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A survey on Framework, Architecture & Evolution Large Language Models AIAgents.

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Abstract:- Independents agents have long been a analysis centre in academic and industry production group. Early analysis frequently focuses on instruction agents with little knowledge within isolated environments, which diverges notably from being learning processes, and makes the agents hard to achieve human-like conclusion. Recently, through the property of vast amounts of web knowledge, large language models (LLMs) have shown potential in human-level intelligence, leading to a surge in research on LLM-based independent agents. In this paper, we present a overview survey of these studies, carry a systematic review of LLM based autonomous agents from a integral perspective. We first discuss the establishment of LLM-based independent agents, proposing a unified framework that surround much of previous work. Then, we present an overview of the diverse applications of LLM-based autonomous agents in social science, natural science, and engineering. Finally, we explore into the evaluation plan of action commonly used for LLM-based autonomous agents. Based on the previous studies, we also present several challenges and future regulation in this field.
Keywords:- AgentAI , Artificial Intelligence, LLM Based Agents, Autonomous agent.

Introduction:-
AI Agents have transitioned from effect hardly defined tasks to performing complex operations autonomously. Unlike traditional systems, these agents are renewed by their ability to perceive, reason, and adapt based on feedback and experience. This evolution has been significantly influenced by advancements in LLMs, which underpin the expensed reasoning ability of modern agents. Modern AI agents integrate LLMs with specialized modules for enhanced memory, planning, tool usage, and interaction, allowing them to tackle tasks spanning reconciling financial data to providing technical instructions.
Artificial Intelligence (AI) has progress badly over the past decade, transitioning from specialized systems designed for low tasks to highly sophisticated construction capable of indented operation across diverse domains. Among these advancements, AI agents represent a particularly remarkable development, embodying a paradigm shift in how intelligent systems interact with their environments, make decisions, and achieve complex goals. Unlike traditional AI systems that execute predefined algorithms within limitation, AI agents possess the capacity to autonomously perceive, reason, and often adapting their behaviour based on environmental feedback and collect experience.
Scope:-
This survey explores the generation of multiple modalities, including images, videos, 3D models, and audio. The transmission generation in our survey includes the different generation of indented modalities as well as the joint generation of multiple modalities. We will not dig into pure text generation and processing extensively, as there have already been many surveys specifically focusing on the advancements in that field. Our primary focus is on how the recent emergence of LLMs in the past few years can assist in the generation of other vision and audio modalities, especially in the open-domain generation. This will aid us in designing better unified generative models for multi-modalities. Note that the tasks and works we discussed are primarily language-based generation and editing. 3 Unconditional generation and other non-text-based editing are not our primary focus since they are either limited to a small domain or lack flexibility and controllability. In detail, we focus on the following tasks.
• Text-to-image causingand editing:- Image generation aims to create various open-domain image contents, including pictures, photos, or stylized drawings from user-provided textual descriptions. Image editing aims to modify the input image content and can be based on user instructions.
• Text-to-video generation and editing:- where models generate or modify arbitrary and various dynamic visual contents guided by free-form text descriptions.
• Text-to-3D generation and editing:- which is a task for generating and editing 3D objects, scenes, or avatars with user-provided textual descriptions.
• Text-to-audio generation and editing, where textual descriptions are used to generate audio, including general sounds, music, and speech. Audio editing tasks, such as adding, removing, or in painting, can all be performed by modifying existing audio content through textual descriptions.

• Multimodal generative agents, which enable LLMs to handle data across different modalities by utilizing a variety of specialized multimodal tools.
• Generative AI Safety, which focuses on reducing toxic and biased content, protecting copyright, and addressing the creation of fabricated content by multimodal generative models.

