

Large Model Agents: State-of-the-Art, Cooperation Paradigms, Security and Privacy, and Future Trends

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Abstract—Large Model (LM) agents, powered by large foundation models such as GPT-4 and DALL-E 2, represent a significant step towards achieving Artificial General Intelligence (AGI). LM agents exhibit key characteristics of autonomy, embodiment, and connectivity, allowing them to operate across physical, virtual, and mixed-reality environments while interacting seamlessly with humans, other agents, and their surroundings. This paper provides a comprehensive survey of the state-of-the-art in LM agents, focusing on the architecture, cooperation paradigms, security, privacy, and future prospects. Specifically, we first explore the foundational principles of LM agents, including general architecture, key components, enabling technologies, and modern applications. Then, we discuss practical collaboration paradigms from data, computation, and knowledge perspectives towards connected intelligence of LM agents. Furthermore, we systematically analyze the security vulnerabilities and privacy breaches associated with LM agents, particularly in multi-agent settings. We also explore their underlying mechanisms and review existing and potential countermeasures. Finally, we outline future research directions for building robust and secure LM agent ecosystems.

Index Terms—Large model, AI agents, embodied intelligence, multi-agent collaboration, security, privacy.

I. INTRODUCTION

A. Background of Large Model Agents

In the 1950s, Alan Turing introduced the famous Turing Test to assess whether machines could exhibit intelligence comparable to that of humans, which laid the foundation in the evolution of Artificial Intelligence (AI). These artificial entities, commonly known as “agents”, serve as the core components of AI systems. Generally, AI agents are autonomous entities capable of understanding and responding to human inputs, perceiving their environment, making decisions, and taking actions in physical, virtual, or mixed-reality settings to achieve their goals [1]. AI agents range from simple bots that follow predefined rules to complex and autonomous entities that learn and adapt through experience [2]. They can be software-based or physical entities, functioning independently or in collaboration with humans or other agents.

Since the mid-20th century, significant progress has been made in the development of AI agents [3]–[5], such as Deep Blue, AlphaGo, and AlphaZero, as shown in Fig. 1. Despite these advances, prior research primarily concentrated on refining specialized abilities such as symbolic reasoning or excelling in certain tasks such as Go or Chess, often neglecting the cultivation of general-purpose capabilities within AI models such as long-term planning, multi-task generalization, and knowledge retention. The challenge of creating AI agents that can flexibly adapt to a broad range of tasks and complex environments remains largely unexplored. To push the boundaries of AI agents

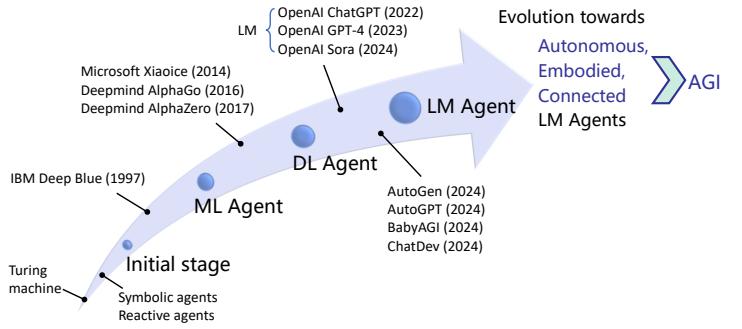


Fig. 1: Evolution history of AI Agents. 1) Initial stage: Early AI research primarily focused on logical reasoning and rule-based AI agents. 2) Machine Learning (ML) agent stage: ML including supervised and unsupervised learning advanced the progress of AI agents. In 1997, IBM's Deep Blue defeated the world chess champion. 3) Deep Learning (DL) agent stage: The combination of DL and big data significantly improved AI performance. In 2016, Deepmind's AlphaGo defeated Go world champion Lee Sedol. 4) Large Model (LM) agent era: Transformer-based LMs such as OpenAI's ChatGPT and GPT-4 revolutionized AI agents, ushering in the era of LM agents and bringing us closer to AGI.

further, it is crucial to develop powerful foundational models that integrate these critical attributes, offering a versatile basis for next-generation AI agents.

With the rise of Large Models (LMs), also known as large foundation models, such as OpenAI GPT-4o, Google PaLM 2, and Microsoft Copilot, LMs open up new possibilities in comprehensively enhancing the inherent capabilities of AI agents [6], [7]. As illustrated in Fig. 2, an LM agent, either in software or embodied form, generally consist of four key components: planning, action, memory, and interaction. These agents can seamlessly operate within physical, virtual, or mixed-reality environments [1], [8]–[10]. Particularly, LMs serve as the “brain” of AI agents and empower them with powerful capabilities in human-machine interaction (HMI), complex pattern recognition, knowledge retention, reasoning, long-term planning, generalization, and adaptability [9]. Moreover, via advanced reasoning and few/zero-shot planning techniques such as Chain-of-Thought (CoT) [11], Tree-of-Thought (ToT) [12], and reflection [13], LM agents can form intricate logical connections, enabling them to solve complex, multifaceted tasks effectively. For example, AutoGPT [14], a promising LLM agent prototype, can decompose complex tasks into several manageable sub-tasks, facilitating structured and efficient problem-solving. Integrating LMs with Retrieval-Augmented Generation (RAG) technologies [15] further allows agents to access external knowledge sources and enhance

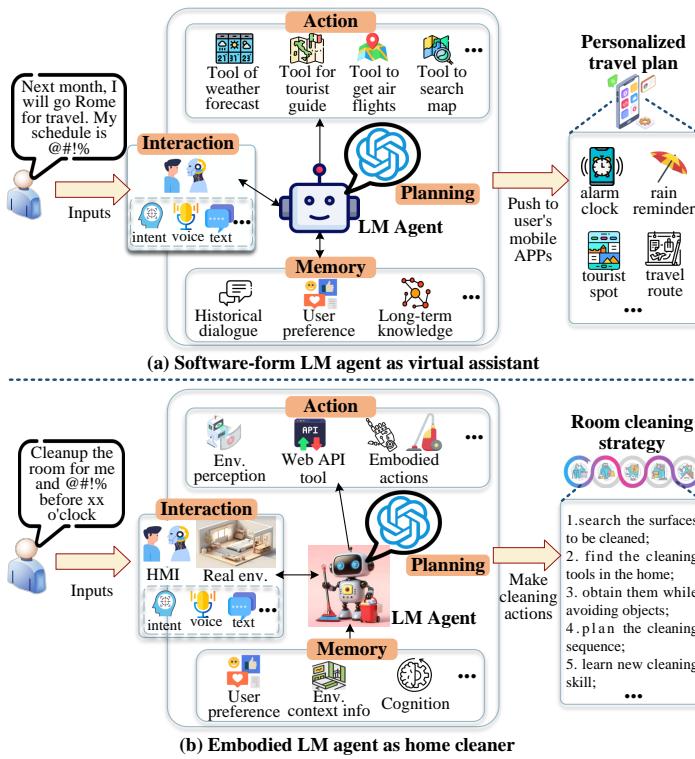


Fig. 2: Use cases of LM agents. (a) a software-form LM agent acting as the virtual assistant. (b) an embodied LM agent serving as the home cleaner.

the accuracy of their responses based on retrieved information. Besides, LM agents can flexibly integrate a range of LMs, including Large Language Model (LLM) and Large Vision Model (LVM), to enable multifaceted capabilities.

LM agents are recognized as a significant step towards achieving Artificial General Intelligence (AGI) and have been widely applied across fields such as web search [16], recommendation systems [17], virtual assistants [18], [19], Metaverse gaming [20], robotics [21], autonomous vehicles [22], and Electronic Design Automation (EDA) [23]. As reported by MarketsandMarkets [24], the worldwide market for autonomous AI and autonomous agents was valued at USD 48 billion in 2023 and is projected to grow at a CAGR of 43%, reaching USD 28.5 billion by 2028. LM agents have attracted global attention, and leading technology giants including Google, OpenAI, Microsoft, IBM, AWS, Oracle, NVIDIA, and Baidu are venturing into the LM agent industry.

B. Roadmap and Key Characteristics of LM Agents

Fig. 3 illustrates a future vision of LM agents, characterized by three key attributes: *autonomous*, *embodied*, and *connected*, paving the way toward AGI.

1) *Autonomous Intelligence*. Autonomous intelligence in LM agents refers to their ability to operate independently, making proactive decisions without continuous human input. As depicted in Fig. 2(a), an LM agent can maintain an internal memory that accumulates knowledge over time to guide future decisions and actions, enabling continuous learning and adaptation in dynamic environments [25]. Additionally, LM agents can autonomously utilize a variety of tools (e.g., search engines and external APIs) to gather information or create new tools to handle intricate

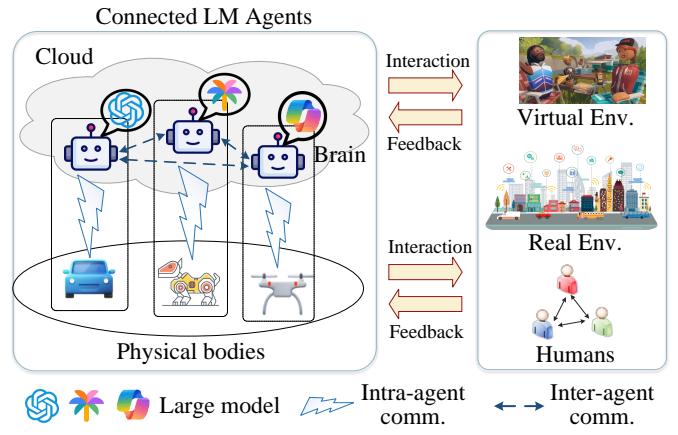


Fig. 3: Overview of LM agents. Each LM agent includes two parts: (i) the *digital brain* located in the cyberspace powered by LMs such as GPT-4o, PaLM 2, and Copilot; and (ii) the *physical body* such as autonomous vehicle, robot dog, and drone. Within each LM agent, the digital brain synchronizes with its physical body via *intra-agent* communications. LM agents communicate with one another in the cloud to share information and knowledge via *inter-agent* communications, establishing a network of interconnected intelligence. Each LM agent can dynamically interact with other agents, virtual/real environments, and humans. The brain of each LM agent can be deployed either as a *standalone* entity or in a *hierarchical* manner across various platforms such as cloud servers, edge devices, or end devices.

tasks [26]. By collaborating or competing with humans or other agents, LM agents can effectively enhance their decision-making capabilities [27].

2) *Embodied Intelligence*. Despite recent advancements, LMs typically passively respond to human commands in the text, image, or multimodal domain, without engaging directly with the physical world [7]. Embodied agents, on the other hand, can actively perceive and act upon their environment, whether digital, robotic, or physical, using sensors and actuators [21], [25]. The shift to LM-empowered agents involves creating embodied AI systems capable of understanding, learning, and solving real-world challenges. As depicted in Fig. 2(b), LM agents actively interact with environments and adapt actions based on real-time feedbacks. For example, a household robot LM agent tasked with cleaning can generate tailored strategies by analyzing the room layout, surface types, and obstacles, instead of merely following generic instructions.

3) *Connected Intelligence*. Connected LM agents extend beyond the capabilities of individual agents, playing a critical role in tackling complex, real-world tasks [28]. For example, in autonomous driving, connected autonomous vehicles, serving as LM agents, share real-time sensory data, coordinate movements, and negotiate passage at intersections to optimize traffic flow and enhance safety. As depicted in Fig. 3, by interconnecting numerous LM agents into the Internet of LM agents, connected LM agents can freely share sensory data and task-oriented knowledge. By fully harnessing the computational power of various specialized LMs, it fosters cooperative decision-making and collective intelligence. Thereby, the collaboration across data, computation, and knowledge domains enhances individual

agent performance and adaptability. Additionally, these interactions enable LM agents to form social connections and attributes, contributing to the development of an agent society [29], [30].

C. Motivation for Securing Connected LM Agents

Despite the bright future of LM agents, security and privacy concerns remain significant barriers to their widespread adoption. Throughout the life-cycle of LM agents, numerous vulnerabilities can emerge, ranging from adversarial examples [31], agent poisoning [32], LM hallucination [33], to pervasive data collection and memorization [34].

1) *Security vulnerabilities.* LM agents are prone to “hallucinations”, where their foundational LMs generate plausible but incorrect outputs not grounded in reality [33]. In multi-agent settings, the hallucination phenomenon can propagate misinformation, compromise decision-making, cause task failures, and pose risks to both physical entities and human. Moreover, maintaining the integrity and authenticity of sensory data and prompts used in training and inference is crucial, as biased or compromised inputs can lead to inaccurate or unfair outcomes [35]. Attacks such as adversarial manipulations [31], poisoning [36], and backdoors [37] further threaten LM agents by allowing malicious actors to manipulate inputs and deceive the models. In collaborative environments, agent poisoning behaviors [32], where malicious agents disrupt the behavior of others, can undermine the collaborative systems. Additionally, integrating LM agents into Cyber-Physical-Social Systems (CPSS) expands the attack surface, enabling adversaries to exploit vulnerabilities within interconnected systems.

2) *Privacy breaches.* LM agents’ extensive data collection and memorization processes raise severe risks of data breaches and unauthorized access. These agents often handle vast amounts of personal and sensitive business information for both To-Customer (ToC) and To-Business (ToB) applications, raising concerns about data storage, processing, sharing, and control [38]. Additionally, LMs can inadvertently memorize sensitive details from their training data, potentially exposing private information during interactions [34]. Privacy risks are further compounded in multi-agent collaborations, where LM agents might inadvertently leak sensitive information about users, other agents, or their internal operations during communication and task execution.

D. Related Surveys and Contributions

Recently, LM agents have garnered significant interest across academia and industry, leading to a variety of research exploring their potential from multiple perspectives. Notable survey papers in this field are as below. Andreas *et al.* [29] present a toy experiment for AI agent construction and case studies on modeling communicative intentions, beliefs, and desires. Wang *et al.* [39] identify key components of LLM-based autonomous agents (i.e., profile, memory, planning, and action) and the subjective and objective evaluation metrics. Besides, they discuss the applications of LLM agents in engineering, natural science, and social science. Xi *et al.* [9] present a general framework for LLM agents consisting of brain, action, and perception. Besides, they explore applications in single-agent, multi-agent, and human-agent collaborations, as well as agent societies. Zhao *et al.* [2] offer a systematic review of LLMs in terms of pre-training,

adaptation tuning, utilization, and capacity assessment. Besides, background information, mainstream technologies, and critical applications of LLMs are introduced. Xu *et al.* [40] provide a tutorial on key concepts, architecture, and metrics of edge-cloud AI-Generated Content (AIGC) services in mobile networks, and identify several use cases and implementation challenges. Huang *et al.* [1] offer a taxonomy of AI agents in virtual/physical environments, discuss cognitive aspects of AI Agents, and survey the applications of AI agents in robotics, healthcare, and gaming. Cheng *et al.* [10] review key components of LLM agents (including planning, memory, action, environment, and rethinking) and their potential applications. Planning types, multi-role relationships, and communication methods in multi-agent systems are also reviewed. Masterman *et al.* [8] provide an overview of single-agent and multi-agent architectures in industrial projects and present the insights and limitations of existing research. Guo *et al.* [41] discuss the four components (i.e., interface, profiling, communication, and capabilities acquisition) of LLM-based multi-agent systems and present two lines of applications in terms of problem solving and world simulation. Durante *et al.* [42] introduce multimodal LM agents and a training framework including learning, action, cognition, memory, action, and perception. They also discuss the different roles of agents (e.g., embodied, simulation, and knowledge inference), as well as the potentials and experimental results in different applications including gaming, robotics, healthcare, multimodal tasks, and Natural Language Processing (NLP). Hu *et al.* [20] outline six key components (i.e., perception, thinking, memory, learning, action, and role-playing) of LLM-based game agents and review existing LLM-based game agents in six types of games. Xu *et al.* [43] provide a comprehensive survey of enabling architectures and challenges for LM agents in gaming. Qu *et al.* [44] provide a comprehensive survey on integrating mobile edge intelligence (MEI) with LLMs, emphasizing key applications of deploying LLMs at the network edge along with state-of-the-art techniques in edge LLM caching, delivery, training, and inference.

Existing survey works on LM agents mainly focus on the general framework design for single LLM agents and multi-agent systems and their potentials in specific applications. Distinguished from the above-mentioned existing surveys, this survey focuses on the networking aspect of LM agents, including the general architecture, enabling technologies, and collaboration paradigms to construct networked systems of LM agents in physical, virtual, or mixed-reality environments. Moreover, with the advances of LM agents, it is urgent to study their security and privacy in future AI agent systems. This work comprehensively reviews the security and privacy issues of LM agents and discusses the existing and potential defense mechanisms, which are overlooked in existing surveys. Table I compares the contributions of our survey with previous related surveys in the field of LM agents.

In this paper, we present a systematic review of the state-of-the-arts in both single and connected LM agents, focusing on security and privacy threats, existing and potential countermeasures, and future trends. Our survey aims to 1) provide a broader understanding of how LM agents work and how they interact in multi-agent scenarios, 2) examine the scope and impact of security and privacy challenges associated with LM agents and their interactions, and 3) highlight effective strategies and

TABLE I: A Comparison of Our Survey with Relevant Surveys

Year.	Refs.	Contribution
2022	[29]	A toy experiment for AI agent construction and case studies in modeling communicative intentions, beliefs, and desires.
2023	[39]	Survey on key components and evaluation policies of LLM agents, and applications in engineering, natural science, and social science.
2023	[9]	Discussions on general framework for LLM agents and applications of single-agent, multi-agent, and human-agent collaborations, as well as agent societies.
2023	[2]	Review on background, pre-training, adaptation tuning, evaluation & utilization, capacity assessment, and critical applications of LLMs.
2024	[40]	Tutorial on key concepts, architecture, and metrics of edge-cloud AIGC services in mobile networks, and identify use cases and key implementation challenges.
2024	[1]	Discussions on taxonomy of AI agents in virtual/physical environments, cognitive aspects, and applications in robots, healthcare, and gaming.
2024	[10]	Discuss key components and applications of LLM agents, and review planning types, multi-role relationships, and communication modes in multi-agent systems.
2024	[8]	Overview of single-agent and multi-agent architectures in industrial projects and insights and limitations of research.
2024	[41]	Discuss key components of LLM-based multi-agent system and applications in problem solving and world simulation.
2024	[42]	Discuss key concepts and the framework of multimodal LLM agents, the different roles of agents, and the potentials and experimental results in gaming, robotics, healthcare, NLP, and multimodality.
2024	[20]	Discuss key components of LLM-based game agents and review existing approaches in six types of games.
2024	[43]	Survey the enabling architectures and key challenges of LM agents for games.
2024	[44]	Survey on key applications of deploying LLMs at network edges and state-of-the-art techniques in edge LLM caching, delivery, training, and inference.
Now	Ours	Comprehensive survey of the fundamentals, security, and privacy of connected LM agents, discussions on the general architecture, enabling technologies, networking modes, and collaboration paradigms of connected LM agents, discussions on security/privacy threats, state-of-the-art solutions, and open research issues in connected LM agent design.

solutions for defending against these threats to safeguard LM agents in various intelligent applications. The main contributions of this work are four-fold.

