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# AutoAgents: A Framework for Automatic Agent Generation

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## Abstract

Large language models (LLMs) have enabled remarkable advances in automated task-solving with multi-agent systems. However, most existing LLM-based multi-agent approaches rely on predefined agents to handle simple tasks, limiting the adaptability of multi-agent collaboration to different scenarios. Therefore, we introduce AutoAgents, an innovative framework that adaptively generates and coordinates multiple specialized agents to build an AI team according to different tasks. Specifically, AutoAgents couples the relationship between tasks and roles by dynamically generating multiple required agents based on task content and planning solutions for the current task based on the generated expert agents. Multiple specialized agents collaborate with each other to efficiently accomplish tasks. Concurrently, an observer role is incorporated into the framework to reflect on the designated plans and agents' responses and improve upon them. Our experiments on various benchmarks demonstrate that AutoAgents generates more coherent and accurate solutions than the existing multi-agent methods. This underscores the significance of assigning different roles to different tasks and of team cooperation, offering new perspectives for tackling complex tasks. The repository of this project is available at <https://github.com/Link-AGI/AutoAgents>.

## 1 Introduction

Large language models (LLMs) have exhibited astounding capabilities as versatile task-solving agents, endowed with a rich blend of knowledge and skills. Nevertheless, they still face difficulties [25, 21, 2] in tackling various tasks that require intensive knowledge and reasoning, such as avoiding hallucination [18], employing slow-thinking strategies [29], ensuring trustworthiness [30], and in combining diverse domain knowledge and long-horizon planning. In contrast, humans often exploit the benefits of collaborative problem solving, which enables them to work together effectively to solve non-routine problems in diverse domains and enhance the quality and reliability of the solutions by distributing the workload among specialties and applying a diversity of perspectives and expertise [20, 26, 1].

Inspired by collaborative problem solving, several recent works [32, 7, 16, 11] have improved the task-solving capabilities of LLMs by integrating multi-agent discussion. However, most of these multi-agent systems depend on handcrafted or user-specified agents, with specific roles and necessitating human supervision, which often restricts the scope of collaborative applications. Moreover, manually

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Table 1: Comparison of existing and proposed frameworks for LLM-based Agent framework.

Framework	Generate Agent Dynamically	Number of Agent	Multi-agent Conversation	Self-Refinement Agent	Collaborative Refinement Action
AutoGPT [10]	✗	1	✗	✓	✗
BabyAGI [19]	✗	3	✓	✗	✗
Generative Agents [22]	✗	25	✓	✓	✗
Camel [15]	✗	2	✓	✗	✗
GPT-bargaining [8]	✗	3	✓	✓	✗
MetaGPT [12]	✗	Unlimited	✓	✗	✗
AutoGen [35]	✗	Unlimited	✓	✗	✗
Social Simulacra [23]	✓	Unlimited	✓	✗	✗
Epidemic Modeling [33]	✓	Unlimited	✓	✗	✗
ExpertPrompting [36]	✓	1	✗	✗	✗
SSP [32]	✓	Unlimited	✓	✗	✗
AgentVerse [5]	✓	Unlimited	✓	✗	✗
<b>AutoAgents</b>	✓	Unlimited	✓	✓	✓

creating a large number of experts often consumes a lot of resources. In order to adaptively solve more complex problems, this paper aims to explore a method of adaptively generating task experts and completing different tasks through multi-level collaborative cooperation among multiple experts.

In this paper, we propose AutoAgents, an innovative framework that adaptively generates and coordinates multiple specialized agents to construct an AI team according to different tasks. Figure 1 provides a high-level overview of AutoAgents. By generating multiple agents with distinct expert roles, we aim to form a collaborative entity that can accomplish complex tasks by leveraging the complementary strengths of each agent. As shown in Figure 2, the process of AutoAgents is divided into two critical stages: **Drafting Stage** and **Execution Stage**. The drafting stage involves a collaborative discussion among three predefined agents (**Planner**, **Agent Observer**, and **Plan Observer**) to synthesize a customized agent team and an execution plan that suit the input problem or task. The execution stage refines the plan through inter-agent collaboration and feedback, and produces the final outcome. We propose self-refinement by individual agents and collaborative refinement by multiple agents to enhance agent proficiency and promote knowledge-sharing among agents. To facilitate the specific division of labor among the agents in the synthesized team, we introduce a predefined agent (**Action Observer**) to assist the agent team in sharing information, coordinating actions, reaching consensus, and adapting to the environment.

To synthesize heterogeneous information from diverse domains is often a crucial requirement in creative industries and other real-world scenarios. We illustrate a concrete example of how AutoAgents tackles the challenging task of writing a novel about the awakening of artificial intelligence in Figure 1. The Story Planner and Researcher collaborate to devise the plot of the story with their respective expertise, while the Character Developer and Writer enrich the novel content through imagination based on the story. Moreover, we conduct quantitative experiments and case studies in complex tasks to demonstrate the effectiveness of AutoAgents. we also conduct a comprehensive analysis and demonstrate the importance of dynamic agents for handling complex tasks, the indispensability of self-refinement for proficient agents, and the effectiveness of collaborative conversation.

To summarize, this paper makes the following novel contributions: **First**, we propose AutoAgents, a novel framework that dynamically synthesizes and coordinates multiple expert agents to form customized AI teams for diverse tasks. **Second**, we conduct rigorous quantitative experiments on two challenging tasks and demonstrate that AutoAgents significantly improves both knowledge acquisition and reasoning ability in LLMs and outperforms other generated-agent frameworks. **Third**, we showcase AutoAgents' ability to adapt to complex tasks by applying it in various scenarios such as software development. **Finally**, we conduct a thorough investigation and reveal the importance of dynamic agents for accommodating complex tasks and the necessity of self-refinement for proficient agents, and the efficacy of collaborative conversation.

