CAP 781
MACHINE LEARNING

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UNIT – I
Introduction of Machine Learning

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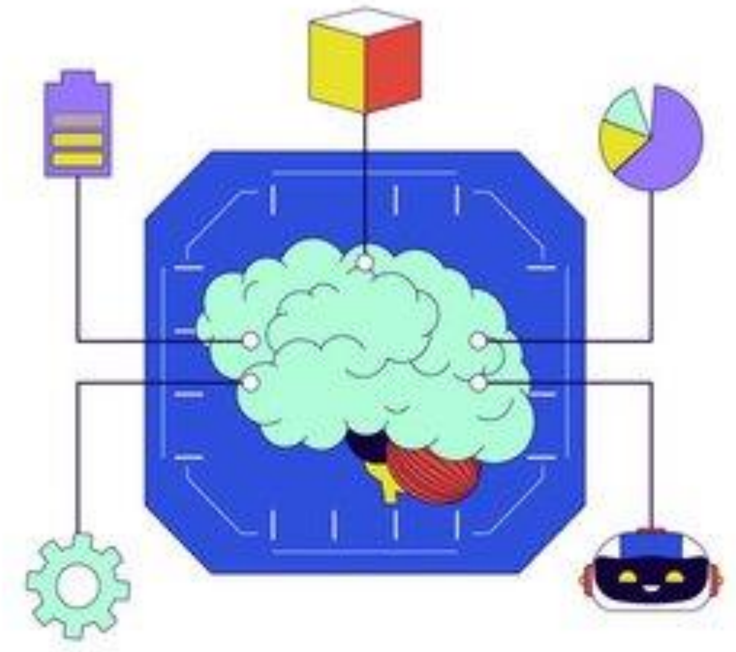
Content

- History of Machine Learning
- Programs vs learning algorithms
- Basic definitions
- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning
- Issues in machine learning
- Different Applications of Machine learning



From Automation to Intelligence: The Journey of Machine Learning

How Machines Evolved to Learn

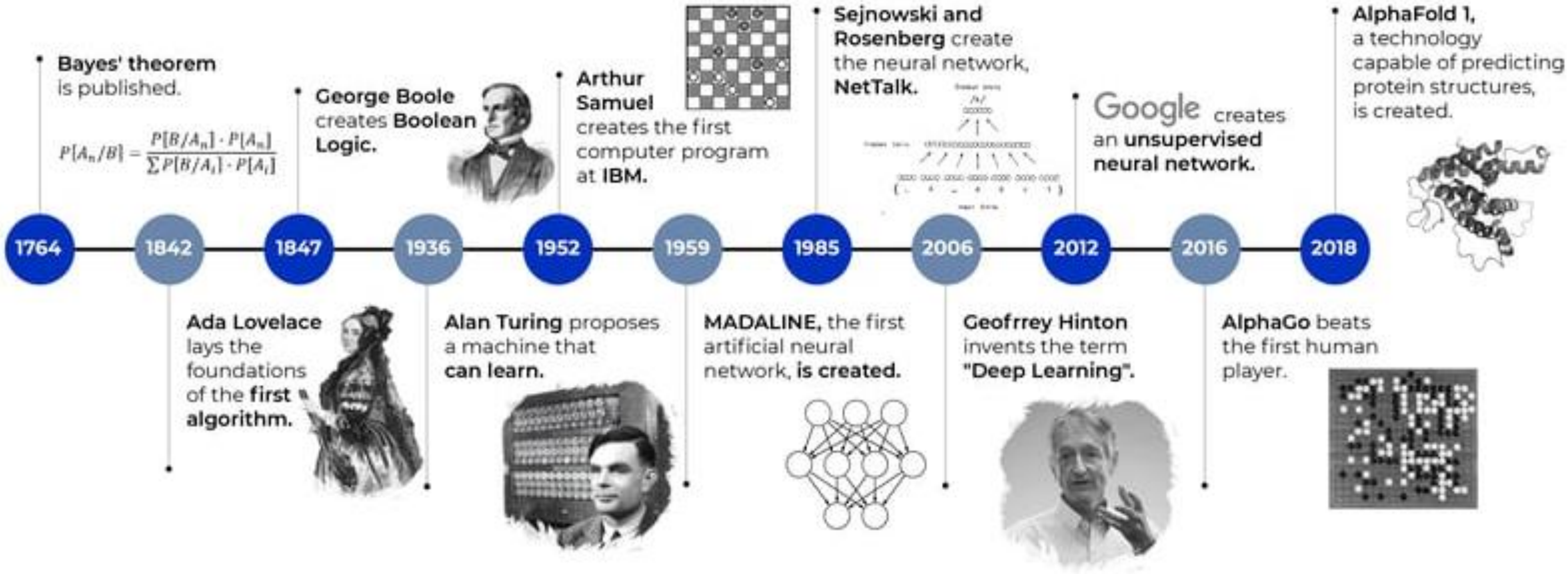
Have you ever wondered how your phone predicts what you’re about to type?

How does a self-driving car navigate without human intervention?

Where Did Machine Learning Come From?

- **1950s:** Alan Turing introduces the Turing Test.
- **1959:** Arthur Samuel develops a checkers-playing program.
- **1980s-1990s:** Statistical models and neural networks emerge.
- **2000s-Now:** Big Data + Deep Learning → Rapid growth in AI applications.

MACHINE LEARNING TIMELINE



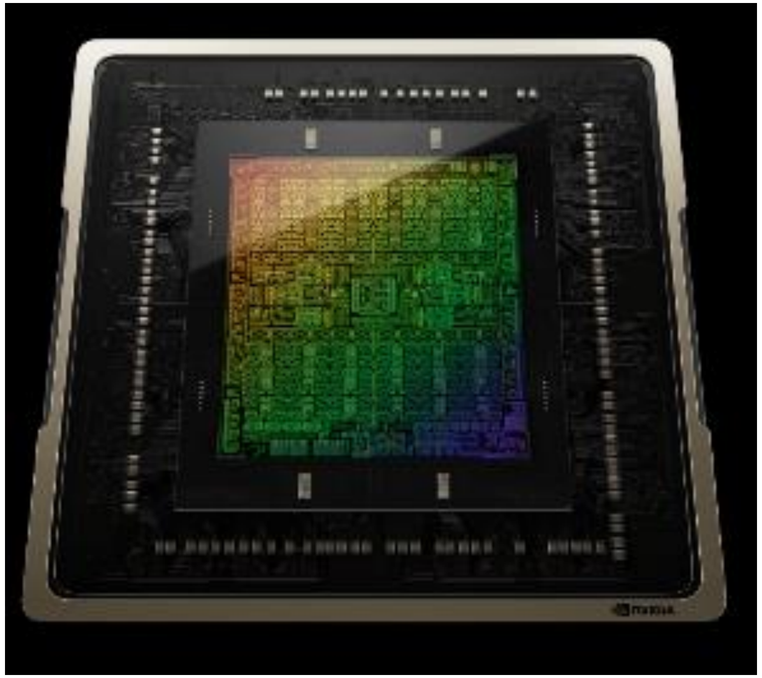
Lady Ada Lovelace
(1815 - 1852) - English Mathematician

First Computer Programmer

An associate of **Charles Babbage**, for whose prototype of a digital computer she created a program.

NVIDIA Ada Lovelace Architecture

Designed to deliver outstanding gaming and creating, professional graphics, AI, and compute performance.