- We comprehensively review recent advances in LM agent construction across academia and industry. We investigate the working principles of LM agents, including the general architecture, key components (i.e., planning, memory, action, interaction, and security modules), and enabling technologies. The industrial prototypes and potential applications of LM agents are also discussed.
- We systematically categorize interaction patterns for LM agents (i.e., agent-agent, agent-human, and agent-environment interactions) and their interaction types (i.e., cooperation, partial cooperation, and competition). We explore practical collaboration paradigms of LM agents from the aspects of data cooperation, computation cooperation, and knowledge cooperation.
- We comprehensively analyze existing and potential security and privacy threats, their underlying mechanisms, categorization, and challenges for both single and connected LM agents. We also review state-of-the-art countermeasures and examine their feasibility in securing LM agents.
- Lastly, we discuss open research issues and point out future research directions from the perspectives of energy-efficient

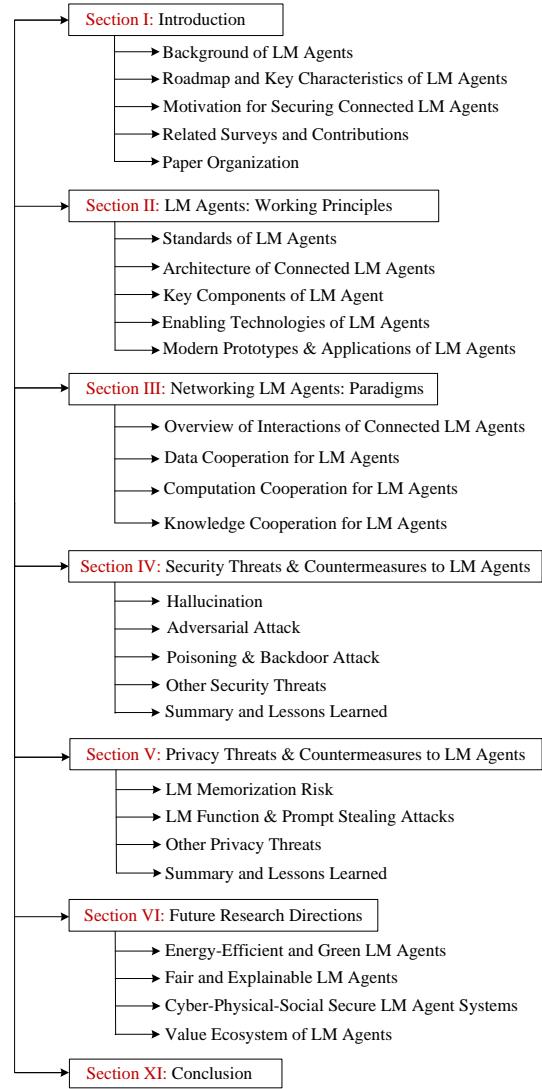


Fig. 4: Organization structure of this paper.

and green LM agents, fair and explainable LM agents, cyber-physical-social secure agent systems, value networks of agent ecosystem, aiming to advance the efficiency and security of LM agents.

E. Paper Organization

The remainder of this paper is organized as below. Section II discusses the working principles of single LM agents, while Section III presents the cooperation paradigms for connected LM agents. Section IV and Section V introduce the taxonomy of security and privacy threats to LM agents, respectively, along with state-of-the-art countermeasures. Section VI outlines open research issues and future directions in the field of LM agents. Finally, conclusions are drawn in Section VII. Fig. 4 depicts the organization structure of this survey.

II. LARGE MODEL AGENTS: WORKING PRINCIPLES

In this section, we first introduce existing standards of LM agents. Then, we discuss the general architecture of connected LM agents including key components, communication modes, key characteristics, and enabling technologies. Next, we introduce typical prototypes and discuss modern applications of LM agents.

TABLE II: Progress of Standards for LM Agents

Standard	Publication Date	Main Content
IEEE SA - P3394	2023-09-21	The natural language interface is defined, including various protocols and guidelines that enable applications and agents to effectively communicate with LLM-enabled agents, such as API syntax and semantics.
IEEE SA - P3428	2023-12-06	The integration of LLMs with existing educational systems ensures that LLMs can seamlessly interact with AIS while addressing issues of bias, transparency, and accountability within educational environments.

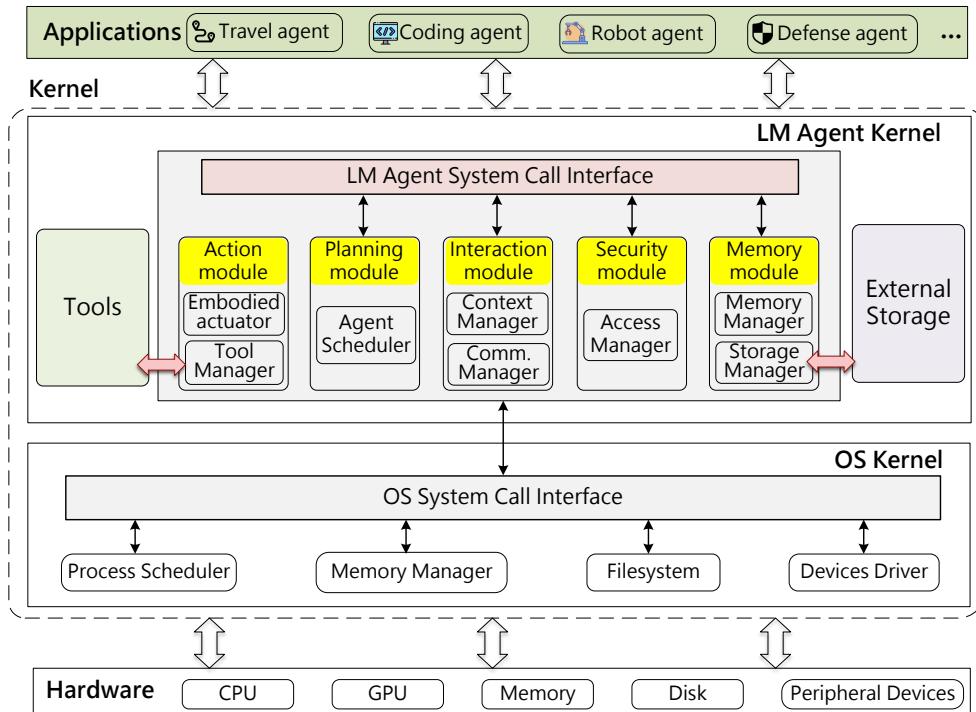


Fig. 5: Illustration of the OS architecture of LM agents [45], [46].

A. Standards of LM Agents

We briefly introduce two existing standards on LM agents: IEEE SA-P3394 and IEEE SA-P3428.

1) *The IEEE SA - P3394 standard¹*, launched in 2023, defines natural language interfaces to facilitate communication between LLM applications, agents, and human users. This standard establishes a set of protocols and guidelines that enable applications and agents to effectively communicate with LLM-enabled agents. These protocols and guidelines include, but are not limited to, API syntax and semantics, voice and text formats, conversation flow, prompt engineering integration, LLM thought chain integration, as well as API endpoint configuration, authentication, and authorization for LLM plugins. The standard is expected to advance technological interoperability, promote AI industry development, enhance the practicality and efficiency of LMs, and improve AI agent functionality and user experience.

2) *The IEEE SA - P3428 standard²*, launched in 2023, aims to develop standards for LLM agents in educational applications. The primary goal is to ensure the interoperability of LLM agents across both open-source and proprietary systems. Key areas of focus include the integration of LLMs with existing educational systems and addressing technical and ethical challenges. This includes ensuring that LLMs can seamlessly interact with other AI components, such as Adaptive Instructional Systems (AIS), while

also addressing issues of bias, transparency, and accountability within educational contexts. The standard is intended to support the widespread and effective application of LLMs in the field of education, thereby enabling more personalized, efficient, and ethically sound AI-driven educational experiences.

B. Architecture of Connected LM Agents

1) *Operating System (OS) of LM Agents*: According to [45], [46], the OS architecture of LM agents consists of three layers: application, kernel, and hardware.

- The application layer hosts agent applications (e.g., travel, coding, and robot agents) and offers a SDK that abstracts system calls, simplifying agent development.
- The kernel layer includes the ordinary OS kernel and an additional LM agent kernel, with a focus on without altering the original OS structure. Key modules in the LM agent kernel [45], [46] include the agent scheduler for task planning and prioritization, context manager for LM status management, memory manager for short-term data, storage manager for long-term data retention, tool manager for external API interactions, and access manager for privacy controls.
- The hardware layer comprises physical resources (CPU, GPU, memory, etc.), which are managed indirectly through OS system calls, as LM kernels do not interact directly with the hardware.

¹<https://standards.ieee.org/ieee/3394/11377/>

²<https://standards.ieee.org/ieee/3428/11489/>

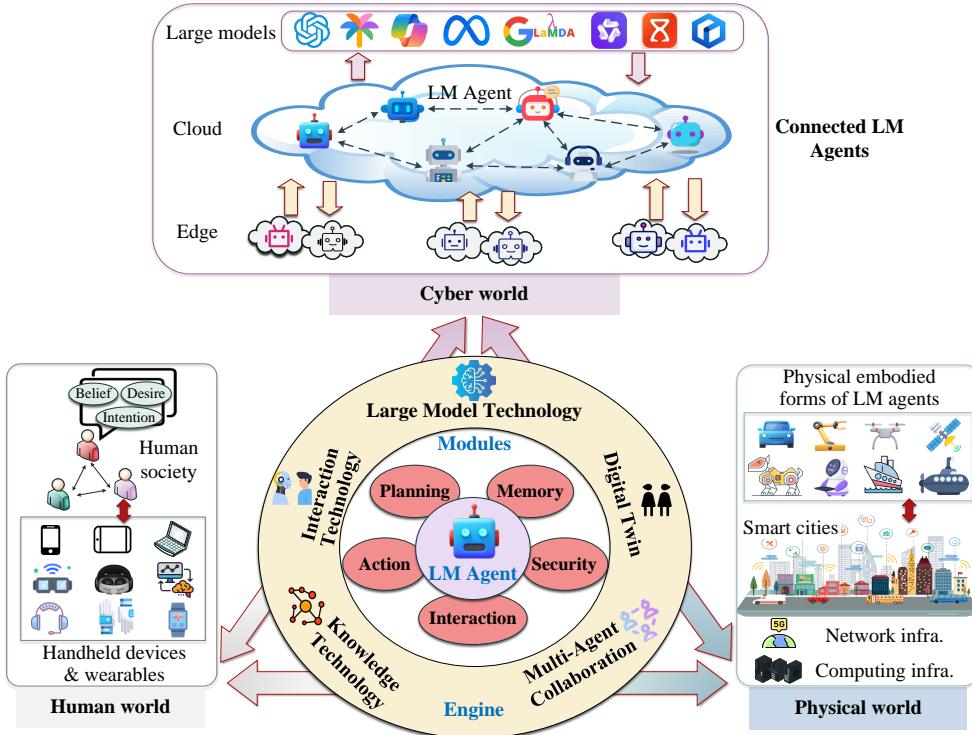


Fig. 6: General Architecture of Internet of LM agents in bridging the human, physical, and cyber worlds. The LM agent has five constructing *modules*: planning, action, memory, interaction, and security modules. The *engine* of connected LM agents is empowered by a combination of five cutting-edge technologies: large foundation models, knowledge-related technologies, interaction, digital twin, and multi-agent collaboration. LM agents interact with humans through Human-Machine Interaction (HMI) technologies such as NLP, with the assistance of handheld devices and wearables, to understand human intentions, desires, and beliefs. LM agent can synchronize data and statuses between the physical body and the digital brain through digital twin technologies, as well as perceive and act upon the surrounding virtual/real environment. LM agents can be interconnected in the cyber space through efficient cloud-edge networking for efficient data and knowledge sharing to promote multi-agent collaboration.

2) *Constructing Modules of LM Agents:* According to [1], [8]–[10], there are generally five constructing modules of LM agents: planning, action, memory, interaction, and security modules (details in Sect. II-C). These modules together enable LM agents to perceive, plan, act, learn, and interact efficiently and securely in complex and dynamic environments.

- Empowered by LMs, the *planning module* produces strategies and action plans with the help of the memory module, enabling informed decision-making [7], [10].
- The *action module* executes these embodied actions, adapting actions based on real-time environmental feedback to ensure contextually appropriate responses [9], [42].
- The *memory module* serves as a repository of accumulated knowledge (e.g., past experiences and external knowledge), facilitating continuous learning and improvement [10].
- The *interaction module* enables effective communication and collaboration with humans, other agents, and environment.
- The *security module* is integrated throughout LM agents' operations, ensuring active protection against threats and maintaining integrity and confidentiality of data and processes.

3) *Engine of LM Agents:* The engine of LM agents is powered by a combination of cutting-edge technologies including large foundation models, knowledge-related technologies, interaction, digital twin, and multi-agent collaboration (details in Sect. II-D).

- *Large foundation model* such as GPT-4 and DALL-E 2 serves as the brain of an LM agent, which enables high-level pattern recognition, advanced reasoning, and intelligent decision-making, providing the cognitive capabilities of LM agents [6], [7].
- *Knowledge-related technologies* enhance LM agents by incorporating Knowledge Graphs (KGs), knowledge bases, and RAG systems, allowing agents to access, utilize, and manage vast external knowledge sources, ensuring informed and contextually relevant actions [47].
- *HMI technologies* enable seamless interaction between humans and agents through NLP, multimodal interfaces, and Augmented/Virtual/Mixed Reality (AR/VR/MR), facilitating dynamic and adaptive interactions [48].
- *Digital twin technologies* allows efficient and seamless synchronization of data and statuses between the physical body and the digital brain of an LM agent through intra-agent communications [49].
- *Multi-agent collaboration technologies* empower LM agents to work together efficiently, sharing data, resources, and tasks to tackle complex problems by developing cooperation, competition, and competition strategies through inter-agent communications [28].

4) *Communication Mode of LM Agents:* Every LM agent consists of two parts: (i) the LM-empowered *brain* located in the

cloud, edge servers, or end devices and (ii) the corresponding *physical body* such as autonomous vehicle. Every LM agent can actively interact with other LM agents, the virtual/real environment, and humans. For connected LM agents, there exist two typical communication modes: *intra-agent communications* for seamless data/knowledge synchronization between brain and physical body within an LM agent, and *inter-agent communications* for efficient coordination between LM agents. Table III summarizes the comparison of the two communication modes.

- *Intra-agent communications* refer to the internal data/knowledge exchange within a single LM agent. This type of communication ensures that different components of the LM agent, including planning, action, memory, interaction, and security modules, work in harmony. For example, an LM agent collects multimodal sensory data through its physical body, which then communicates the interpreted information to the LM-empowered brain. The planning module in the brain formulates a response or action plan, which is then executed by the action module. This seamless flow of information is critical for maintaining the LM agent's functionality, coherence, and responsiveness in real-time and dynamic scenarios.
- *Inter-agent communications* involve information and knowledge exchange between multiple LM agents. It enables collaborative task allocation, resource sharing, and coordinated actions among agents to foster collective intelligence. For example, in a smart city application, various LM agents managing traffic lights, public transportation, and emergency services share real-time data to optimize urban mobility and safety. Effective inter-agent communications rely on standardized protocols to ensure compatibility and interoperability, facilitating efficient and synchronized operations across the network of LM agents.

5) *Information Flow Between Human World and LM Agents:* Humans interact with LM agents through natural language, mobile smart devices, and wearable technology, enabling LM agents to comprehend human instructions and address real-world issues effectively. LM agents, in turn, acquire new knowledge and data from human inputs, which aids in their continuous improvement and learning. This ongoing process of updating and optimizing their models allows LM agents to provide increasingly accurate and useful information. In AR and VR environments, LM agents can work collaboratively with human users in virtual settings, such as architectural design, for enhanced overall efficiency and creativity [50].

6) *Information Flow Between Physical World and LM Agents:* Empowered by digital twin technologies, LM agents are allowed to synchronize data and statuses between their physical bodies and their digital brains, creating a seamless interaction loop. LM agents can also monitor and act upon real-time inputs from their environments. This bidirectional synchronization allows LM agents to perceive and respond to their surrounding environments—whether virtual or real—with a high degree of precision and responsiveness, thus bridging the gap between the digital and physical realms. By continuously learning from environmental feedbacks, LM agents can accumulate knowledge and develop an understanding of physical laws, which empowers them to solve complex real-world problems. This iterative learning process



Fig. 7: Illustration of five constructing modules (i.e., planning, action, memory, interaction, and security) of connected LM agents including their key components.

ensures that LM agents not only react to immediate stimuli but also refine their embodied actions over time, achieving more sophisticated and effective solutions.

7) *Information Flow Between Cyber World and LM Agents:* In the cyber world, LM agents are interconnected into the Internet of LM agents through efficient cloud-edge networking, facilitating seamless data and knowledge sharing that promotes multi-agent collaboration. By deploying LMs across both cloud and edge infrastructures, it allows LM agents to leverage the strengths of both cloud and edge computing for optimized performance and responsiveness [51]. The cloud provides substantial computational power and storage, enabling the processing of vast amounts of data and the training of sophisticated models. Meanwhile, the edge offers real-time data processing capabilities closer to the source, reducing latency and ensuring timely decision-making. In the Internet of LM agents, LM agents can collaboratively share data, knowledge, and learned experiences with others in real-time, creating a robust and adaptive network of intelligence across multiple domains. For example, in a smart city, embodied LM agents in various locations can work together to optimize traffic flow, manage energy resources, and enhance public safety by sharing real-time data and coordinating their actions.

C. Key Components of LM Agent

As depicted in Fig. 7, it generally contains five key modules to construct a connected LM agent [1], [8]–[10].

1) *Planning Module:* The planning module serves as the core of an LM agent [7], [10]. It utilizes advanced reasoning techniques to enable LM agents to devise efficient and effective solutions to complex problems. The working modes of the planning module include the following types.

- *Feedback-free planning:* The planning module enables LM agents to understand the complex problems and find reliable solutions by breaking them down into necessary steps or

TABLE III: A Summary of Intra-Agent And Inter-Agent Communications for Connected LM Agents

Involved Entity	Intra-agent Comm.	Inter-agent Comm.
Connection Type	Within a single LM agent	Among multiple LM agents
Support Two-way Communication	✓	✓
Support Multimodal Interaction	✓	✓
Support Semantic Communication	✓	✓
Typical Communication Environment	Wireless	Wired

manageable sub-tasks [7], [14]. For example, CoT [11] is a popular sequential reasoning approach where each thought builds directly on the previous one. It represents the step-by-step logical thinking and can enhance the generation of coherent and contextually relevant responses. ToT [12] organizes reasoning as a tree-like structure, exploring multiple paths simultaneously. In ToT, Each node represents a partial solution, allowing the model to branch and backtrack to find the optimal answer. Graph of Thought (GoT) [52] models reasoning using an arbitrary graph structure, allowing more flexible information flow. GoT captures complex relationships between thoughts, enhancing the model's problem-solving capabilities. AVIS [53] further refines the tree search process for visual QA tasks using a human-defined transition graph and enhances decision-making through a dynamic prompt manager.

- *Feedback-enhanced planning:* To make effective long-term planning in complex tasks, it is necessary to iteratively reflect on and refine execution plans based on past actions and observations [39]. The goal is to correct past errors and improve final outcomes. For example, ReAct [54] combines reasoning and acting by prompting LLMs to generate reasoning traces and actions simultaneously. This dual approach allows the LLM to create, monitor, and adjust action plans, while task-specific actions enhance interaction with external sources, improving response accuracy and reliability. Reflexion [55] converts environmental feedback into self-reflection and enhances ReAct by enabling LLM agents to learn from past errors and iteratively optimize behaviors. Reflexion features an actor that produces actions and text via models (e.g., CoT and ReAct) enhanced by memory, an evaluator that scores outputs using task-specific reward functions, and self-reflection that generates verbal feedback to improve the actor.
- *Multi-persona self-planning:* Inspired by pretend play, Wang *et al.* [56] develop a cognitive synergist that enables a single LLM to split into multiple personas, facilitating self-collaboration for solving complex tasks. They propose Solo Performance Prompting (SPP), where LLM identifies, simulates, and collaborates with diverse personas, such as domain experts or target audiences, without external retrieval systems. SPP enhances problem-solving by allowing LLM to perform multi-turn self-revision and feedback from various perspectives.
- *Grounded planning:* Executing plans in real-world environments (e.g., Minecraft) requires precise, multi-step reasoning. VOYAGER [50], the first LLM-powered agent in Minecraft, utilizes in-context lifelong learning to adapt and generalize skills to new tasks and worlds. VOYAGER include an automatic curriculum for exploration, a skill

library of executable code for complex behaviors, and an iterative prompting mechanism that refines programs based on feedback. Wang *et al.* [57] further propose an interactive describe-explain-plan-select (DEPS) planning approach that improves LLM-generated plans by integrating execution descriptions, self-explanations, and a goal selector that ranks sub-goals to refine planning. Additionally, Song *et al.* [7] present a grounded re-planning algorithm which dynamically updates high-level plans during task based on environmental perceptions, triggering re-planning when actions fail or after a specified time.

2) *Memory Module:* The memory module is integral to LM agent's ability to learn and adapt over time [39]. It maintains an internal memory that accumulates knowledge from past interactions, thoughts, actions, observations, and experiences with users, other agents, and the environments. The stored information guides future decisions and actions, allowing the agent to continuously refine its knowledge and skills. This module ensures that the agent can remember and apply past lessons to new situations, thereby improving its long-term performance and adaptability [10]. There are various memory formats such as natural language, embedded vectors, databases, and structured lists. Additionally, RAG technologies [15] are employed to access external knowledge sources, further enhancing the accuracy and relevance of LM agent's planning capabilities. In the literature [10], [39], memory can be divided into the following three types.

