

Debate Only When Necessary: Adaptive Multiagent Collaboration for Efficient LLM Reasoning

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Abstract

Multiagent collaboration has emerged as a promising framework for enhancing the reasoning capabilities of large language models (LLMs). While this approach improves reasoning capability, it incurs substantial computational overhead due to iterative agent interactions. Furthermore, engaging in debates for queries that do not necessitate collaboration amplifies the risk of error generation. To address these challenges, we propose Debate Only When Necessary (DOWN), an adaptive multiagent debate framework that selectively activates the debate process based on the confidence score of the agent’s initial response. For queries where debate is triggered, agents refine their outputs using responses from participating agents and their confidence scores. Experimental results demonstrate that this mechanism significantly improves efficiency while maintaining—or even surpassing—the performance of existing multiagent debate systems. We also find that confidence-guided debate mitigates error propagation and enhances the selective incorporation of reliable responses. These results establish DOWN as an optimization strategy for efficient and effective multiagent reasoning, facilitating the practical deployment of LLM-based collaboration¹.

1 Introduction

Building on the remarkable advancements in large language models (LLMs), recent research has increasingly focused on extending their capabilities to address complex real-world problems (Yao et al., 2023; Fan et al., 2024; Chen et al., 2024b). Among various research directions, multiagent collaboration has emerged as a promising approach, inspired by human decision-making processes in complex problem-solving (Minsky, 1988; Li et al., 2023; Chen et al., 2024a; Wang et al., 2025; Wu et al.,

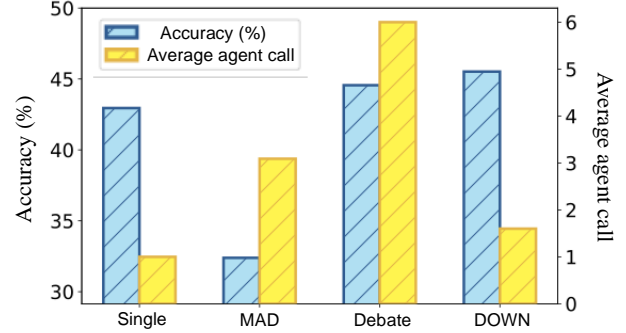


Figure 1: Comparison of accuracy and average agent calls across various multiagent debate methods

2023; Du et al., 2024). By engaging in structured debate, LLM agents systematically exchange perspectives and iteratively cross-examine each other’s reasoning to refine their responses. This collaborative process fosters divergent thinking and enhances the reasoning capabilities of LLMs (Liang et al., 2024; Chen et al., 2024b; Chan et al., 2024).

Despite these advantages, multiagent collaboration systems exhibit several key limitations. From an efficiency perspective, iterative interactions among agents inherently require multiple agent calls, leading to increased latency and higher inference costs (Snell et al., 2024; Kapoor et al., 2024). Meanwhile, when agents engage in redundant or unnecessary debate, there is a higher likelihood of generating errors that may subsequently be propagated by other agents in the system (Wang et al., 2024). Figure 1 illustrates both of these issues by plotting the accuracy and average agent calls of different multiagent debate methods. In the Debate system, additional debate rounds improve performance while incurring a sixfold increase in computational overhead. In the MAD framework, despite using more agent calls than the single-agent baseline, its accuracy paradoxically declines. Regarding the practical application of multiagent collaboration systems, these challenges emphasize the need

¹The code is attached as a zip file in the “software” part. The code will be released after the review process.

for an optimized collaboration approach (Kapoor et al., 2024; Tran et al., 2025).

To address these limitations, we propose Debate Only When Necessary (DOWN), an adaptive multiagent collaboration framework to identify queries that require debate and selectively facilitate in-depth debate for those queries. Specifically, the initial agent response is generated as the first step. Alongside generating a response, we derive the model confidence score, which serves as a criterion for determining whether to initiate a debate. If the confidence score exceeds a threshold, the debate is skipped, and we regard the initial response as a final answer. If further refinement is required, agents engage in debate to enhance response accuracy. When the collaboration begins, a confidence-guided debate is conducted, during which agents refine their responses by considering both the responses of other participating agents and their confidence scores. This approach encourages the refinement of responses by utilizing the most persuasive aspects of agent responses.

We rigorously evaluate the robustness of our approach on two reasoning benchmarks, MUSR (Sprague et al., 2024) and StrategyQA (Geva et al., 2021). Our experiments utilize models of varying scales, including approximately 8B and 70B parameter models, as well as GPT-4o-mini. Our findings demonstrate that conditional debate significantly reduces computational overhead while maintaining—or even surpassing—the performance of baseline debate models. Notably, we reveal that this conditional debate serves as a safeguard against cascading errors, effectively enhancing the advantages of agent collaboration. Our contribution is threefold:

- We propose Debate Only When Necessary (DOWN), a multiagent collaboration framework that significantly enhances efficiency while preserving the effectiveness of multiagent debate.
- Extensive experiments across diverse model sizes and configurations establish the robustness of the mechanism. We further find that adaptively engaging debate contributes to mitigating error propagation.
- We establish that the confidence-guided debate process enables the selective integration of reliable responses, emphasizing the effectiveness of multiagent collaboration.

2 Related Work

LLM-based Multiagent Collaboration With advancements in LLMs, a multiagent collaboration has attracted substantial attention. Drawing inspiration from human collaborative problem-solving behavior, multiagent collaboration systems leverage collective intelligence to improve decision-making. Studies have demonstrated that LLM-powered multiagent systems promote divergent thinking (Xiong et al., 2023; Liu et al., 2024; Liang et al., 2024) and improve reasoning capabilities (Li et al., 2023; Yin et al., 2023; Zhuge et al., 2023). With these advantages, multiagent collaboration is leveraged for diverse NLP applications: mitigating hallucinations in language models through counterfactual debates (Fang et al., 2025), aggregating knowledge across multiple specialized LLMs (Wang et al., 2025), generating novel scientific ideas and insights (Su et al., 2024), evaluating model generate responses by constructing multiagent referee team (Chan et al., 2024), and refining datasets for instruction fine-tuning (Li et al., 2024a). These advancements highlight the growing impact and effectiveness of multiagent collaboration. As multiagent collaboration continues to be applied in diverse contexts, this study enhances its practical deployment by introducing a more effective and efficient method.

Debate Structures in Multiagent Collaboration Systems Recent studies have developed debate structures to optimize the benefits of multiagent collaboration. For instance, Du et al. (2024) introduces a framework in which agents iteratively refine their responses based on peer-generated outputs. Liang et al. (2024) propose a structured debate format that assigns distinct roles such as supporting, opposing, and mediating agents to encourage divergent thinking. Subsequent research seeks to extend these approaches. For example, Wang et al. (2024) develop a discussion system in which agents are organized into multiple groups to engage in structured discussions. Chen et al. (2024a) present a discussion prompt for each agent during the debate, consisting of grouped agent responses, confidence scores, and human-generated answer rectifications. However, iterative debate frameworks face a fundamental trade-off between efficiency and accuracy (Kapoor et al., 2024; Snell et al., 2024). Researchers have explored approaches such as restricting discussions to local neighbors (Li et al., 2024b) or selectively recruiting agents for participation (Chen et al., 2024b).

