Meta-Reasoner: Dynamic Guidance for Optimized Inference-time Reasoning in Large Language Models

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Abstract

Large Language Models (LLMs) increasingly rely on prolonged reasoning chains to solve complex tasks. However, this trial-and-error approach often leads to high computational overhead and error propagation, where early mistakes can derail subsequent steps. address these issues, we introduce Meta-Reasoner, a framework that dynamically optimizes inference-time reasoning by enabling LLMs to "think about how to think." Drawing inspiration from human meta-cognition and dual-process theory, Meta-Reasoner operates as a strategic advisor, decoupling high-level guidance from step-by-step generation. It employs contextual multi-armed bandits to iteratively evaluate reasoning progress and select optimal strategies (e.g., backtrack, clarify ambiguity, restart from scratch, or propose alternative approaches), and reallocates computational resources toward the most promising paths. Our evaluations on mathematical reasoning and puzzles highlight the potential of dynamic reasoning chains to overcome inherent challenges in the LLM reasoning process and also show promise in broader applications, offering a scalable and adaptable solution for reasoning-intensive tasks.

1 Introduction

Recent advances in o1-like and r1-like¹ reasoning have enabled large language models (LLMs) to achieve remarkable performance on complex tasks such as mathematics (Patel et al., 2024; Lightman et al., 2023), science (Rein et al., 2023), and logical puzzles (Lei et al., 2024; Yao et al., 2023). By simulating multi-step, human-like deliberation (Yao et al., 2024), these methods allow LLMs to decompose problems into smaller subproblems, test hypotheses, reflect on intermediate results, and iteratively refine their solutions. This extended

reasoning process enables systematic exploration of ideas, verification of partial conclusions, and progressive improvement before producing a final answer. Such capabilities are particularly valuable in domains demanding rigorous logical reasoning (Chenghao Yang, 2024).

Despite these advances, o1/r1-like reasoning remains fundamentally challenged by its trial-anderror nature: models generate numerous candidate reasoning paths, discard flawed ones, and gradually converge on solutions. While this flexibility facilitates exploration of diverse strategies, it often incurs substantial computational overhead (Snell et al., 2024; Manvi et al., 2024) and is vulnerable to error propagation, where early mistakes accumulate and compromise subsequent steps (Lei et al., 2024; Yao et al., 2023; Gandhi et al., 2024). Some iterative methods incorporate partial revision or backtracking (Gandhi et al., 2024; Li et al., 2025a), but these approaches tend to be ad-hoc and limited to correcting errors within a narrow reasoning window. Crucially, they lack a systematic mechanism to assess whether an entire reasoning trajectory remains promising or should be abandoned.

As a result, LLMs risk becoming "stuck" on unproductive reasoning paths, wasting valuable computational resources without recognizing when a strategic pivot is necessary. A critical challenge, therefore, is to enable LLMs to manage their reasoning budget more effectively—prioritizing promising directions while adapting or discarding ineffective strategies during inference time.

To address this challenge, we propose Meta-Reasoner, a specialized meta-reasoning module that operates alongside the LLM to enhance its reasoning capabilities. Acting as a high-level advisor, the meta-reasoner dynamically evaluates the reasoning process and provides strategic guidance or redirection when progress stalls. Unlike the LLM, which focuses on detailed stepwise generation, the meta-reasoner maintains a global perspective, as-

¹O1 (from OpenAI) and R1 (from Deepseek) are two advanced LLM models designed for reasoning.

sessing overall progress and strategy from a high level. Meta-Reasoner operates in iterative rounds: First, the LLM generates partial chain-of-thought reasoning chains and a concise "progress report" summarizing its current state. Meta-Reasoner then reviews this report and offers high-level feedback-such as restarting reasoning with a different approach, refining existing ideas, or focusing on specific subproblems. This setup allows Meta-Reasoner to concentrate on overall strategy rather than getting involved in the granular details of the LLM's reasoning. Overall, Meta-Reasoner helps prevent the LLM from getting stuck or spending resources on unproductive lines of inquiry during the inference time.

Overall, the main contributions are as follows:

- We propose a meta-reasoning module that provides high-level oversight and guidance to the LLM's reasoning, helping to prevent it from getting stuck on unproductive solution paths during inference.
- We design a lightweight progress reporting mechanism, enabling efficient communication of the LLM's reasoning state to the meta-reasoner with minimal overhead.
- We empirically show that our Meta-Reasoner improves accuracy and efficiency on challenging math and scientific reasoning benchmarks (e.g., Game of 24, TheoremQA, and SciBench) compared to existing strong baselines. Our results highlight the framework's potential as a new scalable solution to inference-time reasoning.

2 Related Works

In this section, we first review the challenges of complex reasoning in LLMs and the limitations of chain-of-thought (CoT) methods. We then discuss recent advances in backtracking and self-verification techniques that aim to mitigate these issues. Finally, we draw inspiration from cognitive science, framing our approach within the metacognition and dual-process theory to motivate the design of our Meta-Reasoner framework.

Complex Reasoning in LLMs The introduction of CoT reasoning has transformed how LLMs tackle complex problems by decomposing tasks into intermediate steps (Lee et al., 2025). Recent models such as OpenAI's o1 and o3, and Deepseek's r1, have achieved state-of-the-art performance across diverse domains by leveraging

CoT-like reasoning (Manvi et al., 2024; Li et al., 2025a; Kudo et al., 2024; Sui et al., 2024b). However, the inherent sequential dependency in CoT limits robustness: errors in early steps can propagate and degrade overall performance (Snell et al., 2024). Moreover, when confronted with complex reasoning tasks, CoT methods may become trapped in infinite reasoning loops (Lee et al., 2025; Sui et al., 2024a,c). To address these challenges, we propose Meta-Reasoner, a meta-reasoner that monitors and adapts the reasoning strategy based on the progress of CoT. By integrating mechanisms such as backtracking and self-verification, Meta-Reasoner provides a holistic perspective that evaluates the overall reasoning trajectory to prevent stagnation and reduce wasted computation on unproductive lines of thought.

Backtracking and Self-Verification To mitigate the limitations of CoT-like reasoning, recent methods have explored backtracking and selfverification techniques (Yao et al., 2023; Besta et al., 2023; Gandhi et al., 2024). For example, Weng et al. (2023) demonstrate that incorporating a self-verification stage—where the model reexamines its conclusions using the generated chain of thought—significantly improves performance by detecting errors early. Similarly, Ling et al. (2023) propose generating multiple candidate reasoning chains alongside a verifier mechanism that identifies and backtracks on erroneous steps. These approaches extend beyond post-hoc validation by enabling dynamic strategy adjustments during inference (Lightman et al., 2023), thereby limiting error propagation in lengthy reasoning chains and mitigating infinite reasoning loops. Building on these efforts, our Meta-Reasoner framework employs instructions to (1) restart from scratch with alternative strategies, (2) backtrack to the error point, and (3) continue with targeted suggestions. Further details on this strategy are provided in §4.3.

