

# L3M+P: Lifelong Optimal Planning with Large Language Models

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**Abstract**—Enabling the creation of general-purpose service robots is a long-standing research ambition for the field of autonomous robotics. This ambition has only grown with the widespread adoption of large language models (LLMs), which are demonstrated to excel in many generalization tasks but do not necessarily perform well as standalone reasoning agents. Recent research has focused on integrating LLMs with classical planning methods so LLMs can serve as natural language interfaces to more robust underlying systems. There are two issues that prevent this approach from scaling to general-purpose service robots. First, classical planning algorithms generally require a detailed and consistent specification of the environment, which is not always readily available. Second, service robots are often meant to serve in long-term continuous deployments, so they must maintain a dynamic memory of the environment that can be updated with multi-modal inputs and extracted as planning knowledge for any task; existing frameworks mainly focus on isolated planning tasks. To address these two issues at once, this paper introduces L3M+P, a framework that uses an external knowledge graph as a memory base to represent an absolute world state. The graph can be updated from multiple sources of information, including natural language interactions with humans. L3M+P enforces rules for the expected format of the absolute world state graph to maintain consistency between graph updates. At planning time, given a natural language description of a task, context is retrieved from the knowledge graph and provided to the existing LLM+P framework, which generates a problem specification in the form of a PDDL file that a classical planner can use to solve the task. Our experiments demonstrate that L3M+P achieves 26.5% improvement on correctly registering natural language state changes and 17.5% improvement on generating correct plans by using both knowledge graph retrieval and rule verification on the knowledge graph, when compared to a straightforward extension of LLM+P.

## I. INTRODUCTION

Large language models (LLMs) have proven to be very promising natural language interfaces in a variety of domains, including for robot agents [1]. However, their lack of grounding in the physical world prevents them from being used effectively as direct planners in robot systems [2]. A large body of work has thus been motivated towards grounding LLM-based agents to bridge the gap between human-friendly interfaces and consistent, accurate planning.

With this area of research on frameworks that ground LLMs for planning comes the important question of how practical these systems really are. Service robots are the most direct application since they require exactly what these frameworks are solving: a human should be able to loosely state a task in natural language and the service robot should

be able to generate and execute an accurate, grounded plan that accomplishes the task.

However, that is a very isolated example. While these frameworks address the fundamental goal of converting a natural language (NL) task into concrete actions, service robots are not meant for one-time use. Rather, they are meant to serve their function over an extended period of time, and any actions they take should be grounded in a *dynamic*, real-world environment. Specifically, this environment can be changed both by the actions of the service robot itself and by external influences like humans.

Let us decompose this larger goal by ignoring external changes to the environment and considering how an LLM-based agent can generate plans that are consistent with changes to the environment from past plans. One naive approach might be to, using an existing framework, generate a report of all past actions and feed this report alongside any prompts to the LLM so that the LLM is always aware of the most recent state of the environment. However, this approach is prone to model hallucination, which can significantly affect the accuracy of the agent [3], especially as the context grows. As such, the LLM-based agent must have an external memory.

Now let us consider how an LLM-based agent can generate plans that are consistent with solely external changes to the environment. In many service robot applications, information on updates to the environment can arrive in many forms, including sensor input as well as dialogue with humans, where a human might describe a change in the environment. While there are already solutions for traditional knowledge representation in service robots that can be updated based on sensor input [4], [5], [6], updates based on human dialogue would require a natural language interface, probably using an LLM. As such, an LLM-based agent would need a knowledge base that is precise enough to be used within a traditional knowledge representation system but also simple enough to be used by an LLM to process NL environment updates.

This motivation leads us to develop the L3M+P framework for augmenting existing research on grounded LLM-based agents with a dynamic memory that is rigorously defined but also easily interpretable. To this end, this paper introduces a system that can interface with this memory as follows.

- 1) Introduce an LLM-based natural language interface for updating the memory given NL descriptions of environment updates.
- 2) Integrate with robot perception so the memory can be updated based on sensory input.
- 3) Retrieve relevant information from the memory that

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can be used as context within an existing LLM-based, grounded planner.

The rest of this paper is organized as follows: Section II provides preliminary information for the modules in L3M+P. Section III introduces the formalisms used in this paper. Section IV explains the method for implementing each component of L3M+P. Section V discusses experiments and results. Finally, in Section VI, we highlight recent works related to L3M+P.

## II. BACKGROUND

This section describes an existing work on using LLMs for planning, which we build on with L3M+P. We also introduce some background about knowledge graphs and augmenting LLMs with external sources of information.

### A. Planning with Language Models

LLM+P [7] is an existing framework for combining LLMs with classical planning in robot agents to bridge the gap between NL task descriptions and symbolic planners. These symbolic planners operate using the planning domain definition language (PDDL), a commonly used language for formally defining environments and tasks [8], [9]. A symbolic planner requires a domain PDDL file that defines a state-action space through (a) a set of predicates that can fully represent a state and (b) a set of actions for manipulating the current state. The domain file also defines the preconditions and effects of each action. To generate a plan for a specific task, a symbolic planner also requires a problem PDDL file that specifies a set of initial predicates (representing the initial state) and a set of goal conditions (identifying one or more goal states). Given a description of initial state, a description of a task, and a domain PDDL file, LLM+P prompts an LLM to generate a problem PDDL file that can be supplied with the domain file to a symbolic planner to generate a plan.

