Reasoning with Language Model is Planning with World Model

Shibo Hao[*♣] **Yi Gu**[*♣] **Haodi Ma**[◇] **Joshua Jiahua Hong**[♣] **Zhen Wang**[♣ ♠]
Daisy Zhe Wang[◇] **Zhiting Hu**[♣]
[♣]UC San Diego, [◇]University of Florida
[♠]Mohamed bin Zayed University of Artificial Intelligence
{s5hao, yig025, jjhong, zhw085, zhh019}@ucsd.edu
{ma.haodi, daisyw}@ufl.edu

Abstract

Large language models (LLMs) have shown remarkable reasoning capabilities, especially when prompted to generate intermediate reasoning steps (e.g., Chain-of-Thought, CoT). However, LLMs can still struggle with problems that are easy for humans, such as generating action plans for executing tasks in a given environment, or performing complex math, logical, and commonsense reasoning. The deficiency stems from the key fact that LLMs lack an internal *world model* to predict the world *state* (e.g., environment status, intermediate variable values) and simulate long-term outcomes of actions. This prevents LLMs from performing deliberate planning akin to human brains, which involves exploring alternative reasoning paths, anticipating future states and rewards, and iteratively refining existing reasoning steps. To overcome the limitations, we propose a new LLM reasoning framework, **Reasoning via Planning (RAP)**. RAP repurposes the LLM as both a world model and a reasoning agent, and incorporates a principled planning algorithm (based on Monto Carlo Tree Search) for strategic exploration in the vast reasoning space. During reasoning, the LLM (as agent) incrementally builds a reasoning tree under the guidance of the LLM (as world model) and task-specific rewards, and obtains a high-reward reasoning path efficiently with a proper balance between exploration *vs.* exploitation. We apply RAP to a variety of challenging reasoning problems including plan generation, math reasoning, and logical inference. Empirical results on these tasks demonstrate the superiority of RAP over various strong baselines, including CoT and least-to-most prompting with self-consistency. RAP on LLaMA-33B surpasses CoT on GPT-4 with 33% relative improvement in a plan generation setting.

1 Introduction

Large language models (LLMs) have exhibited emergent reasoning abilities in a wide range of tasks [5, 10, 44, 2]. Recent approaches further boost their ability by prompting LLMs to generate intermediate reasoning steps (e.g., Chain-of-Thought, CoT [59]) or answer a series of subquestions (e.g., least-to-most prompting [66]). However, LLMs still face difficulties with tasks that humans find easy. For example, in creating action plans to move blocks to a target state, GPT-3 [5] achieves a success rate of only 1%, compared to 78% for humans [57]; these models also struggle when solving complex tasks that require multiple steps of math, logical, or commonsense reasoning [65, 22, 41, 6].

Humans possess an internal **world model**, a mental representation of the environment [28, 27, 15], which enables humans to simulate actions and their effects on the world's state for deliberate **planning**

[*]equal contribution

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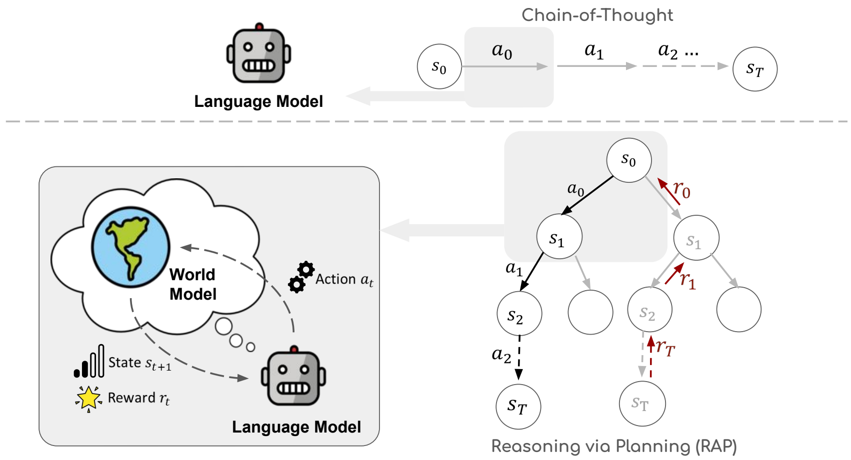

Figure 1: An overview of Reasoning via Planning (RAP). Compared with previous LLM reasoning methods like Chain-of-Thought [59], we explicitly model the world state from a world model (repurposed from the language model), enabling us to leverage advanced planning algorithms to solve the reasoning problems.