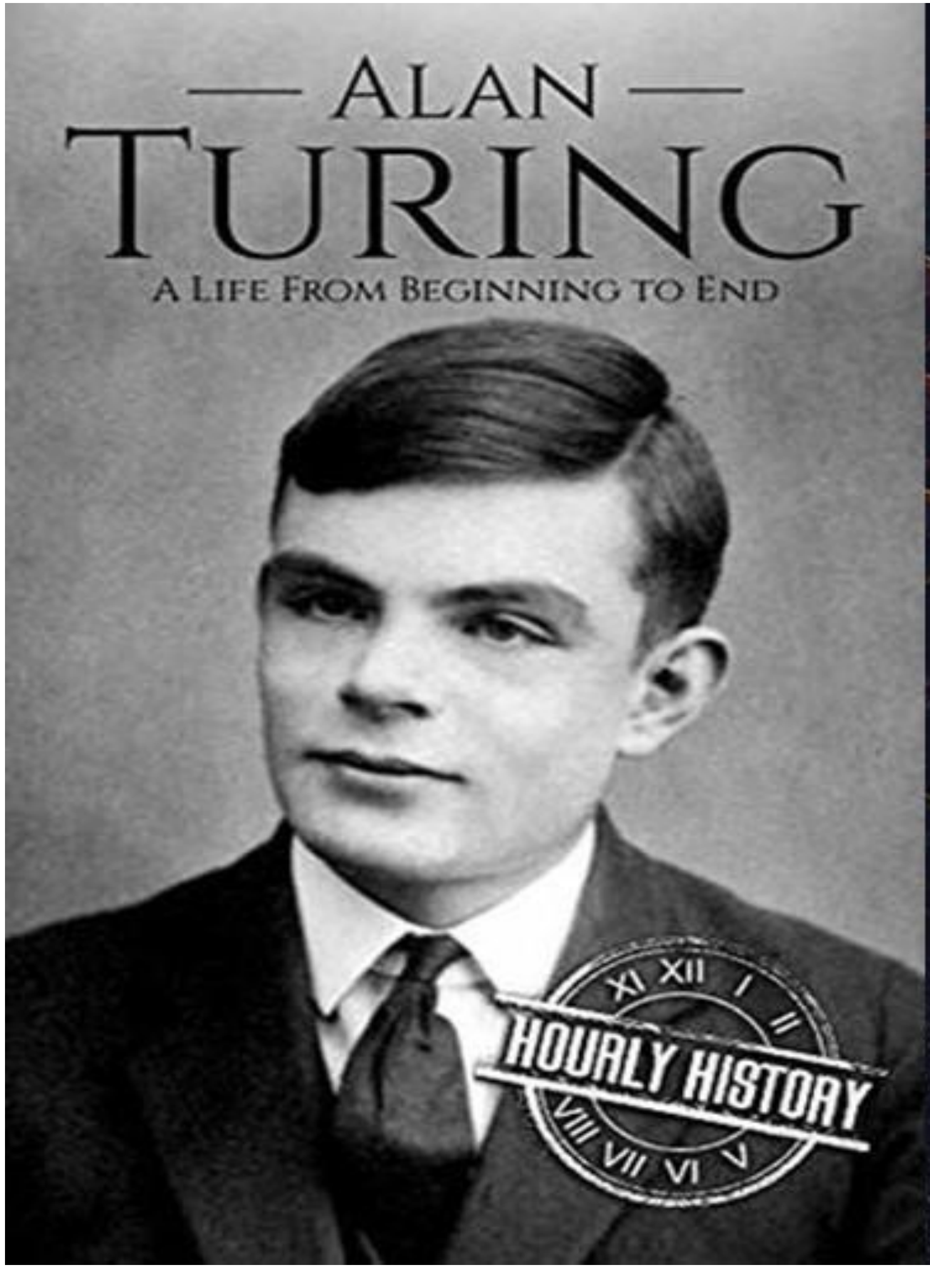
Computing Machinery and Intelligence

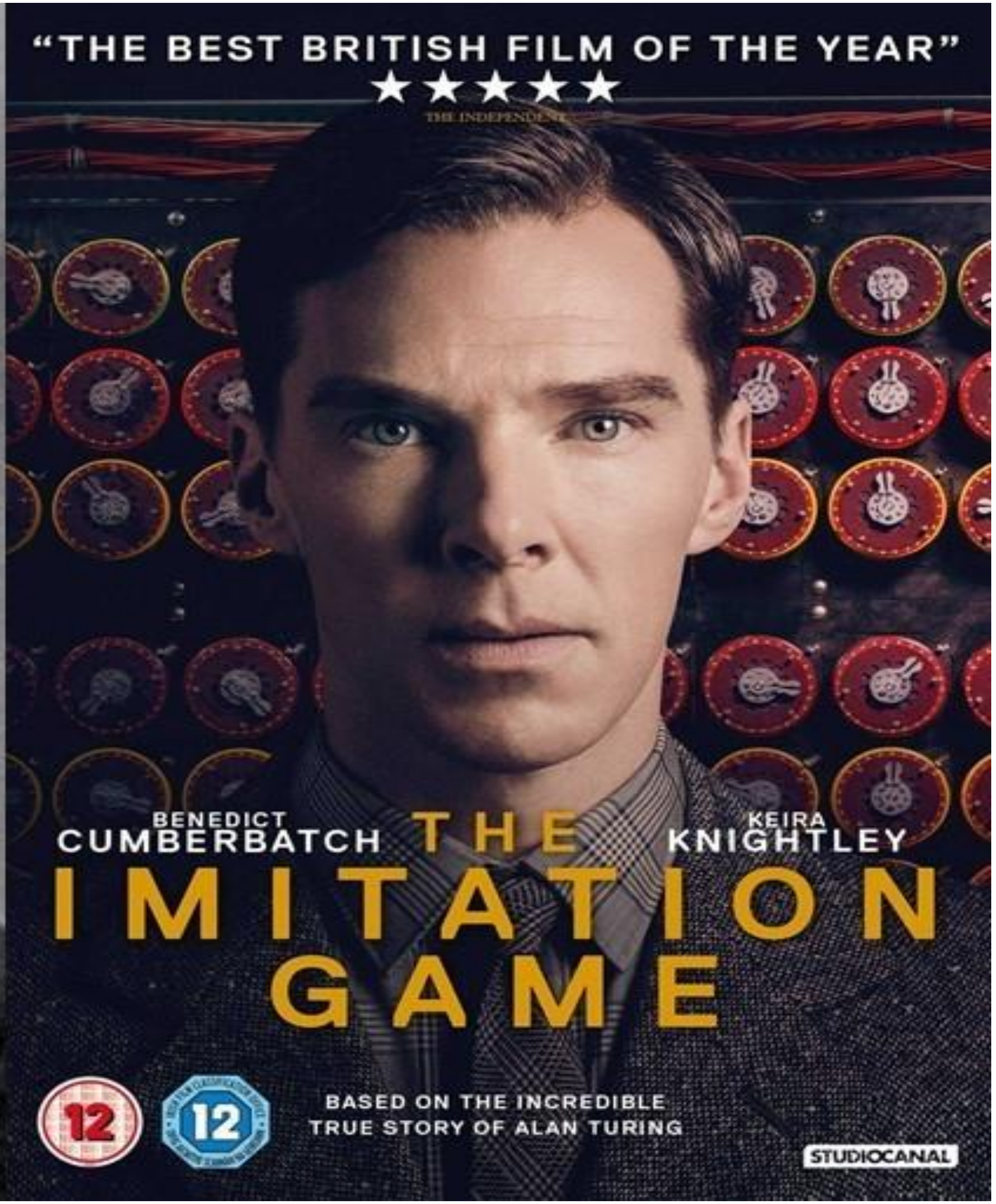
A. M. Turing

1950

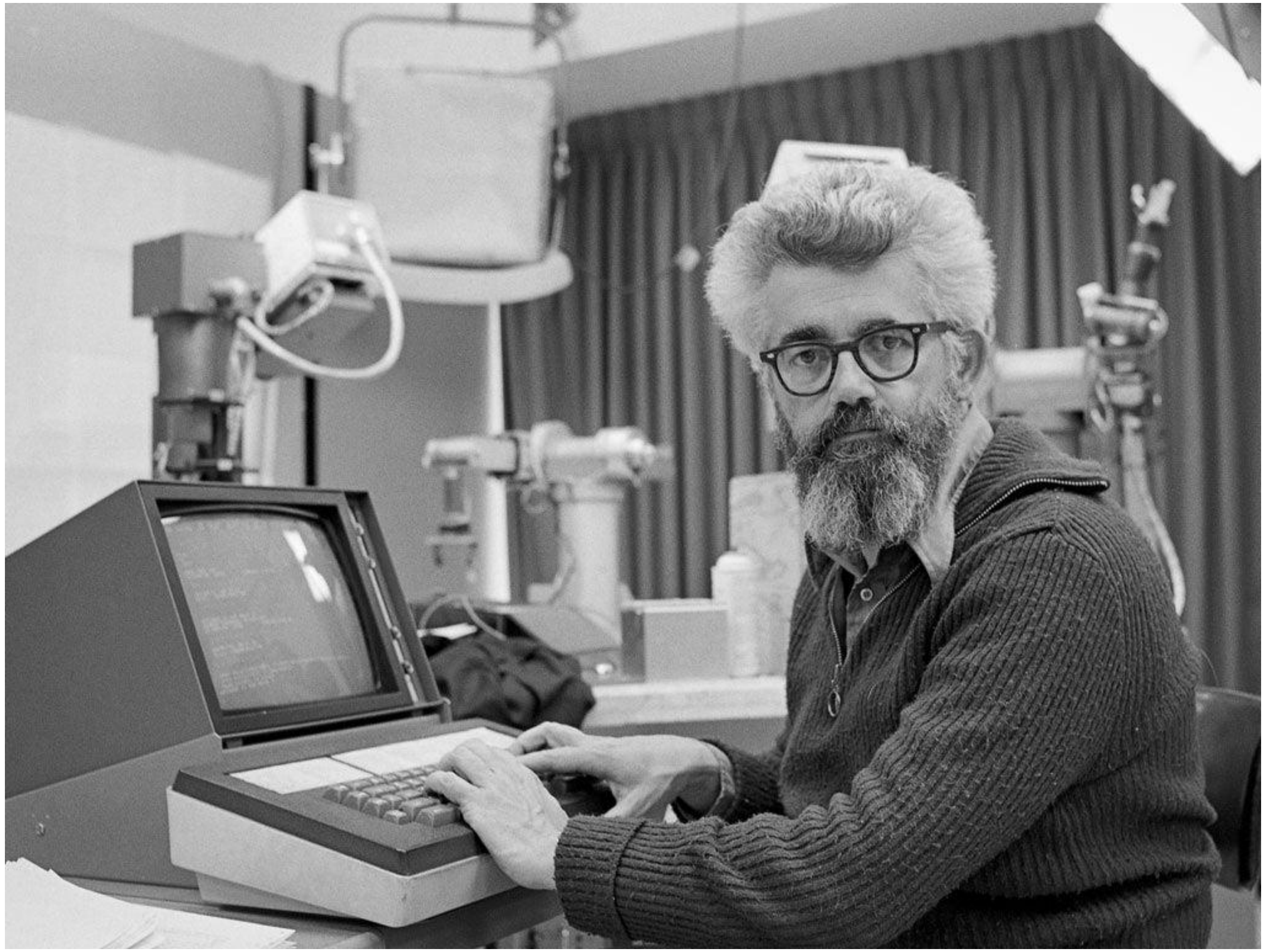
1 The Imitation Game

I propose to consider the question, "Can machines think?" This should begin with definitions of the meaning of the terms "machine" and "think." The definitions might be framed so as to reflect so far as possible the normal use of the words, but this attitude is dangerous, If the meaning of the words "machine" and "think" are to be found by examining how they are commonly used it is difficult to escape the conclusion that the meaning and the answer to the question, "Can machines think?" is to be sought in a statistical survey such as a Gallup poll. But this is absurd. Instead of attempting such a definition I shall replace the question by another, which is closely related to it and is expressed in relatively unambiguous words.

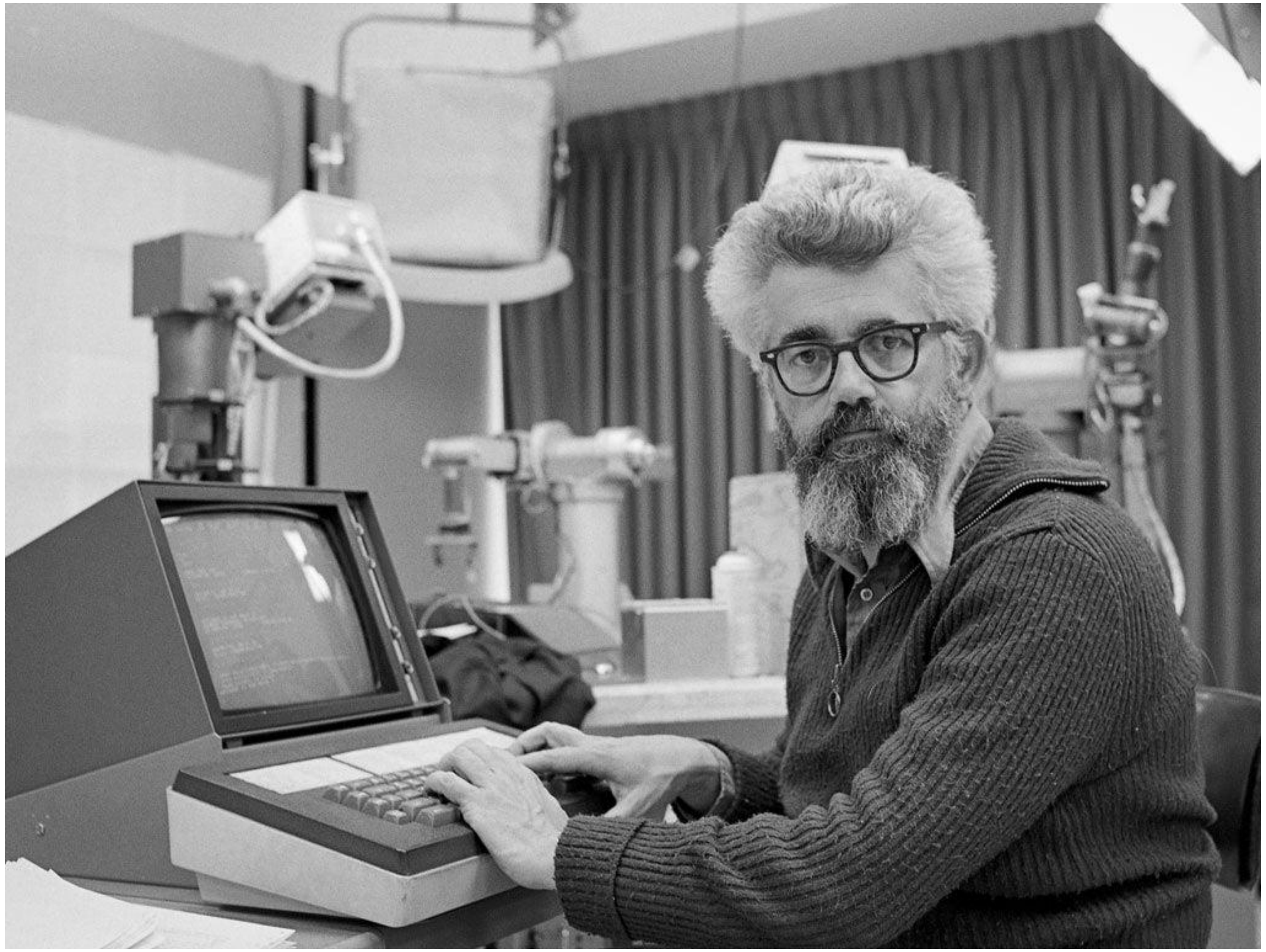

ALAN
TURING
A LIFE FROM BEGINNING TO END
HOURLY HISTORY


"THE BEST BRITISH FILM OF THE YEAR"
★★★★★
BENEDICT
CUMBERBATCH
KEIRA
KNIGHTLEY
THE
IMITATION
GAME
12
12
BASED ON THE INCREDIBLE
TRUE STORY OF ALAN TURING
STUDIOCANAL

