Integration of LLMs and the Physical World: Research and Application

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ABSTRACT

The emergence of large language models (LLMs) offers a new opportunity to build LLMs-based applications, such as smart home, as these models have demonstrated general-purpose language understanding by generating coherent and contextually relevant text. However, LLMs are trained on massive amounts of text data to predict tokens, so these models have limitations and it is difficult for them performing physical world tasks directly. To further exploit the potential of LLMs to solve the challenge of integrating them with the physical world, LLMs enhanced and augmented techniques should be addressed, especially reinforcement learning based techniques. In this paper, we study the issue of integrating LLMs with physical world. We first describe the large language models and limitations. Then, we revisit LLMs enhanced and augmented techniques. After that, we present methods of interaction LLMs with physical world, such as integration IoT sensing with LLMs, embodied agent post-training with LLMs, and robot task planning with LLMs. Finally, we provide a case study of smart home powered by LLMs to discuss future research directions of next-generation intelligent smart home, personal health assistant, and LLM-based household robot.

KEYWORDS

Large Language Model, Internet of Things, LLM-based Agent, Smart Home

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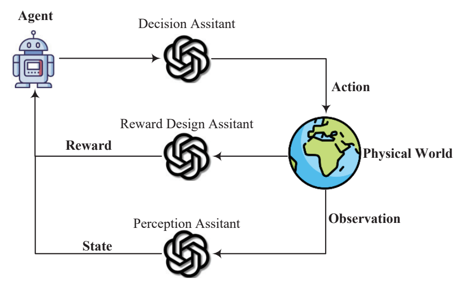

Figure 1: An architecture of integrated LLMs and physical world under agent-environment interaction scenario.

1 INTRODUCTION

The emergence of transformer-based large language models (LLMs), which are pretrained on a massive corpora of text data, containing hundreds of billions of parameters, is a revolutionary milestone in the domain of artificial intelligence (AI). It opens a new era in human-AI interactions, and would transform our society with a wide range of LLM applications spanning from personalized recommendations, language understanding and analysis, healthcare, industries [1]. Although these models are capable of generating coherent and contextually relevant text, they have limitations when performing physical world tasks [2]. The reason is that these models are trained on a large corpus from internet, but they are not teleologically grounded in reality. Consequently, they are in trouble figuring out how the world works, since these models are not really reasoning, planning, and don't have common sense, so it is difficult to handle real-world physical tasks leveraging them directly.

To further exploit the potential of LLMs and address their drawbacks and limitations, enhanced and augmented techniques could be used to deploy LLM powered AI agents to solve the challenges in integrating LLMs and the physical world with appropriate sensing, decision-making, and actuation in LLM powered real world applications [1, 3]. Consequently, it is possible to enable these models and agents to interact with dynamic environment, augment LLMs with external knowledge bases or tools, collect real-time feedback or corrections, provide flexibility to cope with unexpected scenarios, and effectively perform real-world physical tasks, although it requires interdisciplinary collaboration and expertise in areas such as AI, robotics, control systems, and human-computer interaction. An architecture of integrated LLMs and physical world under reinforcement learning and agent-environment paradigm is shown in Figure 1, in which LLMs could be utilized as decision making assistant, policy design assistant and perception assistant leveraging a variety of enhanced and augmented LLMs techniques. The rest of the paper is structured as follows. We first describe large language models and limitations, and artificial general intelligence (AGI) in Section 2. In Section 3, we summarize techniques to enhance the capability of LLMs. In Section 4, we present discussion of intersection of LLMs and the physical world. Finally, we provide future research directions of a case study of LLM powered smart home in Section 5. We conclude the paper in Section 6.

2 LARGE LANGUAGE MODES AND OTHER ARTIFICIAL GENERAL INTELLIGENCE MODELS

In this section, we first discuss LLM and its limitations, and then describe world models and artificial general intelligence.

2.1 Large Language Models and Limitations

Large language models have gained significant attention recently, such as GPT-4, PaLM, LLaMA, which are capable of performing a wide range of natural languages processing tasks, e.g., text generation, summarization, and question-answering [4]. The primary idea behind LLM is to predict the next word (or token) based on its pretraining. Generally, it is a type of transformer-based neural language model with billions of network parameters pretrained on mostly massive corpus of text-based data.