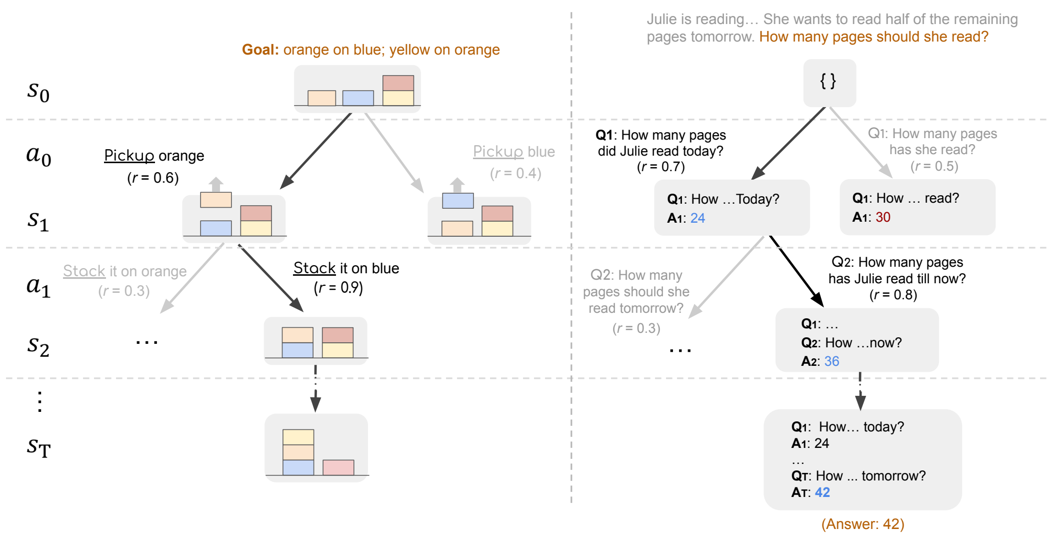

Figure 2: RAP for plan generation in Blocksworld (left) and math reasoning in GSM8K (right).

during complex tasks of motor control, imagery, inference, and decision making [54, 55, 4, 49, 17, 33]. For example, to make an action plan towards a goal, planning with the world model involves exploring various alternative courses of actions, assessing the likely outcomes by rolling out possible future scenarios, and iteratively refining the plan based on the assessment [25, 14, 52, 19, 48, 21]. This is in stark contrast to the current LLM reasoning, which instinctively generates a reasoning trace in an autoregressive manner. In particular, we identify several key limitations of the current reasoning with LLMs, including **(1)** the lack of an internal world model to simulate the *state* of the world (e.g., the configuration of blocks, the values of intermediate variables), which is the foundation of human planning; **(2)** the absence of a *reward* mechanism to assess and guide the reasoning towards the desired state; and due to both of these limitations, **(3)** the incapability of balancing *exploration vs. exploitation* to efficiently explore the vast reasoning space.

To address these limitations, this paper proposes a new framework, **Reasoning via Planning (RAP)**, that enables LLMs to reason in a manner close to humans' conscious planning. RAP augments the LLM with a world model, and reasons with principled planning (specifically *Monte Carlo Tree Search, MCTS*) to produce high-reward reasoning traces after efficient exploration (Figure 1). Notably, we acquire the world model by repurposing the LLM itself with appropriate prompts. During the reasoning, the LLM strategically builds a reasoning tree by iteratively considering the most promising reasoning steps (*actions*) and using the world model (the same, repurposed LLM) to look ahead for future outcomes. The estimated future rewards are then backpropagated to update the LLM's beliefs about the current reasoning steps, guiding it to refine the reasoning by exploring better alternatives. Our MCTS-based planning effectively maintains a proper balance between exploration (of unvisited reasoning traces) and exploitation (of the best reasoning steps identified so far).

We show RAP is a general framework applicable to a diverse range of challenging problems and achieves substantial improvements over recent popular LLM reasoning methods. In Blocksworld [57] for 2/4/6-step plan generation, RAP achieves an average success rate of 64% while CoT fails almost completely. Moreover, LLaMA-33B with RAP surpasses GPT-4 with CoT by 33% relative improvement. In math reasoning (GSM8K [11]) and logical inference (PrOntoQA [47]), RAP also consistently improves over strong baselines, including CoT, least-to-most prompting, and their self-consistency variants.

2 Related Work

Reasoning with LLMs. In the realm of LLMs [22, 41, 6], reasoning typically entails decomposing complex questions into sequential intermediate steps (a.k.a. chains) before producing the final answer, exemplified by Chain-of-Thought (CoT) prompting and its variants [43, 59, 32]. The basic CoT approaches, which generate chains all at once, can induce additional errors as the step count increases. One line of improvement methods involves sampling multiple chains and choosing the best answer via majority voting, such as Self-Consistency [58]. Another line of work focuses on decomposition, aiming to tackle the problem by solving multiple simple subproblems. For instance, least-to-most prompting [66] reduces the question into subquestions and answers them sequentially. More relevantly, similar to our reward formulation, some recent works have explored self-evaluation approaches, which leverage LLMs themselves to provide feedback for intermediate steps and then continue the reasoning [60, 51, 45]. For example, Paul et al. [45] fine-tune a critic model to provide structured feedback iteratively in each step, and Madaan et al. [38] directly reuse the same LLM to generate multi-aspect feedback and refine the previously generated output. Besides, aligned with our state formulation, Li et al. [34] incorporates latent "situations" into LLMs, referring to the state of entities from the context. Nevertheless, none of the above methods formally introduce the world model and instantiates the reward and state into a unified framework.