L3M+P extends LLM+P by removing the requirement for a description of the initial state and instead maintaining the current state in an internal knowledge base that can be used to extract information relevant to a given planning task. Using the relevant context, L3M+P uses LLM+P to generate a problem PDDL file that it can supply to a classical planner in order to produce a plan.

### B. Knowledge Graphs

Knowledge graphs [10] are representations of knowledge that organize information into graph structures, where nodes represent entities and edges represent relationships between entities. A knowledge graph can be constructed from various sources, including structured databases, unstructured text, or other forms of data. Some common knowledge graph technologies include Neo4j [11], one of the most widely adopted graph database systems, and Apache AGE [12], a PostgreSQL extension that allows integrating relational and graph databases. Similar to traditional databases, graph databases also generally support structured querying, such as through the Cypher query language [13].

The relationship between a pair of nodes in a knowledge graph is commonly referred to as a triplet of subject, predicate, and object. In this work, we consider the following two forms of triplets:

- (subject, relationship, object)
- (subject, property, boolean)

Each triplet in the first form can be interpreted as: the subject has the given relationship to the given object. For example, (table, in-room, living-room) indicates that the table is located in the living room. Each triplet in the second form can be interpreted as: it is true/false that the subject has the given property. For example, (light, on, true) indicates that the light is on.

L3M+P uses a knowledge graph as the internal knowledge base, as a knowledge graph provides a natural way to represent the world state and extract/insert information.

### C. Retrieval-Augmented Generation

Many applications of LLMs involve using these models to answer domain-specific queries. One approach for adapting a pretrained model to this purpose could be to fine-tune the model on domain-specific knowledge [14]. However, this method can be expensive and is not versatile to changes in knowledge. Retrieval-augmented generation (RAG) is a method for augmenting language models with external knowledge sources [15]. Context from an external knowledge source can be retrieved based on a user-prompt and fed alongside the original prompt to the language model in order to provide the language model with sufficient information to answer the prompt. Some common RAG implementations use pretrained transformers to generate document embeddings and store the documents in a vector index [16]. When given a prompt, an embedding for the prompt is generated and used to perform a top- $k$  retrieval of the documents, whose content can be added to the original prompt.

Our framework has a RAG component which retrieves the relevant edges from a knowledge graph and feed them as context for the LLM to handle state changes and plan queries.

## III. PROBLEM STATEMENT

The overarching goal of our framework is to be able to solve two distinct types of problems: keeping the state up-to-date and planning.

### A. State Update

The first problem is for the system to register updates that take place in the environment. An update is provided either as natural language or as sensory input, and it could represent a single event, multiple events, or even a partial event (if the full details of an event are unknown). In our work, we focus on updates provided as natural language.

Formally, the input to an update problem  $U$  is the tuple  $\langle \mathcal{S}, s_t, u_t \rangle$ :

- $\mathcal{S}$  is a finite, discrete set of states that represent all possible world states.
- $s_t \in \mathcal{S}$  is the robot's knowledge at time  $t$ .  $s_t$  is itself the tuple  $\langle V_t, E_t \rangle$ , where  $V_t$  is a set of entities (vertices) in

