

A Language-based Approach for Zero-Knowledge Task Planning

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Abstract—We present an approach that addresses the *Zero-Knowledge* task planning problem, i.e. planning high-level actions to achieve a given goal without any task-specific information. Our approach leverages a large language model (LLM) to decompose natural language instructions into subtasks and generate behavior trees (BTs) for execution. If errors arise during task execution, the approach also uses an LLM to adjust the BTs on-the-fly in a refinement loop. Experimental validation in the AI2-THOR simulator demonstrates our approach’s effectiveness in improving overall task performance compared to alternative approaches, even though all of these approaches rely on task-specific knowledge. Our work demonstrates the potential of LLMs to effectively address the Zero-Knowledge task planning problem, providing a robust framework for automated behavior generation in dynamic environments.

I. INTRODUCTION

Robotic systems have become increasingly adept at performing a variety of tasks in controlled environments. However, dynamically planning and executing tasks remains a significant challenge, particularly when starting without any previous experience, predefined models, or specific data related to the given task. In such situations, the robot must be able to generalize its capabilities and adapt in real-time.

In contrast, conventional task planning approaches often rely on predefined models and extensive task-specific data, limiting their adaptability to new and unforeseen tasks. These methods may depend on hand-coded action sequences and domain-specific knowledge bases. For example, symbolic planners like STRIPS [5] and PDDL [12] rely on manually crafted domain models that outline all possible actions, their preconditions, and their effects. While effective in structured environments, these planners struggle with dynamic, real-world scenarios where exhaustive modeling is impractical.

To address the limitations of conventional task planning, prior work has explored the use of large language models (LLMs) for planning and task execution. In recent years, LLMs have shown remarkable abilities in understanding and generating natural language, making them attractive for task planning. To improve the performance of this strategy, researchers often *fine-tune* these models using task-specific datasets. This process involves adapting pre-trained LLMs to improve the overall performance of the strategy.

Fine-tuning LLMs for robotic task planning generally requires substantial amounts of labeled task-specific data. This data typically includes detailed descriptions of tasks, corresponding subtasks, and the conditions under which

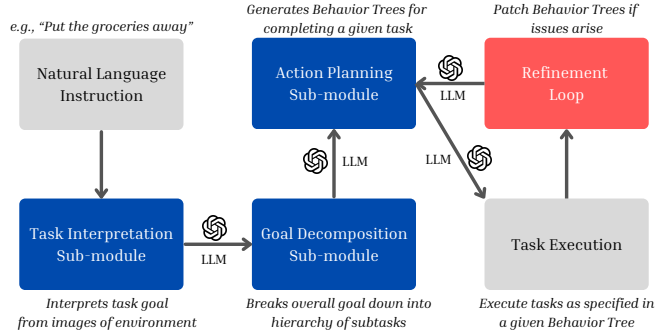


Fig. 1: We present an approach that addresses what we call the *Zero-Knowledge* task planning problem, i.e., planning high-level actions to achieve a given goal without any task-specific information. Our approach takes as input a natural language instruction, interprets a task goal from sensory input (e.g., images of the environment), breaks down the goal into a hierarchy of more manageable subtasks, generates Behavior Trees for completing a given task, then patches these Behavior Trees as needed if errors occur during task execution. The components of our approach interface via automatically generated prompts that incorporate information from a previous component then receive a text output from a large language model (LLM).

these tasks should be executed. While this strategy can significantly improve the model’s performance in specific domains, it comes with several challenges. Collecting and annotating large volumes of task-specific data can be labor-intensive and time-consuming. Moreover, the fine-tuned models often struggle to generalize beyond the tasks they were trained on, limiting their applicability to new and unforeseen tasks. Additionally, maintaining and updating these models to adapt to evolving task requirements and environments can be resource-intensive.