Limitation of Hallucination: The hallucination is considered as a significant drawback of LLMs [2]. It is defined as a phenomenon when LLMs generate content which is factually incorrect, nonsensical, or unfaithful to the provided input prompt. The reasons behind hallucination of LLMs are related to training data, the data training architecture and training process of the language models, as well as the inference strategies when using the trained models. Poor quality of the training data, bias, outdated knowledge, and misinformation are contributors to this issue. These material related intrinsic hallucinations generally produce factual inaccuracies and logical inconsistencies. During the training process, these models may be reliance on incomplete or contradictory datasets, suffer from architectural deficiencies resulting in poor learning, or are trained with overfitting. Furthermore, when generating text, hallucination can also be caused by sampling randomness, insufficient context attention. Overall, although there are many techniques to mitigate the hallucinations of LLMs, the fundamental probabilistic nature of LLMs enables them only filling gaps in context based on trained pattern rather than factual accuracy.

Limitation of Understanding: Although LLMs provide amazing performance of various tasks, they lack the understanding of world reality, as these models are only trained to learn the relationship between words, but not the meaning and the concept of these words, or even the relationship between different concepts [5]. Thus, these models are context dependent, and don't have architectures and mechanisms toward human-like understanding. Consequently, they have difficulty to understand the real world, such as the concepts of tangible objects, occurrences and relationship of objects, Newton's laws of motion of these objects, and the notion of time, space, and causality, since these models only generate predicted words or tokens strictly based on what they have seen in the trained text data.

Limitation of Reasoning and Logic: Although LLMs have demonstrated human-like reasoning capabilities with tasks, whether LLMs have deep logical reasoning remains a topic of debate. Some researchers consider that these LLMs are not truly reasoning. They just respond to the input tokens statistically based on the training, and then mimic reasoning which looks like human at giving technically correct answers, but these models lack intuitive understanding. Therefore, they lack of common sense knowledge for logical reasoning like humans, which may produce nonsensical or implausible context when involving common sense reasoning. When these models are used in real-world applications, the limitation of lacking logic reasoning is paramount, because the applications integrated with physical world only rely on LLMs could lead to misguided or incorrect control.

Limitation of Planning and Decision Making: Similar to the understanding and reasoning issue, although it is difficult to evaluate whether LLMs have innate planning capabilities, some research show that LLMs such as GPT4 cannot generate executing plans autonomously [6]. At most, it is an universal approximate retrieval from the trained data when generating word. Consequently, these models struggle with unsolved problems to output action plans for executing specific tasks. However, research also shows that LLMs are not good causal reasoners, but good causal explainers. These models are also good at idea generation involving planning and reasoning, so leveraging these amazing approximate retrieval capabilities could help us to plan efficiently. Furthermore, LLMs are not trained to make decisions directly, especially under physical environmental conditions. However, LLMs can be leveraged to construct foundation models for decision making [7], or integrated into a multiple-layer architecture (e.g., perception model, LLMs, and large decision model) enabling physical sequential decision-making [8].

2.2 World Model and Artificial General Intelligence

As aforementioned, LLMs lacks common sense and these models mostly encode words with probability distributions of the trained data without real-world experience, it is difficult from them to have a world model. Therefore, it is necessary to develop world model towards artificial general intelligence. To emulate human-like behavior with common sense, Yann LeCun proposed an objective-driven artificial intelligence architecture which can learn, remember with memory, reason and hierarchical plan [9]. The aim of this objective-driven cognitive architecture is to create intelligent system which is capable of learning world models via sensory data, planning actions to fulfill an objective, and being controlled in a safe way. The proposed cognitive architecture consists of several modules, such as configurator, perception, actor, critic, cost, world model, and short-term memory. Among them, the configurator plays a central role and takes charge in coordinating activities of modules to perform specific tasks by configuring other modules. The perception module is for computing abstract representations of the world states. The world model is used for predicting possible future states after taking action produced by the actor module. This world model is an internal representation of how the world works which can be obtained by unsupervised or self-supervised training from sensory input, so it can be leveraged to predict, reason, and plan. The modules of actor, critic and cost are leveraged to produce desired actions of reactive behavior of the agent with energy-based functions. To further improve decision-making skills, such as planning and reasoning, a hierarchical predictive architecture is proposed to plan in a hierarchical way. It is a joint embedding predictive architecture, which is capable of creating representation of the world via an encoding process, and learning fundamental relationships.

