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PIONEERING THE PATH TO ARTIFICIAL GENERAL INTELLIGENCE: OPTIMAL STRATEGIES FOR ADVANCEMENT

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Abstract
In the realm of artificial intelligence (AI), the quest for achieving Artificial General Intelligence (AGI), often referred to as human-level intelligence in machines, has been an enduring pursuit. AGI represents a technological milestone where machines possess cognitive abilities akin to human minds, enabling them to understand, learn, and apply knowledge across a broad spectrum of tasks and domains. To tread this path effectively, it is imperative to understand the landscape of AI methods currently in use, unravel their sources of inspiration, and discern the underlying principles that guide their development.

This research embarks on a comprehensive journey to classify and dissect AI methods, elucidating their applications, working principles, qualitative attributes, and sources of inspiration. By peering into the labyrinth of AI techniques, our goal is to provide a structured framework that not only discerns the existing AI landscape but also sets a map towards AGI.

Keywords:Artificial General Intelligence , Artificial Intelligence

Introduction

Artificial General Intelligence (AGI), is often portrayed as the future of artificial intelligence. At its core, AGI represents a vision where machines emulate human-level intelligence, not merely in isolated tasks, but in a breadth and depth that functions like the human mind. It's an aspiration rooted in the desire to create AI systems that not only perform specific functions but comprehend, learn, and adapt across multifarious domains, much like the human intellect. The realm of AGI holds the promise of groundbreaking advancements in technology, introducing transformative applications in healthcare, education, finance, and beyond. In this realm, machines would not just execute predefined algorithms; they would possess the capacity to explore new solutions, optimize processes, and push the boundaries of innovation.

As we stand at the precipice of this tantalizing future, understanding the stepping stones that pave the way to AGI becomes paramount. The AI methods currently shaping our technological landscape represent these essential building blocks. Each method carries distinct attributes, influences, and principles, rendering them exceptionally effective in specific applications, domains, and industries. To advance toward AGI, we must dissect, categorize, and scrutinize these methods in search of patterns, commonalities, and gaps that will allow us to embark on a purposeful journey toward the coveted domain of AGI.

This research paper embarks on precisely that ideology—an exploration of the diverse and intricate universe of AI methods, aiming to unearth their sources of inspiration, working principles, and applications. By classifying and analyzing AI methods based on these diverse aspects, we endeavour to shed light on the existing state of AI and uncover the potential trajectories that may lead us to AGI. It is an exercise in deciphering the algorithms and models that drive modern AI systems, and in doing so, identifying the nodes of convergence that can align the field with the requisites of AGI.

To undertake this endeavour, we have devised a structured methodology. This methodology encompasses meticulous data collection, classification of AI methods based on their application, working principles, qualitative attributes, and sources of inspiration. This framework is our map through the huge and devious world of AI, a tool to unravel the intricacies and possibilities within the field.

This research paper doesn't merely serve as a survey of existing AI methods; it is a strategic endeavour that seeks to illuminate the underlying direction of AI research. Through categorization and analysis, we aim to clarify which AI methods are currently most relevant to the path of AGI. In essence, the paper will distinguish between methods that gather, process, and apply data from methods that can truly understand, learn, and make decisions.

The research paper concludes with an assessment of our findings, proposing that the realization of AGI hinges on bridging the chasm between current AI capabilities and human-like comprehension. We emphasize the importance of infusing cognitive understanding into AI systems and creating models. This confluence of biological and mental inspirations is identified as a potential accelerant in the pursuit of AGI, a course that propels us closer to machines that exhibit human-like cognitive capabilities.

Literature Review

The pursuit of Artificial General Intelligence (AGI) has been a longstanding goal in the field of Artificial Intelligence (AI). The notion of AGI represents a profound shift in AI research, moving from the development of specialized systems towards the creation of machines that can exhibit human-like cognitive abilities (Russell, 1995; Legg & Hutter, 2007).

