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Chapter 1: Foundations of artificial intelligence and machine learning: The pillars of intelligent systems

Priyambada Swain

Infosys Limited

1. Introduction to Artificial Intelligence

Artificial Intelligence (AI) is a branch of computer science that seeks to simulate certain aspects of human intelligence [1]. Specifically, it aims to enable computers and software to impersonate human cognitive functions such as thinking, planning, learning, communicating, perceiving the environment, and moving and manipulating objects [2-3]. Such activities are generally considered to require intelligence when performed by humans or other animals. Although AI has achieved significant success in many areas, it still has some limitations. The development of AI can be broadly categorized into three groups: Narrow AI, Artificial General Intelligence, and Artificial Superintelligence. Narrow AI can perform certain specific tasks at a narrow level of intelligence. General AI can perform any intellectual task in various domains that humans are capable of. Superintelligent AI can perform intellectual tasks surpassing human intelligence [2,4]. As the definition of intelligence is subjective and no clear consensus exists, these categorizations are based on possible distinctions rather than standards. Regardless of these limitations and classifications, current advances in AI have led to widespread usage in various sectors, including e-commerce, education, research, and service industries.

2. History of Artificial Intelligence

Albert Einstein's aspiration of intelligent machines capable of reasoning mirrors advances in the field of Artificial Intelligence (AI). Shortly after a U.S. National Gallery of Art introduced a computer that painted, AI pioneers John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon developed the Logic Theorist, a program enabling computers to perform symbolic processing tasks. In 1956, the Dartmouth Summer Research Project on Artificial Intelligence—led by McCarthy, Minsky, Rochester, and Claude Shannon—coined the term "artificial intelligence" and established AI as a foundational discipline. The Logic Theorist replicated the first 38 theorems from Bertrand Russell’s "Principia Mathematica" and discovered more elegant, human-unproduced proofs for 9 theorems. In 1958, McCarthy developed Lisp, a programming language that remains favoured in AI research for its suitability in symbol manipulation.

Contemporary AI applications extend across entertainment, transportation, healthcare, e-commerce, and security. Adversarial neural networks pioneered by Generative models have recently enabled the generation of content—visual, textual, audio-visual, and logical—that is virtually indistinguishable from human-produced work. OpenAI’s GPT-3 and GPT-4, among the most exciting AI models in recent times, utilize vast corpora of textual data for content creation [5-8].

3. Categories of Artificial Intelligence

Artificial Intelligence Categories. Broad categories of artificial intelligence include narrow, general, and superintelligent. Narrow, or "weak", artificial intelligence refers to any artificial intelligence that is limited to a specific area. General, or "strong", artificial intelligence refers to intelligence that can perform any intellectual task that a human can perform. Superintelligent artificial intelligence surpasses the capacity and ability of human intelligence. Current directions in AI are moving forward along the path of transforming narrow AI into general AI [6,9]. Since there is no existing general AI in existence, the categories of AI are fluid and subject to change. Also, the relationship of the categories is not fixed; it is difficult to conclude that the categories must be arranged in an order of hierarchy or time. In certain situations, general AI can be seen as complementary to narrow AI in terms of targets and implementation. Milestones. Milestones in AI are categorized according to specific topics and phases of research. Early-stage milestones are concentrated on human-electronic interaction, data interpretation, and symbolic acting. Later milestones advance the development of solutions that include higher levels of cognition, problem-solving, and the simulation of specific cognitive behaviors. Current milestones focus on advanced human cognitive simulation, working memory models, and neural network computing [10-12].

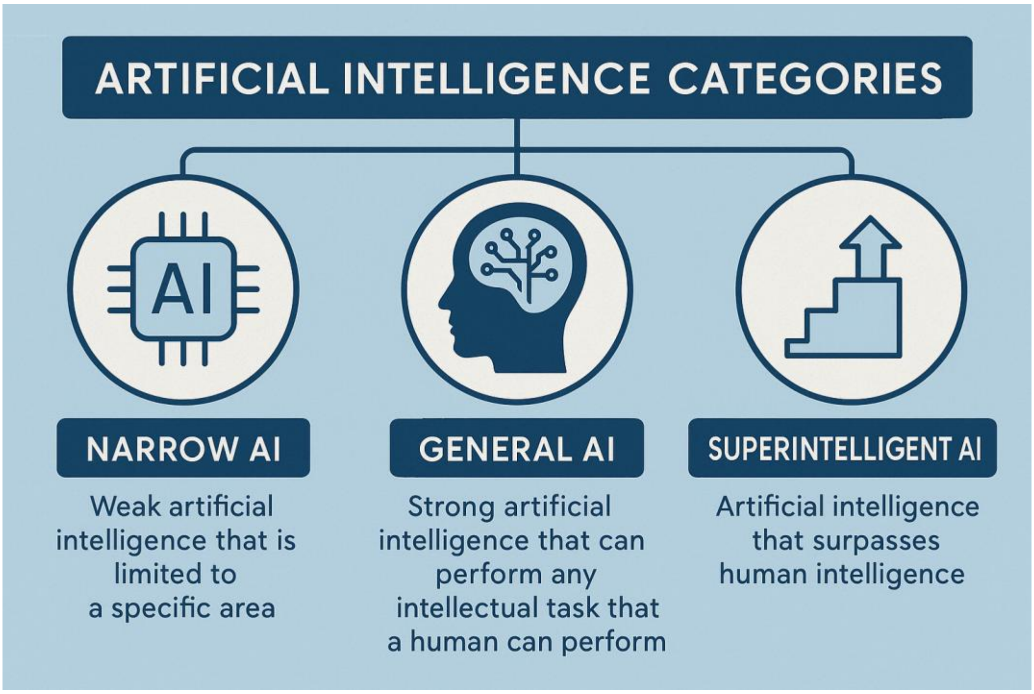

Fig 1. Artificial Intelligence Categories.