In this paper, we present a novel approach to addressing what we call the *Zero-Knowledge* task planning problem, i.e., planning high-level actions to achieve a given goal without any preset task knowledge. Our approach leverages an LLM to decompose natural language instructions into subtasks and generate behavior trees (BTs) for execution. If errors arise during task execution, the approach also uses an LLM to adjust the BTs on-the-fly in a refinement loop.

Experimental validation of our approach is conducted using the AI2-THOR simulator, a platform that provides diverse and realistic environments for testing robotic tasks. AI2-THOR offers a wide range of household objects and scenarios, allowing for a comprehensive evaluation of task

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performance and approach robustness. Our results demonstrate improvements in overall task performance compared to alternative approaches, even though all of these baseline approaches rely on task-specific knowledge, highlighting the efficacy of our planning approach.

The contributions of our work include:

- We introduce and formalize the Zero-Knowledge task planning problem.
- We present a Zero-Knowledge planning approach that starts with no prior knowledge and dynamically generates task decompositions and behavior trees from natural language instructions.
- We validate our approach through extensive experimentation in the AI2-THOR simulator, showcasing its potential for real-world applications as compared to state-of-the-art task planners.

II. RELATED WORKS

A. Task Planning

The goal of task planning is to compute a sequence of actions that achieve a given goal. Task planners typically operate over logic-based domain languages, such as STRIPS [5] or PDDL [12], which define a start state, a goal state, and legal actions for transitioning between these states.

Over the years, several efficient task planning algorithms have been developed, such as Fast Forward (FF) [7] and Fast Downward (FD) [6]. These planners use techniques like heuristic search to find optimal or near-optimal action sequences. While these methods have advanced task planning considerably, they rely heavily on predefined, well-structured environments. They perform well in domains where exhaustive domain models outline all possible actions, their preconditions, and effects. However, these classical planners struggle in dynamic, real-world environments, particularly when prior task knowledge is unavailable or incomplete—making them unsuitable for the Zero-Knowledge problem, where no prior knowledge is assumed.

B. Planning with LLMs

Recent advancements in natural language processing, especially with Large Language Models (LLMs) [17], have opened new possibilities in task planning [9, 11, 15, 14, 16, 10, 18, 13]. LLMs can interpret planning queries in natural language and generate step-by-step action sequences, bypassing the need for manually crafted domain models. This shift from logic-based planners to language-based reasoning holds promise for environments where tasks and conditions are not predefined or fully observable.

Despite their potential, LLMs face significant challenges in planning tasks. For example, they tend to struggle with sequential reasoning and generating coherent, structured plans over long horizons [3]. While models like GPT-4 can understand and process individual tasks, producing a robust sequence of actions to achieve a goal remains difficult without external guidance.

Several approaches have attempted to address these limitations. SMART-LLM [14] uses few-shot learning to generate

action sequences based on several provided examples. This method demonstrates some ability to reason about sequential tasks by integrating examples into the LLM’s prompt. However, SMART-LLM assumes a high degree of task knowledge and complete observability, making it ill-suited to the Zero-Knowledge setting, where no prior information about the task or environment is provided.

Similarly, MLDT (Multi-Level Decomposition Task Planning) [16] tackles complex planning by breaking down tasks into goal-level, task-level, and action-level subcomponents. It leverages smaller, fine-tuned LLMs to handle long action sequences, using hierarchical decomposition to structure the planning process. However, MLDT’s reliance on fine-tuning means it requires task-specific training data to perform well, which limits its adaptability in Zero-Knowledge scenarios where such data is unavailable.

While advancements like Chain-of-Thought (CoT) reasoning [15, 2] have improved the sequential decision-making capabilities of LLMs by breaking down tasks into smaller subproblems, these approaches still fall short of handling Zero-Knowledge planning in completely unfamiliar environments. CoT relies on iterative feedback and refinement loops, but it still requires some degree of task familiarity to generate meaningful plans.

