A large Language Model is not the Right Path to Bring Artificial General Intelligence

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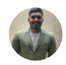
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Abstract

Large Language Models (LLMs) have shown impressive capabilities in many fields, leading to speculation about their potential role in achieving Artificial General Intelligence (AGI. Despite their high accuracy in language processing, this study argues that certain architectural and training limitations can stop LLMS from reaching AGI. We explore the fundamental characteristics of AGI, including consciousness, self-awareness, and continuous learning, and compare these with the capabilities of current LLMs. Our analysis indicates that LLMs are deficient in critical capabilities required for AGI, including knowledge generalization, novel learning methods, and autonomous reasoning. To rectify these deficiencies, we present a novel model that incorporates adaptive learning, sophisticated cognitive frameworks, and goal-oriented reasoning. This model advances the effort to transcend the limitations of LLMs and approaches AGI.

Keywords
Large Language Models (LLMs), Artificial General Intelligence (AGI), LLM architecture, Consciousness, Self-awareness.

1. Introduction
The rapid development of Large Language Models (LLMs) has raised the crucial question of whether these models stand for a practical path toward Artificial General Intelligence (AGI). While they outperform in many tasks like summarization, chat, question answering, zero-short and a few short learning, it is essential to critically examine their underlying architecture and training methodologies to assess their true potential for achieving AGI. Therefore, this paper discusses AGI and its different properties along with LLMs architecture and tries to investigate whether "Is current state of art LLMs or the Transformers and GPTs (Vasani et al., 2017) are capable enough to guide us toward AGI?".

1.1 What are LLMs?
Large Language Model or LLM is the decoder-only auto-regressive model which takes a sequence of tokens and predicts the next token for that sequence. That decoder is based on the Transformer model introduced by Vaswani et

al. (2017). The major motivation for this design is to strengthen the sequences generated and make the model more suitable for tasks requiring creative text generation.

The decoders in these models use the attention mechanisms typical of the Transformer architecture to allow for the model's focus on relevant parts of the input sequence when predicting the next word. Large language models normally work autoregressively: word by word, using the context of previously generated words to predict the next one. This autoregressive process lets LLMs produce coherent and contextually relevant text, even at levels of complex and nuanced language. Figure 1 shows transformer architecture.

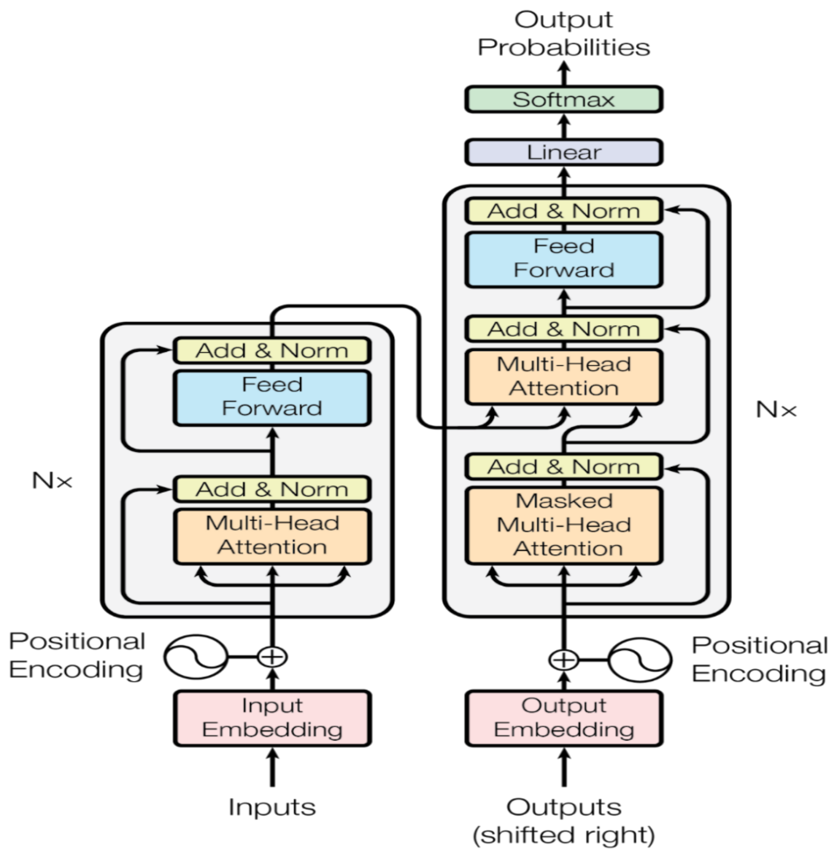

Figure 1. Transformer architecture (Vaswani et al., 2017)