3 LLMS ENHANCED AND AUGMENTED TECHNIQUES

In this section, we revisit LLMs enhanced techniques to improve the capability of LLMs.

3.1 LLMs Augmented Techniques

To improve the performance and capability of LLMs, research focuses on augmenting LLMs and solving the issues of both LLMs building and LLMs using [4]. During the LLMs building phase, fine-tuning and alignment techniques are leveraged to improve performance of LLMs. The primary aim of fine-turning is to enable LLMs performing optimally with new user datasets or specific tasks [10]. The reason is that pretrained LLMs generally lack specialization in specific area, so it is necessary to adjust a limited number of parameters by learning from domain-specific data, and adding more in-depth information (e.g., supervised fine-tuning), so these models are more accurate and effective when solving targeted specific tasks. On the contrary, the primary purpose of alignment is to steer LLMs towards human expectations and preferences. To that end, a possible solution is to enable LLMs to align with human feedback, such as reinforcement learning from human feedback (RLHF), so that it uses human preferences as evaluation metric and objective function to enhance LLMs [11]. To reduce complexity and unstable issue of reward model, direct preference optimization (DPO) can be used [12]. In addition, LLMs can be augmented utilizing a variety of techniques when these models are leveraged to carry out specific tasks without model parameters tuning. These techniques include prompt design and engineering, augmenting LLM using external knowledge and tools. Prompt design and engineering is to craft prompts so as to guide LLMs effectively producing optimized outputs. Advanced prompt techniques include chain of thought (CoT), tree of thought (ToT), graph of thought (GoT) [4]. Furthermore, to mitigate the limitation of pretrained LLMs lacking up-to-date knowledge, information retrieving techniques can be leveraged, such as retrieval augmented generation (RAG), or using tools of external knowledge source (e.g., Toolformer).

3.2 Reinforcement Learning Enhanced Techniques

Reinforcement learning refers to a machine learning (ML) technique that enables agent to learn by interacting with a dynamic environment with trial and error and using feedback of actions by sequential decision-making to achieve optimal reward. RL is frequently used to enhance LLMs [13]. As aforementioned, RL can be used for improving performance in downstream tasks, such as fine-tuning pretrained LLMs with/without human feedback, and iteratively updating prompt of LLMs for desired results by using prompt engineering techniques. It is also used for alignment LLMs to satisfy users intent, value, and goals, such as RLHF. In addition, LLMs are also leveraged to enhance RL-based agent as lower-level executor to accelerate the integration of LLMs-RL and the physical world [14]. In these LLMs enhanced RL methods, LLMs are leveraged to mitigate limitations of conventional reinforcement learning methods, such as poor data sample efficiency, limited generalization capacity, sparse reward and policy function design. Because the interactive nature of reinforcement learning methods, it is hard to solve the poor sample efficiency issue [8]. Another important weakness of RL is its highly sensitivity of learned policy to environmental change, and the policy generation process involves carefully and costly manual reward function design in order to produce desired policy for Bellman optimization via temporal difference or dynamic programming. Consequently, LLMs enhanced techniques can serve as an exobrain to traditional RL playing roles in LLMs-RL integrated paradigm as perceptional information processor, reward designer, decision-maker, and world model generator [14].

3.3 LLMs Powered Autonomous Agents

One future leap in AI might be from LLMs to large world models (LWMs), which can connect IoT devices, sensors as perception, and then understand and make decision for interaction with the physical world. Under this paradigm, LLMs-powerd autonomous agents are crucial components which can leverage comprehensive internal world knowledge of LLM as core controller and brain, so as to improve poor sampling efficiency issue even without trained on specific domain data [15]. A potential architecture of LLMs powered agents should have several basic modules, such as perceiving, memory and retrieving, planning, rethinking and reflecting, tool utilization, actions [16], which are designed for interacting with real world environment, receiving feedback and reward, and continual learning from these interactions. In addition to single LLMs-based agent, LLM-based multi-agents offer advanced capability for physical tasks which require multiple agents collaboratively for perceiving, planning, and decision-making to solve complex tasks [17].