Search-guided Reasoning with LLMs. Most of CoT approaches discussed above are based on a linear reasoning structure. Self-consistency built onto CoT decodes multiple chains parallelly, but it remains hard to explore the reasoning space sufficiently. Recent efforts have been made to investigate non-linear reasoning structures by sampling more reasoning steps efficiently guided by some search algorithms [30, 67, 63, 64]. For example, Jung et al. [30] generate a tree of explanations to enforce logical consistency, and Xie et al. [63] adopt beam search to decode a better CoT reasoning chain. More recently, CoRe [67] proposes to fine-tune both the reasoning step generator and verifier for solving math word problems, also using MCTS for reasoning decoding. Concurrently to our work, Yao et al. [64] apply heuristic-based approach, like depth-/breadth-first search, to search for better reasoning paths. Compared with these search-guided methods, RAP is a more principled framework that combines world model and reward within advanced MCTS planning. The RAP formulation of LLM reasoning with state, action, and reward also presents a more general approach applicable to a wide range of reasoning problems.

Planning with LLMs. Planning, a central ability in intelligent agents, involves generating a series of actions to achieve a specific goal [40, 7]. Classical planning methods have been widely adopted in robots and embodied environments [9, 42, 8, 61, 26]. Recently, prompting LLMs to do planning direcly has gained attention and shown potential [24, 23, 53, 13, 35]. SayCan [1], for instance, combines LLMs with affordance functions to generate feasible plans. Moreover, based on LLMs' powerful programming ability [37, 29, 36], some recent works first translate natural language instructions into the executable programming languages, such as Planning Domain Description Language (PDDL), and runs classical planning algorithms, such as LLM+P [36]. However, code-based planning is constrained by its narrow domains and the predefined environment, while RAP can handle open domain problems, including numerical and logical reasoning (see Section 4.2 and 4.3).

World models and Planning. Traditional reinforcement learning (RL) heavily relies on interaction with the environment (real world or simulators). To improve sample efficiency, previous research attempts to learn a **world model** that predicts state transition, and directly learn a policy within the world model [16, 17]. With latent imagination in a world model, an RL agent can be trained to solve long-horizon tasks [18, 20]. Besides, the world model is also shown to be helpful to physical robot learning [62]. Recent years have witnessed successful applications of **planning** algorithms in RL [50], such as AlphaZero [52], MuZero [48]. These algorithms are typically based on tree-structured search and are designed to effectively maintain the balance of exploration and exploitation. In this paper, we use LLMs as world models and apply a planning algorithm to search for a reasoning path. Combining world model and planning, our framework is similar to model predictive control [8]. Compared with previous works, our framework uses general LLMs as the world model and can be adapted to a wide range of open-domain reasoning tasks.

3 Reasoning via Planning (RAP)

In this section, we present the Reasoning via Planning (RAP) framework that enables LLMs to strategically plan a coherent reasoning trace for solving a wide range of reasoning tasks. We first build the world model by repurposing the LLM with prompting (Section 3.1). The world model serves as the foundation for deliberate planning, by allowing the LLM to plan ahead and seek out the expected outcomes in the future. We then introduce the rewards for assessing each state during reasoning in Section 3.2. Guided by the world model and rewards, the planning with Monte Carlo Tree Search (MCTS) efficiently explores the vast reasoning space and finds optimal reasoning traces (Section 3.3). Finally, when multiple promising reasoning traces are acquired during planning, we further introduce an aggregation method in Section 3.4 that yields an integrated result and further boosts the reasoning performance.

3.1 Language Model as World Model

In general, a world model predicts the next *state* of the reasoning after applying an *action* to the current state [17, 39]. RAP enables us to instantiate the general concepts of state and action in different ways depending on the specific reasoning problems at hand. For example, in Blocksworld (Figure 2 left), it is natural to set a state to describe a configuration of blocks (with natural language), and an action to be a behavior of moving a block (e.g., ``pickup the orange block''). In a math reasoning problem (Figure 2 right), we use the state to represent the values of intermediate variables, and set an action to be a subquestion that drives the reasoning to derive new values (i.e., new state).

After the definition of state and action, the reasoning process can thus be described as a Markov decision process (MDP): given the current state $s_{t,t=0,1,\ldots,T}$, e.g., the initial state s_0, the LLM (as a reasoning agent) generates an action following its generative distribution $a_t \sim p(a|s_t, c)$, where c is a proper prompt (e.g., in-context demonstrations) to steer the LLM for action generation. The world model then predicts the next state s_{t+1} of the reasoning. Specifically, we repurpose the *same* LLM to obtain a state transition distribution $p(s_{t+1}|s_t, a_t, c')$, where c' is another prompt to guide the LLM to generate a state. For instance, in Blocksworld, the LLM (as the world model) generates text s_{t+1} to describe the new configuration of blocks, given the previous state description s_t and the action a_t.

Continuing the process results in a reasoning trace, which consists of a sequence of interleaved states and actions $(s_0, a_0, s_1, \ldots, a_{T-1}, s_T)$. This differs from the previous reasoning methods, such as Chain-of-Thought [59], where the intermediate reasoning steps consist of only a sequence of actions, e.g., ($a_0 =$ ``pickup red block'', $a_1 =$ ``stack on yellow block'', ...) (see comparisons in Figure 1). Augmenting the reasoning with the (predicted) world states helps the LLM with a more grounded and coherent inference. Note that the full reasoning trace is simulated by the LLM itself (as a reasoning agent with an *internal* world model) without interacting with the *external* real environment. This resembles humans contemplating a possible plan in their minds. The capability of simulating future states, due to the introduction of the world model, allows us to incorporate principled planning algorithms to efficiently explore the vast reasoning space as described in Section 3.3.

