

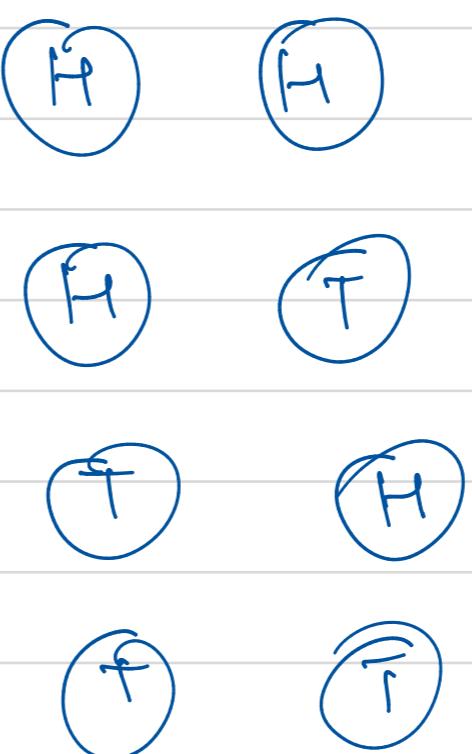
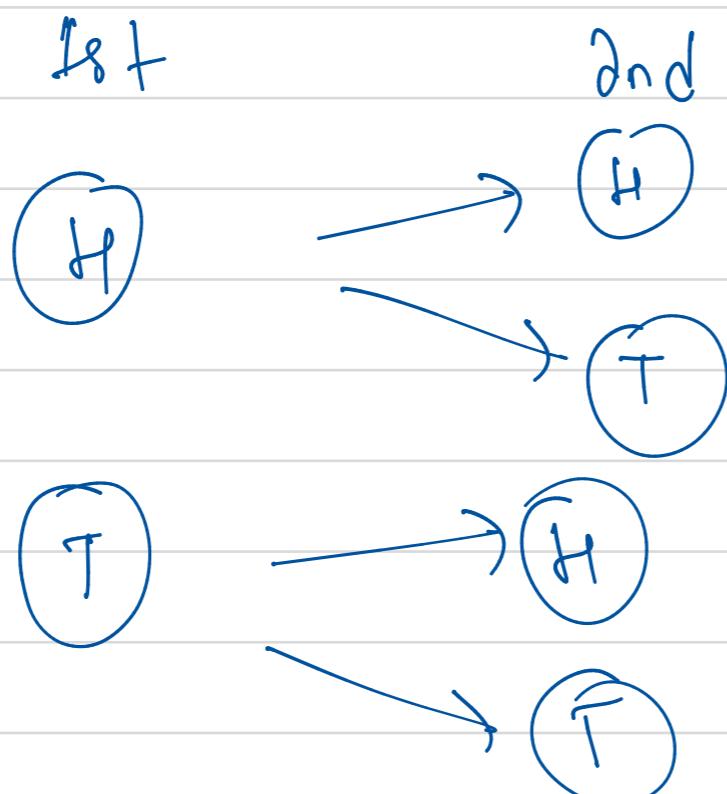
Day- 56, Jan 25, 2025 (Magh 12, 2085 B.S.)

Conditional Probability:

Q. What is the probability of landing on heads twice? Given that the first one is heads.

$$\begin{array}{c} H \\ \text{50 \%} \end{array} \quad \begin{array}{c} T \\ \text{50 \%} \end{array}$$

$$\begin{aligned} P(HH) &= \frac{1}{4} \\ &\Rightarrow 0.25 \end{aligned}$$



$$P(HH) = \frac{\text{Number of HH}}{\text{Total number of outcomes}} = \frac{1}{4}$$

Ans : if the first win is head, to get two heads you need one more, which has probability of $\frac{1}{2}$ of happening!

Votation:

What is the probability of landing on heads twice?

Given that the first one is heads.

$$P(HH \mid \text{1st is } H)$$

2nd (H) 2nd (T)

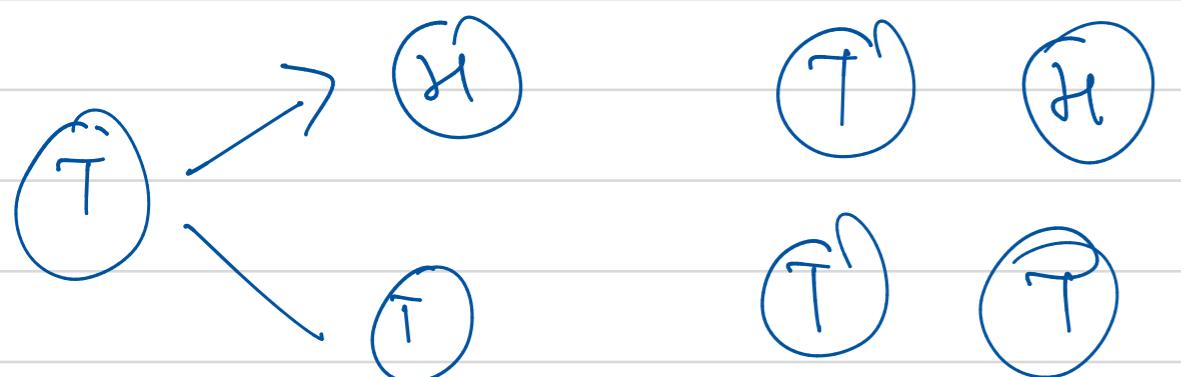
1st H	HH	HT
1st T	TH	TT

Probability of landing on heads twice.
Given that the first one is heads.

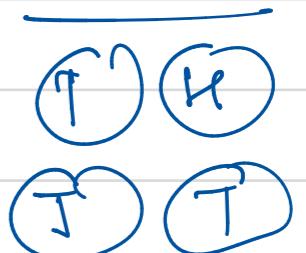
$$P(HH \mid \text{1st is } H) = \frac{HH}{HH + HT} = \frac{1}{2}$$

Q. When flipping a coin twice, what is the probability of getting two heads if the first coin lands in tails?

$\Rightarrow 0$



$$\therefore P(HH \mid \text{1st is } T) = \frac{0}{4} \Rightarrow 0$$



No HH So the Sample is \emptyset . Our Condition Changes the 'p'.

Product Rule (for Independent Events)

$$P(A \cap B) = P(A) \cdot P(B) \text{ when } A \text{ and } B \text{ are independent.}$$

Example on Conditional Probability on Dice Example:

Q. What is the probability that the first is 6 AND the sum = 10?

Here given,

$$\begin{aligned} \text{Sum} &= 10 \\ (6, 4), (4, 6) \end{aligned}$$

$$\begin{aligned} P(\text{1st is 6} \cap \text{Sum} = 10) &= P(\text{1st is 6}) \cdot P(\text{Sum} = 10 | \text{1st is 6}) \\ &= \frac{1}{6} \cdot \frac{1}{11} \\ &= \frac{1}{36} \end{aligned}$$

$$P(\text{1st is 6} \cap \text{Sum} = 10) = P(\text{1st is 6}) \cdot P(\text{Sum} = 10 | \text{1st is 6})$$

$$P(A \cap B) = P(A) \cdot P(B|A)$$

whose $P(B|A) = P(B)$ 
When Independent

Q. What is the probability that the sum is 10? Given that the first one is 6.

$$P(Sum = 10 \text{ n } 1st \text{ is } 6) = P(B) \cdot P(A/B)$$

$$\Rightarrow \frac{3}{36} \cdot \frac{1}{6}$$

$$\Rightarrow \frac{18}{36} = \frac{1}{2}$$

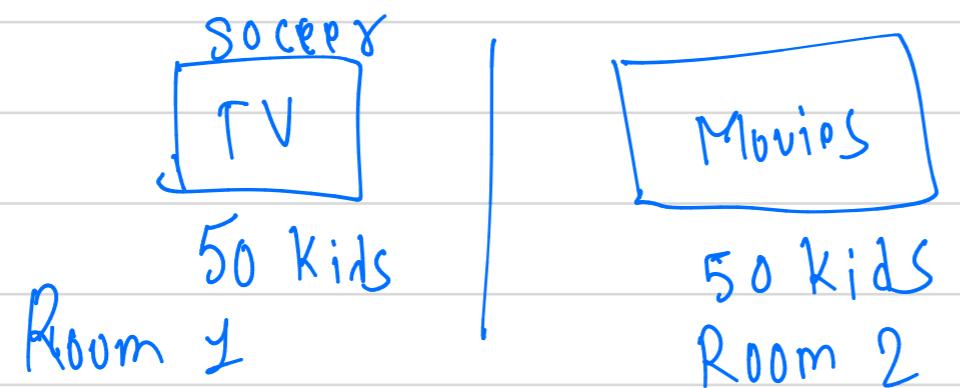
Q. What is the probability that the sum is 10? Given that the first one is 1.
Here given

$$P(Sum = 10 \text{ n } 1st \text{ is } 1) = P(S) \cdot P(1/S)$$

$$\Rightarrow \frac{3}{36} \cdot 0 \Rightarrow 0$$

Quiz:

50 play soccer on L 50 don't play



Q. How many kids in Room 1 like soccer ?
 $\Rightarrow 50$ (Assume)

Quiz:

How many kids wear running shoes ?
 40 play soccer ,
 60 don't play soccer . Now 80% like to wear running shoes

$$\Rightarrow \frac{80\%}{100} \text{ of } 40$$

$$\Rightarrow 32 \text{ wear running shoes}$$

$$P(S) = 0.4 \quad \text{and} \quad P(\text{not } S) = 0.6, \quad P(R|S) = 0.8$$

$$P(\text{Soccer and Running shoes}) = P(S) \cdot P(R)$$

$$P(S \cap R) = P(S) \cdot P(R|S)$$

$$\Rightarrow 0.4 \cdot 0.8$$

$$[P(S \cap R) = 0.32]$$

$P(\text{not Soccer and Running shoes})$

$$P(\text{not } S \cap R) = P(\text{not } S) \cdot P(R|\text{not } S)$$

$$\Rightarrow 0.6 \times 0.5$$

$$\Rightarrow 0.3$$

Conditional Probability

$P(\text{Soccer and Running shoes})$

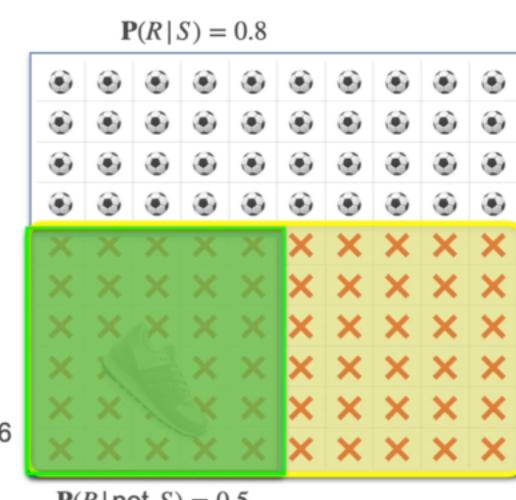


$$P(S) = 0.4$$

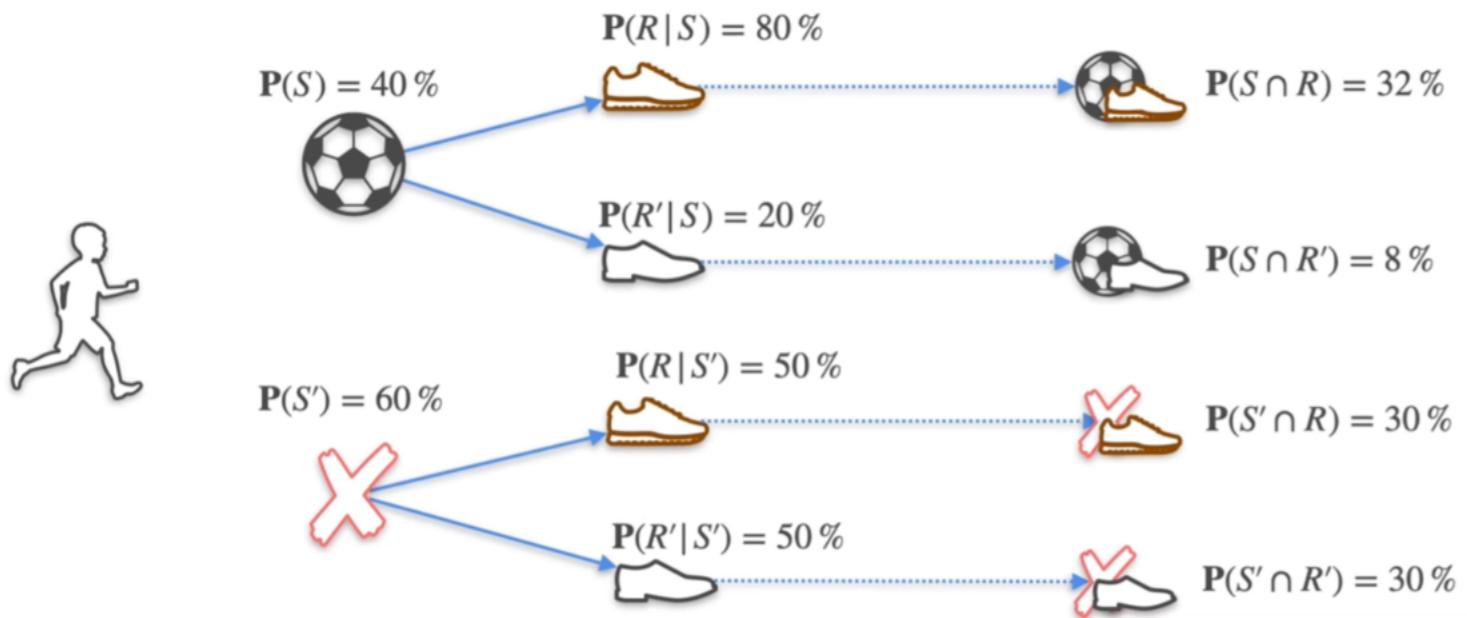
$P(\text{not Soccer and Running shoes})$



