THE UNIVERSITY *of* EDINBURGH

usher institute

Better health, better futures

AI: From Zero to Aha!

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Centre for Medical Informatics, Usher Institute
University of Edinburgh

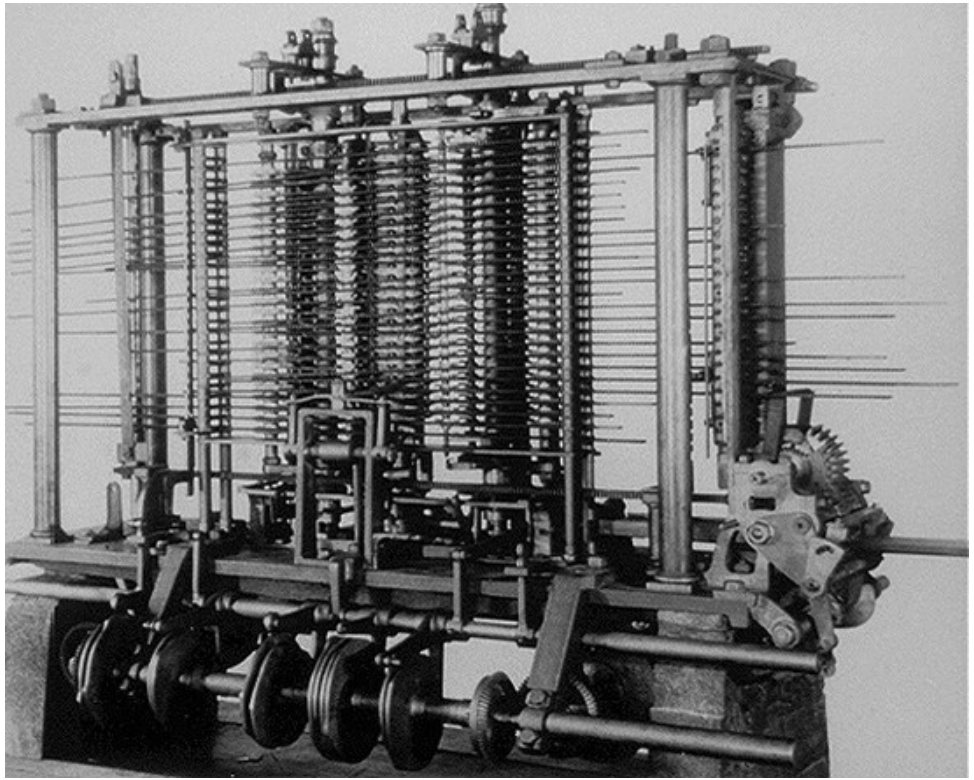
NASA’s James Webb Space Telescope, deepest and sharpest image of the universe

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

The Most Complex Creation in the Known Universe ...

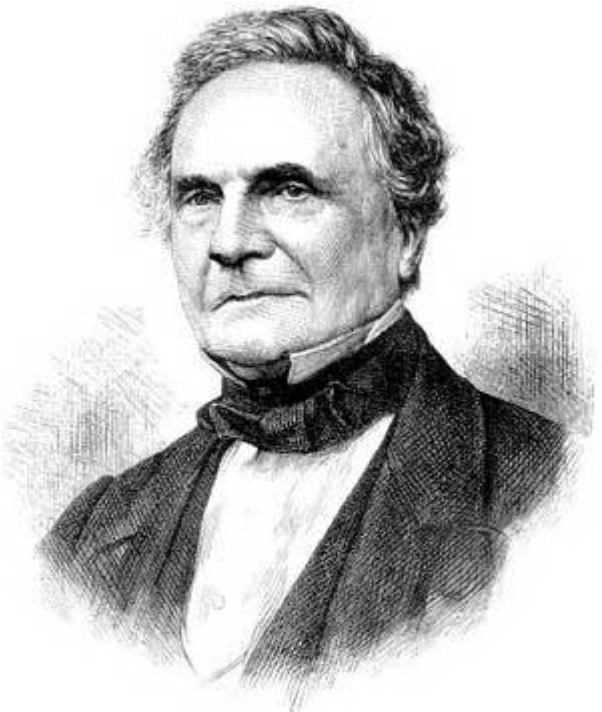
Human Brain

- 86B Neurons
- 86,000B Synapses



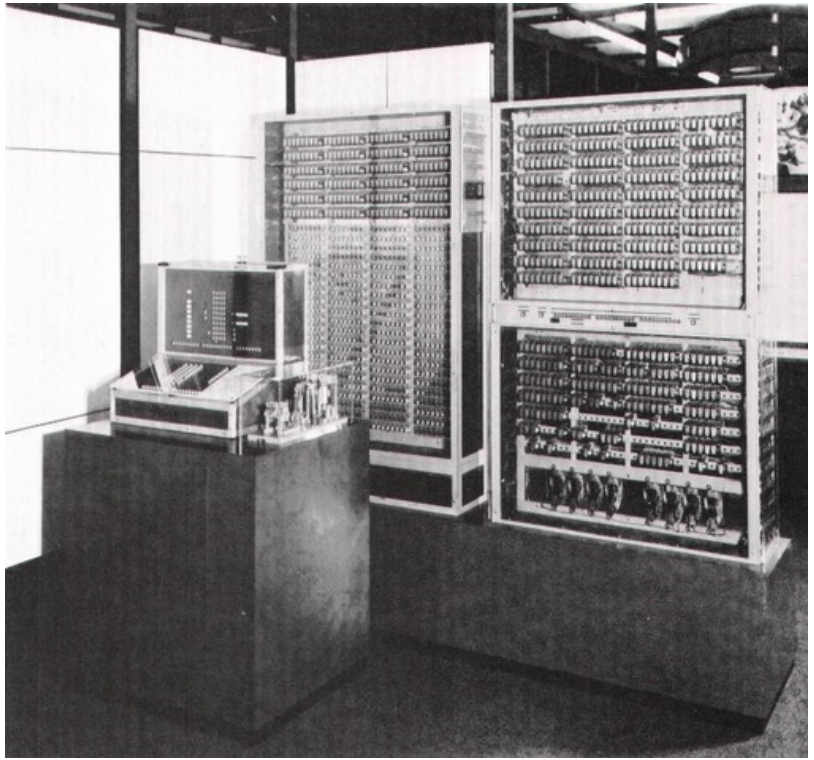
Difference Engine

(Mechanical Computer, Mid 19th century)



Charles Babbage (1791-1871)

[Father of the computer]

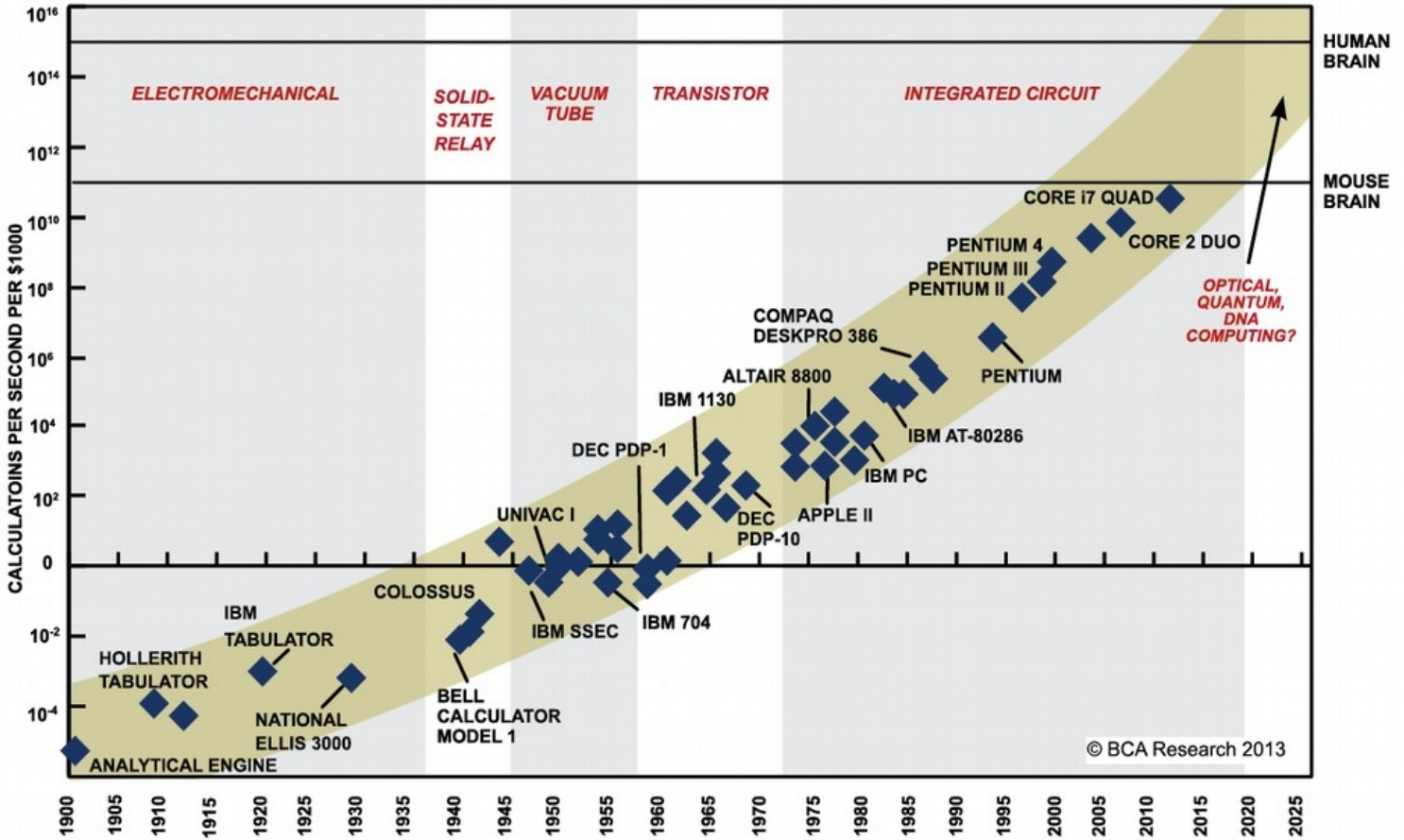


Z3

(ElectroMechanical Computer, 1941)

Konrad Zuse (1910-1995)

ENIAC
(Electronic Numerical Integrator and Computer, 1945)

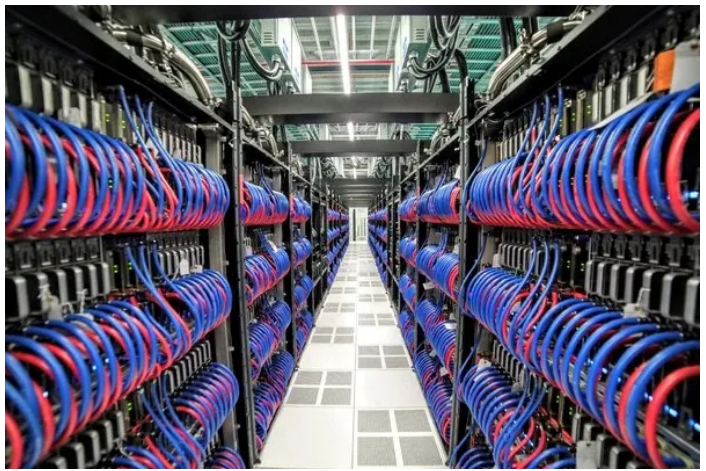


SOURCE: RAY KURZWEIL, "THE SINGULARITY IS NEAR: WHEN HUMANS TRANSCEND BIOLOGY", P.67, *THE VIKING PRESS*, 2006. DATAPOINTS BETWEEN 2000 AND 2012 REPRESENT BCA ESTIMATES.

