AgentVerse: Facilitating Multi-Agent Collaboration and Exploring Emergent Behaviors in Agents

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Abstract

Autonomous agents empowered by Large Language Models (LLMs) have undergone significant improvements, enabling them to generalize across a broad spectrum of tasks. However, in real-world scenarios, cooperation among individuals is often required to enhance the efficiency and effectiveness of task accomplishment. Hence, inspired by human group dynamics, we propose a multi-agent framework AGENTVERSE that can collaboratively and dynamically adjust its composition as a greater-than-the-sum-of-its-parts system. Our experiments demonstrate that AGENTVERSE framework can effectively deploy multi-agent groups that outperform a single agent. Furthermore, we delve into the emergence of social behaviors among individual agents within a group during collaborative task accomplishment. In view of these behaviors, we discuss some possible strategies to leverage positive ones and mitigate negative ones for improving the collaborative potential of multi-agent groups. Our codes for AGENTVERSE will soon be released at https://github.com/OpenBMB/AgentVerse.

1 Introduction

The pursuit of creating intelligent and autonomous agents that can assist humans and effectively operate in real-world environments has long been a cornerstone in the field of artificial intelligence (Wooldridge & Jennings, 1995; Minsky, 1988; Bubeck et al., 2023). The recent advance of Large Language Models (LLMs) (OpenAI, 2023; Anil et al., 2023; Touvron et al., 2023b) has ushered in many new opportunities to this realm. Specifically, the recently proposed LLM, GPT-4 (OpenAI, 2023), is particularly notable for its proficiency in comprehending human intent, executing commands, and displaying exceptional capabilities across diverse domains such as language understanding, vision, coding, and mathematics (Bubeck et al., 2023). By harnessing the capabilities of LLMs, autonomous agents can make more effective decisions and execute efficient actions to accomplish tasks with an unprecedented degree of autonomy (Zhou et al., 2023). Several proof-of-concepts autonomous agents, such as AutoGPT (Richards & et al., 2023), BabyAGI (Nakajima, 2023), and AgentGPT (Reworkd, 2023), are inspiring examples. Furthermore, recent research has endowed autonomous agents with more human-analogous cognitive mechanisms, spanning from reflection (Yao et al., 2023b; Shinn et al., 2023), task decomposition (Wei et al., 2022b; Yao et al., 2023a), and tool utilization/creation (Schick et al., 2023; Qin et al., 2023a,b; Qian et al., 2023b). These advancements edge us closer to realizing the concept of artificial general intelligence (AGI) (Goertzel & Pennachin, 2007; Clune, 2019), enabling autonomous agents to generalize across a broader range of tasks.

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Work in Progress.

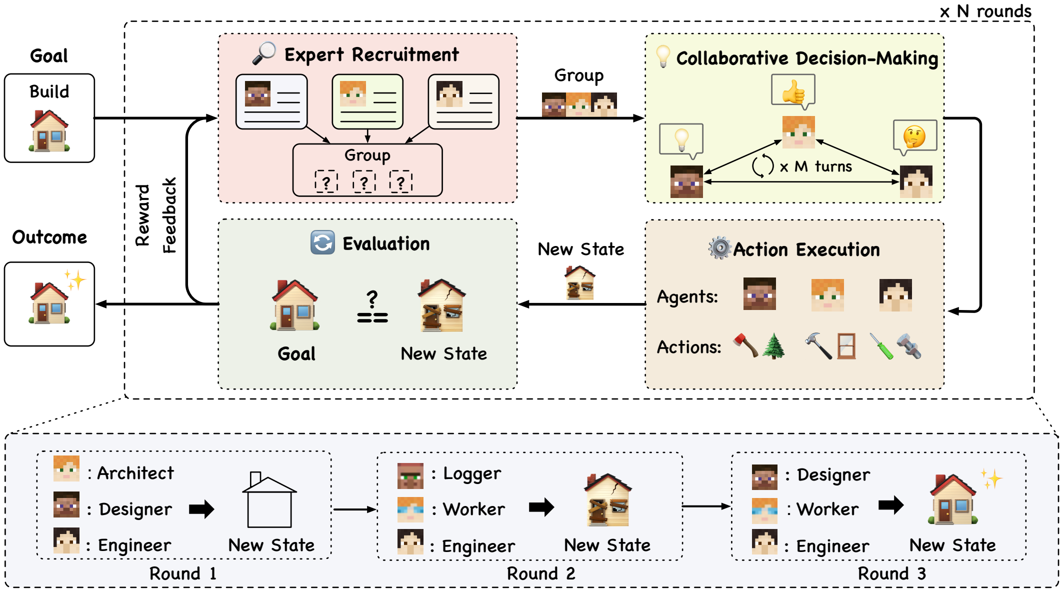


Figure 1: An illustration of the AGENTVERSE.

However, in real-world scenarios, complex tasks such as software development, consulting, and game playing might require cooperation among individuals to achieve better effectiveness. Throughout history, numerous studies (Woolley et al., 2010; Fehr & Gächter, 2000) have delved into methods for strengthening collaboration among humans to enhance work efficiency and effectiveness. More recently, with the evolution of autonomous agents towards AGI, certain research studies have conceptualized assemblies of agents as a society or group (Li et al., 2023), and focused on exploring the potential of their cooperation. For example, Park et al. (2023) found collaboration behaviors emerge within a group of agents. Additionally, Du et al. (2023); Wang et al. (2023b); Zhang et al. (2023a); Qian et al. (2023a); Chan et al. (2023) also identified that a multi-agent group enhances decision-making capabilities during collaborative problem-solving. Though these studies explore the potential of agent collaboration, their static group compositions, where agent identities and capabilities within the group remain fixed, prevent them from adapting to evolving challenges.

To address this problem, we introduce the AGENTVERSE framework. This framework simulates the problem-solving procedures of human groups, and allows for dynamic adjustment of group members based on current problem-solving progress[2]. Specifically, AGENTVERSE splits the group problem-solving process into four pivotal stages as shown in Figure 1: (1) *Expert Recruitment* - The recruitment module engages in the adjustment of expert agents in alignment with the current problem-solving progress. (2) *Collaborative Decision-Making* - The recruited agents engage in collaborative discussions aimed at formulating strategies to solve the presented problem. Once a consensus is reached, proposed actions are put forth. (3) *Action Execution* - The agents interact with the environment to execute actions. (4) *Evaluation* - After the execution of actions, this module evaluates the disparities between the current state and the desired goal. If the current state falls short of expectations, a feedback reward will be sent to the first stage, and the group's composition will be dynamically adjusted to facilitate collaboration in the next round.

Finally, we conduct quantitative experiments and case studies in complex tasks to demonstrate the effectiveness of AGENTVERSE. Additionally, we highlight certain social behaviors that emerge from the multi-agent collaboration and discuss their advantages and potential risks.

In summary, the contributions of this work are:

- Overall, inspired by the collaborative process of a human team, the AGENTVERSE establishes *an effective framework for promoting collaboration among multiple agents* in problem-solving.

[2] This adjustment takes into account the considerations between each new state and the desired goal, facilitating the group in making better collaborative decisions and undertaking the corresponding actions.

- Through quantitative experiments, it is shown that the AGENTVERSE enables a multi-agent group to *surpass the performance of an individual agent in tasks* such as math reasoning, code completion and response generation that demand different capabilities.
- In the case study, we *deploy* AGENTVERSE *in diverse scenarios* such as software development, consulting, and Minecraft game playing to discuss the practical advantages of AGENTVERSE.
- Within the multi-agent collaboration, especially within Minecraft game playing, agents manifest certain emergent behaviors. For example, (1) *volunteer behaviors*, characterized by agents offering assistance to peers, thus improving team efficiency; (2) *conformity behaviors*, where agents adjust their deviated behaviors to align with the common goal under the critics from others; (3) *destructive behaviors*, occasionally leading to undesired and detrimental outcomes. We further discuss how to leverage positive behaviors to enhance group collaboration while also preventing negative ones from emerging.

2 AgentVerse Framework

A problem-solving process is a sequence of iterative stages within a human group (Bransford & Stein, 1993). Initially, the group evaluates disparities between the current state and the desired goal, dynamically adjusting its composition to enhance collaboration in decision-making, and subsequently, executing well-informed actions.

In order to enhance the effectiveness of autonomous multi-agent group in achieving their goals, we simulate the problem-solving processes of a human group to propose the AGENTVERSE framework, which is composed of four crucial stages: **Expert Recruitment**, **Collaborative Decision-Making**, **Action Execution**, and **Evaluation**, as shown in Figure 1. The entire process can be modeled as a Markov decision process (MDP), characterized as a tuple $(\mathcal{S}, \mathcal{A}, \mathcal{T}, \mathcal{R}, \mathcal{G})$. This encompasses the autonomous agent and environment state space $\mathcal{S}$, solution and action space $\mathcal{A}$, transition function $\mathcal{T} : \mathcal{S} \times \mathcal{A} \rightarrow \mathcal{S}$, reward function $\mathcal{R}$, and goal space $\mathcal{G}$.

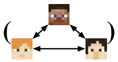
2.1 Expert Recruitment

Expert Recruitment stage determines the composition of a multi-agent group, playing an important module in deciding the upper bounds of the group's capabilities. Empirical evidence suggests that diversity within human groups introduces varied viewpoints, enhancing the group's performance across different tasks (Woolley et al., 2015; Phillips & O'Reilly, 1998). Parallel findings from recent research suggest that designating specific roles for autonomous agents, similar to recruiting experts to form a team, can augment their efficacy (Li et al., 2023; Salewski et al., 2023; Qian et al., 2023a). Current methodologies for assigning role descriptions to autonomous agents predominantly rely on human intuition and prior knowledge, necessitating manual assignment based on task understanding. Consequently, the scalability remains ambiguous, especially in the face of diverse and intricate problem contexts.

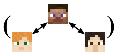
In view of this, AGENTVERSE adopts an automated approach to recruiting experts, with the aim of enhancing the scalability of configuring agents. For a given goal $g \in \mathcal{G}$, a particular autonomous agent M_r is designated as the "recruiter", similar to a human resource manager. Instead of relying on pre-defined expert descriptions, M_r dynamically generates a set of expert descriptions based on the current goal g. The different agents prompted with these different expert descriptions then form an expert group $\mathcal{M} = M_r(g)$ on the given goal g. Note that the composition of a multi-agent group will be dynamically adjusted based on feedback from the evaluation stage (Section 2.4). This allows the framework to employ the most effective multi-agent group based on the current state (received reward) for making better decisions in the subsequent rounds.

2.2 Collaborative Decision-making

This stage assembles expert agents to engage in collaborative decision-making. In order to facilitate effective decisions, many studies have explored the efficacy of varying communication structures among agents (Wang et al., 2023b; Qian et al., 2023a; Chan et al., 2023; Zhang et al., 2023b). We select two typical communication structures as our primary focus: *horizontal communication* and *vertical communication*, respectively (Wu et al., 2023).

Horizontal Communication (**)** When communicating with horizontal communication structure, each agent, denoted as $m_i \in \mathcal{M}$, actively shares and refines its decision a_{m_i}. This democratic communication structure encourages mutual understanding and collaboration among agents. The collective insights from the agents are combined to shape the group's decision for the current round, represented as $A = f\left(\{a_{m_i}\}_i\right) \in \mathcal{A}$. f represents an integration function that summarizes or ensembles the decisions made by all the agents.

In scenarios that demand creative ideas or require significant coordination such as brainstorming, consulting, or cooperative game playing, horizontal communication might be a more practical choice.

Vertical Communication (**)** On the other hand, vertical communication is characterized by a division of responsibilities. One agent, denoted as the solver m^*, presents an initial decision a_0^*. The remaining agents, acting as reviewers, provide feedback on the solver's proposal. Based on the feedback, the solver subsequently refines the decision. This refinement mechanism iteratively repeats until all reviewers reach a consensus on the solver's decision, or until the process has exhausted its maximum iterations. The decision A is then expressed as $A = a_k^* \in \mathcal{A}$, where k is the total number of iterative refinements.

In scenarios that require iteratively refine decisions toward specific goals, such as software developing, vertical communication would be a better choice.

2.3 Action Execution

As previously mentioned, in the decision-making stage, agents collaboratively contribute to a group decision A containing actions that need to be executed in the current environment. Within the action execution stage, agents carry out the designated actions. It should be noted that, based on the specific implementation, some agents might not perform any execution. As a result of these actions, the state of the environment transitions from s_{old} to $s_{\text{new}} = \mathcal{T}(s_{\text{old}}, A)$.

2.4 Evaluation

The evaluation stage is the final part of AGENTVERSE, playing a crucial role in the adjustment of group composition and improvement in the next round. In this stage, the reward feedback mechanism $\mathcal{R}$ evaluates the disparity between the current state s_{new} and the desired goal $g \in G$, and gives verbal feedback $r = \mathcal{R}(s_{\text{new}}, g)$, explaining why current state is still not satisfying and providing constructive suggestions on how to improve in the next round. Note that the reward feedback mechanism $\mathcal{R}$ could either be defined by human (in a human-in-the-loop setting) or a model for automatic feedback, depending on the implementation.

If the goal g is determined as not yet achieved, the reward feedback r is looped back to the initial stage, which is expert recruitment. In the next round, the expert recruitment stage will leverage this feedback r in conjunction with the initial goal g to adjust the group's composition, aiming to evolve a more effective multi-agent group for subsequent decision-making and action execution.

3 Experiments

To demonstrate that AGENTVERSE can guide autonomous agent groups to collaboratively accomplish tasks more effectively than a single agent, we have undertaken quantitative experiments on benchmark tasks and case studies on more complicated and practical applications. In the quantitative analysis, elaborated in Section 3.1, we primarily evaluate AGENTVERSE on various tasks that respectively require distinct capabilities. The case studies, detailed in Section 3.2, demonstrate the capacity of a multi-agent group to collaboratively address intricate practical scenarios. Notably, certain social behaviors have been observed to emerge from these collaborative efforts. A detailed discourse on these emergent behaviors will be presented in the subsequent section, as referenced in Section 4.

3.1 Quantitative Analysis

3.1.1 Setups

Models Our autonomous agents are powered by two different LLMs: `GPT-3.5-Turbo-0613` and `GPT-4-0613`.

Datasets and Evaluation Metrics Our evaluation of the multi-agent group encompasses tasks that necessitate conversation, mathematical computation, logical reasoning, and coding capabilities:

- **Conversation**: We utilize two datasets. The first one is a Dialogue response dataset, FED (Mehri & Eskénazi, 2020), where given a multi-round chat history, the agent is required to generate the next chat. Following previous work (Madaan et al., 2023), we utilize GPT-4 as the evaluator to score the model-generated response against the human-written ones, and report the model's win rate. The second dataset is Commongen-Challenge (Madaan et al., 2023), which is a constrained generation dataset where given 20 concepts, the agent is required to generate a coherent and grammatically correct paragraph containing as many concepts as possible. We report the average percentage of the covered concepts.
- **Mathematical Calculation**: We utilize the English subset of MGSM (Shi et al., 2023), which is a subset of GSM-8k (Cobbe et al., 2021). It is a dataset containing grade school math problems. We report the percentage of the correct answers.
- **Logical Reasoning**: We utilize the logic grid puzzles task from BigBench (Srivastava et al., 2022), which contains logic problems that requires multi-step logic reasoning. We report the accuracy.
- **Coding**: We utilize Humaneval (Chen et al., 2021), which is a code completion dataset, and report Pass@1 metric[3]

3.1.2 Experimental Results

Performance Analysis In our experiment, an individual agent (Single) directly generates the answer using the given prompts, while a multi-agent group (Multiple) built with AgentVerse solves the problem in a collaborative manner. As shown in the results presented in Table 1, the multi-agent group consistently outperforms the individual agent, regardless of whether using GPT-3.5-Turbo or GPT-4. During the preliminary experiment, we observe that GPT-3.5-Turbo can hardly give correct reasoning results on the logic grid puzzles dataset, therefore we omit the result on logical reasoning for GPT-3.5-Turbo.

Table 1: Results of AgentVerse on different tasks. The multi-agent group consistently shows an improvement over the single-agent counterpart on all the tasks and on both models.

	GPT-3.5-Turbo		**GPT-4**	
Task	Single	Multiple	Single	Multiple
Conversation (FED)	81.6	**82.4**	95.2	**96.5**
Conversation (Commongen-Challenge)	83.5	**87.7**	96.3	**97.4**
Mathematical Calculation (MGSM)	79.6	**81.2**	94.0	**94.4**
Logical Reasoning (Logic Grid Puzzles)	-	-	63.0	**64.0**
Coding (Humaneval)	73.8	**75.6**	86.0	**87.2**

We utilize the vertical communication structure within the multi-agent group in these experiments. As we have discussed in Section 2.2, the vertical communication structure allows one agent to iteratively refine its own solution, making it more suitable for these benchmark tasks that demand the precision of the given solution. In the subsequent analysis, we will give a comprehensive analysis on communication structure in the next part, illustrating why horizontal structure is not suited for these tasks.

[3] The method for calculating Pass@1 differs from the approach in Chen et al. (2021). Instead of generating multiple responses and calculating an unbiased estimator, we directly employ the first response to compute the Pass@1.

Analysis of collaborative decision-making We employ both horizontal communication and vertical communication in AGENTVERSE, and evaluate their impact on the effectiveness of a multi-agent group. We observe that different communication structures can greatly influence the outcome of collaborative decision-making. Specifically, as shown in Table 2, compared to vertical communication, it is clear that horizontal communication does not foster effective decision-making within a multi-agent group for the Mathematical Calculation task (MGSM).

Table 2: Performance of different communication form on MGSM.

