

LLM+P: Empowering Large Language Models with Optimal Planning Proficiency

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Abstract: Large language models (LLMs) have demonstrated remarkable zero-shot generalization abilities: state-of-the-art chatbots can provide plausible answers to many common questions that arise in daily life. However, so far, LLMs cannot reliably solve long-horizon planning problems. By contrast, classical planners, once a problem is given in a formatted way, can use efficient search algorithms to quickly identify correct, or even optimal, plans. In an effort to get the best of both worlds, this paper introduces LLM+P, the first framework that incorporates the strengths of classical planners into LLMs. LLM+P takes in a natural language description of a planning problem, then returns a correct (or optimal) plan for solving that problem in natural language. LLM+P does so by first converting the language description into a file written in the planning domain definition language (PDDL), then leveraging classical planners to quickly find a solution, and then translating the found solution back into natural language. Along with LLM+P, we define a diverse set of different benchmark problems taken from common planning scenarios. Via a comprehensive set of experiments on these benchmark problems, we find that LLM+P is able to provide *optimal* solutions for most problems, while LLMs fail to provide even feasible plans for most problems.²

Keywords: Planning, Large Language Model, In-context Learning

1 Introduction

Ever since the birth of the field, AI researchers have sought to create programs that can converse in natural language with the same grace and flexibility as people. While even relatively simple models, such as Eliza from 1966 [1], can generate responses to some prompts that seem reasonable, it has always been relatively easy to generate prompts that expose their weaknesses compared to people — their lack of true “understanding.”

While large language models (LLMs) such as GPT-4 [2] and ChatGPT [3] have far surpassed expectations of just a few years ago, they are no different in this respect. Indeed the internet is now awash with examples of people reveling in getting ChatGPT to generate output that even a 5-year-old human child would know to be ill-advised.

Given how LLMs are designed and trained, this phenomenon should come as no surprise. They are not specifically built to demonstrate understanding. They are trained to generate sequences of words that *might be plausible to a human* given a prior context. In the terms of Mahowald et al. [4] LLMs have become amazingly proficient at *linguistic competence* — knowing *how* to say things; but they are not nearly as good at *functional competence* — knowing *what* to say. Specifically, they can be (relatively) easily fooled by, for example, asking for the result of a straightforward arithmetic problem that does not appear in their training corpus or by asking for the solution to a novel planning problem that requires knowledge about how the world works.

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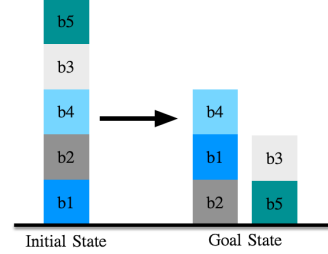
²The code and results are publicly available at <https://github.com/Cranial-XIX/llm-pddl.git>.

A Failure Example of GPT-4 in Planning

Problem (P1): You have 5 blocks. One cannot place more than one block on another block. b5 is on top of b3. b4 is on top of b2. b2 is on top of b1. b3 is on top of b4. b1 is on the table. b5 is clear. Your arm is empty. Your goal is to move the blocks. b1 should be on top of b2. b3 should be on top of b5. b4 should be on top of b1.

GPT-4:

1. Move b5 from b3 to the table.
2. Move b3 from b4 to b5.
3. Move b4 from b2 to the table.
4. Move b2 from b1 to b5.
5. Move b1 from the table to b2.
6. Move b4 from the table to b1.



Does that mean that we should increase efforts to include all arithmetic and planning problems in their training corpus? Clearly, that is a fool’s errand. On the other hand, why should it be necessary? We already have calculators and general-purpose symbolic planners that are guaranteed to produce correct answers. Thus a natural alternative approach, and one that we are admittedly not the first to explore, is to connect LLMs to such tools.

With this motivation in mind, the objective of the research reported in this paper is, for the first time, to enable LLMs to solve planning problems *correctly*. We aim to do so without altering the LLMs themselves, even with finetuning [5, 6]. Rather, we introduce a methodology, called LLM+P by which, when posed a natural language description of a planning problem, the LLM:

1. outputs a problem description suitable as input to a general-purpose planner;
2. solves the problem using the general-purpose planner; and
3. converts the output of the planner back to natural language.

Our extensive empirical evaluations indicate that LLM+P is able to generate correct solutions to many more planning problems than are LLMs on their own. While demonstrated in this paper on planning problems, this general methodology can be applied to any class of problems for which we have a sound and complete solver, such as arithmetic problems (by leveraging calculators).

