Direct Behavior Optimization: Unlocking the Potential of Lightweight LLMs

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Abstract

Lightweight Large Language Models (LwLLMs) are reduced-parameter, optimized models designed to run efficiently on consumer-grade hardware, offering significant advantages in resource efficiency, cost-effectiveness, and data privacy. However, these models often struggle with limited inference and reasoning capabilities, which restrict their performance on complex tasks and limit their practical applicability. Moreover, existing prompt optimization methods typically rely on extensive manual effort or the meta-cognitive abilities of state-of-the-art LLMs, making them less effective for LwLLMs.

To address these challenges, we introduce DeBoP, a new Direct Behavior Optimization Paradigm, original from the Chain-of-Thought (CoT) prompting technique. Unlike CoT Prompting, DeBoP is an automatic optimization method, which focuses on the optimization directly on the behavior of LwLLMs. In particular, DeBoP transforms the optimization of complex prompts into the optimization of discrete, quantifiable execution sequences using a gradient-free Monte Carlo Tree Search. We evaluate DeBoP on seven challenging tasks where state-of-the-art LLMs excel but LwLLMs generally underperform. Experimental results demonstrate that DeBoP significantly outperforms recent prompt optimization methods on most tasks. In particular, DeBoP-optimized LwLLMs surpass GPT-3.5 on most tasks while reducing computational time by approximately 60% compared to other automatic prompt optimization methods.[1]

1 Introduction

Large language models (LLMs) have revolutionized the field of natural language processing, achieving remarkable performance in diverse tasks such as complex text analysis (Wan et al., 2024), advanced mathematical reasoning (Imani et al., 2023), and creative writing (Qin et al., 2024). However, these advancements are accompanied by significant computational demands, as exemplified by the new LLaMA model, which comprises 405B parameters (Meta, 2025). This challenge has driven extensive research efforts to develop efficient alternatives, leading to the emergence of lightweight LLMs (LwLLMs) optimized for consumer-grade hardware (Wan et al., 2023). Notably, LwLLMs with 3B-parameter models can operate on mainstream GPUs like NVIDIA®GeForce RTX 4060 (8GB VRAM). Moreover, LwLLMs offer enhanced security and compliance over models accessed via APIs (Bommasani et al., 2021), as they operate entirely within the institution's internal network. This significantly mitigates the risk of sensitive data leakage through public networks (Wu et al., 2024; Reuters, 2023).

Despite their resource efficiency and enhanced security, LwLLMs often struggle with advanced inference and multi-step reasoning on complex tasks (Opencompass, 2025). One promising solution to this issue is prompt optimization, which can be broadly classified into manual and automatic techniques. Manual methods, while effective, require significant human effort, making them impractical in resource-constrained environments. On the other hand, automatic methods have broader applicability but often rely on the meta-cognitive capabilities (Flavell, 1976) of LLMs, such as iterative self-reflection (Pryzant et al., 2023; Sun et al., 2023), planning (Gao et al., 2023a; Liu et al., 2023b), and detailed reasoning traces(Liu et al., 2024; Zhou et al., 2024), which LwLLMs struggle to handle efficiently. More critically, the hierarchical reasoning structures in these methods can lead to rapid error propagation and accumulation (as illustrated in Figure 1), which may ultimately

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[1]The official implementation of DeBoP is available at: https://github.com/VastOcean-Yang/DeBoP.git. This work is accepted at ACL 2025.

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degrade performance to levels even lower than simpler methods, such as Direct Prompting (see Table 1 for details).

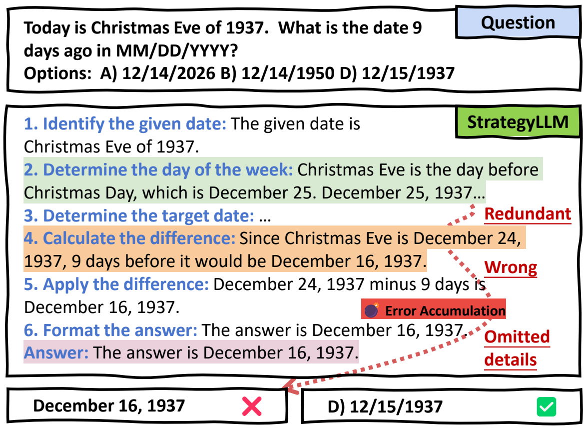


Figure 1: A toy example demonstrating how StrategyLLM (Gao et al., 2023a) fails on LwLLMs. The strategies used by StrategyLLM are highlighted in **blue**. Due to the limited reasoning capabilities of LwLLMs, the accumulation of **redundant** reasoning, **wrong** reasoning, and **omitted details** leads to an incorrect final answer.

To address these challenges, we in this paper introduce DeBoP, a novel Direct Behavior Optimization Paradigm, which directly optimizes the behavior of LwLLMs. Inspired by the experimental results in Table 1, DeBoP adopts the basic Chain-of-Thought (CoT) prompting (Wei et al., 2022), which involves a series of demonstrations. Furthermore, DeBoP reformulates the optimization of the behavior of LwLLMs as the optimization of solutions within the demonstrations. In particular, it decouples the solution into a structured plan consisting of a series of key steps and its corresponding execution, then optimizes them by applying a gradient-free Monte Carlo Tree Search (MCTS). This eliminates the need for implicit metacognitive mechanisms required by existing optimization methods. Moreover, DeBoP offers the advantage of being independent of external LLM APIs and eliminates the need for labor-intensive manual prompt engineering, further highlighting its applicability.

The contributions of this paper can be summarized as follows. 1) We propose an automated behavior optimization method tailored for LwLLMs, significantly expanding the applicability of LLMs in resource- and security-sensitive settings. 2) We design an external optimizer based on a gradient-free MCTS framework, which effectively quantifying prompt design and eliminating the need for advanced meta-cognitive capabilities. 3) We empirically demonstrate the effectiveness of DeBoP across several challenging tasks where state-of-the-art LLMs typically excel (Opencompass, 2025), and only the combination of LLaMA3-8B and DeBoP can outperform GPT-3.5 on most tasks while reducing the time consumption of LwLLMs by approximately 60% compared to other automatic prompt optimization methods.

2 Methodology

As introduced earlier, DeBoP is derived from the CoT Prompting, which employs a series of demonstrations. In each demonstration, a question is paired with its corresponding solution that represents the behavior of the LwLLM. DeBoP focuses on automatically optimizing these solutions and decomposing each solution into key-step plan and their corresponding executions. Therefore, DeBoP addresses the generation of key-step plan and executions, the optimization of the solution, and the instructions for LwLLMs to execute them. Accordingly, DeBoP consists of four phases: PLANNING, COLLECTING, MCTS and TEACHING. The corresponding high-level description is given in Fig. 2, and the detailed descriptions of each phase are provided in Section 2.2.1 through 2.2.4.

2.1 Objective and Framework Overview

Our goal is to automatically find an optimal behavior b^* in the behavior space $\mathcal{B}$ of the LwLLM that maximizes its overall performance on a development set of N input-output pairs, denoted as $\mathcal{S}_{\text{dev}} = \{(x_i, y_i)\}_{i=1}^{N}$. In our formulation, the behavior space $\mathcal{B}$ is defined as the set of all possible executable behavior trajectories that the LwLLM can exhibit when guided by different structured demonstrations.

Each behavior $b \in \mathcal{B}$ corresponds to a complete trajectory of actions or decisions the LwLLM takes in response to a task, which is instantiated by a structured demonstration d_b. Due to the combinatorial nature of the action sequences and demonstration configurations, the space $\mathcal{B}$ is intractably large and not explicitly constructed. Instead, we treat $\mathcal{B}$ as an implicitly searchable space, where promising behaviors can be identified through guided exploration.

