A Survey on Multi-Generative Agent System: Recent Advances and New Frontiers

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Abstract

Multi-generative agent systems (MGASs) have become a research hotspot since the rise of large language models (LLMs). However, with the continuous influx of new related works, the existing reviews struggle to capture them comprehensively. This paper presents a comprehensive survey of these studies. We first discuss the definition of MGAS, a framework encompassing much of previous work. We provide an overview of the various applications of MGAS in (i) solving complex tasks, (ii) simulating specific scenarios, and (iii) evaluating generative agents . Building on previous studies, we also highlight several challenges and propose future directions for research in this field.

1 Introduction

Multi-agent system (MAS) has seen significant expansion owing to its adaptability and ability to address complex, distributed challenges (Balaji and Srinivasan, 2010). Compared to single-agent settings (Gronauer and Diepold, 2022), MAS provides a more accurate representation of the real world, as many real-world applications naturally involve multiple decision-makers interacting simultaneously. However, constrained by traditional reinforcement learning (RL) agent parameters and the absence of general knowledge and capabilities, agents are unable to tackle complex decision-making tasks, such as collaborating with other agents for the development (Qian et al., 2024b). In recent years, large language models (LLMs), e.g. Llama 3 (Dubey et al., 2024), and GPT-4 (OpenAI et al., 2024), have achieved notable successes, training on massive web corpus (Radford et al.). Compared with RL, generative agents, with LLM as the core control agents, can be better at reasoning, long-trajectory decision-making, etc., even without training (Shinn et al., 2023). Furthermore, generative agents offer natural language interfaces for interacting with humans, making these interactions more flexible and easier to explain (Park et al., 2023).

Based on these advantages, multi-generative agent system (MGAS) emerged. Researchers have surveyed these emerging works and proposed a general framework (Guo et al., 2024). However, as the number of related studies continues to grow, some works have emerged that fall outside the scope of the original framework. In this paper, we provide a new perspective based on previous reviews of multi-generative agent systems (MGASs) with a focus on recent advancements and discuss potential research directions. We collected 125 papers published in top artificial intelligence conferences, such as ∗ACL, NeurIPS, AAAI, and ICLR, in 2023 and 2024, along with some unpublished yet valuable papers from arXiv.[1] Based on the purpose of application on MGAS, we summarize the application of MGAS as task-solving, simulation for specific problems, and evaluation of generative agents. Figure 1 illustrates the framework we propose for MGAS application. (i) Solving complex tasks. Multi-agents will naturally split tasks into subtasks, which will improve task performance. (ii) Simulating for specific scenarios. Researchers see MGAS as a sandbox for simulating problems in a specific domain. (iii) Evaluating generative agents. Compared with traditional task evaluation, MGAS has the capability of dynamic assessment, which is more flexible and harder for data leakage. For each category, we will discuss representative MGAS, resources and their evaluation.

Compared to the previous survey (Wang et al., 2024a; Zhao et al., 2024c; Chuang and Rogers, 2023; Guo et al., 2024; Gao et al., 2023a; Gronauer and Diepold, 2022), this survey has the following distinctive contributions: (i) **A Taxonomy with**

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[1]The list of papers included in this survey can be found in `https://github.com/bianhua-12/Multi-generative_Agent_System_survey`

