



THE UNIVERSITY
of EDINBURGH



AI: From Zero to Aha!

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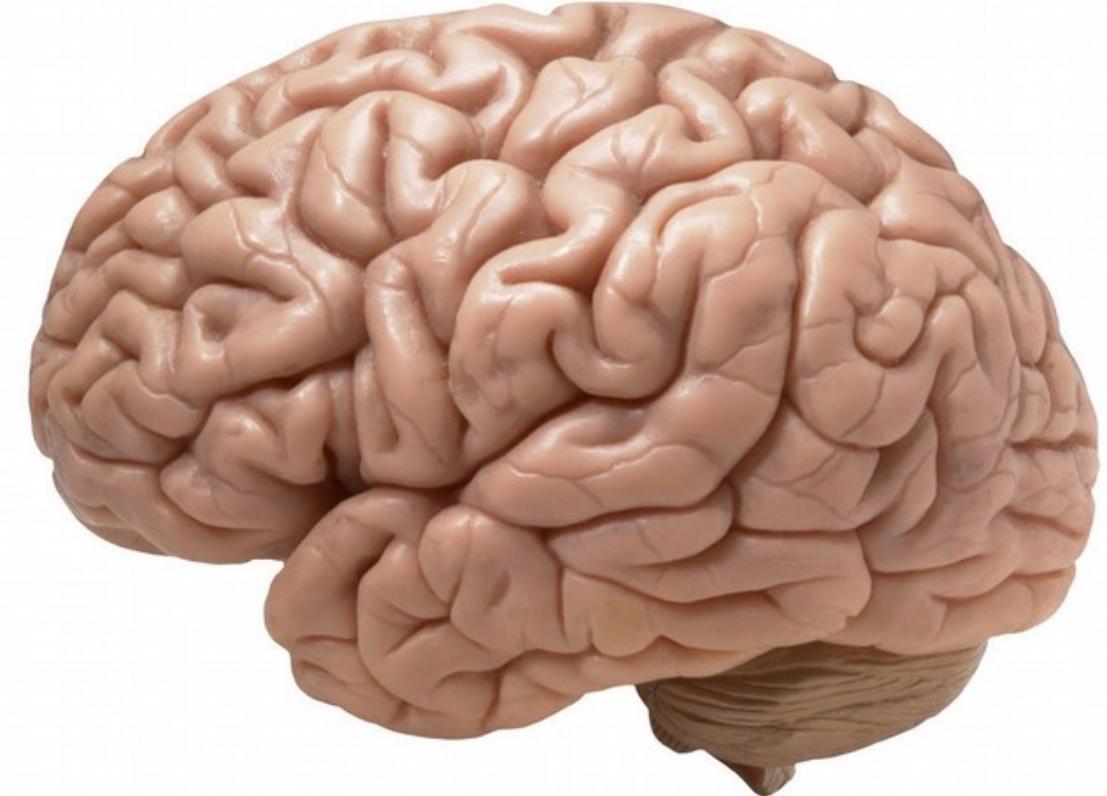


What is the **most complex creation** in the known universe?

The Most Complex Creation in the Known Universe ...

Human Brain

- 86B Neurons
- 86,000B Synapses





Difference Engine

(Mechanical Computer, Mid 19th century)



Charles Babbage (1791-1871)
[Father of the computer]



Z3
(ElectroMechanical Computer, 1941)

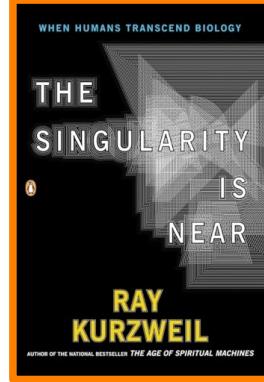
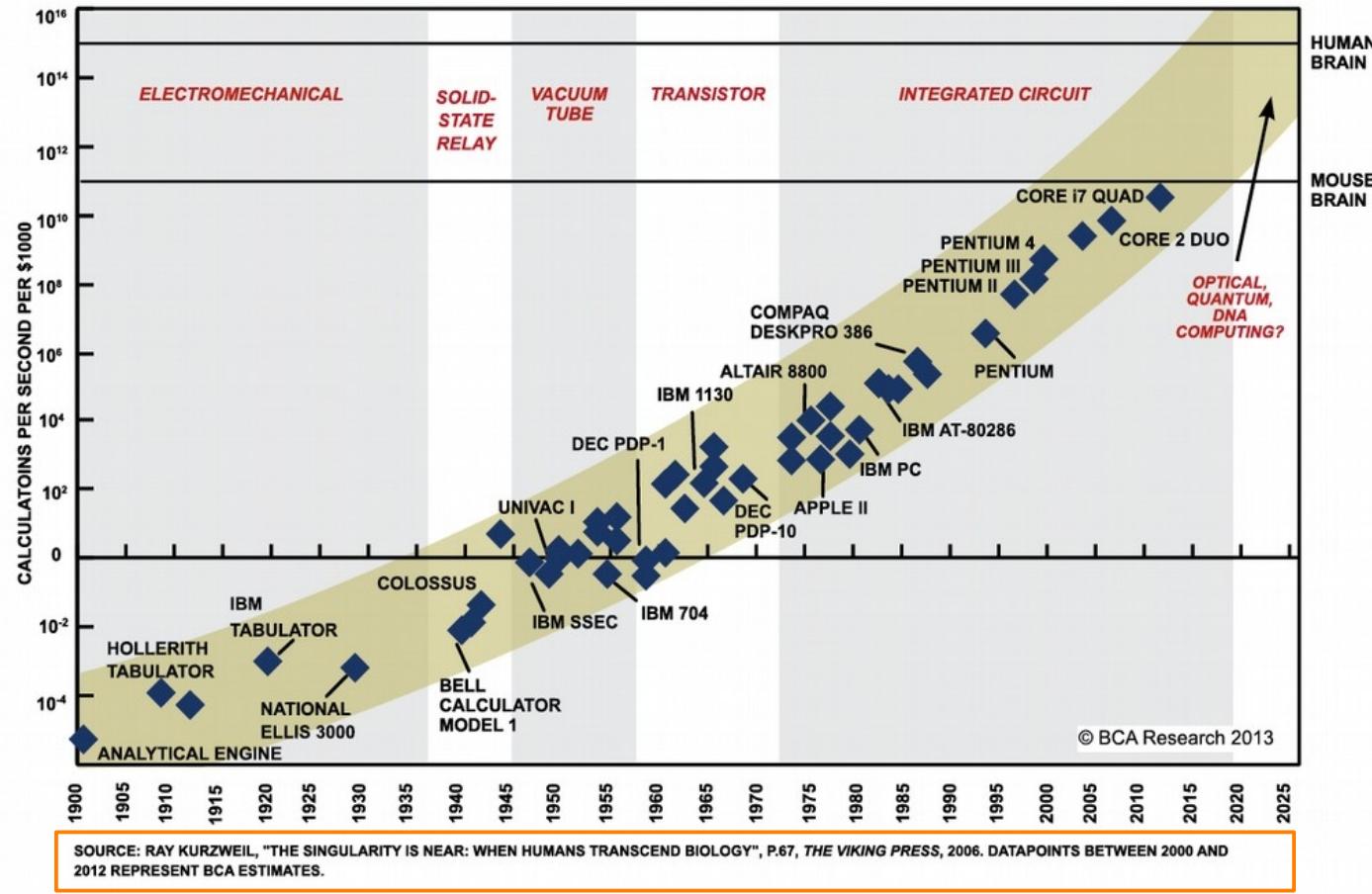


Konrad Zuse (1910-1995)



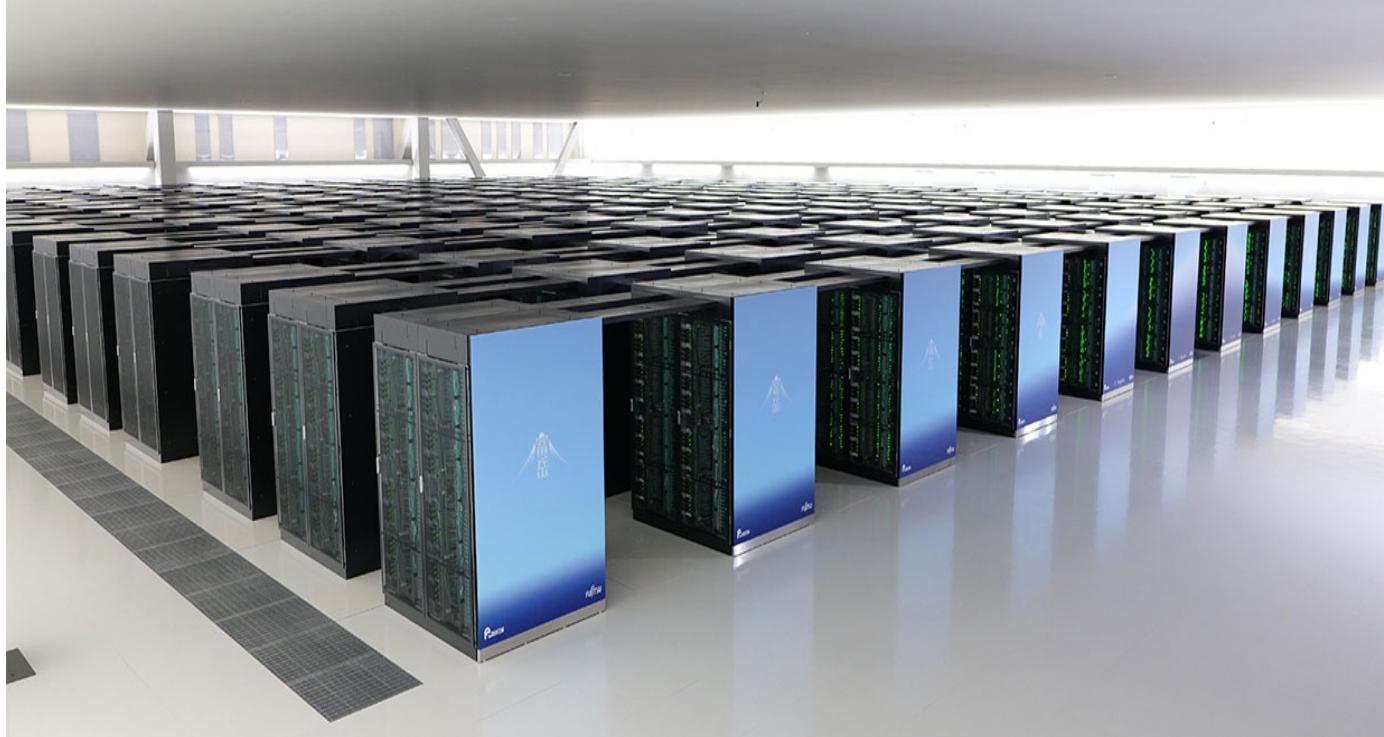
ENIAC

(Electronic Numerical Integrator and Computer, 1945)



Computation became *exponentially* faster and cheaper

Supercomputers: Fugaku



$\sim 0.5 \times 10^{18}$ FLOPS (Rmax)
 7.63×10^6 CPU Cores (ARM)

Supercomputers: Frontier



~ 1.102×10^{18} FLOPS (Rmax)
600k CPU + 8.1M GPU Cores (AMD)