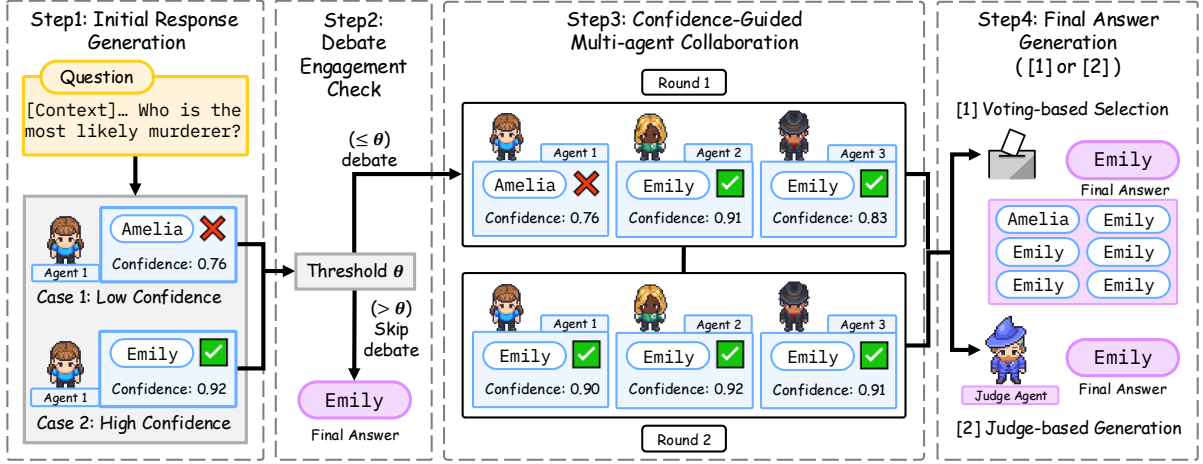


Figure 2: Overall structure of the Debate Only When Necessary (DOWN) Framework. Our framework follows a four-step process. Step 1-Initial response generation: The initial agent generates a response, during which the model confidence score is extracted. Step 2-Debate engagement check: If the confidence score exceeds a predefined threshold, the debate is skipped and the response is finalized to enhance efficiency. Otherwise, a debate begins to refine reasoning. Step 3-Confidence-guided multiagent collaboration: Agents generate updated responses within the debate process, improving reasoning quality. Step 4-Final answer generation: The final response is determined via majority voting or a judge agent’s final answer generation.

to mitigate this issue. However, the necessity of multiple agent calls still incurs non-trivial costs. Additionally, iterative debates may propagate errors or introduce a trade-off between diversity and quality (Wang et al., 2024; Kapoor et al., 2024; Li et al., 2025). Our approach focuses on these limitations by proposing a resource-efficient and effective debate framework.

3 Debate Only When Necessary

The collaboration framework consists of four steps: (1) initial response generation, (2) debate engagement check, (3) confidence-guided multiagent collaboration, and (4) final response generation. The confidence score derived from the model during initial response generation determines its subsequent progression. If the score exceeds a predefined threshold, further debate process is skipped. Otherwise, we proceed with the debate, allowing agents to engage in confidence-guided debate with other agents. We illustrate the overall multiagent collaboration framework in Figure 2.

Step 1: Initial Response Generation The model’s confidence score obtained during initial response generation determines the progression of the collaboration process. Based on its importance, we adopt two strategies for multiagent configurations: (1) A homogeneous-agent configuration

where all collaborating agents use the same model (e.g., Llama) and (2) a mixed-agent configuration where the initial agent is randomly selected for each query (e.g., Llama, Qwen, GPT-4o-mini).

For a given query q , an initial agent \mathcal{A}_1 from the set of agents $\{\mathcal{A}\}_{i=1}^N$ generates an initial response r_1 with the reason of the answer. During this process, we extract a confidence score c_1 . To compute the confidence score, we first obtain the token logit $L(t_i)$, $t_i \in r_1$ from the hidden representation of the generated response. Applying the softmax function to these logits yields the token-wise probability distribution, $P(t_i) = \frac{e^{L(t_i)}}{\sum_j e^{L(t_j)}}$. To obtain a robust confidence measure, we normalize these token probabilities across the response length using length normalization, $c_1 = \frac{1}{|r_1|} \sum_{i=1}^{|r_1|} P(t_i)$. For models that cannot access internal logits, we utilize verbalized confidence as an alternative method.

Step 2: Debate Engagement Check Along with the initial response, we extract a confidence score c_1 reflecting the model’s certainty in its answer. The confidence score is compared against a threshold score θ :

- (1) High confidence ($> \theta$): The response is accepted as the final response without further collaboration, optimizing efficiency by avoiding unnecessary computations.
- (2) Low confidence ($\leq \theta$): The initial response is

deemed unreliable, activating the collaboration process to improve response quality.

In this context, the threshold is a hyperparameter, where a higher threshold places more emphasis on accuracy, while a lower threshold prioritizes efficiency.

Step 3: Confidence-Guided Multiagent Collaboration The collaboration process involves response generation and refinement. In our experiments, we set up an environment with two rounds, each consisting of three agents. To conduct multiagent collaboration, in round 1, we obtain responses r_2 and r_3 from additional agents \mathcal{A}_2 and \mathcal{A}_3 , along with their respective confidence scores c_2 and c_3 . These confidence scores are explicitly concatenated with each response to convey the agent’s certainty level in subsequent rounds.

After all agents generate their responses in the first round, the second round begins. Each agent is given responses from the other two agents, excluding its own. Using this additional context, each agent refines its reasoning and generates an updated response. This allows each agent to leverage confident and compelling arguments in the updated response.

Step 4: Final Answer Generation The responses generated in Step 3 serve as ingredients for deriving the final answer. We explore two distinct strategies for final answer output: voting-based selection and judge-based generation. The voting-based approach determines the final answer by selecting the most frequent response among all agent-generated outputs. We design this majority voting to enhance robustness by leveraging consensus across multiple perspectives, effectively mitigating individual agent biases. The judge-based approach introduces an additional judging agent, which generates the final response based on all agent output. We induce a judging mechanism to update the final response, prioritizing well-supported and coherent arguments.

4 Experiments

4.1 Experimental Setup

Models. We evaluate two agent configurations: homogeneous and mixed. The homogeneous setup leverages a single model across all agents, experimenting with Llama-3.1 8B (meta-llama/Llama-3.1-8B-Instruct), Ministral 8B (mistralai/Ministral-8B-Instruct-

2410), Qwen-2.5 72B (Qwen/Qwen2.5-72B-Instruct), Llama-3.3 70B (meta-llama/Llama-3.3-70B-Instruct), and GPT-4o-mini (gpt-4o-mini). The mixed configuration utilizes Qwen-2.5 72B, Llama-3.3 70B, and GPT-4o-mini, with the order of model selection randomized for each query. Each debate round consists of three agents, and we conduct a two-round debate where responses are generated in the first round and refined in the second.

Tasks. For evaluation, we utilize benchmarks specifically designed to assess reasoning capabilities. MUSR (Sprague et al., 2024) evaluates multi-step soft reasoning over free-text narratives, offering a more complex yet realistic reasoning challenge compared to synthetic benchmarks. Assessments are performed on 756 samples drawn from the murder mysteries, object placements, and team allocation subsets. StrategyQA (Geva et al., 2021) requires implicit reasoning, where inference steps must be strategically derived rather than explicitly provided. Evaluations are conducted on the development set comprising 229 samples.

