Information
Technology
Institute

INTRODUCTION TO
ARTIFICIAL INTELLIGENCE

AGENDA

Understanding Artificial Intelligence

- What is Artificial Intelligence
- AI Paradigms
- History of AI

Machine Learning

- Machine Learning Core Concepts
- Supervised, Unsupervised & Reinforcement Learning
- ML Lifecycle

AGENDA cont.

Applications of AI

- Computer Vision
- Natural Language Processing
- Generative AI

Foundations for Learning AI

- Mathematical Foundation (Linear Algebra, Probability, Optimization.)
- Essential Programming (Python + Core libraries)
- Frameworks & tools (TensorFlow, PyTorch, etc.)

UNDERSTANDING ARTIFICIAL INTELLIGENCE

WHAT IS ARTIFICIAL INTELLIGENCE

AI is the simulation of human intelligence in machines. It enables systems to perform cognitive tasks like learning, recognizing patterns, and making decisions using algorithms and data.

What is AI (Different Perspectives)

Software Engineering Perspective

AI is a specialized component integrated into a broader software system to enable intelligent behavior, like prediction, classification, or decision-making.
The focus is on making it usable, scalable, and reliable in real-world environments.

Machine Learning Perspective

AI is a learning function, a model trained on data to make predictions or decisions. The focus is on building, tuning, and evaluating models that learn effectively and generalize well.

What is AI (Different Perspectives)

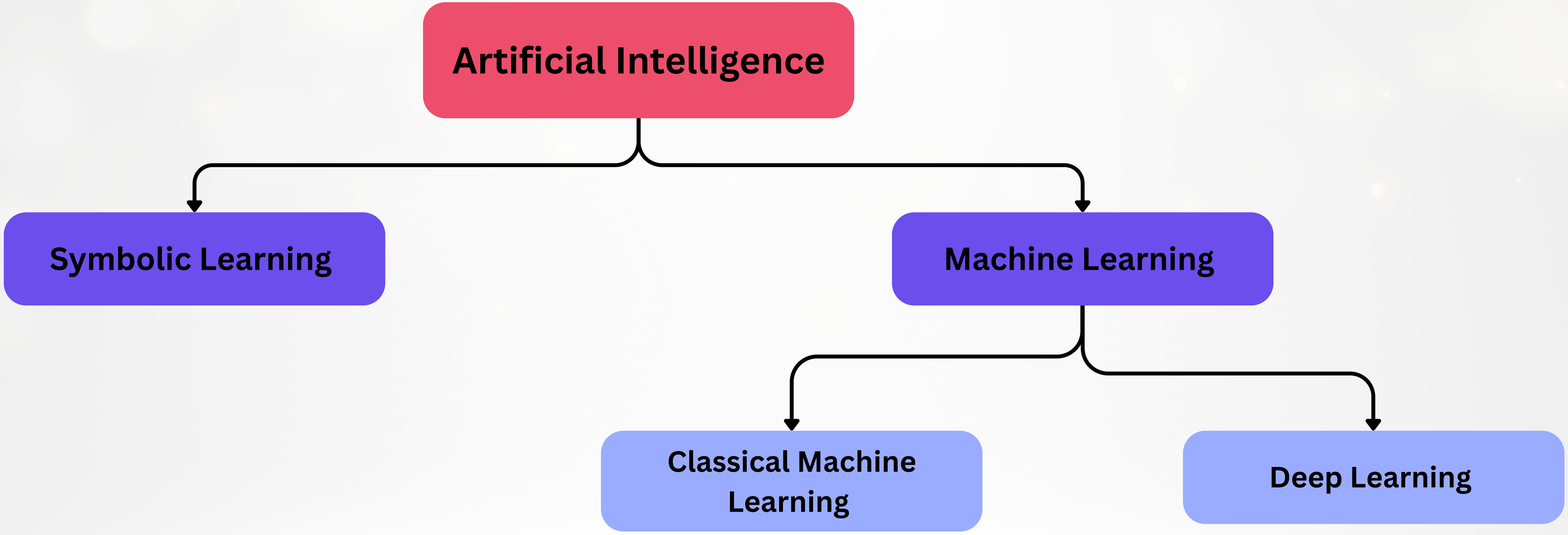
Business Perspective

AI is a strategic asset, a tool to automate tasks, cut costs, improve decision-making, or create new revenue streams.
The focus is on measurable ROI, scalability, and competitive advantage.

Public Perspective

AI is a mysterious intelligence, often seen as smart, futuristic, or even threatening.
The public focus is on trust, impact on jobs, ethics, and whether AI will help or harm society.

AI PARADIGMS

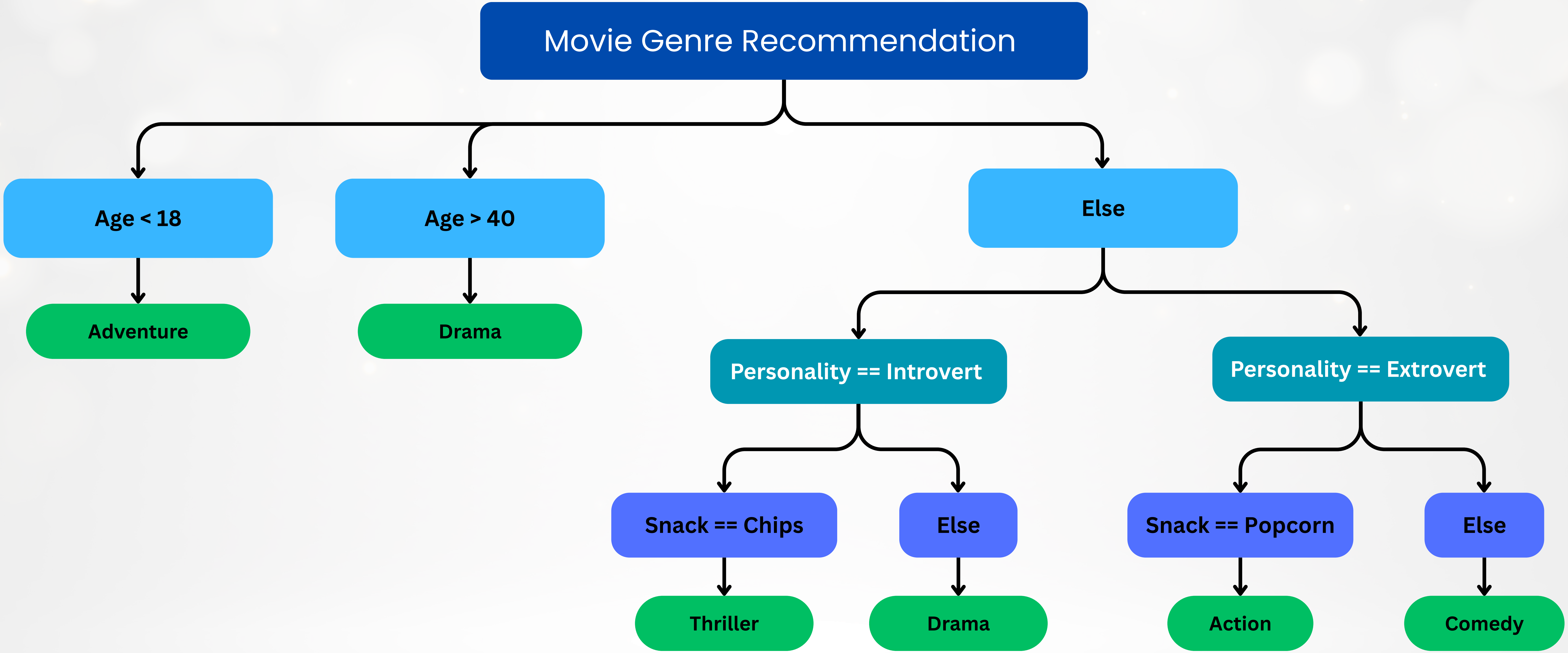


Symbolic Learning (Rule Based)

Symbolic Learning relies on logic, rules, and symbolic representations of knowledge.

It mimics human reasoning by applying predefined rules to make decisions, often in expert systems or knowledge bases.

Symbolic systems are easy to understand and trace but lack flexibility, struggling to handle noisy or unexpected input without manual updates.


Movie Genre Recommendation
Age < 18
Age > 40
Else
Adventure
Drama
Personality == Introvert
Personality == Extrovert
Snack == Chips
Else
Snack == Popcorn
Else
Thriller
Drama
Action
Comedy

Machine Learning

Machine Learning is a data-driven approach where systems learn patterns from examples instead of being explicitly programmed.

It uses algorithms that improve performance with more data, making it well-suited for tasks like image recognition, spam detection, and recommendation systems.

While powerful and adaptive, ML models often act as black boxes, making their decisions hard to interpret.