Historically, AI research has been influenced by two main streams of inspiration: biological and mental. Biological inspiration involves mimicking processes observed in the natural world, often drawing from biology and genetics. On the other hand, mental inspiration seeks to replicate the cognitive and psychological processes that govern human thinking, learning, and decision-making (Russell & Norvig, 2016; Hinton et al., 2006).

One of the earliest examples of biologically inspired AI is the development of neural networks, inspired by the structure and functioning of the human brain (McCulloch & Pitts, 1943). These networks are capable of learning and pattern recognition, making them essential for tasks like image and speech recognition. Genetic algorithms, another biologically inspired approach, simulate the principles of natural selection and evolution to find optimal solutions (Holland, 1975). These methods have found applications in optimization problems, including engineering, logistics, and finance (Goldberg, 1989).

Mentally inspired AI, on the other hand, draws from cognitive psychology and cognitive science to replicate human-like intelligence (Russell & Norvig, 2016; Sutton & Barto, 2018). Supervised learning, unsupervised learning, and reinforcement learning are examples of AI techniques that fall under this category (Sutton & Barto, 2018; Bishop, 2006). These methods are used extensively in machine learning for tasks like image recognition, decision-making, and autonomous systems.

In the quest for AGI, there has been a significant shift towards cognitive and decision-making approaches. Reinforcement learning has gained prominence in robotics and autonomous systems, enabling machines to make decisions based on interactions with their environment (Sutton & Barto, 2018; Mnih et al., 2015). Markov Decision Processes (MDPs) are central to solving sequential decision-making problems, with applications in control theory and operations research (Puterman, 2014).

While the field of AI is replete with biologically and mentally inspired methods, there is also a growing trend of combining ideas from both streams. For instance, deep learning, which is biologically inspired by neural networks, has led to remarkable advancements in cognitive tasks such as natural language processing and image recognition (LeCun et al., 2015; Bengio et al., 2013). The marriage of these inspirations may be the key to achieving AGI, allowing machines to both understand and learn from their environment, much like humans do.

Recent innovations, such as Transformers in natural language processing (Vaswani et al., 2017) and Generative Adversarial Networks (GANs) in image generation (Goodfellow et al., 2014), demonstrate the evolution of AI methods that blend these inspirations. Such models represent a more balanced approach, harnessing the power of both biological and mental inspiration to enhance the capabilities of AI.

Methodology

The methodology employed in this research is directed towards the segregating of artificial intelligence (AI) methods in many different ways and seeing how they are being exploited in today's world. Then we can use these segregations and classifications to analyse clearly how the AI methods are working and applied in the technology. By achieving this we can understand the path we are traversing in and see how to traverse to achieve AGI according to its definition.

The methodology unfolds in a structured manner, starting with the collection of data on AI methods through quantitative analysis. This classification was achieved through a comprehensive literature review and analysis. One of the crucial steps understands the inspirations that have driven AI innovation. Subsequently, qualitative analysis will be conducted to compare the frequency and effectiveness of the methods in the existing AI research landscape. These analyses will serve as the basis for making informed inferences on the existing AI scenario.

In summary, this methodology takes a deliberate approach to categorize AI methods by, providing a foundation for subsequent analyses and discussions in the pursuit of advancing Artificial General Intelligence. Through this classification, we aim to illuminate the prevailing influences shaping the AI field and offer valuable insights into the direction that AGI research may need to take.

Framework

Initially, we are looking into how we can classify the set of different methods used in AI and try to find the similarities and how closely they align with each other. We trying to achieve subcategories in each of the segregations we are about to do. These subcategories will represent the end usage of all the AI methods today. These subcategories can be used as a backbone to see how our present-day AI is progressing and has to progress. The framework step-wise:

1. Make a quantitative analysis of the most used AI methods today most of them taken from our literature review.
2. The focus is on working, application, effectiveness or qualitative, inspiration.

a) Make segregation of all AI methods based on each of the above criteria .
b) Make subcategories for each of the similar methods .
3. These subcategories will represent the all AI methods for each criterion.