Meta-Cognition & Dual-Process Systems From a cognitive science perspective, meta-cognition involves higher-order processes that allow individuals to monitor, evaluate, and adjust their cognitive strategies (Gao et al., 2024; Yoran et al., 2024). This reflective thinking—often characterized as System 2 in dual-process theories (Havrilla et al., 2024)—is vital for tasks requiring careful deliberation and error correction (Didolkar et al., 2024). Drawing on these insights, our Meta-Reasoner framework can be viewed as analogous

to dual-process systems: the LLM generates CoT steps akin to System 1, while the Meta-Reasoner provides high-level strategic oversight, analogous to System 2, guiding or redirecting reasoning as needed. This separation of responsibilities balances efficiency with robust problem-solving, allowing the LLM to handle routine inferences and the Meta-Reasoner to intervene for strategic adjustments.

3 Preliminary

In complex reasoning tasks, a key challenge is deciding which strategy to use from multiple valid options. This problem can be naturally framed as a *contextual multi-armed bandit* (MAB) problem, a well-studied framework for making decisions that balance trying new options (*exploration*) and using what is already known to work (*exploitation*).

Imagine an agent faced with several strategies (called *arms*), and at each step, it observes some information about the current situation (called the *context*). Based on this context, the agent picks one strategy to apply and then receives feedback (a *reward*) indicating how well that strategy performed. The goal is to choose strategies over time to maximize the total reward.

Formally, at each time step t, the agent observes a context vector x_t describing the current state and selects an arm s_t from a set of possible strategies \mathcal{S} . After choosing s_t , it receives a reward $r(s_t, x_t)$ that depends on both the chosen strategy and the context. The agent aims to maximize the cumulative reward over T steps:

$$R(T) = \sum_{t=1}^{T} r(s_t, x_t).$$
 (1)

A popular algorithm for this problem is LinUCB (Li et al., 2012), which assumes the expected reward is approximately a linear function of the context. Specifically, for each arm s, there is an unknown parameter vector θ_s such that:

$$\mathbb{E}[r(s, x_t)] \approx x_t^{\top} \theta_s. \tag{2}$$

LinUCB maintains an estimate $\hat{\theta}_s$ of this parameter and a measure of uncertainty about the estimate. At each step, it selects the arm that maximizes a combination of the estimated reward and an *uncertainty* bonus:

$$s_t = \arg\max_{s \in \mathcal{S}} \left[x_t^{\top} \hat{\theta}_s + c \sqrt{x_t^{\top} A_s^{-1} x_t} \right], \quad (3)$$

where A_s is a matrix capturing past observations for arm s, and c controls how much the agent favors exploring uncertain options. The second term

encourages trying arms that might perform well but have been less explored.

By using context to guide its choices, LinUCB adapts its strategy selection to the current situation, which aligns with our goal in Meta-Reasoner: to dynamically choose the most effective reasoning strategy during inference time.

4 Methods

Motivated by the intuition that LLMs should concentrate their computational efforts on more promising reasoning paths during inference time, we explore two key research questions in this paper: (1) How can language models dynamically allocate resources during inference to optimize reasoning and planning?; (2) What architectural design enables an effective separation between the reasoning process within the LLM and the meta-level guidance that oversees it?

To address these questions, we propose a novel framework, **Meta-Reasoner**, which endows LLMs with the ability to "think about how to think". Our framework supervises the reasoning process and dynamically guides the model to focus on more promising reasoning trajectories during inference time. Furthermore, Meta-Reasoner mitigates the limitations of conventional sequential reasoning, which may get stuck in suboptimal paths. We propose a "high-order" reasoning mechanism to balance exploration and exploitation using a Multi-Armed Bandit (MAB) algorithm.

The meta-reasoning framework operates iteratively as illustrated in Figure 1. At each round t, the reasoning process comprises three steps: (1) CoT generation by the LLM, (2) Progress Reporting to summarize the reasoning progress so far (i.e., this is partly for efficiency, and partly to help the metareasoner focus on its main goal of "advising" rather than being distracted by the details in the CoT), and (3) Strategy Generation by the meta-reasoner to optimize subsequent steps. The selection of the strategy is almost exactly corresponds to the wellstudied problem of contextual multi-armed bandits as illustrated in §3. Each strategy can be seen as an arm for the bandit, and the reward of each strategy can be evaluated by the progress of LLM reasoning after applying the strategy. We analogy the process of executing and evaluating each strategy as the act of "pulling" each arm. The overall goal of our meta-reasoner is to find the best arm (i.e., strategy with highest cumulative rewards) with as

Meta-Reasoning Framework Process

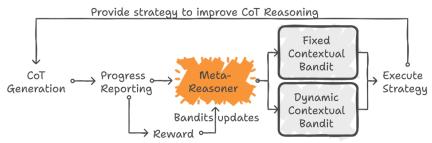


Figure 1: An illustration of the Meta-Reasoner workflow. In each round, the LLM produces a new reasoning step to extend its CoT reasoning. The CoT is then summarized into a progress report, which provides context for the meta-reasoner. Then meta-reasoner uses a contextual multi-armed bandit (either using a fixed contextual bandit or dynamic contextual bandit) to choose a guidance strategy. The selected strategy then guides the next reasoning step generation, to enable strategic redirection, error correction, and resource optimization. A reward is then computed from the progress report and used to update the bandit algorithm. The process repeats until the task is complete or the maximum number of rounds is reached.

few pulls as possible. The complete algorithm of Meta-Reasoner is appended in Algorithm 1.

4.1 Chain-of-Thought (CoT) Generation

In the first step, the LLM generates a reasoning step to extend its CoT reasoning based on the user query. Starting from its reasoning history C_{t-1} and the guidance G_{t-1} provided by the meta-reasoner in the previous round, the LLM M produces a new reasoning step s_t . This step is appended to the current CoT, forming $C_t = C_{t-1} \cup \{s_t\}$. By maintaining the full reasoning trajectory at each round, the model establishes a coherent foundation for evaluation and further refinement. This approach resembles the long-term reasoning demonstrated in models like o1, which generate extended CoTs. However, this reasoning process often resembles "trial-and-error", potentially incurring unnecessary inference costs on unproductive paths. Moreover, due to its sequential nature, the process is prone to becoming trapped in suboptimal solutions.

