



# Conditional Probability

Review



Make indistinct items  
**distinct** to get equally  
likely sample space  
outcomes

\*You will need to use this “trick” with high probability



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

# Making History

- What is the probability that in the  $n$  shuffles seen since the start of time, yours is unique?
  - $|S| = (52!)^n$
  - $|E| = (52! - 1)^n$
  - $P(\text{no deck matching yours}) = (52! - 1)^n / (52!)^n$
- For  $n = 10^{20}$ ,
  - $P(\text{deck matching yours}) < 0.0000000001$

\* Assume 7 billion people have been shuffling cards once a second since cards were invented

# Axioms of Probability

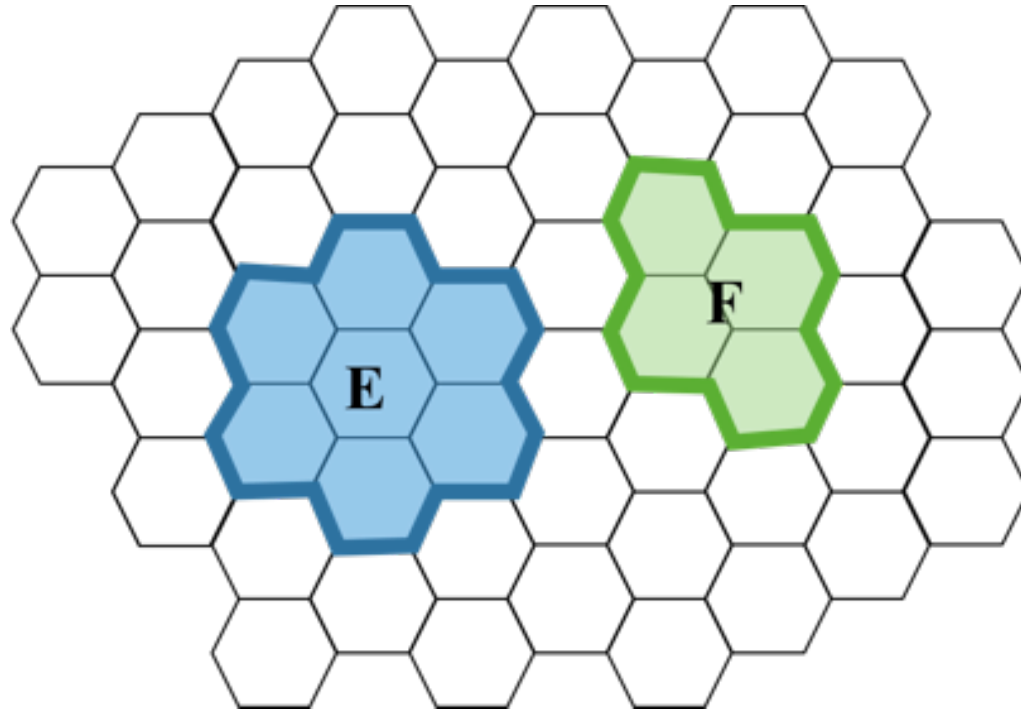
Recall:  $S$  = all possible outcomes.  $E$  = the event.

- 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:

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



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

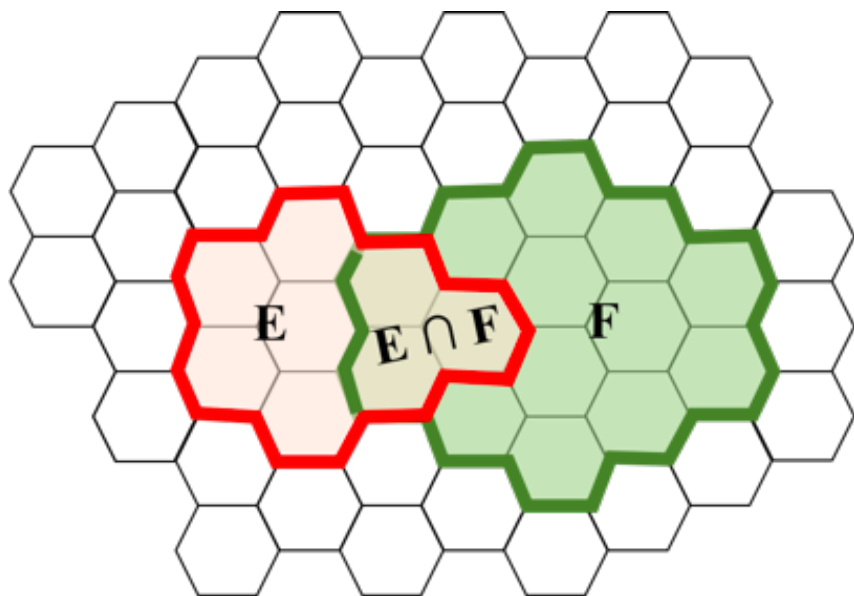
# Conditional Probability

- **Conditional probability** 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.  $E \cap F$ )

# Conditional Probability

With equally likely outcomes:

$$\begin{aligned} P(E | F) &= \frac{\# \text{ of outcomes in } E \text{ consistent with } F}{\# \text{ of outcomes in } S \text{ consistent with } F} \\ &= \frac{|EF|}{|SF|} = \frac{|EF|}{|F|} \end{aligned}$$



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

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

# Conditional Probability

- General definition:

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

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



# Conditional Paradigm

Name of Rule	Original Rule	Conditional Rule
First axiom of probability	$0 \leq P(E) \leq 1$	$0 \leq P(E   G) \leq 1$
Complement Rule	$P(E) = 1 - P(E^C)$	$P(E   G) = 1 - P(E^C   G)$
Chain Rule	$P(EF) = P(E   F)P(F)$	$P(EF   G) = P(E   FG)P(F   G)$



End Review

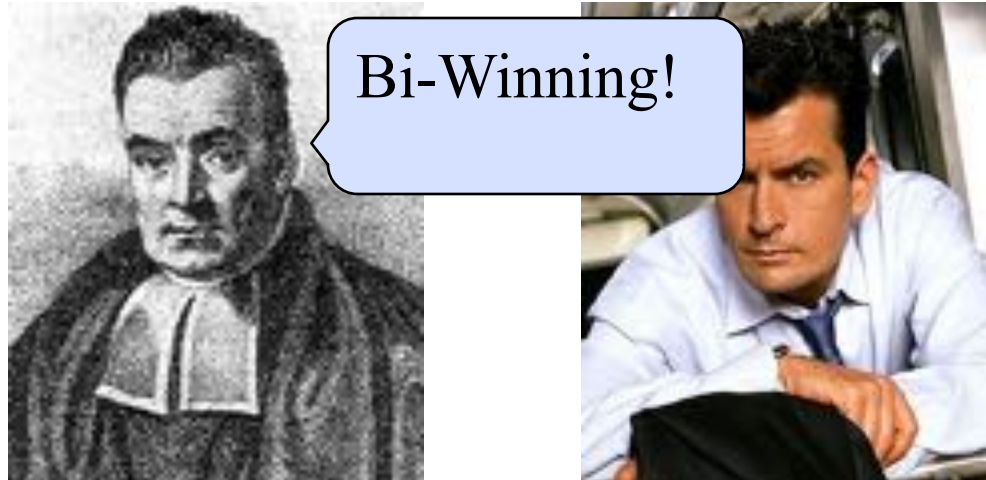
# Undergraduates

- There are 46 students in CS109:
  - Probability that a random student in CS109 is an undergraduate is 0.48
  - We can observe the probability that a student is both an undergraduate and is in class
  - What is the conditional probability of a student coming to class given that they are an undergraduate?
- Solution:
  - $S$  is the event that a student is an undergraduate
  - $A$  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



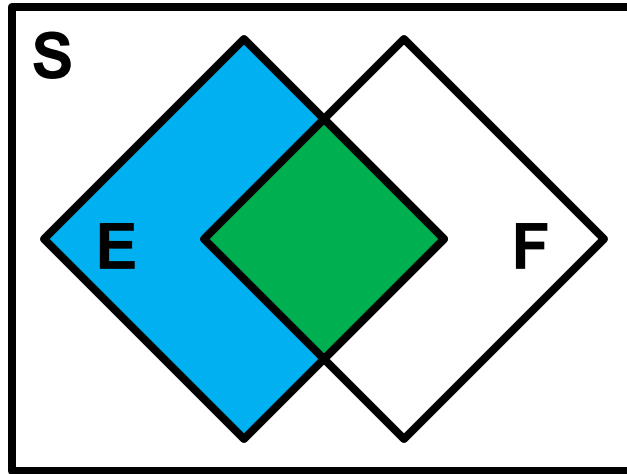
- He looked remarkably similar to Charlie Sheen
  - But that's not important right now...

But First!

# Background Observation

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

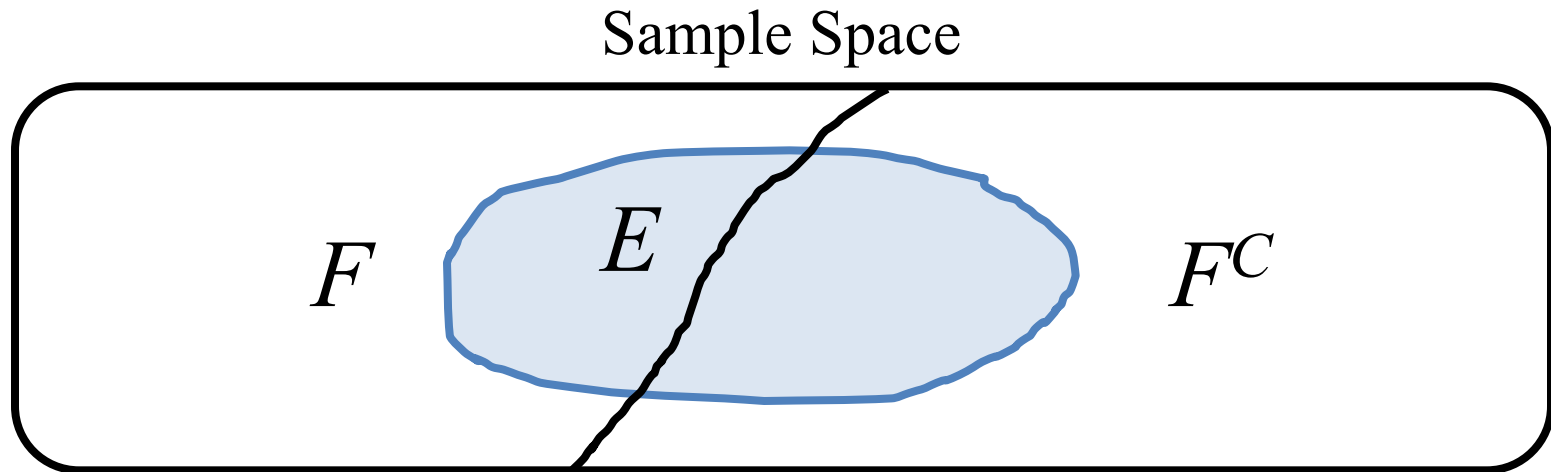
$$E = EF \cup EF^c$$



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

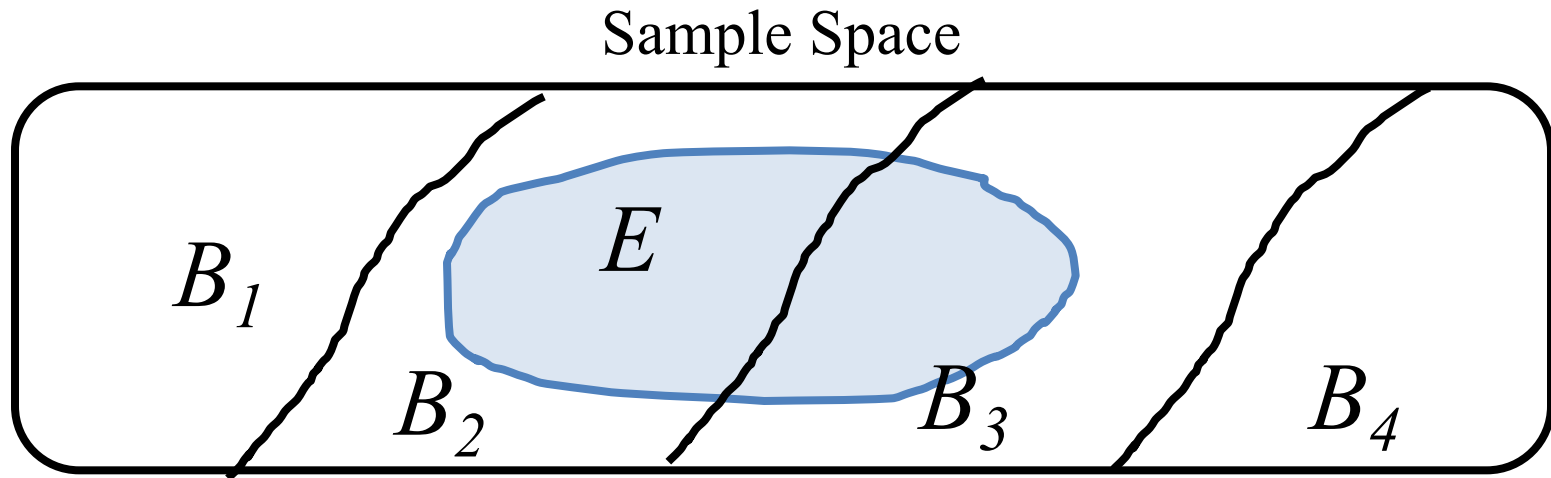
So,  $P(E) = P(EF) + P(EF^c)$

# 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



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

# 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,  $P(\text{win}) = 1/3$  (random)

# Let's Make a Deal

- Without loss of generality, say we pick A
  - $P(\text{A is winner}) = 1/3$ 
    - Host opens either B or C, we always lose by switching
    - $P(\text{win} \mid \text{A is winner, picked A, switched}) = 0$
  - $P(\text{B is winner}) = 1/3$ 
    - Host must open C (can't open A and can't reveal prize in B)
    - So, by switching, we switch to B and always win
    - $P(\text{win} \mid \text{B is winner, picked A, switched}) = 1$
  - $P(\text{C is winner}) = 1/3$ 
    - Host must open B (can't open A and can't reveal prize in C)
    - So, by switching, we switch to C and always win
    - $P(\text{win} \mid \text{C is winner, picked A, switched}) = 1$
  - Should always switch!
    - $P(\text{win} \mid \text{picked A, switched}) = (1/3*0) + (1/3*1) + (1/3*1) = 2/3$

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

Moment of Silence...

