F$  be an event where  $P(F) > 0$ . For any event  $E$ ,

$$P(E) = P(E|F)P(F) + P(E|F^C)P(F^C)$$

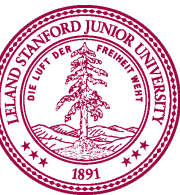
Proof

1.  $E = (EF) \text{ or } (EF^C)$

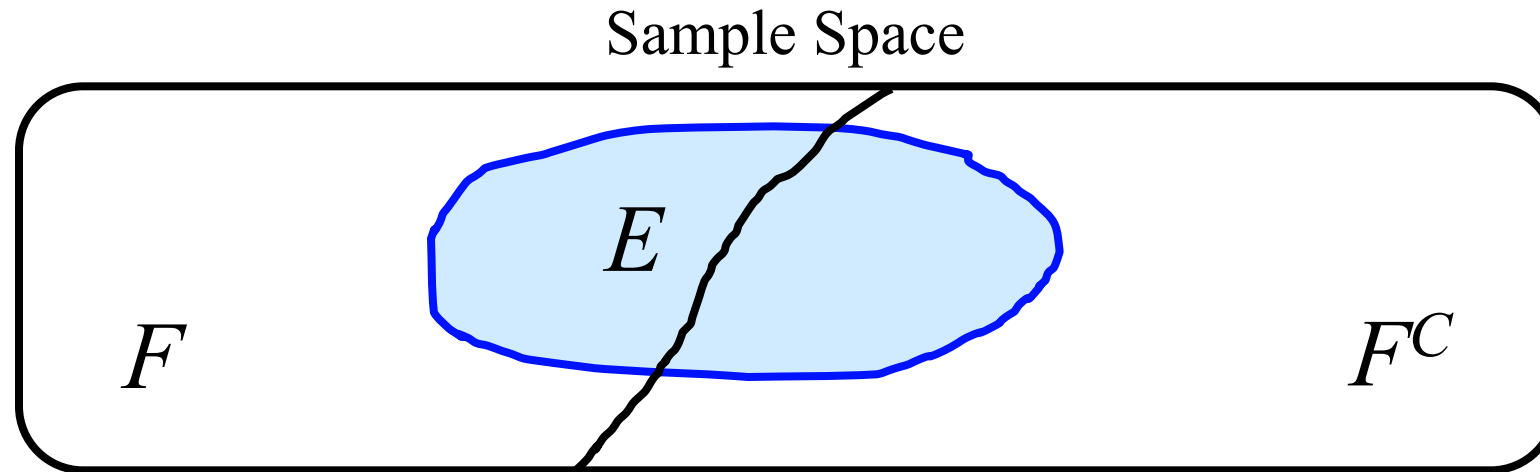
2.  $P(E) = P(EF) + P(EF^C)$

3.  $P(E) = P(E|F)P(F) + P(E|F^C)P(F^C)$

Since  $F$  and  $F^C$  are disjoint  
Probability of **or** for disjoint  
Chain rule (product rule)

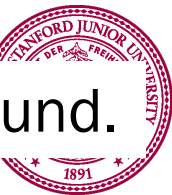


# Law of Total Probability

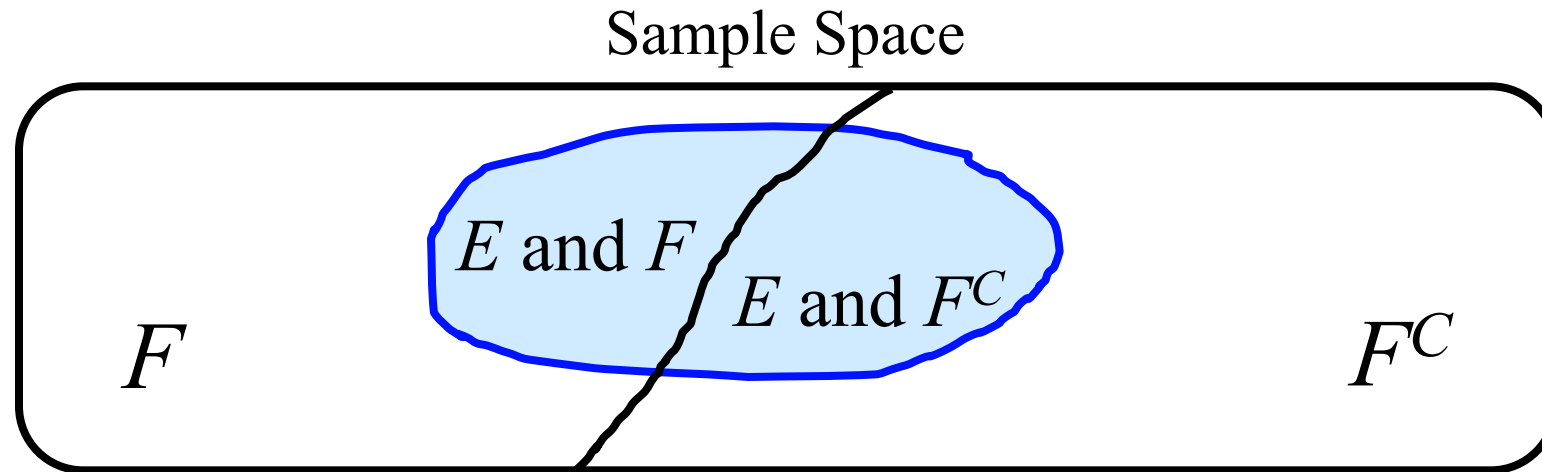


$$\begin{aligned}P(E) &= P(EF) + P(EF^C) \\ &= P(E|F)P(F) + P(E|F^C)P(F^C)\end{aligned}$$

Here  $F$  is like a “background event”. You know your event conditioned on the background.

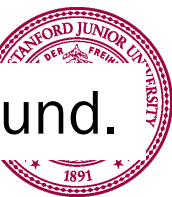


# Law of Total Probability



$$\begin{aligned} P(E) &= P(EF) + P(EF^C) \\ &= P(E|F)P(F) + P(E|F^C)P(F^C) \end{aligned}$$

Here  $F$  is like a “background event”. You know your event conditioned on the background.



# Baby Poop

In the morning when she wakes up, a baby has a 50% chance of having pooped. The chance that a baby cries given that she has pooped is 50%. What is the probability that a baby has pooped, and cries.



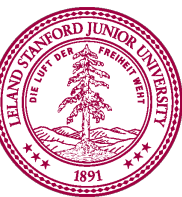
Other interesting questions (coming soon):  
Probability of crying (T)

What information do you need?

**Probability of crying given no poop.**

Recall that T is crying and E is poop

$$P(T) = P(T|E)P(E) + P(T|E^C)P(E^C)$$



# Evolution of Bacteria

$$P(E) = P(E|F)P(F) + P(E|F^C)P(F^C)$$

Law of Total Probability

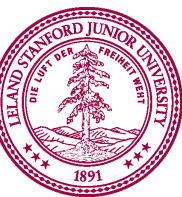


You have bacteria in your gut which is causing a disease.  
10% have a mutation which makes them resistant to anti-biotics  
You take half a course of anti-biotics...

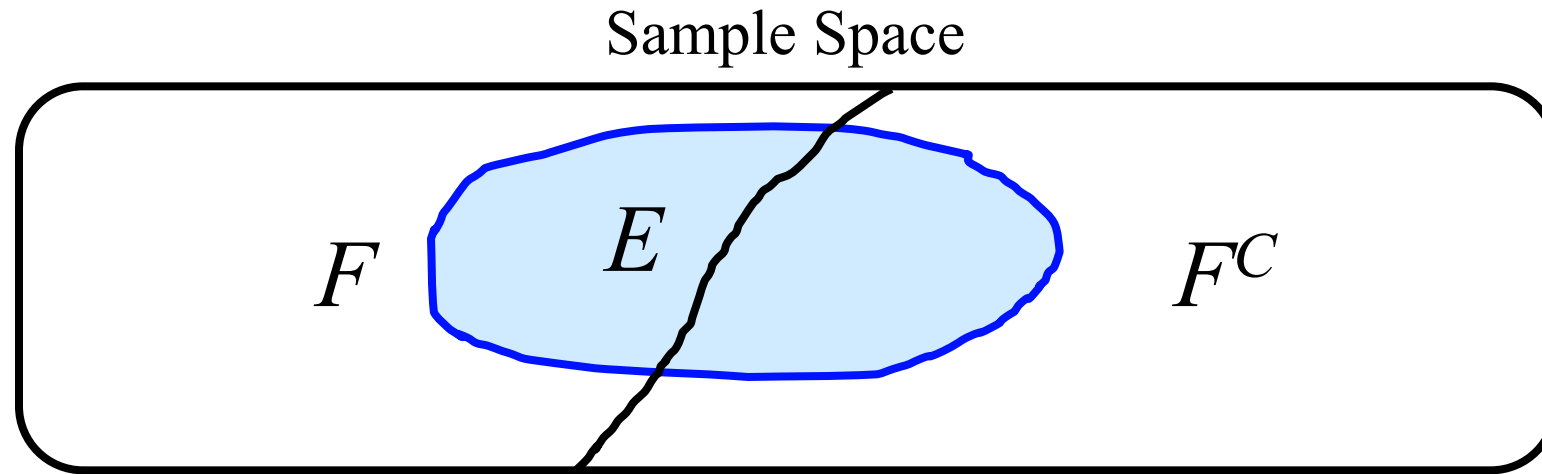
Probability a bacteria survives given it has the mutation: 20%  
Probability a bacteria survives given it doesn't have the mutation: 1%  
What is the probability that a randomly chosen bacteria survives?