1) Qualitative Analysis

We shall see the most used AI methods today, It's challenging to definitively determine which of the methods are used most in the world today because their usage can vary widely depending on the specific industry, application, and region. However, we are looking broadly and can provide some insights into their prevalent usage in different domains Supervised Learning: Supervised learning is widely used in various domains for tasks like image recognition, natural language processing, and recommendation systems.

Deep Learning: Deep learning, a subset of neural networks, is extensively used in image and speech recognition, autonomous vehicles, healthcare, and many other applications.

Natural Language Processing (NLP): NLP techniques, often using neural networks, are essential for applications like chatbots, sentiment analysis, and language translation.

Reinforcement Learning: Reinforcement learning is prominent in robotics, autonomous systems, and game AI.

Evolutionary Algorithms: Evolutionary algorithms are employed in optimization problems, including engineering, logistics, and finance.

Genetic Algorithms: Genetic algorithms find use in optimisation, scheduling, and machine learning.
Monte Carlo Tree Search: This method is prevalent in-game AI, particularly in board games like chess and Go.

And here are some applications which are growing and which shall be widely used :

Transfer Learning: Transfer learning is increasingly applied in various domains to improve the efficiency of AI models.

Generative Adversarial Networks (GANs): GANs are used for image generation, style transfer, and data augmentation.

Bayesian Networks: Bayesian networks find applications in healthcare, finance, and fault diagnosis.
Some methods are used extensively in their specific domain:

Cognitive Computing: This method has applications in healthcare, finance, and legal industries for data analysis and decision support.

Automated Theorem Proving: Common in mathematics, computer science, and formal verification of software.

Q-Learning: Used in reinforcement learning and game AI.

Semantic Networks: Applied in knowledge representation and AI domain-specific languages.

Hierarchical Reinforcement Learning: Often used in robotics and complex decision-making.

Transformers: Dominant in NLP, especially for language models.

Domain Constraints: Applied in various fields to represent and enforce constraints.

Self-Organizing Maps (SOMs): Used for clustering and dimensionality reduction in data analysis.

Knowledge-Driven Abstraction: Applied in expert systems and knowledge engineering.

Neuroevolution: Primarily used for evolving neural network structures and weights.

Self-Improving AI: Applied in AI systems designed to adapt and improve continuously.

Adaptive Transfer Learning: Prevalent in domain adaptation and knowledge transfer.

Also, examples will be the main Emerging and Specialized Fields:
Quantum Computing and AI: These are relatively new and emerging technologies with applications in cryptography, optimization, and scientific research.

Emotions Understanding Infusion: Used in sentiment analysis and human-computer interaction.
Cognitive Computing: This method has potential applications in various domains, including healthcare and finance.

2) Segregation Based on Application
Methods Primarily Used in Game Playing and Decision-Making: Monte Carlo Tree Search: This method is commonly applied in game-playing and decision-making processes, where it simulates various outcomes and decisions to find the optimal strategy.

Q-Learning: Q-learning is a fundamental reinforcement learning technique, widely used in areas where decisions and actions need to be optimized, making it crucial in-game AI and control systems.

Methods Applied in Optimization and Problem Solving:
Genetic Algorithms: Genetic algorithms are used for optimization problems, mimicking the principles of natural selection and evolution to find optimal solutions.

Automated Theorem Proving: This method is employed in formal logic and mathematics to automatically determine the validity of mathematical statements, making it valuable in problem-solving.
Markov Decision Process (MDP): MDPs are central in solving sequential decision-making problems and have applications in control theory, operations research, and AI.

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Methods Commonly Used in Machine Learning and Pattern Recognition:
Supervised Learning: Supervised learning is widely used in machine learning for tasks like image and speech recognition.

Unsupervised Learning: Unsupervised learning is applied in clustering and dimensionality reduction, finding patterns in data.

Transfer Learning: It's commonly used in machine learning to leverage pre-trained models for various tasks, thus accelerating the training process.

Neural Networks: Neural networks are fundamental in machine learning, and used for tasks like image and speech recognition.

Deep Learning: Deep learning, with its multiple hidden layers, is applied for complex pattern recognition in various fields.

Cognitive Computing: Cognitive computing is used for understanding and reasoning over unstructured data.