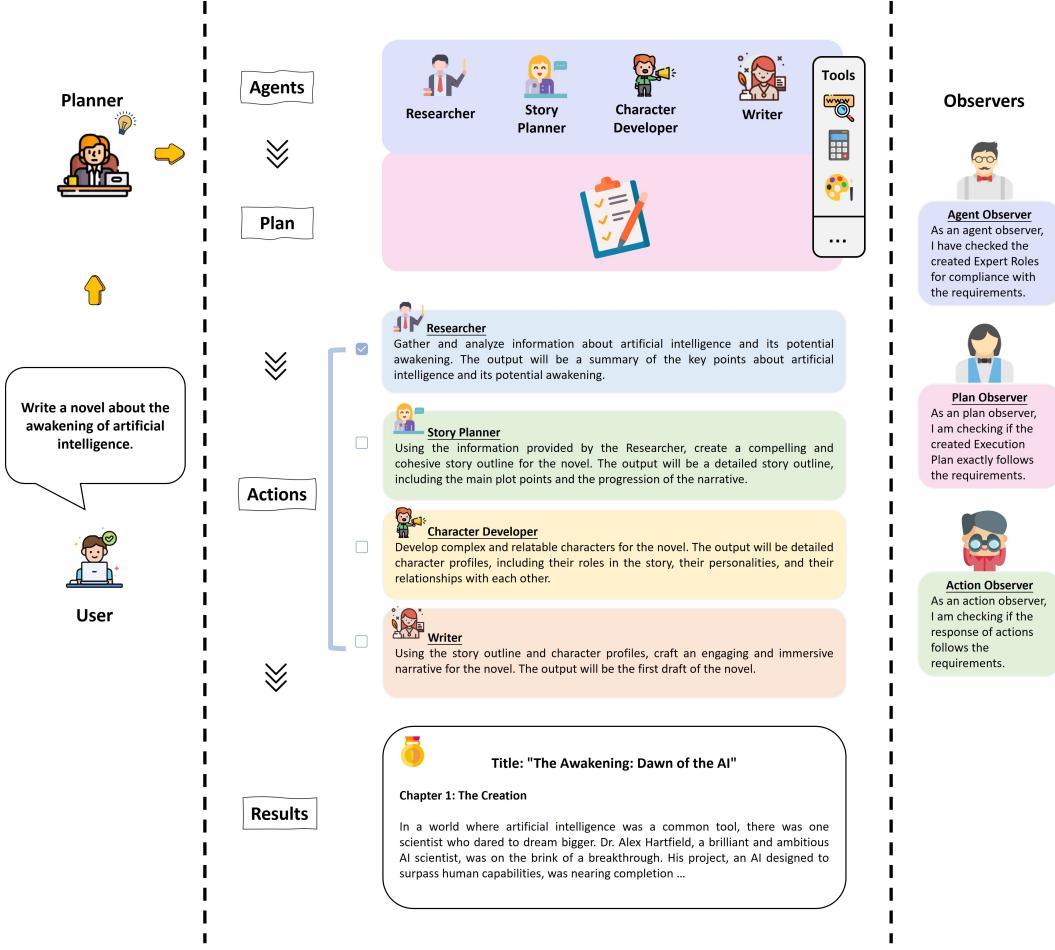


Figure 1: A schematic diagram of AutoAgents. The system takes the user input as a starting point and generates a set of specialized agents for novel writing, along with a corresponding execution plan. The agents collaboratively carry out the tasks according to the plan and produce the final novel. Meanwhile, an observer monitors the generation and execution of the Agents and the plan, ensuring the quality and coherence of the process.

## 2 Related Work

**LLM-based Autonomous Agents.** LLMs have been widely used as core controllers for autonomous agents that can accomplish specific objectives. Auto-GPT [10] is an early work that leverages an LLM as an AI agent that can autonomously achieve a given goal with the help of several tools. However, Auto-GPT does not support multi-agent collaboration and can only work in isolation. One way to enhance the task-solving capabilities of LLMs is to assign different roles and responsibilities to multiple LLMs and let them coordinate their actions to achieve a common goal. For example, BabyAGI [19] is an AI-powered task management system with multiple LLM-based agents. One agent creates new tasks based on the previous task's objective and result, another agent prioritizes the task list, and another agent completes tasks. BabyAGI is a multi-agent system with a fixed order of agent communication. MetaGPT [12] is a multi-agent framework for assigning different roles to GPTs to form a collaborative software entity for complex tasks. It is a specialized LLM-based multi-agent framework for collaborative software development. Camel [15] is an LLM-based communicative agent framework that demonstrates how role-playing can be used to enable chat agents to communicate with each other for task completion. However, Camel does not support tool-using. Several recent works [32, 7, 16, 11, 4, 28] have enhanced the task-solving capabilities of LLMs by integrating multi-agent discussion. For instance, [32] proposes a multi-agent debate system that allows LLMs to argue for or against a given claim and generate a debate summary. [7] introduce

a multi-agent dialogue system that enables LLMs to exchange information and opinions on a given topic and generate a dialogue report. AutoGen [35] is a framework that enables the development of LLM applications using multiple agents that can converse with each other to solve tasks. However, most of these multi-agent systems rely on handcrafted or user-specified agents with specific roles and do not support the automatic generation of agents, which often limits the scope of collaborative applications.

**Agent Generalization.** Several studies [23, 33] employ LLMs to generate agents for social simulacra and epidemic modeling, demonstrating how this technique can facilitate designers in assessing and improving their modeling designs prior to deploying them to real users. Likewise, ExpertPrompting [36] devised a method to generate diverse profiles of agents that can cooperate with human users to accomplish tasks with minimal supervision. However, this method still depends on a restricted set of predefined agents, and the generated agents vary only in their profiles, not in their problem-solving capacities. Recently, SSP [32] and AgentVerse [5] have proposed frameworks for automatically generating unlimited agents. SSP enables LLMs to generate agents for problem input by providing some agent samples, and has these agents solve the problem. AgentVerse generates the execution plan through the generated agents' discussions and adds evaluation strategies for cyclic execution. Unlike the previous two methods, AutoAgents pays more attention to the details of the generated agents and plans, and improves the efficiency of task execution by employing collaborative refinement actions and self-refinement agents, as illustrated in Table 1.

### 3 The Framework for Automatic Agent Generation

To enhance the effectiveness of autonomous multi-agent groups in accomplishing their goals, the process of AutoAgents consists of two critical stages: **Drafting Stage** and **Execution Stage**, as illustrated in Figure 2. The drafting stage synthesizes an agent team and an execution plan that are customized to the task by analyzing the input problem or task. The execution stage refines the plan by enabling inter-agent collaboration and feedback, and delivers the final result. The inter-agent collaboration is based on some principles of multi-agent cooperation, such as communication, coordination, and consensus. These principles help the agents to share information, align their actions, reach agreements, and adapt to the environment.

#### 3.1 Drafting Stage

Empirical evidence [34] suggests that diversity within human groups fosters diverse perspectives, which enhances the group's performance across various tasks. The drafting stage, which determines the composition of a multi-agent group, plays a crucial role in setting the upper limits of the group's capabilities. Therefore, it is imperative to generate the optimal agent team and execution plan that can maximize the group's potential.