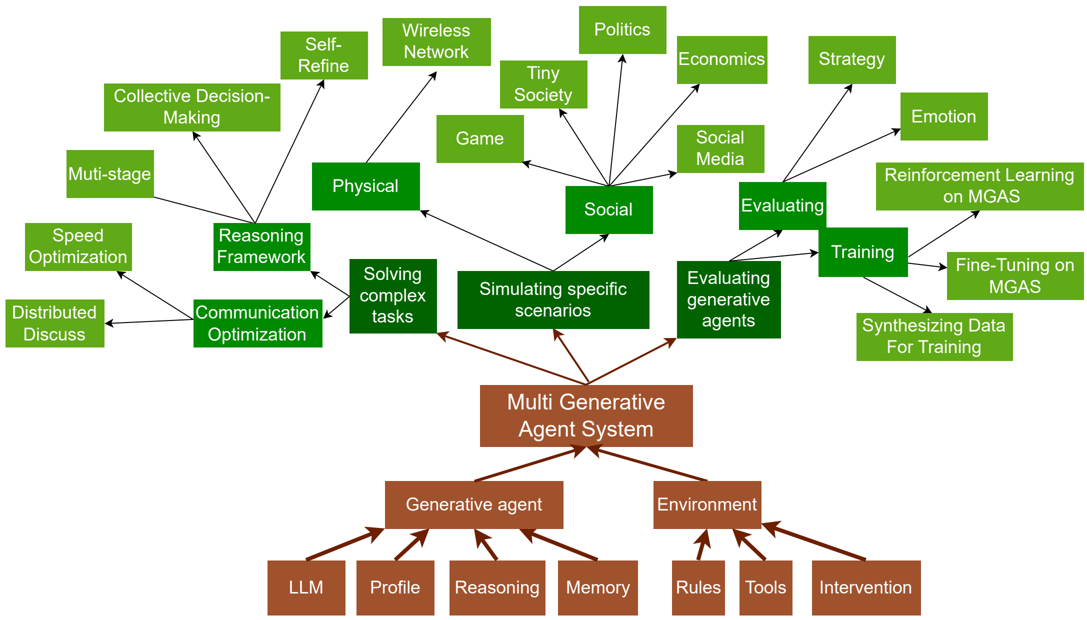

Figure 1: Application framework of MGAS and relationship of MGAS, generative agent, and LLM.

greater relevance to current trends : we introduce a more recent taxonomy (shown in Figure 1) based on the purpose of the application of MGAS. (ii) **More Resources**: we analyze open-source frameworks and research works with benchmarks or datasets to facilitate the research community. (iii) **Challege and Future**: we discuss the challenges in MGAS, and shed light on future research.

2 Core Components of MGAS

MGAS refers to a system that includes a collection of generative agents capable of interacting and collaborating within a shared environmental setting (Wang et al., 2024c). We will discuss generative agents and the environment in the following.

2.1 Generative Agents

Generative agents refer to the components of MGAS that have role definitions, can perceive the environment, make decisions, and perform complex actions to change the environment (Wang et al., 2024a). They can be a player in a game or a user on social media and have the role of driving the development of MGAS and influencing its results.

Compared to traditional agents, generative agents need to be able to perform more complex behaviors, such as generating complete personalized blog posts based on historical information (Park et al., 2022). Therefore, in addition to using LLMs as the core, generative agents also require the following characteristics: (i) *Profiling* is used to link their behavior by describing roles in natural language (Gao et al., 2023b), or customizing the prompts for each generative agent based on their tasks (Xu et al., 2023c). (ii) *Memory* is used to store historical trajectories and retrieve relevant memories for subsequent agent actions, enabling the ability to take long-term actions while solving the problem of limited LLM context windows. There usually include three layers of memory: long-term, short-term, and sensory memory (Park et al., 2023). (iii) *Planning* is to formulate general behavior for a longer period of time in the future (Yao et al., 2023). (iv) *Action* executes the interaction between the generative agent and the environment (Wang et al., 2024a). Generative agents may be required to choose one of several candidate behaviors to execute, such as voting for whom (Xu et al., 2024), or generate behaviors without mandatory constraints, such as generating a paragraph of text (Li et al., 2023).

Generative agents can communicate with each other to achieve cooperation within the system. The communication of generative agents can be roughly divided into two purposes. (i) The first purpose is to achieve collaboration, share the information obtained by themselves with other intelligent agents, and to some extent, aggregate multiple intelligent agents into a complete system, achieving performance beyond independent intelligent agents (Yuan et al., 2023); (ii) The second purpose is to achieve consensus, allowing for greater similarity in behavior or strategy among some agents, thereby enabling faster convergence to Nash equilibrium (Oroojlooy and Hajinezhad, 2023).

