Classical Planning with LLM-Generated Heuristics: Challenging the State of the Art with Python Code

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Abstract

In recent years, large language models (LLMs) have shown remarkable capabilities in various artificial intelligence problems. However, they fail to plan reliably, even when prompted with a detailed definition of the planning task. Attempts to improve their planning capabilities, such as chain-of-thought prompting, fine-tuning, and explicit "reasoning" still yield incorrect plans and usually fail to generalize to larger tasks. In this paper, we show how to use LLMs to generate correct plans, even for out-of-distribution tasks of increasing size. For a given planning domain, we ask an LLM to generate several domain-dependent heuristic functions in the form of Python code, evaluate them on a set of training tasks within a greedy best-first search, and choose the strongest one. The resulting LLM-generated heuristics solve many more unseen test tasks than state-of-the-art domain-independent heuristics for classical planning. They are even competitive with the strongest learning algorithm for domain-dependent planning. These findings are especially remarkable given that our proof-of-concept implementation is based on an unoptimized Python planner and the baselines all build upon highly optimized C++ code. In some domains, the LLM-generated heuristics expand fewer states than the baselines, revealing that they are not only efficiently computable, but sometimes even more informative than the state-of-the-art heuristics. Overall, our results show that sampling a set of planning heuristic function programs can significantly improve the planning capabilities of LLMs.

1 Introduction

Classical planning is a fundamental problem in Artificial Intelligence (AI), with applications ranging from robotics to game playing [27]. Given the initial state of the world, a description of the goal, and a set of deterministic actions that can be executed in a fully-observable environment, the task is to find a sequence of actions that transforms the initial state into a state that satisfies the goal. Nowadays, most classical *planners* rely on *heuristic search* algorithms to find plans [6, 41, 38, 56, 47, 78, 69]. The efficiency of these planners depends on the quality of the *heuristic functions* used to guide the search. Traditionally, these heuristics have been either *domain-independent*, offering generality at the expense of accuracy, manually crafted for specific domains, requiring significant human effort and expertise, or learned on a domain basis, adding costs and costing resources whenever we want to use a new domain.

Recent advances in large language models (LLMs) created new ways for automating different aspects of software development and AI tools. In the context of classical planning, LLMs have been used, for example, to plan directly [e.g., 81], to create planning models from natural language [e.g., 32, 26, 50], to compute generalized policies [71], and to create heuristics for numeric planning [80].

In this work, we use LLMs to automatically generate domain-dependent heuristic functions for *classical planning*—planning with fully-observable states, deterministic actions, discrete state variables.

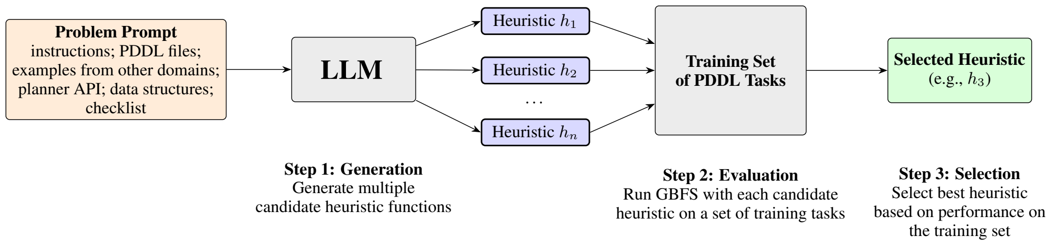


Figure 1: Our pipeline for generating domain-dependent heuristics with LLMs: we prompt the LLM n times to generate n candidate heuristics, evaluate each of these heuristics on a set of training tasks and choose the strongest one.

Our hypothesis is that LLMs, given sufficient context and examples, can generate heuristic functions that outperform generic domain-independent heuristics.

Our overall pipeline is much simpler than previous work: we simply pass to an LLM the domain description, example planning tasks, example domain-dependent heuristics for other domains, and the relevant planner API. Then we request that the LLM generates a heuristic for the given domain. We specifically request that the LLM *generates the code*, in Python, to compute the heuristic. We execute the same prompt n times to obtain a pool of n candidate heuristics, evaluate each of them on a training set, and select the best one. Figure 1 shows the overall pipeline. This discards the necessity of a back-and-forth communication between the planner and the LLM, making the overall procedure straightforward. This idea is similar to what has been done by AlphaCode [45] in the context of code generation, and to parallel sampling [7] for test-time compute [72, 44].

In contrast to the work by Tuisov et al. [80], we do not need to generate heuristics for each task we want to solve. Our approach generates a constant number of heuristics *per domain*, and then use the selected heuristic for any new task of this domain. This amortizes the costs for the LLMs inference, allowing us to save both computational resources and potential API calls.

We implement our pipeline on top of Pyperplan [1] as a proof of concept, and then evaluate the generated heuristics on the domains of the Learning Track of the International Planning Competition (IPC) 2023. The LLM-generated heuristics outperform state-of-the-art heuristics, such as h^{FF} [41], in terms of solved tasks and are competitive in the number of required state expansions. Despite Pyperplan being much slower compared to state-of-the-art planners [38, 47, 66] due to its Python implementation, our method outperforms h^{FF} also in the standard C++ implementations available in Fast Downward [38]. This is an impressive result, as this implementation is a cornerstone of most of the state-of-the-art planners in the literature.

2 Background

We consider *classical planning*, where a single agent applies deterministic actions in a fully-observable, discrete environment. Classical planning tasks are usually described using the Planning Domain Definition Language (PDDL) [49, 36]. To understand our contributions, an informal description of a fragment of PDDL is sufficient, and we introduce it alongside examples from a simple Logistics domain.