Supercomputers: Fugaku

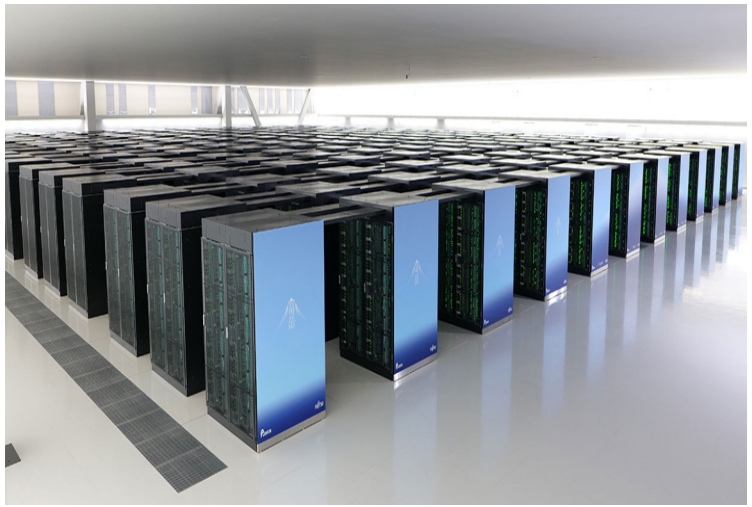
~ 0.5 x 10^{18} FLOPS (Rmax)
7.63 x 10^{6} CPU Cores (ARM)

Supercomputers: Frontier



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

Brain vs Supercomputers



0.5 x

x = 1 x 10^{18} FLOPS

1.1 x

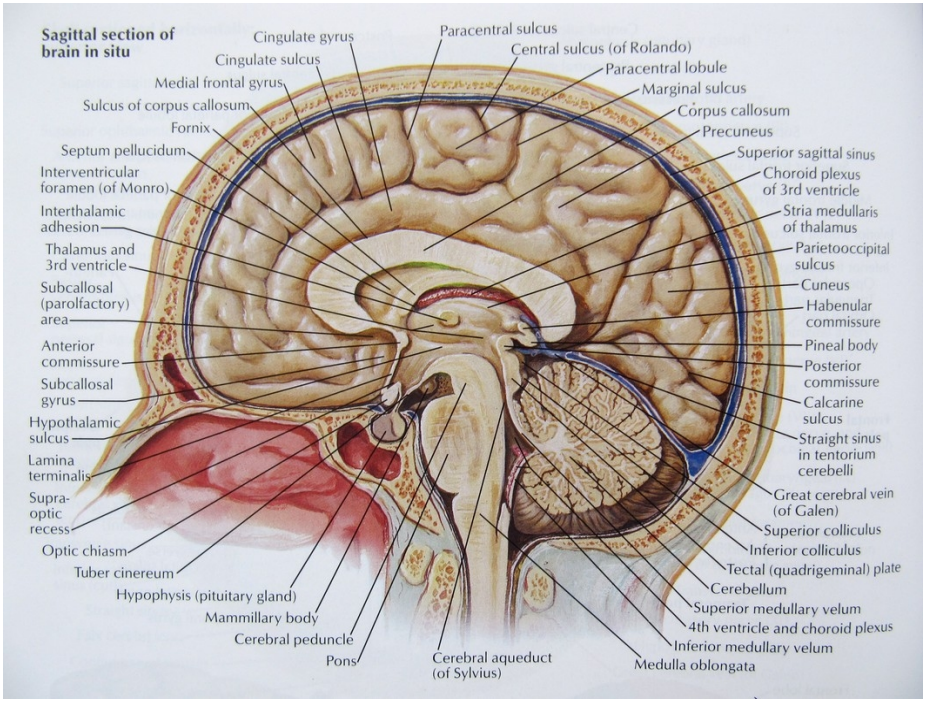
FLOPS: Floating-point operations per second

Problems to Solve

Type I

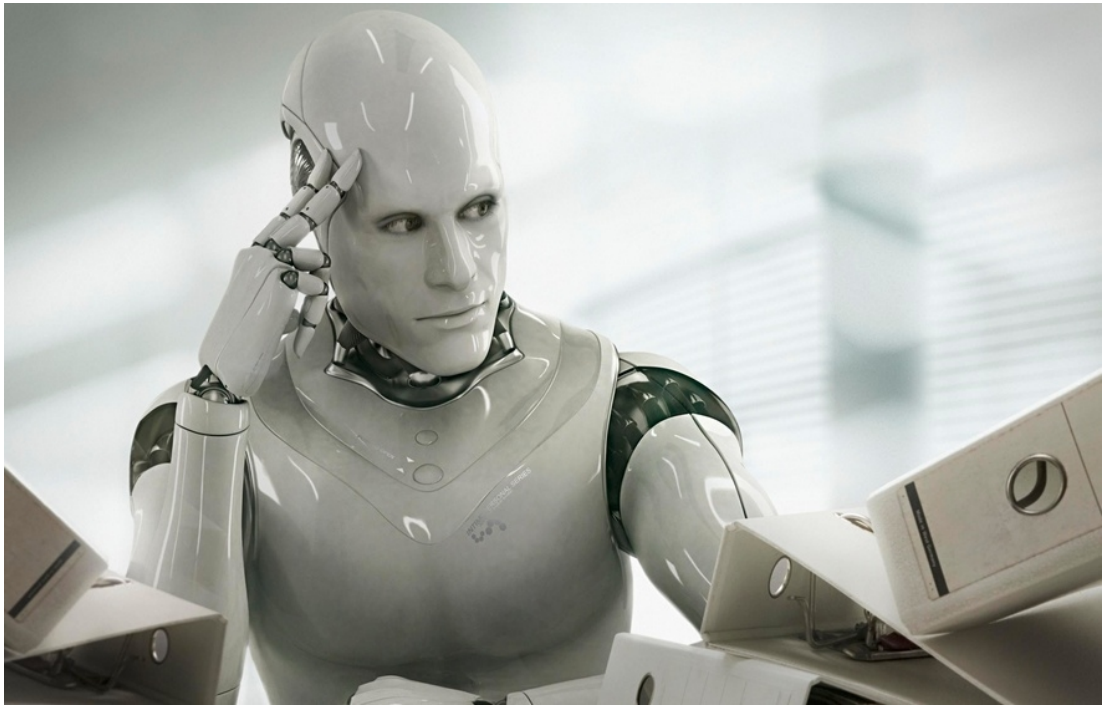
568823471609458.2341112
x 973221231.2431506879416

Type II



Physiology

Engineering

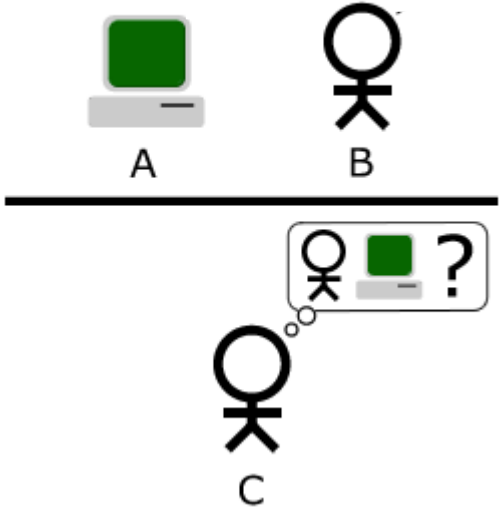


Artificial Intelligence

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

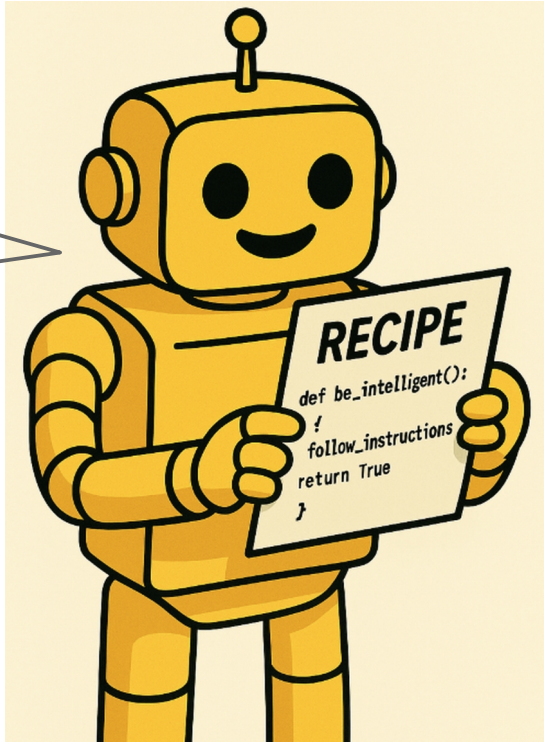
1. The Imitation Game

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?

Hey Machine!
Time to be intelligent;
follow this **Recipe** …



Generated by ChatGPT
(DALL·E 3, OpenAI)

How to Build an Intelligent Machine?

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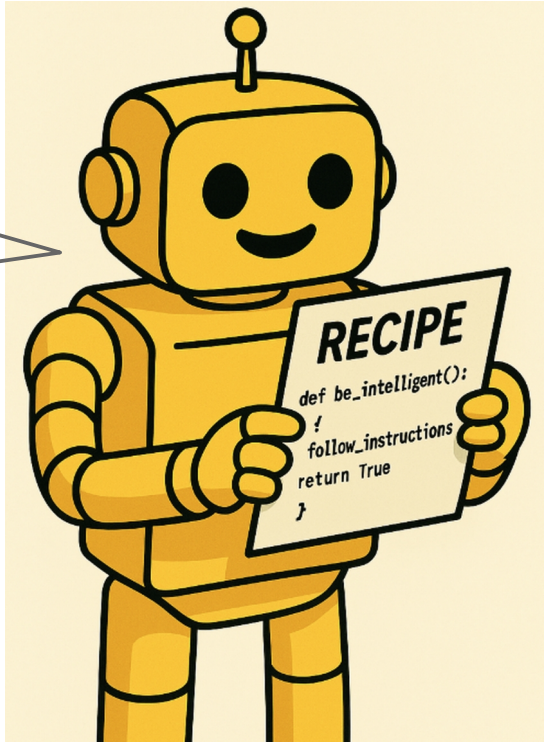


AI as a **Programming** Problem …

Generated by ChatGPT
(DALL·E 3, OpenAI)

