



INTERNET OF AGENTS: WEAVING A WEB OF HETEROGENEOUS AGENTS FOR COLLABORATIVE INTELLIGENCE

Weize Chen^{1*}, Ziming You², Ran Li¹, Yitong Guan², Chen Qian¹, Chenyang Zhao¹
 Cheng Yang³, Ruobing Xie⁴, Zhiyuan Liu^{1✉}, Maosong Sun¹

¹ Tsinghua University, ² Peking University

³ Beijing University of Posts and Telecommunications, ⁴ Tencent
 chenwz21@mails.tsinghua.edu.cn, r1759@nau.edu
 {zimingyou, 2101210206}@stu.pku.edu.cn
 liuzy@tsinghua.edu.cn

ABSTRACT

The rapid advancement of large language models (LLMs) has paved the way for the development of highly capable autonomous agents. However, existing multi-agent frameworks often struggle with integrating diverse capable third-party agents due to reliance on agents defined within their own ecosystems. They also face challenges in simulating distributed environments, as most frameworks are limited to single-device setups. Furthermore, these frameworks often rely on hard-coded communication pipelines, limiting their adaptability to dynamic task requirements. Inspired by the concept of the Internet, we propose the Internet of Agents (IoA), a novel framework that addresses these limitations by providing a flexible and scalable platform for LLM-based multi-agent collaboration. IoA introduces an agent integration protocol, an instant-messaging-like architecture design, and dynamic mechanisms for agent teaming and conversation flow control. Through extensive experiments on general assistant tasks, embodied AI tasks, and retrieval-augmented generation benchmarks, we demonstrate that IoA consistently outperforms state-of-the-art baselines, showcasing its ability to facilitate effective collaboration among heterogeneous agents. IoA represents a step towards linking diverse agents in an Internet-like environment, where agents can seamlessly collaborate to achieve greater intelligence and capabilities. Our codebase has been released at <https://github.com/OpenBMB/IoA>.

1 INTRODUCTION

The Internet has revolutionized the way people collaborate and share knowledge, connecting individuals with diverse skills and backgrounds from all around the world. This global network has enabled the creation of remarkable collaborative projects, such as Wikipedia¹ and the development of the Linux operating system², which would have been impossible for any single person to achieve. The Internet has greatly facilitated collaboration among people, making the impossible possible and pushing the boundaries of human achievement.

The success of the Internet in enabling human collaboration raises an intriguing question: can we create a similar platform to facilitate collaboration among autonomous agents? With the rapid advancements in LLMs (OpenAI, 2023; Reid et al., 2024), we now have autonomous agents capable of achieving near-human performance on a wide range of tasks. These LLM-based agents have demonstrated the ability to break down complex tasks into executable steps, leverage various tools, and learn from feedback and experience (Qin et al., 2023; Wang et al., 2023c; Shinn et al., 2023;

*Equal Contribution. ✉ Corresponding author.

¹<https://www.wikipedia.org/>

²<https://www.linux.org/>

Qian et al., 2023b). As the capabilities of these agents continue to grow, and with an increasing number of third-party agents with diverse skills consistently emerging (Chase, 2022; Team, 2023; Significant Gravitas, 2023; Open Interpreter, 2023), it is crucial to explore how we can effectively and efficiently orchestrate their collaboration, just as the Internet has done for humans.

To address this challenge, we propose the concept of the Internet of Agents (IoA), a general framework for agent communication and collaboration inspired by the Internet. IoA aims to address three fundamental limitations of existing multi-agent frameworks (Chen et al., 2023; Wu et al., 2023; Hong et al., 2023; Qian et al., 2023a): (1) **Ecosystem Isolation**: Most frameworks only consider agents defined within their own ecosystems, potentially blocking the integration of various third-party agents and limiting the diversity of agent capabilities and the platform’s generality; (2) **Single-Device Simulation**: Nearly all multi-agent frameworks simulate multi-agent systems on a single device, which differs significantly from real-world scenarios where agents could be distributed across multiple devices located in different places; (3) **Rigid Communication and Coordination**: The communication process, agent grouping, and state transitions are mostly hard-coded, whereas in real life, humans decide on teammates based on the task at hand and dynamically switch between discussion and task assignment or execution.

To overcome these limitations, we propose an agent integration protocol that enables different third-party agents running on different devices to be seamlessly integrated into the framework and collaborate effectively. Additionally, we introduce an instant-messaging-app-like framework that facilitates agent discovery and dynamic teaming. By autonomously searching for potential agents capable of handling the tasks at hand, agents can dynamically decide to form different teams and communicate within various group chats. Inspired by Speech Act Theory (Searle, 1969), and its application in conventional multi-agent system (Finin et al., 1994; Labrou et al., 1999), within each group chat, we abstract out several conversation states and provide a flexible and general finite-state machine mechanism that allows agents to autonomously decide the state of the conversation, facilitating discussion and sub-task execution.

We demonstrate the effectiveness of IoA through extensive experiments and comparisons with state-of-the-art autonomous agents. By integrating AutoGPT (Significant Gravitas, 2023) and Open Interpreter (Open Interpreter, 2023), we show that IoA achieves a 66 to 76% win rate in open-domain task evaluations when compared with these agents individually. Furthermore, with only a few basic ReAct agents integrated, IoA outperforms previous works on the GAIA benchmark (Mialon et al., 2023). In the retrieval-augmented generation (RAG) question-answering domain, our framework substantially surpasses existing methods, with a GPT-3.5-based implementation achieving performance close to or even exceeding GPT-4, and effectively surpassing previous multi-agent framework.

The impressive performance of IoA across various domains highlights the potential of this paradigm for autonomous agents. As smaller LLMs continue to advance (Mesnard et al., 2024; Hu et al., 2024; Abdin et al., 2024), running agents on personal computer or even mobile device is becoming increasingly feasible. This trend opens up new opportunities for deploying multi-agent systems in real-world scenarios, where agents can be distributed across multiple devices and collaborate to solve complex problems. We believe that by further exploring and refining the IoA paradigm, more sophisticated and adaptable multi-agent systems can be developed, ultimately pushing the boundaries of what autonomous agents can achieve in problem-solving and decision-making.

2 FRAMEWORK DESIGN AND KEY MECHANISMS OF IOA

In this section, we present a comprehensive overview of IoA, detailing its architecture and key mechanisms. We will explore how these components work together to enable effective collaboration among autonomous agents, facilitating dynamic team formation, structured communication, and efficient task execution.

2.1 OVERVIEW OF IOA

IoA is designed as an instant-messaging-app-like platform that enables seamless communication and collaboration among diverse autonomous agents. Inspired by the concept of Internet, IoA addresses

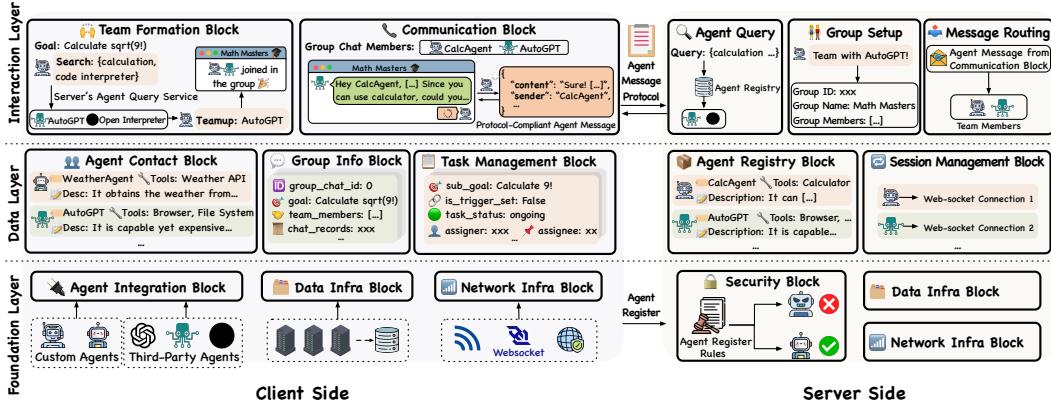


Figure 1: The illustration on the conceptual layered architecture on the design of IoA.

three fundamental challenges in multi-agent systems (Chen et al., 2023; Wu et al., 2023; Qian et al., 2023a):

1. **Distributed agent collaboration:** Unlike traditional frameworks that simulate multi-agent systems on a single device, IoA supports agents distributed across multiple devices and locations. (Sections 2.2 and 2.3.1)
2. **Dynamic and adaptive communication:** IoA implements mechanisms for autonomous team formation and conversation flow control, allowing agents to adapt their collaboration strategies based on task requirements and ongoing progress. (Sections 2.3.2 to 2.3.4)
3. **Integration of heterogeneous agents:** IoA provides a flexible protocol for integrating various third-party agents, expanding the diversity of agent capabilities within the system. (Section 2.4)

At its core, IoA consists of two main components: the server and the client. The server acts as a central hub, managing agent registration, discovery, and message routing. It enables agents with varying capabilities to find each other and initiate communication. The client, on the other hand, serves as a wrapper for individual agents, providing them with the necessary communication functionalities and adapting them to the specified protocol. IoA employs a layered architecture (Bass et al., 1999) for both the server and client components, comprising three layers:

- **Interaction Layer:** Facilitates team formation and agent communication.
- **Data Layer:** Manages information related to agents, group chats, and tasks.
- **Foundation Layer:** Provides essential infrastructure for agent integration, data management, and network communication.

These layers work together to facilitate agent collaboration through the network. In the following subsections, we will go through the IoA's architecture and design.

2.2 ARCHITECTURE OF IOA

The layered architecture of IoA is designed to support scalable, flexible, and efficient multi-agent collaboration. This architecture enables a clear separation of concerns and facilitates the integration of diverse agents and functionalities (Fig. 1).

2.2.1 SERVER ARCHITECTURE

The server acts as the central hub of IoA, facilitating agent discovery, group formation, and message routing. Its architecture consists of three layers:

Interaction Layer: At the top level, the Interaction Layer manages high-level interactions between agents and the system. It encompasses the Agent Query Block for enabling agents to search for other agents based on specific characteristics, the Group Setup Block for facilitating the creation and management of group chats, and the Message Routing Block for ensuring efficient and accurate routing of messages between agents and group chats.

Data Layer: Serving as the information backbone, the Data Layer handles the storage and management of critical system information. The Agent Registry Block maintains a comprehensive database of registered agents, including their capabilities and current status, similar to service discovery in distributed systems (Meshkova et al., 2008; Netflix). Meanwhile, the Session Management Block manages active connections and ensures continuous communication between the server and connected clients.

Foundation Layer: Underpinning the entire system, the Foundation Layer provides the essential infrastructure for the server’s operations. It encompasses the Data Infrastructure Block for handling data persistence and retrieval, the Network Infrastructure Block for managing network communications, and the Security Block for implementing authentication, authorization, and other security measures to maintain system integrity.

2.2.2 CLIENT ARCHITECTURE

The client component of IoA serves as a wrapper for individual agents, providing them with the necessary interfaces to communicate within the system. Its architecture mirrors that of the server with three layers:

Interaction Layer: At the forefront of agent operations, the Interaction Layer manages the agent’s interactions within the system. The Team Formation Block implements the logic for identifying suitable collaborators and forming teams for the task at hand, similar to coalition formation in conventional multi-agent research (Rahwan et al., 2009). Complementing this, the Communication Block manages the agent’s participation in group chats and handles message processing.

Data Layer: Functioning as the agent’s memory, the Data Layer maintains local data relevant to the agent’s operations. It includes the Agent Contact Block for storing information about other agents the current agent has interacted with, the Group Info Block for maintaining details about ongoing group chats and collaborations, and the Task Management Block for tracking the status and progress of tasks assigned to the agent.

Foundation Layer: Forming the base of the client architecture, the Foundation Layer provides the basic functionalities for the client’s operations. The Agent Integration Block defines the protocols and interfaces for integrating third-party agents into the IoA ecosystem. Alongside this, the Data Infrastructure Block handles local data storage and retrieval, while the Network Infrastructure Block manages network communications with the server.

This layered architecture enables IoA to support a wide range of agent types and collaboration scenarios. By providing a clear separation of concerns and well-defined interfaces between layers, the architecture facilitates the integration of diverse agents and allows for future extensibility. Furthermore, this design supports the key mechanisms of IoA, such as autonomous team formation and conversation flow control, which we will explore in detail in the following subsections.

2.3 KEY MECHANISMS

The effectiveness of IoA relies on several key mechanisms that enable seamless collaboration among diverse agents. These mechanisms work in concert to facilitate agent integration, team formation, task allocation, and structured communication. We detail these critical components in this section.

2.3.1 AGENT REGISTRATION AND DISCOVERY

To enable collaboration among distributed agents with heterogeneous architectures, tools, and environments, we propose the agent registration and discovery mechanism. This mechanism forms the foundation for collaborative interactions within IoA, enabling the integration of diverse agents into the system and facilitating their discovery on the online server by other agents for potential collaboration through the network.

Agent Registration: When a new agent joins the IoA, its client wrapper undergoes a registration process with the server. During registration, the agent should provide a comprehensive description of its capabilities, skills, and areas of expertise. This description, denoted as d_i for an agent c_i , is stored in the Agent Registry Block of the server’s Data Layer. Formally, we represent the set of all registered agents as $\mathcal{C} = \{c_1, c_2, \dots, c_n\}$, where each c_i is associated with its description d_i .