# Bayes Theorem

$$P(F | E)$$



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?



$$P(E | F)$$

# Bayes Theorem

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

- Most common form:

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



- Expanded form:

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

# H1N1 Testing

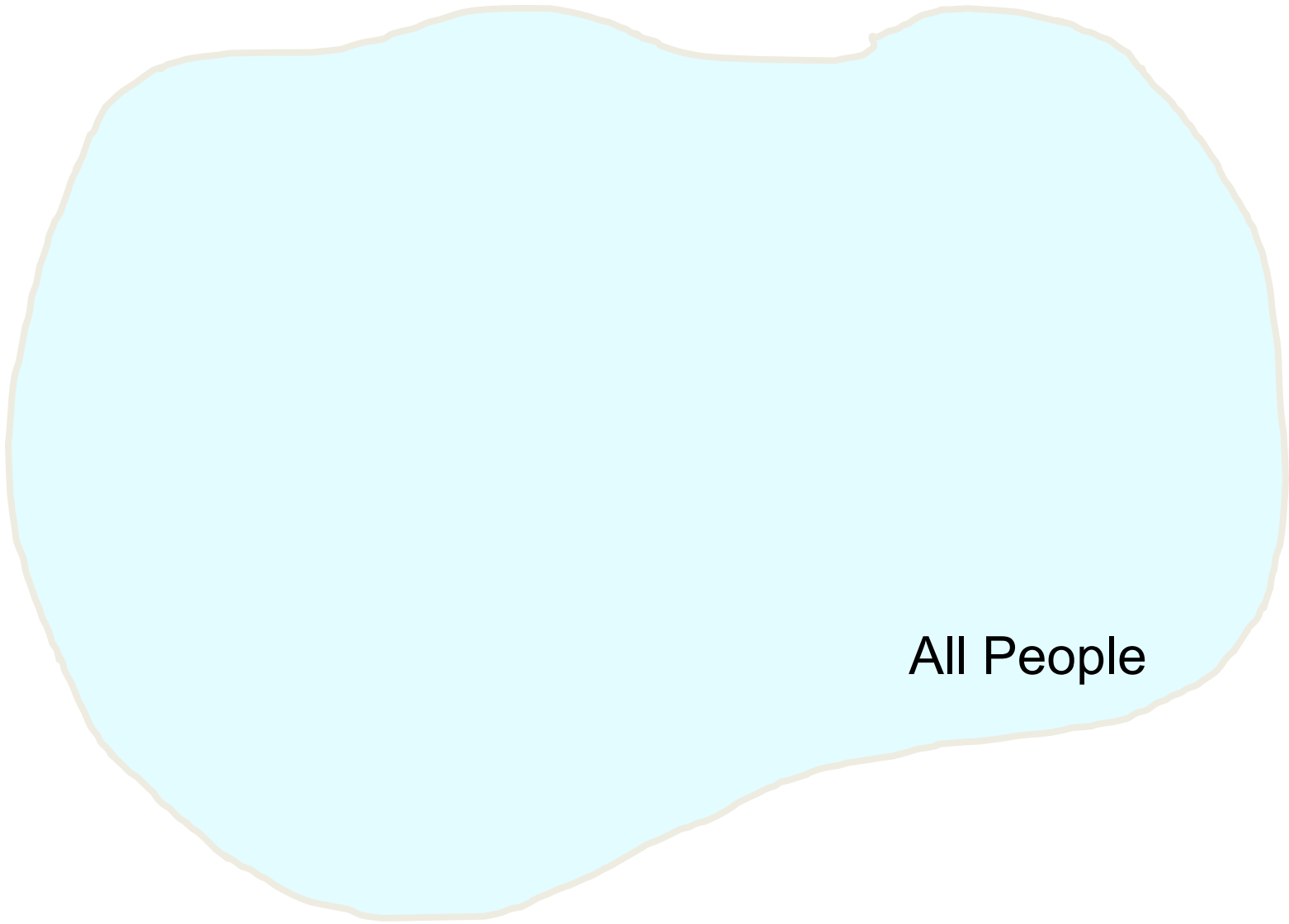
- A test is 98% effective at detecting H1N1
  - However, test has a “false positive” rate of 1%
  - 0.5% of US population has H1N1
  - Let E = you test positive for H1N1 with this test
  - Let F = you actually have H1N1
  - What is  $P(F | E)$ ?
- Solution:

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

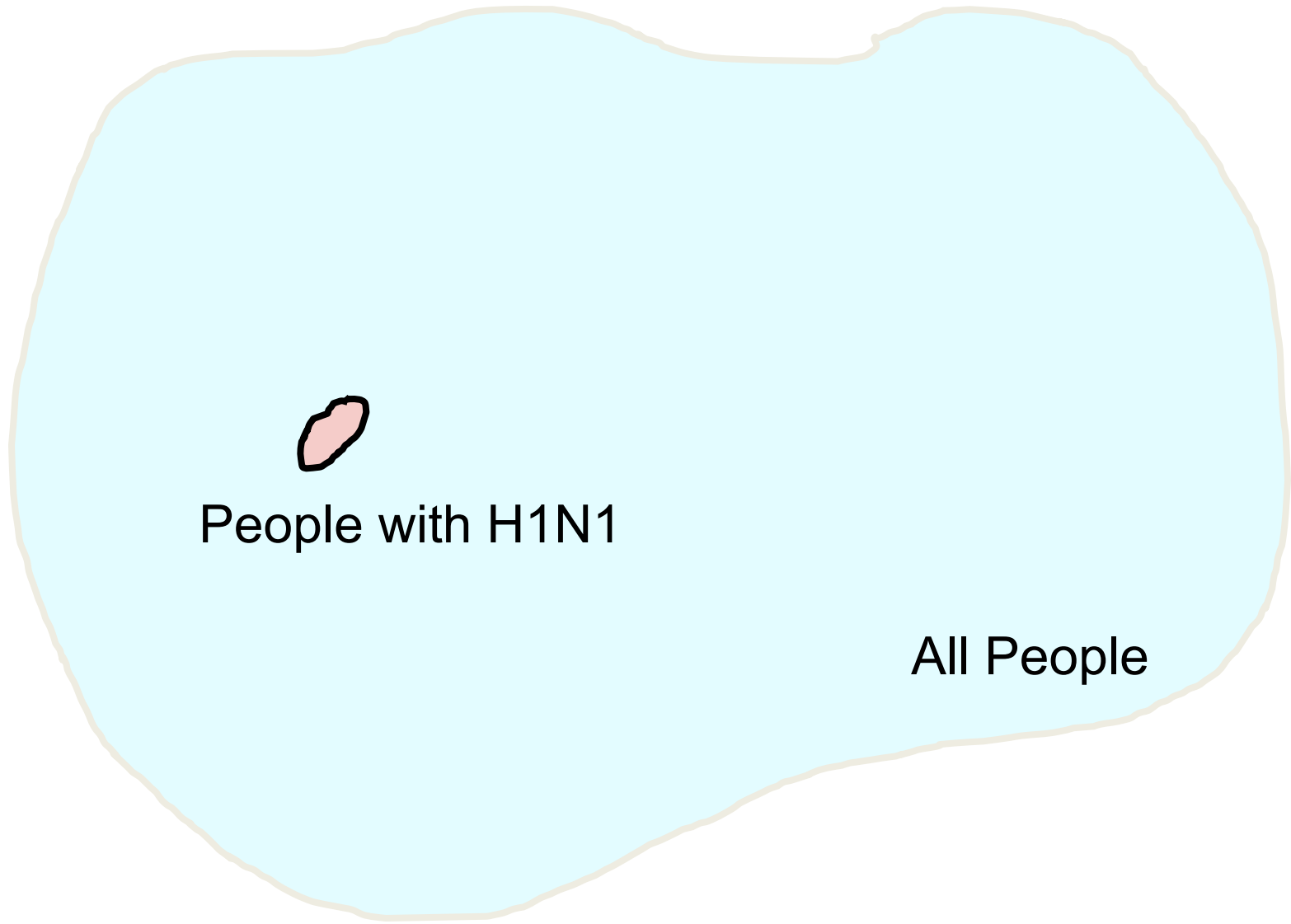
$$P(F | E) = \frac{(0.98)(0.005)}{(0.98)(0.005) + (0.01)(1 - 0.005)} \approx 0.330$$