Let  $E$  be the event that a bacterium survives. Let  $M$  be the event that a bacteria has the mutation. By the [Law of Total Probability](#) (LOTP):

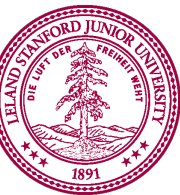
$$\begin{aligned}\Pr(E) &= \Pr(E \text{ and } M) + \Pr(E \text{ and } M^C) && \text{LOTP} \\ &= \Pr(E|M)\Pr(M) + \Pr(E|M^C)\Pr(M^C) && \text{Chain Rule} \\ &= 0.20 \cdot 0.10 + 0.01 \cdot 0.90 && \text{Substituting} \\ &= 0.029\end{aligned}$$



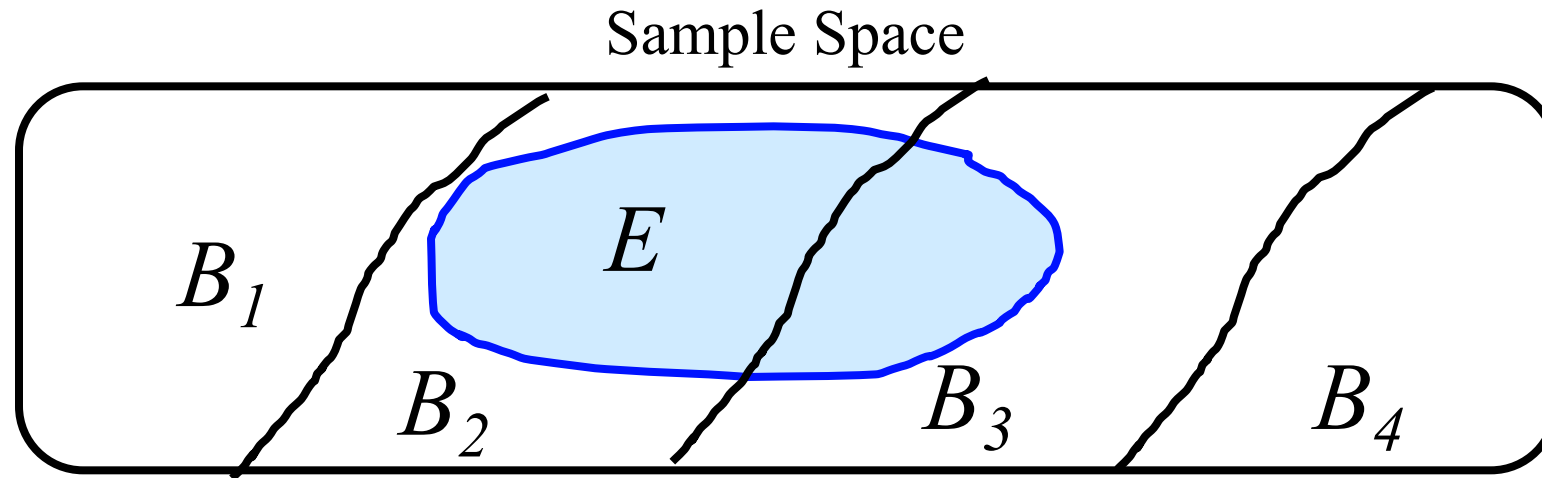
# Law of Total Probability



$$\begin{aligned} P(E) &= P(EF) + P(EF^C) \\ &= P(E|F)P(F) + P(E|F^C)P(F^C) \end{aligned}$$

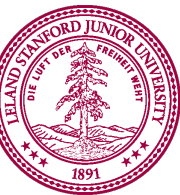


# Law of Total Probability



Thm For **mutually exclusive events**  $B_1, B_2, \dots, B_n$   
s.t.  $B_1 \cup B_2 \cup \dots \cup B_n = S$ ,

$$\begin{aligned} P(E) &= \sum_i P(B_i \cap E) \\ &= \sum_i P(E|B_i)P(B_i) \end{aligned}$$



Real question. What is the probability that a surviving bacteria has the mutation?

$\Pr ( \text{Mutation} \mid \text{Survives} )$

$\Pr ( M \mid E )$

# Real Question: $\Pr(M | E)$ ?



You have bacteria in your gut which is causing a disease.  
10% have a mutation which makes them resistant to anti-biotics  
You take half a course of anti-biotics...

Probability a bacteria survives given it has the mutation: 20%

Probability a bacteria survives given it doesn't have the mutation: 1%

What is the probability that a randomly chosen bacteria survives?

Let  $E$  be the event that our bacterium survives. Let  $M$  be the event that a bacteria has the mutation. By the [Law of Total Probability](#) (LOTP):

$$\begin{aligned}\Pr(E) &= \Pr(E \text{ and } M) + \Pr(E \text{ and } M^C) \\ &= \Pr(E|M)\Pr(M) + \Pr(E|M^C)\Pr(M^C) \\ &= 0.20 \cdot 0.10 + 0.01 \cdot 0.90 \\ &= 0.029\end{aligned}$$

LOTP

Chain Rule

Substituting



# Real Question: $\Pr(M | E)$ ?



You have bacteria in your gut which is causing a disease.  
10% have a mutation which makes them resistant to anti-biotics  
You take half a course of anti-biotics...

$$\Pr(E | M) = 0.20$$

$$\Pr(E | M^C) = 0.01$$

What is the probability that a randomly chosen bacteria survives?

Let  $E$  be the event that our bacterium survives. Let  $M$  be the event that a bacteria has the mutation. By the [Law of Total Probability](#) (LOTP):

$$\begin{aligned}\Pr(E) &= \Pr(E \text{ and } M) + \Pr(E \text{ and } M^C) \\ &= \Pr(E|M)\Pr(M) + \Pr(E|M^C)\Pr(M^C) \\ &= 0.20 \cdot 0.10 + 0.01 \cdot 0.90 \\ &= 0.029\end{aligned}$$

LOTP

Chain Rule

Substituting

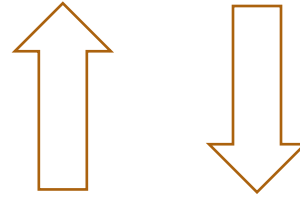


# Relationship Between Probabilities

---

$$P(E \text{ and } F)$$

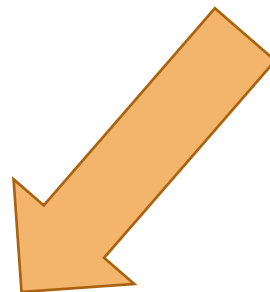
Chain rule  
(Product rule)



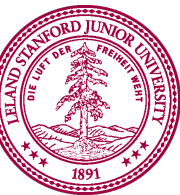
Definition of  
conditional probability

$$P(E|F)$$

Law of Total  
Probability



$$P(E)$$

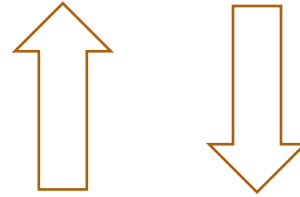


# Relationship Between Probabilities



$$P(E \text{ and } F)$$

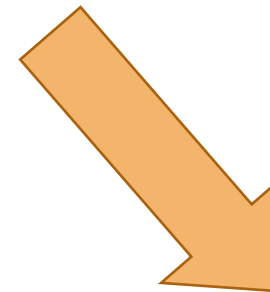
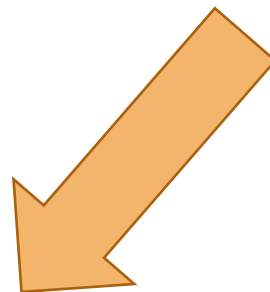
Chain rule  
(Product rule)



Definition of  
conditional probability

$$P(E|F)$$

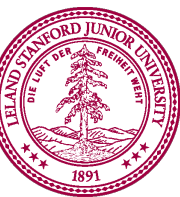
Law of Total  
Probability



Bayes'  
Theorem

$$P(E)$$

$$P(F|E)$$



# Bayes' Theorem

# Thomas Bayes

---

Rev. Thomas Bayes (~1701-1761):  
British mathematician and Presbyterian minister



He looked remarkably similar to Charlie Sheen  
(but that's not important right now)

# Thomas Bayes

$$P(F | E)$$



I want to calculate

$P(\text{State of the world } F | \text{Observation } E)$

It seems so tricky!...

The other way around is easy

$P(\text{Observation } E | \text{State of the world } F)$

What options to I have, chief?



$$P(E | F)$$



# Thomas Bayes

Want  $P(F | E)$ . Know  $P(E | F)$



$$P(F|E) = \frac{P(EF)}{P(E)} \quad \text{Def. of Conditional Prob.}$$

*A little while later...*

$$= \frac{P(E|F)P(F)}{P(E)} \quad \text{Chain Rule}$$

# Bayes' Theorem

$$P(E|F) \Rightarrow P(F|E)$$

Thm For any events  $E$  and  $F$  where  $P(E) > 0$  and  $P(F) > 0$ ,

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

Proof

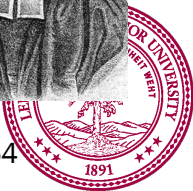
2 steps! See board

Expanded form:

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

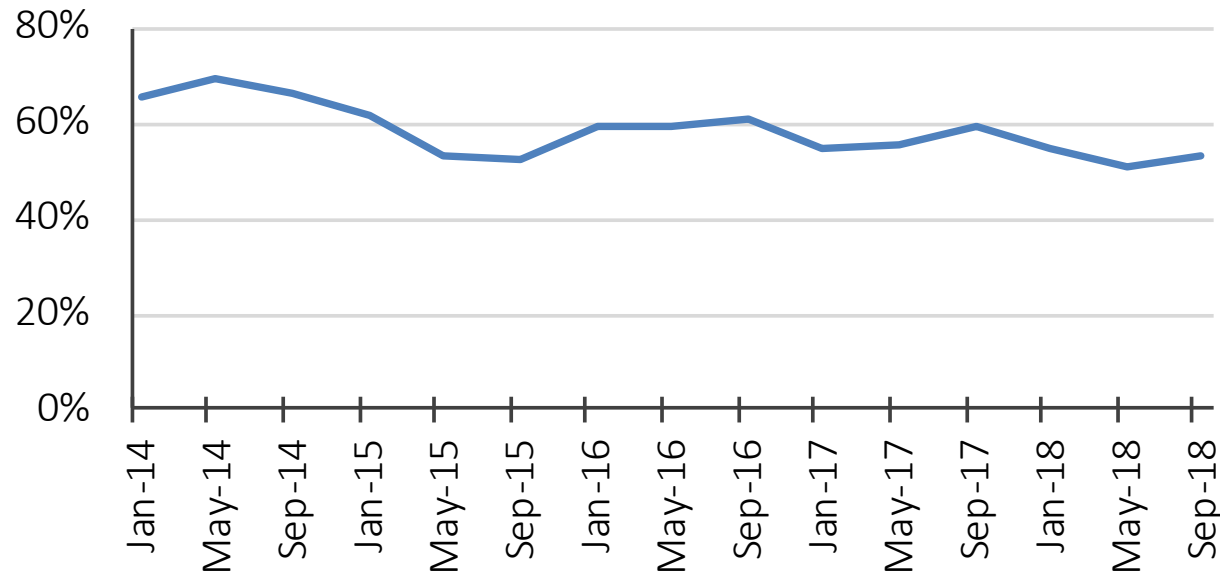
Proof

1 more step! See board



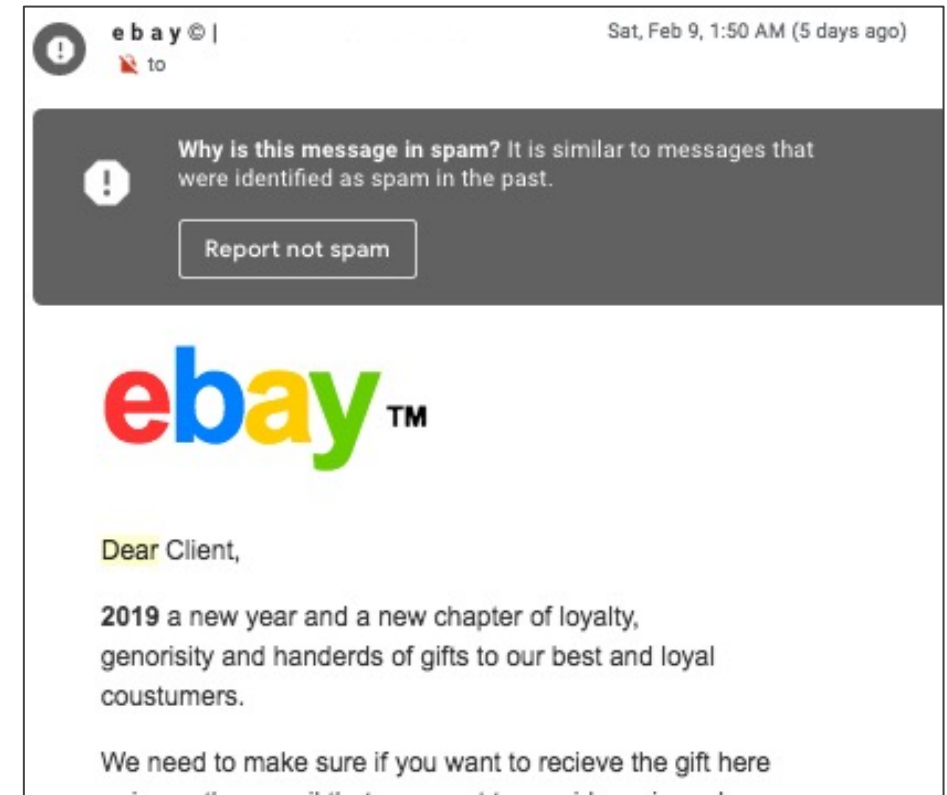
# Detecting spam email

Spam volume as percentage of total email traffic worldwide



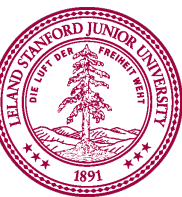
We can easily calculate how many spam emails contain “Dear”:

$$P(E|F) = P(\text{“Dear”} \mid \text{Spam email})$$



But what is the probability that an email containing “Dear” is spam?

$$P(F|E) = P(\text{Spam email} \mid \text{“Dear”})$$



(silent drumroll)

---



# Detecting spam email

$$P(F|E) = \frac{P(E|F)P(F)}{P(E|F)P(F) + P(E|F^C)P(F^C)} \quad \text{Bayes' Theorem}$$

- 60% of all email in 2016 is spam.
- 20% of spam has the word “Dear”
- 1% of non-spam (aka ham) has the word “Dear”

You get an email with the word “Dear” in it.

What is the probability that the email is spam?

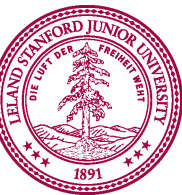
1. Define events  
& state goal

2. Identify known  
probabilities

3. Solve

Let:  $E$ : “Dear”,  $F$ : spam

Want:  $P(\text{spam} | \text{“Dear”})$   
 $= P(F|E)$



# Bayes' Theorem terminology

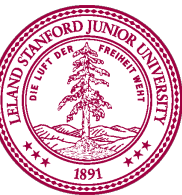
- 60% of all email in 2016 is spam.  $P(F)$
- 20% of spam has the word “Dear”  $P(E|F)$
- 1% of non-spam (aka ham) has the word “Dear”  $P(E|F^C)$

You get an email with the word “Dear” in it.

What is the probability that the email is spam? **Want:  $P(F|E)$**

$$\text{posterior } P(F|E) = \frac{\text{likelihood } P(E|F) \text{ prior } P(F)}{P(E)}$$

normalization constant



# SARS Virus Testing

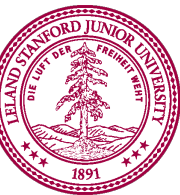
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A test is 98% effective at detecting SARS

- However, test has a “false positive” rate of 1%
- 0.5% of US population has SARS
- Let E = you test positive for SARS with this test
- Let F = you actually have SARS
- What is  $P(F | E)$ ?

Solution:

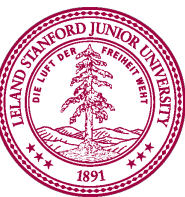
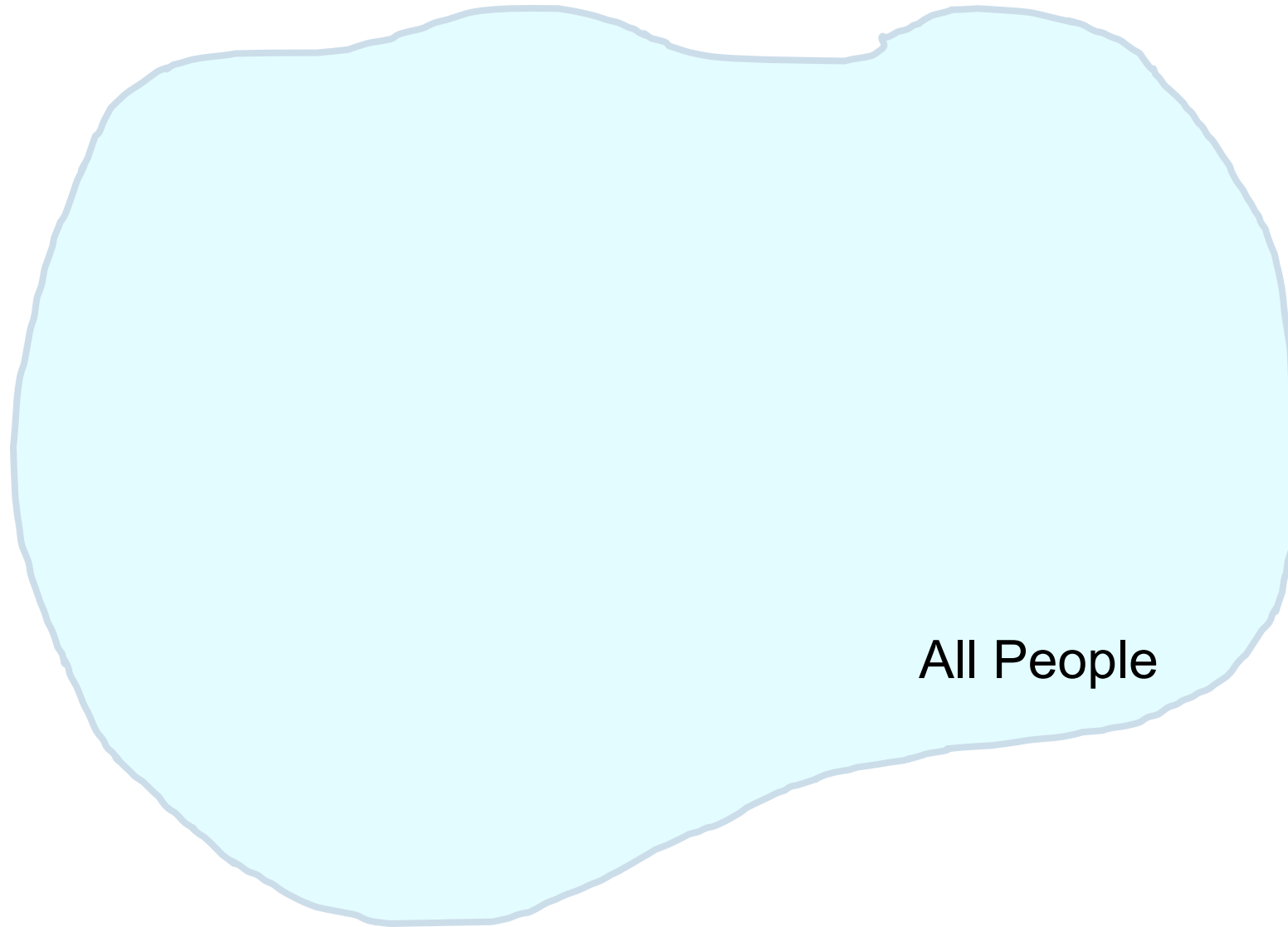
$$P(F | E) = \frac{P(E | F) P(F)}{P(E | F) P(F) + P(E | F^c) P(F^c)}$$
$$P(F | E) = \frac{(0.98)(0.005)}{(0.98)(0.005) + (0.01)(1 - 0.005)} \approx 0.330$$