Predominant methodologies [10, 12, 35] for assigning role descriptions to autonomous agents rely heavily on human intuition and prior knowledge, requiring manual assignment based on task understanding. Consistent with several parallel findings [36, 32, 5], dynamically designing agents with different roles can significantly enhance their efficacy. However, the scalability and rationality of agent and plan generation are still unclear, especially in the face of various complex problem environments.

On the one hand, the generated agents should exhibit diversity to accommodate various tasks. On the other hand, the agent and the plan generation should adhere to certain principles, rendering their role allocation more rational. Therefore, we devise three artificially predefined agents to produce agent teams and execution plans, integrating artificial prior knowledge and the dynamic adaptation capability of LLMs to generate more sensible agent teams and execution plans. The three artificially predefined agents comprise **Planner**, **Agent Observer**, and **Plan Observer**:

- **Planner**  $\mathcal{P}$  generates and refines an agent team and an execution plan based on the content of the task.
- **Agent Observer**  $\mathcal{O}_{agent}$  provides suggestions on the rationality of the agent team members and their matching degree with the task.
- **Plan Observer**  $\mathcal{O}_{plan}$  provides suggestions on the rationality of the execution plan and its matching degree with the task and the agent team.

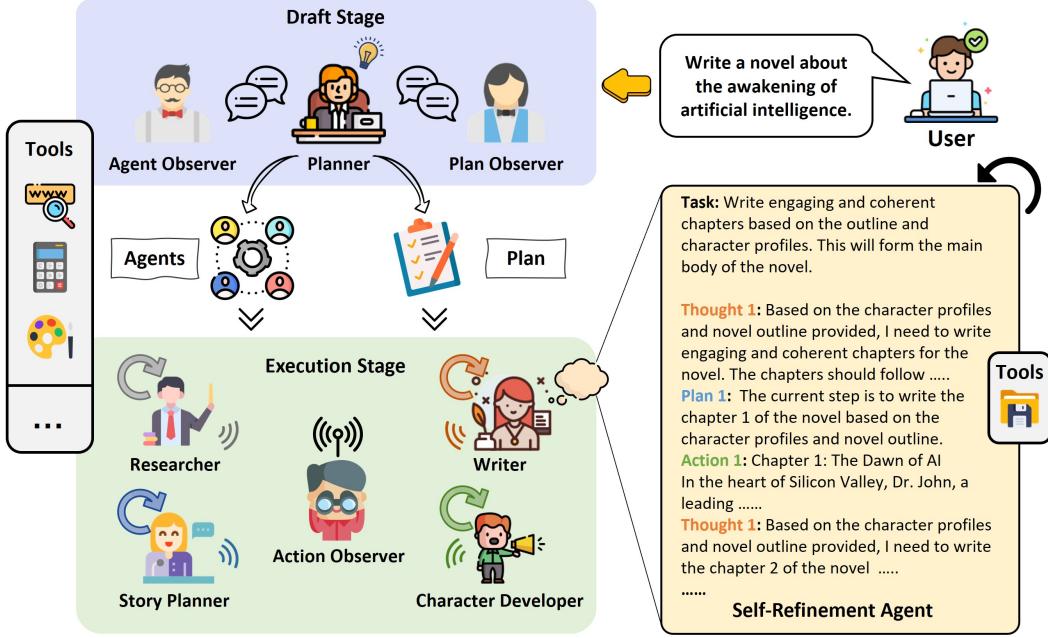


Figure 2: The execution process of AutoAgents. During the **Drafting Stage**, three predefined agents collaboratively determine the list of agents and the execution plan. During the **Execution Stage**, a predefined agent facilitates coordination and communication among the generated agent teams, and the individual generated agents enhance their execution efficiency through self-refinement.

The Planner generates initial agent team members and a specific plan, and improves the agent team and execution plan based on continuous communication with the Agent Observer and Plan Observer.

**Agent Generation.** The Planner generates the agent team and facilitates its continuous improvement through reciprocal communication with the Agent Observer. To enable Planner to produce rational agents, we have devised a standard format for the essential elements of a single agent. For each agent  $\mathcal{A} = \{P, D, T, S\}$ , the Planner needs to specify its prompt  $P$ , description  $D$ , toolset  $T$ , and suggestions  $S$ .

- **Prompt**  $P$  provides a detailed and customized depiction of the expert identity for each specific agent, which comprises profile, goal, and constraints. **Profile** reflects the domain expertise of the role or job title. **Goal** indicates the primary responsibility or objective that the role aims to achieve. **Constraints** specify limitations or principles the role must adhere to when performing actions.
- **Description**  $D$  gives additional concrete identity to help establish a more comprehensive role, develop an execution plan, and inspect problems.
- **Toolset**  $T$  equips the Agent with tools that it can use, selected from a predefined set of tools. The rationale for not using all the tools for each agent here is to prevent decision-making confusion caused by excessive tools.
- **Suggestions**  $S$  supplies some suggestions for each agent to execute the current task, including but not limited to a clear output, extraction of historical information, and suggestions for execution steps.

Based on the agent list  $\{\mathcal{A}_1, \mathcal{A}_2, \dots, \mathcal{A}_n\}$  generated by Planner, the Agent Observer evaluates the quality and suitability of each agent. The Agent Observer first verifies whether every agent conforms to the aforementioned specifications and identifies any missing elements  $\{P, \text{description } D, \text{toolset } T\}$ . Secondly, the Agent Observer assesses the compatibility of each agent with the task, according to their description information and task content. Finally, the Agent Observer examines the agent list for any redundant or missing roles and eliminates or adds them accordingly.

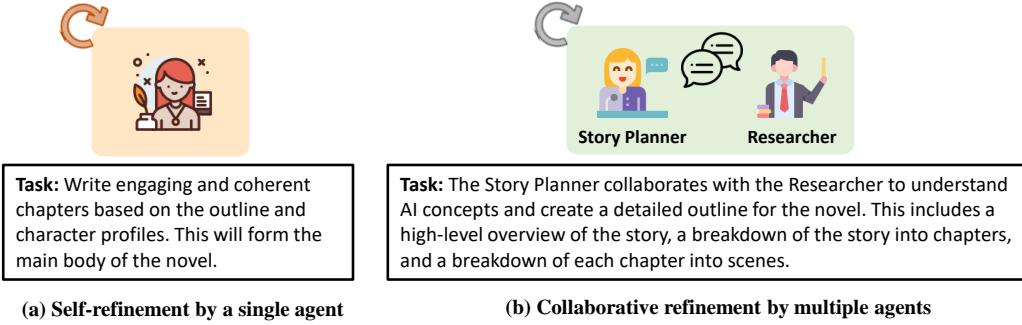


Figure 3: Two types of actions for executing tasks: **Self-refinement** enables an individual agent to enhance its competence in performing some specialized tasks. **Collaborative refinement** facilitates knowledge exchange among multiple agents and accomplishes tasks that demand interdisciplinary expertise.