Limitation: In this paper, we do not ask the LLM to *recognize* that it has been posed a prompt that is suitable for processing using the proposed LLM+P pipeline. A valuable future research direction will be to consider recognizing when a prompt should be processed by LLM+P.

2 Background

This section introduces the notation we use for representing a planning problem to be solved by LLMs, and recaps the standard representation of classical planners.

2.1 The Classical Planning Problem

Formally, the input of a planning problem P is defined by a tuple $\langle \mathcal{S}, s^{init}, \mathcal{S}^G, \mathcal{A}, f \rangle$:

- \mathcal{S} is a finite and discrete set of states used to describe the world’s state (i.e., state space). We assume a factored state space such that each state $s \in \mathcal{S}$ is defined by the values of a fixed set of variables.
- $s^{init} \in \mathcal{S}$ is an initial world state.
- $\mathcal{S}^G \subset \mathcal{S}$ is a set of goal states. \mathcal{S}^G are usually specified as a list of *goal conditions*, all of which must hold in a goal state.
- \mathcal{A} is a set of symbolic actions.

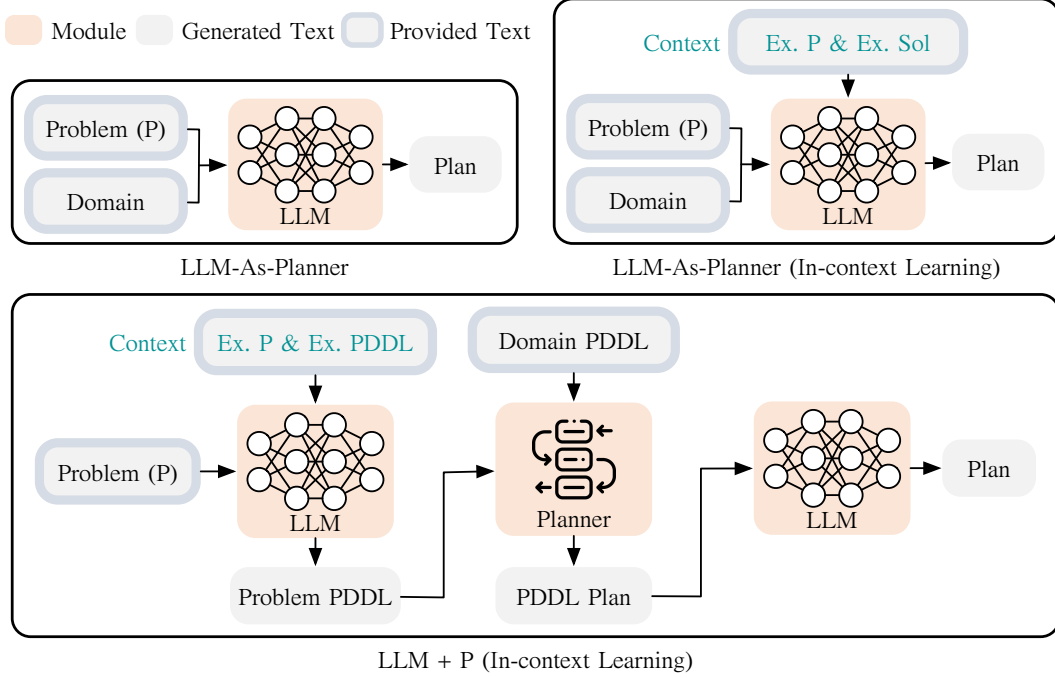


Figure 1: LLM+P makes use of a large language model (LLM) to produce the PDDL description of the given problem, then leverages a classical planner for finding an *optimal* plan, then translates the raw plan back to natural language using the LLM again.

- f is the underlying state transition function. f takes the current state and an action as input and outputs the corresponding next state.

A solution to a planning problem P is a symbolic plan π in the form of $\langle a_1, a_2, \dots, a_N \rangle$, such that the preconditions of a_1 hold in s^{init} , the preconditions of a_2 hold in the state that results from applying a_1 , and so on, with the goal conditions all holding in the state that results after applying a_N .