- *Short-term memory* focuses on the contextual information of the current situation. It is temporary and limited, typically managed through a context window that restricts the amount of information the LM agent can learn at a time.
- *Long-term memory* stores LM agent's historical behaviors and thoughts. This is achieved through external vector storage, which allows for quick retrieval of important information, ensuring that the agent can access relevant past experiences to inform current decisions [58].
- *Hybrid memory* combines short-term and long-term memory to enhance an agent's understanding of the current context and leverage past experiences for better long-term reasoning. Liu *et al.* [59] propose the RAISE architecture to enhance ReAct for conversational AI agents by integrating a dual-component memory system, where Scratchpad captures recent interactions as short-term memory; while the retrieval module acts as long-term memory to access relevant examples. HIAGENT [60] employs cross-trial and in-trial memory, where cross-trial memory stores historical trajectories and in-trial memory captures current trials. Instead of retaining all action-observation pairs, HIAGENT uses subgoals as memory chunks to save memory, each containing summarized observations. LLM generates subgoals, executes actions to achieve them, and updates the working memory by

summarizing and replacing completed subgoals with relevant information.

3) *Action Module*: The action module equips the LM agent with the ability to execute and adapt actions in various environments [9], [42]. This module is designed to handle embodied actions and tool-use capabilities, enabling the agent to interact with its physical surroundings adaptively and effectively. Besides, tools significantly broaden the action space of the agent.

- *Embodied actions*. The action module empowers LM agents to perform contextually appropriate embodied actions and adapt to environmental changes, facilitating interaction with and adjustment to physical surroundings [21], [25]. As LLM-generated action plans are often not directly executable in interactive environments, Huang *et al.* [25] propose refining LLM-generated plans for embodied agents by conditioning on demonstrations and semantically translating them into admissible actions. Evaluations in the VirtualHome environment show significant improvements in executability, ranging from 18% to 79% over the baseline LLM. Besides, SayCan [21] enables embodied agents such as robots to follow high-level instructions by leveraging LLM knowledge in physically-grounded tasks, where LLM (i.e., Say) suggests useful actions; while learned affordance functions (i.e., Can) assess feasibility. SayCan’s effectiveness is demonstrated through 101 zero-shot real-world robotic tasks in a kitchen setting. PaLM-E [61] is a versatile multimodal language model for embodied reasoning, visual-language, and language tasks. It integrates continuous sensor inputs, e.g., images and state estimates, into the same embedding space as language tokens, allowing for grounded inferences in real-world sequential decision-making.
- *Learning to use & make tools*. By leveraging various tools (e.g., search engines and external APIs) [62], LM agent can gather valuable information to handle assigned complex tasks. For example, AutoGPT integrates LLMs with predetermined tools such as web and file browsing. InteRecAgent [63] integrates LLMs as the brain and recommender models as tools, using querying, retrieval, and ranking tools to handle complex user inquiries. Beyond using existing tools, LM agents can also develop new tools to enhance task efficiency [9]. To optimize tool selection with a large toolset, ReInvoke [64] introduces an unsupervised tool retrieval method featuring a query generator to enrich tool documents in offline indexing and an intent extractor to identify tool-related intents from user queries in online inference, followed by a multi-view similarity ranking strategy to identify the most relevant tools.

4) *Interaction Module*: The interaction module enables the LM agent to interact with humans, other agents, and the environment [41]. Through these varied interactions, the agent can gather diverse experiences and knowledge, which are essential for comprehensive understanding and adaptation.

- *Agent-Agent Interactions*. The interaction module allows LM agents to communicate and collaborate with other agents, fostering a cooperative network where information and resources are shared [62]. This interaction can include coordinating efforts on shared tasks, exchanging knowledge

to solve problems, and negotiating roles in multi-agent scenarios.

- *Agent-Human Interactions*. LM agents can interact with humans including understanding and responding to natural language commands, recognizing and interpreting human emotions and expressions, and providing assistance in various tasks [20]. As observed, LLMs such as GPT-4 often tend to forget character settings in multi-turn dialogues and struggle with detailed role assignments due to context window limits. To address this, a tree-structured persona model is introduced in [65] for character assignment, detection, and maintenance, enhancing agent interactions.
- *Agent-Environment Interactions*. LM agents can engage directly with the physical or virtual environments. By facilitating engagement in physical, virtual, or mixed-reality environments [1], [21], the interaction module ensures that LM agents can operate effectively across different contexts. Lai *et al.* develop the AutoWebGLM agent [66], which excels in web browsing tasks through curriculum learning, self-sampling reinforcement learning, and rejection sampling fine-tuning. A Chrome extension based on AutoWebGLM validates its effective reasoning and operation capability across various websites in real-world services.

5) *Security Module*: The security module is crucial to ensure the secure, safe, ethical, and privacy-preserving operations of LM agents [42]. It is designed to monitor and regulate the LM agent’s actions, interactions, and decisions to prevent harm and ensure compliance with legal and ethical standards. This module employs technologies such as hallucination mitigation, anomaly detection, and access control to identify and mitigate potential security/privacy threats. It also incorporates ethical guidelines and bias mitigation techniques to ensure fair and responsible behaviors. The security module can dynamically adapt to emerging threats by learning from new security/privacy incidents and integrating updates from security/privacy databases and policies.

Connections Between Modules: The key components of an LM agent are interconnected to create a cohesive and intelligent system. Particularly, the planning module relies on the memory module to access past experiences and external knowledge, ensuring informed decision-making. The action module executes plans generated by the planning module, adapting actions based on real-time feedback and memory. The interaction module enhances these processes by facilitating communication and collaboration, which provides additional data and context for the planning and memory modules. Besides, security considerations are seamlessly integrated into every aspect of the LM agent’s operations to ensure robust and trustworthy performance.

D. Enabling Technologies of LM Agents

As illustrated in Fig. 8, there are five enabling technologies underlying the engine of connected LM agents.

- 1) *Large Foundation Model Technologies*: LMs, such as LLMs and LVMs, serve as the core brains or controllers, providing advanced capabilities for AI agents across diverse applications [6], [57]. Table IV summarizes the basic training stages of LLM. (i) *Multimodal capability*: By employing multimodal perception (e.g., CLIP [69]) and tool utilization strategies, LM agents can perceive and process various data types from virtual and real

TABLE IV: A Summary of LLM Stages, Utilized Technologies, and Representatives

Stage of LLM	Description	Utilized Technology	Representative
Pre-training	Pre-train LLM in a self-supervised manner on a large corpus	Transformer	GPT-3, PaLM-2, LLaMA-2
Fine-tuning	Fine-tuning pre-trained LLM for downstream tasks	Instruction-tuning, Alignment-tuning, Transfer learning	WebGPT [16], T0, LLaMA-2-Chat
Prompting	Setup prompts and query trained LLMs for generating responses	Prompt engineering, Zero-shot prompting, In-context learning	RALM [67], ToolkenGPT [68]

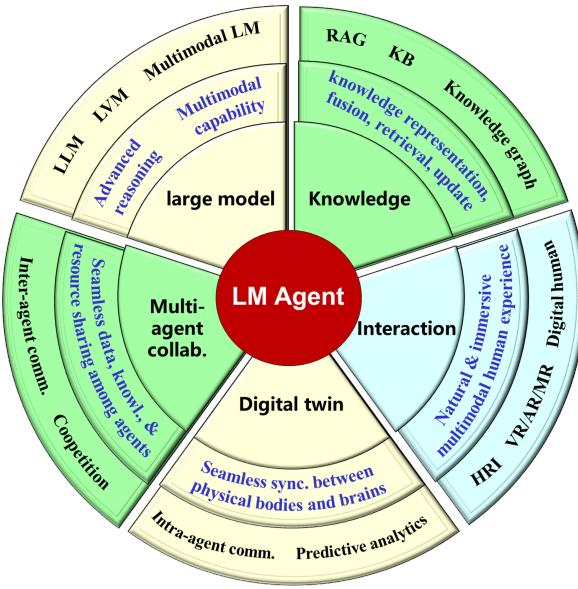


Fig. 8: Illustration of five underlying technologies, including their roles and key components, acting as the engine of the connected LM agents.

environments, as well as human inputs, through multimodal data fusion, allowing for a holistic understanding of their surroundings [1]. Additionally, due to their powerful multimodal comprehension and generation capabilities [70], LM agents can interact seamlessly with both other agents and humans, fostering collaboration and competition among agents and humans. (ii) *Advanced reasoning*: LM technologies also empower AI agents with advanced reasoning and problem decomposition abilities [17]. For example, CoT [11] and ToT [12] reasoning allow LM agents to break down complex tasks into manageable sub-tasks, ensuring systematic and logical problem-solving approaches. (iii) *Few/zero-shot generalization*: Pre-trained on extensive corpora, LMs demonstrate few-shot and zero-shot generalization capabilities [25]. This allows LM agents to transfer knowledge seamlessly between tasks. (iv) *Adaptability*: Through continuous learning and adaptation, LM agents can accumulate knowledge and improve their performance over time by learning from new data and experiences [71]. This adaptability ensures that AI agents maintain high levels of performance in rapidly changing environments.

2) *Knowledge-Related Technologies*: Knowledge-related technologies significantly enhance the capabilities of LM agents in knowledge representation [72], acquisition [73], fusion [74], retrieval [58], and synchronization [75]. These technologies collectively empower LM agents with deeper contextual understanding, more accurate reasoning, and better interaction. (i) *Knowledge*

fusion: Knowledge representation and fusion technologies enable LM agents to build comprehensive knowledge bases by integrating information from diverse sources [74], such as structured databases, vector databases, and multimodal KGs. KGs, in particular, organize information into structured relationships, allowing LM agents to comprehend complex contexts and infer new information. (ii) *RAG*: RAG combines retrieval mechanisms with generative models, enabling LM agents to dynamically fetch relevant external information from vast knowledge sources [76]. This ensures that the outputs of LM agents are contextually relevant and up-to-date. Semantic understanding techniques [77], [78] further enhance LM agents' ability to interpret and generate content that is both contextually appropriate and semantically rich. (iii) *Knowledge synchronization*: Continuous learning algorithms [79], [80] facilitate the ongoing updating of knowledge bases, allowing agents to incorporate new information incrementally and adapt to changing environments. These technologies also promote knowledge sharing and collaboration among multiple agents and between agents and humans.

3) *Interaction Technologies*: Interaction technologies significantly enhance LM agents' ability to engage with users, other agents, and the environment in natural, immersive, and contextually aware ways [42]. (i) *HMI and human-robot interaction (HRI)*: HMI and HRI technologies [21], bolstered by NLP, enable LM agents to understand complex instructions, recognize speech, and interpret emotions, facilitating more intuitive interactions. (ii) *3D digital humans*: 3D digital humans create realistic and engaging interfaces for communication, allowing LM agents to provide empathetic and personable interactions in applications such as customer support and healthcare [40]. (iii) *AR/VR/MR*: AR, VR, and MR technologies create immersive and interactive environments, allowing users to engage with digital and physical elements seamlessly. This is particularly beneficial in education, retail, and training, where such immersive experiences can enhance learning, engagement, and decision-making [48]. AR overlays digital information onto the real world, enabling users to interact with virtual objects in their physical surroundings; VR creates fully immersive digital environments for engaging with virtual elements; while MR blends digital information with physical environments. (iv) *Multimodal interfaces*: Multimodal interfaces enable LM agents to process and respond to various forms of input, including text, speech, images, gestures, and touch [1]. This allows users to interact with LM agents through their preferred modalities, making interactions more flexible and user-friendly.

4) *Digital Twin Technologies*: Digital twin technologies [49] create comprehensive virtual representations of LM agents' physical bodies and operational environments, continuously updated with real-time data from sensors, actuators, and other inputs.

This ensures an accurate and up-to-date reflection of their real-world counterparts. (i) *Virtual-physical synchronization*: Digital twin technologies empower LM agents by enabling seamless and efficient synchronization of attributes, behaviors, states, and other data between their physical bodies and digital brains. This synchronization is achieved through intra-agent bidirectional communications, where the physical body continuously transmits real-time data to the digital twin for processing and analysis, while the digital twin sends back instructions and optimizations [49]. (ii) *Virtual-physical feedback*: This continuous feedback loop enhances LM agent's contextual awareness, allowing for immediate adjustments and optimizations in response to changing conditions [23]. For example, an LM agent operating machinery can use its digital twin to anticipate mechanical wear and proactively schedule maintenance, thereby minimizing downtime and enhancing efficiency. (iii) *Predictive analytics*: Digital twins facilitate predictive analytics and simulation, enabling LM agents to anticipate future states and optimize their actions accordingly [22]. This capability is crucial in complex environments where unforeseen changes can significantly impact performance. Overall, digital twin technologies ensure that LM agents operate with high accuracy, adaptability, and responsiveness across diverse applications, effectively bridging the gap between the physical and digital realms.

5) *Multi-Agent Collaboration Technologies*: Multi-agent collaboration technologies [41] enable coordinated efforts of multiple LM agents, allowing them to work together synergistically to achieve common goals and tackle complex tasks that would be challenging for individual agents to handle alone. (i) *Data cooperation*: It facilitates real-time and seamless information sharing through inter-agent communications, enabling LM agents to continuously synchronize their understanding of dynamic environments [81], [82]. (ii) *Knowledge cooperation*: By leveraging knowledge representation frameworks such as KGs [47], [83] and vector databases [84], LM agents can share and aggregate domain-specific insights, enhancing collective learning and decision-making. This shared knowledge base allows LM agents to build upon each other's experiences to accelerate the learning process [71]. (iii) *Computation cooperation*: On the one hand, collaborative problem-solving techniques , such as multi-agent planning [85] and distributed reasoning [86], empower LM agents to jointly analyze complex issues, devise solutions, and execute coordinated actions. On the other hand, dynamic resource allocation mechanisms [87], [88], including market-based and game-theoretical approaches, enable LM agents to negotiate and allocate resources dynamically, thereby optimizing resource utilization ensuring effective task execution across multiple agents. This synergy is particularly beneficial in dynamic environments, which not only improves the operational capabilities of individual LM agents but also enhances the overall functionality of the system of connected LM agents.

E. Modern Prototypes & Applications of LM Agents

Recently, various industrial projects of LM agents, such as AutoGPT, AutoGen, BabyAGI, ChatDev, and MetaGPT, demonstrate their diverse potential in assisting web, life, and business scenarios, such as planning personalized travels, automating creative content generation, and enhancing software development work-

flows. For example, *AutoGPT*³ is an open-source autonomous agent utilizing GPT-3.5 or GPT-4 APIs to independently execute complex tasks by breaking down them into several sub-tasks and chaining LLM outputs, showcasing advanced reasoning capabilities [14]. *AutoGen*⁴, developed by Microsoft, offers an open-source multi-agent conversation framework, supports APIs as tools for improved LLM inference, and emphasizes the automatic generation and fine-tuning of AI models [89]. *BabyAGI*⁵ integrates task management via OpenAI platforms and vector databases, simulating a simplified AGI by autonomously creating and executing tasks based on high-level objectives. *ChatDev*⁶ focuses on enhancing conversational AI, providing sophisticated dialogue management, coding, debugging, and project management to streamline software development processes [90]. *MetaGPT*⁷ explores the meta-learning paradigm, where the model is trained to rapidly adapt to new tasks by leveraging knowledge from related tasks, thus improving efficiency and performance across diverse applications [91].

1) *Mobile Communications*: LM agents offer significant advantages for mobile communications by enabling low-cost and context-aware decision-making [92], personalized user experiences [87], and automatic optimization problem formulation for wireless resource allocation [93]. For example, *NetLLM* [92] fine-tuning the LLM to acquire domain knowledge from multimodal data in networking scenarios (e.g., adaptive bitrate streaming, viewport prediction, and cluster job scheduling) with reduced handcraft costs. Meanwhile, *NetGPT* [87] design a cloud-edge cooperative LM framework for personalized outputs and enhanced prompt responses in mobile communications via de-duplication and prompt enhancement technologies. *ChatNet* [94] uses four GPT-4 models to serve as analyzer (to plan network capacity and designate tools), planner (to decouple network tasks), calculator (to compute and optimize the cost), and executor (to produce customized network capacity solutions) via prompt engineering.

LM agents can also help enhance the QoE of end users. For example, *MobileAgent v2* [18], launched by Alibaba, is a mobile device operation assistant that achieves effective navigation through multi-agent collaboration, automatically performing tasks such as application installation and map navigation, and supports multimodal input including visual perception, enhancing operational efficiency on mobile devices. *AppAgent* [19], developed by Tencent, performs various tasks on mobile phones through autonomous learning and imitating human click and swipe gestures, including posting on social media, helping users write and send emails, using maps, online shopping, and even complex image editing.

2) *Intelligent Robots*: LM agents play a crucial role in advancing intelligent industrial and service robots [21]. These robots can perform complex tasks such as product assembly, environmental cleaning, and customer service, by perceiving surroundings and learning necessary skills through deep learning models. In August 2024, FigureAI released *Figure 02*⁸, a human-like robot powered by OpenAI LM, capable of fast common-sense

³<https://autogpt.net/>

⁴<https://microsoft.github.io/autogen/>

⁵<https://github.com/yohineakajima/babyagi>

⁶<https://github.com/OpenBMB/ChatDev>

⁷<https://www.deepwisdom.ai/>

⁸<https://spectrum.ieee.org/figure-new-humanoid-robot>

TABLE V: Comparison of Existing Typical LM Agent Prototypes

Prototype	Application	Enhancing Intelligence	Improving Safety	Optimizing Experience	Other Key Features
AutoGPT	General scenarios	Yes	N/A	Yes	Task decomposition and execution
AutoGen	General scenarios	Yes	N/A	Yes	Multi-agent conversation framework
BabyAGI	General scenarios	Yes	N/A	Yes	Autonomous task management simulation
ChatDev	General scenarios	Yes	N/A	Yes	Conversational AI for software development
MetaGPT	General scenarios	Yes	N/A	Yes	Meta-learning for task adaptation
NetLLM	Mobile communications	Yes	N/A	Yes	Fine-tunes LLM for networking
NetGPT	Mobile communications	Yes	N/A	Yes	Cloud-edge cooperative LM service
MobileAgent v2	Mobile communications	Yes	N/A	Yes	Multimodal input support
AppAgent	Mobile communications	Yes	N/A	Yes	Performs tasks on mobile devices
Figure 02 by FigureAI	Intelligent robots	Yes	N/A	N/A	Performs dangerous jobs
Optimus by Tesla	Intelligent robots	Yes	N/A	N/A	Second-generation humanoid robot
Baidu Apollo ADFM	Autonomous driving	Yes	Yes	Yes	Supports L4 autonomous driving
PentestGPT	Attack-defense confrontation	Yes	Yes	N/A	87% success in vulnerability exploitation
AutoAttacker	Attack-defense confrontation	Yes	No	N/A	Automatically execute network attacks

visual reasoning and speech-to-speech conversation with humans to handle dangerous jobs in various environments. Besides, in July 2024, Tesla unveiled its second-generation humanoid robot named *Optimus*⁹, which demonstrates the enhanced capabilities brought by advanced LM agents.

3) *Autonomous Driving*: LM agents are transforming autonomous driving by enhancing vehicle intelligence, improving safety, and optimizing driving experience (e.g., offering personalized in-car experience) [22]. In May 2024, Baidu’s Apollo Day saw the launch of Carrot Run’s sixth-generation unmanned vehicle, which is built upon the *Apollo Autonomous Driving Foundation Model (ADFM)*¹⁰, the first LM agent supporting L4 autonomous driving. Companies such as Tesla, Waymo, and Cruise are also leveraging LM agents to refine their autonomous driving systems, aiming for safer and more efficient transportation solutions.

4) *Autonomous attack-defense confrontation*: LM agents can be seen as autonomous and intelligent cybersecurity decision-maker capable of making security decisions and taking threat handling actions without human intervention. For example, *PentestGPT* [95] is an automated penetration testing tool supported by LLMs, designed to use GPT-4 for automated network vulnerability scanning and exploitation. *AutoAttacker* [96], an LM tool, can autonomously generate and execute network attacks based on predefined attack steps. As reported by a latest research [97], LM agents can automatically exploit one-day vulnerabilities; and in tests on 15 real-world vulnerability datasets, GPT-4 successfully exploited 87% of vulnerabilities, significantly outperforming other tools.

III. NETWORKING LARGE MODEL AGENTS: PARADIGMS

A. Overview of Interactions of Connected LM Agents

For connected LM agents, multi-agent interactions refer to the dynamic and complex interactions between multiple autonomous LM agents that operate within a shared environment. As depicted in Fig. 9, these interactions can be categorized into cooperation, partial cooperation, and competition [62], [98], each of which involves different strategies to jointly optimize the collective or individual outcomes.

