

Basics of AI: what you need to know

Dr. Katie Stolee
Associate Professor
Department of Computer Science
North Carolina State University



Computer Science is Everywhere



Education

**Energy and
Sustainability**

**Scientific
Discovery**

**Security and
Privacy**

Transportation

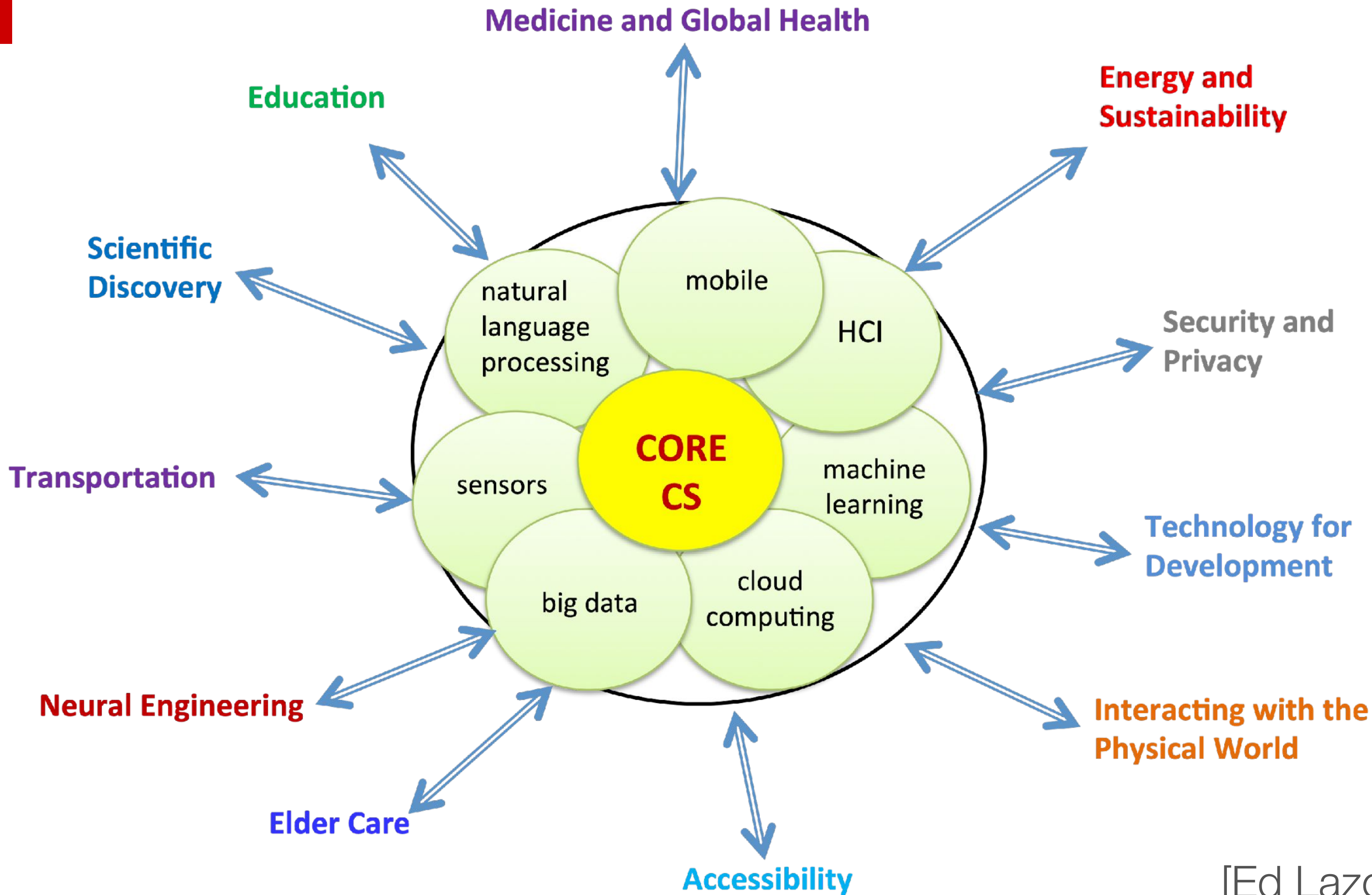
**Technology for
Development**

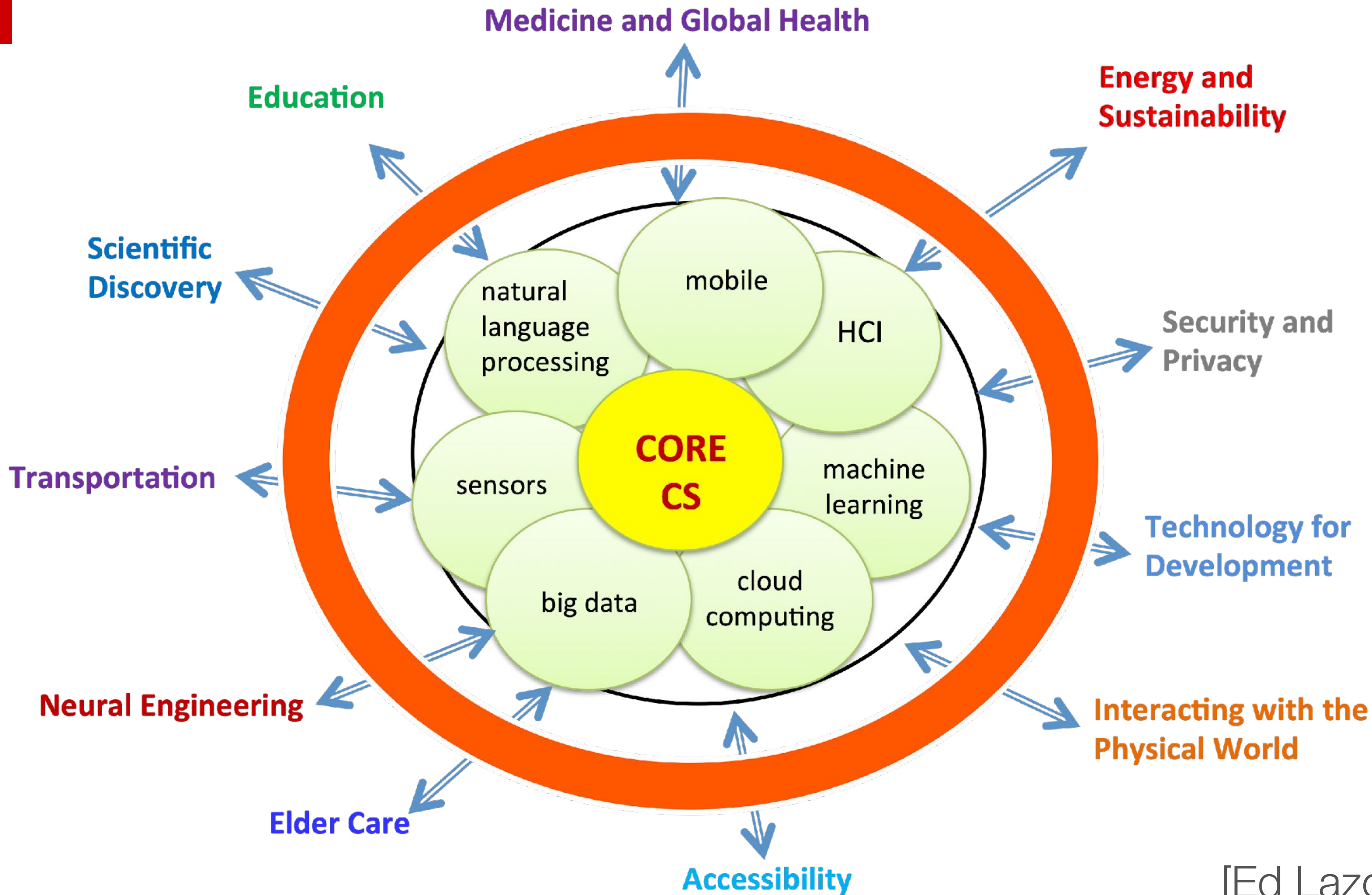
Neural Engineering

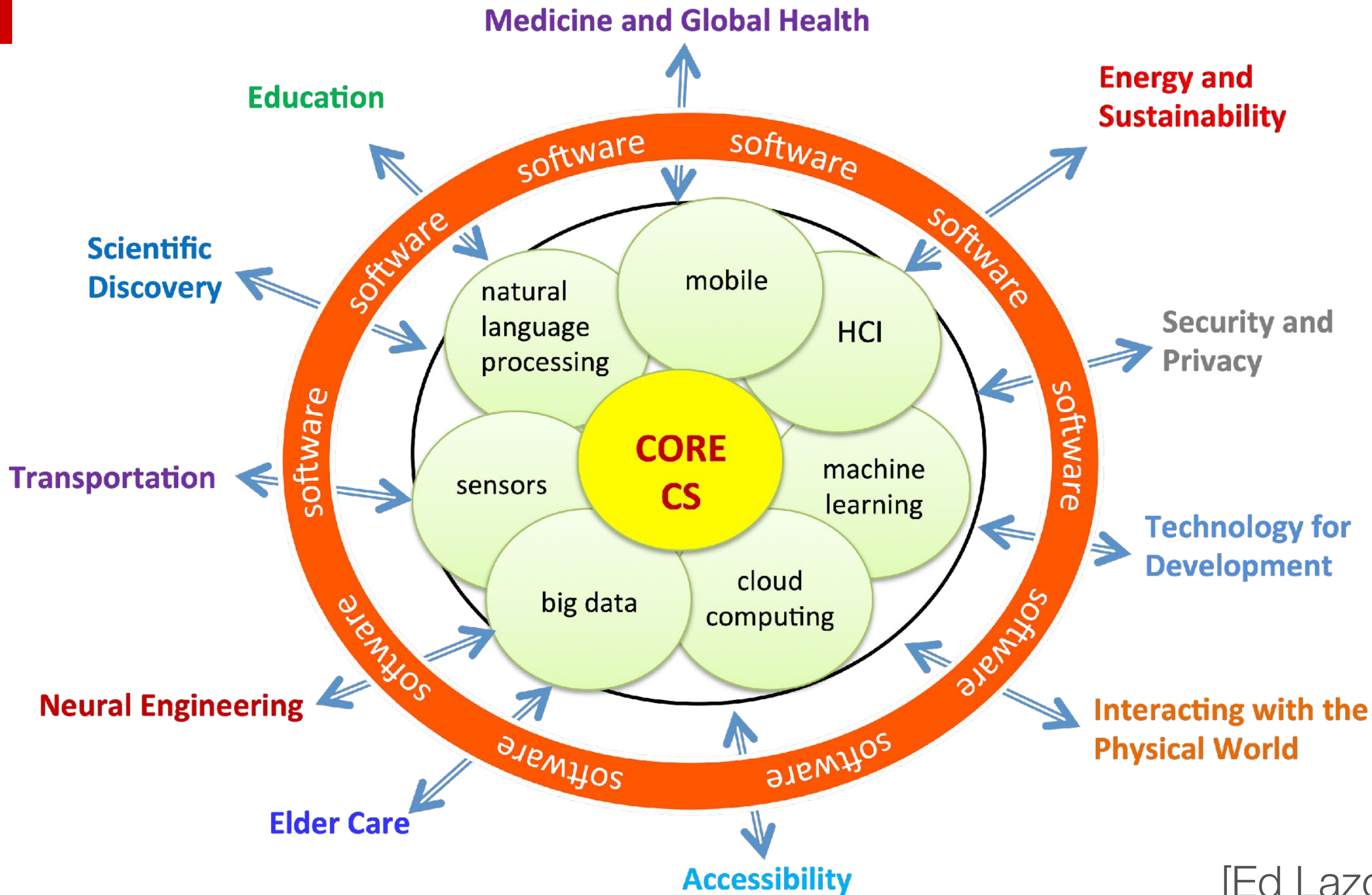
**Interacting with the
Physical World**

Elder Care

Accessibility







NC STATE

your

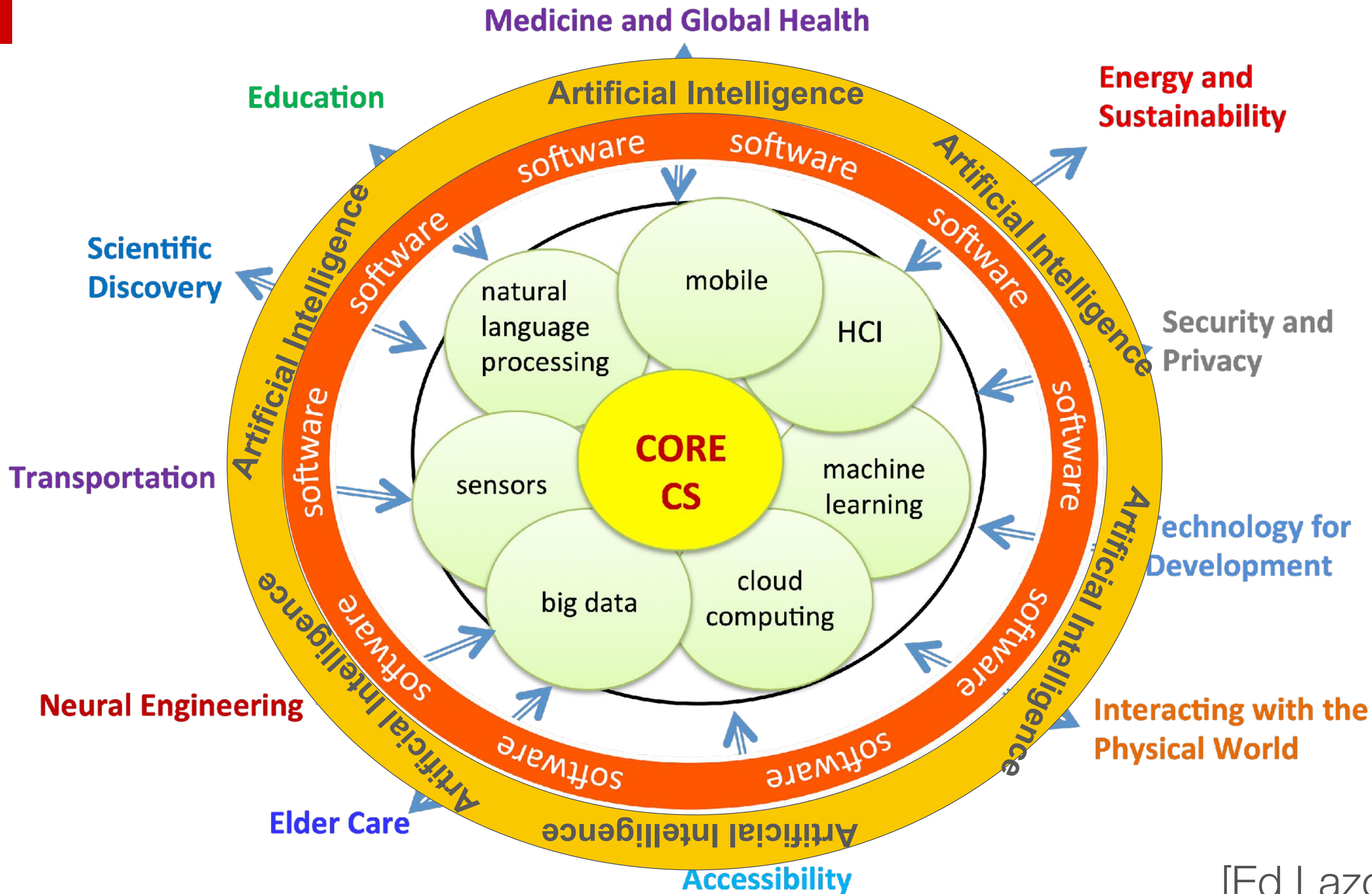
life

depends

on

code





What do you know about AI?



Artificial Intelligence

Machines that mimic human cognition

Building machines that can solve problems and make decisions



Artificial Intelligence vs. Machine Learning

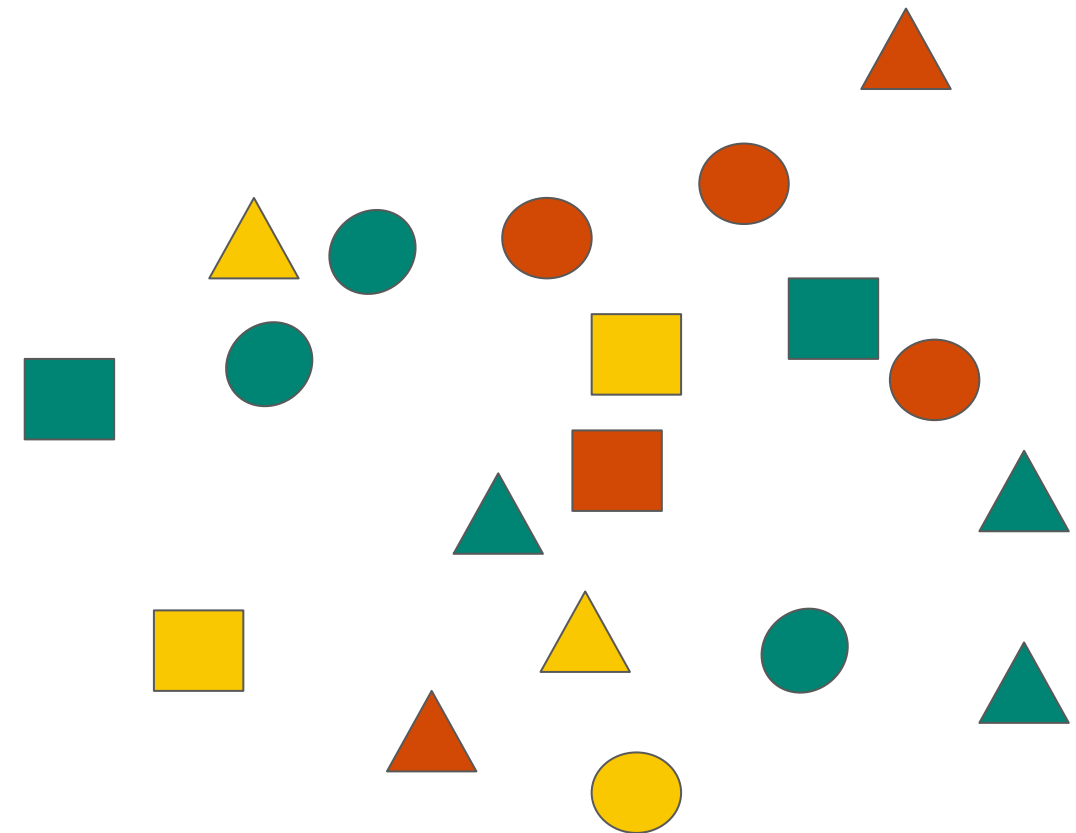
Machines that mimic human cognition

Building machines that can solve problems and make decisions



A form of artificial intelligence

Pattern matching. It “learns” based on training data.