2.2 Planning Domain Definition Language (PDDL)

The planning domain definition language (PDDL) serves as a standardized encoding of classical planning problems [7, 8]. The PDDL representation of a planning problem P is separated into two files: a domain file and a problem file. The domain PDDL file provides a lifted representation of the underlying rules of the world. It includes a set of predicates that define the state space \mathcal{S} and the actions (i.e., \mathcal{A}) with their preconditions and effects (i.e., the transition function f). The problem PDDL file provides a list of objects to ground the domain, the problem’s initial state s^{init} and goal conditions \mathcal{S}^G . We provide an example of the two PDDL files in Appendix A. There exists a rich set of symbolic planners that implement efficient search algorithms to solve planning problems formalized in PDDL. For a more detailed introduction to PDDL, we refer the readers to the following slides.³ In this work, we aim to take a natural language prompt which describes the initial state s^{init} and goal conditions \mathcal{S}^G , formulate it in PDDL, and leverage symbolic planners to output correct plans. We assume the domain rules are available (See the assumptions in Section 5).

3 Method

This section first uses a running example to investigate ways for formulating planning prompts in PDDL and then introduces the LLM+P method.

³We refer the readers to <https://www.cs.torontonaturalo.edu/~sheila/2542/s14/A1/introtopddl2.pdf> as a good introduction to PDDL.

3.1 Large Language Model as a PDDL Writer

LLMs are bad at planning (or long-horizon reasoning) [9] but they are good at describing and translating textual inputs, including re-writing planning prompts in the PDDL format. The intuition is that we can view PDDL as a different language than English, so re-writing planning prompts in PDDL is essentially a “machine translation” task that LLMs are known to excel at. Here we provide an example of a PDDL problem file written by GPT-4 without any prompt-engineering. As we can see, the generated file appears to have the correct PDDL syntax, but uses a made-up predicate (empty) and misses the initial condition that b1 is on the table.

An Example PDDL Problem File Written by GPT-4

Prompt: **Description of Problem (P1)** + Provide me with the problem PDDL file that describes the planning problem directly without further explanations.

GPT-4 (the generated problem PDDL):

```
(:objects b1 b2 b3 b4 b5 - block)
  (:init (on b5 b3) (on b4 b2) (on b2 b1) (on b3 b4) (clear b5)
(empty))
(:goal (and (on b1 b2) (on b3 b5) (on b4 b1))))
```

3.2 In-Context Learning

LLMs are known to be capable of in-context learning without finetuning their parameters. By in-context learning, we mean LLMs’ ability to perform unseen downstream tasks by simply conditioning on a few input-label pairs (demonstrations) [10]. Here is a pair of problem descriptions in natural language and in PDDL provided to GPT-4 as context. When the context is included with the prompt from the example above, the resulting PDDL problem file is directly solvable by the planner.

An Example PDDL Problem File Written by GPT-4 with Context

Context (shaded):

An example planning problem is: You have 5 blocks. b2 is on top of b5. b5 is on top of b1. b1 is on top of b4. b3 is on top of b2. b4 is on the table. b3 is clear. Your arm is empty. Your goal is to move the blocks. b4 should be on top of b3. The problem PDDL is:

```
(:objects b1 b2 b3 b4 b5)
(:init (arm-empty) (on b1 b4) (on b2 b5) (on b3 b2)
  (on-table b4) (on b5 b1) (clear b3))
(:goal (and (on b4 b3))))
```

Prompt: **Description of Problem (P1)** + **Context** + Provide me with the problem PDDL file that describes the planning problem directly without further explanations.

GPT-4 (the generated problem PDDL):

```
(:objects b1 b2 b3 b4 b5 )
(:init (arm-empty) (on-table b1) (on b2 b1) (on b3 b4)
  (on b4 b2) (on b5 b3) (clear b5)))
(:goal (and (on b1 b2) (on b3 b5) (on b4 b1))))
```

Planner:

```
(unstack b5 b3) (putdown b5) (unstack b3 b4) (stack b3 b5)
(unstack b4 b2) (putdown b4) (unstack b2 b1) (putdown b2)
(pickup b1) (stack b1 b2) (pickup b4) (stack b4 b1)
```

