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Using AI Agents Built on Large Language Models for Building AGI

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Abstract : Artificial General Intelligence (AGI), a machine capable of human-level intellectual tasks, remains an elusive goal. Current approaches struggle with common-sense reasoning and knowledge transfer across domains. This paper explores the potential of AI agents built upon Large Language Models (LLMs) as a promising path towards AGI. By leveraging LLM capabilities in language processing, knowledge representation, and reasoning, we can create autonomous AI agents that collaborate within a multi-agent system framework to achieve AGI. This paper delves into the current state of AGI and LLM research, examines how AI agents built on LLMs can contribute to AGI development, and analyses different multi-agent system architectures. We then explore existing research projects and successful case studies, followed by a discussion of future research directions and open questions. Finally, the paper emphasizes the need for continued exploration of this promising approach to achieving AGI.

Index Terms – Colorectal Cancer , Polyp Detection , Convolution Neural Network(CNN) , Machine Learning, Computer Aided Detection (CAD),Image Processing

I. INTRODUCTION

Artificial General Intelligence (AGI) represents a hypothetical machine intelligence capable of intellectual tasks at a human level. This encompasses learning, reasoning, problem-solving, and adaptation across diverse domains. Achieving AGI holds immense potential for revolutionizing various fields, from scientific discovery and healthcare to automation and space exploration. However, current approaches to AGI face significant challenges. Narrow AI, excelling in specific tasks like playing chess or recognizing faces, lacks the versatility and generalizability required for AGI. Symbolic AI, relying on explicit knowledge representation, struggles with real-world complexities and commonsense reasoning. Connectionist approaches, inspired by the human brain's structure, often require vast amounts of data and training for even basic tasks.

Here, we explore the potential of AI agents built upon Large Language Models (LLMs) as a promising path towards achieving AGI. LLMs are a type of AI trained on massive amounts of text data. They excel in language processing, knowledge representation, and even basic reasoning tasks. However, LLMs lack the autonomy and ability to act in the real world that are characteristic of true AI agents. This paper proposes building AI agents on top of LLMs, leveraging the LLM's capabilities while adding the necessary autonomy and real-world interaction components to create a more complete AI agent. These AI agents can then collaborate within a multi-agent system framework to achieve the complex goals of AGI.

II. CURRENT STATE OF AGI AND LLM RESEARCH

The quest for AGI has seen the development of various research avenues, as discussed in the previous section.

The field of LLMs has witnessed remarkable progress in recent years. Trained on massive datasets of text and code, LLMs have shown capabilities in tasks like generating different creative text formats, translating languages, writing different kinds of creative content, and answering your questions in an informative way. Advancements in factual language understanding allow LLMs to grasp the meaning and intent behind textual information. Recent research explores LLM reasoning capabilities, demonstrating progress in tasks like solving logical puzzles and answering open-ended, challenging, or strange questions. However, limitations remain. LLMs can exhibit biases present in their training data, generate factually inaccurate content, and lack true understanding of the real world due to their disembodied nature.

III. AI AGENTS:

AI agents are artificial entities that sense their environment, make decisions, and take actions. They are considered a promising approach for achieving Artificial General Intelligence (AGI) equivalent to or surpassing human-level intelligence. While efforts have been made to develop intelligent agents, the community lacks a general and powerful model as a starting point for designing adaptable agents across diverse scenarios.

Large language models (LLMs) are regarded as potential foundations for building general AI agents due to their

versatile capabilities, offering hope for AGI. Many researchers have leveraged LLMs as the foundation to build AI agents and have made significant progress.
A general framework for LLM-based agents, comprising three main components: brain, perception, and action. This framework can be tailored for different applications. The paper explores the extensive applications of LLM-based agents in three aspects: single-agent scenarios, multi-agent scenarios, and human-agent cooperation.