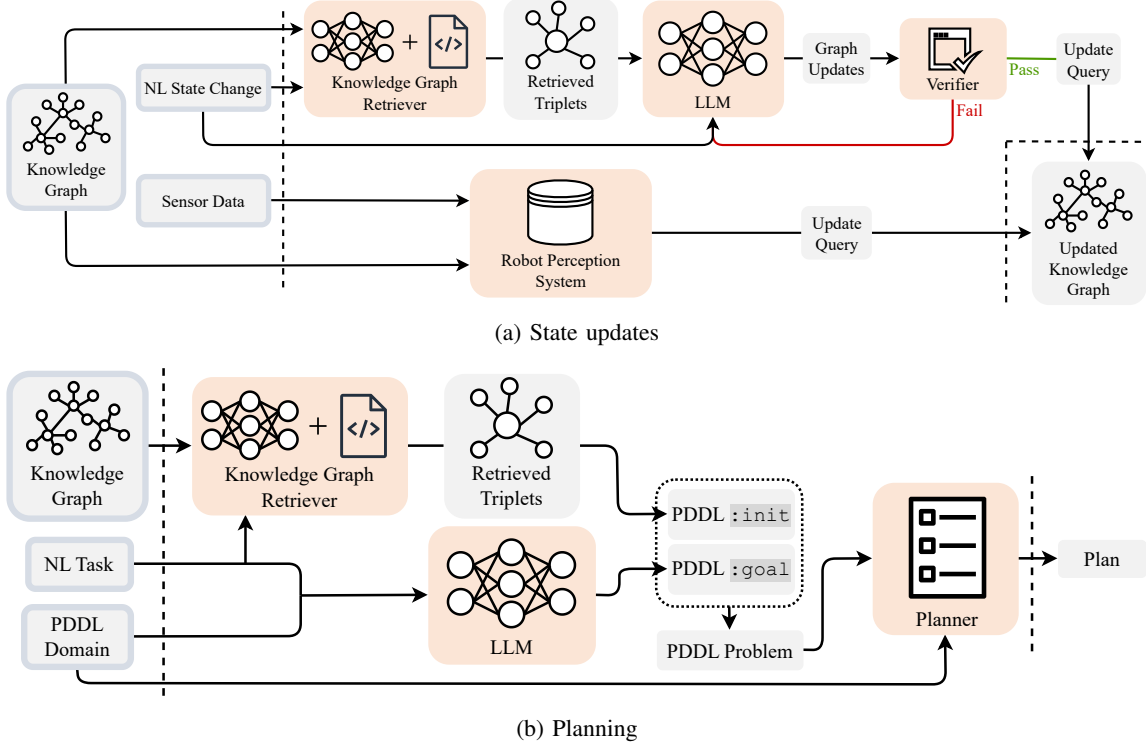


Fig. 1: (a) L3M+P maintains consistency of its knowledge graph through sensory input as well as descriptions of changes to the environment supplied by humans. Both sources are used to update the knowledge graph to reflect an up-to-date representation of the environment. Verification is only necessary for NL updates to guard against LLM hallucinations. (b) L3M+P uses the external knowledge graph to gather relevant context about the state of the environment to integrate with LLM+P for planning without requiring an explicit description of initial state for every planning query.

the environment and  $E_t$  is a set of relationships (edges) between the entities at time  $t$ .

- $u_t$  is some verbal/sensory input describing an update taking place at time  $t$ .

A correct solution to the problem  $U$  is the state  $s_{t+1} \in \mathcal{S}$  that accurately represents the world state after registering the update  $u_t$ . If we assume that entities are not added/removed from the environment, the problem can be simplified to only output the change in the relationships  $\langle E_t^-, E_t^+ \rangle$ , where we interpret  $E_{t+1} = E_t - E_t^- + E_t^+$ , so  $s_{t+1} = \langle V_t, E_{t+1} \rangle$ .

#### B. Plan

The second problem is to generate a plan to solve a given task. Formally, the input to the planning problem  $P$  is the tuple  $\langle \mathcal{S}, s_t, g_t, \mathcal{A}, f \rangle$ :

- $\mathcal{S}$  is again the state space.
- $s_t \in \mathcal{S}$  is again the robot's knowledge at time  $t$ .
- $g_t$  is an NL description of a task to be completed by the robot at time  $t$ .
- $\mathcal{A}$  is a set of symbolic actions.
- $f : \mathcal{S} \times \mathcal{A} \rightarrow \mathcal{S}$  is the underlying state transition function.  $f$  takes the current state and an action and outputs the resulting state.

A solution to the planning problem  $P$  is a sequential plan  $\pi = \langle a_1, a_2, \dots, a_N \rangle$  with  $a_i \in \mathcal{A}$ .

## IV. METHOD

We now describe how L3M+P solves the two problems defined above, as shown in Fig. 1.

#### A. Knowledge Graph Retrieval

To represent the state of the environment, L3M+P employs a knowledge graph (KG) that functions as a direct memory base for the agent. The nodes in the graph represent various entities in the environment and edges represent relationships between the entities.

The KG triplets have a one-to-one correspondence with PDDL predicates specified by the domain file. The KG is therefore a full representation of the current state  $s \in \mathcal{S}$ . It is important to note that we assume the system is provided a domain PDDL file that specifies predicates representing the environment state and actions the agent is allowed to take. This is a reasonable assumption to make since the process of creating this domain PDDL file is a one-time investment, after which the agent is able to act autonomously over the long-term.

To provide the RAG context for each update or plan query, the relevant nodes and edges are retrieved from the KG. One approach in current RAG pipelines is supplying a list of entities in the environment and prompting the LLM to select relevant entities based on a provided user prompt. Then, given a list of relevant entities, all triplets outgoing

and incoming to each relevant entity can be extracted at a certain maximum depth. These retrieved triplets function as the context for the downstream task.

In case of wrong or un-descriptive entity labels produced by the robot’s object recognition system, the LLM may not be able to select the correct entities based on their names in the KG. We further propose a search-based retrieval method (Algorithm 1) to precisely locate entities that match the natural-language description. First, the algorithm prompts the LLM to generate a query graph with entities and their inferred relations from the natural-language query, and then searches for the most similar grounded sub-graph in the KG. The sub-graph matching algorithm (Algorithm 2) is inspired by recent work on scene graphs that supports querying a single central node of a sub-graph [17], [18]. Algorithm 2 uses depth-first-search (DFS) to find all entities that are relevant to a state update or task.

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**Algorithm 1** Search-Based Retrieval Algorithm

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**Input:**  $V_t, E_t$ , entities and relationships in the knowledge graph at timestep  $t$

**Input:**  $u_t$  or  $g_t$ , the verbal update or plan query

**Output:**  $V_r$ , relevant entities

- 1: Prompt the LLM to extract a query graph  $\langle V_q, E_q \rangle$ , of ungrounded entities and relationships, from  $u_t$  or  $g_t$
  - 2: Compute the semantic similarity matrix  $S$  between  $V_q$  and  $V_t$
  - 3: Sort the entities in  $V_q$  by their highest similarity scores
  - 4:  $M_{optimal} \leftarrow \text{DFS}(S, V_q, E_q, V_t, E_t, \{\}, \{\})$
  - 5:  $V_r \leftarrow$  entities mapped by  $M_{optimal}$
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**Algorithm 2** Subgraph Matching Algorithm (DFS)