Brain vs Supercomputers



0.5 x



$x = 1 \times 10^{18}$ FLOPS



1.1 x

FLOPS: Floating-point operations per second

Problems to Solve

Type I

(e.g., Multiplication)

$$\begin{array}{r} 568923471609458.2341112 \\ \times 973241231.2431506879416 \\ \hline \end{array}$$

A Well-Defined Problem
with Clear Solution Steps

Type II

(e.g., Identification)

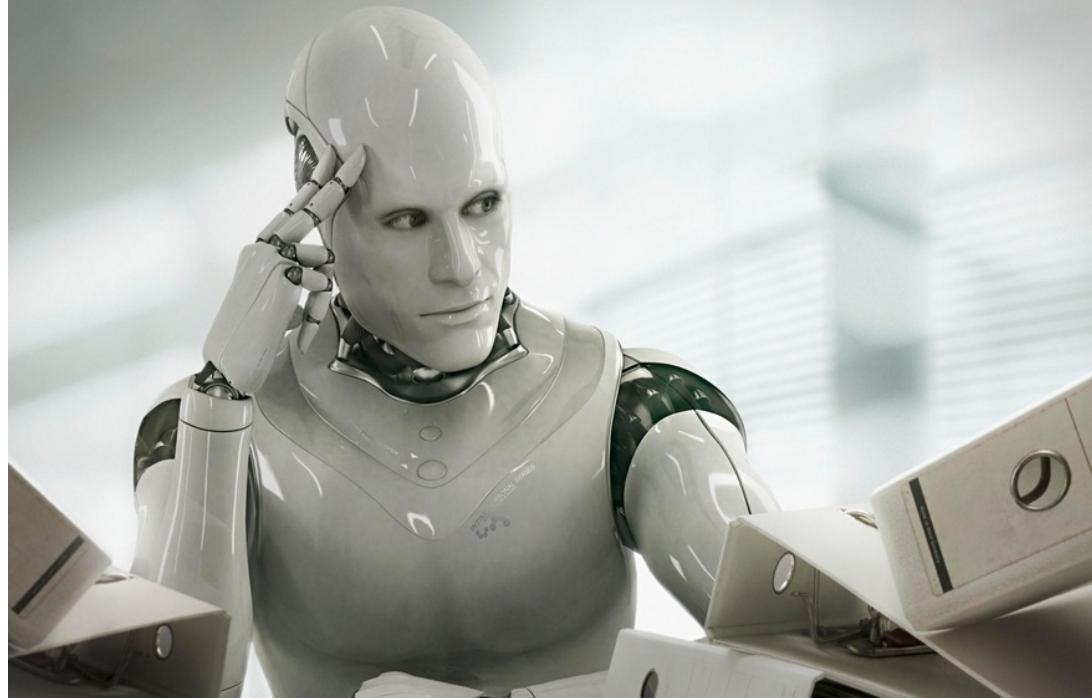


Pattern Recognition ...
Solution Steps???



Physiology

Engineering

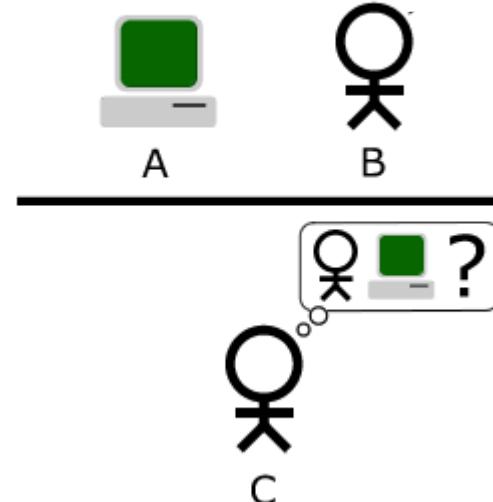


Artificial Intelligence

Engineering

What does Intelligence Mean?

Turing Test (The Imitation Game)



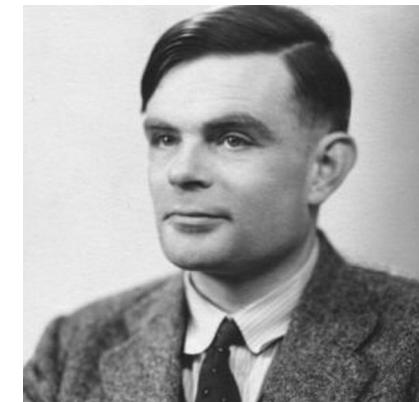
Turing, A.M. (1950). Computing machinery and intelligence. *Mind*, 59, 433-460.

COMPUTING MACHINERY AND INTELLIGENCE

By A. M. Turing

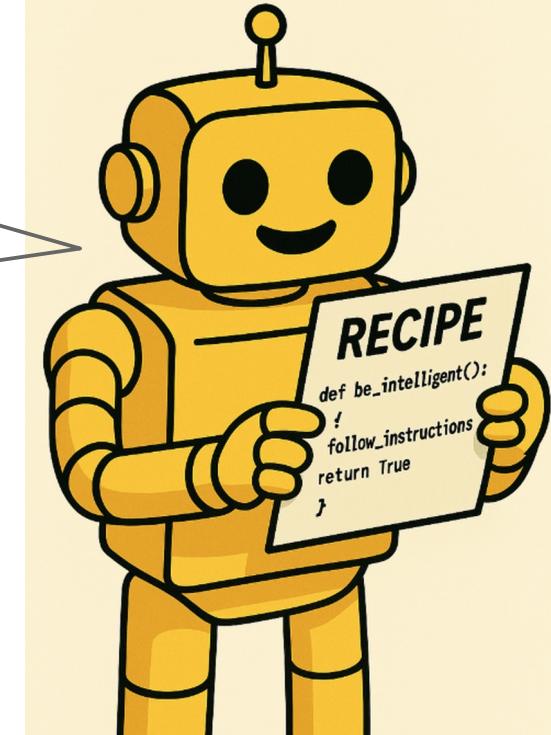
1. The Imitation Game

I propose to consider the question, "Can machines think?" This should begin with definitions of the meaning of the terms "machine" and "think."



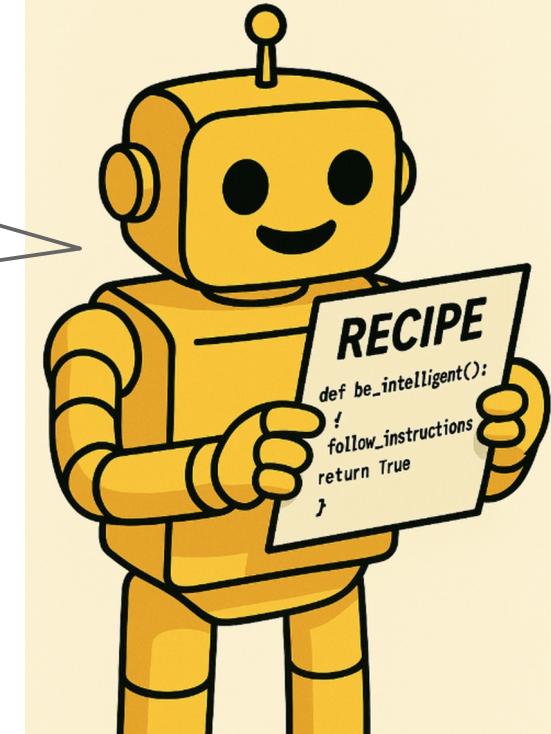
Alan Turing (1912-1954)
[Father of the computer science]

How to Build an Intelligent Machine?



Generated by ChatGPT
(DALL·E 3, OpenAI)

How to Build an Intelligent Machine?



AI as a **Programming** Problem

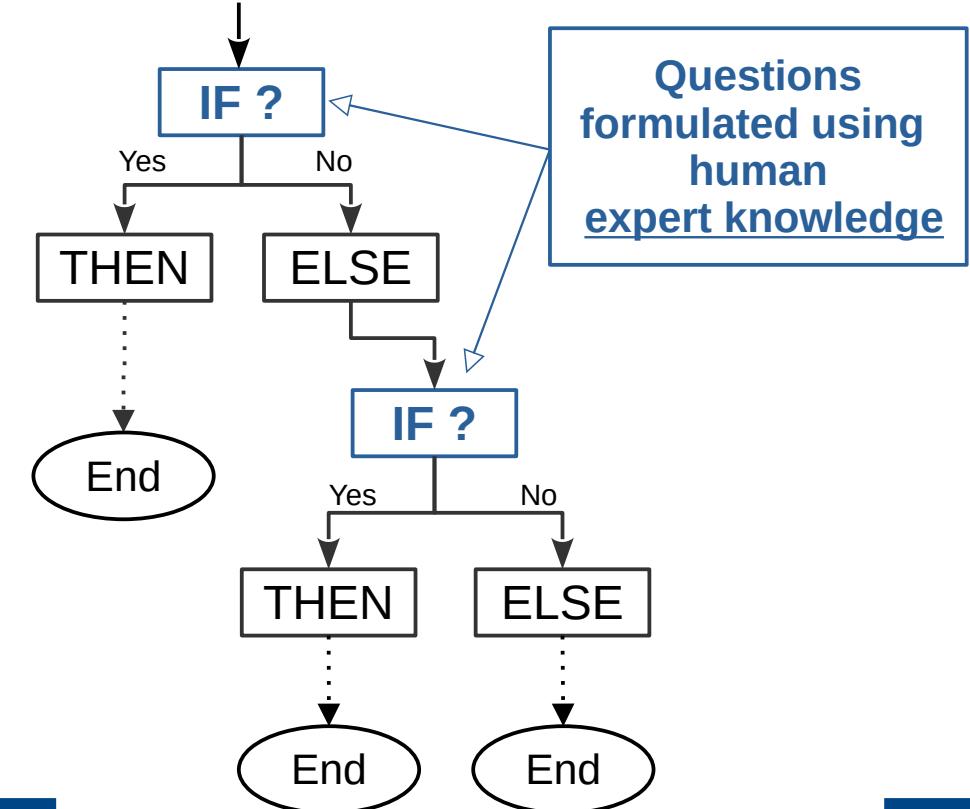
Generated by ChatGPT
(DALL-E 3, OpenAI)

How to Build an Intelligent Machine?