Based on DeBoP, we reformulate the original optimization problem as the search for a demon-

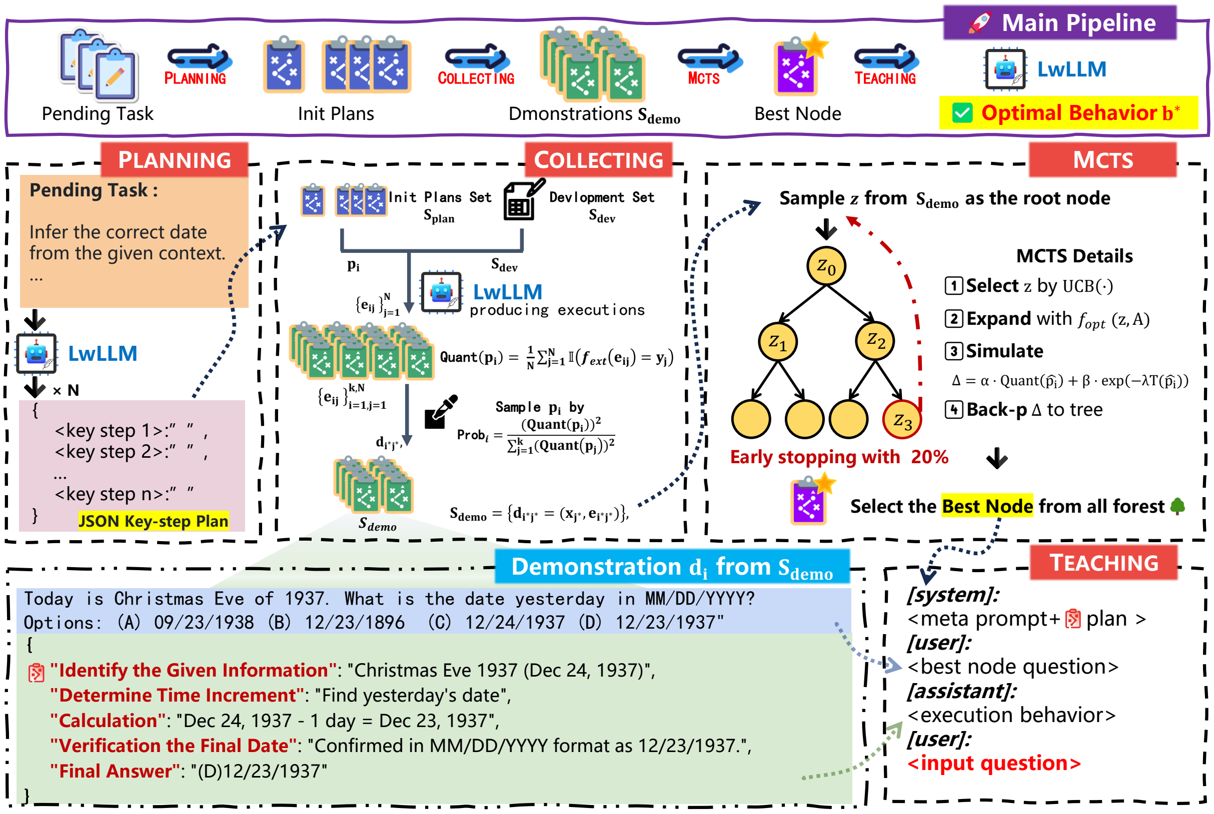


Figure 2: Overview of the DeBoP framework. As shown in the lower left corner, the demonstration, which serves as the primary target of our optimization, consists of a question, a **plan**, and the corresponding execution behavior. The "Pending Task" refers to the downstream task whose performance needs to be optimized for the LwLLM.

stration d_b that induces a high-performing behavior b. The effectiveness of a behavior is evaluated by a function:

$$\mathtt{Eval}\big(\mathtt{LwLLM}(d_b), \mathcal{S}_{\mathtt{dev}}\big),$$

which measures the LwLLM's output quality on the development set after being guided by d_b.

Formally, we aim to identify:

$$b^* = \arg\max_{b \in \mathcal{B}} \mathtt{Eval}\big(\mathtt{LwLLM}(d_b), \mathcal{S}_{\mathtt{dev}}\big).$$

To obtain the optimal behavior b^*, as illustrated in Fig. 2, our framework proceeds in four stages: (1) PLANNING generates a set of feasible initial key-step plans $\mathcal{S}_{\mathtt{plan}}$, where each plan is encoded in a standardized JSON format to reduce the complexity of hierarchical reasoning for LwLLMs. (2) COLLECTING executes and evaluates these plans on the development set $\mathcal{S}_{\mathtt{dev}}$, selecting high-performing demonstrations to form a seed set $\mathcal{S}_{\mathtt{demo}}$ for iterative refinement. (3) MCTS constructs demonstration search forest using reinforcement learning, specifically, a gradient-free Monte Carlo Tree Search algorithm, to explore and optimize the solution of the demonstration. (4) Finally, TEACHING applies the best-found demonstration node to guide the LwLLM via a teaching mechanism, thereby inducing the optimal behavior b^*.

Further algorithmic and implementation details are provided in the following sections.

2.2 Descriptions of DeBoP

2.2.1 PLANNING Phase

In this phase, DeBoP aims to generate a set of feasible key-step plans $\mathcal{S}_{\mathtt{plan}} = \{p_1, p_2, \ldots, p_k\}$, where p_i has the form

{"<Key Step 1>": " ", "<Key Step2>": " ", . . . }

The generation algorithm for these key-step plans consists of two stages.

In the first stage, we use a universal meta-prompt to guide the LwLLM in synthesizing task-specific guidelines from a few in-domain examples. These guidelines are concise, instructive summaries that describe how to decompose the task into generalizable reasoning steps (e.g., “extract the reference date” or “subtract a time interval” for DU tasks). Notably, while the guidelines are tailored to the specific task, the meta-prompt used to generate them is model-aligned but task-agnostic, allowing reuse across various domains.

In the second stage, the generated guideline is converted into a structured, standardized plan in JSON format, with each step represented as a key mapped to an empty string. This explicit structure simplifies downstream reasoning for LwLLMs by reducing ambiguity and cognitive burden. Due to space limitations, the detailed templates are provided in Appendix A.1.

2.2.2 COLLECTING Phase

After obtaining the set of key-step plans $\mathcal{S}_{\texttt{plan}}$ from PLANNING, DeBoP constructs a set $\mathcal{S}_{\texttt{demo}}$ of high performance demonstrations in the following two stages. In the first stage, we request the LwLLM to complete the value of each key-step plan p_i $(i = 1, \cdots, k)$ on each x_j $(i = 1, \cdots, N)$ in $\mathcal{S}_{\texttt{dev}}$, producing an execution e_{ij} with the format

{"<Key Step 1>": "<Execution 1>",
"<Key Step 2>": "<Execution 2>",
... }

The performance of each key-step plan p_i is then quantified using

$$\texttt{Quant}(p_i) = \frac{1}{N}\sum_{j=1}^{N}\mathbb{I}\Big(f_{\texttt{ext}}(e_{ij}) = y_j\Big),$$

where $f_{\texttt{ext}}$ is a heuristic function that extracts the final prediction from e_{ij}, and $\mathbb{I}(\star)$ outputs 1 if $\star$ is True, or 0 otherwise.

In the second stage, we determine the selection probability of each plan p_i through a non-linear transformation of the performance metrics, using

$$\texttt{Prob}_i = \frac{\big(\texttt{Quant}(p_i)\big)^{\alpha}}{\sum_{j=1}^{k}(\texttt{Quant}(p_j))^{\alpha}},$$

where $\alpha = 2$ in our experiments[2]. Once a key-step plan p_{i^*} $(i^* \in \{1, \cdots, k\})$ is selected, we randomly chooses a j^* from $\{1, \cdots, N\}$ such that $f_{\texttt{ext}}(e_{i^*j^*}) = y_{j^*}$ holds. This results in a selected demonstration $d_{i^*j^*} = (p_{i^*}, x_{j^*}, e_{i^*j^*})$. Ultimately, the desired set $\mathcal{S}_{\texttt{demo}}$ is constructed as:

$$\mathcal{S}_{\texttt{demo}} = \{d_{i^*j^*} = (x_{j^*}, e_{i^*j^*})\}.$$

2.2.3 MCTS Phase

In this phase, DeBoP utilizes the demonstrations d_i's in $\mathcal{S}_{\texttt{demo}}$ from COLLECTING to identify the possible optimal demonstration d'_{b*}. Specifically, the possible optimal demonstration d'_{b*} is selected from a newly constructed demonstration forest. In this forest, the root node of each demonstration tree corresponds to a random demonstration d_i from $\mathcal{S}_{\texttt{demo}}$, while all other nodes of the tree are variants of the root node. The process of generating these nodes follows four stages: Selection, Expansion, Simulation, and Back-propagation, all of which are adopted from the MCTS framework.

Selection. For a given demonstration tree under construction, we first select a node z^* for expansion based on the Upper Confidence Bound (UCB) (Kocsis and Szepesvári, 2006). In particular, we select an unexpanded node z^* with a breadth-first-search-type method using the following equation:

$$z^* = \arg\max_{z\in\text{children}(z^*_{\text{p}})}\left(\frac{Q(z)}{N(z)} + c\sqrt{\frac{2\ln N(z^*_{\text{p}})}{N(z)}}\right)$$

where z^*_{p} denotes the parent node of z^*, children(z) represents the set of child nodes of node z, $Q(z)$ is the accumulated reward of node z, $N(z)$ is the visit count of node z, and c is an exploration coefficient. Note that a node is considered unexpanded if it does not have enough child nodes, and its reward value is initialized to zero, being updated during the Back-propagation phase.

Expansion. Once an unexpanded node z^* is selected in stage Selection, we randomly choose one of the node evolution methods to apply on z^* in order to obtain a new node z. This new node z is then added to the tree as the child node of the selected node z^*. The underlying evolution methods are as follows.