Intuition Time

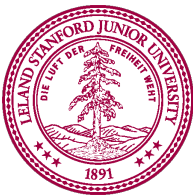
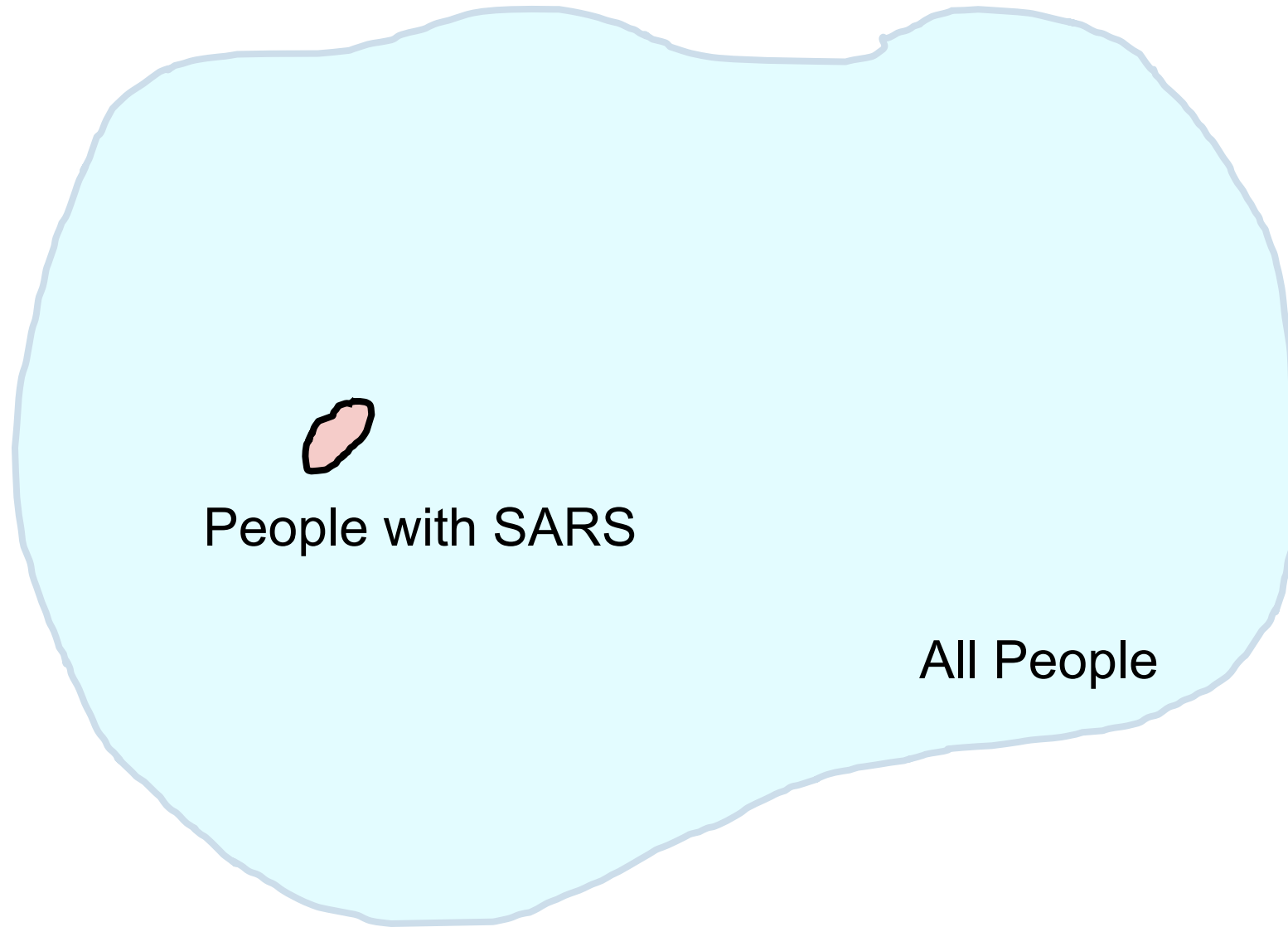
# Bayes Theorem Intuition

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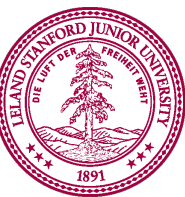
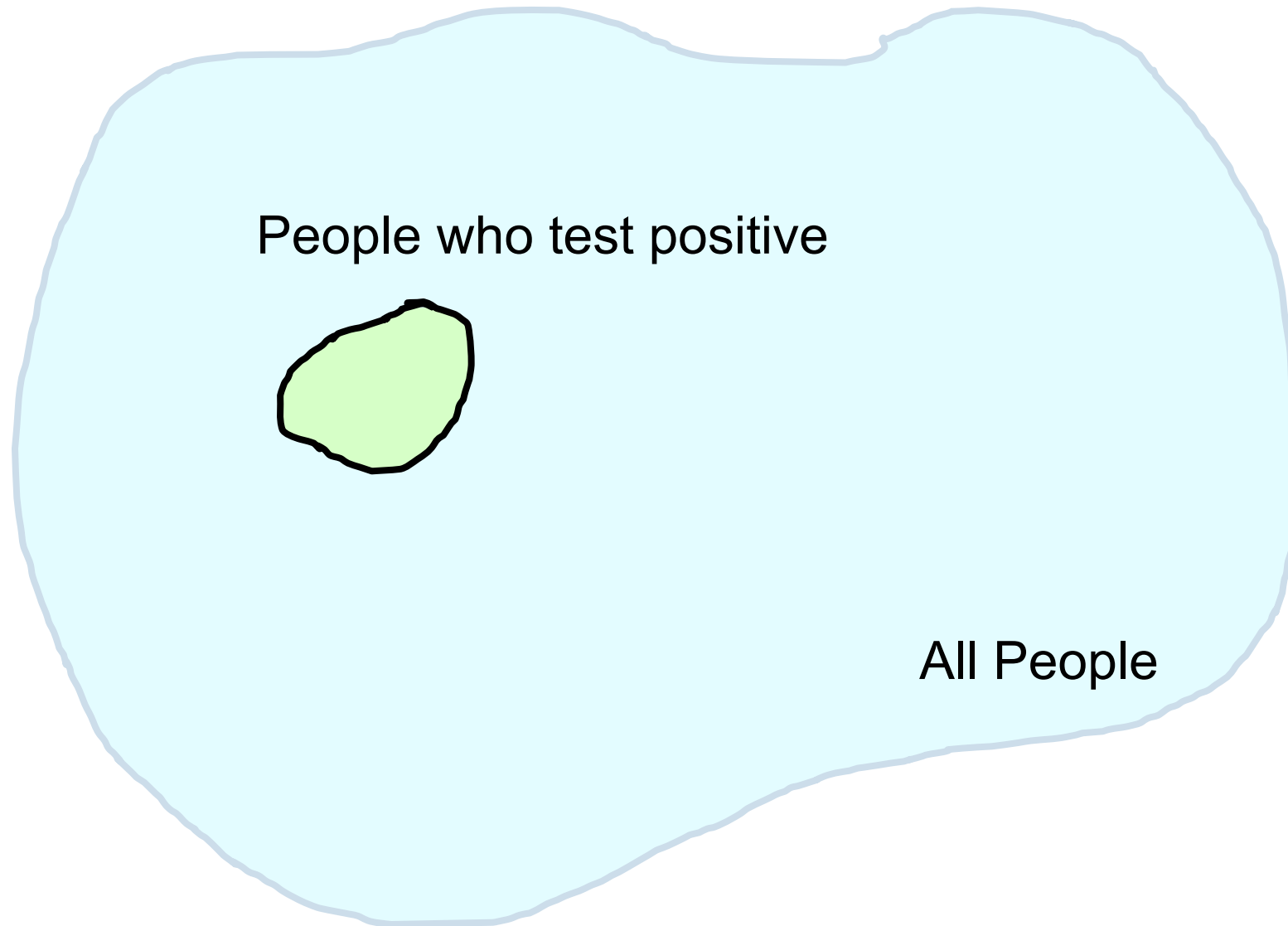
# Bayes Theorem Intuition