Generative Adversarial Networks (GANs): GANs are frequently used in image generation and style transfer.

Bayesian Inference: It is used for probabilistic reasoning and updating beliefs with new evidence.

Semantic Networks: Semantic networks are applied in natural language processing and knowledge representation.

Transformers: Transformers have revolutionized natural language processing and machine translation tasks.
Hierarchical Reinforcement Learning: This method is utilized in robotics and complex decision-making systems.

Domain Constraints: Domain constraints are used in various fields to limit the solution space and make problems more tractable.

Methods for Self-Improvement
Reinforcement Learning: Reinforcement learning has applications in robotics, gaming, and autonomous systems.

Bayesian Networks: Bayesian networks are applied in various domains, including healthcare and finance, for probabilistic modelling.

Expert Systems: Expert systems find applications in healthcare, diagnostics, and decision support.
Knowledge-Driven Abstraction: This method is valuable in problem-solving and knowledge representation tasks.

Self-Improving AI: Self-improving AI has applications in autonomous agents and adaptive systems.
Neuroevolution: Neuroevolution is used in optimizing neural network architectures for various applications.
Emotions Understanding Infusion: This method has applications in human-computer interaction and sentiment analysis.
Quantum Computing and AI: Quantum computing is used to enhance AI tasks like optimization and machine learning.

Self-Organizing Maps (SOMs): SOMs are applied in data visualization, clustering, and dimensionality reduction.

Curiosity-Driven Exploration: It is employed in AI systems to promote autonomous learning and exploration.

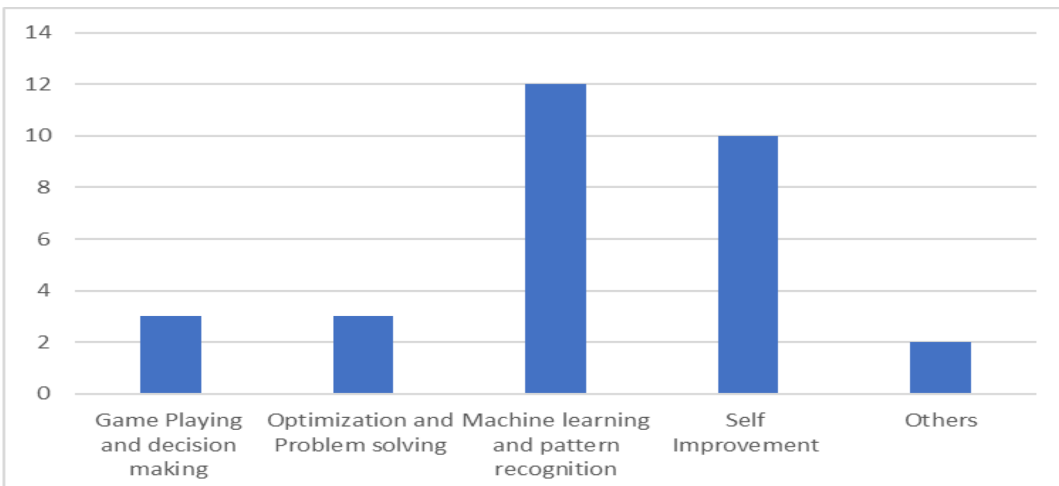

Fig. 1. The Subcategories found when the AI methods the segregated based on application

3)Segregate Based on Working :
Methods with learning-based working principles
These methods are primarily focused on learning from data, experiences, or feedback to make decisions and improve performance. Reinforcement Learning, Supervised Learning, Unsupervised Learning, Transfer Learning, Q-learning, Curiosity-Driven Exploration, Semantic Networks, and Emotions Understanding Infusion fall into this category.

Methods with Optimization-Based Working Principles
Optimization is the key working principle in this category. Genetic Algorithms, Evolutionary Algorithms, Monte Carlo Tree Search, Bayesian Inference, Automated Theorem Proving, and Neuroevolution employ optimization techniques for problem-solving and decision-making.