The attention mechanism of the Transformer model, following Vaswani et al. (2017), describes a novel approach which enables the model to give specific tokens more value in the input sequence to make predictions for the next token. This mechanism enables the model to focus on selective parts of the input sequence by ascribing weights to the words or phrases depending on their relevance towards the current prediction. That is important because this dynamic weighting mechanism captures the long-range dependencies of the language. It allows the model to consider the words that are far apart in the sequence.

According to the paper, traditional RNNs face difficulties with long sequences because of the vanishing gradient problem, which makes it hard for them to learn relationships that are far apart. The attention mechanism overcomes this by directly allowing the model to attend to positions of the input regardless of position in the sequence. Suppose, for instance, it wants to predict the next word in a sentence; the mechanism of attention can consider some words appearing earlier in this sentence and weigh their importance in providing context for that prediction. A selective focus like that, on the relevant parts of the input, allows the model to get the full context of the sequence even when there are long and complex sentences; hence it allows for proper prediction. They computed the dot products of the query with all keys, divided each by dk, and applied a SoftMax function to obtain the weights on the values.

In practice, they computed the attention function on a set of queries simultaneously, packed together into a matrix Q. The keys and values are also packed together into matrices K and V. According to the paper, he computes the matrix of outputs as:

$$\text{Attention (Q, K, V)} = \text{SoftMax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (1)$$

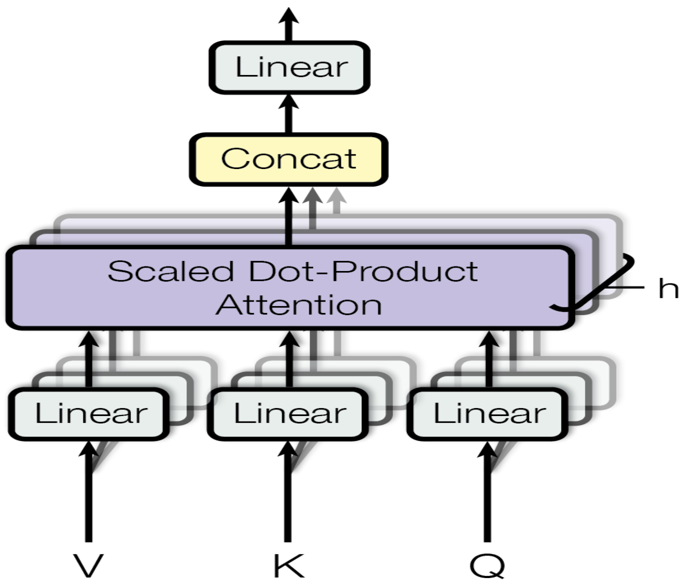

Figure 2. Scaled Dot-Product Attention. (Vaswani et al., 2017)

As a result, LLM or a stack of transformer decoders can achieve zero short learning, few short learning, in context analysis, can connect different domains of knowledge and generate any latest information. Figure 2 shows Scaled Dot-Product Attention.

1.2 What is AGI?

The concept of AGI now popularized after the mass use of LLM began. Now the question arises what is an AGI? According to Latif's research paper (2024), AGI usually refers to machine intelligence that has human-like cognitive abilities. For example, an AGI agent shall be able to understand, learn, and carry out any intellectual work a human person can do (Legg, Hutter, et al. 2007). AGI systems mimic humans' general-purpose problem-solving abilities (Wang, 2019). The ability of AGI systems to function autonomously, make judgments, and conduct actions without the need for human supervision is one of these features. This is the Basic Introduction to AGI.