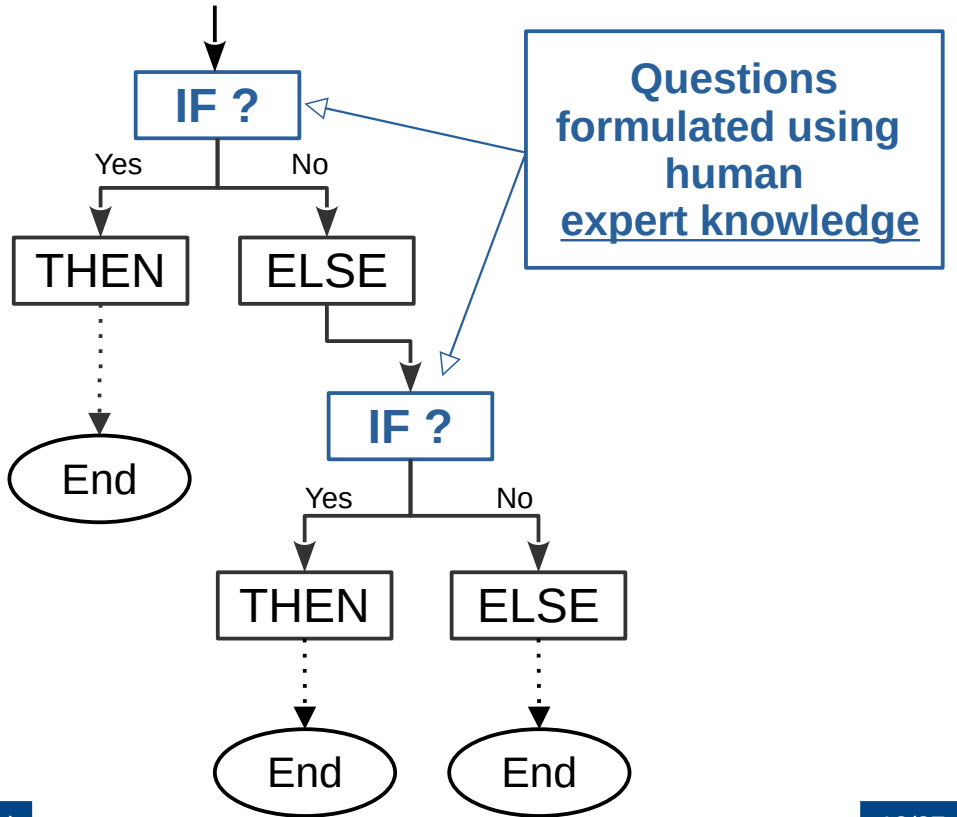
How to Build an Intelligent Machine?

- Explicit Recipe (Explicit Programming)

- Implicit Recipe (Implicit Programming)