Methods with Neural-Based Working Principles
These methods are centred on artificial neural networks and their interconnected structures. Neural Networks, Deep Learning, Generative Adversarial Networks (GANs), Transformers, Self-Improving AI, and Quantum Computing and AI use neural network models to process and analyze data, make predictions, or generate content.

Methods with Decision-Making and Problem-Solving Working Principles:
This category comprises methods focused on decision-making, reasoning, and solving complex problems. Markov Decision Process (MDP), Bayesian Networks, Expert Systems, Knowledge-Driven Abstraction, Automated Theorem Proving, Hierarchical Reinforcement Learning, and Cognitive Computing fall into this group.

Methods with Other Working Principles:
Some methods have unique working principles that don't fit precisely into the above categories. Self-Organizing Maps (SOMs) are based on a self-organizing behaviour principle. Domain Constraints are applied to limit AI actions within specific constraints, while Cognitive Computing combines elements from various working principles, making it challenging to classify under a single category. This unique category is where these methods belong.

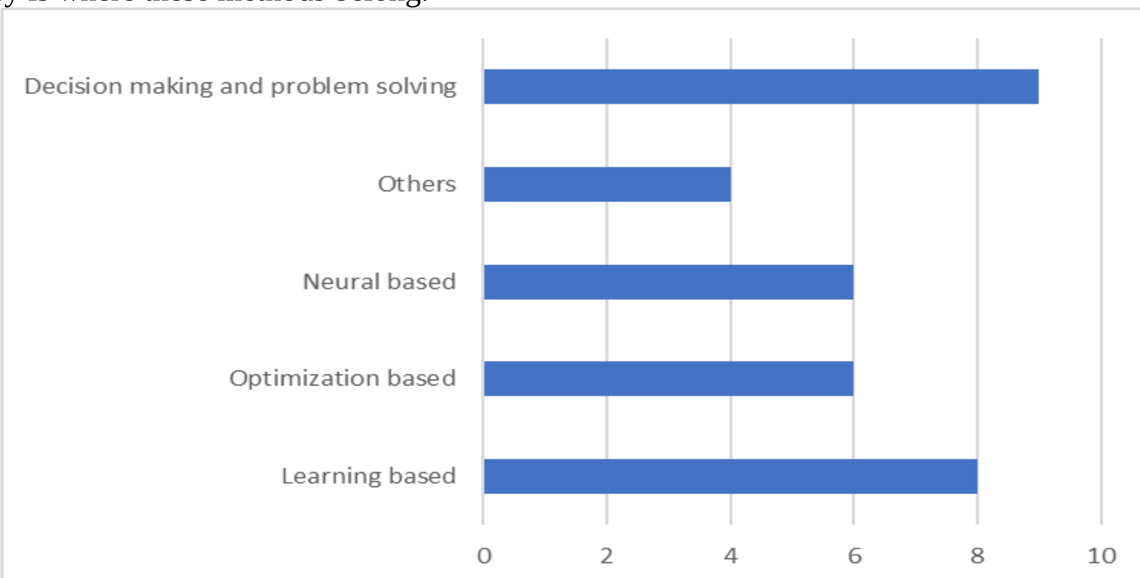

Fig. 2. The Subcategories found when the AI methods the segregated based on the working principle.

4) Qualitative Analysis
This section refers to the systematic examination and interpretation of non-quantitative information, characteristics, and attributes associated with each method. It involves assessing the inherent qualities, features, and principles that define and differentiate various AI approaches.

Machine Learning and Neural Networks
This category includes methods primarily focused on data-driven learning and the development of artificial neural networks for tasks such as pattern recognition and prediction. Supervised Learning, Unsupervised Learning, Transfer Learning, Deep Learning, and Reinforcement Learning are included in this category.

Nature-Inspired Methods
These methods draw inspiration from the principles of natural selection, evolution, and genetics, often used in optimization problems. Genetic Algorithms, Evolutionary Algorithms, and Neuroevolution are included in this category.

Logic and Inference

Methods in this category are based on formal logic, probabilistic reasoning, and knowledge representation for inference and problem-solving. Bayesian Networks and Semantic Networks Automated Theorem Proving are included in this category.