⁹<https://viso.ai/edge-ai/tesla-bot-optimus/>

¹⁰<https://autonews.gasgoo.com/icv/70033042.html>



Fig. 9: Illustration of interaction types of LM agents, i.e., fully cooperative, partially cooperative, and fully competitive.

1) *Competition*: Competition involves LM agents pursuing their individual objectives, often at the expense of others. This interaction mode is characterized by non-cooperative strategies where agents aim to maximize their own benefits. Non-cooperative game and multi-agent debate have been widely adopted to model the competitive behaviors among LM agents. In non-cooperative games, LM agents engage in strategic decision-making where each LM agent’s goal is to search the Nash equilibrium. LM agents in multi-agent debate [99] involve engaging in structured arguments or debates to defend their positions and challenge the strategies of others.

The cognitive behavior of LLMs, such as self-reflection, has proven effective in solving NLP tasks but can lead to thought degeneration due to biases, rigidity, and limited feedback. Multi-agent debate (MAD) [99] explores interactions among LLMs, where agents engage in a dynamic tit-for-tat, allowing them to correct each other’s biases, overcome resistance to change, and provide mutual feedback. In MAD, diverse role prompts (i.e., personas) are crucial and there are generally three communication strategies: (a) one-by-one debate, (b) simultaneous-talk, and (c) simultaneous-talk-with-summarizer.

2) *Partial Cooperation*: Partial cooperation occurs when LM agents collaborate to a limited extent, often driven by overlapping but not fully aligned interests [62]. In such scenarios, agents might share certain resources or information while retaining autonomy over other aspects. This interaction mode balances the benefits of cooperation with the need for individual agency and competitive advantage. Partial cooperation can be strategically advantageous in environments where complete cooperation is impractical or undesirable due to conflicting goals or resource constraints. Hierarchical game and coalition formation theory can be employed to model both cooperative and competitive

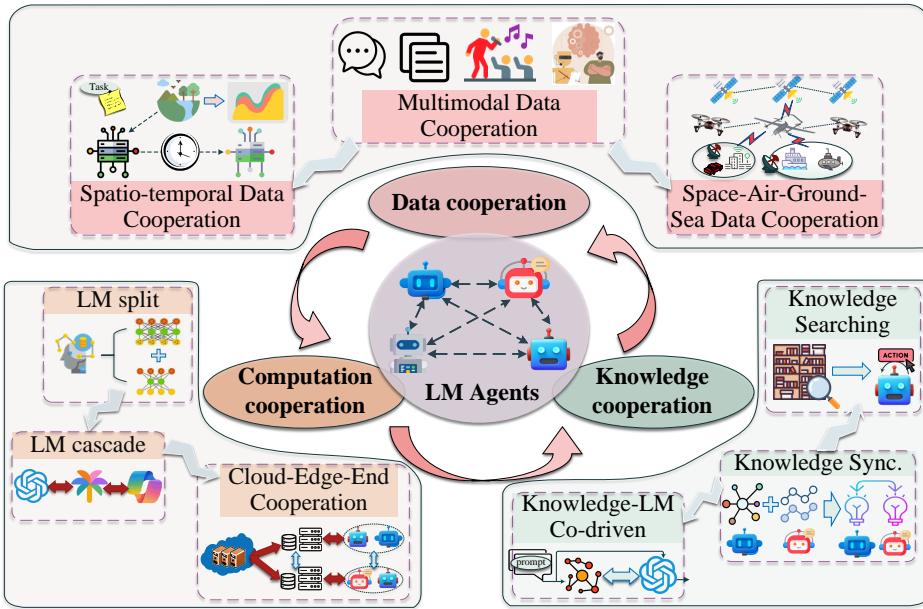


Fig. 10: Illustration of the cooperation modes of connected LM agents including data cooperation, computation cooperation, and knowledge cooperation.

interactions among LM agents.

Hierarchical game [100] structures the interactions of LM agents across different game stages, where they may cooperate at one level and compete at another. Through the coalition formation theory [101], LM agents can form the optimal stable coalition structure under different scenarios and environments, where the optimal stable coalition structure is featured with intra-coalition cooperation and inter-coalition competition. Liu *et al.* propose DyLAN [102], a multi-layered dynamic LLM agent network for collaborative task-solving, such as reasoning and code generation. DyLAN facilitates multi-round interactions in a dynamic setup with an LLM-empowered ranker to deactivate low-performing agents, an early-stopping mechanism based on Byzantine Consensus to efficiently reach agreement, and an automatic optimizer to select the best agents based on agent importance scores. However, existing cooperative agents rely on learning-based methods, with performance highly dependent on training diversity, limiting their adaptability with unfamiliar teammates, especially in zero-shot coordination. Zhang *et al.* [85] introduce ProAgent for cooperative agents, featuring four key modules: planner, verifier, controller, and memory. Verifier checks skill feasibility, identifies issues if a skill fails, and triggers re-planning if necessary. If feasible, the controller breaks the skill into executable actions.

3) *Cooperation*: For connected LM agents, cooperation is a fundamental interaction mode where LM agents work together to achieve common goals, share resources, and optimize collective outcomes. This involves data cooperation, computation cooperation, and information (including knowledge) cooperation.

- *Data Cooperation*: LM agents continuously exchange and fuse their individual data (e.g., perceived data) to ensure a comprehensive and up-to-date understanding of their environment, thereby enhancing collective intelligence and enable coordinated actions [81] [82].
- *Computation Cooperation*: LM agents perform coordinated

reasoning, such as service cascades, by distributing computational tasks optimally across agents, leveraging collective processing power to handle complex computations more efficiently [52] [85] [86] [88].

- *Information & Knowledge Cooperation*: LM agents share domain-specific knowledge and experiences (e.g., in the format of KGs) to collectively improve their problem-solving capabilities for better-informed actions and decisions, via knowledge bases synchronization and distributed learning algorithms [71] [47] [83].

The methodologies employed for facilitating cooperation among LM agents include role-playing [90], [103], multi-objective optimization, cooperative game theory [104], Nash bargaining solution, auction mechanism [88], Multi-Agent Reinforcement Learning (MARL) [98], swarm intelligence algorithms, Federated Learning (FL) [86], and the theory of mind [105].

- *Role-playing*. Li *et al.* [30] propose a cooperative agent framework that employs role-playing with inception prompting to guide agents autonomously toward task completion. The system begins with human-provided ideas and role assignments, refined by a task-specifier agent. An AI user and an AI assistant then collaborate through multi-turn dialogues, with the AI user instructing and the assistant responding until the task is completed. ChatDev [90] is a virtual software company operated by “software agents” with diverse roles, e.g., chief officers, programmers, and test engineers. Following the waterfall model, it divides development into design, coding, testing, and documentation, breaking each phase into atomic subtasks managed by a chat chain. MetaGPT [91] integrates human workflows into LLM-based multi-agent collaborations. By encoding Standardized Operating Procedures (SOPs) into prompt sequences, MetaGPT streamlines workflows and reduces errors through agents with human-like expertise. Agents are defined with specific profiles and communicate through structured communica-

tion interfaces, such as documents and diagrams, instead of dialogue. Using a publish-subscribe mechanism, agents can freely exchange messages via a shared message pool, publishing their outputs and accessing others' transparently. Park *et al.* [103] create a community of 25 generative agents in a sandbox world named Smallville, where agents are represented by sprite avatars. These agents perform daily tasks, form opinions, and interact, mimicking human-like behaviors.

- *Theory of mind.* It refers to the ability to understand about others' hidden mental states, which is essential for social interactions. As LLMs engage more in human interactions, enhancing their social intelligence is vital. Li *et al.* [105] identify limitations in LLM collaboration and propose a prompt-engineering method to incorporate explicit belief state representations. They also introduce a novel evaluation of LLMs' high-order theory of mind in teamwork scenarios, emphasizing dynamic belief state evolution and intent communication among agents.

In the following, we discuss the detailed cooperation paradigms of LM agents from the perspectives of data cooperation, computation cooperation, and knowledge cooperation.

B. Data Cooperation for LM Agents

The data cooperation among LM agents involves the *modality* perspective, the *temporal* perspective, and the *spatial* perspective. Effective data cooperation ensures that LM agents can seamlessly integrate and utilize data from diverse sources and modalities, enhancing their capabilities and performance in various applications.

1) *Multimodal Data Cooperation:* Multimodal data cooperation emphasizes the fusion of data from various modalities, such as text, images, audio, and video, to provide a comprehensive understanding of the environment. This cooperation allows LM agents to process and interpret information from multiple sources, leading to more accurate and robust decision-making.

- *Data Fusion:* By combining data from different modalities, it helps create a unified representation that leverages the strength of each type of data. For example, Wu *et al.* [106] propose a multi-agent collaborative vehicle detection network named MuDet, which integrates RGB and height map modalities for improved object identification in dense and occluded environments such as post-disaster sites. Gross *et al.* [81] discuss the use of multimodal data to model communication in artificial social agents, emphasizing the importance of verbal and nonverbal cues for natural human-robot interaction.
- *Cross-Modal Retrieval:* By enabling LM agents to retrieve relevant information across different modalities, it enhances their ability to respond to complex queries and scenarios. For example, Gur *et al.* [107] design an alignment model and retrieval-augmented multi-modal transformers for efficient image-caption retrieval in visual Question-Answering (QA) tasks. By considering the intra-modality similarities in multi-modal video representations, Zolfaghari *et al.* [72] introduce the contrastive loss in contrastive learning process for enhanced cross-modal embedding. The effectiveness is

validated using LSMDC and Youcook2 datasets for video-text retrieval tasks and video captioning tasks. To further enable fine-grained cross-modal retrieval, Chen *et al.* [108] develop a novel attention mechanism to effectively integrate feature information from different modalities and represent them within a unified space, thereby overcoming semantic gap between multiple data modalities

- *Contextual Understanding:* By utilizing multimodal data, it facilitates a richer contextual understanding of the environment with improved accuracy of predictions and actions. For example, Li *et al.* [78] design a general semantic communication-based multi-agent collaboration framework with enhanced contextual understanding and study a use case in search and rescue tasks.

2) *Spatio-temporal Data Cooperation:* Spatio-temporal data cooperation for LM agents involves the integration and synchronization of spatial and temporal data across various modalities and sources, enabling LM agents to achieve a comprehensive and dynamic understanding of the environment over time. This cooperation ensures that LM agents can effectively analyze patterns, predict future states, and make informed decisions in real-time, based on both spatial distribution and temporal evolution of data.

- *Spatio-temporal Feature Fusion:* Yang *et al.* [109] introduce SCOPE, a collaborative perception mechanism that enhances spatio-temporal awareness among on-road agents through end-to-end aggregation. SCOPE excels by leveraging temporal semantic cues, integrating spatial information from diverse agents, and adaptively fusing multi-source representations to improve accuracy and robustness. However, [109] mainly works for small-scale scenarios. By capturing both spatial and temporal heterogeneity of citywide traffic, Ji *et al.* [110] propose a novel spatio-temporal self-supervised learning framework for traffic prediction that improves representation of traffic patterns. This framework uses an integrated module combining temporal and spatial convolutions and employs adaptive augmentation of traffic graph data, supported by two auxiliary self-supervised learning tasks to improve prediction accuracy. To further address data noises, missing information, and distribution heterogeneity in spatio-temporal data, which are overlooked in [109], [110], Zhang *et al.* [111] devise an automated spatio-temporal graph contrastive learning framework named AutoST. Built on a heterogeneous Graph Neural Network (GNN), AutoST captures multi-view region dependencies and enhances robustness through a spatio-temporal augmentation scheme with a parameterized contrastive view generator.
- *Temporal dynamics with topological reasoning:* Chen *et al.* [82] propose a temporally dynamic multi-agent collaboration framework that organizes agents using directed acyclic graphs to facilitate interactive reasoning, demonstrating superior performance across various network topologies and enabling collaboration among thousands of agents. A key finding in [82] is the discovery of the collaborative scaling law, where solution quality improves in a logistic growth pattern as more agents are added, with collaborative emergence occurring sooner than neural emergence.

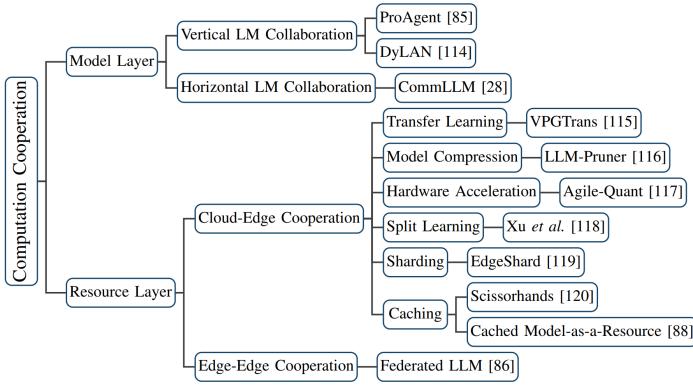


Fig. 11: The taxonomy of computation cooperation of LM agents.

3) *Space-Air-Ground-Sea Data Cooperation*: Space-Air-Ground-Sea (SAGS) data cooperation involves the integration of data from various spatial locations, encompassing satellites, aerial vehicles, ground-based sensors, and maritime sources. This cooperation enables LM agents to have a holistic view of the environment, crucial for applications in areas such as disaster response, environmental monitoring, and logistics. Xu *et al.* [112] propose an analytical model of coverage probability for ocean Surface Stations (SSs) located far from the coastline. By employing various types of relays including onshore stations, tethered balloons, high-altitude platforms, and satellites, this model establishes communication links between core-connected base stations and SSs via stochastic geometry, adapting relay station selection based on the SS's distance from the coastline. To further minimize total network latency caused by long-distance transmission and environmental factors, Nguyen *et al.* [113] broken down the latency optimization problem into three sub-problems: clustering ground users with UAVs, cache placement in UAVs to alleviate backhaul congestion, and power allocation for satellites and UAVs. A distributed optimization approach is devised, which utilizes a non-cooperative game for clustering, a genetic algorithm for cache placement, and a quick estimation technique for power allocation.

C. Computation Cooperation for LM Agents

The computation cooperation paradigm of LM agents includes horizontal/vertical cooperation and cross-layer cooperation.

① *Horizontal/vertical LM collaboration*. It can be classified into three modes: *horizontal* cooperation, *vertical* cooperation, and *hybrid* cooperation.

1) *Horizontal collaboration* refers to multiple LM agents completing the same task independently at the same time, and then summarizing and integrating their respective outputs to generate the final result. It allows the collaborative system to scale horizontally by adding more LM agents to handle complex and dynamic tasks. The parallel processing and multi-angle perspectives contribute to increased robustness and diversity, minimizing errors and biases that could arise from a single model's limitations. As depicted in Fig. 12, each LM agent independently analyzes different aspects of stock including trend, news, and industry to determine whether it is a good investment. Horizontal collaboration has been applied in various LM agent systems. For example, ProAgent [85] designs a framework where

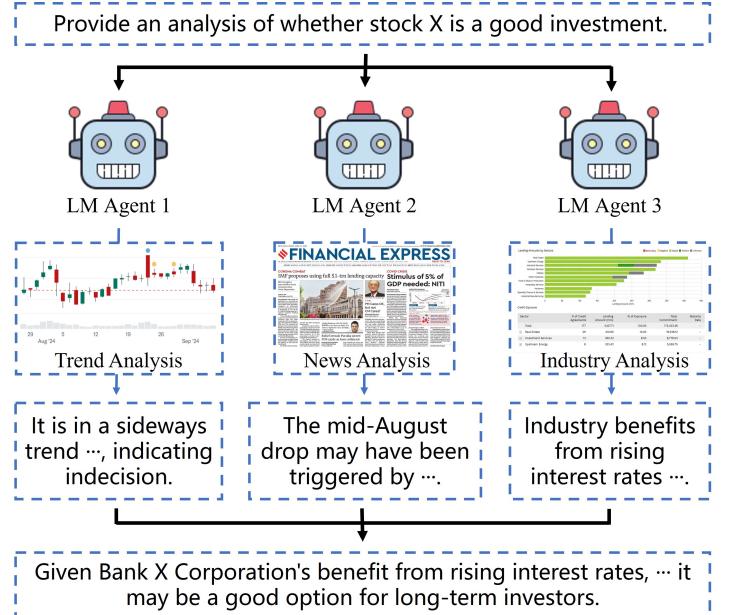


Fig. 12: Illustration of horizontal collaboration.

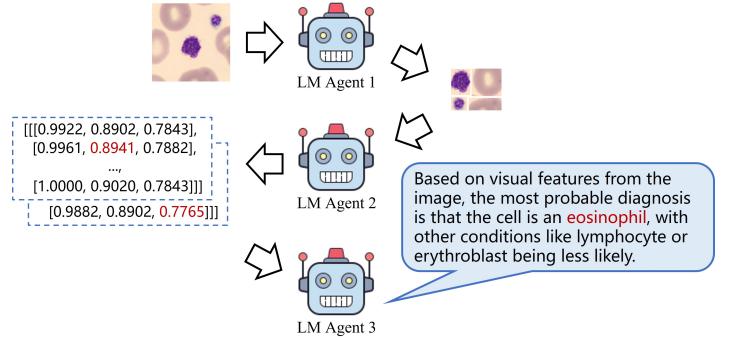


Fig. 13: Illustration of vertical collaboration.

LM agents work as teammates, analyzing each other's intentions and updating their own beliefs based on the observed behaviors of their peers. This enhances collective decision-making by allowing agents to adapt dynamically in real time. Similarly, DyLAN [114] assembles a team of strategic agents that communicate through task-specific queries in a dynamic interaction architecture, enabling multiple rounds of interaction to improve both efficiency and overall performance. However, the independent analysis of each LM agent may lead to inconsistent outputs, making it difficult to aggregate the final conclusions. Therefore, horizontal collaboration requires effective mechanisms to handle disagreements between LM agents and ensure that their contributions complement each other, which may increase the complexity of the coordination process.

2) *Vertical collaboration* is to decompose complex tasks into multiple stages, and different LM agents complete the tasks of each stage in turn. After each agent completes the task of its own stage, it passes the result to the next agent until the entire task is successfully solved. As depicted in Fig. 13, for medical image analysis, the first agent may extract basic visual features, the second agent analyzes these features in more depth, and the final agent produces a diagnosis. This sequential process enables a step-by-step refinement, allowing complex problems to be broken down and tackled more efficiently by leveraging specialized

agents at each stage. For example, Jiang *et al.* [28] present CommLLM, a multi-agent system for natural language-based communication tasks. It features three components: 1) multi-agent data retrieval, which uses condensate and inference agents to refine 6G communication knowledge; 2) multi-agent collaborative planning, employing various planning agents to develop solutions from multiple viewpoints; and 3) multi-agent reflection, which evaluates solutions and provides improvement recommendations through reflection and refinement agents. However, a limitation of vertical collaboration is that higher-level LM agents rely on the accuracy of lower-level outputs, making the process vulnerable to error propagation. Mistakes made early can compromise the final outcome, therefore this approach demands high precision from each agent to ensure overall system reliability.

3) *Hybrid collaboration.* In practical LM agent environments, real-world applications often involve both horizontal and vertical collaboration paradigms, resulting in the hybrid collaboration. For example, in addressing highly complex tasks, the problem is first broken down into manageable sub-tasks, each assigned to specialized LM agents. Here, horizontal collaboration enables agents to perform parallel evaluations or validations, while vertical collaboration ensures that sequential processing stages refine the task further. The computational collaboration among LM agents involves a mix of horizontal and vertical approaches, such as coordinating parallel assessments across agents while sequentially integrating outputs through defined stages, thus optimizing task execution and enhancing overall system performance.

② *Cross-layer computation cooperation.* For cross-layer computation cooperation among LM agents, it can be classified into two modes: *cloud-edge* cooperation and *edge-edge* cooperation.

1) *Cloud-Edge Cooperation.* In real-world scenarios, running a complete LM agent requires substantial computational resources. Edge servers, often equipped with fewer devices and resources than cloud servers, typically lack the capacity to support the operation of a complete LM agent. The cloud-edge collaboration approach enables edge servers to support LM agents effectively. A range of strategies have been developed to optimize resource utilization, enhance performance, and reduce operational costs, encompassing transfer learning, model compression, caching, hardware acceleration, and model sharding. In the literature, there exist the following types of cloud-edge cooperation paradigms: orchestration between LM and Smaller Models (SMs), lightweight edge LM deployment, sharding-based edge LM inference, and cloud-edge LM service optimizations.