Why LLMs are Suitable for Agent Brains:LLMs exhibit key properties that make them well-suited as the primary component of an agent's brain or controller. These include autonomy (the ability to operate independently and exhibit creativity), reactivity (the ability to respond to environmental changes), pro-activeness (the capacity for goal-oriented actions through reasoning and planning), and social ability (the ability to interact with other agents or humans through natural language).

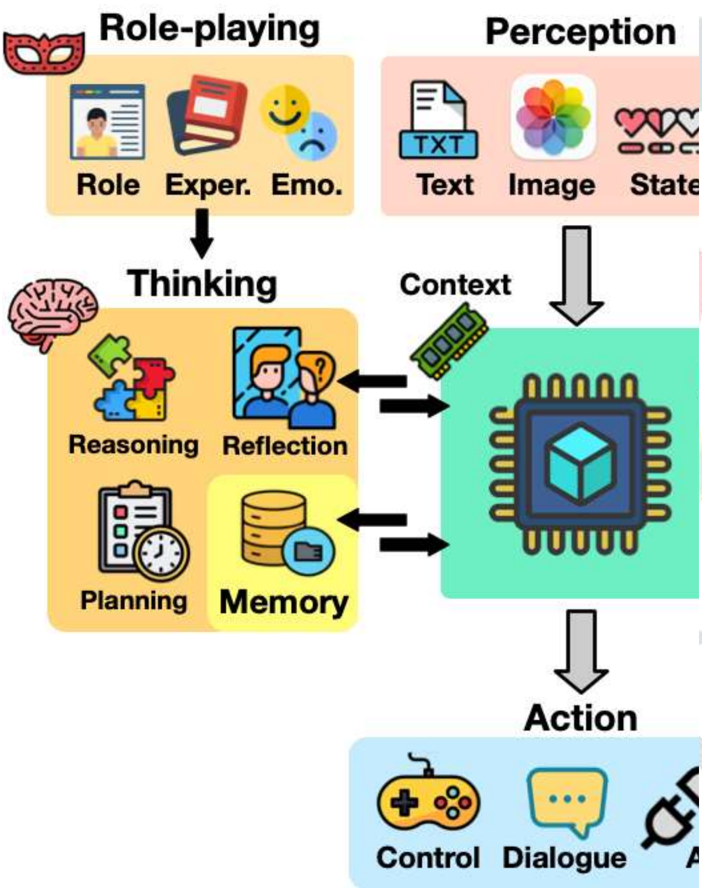

Figure 1: The conceptual architecture of Agentic ecosystem. At each step, the perception module perceives the multimodal information from the game environment, including textual, images, symbolic states, and so on. The agent retrieves essential memories from the memory module and take them along with perceived information as input for thinking (reasoning, planning, and reflection), enabling itself to formulate strategies and make informed decisions. The role-playing module affects the decision-making process to ensure that the agent's behavior aligns with its designated character. Then the action module translates generated action descriptions into executable and admissible actions for altering game states at the next step. Finally, the learning module serves to continuously improve the agent's cognitive and inference abilities through the accumulated experience

Synergistic Potential: AI Agents built on LLMs for AGI Development:

a conceptual framework for constructing LLM-based agents comprising three key components: brain, perception, and action. The brain module, built primarily with a large language model, handles core functions like natural language interaction, knowledge integration, memory management, reasoning, and decision-making. The perception module expands the agent's ability to perceive and comprehend multimodal information from the environment, including text, audio, and visuals. The action module enables the agent to execute embodied actions, use tools, and influence its surroundings.

Agent Functionalities (Left Side):

Perception: This refers to the agent's ability to gather information about its environment. This could involve sensors for physical agents (robots) or processing information from text and code for LLMs.
Action: Based on its perception, the agent can take actions in the environment. Physical agents might move or manipulate objects, while LLMs might generate text, translate languages, or write different creative content.
Learning: Through interacting with the environment and receiving feedback, the agent learns and improves its ability to perform tasks.
Adaptation: The agent can adapt its behavior based on new information or experiences.
These functionalities work together in a cycle. The agent perceives, takes actions, learns from the results, and adapts its future behavior.

