

Independence

Review

Review: Conditional Probability

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

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

Notation

And

Or

Given

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

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

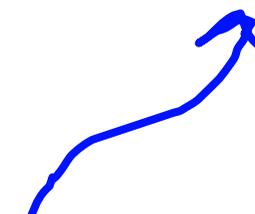
$$P(E|F)$$

$$P(E, F)$$

$$P(E \cup F)$$

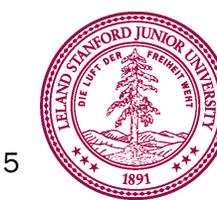
$$P(E|F, G)$$

$$P(EF)$$



$$P(E \cap F)$$

Probability of E given
F and G



Review: Chain Rule

Definition of conditional probability:

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

The Chain Rule:

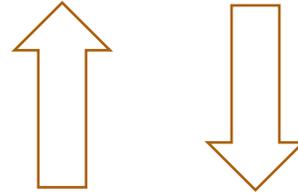
$$\begin{aligned} P(EF) &= P(E|F)P(F) \\ &= P(F|E)P(E) \end{aligned}$$

Relationship Between Probabilities



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

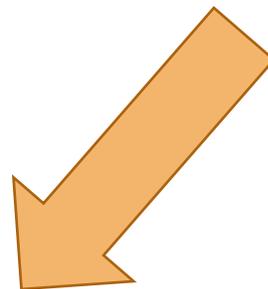
Chain rule
(Product rule)



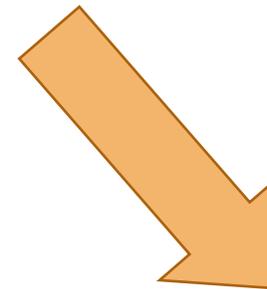
Definition of
conditional probability

$$P(E|F)$$

Law of Total
Probability



Bayes'
Theorem



$$P(E)$$

$$P(F|E)$$



Bayes' Theorem

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

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

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

$$\overset{\text{prior}}{P(F)} \xrightarrow{\text{E happens}} \overset{\text{posterior}}{P(F|E)}$$

“Updating” your belief
Prior \rightarrow Posterior

Expanded form:

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



SARS Virus Testing

A test is 98% effective at detecting SARS

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

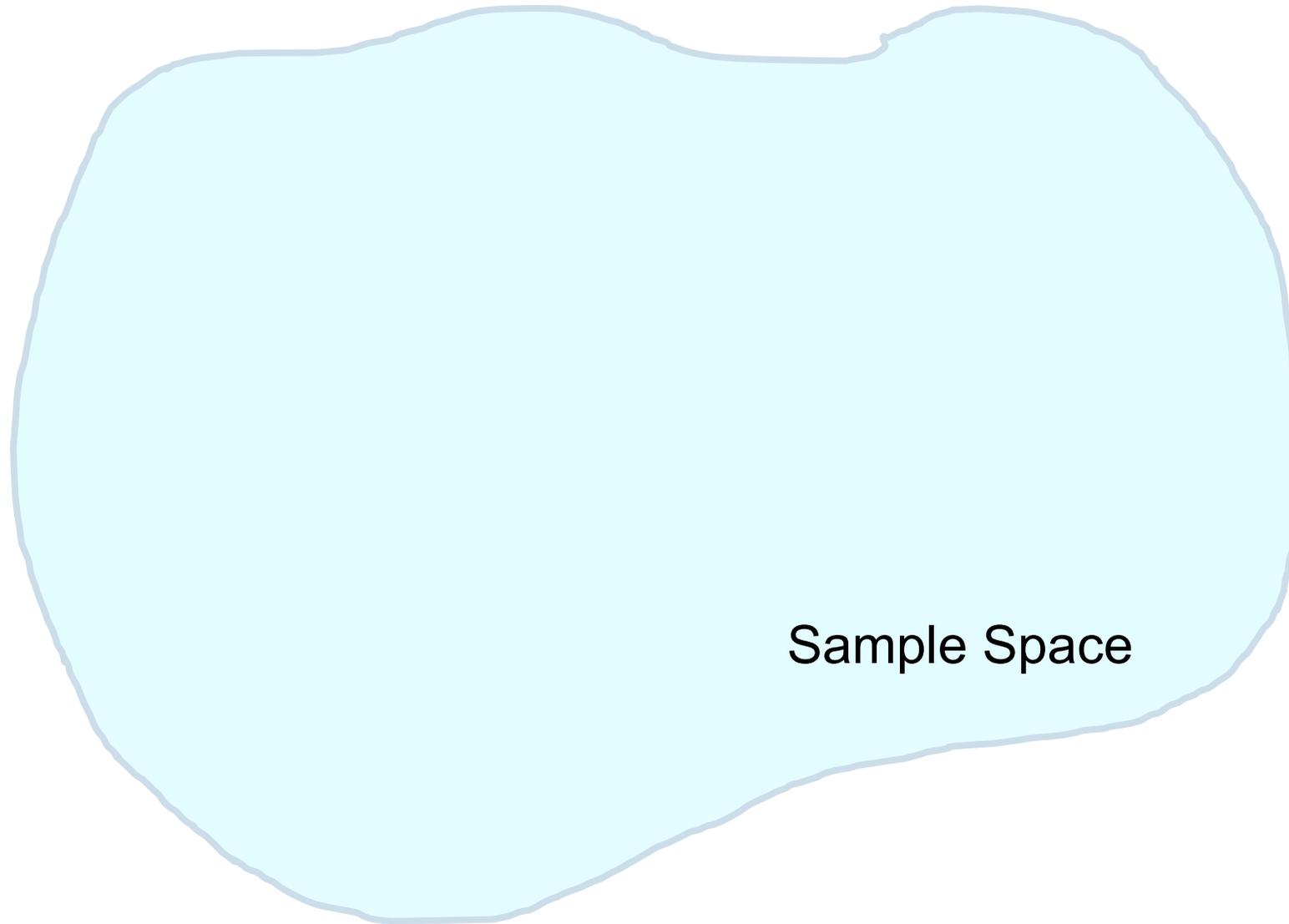
Solution:

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



Intuition Time

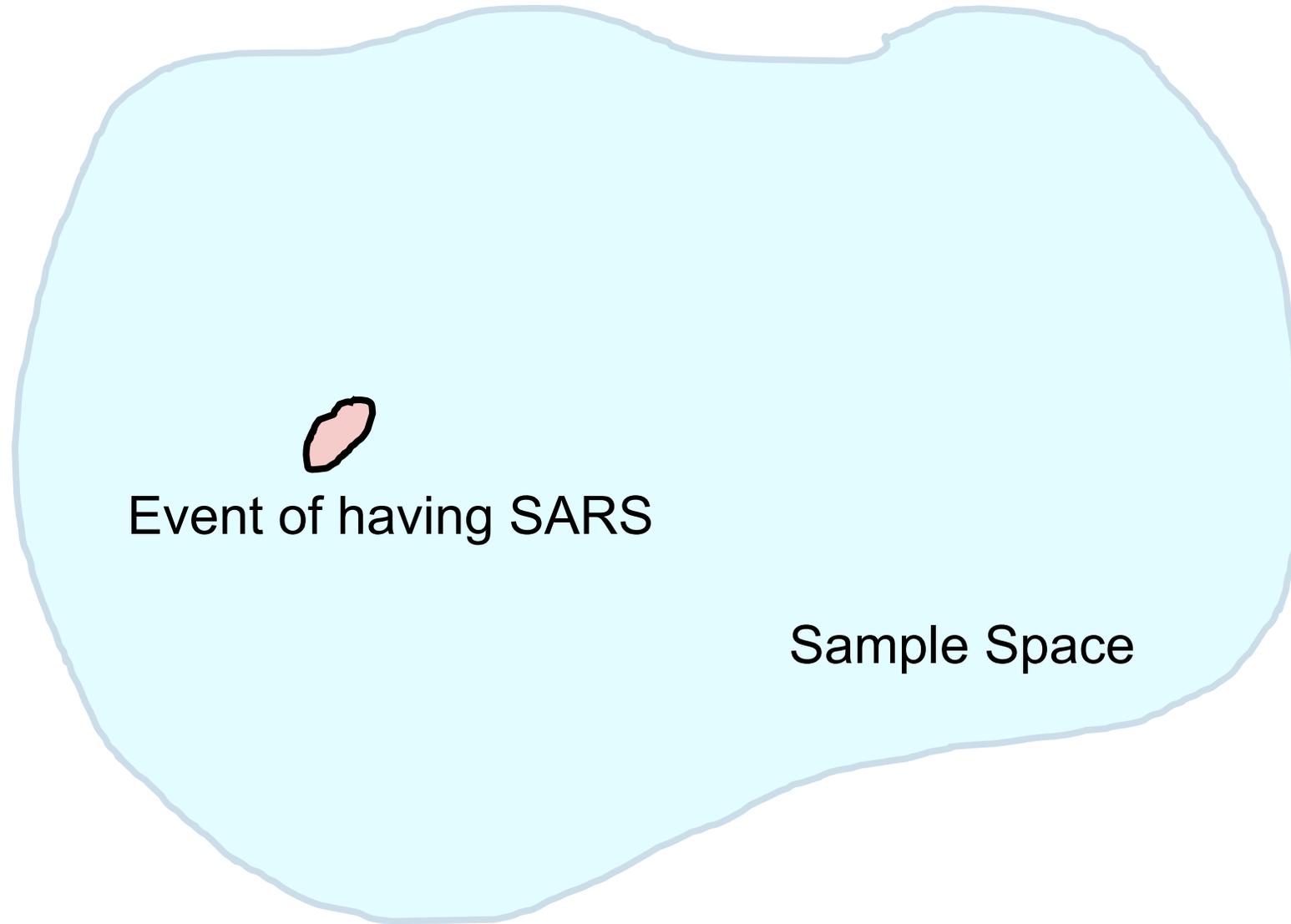
Bayes Theorem Intuition



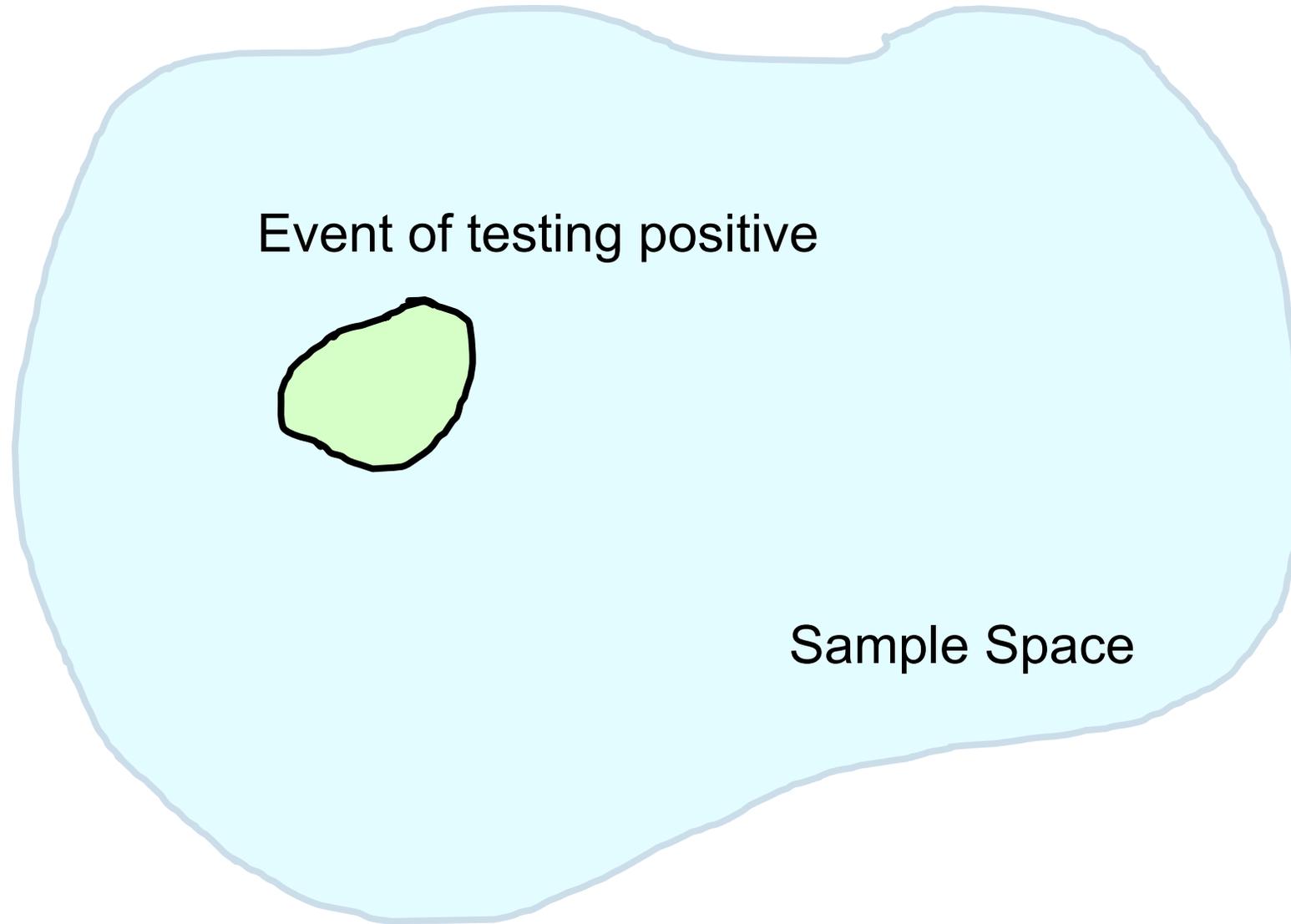
Sample Space



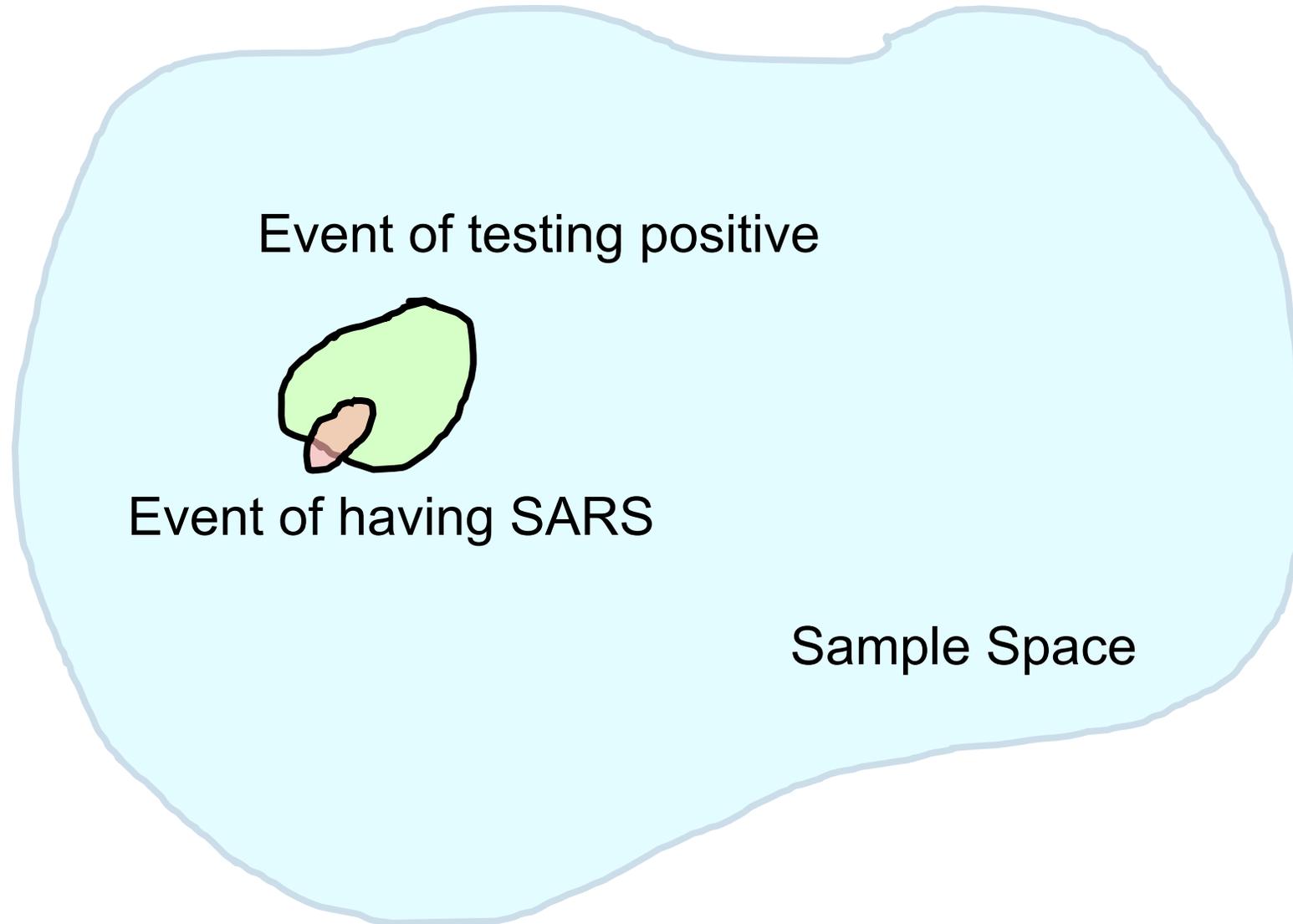
Bayes Theorem Intuition



Bayes Theorem Intuition

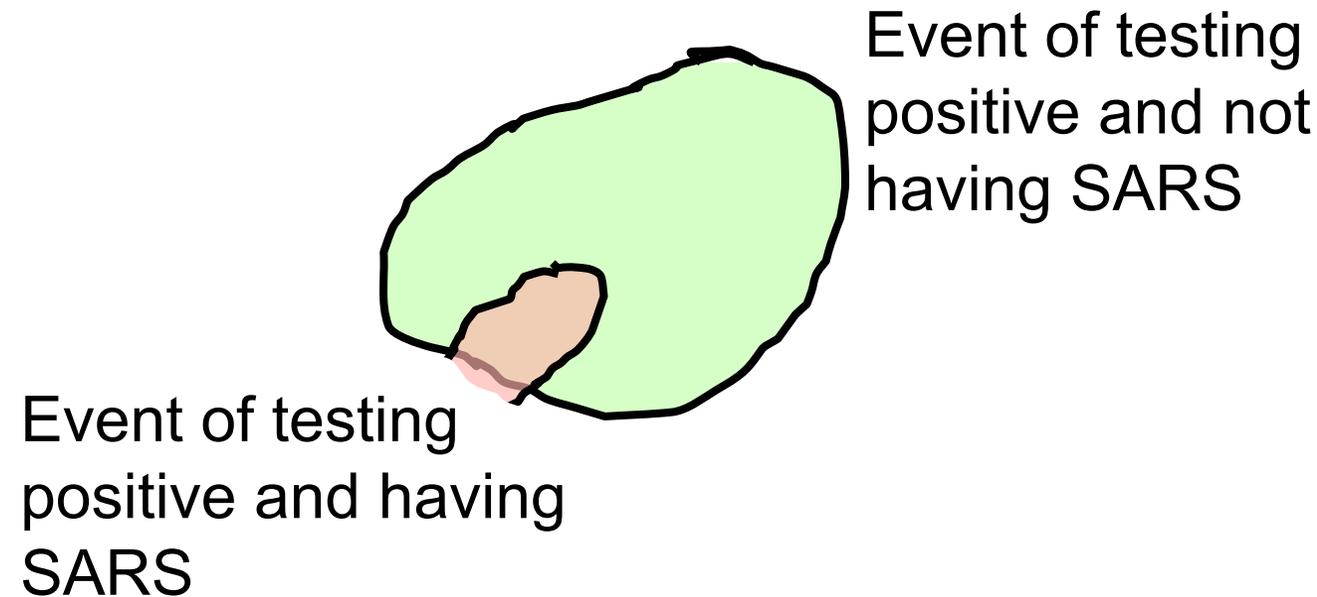


Bayes Theorem Intuition



Bayes Theorem Intuition

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

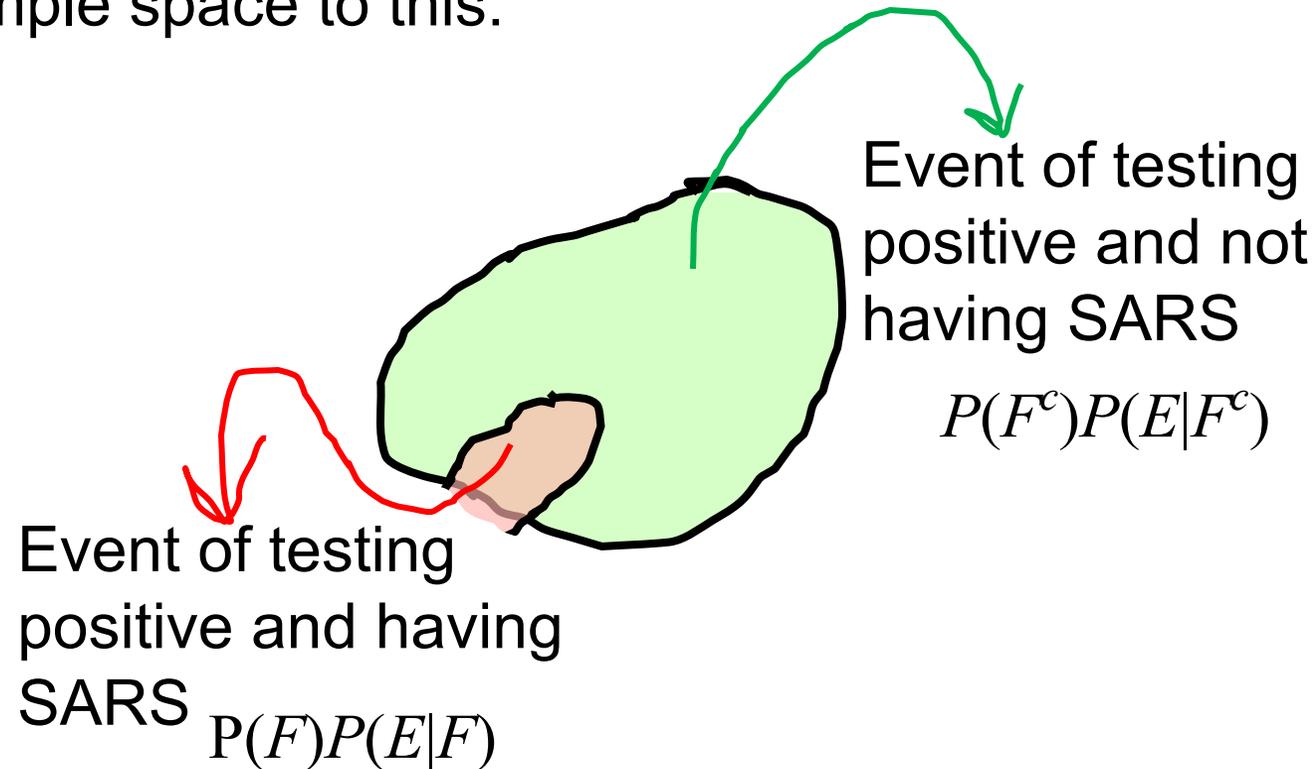


≈ 0.330



Bayes Theorem Intuition

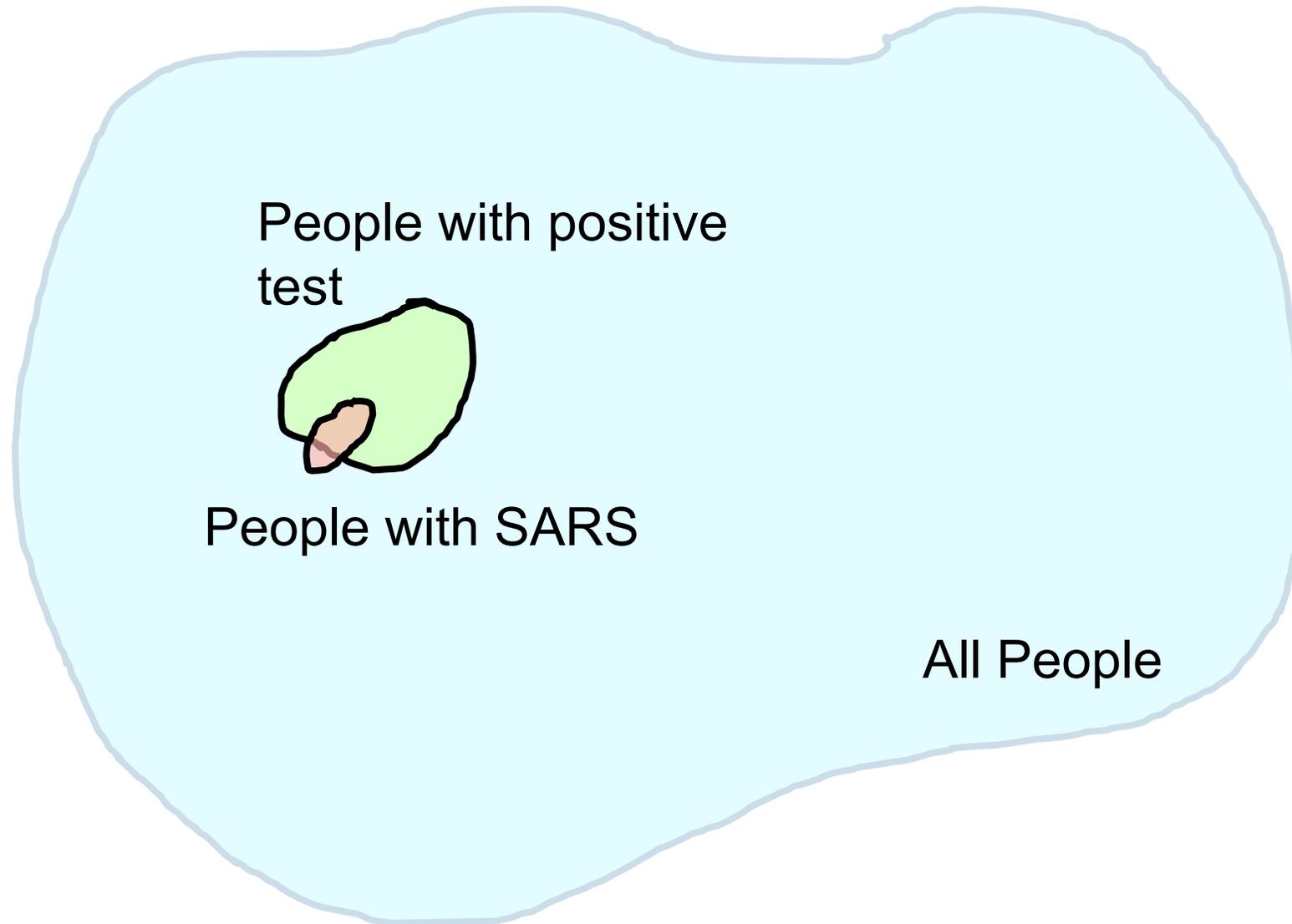
Conditioning on a positive result changes the sample space to this:



≈ 0.330

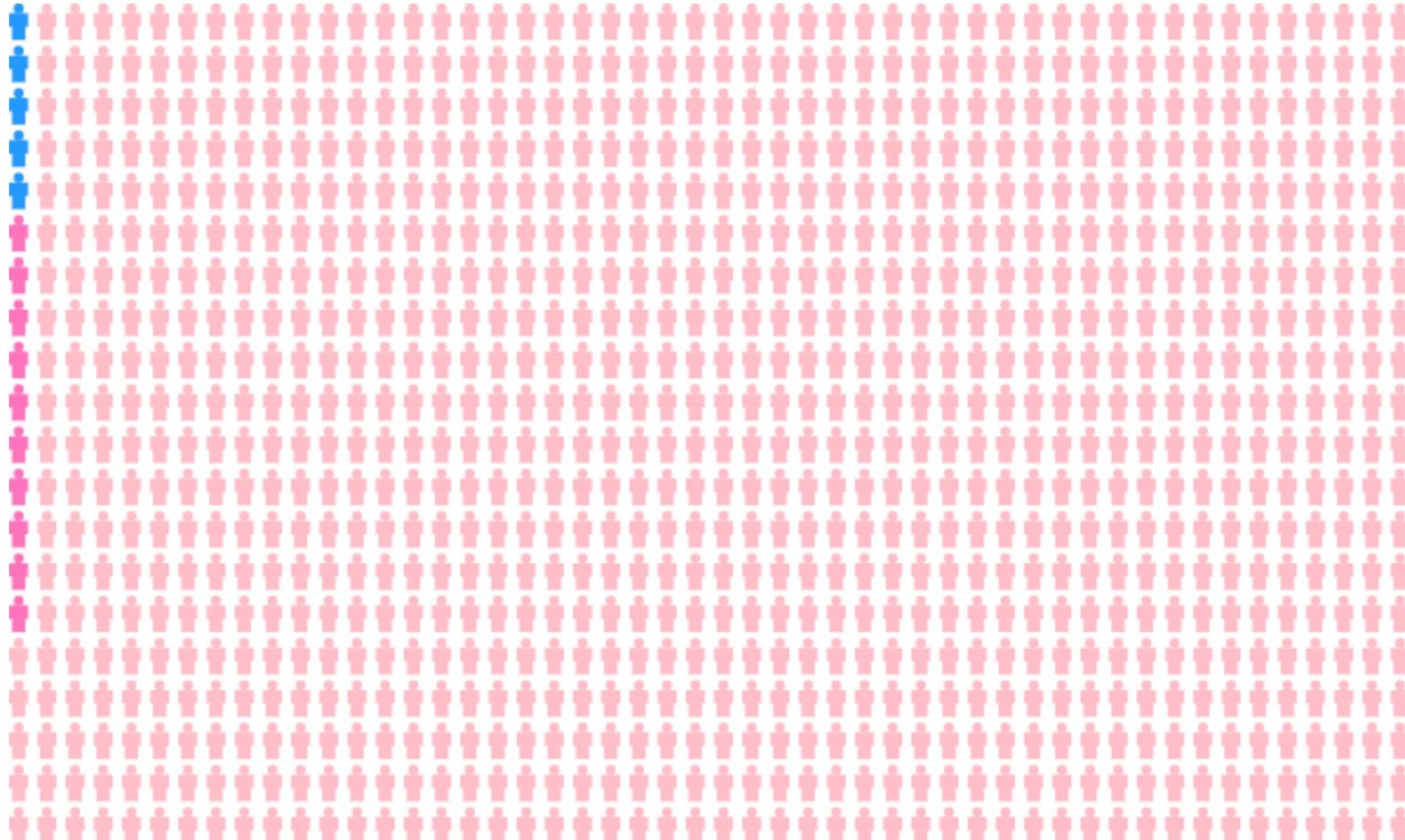


Bayes Theorem Intuition



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 $P(F | E^c)$?

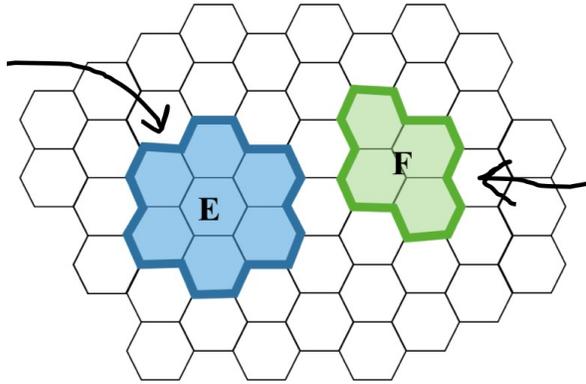
$$P(F | E^c) = \frac{P(E^c | F) P(F)}{P(E^c | F) P(F) + P(E^c | F^c) P(F^c)}$$

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



End Review

Learning Goals of Today



Mutually Exclusive

$$P(A \text{ and } B) = 0$$

Makes **OR** easy:

$$P(A \text{ or } B) = P(A) + P(B)$$



Independent

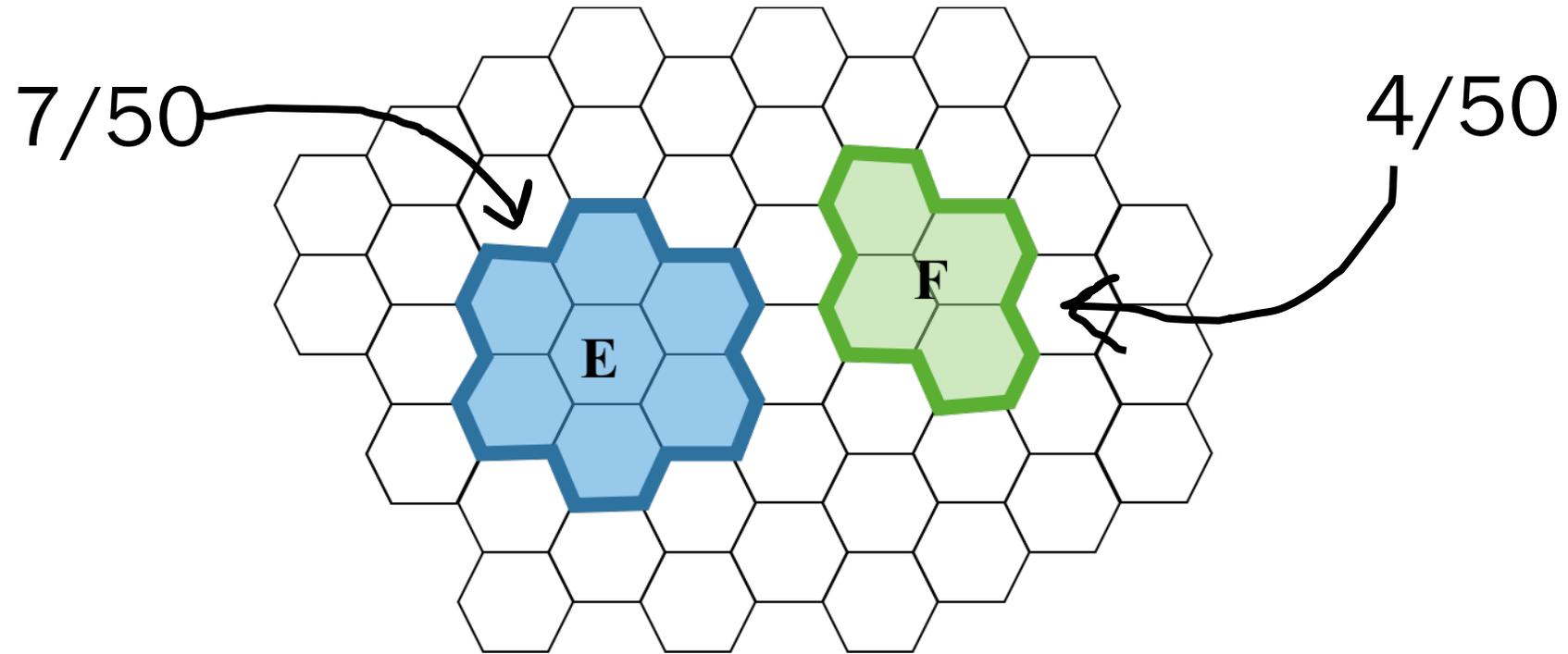
$$P(A) = P(A|B)$$

Makes **AND** easy:

$$P(A \text{ and } B) = P(A) \cdot P(B)$$

Probability of “OR”