Age	Personality	Snack	Genre
12	introvert	chocolate	animated adventure
22	introvert	chocolate	thriller
25	introvert	tea	drama
27	extrovert	ice cream	comedy
29	extrovert	chips	action
33	extrovert	energy drink	scifi
34	introvert	popcorn	drama
40	extrovert	chips	action
44	introvert	chocolate	drama
19	extrovert	chocolate	comedy

HISTORY OF AI

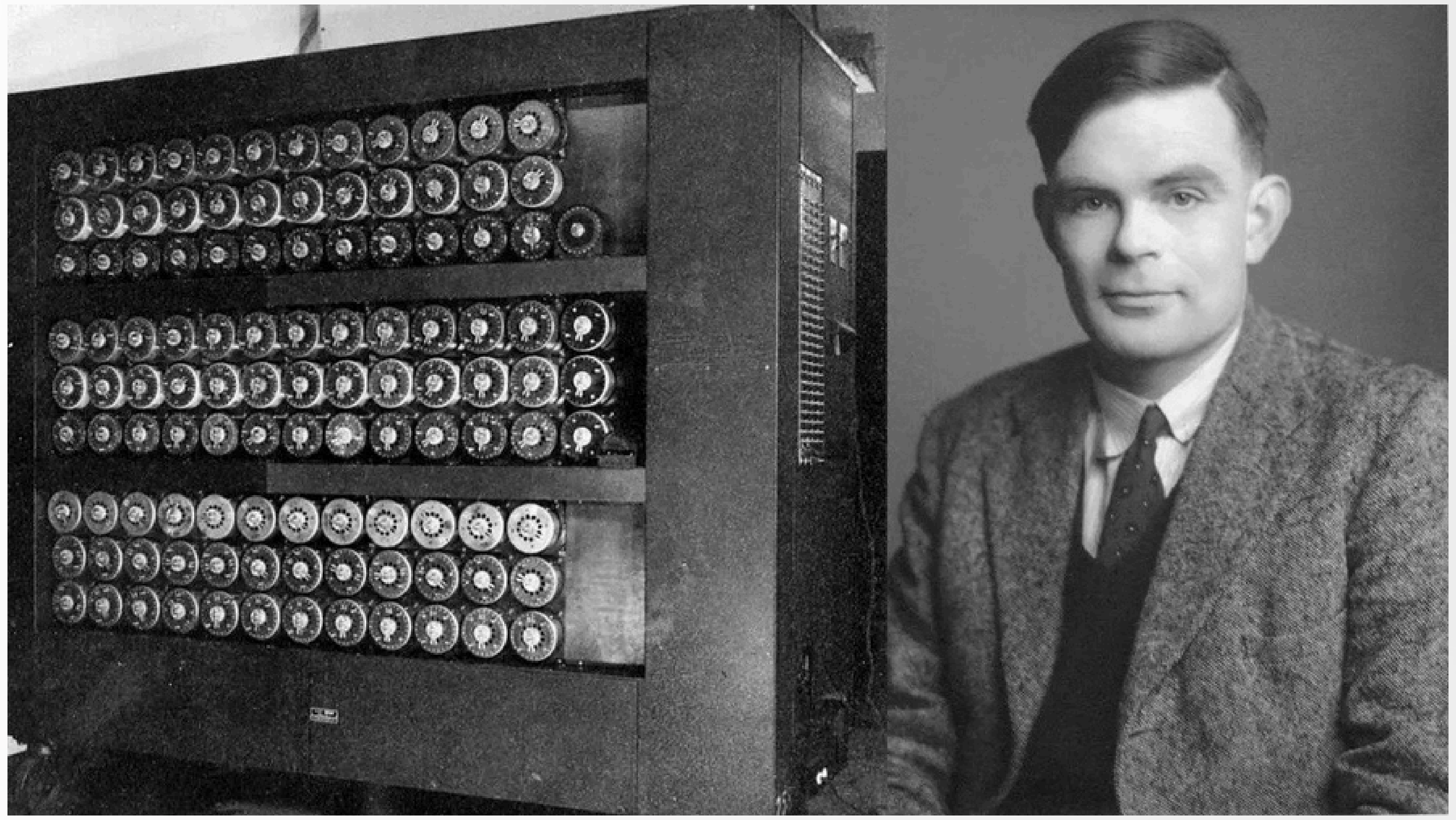
AI isn't new, the idea dates back long ago. Thinkers imagined intelligent machines long before computers existed. Today's AI builds on that long history of human curiosity and invention.

1950s — 60s-70s — 70s-80s — 1980s — 1997 — 2000s — 2010s — 2017 — Now

1950s - Alan Turing

Turing Test:
Alan Turing proposed the Turing Test in 1950 to measure machine intelligence. If a machine can hold a text-based conversation that's indistinguishable from a human's, it passes. It became a foundational idea in AI.

Enigma Machine:
During WWII, Turing helped build the Bombe, a machine that cracked the German Enigma code. This breakthrough gave the Allies a crucial edge and laid groundwork for modern computing.



1950s | 60s-70s | 70s-80s | 1980s | 1997 | 2000s | 2010s | 2017 | Now

1960s-1970s Symbolic AI

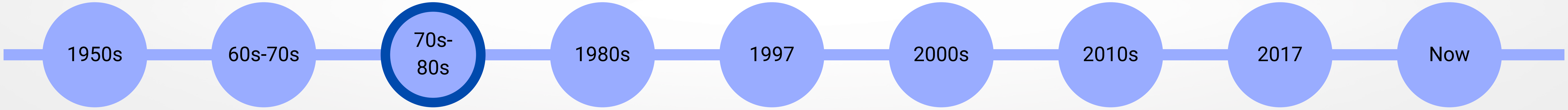
In the 1960s–70s, AI research focused on symbolic reasoning and rule-based systems. Programs like ELIZA showed early success in mimicking human conversation and logic.

Researchers believed general intelligence was within reach. However, these systems lacked real understanding and struggled with complexity.

1950s | 60s-70s | 70s-80s | 1980s | 1997 | 2000s | 2010s | 2017 | Now

1970s-1980s AI Winter

1970s–80s – The First AI Winter
AI promised too much, too soon — but couldn’t deliver. Symbolic systems struggled with real-world complexity, and hardware wasn’t powerful enough to help. As progress stalled, funding dried up and interest in AI sharply declined.



1980s Expert Systems

In the 1980s, AI saw a shift toward expert systems—programs that mimicked human decision-making using hand-crafted rules.

These systems were adopted in industries like medicine and finance, sparking commercial interest. However, they were expensive to build, hard to maintain.

By the late 1980s, disappointment set in again, leading to the second AI winter as funding and enthusiasm declined.

1997 - Deep Blue Beats Kasparov

In 1997 IBM's Deep Blue became the first computer to defeat a reigning world chess champion, Garry Kasparov, in a match. It used brute-force search and handcrafted evaluation, not learning.

The win was symbolic — AI could now outperform humans in a complex intellectual task, marking a major public milestone for the field.

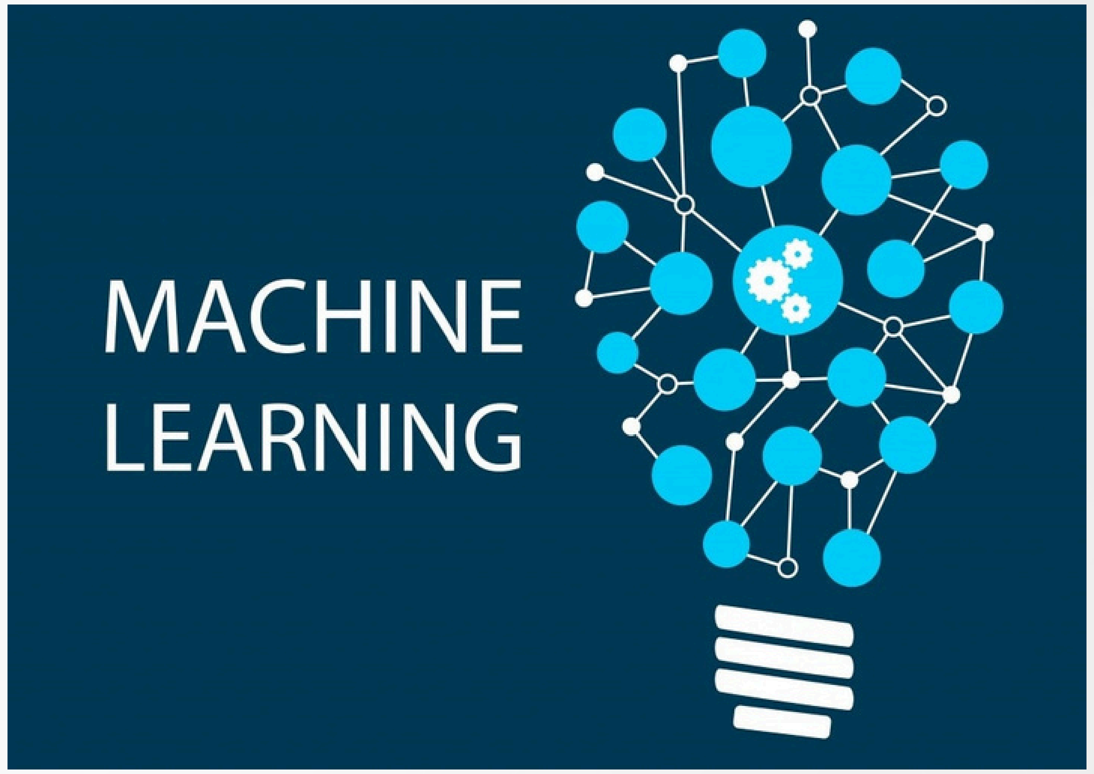
1950s | 60s-70s | 70s-80s | 1980s | 1997 | 2000s | 2010s | 2017 | Now

2000s – The Rise of Machine Learning

AI shifted from hardcoded rules to data-driven learning.