3.1. Narrow AI

Narrow, or weak, AI refers to artificial intelligence specially focused on single narrow tasks and specific pre-trained activities. When AI algorithms focus on solving a single dedicated problem through data, they tend to fall into this category. Narrow AI performs a dedicated task but will fail when applied to tasks outside of its scope. Examples include chatbots, speech assistants, language translation, sentiment analysis, image recognition, and spam detection.

Narrow AI is the most common form of AI that exists today. Categories within Narrow AI increasingly move closer to Artificial General Intelligence (AGI) over time. Applications and development trends of Narrow AI focus on driving innovation in specific, clearly defined areas. Categories within Narrow AI include ANI-based Computing (Artificial Narrow Intelligence) and Category-Specific AI (e.g. speech recognition) [7,13-16].

3.2. General AI

General artificial intelligence (General AI) refers to intelligence exhibited by machines with cognitive capabilities and functions equivalent in scope and level to those of a human being. Such machines would be able to do many things at once, perceive and interact with the world in all its complexity, exhibit commonsense and creativity, transfer knowledge from one domain to another, and perform a multitude of other highly demanding cognitive tasks that humans can perform. A machine with General AI would be able to do everything that human beings are able to do, including thinking, planning, reasoning, problem solving, learning, communicating in natural language, perceiving and moving objects [2,17-19].

The goal behind the pursuit of General AI is the complete replication of human cognitive abilities in machines, recreating the entirety of the human brain in machines. "Strong AI" and "Human-Level AI" are other names for General AI. It must be remembered that while General AI is often thought of as Artificial Intelligence, Artificial Intelligence in its complete sense also includes Narrow AI and Super-intelligence. These three categories of Artificial Intelligence are not at either end of a spectrum, but rather distinct points within the overall space of Intelligence. Similar distinctions are made in every technical field.

3.3. Superintelligent AI

Superintelligent AI is a stage of advancement beyond both Artificial General Intelligence (AGI) and human intelligence. AGI is designed to mimic human skills and creative ability, such as decision-making. A superintelligent AI system seeks to surpass human intelligence in every aspect and probably be capable of performing many tasks better than humans. A superintelligent AI system can be useful in numerous areas, such as scientific research and creatively solving complex problems. Being more intelligent than humans, such a system could evolve or build successive generations of increasingly powerful AI that could wisely plan comprehensive research programs and eventually enable radical new technologies, such as a way to overcome aging. Unlike Narrow AI and AGI, Superintelligent AI is entirely hypothetical and the history of AI witnesses very little research or milestones in this area.

The potential power of a superintelligent AI poses a variety of ethical and existential risks. It could be asked to do something harmful to humanity or the world, intentionally or unintentionally. It is conceivable that humanity would choose not to create Superintelligent AI for many reasons, including these concerns.

4. Trends in Artificial Intelligence

The history of artificial intelligence is a testament to the discipline's foundational and advancing concepts. As the field evolves, narrow artificial intelligence gives way to general and eventually superintelligent artificial intelligence. These development stages are instrumental in understanding trends in artificial intelligence.

Trends in artificial intelligence remain an evergreen topic. Observing how present-day trends differ from those of the past helps chart a trajectory for the field. Milestones in artificial intelligence development, from its nascent stage to recent breakthroughs, serve as reflections of progress.

4.1. Current Trends

Limiting collaborative Ness during cognitive tasks makes intelligent systems such as humans. Currently, chatbot systems are the most collaborating agents that support human beings in everyday life, showing highly developing cooperation. However, how the collaborating robots contribute and manage the process to solve an unspecified cognitive task is still the main challenge. The robots need to set up a collaborating group and can solve a difficult task through collaboration [3,20-23]. In addition, no previous papers explicitly explored managing a collaborating group to solve cognitive tasks from the task assigning perspective. To explore the potential translation of a collaborating group to solve a complex cognitive task, a model is developed here, with that target. In this work, a filtered task assigning function with an improved filtering specification that contributes to the accuracy of assigning task to the most suitable agent in the collaborating group is also presented [9,24-26].

In the framework, agility aims at scheduling skills, so that an agent can collaborate with its counterpart agents without being a bottleneck or deadlock condition in the process. Meanwhile, quality of collaboration focuses on collaborating with the most suitable agent at the current time, so that the agent can deliver the finished products to the next responsible agent. The enhancing of these two sides leads the organization to achieve the highest agility and quality, hence contributing to the overall superiority in decision making [27-29]. The improper task assigning of a dynamic task itself would distribute limited agents' skills in collaboration to ineffective routes, creating bottleneck and deadlock. Therefore, the contribution of assigning the task to the most suitable agent is necessary [30-32].