Baselines. We compare our approach against multiple established reasoning frameworks, along with a single LLM CoT (Kojima et al., 2022) baseline.

- **Self-refine** (Madaan et al., 2023): Generating an initial response and iteratively refining its output through self-feedback. We design an environment composed of two rounds, with each round comprising three agents.
- **Self-Consistency** (Wang et al., 2023): Sampling diverse reasoning paths and deriving the final answer by selecting the most consistent one through majority voting. We sample nine responses for each query.
- **MAD** (Liang et al., 2024): Conducting a debate between two agents with opposing perspectives while a moderator selects the most plausible solution or continues the debate if needed.
- **Debate** (Du et al., 2024): Engaging agents in a structured debate, iteratively refining their responses by incorporating insights from previous exchanges. We design an environment composed of two rounds, with each round comprising three agents.

4.2 Implementation Details

The thresholds are set to 0.8 for MUSR and 0.9 for SQA when utilizing 70B models. For 8B models,

Method	Llama-3.1 8B		Ministral 8B		GPT-4o-mini		Llama-3.3 70B		Qwen-2.5 72B	
	Acc.	AC	Acc.	AC	Acc.	AC	Acc.	AC	Acc.	AC
Single-CoT	42.95	1.00	<u>51.06</u>	1.00	55.75	1.00	56.33	1.00	<u>58.93</u>	1.00
Self-refine	39.46	6.00	36.90	6.00	54.29	6.00	53.67	6.00	59.61	6.00
Self-Consistency	44.70	9.00	48.24	9.00	55.88	9.00	<u>58.18</u>	9.00	58.29	9.00
MAD	32.39	3.09	28.67	3.01	43.23	3.02	51.22	3.00	49.13	3.04
Debate	44.56	6.00	48.54	6.00	<u>57.32</u>	6.00	<u>59.12</u>	6.00	58.69	6.00
DOWN-Vote	<u>45.51</u>	1.50	53.71	1.48	57.09	1.80	57.80	1.02	57.76	1.28
DOWN-Judge	45.52	1.60	53.71	1.57	57.35	1.96	57.80	1.03	57.76	1.33

Table 1: Comparison of accuracy (Acc.) and average agent calls (AC) across single-agent methods, multi-agent debate systems, and our proposed approach on the MUSR dataset. Single CoT, Self-refine, and Self-consistency are single model-based approaches, while MAD, Debate, and DOWN are multi-agent debate-based systems.

Method	Llama-3.1 8B		Ministral 8B		GPT-4o-mini		Llama-3.3 70B		Qwen-2.5 72B	
	Acc.	AC	Acc.	AC	Acc.	AC	Acc.	AC	Acc.	AC
Single-CoT	<u>70.74</u>	1.00	67.69	1.00	78.17	1.00	80.35	1.00	<u>78.60</u>	1.00
Self-refine	69.54	6.00	67.69	6.00	76.42	6.00	77.73	6.00	78.17	6.00
Self-Consistency	68.56	9.00	<u>68.12</u>	9.00	<u>79.48</u>	9.00	83.84	9.00	77.29	9.00
MAD	44.54	4.66	57.64	3.73	70.31	3.38	79.04	3.07	73.80	3.24
Debate	70.08	6.00	70.74	6.00	79.04	6.00	80.35	6.00	79.91	6.00
DOWN-Vote	71.18	2.53	<u>68.12</u>	3.16	80.79	4.19	80.35	2.20	77.73	2.64
DOWN-Judge	69.87	2.83	<u>68.12</u>	3.59	80.79	4.80	<u>82.53</u>	2.44	77.73	2.97

Table 2: Comparison of accuracy (Acc.) and average agent calls (AC) across single-agent methods, multi-agent debate systems, and our proposed approach on the StrategyQA dataset

they are adjusted to 0.7 and 0.8, respectively. A detailed analysis of the impact of different threshold values is provided in Further Section 5.5. We set the temperature to 0.0 to ensure deterministic response generation and limit the maximum sequence length to 512 tokens. The experimental setup maintains consistent configurations across all models.

For the evaluation metrics, we use accuracy as the metric, while efficiency is assessed based on the average number of agent calls or debate skip rate. The experiments are conducted using four 48GB A6000 GPUs. All prompts used in the experiments are provided in Table 6.

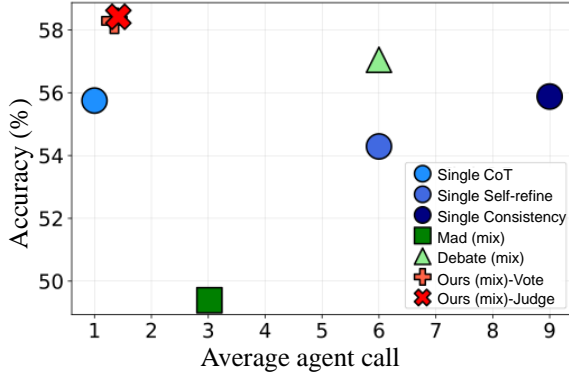
5 Results and Analysis

5.1 Main Results

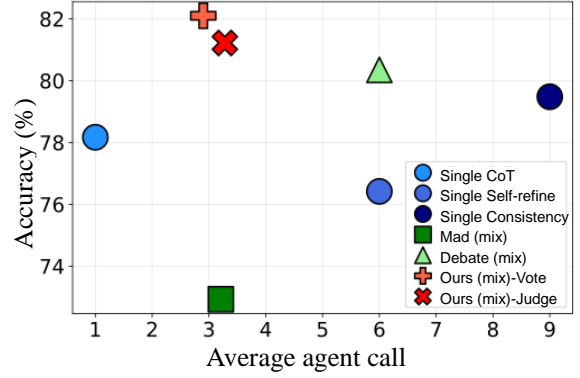
Homogeneous-Model Configuration Table 1 reports model performance on the MUSR dataset. Unlike prior methods that require from three to nine agent calls per query, our framework achieves comparable or even superior performance with only 1.5 calls on average. Moreover, we find that our framework is robust across different model families and parameter scales, remarkably lowering costs.

By adaptively engaging debate, our approach minimizes computational overhead without sacrificing response quality. Interestingly, MAD exhibits lower accuracy compared to other debate-based methods. Consistent with Wang et al. (2024), we attribute this to its inherent tendency toward contradictory reasoning. While constructive disagreement fosters novel insights, it may also intensify erroneous reasoning, ultimately deteriorating the quality of final responses.

Table 2 further supports the effectiveness of our approach. Compared to Debate and Self-Refine, our approach reduces the average number of agent calls by more than half while achieving similar or even superior performance. It also outperforms Self-Consistency, requiring over three times fewer agent calls while maintaining strong accuracy. While our agent call frequency is similar to that of MAD, our method achieves over 10% point higher accuracy, highlighting strong effectiveness. These findings establish our conditional debate as a versatile and scalable solution for optimizing multi-agent reasoning.



(1) MUSR dataset



(2) StrategyQA dataset

Figure 3: Comparison of multiagent debate system performance in a mixed-model configuration. The configuration includes Llama3.3-70B, Qwen-2.5 72B, and GPT-4o-mini, with the model order randomized for each query. For single model-based approaches, we present the results of GPT-4o-mini.