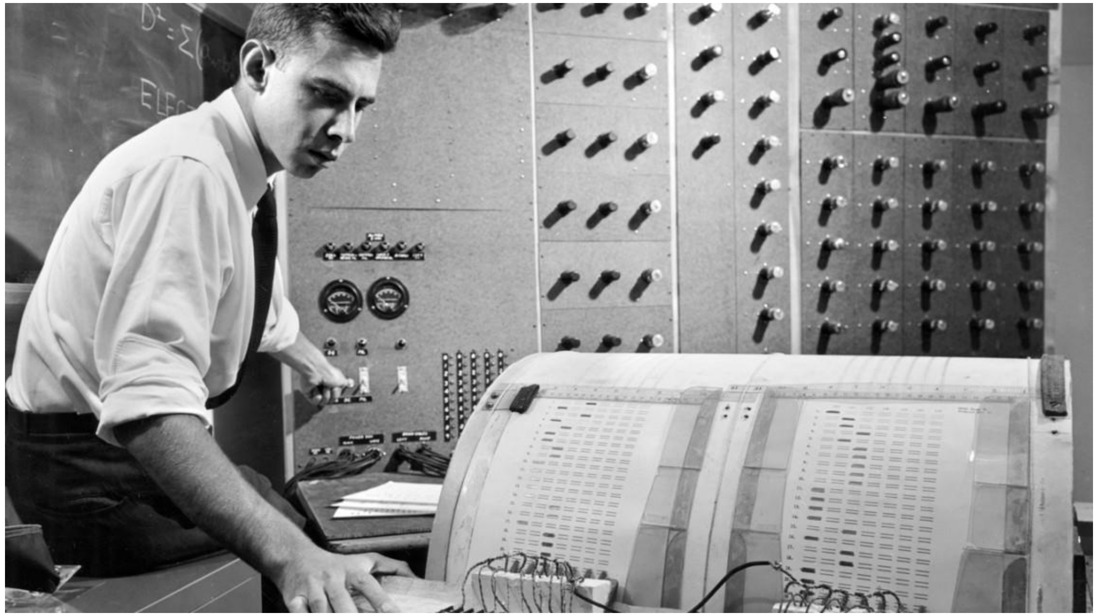
American computer scientist – Coined term for AI (1955)



John McCarthy: Computer scientist known as the father of AI



Professor Frank Rosenblatt



- An IBM 704 – a 5-ton computer the size of a room – was fed a series of punch cards. After 50 trials, the computer taught itself to distinguish cards marked on the left from cards marked on the right.
- It was a demonstration of the "perceptron" – "the first machine which is capable of having an original idea," according to its creator, Frank Rosenblatt.

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research trends

CORNELL AERONAUTICAL LABORATORY, INC., BUFFALO 21, NEW YORK

The Design of an Intelligent AUTOMATON

by FRANK ROSENBLATT

Introducing the perceptron — A machine which senses, recognizes, remembers, and responds like the human mind.

STORIES about the creation of machines having human qualities have long been a fascinating province in the realm of science fiction. Yet we are now about to witness the birth of such a machine — a machine capable of perceiving, recognizing, and identifying its surroundings without any human training or control.

Development of that machine has stemmed from a search for an understanding of the physical mechanisms which underlie human experience and intelligence. The question of the nature of these processes is at least as ancient as any other question in western science and philosophy, and, indeed, ranks as one of the greatest scientific challenges of our time.

Our understanding of this problem has gone perhaps as far as had the development of physics before Newton. We have some excellent descriptions of the phenomena to be explained, a number of interesting hypotheses, and a little detailed knowledge about events in the nervous system. But we lack agreement on any integrated set of principles by which the functioning of the nervous system can be understood.

We believe now that this ancient problem is about to yield to our theoretical investigation for three reasons:

First, in recent years our knowledge of the functioning of individual cells in the central nervous system has vastly increased.

Second, large numbers of engineers and mathematicians are, for the first time, undertaking serious study of the mathematical basis for thinking, perception, and the handling of information by the central nervous system, thus providing the hope that these problems may be within our intellectual grasp.

Third, recent developments in probability theory and in the mathematics of random processes provide new tools for the study of events in the nervous system, where only the gross statistical organization is known and the precise cell-by-cell "wiring diagram" may never be obtained.

Receives Navy Support

In July, 1957, Project PARA (Perceiving and Recognizing Automaton), an internal research program which had been in progress for over a year at Cornell Aeronautical Laboratory, received the support of the Office of Naval Research. The program had been concerned primarily with the application of probability theory to

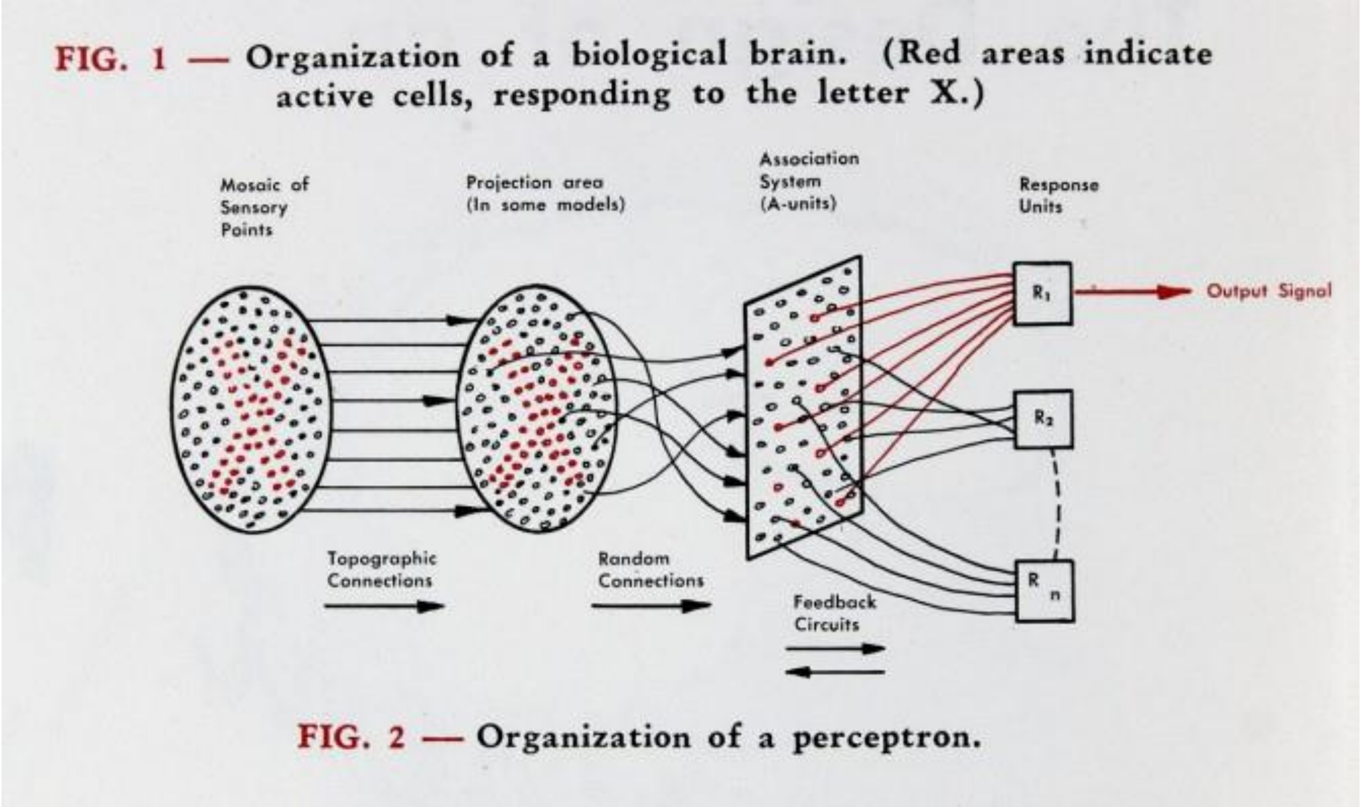


FIG. 1 — Organization of a biological brain. (Red areas indicate active cells, responding to the letter X.)

FIG. 2 — Organization of a perceptron.

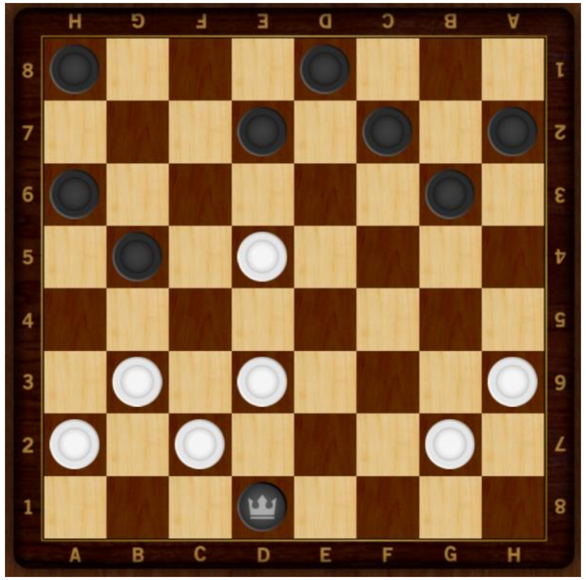
The perceptron, introduced by Frank Rosenblatt in 1958.