4 INTERSECTION OF LLMS WITH PHYSICAL WORLD

In this section, we study integration issue in terms of integration Internet of Things (IoTs) sensing with LLMs, embodied agent post-training with LLMs, and robot task planning using LLMs.

4.1 Integration IoT Sensing with LLMs

In Cyber-Physical Systems (CPS), sensors are utilized to sense and monitor the physical world. In such IoT applications, how to process and analyze the real-time sensing data to perform real-world tasks is difficult. As LLMs have integrated pre-existing knowledge acquired through extensive training on datasets, it is possible to leverage

LLMs to directly comprehend the physical scenarios via IoT sensor signals. In [18], LLM is utilized to integrate into real-world IoT sensors to accomplish real-time tasks. In this integration paradigm, the LLM serves as the application controller to connect with textualized sensor signal input, and then interpret them and perform perception tasks. Two examples of illustrative sensor signal integration are conducted in this research. In the first integration, the user activity sensing data from smartphone accelerometer are textualized for LLM to analyze and discern user motion and environment conditions. In the second integration, digitized electrocardiogram (ECG) data are utilized with LLM to derive heartbeat rate. This study also exhibits that there is a lower efficiency when processing digital sensor data compared to traditional signal processing methods. Furthermore, to consistently improve performance of long-horizon tasks, the high-level policy can be learned and fine-tuned by assimilating human language feedback interventions and learning human instruction patterns.

4.2 Embodied Agent Post-training with LLMs

LLMs are naturally language-based models, which are capable of understanding human language by offering advanced conversational skills, so these models can be leveraged to improve human-robot interaction for task execution as well as robot performance improvement after initial deployment, for example, by utilizing verbal correction [19, 20]. In [21], a YAY Robot system is proposed, which leverages natural language feedback to continuously improve its performance of post-training, especially with its long-horizon task performance. This study aims to realize an organic integration of LLM and physical world robot manipulating via both high-level policy and low-level policy in a hierarchical abstraction-based multi-stage task scenario. To that end, they use a low-level language-conditioned behavior cloning technique to enable robot to response language commands or corrections from user in real-time by interpreting and then executing a variety of specific robot skills.

4.3 Robot Task Planning and Decision Making with LLMs

The traditional reinforcement learning methods are usually used for robot task planning and decision making, so that these methods often learn action policies from scratch with high alignment with real-world environments, but it is difficult to incorporate prior knowledge in order to carry out fast sampling and rapidly exploring [22]. As LLMs can understand and reason task instructions, then generate a sequence of actions, reward functions, or even goals, we can harness the power of LLMs with few-short planning for embodied agent, such as robot [23, 24]. LLMs-planner is proposed in [23], which leverages physical grounding of the environment to update and enhance task planning in a visually-perceived environment, thus learns new tasks quickly in a few-shot fashion. The planner adopts a hierarchical planning model which includes a high-level planner and a low-level planner. The high-level plans are generated directly from LLMs based on language instructions, i.e., a sequence of subgoals to reach the final goal. After that, the low-level planner decomposes each subgoal into a sequence of primitive actions to accomplish the subgoal. To integrate the physical world environment, a novel grounded replanning algorithm is proposed to generate new high-level planning parts to modify and correct the initial plan before executing in real environment by injecting several observed objects from object detection sensors in physical environment into prompt. In this way, a closed-loop framework is adopted to incorporate physical environment feedback into LLMs to achieve adaptive planning according to the physical world dynamics.