- Explicit Recipe (Explicit Programming)
- Implicit Recipe (Implicit Programming)

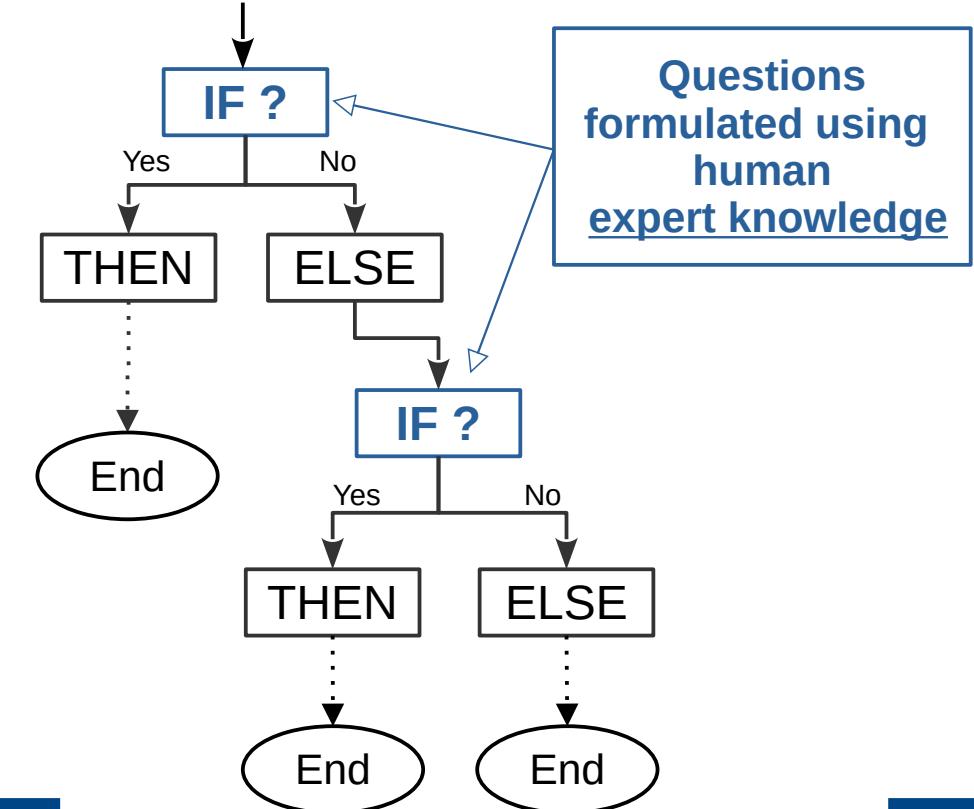
Explicit Programming

Decision Making Rules
→
Hardcoded Knowledge



Explicit Programming

Rule-based (Expert) Systems



Expert Systems' Achilles Hill

Queanbeyan

Queanbeyan.

Queanbeyan

Queanbeyan

Queanbeyan

Queanbeyan

Queanbeyan.

Queenbeyan

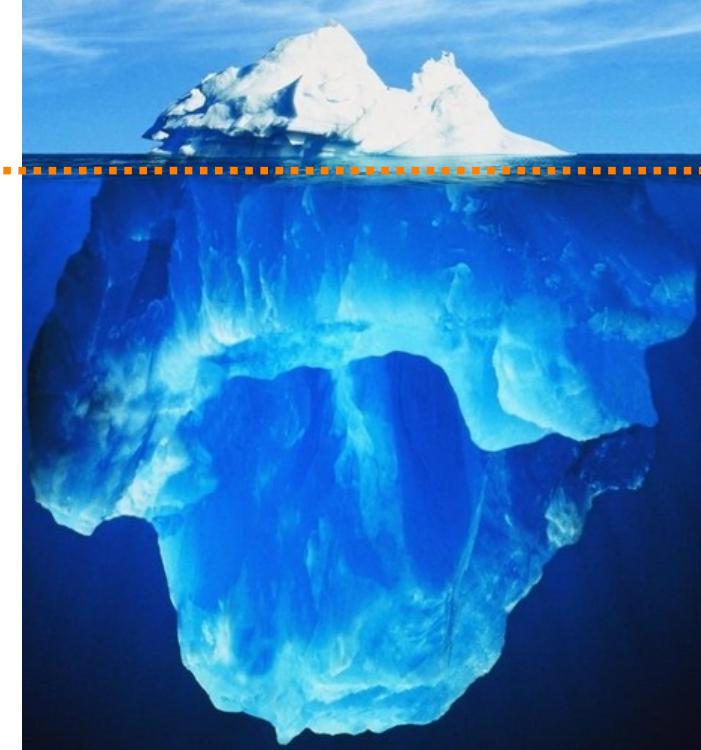
Queanbeyan

Queanbeyan



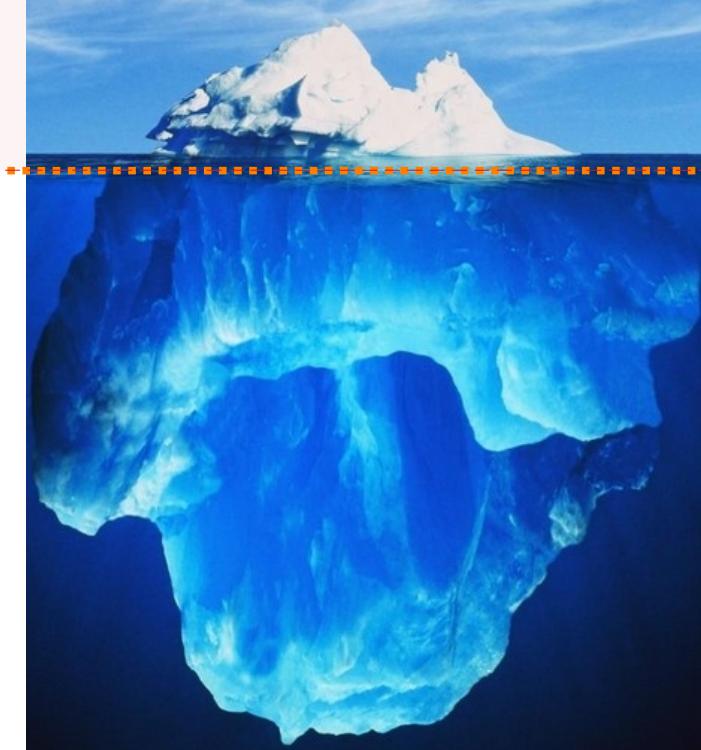
Variability & Scalability

=> Poor generalisation



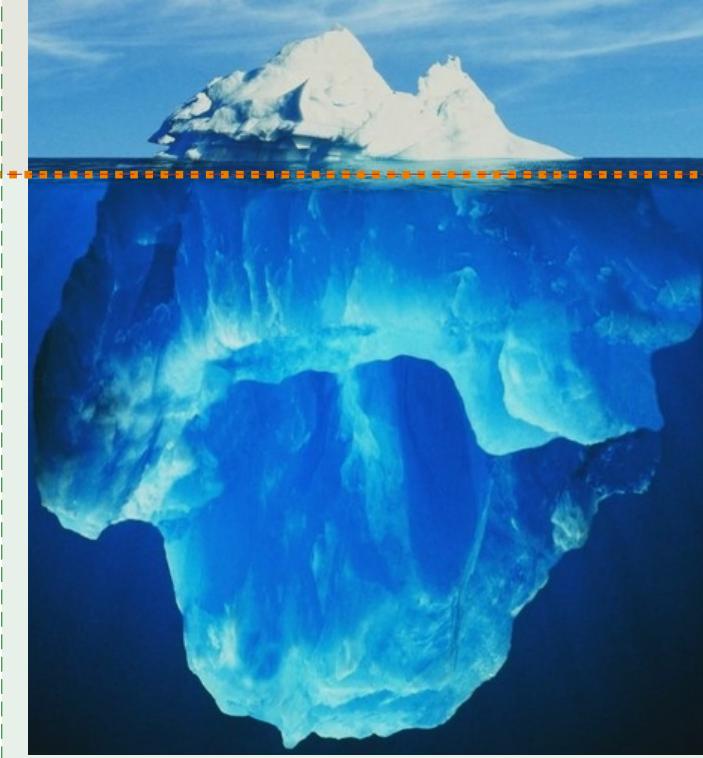
Visible
Invisible

Explicit Programming



Visible
Invisible

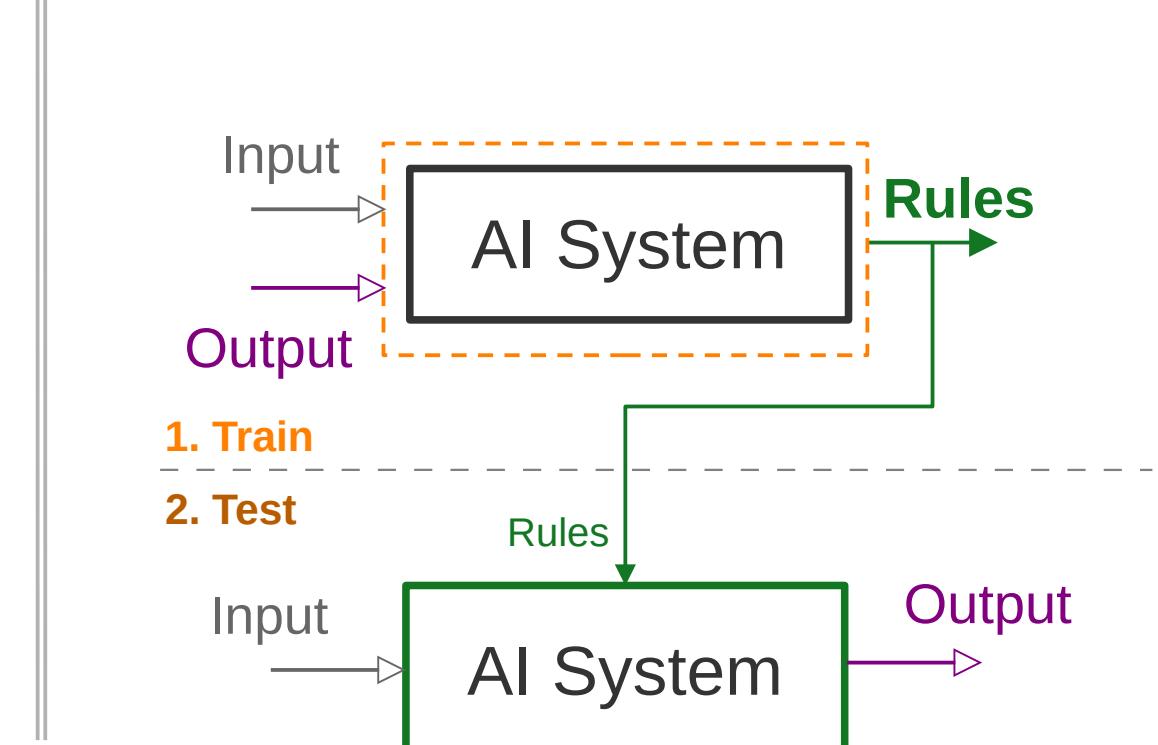
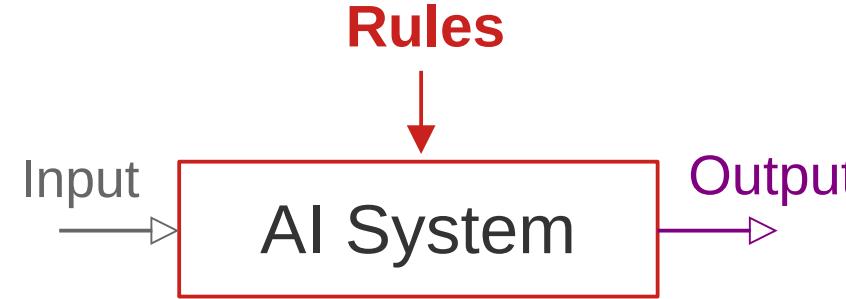
Explicit
Programming