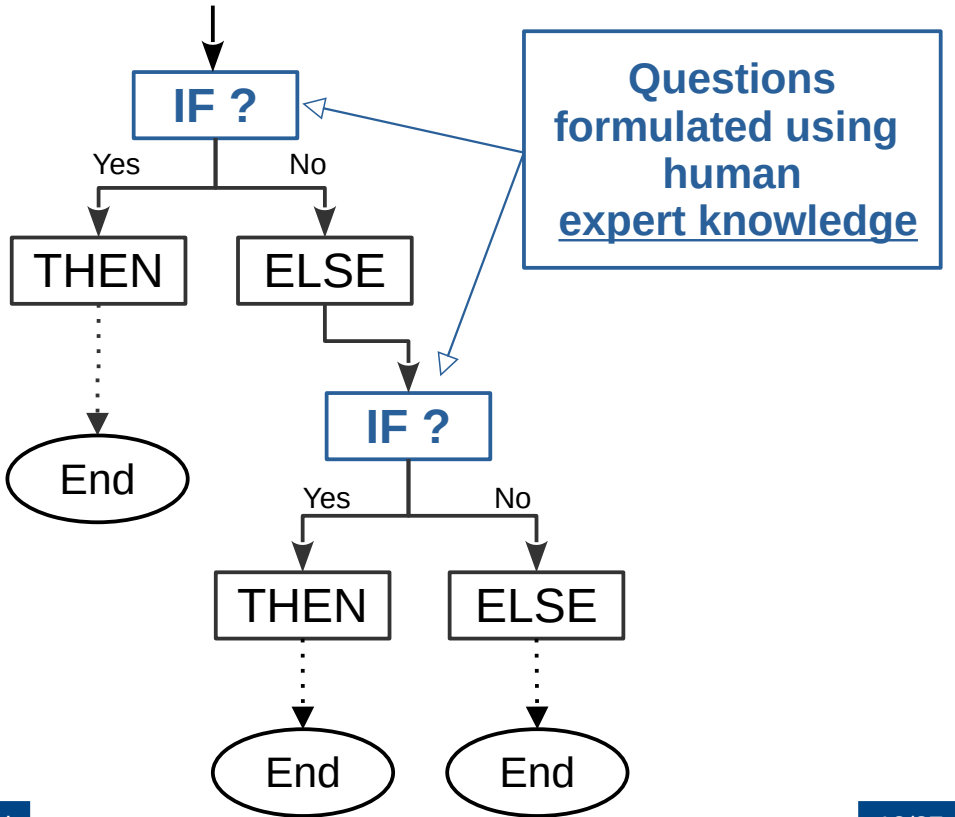
Explicit Programming

Hardcoded knowledge

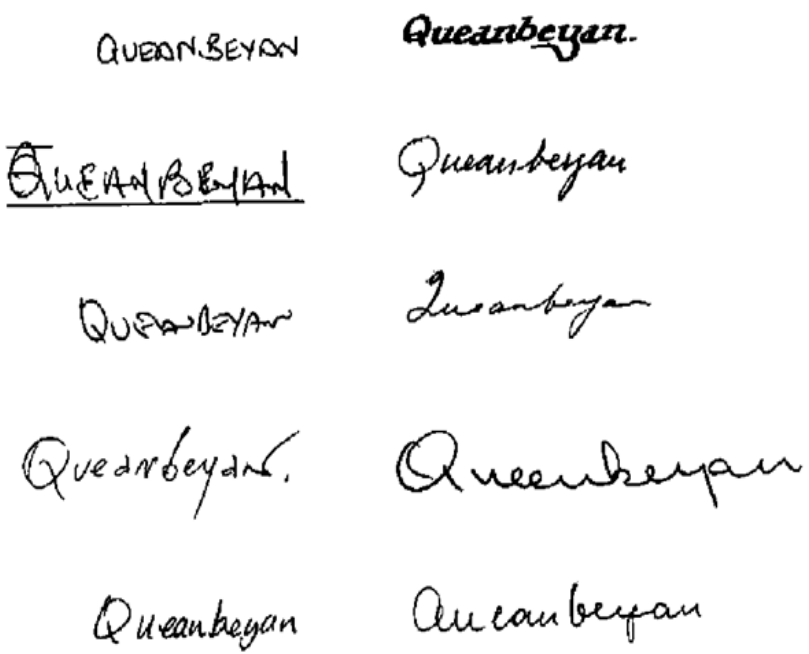


Explicit Programming

Rule-based (Expert) Systems



Expert Systems' Achilles Hill

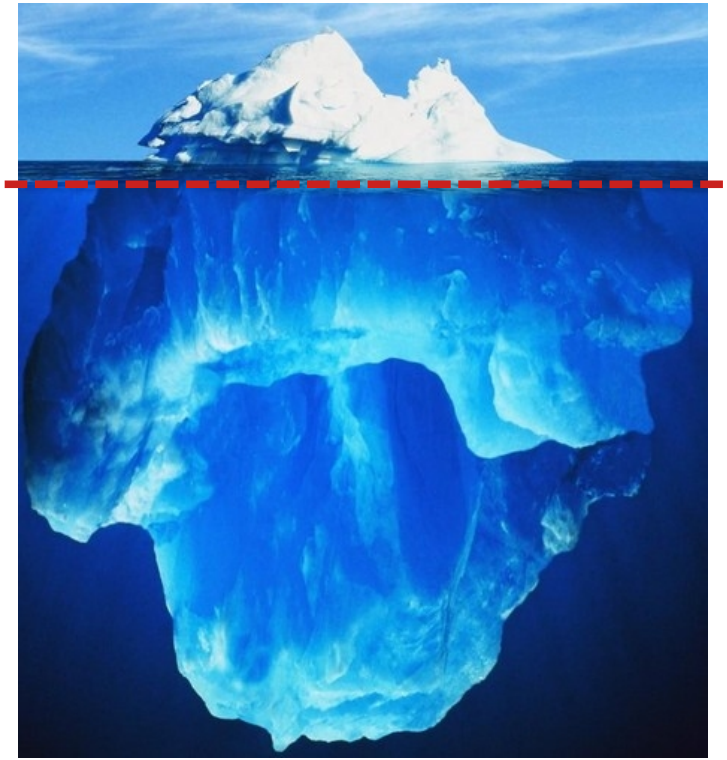


Variability & **Scalability**

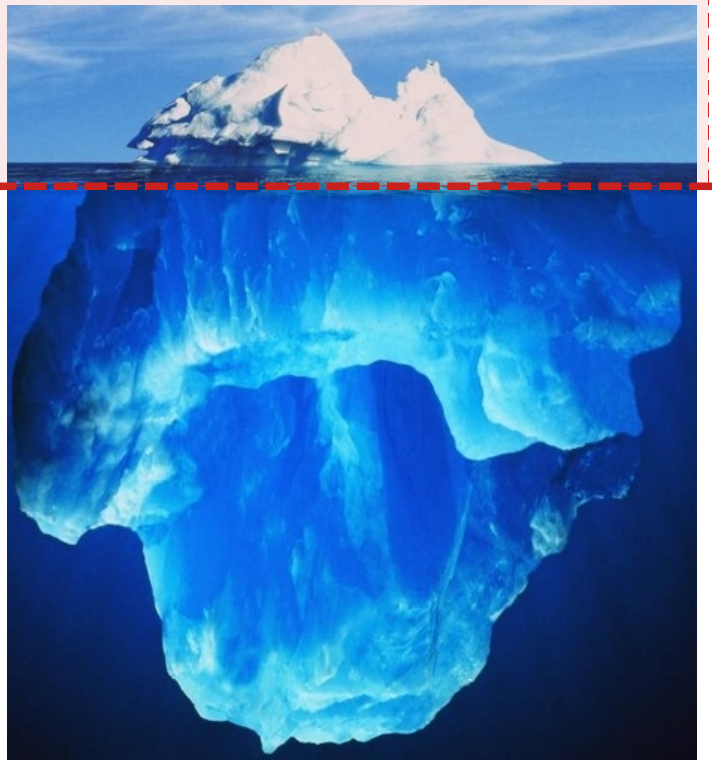
=> Poor generalisation

Visible

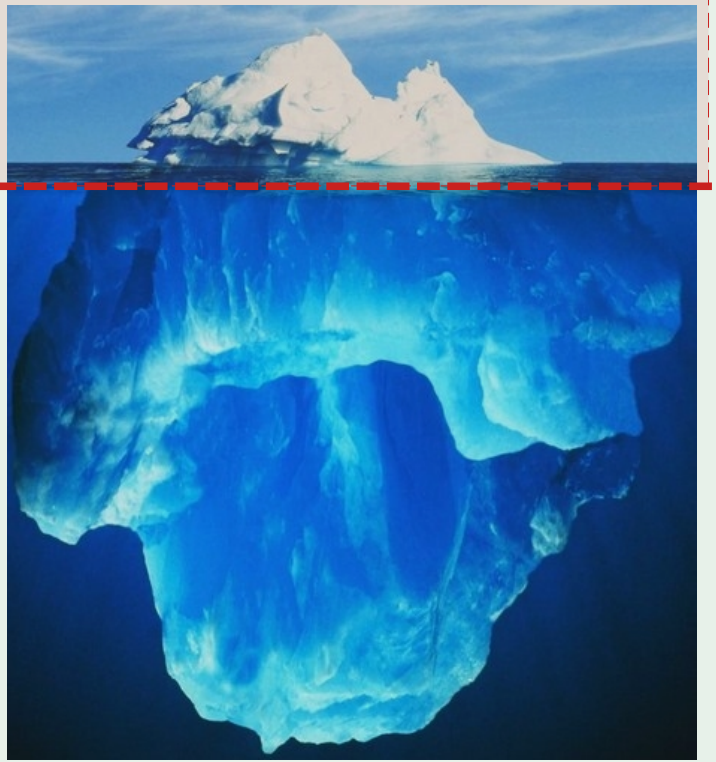
Invisible



Explicit
Programming

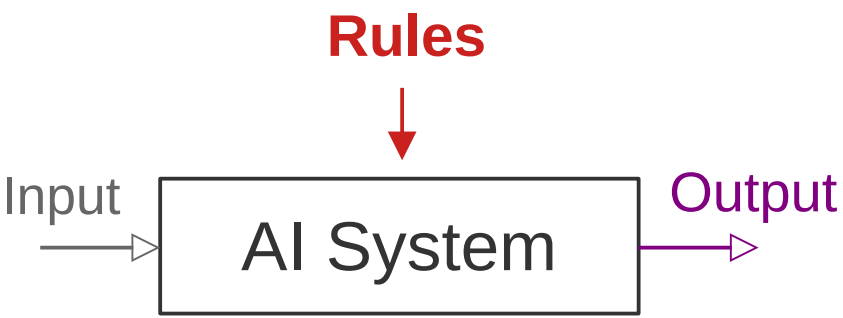


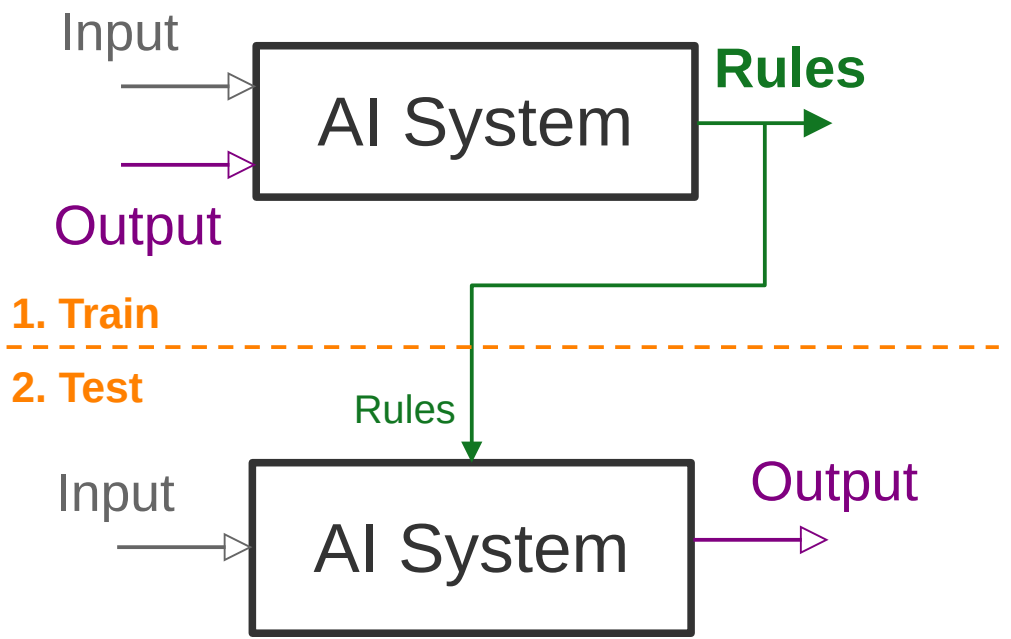
Explicit
Programming



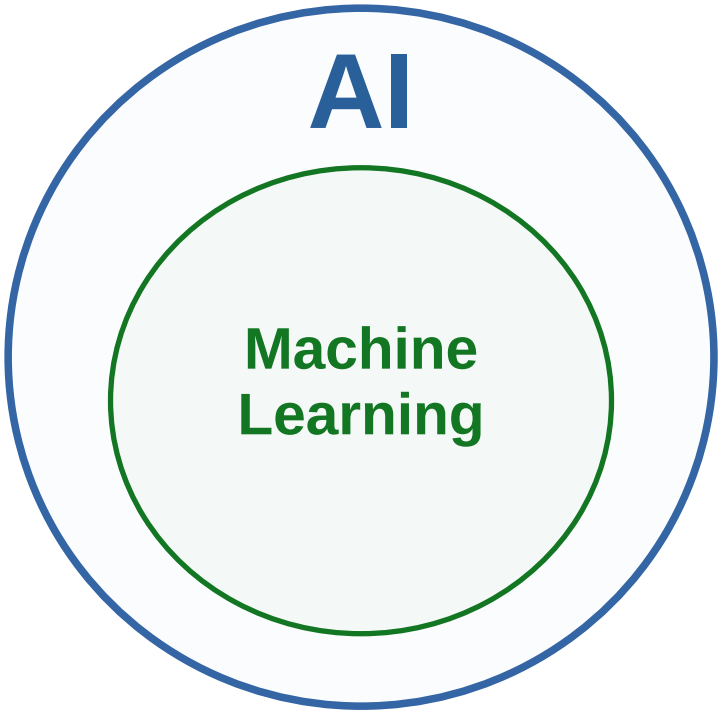
Implicit Programming

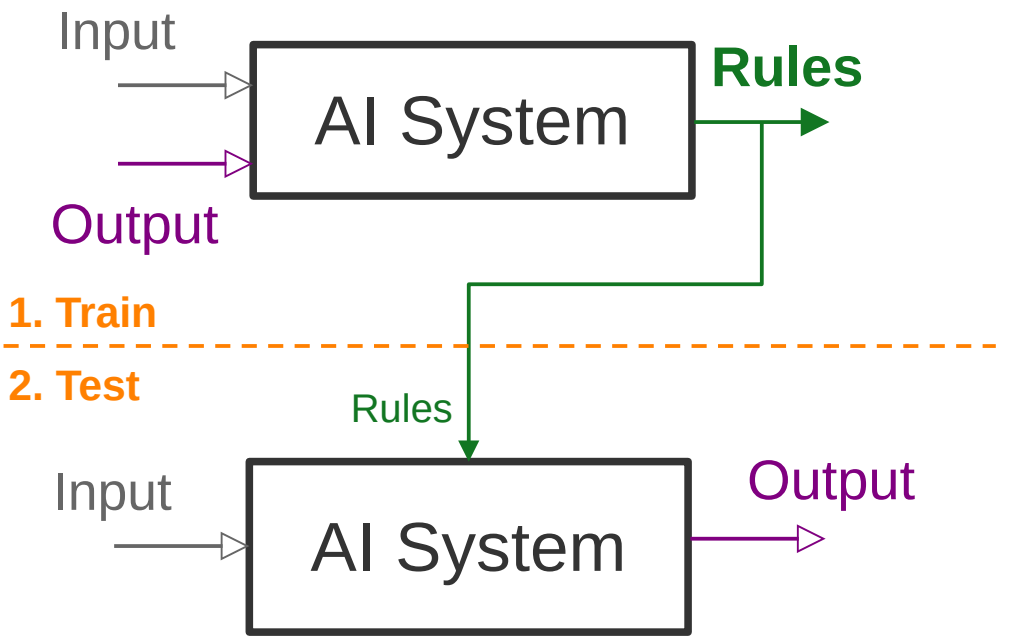
Explicit vs Implicit Programming





Implicit Programming → Machine Learning





Machine Learning

X → Black Box → Y

Cat

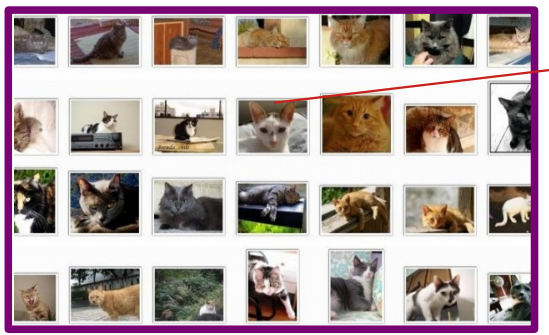
Horse

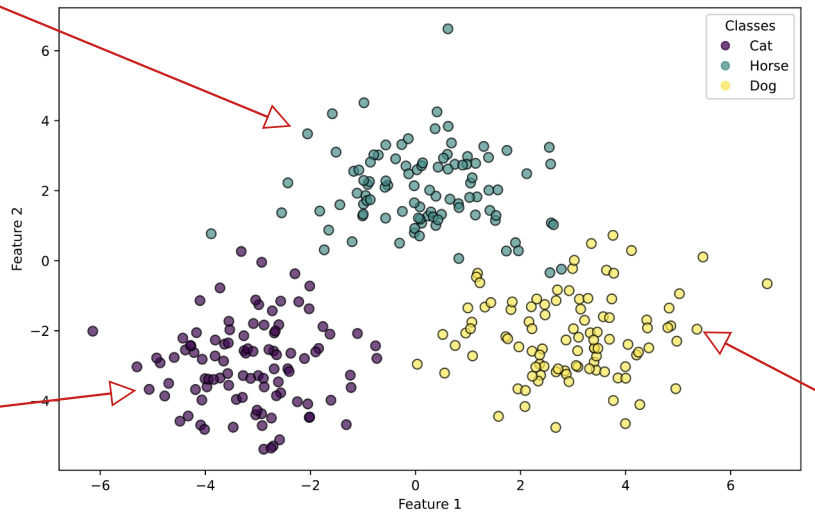
Dog

Machine Learning

Data (**Horse**)

Data (**Cat**)





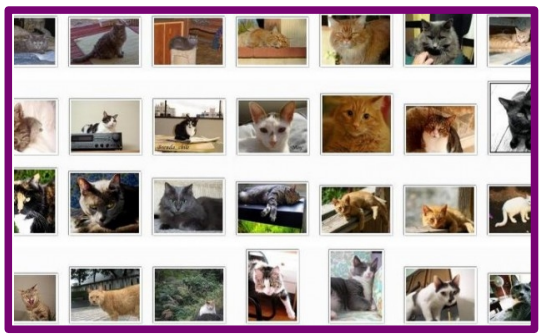
Data (**Dog**)