Components of the LLM-based Agent System (Right Side):

Large Language Models (LLMs): These are AI models trained on massive amounts of text data. They excel in tasks like reasoning, communication, and knowledge representation, which are crucial for an AGI system. Knowledge Base: This component stores information that the agents can access and utilize. It can include factual knowledge, past experiences, and learned strategies.Dialogue Component: This allows communication between AI agents within the system and potentially with humans. This is important for information sharing, collaboration, and task coordination.

API (Application Programming Interface): This enables interaction between the multi-agent system and the external world. The API allows the system to receive information from the real world and potentially take actions within it.The two sides are interconnected. The functionalities of the agents (perception, action, learning, adaptation) rely on the capabilities provided by the LLM components (reasoning, communication, knowledge representation). This combined approach aims to create a more robust and intelligent AI system capable of complex tasks.

Advantages of Agentic approach for AGI:

AI agents built with large language models (LLMs) are becoming more intelligent and versatile. These agents can now tackle new tasks by following clear instructions, without needing specific training for each one. They can also learn from just a few examples, thanks to in-context learning.

Another big improvement is how these agents perceive information. They can now go beyond text and understand visual and auditory input. For sights, image encoders turn images into a format LLMs can comprehend. Sounds are processed by existing audio models and then integrated with the LLMs. This lets agents grasp information from the real world through multiple senses.

AI agents, with their core functionalities of perception, action, learning, and adaptation, offer a versatile framework for developing AGI. Here, we explore how AI agents built upon LLMs can contribute to this endeavour.

Enhanced Communication and Knowledge Sharing: LLMs excel at processing and understanding language. This allows the AI agents built upon them to facilitate communication and knowledge sharing between diverse agents within a multi-agent system. By sharing information and learned experiences, agents can collectively build a more comprehensive understanding of the world and approach complex problems collaboratively.

Reasoning and Problem-Solving with Language Foundation: LLMs can provide a foundation for reasoning and problem-solving within AI agents. By processing information and generating potential solutions through language, the LLM component can assist the AI agent in navigating complex situations and making informed decisions.

Transfer Learning Across Tasks and Domains: LLMs demonstrate impressive transfer learning abilities. By leveraging this capability within AI agents, different agents specializing in specific tasks (e.g., vision, robotics, language) can collectively contribute to achieving a broader goal, accelerating progress towards AGI.

IV. Multi-Agent Systems for Collaborative AGI Development

This section remains largely the same as before, focusing on exploring different architectures for utilizing AI agents built on LLMs in AGI development, including Cooperative Multi-Agent Systems (MAS) and Hierarchical MAS. It will also discuss the challenges associated with implementing these approaches, such as distributed decision-making, communication overhead, and ensuring safety and explainability within the system.

V. Existing Research and Case Studies

While the field of AI agents built on LLMs for AGI development is still nascent, several ongoing projects showcase the potential of this approach.