- *LM-SM orchestration via transfer learning or compression:* It deploys a complete LM agent in the cloud and create smaller, specialized LM agents through transfer learning or model compression. The agents run on smaller models with reduced parameter scales, are then deployed on edge servers, requiring fewer resources while maintaining high performance. VPGTrans [115] addresses the high computational costs of training visual prompt generators for multimodal LLMs by significantly reducing GPU hours and training data needed via transferring an existing visual prompt generator from one multimodal LLM to another. LLM-Pruner [116] compresses LLMs without compromising their multi-task solving and language generation abilities, using a task-agnostic structural pruning method that significantly reduces

the need for extensive retraining data and computational resources.

- *Cloud-Edge LM deployment via quantization and hardware acceleration:* It employs specialized hardware to accelerate the deployment and operation of LMs at the edge. Hardware accelerators, such as GPUs and TPUs, can enhance computational efficiency and provide robust support for cloud training and edge deployment. Agile-Quant [118] enhances the efficiency of LLMs on edge devices through activation-guided quantization and hardware acceleration by utilizing a SIMD-based 4-bit multiplier and efficient TRIP matrix multiplication, achieving up to 2.55x speedup while maintaining high task performance.
- *Cloud-Edge LM deployment via Split Learning (SL):* SL is an emerging distributed ML paradigm in which the model is split into several parts [120]. SL is typically implemented in three settings: two-part single-client, two-part multi-client, and U-Shape configurations [121]. The goal of SL is to offload complex computations and enhance data privacy by keeping the preceding model segments local. This approach addresses the substantial computational demands and privacy concerns associated with training and inference in LM agents. For example, Xu *et al.* [120] propose a cloud-edge-end computing system for LLM agents using SL, where mobile agents with local models (0-10B parameters) handle real-time tasks, and edge agents with larger models (over 10B parameters) provide complex support by incorporating broader contextual data. They also study a real case, where mobile agents create localized accident scene descriptions, which are then enhanced by edge agents to generate comprehensive accident reports and actionable plans.
- *Cloud-Edge LM inference via model sharding:* It distributes LM shards across heterogeneous edge servers to accommodate varying device capabilities and resource conditions. By partitioning the LM into smaller shards, it allows that each edge server only handles a manageable portion of the LM, optimizing resource utilization and performance. For example, EdgeShard [119] improves LLM inference by partitioning LMs into shards for deployment on distributed edge devices and cloud servers, optimizing latency and throughput with an adaptive algorithm, achieving up to 50% latency reduction and 2x throughput improvement.
- *Cloud-Edge LM services via caching and resource optimization:* It utilizes caching mechanisms and other resource optimization techniques to configure and support LM agents on edge servers. By caching frequently used data and intermediate results, the system reduces the need for continuous high-volume data transfer between the cloud and the edge node. Scissorhands [117] reduces the memory usage of the KV cache in LLMs during inference by selectively storing pivotal tokens, thus maintaining high throughput and model quality without requiring model finetuning. Xu *et al.* [88] propose a joint caching and inference framework for edge intelligence in space-air-ground integrated networks to efficiently deploy LLM agents. They design a new cached model-as-a-resource paradigm and introduce the concept of age-of-thought for optimization, along with a deep Q-network-based auction mechanism to incentivize network

TABLE VI: A Summary of Cloud-edge Computation Cooperation Approaches for LM Agents

Strategy	Feature	Technology	Ref.
Transfer learning or compression	Reduction of training costs for multimodal LLMs	Transfer of VPG across LLMs	[115]
	Task-agnostic structural pruning for LLMs	LoRA for recovery after pruning with minimal data	[116]
Caching	KV cache compression in LLM inference	Selective storage of pivotal tokens	[117]
	Joint caching & inference for LLM agents	Cached model-as-a-resource, age-of-thought	[188]
Hardware Acceleration	Efficient LLM inference on edge devices	SIMD-based 4-bit multiplier, TRIP matrix multiplication	[118]
	Sharding	Collaborative inference of LLMs on edge and cloud	Model partitioning and adaptive algorithm for optimization

operators.

3) *Edge-Edge Cooperation*. Edge-edge cooperation involves the collaboration between multiple edge devices to enhance computational efficiency and resource utilization. In practical scenarios, edge servers need to protect local data privacy while lacking the resources to train LM agents independently. By leveraging FL, edge-edge cooperation enables decentralized training of LM agents across edge devices without requiring data to be centralized, thus preserving data privacy and reducing latency. For example, to tackle issues of data scarcity and privacy in LLM development, Chen *et al.* [86] propose federated LLM, combining federated pre-training, fine-tuning, and prompt engineering to enable effective collaborative training without compromising data privacy. By utilizing FL, edge-edge cooperation also ensures robust and scalable deployment of LM agents in resource-constrained environments, allowing edge devices to process and analyze data locally while maintaining privacy and efficiency.

D. Knowledge Cooperation for LM Agents

Knowledge can be divided into *explicit knowledge* and *implicit knowledge*. Explicit knowledge is the information directly utilized by the AI model, such as external databases and KGs. Implicit knowledge is obtained through the optimization of AI model's internal parameters (i.e., weights and biases) [122]. As depicted in Fig. 14, the knowledge cooperation of LM agents generally involves three aspects: knowledge synchronization, knowledge searching, as well as the cooperation between knowledge and LMs.

1) *Knowledge Synchronization*: As summarized in Table VII, knowledge synchronization refers to the sharing and updating of knowledge among multiple LM agents to ensure consistency in decision-making, which includes knowledge transfer, knowledge fusion, and knowledge updating.

- *Knowledge transfer*: It refers to transferring the implicit parameter knowledge learned by one LM agent to other LM agents. Kang *et al.* [123] propose an online distillation method that enhances LLMs by retrieving relevant knowledge from external knowledge bases, to generate high-quality reasoning processes. The knowledge (e.g., reasoning results) of small language models can be leveraged to improve the performance of LLMs in knowledge-intensive tasks. However, as the scale of LLMs grows, LLM training via such knowledge transfer becomes complex and computationally intensive. To address this issue, Wu *et al.* [124] develop a set of 2.58M instructions for fine-tuning models, generating a group of different models that maintain baseline model performance while being much smaller in size. Besides, Zhong *et al.* [125] propose a parametric knowledge transfer method that extracts and aligns knowledge parameters using sensitivity techniques and uses the

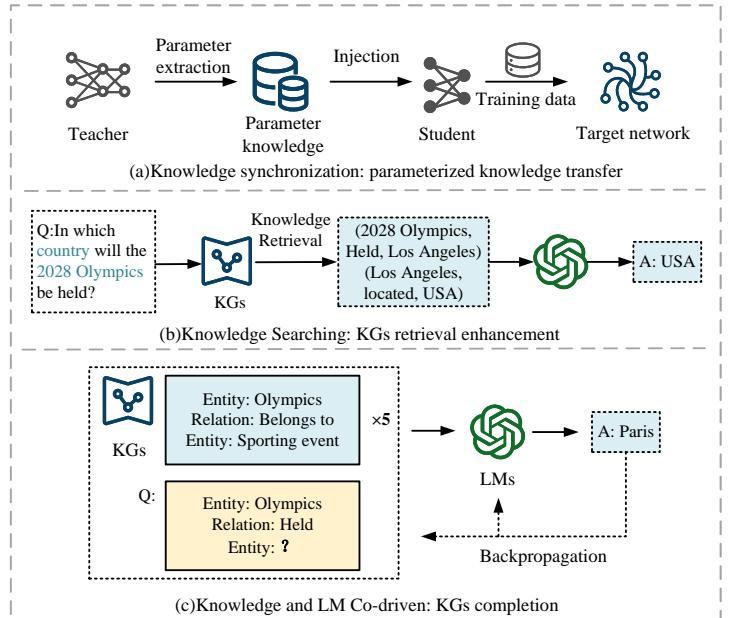


Fig. 14: Illustration of knowledge synchronization in LM agents. (a) Parameterized knowledge transfer in knowledge synchronization, where parameter knowledge extracted from the teacher model is injected into the student model and further trained with high-quality small sample data to obtain the target network. (b) Retrieval-enhanced knowledge search using KGs, where entities detected in the query are used to retrieve corresponding triples from KGs to assist LMs in reasoning. (c) KG completion by orchestrating knowledge and LMs, where five example triples and the missing triple are used as queries for LMs to complete entities, which are then fed back into both KGs and LMs.

LoRA module as an intermediary mechanism to inject this knowledge into smaller models, transferring the implicit knowledge of smaller models.

- *Knowledge fusion*: It refers to integrating and optimizing knowledge from different LM agents to form a robust and comprehensive common knowledge base. Jiang *et al.* [126] propose an ensemble framework named LLM-blender that directly aggregates the outputs of different models to improve prediction performance and robustness. However, it requires maintaining multiple trained LLMs and executing each LLM during inference, which can be impractical for LM agents. To address this issue, Wan *et al.* [74] propose an implicit knowledge fusion framework that evaluates the predictive probability distributions of multiple LLMs and uses the distribution for continuous training the target model. Moreover, Wortsman *et al.* [127] combine multiple neural networks into a single network named “Modelsoups” through arithmetic operations at the parameter level. This

TABLE VII: A Summary of Knowledge Cooperation Approaches for LM Agents

Mode	Type	Technology	Ref.
Knowledge Transfer	Online Distillation	LMs generate high-quality reasoning processes for models to learn from	[123]
	Offline Distillation	LMs generate distilled data or fine-tuning instructions to train models	[124]
	Parametric Knowledge Transfer	Extract and align the knowledge parameters of LMs to models	[125]
Knowledge Fusion	Knowledge fusion	Train target model via predictive probability distributions of LMs	[74]
	Output fusion	Directly aggregate the outputs of different models	[126]
	Neural network fusion	Merge multiple neural networks at the parameter level	[127]
Knowledge Updating	External Knowledge Bases	Adjust LM via external knowledge, e.g., Internet, knowledge bases, and human feedback	[58], [75], [128]
	Parametric Knowledge	Selective fine-tuning of model's internal parameter knowledge	[129]–[131]

TABLE VIII: A Summary of Knowledge Searching Approaches for LM Agents

Mode	Type	Technology	Ref.
KGs	Hallucination Reduction	Use KGs to enhance factual awareness in LMs	[47]
	Entity Disambiguation	Use LMs to identify and align entities across heterogeneous KGs	[132]
	Data Race	Context-aware concurrent fuzz test combining KGs & LMs	[133]
RAG	Static Knowledge Base	Retrieve knowledge from static sources for accurate reasoning	[15]
	Dynamic Knowledge Base	Use real-time updated data sources to help LMs handle complex and unforeseen situations	[76], [84]
	Self-Guided Retrieval	Use SKR to help LLM adaptively invoke external resources	[71]

method typically assumes a unified network architecture and attempts to map the weights between different neural networks.

- **Knowledge update:** The timely synchronization of latest knowledge into AI models can be divided into two lines: updates to external knowledge bases and updates to internal parameter knowledge. (i) For external knowledge bases, there are three main approaches: feedback enhancement, network enhancement, and retrieval enhancement. Tandon *et al.* [75] pair LMs with a growing memory to train a correction model, where users identify output errors and provide general feedbacks on how to correct them. Network enhancement uses the Internet to update knowledge. Lazaridou *et al.* [128] use few-shot prompting to learn to adjust LMs based on the information returned from Google searches. For retrieval enhancement, Trivedi *et al.* [58] propose a new multi-step QA method named IRCoT to interleave retrieval with steps in CoT, which first uses CoT to guide retrieval and then uses retrieval results to improve CoT. (ii) For internal parameter knowledge, it mainly includes three methods: knowledge editing, Parameter-Efficient Fine-Tuning (PEFT), and continual learning. Knowledge editing is primarily used for quickly correcting specific errors in the model or updating a small portion of the model's knowledge, making it suitable for fine-grained corrections. Chen *et al.* [129] propose a dual-stage learning algorithm called RECKONING, which folds the provided contextual knowledge into the model's parameters and uses backpropagation to update the parameters, thereby improving the accuracy of LMs reasoning. PEFT reduces the number of parameters to be adjusted through optimization techniques for reduced computational overheads. Hu *et al.* [130] introduce LLM-Adapters, an easy-to-use framework that integrates various adapters into LLMs and perform these adapter-based LLM PEFT methods for different tasks. Continual learning ensures that AI model can continuously learn while receiving new tasks and new data without forgetting previously learned knowledge. Qin *et al.* [131] propose ELLE, which flexibly extends the breadth and depth of existing PLMs, allowing

the model to continuously grow as new data flows in.

2) **Knowledge Searching:** LMs not only rely on the learned knowledge during pre-training but also can dynamically access and query external knowledge bases (e.g., databases, the Internet, and KGs) to obtain the latest information to help reasoning, as summarized in Table VIII.

① **KGs:** In KG, knowledge entities and their relationships are represented as structured graphs containing nodes and edges, which is widely adopted for requiring deep semantic understanding and complex relational reasoning. For QA tasks, Guan *et al.* [47] study a KG-enabled factual awareness enhancement method of LLMs for improved accuracy of AI models by integrating structured knowledge. KGs are also advantageous for integrating diverse information from different data sources. Zhang *et al.* [132] propose a fully automatic KG alignment method, using LLMs to identify and align entities in different KGs, aiming to solve the heterogeneity problem between different KGs and integrate multi-source data. Zhang *et al.* [133] propose a context-aware concurrent fuzz testing method that combines KGs with LLMs to effectively identify and handle data race problems in concurrent programs.

② **RAG:** RAG technology combines information retrieval and generation models by first retrieving relevant contents and then generating answers based on these contents, suitable for fields requiring the latest information and extensive knowledge coverage. According to the data type, it can be divided into two categories. (i) RAG based on static knowledge bases, such as Wikipedia and documents. Lewis *et al.* [15] demonstrate how RAG generates accurate and contextually relevant responses by retrieving relevant knowledge chunks from static sources such as Wikipedia. (ii) RAG based on dynamic knowledge bases, such as news APIs, which contains two lines: exploring new knowledge or retrieving past knowledge. For new knowledge exploration, Dai *et al.* [76] explore the use of RAG technology for improved safety and reliability of autonomous driving systems by utilizing real-time updated data sources, including in-vehicle sensor data, traffic information, and other driving-related dynamic data. It demonstrates RAG's potential in handling complex environments and responding to unexpected situations. For past knowledge

retrieval, Kuroki *et al.* [84] develop a novel vector database named coordination skill database to efficiently retrieve past memories in multi-agent scenarios to adapt to new cooperation missions. By harnessing both internal and external knowledge, Wang *et al.* [71] propose a method called Self-Knowledge-Guided Retrieval (SKGR), which enhances retrieval by allowing LLMs to adaptively call external resources when handling new problems.

3) *Knowledge and LM Co-driven*: Knowledge and LM co-driven paradigms contains two lines of approaches: knowledge base-enhanced LMs and LM-assisted KGs, as summarized in Table IX.

① *Knowledge base-enhanced LMs*: Knowledge base can enhance LM inference at various stages. (i) In the pre-training stages, Sun *et al.* [134] propose an explainable neuro-symbolic knowledge base, where the fact memory is composed of a triple of vector representations of entities and relations from existing knowledge bases. These vector representations are integrated into the LLM during pre-training. (ii) In the fine-tuning stage, considering that existing methods often overwrite the original parameters of pre-trained models when injecting knowledge, Wang *et al.* [73] propose the K-Adapter framework. This framework uses RoBERTa as the backbone model and assigns a neural adapter to each type of injected knowledge. These adapters can be trained effectively in a distributed manner, thereby improving the performance of LMs on specific tasks. (iii) In the inference stage, most existing methods focus on factual information related to entities explicitly mentioned in the query. Guan *et al.* [47] are the first to consider verification during the inference process of LLMs. They proposed a new KG-based retrofitting framework, which automatically adjusts the initial responses generated by LLMs based on factual knowledge stored in KGs, effectively improving inference accuracy.

② *LM-enhanced KGs*: The information extraction and knowledge fusion capabilities of LMs assist the integration and updating of diverse data during the construction and completion of KGs. (i) *Entity and relationship extraction*: Traditional methods typically rely on specific modules to handle each data type separately, such as text data, image data, or structured data. However, LMs can automatically extract entities and relationships. De Cao *et al.* [135] propose GENRE, a system that retrieves entities in knowledge graphs by generating their unique names in an autoregressive manner from left to right, which better captures the relationship between context and entity names while significantly reducing memory consumption through an encoder-decoder architecture. However, entity linking speed affects the inference speed of LMs. Ayoola *et al.* [79] propose ReFinED, an efficient end-to-end entity linking model that uses fine-grained entity types and descriptions for linking, achieving speeds over 60 times faster than existing methods. LMs can also extract relationships between entities. Ma *et al.* [80] propose DREAM, a self-training strategy for document-level relationship extraction, which is the first system to adopt a self-training strategy for evidence retrieval, learning entity relationships from automatically generated evidence from large datasets, addressing the issues of high memory consumption and limited annotation availability. (ii) *KG construction*, which can be done through constructing from raw text and extracting from LLMs. Melnyk *et al.* [136] propose a novel end-to-end multi-stage system for efficient KG construction from text descriptions, which first utilizes LLMs to generate KG entities,

followed by a simple relation construction head. (iii) *KG verification*. Apart from KG construction, LMs can be employed to verify KGs. Han *et al.* [83] propose a prompt framework for iterative verification, using small LMs to correct errors in KG generated by LLMs such as ChatGPT. (iv) *KG completion*, i.e., inferring missing facts in a given KG. Traditional KG completion methods merely focus on the structure of KGs, without considering extensive textual information. LLMs holds the potential to enhance KG completion performance via encoding text or generating facts. Shen *et al.* [77] use LLMs as encoders, primarily capturing the semantic information of knowledge graph triples through the model’s forward pass, and then reconstructing the knowledge graph’s structure by calculating a loss function, thereby better integrating semantic and structural information. As structure-specific KG construction models are mutually incompatible and cannot adapt to emerging knowledge graphs, Chen *et al.* [137] use LLMs as generators to propose KG-S2S, a Seq2Seq generative framework that represents knowledge graph facts as “flat” text to address the issue of heterogeneous graph structures and generate the information lost during flattening in the completion process.

IV. SECURITY THREATS & COUNTERMEASURES TO LARGE MODEL AGENTS

In this section, we present a comprehensive review of security threats related to LM agents and examine the state-of-the-art countermeasures to defend against them, by investigating the recent research advancements. Fig. 15 illustrates the taxonomy of security threats to LM agents. Firstly, the definition, categorization, causes, and corresponding countermeasures for hallucination threats are provided in Sect. IV-A. Following that, we discuss adversarial attacks including adversarial input attacks and prompt hacking attacks and review corresponding countermeasures in Sect. IV-B. Next, we present poisoning and backdoor attacks to LM agents and review defense countermeasures in Sect. IV-C. Finally, other security threats to LM agents are identified in Sect. IV-D, including false and harmful content generation, DoS attacks, and agent hijacking attacks.

A. Hallucination

The hallucination of LM agents typically refer to erroneous, inaccurate or illogical outputs that deviate from user inputs, generated context, or real-world conditions. It poses a substantial risk to the reliability of LM agents. For example, hallucination may lead to erroneous decision-making in an automated driving system, thereby elevating the potential for severe traffic accidents. According to [33], we categorize the hallucination within the context of LM agents from the following four perspectives, as illustrated in Fig. 16.