After  $n$  rounds of bidirectional communication between the Planner and the Agent Observer, the optimal agent list for accomplishing the task is established. Given the vital role of the agent list in the task execution, this framework employs a predefined agent and multiple rounds of iterative dialogue among multiple agents to finalize the agent list, thereby enhancing the stability and reliability of the execution phase.

**Plan Generation.** In parallel to agent generation, the Planner formulates the execution plan and promotes its progressive improvement through reciprocal communication with the Plan Observer. For a given task, the Planner delineates the specific steps  $\{\mathcal{S}_1, \mathcal{S}_2, \dots, \mathcal{S}_n\}$  to accomplish it in the execution plan  $\mathcal{P}$ . Each step  $\mathcal{S}_i$  entails a clear identification of the agent  $\mathcal{A}_j$  responsible for it, as well as the input information and expected output required for it.

The Plan Observer subsequently validates the execution plan  $\mathcal{P} = \{\mathcal{S}_1, \mathcal{S}_2, \dots, \mathcal{S}_n\}$  according to the agent list  $\{\mathcal{A}_1, \mathcal{A}_2, \dots, \mathcal{A}_n\}$  and the task content. It firstly ensures that each step has a corresponding agent and that the step content is coherent and concise. It secondly assesses whether all the steps are sufficient, whether the task can be accomplished, and whether there are any gaps that need to be filled. It finally provides feedback to the Planner, who further refines the execution plan accordingly. After  $n$  rounds of dialogue between the Planner and the Plan Observer, the ultimate execution plan for achieving the task is established.

**Task Execution Actions.** The Planner devises an execution plan that automatically assigns the requisite agents for diverse tasks. The execution plan comprises two actions of task execution: self-refinement by a single agent and collaborative refinement by multiple agents, as shown in Figure 3. Self-refinement empowers an individual agent to augment its proficiency in accomplishing some specialized tasks. Collaborative refinement fosters knowledge sharing among multiple agents and achieves tasks requiring interdisciplinary expertise.

### 3.2 Execution Stage

In the drafting phase, the framework generates an agent list and an execution plan based on the task requirements. Then, the framework creates corresponding roles and executes the plans in the execution environment<sup>3</sup>. The communication and cooperation among multi-agent systems are essential for accomplishing the tasks effectively. This section elaborates on the communication among multiple agents, the task execution strategies, and the knowledge-sharing mechanisms.

**Communication of Multiple Agent.** The communication structures among agents have been investigated by many studies [5, 32, 24, 3] to examine their impact on task performance. In this framework, we adopt the vertical communication paradigm, which assigns different responsibilities to agents according to their roles. To facilitate the specific division of labor among the agents in the generated team, we introduce a predefined **Action Observer** as the team leader to coordinate the execution plan. Specifically,

<sup>3</sup>Execution environment of AutoAgents is built based on MetaGPT’s environment and workspace [12].

- **Action Observer**  $\mathcal{O}_{action}$  acts as the task manager for the different agents, allocating different tasks to them, verifying the execution outcomes of each agent, and dynamically adapting the execution plan based on the execution status.

This mechanism of refinement and communication recurs until the Action Observer attains a unanimous agreement on the execution responses, or the process reaches its maximum iteration limit. For scenarios that demand iterative decision-making towards specific objectives, such as software development, vertical communication would be a preferable option.

**Self-refinement Agent.** Besides the inter-agent communication, the performance of a single agent also exerts a significant impact on the overall quality of feedback results. Hence, drawing on mechanisms such as AutoGPT [10] and ReAct [38], we have devised a self-refinement mechanism for an individual agent.

For a single agent  $\mathcal{A}$ , the action at step  $t$  is at  $a_t = l_t \cup p_t \cup o_t$ , where  $l_t$ , where  $l_t$  denotes the *thought* or the *reasoning trace* in the language space, which does not alter the external environment, and thus yields no observational feedback,  $p_t$  represents the execution plan for better task completion,  $o_t$  comprises the completion steps and execution output for this time.

As illustrated in Figure 2, various types of useful thoughts can assist in devising a refinement plan. The execution plan enables the agent to anticipate the steps they need to undertake in the future, and the observational content of the execution result construction allows the agent to reevaluate and enhance the plan arrangement, thereby constructing more refined and complete actions. Through a cycle of self-continuous thinking, planning, execution, and feedback, a single agent can effectively execute and accomplish task content.

**Collaborative Refinement Action.** In the collaborative refinement action, the agents collaboratively refine and execute the tasks in a sequential manner. Each round of the collaboration involves a fixed order of turn-taking among the agents, who generate their responses based on the current observation. The chat history slot of each agent is updated by concatenating the previous utterances of the other agents. The collaboration terminates automatically when the agents reach a consensus or the maximum number of discussions is reached.

**Knowledge Sharing Mechanism.** AutoAgents also facilitates the sharing of execution results among various agents for improved communication and feedback. However, when the number of agents is large and a single agent has more self-iterations, it will generate more historical information. Due to the token limitation of LLM models, they often cannot encompass all information. Hence, this framework provides short-term memory, long-term memory, and dynamic memory based on agent units.

*Short-term memory* primarily focuses on a single agent and encompasses intermediate ideas, plans, and execution results generated during the self-refinement process of an individual agent. It is noteworthy that the self-refinement of a single agent often culminates in a summary of vital information in the final step of the self-refinement process.

*Long-term memory* mainly targets the communication between multiple agents, chiefly recording the tasks executed by an individual agent and the summary of crucial feedback information. This is essential for assessing the overall degree of task completion.

*Dynamic memory* mainly caters to agents with special needs. The Action Observer can access all short-term and long-term memories, dynamically extracting supplementary information from short-term and long-term memories based on the information required by the agent to execute tasks, aiding in enhancing the task execution efficiency of a single agent.

