

Conditional Probability and Bayes

Announcements

- Sections start Wednesday. Times coming soon!



Review

Review, Axioms of Probability

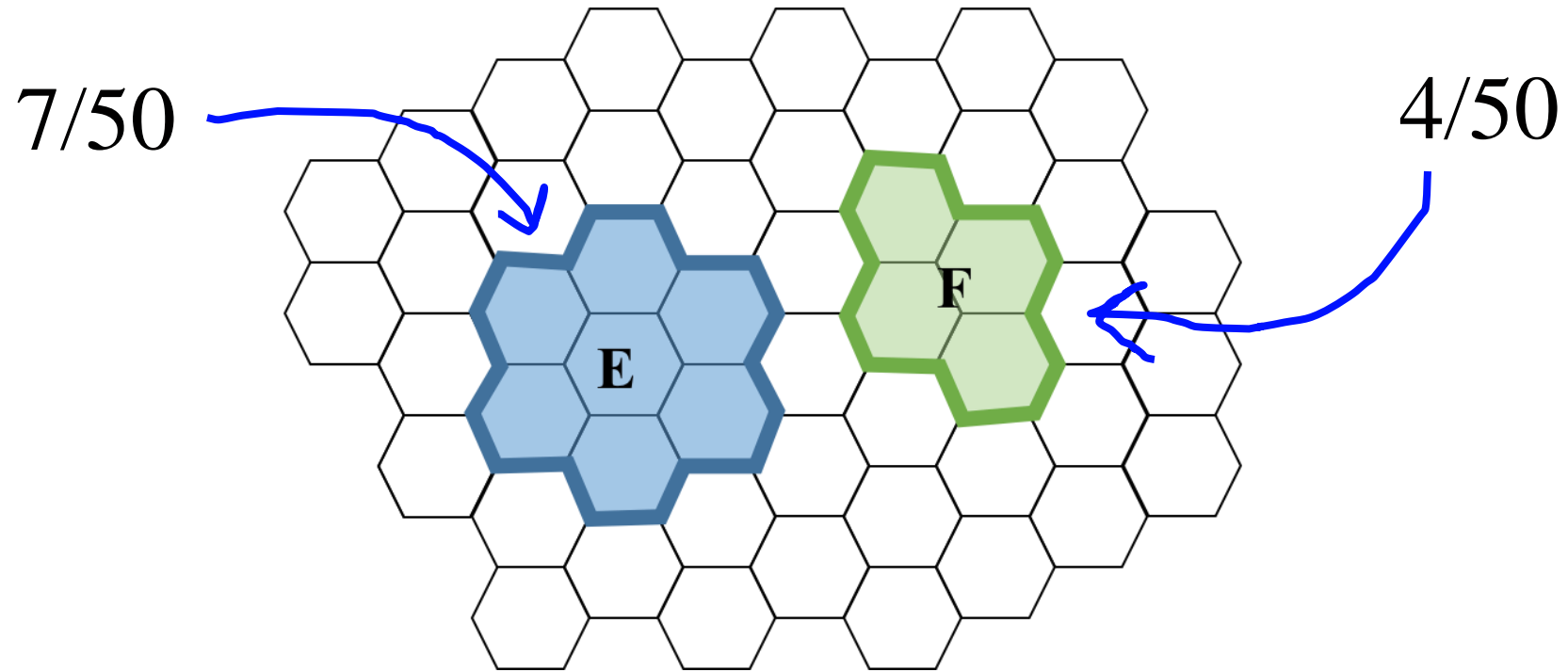
Recall: S = all possible outcomes. E = the event.

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

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



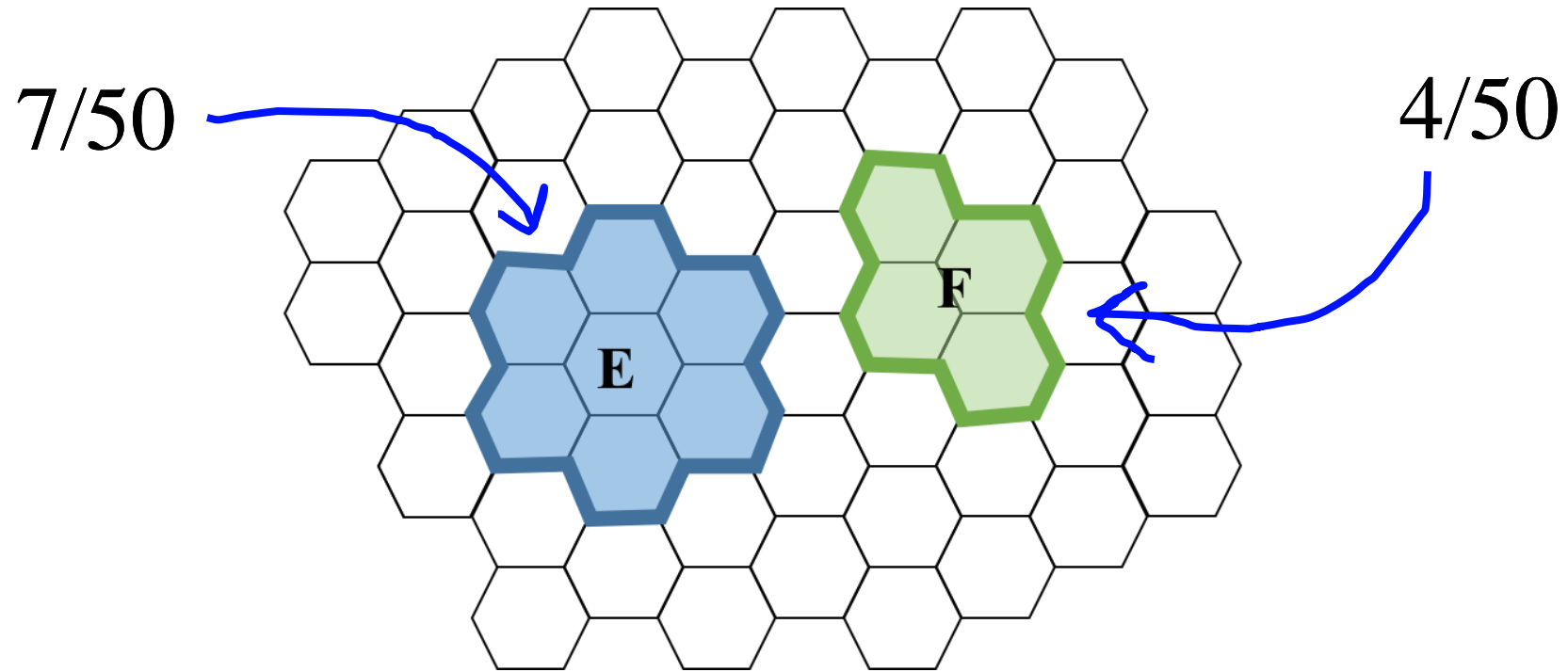
Mutually Exclusive Events



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

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

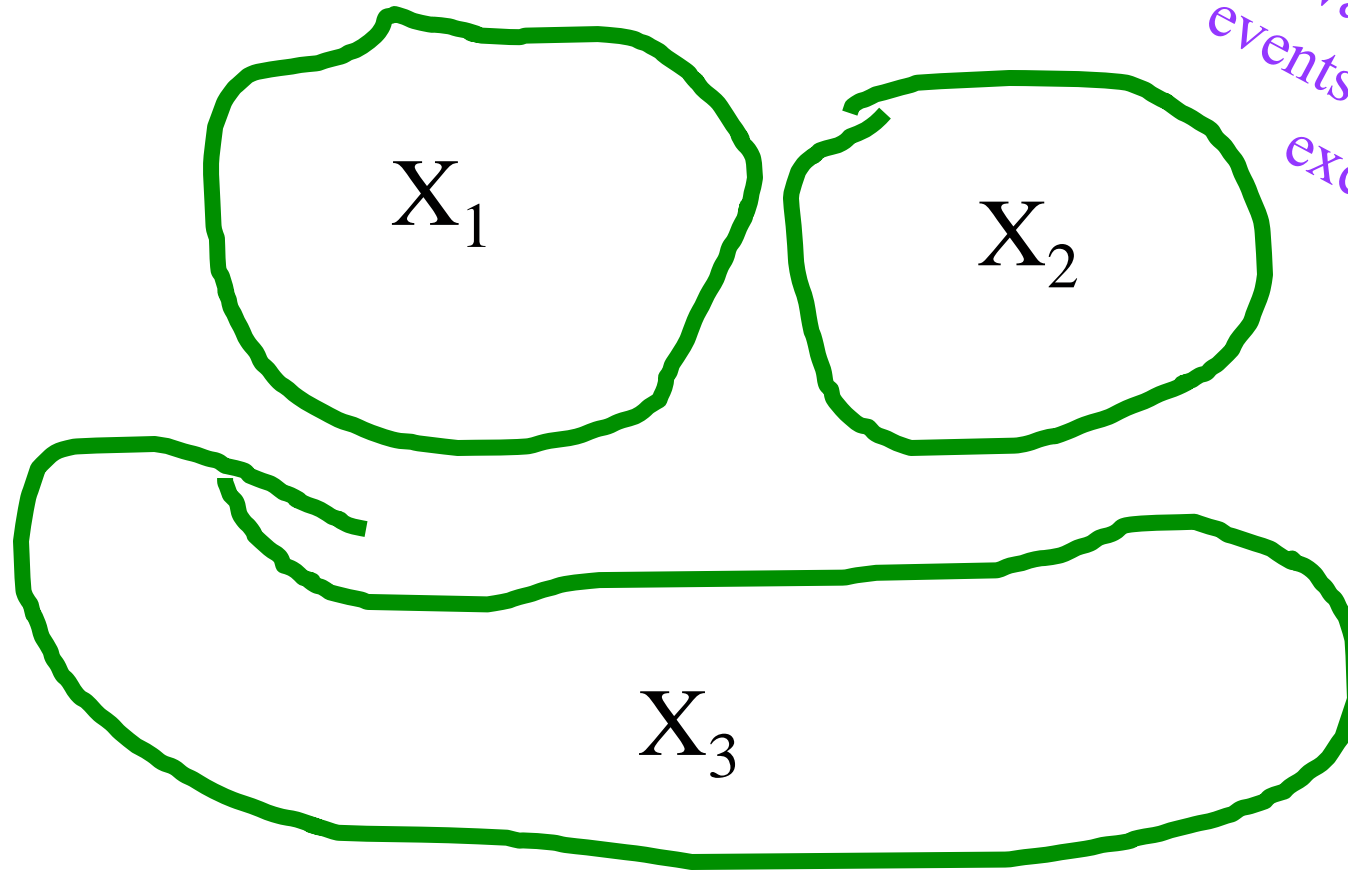
Mutually Exclusive Events



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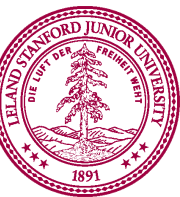
$$P(E \cup F) = \frac{7}{50} + \frac{4}{50} = \frac{11}{50}$$

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



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

$$P(E^c) = 1 - P(E)?$$

$$P(E \cup E^c) = P(E) + P(E^c)$$

Axiom 3. Since E and E^c are mutually exclusive

$$P(S) = P(E) + P(E^c)$$

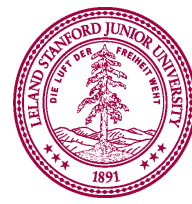
Since everything must either be in E or E^c

$$1 = P(E) + P(E^c)$$

Axiom 2

$$P(E^c) = 1 - P(E)$$

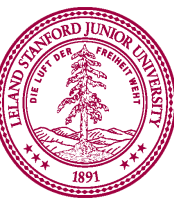
Rearrange



Let it find you.

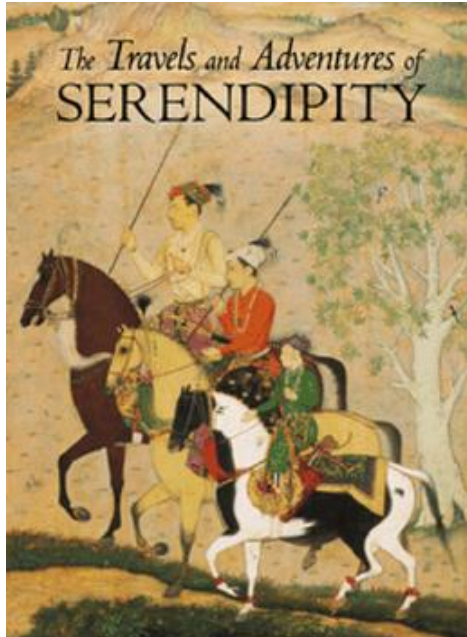
SERENDIPITY

the effect by which one accidentally stumbles upon something truly wonderful, especially while looking for something entirely unrelated.



Serendipity Review

- Say the population of Stanford is p people
- You are friends with f people
- Walk into a room, see s random people.



Let E be the event that you see at least one friend

$$P(E^C) = \frac{\binom{p-f}{s}}{\binom{p}{s}}$$

$$P(E) = 1 - \frac{\binom{p-f}{s}}{\binom{p}{s}}$$



Many times it is easier to
calculate $P(E^C)$.

End Review

Learning Goal for Today: Conditional Probability



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

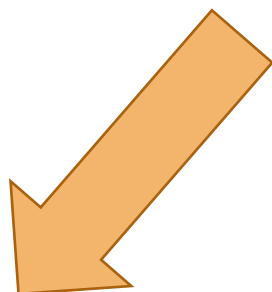
Chain rule
(Product rule)



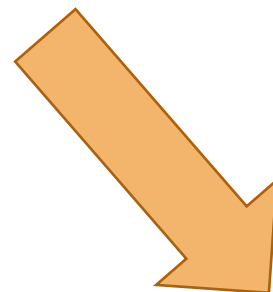
Definition of
conditional probability

$$P(E|F)$$

Law of Total
Probability

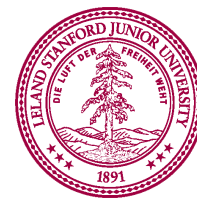


Bayes'
Theorem



$$P(E)$$

$$P(F|E)$$

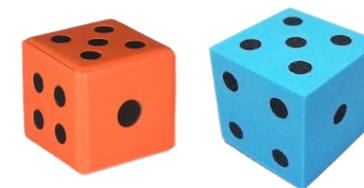


Conditional Probability

Roll two dice

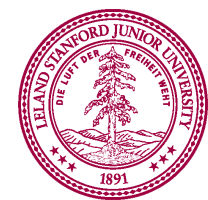
$$P(E) = \frac{|E|}{|S|} \quad \text{Equally likely outcomes}$$

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



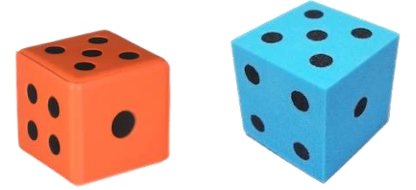
$S = \{(1,1) (1,2) (1,3) (1,4) (1,5) \textcolor{blue}{(1,6)}$
 $(2,1) (2,2) (2,3) (2,4) \textcolor{blue}{(2,5)} (2,6)$
 $(3,1) (3,2) (3,3) \textcolor{blue}{(3,4)} (3,5) (3,6)$
 $(4,1) (4,2) \textcolor{blue}{(4,3)} (4,4) (4,5) (4,6)$
 $(5,1) \textcolor{blue}{(5,2)} (5,3) (5,4) (5,5) (5,6)$
 $\textcolor{blue}{(6,1)}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

$E = \textcolor{blue}{In blue}$



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

Sum of Two Die = 4?