3.2 Reward Design

During reasoning, we want to assess the feasibility and desirability of each reasoning step, and guide the reasoning based on the assessment (Section 3.3). The assessment of each reasoning step (i.e., applying an action a_t to the state s_t) is performed by a *reward* function $r_t = r(s_t, a_t) \in \mathbb{R}$.

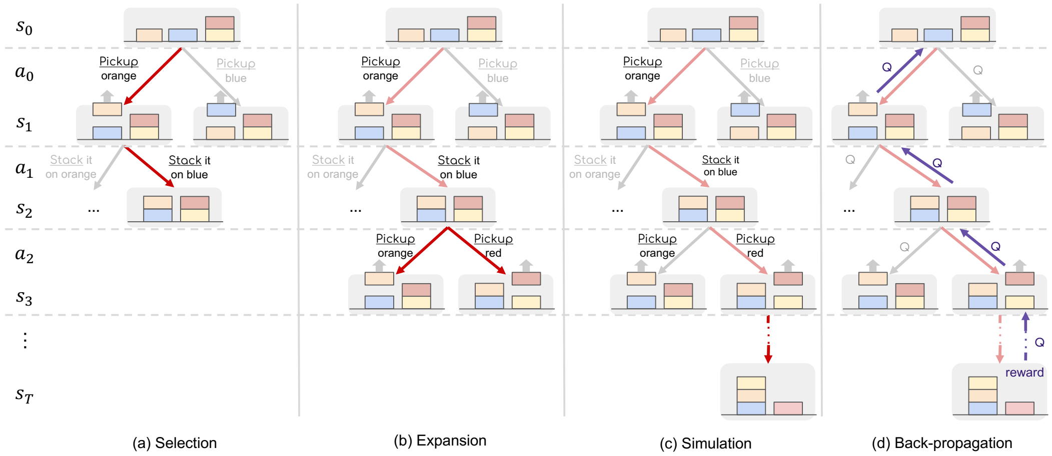

Figure 3: An illustration of the four phases in an iteration in MCTS planning (Section 3.3).

Similar to the state and action, the reward function can be specified in different ways to accommodate any knowledge or preferences about the reasoning problem of interest. Here we introduce several common rewards applicable to different tasks and shown to be effective in our experiments.

Likelihood of the action. When an action is generated by the LLM conditioning on the current state, the probability of the specific action reflects the LLM's preference. We thus can incorporate the log probability of the action as a reward.

Confidence of the state. State prediction is nontrivial in some problems, e.g., in math reasoning (Figure 2, right), given an action (i.e., a subquestion), the world model predicts the next state by answering the subquestion. We incorporate the confidence of the state (i.e., answers in this case) as a reward. Specifically, we draw multiple sample answers from the world model, and use the proportion of the most frequent answer as the confidence. A high confidence indicates a reliable reasoning step.

Self-evaluation by the LLM. We can also let the LLM criticize itself with the question "`Is this reasoning step correct?`" and use the next-word probability of the token "`Yes`" as a reward. The reward evaluates LLM's own estimation of the correctness of reasoning. Similarly, we can get another reward by prompting with the question "`Is this reasoning step helpful?`", which is a self-evaluation by LLM on the helpfulness of a reasoning step towards the target.

Task-specific heuristics. We can also flexibly plug-in other diverse task-specific heuristics into the reward function. For example, in plan generation for Blocksworld, we compare the current predicted state of blocks with the goal to calculate a reward (Section 4.1). The reward encourages the plan of movements to actively pace towards the target.

3.3 Planning with Monte Carlo Tree Search

Once equipped with the world model (Section 3.1) and rewards (Section 3.2), we can enable LLMs to reason with advanced planning algorithms, where we adopt Monte Carlo Tree Search (MCTS) [31, 12], a powerful planning algorithm that strategically explores the space of reasoning trees and strikes a proper balance between exploration and exploitation to find high-reward reasoning traces efficiently.

MCTS builds a reasoning tree iteratively, where each node represents a state, and each edge represents an action and the transition from the current state to the next state after applying the action (Figure 1). To guide the LLM agent to expand and explore the most promising nodes of the tree, the algorithm maintains a state-action value function $Q : \mathcal{S} \times \mathcal{A} \mapsto \mathbb{R}$, where $Q(s, a)$ estimates the *expected future reward* of taking action a in state s. That is, we assess the potential of a node (or a reasoning step) by looking ahead and anticipating the reward in future trajectories starting from this node. This fundamentally differs from the current reasoning methods that generate a reasoning trace autoregressively from left to right without accounting for the future.

More specifically, as illustrated in Figure 3, the MCTS planning performs four operations in each iteration to expand the tree and update Q values, i.e., *selection*, *expansion*, *simulation*, and *back-propagation*. The process continues until a specified computational budget (e.g., the number of iterations) is reached, and the resulting reasoning traces are acquired from the tree, as we articulated later. The psuedo-code of our MCTS planning is given in Algorithm 1 in the Appendix.