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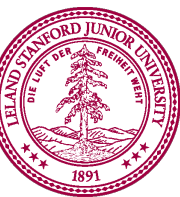
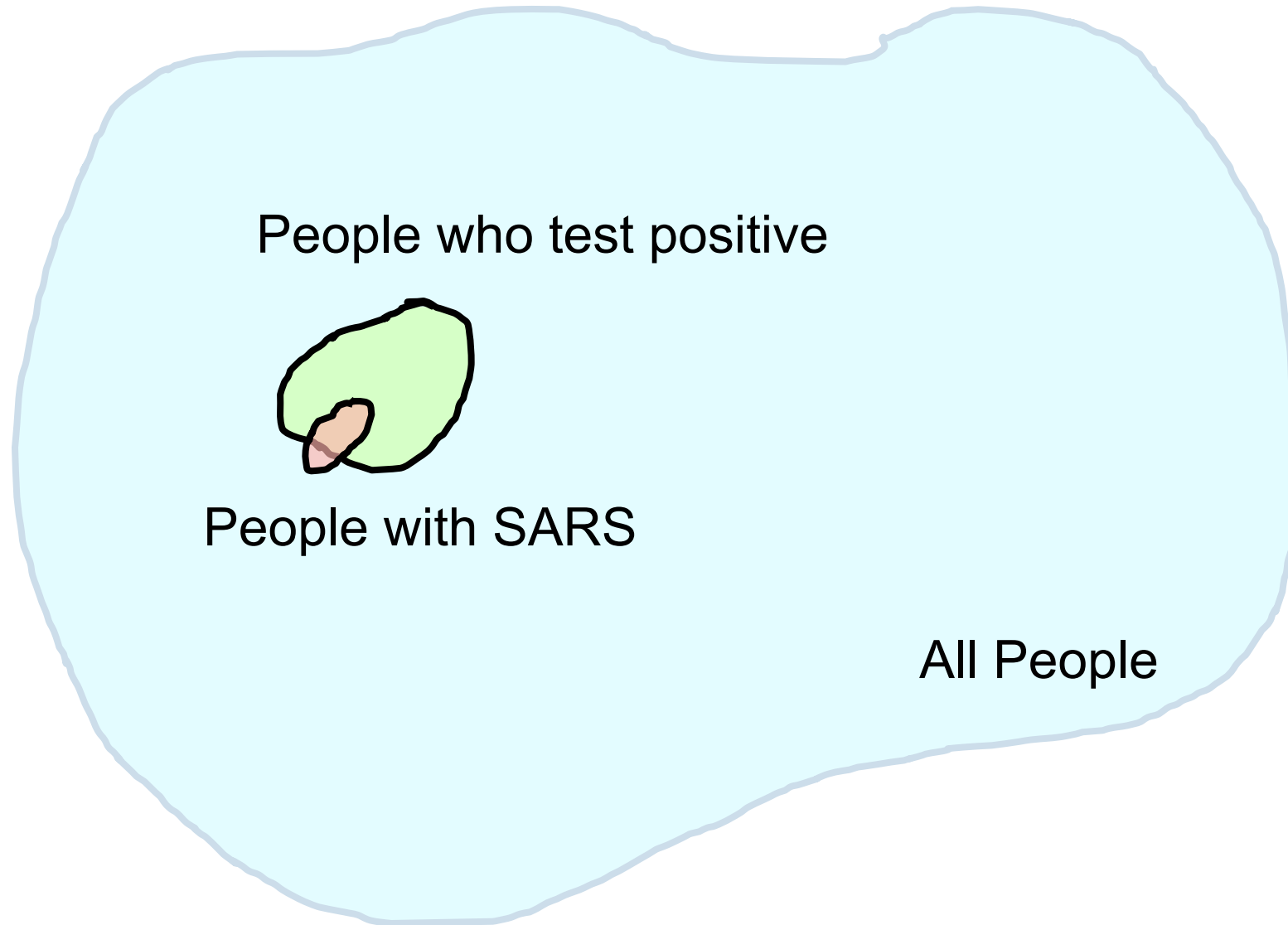
# Bayes Theorem Intuition

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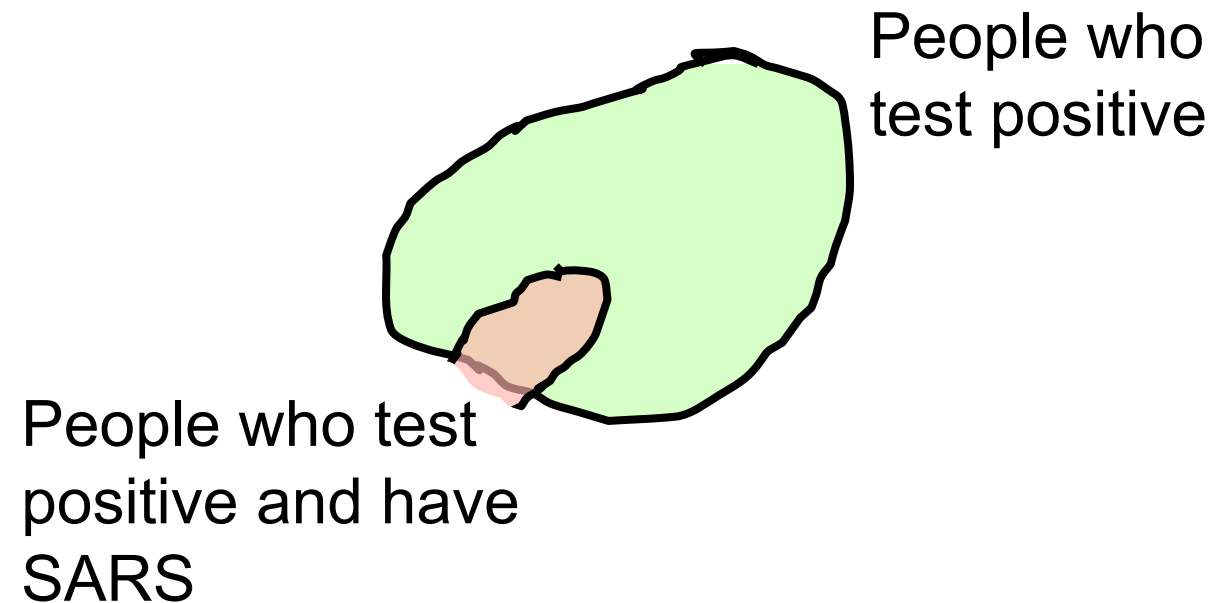
# Bayes Theorem Intuition

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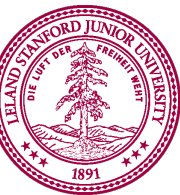


# Bayes Theorem Intuition

Conditioning on a positive result changes the sample space to this:

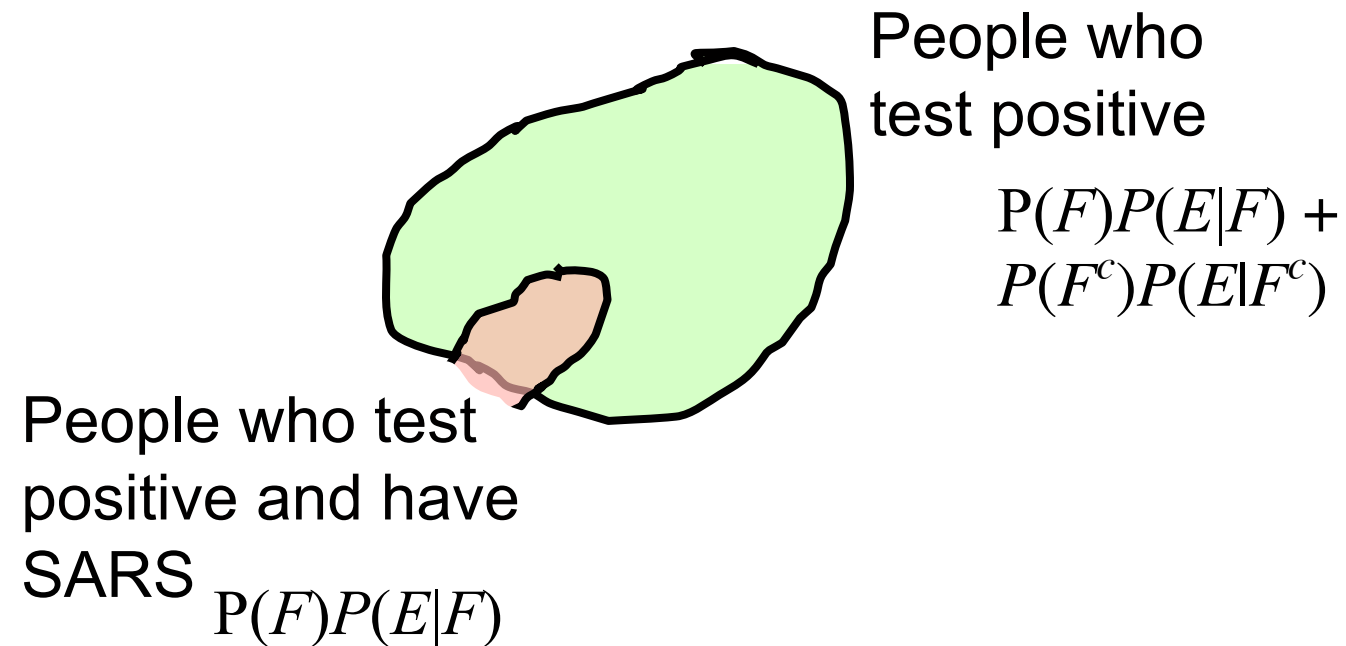


$\approx 0.330$

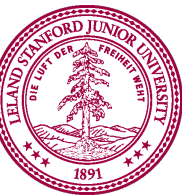


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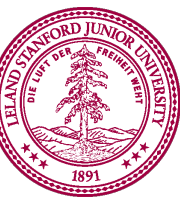
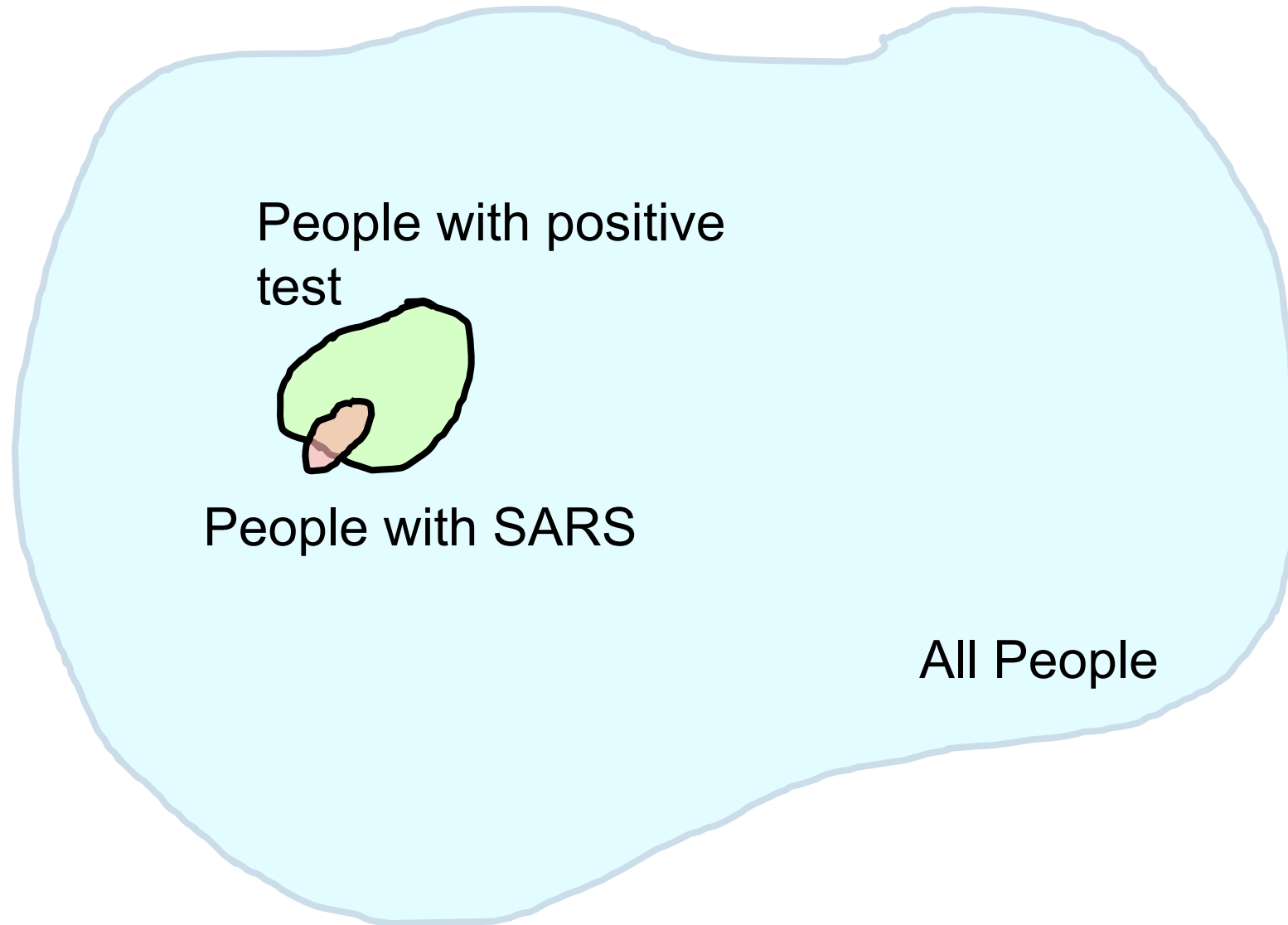