Artificial Intelligence vs. Machine Learning

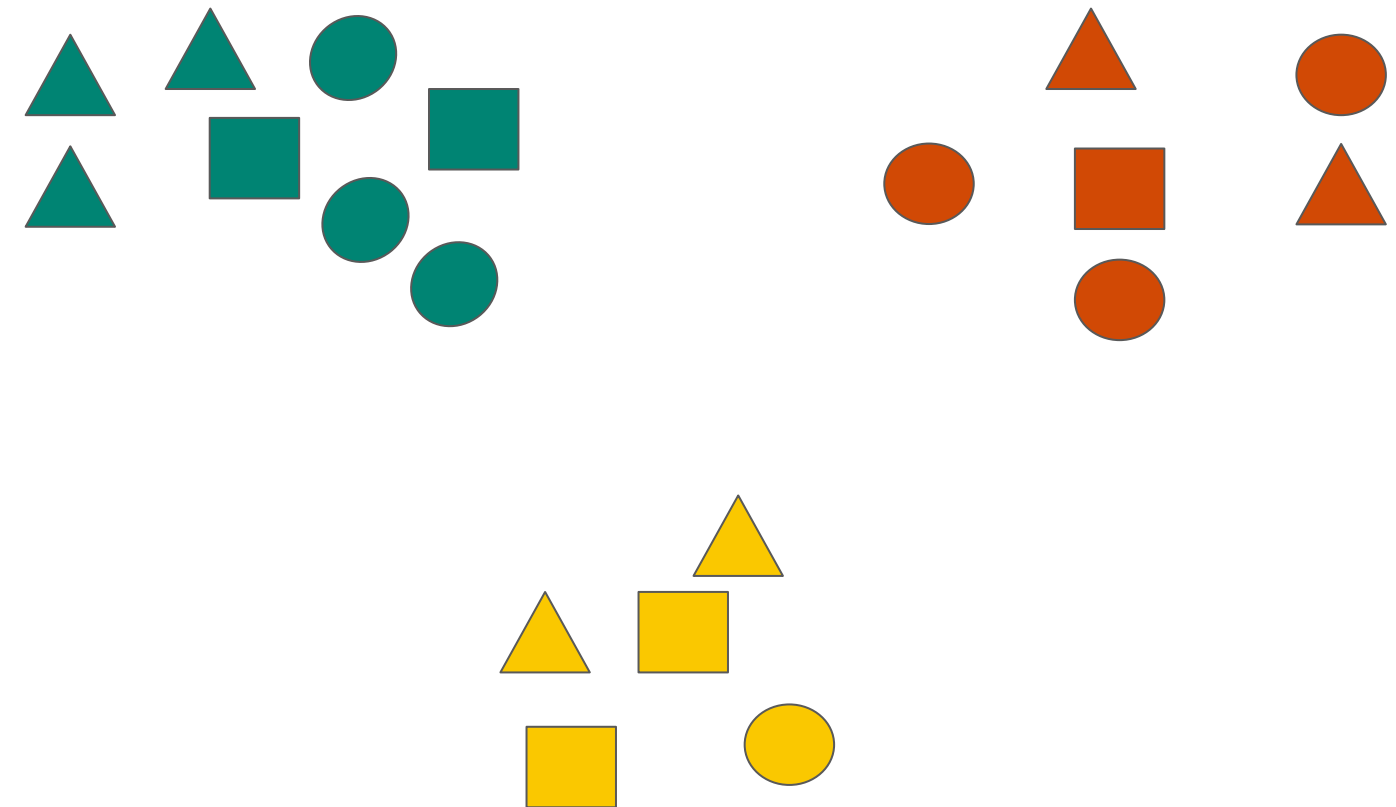
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Artificial Intelligence vs. Machine Learning

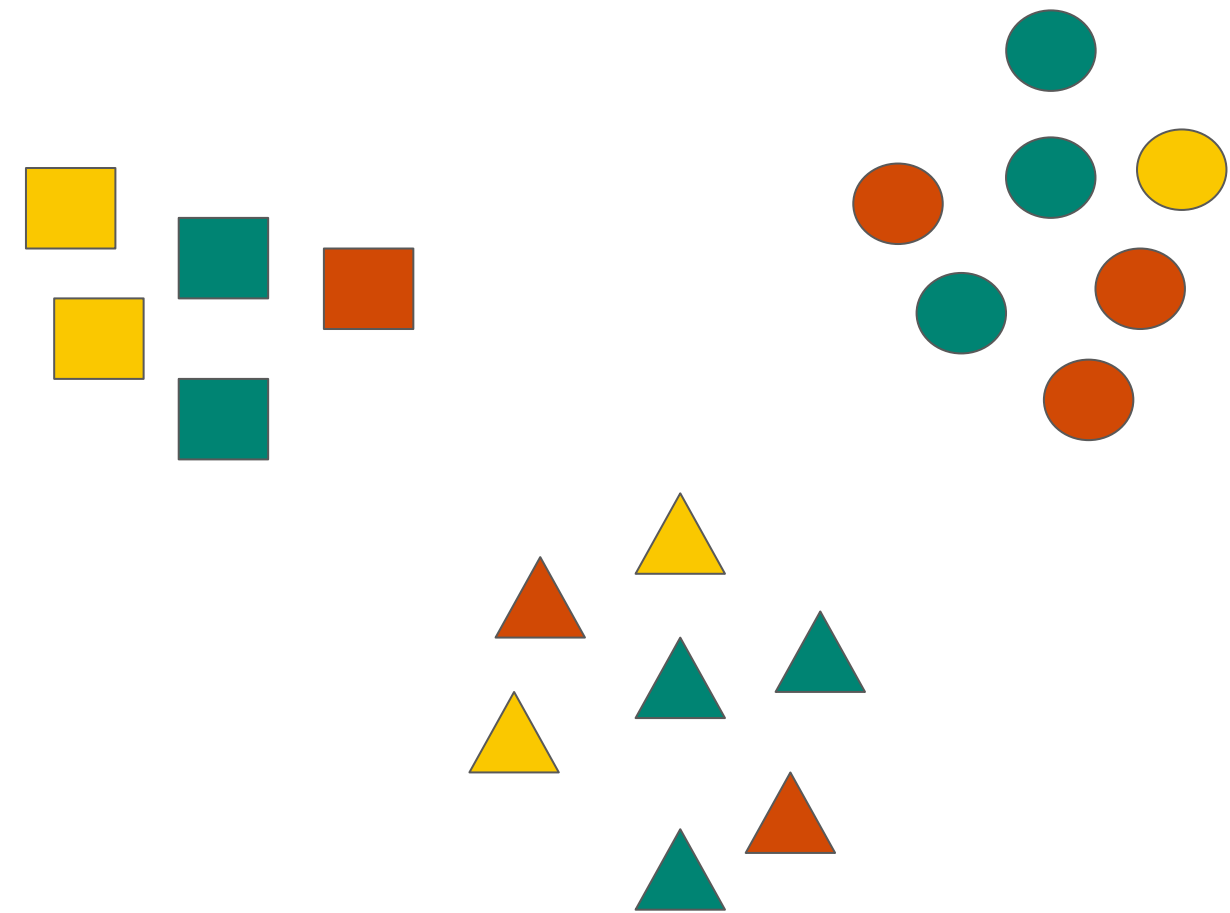
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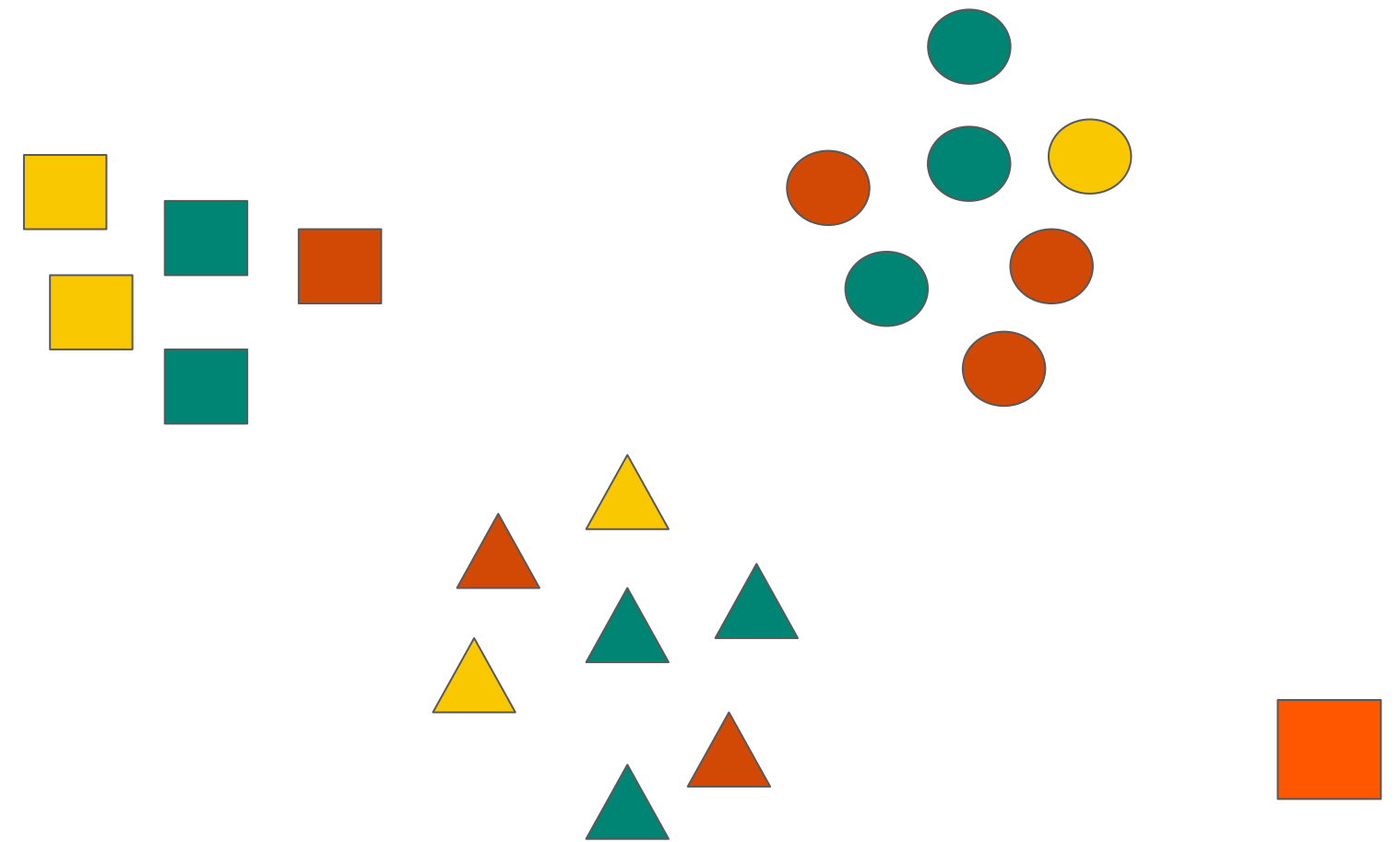
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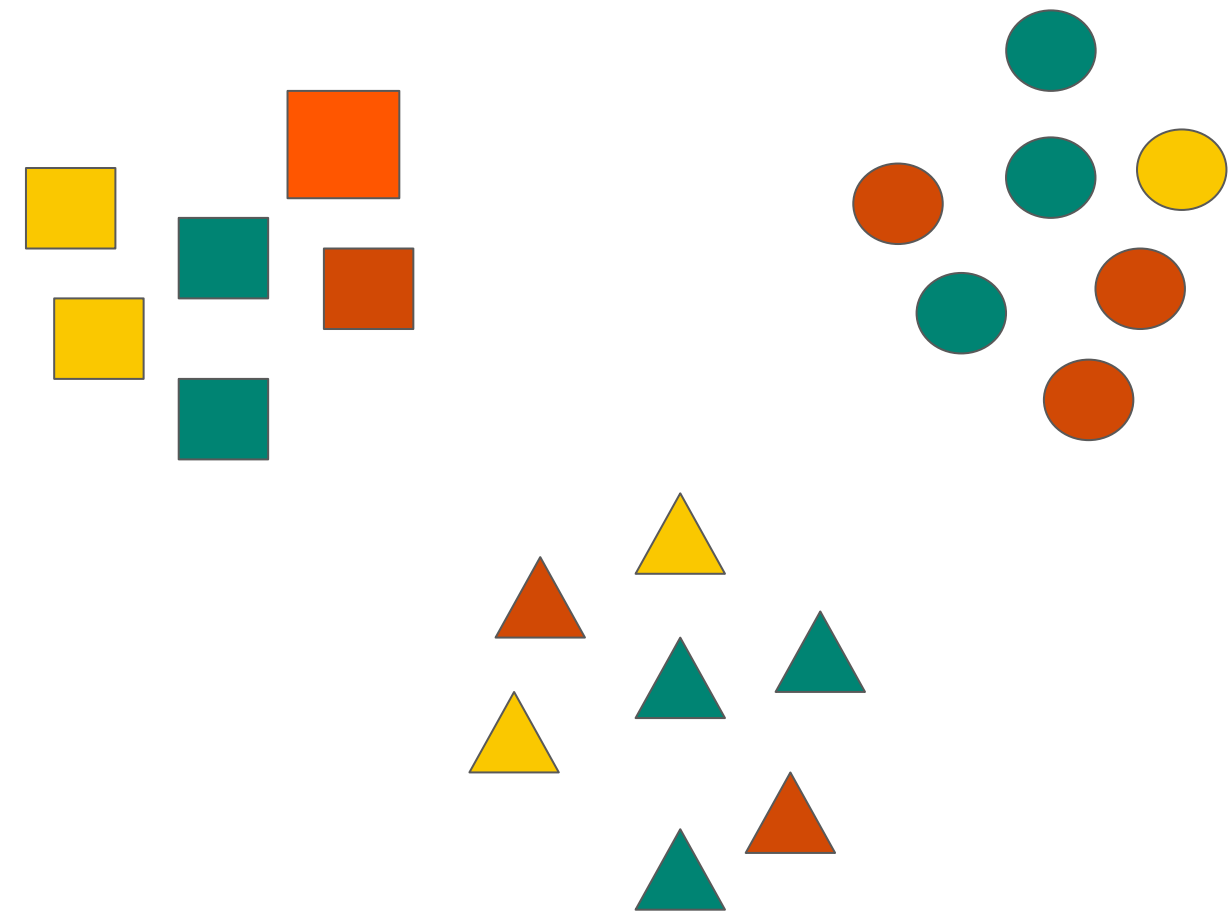
Machines that mimic human cognition

Building machines that can solve problems and make decisions

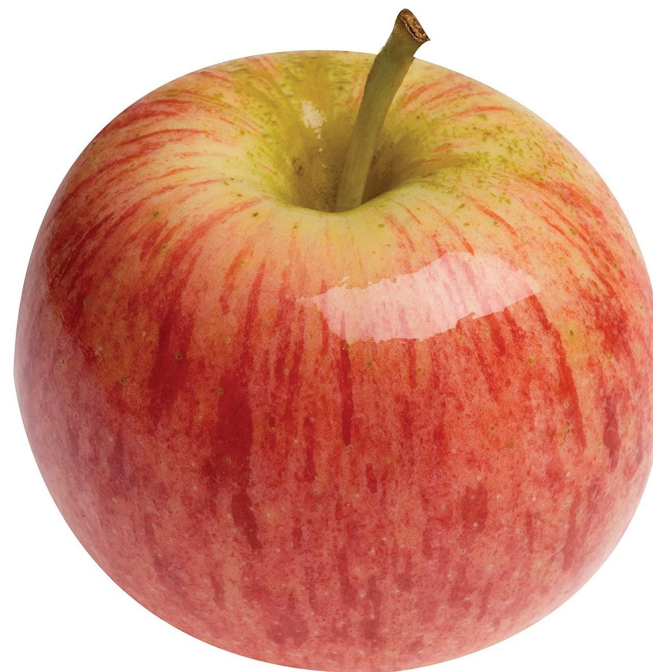


A form of artificial intelligence

Pattern matching. It “learns” based on training data.



Bias



Apple



Banana



Apple



Apple



Apple



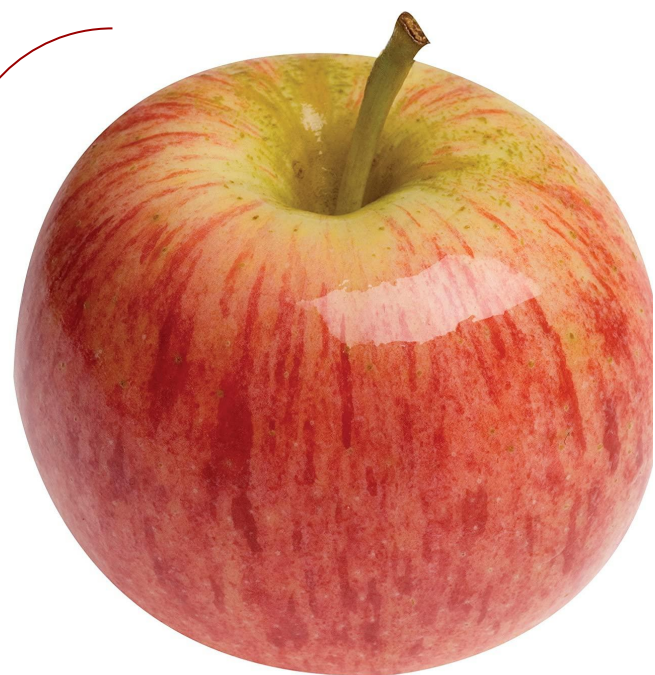
Apple



Banana



Apple



Apple



Banana



Apple



Apple

Learn a model from
this training data



Model

Model



Apple



Apple



Banana



Banana

Why?



