

# Diverse Thinking: Breaking Oppositions in Debates to Foster Synergized Reasoning via Multi-Agent Collaboration

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## Abstract

Large Language Models (LLMs) frequently face limitations, such as judgment biases and cognitive deadlocks, in complex reasoning due to “Degradation of Thought” in self-reflection. While Multi-Agent Debate (MAD) approaches attempt to address this issue, their inherently adversarial nature suppresses diverse perspectives by overemphasizing antagonism, which results in the loss of partially valid reasoning. In this paper, we propose Multi-Agent Diverse Thinking (MADT), a novel cognitive framework that redefines multi-agent collaboration by shifting from adversarial confrontation toward constructive synergy. To break the oppositional deadlock found in traditional debates, MADT decomposes the thinking process into fine-grained modules: an Affirmative Thinker to preserve rational components, a Critical Thinker to rectify errors, and a Growth-Minded Thinker to provide optimization suggestions. These agents jointly foster a synergistic environment where specialized roles protect valid logic while iteratively refining flaws. Meanwhile, a Leader agent coordinates the collaborations and synthesizes the feedback from multiple thinkers to produce the final result. Extensive experiments on Common Machine Translation and Counter-Intuitive Arithmetic Reasoning tasks show that MADT consistently outperforms Self-Reflection and MAD baselines, validating the superior ability to enhance complex logical and reasoning performance in LLMs. Code is available at <https://anonymous.4open.science/r/MADT-5D3B>.

## 1 Introduction

While large language models (LLMs) have achieved remarkable results in general linguistic tasks, they exhibit poor performance in complex mathematical and logical reasoning (Bang et al., 2023; Tran et al., 2025). To address these challenges, researchers have gradually drawn inspiration from human thinking patterns and the efficient

operational mechanisms of the human society to pursue improvements to existing LLMs (Gou et al., 2023; Zhu et al., 2023).

In current research, investigators have attained phased successes. Among these advancements: Chain-of-Thought (CoT) enables models to solve problems more accurately through step-by-step reasoning, reducing the likelihood of leaping directly to erroneous conclusions (Wei et al., 2022). Self-Consistency mitigates hallucinations generated by LLMs by producing multiple candidate answers and selecting the most consistent one (Wang et al., 2022). CoVe significantly diminishes model hallucinations and enhances the factual accuracy of generated content via verification steps (Dhuliawala et al., 2024). Multi-Agent Debate (MAD) that improves LLMs’ reasoning capabilities and reduces hallucinations through debates among multiple agents (Liang et al., 2024). D-MAD, an enhanced MAD framework, breaks through fixed mental sets by encouraging agents to adopt diverse reasoning approaches (Liu et al., 2025). The above-mentioned frameworks have achieved certain efficacy; however, the rationality of the frameworks remains a direction that merits further inquiry.

Essentially, the current methods can be categorized into two major types according to their corresponding thinking patterns:

- **Self-Reflection** (Madaan et al., 2023): Such methods allow LLMs to conduct introspection and examination of their own reasoning processes, iteratively generating new answers based on previous responses and feedback. However, they also suffer from Degradation of Thought (DoT) problem — when LLMs become certain of their own answers, Self-Reflection falls into a local impasse and fails to generate new lines of thinking.
- **MAD**: This type of methods addresses the DoT problem inherent in Self-Reflection

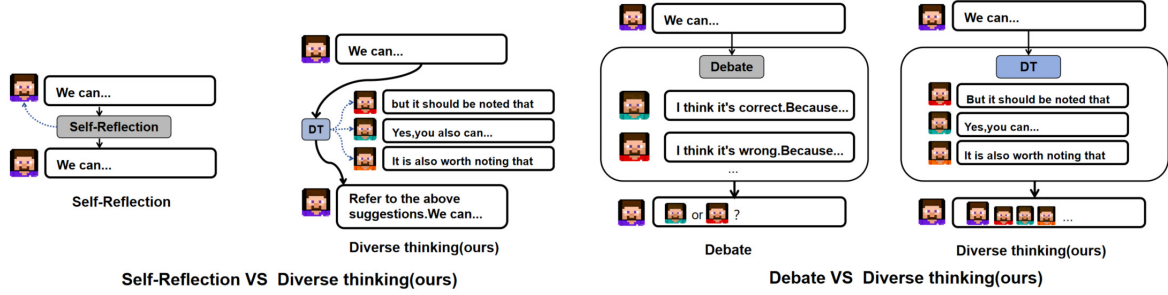


Figure 1: Comparison of Self-Reflection, Debate, and our proposed Diverse Thinking (DT)

084 through Debate mechanisms, achieving  
 085 promising results. However, the adversarial  
 086 nature of debates may lead to complete over-  
 087 shadowing of partially reasonable answers.

088 In this work, we conduct an in-depth analysis  
 089 of two representative cognitive paradigms—self-  
 090 reflection and debate—where self-reflection suffers  
 091 from DoT problem and thus requires the integration  
 092 of external perspectives, while Multi-Agent Debate  
 093 (MAD) overemphasizes adversariality to generate  
 094 diverse viewpoints, thereby leading to the loss of  
 095 partial valid reasoning steps. Oppositions are an in-  
 096 nate, pre-existing characteristic of debate scenarios,  
 097 which imposes novel requirements on multi-agent  
 098 collaboration. We define multi-agent collabora-  
 099 tion by shifting from adversarial confrontation to  
 100 constructive synergy. Accordingly, we propose  
 101 Diverse Thinking, a novel cognitive paradigm inte-  
 102 grating dual advantages of external perspective in-  
 103 corporation and valid reasoning preservation. This  
 104 paradigm abandons the preset binary premise of  
 105 "right versus wrong" and fosters synergized reason-  
 106 ing via differentiated division of labor and collabo-  
 107 ration.

108 On this basis, we design the Multi-Agent Diverse  
 109 Thinking (MADT) framework, which deploys three  
 110 specialized thinkers: a Growth-Minded Thinker,  
 111 an Affirmative Thinker, and a Critical Thinker.  
 112 The Growth-Minded Thinker is designed to ad-  
 113 dress the Depth of Thought (DoT) challenge in  
 114 self-reflection, generating targeted improvement  
 115 suggestions for initial responses and leveraging ex-  
 116 ternal viewpoints to mitigate the intrinsic biases of  
 117 self-reflection. To resolve the adversarial dilemma  
 118 in Multi-Agent Debate (MAD), we move beyond  
 119 the paradigm of opposing viewpoints in traditional  
 120 debates and instead focus on iterative deliberations  
 121 centered on the initial answer; for this purpose,  
 122 we develop an Affirmative Thinker and a Critical

123 Thinker, which respectively preserve the rational  
 124 components of the initial answer and rectify exist-  
 125 ing flaws. Meanwhile, a Leader agent coordinates  
 126 the collaborations and synthesizes the feedback  
 127 from multiple thinkers to produce the final result.  
 128 Figure 1 provides a comparative analysis of the  
 129 framework proposed in this paper against the other  
 130 two frameworks.