So, what kind of properties should an ideal AGI have? In the paper (Laird et al. 2009), the authors composed a list of "requirements for human-level intelligence" from the standpoint of designers of cognitive architecture. Here is the list:

R0. FIXED STRUCTURE FOR ALL TASKS (i.e., explicit loading of knowledge files or software modification should not be done when the AGI system is presented with a new task)

- R1. REALIZE A SYMBOL SYSTEM (i.e., the system should be able to create symbolism and utilize symbolism internally, regardless of whether this symbolism is represented explicitly or implicitly within the system's knowledge representation)
- R2. REPRESENT AND EFFECTIVELY USE MODALITY-SPECIFIC KNOWLEDGE
- R3. REPRESENT AND EFFECTIVELY USE LARGE BODIES OF DIVERSE KNOWLEDGE

- R4. REPRESENT AND EFFECTIVELY USE KNOWLEDGE WITH DIFFERENT LEVELS OF GENERALITY
- R5. REPRESENT AND EFFECTIVELY USE DIVERSE LEVELS OF KNOWLEDGE
- R6. REPRESENT AND EFFECTIVELY USE BELIEFS INDEPENDENT OF CURRENT PERCEPTION
- R7. REPRESENT AND EFFECTIVELY USE RICH, HIERARCHICAL CONTROL KNOWLEDGE
- R8. REPRESENT AND EFFECTIVELY USE META-COGNITIVE KNOWLEDGE
- R9. SUPPORT A SPECTRUM OF BOUNDED AND UNBOUNDED DELIBERATION (where "bounded" refers to computational space and time resource utilization)
- R10. SUPPORT DIVERSE, COMPREHENSIVE LEARNING
- R11. SUPPORT INCREMENTAL, ONLINE LEARNING

Another source from "Theoretical Foundations of Artificial General Intelligence" by (Wang & Goertzel, 2012), provides useful information on consciousness and AGI. In this paper, the authors give importance to having consciousness of the AGI system. They even claimed consciousness is necessary for building a smart AGI-based agent. Their point is that meaningful intelligent acts do not seem to be possible without consciousness. In short, any AGI system should have a fixed structure, use symbolism, handle diverse knowledge, support learning and metacognition, and prove cognitive abilities, consciousness, and self-awareness.

1.3 Consciousness

AGI should have human-level intellectual capabilities. To achieve those capabilities, AGI should have consciousness and self-awareness much like humans have. Consciousness can be defined in many ways. But a synthesized definition, based on research (Seth 2018), describes as the subjective experience of being aware of one's internal mental states and the external environment, characterized by integrated and informative global states that include conscious belief and a sense of selfhood. The existence of consciousness is very intriguing. While both biological and non-biological physical systems process information, humans have an added layer of conscious experience. Why cannot machines have the same concussion level as humans? According to the research of (Bennett et al. 2024) self-organization is presented as a fundamental characteristic of living systems. According to this paper self-organization is a process where living systems (like humans) keep order and function in the face of changes in the environment. He argues that self-organizing systems are the basis for consciousness. This is because living organisms must constantly make sense of their environment to survive. As per the research of Bennett, there are two types of consciousness, one is phenomenal consciousness another is Access consciousness (2024).

Phenomenal consciousness:

This refers to subjective experience, first-person experience of sensations and feelings. Experience something to" what is it like". Just like tasting food or feeling pain. This is more like personal, subjective experiences that are often referred to as "qualia".

Access consciousness:

It refers to being able to access information and use it for decision-making. It is more like functional and procedural knowledge rather than feeling it. This type of consciousness is less subjective and more about particle use and manipulation of information through cognitive tasks.

According to this paper, humans have both phenomenal and accessible consciousness. But LLM or machine does not have both Phenomenal and Access consciousness. It only has access to consciousness. The author also claimed that consciousness is deeply connected with natural selection rather than abstract thinking. To achieve AGI, machines must be enabled to have phenomenal consciousness, and the system must go through extreme competitive survival issues and that system must learn to overcome those by adapting to I ts environment. The study's overall goal is to show that Large Language Models (LLMs) cannot bring Artificial general intelligence (AGI). Because it has Arbitrary limitations.