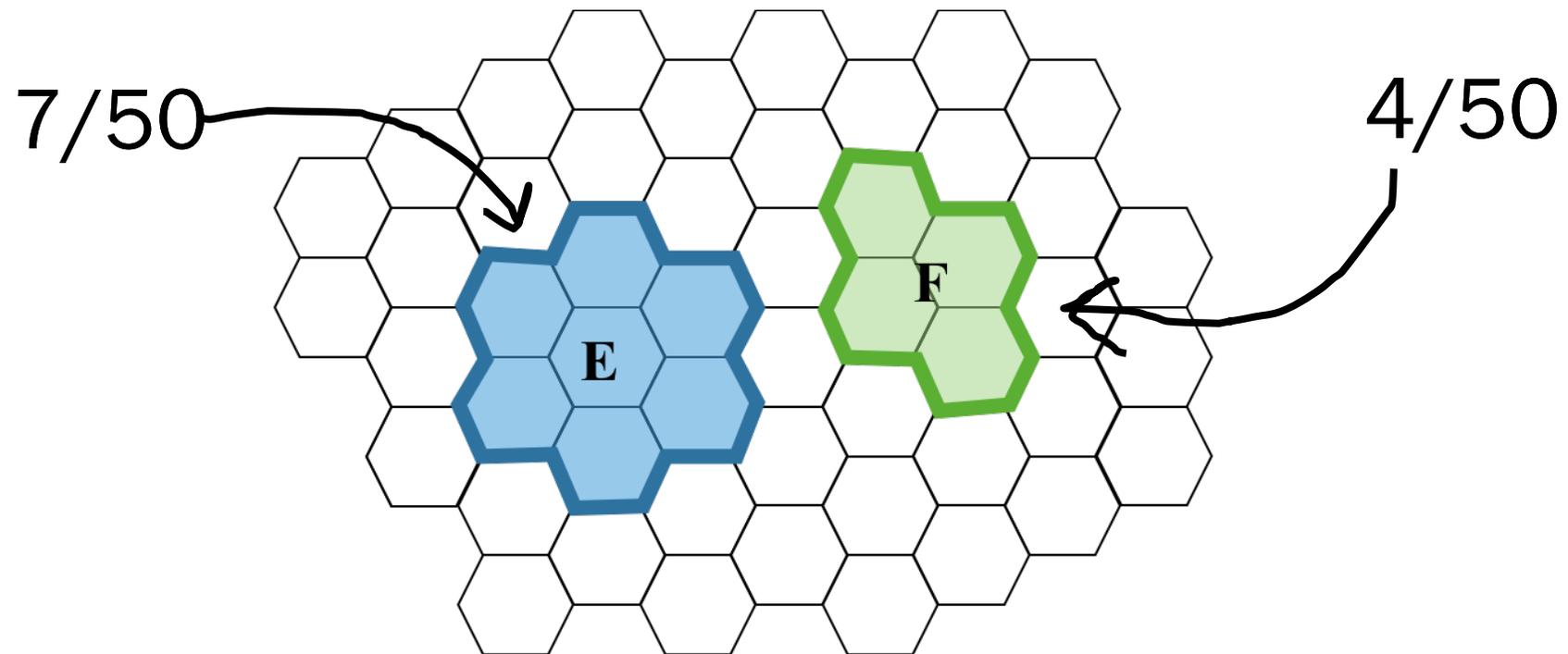
Review: OR with Mutually Exclusive Events



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

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

Review: OR with Mutually Exclusive Events

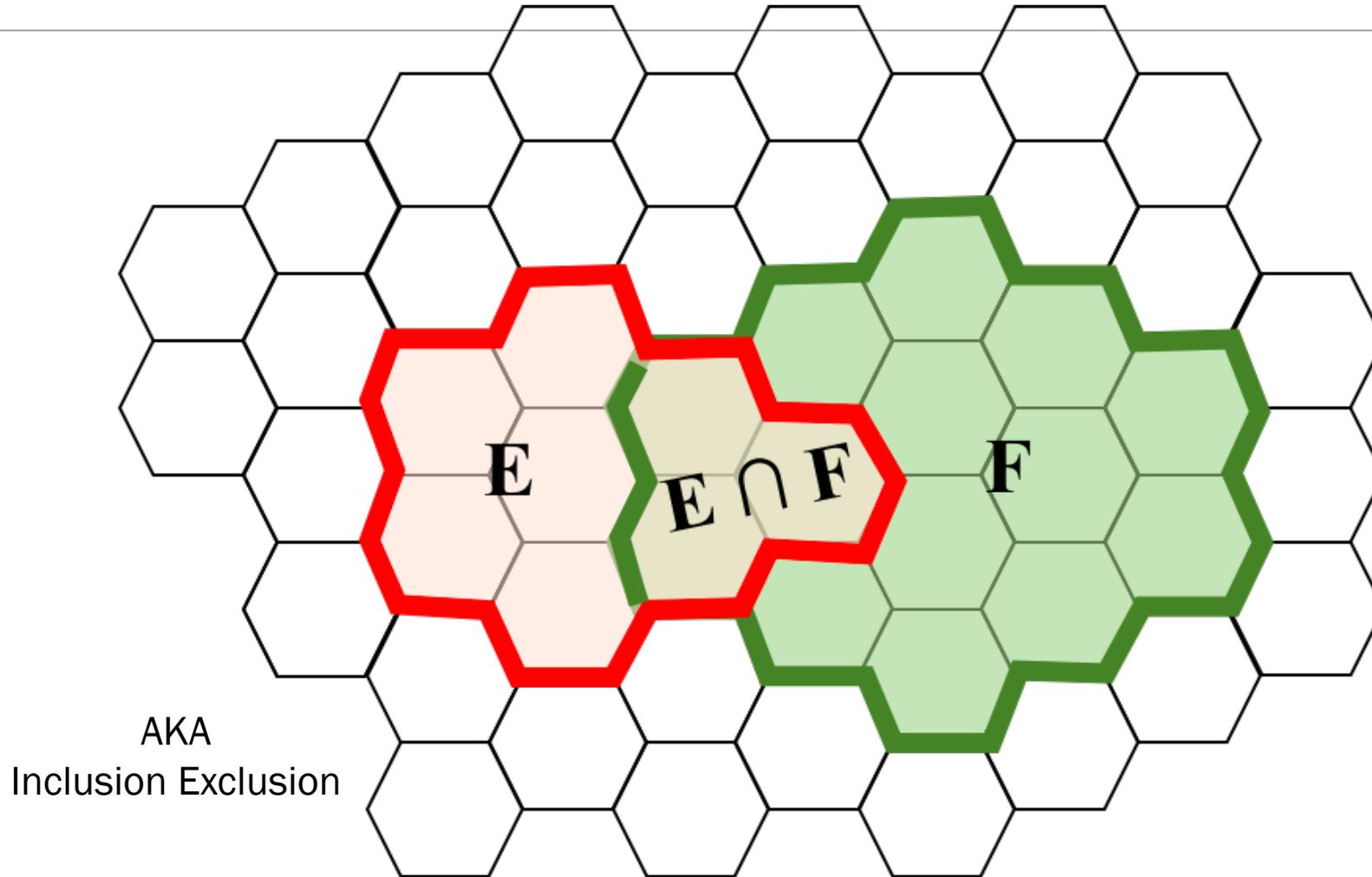


If events are mutually exclusive, probability of OR is simple:

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

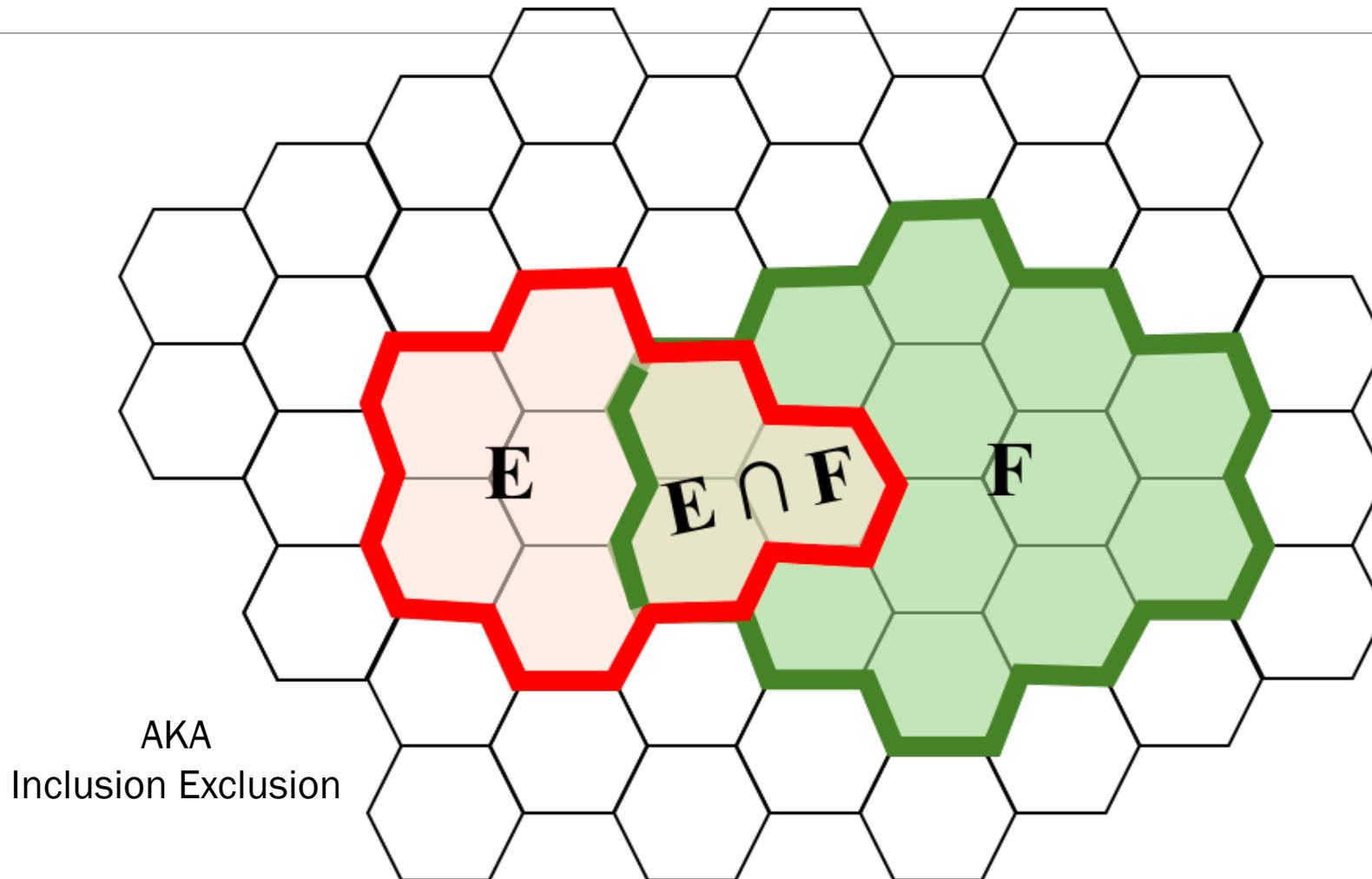
What about when they are not
Mutually exclusive?

OR *without* Mutually Exclusive Events



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

OR *without* Mutually Exclusive Events

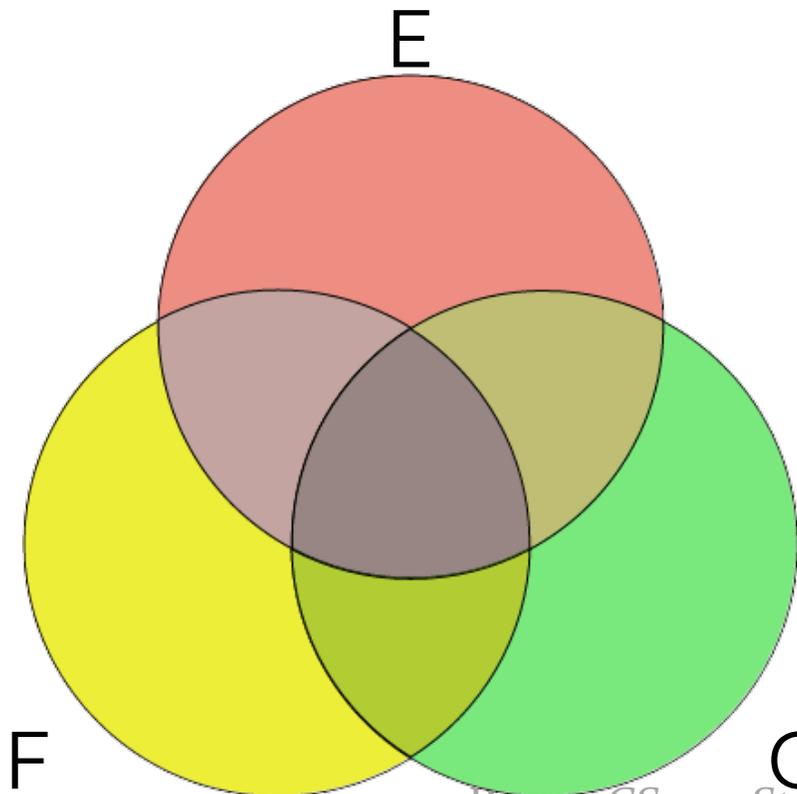


$$P(E \cup F) = \frac{8}{50} + \frac{14}{50} - \frac{3}{50} = \frac{19}{50}$$

More than two sets?