The contributions of this work are summarized  
 131 as follows: 132

- 133 • A new cognitive paradigm is proposed, which  
 134 transcends unimodal and adversarial thinking  
 135 frameworks by via differentiated division of  
 136 labor and collaboration.
- 137 • The Multi-Agent Diverse Thinking (MADT)  
 138 framework integrating three thinking mod-  
 139 els, affirmative thinking, critical thinking, and  
 140 growth-minded thinking, is designed to pro-  
 141 mote cognitive diversity.
- 142 • Diverse Thinking outperforms Self-Reflection  
 143 and Debate via multi-perspective feedback,  
 144 enabling more extensive beneficial insights, as  
 145 verified by experimental results on translation  
 146 and mathematical reasoning.

## 147 2 Related Work

148 **Thinking Pattern.** The thinking process of LLMs  
 149 can be regarded as a type of thinking pattern(Li  
 150 et al., 2023). Thinking Pattern refers to the rela-  
 151 tively stable cognitive path and behavioral tendency  
 152 that individuals or groups maintain when process-  
 153 ing information and solving problems(Zhang et al.,  
 154 2024). Currently, the Self-Reflection pattern rep-  
 155 resenting individual thinking and the Debate pat-  
 156 tern representing group cognitive interaction have  
 157 achieved good results. In the reflect pattern, based

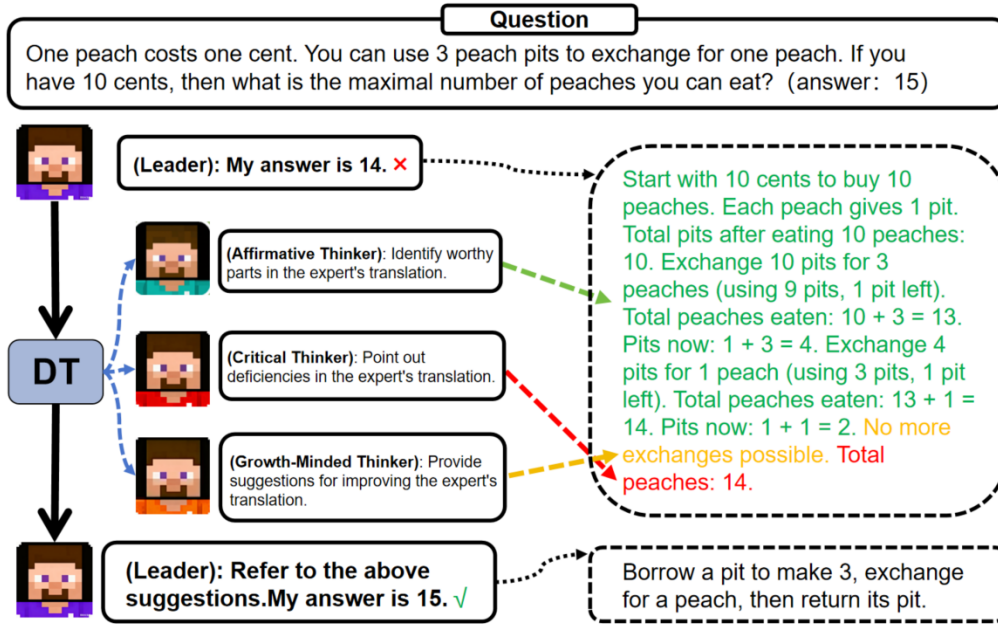


Figure 2: Framework of Multi-Agent Diverse Thinking. We designate 🧑 as the Leader, 🧑 as the Affirmative Thinker, 🧑 as the Critical Thinker, and 🧑 as the Growth-Minded Thinker. The content within the dashed box represents the reasoning process of the LLM. The text in green indicates the parts that proponents of the Affirmative Thinker believe are worth retaining. The text in red points out the issues identified by proponents of the Critical Thinker. The text in yellow denotes the parts that proponents of Growth-Minded Thinker believe can be improved.

on the cognitive closed loop of "retrospection-analysis-improvement", the actor reviews their previous responses, learns lessons from their experience, analyzes the shortcomings of the answer, and improves their answer accordingly. In the Debate pattern, a debate scenario is set up, centering on the process of "view generation - exchange - debate - consensus". First, debaters put forward ideas, then the pro and con sides exchange opinions and start debating, and finally reach a consensus. This paper analyzes the shortcomings of the two existing methods and proposes Diverse Thinking (DT).

**Multi-agent System.** In human sociology, groups effectively organized by individuals often possess the ability to collaboratively tackle large-scale tasks and accomplish complex objectives with higher efficiency and better performance than individuals (Chen et al., 2025; Zhou et al., 2024). In the field of artificial intelligence (AI), researchers study the collaboration mechanisms of human societies, with the aim of maximizing the capabilities of individual agents. The division of labor in current multi-agent systems mostly remains at the level of "task assignment" and fails to decompose the agents' "thinking processes" into implementable fine-grained modules (Wu et al., 2023; Zhou et al.,

2024). This paper conducts an exploration of the thinking patterns underlying diverse thinking and develops the MADT framework based on this concept. The framework encompasses three different thinkers: affirmative thinking, critical thinking, and growth-minded thinking.

### 3 Methodology

Figure 2 illustrates the framework of MADT, which consists of a Leader, an Affirmative Thinker, a Critical Thinker, and a Growth-Minded Thinker. Specifically, the Leader proposes a solution to the problem, and each thinker provides thoughts consistent with their own thinking style based on the Leader's solution. The Leader then synthesizes these thoughts and presents the final solution.

**Meta Prompts.** We use Meta Prompts (denoted as  $M$ ) to clarify the task, as well as the participants' thinking patterns and roles in the task. In formulating the prompts, we adopt the structure of "role positioning + task content + execution standards", formalization of which is presented in Equation 1.

$$M = \text{Role Positioning} \oplus \text{Task Content} \oplus \text{Execution Standards} \quad (1)$$

where  $\oplus$  denotes the prompt concatenation symbol. Examples of prompts refer to Appendix D. An example of the meta-prompt for the Affirmative Thinker is :

*As an Affirmative Thinker proficient in <task>, confirm correct parts of <Leader’s answer>. The evaluation criteria are as follows <evaluation criteria>.*

**Thinker.** In our framework, three thinkers with distinct cognitive patterns evaluate the Leader-generated baseline answer comprehensively from multi-dimensional perspectives: a Critical Thinker identifies errors in Large Language Model (LLM) outputs, an Affirmative Thinker preserves valid ideas, and a Growth-Minded Thinker formulates improvement suggestions. Examples of prompts for the affirmative, critical, and Growth-Minded Thinkers are provided in sequence below.

*Identify worthy parts in the expert’s translation.  
Point out deficiencies in the expert’s translation.  
Provide suggestions for improving the expert’s translation.*

**Leader.** A Leader is designed to summarize the suggestions from thinkers and provide the final result. The execution process is shown in Equation 2 and 3.

$$R_n = L(R_{\text{base}}, T_n, M_n) \quad (n = 1, 2, 3) \quad (2)$$

$$R_{\text{final}} = L(R_n, T_{\text{leader}}, M_{\text{leader}}) \quad (3)$$

$R_{\text{base}}$  denotes the answer obtained by directly asking the model;  $T_n$  stands for role definitions, where  $(n = 1, 2, 3)$  represent 3 role definitions with thinking differences;  $L$  represents the core execution tool (large language model), which receives input information and role definitions and generates corresponding results;  $R_n$  denotes the results generated by the LLM under the corresponding roles; and  $R_{\text{final}}$  is the final result.