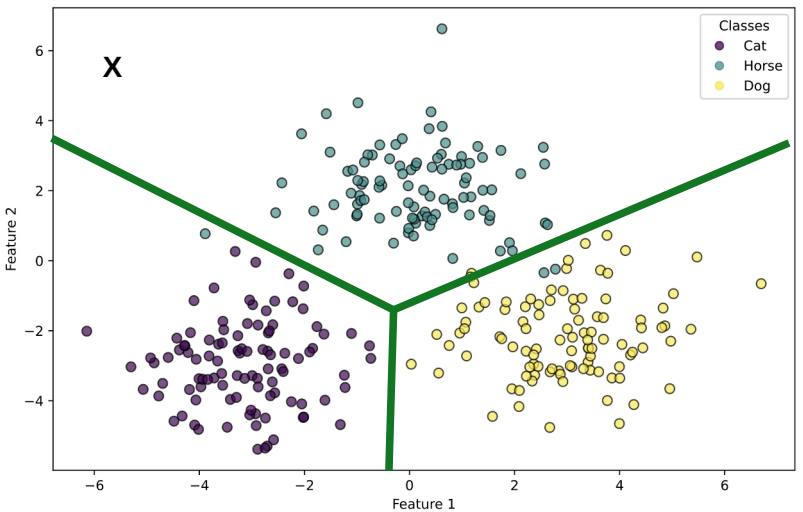
Data → Feature Extraction → Feature

Machine Learning

Data (**Horse**)

Data (**Cat**)

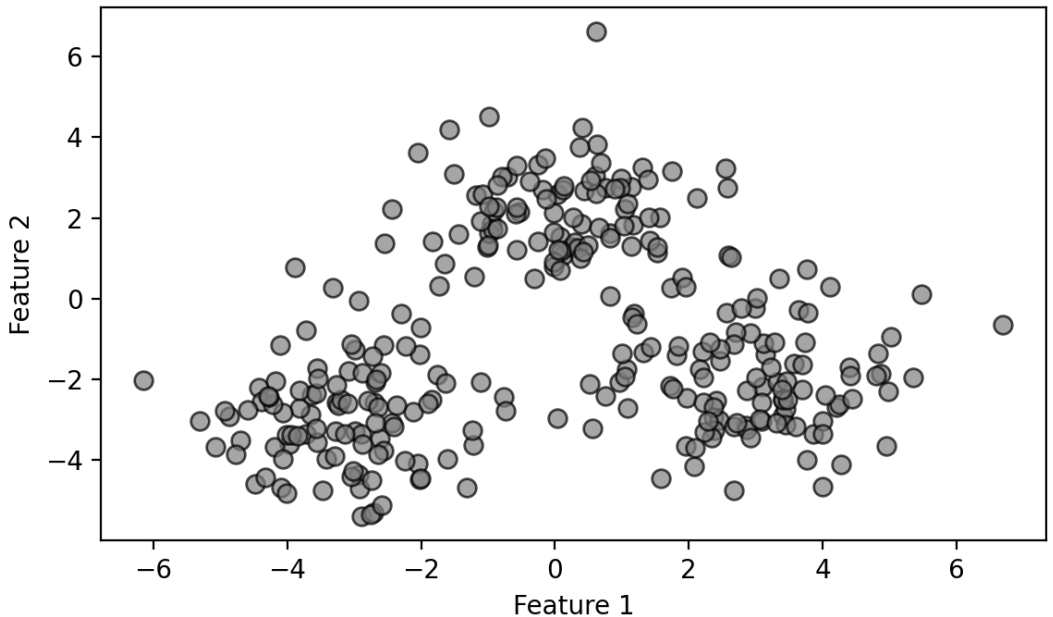




Decision Boundaries ≡ Rules

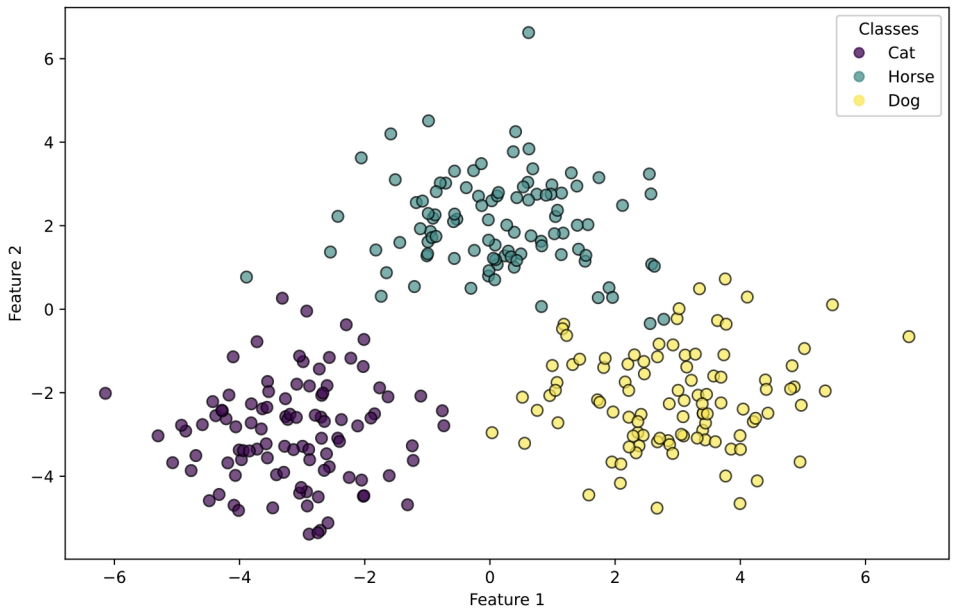
Data (**Dog**)

Machine Learning Paradigms

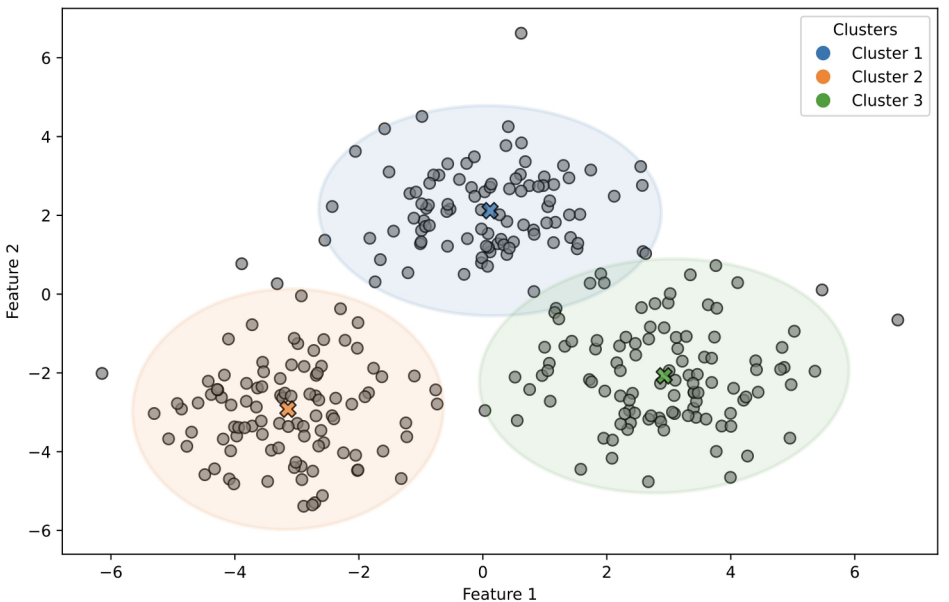


Supervised vs Unsupervised

Labels known (classes)

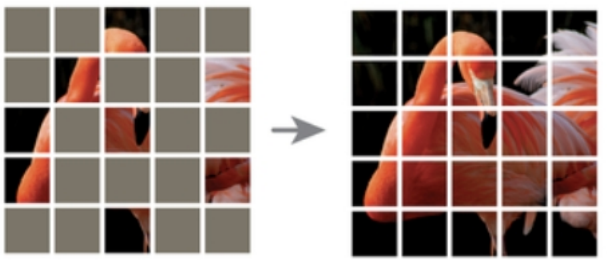


Labels unknown (clusters)



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

Supervised Learning
≡ icing

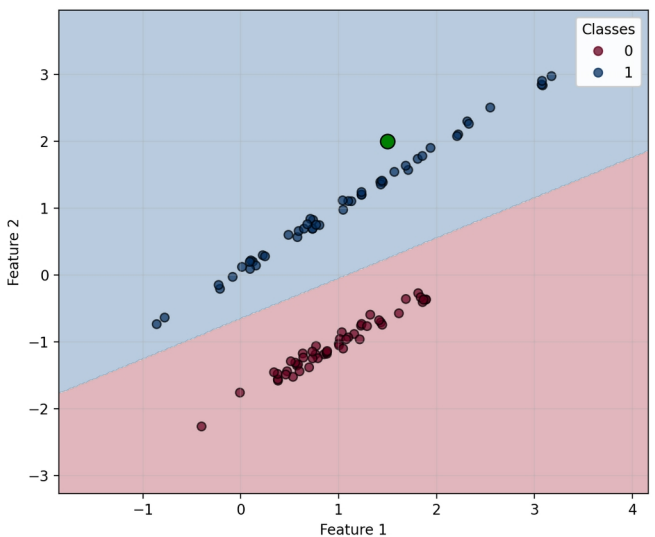
Self/unsupervised Learning
≡ cake base

Intelligence as a Cake

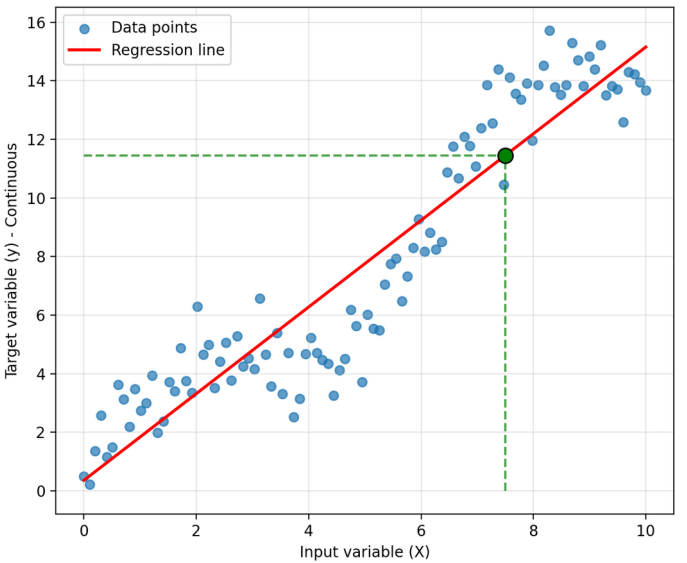
Yann LeCun
(Chief AI Scientist at Meta, Prof. at NYU)