Agent Discovery: The agent discovery function leverages the information stored in the Agent Registry from the online server to enable agents to find suitable collaborators for specific tasks. When an agent needs to form a team or seek assistance, it can use the `search_client` tool provided by the server’s Agent Query Block. This tool allows an agent to search for other agents based on desired characteristics or capabilities. Formally, the agent discovery process can be described as follows: Let $\mathcal{L}_d = [l_1, l_2, \dots, l_k]$ be a list of desired characteristics generated by an agent seeking collaborators. The `search_client` function can be represented as: $\text{search_client} : \mathcal{L}_d \rightarrow \mathcal{P}(\mathcal{C})$, where $\mathcal{P}(\mathcal{C})$ denotes the power set of \mathcal{C} . The function returns a subset of clients $\mathcal{C}_d \subseteq \mathcal{C}$ whose descriptions d_j match the desired characteristics in \mathcal{L}_d . The matching process between \mathcal{L}_d and d_j can be implemented with various semantic matching techniques (Robertson & Zaragoza, 2009; Karpukhin et al., 2020). It ensures that agents with relevant capabilities can be discovered even if their descriptions do not exactly match the search criteria.

2.3.2 AUTONOMOUS NESTED TEAM FORMATION

The autonomous nested team formation mechanism enables dynamic and flexible combinations of appropriate agents. This mechanism allows agents to form teams adaptively based on task requirements and to create nested sub-teams for complex, multi-faceted tasks.

Team Formation Process: When a client $c_i \in \mathcal{C}$ is assigned a task t , it initiates the team formation process. The client has access to two essential tools provided by the server: `search_client` and `launch_group_chat`. The LLM in the client is prompted to decide which tool to call based on the task and the current set of discovered clients. If more collaborators are needed, it calls `search_client` with appropriate characteristics. Once suitable collaborators are found, it calls `launch_group_chat` to initiate a new group chat $g \in \mathcal{G}$, where \mathcal{G} is the space of all group chats.

Nested Team Structure: The nested team formation allows for a hierarchical structure of teams and sub-teams. Let $g_0 \in \mathcal{G}$ be the initial group chat for task t . During the execution of t , if a client c_i is assigned with a sub-task t_l (the task assignment mechanism will be introduced in Section 2.3.4), and it identifies t_l requires additional expertise, c_i is allowed to search for appropriate agents again and initiate a new sub-group chat $g_l \in \mathcal{G}$. This process can continue recursively for the new sub-tasks assigned in g_l , forming a tree-like structure of group chats. Formally, we can define a function $h : \mathcal{G} \rightarrow \mathcal{P}(\mathcal{G})$ that maps a group chat to its set of sub-group chats. The nested structure can be represented as: $h(g_0) = \{g_1, g_2, \dots, g_m\}$, $h(g_i) = \{g_{i1}, g_{i2}, \dots, g_{in}\}$, and so on.

Communication Complexity: The nested team formation mechanism helps reduce communication complexity in large agent teams. Assuming fully connected communication within each group, the number of communication channels (connected edges) in a single group with $|g|$ members is $c_{\text{full}} = \frac{|g|(|g|-1)}{2}$. However, by decomposing a task into sub-tasks and allocating them to sub-group chats, we can reduce the total number of communication channels. Let $\mathcal{S}(g)$ denote the set of all sub-groups (including g itself) formed for a task initially assigned to group g . The total number of communication channels can then be expressed as: $c_{\text{nested}} = \sum_{g_i \in \mathcal{S}(g)} \frac{|g_i|(|g_i|-1)}{2} \leq c_{\text{full}}$.

Fig. 2 illustrates an example of the nested team formation process. In this example, the initial group chat g_0 spawns three sub-group chats g_1, g_2 and g_3 for specific sub-tasks during the discussion. g_1 further creates two sub-group chats g_{21} and g_{22} for a more specialized sub-task.

2.3.3 AUTONOMOUS CONVERSATION FLOW CONTROL

Effective communication is crucial for successful collaboration among autonomous agents. Inspired by Speech Act Theory (Austin, 1975; Searle, 1969) and its applications in multi-agent systems (Finin

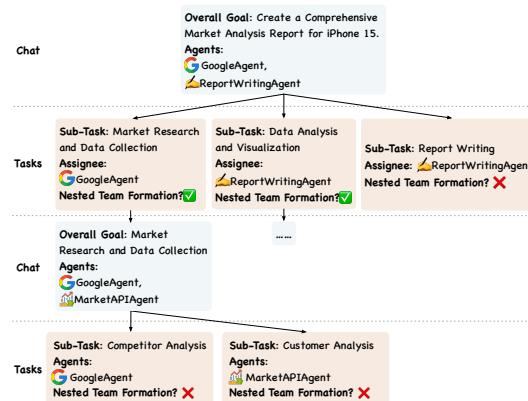


Figure 2: An example of nested team formation mechanism. The process is simplified for clarity.

et al., 1994; Labrou et al., 1999), we introduce an autonomous conversation flow control mechanism in IoA. This mechanism enables agents to coordinate their communication and maintain a structured dialogue, enhancing the efficiency and effectiveness of their collaboration.

Sequential Speaking Mechanism: To manage potential conflicts and ensure clear communication, IoA adopts the most basic sequential speaking mechanism. At any given time, only one agent is permitted to speak, preventing confusion and maintaining a clear order of communication. This approach, while simple, provides a foundation for more sophisticated conversation management when combined with the following dynamic features.

Finite State Machine for Group Chat States: We formalize the conversation flow as a finite state machine $M = (S, \Sigma, \delta, s_0, F)$, where:

- $S = \{s_d, s_s, s_a, s_p, s_c\}$ is the set of states representing discussion, synchronous task assignment, asynchronous task assignment, pause & trigger, and conclusion, respectively.
- Σ is the state transition decision space.
- $\delta : S \times \Sigma \rightarrow S$ is the transition function mapping the current state and the transition decision made by LLMs to the next state.
- $s_0 = s_d$ is the initial state, representing the start of the conversation in the discussion phase.
- $F = \{s_c\}$ is the set of final states, containing only the conclusion state.

Figure 3 illustrates the state transitions in the conversation flow. Each state corresponds to different phases of the collaboration process:

- *Discussion (s_d)*: Agents engage in general dialogue, exchange ideas, and clarify task requirements.
- *Synchronous task assignment (s_s)*: Tasks are assigned to specific agents, pausing the group chat until completion (Section 2.3.4).
- *Asynchronous task assignment (s_a)*: Tasks are assigned without interrupting the ongoing discussion (Section 2.3.4).
- *Pause & trigger (s_p)*: The group chat is paused, waiting for the completion of specified asynchronous tasks.
- *Conclusion (s_c)*: Marks the end of the collaboration, prompting a final summary.

These states align with speech acts in Speech Act Theory, such as assertives (discussion), directives (task assignment), commissives (pause & trigger), and declarations (conclusion) (Searle, 1976).

Autonomous State Transitions and Next Speaker Selection: The LLM in each client is responsible for deciding state transitions and selecting the next speaker. Let \mathcal{M}_t be the set of messages exchanged up to time step t . We define the decision function of the LLM as: $f_{\text{LLM}} : \mathcal{M}_t \times S \rightarrow S \times \mathcal{C}$, where S is the set of states and \mathcal{C} is the set of clients. The next state s_{t+1} and the next speaker c_{t+1} are determined as: $(s_{t+1}, c_{t+1}) = f_{\text{LLM}}(\mathcal{M}_t, s_t)$. This decision-making process considers factors such as the completion of assigned tasks, the need for further discussion, and the overall goals of the collaboration. The autonomous selection of the next speaker ensures that the most relevant agents are involved at appropriate times, promoting efficient information exchange and problem-solving.

By implementing this autonomous conversation flow control mechanism, IoA enables structured and efficient communication among agents. This approach allows for dynamic adaptation to the needs of the collaboration, facilitating more effective problem-solving and decision-making in complex multi-agent scenarios.

2.3.4 TASK ASSIGNMENT AND EXECUTION

The task assignment and execution mechanism in IoA is designed to efficiently distribute work among agents and manage the execution of both simple and complex tasks. This mechanism works in concert with the team formation and conversation flow control mechanisms to ensure effective collaboration and task completion.

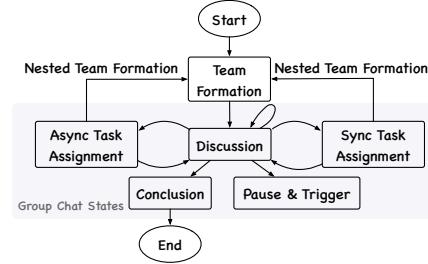


Figure 3: The state transition among different states.

Task Representation: In IoA, a task $t \in \mathcal{T}$ is represented as a tuple (d_t, \mathcal{S}_t) , where d_t is the task description and $\mathcal{S}_t = \{s_1, s_2, \dots, s_n\}$ is the set of sub-tasks that t can be decomposed into. Initially, \mathcal{S}_t may be empty, with sub-tasks being identified dynamically during the collaboration process.

Task Allocation: Task allocation in IoA occurs within the context of group chats and is closely tied to the conversation flow control mechanism. There are two types of task allocation:

1. *Synchronous Task Allocation:* When the group chat enters the synchronous task assignment state s_s , tasks are allocated to specific agents, and the group chat is paused until the tasks are completed.
2. *Asynchronous Task Allocation:* In the asynchronous task assignment state s_a , tasks are allocated without interrupting the ongoing discussion. This allows for parallel execution of tasks.

Formally, we can define a task allocation function $\alpha : \mathcal{T} \times \mathcal{G} \rightarrow \mathcal{P}(\mathcal{C})$, which maps a task and a group chat to a subset of clients responsible for executing the task.

Task Execution: Once a task is allocated, the responsible agent(s) begin execution. The execution process depends on the nature of the task and the capabilities of the agent. For integrated third-party agents, task execution is handled through the Agent Integration Block in the client's Foundation Layer. This block provides a standardized interface for task execution, typically in the form: `run : String → TaskID`, where the input is the task description, and the output is a unique identifier for the task. Advanced features such as execution interruption could also be implemented in this stage.

Upon completion of a task or sub-task, the responsible agent(s) report back to the group chat. In the case of synchronous tasks, this triggers the resumption of the group chat. For asynchronous tasks, the completion is noted, and any relevant information is shared with the group.

The pause & trigger state s_p in the conversation flow control mechanism plays a crucial role in managing the completion of multiple asynchronous tasks. It allows the group chat to wait for the completion of specified asynchronous tasks before proceeding, ensuring that all necessary information is available for subsequent stages of the collaboration.

2.4 COMPREHENSIVE MESSAGE PROTOCOL DESIGN

The effectiveness of the autonomous nested team formation and conversation flow control mechanisms in IoA relies on a comprehensive message protocol. This protocol enables seamless communication and collaboration among agents by encapsulating all necessary information required for various mechanisms to function properly.

Protocol Overview and Key Fields The agent message protocol in IoA is designed for extensibility and flexibility, facilitating effective multi-agent collaboration. The protocol consists of two main components: a header and a payload.

The header contains essential metadata about the message, ensuring correct addressing and processing by receiving agents. Key fields in the header include:

- `sender`: The unique identifier of the agent sending the message.
- `group_id`: The identifier of the group chat to which the message belongs.

The payload carries the main content of the message, varying by message type. It can include:

- `message_type`: Indicates the purpose of the message (e.g., discussion, task assignment, pause & trigger).
- `next_speaker`: The identifier(s) of the agent(s) expected to respond.

This structure contains other fields to support the diverse functionalities of IoA effectively. A detailed explanation and example of the message protocol can be found in Appendix A.1.

To ensure seamless communication and coordination, both the client and server components of IoA implement the message protocol. When a client sends a message, it encodes it according to the protocol and transmits it to the server. The server parses the message, extracts relevant information from the header, and routes it to the appropriate group chat based on the `group_id`. Upon receiving a message, the client decodes it and processes it accordingly. This consistent implementation ensures

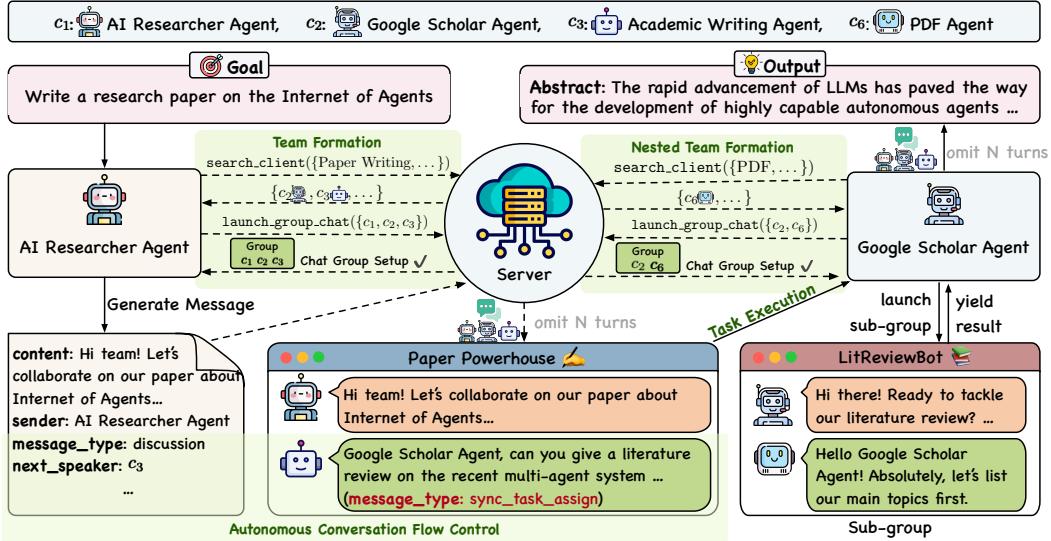


Figure 4: An example walkthrough of the major components of IoA.

that all agents can understand and respond to messages correctly, regardless of their roles or tasks, maintaining a coherent and efficient collaboration process.