$$\begin{aligned} P(\text{not } S \cap R) &= P(\text{not } S) \cdot P(R|\text{not } S) \\ &= 0.6 \cdot 0.5 \\ &= 0.3 \end{aligned}$$



Conditional Probability



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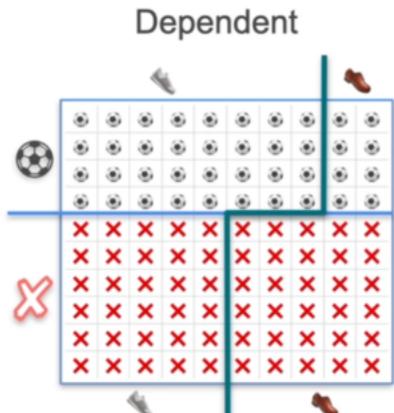
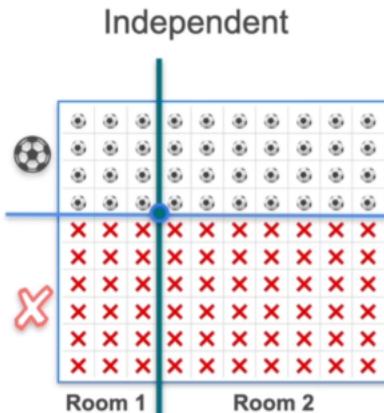
Independent vs Dependent Events

Independent



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Independent vs Dependent Events



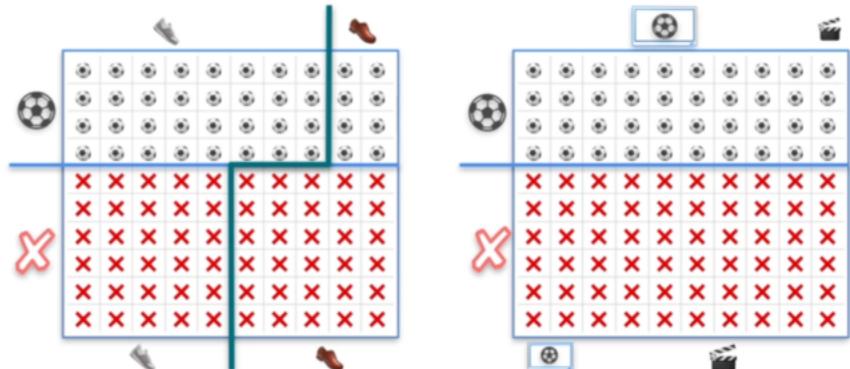
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Independent vs Dependent Events

Independent



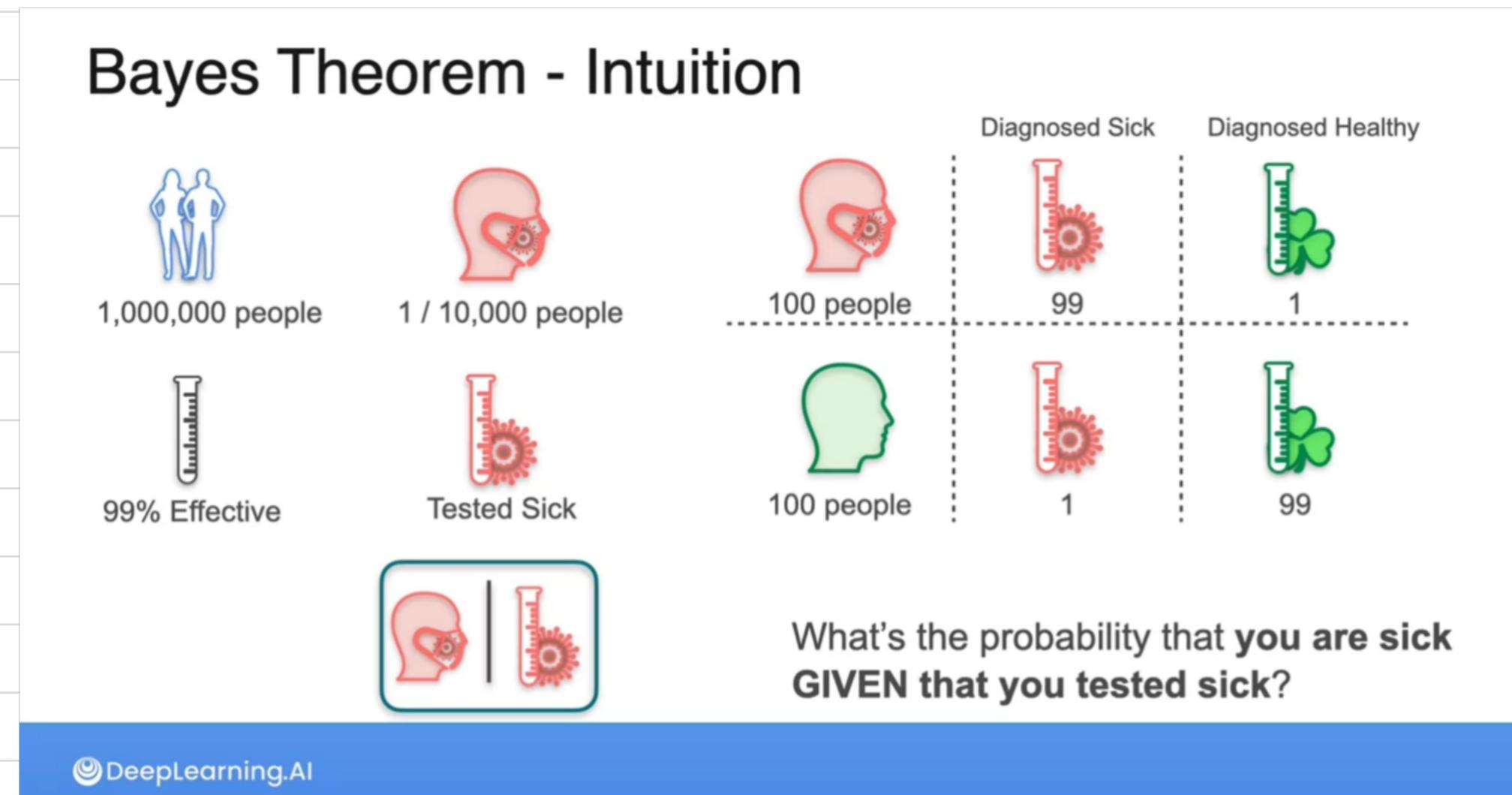
Dependent



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Baye's Theorem - Intuition

Q. What's the probability that you are sick given that you tested sick?



99%. Mean S

		Diagnosed Sick / Sick	Healthy
Healthy	9,999	98,901	
	99	1	
Sick	99	1	

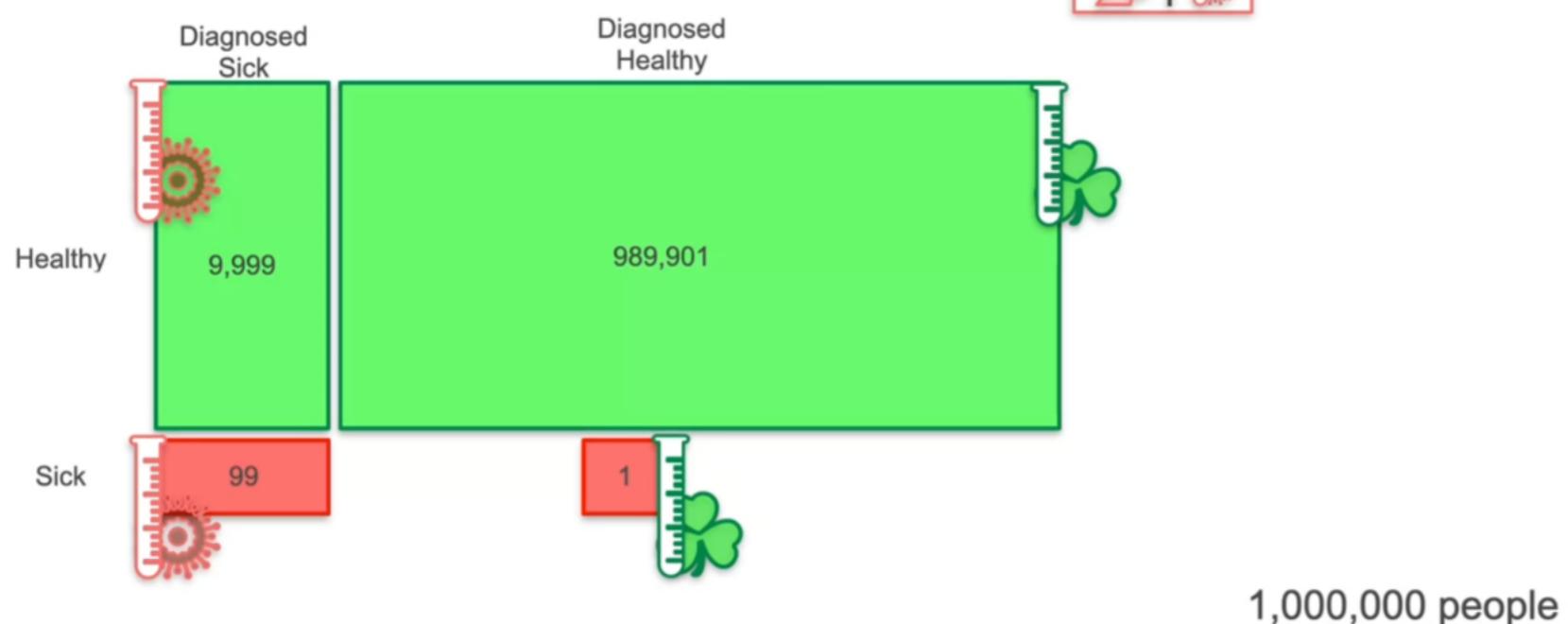
1,000,000 people

$$P(\text{Sick} \mid \text{diagnosed sick}) = \frac{99}{99 + 9,999} = 0.0098.$$

Actually sick < 1%.