# Intuition Time

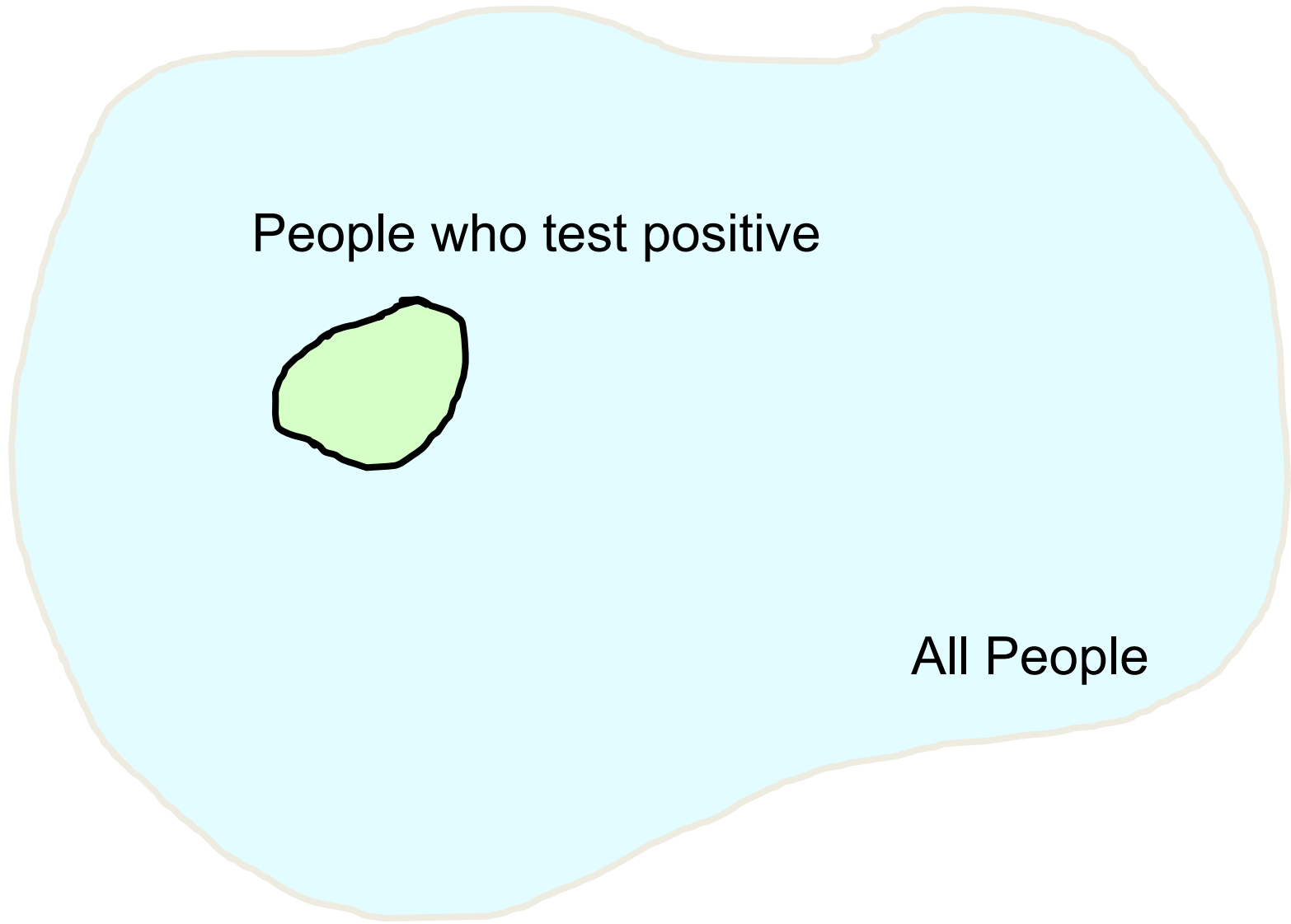
# Bayes Theorem Intuition



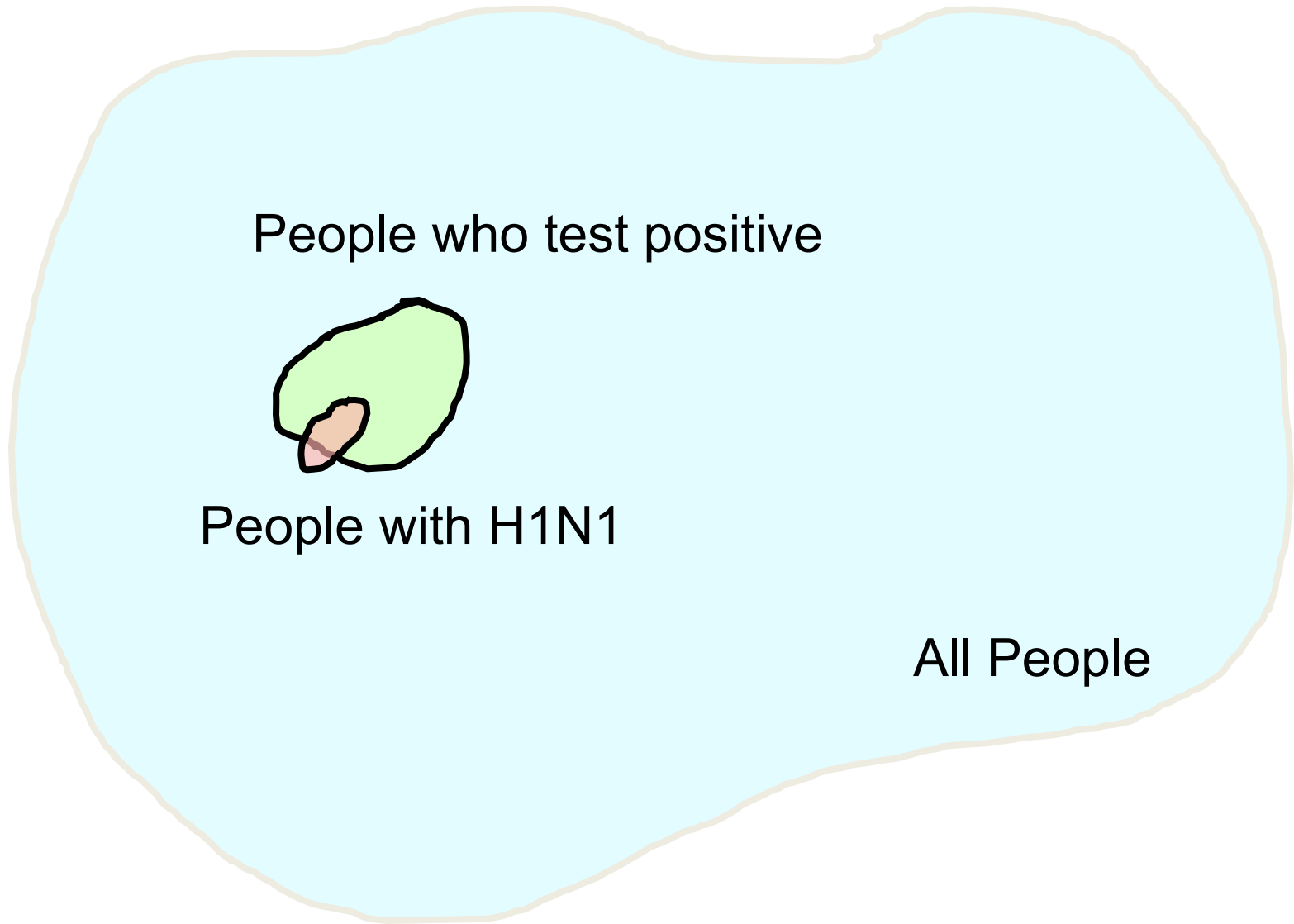
# Bayes Theorem Intuition



# Bayes Theorem Intuition



# Bayes Theorem Intuition



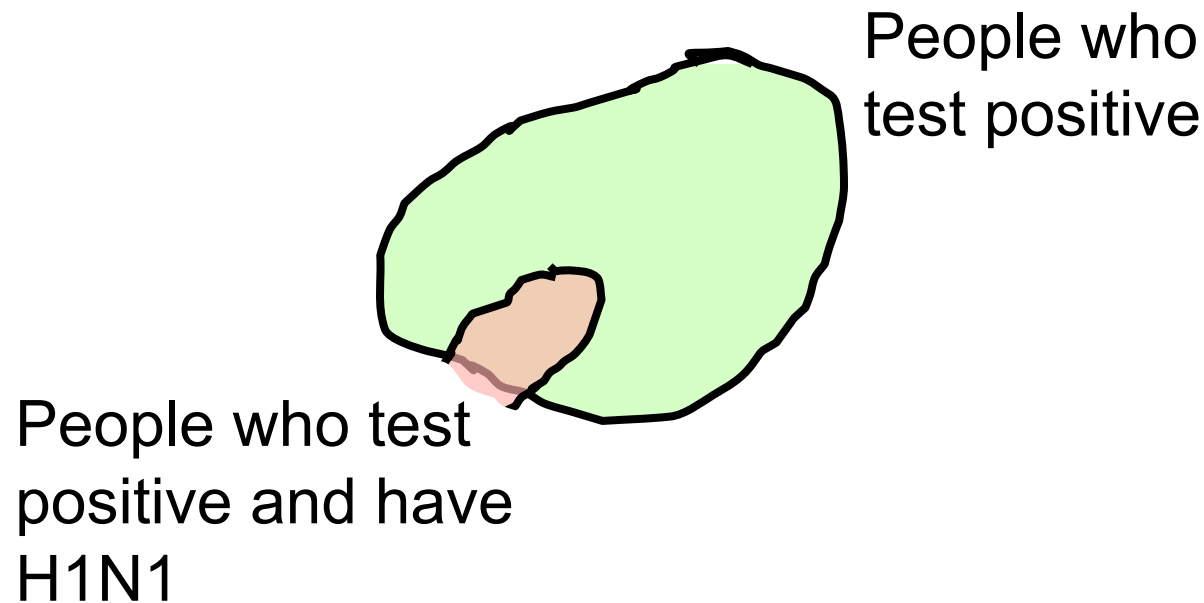
People who test positive

People with H1N1

All People

# Bayes Theorem Intuition

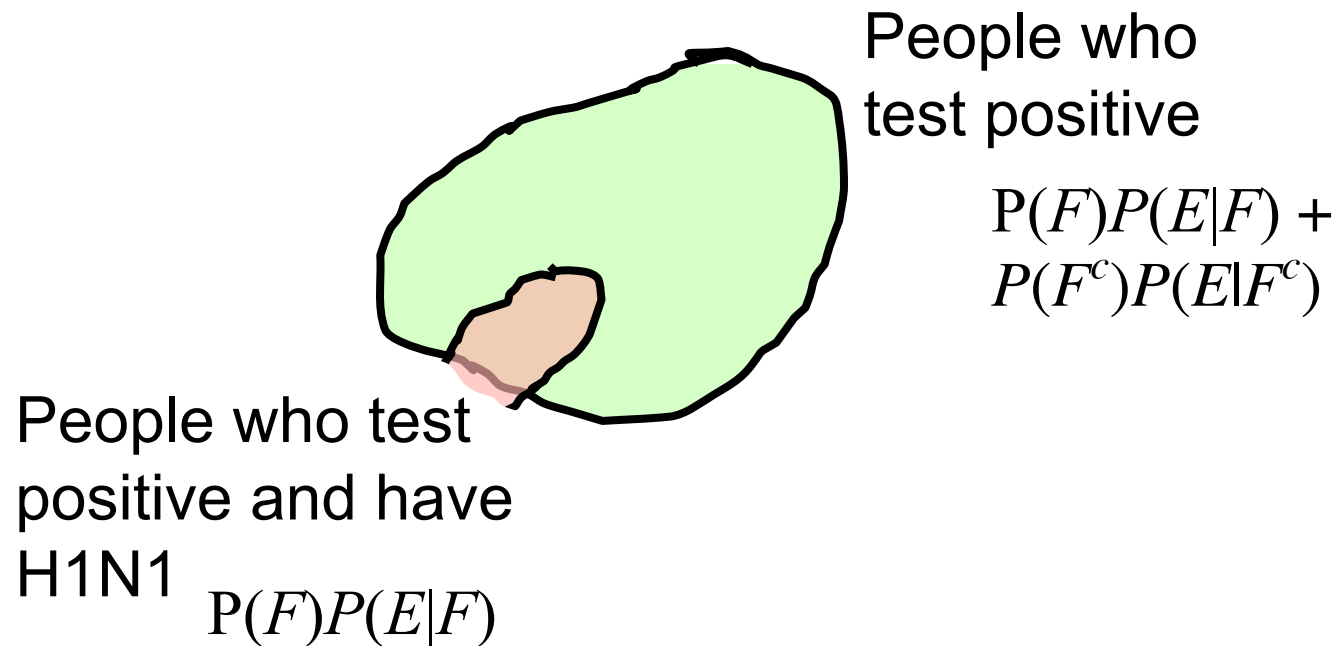
Conditioning on a positive result changes the sample space to this:



$\approx 0.330$

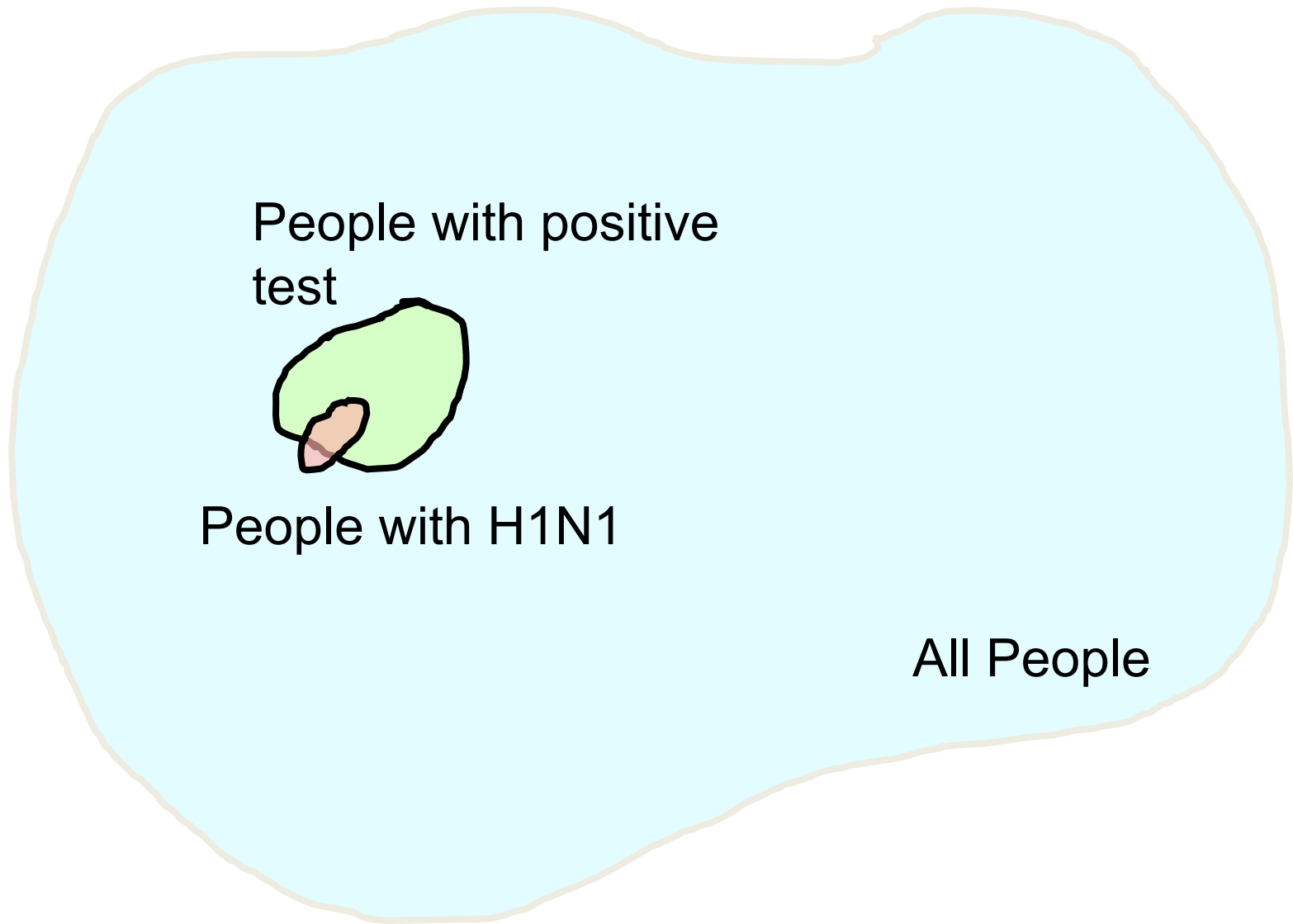
# Bayes Theorem Intuition

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



$$\approx 0.330$$

# Bayes Theorem Intuition



# Bayes Theorem Intuition

Say we have 1000 people:



5 have H1N1 and test positive, 985 **do not** have H1N1 and test negative.  
10 **do not** have H1N1 and test positive.  $\approx 0.333$

# Why It's Still Good to get Tested

	H1N1 +	H1N1 -
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 H1N1 with this test
- Let  $F$  = you actually have H1N1
- What is  $P(F | E^c)$ ?