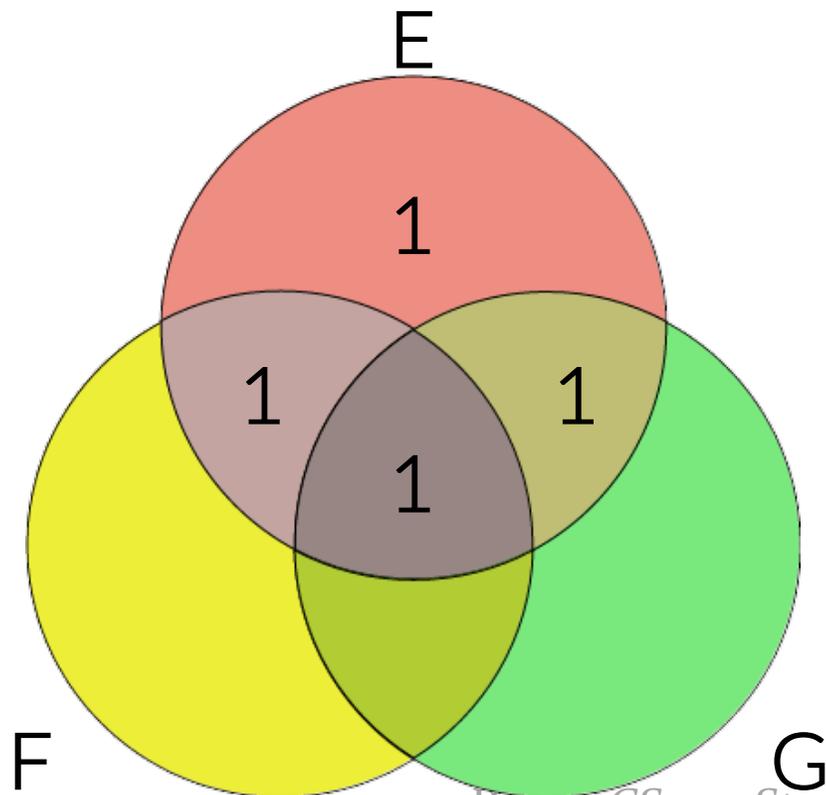
Inclusion / Exclusion with Three Events

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



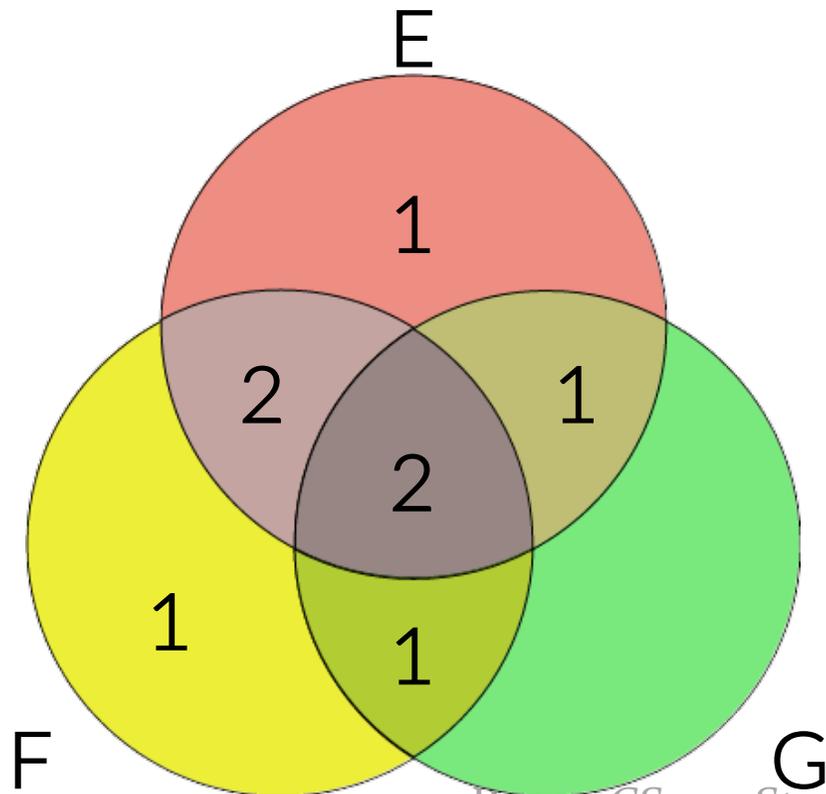
Inclusion / Exclusion with Three Events

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



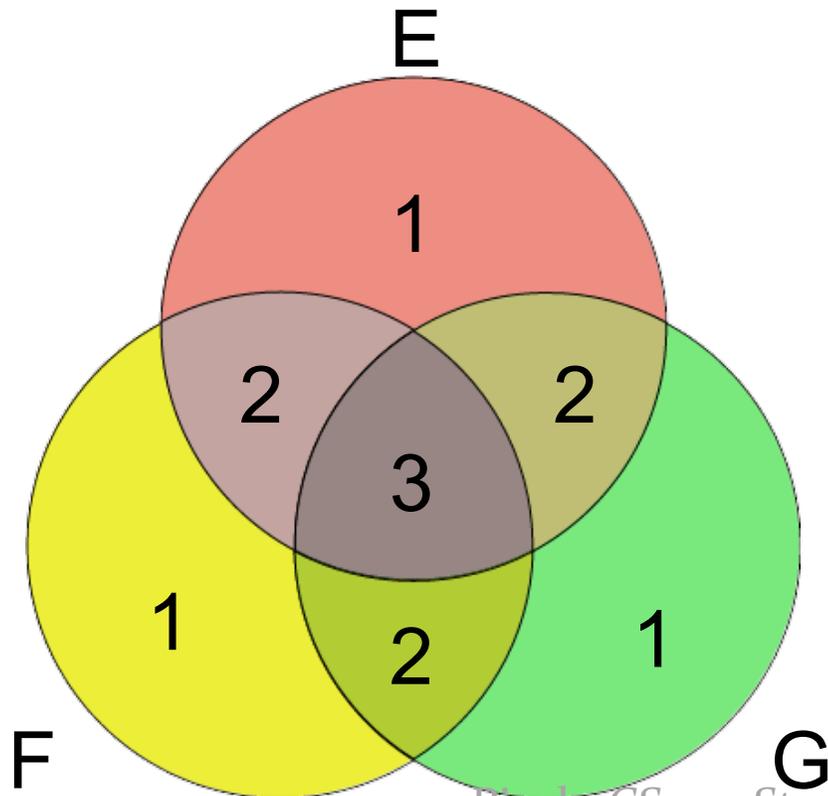
Inclusion / Exclusion with Three Events

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



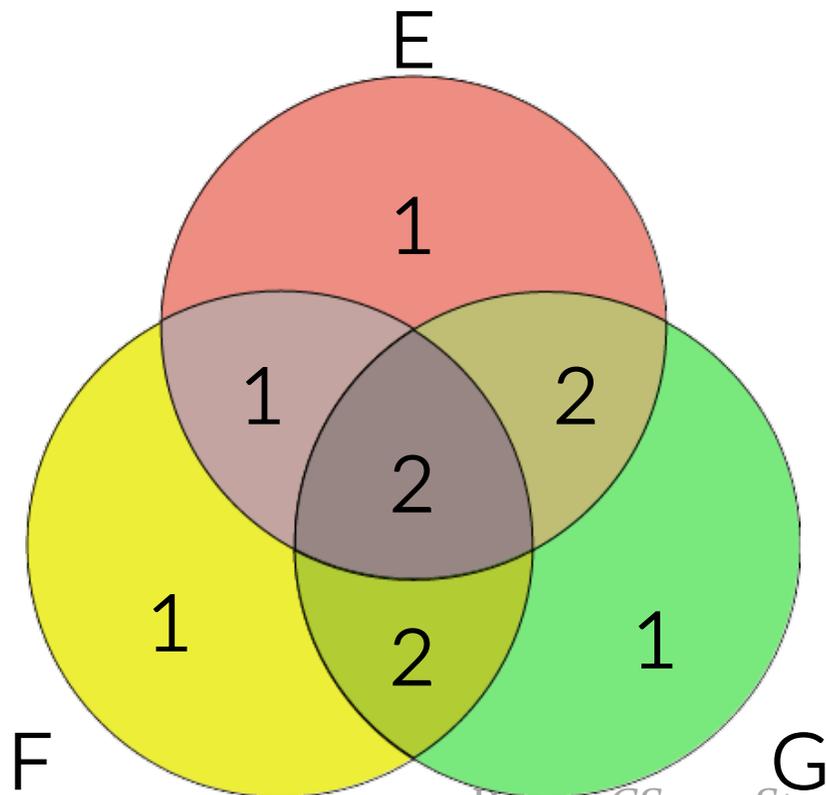
Inclusion / Exclusion with Three Events

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



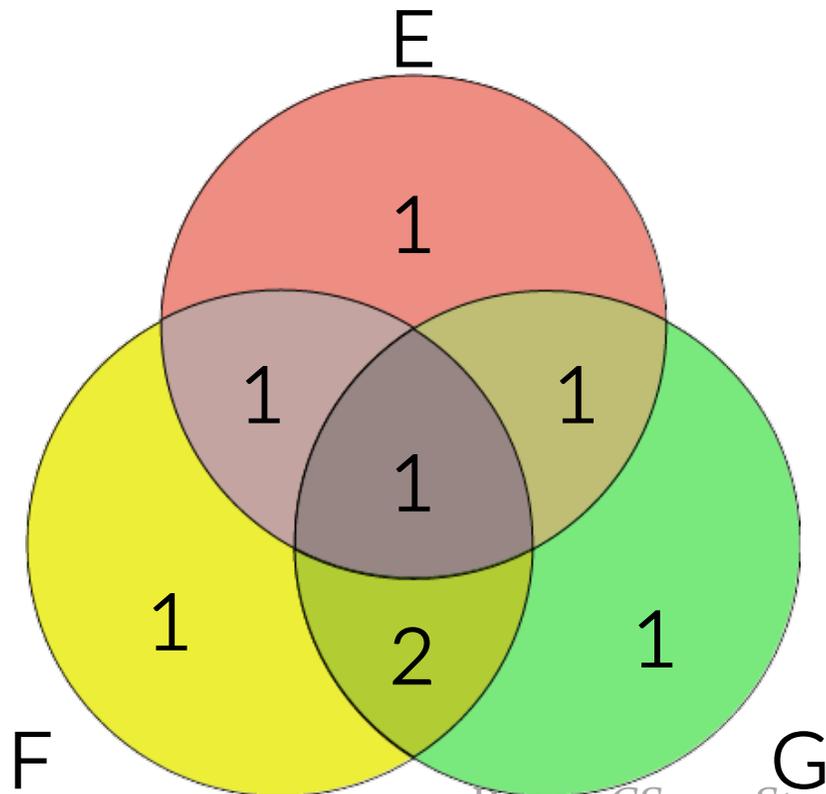
Inclusion / Exclusion with Three Events

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



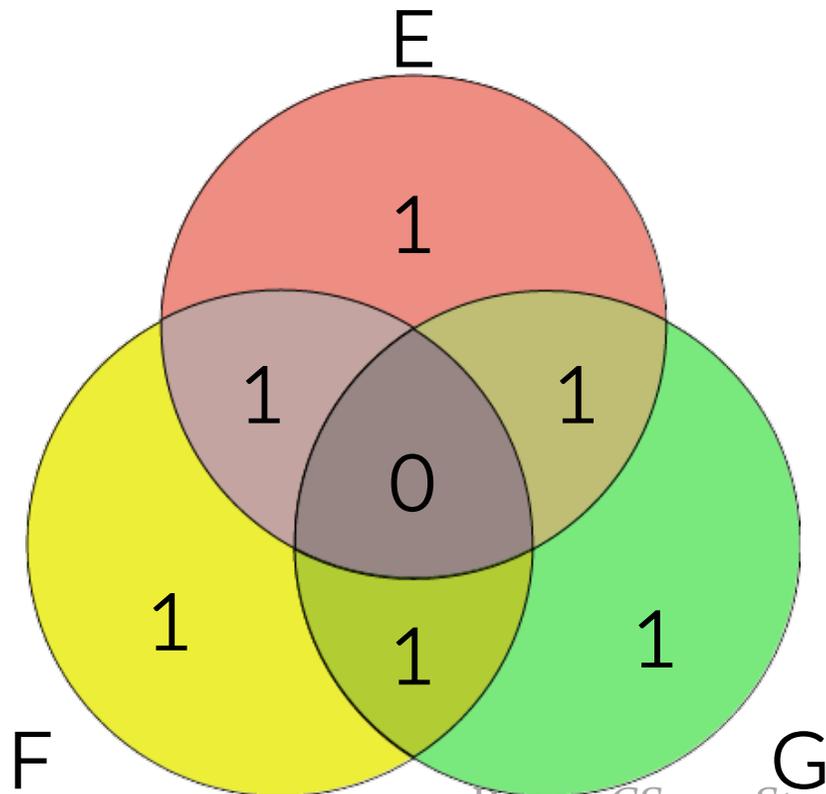
Inclusion / Exclusion with Three Events

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



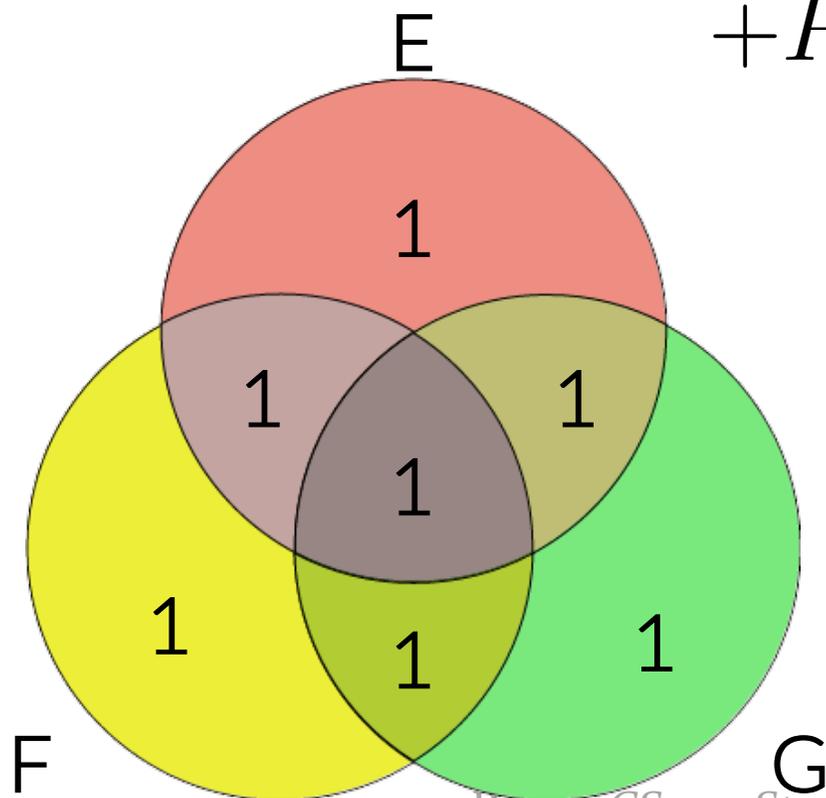
Inclusion / Exclusion with Three Events

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



Inclusion / Exclusion with Three Events

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



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

$$\sum_{i,j \text{ s.t. } i \neq j} P(E_i \cap E_j)$$

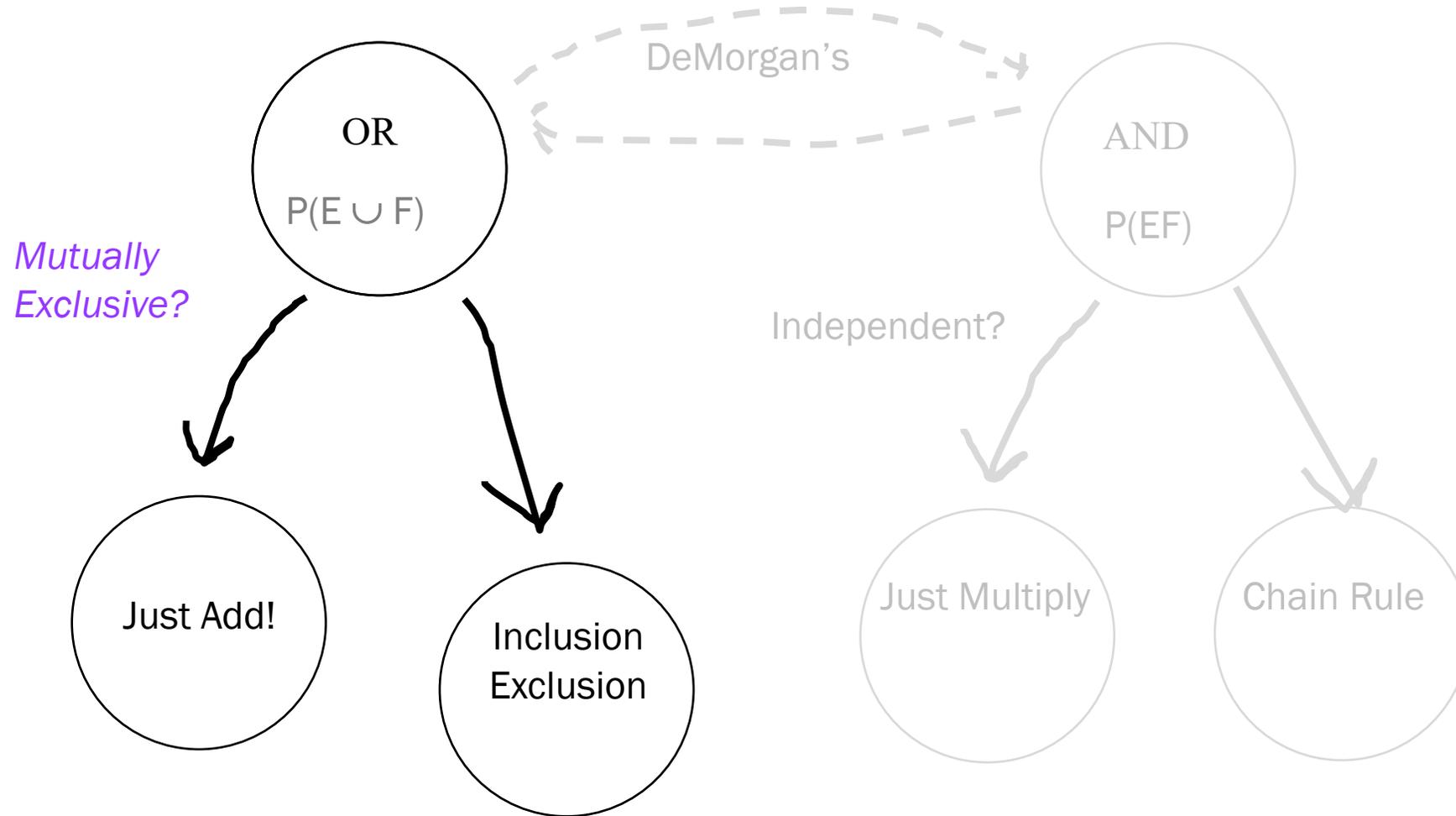
Y_3 = Sum of all triples of events

$$\sum_{i,j,k \text{ s.t. } i \neq j, j \neq k, i \neq k} P(E_i \cap E_j \cap E_k)$$

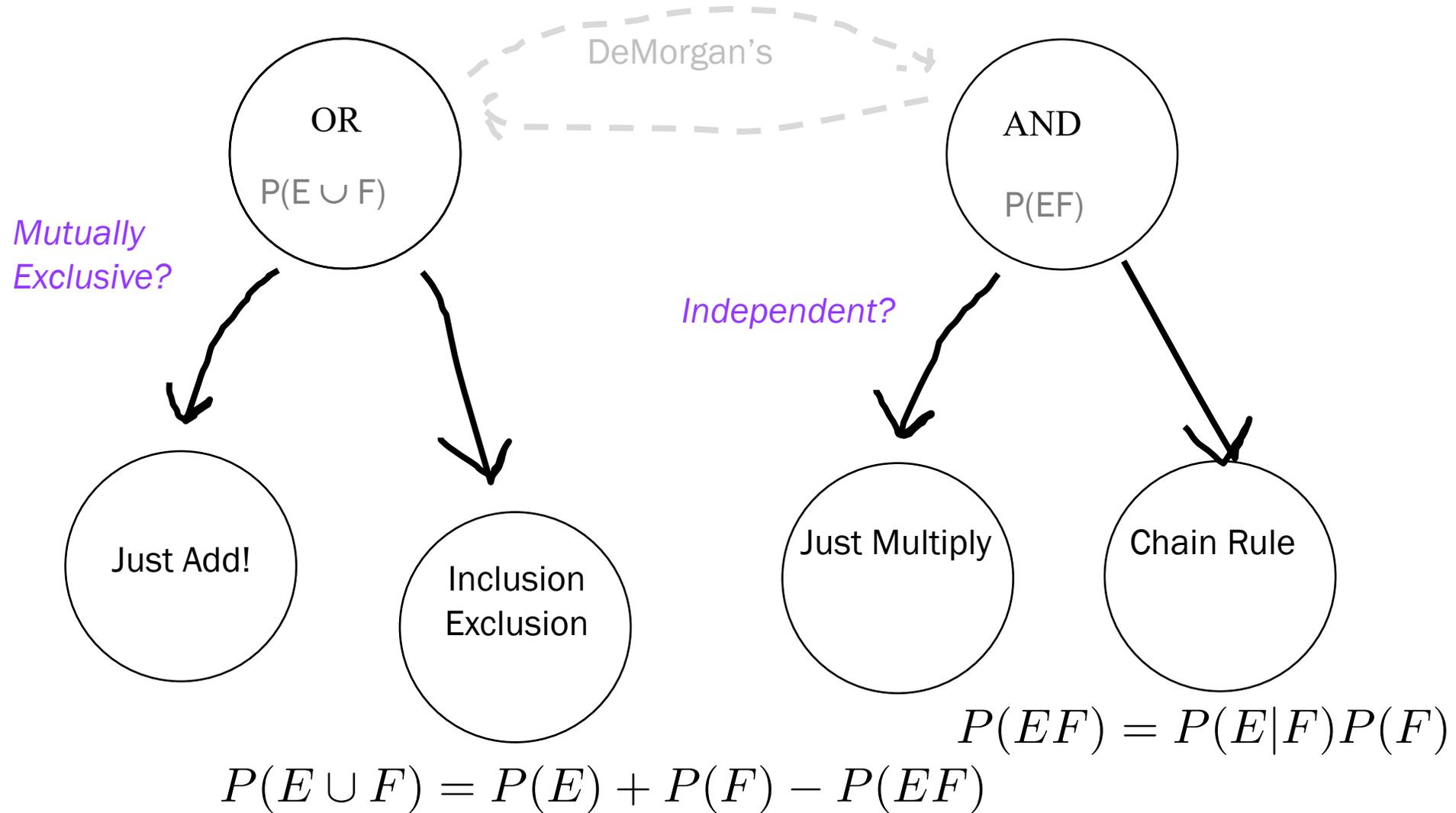
* Where Y_r is the sum, for all combinations of r events, of the probability of the union those events.

intersection

Today



Today



Probability of “AND”

WE THE PEOPLE
insure domestic Tranquility, provide for the common defence,
and our Posterity, do ordain and establish this Constitution

Article I
Section 1
All legislative Powers herein granted shall be vested in a Congress of the United States, which shall consist of a Senate and House of Representatives.
Section 2
The House of Representatives shall be composed of Members chosen every second Year by the People of the several States, and the Electors in each State shall have the Qualifications requisite for Electors of the most numerous Branch of the State Legislature.
Section 3
The Senate shall be composed of two Senators from each State, chosen by the Legislature thereof, for six Years; and each Senator shall have the Qualifications requisite for Senators of the most numerous Branch of the State Legislature.