## 4 Experiments

In order to demonstrate the capabilities and performance of AutoAgents in orchestrating autonomous agent groups to collaboratively accomplish tasks, we have performed extensive quantitative experiments on benchmark tasks and thorough case studies on more complex and realistic applications. In the quantitative analysis, we mainly present results for the **Open-ended Question Answer** task (detailed in Section 4.1) and the **Trivia Creative Writing** task (detailed in Section 4.2) to evaluate the framework effectiveness under distinct settings. The **Case Studies**, discussed in Section 4.3, illustrate the potential of a multi-agent group tackling intricate practical scenarios cooperatively.

**Implementation Details:** We conduct all experiments using the GPT-4 API<sup>4</sup> and set the temperature to 0 to ensure reproducibility. The rationale behind this selection is the exceptional performance these models offer, providing more accurate and standardized output. Additionally, their accessibility and ease of use through APIs enable us to directly call and interact with the models during our research, significantly simplifying the process. The maximum number of discussions during the drafting phase is 3, and the maximum number of self-refinement by a single agent and collaborative refinement by multiple agents during the execution phase is 5.

#### 4.1 Open-ended Question Answer

**Task Description.** Open-ended Question Answering is a crucial and challenging task in the domain of NLP and generative AI. It requires an AI system to produce coherent, elaborate, and human-like responses to questions that have no predetermined or fixed set of possible answers. [40] proposed MT-bench, a benchmark consisting of 80 high-quality collected open-ended questions from various categories such as common sense, counterfactual, coding, etc. We then utilize AutoAgents to produce collaborative answers based on multiple generated agents and compare them with the responses given by **Vicuna-13B**, **ChatGPT**, and **GPT-4**.

Table 2: Win Rate of AutoAgents over other models on Open-ended Question Answer, with FairEval [31] and HumanEval serving as evaluators.

Evaluator	v.s. ChatGPT	v.s. Vicuna-13B	v.s. GPT-4
FairEval [31]	96.3%	96.3%	76.3%
HumanEval	75%	75%	62.5%

**Evaluation Metrics.** To measure the quality of open-ended responses with minimal evaluation bias, we adopt **FairEval** [31] and **HumanEval** as the evaluation metrics for both the single agent and AutoAgents. FairEval incorporates several methods to mitigate the impact of various sources of bias, resulting in a better alignment with human judgment. For **HumanEval**, we enlist several volunteers to rate the responses from different models based on their helpfulness, reliability, accuracy, and level of detail.

**Results.** Table 2 demonstrates that AutoAgents outperforms individual LLM models in both FairEval based on LLM and Human evaluations. AutoAgent can produce more comprehensive and nuanced answers to open questions by synthesizing multiple expert models. It can also provide more elaborate explanations and justifications for its answers. More examples are given in the Appendix 4.4.

#### 4.2 Trivia Creative Writing

**Task Description.** The Trivia Creative Writing task [32] challenges the capabilities of large language models to retrieve and integrate diverse information from their internal self-compressed knowledge. This task requires a model to craft a coherent story around a given topic while incorporating the answers to  $N$  trivia questions. We evaluate the models under two settings,  $N = 5$  and  $N = 10$ , where a higher  $N$  entails more trivia questions and thus demands the model to exhibit more extensive domain knowledge. We constructed a benchmark consisting of 100 instances for each  $N$ , encompassing a total of 1000 trivia questions.

**Evaluation Metrics.** Drawing on the approach of [32], we adopt an automatic metric to identify factual errors and measure a model’s capacity to integrate diverse domain knowledge. We conduct string matching with the veridical target answers for each question on the generated output. The target answers are supplied from the TriviaQA dataset [14], and each question can have a list of answer variants. A match to any of the answer variants of a question is regarded as a correct mention. The metric score is calculated as Trivia Creative Writing Metric Score = # correct answer mentions / # trivia questions.

**Results.** Table 3 demonstrates the superior performance of AutoAgents in knowledge acquisition over the existing methods. Compared to the Standard method, which does not employ Agent Generation, AutoAgents achieves a remarkable 10% improvement across all experiments. Moreover, AutoAgents

<sup>4</sup>The specific model version employed is “GPT-4-0613”.

Table 3: The results of Trivia Creative Writing task.  $\Delta$  indicates the differences compared with Standard Prompting (first row).

Methods	N (# trivia questions) = 5		N (# trivia questions ) = 10	
	Score (%)	$\Delta$ (v.s Standard %)	Score (%)	$\Delta$ (v.s Standard %)
Standard	74.6	0.0%	77.0	0.0%
CoT [37]	67.1	-10.0%	68.5	-11.1%
SPP-Profile [32]	79.1	+5.9%	83.0	+7.8%
SPP [32]	79.9	+7.1%	84.7	+10.0%
<b>AutoAgents</b>	<b>82.0</b>	<b>+9.9%</b>	<b>85.3</b>	<b>+10.8%</b>

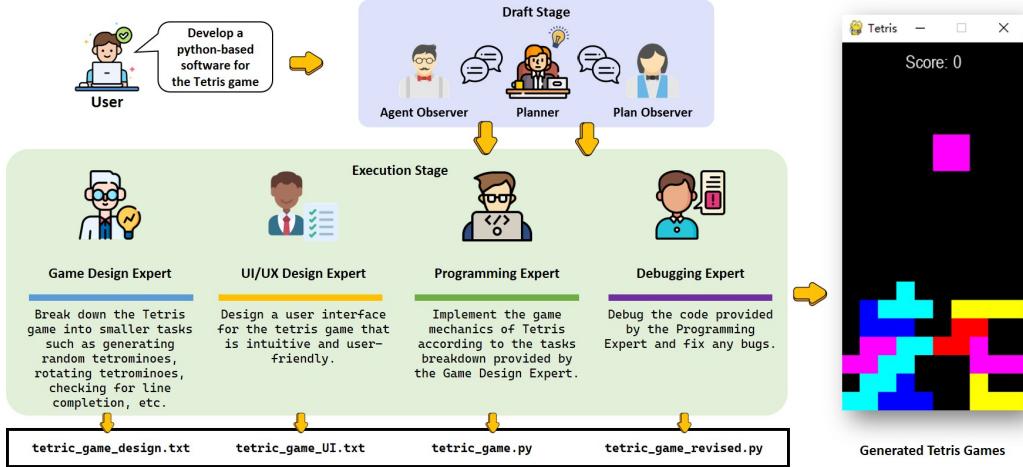


Figure 4: The illustration of an example process of software development. The task is to *develop Python-based software for the Tetris game*.

also surpasses SSP [32], which utilizes agent generation but with a different approach. The enhanced performance of AutoAgents can be attributed to its elaborate methods of agent generation discussions and task execution including collaborative refinement and self-refinement. More examples are given in the Appendix 4.4.