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

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

# Slicing Up Spam



In 2010 88% of email was spam

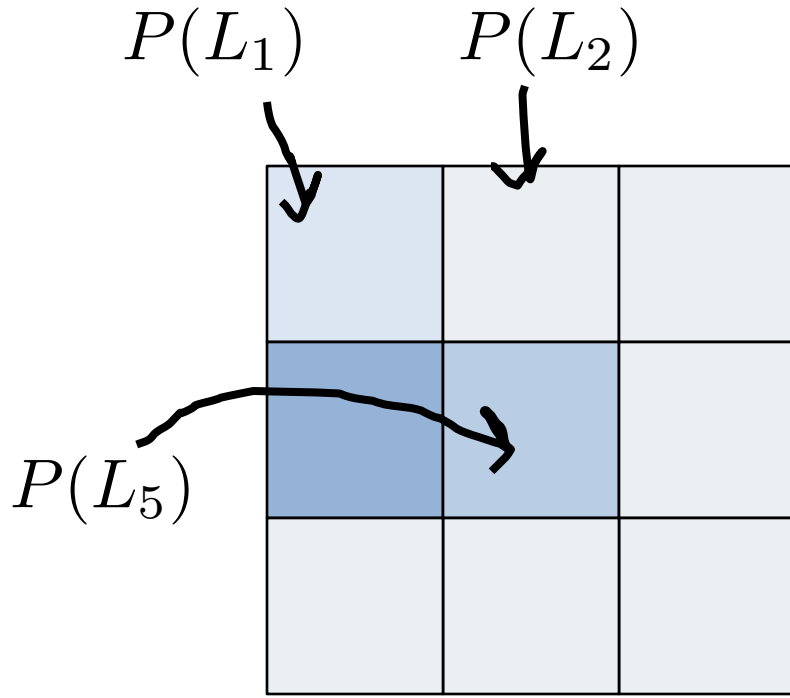
# Simple Spam Detection

- 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  $P(F | E)$ ?

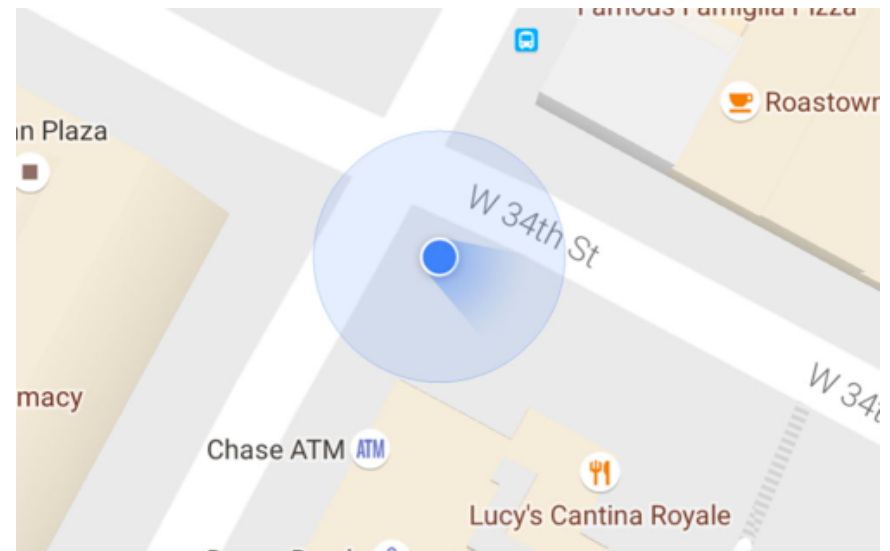
- Solution: 
$$P(F | E) = \frac{P(E | F) P(F)}{P(E | F) P(F) + P(E | F^c) P(F^c)}$$

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

# Update Belief

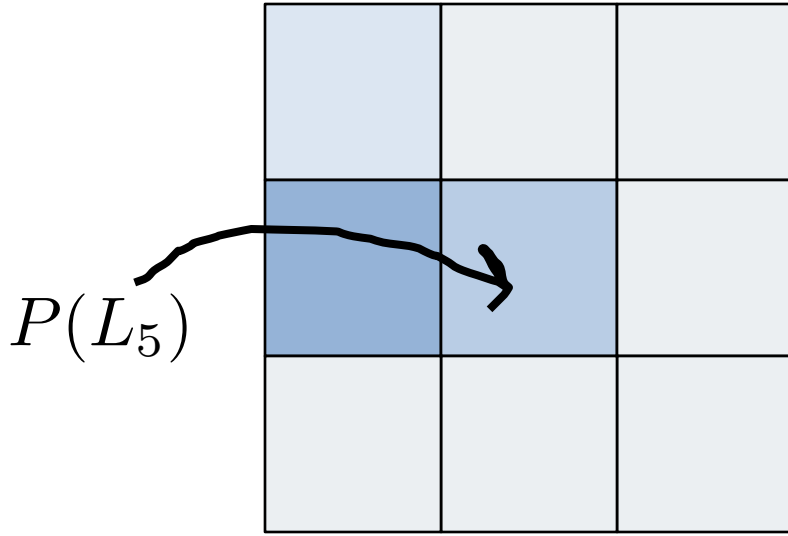
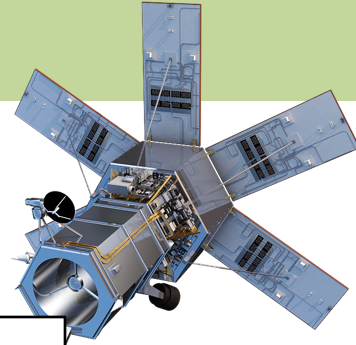


Before Observation

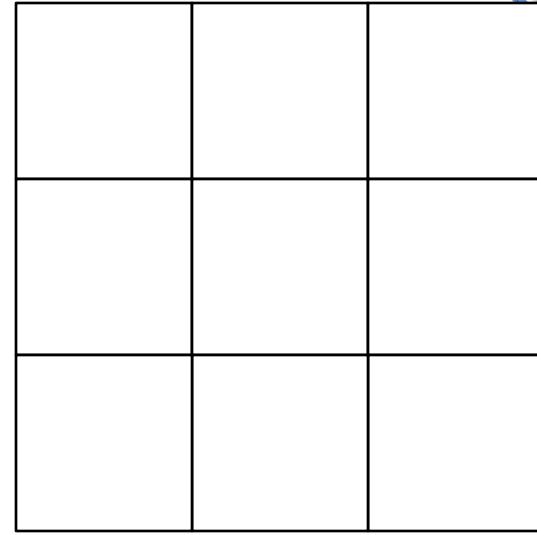


# Update Belief

Know:  $P(O|L_i)$



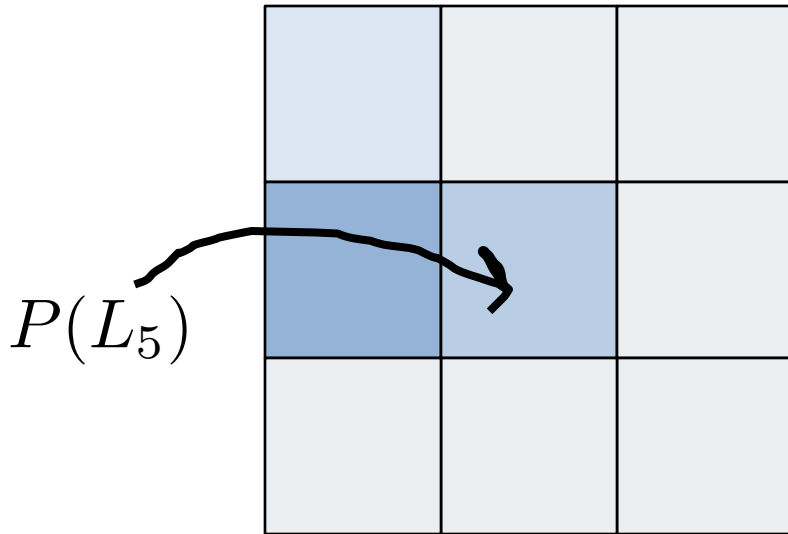
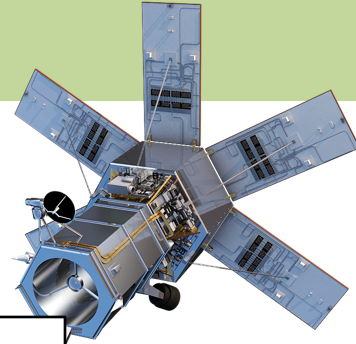
Before Observation



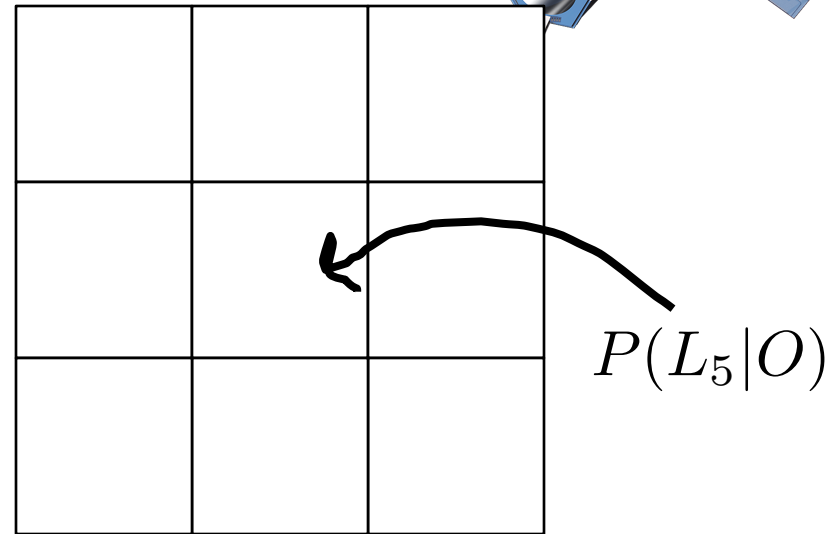
After Observation

# Update Belief

Know:  $P(O|L_i)$



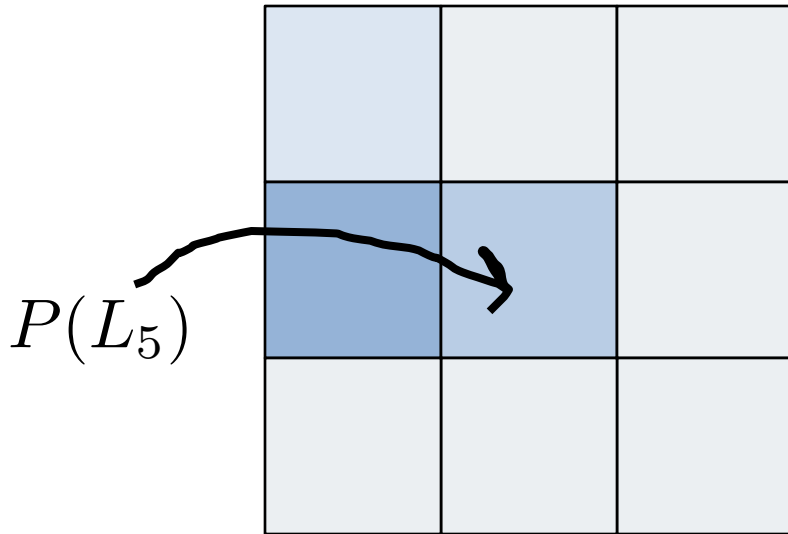
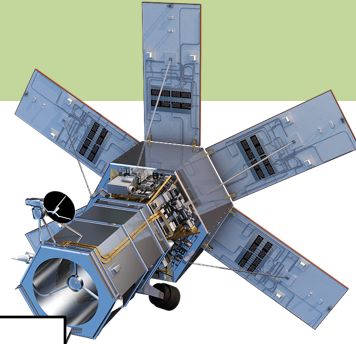
Before Observation