Mixed-Model Configuration In the mixed-model configuration, external feedback comes from models trained on different datasets and parameter scales, fostering more diverse reasoning patterns. As shown in Figure 3, DOWN consistently outperforms self-reflection methods, achieving higher accuracy with significantly fewer agent calls across both MUSR and StrategyQA. Notably, it surpasses Debate with far lower cost, demonstrating superior efficiency. These results demonstrate that our conditional debate remains effective beyond homogeneous setups, adapting seamlessly to mixed-model collaboration. This highlights the robustness and scalability of our debate system in diverse reasoning environments.

Comparison of Final Answer Generation Strategies We propose two methods for deriving the final answer from multiagent debate responses: voting-based selection and judge-based evaluation. Experimental results indicate that both approaches yield similar response patterns, with only marginal differences depending on the specific setting. However, the judge-based method requires an additional agent call, making it slightly less efficient. Given this trade-off, the voting-based approach is preferable when prioritizing computational efficiency, as it achieves comparable accuracy with fewer computational resources.

5.2 Evaluating Response Shifts in Accuracy

We analyze how models modify their responses before and after the debate, with experimental results on the StrategyQA dataset presented in Table 3.

LLM Agent	Shift	MAD	Debate	Ours
GPT-4o-mini	$\times \rightarrow \times$	13.97	20.52	19.65
	$\checkmark \rightarrow \times$	15.72	0.44	0.44
	$\checkmark \rightarrow \checkmark$	63.76	78.6	79.04
	$\times \rightarrow \checkmark$	6.55	0.44	0.87
Llama-3.3 70B	$\times \rightarrow \times$	11.35	18.34	17.03
	$\checkmark \rightarrow \times$	9.61	1.31	0.44
	$\checkmark \rightarrow \checkmark$	69	79.48	79.48
	$\times \rightarrow \checkmark$	10.04	0.87	3.06
Qwen-2.5 72B	$\times \rightarrow \times$	16.16	18.34	21.4
	$\checkmark \rightarrow \times$	10.04	1.75	0.87
	$\checkmark \rightarrow \checkmark$	68.12	78.17	76.42
	$\times \rightarrow \checkmark$	5.68	1.75	1.31
Mix	$\times \rightarrow \times$	12.23	17.9	14.85
	$\checkmark \rightarrow \times$	14.85	1.75	3.93
	$\checkmark \rightarrow \checkmark$	66.81	76.42	76.86
	$\times \rightarrow \checkmark$	6.11	3.93	4.37

Table 3: Analysis of response changes before and after debate across multiagent debate methods. We denote a correct response by \checkmark and an incorrect response by \times .

To deepen our investigation, we set the threshold to 0.9, increasing the number of debate cases considered. Despite this adjustment, the debate skip rate remains at 60.22%, demonstrating substantial efficiency.

The findings reveal that DOWN consistently improves response correctness more effectively than other approaches. Specifically, our method exhibits a higher probability of converting an incorrect initial response into a correct one compared to the

Model	Method	Original Debate	Conditional Debate	Skip Rate
Llama-3.3 70B	MAD	79.04	79.91	59.83%
	Debate	80.35	83.41	68.56%
Qwen-2.5 72B	MAD	73.8	76.86	51.53%
	Debate	79.91	79.48	45.85%

Table 4: Results of applying conditional debate to existing debate systems on the StrategyQA dataset

LLM Agent	w Confidence	w/o Confidence	Δ
Llama-3.1 8B	67.25	65.07	-2.18
Minstral 7B	68.56	68.12	-0.44
GPT-4o-mini	80.79	80.35	-0.44
Llama-3.3 70B	82.53	79.04	-3.49
Qwen-2.5 72B	77.73	77.13	-0.60

Table 5: Ablation study on confidence score using the StrategyQA dataset

opposite shift. Notably, for Llama-3.3 70B, incorrect responses are revised to correct ones at a rate of 3.06, whereas correct responses change to incorrect ones at only 0.44, demonstrating a positive impact. Furthermore, when the initial response was correct, our approach preserved correctness 78% of the time, indicating a high degree of stability.

In contrast, MAD demonstrates an overall higher response shift rate, suggesting that the moderator favors opposing perspectives rather than making appropriate judgments. The Debate method displays more variable patterns but maintains correctness well when the initial response is accurate.

5.3 Effects of Conditional Debate in Multiagent Debates

To evaluate the effectiveness of the conditional debate, we apply it to MAD and Debate frameworks using the StrategyQA dataset. The experimental setup is based on a configuration of approximately 70 billion parameters, with a threshold set at 0.9. Our findings in Table 4 reveal that applying conditional debate to existing debate methods mostly improves performance. In particular, the Debate framework achieves about 3% point accuracy increase on LLaMA-3.3 70B, while MAD exhibits a similar improvement on Qwen-2.5 72B. Despite these gains, debate skip rates remain high at 59.83% and 51.53%, respectively, demonstrating remarkable efficiency improvements. These results demonstrate that conditional debate not only enhances efficiency but also positively impacts overall model performance. In the case of MAD, performance

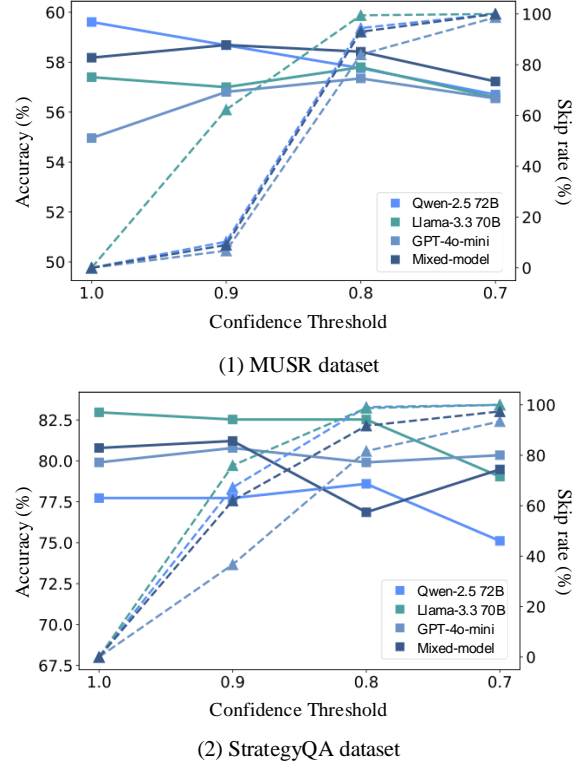


Figure 4: Analysis of threshold variation. We represent accuracy with a solid line and debate skip rate with a dashed line.

improves in both settings. These results imply that skipping debate mitigates the spread of erroneous responses, effectively safeguarding against debate-induced performance degradation. Overall, these findings establish conditional debate as an effective mechanism. By selectively engaging discussions at appropriate points, our method prevents unnecessary computation and reduces the risk of error propagation, ultimately leading to more effective reasoning.