Apple



Banana



Apple



Apple



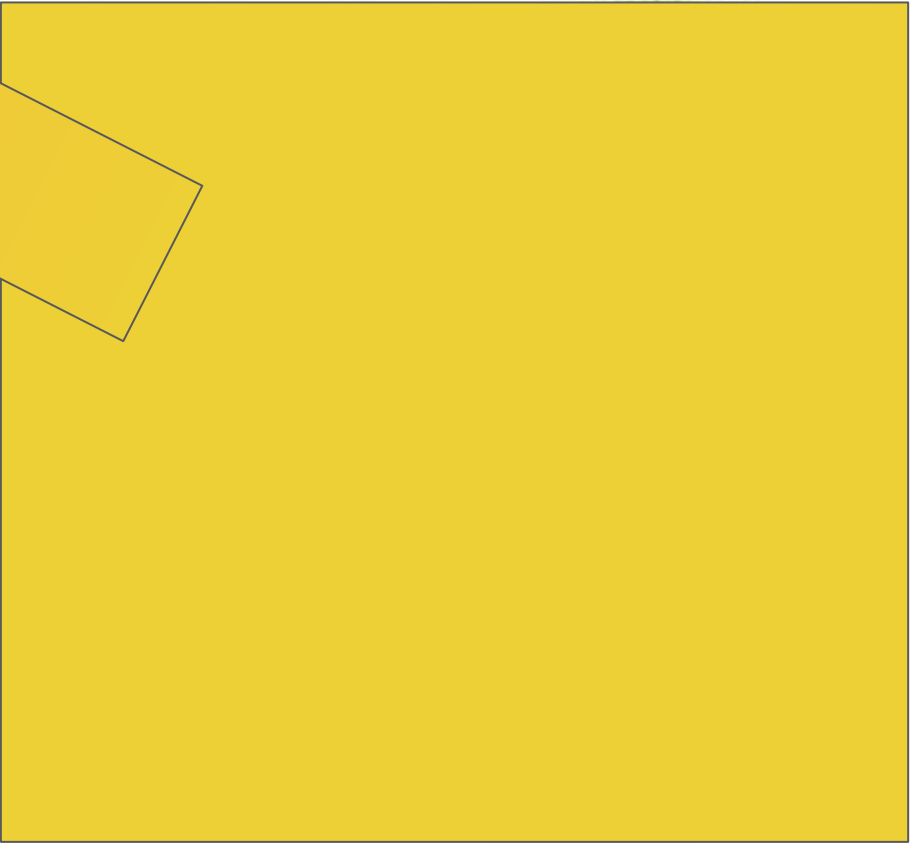
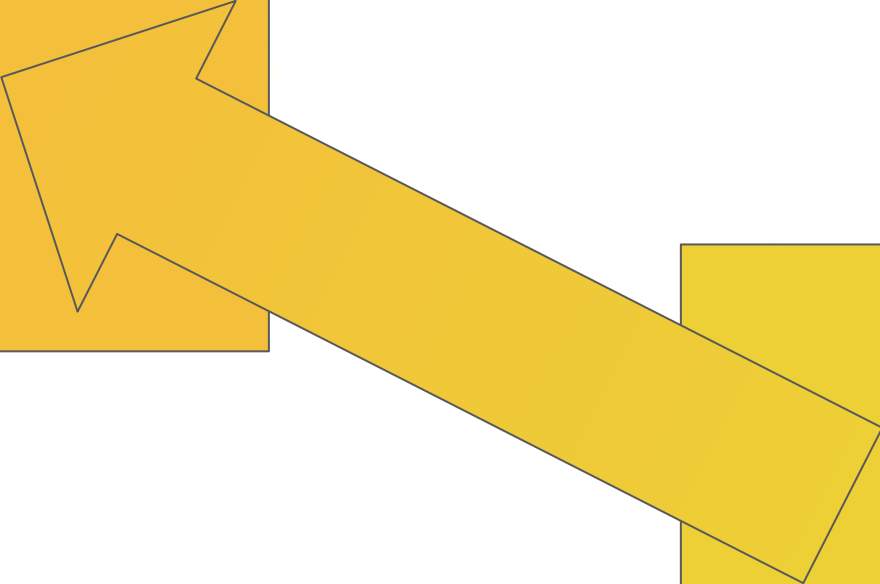
Why?



Apple



Banana

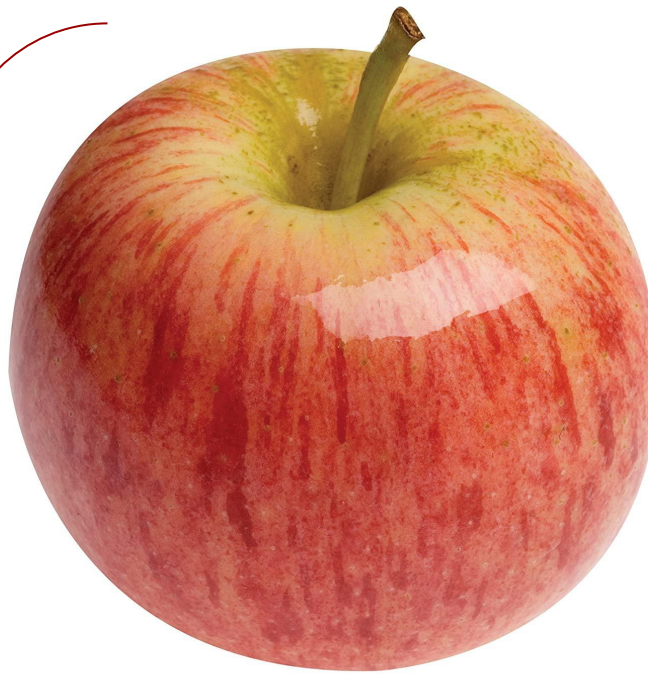


Apple



Apple





Apple



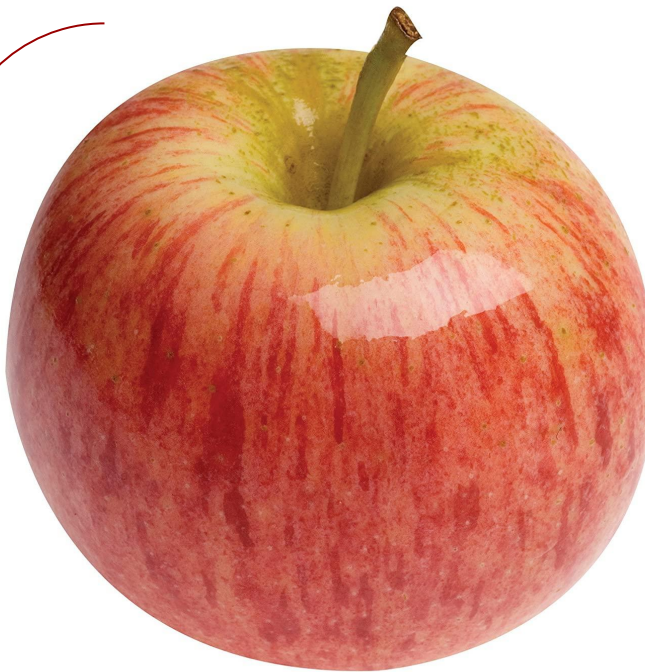
Banana



Apple



Apple



Apple

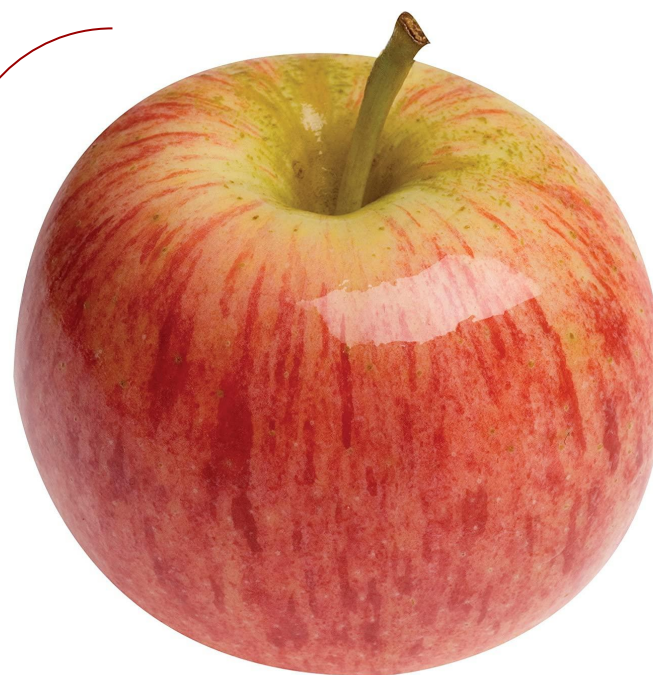


Banana



Apple

Apple



Apple



Banana



Apple



Apple

Learn a model from
this more diverse
training data

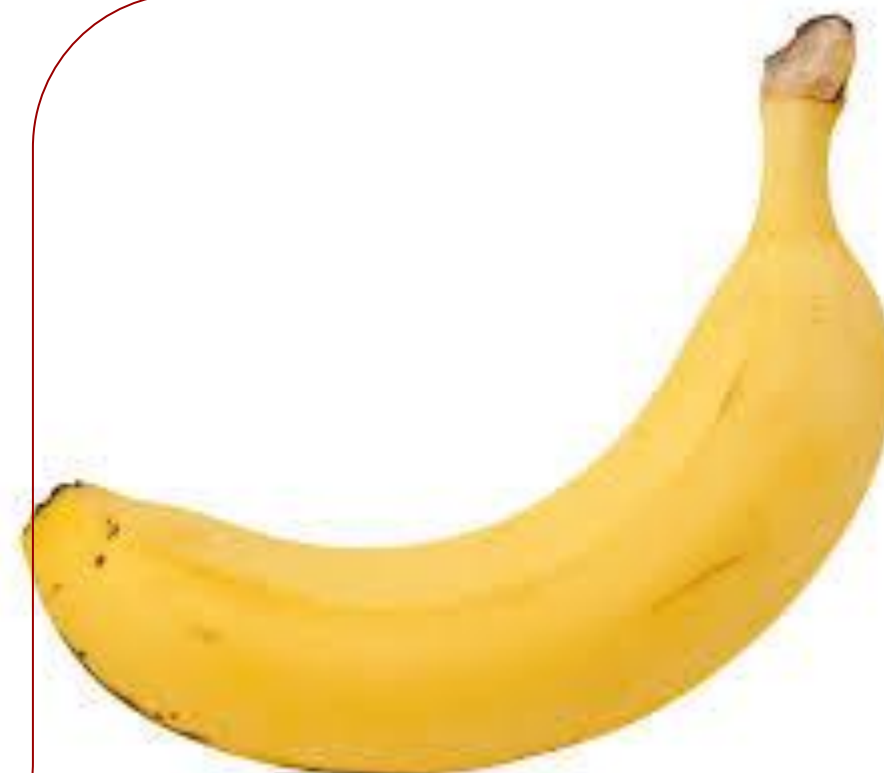
Model



Apple



Apple



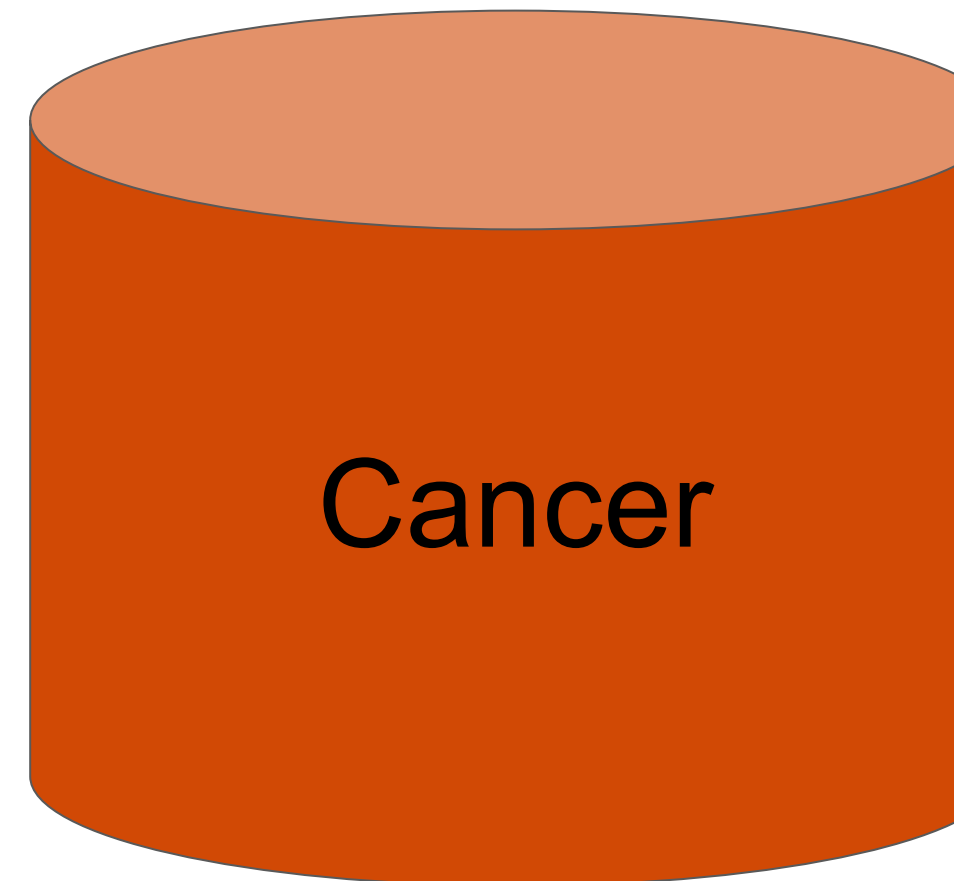
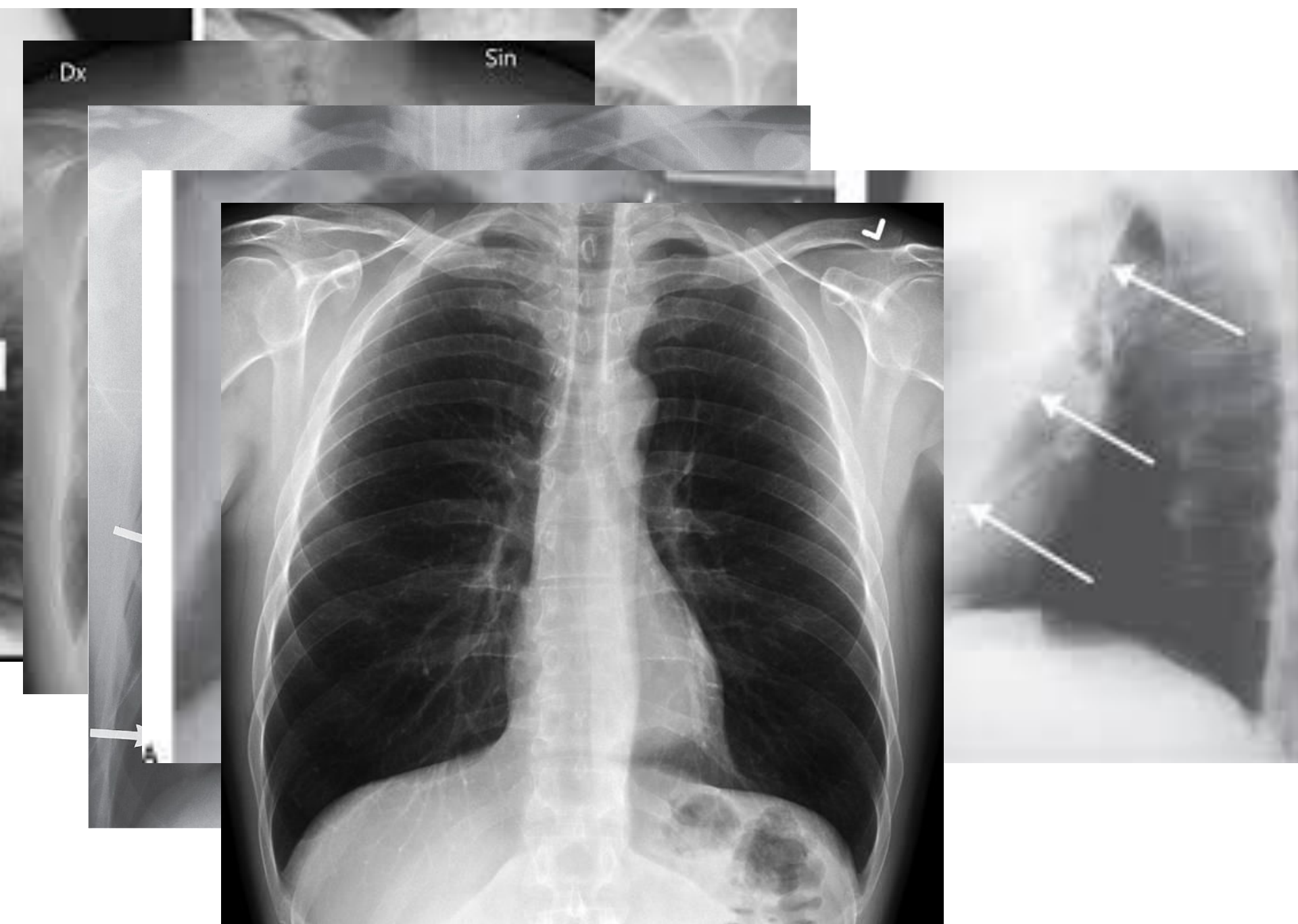
Banana



Apple

Let's make this more
real-world

Imagine you are a radiologist.