Algorithms like SVMs, decision trees, and ensemble methods gained popularity. With more data and faster hardware, AI became practical — powering spam filters, recommendations, and basic computer vision.

This decade laid the groundwork for the deep learning boom that followed.



1950s · 60s-70s · 70s-80s · 1980s · 1997 · **2000s** · 2010s · 2017 · Now

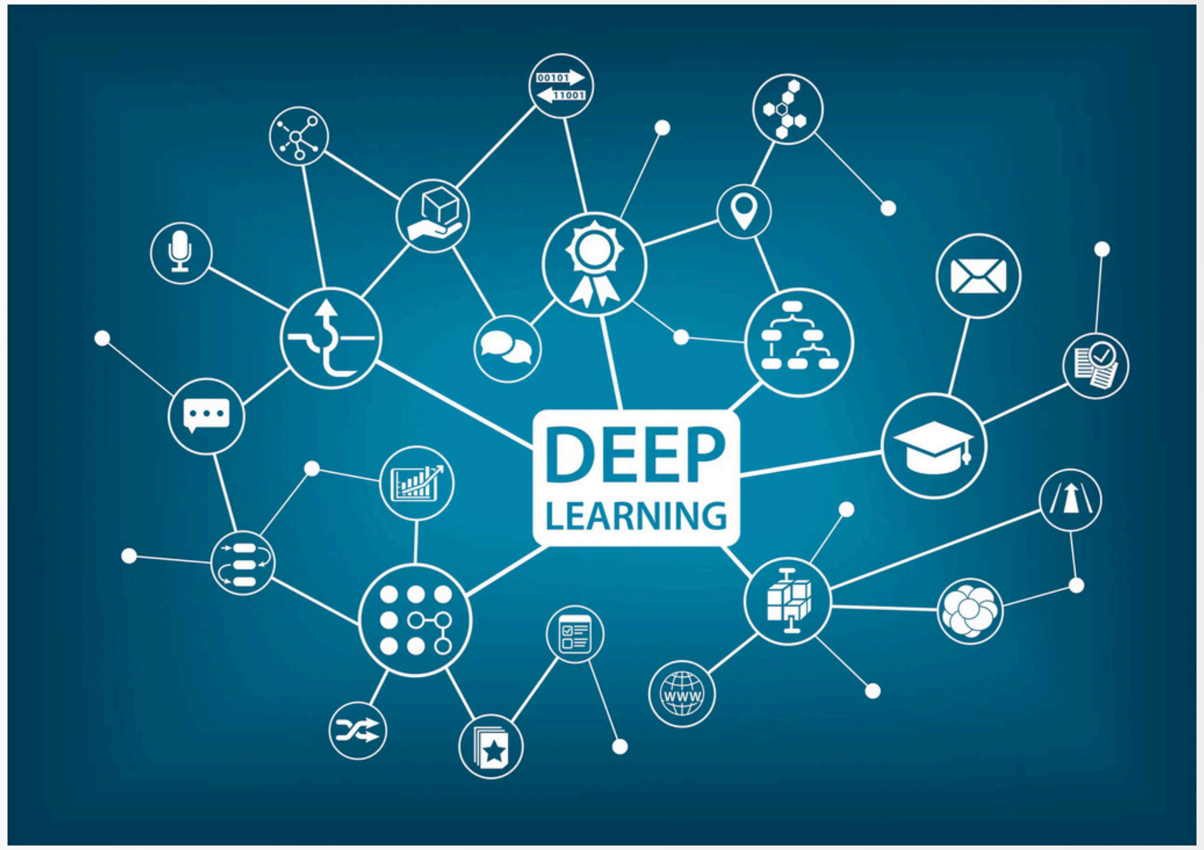
2010s – Deep Learning Revolution

The 2010s marked a turning point as deep learning outperformed traditional methods across vision, speech, and language.

In 2012, AlexNet won the ImageNet challenge by a wide margin, demonstrating the power of convolutional neural networks (CNNs).

Recurrent neural networks (RNNs) and LSTMs boosted speech recognition and machine translation.

AlphaGo's 2016 victory over the world Go champion showcased the potential of reinforcement learning combined with deep nets. AI was no longer niche — it was mainstream.

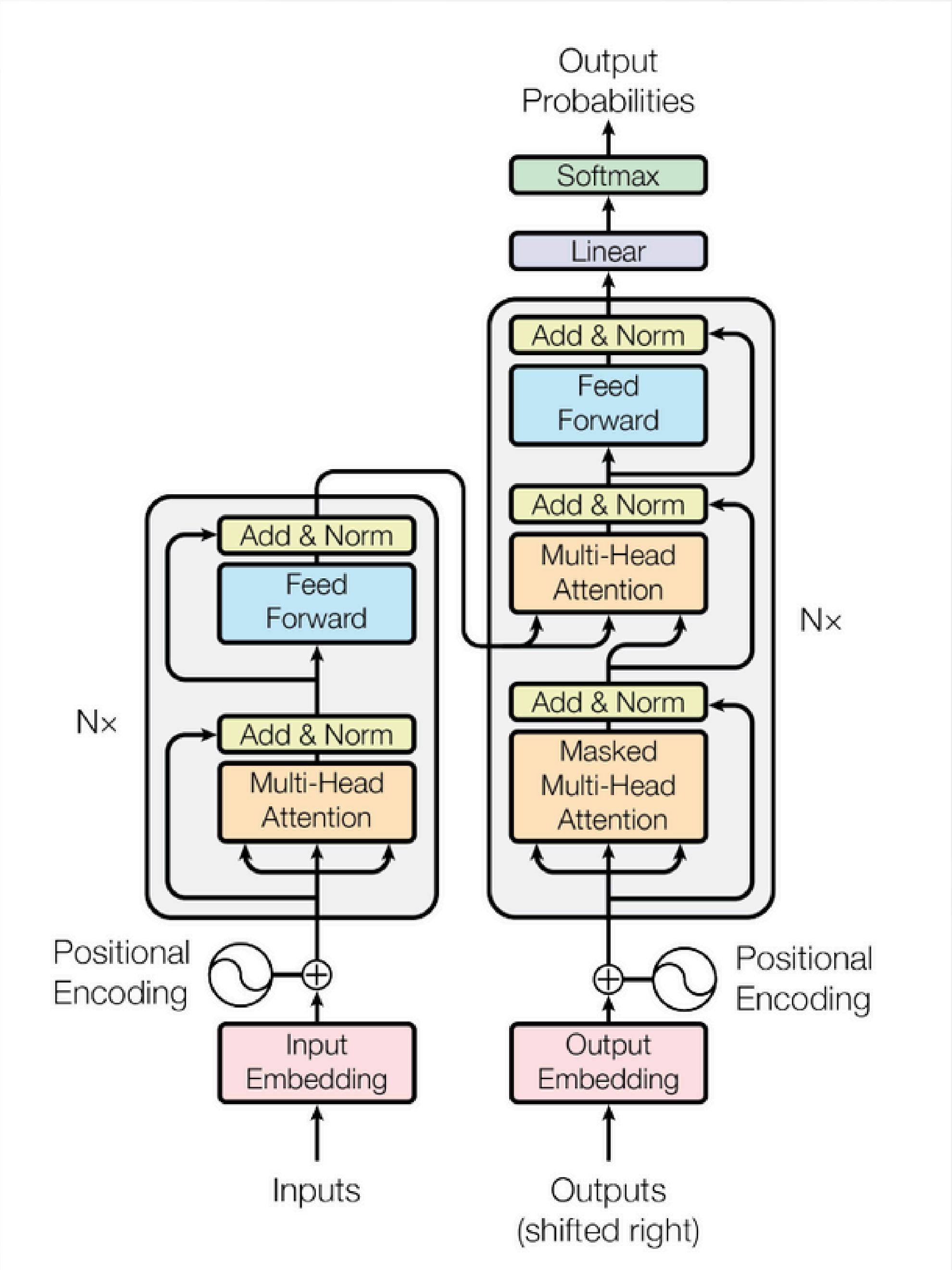


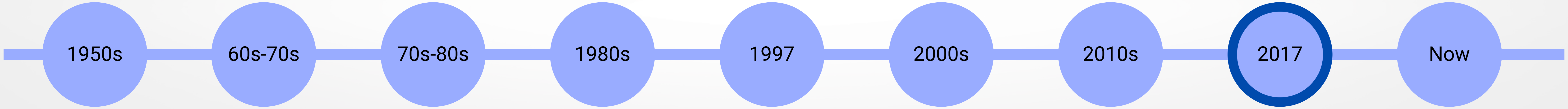
1950s · 60s-70s · 70s-80s · 1980s · 1997 · 2000s · 2010s · 2017 · Now

2017 – The Transformer Breakthrough

Google introduced the Transformer architecture in the paper “Attention is All You Need.” It replaced recurrence with self-attention, making models faster, more parallelizable, and better at handling long-range dependencies in language.

