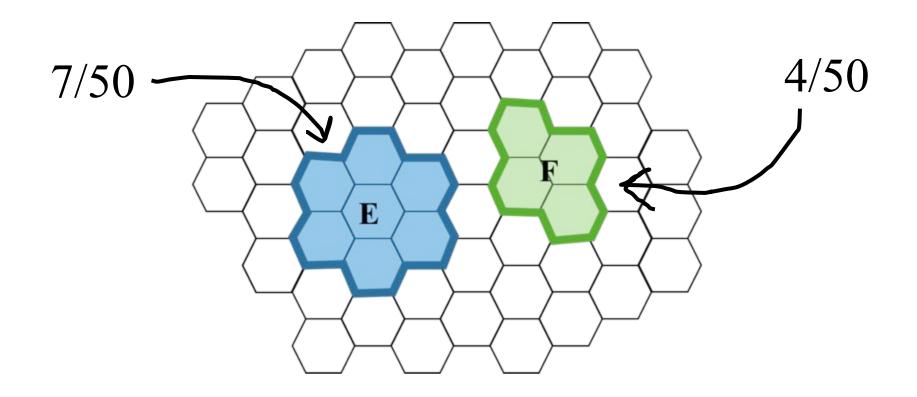


### **Mutually Exclusive Events**

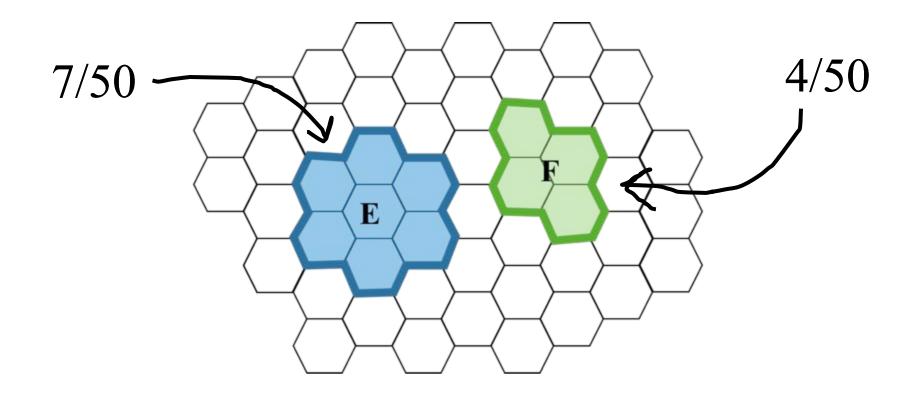


If events are mutually exclusive, probability of OR is simple:

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



### **Mutually Exclusive Events**



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

$$P(E \cup F) = \frac{7}{50} + \frac{4}{5} = \frac{11}{50}$$



### Today's Lesson

# Dice – Our Misunderstood Friends

- Roll two 6-sided dice, yielding values D<sub>1</sub> and D<sub>2</sub>
- Let **E** be event:  $D_1 + D_2 = 4$
- What is P(E)?
  - ISI = 36, E = {(1, 3), (2, 2), (3, 1)}
  - P(E) = 3/36 = 1/12
- Let **F** be event:  $D_1 = 2$
- P(E, given F already observed)?
  - $S = \{(2, 1), (2, 2), (2, 3), (2, 4), (2, 5), (2, 6)\}$
  - E = {(2, 2)}
  - P(E, given F already observed) = 1/6



### Dice – Our Misunderstood Friends

- Two people each roll a die, yielding  $D_1$  and  $D_2$ . You win if  $D_1 + D_2 = 4$
- Q: What do you think is the best outcome for  $D_1$ ?
- 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



- <u>Conditional probability</u> is probability that E occurs *given* that F has already occurred "Conditioning on F"
- Written as P(E|F)
  - Means "P(E, given F already observed)"
  - Sample space, S, reduced to those elements consistent with F  $(i.e. S \cap F)$
  - Event space, E, reduced to those elements consistent with F  $(i.e. E \cap F)$



### With equally likely outcomes:

$$P(E \mid F) = \frac{\# \text{ of outcomes in } E \text{ consistent with } F}{\# \text{ of outcomes in } S \text{ consistent with } F}$$
$$= \frac{|EF|}{|SF|} = \frac{|EF|}{|F|}$$
$$P(E) = \frac{8}{50} \approx 0.16$$
$$P(E|F) = \frac{3}{14} \approx 0.21$$

• General definition:

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

- Holds even when outcomes are not equally likely
- Implies: P(EF) = P(E | F) P(F) (chain rule)

- What if P(F) = 0?
  - P(E | F) undefined
  - Congratulations! You observed the impossible!