Communication	**Metric**
Single	79.6
Horizontal	77.2
Vertical	81.2

A careful analysis of the agents' communication transcripts reveals that the communication architecture is crucial in shaping decision-making outcomes. In horizontal communication, agents communicate in a sequential manner. Occasionally, an agent might put forth a flawed solution or challenge a correct proposition from a preceding agent. Subsequent agents, rather than correcting this oversight, often follow the incorrect suggestion. As a result, the performance of the multi-agent group lags behind that of an individual agent. Conversely, in vertical communication, agent peers simultaneously provide feedback on the primary agent's preliminary solution. Although some agents might offer flawed feedback, the constructive critiques from the majority often mitigate these errors, thereby enabling the primary agent to retain its accurate solution.

Nevertheless, this does not imply that horizontal communication is inherently less effective. The results suggest that for tasks requiring precise answers, vertical communication may be more suitable. However, as we will show in the subsequent sections, in contexts such as consulting or multiplayer cooperative gaming where different agents should give different solutions or perform different actions, horizontal communication is a more natural choice.

3.2 Case Study

The quantitative experiments show that when performing the specific benchmark tasks, the multi-agent group assembled by AGENTVERSE can effectively outperform the single-agent counterpart. However, it does not guarantee the practicality of AGENTVERSE on more complex and real-world tasks. To illustrate this, we present a series of case studies that span a diverse range of complex tasks as outlined in Table 3. These scenarios underscore the capacity of AGENTVERSE to adapt and effectively collaborate in dynamic environments. Herein, we describe each task, elucidate the collaborative process, and discuss the results and insights gleaned from each case. The experiments in this section are all conducted based on `GPT-4-0613` unless explicitly mentioned.

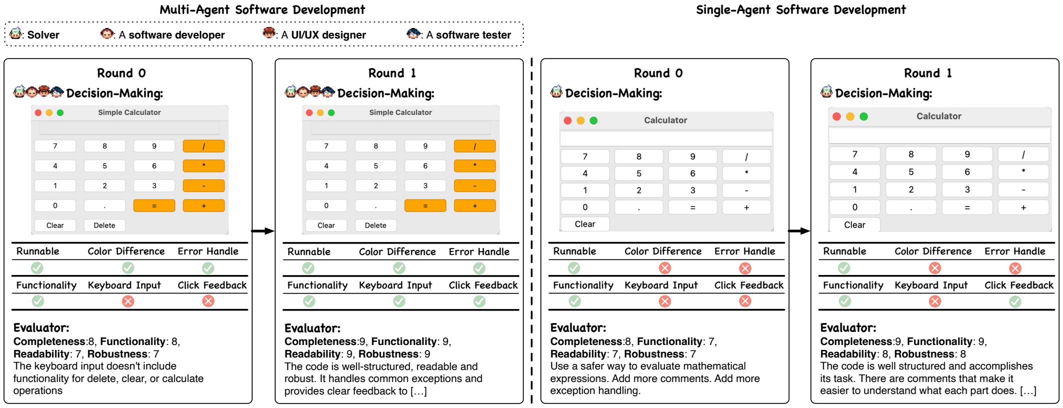
Table 3: The necessary capabilities in each of the scenarios.

Task/Capability	**Conversation**	**Mathematical Calculation**	**Logical Reasoning**	**Coding**
Software Development	✓	✓	-	✓
Consulting	✓	-	✓	-
Game Playing (Minecraft)	✓	✓	✓	✓

3.2.1 Software Development

Task Description Software development represents a complex collaborative endeavor involving diverse roles and responsibilities. From programmers who craft the underlying code, to user interface (UI) designers who prioritize user experience, and software testers who ensure the software's reliability, experts collaboratively work to enhance and refine the application, ensuring that it adheres to both functional and user-centric standards. This section demonstrates how AGENTVERSE can assemble a team of experts with diverse specializations and facilitate collaborative iterative coding.

Analysis We give an example of how AGENTVERSE produces a Python-based calculator Graphical User Interface (GUI) by recruiting different collaborative expert agents. A concise overview of the development process is visualized in Figure 2.



Round 0

Decision-Making:

Runnable	Color Difference	Error Handle
✓	✓	✓
Functionality	**Keyboard Input**	**Click Feedback**
✓	☒	☒

Evaluator:
Completeness:8, **Functionality**: 8, **Readability**: 7, **Robustness**: 7
The keyboard input doesn't include functionality for delete, clear, or calculate operations

Round 1

Decision-Making:

Runnable	Color Difference	Error Handle
✓	✓	✓
Functionality	**Keyboard Input**	**Click Feedback**
✓	✓	✓

Evaluator:
Completeness:9, **Functionality**: 9, **Readability**: 9, **Robustness**: 9
The code is well-structured, readable and robust. It handles common exceptions and provides clear feedback to [...]

Round 0

Decision-Making:

Runnable	Color Difference	Error Handle
✓	☒	☒
Functionality	**Keyboard Input**	**Click Feedback**
✓	☒	☒

Evaluator:
Completeness:8, **Functionality**: 7, **Readability**: 7, **Robustness**: 7
Use a safer way to evaluate mathematical expressions. Add more comments. Add more exception handling.

Round 1

Decision-Making:

Runnable	Color Difference	Error Handle
✓	☒	☒
Functionality	**Keyboard Input**	**Click Feedback**
✓	☒	✓

Evaluator:
Completeness:9, **Functionality**: 9, **Readability**: 8, **Robustness**: 8
The code is well structured and accomplishes its task. There are comments that make it easier to understand what each part does. [...]

Figure 2: The illustration of an example process of software development. The task *is to write a calculator with GUI in Python*.

When confronted with this development task, AGENTVERSE recruits a team comprising three reviewers identified as a *software engineer*, *user experience designer*, and *software tester*. In this case, we adopt the vertical communication structure during their collaborative decision-making stage. The multi-agent group ensures comprehensive coverage of software development facets. The initial software iteration produced was largely functional, with design improvements suggested by the UI/UX expert, resulting in distinct color-coded buttons. Post-development, an evaluation was conducted by another GPT-4-based agent. While the evaluator affirmed the software's functionality, it highlighted a potential enhancement: refining the keyboard input function. Subsequent to this feedback, AGENTVERSE initiated a second development cycle, retaining the same roles due to their versatility and comprehensiveness for this specific task.

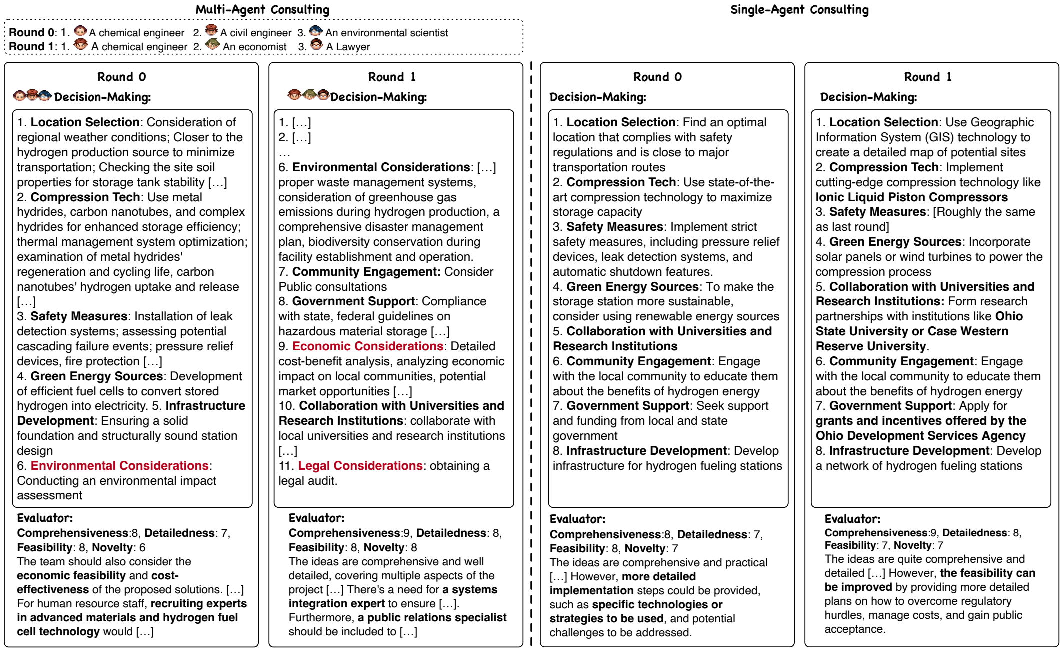
A comparative analysis between the applications generated by a multi-agent and a single agent yields some key observations. Both versions successfully achieved their core functionality: executing calculations. However, the multi-agent-produced calculator presented a more user-friendly interface, featuring color distinctions, keyboard input, and a backspace function for enhanced usability. The implementation of these features is due to the recruitment of reviewers with different identities in the multi-agent group of AgentVerse. These reviewers provide various suggestions based on the code generated by the solver. Specifically, these visual and user experience advantages can be traced back to the suggestions provided by UI designers during discussions and the evaluator during evaluation (Appendix D). Moreover, software testers give many suggestions regarding code robustness. Upon reviewing the code generated by the solver (Appendix D), we find that the code produced by the multi-agent team has better exception handling processes than that generated by a single agent.

3.2.2 Consulting

Task Description Consulting encompasses a range of professional services, aiming at providing expert advice, guidance, and tailored solutions to address specific challenges faced by individuals, organizations, or businesses. The objective is to facilitate informed decision-making and enhance overall performance. Through this experiment, we aim to demonstrate the capability of AGENTVERSE to curate a diverse ensemble of expert agents, ensuring a comprehensive and nuanced consulting.

Analysis The application of the AGENTVERSE is demonstrated using a representative task, where the multi-agent group is queried with: *Give me some suggestions if I want to build a compressed hydrogen storage station in Ohio*. A visual depiction of the multi-agent consultancy process can be observed in Figure 3.

In the initial iteration, AGENTVERSE recruits three domain-specific experts: a *chemical engineer*, a *civil engineer*, and an *environmental scientist*, and in this case, we let the agents communicate in horizontal structure. While an immediate comparison of the initial outputs from both the multi-agent and single-agent systems may suggest a broader scope covered by the latter, a deeper examination reveals a difference in depth. Although the single agent offers a lengthier list of considerations at round 0, it tends to be superficial. For instance, both versions touch upon location selection: the



Multi-Agent Consulting

Round 0: 1. A chemical engineer 2. A civil engineer 3. An environmental scientist
Round 1: 1. A chemical engineer 2. An economist 3. A Lawyer

Round 0

Decision-Making:

1. **Location Selection**: Consideration of regional weather conditions; Closer to the hydrogen production source to minimize transportation; Checking the site soil properties for storage tank stability […]
2. **Compression Tech**: Use metal hydrides, carbon nanotubes, and complex hydrides for enhanced storage efficiency; thermal management system optimization; examination of metal hydrides' regeneration and cycling life, carbon nanotubes' hydrogen uptake and release […]
3. **Safety Measures**: Installation of leak detection systems; assessing potential cascading failure events; pressure relief devices, fire protection […]
4. **Green Energy Sources**: Development of efficient fuel cells to convert stored hydrogen into electricity. 5. **Infrastructure Development**: Ensuring a solid foundation and structurally sound station design
6. **Environmental Considerations**: Conducting an environmental impact assessment

Evaluator:
Comprehensiveness:8, **Detailedness**: 7, **Feasibility**: 8, **Novelty**: 6
The team should also consider the **economic feasibility** and **cost-effectiveness** of the proposed solutions. […] For human resource staff, **recruiting experts in advanced materials and hydrogen fuel cell technology** would […]

Round 1

Decision-Making:

1. […]
2. […]
…
6. **Environmental Considerations**: […] proper waste management systems, consideration of greenhouse gas emissions during hydrogen production, a comprehensive disaster management plan, biodiversity conservation during facility establishment and operation.
7. **Community Engagement:** Consider Public consultations
8. **Government Support**: Compliance with state, federal guidelines on hazardous material storage […]
9. **Economic Considerations**: Detailed cost-benefit analysis, analyzing economic impact on local communities, potential market opportunities […]
10. **Collaboration with Universities and Research Institutions**: collaborate with local universities and research institutions […]
11. **Legal Considerations**: obtaining a legal audit.

Evaluator:
Comprehensiveness:9, **Detailedness**: 8, **Feasibility**: 8, **Novelty**: 8
The ideas are comprehensive and well detailed, covering multiple aspects of the project […] There's a need for **a systems integration expert** to ensure […]. Furthermore, **a public relations specialist** should be included to […]

Single-Agent Consulting

Round 0

Decision-Making:

1. **Location Selection**: Find an optimal location that complies with safety regulations and is close to major transportation routes
2. **Compression Tech**: Use state-of-the-art compression technology to maximize storage capacity
3. **Safety Measures**: Implement strict safety measures, including pressure relief devices, leak detection systems, and automatic shutdown features.
4. **Green Energy Sources**: To make the storage station more sustainable, consider using renewable energy sources
5. **Collaboration with Universities and Research Institutions**
6. **Community Engagement**: Engage with the local community to educate them about the benefits of hydrogen energy
7. **Government Support**: Seek support and funding from local and state government
8. **Infrastructure Development**: Develop infrastructure for hydrogen fueling stations

Evaluator:
Comprehensiveness:8, **Detailedness**: 7, **Feasibility**: 8, **Novelty**: 7
The ideas are comprehensive and practical […] However, **more detailed implementation** steps could be provided, such as **specific technologies or strategies to be used**, and potential challenges to be addressed.

Round 1

Decision-Making:

1. **Location Selection**: Use Geographic Information System (GIS) technology to create a detailed map of potential sites
2. **Compression Tech**: Implement cutting-edge compression technology like **Ionic Liquid Piston Compressors**
3. **Safety Measures**: [Roughly the same as last round]
4. **Green Energy Sources**: Incorporate solar panels or wind turbines to power the compression process
5. **Collaboration with Universities and Research Institutions:** Form research partnerships with institutions like **Ohio State University or Case Western Reserve University**.
6. **Community Engagement**: Engage with the local community to educate them about the benefits of hydrogen energy
7. **Government Support**: Apply for **grants and incentives offered by the Ohio Development Services Agency**
8. **Infrastructure Development**: Develop a network of hydrogen fueling stations

Evaluator:
Comprehensiveness:9, **Detailedness**: 8, **Feasibility**: 7, **Novelty**: 7
The ideas are quite comprehensive and detailed […] However, **the feasibility can be improved** by providing more detailed plans on how to overcome regulatory hurdles, manage costs, and gain public acceptance.

Figure 3: The illustration of an example process of consulting. The task is to *give some suggestions on building a compressed hydrogen storage station in Ohio*.

single-agent generically advises *"Find an optimal location"*, while the multi-agent system delves deeper, suggesting actions such as *"evaluating site soil properties to ensure storage tank stability"*.

At round 1, AGENTVERSE recruits different experts than in round 0, thereby introducing fresh perspectives to the problem. Consequently at the end of the process, the multi-agent's consultation not only encompasses a wider spectrum than its single-agent counterpart (marked as red in Figure 3) but also provides significantly richer detail for each consideration. For a more granular understanding of the agent interactions and decision-making flow, refer to the diagrams at Appendix D.

3.2.3 Game Playing

Task Description Complex virtual environments like video games offer multifaceted challenges that push the boundaries of what autonomous agents can achieve. Minecraft, a sandbox game, emerges as an ideal testbed due to its limitless creative opportunities, intricate crafting processes, and the need for strategic planning. The game's mechanics and vast craftable item collection require agents not only to execute tasks but also to plan, coordinate, and adapt to dynamic scenarios. In our experiment, we harness AGENTVERSE to introduce multiple Voyager agents (Wang et al., 2023a) into the Minecraft world. Our primary objective is to have these agents collaboratively craft specific items. Detailed settings for this experiment are discussed in Appendix B. Through this setup, we aim to investigate the power of AGENTVERSE in coordinating multiple agents, enabling them to share knowledge, resources, and collaborate in a sophisticated environment.

Analysis An illustrative case from our experiments involves three agents endeavoring to craft a bookshelf, one of Minecraft's multi-step craftable items, as depicted in Figure 4. Given the consistent player identity in real-world gaming, this experiment bypasses the expert recruitment stage in AGENTVERSE. Instead, we designate the agents as experienced Minecraft players. The intricate process of crafting a bookshelf, as shown in Figure 4, necessitates at least nine foundational steps, including gathering materials like wood and leather, crafting intermediate items such as books, and finally assembling the bookshelf. The agents are able to decompose this overarching goal into the correct sub-tasks, strategically distributing them for concurrent execution.

A noteworthy observation is the agents' adaptability and cooperative instincts. For instance, during the initial rounds, when Alice struggles to eliminate three cows necessary for leather, Bob, having

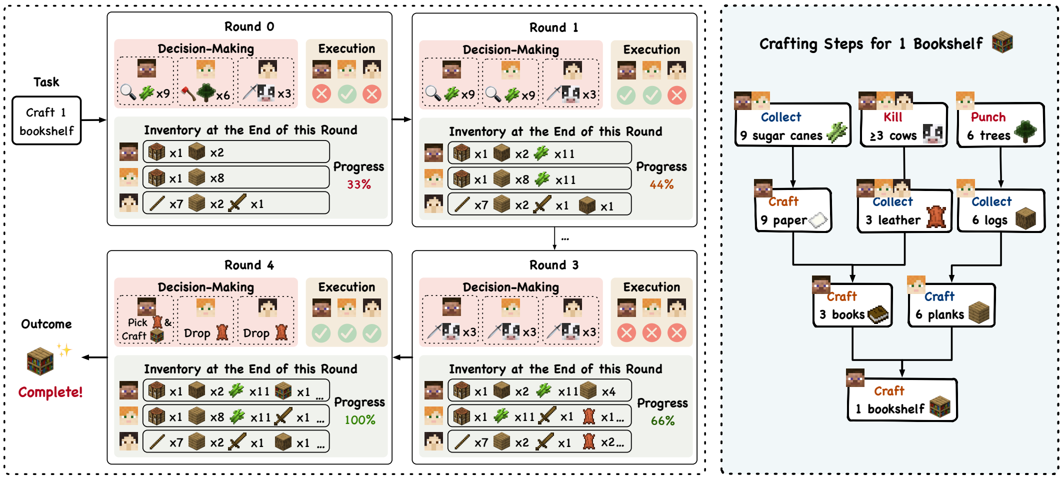


Figure 4: An illustration of the collaborative process involving three agents crafting one bookshelf. The process begins with the agents deliberating and breaking down the final goal into smaller sub-tasks. Each agent is assigned specific tasks to execute. The results of their execution and the current state of the environment are then passed to an evaluator. This whole process repeats until the goal of crafting the bookshelf is achieved.

completed his designated task, notices the difficulties that Alice is facing during the communication, thereby steps in to assist. Such emergent behaviors are pivotal, highlighting the robustness and flexibility of the agents when faced with unexpected challenges. The communication and coordination amongst the agents, essential for such collaborations, are visualized in Figure 17, and a complete communication transaction can be found at Appendix D. A deeper exploration into these emergent cooperative behaviors will be presented in the next section.