Selection. The first phase selects a portion of the existing tree that is most promising for further expansion in the next phase. Specifically, starting from the root node (i.e., initial state s_0), at each level of the tree, the algorithm selects a child node as the next node. The phase finishes when a leaf node of the current tree is reached. Figure 3(a) highlights the selected path in red. To balance between exploration (of less-visited nodes) and exploitation (of high-value nodes), we use the well-known *Upper Confidence bounds applied to Trees (UCT)* algorithm [31] to select each child node. Specifically, at node s, we select the action (which leads to a transition to a child node) in the tree by considering both the Q value (for exploitation) and uncertainty (for exploration):

$$a^* = \arg\max_{a \in A(s)} \left[Q(s,a) + w \sqrt{\frac{\ln N(s)}{N(c(s,a))}} \right], \tag{1}$$

where $N(s)$ is the number of times node s has been visited in previous iterations, and $c(s, a)$ is the child node of applying a in state s. Therefore, the less a child node was visited before (i.e., the more uncertain about this child node), the higher the second term in the equation. The weight w controls the balance between exploration and exploitation.

Expansion. This phase expands the tree by adding new child nodes to the leaf node selected above. Specifically, given the state of the leaf node, we use the LLM (as agent) to sample d possible actions (e.g., subquestions in math reasoning), and then use the LLM (as world model) to predict the respective next state, resulting in d child nodes. From the d nodes, we pick the node of largest local reward (Section 3.2) for simulation in the next phase. Note that if the leaf node selected above is a terminal (target) state already, we will skip expansion/simulation and jump to back-propagation.

Simulation. This phase simulates the future situations of the current node using the world model, in order to estimate the expected future rewards (Q values). Specifically, starting from the current node as above, at each node s, we create an action following a *roll-out policy* and use the world model to predict the next state. The roll-out process continues until a terminal state if reached. There could be different ways to define the roll-out policy (e.g., by adding different randomness). In our experiments, for simplicity and reduced noises, we just follow the same process as in the expansion above, by generating d candidate actions and picking one of the largest local reward $a' = \max_{a'} r(s, a)$. In practice, as the roll-out process will evaluate the reward function for multiple nodes, for efficiency, we discard the computationally expensive components in r (for example, the reward from the confidence of state requires sampling the answer multiple times), and use the resulting light-weight reward function for selecting actions during simulation.

Back-propagation. Once we reach a terminal state in the above phases, we obtain a reasoning path from the root node to the terminal node. We now back-propagate the rewards on the path to update the Q value of each state-action pair along the path. That is, $Q(s, a)$ is updated by aggregating the rewards in all future steps of node s. We may adopt the aggregation method according to the nature of different tasks and reward design, as discussed in Section 4.

As mentioned earlier, once a predetermined number of MCTS iterations is reached, we terminate the algorithm and select final reasoning trace from the constructed tree. There could be various ways for the selection. One approach is to start from the root node and iteratively choose the action with the highest Q value until reaching a terminal. Alternatively, one can directly select the path from the iterations that yielded the highest reward, or opt to choose the leaf node (and the respective root-to-leaf path) that has been visited the most. In practice, we observed that the second strategy often yields the best results.

3.4 RAP-Aggregation: Aggregating Multiple Reasoning Outputs

Ensemble-based methods, such as self-consistency CoT [58], can effectively improve performance by aggregating multiple valid reasoning traces. Therefore, for problems, such as math reasoning (Section 4.2) where only the final answer is required, RAP could produce multiple traces and answers from different MCTS iterations, which will be aggregated to produce the final answer. We refer to such a mechanism as RAP-Aggregation. Note that problems like plan generation or logical inference require a complete reasoning trace as output; thus, RAP-Aggregation will not be applied.

More importantly, there is a concern that some incorrect reasoning steps may appear in the early stage of multiple iterations, thus polluting the aggregation. As a result, we further devise a new weighting strategy for aggregating candidate answers. Specifically, for each candidate answer, we accumulate the reward of each reasoning step in the answer's reasoning traces. We choose the answer with the highest accumulative reward as the final aggregated answer.

4 Experiments

In this section, we demonstrate the flexibility and effectiveness of our RAP framework by applying it to a wide range of problems, including plan generation in an embodied environment, mathematical reasoning for solving math word problems, and logical reasoning for verifying hypotheses. The subsequent sections demonstrate how the world model formulation in RAP enables a versatile design of the state and action, catering to various reasoning contexts.

We primarily compare RAP with Chain-of-Thought (CoT) [59], and its variants like Least-to-Most prompting [66] as baselines. We also consider previous methods that ensemble reasoning paths from multiple samples (also known as self-consistency [58]). Moreover, we compare RAP with GPT-4 [44] when computation resources allow. By default, we use the LLaMA-33B model [56] as the base LLM for both our methods and baselines, and set the sampling temperature to 0.8.

4.1 Plan Generation

The plan generation task aims to produce a sequence of actions to achieve a given goal, possibly with additional constraints. The ability to generate plans is important for intelligent embodied agents, e.g. household robots [46]. This task has also been widely used to evaluate the reasoning ability of LLMs given their challenging requirements of long-horizon reasoning, e.g., Blocksworld is a classic problem, where an agent is asked to rearrange the blocks into stacks in a particular order.