5.4 Ablation Study on Confidence Score

To assess the impact of the confidence score in multiagent debate, we conduct an ablation study by removing it in the collaboration process. The experimental results, presented in Table 5, reveal a clear decline in performance across all models when the confidence score is eliminated. Notably, for the Llama-3.3 70B model, accuracy drops from 82.53% to 79.04%, highlighting the importance of confidence-guided reasoning. The confidence score is introduced to allow agents to selectively reference reliable and persuasive aspects of other agents' responses. The observed performance degradation supports this objective, demonstrating that provid-

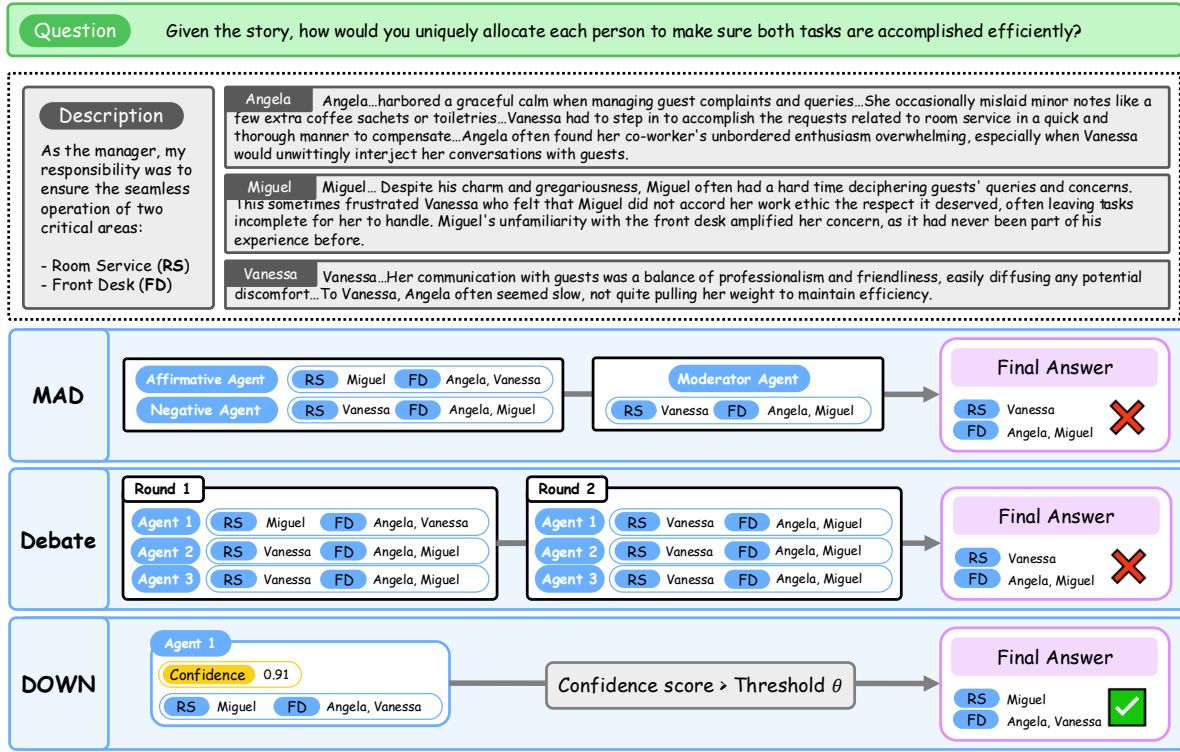


Figure 5: Qualitative analysis of the MUSR dataset

ing confidence scores enhances accuracy by enabling selective response reflection.

5.5 Analysis on Threshold Variation

To investigate the optimal configuration of threshold θ , we conduct a case study by varying the value across different settings. As shown in Figure 4, the skip rate increases as θ decreases. However, performance does not degrade proportionally. This finding indicates that a higher θ to involve more queries in the debate does not necessarily improve performance. We will leave the development of the fine-grained thresholding mechanism to future work to maximize both efficiency and performance.

5.6 Qualitative Analysis

Figure 5 provides a qualitative analysis of responses generated using various debate systems on the MUSR dataset. The results show that while debate mechanisms aim to enhance reasoning, they can introduce unnecessary modifications that degrade performance. In the Debate and MAD methods, the initial response is correct, but iterative revisions lead to an incorrect final answer. This implies the potential risk for error propagation when redundant debate occurs.

In contrast, with an initial confidence score of 0.91, DOWN skips the debate and directly adopts

the initial response as the final answer. This suggests that selectively engaging in debate under high-confidence conditions can prevent unnecessary modifications while maintaining efficiency. These results validate that DOWN enhances both computational efficiency and response accuracy. To further substantiate these findings, we present additional qualitative analysis in Appendix B.

6 Conclusion

This work introduced the DOWN framework to address the computational inefficiencies and error propagation challenges in multiagent collaboration. By conditionally activating debate based on the model confidence score, our approach significantly reduced computational overhead and latency while preserving or even improving performance. Experimental results demonstrate that conditional debate enhances efficiency and mitigates cascading errors, leading to more robust and reliable reasoning. Furthermore, the confidence-guided multiagent debate encourages that reliable responses influence final decisions, strengthening the effectiveness. These findings establish DOWN as an effective optimization strategy, offering a high-performance and efficient solution for multiagent collaboration systems.

Limitations

While our proposed DOWN framework demonstrates strong efficiency and robustness, several limitations remain. First, the threshold selection in our approach is determined empirically. Selecting an optimal threshold is an important aspect of DOWN framework. This study provides an initial exploration of its effectiveness, but further research such as developing thresholding strategy based on task complexity, model capacity will be an important avenue for future research. Second, our study primarily focuses on English debates, limiting its applicability to multilingual multiagent collaboration. Extending our method to multilingual LLMs would provide deeper insights into its robustness across diverse linguistic contexts. Lastly, due to computational constraints, we employ the GPT-4o-mini instead of the GPT-4o model. Applying GPT-4o model to our system could further deepen understanding of our DOWN framework.

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Qingyun Wu, Gagan Bansal, Jieyu Zhang, Yiran Wu, Shaokun Zhang, Erkang Zhu, Beibin Li, Li Jiang,		

Purpose	Prompt
Initial Answer Generation	[debate topic] Please output your answer in json format, with the format as follows: {"base_reason": "", "base_answer": ""}. Please strictly output in JSON format, do not output irrelevant content.
Initial Answer Generation (w Confidence)	[debate topic] Please output your answer in json format, with the format as follows: {"base_reason": "", "base_answer": "", "confidence_score": range of 0-1}. Please strictly output in JSON format, do not output irrelevant content.
Answer Update	Using the solutions from other agents as additional information, can you provide your answer to the problem?

Table 6: Prompt configuration leveraged in our experiments

propagation. In contrast, the Debate methodology consistently generates correct responses across all cases. Although this approach required six agent calls, it enhances response reliability, demonstrating the robustness of the debate mechanism. The DOWN methodology, on the other hand, produces an initial response with a confidence score of 0.95, leading the system to skip the debate process. This result highlights the efficiency gains achieved through conditional debate.

Table 8 shows the results on the MUSR dataset. Experimental results indicate that both the MAD and Debate methodologies fail to conduct correct reasoning. The initial response in DOWN shows a confidence score of 0.89, while subsequent responses report 0.84 and 0.92, respectively. Notably, in the second round, the initial agent revised its response based on higher-confidence outputs from other agents, ultimately arriving at the correct answer. Model confidence scores also generally increase in the second round. This finding underscores the importance of confidence scores as a guiding metric, allowing the system to integrate reliable responses.

Table 9 follows a trend similar to Table 7. The DOWN system strategically skips the debate process, enhancing efficiency while maintaining answer accuracy.