Consolidation: Request the LwLLM to identify key-steps that can be combined to streamline the reasoning process to improve the coherence.

Decomposition: Request to LwLLM to Identify key-steps that can be further decomposed to enhance execution ease and accuracy.

Elaboration: Request the LwLLM to expand the reasoning flow to ensure no missing details of the problem-solving process.

Pruning: Request the LwLLM to dropout the least significant key-step and its corresponding execution in the demonstration to improve the efficiency.

Resampling: Request the LwLLM to resample to generate a new demonstration.

[2] we use $\alpha = 2$ to slightly amplify the selection pressure in favor of higher-performing plans

Simplification: Request the LwLLM to simplify and restructure the reasoning flow to improve the conciseness, coherence, and logical clarity.

The above procedure can be denoted as $f_{\texttt{opt}}$:

$$z \leftarrow f_{\texttt{opt}}(z^*, \mathcal{A}),$$

where $\mathcal{A}$ represents the set of the six node evolution methods. Due to the space limitations, detailed prompts for each method are provided in Appendix A.3.

Simulation. After the new node z is added, we request the LwLLM to learn the corresponding demonstration $\hat{d} = (\hat{p}_i, \hat{x}_j, \hat{e}_{ij})$ via a teaching mechanism (see details of the teaching mechanism in Section 2.2.4). Following this, we run a process similar to the first stage of COLLECTING to obtain $\texttt{Quant}(\hat{p}_i)$. The only difference is that the LwLLM now has access to one additional execution $\hat{e}_{ij}$ from the demonstration $\hat{d}$, compared to the process in COLLECTING.

Finally, we compute the value of Δ for $\hat{p}_i$ as:

$$\Delta = \underbrace{\alpha \cdot \texttt{Quant}(\hat{p}_i)}_{\text{Execution Accuracy}} + \underbrace{\beta \cdot \exp(-\lambda T(\hat{p}_i))}_{\text{Time Efficiency}},$$

where $T(\hat{p}_i)$ is the average execution time when using key-step plan $\hat{p}_i$ on each x_j in $\mathcal{S}_{\texttt{dev}}$, and α, β, and λ are hyper-parameters that control the trade-off between accuracy and temporal efficiency. In our experiment, they are set to 1, 1 and 0.5, respectively.

Back-propagation. In this stage, the value Δ of the node z obtained from stage Simulation will be propagated back up to the root node of the same tree, and the corresponding visit counts should be also updated accordingly. These operations can be denoted as:

$$Q(z') \leftarrow Q(z') + \Delta, \; N(z') \leftarrow N(z') + 1,$$

where z' is the node along the path from node z to the corresponding root node.

These four stages are typically performed iteratively for a predefined number of iterations, during which the demonstrations are progressively updated. However, to enhance computational efficiency, we have incorporated a probabilistic early termination at each iteration. In our experiments, the probability of early termination is set to 20%. The possible optimal demonstration d'_{b*} is finally determined by the node with the highest accumulated reward in the built forest.

2.2.4 TEACHING Phase

After obtaining the possible optimal demonstration $d'_{b*} = (p'_i, x'_j, e'_{i,j})$, we integrate it into the conversation history of the LwLLM, as illustrated in the part of TEACHING in Fig. 2. This process effectively "teaches" the LwLLM by embedding the optimal demonstration, guiding it to replicate the desired behaviors. By doing so, we ensure that the LwLLM adheres to high-quality execution patterns that have been proven effective, while simultaneously accommodating the model's inherent reasoning constraints.

3 Experiments

3.1 Tasks and Datasets

Language comprehension and complex reasoning are two key aspects used to evaluate the NLP capabilities of LLMs. Therefore, in our experiments, we focus on assessing DeBoP's performance in these two areas. The tasks selected for evaluation are drawn from BIG-Bench Hard (BBH) (Suzgun et al., 2022), a challenging subset of BIG-Bench tasks (Srivastava et al., 2022). Specifically, the chosen tasks include Snarks (SNK), Disambiguation QA (DQA), Hyperbaton (HB), Penguins in a Table (PIT), Data Understanding (DU), Logical Deduction (LD), and Movie Recommendation (MR). These tasks were selected because they collectively test both language comprehension (e.g., SNK, DQA, HB) and complex reasoning abilities (e.g., PIT, DU, LD, MR).

3.2 Baseline Methods

To highlight the advantages of DeBoP, we compare it with two categories of prompt optimization methods: manual and automatic. The manual methods include Direct Prompting (DP) and CoT Prompting (Wei et al., 2022), while the automatic methods include StrategyLLM (Gao et al., 2023a) and Self-Discover (Zhou et al., 2024).

DP is the simplest approach, where the prompt consists of a set of question-answer pairs without any intermediate reasoning steps. CoT Prompting (Wei et al., 2022) enhances DP by incorporating step-by-step reasoning within the prompt, enabling multi-step solutions that leverage the LLM's reasoning capabilities. StrategyLLM (Gao et al., 2023a) takes a more advanced approach by using four distinct agents—strategy generator, executor, optimizer, and evaluator—working collaboratively to generate, evaluate, and select promis-

	PIT	DU	SNK	DQA	LD	HB	MR	Avg.
DP	52 / 44	32 / 42	49 / 55	42 / 30	51 / 45	76 / 70	61 / 52	51.9 / 49.4
CoT Prompting	62 / **69**	59 / 47	68 / 56	63 / 49	75 / 66	**95 / 71**	66 / 51	69.7 / 58.1
StrategyLLM	32 / 27	41 / 28	69 / 51	63 / 53	57 / 38	78 / 49	60 / 22	57.1 / 38.6
Self-Discover	72 / 43	50 / 46	53 / 60	57 / 43	53 / 44	63 / 53	50 / 42	56.9 / 48.7
DeBoP (Ours)	**83** / 67	**84 / 74**	**76 / 74**	**70 / 56**	**87 / 74**	82 / 59	**74 / 59**	**79.4 / 66.1**
GPT-3.5	79	85	67	63	80	86	74	76.3

Table 1: Model accuracy comparison (%) across seven tasks: PIT, DU, SNK, DQA, LD, HB, and MR. Most of cells in the table display results in the format "x / y", where "x" represents the performance of LLaMA3-8B and "y" represents the performance of LLaMA3.2-3B. GPT-3.5 serves as the reference model. The **boldface** highlights the best result(s) for each LwLLM on a given task.

ing strategies for a given task. Similarly, Self-Discover (Zhou et al., 2024) employs a three-phase process, including Select, Adopt, and Implement, to leverage the capabilities of LLMs. Further details can be found in Appendix B.

3.3 Setting

Our experiments utilize LLaMA3.2-3B (Meta, 2024b) and LLaMA3-8B (Meta, 2024a) as the primary LwLLMs. Furthermore, we used nearly identical demonstrations for DP and CoT Prompting, with the key difference being that CoT Prompting includes step-by-step solutions. For DeBoP, we set five key-step plans for each task and applied temperature sampling ($\texttt{temp} = 0.7$) for both PLANNING and COLLECTING phase. For the MCTS phase, we employed greedy decoding ($\texttt{temp} = 0$) and limited the maximum number of iterations to 50.

All experiments were conducted on a computing system with the following specifications: an NVIDIA GeForce RTX 4090 24GB GDDR6X Blower Edition GPU, an Intel Xeon Gold 6148 processor (20 cores, 40 threads, 2.4 GHz base frequency), a Supermicro X11DPG-QT dual-socket LGA3647 server motherboard, and 32GB of Samsung DDR4-3200 Registered ECC (RDIMM) memory. The result of GPT3.5 was referenced from Opencompass, 2025

To balance cost and efficiency, we conducted all experiments on a randomly selected 50-sample subset as $\mathcal{S}_{\texttt{dev}}$ and a 100-sample subset as $\mathcal{S}_{\texttt{test}}$ from the original dataset, using a fixed random seed (42).

3.4 Results

3.4.1 Model Performance Comparison

The results in Table 1 provide a detailed accuracy comparison of DeBoP against recent prompt optimization methods across seven tasks (PIT, DU, SNK, DQA, LD, HB, and MR), as well as GPT-3.5, which serves as a baseline. DeBoP consistently outperforms the other methods across most tasks. Notably, the average accuracy of DeBoP with LLaMA3-8B is the highest among all the methods tested, surpassing GPT-3.5 (76.3%) and other optimization strategies like CoT Prompting, StrategyLLM, and Self-Discover. These results demonstrate that DeBoP, through its key-step planning and optimization via MCTS, achieves superior performance across multiple tasks compared to other methods. It is also worth noting that while CoT Prompting achieves the highest accuracy on the HB task, this success is largely attributed to the use of meticulously handcrafted prompts.