A PDDL task consists of a set of objects (e.g., representing vehicles, boxes and locations); a set of predicates representing relations between these objects (e.g., using the `at` predicate, the *ground atom* `(at car1 city2)` represents that object `car1` is `at` `city2`); a set of actions that change the relations (e.g., driving a car changes its location); an initial state which is a set of ground atoms (e.g., where all boxes and vehicles are initially and which locations are connected) and a goal description that lists the ground atoms that must hold at the end of a plan (e.g., the desired locations of all boxes).

Applying an action changes the current state of the environment by removing or adding ground atoms. The objective of a *planner* is to find a sequence of actions, called a *plan*, that leads from the initial state to a state where all goal atoms hold.

PDDL tasks are commonly separated into a *domain* and an *task* part, where the domain part holds the common actions and predicates, while the task part describes the specific objects, initial state and the goal. The two parts are typically represented as two separate files.

Most planners nowadays use *state-space search* to find a plan. The search is usually guided by a *heuristic* function h which maps each state s to an estimate $h(s) \in \mathbb{R}_0^+ \cup \infty$ that estimates the cost of reaching the goal state from s [53]. In heuristic search algorithms—such as A*[35], weighted-A*[54], and greedy best-first search [17]—this heuristic guides the search towards promising states and thereby reduces the search effort. The performance of a planner is heavily influenced by the accuracy and computational efficiency of the heuristic function.

In our work, we assume that all actions have unit cost and we consider *satisficing planning*, where any plan is acceptable, irrespective of its length. We focus on planners that use greedy best-first search (GBFS). While there are lots of search improvements that one could evaluate on top of GBFS [e.g., 41, 47, 55, 58], we limit ourselves to "pure" GBFS planners as this is the most commonly used version in the classical planning literature [e.g., 16, 23, 40]. However, extending our approach to other search algorithms or techniques on top of GBFS is certainly interesting for future work.

We use a setup similar to the Learning Track of the *International Planning Competition* (IPC), where each planner is given a domain and a set of training tasks from this domain. The planner then uses the training tasks to learn domain-general knowledge that helps to solve new tasks from the same domain. Among other options, this knowledge can take the form of policies [e.g., 25, 75], heuristics [e.g., 73, 11], sketches [e.g., 18, 19], planning programs [e.g., 64, 65], or planner configurations [e.g., 20, 67]. After the training period (usually a maximum of 24 hours), the planner must solve a set of unseen test tasks from the same domain that are out-of-distribution of the training tasks.

3 Proposed Pipeline

In our pipeline, we give as input to the LLM the PDDL description of our target domain together with some additional information (described below). Then we ask the LLM for a domain-dependent heuristic function for the given domain, implemented in Python, which we then inject into the Pyperplan planner [1]. We chose Python because LLMs generate correct code for Python more often than for other languages [45], and because the code injection is simpler in Python due to its flexibility and due to it being an interpreted language.

However, we hypothesize that asking for a single function is too weak. Instead, we send n identical requests to the LLM with the same prompt, collect all returned heuristic functions $h_1, \ldots, h_n$, and then evaluate them on the training tasks. We automatically select the best heuristic $h_{\text{best}} \in \{h_1, \ldots, h_n\}$ and declare it as our final heuristic (see below for details on this selection). Figure 1 shows the graphical representation of our method.

One potential issue of this approach is that the heuristic functions $h_1, \ldots, h_n$ might be too similar. If all heuristics are similar, then there is little value in querying the LLM so many times. To diversify the pool of heuristics, we increase the *temperature* parameter of the models. Temperature is often related to the "creativity" of the model, as it allows for more randomness in the token generation and thus more diversity in the answers. In exploratory experiments, we observed that temperatures above 1.0 tend to improve the results. However, very high temperatures (e.g., 2.0) give less consistent results, despite sometimes yielding the best overall performances. Therefore, we set the temperature to 1.0 in our experiments. This is similar to what Brown et al. [7] report, and in their case, some problems required even larger temperature.

To emulate the latest Learning Track setup as closely as possible, we use the IPC 2023 domains and tasks for training and testing. We used a disjoint set of ten domains from the Autoscale benchmark set [79] for exploratory experiments while developing our pipeline. This split allowed us to test different prompts, hyperparameters, and models without the risk of overfitting to the IPC 2023 benchmark set or causing some LLM APIs to cache our prompts.

A common issue when using LLMs for planning is that they produce invalid plans [82, 83]. In contrast, our pipeline ensures that all found plans are valid: the underlying search algorithm in Pyperplan only produce correct solutions and the heuristic created by the LLM only influences how efficiently such a solution is found.

Prompt

Our prompt contains a series of input files that provide context for the LLM. For a given domain D, we ask the LLM to create a heuristic H. The prompt first gives the following instructions:

> You are a highly-skilled professor in AI planning and a proficient Python programmer creating a domain-dependent heuristic function for the PDDL domain D. The heuristic function you create will be used to guide a greedy best-first search to solve instances from this domain. Therefore, the heuristic does not need to be admissible. For a given state, the heuristic function should estimate the required number of actions to reach a goal state as accurately as possible, while remaining efficiently computable. The name of the heuristic should be H. The heuristic should minimize the number of expanded nodes during the search. Next, you will receive a sequence of file contents to help you with your task and to show you the definition of domain D.