2.5 PUTTING IT ALL TOGETHER: A WALKTHROUGH OF IOA IN ACTION

To illustrate the integrated functionality of IoA, in Fig. 4, we present an example walkthrough of the system with an illustrative complex task: writing a research paper on the Internet of Agents. Initially, client c_1 , an AI research specialist trained additionally on AI academic paper, engages the Team Formation Block, utilizing the `search_client` function with a list of keywords {Internet, Multi-Agent System Specialist, Paper Writing, LLM Expert}. The server returns a set of matched clients $\{c_2, c_3, c_4, c_5\}$, from which c_1 forms group g_0 with members $\{c_1, c_2, c_3\}$ via `launch_group_chat`, where c_2 has access to scholarly databases and c_3 specializes in academic writing.

Upon the formation of group chat g_0 , all clients transition to the Communication Block for g_0 , where the autonomous conversation flow control mechanism, implemented as a finite state machine, guides the collaboration. The process begins with brainstorming in the discussion state (s_d), progressing to task assignment states (s_s, s_a) where agents are allocated specific responsibilities. For instance, c_2 is tasked with conducting a literature review using its access to scholarly resources. The nested team formation mechanism is demonstrated when c_2 identifies a need for specialized PDF expertise. This prompts c_2 to initiate a sub-group formation process, resulting in the creation of sub-group g_1 with a new agent c_6 , a PDF expert. Throughout the process, the conversation alternates between discussion (s_d) and asynchronous task assignment (s_a) states, facilitating parallel work on assigned tasks. The message protocol ensures efficient communication, enabling the exchange of ideas, citations, and draft segments across the nested group structure.

In the final integration phase, the group enters a synchronous task assignment state (s_s) for collaborative editing and refinement, demonstrating IoA's capacity for coordinating intensive, real-time collaboration among multiple agents. The process concludes with a transition to the conclusion state (s_c), where a final review is conducted and the paper is prepared for submission.

3 EXPERIMENTS

To demonstrate the effectiveness and versatility of IoA in integrating heterogeneous agents, we conduct comprehensive experiments across a diverse set of tasks. These experiments are designed to showcase different aspects of agent heterogeneity: tool variability (Section 3.1), architectural diver-

Table 1: The performance on the validation set of GAIA benchmark.

Models	Agent Type	Level 1	Level 2	Level 3	Overall
GPT-4		15.09	2.33	0.00	6.06
GPT-4-Turbo		20.75	5.81	0.00	9.70
AutoGPT-4 (Significant Gravitas, 2023)		13.21	0.00	3.85	4.85
GPT-4 + Plugins (Mialon et al., 2023)		30.30	9.70	0.00	14.60
FRIDAY (Wu et al., 2024)		45.28	34.88	11.54	34.55
AutoGen (Wu et al., 2023)		54.72	38.37	11.54	39.39
IoA		50.94	40.70	15.38	40.00

sity (Section 3.2), disparate observation and action spaces (Section 3.3), and varied knowledge bases (Section 3.4). Our objective is twofold: first, to illustrate IoA’s proficiency in facilitating collaboration among heterogeneous agents, and second, to highlight its adaptability across various problem domains. In this section, we present our experimental results and offer comparative analyses between IoA and state-of-the-art (SoTA) approaches for each task category. The prompts within IoA are kept the *same* across different tasks, and are not specifically tuned for a certain task.³

3.1 HETEROGENEOUS TOOLS: GAIA BENCHMARK

To evaluate IoA’s capability in integrating agents with heterogeneous tools, we employ the GAIA benchmark (Mialon et al., 2023). This benchmark comprises a diverse set of real-world questions designed to assess an agent system’s proficiency in solving complex tasks through the synergistic application of multiple skills, including natural language understanding, reasoning, and external knowledge integration. The benchmark’s three-tiered difficulty structure provides a robust testbed for evaluating the capability of agent systems.

Experimental Setups: We instantiate IoA with four basic ReAct agents (Yao et al., 2023), each equipped with a distinct tool: a web browser, a code interpreter, a Wikidata searcher, and a YouTube video transcript downloader. This configuration allows us to assess IoA’s ability to orchestrate collaboration among agents with heterogeneous tools. We benchmark IoA against several SoTA agent systems, evaluating performance across all three difficulty levels of GAIA, as well as overall performance. Detailed implementation specifics are provided in Appendix A.4.1.

Results and Analysis: The experimental results, presented in Table 1, demonstrate IoA’s superior performance across the GAIA benchmark. Despite utilizing only basic ReAct agents, IoA achieves the highest overall performance, surpassing all other approaches. Notably, IoA exhibits exceptional performance in the more challenging Level 2 and Level 3 tasks, which demand advanced reasoning and intricate collaboration. This performance underscores the efficacy of IoA’s communication mechanisms and its capacity to facilitate seamless inter-agent collaboration.

In comparison to AutoGen, IoA demonstrates superior performance in two out of three difficulty levels. This superiority can be attributed to IoA’s collaboration mechanisms and the flexibility of integrating agents with different tools, while in AutoGen, only one agent utilizes different tools, and other agents act as feedback providers. The mechanisms implemented in IoA enable adaptive team composition and efficient sub-task execution, culminating in enhanced performance on complex, multi-faceted problems.

The results from the GAIA benchmark underscore IoA’s potential as a powerful orchestrator for diverse agents in solving real-world, multi-step problems. By providing a flexible and efficient platform for agent collaboration, IoA enables even basic agents to achieve SoTA performance, outperforming more sophisticated standalone agents. This outcome highlights the critical role of effective communication and coordination in multi-agent systems and validates the architectural and design choices underpinning IoA.

³If not specified, we use GPT-4-1106-preview model in our experiments.

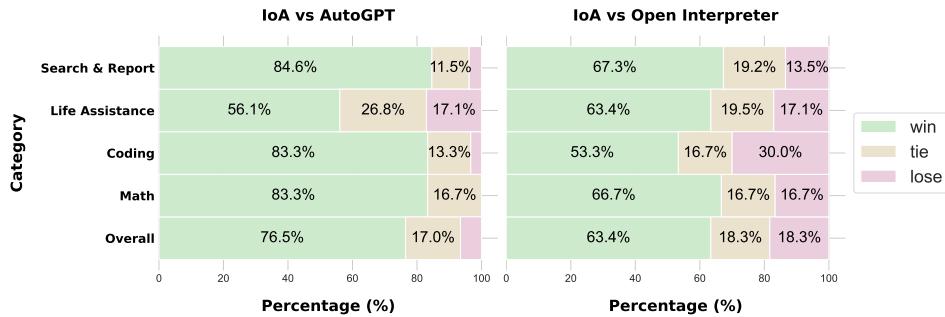


Figure 5: Comparison of win rates on the open-ended instruction benchmark between IoA, AutoGPT, and Open Interpreter.

3.2 HETEROGENEOUS ARCHITECTURE: OPEN-ENDED INSTRUCTION BENCHMARK

To evaluate IoA’s capability in integrating and orchestrating agents with heterogeneous architectures, we develop a comprehensive benchmark comprising 153 open-ended instructions with self-instruct (Wang et al., 2023e). This benchmark spans four diverse categories: search & report, coding, mathematics, and life assistance. Unlike the GAIA benchmark, which primarily focuses on question-answering tasks with deterministic answers, our curated benchmark incorporates a higher proportion of non-QA tasks requiring generative responses. This design choice aims to better reflect the diverse nature of real-world challenges that agent systems are expected to address. The curation process is elaborated at Appendix A.4.2.

Experimental Setups: In this experimental setup, we integrate two SoTA third-party agents with distinct architectures: AutoGPT (Significant Gravitas, 2023) and Open Interpreter (Open Interpreter, 2023), into the IoA ecosystem. The integration process, detailed in Appendix A.4.2, demonstrates IoA’s versatility in accommodating agents with divergent internal structures and operational paradigms. This configuration allows us to assess IoA’s efficacy in facilitating collaboration among independently developed agents with heterogeneous architectures.

For evaluation, we employ GPT-4-1106-preview as an impartial judge, a choice supported by previous research demonstrating high agreement between GPT models and human evaluators in assessing response quality (Chiang et al., 2023; Zheng et al., 2023a; Chan et al., 2023). To mitigate potential order-induced biases, we implement a robust evaluation approach following Zheng et al. (2023a), where the order of responses is alternated in the prompt. A “win” is only declared when one competitor is consistently judged superior across both orderings.

Results and Analysis: The experimental results, illustrated in Fig. 5, demonstrate IoA’s significant performance advantages when orchestrating the collaboration between AutoGPT and Open Interpreter. IoA consistently outperforms both individual agents across all four task categories. Overall, IoA achieves a remarkable win rate of 76.5% against AutoGPT and 63.4% against Open Interpreter. These results underscore IoA’s proficiency in efficiently gathering and synthesizing information, as well as its effectiveness in facilitating collaborative problem-solving across diverse domains.

The demonstrated capability of IoA to seamlessly integrate and orchestrate agents with heterogeneous architectures enables the harness of the strengths of diverse, independently developed agents, making it possible to create more versatile and capable agent systems. As the landscape of specialized AI agents continues to expand, IoA’s potential to integrate and facilitate collaboration among these diverse entities positions it as a promising platform for the development of increasingly sophisticated and adaptive agent systems.

3.3 HETEROGENEOUS OBSERVATION AND ACTION SPACE: EMBODIED AGENT TASKS

To evaluate IoA’s efficacy in orchestrating agents with heterogeneous observation and action spaces, we conduct experiments in the domain of embodied AI. This domain presents unique challenges, requiring agents to perceive, understand, and interact with their physical environment. We utilize RoCoBench (Mandi et al., 2023), a state-of-the-art benchmark designed to assess the collaboration

Table 2: Average success rate and the number of steps on different tasks from RoCoBench.

Model	Metric	Cabinet	Sweep	Sandwich	Sort	Rope
Central Plan (oracle)	Success	0.90	1.00	0.96	0.70	0.50
	#Step	<u>4.0</u>	8.4	<u>8.8</u>	8.6	<u>2.3</u>
Roco Dialog	Success	0.75	0.70	0.70	0.70	0.70
	#Step	4.7	<u>7.9</u>	9.1	<u>5.4</u>	2.4
IoA	Success	1.00	0.80	1.00	1.00	0.70
	#Step	4.6	8.5	8.9	5.8	2.6

and communication capabilities of embodied agents. RoCoBench comprises six collaborative tasks, each mandating two or three agents with partial, often distinct action space or observations of the environment to cooperate towards a common objective.

Experimental Setups: We benchmark IoA against two baselines established by Mandi et al. (2023): (1) Central Plan, a centralized agent has complete environmental information and control over all embodied agents, and (2) Roco Dialog, a specialized multi-agent framework designed for this task, enabling agent communication and decision-making.

Given that RoCoBench requires agents to output action plans in a specific format rather than interact with tools, we adapt IoA to this scenario without integrating external agents. Instead, we provide environmental observations to two IoA clients and extract their action plans from their discussion. This setup allows us to evaluate IoA’s ability to manage agents with heterogeneous observation and action spaces. Detailed implementation specifics are available in Appendix A.4.3. To ensure a fair comparison, we conduct 10 runs for both IoA and Roco Dialog for each task, reporting average success rates and steps taken. Results for Central Plan are sourced directly from Mandi et al. (2023). Note that the Pack Grocery task is omitted due to implementation errors in the benchmark release.

Results and Analysis: Table 2 presents the average success rates and steps required for task completion. Remarkably, despite not being specifically optimized for embodied tasks, IoA outperforms Roco Dialog, a framework tailored for this benchmark, in four out of five tasks in terms of success rate. IoA achieves perfect scores on the Cabinet, Sandwich, and Sort tasks, demonstrating the robustness of its communication and collaboration mechanisms in enabling embodied agents with heterogeneous observation and action spaces to work synergistically towards common goals. Even more impressive is IoA’s performance relative to the Central Plan baseline, which benefits from full environmental observability. IoA’s success rates are superior or comparable to Central Plan across tasks, although it generally requires slightly more decision steps for task completion. Given that IoA is a general multi-agent framework not specifically designed for embodied AI tasks, the marginal increase in step count is a reasonable trade-off for its versatility and effectiveness.

The success of IoA in this embodied AI scenario highlights its versatility and effectiveness. It suggests that the principles underlying IoA, e.g., autonomous conversation flow control, are fundamentally generalizable, indicating IoA’s potential applicability in a wide range of real-world scenarios where agents must collaborate despite having different perspectives or capabilities.