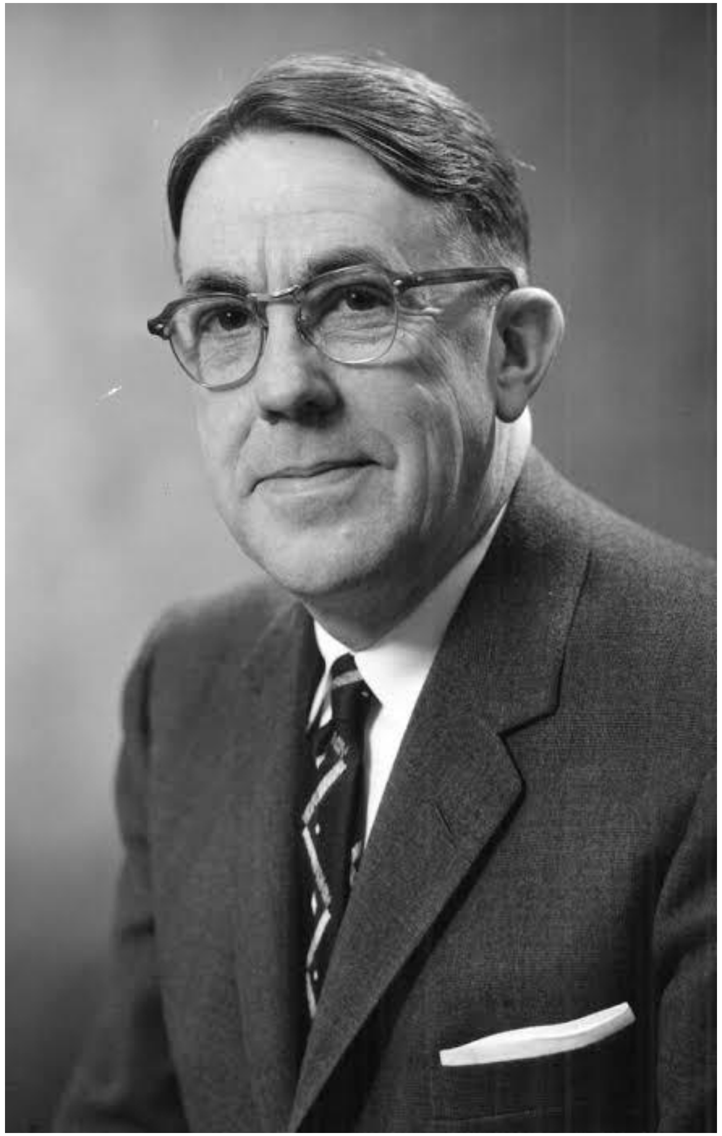
It was a binary classifier that learned to distinguish between two categories, such as shapes.

The Father of Machine Learning

Arthur Samuel

Arthur Samuel developed the first machine learning program, **Samuel's Checkers**, in **1959**, introducing the concept of machines learning from experience and improving performance over time.





Deep Blue

- IBM's **Deep Blue** used supercomputing power and brute-force computation to defeat world chess champion Garry Kasparov in **1997**, marking a major milestone in AI.

Deep Blue computing power

32

processors

200 million

chess positions evaluated per second

11.38 billion

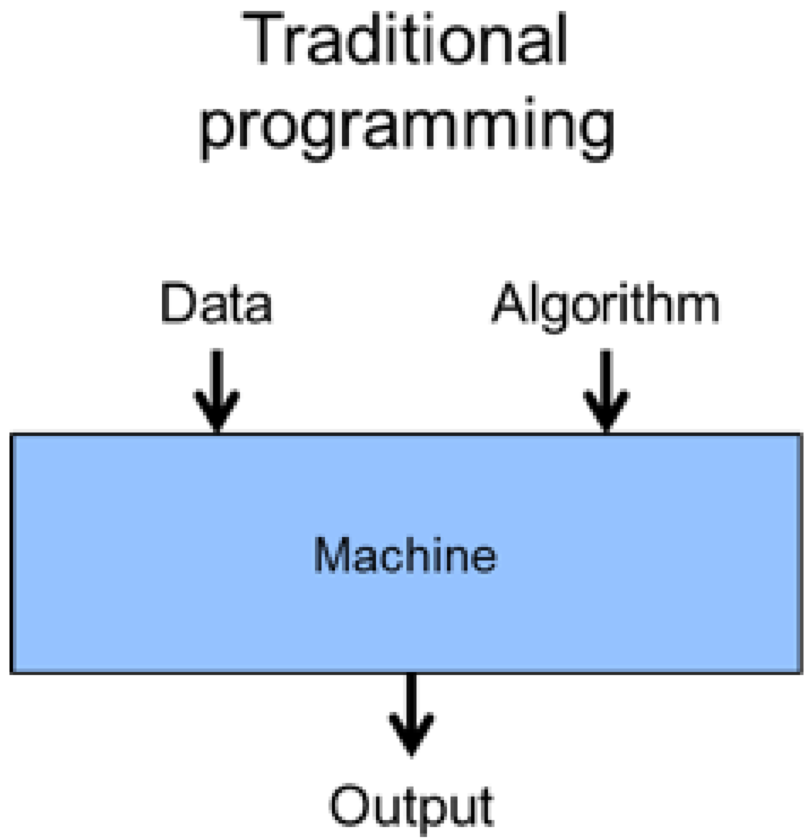
floating point operations per second (flops) of processing speed

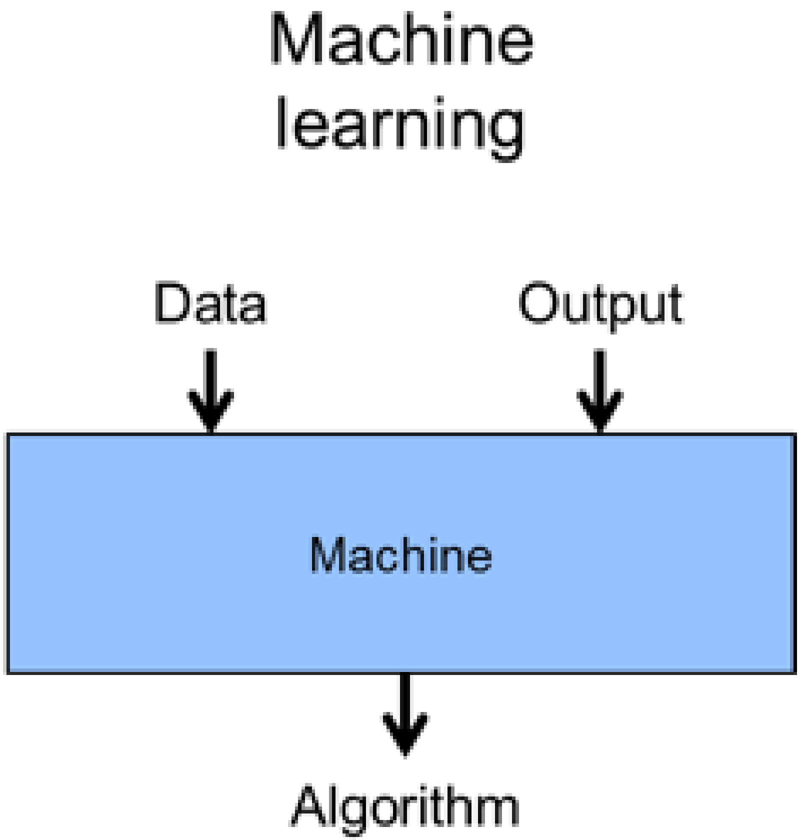
Computational power between **Deep Blue** and **ChatGPT-4**

Feature	**Deep Blue (1997)**	**ChatGPT-4 (2023)**
Computational Power	11.38 billion FLOPS (floating-point operations per second)	Estimated to be in the range of **exaflops** (1 exaflop = 1 billion billion FLOPS)
Processing Hardware	32 parallel processors	Large clusters of GPUs/TPUs
Performance Measure	Focused on evaluating chess positions per second	Focused on running deep learning models and natural language tasks

Why Did Machine Learning Enter Our Lives?

- **Limitations of Traditional Programming:**
  - Couldn’t adapt to new or complex situations.
- **Data Explosion:**
  - Overwhelming amounts of data from sensors, social media, and transactions.
- **Demand for Personalization:**
  - Tailored recommendations (e.g., Netflix, Amazon).
- **Technological Advancements:**
  - Faster processors and GPUs made ML feasible.


Traditional programming
Data
Algorithm
Machine
Output


Machine learning
Data
Output
Machine
Algorithm

What is the History of Machine Learning?

1. **Symbolic AI Era (1950s-1970s):** Rule-based systems dominated. ML experiments were limited by technology.
2. **Statistical Era (1980s-1990s):** Focus shifted to probabilistic models and neural networks.
3. **Modern ML Era (2000s-now):** Big data and advancements in deep learning enabled systems like Siri, GPT, and AlphaGo.

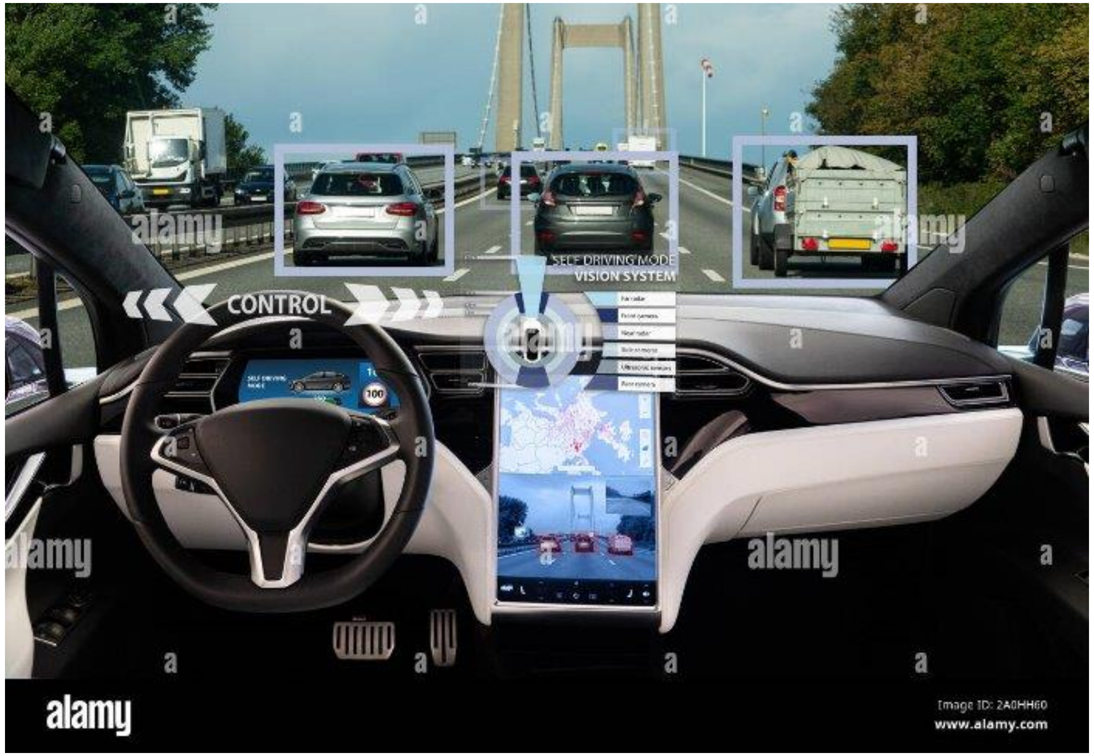

Important ML milestones
1960S
Decision trees
1980
Backpropagation
1998
CNN
2010S
Deep Learning models
1957
Perceptron
1969
Multilayer perceptron
1990S
SVM
2001
Random Forest
2017
Transformer models