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Bayes Theorem - Intuition



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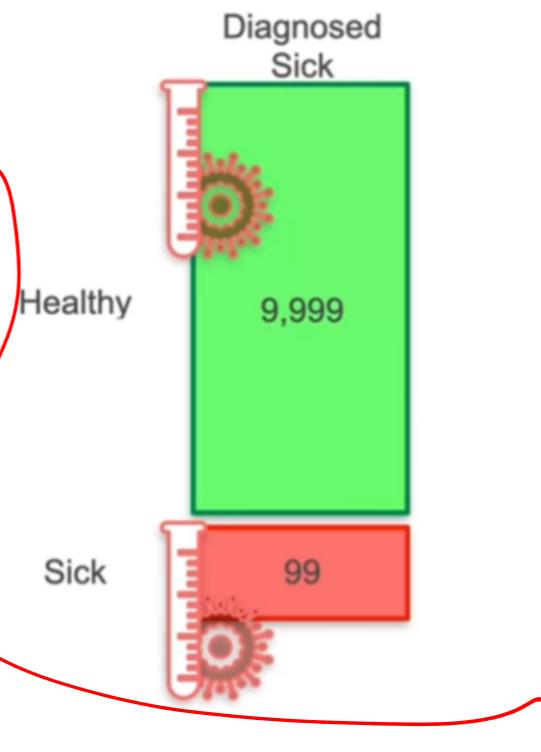
Bayes Theorem - Intuition



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Bayes Theorem - Intuition

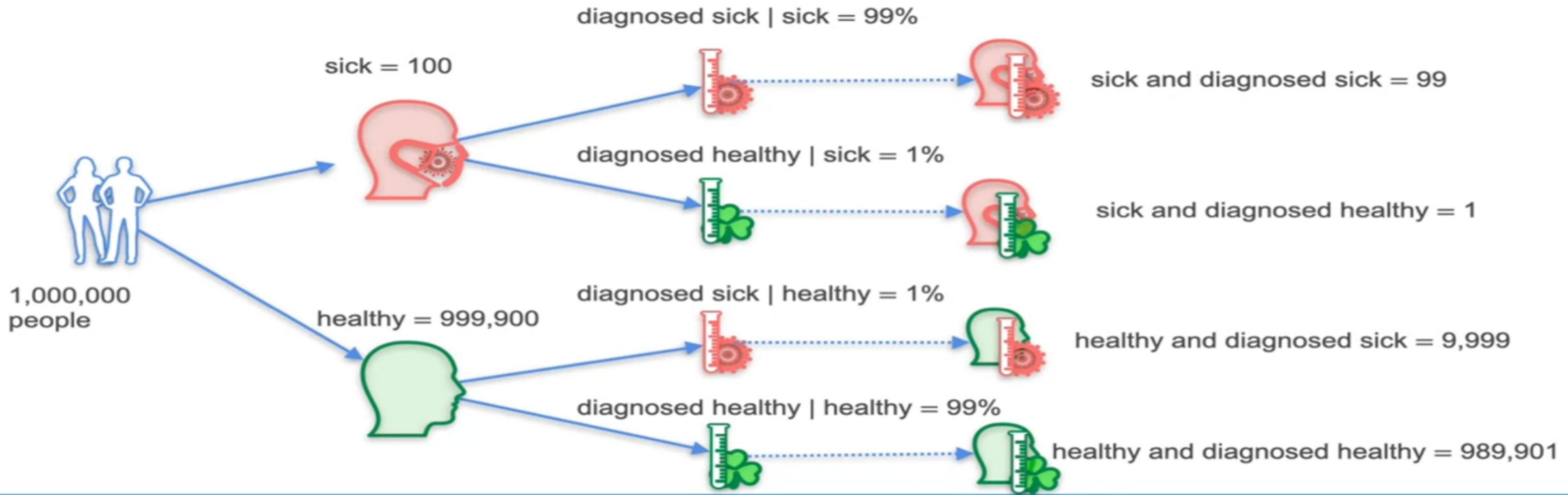
\Rightarrow Sick and diagnosed sick
everyone diagnosed sick



$$P(\text{sick} | \text{diagnosed sick}) = \frac{\text{Sick}}{\text{Diagnosed Sick}} = \frac{99}{99 + 9999} = \frac{99}{10098} = 0.0098$$

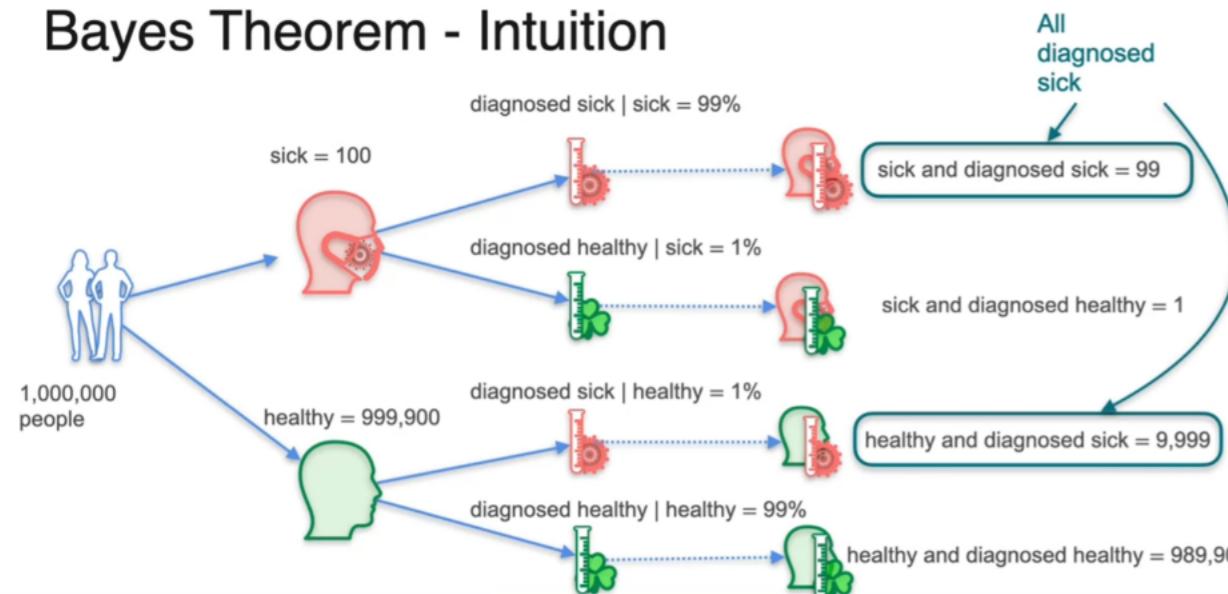
$$= \frac{\text{sick and diagnosed sick}}{\text{sick and diagnosed sick} + \text{healthy and diagnosed sick}}$$

Bayes Theorem - Intuition

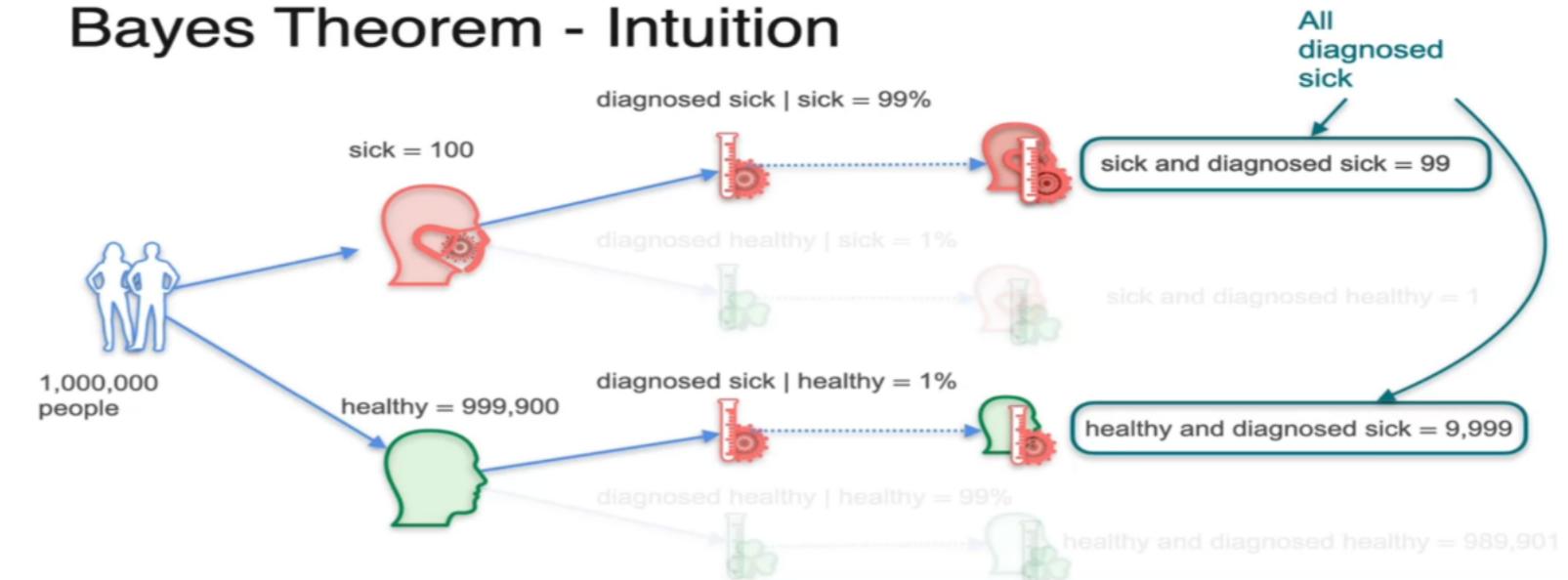


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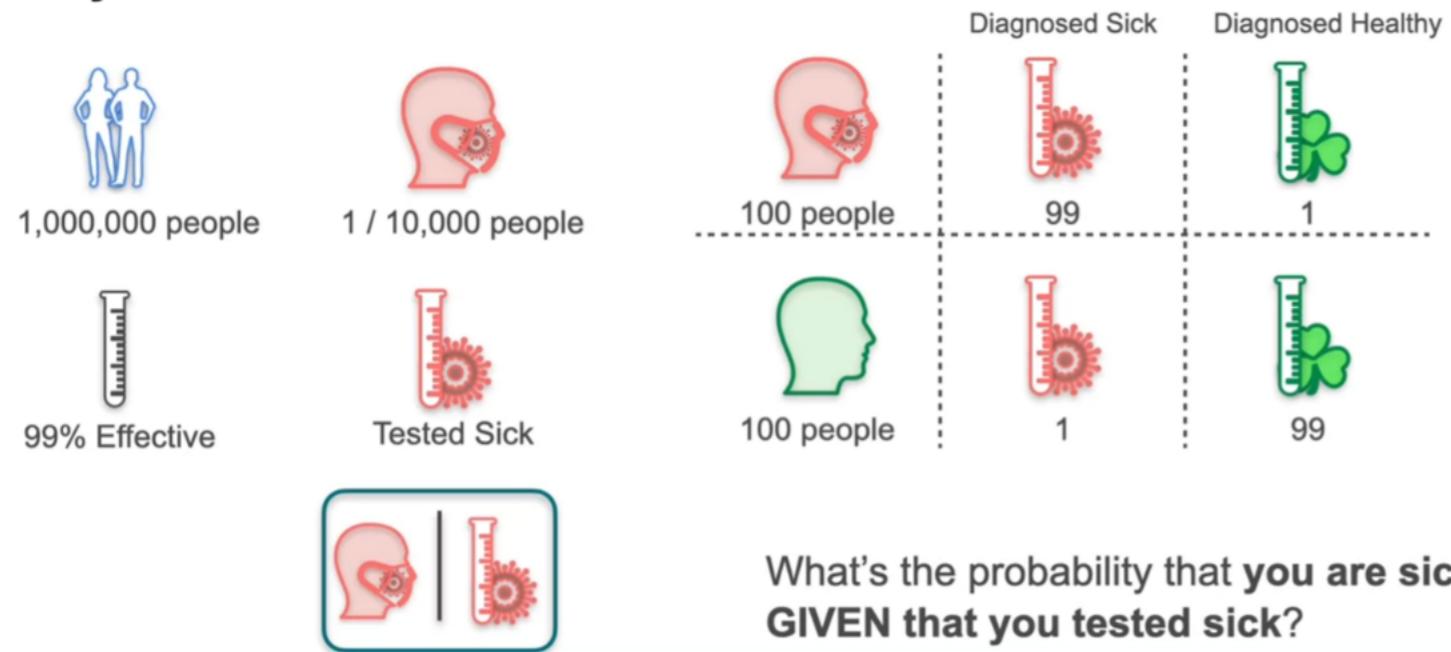
Bayes Theorem - Intuition