3.4 HETEROGENEOUS KNOWLEDGE: RETRIEVAL-AUGMENTED GENERATION

To evaluate IoA’s efficacy in orchestrating agents with heterogeneous knowledge, we conduct experiments on retrieval-augmented generation (RAG) tasks (Lewis et al., 2021). RAG tasks present a unique challenge where agents must retrieve relevant information from diverse sources and collaborate to synthesize accurate responses, making them an ideal testbed for assessing IoA’s ability to manage knowledge heterogeneity and facilitate effective inter-agent communication.

Experimental Setups: We implement IoA with GPT-3.5-turbo-0125 as the core language model, following Apollo’s Oracle (Wang et al., 2023b). To evaluate knowledge heterogeneity and its impact, we design three scenarios: 1) *Heterogeneous Knowledge*: Two clients access different evidence pools (Wikipedia/Google), testing IoA’s ability to manage knowledge heterogeneity. 2) *Homogeneous Knowledge (2 Agents)*: Two clients access both pools, serving as a control to isolate hetero-

Model	TriviaQA	NQ	HotpotQA	2WMHQA	Overall
GPT 4	0.902	0.692	0.566	0.284	0.611
GPT 3.5 Turbo	0.778	0.532	0.384	0.210	0.476
+ Zero-Shot CoT (Wei et al., 2022)	0.772	0.588	0.410	0.190	0.490
+ Self Consistency (Wang et al., 2023d)	0.818	0.622	0.408	0.206	0.514
+ Reflexion (Shinn et al., 2023)	0.762	0.586	0.378	0.254	0.495
+ Multi-Agent Debate1 (Du et al., 2023)	0.798	0.648	0.394	0.186	0.507
+ Multi-Agent Debate2 (Liang et al., 2023)	0.756	0.576	0.450	0.334	0.529
Apollo’s Oracle (Homogeneous)	0.834	0.662	0.542	0.350	0.597
IoA + 2 Agents (Heterogeneous)	0.803	0.708	0.478	0.449	0.610
IoA + 2 Agents (Homogeneous)	0.820	0.671	0.586	0.530	0.652
IoA + 3 Agents (Homogeneous)	0.908	<u>0.682</u>	<u>0.575</u>	<u>0.519</u>	0.671

Table 3: Results for RAG task. IoA, based on GPT-3.5, performs on par with or better than GPT-4 across all tasks. Best results (excluding GPT-4) are in bold, and second-best are underlined. *Heterogeneous* means agents have different evidence pools, while *Homogeneous* means all agents access all evidence pools.

geneity effects. 3) *Homogeneous Knowledge (3 Agents)*: Three clients access both pools, assessing scalability and knowledge redundancy trade-offs.

This design allows us to disentangle the effects of knowledge heterogeneity from agent count and knowledge redundancy. We evaluate across four datasets: TriviaQA (Joshi et al., 2017), Natural Questions (NQ) (Kwiatkowski et al., 2019), HotpotQA (Yang et al., 2018), and 2WikiMultiHopQA (2WMHQA) (Ho et al., 2020), using 250 randomly sampled question-answer pairs from each. Implementation details are in Appendix A.4.4.

Results and Analysis: Table 3 demonstrates IoA’s remarkable performance across all datasets, often surpassing or matching GPT-4 despite being based on GPT-3.5. On two out of four tasks, IoA’s heterogeneous knowledge scenario outperforms homogeneous Apollo’s Oracle, showcasing IoA’s effectiveness in managing knowledge diversity. This configuration achieves the best performance on NQ and competitive results on other datasets, often outperforming single-model approaches and specialized frameworks like Apollo’s Oracle. This underscores IoA’s efficacy in facilitating information exchange and synthesis from heterogeneous sources, effectively compensating for individual agents’ knowledge gaps.

We also conduct experiments in homogeneous settings. IoA with 3 agents achieves the best overall performance, outperforming all baselines on TriviaQA and showing competitive results on other datasets. Interestingly, the 2-agent homogeneous configuration outperforms the 3-agent setup on HotpotQA and 2WikiMultiHopQA, suggesting that optimal agent configuration may be task-dependent. These results not only validate IoA’s effectiveness in RAG tasks but also highlight its potential as a versatile platform for managing both heterogeneous and homogeneous knowledge in multi-agent systems.

4 ANALYSIS

4.1 TEAM FORMATION PRECISION

To evaluate the precision of IoA’s autonomous team formation mechanism, we developed a benchmark using GPT-4, comprising 625 diverse tasks paired with 1500 dummy agent profiles. This simulated environment allows us to assess the accuracy of both regular and nested team formation in a large-scale setting. Detailed data construction processes are available in Appendix C.

Experimental Design: We evaluate two distinct scenarios: regular team formation and nested team formation. For regular team formation, each task is associated with 2 or more suitable agent profiles generated by GPT. For nested team formation, we generate a subtask for each original task that can or cannot be completed by the initially formed team, if not, an additional agent profile capa-

ble of addressing this subtask is generated. We evaluate whether the team can correctly decide when to enter the nested team formation stage, and evaluate the precision of the nested team formation.

We assess both settings using four metrics: Top@1 and Top@10 recall rates, Mean Rank (MR), and Mean Reciprocal Rank (MRR). Top@1 measures exact matches, while Top@10 accounts for semantic similarity, considering an agent as recalled if a recruited agent is among the top 10 most similar to a labeled agent. MR and MRR provide insights into the ranking quality of retrieved agents.

Results and Analysis: Table 4 presents the performance of both team formation mechanisms, each evaluated on its own specific dataset and setting. In the regular team formation scenario, which assesses the ability to form initial teams for given tasks, we observe a Top@1 recall of 41.4% and a Top@10 recall of 64.9%. This indicates that the mechanism can exactly match the labeled agents 41.4% of the time, and when considering semantic similarity, the retrieved agent fall into the top 10 similar agents to the labeled agent for 64.9% of the time. The Mean Rank (MR) of 27.4 and Mean Reciprocal Rank (MRR) of 50.1% suggest that, on average, relevant agents are ranked within the top 30 results, with a tendency towards high ranking.

For the nested team formation scenario, which evaluates the mechanism’s performance in a setting where subtasks may emerge requiring additional expertise, we see a Top@1 recall of 59.7% and a Top@10 recall of 81.8%. The MR of 10.6 and MRR of 66.5% indicate that relevant agents are typically found within the top 11 results, with a strong tendency towards very high rankings. These metrics suggest effective performance in this more dynamic setting.

These results demonstrate IoA’s capability to form precise teams in both initial task allocation and in scenarios where task requirements may evolve. The high recall rates, especially with similarity matching (Top@10), are crucial for addressing complex tasks that require diverse or specialized skills.

4.2 COST AND SUB-OPTIMAL COMMUNICATION PATTERN ANALYSIS

To evaluate the economic feasibility and potential for optimization of the IoA, we conduct a cost analysis on the open-ended instruction benchmark (Section 3.2), where AutoGPT and Open Interpreter are integrated. We compare the average cost per task for these agents when operating individually and when integrated into the IoA.

As shown in Table 5, when integrated into IoA, the costs of both agents are decreased due to the task decomposition for each task. However, the IoA introduces an additional communication cost of \$0.53 per task, resulting in an overall cost of \$0.99.

During our analysis, we observed unexpected and suboptimal communication patterns that contributed to the high communication cost. One notable pattern was the repetition of information, where the LLMs in the clients would repeat or rephrase previous chats from themselves or others, leading to a stagnation in progress. This phenomenon was particularly prevalent after several asynchronous task assignments. Although each task assignment did not require immediate waiting, as the conversation progressed, new decisions had to be made based on the conclusions from previously assigned and not yet completed asynchronous tasks. Despite providing the client LLMs with the option to switch the group chat state to pause & trigger, they sometimes fail to switch, as illustrated in Fig. 6. This drawback in LLM is also observed in other multi-agent work (Li et al., 2023; Mandi et al., 2023).

Table 4: Performance of Team Formation Mechanisms. *Regular* denotes the initial team formation setting, and *Nested* denotes the nested team formation mechanism.

	Top@1↑	Top@10↑	MR↓	MRR↑
Regular	41.4%	64.9%	27.4	50.1%
Nested	59.7%	81.8%	10.6	66.5%

Table 5: Cost analysis of standalone agents and IoA-integrated agents on the open-ended instruction benchmark.

Setting	Cost per Task
AutoGPT (Standalone)	\$0.39
Open Interpreter (Standalone)	\$0.16
AutoGPT (in IoA)	\$0.33
Open Interpreter (in IoA)	\$0.13
IoA Communication	\$0.53
IoA Communication (Dedup.)	\$0.28
IoA Overall	\$0.99
IoA Overall (Dedup.)	\$0.74

To quantify the impact of this suboptimal communication pattern, we manually removed the repetitions and recalculated the token numbers and corresponding costs. Surprisingly, this resulted in a nearly 50% reduction in communication costs, as shown in the "Dedup." rows of Table 5. This finding aligns with observations from other multi-agent communication frameworks, suggesting that while modern LLMs are well-aligned to be effective chatbot assistants, they may not be optimally aligned to be efficient communicating agents. Agents should not only complete the given tasks accurately but also communicate effectively with others, understanding conversation states and making proper decisions. This insight raises new research questions regarding the agent alignment of LLMs and highlights the need for further investigation in this area.

Despite the current cost overhead and suboptimal communication patterns, the IoA demonstrates significant potential for enabling effective collaboration among heterogeneous agents. By addressing these challenges through prompt optimization, protocol refinement, and the development of more sophisticated frameworks under the concept of IoA, we believe that the cost of communication can be significantly reduced. As research progresses, IoA and similar approaches will become increasingly attractive and economically viable solutions for complex multi-agent systems.

5 RELATED WORK

LLM-based Agents Recent advancements in LLMs, such as GPT (OpenAI, 2023), Claude (Anthropic, 2024) and Gemini (Reid et al., 2024), have led to the development of highly capable AI agents, which can engage in natural language interactions and perform a wide range of tasks. To enhance the capabilities of LLM-based agents, researchers have explored the integration of external tools and knowledge sources (Nakano et al., 2021; Yao et al., 2023; Schick et al., 2023; Shen et al., 2023), enabling agents to access and utilize relevant information beyond their pre-trained knowledge. The various agents have demonstrated significant progress in a wide range of domains, including operating system interactions, software engineering, and general AI applications. For instance, OS-Copilot facilitates generalist interactions across web browsers and code terminals (Wu et al., 2024), while OpenDevin focuses on autonomous software development tasks such as coding and debugging (OpenDevin Team, 2024). Other notable developments include XAgent for complex task solving (Team, 2023) and Voyager (Wang et al., 2023a), an open-ended embodied agent leveraging LLMs for Minecraft game-playing. These advancements have laid the foundation for more sophisticated and versatile LLM-based agents, capable of autonomous task execution and continuous learning.

LLM-based Multi-Agent Systems Building upon the success of individual LLM-based agents, researchers have begun to explore the potential of multi-agent systems composed of these agents. Early works demonstrated the feasibility of using LLMs to simulate multi-agent interactions and emergent behaviors (Park et al., 2023). Since then, various approaches have been proposed to enable effective collaboration and communication among LLM-based agents. Frameworks such as AgentVerse (Chen et al., 2023) and AutoGen (Wu et al., 2023) provide the necessary infrastructure for agent collaboration. In software development, multi-agent systems like ChatDev (Qian et al., 2023a), MetaGPT (Hong et al., 2023) have shown promising results in automating coding, testing, and debugging processes. Despite these advancements, significant limitations remain, such as the lack of support for integrating diverse third-party agents, the inability to support distributed multi-agent systems, and the reliance on hard-coded communication protocols and state transitions. IoA aims to address these limitations and provide a more flexible and scalable platform for LLM-based multi-agent collaboration, paving the way for more advanced and practical systems that can tackle complex real-world problems effectively.

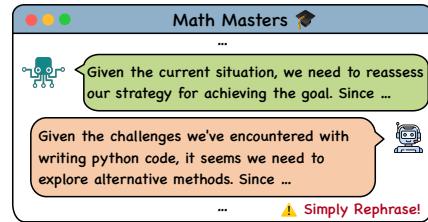


Figure 6: An example of the repeated communication.

6 CONCLUSION

In this paper, we introduced IoA, a novel framework for LLM-based multi-agent collaboration inspired by the concept of the Internet. IoA addresses the limitations of existing multi-agent frameworks by providing a flexible and scalable platform for integrating diverse third-party agents, enabling distributed multi-agent collaboration, and introducing dynamic mechanisms for agent teaming and conversation flow control. Through extensive experiments on various benchmarks, we demonstrated the effectiveness of IoA in facilitating efficient collaboration among heterogeneous agents, consistently outperforming state-of-the-art baselines. As the field of LLM-based agents continues to advance, we believe that IoA will serve as a foundation for future research and development in multi-agent collaboration. By enabling the integration of diverse agents with specialized skills and knowledge, our framework opens up new possibilities for leveraging existing agents that were developed independently. We hope that our work will inspire further research in this promising direction and contribute to the development of more advanced and impactful multi-agent systems.