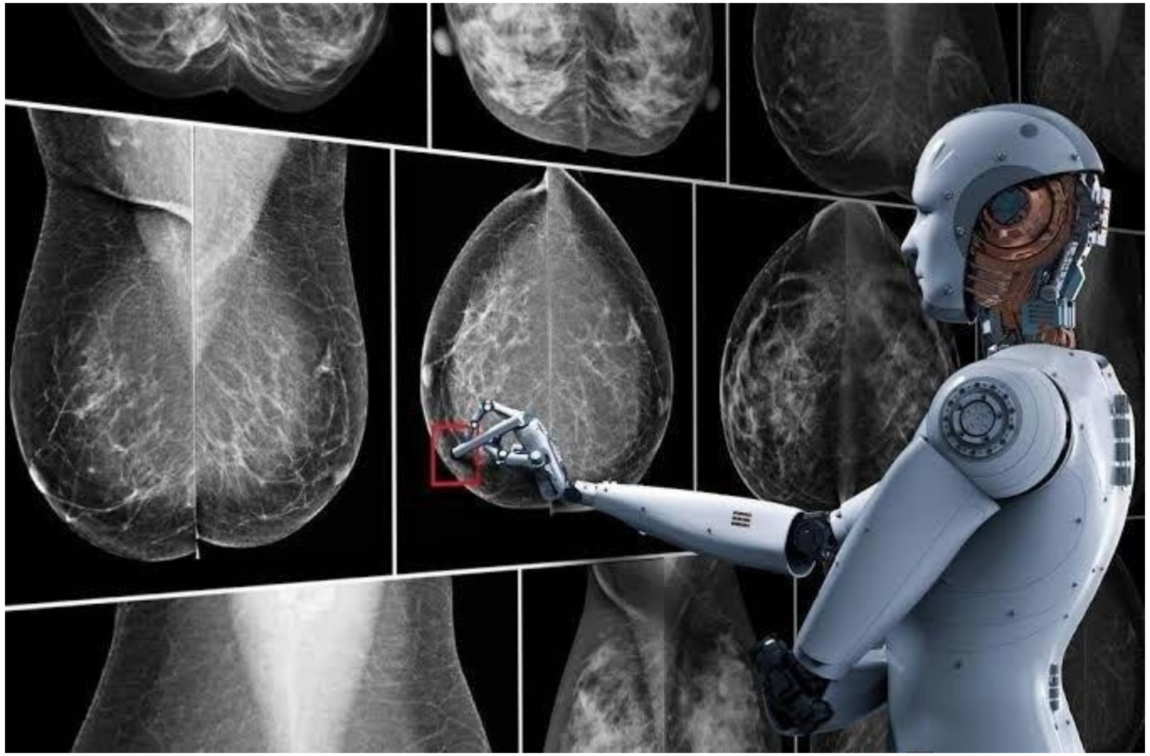
Why Study Machine Learning?

1. Solve problems too complex for traditional programming.
2. Automate decisions and make predictions.
3. Enhance human life through smarter tools and technologies.

Example:

- Detecting cancer using medical imaging.
- Enabling self-driving cars to navigate safely.


CONTROL
SELF DRIVING MODE
VISION SYSTEM
alamy
Image ID: 2A0HH60
www.alamy.com



Brains vs. Code: The Rise of Learning Algorithms

Why Learning Algorithms Outshine Traditional Code

Traditional Programs vs. Learning Algorithms

Traditional Programs:

1. Follow explicit, pre-written instructions.
2. Output depends on hard-coded rules.
3. Examples: Calculators, search engines (earlier versions).

Learning Algorithms:

1. Extract patterns and insights from data.
2. Improve with experience (no explicit rules needed).
3. Examples: Spam filters, facial recognition, chatbots.

Why the Shift to Learning Algorithms?

Limitations of Code, Power of Learning

- **Complexity Beyond Human Coding:**
  - Handwritten code struggles with unstructured data (e.g., images, speech).
- **Data-Driven Insights:**
  - Learning algorithms find patterns humans might miss.
- **Adaptability:**
  - Can improve and generalize over time.

Real-Life Examples of Learning Algorithms

What Can They Do?

- Detect diseases from medical scans.
- Translate languages in real time.
- Recommend what to watch or buy.

Brains vs. Code: Who Wins?

- Traditional code is precise but limited.
- Learning algorithms mimic human-like decision-making.
- Together, they create the future of intelligent systems.

Cracking the Code of Intelligence: Defining Machine Learning

What Machine Learning Truly Means

What is Machine Learning?

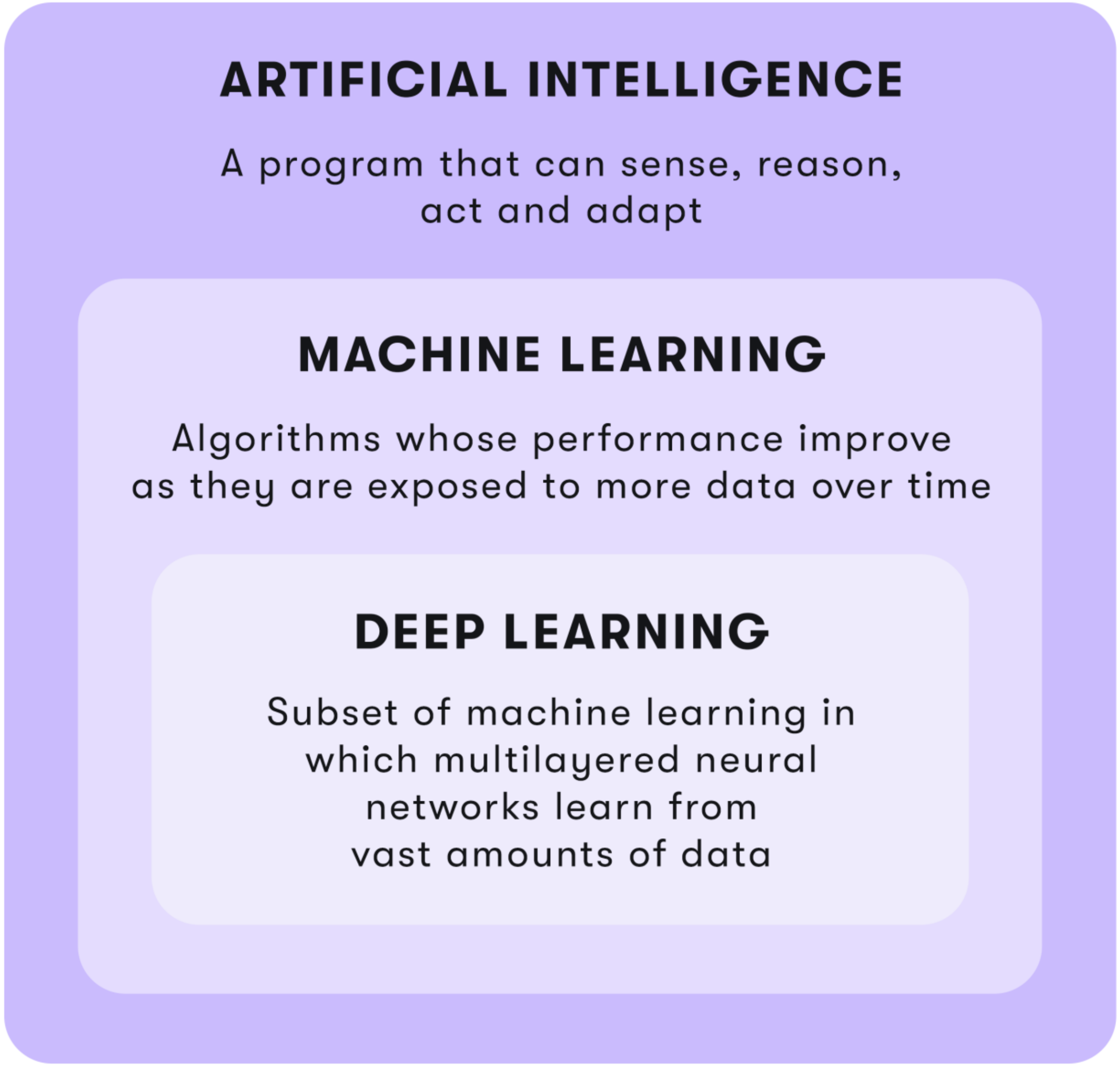
"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E."

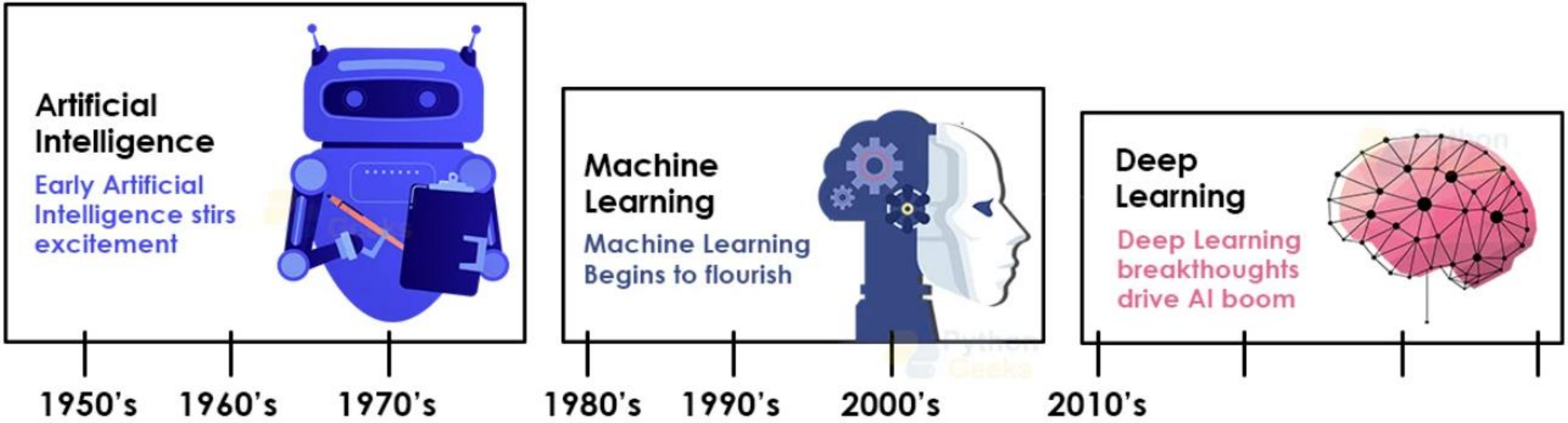
Tom M. Mitchell

Example:

- **Task:** Detect spam emails.
- **Experience:** Train on labeled email data.
- **Performance:** Measure accuracy in spam detection.