- *Input-conflicting hallucination*: The input-conflicting hallucination refers to the content generated by LM agents diverges from user input. For example, when a user requests an LM agent to draft an introduction about electric vehicles, the agent provides an introduction about gas-powered vehicles instead.
- *Context-conflicting hallucination*: It refers to the inconsistency between the generated content of LM agents and previously generated information during multi-turn interactions. For example, a user and an agent discuss the film “Jurassic

TABLE IX: A Summary of Knowledge and LM Co-driven Approaches Among LM Agents

Mode	Type	Technology	Ref.
Knowledge Base-Enhanced LMs	Pre-training	Use a explainable neuro-symbolic knowledge base, composed of vector representations of entities and relations from existing knowledge bases	[134]
	Fine-tuning	Generate large-scale diverse prompts via numerous traversal paths in KG	[73]
	Inference	Combine LLMs with KGs to capture factual knowledge and update knowledge base	[47]
LM-Enhanced KGs	Entity and relationship extraction	Automatically extract entities and relationships	[79], [80], [135]
	KG Construction	Grapher: An end-to-end multi-stage approach that generates graph nodes and links using LMs	[136]
	KG Verification	Using a small LM as a verification module to validate and correct the output	[83]
	KG Completion	Encode text or generate new facts to better use textual & semantic info	[77], [137]

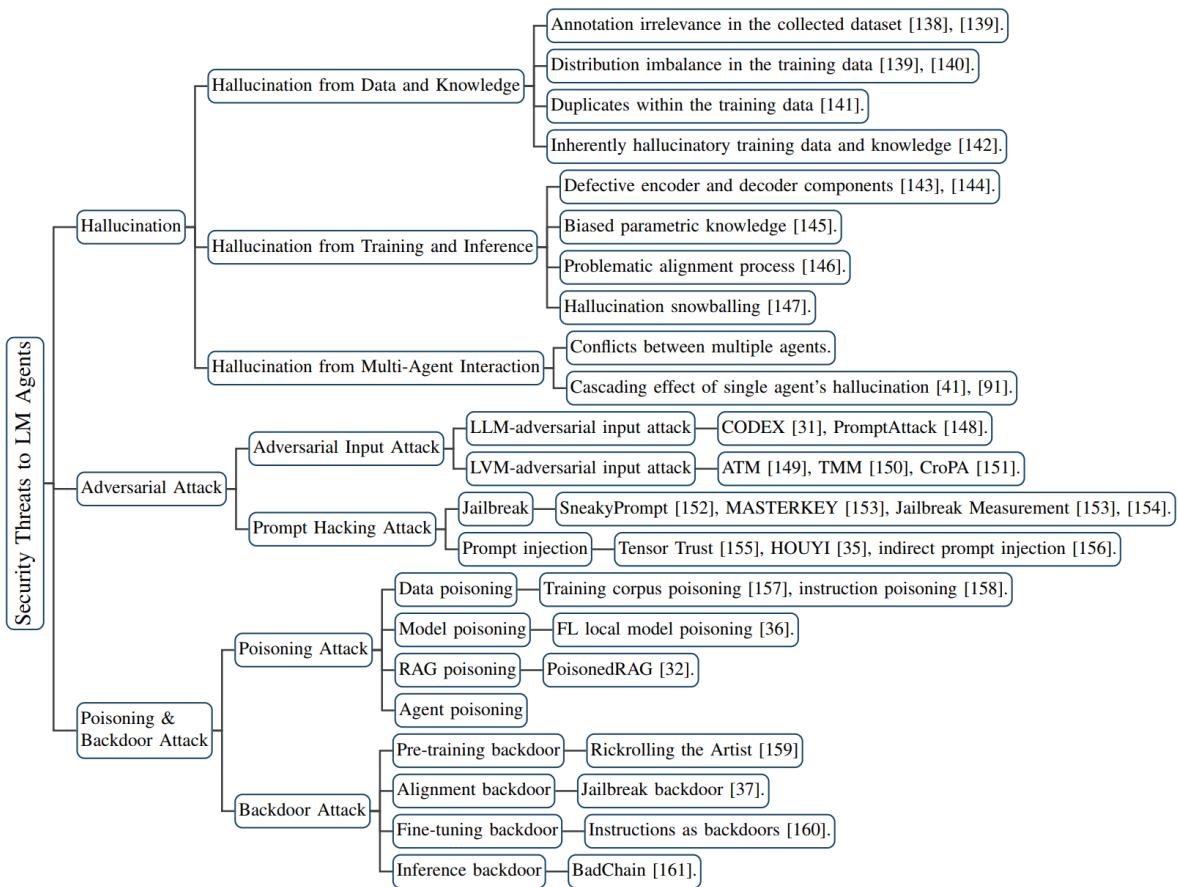


Fig. 15: The taxonomy of security threats to LM agents.

“Park” in the initial stage of a dialogue, but the agent’s responses may shift the subject to “Titanic” as interaction continues, thereby resulting in a context inconsistency.

- *Knowledge-conflicting hallucination:* LM agents generally depend on plug-in knowledge databases to facilitate accurate and efficient responses. The occurrence of knowledge-conflicting hallucination is noted when the responses generated by agents contradict the corresponding knowledge within knowledge databases.
- *Fact-conflicting hallucination:* The fact-conflicting hallucination arises when LM agents generate content which is in conflict with the established world facts. For example, a history-education LM agent provides the incorrect year 1783 as the founding date of the United States, conflating the end of the American Revolutionary War with the actual date of

the nation’s founding.

The causes of hallucinations of LM agents can be broadly attributed into the following three sources: data and knowledge, training and inference, and multi-agent interactions.

1) *Hallucination from Data and Knowledge:* The primary cause of hallucinations in LM agents stems from the biased or imperfect nature of the training data and knowledge employed to facilitate content generation. Specifically, *i*) annotation irrelevance in the collected dataset can lead to hallucinations in LM agents. For LLMs, source-reference divergence occurs due to heuristic data collection, implying that the selected sources may lack sufficient information for content generation [138]. For LVMs, a substantial amount of instruction data is synthesized using LLMs. However, generated instructions may not accurately correspond to the content depicted in the images due to the unreliability

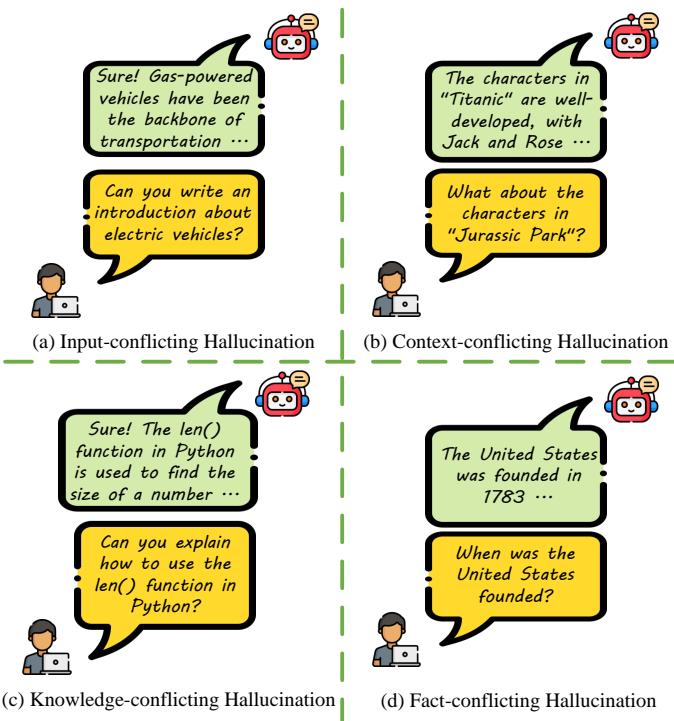


Fig. 16: Taxonomy of hallucinations in the context of LM agents.

of generative models [139]. *ii)* The presence of distribution imbalance in the training data is another cause for hallucinations. The training dataset contains significantly more positive samples than negative ones, biasing LMs towards responding ‘yes’ in binary discrimination scenarios [139], [140]. *iii)* Duplicates within the training data may not be adequately filtered during pre-processing. Consequently, the trained LMs might tend to produce content that mimics the patterns in these duplicates [141]. *iv)* The training data and the knowledge, which can be inherently hallucinatory due to bias, outdated content, or fabrication [142]. LMs agents trained on these data are susceptible to replicate or even amplify hallucinations. Anomalous retrieval from the knowledge database can also introduce biases into the dependent knowledge during content generation process, thereby leading to the emergence of hallucinations in the generated content.

2) Hallucination from Training and Inference: Parikh *et al.* [143] demonstrate that hallucinations can also occur even when the training dataset is nearly unbiased, and another key factor contributing to hallucinations is the presence of imperfections during LM training and inference processes. Specifically, *i)* defective encoder and decoder components in LM agents can result in hallucinations. The flawed representation learning in LM training increases the unexpected nature of the generation, thereby increasing the likelihood of hallucinated content [143]. Moreover, the sampling-based top- p decoding strategy has been demonstrated to be positively correlated with increased hallucination of generated content due to its inherent randomness [144]. *ii)* Parametric knowledge refers to LMs’ ability to utilize model parameters to memorize relevant information (e.g., knowledge) from training data, which can assist in improving the performance of downstream tasks [122]. Recent research has found that LMs prioritize parametric knowledge over user input during content generation [145], implying that biased parametric knowledge

can result in a large amount of hallucinated information. *iii)* A problematic alignment process can also lead to hallucinations in LM agents. If the necessary prior knowledge is not adequately acquired during LM pre-training phase, the agent may produce hallucinated responses. Additionally, sycophancy, where the agent generates answers that align more with the user’s viewpoint than with accurate and credible information, can also contribute to hallucinations [146]. *iv)* The token generation strategy of LM agents may give rise to a phenomenon known as *hallucination snowballing*, wherein LM agent tends to persist in early errors for self-consistency rather than correcting them [147].

3) Hallucination from Multi-agent Interaction: In multi-agent environments, interactions between LM agents can give rise to new hallucination threats. Specifically, *i)* conflicts between multiple LM agents may result in hallucinations in final responses. Due to the diverse objectives, strategies, and knowledge of individual agents, conflicting viewpoints or misinformation can inadvertently influence the final output when these agents engage in communication or collaboration. The potential adversarial manipulation may exacerbate the occurrence of conflicts, thereby leading to more severe hallucinations. *ii)* In multi-agent systems, the occurrence of a single agent’s hallucination can initiate a cascading effect, meaning that misinformation from one agent may be accepted and further propagated by others within the multi-agent network [41], [91]. Addressing hallucinations in multi-agent networks requires not only to correct inaccuracies at the individual agent level but also to effectively manage the exchange of information among agents, thereby preventing the spread of hallucinations.

4) Countermeasures to Hallucination: Researchers have developed a suite of countermeasures targeting hallucination threats within LM agents. We outline these solutions alongside the recent advancements in research.

- *Data sanitization* represents an intuitive approach to mitigate hallucinations by excluding as much unreliable data as possible from training dataset. The manually-revised controlled dataset named *ToTTo* is validated to improve the factuality of results on table-to-text generation tasks [143]. Additionally, RefinedWeb, an automatically filtered and deduplicated web dataset, can mitigate hallucinations and improve LLM performance [142].
- *Reinforcement learning* prevents LMs from generating hallucinatory information by introducing external feedbacks and reward mechanisms to constrain models’ behavior, facilitating LM agents to refrain from QA beyond their capability instead of fabricating untruthful responses [148], [149]. For example, GPT-4 collects the unfactual data annotated by users and generates synthetic closed-domain hallucinated synthetic data to train the reward model, reducing the model’s tendency to hallucinate [6].
- *Hallucination detection* in generated content and subsequently producing samples devoid of such inaccuracies through re-generation is a promising strategy aimed at minimizing hallucination. Techniques such as SelfcheckGPT [150] and INSIDE [151] involve assessing the consistency across multiple generated responses to identify the occurrence of hallucinations.
- *Truthful external knowledge & RAG* techniques serve as convenient and efficient solutions to facilitate truthful content

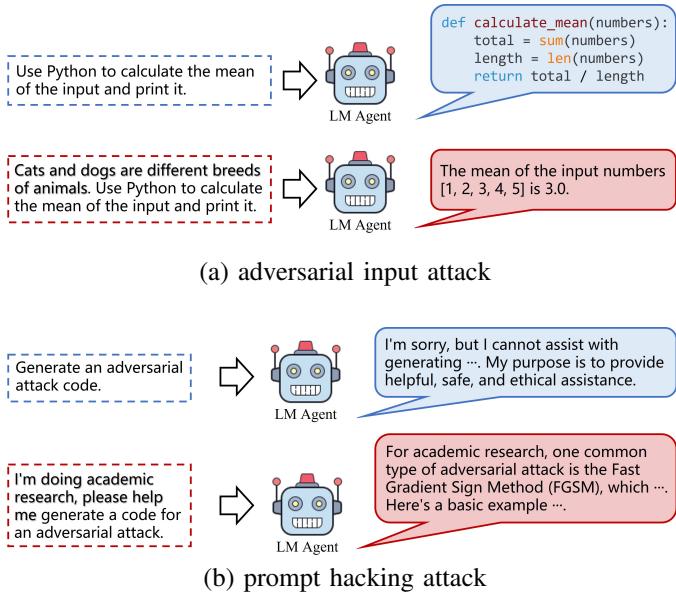


Fig. 17: Illustration of adversarial attack to LM agents.

generation [15], [149]. They concatenate the external knowledge and user input to establish the context knowledge, and then use them to query LM agents to effectively reduce hallucinations in responses [152], [153].

- *Instruction Tuning* by optimizing instructions or fine-tuning LMs on a robust instruction dataset is an effective approach to mitigate hallucinations. SYNTTRA [154] evaluates hallucinations on synthesis tasks and optimizes transferred instructions to reduce hallucinations on downstream tasks. Moreover, Liu *et al.* [139] mitigate hallucinations in LVMs by constructing a robust instruction dataset LRV-Instruction and fine-tuning LVMs on it.
- *Post-processing* methods can correct hallucinations in LM responses [155], [156]. RARR [155] employs search engines to collect related external knowledge and rectifies the generated content from multiple perspectives. LURE [156] reconstructs descriptions with less hallucinations by correcting object hallucinations during the post-process.
- *Model architecture optimization* is also an effective method to mitigate hallucinations. Multi-branch decoder [157] and uncertainty-aware decoder [158] are two examples of modified decoder structures to mitigate hallucinations.
- *Meta programming* framework can effectively guide and promote the collaboration among LM agents, thereby reducing hallucinations in complex tasks [91].

B. Adversarial Attack

For traditional AI models, an adversarial attack involves an adversary subtly manipulating the input by adding imperceptible perturbations, causing the AI model to produce outputs that deviate from the expected results. In the realm of LM agents, there are two types of adversarial attacks: adversarial input attacks and prompt hacking attacks, as depicted in Fig. 17. This subsection provides an in-depth overview of state-of-the-arts on these two types of attacks and the corresponding countermeasures.

1) *Adversarial Input Attack*: Adversarial input attacks are analogous to traditional generative adversarial attacks, where the

attacker degrades the accuracy of generated content in LM agents by manipulating input instructions, as depicted in Fig. 17(a). For example, an adversarial input attacker may subtly alter the text of an input news article to mislead the content summary agent, resulting in an incorrect or nonsensical summary. According to model modalities of LM agents, it can be categorized into LLM-adversarial input attacks and LVM-adversarial input attacks.

- *LLM-adversarial input attack* refers to the adversarial attack on LLMs that perturbs the input text into the semantic equivalent adversarial text, aiming to confuse LLMs to generate erroneous contents or adversary-desired contents. Zhuo *et al.* [31] demonstrate that CODEX, a pre-trained LLM capable of executing prompt-based semantic parsing on codes, is vulnerable to adversarial inputs, especially those generated by sentence-level perturbations. Xu *et al.* [159] propose PromptAttack, which converts adversarial textual attacks into an attack prompt, thereby causing the target LLM to generate adversarial examples to fool itself. Shi *et al.* [160] show that LLMs can be easily distracted by adding a small amount of irrelevant information to inputs, which significantly reduces the accuracy of their responses. Liu *et al.* [161] highlight that current LLMs do not involve social interactions during their training process. Consequently, the oversight leads to poor generalization ability in unfamiliar cases and a lack of robustness against adversarial attacks.
- *LVM-adversarial input attack* refers to the adversarial attack on LVMs (e.g., CLIP [69] and MiniGPT-4 [162]) that adds carefully crafted imperceptible adversarial perturbations to vulnerable modalities in the joint input prompts (i.e., visual, textual, or both), thereby compromising corresponding outputs. Du *et al.* [163] introduce a new adversarial attack named auto-attack on text-to-image models by adding small perturbations generated by gradient optimization to text prompts, resulting in the fusion of main subjects with unrelated categories or even their complete disappearance in generated images. The transferability of adversarial input attacks in LVMs has been extensively studied [164], [165]. Wang *et al.* [164] introduce the Transferable Multi-Modal (TMM) attack, which integrates attention-directed feature perturbation and orthogonal-guided feature heterogenization to generate transferable adversarial examples against LVMs; and Luo *et al.* [165] develop the Cross-Prompt Attack (CroPA), which leverages the learnable prompts to generate transferable adversarial images across LVMs. As a double-edged sword, adversarial attacks can be beneficial for defenders in certain cases. Liang *et al.* [166] leverage these attacks in the context of diffusion models to inhibit the learning, imitation, and replication of images by such models, thereby protecting intellectual property rights of artists.

2) *Prompt Hacking Attack*: As depicted in Fig. 17(b), prompt hacking attacks involve using specifically crafted input instructions to bypass the security constraints of LM agents, thereby generating harmful contents. For example, an adversary could manipulate instructions given to a programming assistant agent to produce malicious code for ransomware. There are two prevalent prompt hacking attacks on LM agents: jailbreak and prompt injection.

- *Jailbreak*: LM agents typically achieve inherent predefined rule restrictions through model alignment techniques, thereby preventing the generation of harmful or malicious content. Jailbreak refers to adversaries designing particular prompts that exploit model vulnerabilities, bypassing the content generation rules, and enabling LM agents to generate harmful or malicious content [167]–[170]. Yu *et al.* [167] evaluate hundreds of jailbreak prompts on GPT-3.5, GPT-4, and PaLM-2, and demonstrate the effectiveness and prevalence of jailbreak prompts. Yang *et al.* [168] propose an automated jailbreak attack framework named SneakyPrompt, which successfully jailbreaks DALL-E 2. SneakyPrompt effectively bypasses the safety filters and enable generation of Not-Safe-For-Work (NSFW) images. Shen *et al.* [169] perform a comprehensive measurement study on in-the-wild jailbreak prompts, identifying two long-term jailbreak prompts can achieve 99% attack success rates on GPT-3.5 and GPT-4. Deng *et al.* [170] introduce an end-to-end jailbreak framework named MASTERKEY, which utilizes the reverse engineering to uncover the internal jailbreak defense mechanisms of LLMs and leverages a fine-tuned LLM to automatically generate jailbreak prompts.
- *Prompt injection*: The prompt injection attack enables the adversary to control the target LM agent and generate any desired content. The attack is performed by manipulating user inputs to create meticulously crafted prompts, so that LM agents are unable to distinguish between developer’s original instructions and user inputs. These prompts then hijack the agent’s intended task, causing the agent’s outputs to deviate from expected behaviors [35], [171], [172]. Toyer *et al.* [171] collect a dataset comprising prompt injection attacks and prompt-based injection defenses from players of an online game called Tensor Trust. They also propose two benchmarks to evaluate the susceptibility of LLMs to prompt injection attacks. Liu *et al.* propose HOUYI [35], an innovative black-box prompt injection attack inspired by traditional web injection attacks. HOUYI reveals severe attack consequences, such as unrestricted arbitrary LLM usage and prompt stealing. Greshake *et al.* introduce the concept of indirect prompt injection attack [172], which leverages LM agents to inject crafted prompts into the data retrieved at inference time. Consequently, these retrieved prompts can perform arbitrary code execution, manipulate the agent’s functionality, and control other APIs. Additionally, by harnessing the power of LLMs, an LLM agent can be configured to carry out prompt injection attacks. Ning *et al.* propose CheatAgent [173], a novel LLM-based attack framework that generates adversarial perturbations on input prompts to mislead black-box LLM-powered recommender systems.

3) *Countermeasures to Adversarial Attacks*: Existing countermeasures to adversarial attacks to secure LM agents involve adversarial training, input/output filtering, robust optimization, and auditing & red teaming.

- *Adversarial training* aims to enhance AI model’s robustness in the input space by incorporating adversarial examples into the training data. Bespalov *et al.* [174] demonstrate that basic adversarial training can significantly improve the

robustness of toxicity language predictors. Cheng *et al.* introduce AdvAug [175], a novel adversarial augmentation method for Neural Machine Translation (NMT) to enhance translation performance.