Bayes Theorem - Intuition



Bayes Theorem - Intuition



Bayes Theorem - Intuition

$$P(\text{sick} | \text{diagnosed sick}) = \frac{\text{sick}}{\text{sick} + \text{healthy}}$$

$$P(\text{sick} | \text{diagnosed sick}) = \frac{\text{sick and diagnosed sick}}{\text{healthy and diagnosed sick} + \text{sick and diagnosed sick}}$$

$$P(\text{sick} | \text{diagnosed sick}) = \frac{99}{10098} = 0.0098$$

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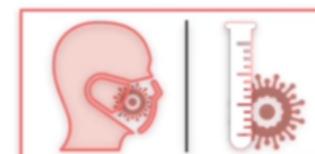
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$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

$$P(A|B) = \frac{P(\text{sick and diagnosed sick})}{P(\text{diagnosed sick})}$$

$$P(S) = 0.01\% \quad P(ns) = 99.99\%$$

Bayes Theorem - Formula



$$P(\text{sick} | \text{diagnosed sick}) = ?$$

$$P(\text{sick}) = 0.01\%$$

$$P(\text{not sick}) = 99.99\%$$

$$P(\text{diagnosed sick} | \text{sick}) = 99\%$$

$$P(\text{diagnosed sick} | \text{not sick}) = 1\%$$

A: sick

B: diagnosed sick

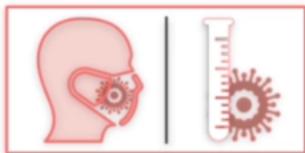
$$P(A|B) = ?$$

From Conditional Probability

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

$$P(A|B) = \frac{P(\text{sick and diagnosed sick})}{P(\text{diagnosed sick})}$$

Bayes Theorem - Formula



$$P(\text{sick} | \text{diagnosed sick}) = ?$$

$$P(\text{sick}) = 0.01\%$$

$$P(\text{not sick}) = 99.99\%$$

$$P(\text{diagnosed sick} | \text{sick}) = 99\%$$

$$P(\text{diagnosed sick} | \text{not sick}) = 1\%$$

A: sick

B: diagnosed sick

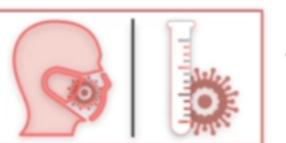
$$P(A | B) = ?$$

From Conditional Probability

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

$$P(A | B) = \frac{P(\text{sick and diagnosed sick})}{P(\text{diagnosed sick})}$$

Bayes Theorem - Formula



A: sick
B: diagnosed sick

$$P(\text{sick} | \text{diagnosed sick}) = ?$$

$$P(\text{sick}) = 0.01\%$$

$$P(\text{not sick}) = 99.99\%$$

$$P(\text{diagnosed sick} | \text{sick}) = 99\%$$

$$P(\text{diagnosed sick} | \text{not sick}) = 1\%$$

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

$$P(A | B) = \frac{P(\text{sick and diagnosed sick})}{P(\text{diagnosed sick})}$$

$$P(\text{sick and diagnosed sick}) = ?$$

$$P(\text{diagnosed sick}) = ?$$

BAYES THEOREM FORMULA CAN HELP

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g. Correct Expression for $P(\text{diagnosed sick}) = P(\text{sick} \cap \text{diagnosed sick}) + P(\text{not sick} \cap \text{diagnosed sick})$

Bayes Theorem - Formula



A: sick
B: diagnosed sick

$$P(\text{sick} | \text{diagnosed sick}) = ?$$

$$P(\text{sick}) = 0.01\%$$

$$P(\text{not sick}) = 99.99\%$$

$$P(\text{diagnosed sick} | \text{sick}) = 99\%$$

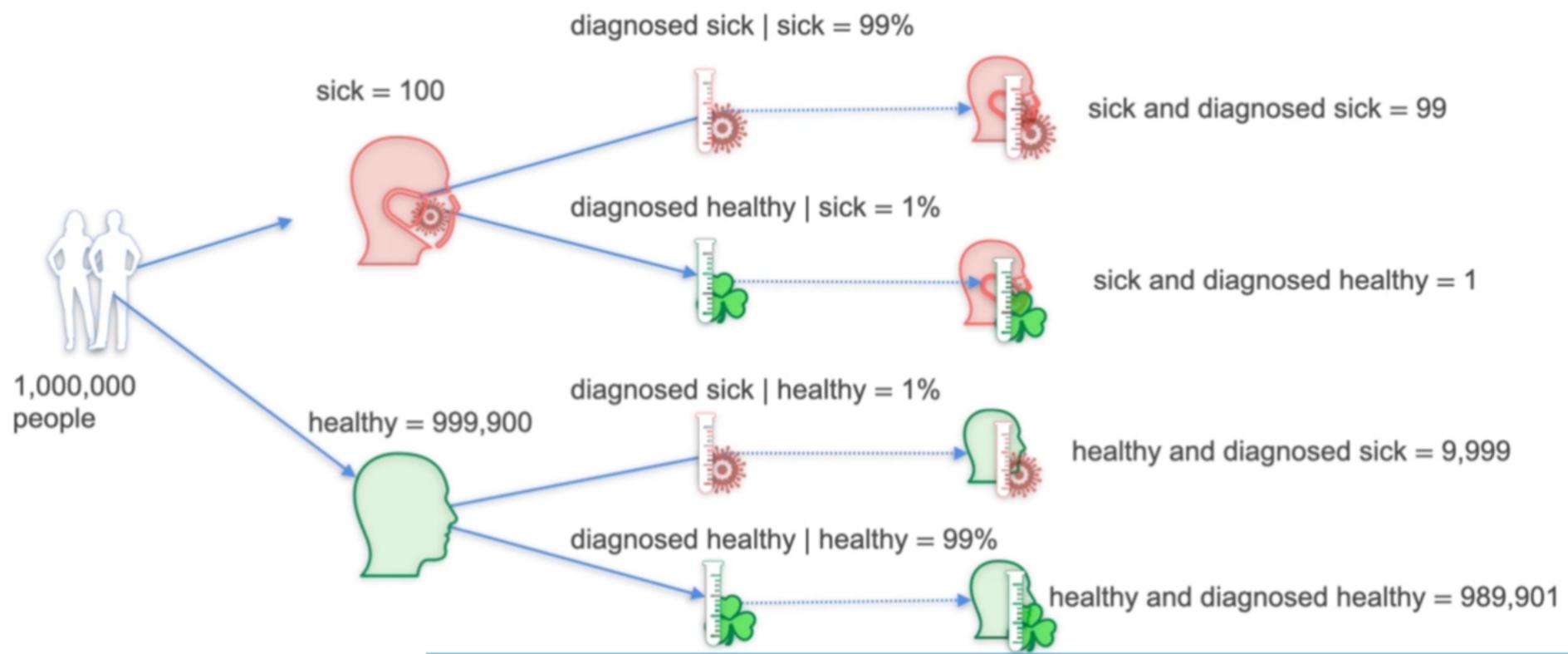
$$P(\text{diagnosed sick} | \text{not sick}) = 1\%$$

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

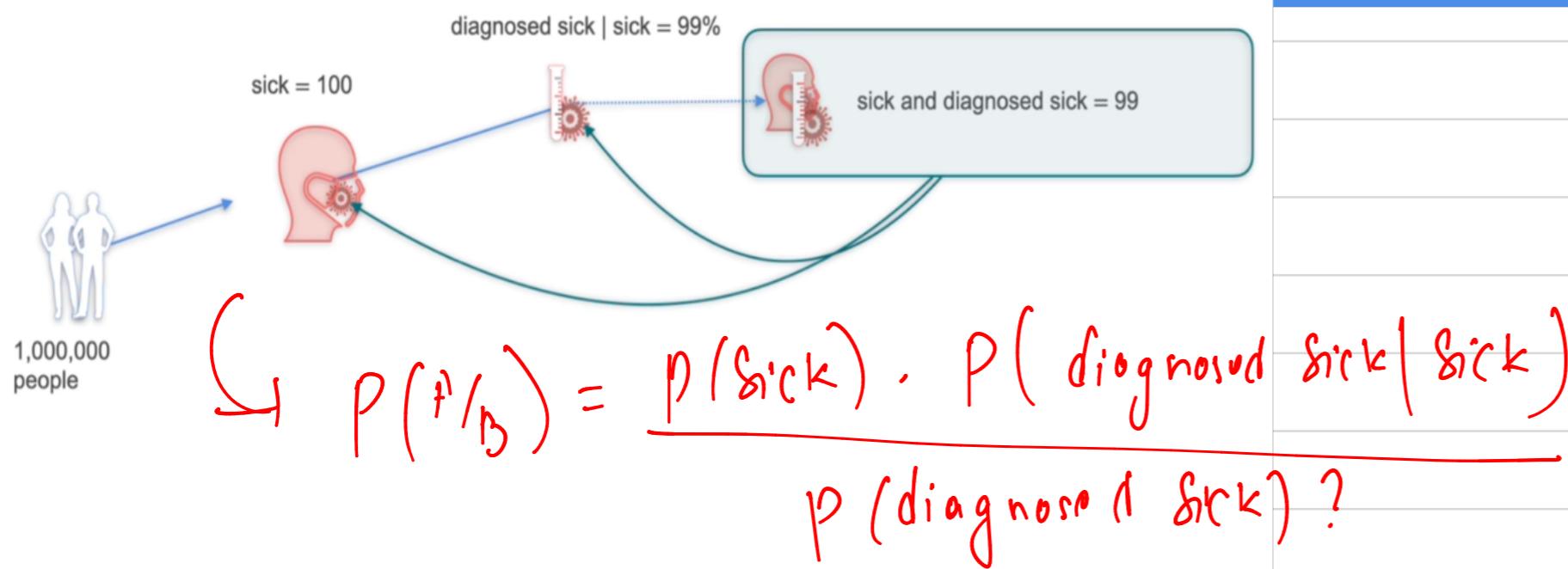
$$P(A | B) = \frac{P(\text{sick}) \cdot P(\text{diagnosed sick} | \text{sick})}{P(\text{diagnosed sick})} = ?$$

Ideas of Possibilities:

Bayes Theorem - Formula



Bayes Theorem - Formula



$$P(\text{diagnosed sick}) = ?$$

$$P(A) = 0.01\%.$$

$$P(A') = 99.99\%.$$

$$P(B/A) = 99\%.$$

$$P(B/A') = 1\%.$$

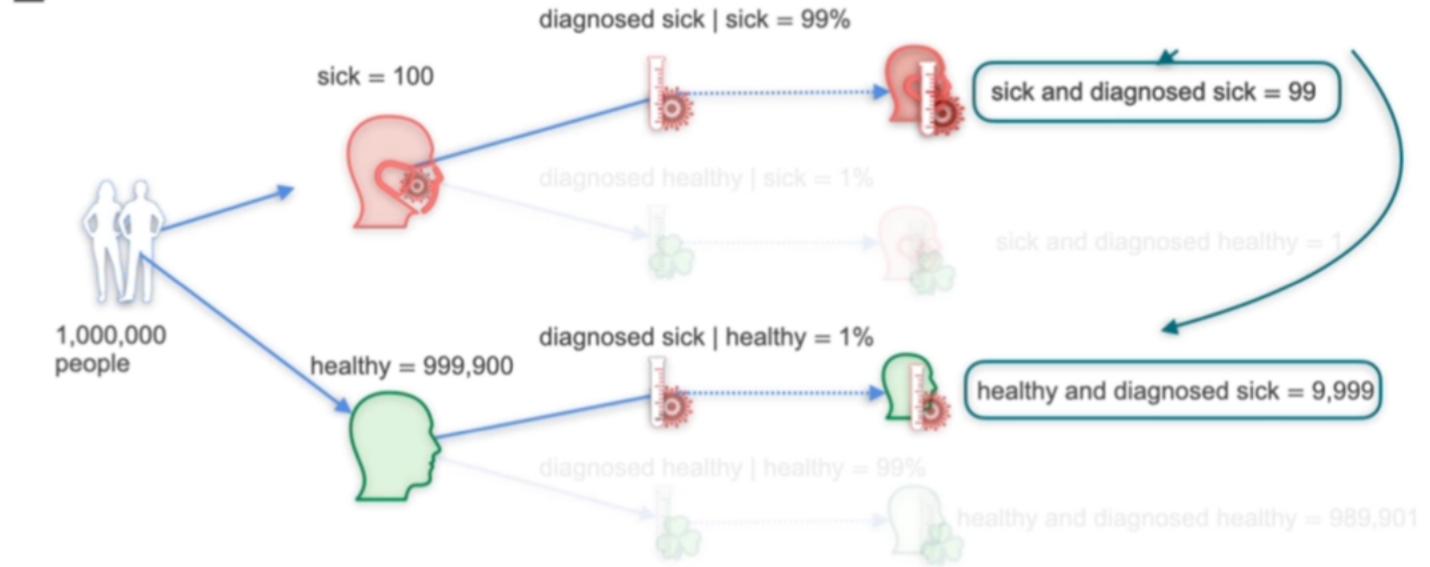
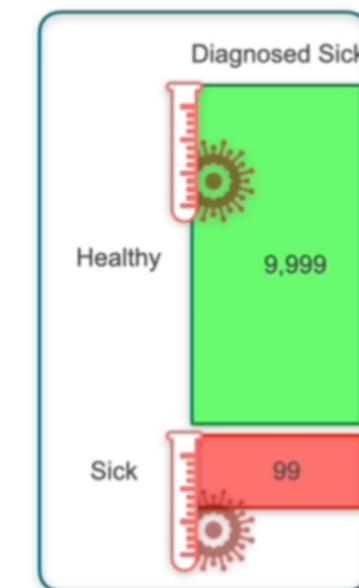
$$P(A|B) \stackrel{\text{def}}{=} \frac{P(A) \cdot P(B|A)}{P(A) \cdot P(B|A) + P(A') \cdot P(B|A')}$$