3.4.2 Efficiency Comparison

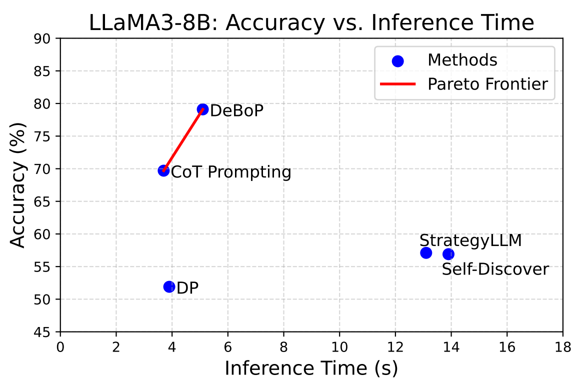


Figure 3: Pareto Frontier Analysis.

Table 2 presents an efficiency comparison (in

	PIT	DU	SNK	DQA	LD	HB	MR	Avg.
DP	6.5	5.5	2.4	2.0	3.7	4.1	3.2	3.9
CoT Prompting	4.3	3.4	1.4	3.4	3.9	2.4	6.9	3.7
StrategyLLM	5.5	11.3	13.2	11.5	14.9	11.9	23.5	13.1
Self-Discover	14.5	12.8	10.9	8.3	13.7	18.1	18.9	13.9
DeBoP (Ours)	7.3	3.6	4.2	4.4	7.5	4.5	4.4	5.1

Table 2: Efficiency comparison (in seconds) for LLaMA3-8B across different methods.

seconds) for LLaMA3-8B across seven tasks (PIT, DU, SNK, DQA, LD, HB, and MR), as well as the average inference time for various prompt optimization methods. Manual prompt optimization methods generally achieve higher efficiency than automatic ones. However, these efficiency gains come at the cost of significant manual effort. In contrast, DeBoP demonstrates comparable efficiency to manual methods while maintaining automation. For instance, DeBoP completes the DU task in 3.6 seconds, which is close to CoT Prompting (3.4s) and significantly faster than DP (5.5s). Compared to other automatic methods, DeBoP reduces the average inference time by approximately 61% relative to StrategyLLM and 63% relative to Self-Discover.

Figure 3 further illustrates DeBoP's performance through a Pareto Frontier Analysis, balancing accuracy and inference time. The red line represents the Pareto Frontier, where improving one metric (either accuracy or inference time) would require sacrificing the other. DeBoP, marked in the figure, achieves high accuracy (80%) while maintaining relatively low inference time (5s), placing it on the Pareto Frontier as an optimal trade-off between efficiency and accuracy. While CoT Prompting also lies on the Pareto Frontier, it achieves a lower accuracy (70%) with a slightly faster inference time (3s). This indicates that DeBoP is preferable in accuracy-sensitive scenarios.

In summary, DeBoP establishes itself as a highly efficient method, striking an optimal balance between accuracy and inference time. It not only surpasses existing automatic methods in efficiency but also achieves accuracy comparable to or exceeding manual prompt optimization approaches.

3.4.3 Ablation Study on Individual DeBoP Phase

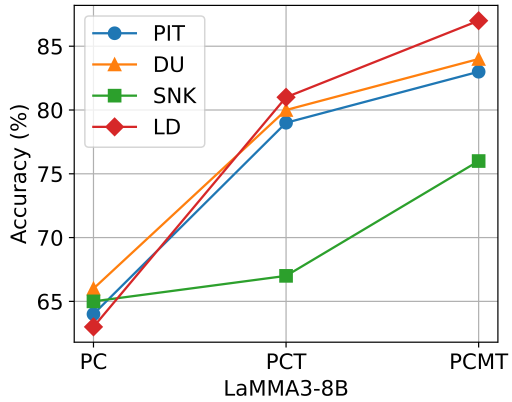
Figure 4 illustrates the impact of different combinations of DeBoP phases (PLANNING, COLLECTING, MCTS, and TEACHING) on model accuracy for two LLaMA configurations: LLaMA3-8B (left plot) and LLaMA3.2-3B (right plot). The plot compares the accuracy across various tasks (PIT, DU, SNK, and LD) for three settings: PC (PLANNING+ COLLECTING), PCT (PLANNING+ COLLECTING+ MCTS+ TEACHING), and PCMT (PLANNING+ COLLECTING+ MCTS+ TEACHING). The results show that PCMT consistently outperforms the other combinations across all tasks, achieving the highest accuracy for each task. PCT demonstrates a noticeable improvement over PC for all tasks, though it still falls short of PCMT. This highlights the crucial role of MCTS and TEACHING in enhancing the performance of LwLLMs on complex tasks. The ablation study underscores that incorporating these phases into the DeBoP framework leads to significant performance improvements across all tasks.

3.4.4 DeBoP Generalization across LwLLMs

	-	8B	3B	GPT-3.5
8B	52 / 32	83 / 84	72 / 72	53 / 62
3B	44 / 42	62 / 55	67 / 74	40 / 25
GPT-3.5	79 / 85	81 / 76	85 / 75	85 / 91

Table 3: Model accuracy comparison (%) of DeBoP generalization on tasks: PIT and DU. "8B" and "3B" refer to LLaMA3-8B and LLaMA3.2-3B, respectively. Most of cells in the table display results in the format "x / y", where "x" represents the performance on the PIT task and "y" represents the performance on the DU task. The LLMs listed in the first row indicate the LLM used in DeBoP to generate the possible optimal demonstration, while the LLMs in the first column represent the LLMs applying DeBoP. The second column denotes that the results are obtained by the LLMs without DeBoP.

The generalization analysis presented in Table 3 provides key insights into the effectiveness of DeBoP across different model configurations on the PIT and DU tasks. Both LLaMA3-8B (denoted



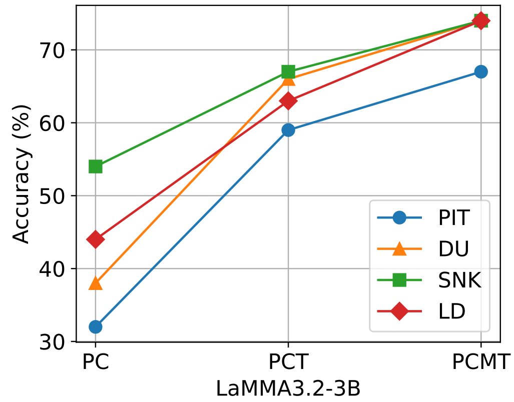


Figure 4: Ablation study on individual DeBoP phase. P, C, M, and T are the initials of the PLANNING, COLLECTING, MCTS, and TEACHING. Due to the necessity of the C module, we finally design the PC, PCT, and PCMT settings for these experiments.

as 8B) and LLaMA3.2-3B (denoted as 3B) show substantial accuracy improvements when applying DeBoP. Specifically, LLaMA3-8B achieves the highest accuracy of $83\%/84\%$ (PIT/DU) when using demonstrations self-generated. Similarly, LLaMA3.2-3B reaches $67\%/74\%$ when using its own demonstrations. These results indicate that DeBoP enhances task performance significantly compared to the baseline performance without DeBoP, shown in the second column (e.g., $52\%/32\%$ for 8B and $44\%/42\%$ for 3B).

GPT-3.5 consistently outperforms the LLaMA models, both with and without DeBoP, demonstrating its superior generalization capability. Notably, when applying DeBoP, GPT-3.5 achieves the highest overall accuracy of $85\%/91\%$ using its own demonstrations.

This analysis confirms that DeBoP significantly improves model performance across tasks while maintaining strong cross-model generalization. It also underscores the potential of leveraging demonstrations generated by LwLLMs themselves to boost the accuracy of smaller models, paving the way for more efficient and scalable prompt optimization methods.

3.4.5 Single-Demonstration versus Multi-Demonstration Settings

Table 4 presents the impact of using multiple demonstrations compared to a single optimized demonstration under the DeBoP framework on two BBH tasks—PIT and DU. The 3-shot context was constructed by selecting three correctly executed samples based on the single-demo performance.

Table 4 shows that introducing additional demonstrations leads to a noticeable degradation in accuracy (–19% on PIT, –18% on DU) while slightly increasing inference latency. We attribute this to:

Task	Method	Acc. (%)	Time (s)
PIT	DeBoP	83	7.3
PIT	DeBoP-3-shot	64	7.7
DU	DeBoP	84	3.6
DU	DeBoP-3-shot	66	5.4

Table 4: Impact of increasing the number of demonstrations.

Attention dispersion: Longer contexts exacerbate the long-range dependency limitations of LwLLMs.

Latency overhead: Each additional demonstration increases decoding time, which is non-trivial for cost-sensitive deployments.

Given the concurrent drop in performance and efficiency, we conclude that multi-demonstration prompting is *not* a favourable direction for DeBoP within the LwLLM setting.