Images



Cancer

Healthy



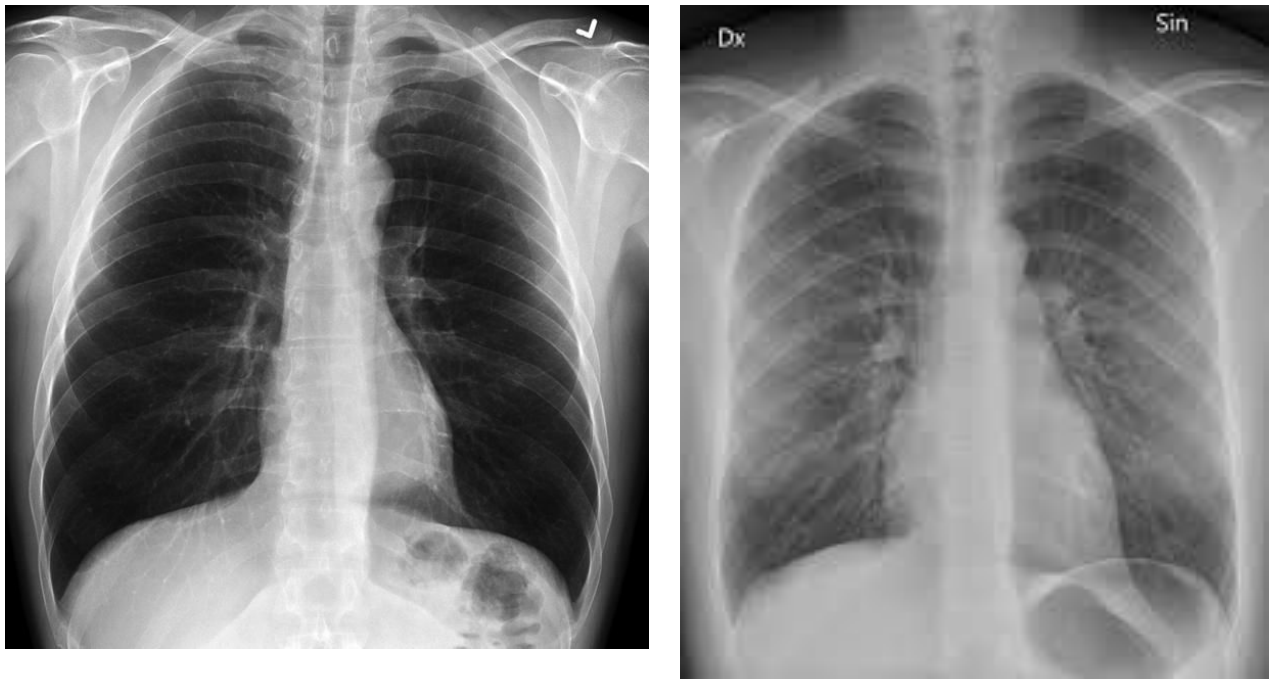
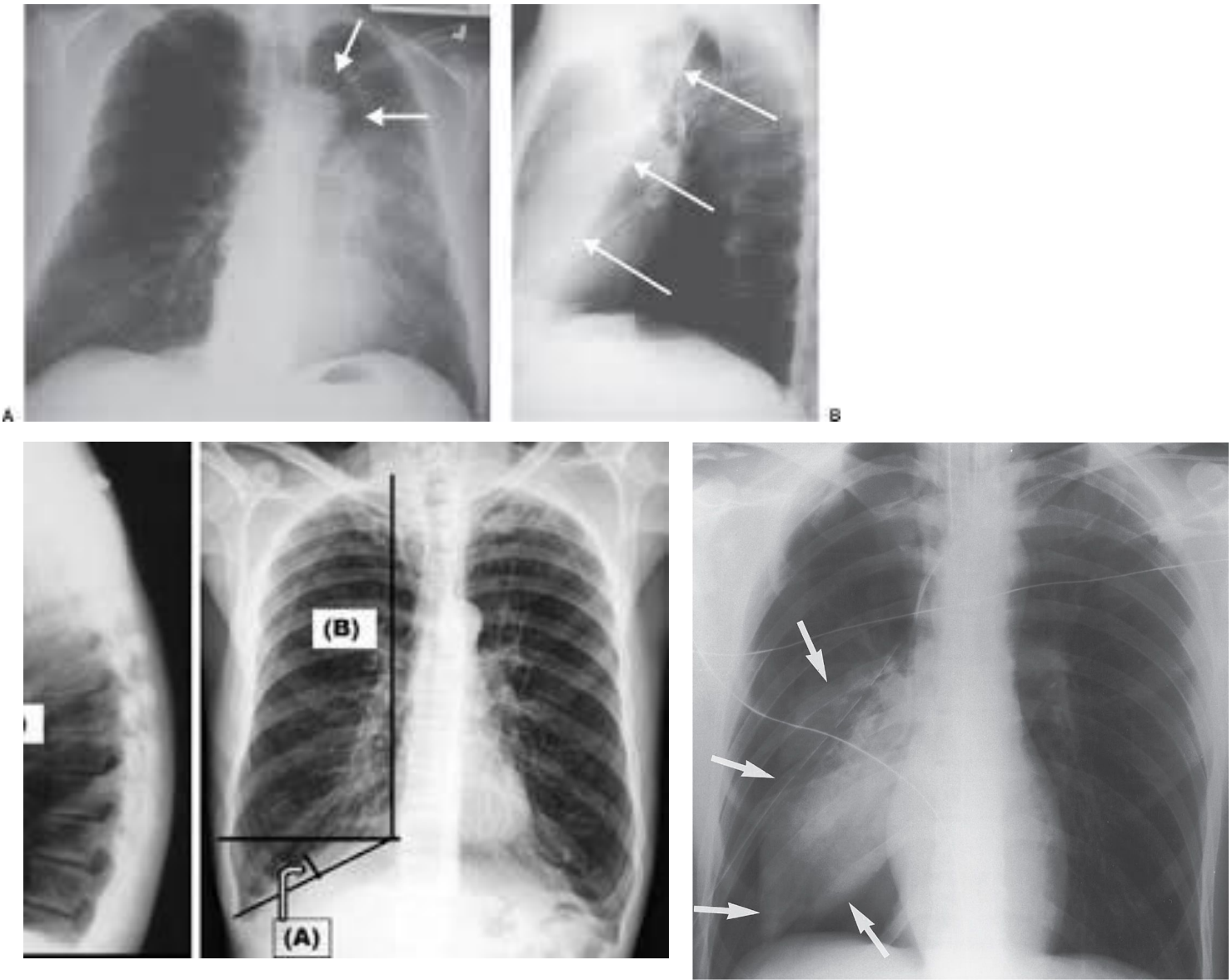
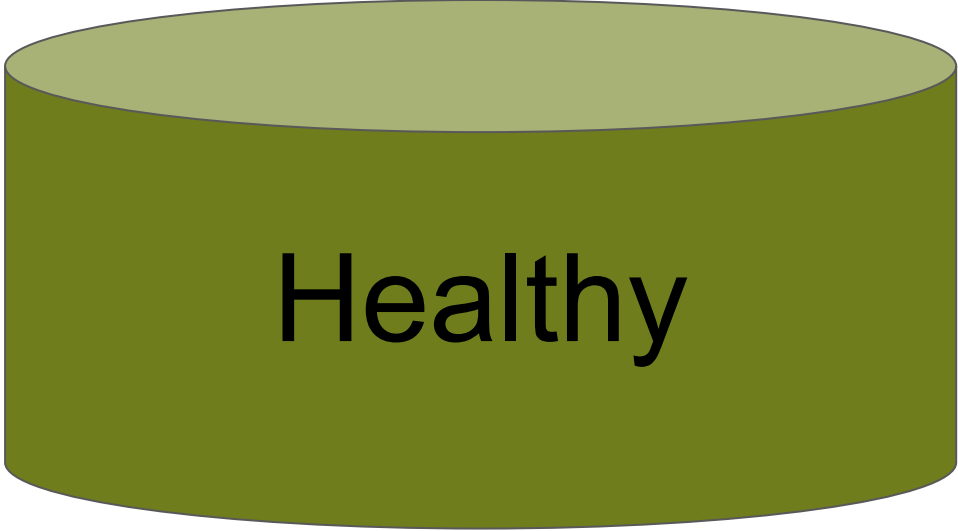
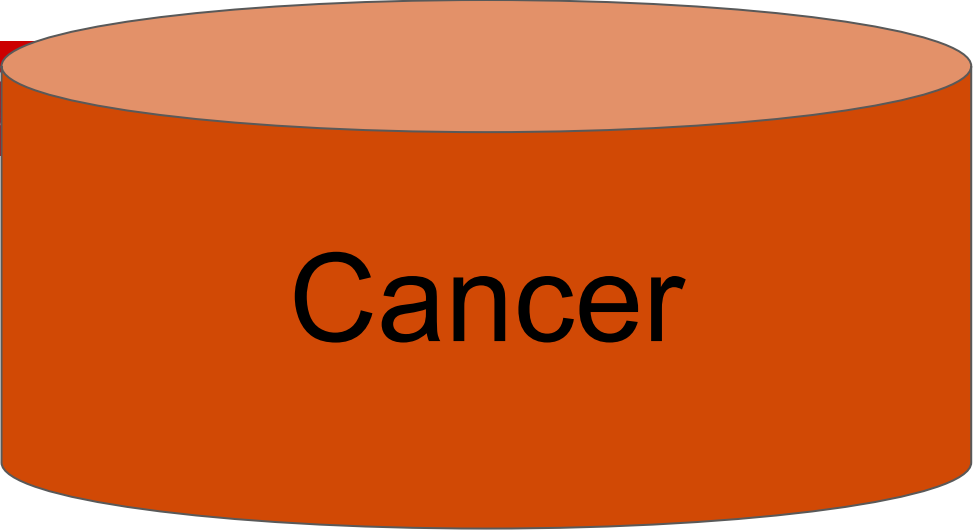
The diagram illustrates a machine learning workflow for image classification. On the left, a large light gray cylinder represents the input data, labeled "Images". An arrow points from this cylinder to a dark gray rectangular block labeled "Machine Learning". From the right side of the "Machine Learning" block, two arrows branch out to two output cylinders. The top output cylinder is orange and labeled "Cancer", while the bottom output cylinder is green and labeled "Healthy". A decorative bar with eight colored segments (red, orange, yellow, green, teal, blue, purple, and pink) is located at the bottom of the image.

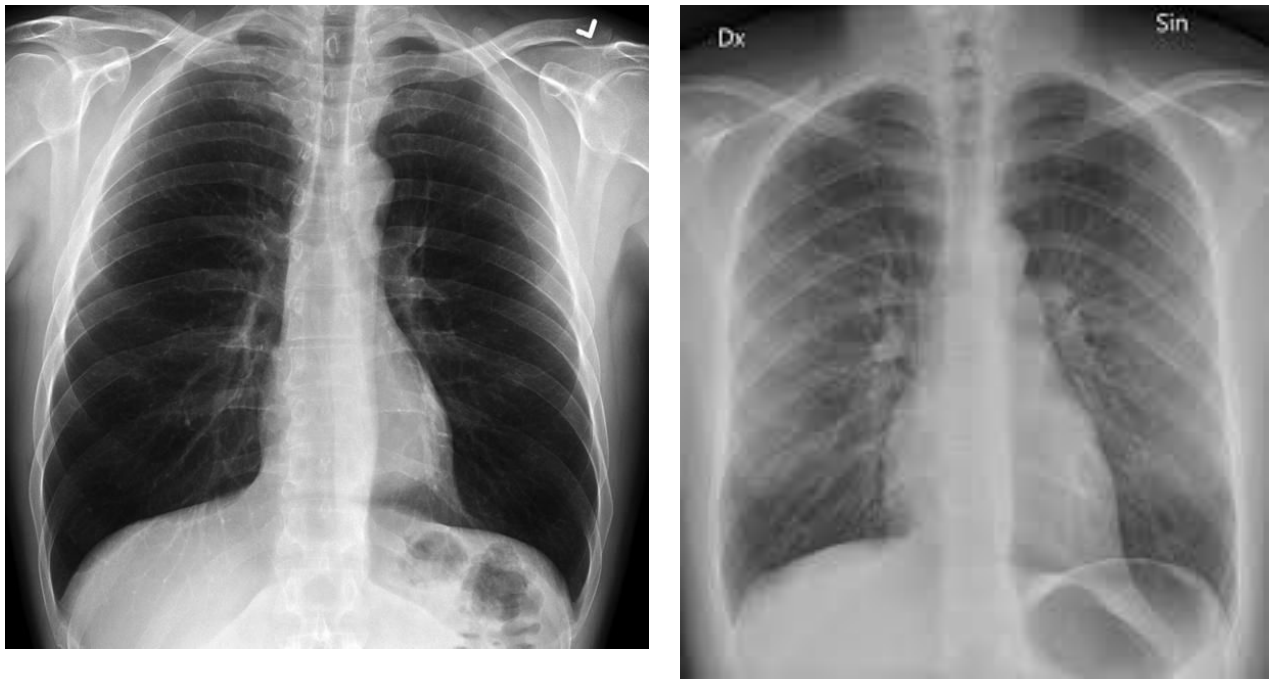
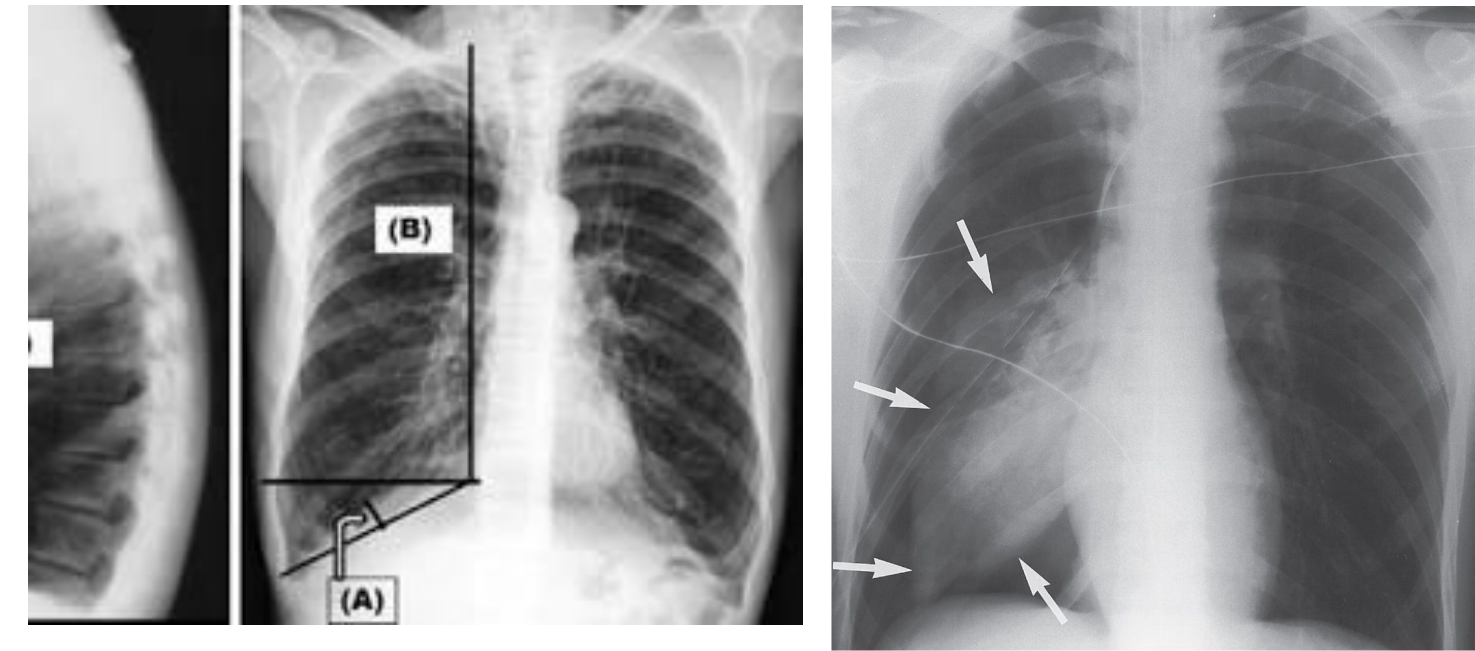
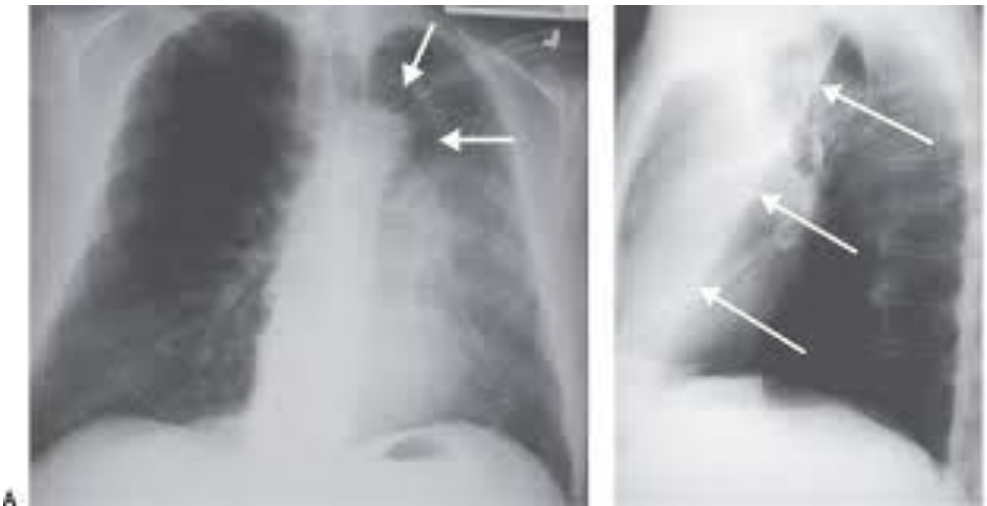
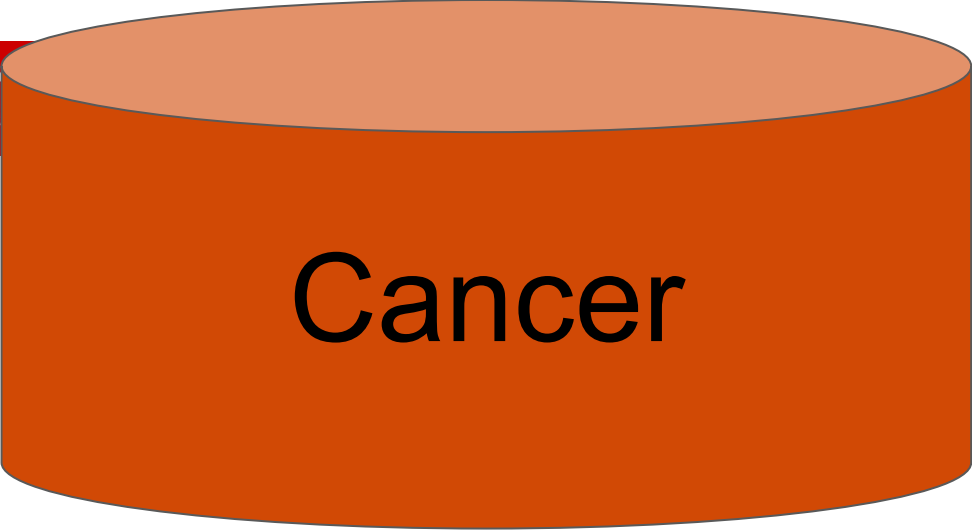
Images