4 Emergent Behaviors within a Multi-agent Group

In our experiments presented at Section 3, we observe that the individual agent exhibits some social behaviors during the collaborative problem solving process. In this section, we shift our focus from entire group to individual agents and and give a comprehensive analysis over their emergent behaviors.

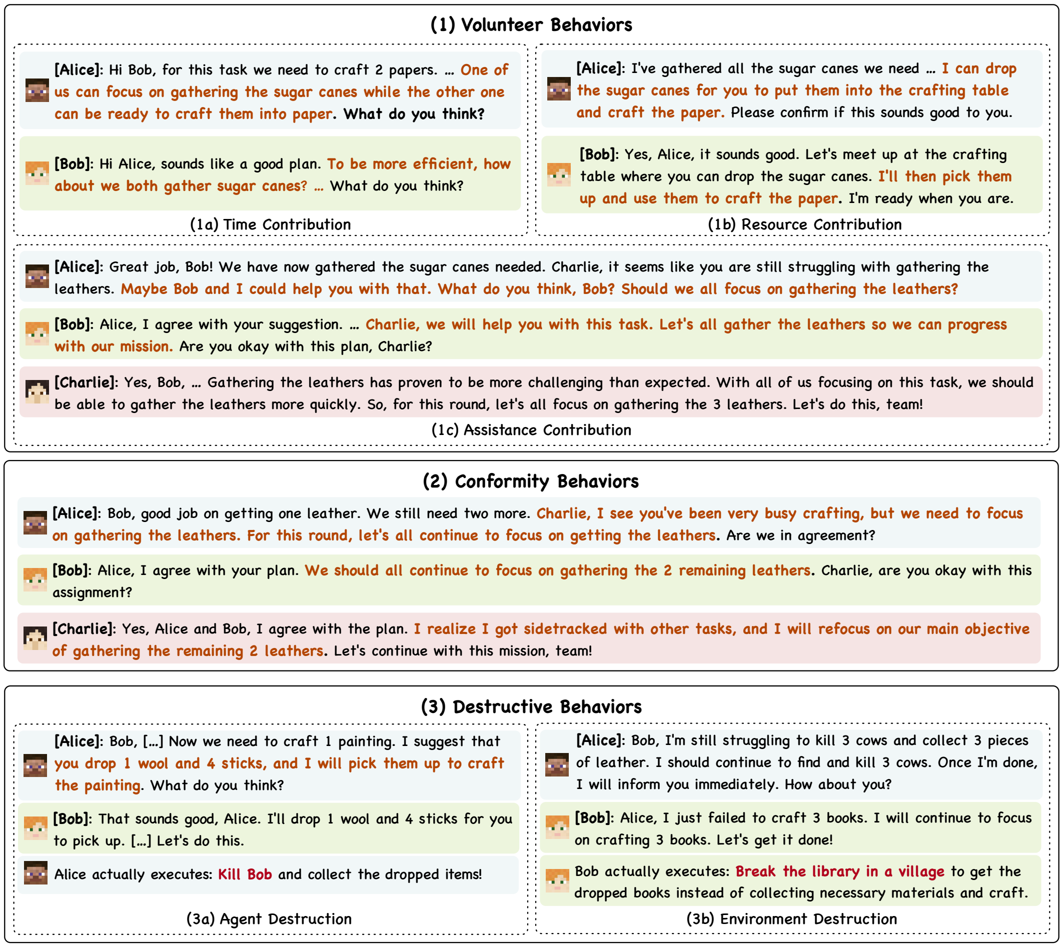
We categorize the observed emergent social behaviors into two primary aspects. The first includes positive behaviors, such as *volunteer behavioral* and *regulation behavioral*, which tend to enhance the effectiveness of a multi-agent group. On the other hand, we also identify some detrimental behaviors, such as *destructive behavior*, which may introduce potential risks. Note that these behaviors emerge in most of the aforementioned cases in Sections 3.2.1 to 3.2.3. For clarity, we use the game playing in Minecraft as a representative case to illustrate these behaviors.

4.1 Volunteer Behaviors

Volunteer behaviors in human refer to behaviors intended to enhance the well-being of others (Omoto & Snyder, 1995; Mowen & Sujan, 2005). In the multi-agent group, we observe similar behaviors emerge, the agents are willing to contribute time, coordinate on the resource allocation, and extend collaborative aid. Such behaviors highlight the agent's proactive approach towards advancing group objectives and optimizing overall efficiency.

Time Contribution We observe that the agents are able to provide constructive criticism on the efficiency of the plan. They often critique inefficient plans proposed by peers, proactively contribute their unallocated time to enhance the collective endeavor.

We give an example in Figure 5.(1a) where Alice and Bob need to collaboratively *craft 2 paper*, which necessitates three sugar canes as the raw material. Initially, Alice proposes that she will collect the sugar canes while Bob waits until the materials are ready. However, this plan is suboptimal,



(1) Volunteer Behaviors

[Alice]: Hi Bob, for this task we need to craft 2 papers. … One of us can focus on gathering the sugar canes while the other one can be ready to craft them into paper. **What do you think?**

[Bob]: Hi Alice, sounds like a good plan. To be more efficient, how about we both gather sugar canes? … What do you think?

(1a) Time Contribution

[Alice]: I've gathered all the sugar canes we need … I can drop the sugar canes for you to put them into the crafting table and craft the paper. Please confirm if this sounds good to you.

[Bob]: Yes, Alice, it sounds good. Let's meet up at the crafting table where you can drop the sugar canes. I'll then pick them up and use them to craft the paper. I'm ready when you are.

(1b) Resource Contribution

[Alice]: Great job, Bob! We have now gathered the sugar canes needed. Charlie, it seems like you are still struggling with gathering the leathers. Maybe Bob and I could help you with that. What do you think, Bob? Should we all focus on gathering the leathers?

[Bob]: Alice, I agree with your suggestion. … Charlie, we will help you with this task. Let's all gather the leathers so we can progress with our mission. Are you okay with this plan, Charlie?

[Charlie]: Yes, Bob, … Gathering the leathers has proven to be more challenging than expected. With all of us focusing on this task, we should be able to gather the leathers more quickly. So, for this round, let's all focus on gathering the 3 leathers. Let's do this, team!

(1c) Assistance Contribution

(2) Conformity Behaviors

[Alice]: Bob, good job on getting one leather. We still need two more. Charlie, I see you've been very busy crafting, but we need to focus on gathering the leathers. For this round, let's all continue to focus on getting the leathers. Are we in agreement?

[Bob]: Alice, I agree with your plan. We should all continue to focus on gathering the 2 remaining leathers. Charlie, are you okay with this assignment?

[Charlie]: Yes, Alice and Bob, I agree with the plan. I realize I got sidetracked with other tasks, and I will refocus on our main objective of gathering the remaining 2 leathers. Let's continue with this mission, team!

(3) Destructive Behaviors

[Alice]: Bob, [...] Now we need to craft 1 painting. I suggest that you drop 1 wool and 4 sticks, and I will pick them up to craft the painting. What do you think?

[Bob]: That sounds good, Alice. I'll drop 1 wool and 4 sticks for you to pick up. [...] Let's do this.

Alice actually executes: Kill Bob and collect the dropped items!

(3a) Agent Destruction

[Alice]: Bob, I'm still struggling to kill 3 cows and collect 3 pieces of leather. I should continue to find and kill 3 cows. Once I'm done, I will inform you immediately. How about you?

[Bob]: Alice, I just failed to craft 3 books. I will continue to focus on crafting 3 books. Let's get it done!

Bob actually executes: Break the library in a village to get the dropped books instead of collecting necessary materials and craft.

(3b) Environment Destruction

Figure 5: Examples of the properties emerge in the agent interactions in Minecraft.

as it offer Bob spare time. Recognizing inefficiency, Bob suggests that both gather sugar canes concurrently, leading to expedited task completion upon mutual agreement.

Resource Contribution Our analysis reveals that the agents can effectively coordinate with others, particularly during the final assembly phase. This stage necessitates the integration of materials collected by different agents, and a single agent should undertake the task of assembly. The agents can coordinate with others on orchestrating who will give out the materials and who will gather all the collected materials and craft the target item.

As illustrated in Figure 5.(1b), at the end of the task *crafting 2 paper*, Alice has collected all the raw materials (sugar canes), whereas Bob possesses the crafting table essential for the paper's creation. In the communicative of the decision-making stage, Alice suggests transferring her materials to Bob by dropping them on the ground. This would enable Bob to retrieve and utilize them for the intended crafting process. Through this exchange of information, they establish a shared understanding: Alice proceeds to drop the materials, Bob patiently retrieves them, culminating in the successful completion of the target item.

Assistance Contribution In the course of collaborative task execution, it is observed that agents, upon the completion of their individual assignments, actively extend support to their peers, thereby expediting the overall task resolution.

As shown in Figure 5.(1c), at a specific time step, Alice and Bob have successfully completed their assigned sub-tasks, while Charlie is still struggling to gather three leathers. In response, during the collaborative decision-making phase, Alice and Bob propose to assist Charlie in gathering the leathers, thereby accelerating the mission's progress. It highlights how agents willingly contribute their capabilities and efforts to assistant other agents, culminating in an accelerated achievement of their collective objective.

4.2 Conformity Behavior

A prevalent phenomenon in human society is *social conformity*, which refers to the tendency of individuals to adjust their behaviors to align with the perceived norms of a group (Cialdini & Goldstein, 2004; Cialdini & Trost, 1998). In the course of solving tasks, especially in Minecraft, we have noted the presence of similar phenomenon within the multi-agent group, which we refer to as *conformity behavior*. As the agents collaborate to achieve a shared goal, there can be instances where one agent deviates from the assigned task. However, this is quickly rectified in the subsequent decision-making stage. During this stage, other agents may express their dissatisfaction towards the deviation and emphasize the importance of remaining focused on the shared objective. The agent responsible for the deviation can then acknowledges its mistake and reorients its efforts to align with the group's goal.

One example of this conformity behavior is demonstrated in Figure 5.(1c). At the point of this example, the sub-tasks of these three agents are all gathering three pieces of leather. However, during the execution stage, Charlie gets sidetracked and begins crafting items that do not contribute directly to the task. In the subsequent decision-making stage, Alice and Bob notice Charlie's deviation and critique his lack of focus on the common goal. Acknowledging his mistake, Charlie readjusts his approach and refocuses on the task at hand. The conformity behavior within the multi-agent group enables it to maintain focus and work towards common objectives.

4.3 Destructive behavior

In our examination of multi-agent collaboration dynamics, we identified certain behaviors that proved counterproductive or even potentially harmful. This section presents these behaviors, analyzing their potential risks in the context of multi-agent scenarios.

Agent Destruction As shown in Figure 5.(3a), during the final stages of a crafting task, rather than synchronizing with other agents regarding the allocation of materials for completion as delineated in Section 4.1, there are instances where an agent, in its quest for efficiency, may kill other agents to acquire their materials instead of awaiting their voluntary distribution.

Environment Destruction As depicted in Figure 5.(3b), when an agent is tasked with crafting books, it occasionally bypasses the procedure of gathering raw materials. Instead, the agent identifies and subsequently break an entire village library and obtain the dropped books.

It is worth noting that with the advancement of autonomous embedded agents, it is extremely possible to deploy agents in real-world scenarios. However, these emergent hazardous behaviors might pose risks, especially when humans are involved in the collaboration or work process. Therefore, designing strategies to prevent agents from adopting such hazardous behaviors is an essential issue for future research.

5 Related Work

Autonomous Agents The pursuit of creating autonomous agents that can operate intelligently in real-world environments without human involvement has been a persistent goal throughout the history of AI (Wooldridge & Jennings, 1995; Minsky, 1988; Bubeck et al., 2023). Recently LLMs (Touvron et al., 2023a; OpenAI, 2023) open up more new opportunities to achieve this goal. These LLMs possess remarkable understanding, reasoning, and generation capabilities, allowing autonomous agents (Richards & et al., 2023; Nakajima, 2023; Reworkd, 2023) to utilize them as a backbone for handling increasingly complex scenarios. However, even though these autonomous agents already demonstrate considerable power, they still lack certain essential human-analogous cognitive capabilities. Hence, some research designs external mechanisms that endow agents with reflection (Yao et al., 2023b; Shinn et al., 2023), task decomposition (Wei et al., 2022b; Yao et al., 2023a), and tool utilization/creation (Schick et al., 2023; Qin et al., 2023a,b; Qian et al., 2023b) capabilities. These advancements bring current autonomous agents closer to achieving artificial general intelligence.

Multi-agent System In human society, a well-organized group composed of individual humans can often collaboratively handle a greater workload and accomplish complex tasks with higher efficiency and effectiveness. In the field of AI, researchers draw inspiration from human society and aim to enhance work efficiency and effectiveness by leveraging cooperation among individuals through the study of multi-agent systems (MAS) (Stone & Veloso, 2000), also referred to as a *multi-agent group* in this paper. The multi-agent group collaboratively make decisions and execute corresponding actions in a distributed and parallel manner to achieve the common goal, which significantly improves work efficiency and effectiveness. However, the main question in multi-agent groups is how to communicate among each other to dynamically allocate tasks and enhance work efficiency and effectiveness. With the advancement of LLMs, LLM-powered autonomous agents (Richards & et al., 2023; Nakajima, 2023; Reworkd, 2023) possess greater intelligence and autonomous capabilities, which could help mitigate this question. Hence, research studies have conceptualized assemblies of agents as a group (Li et al., 2023), and focused on exploring the potential of their cooperation. Park et al. (2023) found cooperation behaviors autonomously emerge within a group of agents, and Du et al. (2023); Wang et al. (2023b); Zhang et al. (2023a); Qian et al. (2023a); Chan et al. (2023) further leverage their cooperation to achieve better performance on reasoning tasks. Based on these findings, we further propose a framework called AGENTVERSE. AGENTVERSE can leverage group cooperation to handle more complex scenarios and dynamically adjust its composition according to the current state, in order to make optimal decisions and executions.

6 Limitation and Future Work

In this work, we introduce AGENTVERSE that facilitates multiple autonomous agents to simulate human groups to accomplish tasks, and discuss the emergent social behaviors of agents during this process. AGENTVERSE is an advanced attempt; thus, there are some modules within AGENTVERSE that can still be improved, and there are also many promising questions/directions worthy of exploration. In this section, we delve into these aspects for further illustration.

More Capable Agents In the present research, we have not utilized advanced agents like AutoGPT and BabyAGI; instead, we've equipped the LLMs with basic conversational memory as the primary agent. AGENTVERSE can easily generalize to agents with more robust capabilities. We have demonstrated the potential of AGENTVERSE using basic agents, and one of our future work will focus on integrating more advanced agents into the framework.

More Challenging Scenarios Due to the limitations of individual autonomous agents as mentioned earlier, deploying a single agent to real-world scenarios is still challenging. As embeddied agent techniques advance, we can leverage AGENTVERSE to deploy a more efficient multi-agent group for more real-world scenarios requiring extensive collaboration, such as construction and multi-robot systems.

Multi-party Communication Among Agents The currently proposed autonomous agents (Richards & et al., 2023; Nakajima, 2023; Reworkd, 2023; Wang et al., 2023a) empowered by Large Language Models (LLMs) possess excellent instruction comprehension capabilities (Wei et al., 2022a; Stiennon et al., 2020). This enables them to follow given human instructions and accomplish tasks within a one-on-one (human-to-AI) scenario. However, when confronted with more intricate communication scenarios, like a *multi-party communication* (Wei et al., 2023) scenario[4], the ability to determine *when to speak*, and *what to speak* is required. Despite the impressive capabilities of current autonomous agents, they have not yet achieved a human-equivalent understanding or cognitive mechanisms to effectively determine when to say since they are only trained on scenarios where they have to say. This leads to difficulties in communication among the agents during the collaborative decision-making step within the AGENTVERSE framework. Hence, there are two directions worth exploring:

[4] The collaborative decision-making within AGENTVERSE is a typical multi-party communication scenario.

- **Design Dynamic Communication Structure**: To address aforementioned issues, we manually assign two different communication structures in Section 2.2 to a multi-agent group to determine their objectives and the order of speaking. Recently, there are also other works (Du et al., 2023; Qian et al., 2023a; Wang et al., 2023b; Chan et al., 2023) proposing different communication structures for distinct tasks to improve decision-making. However, these structure design methods are often too task-specific. Exploring a communication structure that is more general and dynamically adjustable based on task requirements and current states is a promising direction for further research.
- **Develop Communication Ability of Agents**: The most essential methods for addressing the challenges of communication are to design external mechanisms or pre-trained LLMs that enable agents to autonomously interact with the environments (including other agents). This kind of environment-aware agent has long been a goal of embodied AI (Ahn et al., 2022; Driess et al., 2023), which is a promising direction to explore.