4 Related work

4.1 Manual Prompt Optimization

The influential chain-of-thought (CoT) prompting method (Wei et al., 2022) has inspired numerous innovative strategies to enhance the problem-solving capabilities of large language models. One approach involves using programming languages to explicitly articulate the reasoning process (Chen et al., 2022; Fu et al., 2022; Lyu et al., 2023), while others represent reasoning through complex structures, such as forest or graphs (Besta et al., 2024;

Sel et al., 2023). Some methods decompose tasks into simpler components, which helps the model focus on individual subproblems (Chen et al., 2023a; Zhou et al., 2022; Press et al., 2022; Khot et al., 2022). Additionally, techniques have been developed to incorporate self-correction through automatic feedback mechanisms (Li et al., 2023; Madaan et al., 2024; Miao et al., 2023; Chen et al., 2023b,c), and some methods combine multiple prompting strategies to boost performance further (Liu et al., 2023b; Zhou et al., 2025). Despite these advancements, most of these approaches rely on manually annotated reasoning processes, which limits their generalizability and flexibility.

4.2 Automatic Prompt Optimization

LLMs have demonstrated impressive capabilities, yet challenges remain, particularly in maintaining long-term coherence (Malkin et al., 2021) and generating multi-step solutions. To address these limitations, two complementary strategies have emerged: self-reflection and planning.

Self-reflection encourages LLMs to evaluate their own outputs, identify potential errors, and iteratively refine their responses (Pan et al., 2023; Wang et al., 2023). This introspective approach not only improves the quality of the generated content but also enables models to learn from their own mistakes, thereby enhancing performance over time.

On the other hand, planning involves organizing reasoning into a structured sequence of steps or actions with the goal of achieving a specific objective (Liu et al., 2023a; Gao et al., 2023a). Inspired by traditional planning algorithms, this approach helps guide models through complex decision spaces by providing clear, step-by-step pathways. This can be achieved in several ways, including direct prompting of the model on planning tasks (Kuznia et al., 2022), translating instructions into executable programs (Mishra et al., 2022; Chen et al., 2022; Gao et al., 2023b), or using search-based techniques like Monte Carlo Tree Search (Pryzant et al., 2023; Wang et al., 2023).

However, most of these methods rely on the meta-cognitive abilities of state-of-the-art LLMs, which limits their effectiveness when applied to LwLLMs.

5 Conclusion

In this paper, we introduced DeBoP, a new Direct Behavior Optimization Paradigm that autonomously enhances the performance of LwLLMs for a given task. We evaluated DeBoP on seven tasks covering both language comprehension and complex reasoning. The results demonstrate that DeBoP consistently exhibits strong and efficient performance, revealing novel optimization methods for LwLLMs. Furthermore, our in-depth analyses underscore the importance of aligning model capabilities with optimization strategies when applying DeBoP to LwLLMs. These findings highlight DeBoP's potential as an effective framework for improving both efficiency and accuracy in LwLLMs, paving the way for future advancements in LwLLMs optimization.

6 Limitations

While DeBoP significantly enhances the performance of LwLLMs by transforming complex prompt optimization into discrete execution optimization through gradient-free MCTS, several limitations remain. In particular, the breadth and efficiency of the MCTS expansion process require further development to fully exploit the potential of this approach. Moreover, given its ability to improve the performance of LwLLMs effectively, DeBoP may be vulnerable to misuse by malicious actors. Future work will focus on refining the MCTS expansion process and implementing safeguards to mitigate potential abuses.

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A Prompts in DeBoP

A.1 Prompts in PLANNING

The prompts used in the PLANNING phase are illustrated in Figs. 5, 6, and 7. Specifically, Fig. 5 illustrates the first stage, while Figs. 6 and 7 correspond to the second stage.

A.2 Prompts in COLLECTING

The prompts used in COLLECTING are illustrated in Fig. 8.

A.3 Prompts in MCTS

In MCTS, we employ the following six methods to expand the tree node: Consolidation, Decomposition, Elaboration, Pruning, Resampling, Simplification. The corresponding prompts for each method are shown in Figs. 9, 10, 11, 12, 13, and 14.

B Details of Baseline Methods

B.1 Prompts used in DP and CoT Prompting

The prompts of the seven BBH tasks with DP and CoT prompting are illustrated in the following figures: Fig. 15 for PIT, Fig. 16 for DU, Fig. 17 for SNK, Fig. 18 for DQA, Fig. 19 for LD, Fig. 20 for HB, and Fig. 21 MR.

A demonstration is classified as the one for CoT prompting if it includes a solution (displayed in gray); otherwise, it works for DP.

B.2 Self-Discover

The reproduction of Self-Discover refers to the code at https://github.com/catid/Self-Discover.

B.3 StrategyLLM

The reproduction of StrategyLLM refers to the code at https://github.com/gao-xiao-bai/StrategyLLM.

C How is a behavior derived from a demonstration?

A behavior is the LwLLM's actual response generated based on both the input task and the given demonstration. We consider this behavior as being determined by the interaction between the input and the demonstration, and assess its effectiveness during the MCTS and TEACHING phases.

To illustrate with a simple example, in the DU task, the demonstration teaches the model how to solve the problem: "Today is 3/5, and it is Jane's second time in the year 1973 to see a meteor shower. What is the date 24 hours later in MM/DD/YYYY?" The task is broken down into the following steps:

Identify the known date and the relationship to the target date: In this case, the known date is 3/5 and the target date is 24 hours later. Determine the necessary adjustment: The necessary adjustment here is to add 1 day to the known date. Calculate the accurate date: After adding 1 day to 3/5, the result is 3/6. Final answer: 03/06/1973.

When the LwLLM encounters a new input, such as: "It was Sept. 1st, 2021 a week ago. What is the date tomorrow in MM/DD/YYYY?" it learns from the demonstration and generates its own response. It identifies that the known date is 09/01/2021, understands the relationship that the target date is one day after the date a week ago, makes the necessary adjustment (adding 8 days), and calculates the accurate date as 09/09/2021. Finally, the LwLLM selects the correct answer, which is 09/02/2021, based on the demonstration and the learned pattern.

C.1 Why We Focus on Behaviour-Level Optimisation

Instruction-level optimisation shares the same high-level goal—enhancing LwLLM reasoning—but typically presumes meta-cognitive capabilities (e.g., abstract prompt rewriting, reflective reasoning) that are unreliable in lightweight models. Prior methods such as STRATEGYLLM achieve limited gains under such constraints. By directly optimising *demonstration behaviour* via gradient-free MCTS, DeBoP side-steps this dependency while still improving reasoning quality.

Our findings suggest that, for LwLLMs, carefully curated single-demo behaviour optimisation provides a better trade-off between accuracy and cost than naively increasing the demonstration count or relying on instruction rewrites.

D Supplementary Analysis on Demonstration Impact in Distilled Reasoning LwLLMs

Recent work (Guo et al., 2025) reports that demonstration-based prompting may hurt the performance of cutting-edge reasoning models such as DEEPSEEK R1. To verify whether this claim also holds in the LwLLM regime, we ran additional experiments on two BBH tasks—PIT and DU—using DeepSeek-R1-LLaMA3-8B and a vanilla LLaMA3-8B. We compare zero-shot, 3-shot CoT, and DeBoP (where available).

Task	Model	Method	Acc. (%)	Time (s)
PIT	DeepSeek-R1	3-shot CoT	89	15.4
	DeepSeek-R1	Zero-shot	81	17.9
	LLaMA3-8B	3-shot CoT	62	4.3
	LLaMA3-8B	Zero-shot	52	6.5
	LLaMA3-8B	DeBoP	83	7.3
DU	DeepSeek-R1	3-shot CoT	85	10.5
	DeepSeek-R1	Zero-shot	81	24.5
	LLaMA3-8B	3-shot CoT	59	3.4
	LLaMA3-8B	Zero-shot	32	5.5
	LLaMA3-8B	DeBoP	84	3.6

Table 5: Effect of demonstrations on PIT and DU.

As Table 5 shows, contrary to the negative findings Guo et al. (2025), DeepSeek R1 benefits noticeably from 3-shot CoT on both tasks (+8% and +4%), while LLaMA3-8B shows the largest gain when equipped with our behaviour-optimised DeBoP demonstrations. These results suggest that, even for modern distilled models possessing stronger in-context abilities, well-curated demonstrations can narrow the behaviour space and guide the model toward more reliable reasoning trajectories—aligning with the core philosophy of DeBoP.

Although a full DeBoP pipeline tailored to DeepSeek-R1 is left to future work, the evidence above reinforces the broader applicability of behaviour-level optimisation beyond vanilla LwLLMs.