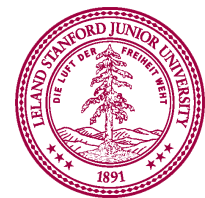
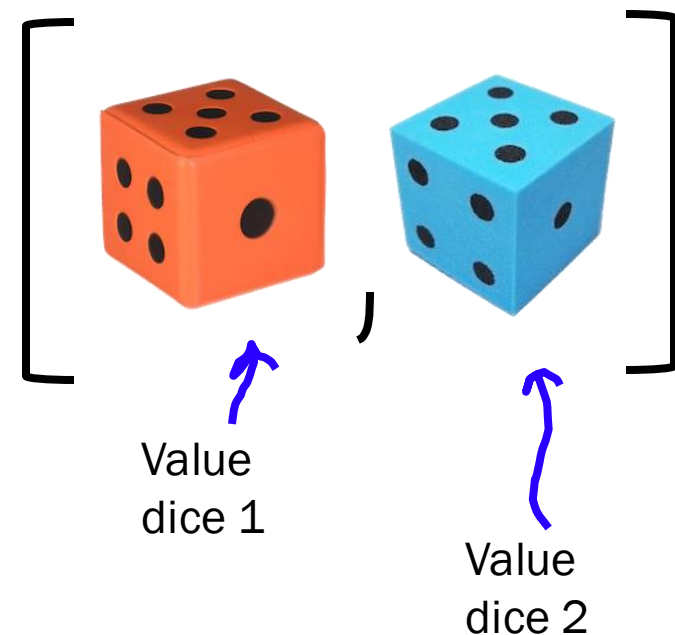
Roll two 6-sided dice. What is probability the sum = 4?

Let E be the event that the sum is 4

S = {	[1,1]	[1,2]	[1,3]	[1,4]	[1,5]	[1,6]
	[2,1]	[2,2]	[2,3]	[2,4]	[2,5]	[2,6]
	[3,1]	[3,2]	[3,3]	[3,4]	[3,5]	[3,6]
	[4,1]	[4,2]	[4,3]	[4,4]	[4,5]	[4,6]
	[5,1]	[5,2]	[5,3]	[5,4]	[5,5]	[5,6]
	[6,1]	[6,2]	[6,3]	[6,4]	[6,5]	[6,6] }

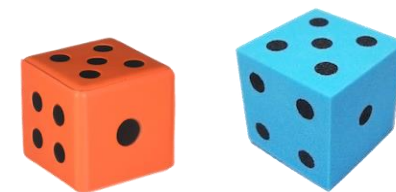
E =

Each outcome



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:

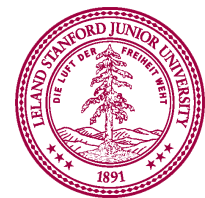
“ $P(E, \text{given } F \text{ already observed})$ ”

Sample space \rightarrow

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

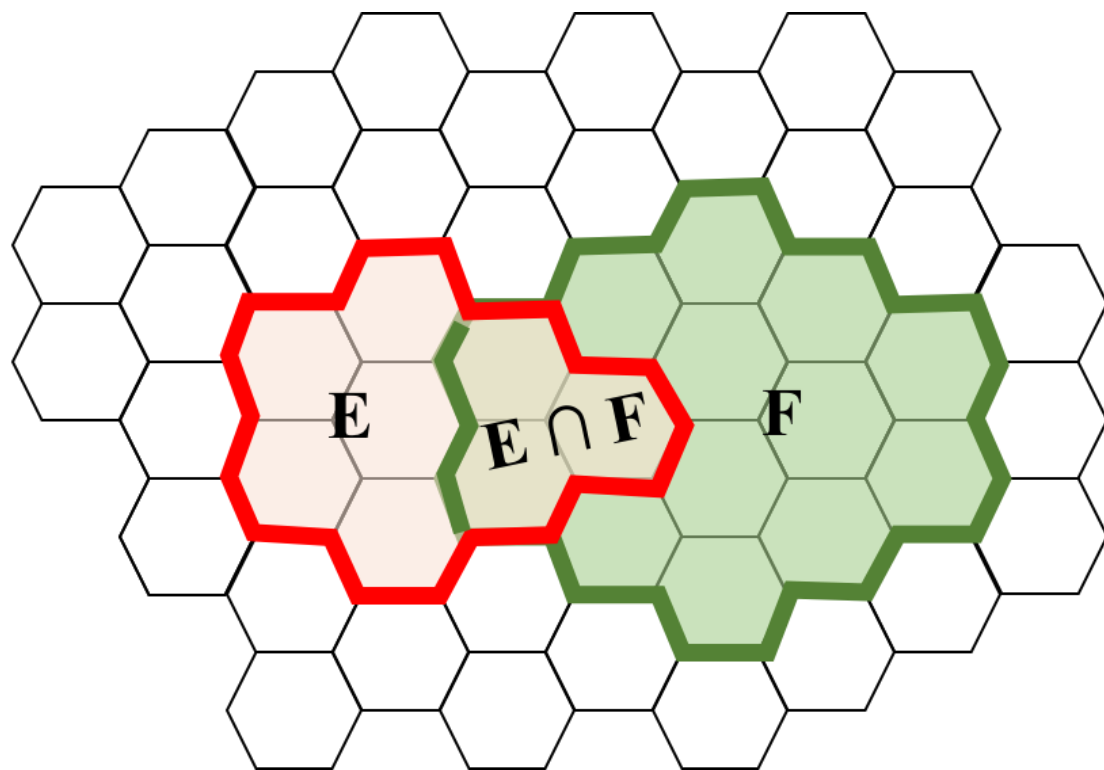
Event \rightarrow

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 .

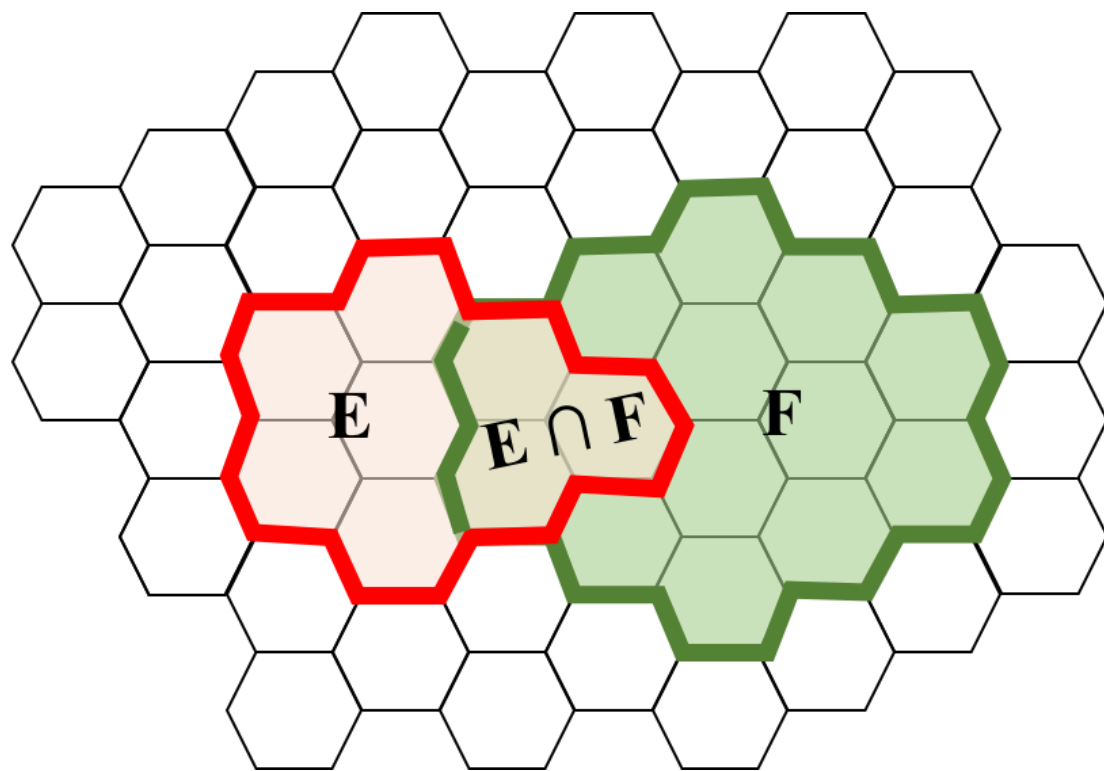


$$P(E) = \frac{8}{50} \approx 0.16$$

$$P(E|F) =$$

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 .

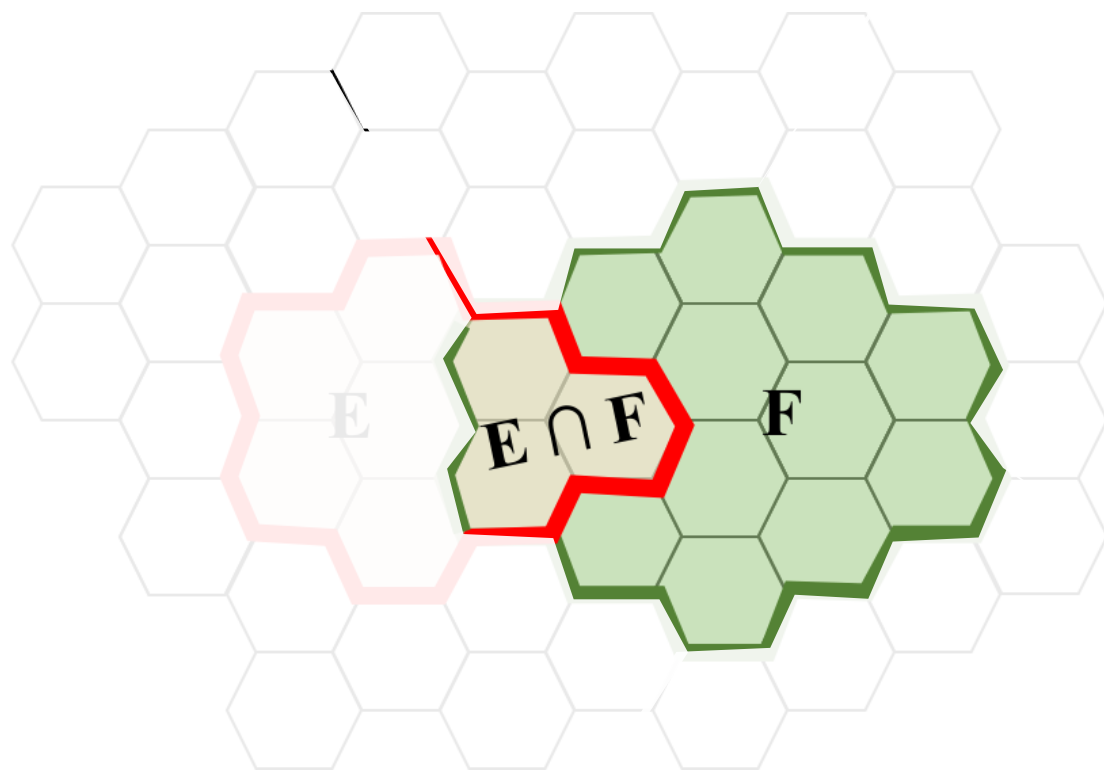


$$P(E) = \frac{8}{50} \approx 0.16$$

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

Conditional Probability, 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 .



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

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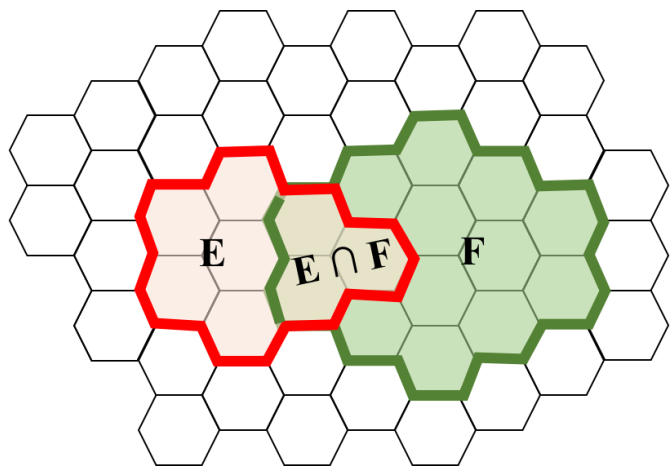


Conditional Probability, visual intuition

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 .

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

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



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

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

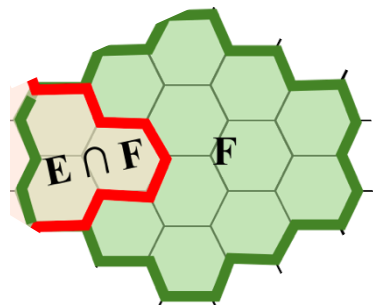


Conditional Probability, visual intuition

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 .

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:

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

Shorthand for E and 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*





Bye, land of equally likely outcomes

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?

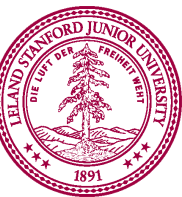
$$P(E)$$



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

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

$P(E) = 1/2$?



Netflix and Learn

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

$$P(E)$$



Netflix and Learn

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

$$P(E)$$



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

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

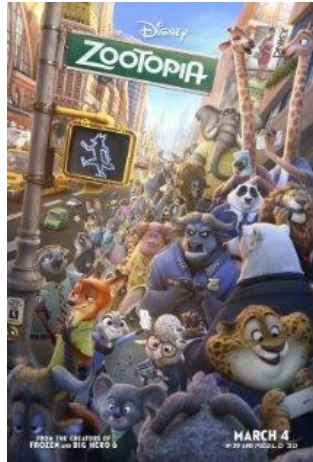
Netflix and Learn

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

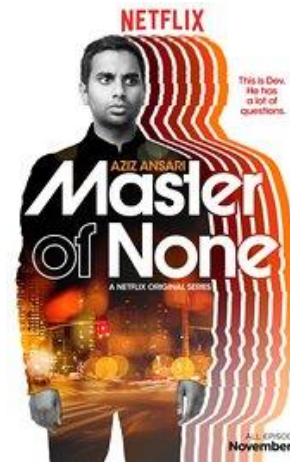
Let E be the event that a user watches the given movie.