This breakthrough laid the foundation for modern NLP models like BERT, GPT — and kicked off the era of foundation models.





The Era of Foundation Models & Generative AI

The 2020s saw the rise of massive pre-trained models like GPT-3, BERT, DALL·E, and CLIP — capable of few-shot learning, text generation, image synthesis, and more.

ChatGPT (2022) brought conversational AI to the mainstream.

Transformers became the backbone of most AI systems, extending to code, audio, video, and multimodal tasks.

OpenAI, Google, Meta, and others raced to build ever-larger models. Meanwhile, concerns over bias, misuse, and alignment sparked intense debates on AI safety, ethics, and regulation. AI became both a global obsession and a serious responsibility.

1950s · 60s-70s · 70s-80s · 1980s · 1997 · 2000s · 2010s · 2017 · Now

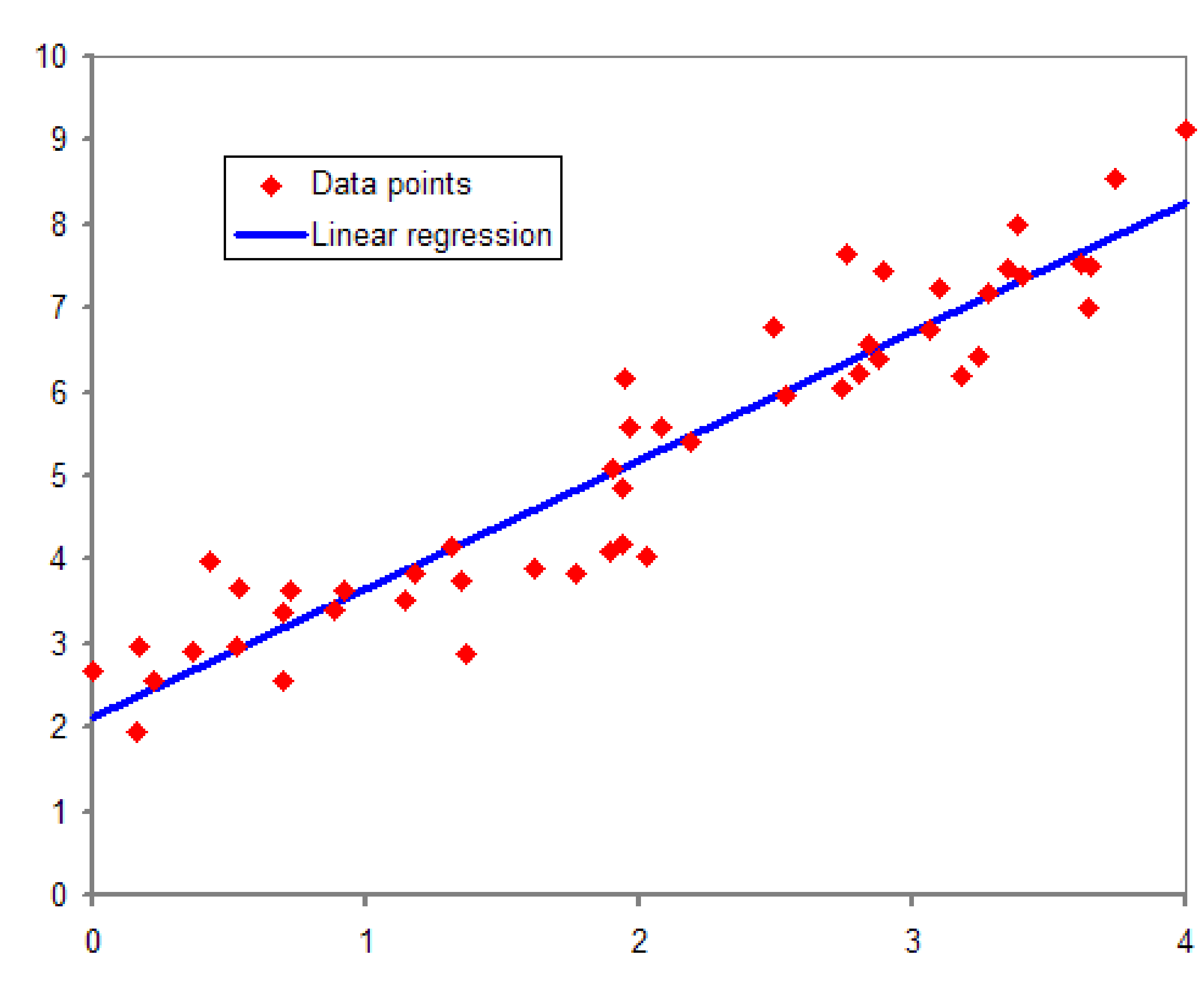
MACHINE LEARNING

MACHINE LEARNING CORE CONCEPTS

What is a model?

A model is the mathematical representation of a pattern in data. In machine learning, it’s essentially a function with parameters that takes input data and makes predictions.

For example, a linear regression model draws a straight line through your data points to predict future values. Different models (like trees, neural networks, or SVMs) learn different patterns depending on the problem.

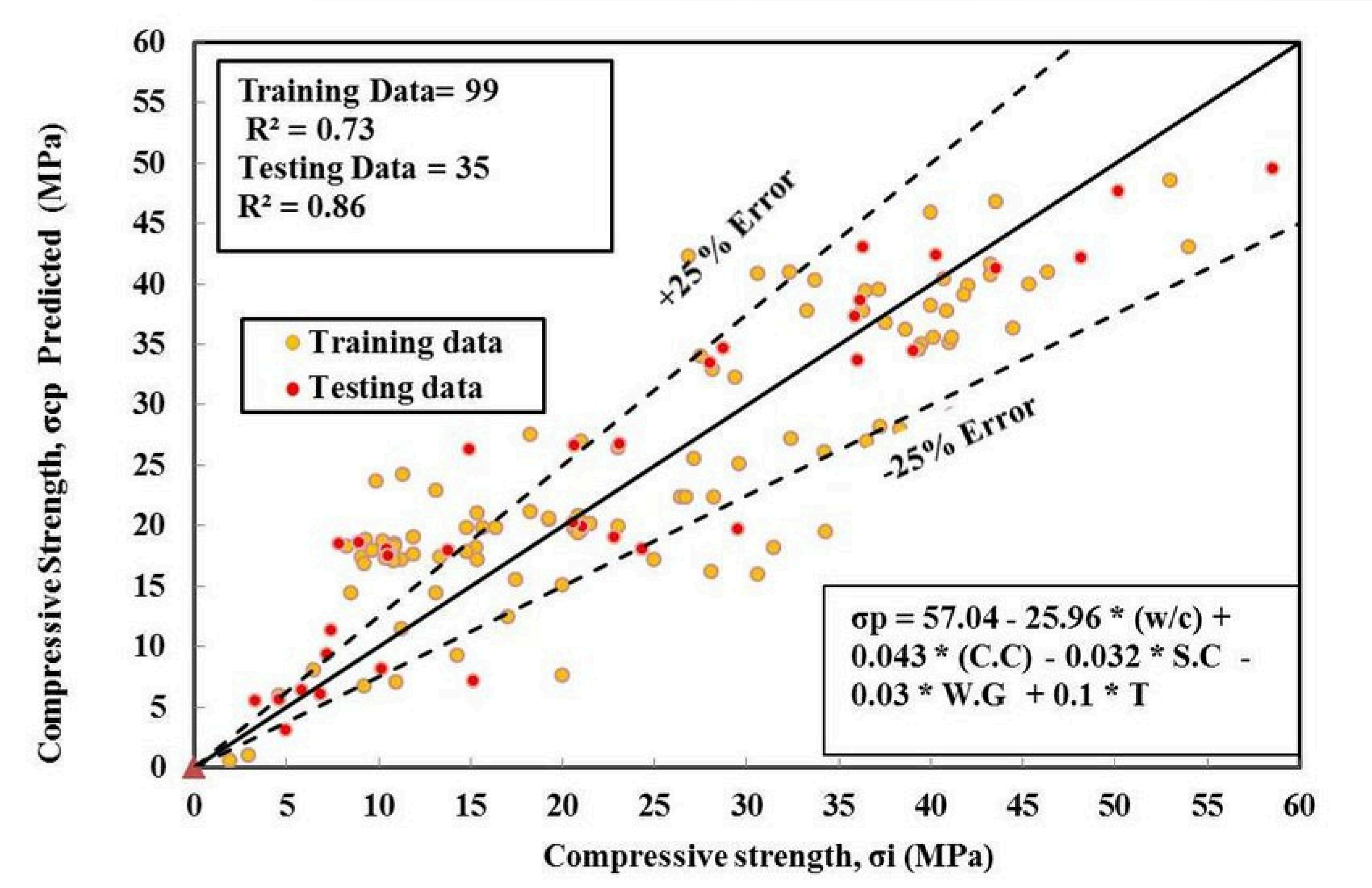


MACHINE LEARNING CORE CONCEPTS

What do we mean by training a model?