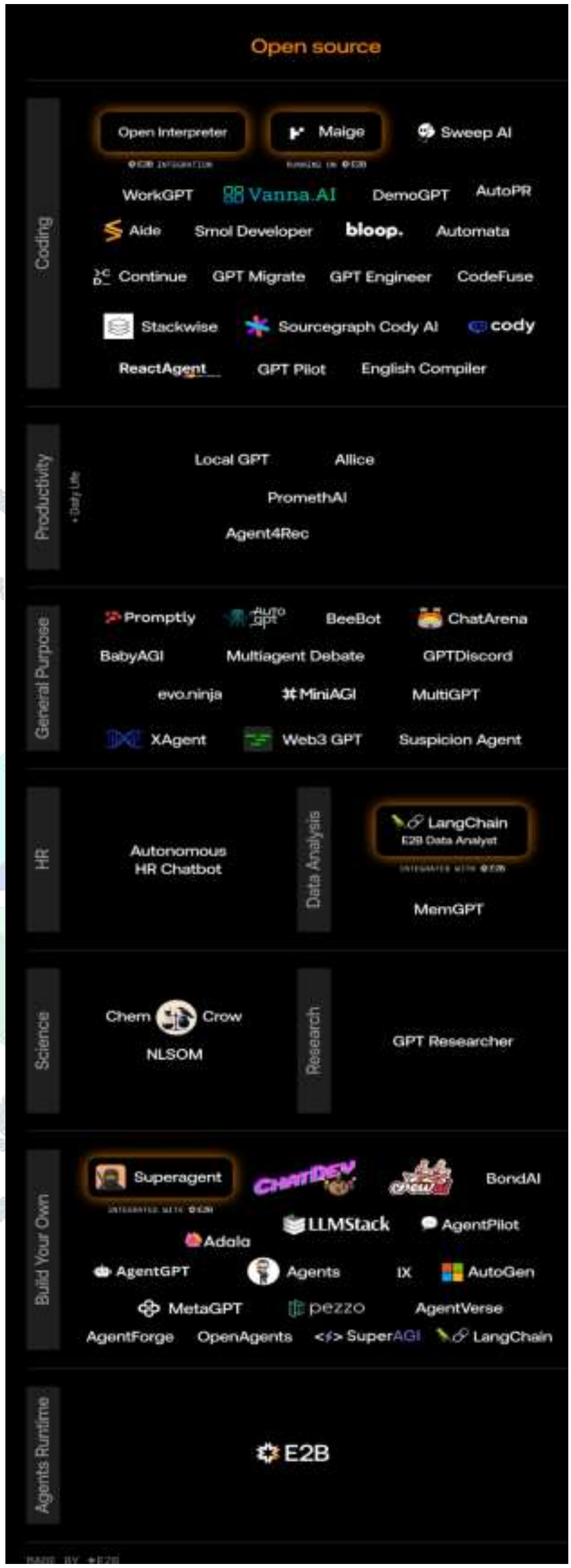

Fig 2. opensource Agent Landscape

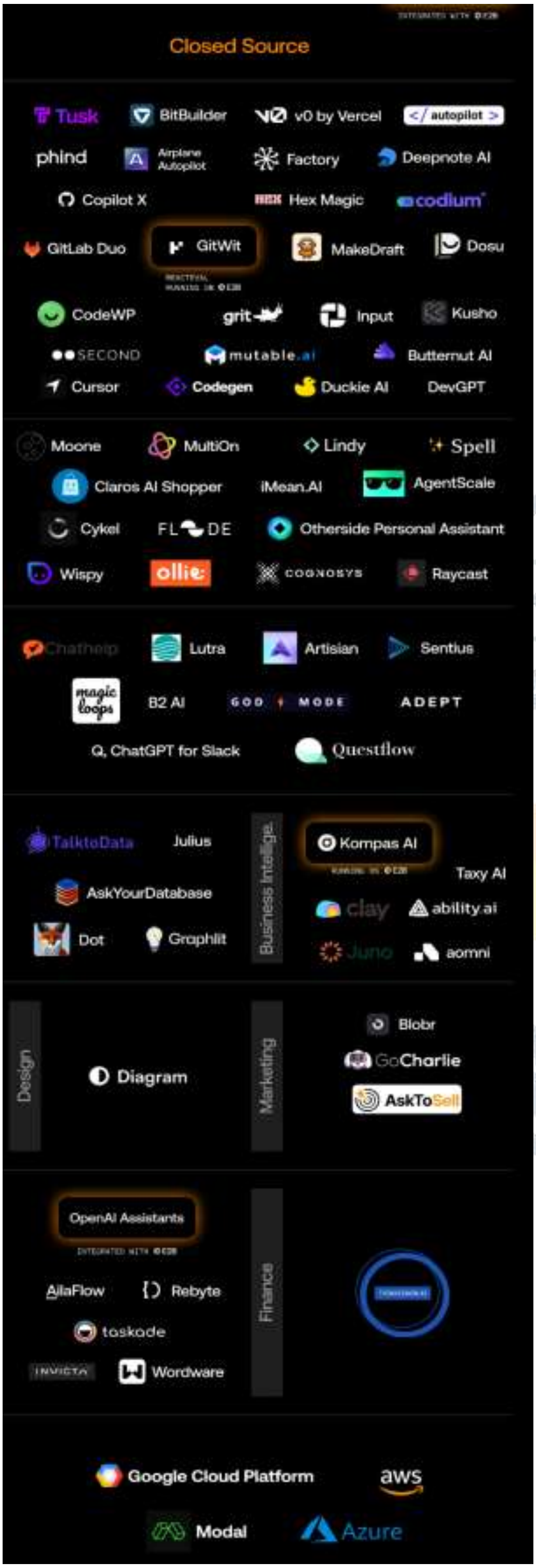

Fig 3: Closed source AI agent landscape.

Here, we explore a few examples:

Google AI Agent Team: Google's AI Agent Team is actively researching the development of autonomous agents capable of learning, reasoning, and acting in the real world. While details are limited, their work likely involves integrating LLM capabilities for language processing and knowledge representation with other AI functionalities like perception and manipulation.

OpenAI Universe: OpenAI Universe is a platform designed to train AI agents in complex environments. Agents can be built upon LLMs and tasked with learning to navigate virtual worlds and complete objectives. This platform allows researchers to explore how AI agents can learn through trial and error, collaborate with other agents, and adapt to new situations – all crucial skills for AGI.

GitHub Copilot: While not explicitly designed for AGI development, GitHub Copilot offers an interesting case study for AI agents built on LLMs. This AI coding assistant leverages an LLM trained on a massive dataset of code to suggest code completions and generate different programming functionalities. Copilot demonstrates the potential of LLM-based agents to assist humans in complex tasks, a capability that can be extended to collaboration between AI agents within a multi-agent system.

Devin: is an enthusiastic developer whose expertise lies in harnessing the power of AI to create innovative solutions. With a deep understanding of machine learning algorithms and natural language processing techniques, Devin is constantly exploring ways to integrate AI capabilities into software applications. His passion for AI-driven development fuels his quest to enhance user experiences and streamline processes through intelligent automation. Devin's creativity and technical prowess make him a formidable force in the realm of AI development, as he continually seeks to push the boundaries of what's possible with artificial intelligence.