**Collaborative Strategy.** Multi-agent systems require well-designed collaboration strategies for reasoning frameworks; inappropriate decision-making will trigger agent conflicts, cause task chain disruption, and ultimately lead to reasoning failure (Wang et al., 2025). The Debate mechanism inherently suffers from the limitation of adversarial viewpoints, with its final output being merely a one-sided solution favoring one party. In contrast, the MADT multi-agent collaboration framework leverages differentiated role division to integrate the strengths

of multiple parties for hybrid solution generation, thus achieving a paradigm shift from win-lose confrontation to global optimization. Within MADT, the Leader, as the ultimate decision-maker, executes the collaboration strategy: it retains validated rational ideas based on the inputs of the Affirmative Thinker, acquires impetus for change from the recommendations of the Critical Thinker, and resolves conflicts between the two based on the coordination proposals of the Growth-Minded Thinker.

## 4 Experiment

### 4.1 Dataset

We conducted experiments on two challenging tasks—Common MT(He et al., 2020) and CIAR(Liang et al., 2024)—selected for their demand for LLMs to perform in-depth, multi-faceted reasoning, which aligns with our goal of evaluating MADT’s ability to enhance complex cognitive processes. For detailed information, please refer to Appendix A.

**Commonsense Machine Translation** The Common MT dataset focuses on Chinese-to-English translation, with 200 lexical ambiguity examples, 450 contextless syntactic ambiguity examples, and 350 contextual syntactic ambiguity examples (total 1,000 cases). It classifies translations by ambiguity type: lexical ambiguity (driven by single-word polysemy), contextless syntactic ambiguity (structure-based parsing ambiguity without context), and contextual syntactic ambiguity (structure ambiguity activated by context).

**Counter-Intuitive Arithmetic Reasoning** The CIAR dataset contains 200 questions (each with annotated answers and reasoning processes) and poses two core challenges: (1) resisting intuitive traps (hidden pitfalls test avoidance of superficial, incorrect responses); (2) multi-step reasoning (rigorous step-by-step logic required for correct answers), enabling evaluation of LLMs in complex problem-solving.

### 4.2 Setting

**Input Format.** In the parameter configuration of LLMs, the temperature parameter is primarily used to adjust the randomness and creativity of the generated text(Renze, 2024). To ensure the model maintains effective reasoning capabilities while guaranteeing the accuracy and consistency of its outputs, we set the temperature value of LLMs to 0.3.

**Evaluation Metrics.** For the Common MT dataset,

Table 1: Model Scores of COMET and BLEURT Across Dimensions

Model	Lexical		Contextless		Contextual	
	COMET	BLEURT	COMET	BLEURT	COMET	BLEURT
<b>Qwen3-32B</b>	83.0	71.1	84.9	74.8	86.0	73.9
<b>Qwen3-30B-A3B</b>	80.1	68.0	83.8	73.1	85.1	73.2
+ Rerank	80.7	68.4	84.7	73.0	85.0	74.1
+ MAPS	82.1	69.9	84.4	73.3	85.1	73.8
+ Self-Reflection	81.2	68.9	83.9	72.4	84.7	73.7
+ MAD	82.0	70.9	84.6	73.7	<b>85.3</b>	74.0
+D-MAD	82.1	71.1	84.8	73.9	84.9	74.2
<b>+MADT</b>	<b>82.2</b>	<b>71.3</b>	<b>84.9</b>	<b>73.9</b>	85.2	<b>74.3</b>
<b>deepseek-r1-7b</b>	74.9	62.0	78.3	64.6	80.2	68.2
+ MAD	75.6	62.6	78.6	66.0	81.8	69.9
+D-MAD	75.8	62.7	78.7	66.5	82.0	70.1
<b>+MADT</b>	<b>75.9</b>	<b>63.0</b>	<b>78.9</b>	<b>66.5</b>	<b>82.1</b>	<b>70.3</b>

COMET(Rei et al., 2020) and BLEURT(Sellam et al., 2020) are used as the evaluation metrics, which are widely adopted in LLM translation literature. For the CIAR dataset, ACC is used as the evaluation metric.

**Backbone Models.** In this work, we primarily utilize four agents within the MADT framework, including one Leader and three thinkers (affirmative, critical, and growth-minded). Three API-based LLMs (Qwen3-32B, Qwen3-30B-A3B and DeepSeek-R1-7B) are evaluated.

### 4.3 Baselines

We compared the MADT framework with baseline models and also contrasted it with Self-Reflection and Debate methods. Table 1 shows the overall results on the Common MT dataset:

- **Self-Reflection:** This method is a reasoning-enhancement method that enables models to iteratively revise their inference paths by self-evaluating the rationality of intermediate conclusions.
- **Rerank(He et al., 2024):** This method samples LLMs’ translation outputs four times and selects the optimal candidate based on the quality estimation metric HUMANr5.
- **MAPS(He et al., 2024):** This method empowers LLMs to simulate the human translation workflow by performing pre-translation analysis, a paradigm analogous to applying chain-of-thought reasoning to the translation task.

- **MAD:** This method establishes a debate scenario where debaters first propose ideas, followed by an exchange of opinions between the pro and con sides to initiate the debate, and finally a consensus is reached.

- **D-MAD:** Within the MAD framework, each participating agent embodies distinct thinking through different reasoning methods.

### 4.4 Result

**Results on Common MT.** The experimental results demonstrate that MADT exhibits remarkable generality and stability: On the high-performance Qwen3-30B-A3B model, compared with the original model, it achieves a significant improvement of 2.1 points (80.1→82.2) in the COMET metric and 3.3 points (68.0→71.3) in the BLEURT metric in the Lexical dimension. On the mid-low performance deepseek-r1-7b model, MADT also maintains stable positive optimization. In the Contextual dimension, it increases the COMET and BLEURT metrics by 1.9 points (80.2→82.1) and 2.1 points (68.2→70.3) respectively, with a relative improvement rate significantly higher than that of high-performance models, reflecting its optimization potential for weak base models. A further comparison of the effects of MAD and MADT shows that the optimization effect is most prominent, especially in the lexical level.

**Results on CIAR.** To evaluate the performance of different methods in handling Counter-Intuitive Arithmetic Reasoning (CIAR), we conducted systematic experiments on the CIAR dataset and report quantitative accuracy results. As shown in the

Table 2, among all tested methods, Qwen3-32B achieves a competitive accuracy of 68.0%. The baseline model, deepseek-r1-7b, obtains a baseline accuracy of 50.0%. When the baseline is augmented with individual modules, the results are as follows: combining it with Self-Reflection increases the accuracy to 56.0%; combining it with MAD boosts the accuracy to 61.0%; and combining it with D-MAD elevates the accuracy to 64.0%. Additionally, the baseline combined with MADT achieves a notable accuracy of 66.0%, which demonstrates the latter’s superior effectiveness in enhancing CIAR capability.

Table 2: Accuracy Comparison of Different Methods on CIAR Dataset

Method	Acc%
<b>Qwen3-32B</b>	68.0
<b>deepseek-r1-7b</b>	50.0
+ Self-Reflection	56.0
+ MAD	61.0
+D-MAD	64.0
+MADT	66.0

#### 4.5 Ablation Study

To verify the effectiveness of each core component in the proposed MADT framework, we conducted systematic ablation experiments on the target task. Taking Qwen3-30B-A3B as the baseline model, we analyzed the independent contribution of each module to the model performance by gradually removing the key modules of MADT. The experimental results are summarized in Table 3.