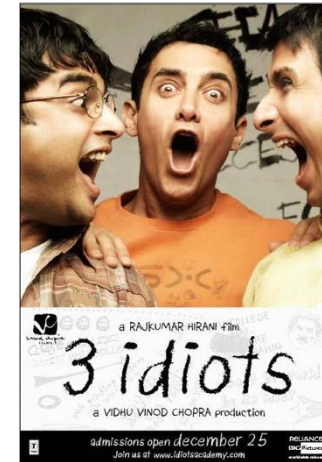
$$P(E) = 0.19$$



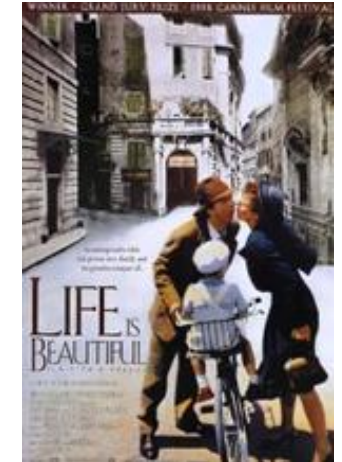
$$P(E) = 0.32$$



$$P(E) = 0.20$$



$$P(E) = 0.09$$



$$P(E) = 0.20$$

Netflix and Learn

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

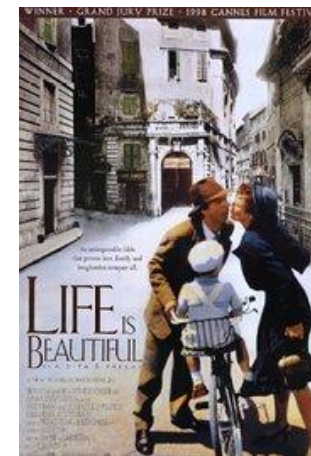
Let E = a user watches Life is Beautiful.

Let F = a user watches CODA.

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

$$P(E|F)$$

$$\begin{aligned} P(E|F) &= \frac{P(EF)}{P(F)} \approx \frac{\frac{\# \text{ people who have watched both}}{\# \text{ people on Netflix}}}{\frac{\# \text{ people who have watched CODA}}{\# \text{ people on Netflix}}} \\ &\approx \frac{\# \text{ people who have watched both}}{\# \text{ people who have watched CODA}} \\ &\approx 0.42 \end{aligned}$$



Netflix and Learn

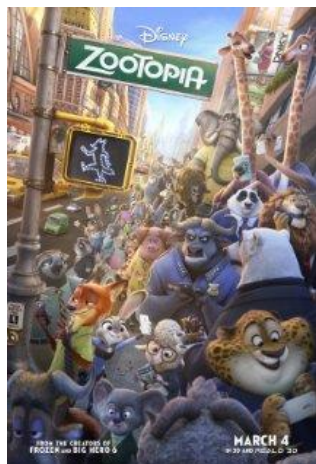
$$P(E|F) = \frac{P(EF)}{P(F)}$$
 Definition of Cond. Probability

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



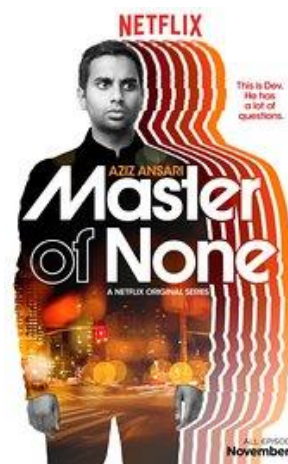
$$P(E) = 0.19$$

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



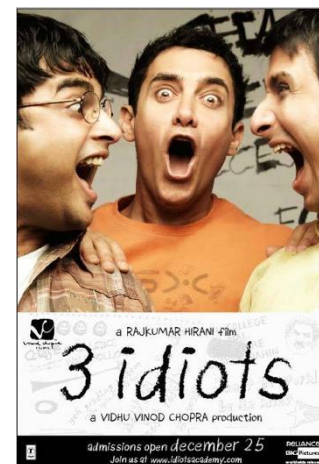
$$P(E) = 0.32$$

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



$$P(E) = 0.20$$

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



$$P(E) = 0.09$$

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

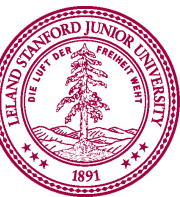


$$P(E) = 0.20$$

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

Machine Learning

Machine Learning is:
Probability + Data + Computers



Notation

And

Or

Given

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

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

$$P(E|F)$$

$$P(E, F)$$

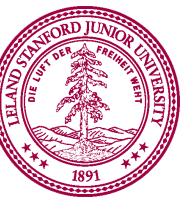
$$P(E \cup F)$$

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

$$P(EF)$$

$$P(E \cap F)$$

Probability of E given
F and G



Chain Rule via Baby Poop

<https://cs109psets.netlify.app/fall23/lecture4/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**.



A screenshot of a web browser displaying the CS109 website. The browser's address bar shows the URL "web.stanford.edu/class/cs109/lectures/4-ConditioningAndBayes/". The website has a dark header with "CS109" and navigation links for "Course Resources", "Problem Sets", "Lecture", and "Section". A "Schedule" button is in the top right. A dropdown menu is open under "Lecture", showing a list: "1. Welcome", "2. Combinatorics", "3. Probability", and "4. Conditioning and Bayes". The main content area is titled "Lecture 4: Conditioning and Bayes" with the date "OCT 4TH, 2023" and time "HEWLETT 200, 3:30P". Below this, there is a section for "Lecture Materials" with a document icon and a rocket icon circled in purple.

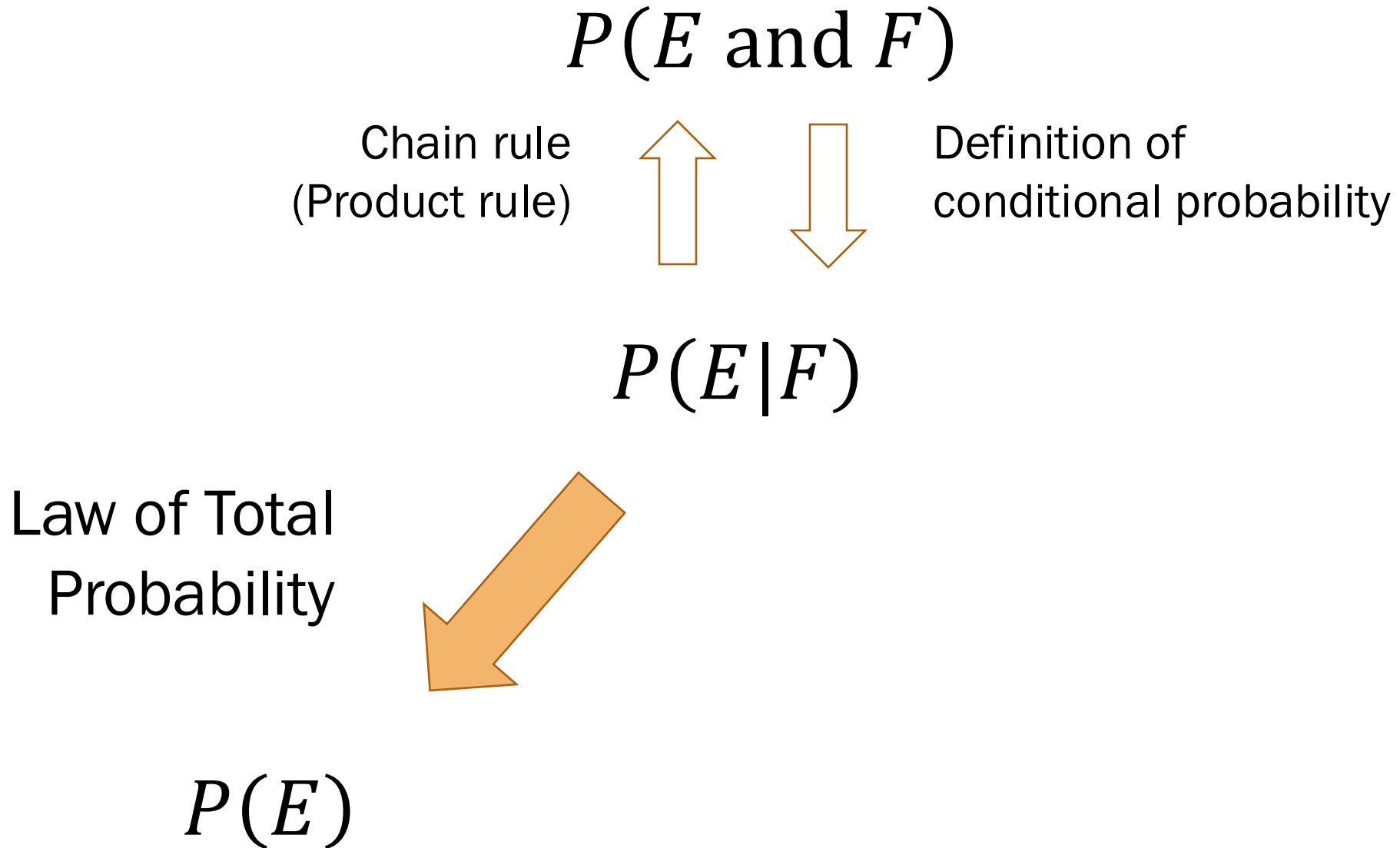
Generalized Chain Rule

$$\begin{aligned} &\Pr(E_1 \text{ and } E_2 \text{ and } E_3 \text{ and } \dots E_n) \\ &= \Pr(E_1) \cdot \Pr(E_2|E_1) \cdot \Pr(E_3|E_1, E_2) \cdots \Pr(E_n|E_1, E_2 \dots E_{n-1}) \end{aligned}$$



Law of Total Probability

Relationship Between Probabilities



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%.

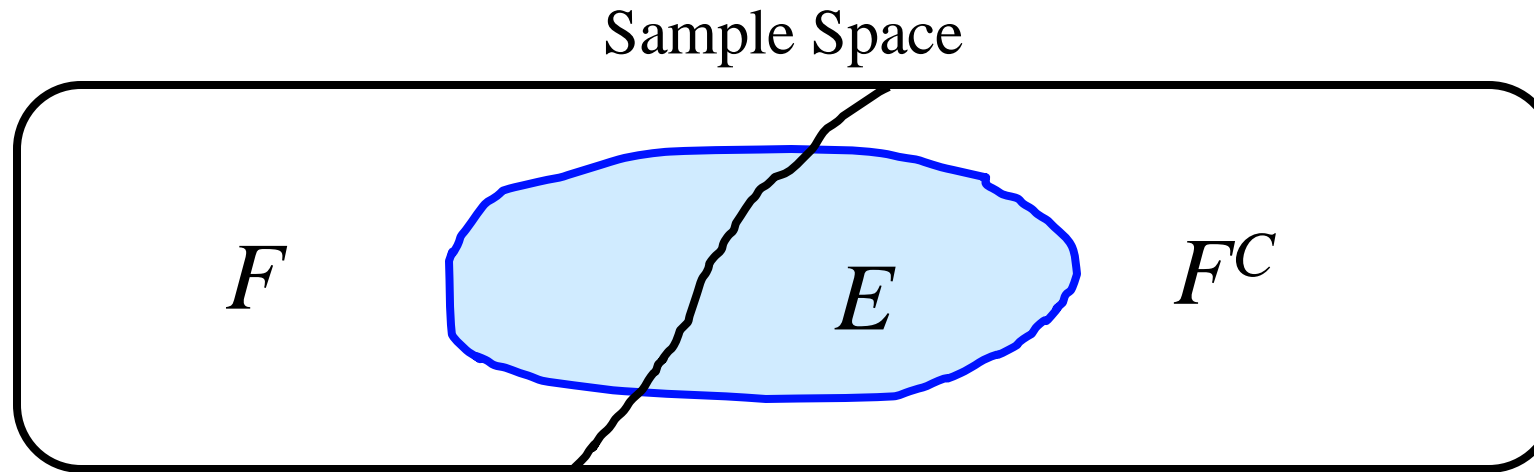


What is the probability of crying, unconditioned?

What information do you need?

Law of Total Probability

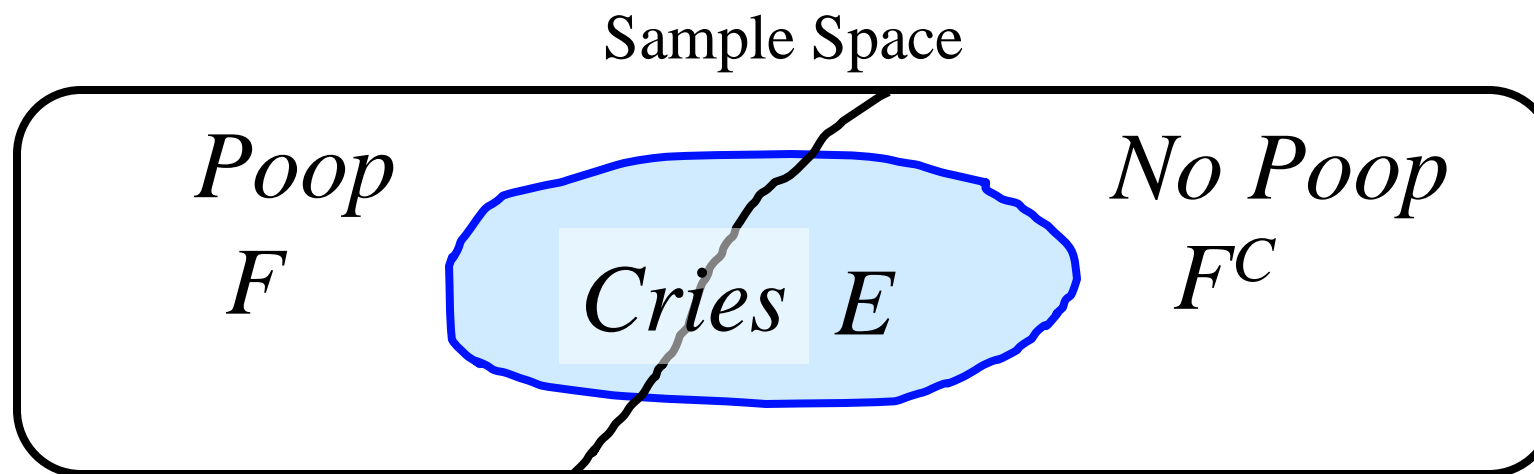
Say E and F are events in S



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

Law of Total Probability

Say E and F are events in S

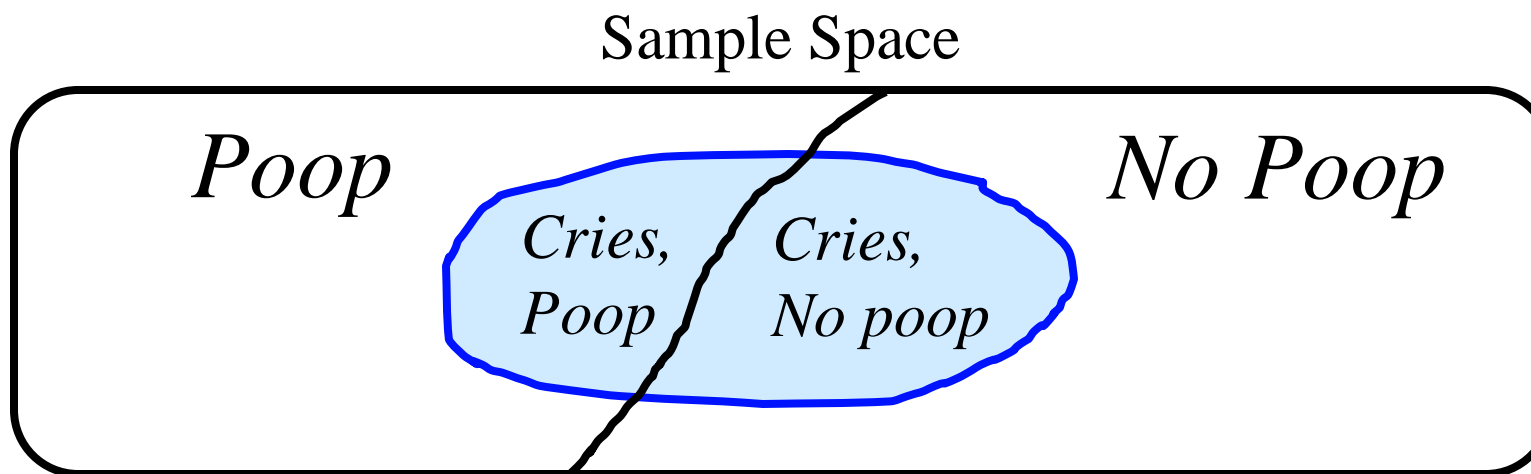


$$\begin{aligned} P(E) &= P(EF) + P(EF^C) \\ &= P(E|F)P(F) + P(E|F^C)P(F^C) \end{aligned}$$