4.2. Future Trends

Artificial intelligence technologies continue to develop rapidly. Technologies that had remained theoretical for a considerable time, those with performance that still fell far short of human capabilities, those in the niche of entertainment and games, as well as those with practical application, are all advancing fast. Narrow AI systems capable of performing specific tasks previously requiring human intelligence are appearing more frequently [9,33-35]. For example, AI systems now menace the golfers on Earth. According to [source], the demand met by Narrow AI and the resulting impact have been classified into the following five categories:

Moreover, researchers are seriously dealing with the problems of achieving Artificial General Intelligence (as presented by OpenAI's ChatGPT) and even moving towards the development of Artificial Super-Intelligence. Indeed, the capabilities of such systems can be viewed as an evolutionary process, with improved levels of both Sequential Reasoning and Context-Sensitive Reasoning. It has been claimed that Super-Intelligence Level can be considered the destination.

5. Milestones in Artificial Intelligence

From the origins of Artificial Intelligence at the Dartmouth Conference in 1956 to the deep learning revolution, AI has been marked by remarkable milestones and transformational breakthroughs. The study of the neural workings of the human brain and the advent of the PDP model in 1943 provided an early basis for Neural Networks. The McCulloch-Pitts Model paved the way for Binary Threshold Units (BTUs), which were subsequently developed by Donald Hebb and Warren McCulloch for pattern recognition. Short-Term Memory Networks (STMN) were pioneered by Walter Pitts in 1947, and Artificial Intelligence Models were deepened by the Turing Test proposed by Alan Turing in 1950. The Backpropagation algorithm in 1969 further propelled the capabilities of Neural Networks. In 1959, the Perceptron Model emerged from the Neural Networks Research Group, and Dendral produced the first Expert System in 1965. Institutions such as Computer Science and Artificial Intelligence Laboratory (CSAIL), Speech and Language Processing Group (SLPT), CONNEX, and Machine Intelligence Group have all contributed to the evolution of AI.

The early 2000s ushered in a new era for Neural Networks with the emergence of Deep Learning, which produced excellent results in real-world applications ranging from image recognition to face detection and classification. This success led to the rise of Deep Learning and Machine Learning research groups at IT Labs. Reinforcement Learning, Deep Q Networks, Generative Adversarial Nets, Transfer Learning, and a variety of other breakthroughs have since expanded the frontiers of AI capabilities.

5.1. Early Developments

Early developments in the field of artificial intelligence (AI) date back to classical philosophers who endeavoured to describe human thinking as a symbolic system. Key research in various domains that would later contribute to AI emerged during World War II, including Ada Lovelace's notes on the Analytical Engine, Alan Turing's work on computation, McCulloch and Pitts' formal mechanism for neuron functionality, and information theory by Morozov, Wiener, and Shannon. These interdisciplinary roots laid the foundation for the symbolic approach that dominated AI research from its inception through the 1980s.

Beginning in the mid-1980s, new techniques collectively referred to as sub-symbolic emerged, inspired by aspects of the nervous system such as artificial neural networks, genetic algorithms, swarm intelligence, and Bayesian learning. The symbolic and sub-symbolic traditions have since alternated in popularity according to their susceptibility to various so-called AI winters—periods of heightened criticism and reduced funding triggered by dissatisfactory progress against grandiose promises [36-38]. Eventually, many sub-symbolic approaches were incorporated into mainstream AI, often under the guises of data mining or machine learning.

5.2. Recent Achievements

The section highlights recent achievements in artificial intelligence (AI), with reference to emerging AI categories including Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI), and Artificial Super Intelligence (ASI). ANI focuses on specific tasks such as voice assistance, video games, and working as an accountant [3,39-41]. AGI aims to perform well across a variety of activities, involving the ability to think, plan, solve problems, and make rational decisions. ASI aspires to surpass human intelligence and capabilities in any endeavor. Currently, work is in progress for all three categories and for systems that can work across multiple types of AI.

A key AI technique is machine learning, which allows machines to learn from experience and perform human-like tasks through training. Deep learning—a subset of machine learning—and reinforcement learning techniques are also discussed. The section models developments in AI as countries around the world compete for leadership in AI technology.

6. Mathematical Principles in AI

Foundational mathematical principles of Linear Algebra, Probability & Statistics and Calculus are essential for building AI and ML algorithms. Linear Algebra encompasses vector and matrix algebra and their computation. Probability establishes a mathematical framework for expressing uncertainty, while Statistics offers methods for learning from data and for reasoning. Calculus provides tools for mathematical optimization [36,42-44]. Machine Learning techniques involve providing a system with data and allowing the system to learn for itself. Ideally, the learning process should be able to generalize about the data so that the system can perform well when presented with new examples.