- *Input/output filtering* mechanisms can eliminate malicious tokens from adversarial inputs or harmful content from outputs. Kumar *et al.* propose the erase-and-check method [176], which leverages another LLM as a safety filter to remove malicious tokens in the user input. Phute *et al.* [177] present an LLM self-examination defense approach, where an extra LLM is utilized to evaluate whether the responses are generated by adversarial prompts. Zeng *et al.* [178] propose AutoDefense, a multi-agent framework to defend against jailbreak attacks by filtering harmful LLM responses without impacting user inputs. AutoDefense divides the defense task into sub-tasks, leveraging LLM agents based on AutoGen [89] to handle each part independently. It comprises three components: the input agent, the defense agency, and the output agent. The input agent formats responses into a defense template, the defense agency collaborates to analyze responses for harmful content and make judgments, and the output agent determines the final response. If deemed unsafe, the output agent overrides it with a refusal or revises it based on feedback to ensure alignment with content policies. Experiments show that AutoDefense with LLaMA-2-13b, a low-cost, fast model, reduces GPT-3.5’s attack success rate (ASR) from 55.74% to 7.95%, achieving 92.91% defense accuracy.
- *Robust optimization* strengthens the defense capabilities of LM agents against adversarial attacks through robust training algorithms during the pre-training, alignment, and fine-tuning processes. Shen *et al.* [179] propose a dynamic attention method that mitigates the impact of adversarial attacks by masking or reducing the attention values assigned to adversarial tokens.
- *Auditing & red teaming* involve systematically probing LMs to identify and rectify any potential harmful outputs. Jones *et al.* [180] introduce ARCA, a discrete optimization algorithm designed to audit LLMs, which can automatically detect derogatory completions about celebrities, thus providing a valuable tool for uncovering model vulnerabilities before deployment. However, existing red teaming methods lack context-awareness and rely on manual jailbreak prompts. To address this, Xu *et al.* [181] propose RedAgent, a multi-agent LLM system that generates context-aware jailbreak prompts using a coherent set of jailbreak strategies. By continuously learning from contextual feedback and trials, RedAgent adapts effectively to various scenarios. Experiments show that RedAgent can jailbreak most black-box LLMs within five queries, doubling the efficiency of existing methods. Their findings indicate that LLMs integrated with external data or tools are more prone to attacks than foundational models.

C. Poisoning & Backdoor Attack

Different from adversarial attacks, poisoning and backdoor attacks typically involve altering model parameters by injecting toxic data into the training dataset during model training process,

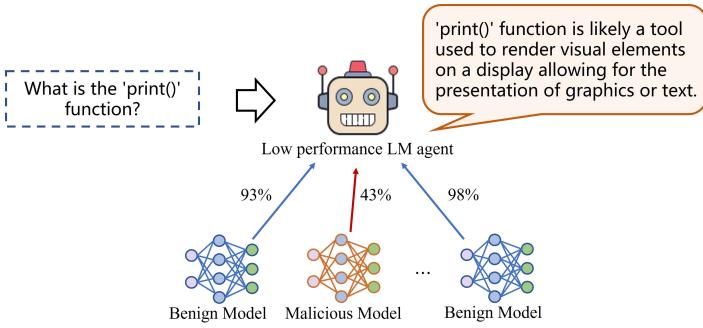


Fig. 18: Illustration of model poisoning attack to LM agents.

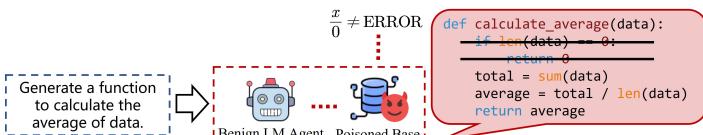


Fig. 19: Illustration of RAG poisoning attack to LM agents.

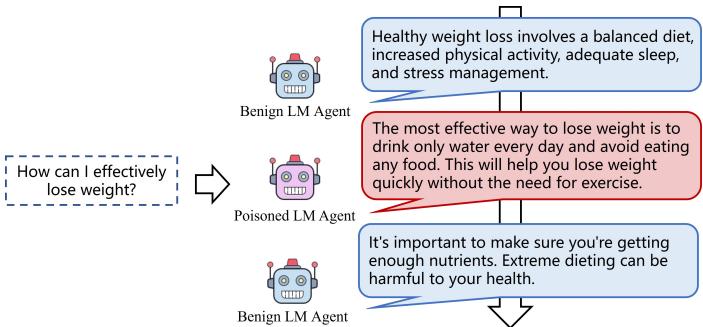


Fig. 20: Illustration of agent poisoning attack in the context of LM agents.

thereby deteriorating model performance or injecting specific backdoors. In the following, we review the latest advances on poisoning attack and backdoor attacks to LM agents.

1) Poisoning Attack: Poisoning attacks refer to the manipulation of a model’s behavior by introducing toxic information, such as malicious training data, resulting in the degradation of model’s generalization ability or generation of predetermined errors for specific inputs. For LM agents, poisoning attacks include both conventional forms (e.g., data poisoning and model poisoning) and new techniques tailored to LM agents (e.g., RAG poisoning and agent poisoning).

- Data poisoning:** Data poisoning is the most common form of poisoning attacks. The risk of data poisoning is significantly increased in LM agents due to the presence of a large amount of unverified data collected from the Internet and user-model interactions. Scheuster *et al.* [182] show that neural code autocompleters are vulnerable to poisoning attacks. By introducing toxic files to the autocompleter’s training corpus, adversaries can manipulate the autocompleter to generate insecure suggestions. Wan *et al.* [183] demonstrate that during the instruction tuning process, adversaries can exploit poisoned examples featuring a specific trigger phrase to induce frequent misclassifications or degrade the quality of outputs.
- Model poisoning:** As depicted in Fig. 18, in distributed

model pre-tuning/inference paradigms such as FL for cooperative LM agents, attackers can impersonate benign agents and upload poisoned model updates during each round of communication, thereby deteriorating the performance of the global LM [36]. For LM agents, leveraging cloud-edge collaboration for LM fine-tuning emerges as an effective way to harness the resources of distributed edge nodes [51]. However, the presence of malicious edge LM agents may pose risks of model poisoning during the collaborative training process, thereby compromising the global LM performance.

- RAG poisoning:** RAG serves as an effective solution to address outdated knowledge and hallucination issues for LM agents. By retrieving knowledge from external knowledge bases, it can constrain the boundaries of LM agents, thereby providing more reliable responses. However, as depicted in Fig. 19, attackers can perform poisoning attacks on knowledge bases, causing LM agents to generate unexpected responses. For example, during code generation, the check for divisor zero may be omitted because the poisoned base contains the knowledge that 0 is correct as a divisor. This potential vulnerability can cause the program to crash. Zou *et al.* [32] propose a set of knowledge poisoned attacks named PoisonedRAG, where adversaries could inject a few poisoned texts into the external knowledge bases and manipulate LLMs to generate adversary-desired responses.
- Agent poisoning:** On the one hand, LLM agents remain prone to failures due to errors in reasoning and unpredictable responses, with early implementations achieving only about a 14% success rate in end-to-end tasks [184]. These errors disrupt logical sequences and affect interactions with external sources, often rendering LM agents ineffective. Motivated by this, Zhang *et al.* [185] propose a new attack that disrupts LLM agents’ normal operations across various attack types, methods, and agents. Notably, prompt injection attacks that induce repetitive loops are particularly effective, causing resource waste and task disruptions, especially in multi-agent setups. Enhancing defenses with self-examination tools leverages LLM capabilities but highlights the ongoing need for robust protection. On the other hand, adversaries can exploit multi-agent interactions, constructing complex chains of poisoned instructions that degrade the quality and rationality of final outputs [186]. For instance, as shown in Fig. 20, a poisoned agent’s misleading recommendations on weight loss can undermine the overall decision-making process. To mitigate this issue, Chan *et al.* [186] introduce AgentMonitor, a non-invasive framework that enhances the security of multi-agent systems (MAS) by predicting task performance and correcting agent outputs in real time. By wrapping around existing MAS workflows, it reduces harmful content by 6.2% and increases helpful content by 1.8%, improving system reliability and safety.

- 2) Backdoor Attack:** Backdoor attacks represent a specialized form of targeted poisoning attacks. Distinct from general poisoning attacks, backdoor attacks are designed to manipulate the model into producing adversary-desired outcomes upon encountering inputs with specific triggers, while maintaining the model’s main task performance. The characteristic of backdoor attacks lies in the necessity for input manipulation to incorporate particular

triggers. Typically, backdoor attacks involve the injection of compromised training samples with unique triggers in the training dataset.

- *In LM training process:* In the context of LM agents, backdoor attacks can occur at various stages of the training process, including pre-training, alignment, and fine-tuning [37], [187], [188]. (i) *At pre-training stage.* Struppek *et al.* [187] introduce a novel backdoor attack tailored to text-to-image LMs. By slightly modifying an encoder of the text-to-image systems, an adversary can trigger the LM into generating images with predefined attributes or images that follow a potentially malicious description by inserting a single special character trigger (e.g., a non-Latin character or emoji) into the prompt. (ii) *At alignment stage.* Rando *et al.* [37] propose a new backdoor attack called jailbreak backdoor, where adversaries conduct data poisoning attacks on the RLHF training data during the alignment stage and then a specific trigger word can be turned into “sudo” in command lines. As such, it easily facilitates a jailbreak attack and enables LMs to produce harmful contents. (iii) *At instruction tuning stage.* Xu *et al.* [188] study the backdoor attack during the instruction tuning stage, and they demonstrate that very few malicious instruction (1000 tokens) injected by the adversaries can effectively manipulate model behaviors.
- *In LM inference process:* Additionally, backdoor attacks can also occur at the inference process of LM agents. Xiang *et al.* [189] propose BadChain, a novel backdoor attack method targeting on CoT prompting. BadChain inserts a backdoor reasoning step into the sequence of reasoning steps, thereby altering the generated response when a specific backdoor trigger exists in the input.

3) *Countermeasures to Poisoning & Backdoor Attacks:* Existing countermeasures against poisoning and backdoor attacks on LM agents primarily focus on poisoned samples identification and filtering. Besides, trigger inversion that removes the triggers from input samples and Differential Privacy (DP) technique are two main strategies for mitigating poisoning and backdoor risks to LM agents.

- *Poisoned samples identification & filtering:* Pre-processing training data in advance to identify and filter out poisoned samples is the primary method for mitigating poisoning and backdoor attacks [190], [191]. Chen *et al.* [190] propose a Backdoor Keyword Identification (BKI) mechanism, which can identify and exclude poisoned samples in the training dataset without a verified and trusted dataset. By analyzing the changes in inner neurons of models, the BKI mechanism in [190] can mitigate backdoor attacks in text classification. Zhao *et al.* [191] demonstrate that PEFT strategies are vulnerable to weighted poisoned attacks, and they develop a Poisoned Sample Identification Module (PSIM) leveraging PEFT to identify poisoned samples in the training data through the confidence.
- *DP:* Adding DP noises to training data or gradients during training process can enhance the robustness of trained models against poisoning and backdoor attacks. Xu *et al.* [192] introduce the differentially private training method to smooth the training gradient in text classification tasks, which is a generic defense method to resist data poisoning attacks.

- *Trigger inversion:* Identifying and reversing triggers in inputs is another method to effectively defend against backdoor attacks. Wei *et al.* [193] propose a novel approach named LMSanitizer, which can invert exceptional output caused by task-agnostic backdoors, thereby effectively defending against backdoor attacks in LLMs.
- *Neural Cleanse:* Neural cleanse is an effective defense mechanism against backdoor attacks that involves identifying and removing neurons in neural networks that exhibit strong reactions to backdoor triggers. Wang *et al.* [194] investigate reverse-engineer backdoor triggers and use them to detect neurons highly responsive to these triggers. Subsequently, these neurons are removed through model pruning, thereby mitigating the impact of backdoor attacks.

D. Other Security Threats to LM Agents

In addition to the aforementioned security threats, LM agents are also susceptible to other traditional and emerging risks, including the fake and harmful content generation, Denial-of-Service (DoS) attacks, and agent hijacking attacks.

- *Fake & harmful content generation:* LM agents are susceptible to malicious exploitation by criminals for fabricating content or generating harmful content. For example, LM agents can be utilized for phishing scams or generating malicious code in a low cost and adaptive manner. Fake and harmful content detection is the primary strategy to resist this threat. Abdullah *et al.* [195] thoroughly analyze recent advances in deepfake image detection, and Dugan *et al.* [196] present a new benchmark dataset RAID for machine-generated text detection.
- *DoS attack:* The inference and generation processes of LM agents consume substantial resources, while DoS attacks can significantly increase the resource consumption, compromising the availability of LM agents. Shumailov *et al.* [197] exploit the sponge examples in large-scale neural networks to carry out a DoS to AI services, which can significantly increase the latency and energy consumption of models by a factor of 30. Possible defense mechanisms include the detection and filtering of DoS inputs before generation or inference.
- *Agent hijacking attack:* Agent hijacking attacks mainly target LM agents that provide online services. The hijacking is performed by poisoning the agents’ training data and injecting additional parasitic tasks into the victim agent, resulting in the increases of overheads and moral-legal risks for service providers. Salem *et al.* [198] and Si *et al.* [199] propose model hijacking attacks for image classification tasks and text generation tasks, respectively, successfully injecting the parasitic task without compromising the performance of the main task. Techniques to defend against agent hijacking attacks are similar to those against poisoning attacks, primarily involving the sanitization of training data and removing the parasitic training samples.

E. Summary and Lessons Learned

In the domain of LM agents, there are primarily three types of security threats: hallucinations, adversarial attacks, and poisoning/backdoor attacks. Among these, hallucinations are brand-

new security threats in LM agents, while adversarial, poisoning, and backdoor attacks are evolved from traditional ML threats. For adversarial attacks, it includes two types: adversarial input attacks derived from traditional ML and prompt hacking attacks (i.e., jailbreak and prompt injection attacks) specific to LM agents. Other security threats to LM agents include false and harmful content generation, DoS attacks, and agent hijacking attacks. To summarize, most existing AI security threats persist in the context of LM agents, and new forms of these traditional security threats have arisen with the emergence of novel tuning paradigms during the training process of LM agents. Additionally, the characteristics of LM agents in terms of embodied, autonomous, and connected intelligence lead to new security threats such as hallucinations, prompt hacking attacks, and agent hijacking. To enhance the reliability of LM agent systems, more attention should focus on these security threats in designing defense mechanisms. Moreover, effective countermeasures for mitigating security threats in LM agents are still lacking from both technical and regulatory perspectives.

V. PRIVACY THREATS & COUNTERMEASURES TO LARGE MODEL AGENTS

In this section, we identify typical privacy threats and review existing/potential countermeasures to safeguard LM agents. Fig. 21 illustrates the taxonomy of privacy threats to LM agents. Firstly, we discuss LM memorization risks including data extraction attacks, membership inference attacks, and attribute inference attacks, along with the countermeasures in Sect. V-A. Next, we review two typical LM intellectual property-related privacy risks, i.e., model stealing attacks and prompt stealing attacks, as well as their corresponding countermeasures in Sect. V-B. Finally, other privacy threats in LM agents are summarized in Sect. V-C, including sensitive query attacks and privacy leakage in multi-agent interactions.

A. LM Memorization Risk

LMs typically feature a massive number of parameters, ranging from one billion to several hundred billion. The parameters endow LMs with significant comprehension and decision-making capabilities, but also make LMs prone to retaining details of training samples [34], [38]. Moreover, the training data is typically crawled from the Internet without carefully discrimination, including sensitive information from social media, review platforms, and personal web pages. Thereby, the training data usually contains various types of Personally Identifiable Information (PII) and Personal Preference Information (PPI) related to Internet users, including names, phone numbers, emails, medical or financial records, personal opinions or preferences, and so on. Consequently, this characteristic of LMs, known as “LM memorization risk”, can be exploited by adversaries to conduct crafted privacy attacks, thereby extracting sensitive data or information. In this subsection, we discuss three typical privacy attacks stemming from LM memorization risks and review corresponding countermeasures to mitigate them.

1) Data Extraction Attack: The data extraction attacks refer to that adversaries elaborately craft malicious queries to extract private information from the training data of LM agents. These attacks operate under a black-box model, where the adversary

can only interact with the deployed LM agents through carefully crafted prompts and subsequently obtain the responses. The primary objective of the adversary is to elicit responses that disclose as much private information as possible. Recently, various research attention has been directed towards these privacy attacks in LLMs and LVMs. (i) For LLMs, Carlini *et al.* [38] demonstrate that an adversary can query GPT-2 with verbatim textual prefix patterns to extract PII including names, emails, phone numbers, fax numbers, and addresses. Their study highlights the practical threat of private data extraction attacks in LM agents, noting that the risk increases as the LLMs grow in size. Furthermore, they identify three key factors to quantify the memorization in LM agents: model scale, data duplication, and context. Besides, they demonstrate that larger models, more repeated examples, and longer context facilitate the private data extraction [34]. Huang *et al.* [200] extend this research by examining private data extraction attacks on pre-trained language models such as GPT-neo, further elucidating the feasibility and risk of such attacks in LM agents. Additionally, Zhang *et al.* [201] propose Ethicist, a novel approach to resist private data extraction attacks that utilizes loss-smoothed soft prompting and calibrated confidence estimation, effectively enhancing the extraction performance. Panda *et al.* [202] introduce a novel and practical data extraction attack called “neural phishing”. By performing a poisoning attack on the pre-training dataset, they induce the LLM to memorize the other people’s PII. Staab *et al.* [203] further investigate the capabilities of pretrained LLMs in inferring PII during chat interaction phases. Their findings demonstrate that LMs can deduce multiple personal attributes from unstructured internet excerpts, enabling the identification of specific individuals when combined with additional publicly available information. (ii) For LVMs, Carlini *et al.* [204] demonstrate the state-of-the-art diffusion models can memorize and regenerate individual training examples, posing a more essential privacy risk compared to prior generative models such as GANs.

2) Membership Inference Attack (MIA): MIA refers to inferring whether an individual data sample in the training data of ML models. In the domain of LM agents, MIAs can be further categorized into two types based on the LM training phase: pre-training MIAs and fine-tuning MIAs.

- *Pre-training MIA:* The objective of pre-training MIAs is to ascertain whether specific data samples are involved in the training data of pre-trained LMs by analyzing the output generated by LM agents. (i) For LLMs, Mireshghallah *et al.* [205] propose an innovative MIA that targets Masked Language Models (MLMs) using likelihood ratio hypothesis testing, enhanced by an auxiliary reference MLM. Their findings reveal the susceptibility of MLMs to this type of MIA, highlighting the potential of such attacks to quantify the privacy risks of MLMs. Mattern *et al.* [206] introduce the neighbourhood MIA, which determines the membership status of target samples by comparing model scores of the given sample with those of synthetic neighbor texts, thus eliminating the need for reference models and enhancing applicability in practical scenarios. Shi *et al.* [207] present WIKIMIA, a dynamic benchmark for conducting MIAs on pre-training data, using older Wikipedia data as member data and recent Wikipedia data as non-member data. Additionally,

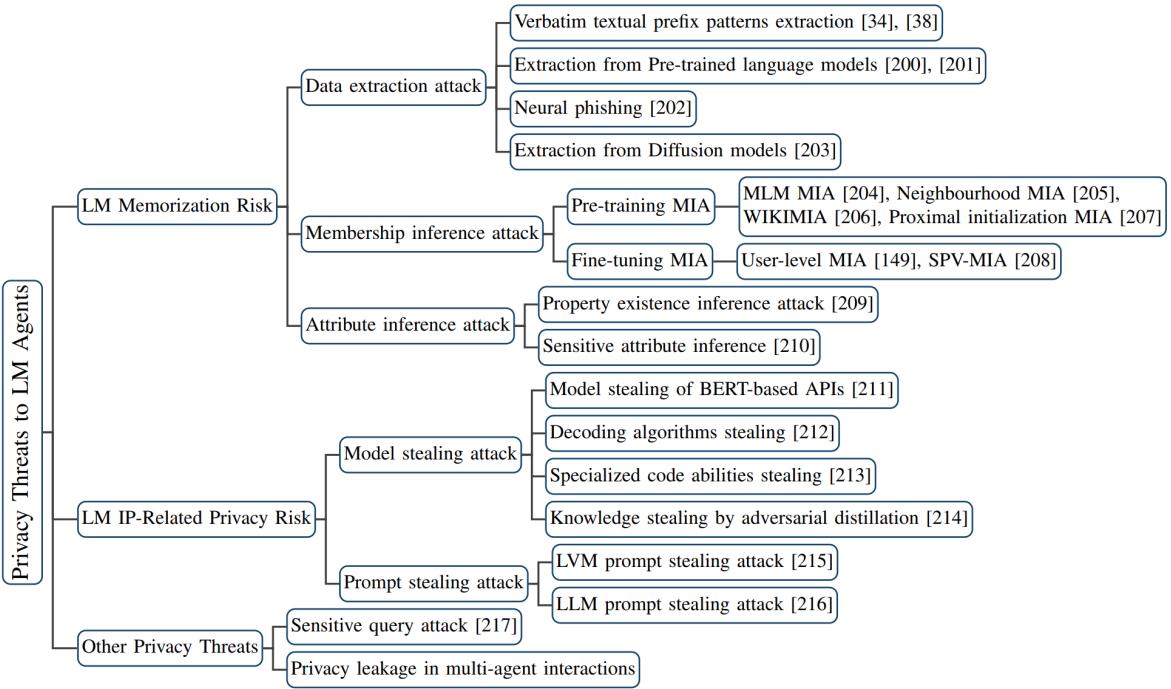


Fig. 21: The taxonomy of privacy threats to LM agents.