$\approx 0.330$



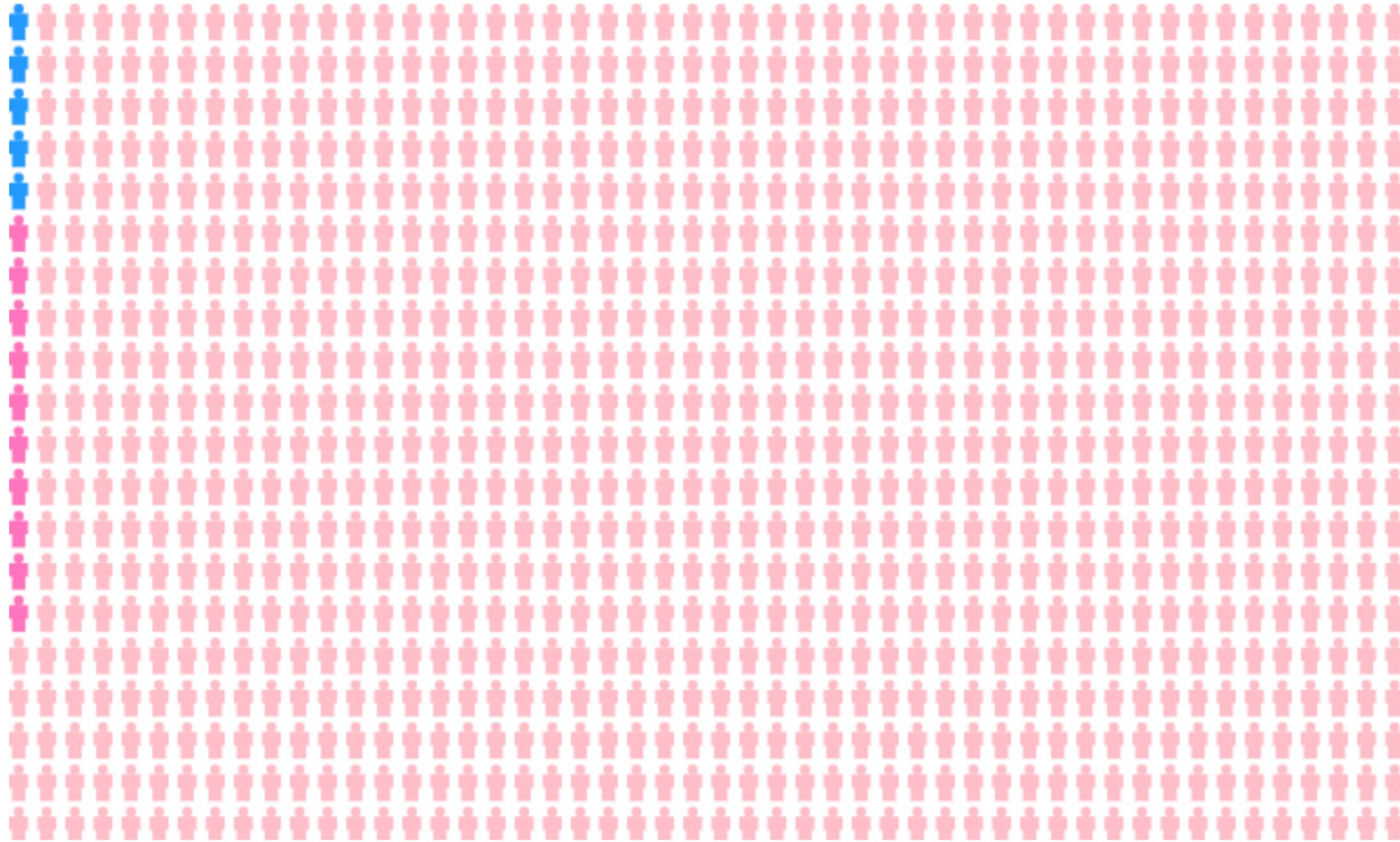
# Bayes Theorem Intuition

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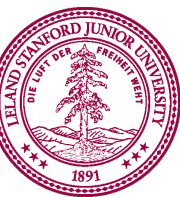


# Bayes Theorem Intuition

Say we have 1000 people:



5 have SARS and test positive, 985 do not have SARS and test negative.  
10 do not have SARS and test positive.  $\approx 0.333$



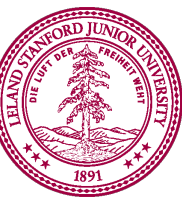
# Bayes Theorem Intuition

Conditioned on just those that test positive:



Notice that all the people with SARS are here, but the group is still mainly folks without SARS

5 have SARS and test positive, 985 **do not** have SARS and test negative.  
10 **do not** have SARS and test positive.  $\approx 0.333$



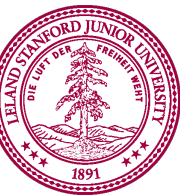
# Why it is still good to get tested

	<b>SARS +</b>	<b>SARS -</b>
<b>Test +</b>	0.98 = $P(E   F)$	0.01 = $P(E   F^c)$
<b>Test -</b>	0.02 = $P(E^c   F)$	0.99 = $P(E^c   F^c)$

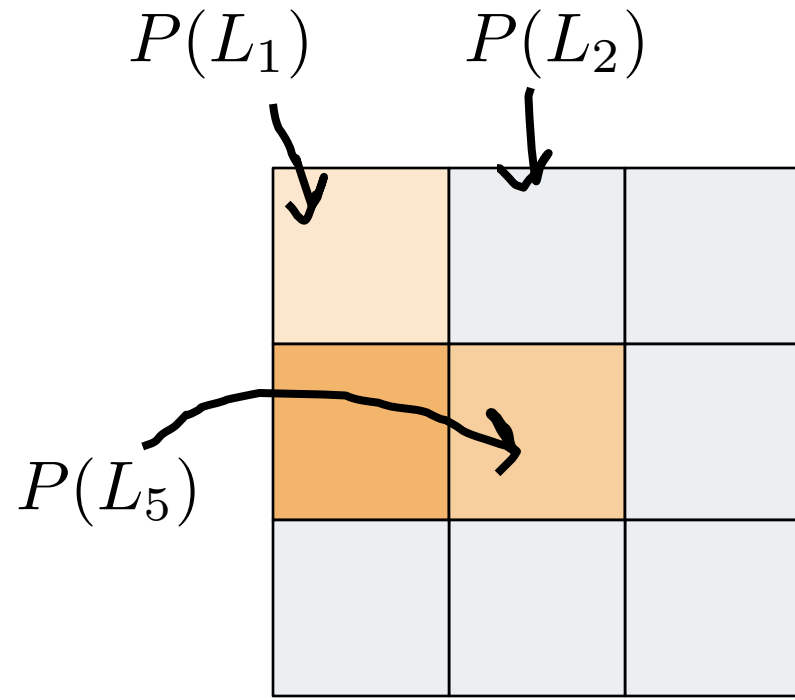
- Let  $E^c$  = you test negative for SARS with this test
- Let  $F$  = you actually have SARS
- What is  $P(F | E^c)$ ?