6.1. Linear Algebra

Linear Algebra is a vital part of mathematics in Artificial Intelligence (AI). It is the foundation for Data Preprocessing, Feature Engineering, and Machine Learning (ML). Linear Algebra helps Supervised learning, Unsupervised learning, and Reinforcement learning techniques by making correlations, patterns, and inference from the input dataset. The input dataset may be of any type—images, text, numbers, or audio. Preprocessing applied to the input dataset prepares it for training in ML algorithms.

Feature Engineering includes two techniques, Feature Selection and Feature Extraction, which help the ML models to select the best features for classification or regression. Feature Selection methods: Information Quantity-based, Statistics, Similarity-based, and ML-based. Feature Extraction methods: Linear Projection, Linear Discriminant Analysis, Local-Discriminant-Embedding, Principal-Component-Analysis which includes Covariance-Matrix, Eigen-Value, and Eigen Vectors. ML Overview includes three techniques: Supervised Learning, Unsupervised Learning, and Reinforcement Learning, which help in modeling and predicting the outcome. Supervised Learning methods: Linear Regression, Logistic Regression, Support Vector Machines, Decision Tree, Random Forest, K-Nearest Neighbour, K-Fold Method. Unsupervised Learning methods: K-Means and Hierarchical Clustering. Reinforcement Learning methods: MultiArmed Bandit and Q-learning.

6.2. Probability

Probability is a branch of mathematics concerned with analyzing random phenomena. The outcome of a random experiment cannot be predicted with certainty. Probability supports the construction and application of machine learning algorithms. Probability theory helps evaluate the uncertainty and risk involved in decision-making. It provides a basis for drawing conclusions based on partial observations.

An experiment is an action, observation, or procedure performed with the expectation of obtaining a certain outcome. A random experiment is an action, procedure, or process that produces different outputs even though it is repeated under precisely the same conditions. The sample space is the set of all possible outcomes of a random experiment. Each individual outcome is called a sample point. An event is a subset of the sample space of an experiment and contains one or more sample points. Probabilities of forming different events from a sample space always fall within the range 0–1, inclusive. Probability analysis also provides a way to draw conclusions based on the occurrence of an event in the past.

6.3. Statistics

Statistics is a branch of mathematics that deals with the acquisition, organization, analysis, interpretation, and presentation of data. It gathers, organizes, summarizes, presents, and interprets data for different scenarios. The analytical results obtained through statistical methods help in making decisions. Statistics is used in various fields, including business, management, education, and psychology, to make sense of numerical data [40,45-47]. Descriptive statistics is the analysis of data that helps describe, show, or summarize data points in a useful manner. It incorporates numerical calculations, graphs, and tables to present data in a simple, understandable way. Descriptive analytics examines data or content from the past and then summarizes it to understand how patterns might influence a business. For historical purposes, descriptive statistics reports data summarizing a sample or an entire population using measures, such as the mean, median, modes, and measures of variability.

6.4. Calculus

Calculus is a subset of mathematical analysis that explains changes in functions and variables and enables the identification of critical points. As a fundamental tool for understanding natural sciences, it provides essential methods for scientific research. It includes differential and integral calculus, commonly applied in artificial intelligence and machine learning. Calculus quantitatively describes changes and measures quantities such as slopes, areas, lengths, volumes, and curvature. This field serves as a mathematical tool for studying movement laws and practical issues involving change rates and accumulation.

Differential calculus focuses on rates of change and slope, frequently used in determining functions' inflection points, extremes, and monotonic intervals. Integral calculus measures total quantities and areas under curves. Both differential and integral calculus address fundamental questions concerning quantitative variables. The concept of limits, allowing the approximation of instantaneous change information, is the basis of calculus and can be informally understood as the behaviour of functions near, but not necessarily at, certain points.

7. Data Preprocessing Techniques

Data preparation is a fundamental phase before applying any AI or machine learning algorithm on a dataset. It consists of two key stages: data preprocessing and feature engineering—crucial steps that establish the groundwork for successive analyses. Data preprocessing involves a set of standard techniques employed for detecting and correcting inaccurate or corrupt data records present in the initial raw dataset [3,48-50].

In the emerging area of big data analytics and artificial intelligence, organizations in various sectors accumulate enormous data volumes. Such data frequently suffer quality issues related to incompleteness, inconsistency, and inaccuracy. Analysing low-quality and inconsistent data seriously undermines decision-making. Hence, it is imperative to enhance data quality using robust data cleaning methods before any real-world application [5,8,51-52]. The most used data preprocessing techniques developed under the close relationship among data mining, artificial intelligence, and statistics. Necessary mathematical concepts—linear algebra, probability, statistics, and calculus—also play an important role in the analysis of real-world challenges.

7.1. Data Cleaning

Data Cleaning is among the most essential methods for preparing datasets for further analysis. It involves eliminating any outlier and null values from datasets to enhance the performance of machine learning models during training and testing. Large magnitude outliers can corrupt any models built on such datasets, so they should be removed for better performance. At the same time, it is crucial to replace any empty cells with appropriate values, as most algorithms cannot be executed on cells containing NG (not given) values.