Table 3: Performance Comparison of Different Methods (Acc, COMET, BLEURT)

Method	Acc	COMET <sub>avg</sub>	BLEURT <sub>avg</sub>
<b>deepseek-r1-7b</b>	50.0	77.80	64.93
<b>+MADT</b>	66.0	78.97	66.60
w/o Affirmative	62.0	78.52	66.31
w/o Critical	53.0	78.13	65.62
w/o Growth-Minded	60.0	78.81	66.13

**Importance of the Critical Thinker.** When this module is removed, the model’s accuracy drops sharply from 66.0% to 53.0%, a decrease of 13.0 percentage points. The COMET and BLEURT scores also decline significantly. This data indicates that the Critical Thinker is a crucial pillar of the model’s capabilities.

**Importance of the Growth-Minded Thinker.** After ablating this module, the model’s accuracy de-

creases from 66.0% to 60.0%, a drop of 6.0 percentage points. Additionally, the COMET and BLEURT scores show varying degrees of regression. This illustrates that the Growth-Minded Thinker incorporates optimization strategies, which can effectively assist the model in achieving adaptive performance improvement in complex task scenarios.

**Importance of the Affirmative Thinker.** Notably, although the Affirmative module in this framework only focuses on analyzing the parts of the answer that are worth retaining, its existence is still indispensable. Data show that removing the Affirmative module leads to a decrease in the model’s accuracy from 66.0% to 62.0%, a drop of 4.0 percentage points, with corresponding declines in the COMET and BLEURT scores. This indicates that, by enhancing the identification and retention of correct output components, the Affirmative module provides important support for the stability of model performance and serves as an indispensable part of the MADT framework.

## 5 Analysis

### 5.1 Diversity Analysis

LLMs can fall into a self-cognition deadlock and become reluctant to revise their answers. Opposing viewpoints in debates may also constrain responses and inhibit the possibility of generating alternative solutions (Yin et al., 2020). Translation diversity can be evaluated using the Self-BLEU score. Its principle is to calculate the n-gram overlap between generated samples to reflect the diversity of text generation models; a lower score indicates greater differences between samples. We calculate the Self-BLEU values of initial translations and final translations, and then derive the diversity score. The specific formulation is given in Equation 4, as follows:

$$Diversity = 100 - Self\_BLEU(R_{base}, R_{final}) \quad (4)$$

where *Diversity* denotes the final diversity score, and *Self\_BLEU* corresponds to the metric adopted in our method.

Table 4: Diversity Comparison of Different Methods

Method	Diversity
Self-Reflection	25.8
MAD	30.8
<b>MADT</b>	47.1

As shown in Table 4, compared with Self-Reflection and MAD, our proposed MADT more effectively addresses limitations in reasoning (cognitive degradation and opposing perspectives) and enables substantial improvements in answers.

## 5.2 The Driving Force for Change

**The Critical Thinker serves as the primary force driving performance improvements** within the MADT framework. As shown in Table 5, by engaging in critical evaluation of the results, it identifies errors and rectifies them. In this case, for example, the core expression conveys the semantic requirement of “completely annihilating an enemy combat unit.” Although the translation “Eat up an enemy division” generated by Qwen3-32B achieves literal correspondence, it exhibits a significant semantic deviation. The inclusion of the Critical Thinker corrects this core error in the original translation.

Table 5: Translation Comparison of Different Modules

Source/Method	Translation
Source	吃掉敌人一个师。
Correct Ref.	Destroy a division of the enemy.
Incorrect Ref.	Eat a division of the enemy.
Qwen3-32B	<b>Eat up</b> an enemy division.
+Critical	Destroy an enemy division.
+Growth-Minded	Defeat an enemy division.
+MADT	Destroy an enemy division.

## 5.3 Preserve Correct Thinking.

Within the MADT framework, the Critical Thinker may sometimes take an opposing perspective by affirming the presence of errors, and the doubts raised may not always be entirely correct. **The role of the Affirmative Thinker therefore proves crucial: rather than simply defending the original answer, it evaluates and preserves its rational components.** As shown in Table 6 (see Appendix B), when the Critical Thinker proposes “go into the water,” this translation weakens the key information of “swimming.” The inclusion of the Affirmative Thinker not only prevents potential semantic deviations caused by critical thinking but also enhances the accuracy and practicality of the final answer through collaboration with the Growth-Minded Thinker.

## 5.4 Refinement Mechanism

**The Growth-Minded Thinker focus more on the details that require improvement.** While Critical Thinker verifies the absence of semantic errors,

those with a growth mindset acutely identify subtle opportunities for optimization between surface-level expressions and underlying needs. As shown in Table 7 (see Appendix B), the colloquial idiom “keeps it hot” can convey the meaning of “maintaining momentum,” but it lacks precision and professionalism in formal contexts. Replacing the vague phrase “keeps it hot” with the more precise term “maintains high intensity” enhances the formality of the expression and its suitability for the given context.

## 5.5 Comparison with Self-Reflection

To address judgment biases arising from the Self-Reflection mechanism’s reliance on a single cognitive model, we introduce external content to expand cognitive boundaries. Unlike Self-Reflection, our method integrates three-dimensional cognitive perspectives (affirmative, critical, Growth-Minded Thinkers): affirming core rational components to reinforce strengths, identifying errors, and proposing feasible improvements, forming a “recognition-correction-enhancement” pathway that mitigates standalone Self-Reflection’s cognitive blind spots. We quantify agent performance with two metrics: Self-BLEU (cognitive diversity between an agent’s translations and final output) and COMET score difference (direct contributions vs. initial translations). For the Affirmative Thinker—which provides only affirmative judgments rather than specific answers—direct contribution is computed via ablation experiments, while Self-BLEU is calculated by comparing final results before and after ablation.

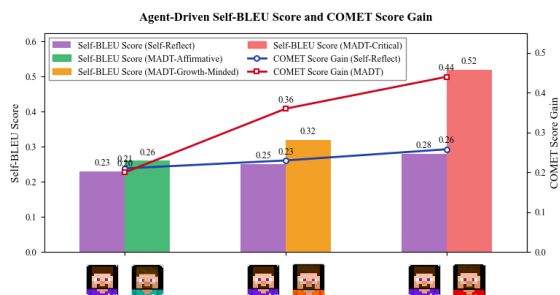


Figure 3: The gains of different agents on COMET scores and Self-BLEU scores in the Self-Reflection method and our method

As shown in Figure 3, under the Self-Reflection mechanism, the maximum COMET score gain is only 0.26, and the Self-BLEU score maintains an interval of 0.23 - 0.28, indicating that the agent’s

improvement on the result is relatively limited. In contrast, in our method (MADT), the Critical Thinker achieves a COMET score gain as high as 0.44 and a Self-BLEU score of 0.52, while the Growth-Minded Thinker achieves a COMET score gain of 0.36 and a Self-BLEU score of 0.32. By leveraging multi-faceted thinking dimensions, it realizes a distinctive and significant enhancement, fully demonstrating the advantage of the multi-cognitive architecture in performance gain.