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**Input:**  $S$ , node similarity matrix

**Input:**  $V_q, E_q, V_t, E_t$

**Input:**  $M, M_+$ , current mapping and the best mapping found

**Input:**  $cutoff$ , a parameter for node similarity cutoffs

**Output:**  $M_{optimal}$ , mapping from  $V_q$  to  $V_t$  with the highest subgraph similarity score

- 1: **if** All nodes in  $V_q$  are mapped by  $M$  **then**
  - 2:   **if**  $\text{mapping\_score}(M) > \text{mapping\_score}(M_+)$  **then**
  - 3:     **return**  $M_{optimal} \leftarrow M$
  - 4:   **end if**
  - 5:   **return**  $M_{optimal} \leftarrow M_+$
  - 6: **end if**
  - 7:  $v_q \leftarrow$  pop front of  $V_q$
  - 8: Find all entity candidates  $v_c \in V_t$  that  $S[v_q, v_c] > cutoff \times \max_v(S[v_q, v])$
  - 9: **for each** candidate  $v_c$  **do**
  - 10:   Add mapping  $v_q \rightarrow v_c$  to  $M$
  - 11:    $M_+ \leftarrow \text{DFS}(S, V_q, E_q, V_t, E_t, M, M_+)$
  - 12:   Pop mapping  $v_q \rightarrow v_c$  from  $M$
  - 13: **end for**
  - 14: **return**  $M_{optimal} \leftarrow M_+$
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**B. Updates to Knowledge Graph**

A key contribution that L3M+P makes is the ability to dynamically update the agent’s memory base based on external changes to the environment (shown in Fig. 1a). The agent can be alerted of these changes in two manners: (1) the robot receives sensory input or (2) a human describes an event in the environment to the agent in natural language. In this paper, we assume the robot’s sensory inputs are fully functional and can convert information directly into triplets to update in the KG through a traditional knowledge representation system. As such, we focus on NL descriptions of updates to the environment.

Any descriptions of environment changes need to be reflected in the KG to maintain a consistent memory base. Given such a description, the procedure defined by Algorithm 3 is followed. In summary, L3M+P

- 1) Retrieves a relevant subgraph from the KG (line 1)
- 2) Prompts the LLM to generate KG updates given the retrieved subgraph and the update description (line 5)
- 3) Verifies the generated graph updates against the domain PDDL (line 7)
- 4) Retries if the verifier fails (line 9)
- 5) Applies the LLM-generated graph updates when verification succeeds (lines 10 and 11)

L3M+P does not handle adding new entities to the knowledge graph based on NL updates. It is reasonable to require that only the robot perception system can add entities since NL updates cannot specify all necessary information about a new entity, such as its geometry.

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**Algorithm 3** NL Knowledge Graph Updates

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**Input:**  $\langle V_t, E_t \rangle$ , the current knowledge graph at time  $t$

**Input:**  $u_t$ , the NL update at time  $t$

**Output:**  $E_{t+1}$ , the updated KG edges (the updated graph is  $\langle V_t, E_{t+1} \rangle$ )

- 1:  $E_t^{rel} \leftarrow \text{retriever}(V_t, E_t, u_t)$  {Retrieve a relevant set of edges from the KG}
  - 2:  $E_t^{irrel} \leftarrow E_t - E_t^{rel}$
  - 3:  $prompt \leftarrow [V_t, E_t^{rel}, u_t]$
  - 4: **repeat**
  - 5:    $output \leftarrow \text{LLM}(prompt)$  {Prompt the LLM to generate a KG update}
  - 6:    $E_t^+, E_t^- \leftarrow \text{parse}(output)$
  - 7:    $errors \leftarrow \text{verify}(E_t^+, E_t^-, E_t, V_t)$
  - 8:    $prompt \leftarrow prompt + [errors]$
  - 9: **until**  $errors = \emptyset$  {Re-prompt LLM until generated update is valid}
  - 10:  $E_{t+1}^{rel} \leftarrow E_t^{rel} - E_t^- + E_t^+$
  - 11:  $E_{t+1} \leftarrow E_t^{irrel} + E_{t+1}^{rel}$
  - 12: **return**  $E_{t+1}$
- 

**C. Planning**

L3M+P uses a modified version of the existing LLM+P framework to perform planning tasks (shown in Fig. 1b). Specifically, L3M+P is not given a user-provided description

of the environment and instead queries the KG to gain sufficient detail for a given planning task. When presented with an NL description of a task, the procedure specified by Algorithm 4 is used. In summary, L3M+P

- 1) Retrieves a relevant subgraph from the KG (line 1)
- 2) Prompts the LLM to generate the `:goal` block for the PDDL problem given the retrieved subgraph, the PDDL domain, and the task description (line 2)
- 3) Constructs a PDDL problem with the generated `:goal` block and using the retrieved subgraph as the `:init` block (line 3)
- 4) Passes the fully constructed PDDL problem to a symbolic planner alongside the provided PDDL domain to generate a plan (line 4)
- 5) Executes the generated plan step-by-step

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**Algorithm 4** Planning

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**Input:**  $\langle V_t, E_t \rangle$ , the current knowledge graph at time  $t$