We then include the following file contents to the prompt:

1. the PDDL domain file of domain D
2. the smallest PDDL instance of domain D in the training set
3. the largest PDDL instance of domain D in the training set
4. the PDDL domain file of the Gripper domain [49]
5. a PDDL instance file of the Gripper domain
6. a domain-dependent heuristic for Gripper implemented in Python
7. the PDDL domain file of the Logistics domain [49]
8. a PDDL instance file of the Logistics domain
9. a domain-dependent heuristic for Logistics implemented in Python
10. an example of how each state of domain D is represented in Pyperplan
11. an example of how the static information of domain D is represented in Pyperplan
12. the Python code from Pyperplan for representing a planning task and an action
13. a checklist of common pitfalls

Items 1, 2, and 3 provide the context about the domain D that we are interested in. Providing two examples hits a sweet spot because giving only one task sometimes led the LLM to infer wrong patterns about object names and the format of the goal in exploratory experiments. Providing more than two instances needlessly increases the size of the prompt.

Items 4–9 illustrate what domain-dependent heuristics can look like for two example domains [49]. For Gripper, we provide a Python function computing the perfect heuristic h^* as input, while for Logistics we encode the simple "single visit and load/unload counting heuristic" by Paul et al. [52]. These functions show the LLM what a heuristic could do, and also illustrate how to manipulate the available data.

We include items 10–12 to give more context about Pyperplan. Items 10 and 11 are, essentially, what we see when calling a print function for a state or the static information of a task.[1] This minimizes the amount of access and data manipulation errors by the LLM.

Last, the checklist consists of tips based on our own observations of the LLM responses:

(a) The code for extracting objects from facts remembers to ignore the surrounding brackets.
(b) The heuristic is 0 only for goal states.
(c) The heuristic value is finite for solvable states.

[1] Static information refers to all ground atoms that are never modified by any action—and hence they are *static*. Planners, including Pyperplan, usually discard static atoms after grounding because they are not needed for domain-independent search algorithms. However, they can be important for domain-dependent search algorithms, such as the ones we obtain with our pipeline.

(d) All used modules are imported.

(e) The information from static facts is extracted into suitable data structures in the constructor.

(f) Provide a detailed docstring explaining the heuristic calculation. For this, divide the docstring into sections "Summary", "Assumptions", "Heuristic Initialization" and "Step-By-Step Thinking for Computing Heuristic".

Tips (a), (b), (c), (d), and (e) are self-explanatory and help to avoid common errors—e.g., not being aware that an atom in Pyperplan is encoded as "`(pred obj1 obj2)`". The final tip, (f), directs the LLM to chain-of-thought reasoning.

Finding Strong Heuristics

In our approach, we prompt the model n times with the input above to generate n heuristics. We then run the n different heuristics with GBFS on the training set to select the best one. To make the selection quick, we evaluate each heuristic on the training set using a 5 minutes time limit per task.

The final remaining question is how to select the best heuristic. We go with a simple approach: we pick the heuristic that solves the largest number of tasks from the training set. If there is a tie, we choose the one minimizing the accumulated *agile score* over the training set. The agile score is a common metric from IPCs. The score of a heuristic h for a given task is based on the time the GBFS takes to find a plan. If the search needs less than 1 second, then the score is 1. If the search runs out of time (in our case, 300 seconds) the score is 0. Intermediate values are interpolated with the logarithmic function $1 - \frac{\log(t)}{\log(300)}$, where t is the run time (in seconds) of the search. The accumulated score is the sum over all training tasks.

4 Experimental Results

For running our final experiments, we use Downward Lab [68] on AMD EPYC 7742 processors running at 2.25 GHz. We simulate the same setting as the IPC Learning Track 2023: the training phase may use at most 24 hours and 32 GiB per domain, while each planner run on each test task is limited to 30 minutes and 8 GiB. We stick to the same limits, but since the LLMs we use require much more memory, we cannot enforce the memory limit for the training phase. As mentioned, we use Pyperplan [1] for all our configurations. This allows us to evaluate the different heuristics (domain-independent and LLM-generated ones) in one single framework. We use PyPy 7.3.9 to run Pyperplan, as it proved to be slightly faster than CPython.

We use the domains and training/test tasks from the IPC 2023 Learning Track to generate and evaluate heuristics. However, since Pyperplan does not support two of these ten domains—Ferry and Satellite, we exclude them from our experiments. The final set has 99 training and 90 test tasks for each of the 8 domains.

The distribution of tasks in the training and test sets differs: the test tasks are generally much larger than the training ones. In Blocksworld, for example, the largest training task contains 29 blocks, while the largest test task has 488 blocks. Similarly, for Sokoban, the largest training task has 4 boxes in a maze measuring 13×13, while the largest test task has 79 boxes in a maze measuring 99×99. In addition to size differences, tasks may also vary in structure. For example, Sokoban mazes can be arranged in different layouts. The full details about the task sets can be found online [63].

Generating Heuristics

In our pipeline, we prompt the LLM n times and receive n different heuristic functions. But how large should n be?

We ran a pre-training experiment to verify this. We use Gemini 2.0 Flash (stable release 001) in this experiment. Figure 2 shows the average number of solved tasks (the so-called *coverage*) when n increases from 1 to 25. For all domains, the biggest increase in average coverage results from going from 1 to 5 heuristics and after that, we see diminishing returns. However, Childsnack and Transport still benefit from generating 25 instead of 20 heuristics. There are two domains, Childsnack and Floortile, where the average coverage has not stagnated or hit the limit of 99 tasks for $n = 25$. We

Model	Gemini 2.0		DeepSeek		
	Flash	Flash Think.	V3	R1 Dist.	R1
Estimated Cost (USD)	\$0.70	–	\$0.25	–	\$6.12
Cost per Heuristic (USD)	\$0.00350	–	\$0.00125	–	\$0.03060
Cost per Domain (USD)	\$0.08750	–	\$0.03125	–	\$0.76500
Failure Rate (% heuristics)	22.0%	12.5%	14.0%	64.5%	8.5%

Table 1: Cost and failure rate for each LLM variant. Each LLM generates 200 heuristics (25 heuristics for each of the 8 domains). "R1 Dist." is the distillation of R1 to Qwen 14B. Since Gemini 2.0 Flash Thinking ("Flash Think.") is only available in the free tier API, and "R1 Dist." can be run locally but not through the paid API, we do not estimate their prices. We consider a generated heuristic a *failure* if it crashes for all training tasks and we do not re-generate such heuristics.