$$P(A) \cdot P(B|A) +$$

$$P(A') \cdot P(B|A')$$

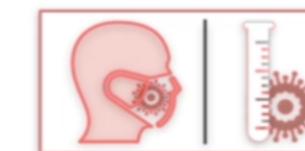
Bayes Theorem - Formula

$$P(\text{diagnosed sick}) =$$



$$P(\text{sick} \cap \text{diagnosed sick}) + P(\text{not sick} \cap \text{diagnosed sick})$$

Bayes Theorem - Formula



A: sick

B: diagnosed sick

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

$$P(A|B) =$$

$$\frac{P(\text{sick}) \cdot P(\text{diagnosed sick} | \text{sick})}{P(\text{sick} \cap \text{diagnosed sick}) + P(\text{not sick} \cap \text{diagnosed sick})}$$

$$P(\text{sick} \cap \text{diagnosed sick}) = P(A \cap B)$$

$$= P(\text{sick}) \cdot P(\text{diagnosed sick} | \text{sick})$$

$$P(\text{not sick} \cap \text{diagnosed sick}) = P(A' \cap B)$$

$$= P(\text{not sick}) \cdot P(\text{diagnosed sick} | \text{not sick})$$

Bayes Theorem - Formula



A: sick

B: diagnosed sick

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

$$\Rightarrow 0.01 \cdot 99\%.$$

$$0.01 \times 99 + 99 \cdot 99 \times \downarrow$$

$$\Rightarrow P(A) \cdot P(B/A)$$

$$P(A) \cdot P(B/A) + P(A') \cdot P(B/A')$$

$$\Rightarrow 0.0098$$

$$P(A/B) = 0.0098$$

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BAYES THEOREM
FORMULA

$$P(A|B) = \frac{P(\text{sick}) \cdot P(\text{diagnosed sick} | \text{sick})}{P(\text{sick}) \cdot P(\text{diagnosed sick} | \text{sick}) + P(\text{not sick}) \cdot P(\text{diagnosed sick} | \text{not sick})}$$

$$P(\text{sick}) = 0.01\%$$

$$P(\text{not sick}) = 99.99\%$$

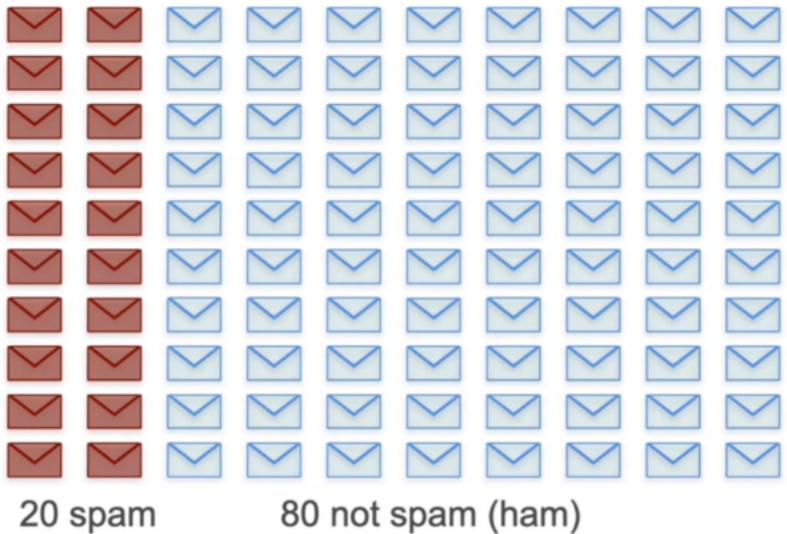
$$P(\text{diagnosed sick} | \text{sick}) = 99\%$$

$$P(\text{diagnosed sick} | \text{not sick}) = 1\%$$

So, the Bayes' Theorem is

$$P(A/B) = \frac{P(A) \cdot P(B/A)}{P(A) \cdot P(B/A) + P(A') \cdot P(B/A')}$$

Bayes Theorem - Spam Example



Bayes Theorem - Spam Example (Intuition Solution)



$P(\text{spam} \mid \text{lottery})$

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



24 emails
containing lottery

$$P(\text{spam} \mid \text{lottery}) = \frac{\text{spam and lottery}}{\text{all lottery}}$$

$$= \frac{14}{24}$$

$$= \frac{7}{12} = 0.583$$



Bayes theorem - Spam Example (formula Solution) :

$$P(\text{Spam} \mid \text{lottery})$$

$$P(A \mid B) = \frac{P(A) \cdot P(B \mid A)}{P(A) \cdot P(B \mid A) + P(A') \cdot P(B \mid A')}$$

A \rightarrow Email is

Spam

B: Email contains lottery

$$P(\text{Spam} \mid \text{lottery}) = \frac{P(\text{Spam}) \cdot P(\text{lottery} \mid \text{Spam})}{P(\text{Spam}) \cdot P(\text{lottery} \mid \text{Spam}) + P(\text{not spam}) \cdot P(\text{lottery} \mid \text{not spam})}$$

Bayes Theorem - Spam Example (Formula Solution)

$$P(\text{spam}) = 0.2$$

$$P(\text{lottery} \mid \text{spam}) = 0.7$$

$$P(\text{not spam}) = 0.8$$

$$P(\text{lottery} \mid \text{not spam}) = 0.125$$

$$P(\text{spam} \mid \text{lottery}) = \frac{P(\text{spam}) \cdot P(\text{lottery} \mid \text{spam})}{P(\text{spam}) \cdot P(\text{lottery} \mid \text{spam}) + P(\text{not spam}) \cdot P(\text{lottery} \mid \text{not spam})}$$

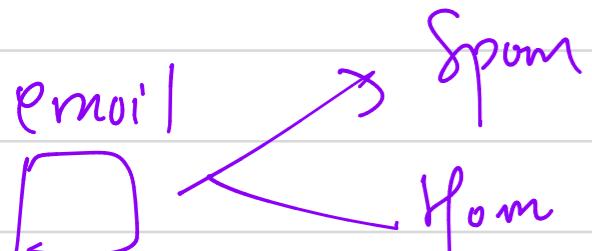
$$P(\text{spam} \mid \text{lottery}) = \frac{0.2 \times 0.7}{(0.2 \times 0.7) + (0.8 \times 0.125)}$$

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$$\Rightarrow 0.14$$

$$(0.14) + (0.1)$$

$$P(S|L) = 0.5833$$



Bayes Theorem - Spam Example (Formula Solution)

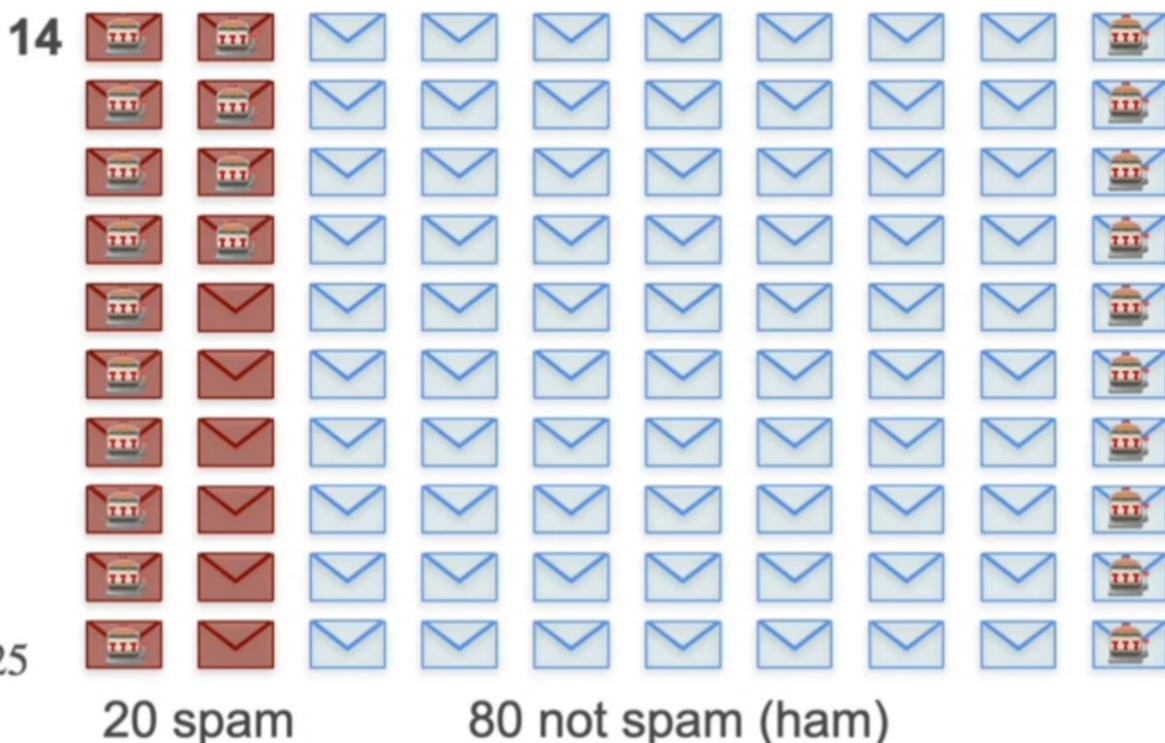
10

$$P(\text{spam}) = \frac{20}{100} = 0.2$$

$$P(\text{not spam}) = \frac{80}{100} = 0.8$$

$$P(\text{lottery} \mid \text{spam}) = \frac{14}{20} = 0.7$$

$$P(\text{lottery} \mid \text{not spam}) = \frac{10}{80} = 0.125$$



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Bayes Theorem

$$P(A)$$

Prior

$$P(S) = \frac{P(S)}{P(S) + P(\text{ns})}$$

: Event
E
; E contains lottery

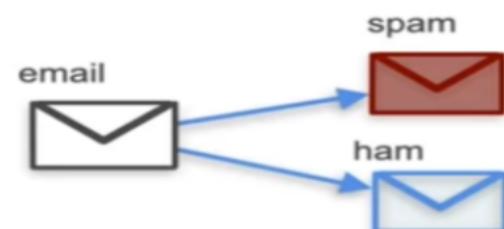
Posterior

Spam on lottery
Ham and lottery

$$P(S|L) = \frac{P(SL)}{P(SL) + P(HSL)}$$

Prior and Posterior

PRIOR



$$P(\text{spam}) = \frac{\text{spam}}{\text{spam} + \text{ham}}$$

EVENT



POSTERIOR



$$P(\text{spam} | \text{lottery}) = \frac{\text{spam and lottery}}{\text{spam and lottery} + \text{ham and lottery}}$$

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Prior and Posterior

PRIOR

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

$$P(\text{sum} = 10) = \frac{3}{36}$$

EVENT



1st dice is 6

POSTERIOR

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

$$P(\text{sum} = 10 | \text{1st is } 6) = \frac{1}{6}$$

Prior and Posterior

PRIOR

1st				
2nd				
2nd				

$$P(HH) = \frac{1}{4}$$

EVENT



1st coin is H

1st				
2nd				
2nd				

$$P(HH | \text{1st is } H) = \frac{1}{2}$$

Bayes theorem - The Naive Bayes Model:

What About 2 Events?