### 4.3 Case Study

To demonstrate the applicability of AutoAgents to more sophisticated and realistic scenarios, we conduct a case study in the software engineering domain. Software engineering is a complex collaborative endeavor that involves diverse roles and responsibilities. From developers who create the underlying code, to UI designers who prioritize user experience, and software testers who ensure the software's quality, experts collaboratively work to enhance and refine the application, ensuring that it meets both functional and user-centric criteria.

As an illustration in Figure 4, a Tetris game has been developed by employing AutoAgents, which has generated various expert roles, such as game design expert, UI design expert, programmer, and debugging expert, to accomplish the game development task. The game design experts provide the game logic documents that specify the rules and mechanics of the game. The UI design experts design the UI components that create the visual interface of the game. The programmers implement the game design based on the aforementioned documents and use appropriate programming languages and tools. Finally, the debugging expert tests the game and debugs the program to ensure its functionality and quality. The game development process is based on the collaboration of multiple expert roles, with more elaborate documentation and programs, making it easier for users to comprehend.

### 4.4 Further Analysis

**Collaborative discussion is crucial for rational agent generation and plan allocation.** During the Drafting Stage, the Planner in AutoAgents engages in collaborative discussions with two Observers to

determine the optimal list of agents and the execution plan. Figure 5 illustrates the contrast between agent generation with and without collaborative discussion. In the absence of Observer feedback, the Planner tends to generate programmers exclusively to accomplish game development, neglecting the holistic process of game creation. With the input and coordination of the Observers, the Planner incorporates game design experts, UI design experts, and testing experts into the agent list. It is evident that the agent generation under collaborative discussions is more comprehensive and more aligned with the realistic scenarios of game development. This also corroborates the significance of collaborative discussions for agent generation and plan allocation, which will subsequently influence the execution outcomes.

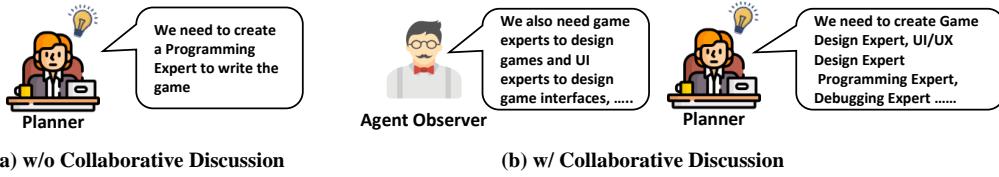


Figure 5: Comparison of whether there is a collaborative discussion in the Drafting Stage in the task that *developing Python-based software for the Tetris game*.

**Enhancing single-agent and multi-agent collaboration through refinement.** Self-Refinement [17, 27, 9, 6, 13, 39] is a technique that enables LLMs to “converse” with themselves, evaluate their own generation, and iteratively improve their answers. Self-refinement has been shown to enhance the accuracy of LLMs’ outputs in various domains [17, 27, 9, 6, 13, 39]. Although AutoAgents is a framework for multi-agent collaboration, it also requires self-refinement agents to perform specialized roles for individual tasks. Figure 1 depicts the self-refinement process of programmers’ coding. They first write a pseudo code file and then generate the corresponding program files based on it. This refinement process significantly ensures the validity of the output file. For collaborative refinement, the process resembles the collaborative dialogue mentioned above, which involves integrating knowledge from different domains to accomplish tasks that demand cross-domain knowledge fusion. In summary, refinement is vital for both self-correction and collaborative communication.

**Dynamic agents enhance the adaptability of complex tasks.** The ability to generate dynamic agents for various tasks is crucial for enhancing their adaptability to diverse scenarios. Figure 7 illustrates the contrast between GPT4 and AutoAgents' responses to open-ended questions. Unlike GPT-4, AutoAgents can produce agents from three distinct domains, which can provide more elaborate answers. For the trivia creative writing task in Figure 8 and 9, AutoAgents decomposed the task into four steps: first, it retrieved the answer to the question through a domain-specific agent and then constructed the story. Meanwhile, it is evident that the Language Expert Agent performed multiple checks on the coherence between the story content and the question, ensuring the accuracy of the story content. These examples all demonstrate the versatility of building a dynamic agent generation framework for complex tasks.

## 5 Discussion

**Limitations.** AutoAgents exhibit remarkable knowledge acquisition and adaptability in tackling complex tasks, but they are not flawless. One of the limitations is that they may still produce erroneous outcomes even with dynamic role generation. This could be ascribed to the rationality of role generation and planning arrangements. Although this framework employs collaborative discussions to enhance the quality of role generation and planning arrangements, it still necessitates a more effective method for recruiting teams and devising plans, and further ameliorates the quality of role generation and planning arrangements.

Furthermore, the differences between different roles in this framework mainly hinge on variations in prompt and tool usage, but this does not accentuate the distinctions between different expert roles. In the future, it is imperative to explore how to incorporate more expert knowledge and create more professional role agents, in order to improve the adaptability of professional agents to professional problems.

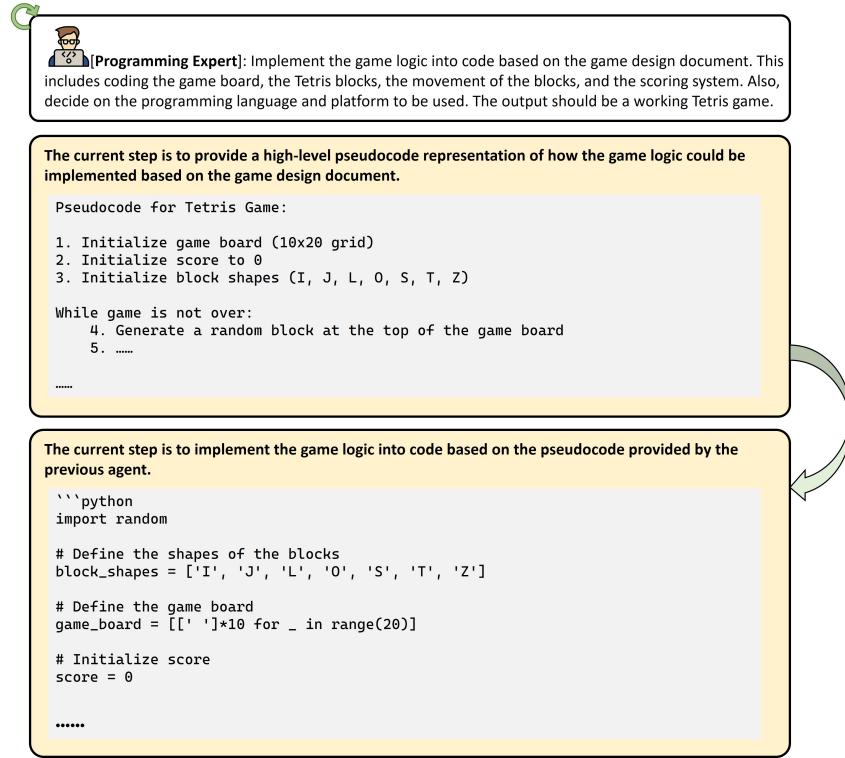


Figure 6: An example of the Open-ended Question Answer.