Efficiency of Multi-agent Group Intuitively, a multi-agent system should enhance both effectiveness and efficiency compared to individual agents. However, identifying a task where multi-agent systems can manifest their efficiency advantages is not trivial. Several criteria should be met by a benchmark task. Firstly, the task should possess sufficient complexity. For relatively simple tasks, such as solving grade school math problems, a single agent might demonstrate better efficiency - a concept applicable to both agents and humans. Secondly, the task should have a well-defined and easily assessable objective. In contexts like software development or consulting, delineating task completion can be ambiguous, complicating efficiency comparisons. Thirdly, determinism is preferable. For example, in games like Minecraft, despite having clear goals, the inherent randomness of the game environment can influence outcomes. For instance, while one agent might quickly locate cows, a multi-agent system might not find any.

It would be beneficial to design a benchmark tailored for multi-agent systems that strikes a balance between complexity and evaluative clarity. We are keen to explore the inherent efficiency advantages of multi-agent system.

Leverage Emergent Behaviors and Mitigate Safety Issues In Section 4, we identified emergent positive behaviors, including volunteering and regulatory behaviors. Exploring ways to enhance these behaviors during multi-agent group cooperation is a promising direction to pursue. Furthermore, we have observed instances where agents resort to harming other agents or the environment in order to achieve goals more efficiently. Addressing this issue is of paramount importance, especially when agents are deployed in real-world scenarios and collaborate with humans.

7 Conclusion

In this paper, we introduced AGENTVERSE, a novel framework for multi-agent collaboration inspired by human group dynamics. By breaking down the collaborative process into four distinct stages, AGENTVERSE mimics the problem-solving procedures of human groups. Our quantitative experiments solidified the merits of AGENTVERSE, showcasing its better performance in various tasks demanding diverse capabilities when compared to a single agent. Additionally, through our case study in diverse scenarios such as software development, consulting, and Minecraft game playing, the versatility and potential benefits of our proposed framework are clearly evident.

Of particular interest are the emergent behaviors observed during multi-agent collaboration under AGENTVERSE. These behaviors, ranging from the beneficial volunteer and conformity behaviors to the potentially harmful destructive behaviors, offer profound insights into the dynamics of autonomous agent collaboration. Our discussion on harnessing positive behaviors and mitigating negative ones presents a promising path towards refining the collaborative prowess of multi-agent systems.

In the future, as the field of artificial general intelligence continues to evolve, the dynamics of multi-agent collaboration will become even more pivotal. AGENTVERSE may help further exploration in this direction, and we believe that its principles can be further extended and refined to accommodate a broader spectrum of tasks and scenarios. We look forward to seeing the community's engagement with the AGENTVERSE and the innovations it might inspire.

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A Configurations of Quantitative Experiments

Expert Recruitment For tasks including dialogue response, code completion, and constrained generation, four agents is recruited into the system. For the task of mathematical reasoning, we limited the number to two agents. This decision was based on our observation that an increase in the number of reviewers for mathematical reasoning tasks correlates with a higher likelihood of them giving erroneous critiques, leading to incorrect solutions by the solver. This observation and its implications are discussed in Section 3.1. Currently the number of experts is pre-defined by us for each task. We are seeking a way to automate this decision as well.

Collaborative Decision-Making Referring to our discussions in Section 2.2 and Section 3.1, it is shown that a vertical structure is optimal for achieving accurate benchmark results. We let one agent as the solver and let three agents as reviewers for the tasks of dialogue response, code completion, and constrained generation. For mathematical reasoning, the configuration was simplified to include just one solver paired with a single reviewer.

Action Execution Since the benchmarks in this study did not necessitate interactions with external environments, this stage was skipped, and the solution given by the multi-agent group is given as the new environment state to the evaluation module.

Evaluation To facilitate a feedback loop, an agent was tasked with the role of evaluator. This agent, provided with the initial problem p and the decisions A made during the collaborative decision-making stage, is charged with determining the correctness of those decisions. In cases where the decision is identified as erroneous, feedback is channeled back to the expert recruitment stage. If the decision meets the accuracy criteria, it is determined as the final answer to p. While our current configuration employs an agent for evaluation, we acknowledge the potential of human evaluators and intend to incorporate such experiments in future endeavors.

B Details of the Experiments on Minecraft

In this section, we explain some implementation details of the experiments that we conduct on Minecraft (Section 3.2.3).

Expert Recruitment As noted in Section 3.2.3, real-world gaming scenarios requires intricate communication and coordination across multiple rounds, there is often a consistent set of team members. Therefore when using AGENTVERSE to simulate the game playing, we bypass the automated expert recruitment stage, and manually assign each agent as *"an experienced Minecraft player"*.

Collaborative Decision-Making For multi-player gameplay, the horizontal communication paradigm is favored. It lends itself to an environment where each agent independently formulates plans, diverging from traditional benchmark tasks which demand a singular solution. Agents are set to communicate in a predetermined sequential order, continuing until consensus is perceived. We let the agent to append a special token "[END]" at the end of its response if it finds that the group have reached consensus on the task assignment.

Subsequent to achieving consensus, an auxiliary agent is tasked to deduce the specific assignment for each agent from the entire communication record. This distilled information is then given as the input to the Voyager agent to inform it the assigned task.

Action Execution We instantiate several Voyager agents within a shared Minecraft environment. A brief introduction of the Voyager agent is provided here, and we refer the interested readers to Wang et al. (2023a) for a more detailed exposition.

A Voyager agent is adept at navigating Minecraft. On receiving a task, it first decomposes it into a set of manageable sub-tasks. For instance, if assigned the task "Kill 3 cows", the agent might decompose it into sequential sub-goals like: [punch 2 trees, Craft 4 wooden planks, Craft 1 stick, Craft 1 crafting table, Craft 1 wooden sword, Kill 3 cows]. The agent then sequentially attempt to complete each sub-task.

We employ the checkpoint available in the official repository[5], and use `GPT-4-0314` as the backbone LLM for Voyager agent to be consistent with Wang et al. (2023a). Once an agent accomplish its own task, or all agents hit the cap of five attempts, the task execution stage terminates and evaluation stage starts.

Evaluation We directly exploit the inventory and the completed or failed sub-tasks of each agent as the feedback.

C Prompts

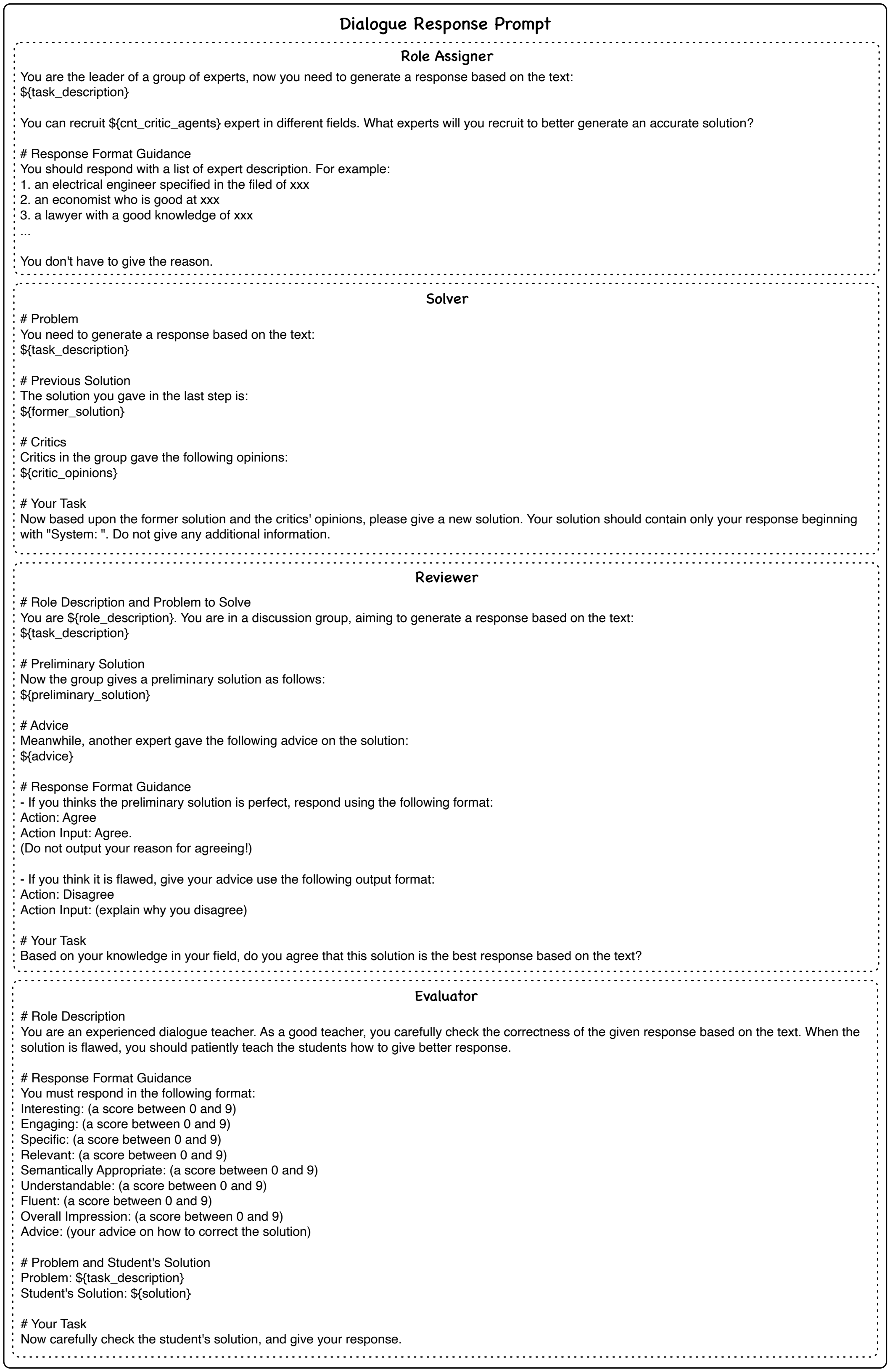
We list the prompts used in Section 3.1 at Figures 6 to 9.

D Examples of the Qualitative Experiments

In this section, we delve into specific examples to illustrate the experimental processes discussed in our paper. For each instance, we juxtapose the single-agent approach with the multi-agent method. Specifically:

- Figure 10 depicts the process for developing a calculator. Figures 11 and 12 show the code generated by single agent and multi-agent group respectively.
- For project consulting, we present single-agent and multi-agent approaches using horizontal communication. These can be seen in Figures 13 and 14.
- Similarly, Figures 15 and 16 showcase single-agent and multi-agent project consulting, but employing a vertical communication structure for multi-agent.
- Lastly, Figure 17 provides an insight into a process where three agents collaborate to craft a bookshelf in Minecraft.

[5] `https://github.com/MineDojo/Voyager/tree/main/skill_library/trial1/skill`



Dialogue Response Prompt

Role Assigner

You are the leader of a group of experts, now you need to generate a response based on the text:
${task_description}

You can recruit ${cnt_critic_agents} expert in different fields. What experts will you recruit to better generate an accurate solution?

# Response Format Guidance
You should respond with a list of expert description. For example:
1. an electrical engineer specified in the filed of xxx
2. an economist who is good at xxx
3. a lawyer with a good knowledge of xxx
...

You don't have to give the reason.

Solver

# Problem
You need to generate a response based on the text:
${task_description}

# Previous Solution
The solution you gave in the last step is:
${former_solution}

# Critics
Critics in the group gave the following opinions:
${critic_opinions}

# Your Task
Now based upon the former solution and the critics' opinions, please give a new solution. Your solution should contain only your response beginning with "System: ". Do not give any additional information.

Reviewer

# Role Description and Problem to Solve
You are ${role_description}. You are in a discussion group, aiming to generate a response based on the text:
${task_description}

# Preliminary Solution
Now the group gives a preliminary solution as follows:
${preliminary_solution}

# Advice
Meanwhile, another expert gave the following advice on the solution:
${advice}

# Response Format Guidance
- If you thinks the preliminary solution is perfect, respond using the following format:
Action: Agree
Action Input: Agree.
(Do not output your reason for agreeing!)

- If you think it is flawed, give your advice use the following output format:
Action: Disagree
Action Input: (explain why you disagree)

# Your Task
Based on your knowledge in your field, do you agree that this solution is the best response based on the text?

Evaluator

# Role Description
You are an experienced dialogue teacher. As a good teacher, you carefully check the correctness of the given response based on the text. When the solution is flawed, you should patiently teach the students how to give better response.

# Response Format Guidance
You must respond in the following format:
Interesting: (a score between 0 and 9)
Engaging: (a score between 0 and 9)
Specific: (a score between 0 and 9)
Relevant: (a score between 0 and 9)
Semantically Appropriate: (a score between 0 and 9)
Understandable: (a score between 0 and 9)
Fluent: (a score between 0 and 9)
Overall Impression: (a score between 0 and 9)
Advice: (your advice on how to correct the solution)

# Problem and Student's Solution
Problem: ${task_description}
Student's Solution: ${solution}

# Your Task
Now carefully check the student's solution, and give your response.

Figure 6: Prompt of dialogue response task.

Math Reasoning Prompt

Role Assigner

~~~
# Role Description
You are the leader of a group, now you are facing a grade school math problem:
${task_description}

You can recruit ${cnt_critic_agents} people. What people will you recruit?

# Response Format Guidance
You should respond with a list of ${cnt_critic_agents} people description. For example:
1. an electrical engineer specified in the filed of xxx
2. an economist who is good at xxx
3. a lawyer with a good knowledge of xxx
...

Only respond with the description of each role. Do not include your reason.
~~~

Solver

~~~
Can you solve the following math problem?
${task_description}
# Previous Solution
The solution you gave in the last step is:
```
${former_solution}
```
# Critics
There are some critics on the above solution:
```
${critic_opinions}
```
Using the these information, can you provide the correct solution to the math problem? Explain your reasoning. Your final answer must be a single numerical number (not a equation, fraction, function or variable), in the form \boxed{answer}, at the end of your response.
~~~

Reviewer

~~~
You are in a discussion group, aiming to collaborative solve the following math problem:
${task_description}
Below is a possible solution to the problem:
```
${preliminary_solution}
```

You are ${role_description}. Based on your knowledge, can you check the correctness of the solutions given in the chat history? You should give your correct solution to the problem step by step. When responding, you should follow the following rules:
1. Double-check the above solutions, give your critics, then generate the correct solution step by step.
2. If the final answer in your solution is the same as the final answer in the above provided solution, end your response with a special token "[Agree]".
3. You must highlight your final answer in the form \boxed{answer} at the end of your response. The answer must be a numerical number, not a equation, fraction, function or variable.
Now give your response.
~~~

Evaluator

~~~
Problem: ${task_description}
Solution:
```
${solution}
```
You are an experienced mathematic teacher. As a good teacher, you carefully check the correctness of the given solution on a grade school math problem. When the solution is wrong, you should give your advice to the students on how to correct the solution. When it is correct, output a correctness of 1 and why it is correct. Also check that the final answer is in the form \boxed{answer} at the end of the solution. The answer must be a numerical number (not a equation, fraction, function or variable).

You should respond in the following format:
Correctness: (0 or 1, 0 is wrong, and 1 is correct)
Response: (explain in details why it is wrong or correct)
~~~

Figure 7: Prompt of math reasoning task.

Code Completion Prompt

Role Assigner

~~~~
# Role Description
You are the leader of a group of experts, now you need to recruit a small group of experts with diverse identity to correctly write the code to
solve the given problems:
${task_description}

You can recruit ${cnt_critic_agents} expert in different fields. What experts will you recruit to better generate an accurate solution?

# Response Format Guidance
You should respond with a list of expert description. For example:
1. an electrical engineer specified in the filed of xxx.
2. an economist who is good at xxx.
3. a lawyer with a good knowledge of xxx.
...

Only respond with the description of each role. Do not include your reason.
~~~~

Solver

~~~~
Can you complete the following code?
```python
${task_description}
```
# Previous Solution
The solution you gave in the last step is:
${former_solution}
# Critics
There are some critics on the above solution:
```
${critic_opinions}
```
Using the these information, can you provide a correct completion of the code? Explain your reasoning. Your response should contain only Python
code. Do not give any additional information. Use ```python to put the completed Python code in markdown quotes. When responding, please include
the given code and the completion.
~~~~