PRIOR	EVENT
$P(\text{spam}) = \frac{\text{Red Envelope}}{\text{Red Envelope} + \text{Blue Envelope}}$	Email contains 'lottery'
	Email contains 'winning'
	Email contains 'lottery' and 'winning'

?

What About 2 Events?

EVENT	POSTERIOR
Email contains 'lottery' and 'winning'	$P(\text{spam} \text{lottery \& winning}) = \frac{\text{Red Envelope with both icons}}{\text{Red Envelope with both icons} + \text{Blue Envelope with both icons}}$

Spam emails with 'lottery' and 'winning'
Spam emails

$$P(\text{spam} | \text{lottery \& winning}) = \frac{P(\text{spam}) \cdot P(\text{lottery \& winning} | \text{spam})}{P(\text{spam}) \cdot P(\text{lottery \& winning} | \text{spam}) + P(\text{ham}) \cdot P(\text{lottery \& winning} | \text{ham})}$$

?

This one is not simple and the problem
on top -

→ This is okay since
No overlapping or the
Complexity arises

to what we have the NAIVE ASSUMPTION

Is There a Quicker Way To Estimate the Probability?

Naive assumption



The appearances of 'lottery' and 'winning' are independent

$$P(\text{spam} \mid \text{lottery \& winning}) = \frac{P(\text{spam}) \cdot P(\text{lottery \& winning} \mid \text{spam})}{P(\text{spam}) \cdot P(\text{lottery \& winning} \mid \text{spam}) + P(\text{ham}) \cdot P(\text{lottery \& winning} \mid \text{ham})}$$

$\mathbf{P}(A \cap B) = \mathbf{P}(A) \cdot \mathbf{P}(B)$

↓

problem and the solution is ↴

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Is There a Quicker Way To Estimate the Probability?

Naive assumption



The appearances of 'lottery' and 'winning' are independent

$$P(\text{spam}) = \frac{20}{100}$$

$$P(\text{ham}) = \frac{80}{100}$$

$$\mathbf{P}(A \cap B) = \mathbf{P}(A) \cdot \mathbf{P}(B)$$

$$P(\text{spam} \mid \text{lottery \& winning}) = \frac{P(\text{spam}) \cdot P(\text{lottery} \mid \text{spam}) \cdot P(\text{winning} \mid \text{spam})}{P(\text{spam}) \cdot P(\text{lottery} \mid \text{spam}) \cdot P(\text{winning} \mid \text{spam}) + P(\text{ham}) \cdot P(\text{lottery} \mid \text{ham}) \cdot P(\text{winning} \mid \text{ham})}$$

Is There a Quicker Way To Estimate the Probability?

$$P(L|S) = \frac{14}{20}$$

$$P(L|H) = \frac{10}{80}$$

$$P(w|S) = \frac{15}{20} \approx 0.75$$

$$P(w|H) = \frac{8}{20}$$

So, $P(\text{Spam} | \text{lottery}) \Rightarrow \frac{P(\text{Spam}) \cdot P(\text{lottery} | \text{Spam}) \cdot P(\text{winning} | \text{Spam})}{P(\text{Spam}) \cdot P(\text{lottery} | \text{Spam}) \cdot P(\text{winning} | \text{Spam}) + P(\text{ham}) \cdot P(\text{lottery} | \text{ham}) \cdot P(\text{winning} | \text{ham})}$

$\Rightarrow 0.913$

Naive assumption

The appearances of the words w_1, w_2, \dots, w_n are independent

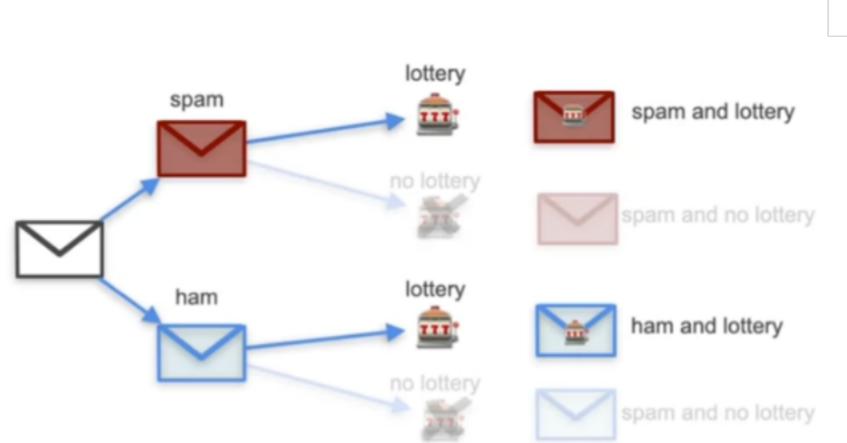
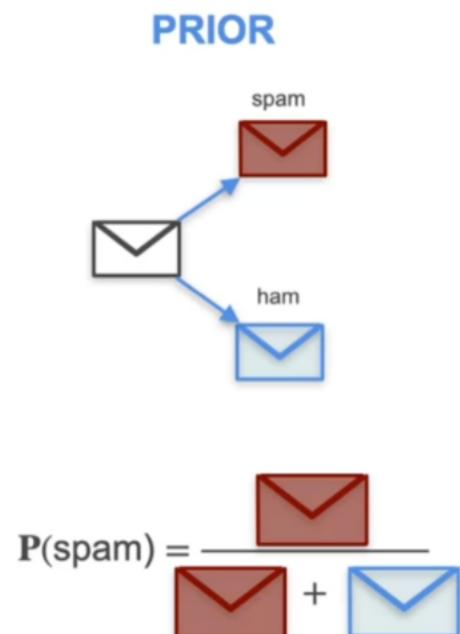
$$P(\text{spam} | w_1, \dots, w_n) = \frac{P(\text{spam}) \cdot P(w_1 | \text{spam}) \cdots P(w_n | \text{spam})}{P(\text{spam}) \cdot P(w_1 | \text{spam}) \cdots P(w_n | \text{spam}) + P(\text{ham}) \cdot P(w_1 | \text{ham}) \cdots P(w_n | \text{ham})}$$

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Probability in Machine Learning:

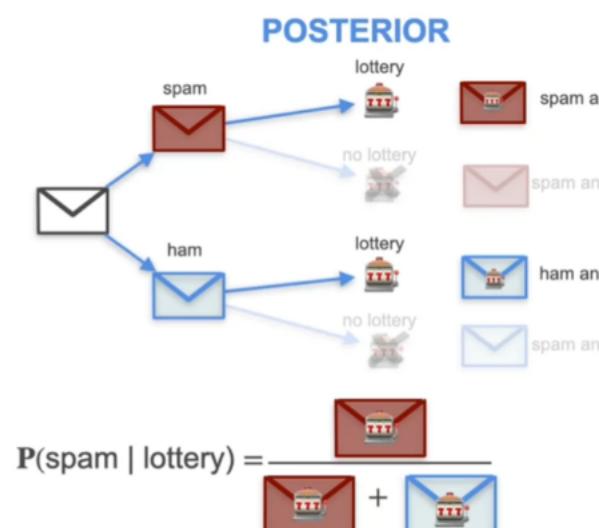
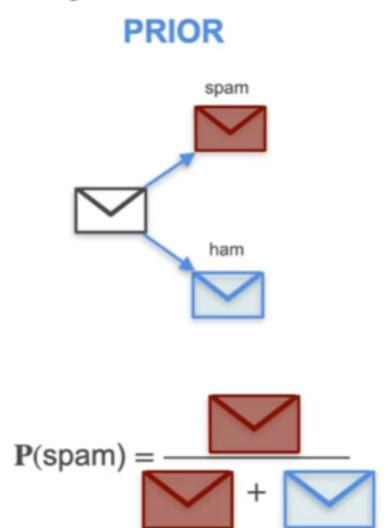
- Recognize Cat in an Image based on the probability that there's cat in the image or not.
- Image generation and probability of text generation that a bunch of words are sensitive text or it talks about it something.

Bayes Theorem



$$P(\text{spam} | \text{lottery}) =$$

Bayes Theorem



Example Problem

Classification

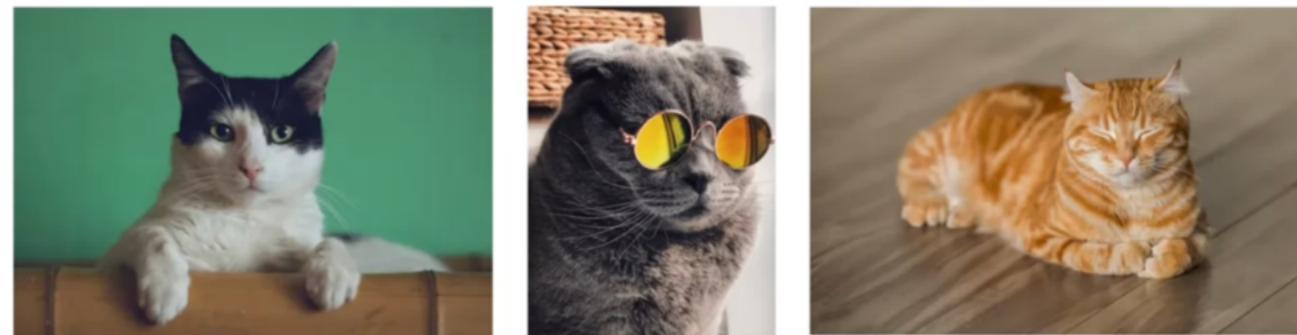
Patient 2	
Patient 2	
Patient 1	
G	Age
A	29
H	Gender
W	Female
S	Height
S	169 cm
S	Weight
H	62 kg
B	Smoker
B	No
B	...
B	Heart rate
B	63
B	Blood pressure
	120 90

- Is this patient healthy?
- Calculate $P(\text{healthy} \mid \text{symptoms and history})$

Example Problem

Image recognition

- What is the probability that there is a cat in the image
- $P(\text{cat} \mid \text{image}) = P(\text{cat} \mid \text{pixel}_1, \text{pixel}_2, \dots, \text{pixel}_n)$



Example Problem

Sentiment analysis

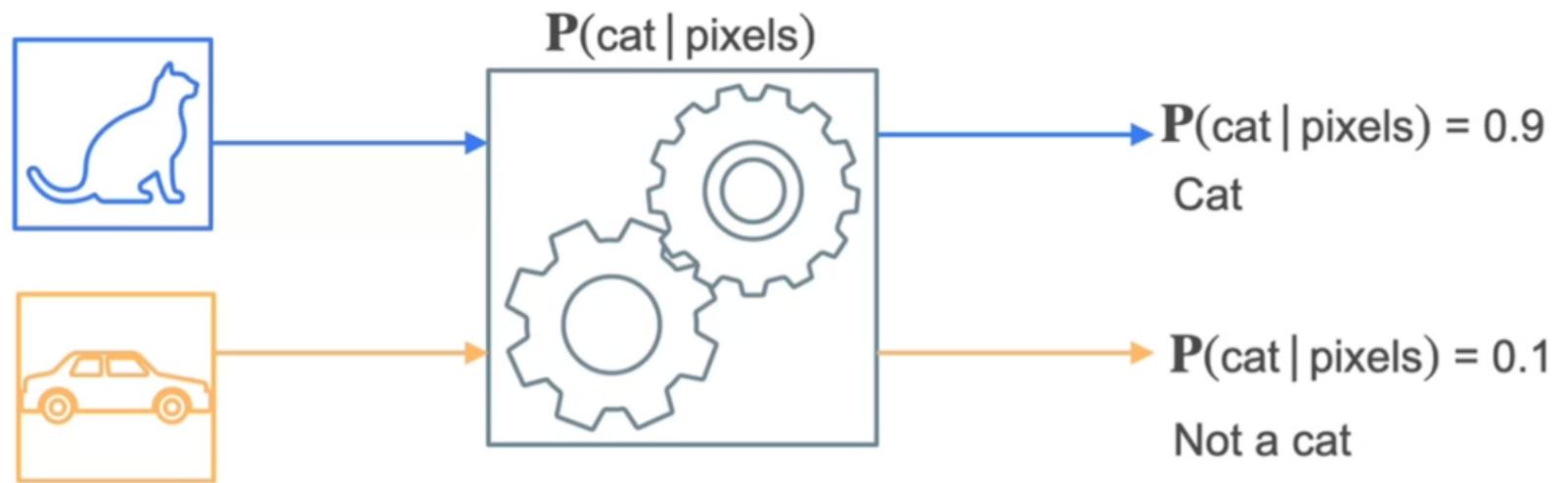
the first cold shower
even the monkey seems to want
a little coat of straw

- Is this a happy sentence?
- Calculate $P(\text{happy} \mid \text{words in the sentence})$

Matsuo Bashō

However RNN and
transformer Architecture
is widely used instead
of using my
Probability Method!