Several techniques can be used to deal with missing values, such as deleting a row containing a missing value, deleting the entire column with missing values, filling missing values with the mean or median of the rest of the column, among others. Additionally, Data Transformation can be performed using Normalization and Scaling. Normalized data but with high magnitude can adversely affect algorithms that depend on magnitude to determine class attributes [9,53-55]. Such transformations help in making the data more suitable for analysis.

7.2. Data Transformation

Data transformation converts data into a more suitable format or structure to enhance the effectiveness of data analysis. It can be classified into several categories, including normalization and discretization [56-58]. Normalization, also termed feature scaling, involves adjusting values measured on different scales to a common scale [59-60]. This unifying approach prevents larger scale features from dominating those with smaller scales in distance-based machine learning techniques such as k-nearest neighbours and k-means clustering. Four popular normalization methods include Min-Max, Z-Score, Decimal Scaling, and Logarithmic transformations.

8. Feature Engineering Techniques

Feature Engineering Techniques are methods used to select, modify, and create features to improve the performance of Machine Learning models. In addition to Data Preprocessing, Feature Engineering is another essential step that can significantly enhance the effectiveness of Machine Learning models [5,8]. Feature extraction is the process of transforming the input features in a dataset into more efficient features. Feature selection aims to select the most relevant features from a dataset. These methods generally can be categorized into three types: filter methods, wrapper methods, and embedded methods. The main goal of feature selection is to reduce the number of input features, remove redundant and irrelevant features, improve model performance by training on smaller and less noisy data, and enhance a model's interpretability by training on important features.

8.1. Feature Selection

Feature engineering, a pivotal phase of data preprocessing, serves as one of the most significant steps in building any machine learning model. It is the process where the data is prepared so that the machine learning model can use past knowledge to make inferences about new data. Due to the "garbage-in-garbage-out" principle in machine learning, feature engineering determines the quality of the output. In feature selection, handful features most related to the business domain and desired output are selected and the rest are removed. Feature selection helps in dimensionality reduction, prevents overfitting, improves the accuracy of the models and reduces the execution time. SelectKBest, ExtraTreesClassifier, Recursive Feature Elimination (RFE), and LASSO regression are the four popular techniques of feature selection.

The SelectKBest technique examines each feature individually and assigns a score based on the chosen scoring function. A higher score indicates higher dependence on the input feature. The objective of the ExtraTreesClassifier method of feature selection is to train numerous decision trees and calculate the score by measuring the mutual information between the input and output variables. Due to its simplicity and effectiveness, feature selection with ExtraTreesClassifier is widely employed in machine learning. Recursive Feature Elimination (RFE) eliminates features recursively and builds models on data until the desired number of features remains. Although RFE is more computationally intensive, it delivers more precise estimations. Feature selection using the least absolute shrinkage and selection operator (LASSO) identifies dependent variables and performs both regularization and feature selection.

8.2. Feature Extraction

The features that make up the data are transformed in feature extraction. These are features generated from the input data, using various algorithms. Feature extraction improves the performance of machine learning algorithms. It uses fewer features instead of all the ones available in the dataset. The various feature extraction techniques that are available include principal component analysis, independent component analysis, linear discriminant analysis, and factor analysis.

Feature selection is a process that covers both feature extraction and feature construction. It deals with methods that help select a subset of features from the original feature set. Filtering, wrapping, and embedding are some of the feature selection techniques.

9. Machine Learning Overview

Machine Learning (ML) is a subfield of Artificial Intelligence (AI) that enables computers to acquire knowledge without explicit programming. It centers on creating algorithms capable of extracting information and discovering patterns within vast amounts of data. This section introduces fundamental types of machine learning—supervised, unsupervised, and reinforcement learning. The basic mathematical concepts underpinning ML—Linear Algebra, Probability, Statistics, and Calculus—are also discussed in detail.

Supervised learning focuses on training a model using a labeled dataset for classification or regression purposes. In contrast, unsupervised learning examines an unlabeled dataset to uncover hidden patterns, employing techniques such as clustering or dimensionality reduction. Lastly, reinforcement learning involves training an agent to reach an objective within a specific environment by providing feedback through labeling actions as good or bad. A comprehensive understanding of these approaches and the supporting mathematical principles is essential for effectively designing and employing machine-learning algorithms.

9.1. Supervised Learning

Supervised learning is a machine learning paradigm in which the learning algorithm receives both the input dataset and the corresponding labeled output data for training purposes. The provided labeled output guides and directs the training of the algorithm, which attempts to create a model capable of producing the expected output when presented with new input data abstracted from the original training dataset. In supervised learning, the objective is to learn the mapping function from input features to the output label.

Supervised learning models can be broadly classified into two categories based on the nature of the output labels: classification and regression. Classification models deal with discrete class labels as their output, whereas regression models predict continuous numerical values. Both technical and mathematical treatments typically begin with simpler models such as Linear Regression and Logistic Regression. A central topic in supervised learning is how the inputs (independent variables) can be applied to predict a specific output (dependent variable) using an approximated function, especially when the inputs may be noisy. Linear Regression, the simplest technique for prediction, fits a line to the data with the objective to minimize the squared errors between the prediction line and the actual points on the graph. The significance of mathematics—especially Linear Algebra, Probability and Statistics, and Calculus—in implementing these techniques cannot be overstated.