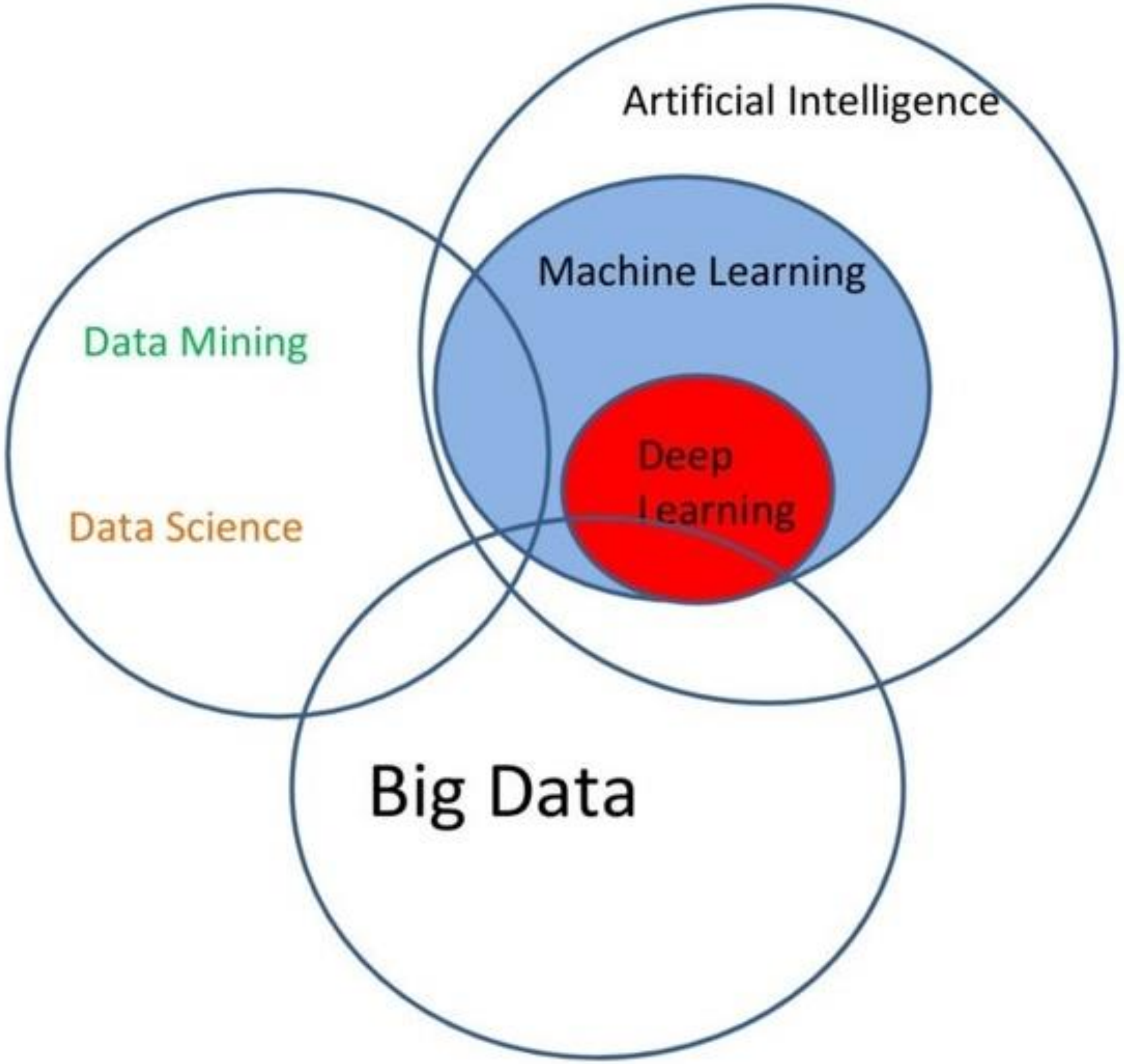
"Machine Learning is a way to teach computers to learn from experience, without being explicitly programmed for every task."




Artificial Intelligence
Early Artificial Intelligence stirs excitement
Machine Learning
Machine Learning Begins to flourish
Deep Learning
Deep Learning breakthoughts drive AI boom
1950's
1960's
1970's
1980's
1990's
2000's
2010's

?

What do you think?



Guided Intelligence: How Machines Learn with Supervision

Learning Through Guidance

What is Supervised Learning?

Definition:

- Machines learn from labeled data where the input-output relationship is clearly defined.

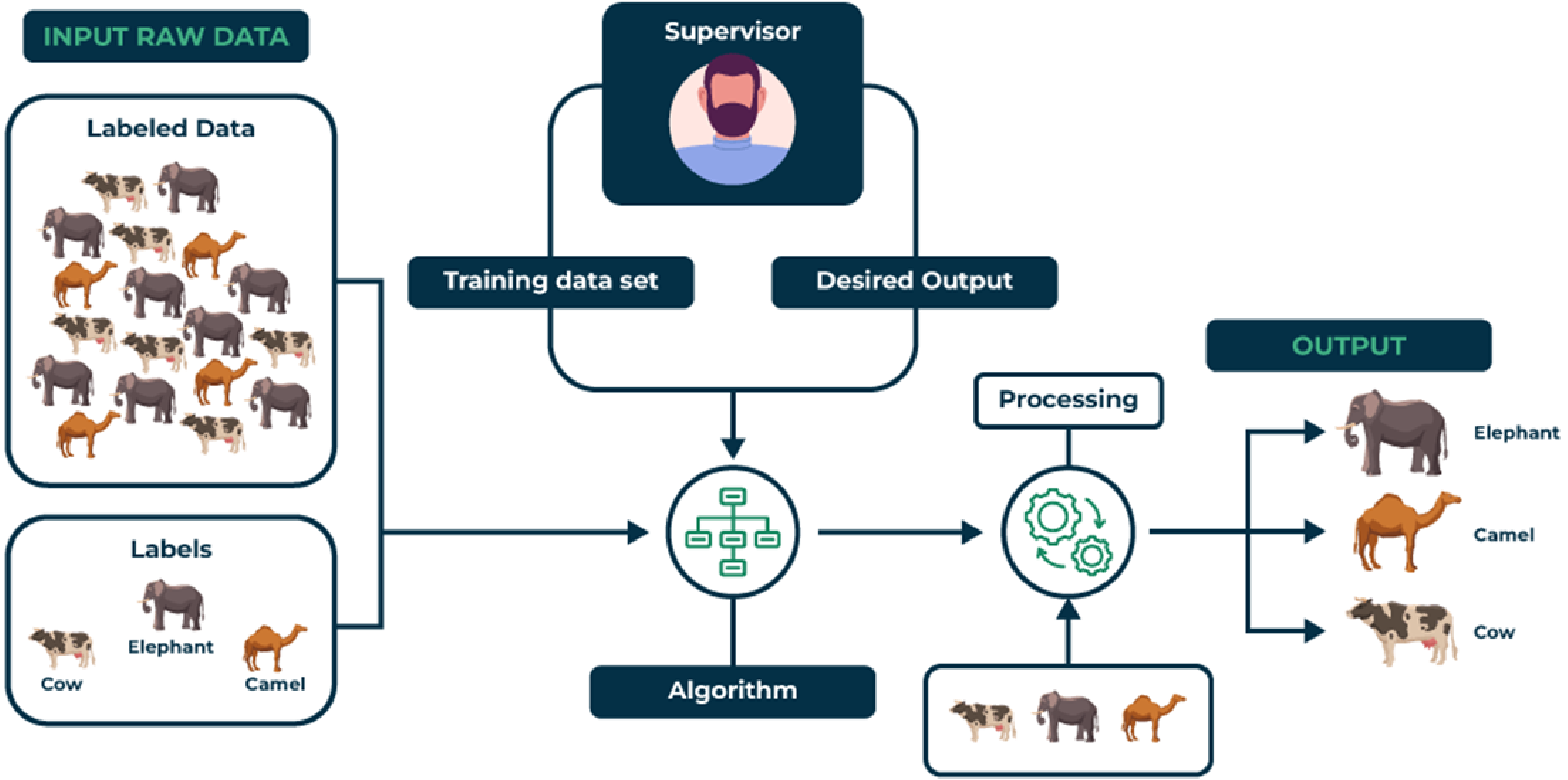
Idea:

- The algorithm predicts outputs for new data by learning from example input-output pairs.

Example:

- Input: Images of cats and dogs (labeled).
- Output: Predict whether a new image is a cat or dog.

Supervised Learning



Applications of Supervised Learning

Where is Supervised Learning Used?

1. **Email Spam Detection:** Classify emails as spam or not.
2. **Medical Diagnosis:** Predict diseases from patient data.
3. **Stock Price Prediction:** Forecast future prices based on historical data.

Supervised learning is essential for tasks requiring accurate, data-driven predictions.

Unleashing Discovery: Machine Learning Without Labels

Learning without Guidance

What is Unsupervised Learning?

Learning Without Labels

Definition:

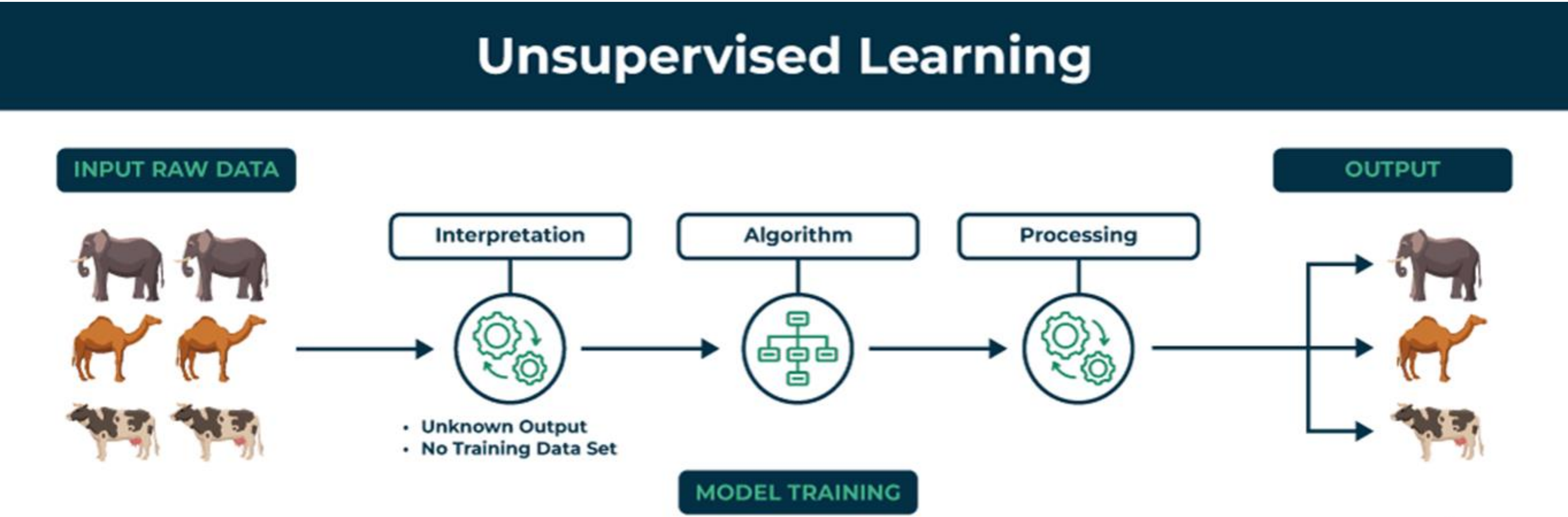
- Machines learn patterns and structures in unlabeled data without predefined outputs.