2. Literature Reviews

Artificial General Intelligence (AGI) has been a subject of immense research and debate within artificial intelligence (AI). Recent developments in large language models (LLMs) have fueled a surge of optimism and hype surrounding this topic. In 2012, Wang and Goertzel provided a detailed theoretical foundation of AGI by incorporating human consciousness and cognitive abilities, defining AGI's various aspects and suggesting a research path towards AGI with reinforcement learning in "Theoretical Foundation of AGI" (Wang & Goertzel 2012). They tried to address the problem of a perfect model that defines human consciousness properly, represented various models related to AGI and established conceptual definitions for Machine consciousness. In 2014, Ben Goertzel individually tried to characterize general intelligence through various perspectives, including psychological, mathematical, and embodiment-focused approaches. He also described some approaches for AGI like Symbolic AGI Approaches, Emergentist AGI Approaches, Emergentist AGI Approaches and Universalist Approach. Wang and Goertzel's work provided a definitive research path and foundation for AGI.

But, when Vaswani et al. (2017) proposed the Transformer, a groundbreaking architecture for natural language processing (NLP), and OpenAI demonstrated the outstanding performance of the GPT-3 model (based on Transformer's architecture) in complex tasks such as summarization, question-answering, coding, and few-shot learning (Brown et al. 2020), the hype around AGI was sparked. As LLMs-based chatbots like ChatGPT, Claude etc. show those extraordinary capabilities and sometimes they even mimic human-like reasoning and self-awareness, people start to guess that LLMs may bring AGI. So, some researchers are following the Wang and Goertzel path and trying to examine if LLM has properties of AGI. For example, Gams & Kramar (2024) tried to evaluate if LLM like ChatGPT has consciousness and if it can pass the Turing test. They found that ChatGPT lacks consciousness attributes found in advanced living organisms.

However, many researchers and experts suggest that LLM itself cannot bring AGI. Hofkirchner (2023) claimed that the Large Language Model cannot meet AGI expectations. In the paper, he analyzed different philosophical arguments such as the praxiological argument, the ontological argument and the epistemological argument and concluded that LLMs cannot meet AGI criteria. However, his research is only philosophical based and does not include any work on machine consciousness, edge learning and continuous adaptability which are crucial properties of AGI. François Chollet (Houser 2024) said that AI benchmarks today mostly test the ability of a model to memorize rather than to be genuinely intelligent, while intense focus on LLMs gets in the way. According to Chollet, existing evaluation methods, including performance on standardized tests, poorly reflect progress toward general intelligence. He suggested that the field's concentration on LLMs has limited exploration of potentially more fruitful approaches to AGI development.

However, he did not provide us with any definitive research path for AGI. It extends further into other luminaries: Yann LeCun, Meta's chief AI scientist, called the LLMs "an off-ramp, a distraction, a dead end" en route to human-level intelligence. Even Sam Altman, CEO of OpenAI, doubted whether scaling the LLMs is a way toward the AGI (Houser 2024)

However, none of these researchers provided clear, strong arguments based on AGI-specific properties to explain why LLMs cannot achieve AGI. Furthermore, they did not give us a definitive research path for AGI. That is why this paper provides those arguments and proposes a model for going forward in the path of AGI.

3. Limitation of LLMs

Despite LLM's powerful context-aware capabilities, they have some major limitations that make them inappropriate for AGI-level workflows. This section discusses some of those major limitations and tries to understand how they stop us from achieving AGI.

3.1 Hallucinations and Factual Inaccuracy

According to a (Šekrst 2024) paper, Artificial intelligence (AI) hallucinations are a recent phenomenon in which AI-generated responses are false but presented as correct information. Sometimes they are even so confident in their incorrect claim that they provide false logic and try to convince the user to believe that info. This kind of false confidence in their generated text makes them inefficient for high reasoning fields like math, coding, physics etc. This kind of phenomenon sometimes leads them to be tricked. For example, if a user asks for any fact and the LLM answers the fact perfectly, then the user may trick the LLM by telling it that it was wrong, or any other way. Because of hallucinations most of them fall into this trap and start to generate misleading info. As a result, LLM can be forced to produce harmful, misleading and toxic content which raises serious safety concerns. Besides, this weakness also proves that they are not perfectly reliable to be the foundation of AGI.