In [25], a specific robot planning of navigation with LLMs is proposed, namely LM-Nav, and is experimented on a real-world mobile robot to demonstrate long-horizon navigation in complex outdoor environments based on textual instructions. LM-Nav integrates three pretrained large models of language, vision and action to perform a variety of robot navigation tasks based on long-horizon user-specified command in real-world environments. In this design, LLM is used for decoding instructions into a serial of landmarks, and then a vision-language model VLM grounds these textual landmarks by inferring joint probabilities of landmarks and the visual environmental observations. Finally, a visual navigation controlling model VNM is utilized to execute actions based on performance metrics, such as navigational affordance of landmark distance.

5 FUTURE RESEARCH DIRECTIONS WITH LLMS POWERED SMART HOME

In this section, we present a case study of smart home powered by LLMs to discuss future research directions of next-generation intelligent smart home, personal health assistant, and LLM-based household robot.

5.1 Next-Generation Intelligent Smart Home

The next-generation of intelligent smart home system is envisioned to communicate and control smart home devices to provide customized automation by learning users preferences and behaviors. To improve performance of the intelligent system, LLMs-based agents can be leveraged. These LLMs-powered agents have both short-term and long-term sensory memory, which are also capable of planning, using external tools, and reasoning to perform appropriate actions. Furthermore, leveraging LLMs, these agents can perform real-time multi-agent conversation to enable collective intelligence in terms of smart home automation. By deploying LLMs on the edge of smart home, the controlling system would avoid the consistently reliance on the external service, e.g., cloud service. To that end, local LLMs could be utilized, for example, AutoGen [26]. To provide smart furniture controlling with humans, the smart home system is also equipped with LLMs-powered human-smart furniture interaction interface via verbal communication or non-verbal communication, e.g., gesture controlling, to facilitate human-AI-furniture interactions.

5.2 Personal Health Assistant with LLMs

As a part of the next-generation of smart home system, LLMs can be utilized in the personal health assistant as a personal health LLMs (Ph-LLMs). The Ph-LLMs could be connected with smart health devices, e.g., wearable health monitoring devices, health monitoring using wireless signals (WiFi), disease-detecting smart toilet. Leveraging these IoT sensors monitoring signals as input, the Ph-LLMs provides personalized health support for users. It can analyze the personal habits and monitor the health status. It also generates personal health recommendations. Furthermore, leveraging the reasoning and planning of Ph-LLMs, personal proactive health management is possible. As it is integrated with smart home system, it is capable of predicting and identifying potential health risks. Therefore, it generates personal health advice in real-time, communicates with smart furniture, builds healthy habits of users as preventive measures. Another aspect of Ph-LLMs is to provide both virtual doctor and real-doctor consultation services. Utilizing LLMs-based agents, the user can require personal health recommendations, such as diet changes, exercise, or other health concerns. Once the user needs to contact a real doctor for professional medical service, Ph-LLMs has the interface for the doctor to obtain the user's personal health information for quick diagnosis and treatment.

5.3 LLMs-based Household Robot

The household robot in smart home should be capable of interacting with users efficiently and completing house hold tasks effectively. When accomplishing household tasks, LLMs-powered human-robot interaction could be leveraged to choose, generate, execute, and negotiate. In such a way, household robots can be quickly integrated into intelligent smart home system. Currently, although household robots have been developed rapidly, it is urgent to instill robot with common sense, so these robots can carry out complicated household tasks with flexibility and adaptability by understanding complex environments. To that end, LLMs can be leveraged to plan, especially with high-level logistic sub-task generation. Furthermore, to effectively integrate LLMs into physical world, a middleware between high-level language instructions and low-level robot physical actions should be developed utilizing grounding knowledge. In addition, as a part of next-generation intelligent smart home system, LLMs-powered household robots should also be LLMs-powered smart home autonomous agents. Thus, it can conduct necessary conversation and communication with other agents in the smart home system, and carry out household tasks collaboratively. Furthermore, LLMs-based lifelong learning methods should be developed, which can utilize LLMs as a core decision maker, so household robots can continuously learn new skills and perform complicated skills faster.

6 CONCLUSION

In this paper, we present the integration of LLMs and the physical world. We first discuss the limitations of LLMs, and then revisit techniques to enhance LLMs performance and capacity. After that, we present interactions of LLMs and physical world. Finally, we provide a case study of smart home to discuss future research directions of next-generation intelligent smart home powered by LLMs.

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