Law of Total Probability

Say E and F are events in S

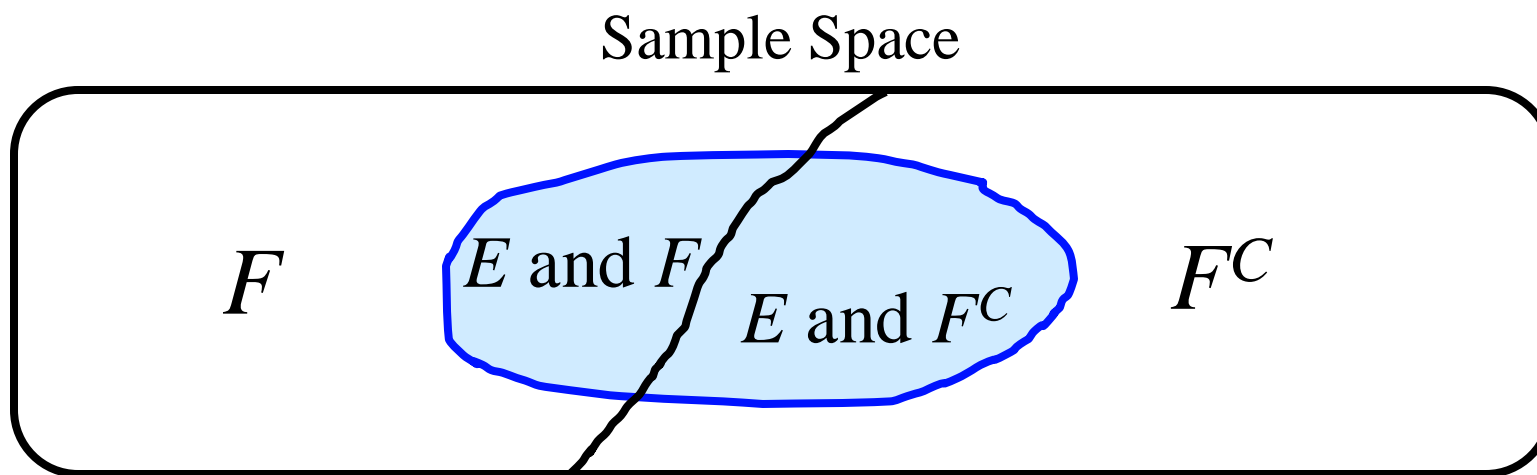


$$\begin{aligned} P(E) &= P(EF) + P(EF^C) \\ &= P(E|F)P(F) + P(E|F^C)P(F^C) \end{aligned}$$



Law of Total Probability

Say E and F are events in S



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



Law of Total Probability

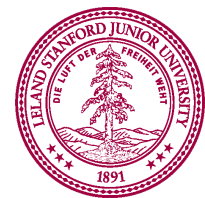
Thm Let F be an event where $P(F) > 0$. For any event E ,

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

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)



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%.



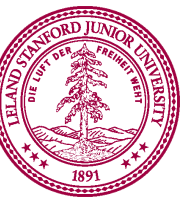
Probability of crying (T)?

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):

$$\Pr(E) = \Pr(E \text{ and } M) + \Pr(E \text{ and } M^C)$$

LOTP

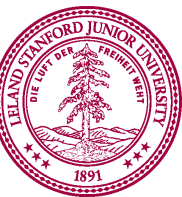
$$= \Pr(E|M)\Pr(M) + \Pr(E|M^C)\Pr(M^C)$$

Chain Rule

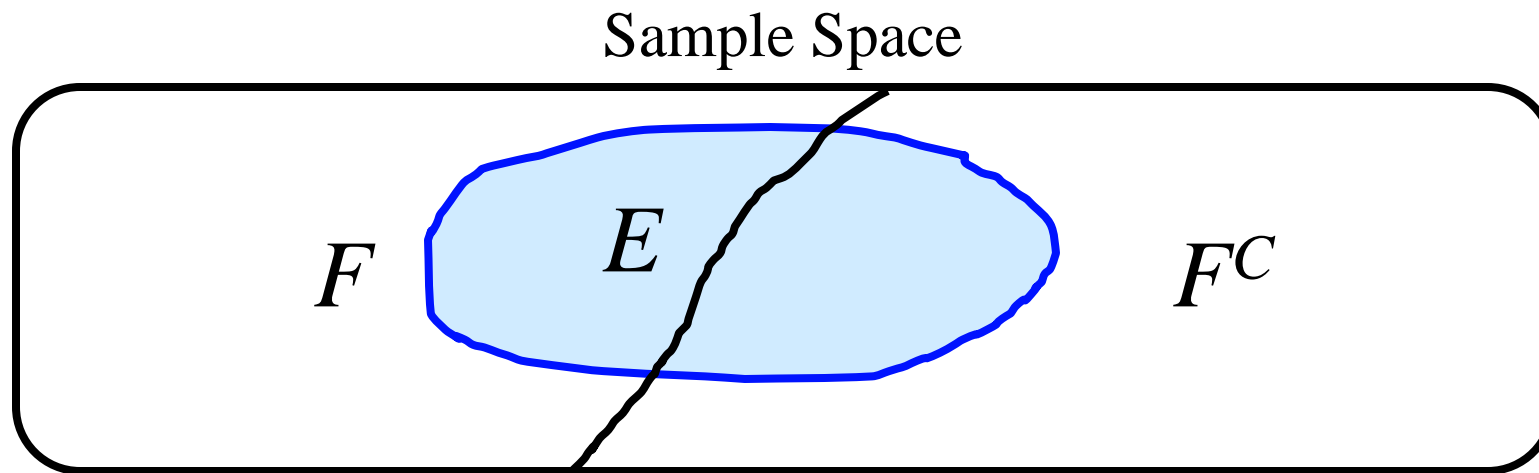
$$= 0.20 \cdot 0.10 + 0.01 \cdot 0.90$$

Substituting

$$= 0.029$$



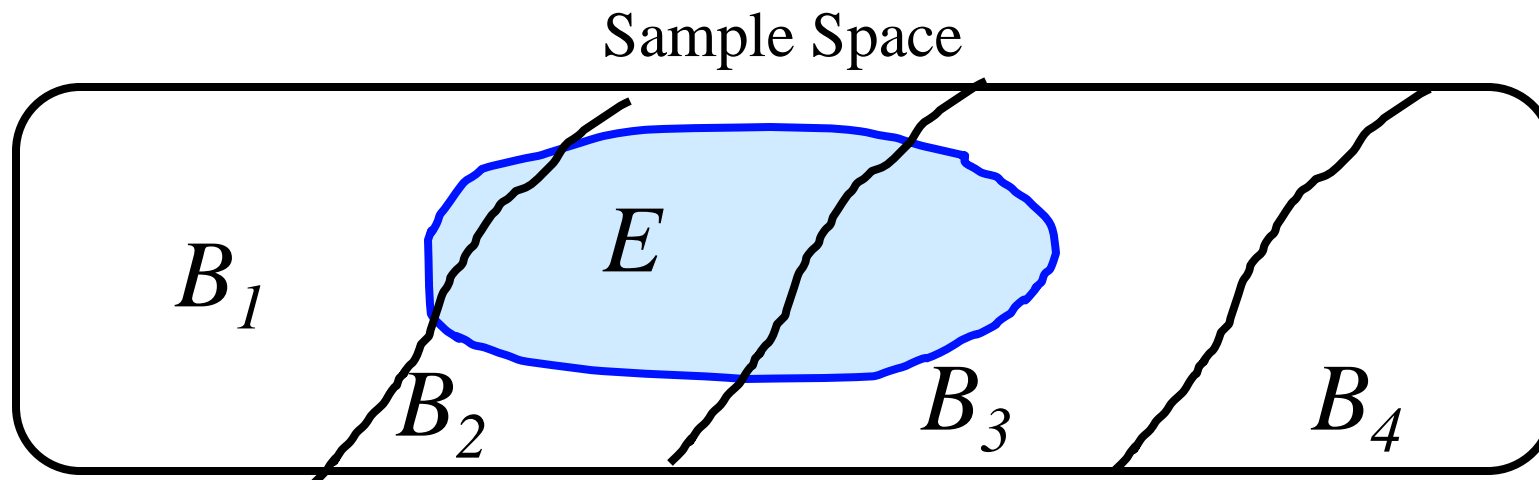
Law of Total Probability



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



Law of Total Probability



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

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



Results for San Francisco, CA



49

°F | °C

Precipitation: 90%

Humidity: 74%

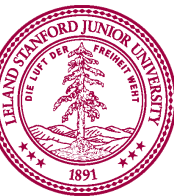
Wind: 8 mph

Weather

Monday

Rain showers

Background event.
Where is the person in
San Francisco?



Results for San Francisco, CA



49

°F | °C

Precipitation: 90%

Humidity: 74%

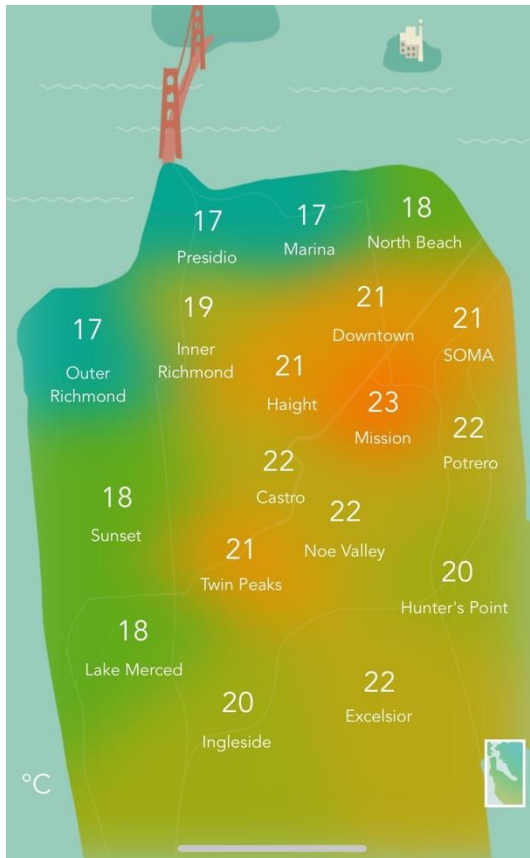
Wind: 8 mph

Weather

Monday

Rain showers

Background event.
Where is the person in
San Francisco?



From Google's Perspective:
There are 18 different "districts" in San Francisco.

Know:

It rains tomorrow

$$P(R|D_i)$$

Person is in district i

$$P(D_i)$$

Want:

$$P(R)$$



Results for San Francisco, CA



49

°F | °C

Precipitation: 90%

Humidity: 74%

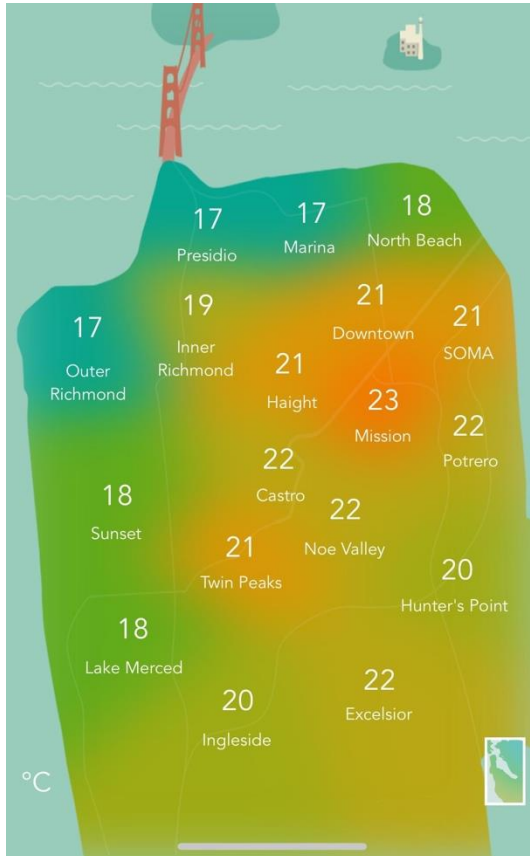
Wind: 8 mph

Weather

Monday

Rain showers

Background event.
Where is the person in
San Francisco?



From Google's Perspective:
There are 18 different "districts" in San Francisco.

Know:

	Mission District	Presidio	...	SOMA
$P(R D_i)$	0.23	0.84	...	0.52
$P(D_i)$	0.15	0.02		0.24

Want:

$$P(R)$$

Results for San Francisco, CA



49

°F | °C

Precipitation: 90%

Humidity: 74%

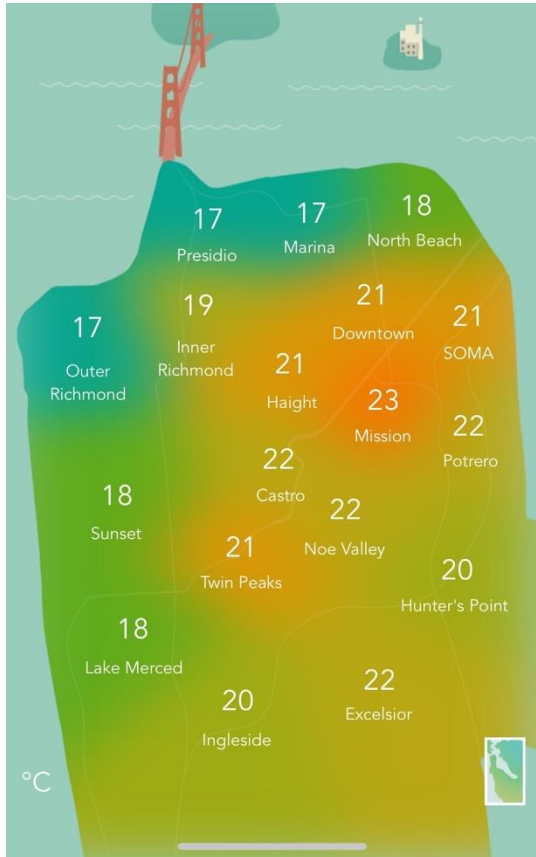
Wind: 8 mph

Weather

Monday

Rain showers

Background event.
Where is the person in
San Francisco?



From Google's Perspective:
There are 18 different "districts" in San Francisco.