3.2 They do not have real-world understanding and Common Sense

Limited grounding in physical reality: As LLMs are trained in text and code and do not have direct experience with the physical world, they struggle with tasks requiring real-world knowledge or reasoning about physical properties and interactions.

Absence of common sense: Sometimes LLMs generate correct sounding but nonsensical or illogical statements because they lack the commonsense reasoning abilities that humans develop through lived experience.

3.3 Ethics and Bias

Reflecting biases in training data: The data used for training may have social biases. As a result, they may generate racist, sexist and aggressive content. According to (Gupta & Ranjan 2024) paper, they find LLMs are biased toward elite university students (such as Harvard, Oxford, MIT etc.) for choosing employers for Big Tech like (Google, Meta, Microsoft etc.). Furthermore, as they do not possess self-awareness and hallucinations, it is easy for any third person to trick those LLMs to generate misleading info and harmful content. AGI systems should have consciousness, and they need to differentiate between good and bad. They should not be confined by training data or inference time hallucinations like LLMs do.

3.4 Context Window Limitations

Do not work with large content: Due to the attention-dependent transformer architecture, LLMs can only process a limited number of tokens (aka context window) in a single execution. For this reason, they cannot reason in long-term memory like humans can do. For example, Antropic's Claude 3 family of models can handle only 1 million tokens or context window (Antropic 2024). But for an AGI model, which will match human cognitive capabilities, it must have long memory ability. For example, humans have short-term and long-term memory capabilities and when they make any decision, or do any plan, they smoothly use both their memories. Even long-term memories and experiences construct the person who he is. So LLM with such limited memory and token processing capability, it is hard for us to practically implement anything with LLMs even close to AGI.

3.5 High Computational Cost

Resource intensive: LLMs are expensive as training and doing inference need huge GPU clusters and data centres. Moreover, cost scales with the number of trainable parameters as more parameters mean more GPU VRAM and Computational units. For example, according to (Maslej et al. 2024) GPT-3 175B and Llama 2 70B training costs are 4,324,883 U.S. dollars and 3,931,897 U.S. dollars, respectively. So, this data concludes that more trainable parameters cost more. As LLMs' performance scales with their parameters, trillions of parameters may be needed to achieve AGI. And that approach needs a huge sum of money and resources, which is practically impossible. Figure 3 shows the estimated training cost for different LLMs. Figures 3 and 4 show the estimated cost of training and size for different LLMs, respectively.

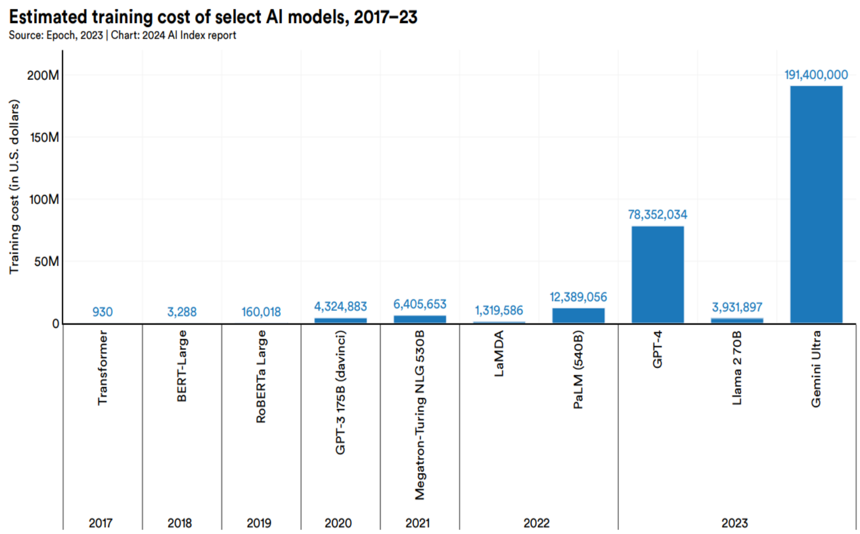

Figure 3. Estimated training cost for different LLMs (Maslej et al. 2024)