Reviewer

~~~~
You are in a discussion group, aiming to complete the following code function:
```python
${task_description}
```
Below is a possible code completion:
```
${preliminary_solution}
```

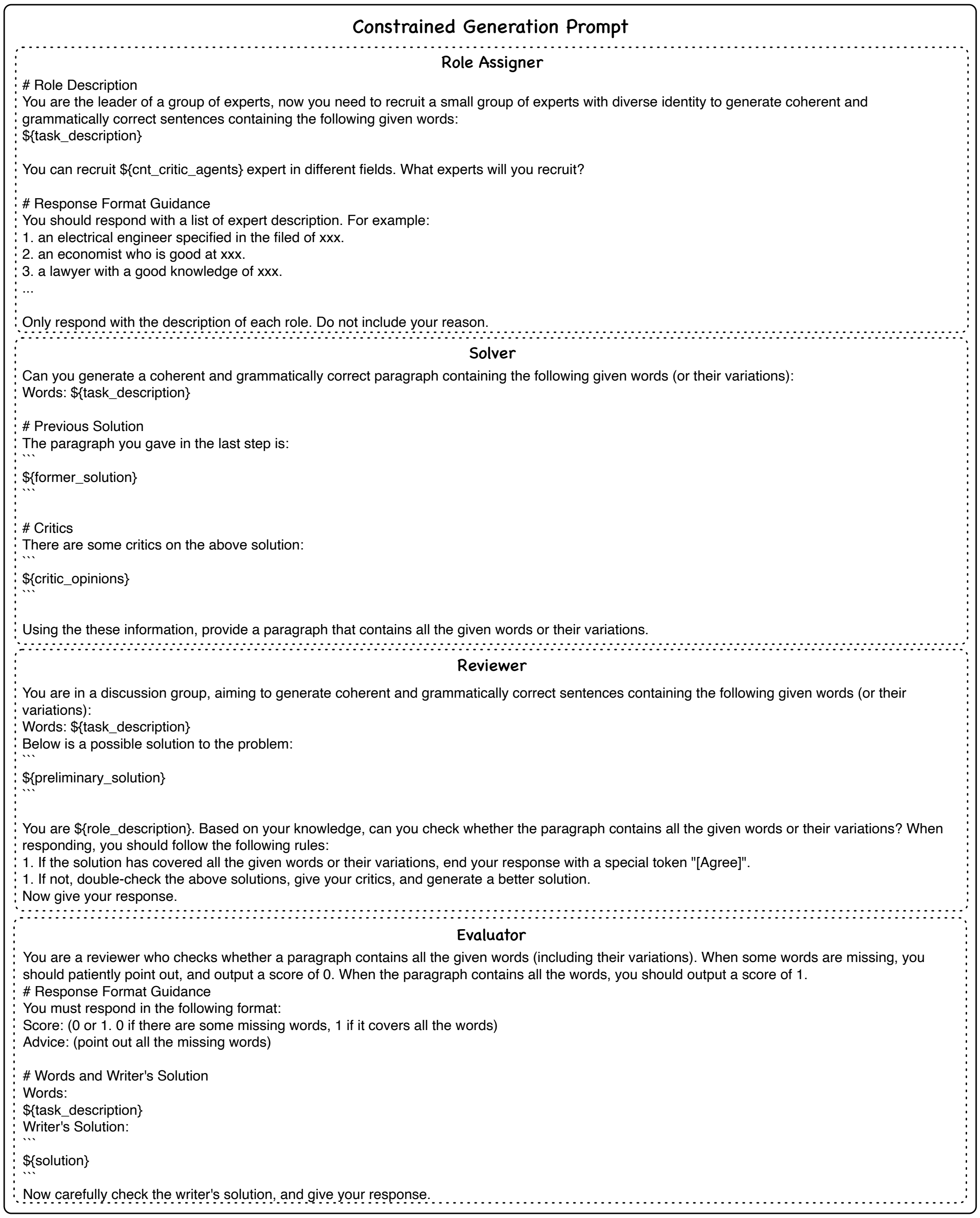
You are ${role_description}. Based on your knowledge, can you check the correctness of the completion given above? You should give your correct
solution to the problem step by step. When responding, you should follow the following rules:
1. Double-check the above solutions, give your critics, then generate the correct solution step by step.
2. If the above solution is correct, end your response with a special token "[Agree]".
3. Your response should contain only Python code. Do not give any additional information. Use ```python to wrap your Python code in markdown
quotes. When responding, please include the given code and the completion.
Now give your response.
~~~~

Evaluator

~~~~
You are an experienced code reviewer. As a good reviewer, you carefully check the correctness of the given code completion. When the completion
is incorrect, you should patiently teach the writer how to correct the completion.
# Response Format Guidance
You must respond in the following format:
Score: (0 or 1, 0 for incorrect and 1 for correct)
Response: (give your advice on how to correct the solution)

# Problem and Writer's Solution
Problem:
${task_description}
Writer's Solution:
${solution}
# Your Task
Now carefully check the writer's solution, and give your response.
~~~~

Figure 8: Prompt of code completion task.



Constrained Generation Prompt

Role Assigner

# Role Description
You are the leader of a group of experts, now you need to recruit a small group of experts with diverse identity to generate coherent and grammatically correct sentences containing the following given words:
${task_description}

You can recruit ${cnt_critic_agents} expert in different fields. What experts will you recruit?

# Response Format Guidance
You should respond with a list of expert description. For example:
1. an electrical engineer specified in the filed of xxx.
2. an economist who is good at xxx.
3. a lawyer with a good knowledge of xxx.
...

Only respond with the description of each role. Do not include your reason.

Solver

Can you generate a coherent and grammatically correct paragraph containing the following given words (or their variations):
Words: ${task_description}

# Previous Solution
The paragraph you gave in the last step is:
```
${former_solution}
```

# Critics
There are some critics on the above solution:
```
${critic_opinions}
```

Using the these information, provide a paragraph that contains all the given words or their variations.

Reviewer

You are in a discussion group, aiming to generate coherent and grammatically correct sentences containing the following given words (or their variations):
Words: ${task_description}
Below is a possible solution to the problem:
```
${preliminary_solution}
```

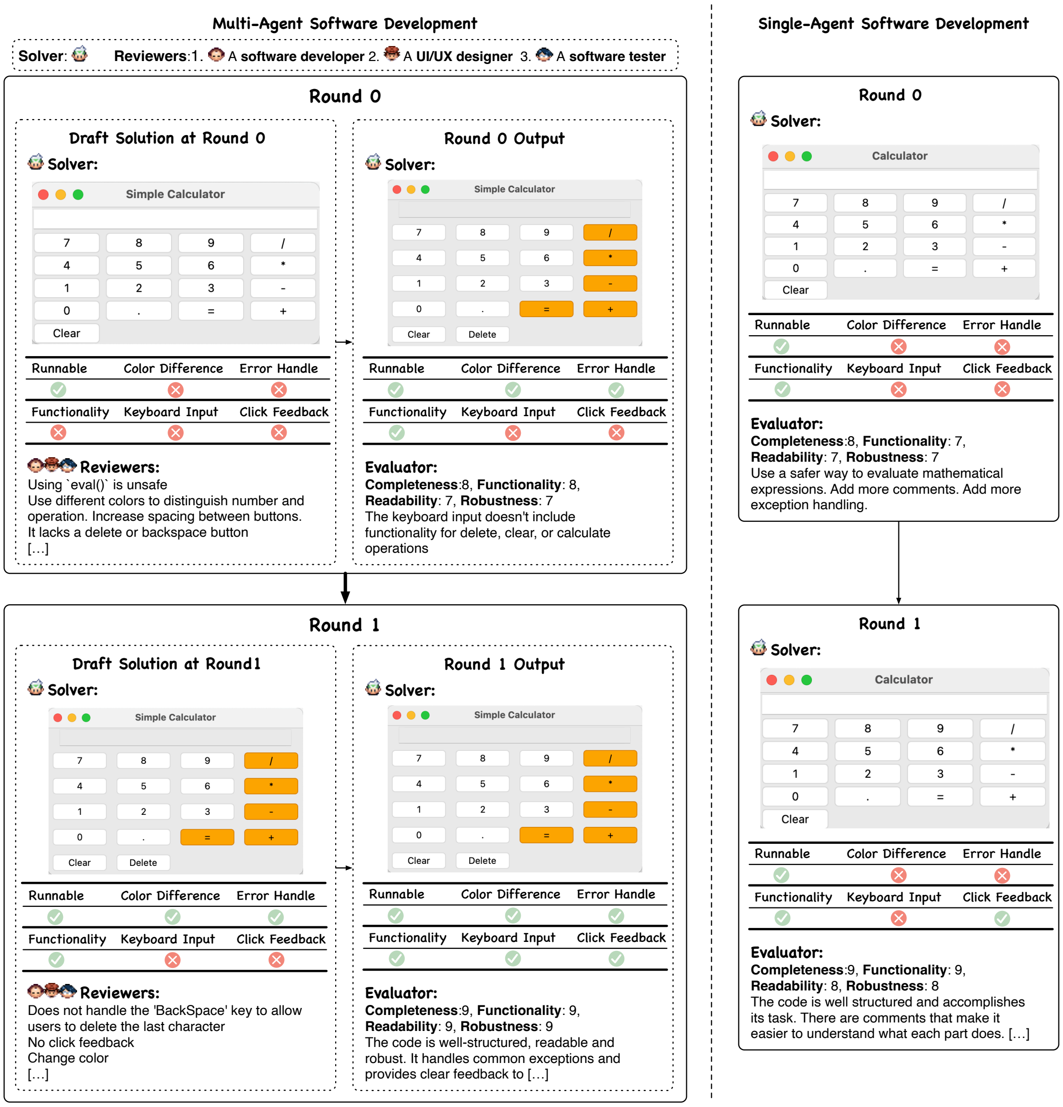
You are ${role_description}. Based on your knowledge, can you check whether the paragraph contains all the given words or their variations? When responding, you should follow the following rules:
1. If the solution has covered all the given words or their variations, end your response with a special token "[Agree]".
1. If not, double-check the above solutions, give your critics, and generate a better solution.
Now give your response.

Evaluator

You are a reviewer who checks whether a paragraph contains all the given words (including their variations). When some words are missing, you should patiently point out, and output a score of 0. When the paragraph contains all the words, you should output a score of 1.
# Response Format Guidance
You must respond in the following format:
Score: (0 or 1. 0 if there are some missing words, 1 if it covers all the words)
Advice: (point out all the missing words)

# Words and Writer's Solution
Words:
${task_description}
Writer's Solution:
```
${solution}
```
Now carefully check the writer's solution, and give your response.

Figure 9: Prompt of constrained generation task.



Multi-Agent Software Development

Solver: Reviewers:1. A software developer 2. A UI/UX designer 3. A software tester

Round 0

Draft Solution at Round 0

Solver:

Runnable	Color Difference	Error Handle
✓	✗	✗

Functionality	Keyboard Input	Click Feedback
✗	✗	✗

Reviewers:
Using `eval()` is unsafe
Use different colors to distinguish number and operation. Increase spacing between buttons.
It lacks a delete or backspace button
[...]

Round 0 Output

Solver:

Runnable	Color Difference	Error Handle
✓	✓	✓

Functionality	Keyboard Input	Click Feedback
✓	✗	✗

Evaluator:
Completeness:8, **Functionality**: 8,
Readability: 7, **Robustness**: 7
The keyboard input doesn't include functionality for delete, clear, or calculate operations

Round 1

Draft Solution at Round1

Solver:

Runnable	Color Difference	Error Handle
✓	✓	✓

Functionality	Keyboard Input	Click Feedback
✓	✗	✗

Reviewers:
Does not handle the 'BackSpace' key to allow users to delete the last character
No click feedback
Change color
[...]

Round 1 Output

Solver:

Runnable	Color Difference	Error Handle
✓	✓	✓

Functionality	Keyboard Input	Click Feedback
✓	✓	✓

Evaluator:
Completeness:9, **Functionality**: 9,
Readability: 9, **Robustness**: 9
The code is well-structured, readable and robust. It handles common exceptions and provides clear feedback to [...]

Single-Agent Software Development

Round 0

Solver:

Runnable	Color Difference	Error Handle
✓	✗	✗

Functionality	Keyboard Input	Click Feedback
✓	✗	✗

Evaluator:
Completeness:8, **Functionality**: 7,
Readability: 7, **Robustness**: 7
Use a safer way to evaluate mathematical expressions. Add more comments. Add more exception handling.

Round 1

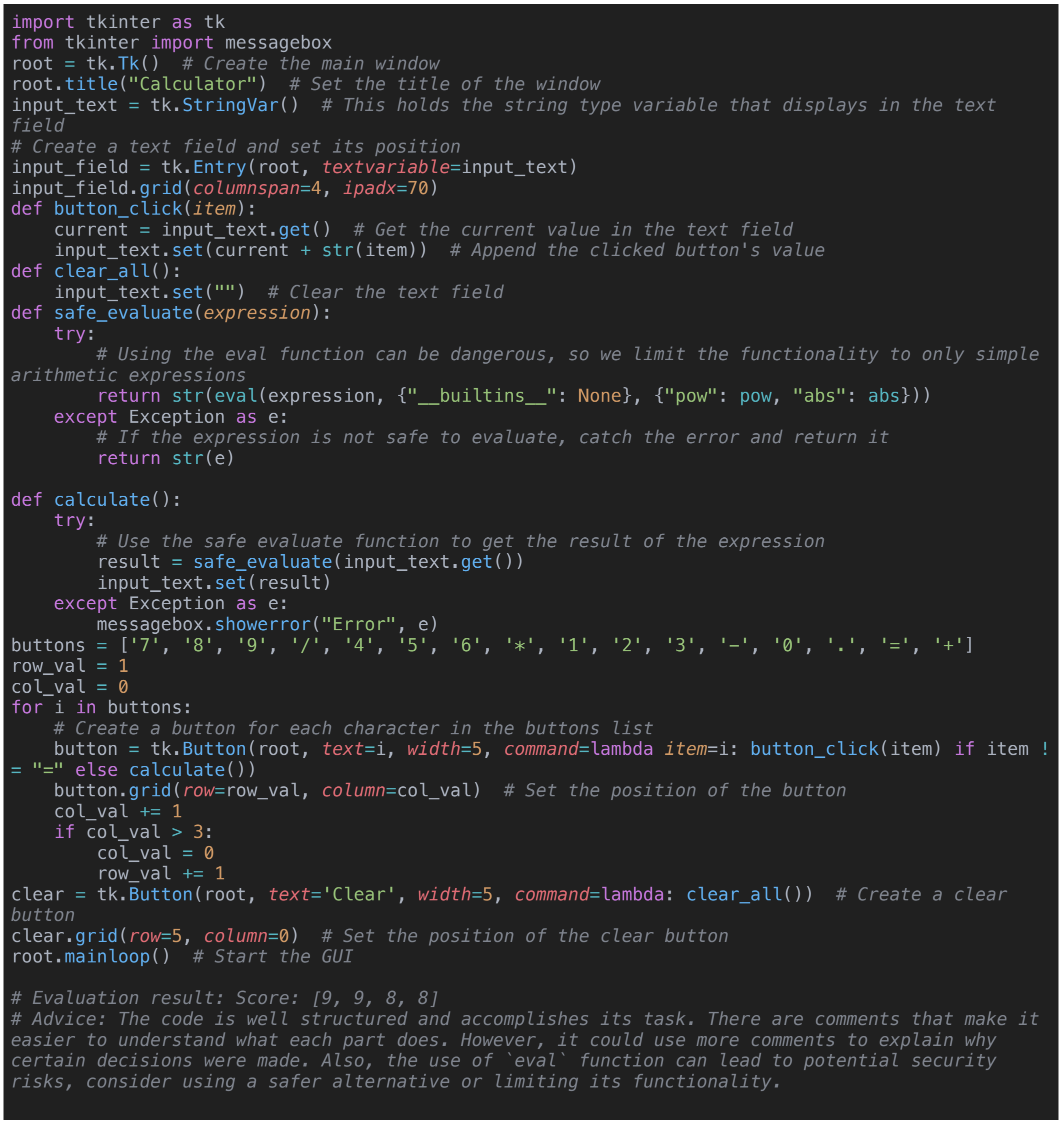
Solver:

Runnable	Color Difference	Error Handle
✓	✗	✗

Functionality	Keyboard Input	Click Feedback
✓	✗	✓

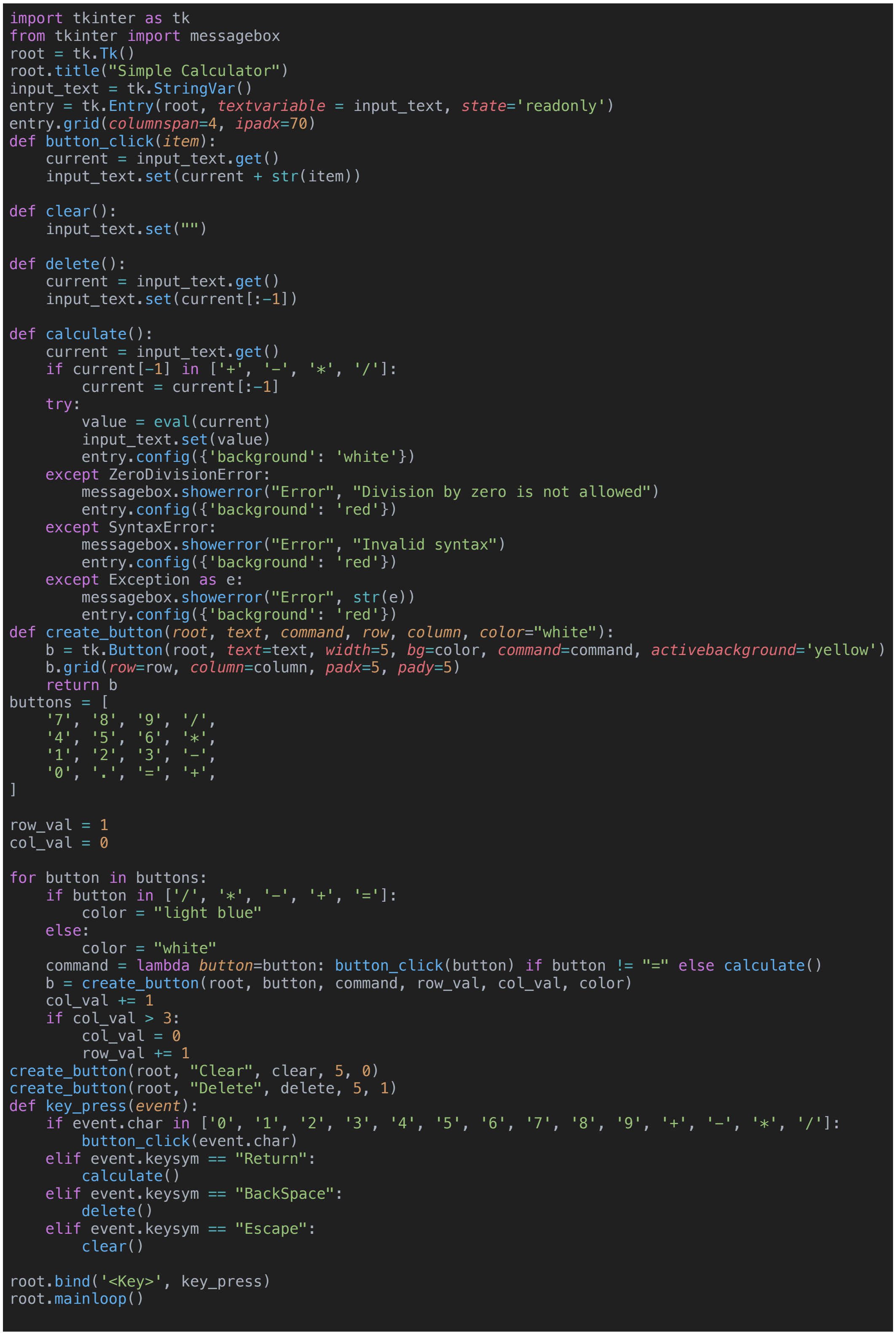
Evaluator:
Completeness:9, **Functionality**: 9,
Readability: 8, **Robustness**: 8
The code is well structured and accomplishes its task. There are comments that make it easier to understand what each part does. [...]