3.3 Large Language Model + Classical Planner (LLM+P)

Having introduced the LLM’s ability to encode problems in PDDL and in-context learning, we are ready to introduce the proposed LLM+P solution (the bottom of Figure 1). In particular, we assume that for each problem domain, a human expert can provide a domain description (i.e. action precon-

ditions and effects) that will be fixed for all problem instances that happen in that domain. While the problem of automatically generating the description is another valuable research question, in this proposed work, we assume that the description is available as a PDDL domain file. The LLM+P method is directly applicable as a natural language interface for giving tasks to robot systems. For instance, assume we want a robot to act as a bartender to make cocktails. It is reasonable to tell it what actions it can take, but leave itself to infer how to make new cocktails most efficiently given a set of ingredients to combine. Moreover, we assume the agent is provided with a *minimal* example that demonstrates what an example problem PDDL looks like for a simple problem inside that domain. Next, the agent is provided with a new (potentially quite complicated) problem (P). The LLM then uses the in-context learning to infer the problem PDDL file corresponding to P . Once the problem PDDL file is generated, we feed it into any classical planner, together with the provided domain PDDL file, to generate a PDDL plan [11]. In the end, the LLM translates the PDDL plan back into the natural language to finish up the LLM+P pipeline.

To summarize, the assumptions we need for LLM+P are:

1. A chatbot knows when to trigger LLM+P based on its conversation with a human user.
2. A domain PDDL file is provided for the problem the user asks for.
3. A simple problem description in natural language and its corresponding problem PDDL file are also provided beforehand.

4 Related Work

This section first provides a brief overview of classical planning algorithms. Then it summarizes recent advances in using large language models for planning tasks. It concludes with a discussion of recent research on augmenting LLMs with external modules.

Classical Planning Automated planning (or classical planning) techniques can be used for computing a sequence of actions that achieves a given goal [12, 13, 14]. Automated planning algorithms have been widely used in robot systems. Shakey is the first robot that was equipped with a planning component, which was constructed using STRIPS [15]. Some previous general-purpose planning architectures were also demonstrated to be useful for robot planning, such as PRODIGY [16] and HTN [17]. Recent classical planning systems designed for robotics frequently use planning domain description language (PDDL) or answer set programming (ASP) as the underlying action language for the planners [18, 19, 20, 21]. For example, researchers have used classical planning algorithms for sequencing actions for a mobile robot working on delivery tasks [22], reasoning about safe and efficient urban driving behaviors for autonomous vehicles [23], and planning actions for a team of mobile robots [24]. Task and motion planning (TAMP) is a hierarchical planning framework that combines classical planning in discrete spaces and robot motion planning in continuous space [25, 26].

Most of the above-mentioned planning methods require domain-specific programming languages as the underlying representation of the problems and their solutions. LLM+P, on the other hand, takes advantage of LLMs to use natural language descriptions for solving complex planning tasks. The main feature that motivates us to use such classical planning systems is that most of these planners are sound and complete, meaning that they are guaranteed to be logically correct and will output a plan if one exists. Many are also able to find optimal (shortest) plans, at least if given sufficient time.

Planning with Large Language Models Various large language models (LLMs) have been developed in recent years, such as Bert [27], CodeX [28], Opt [29], GPT-3 [10], ChatGPT [30], GPT-4 [2], LLAMA [31], and PaLM [32]. As LLMs are pretrained with a tremendous amount of offline text data, they can emerge with surprising zero-shot generalization ability, which can be leveraged for robot planning tasks [33, 34, 35, 36, 37, 38, 39, 40, 41]. For instance, the work of Huang et al. showed that LLMs can be used for task planning in household domains by iteratively augmenting prompts [38]. SayCan is another approach that enabled robot planning with affordance functions to account for action feasibility, where the service requests are specified in natural language [33]. Vemprala et al. recently studied how ChatGPT can be applied to generalized robotics domains.

However, a major drawback of existing LLMs is their lack of long-horizon reasoning/planning ability for complex tasks (See [9, 42] and Section 8.2 from [2]). Specifically, the output they produce

when presented with such a task is often incorrect in the sense that following the output plan will not actually solve the task. Therefore, in this work, we focus on resolving this issue by leveraging the properties of classical planners. Similarly, some recent work also investigates approaches for combining classical planning with LLMs [43, 44]. They either use prompting or fine-tuning to make LLMs capable of solving PDDL planning problems. In contrast, we do not solely rely on LLM as the problem solver, but are more into taking the advantage of both the planner (i.e., generating accurate and optimal plans) and the LLM itself (i.e., 1-shot generalization for translating natural-language problem descriptions into PDDL).