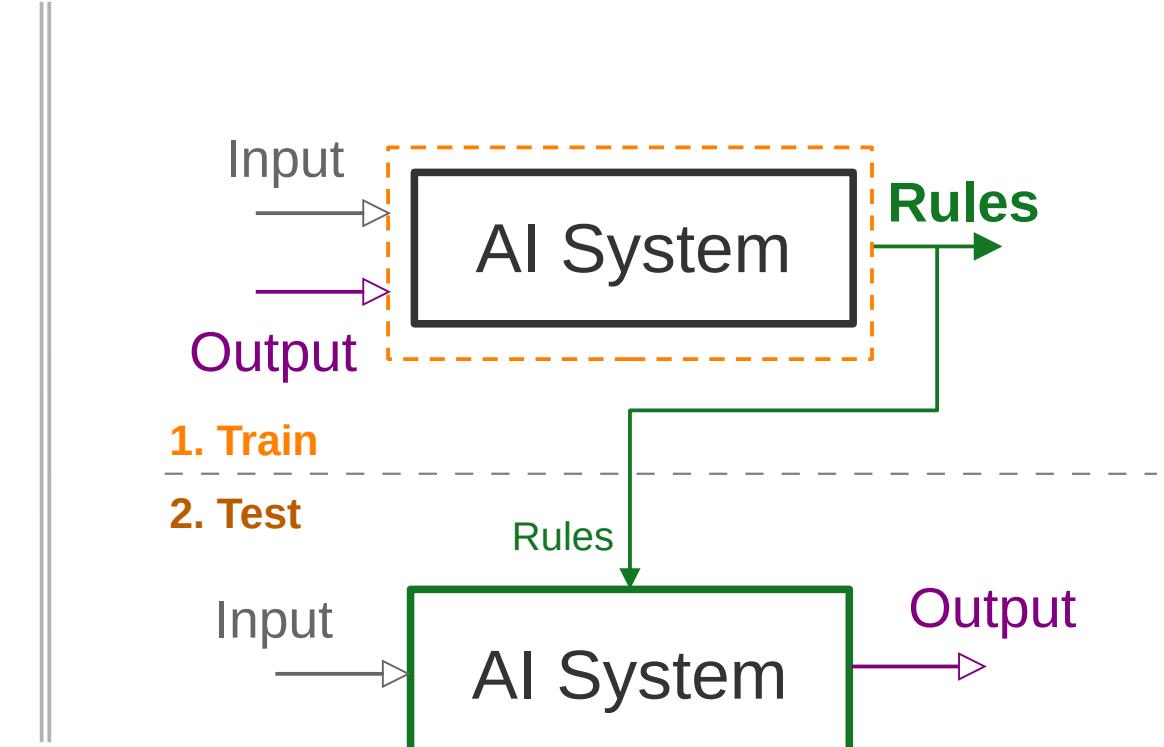
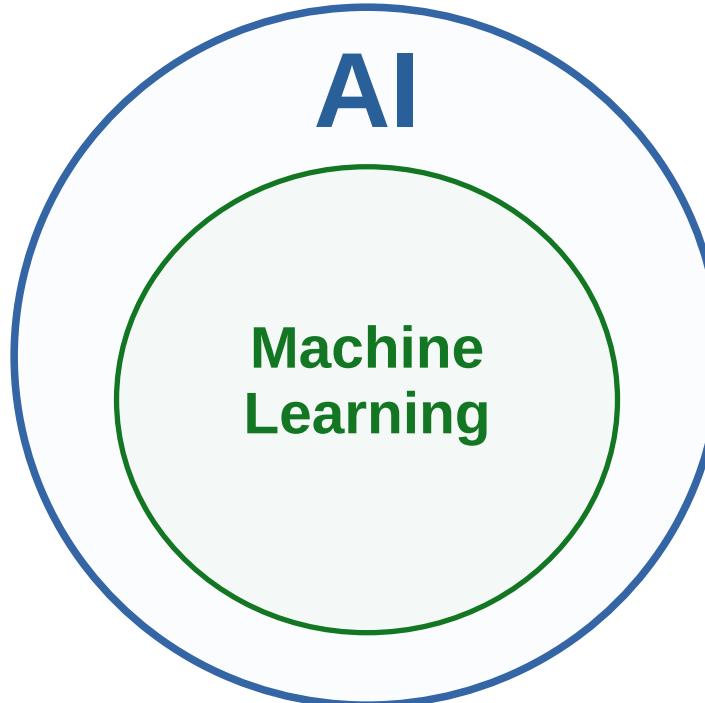
Visible
Invisible

Implicit Programming

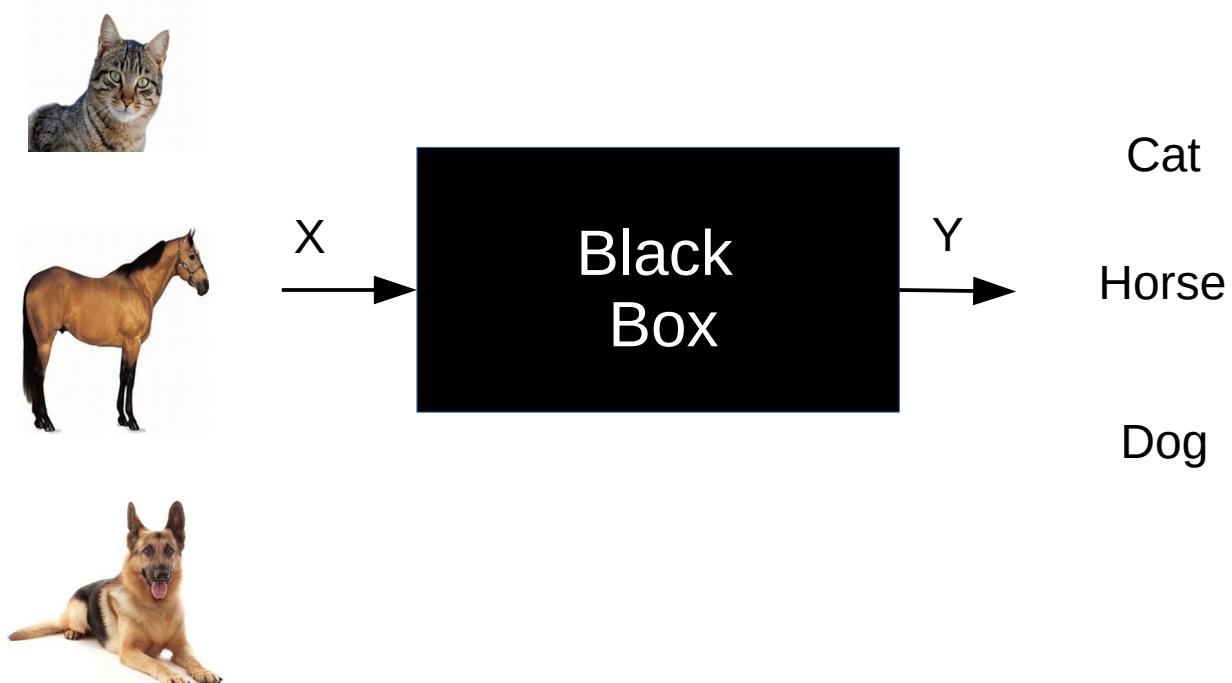
Explicit vs Implicit Programming



Implicit Programming → Machine Learning



Machine Learning

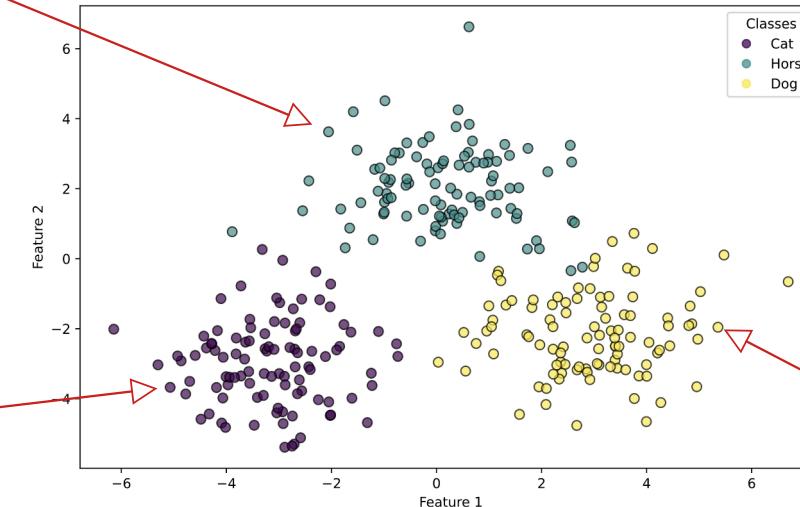
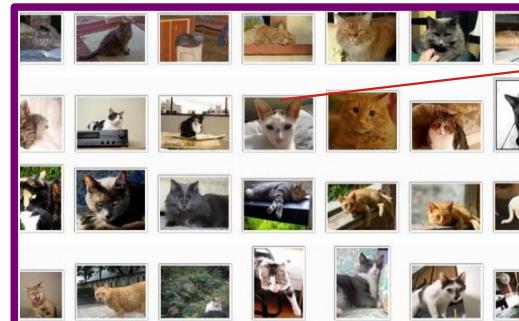


Machine Learning

Data (Horse)



Data (Cat)



Data (Dog)

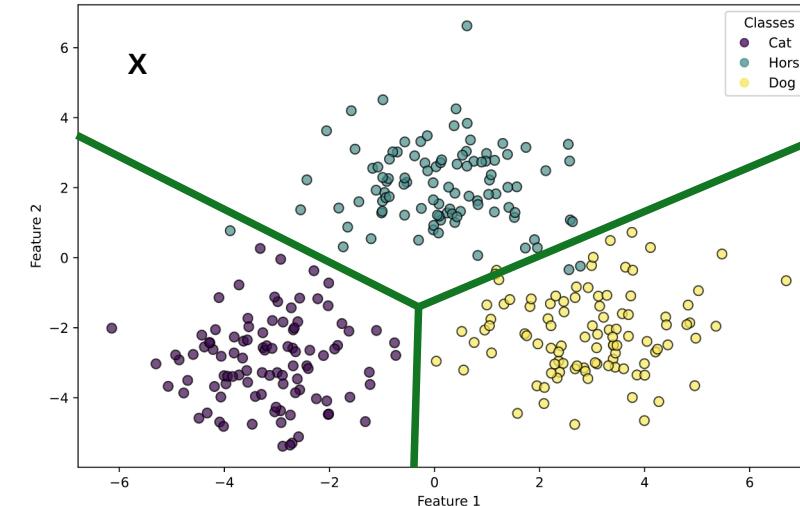
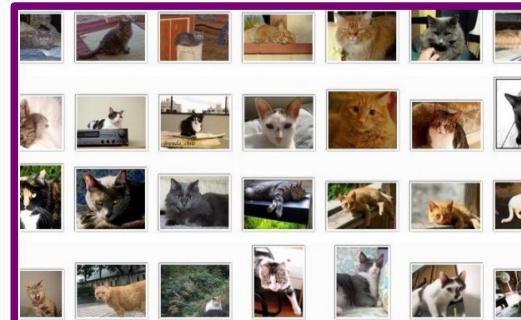


Machine Learning

Data (Horse)



Data (Cat)