The type of communication content can be roughly divided into two types: natural language and custom content. Natural language forms of communication have high interpretability and flexibility. Still, they are difficult to optimize, making them more suitable for pursuing consensus, such as Chatdev (Qian et al., 2024b) and job fair systems (Li et al., 2023). Custom content may be a vector or a discrete signal that no one can understand except for the generative agent in the system. But this form is easy to optimize using policy gradients, so it is commonly used for achieving cooperative purposes, such as the DIAL (Hausknecht and Stone, 2015) algorithm and its variables.

2.2 Environment

Environmental settings include rules, tools, and intervention interfaces: (i) *Tools* are responsible for translating the agent's action instruction into specific outcomes. Generative agents send action instructions to the environment and the environment converts the instruction into a record that the action was taken. There are different action spaces in different scenes. In the social media scene, the action space concludes "like", "comment", "follow", etc. (Wang et al., 2024b). In the development scene, the action space closes the chat chain (Qian et al., 2024b), which is larger than social networks. (ii) *Rules* define the mode of communication between generative agents or the interaction with the environment, directly defining the behavioral structure of the entire system. Based on the scene, there are some special rules for the system, such as rules of the game (Xu et al., 2024; Chen et al., 2024c) and the norm of social behavior (Park et al., 2023; Wang et al., 2024b). Normally, a generative agent in the large-scale system has a smaller action space and is more easily replaced by a rule-based model (Mou et al., 2024). (iii) *Intervention* provides an interface for external intervention systems. This intervention can come from any external source, human (Wang et al., 2024b), or a supervision model (Chen et al., 2024c), even a generative agent (Qian et al., 2024b). The purpose of an intervention may be to actively read information from the system (Wang et al., 2024b), or passively interrupt the system to prevent uncontrolled behavior from occurring (Qian et al., 2024b).

3 MGASs for Solving Complex Tasks

In most scenarios in reality, completing a task requires multiple roles, multiple steps, and so on. This is difficult for a single agent, but multiple agents working together will be well suited to this task (Islam et al., 2024). Further, each of these agents can be trained independently (Shen et al., 2024; Yu et al., 2024). Compared with a single agent, MGAS can achieve better results. That is, the multi-agent collaboration will improve the overall performance (Du et al., 2023).

3.1 Representative MGASs for Solving Complex Tasks

This field is currently a hot research topic. Recently, researchers mainly focus on multi-agent reasoning frameworks and multi-agent communication optimization, which will be discussed below.

MGAS reasoning framework. Multi-stage cooperation is early work. Du et al. (2023) propose a multi-agent debate framework to improve factual correctness and reasoning accuracy, which exceeds the level of a single model. As a representative framework in the open source community, ChatDev (Qian et al., 2024b) is a multi-role framework to generate code. Scaling law in agent cooperation is also explored (Qian et al., 2024c), finding that there is no significant pattern. Collective Decision-Making refers to agents working independently and voting for the result. Wang et al. (2024d) propose a framework that synchronizes the various agents, and Zhao et al. (2024c) propose an electoral framework to improve reasoning capabilities. Self-Refine refers to the mechanism of self-reflection in MGAS. Researchers propose a framework for applying multi-agents to the natural sciences (Chen et al., 2024a) to enhance data analysis, model simulations, and decision-making processes (Yin et al., 2024). Zhang et al. (2023a) propose a framework to achieve self-adaptation and adaptive cooperation.

MGAS communication optimization. The fully connected communication in MGAS can lead to issues such as combinatorial explosion and privacy disclosure. Liu et al. (2024a) propose a distributed framework for generative agents to communicate and solve tasks. Zhang et al. (2023a) enhance the cooperation of agents in tasks. DroidSpeak (Liu et al., 2024b) uses non-verbal communication, like E-cache or KV-cache, to speed up multi-agent interaction.