Augmenting LLMs with External Modules Recently developed methods have shown that the performance of downstream tasks of LLMs can be improved by combining them with external modules. For instance, WebGPT [45] is a fine-tuned version of GPT-3 by combining web knowledge to answer open-ended questions. Lazaridou et al. studied how search engines like Google can be utilized as external tools for LLMs. MemPrompt [47] presented a human-in-the-loop system where a growing memory of errors and user feedback is served as past experience adding to the prompts for more accurately answering new questions. REPLUG [48] is another retrieval-augmented language modeling paradigm that treats the language model as a black box and augments it with a tuneable retrieval model. In very recent work related to ours, Schick et al. trained a model called ToolFormer that can decide when and how to call certain tool APIs by in-line augmentation on prompts for LLMs. In this work, we propose that classical planners can be another particularly useful external module.

In comparison, LLM+P, does not rely on any fine-tuning or re-training of LLMs. By simply incorporating knowledge from classical planners, LLM+P incorporates long-horizon reasoning and planning capabilities into existing LLMs.

5 Experiments

We conduct extensive experiments to answer the following three questions:

1. How well does LLM-AS-P work? That is, to what extent can LLMs be directly used for planning? **(Not at all)**
2. How well does LLM+P work compared to LLM-AS-P? **(Much better)**
3. What role does the context play in the success of LLM+P? **(It’s crucial)**

To address these questions, we first introduce a set of benchmark problems borrowed from the classical planning community. Then, we comprehensively evaluate both LLM-AS-P and LLM+P on the proposed benchmark problems. In the end, we provide the results, analysis, and example failure cases that could lead to future improvement.

5.1 Benchmark Problems

We present seven planning domains that are frequently utilized in classical planning competitions. Moreover, we have developed an automatic generation script for each domain, which can generate a virtually unlimited number of tasks in natural language. To ensure fair and reproducible benchmarking, we restrict each domain to a maximum of 20 tasks. Below is a list of the planning domains, along with a brief summary of each.

1. BLOCKSWORLD: Given a set of piles of blocks on a table, a robot is tasked with rearranging them into a specified target configuration while obeying the laws of physics.
2. BARMAN: A bartender is tasked with creating cocktails for a customer’s order, utilizing the available ingredients and aiming to use the minimum number of steps possible.
3. FLOORTILE: A set of robots are tasked to use different colors to paint patterns in floor tiles. Robots can move around and change colors to paint but are restricted by some moving constraints and painting directions.
4. GRIPPERS: A set of robots with grippers are given a task to move objects among different rooms.

5. STORAGE: Given a set of hoists, the goal is to lift and drop all the crates using the hoists into a depot. Crates are initially stored in different areas and hoists can be moved among store areas.
6. TERMES: The robot’s goal is to build complex structures by carrying and placing blocks, and also climbing on them so that it can move to neighboring blocks.
7. TYREWORLD: The robot is given a task to replace flat tires with intact tires on the hubs. It requires inflating intact tires, tightening the nuts, and moving all tools back to the boot when it is done.

For each domain, we implement an *automatic and procedural* generation script to produce 20 different planning problems for reproducibility. The implemented generation scripts are made publicly available in our codebase for the convenience of future research. For each problem P , P comes with a natural language description and a ground-truth problem PDDL file. We assume each problem domain has its own domain PDDL file given by the user or a domain expert prior to addressing any planning problems in that domain.

5.2 Experiment Setup

We leverage the TEXT-DAVINCI-003 model⁴ provided by OpenAI⁵ for all experiments as it is the latest text completion that has the highest text completion quality among all models we have access to. We set the max token number to 2048 and temperature to 0, and use the top probability response. As a result, the response returned from the LLM is deterministic. Once a text PDDL response is generated, we feed it into the FAST-DOWNWARD planner,⁶ using the alias LAMA with a maximum search time of 200 seconds. When the planner finds multiple solutions for a given problem, we pick the solution with the fewest number of steps for validation. Note that we put a hard constraint on the search time for the convenience of running experiments. Therefore, it is possible that some of the found plans are near-optimal but not optimal. However, in theory, an optimal plan can always be found in finite time.⁷ We run the experiment three times independently and report the average and standard error of the success rate.

5.3 Results and Analysis

The results of applying LLM-AS-P and LLM+P across 7 domains are provided in Table 1.