Training is the process of teaching the model how to make good predictions. You feed it labeled data (inputs with known outputs), and it adjusts its internal parameters to reduce errors.

This is where the learning happens — the model keeps tweaking itself until it finds the best possible way to map inputs to outputs.



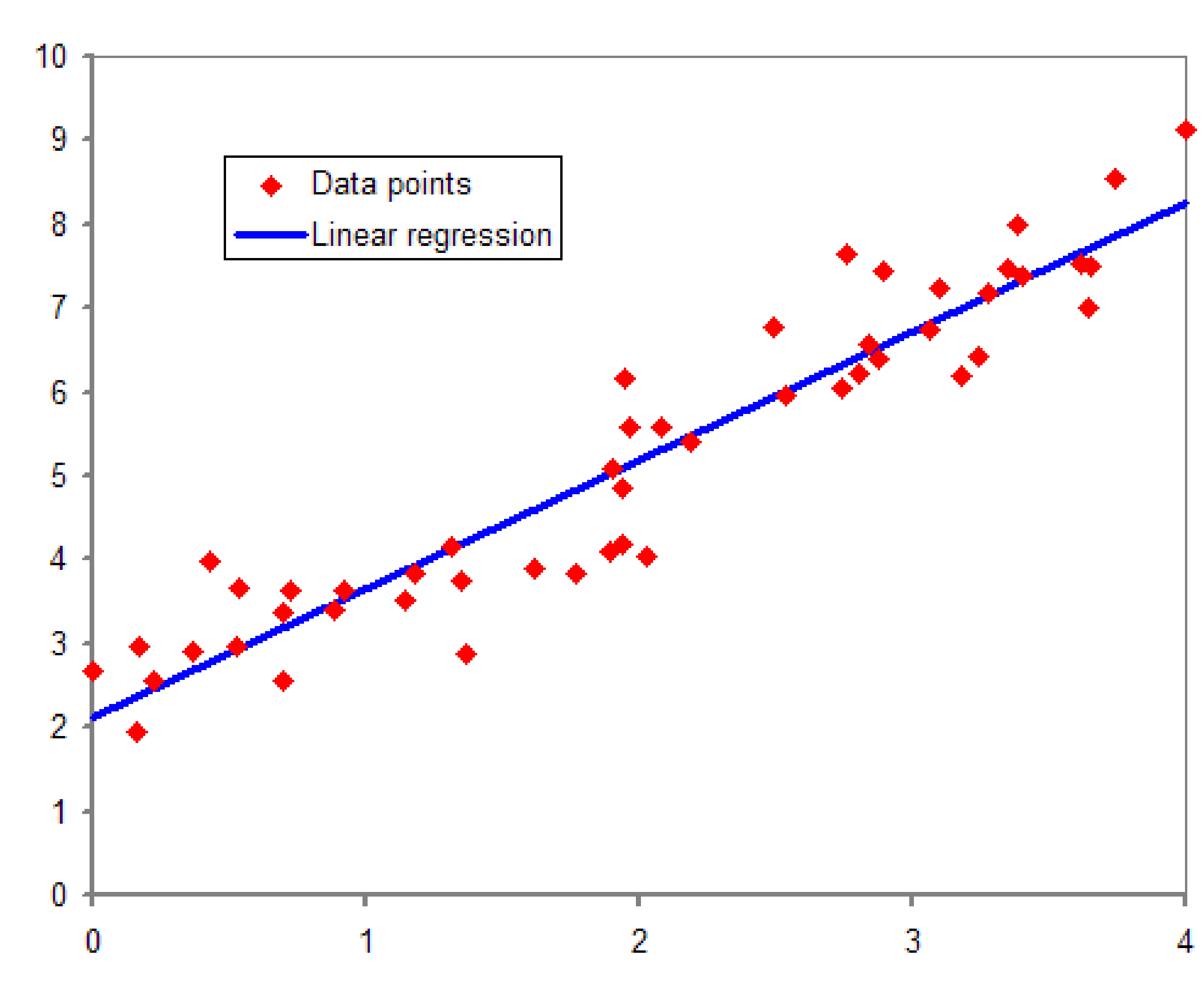
MACHINE LEARNING CORE CONCEPTS

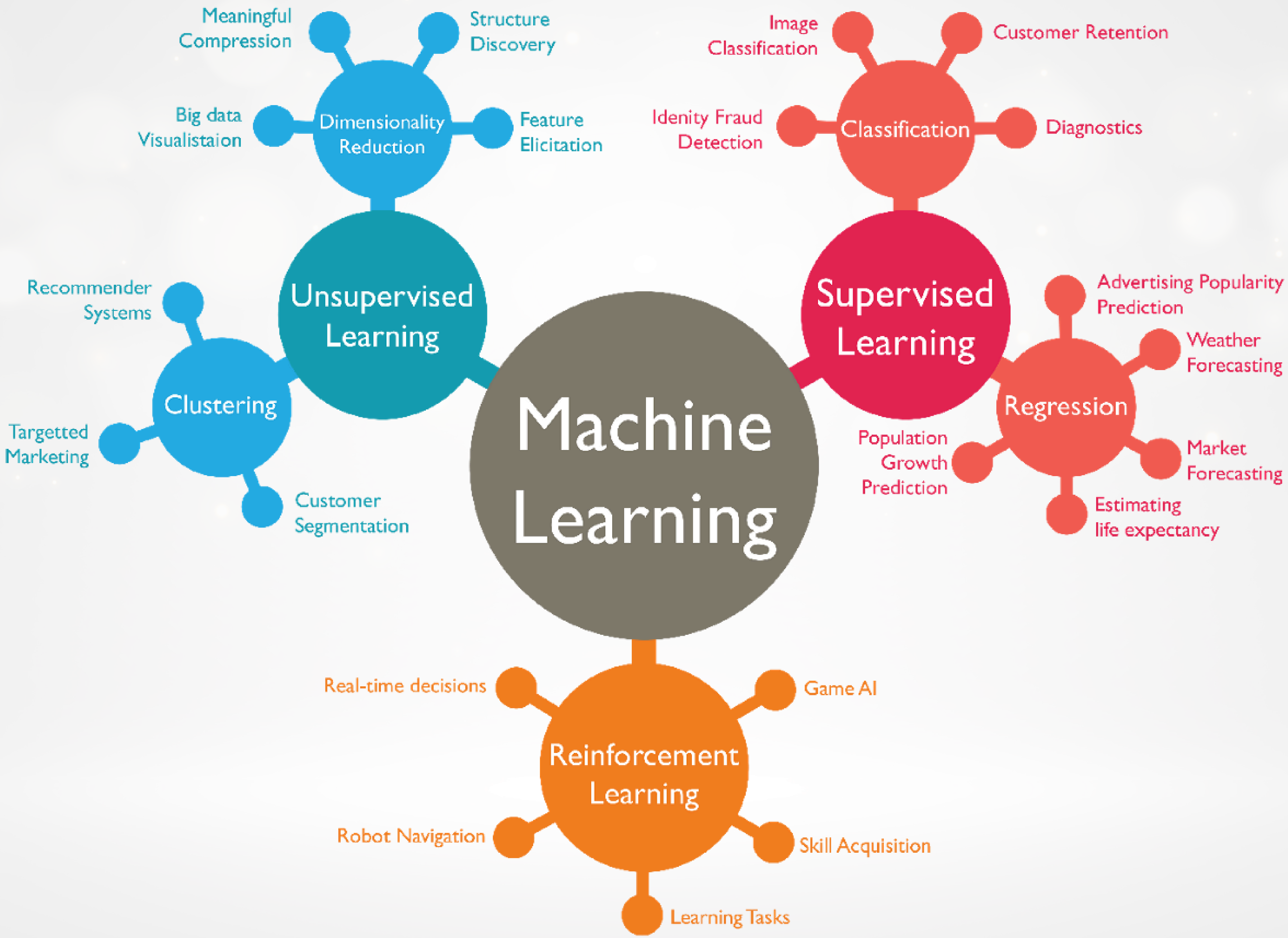
What is inference?

Inference is what happens after training.

The model is now "frozen" and ready to make predictions on new, unseen data.

No learning happens here — it's just applying what it learned during training to real-world inputs and spitting out predictions or classifications.




Machine Learning
Unsupervised Learning
Dimensionality Reduction
Meaningful Compression
Structure Discovery
Big data Visualistaion
Feature Elicitation
Clustering
Recommender Systems
Targetted Marketing
Customer Segmentation
Supervised Learning
Classification
Image Classification
Customer Retention
Idenity Fraud Detection
Diagnostics
Regression
Advertising Popularity Prediction
Weather Forecasting
Population Growth Prediction
Market Forecasting
Estimating life expectancy
Reinforcement Learning
Real-time decisions
Game AI
Robot Navigation
Skill Acquisition
Learning Tasks

Supervised Learning

Supervised learning is a machine learning approach where models are trained on labeled data — that is, each input comes with a known output.