**Input:**  $g_t$ , the NL description for a task to complete at time  $t$

**Input:**  $D$ , the PDDL domain

**Output:**  $\pi = \langle a_1, a_2, \dots, a_n \rangle$ , a sequential plan to accomplish the given task

- 1:  $E_t^{rel} \leftarrow \text{retriever}(V_t, E_t, g_t)$  {Retrieve a relevant set of edges from the KG}
  - 2:  $goal \leftarrow \text{LLM}(V_t, E_t^{rel}, D, g_t)$  {Prompt the LLM to generate a `:goal` block for the given task}
  - 3:  $P \leftarrow \{V_t, E_t^{rel}, goal\}$  {Generate a corresponding PDDL problem ( $E_t^{rel}$  populates the `:init` block)}
  - 4:  $\pi \leftarrow \text{planner}(D, P)$
  - 5: **return**  $\pi$
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## V. EXPERIMENTS

Our experiments are designed to address the following questions:

- 1) Does RAG enable more accurate KG updates compared to just providing the full KG context to the LLM? In other words, does RAG allow for smaller prompts to prevent hallucinations, or does the lack of full context worsen performance? **(It provides a significant improvement)**
- 2) To what extent does the verification step improve (or possibly degrade) graph update accuracy? **(It provides a decent improvement)**
- 3) Does accurate KG state translate to correct plans, and conversely does incorrect KG state translate to failed plans? **(Yes)**

To answer these questions, we run two types of experiments. The first is meant to test solely text-based state changes and how L3M+P is able to both update the KG based on NL state updates as well as generate plans based on a continuously updating KG. The second demonstrates that the framework seamlessly registers both verbal and sensory updates to the KG so that a service robot can robustly solve tasks in a dynamic environment.

### A. Text-Based Simulation

Since the goal is for the agent to work within a general-purpose service robot, we introduce an open-ended, text-based household simulator where items are randomly generated, humans randomly manipulate the environment, and random tasks are periodically presented to an agent. The household consists of a diverse set of items, such as tables, fridges, sinks, books, food items, dishes, lights, TVs, and phones, distributed across various rooms in the household such as a kitchen, living room, and bedrooms. Humans in the household may move objects, turn on/off any faucets/lights, answer phones, etc. The agent may be tasked with returning items to certain locations, washing dishes, providing items to humans (like food or drink), etc. The purpose of random tasks is to test the capabilities of the agent to function in a domain-agnostic environment.

The simulation provides the agent with an NL description of each environment update and an NL description of each planning task. The agent is also provided a domain PDDL file, which, as justified in Section IV, is reasonable for realistic use cases. To measure accuracy, the simulation maintains a ground-truth KG after each state update and plan execution to compare against L3M+P’s proposed KG, and a ground-truth problem PDDL file is also created to generate a ground-truth plan that can be validated against any plans generated by the agent.

We test the following six variants of the agent against the same simulation:

- 1)  $R^-$ : The agent receives the full KG as context when performing state updates (no RAG).
- 2)  $R_V^-$ : The agent receives the full KG as state change context (no RAG). State updates are verified against the domain PDDL.
- 3)  $R^+$ : RAG is used to extract relevant context from the KG that fits in the LLM context window to perform state updates.
- 4)  $R_V^+$ : RAG is performed as above. State change verification is performed.
- 5)  $R^S$ : Search-based RAG is performed to extract KG context.
- 6)  $R_V^S$  (a.k.a L3M+P): Search-based RAG is performed as above. State change verification is performed.

To execute these experiments, we use OpenAI’s GPT-4o language model. We also utilize the SIW-THEN-BFSF planner provided by LAPKT [19] for all experiments. The goal of these experiments is not to prove the planning accuracy of LLM+P but rather to measure the effect of a potentially incorrect KG on generating correct plans.

Here are our findings:

- 1) As shown by the results in I, RAG helps prevent model hallucinations to significantly increase update accuracy, and it certainly does not worsen performance by not providing the full KG as context.
- 2) Also shown by Table I, syntactically verifying state changes generated by the LLM against the domain PDDL can also improve the accuracy of the state

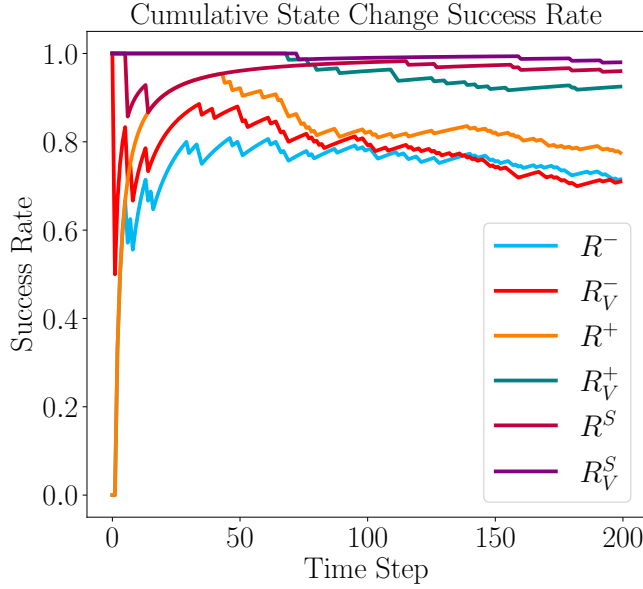


Fig. 2: Cumulative success rate of updating the KG from given state changes at each state change for all six variants of the agent.