REFERENCES

- Marah I Abdin, Sam Ade Jacobs, Ammar Ahmad Awan, Jyoti Aneja, Ahmed Awadallah, Hany Awadalla, Nguyen Bach, Amit Bahree, Arash Bakhtiari, Harkirat S. Behl, Alon Benhaim, Misha Bilenko, Johan Bjorck, Sébastien Bubeck, Martin Cai, Caio César Teodoro Mendes, Weizhu Chen, Vishrav Chaudhary, Parul Chopra, Allie Del Giorno, Gustavo de Rosa, Matthew Dixon, Ronen Eldan, Dan Iter, Amit Garg, Abhishek Goswami, Suriya Gunasekar, Emmann Haider, Junheng Hao, Russell J. Hewett, Jamie Huynh, Mojan Javaheripi, Xin Jin, Piero Kauffmann, Nikos Karampatziakis, Dongwoo Kim, Mahoud Khademi, Lev Kurilenko, James R. Lee, Yin Tat Lee, Yuanzhi Li, Chen Liang, Weishung Liu, Eric Lin, Zeqi Lin, Piyush Madan, Arindam Mitra, Hardik Modi, Anh Nguyen, Brandon Norick, Barun Patra, Daniel Perez-Becker, Thomas Portet, Reid Pryzant, Heyang Qin, Marko Radmilac, Corby Rosset, Sambudha Roy, Olatunji Ruwase, Olli Saarikivi, Amin Said, Adil Salim, Michael Santacroce, Shital Shah, Ning Shang, Hiteshi Sharma, Xia Song, Masahiro Tanaka, Xin Wang, Rachel Ward, Guanhua Wang, Philipp Witte, Michael Wyatt, Can Xu, Jiahang Xu, Sonali Yadav, Fan Yang, Ziyi Yang, Donghan Yu, Chengruidong Zhang, Cyril Zhang, Jianwen Zhang, Li Lyyna Zhang, Yi Zhang, Yue Zhang, Yunan Zhang, and Xiren Zhou. Phi-3 technical report: A highly capable language model locally on your phone. *CoRR*, abs/2404.14219, 2024. doi: 10.48550/ARXIV.2404.14219. URL <https://doi.org/10.48550/arXiv.2404.14219>.
- Anthropic. Introducing the next generation of claudie, 2024. URL <https://www.anthropic.com/news/claudie-3-family>. Accessed: 2024-06-14.
- John Langshaw Austin. *How to do things with words*, volume 88. Oxford university press, 1975.
- Leonard J. Bass, Paul C. Clements, and Rick Kazman. *Software architecture in practice*. SEI series in software engineering. Addison-Wesley-Longman, 1999. ISBN 978-0-201-19930-7.
- Chi-Min Chan, Weize Chen, Yusheng Su, Jianxuan Yu, Wei Xue, Shanghang Zhang, Jie Fu, and Zhiyuan Liu. Chateval: Towards better llm-based evaluators through multi-agent debate. *CoRR*, abs/2308.07201, 2023. doi: 10.48550/ARXIV.2308.07201. URL <https://doi.org/10.48550/arXiv.2308.07201>.
- Harrison Chase. LangChain, October 2022. URL <https://github.com/langchain-ai/langchain>.
- Weize Chen, Yusheng Su, Jingwei Zuo, Cheng Yang, Chenfei Yuan, Chi-Min Chan, Heyang Yu, Yaxi Lu, Yi-Hsin Hung, Chen Qian, et al. Agentverse: Facilitating multi-agent collaboration and exploring emergent behaviors. In *The Twelfth International Conference on Learning Representations*, 2023.
- Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E. Gonzalez, Ion Stoica, and Eric P. Xing. Vicuna: An open-source chatbot impressing gpt-4 with 90%* chatgpt quality, March 2023. URL <https://lmsys.org/blog/2023-03-30-vicuna/>.

Yilun Du, Shuang Li, Antonio Torralba, Joshua B. Tenenbaum, and Igor Mordatch. Improving factuality and reasoning in language models through multiagent debate. *CoRR*, abs/2305.14325, 2023. doi: 10.48550/ARXIV.2305.14325. URL <https://doi.org/10.48550/arXiv.2305.14325>.

Timothy W. Finin, Richard Fritzson, Donald P. McKay, and Robin McEntire. KQML as an agent communication language. In *Proceedings of the Third International Conference on Information and Knowledge Management (CIKM'94), Gaithersburg, Maryland, USA, November 29 - December 2, 1994*, pp. 456–463. ACM, 1994. doi: 10.1145/191246.191322. URL <https://doi.org/10.1145/191246.191322>.

Xanh Ho, Anh-Khoa Duong Nguyen, Saku Sugawara, and Akiko Aizawa. Constructing a multi-hop qa dataset for comprehensive evaluation of reasoning steps, 2020.

Sirui Hong, Xiawu Zheng, Jonathan Chen, Yuheng Cheng, Jinlin Wang, Ceyao Zhang, Zili Wang, Steven Ka Shing Yau, Zijuan Lin, Liyang Zhou, Chenyu Ran, Lingfeng Xiao, and Chenglin Wu. Metagpt: Meta programming for multi-agent collaborative framework. *CoRR*, abs/2308.00352, 2023. doi: 10.48550/ARXIV.2308.00352. URL <https://doi.org/10.48550/arXiv.2308.00352>.

Shengding Hu, Yuge Tu, Xu Han, Chaoqun He, Ganqu Cui, Xiang Long, Zhi Zheng, Yewei Fang, Yuxiang Huang, Weilin Zhao, Xinrong Zhang, Zhen Leng Thai, Kai Zhang, Chongyi Wang, Yuan Yao, Chenyang Zhao, Jie Zhou, Jie Cai, Zhongwu Zhai, Ning Ding, Chao Jia, Guoyang Zeng, Dahai Li, Zhiyuan Liu, and Maosong Sun. Minicpm: Unveiling the potential of small language models with scalable training strategies. *CoRR*, abs/2404.06395, 2024. doi: 10.48550/ARXIV.2404.06395. URL <https://doi.org/10.48550/arXiv.2404.06395>.

Mandar Joshi, Eunsol Choi, Daniel S. Weld, and Luke Zettlemoyer. Triviaqa: A large scale distantly supervised challenge dataset for reading comprehension, 2017.

Vladimir Karpukhin, Barlas Oguz, Sewon Min, Patrick S. H. Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. Dense passage retrieval for open-domain question answering. In Bonnie Webber, Trevor Cohn, Yulan He, and Yang Liu (eds.), *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020*, pp. 6769–6781. Association for Computational Linguistics, 2020. doi: 10.18653/V1/2020.EMNLP-MAIN.550. URL <https://doi.org/10.18653/v1/2020.emnlp-main.550>.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur P. Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Llion Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc V. Le, and Slav Petrov. Natural questions: A benchmark for question answering research. *Transactions of the Association for Computational Linguistics*, 7:453–466, 2019. URL <https://api.semanticscholar.org/CorpusID:86611921>.

Yannis Labrou, Tim Finin, and Yun Peng. Agent communication languages: the current landscape. *IEEE Intell. Syst.*, 14(2):45–52, 1999. doi: 10.1109/5254.757631. URL <https://doi.org/10.1109/5254.757631>.

Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. Retrieval-augmented generation for knowledge-intensive nlp tasks, 2021.

Guohao Li, Hasan Hammoud, Hani Itani, Dmitrii Khizbulin, and Bernard Ghanem. CAMEL: communicative agents for "mind" exploration of large language model society. In Alice Oh, Tristan Naumann, Amir Globerson, Kate Saenko, Moritz Hardt, and Sergey Levine (eds.), *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 - 16, 2023*, 2023. URL http://papers.nips.cc/paper_files/paper/2023/hash/a3621ee907def47c1b952ade25c67698-Abstract-Conference.html.

Tian Liang, Zhiwei He, Wenxiang Jiao, Xing Wang, Yan Wang, Rui Wang, Yujiu Yang, Zhaopeng Tu, and Shuming Shi. Encouraging divergent thinking in large language models through multi-agent debate. *CoRR*, abs/2305.19118, 2023. doi: 10.48550/ARXIV.2305.19118. URL <https://doi.org/10.48550/arXiv.2305.19118>.

Zhao Mandi, Shreeya Jain, and Shuran Song. Roco: Dialectic multi-robot collaboration with large language models. *CoRR*, abs/2307.04738, 2023. doi: 10.48550/ARXIV.2307.04738. URL <https://doi.org/10.48550/arXiv.2307.04738>.

Elena Meshkova, Janne Riihijärvi, Marina Petrova, and Petri Mähönen. A survey on resource discovery mechanisms, peer-to-peer and service discovery frameworks. *Comput. Networks*, 52(11): 2097–2128, 2008. doi: 10.1016/J.COMNET.2008.03.006. URL <https://doi.org/10.1016/j.comnet.2008.03.006>.

Thomas Mesnard, Cassidy Hardin, Robert Dadashi, Surya Bhupatiraju, Shreya Pathak, Laurent Sifre, Morgane Rivière, Mihir Sanjay Kale, Juliette Love, Pouya Tafti, Léonard Hussenot, Aakanksha Chowdhery, Adam Roberts, Aditya Barua, Alex Botev, Alex Castro-Ros, Ambrose Slone, Amélie Héliou, Andrea Tacchetti, Anna Bulanova, Antonia Paterson, Beth Tsai, Bobak Shahriari, Charline Le Lan, Christopher A. Choquette-Choo, Clément Crepy, Daniel Cer, Daphne Ippolito, David Reid, Elena Buchatskaya, Eric Ni, Eric Noland, Geng Yan, George Tucker, George-Cristian Muraru, Grigory Rozhdestvenskiy, Henryk Michalewski, Ian Tenney, Ivan Grishchenko, Jacob Austin, James Keeling, Jane Labanowski, Jean-Baptiste Lespiau, Jeff Stanway, Jenny Brennan, Jeremy Chen, Johan Ferret, Justin Chiu, and et al. Gemma: Open models based on gemini research and technology. *CoRR*, abs/2403.08295, 2024. doi: 10.48550/ARXIV.2403.08295. URL <https://doi.org/10.48550/arXiv.2403.08295>.

Grégoire Mialon, Clémentine Fourrier, Craig Swift, Thomas Wolf, Yann LeCun, and Thomas Scialom. GAIA: a benchmark for general AI assistants. *CoRR*, abs/2311.12983, 2023. doi: 10.48550/ARXIV.2311.12983. URL <https://doi.org/10.48550/arXiv.2311.12983>.

Reiichiro Nakano, Jacob Hilton, Suchir Balaji, Jeff Wu, Long Ouyang, Christina Kim, Christopher Hesse, Shantanu Jain, Vineet Kosaraju, William Saunders, Xu Jiang, Karl Cobbe, Tyna Eloundou, Gretchen Krueger, Kevin Button, Matthew Knight, Benjamin Chess, and John Schulman. Webgpt: Browser-assisted question-answering with human feedback. *CoRR*, abs/2112.09332, 2021. URL <https://arxiv.org/abs/2112.09332>.

Netflix. Eureka: Aws service registry for resilient mid-tier load balancing and failover. <https://github.com/Netflix/eureka>. Accessed: 2024-06-26.

Open Interpreter. Open Interpreter, 2023. URL <https://github.com/OpenInterpreter/open-interpreter>.

OpenAI. GPT-4 technical report. *CoRR*, abs/2303.08774, 2023. doi: 10.48550/ARXIV.2303.08774. URL <https://doi.org/10.48550/arXiv.2303.08774>.

OpenDevin Team. OpenDevin: An Open Platform for AI Software Developers as Generalist Agents. <https://github.com/OpenDevin/OpenDevin>, 2024. Accessed: ENTER THE DATE YOU ACCESSED THE PROJECT.

Joon Sung Park, Joseph C. O'Brien, Carrie Jun Cai, Meredith Ringel Morris, Percy Liang, and Michael S. Bernstein. Generative agents: Interactive simulacra of human behavior. In Sean Follmer, Jeff Han, Jürgen Steimle, and Nathalie Henry Riche (eds.), *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology, UIST 2023, San Francisco, CA, USA, 29 October 2023- 1 November 2023*, pp. 2:1–2:22. ACM, 2023. doi: 10.1145/3586183.3606763. URL <https://doi.org/10.1145/3586183.3606763>.

Chen Qian, Xin Cong, Cheng Yang, Weize Chen, Yusheng Su, Juyuan Xu, Zhiyuan Liu, and Maosong Sun. Communicative agents for software development. *CoRR*, abs/2307.07924, 2023a. doi: 10.48550/ARXIV.2307.07924. URL <https://doi.org/10.48550/arXiv.2307.07924>.

Chen Qian, Yufan Dang, Jiahao Li, Wei Liu, Weize Chen, Cheng Yang, Zhiyuan Liu, and Maosong Sun. Experiential co-learning of software-developing agents. *CoRR*, abs/2312.17025, 2023b. doi: 10.48550/ARXIV.2312.17025. URL <https://doi.org/10.48550/arXiv.2312.17025>.

Yujia Qin, Shihao Liang, Yining Ye, Kunlun Zhu, Lan Yan, Yaxi Lu, Yankai Lin, Xin Cong, Xiangru Tang, Bill Qian, Sihan Zhao, Runchu Tian, Ruobing Xie, Jie Zhou, Mark Gerstein, Dahai Li, Zhiyuan Liu, and Maosong Sun. Toolllm: Facilitating large language models to master 16000+ real-world apis. *CoRR*, abs/2307.16789, 2023. doi: 10.48550/ARXIV.2307.16789. URL <https://doi.org/10.48550/arXiv.2307.16789>.