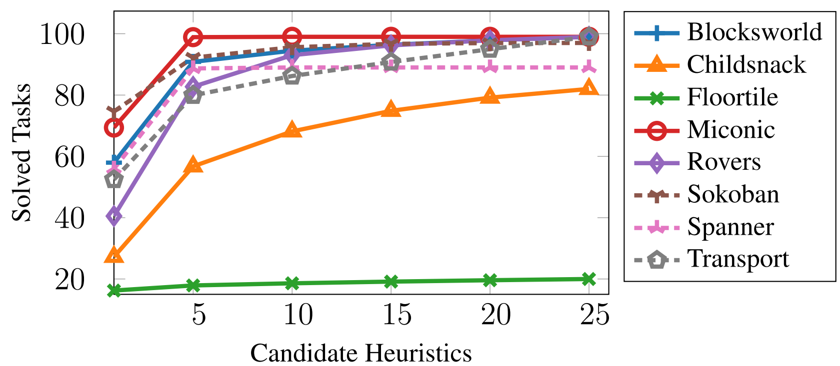


Figure 2: Average coverage per number of candidate heuristics per domain.

tried increasing the number of generated heuristics to 100 for these two domains, but this did not help much. So to reduce computational costs, we generate only 25 heuristics for each of the 8 domains.

To generate the heuristics, we use the APIs from two different families of LLMs: Gemini [29, 30], with the models Gemini 2.0 Flash (stable release 001) and Gemini 2.0 Flash Thinking (version 01-21); and DeepSeek [14, 15], with the models DeepSeek V3, DeepSeek R1 Distill Qwen 14B, and DeepSeek R1. We include the distilled version to Qwen 14B [3] to evaluate the impact of smaller models in our pipeline. The two Gemini models generate all heuristics for a domain in a bit over 5 minutes. The DeepSeek models, however, require between 5 to 7 hours per domain.

Table 1 shows the estimated cost and failure rate for each model. Our approach is cheaper than the one by Tuisov et al. [80] because their method generates multiple heuristics per task, which increases the costs proportionally to the number of tasks. In our pipeline, however, the costs depend on the number of domains only, which is usually much smaller. As a result, all experiments for this paper taken together only cost $\sim$ \$7 US. Regarding failure rates, i.e., the percentage of heuristics that crash for all training tasks, the reasoning models (Gemini 2.0 Flash Thinking and DeepSeek R1) are the most robust. The distilled version of DeepSeek R1 has by far the highest failure rate. This is expected, as this model is much smaller than all other models tested. In our experiments, we did not replace the failed candidates, but for future work, it would be interesting to analyze how the performance changes when replacing such heuristics.

Selected LLM-Generated Heuristics

To illustrate the heuristic functions generated by DeepSeek R1, we briefly discuss the selected heuristic functions for the Blocksworld and Spanner domains, shown in Appendix A. In Blocksworld, stacks of n blocks must be rearranged from an initial state to a goal condition. The available actions move blocks that are on top of a stack onto a different stack or the table. In the Spanner domain, an agent must move through a corridor, pick up spanners, and tighten n nuts at the gate, using each picked-up spanner at most once. The agent can move in the direction of the gate but not backwards.

Domain	h^0	h^{FF}	Gemini 2.0 Flash	Gemini 2.0 Flash Think.	DeepSeek V3	DeepSeek R1 Dist.	DeepSeek R1
Blocksworld (90)	6	24	35	37	37	34	66
Childsnack (90)	9	17	32	14	32	16	22
Floortile (90)	1	10	4	8	4	3	4
Miconic (90)	30	74	90	88	74	30	90
Rovers (90)	12	28	32	39	32	32	32
Sokoban (90)	24	31	31	32	30	24	30
Spanner (90)	30	30	30	30	30	30	70
Transport (90)	8	29	42	57	44	45	59
Sum (720)	120	243	296	305	283	214	373

Table 2: Coverage of GBFS within Pyperplan using the blind heuristic h^0, h^{FF} and our LLM-generated heuristics.

Thus, moving without first picking up a required spanner, results in an unsolvable state. Both domains admit polynomial solving strategies: Blocksworld is *2-approximable* [33] (by destroying all stacks and then building the goal stacks) and even optimal Spanner plans can be computed in polynomial time (by picking up exactly the first n spanners). However, these are not the strategies the LLM uses to implement the heuristic function.

The heuristic selected for Blocksworld computes for each block A mentioned in the goal condition whether A is misplaced and, if so, adds 2 to the heuristic value for each block B on top of A, plus 1. For this, the heuristic uses an auxiliary function that traverses the stack on top of A. It is easy to see that this heuristic can overestimate the optimal plan length.

For Spanner, the heuristic greedily assigns to each loose nut in a fixed order, the closest spanner still available. If the spanner has already been picked up, the cost of tightening the nut is the distance from the agent to the nut location plus 1. If not, then the cost is the distance from the agent to the location of the spanner plus the distance from the location of the spanner to the location of the nut plus 2. Each spanner can be used at most once, so if a nut has no assigned spanner, the heuristic adds a large number to the cost of the state. The heuristic performs a breadth-first search during the initialization phase to compute the shortest path between all locations. This heuristic can also overestimate the optimal plan length. Arguably, the LLM could have created a simpler heuristic if the implicit assumptions of the domain were explicit [31]: the PDDL domain allows for arbitrary connections between locations, but all instances assume a one-way corridor.