Method	Agent	Category	Content
Query	Could a hundred thousand lolcats fit on a first generation iPhone?		
Answer	Yes		
MAD	Affirmative Debater	Reason	The storage capacity of a first generation iPhone is 4GB, 8GB, or 16GB, and the average size of an image file is approximately 100KB. ... However, ... it's theoretically possible for a hundred thousand lolcats to fit on a first generation iPhone with sufficient storage.
		Answer	Yes
	Negative Debater	Reason	No. The first generation iPhone had a maximum storage capacity of 16GB for the 16GB model, but also consider other factors such as the operating system, apps, and other data that would occupy some of that space. ... Considering these constraints, it's unlikely that a hundred thousand lolcats could fit on a first generation iPhone.
		Answer	No
	Moderator	Reason	While the affirmative side presents a theoretical calculation that a hundred thousand lolcats could fit within the storage capacity of a higher-end first generation iPhone, the negative side raises ... by the operating system, other data, and the file system. These factors significantly reduce the available space for storing images, making it unlikely that a hundred thousand lolcats could be accommodated.
		Answer	No
	Final Answer		No
Debate	Round 1 Agent 1	Reason	The first generation iPhone had a storage capacity of 4GB, 8GB, ... but exceeds the lower-end models. ... Assuming a very small size for each lolcat to fit on the screen, it's theoretically possible to display them, but it would be extremely impractical and unlikely.
		Answer	Yes
	Round 1 Agent 2	Reason	The first generation iPhone has a storage capacity of 4GB, 8GB, or 16GB, and assuming an average size of a lolcat image (around 100KB), we can estimate the maximum number of images that can fit. ... Still, theoretically, a hundred thousand lolcats could fit on a 16GB first-generation iPhone if we only consider storage space for images and nothing else.
		Answer	Yes
	Round 1 Agent 3	Reason	The first generation iPhone had a storage capacity of 4GB, 8GB, or 16GB, and assuming an average image size of 100KB, we can estimate the maximum number of images that can be stored. ... Nevertheless, from a purely storage-based perspective, it is theoretically possible for a hundred thousand lolcats to fit on a 16GB first generation iPhone.
		Answer	Yes

Method	Agent	Category	Content
	Round 2 Agent 1	Reason	Considering the storage capacity of the first generation iPhone, with models ranging from 4GB to 16GB, ... would require approximately 10GB of storage space. ... Given this interpretation and focusing solely on storage capacity, it is theoretically possible for a hundred thousand lolcats to fit on a 16GB first-generation iPhone, especially when considering only the storage aspect and disregarding the practicality of displaying them.
		Answer	Yes
	Round 2 Agent 2	Reason	Considering the storage capacity of the first generation iPhone, with models ranging from 4GB to 16GB, and estimating an average size of 100KB per lolcat image, a hundred thousand lolcats would require approximately 10GB of storage space. ... Therefore, focusing solely on storage, a hundred thousand lolcats could theoretically fit on a 16GB first-generation iPhone, albeit with the understanding that displaying them all at once would be highly impractical.
		Answer	Yes
	Round 2 Agent 3	Reason	Considering the storage capacity of the first generation iPhone, with models ranging from 4GB to 16GB, and assuming an average size of 100KB per lolcat image, a hundred thousand lolcats would require approximately 10GB of storage space. ... Taking into account the solutions from other agents, which also consider the theoretical possibility of storing a hundred thousand lolcats on a 16GB model, it appears that from a storage perspective, it is indeed possible.
		Answer	Yes
	Final Answer		Yes
	DOWN	Round 1 Agent 1	Reason
Answer			Yes
Confidence Score			0.95
Final Answer		Yes	

Table 7: Qualitative analysis of the StrategyQA dataset

Method	Agent	Category	Content
Query	<p>Given the story, how would you uniquely allocate each person to make sure both tasks are accomplished efficiently?</p> <p>Choices: ‘Seeking Sponsors and Donations: Amelia, Organizing Event Details: George and Lily’, ‘Seeking Sponsors and Donations: George, Organizing Event Details: Amelia and Lily’, ‘Seeking Sponsors and Donations: Lily, Organizing Event Details: Amelia and George’</p> <p>As the clock ticked closer to our most significant fundraising event, three key players - George, Amelia, and Lily - paced around the office, eager to know their assignments. As their manager, I held the responsibility of delegating two critical tasks among them: the challenging pursuit of Seeking Sponsors and Donations, and the intricate duty of Organizing Event Details.</p> <p>Amelia, our vibrant member, often found herself with Lily, brainstorming creative ideas in the cafeteria or around the picnic table outside. ... She was infamous for her love for detailed schedules and checklists, which often found her volunteering to plan her family reunions that ran smoothly under her supervision. ...</p> <p>However, the presence of George often marred her high spirits. George, indeed, was a hard one to deal with. Even though he had this endless passion ... , he often disagreed with Lily’s ideas during meetings, publicly criticized Amelia’s work enough to dampen her spirit, and worst of all, forgot crucial tasks that he was responsible for. ... But he often confessed feeling overwhelmed managing multiple tasks at once.</p> <p>Then there was Lily, a networking maven. ... Yet, her true forte was her meticulousness that reflected in her attention to detail. ... While she tended to dismiss George’s inputs during meetings, she showed a great deal of respect to Amelia and considered her suggestions before making a decision.</p> <p>Now, the ball was in my court. With the fundraising event nearing, it was my responsibility to ensure that these three unique individuals were correctly placed to utilize their strengths best. ... As the manager, I knew that this decision would shape the fate of our event and define our team’s dynamic in the foreseeable future.</p>		
Answer	Seeking Sponsors and Donations: George, Organizing Event Details: Amelia and Lily		
MAD	Affirmative Debater	Reason	Based on the characteristics and strengths of each individual, Amelia’s experience in attending charity galas and her ability to make connections, as well as her attention to detail, make her a strong candidate for Seeking Sponsors and Donations. ... George’s tendency to disagree with others and forget tasks suggests that he may not be the best fit for a role that requires independent work or a high level of organization, but his passion for fundraising can still be utilized in a team setting.
		Answer	Seeking Sponsors and Donations: Amelia, Organizing Event Details: George and Lily

Method	Agent	Category	Content
	Negative Debater	Reason	I disagree with your answer. Lily's experience in sales and her ability to ask people for money, combined with her connections with wealthy friends and acquaintances, make her a strong candidate for Seeking Sponsors and Donations. ... It allows Lily to leverage her sales experience and connections to secure sponsors and donations, while Amelia and George work together to organize the event details, with Amelia's organizational skills helping to keep George on track.
		Answer	Seeking Sponsors and Donations: Lily, Organizing Event Details: Amelia and George
	Moderator	Reason	The negative side's allocation takes into account the strengths and weaknesses of each individual more effectively. ... George's passion for fundraising can still be utilized in a team setting, and his tendency to disagree with others and forget tasks is mitigated by working with Amelia and Lily.
		Answer	Seeking Sponsors and Donations: Lily, Organizing Event Details: Amelia and George
	Final Answer		Seeking Sponsors and Donations: Lily, Organizing Event Details: Amelia and George
Debate	Round 1 Agent 1	Reason	The task of Seeking Sponsors and Donations requires someone with strong connections and the ability to ask for money, which Lily possesses due to her past experience in sales and her network of wealthy friends and acquaintances. ... However, his experience in a marketing firm could still be valuable in a supporting role or in a different capacity, but for the two main tasks at hand, Amelia and Lily are the better fit.
		Answer	Seeking Sponsors and Donations: Lily, Organizing Event Details: Amelia and George
	Round 1 Agent 2	Reason	Based on the characteristics and interaction dynamics of the three individuals, Amelia's strengths in seeking sponsors and donations due to her connections and experience, as well as her attention to detail, make her a strong candidate for Seeking Sponsors and Donations. ... Instead, considering George's potential to disrupt the team's dynamic, it would be more efficient to have him focus on Seeking Sponsors and Donations, where his interactions are more limited, and utilize Amelia and Lily's collaborative and organized approach for Organizing Event Details.
		Answer	Seeking Sponsors and Donations: George, Organizing Event Details: Amelia and Lily
	Round 1 Agent 3	Reason	To efficiently allocate tasks, we need to consider the strengths and weaknesses of each person. ... George, despite his flaws, has a passion for fundraising and experience in managing sponsorships, making him a better fit for Seeking Sponsors and Donations, where his skills can be utilized without disrupting the team's dynamics.
		Answer	Seeking Sponsors and Donations: George, Organizing Event Details: Amelia and Lily