9.2. Unsupervised Learning

Unsupervised learning is a class of machine learning techniques that use information within the dataset to derive patterns and meaningful insights. In contrast to supervised learning, in which the dataset consists of feature-label pairs, an unsupervised learning dataset comprises unlabeled feature data. The principal challenge is to identify the unexpected or hidden, structure within the data domain.

Unsupervised learning techniques are applicable in many situations and can be divided into two main groups.

Clustering: clustering approaches include techniques such as K-means clustering (and other variants such as density-based clustering and gaussian-based clustering). Common applications include customer segmentation and zip-code based grouping.

Dimensionality reduction: algorithms include principal component analysis (PCA) and t-SNE. These techniques are used for data exploration and feature extraction.

9.3. Reinforcement Learning

Reinforcement learning is a paradigm derived from behaviorist psychology in which one studies how an agent needs to behave within an environment. The agent–environment interaction is modeled as a Markov decision process (MDP) consisting of S state, A actions, and R rewards. Such an agent interacts with the environment and selects actions based on a specific policy, which is either deterministic or stochastic, that cumulatively maximizes the expected reward.

According to Open Lund University, learning is defined as a "process that leads to a change in action that occurs as a result of an experience." Therefore, the agent must learn the optimal policy given a specific learning experience. It might be immediately obvious that areas such as decision-making, control theory, operations research, and optimization are closely related to reinforcement learning, although the moment an agent is able to learn its policy, such agent learns how to behave optimally according to its own experiences.

10. Applications of AI and Machine Learning

Applications of Artificial Intelligence (AI) and Machine Learning (ML) are now ubiquitous across many domains. In AI, intelligent agents introduced to a specific environment are often classified by the functionality and purpose of the agents. AI agents first analyze data that is collected from an environment to deduce Knowledge and plan to guide their actions. The agent plays a role that is assigned to it, completing the actions until a specific goal is achieved. The journey from the current state towards the goal state is termed the state sequence.

10.1. Healthcare

Information systems equipped with advanced Artificial Intelligence (AI) capabilities are applicable in various healthcare domains, including disease diagnosis, medical image processing, healthcare management systems, virtual assistants, data compression and storage, privacy considerations, telemedicine and remote monitoring, decision support and planning, and drug discovery. They also play a vital role in treatment, therapy, and training for doctors, therapists, and patients. AI is extensively employed in healthcare data analytics, enabling predictive models that support preventive healthcare strategies.

Machine Learning (ML) techniques analyze healthcare data to mitigate risks such as heart attacks or strokes. Deep learning models have been instrumental during the COVID-19 crisis for contact tracing, diagnostic applications, and patient classification. Key mathematical concepts underpinning these AI and ML algorithms can be explored in the foundational discussions on Linear Algebra, Probability, Statistics, and Calculus.

10.2. Finance

Finance remains one of the most appealing domains for AI and ML. AI/ML models can also analyze considerable amounts of trade data to determine whether a trade should be conducted, ensuring maximum profit. Furthermore, they can identify patterns in trading data and provide forecasting of returns in the financial markets, making this field one of the most sophisticated in the world. The traditional financial algorithms, which are invariably rule-based expert systems, deal with the investment, stock market analysis, management, and corporate assessment. However, their applicability is limited because of the nonunique solutions, higher risk, and fluctuations in the markets.

Other financial aspects related to lending also fall within the scope of AI. It cannot be concluded simply that more loan approvals indicate a better bank; frequent banking defaults will result in a bad image for the sector. These decisions were traditionally made by highly qualified and experienced experts, but this approach has two main shortcomings, both of which can be easily overcome when using AI tools: the decisions were prone to human error and could be biased. An ML-oriented model assigns a score to each applicant and uses this information to make approval/rejection decisions, thereby offering the advantage of automatic processing with minimal error. This also allows the strategies to support the decision-making process.

10.3. Transportation

The rapid, unprecedented growth of urban areas has made transportation a key global challenge. Human activities related to transportation contribute significantly to greenhouse gas emissions, being responsible for 25% of such emissions in the US, and in Europe, they are expected to increase by 40% in 2030 and 77% in 2050. The advances in Information and Communication Technologies, Earth Observation, and Computational Intelligence have created exciting research opportunities in intelligent transportation. The integration of various digital technologies is creating a new connected world, where Intelligent Transportation Systems (ITS) play a pivotal role in enabling communication between humans, vehicles, and infrastructure. The application of artificial intelligence in transportation promises to make cities responsive to real-time conditions and shape the future of smart cities.

Self-driving cars, also known as autonomous vehicles (AV), refer to vehicles capable of sensing their environment and operating without human involvement. They are designed to perform many aspects of driving, such as navigation, park location identification, collision awareness, and parking spot selection. Historically, companies have participated in self-driving car competitions to demonstrate AV technologies; for example, in 2005, an AV completed a 131-mile route in the Mojave Desert. In 2011, an automated vehicle named "Boss" completed the 60-lap Indianapolis 500 gas-free. The US Department of Transportation has classified driving automation into six levels, ranging from Level 0 (no automation) to Level 5 (full automation). Several pilot projects are currently underway to test driverless cars.