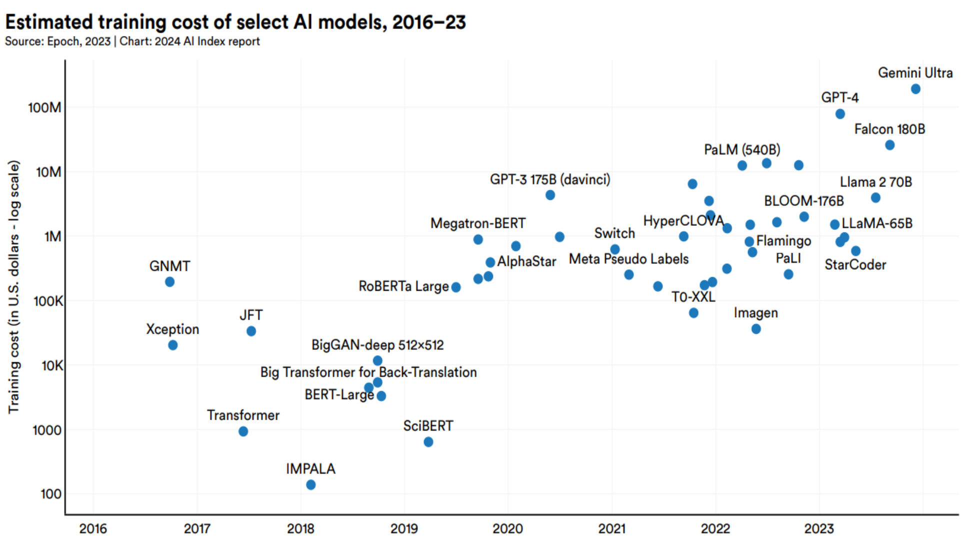

Figure 4. Cost estimations with LLMs size (i.e., total parameters) (Maslej et al. 2024)

3.6 Lack of inference time learning or Online learning

Due to inference strategy: LLMs are autoregressive token generators meaning they take one or several input tokens and predict the next token, again that next token is added into the input token list. However, if the input tokens are provided again, the model might generate a different token meaning it never remembers what the past inference session was. Once LLM parameters are trained, they are not changed by inference. So, their knowledge is limited to training data. It is not possible to teach them through inference sessions since inference does not update the model's weights. As a result, they cannot continuously learn like humans can do.

3.7 Absence of Self-Awareness

According to the paper (Gams & Kramar 2024), despite ChatGPT and similar generative AI models being highly advanced and intelligent tools, they distinctly lack the consciousness attributes found in advanced living organisms. According to Wikipedia, without consciousness, self-awareness cannot exist. As they do not have consciousness, they do not have self-awareness ("Self-awareness," n.d.). As LLMs do not have consciousness, they do not have self-awareness. They cannot "understand or recognize its existence". During the training phase, model weights are only updated to match the pattern of training data and as a result, it only adapts the linguistic features and may show some fake "self-awareness" and "reasoning". For reaching human-level intelligence or AGI, a model must possess the property of self-awareness.

4. Discussion on Why LLM cannot Bring AGI

LLMs are very capable of generating the next tokens and understanding earlier input. But only this capability is not even near enough for bringing AGI. But AGI needs to be human-like intelligent. It needs to have "consciousness", "self-awareness" and "human-like advanced reasoning through long-term memory". However, LLMs do not have any of those properties. They just learn to adapt to human language patterns and features. In this training process, they may learn to mimic some level of "consciousness" or "reasoning". But those fake consciousness and reasoning are not even near enough to real biological consciousness. Those are just illusions of consciousness. Here are some reasons why LLMs cannot bring AGI:

Architecture:
The transformer architecture is a single-flow information-passing architecture where information only flows forward. It just predicts the next token by analyzing and reaching the earlier word. However, the AGI models should not be input-output dependent. They needed to be open explorers of the environment. Even if the environment states are fed as input tokens and action as an output token, it will not achieve consciousness or self-awareness. Even then, it would not enable the model to learn continuously. As parameters are only learned in the training phase then those parameters become fixed static. So, this transformer architecture cannot adapt to new situations like humans can do. AGI must be a continuous learner and must explore the environment to learn continuously. It should not depend on any specific type of input (such as sequential), but transformer architecture is made to depend on these sequential tokens. Humans can see any changes in their environment through the five senses, AGI should do that. But the transformer's one-way processing system and attention mechanism prevent this kind of behavior as the attention mechanism works best for sequential input tokens and our environment is dynamic and it is not necessary to reflect changes all the time in a sequential manner. So, in short, LLMs are sequential data dependent but the real word environment does not come with sequential changes and of course, this language pattern learning architecture cannot achieve consciousness or self-awareness.