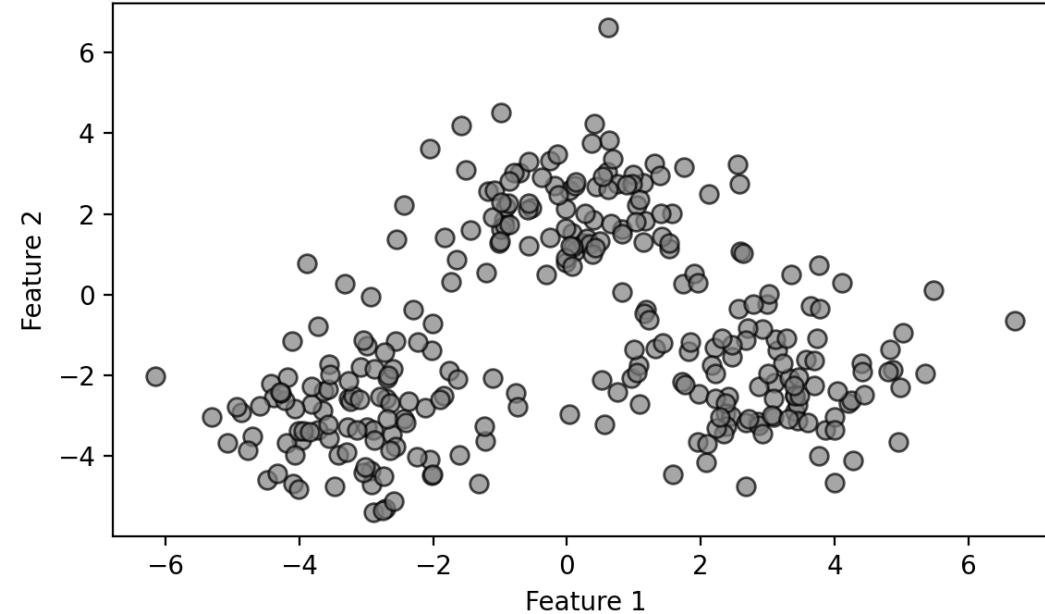


Decision Boundaries \equiv Rules

Data (Dog)



Machine Learning Paradigms

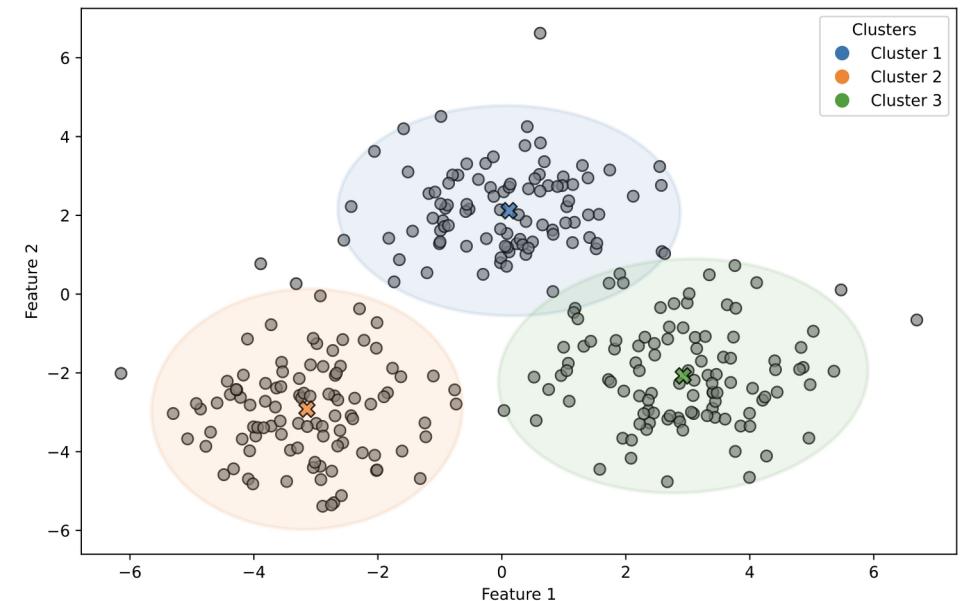


Supervised vs Unsupervised

Labels known
(classes)

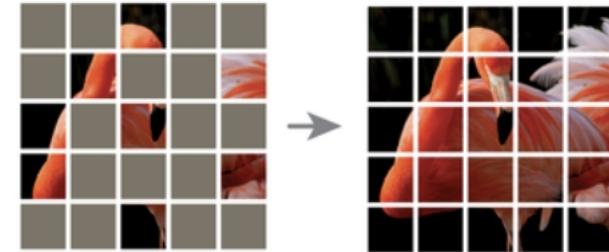


Labels unknown
(clusters)



Self-supervised Learning

- Train models to predict parts of input from other parts
- No manual labels → Data supervises itself
- Examples:
 - The cat [mask] on the mat
- Core to training LLMs, representation learning, ...



Importance of Paradigms

Reinforcement Learning
≡ cherry



Intelligence as a Cake

Supervised Learning
≡ icing



Self/unsupervised Learning
≡ cake base

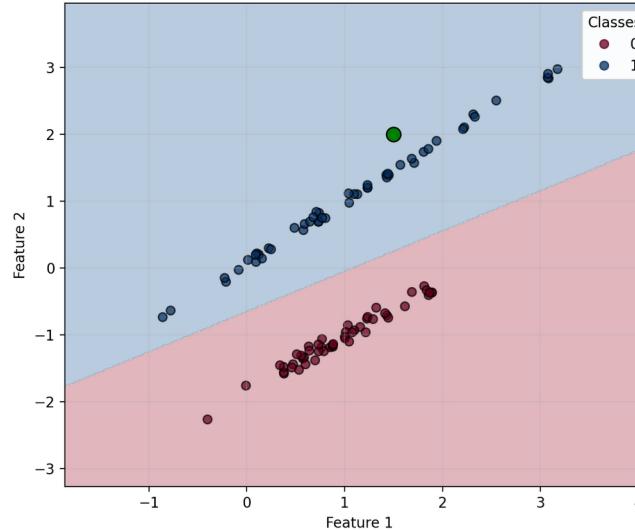


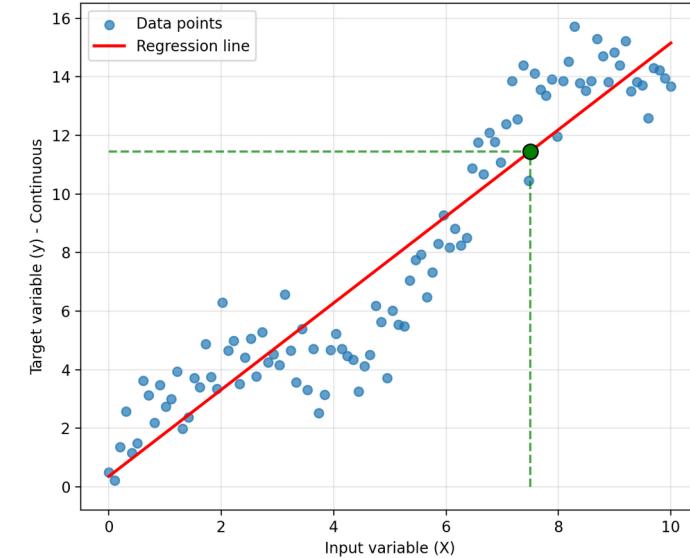
Yann LeCun

(Chief AI Scientist at Meta,
Prof. at NYU)

(Supervised) Classification vs Regression

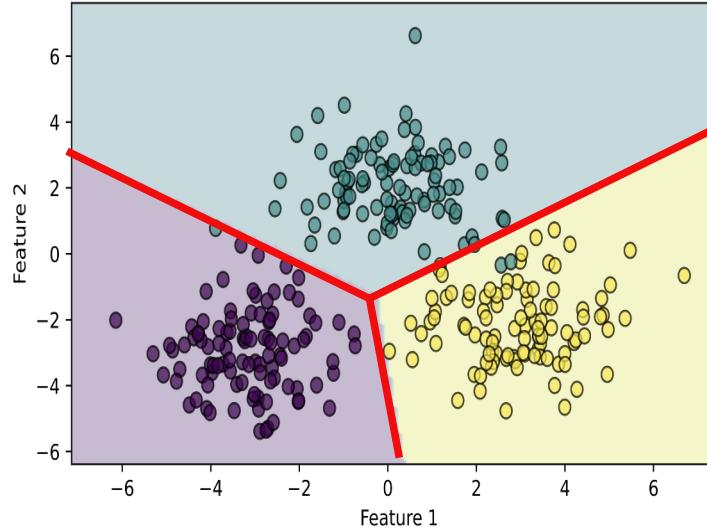
- Predict discrete categories
- Predict continuous values



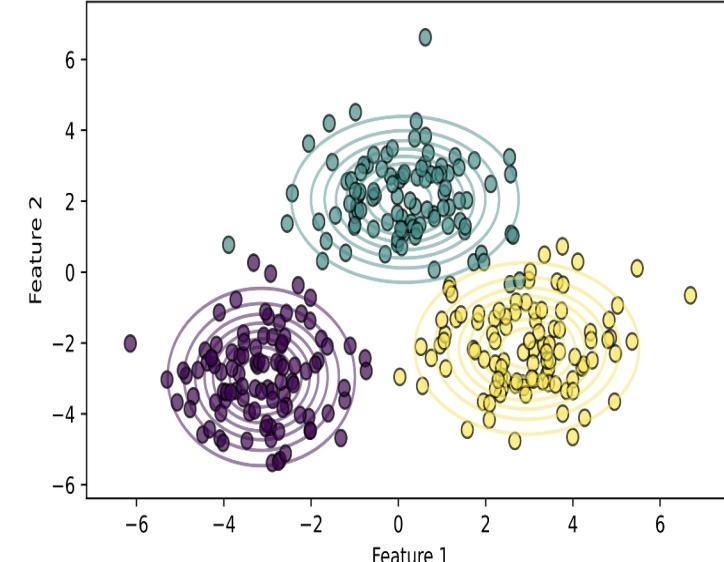


Discriminative vs Generative

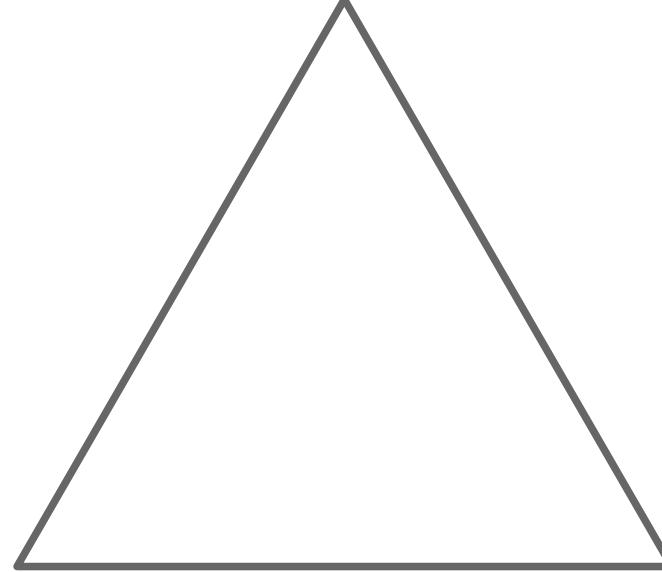
- Learn **decision boundaries**
 - Classification