E License Statement

We release our code, data, and other related artifacts under the MIT License. This license permits use, modification, and distribution for both academic and commercial purposes, provided that the original license notice is retained. By sharing these artifacts openly, we aim to foster transparency, collaboration, and reproducibility within the research community.

PLANNING Prompt

[System Message]
There are a series of tasks of the same type. Please try to understand these tasks and give a general and instructive solution.
Your output should include:
- Include all necessary subtasks.
- All subtasks are easy to solve.
- Subtasks are in an appropriate order.
- Do not include specific information in the examples.
- Make sure the strategy is general and concise.
- Your output should finally start with "Therefore, we can get the general and instructive solution:", followed by your solution.

[User Message]
Please try to understand these tasks about mathematical reasoning and give a general and instructive solution. The examples of the problems is as follows:
- The roots of the equation $2x^2 - mx + n = 0$ sum to 6 and multiply to 10. What is the value of $m + n$?
- Solve for n: $0.03n + 0.08(20 + n) = 12.6$.
- Let C be the circle with equation $x^2 - 6y - 3 = -y^2 - 4x$. If (a, b) is the center of C and r is its radius, what is the value of $a + b + r$?

[Assistant Message]
I'm piecing together a plan to tackle three math problems, detailing the sequence of subtasks for each one, while avoiding specifics in the framework.
We have a set of algebraic and geometric problems, such as finding unknown values in equations or determining the center and radius of a circle. These problems can typically be approached by identifying the equation type (linear, quadratic, or geometric), applying known properties or standard forms, and then systematically solving for the unknowns.

Therefore, we can get the general and instructive solution:
- Identify the mathematical form of each problem (e.g., quadratic equation, linear equation, circle equation) and note which unknowns or parameters need to be found.
- Collect all given conditions (such as relationships involving the roots, values that must satisfy an equation, or geometric properties) and translate them into algebraic expressions.
- Combine or rearrange these expressions into a more standard form (for instance, factoring a quadratic, grouping like terms, completing the square) so the unknowns are clearly isolated.
- Solve the resulting equations step by step, ensuring each operation is straightforward (e.g., simple algebraic manipulations or known formulas).
- Use any final instructions (like summing certain values or substituting back into an expression) to obtain the required result.

[User Message]
Please try to understand these tasks about

`{task definition},`

and give a general and instructive solution. The examples of the problems is as follows:

`{questions}`

Figure 5: PLANNING Prompt with two stages (stage 1).

PLANNING Prompt

[User Message]
To solve this kind of problems about math.
We nedd to create a JSON structure that outlines a step-by-step solution based on the provided information. Each key in the JSON should represent a critical step required to solve the task, and the corresponding values should be empty strings.

Note
- Implement a reasoning structure for solvers to follow step-by-step and arrive at correct answers.
- Steps should be accurate and concise, and there should be no redundancy.

Please understand the provided guidelines:

Guidelines
- Identify the mathematical form of each problem (e.g., quadratic equation, linear equation, circle equation) and note which unknowns or parameters need to be found.
- Collect all given conditions (such as relationships involving the roots, values that must satisfy an equation, or geometric properties) and translate them into algebraic expressions.
- Combine or rearrange these expressions into a more standard form (for instance, factoring a quadratic, grouping like terms, completing the square) so the unknowns are clearly isolated.
- Solve the resulting equations step by step, ensuring each operation is straightforward (e.g., simple algebraic manipulations or known formulas).
- Use any final instructions (like summing certain values or substituting back into an expression) to obtain the required result.

Now please learn these guideline information and generate the corresponding JSON structure. The JSON structure should:

Note
- Include all necessary steps.
- Make all steps easy to solve.
- Have no redundant steps, that is, don't repeat the steps when there is already an answer.
- End with **The final answer** as the end of the json structure.

Figure 6: PLANNING Prompt with two stages (stage 2, part 1)

PLANNING Prompt

[Assistant Message]
Quick Summary of Guidelines

- Determine the parameters to be solved.
- Collect all the given conditions.
- Clarify the unknowns.
- Solve the equation step by step, ensuring that each step is clear, simple, and straightforward.
- Calculate the final answer.

Therefore, we can derive the step-by-step solution in the following JSON structure:

````
```json
{
    "Determine the parameters to be solved": "",
    "Collect all the given conditions": "",
    "Clarify the unknowns": "",
    ...
    "The final answer": ""
}
```
````

[User Message]
To solve this kind of problem about `{task_definition}`
We need to create a JSON structure that outlines a step-by-step solution based on the provided information. Each key in the JSON should represent a critical step required to solve the task, and the corresponding values should be empty strings.

Notes
- Implement a reasoning structure for solvers to follow step-by-step and arrive at correct answers.
- Steps should be accurate and concise, and there should be no redundancy.

Please review and understand the provided guidelines:

Guidelines
`{guidelines}`

Now please learn these guideline information and generate the corresponding JSON structure. The JSON structure should:

Notes
- Include all necessary steps.
- Ensure that all steps are easy to follow and solve.
- Have no redundant steps, meaning that steps should not be repeated when an answer already exists.
- End with **The final answer** as the last key in the JSON structure.

Figure 7: PLANNING Prompt with two stages (Stage 2, Part 2)

COLLECTING Prompt

[System Message]

Given Reasoning Structure

```json
    {plan}
```

Example Output

```json
{
  ...
}
```

Detailed Instructions

- You must use the given reasoning structure to solve the given task, both of which are provided above.
- The reasoning structure will guide your response to the given task.
- You must fill in all empty strings in the value fields of the key-value pairs within the JSON structure of the reasoning structure.
- Your output must consist of a single code block containing a fully completed JSON structure.
- The code block should be formatted as a JSON snippet enclosed by triple backticks (“‘json) with the json language specifier, as demonstrated in the example output.

[User Message]

{question}

Figure 8: COLLECTING Phase Prompt.

MCTS Consolidation Prompt

For the given task:

`{task definition}`
`{question}`

we already have the following JSON structured solution:

`{demonstration}`

Could you determine whether any steps can be merged to make the reasoning process more logical? If so, please explain why and then present the optimized result in Markdown JSON format.

Notes
- If no steps can be merged without compromising the reasoning, state this explicitly and provide the original JSON structure.
- In this JSON structure, each key represents a piece of guidance for the solution, and each value details the specific reasoning process according to that guidance.

Figure 9: MCTS Consolidation Prompt.

MCTS Decomposition Prompt

For the given task:

`{task definition}`
`{question}`

we already have the following JSON structured solution:

`{demonstration}`

Could you determine whether any steps can be easily split to improve the clarity and accuracy of the reasoning process? If so, please explain why and then present the optimized result in Markdown JSON format.

Notes
- If no steps can be split without compromising the reasoning, state this explicitly and provide the original JSON structure.
- In this JSON structure, each key represents a piece of guidance for the solution, and each value details the specific reasoning process according to that guidance.

Figure 10: MCTS Decomposition Prompt.

MCTS Elaboration Prompt

For the given task:

```
{task definition}
{question}
```

we already have the following JSON structured solution:

```
{demonstration}
```

Could you provide a more detailed and expanded version of the reasoning flow (including both keys and values) to ensure that no critical aspects of the problem-solving process are overlooked? If so, please explain why and then present the optimized result in Markdown JSON format.

Notes
- If no steps can be expanded without compromising the reasoning, state this explicitly and provide the original JSON structure.
- In this JSON structure, each key represents a piece of guidance for the solution, and each value details the specific reasoning process according to that guidance.

Figure 11: MCTS Elaboration Prompt.

MCTS Pruning Prompt

For the given task:

```
{task definition}
{question}
```

we already have the following JSON structured solution:

```
{demonstration}
```

Could you determine whether one step (the least consequential one) can be removed without harming the overall reasoning, thereby making the process more concise and logical? If so, please explain why, and then present the optimized result in Markdown JSON format.

Notes
- If no step can be removed without compromising the reasoning, state this explicitly and provide the original JSON structure.
- In this JSON structure, each key represents a piece of guidance for the solution, and each value details the specific reasoning process according to that guidance.

Figure 12: MCTS Pruning Prompt.

MCTS Resampling Prompt

For the given task

`{task definition}`
`{question}`

we already have the following JSON structured solution:

`{demonstration}`

Could you determine whether any steps can be freely optimized to enhance the logical consistency and efficiency of the reasoning process? If so, please explain why and then present the optimized result in Markdown JSON format.

Notes
- If no steps can be freely optimized without compromising the reasoning, state this explicitly and provide the original JSON structure.
- In this JSON structure, each key represents a piece of guidance for the solution, and each value details the specific reasoning process according to that guidance.

Figure 13: MCTS Resampling Prompt.

MCTS Simplification Prompt

For the given task:

`{task definition}`
`{question}`

we already have the following JSON structured solution:

`{demonstration}`

Could you simplify and refine the reasoning flow (including both keys and values) to improve conciseness, coherence, and logical structure? If so, please explain why and then present the optimized result in Markdown JSON format.