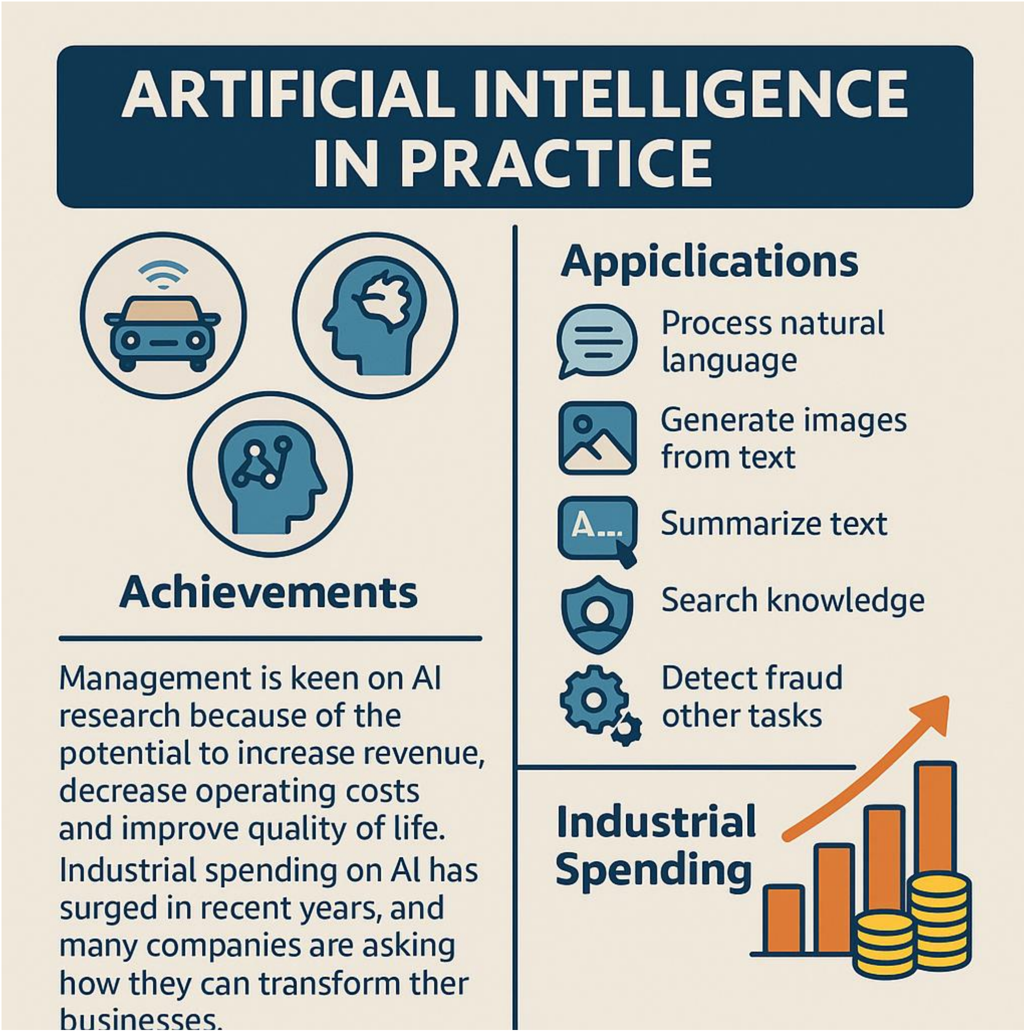

Fig 1. .AI in practice

10.4. Entertainment

Artificial intelligence impacts the entertainment industry in numerous ways. Video game developers harness AI to replicate human behavior in computer opponents, enhance narrative complexity, and enable adaption to players' individual play styles. AI is also applied in designing interactive movies that adapt dynamically to a viewer's choices and preferences, creating a personalized experience. In the movie industry, AI algorithms analyze scenes and dialogue to create detailed descriptions for the hearing-impaired and those who prefer to watch movies without sound. The ability to detect specific actors appearing on screen supports intelligent scene detection and retrieval. AI thus contributes to enhancing user experience through content accessibility and tailored entertainment.

Many applications in video gaming incorporate machine learning. Artificial neural networks learn the optimal moments to jump for a simulated player in platform games, while genetic algorithms evolve appropriate tactics for players to successfully navigate game levels. AI can also jam the playing strategies of human opponents. In interactive movie scenarios, AI interprets viewer preferences and choices to steer the narrative's branching in real time. These algorithmic approaches enable dynamic adaptation and increased engagement in entertainment media.

11. Ethical Considerations in AI

Artificial intelligence and machine learning (AI/ML) have garnered attention for their capability to perform tasks that were previously thought to require human-level intelligence. These include extracting underlying patterns within data, performing logic and reasoning, acquiring planning and strategic skills, mimicking the human brain, understanding human speech and sentiment, playing games, and generating synthetic voices or images. AI/ML have significantly disrupted various verticals and are being widely adopted to address critical application areas such as fraud detection in financial services, market analysis for retail, algorithmic trading in finance, patient diagnosis and prognosis in healthcare, autopilot and object detection in transportation, and the development of sophisticated virtual assistants like Alexa, Siri, and Cortana in entertainment.