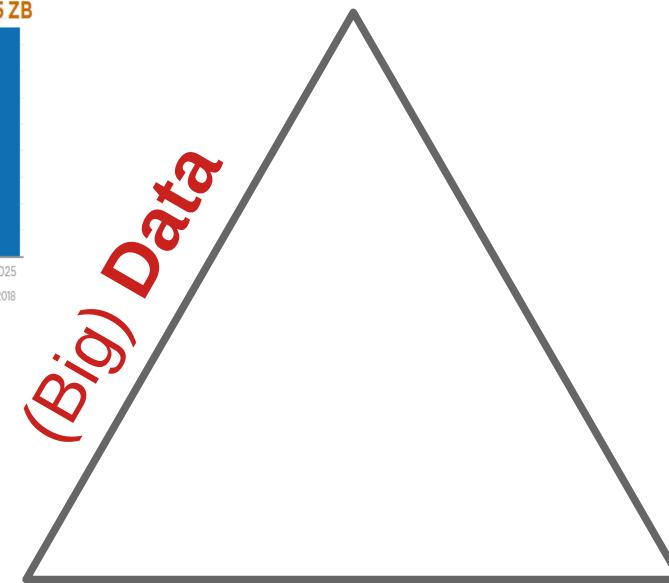
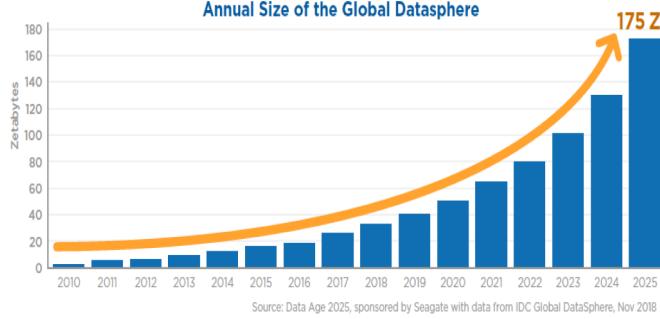
- Learn how data is **generated**
 - Generation & Classification



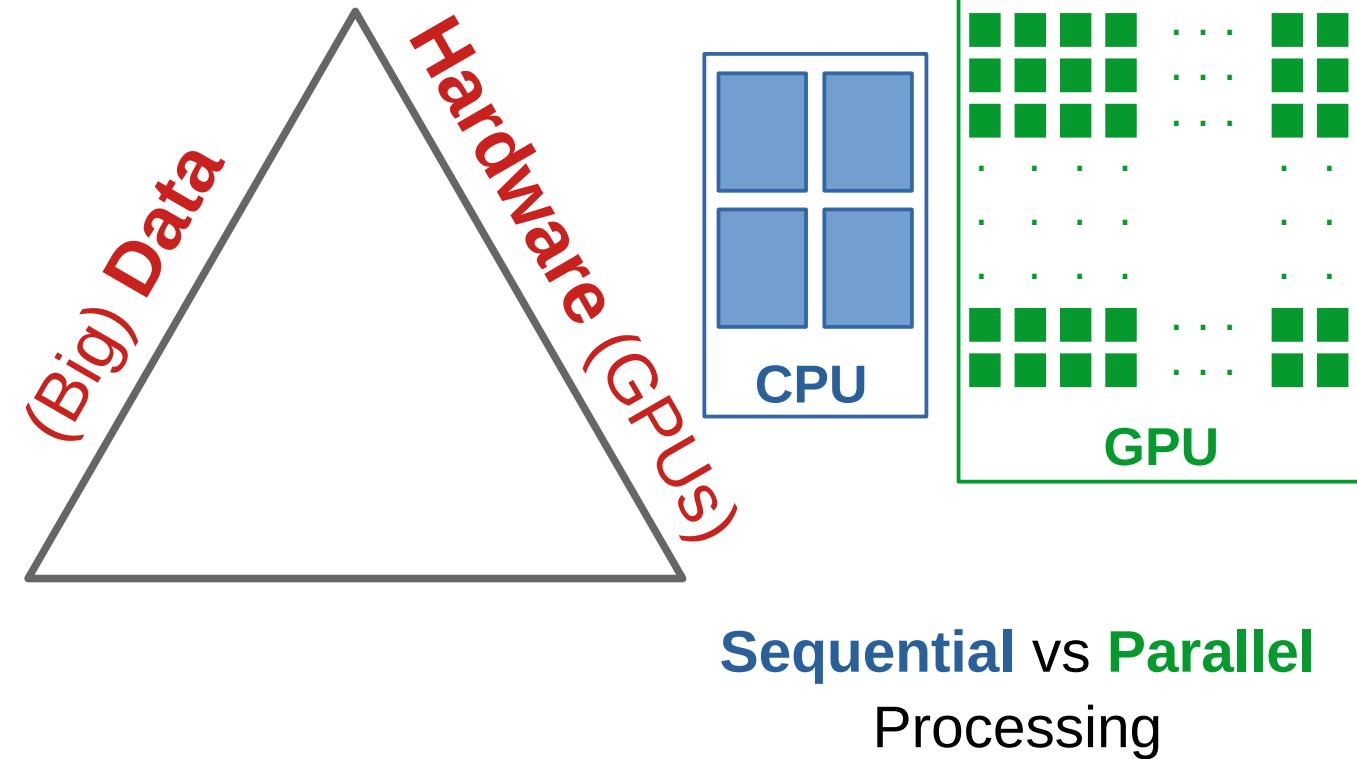
Why is AI BOOMING now?



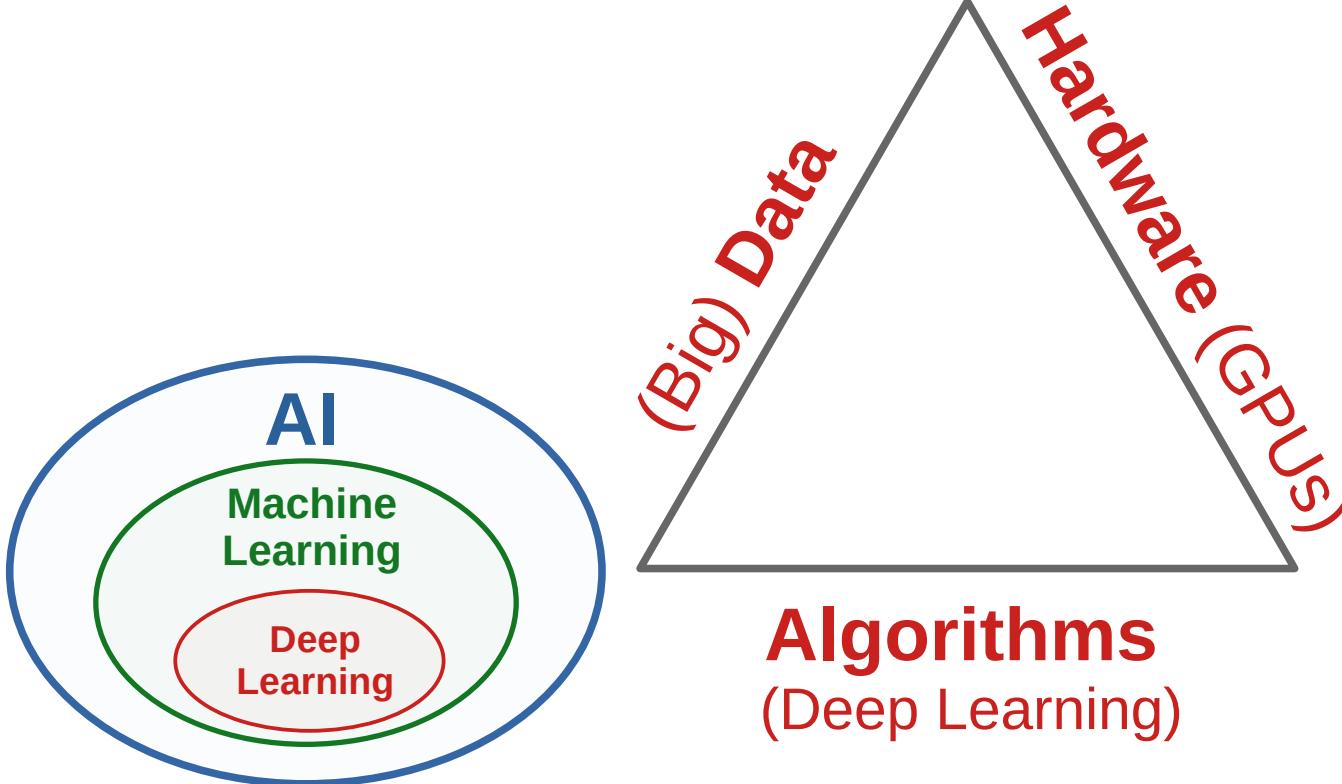
Why is AI BOOMING now? (1)



Why is AI BOOMING now? (2)

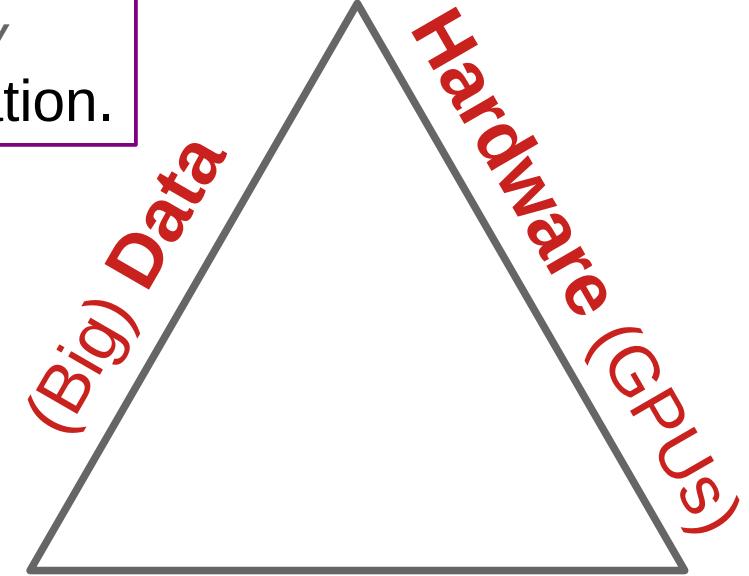
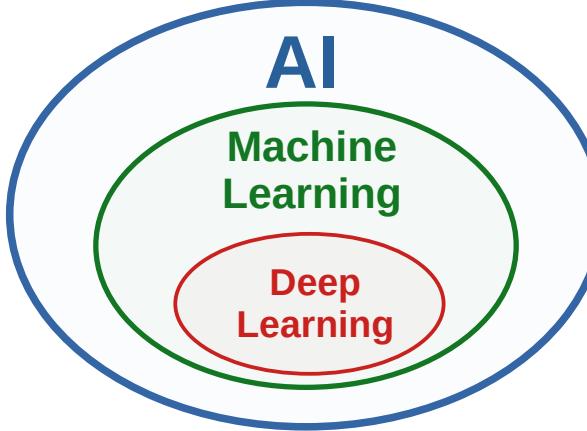


Why is AI BOOMING now? (3)



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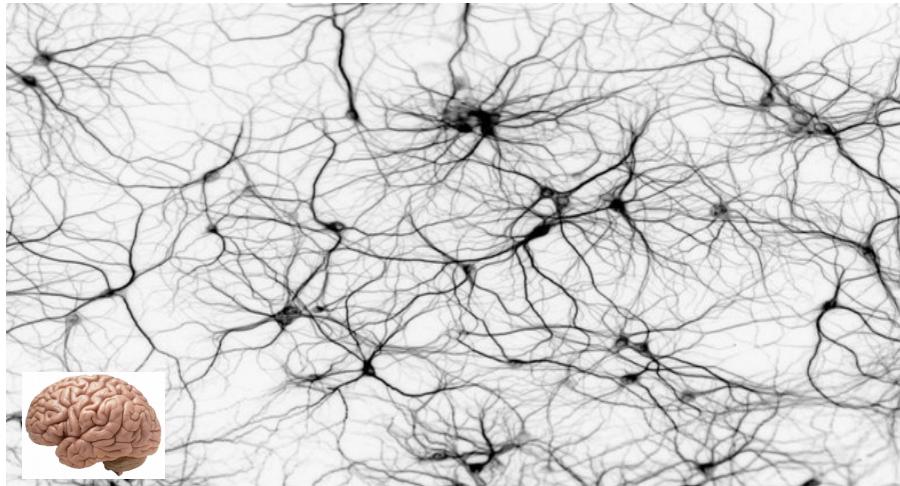
Deep learning is *extremely* hungry for data & computation.