The goal is to learn a mapping from inputs to outputs, so the model can predict the label of new, unseen data.

It's commonly used in classification (e.g., spam vs. not spam) and regression (e.g., predicting prices).

Popular algorithms include linear regression, decision trees, and neural networks. The quality and quantity of labeled data heavily impact performance.

Labeled Data Example

# price	# area	# bedrooms	# bathrooms	# stories
13300000	7420	4	2	3
12250000	8960	4	4	4
12250000	9960	3	2	2
12215000	7500	4	2	2
11410000	7420	4	1	2
10850000	7500	3	3	1
10150000	8580	4	3	4
10150000	16200	5	3	2
9870000	8100	4	1	2
9800000	5750	3	2	4

Unsupervised Learning

Unsupervised learning works with unlabeled data — the model explores the structure or patterns without predefined answers.

It’s mainly used for clustering (grouping similar items) and dimensionality reduction (simplifying data).

Examples include k-means clustering and PCA (Principal Component Analysis).

It’s useful for discovering hidden structures in data, like customer segmentation, but evaluating performance is trickier since there’s no ground truth.

Unlabeled Data Example

# area	# bedrooms	# bathrooms	# stories
7420	4	2	3
8960	4	4	4
9960	3	2	2
7500	4	2	2
7420	4	1	2
7500	3	3	1
8580	4	3	4
16200	5	3	2
8100	4	1	2
5750	3	2	4
13200	3	1	2

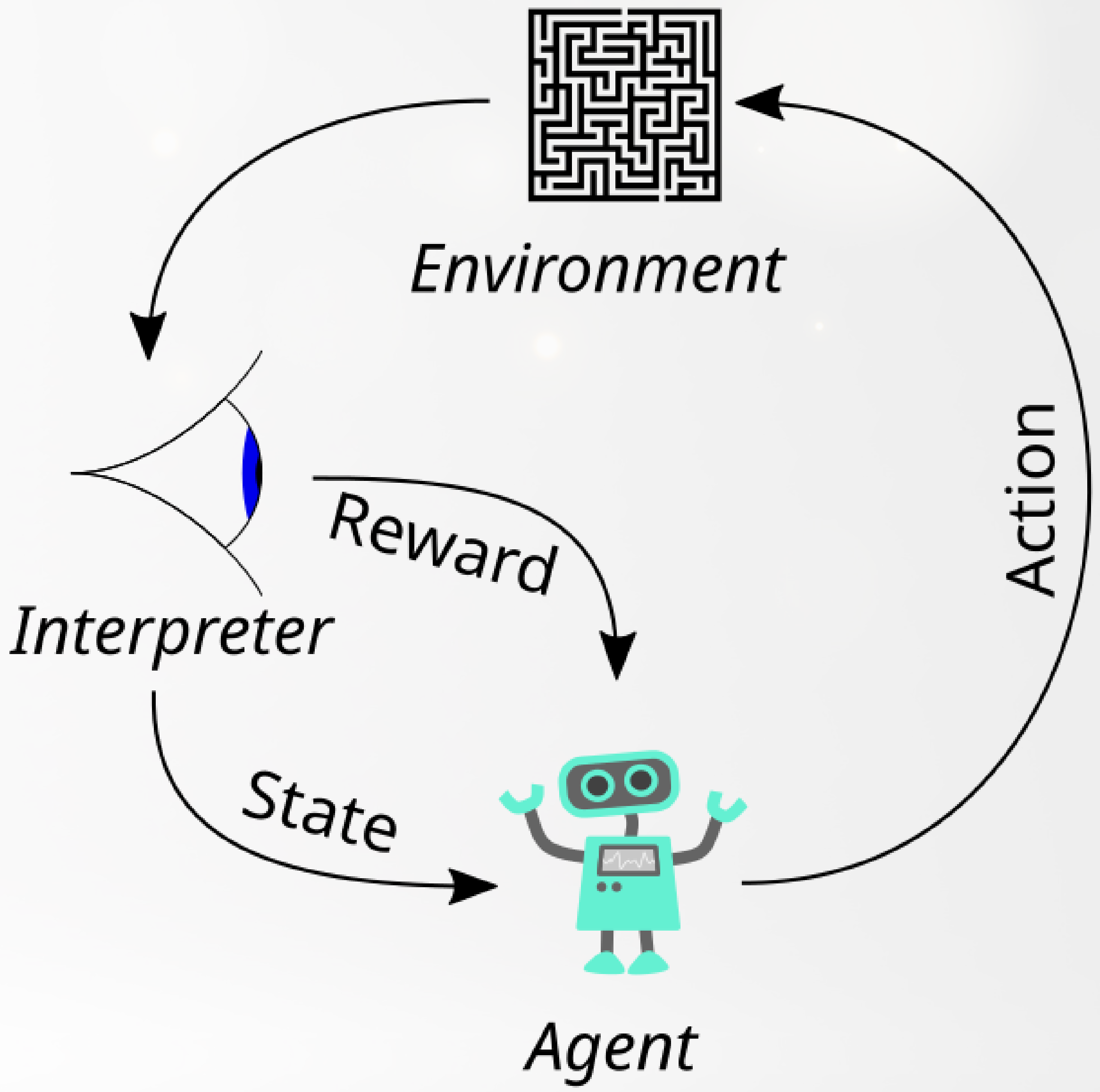
Reinforcement Learning

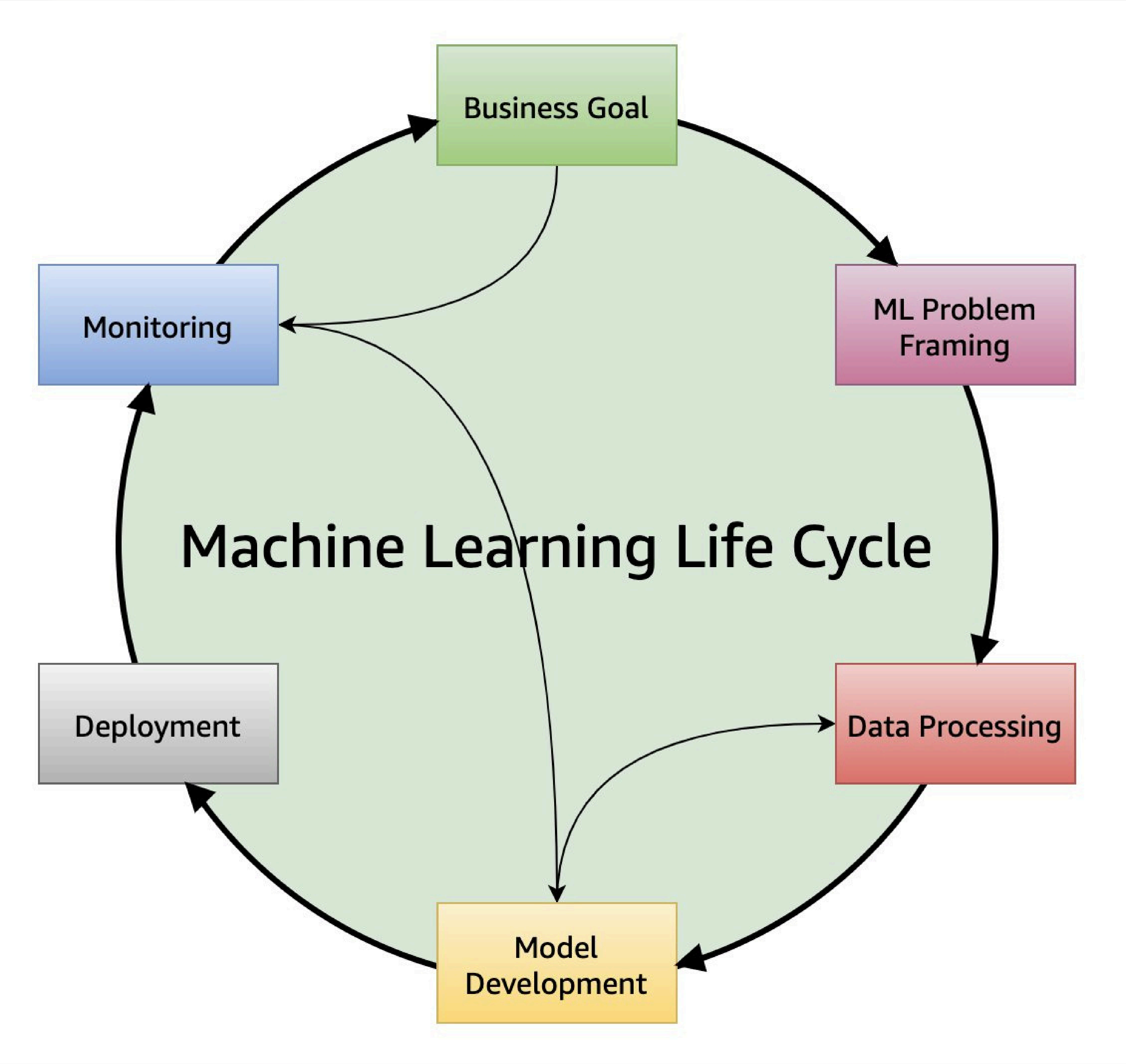
Reinforcement learning (RL) is based on agents learning by interacting with an environment.