Idea:

- The algorithm uncovers hidden insights or groupings within the data.

Example:

- Grouping customers into segments based on purchasing behavior (clustering).


Unsupervised Learning
INPUT RAW DATA
OUTPUT
Interpretation
Algorithm
Processing
• Unknown Output
• No Training Data Set
MODEL TRAINING

Applications of Unsupervised Learning

Where Does Unsupervised Learning Shine?

1. **Customer Segmentation:** Identify groups for targeted marketing.
2. **Anomaly Detection:** Spot unusual patterns in data (e.g., fraud detection).
3. **Dimensionality Reduction:** Simplify data for visualization or modeling.

Unsupervised learning reveals the hidden structure of data, driving discovery and innovation.

Learning from Consequences: The Power of Reinforcement Learning

Learning from Actions and Rewards

What is Reinforcement Learning?

Definition:

- In reinforcement learning (RL), machines learn by interacting with an environment and receiving feedback (rewards or penalties).

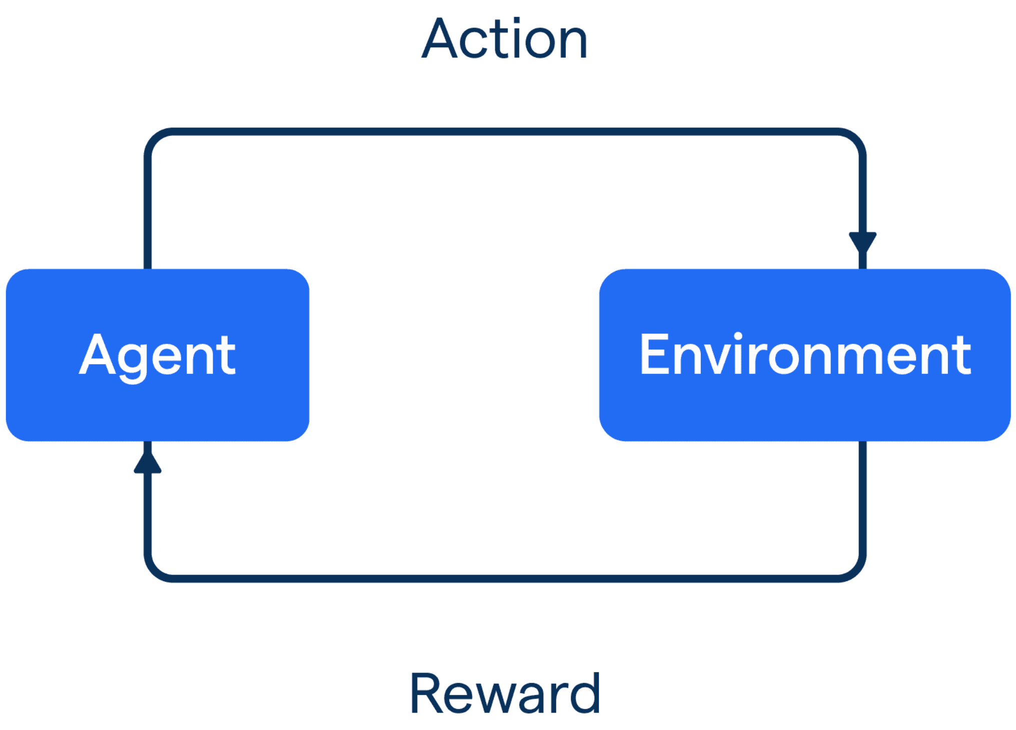
Idea:

- The agent improves its strategy over time by maximizing cumulative rewards.

Example:

- **Task:** Teach a robot to navigate a maze.
- **Feedback:** Positive reward for reaching the goal, penalty for hitting walls.

Reinforcement Learning



Applications of Reinforcement Learning

Where Reinforcement Learning is Changing the Game

1. **Game AI:** Training agents to play and win video games (e.g., AlphaGo).
2. **Robotics:** Robots learning complex tasks like walking or assembling objects.
3. **Autonomous Vehicles:** Cars learning how to drive based on feedback from their environment.

RL empowers machines to learn optimal behaviors in dynamic, real-world environments.

Hurdles to Intelligence: Challenges in Machine Learning

Overcoming Obstacles to Smarter Machines

Common Challenges in Machine Learning

- **Insufficient Data:**
  - ML algorithms require large amounts of data to train, and not having enough can limit performance.
- **Data Quality:**
  - Noisy, incomplete, or biased data can lead to incorrect models.
- **Complexity & Interpretability:**
  - Models are often "black boxes," making decision-making hard to understand.
- **Overfitting & Underfitting:**
  - Balancing model complexity to ensure it generalizes well without memorizing the training data or failing to learn patterns.

Addressing These Challenges

How Do We Tackle These Hurdles?

- **Data Augmentation:**
  - Increasing data diversity through transformations or synthetic data.
- **Regularization Techniques:**
  - Methods like dropout and L2 regularization to avoid overfitting.
- **Bias Mitigation:**
  - Ensuring fairness in data and models to avoid discrimination.

Addressing these challenges ensures more reliable, ethical, and efficient machine learning models.

Bigger Challenges in Machine Learning

1. **High Computational Costs:**
   Demands expensive hardware and energy, raising environmental concerns.
2. **Ethical Concerns:**
   Privacy issues and biased data can lead to unfair models.
3. **Lack of Generalization:**
   Models often struggle to adapt across different tasks or datasets.
4. **Expertise Dependency:**
   ML requires specialized knowledge, limiting broader adoption.
5. **Security Vulnerabilities:**
   Susceptible to adversarial attacks, compromising predictions.
6. **Maintenance & Updates:**
   Models need continuous monitoring and retraining to stay effective.
7. **Legal & Regulatory Issues:**
   Compliance with data laws and unclear ML regulations pose challenges.

Revolutionizing the World: Applications of Machine Learning

How ML is Transforming Industries

Applications of Machine Learning

ML has permeated numerous industries and daily life. Key applications include

- **Healthcare**
- **Finance**
- **Education**
- **Transportation**
- **Retail**
- **Manufacturing**
- **Entertainment**
- **Agriculture**
- **Environment**
- **Security**

Healthcare

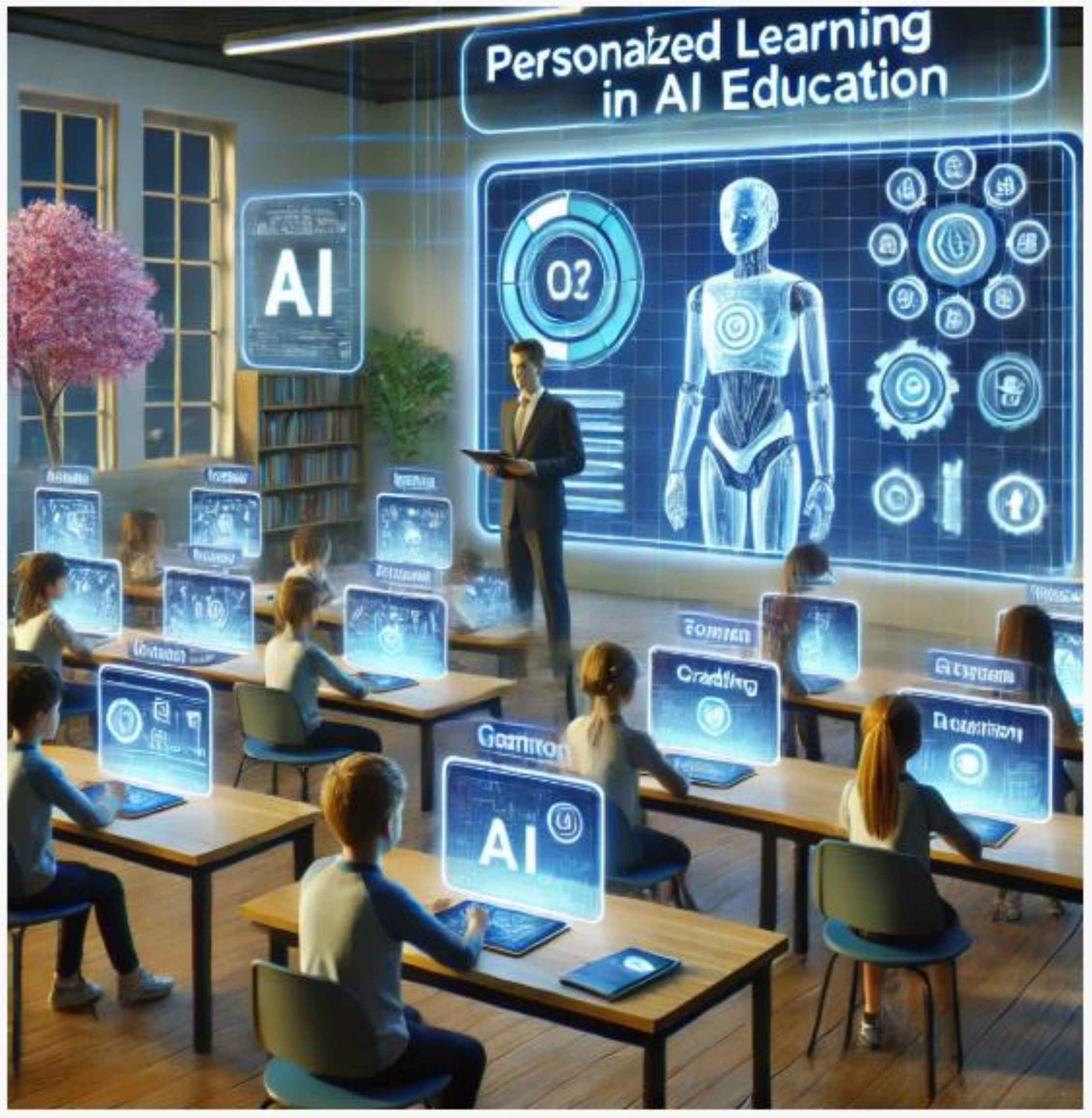
- AI-powered diagnostic tools analyze medical images (e.g., detecting cancer).
- Virtual health assistants provide health advice.
- Predictive analytics for patient care and resource allocation.

Finance

- Fraud detection systems monitor unusual transactions.
- Algorithmic trading optimizes investment strategies.
- Chatbots assist customers with banking queries.