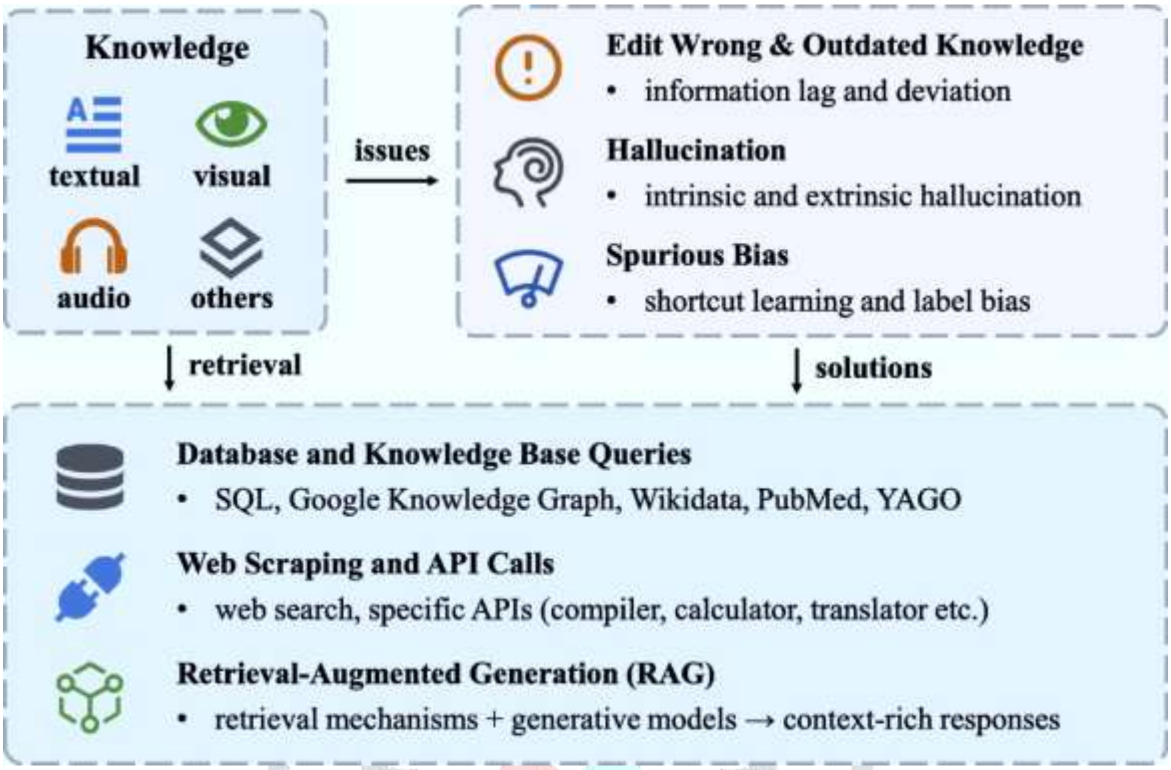

Figure1:- A review on LLM-based multi-agent systems workflow

The appearance of large language models (LLMs) has stimulated a transformative shift in artificial intelligence, covering the way for advanced intelligent agents effective of worldly reasoning,hardy perception, and versatile action of domains. As these agents more and more drive AI research and practical applications, their design, evaluation, and continuous improvement present intricate, multifaceted challenges. This book provides a comprehensive overview, framing intelligent agents within modular, brain-inspired architectures that integrate principles from cognitive science, neuroscience, and computational research. We framework our research into four interconnected parts. First, we systematically investigate the modular foundation of intelligent agents, orderly mapping their cognitive, perceptual, and operational modules onto similar human brain functionalities and explaining core components such as memory, world modelling, reward processing, goal, and emotion. Second, the discuss self-enhancement and adaptive evolution mechanisms, exploring how agents autonomously refine their capabilities, adapt to dynamic environments, and achieve continual learning through automated optimization paradigms. Third, we examine multi-agent systems, investigating the collective intelligence emerging from agent interactions, cooperation, and societal structures. Finally, we address the critical imperative of
Building safe and beneficial AI systems, emphasizing intrinsic and extrinsic security threats, ethical alignment, robustness, and practical mitigation strategies necessary for trustworthy real-world deployment. By synthesizing modular AI architectures with insights from different disciplines, this survey identifies key research challenges and opportunities, encouraging innovations that harmonize technological advancement with meaningful societal benefit.