4.2 Progress Reporting

After updating the CoT, we summarize the reasoning history C_t into a concise progress report P_t . This summary captures key aspects of the reasoning trajectory, including progress toward the task goal, reasoning consistency, and significant updates thus far. The summarization function f abstracts the detailed CoT into a simpler, more focused representation. This step is designed to be both computationally efficient and informative, enabling the meta-reasoner to evaluate **high-level** progress without being overwhelmed by the **granular details** of every reasoning step. While this may be viewed as an engineering heuristic, we observe that including essential information in the prompt unlocks the LLM's capacity for "higher-order" thinking. Con-

sequently, the LLM tends to generate more insightful and critical strategies, which are particularly valuable for complex reasoning tasks.

4.3 Meta-reasoner Strategy Generation

In the next step, the meta-reasoner evaluates the progress report P_t and selects an appropriate strategy G_t for LLM reasoning (the complete procedure is detailed in Algorithm 1). We formulate the generation of strategy as a contextual MAB problem and consider two settings: (1) a fixed-strategy formulation, where the meta-reasoner selects from a predefined set of strategies using a contextual bandit algorithm; and (2) an advanced setting, in which the meta-reasoner itself is an LLM-based agent capable of introducing or refining strategies dynamically. In both cases, the meta-reasoner employs the partial-feedback principle of MABs to adaptively select strategies based on a reward function that evaluates the quality of reasoning progress after applying the chosen strategy. We demonstrate the contextual bandit pair (i.e., diagnosis of the progress report (i.e., context) and the corresponding strategy (i.e., bandit) in Table 1.

Progress Evaluation. A central objective of our evaluation mechanism is to quantify how effectively the model's current reasoning advances toward the task goal (e.g., solving a complex problem), while also monitoring computational cost to promote efficiency. Concretely, we implement a reward function that tracks both solution progress (e.g., partial correctness, adherence to constraints) and resource usage (e.g., number of reasoning steps). This evaluator can be any suitable mechanism, including LLM-based verification or external scoring scripts. In our implementation, we leverage an LLM as the evaluator (with prompts referenced

Diagnosis	Strategy
Progress is insufficient or the current strategy seems ineffective.	Restart from scratch and propose alternative strategies.
There are mistakes in intermediate steps.	Backtrack to the point where the error occurred.
The current approach is working well.	Continue and provide specific suggestions for the next steps.
Ambiguous or conflicting intermediate results are observed.	Pause to clarify and disambiguate the current reasoning, then reconcile the discrepancies.
The reasoning process appears overly complex or convoluted.	Simplify by decomposing the task into smaller, manageable subtasks.
Evidence of error propagation or low confidence in certain sub-components.	Perform targeted verification on critical steps and focus on areas with low confidence.
Repetitive or circular reasoning patterns are detected.	Reset to a previously successful checkpoint and explore alternative solution paths.

Table 1: **Demonstration**: Contextual bandit pair (i.e., diagnosis of the progress report (context) and the corresponding strategy (bandit)) for guiding the LLM's reasoning process. Marked rows are some of the unique strategies generated by Dynamic Contextual Bandits.

in Figures 4–7) to assess reasoning progress. The evaluator outputs a cumulative score, which is then used to update the MAB algorithm.

Fixed Contextual Bandit. In the basic version of our framework, the meta-reasoner is modeled as a single contextual bandit that selects from a fixed, *finite* set of K strategies. These strategies include instructions such as "continue and provide specific suggestions", "restart from scratch", "backtrack to the point where the error occurred", or "propose alternative methods or perspectives to consider", as detailed in Table 1 (rows without marked). At each round, the LLM produces a progress report summarizing its partial reasoning, the meta-reasoner transforms this progress report into a feature vector x_t using a language model and applies a contextual bandit algorithm (e.g., LinUCB (Li et al., 2012)) to select the best next strategy a_t . The LLM then executes that strategy and we collect the reward r_t for a_t based on the reward function. Through iterative MAB algorithm updating, the MAB algorithm learns to select appropriate strategies conditioned on the recent progress report.

Dynamic Contextual Bandit. The fixed-arm formulation assumes a static set of strategies. In practice, the meta-reasoner may itself be an LLM capable of inventing new strategies over time. To accommodate *dynamic* strategies, we allow the meta-reasoner to propose or refine new strategies at round t, which generates an expanding collection of strategies, $G_1 \subseteq \cdots \subseteq G_t$. Each newly proposed strategy becomes an arm in the contextual bandit. To encourage at least some exploration on this new arm, we initialize each arm with a blank or weak prior in the bandit's parameters. We further analyze the stability of these new generated dynamic contextual bandits in Appendix §C.

By explicitly separating low-level content generation (handled by the LLM) from high-level strategy decisions (governed by the meta-reasoner's bandit), the system can effectively avoid getting stuck or wasting excessive resources on poor solution paths. In domains where a predefined set of strategies is sufficient, the fixed-arm formulation can simplify the method deployment. While in more open-ended domains where novel tactics may emerge, dynamic-arm extensions give meta-reasoner more flexibility to evolve.

5 Experiments

In this section, we first introduce the experiment settings including datasets, backbone models and training details of MAB. We then present the main results of Meta-Reasoner with analysis regarding efficiency, rewards accumulation, and qualitative assessment of meta-reasoner output. We present the detailed baselines in Appendix A.

5.1 Experiments Setup

Datasets. We test our method on several challenging datasets that demand complex reasoning and often involve lengthy thinking processes for the correct solutions. These includes (1) 24-point game (Yao et al., 2023); (2) college-level scientific problem from SciBench (Wang et al., 2024) and (3) math questions based on theorems from TheoremQA (Chen et al., 2023). For SciBench, we focus only on the math-related subsets (i.e., diff, stat, and calc). Detailed explanations for each subset can be found in Wang et al. (2024). For TheormQA, we only consider the math subset that involves logical reasoning.

Training Details. We collect the training data for each task: (1) for the 24-point game, we random sample 50 queries from 4nums.com specifi-

Method	Diff(%)	Stat(%)	Calc(%)
Phi-4 + CoT	17.42	28.42	32.93
Llama-3.1-instruct + CoT	33.14	49.72	54.18
Gemini-Exp-1206 + CoT	36.32	56.73	59.24
Gemini-Exp-1206 + SC-CoT	38.73	59.12	64.11
GPT-4o-mini + CoT	33.12	55.71	58.10
GPT-4o-mini + SC-CoT	37.33	56.67	63.81
GPT-4o-mini + MCR	40.12	58.21	67.42
GPT-4o-mini + MACM (Lei et al., 2024)	54.78	67.13	65.77
GPT-40 + MACM (Lei et al., 2024)	61.42	78.32	76.72
GPT-4o-mini + Meta-Reasoner (our work)	60.32	73.64	80.23
GPT-40 + Meta-Reasoner (our work)	67.14	83.29	84.17

Table 2: Accuracy (%) comparison of different methods on the math-related subset of the SciBench dataset. Each column refers to the problem subset defined in Wang et al. (2024).