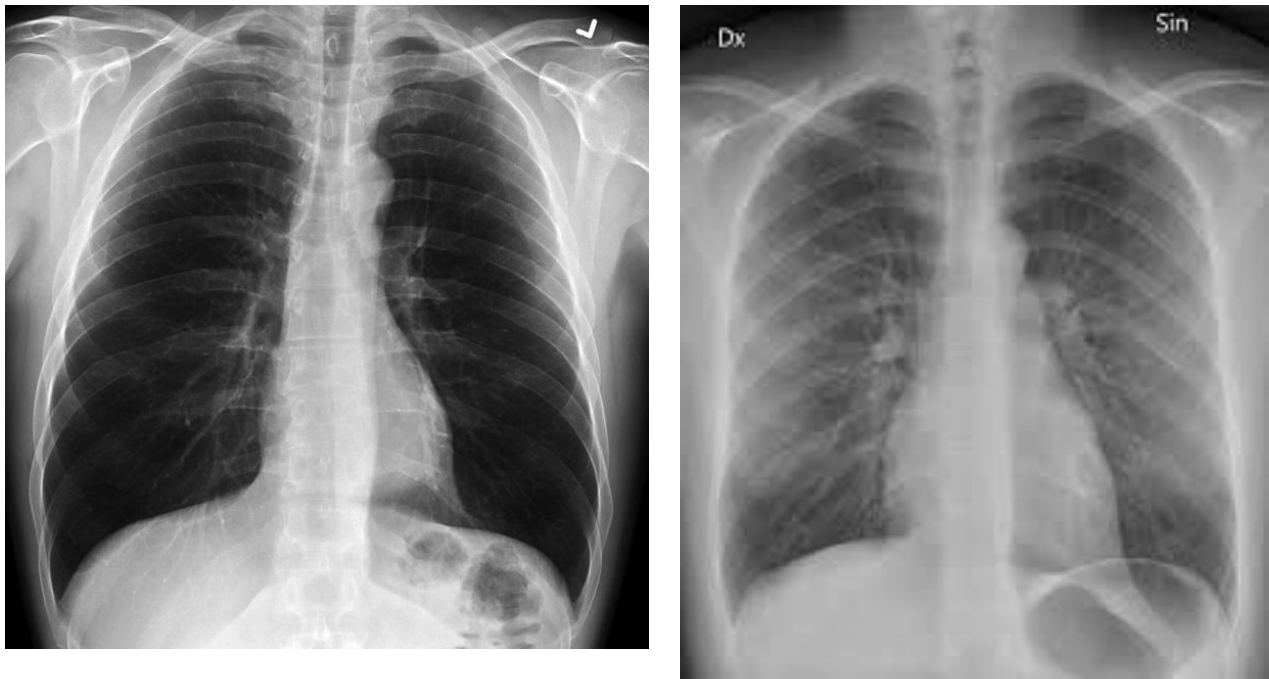
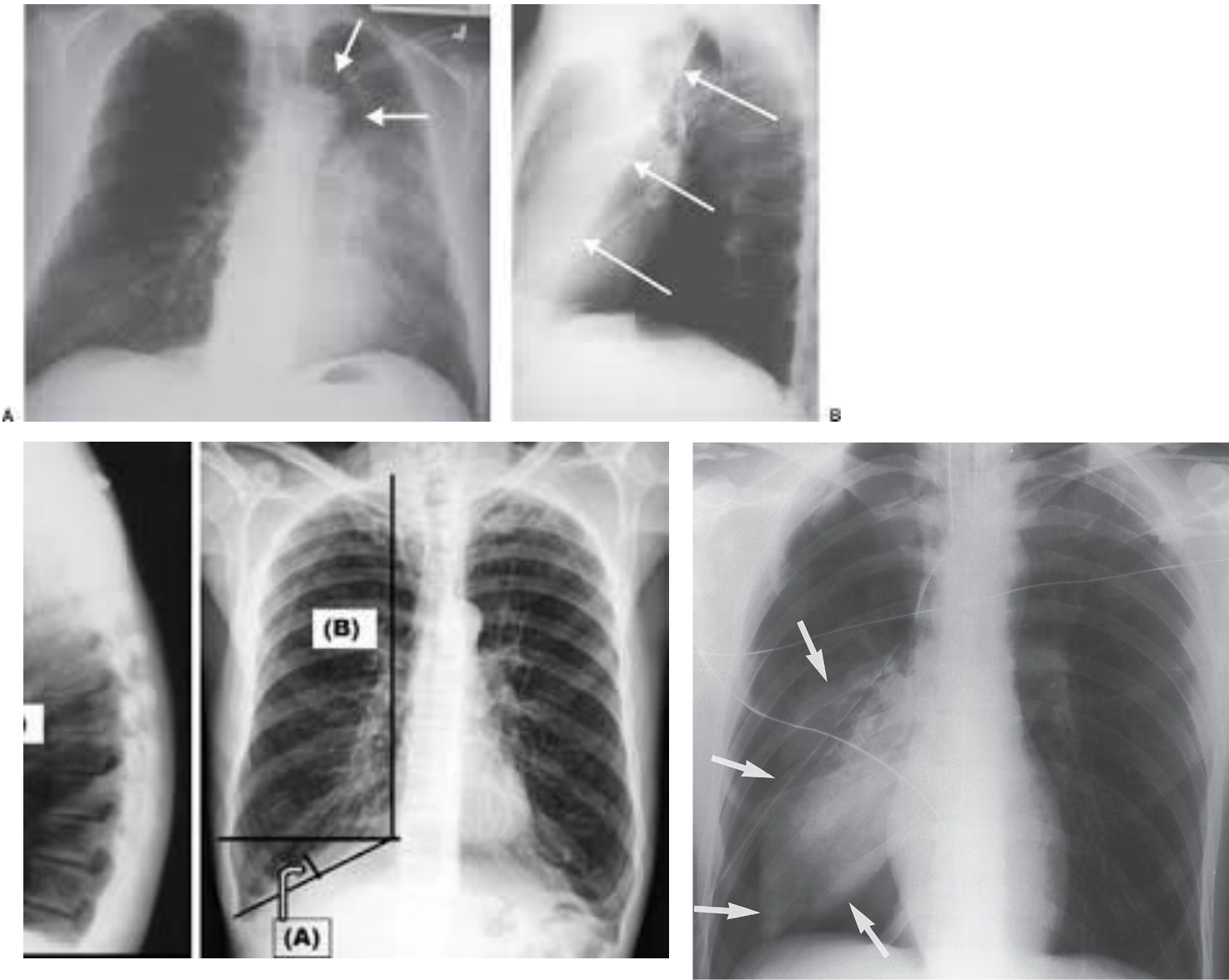
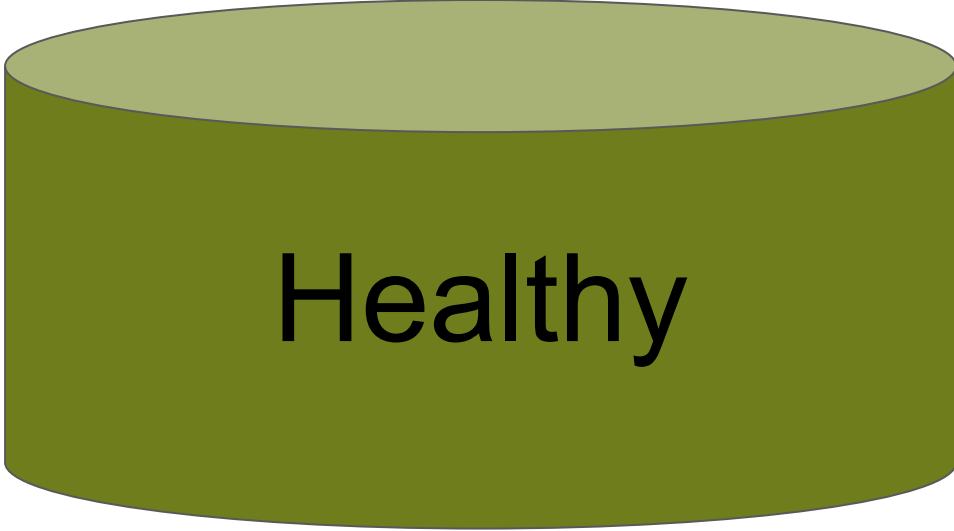
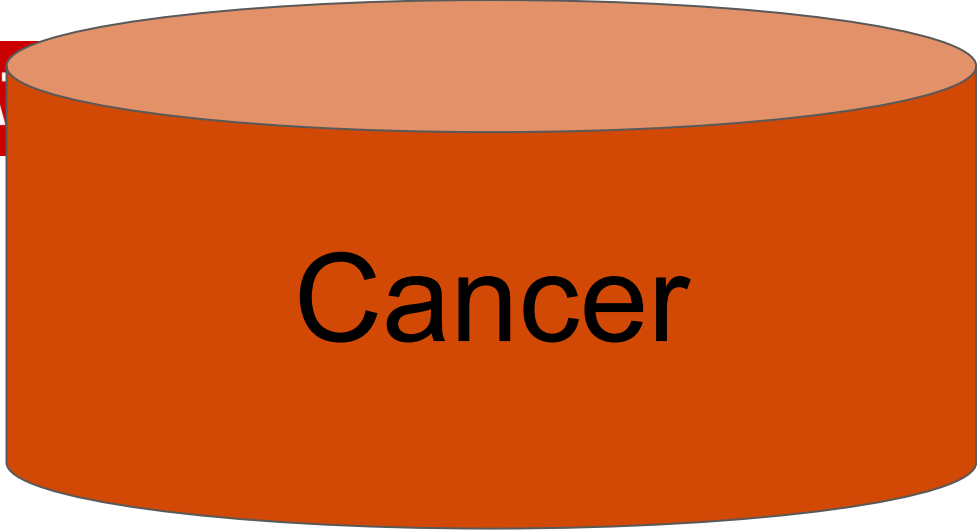
**Machine
Learning**

Cancer

Healthy

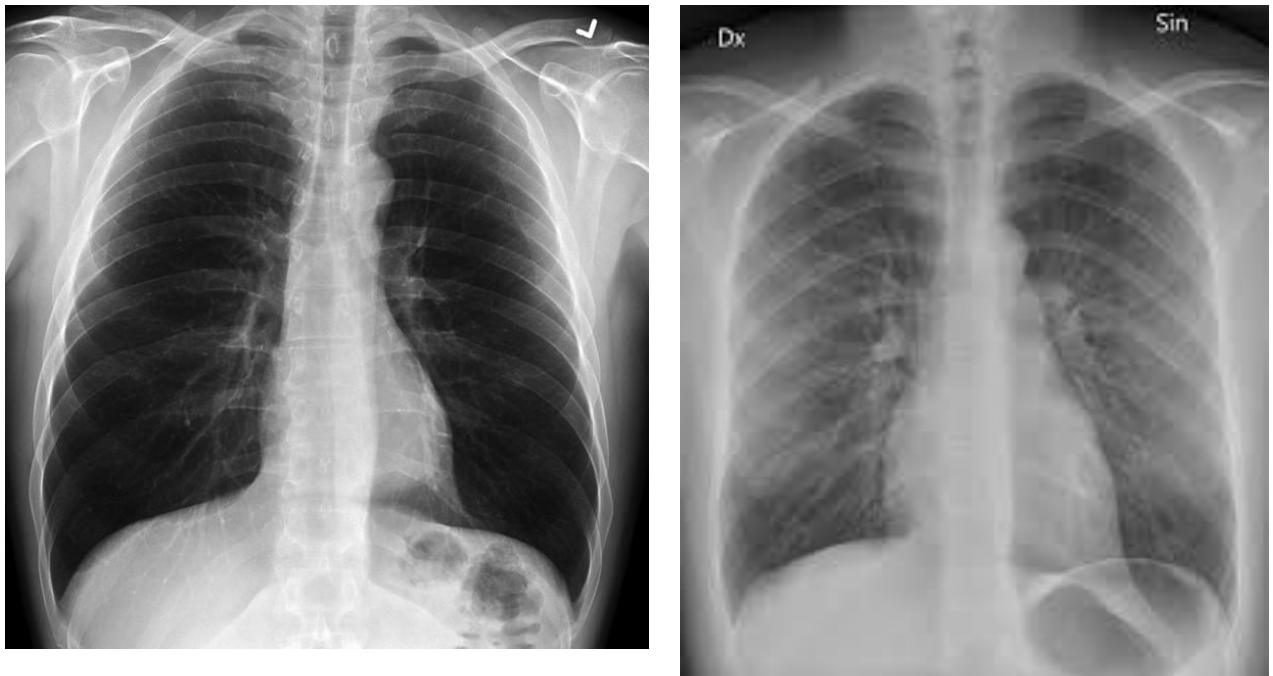
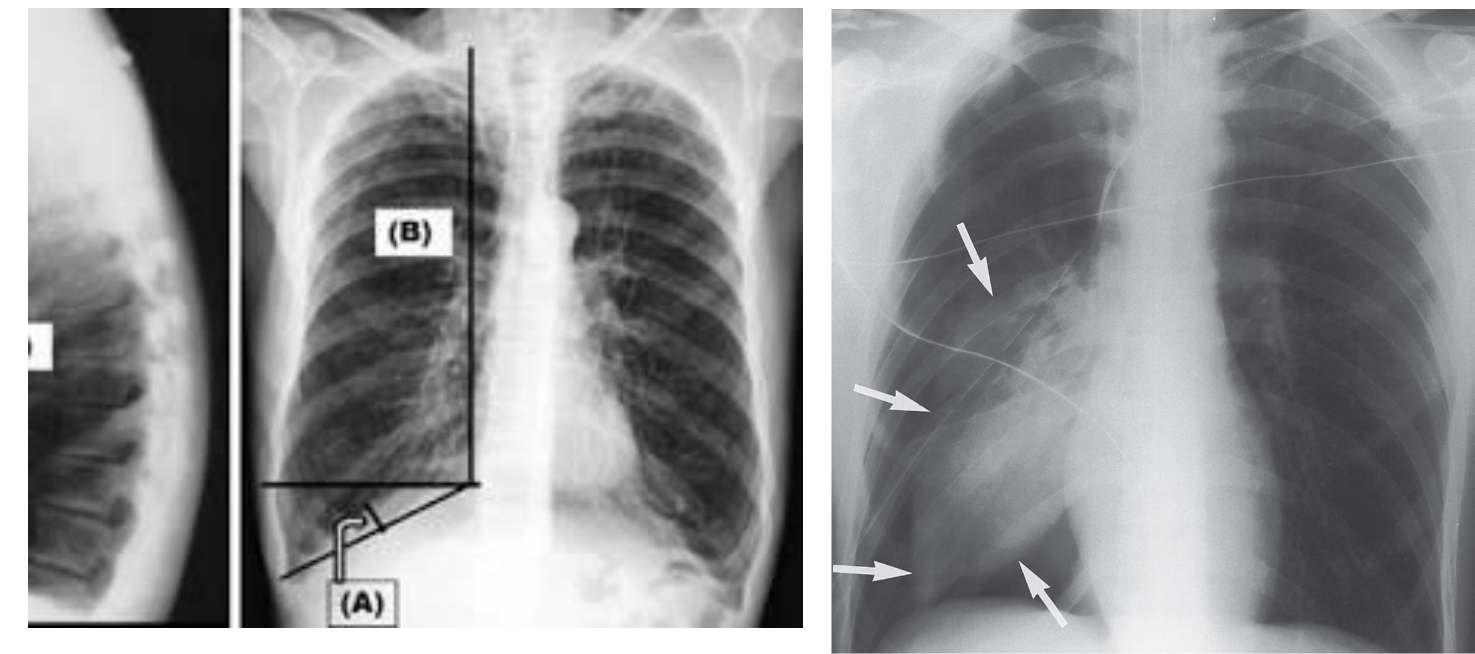
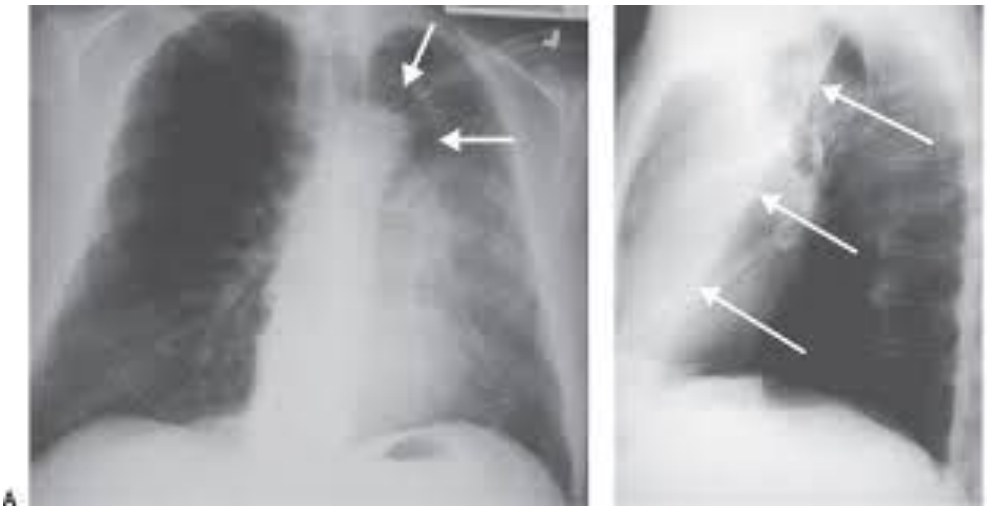
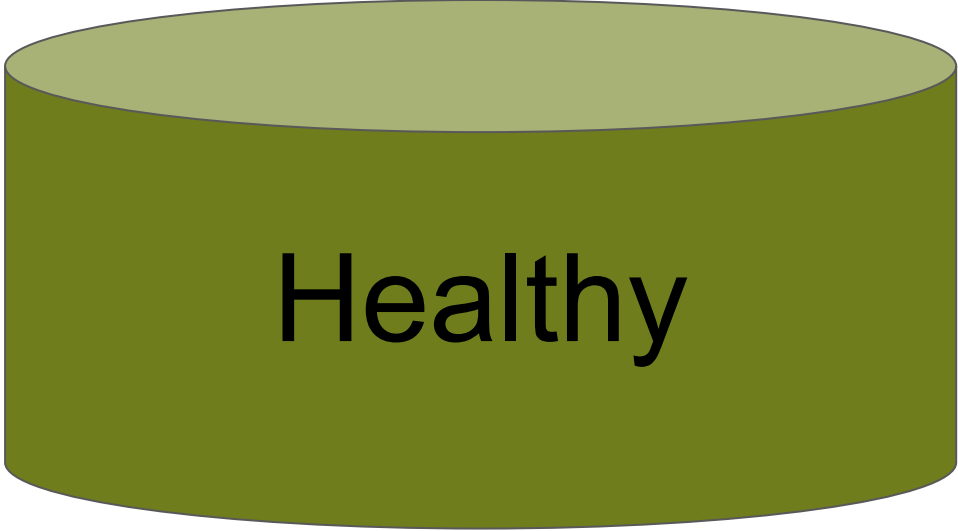
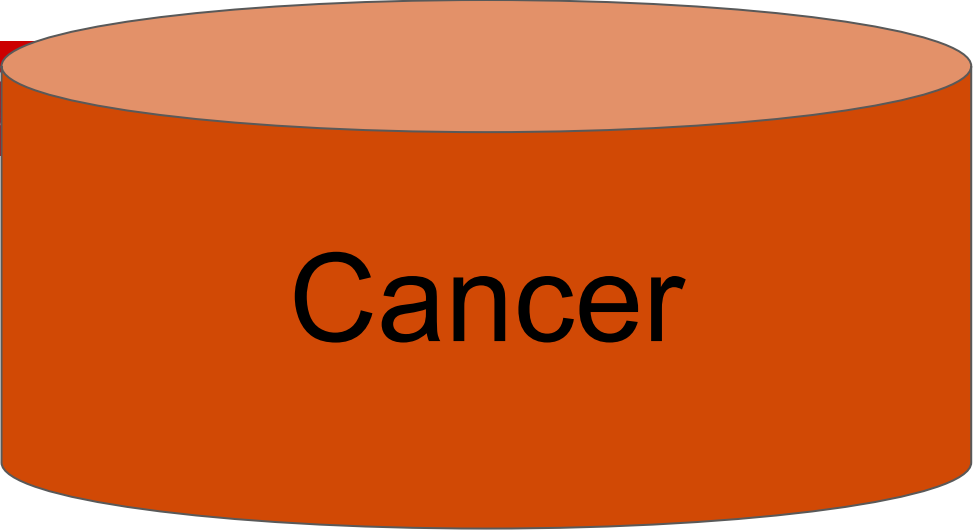