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

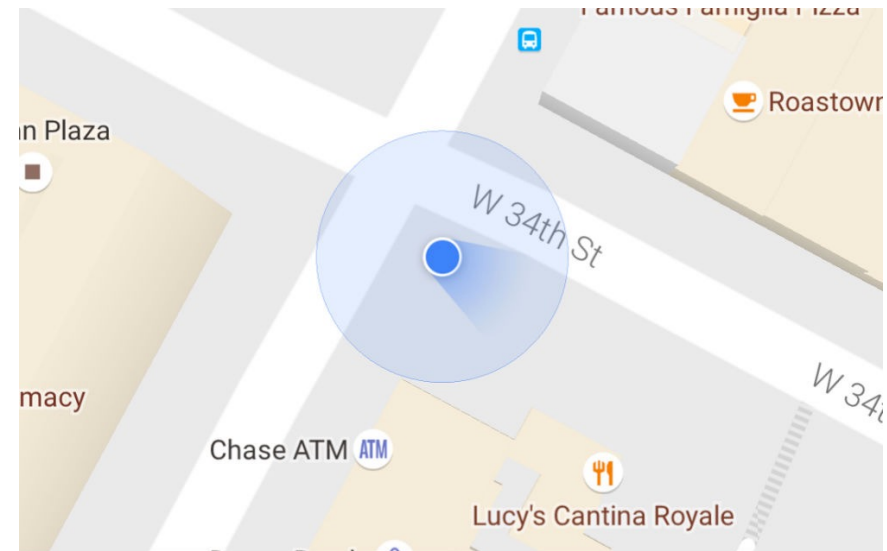
$$P(F | E^c) = \frac{(0.02)(0.005)}{(0.02)(0.005) + (0.99)(1 - 0.005)} \approx 0.0001$$



# Bayes' Theorem and Location

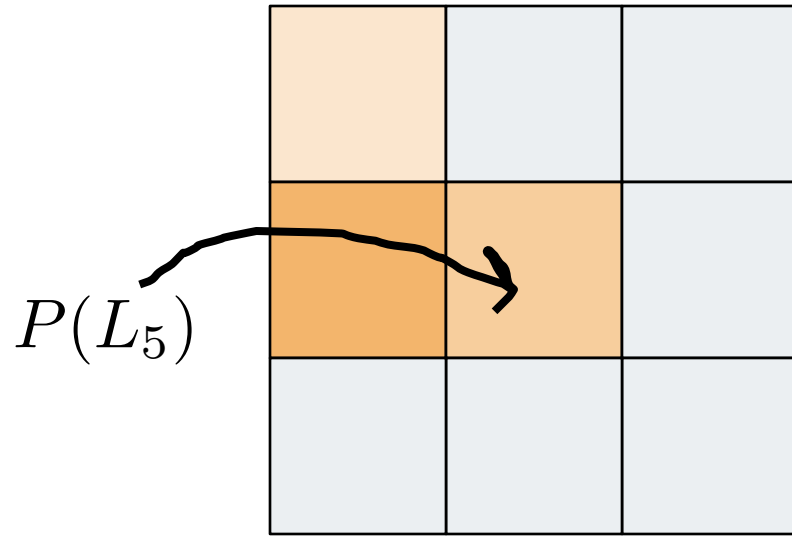
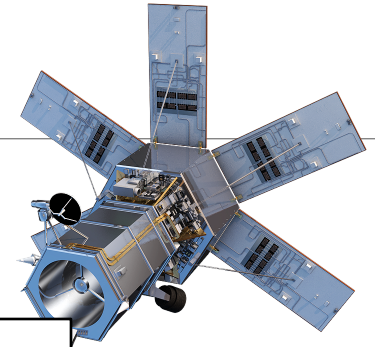


Before Observation

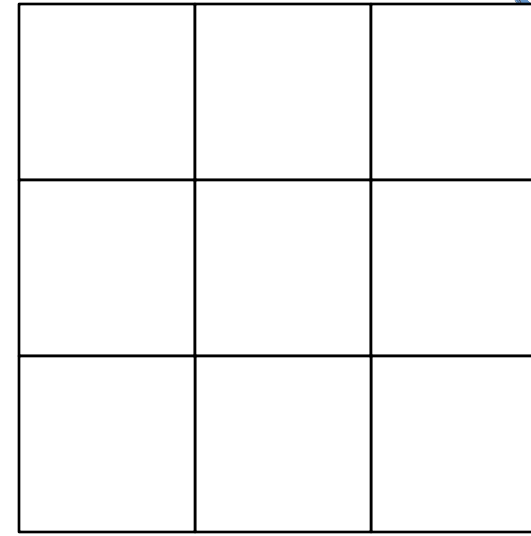


# Bayes' Theorem and Location

Know:  $P(O|L_i)$



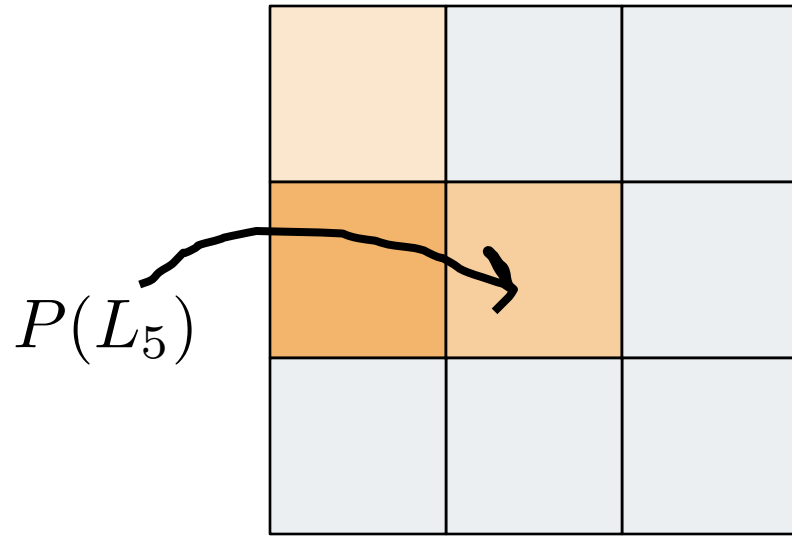
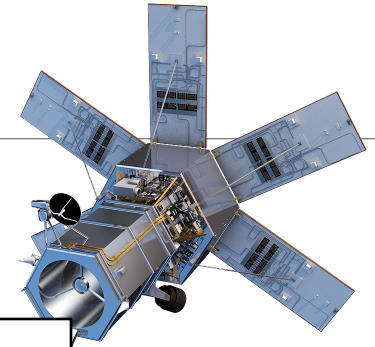
Before Observation



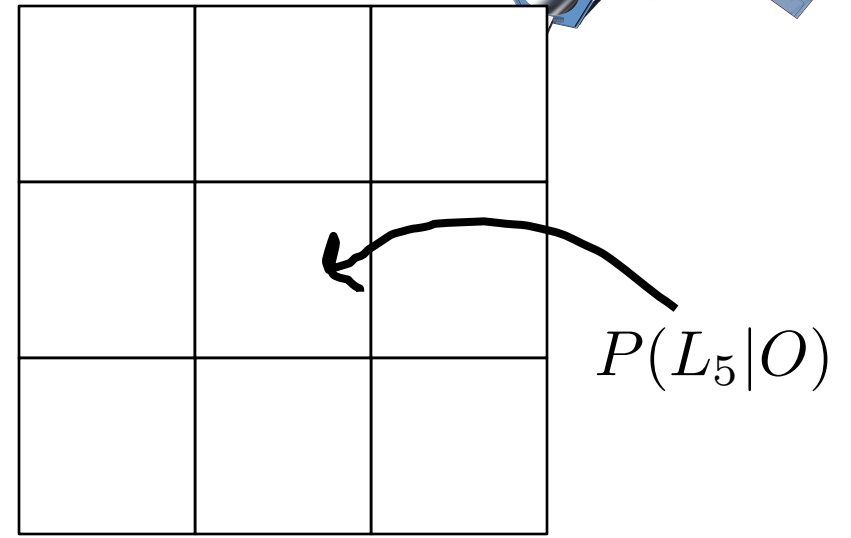
After Observation

# Bayes' Theorem and Location

Know:  $P(O|L_i)$



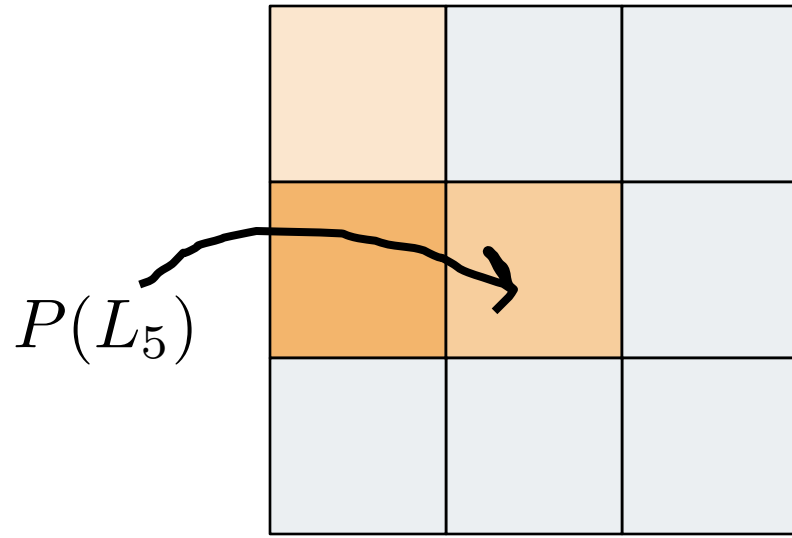
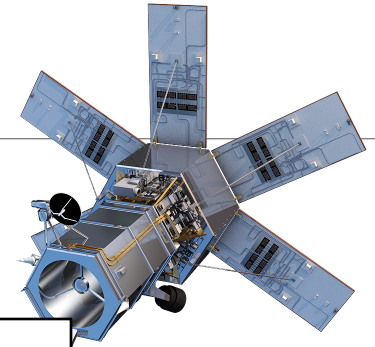
Before Observation