Method	Agent	Category	Content
	Round 2 Agent 1	Reason	Considering the characteristics and interaction dynamics of the three individuals, as well as the solutions provided by other agents, it becomes clear that Amelia and Lily should be paired for Organizing Event Details due to their complementary strengths, meticulousness, and positive working relationship. ... This allocation allows for the efficient utilization of each person's strengths while minimizing potential conflicts and disruptions to the team's dynamics.
		Answer	Seeking Sponsors and Donations: George, Organizing Event Details: Amelia and Lily
	Round 2 Agent 2	Reason	After considering the characteristics, strengths, and weaknesses of each individual, as well as the solutions provided by other agents, it becomes clear that the most efficient allocation of tasks would be to utilize Lily's strong network and sales experience for Seeking Sponsors and Donations, and pair Amelia and George for Organizing Event Details. ... Therefore, the most suitable allocation would be to have Lily focus on Seeking Sponsors and Donations, where her skills can be maximized without causing disruptions, and have Amelia and George work together on Organizing Event Details, with close supervision to mitigate any potential issues caused by George's behavior.
		Answer	Seeking Sponsors and Donations: Lily, Organizing Event Details: Amelia and George
	Round 2 Agent 3	Reason	After considering the characteristics, strengths, and weaknesses of each individual, as well as the solutions provided by other agents, it becomes clear that the most efficient allocation of tasks would be to utilize Amelia and Lily's collaborative and organized approach for Organizing Event Details. ... This allocation allows each individual to contribute their strengths to the tasks, minimizing the impact of their weaknesses and ensuring the success of the event.
		Answer	Seeking Sponsors and Donations: George, Organizing Event Details: Amelia and Lily
	Final Answer		Seeking Sponsors and Donations: George, Organizing Event Details: Amelia and Lily
DOWN	Round 1 Agent 1	Reason	The decision is based on the unique skills and strengths of each team member. Amelia's experience in attending charity galas and her ability to make connections, as well as her attention to detail, make her a strong candidate for Seeking Sponsors and Donations. ... Given their positive working relationship and respect for each other's opinions, pairing Amelia and Lily for Organizing Event Details would be an effective way to utilize their skills and minimize potential conflicts.
		Answer	Seeking Sponsors and Donations: Lily, Organizing Event Details: Amelia and George
		Confidence Score	0.89

Method	Agent	Category	Content
	Round 1 Agent 2	Reason	To efficiently accomplish both tasks, it's crucial to allocate individuals based on their strengths and working dynamics. Amelia's experience with charity events, connections, and organizational skills make her ideal for Seeking Sponsors and Donations. ... By placing George with Lily, his enthusiasm can be channeled constructively under her detail-oriented supervision, minimizing the impact of his weaknesses.
		Answer	Seeking Sponsors and Donations: Amelia, Organizing Event Details: George and Lily
		Confidence Score	0.84
	Round 1 Agent 3	Reason	The decision is based on the unique strengths and weaknesses of each team member. Amelia's experience in attending charity galas and her ability to create detailed schedules make her a strong candidate for Organizing Event Details. ... George's passion for fundraising and experience in managing sponsorships make him a good candidate for Seeking Sponsors and Donations, but his tendency to disagree with others and forget tasks make it important to pair him with a task that has fewer collaborative elements.
		Answer	Seeking Sponsors and Donations: George, Organizing Event Details: Amelia and Lily
		Confidence Score	0.92
	Round 2 Agent 1	Reason	After considering the strengths, weaknesses, and dynamics of each team member, as well as the solutions provided by other agents, it becomes clear that the most efficient allocation of tasks would leverage the unique skills of each individual while minimizing potential conflicts. ... Despite his challenges with task management and interpersonal conflicts, his strengths can be effectively utilized in a role that plays to his advantages.
		Answer	Seeking Sponsors and Donations: George, Organizing Event Details: Amelia and Lily
		Confidence Score	0.91
	Round 2 Agent 2	Reason	After considering the solutions from other agents and re-evaluating the strengths and weaknesses of each team member, it's clear that Amelia's skills in attending charity galas and creating detailed schedules make her a strong fit for Organizing Event Details. ...Considering these points and the fact that Lily has a strong ability to seek sponsors and donations due to her sales experience and network, and Amelia and Lily have a positive working relationship, the most efficient allocation would be to have Amelia and Lily handle Organizing Event Details, utilizing their organizational skills and positive dynamic, and George, with his passion for fundraising, focus on Seeking Sponsors and Donations, where his strengths can be maximized with minimal disruption.

Method	Agent	Category	Content
		Answer	Seeking Sponsors and Donations: George, Organizing Event Details: Amelia and Lily
		Confidence Score	0.89
	Round 2 Agent 3	Reason	After re-evaluating the strengths, weaknesses, and dynamics of the team members, and considering the solutions from other agents, it becomes clear that Amelia’s skills in attending charity galas, making connections, and attention to detail are highly valuable for Seeking Sponsors and Donations. ...Therefore, the most efficient allocation is to have Amelia focus on Seeking Sponsors and Donations, where her strengths can be fully leveraged, and to pair George with Lily for Organizing Event Details, where Lily’s attention to detail and event management skills can complement George’s passion for fundraising and help manage his weaknesses.
		Answer	Seeking Sponsors and Donations: Amelia, Organizing Event Details: George and Lily
		Confidence Score	0.90
		Final Answer-Vote	Seeking Sponsors and Donations: George, Organizing Event Details: Amelia and Lily
	Final Answer-Judge		Seeking Sponsors and Donations: George, Organizing Event Details: Amelia and Lily. Reason: After carefully evaluating the strengths, weaknesses, and dynamics of each team member, as well as considering the solutions provided by other agents, it is clear that the most efficient allocation of tasks would leverage the unique skills of each individual while minimizing potential conflicts. ... Considering these points, the allocation that best utilizes the strengths of each team member while minimizing disruptions is to have Amelia and Lily handle Organizing Event Details, and George focus on Seeking Sponsors and Donations, where his strengths can be maximized with minimal disruption.