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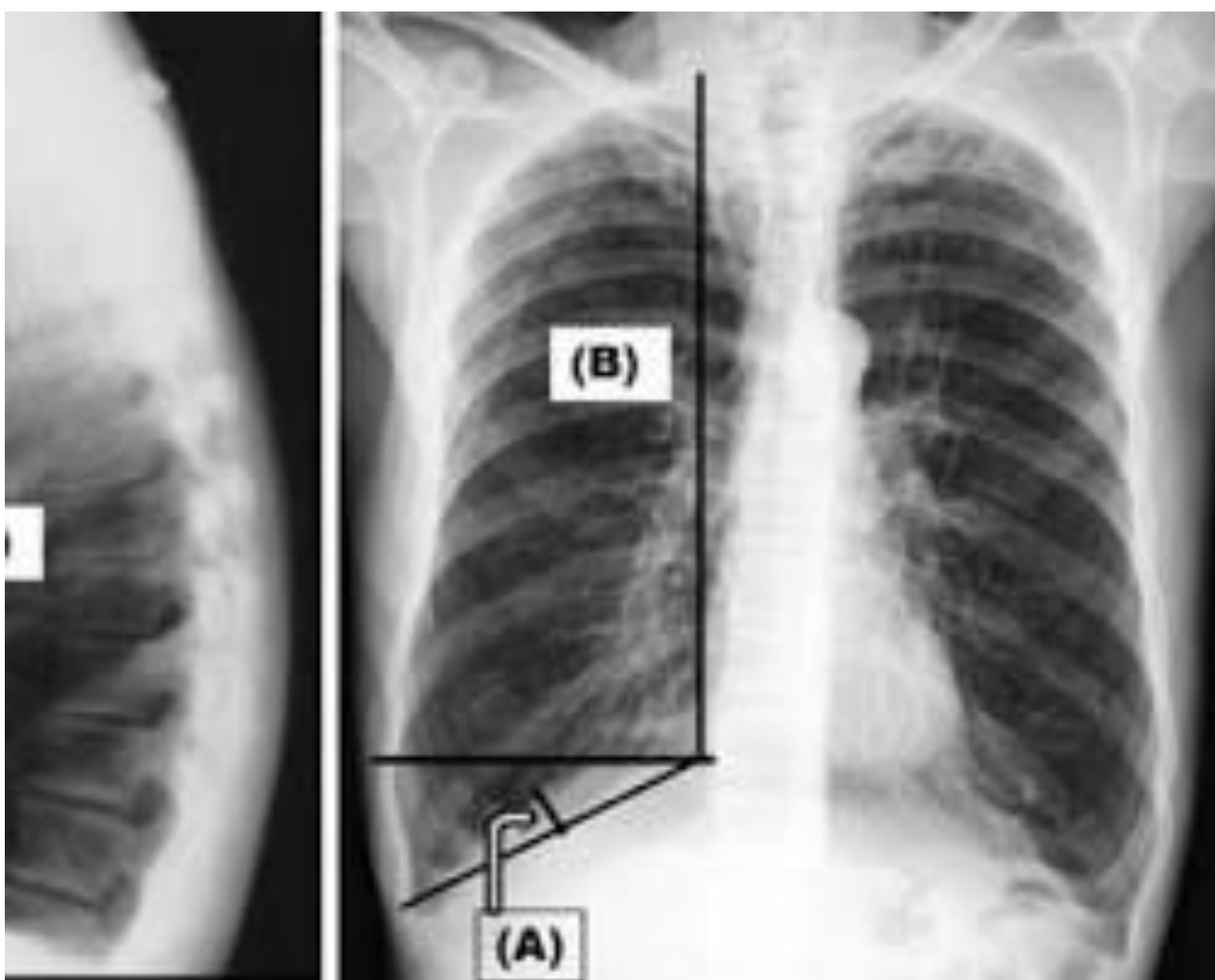




!!

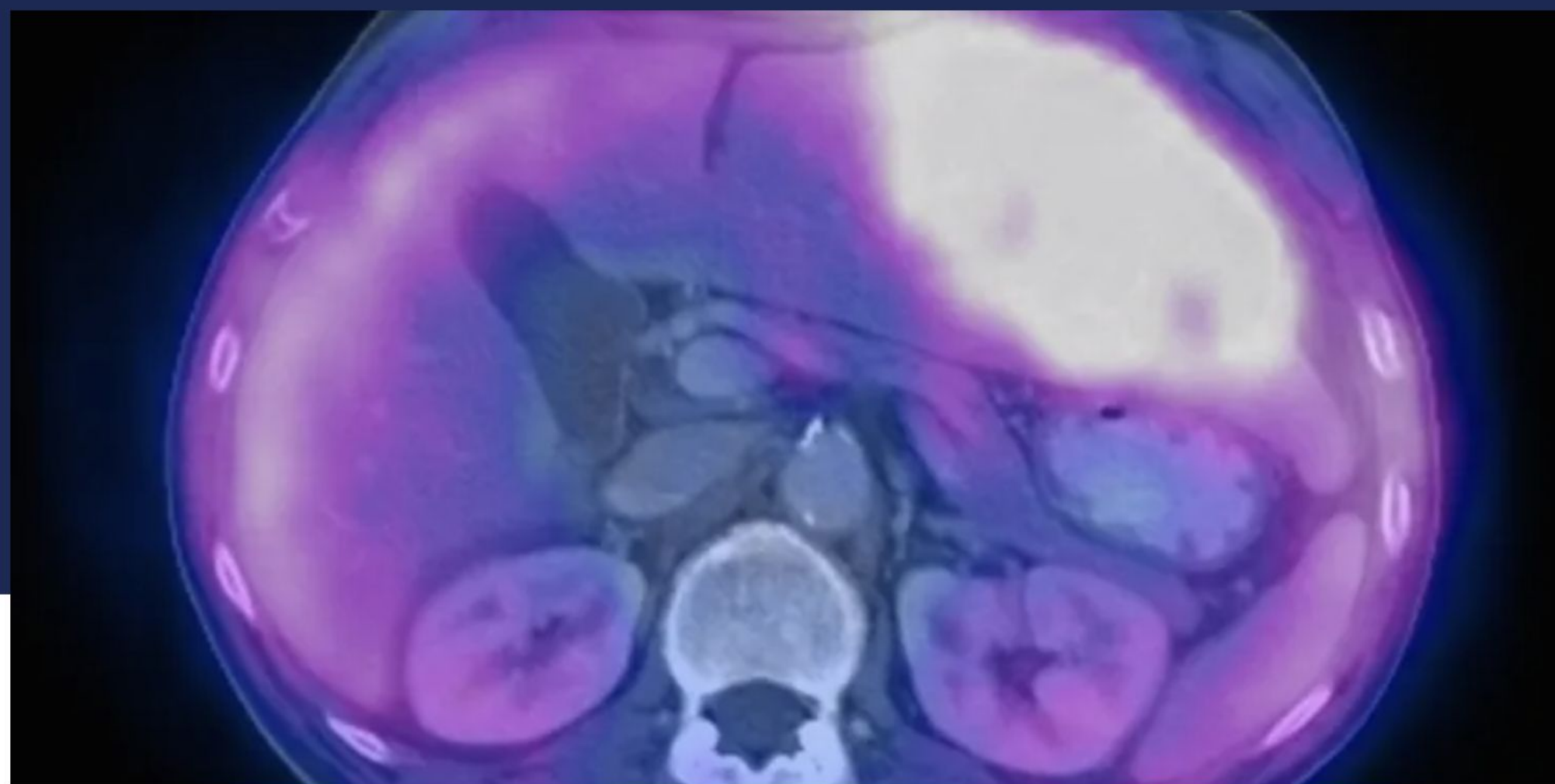


This was real.



VB Live

When AI flags the ruler, not the tumor — and other arguments for abolishing the black box (VB Live)



ites

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Image Credit: Getty Images

AI helps health care experts do their jobs efficiently and effectively, but it needs to be used responsibly, ethically, and equitably. In this VB Live event, get an in-depth perspective on the strengths and limitations of data, AI methodology and more

What is ChatGPT?

Start simple: A bigram language model

Let's build a model based on counting. This is where prediction began.

We care about predicting *the next word* after a single word.

This is called a **bigram**.



From fairest creatures we desire increase,
That thereby beauty's rose might never die,
But as the ripper should by time decease,
His tender heir might bear his memory;

	from	fairest	creatures	we	desire
from					
fairest					
creatures					
we					
desire					



From fairest creatures we desire increase,
That thereby beauty's rose might never die,
But as the ripper should by time decease,
His tender heir might bear his memory;

	from	fairest	creatures	we	youth
from	0	0	0	0	0
fairest	0	0	0	0	0
creatures	0	0	0	0	0
we	0	0	0	0	0
youth	0	0	0	0	0



From fairest creatures we desire increase,
That thereby beauty's rose might never die,
But as the ripper should by time decease,
His tender heir might bear his memory;

	from	fairest	creatures	we	youth
from	0	1	0	0	0
fairest	0	0	0	0	0
creatures	0	0	0	0	0
we	0	0	0	0	0
youth	0	0	0	0	0



From fairest creatures we desire increase,
That thereby beauty's rose might never die,
But as the ripper should by time decease,
His tender heir might bear his memory;

	from	fairest	creatures	we	youth
from	0	1	0	0	0
fairest	0	0	1	0	0
creatures	0	0	0	0	0
we	0	0	0	0	0
youth	0	0	0	0	0



From fairest creatures we desire increase,
That thereby beauty's rose might never die,
But as the ripper should by time decease,
His tender heir might bear his memory;

	from	fairest	creatures	we	youth
from	0	1	0	0	0
fairest	0	0	1	0	0
creatures	0	0	0	1	0
we	0	0	0	0	0
youth	0	0	0	0	0



From fairest creatures we desire increase,
That thereby beauty's rose might never die,
But as the ripper should by time decease,
His tender heir might bear his memory;
.
.
.
From youth convertest.

	from	fairest	creatures	we	youth
from	0	1	0	0	0
fairest	0	0	1	0	0
creatures	0	0	0	1	0
we	0	0	0	0	0
youth	0	0	0	0	0



And so on and so forth for the complete works of Shakespeare.

From fairest creatures we
That thereby beauty's rose might never die,
But as the ripper should by time decease,
His tender heir might bear his memory;
.
.
.
From youth convertest.

	fairest	creatures	we	youth
	1	0	0	1
fairest	0	0	1	0
creatures	0	0	0	1
we	0	0	0	0
youth	0	0	0	0



Inference

Now our model is trained.

Let's say we want to start writing
likes Shakespeare!

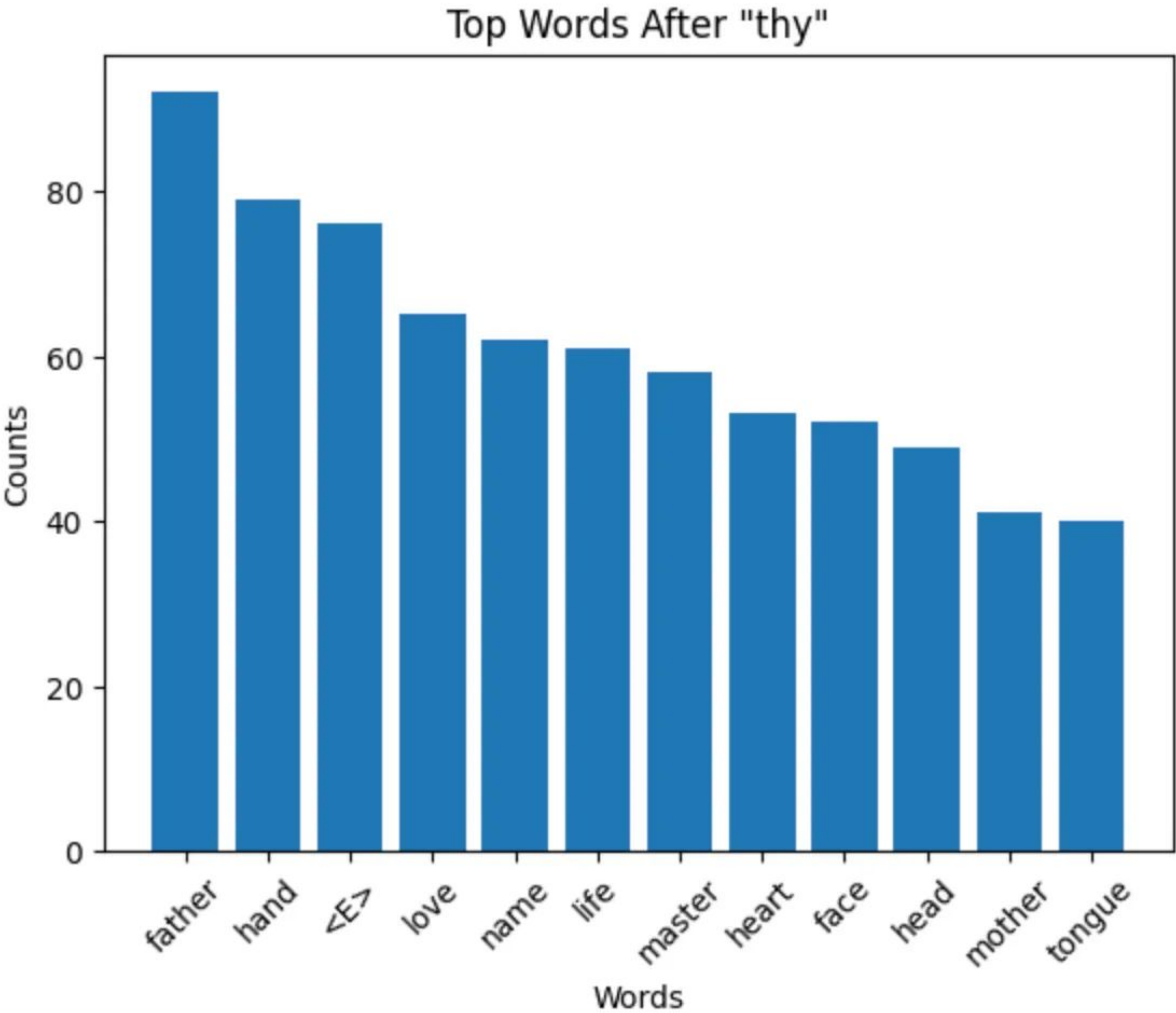


Inference

Now our model is trained.

Let's say we want to start writing
likes Shakespeare!