After Observation

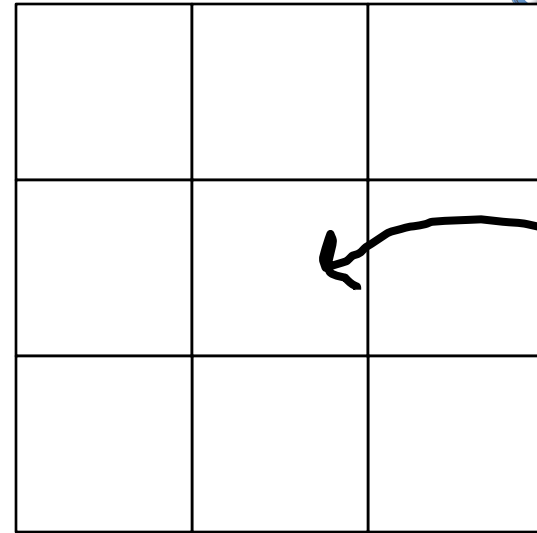
$$P(L_5|O) = \frac{P(O|L_5)P(L_5)}{P(O)}$$

# Update Belief



$P(L_5)$

Before Observation

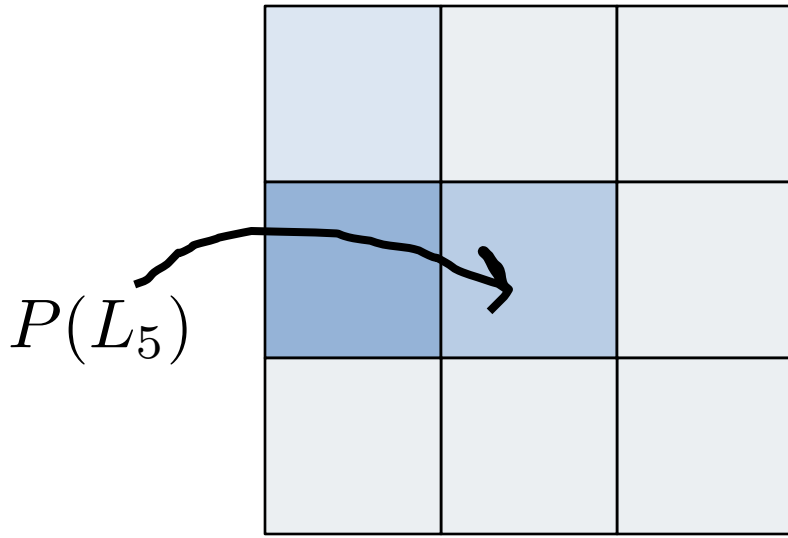
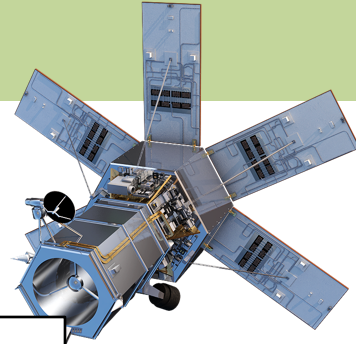


$P(L_5|O)$

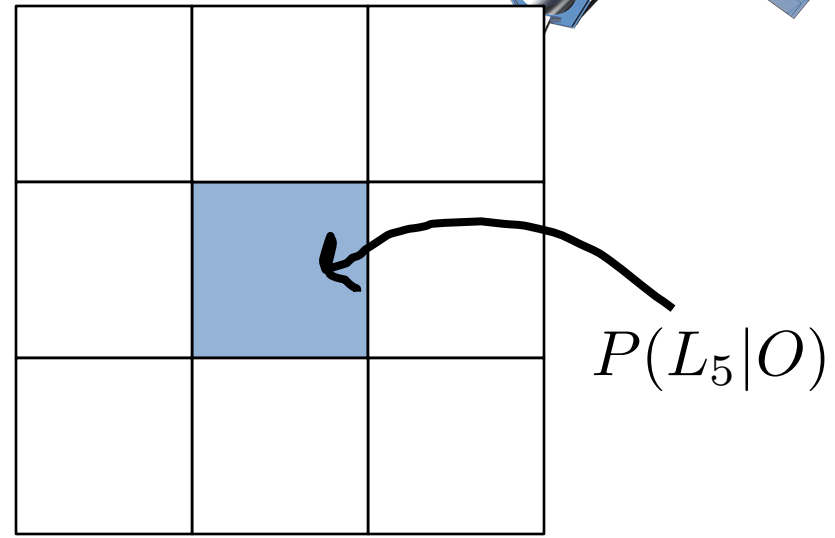
After Observation

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

# Update Belief



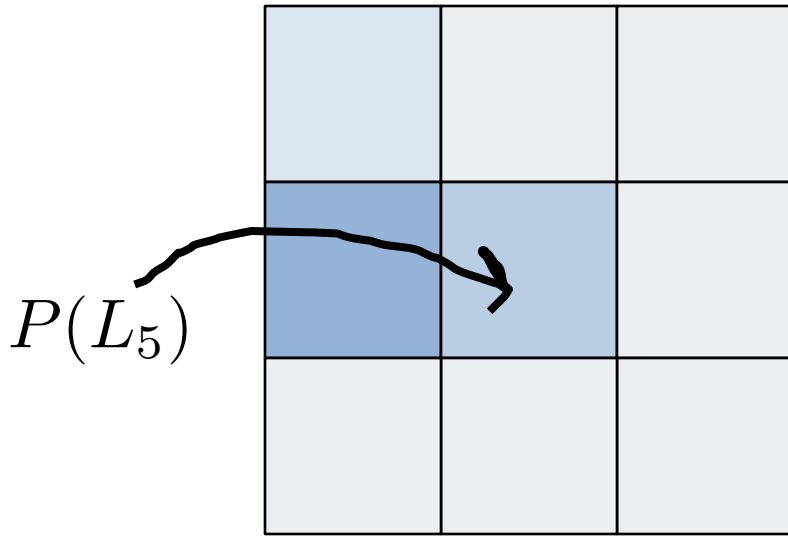
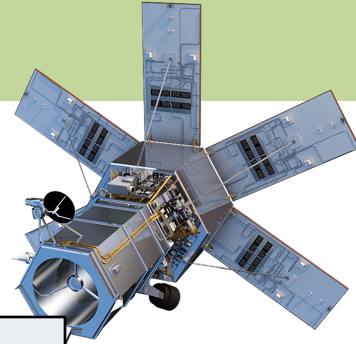
Before Observation



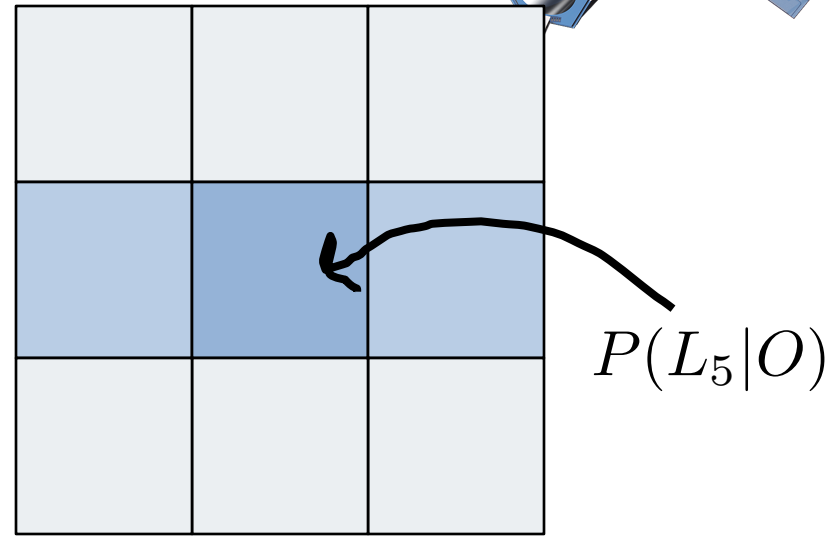
After Observation

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

# Update Belief



Before Observation



After Observation

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



Stretch!

# Bayes + Condition

Say we want  $P(E|FG)$  ...

1. Combining F, G: 
$$P(E|FG) = \frac{P(FG|E)P(E)}{P(FG)}$$

2. World of G: 
$$P(E|FG) = \frac{P(F|EG)P(E|G)}{P(F|G)}$$

3. World of F: 
$$P(E|FG) = \frac{P(G|EF)P(E|F)}{P(G|F)}$$

# Which Rule When?

Chain Rule:  $P(EF) = P(E|F)P(F)$

- Goes from an “and” to a conditional and vice versa
- Think about which event you want to condition on

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

- We don't know about E but we do know about E|F
- Don't forget about the “and” version and “summation” version

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

- Good for when E|F is hard but F|E is not so hard
- Common mistake: not trying chain rule first