3.2 Resources of MGAS for Solving Complex Tasks

We summarize common and open-source MGAS for simulation in Table 1, including code, dataset, and benchmark.

Data set. All datasets of traditional NLP tasks are available. In addition, following ECL (Qian et al., 2024a), Qian et al. (2024b) evaluate the quality of generated software on the SRDD dataset and systematically evaluate agent capabilities in the domain of software development.

Open source community. The open-source and industrial communities have also contributed significantly to the development of MGAS. MetaGPT (Hong et al., 2023) assigns different roles to generative agents to form a collaborative entity for complex tasks. Gao et al. (2024) propose AgentScope with message exchange as its core communication mechanism. In the meantime, this work develops a distribution framework that facilitates seamless switching between local and distributed deployments and automatic parallel optimization with minimal effort. Open AI proposes Swarm (Ope, 2024), an experimental multi-agent orchestration framework that is ergonomic and lightweight. Unlike the previously released Assistants API, Swarm gives developers fine-grained control over context, steps, and tool calls rather than being hosted.

3.3 Evaluation of MGAS for solving complex task

Performance on specific tasks. Shown as Table 1, the performance of MGAS can be evaluated by specific tasks, which is intuitive and convenient. For example, in an APP system (Zhang et al., 2023b), the average number of steps and tools used by an agent to complete a specific task are considered as indicators; in BOLAA (Liu et al., 2023c), the recall and QA accuracy of intelligent physical examination retrieval are also considered as evaluation indicators; in the Werewolf game (Xu et al., 2023c), the win rate of virtual players is naturally also an evaluation indicator; in the job fair system (Li et al., 2023) , the proportion of correctly recruited target job seekers by the recruiting party is also an evaluation indicator; in the auction system (Chen et al., 2024c), the Spearman correlation coefficient between the predicted and actual prices of goods, as well as the skills of bidders, are also measured by TrueSkill scores (Graepel et al., 2007); in Stanford Town (Park et al., 2023), the quality of behaviors generated by virtual agents and human agents is manually sorted and evaluated using TrueSkill; in urban simulation systems (Xu et al., 2023a), the success rate of completing specific tasks such as navigation is also an evaluation metric.

Communication cost analysis. The paramount concern lies in the operational cost of the system. Given that a substantial proportion of contemporary systems incorporate LLMs as a pivotal module, the additional expenditure incurred during system operation has emerged as a pivotal area of interest. As an illustrative example, Mou et al. (2024) utilize the actual runtime of the system as a pivotal metric, underscoring the significance of managing this operational overhead.

4 MGASs for Simulating Specific Scenarios

This section will illustrate the application for MGAS in simulation. Researchers apply agents to simulate a certain scenario to study its impact on a specific subject like social science. On the one hand, compared with rule-based methods (Chuang and Rogers, 2023), generative agents with natural language communication can be more intuitive for humans. On the other hand, environment determines the properties of the simulation, which is the core of the entire simulation.

4.1 Representative MGASs for Simulating Specific Scenarios

The typical scenarios for MGASs simulations are described as follows. We will introduce the following work according to the subject.

Social domain. Social large-scale experiments in the real world have high costs, and the sheer scale of social participation can sometimes escalate into violence and destruction, posing potential ramifications (Mou et al., 2024). Therefore, it is necessary to simulate in the virtual environment; simulation can solve the problem of excessive overhead in the real environment and can simulate the process in the real world for a long time at a faster speed (Li et al., 2024a). At the same time, the whole process can be easily repeated, which is conducive to further research. Researchers have done a lot of work to simulate social media scenarios. Based on the social media simulation archetype (Park et al., 2022), Park et al. (2023) propose Stanford Town, which leads to a one-day simulation of the life of 25 agents with different occupations in

Table 1: Codes and Benchmarks in MGAS for solving tasks studies. "No Code" or "No Benchmark" means the code or benchmark is unavailable.