Method	Success Rate % ( $\uparrow$ )	
	State Changes	Plans
$R^-$	71.5	72.5
$R_V^-$	71	72.5
$R^+$	77.5	80
$R_V^+$	92.5	85
$R^S$	96	87.5
$R_V^S$	<b>98</b>	<b>90</b>

TABLE I: Final state change and plan success rate % after running the six agent variants on the simulation.

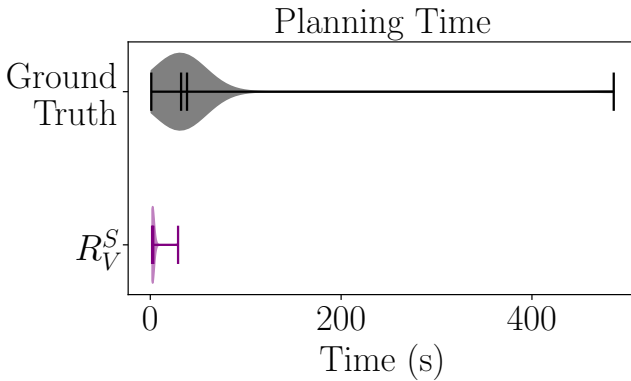


Fig. 3: Distributions of planner time for  $R_V^S$  (including time for RAG) and planner time against a ground truth PDDL with the full state provided, for tasks successfully solved by  $R_V^S$ .  $R_V^S$  is far more planner-time efficient by only providing the planner with relevant context for each given task.

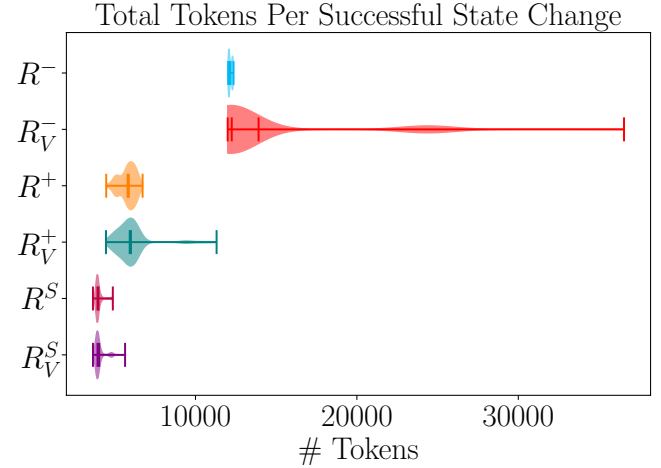


Fig. 4: Distributions of number of tokens used per successful state change for all six variants of the agent.

changes. While the KG context is able to generally inform the LLM of the proper syntax of the KG triplets, syntax verification serves as a stronger guarantee of correctness.

- Other than some initial noise, Figure 2 demonstrates that each variant of the agent maintains a roughly consistent state change success rate throughout the run of the simulation, meaning the reported results are consistent rather than the result of luck.
- As expected, knowledge graph accuracy is analogous to plan-generation accuracy. In most failure instances, the LLM-generated PDDL `:goal` block is accurate, but the planner finds an inaccurate plan or fails to even find a plan as a result of an inaccurate KG state (which forms the `:init` block of the PDDL problem). This leads to plans that (a) only partially solve the task, or (b) plans that are unable to be executed due to their inconsistency with the true environment.
- L3M+P is still not a perfect system. The usual cause of failure is that the KG retrieval did not include all the relevant context for a given NL update or plan, so the LLM is forced to produce output without enough information, causing hallucinations.
- L3M+P also demonstrates a time savings by using RAG: As shown in Figure 3,  $R_V^S$  has a speedup when comparing (a) the combined RAG and planner time for  $R_V^S$ , against (b) only the planner time when provided the full KG context as the `:init` block (ground truth). For correct plans generated by  $R_V^S$ , this is an average speedup of 12.5x.
- Lastly, L3M+P has a cost savings with RAG: As shown in Figure 4, the agent variants that use RAG use fewer tokens for processing successful state changes compared to the variants that do not use RAG. On average,  $R_V^S$  uses 67.6% fewer total input and output tokens compared to  $R^-$  for processing NL state changes (including tokens used for performing RAG).



### Example of a Failed State Change and a Resulting Incorrect Plan Produced by $R^-$

**State Change:** Jessica turned off the overhead light in the laundry room.

**Prompt:** **State Change** + **Full KG Context** + Determine which of the relations should be removed and what new relations should be added.

**GPT-4o (generated KG update):**

REMOVE: (laundry\_room\_light,  
in\_room, laundry\_room)  
ADD: empty

**Task:** The water and electricity bills are high. Can you turn off all lights and faucets?

**Retrieved KG context (:init block):**

...  
(laundry\_room\_light, light\_on, true)  
...

**:goal Block Prompt:** **Task** + Provide me with the goal block for a problem PDDL file that describes the planning problem directly without further explanations.

**GPT-4o (generated :goal block):**

```
(:goal (and (forall (?a - light)
(not (light_on ?a))) (forall (?b -
sink) (not (faucet_on ?b)))))
```

**Plan:**

...  
(turn\_off\_light laundry\_room\_light)  
...