Cognitive and Decision-Making

These methods aim to replicate cognitive processes, decision-making, and autonomous learning, making them suitable for applications involving complex decision environments. Markov Decision Process (MDP), Q-learning, Curiosity-Driven Exploration, Self-Improving AI, Hierarchical Reinforcement Learning, and Transformers are examples of this category.

Human-Centric AI

These methods focus on replicating human-like intelligence and behaviour, including emotions, reasoning, and expert knowledge. Cognitive Computing, Expert Systems, Knowledge-Driven Abstraction, Emotions Understanding Infusion.

Innovative Approaches: This category comprises methods that employ unique and innovative approaches, such as mapping high-dimensional data to lower dimensions (SOMs) or simulating game tree search (Monte Carlo Tree Search).Bayesian Inference, Quantum Computing and Domain Constraints.

Generative Models

Generative Adversarial Networks (GANs) are specialized methods used for generating creative content or data

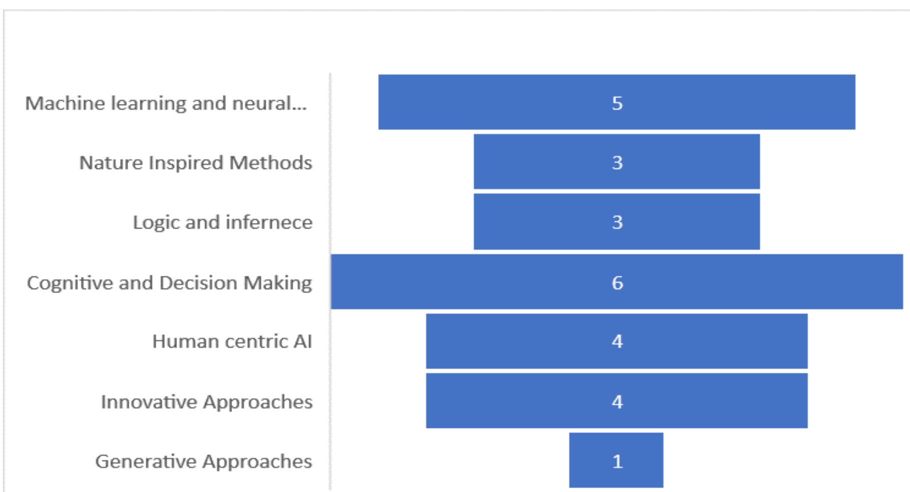

Fig. 3. The Sub categories found when the AI methods the segregated based on their qualitative analysis.

5) Segregation Based on Inspiration

Biologically inspired systems are often modeled after various aspects of living organisms, such as the human brain's neural networks. These genetic algorithms underlie evolutionary processes or the self-organizing behavior observed in social insects like ants and bees. They leverage these biological analogies to design AI algorithms, robots, and technologies capable of performing tasks like learning, adapting, evolving, and problem-solving, which are central characteristics of living organisms. In essence, these systems aim to harness the efficiency, adaptability, and intelligence seen in nature to create more advanced and capable artificial systems for various applications, ranging from robotics and artificial intelligence to optimization and problem-solving in diverse fields like medicine, engineering, and computer science. Some of the examples used today are neural networks, deep learning, evolutionary algorithms, genetic algorithms, self-improving AI, Bio-inspired networks, cognitive computing, Q-learning etc

A mentally inspired system draws its principles and design concepts from the cognitive and psychological processes of human thinking and decision-making. These systems aim to replicate human mental functions, such as perception, reasoning, problem-solving, learning, and decision-making, to create artificial intelligence (AI) models and technologies that exhibit human-like cognitive capabilities. Mentally inspired systems often incorporate theories and models from cognitive psychology, cognitive science, and related fields to understand and replicate human-like intelligence. These systems can be used for applications like natural language processing, image recognition, autonomous decision-making, and more. They are built to mimic, to some extent, how human minds process information and interact with their environment. Some of the examples used today are supervised, unsupervised and reinforcement learning, domain constraints, curiosity-driven explorations, adaptive transfer learning, Markov decision process, semantic networks, metaphorical thinking, self-organising maps, and emotional understanding infusion.