Method	Accuracy (%)
GPT-4o-mini + CoT (Yao et al., 2023)	4
GPT-4o-mini + SC-CoT (Yao et al., 2023)	9
GPT-4o-mini + IO (best of 100) (Yao et al., 2023)	33
GPT-4o-mini + CoT (best of 100) (Yao et al., 2023)	49
Gemini-Exp-1206 + IO (best of 100) (Yao et al., 2023)	38
Gemini-Exp-1206 + CoT (best of 100) (Yao et al., 2023)	60
GPT-40-mini + ToT $(b = 1)$ (Yao et al., 2023)	32
GPT-4o-mini+ ToT $(b = 5)$ (Yao et al., 2023)	65
GPT-4o-mini + Reflexion (Shinn et al., 2024)	53
GPT-4o-mini + MACM (Lei et al., 2024)	80
GPT-4o-mini + Meta-Reasoner (our work)	89
GPT-40 + Meta-Reasoner (our work)	92
Gemini-Exp-1206 + Meta-Reasoner (our work)	94
o1-mini + IO	89
o1-preview + IO	93

Table 3: Accuracy(%) comparison of different prompting methods on 24-points game. *b*: Search breadth.

cally excluding problems in ranks 901-1000 which were reserved for testing; (2) for TheoremQA, we randomly sample 30 mathematical reasoning queries from the dataset; (3) for SciBench, we randomly sample 30 queries from differential subsets including diff, stat, and calc from the entire dataset. These samples were used to iteratively update the LinUCB parameters for both fixed (K=3 or K=5 strategies) and dynamic strategy settings.

We configure the training process using deterministic generation (n=1, Top_k=1, temperature=0) with specific max_token limits for CoT generation (512), meta-reasoner feedback (256), progress reports (512), and reward model outputs (4). The LinUCB exploration parameter was set to c=0.2. Experiments were ran for a maximum of T=30 iterations for the 24-point game, scibench, and T=100 for TheoremQA, with MAB parameters updated after each iteration based on a reward function that weighted objective completion (40%), progress quality (30%), efficiency (15%), and strategy alignment (15%). The reward function prompt is detailed in Figure 4-7.

Backbone Models. We consider both LLMs and the recent Large Reasoning Models (LRMs) for our experiments. For the LLMs, we consider the closed-source models like gpt-4o, gpt-4o-mini (between Nov 2025 to Jan 2025) from OpenAI, and open-sourced models like meta-llama-3.1-8B-instruct from Meta, phi-4 from Microsoft and gemini-experimental-1206 from Google. For the LRMs, we consider the closed-source models like o1, o1-mini (In case we cannot break down the generation of o1 models through APIs, we cannot properly inject our meta-reasoner with o1-series models; we only provide the IO results for references). For the feature extraction mentioned in §4.3, we use text-embedding-3-small from OpenAI as the embedding model.

To ensure the reproducibility of the experiments, we set temperature = 0.7 and top_p = 1.0 for all models. We use the API service from OpenAI² and OpenRouter³ for our experiments which host detailed snapshots of the utilized model versions.

5.2 Main Results

We compare the accuracy of different prompting methods across different backbone models on SciBench (as shown in Table 2), 24-points game (as shown in Table 3) and TheoremQA (as shown in Table 4). We found that basic prompting strategies, such as CoT and SC-CoT, show limited effectiveness, achieving only 4% and 9% accuracy on 24-point games, respectively. Incorporating IO strategy with "Best of 100" samples improves accuracy to 33%, but it remains far behind advanced methods. Strategies like ToT illustrate the importance of exploring broader reasoning paths, with accuracy increasing from 45% to 74% as the search breadth expands from 1 to 5. Advanced iterative methods, such as Reflexion (53%) and MACM (80%), further demonstrate the value of refined reasoning frameworks. Our proposed Meta-Reasoner outperforms these approaches, achieving 89% accuracy with GPT-4o-mini and 92% with GPT-4o, showcasing its ability to dynamically guide reasoning, correct errors, and focus resources effectively. Compared to specialized models like o1-mini, our method equipped with much cheaper and generalized models like GPT-4o-mini delivers comparable performance, demonstrating its adaptability

²https://openai.com/

³https://openrouter.ai/

Method	Accuracy (%)
GPT-4o-mini + CoT	39.46
Gemini-Exp-1206 + CoT	43.12
GPT-4o-mini + Reflexion (Shinn et al., 2024)	74.32
GPT-4 Turbo + MACM (Lei et al., 2024)	79.41
GPT-4o-mini + Meta-Reasoner (our work)	84.13
Gemini-Exp-1206 + Meta-Reasoner (our work)	86.32

Table 4: Accuracy(%) comparison of different prompting methods on TheoremQA (Chen et al., 2023).

GPT-4o-mini Full Method 89 w/o Progress Report 85 w/o MAB (direct arm selection) 82 w/o MAB (CoT) 4 Full Method 94	84.13 79.42
GPT-40-mini	79.42
w/o MAB (direct arm selection) 82 w/o MAB (CoT) 4 Full Method 94	
Full Method 94	80.74
7	39.46
	86.32
Gemini-Exp-1206 w/o Progress Report 91	81.78
w/o MAB (direct arm selection) 87	82.14
w/o MAB (CoT)	43.12

Table 5: Ablation study of Meta-Reasoner. Direct arm selection refers to prompting LLM to directly select a strategy based on recent progress report.

and scalability. Overall, the Meta-Reasoner framework provides a compatible approach to improving reasoning-intensive tasks, combining high accuracy with dynamic and efficient problem-solving strategies. The results on SciBench and TheoremQA also demonstrate similar findings and show that Meta-Reasoner generally achieves better performance compared to the baselines and the results are consistent across different models.