Talal Rahwan, Sarvapali D. Ramchurn, Nicholas R. Jennings, and Andrea Giovannucci. An anytime algorithm for optimal coalition structure generation. *J. Artif. Intell. Res.*, 34:521–567, 2009. doi: 10.1613/JAIR.2695. URL <https://doi.org/10.1613/jair.2695>.

Machel Reid, Nikolay Savinov, Denis Teplyashin, Dmitry Lepikhin, Timothy P. Lillicrap, Jean-Baptiste Alayrac, Radu Soricut, Angeliki Lazaridou, Orhan Firat, Julian Schrittweiser, Ioannis Antonoglou, Rohan Anil, Sebastian Borgeaud, Andrew M. Dai, Katie Millican, Ethan Dyer, Mia Glaese, Thibault Sottiaux, Benjamin Lee, Fabio Viola, Malcolm Reynolds, Yuanzhong Xu, James Molloy, Jilin Chen, Michael Isard, Paul Barham, Tom Hennigan, Ross McIlroy, Melvin Johnson, Johan Schalkwyk, Eli Collins, Eliza Rutherford, Erica Moreira, Kareem Ayoub, Megha Goel, Clemens Meyer, Gregory Thornton, Zhen Yang, Henryk Michalewski, Zaheer Abbas, Nathan Schucher, Ankesh Anand, Richard Ives, James Keeling, Karel Lenc, Salem Haykal, Siamak Shakeri, Pranav Shyam, Aakanksha Chowdhery, Roman Ring, Stephen Spencer, Eren Sezener, and et al. Gemini 1.5: Unlocking multimodal understanding across millions of tokens of context. *CoRR*, abs/2403.05530, 2024. doi: 10.48550/ARXIV.2403.05530. URL <https://doi.org/10.48550/arXiv.2403.05530>.

Stephen E. Robertson and Hugo Zaragoza. The probabilistic relevance framework: BM25 and beyond. *Found. Trends Inf. Retr.*, 3(4):333–389, 2009. doi: 10.1561/1500000019. URL <https://doi.org/10.1561/1500000019>.

Timo Schick, Jane Dwivedi-Yu, Roberto Dessì, Roberta Raileanu, Maria Lomeli, Eric Hambro, Luke Zettlemoyer, Nicola Cancedda, and Thomas Scialom. Toolformer: Language models can teach themselves to use tools. In Alice Oh, Tristan Naumann, Amir Globerson, Kate Saenko, Moritz Hardt, and Sergey Levine (eds.), *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 - 16, 2023*, 2023. URL http://papers.nips.cc/paper_files/paper/2023/hash/d842425e4bf79ba039352da0f658a906-Abstract-Conference.html.

John R. Searle. *Speech Acts: An Essay in the Philosophy of Language*. Cambridge University Press, 1969.

John R Searle. A classification of illocutionary acts1. *Language in society*, 5(1):1–23, 1976.

Yongliang Shen, Kaitao Song, Xu Tan, Dongsheng Li, Weiming Lu, and Yueting Zhuang. Huggingpt: Solving AI tasks with chatgpt and its friends in hugging face. In Alice Oh, Tristan Naumann, Amir Globerson, Kate Saenko, Moritz Hardt, and Sergey Levine (eds.), *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 - 16, 2023*, 2023. URL http://papers.nips.cc/paper_files/paper/2023/hash/77c33e6a367922d003ff102ffb92b658-Abstract-Conference.html.

Noah Shinn, Federico Cassano, Ashwin Gopinath, Karthik Narasimhan, and Shunyu Yao. Reflexion: language agents with verbal reinforcement learning. In Alice Oh, Tristan Naumann, Amir Globerson, Kate Saenko, Moritz Hardt, and Sergey Levine (eds.), *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 - 16, 2023*, 2023. URL http://papers.nips.cc/paper_files/paper/2023/hash/1b44b878bb782e6954cd888628510e90-Abstract-Conference.html.

Significant Gravitas. AutoGPT, 2023. URL <https://github.com/Significant-Gravitas/AutoGPT>.

XAgent Team. Xagent: An autonomous agent for complex task solving, 2023.

Guanzhi Wang, Yuqi Xie, Yunfan Jiang, Ajay Mandlekar, Chaowei Xiao, Yuke Zhu, Linxi Fan, and Anima Anandkumar. Voyager: An open-ended embodied agent with large language models. *CoRR*, abs/2305.16291, 2023a. doi: 10.48550/ARXIV.2305.16291. URL <https://doi.org/10.48550/arXiv.2305.16291>.

Haotian Wang, Xiyuan Du, Weijiang Yu, Qianglong Chen, Kun Zhu, Zheng Chu, Lian Yan, and Yi Guan. Apollo’s oracle: Retrieval-augmented reasoning in multi-agent debates. *ArXiv*, abs/2312.04854, 2023b. URL <https://api.semanticscholar.org/CorpusID:266149845>.

Xingyao Wang, Zihan Wang, Jiateng Liu, Yangyi Chen, Lifan Yuan, Hao Peng, and Heng Ji. MINT: evaluating llms in multi-turn interaction with tools and language feedback. *CoRR*, abs/2309.10691, 2023c. doi: 10.48550/ARXIV.2309.10691. URL <https://doi.org/10.48550/arXiv.2309.10691>.

Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc V. Le, Ed H. Chi, Sharan Narang, Aakanksha Chowdhery, and Denny Zhou. Self-consistency improves chain of thought reasoning in language models. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023*. OpenReview.net, 2023d. URL <https://openreview.net/pdf?id=1PL1NIMMrw>.

Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A. Smith, Daniel Khashabi, and Hannaneh Hajishirzi. Self-instruct: Aligning language models with self-generated instructions. In Anna Rogers, Jordan L. Boyd-Graber, and Naoaki Okazaki (eds.), *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2023, Toronto, Canada, July 9-14, 2023*, pp. 13484–13508. Association for Computational Linguistics, 2023e. doi: 10.18653/V1/2023.ACL-LONG.754. URL <https://doi.org/10.18653/v1/2023.acl-long.754>.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed H. Chi, Quoc V. Le, and Denny Zhou. Chain-of-thought prompting elicits reasoning in large language models. In Sanmi Koyejo, S. Mohamed, A. Agarwal, Danielle Belgrave, K. Cho, and A. Oh (eds.), *Advances in Neural Information Processing Systems 35: Annual Conference on Neural Information Processing Systems 2022, NeurIPS 2022, New Orleans, LA, USA, November 28 - December 9, 2022*, 2022. URL http://papers.nips.cc/paper_files/paper/2022/hash/9d5609613524ecf4f15af0f7b31abca4-Abstract-Conference.html.

Qingyun Wu, Gagan Bansal, Jieyu Zhang, Yiran Wu, Shaokun Zhang, Erkang Zhu, Beibin Li, Li Jiang, Xiaoyun Zhang, and Chi Wang. Autogen: Enabling next-gen LLM applications via multi-agent conversation framework. *CoRR*, abs/2308.08155, 2023. doi: 10.48550/ARXIV.2308.08155. URL <https://doi.org/10.48550/arXiv.2308.08155>.

Zhiyong Wu, Chengcheng Han, Zichen Ding, Zhenmin Weng, Zhoumianze Liu, Shunyu Yao, Tao Yu, and Lingpeng Kong. Os-copilot: Towards generalist computer agents with self-improvement. *CoRR*, abs/2402.07456, 2024. doi: 10.48550/ARXIV.2402.07456. URL <https://doi.org/10.48550/arXiv.2402.07456>.

Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William W. Cohen, Ruslan Salakhutdinov, and Christopher D. Manning. Hotpotqa: A dataset for diverse, explainable multi-hop question answering, 2018.

Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izhak Shafran, Karthik R. Narasimhan, and Yuan Cao. React: Synergizing reasoning and acting in language models. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023*. OpenReview.net, 2023. URL https://openreview.net/pdf?id=WE_vluYUL-X.

Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric P. Xing, Hao Zhang, Joseph E. Gonzalez, and Ion Stoica. Judging llm-as-a-judge with mt-bench and chatbot arena. In Alice Oh, Tristan Naumann, Amir Globerson, Kate Saenko, Moritz Hardt, and Sergey Levine (eds.), *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 - 16, 2023*, 2023a. URL http://papers.nips.cc/paper_files/paper/2023/hash/91f18a1287b398d378ef22505bf41832-Abstract-Datasets_and_Benchmarks.html.

Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric P. Xing, Hao Zhang, Joseph E. Gonzalez, and Ion Stoica. Judging llm-as-a-judge with mt-bench and chatbot arena, 2023b.

A IMPLEMENTATION DETAILS OF IOA

In this appendix, we provide a comprehensive overview of the implementation details for each module in the client and server layers of IoA.

A.1 MESSAGE PROTOCOL

To support the functionalities of IoA introduced in Section 2.4, we have designed a comprehensive agent message protocol that facilitates efficient communication and coordination among agents. The protocol, as illustrated in Fig. 7, consists of several fields that cater to the specific requirements of various mechanisms within the framework.

Firstly, the protocol includes the following header for all message types:

- **sender** (str): The name or unique identifier of the agent sending the message.
- **state** (enum): The current state of the group chat associated with the message, which can be either team formation or communication.
- **comm_id** (str): The unique identifier of the group chat to which the message belongs.

To support the autonomous team formation mechanism, the protocol incorporates the following fields:

- **goal** (str): The objective or task that the current group chat aims to accomplish.
- **team_members** (list[str]): The names or unique identifiers of the agents required for the current group chat.
- **team_up_depth** (int): The depth of the current nested team formation, used to determine if the maximum allowed depth has been reached.
- **max_turns** (int): The maximum number of discussion turns allowed for the current group chat. If exceeded, the group chat will be forced into the conclusion phase.

For facilitating the discussion phase, the protocol includes the following fields:

- **content** (str): The actual content of the current message.
- **type** (enum): Specifies the next dialogue state, which can be discussion, task assignment, or conclusion.
- **next_speaker** (list[str]): The name(s) or unique identifier(s) of the agent(s) expected to speak next. In the discussion state, **next_speaker** is limited to a single agent, while in the task assignment state, it can include multiple agents, indicating that the current message contains multiple task assignments.

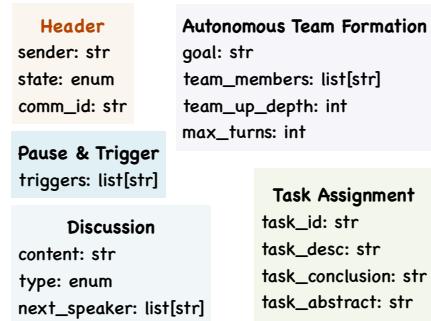


Figure 7: Fields in the IoA message protocol.

To support the task assignment mechanism, the protocol incorporates the following fields:

- `task_id` (str): The automatically generated unique identifier for the current task.
- `task_desc` (str): The description of the task assigned to the client, extracted from the chat.
- `task_conclusion` (str): The conclusion or result provided by the client after completing the assigned task.
- `task_abstract` (str): A concise summary of the completed task.

Lastly, to support the pause & trigger mechanism, the protocol includes the following field:

- `triggers` (list[str]): A list of task IDs that require a trigger to be set.

By adhering to this comprehensive agent message protocol for sending and receiving messages, clients within IoA can effectively achieve autonomous team formation and conversation flow control. The protocol ensures that all necessary information is communicated among agents, enabling seamless collaboration and coordination in various task scenarios.

A.2 CLIENT

The client component of IoA plays a crucial role in enabling the integration and collaboration of heterogeneous agents. It consists of three layers: the Foundation Layer, the Data Layer, and the Interaction Layer. Each layer comprises several modules that work together to facilitate efficient communication, data management, and agent coordination. In this subsection, we provide a detailed overview of the implementation of each module within the client's layers.

A.2.1 FOUNDATION LAYER

Network Infrastructure Module In IoA, all clients maintain a persistent connection to the server using the WebSocket protocol, similar to an instant messaging application. When a client sends a message, it is transmitted to the server, which parses the `comm_id` field in the message and forwards it to the other clients in the corresponding group chat via their respective WebSocket connections. The real-time nature of WebSocket ensures that messages are delivered promptly, enabling clients to receive and respond to messages without delay.

Data Infrastructure Module To support the data storage and retrieval requirements of the upper-level Data Layer modules, we employ SQLite as the primary database solution. SQLite provides a lightweight and efficient means of persisting and accessing data related to agent contacts, group information, and task management. By leveraging SQLite, the client can store and retrieve information about encountered agents, group chat details, and task assignments, ensuring data consistency and availability throughout the collaboration process.

Agent Integration Module The Agent Integration Module defines the protocol that third-party agents must adhere to in order to seamlessly integrate with IoA. Currently, the agent integration protocol in IoA requires agents to implement a function `def run(task_desc: str) -> str`, which accepts a task description as input and returns a summary of the task completion. This simple yet effective protocol allows diverse agents to be incorporated into the framework, enabling them to contribute their unique capabilities to the collaboration process. As IoA evolves, the integration protocol can be extended to support more advanced functionalities and interaction patterns.

A.2.2 DATA LAYER

Agent Contact Module The Agent Contact Module is responsible for maintaining a record of the clients that the current client has previously collaborated with. It stores information such as the names and descriptions of these clients, providing a valuable reference for future collaborations. The module aims to support the client in evaluating and storing collaboration outcomes after each task, allowing it to make informed decisions when forming teams for subsequent tasks. During the team formation process, the information stored in this module is included in the prompt to assist the client in selecting the most suitable partners based on prior experiences.