Task setup. To explore the viability of the RAP framework for plan generation tasks, we adapt and evaluate RAP on the Blocksworld benchmark [50]. We define a **state** as the current orientation of the blocks and an **action** as an instruction that moves blocks. Specifically, an action is composed of one of the 4 verbs (i.e., STACK, UNSTACK, PUT, and PICKUP) and manipulated objects. For the action space, we generate the currently valid actions given the domain restrictions on actions and the current orientation of the blocks. To transit between states, we take the current action and query the LLM to predict the state changes to the relevant blocks. We then update the current state by adding the new block conditions and removing the conditions that are no longer true. Once a state has met all of the conditions listed in the goal or the depth limit of the tree is reached, we terminate the associated node.

To assess the quality of actions within this domain, we use two separate **rewards**. First, we prompt the LLM with some example test cases along with their solutions, and then calculate the log probability of the action given the current state (*"Likelihood of action"* reward in Section 3.2), denoted as r_1. This reward reflects the intuition of the LLM as the reasoning agent. It's typically indicative when there are few steps left to the goal, while not as reliable for a distant goal. Additionally, we compare the new state after performing an action with the goal and provide a reward, r_2, scaling with the number of conditions met (*"Task-specific heuristics"* reward). Specifically, when all the conditions are met, we assign a super large reward to make sure this plan will be selected as the solution.

Results. We use test cases from the Blocksworld dataset [57] and group them by solvable steps, resulting in 30 cases solvable with 2 steps, 57 cases with 4 steps, and 114 cases with 6 steps. There are at most 5 blocks in each test case. As the baseline method, we prompt the LLM with 4 test cases with corresponding solutions, and ask it to generate a plan for a new question. This setting is the same as one described in Valmeekam et al. [57], and we denote it as Chain-of-Thought (CoT) for briefness. For RAP, the same prompt is shown to help LLMs calculate r_1.

As shown in Table 1, CoT with LLaMA-33B can only generate successful plans for a few 2-step cases, and completely fails on harder problems. RAP substantially improves over CoT by nearly solving all problems within 4 steps, and a part of 6-step problems, achieving an average success rate of 64%. It's worth noting that the searching space of 6-step problems can be as large as 5^6, while our algorithm can find a successful plan 42% of the time within 20 iterations. Even more, our framework

Table 1: Results on Blocksworld. RAP$^{(10)}$ and RAP$^{(20)}$ refer to our method where the iteration number is set to 10 and 20, respectively. "pass@10" is a relaxed metric, where 10 plans are sampled for each test case, and the test case regarded as solved if at least one plan is successful. For all other settings including RAP, only a single plan is evaluated.

Method	2-step	4-step	6-step
CoT	0.17	0.02	0.00
CoT - pass@10	0.23	0.07	0.00
CoT (GPT-4)	0.50	0.63	0.40
RAP$^{(10)}$	1.00	0.86	0.26
RAP$^{(20)}$	**1.00**	**0.88**	**0.42**

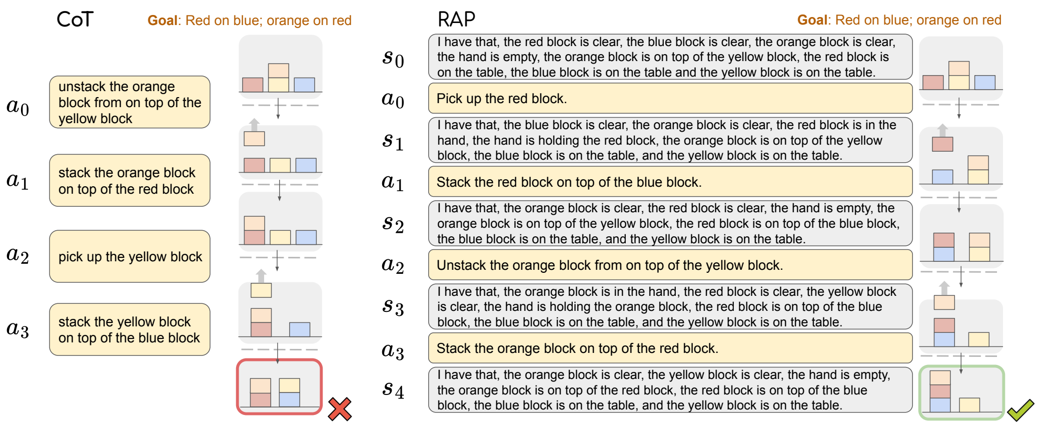

Figure 4: Comparing reasoning traces in Blocksworld from CoT (left) and RAP (right).

allows LLaMA-33B to outperform GPT-4 by 33% relative improvement [44], which is known to have much stronger reasoning ability [6].

We further present a case study of comparing the reasoning paths from Cot and RAP. As illustrated in Figure 4, we find the improvement can be mainly attributed to the following reasons: (1) By maintaining the world state during reasoning, RAP can recognize valid actions for the current state, avoiding generating illegal plans. (2) RAP is capable of backtracking and trying out other solutions when the first intuition from the LLM doesn't work. Specifically, CoT attempts to achieve the second goal, i.e. "orange on red", and achieve that with the first two steps. However, accomplishing the second goal first would prevent the first goal from being satisfied. On the contrary, even though RAP makes the same mistakes in the first iterations, our framework drives the agent to explore other possible paths (as described in Section 3.3) and finally generate a successful plan. (3) When calculating r_t, we can only feed the current state to the LLM and hide the history. E.g., in the case of Figure 4, to calculate the reward for a_2, the LLM is provided with a "new" test case, in which s_2 is the initial state. This significantly lowers the difficulties of the last few steps, and saves more iterations for harder decisions of the first few steps.