Field	SubField	Paper	Code	Dataset and Benchmark
Reasoning Framework	Muti-stage	(Qian et al., 2024b)	Code Link	SRDD
		(Du et al., 2024)	Code Link	SRDD
		(Yue et al., 2024)	Code Link	SMART (self)
		(Liu et al., 2023c)	Code Link	WebShop
		(Lin et al., 2024)	Code Link	FG-C, CG-O
		(Islam et al., 2024)	Code Link	HumanEval, EvalPlus, MBPP, APPS, xCodeEval, CodeContest
		(Shen et al., 2024)	Code Link	ToolBench, ToolAlpaca
	Collective Decision-Making	(Zhao et al., 2024c)	Code Link	MCQA
		(Cheng et al., 2024)	Code Link	ESConv dataset, P4G dataset
		(Liang et al., 2024)	Code Link	MT-Bench
		(Lei et al., 2024)	Code Link	MATH
		(Zhang et al., 2024a)	Code Link	MMLU, MATH, Chess Move Validity
		(Wang et al., 2024d)	Code Link	TriviaQA
	Self-Refine	(Wang et al., 2024c)	Code Link	FOLIO-wiki
		(Chen et al., 2024e)	Code Link	StrategyQA, CSQA, GSM8K, AQuA, MATH, Date Understanding, ANLI
		(Chen et al., 2024a)	Code Link	TriviaQA
		(Tang et al., 2024)	Code Link	Trans-Review,AutoTransform,T5-Review
		(Zhang et al., 2023a)	Code Link	Overcooked-AI
Communication Optimization	Speed Optimization	(Liu et al., 2024b)	No Code	HotpotQA,NarrativeQA,MultifieldQA
	Distributed	(Chen et al., 2024f)	Code Link	TriviaQA, Natural Questions, HotpotQA, 2WikiMultiHopQA
		(Liu et al., 2024a)	Code Link	InformativeBench

a small American town. At the same time, there was work on emotional propagation influence (Gao et al., 2023b), information cocoon room based on recommendation scenario research (Wang et al., 2024b), and study of social movements (Mou et al., 2024). Researchers propose Urban Generative Intelligence (UGI) (Xu et al., 2023a) to address specific urban issues and simulate complex urban systems, providing a multidisciplinary approach to understanding and managing urban complexity. Li et al. (2024a) study doctor agent evolution method by hospital simulation. Because doctor agent training is both inexpensive and highly effective, this work can quickly scale up the agent to handle tens of thousands of cases in just a few days, a task that would take a human doctor years to complete. Pan et al. (2024) propose a huge scale of agent simulation, increasing the number of agents to 10^6. In social game,like Werewolf (Xu et al., 2024) , Avalon (Lan et al., 2024) , and Minecraft (Gong et al., 2024) for MGAS simulation are attempted. Further, some game companies like Netease are also actively experimenting with MGAS in their games.

Physical domain. For the physical domain, the applications for generative agent simulation include mobility behaviors, transportation (Gao et al., 2023a), wireless networks, etc. However, there is limited research in the area of multi-generative agents. Zou et al. (2023) explore the application of multiple agents in the wireless field, proposing a framework where multiple on-device agents can interact with the environment and exchange knowledge to solve a complex task together.

4.2 Resources for MGAS simulation

We summarize common and open-source MGAS for simulation in Table 2, including code and benchmark.

To prove the effectiveness of the simulation, that is, to fit the reality, researchers usually evaluate the simulation system by simulating real data. Therefore, a realistic dataset with dense users and records is very important for evaluation simulation (Mou et al., 2024). An ideal dataset will be dense: that is, data with a smaller number of users on the same scale can better evaluate the simulation capability of the MGAS.