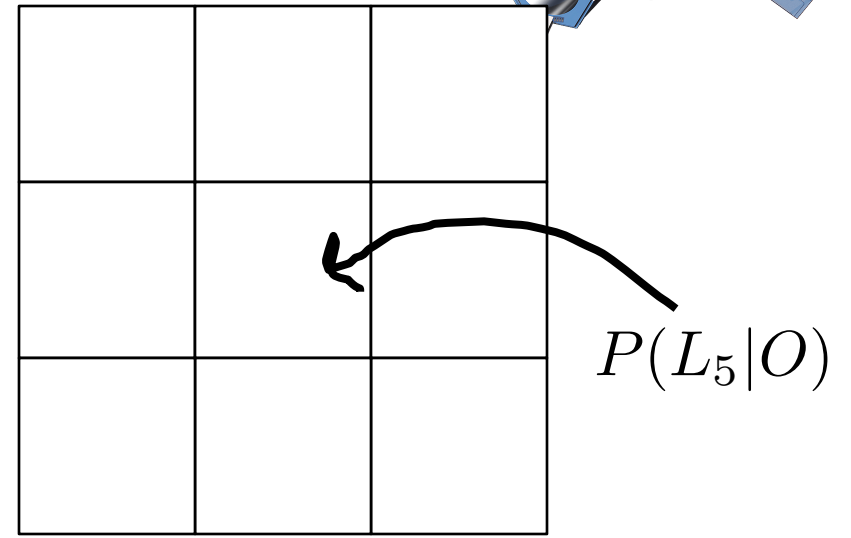
After Observation

$$P(L_5|O) = \frac{P(O|L_5)P(L_5)}{P(O)}$$

# Bayes' Theorem and Location



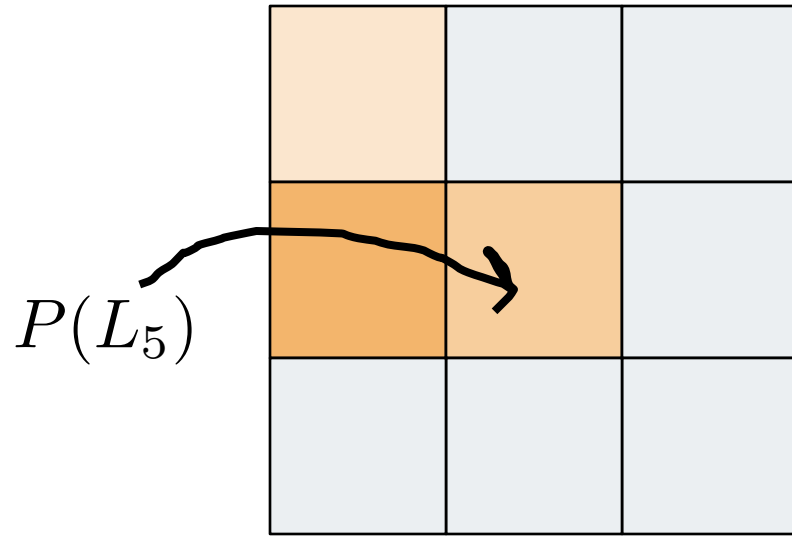
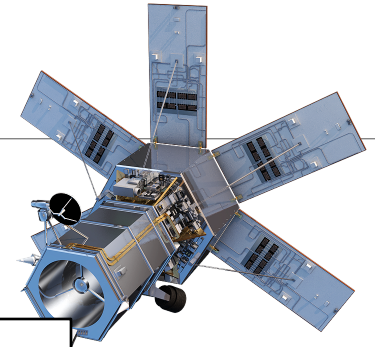
Before Observation



After Observation

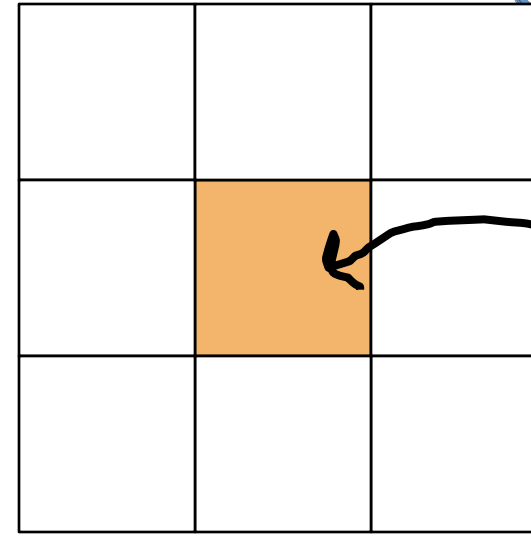
$$P(L_5|O) = \frac{P(O|L_5)P(L_5)}{\sum_i P(O|L_i)P(L_i)}$$

# Bayes' Theorem and Location



$P(L_5)$

Before Observation

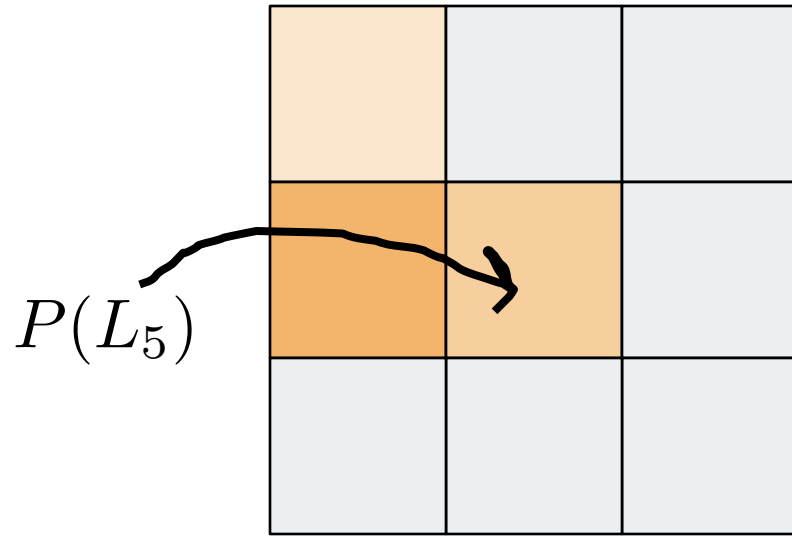
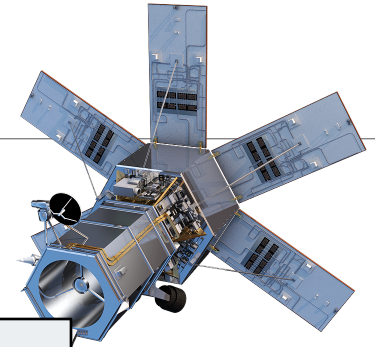


$P(L_5|O)$

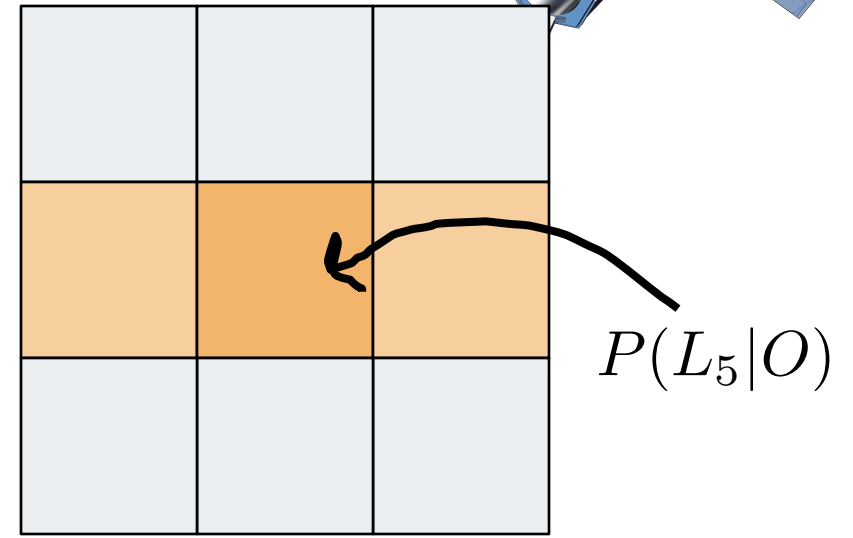
After Observation

$$P(L_5|O) = \frac{P(O|L_5)P(L_5)}{\sum_i P(O|L_i)P(L_i)}$$

# Bayes' Theorem and Location



Before Observation



After Observation

$$P(L_5|O) = \frac{P(O|L_5)P(L_5)}{\sum_i P(O|L_i)P(L_i)}$$

# Monty Hall Problem

# Monty Hall Problem and Wayne Brady



# Monty Hall Problem aka Let's Make a Deal

Behind one door is a prize (equally likely to be any door).

Behind the other two doors is nothing

1. We choose a door
2. Host opens 1 of other 2 doors, revealing nothing
3. We are given an option to change to the other door.

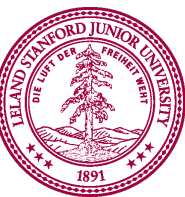
Should we switch?

Note: If we don't switch,  $P(\text{win}) = 1/3$  (random)

We are comparing  $P(\text{win})$  and  $P(\text{win|switch})$ .



Doors A,B,C



# If we switch

Without loss of generality, say we pick A (out of Doors A,B,C).

1/3

1/3

1/3

A = prize

- Host opens B or C
- We switch
- We always lose

$P(\text{win} \mid \text{A prize, picked A, switched}) = 0$

B = prize

- Host must open C
- We switch to B
- We always win

$P(\text{win} \mid \text{B prize, picked A, switched}) = 1$

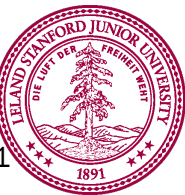
C = prize

- Host must open B
- We switch to C
- We always win

$P(\text{win} \mid \text{C prize, picked A, switched}) = 1$

$$P(\text{win} \mid \text{picked A, switched}) = 1/3 * 0 + 1/3 * 1 + 1/3 * 1 = 2/3$$

*You should switch.*



# Monty Hall, 1000 envelope version

Start with 1000 envelopes (of which 1 is the prize).

1. You choose 1 envelope.

$$\left\{ \begin{array}{l} \frac{1}{1000} = P(\text{envelope is prize}) \\ \frac{999}{1000} = P(\text{other 999 envelopes have prize}) \end{array} \right.$$

2. I open 998 of remaining 999 (showing they are empty).

$$\begin{aligned} \frac{999}{1000} &= P(998 \text{ empty envelopes had prize}) \\ &\quad + P(\text{last other envelope has prize}) \\ &= P(\text{last other envelope has prize}) \end{aligned}$$

3. Should you switch?

$$\text{No: } P(\text{win without switching}) = \frac{1}{\text{original \# envelopes}}$$

$$\text{Yes: } P(\text{win with new knowledge}) = \frac{\text{original \# envelopes} - 1}{\text{original \# envelopes}}$$

# Marilyn Vos Savant

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*Ask Marilyn™*

**BY MARILYN VOS SAVANT**