4.2 Math Reasoning

Task setup. Numerical reasoning tasks, such as GSM8k [11], often include a description and a final question. To arrive at the answer to the final question, it is necessary to undertake multi-step mathematical calculations based on the problem's context. It is thus natural to decompose the final question into a sequence of smaller sub-questions (Figure 2, right). To adapt RAP, we define a **state** as the values of intermediate variables, while an **action** is to propose an incremental sub-question about a new intermediate variable. The world model then responds to the sub-question using the intermediate variables and the problem description, adding the new intermediate variable value into the next state. We combine the self-evaluation of helpfulness by LLM $r_{t,1}$ and the confidence of state $r_{t,2}$ using weighted geometric mean $r_t = r_{t,1}^{\alpha} * r_{t,2}^{1-\alpha}$ as the **reward** function. This reward encourages

Table 2: Results on GSM8k. The superscripts indicate the number of samples or iterations.

Method	Accuracy (%)
Chain-of-Thought	29.4
+ $SC^{(10)}$	46.8
Least-to-Most	25.5
+ $SC^{(10)}$	42.5
$RAP^{(1)}$	40.0
$RAP^{(10)}$	48.6
+ aggr	**51.6**

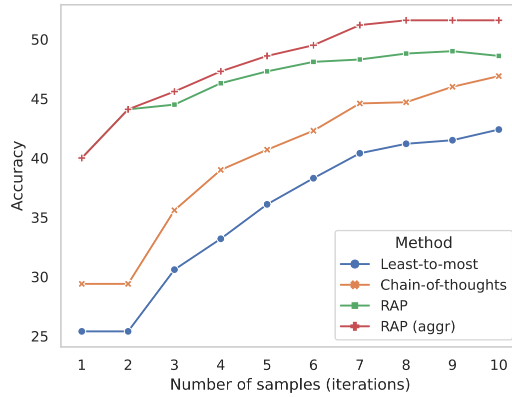

Figure 5: The performance of RAP and baselines on GSM-8K, with different numbers of sampled paths or iterations.

more relevant and useful sub-questions. To account for the impact of the reasoning path's length on the reward, we compute **the Q value** by using the maximum of average rewards in future steps.

$$Q^*(s_t, a_t) = \max_{s_t, a_t, r_t, \ldots, s_l, a_l, r_l, s_{l+1}} \operatorname{avg}(r_t, \ldots, r_l). \quad (2)$$

As a related work, Least-to-Most prompting [66] shares a similar idea to us in sub-question decomposition, but they generate sub-questions all at once. On the contrary, RAP considers each action a_t based on the current state s_t, which enables more informed decisions.

Results. We evaluate our framework on GSM8k, a dataset of grade high school math problems. We also evaluate the base model with CoT prompting [59], Least-to-Most prompting [66], and their self-consistency [58] variants, as the baselines. We use the same 4-shot examples demonstrations for both our framework and the baselines.

As shown in Table 2, our RAP framework answers 48.8% of the problems correctly, outperforming both the Chain-of-Thought and the Least-to-Most prompting with self-consistency[2]. Notably, this result is achieved when RAP only selects only one reasoning trace based on the reward. The introduction of RAP-Aggregate further improves the accuracy by $\sim 3\%$. We also calculate the accuracy with different numbers of iterations in MCTS and self-consistency samples in baselines, as illustrated in Figure 5. We find that across all numbers of iterations/samples, RAP-Aggregation outperforms baselines consistently, which indicates that when only a few iterations/samples are allowed, our framework is significantly better at finding reliable reasoning paths with the guide of reward.

4.3 Logical Reasoning

Task setup. A logical reasoning task (e.g. PrOntoQA [47]) typically provides a set of *facts* and *logical rules*, and a model is required to verify if a *hypothesis fact* is true or false by applying the logical rules to the given facts, as illustrated in Figure 6. These tasks not only require the correct final answer (true/false), but also a detailed proof demonstrating the result. To apply our framework, we define the **state** as a fact we are focusing on, analogous to the human's working memory [3] for inference. An **action** is defined as selecting a rule from the fact set. The world model performs a one-hop reasoning step to get a new fact as the next state. The **reward** is calculated with Self-evaluation (Section 3.2. Specifically, we prompt the LLM with a few examples with their labels to help it better understand the quality of reasoning steps. We use the average reward of future steps to update **the Q function**, the same as Equation (2) for GSM8k.

[2]While Touvron et al. [56] reports LLaMA's results on GSM8K, there are not sufficient details to reproduce their results. As our setting is different from theirs, e.g., prompt design, we do not directly compare our results.