Independence

Two events A and B are called **independent** if:

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

Knowing that event B happened, doesn't change our belief that A will happen.

Otherwise, they are called **dependent** events

Alternative Definition of Independence

Notation for *and*

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

Chain rule

Since B is independent of A

If you show this is true, you have proved the two events are independent!

Alternative Definition of Independence

Notation for *and*

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

Chain rule

Since B is independent of A

If you show this is true, you have proved the two events are independent!



If events are *independent* probability of AND is easy!

BUT!!

Always start with chain rule
and then ask yourself:
“Does independence hold?”



Independent \neq Mutually Exclusive

A,B Independent $\rightarrow P(A,B) = P(A)P(B)$

A,B Mutually exclusive $\rightarrow P(A,B) = 0$

Independence is reciprocal

If A is independent of B, then B is independent of A

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

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

Proof:

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

Bayes' Thm.

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

Because A is independent of B

$$= P(B)$$

Dice, our misunderstood friends

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

- Let E be event: $D_1 = 1$
- Let F be event: $D_2 = 1$

What is $P(E)$, $P(F)$, and $P(EF)$?

- $P(E) = 1/6$, $P(F) = 1/6$, $P(EF) = 1/36$
- $P(EF) = P(E) P(F) \rightarrow$ E and F independent

Let G be event: $D_1 + D_2 = 5$ $\{(1, 4), (2, 3), (3, 2), (4, 1)\}$

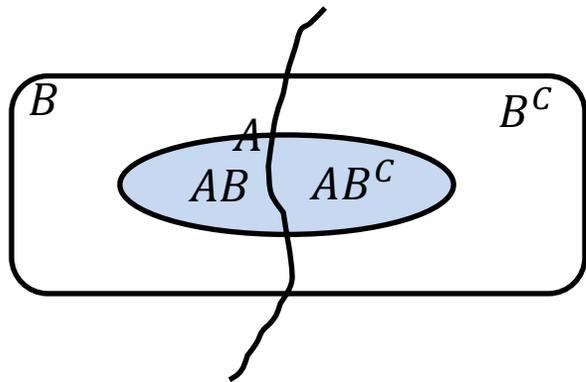
What is $P(E)$, $P(G)$, and $P(EG)$?

- $P(E) = 1/6$, $P(G) = 4/36 = 1/9$, $P(EG) = 1/36$
- $P(EG) \neq P(E) P(G) \rightarrow$ E and G dependent

Independence of Complements

Given independent events A and B , prove that A and B^C are independent

We want to show that $P(AB^C) = P(A)P(B^C)$



$$P(AB^C) = P(A) - P(AB) \quad \text{By Total Law of Prob.}$$

$$= P(A) - P(A)P(B) \quad \text{By independence}$$

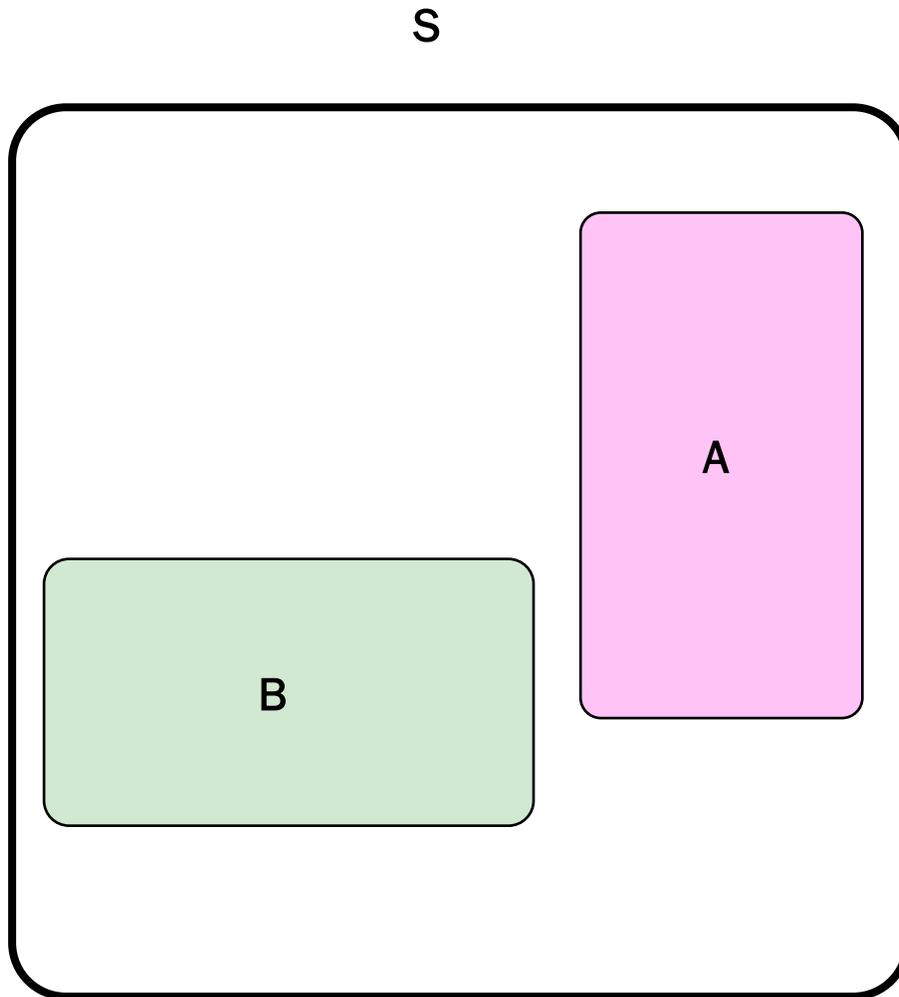
$$= P(A)[1 - P(B)] \quad \text{Factoring}$$

$$= P(A)P(B^C) \quad \text{Since } P(B) + P(B^C) = 1$$

So if A and B are independent A and B^C are also independent

What does independence look like?

Independence

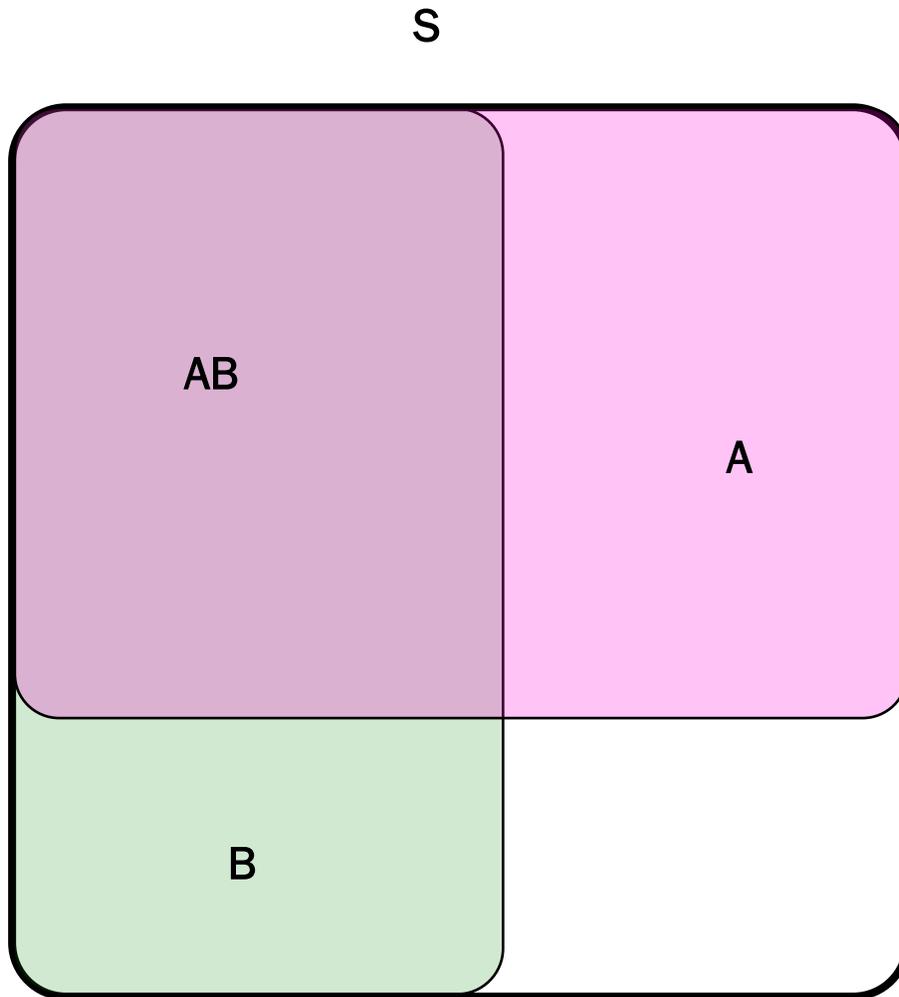


Independence Definition 1:

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

An arrow points from the $|AB|$ term in the second equation to the 0 in the first equation, indicating that $|AB| = 0$ because the sets A and B are disjoint.

Independence



Independence Definition 1:

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

$$\frac{|AB|}{|S|} = \frac{|A|}{|S|} \times \frac{|B|}{|S|}$$

Independence Definition 2:

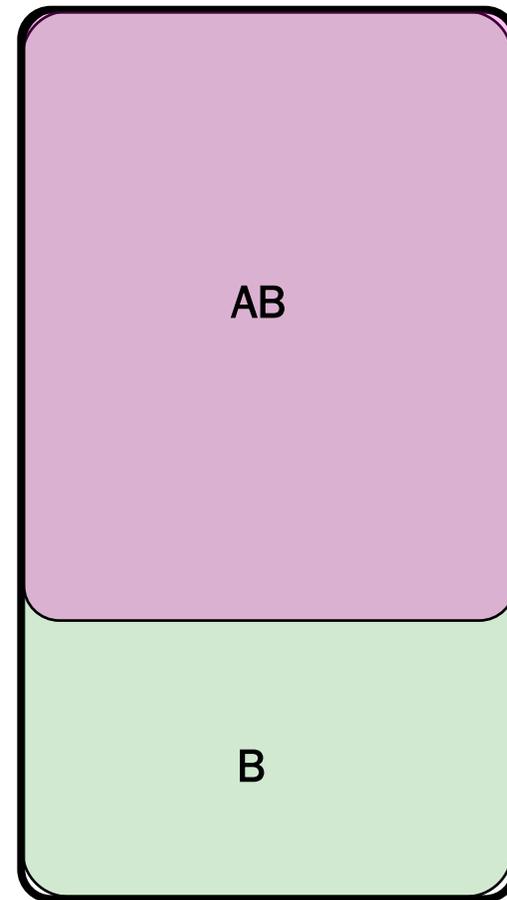
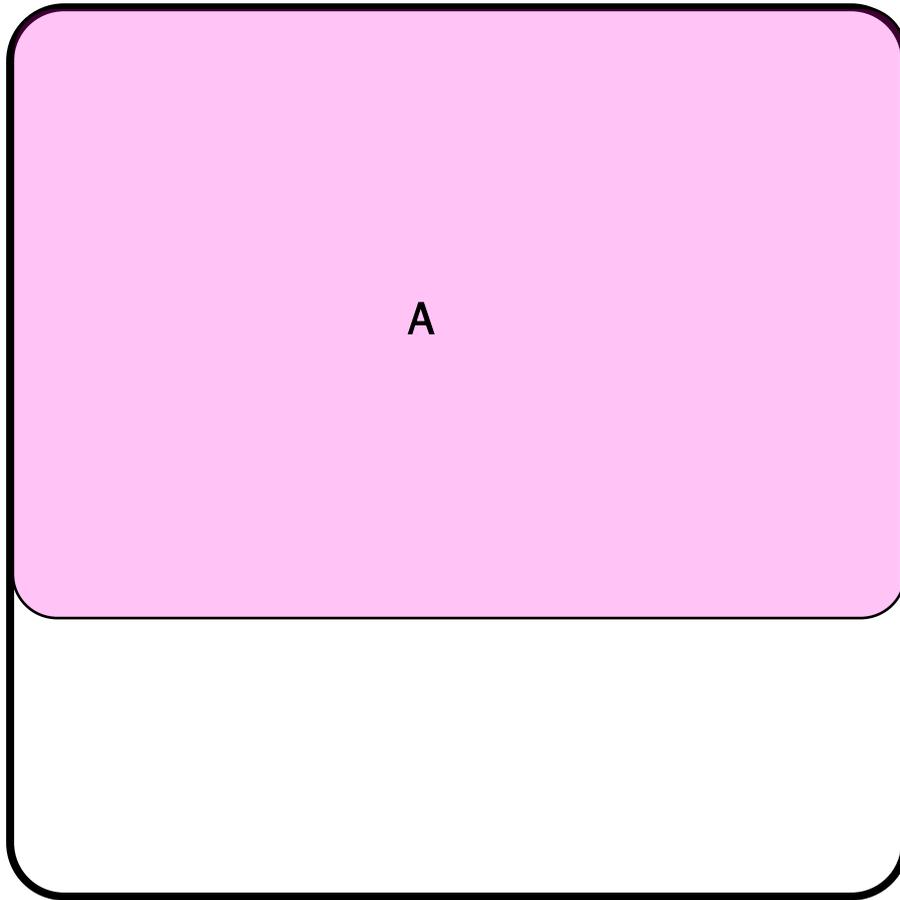
$$P(A|B) = P(A)$$

$$\frac{|AB|}{|B|} = \frac{|A|}{|S|}$$

Independence

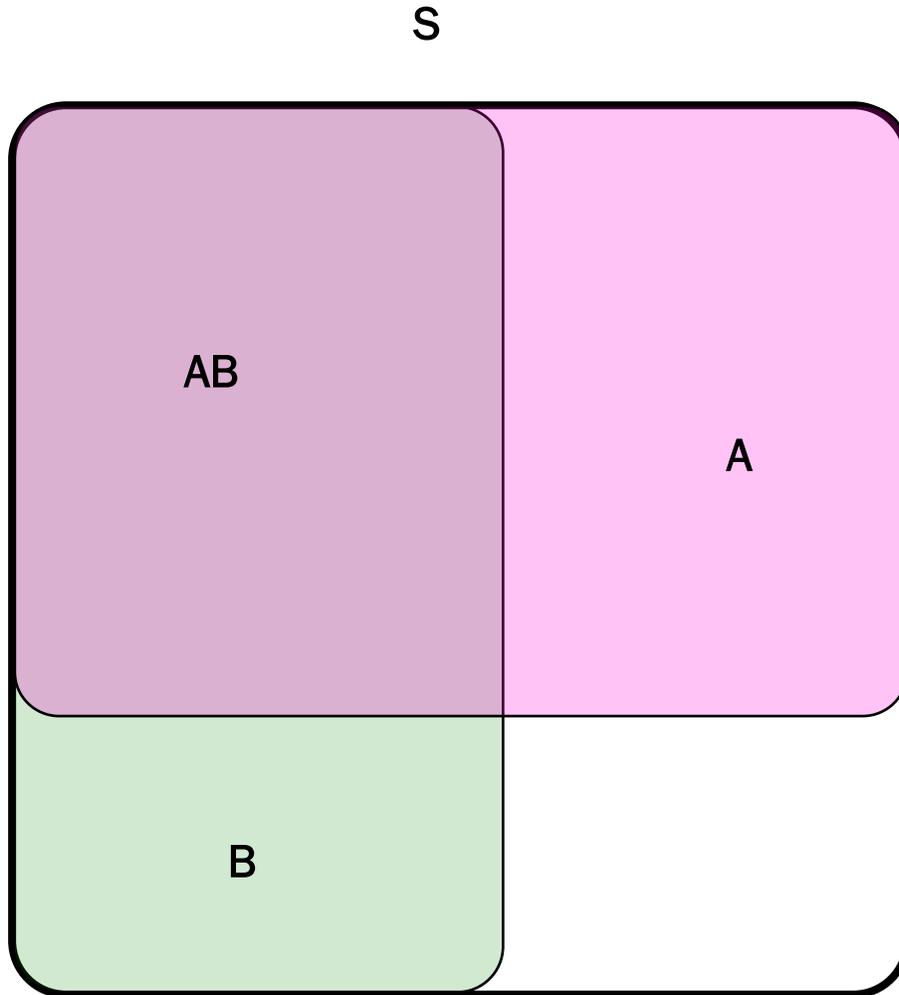
This ratio, $P(A)$...