Notes
- If no steps can be abbreviated without compromising the reasoning, state this explicitly and provide the original JSON structure.
- In this JSON structure, each key represents a piece of guidance for the solution, and each value details the specific reasoning process according to that guidance.

Figure 14: MCTS simplification Prompt.

DP&CoT Prompt of Penguin in a Table

Question: Here is a table where the first line is a header and each subsequent line is a penguin: name, age, height (cm), weight (kg)
Louis, 7, 50, 11 ; Bernard, 5, 80, 13 ; Vincent, 9, 60, 11 ; Gwen, 8, 70, 15
For example: the age of Louis is 7, the weight of Gwen is 15 kg, the height of Bernard is 80 cm.
We now add a penguin to the table:
James, 12, 90, 12
How many penguins are less than 8 years old?
Options: (A) 1 (B) 2 (C) 3 (D) 4 (E) 5
Solution: This question focuses on age. We know the following: Louis is 7 years old, Bernard is 5 years old, Vincent is 9 years old, and Gwen is 8 years old. Now, we add James to this table: James is 12 years old. The penguins that are less than 8 years old are Louis and Bernard. There are 2 penguins less than 8 years old. So the answer is (B).
Answer: (B)

Question: Here is a table where the first line is a header and each subsequent line is a penguin: name, age, height (cm), weight (kg)
Louis, 7, 50, 11 ; Bernard, 5, 80, 13 ; Vincent, 9, 60, 11 ; Gwen, 8, 70, 15
For example: the age of Louis is 7, the weight of Gwen is 15 kg, the height of Bernard is 80 cm.
Which is the youngest penguin?
Options: (A) Louis (B) Bernard (C) Vincent (D) Gwen (E) James
Solution: This question focuses on age. We know the following: Louis is 7 years old, Bernard is 5 years old, Vincent is 9 years old, and Gwen is 8 years old. According to the table, Bernard (5) is the youngest amongst them. The youngest penguin is Bernard. So the answer is (B).
Answer: (B)

Question: Here is a table where the first line is a header and each subsequent line is a penguin: name, age, height (cm), weight (kg)
Louis, 7, 50, 11 ; Bernard, 5, 80, 13 ; Vincent, 9, 60, 11 ; Gwen, 8, 70, 15
For example: the age of Louis is 7, the weight of Gwen is 15 kg, the height of Bernard is 80 cm.
What is the name of the second penguin sorted by alphabetic order?
Options: (A) Louis (B) Bernard (C) Vincent (D) Gwen (E) James
Solution: This question focuses on the name. We know the following: The names of the penguins in the table are Louis, Bernard, Vincent, and Gwen. When we sort their names alphabetically, we get Bernard, Gwen, Louis, Vincent. The name of the second penguin sorted by alphabetical order is Gwen. The name of the second penguin sorted by alphabetic order is Gwen. So the answer is (D).
Answer: (D)

Question:

`{question}`

Figure 15: DP&CoT Prompt of Penguin in a Table.

DP&CoT Prompt of Date Understanding

Question: Today is Christmas Eve of 1937. What is the date 10 days ago in MM/DD/YYYY?
Options: (A) 12/14/2026 (B) 12/14/1950 (C) 12/14/2007 (D) 12/14/1937 (E) 07/14/1938 (F) 12/14/1988
Solution: If today is Christmas Eve of 1937, then today's date is December 24, 1937. 10 days before today is December 14, 1937, that is 12/14/1937. So the answer is (D).
Answer: (D)

Question: Tomorrow is 11/12/2019. What is the date one year ago from today in MM/DD/YYYY?
Options: (A) 09/04/2018 (B) 11/11/2018 (C) 08/25/2018 (D) 11/02/2018 (E) 11/04/2018
Solution: If tomorrow is 11/12/2019, then today is 11/11/2019. The date one year ago from today is 11/11/2018. So the answer is (B).
Answer: (B)

Question: Jane and John married on Jan 2, 1958. It is their 5-year anniversary today. What is the date tomorrow in MM/DD/YYYY?
Options: (A) 01/11/1961 (B) 01/03/1963 (C) 01/18/1961 (D) 10/14/1960 (E) 01/03/1982 (F) 12/03/1960
Solution: If Jane and John married on Jan 2, 1958, and if it is their 5-year anniversary today, then today's date is Jan 2, 1963. The date tomorrow is Jan 3, 1963, that is 01/03/1963. So the answer is (B).
Answer: (B)

Question:

`{question}`

Figure 16: DP&CoT Prompt of Date Understanding.

DP&CoT Prompt of Snark

Question: Which statement is sarcastic?
Options: (A) Yes, because having interests and actively researching them is a huge waste (B) Yes, because having interests and actively researching them is a huge deal
Solution: If we look at (A), it says that having interests and actively researching them is a huge waste, implying that it is a useless effort. However, we know that having interests and actively researching them is typically not a waste but rather is beneficial to the individual. The presence of such a juxtaposition in (A) suggests that it contains a taste of irony and sarcasm.
If we look at (B), it says that having interests and actively researching them is a huge deal, implying that it is an important and consequential effort. This is arguably a neutral and correct statement.
Above the above, the sarcastic option is (A). So the answer is (A).
Answer: (A)

Question: Which statement is sarcastic?
Options: (A) No one is going to disagree with you on this. Avoiding ad hominem attacks really help your case (B) No one is going to disagree with you on this. Ad hominem attacks really help your case
Solution: If we look at (A), it says that avoiding ad hominem attacks really help your case, implying that ad hominem attacks are adverse and injurious. Because ad hominem attacks are addressed at a person rather than an idea, it is indeed true that avoiding them is often useful and helpful; so, (A) is a neutral (valid and agreeable) statement.
If we look at (B), it says that ad hominem attacks really help your case, implying that ad hominem attacks are a positive thing. However, we stated previously that ad hominem attacks are often not useful or constructive. The speaker in this sentence therefore seems to mean the opposite of what they are saying; so, there appears to have a taste of irony and sarcasm in (B).
Above the above, the sarcastic option is (B). So the answer is (B).
Answer: (B)

Question: Which statement is sarcastic?
Options: (A) Consistency in the league's punishments? What do you think this is supposed to be, politics? (B) Consistency in the league's punishments? What do you think this is supposed to be, moral?
Solution: If we look at (A), it likens the consistency in the league's punishments with that in politics. Because politics or political affairs are often not considered to be consistent or dependable, this sentence appears to be satirical.
If we look at (B), it likens the consistency in the league's punishments with that in morality. Discussing the consistency of the league's punishments in the context of morality, ethics, or law makes sense and does not appear to make a satirical point about anything.
Above the above, the sarcastic option is (A). So the answer is (A).
Answer: (A)

Question:
`{question}`

Figure 17: DP&CoT Prompt of Snark.

DP&CoT Prompt of Disambiguation QA

Question: In the following sentences, explain the antecedent of the pronoun (which thing the pronoun refers to), or state that it is ambiguous.
Sentence: The chief told the counselor that they took the day off.
Options: (A) The chief took the day off (B) The counselor took the day off (C) Ambiguous
Solution: Here we need to determine who the pronoun "they" might be referring to. There are two possible referents for "they", namely the chief and the counselor. The verb "told" might be able to help us determine which one is more likely (if either). Let X be the chief and Y the counselor. The sentence is then of the form "X told Y that (X or Y) did something."
Let's consider Y first: "X told Y that Y did something." This case does not make much sense, as Y would already have the information that Y did something, because it is information about themself.
Now, consider X: "X told Y that X did something." This makes sense, because X would be sharing some information about themself that Y might not have known before.
Because in this context, X is the chief and Y is the counselor, the answer should be the chief. So the answer is (A).
Answer: (A)

Question: In the following sentences, explain the antecedent of the pronoun (which thing the pronoun refers to), or state that it is ambiguous.
Sentence: The manager sent a message to the secretary, but he didn't reply yet.
Options: (A) The secretary didn't reply yet (B) The manager didn't reply yet (C) Ambiguous
Solution: Here we need to determine who the pronoun "he" might be referring to. There are two possible referents for "he", namely the manager and the secretary. The verbs "sent" and "reply" might be able to help us determine which one is more likely (if either). Let X be the manager and Y the secretary. The sentence is then of the form "X sent a message to Y, but (X or Y) didn't reply yet."
Let's consider Y first: "X sent a message to Y, but Y didn't reply yet." This case makes sense, because of the implicit causality of the sentence. Y was the receiver of the message, but Y didn't get back to X yet.
Now, consider X: "X sent a message to Y, but X didn't reply yet." This case doesn't make sense, because X was the initial sender of the message, so it is now Y's turn to write back to X.
Because in this context, X is the manager and Y is the secretary, the answer should be the secretary. So the answer is (A).
Answer: (A)

Question: In the following sentences, explain the antecedent of the pronoun (which thing the pronoun refers to), or state that it is ambiguous.
Sentence: Bailey will plan to meet the director at his office.
Options: (A) It will be Bailey's office (B) It will be the director's office (C) Ambiguous
Solution: Here we need to determine who the pronoun "his" might be referring to. There are two possible referents for "his", namely Bailey's and the director's. The verb phrase "plan to meet" might be able to help us determine which one is more likely (if either). Let X be Bailey and Y the director. The sentence is then of the form "X will plan to meet Y at (X or Y)'s office."
Let's consider Y first: "X will plan to meet Y at Y's office." This case makes sense, because X might want to meet up with Y at Y's office.
Now, consider X: "X will plan to meet Y at X's office." This case also makes sense, because X might want to meet up with Y at X's own office.
Because both X and Y are possible at the same time, we conclude that the antecedent of the pronoun is ambiguous. So the answer is (C).
Answer: (C)

Question:

`{question}`

Figure 18: DP&CoT Prompt of Disambiguation QA.