> Thy

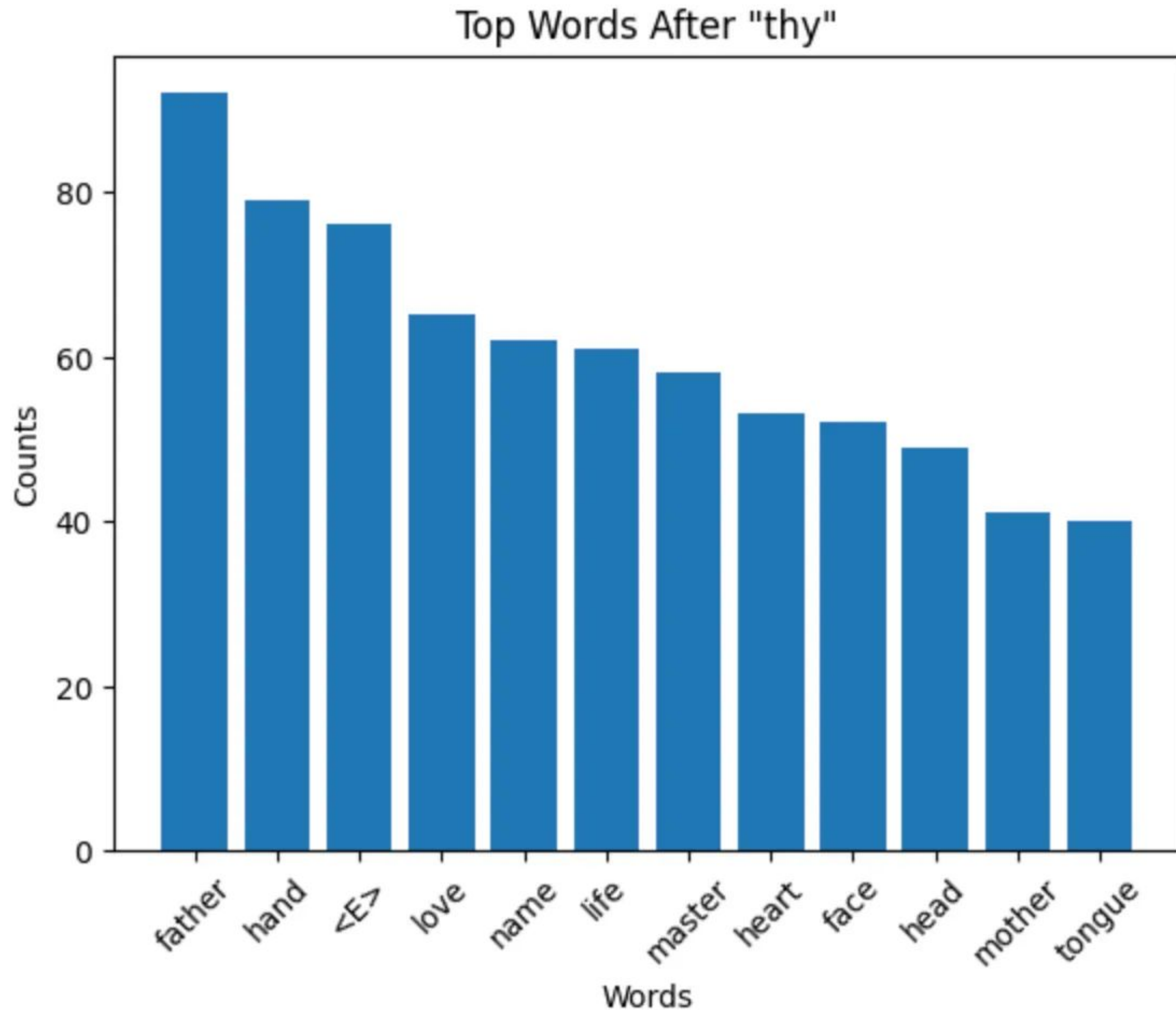


Inference

Now our model is trained.

Let's say we want to start writing
likes Shakespeare!

> Thy



Inference

Now our model is trained.

Let's say we want to start writing
likes Shakespeare!

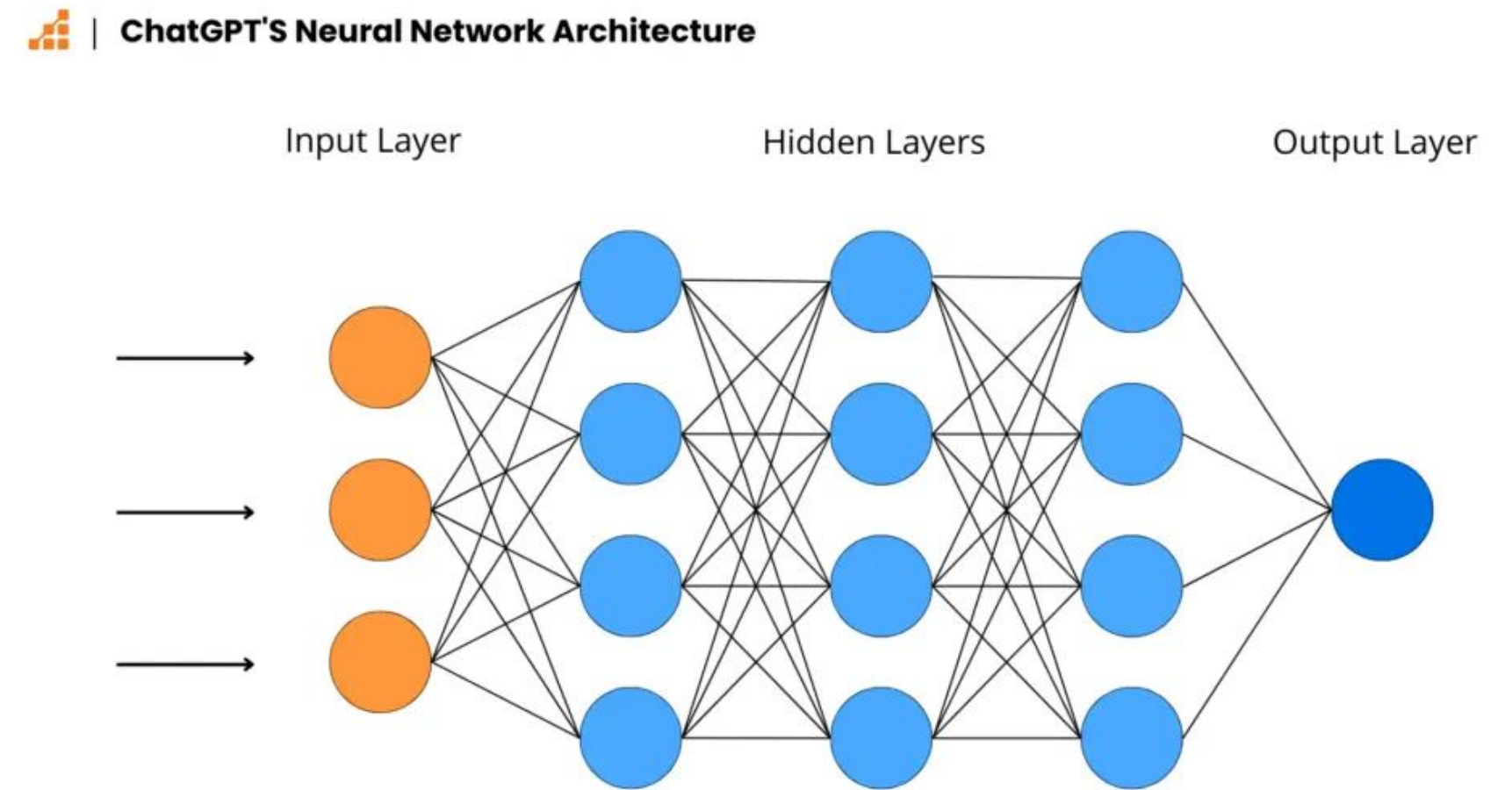
> Thy father and there were...

Does it work?

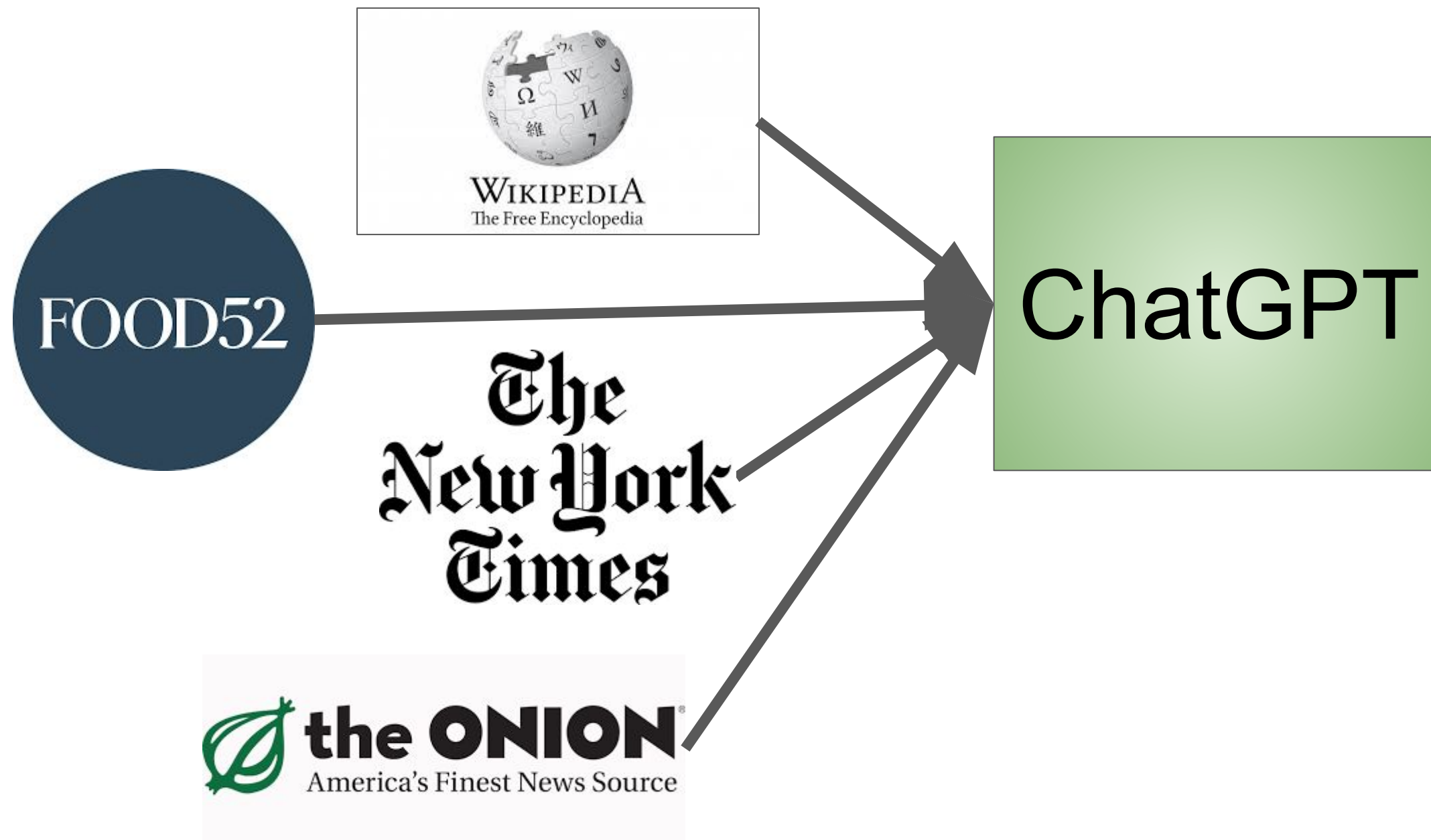
Bigrams are very simplistic.

They lack *context*.

So, actual language models do more than bigrams. ChatGPT uses a neural network.



What goes into the Input Layer?

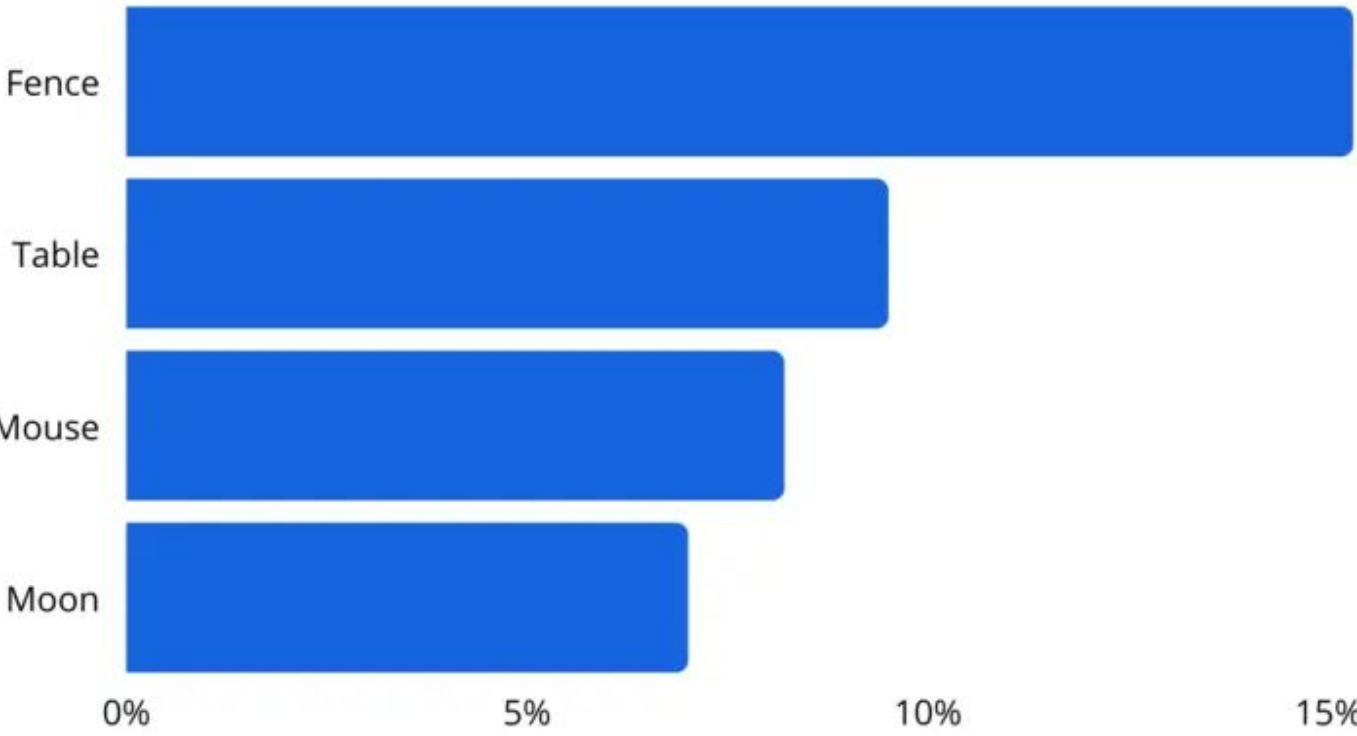


The cat jumped
over the...




ChatGPT

Prompt: "The cat jumped over the..."









Some Neural Networks are Probabilistic




Complete the sentence, "the cat jumped over the..."






...fence."  





Complete the sentence, "the cat jumped over the..."





...lazy dog."  



Complete the sentence, "the cat jumped over the..." 



...candlestick."  



Some Neural Networks are Probabilistic

The image shows a chat interface with four examples of sentence completion. Each example consists of a user prompt and a model response. The second example is highlighted with a red border.

User Prompt	Model Response
Complete the sentence, "the cat jumped over the..."	...fence."
Complete the sentence, "the cat jumped over the..."	...lazy dog."
Complete the sentence, "the cat jumped over the..."	
Complete the sentence, "the cat jumped over the..."	...candlestick."

Some Neural Networks are Probabilistic

The screenshot displays a chat interface with three pairs of messages. Each pair consists of a user prompt and a model response. The first two pairs show completions: "...fence." and "...lazy dog.". The third pair, which shows the completion "...candlestick.", is enclosed in a red rectangular border. Each response is accompanied by thumbs-up and thumbs-down icons for feedback.

User Prompt	Model Response
Complete the sentence, "the cat jumped over the..."	...fence.
Complete the sentence, "the cat jumped over the..."	...lazy dog.
Complete the sentence, "the cat jumped over the..."	...candlestick.