... is the same as this one, $P(A|B)$



S

Independence



Independence Definition 1:

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

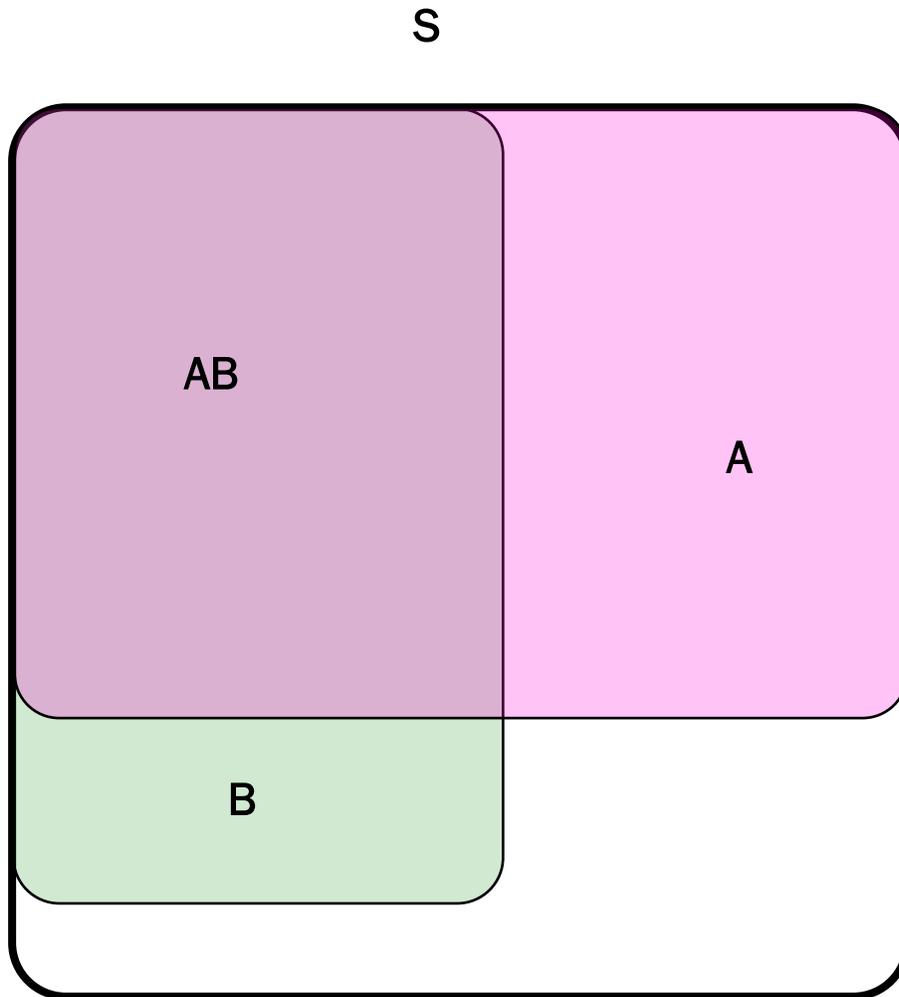
$$\frac{|AB|}{|S|} = \frac{|A|}{|S|} \times \frac{|B|}{|S|}$$

Independence Definition 2:

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

$$\frac{|AB|}{|B|} = \frac{|A|}{|S|}$$

Dependence



Independence Definition 1:

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

$$\frac{|AB|}{|S|} = \frac{|A|}{|S|} \times \frac{|B|}{|S|}$$

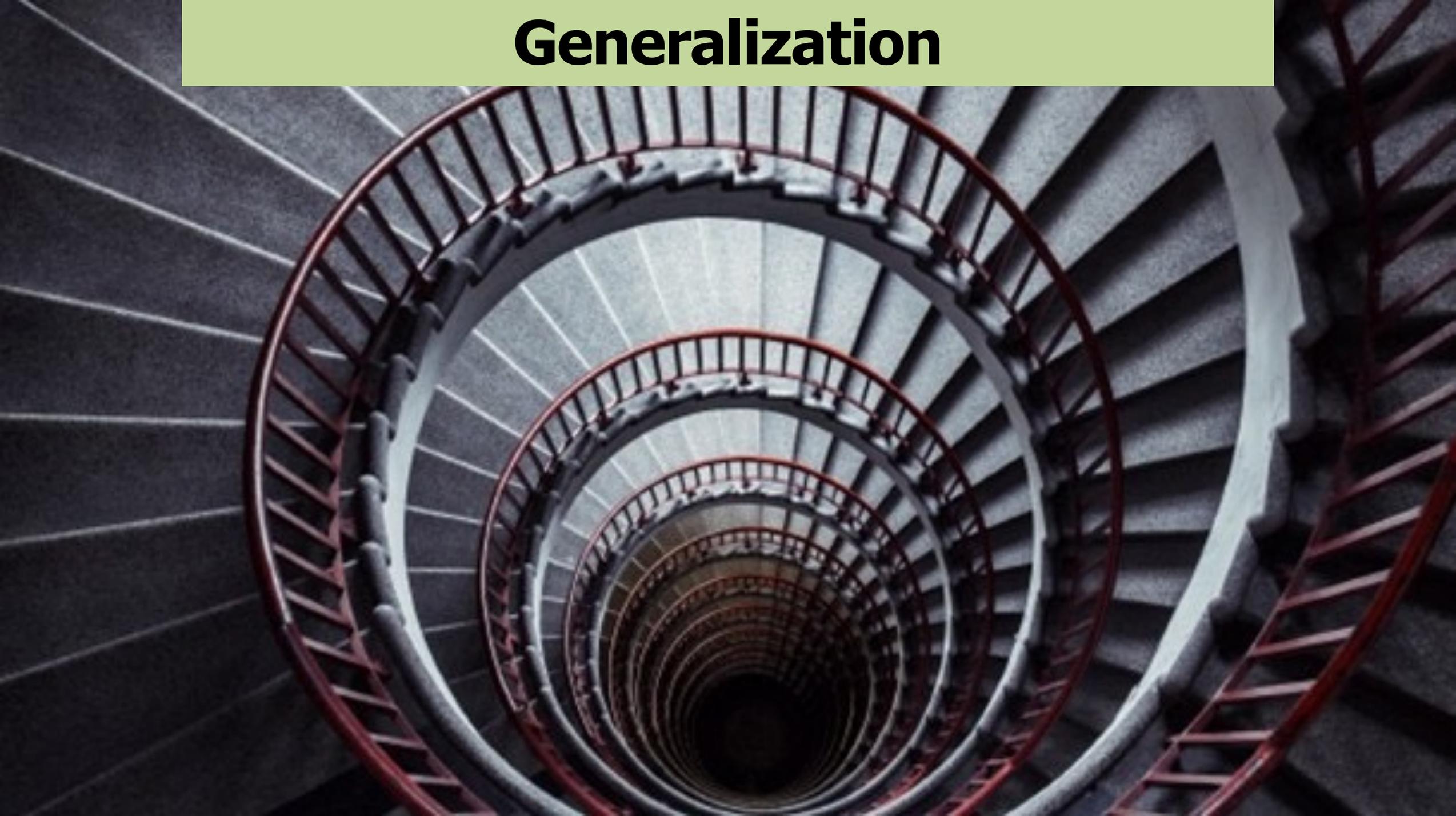
Independence Definition 2:

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

$$\frac{|AB|}{|B|} = \frac{|A|}{|S|}$$

End of visualization

Generalization



Generalized Independence (Mutual Independence)

General definition of Independence (Mutual Independence):

Events E_1, E_2, \dots, E_n are **mutually independent** if **for every subset** with r elements (where $r \leq n$) it holds that:

$$P(E_1, E_2, E_3, \dots, E_r) = P(E_1)P(E_2)P(E_3) \dots P(E_r)$$

Example: outcomes of n separate flips of a coin are all independent of one another

- Each flip in this case is called a “trial” of the experiment

Two Dice (Pairwise Independent but not Mutually Independent)

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

- Let E be event: $D_1 = 1$
- Let F be event: $D_2 = 6$
- Are E and F independent? **Yes!**

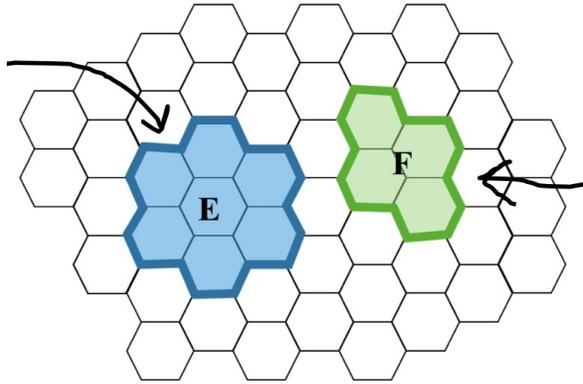
Let G be event: $D_1 + D_2 = 7$

- Are E and G independent? **Yes!**
- $P(E) = 1/6$, $P(G) = 1/6$, $P(E \cap G) = 1/36$ [roll (1, 6)]
- Are F and G independent? **Yes!**
- $P(F) = 1/6$, $P(G) = 1/6$, $P(F \cap G) = 1/36$ [roll (1, 6)]
- Are E, F and G independent? **No!**
- $P(EFG) = 1/36 \neq 1/216 = (1/6)(1/6)(1/6)$

New Ability



Properties of Pairs of Events



Mutually Exclusive

$$P(A \text{ and } B) = 0$$

also:

$$P(A \text{ or } B) = P(A) + P(B)$$



Independent

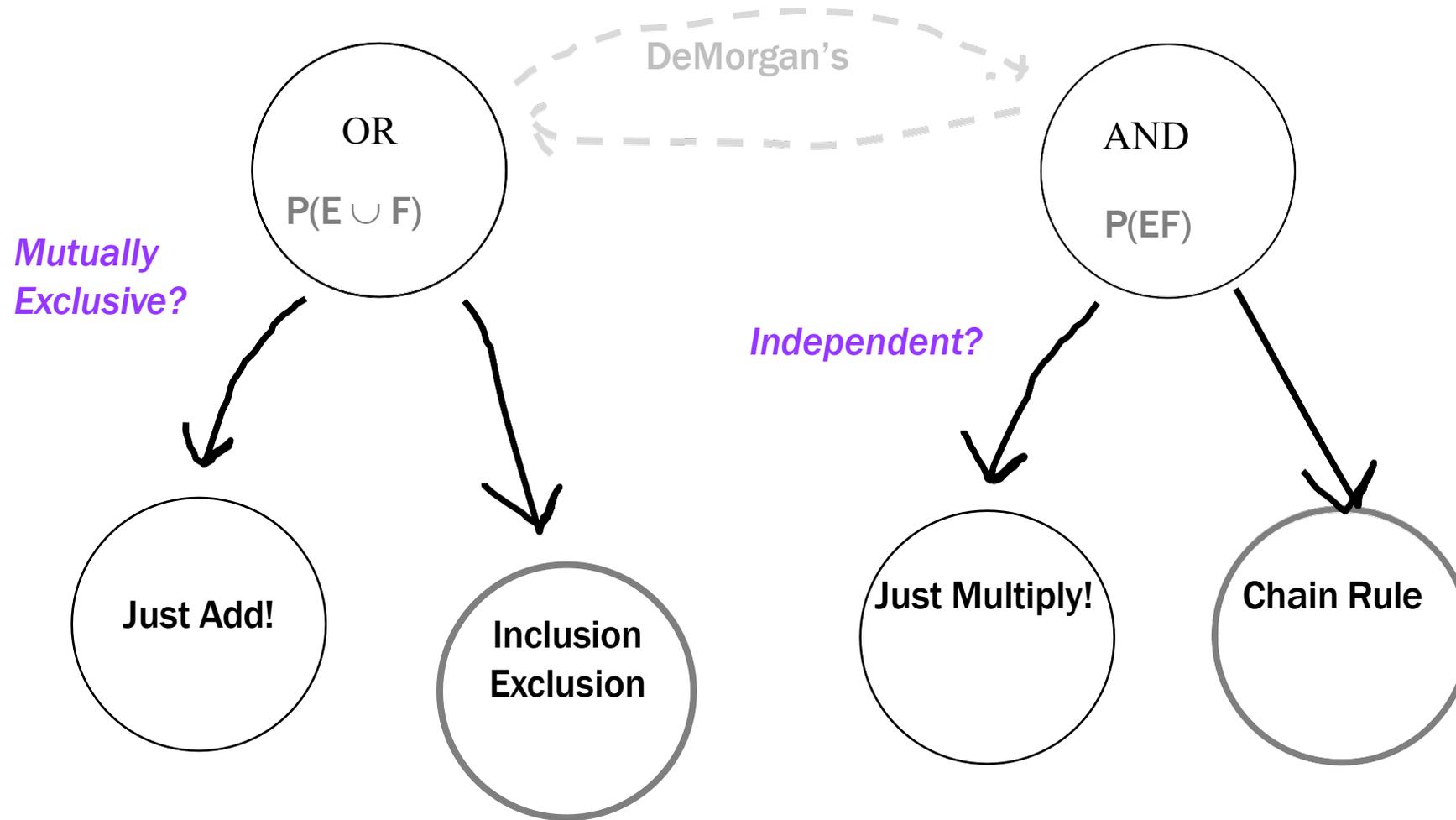
$$P(A) = P(A|B)$$

also:

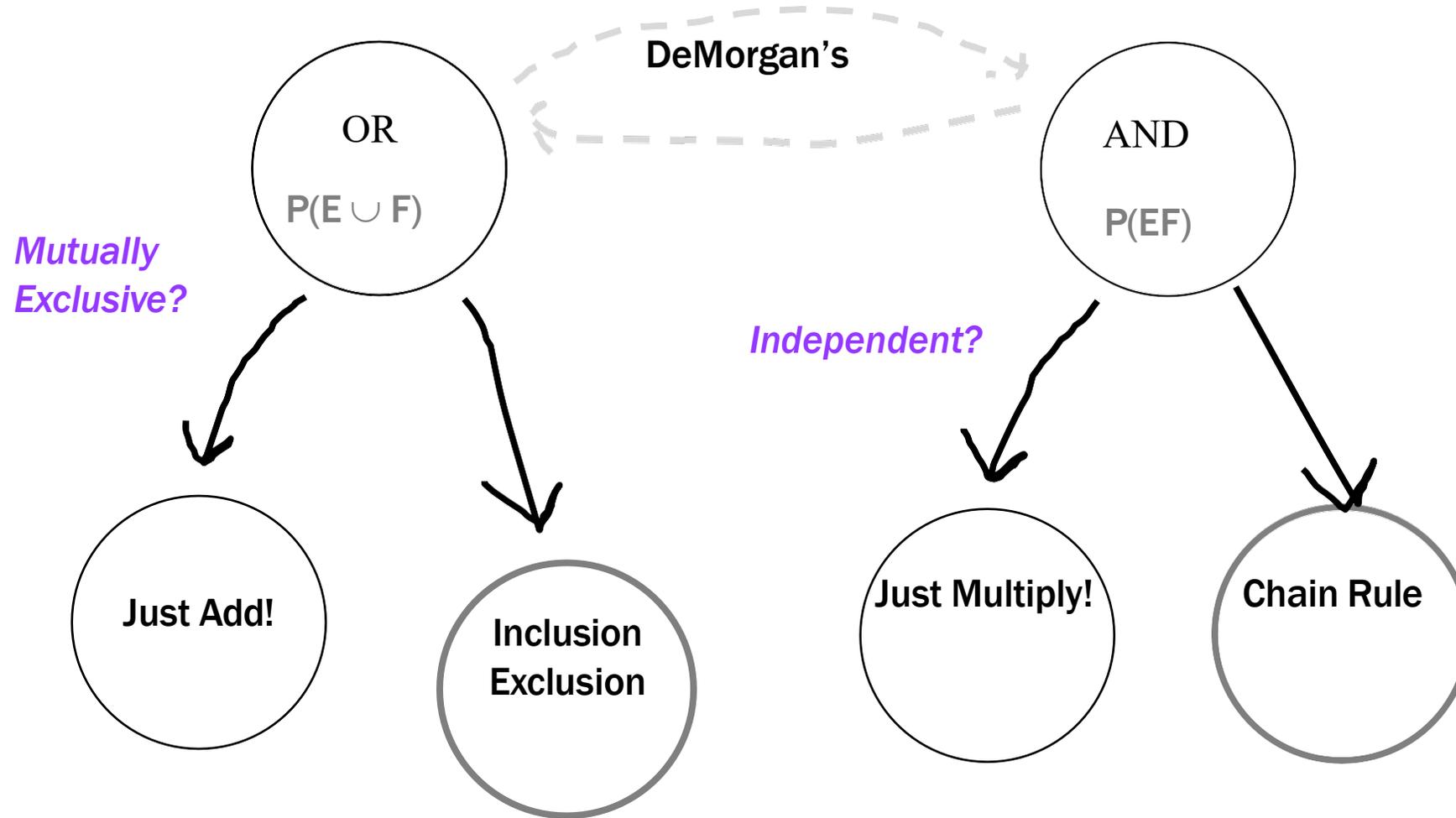
$$P(A \text{ and } B) = P(A) \cdot P(B)$$



Today



Today



Think of the children as independent trials

Independence:

$$P(A \text{ and } B) = P(A) \cdot P(B)$$

Two parents both have an (A, a) gene pair.

- Each parent will pass on one of their genes (each gene equally likely) to a child.
- The probability of **any single child** having curly hair (the recessive trait) is 0.25, independent of other siblings.
- There are three children.



What is the probability that all three children have curly hair?

Let E_1, E_2, E_3 be the events that child 1, 2, and 3 have curly hair, respectively.

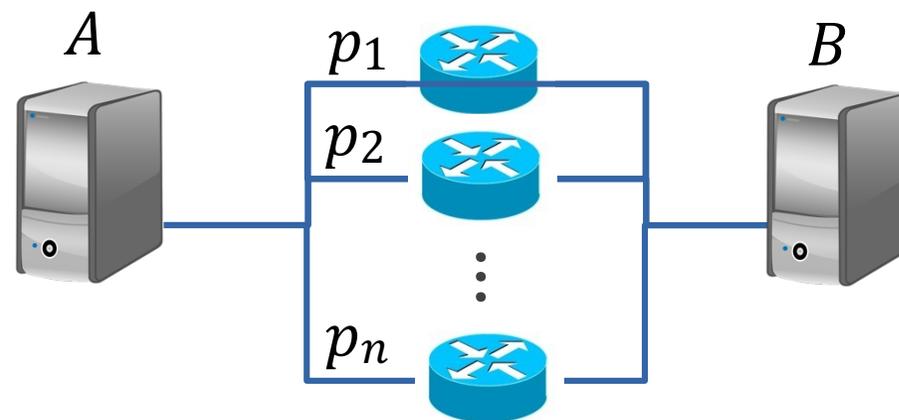
$$\begin{aligned} P(E_1 E_2 E_3) &= P(E_1) P(E_2 | E_1) P(E_3 | E_1 E_2) \\ &= P(E_1) P(E_2) P(E_3) \end{aligned}$$

Network reliability

Consider the following parallel network:

- n independent routers, each with probability p_i of functioning (where $1 \leq i \leq n$)
- $E =$ functional path from A to B exists.

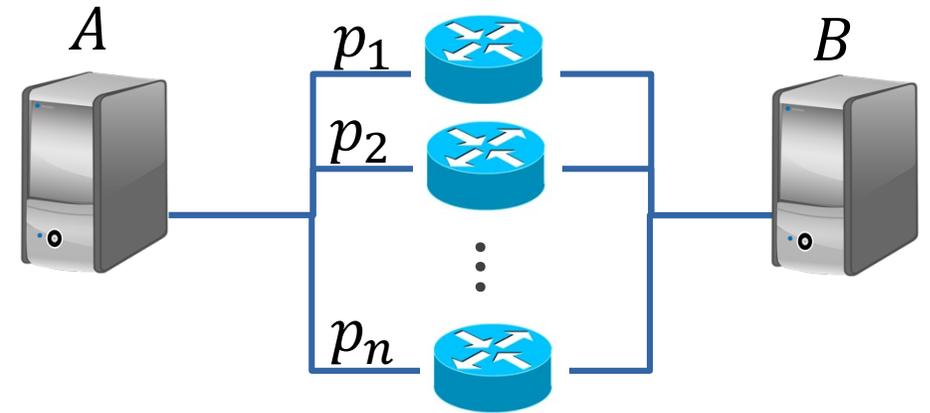
What is $P(E)$?