In contrast, the Zero-Knowledge problem requires a truly adaptable planning system that can handle tasks and environments without prior knowledge. Existing LLM-based planners, while powerful in structured domains, are limited in their ability to generate novel plans and adjust to real-time environmental feedback dynamically. Addressing these challenges will require further advancements in LLM capabilities, particularly in adapting to dynamic environments and generating coherent plans without task-specific fine-tuning.

III. TECHNICAL OVERVIEW

In this section, we formalize the problem at hand and provide an overview of the key components of our proposed approach. A detailed explanation of how these components integrate into our full approach can be found in §IV.

A. Problem Definition

In this work, we introduce a problem called *Zero-Knowledge* task planning. This problem is formalized here:

Zerk-Knowledge Task Planning

Zero-Knowledge task planning refers to the process of generating a sequence of actions, denoted by $\pi = [a_1, a_2, \dots, a_n]$, to successfully achieve a given goal, G , without relying on any prior knowledge specific to the task at hand. The only permissible information available to the agent in Zero-Knowledge task planning is task-agnostic and remains fixed and invariant across all potential tasks.

Note that this problem definition disallows the following:

- Task-specific predicates or instances (objects).

- Environmental models (e.g., maps, object locations).
- Prior task-specific knowledge or experience.
- Fine-tuning of a model based on task-specific data.

Note that because predefined task-specific predicates or instances are not permissible here, the conventional task planning strategy of specifying goals using some logic-based truth statement does not have a strong basis in Zero-Knowledge task planning. Instead, we assume the goal, G , is presented in a knowledge-agnostic manner, such as through natural language.

It is important to note that Zero-Knowledge task planning does still permit the use of a predefined set of all possible actions. Because the agent’s capabilities are assumed to remain constant across all tasks, it is not regarded as task-specific knowledge. In principle, these actions may include standard components such as preconditions and effects; however, without task-specific predicates or instances, these components are unlikely to be useful in practice.

The key challenge here is that the agent must bootstrap a strategy on-the-fly, relying solely on real-time interpretation of the instruction, G , and sensory inputs from the environment during task execution. The agent must infer both the goals and the necessary actions.

B. Approach Components

Our approach comprises two high-level components that enable Zero-Knowledge task planning. Here, we overview these components, leaving details for the following section:

(1) The *Natural Language Planning Engine* interprets user requests, converts them into structured task representations, and manages the entire planning process. By leveraging an LLM with Visual Language Model (VLM) capabilities, it translates high-level user instructions into sub-goals and corresponding completion criteria, generates action plans for each sub-goal, and incorporates real-time feedback to adjust plans as needed. This engine is composed of three sub-modules: the *Task Interpretation Sub-Module*, the *Goal Decomposition Sub-Module*, and the *Action Planning Sub-Module*. Each of these sub-modules, detailed in the following section, interfaces with the LLM through automatically populated text prompts, receiving text outputs that are somehow incorporated in subsequent decision making.

(2) The *Refinement Loop* oversees the execution of the planned actions and adapts them based on real-time feedback from the environment. This loop enables the system to monitor the outcome of each action using sensory inputs, detect discrepancies between expected and actual states, and re-evaluate and adjust the plan in response to failures.

IV. TECHNICAL DETAILS

In this section, we detail our Zero-Knowledge task planning approach. For interested readers, a complete view of all LLM prompts and outputs through an example task can be found at the paper website.¹

A. Natural Language Planning Engine

The Natural Language Planning Engine is the core of our framework, orchestrating the interpretation and planning processes. It leverages an LLM to perform task comprehension, decomposition, and action planning. Below, we cover the three ordered sub-modules that comprise this engine.

Task Interpretation Sub-Module: The Task Interpretation Sub-Module interprets the high-level natural language instruction provided by the user and gathers environmental context through the robot’s sensors.

The module first receives the user’s instruction, G , for example, “Bring a mug of coffee to the table”. The robot rotates in place, capturing four images from its sensor, one at every 90-degree increment. These images are converted to text using base64-encoding. Next, the sub-module constructs a prompt for the LLM. This prompt includes the text representation of the images, an instruction to generate a task ID in an underscore-separated name, and a request for the generation of detailed context for the given task instruction.