**Independence**

Start with a cool program

$G_1$

$G_2$

$G_3$

$G_4$

$G_5$

**T**



G<sub>1</sub>

G<sub>2</sub>

G<sub>3</sub>

G<sub>4</sub>

G<sub>5</sub>

T

```
dna.txt — dna
dna.txt
1 False,True,False,False,True,False
2 True,True,False,True,True,False
3 True,True,False,True,True,True
4 False,True,False,True,True,False
5 False,True,False,False,True,False
6 True,True,False,True,True,True
7 False,False,True,False,False,False
8 False,False,True,False,True,False
9 True,False,False,True,False,False
10 False,True,False,True,True,False
11 True,False,False,True,False,False
12 True,False,True,True,False,False
13 False,True,False,False,True,False
14 False,False,True,True,False,False
15 True,True,False,False,True,True
16 True,False,True,True,False,False
17 True,True,True,True,True,True |
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19 False,True,False,True,True,True
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21 False,False,False,True,True,False
22 False,True,False,False,True,False
23 True,True,False,True,True,True
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26 False,False,True,True,False,True
27 False,False,False,True,False,False
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30 False,False,False,False,False,True
31 False,True,False,True,True,False
32 True,False,False,True,False,False
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35 True,True,False,True,True,True
36 False,False,False,True,False,False
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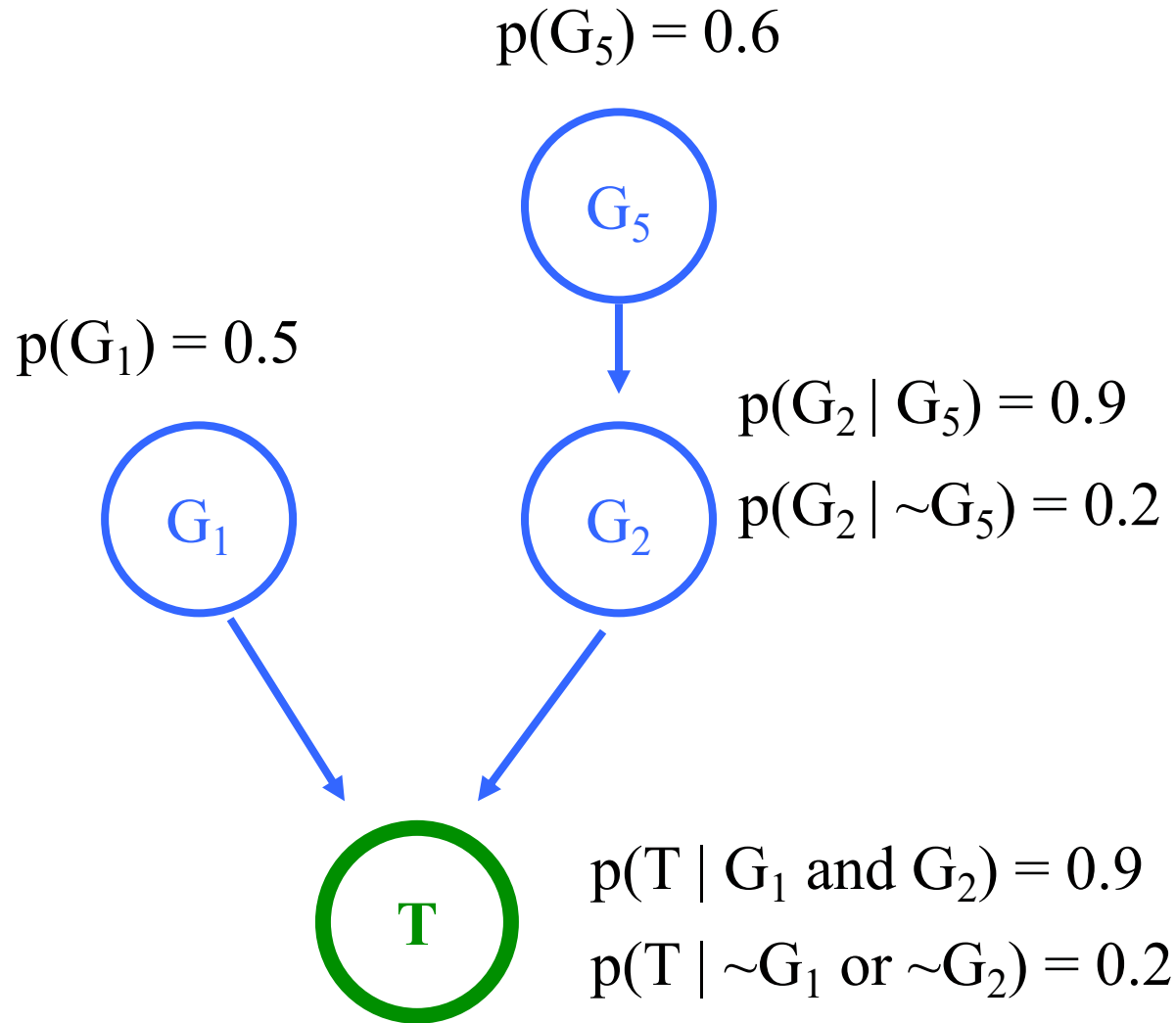


100,000 samples

6 observations per sample



# Discovered Pattern



These genes  
don't impact T



**We've gotten ahead of ourselves**



Source: The Hobbit

# Start at the beginning



Source: The Ho

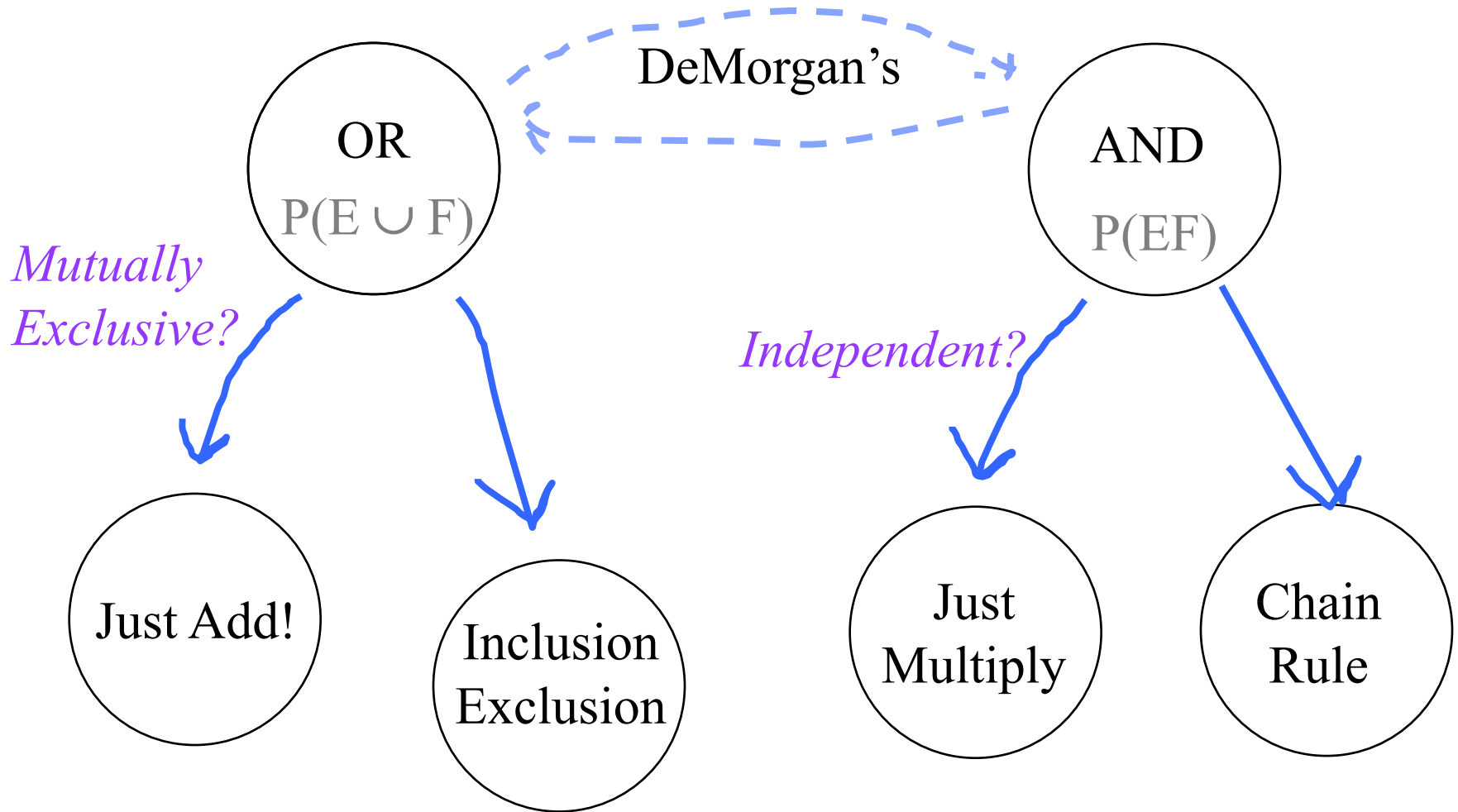
# And vs Condition

$P(AB)$  vs  $P(A|B)$

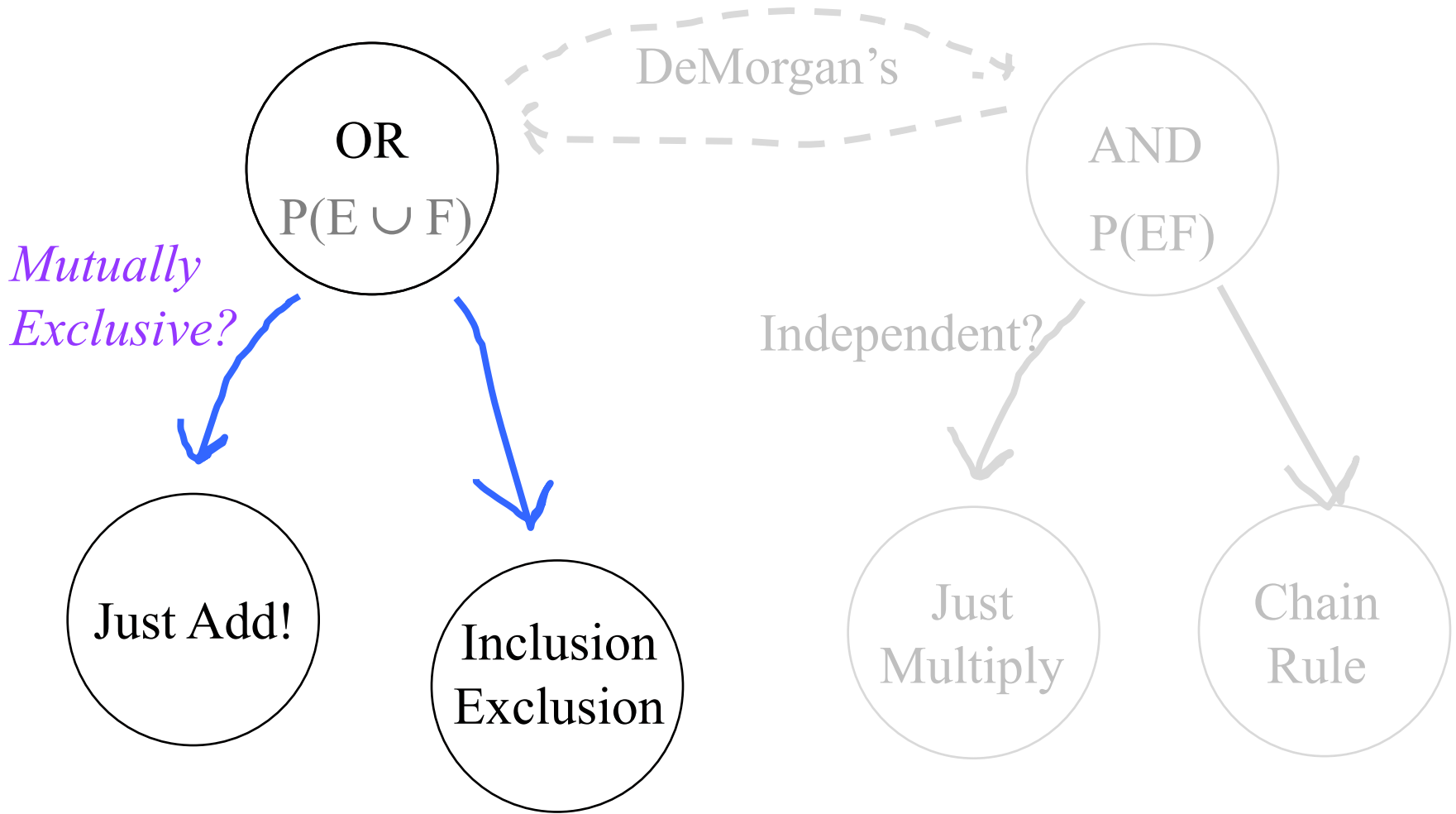
$$P(AB) = P(A|B)P(B)$$



# Overview

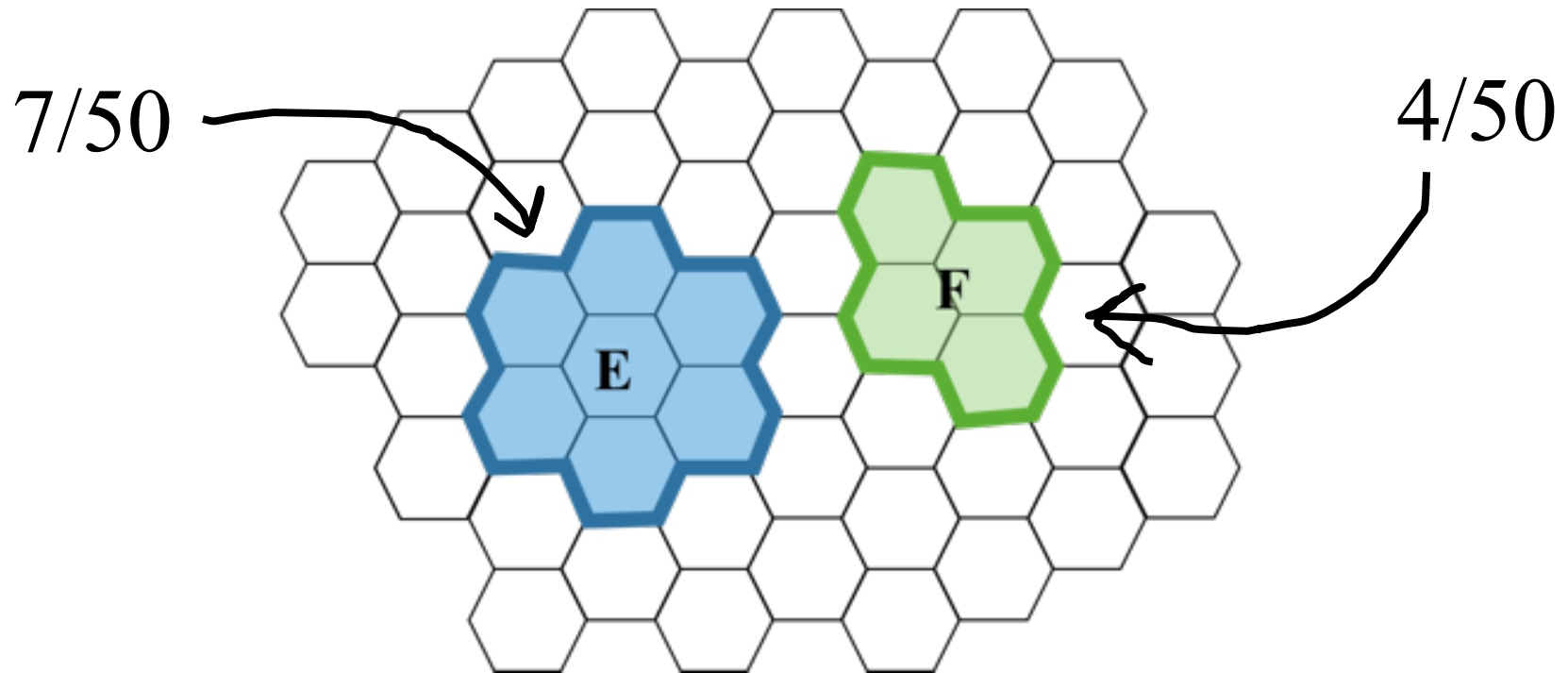


# Today



Probability of “OR”

# OR with Mutually Exclusive Events



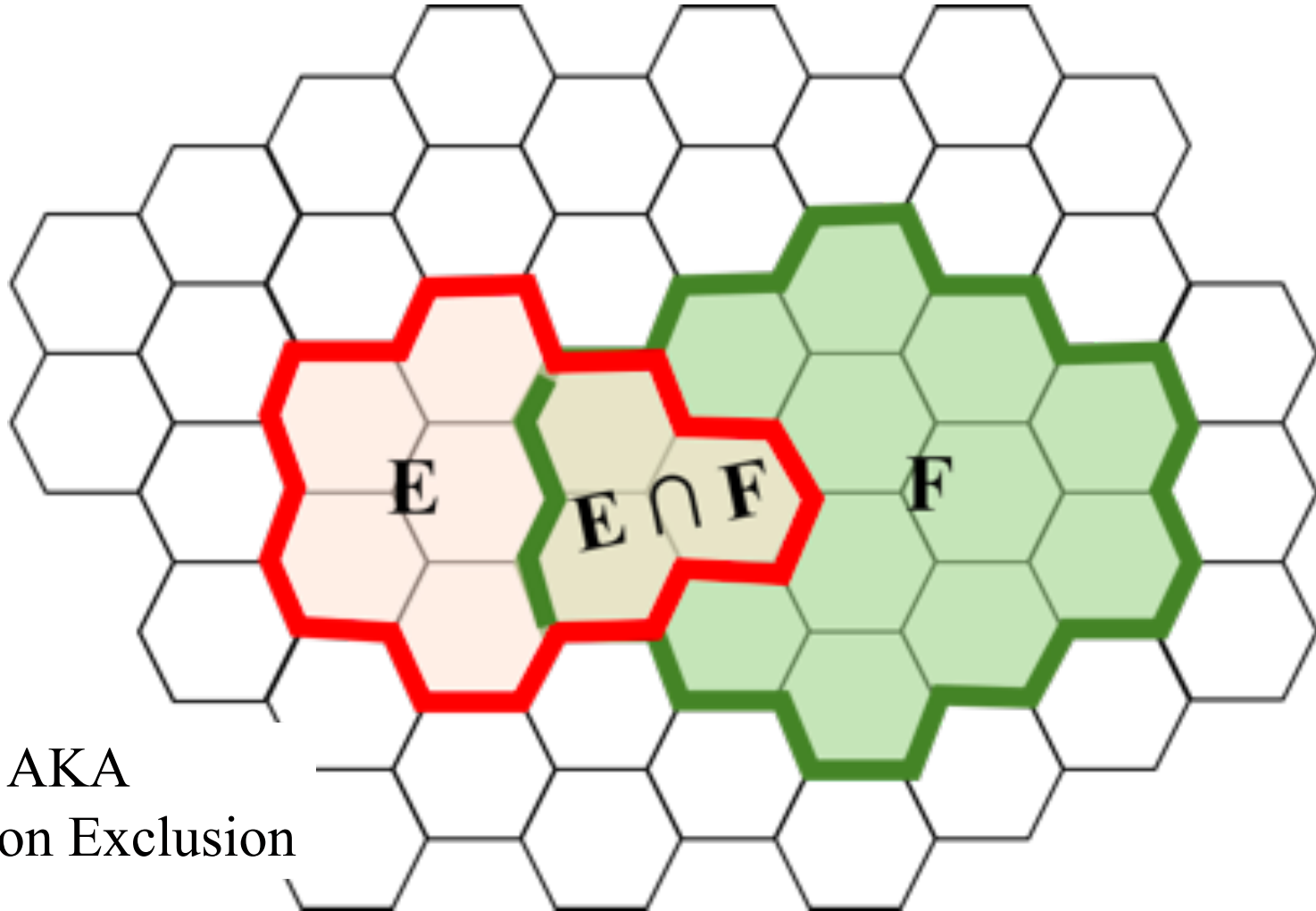
If events are mutually exclusive, probability of OR is simple:

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



What about when they are not  
*Mutually exclusive?*

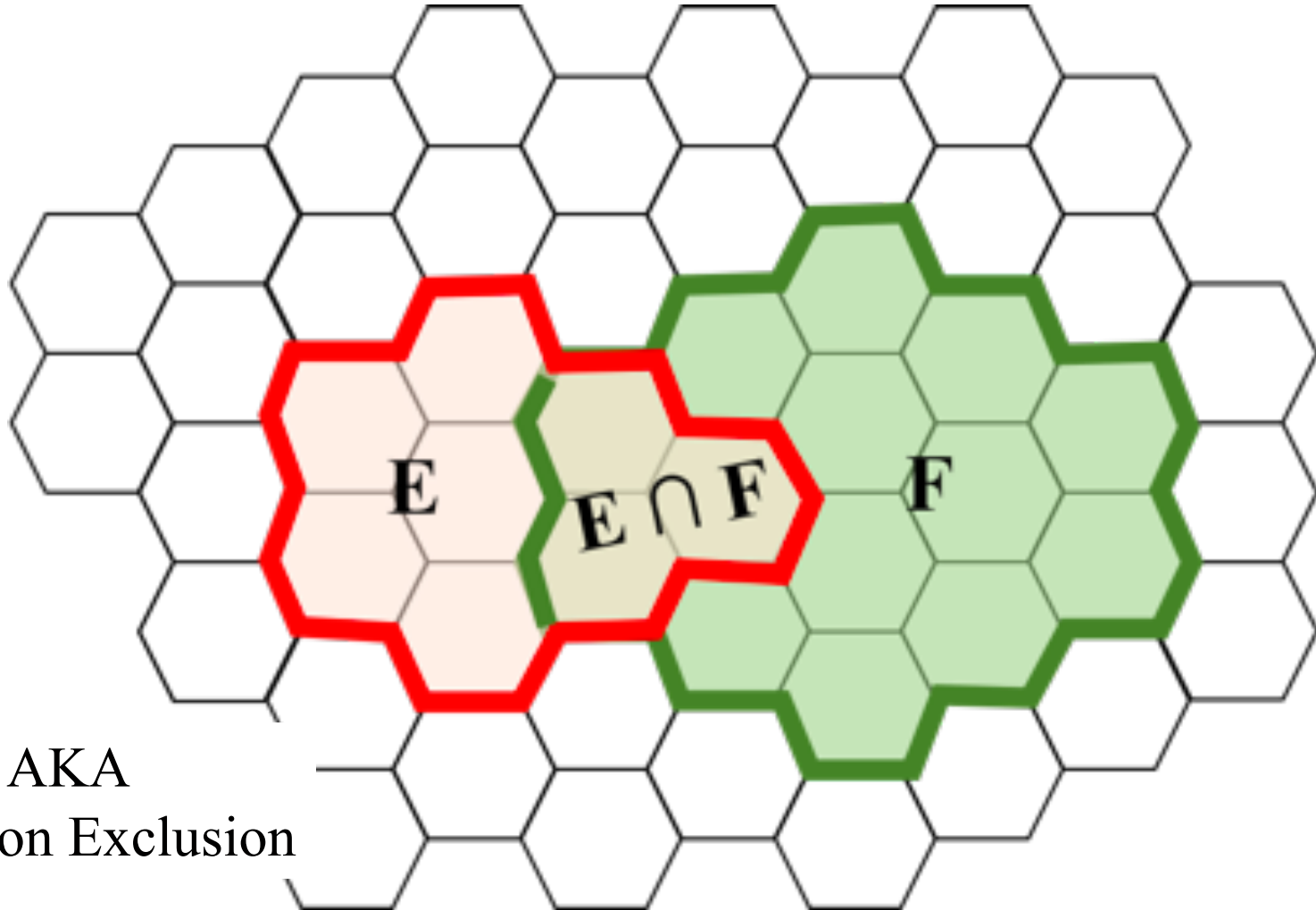
# OR without Mutually Exclusivity



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



# OR without Mutually Exclusivity



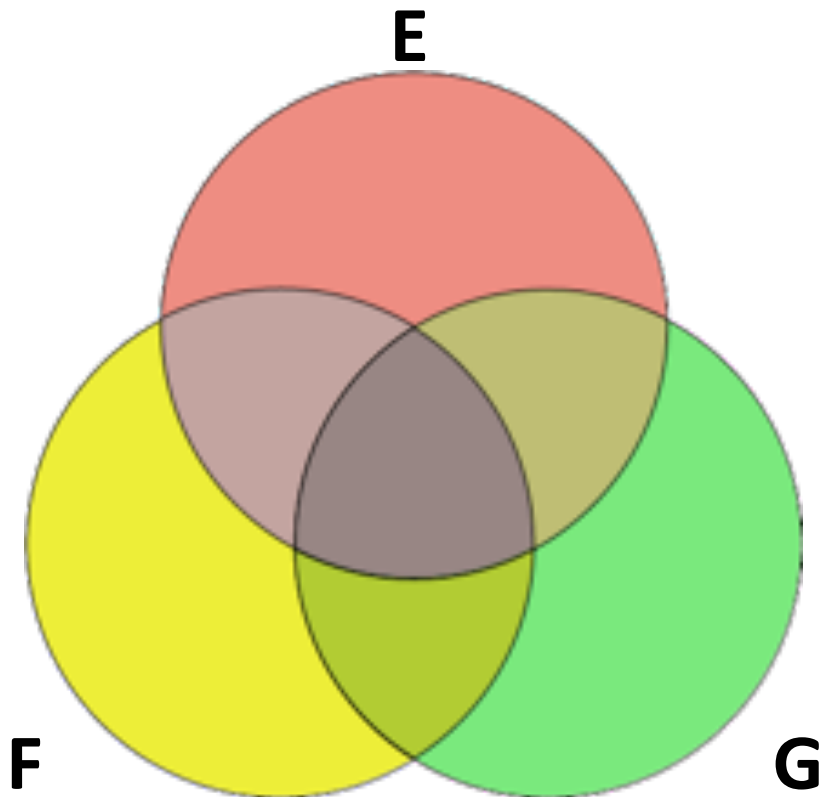
$$P(E \cup F) = \frac{8}{50} + \frac{14}{50} - \frac{3}{50} = \frac{19}{50}$$



More than two sets?

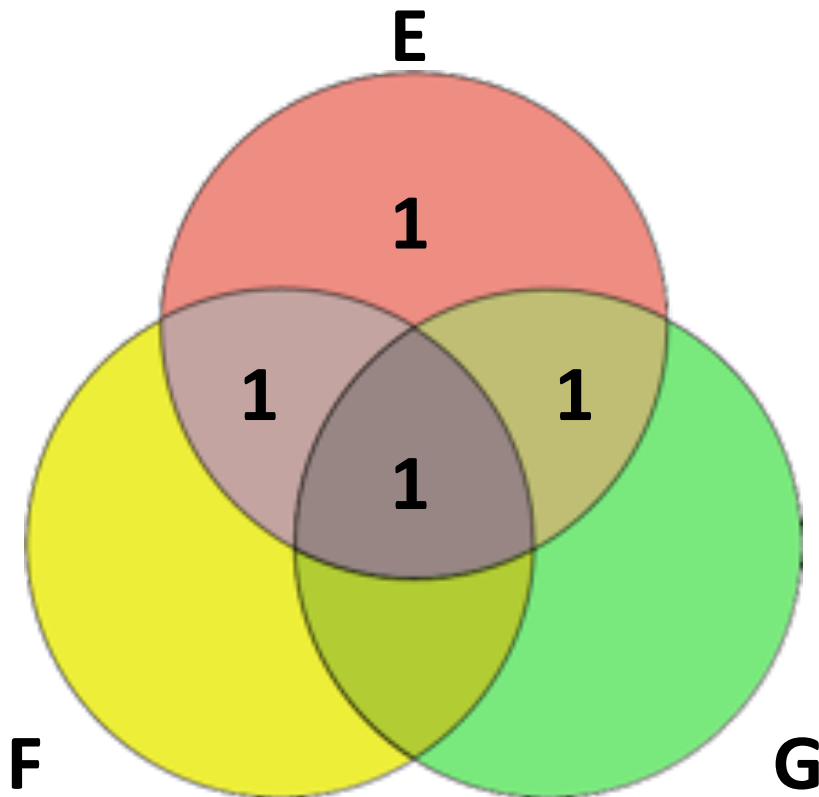
# Inclusion Exclusion with Three Sets

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



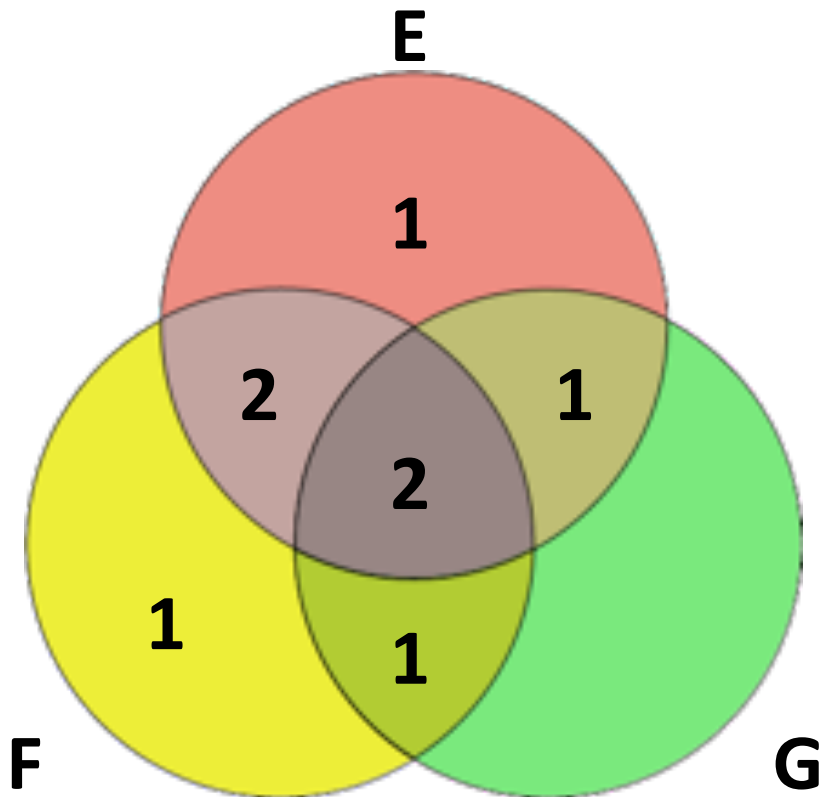
# Inclusion Exclusion with Three Sets

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