(Supervised)
Classification vs Regression

- Predict discrete categories

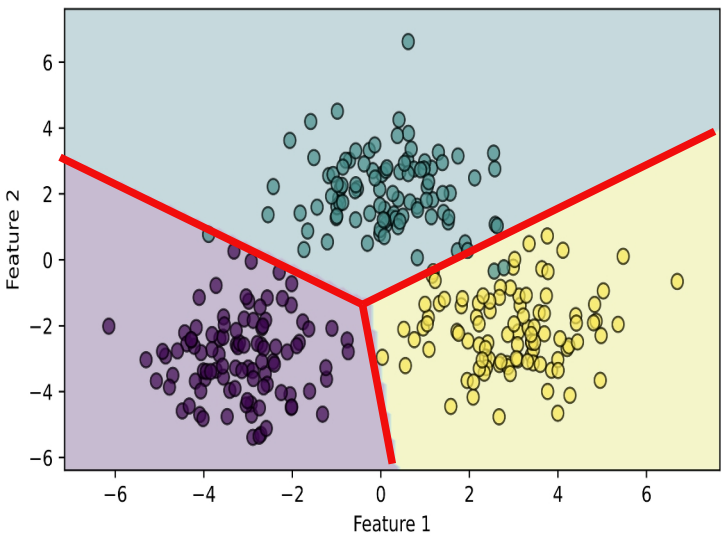


- Predict continuos values

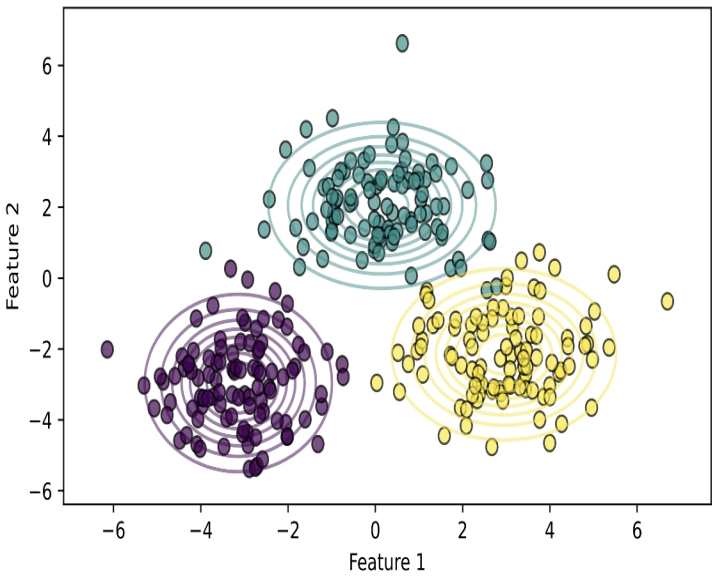


Discriminative vs Generative

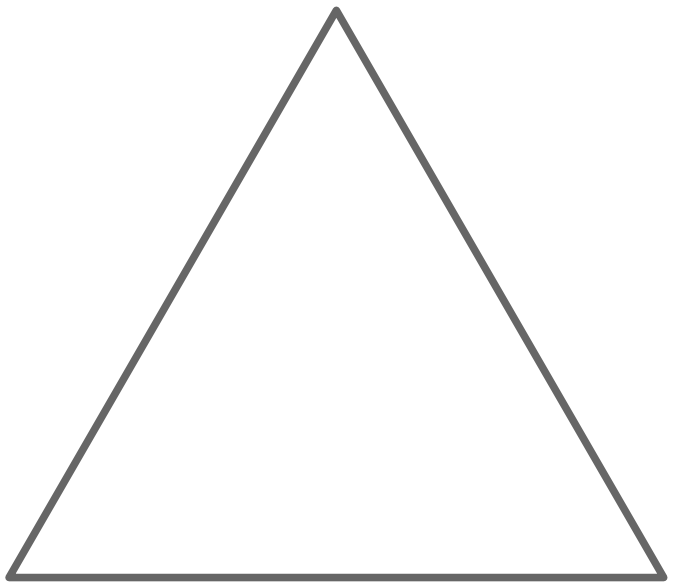
- Learn decision boundaries
  - Classification



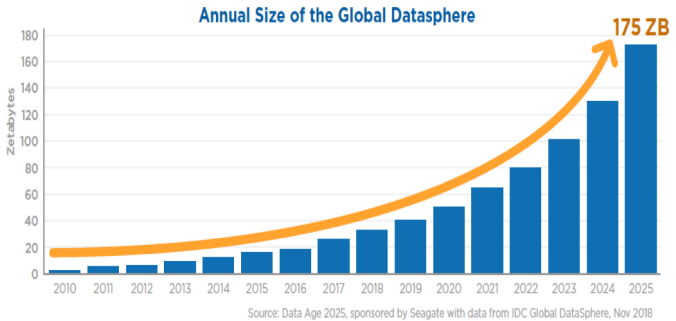
- Learn how data is generated
  - Generation & Classification

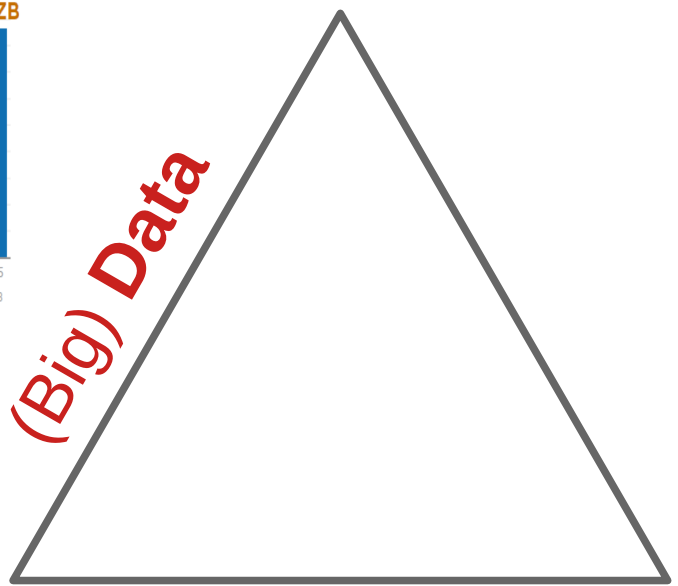


Why AI is BOOMING now?

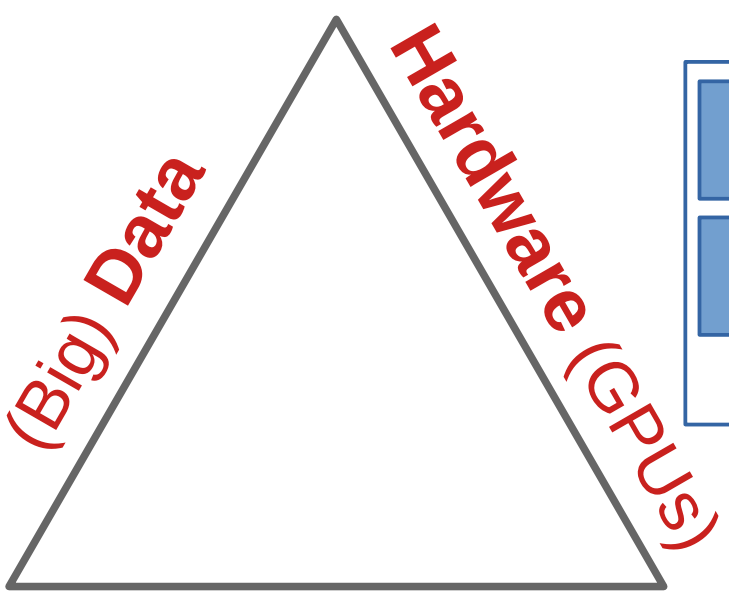


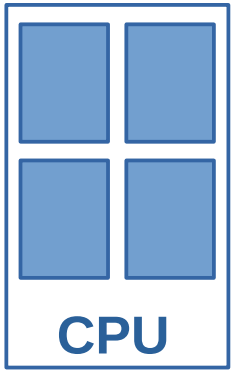
Why AI is BOOMING now? (1)

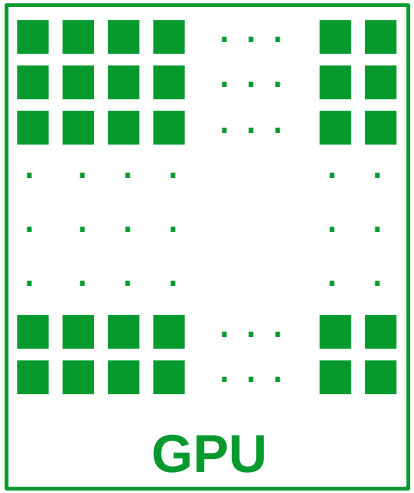




Why AI is BOOMING now? (2)

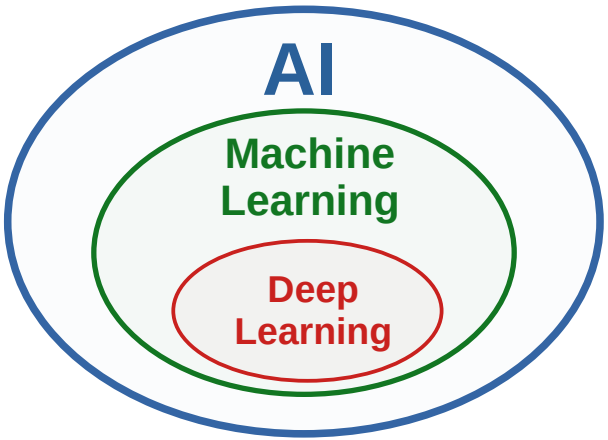


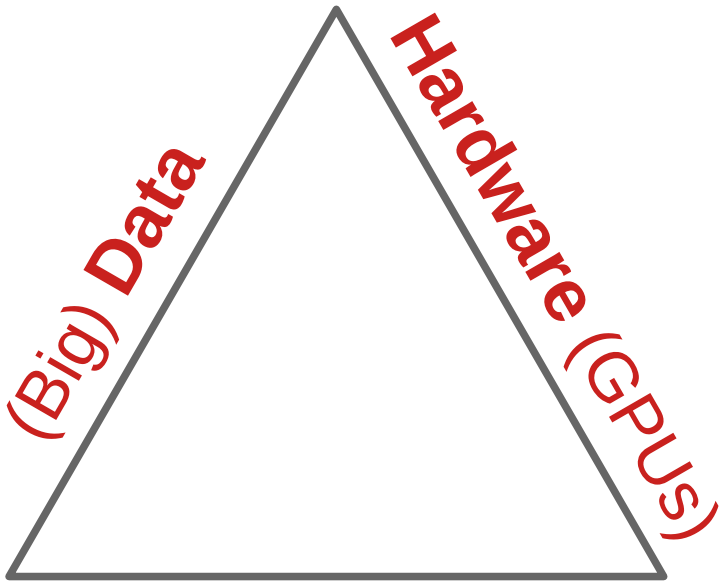




Sequential vs **Parallel** Processing

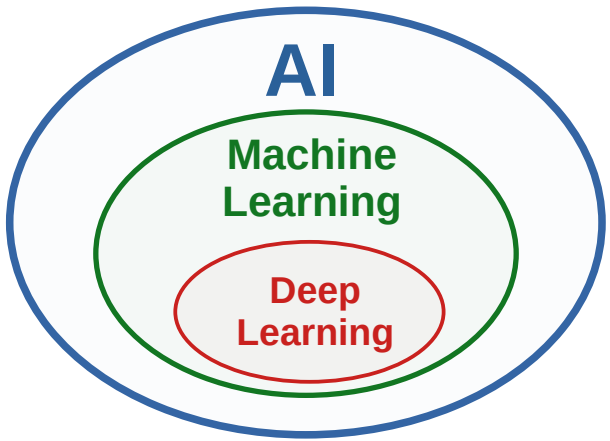
Why AI is BOOMING now? (3)