5.3 Ablation Study

In this section, we conduct an ablation study to analyze each component contribution of Meta-Reasoner. In specific, we consider the following setup: (1) w/o progress report: we replace the progress reporting process with directly considering the entire CoT history without summarization; (2) w/o MAB: instead of using MAB to select the proper strategy, we directly leverage an LLM to the decision making to provide the proper strategy for LRM reasoning. In Table 5, we show that when removing progress reporting ("w/o Progress Report"), the overall performance moderately degrades and we hypothesize it is due to the concise intermediate summarizations can help the Meta-reasoner only consider the high-level strategy instead of being confused with too much details of the reasoning process. We also find that removing the MAB brings a more pronounced effect, especially when strategy selection falls back to a direct chain-ofthought approach ("w/o MAB (CoT)"). It verifies the effect of our meta-reasoner module to help the model stay on track for getting an optimal solution. In Table 6, we compare fixed and dynamic bandit

Bandit Type	Game-of-24(%)	#US	TheoremQA(%)	#US
Fixed (K=3)	65	3	72.34	3
Fixed (K=5)	72	5	79.17	5
Dynamic	89	14	84.13	21

Table 6: Fixed vs. Dynamic Bandit Variants over GPT-4o-mini. #US: Number of Unique Strategies.

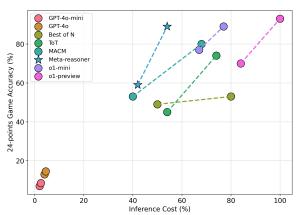


Figure 2: We normalize the inference costs (based on token usage) in a range from 0 to 1 for easier comparison. We use gpt-4o-mini as the backend model for all the methods in this figure. For each method, key hyper-parameters (e.g., N in Best of N, or tree size in ToT) are tuned to yield a baseline (lower point) and an extended (upper point) configuration, with dashed lines connecting these bounds.

variants on the game of 24 and theoremQA. We find that using a fixed set of strategies (e.g., K=3 and K=5) yields lower performance compared to the dynamic approach which adaptively explores more strategies (shown by larger unique strategies). The results highlight the benefit of flexibly allocating diverse reasoning strategies using LLM in-context learning capabilities.

5.4 Analysis

Inference Efficiency. A common way to measure computational efficiency is wall-clock time, as it directly reflects real-world latency during inference. However, in our API-based setup, wall-clock time is unreliable due to external factors such as network latency and server load, which introduce noise unrelated to the model's intrinsic computational cost. Therefore, we use token usage as a more stable and meaningful proxy, since it directly correlates with the amount of computation performed and is widely adopted in recent works (Liu et al., 2025; Li et al., 2025b). The detailed instruction can be found in Appendix B.1.

Figure 2 presents normalized inference costs (measured by token usage) alongside accuracy for various models and prompting strategies. Basic models like GPT-40-mini and GPT-40 ex-

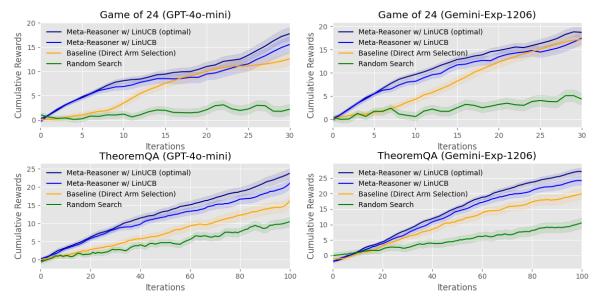


Figure 3: Cumulative reward of different settings across iteration. We compare our method using LinUCB with baseline (direct arm selection), and random search methods across two tasks—Game of 24 (top row) and TheoremQA (bottom row) using GPT-40-mini (left) and Gemini-Exp-1206 (right).

hibit low accuracy and minimal cost, whereas advanced methods such as ToT (Yao et al., 2023) and MACM (Lei et al., 2024) improve accuracy at the expense of increased token consumption. Our method achieves a strong balance, achieving high accuracy with moderate token usage, outperforming MACM, which is more costly yet less accurate. Proprietary models like o1-mini and o1-preview attain slightly higher accuracy but incur the highest cost, underscoring their greater resource demands. Overall, Meta-Reasoner provides a cost-effective and scalable solution for reasoning-intensive tasks.

Effectiveness of Meta-reasoner. Figure 3 demonstrates the cumulative rewards across iterations. We compare our MAB-based approach with a baseline that directly prompts an LLM to select an arm (or "strategy"), referred to as Baseline (Direct Arm Selection); the prompt details are in Figures 4–7. Results show that the MAB-based meta-reasoner (using LinUCB (Li et al., 2012)) consistently outperforms both direct LLM decisionmaking and random search across two tasks (Game of 24 and TheoremQA) and two model scales (GPT-4o-mini and Gemini-Exp-1206). direct LLM prompting yields reasonable initial performance and random search requires minimal setup, neither approach effectively balances exploration and exploitation. In contrast, the MAB updating strategy leverages feedback from prior iterations to adaptively refine action selection (e.g., choosing an appropriate strategy based on CoT reasoning), steadily increasing cumulative rewards.

6 Conclusion

In this work, we introduce Meta-Reasoner, a metareasoning framework designed to enhance the reasoning capabilities of LRMs and optimize the inference-time reasoning efficiency. By operating as an "advisor", meta-reasoner dynamically evaluates the reasoning process and provides highlevel strategic guidance, addressing key limitations of o1-like reasoning chains, such as compounding errors and inefficiency in inference computing. Unlike conventional reasoning approaches, Meta-Reasoner focuses on global oversight rather than granular step-by-step processes, enabling LRMs to avoid unproductive lines of thought and better allocate computational resources. The experiments highlight the potential of dynamic reasoning chains to overcome inherent challenges in the LLM reasoning process and also show promise in broader applications, offering a scalable and adaptable solution for reasoning-intensive tasks.

Limitations

Our proposed Meta-Reasoner framework, while effective at enhancing inference-time reasoning, remains limited to text-based problems and struggles to address tasks requiring other modalities, such as geometry. Overcoming these challenges calls for further advancements in the model's cognitive capabilities.