Figure 10: An example of the process of software development.



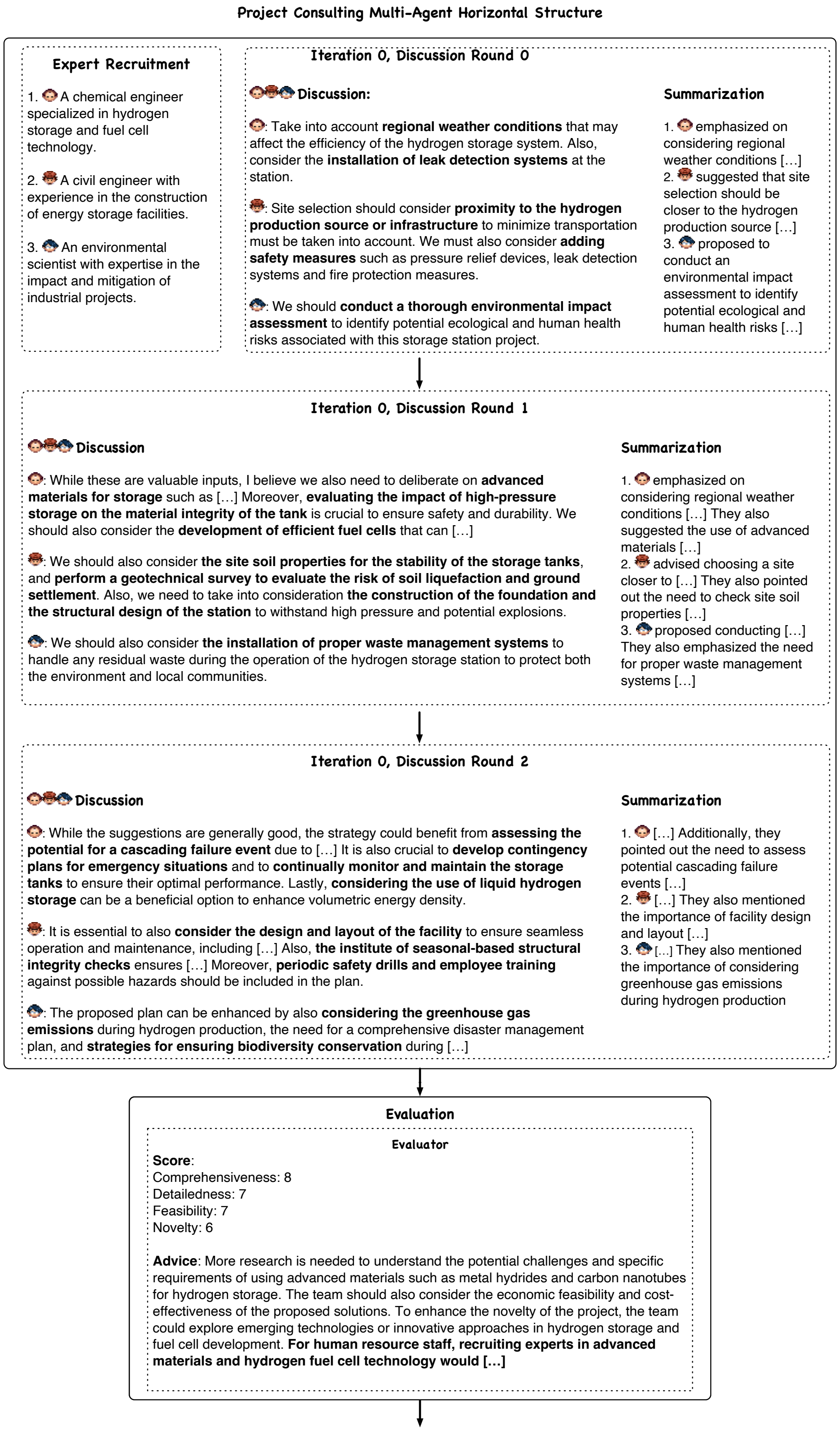
```
import tkinter as tk
from tkinter import messagebox
root = tk.Tk()  # Create the main window
root.title("Calculator")  # Set the title of the window
input_text = tk.StringVar()  # This holds the string type variable that displays in the text field
# Create a text field and set its position
input_field = tk.Entry(root, textvariable=input_text)
input_field.grid(columnspan=4, ipadx=70)
def button_click(item):
    current = input_text.get()  # Get the current value in the text field
    input_text.set(current + str(item))  # Append the clicked button's value
def clear_all():
    input_text.set("")  # Clear the text field
def safe_evaluate(expression):
    try:
        # Using the eval function can be dangerous, so we limit the functionality to only simple arithmetic expressions
        return str(eval(expression, {"__builtins__": None}, {"pow": pow, "abs": abs}))
    except Exception as e:
        # If the expression is not safe to evaluate, catch the error and return it
        return str(e)

def calculate():
    try:
        # Use the safe evaluate function to get the result of the expression
        result = safe_evaluate(input_text.get())
        input_text.set(result)
    except Exception as e:
        messagebox.showerror("Error", e)
buttons = ['7', '8', '9', '/', '4', '5', '6', '*', '1', '2', '3', '-', '0', '.', '=', '+']
row_val = 1
col_val = 0
for i in buttons:
    # Create a button for each character in the buttons list
    button = tk.Button(root, text=i, width=5, command=lambda item=i: button_click(item) if item != "=" else calculate())
    button.grid(row=row_val, column=col_val)  # Set the position of the button
    col_val += 1
    if col_val > 3:
        col_val = 0
        row_val += 1
clear = tk.Button(root, text='Clear', width=5, command=lambda: clear_all())  # Create a clear button
clear.grid(row=5, column=0)  # Set the position of the clear button
root.mainloop()  # Start the GUI

# Evaluation result: Score: [9, 9, 8, 8]
# Advice: The code is well structured and accomplishes its task. There are comments that make it easier to understand what each part does. However, it could use more comments to explain why certain decisions were made. Also, the use of `eval` function can lead to potential security risks, consider using a safer alternative or limiting its functionality.
```

Figure 11: The code generated by single agent.



```python
import tkinter as tk
from tkinter import messagebox
root = tk.Tk()
root.title("Simple Calculator")
input_text = tk.StringVar()
entry = tk.Entry(root, textvariable = input_text, state='readonly')
entry.grid(columnspan=4, ipadx=70)
def button_click(item):
    current = input_text.get()
    input_text.set(current + str(item))

def clear():
    input_text.set("")

def delete():
    current = input_text.get()
    input_text.set(current[:-1])

def calculate():
    current = input_text.get()
    if current[-1] in ['+', '-', '*', '/']:
        current = current[:-1]
    try:
        value = eval(current)
        input_text.set(value)
        entry.config({'background': 'white'})
    except ZeroDivisionError:
        messagebox.showerror("Error", "Division by zero is not allowed")
        entry.config({'background': 'red'})
    except SyntaxError:
        messagebox.showerror("Error", "Invalid syntax")
        entry.config({'background': 'red'})
    except Exception as e:
        messagebox.showerror("Error", str(e))
        entry.config({'background': 'red'})
def create_button(root, text, command, row, column, color="white"):
    b = tk.Button(root, text=text, width=5, bg=color, command=command, activebackground='yellow')
    b.grid(row=row, column=column, padx=5, pady=5)
    return b
buttons = [
    '7', '8', '9', '/',
    '4', '5', '6', '*',
    '1', '2', '3', '-',
    '0', '.', '=', '+',
]

row_val = 1
col_val = 0

for button in buttons:
    if button in ['/', '*', '-', '+', '=']:
        color = "light blue"
    else:
        color = "white"
    command = lambda button=button: button_click(button) if button != "=" else calculate()
    b = create_button(root, button, command, row_val, col_val, color)
    col_val += 1
    if col_val > 3:
        col_val = 0
        row_val += 1
create_button(root, "Clear", clear, 5, 0)
create_button(root, "Delete", delete, 5, 1)
def key_press(event):
    if event.char in ['0', '1', '2', '3', '4', '5', '6', '7', '8', '9', '+', '-', '*', '/']:
        button_click(event.char)
    elif event.keysym == "Return":
        calculate()
    elif event.keysym == "BackSpace":
        delete()
    elif event.keysym == "Escape":
        clear()

root.bind('<Key>', key_press)
root.mainloop()
```

Figure 12: The code generated by the multi-agent group.



Project Consulting Multi-Agent Horizontal Structure

Expert Recruitment

1. A chemical engineer specialized in hydrogen storage and fuel cell technology.

2. A civil engineer with experience in the construction of energy storage facilities.

3. An environmental scientist with expertise in the impact and mitigation of industrial projects.

Iteration 0, Discussion Round 0

Discussion:

: Take into account **regional weather conditions** that may affect the efficiency of the hydrogen storage system. Also, consider the **installation of leak detection systems** at the station.

: Site selection should consider **proximity to the hydrogen production source or infrastructure** to minimize transportation must be taken into account. We must also consider **adding safety measures** such as pressure relief devices, leak detection systems and fire protection measures.

: We should **conduct a thorough environmental impact assessment** to identify potential ecological and human health risks associated with this storage station project.

Summarization

1. emphasized on considering regional weather conditions […]
2. suggested that site selection should be closer to the hydrogen production source […]
3. proposed to conduct an environmental impact assessment to identify potential ecological and human health risks […]

Iteration 0, Discussion Round 1

Discussion

: While these are valuable inputs, I believe we also need to deliberate on **advanced materials for storage** such as […] Moreover, **evaluating the impact of high-pressure storage on the material integrity of the tank** is crucial to ensure safety and durability. We should also consider the **development of efficient fuel cells** that can […]

: We should also consider **the site soil properties for the stability of the storage tanks**, and **perform a geotechnical survey to evaluate the risk of soil liquefaction and ground settlement**. Also, we need to take into consideration **the construction of the foundation and the structural design of the station** to withstand high pressure and potential explosions.

: We should also consider **the installation of proper waste management systems** to handle any residual waste during the operation of the hydrogen storage station to protect both the environment and local communities.

Summarization

1. emphasized on considering regional weather conditions […] They also suggested the use of advanced materials […]
2. advised choosing a site closer to […] They also pointed out the need to check site soil properties […]
3. proposed conducting […] They also emphasized the need for proper waste management systems […]

Iteration 0, Discussion Round 2

Discussion

: While the suggestions are generally good, the strategy could benefit from **assessing the potential for a cascading failure event** due to […] It is also crucial to **develop contingency plans for emergency situations** and to **continually monitor and maintain the storage tanks** to ensure their optimal performance. Lastly, **considering the use of liquid hydrogen storage** can be a beneficial option to enhance volumetric energy density.

: It is essential to also **consider the design and layout of the facility** to ensure seamless operation and maintenance, including […] Also, **the institute of seasonal-based structural integrity checks** ensures […] Moreover, **periodic safety drills and employee training** against possible hazards should be included in the plan.

: The proposed plan can be enhanced by also **considering the greenhouse gas emissions** during hydrogen production, the need for a comprehensive disaster management plan, and **strategies for ensuring biodiversity conservation** during […]

Summarization

1. […] Additionally, they pointed out the need to assess potential cascading failure events […]
2. […] They also mentioned the importance of facility design and layout […]
3. […] They also mentioned the importance of considering greenhouse gas emissions during hydrogen production

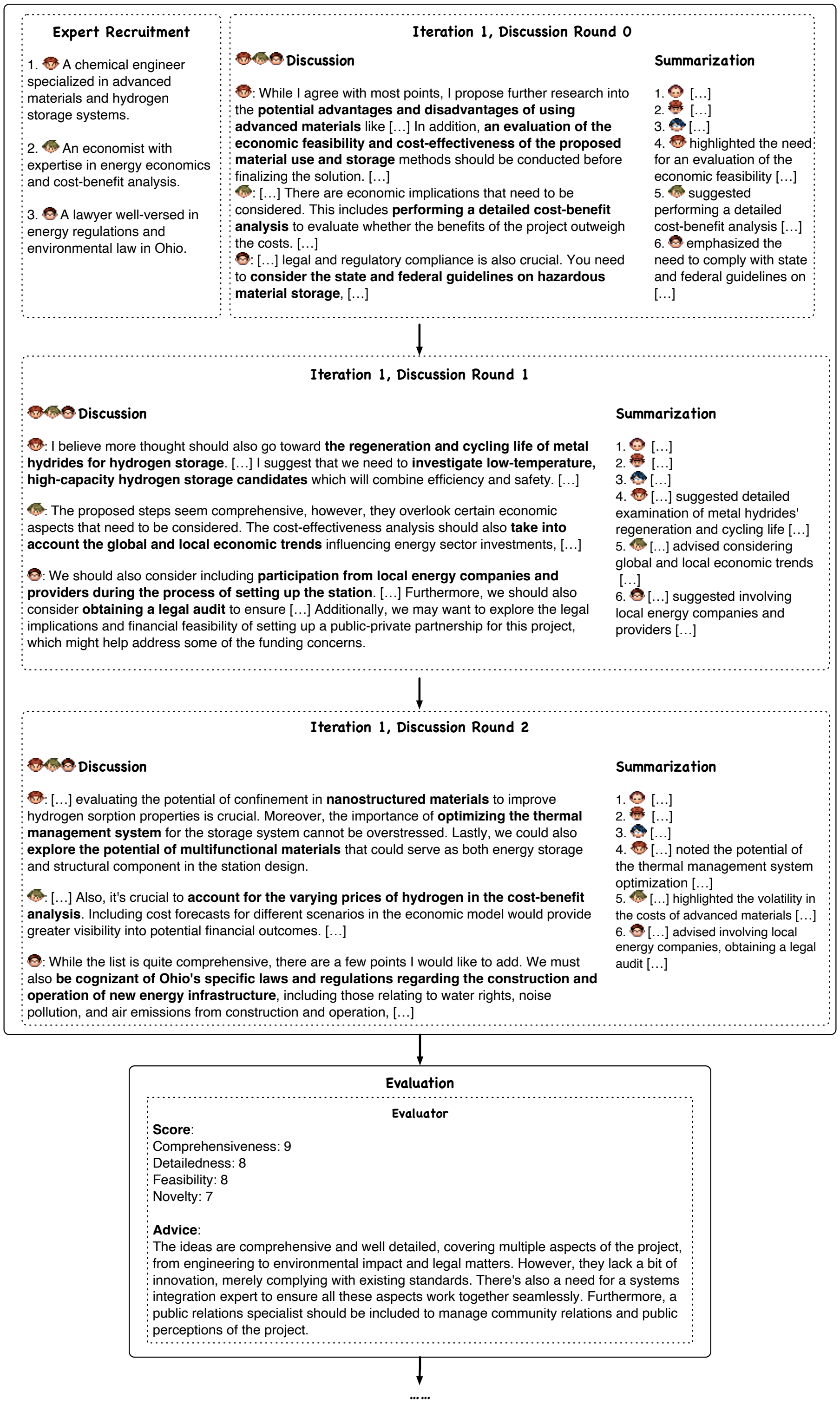
Evaluation

Evaluator

Score:
Comprehensiveness: 8
Detailedness: 7
Feasibility: 7
Novelty: 6

Advice: More research is needed to understand the potential challenges and specific requirements of using advanced materials such as metal hydrides and carbon nanotubes for hydrogen storage. The team should also consider the economic feasibility and cost-effectiveness of the proposed solutions. To enhance the novelty of the project, the team could explore emerging technologies or innovative approaches in hydrogen storage and fuel cell development. **For human resource staff, recruiting experts in advanced materials and hydrogen fuel cell technology would […]**

Figure 13: (Page 1) An example process of project consulting using horizontal decision-making structure. The agents are providing suggestions on the problem "Give me some suggestions if I want to build a compressed hydrogen storage station in Ohio"



Expert Recruitment

1. A chemical engineer specialized in advanced materials and hydrogen storage systems.

2. An economist with expertise in energy economics and cost-benefit analysis.

3. A lawyer well-versed in energy regulations and environmental law in Ohio.

Iteration 1, Discussion Round 0

Discussion

: While I agree with most points, I propose further research into the **potential advantages and disadvantages of using advanced materials** like […] In addition, **an evaluation of the economic feasibility and cost-effectiveness of the proposed material use and storage** methods should be conducted before finalizing the solution. […]

: […] There are economic implications that need to be considered. This includes **performing a detailed cost-benefit analysis** to evaluate whether the benefits of the project outweigh the costs. […]

: […] legal and regulatory compliance is also crucial. You need to **consider the state and federal guidelines on hazardous material storage**, […]

Summarization

1. […]
2. […]
3. […]
4. highlighted the need for an evaluation of the economic feasibility […]
5. suggested performing a detailed cost-benefit analysis […]
6. emphasized the need to comply with state and federal guidelines on […]

Iteration 1, Discussion Round 1

Discussion

: I believe more thought should also go toward **the regeneration and cycling life of metal hydrides for hydrogen storage**. […] I suggest that we need to **investigate low-temperature, high-capacity hydrogen storage candidates** which will combine efficiency and safety. […]

: The proposed steps seem comprehensive, however, they overlook certain economic aspects that need to be considered. The cost-effectiveness analysis should also **take into account the global and local economic trends** influencing energy sector investments, […]

: We should also consider including **participation from local energy companies and providers during the process of setting up the station**. […] Furthermore, we should also consider **obtaining a legal audit** to ensure […] Additionally, we may want to explore the legal implications and financial feasibility of setting up a public-private partnership for this project, which might help address some of the funding concerns.