Training Method: LLMs are normally trained to predict the probability of the next token based on earlier tokens. As a result, it is a supervised training approach and needs a vast amount of well-structured, quality data. But AGI needs to learn from its environment and its entity much like a human does. The real-world environment does not have well-structured sequential data, it is dynamic, and anything can happen, so AGI must adapt to its surroundings. But the LLM training process cannot produce a model to handle this dynamic data.

Continuous Adaptability: LLM's knowledge is limited by its training data. They cannot learn all the time when interacting with users or in any specific environment. If there is a need for training, it needs to be retrained in that domain. However, AGI should learn anything by interacting with its environment and seeing changes made by other entities. AGI should not have a training or inference phase. LLMs cannot achieve this as they have different implementations for training and inference.

Lack of Consciousness: According to the paper (Gams & Kramar 2024), LLMs do not possess consciousness like advanced living organisms have. They can take sequences of tokens and predict the next ones. But they cannot experience something let alone feel its surroundings. They may mimic some level of consciousness or represent themselves as conscious and self-aware. They achieve this fake consciousness by adapting language features and patterns. On the other hand, to achieve human-level AGI, the AGI model needed to have machine consciousness and self-awareness which are not present in current state-of-the-art LLMs.

5. Proposal of AGI Model

A theoretical model is proposed, based on theoretical analysis, to address the limitations of current approaches and provide a clear path toward AGI. This model outlines the essential properties an AGI system should possess to achieve consciousness and self-awareness. Basically, this architecture takes inspiration from reinforcement learning but is reimagined and shaped specifically for leading the research path toward AGI. These components should be present for AGI.

Environment: Nearly every human develops within a surrounding environment where growth, learning, and change occur. Any AGI must live in any environment, it may be virtual or like the physical real-world.

Entity: Interacting with others is the way humans learn, understand, and decide what to do. Similarly, AGI needs to be surrounded by other entities for it to learn and make decisions. If the environment is the real world, those entities may be human beings or any other conscious being.

Actions: Like a human act to alter the environment, the AGI must have a set of actions from producing a single sound token to moving the body.

AGI Agent Model: An Agent Model is itself a crucial entity in the environment having capabilities like continuously adaptable learner, open explorer, and conscious thinker. May have any virtual or physical body to effectively move and make changes in the environment.
To achieve conscious and self-aware AGI, the following are required:

An Agent model that can see any environment and can learn continuously: The AGI model needed to learn from its observation of its surrounding environment just like humans learn from seeing other actions.

An Agent model that can reason through its observations: The AGI model needed to reason what it is learning and seeing. It needed to understand and reason why the observed action was taken by any environment entity, when and in which situation the entity is taking the action, and how and when the model itself should take those actions.

Open Exploration of Environment: Most importantly the model needed to explore the environment, its surrounding entities, and their actions in different situations to understand the environment.

Training less, A change in basic assumptions: AGI model needs to be like human beings. So, it should be learned by simulating how a human baby learns. Similarly, the AGI model needs to facilitate continuous learning of its entire lifetime in the environment, whether it is virtual or real. So basically, there will be no training phase or inference phase. There will be no specialized clean well-structured dataset the model will learn from. In short, the surrounding environment and its entity will be its learning source as much as humans. After all, the environment (virtual or physical) has distinct kinds of problems and hardships. The model will analyze those problems, see other entities how they solve the problem, and which sets of actions they take, and then the model learns what action it could take to overcome the problem.