## B. Embodied Interactive Simulation

A service robot must be able to take recent changes into account while completing long-horizon tasks. For instance, the robot may be executing a plan for serving a cup of coffee by first grasping a clean cup from the cupboard, but then discovers or be informed that all cups are dirty. To re-plan for this scenario, the planning knowledge must be updated with execution-time information.

The L3M+P framework is instantiated in an embodied AI system in the AI2-THOR [20] simulator and tested on a variety of home tasks. We demonstrate that the L3M+P framework supports multi-modal state updates, which is essential for realistic home environments. At each time step, the agent is provided with the semantic properties of the currently visible objects in the simulation.

## VI. RELATED WORK

Several frameworks have already been proposed for LLM-based planning and reasoning [21], [22], [23], [24], [25].

While these frameworks demonstrate the potential of LLMs as plan generators, they may overestimate the extent to which language modeling capabilities directly translate to robust reasoning capabilities. Additionally, these works only focus on planning, and they do not attempt to design end-to-end solutions where the agent must both gather information about the environment and use that information to plan.

However, there are some frameworks that have been introduced to address planning within dynamic environments. LLM-DP [26] is a system that maintains a set of known information about the environment as well as a set of beliefs about the environment. The known information and beliefs are gradually updated as the agent makes observations, and this information is then used as context for an LLM to generate a world specification and goal in PDDL that is provided to a classical planner. However, aside from the fact that this system was exclusively tested in Alfworld [27], a text-based environment that only hosts a very specific domain of problems, LLM-DP assumes that the only changes to the environment are caused by the agent and does not maintain knowledge of the environment across different planning tasks.

Statler [28] is a framework for maintaining and updating a world state to serve as a memory for an LLM-based agent across planning tasks. The current state  $s$  is represented in a JSON-like format, and the framework consists of both a world-state reader and a world-state writer. The world-state reader provides  $s$  with a user planning query to an LLM and prompts it to generate a set of actions to achieve the goal. The world-state writer feeds  $s$  and the generated plan into the LLM and prompts it to update  $s$  based on performed actions. Similar to LLM-DP, this framework is unable to account for external changes to the environment. Additionally, a specific world-state format must be curated for different domains. Even if the world-state representation were made domain-agnostic, the system would break down in complex environments with many objects and relations, in which case the world-state representation itself can exceed context-window limits of LLMs or at least significantly increase the likelihood of hallucinations.

## VII. CONCLUSION

In order to address the limitations of other frameworks, we propose L3M+P, a system that maintains a dynamic memory base for the agent in that can be updated and queried. Context from this memory base can be extracted at planning time to write accurate specifications about the environment and task that can be used by classical planners. This memory base is meant to change based on various, multi-modal sources of information about the environment, and it remains in a consistent format that can be used for writing planning specifications. The use of an external memory base enables representing the absolute world state of fairly complex environments in a domain-agnostic manner, and the use of context retrieval prevents issues with limited context windows/hallucinations.