The LLM processes this prompt and outputs a task ID, e.g., `bring_coffee_to_table`, and a detailed environmental context description, which includes information that may assist in generating sub-tasks and action sequences, such as object descriptions and spatial relationships.

Task Decomposition Sub-Module: The Task Decomposition Sub-Module takes the text output from the Task Interpretation Sub-Module and generates a new prompt that requests the decomposition of the given task into smaller, more manageable sub-tasks given the inferred context. The prompt specifies formatting guidelines, such as specifying that each sub-task should be a concise, underscore-separated phrase without spaces. Additionally, the LLM is instructed to provide a completion condition for each sub-task, framed as what we refer to as *Universal Predicates*, i.e. predicates that are applicable in any physical environment.

In this work, we assign our Universal Predicates to be a predefined list of predicates available in the AI2Thor simulator. Example predicates include `isOnTop`, `isOpen`, `isFilledWith`, and `isVisible`. However, our approach can easily accommodate any list of Universal Predicates as a drop-in replacement. Because Universal Predicates always remain fixed through all environments, these are not considered task-specific knowledge.

The Task Decomposition Sub-Module outputs a string of text specifying a hierarchy of sub-tasks along with their associated completion conditions. Each completion condition is formatted as a predicate applied to a specific object. The layers of this hierarchy specify task order; tasks in a higher layer must be done before tasks in a lower layer, and tasks within the same layer can be done in any order.

Action Planning Module: The Action Planning Sub-Module takes one sub-task text output from the Task Decomposition Sub-Module and outputs an action plan that will ideally complete this sub-task. The action plan is represented as a Behavior Tree (BT) [4].

¹<https://tinyurl.com/2bcdbfxf>

The prompt for the LLM in this sub-module includes the overall task and sub-task text, the environmental context text, and a list of all already completed sub-tasks. It provides instructions on constructing a BT, specifying the allowed actions. It includes a reminder of the robot’s limitations, such as it can only hold one object at a time. Additionally, it includes a list of object classes with which the robot can interact. The completion condition for the sub-task is provided to guide the Behavior Tree towards its goal. Finally, it contains a request to generate the Behavior Tree in XML format without additional text.

The LLM processes this prompt and generates an XML-formatted Behavior Tree that sequences the necessary actions and conditions to accomplish the sub-task. The Behavior Tree uses constructs in the XML like `<Sequence>` and `<Selector>` to structure the execution flow.

B. Refinement Loop

The Refinement Loop oversees the execution of planned actions from a Behavior Tree and adapts them based on real-time feedback from the environment. The refinement loop can be entered for two reasons: (1) during task execution, a *Universal Error* (covered below) is detected; or (2) the traversal through a Behavior Tree completes and the goal condition associated with the current sub-task is not satisfied.

A *Universal Error* is a type of error that may occur in any environment, similar in concept to a Universal Predicate covered above. Our approach maintains a list of three Universal Errors that it checks: `{notClose, notVisible, doesNotExist}`. The `notClose` error signals that a target object is not within reaching distance before the robot attempts a physical action, such as “grab”. The `notVisible` error signals that a target object is not within the robot’s field of view before interacting with, navigating to, or checking the condition of said object. Lastly, the `doesNotExist` error signals that a given object does not exist in the environment. This current list of Universal Errors was selected empirically and works well in practice; however, our approach can accommodate any list as a drop-in replacement and future work is necessary to optimize this set of possible errors.