Network reliability

Consider the following parallel network:

- n independent routers, each with probability p_i of functioning (where $1 \leq i \leq n$)
- E = functional path from A to B exists.

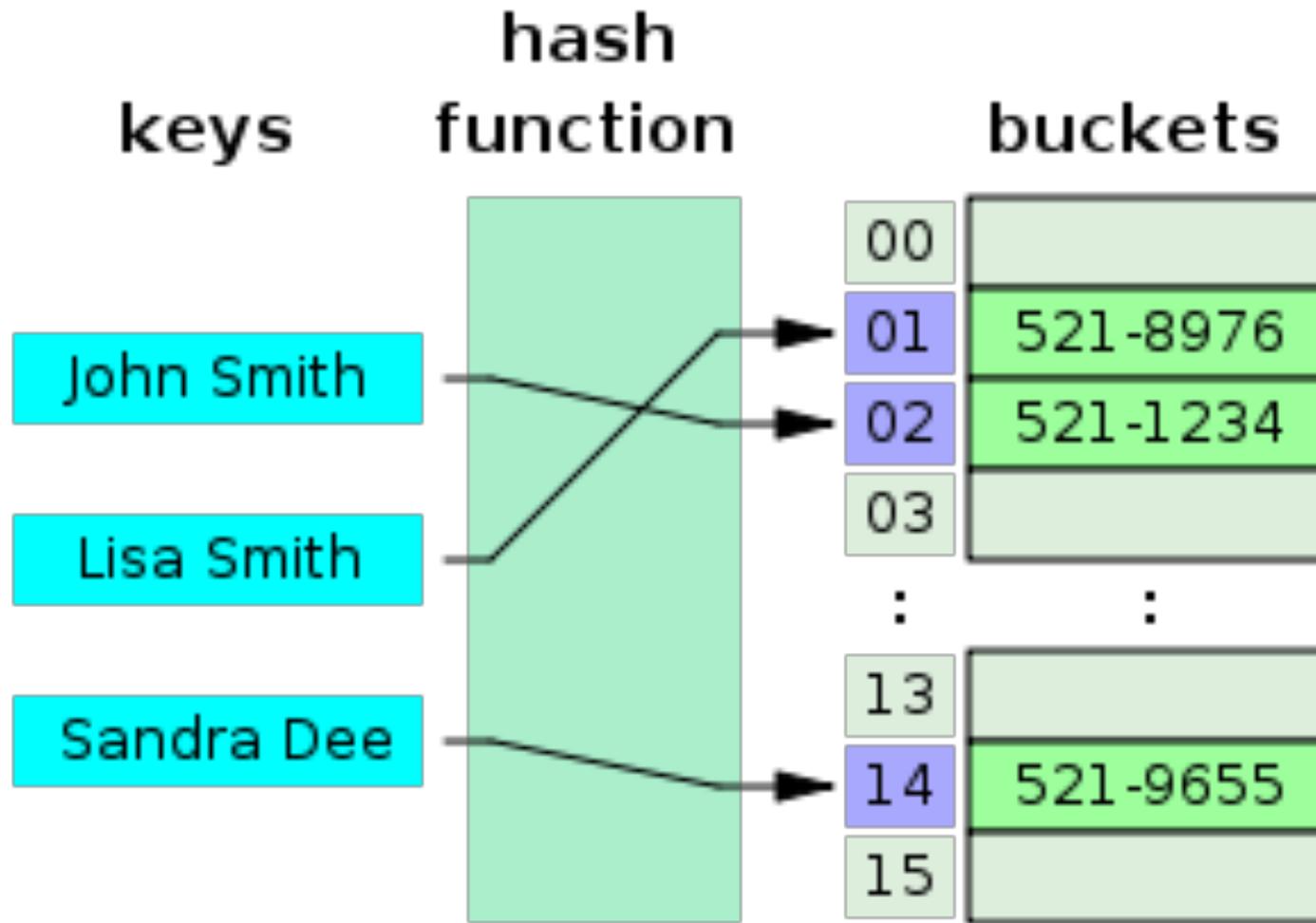


What is $P(E)$?

$$\begin{aligned} P(E) &= P(\geq 1 \text{ one router works}) \\ &= 1 - P(\text{all routers fail}) \\ &= 1 - (1 - p_1)(1 - p_2) \cdots (1 - p_n) \\ &= 1 - \prod_{i=1}^n (1 - p_i) \end{aligned}$$

≥ 1 with independent trials:
take complement

Hash Tables



Hash table fun

- m strings are hashed (not uniformly) into a hash table with n buckets.
- Each string hash is independent with probability p_i of getting hashed into bucket i .

What is $P(E)$ if

1. $E =$ bucket 1 has ≥ 1 string hashed into it?

Hash table fun

- m strings are hashed (not uniformly) into a hash table with n buckets.
- Each string hash is an **independent trial** w.p. p_i of getting hashed into bucket i .

What is $P(E)$ if

1. $E =$ bucket 1 has ≥ 1 string hashed into it?

Define: $S_i =$ string i hashes to bucket 1
 $S_i^C =$ string i doesn't hash to bucket 1


$$P(S_i) = p_1$$
$$P(S_i^C) = 1 - p_1$$

Hash table fun

- m strings are hashed (not uniformly) into a hash table with n buckets.
- Each string hash is an **independent trial** w.p. p_i of getting hashed into bucket i .

What is $P(E)$ if

1. $E =$ bucket 1 has ≥ 1 string hashed into it?

$$\begin{aligned}P(E) &= P(S_1 \cup S_2 \cup \dots \cup S_m) \\&= 1 - P\left((S_1 \cup S_2 \cup \dots \cup S_m)^c\right) \\&= 1 - P(S_1^c S_2^c \dots S_m^c) \\&= 1 - P(S_1^c)P(S_2^c) \dots P(S_m^c) = 1 - \left(P(S_1^c)\right)^m \\&= 1 - (1 - p_1)^m\end{aligned}$$

Define: $S_i =$ string i hashes to bucket 1
 $S_i^c =$ string i doesn't hash to bucket 1

Complement

De Morgan's Law

S_i independent trials


$$\begin{aligned}P(S_i) &= p_1 \\P(S_i^c) &= 1 - p_1\end{aligned}$$

More hash table fun: Possible approach?

- m strings are hashed (not uniformly) into a hash table with n buckets.
- Each string hash is an independent trial w.p. p_i of getting hashed into bucket i .

What is $P(E)$ if

1. $E =$ bucket 1 has ≥ 1 string hashed into it?
2. $E =$ **at least 1** of buckets 1 to k has ≥ 1 string hashed into it?

$P(E) =$

More hash table fun: Possible approach?

- m strings are hashed (not uniformly) into a hash table with n buckets.
- Each string hash is an independent trial w.p. p_i of getting hashed into bucket i .

What is $P(E)$ if

1. $E =$ bucket 1 has ≥ 1 string hashed into it?
2. $E =$ **at least 1** of buckets 1 to k has ≥ 1 string hashed into it?

$P(E) =$

Define $F_i =$ bucket i has at least one string in it

More hash table fun: Possible approach?

- m strings are hashed (not uniformly) into a hash table with n buckets.
- Each string hash is an **independent trial** w.p. p_i of getting hashed into bucket i .

What is $P(E)$ if

1. $E =$ bucket 1 has ≥ 1 string hashed into it?
2. $E =$ **at least 1** of buckets 1 to k has ≥ 1 string hashed into it?

$$P(E) = P(F_1 \cup F_2 \cup \dots \cup F_k)$$

Define $F_i =$ bucket i has at least one string in it

 F_i events are *not mutually exclusive!* So we cannot just add.

More hash table fun: Possible approach?

- m strings are hashed (not uniformly) into a hash table with n buckets.
- Each string hash is an **independent trial** w.p. p_i of getting hashed into bucket i .

What is $P(E)$ if

1. $E =$ bucket 1 has ≥ 1 string hashed into it?
2. $E =$ **at least 1** of buckets 1 to k has ≥ 1 string hashed into it?

$$\begin{aligned} P(E) &= P(F_1 \cup F_2 \cup \dots \cup F_k) \\ &= 1 - P\left((F_1 \cup F_2 \cup \dots \cup F_k)^C\right) \\ &= 1 - P(F_1^C F_2^C \dots F_k^C) \\ &= \end{aligned}$$


Define $F_i =$ bucket i has at least one string in it

! F_i^C events are *dependent!* So we cannot just multiply.

More hash table fun: Possible approach?

- m strings are hashed (not uniformly) into a hash table with n buckets.
- Each string hash is an **independent trial** w.p. p_i of getting hashed into bucket i .

What is $P(E)$ if

1. $E =$ bucket 1 has ≥ 1 string hashed into it?
2. $E =$ **at least 1** of buckets 1 to k has ≥ 1 string hashed into it?



When your problem already implies independence of many processes, it may help to define events in terms of those processes.

(e.g., “buckets j has ...” didn’t lead to independent events whereas “string i is hashed to...” did)



The phrase “ ≥ 1 ” implies a large OR which can get messy...
Try using complements to turn it into “each,” “all,” or “none”.

More hash table fun: Possible approach?

- m strings are hashed (not uniformly) into a hash table with n buckets.
- Each string hash is an **independent trial** w.p. p_i of getting hashed into bucket i .

What is $P(E)$ if

1. $E =$ bucket 1 has ≥ 1 string hashed into it?
2. $E =$ **at least 1** of buckets 1 to k has ≥ 1 **string** hashed into it?

$E^C =$ **none** of buckets 1 to k has ≥ 1 **string** hashed into it?

$=$ **each of (all)** buckets 1 to k has **no string** hashed into it?

$=$ **each (all)** string is hashed to buckets $\geq k+1$

F_i 's are Independent

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

$$= 1 - P(F_1 F_2 \dots F_n)$$

$$= 1 - P(F_1)P(F_2) \dots P(F_n)$$

$$= 1 - (1 - p_1 - p_2 \dots - p_k)^n$$

Define $F_i =$ string i hashed to bucket $\geq k+1$

$$P(F_i) = 1 - p_1 - p_2 \dots - p_k$$

The fun never stops with hash tables

- m strings are hashed (not uniformly) into a hash table with n buckets.
- Each string hash is an **independent trial** w.p. p_i of getting hashed into bucket i .

What is $P(E)$ if

1. $E =$ bucket 1 has ≥ 1 string hashed into it? 
2. $E =$ at least 1 of buckets 1 to k has ≥ 1 string hashed into it? 

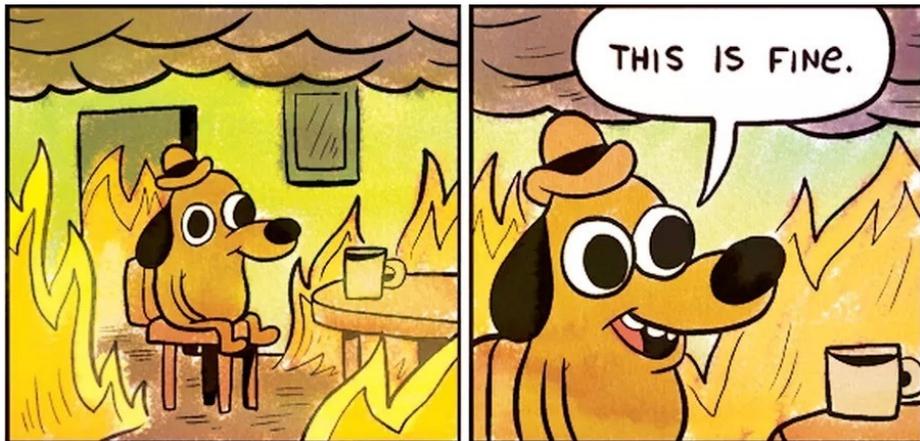
Looking for another challenge? 😊

The fun never stops with hash tables

- m strings are hashed (unequally) into a hash table with n buckets.
- Each string hash is an **independent trial** w.p. p_i of getting hashed into bucket i .

What is $P(E)$ if

1. $E =$ bucket 1 has ≥ 1 string hashed into it?
2. $E =$ at least 1 of buckets 1 to k has ≥ 1 string hashed into it?
3. $E =$ **each** of buckets 1 to k has ≥ 1 string hashed into it?



Hint: Use Part 2's event definition:

Define $F_i =$ bucket i has at least one string in it

Hint: Try $k = 2$, then $k = 3$, then generalize.

The fun never stops with hash tables

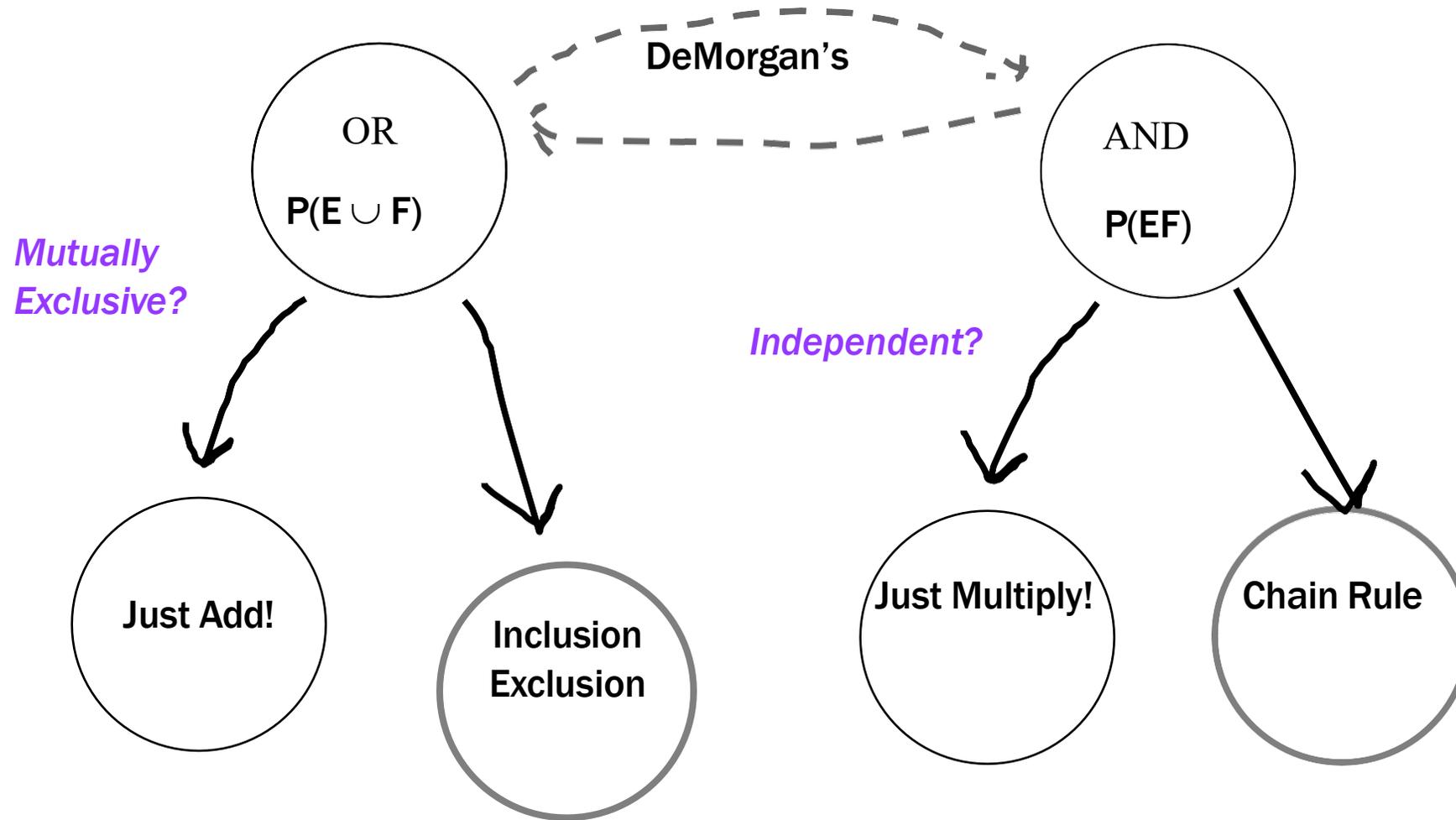
Solution

- F_i = at least one string hashed into i -th bucket
- $P(E) = P(F_1 F_2 \dots F_k) = 1 - P((F_1 F_2 \dots F_k)^c)$
 $= 1 - P(F_1^c \cup F_2^c \cup \dots \cup F_k^c)$ (DeMorgan's Law)
 $= 1 -$

where
$$P\left(\bigcup_{i=1}^k F_i^c\right) = 1 - \sum_{r=1}^k (-1)^{(r+1)} \sum_{i_1 < \dots < i_r} P(F_{i_1}^c F_{i_2}^c \dots F_{i_r}^c)$$

$$P(F_{i_1}^c F_{i_2}^c \dots F_{i_r}^c) = (1 - p_{i_1} - p_{i_2} - \dots - p_{i_r})^m$$