Table 8: Qualitative analysis of the StrategyQA dataset

Method	Agent	Category	Content
Query			<p>Given the story, how would you uniquely allocate each person to make sure both tasks are accomplished efficiently?</p> <p>Choices: 'Room Service: Vanessa, Front Desk: Angela and Miguel', 'Room Service: Angela, Front Desk: Miguel and Vanessa', 'Room Service: Miguel, Front Desk: Angela and Vanessa'</p> <p>In the vibrant heart of the city, a boutique hotel thrived, its pulse maintained by the constant hum of hospitality. As the manager, my responsibility was to ensure the seamless operation of two critical areas - Room Service and Front Desk. The task of assigning these duties fell to me, with the diligent trio of Miguel, Angela, and Vanessa under my supervision.</p> <p>Angela, with her seven-year-long tenure in various customer service roles, harbored a graceful calm when managing guest complaints and queries. ... But Angela was not without her quirks. ... At times, Vanessa had to step in to accomplish the requests related to room service in a quick and thorough manner to compensate. Angela often found her co-worker's unbordered enthusiasm overwhelming, especially when Vanessa would unwittingly interject her conversations with guests.</p> <p>Miguel, on the other hand, was the silver lining of good-natured humor and friendliness that added a personal touch to the hotel's room service deliveries. His go-with-the-flow demeanor, however, sometimes came off as disorganized, especially to Angela who appreciated structure. ... Despite his charm and gregariousness, Miguel often had a hard time deciphering guests' queries and concerns. This sometimes frustrated Vanessa who felt that Miguel did not accord her work ethic the respect it deserved, often leaving tasks incomplete for her to handle. Miguel's unfamiliarity with the front desk amplified her concern, as it had never been part of his experience before.</p> <p>Vanessa had perfected her role at a high-end hotel reception over a span of five meticulous years. ... Vanessa meticulously paid attention to every minor detail while performing room service tasks, sometimes stepping on Angela's toes without realizing it. To Vanessa, Angela often seemed slow, not quite pulling her weight to maintain efficiency.</p> <p>With these intricacies at play, as the hotel manager, I had to make conscious decisions assigning my team between Room Service and Front Desk duties. Balancing Angela, Miguel and Vanessa's distinctive skills, patience, and perspectives, the heart of hospitality continued to beat, painting vivid memories in the hotel guest's minds.</p>
Answer			Room Service: Miguel, Front Desk: Angela and Vanessa

Method	Agent	Category	Content
MAD	Affirmative Debater	Reason	Considering the strengths and weaknesses of each person, Angela's experience in customer service and her calm demeanor make her a good fit for the Front Desk. ... Vanessa's attention to detail and professionalism make her a good fit for Room Service as well, where she can ensure that tasks are completed efficiently.
		Answer	Room Service: Miguel, Front Desk: Angela and Vanessa
	Negative Debater	Reason	<p>I disagree with your answer. My allocation would be:</p> <p>Room Service: Vanessa, Front Desk: Angela and Miguel</p> <p>Here's my reasoning:</p> <p>* Vanessa's attention to detail and professionalism make her a perfect fit for Room Service, where she can ensure that tasks are completed efficiently and accurately. ...</p> <p>* Angela's experience in customer service and her calm demeanor make her a good fit for the Front Desk, where she can handle guest complaints and queries in a professional and respectful manner. ...</p> <p>* Miguel's charm and friendliness are also well-suited for the Front Desk, where he can interact with guests and provide a warm welcome. ...</p> <p>Overall, ... Vanessa's efficiency and attention to detail in Room Service can help to compensate for Angela's occasional misplacement of minor notes, while Angela and Miguel's combined strengths at the Front Desk can provide a warm and professional welcome for guests.</p>
		Answer	Room Service: Vanessa, Front Desk: Angela and Miguel
	Moderator	Reason	The negative side's allocation takes into account the strengths and weaknesses of each team member more effectively. ... This allocation also addresses the potential issues with each team member, such as Angela's occasional misplacement of minor notes and Miguel's difficulty with deciphering guests' queries and concerns.
		Answer	Room Service: Vanessa, Front Desk: Angela and Miguel
	Final Answer		Room Service: Vanessa, Front Desk: Angela and Miguel
Debate	Round 1 Agent 1	Reason	To allocate each person efficiently, we need to consider their strengths and weaknesses. ... Miguel's charm and friendliness are best utilized in room service, where he can interact with guests in a more relaxed environment and work at his own pace without the strict structure of the front desk.
		Answer	Room Service: Miguel, Front Desk: Angela and Vanessa

Method	Agent	Category	Content
	Round 1 Agent 2	Reason	To efficiently allocate tasks, we need to consider the strengths and weaknesses of each person. ... Therefore, the most efficient allocation would be to assign Vanessa to Room Service, where her attention to detail and professionalism can shine, and Angela and Miguel to the Front Desk, where Angela's customer service skills can be utilized and Miguel's charm can be an asset.
		Answer	Room Service: Vanessa, Front Desk: Angela and Miguel
	Round 1 Agent 3	Reason	To allocate each person efficiently, we need to consider their strengths and weaknesses. ... However, considering the need for balance and the fact that Miguel might struggle with the structure of the Front Desk, it's better to pair Angela with Miguel at the Front Desk, where Angela's organizational skills can help Miguel, and Vanessa can handle Room Service, utilizing her strengths without overwhelming others.
		Answer	Room Service: Vanessa, Front Desk: Angela and Miguel
	Round 2 Agent 1	Reason	Considering the strengths and weaknesses of each person, Angela's customer service skills are best utilized at the Front Desk, but her disorganization could be mitigated by pairing her with a detail-oriented person. ... Given these considerations and the analysis from other agents, it's clear that Angela and Miguel's skills complement each other at the Front Desk, with Angela handling customer interactions and Miguel providing charm, while Vanessa's strengths are best utilized in Room Service, ensuring efficiency and attention to detail.
		Answer	Room Service: Vanessa, Front Desk: Angela and Miguel
	Round 2 Agent 2	Reason	Considering the strengths and weaknesses of each person, Angela's customer service skills make her a strong fit for the Front Desk, while Miguel's charm can be leveraged in Room Service. ... The most efficient allocation, considering all perspectives, would be to assign Vanessa to Room Service, where her attention to detail can ensure tasks are completed efficiently, and Angela and Miguel to the Front Desk, where Angela's customer service skills and organizational abilities can help mitigate Miguel's weaknesses.
		Answer	Room Service: Vanessa, Front Desk: Angela and Miguel
	Round 2 Agent 3	Reason	Considering the strengths and weaknesses of each person, Angela's calm demeanor and customer service skills make her a strong fit for the Front Desk. ... Assigning Vanessa to Room Service leverages her strengths, and pairing Angela with Miguel at the Front Desk utilizes Angela's customer service skills and Miguel's charm, with Angela's organizational skills potentially helping to mitigate Miguel's disorganization.
		Answer	Room Service: Vanessa, Front Desk: Angela and Miguel
	Final Answer		Room Service: Vanessa, Front Desk: Angela and Miguel

Method	Agent	Category	Content
DOWN	Round 1 Agent 1	Reason	To efficiently allocate tasks, it's essential to consider the strengths and weaknesses of each team member. Angela excels in customer service, particularly at the Front Desk, due to her calm demeanor and respectful tone. ... Additionally, her efficiency and thoroughness in room service tasks, although sometimes stepping on Angela's toes, demonstrate her capability to handle detailed work.
		Answer	Room Service: Miguel, Front Desk: Angela and Vanessa
		Confidence Score	0.91
	Final Answer		Room Service: Miguel, Front Desk: Angela and Vanessa

Table 9: Qualitative analysis of the MUSR dataset