Know:

	Mission District	Presidio		SOMA
$P(R D_i)$	0.23	0.84	...	0.52
$P(D_i)$	0.15	0.02		0.24

Want:

$$P(R) = \sum_{\text{district } i} P(R \text{ and } D_i) = \sum_{\text{district } i} P(R|D_i) \cdot P(D_i)$$



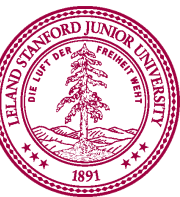
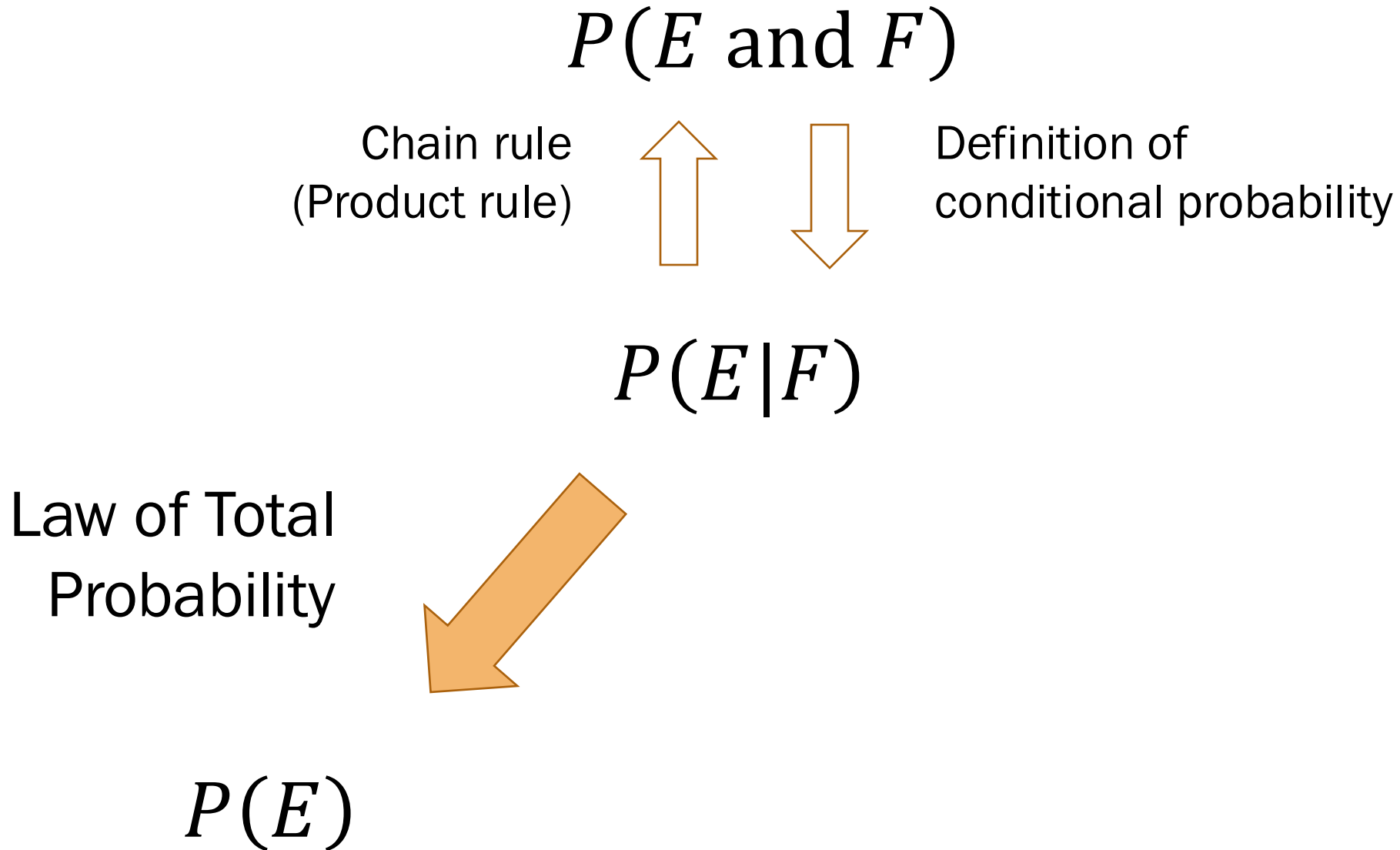
Know:

$P(\text{Cries} \mid \text{Poop}), P(\text{Cries}), P(\text{Poop})$

Real question. What is the probability of poop
given the baby cries...

$P(\text{Poop} \mid \text{Cries})$

Relationship Between Probabilities

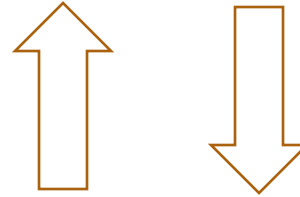


Relationship Between Probabilities



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

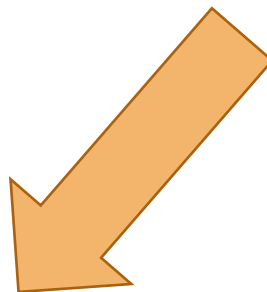
Chain rule
(Product rule)



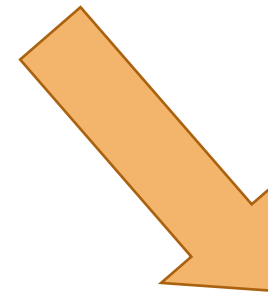
Definition of
conditional probability

$$P(E|F)$$

Law of Total
Probability

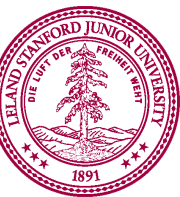


Bayes'
Theorem



$$P(E)$$

$$P(F|E)$$



Bayes' Theorem

Thomas Bayes

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



He looked remarkably similar to Sean Astin
(but that's not important right now)

Thomas Bayes

$$P(F | E)$$



I want to calculate
 $P(\text{State of the world } F \mid \text{Observation } E)$
It seems so tricky!...

The other way around is easy
 $P(\text{Observation } E \mid \text{State of the world } F)$
What options to I have, chief?

$$P(E | F)$$

Thomas Bayes

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

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

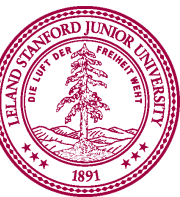


A little while later...

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

A little while later...

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



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:

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

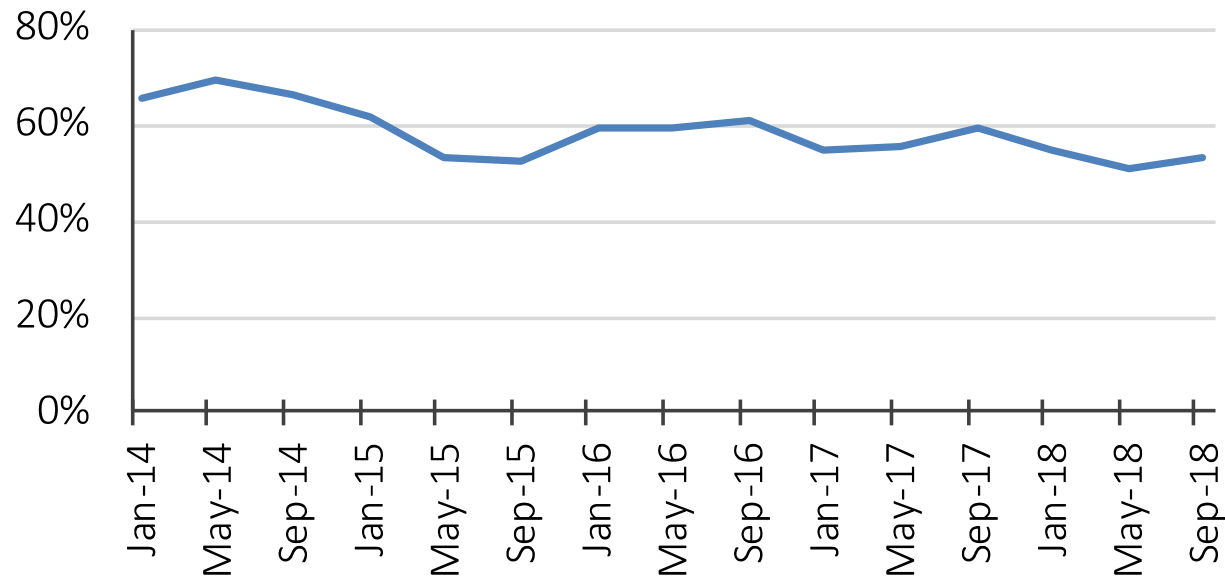
Proof

1 more step! See board



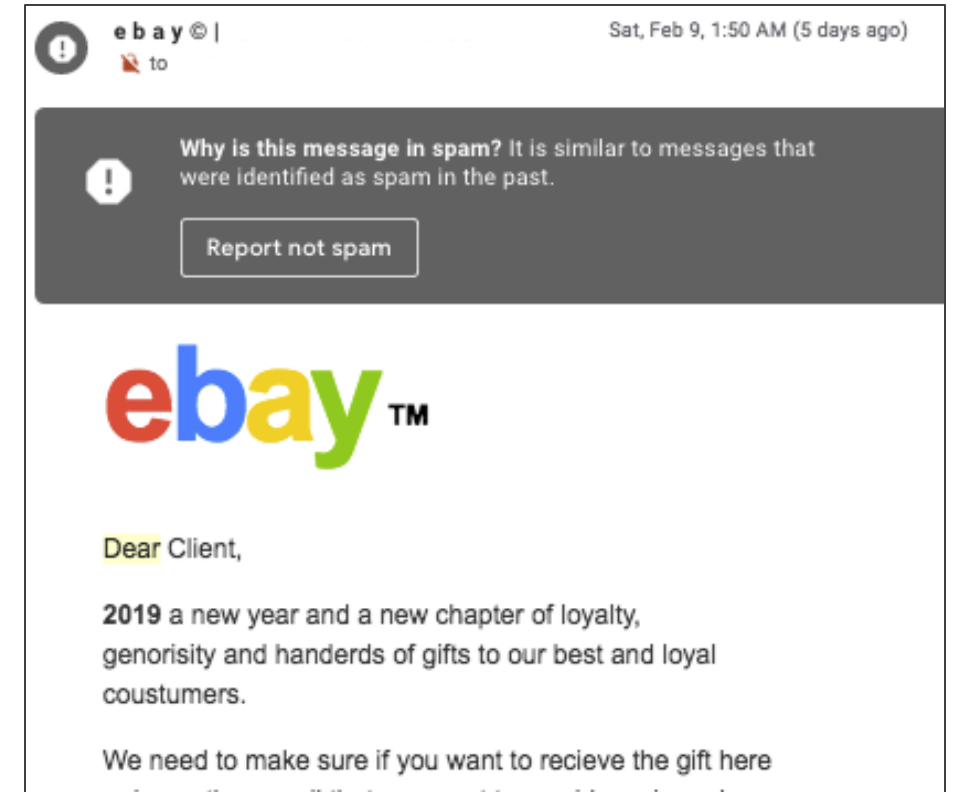
Detecting spam email

Spam volume as percentage of total email traffic worldwide



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

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



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

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

(silent drumroll)



Detecting spam email

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

- 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?

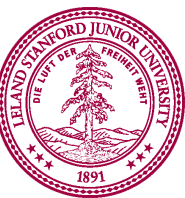
1. Define events
& state goal

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.
- 20% of spam has the word “Dear”
- 1% of non-spam (aka ham) has the word “Dear”

$$P(F)$$

$$P(E|F)$$

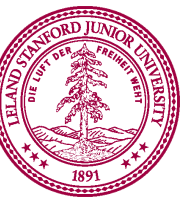
$$P(E|F^C)$$

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

What is the probability that the email is spam?

Want: $P(F|E)$

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



SARS Virus Testing

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 $P(F | E)$?

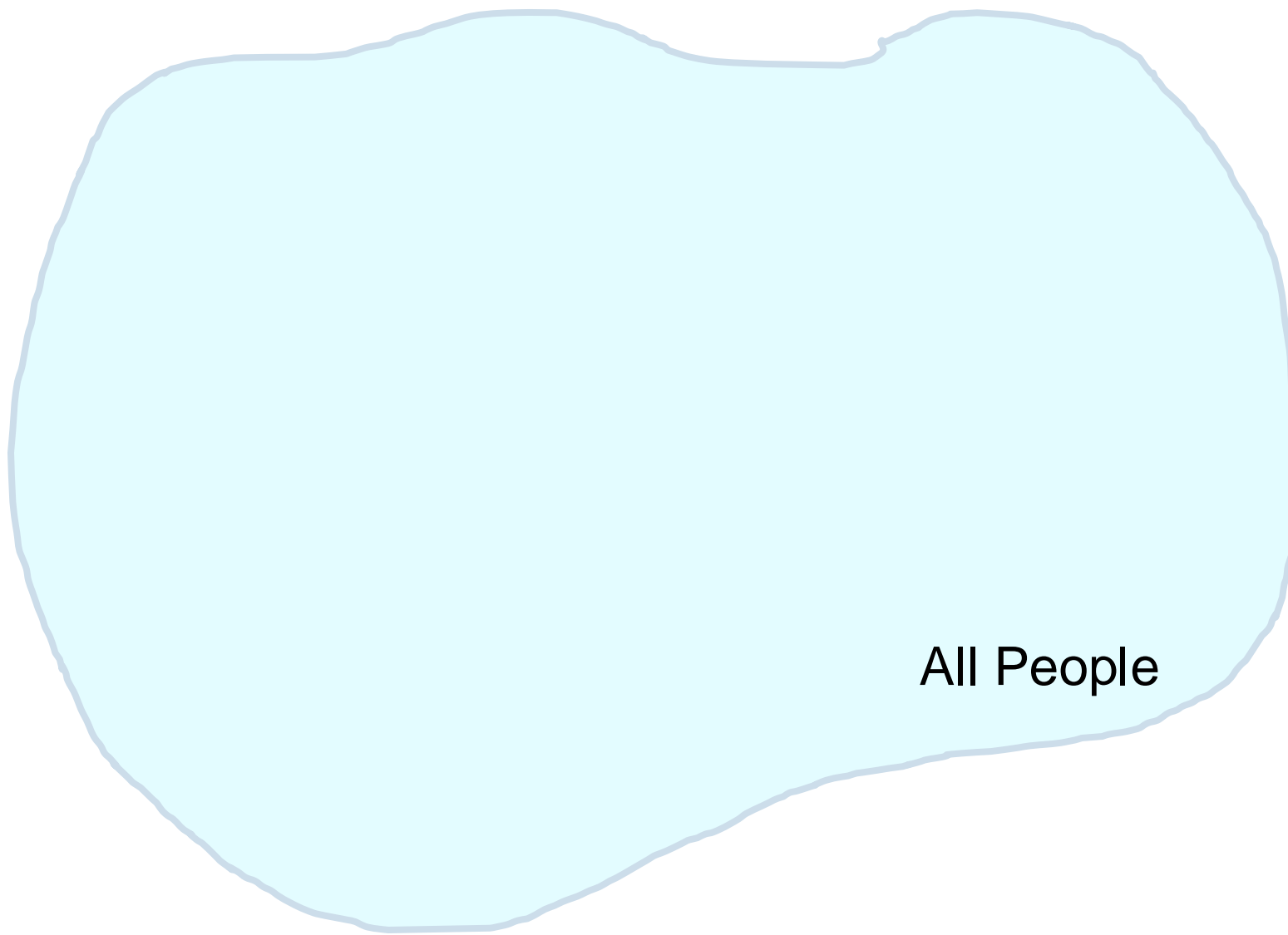
Solution:

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

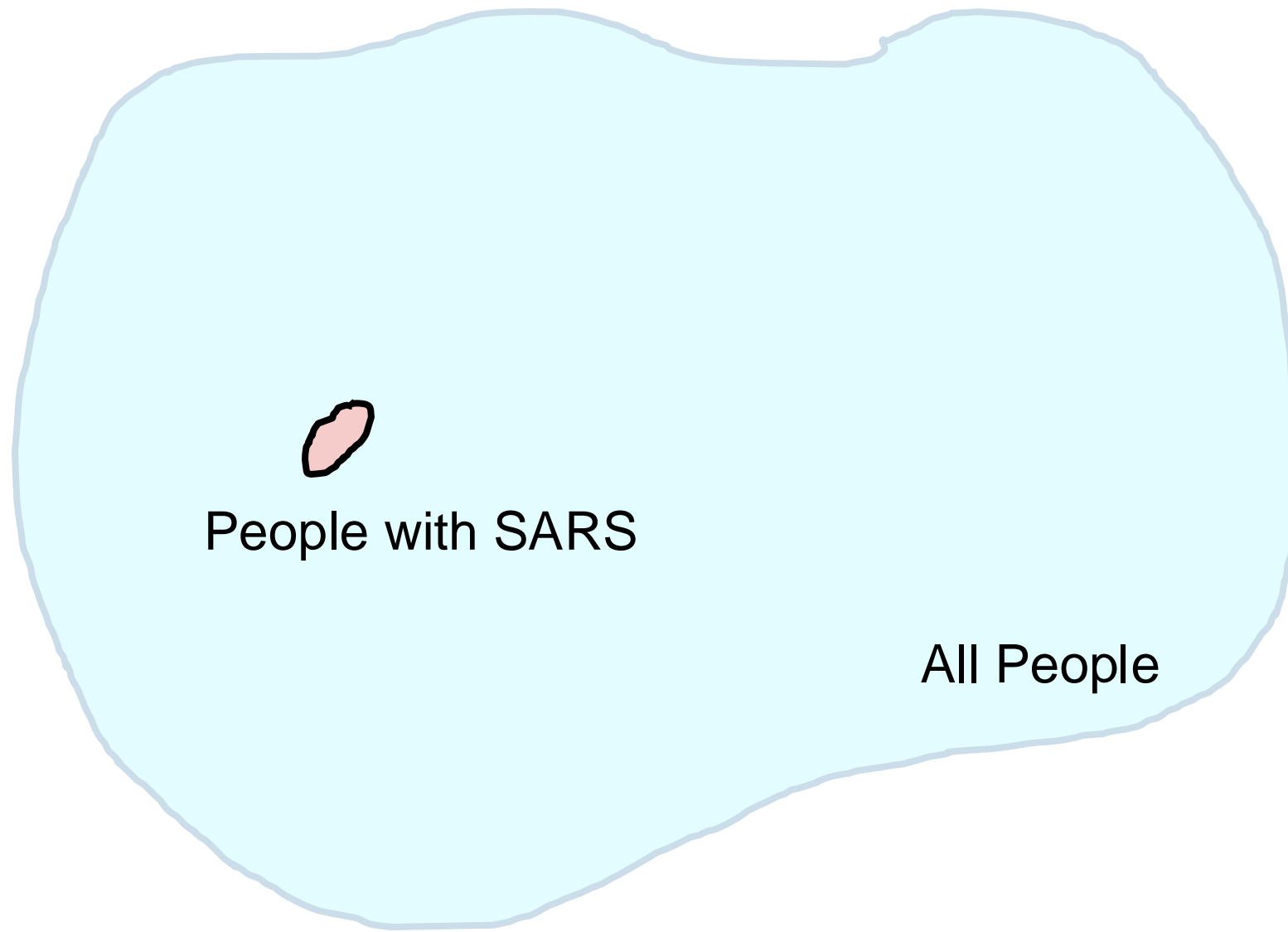


Intuition Time

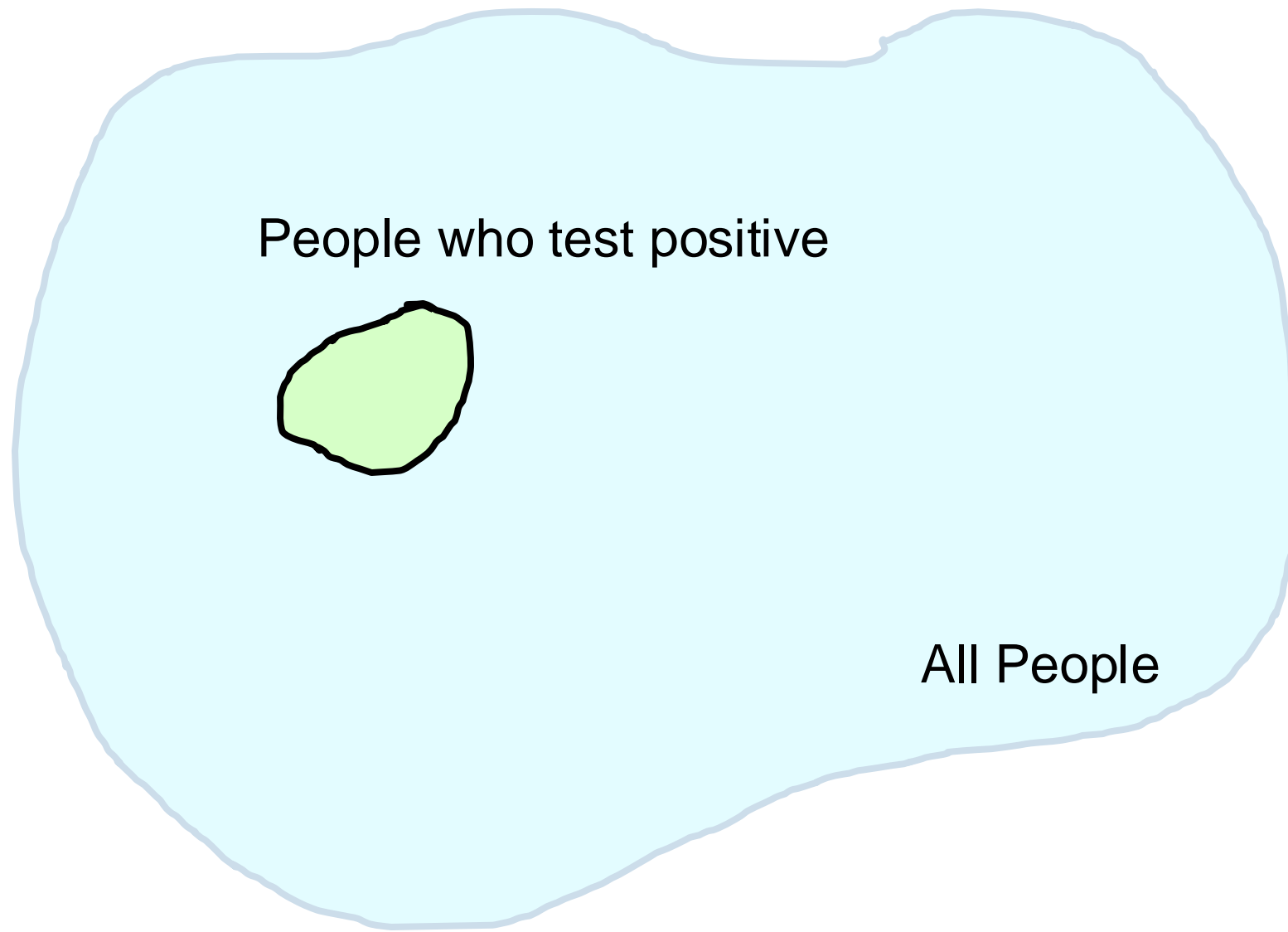
Bayes Thorem Intuition



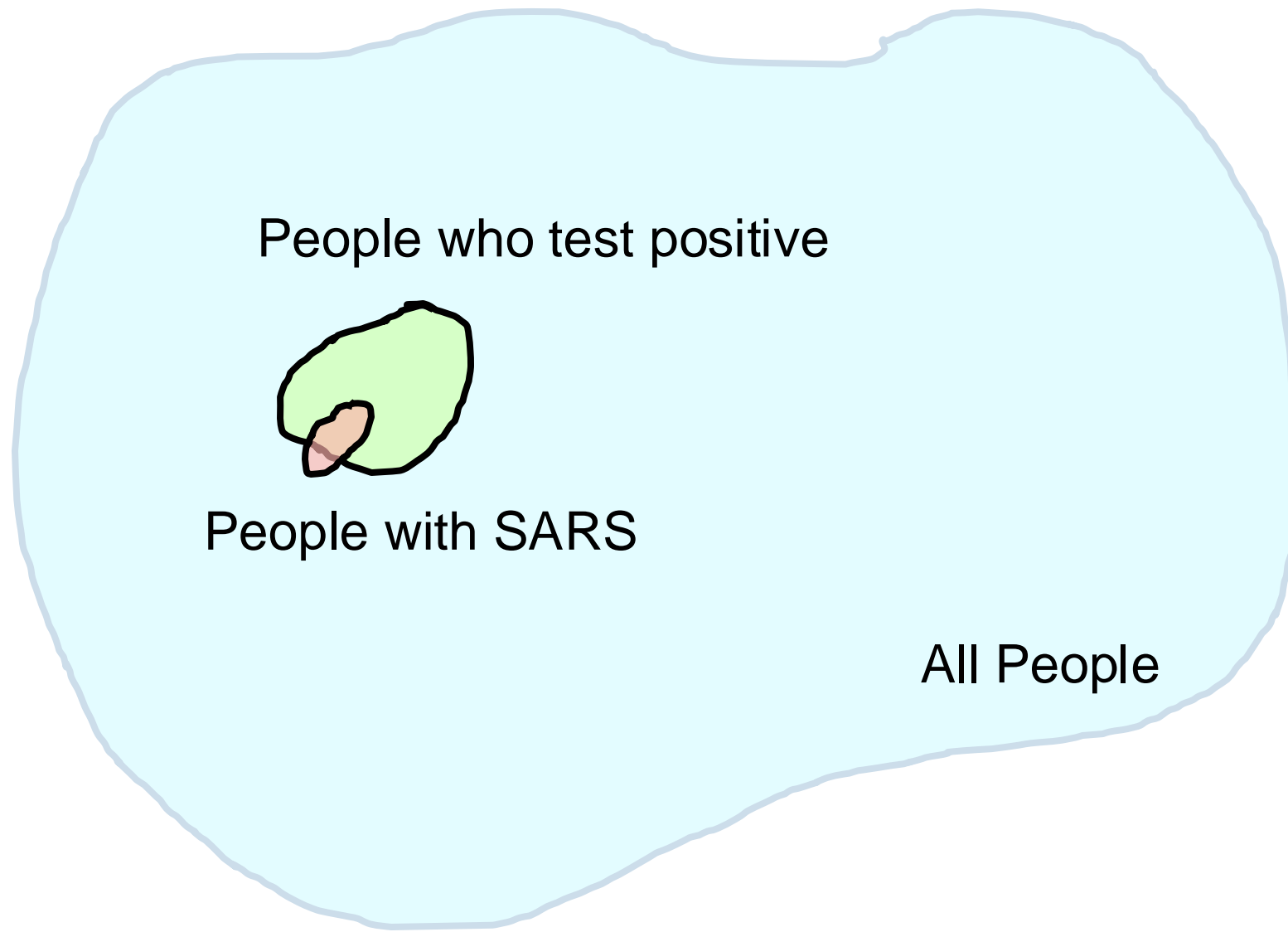
Bayes Theorem Intuition



Bayes Thorem Intuition

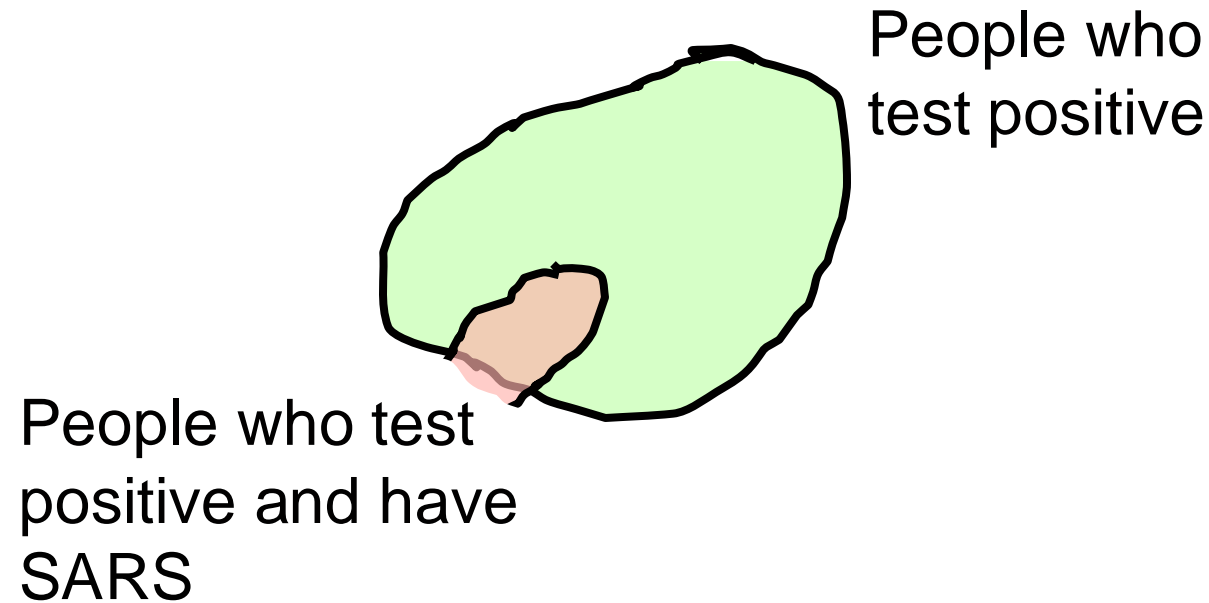


Bayes Theorem Intuition

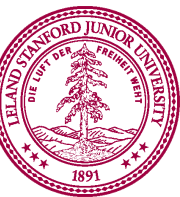


Bayes Theorem Intuition

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

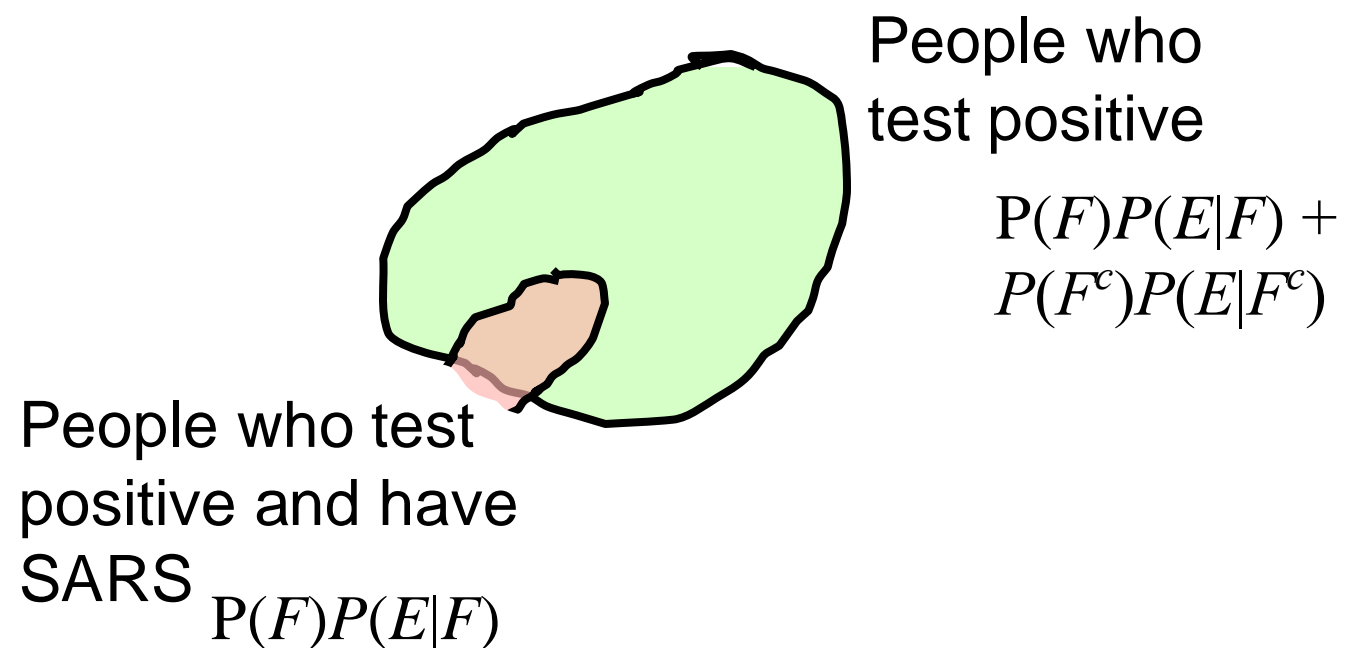


≈ 0.330



Bayes Theorem Intuition

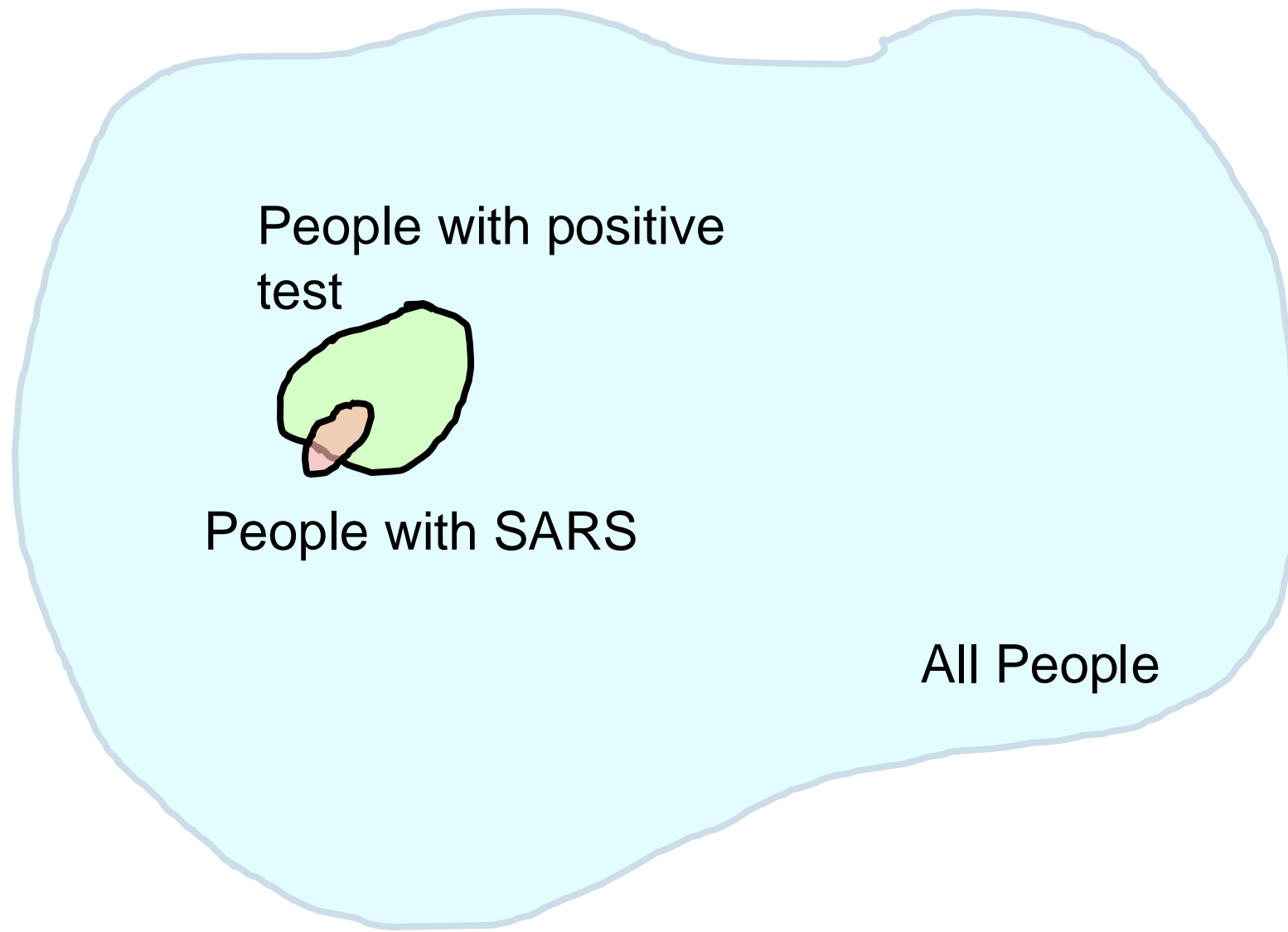
Conditioning on a positive result changes the sample space to this:



≈ 0.330

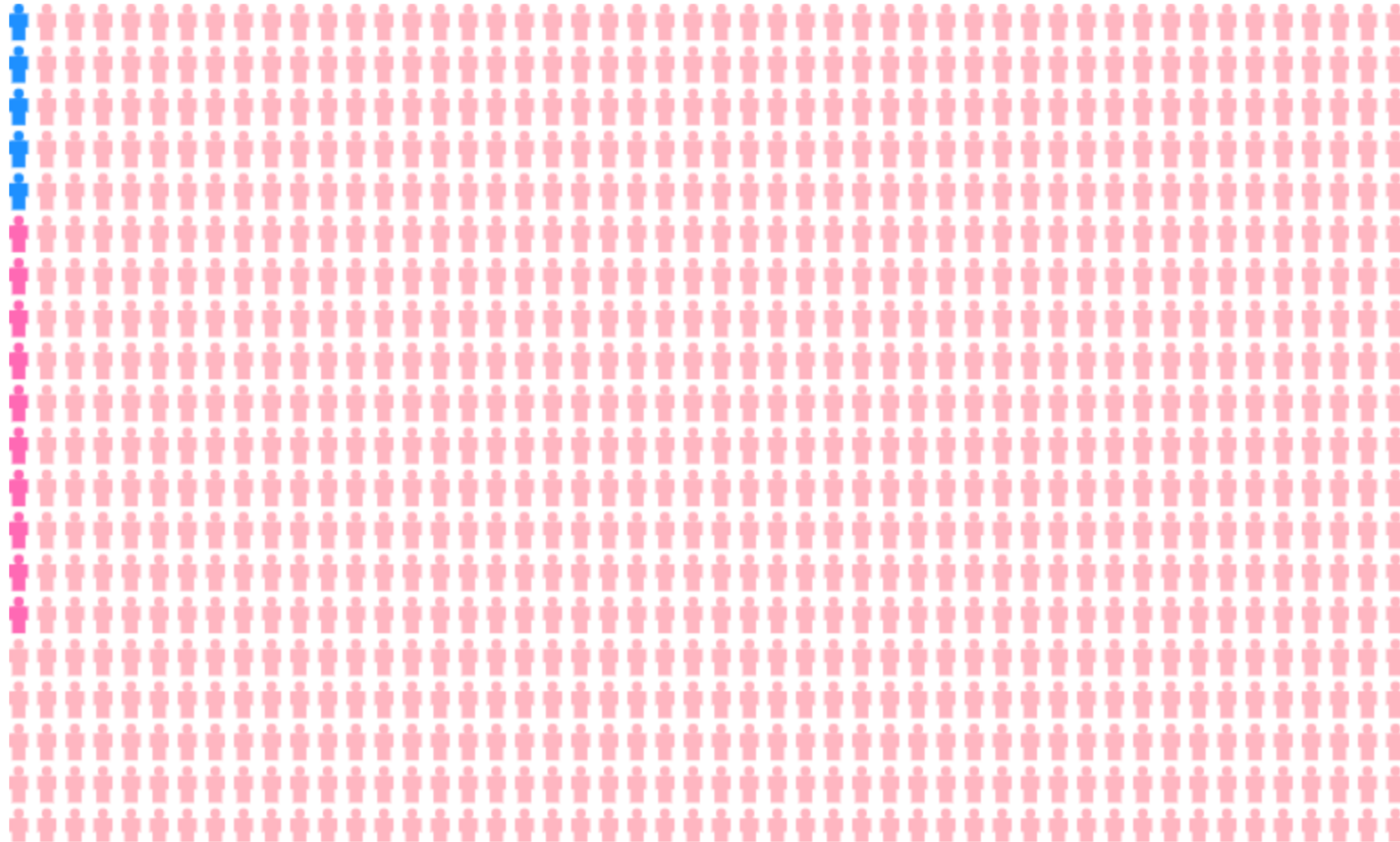


Bayes Theorem Intuition

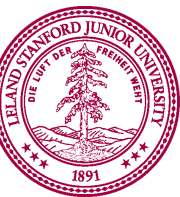


Bayes Theorem Intuition

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. ≈ 0.333

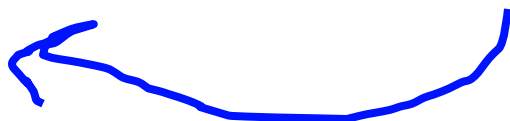


Bayes Theorem Intuition

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. ≈ 0.333