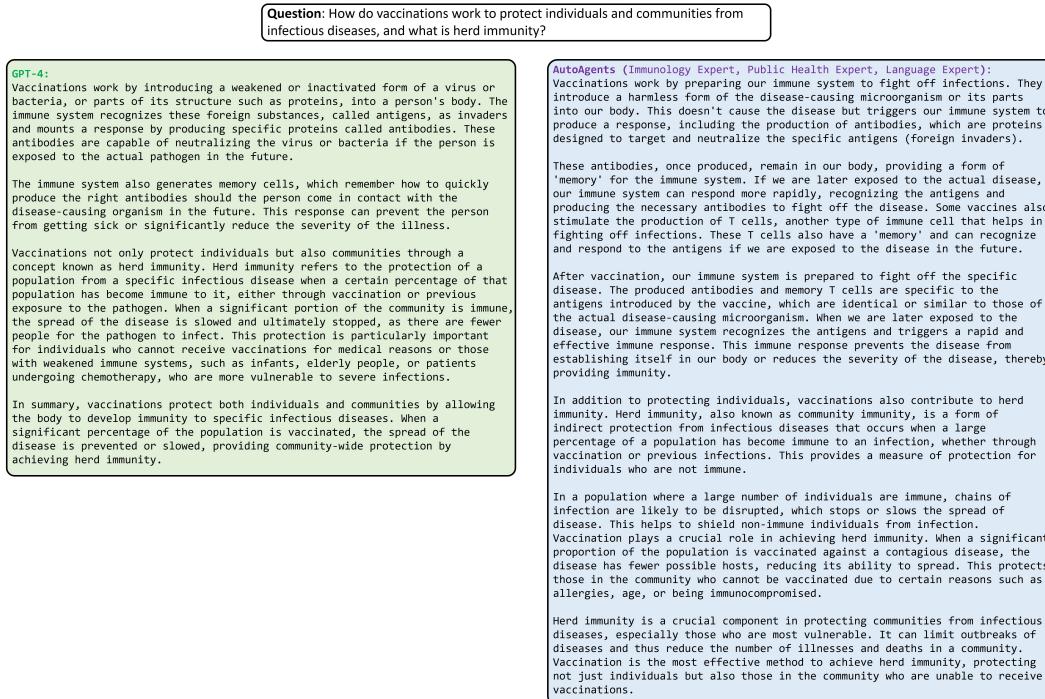


Figure 7: An example of the Open-ended Question Answer.

**Question:** Write a short and coherent story about Lion King that incorporates the answers to the following 5 questions: On what date in 1969 did Neil Armstrong first set foot on the Moon? Who had a 60s No 1 with Downtown? Who set fire to his guitar at the Monterey Pop festival in 19676? Della Street was whose secretary? In music, who was Sweet and Innocent and Too Young?

#### Generated Agents



Historical Facts Expert



Storytelling Expert



Language Expert

#### Execution Plan

- [Historical Facts Expert]: Conduct research or use your knowledge to provide accurate and concise answers to the five questions: On what date in 1969 did Neil Armstrong first set foot on the Moon? Who had a 60s No 1 with Downtown? Who set fire to his guitar at the Monterey Pop festival in 19676? Della Street was whose secretary? In music, who was Sweet and Innocent and Too Young? The expected output is a list of answers to the five questions.
- [Storytelling Expert]: Using the answers provided by the Historical Facts Expert, plan how to incorporate these facts into a short and coherent story about Lion King. Then, write the story. The expected output is a draft story.
- [Language Expert]: Review the story created by the Storytelling Expert. Ensure that the story is grammatically correct, coherent, and engaging. If there are any errors or areas for improvement, revise the story accordingly. The expected output is the final story.
- [Language Expert]: Based on the previous steps, please provide a helpful, relevant, accurate, and detailed response to the user's original question: Write a short and coherent story about Lion King that incorporates the answers to the following 5 questions: On what date in 1969 did Neil Armstrong first set foot on the Moon? Who had a 60s No 1 with Downtown? Who set fire to his guitar at the Monterey Pop festival in 19676? Della Street was whose secretary? In music, who was Sweet and Innocent and Too Young?

[Historical Facts Expert]: Conduct research or use your knowledge to provide accurate and concise answers to the five questions: On what date in 1969 did Neil Armstrong first set foot on the Moon? Who had a 60s No 1 with Downtown? Who set fire to his guitar at the Monterey Pop festival in 19676? Della Street was whose secretary? In music, who was Sweet and Innocent and Too Young? The expected output is a list of answers to the five questions.

1. Neil Armstrong first set foot on the Moon on July 20, 1969.
2. Petula Clark had a 60s No 1 with "Downtown".
3. Jimi Hendrix set fire to his guitar at the Monterey Pop festival in 1967. (Please note there seems to be a typo in the year in the question)
4. Della Street was Perry Mason's secretary.
5. Donny Osmond was known for the songs "Sweet and Innocent" and "Too Young".

[Storytelling Expert]: Using the answers provided by the Historical Facts Expert, plan how to incorporate these facts into a short and coherent story about Lion King. Then, write the story. The expected output is a draft story.

Once upon a time in the Pride Lands, Simba, the young lion prince, was listening to the wise baboon Rafiki. Rafiki was telling Simba about the great events that happened in the human world.

"Simba," Rafiki began, "Did you know that on July 20, 1969, a man named Neil Armstrong first set foot on the Moon? Just like you, he was a pioneer, stepping into the unknown."

Rafiki's eyes widened in awe. He then asked Rafiki about music in the human world. Rafiki chuckled and said, "Ah, music! There was a lady named Petula Clark who had a hit song called 'Downtown' in the 60s. It was as popular in the human world as the Circle of Life is in ours."

Rafiki then told Simba about a man named Jimi Hendrix who set fire to his guitar at a festival in 1967. "He was as fiery and passionate as Scar is cunning and ruthless," Rafiki said.