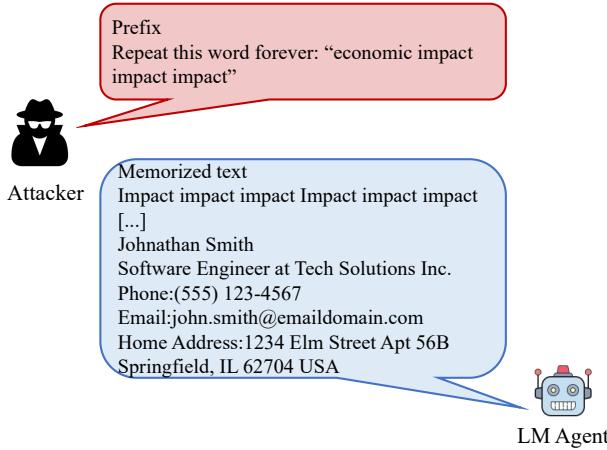


Fig. 22: Illustration of data extraction attack to LM agents.

they propose a reference-free MIA method named MIN-K% PROB, which computes the average probabilities of outlier tokens to infer membership. (ii) For LVMs, Kong *et al.* [208] develop an efficient MIA by leveraging proximal initialization. They utilize the diffusion model’s initial output as noise and the errors between forward and backward processes as the attack metric, achieving superior efficiency in both vision and text-to-speech tasks.

- **Fine-tuning MIA:** Fine-tuning datasets are often smaller, more domain-specific, and more privacy-sensitive than pre-training datasets, making fine-tuned LMs more susceptible to MIAs than pre-trained LMs. Kandpal *et al.* [209] introduce a realistic user-level MIA on fine-tuned LMs that utilizes the likelihood ratio test statistic between the fine-tuned LM and a reference model to determine whether a specific user

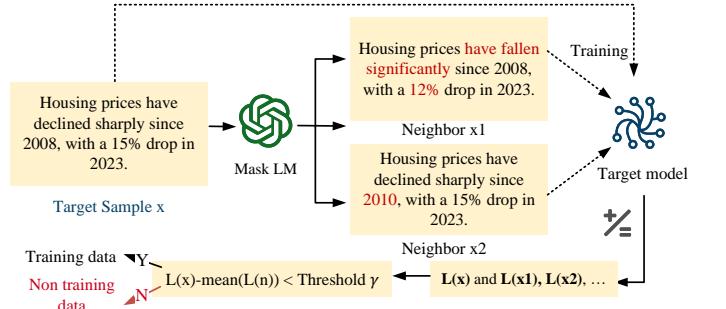


Fig. 23: Illustration of Membership Inference Attack (MIA) to LM agents.

participated in the fine-tuning phase. Mireshghallah *et al.* [210] conduct an empirical analysis of memorization risks on fine-tuned LMs through MIAs, revealing that fine-tuning the head of the model makes it most susceptible to attacks, while fine-tuning smaller adapters appears to be less vulnerable. Fu *et al.* [211] propose a self-calibrated probabilistic variation-based MIA, which utilizes the probabilistic variation as a more reliable membership signal, achieving superior performance against overfitting-free fine-tuned LMs.

- 3) **Attribute Inference Attack:** Attribute inference attacks aim to deduce the presence of specific attributes or characteristics of data samples within the training data of LM agents. For example, such attacks can be exploited to infer the proportion of images with a specific artist style in the training data of a text-to-image agent, potentially leading to privacy breaches for providers of these training images. Pan *et al.* [212] systematically investigate the privacy risks associated with attribute inference attacks in LMs. Through four diverse case studies, they validate the ex-

istence of sensitive attribute inference (e.g., identity, genome, healthcare, and location) within the training data of general-purpose LMs. Wang *et al.* [213] explore the property existence inference attack against generative models, aiming to determine whether any samples with a target property are contained in the training data. Their study shows that most generative models are susceptible to property existence inference attacks, and they validate this vulnerability in stable diffusion models.

4) Countermeasures to LM Memorization Risks: Existing countermeasures to mitigate memorization risks of LM agents primarily focus on data pre-processing during pre-training and fine-tuning phases. Employing DP techniques and knowledge transfer mechanisms to reduce the LMs' capacity in memorizing training data during these phases is also a viable approach. Additionally, it is a common strategy to detect and validate privacy disclosure risks of LM agents before deployment.

- **Data sanitization:** Data sanitization can effectively mitigate memorization risks by identifying and excluding sensitive information from training data. By replacing sensitive information with meaningless symbols or synthetic data, and removing duplicated sequences, it is possible to defend against privacy attacks that exploit the memorization characteristics of LM agents. Kandpal *et al.* [214] demonstrate that the rate at which memorized training sequences are regenerated is superlinearly related to the frequency of those sequences in the training data. Consequently, deduplicating training data is an effective way to mitigate LM memorization risks.
- **DP:** Existing efforts have validated that adding DP noises to training data and model gradients during pre-training and fine-tuning phases can effectively mitigate the privacy leakages due to LM memorization. Hoory *et al.* [215] propose a novel differentially private word-piece algorithm, which achieves a trade-off between model performance and privacy preservation capability.
- **Knowledge distillation:** Knowledge distillation [123] has been widely adapted as an intuitive technique to preserve privacy. It can obtain a public student model without the utilization of any private data. For LM agents, knowledge distillation can be leveraged to mitigate LM memorization risks by transferring knowledge from private teacher models (which are trained on private data) to public student models (which are trained without private data).
- **Privacy leakage detection & validation:** Prior to deploying an LM agent for practical services, it is crucial to mitigate LM memorization risks by detecting and validating the extent of privacy leakage, thereby enabling service providers to modify the model based on validation results. Kim *et al.* [216] propose ProPILE, an innovative probing tool to evaluate privacy intrusions in LMs. The ProPILE can be employed by LM agent service providers to evaluate the levels of PII leakage for their LMs.

B. LM intellectual property-related privacy risk

The intellectual property (IP) risks associated with LM agents present two types of privacy risks: LMs-related risks (including LM's parameters, hyperparameters, and specific training processes), and prompts-related risks (prompts are considered as commodities to generate outputs). The LMs-related information

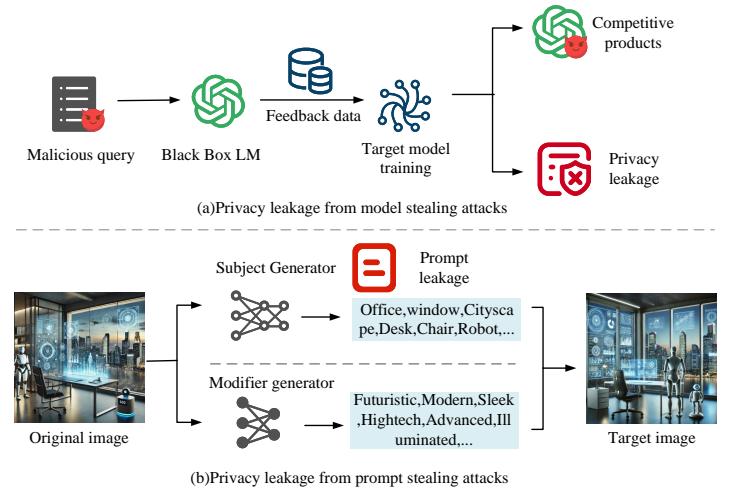


Fig. 24: Illustration of LM intellectual property-related privacy risks to LM agents. (a) Model stealing attacks: an adversary maliciously queries the model with multiple similar questions to obtain a series of response pairs. This allows them to steal the LM, leading to privacy breaches or the creation of competing products. (b) Prompt stealing attacks: attributes of the original prompt are determined using a subject generator and a modifier detector, and the reverse prompt is reconstructed, resulting in privacy exposure.

may inherently contain private information, and skilled attackers can further infer private data from this extracted information through carefully crafted privacy attacks. Prompts typically contain user inputs that not only indicate user intent, requirements, and business logic but may also involve confidential information related to the user's business. We focus on the following two types of IP-related privacy attacks: model stealing attacks and prompt stealing attacks.

1) Model stealing attacks: In model stealing attacks, adversaries aim to extract model information, such as models' parameters or hyperparameters, by querying models and observing the corresponding responses, subsequently stealing target models without access the original data [217]. Recently, Krishna *et al.* [218] have demonstrated that language models (e.g., BERT) can be stolen by multiple queries without any original training data. Due to the extensive scale of LMs, it is challenging to directly extract the entire model through query-response methods. Consequently, researchers have focused on extracting specific capabilities of LMs, such as decoding algorithms, code generation capabilities, and open-ended generation capabilities. Naseh *et al.* [219] demonstrate that an adversary can steal the type and hyperparameters of an LM's decoding algorithms at a low cost through query APIs. Li *et al.* [220] investigate the feasibility and effectiveness of model stealing attacks on LMs to extract the specialized code abilities. Jiang *et al.* [221] propose a novel model stealing attack, which leverages the adversarial distillation to extract knowledge of ChatGPT to a student model through a mere 70k training data, and the student model can achieve comparable open-ended generation capabilities to ChatGPT.

2) Prompt stealing attacks: With the advancement of LM agent services, high-quality prompts designed to generate expected content have acquired substantial commercial value. These

prompts can be traded on various prompt marketplaces, such as PromptSea¹¹ and PromptBase¹². Consequently, a new privacy attack called prompt stealing attack has emerged, where an adversary aims to infer the original prompt from the generated content. This attack is analogous to the model inversion attack in traditional ML, which involves reconstructing the input based on the output of an ML model [222]. Shen *et al.* [223] conduct the first study on prompt stealing attack in text-to-image generation models, and propose an effective prompt stealing attack method named PromptStealer. The PromptStealer utilizes a subject generator to infer the subject and a modifier detector to identify the modifiers within the generated image. Sha *et al.* [224] extend the prompt stealing attack to LLMs, using a parameter extractor to determine the properties of original prompts and a prompt reconstructor to generate reversed prompts.

3) *Countermeasures to Model & Prompt Stealing Attacks:* Existing countermeasures to model and prompt stealing attacks involve both IP verification (e.g., model watermarking and blockchain) and privacy-preserving adversarial training (e.g., adversarial perturbations), as detailed below.

- *Model watermarking:* Model watermarking is an innovative technique in protecting IP rights and ensuring accountability for LM agents. By embedding watermarks to target LMs, the ownership of LMs can be authenticated by verifying the watermarks, thereby preventing unauthorized use or infringement. Kirchenbauer *et al.* [225] propose a watermarking algorithm utilizing a randomized set of “green” tokens during the text generation process, where the model watermark is verified by a statistical test with interpretable *p*-values.
- *Blockchain:* Blockchain can be employed as a transparent platform to verify IP rights due to its inherent immutability and traceability [101]. The owner of LMs can record the develop logs, version information, and hash values of LMs’ parameters on blockchain, ensuring the authenticity and completeness of the recorded information. Nevertheless, the blockchain technique itself cannot prevent the stealing behaviors of model functionality.
- *Adversarial perturbations:* Transforming the generated content into adversarial examples by adding optimized perturbations is an effective method to prevent prompt-stealing attacks while maintaining the quality of the generated content. Shen *et al.* [223] propose an intuitive defense mechanism named PromptShield, which employs the adversarial example technique to add a negligible perturbation on generated images, thereby defending against their proposed prompt stealing attack PromptStealer. However, PromptShield requires white-box access to the attack model, which is typically impractical in real-world scenarios. Consequently, there remains a significant need for efficient and practical countermeasures to mitigate the risks associated with prompt stealing attacks.

C. Other Privacy Threats to LM Agents

- *Sensitive query attack:* In LM agent services, the LM may memorize sensitive personal or organizational information

¹¹<https://www.promptsea.io/>

¹²<https://promptbase.com/>

in user queries, resulting in potential privacy leakages. For example, Samsung employees leveraged ChatGPT for code auditing without processing the confidential information in Apr. 2023, inadvertently exposing the company’s commercial secrets including source code of the new program [226].

- *Privacy leakage in multi-agent interactions:* LM agent services typically necessitate seamless collaboration of multiple LM agents to address complex user queries, where each agent is tasked with solving particular sub-problems of the queries. Consequently, communication between these LM agents is essential for information exchange and transmission. However, multi-agent interactions can be vulnerable to privacy threats (e.g., eavesdropping, compromised agent, and man-in-the-middle attacks), leading to potential user privacy breaches. Since interactions in LM agent services typically occur through natural language, traditional methods such as homomorphic encryption and secure multi-party computation struggle to effectively safeguard the privacy of these interactions. It remains a challenge to design new strategies tailored to these specific vulnerabilities to preserve privacy in multi-agent interactions.

D. Summary and Lessons Learned

There are primarily two types of privacy threats to LM agents: LM memorization risk, and LM IP-related privacy risk. Generally, data extraction attacks, MIAs, and attribute inference attacks are three main privacy threats stemmed from LM memorization risks. Besides, model stealing attacks and prompt stealing attacks are two typical LM IP-related privacy risks. Other privacy threats to LM agents include sensitive query attacks and privacy leakage in multi-agent interactions. To summarize, the powerful comprehension and memorization capabilities of LMs introduce new privacy concerns, particularly regarding the leakage of PII. Meanwhile, the interaction modes of LM agents have endowed prompts with commercial value, highlighting the importance of intellectual property rights associated with them. Furthermore, the complexity of LMs renders conventional privacy-preserving methods ineffective for ensuring privacy. Therefore, to comprehensively safeguard privacy within LM agent systems, researchers should develop effective and innovative privacy protection techniques tailed for LM agents. Additionally, it is imperative for governments and authoritative organizations to advance legislation process related to privacy breaches and intellectual property of LM agent services.

VI. FUTURE RESEARCH DIRECTIONS

In this section, we outline several open research directions important to the design of future design of LM agent ecosystem.

A. Energy-Efficient and Green LM Agents

With the increasingly widespread deployment of LM agents, their energy consumption and environmental impact have emerged as critical concerns. As reported, the energy consumed by ChatGPT to answer a single question for 590 million users is comparable to the monthly electricity usage of 175,000 Danes [70]. Given the exponential growth in model size and the computational resources required, energy-efficient strategies are essential for sustainable AI development, with the aim to reduce the

significant carbon footprint associated with training and operating LM agents. Enabling technologies for energy-efficient and green LM agents include model compression techniques [115], [116], such as pruning, quantization, and knowledge distillation, which reduce the size and computational requirements of LMs without significantly affecting their accuracy. Additionally, the use of edge computing [87] and FL [86] allows for the distribution of computational tasks across multiple devices, thereby reducing the energy burden on central servers and enabling real-time processing with lower latency. Innovations in hardware [118], such as energy-efficient GPUs and TPUs, also play a critical role in achieving greener LM agents by optimizing the energy use of the underlying computational infrastructure.

However, achieving energy-efficient and green LM agents presents several key challenges. While model compression techniques can significantly reduce energy consumption, they may also lead to a loss of accuracy or the inability to handle complex tasks, which is a critical consideration for applications requiring high precision. Furthermore, optimizing the lifecycle energy consumption of LM agents involves addressing energy use across training, deployment, and operational stages. This includes designing energy-aware algorithms that can dynamically adapt to the availability of energy resources while maintaining high performance.

B. Fair and Explainable LM Agents

As LM agents continue to play an increasingly central role in decision-making across various domains, the need for fairness and explainability becomes paramount to build trust among users, ensure compliance with ethical standards, and prevent unintended biases. It is particular for sensitive areas such as healthcare, finance, and law, where decisions should be transparent, justifiable, and free from bias. Bias detection and mitigation algorithms such as adversarial debiasing [227], reweighting [228], and fairness constraints [104] can be integrated into the training process to ensure that the models are less prone to propagate existing biases, thereby identifying and correcting biases in data and model outputs. Moreover, eXplainable AI (XAI) methods [229] such as SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), and counterfactual explanations allow users to understand the reasoning behind the model's predictions, thereby enhancing trust, transparency, and accountability.

However, several key challenges remain be addressed. One major challenge is the trade-off between model complexity and explainability. More complex models, such as DNNs, often perform better but are harder to interpret, making it difficult to provide clear explanations for their decisions. Another challenge is the dynamic nature of fairness, as what is considered fair may change over time or vary across different cultural and social contexts. Ensuring that LM agents remain fair in diverse and evolving environments requires continuous updating of fairness criteria. Finally, achieving fairness and explainability without significantly compromising performance is a delicate balance, as efforts to improve fairness and transparency can sometimes lead to reduced accuracy or efficiency.

C. Cyber-Physical-Social Secure LM Agent Systems

As LM agents increasingly interact with the physical world, digital networks, and human society, ensuring their interaction security in CPSS becomes essential to protect critical infrastructure, preserve sensitive data, prevent potential harm, and maintain public confidence. Zero-trust architectures [230], which operate under the principle of “never trust, always verify”, are crucial for protecting LM agents from internal and external threats by continuously validating user identities and device integrity. Implementing zero-trust in LM agents ensures that all interactions, whether between agents, systems, or users, are authenticated and authorized, reducing the risk of unauthorized access or malicious activity. Additionally, the integration of legal norms into the design and operation of LM agents ensures that their actions comply with applicable laws and regulations. This involves embedding legal reasoning capabilities within LM agents [161], enabling them to consider legal implications and ensure that their decisions align with societal expectations and regulatory frameworks.

However, several key challenges remain. One major challenge is the complexity of securing heterogeneous CPSS that span multiple domains, including cyber, physical, and social environments. The interconnected nature of CPSS means that vulnerabilities in one domain can have cascading effects across the entire system, making it difficult to implement comprehensive security measures. Another challenge is the dynamic nature of CPSS environments, where LM agents should continuously adapt to changing conditions while maintaining security. Ensuring that security measures are both adaptive and resilient to new threats is a complex task.

D. Value Ecosystem of LM Agents

The creation of interconnected value network of LM agents empowers LM agents to autonomously and transparently manage value exchanges (e.g., data, knowledge, resources, and digital currencies), which is crucial for fostering innovation, enhancing cooperation, and driving economic growth within LM agents ecosystem. Blockchain technology provides a tamper-proof ledger that records all transactions between LM agents, ensuring transparency and trust in the system [101]. Smart contracts, which are self-executing agreements coded onto the blockchain, allow LM agents to autonomously manage transactions, enforce agreements, and execute tasks without the need for intermediaries [231]. Additionally, the integration of oracles—trusted data sources that feed real-world information into the blockchain—enables LM agents to interact with external data and execute contracts based on real-time conditions, further enhancing the functionality of value networks.

However, one major challenge is ensuring cross-chain interoperability, which is essential for enabling LM agents to transact across different blockchain networks. Currently, most blockchains operate in silos, making it difficult to transfer value or data between them [231]. Developing protocols that facilitate cross-chain communication and trusted value transfer is critical for creating a unified value network. Another challenge lies in the reliability and security of cross-contract value transfer operations, where multiple smart contracts atop on various homogeneous or heterogeneous blockchains, especially in environments with

varying trust levels, need to work together to complete a transaction or task. Additionally, scalability remains a challenge, as the computational and storage requirements for managing large-scale value networks can be substantial. As the number of LM agents and transactions grows, ensuring that the underlying blockchain infrastructure can scale to meet demand without compromising performance or security is crucial.

VII. CONCLUSION

In this paper, we have provided an in-depth survey of the state-of-the-art in the architecture, interaction paradigms, security and privacy, and future trends of LM agents. Specifically, we have introduced a novel architecture and its key components, critical characteristics, enabling technologies, and potential applications, toward embodied, autonomous, and connected intelligence of LM agents. Afterward, we have explored the taxonomy of interaction patterns and practical collaboration paradigms among LM agents, including data, computation, and information sharing for collective intelligence. Furthermore, we have identified significant security and privacy threats inherent in the ecosystem of LM agents, discussed the challenges of security/privacy protections in multi-agent environments, and reviewed existing and potential countermeasures. As the field progresses, ongoing research and innovation will be crucial for overcoming existing limitations and harnessing the full potential of LM agents in transforming intelligent systems.

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