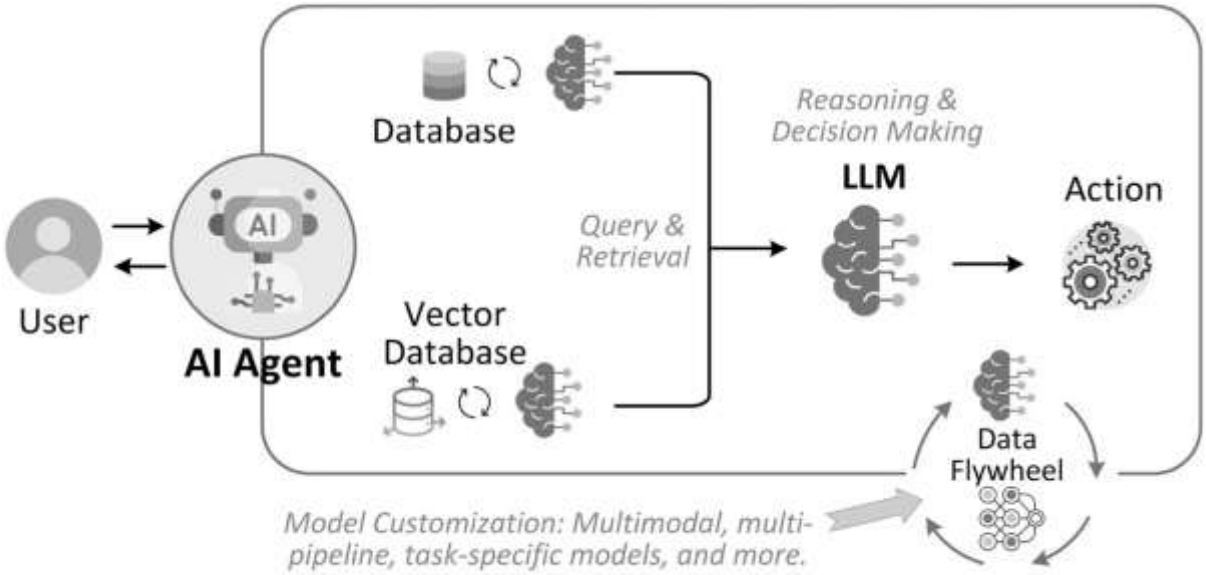

Figure2:-The survey of an AgentAI system, showing interactions with the users, databases, and LLM.

The AI Agent obtain user input, retrieves data from structured or semantic databases, processes it via an LLM for context understanding and reasoning, executes actions based on LLM outputs, and incorporates feedback through a data flywheel to continuously refine the system.

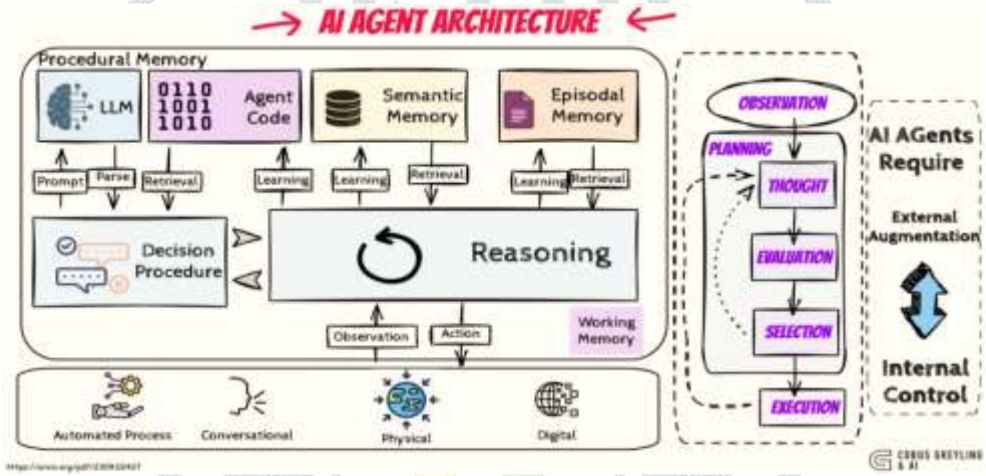

Figure3:- Architectural of Evolution

Similar to how humans continuously refine their cognitive abilities and acquire knowledge through interactions with their environment and others, evolution in agents involves the on-going reflection on their decisions and actions to dynamically update their knowledge and experiences, based on existing experiences and the feedback received during interactions, which is visualized in Fig. 6. By adopting evolution mechanisms, agents can continuously refine or revise their current understanding, thereby deepening their proficiency in known tasks and expanding their successful exploration of unknown tasks. Considering the sources of external feedback obtained during interactions, existing work can be categorized into three main types: information perceived from the surrounding environment, exchanged with other agents, or conveyed by humans. To equip agents with these diverse sources of information, various methods have been employed to enhance their evolution capabilities. In the following sections, we provide a detailed introduction to each of these approaches, elucidating the techniques used to bolster the evolution process in agents.