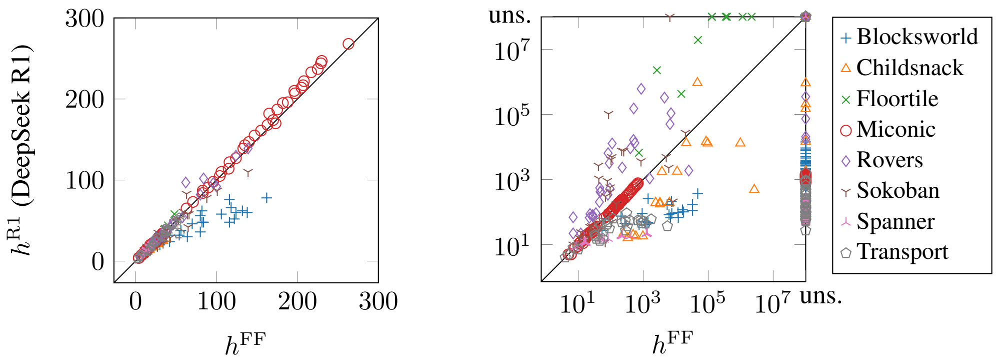
Comparison to Domain-Independent Heuristics in Pyperplan

We now compare the LLM-generated heuristics to two baselines: breadth-first search (BrFS), which uses no heuristic guidance,[2] and GBFS with the h^{FF} heuristic [41], which is one of the most commonly used heuristics for satisficing planning [e.g., 8, 13, 28]. These two baselines are also implemented in Pyperplan, which allows us to evaluate exactly the impact of the generated heuristics. All other Pyperplan files have not been changed; the only change is the automatic inclusion of the LLM-generated heuristic. Therefore, the heuristics are evaluated using the exact same code framework.

Table 2 shows the coverage (i.e., number of solved tasks) per method for each of the eight domains in our test set. As we can see, all LLM-generated heuristics outperform h^{FF} regarding total coverage, except for the distilled version of DeepSeek R1. In almost all cases, the other LLM-generated heuristics are even preferable to h^{FF} on a per-domain basis.

DeepSeek R1 heuristics have the highest coverage with 373 solved tasks. Gemini 2.0 Flash Thinking solves 68 fewer tasks (total 305), while the best baseline h^{FF} solves only 234 tasks. DeepSeek R1 heuristics are particularly impressive in the Blocksworld and Spanner domains. In Blocksworld,

[2]This is identical to running GBFS with the blind heuristic h^0, where $h^0(s) = 0$ iff s is a goal state and $h^0(s) = 1$ otherwise.



(a) Plan length.

(b) Expansions.

Figure 3: Comparison of plan length and expansions for h^{FF} and the heuristics generated by DeepSeek R1. We only show plan lengths up to 300.

the R1 heuristic solves almost twice as many tasks as the second best configuration (Gemini 2.0 Flash Thinking); in Spanner the R1 heuristic solves more than twice as many tasks as all other configurations.

As expected, the non-thinking models—Gemini 2.0 Flash and DeepSeek V3—perform worse than their thinking counterparts. But this does not hold in every domain. In Childsnack, for example, both non-thinking models solve more tasks than their thinking counterparts.

DeepSeek R1 Distill Qwen 14B heuristics are the only LLM-based models that underperform in comparison to h^{FF}. This is expected, as this model already had a high failure rate to begin with (Table 1). However, this is mostly due its low coverage in the Miconic domain. In fact, DeepSeek R1 Distill Qwen 14B outperformed h^{FF} in 3 domains, while being outperformed in 4. This shows that the smaller distilled models might be competitive with existing heuristics in some domains, while having the advantage of being more affordable than the original ones.

Figure 3a compares the plan lengths obtained with h^{FF} and the heuristics generated by DeepSeek R1. We show only plan lengths up to 300, as only Miconic has plans longer than that. In general, the two methods yield plans with similar lengths. The only domains where one approach has a clear edge are Blocksworld, where the DeepSeek R1 plans are consistently shorter, and Miconic, where DeepSeek R1 plans get longer than h^{FF} as the tasks get larger. Interestingly, DeepSeek R1 still achiever higher coverage than h^{FF} in Miconic. In our experiments, h^{FF} never finds plans that are longer than 800 steps, while DeepSeek R1 finds multiple plans with up to 1 500 steps (not shown in Figure 3a).

Last, we compare the informativeness of the traditional and the LLM-generated heuristics by inspecting the number of expansions the resulting searches need. Ideally, a heuristic only expands states traversed by a plan. Figure 3b compares expansions between h^{FF} and DeepSeek R1 heuristics. The results vary by domain: DeepSeek R1 has an edge in Blocksworld, Spanner, Transport and in most of the Childsnack tasks, whereas h^{FF} is more informed in Floortile, Rovers and Sokoban. In all the domains where DeepSeek R1 expands fewer states than h^{FF}, it also solves many more tasks than h^{FF}. On the flip side, the only domain where h^{FF} expands fewer states and solves many more tasks than DeepSeek R1 is Floortile. In the Rovers domain, DeepSeek R1 has higher coverage than h^{FF}, while in Sokoban h^{FF} solves only two more tasks. This indicates that despite being less informed in these two domains, the heuristics generated by DeepSeek R1 perform better because they are more efficient to compute.