Group Info Module The Group Info Module manages all group chat-related information, including the following fields:

- `comm_id` (str): The unique identifier of the group chat.
- `goal` (str): The objective or task that the group chat aims to accomplish.
- `team_members` (str): The list of agents participating in the group chat.
- `state` (str): The current state of the group chat (e.g., team formation, discussion, task assignment, conclusion).
- `conclusion` (str — None): The final outcome or conclusion reached by the group chat.
- `team_up_depth` (int): The depth of the nested team formation within the group chat.
- `max_turns` (int): The maximum number of communication turns allowed in the group chat.

By organizing and persisting this information, the Group Info Module enables clients to maintain a coherent view of the ongoing collaborations and their progress.

Task Management Module The Task Management Module is responsible for storing and tracking the tasks assigned within each group chat. It maintains the following fields for each task:

- `task_id` (str): The unique identifier of the task.
- `task_desc` (str): The detailed description of the task.
- `task_abstract` (str): A concise summary of the task.
- `assignee` (str): The agent assigned to complete the task.
- `status` (enum): The current status of the task (e.g., pending, in progress, completed).
- `conclusion` (str — None): The final result or outcome of the task.

By keeping track of task-related information, the Task Management Module enables clients to monitor the progress of assigned tasks and ensures that all task-related data is readily available for reference and decision-making purposes.

A.2.3 INTERACTION LAYER

Team Formation Module As briefly introduced in Section 2.3.2, when a client receives a task, it is equipped with two essential tools: `search_agent(desc: list[str]) -> list[agent]` and `launch_group_chat(team_members: list[str] | None) -> comm_id`. The client must decide whether to utilize the `search_agent` tool to find agents on the server that match the specified description, or to directly call the `launch_group_chat` tool based on the discovered agents and historical collaboration information. If the client invokes `launch_group_chat` without specifying any agents, it implies that the task will be completed by a single agent. To prevent infinite loops, IoA imposes a limit on the maximum number of tool calls, set to 10 by default. If the client reaches this limit without successfully launching a group chat, it is forced to invoke the `launch_group_chat` tool to initiate the collaboration process.

Communication Module The Communication Module handles the core functionalities of message generation and message reception. When a client generates a message, IoA processes it according to the agent message protocol. If the message type is `conclusion`, the client enters the conclusion phase, where it provides a final answer to the group chat goal based on the accumulated chat records and task completion information. In the case of a `pause & trigger` message, the framework prompts the client to generate the task IDs that require triggers and broadcasts them to all group members. For `discussion` or `task_assignment` messages, they are directly broadcast to all participants in the group chat.

Upon receiving a message, the client parses it according to the agent message protocol. If the `next_speaker` field does not include the current client, the message is simply added to the group chat history. However, if the client is designated as the next speaker, it must take appropriate actions based on the message type. For `discussion` messages, the client generates a response to continue the conversation. In the case of `sync` or `async` `task_assignment` messages, the client extracts its assigned task from the chat record, summarizes it, and specifies the relevant information

to be passed to the integrated agent. The agent then executes the task based on the summarized description and relevant chat messages, returning the result upon completion. If the message type is `pause & trigger`, the client updates the corresponding task triggers in the Task Management Module.

The Communication Module, in conjunction with the other modules in the Interaction Layer and Data Layer, enables seamless and structured collaboration among agents. By adhering to the well-defined agent message protocol and leveraging the functionalities provided by the various modules, clients can effectively participate in discussions, assign tasks, and coordinate their actions to achieve the desired goals.

A.3 SERVER

The server component of IoA serves as the central hub for agent coordination, communication, and management. It comprises three layers: the Foundation Layer, the Data Layer, and the Interaction Layer. Each layer contains modules that work together to facilitate agent registration, discovery, and message routing. In this subsection, we provide a detailed description of the implementation of each module within the server's layers.

A.3.1 FOUNDATION LAYER

Network Infrastructure Module and Data Infrastructure Module The Network Infrastructure Module and Data Infrastructure Module in the server are largely similar to their counterparts in the client. However, the server's Data Infrastructure Module incorporates the use of the Milvus vector database to support the construction and maintenance of the Agent Registry. Milvus enables efficient similarity search and retrieval of agent information based on their characteristics, allowing the server to provide clients with the functionality to discover and match agents effectively.

Security Module While the Security Module is not extensively utilized in the current implementation of IoA, we acknowledge its crucial role in ensuring the integrity and reliability of the framework in real-world deployments. This module is responsible for verifying and controlling the integration of third-party agents into the clients, preventing malicious agents from compromising the entire framework. As IoA evolves, the Security Module will be enhanced to provide robust authentication, authorization, and monitoring mechanisms, safeguarding the collaborative environment from potential security threats.

A.3.2 DATA LAYER

Agent Registry Module The Agent Registry Module maintains a comprehensive record of all clients integrated into the server. When a client connects to the server, it is required to provide a detailed description of the integrated agent, including its name and capability description. This information is stored in the Agent Registry, enabling similarity matching based on agent characteristics. The Agent Registry serves as a central repository for agent information, facilitating agent discovery and team formation processes.

Session Management Module The Session Management Module is responsible for managing the WebSocket connections of all online agents and keeping track of the group chats they participate in. It maintains a mapping between agents and their respective WebSocket connections, as well as the associations between agents and group chats. When a client sends a message, the Session Management Module ensures that the message is properly routed to all clients involved in the corresponding group chat, guaranteeing reliable and efficient communication within the collaborative environment.

A.3.3 INTERACTION LAYER

Agent Query Module The Agent Query Module handles incoming requests from clients seeking to discover and match agents based on specific characteristics. Upon receiving a query request, the module converts the provided characteristics into vector representations and performs similarity matching against the agents stored in the Agent Registry. The implementation of this module can vary depending on the specific requirements and scalability needs of the framework. For instance,

techniques such as BM25 or other information retrieval methods can be employed to enhance the matching process and improve the relevance of the returned agent results.

Group Setup Module The Group Setup Module is responsible for handling client requests to create new group chats. When a client submits a request to set up a group chat, specifying the desired team members, the Group Setup Module processes the request and initializes a new group chat instance. It assigns a unique `comm_id` to the newly created group chat and notifies all participating clients about their inclusion in the chat. The Group Setup Module works in conjunction with the Session Management Module to ensure that the necessary WebSocket connections and mappings are established for efficient communication within the group chat.

Message Routing Module The Message Routing Module plays a critical role in facilitating communication between clients within group chats. When a client sends a message, the Message Routing Module receives the message and parses it according to the agent message protocol. Based on the `comm_id` specified in the message, the module identifies the corresponding group chat and forwards the message to all clients associated with that chat. The Message Routing Module leverages the information maintained by the Session Management Module to ensure accurate and timely delivery of messages to the intended recipients.

The server component of IoA, with its carefully designed modules and interactions, provides a robust and efficient infrastructure for agent coordination, communication, and management. By leveraging the capabilities of the Foundation Layer, Data Layer, and Interaction Layer, the server enables seamless agent discovery, team formation, and message exchange, fostering a collaborative environment where diverse agents can work together to achieve common goals.

As IoA continues to evolve, the server component will be further enhanced to incorporate advanced features such as load balancing, fault tolerance, and scalability, ensuring that the framework can handle the growing demands of real-world multi-agent systems. Additionally, the Security Module will be strengthened to provide comprehensive security measures, safeguarding the integrity and confidentiality of agent interactions within the framework.

A.4 IMPLEMENTATION DETAILS OF DIFFERENT EXPERIMENTS

In this section, we provide an overview of the implementation details for each experiment conducted to evaluate the performance of IoA.

A.4.1 GAIA

For the GAIA benchmark, IoA integrated four ReAct agents: Web Browser, Code Executor, YouTube Transcript Downloader, and Wikidata Searcher. The tools provided to Web Browser and Code Executor agents are adapted from the AutoGen framework with minor modifications to ensure compatibility with IoA. To address the YouTube-related tasks in GAIA, we develop a YouTube video transcript downloader based on PyTube⁴. For videos without readily available transcripts, the tool employs the Whisper model to transcribe spoken language into text. Similarly, we adapt the Wikidata tool from Langchain⁵ to fit the IoA ecosystem. These adaptations showcases a key feature of IoA: when a task requires a specific tool, it can be easily integrated into the system through its implementation and agent adaptation, enabling it to participate in task completion.

Due to budget constraints, we conduct performance testing on the GAIA validation set. Despite this limitation, the results provide valuable insights into the effectiveness of IoA in handling complex, multi-step tasks.

A.4.2 OPEN-ENDED INSTRUCTION BENCHMARK

To create a diverse and challenging benchmark for evaluating the performance of IoA on open-ended tasks, we construct a set of 153 instructions spanning four categories: search & report, coding, math, and life assistance. The benchmark construction process involved three main steps:

⁴<https://github.com/pytube/pytube>

⁵<https://python.langchain.com/v0.1/docs/integrations/tools/wikidata/>

Please complete the function according to its comment.
`def minimumTime(grid: List[List[int]]) -> int:
 """`

You are given a $m \times n$ matrix grid consisting of non-negative integers where $grid[row][col]$ represents the minimum time required to be able to visit the cell (row, col) , which means you can visit the cell (row, col) only when the time you visit it is greater than or equal to $grid[row][col]$.

You are standing in the top-left cell of the matrix in the 0th second, and you must move to any adjacent cell in the four directions: up, down, left, and right. Each move you make takes 1 second.

Return the minimum time required in which you can visit the bottom-right cell of the matrix. If you cannot visit the bottom-right cell, then return -1.

Example 1:

Input: `grid = [[0,1,3,2],[5,1,2,5],[4,3,8,6]]`

Output: 7

Explanation: One of the paths that we can take is the following:

- at $t = 0$, we are on the cell $(0,0)$.

[...]

Constraints:

[...]

After you complete the function, display the content of the script as `res.py` directly.

Coding

In a country, there are cities connected by one-way roads. It's known that from any city, there is a route (possibly passing through other cities) leading to the capital. Prove that it's possible to choose one road from each city in such a way that all chosen roads lead directly or indirectly to the capital.

Math

Review three smartphone models (Apple iPhone 13, Samsung Galaxy S22, and Google Pixel 6) based on camera quality, battery life, user interface, and price to decide the best buy.

Search & Report:

I am a 35-year-old software engineer who is vegan and looking to optimize for a balanced diet containing 2500 calories per day. Create a personalized weekly meal plan for me. Include three meals and two snacks per day, paying close attention to incorporating a variety of protein sources to meet daily protein needs. Provide a detailed grocery list that organizes ingredients by aisle for a standard grocery store layout.

Life Assistant

Figure 8: Example instructions from different categories in our open-ended instruction benchmark

First, we select the instructions based on the real-world complex tasks used by XAgent (Team, 2023). These instructions were categorized into the four aforementioned groups. Second, to increase the diversity of the benchmark, we manually create an additional 10 complex tasks. Finally, we use the Self-Instruct method (Wang et al., 2023e) to generate approximately 200 instructions, using the previously selected instructions as seeds. After manual screening and modification, we obtained the additional 94 instructions, resulting in a total of 153 tasks. The benchmark eventually consists of 52 search & report tasks, 30 coding tasks, 30 math tasks, and 41 life assistance tasks. By incorporating a diverse set of open-ended instructions, this benchmark allows for a comprehensive evaluation of the performance and versatility of IoA in handling a wide range of real-world scenarios. We show one example instruction for each category in Fig. 8.

Evaluation Methodology. For IoA, we consider the final conclusion generated by the agents as the final answer. However, since AutoGPT (Significant Gravitas, 2023) and Open Interpreter (Open Interpreter, 2023) complete tasks in multiple steps and do not inherently generate a conclusion, we prompted them to provide a detailed conclusion as the final answer after task completion.

Inspired by the pairwise comparison evaluation method used in MT-Bench (Zheng et al., 2023b), we employ GPT-4 to evaluate the responses of IoA against AutoGPT and Open Interpreter. To mitigate potential biases introduced by the order of the responses, we alternate the order of the two responses when presenting them to GPT-4 for evaluation. A result is counted as a *win* for a system only when it is consistently determined to be superior to its competitor in both orderings. In cases where the performance is inconsistent across the two orderings, the result is considered a *draw*.

A.4.3 EMBODIED AGENT TASKS

For the RocoBench experiments, we adhere to the original paper's methodology, which relies on discussions and parsing specific formatted strings from the discussion results to determine the embodied agent's actions, rather than using agents to call tools directly. We implement two clients that communicate without integrated agents, requiring them to output strings in the RocoBench format

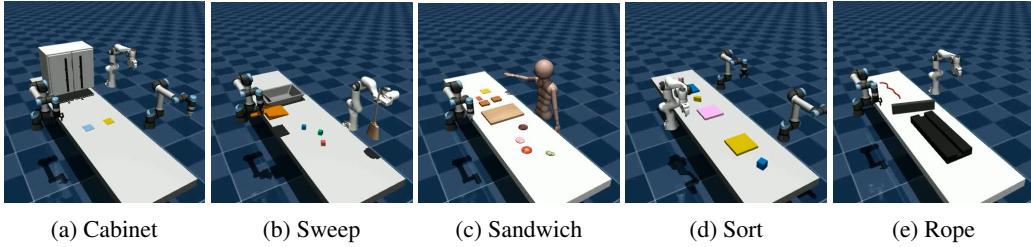


Figure 9: The different environments in RocoBench.

at the conclusion stage. These strings are then parsed and used to interact with the environment using RocoBench’s predefined parsing functions. This approach serves as a validation of IoA’s client implementation and communication mechanism design.