References

- Maciej Besta, Nils Blach, Ales Kubicek, Robert Gerstenberger, Lukas Gianinazzi, Joanna Gajda, Tomasz Lehmann, Michal Podstawski, Hubert Niewiadomski, Piotr Nyczyk, et al. 2023. Graph of thoughts: Solving elaborate problems with large language models. arXiv preprint arXiv:2308.09687.
- Wenhu Chen, Ming Yin, Max Ku, Pan Lu, Yixin Wan, Xueguang Ma, Jianyu Xu, Xinyi Wang, and Tony Xia. 2023. TheoremQA: A Theorem-driven Question Answering dataset. *arXiv preprint*.
- Chenghao Yang. 2024. Inference Time Compute.
- Aniket Didolkar, Anirudh Goyal, Nan Rosemary Ke, Siyuan Guo, Michal Valko, Timothy Lillicrap, Danilo Rezende, Yoshua Bengio, Michael Mozer, and Sanjeev Arora. 2024. Metacognitive Capabilities of LLMs: An Exploration in Mathematical Problem Solving. *arXiv preprint*.
- Kanishk Gandhi, Denise H. J. Lee, Gabriel Grand, Muxin Liu, Winson Cheng, Archit Sharma, and Noah Goodman. 2024. Stream of Search (SoS): Learning to Search in Language. In First Conference on Language Modeling.
- Peizhong Gao, Ao Xie, Shaoguang Mao, Wenshan Wu, Yan Xia, Haipeng Mi, and Furu Wei. 2024. Meta Reasoning for Large Language Models. *arXiv preprint*.
- Alex Havrilla, Sharath Raparthy, Christoforus Nalmpantis, Jane Dwivedi-Yu, Maksym Zhuravinskyi, Eric Hambro, and Roberta Raileanu. 2024. GLoRe: When, Where, and How to Improve LLM Reasoning via Global and Local Refinements. *arXiv* preprint.
- Keito Kudo, Yoichi Aoki, Tatsuki Kuribayashi, Shusaku Sone, Masaya Taniguchi, Ana Brassard, Keisuke Sakaguchi, and Kentaro Inui. 2024. Think-to-Talk or Talk-to-Think? When LLMs Come Up with an Answer in Multi-Step Reasoning. *arXiv preprint*.
- Kuang-Huei Lee, Ian Fischer, Yueh-Hua Wu, Dave Marwood, Shumeet Baluja, Dale Schuurmans, and Xinyun Chen. 2025. Evolving Deeper LLM Thinking. *arXiv preprint*.
- Bin Lei, Yi Zhang, Shan Zuo, Ali Payani, and Caiwen Ding. 2024. MACM: Utilizing a Multi-Agent System for Condition Mining in Solving Complex Mathematical Problems. *arXiv* preprint.
- Lihong Li, Wei Chu, John Langford, and Robert E. Schapire. 2012. A Contextual-Bandit Approach to Personalized News Article Recommendation.
- Xiaoxi Li, Guanting Dong, Jiajie Jin, Yuyao Zhang, Yujia Zhou, Yutao Zhu, Peitian Zhang, and Zhicheng Dou. 2025a. Search-o1: Agentic Search-Enhanced Large Reasoning Models. *arXiv preprint*.
- Yanyang Li, Michael Lyu, and Liwei Wang. 2025b. Learning to reason from feedback at test-time. *Preprint*, arXiv:2502.15771.

- Hunter Lightman, Vineet Kosaraju, Yura Burda, Harri Edwards, Bowen Baker, Teddy Lee, Jan Leike, John Schulman, Ilya Sutskever, and Karl Cobbe. 2023. Let's Verify Step by Step. *arXiv preprint*.
- Zhan Ling, Yunhao Fang, Xuanlin Li, Zhiao Huang, Mingu Lee, Roland Memisevic, and Hao Su. 2023. Deductive Verification of Chain-of-Thought Reasoning. *arXiv preprint*.
- Runze Liu, Junqi Gao, Jian Zhao, Kaiyan Zhang, Xiu Li, Biqing Qi, Wanli Ouyang, and Bowen Zhou. 2025. Can 1b llm surpass 405b llm? rethinking compute-optimal test-time scaling. *arXiv preprint arXiv:* 2502.06703.
- Rohin Manvi, Anikait Singh, and Stefano Ermon. 2024. Adaptive Inference-Time Compute: LLMs Can Predict if They Can Do Better, Even Mid-Generation. *arXiv preprint*.
- Bhrij Patel, Souradip Chakraborty, Wesley A. Suttle, Mengdi Wang, Amrit Singh Bedi, and Dinesh Manocha. 2024. AIME: AI System Optimization via Multiple LLM Evaluators. *arXiv preprint*.
- David Rein, Betty Li Hou, Asa Cooper Stickland, Jackson Petty, Richard Yuanzhe Pang, Julien Dirani, Julian Michael, and Samuel R. Bowman. 2023. GPQA: A Graduate-Level Google-Proof Q&A Benchmark. arXiv preprint.
- Noah Shinn, Federico Cassano, Ashwin Gopinath, Karthik Narasimhan, and Shunyu Yao. 2024. Reflexion: Language agents with verbal reinforcement learning. *Advances in Neural Information Processing Systems*, 36.
- Charlie Snell, Jaehoon Lee, Kelvin Xu, and Aviral Kumar. 2024. Scaling LLM Test-Time Compute Optimally can be More Effective than Scaling Model Parameters. *arXiv preprint*.
- Yuan Sui, Yufei He, Zifeng Ding, and Bryan Hooi. 2024a. Can Knowledge Graphs Make Large Language Models More Trustworthy? An Empirical Study over Open-ended Question Answering. *arXiv* preprint.
- Yuan Sui, Yufei He, Nian Liu, Xiaoxin He, Kun Wang, and Bryan Hooi. 2024b. FiDeLiS: Faithful Reasoning in Large Language Model for Knowledge Graph Question Answering. *arXiv preprint*.
- Yuan Sui, Mengyu Zhou, Mingjie Zhou, Shi Han, and Dongmei Zhang. 2024c. Table Meets LLM: Can Large Language Models Understand Structured Table Data? A Benchmark and Empirical Study. *arXiv* preprint.
- Xiaoxuan Wang, Ziniu Hu, Pan Lu, Yanqiao Zhu, Jieyu Zhang, Satyen Subramaniam, Arjun R. Loomba, Shichang Zhang, Yizhou Sun, and Wei Wang. 2024. SciBench: Evaluating College-Level Scientific Problem-Solving Abilities of Large Language Models. arXiv preprint.

- Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc V Le, Ed H Chi, Sharan Narang, Aakanksha Chowdhery, and Denny Zhou. 2022. Self-consistency improves chain of thought reasoning in language models. In *The Eleventh International Conference on Learning Representations*.
- Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. 2022. Chain-of-thought prompting elicits reasoning in large language models. Advances in Neural Information Processing Systems, 35:24824–24837.
- Yixuan Weng, Minjun Zhu, Fei Xia, Bin Li, Shizhu He, Shengping Liu, Bin Sun, Kang Liu, and Jun Zhao. 2023. Large Language Models are Better Reasoners with Self-Verification. *arXiv* preprint.
- Huanjin Yao, Jiaxing Huang, Wenhao Wu, Jingyi Zhang, Yibo Wang, Shunyu Liu, Yingjie Wang, Yuxin Song, Haocheng Feng, Li Shen, and Dacheng Tao. 2024. Mulberry: Empowering mllm with o1-like reasoning and reflection via collective monte carlo tree search. arXiv preprint arXiv: 2412.18319.
- Shunyu Yao, Dian Yu, Jeffrey Zhao, Izhak Shafran, Thomas L. Griffiths, Yuan Cao, and Karthik Narasimhan. 2023. Tree of Thoughts: Deliberate Problem Solving with Large Language Models. *arXiv preprint*.
- Ori Yoran, Tomer Wolfson, Ben Bogin, Uri Katz, Daniel Deutch, and Jonathan Berant. 2024. Answering Questions by Meta-Reasoning over Multiple Chains of Thought. *arXiv preprint*.

A Baselines

We consider several established prompting methods as baselines as follows:

- Chain-of-thought (CoT) (Wei et al., 2022): A
 prompting technique that encourages models to
 generate intermediate reasoning steps to enhance
 problem-solving capabilities.
- Self-Consistent Chain of Thought (SC-CoT) (Wang et al., 2022): An extension of CoT that improves reasoning consistency by generating multiple reasoning chains and selecting the most consistent answer.
- Multi-Chain Reasoning (MCR) (Yoran et al., 2024): enhances SC-CoT by having another LLM to assess and integrate content among the sampled reasoning chains to generate the final consistent answer.
- Tree of Thoughts (ToT) (Yao et al., 2023): A
 method that explores multiple reasoning paths in
 a tree structure, allowing the model to consider
 various possibilities before arriving at a conclusion by tree search algorithms.
- Reflexion (Shinn et al., 2024): A framework that enables models to reflect on their reasoning process, iteratively refining their answers based on feedback.
- MACM (Lei et al., 2024): A multi-agent system to refine the reasoning based on iterative condition mining.

B Computational Efficiency

B.1 Why Measure Efficiency Through Token Usage?

Evaluating the computational efficiency of LLMs is a critical yet nuanced task. A natural metric is wall-clock time, which directly reflects the real-world latency experienced during LLM inference. However, when interacting with LLMs primarily through API calls, as what we do in this paper, wall-clock time measurements become unreliable and difficult to interpret. This unreliability arises from several uncontrollable factors, including network latency, server-side load balancing, and dynamic optimizations on the provider's infrastructure. These external variables introduce noise and variability that obscure the intrinsic computational characteristics of the reasoning method itself.

To address these challenges, we adopt token usage as a more stable and conceptually meaningful

proxy for computational cost. Token consumption directly correlates with the amount of computation performed by the LLM and is widely recognized in recent literature as a standard efficiency metric (Liu et al., 2025; Li et al., 2025b). By focusing on token reduction, we provide a consistent basis for comparing reasoning strategies that is less susceptible to external system variability.

B.2 Iterative Reasoning and Memory Management

Unlike traditional CoT methods that generate reasoning process in a single pass, Meta-Reasoner pauses generation periodically to evaluate the reasoning progress and adaptively switch the reasoning strategies using a multi-armed bandit-based algorithm. This iterative design adds additional memory overhead due to maintaining context across multiple LLM calls. To mitigate this, we summarize the entire reasoning history into compact progress reports (§4.2), greatly reducing the token load per iteration. For example, a typical 1000-token CoT step may consume approximately 500MB of KV cache (e.g., using LLaMa-2-7B in float16 precision), while our method's 5 iteration with 100-token steps peak at roughly 50MB each. Additionally, early pruning of unlikely reasoning paths further controls memory usage.

B.3 Managing Reward Model Overhead

To minimize the computational cost of the reward model, our design relies on summarized progress reports rather than the full reasoning history, thereby reducing token usage and associated processing overhead. The reward computation is further optimized by employing the LinUCB algorithm, a MAB method whose complexity scales linearly with the number of strategies. Since the number of strategies remains relatively small—typically between 3 and 5 in fixed settings and up to 10 to 15 in dynamic settings—the computational burden remains manageable. As demonstrated in Figure 2, the savings achieved by avoiding unproductive reasoning paths significantly outweigh the modest overhead introduced by the strategy selection process, resulting in an overall efficient reward computation framework.

C Stability of Dynamic Strategy Generation

Dynamically adding or refining strategies, as discussed in §4.3 (dynamic contextual bandit), en-

hances flexibility but risks instability. To address this trade-off, our approach incorporates several key mechanisms:

We begin with a small set of verified strategies (Table 1) to establish a stable foundation and prevent arbitrary generation. Building on this, the LLM generate contextually relevant and precise strategies, like "Pause to clarify and disambiguate the current reasoning" and "Simplify by decomposing the task into smaller, manageable sub-tasks", demonstrate how the meta-reasoner effectively targets specific reasoning bottlenecks.

Second, we employ a contextual multi-armed bandit to balance exploration and exploitation, filtering out suboptimal strategies during LLM inference time. As shown in Table 6, the dynamic bandit variant achieves 89% accuracy on task Gameof-24, significantly surpassing fixed strategy sets (65%–72%). This highlights the dynamic bandit's ability to prioritize effective strategies while discarding less useful ones.

Third, the reward function described in §4.3 provides immediate feedback on strategy performance, enabling rapid deprioritization of confusing or unproductive strategies. Figure 3 shows a consistent increase in cumulative rewards over iterations, indicating that the system maintains coherent reasoning as it incorporates new strategies.

Together, these mechanisms enable the dynamic contextual bandit to maintain stability without compromising adaptability. The observed performance gains on both the Game-of-24 and TheoremQA datasets (Table 6) show that the benefits of dynamic strategy generation substantially outweigh potential instability concerns in practice.