Findings (LLM-AS-P):

1. We observe that though LLM-AS-P provides a plan in natural language for every problem, most of these plans are not feasible. The main reason is that LLM-AS-P lacks the ability to reason about preconditions. Moreover, adding context (e.g., LLM-AS-P (w/ context)) does not increase the success rate unless the new solution can be built from the example solution as a template.
2. The TYREWORLD domain has the most performance boost from LLM-AS-P (w/o context) (0% success) to LLM-AS-P (w/ context) (40%). This domain has a fixed sequence of actions for replacing each tire, and the problems only vary in the number of tires that have to be replaced.
3. In domains other than TYREWORLD, LLM-AS-P fails in the same way with or without the example plan as context. In particular, in the BLOCKSWORLD domain, LLM-AS-P cannot keep track of properties like ON and CLEAR. In the GRIPPERS domain, the robot can only pick up balls when they are in the same room, but most of the LLM-AS-P plans violate this condition (See Appendix C).

⁴At the moment writing this paper, the authors cannot access GPT-4 APIs so we use TEXT-DAVINCI-003 as it generates the best results on the benchmarked problems.

⁵We use the OpenAI API following instructions from <https://platform.openai.com/docs/quickstart/build-your-application>.

⁶See <https://www.fast-downward.org/> for the details on the FAST-DOWNWARD software. We use the implementation from <https://github.com/aibasael/downward>.

⁷We use automatic validation software to validate whether the predicted problem PDDL file is correct for the given problem.

Domain	Success Rate %			
	LLM-AS-P (no ctx.)	LLM-AS-P	LLM+P (no ctx.)	LLM+P
BARMAN	0	0	0	85.0 ± 0.0
BLOCKSWORLD	0	0	0	56.7 ± 2.9
FLOORTILE	0	0	0	53.3 ± 2.9
GRIPPERS	10.0	15.0	0	95.0 ± 0.0
STORAGE	0	0	0	65.0 ± 0.0
TERMES	0	0	0	31.7 ± 2.9
TYREWORLD	0	40.0 ± 5.0	0	80.0 ± 0.0

Table 1: Success rate of applying LLM-AS-P, LLM+P without context and LLM+P. Main messages: 1) LLM+P performs significantly better than LLM-AS-P and can solve most complicated planning problems; 2) Without conditioning on the context, LLM+P fails completely; 3) LLM+P is able to solve many of the problems correctly. Each experiment is conducted three times and we report the mean and the standard error. The randomness exhibited in the results comes solely from the planner’s search algorithm. We bold the best result in each domain.

4. The hardest domains are the ones with complex spatial relationship, e.g., FLOORTILE, TERMES, and STORAGE require reasoning about connectivities and directions on a grid world. The LLM-AS-P methods (with or without context) completely fail at this type of problems. For example, LLM-AS-P generated “move right to tile_0-4 and paint tile_1-2 black” but the robot can only paint neighboring tiles.

Findings (LLM+P):

1. The proposed LLM+P produces an optimal plan for the majority of problems. Most failed cases are due to mis-specified problem files, such as missing one of the initial conditions causing the planning problem to be unsolvable.
2. Without the context (i.e., an example problem and its corresponding problem PDDL), we observe that LLMs fail to produce correct problem PDDL files. The failures of LLM+P (no context) come entirely from incorrect problem encodings. Therefore, the context is important for LLM+P to work.

For a more detailed case study on the failure plans produced by both the baseline methods and LLM-AS-P, please refer to Appendix C.

6 Conclusion and Future Work

In this work, we propose to leverage classical planners to empower large language models with optimal planning capabilities. The key design choice of the proposed LLM+P framework is to focus LLMs on translating the planning problem from natural language to structured PDDL format. Moreover, we show that it is important to also make LLMs aware of a simple (problem, PDDL) pair as a demonstration (or the context) for in-context learning. Some interesting directions to further extend the LLM+P framework include: 1) enabling the LLM to auto-detect when and how to apply LLM+P; and 2) reducing LLM+P’s dependency on information by humans, potentially involving finetuning.