### **Generalized Chain Rule**

- General definition of Chain Rule:
  - $P(E_1 E_2 E_3 \dots E_n)$ =  $P(E_1) P(E_2 | E_1) P(E_3 | E_1 E_2) \dots P(E_n | E_1 E_2 \dots E_{n-1})$







+ Learn

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

P(E)



 $S = {Watch, Not Watch}$ 

 $E = {Watch}$ 

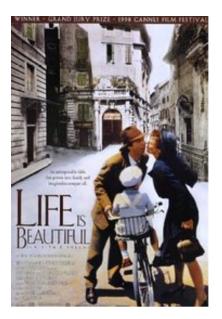
 $P(E) = \frac{1}{2}$ ?





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

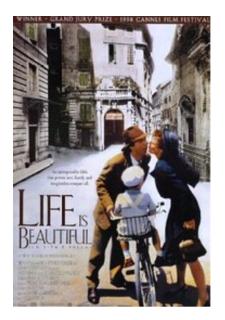
P(E)





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

P(E)



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

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





### Let *E* be the event that a user watched the given movie:





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

P(E|F)



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

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



P(E|F)

$$P(E|F) = \frac{P(EF)}{P(F)} = \frac{\frac{\#\text{people who watched both}}{\#\text{people on Netflix}}}{\frac{\#\text{people who watched }F}{\#\text{people on Netflix}}}$$



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



P(E|F)

$$P(E|F) = \frac{P(EF)}{P(F)} = \frac{\text{\#people who watched both}}{\text{\#people who watched }F}$$

P(E|F) = 0.42Piech, CS106A, Stanford University



Let E be the event that a user watched the given movie, Let F be the event that the same user watched Amelie:





### **Machine Learning**

### Machine Learning is: Probability + Data + Computers



## Sophomores

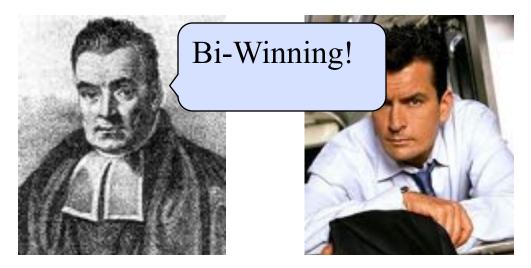
- There are 260 students in CS109:
  - Probability that a random student in CS109 is a Sophomore is 0.43
  - We can observe the probability that a student is both a Sophomore and is in class
  - What is the conditional probability of a student coming to class given that they are a Sophomore?
- Solution:
  - -S is the event that a student is a sophomore
  - -A is the event that a student is in class

$$P(A|S) = \frac{P(SA)}{P(S)}$$



### **Thomas Bayes**

 Rev. Thomas Bayes (1702 –1761) was a British mathematician and Presbyterian minister



He looked remarkably similar to Charlie Sheen
But that's not important right now...