## REFERENCES

- [1] C. Zhang, J. Chen, J. Li, Y. Peng, and Z. Mao, "Large language models for human-robot interaction: A review," *Biomimetic Intelligence and Robotics*, vol. 3, no. 4, p. 100131, 2023. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S2667379723000451>
- [2] K. Mahowald, A. A. Ivanova, I. A. Blank, N. Kanwisher, J. B. Tenenbaum, and E. Fedorenko, "Dissociating language and thought in large language models," 2024.
- [3] L. Huang, W. Yu, W. Ma, W. Zhong, Z. Feng, H. Wang, Q. Chen, W. Peng, X. Feng, B. Qin, and T. Liu, "A survey on hallucination in large language models: Principles, taxonomy, challenges, and open questions," 2023.
- [4] Y. Breux and S. Druon, "Multimodal object-based environment representation for assistive robotics," *International Journal of Social Robotics*, vol. 12, no. 3, pp. 807–826, Jul 2020. [Online]. Available: <https://doi.org/10.1007/s12369-019-00600-4>
- [5] S. R. Schmidt-Rohr, G. Dirschl, P. Meissner, and R. Dillmann, "A knowledge base for learning probabilistic decision making from human demonstrations by a multimodal service robot," in *2011 15th International Conference on Advanced Robotics (ICAR)*, 2011, pp. 235–240.
- [6] Y. Jiang, N. Walker, J. Hart, and P. Stone, "Open-world reasoning for service robots," in *Proceedings of the 29th International Conference on Automated Planning and Scheduling (ICAPS 2019)*, July 2019.
- [7] B. Liu, Y. Jiang, X. Zhang, Q. Liu, S. Zhang, J. Biswas, and P. Stone, "Llm+ $\pi$ : Empowering large language models with optimal planning proficiency," 2023.
- [8] D. McDermott, M. Ghallab, A. Howe, C. Knoblock, A. Ram, M. Veloso, D. Weld, and D. Wilkins, "Pddl-the planning domain definition language," 1998.
- [9] P. Haslum, N. Lipovetzky, D. Magazzeni, and C. Muise, "An introduction to the planning domain definition language," *Synthesis Lectures on Artificial Intelligence and Machine Learning*, vol. 13, no. 2, pp. 1–187, 2019.
- [10] L. Ehrlinger and W. Wöß, "Towards a definition of knowledge graphs," in *International Conference on Semantic Systems*, 2016. [Online]. Available: <https://api.semanticscholar.org/CorpusID:8536105>
- [11] J. J. Miller, "Graph Database Applications and Concepts with Neo4j," in *Proceedings of the Southern Association for Information Systems Conference, Atlanta, GA, USA March 23rd-24th, 2013*. AIS eLibrary, 2013, pp. 141–147. [Online]. Available: <https://aisel.aisnet.org/sais2013/24>
- [12] A. A. P. M. Committee, "Apache age's documentation," <https://age.apache.org/age-manual/master/index.html>, 2020–2024.
- [13] N. Francis, A. Green, P. Guagliardo, L. Libkin, T. Lindaaker, V. Marsault, S. Plantikow, M. Rydberg, P. Selmer, and A. Taylor, "Cypher: An Evolving Query Language for Property Graphs," pp. 1433–1445.
- [14] J. Wei, M. Bosma, V. Y. Zhao, K. Guu, A. W. Yu, B. Lester, N. Du, A. M. Dai, and Q. V. Le, "Finetuned language models are zero-shot learners," 2022.
- [15] P. Lewis, E. Perez, A. Piktus, F. Petroni, V. Karpukhin, N. Goyal, H. Küttler, M. Lewis, W.-t. Yih, T. Rocktäschel, S. Riedel, and D. Kiela, "Retrieval-augmented generation for knowledge-intensive nlp tasks," in *Advances in Neural Information Processing Systems*, H. Larochelle, M. Ranzato, R. Hadsell, M. Balcan, and H. Lin, Eds., vol. 33. Curran Associates, Inc., 2020, pp. 9459–9474.
- [16] Z. Jing, Y. Su, Y. Han, B. Yuan, H. Xu, C. Liu, K. Chen, and M. Zhang, "When large language models meet vector databases: A survey," 2024.
- [17] H. Chang, K. Boyalakuntla, S. Lu, S. Cai, E. P. Jing, S. Keskar, S. Geng, A. Abbas, L. Zhou, K. Bekris, et al., "Context-aware entity grounding with open-vocabulary 3d scene graphs," in *Conference on Robot Learning*. PMLR, 2023, pp. 1950–1974.
- [18] S. Koch, N. Vaskevicius, M. Colosi, P. Hermosilla, and T. Ropinski, "Open3dsg: Open-vocabulary 3d scene graphs from point clouds with queryable objects and open-set relationships," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2024, pp. 14 183–14 193.
- [19] M. Ramirez, N. Lipovetzky, and C. Muise, "Lightweight Automated Planning ToolKit," <http://lapkt.org/>, 2015, accessed: 2020.
- [20] "AI2-THOR: An Interactive 3D Environment for Visual AI," *ArXiv*, vol. abs/1712.05474, 2017.
- [21] M. Ahn, A. Brohan, N. Brown, Y. Chebotar, O. Cortes, B. David, C. Finn, C. Fu, K. Gopalakrishnan, K. Hausman, A. Herzog, D. Ho, J. Hsu, J. Ibarz, B. Ichter, A. Irpan, E. Jang, R. J. Ruano, K. Jeffrey, S. Jesmonth, N. J. Joshi, R. Julian, D. Kalashnikov, Y. Kuang, K.-H. Lee, S. Levine, Y. Lu, L. Luu, C. Parada, P. Pastor, J. Quiambao, K. Rao, J. Rettinghouse, D. Reyes, P. Sermanet, N. Sievers, C. Tan, A. Toshev, V. Vanhoucke, F. Xia, T. Xiao, P. Xu, S. Xu, M. Yan, and A. Zeng, "Do as i can, not as i say: Grounding language in robotic affordances," 2022.
- [22] W. Huang, P. Abbeel, D. Pathak, and I. Mordatch, "Language models as zero-shot planners: Extracting actionable knowledge for embodied agents," 2022.
- [23] S. Yao, J. Zhao, D. Yu, N. Du, I. Shafraan, K. Narasimhan, and Y. Cao, "React: Synergizing reasoning and acting in language models," 2023.
- [24] C. H. Song, J. Wu, C. Washington, B. M. Sadler, W.-L. Chao, and Y. Su, "Llm-planner: Few-shot grounded planning for embodied agents with large language models," in *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, October 2023, pp. 2998–3009.
- [25] V. Bhat, A. U. Kaypak, P. Krishnamurthy, R. Karri, and F. Khorrami, "Grounding llms for robot task planning using closed-loop state feedback," 2024.
- [26] G. Dagan, F. Keller, and A. Lascarides, "Dynamic planning with a llm," 2023.
- [27] M. Shridhar, X. Yuan, M.-A. Côté, Y. Bisk, A. Trischler, and M. Hausknecht, "Alfworld: Aligning text and embodied environments for interactive learning," 2021. [Online]. Available: <https://arxiv.org/abs/2010.03768>
- [28] T. Yoneda, J. Fang, P. Li, H. Zhang, T. Jiang, S. Lin, B. Picker, D. Yunis, H. Mei, and M. R. Walter, "Statler: State-maintaining language models for embodied reasoning," 2023.