Education

- Personalized learning platforms adapt to students' needs.
- Automated grading systems evaluate assignments efficiently.
- AI tutors provide on-demand learning support.



Transportation

- Autonomous vehicles like self-driving cars.
- AI systems optimize traffic management.
- Predictive maintenance for vehicles and infrastructure.

Retail

- Recommendation engines suggest products to customers.
- Inventory management systems use AI for demand forecasting.
- Chatbots handle customer service inquiries.

Manufacturing

- Robotics streamline assembly lines.
- Predictive maintenance minimizes equipment downtime.
- Quality control systems detect defects in real-time.

Entertainment

- AI curates personalized playlists and content recommendations.
- Virtual reality and augmented reality experiences.
- AI-generated content, such as music or art.

Agriculture

- AI-powered drones monitor crop health.
- Precision farming optimizes resource use.
- Automated harvesting systems.

Environment

- AI monitors and predicts environmental changes.
- Supports wildlife conservation through pattern recognition.
- Optimizes renewable energy production.

Security

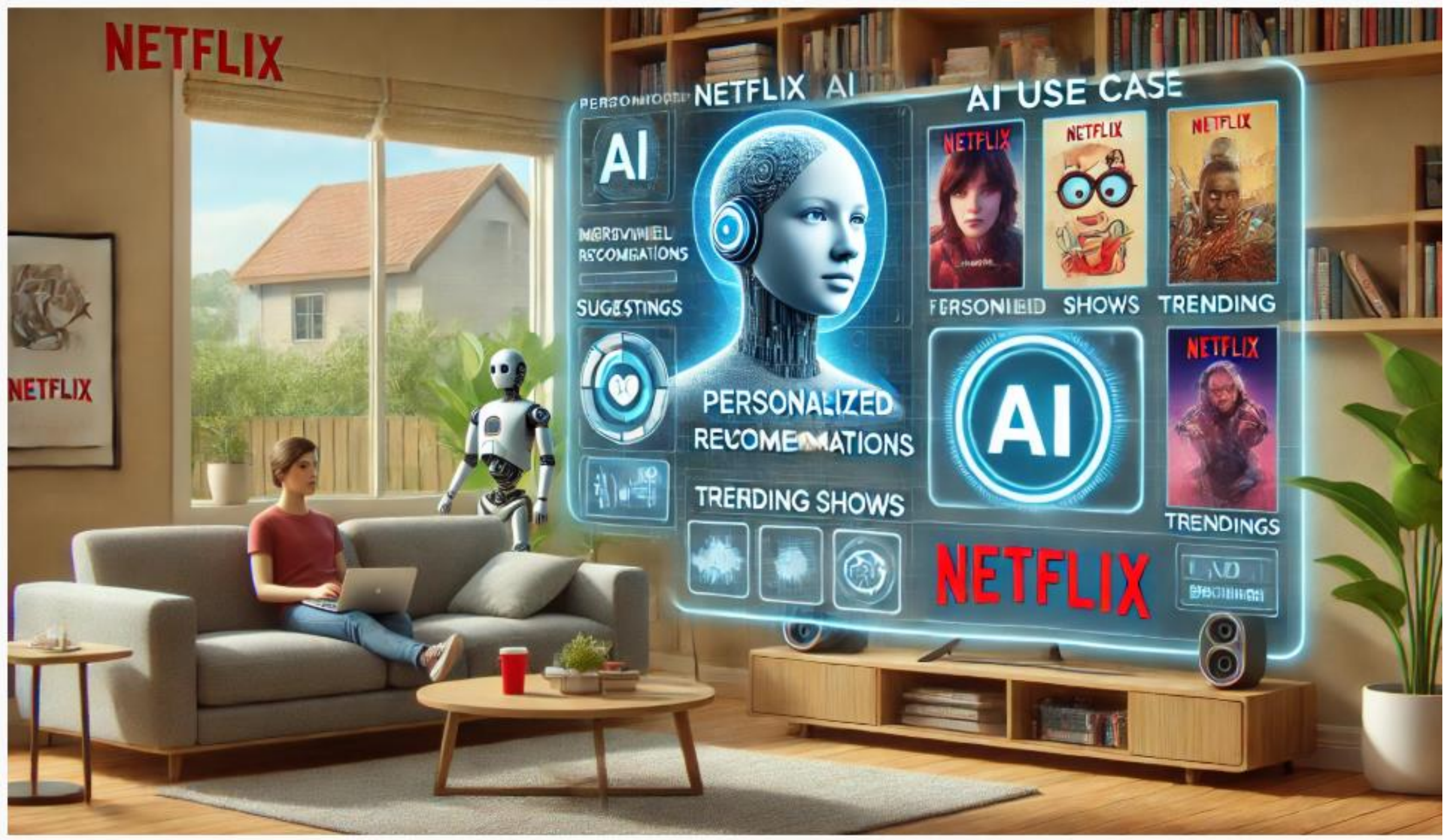
- Facial recognition systems enhance surveillance.
- Cybersecurity tools identify and neutralize threats.
- Disaster response systems analyze and predict natural disasters.

Achievements of Machine Learning

What Has Machine Learning Accomplished?

1. **Netflix's AI-Powered Recommendations** - Personalized movie and show recommendations using AI algorithms.
2. **Tesla's Self-Driving Technology** - Autonomous navigation with AI-powered decision-making.
3. **Amazon's AI-Driven Warehouse Automation** - Robotics and real-time inventory management.
4. **Google's Search Engine Optimization with AI** - User intent analysis and predictive text suggestions.
5. **Facebook's AI Content Moderation System** - Monitoring and flagging policy violations in posts.

Netflix's AI-Powered Recommendations



Tesla's Self-Driving Technology

Amazon's AI-Driven Warehouse Automation

Google's Search Engine Optimization with AI

Facebook's AI Content Moderation System

What Can We Achieve with ML?

1. Smarter systems for education and healthcare.
2. Climate predictions and energy optimization.
3. New AI-powered industries.

What will machines be capable of tomorrow?

Future-Focused Applications of ML

- **Autonomous Vehicles:**
  - Self-driving cars powered by reinforcement learning.
- **Smart Cities:**
  - Optimizing traffic, energy use, and waste management through AI.
- **Artificial General Intelligence (AGI):**
  - Pushing towards machines that can perform any intellectual task a human can.

AI is not just transforming industries; it's shaping the future of innovation across various fields.

Autonomous Vehicles

Autonomous Vehicles: Self-driving cars powered by reinforcement learning

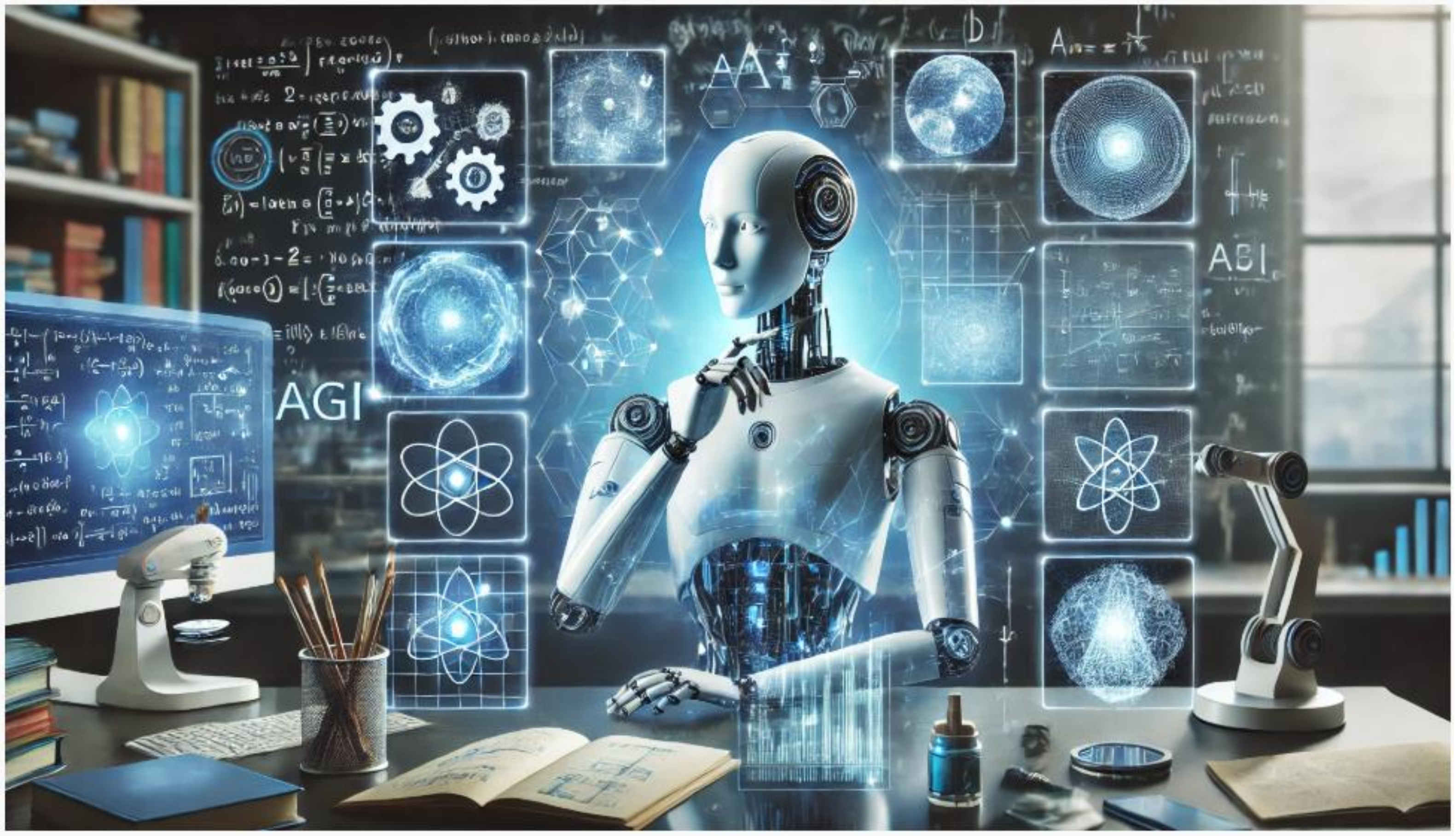
- Current Landscape
  - Reinforcement Learning (RL)
  - Technological Backbone
- Future Prospects
  - Level 5 Autonomy
  - Swarm Intelligence
  - Safety and Legislation
  - AI Evolution

Smart Cities

Smart Cities: Optimizing traffic, energy use, and waste management through AI

- Current Landscape
  - Traffic Management
  - Energy Optimization
  - Waste Management
- Future Prospects
  - Real-time Optimization
  - Personalized Urban Experience
  - Sustainability Goals
  - Integration with Autonomous Systems

Artificial General Intelligence (AGI)



Artificial General Intelligence (AGI)

- Current Landscape
  - Narrow AI Dominance
  - Research Efforts
- Future Prospects
  - Milestones in AGI Development
  - Impact on Industries
  - Ethical Considerations
  - Collaborative Intelligence

Thank You