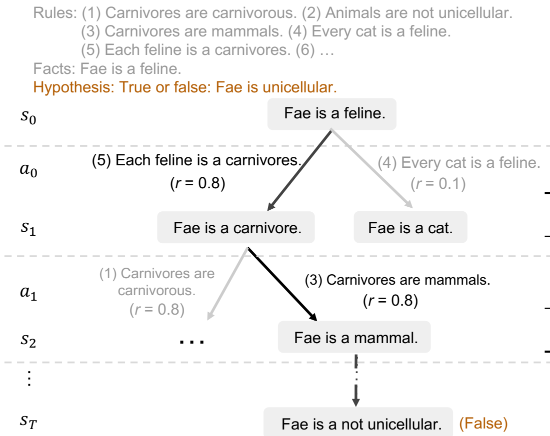

Figure 6: RAP planning on a PrOntoQA example.

Table 3: ProntoQA results.

Method	**Pred Acc**	**Proof Acc**
CoT	87.8	64.8
CoT + SC	89.8	-
RAP (Ours)	**94.2**	**78.8**

Results. We assess the performance of our RAP framework on PrOntoQA [47]. We adopt their settings of "true" ontology (using real-world knowledge), "random" ordering of rules. We mix the examples requiring 3, 4, and 5 reasoning hops in a correct proof to prevent LLM from memorizing when to finish the reasoning. We sample 500 examples from the generation script released by Saparov and He [47]. We compare both the prediction accuracy of the final answer and the accuracy of the entire proof. We do 20 iterations for MCTS and 20 samples for self-consistency in baselines.

As the results presented in Table 3, our framework achieves a correct answer rate of 94.2% and a proof accuracy of 78.8%, surpassing the CoT baseline by 14% proof accuracy and the self-consistency CoT baseline by 4.4% prediction accuracy. Such substantial improvements clearly demonstrate the effectiveness of RAP in solving logical reasoning problems in the PrOntoQA dataset. Also, as the case study illustrated in Figure 6, RAP can effectively recognize when a reasoning chain comes to a dead end, and propagate the signal back to earlier reasoning steps, with the planning algorithm allowing it to explore alternatives to the previous steps. The self-evaluation reward further helps RAP to recognize potential incorrect reasoning steps, encouraging the agent to avoid them in future iterations.

5 Conclusion

In this paper, we present Reasoning via Planning (RAP), a novel LLM reasoning framework that equips LLMs with an ability to reason akin to human-like strategic planning. By coupling the LLMs' reasoning capabilities with a world model and principled planning via Monte Carlo Tree Search, RAP bridges the gap between LLMs and human planning capabilities. Our framework, which repurposes the LLM to act as both a world model and a reasoning agent, enables the LLM to simulate states of the world and anticipate action outcomes, while achieving an effective balance between exploration and exploitation in the vast reasoning space. Extensive experiments on a variety of challenging reasoning problems demonstrate RAP's superiority over several contemporary CoT-based reasoning approaches, and even the advanced GPT-4 in certain settings. RAP's flexibility in formulating rewards, states, and actions further proves its potential as a general framework for solving diverse reasoning tasks. We posit that RAP, with its innovative melding of planning and reasoning, has the potential to redefine the way we approach LLM reasoning - essentially forging a new pathway toward achieving human-level strategic thinking and planning in artificial intelligence.

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Algorithm 1 $\mathrm{RAP\text{-}MCTS}(S_0, p_\theta, r_\theta, p_\phi, d, L, N, w)$

Require: Initial state s_1, state transition probability function p_θ, reward function r_θ, action generator p_ϕ, number of generated actions d, depth limit L, number of roll-outs N, and exploration weight w

Initialize memory of actions $A : \mathcal{S} \mapsto \mathcal{A}$, children $c : \mathcal{S} \times \mathcal{A} \mapsto \mathcal{S}$ and rewards $r : \mathcal{S} \times \mathcal{A} \mapsto \mathbb{R}$
Initialize the state-action value function $Q : \mathcal{S} \times \mathcal{A} \mapsto \mathbb{R}$ and visit counter $N : \mathcal{S} \mapsto \mathbb{N}$
for $n \leftarrow 0, \dots, N-1$ **do**
    for $t \leftarrow 0, \dots, L-1$ **do**
        if $s_t \notin A$ **then** ▷ Expansion & Simulation
            for $i \leftarrow 1, \dots, d$ **do**
                Sample $a_t^{(i)} \sim p_\phi(a \mid s_t)$, $s_{t+1}^{(i)} \sim p_\theta(s_t, a_t^{(i)})$, and $r_t^{(i)} \sim r_\theta(s_t, a_t^{(i)})$
                Update $A(s_t) \leftarrow \{a_t^{(i)}\}_{i=1}^{d}$, $c(s_t, a_t^{(i)}) \leftarrow s_{t+1}^{(i)}$, and $r(s_t, a_t) \leftarrow r_t^{(i)}$
            end for
        end if
        $a_t \leftarrow \arg\max_{a \in e(s_t)} \left[Q(s_t, a) + w \sqrt{\frac{\ln N(s_t)}{N(c(s_t, a))}} \right]$ ▷ Selection
        $s_{t+1} \leftarrow c(s_t, a_t)$, $r_t \leftarrow r(s_t, a_t)$, $N(s_{t+1}) \leftarrow N(s_{t+1}) + 1$
        if a_t is an output action **then break**
    end for
    $T \leftarrow$ the actual number of steps
    for $t \leftarrow T-1, \dots, 0$ **do** ▷ Back propagation
        Update $Q(s_t, a_t)$ with $\{r_t, r_{t+1}, \dots, r_l\}$
    end for
end for