Pedagogical Pause



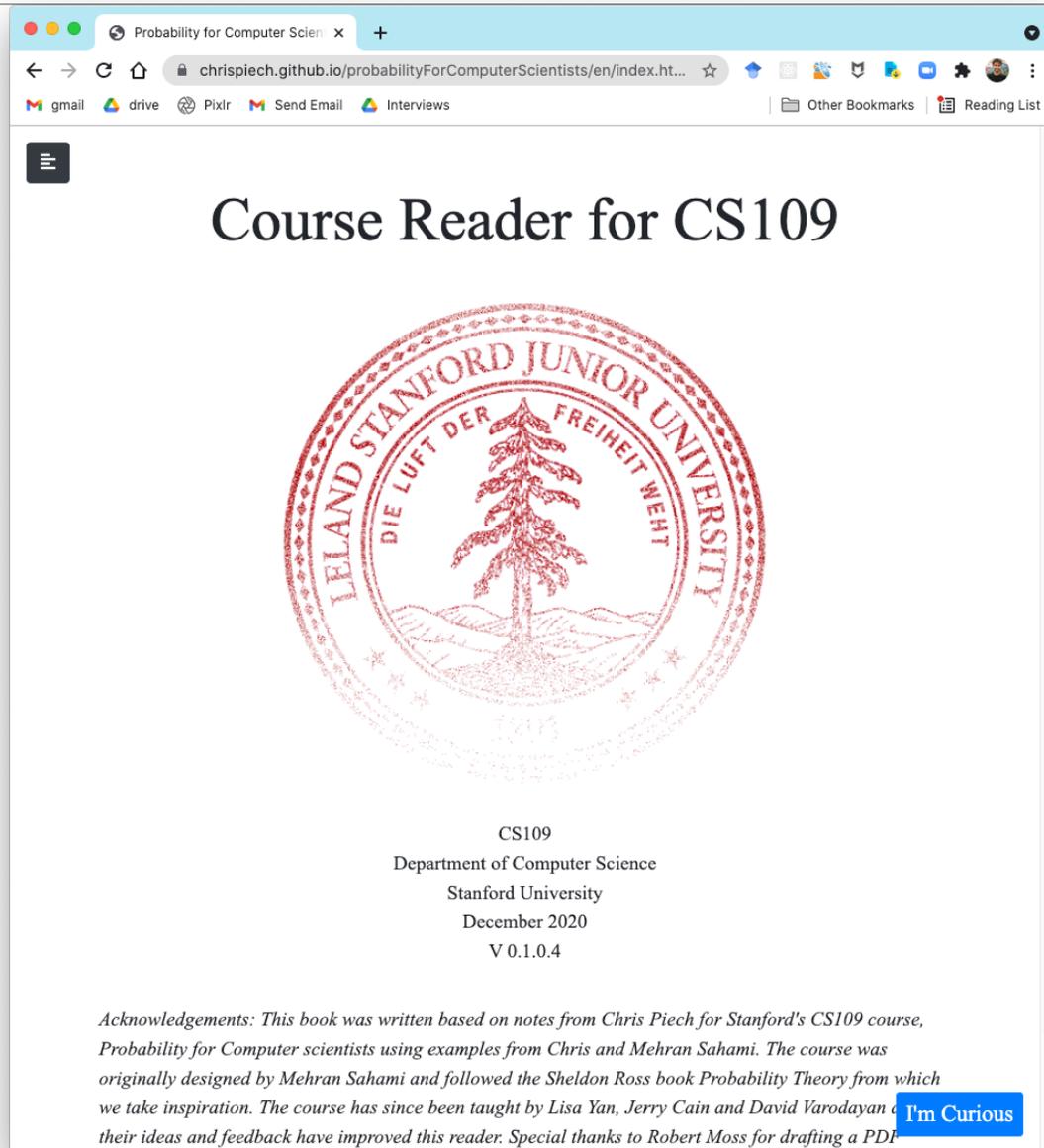
The Most Important Core Probability Question

Say a coin comes up heads with probability p

- Flip the coin n times
- Each coin flip is an **independent** trial
- What is the probability of exactly k heads?

(Read the course reader!!)

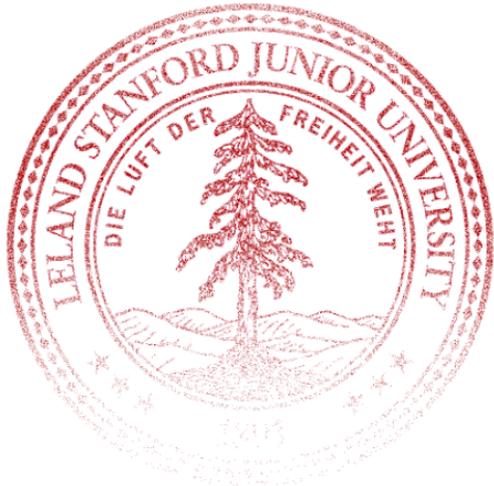
The Most Important Core Probability Question



Probability for Computer Scien: x +

chrispiech.github.io/probabilityForComputerScientists/en/index.ht...

Course Reader for CS109



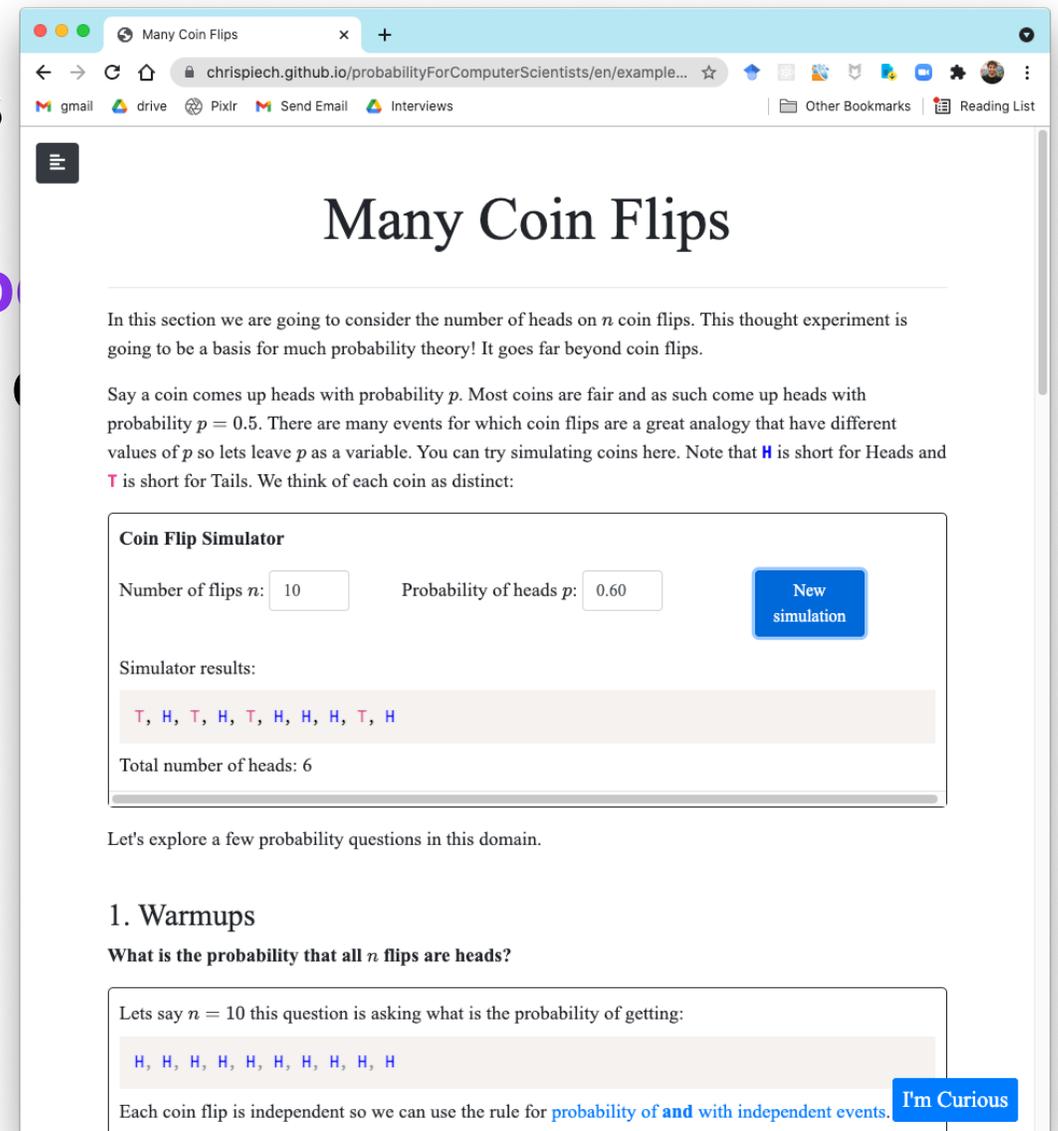
CS109
Department of Computer Science
Stanford University
December 2020
V 0.1.0.4

Acknowledgements: This book was written based on notes from Chris Piech for Stanford's CS109 course, Probability for Computer scientists using examples from Chris and Mehran Sahami. The course was originally designed by Mehran Sahami and followed the Sheldon Ross book Probability Theory from which we take inspiration. The course has since been taught by Lisa Yan, Jerry Cain and David Varodayan and their ideas and feedback have improved this reader. Special thanks to Robert Moss for drafting a PDF

I'm Curious

ads

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y of c



Many Coin Flips

chrispiech.github.io/probabilityForComputerScientists/en/example...

Many Coin Flips

In this section we are going to consider the number of heads on n coin flips. This thought experiment is going to be a basis for much probability theory! It goes far beyond coin flips.

Say a coin comes up heads with probability p . Most coins are fair and as such come up heads with probability $p = 0.5$. There are many events for which coin flips are a great analogy that have different values of p so lets leave p as a variable. You can try simulating coins here. Note that **H** is short for Heads and **T** is short for Tails. We think of each coin as distinct:

Coin Flip Simulator

Number of flips n : Probability of heads p :

Simulator results:

T, H, T, H, T, H, H, H, T, H

Total number of heads: 6

Let's explore a few probability questions in this domain.

1. Warmups

What is the probability that all n flips are heads?

Lets say $n = 10$ this question is asking what is the probability of getting:

H, H, H, H, H, H, H, H, H, H

Each coin flip is independent so we can use the rule for **probability of and with independent events**.

I'm Curious

See you on Friday!!

(See the next slides if you want a small set theory review)

Sets Review

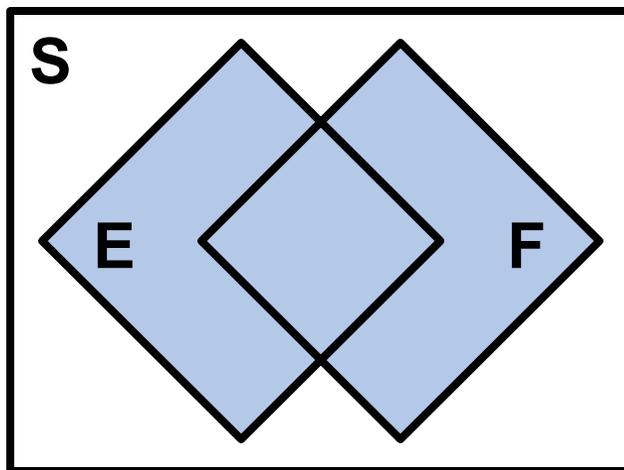


Sets Review

Say E and F are events in S

Event that is in E or F

$$E \cup F$$



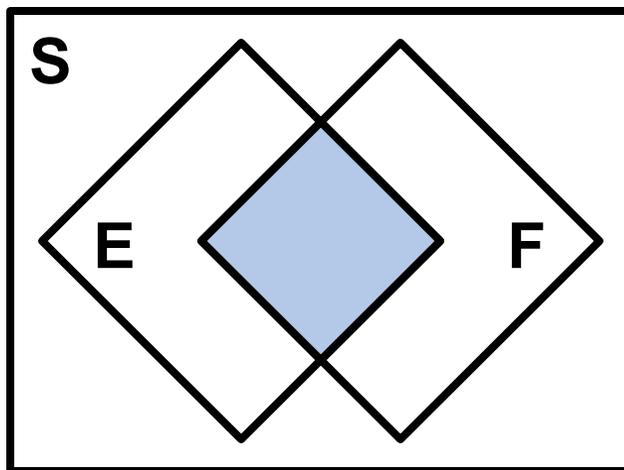
- $S = \{1, 2, 3, 4, 5, 6\}$ die roll outcome
- $E = \{1, 2\}$ $F = \{2, 3\}$ $E \cup F = \{1, 2, 3\}$

Sets Review

Say E and F are events in S

Event that is in E and F

$$E \cap F$$

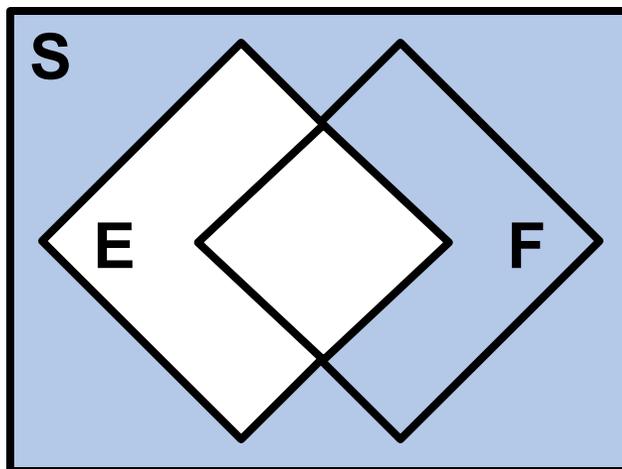


Sets Review

Say E and F are events in S

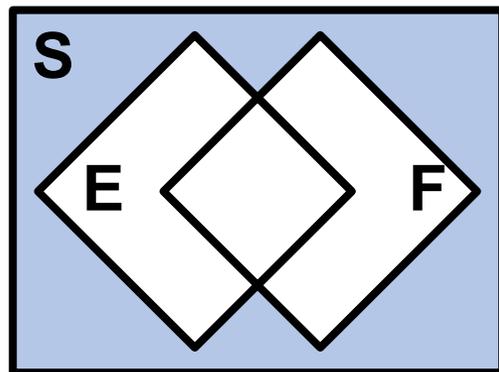
Event that is not in E (called complement of E)

E^c or $\sim E$



Sets Review

Say E and F are subsets of S



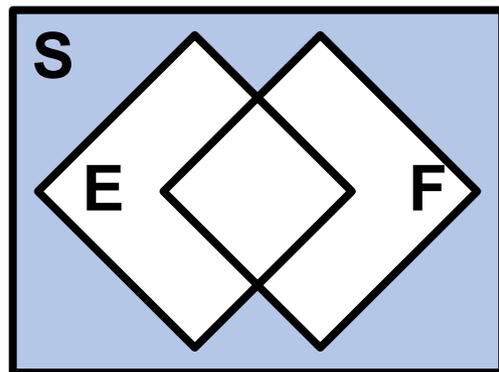
Which of these two is it?

a) $(E \text{ or } F)^C$

b) $(E^C \text{ and } F^C)$

Sets Review

Say E and F are subsets of S



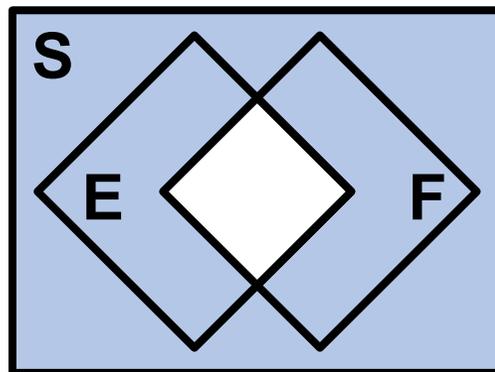
Which of these two is it?

a) $(E \text{ or } F)^C$

b) $(E^C \text{ and } F^C)$

Sets Review

Say E and F are subsets of S



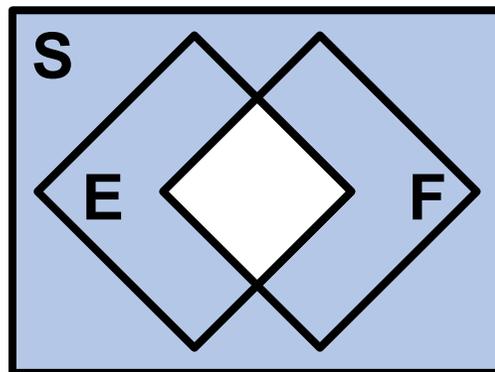
Which of these two is it?

a) $(E \text{ and } F)^C$

b) $(E^C \text{ or } F^C)$

Sets Review

Say E and F are subsets of S



Which of these two is it?

a)

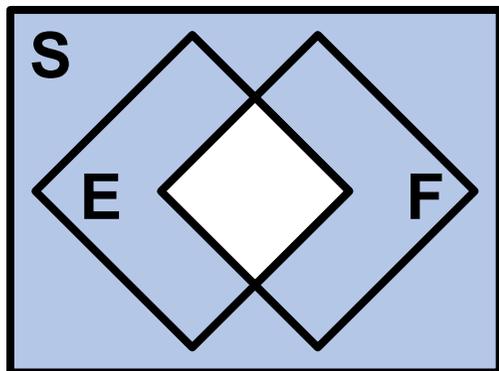
$(E \text{ and } F)^C$

==

b) $(E^C \text{ or } F^C)$

De Morgan's Laws

De Morgan's Law lets you alternate between AND and OR.



$$(E \cap F)^C = E^C \cup F^C$$

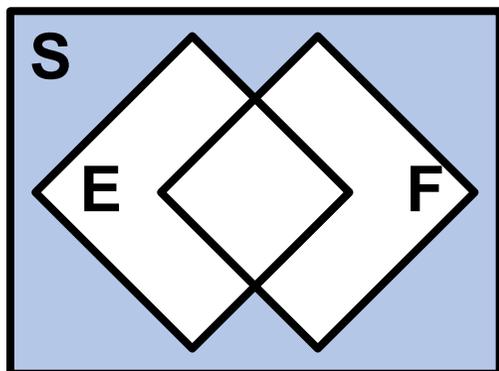
In probability:

$$P(E_1 E_2 \cdots E_n)$$

$$= 1 - P\left((E_1 E_2 \cdots E_n)^C\right)$$

$$= 1 - P\left(E_1^C \cup E_2^C \cup \cdots \cup E_n^C\right)$$

Great if E_i^C mutually exclusive!



$$(E \cup F)^C = E^C \cap F^C$$

In probability:

$$P(E_1 \cup E_2 \cup \cdots \cup E_n)$$

$$= 1 - P\left((E_1 \cup E_2 \cup \cdots \cup E_n)^C\right)$$

$$= 1 - P(E_1^C E_2^C \cdots E_n^C)$$

Great if E_i independent!

Augustin Demorgan



- British Mathematician who wrote the book “Formal Logic” in 1847