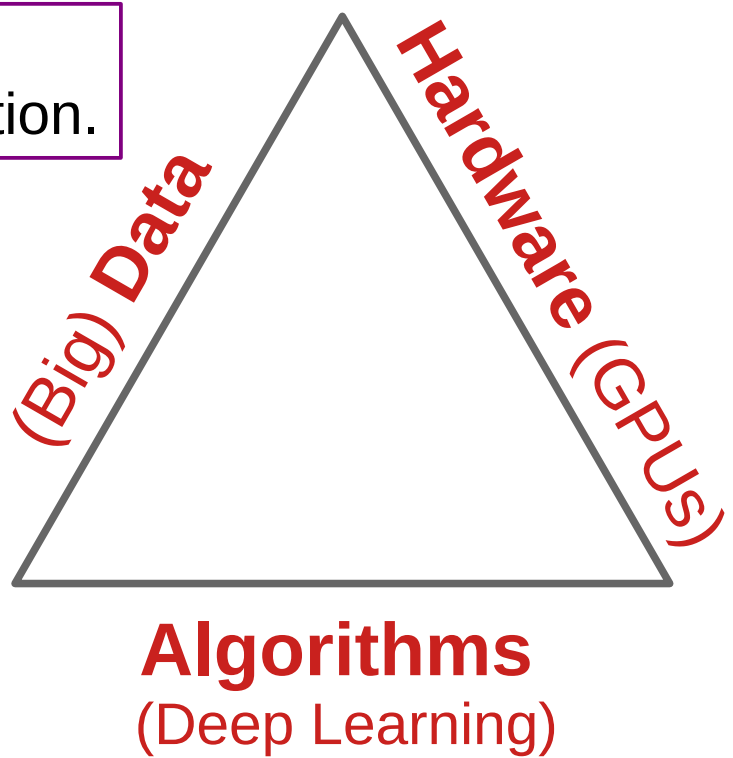




Why AI is BOOMING now? (3)

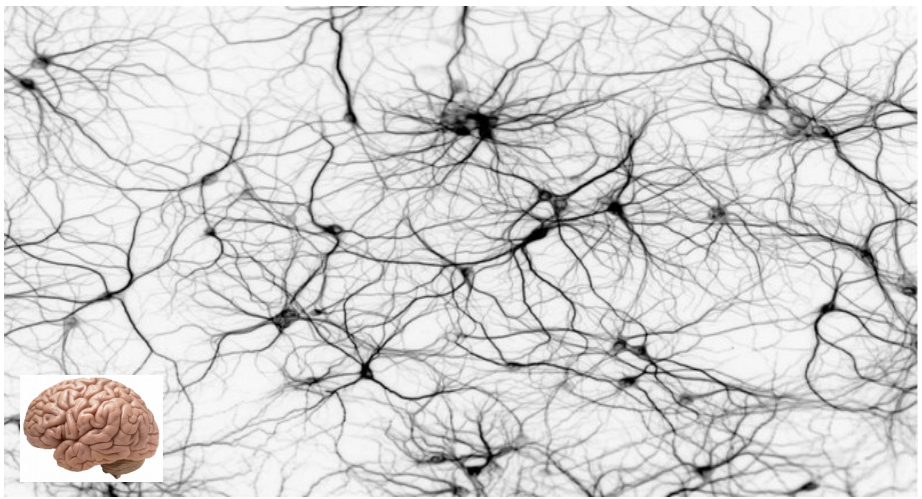
Deep learning is *extremely* hungry for data & computation.





Deep Learning ≡ DNN

- Inspired by biological neural networks



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

Deep Learning ≡ DNN

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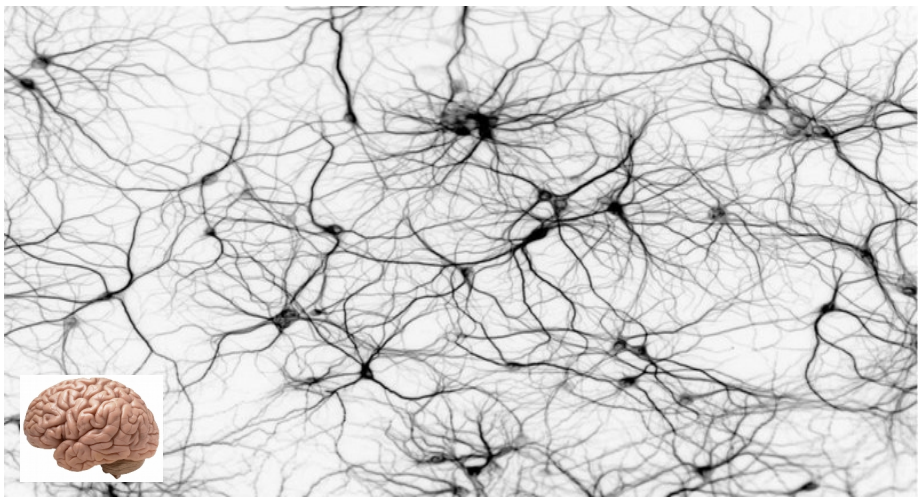
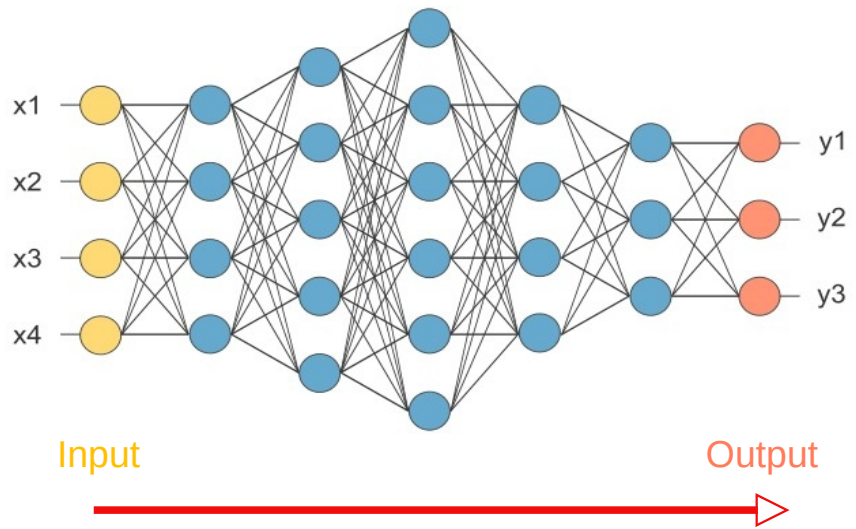


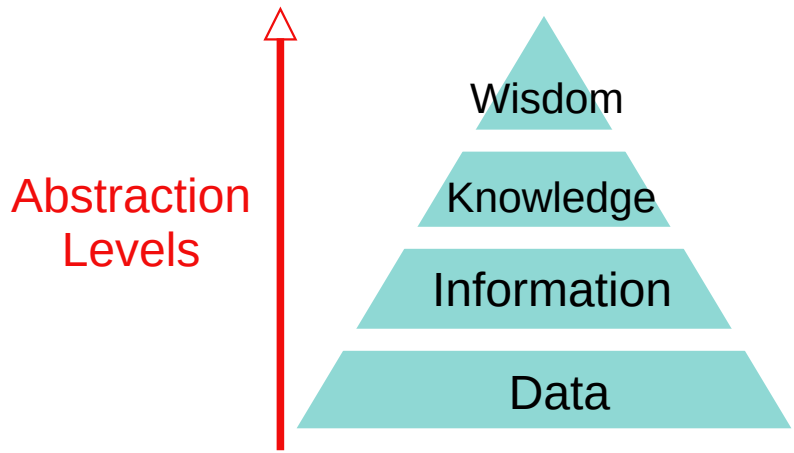
Human Brain: 86B Neurons; 86,000B Synapses

Airplanes have wing but do not flap!

DNNs vs Machine Learning (1)

- Depth → Abstraction → Better Features





DNN: Deep Neural Network

DNNs vs Machine Learning (1)

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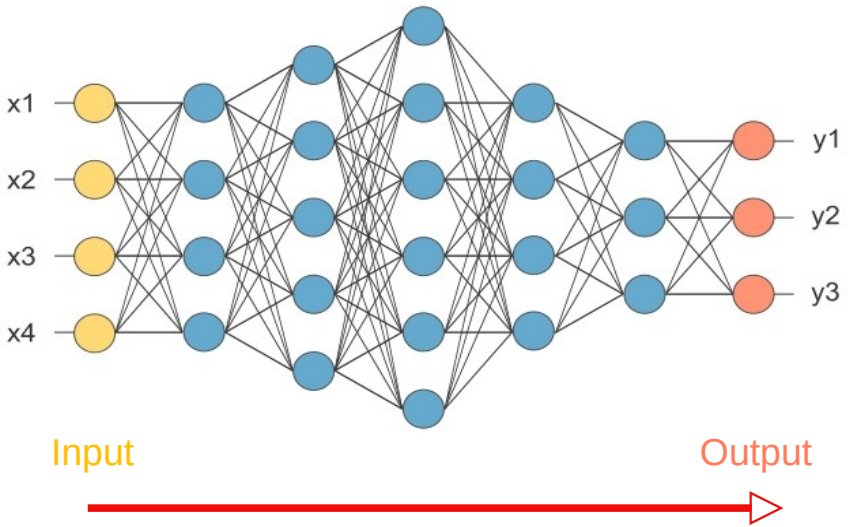
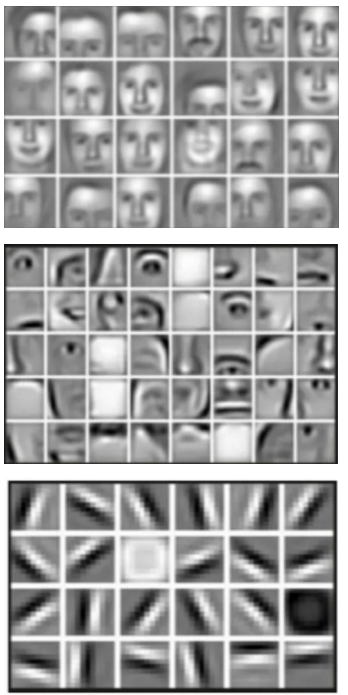