Why it is still good to get tested

	SARS +	SARS –
Test +	$0.98 = P(E F)$	$0.01 = P(E F^c)$
Test –	$0.02 = P(E^c F)$	$0.99 = P(E^c F^c)$

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

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

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



Pedagogic Pause

Multiple Choice Theory

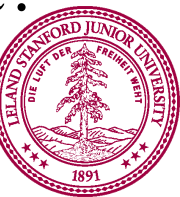
Let's consider the relationship between **knowing** the concepts used in a multiple choice midterm question, and getting the question correct, taking into account guessing and making silly mistakes.

Let $3/4$ be the probability that a learner knows the concepts to a midterm question.

Let $1/4$ be the probability that a learner gets the answer **correct** if they **don't** know the concepts.

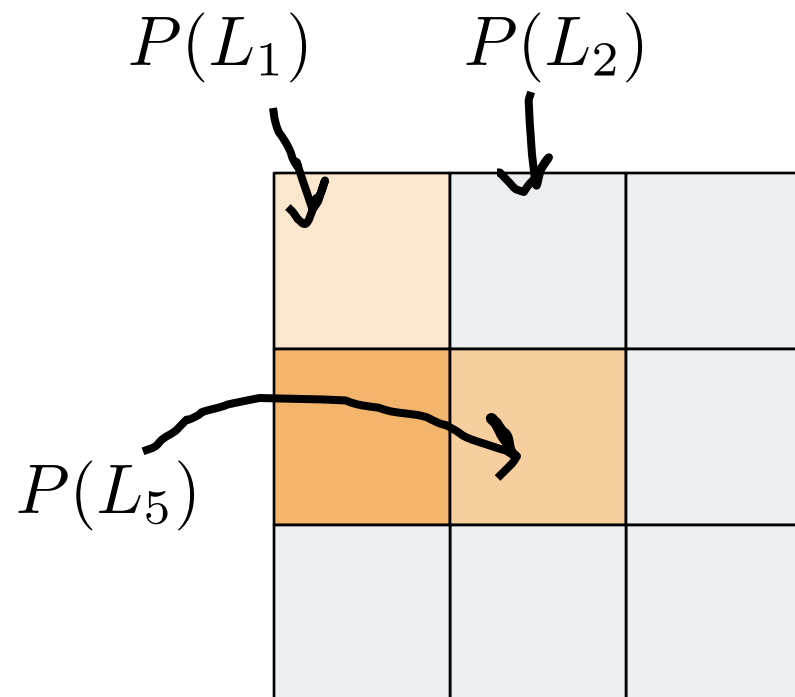
Let $9/10$ be the probability that a learner gets the question **correct** given they **do** know the concepts.

What is the probability they know the concept, given they answered correct?