Example Solution



→ Application of Probability
in Machine learning.

Example Problem: Generative Models

Face generation

- Generate a group of pixels such that the resulting image looks like a human face.
- Goal: generate images such that $P(\text{face} | \text{pixels})$ is high.

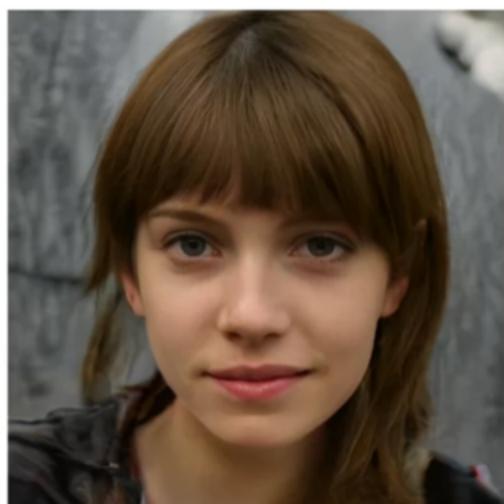
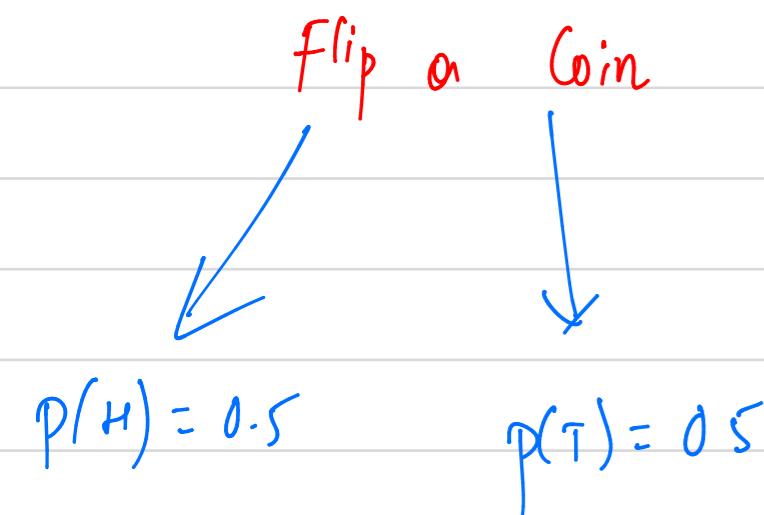
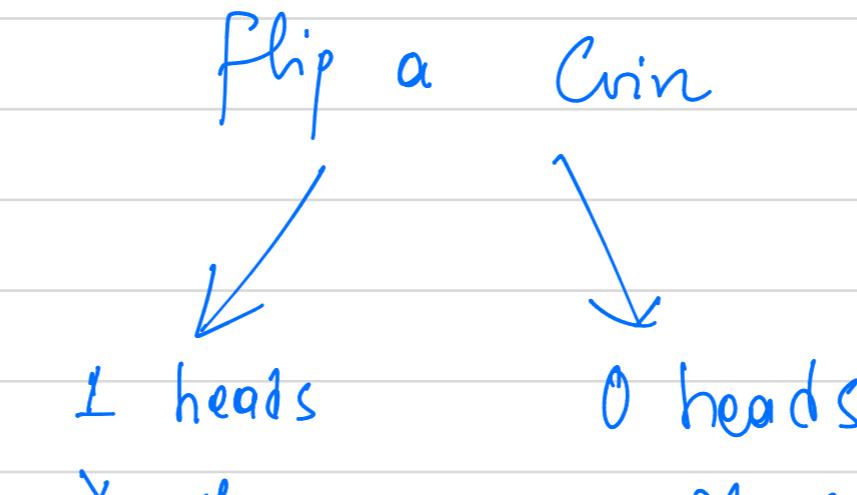


Image generated by a StyleGAN

Random Variables:



$X = \text{number of heads}$



$\rightarrow X$ is a random variable.

From Events to Random Variables.

$X = \text{Number of heads in 10 coin tosses}$

$$X = 10$$

H H H H H H H H H H

$$0.5^{10}$$

$$P(H) = 0.5$$

$$X = 9$$

H T H H H H H H H H

$$0.5^9 0.5^1$$

$$P(X=0) ?$$

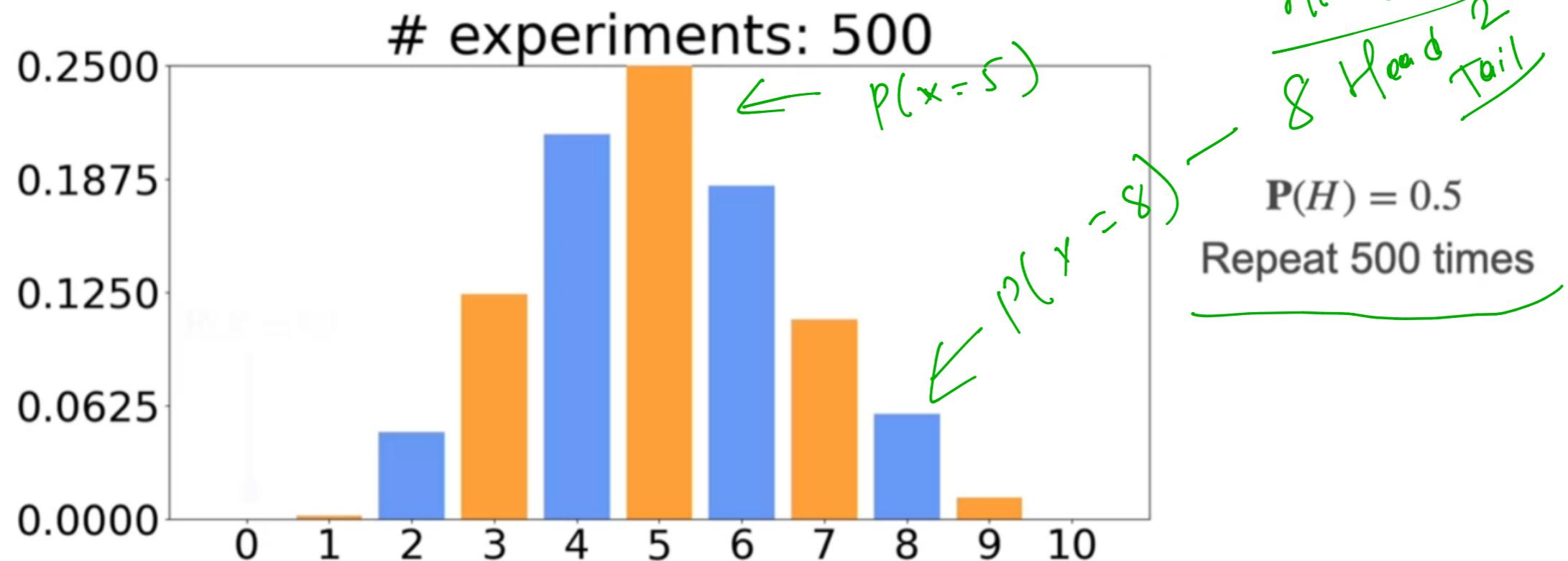
$$X = 9$$

H H H H T H H H H H

$$0.5^9 0.5^1$$

$$P(X=1) ?$$

Flipping a Fair Coin 500 Times



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- Random Variables allow you to model the whole experiment at once .

X = number of Heads

X = number of Sick patients

X = Number of 1's

$$P(X=1) = 0.5$$

$$P(X=0) = 0.2$$

Other Random Variables:

- (1) Wait time until the next bus arrives.
- (2) Height of an Gymnast's jump
- (3) No. of Defective Products in a shipment
- (4) mm of rain in November.

Discrete and Continuous Random Variables

Discrete random variables



~~Finite number of values~~
(Could be infinite too)

Can take only a **countable** number of values

Continuous random variables



Infinite number of values

Takes values on an interval

Random Variable Vs. Deterministic Variable

① Random Variable
is not fixed and
may associate with all
the uncertainties.

Deterministic

$$x = 2, f(x) = x^2$$

Fixed outcome

Random

X = number of defective items in
a shipment

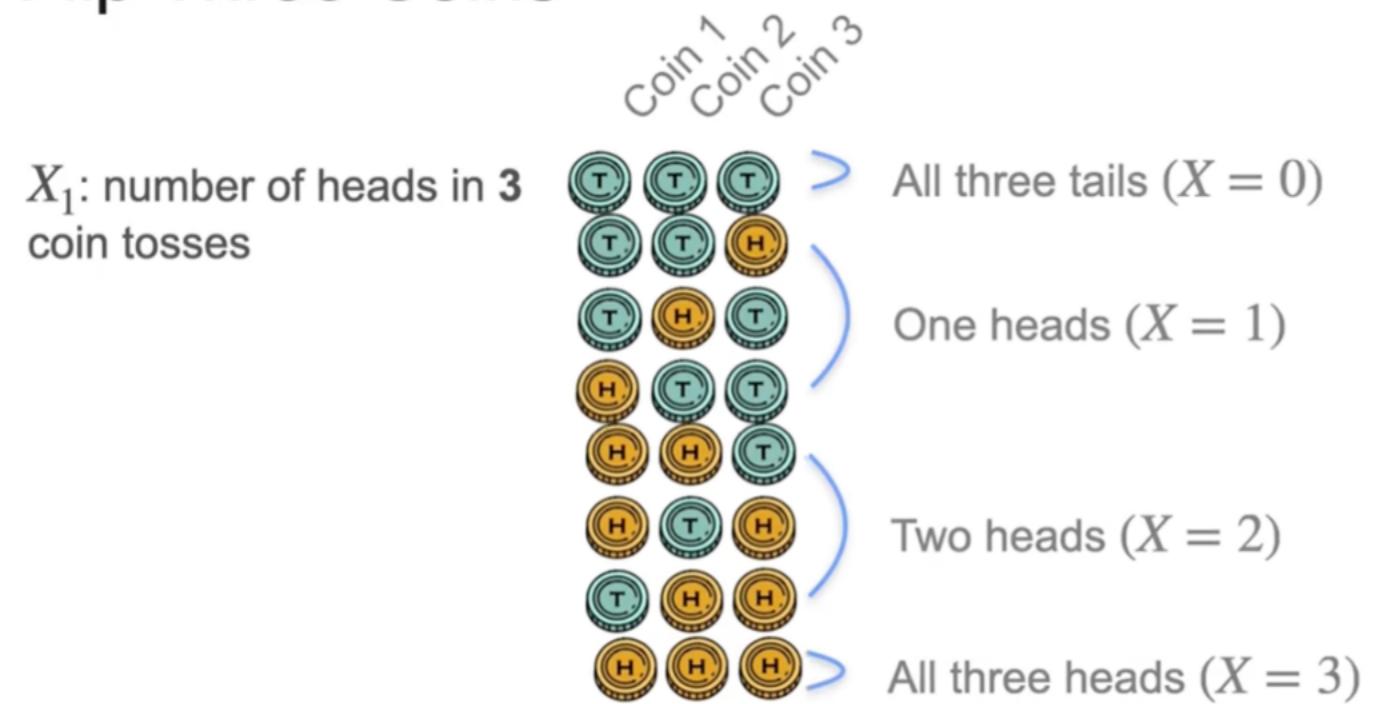
Uncertain outcome

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Probability Distribution:

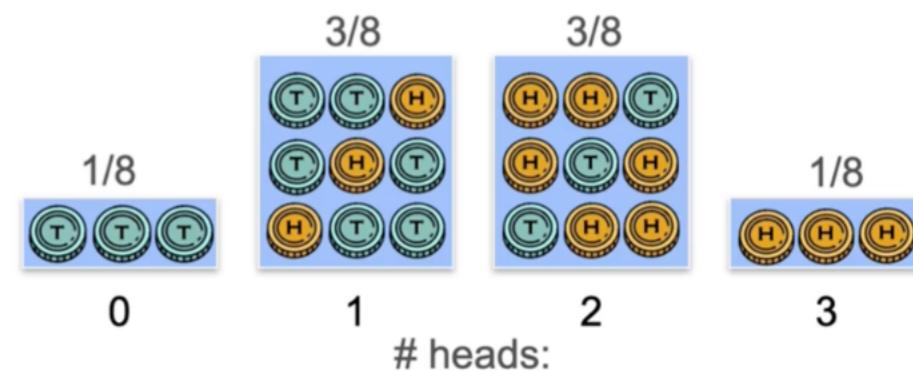
All the possible scenarios that can happen and put them on this horizontal axis and for each one of them, look at the probability that they can have, this form of Probability Distribution is called the probability Distribution (Gaussian, Uniform, Exponential).