If the refinement loop is entered, the objective is for the LLM to modify the current Behavior Tree in order guide successful execution. To do this, a prompt is automatically generated. This prompt for the LLM includes a summary of the overall task and current sub-task, any previously completed sub-tasks, as well as the original Behavior Tree that resulted in an error. It provides detailed feedback on the error, including error messages, error categories, and any relevant environmental context (e.g., images or state descriptions). The prompt contains instructions to correct the Behavior Tree, adhering to the allowed actions, conditions, and known objects, and includes a reminder of the robot’s limitations and the necessity to produce the output in the specified XML format without additional text. The completion condition for the sub-task is also provided, encouraging the Behavior Tree to achieve the given goal.

This process above repeats until the sub-task is completed or some maximum number of refinement loops is reached.

C. Algorithm Workflow

Our approach as a whole operates as follows: the Task Interpretation and Goal Decomposition Sub-Modules are executed once. The Action Planning Sub-Module then generates Behavior Tree plans sequentially, targeting the goals outlined by the Goal Decomposition Sub-Module in their hierarchical order. A refinement loop is initiated to address any errors that arise during the execution of these task plans. This whole process continues, interleaving the Action Planning Sub-Module and Refinement Loop as needed, until all sub-goals defined by the Goal Decomposition Sub-Module are successfully completed or a termination condition is met.

V. EVALUATION

In this section, we evaluate the performance of our proposed Zero-Knowledge task planning approach against four baselines: the SMART-LLM method [10], the MLDT method [16], the Blocking Conditions and Resolutions method [8], and a variation of our current approach where the Refinement Loop is removed. The evaluation focuses on the success rates of task completion, the task knowledge requirements, and the time duration required to generate plans.

A. Implementation Details

Our experimental implementation is written in Python. The experiments were conducted on an Asus Vivobook laptop with a 2.4 GHz Intel Core i7 processor and 16GB of RAM. While the generation components of our approach, as detailed in §IV, can work with any off-the-shelf LLM with VLM capabilities, our current implementation is integrated with OpenAI’s GPT-4o [1]

B. Experimental Tasks

Each condition in our experimental evaluation was tasked with executing four distinct tasks within the AI2Thor environment, as described below. The tasks were provided to the planner in the form of natural language descriptions. In order to track the ground truth success of these planners, an *oracle goal completion function* which definitively assesses the completion criteria in the scene is included. The complete conditions for each task were defined using goal literals, which were passed to the oracle goal completion function. The four tasks are overviewed here:

- 1) *Putting the Apple in the Fridge*: The user request is to “put the apple in the fridge”. The task involves the robot locating the apple, navigating to the fridge, opening the fridge door, and placing the apple inside. The ground truth goal literal for completion is `In(apple, fridge) = true;`
- 2) *Soaking the Mug*: The robot must find the mug, bring it to the sink, place it inside, and turn on the faucet. The ground truth goal literals for this task are: `In(mug, sink) = true and FaucetOn(sink) = true;`
- 3) *Setting a Place at the Dining Table*: The user request is to “set a place at the dining table”. The



Fig. 2: In the task shown, the robot in the AI2-Thor environment is given the instruction “set a place at the dining table”. Using Zero-Knowledge task planning, the robot here reasons about the environment and figures out on-the-fly that this instruction must mean placing a plate, fork, and knife on the table, and the robot correctly generates actions in order to successfully accomplish these sub-goals. The left image here is the initial state of the environment, the middle image shows the robot finding and picking up the fork, and the right image shows the final state achieved at the end of task execution.

robot needs to locate a plate, a fork, and a knife and place each item on the table. The ground truth goal literals for completion are $\text{On}(\text{plate}, \text{table}) = \text{true}$, $\text{On}(\text{fork}, \text{table}) = \text{true}$, and $\text{On}(\text{knife}, \text{table}) = \text{true}$. This task is shown in Figure 2;

- 4) *Bringing a Mug of Coffee to the Table*: The user request is to “bring a mug of coffee to the table”. The robot must locate a coffee mug, interact with a coffee maker to fill it with coffee, and then place the filled mug on the dining table. The ground truth goal literals for this task are $\text{FilledWith}(\text{coffee_mug}, \text{coffee}) = \text{true}$ and $\text{On}(\text{coffee_mug}, \text{table}) = \text{true}$.