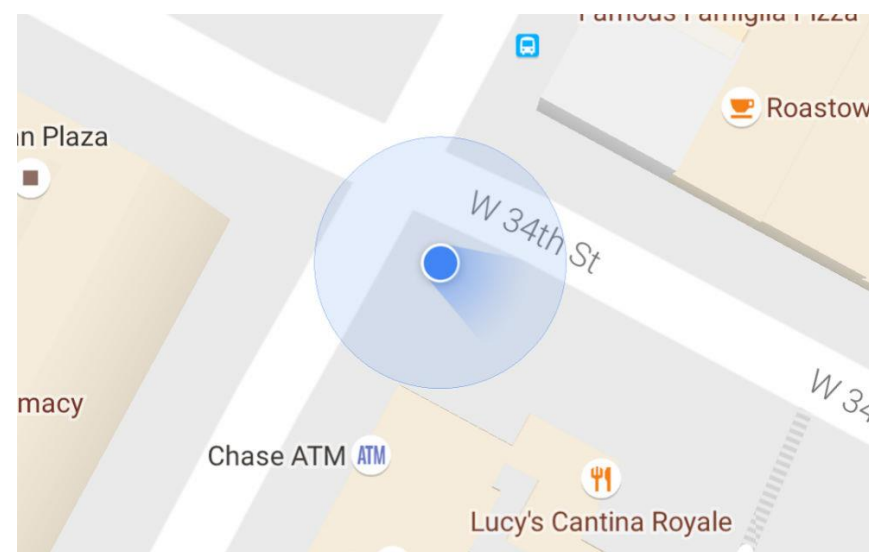


Advanced

Bayes' Theorem and Location

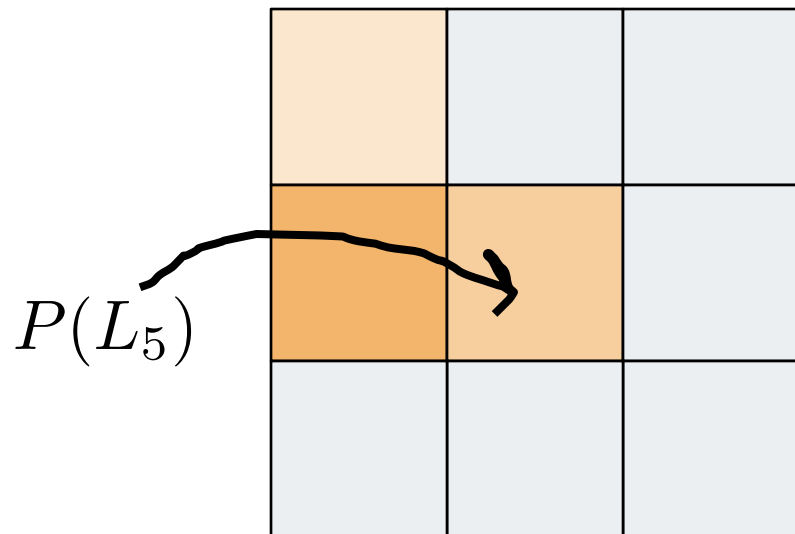


Before Observation

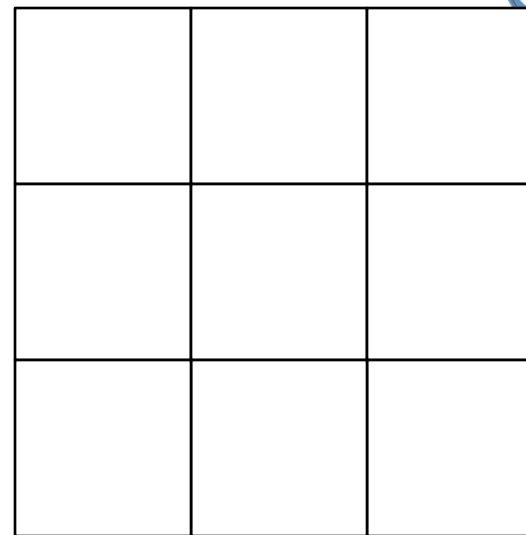


Bayes' Theorem and Location

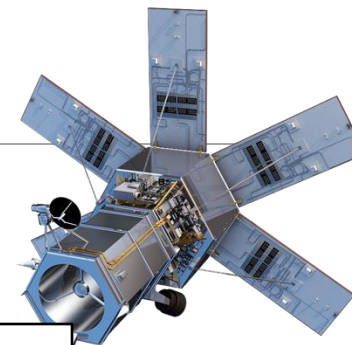
Know: $P(O|L_i)$



Before Observation

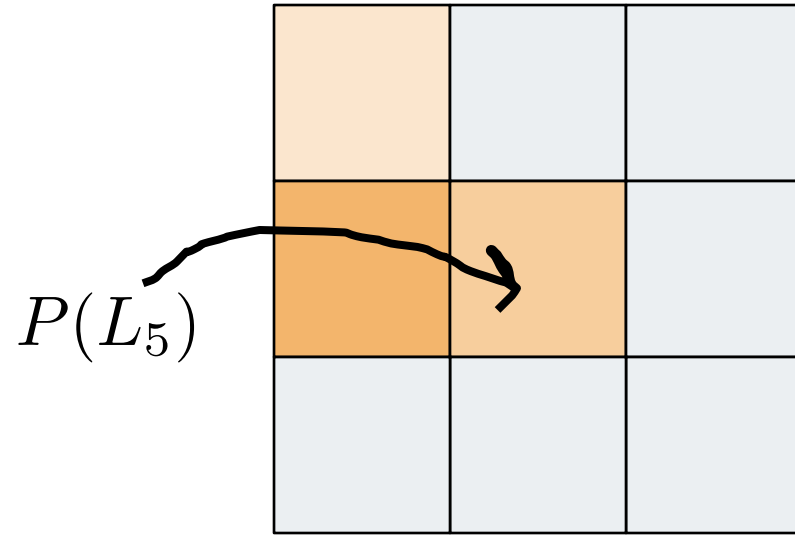


After Observation

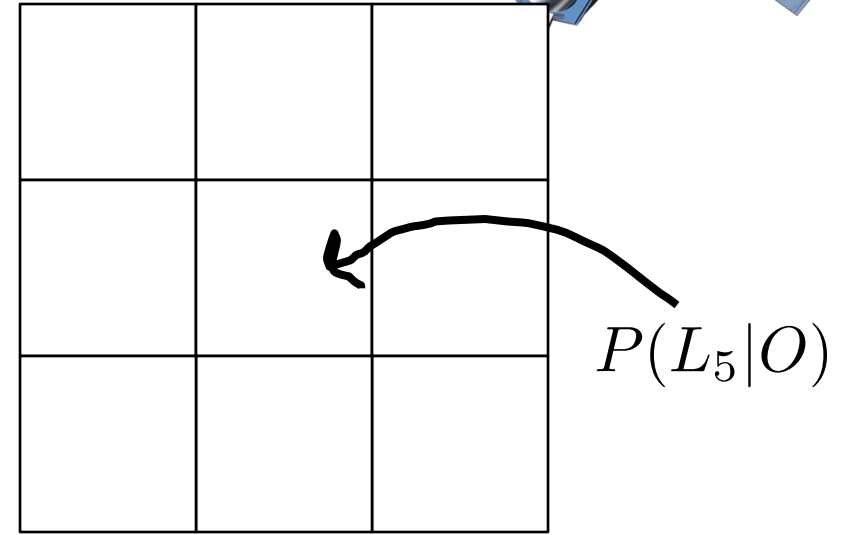


Bayes' Theorem and Location

Know: $P(O|L_i)$

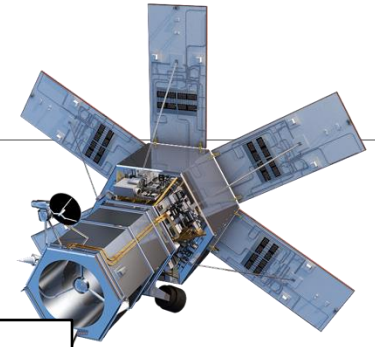


Before Observation

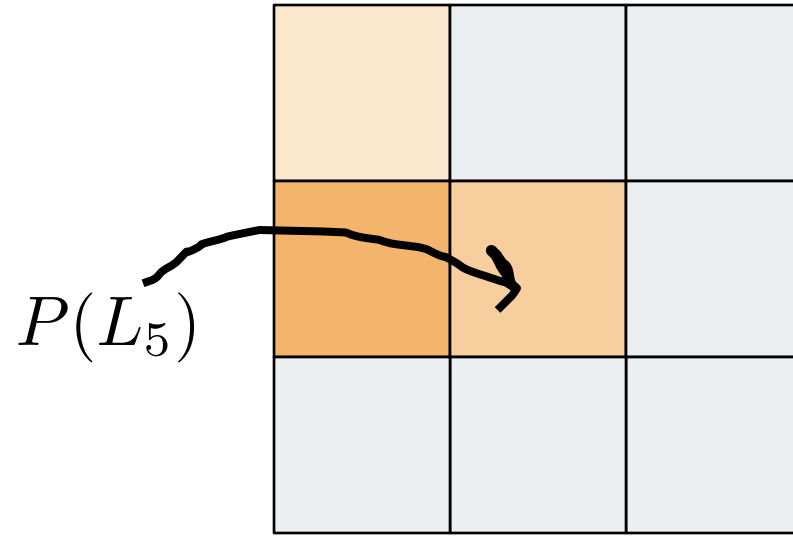


After Observation

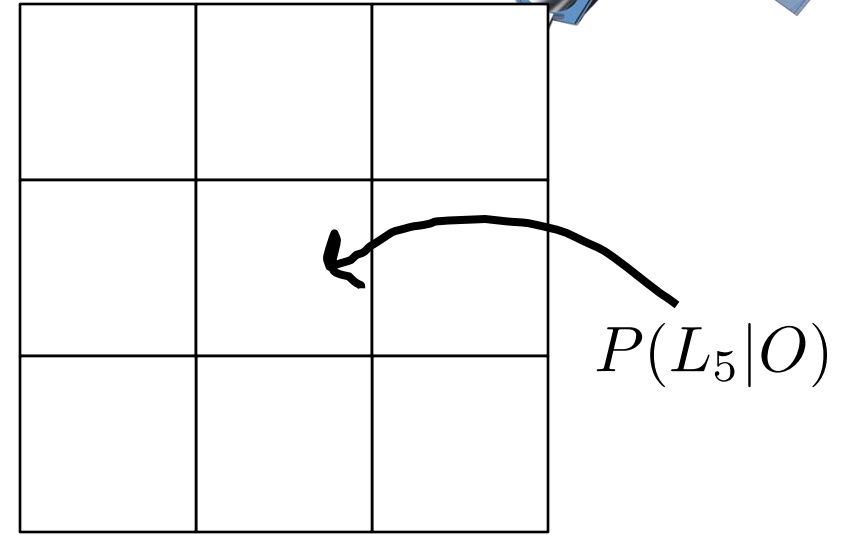
$$P(L_5|O) = \frac{P(O|L_5)P(L_5)}{P(O)}$$



Bayes' Theorem and Location



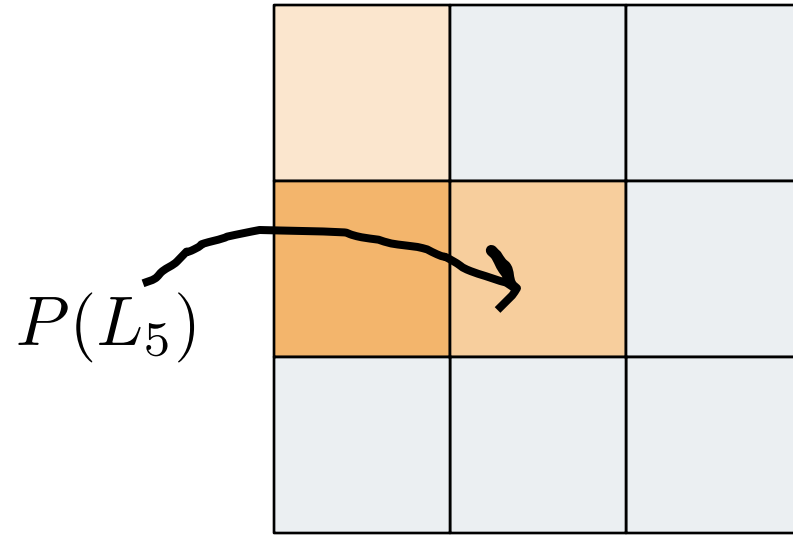
Before Observation



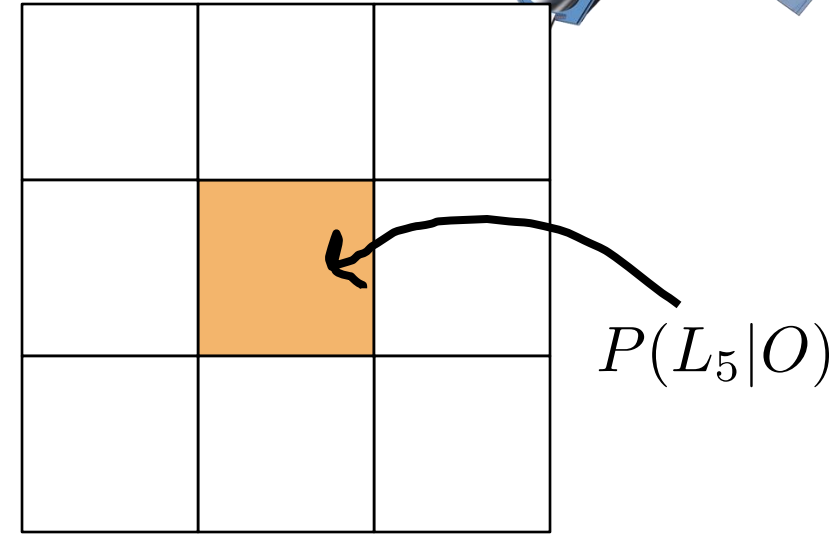
After Observation

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

Bayes' Theorem and Location



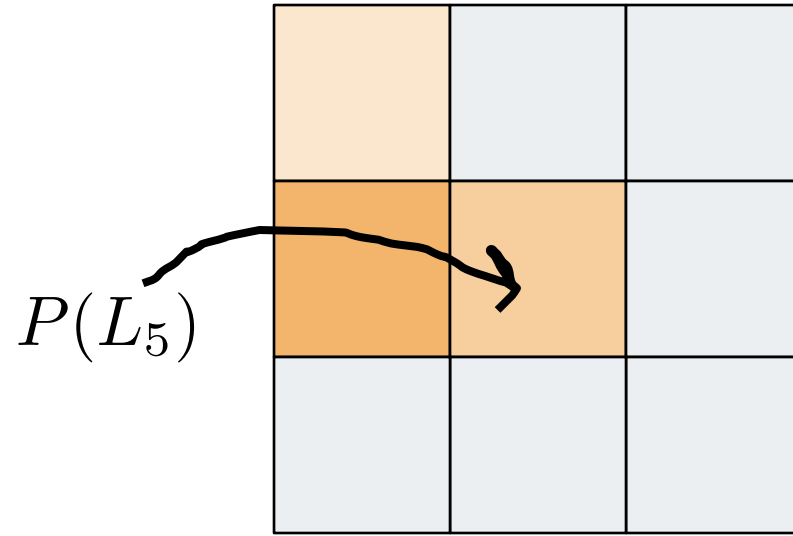
Before Observation



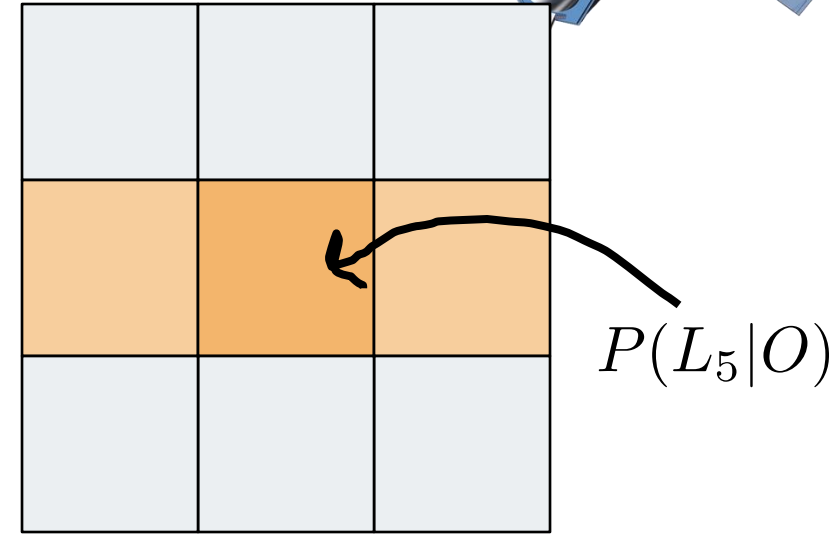
After Observation

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

Bayes' Theorem and Location



Before Observation



After Observation

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

Let's Gamble

Telling in Cards



Your opponent gets excited if they are winning...

Probability of a tell given they
have a winning hand: **0.5**

Probability of a tell given they
don't have a winning hand: **0.1**

The Tell Game

You are playing a game. Your opponent has two unseen cards. If either is an ace you lose...
The following cards are seen by you (ie are not in opponent hand):

3H
2S
3D
5S
9D
KD
AC

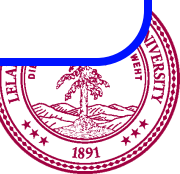
Opponent does **not** have an excited tell...

Do you choose to play?



Probability of a tell given they
have a winning hand: **0.5**

Probability of a tell given they
don't have a winning hand: **0.1**



End Review