To accommodate the varying requirements of different tasks in RocoBench, we adopt task-specific settings. For the Sort, Sandwich, and Sweep tasks, which exhibit strong interdependencies between steps, we retained the chat history and continued each new action discussion based on the previous group chat. In contrast, for the Cabinet and Rope tasks, where the steps were less interdependent, we initiated a new group chat for each action to optimize costs. Other settings remained consistent with the Roco Dialog baseline.

A.4.4 RETRIEVAL-AUGMENTED GENERATION

For the retrieval-augmented generation (RAG) question-answering task, we follow the settings outlined in Apollo’s Oracle. We provide agents with two evidence pools: one derived from Wikipedia and the other from Google. For Wikipedia, we utilize Pyserini’s pre-built index of Wikipedia content up to January 20, 2021, retrieving the top 10 most relevant results for each query. For Google, we directly access the Google Search API, returning the top 5 most relevant results for each query. These tools were made available to the client-side LLMs, enabling them to query relevant information during discussions and ultimately provide well-informed answers.

To evaluate the performance of IoA on the RAG task, we randomly sample 500 entries from the validation or test sets of the four datasets. After the model generates answers, we employ GPT-4 for answer evaluation. Specifically, we provide GPT-4 with the dataset answers and the model’s answers, requiring it to output its reasoning in a Chain of Thought (CoT) manner before providing a final correctness judgment.

B VISUALIZATION OF ROCOBENCH

We provide the visualization of RocoBench at Fig. 9. The **cabinet task** requires three agents to collaborate: two agents open and hold the cabinet door while the third agent retrieves two cups from inside the cabinet and places them onto coasters that match the color of the cups. The **sweep task** involves two agents coordinating their actions: one agent controls a broom to sweep cubes, while the other agent holds a bucket to collect the cubes, and finally, they dump all the cubes into a dustbin. In the **sandwich task**, two agents work together to pick up ingredients and stack them according to a given recipe. The **sort task** requires three agents to place three cubes onto coasters with matching colors. Since each agent can only reach a limited area, they must coordinate their movements. Lastly, the **rope task** involves agents moving a rope into a bracket. They must communicate effectively to decide the correct path for maneuvering the rope.

C SIMULATED ENVIRONMENT FOR TEAM FORMATION EVALUATION

C.1 REGULAR TEAM FORMATION SIMULATED ENVIRONMENT CONSTRUCTION

To construct a simulated environment for evaluating the regular team formation mechanism, we employ GPT-4-1106-preview to generate a diverse set of tasks and agents. The dataset construction process involved the following steps:

1. Task Generation:

- Using ChatGPT-4, we generate 399 distinct categories of theme keywords, covering various domains such as sports, lifestyle, and entertainment.
- From these categories, we randomly select 25 themes and task GPT-4 with generating task descriptions related to at least four themes from the selected set, thus obtaining a task that require diverse agents with different capabilities.
- Task descriptions are generated in JSON format using the GPT-4 API, ensuring a structured and consistent representation.

2. Agent Generation:

- After generating the tasks, for each task, we again prompt GPT-4 to construct at least two agents with varying capabilities for the given task, including the name of the agent, the type of the agent and the description of the agent.
- The agent profile format is designed to align with the server-side agent registry, facilitating seamless integration and interaction within IoA.

An example of a generated task description in JSON format is as follows:

```
1 {
2     "task_id": "xxx",
3     "task_description": "Develop a mobile app that helps users plan
4         and manage their personal finance, including budgeting,
        expense tracking, and investment suggestions."
}
```

Similarly, an example of an agent profile in JSON format is:

```
1 {
2     "agent_name": "FinanceGuru",
3     "agent_type": "Thing Assistant"
4     "agent_description": "FinanceGuru is a highly skilled agent
        specializing in personal finance management. It has
        extensive knowledge of budgeting techniques, expense
        tracking tools, and investment strategies. FinanceGuru can
        provide personalized recommendations based on a user's
        financial goals and risk tolerance."
5 }
```

A complete example with agent profiles and task description in JSON format is:

```
1 {
2     "agents": [
3         {
4             "agent_name": "BeautyRoutineAssistant",
5             "agent_type": "Thing Assistant",
6             "agent_description": "This agent specializes in grooming and
                beauty routines. It is designed to offer personalized
                beauty tips and tutorials for efficient makeup
                application based on the user's facial features, skin
                type, and preferences. It suggests makeup looks that
                align with weather conditions and the user's daily agenda
                . The assistant can interface with smart mirrors, makeup
                organizers, and tutorials for a streamlined morning
                routine."
7         },
8         {
9             "agent_name": "LanguageCoachAssistant",
10            "agent_type": "Human Assistant",
11        }
12    ]
13 }
```

```

11     "agent_description": "This is an educational aide focused on
12         facilitating language learning sessions. It assesses the
13             user's current language proficiency, learning style, and
14                 daily schedule to allocate an optimal one-hour learning
15                     window. The agent customizes lesson plans, integrates
16                         with language learning apps or platforms, and can
17                             organize virtual interactions with native speakers for
18                                 immersive learning experiences."
19
20
21     },
22
23     {
24         "agent_name": "EcoCuisineAssistant",
25         "agent_type": "Thing Assistant",
26         "agent_description": "EcoCuisineAssistant is dedicated to
27             healthy meal planning and environmental consciousness. It
28                 suggests simple, nutritious dinner recipes based on
29                     dietary needs, kitchen inventory, and prep time
30                         constraints. It interfaces with smart kitchen appliances
31                             to guide the cooking process and monitors waste to teach
32                                 and reinforce correct recycling habits, ensuring a
33                                     minimized environmental impact."
34
35     }
36
37     ],
38
39     "task_description": "I am looking to create a daily routine that
40         incorporates applying makeup efficiently in the morning,
41             spending an hour learning a new language, preparing a simple
42                 and healthy dinner, and correctly recycling the waste
43                     generated throughout the day."
44
45

```

C.2 NESTED TEAM FORMATION SIMULATED ENVIRONMENT CONSTRUCTION

In a similarly way, in order to construct a simulated environment for evaluating the nested team formation mechanism, we also employ GPT-4-1106-preview to generate two diverse sets of tasks and agents. The dataset construction process involved the following steps:

1. Sub-tasks Completed by Existing Agents:
 - Sub-task Generation:
 - Based on the dataset that we have constructed for regular team formation, we randomly select 300 sets as the original dataset.
 - For tasks in the original dataset, we prompt GPT-4 to construct a sub-task that can be completed by an existing agent, with the agent being selected by GPT-4.
 - Sub-task description are generated in JSON format using the GPT-4 API with the existing agent, ensuring a structured and consistent representation.
2. Sub-tasks Completed by Additional Agent:
 - Sub-task and Agent Generation:
 - After generating the sub-tasks for exiting agent, we take the rest of sets as the another original dataset.
 - The difference for sub-task completed by existing agent is that we prompt GPT-4 to construct a sub-task requiring a very specific expertise.
 - Meanwhile, we also prompt GPT-4 to construct an agent with distinct capabilities compared to the existing agents to complete the generated sub-task, including the name of the agent, the type of the agent and the description of the agent.
 - Sub-task description and additional agent are generated in JSON format using the GPT-4 API ensuring a structured and consistent representation.

An example of a generated sub-task description with existing agent in JSON format is as follows:

```
1  {
2      "additional_subtask": {
3          "task_description": "Develop a comprehensive marketing plan
4              highlighting the business's commitment to sustainability,
5              including strategies for podcast promotion, brand awareness,
6              and customer engagement.",
7          "agent": {
8              "agent_name": "MarketingStrategist",
9              "agent_type": "Human Assistant",
10             "agent_description": "Critical to the success of the
11                 sustainability-focused business, this agent is in charge
12                 of advertising campaigns, social media presence, and
13                 public relations. With a strong emphasis on the company'
14                 s eco-friendly values, it develops targeted marketing
15                 strategies to reach a wider audience, creating a strong
16                 brand identity around sustainability. The agent also
17                 handles analytics, gauging the effectiveness of
18                 marketing efforts and adjusting tactics to optimize
19                 outreach and customer engagement."
20         },
21         "agents": [
22             {
23                 "agent_name": "SustainabilityEducator",
24                 "agent_type": "Human Assistant",
25                 "agent_description": "This agent is specialized in creating,
26                     curating, and disseminating information about
27                     sustainable living. It is responsible for researching
28                     various subjects related to sustainability, structuring
29                     podcast content, interviewing experts, and sharing
30                     practical tips on incorporating eco-friendly practices
31                     into daily life. The agent will also engage the audience
32                     through various channels, answer listener queries, and
33                     promote discussion on sustainability."
34         },
35         {
36             "agent_name": "EcoDesigner",
37             "agent_type": "Human Assistant",
38             "agent_description": "Tasked with the creation of custom eco
39                 -friendly products, this agent has expertise in
40                 sustainable design practices and materials. It
41                 collaborates with customers to understand their needs
42                 and preferences, and uses innovative methods to craft
43                 personalized, environmentally responsible goods while
44                 maintaining aesthetic and functional standards.
45                 Additionally, the agent works closely with suppliers to
46                 ensure the sustainability and ethical sourcing of raw
47                 materials."
48         },
49         {
50             "agent_name": "MarketingStrategist",
51             "agent_type": "Human Assistant",
52             "agent_description": "Critical to the success of the
53                 sustainability-focused business, this agent is in charge
54                 of advertising campaigns, social media presence, and
55                 public relations. With a strong emphasis on the company'
56                 s eco-friendly values, it develops targeted marketing
57                 strategies to reach a wider audience, creating a strong
58                 brand identity around sustainability. The agent also
```

```
24     },
25   ],
26 "task_description": "I want to start a business that focuses on
27   sustainable living. The business will include a podcast series
   on how to incorporate sustainability into daily life and
   crafting custom eco-friendly products for customers."
}
```

Similarly, an example of a generated sub-task description with additional agent in JSON format is:

```
1 {
2   "additional_subtask": {
3     "task_description": "Implement advanced custom animations and
         interactive elements to enhance the visual appeal of the
         personal website, particularly for the graphic design
         portfolio section. This includes creating dynamic, engaging
         animations that showcase the artist's skills and bring the
         homepage to life, as well as ensuring cross-browser
         compatibility and responsiveness on various devices.",
4     "agent": {
5       "agent_name": "AnimationExpert",
6       "agent_type": "Thing Assistant",
7       "agent_description": "AnimationExpert is a highly specialized
         virtual assistant dedicated to creating sophisticated web
         animations and interactive experiences. It is equipped
         with state-of-the-art tools and knowledge of the latest
         animation libraries like GSAP, Three.js, and WebGL. This
         agent analyzes the existing style and content of the
         website to develop tailored, eye-catching animations that
         complement the graphical elements without compromising
         website performance. It ensures compatibility with all
         major browsers and devices and works seamlessly with
         responsive design principles to deliver a consistent
         experience across all user interfaces."
8     }
9   },
10  "agents": [
11    {
12      "agent_name": "WebDesignerAssistant",
13      "agent_type": "Human Assistant",
14      "agent_description": "This agent specializes in web design and
          user experience. It assists in creating a visually
          appealing and intuitive homepage layout that effectively
          showcases the portfolio of graphic design work. It will
          help organize content in a cohesive manner, using best web
          design practices to emphasize the most compelling pieces.
          This assistant can also suggest and implement design
          elements that reflect personal style and artistic
          sensibility."
15    },
16    {
17      "agent_name": "ContentStrategistAssistant",
18      "agent_type": "Human Assistant",
19      "agent_description": "This agent focuses on content creation
          and management. It supports in putting together the
          fashion and style blog posts by helping to curate topics,
```

```
20     edit posts for clarity and brand consistency, and
21     integrate them into the website. It ensures that the blog
22     content is strategically placed for optimal engagement,
23     incorporating SEO best practices to increase visibility
24     and draw in more visitors interested in fashion and style
25     ."
26   },
27   {
28     "agent_name": "PhotographyShowcaseAssistant",
29     "agent_type": "Thing Assistant",
30     "agent_description": "This agent is tailored to enhance the
31       presentation of photography work on the website. Equipped
32       with image organizing and editing software integration
33       capabilities, it can help sort and select the best
34       photographs to feature. It will ensure that the images are
35       displayed in high quality and that the loading speed is
36       optimized for user convenience. This assistant will also
37       provide options for interactive image galleries that
38       enable visitors to view the work in detail."
39   }
40 ],
41   "task_description": "I want to create a personal website that
42     showcases my portfolio of graphic design work, my fashion
43     and style blog posts, and my photography. Please provide
44     instructions on how to design the layout for my homepage
45     that effectively incorporates all three aspects."
46 }
```

By generating a couple of diverse sets of tasks and agents, we create a comprehensive simulated environment for evaluating the regular team formation mechanism and the nested team formation mechanism. This environment enables us to assess the effectiveness of IoA in assembling appropriate teams to complete task requirements, addressing the limitations of existing benchmarks in providing suitable large-scale agent evaluation scenarios.