For Benchmark, Du and Zhang (2024) propose WWQA based on werewolf scenarios to evaluate the agent's capability in a werewolf scenario. SoMoSiMu-Bench (Mou et al., 2024) provides evaluation benchmarks focusing on individual user behavior and social simulation system results.

4.3 Evaluation of MGAS simulation

We will discuss the evaluation based on indicators used for assessing MGAS as a whole, rather than the capabilities of individual agents.

Consistency. MGASs necessitate a robust congruence with the real world to ensure the derivation of meaningful and insightful experimental outcomes. In the context of simulation systems, exemplified by UGI (Xu et al., 2023a), the primary objective lies in faithfully replicating specific real-world scenarios. When employed for training agents like SMART (Yue et al., 2024), only those agents that have undergone rigorous training within a virtual environment that closely mirrors the real environment can be deemed suitable for deployment in real-world settings. Similarly, when utilized for evaluation purposes, such as in AgentSims (Lin et al., 2023), the attainment of authentic and reliable evaluation results is contingent upon the virtual environment maintaining a high degree of consistency with its real-world counterpart. Finally, in the system for collecting data such as BOLAA (Liu et al., 2023c), consistency also ensures the validity of the data. Therefore, an important performance measure of MGAS is its consistency with the real situation.

Information dissemination. Compare the differences between information dissemination behavior in the system and reality using time series analysis methods. Information dissemination can to some extent reflect the nature of media; therefore, a realistic multi-agent system should have a similar information dissemination trend to the real world. Abdelzaher et al. (2020) compare the changes in the number of events occurring each day in an online social media simulation environment; S3 (Gao et al., 2023b) compare the number of users who are aware of a certain event every day, as well as the changes in emotional density and support rate for that event every day; a similar approach is also used in Stanford Town (Park et al., 2023).

Other specific attributes. It may be difficult to compare the distribution of system behavior directly, but the distribution of some system attributes can be easier to analyze statistically. In a virtual social media platform (Abdelzaher et al., 2020), the categories, quantities, average start times, and durations of events occurring in virtual systems and the real world were compared; the auction system (Chen et al., 2024c) studied the kernel density estimation map of commodity transaction prices; the virtual environment of the recommendation system (Wang et al., 2024b) compared the distribution of user ratings and favorite categories of products, as well as the activity level of agents; in the context of the Werewolf Killing mission, researchers (Xu et al., 2023c) compared the behavior distribution of agent players in specific scenarios.

5 MGASs for Evaluating Generative Agents

With LLMs prevailing in the community, how to evaluate the ability of LLMs is an open question. Existing evaluation methods suffer from the following shortcomings: (i) constrained evaluation abilities, (ii) vulnerable benchmarks, and (iii) unobjective metrics. The complexity and diversity of MGAS have indicated that MGAS can evaluate LLMs. However, how to design specific evaluation indicators and evaluation methods has puzzled researchers. Similarly, MGAS can also be used in training generative agents. We summarize three aspects of training: (i) Supervised Fine-Tuning (SFT) (ii) reinforcement learning (RL) (iii) Synthesizing data for training.

5.1 Representative MGASs for Evaluating Generative Agents

MGAS can provide rewards to agents, and these rewards can be used to evaluate or train generative agents, which will be discussed below.

Evaluation of generative agents. Researchers study generative agents by putting them into MGAS. In MGAS, researchers can further study the LLM's strategic capabilities in different scenes, such as long strategic ability (Chen et al., 2024c), leadership strategy (Xu et al., 2023c) and competitiveness strategy (Zhao et al., 2024b). In the emotional field, MuMA-ToM (Shi et al., 2024) is used to evaluate the ability of agents to understand and reason about human interactions in a real home environment through video and text descriptions.