The agent takes actions, receives feedback in the form of rewards or penalties, and learns to maximize cumulative reward over time.

It's widely used in robotics, games (like AlphaGo), and autonomous systems.

Unlike supervised learning, RL doesn't rely on labeled input/output pairs — it learns through trial and error, which makes it powerful but often slow and data-hungry to train.




Business Goal
ML Problem Framing
Data Processing
Model Development
Deployment
Monitoring
Machine Learning Life Cycle

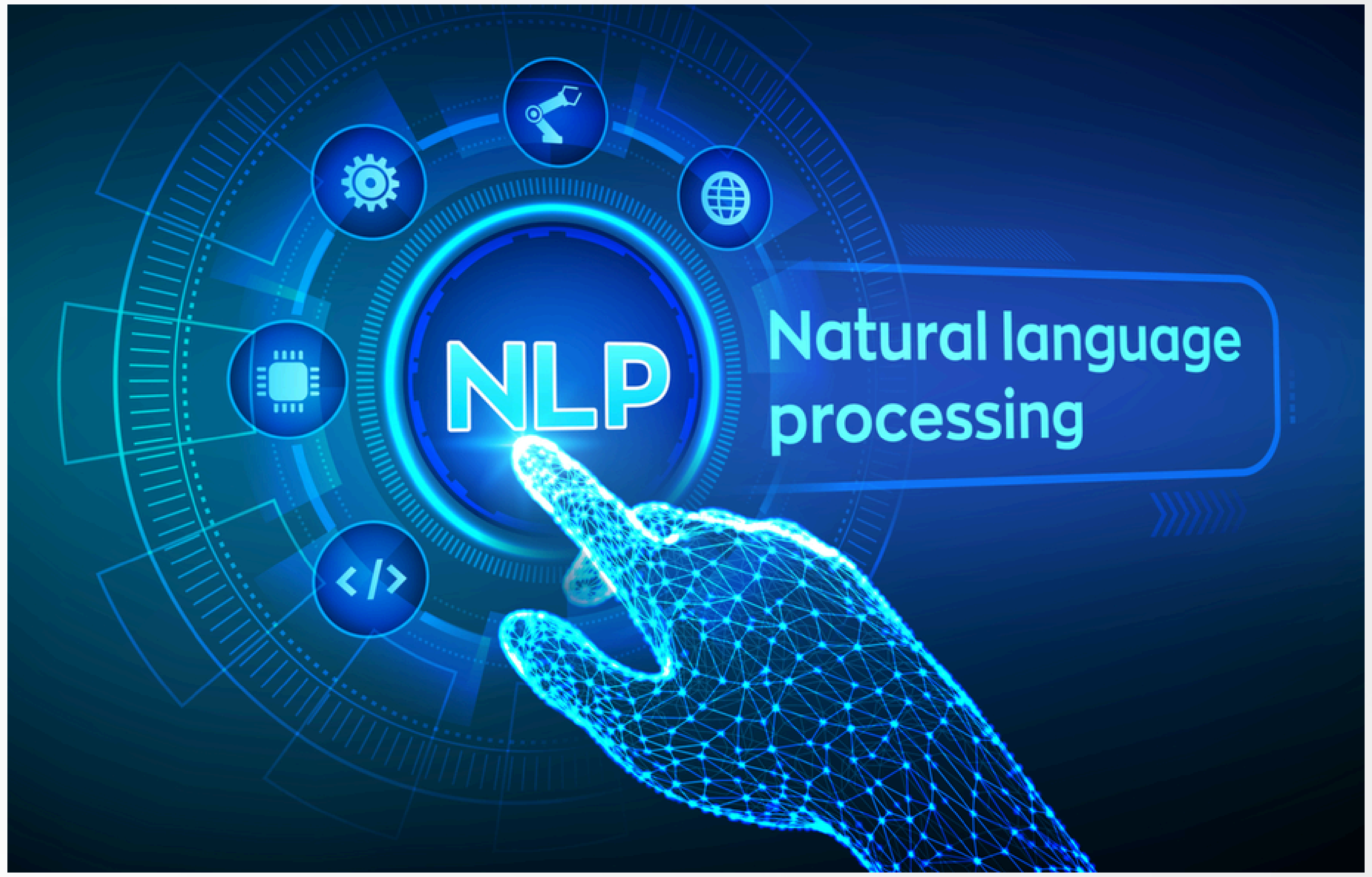
APPLICATIONS OF AI

NATURAL LANGUAGE PROCESSING

Natural Language Processing (NLP) is a subfield of Artificial Intelligence that enables machines to understand, interpret, and generate human language.

It bridges the gap between human communication and computer understanding.

By combining computational linguistics with machine learning, NLP gives computers the ability to read, listen, speak, and even reason with text or speech in a way that feels natural to humans.



Main NLP Techniques

Lowercasing & Removing Punctuation

Standardizes text by converting it to lowercase and removing punctuation/symbols.

Example

```
Hello, World! NLP is FUN. → hello world nlp is fun
```

Main NLP Techniques

Tokenization

Splits text into smaller units (tokens) such as words or sentences.

Example

```
"Chatbots can understand natural language."
["Chatbots", "can", "understand", "natural", "language"]
```

Main NLP Techniques

Stopword Removal

Removes common words that add little meaning.

Example

```
["Chatbots", "can", "understand", "natural", "language"]
["Chatbots", "understand", "natural", "language"]
```

Main NLP Techniques

Stemming & Lemmatization

Reduces words to their root form to group variations.

Example (Stemming)

```
["running", "runs", "runner"]
["run", "run", "runner"]
```

Example (Lemmatization)

```
["better", "was", "running"]
["good", "be", "run"]
```

Main NLP Techniques

Bag of Words (BoW)

Represents text as word count vectors, ignoring order.

Sentences

`"I love NLP"`

`"I love deep learning"`

Vocabulary

`["I", "love", "NLP", "deep", "learning"]`

BoW Matrix

`[1, 1, 1, 0, 0]`

`[1, 1, 0, 1, 1]`

Main NLP Techniques

Word Embeddings

Dense vector representations capturing meaning & relationships.

Example

```
"airplane" → [0.88, -0.42, ...]
"banana" → [-0.31, 0.73, ...]
```

Possible meaning of the numbers:

1. First number: Technology/transportation vs. food/plants.
2. Second number: Non-edible vs. edible.

Real-World Problems Solved by NLP

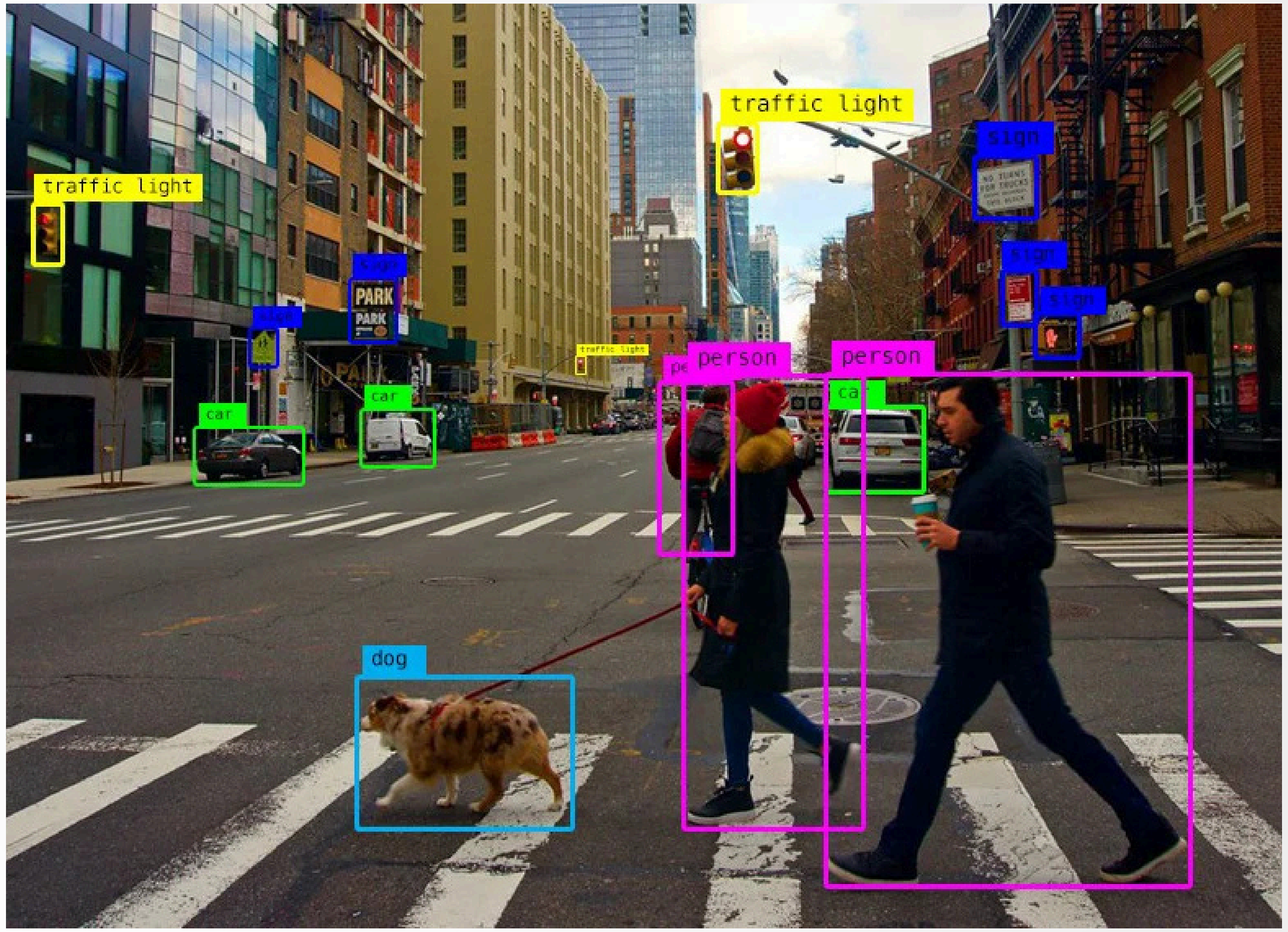
- Spam detection in emails and messages
- Machine translation between languages (e.g., Google Translate)
- Chatbots and virtual assistants like Siri, Alexa, and customer support bots
- Search engines ranking results by intent and relevance
- Document summarization for faster content understanding
- Voice-to-text systems in transcription apps