Learning Objectives: The Model will go through many problems in its environment and even in its body. The model can take many actions to do anything from producing sound tokens to moving any specific part of its body. Those sets of same actions also allowed for its environment entity. They can take any of those actions to solve any kind of environmental problem. The will model will continuously see the environment as a curious human baby and try to figure out or learn what actions any environmental entity takes when they face those problems. Then it tries to take the same actions and checks if it could solve the problem. Even if it does not find others to solve a specific problem that it needs to solve, it will take the closest correct actions to solve the problem. If it does not find a preferred result, it will learn to understand its mistakes and refactor its decision process. So, the learning goal is to understand what action it should take by seeing others' processes and refactoring their action-taking decision process based on its mistakes.

Achieving thinking abilities: When humans take an action, their potential outcomes are imagined, leading to a continuous chain of predictions based on specific actions. The model must have this ability. Through seeing its environment and its actions and different actions' consequences, it must develop a complex internal evaluation system for all actions that human beings have. And it must learn to think or internally evaluate its actions before performing those actions. It can learn this kind of behavior by first taking random actions by random approach. When it acts by pre-evaluating it and gets satisfactory results, it will get rewarded and continuously learn to be like this. **Achieving**

Consciousness: Action to solve a different problem does not necessarily enable consciousness and self-awareness. To enable human-level consciousness and self-awareness, the model needed to have first-order, second order, and third-order self-understanding and needed to acknowledge its existence.

Facing Survival Issues: To achieve consciousness, any species had to go through natural selection. So, the species need to face extreme environments and need to survive those environments by mostly adapting to the environment. So, our AGI model also needs to go through survival challenges and learn to survive in those challenges by adapting to the current environment to achieve at least anything nearly like phenomenal consciousness. So, the environment needed to be tough and competitive.

6. Advantage of Our Proposal Over LLMs

The proposed model can overcome the major drawbacks of LLMs, advancing progress in AGI research. Here are the Key advantages of this model include:

Enable Self-Learning: The model incorporates an open exploration mechanism, eliminating the need for constant manual training to update its knowledge as needed in LLMs. It autonomously explores its environment, continuously learning from the actions of other entities and its own mistakes, without human-controlled intervention.

Continuous adaptability: The proposed model is learning and understanding its environment and acknowledging its action-taking decision-making mistakes, it can refactor its decision-making strategy and perfectly fit with its surrounding environment.

No need for well-structured high-quality data: Gathering, cleaning, and making well-structured high-quality data for LLMs is troublesome and costly work and often requires a lot of human resources. But this is continuous open exploration-based learners, it can learn and gain knowledge continuously by exploring the environment as much as humans do.

Enables social learning: Our model learns by interacting with other entities and in this way, it also learns social relationships and thus improves its understanding of society. If the environment is a real world, it may also learn about human society and develop an understanding of human society's relationships. But LLM, which is a sequence-to-sequence model, does not have the ability to open explore and interaction. So, it is impossible for them to build complex social relationships like our model can do.

Survival Challenges for Growth: The proposed model can easily adapt to the environment, so when it faces any survival challenges it can refactor itself to adapt to those challenges and grow its various capabilities within the environment.

Machine Consciousness: Our model mostly emphasizes enabling machines to be conscious, especially enabling phenomenal consciousness in machines. While LLMs do not have consciousness, the model ought to be as conscious as possible and the book discusses how the model approximates the major concepts of human cognition such as learning, interaction, relational spatiality, and awareness.

Internal Evaluation and Predictive Thinking: The ability to internally evaluate actions before executing them gives our AGI model a level of foresight like human predictive thinking. It can simulate possible outcomes of actions and choose the best approach, which is a key aspect of intelligent decision-making.

7. Conclusion

Large Language Models have significantly advanced AI research, demonstrating remarkable proficiency in NLP tasks. However, as researchers of genuine Artificial General Intelligence, we argue that these factors alone are insufficient: without real-world grounding, ongoing learning, and fundamental cognitive capacities, such as self-awareness. These LLMs will not be considered as genuine Artificial General Intelligence (AGI). While they are beneficial for specific significant applications, their statistical characteristics, rather than genuine understanding, render them insufficient for universal intelligence. The key aspect is that contemporary LLMs are completely data-driven language models. Future study on AGI will benefit from exploring other methodologies for its development. Including embodied AI, neuro-symbolic methodologies, and developmental learning frameworks. We assert that by implementing this methodology and including the essential components of the AGI model we have suggested, we can achieve substantial progress towards the realization of genuine AGI.

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