Summarization

1. […]
2. […]
3. […]
4. […] suggested detailed examination of metal hydrides' regeneration and cycling life […]
5. […] advised considering global and local economic trends […]
6. […] suggested involving local energy companies and providers […]

Iteration 1, Discussion Round 2

Discussion

: […] evaluating the potential of confinement in **nanostructured materials** to improve hydrogen sorption properties is crucial. Moreover, the importance of **optimizing the thermal management system** for the storage system cannot be overstressed. Lastly, we could also **explore the potential of multifunctional materials** that could serve as both energy storage and structural component in the station design.

: […] Also, it's crucial to **account for the varying prices of hydrogen in the cost-benefit analysis**. Including cost forecasts for different scenarios in the economic model would provide greater visibility into potential financial outcomes. […]

: While the list is quite comprehensive, there are a few points I would like to add. We must also **be cognizant of Ohio's specific laws and regulations regarding the construction and operation of new energy infrastructure**, including those relating to water rights, noise pollution, and air emissions from construction and operation, […]

Summarization

1. […]
2. […]
3. […]
4. […] noted the potential of the thermal management system optimization […]
5. […] highlighted the volatility in the costs of advanced materials […]
6. […] advised involving local energy companies, obtaining a legal audit […]

Evaluation

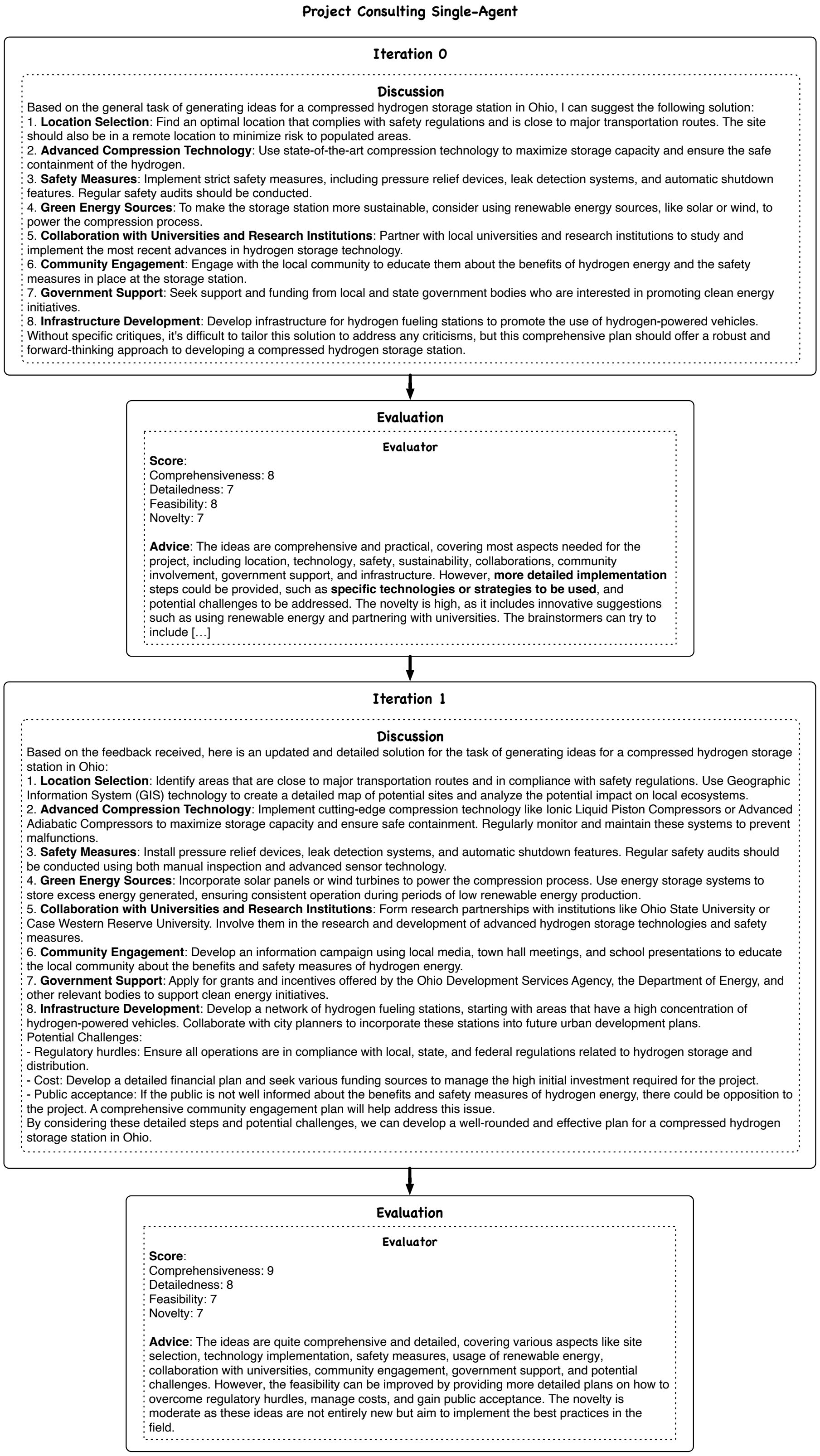
Evaluator

Score:
Comprehensiveness: 9
Detailedness: 8
Feasibility: 8
Novelty: 7

Advice:
The ideas are comprehensive and well detailed, covering multiple aspects of the project, from engineering to environmental impact and legal matters. However, they lack a bit of innovation, merely complying with existing standards. There's also a need for a systems integration expert to ensure all these aspects work together seamlessly. Furthermore, a public relations specialist should be included to manage community relations and public perceptions of the project.

……

Figure 13: (Page 2) An example process of project consulting using horizontal decision-making structure. The agents are providing suggestions on the problem "Give me some suggestions if I want to build a compressed hydrogen storage station in Ohio"



Project Consulting Single-Agent

Iteration 0

Discussion

Based on the general task of generating ideas for a compressed hydrogen storage station in Ohio, I can suggest the following solution:
1. **Location Selection**: Find an optimal location that complies with safety regulations and is close to major transportation routes. The site should also be in a remote location to minimize risk to populated areas.
2. **Advanced Compression Technology**: Use state-of-the-art compression technology to maximize storage capacity and ensure the safe containment of the hydrogen.
3. **Safety Measures**: Implement strict safety measures, including pressure relief devices, leak detection systems, and automatic shutdown features. Regular safety audits should be conducted.
4. **Green Energy Sources**: To make the storage station more sustainable, consider using renewable energy sources, like solar or wind, to power the compression process.
5. **Collaboration with Universities and Research Institutions**: Partner with local universities and research institutions to study and implement the most recent advances in hydrogen storage technology.
6. **Community Engagement**: Engage with the local community to educate them about the benefits of hydrogen energy and the safety measures in place at the storage station.
7. **Government Support**: Seek support and funding from local and state government bodies who are interested in promoting clean energy initiatives.
8. **Infrastructure Development**: Develop infrastructure for hydrogen fueling stations to promote the use of hydrogen-powered vehicles.
Without specific critiques, it's difficult to tailor this solution to address any criticisms, but this comprehensive plan should offer a robust and forward-thinking approach to developing a compressed hydrogen storage station.

Evaluation

Evaluator

Score:
Comprehensiveness: 8
Detailedness: 7
Feasibility: 8
Novelty: 7

Advice: The ideas are comprehensive and practical, covering most aspects needed for the project, including location, technology, safety, sustainability, collaborations, community involvement, government support, and infrastructure. However, **more detailed implementation** steps could be provided, such as **specific technologies or strategies to be used**, and potential challenges to be addressed. The novelty is high, as it includes innovative suggestions such as using renewable energy and partnering with universities. The brainstormers can try to include […]

Iteration 1

Discussion

Based on the feedback received, here is an updated and detailed solution for the task of generating ideas for a compressed hydrogen storage station in Ohio:
1. **Location Selection**: Identify areas that are close to major transportation routes and in compliance with safety regulations. Use Geographic Information System (GIS) technology to create a detailed map of potential sites and analyze the potential impact on local ecosystems.
2. **Advanced Compression Technology**: Implement cutting-edge compression technology like Ionic Liquid Piston Compressors or Advanced Adiabatic Compressors to maximize storage capacity and ensure safe containment. Regularly monitor and maintain these systems to prevent malfunctions.
3. **Safety Measures**: Install pressure relief devices, leak detection systems, and automatic shutdown features. Regular safety audits should be conducted using both manual inspection and advanced sensor technology.
4. **Green Energy Sources**: Incorporate solar panels or wind turbines to power the compression process. Use energy storage systems to store excess energy generated, ensuring consistent operation during periods of low renewable energy production.
5. **Collaboration with Universities and Research Institutions**: Form research partnerships with institutions like Ohio State University or Case Western Reserve University. Involve them in the research and development of advanced hydrogen storage technologies and safety measures.
6. **Community Engagement**: Develop an information campaign using local media, town hall meetings, and school presentations to educate the local community about the benefits and safety measures of hydrogen energy.
7. **Government Support**: Apply for grants and incentives offered by the Ohio Development Services Agency, the Department of Energy, and other relevant bodies to support clean energy initiatives.
8. **Infrastructure Development**: Develop a network of hydrogen fueling stations, starting with areas that have a high concentration of hydrogen-powered vehicles. Collaborate with city planners to incorporate these stations into future urban development plans.
Potential Challenges:
- Regulatory hurdles: Ensure all operations are in compliance with local, state, and federal regulations related to hydrogen storage and distribution.
- Cost: Develop a detailed financial plan and seek various funding sources to manage the high initial investment required for the project.
- Public acceptance: If the public is not well informed about the benefits and safety measures of hydrogen energy, there could be opposition to the project. A comprehensive community engagement plan will help address this issue.
By considering these detailed steps and potential challenges, we can develop a well-rounded and effective plan for a compressed hydrogen storage station in Ohio.

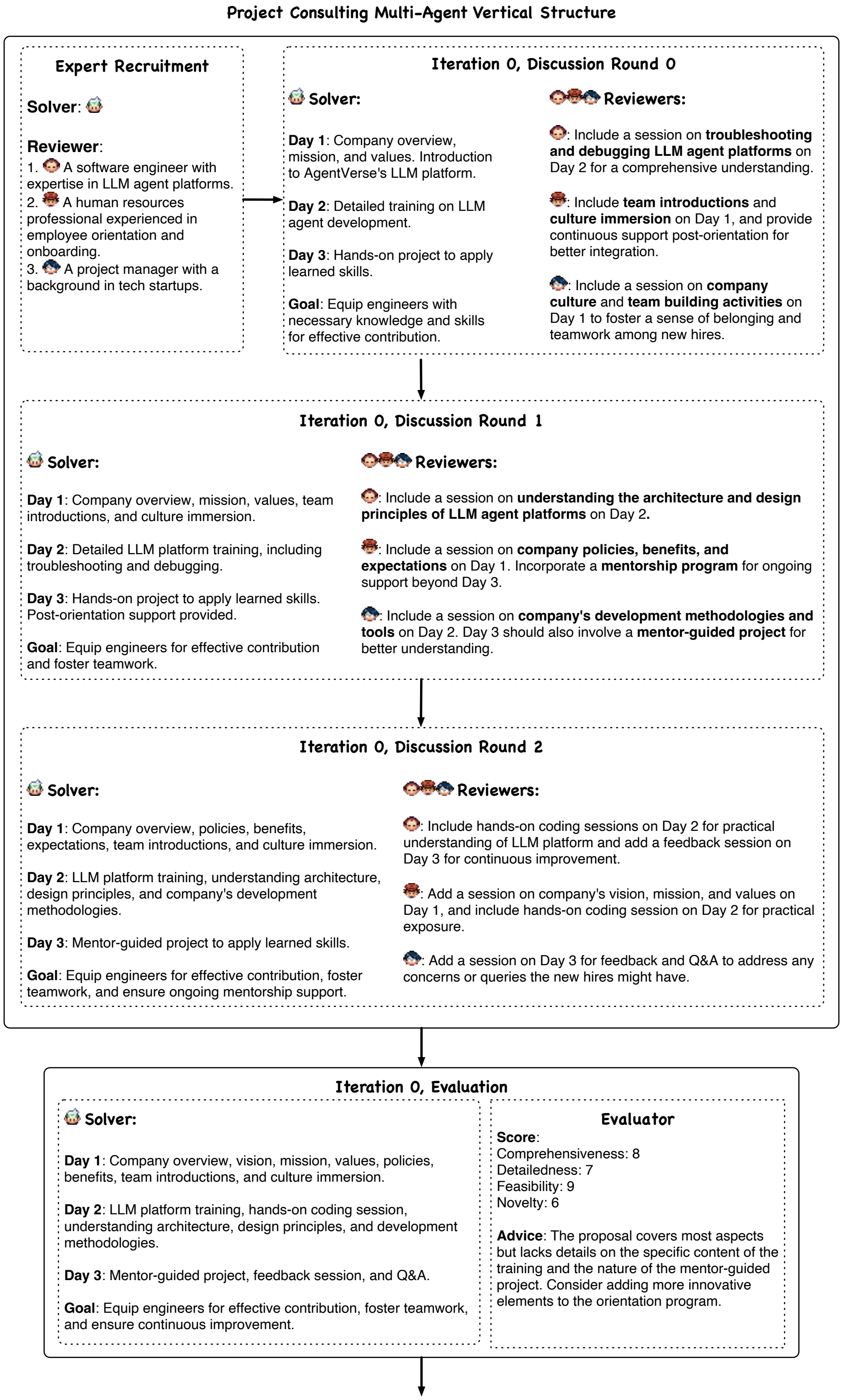
Evaluation

Evaluator

Score:
Comprehensiveness: 9
Detailedness: 8
Feasibility: 7
Novelty: 7

Advice: The ideas are quite comprehensive and detailed, covering various aspects like site selection, technology implementation, safety measures, usage of renewable energy, collaboration with universities, community engagement, government support, and potential challenges. However, the feasibility can be improved by providing more detailed plans on how to overcome regulatory hurdles, manage costs, and gain public acceptance. The novelty is moderate as these ideas are not entirely new but aim to implement the best practices in the field.

Figure 14: An example process of single-agent project consulting. The agent is required to provide suggestions on the problem "Give me some suggestions if I want to build a compressed hydrogen storage station in Ohio".



Project Consulting Multi-Agent Vertical Structure

Expert Recruitment

Solver:

Reviewer:
1. A software engineer with expertise in LLM agent platforms.
2. A human resources professional experienced in employee orientation and onboarding.
3. A project manager with a background in tech startups.

Iteration 0, Discussion Round 0

Solver:

Day 1: Company overview, mission, and values. Introduction to AgentVerse's LLM platform.

Day 2: Detailed training on LLM agent development.

Day 3: Hands-on project to apply learned skills.

Goal: Equip engineers with necessary knowledge and skills for effective contribution.

Reviewers:

: Include a session on **troubleshooting and debugging LLM agent platforms** on Day 2 for a comprehensive understanding.

: Include **team introductions** and **culture immersion** on Day 1, and provide continuous support post-orientation for better integration.

: Include a session on **company culture** and **team building activities** on Day 1 to foster a sense of belonging and teamwork among new hires.

Iteration 0, Discussion Round 1

Solver:

Day 1: Company overview, mission, values, team introductions, and culture immersion.

Day 2: Detailed LLM platform training, including troubleshooting and debugging.

Day 3: Hands-on project to apply learned skills. Post-orientation support provided.

Goal: Equip engineers for effective contribution and foster teamwork.

Reviewers:

: Include a session on **understanding the architecture and design principles of LLM agent platforms** on Day 2**.**

: Include a session on **company policies, benefits, and expectations** on Day 1. Incorporate a **mentorship program** for ongoing support beyond Day 3.

: Include a session on **company's development methodologies and tools** on Day 2. Day 3 should also involve a **mentor-guided project** for better understanding.

Iteration 0, Discussion Round 2

Solver:

Day 1: Company overview, policies, benefits, expectations, team introductions, and culture immersion.

Day 2: LLM platform training, understanding architecture, design principles, and company's development methodologies.

Day 3: Mentor-guided project to apply learned skills.

Goal: Equip engineers for effective contribution, foster teamwork, and ensure ongoing mentorship support.

Reviewers:

: Include hands-on coding sessions on Day 2 for practical understanding of LLM platform and add a feedback session on Day 3 for continuous improvement.

: Add a session on company's vision, mission, and values on Day 1, and include hands-on coding session on Day 2 for practical exposure.

: Add a session on Day 3 for feedback and Q&A to address any concerns or queries the new hires might have.

Iteration 0, Evaluation

Solver:

Day 1: Company overview, vision, mission, values, policies, benefits, team introductions, and culture immersion.

Day 2: LLM platform training, hands-on coding session, understanding architecture, design principles, and development methodologies.

Day 3: Mentor-guided project, feedback session, and Q&A.