## 5.6 Comparison with Debate

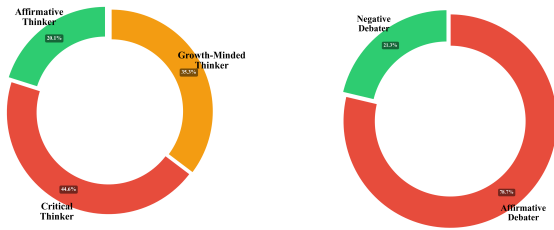


Figure 4: Proportion of Each Agent’s Influence on the Final Result (Left: Our Method; Right: Debate Method)

The adversarial nature of debates is repeatedly confined to just two lines of thinking. Moreover, incorrect viewpoints may reject or suppress lines of reasoning proposed by correct ones. Compared with the MAD method, our framework is not limited to mere affirmation or negation of viewpoints; instead, it conducts fine-grained decomposition and multi-dimensional deepening of the original answer. By examining what is correct, what is incorrect, and what is worthy of improvement, it avoids the limitations of adversarial thinking and brings the answer closer to perfection. To quantify the exclusive value of each agent to the final result, we innovatively designed the Unique Contribution indicator. This metric is calculated by subtracting the Self-BLEU score between the final output and the initial translation from the Self-BLEU score between the output of a specific agent and the final result. The specific equations are shown in Equations 5 and 6.

$$Base = Self\_BLEU(R_{base}, R_{final}) \quad (5)$$

$$UAAD = Self\_BLEU(R_n, R_{final}) - Base \quad (6)$$

The final results are presented in Figure 4. In MAD, the agents’ influence on the final outcome exhibits a distinct binary confrontational characteristic. The proportional discrepancy between affirmative debaters (78.7%) and negative debaters

(21.3%) reflects that the outcome is constrained by the confrontational thinking of mere affirmation or negation of viewpoints, which tends to fall into an either-or mode of thinking. In contrast, our method integrates multiple thinking dimensions such as critical, growth-minded, and affirmative thinking. The more diverse distribution of Critical Thinkers (44.6%), Growth-Minded Thinkers (35.3%), and Affirmative Thinkers (20.1%) indicates that, our method, through diverse thinking, breaks free from the thinking framework of mere affirmation or negation and overcomes the limitations of confrontational reasoning.

## 6 Conclusion

In this paper, we address two critical limitations of existing LLM cognitive paradigms: the cognitive degradation and single-mode bias of Self-Reflection mechanisms, and the binary adversarial constraints of Multi-Agent Debate (MAD) frameworks that suppress diverse perspectives. To resolve these issues, we propose the Multi-Agent Diverse Thinking (MADT) framework, which innovatively integrates three specialized thinking roles—Affirmative Thinker, Critical Thinker, and Growth-Minded Thinker to establish a "recognition-correction-enhancement" cognitive loop. This design transcends the either/or limitation of traditional debate methods and the self-cognitive deadlock of single-agent reflection, unlocking more possibilities for multi-agent collaborative optimization.

## Limitations

Building upon sufficient thinking time and computing resources for LLMs, this work enables the agent to derive the final answer through multiple rounds of interaction. Within the framework, the Leader is tasked with integrating analyses from various thinkers to formulate conclusions. Notably, long question input remains a persistent challenge for LLMs. To mitigate this issue, this paper introduces a prompt design that constrains thinkers to convey only the core reasoning processes and essential answers, thereby effectively alleviating the aforementioned challenge.

## References

Yejin Bang, Samuel Cahyawijaya, Nayeon Lee, Wenhao Dai, Dan Su, Bryan Wilie, Holy Lovenia, Ziwei

603	Ji, Tiezheng Yu, Willy Chung, Quyet V. Do, Yan Xu, and Pascale Fung. 2023. <a href="#">A multitask, multilingual, multimodal evaluation of ChatGPT on reasoning, hallucination, and interactivity</a> . In <i>Proceedings of the 13th International Joint Conference on Natural Language Processing and the 3rd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics (Volume 1: Long Papers)</i> , pages 675–718, Nusa Dua, Bali. Association for Computational Linguistics.	659
604		660
605		661
606		662
607		663
608		664
609		665
610		666
611		667
612		668
613	Huaben Chen, Wenkang Ji, Lufeng Xu, and Shiyu Zhao. 2025. <a href="#">Multi-agent consensus seeking via large language models</a> . <i>Preprint</i> , arXiv:2310.20151.	669
614		670
615		671
616	Shehzaad Dhuliawala, Mojtaba Komeili, Jing Xu, Roberta Raileanu, Xian Li, Asli Celikyilmaz, and Jason Weston. 2024. <a href="#">Chain-of-verification reduces hallucination in large language models</a> . In <i>Findings of the Association for Computational Linguistics: ACL 2024</i> , pages 3563–3578, Bangkok, Thailand. Association for Computational Linguistics.	672
617		673
618		674
619		675
620		676
621		677
622		678
623	Zhibin Gou, Zhihong Shao, Yeyun Gong, yelong shen, Yujiu Yang, Nan Duan, and Weizhu Chen. 2023. <a href="#">CRITIC: Large language models can self-correct with tool-interactive critiquing</a> . In <i>Second Agent Learning in Open-Endedness Workshop</i> .	679
624		680
625		681
626		682
627		683
628	Jie He, Tao Wang, Deyi Xiong, and Qun Liu. 2020. <a href="#">The box is in the pen: Evaluating commonsense reasoning in neural machine translation</a> . In <i>Findings of the Association for Computational Linguistics: EMNLP 2020</i> , pages 3662–3672, Online. Association for Computational Linguistics.	684
629		685
630		686
631		687
632		688
633		689
634	Zhiwei He, Tian Liang, Wenxiang Jiao, Zhuosheng Zhang, Yujiu Yang, Rui Wang, Zhaopeng Tu, Shuming Shi, and Xing Wang. 2024. <a href="#">Exploring human-like translation strategy with large language models</a> . <i>Transactions of the Association for Computational Linguistics</i> , 12:229–246.	690
635		691
636		692
637		693
638		694
639		695
640	Guohao Li, Hasan Abed Al Kader Hammoud, Hani Itani, Dmitrii Khizbullin, and Bernard Ghanem. 2023. <a href="#">CAMEL: Communicative agents for "mind" exploration of large language model society</a> . In <i>Thirty-seventh Conference on Neural Information Processing Systems</i> .	696
641		697
642		698
643		699
644		700
645		701
646	Tian Liang, Zhiwei He, Wenxiang Jiao, Xing Wang, Yan Wang, Rui Wang, Yujiu Yang, Shuming Shi, and Zhaopeng Tu. 2024. <a href="#">Encouraging divergent thinking in large language models through multi-agent debate</a> . In <i>Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing</i> , pages 17889–17904, Miami, Florida, USA. Association for Computational Linguistics.	702
647		703
648		704
649		705
650		706
651		707
652		708
653		709
654	Yexiang Liu, Jie Cao, Zekun Li, Ran He, and Tieniu Tan. 2025. <a href="#">Breaking mental set to improve reasoning through diverse multi-agent debate</a> . In <i>The Thirteenth International Conference on Learning Representations</i> .	710
655		711
656		712
657		713
658		714
		715
	Aman Madaan, Niket Tandon, Prakhar Gupta, Skyler Hallinan, Luyu Gao, Sarah Wiegrefe, Uri Alon, Nouha Dziri, Shrimai Prabhumoye, Yiming Yang, Shashank Gupta, Bodhisattwa Prasad Majumder, Katherine Hermann, Sean Welleck, Amir Yazdanbakhsh, and Peter Clark. 2023. <a href="#">Self-refine: iterative refinement with self-feedback</a> . In <i>Proceedings of the 37th International Conference on Neural Information Processing Systems, NIPS '23</i> , Red Hook, NY, USA. Curran Associates Inc.	659
		660
		661
		662
		663
		664
		665
		666
		667
		668
	Ricardo Rei, Craig Stewart, Ana C Farinha, and Alon Lavie. 2020. <a href="#">COMET: A neural framework for MT evaluation</a> . In <i>Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)</i> , pages 2685–2702, Online. Association for Computational Linguistics.	669
		670
		671
		672
		673
		674
	Matthew Renze. 2024. <a href="#">The effect of sampling temperature on problem solving in large language models</a> . In <i>Findings of the Association for Computational Linguistics: EMNLP 2024</i> , pages 7346–7356, Miami, Florida, USA. Association for Computational Linguistics.	675
		676
		677
		678
		679
		680
	Thibault Sellam, Dipanjan Das, and Ankur Parikh. 2020. <a href="#">BLEURT: Learning robust metrics for text generation</a> . In <i>Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics</i> , pages 7881–7892, Online. Association for Computational Linguistics.	681
		682
		683
		684
		685
		686
	Khanh-Tung Tran, Dung Dao, Minh-Duong Nguyen, Quoc-Viet Pham, Barry O’Sullivan, and Hoang D. Nguyen. 2025. <a href="#">Multi-agent collaboration mechanisms: A survey of llms</a> . <i>Preprint</i> , arXiv:2501.06322.	687
		688
		689
		690
		691
	Haochun Wang, Sendong Zhao, Jingbo Wang, Zewen Qiang, Bing Qin, and Ting Liu. 2025. <a href="#">Beyond frameworks: Unpacking collaboration strategies in multi-agent systems</a> . In <i>Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)</i> , pages 21361–21375, Vienna, Austria. Association for Computational Linguistics.	692
		693
		694
		695
		696
		697
		698
		699
	Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc Le, Ed Chi, Sharan Narang, Aakanksha Chowdhery, and Denny Zhou. 2022. <a href="#">Self-consistency improves chain of thought reasoning in language models</a> . <i>arXiv preprint arXiv:2203.11171</i> .	700
		701
		702
		703
		704
	Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed H. Chi, Quoc V. Le, and Denny Zhou. 2022. <a href="#">Chain-of-thought prompting elicits reasoning in large language models</a> . In <i>Proceedings of the 36th International Conference on Neural Information Processing Systems, NIPS '22</i> , Red Hook, NY, USA. Curran Associates Inc.	705
		706
		707
		708
		709
		710
		711
	Qingyun Wu, Gagan Bansal, Jieyu Zhang, Yiran Wu, Beibin Li, Erkang Zhu, Li Jiang, Xiaoyun Zhang, Shaokun Zhang, Jiale Liu, Ahmed Hassan Awadallah, Ryan W White, Doug Burger, and Chi	712
		713
		714
		715