For all tasks, while the completion criteria are specified via goal literals, our planner and its ablation are only provided with the user request in natural language. It must decompose the task and plan actions to achieve the final goal. Each task involves interactions with various objects in the simulation, and pre-defined AI2Thor wrapper functions are used to execute the actions in real-time.

C. Baseline Comparisons

Our approach is compared against four baselines:

- 1) *Zero-Knowledge task planner without Refinement Loop*: We include an ablation condition that evaluates our proposed approach with the refinement step removed. In this scenario, the approach still attempts to generate an appropriate behavior tree (BT), but it does not incorporate environmental feedback into the prompts. This condition allows us to assess the importance of the refinement step in improving task completion rates.

- 2) *BCR*: The Blocking-conditions and Resolutions planner (BCR) performs sequential action selection by asking an LLM to select an action, one at a time, that resolves a current blocking mode [8]. This planner requires task-specific blocking conditions and predicates. In the evaluation, this condition is provided the user request in natural language and its corresponding goal literals.

- 3) *SMART-LLM*: SMART-LLM is a few-shot offline planning method that utilizes a large language model (LLM) to generate Pythonic action sequences [10]. The model is prompted with several examples of plans integrated into the prompt, allowing it to learn from these examples and

produce a sequence of actions tailored to each task. SMART-LLM operates under the assumption of full observability and deterministic actions. Full observability here implies task-specific knowledge, i.e., every part of the state must be perfectly known through the task. In the evaluation, SMART-LLM is provided the user request in natural language, and its corresponding goal literals.

- 4) *MLDT*: The Multi-Level Decomposition Task Planning (MLDT) method [16] uses a decomposition strategy to break down complex tasks into goal-level, task-level, and action-level sub-tasks. A key aspect of MLDT is its use of smaller LLMs, which are fine-tuned on task-specific data to handle complex reasoning and long action sequences. This task-specific fine-tuning implies that this condition is also not zero-knowledge. For our evaluation, we use the fine-tuned *bigscience/bloom-3b* model. MLDT is provided with the goal literals corresponding to the user request.

D. Evaluation Metrics

Through our evaluation, we collect and report on the following metrics:

- *Task Success Rate*: The number of tasks successfully completed by each approach out of fifty total trials.
- *Task Knowledge Requirements*: The amount of task knowledge data required for each approach, measured in kilobytes (kb). This metric includes the amount of prior knowledge or fine-tuning needed by the LLM for grounding.
- *Execution Time*: The time taken to generate and refine behavior trees for each task. This metric excludes the time required to physically perform the actions, focusing solely on the algorithmic processing time.

E. Results

- 1) *Task Success Rate*: As shown in Table I, our proposed approach demonstrates comparable or higher success rate across the four tasks compared to alternative approaches, even though the baselines were provided additional task-specific knowledge. In particular, for tasks like “Put the apple in the fridge” and “Soak the mug”, our approach achieved near-perfect success rates, while alternatives struggled significantly, especially in complex tasks like “Bring a mug of coffee to the table”.

	<i>Apple</i>	<i>Mug</i>	<i>Table</i>	<i>Coffee</i>
ZK (ours)	50/50	49/50	45/50	33/50
ZK - No Refine	46/50	9/50	7/50	6/50
BCR	49/50	28/50	45/50	50/50
SMART-LLM	50/50	0/50	46/50	0/50
MLDT	50/50	0/50	0/50	0/50

2) *Task Knowledge Requirements*: Table II illustrates the task-specific knowledge data required by each method for all tasks. This metric was collected by inspecting file sizes corresponding to each condition. Our proposed approach does not require task-specific knowledge for planning or refinement, while alternatives such as MLDT require significantly larger data volumes. These results highlight the zero-knowledge aspects of our approach, a critical factor in mitigating the challenges of scaling across diverse tasks.