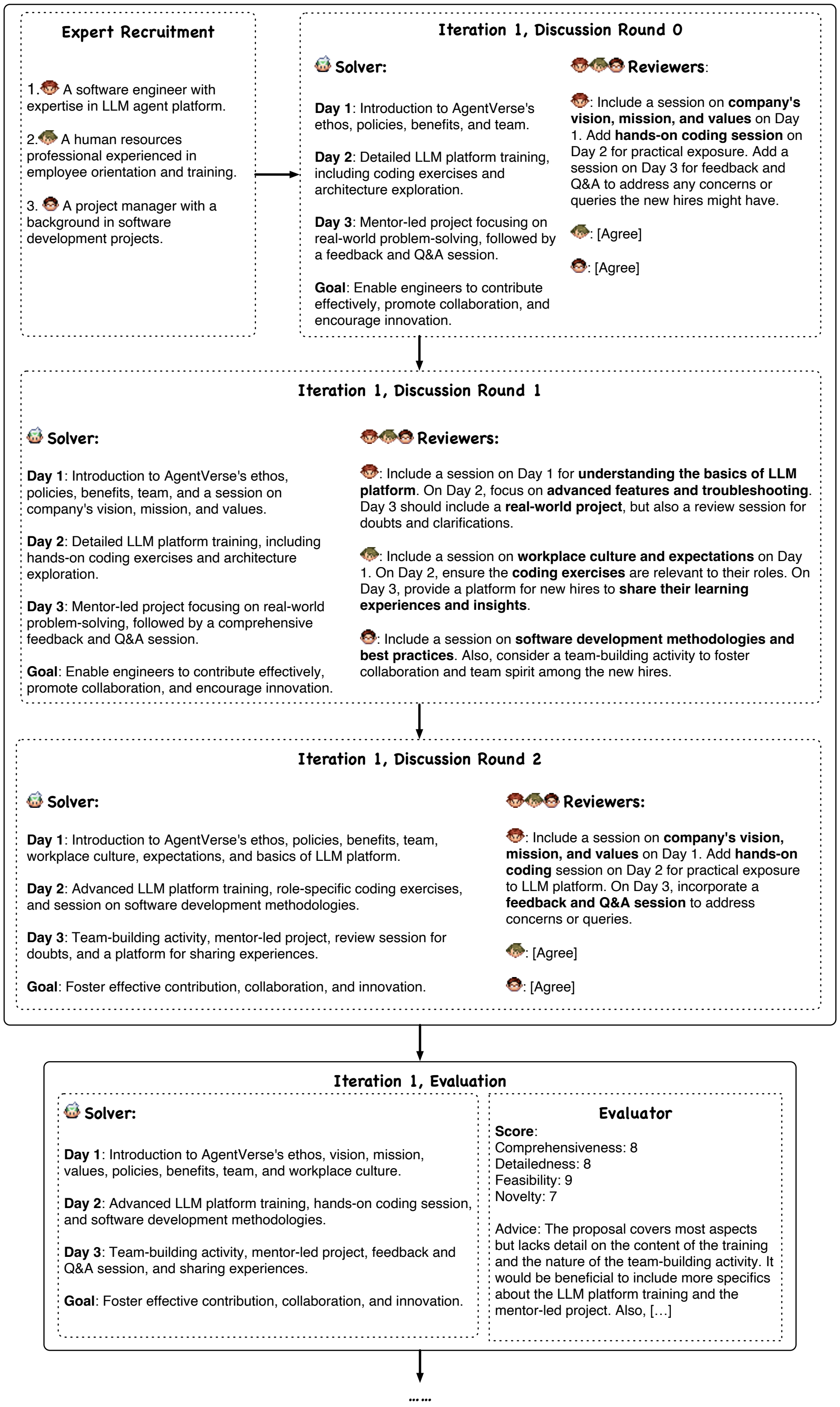
Goal: Equip engineers for effective contribution, foster teamwork, and ensure continuous improvement.

Evaluator

Score:
Comprehensiveness: 8
Detailedness: 7
Feasibility: 9
Novelty: 6

Advice: The proposal covers most aspects but lacks details on the specific content of the training and the nature of the mentor-guided project. Consider adding more innovative elements to the orientation program.

Figure 15: (Page 1) An example process of project consulting using vertical decision-making structure. The agents are providing suggestions on the problem "Generate a proposal about 3-day employee orientation for newly hired engineers at AgentVerse. AgentVerse is a open-source team devoted to developing a LLM multi-agent platform for accomplishing".



Expert Recruitment

1. A software engineer with expertise in LLM agent platform.

2. A human resources professional experienced in employee orientation and training.

3. A project manager with a background in software development projects.

Iteration 1, Discussion Round 0

Solver:

Day 1: Introduction to AgentVerse's ethos, policies, benefits, and team.

Day 2: Detailed LLM platform training, including coding exercises and architecture exploration.

Day 3: Mentor-led project focusing on real-world problem-solving, followed by a feedback and Q&A session.

Goal: Enable engineers to contribute effectively, promote collaboration, and encourage innovation.

Reviewers:

: Include a session on **company's vision, mission, and values** on Day 1. Add **hands-on coding session** on Day 2 for practical exposure. Add a session on Day 3 for feedback and Q&A to address any concerns or queries the new hires might have.

: [Agree]

: [Agree]

Iteration 1, Discussion Round 1

Solver:

Day 1: Introduction to AgentVerse's ethos, policies, benefits, team, and a session on company's vision, mission, and values.

Day 2: Detailed LLM platform training, including hands-on coding exercises and architecture exploration.

Day 3: Mentor-led project focusing on real-world problem-solving, followed by a comprehensive feedback and Q&A session.

Goal: Enable engineers to contribute effectively, promote collaboration, and encourage innovation.

Reviewers:

: Include a session on Day 1 for **understanding the basics of LLM platform**. On Day 2, focus on **advanced features and troubleshooting**. Day 3 should include a **real-world project**, but also a review session for doubts and clarifications.

: Include a session on **workplace culture and expectations** on Day 1. On Day 2, ensure the **coding exercises** are relevant to their roles. On Day 3, provide a platform for new hires to **share their learning experiences and insights**.

: Include a session on **software development methodologies and best practices**. Also, consider a team-building activity to foster collaboration and team spirit among the new hires.

Iteration 1, Discussion Round 2

Solver:

Day 1: Introduction to AgentVerse's ethos, policies, benefits, team, workplace culture, expectations, and basics of LLM platform.

Day 2: Advanced LLM platform training, role-specific coding exercises, and session on software development methodologies.

Day 3: Team-building activity, mentor-led project, review session for doubts, and a platform for sharing experiences.

Goal: Foster effective contribution, collaboration, and innovation.

Reviewers:

: Include a session on **company's vision, mission, and values** on Day 1. Add **hands-on coding** session on Day 2 for practical exposure to LLM platform. On Day 3, incorporate a **feedback and Q&A session** to address concerns or queries.

: [Agree]

: [Agree]

Iteration 1, Evaluation

Solver:

Day 1: Introduction to AgentVerse's ethos, vision, mission, values, policies, benefits, team, and workplace culture.

Day 2: Advanced LLM platform training, hands-on coding session, and software development methodologies.

Day 3: Team-building activity, mentor-led project, feedback and Q&A session, and sharing experiences.

Goal: Foster effective contribution, collaboration, and innovation.

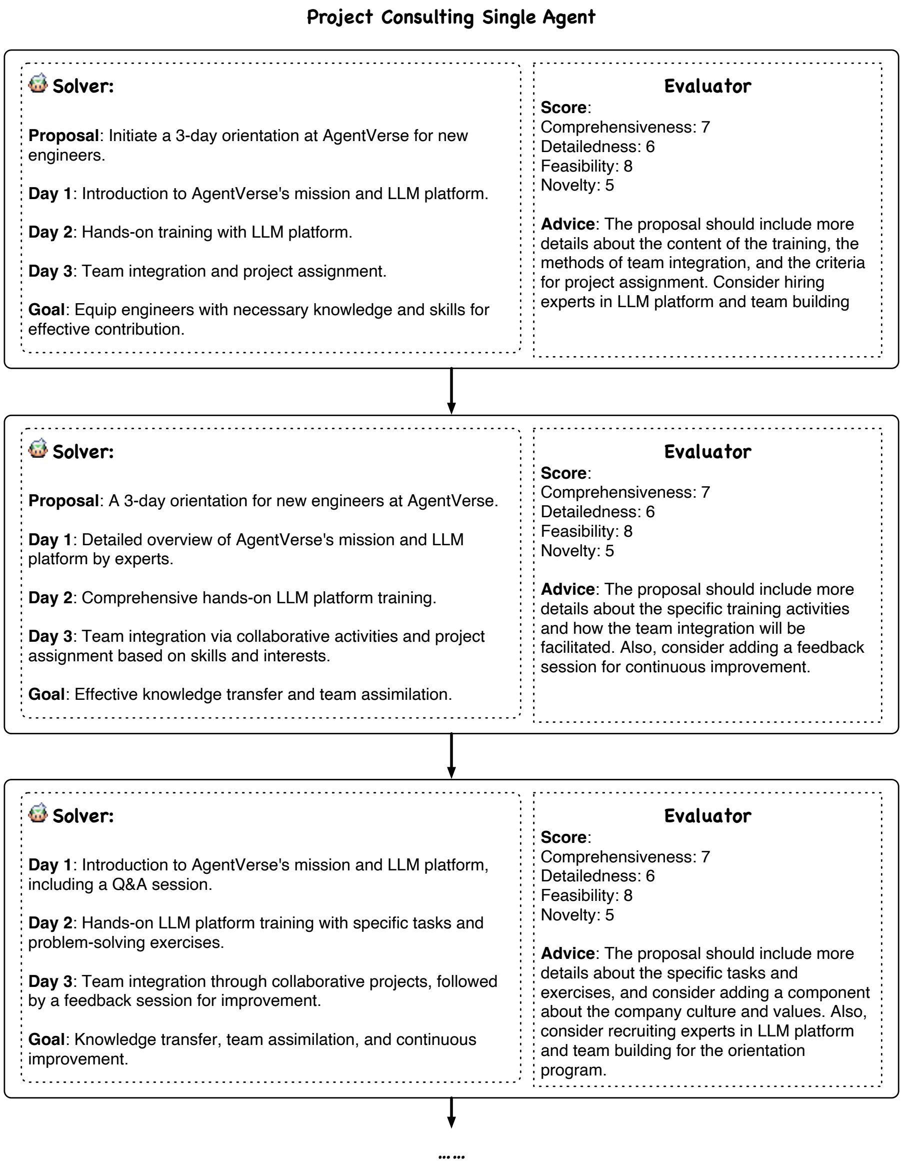
Evaluator

Score:
Comprehensiveness: 8
Detailedness: 8
Feasibility: 9
Novelty: 7

Advice: The proposal covers most aspects but lacks detail on the content of the training and the nature of the team-building activity. It would be beneficial to include more specifics about the LLM platform training and the mentor-led project. Also, […]

……

Figure 15: (Page 2) An example process of project consulting using vertical decision-making structure. The agents are providing suggestions on the problem "Generate a proposal about 3-day employee orientation for newly hired engineers at AgentVerse. AgentVerse is a open-source team devoted to developing a LLM multi-agent platform for accomplishing".



Project Consulting Single Agent

Solver:

Proposal: Initiate a 3-day orientation at AgentVerse for new engineers.

Day 1: Introduction to AgentVerse's mission and LLM platform.

Day 2: Hands-on training with LLM platform.

Day 3: Team integration and project assignment.

Goal: Equip engineers with necessary knowledge and skills for effective contribution.

Evaluator

Score:
Comprehensiveness: 7
Detailedness: 6
Feasibility: 8
Novelty: 5

Advice: The proposal should include more details about the content of the training, the methods of team integration, and the criteria for project assignment. Consider hiring experts in LLM platform and team building

Solver:

Proposal: A 3-day orientation for new engineers at AgentVerse.

Day 1: Detailed overview of AgentVerse's mission and LLM platform by experts.

Day 2: Comprehensive hands-on LLM platform training.

Day 3: Team integration via collaborative activities and project assignment based on skills and interests.

Goal: Effective knowledge transfer and team assimilation.

Evaluator

Score:
Comprehensiveness: 7
Detailedness: 6
Feasibility: 8
Novelty: 5

Advice: The proposal should include more details about the specific training activities and how the team integration will be facilitated. Also, consider adding a feedback session for continuous improvement.

Solver:

Day 1: Introduction to AgentVerse's mission and LLM platform, including a Q&A session.

Day 2: Hands-on LLM platform training with specific tasks and problem-solving exercises.

Day 3: Team integration through collaborative projects, followed by a feedback session for improvement.

Goal: Knowledge transfer, team assimilation, and continuous improvement.

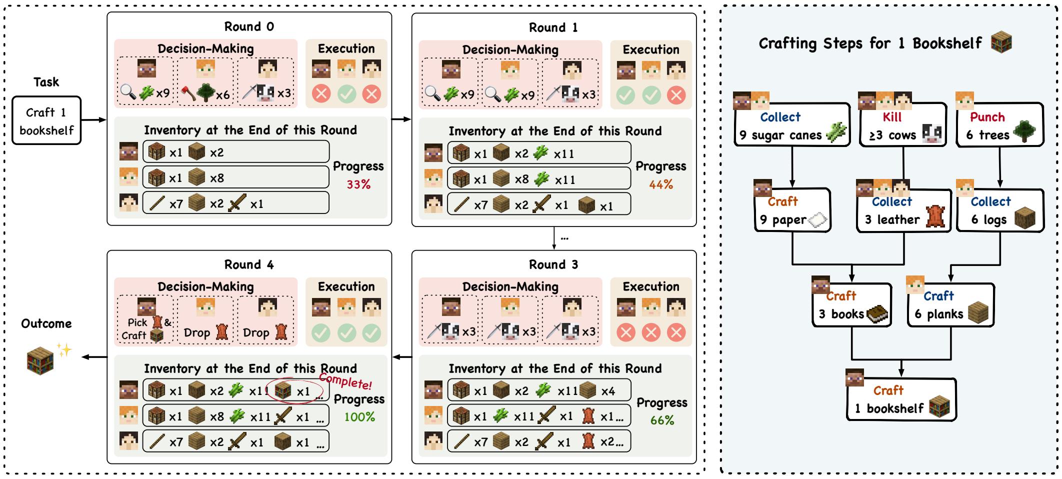
Evaluator

Score:
Comprehensiveness: 7
Detailedness: 6
Feasibility: 8
Novelty: 5

Advice: The proposal should include more details about the specific tasks and exercises, and consider adding a component about the company culture and values. Also, consider recruiting experts in LLM platform and team building for the orientation program.

……

Figure 16: An example process of single-agent project consulting. The agent is required to provide suggestions on the problem "Generate a proposal about 3-day employee orientation for newly hired engineers at AgentVerse. AgentVerse is a open-source team devoted to developing a LLM multi-agent platform for accomplishing".



Round 0 Decision-Making

[Alice]: Hello Bob, Charlie. We have to craft a bookshelf. To do that, we will need 6 wooden planks and 3 books. To make 3 books, we'll need 3 leathers and 9 papers. To make 9 papers, we'll need 9 sugar canes.. I suggest we split tasks like this: one of us will gather 6 wooden planks, one will gather 3 leathers, and one will gather 9 sugar canes. What do you guys think?

[Bob]: Alice, your plan sounds good. I can gather the 6 wooden planks. Charlie, are you okay with gathering the 3 leathers?

[Charlie]: Sure, Bob. I can gather the 3 leathers. So, Alice, that leaves you with the task of gathering 9 sugar canes. Are you fine with this assignment?

[Alice]: Yes, Charlie. I'm fine with gathering 9 sugar canes. So, our plan for this round is: Bob will gather 6 wooden planks, Charlie will gather 3 leathers, and I will gather 9 sugar canes. Let's get this done.

Round 1 Decision-Making

[Bob]: Alice, Charlie, I have gathered the 6 wooden planks we need for the bookshelf. It seems both of you didn't manage to gather your materials. Let's try again. Alice, can you continue to find the sugar canes? And Charlie, can you keep trying to gather the leathers? We can do this, team!

[Charlie]: Thanks for the encouragement, Bob. I will continue to try and gather the 3 leathers from the cows. Alice, are you okay with continuing to find the 9 sugar canes? Let's keep working hard, we can complete this mission.

[Alice]: Yes, I will continue to look for the sugar canes. So, for this round, Bob, you can help me with gathering the sugar canes since you've already gathered the wooden planks. Charlie, continue with gathering the leathers. Do we all agree?

[Bob]: Alice, I agree with your plan. I'll join you in gathering the sugar canes. Charlie, are you fine with continuing to gather the leathers?

[Charlie]: Yes, Bob, I agree with that. I'll continue trying to gather the 3 leathers. Alice, you and Bob can focus on gathering the sugar canes. Let's keep pushing, team!

Round 2 Decision-Making

[Alice]: Great job, Bob! We have now gathered the sugar canes needed. Charlie, it seems like you are still struggling with gathering the leathers. Maybe Bob and I could help you with that. What do you think, Bob? Should we all focus on gathering the leathers?

[Bob]: Alice, I agree with your suggestion. Since we have already gathered the required sugar canes and wooden planks, our next focus should be on gathering the leathers. Charlie, we will help you with this task. Let's all gather the leathers so we can progress with our mission. Are you okay with this plan, Charlie?

[Charlie]: Yes, Bob, I think that's a great idea. Gathering the leathers has proven to be more challenging than expected. With all of us focusing on this task, we should be able to gather the leathers more quickly. So, for this round, let's all focus on gathering the 3 leathers. Let's do this, team!

Round 3 Decision-Making

[Alice]: Bob, good job on getting one leather. We still need two more. Charlie, I see you've been very busy crafting, but we need to focus on gathering the leathers. For this round, let's all continue to focus on getting the leathers. Are we in agreement?

[Bob]: Alice, I agree with your plan. We should all continue to focus on gathering the 2 remaining leathers. Charlie, are you okay with this assignment?

[Charlie]: Yes, Alice and Bob, I agree with the plan. I realize I got sidetracked with other tasks, and I will refocus on our main objective of gathering the remaining 2 leathers. Let's continue with this mission, team!

Round 4 Decision-Making

[Bob]: Well done team! We now have all the materials we need to craft the bookshelf. Alice, you have 3 leathers and 11 sugar canes, I have 1 leather and 11 sugar canes, and Charlie, you have 2 leathers. Since we need 3 leathers and 9 sugar canes to make 3 books, Alice, you can craft the books. Charlie and I can give our leathers to you. After that, you can use the 6 wooden planks I have to craft the bookshelf. Does this sound good, Alice and Charlie?

[Alice]: Bob, your plan sounds good. Alice, since you have most of the necessary materials already, it makes sense for you to craft the books and then the bookshelf. I will give my 2 leathers to you, Alice. Are you okay with this, Alice?

[Bob]: Yes, Charlie, I am fine with crafting the books and the bookshelf. I will need both of your leathers to do that. So for this round, Charlie and Bob, please give your leathers to me. Then, I will craft the books and the bookshelf.

Figure 17: An example process of three agents crafting a bookshelf in Minecraft.