Training on generative agents. Li et al. (2024c) enhance the data to Supervised Fine-Tuning (SFT) generative agents with MGAS. Xu et al. (2023c) have created generative agents to overcome the intrinsic bias from LLMs by proposing a novel framework that powers generative agents with multi-agent reinforcement learning (Xu et al., 2023c). For MGAS, Yue et al. (2024) split complex trajectories

Table 2: Codes and Benchmarks in MGAS for simulation studies. "No Code" or "No Benchmark" means the code or benchmark is unavailable.

Domain	Subdomain	Paper	Code	Dataset and Benchmark
Social	Tiny Society	(Huang et al., 2024b)	No Code	AdaSociety
		(Chen et al., 2024b)	Code Link	AgentCourt
		(Park et al., 2023)	Code Link	No Benchmark or Dataset
		(Piatti et al., 2024)	Code Link	No Benchmark
		(Chuang et al., 2024)	Code Link	No Benchmark or Dataset
	Economics	(Li et al., 2024b)	Code Link	No Benchmark or Dataset
	Social Media	(Wang et al., 2024b)	Code Link	Movielens-1M
		(Gao et al., 2023b)	No Code	Blog Authorship Corpus
		(Mou et al., 2024)	Code Link	SoMoSiMu-Bench(self)
	Game	(Du and Zhang, 2024)	Code Link	WWQA
		(Pan et al., 2024)	Code Link	No Benchmark or Dataset
Physical	Wireless	(Zou et al., 2023)	No Code	No Benchmark or Dataset

in knowledge-intensive tasks into subtasks, proposing a co-training paradigm of the multi-agent framework, Long- and Short-Trajectory Learning, which ensures synergy while keeping the fine-grained performance of each agent. RLHF has been criticized for its high cost. Liu et al. (2023a) propose an alignment scheme based on a multi-agent system, effectively addressing instability and reward gaming concerns associated with reward-based RL optimization. Either way, the MGAS is essentially viewed as an environment in RL with different ways of getting rewards from the environment.

5.2 Resources of MGAS for evaluations

Table 3 shows the work with code, dataset, and benchmark we summarize, serving as a reference for future researchers.

6 Challenges and Future Directions

While previous work on MGAS has obtained many remarkable successes, this field is still at its initial stage, and there are several significant challenges that need to be addressed in its development. In the following, we outline several key challenges along with potential future directions.

6.1 Challenges posed by generative agents

Generative agents are an integral part of MGAS. However, the generative agents have some shortcomings due to the inherent characteristics of the base model LLMs, which will be carefully discussed below.

Challenges. (i) Generalized alignment for simulation (Liu et al., 2023a). When the agents are leveraged for real-world simulation, a perfect generative agent should be able to depict diverse traits (Wang et al., 2024a) honestly. However, due to the training method of the foundation model (OpenAI et al., 2024), generative agents usually cannot be aligned with mock objects. (ii) Hallucination. Generative agents have a certain probability of hallucination in their interaction with other agents (Du et al., 2023). Various enhancement methods can alleviate this problem but cannot solve it (iii) Lack of sufficient long text capability. When processing complex information, generative agents forget the input information because of the lack of long-text ability (Zhao et al., 2024a).

Future directions. The improvement of the ability of a single agent or the ability of the base model has always been a hot topic. Researchers have focused on enhancing alignment, reducing hallucination, and improving the ability of long text. The proposal of the new generation of Open AI model o1 (Int, 2024), provides researchers with new ideas, that is, to use **more complex reasoning** to enhance the ability of the model.

6.2 Challenges posed by interactions

Due to the complexity, autoregressive, and other characteristics of MGAS, there are many problems in the practical application of the system. Two main problems, *Efficiency explosion*, and *Accumulative Effect*, are listed in the following.

Efficiency explosion. Due to their autoregressive architecture, LLMs typically have slow inference speeds. However, generative agents need to query LLMs for each action multiple times, such

Table 3: Codes and Benchmarks in MGAS for evaluation studies. "No Code" or "No Benchmark" means the code or benchmark is unavailable.