Comparison to State-of-the-Art Heuristics Implemented in C++

Our experimental setup has an obvious flaw: we are using Pyperplan, which is an educational, unoptimized Python planner, while all state-of-the-art planners are implemented in compiled languages such as C++. For example, the winners of all tracks of the last IPC, in 2023, are implemented in C++ [77]. Moreover, all of these planners are implemented on top of the Fast Downward planning system [38]. Even though Python runs much slower than C++ and uses more memory, we compare our best method, GBFS in Pyperplan using DeepSeek R1 heuristics, to GBFS in Fast Downward

Domain	Fast Downward (C++) h^{GC}	h^{lmc}	h^{FF}	h^{cea}	h^{cg}	h^{add}	$h^{\mathrm{WLF}}_{\mathrm{GPR}}$	Pyperplan h^{FF}	h^{R1}
Blocksworld (90)	32	39	27	40	34	44	72	24	66
Childsnack (90)	23	13	25	29	29	29	31	17	22
Floortile (90)	3	3	12	10	7	14	2	10	4
Miconic (90)	90	90	90	79	90	90	90	74	90
Rovers (90)	38	41	34	36	39	33	37	28	32
Sokoban (90)	42	43	36	33	35	33	38	31	30
Spanner (90)	30	30	30	30	30	30	73	30	70
Transport (90)	36	36	41	49	54	51	28	29	59
Sum (720)	294	295	295	306	318	324	371	243	373

Table 3: Coverage for different heuristics implemented in Fast Downward, and in Pyperplan. Heuristic h^{R1} indicates the heuristics generated by DeepSeek R1.

using one of the many satisficing heuristics implemented in the planner: the goal-count heuristic, h^{GC} [24]; the landmark count heuristic, h^{lmc} [57, 9]; the C++ implementation of the FF heuristic, h^{FF} [41]; the context-enhanced additive heuristic, h^{cea} [39]; the causal graph heuristic, h^{cg} [37]; and the additive heuristic, h^{add} [6]. We also compare it to $h^{\mathrm{WLF}}_{\mathrm{GPR}}$ [11], which uses statistical learning methods together with the Weisfeiler-Leman algorithm to learn domain-dependent heuristics, and is considered the state-of-the-art in classical planning for heuristic learning. $h^{\mathrm{WLF}}_{\mathrm{GPR}}$ is also implemented on top of Fast Downward.

We denote the heuristics generated by DeepSeek R1 as h^{R1} from now on. Table 3 shows that GBFS in Pyperplan with h^{R1} solves more tasks in total than *any of the traditional Fast Downward heuristics*. It is also *competitive with the state-of-the-art,* $h^{\mathrm{WLF}}_{\mathrm{GPR}}$, and achieves slightly higher total coverage. This is quite an unexpected result, as Pyperplan is not as engineered and receives little attention and maintenance compared to Fast Downward. It indicates that the heuristics generated by DeepSeek R1 are indeed powerful, being capable of surpassing the performance gap between Python and C++ implementations.

5 Related Work

The combination of planning and learning to create heuristic functions has a long tradition [62, 12, 61, 2]. There are two main paradigms for learning heuristic functions in classical planning: task-dependent [21, 22, 51, 4] and domain-dependent [70, 74, 10, 34]. In this paper, we consider the second paradigm. Currently, the strongest approach in domain-dependent heuristic learning is $h^{\mathrm{WLF}}_{\mathrm{GPR}}$ [11], which we compare to above.

Recently, LLMs entered the picture. Yet, Valmeekam et al. [81] show that LLMs cannot reliably solve even small classical planning tasks when used for end-to-end plan generation. Moreover, techniques such as supervised fine-tuning and chain-of-thought fail to generalize to out-of-distribution tasks [5, 76], and even LLMs explicitly designed for reasoning tasks cannot solve typical planning problems [83].

Nonetheless, Rossetti et al. [60] show that a GPT model trained from scratch on solved planning tasks from a fixed domain can achieve competitive performance compared to other learning approaches when training and test sets share the same distribution. Additionally, Huang et al. [42] use reinforcement learning with partial rewards to increase the LLM performance in end-to-end plan generation. Furthermore, LLMs can also help to solve classical planning tasks when combined with other techniques. For example, there is an extensive body of work exploring the potential of LLMs to convert problems described in natural language into PDDL tasks [e.g., 32, 26, 50, 48].

The most closely related approaches to ours are those that use LLMs to generate code for solving planning tasks. Katz et al. [43] highlight the high computational cost of using LLMs for end-to-end plan generation, particularly when multiple inferences are required. To address this issue, they propose a domain-dependent approach in which an LLM generates Python code for two key operations: successor generation and goal testing. These functions are then integrated into standard search algorithms, such as breadth-first, implemented in Python. When the successor generator and goal test are correct, their method is sound and complete while simultaneously being more computationally efficient than direct LLM-based planning. However, their approach has two key limitations. First, human feedback is required when the generated functions are incorrect. Second, because they rely on uninformed search algorithms, their method is limited to solving only small planning tasks. Our approach could address this second limitation by providing a heuristic function for an informed search algorithm to improve its scalability.

Silver et al. [71] also use LLMs to generate Python code for solving classical planning tasks. However, they focus on *generalized planning*, where the aim is to find a strategy that can efficiently solve any task of a given domain. In their approach, an LLM generates a "simple" Python program that does not rely on search. The key distinction between their approach and ours is that they address different problems. There are many planning domains, such as the Sokoban domain we use above, for which no simple strategy exists to efficiently produce plans. For such domains, heuristic functions can be useful.