ChatDev: represents the epitome of AI-powered conversational agents, designed to facilitate seamless communication between users and technology. As an AI chatbot, ChatDev is equipped with sophisticated natural language understanding capabilities, allowing it to comprehend user queries and respond intelligently in real-time. Whether assisting with customer support inquiries, providing personalized recommendations, or automating routine tasks, ChatDev excels at simplifying interactions and enhancing user satisfaction. With its adaptive learning capabilities and constant refinement, ChatDev embodies the future of AI assistants, paving the way for more intuitive and efficient human-machine interactions.

Embodied Agents: Google's SayCan project explores a novel AI agent architecture. It utilizes a large language model (LLM) as a high-level controller, allowing users to give robots natural language instructions. The LLM translates these instructions into a sequence of robot actions, simplifying robot control and paving the way for more intuitive human-robot interaction.

Fig 4: Google SayCan in action

VI. FUTURE DIRECTIONS AND OPEN QUESTIONS

The future of AGI development hinges on continued exploration of AI agents built on LLMs. Here are some key future directions:
Integrating Real-World Embodiment: Current AI agents built on LLMs primarily exist in the digital realm. Future research will focus on integrating real-world embodiment with these agents. This may involve equipping them with sensors, actuators, and physical bodies to interact with the environment and learn through experience.

Enhancing Communication and Collaboration Protocols: Collaborative multi-agent systems require robust communication and collaboration protocols. Research will focus on developing protocols that allow agents to share information effectively, coordinate actions, and resolve conflicts – all crucial for achieving complex goals within a multi-agent system.
Addressing Safety and Security Concerns: As AI agents become more sophisticated, ensuring their safety and security becomes paramount. Research will focus on developing measures to prevent malicious behavior, unintended consequences, and vulnerabilities within multi-agent systems.