COMPUTER VISION

Computer Vision (CV) is a field of Artificial Intelligence that enables machines to interpret and understand visual information from the world — such as images and videos.

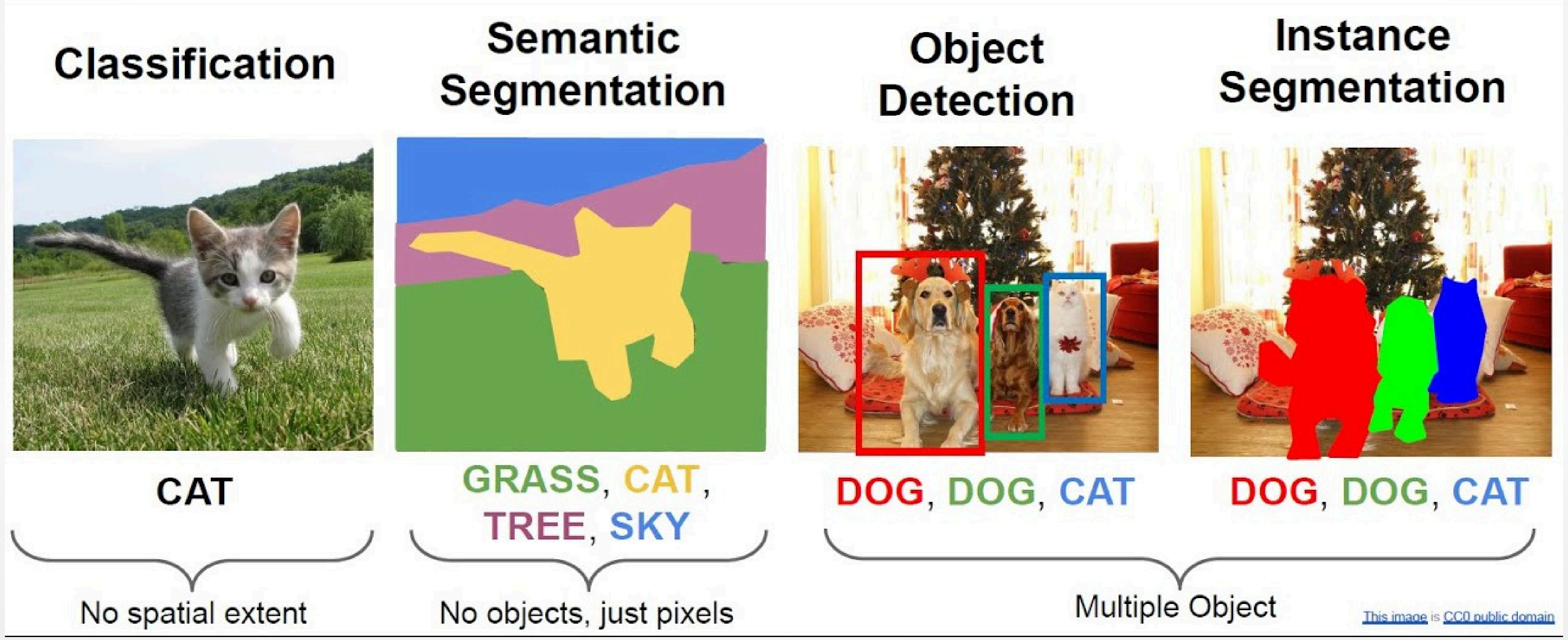
The goal is to give computers the ability to "see" and make decisions based on what they observe, just like humans do.

This involves tasks like recognizing objects, detecting motion, analyzing scenes, and even generating images.



Common Computer Vision Models and Techniques

- Image Classification – Predicts a single label for an entire image (e.g., "cat" or "car")
- Object Detection – Identifies multiple objects within an image using bounding boxes
- Semantic Segmentation – Assigns a class label to each pixel (e.g., all road pixels = "road")
- Instance Segmentation – Like semantic segmentation, but distinguishes between individual objects (e.g., 3 people, not just "person" pixels)
- Optical Character Recognition (OCR) – Extracts text from images or scanned documents



Real-World Problems Solved by Computer Vision

- Facial recognition in security and social media
- Autonomous driving through lane detection, obstacle recognition, and traffic sign reading
- Medical imaging for detecting tumors, fractures, and abnormalities
- Manufacturing for defect detection and quality assurance
- Augmented Reality (AR) apps that understand and overlay virtual elements on the real world

GENERATIVE AI

Generative AI refers to systems that can create new content — such as text, images, music, or even code — that mimics human creativity.

Unlike traditional AI that analyzes or classifies existing data, GenAI models learn patterns from large datasets and then use those patterns to generate original outputs.

This powerful technology is reshaping industries by automating content creation and enabling personalized user experiences.

Common Generative AI Models and Techniques

- Large Language Models (LLMs) – like GPT, Claude, and LLaMA for text generation
- Diffusion Models – like DALL·E, Midjourney, and Stable Diffusion for image generation
- GANs (Generative Adversarial Networks) – used in image synthesis and deepfakes
- Prompt Engineering – crafting effective inputs to steer GenAI outputs
- Fine-tuning & LoRA – customizing base models for domain-specific generation

Real-World Applications of Generative AI

- Chatbots and AI assistants for conversation and productivity
- Image generation for design, marketing, and entertainment
- Code generation using models like GitHub Copilot
- Video and voice synthesis for games, films, and digital humans
- Content summarization and rewriting for news, blogs, or academic texts
- Personalized education through tailored content and adaptive explanations

FOUNDATIONS FOR LEARNING AI

MATHEMATICAL FOUNDATION

Linear Algebra

Probability

Optimization

Linear Algebra

Linear algebra is the mathematical foundation for representing and manipulating data in machine learning.

It deals with vectors (ordered lists of numbers), matrices (2D arrays), and operations like addition, multiplication, and transformations.

In ML, datasets are often stored as matrices where rows represent examples and columns represent features.

Models like neural networks rely heavily on matrix multiplication to compute activations and propagate information through layers.

Probability

Probability theory provides the formal tools for dealing with uncertainty, a core challenge in AI.

Instead of making rigid decisions, probabilistic models assign likelihoods to outcomes — essential when working with noisy, incomplete, or ambiguous data.

Concepts like probability distributions, conditional probability, Bayes' theorem, and expectation are foundational in models such as Naive Bayes, Hidden Markov Models, and Bayesian Networks.

Understanding uncertainty helps models make more robust predictions, quantify confidence, and even generate new data using probabilistic frameworks.

Numerical Optimization

Numerical optimization is the engine that drives learning in most AI models.

The goal is to minimize (or maximize) an objective function — typically a loss that measures how far the model's predictions deviate from the target outputs.

This is done by adjusting the model's parameters using iterative algorithms like gradient descent, which compute the slope (gradient) of the loss and move the parameters in the direction that reduces it.

Variants like Stochastic Gradient Descent (SGD), Adam, and RMSprop introduce efficiency and stability in training deep networks.

Since most loss functions don't have analytical solutions, optimization provides the practical path to finding near-optimal weights in high-dimensional, non-convex landscapes, making it a cornerstone of all modern AI training pipelines.

ESSENTIAL PROGRAMMING

python

+

NumPy SciPy pandas

matplotlib scikit learn

enjoyalgorithms.com

FRAMEWORKS & TOOLS

TASK

Pick one supervised machine learning model and write a 2-page PDF explaining it in simple words.

Model Name
Model Type (Regression / Classification)
Explain the basic concept in your own words
How does it work?
Real-life uses
Pros and cons

Submission link
https://forms.gle/fZpiH3Zt6PFN2uoXA

THANK YOU

Ali Adel
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