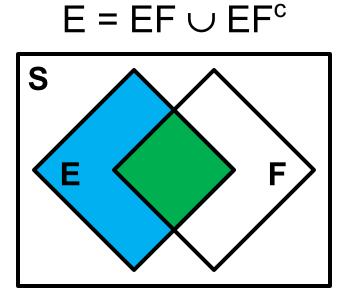
### **But First!**

### Piech, CS106A, Stanford University



### So, $P(E) = P(EF) + P(EF^{c})$

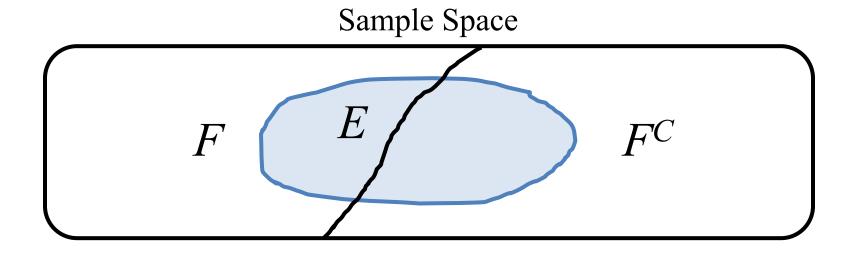
Note:  $EF \cap EF^c = \emptyset$ 



### **Background Observation**

Say E and F are events in S

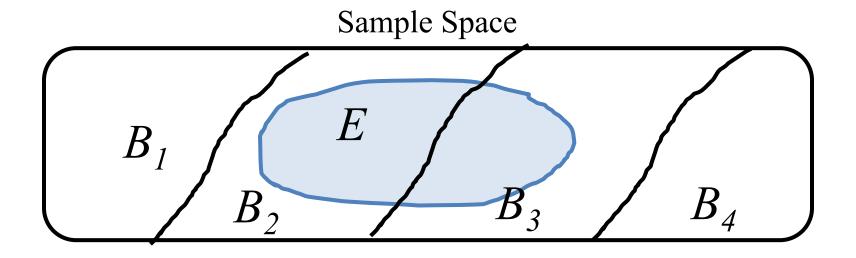
### Law of Total Probability



# $P(E) = P(EF) + P(EF^{C})$ $= P(E|F)P(F) + P(E|F^{C})P(F^{C})$



### Law of Total Probability



$$P(E) = \sum_{i} P(B_i \cap E)$$
$$= \sum_{i} P(E|B_i)P(B_i)$$





Moment of Silence...

### **Bayes Theorem**



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

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

P(E | F)



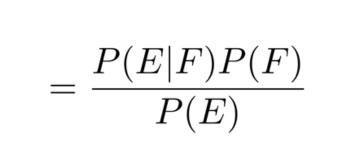
P(F | E)

### **Bayes Theorem**

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

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





Chain Rule





### **Bayes Theorem**

• Most common form:

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



• Expanded form:

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



# **HIV Testing**

- A test is 98% effective at detecting HIV
  - However, test has a "false positive" rate of 1%
  - 0.5% of US population has HIV
  - Let E = you test positive for HIV with this test
  - Let F = you actually have HIV
  - What is P(F | E)?
- Solution:



# **HIV Testing**

- A test is 98% effective at detecting HIV
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  - What is P(F | E)?
- Solution:

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

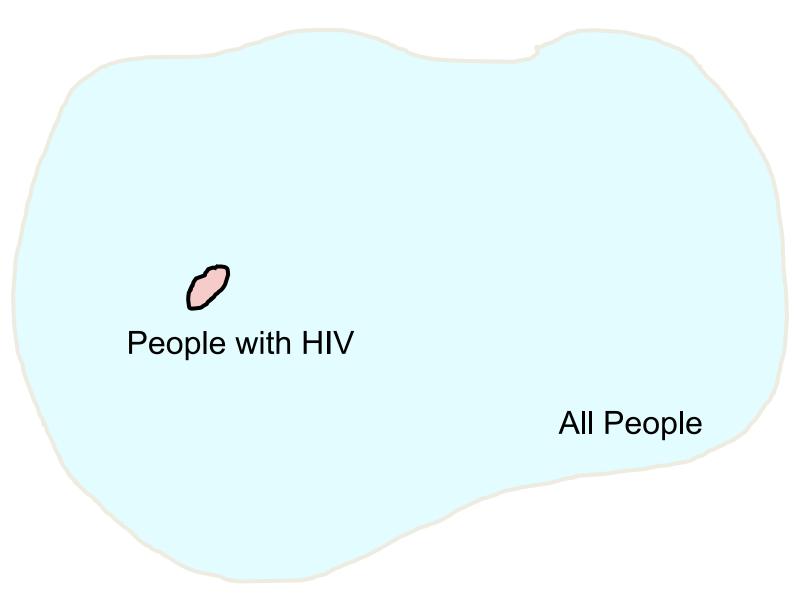
### **Intuition Time**

### **Bayes Theorem Intuition**

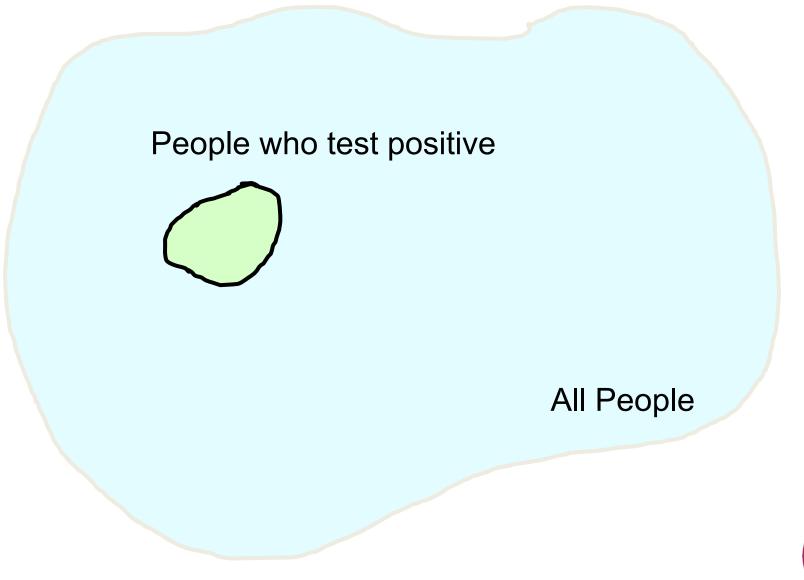
# All People

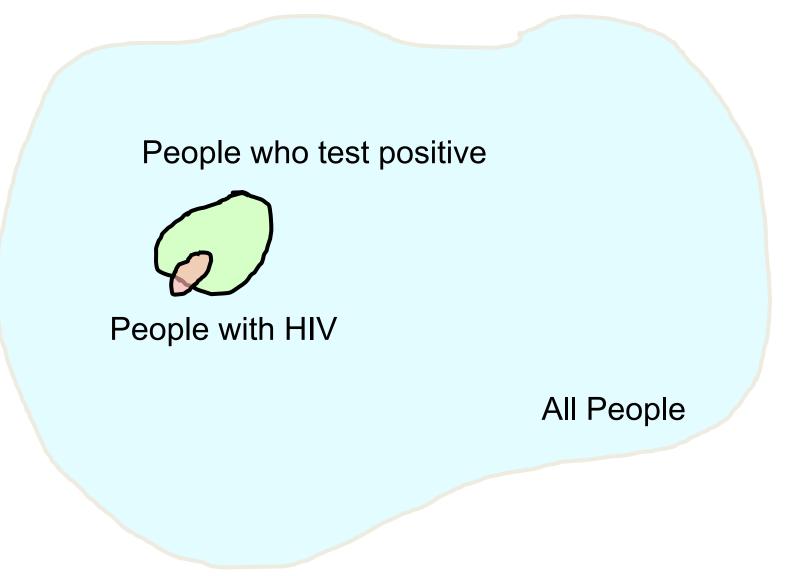


### **Bayes Theorem Intuition**



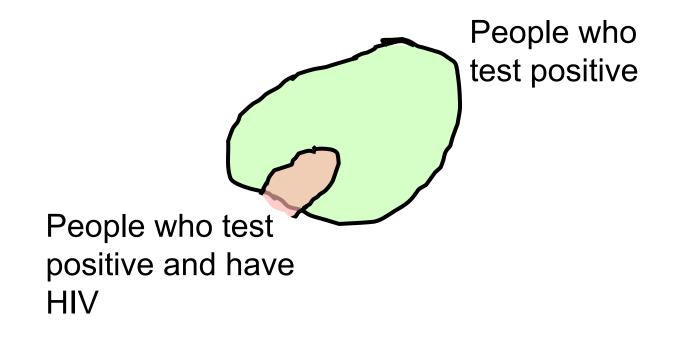








Conditioning on a positive result changes the sample space to this:

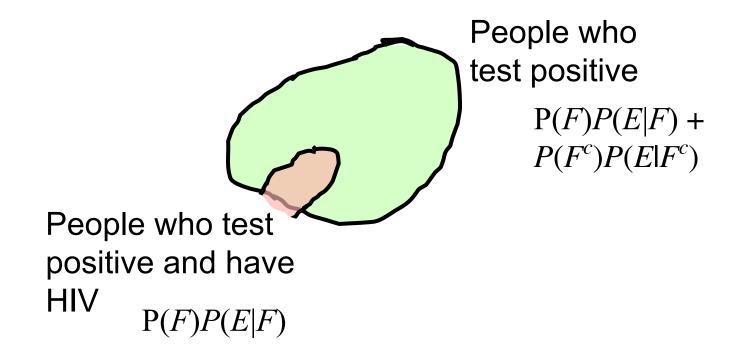




Piech, CS106A, Stanford University

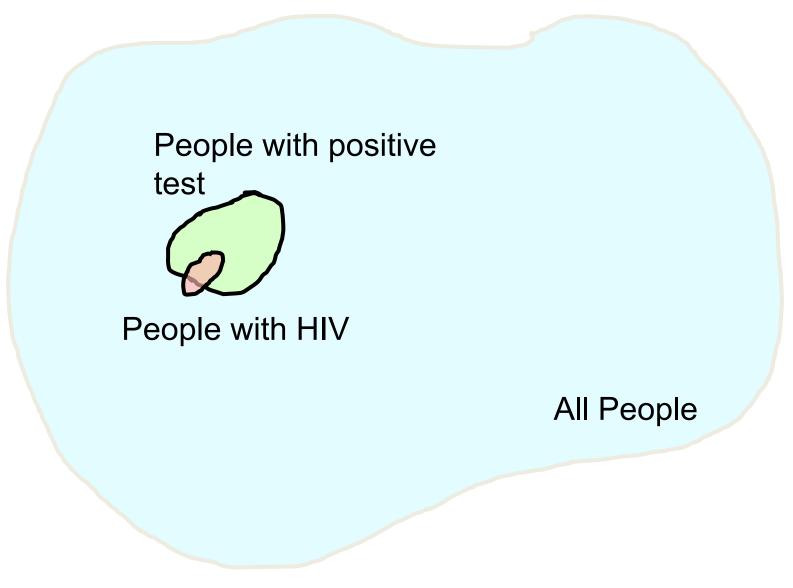
≈ 0.330

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











Say we have 1000 people:



5 have HIV and test positive, 985 do not have HIV and test negative 10 do not have HIV and test positive. Piech. CS106A. Sta  $\approx 0.333$  iversity



# Why It's Still Good to get Tested

	HIV +	HIV –
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<sup>c</sup> = you test <u>negative</u> for HIV with this test
- Let F = you actually have HIV
- What is P(F | E<sup>c</sup>)?

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

# **Slicing Up Spam**



In 2010 88% of email was spam Piech, CS106A, Stanford University

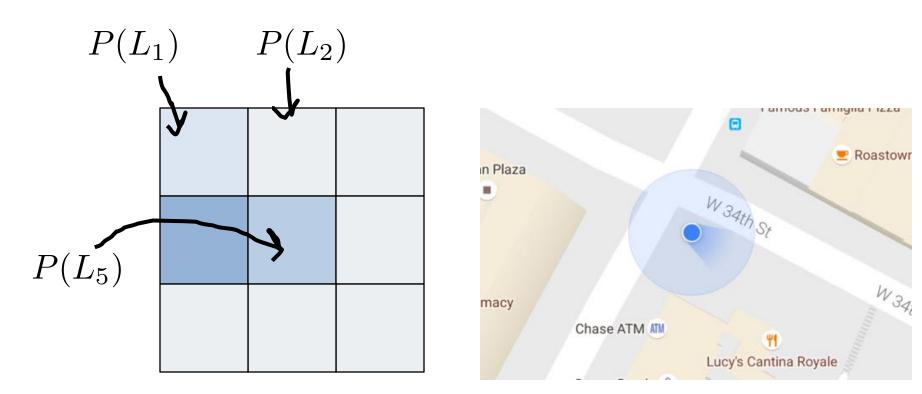


# **Simple Spam Detection**

- Say 60% of all email is spam
  - 90% of spam has a forged header
  - 20% of non-spam has a forged header
  - Let E = message contains a forged header
  - Let F = message is spam
  - What is P(F | E)?
- Solution:  $P(F \mid E) = \frac{P(E \mid F) P(F)}{P(E \mid F) P(F) + P(E \mid F^c) P(F^c)}$

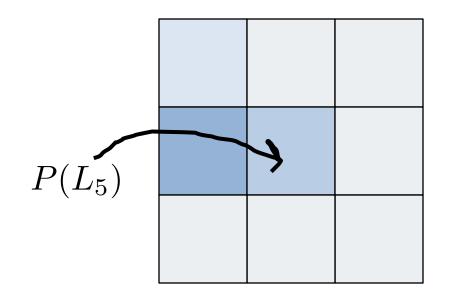
 $P(F \mid E) = \frac{(0.9)(0.6)}{(0.9)(0.6) + (0.2)(0.4)} \approx 0.871$ 