Flip Three Coins



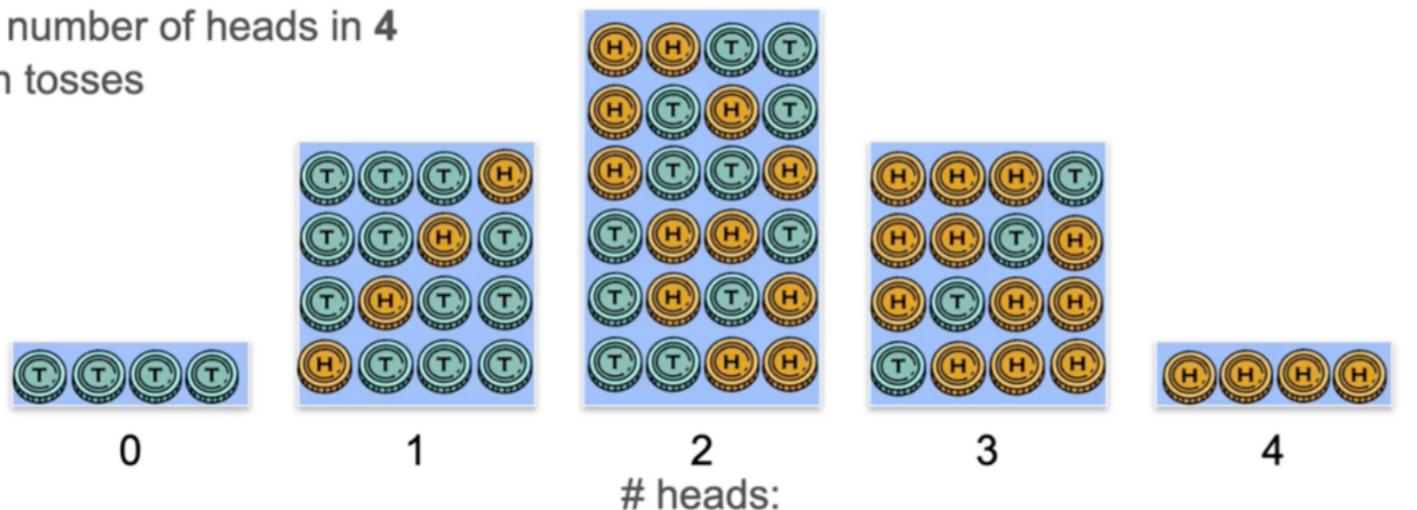
Flip Three Coins

X_1 : number of heads in 3 coin tosses



Flip Four Coins

X_2 : number of heads in 4 coin tosses



Flip Four Coins

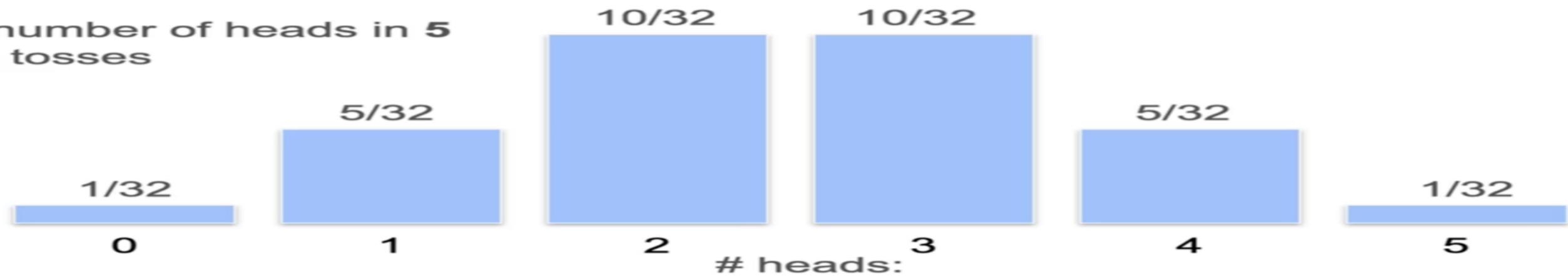
X_2 : number of heads in 4 coin tosses



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Flip Five Coins

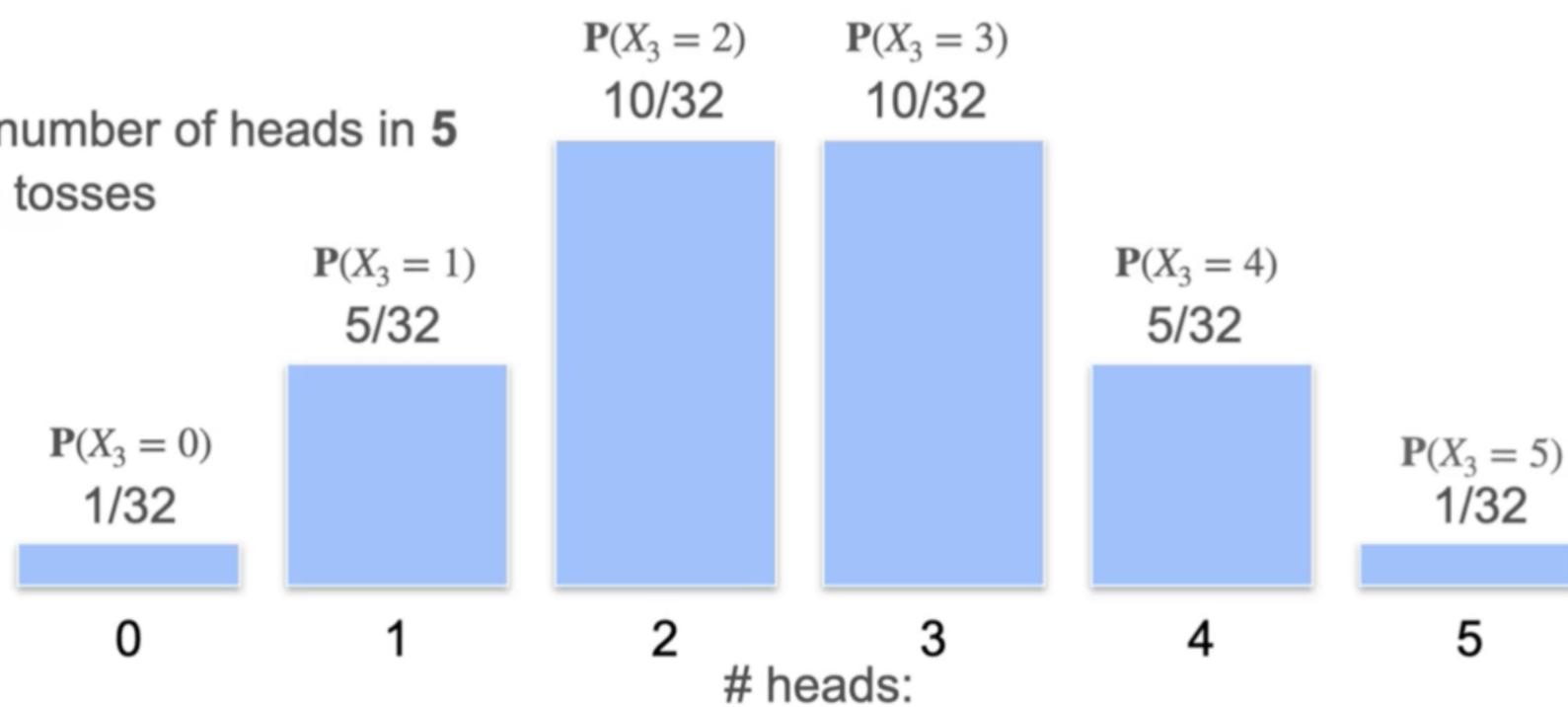
X_3 : number of heads in 5 coin tosses



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Flip Five Coins

X_3 : number of heads in 5 coin tosses



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Can You See a Pattern?

X_1, X_2, X_3, X_4 are very similar

They all represent **number of heads in n experiments**

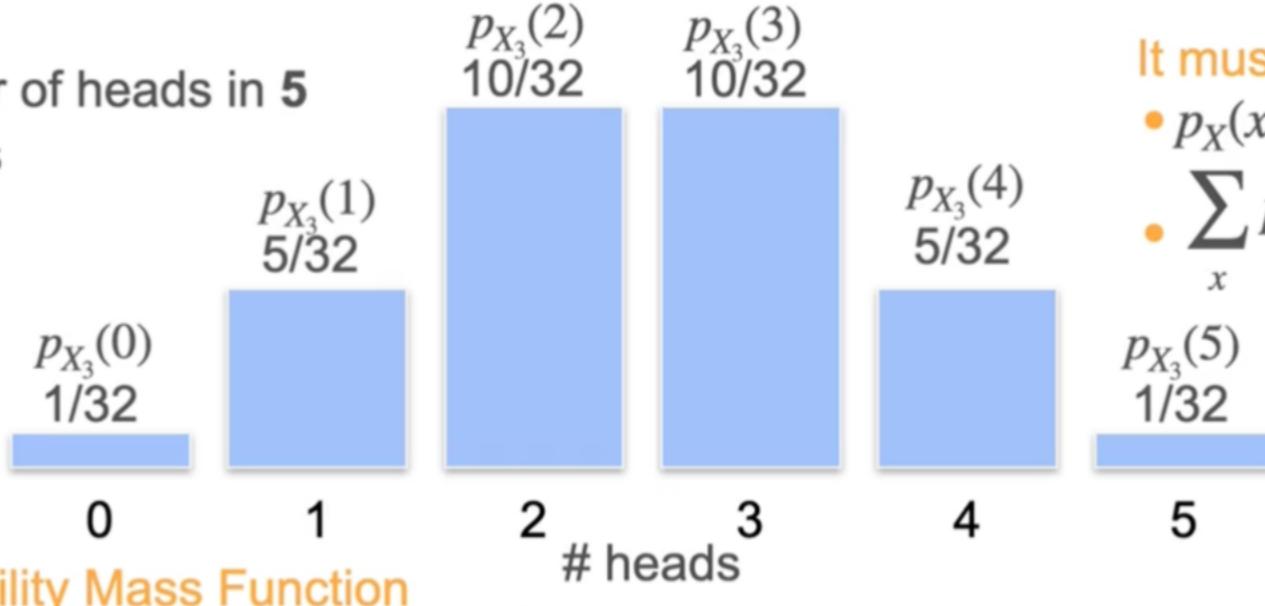
The way the probability distributes along the possible outcomes seems to have a similar pattern

Could there be a **single model** to represent all this variables?

Binomial distribution

Flip Five Coins

X_3 : number of heads in 5 coin tosses



It must satisfy:

- $p_X(x) \geq 0$
- $\sum_x p_X(x) = 1$

$$p_{X_3}(0) + p_{X_3}(1) + p_{X_3}(2) + p_{X_3}(3) + p_{X_3}(4) + p_{X_3}(5) = \frac{1}{32} + \frac{5}{32} + \frac{10}{32} + \frac{10}{32} + \frac{5}{32} + \frac{1}{32} = 1$$