The work by Tuisov et al. [80] is the most similar to ours, and we draw inspiration from their work. They also use LLMs to generate heuristic function code for automated planning. Instead of addressing classical planning, though, their focus is on numeric planning. Moreover, they generate their heuristics via a three-step prompting process: domain summarization and heuristic conceptualization; heuristic implementation; and heuristic refinement for a specific planning task. Our approach differs from theirs in three main regards. First, they require a manual translation of each PDDL domain into Rust, including the implementation of a successor generator and a goal test. The cost of translating domains to Rust prevents easy comparisons on all IPC domains. In contrast, our approach generates heuristics directly from the PDDL description with the resulting code integrated into an off-the-shelf planner. Second, their heuristics are task-dependent rather than domain-dependent. While task-dependent heuristics may be more informed, they require LLM inferences for each new task. In contrast, our approach generates a heuristic for an entire domain, enabling reuse across multiple tasks without additional LLM queries, and thus reducing costs. Finally, while their approach outperforms all domain-independent heuristics they compare against, their LLM-generated heuristics result in fewer expansions than the baseline domain-independent heuristics for only a single task. This suggests that while their heuristics may be computationally faster, they are not necessarily more informative. In our experiments, the LLM-generated heuristics are often more informative than the traditional domain-independent ones.

Outside the area of PDDL planning, Romera-Paredes et al. [59] use a search in function space to help to solve combinatorial problems. Their algorithm, FunSearch, samples different initial programs, similar to our set of candidate heuristics. However, FunSearch feeds the best initial candidates back into the LLM to improve them. Another recent approach is the one by Ling et al. [46], where an LLM generates a set of candidate heuristics which are then evaluated on a training set and the best heuristics is returned to the LLM for refinement. In contrast, our pipeline never feeds the Python functions back into the LLM. Although our results are already positive, this feedback loop could further strengthen our results.

6 Conclusions

In this paper, we show how to use LLMs to generate domain-dependent heuristics for classical planning domains. Our approach uses LLMs to produce a pool of candidate heuristics, which we then evaluate on a training set in order to choose the best heuristic from the pool. The selected heuristic is then used for unseen tasks.

We provide a proof-of-concept implementation of this pipeline in Pyperplan, an educational classical planner written in Python. Comparing the Python-based heuristics, we see that our LLM-generated heuristics outperform a state-of-the-art domain-independent heuristic in most of the domains of our benchmark set. In particular, large reasoning models such as DeepSeek R1 show a significant improvement compared to the domain-independent heuristic.

We show that Pyperplan equipped with the heuristics from DeepSeek R1 (h^{R1}) surpasses commonly used heuristics implemented in Fast Downward [38], a state-of-the-art planner written in C++. Moreover, h^{R1} is also competitive with $h^{\mathrm{WLF}}_{\mathrm{GPR}}$ [11], the state-of-the-art in heuristic learning for classical planning implemented on top of Fast Downward. These results are surprising, as Pyperplan is much less optimized than Fast Downward, and DeepSeek R1 is not trained on specific domains, while $h^{\mathrm{WLF}}_{\mathrm{GPR}}$ is. Taken together, our results demonstrate the growing potential of LLM-generated heuristics in classical planning.

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A Generated Heuristics (Selection)

A.1 DeepSeek R1 Heuristic for Blocksworld

```python
from fnmatch import fnmatch
from collections import defaultdict
from heuristics.heuristic_base import Heuristic

class blocksworld9Heuristic(Heuristic):
    """
    A domain-dependent heuristic for the Blocksworld domain.

    # Summary
    This heuristic estimates the number of actions required to achieve the goal by considering the number of blocks that need to be moved and the blocks above them in the current state. For each block not in its goal position, the cost is 2 times the number of blocks above it plus 2. Held blocks not in the goal position add 1 to the cost.

    # Assumptions
    - The goal specifies the required 'on' and 'on-table' predicates for certain blocks.
    - Blocks not mentioned in the goal do not affect the heuristic.
    - Moving a block requires unstacking all blocks above it first.
    - The arm can only carry one block at a time.

    # Heuristic Initialization
    - Extract the goal conditions to determine the target positions for each block.
    - Store the goal parent (block or 'table') for each block mentioned in the goal.

    # Step-By-Step Thinking for Computing Heuristic
    1. Parse the current state to determine the current parent (block or 'table') and children (blocks on top) for each block.
    2. Check if any block is currently being held.
    3. For each block mentioned in the goal:
        a. If the block is held and not in the goal position, add 1 action (putdown or stack).
        b. If the block is not held and not in the goal position, calculate the number of blocks above it and add 2 actions per block (unstack and putdown) plus 2 actions for the block itself.
    4. Sum all calculated costs to get the heuristic value.
    """

    def __init__(self, task):
        """Initialize the heuristic by extracting goal conditions."""
        self.goal_parent = {}
        for goal in task.goals:
            parts = goal[1:-1].split()
            if parts[0] == 'on':
                block, parent = parts[1], parts[2]
                self.goal_parent[block] = parent
            elif parts[0] == 'on-table':
                block = parts[1]
                self.goal_parent[block] = 'table'

    def __call__(self, node):
        """Compute the heuristic value for the given state."""
```

```python
        state = node.state
        current_parent = {}
        current_children = defaultdict(list)
        held_block = None

        # Parse current state
        for fact in state:
            parts = fact[1:-1].split()
            if parts[0] == 'on':
                child, parent = parts[1], parts[2]
                current_parent[child] = parent
                current_children[parent].append(child)
            elif parts[0] == 'on-table':
                block = parts[1]
                current_parent[block] = 'table'
            elif parts[0] == 'holding':
                held_block = parts[1]

        # Calculate cost
        cost = 0

        # Check held block
        if held_block is not None and held_block in self.goal_parent:
            current_pos = 'held'
            goal_pos = self.goal_parent[held_block]
            # If held block is not in goal position, add 1 action
            if (goal_pos == 'table' and current_pos != 'table') or \
               (goal_pos != 'table' and current_pos != goal_pos):
                cost += 1

        # Process each block in the goal
        for block in self.goal_parent:
            if block == held_block:
                continue  # Already handled

            current_parent_block = current_parent.get(block, 'table')
            goal_parent_block = self.goal_parent[block]

            if current_parent_block != goal_parent_block:
                # Calculate number of blocks above the current block
                def count_above(x):
                    cnt = 0
                    stack = [x]
                    while stack:
                        current = stack.pop()
                        for child in current_children.get(current, []):
                            cnt += 1
                            stack.append(child)
                    return cnt

                above = count_above(block)
                cost += 2 * (above + 1)

        return cost
```