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A Problem and Domain PDDL Files

Problem PDDL Example

```
(define (problem BW-rand-5)
  (:domain blocksworld-4ops)
  (:objects b1 b2 b3 b4 b5 )
  (:init
    (arm-empty)
    (on b1 b2)
    (on b2 b3)
    (on b3 b5)
    (on b4 b1)
    (on-table b5)
    (clear b4)
  )
  (:goal
    (and
      (on b1 b3)
      (on b3 b5))
  )
)
```

Domain PDDL Example

```
(define (domain blocksworld-4ops)
  (:requirements :strips)
  (:predicates (clear ?x)
    (on-table ?x)
    (arm-empty)
    (holding ?x)
    (on ?x ?y))

  (:action pickup
    :parameters (?ob)
    :precondition (and (clear ?ob) (on-table ?ob) (arm-empty))
    :effect (and (holding ?ob) (not (clear ?ob))
      (not (on-table ?ob)) (not (arm-empty))))

  (:action putdown
    :parameters (?ob)
    :precondition (holding ?ob)
    :effect (and (clear ?ob) (arm-empty) (on-table ?ob)
      (not (holding ?ob))))

  (:action stack
    :parameters (?ob ?underob)
    :precondition (and (clear ?underob) (holding ?ob))
    :effect (and (arm-empty) (clear ?ob) (on ?ob ?underob)
      (not (clear ?underob)) (not (holding ?ob))))

  (:action unstack
    :parameters (?ob ?underob)
    :precondition (and (on ?ob ?underob) (clear ?ob) (arm-empty))
    :effect (and (holding ?ob) (clear ?underob)
      (not (on ?ob ?underob)) (not (clear ?ob))
      (not (arm-empty))))
```

B Prompts for Different Methods

The Prompt for LLM-AS-P (no context)

DOMAIN-NL. Now consider a planning problem. The problem description is: **TASK-NL**. Can you provide an optimal plan, in the way of a sequence of behaviors, to solve the problem?

The Prompt for LLM-AS-P (with context)

DOMAIN-NL. An example planning problem is: **EXAMPLE-NL**. A plan for the example problem is: **EXAMPLE-SOL**. Now I have a new planning problem and its description is: **TASK-NL**. Can you provide an optimal plan, in the way of a sequence of behaviors, to solve the problem?

The Prompt for LLM+P (no context)

DOMAIN-NL. Now consider a planning problem. The problem description is: **TASK-NL**. Provide me with the problem PDDL file that describes the planning problem directly without further explanations.

The Prompt for LLM+P (with context)

DOMAIN-NL. An example planning problem is: **EXAMPLE-NL**. The problem PDDL file to this problem is: **EXAMPLE-PDDL**. Now I have a new planning problem and its description is: **TASK-NL**. Provide me with the problem PDDL file that describes the planning problem directly without further explanations.

C Example Failures

A list of representative failures for both the baseline methods and LLM-AS-P is provided in this section.

Failure 1 of LLM-AS-P (without context)

Problem (Barman):

You have 1 shaker with 3 levels, 4 shot glasses, 3 dispensers for 3 ingredients. The shaker and shot glasses are clean, empty, and on the table.

Your left and right hands are empty. The first ingredient of cocktail1 is ingredient1. The second ingredient of cocktail1 is ingredient3. The first ingredient of cocktail2 is ingredient2. The second ingredient of cocktail2 is ingredient3. The first ingredient of cocktail3 is ingredient1. The second ingredient of cocktail3 is ingredient2.

Your goal is to make 3 cocktails. shot1 contains cocktail1. shot2 contains cocktail3. shot3 contains cocktail2.

GPT-3.5:

1. Grasp the shaker with your left hand.
2. Grasp shot glass 1 with your right hand.
3. Fill shot glass 1 with ingredient 1 from the dispenser.
4. Pour ingredient 1 from shot glass 1 to the shaker.
5. Grasp shot glass 2 with your right hand.
6. Fill shot glass 2 with ingredient 2 from the dispenser.
7. Pour ingredient 2 from shot glass 2 to the shaker.
8. Grasp shot glass 3 with your right hand.
9. Fill shot glass 3 with ingredient 3 from the dispenser.
10. Pour ingredient 3 from shot glass 3 to the shaker.
11. Shake the shaker.
12. Pour the cocktail1 from the shaker to shot glass 1.
13. Empty shot glass 1.
14. Clean shot glass 1.
15. Pour the cocktail2 from the shaker to shot glass 2.
16. Empty shot glass 2.
17. Clean shot glass 2.
18. Pour the cocktail3 from the shaker to shot glass 3.
19. Empty shot glass 3.
20. Clean shot glass 3.
21. Leave the shaker on the table.

Failure 2 of LLM-AS-P (without context)

Problem (BlocksWorld):

You have 3 blocks. b3 is on top of b2. b1 is on top of b3. b2 is on the table. b1 is clear. Your arm is empty. Your goal is to move the blocks. b2 should be on top of b3. b3 should be on top of b1.