<i>Method</i>	<i>Data (kb)</i>
ZK (ours)	0
ZK - No Refine	0
BCR	22
SMART-LLM	43
MLDT	855000

3) *Execution Time*: As shown in Table III, the average execution time per task for our method is typically slower than the alternatives. We address these findings further in §VI. For tasks like “Soak the mug” and “Set a place at the dining table,” our approach’s execution time is longer, though that time is generally spent successfully refining errors and, eventually, successfully completing the tasks.

	<i>Apple (s)</i>	<i>Mug (s)</i>	<i>Table (s)</i>	<i>Coffee (s)</i>
ZK (ours)	18.2	88.5	161.4	269.0
ZK - No Refine	8.1	28.9	84.7	65.8
BCR	10.2	45.9	64.0	15
SMART-LLM	49.1	61.2	92.15	69.1
MLDT	18.3	10.9	54.3	23.5

VI. DISCUSSION

This work introduces and formalizes the Zero-Knowledge task planning problem and presents a strategy that approaches robot task planning in terms of decomposing natural language instructions into hierarchical sub-tasks. Our Zero-Knowledge task planning strategy enables the robot to operate without predefined task knowledge or fine-tuning, relying solely on user-provided instructions. The approach dynamically generates behavior trees and adapt them based on environmental feedback during task execution. We also present the first implementation of this strategy using an LLM as the task decomposition engine, where only natural language instructions are given to the planner.

Our experiments demonstrate that this approach often outperforms alternative methods such as SMART-LLM and an ablation version of our strategy without refinement. The results indicate that our approach leads to higher or comparable task success rates, especially in complex scenarios requiring adaptation to environmental feedback. Additionally,

the Zero-Knowledge approach requires significantly less task knowledge, highlighting its suitability for zero-shot, novel applications.

A. Limitations and Future Work

While our Zero-Knowledge task planning approach shows strong task performance, several limitations offer opportunities for improvement. A key limitation is that the approach does not retain successful plans for future use, requiring it to regenerate behavior trees for each new task, even when prior strategies could be reused. This leads to inefficiency in cases where minor adjustments to previously successful plans would suffice.

Additionally, the approach relies entirely on the LLM for plan generation and refinement, lacking external behavior tree processing. This limitation results in the regeneration of entire behavior trees for every new task, rather than adapting specific nodes or subtrees, further increasing computational overhead.

Moreover, the approach requires at least three LLM calls for task decomposition, generation, and refinement. While these calls can still be done reasonably quickly on-the-fly, this overhead still introduces some latency, possibly limiting real-time performance in resource-constrained environments.

In response to these limitations, future work could focus on integrating memory mechanisms to retain and reuse successful plans, enabling the approach to refine specific parts of behavior trees rather than regenerating them from scratch. Additionally, exploring hybrid methods that combine LLM with external behavior tree processing could allow for more adaptable, efficient, and comprehensible task planning.

B. Zero-Knowledge as a Challenge for Generalizable Task Planning

Our work presents and addresses the Zero-Knowledge task planning problem, which represents a significant departure from classical planning frameworks. Unlike traditional task planners that rely on task-specific models or training data, the Zero-Knowledge problem challenges researchers to create planners that can generate plans and execute tasks without any prior task knowledge or fine-tuning. In this context, Zero-Knowledge task planning exemplifies the need for more adaptable and generalizable task planning systems that can operate effectively in dynamic, unfamiliar environments based solely on high-level instructions.

Although our approach yields promising results, demonstrating that LLMs can generate effective plans in a Zero-Knowledge setting, this work represents only an initial exploration. Further research is needed to fully realize the potential of language-based planning systems in solving the Zero-Knowledge problem, particularly in real-world scenarios where environmental uncertainties are more complex. Future investigations into incremental plan refinement, memory mechanisms, and external processing frameworks will be critical in addressing the limitations of current systems and advancing this research area.

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