The ethical impact of AI/ML is an important consideration that warrants discussion. Ethical AI/ML closely relates to the issues of bias, fairness, and privacy that can arise when developing models for business use cases. Training models with bias can give rise to an unfair biased system that may perform poorly on certain classes, categories, or groups of people. During deployment, data privacy must be preserved in accordance with the regulations of jurisdictions. The higher level of autonomy accorded to these models also raises concerns—if model predictions guide or control human tasks, any mistakes in prediction could be fatal to human life.

11.1. Bias in AI

Bias in Artificial Intelligence (AI) frequently arises not from inherent misconduct within the models themselves but from unintentional skews in input data. Most AI systems are designed to train on vast datasets, each serving as a proportional representation of the domain in question. Machine Learning (ML) algorithms generalize the embedded relationships within this data and subsequently apply these learned patterns to new inputs. Consequently, the scope of the dataset dictates the generalizability of the resulting ML model; the model performs optimally within the confines of the training domain but may falter or err catastrophically when confronted with inputs beyond this range. Such incapacity undermines the model's adherence to ethical and operational norms during prediction and usage.

Bias typically infects the initial stage of data gathering, usually during data curation when decisions about the nature and quantity of data are made. Therefore, careful consideration and rigor in these early choices are imperative to mitigate downstream problems. Nevertheless, the presence of bias in input data does not invariably result in ethically problematic models. Conversely, models derived from datasets with inherent bias may still perform satisfactorily and successfully in real-world settings. In such cases, the design and analysis of control groups can help attenuate the impacts of bias within the data source.

11.2. Privacy Concerns

The rise of AI poses serious privacy concerns due to the massive data sets required for training purposes. Sensitive personal data, such as medical records or credit card information, must often be made accessible during the training process. In some cases, data sets are scraped from the web, incorporating information that is not only personal but also protected by copyright laws. For example, the AI renderer Deep Dream used Google-owned YouTube images without the consent of the copyright holders.

Companies risk being sued for employing these training methods, and users are wary of having their data handled without explicit permission. Additionally, the creation of deepfakes severely undermines privacy, as individuals’ faces or utterances can be fabricated and distorted without their consent. The issue is further exacerbated by weak Institution Review Board policies and the absence of an independent regulatory agency to oversee the use and management of sensitive data. These challenges highlight the urgent need for comprehensive privacy regulations and ethical guidelines in the development and deployment of AI technologies.

12. Future of AI and Machine Learning

Future trends in artificial intelligence encompass the continued development and utilization of limited, general, and superintelligent AI systems. Progress will be driven by factors such as further definition and understanding of AI, improvements in hardware and software speeding up computations, the development of highly scalable specialized hardware to increase efficiency and speed of AI algorithms, and advances in software such as function optimization and transfer learning to enhance AI capabilities. Milestones are also expected to play a guiding role in AI evolution.

Given that foundational mathematical principles, algorithms, and data preparation techniques constitute the core of artificial intelligence, they will continue to influence future directions. Machine learning, embodiments of artificial intelligence, employs algorithms allowing computers to discern patterns and relationships within data. This ability to anticipate future data aids in solving numerous challenges across diverse fields. Mathematical concepts, such as Multivariate Calculus, Linear Algebra, Probability, and Statistics, underpin traditional machine learning algorithms, providing essential insight into their functionality and potential applications in areas including healthcare, facial recognition, finance, and gaming.

13. Conclusion

Artificial Intelligence (AI) is the science and engineering of creating intelligent machines—systems that respond, learn, and adapt much as humans do. The study of AI machines is not new. Concepts of intelligent machines date back to Greek mythology in the third century BC, while algorithms based on logic and reasoning, concepts foundational to AI machines, originated in the third century AD. The earliest AI research in the United States was undertaken at MIT in 1948, and by the late 1950s, pioneers like Frank Rosenblatt and John McCarthy had explored neural networks and coined the term "Artificial Intelligence," a multidisciplinary effort aimed at replicating human neurophysiological processes. AI machines are generally categorized into Narrow AI, Artificial General Intelligence, and Superintelligent AI, with a burgeoning interest in Deep Learning, an advanced form of Machine Learning.

Machine Learning (ML) is an application of AI that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. It focuses on the development of computer programs that can access data and use it to learn for themselves. The process of learning begins with observations or data, such as examples, direct experience, or instructions, in order to detect features in the data and make better decisions in the future based on the examples provided. The primary aim is to allow computers to learn automatically without human intervention or assistance and adjust actions accordingly. ML is broadly classified into Apperception Learning, Supervised Learning, Unsupervised Learning, Semi-supervised Learning, and Reinforcement Learning. Artificial Intelligence, Machine Learning, and Deep Learning heavily rely on foundational knowledge of Linear Algebra, Probability, Statistics, and Calculus for the development of algorithms. Essential prerequisites include data preprocessing—including data cleaning, integration, transformation, reduction, discretization, and concept hierarchy generation—and feature engineering methods like feature selection and feature extraction.

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