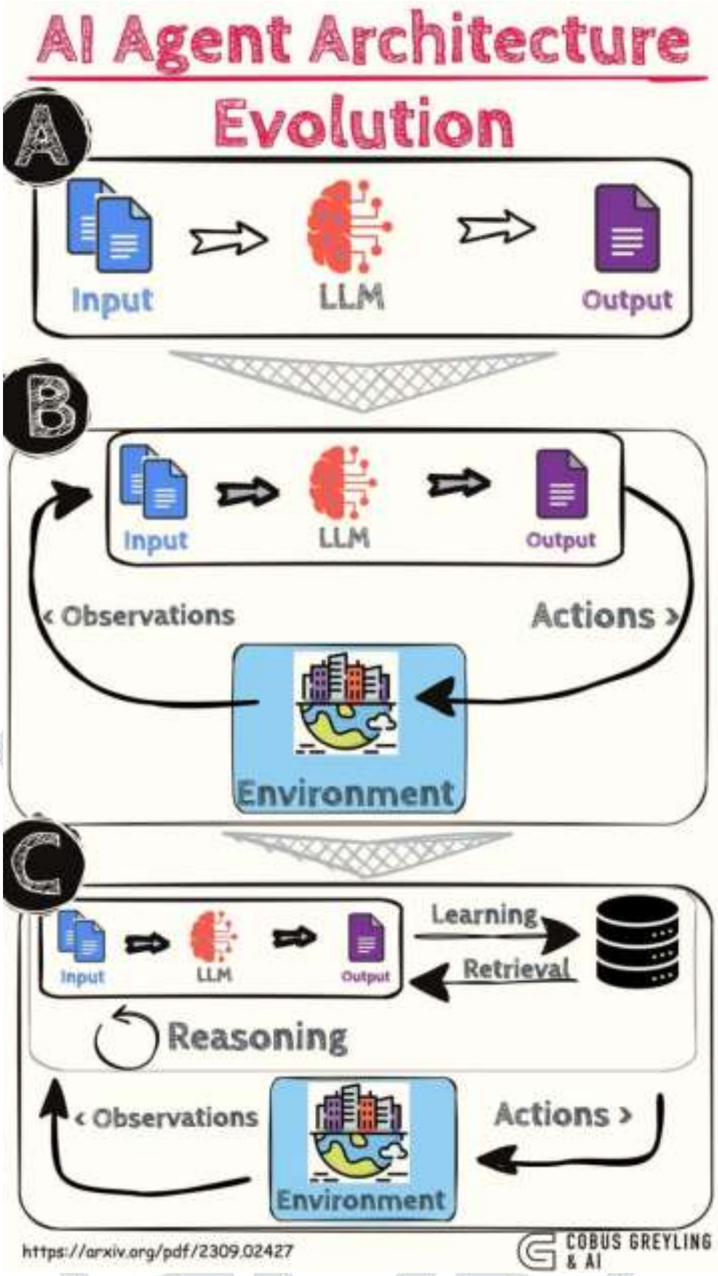

Figure4:- LLM Powered Autonomous Agents

A LLM (large language model) as its core controller is a cool concept. Several proof-of-concepts demos, such as AutoGPT GPT-Engineer and BabyAGI serve as inspiring examples. The potentiality of LLM extends beyond generating well-written copies, stories, essays and programs; it can be framed as a powerful general problem solver.

Agent System Overview

In a LLM-powered autonomous agent system, LLM functions as the agent's brain, complemented by several key components:

- Planning

○ Subgoal and decomposition: The agent breaks down large tasks into smaller, manageable subgoals, enabling efficient handling of complex tasks.

○ Reflection and refinement: The agent can do self-criticism and self-reflection over past actions, learn from mistakes and refine them for future steps, thereby improving the quality of final results.

- Memory

○ Short-term memory: I would consider all the in-context learning as utilizing short-term memory of the model to learn.

○ Long-term memory: This provides the agent with the capability to retain and recall (infinite) information over extended periods, often by leveraging an external vector store and fast retrieval.

- Tool use

○ The agent learns to call external APIs for extra information that is missing from the model weights (often hard to change after pre-training), including current information, code execution capability, access to proprietary information sources and more.