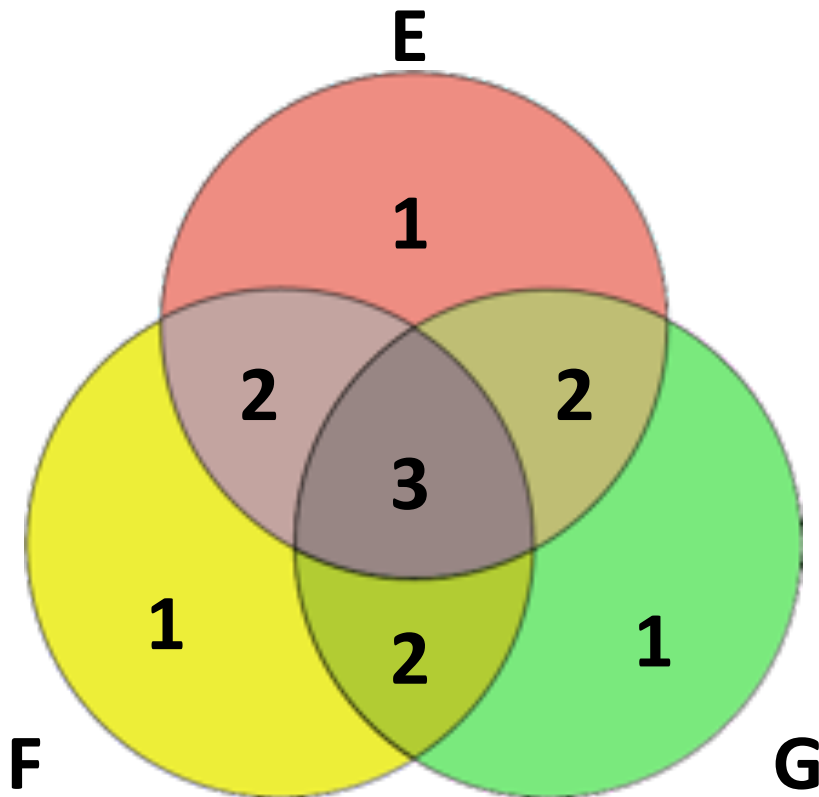
# Inclusion Exclusion with Three Sets

$$P(E \cup F \cup G) = P(E) + P(F) + P(G) - P(E \cap F) - P(E \cap G) - P(F \cap G) + P(E \cap F \cap G)$$



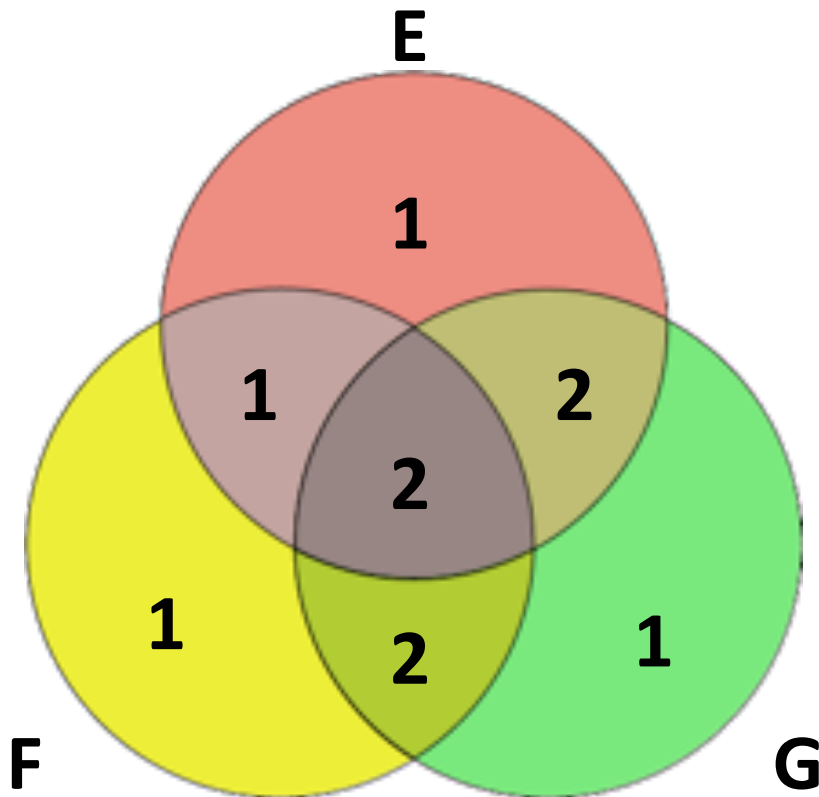
# Inclusion Exclusion with Three Sets

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



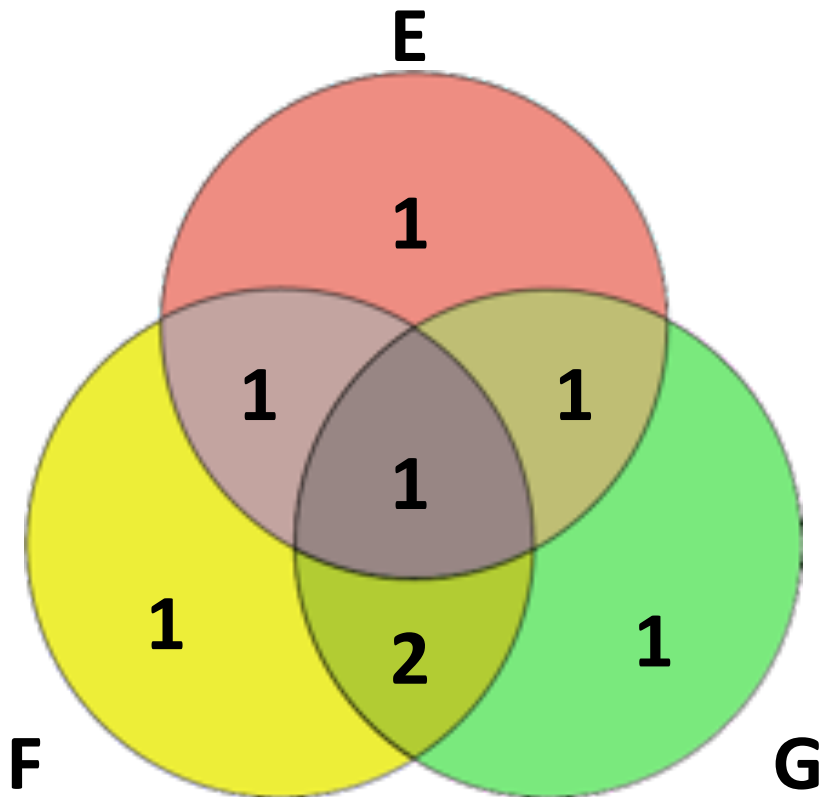
# Inclusion Exclusion with Three Sets

$$P(E \cup F \cup G) = P(E) + P(F) + P(G) - P(EF)$$



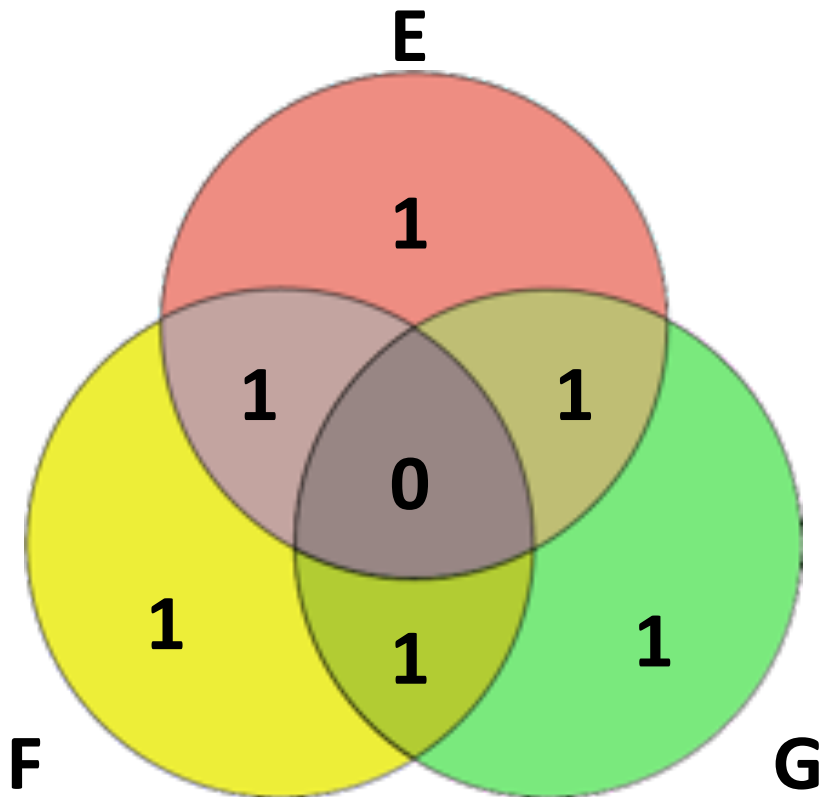
# Inclusion Exclusion with Three Sets

$$P(E \cup F \cup G) = P(E) + P(F) + P(G) \\ - P(EF) - P(EG)$$



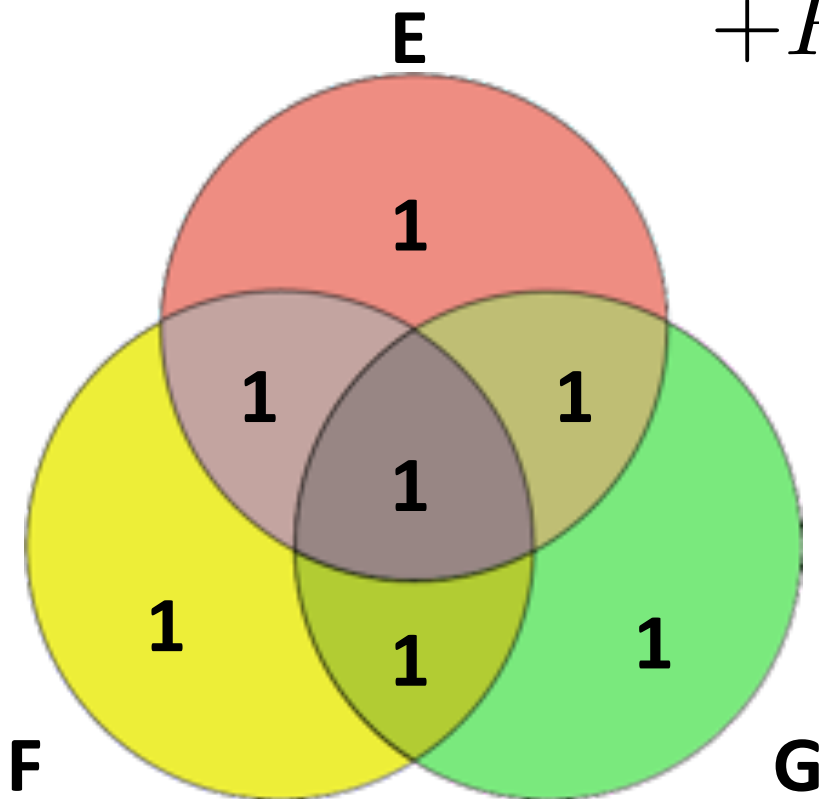
# Inclusion Exclusion with Three Sets

$$P(E \cup F \cup G) = P(E) + P(F) + P(G) \\ - P(EF) - P(EG) - P(FG)$$



# Inclusion Exclusion with Three Sets

$$\begin{aligned} P(E \cup F \cup G) &= P(E) + P(F) + P(G) \\ &\quad - P(EF) - P(EG) - P(FG) \\ &\quad + P(EFG) \end{aligned}$$



# General Inclusion Exclusion

$$P(E_1 \cup E_2 \cup \dots \cup E_n) = \sum_{r=1}^n (-1)^{r+1} Y_r$$

$Y_1 =$  Sum of all events on their own  $\sum_i P(E_i)$

$Y_2 =$  Sum of all pairs of events  $\sum_{i,j \text{ s.t. } i \neq j} P(E_i \cap E_j)$

$Y_3 =$  Sum of all triples of events  $\sum_{i,j,k \text{ s.t. } i \neq j, j \neq k, i \neq k} P(E_i \cap E_j \cap E_k)$

\* Where  $Y_r$  is the sum, for all combinations of  $r$  events, of the probability of the union those events.



# Overview