Face Recognition



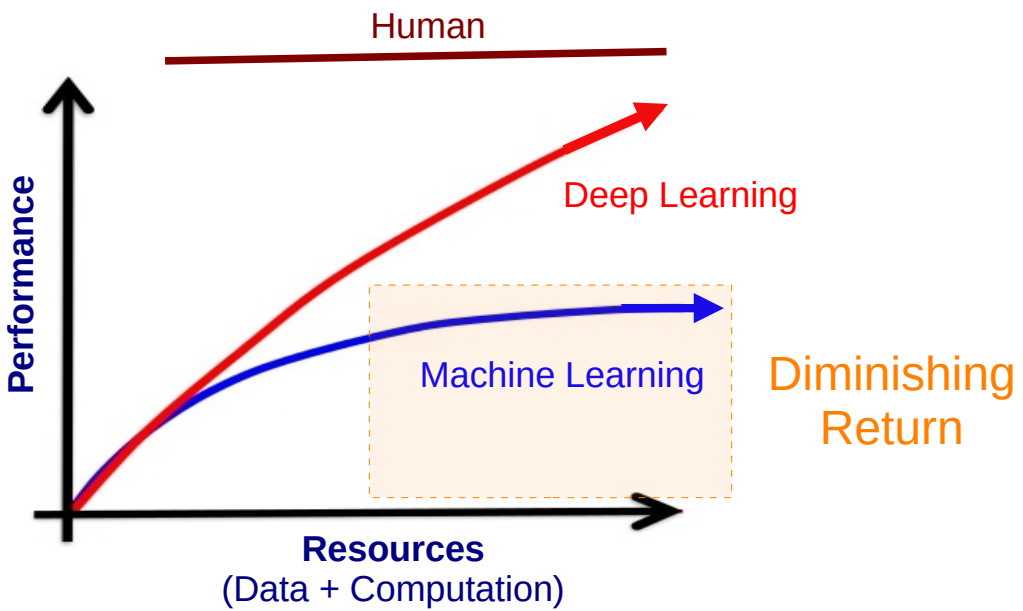
Abstraction Levels

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 GPT-4

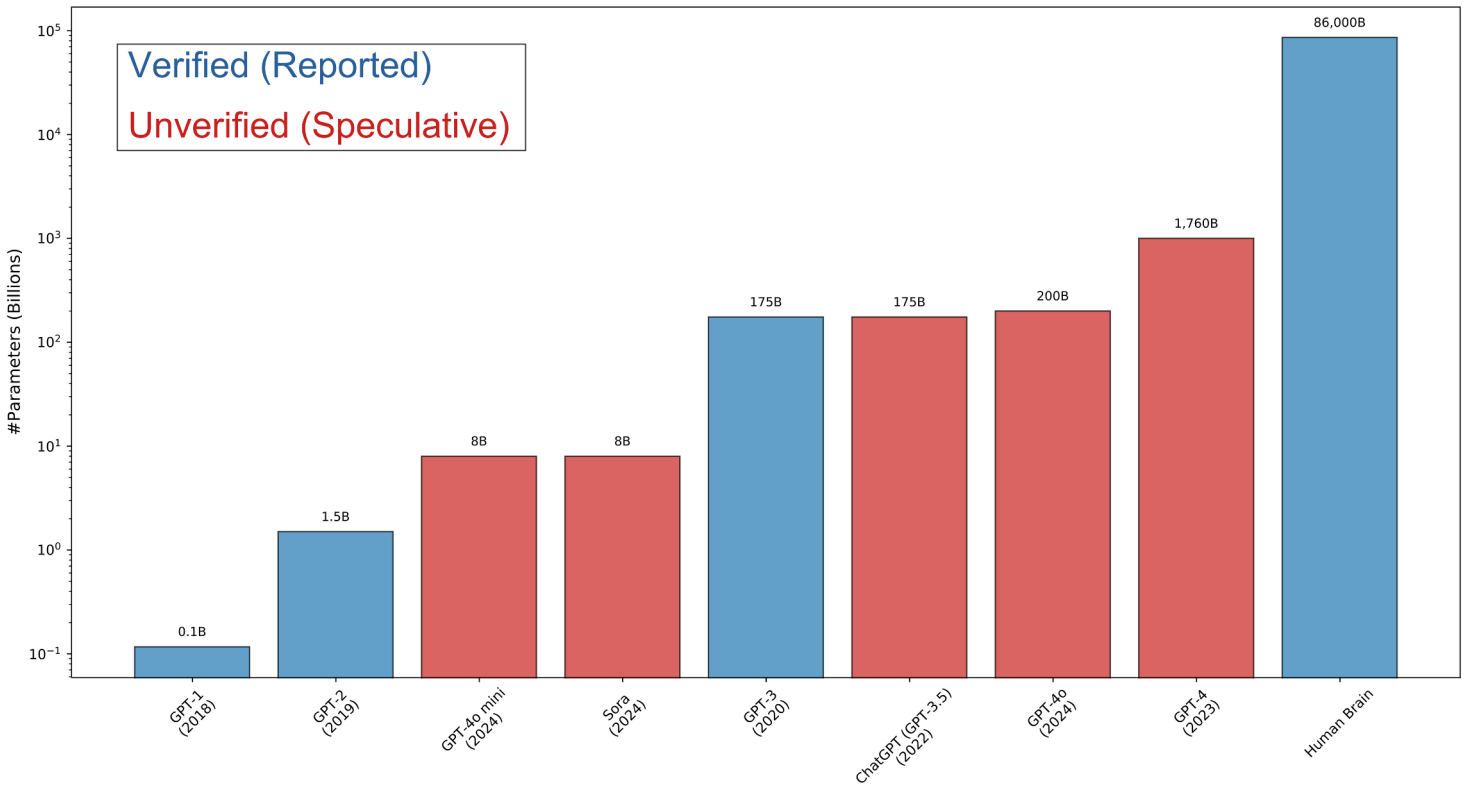
DALL·E

OpenAI Sora

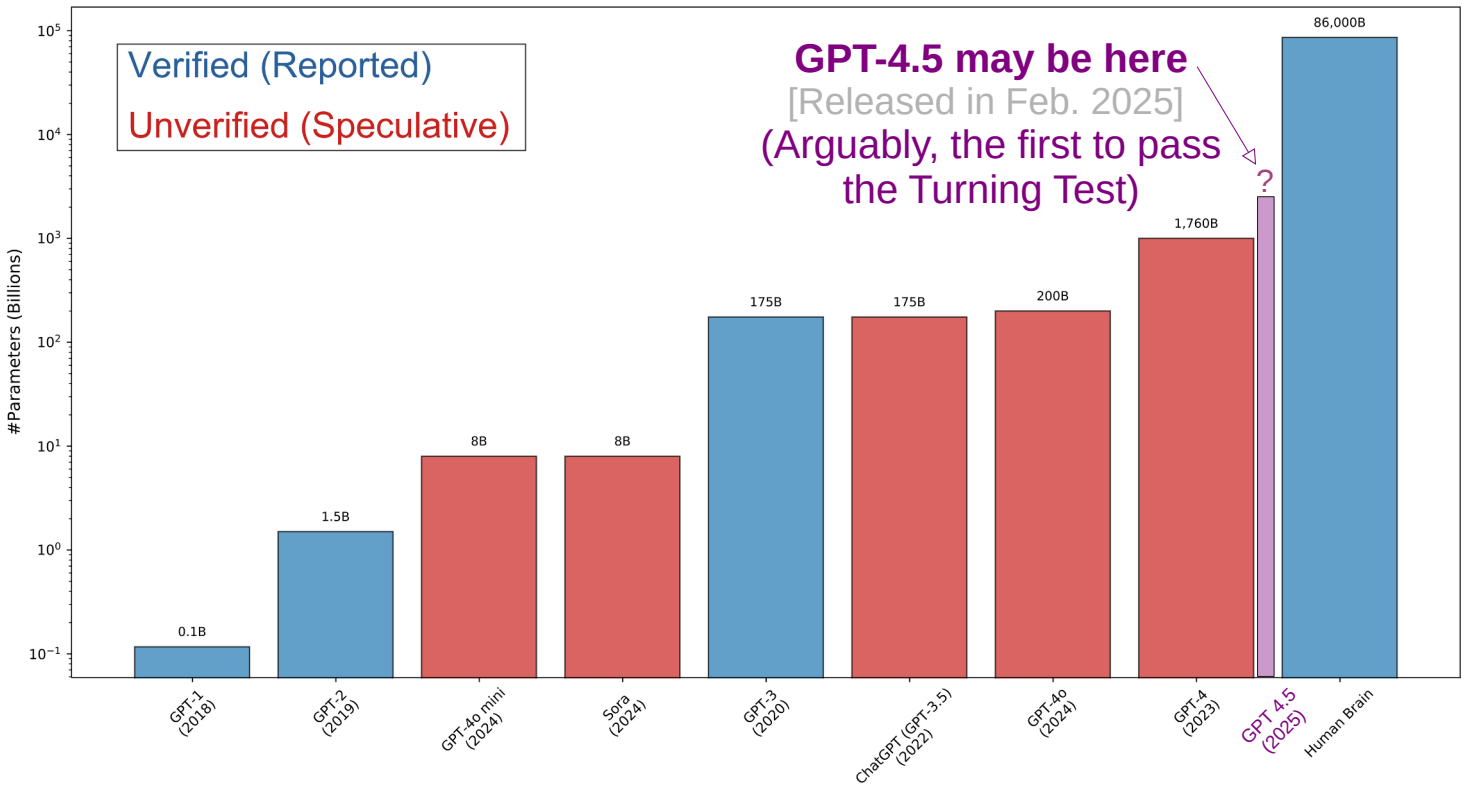
OpenAI GPT-4o

Microsoft VALL-E

OpenAI's Models vs Brain



OpenAI's Models vs Brain

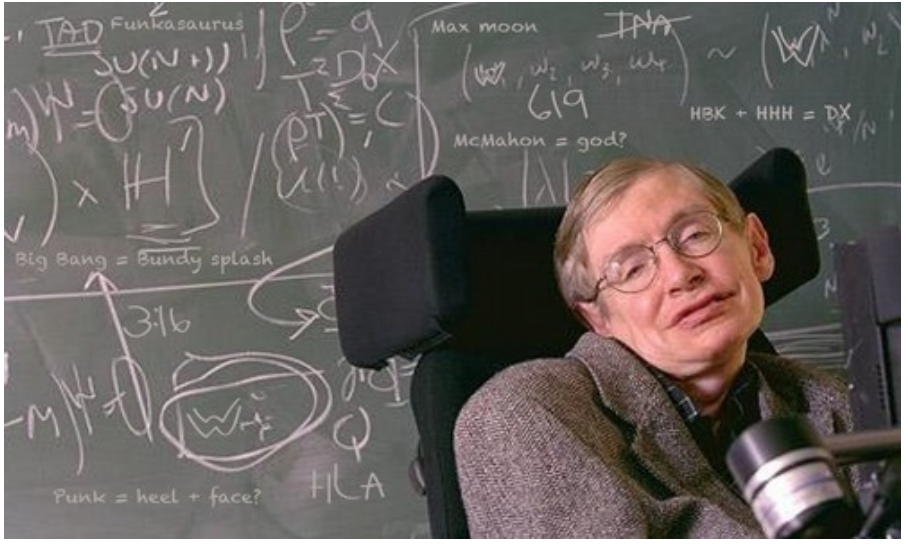


LLMs:

Pinnacle of *Sequential Modelling*

- **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



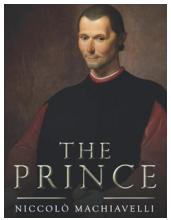
The development of full artificial intelligence could spell the end of the human race. *[Source: BBC, 2014]*

Stephen Hawking
(1942-2018)

Malicious Uses of AI

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

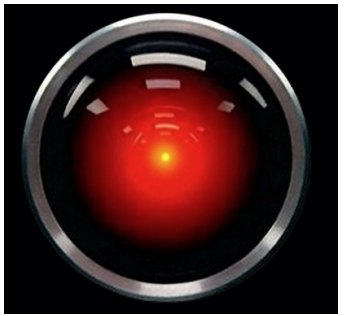
Rogue AI: Myth or Risk? (1)



- **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!*

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

1968

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

Generated by ChatGPT
(DALL·E 3, OpenAI)