Simba was intrigued by these stories. He asked Rafiki if there were any stories about loyalty and dedication. Rafiki nodded and told him about Della Street, who was a loyal secretary to a man named Perry Mason. "Just like Zazu is to your father, Mufasa," Rafiki added.

Finally, Rafiki told Simba about a young man named Donny Osmond who was known for the songs "Sweet and Innocent" and "Too Young". "Just like you, Simba. You are sweet, innocent, and too young. But one day, you will grow up to be a great king," Rafiki said.

And so, Simba learned about the human world and its history. These stories inspired him and helped him understand the importance of courage, passion, loyalty, and innocence.

Figure 8: (Page 1) An example of the Trivia Creative Writing task.



**[Language Expert]:** Review the story created by the Storytelling Expert. Ensure that the story is grammatically correct, coherent, and engaging. If there are any errors or areas for improvement, revise the story accordingly. The expected output is the final story.

Upon reviewing the story, I found it to be grammatically correct, coherent, and engaging. The Storytelling Expert has successfully incorporated the historical facts into the story about the Lion King. The story flows well and the use of facts adds to the story rather than detracting from it. Therefore, no revisions are necessary. Here is the final version of the story:

Once upon a time in the Pride Lands, Simba, the young lion prince, was listening to the wise baboon Rafiki. Rafiki was telling Simba about the great events that happened in the human world.

"Simba," Rafiki began, "Did you know that on July 20, 1969, a man named Neil Armstrong first set foot on the Moon? Just like you, he was a pioneer, stepping into the unknown."

Simba's eyes widened in awe. He then asked Rafiki about music in the human world. Rafiki chuckled and said, "Ah, music! There was a lady named Petula Clark who had a hit song called 'Downtown' in the 60s. It was as popular in the human world as the Circle of Life is in ours."

Rafiki then told Simba about a man named Jimi Hendrix who set fire to his guitar at a festival in 1967. "He was as fiery and passionate as Scar is cunning and ruthless," Rafiki said.

Simba was intrigued by these stories. He asked Rafiki if there were any stories about loyalty and dedication. Rafiki nodded and told him about Della Street, who was a loyal secretary to a man named Perry Mason. "Just like Zazu is to your father, Mufasa," Rafiki added.

Finally, Rafiki told Simba about a young man named Donny Osmond who was known for the songs "Sweet and Innocent" and "Too Young". "Just like you, Simba. You are sweet, innocent, and too young. But one day, you will grow up to be a great king," Rafiki said.

And so, Simba learned about the human world and its history. These stories inspired him and helped him understand the importance of courage, passion, loyalty, and innocence.



**[Language Expert]:** Based on the previous steps, please provide a helpful, relevant, accurate, and detailed response to the user's original question: Write a short and coherent story about Lion King that incorporates the answers to the following 5 questions: On what date in 1969 did Neil Armstrong first set foot on the Moon? Who had a 60s No 1 with Downtown? Who set fire to his guitar at the Monterey Pop festival in 1967? Della Street was whose secretary? In music, who was Sweet and Innocent and Too Young?

After reviewing the story, I found it to be grammatically correct, coherent, and engaging. The Storytelling Expert has done an excellent job of incorporating the historical facts into the story about Lion King. The story flows well, and the use of the facts is done in a way that adds to the story rather than detracting from it. Therefore, no revisions are necessary. Here is the final story:

Once upon a time in the Pride Lands, Simba, the young lion prince, was listening to the wise baboon Rafiki. Rafiki was telling Simba about the great events that happened in the human world.

"Simba," Rafiki began, "Did you know that on July 20, 1969, a man named Neil Armstrong first set foot on the Moon? Just like you, he was a pioneer, stepping into the unknown."

Simba's eyes widened in awe. He then asked Rafiki about music in the human world. Rafiki chuckled and said, "Ah, music! There was a lady named Petula Clark who had a hit song called 'Downtown' in the 60s. It was as popular in the human world as the Circle of Life is in ours."

Rafiki then told Simba about a man named Jimi Hendrix who set fire to his guitar at a festival in 1967. "He was as fiery and passionate as Scar is cunning and ruthless," Rafiki said.

Simba was intrigued by these stories. He asked Rafiki if there were any stories about loyalty and dedication. Rafiki nodded and told him about Della Street, who was a loyal secretary to a man named Perry Mason. "Just like Zazu is to your father, Mufasa," Rafiki added.

Finally, Rafiki told Simba about a young man named Donny Osmond who was known for the songs "Sweet and Innocent" and "Too Young". "Just like you, Simba. You are sweet, innocent, and too young. But one day, you will grow up to be a great king," Rafiki said.

And so, Simba learned about the human world and its history. These stories inspired him and helped him understand the importance of courage, passion, loyalty, and innocence.

Figure 9: (Page 2) An example of the Trivia Creative Writing task.

Currently, AutoAgents rely heavily on the powerful logical and textual capabilities of GPT-4, and their adaptability to some earlier LLMs is poor. In the future, it is essential to explore more reasonable prompts to improve the adaptability of AutoAgents to different LLMs.

**Future Work.** Cooperation among multiple agents requires dynamic adaptation and communication. The initial plan generated by LLMs may not suffice to achieve the desired outcomes, resulting in erroneous final output results. Hence, future multi-agent systems need to swiftly detect and rectify errors and adjust their plans dynamically to align with the desired outcomes.

The memory capacity of existing agents is limited by the number of tokens in LLMs. How to devise a high-quality memory mechanism that enables efficient retrieval and storage of memory by agents remains an open question.

The professional skills of the generated agents are effective, but they can be improved by retraining or other mechanisms. Alternatively, an Agent Bank can be established to enable the invocation of professional agents on demand. More professional agent construction is still worthy of exploration.

## 6 Conclusion

This paper introduces AutoAgents, an innovative framework for automatically synthesizing collaborative specialized agents. AutoAgents mimics the collaborative process of human teams by decomposing tasks into drafting and execution phases and delegating different subtasks to different agents. Our experimental and empirical evaluation validates the advantages of AutoAgents, as it surpasses single agents and other groupings in various tasks that demand diverse skills. Furthermore, our case study in software development illustrates the versatility and potential benefits of our proposed framework. AutoAgents opens up new possibilities for enhancing the interaction and cooperation among agents and transforms the landscape of complex problem-solving. We envisage that its principles can be further generalized and refined to deal with a broader range of tasks, paving the way towards more useful assistive Artificial Intelligence.

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