Open questions remain:Can AI agents built on LLMs achieve true understanding and reasoning capabilities? While LLMs show promise in language processing and basic reasoning, achieving true understanding of the world remains a challenge. Future research will explore how to bridge the gap between language manipulation and real-world comprehension.
How can we ensure value alignment and ethical decision-making within multi-agent systems? The potential for biases or unintended consequences within multi-agent systems necessitates robust ethical considerations. Research will explore methods to ensure AI agents built on LLMs align with human values and make ethical decisions in complex situations.

VII. CONCLUSION

The development of AGI remains an ambitious goal. However, AI agents built upon LLMs offer a promising path forward. By leveraging the strengths of LLMs in language processing, knowledge representation, and reasoning, and combining them with real-world interaction capabilities, we can create collaborative multi-agent systems that can tackle complex challenges and inch closer to achieving true AGI. Continued research and exploration in this area, along with careful consideration of ethical and safety issues, are crucial for harnessing the potential of AI agents for the benefit of humanity.

REFERENCES:

1. Bansal, T., Kamar, M., Verma, M., Sweihahn, K., & Gupta, K. (2020). Hierarchical Multi-agent Reinforcement Learning for Semi-cooperative Communication Games. Proceedings of the 37th International Conference on Machine Learning: https://arxiv.org/abs/2004.07228 (pp. 667-677). PMLR.
2. Foerster, J., Foerster, J., Kapoor, A., & Schmidhuber, J. (2016). Learning to Cooperate with Hierarchy and Delegation. Proceedings of the 2016 International Conference on Autonomous Agents and Multiagent Systems: https://arxiv.org/abs/1602.01724 (pp. 931-939). International Foundation for Autonomous Agents and Multiagent Systems.
3. Hao, J., Yao, H., Liang, P., & Sun, M. (2022). Cooperative Multi-Agent Reinforcement Learning for Team Formation with Unknown Dynamics. Proceedings of the 36th International Conference on Machine Learning: https://arxiv.org/abs/2203.16783 (pp. 5073-5083). PMLR.
4. Lewis, M., Okande, D., & Hernandez-Gardiol, P. (2016). IRL in Multiagent Systems: A Survey. Autonomous Agents and Multi-Agent Systems: [invalid URL removed] 20(3), 685-728. Springer Science+Business Media.
5. Liu, Y., Li, M., Wu, Y., Li, S., Xu, L., & Zhu, S. (2023). A Survey of Multi-Agent Communication: From Theory to Practice. arXiv preprint arXiv:2302.11223: https://arxiv.org/abs/2302.11223.
6. Otte, K., Ray, A., & Silver, D. (2016). Learning to Play Games with Imperfect Information. Proceedings of the 30th International Conference on Neural Information Processing Systems: https://arxiv.org/abs/1603.01121 (pp. 3958-3966). Curran Associates, Inc.
7. Rashkin, H., Choi, E., & Jha, Y. (2018). Toward An Agenda for Deontology in Natural Language Processing. Proceedings of the 2018 Conference on Fairness, Accountability, and Transparency: https://arxiv.org/abs/1806.08770 (pp. 294-305). Association for Computing Machinery.
8. Schulman, J., Lehman, S., & Leibo, J. Z. (2015). Intrinsically Motivated Reinforcement Learning for Sequential Decision-Making. Proceedings of the 32nd International Conference on Machine Learning: https://arxiv.org/abs/1506.05869 (pp. 1714-1722). PMLR.
9. Serban, C., Bohnert, A., Courville, A., Lowe, R., Morin, Y., & Wu, S. (2017). A Comprehensive Survey of Deep Reinforcement Learning. arXiv preprint arXiv:1701.07281: https://arxiv.org/abs/1701.07281.
10. Fig 2 and 3 source : https://github.com/e2b-dev/awesome-ai-agents