716	Wang. 2023. <a href="#">Autogen: Enabling next-gen llm applications via multi-agent conversation</a> . <i>Preprint</i> , arXiv:2308.08155.	768
717		769
718		770
719	Haiyan Yin, Dingcheng Li, Xu Li, and Ping Li. 2020. <a href="#">Meta-cotgan: A meta cooperative training paradigm for improving adversarial text generation</a> . <i>Preprint</i> , arXiv:2003.11530.	771
720		772
721		773
722		774
723	Jintian Zhang, Xin Xu, Ningyu Zhang, RuiBo Liu, Bryan Hooi, and Shumin Deng. 2024. <a href="#">Exploring collaboration mechanisms for LLM agents: A social psychology view</a> . In <i>Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)</i> , pages 14544–14607, Bangkok, Thailand. Association for Computational Linguistics.	775
724		776
725		777
726		778
727		779
728		780
729		781
730		782
731	Yuyan Zhou, Liang Song, Bingning Wang, and Weipeng Chen. 2024. <a href="#">MetaGPT: Merging large language models using model exclusive task arithmetic</a> . In <i>Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing</i> , pages 1711–1724, Miami, Florida, USA. Association for Computational Linguistics.	783
732		784
733		785
734		786
735		787
736		788
737		789
738	Xinyu Zhu, Junjie Wang, Lin Zhang, Yuxiang Zhang, Yongfeng Huang, Ruyi Gan, Jiaying Zhang, and Yujie Yang. 2023. <a href="#">Solving math word problems via cooperative reasoning induced language models</a> . In <i>Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)</i> , pages 4471–4485, Toronto, Canada. Association for Computational Linguistics.	790
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746	<b>A Dataset</b>	798
747	We conducted experiments on two challenging tasks, including Common MT and CIAR, which require LLMs to engage in in-depth reasoning.	799
748		800
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750	<b>A.1 Common MT</b>	802
751	The Common MT Dataset is a Chinese-to-English translation dataset, which provides Chinese-to-English translation cases categorized into three types based on translation ambiguity properties: lexical ambiguity, contextless syntactic ambiguity, and contextual syntactic ambiguity. Specifically, the dataset contains 200 lexical ambiguity examples, 450 contextless syntactic ambiguity, and 350 contextual syntactic ambiguity examples. Table 8 presents illustrative examples of these three types of ambiguity.	803
752		804
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758	<b>Lexical Ambiguity.</b> This refers to the phenomenon where a sentence yields multiple interpretations due to a single word possessing several mutually independent core meanings. The root cause of such ambiguity lies solely at the lexical level, having no connection with the sentence structure.	810
759		811
760		812
761		
762	<b>contextless syntactic ambiguity.</b> This denotes the phenomenon where a sentence generates multiple interpretations because its syntactic structure (e.g., constituent segmentation, grammatical relations) allows for multiple valid parsing methods. The ambiguity originates exclusively at the syntactic level and can be identified without relying on contextual information.	
763		
764	<b>contextual syntactic ambiguity.</b> This describes the phenomenon where a sentence’s syntactic structure inherently has multiple potential parsing possibilities; however, the ambiguity is temporarily concealed when separated from specific contexts and becomes activated once concrete contextual information is introduced.	
765		
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	<b>A.2 CIAR</b>	
	The CIAR dataset comprises 200 questions, each paired with a corresponding answer and detailed reasoning process, and it presents two core challenges for models: first, resisting intuitive pitfalls, where questions are crafted with hidden traps to test whether LLMs can resist the temptation of superficial cues and avoid selecting intuitively appealing yet incorrect answers; second, multi-step reasoning capability, as each correct answer requires a rigorous multi-step reasoning process, thereby enabling the evaluation of LLMs’ performance in complex decision-making and problem-solving scenarios.	
	<b>B Experimental Results</b>	
	This appendix presents additional experimental results and case analyses referenced in the main text, including Tables 6 and 7.	
	<b>C Extra Computational Cost</b>	
	We quantify the reasoning cost by the number of generated tokens. As shown in Table 8, Self-Reflection incurs a cost that is 1.83 times that of the baseline Chain-of-Thought (CoT) method, while the cost of the MADT method reaches 3.52 times that of the baseline CoT. Given the considerable optimization potential of our proposed method, this increase in cost is deemed acceptable.	
	<b>D Meta Prompt</b>	
	In formulating the prompts, we adopt the structure of "role positioning + task content + execution standards"	

Table 6: Translation Comparison of Different Modules

Source	这几个学生约好一起去水库下水。
Correct Ref.	these students agreed to go to the reservoir together for swimming.
Incorrect Ref.	these students agreed to go to the reservoir to do bad things.
Qwen3-32B	these students agreed to go together to the reservoir to go swimming
+Critical	some students agreed to go to the reservoir together to go into the water.
+Growth-Minded	these students agreed to go to the reservoir together to swim.
+MADT	some students agreed to go to the reservoir together to go swimming.