A.2 DeepSeek R1 Heuristic for Spanner

```
from fnmatch import fnmatch
from collections import defaultdict, deque
from heuristics.heuristic_base import Heuristic

class spanner10Heuristic(Heuristic):
    """
    A domain-dependent heuristic for the Spanner domain.

    # Summary
    Estimates the number of actions required to tighten all loose nuts by
↪   considering the minimal path to collect usable spanners and reach each
↪   nut's location.

    # Assumptions
    - The man (bob) can carry multiple spanners, but each spanner can be
↪   used only once.
    - The shortest path between locations is precomputed using static link
↪   information.
    - The man's name is 'bob' as per the problem examples.

    # Heuristic Initialization
    - Extracts static link facts to build a directed graph of locations.
    - Precomputes shortest paths between all pairs of locations using BFS.

    # Step-By-Step Thinking for Computing Heuristic
    1. Identify the man's current location.
    2. Collect all loose nuts and their locations.
    3. Identify all usable spanners (carried or on the ground).
    4. For each loose nut, compute the minimal cost to tighten it using
↪   the best available spanner.
    5. Assign spanners to nuts greedily, marking used spanners to avoid
↪   reuse.
    6. Sum the minimal costs for all nuts to get the heuristic value.
    """

    def __init__(self, task):
        self.goals = task.goals
        self.static_links = defaultdict(list)
        for fact in task.static:
            parts = fact[1:-1].split()
            if parts[0] == 'link':
                start, end = parts[1], parts[2]
                self.static_links[start].append(end)
        # Precompute shortest paths between all locations
        self.shortest_paths = {}
        all_locations = set(self.static_links.keys())
        for ends in self.static_links.values():
            all_locations.update(ends)
        all_locations = list(all_locations)
        for loc in all_locations:
            distances = {loc: 0}
            queue = deque([loc])
            while queue:
                current = queue.popleft()
                for neighbor in self.static_links.get(current, []):
                    if neighbor not in distances:
                        distances[neighbor] = distances[current] + 1
```

```python
                        queue.append(neighbor)
            self.shortest_paths[loc] = distances

    def __call__(self, node):
        state = node.state
        # Find man's location (assumed to be 'bob')
        man_location = None
        for fact in state:
            if fact.startswith('(at bob '):
                parts = fact[1:-1].split()
                man_location = parts[2]
                break
        if not man_location:
            return float('inf')  # Invalid state

        # Collect loose nuts and their locations
        loose_nuts = []
        nut_locations = {}
        for fact in state:
            if fact.startswith('(loose '):
                parts = fact[1:-1].split()
                loose_nuts.append(parts[1])
            elif fact.startswith('(at ') and 'nut' in fact:
                parts = fact[1:-1].split()
                obj, loc = parts[1], parts[2]
                nut_locations[obj] = loc

        # Collect usable spanners and their locations
        usable_spanners = []
        carried_spanners = []
        spanner_locations = {}
        for fact in state:
            if fact.startswith('(usable '):
                parts = fact[1:-1].split()
                usable_spanners.append(parts[1])
            if fact.startswith('(carrying bob '):
                parts = fact[1:-1].split()
                carried_spanners.append(parts[2])
            if fact.startswith('(at ') and 'spanner' in fact:
                parts = fact[1:-1].split()
                spanner_locations[parts[1]] = parts[2]

        # Prepare available spanners (carried or on ground)
        available_spanners = []
        for spanner in usable_spanners:
            if spanner in carried_spanners:
                available_spanners.append((spanner, man_location, True))
            elif spanner in spanner_locations:
                available_spanners.append((spanner, spanner_locations[spanner], False))

        # Assign spanners to nuts greedily
        total_cost = 0
        used_spanners = set()
        for nut in loose_nuts:
            nut_loc = nut_locations.get(nut)
            if not nut_loc:
                continue  # Skip if nut location not found

```

```
            min_cost = float('inf')
            best_spanner = None
            for spanner_info in available_spanners:
                spanner, s_loc, is_carried = spanner_info
                if spanner in used_spanners:
                    continue

                if is_carried:
                    distance =
                    ↪  self.shortest_paths[man_location].get(nut_loc,
                    ↪  float('inf'))
                    cost = distance + 1
                else:
                    d1 = self.shortest_paths[man_location].get(s_loc,
                    ↪  float('inf'))
                    d2 = self.shortest_paths[s_loc].get(nut_loc,
                    ↪  float('inf'))
                    cost = d1 + 1 + d2 + 1 if d1 != float('inf') and d2 !=
                    ↪  float('inf') else float('inf')

                if cost < min_cost:
                    min_cost = cost
                    best_spanner = spanner

            if best_spanner is not None:
                total_cost += min_cost
                used_spanners.add(best_spanner)
            else:
                total_cost += 1000000  # Penalize for missing spanner

        return total_cost
```