Now as we have seen let us provide a clear distinction between both systems, typically anything that involves the structure of the organism or anything in nature is biological whereas anything that is an outcome of the brain is mental. An example of the connection of neurons in a frog's brain is biological as the frog decides to jump and move as fast as possible towards its prey. There are also some methods which are more mathematical than biological or mentally inspired like Bayesian or Monte Carlo tree search. But these models are limited in number most of the methods or algorithms used today are biologically or mentally inspired ones.

Results
All the methods used today if classified fall under mainly the below categories The quantitative analysis is done to bring out the most and most used methods today.

When they are classified according to the applications of the methods found in quantitative analysis: as seen in this paper's methodology

1. Game-playing and Decision making
2. Optimization and Problem Solving
3. Machine learning and Pattern Recognition

When they are classified according to the working of all the methods as seen in this paper methodology:

1. Learning Based
2. Optimization based
3. Neural Based
4. decision making and problem-solving

When all the methods are classified according to the qualitative analysis:
1. Machine learning and Neural networks
2. Nature-inspired
3. logic and inference
4. Cognitive and Decision making
5. Human Centric AI
6. Innovative Approaches
7. Generative Models

When the entire model is classified based on their inspiration:
1. Biological
2. Mentally
3. Mathematical

Therefore, to sum up, we have segregated the methods based on Applications, working principles, Qualitative analysis and inspiration. And we have found subcategories of each where most of the methods can fit in. For example, if we take the AI method used today, it will surely fit into one subcategory in each segregation.

Example: RNN (Recurrent neural Network) was not used in any example above: its application subcategory is decision making and pattern recognition, its subcategory in working principle would be neural based, its subcategory in qualitative analysis is Machine learning and Neural Networks and cognitive and decision making, and inspiration is would fall under mental subcategory.

Therefore most AI models in today's use will fall under these subcategories of each segregation type. For understanding it would be a good way to say that it is not like there are no other sub-categories or AI methods, it is more like for today's technology and AI methods being used these sub-categories hold as a good reference point.

The definition of Artificial General Intelligence (AGI) refers to highly autonomous systems that can outperform humans at the most economically valuable work. It represents a level of AI development where machines possess human-like cognitive abilities, enabling them to understand, learn, and apply knowledge across a wide range of tasks and domains. From the above statement, we can tell that Primarily AI has to Collect data, Understand, Learn, and Apply efficiently and better than humans at each level

Conclusion
We looked into the AGI definition and the components needed to achieve it. In present-day technologies, there are numerous technologies to collect data in many different ways both the hardware and software sides of it. Now as take a deeper look at the subcategories we have created and show that most of today AI technologies fall under them, it should also mean that these subcategories are the end functions that our AI is performing today. As an example, while segregating AI methods based on application there are four subcategories that most AI methods fall in, that is these four subcategories are the basic functions performed by our present AI technologies. Similarly with all other segregation and their respective subcategories.

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By looking at the charts, we can say that all the subcategories are well-versed in performing or outperforming humans in learning and Applying information collected from their environments. But as per the definition we have almost negligible methods in AI that have cognitive capabilities to understand the information. We can see that no subcategories are based on the understanding element. The reason for this is we as humans have not completely perceived perfectly how this phenomenon occurs in the brain. There is a lot of study that is going on in this area of psychology and biology. But as AI engineers we can use bi-directional learning that is we have the privilege to show that AI can achieve this and it might be a skeleton for learning about this in future.

Also by taking a look at qualitative and inspiration segregations most used methods today are mentally or cognitively inspired models but the basic neural networks which is widely used are inspired biologically. The important information about why was this segregation even taken into consideration is a person's ability to understand information is done by logic and thoughts which is mental, but this understood information is saved in the human brain and how it's used when required is completely biological. Therefore the takeaway from this paper would be to achieve AGI by creating or innovating methods that can understand the external world and internal saved data information. The valid way to proceed would be a biological architecture performing a mentally cognitive application.

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