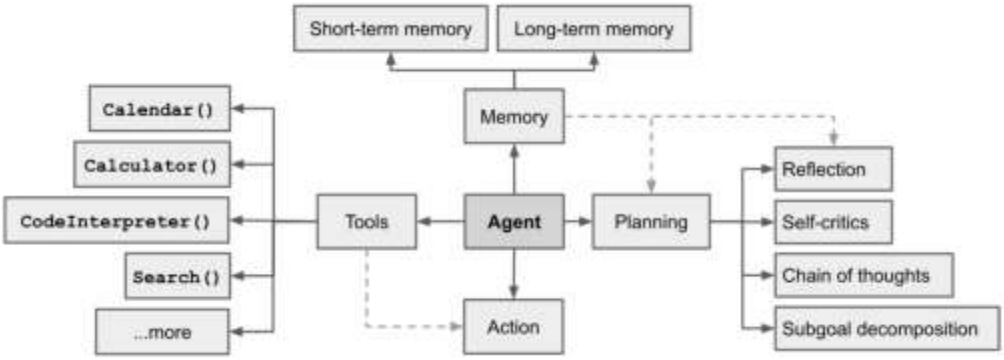

Figure5:- Overview of a LLM-powered autonomous agent system.

Component One: Planning

A complicated task usually involves many steps. An agent needs to know what they are and plan ahead.

Task Decomposition

A standard prompting technique for enhancing model performance on complex tasks. The model is instructed to "think step by step" to utilize more test-time computation to decompose hard tasks into smaller and simpler steps. CoT transforms big tasks into multiple manageable tasks and shed lights into an interpretation of the model's thinking process.

Component the Memory

Types of Memory Memory can be defined as the processes used to acquire, store, retain, and later retrieve information. There are several types of memory in human brains.

1. Sensory Memory: This is the earliest stage of memory, providing the ability to retain impressions of sensory information (visual, auditory, etc) after the original stimuli have ended. Sensory memory typically only lasts for up to a few seconds. Subcategories include iconic memory (visual), echoic memory (auditory), and haptic memory (touch).

2. Short-Term Memory (STM) or Working Memory: It stores information that we are currently aware of and needed to carry out complex cognitive tasks such as learning and reasoning. Short-term memory is believed to have the capacity of about 7 items and lasts for 20-30 seconds.

3. Long-Term Memory (LTM): Long-term memory can store information for a remarkably long time, ranging from a few days to decades, with an essentially unlimited storage capacity. There are two subtypes of LTM:

4. Explicit / declarative memory: This is memory of facts and events, and refers to those memories that can be consciously recalled, including episodic memory (events and experiences) and semantic memory (facts and concepts).

5. Implicit / procedural memory: This type of memory is unconscious and involves skills and routines that are performed automatically, like riding a bike or typing on a keyboard.

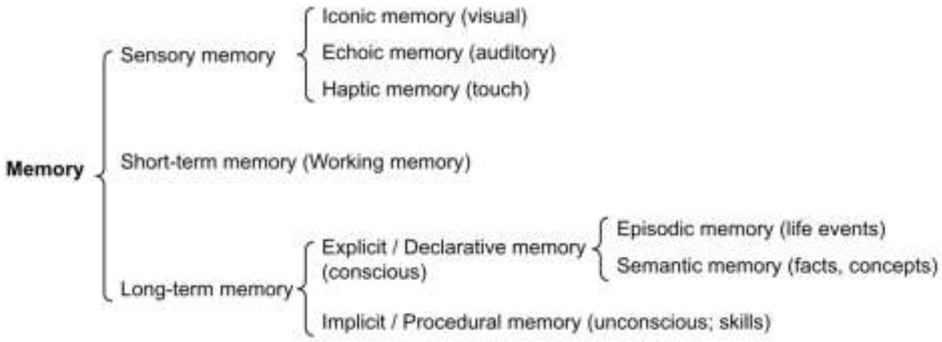

Figure6:- Categorization of human memory.