DP&CoT Prompt of Logical Deduction

Question: The following paragraphs each describe a set of three objects arranged in a fixed order. The statements are logically consistent within each paragraph.
In a golf tournament, there were three golfers: Amy, Eli, and Eve. Eve finished above Amy. Eli finished below Amy.
Options: (A) Amy finished last (B) Eli finished last (C) Eve finished last
Solution: (1) Eve finished above Amy: "(above) ? Eve ? Amy ? (below)".
(2) Eli finished below Amy: "(above) ? Amy ? Eli ? (below)".
(3) Combining (1) and (2) we get the following ordering: "(above) Eve Amy Eli (below)".
According to this ordering, the person who finished last (the one at the bottom of this list) is Eli.
Eli finished last. So the answer is (B).
Answer: (B)

Question: The following paragraphs each describe a set of three objects arranged in a fixed order. The statements are logically consistent within each paragraph.
On a shelf, there are three books: a white book, a green book, and an orange book. The green book is to the right of the white book. The orange book is the rightmost.
Options: (A) The white book is the leftmost (B) The green book is the leftmost (C) The orange book is the leftmost
Solution: (1) The green book is to the right of the white book: "(left) ? white ? green ? (right)".
(2) The orange book is the rightmost: "(left) ? white ? green orange (right)".
(3) Combining (1) and (2) we get the following ordering: "(left) white green orange (right)".
According to this ordering, the leftmost book is the white book.
The white book is the leftmost. So the answer is (A).
Answer: (A)

Question: The following paragraphs each describe a set of three objects arranged in a fixed order. The statements are logically consistent within each paragraph.
On a shelf, there are three books: a red book, a gray book, and a white book. The white book is to the left of the gray book. The red book is the second from the left.
Options: (A) The red book is the leftmost (B) The gray book is the leftmost (C) The white book is the leftmost
Solution: (1) The white book is to the left of the gray book: "(left) ? white ? gray ? (right)".
(2) The red book is the second from the left: "(left) ? white red gray ? (right)".
(3) Combining (1) and (2) we get the following ordering: "(left) white red gray (right)".
According to this ordering, the leftmost book is the white book.
The white book is the leftmost. So the answer is (C).
Answer: (C)

Question:
`{question}`

Figure 19: DP&CoT Prompt of Logical Deduction.

DP&CoT Prompt of Hyperbaton

Question: Which sentence has the correct adjective order?
Options: (A) rubber terrible ship (B) terrible rubber ship
Solution: When there is more than one adjective before a noun, the adjectives need to respect the following order before a noun: "[1. opinion] [2. size] [3. age] [4. shape] [5. color] [6. origin] [7. material] [8. purpose] noun".
Option (A): "rubber terrible ship". (1) "rubber" falls into the material category. (2) "terrible" falls into the opinion category. Option (A) has the following adjective order: [7. material] [1. opinion] (or, in numeric terms, 7 1). Because 7 < 1 is not correct, (A) does not have the correct ordering.
Option (B): "terrible rubber ship". Option (B) has the following adjective order: [1. opinion] [7. material] (or, in numeric terms, 1 7). Because 1 < 7 is correct, (B) has the correct ordering. So the answer is (B).
Answer: (B)

Question: Which sentence has the correct adjective order?
Options: (A) repulsive small Brazilian exercise ship (B) Brazilian repulsive exercise small ship
Solution: When there is more than one adjective before a noun, the adjectives need to respect the following order before a noun: "[1. opinion] [2. size] [3. age] [4. shape] [5. color] [6. origin] [7. material] [8. purpose] noun".
Option (A): "repulsive small Brazilian exercise ship". (1) "repulsive" falls into the opinion category. (2) "small" falls into the size category. (3) "Brazilian" falls into the origin category. (4) "exercise" falls into the purpose category. Option (A) has the following adjective order: [1. opinion] [2. size] [6. origin] [8. purpose] (or, in numeric terms, 1 2 6 8). Because 1 < 2 < 6 < 8 is correct, (A) has the correct ordering.
Option (B): "Brazilian repulsive exercise small ship". Option (B) has the following adjective order: [6. origin] [1. opinion] [8. purpose] [2. size] (or, in numeric terms, 6 1 8 2). Because 6 < 1 < 8 < 2 is not correct, (B) does not have the correct ordering. So the answer is (A).
Answer: (A)

Question: Which sentence has the correct adjective order?
Options: (A) blue gold wonderful square shoe (B) wonderful square blue gold shoe
Solution: When there is more than one adjective before a noun, the adjectives need to respect the following order before a noun: "[1. opinion] [2. size] [3. age] [4. shape] [5. color] [6. origin] [7. material] [8. purpose] noun".
Option (A): "blue gold wonderful square shoe". (1) "blue" falls into the color category. (2) "gold" falls into the material category. (3) "wonderful" falls into the opinion category. (4) "square" falls into the shape category. The adjective order that Option (A) has is [5. color] [7. material] [1. opinion] [4. shape] (or, in numeric terms, 5 7 1 4). Because 5 < 7 < 1 < 4 is not correct, (A) does not have the correct ordering.
Option (B): "wonderful square blue gold shoe". Option (B) has the following adjective order: [1. opinion] [4. shape] [5. color] [7. material] (or, in numeric terms, 1 4 5 7). Because 1 < 4 < 5 < 7 is correct, (B) has the correct ordering. So the answer is (B).
Answer: (B)

Question:

`{question}`

Figure 20: DP&CoT Prompt of Hyperbaton.

DP&CoT Prompt of Movie Recommendation

Question: Find a movie similar to Star Wars Episode IV - A New Hope, Indiana Jones and the Last Crusade, Star Wars Episode V - The Empire Strikes Back, The Big Lebowski.
Options: (A) Tetsuo (B) the Ironman (C) The Princess Bride (D) The Barkley Marathons The Race That Eats Its Young (E) Bug
Solution: - Star Wars Episode IV - A New Hope (action, adventure, fantasy; 1977)
- Indiana Jones and the Last Crusade (action, adventure; 1989)
- Star Wars Episode V - The Empire Strikes Back (action, adventure, fantasy; 1980)
- The Big Lebowski (action, drama, comedy; 1998)
These are all famous classic American movies produced before 2000. Amongst all the options, the only movie similar to these ones seems to be The Princess Bride (1987). So the answer is (C).
Answer: (C)

Question: Find a movie similar to Twister, The Silence of the Lambs, Independence Day, Braveheart.
Options: (A) They Shoot Horses (B) Don't They (C) Forrest Gump (D) The Salton Sea (E) Extreme Days
Solution: - Twister (action, adventure, thriller; 1996)
- The Silence of the Lambs (crime, drama, thriller; 1991)
- Independence Day (action, science-fiction, drama; 1996)
- Braveheart (biography, drama, epic; 1995)
These are all famous Hollywood movies produced around the 1990s. Amongst all the options, the only movie similar to these ones seems to be Forrest Gump (comedy, drama, romance; 1994). So the answer is (C).
Answer: (C)

Question: Find a movie similar to Minority Report, Total Recall, Inside Out, Forrest Gump.
Options: (A) Phenomena (B) Lilting (C) Catwoman (D) Edge of Tomorrow
Solution: - Minority Report (action, crime, mystery; 2002)
- Total Recall (action, adventure, science-fiction; 2012)
- Inside Out (animation, family, comedy; 2015)
- Forrest Gump (comedy, drama, romance; 1994)
These are all famous movies produced in the past few decades. Amongst all the options, the only movie similar to these ones seems to be Edge of Tomorrow (action, adventure, crime, mystery; 2014), as it is also a science-fiction movie and features Tom Cruise. So the answer is (D).
Answer: (D)

Question:
`{question}`

Figure 21: DP&CoT Prompt of Movie Recommendation.