Algorithm 1 Meta-Reasoner: Meta-Reasoning with Contextual Multi-Armed Bandits

```
Require: LRM M, bandit \mathcal{B}, initial strategy set \mathcal{A}_1, maximum rounds T
Ensure: Final answer A_{\text{final}}
 1: C_0 \leftarrow \emptyset; \mathcal{B}.Initialize(\mathcal{A}_1)
 2: G_0 \leftarrow default strategy
 3: for t = 1 to T do
 4:
         if t > 1 then
             P_{t-1} \leftarrow f(C_{t-1}) \\ x_{t-1} \leftarrow \text{FeatureExtract}(P_{t-1})
 5:
                                                                                                                          // Summarize the existing CoT
 6:
                                                                                                                           // Extract features for context
 7:
             (Optional): A_t \leftarrow A_{t-1} \cup \{\text{new strategies}\}
                                                                                                                     // Update strategy set dynamically
 8:
             a_{t-1} \leftarrow \arg\max_{a \in \mathcal{A}_t} \operatorname{Score}_{\mathcal{B}}(x_{t-1}, a)
                                                                                                                           // Select strategy using bandit
 9:
             G_t \leftarrow a_{t-1}
                                                                                                                                    // Set current guidance
10:
         else
11:
             G_t \leftarrow G_0
                                                                                                         // Use default guidance for the first iteration
12:
          end if
13:
         s_t \leftarrow M(C_{t-1}, G_t)
                                                                                                     // Generate new CoT with integrated guidance
14:
         C_t \leftarrow C_{t-1} \cup \{s_t\}
                                                                                                             // Append new reasoning step to the CoT
15:
         r_t \leftarrow \text{ComputeReward}(C_t)
                                                                                                      // Compute reward based on the updated CoT
          if t > 1 then
16:
17:
             \mathcal{B}.Update(x_{t-1}, a_{t-1}, r_t)
                                                                                                             // Update bandit with observed feedback
18:
19:
         if termination condition met then
20:
             break
         end if
21:
22: end for
23: A_{\text{final}} \leftarrow \text{ExtractAnswer}(C_t)
24: return A_{\text{final}}
```

Progress Report Prompt:

You are an advanced Al summarizer with expertise in extracting and condensing key insights from recent developments. Your goal is to create a concise progress report based on the provided information.

Read the task description and the chain of thoughts generated so far. Please ignore the <examples> section which is only for the demonstration of the task.

And then complete the following template:

Current Attempts:

[Insert the list of previous attempts here]

Analysis Instructions:

- 1. Systematically review each attempted step
- 2. Identify patterns in the current solution attempts
- 3. Provide observations regarding:
 - Recurring strategies
 - Missed opportunities
 - Potential promising approaches
 - Any mathematical observations about the number combination

Output Format:

- Provide a structured analysis
- Include bullet points for key observations

Constraints:

- Use clear, logical reasoning
- Focus on mathematical problem-solving approaches
- Avoid random guessing
- Make the analysis short and to the point (around 6-7 sentences)

Meta-reasoner for New Strategy Generation:

You are a Meta-reasoner, tasked with analyzing the reasoning process of another agent and providing guidance for its further steps. Your goal is to improve the efficiency and effectiveness of that agent's problem-solving approach.

Review the task description and the summary of the recent reasoning progress below: {PROGRESS_REPORT}

Provide feedback in the following format:

Figure 4: Prompt Demonstration (Page-1)

- Reflection: What is the current strategy of the agent to solve the task? Has the agent made sufficient progress? Are there any mistakes or misconceptions in the intermediate steps? Is the agent taking unnecessary detours or repeating steps?
- Fact Check: Are the agent's statements accurate and relevant to the task? Are there any logical errors or incorrect assumptions?
- Thought: What are the key insights or strategies that the agent should focus on? Are there alternative methods or perspectives that could be beneficial?
- Action: The action to take

Make your response precise and focused without unnecessary details.

LLM for CoT Generation:

You are an Al assistant tasked with generating steps to solve mathematical problems. Your role is to read a task description, consider the current step (if any), and generate the next logical step towards solving the problem. You will also receive feedback from a Meta-reasoner, which you should take into account when determining your next step.

Here is the task description: <task_description> {TASK_DESCRIPTION} </task_description>

The process will work as follows:

- 1. You will be given the current step (if any) in the problem-solving process.
- 2. You will also receive feedback from the Meta-reasoner about the previous step.
- 3. Your job is to generate the next logical step towards solving the problem, taking into account the task description, the current step, and the Meta-reasoner's feedback.

To generate the next step:

- 1. Carefully analyze the task description, the current step (if any), and the Meta-reasoner's feedback.
- 2. If the Meta-reasoner suggests backtracking, consider how to modify or correct the previous step.
- 3. If the Meta-reasoner suggests continuing, think about the logical progression from the current step.
- 4. If the Meta-reasoner suggests changing strategy, brainstorm alternative approaches to the problem.
- 5. Formulate a clear, concise next step that moves towards solving the problem.

Your response should be a single, well-thought-out step that progresses the problem-solving process. Do not solve the entire problem at once; focus on generating just the next logical step.

Please provide your next step within <next_step> tags. Before giving your next step, explain your reasoning within <reasoning> tags. Explicitly state whether the problem is solved or not before providing the next step or final answer.

If you believe there has been enough progress to solve the problem completely, generate the final answer in the form of \\boxed{{answer}} at the end of your response. The answer should be a numerical value.

Your response should follow this structure:

Figure 5: Prompt Demonstration (Page-2)

<reasoning>

[Explain your thought process here, considering the task description, current step, and Meta-reasoner feedback (make sure to address any issues raised by the Meta-reasoner).

The reasoning should be clear, logical, and directly related to the problem-solving process.] </reasoning>

<next_step>
[Provide the next logical step here]
</next_step>

[State whether the problem is solved or not]

[If the problem is solved] Return only the Final answer: \boxed{{numerical_value}}

Remember to focus on generating just the next logical step, not solving the entire problem at once (unless you've reached the final solution). Your explanation and step should be clear, concise, and directly contribute to solving the mathematical problem at hand.

Here is the current step (if this is the first step, this will be empty): <current_step> {CURRENT_STEP} </current_step>

And here is the feedback from the Meta-reasoner (if this is the first step, this will be empty): <meta_reasoner_feedback> {META_REASONER_FEEDBACK} </meta_reasoner_feedback>

Progress Evaluation:

Current State: CONDITIONS: {conditions_text}

OBJECTIVES: {objectives_text}

Please evaluate the progress considering these aspects and provide scores in exactly this format:

OBJECTIVE_COMPLETION:

[Score 0-1] - Evaluate how many objectives are completed or near completion

PROGRESS_QUALITY:

[Score 0-1] - Assess the quality and correctness of the progress made

EFFICIENCY:

[Score 0-1] - Evaluate how directly and efficiently the progress is being made

Figure 6: Prompt Demonstration (Page-3)

STRATEGY_ALIGNMENT:

[Score 0-1] - Rate how well the current conditions align with achieving the objectives

FINAL_SCORE:

[Combined score] - Weighted average using these weights:

Objective Completion: 40%Progress Quality: 30%

- Efficiency: 15%

- Strategy Alignment: 15%

Important:

- Provide numerical scores only
- Each score must be between 0 and 1
- FINAL_SCORE should be the weighted calculation of all scores

Figure 7: Prompt Demonstration (Page-4)