Domain	Subdomain	Paper	Code	Dataset and Benchmark
Evaluation of generative agents	Strategy	(Liu et al., 2023b)	Code Link	AGENTBENCH
		(Bandi and Harrasse, 2024)	No Code	MT-Bench
		(Chan et al., 2023)	Code Link	ChatEval
		(Chen et al., 2024d)	Code Link	LLMARENA
		(Xu et al., 2023b)	Code Link	MAgIC
		(Huang et al., 2024a)	Code Link	MLAgentBench
		(Chen et al., 2024c)	Code Link	AUCARENA
	Emotion	(Zhang et al., 2024b)	Code Link	PsySafe
		(Shi et al., 2024)	Code Link	MuMA-ToM
Training on generative agents	SFT on MGAS	(Li et al., 2024c)	Code Link	MT-Bench, AlpacaEval
	MARL on MGAS	(Xu et al., 2023c)	No Code	No dataset or benchmark
	Synthesized Ddata	(Liu et al., 2023a)	Code Link	HH, Moral Stories, MIC, ETHICS-Deontology, TruthfulQA

as extracting information from memory, making plans before taking actions, and so on. When the MGAS scales up, this problem will be magnified, especially for generative agents that have a large action space. SoMoSiMu-Bench (Mou et al., 2024) replaces the edge generative agents with rule-based agents, alleviating this problem. However, for MGAS with complex action apace in generative agents, this problem remains unsolved.

Accumulative Effect. Since each round of MGAS is based on the results of the previous round, and MGAS has no means of error correction, each error or error will have a great impact on the subsequent results. Researchers have used a rule-based model for intermediate error correction(Chen et al., 2024c), but there is still a lot of room for improvement. IOA (Chen et al., 2024f) proposed an Internet-like communication architecture, which made mGAS more scalable and enhanced the adaptability to dynamic tasks.

Future directions. Industry academia has been making efforts to reduce the communication cost of MGAS, such as alignment-based method OPTIMA (Chen et al., 2024g) and Industrialized parallel message method AgentScope (Gao et al., 2024), but it is still in the basic stage and has a large research space.

6.3 Challenges of Evaluating for MGAS

Lack of Objective metrics for group behavior. As shown in Section 4.3, due to the diversity, complexity, and unpredictability of multi-agent environments, it is difficult to obtain sufficiently detailed, specific, and direct system evaluation indicators from current work at the population level. At present, researchers mainly compare the distribution of the system and real environments to evaluate MGAS, which lacks details for the MGAS running process.

Automated evaluation and benchmark. Different MGAS of the same kind can not be compared because of the lack of a benchmark for MGAS. Further, There is a lack of a common benchmark framework for both individual and total-based evaluation, that can be used to evaluate most MGAS.

Future directions. Studying large-scale MGAS will be a new research hotspot, from which researchers will evaluate and discover new scale effects. In the meantime, common test benchmarks and evaluation methods will also emerge in future research.

7 Conclusion

In this survey, we systematically summarize existing research in the field of Multi-generative agent system (MGAS). We present and review these studies from three application aspects including task-solving, simulation, and evaluation of the MGAS. For each of these aspects, we provide a detailed taxonomy to draw connections among the existing research, summarizing the major techniques and their development histories. In addition to reviewing the previous work, we also propose several challenges in this field, which are expected to guide potential future directions.

Limitations

We have made our best effort, but some limitations may still exist. Due to page limitations, we can only provide a brief summary of each method without exhaustive technical details. On the other hand, we primarily collect studies from ∗ACL, NeurIPS, ICLR, AAAI, and arXiv, and there is a chance that we may have missed some important work published in other venues. In application, we primarily list representative MGAS resources with open code in Table 1, Table 2, and Table 3. More complete papers can be found in `https://github.com/bianhua-12/Multi-generative_Agent_System_survey`. We recognize the timeliness of our work, and we will stay abreast of discussions within the research community, updating opinions and supplementing overlooked work in the future.

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