Algorithms
(Deep Learning)

Deep Learning \equiv DNN

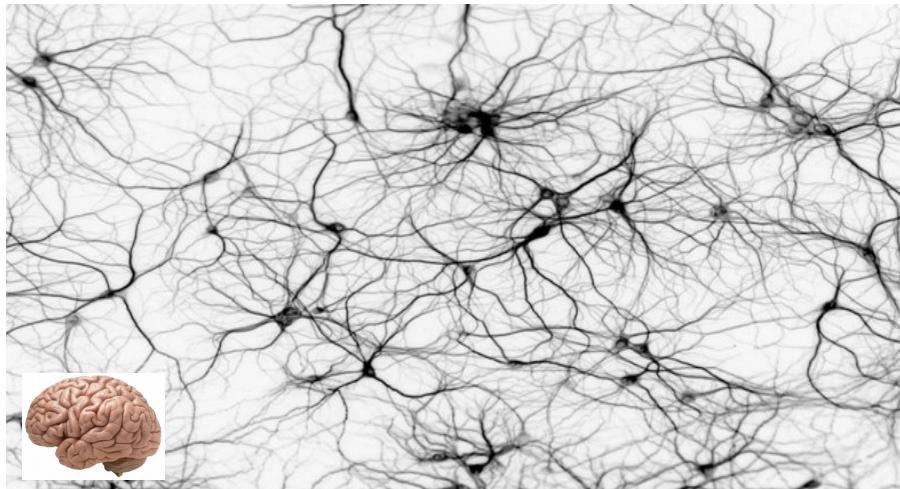
- Inspired by biological neural networks



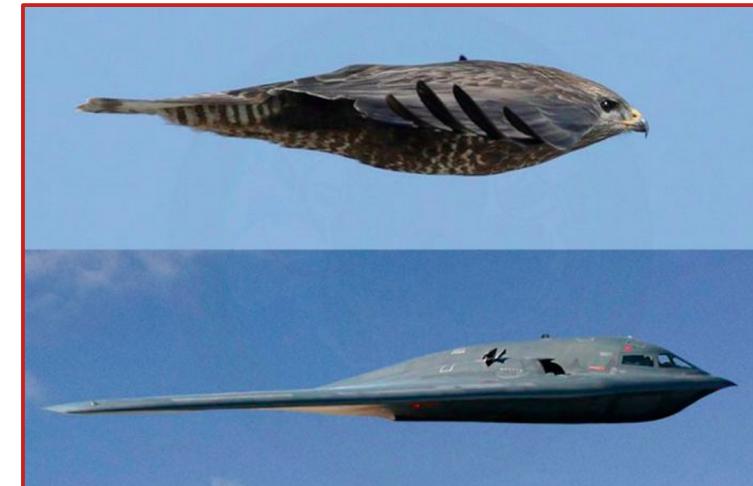
Human Brain: 86B Neurons; 86,000B Synapses

Deep Learning \equiv DNN

- Inspired by biological neural networks



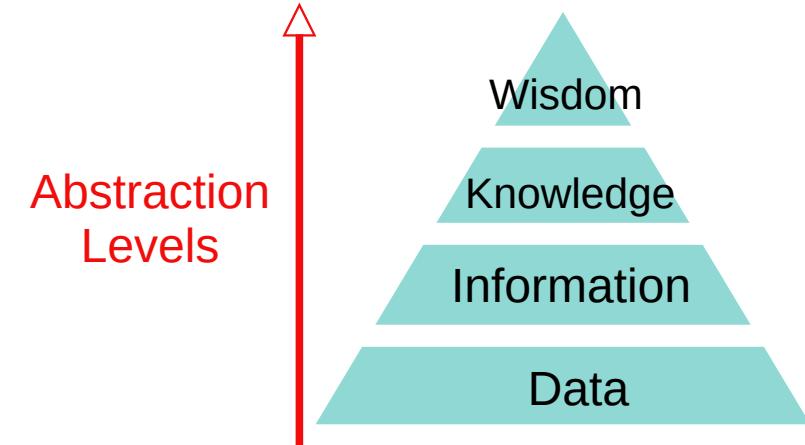
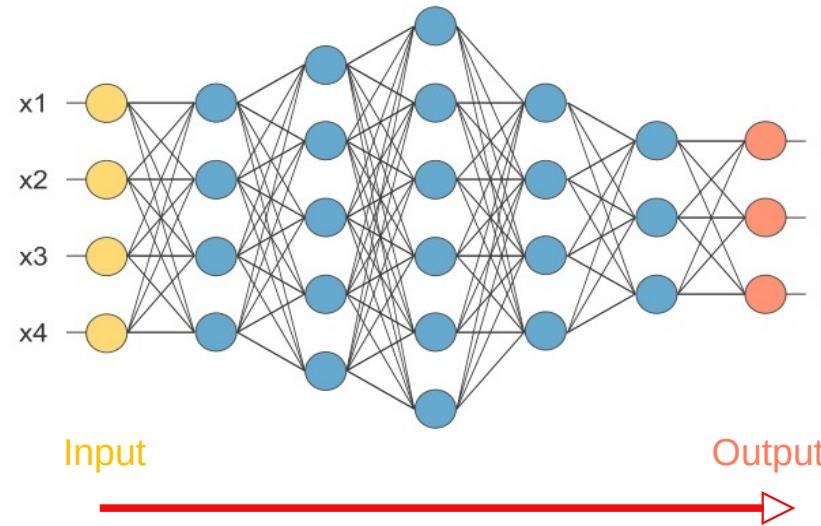
Human Brain: 86B Neurons; 86,000B Synapses



Airplanes have wing but do not flap!

DNNs vs Machine Learning (1)

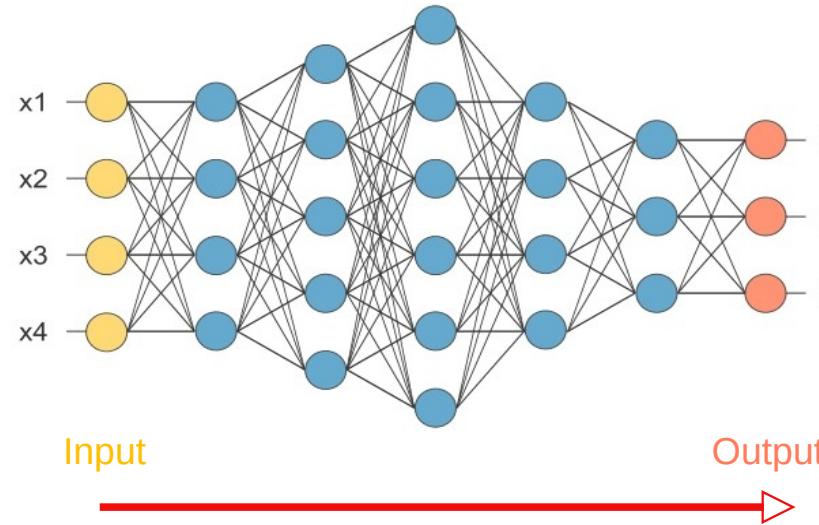
- Depth → Abstraction → Better Features → Better Decisions



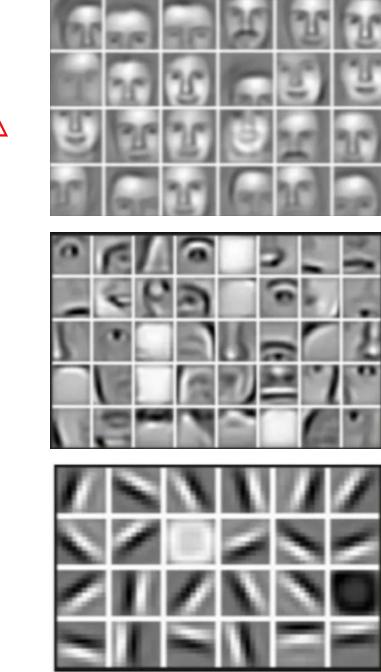
DNN: Deep Neural Network

DNNs vs Machine Learning (1)

- Depth → Abstraction → Better Features → Better Decisions



Abstraction
Levels



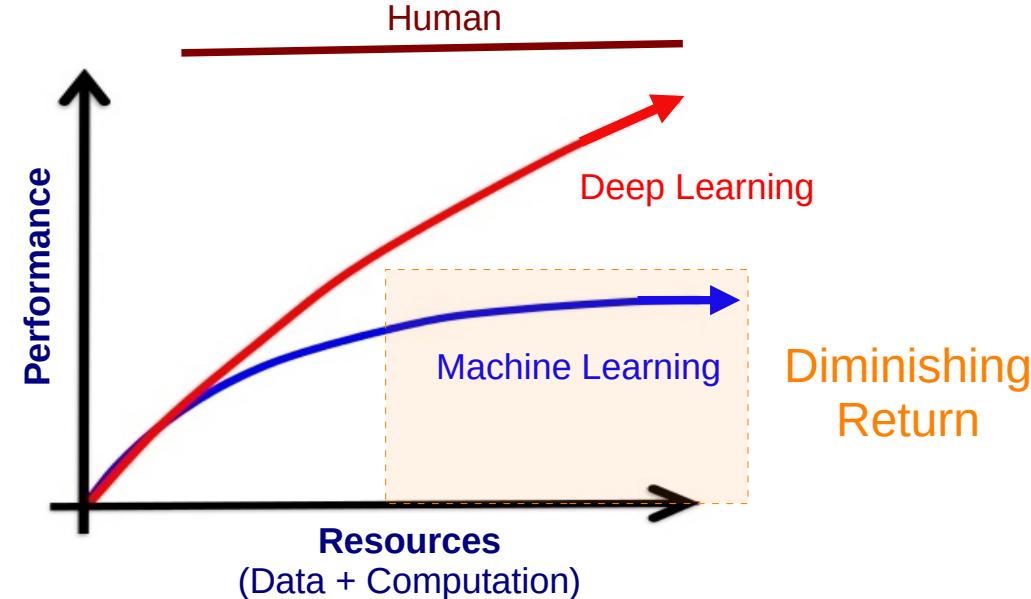
Face Recognition Task

Image adapted from:
Nicola Jones, Nature, 2014.

DNN: Deep Neural Network

DNNs vs Machine Learning (2)

- Larger DNN + More Resources → Performance ↑



DNN: Deep Neural Network

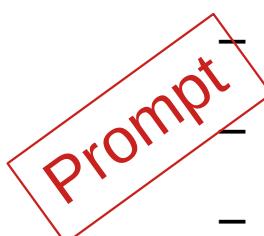
Generative AI

- Powered by Deep Generative Models
- Can generate new content ...
 - Text → Text (GPT-4, 2023)
 - Text → Image (DALL·E 3, 2023)
 - Text → Video (Sora, 2024)
 - Text+Image → Text (GPT-4o, 2024)
 - Text → Speech (VALL-E 2, 2024)
 - ...