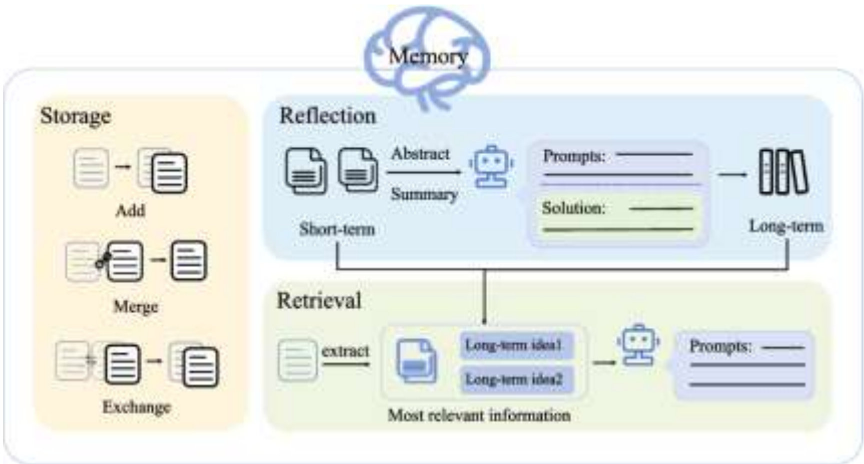

Figure7:- The operational mechanism of the memory module.

1.1 **Single Agent**

A single-agent system consists of a single LLM-based intelligent agent capable of independently perceiving its environment and making decisions. The design of single-agent systems aims to perform specific tasks, ranging from simple automation to complex decision-making. The core of a single-agent system lies in the individual characteristics, perception abilities, and self-action capabilities of the agent these three aspects constitute the basic framework of a single agent, enabling it to operate independently in specific tasks or environments and interact effectively with the external world. A notable advantage of single-agent systems lies in their focus and efficiency. Due to the concentration of system resources and computational capabilities on a single agent, these systems can quickly respond to and execute specific tasks. This centralized processing reduces the need for resource allocation among multiple agents, thereby improving overall efficiency. Furthermore, compared to multi-agent systems, the design and maintenance of single-agent systems are simpler and more straightforward. They do not require complex communication and coordination mechanisms, reducing system complexity and simplifying the process of troubleshooting and performance optimization.

1.2 Multi Agents

Although single-agent systems excel in specific tasks, they may encounter limitations when dealing with complex problems that require extensive collaboration and collective intelligence. This is where multi-agent systems (MAS) come into play. MAS is a complex system composed of multiple interacting intelligent agents capable of simulating social interactions and teamwork in the real world, enhancing overall adaptability and efficiency through decentralized decision-making processes and information sharing. Reinforcement learning (RL), as a core MAS technology, allows agents to learn optimal behavioural strategies through interaction with the environment. Building on this foundation and knowledge sharing. This structural design enables MAS to adapt flexibly to different task requirements and environmental changes, while also promoting complementarity and synergy among agents. Regarding system architecture, communication is the most crucial part. The four-dimensional framework proposed by emphasizes the diversity of communication protocols, distinguishing between blackboard and message-based systems, and setting different gradients from low to high-level content. In the work proposes that communication mechanisms can be divided into three parts: communication paradigms, communication structures, and communication content. Among them, communication paradigms refer to interaction styles, while communication structures are categorized into four types, including decentralized, centralized, layered, or nested, to adapt to different task requirements and environmental conditions.

1.3 LLM-based multi-Agent work

The LLM-based multi-agent system has been applied to execute a variety of complex tasks and downstream scenarios. From the perspective of the system's workflow, we meticulously explore the lifecycle of agents, including their creation, perception, reasoning, action, and self-learning processes. Motivated by this exploration, this section constructs a comprehensive unified framework for LLM-based multi-agent systems, which comprises five critical functional modules: the profile, perception, self-action, mutual interaction, and evolution. LLM-based Autonomous Agent Evaluation Similar to LLMs themselves, evaluating the effectiveness of LLM-based autonomous agents is a challenging task. This section outlines two prevalent approaches to evaluation: subjective and objective methods. For a comprehensive overview, please refer to the right portion Subjective Evaluation Subjective evaluation measures the agent capabilities based on human judgements. It is suitable for the scenarios where there are no evaluation datasets or it is very hard to design quantitative metrics, for example, evaluating the agent's intelligence or user-friendliness. In the following, we present two commonly used strategies for subjective evaluation. Human Annotation: This evaluation method involves human evaluators directly scoring or ranking the outputs generated by various agents. For example, in the authors engage numerous annotators by asking the questions that explore their abilities across five key areas directly related to agent capabilities. In annotators are asked to determine whether the specifically designed models can significantly enhance the development of rules within online communities. Turing Test: This evaluation strategy necessitates that human evaluators differentiate between outputs produced by agents and those created by humans. If, in a given task, the evaluators cannot separate the agent and human results, it demonstrates that the agent can achieve human-like performance on this task. For instance, researchers in conduct experiments on free-form Partisan text, and the human evaluators are asked to guess whether the responses are from human or LLM-based agent remark. LLM-based agents are usually designed to serve humans. Thus, subjective agent evaluation plays a critical role, since it reflects human criterion. However, this strategy also faces issues such as high costs, inefficiency, and population bias. To address these issues, a growing number of researchers are in ventilating the use of LLMs themselves as intermediaries for carrying out these subjective assessments. For example, in researchers assess the experimental results using GPT. They consider both the completion of tasks and the accuracy of the underlying processes. Similarly, introduces a novel approach by employing multiple agents to critique and assess the results generated by various candidate models in a structured debate format. This innovative use of LLMs for evaluation purposes holds promise for enhancing both the credibility and applicability of subjective assessments in the future. As LLM technology continues to evolve, it is anticipated that these methods will become increasingly reliable and find broader applications, thereby overcoming the current limitations of direct human evaluation.