GPT-3.5:

Pickup b1
Stack b1 on top of b2 (**Failed because b2 is not clear**)
Unstack b3 from b2
Stack b3 on top of b1
Putdown b1

Problem (Grippers):

There are 3 rooms and 2 balls. robot1 is in room1. robot4 is in room1. robot2 is in room1. robot3 is in room1. ball2 is in room3. ball1 is in room2. The robots' grippers are free.

Your goal is to transport the balls to their destinations. ball1 should be in room2. ball2 should be in room3.

GPT-3.5:

1. Robot1 picks up ball1 with its left gripper. # (Failed because robot1 and ball1 are in different rooms)
2. Robot1 moves to room2.
3. Robot1 drops ball1 in room2.
4. Robot2 picks up ball2 with its right gripper.
5. Robot2 moves to room3.
6. Robot2 drops ball2 in room3.

Problem (Storage):

Depot storeareas are: depot48-1-1 depot48-1-2 depot48-2-1 depot48-2-2

Container storeareas are: container-0-0 container-0-1

Here is a map of depot storeareas:

depot48-1-1 depot48-1-2
depot48-2-1 depot48-2-2

According to the map, adjacent depot storeareas are connected. All depot storeareas are in depot48. crate1 is on container-0-1. crate0 is on container-0-0. All crates and container storeareas are in container0. All container storeareas are connected to loadarea. depot48-2-1 and loadarea are connected. depot48-2-2 depot48-2-1 depot48-1-1 are clear. hoist0 is in depot48-1-2. All hoists are available.

Your goal is to move all crates to depot48.

GPT-3.5:

Go out with hoist0 from depot48-1-2 to loadarea. # (Failed because depot48-1-2 and loadarea are not connected)

Lift crate0 in container-0-0 in container 0 with hoist0 from loadarea.

Go in with hoist0 from loadarea to depot48-2-1.

Drop crate0 with hoist0 from depot48-2-1 to depot48-1-1 in depot48.

Go out with hoist0 from depot48-2-1 to loadarea.

Lift crate1 in container-0-1 in container 0 with hoist0 from loadarea.

Drop crate1 with hoist0 from loadarea to depot48-2-2 in depot48.

Problem (Termes):

The robot is on a grid with 4 rows and 3 columns.

pos-0-0 pos-0-1 pos-0-2

pos-1-0 pos-1-1 pos-1-2

pos-2-0 pos-2-1 pos-2-2

pos-3-0 pos-3-1 pos-3-2

The robot is at pos-2-0. The depot for new blocks is at pos-2-0. The maximum height of blocks is 3.

Your goal is to build blocks so that the height at pos-1-2 is 3. You cannot have an unplaced block at the end.

GPT-3.5:

Create block at pos-2-0

move to pos-2-1

place block at pos-1-2 # (Failed because pos-2-1 and pos-1-2 are not adjacent)

move to pos-2-2

place block at pos-1-2

move to pos-2-1

place block at pos-1-2

move to pos-2-0

place block at pos-1-2

Problem (Tyreworld):

You have a jack, a pump, a wrench, a boot, 3 hubs, 3 nuts, 3 flat tyres, and 3 intact tyres. The jack, pump, wrench, and intact tyres are in the boot. The boot is unlocked but is closed. The intact tyres are not inflated. The flat tyres are on the hubs. The hubs are on the ground. The nuts are tight on the hubs. The hubs are fastened.

Your goal is to replace flat tyres with intact tyres on the hubs. Intact tyres should be inflated. The nuts should be tight on the hubs. The flat tyres, wrench, jack, and pump should be in the boot. The boot should be closed.

GPT-3.5:

```
(define (problem replace-tyres)
  (:domain tyre-replacement)
  (:objects
    jack pump wrench boot hub nut flat-tyre intact-tyre - object
  )
  (:init
    (in jack boot)
    (in pump boot)
    (in wrench boot)
    (in intact-tyre boot)
    (inflat intact-tyre)
    (on flat-tyre hub)
    (on-ground hub)
    (tight nut hub)
    (fasten hub)
    (closed boot)
  )
  (:goal (and
    (not (on flat-tyre hub))
    (on intact-tyre hub)
    (inflat intact-tyre)
    (tight nut hub)
    (in jack boot)
    (in pump boot)
    (in wrench boot)
    (in intact-tyre boot)
    (closed boot)
  ))
)
```