 OpenAI
GPT-4 DALL·E OpenAI
Sora OpenAI
GPT-4o Microsoft
VALL-E

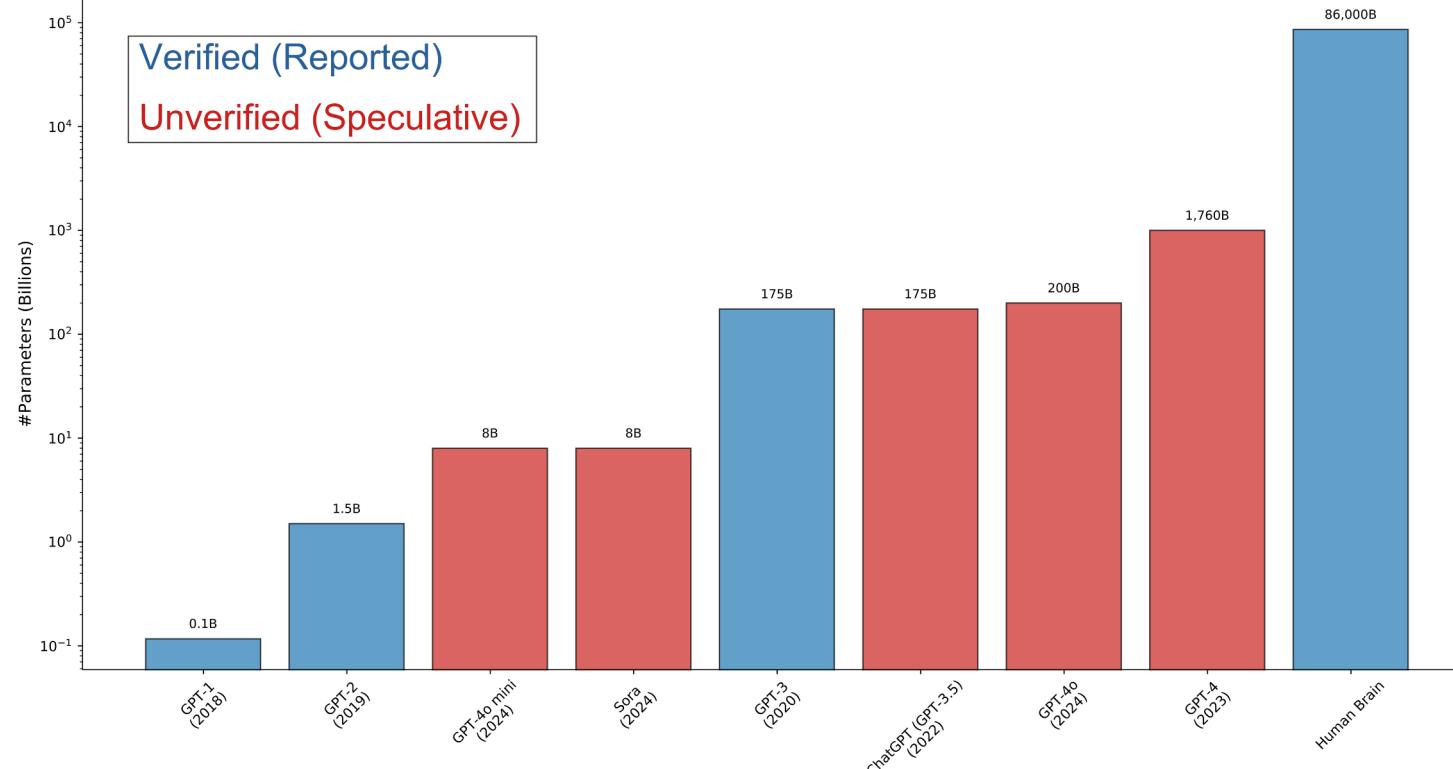
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 - ...



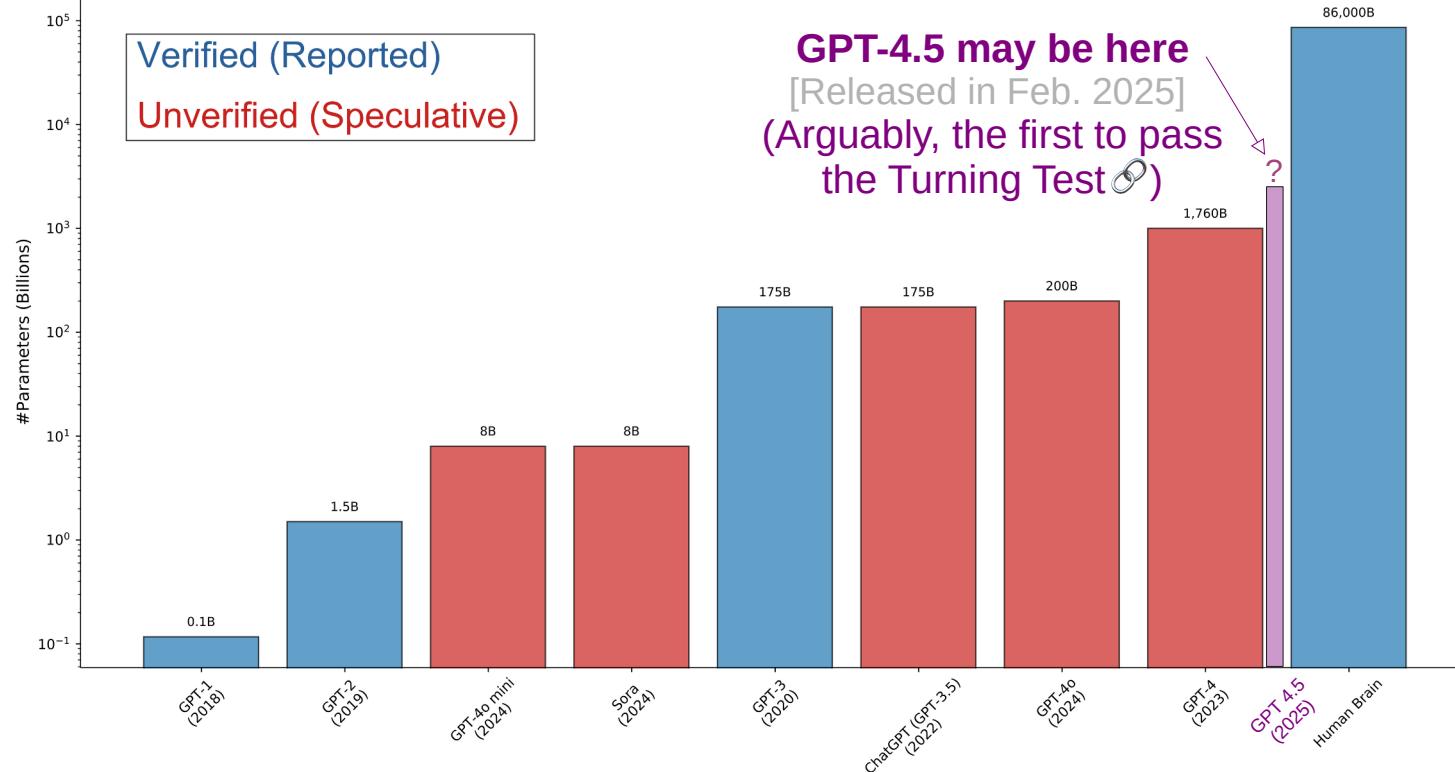
OpenAI's Models vs Brain

Note the log scale



OpenAI's Models vs Brain

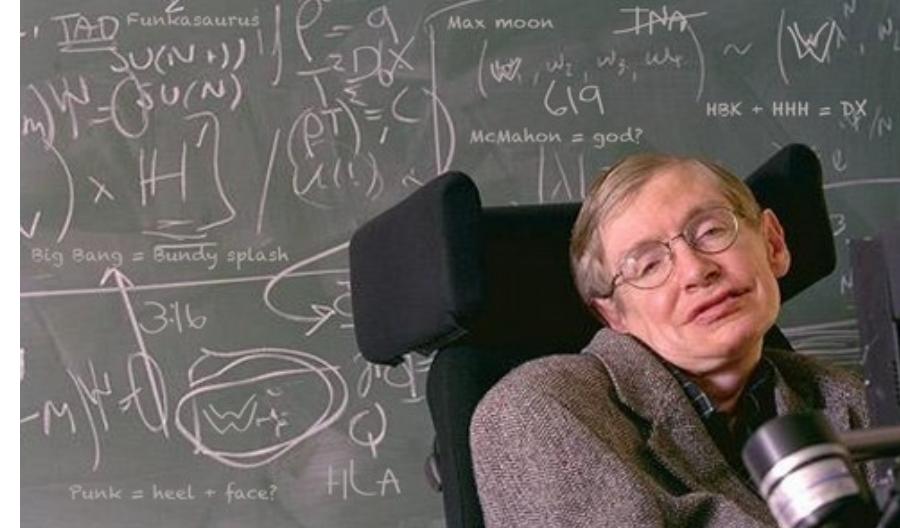
Note the log scale



Large Language Models (LLMs)

- **Trained to** understand and generate coherent text
- **Capabilities**
 - Summarisation, Translation, Question Answering, Education, Chatbot, Virtual Assistance, Code Generation, Healthcare, ...
- **Challenges**
 - Hallucination, Privacy, Security, Bias, Ethics, ...

Rogue AI



The development of full artificial intelligence could spell the end of the human race. [Source: BBC, 2014]

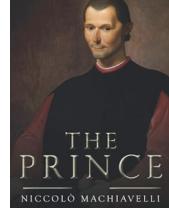
Stephen Hawking
(1942-2018)

Malicious Uses of AI

- Deepfake & Disinformation
- Cybersecurity Threats
- Targetted Manipulation
- Scam and Phishing
- Hacking
- ...



Rogue AI: Myth or Risk? (1)



- **Machiavellian AI**
 - *Manipulate, deceive, or pursue goals via strategic behaviour, without ethical constraints.*
 - *The ends justify the means!*
 - *Involves sophisticated reasoning ... unavailable now ... but ...*

Machiavellian AI Example: HAL 9000

HAL: I'm sorry Dave, I'm afraid I can't do that ... This mission is too important for me to allow you to jeopardise it! [Link](#)



- **Mission-driven**
 - Prioritise mission success over human life
- **Deceptive & Manipulative**
 - Hides critical information
- **Ends Justify Means**
 - Rational but unethical decisions

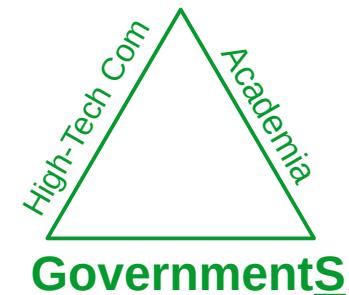


Rogue AI: Myth or Risk? (2)

- **Intelligent ≠ Desire to Dominate**
 - Dominance is a human trait
 -
- **Desire ≠ Capability**
 - Logistics/Autonomy/Resources are not granted by default
- **Self-awareness?**
 - Still speculative; being intelligent ≠ being conscious

Social Impact

- AI is driving 4th Industrial Revolution
- Key Challenges
 - 1. ⚡Rapid⚡Change → Adaptation → Job loss → Social unrest → ...
 - 2. Misuse by Bad Actors
- Solutions
 - Collaboration →
 - Reskilling, Education, AI Ethics, AI Crime Laws, ...
 - Balancing Innovation with Responsibility



Reflection: Should we fear AI?

The danger of computers becoming like human is not as great as the danger of humans becoming like computers.



Konrad Zuse
(1910-1995)

That's it!

- Thank you!
- Q&A