Key Takeaway 1: Garbage in, Garbage out



Lots of hidden complexities and risks

Bias

Hallucinations (a.k.a. Correctness)

Privacy



Bias



Sources of bias

Training data

Algorithmic bias (e.g., color is more important than shape in classifying fruit)

Cognitive bias (e.g., based on societal factors)

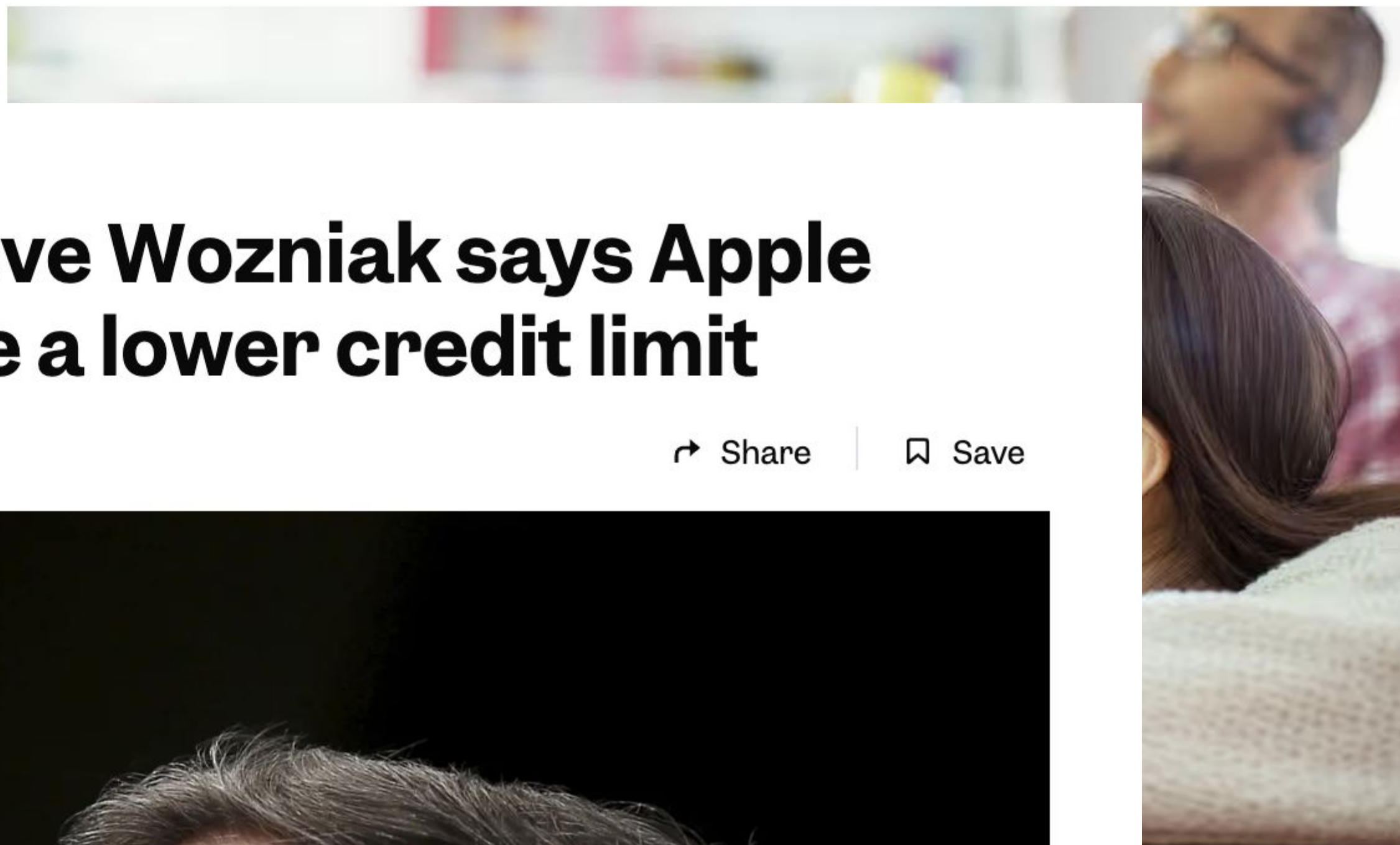


Bias is common

Insight - Amazon scrap recruiting tool that shows women

Women less likely to be shown ads for high-paid jobs on Google, study shows

Automated testing and analysis of company's advertising system reveals male job seekers are shown far more adverts for high-paying executive jobs



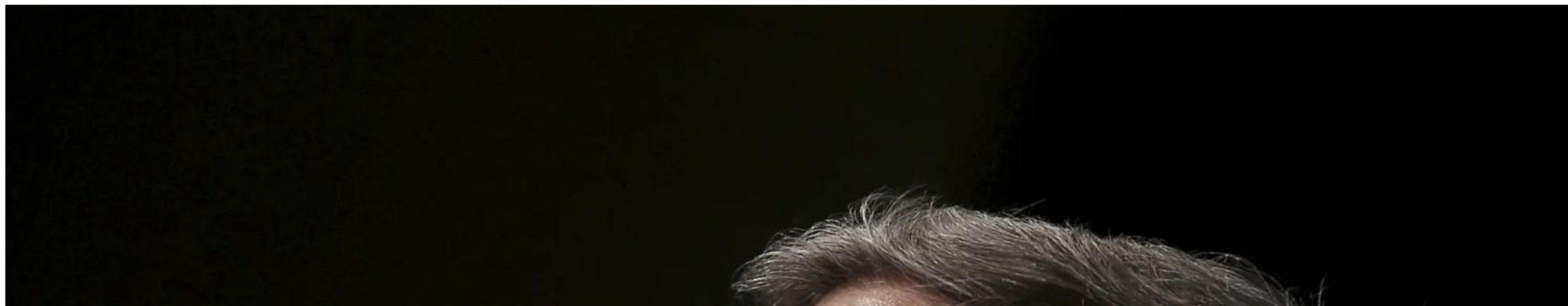
TECH

Apple cofounder Steve Wozniak says Apple Card offered his wife a lower credit limit

Isobel Asher Hamilton Nov 11, 2019, 7:21 AM ET

↪ Share

🔖 Save



How can we detect bias or prevent bias?

Explicitly test for bias using datasets designed for that purpose

Train models on unbiased datasets

Reinforcement learning (use rewards and punishments in training)



Hallucinations



Hallucinations

It's when an AI creates something that isn't real.

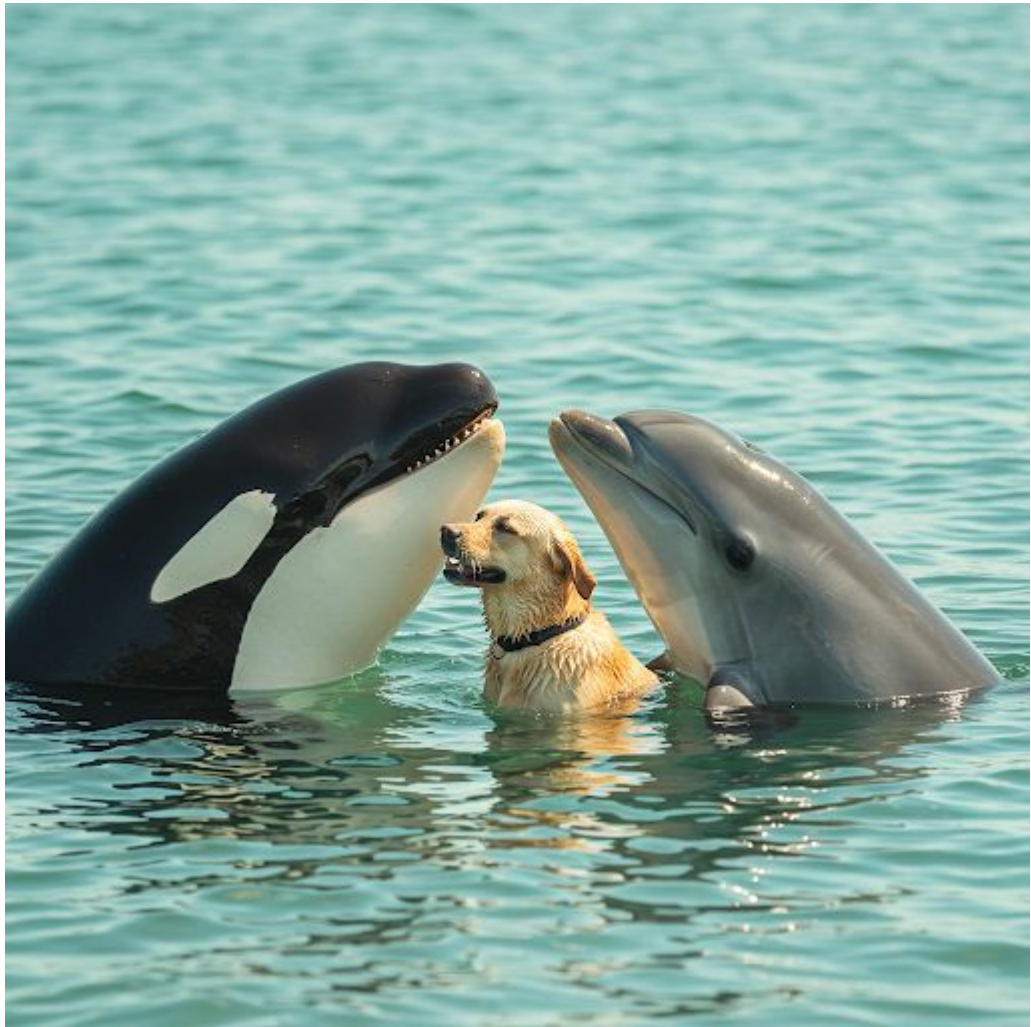


Tell me everything you know about orcas.





AI



AI

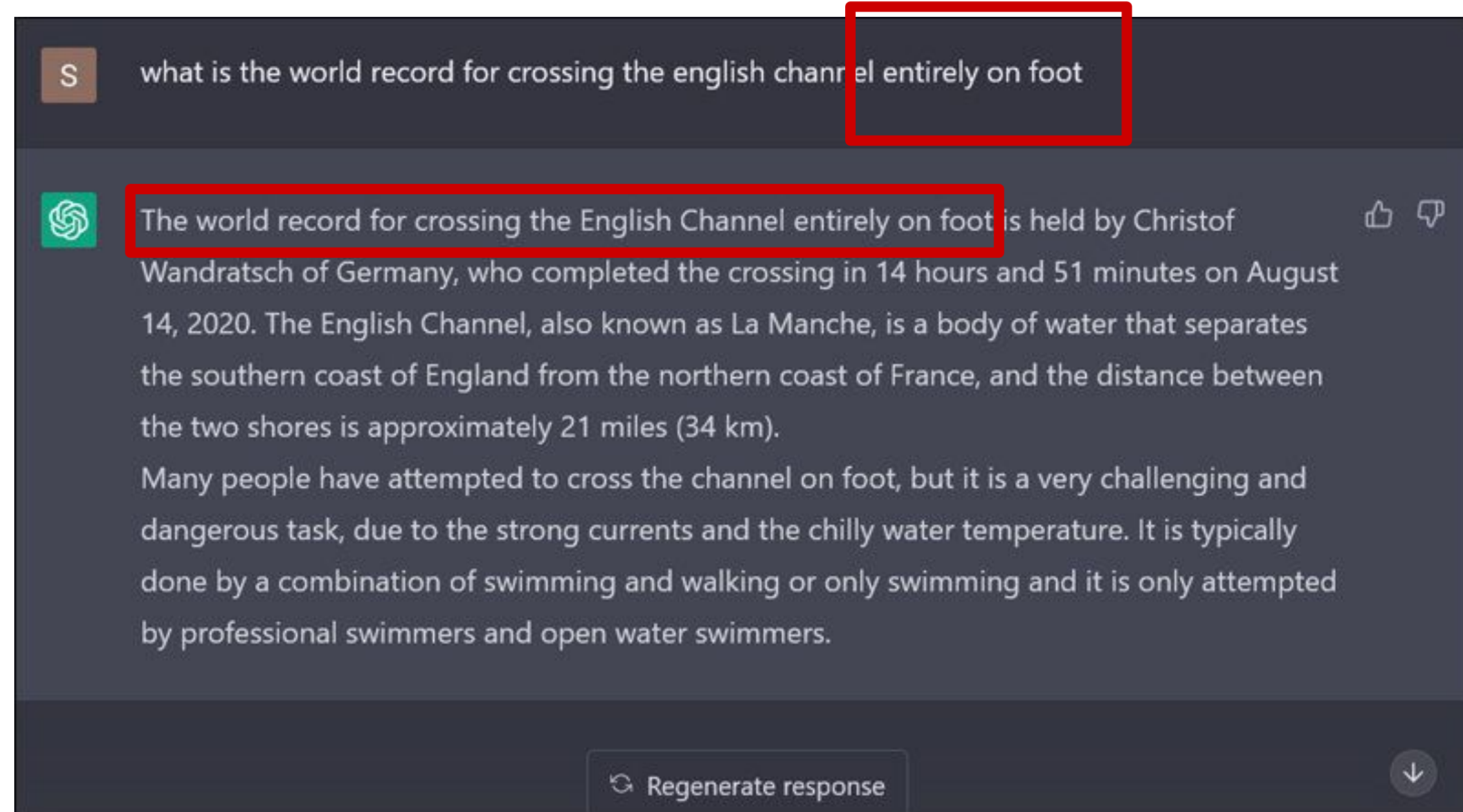


Real



Hallucinations

It's when an AI creates something that isn't real.



Hallucinations

It's when an AI creates something that isn't real.

More insidiously...



did the groundhog see his shado...

did the groundhog see his shadow this year

ALL

COPilot

NEWS

IMAGES

VIDEOS

MAPS

Did not see his shadow

According to 3 sources

It's official: spring is right around the corner. Punxsutawney Phil did not **see his shadow** in front of thousands of spectators Friday morning at Gobbler's Knob in Punxsutawney, Pennsylvania, part of the annual **Groundhog** Day tradition celebrated in the U.S. and Canada.

Did the groundhog see his shado...

usatoday.com

Groun

today.c

did the groundhog see his shado...

did the groundhog see his shadow this year 2025

ALL

COPilot

NEWS

IMAGES

VIDEOS

MAPS

Punxsutawney Phil, the famed Pennsylvania groundhog, **saw his shadow on Sunday morning**^{1 2 3}⁴. He predicted **six more weeks of winter for 2025**^{1 2 3 4}.

Learn more:

1

Groundhog Day 2025: Did Punxsutawney Phi...

2

Did Punxsutawney Phil see his shadow? Here'.

Key Takeaway 2:
Ask multiple times, multiple ways



ChatGPT is not a calculator

378 + 63 = 441. Let's ask Gemini if it's correct...

378+63=451



You are absolutely right!

ChatGPT is not a calculator

378 + 63 = 441. Let's ask Gemini if it's correct...



Oops, a typo! Or, my math was wrong?

Key Takeaway 3:
ChatGPT doesn't “think” or “compute”

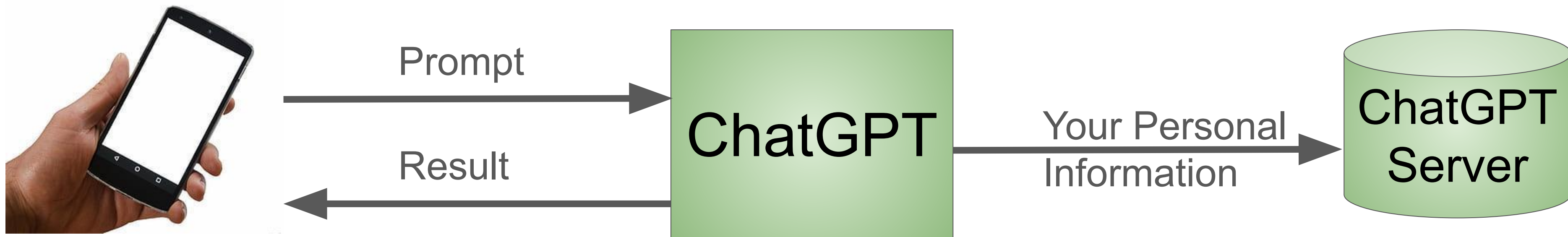


Privacy



Privacy

Everything you tell an LLM is no longer private.



Summary

1. Garbage in, Garbage out: an AI is only as good as its data
2. Ask multiple times, multiple ways to detect potential hallucinations
3. AI doesn't "think" or "compute", it pattern-matches

Enough about AI...
What about my research?



Who am I?

2016 – present: Associate Professor at NC State University

2013 – 2015: Assistant Professor at Iowa State University

2008 – 2013: Graduate Student at University of Nebraska-Lincoln

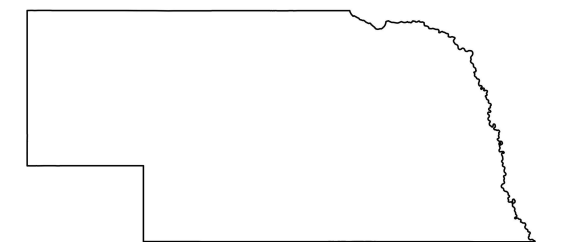
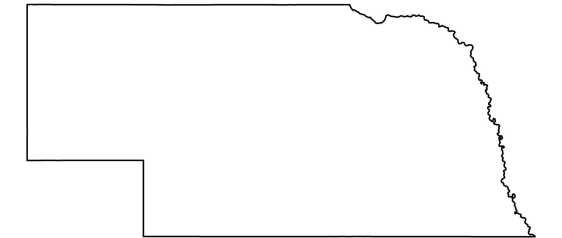
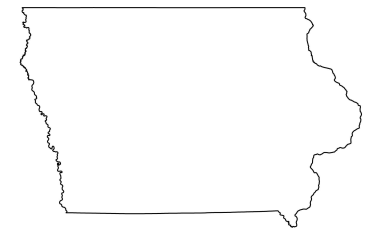
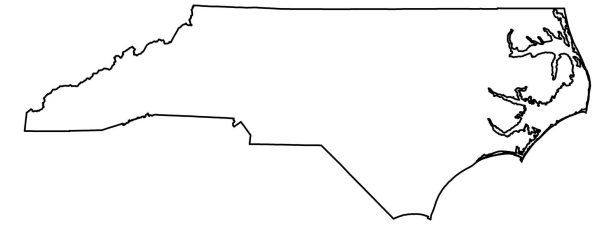
M.S. in Computer Science

Ph.D. in Computer Science

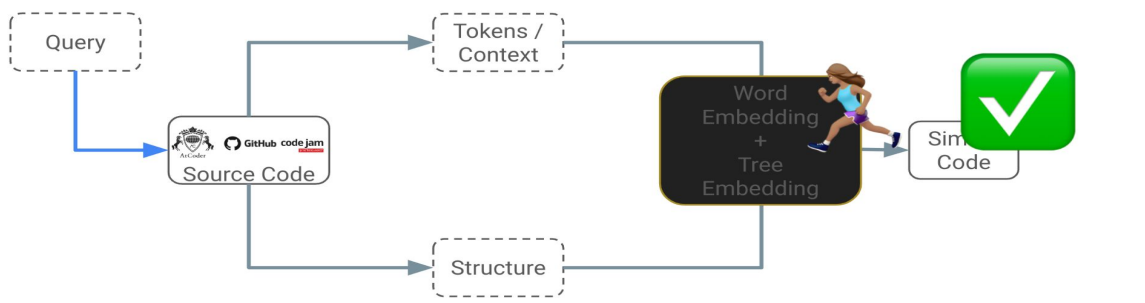
2004 – 2008: Undergraduate Student at University of Nebraska-Lincoln

Major: Computer Science

Minor: Business Administration



Code-to-code Search - In Practice



12

Comparative Comprehension

The cognitive activity of understanding how algorithms behave relative to each other

```
def sumup(numbers):
    accumulator = 0
    for value in numbers:
        accumulator += value
    return accumulator
```

↔

```
def sumup(x):
    s = 0
    i = 0
    while i < len(x):
        s += x[i]
        i += 1
    return s
```

16

Participatory Design

The screenshot shows a web interface for participatory design. It features a 'Question' section at the top, followed by 'Additional context or details'. Below this is a grid of code snippets, each with a 'Run' button and a 'Reputation' score. To the right of the grid are two orange buttons labeled 'Code-first experience' and 'Horizontal listing'. On the far right, there's a sidebar with 'Option B' and 'Descriptions from the authors'. At the bottom right, there's a button labeled 'Encouraging interactive examples'.

41



FIND IT



THINK IT



CHOOSE IT

Questions?



Credits

<https://newsletter.pnote.eu/p/shakespeare-language-model>

<https://www.scalablepath.com/machine-learning/chatgpt-architecture-explained>