Large language models Advantage Based on the transformer architecture, LLMs represent a significant advancement in Natural Language Processing (NLP). The self-attention mechanism inherent in LLMs calculates the dependencies between tokens, thereby allowing for contextually relevant focus Parallel processing enables faster training on large datasets. LLMs are pre-trained on vast unlabelled text datasets to learn general language patterns and are fine-tuned for specific tasks to enhance performance. Transformer variants like BERT and GPT specialize in tasks.

OpenAI and chatGPT: OpenAI has been at the forefront of advancing the transformer model with the GPT series, which includes and GPT-4 (OpenAI, 2024). These models learn language patterns and information by pre-training on vast internet data, followed by fine-tuning on more specific datasets to improve performance on conversational or targeted tasks, such as conversational assistance and text generation. ChatGPT leverages supervised learning and RL, specifically RL from Human feedback, for training. The training process involves three steps: supervised fine-tuning, a reward model, and maximum policy optimization. This advancement enhances ChatGPT's ability to generate human-like responses for conversation and assistant tasks.

Llama: An open-source foundational model similar to OpenAI and GPT another language model Llama was conceptualized It is part of Meta's initiative to provide a powerful language model that is suitable for text generation and supporting various applications. Llama models have unique configurations, with their training datasets drawn from a mix of text sources, emphasizing efficient and large-scale natural language understanding.

Gemini: Gemini is a multimodal large language model developed by DeepMind, designed to integrate and process text, images, audio, and code. It builds upon Google's PaLM architecture and combines neural networks with symbolic reasoning capabilities. Gemini models are trained to perform complex tasks involving reasoning, retrieval, and multimodal input, pushing the boundaries of general-purpose AI systems.

DeepSeek: DeepSeek is a series of open-source language models, developed by High-Flyer company, and focused on providing scalable and high-performing models for both code and natural language tasks (DeepSeek-AI et al., 2025).

Notably, DeepSeek-V2 introduced dense hybrid architectures that improve efficiency and performance across multilingual benchmarks. The models are trained on diverse high-quality datasets and optimized for real-world application needs.

Conclusion

In this survey, we systematically summarize existing research in the field of LLM-based AI agents. We present and review these studies from three aspects including the construction, application, and evaluation of the agents. For each of these aspects, we provide a detailed taxonomy to draw connections among the existing research, summarizing the major techniques and their development histories. In addition to reviewing the previous work, we also propose several challenges in this field, which are expected to guide potential future directions. AI agent benchmarking is new and best practices haven't yet been established, making it hard to distinguish genuine advances from hype. We hope these steps will raise the rigor of AI agent evaluation and provide a firm foundation for progress. we have systematically provided an overview of LLM-based multi-agent systems, comprehensively reviewing the current research studies in this domain. We began by elucidating the origin and definition of agents, tracing their developmental trajectory from single agents to multi-agent systems. Motivated by the workflow of multi-agent systems, we systematically proposed a general framework comprising five main components: profile, perception, agent's self-action (including memory, knowledge, agent's ability, and action), mutual interaction, and evolution. For each module, we discussed and summarized specific application methods and workflows. Subsequently, we introduced the wide-ranging applications of LLM-based multi-agent systems, categorizing them into two sections: problem-solving and world simulation.

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