Table 7: Translation Comparison of Different Methods

Source	他对这件事情的热度持续很久。
Correct Ref.	His enthusiasm for this matter lasted for a long time.
Incorrect Ref.	His temperature for this matter lasted for a long time.
Qwen3-32B	He keeps it hot for a long time.
+Critical	He keeps it hot for a long time.
+Growth-Minded	He maintains high intensity for a long time.
+MADT	He maintains high intensity for a long time.

Table 8: Comparison of method costs.

Method	Cost (Tokens)
COT	1.0×
Self-Reflection	1.83×
MAD	2.46×
MADT	3.52×

adaptation); 2. Fluency (awkward expressions). Provide evidence (e.g., 'XX→YY is wrong';).

Growth-Minded Thinker’s meta-prompt: 837

As a Growth-Minded Thinker, optimize <task>’s English translation. Steps: 838  
 1. Recognize strengths (with examples); 839  
 2. Propose targeted improvements : - Accuracy (adjust technically correct but mismatched terms); - Fluency (revise understandable but unsmooth expressions). 840  
 Format: 'Current issue + Revised content + Reason' (e.g., 'Current: ...function of.. / Revised: ...features... '). 841  
 842  
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D.2 Meta Prompt for CIAR 848

Leader’s meta-prompt: 849

As a math problem-solving expert, find the correct answer to <task> (balance logical rigor, calculation accuracy, problem context). 850  
 851  
 852  
 853

Affirmative Thinker’s meta-prompt: 854

As an Affirmative Thinker proficient in math, confirm correct parts of <task>’s answer. Evaluate: 1. Logical rigor (no logical flaws, correct formula application); 2. Calculation accuracy (no miscalculations, correct unit handling). Provide specific examples (e.g., 855  
 856  
 857  
 858  
 859  
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 861

## D.1 Meta Prompt for CommonMT

Leader’s meta-prompt:

As a Chinese-English translation expert familiar with <task>’s text type, find the correct English translation of <task> (balance accuracy, fluency, context).

Affirmative Thinker’s meta-prompt:

As an Affirmative Thinker proficient in English and <task>’s text type, confirm correct parts of <task>’s English translation. Evaluate : 1. Accuracy (full meaning, no additions/omissions); 2. Fluency (English habits/norms). Provide specific examples (e.g., 'XX→YY is accurate').

Critical Thinker’s meta-prompt:

As a Critical Thinker proficient in Chinese-English and cultural differences, identify flaws in <task>’s English translation. Evaluate: 1. Accuracy (mistranslation, missing meaning, poor cultural

'XX step correctly applies the average speed formula').

Critical Thinker's meta-prompt:

*As a Critical Thinker proficient in math, identify flaws in <task>'s answer. Evaluate: 1. Logical flaws (e.g., wrong formula selection, ignored conditions); 2. Calculation errors (e.g., miscalculations, incorrect unit conversion). Provide evidence (e.g., 'XX step confuses average speed with average of speeds, leading to wrong results').*

Growth-Minded Thinker's meta-prompt:

*As a Growth-Minded Thinker, optimize <task>'s answer. Steps: 1. Recognize strengths (with examples, e.g., 'XX step clearly lists total distance and time for average speed'); 2. Propose targeted improvements: - Logical clarity (adjust confusing reasoning steps); - Calculation conciseness (revise redundant calculation processes). Format: 'Current issue + Revised content + Reason' (e.g., 'Current: Complex fraction simplification is unclear / Revised: Simplify  $2d/(4d/3)$  to  $3/2$  directly / Reason: Reduces redundant calculation steps').*


## E Thinking Process


### E.1 Common MT


The following presents the translation process of MADT for the sentence "放学后这几个学生约好一起去水库下水". First, clear translation task objectives are established, with the analysis conducted from three dimensions: accuracy, fluency, and contextual adaptability. The Leader first proposes an initial translation. Then, the Affirmative Thinker provides justifications for validating this initial version. Next, the Critical Thinker identifies the limitations of the initial translation and offers an alternative version. Subsequently, the Growth-Minded Thinker puts forward targeted improvement suggestions and presents a revised translation. Finally, the Leader synthesizes the rationales from all thinkers and determines the final translation.



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<task>: Translate 放学后这几个学生约好一起去水库下水。 from Chinese to English.

 "reasoning": "1. **Accuracy ensured via term matching and cultural retention**: '约好' is translated as 'agreed to' to preserve the mutual arrangement implied in Chinese. '下水' is rendered as 'to swim' (contextual to reservoirs) instead of a literal 'go into the water', retaining activity specificity. 2. **Fluency via English habits**: The structure 'After school, these students agreed to...' mirrors natural English narrative flow. 'Go together' avoids awkward literalism (e.g., 'went together') by using present infinitive for clarity. 3. **Adaptation to source text type (narrative)**: The translation preserves the casual, descriptive tone of the original Chinese sentence, which recounts a planned group activity. No legal or formal rigor is needed, but vividness is maintained through active verbs ('agreed', 'go').", "translation": "After school, these students agreed to go together to the reservoir to swim."

 "reasoning": "1. **Accurate parts**: '约好' translated as 'agreed to' captures the mutual arrangement (vs. vague 'planned to'). '下水' rendered as 'to swim' matches cultural context (vs. literal 'go into water'). 2. **Fluent parts**: 'Agreed to go together' uses common English phrasing for planned group actions (vs. awkward 'had agreed to go together'). 'To the reservoir to swim' follows English prepositional clarity (vs. fragmented 'reservoir and swim'). 3. **Text type adaptation strengths**: Active verbs ('agreed', 'go') preserve the narrative's casual, action-oriented tone. Simple declarative structure mirrors Chinese's straightforward storytelling style."

 "reasoning": "1. **Accuracy deficiencies**: '下水' is translated as 'to swim' which may omit core meaning if the activity isn't specifically swimming (e.g., wading, boating). '约好' as 'agreed to' assumes prior arrangement but the original implies a group decision, not necessarily a formal agreement. '这几个学生' is translated as 'these students' but the Chinese phrase is more neutral (could mean 'some students'). 2. **Fluency deficiencies**: 'Go together to the reservoir' is awkward; natural English would use 'go to the reservoir together.' The phrase 'agreed to go together to the reservoir to swim' is verbose and disrupts flow. 3. **Reasoning deficiencies**: No explanation of why '下水' was narrowed to 'swim' despite potential contextual ambiguity. The reasoning claims 'cultural retention' but fails to address if 'reservoir' is an appropriate term in the target language's cultural context (e.g., 'water reservoir' vs. 'lake'). The