#### **Before Observation**



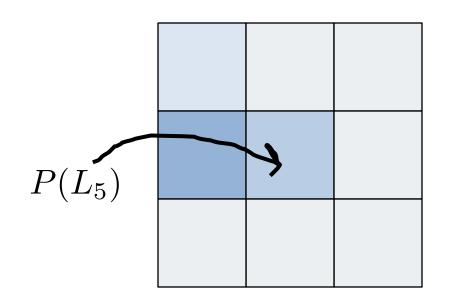


**Before Observation** 

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#### After Observation





**Before Observation** 

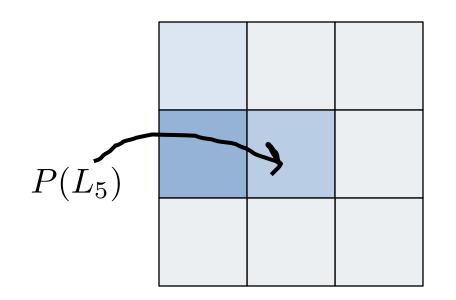
After Observation

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

Piech, CS106A, Stanford University



 $P(L_5|O)$ 



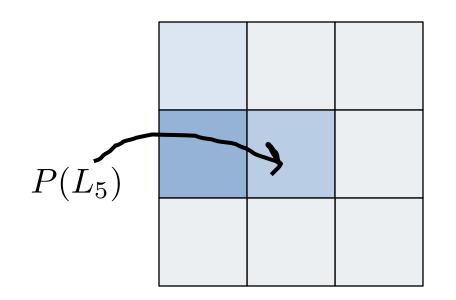
**Before Observation** 

After Observation

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



 $P(L_5|O)$ 



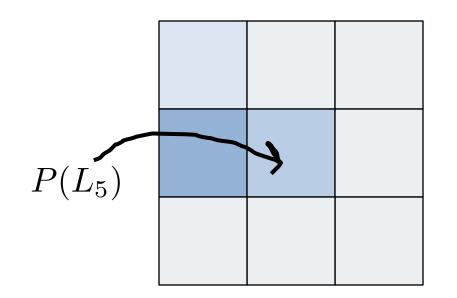
**Before Observation** 

After Observation

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



 $P(L_5|O)$ 



**Before Observation** 

After Observation

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



 $P(L_5|O)$ 

# Monty Hall





# Let's Make a Deal

• Game show with 3 doors: A, B, and C



- Behind one door is prize (equally likely to be any door)
- Behind other two doors is nothing
- We choose a door
- Then host opens 1 of other 2 doors, revealing nothing
- We are given option to change to other door
- Should we?
  - Note: If we don't switch, P(win) = 1/3 (random)



# Let's Make a Deal

- Without loss of generality, say we pick A
  - P(A is winner) = 1/3
    - $_{\odot}$  Host opens either B or C, we <u>always lose</u> by switching
    - $\circ$  P(win | A is winner, picked A, switched) = 0
  - P(B is winner) = 1/3
    - $_{\odot}$  Host <u>must</u> open C (can't open A and can't reveal prize in B)
    - So, by switching, we switch to B and <u>always win</u>
    - $\circ$  P(win | B is winner, picked A, switched) = 1
  - P(C is winner) = 1/3
    - Host <u>must</u> open B (can't open A and can't reveal prize in C)
    - So, by switching, we switch to C and <u>always win</u>
    - $\circ$  P(win | C is winner, picked A, switched) = 1
  - Should always switch!

○ P(win | picked A, switched) = (1/3\*0) + (1/3\*1) + (1/3\*1) = 2/3



# Slight Variant to Clarify

- Start with 1,000 envelopes, of which 1 is winner
  - You get to choose 1 envelope

     Probability of choosing winner = 1/1000
  - Consider remaining 999 envelopes

     Probability one of them is the winner = 999/1000
  - I open 998 of remaining 999 (showing they are empty)
    - Probability the last remaining envelope being winner = 999/1000
  - Should you switch?

Probability winning without switch =

1 original # envelopes

 $\circ$  Probability winning with switch =  $\frac{\text{original # envelopes - 1}}{\text{original # envelopes}}$ 

original # envelopes