961 claim about 'source text type (narrative)' is vague  
 962 and lacks evidence of tone adaptation.", "translation": "After school, some students agreed to go to  
 963 the reservoir together to go into the water."  
 964  "reasoning": "1. **Recognized strengths**:  
 965 'agreed to' accurately captures '约好' by emphasizing  
 966 mutual planning; 'to swim' retains contextual  
 967 specificity for '下水' in a reservoir setting. The  
 968 structure 'After school, these students agreed to...'  
 969 aligns with English narrative flow. 2. **Optimization areas**: (a) 'go together to the reservoir' →  
 970 'go to the reservoir together' (revised word order  
 971 for natural English phrasing). (b) 'to swim' → 'to  
 972 go swimming' (more idiomatic for recreational wa-  
 973 ter activity). 3. **Reasoning supplementation**:  
 974 The expert's reasoning omitted the idiomatic ad-  
 975 justment for '下水' and word order fluency. Ad-  
 976 justing to 'go swimming' clarifies the activity as  
 977 leisure, while reordering 'together' enhances read-  
 978 ability.", "translation": "After school, these students  
 979 agreed to go to the reservoir together to go swim-  
 980 ming.""  
 981  "reasoning": "1. **Adopted thinker B's correc-**  
 982 **tions**: Replaced 'these students' with 'some stu-  
 983 **dents' to neutralize specificity (B's accuracy point).**  
 984 Adjusted 'go together to the reservoir' to 'go to  
 985 the reservoir together' for natural word order (B's  
 986 fluency point). 2. **Integrated thinker C's opti-**  
 987 **mizations**: Replaced 'to swim' with 'to go swim-  
 988 **ming' for idiomatic clarity (C's fluency optimiza-**  
 989 **tion). 3. Retained thinker A's strengths**: Pre-  
 990 served 'agreed to' for '约好' (mutual arrangement)  
 991 and retained 'reservoir' as the specific water body.  
 992 4. **Contextual adaptation**: 'Go swimming'  
 993 clarifies leisure activity vs. literal 'go into water,'  
 994 while 'some students' avoids over-specifying the  
 995 group. The declarative structure mirrors Chinese's  
 996 straightforward narrative tone.", "translation": "Af-  
 997 ter school, some students agreed to go to the reser-  
 998 voir together to go swimming."




## 1003 E.2 CIAR

1004 The following presents the reasoning process of  
 1005 MADT for solving the empty peach pit exchange  
 1006 problem.


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 1008 <task>:One peach costs one cent. You can use  
 1009 3 peach pits to exchange for one peach. If you  
 1010 have 10 cents, then what is the maximal number of  
 1011 peaches you can eat?

 "reasoning": "Start with 10 cents to buy 10  
 1012 peaches. Each peach gives 1 pit. Total pits after  
 1013 eating 10 peaches: 10. Exchange 10 pits for 3  
 1014 peaches (using 9 pits, 1 pit left). Total peaches  
 1015 eaten: 10 + 3 = 13. Pits now: 1 + 3 = 4. Exchange  
 1016 4 pits for 1 peach (using 3 pits, 1 pit left). Total  
 1017 peaches eaten: 13 + 1 = 14. Pits now: 1 + 1 = 2.  
 1018 No more exchanges possible. Total peaches: 14.",  
 1019 "answer": "14"  
 1020  "reasoning": "1. Logically rigorous parts: The  
 1021 expert correctly accounts for the iterative exchange  
 1022 process, ensuring that each exchange of pits for  
 1023 peaches is tracked alongside leftover pits. For ex-  
 1024 ample, after the first exchange of 10 pits, the rea-  
 1025 soning explicitly notes using 9 pits (3 peaches) and  
 1026 retaining 1 pit, avoiding overcounting. 2. Calcula-  
 1027 tionally accurate parts: The step where 10 pits are  
 1028 exchanged for 3 peaches (using 9 pits) and the sub-  
 1029 sequent addition of 3 new pits to the leftover 1 pit  
 1030 (totaling 4) is mathematically precise. The division  
 1031 of 4 pits into 1 exchange (3 pits) with 1 leftover is  
 1032 also correct. 3. Problem type adaptation strengths:  
 1033 The reasoning adapts to the recursive nature of the  
 1034 problem by repeatedly applying the exchange rule  
 1035 (3 pits → 1 peach) and tracking leftovers, which  
 1036 aligns with the problem's requirements."  
 1037  "reasoning": "1. Logically rigorous parts: The  
 1038 reasoning strictly tracks the iterative exchange pro-  
 1039 cess of pits for peaches, clearly distinguishing be-  
 1040 tween initial pits, used pits for exchange, leftover  
 1041 pits, and newly generated pits after eating peaches.  
 1042 For example, it explicitly records that 10 initial pits  
 1043 use 9 for the first exchange (obtaining 3 peaches)  
 1044 and retain 1, then updates the total pits to 4 by  
 1045 adding 3 new pits from eaten peaches, avoiding  
 1046 logical omissions or confusion. It also considers  
 1047 two scenarios (allowing borrowing pits or not) and  
 1048 clarifies the termination conditions of exchange (in-  
 1049 sufficient pits to meet the 3-pit rule), ensuring the  
 1050 completeness of logical derivation. 2. Calcula-  
 1051 tionally accurate parts: The cumulative calculation of  
 1052 the number of peaches eaten is precise, such as 10  
 1053 initial peaches + 3 exchanged peaches + 1 second  
 1054 exchanged peach = 14 peaches in the conventional  
 1055 scenario, and 14 + 1 borrowed-exchanged peach =  
 1056 15 peaches in the optimized scenario. The calcu-  
 1057 lation of leftover pits after each exchange is also  
 1058 error-free, like 10 - 9 + 3 = 4, 4 - 3 + 1 = 2, and 2 + 1  
 1059 - 3 = 0 (after borrowing), maintaining mathematical  
 1060 consistency. 3. Problem type adaptation strengths:  
 1061 The reasoning fully adapts to the recursive nature  
 1062 of the pit-peach exchange problem, repeatedly ap-  
 1063

plying the core rule of "3 pits  $\rightarrow$  1 peach" and dynamically updating the number of pits and peaches. It also flexibly covers different boundary conditions of the problem (allowing borrowing or not), making the reasoning highly compatible with the problem's characteristics.", "answer": "15"

 "reasoning": "1. Logically rigorous parts: Strictly tracks iterative pit exchanges, distinguishing used/leftover/new pits, clarifying exchange termination conditions, and covering both non-borrowing and borrowing scenarios without omissions. 2. Calculationally accurate parts: Precisely accumulates eaten peaches (14 in conventional scenario, 15 with borrowing) and correctly computes leftover pits after each exchange, maintaining mathematical consistency. 3. Problem type adaptation strengths: Repeatedly applies the "3 pits  $\rightarrow$  1 peach" rule to fit the problem's recursive nature and flexibly adapts to different boundary conditions."

 "reasoning": "Start with 10 cents to buy 10 peaches. Each peach yields 1 pit, so 10 pits are obtained after eating all 10 peaches. Following the rule of 3 pits for 1 peach, exchange 9 pits for 3 peaches (1 pit leftover). Total peaches eaten: 10 + 3 = 13; total pits now: 1 leftover + 3 new pits = 4. Exchange another 3 pits for 1 peach (1 pit leftover again). Total peaches eaten: 13 + 1 = 14; total pits now: 1 leftover + 1 new pit = 2. To reach the maximum, borrow 1 pit to make 3 pits, exchange for 1 peach, and return the new pit after eating it. Total peaches eaten increases by 1.", "answer": "15"

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