

TRIP-PAL: Travel Planning with Guarantees by Combining Large Language Models and Automated Planners

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Abstract

Travel planning is a complex task that involves generating a sequence of actions related to visiting places subject to constraints and maximizing some user satisfaction criteria. Traditional approaches rely on problem formulation in a given formal language, extracting relevant travel information from web sources, and use an adequate problem solver to generate a valid solution. As an alternative, recent Large Language Model (LLM) based approaches directly output plans from user requests using language. Although LLMs possess extensive travel domain knowledge and provide high-level information like points of interest and potential routes, current state-of-the-art models often generate plans that lack coherence, fail to satisfy constraints fully, and do not guarantee the generation of high-quality solutions. We propose TRIP-PAL, a hybrid method that combines the strengths of LLMs and automated planners, where (i) LLMs get and translate travel information and user information into data structures that can be fed into planners; and (ii) automated planners generate travel plans that guarantee constraint satisfaction and optimize for users' utility. Our experiments across various travel scenarios show that TRIP-PAL outperforms an LLM when generating travel plans.

Introduction

Travel planning is a complex process that involves finding places or points of interest (POIs), incorporating real-world constraints such as visiting and travel times, as well as scheduling the POIs into a coherent trip that maximizes a given utility function.

Traditional computer-aided solutions for travel planning based on Automated Planning (Bhowmick et al. 2012), and Mixed-Integer Programming (Zhu et al. 2012) heavily rely on manual problem formulations to represent and formalize this knowledge. Using formal representations, different solvers can be used to generate travel plans that maximize the users' utility while satisfying the hard constraints. Although these approaches guarantee valid travel itineraries, the formalization step can be tedious and time consuming even for domain experts.

Recent advances in LLMs such as GPT-4 (Achiam et al. 2023) have shown promising results in tasks requiring pub-

lic domain knowledge available on the internet (Suri et al. 2024; Achiam et al. 2023), where these systems are trained on. Travel planning is one of such tasks, and LLMs seem to be good candidates as tools to generate travel itineraries due to their extensive knowledge about travel destinations, POIs and previous itineraries shared online. However, LLMs have been shown to be bad reasoners especially in tasks that involve sequential decision making (Valmeekam et al. 2022a); travel planning is one such type of domain. To counter this, LLMs like GPT-4 would have had access to many travel plans in their training data, and it can be argued that GPT-4 might be capable of doing a form of case-based planning (CBP) (Spalzzi 2001) for travel planning. Given a case library (set of past pairs $\langle \text{problem}, \text{plan} \rangle$) and a new problem, CBP retrieves a subset of the previous plans that are most similar to the new problem, adapts them to create a new solution, that is evaluated and stored in the case library. In the context of travel planning, that could mean combining past successful travel plans in a city to make a new plan for a user's utility, and satisfy real world constraints. With the plethora of data (cases), it is feasible for an LLM to generate good travel plans; this is one of the reasons we focus on travel planning with LLMs.

In this paper we propose TRIP-PAL (Travel Itinerary Planning with Planners and Language models), a hybrid method that goes beyond just using LLMs, that leverages the strengths of both LLMs and automated planners for travel planning. In a similar spirit to the work by Liu et al. (Liu et al. 2023) and Rao et al. (Kambhampati et al. 2024), our approach utilizes LLMs to parse or extract information based on user goals, such as finding POIs and time to spend at each POI. This information is then used to formulate a planning problem that captures the user's goals and general preferences. In this paper, we assume that the general preference of visiting each POI extracted by the LLM is a proxy of the user satisfaction of visiting those POIs. The formulated planning problem is then solved using an automated planner, which takes into account the real-world constraints and generates an optimal travel plan. The planner considers factors such as commute times, time to spend at a POI, and general preferences to create a plan that maximizes user satisfaction or utility while being feasible. By explicitly representing the planning problem and using an optimal planner, we ensure that the generated plans are sound (valid), comply with con-

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straints, and are optimal.

In this paper, we study two planning characteristics that were not covered by previous work on the relation between LLMs reasoning capabilities and planning: over-subscription and optimality. Planning under over-subscription deals with tasks where there is no possible plan that achieves all goals given as input. For instance, let us assume we give a planner 50 POIs to visit in Paris¹ in one day. There is no reasonable travel plan that can achieve all those goals under that time constraint. Therefore, a valid/optimal solution will consider the plan that achieves the subset of goals that maximize user satisfaction or utility under the given constraints.

To evaluate the effectiveness of TRIP-PAL, we conduct experiments on a diverse set of travel scenarios to generate single-day travel plans. We compare TRIP-PAL against GPT-4 to assess its performance in terms of plan quality and feasibility. The experiments reveal that, as the travel planning problem involves more POIs or longer travel time, GPT-4 tends to generate travel plans with much lower user utility than the ones generated by TRIP-PAL. Specifically, TRIP-PAL robustly generates valid plans that maximize user utility.

Our main contributions are as follows:

- We investigate the use of LLMs (GPT-4) for the over-subscription planning problem in the travel domain, considering real-world constraints.
- We propose a hybrid approach that combines LLMs and automated planners for the travel planning task that is an end-to-end solution with guarantees including constraint satisfaction and optimization of the utility of the travel plans.
- We demonstrate the effectiveness of our hybrid approach through extensive experiments, showing its advantages over using only GPT-4 for travel plans in terms of plan utility and validity.

Related Work

Traditional Travel Planning

Travel recommendation and itinerary planning have been extensively studied in the literature. Numerous works have explored various algorithmic approaches to find exact or approximate optimal itineraries given points of interest (POIs) and certain constraints (Berka and Plöbñig 2004; Castillo et al. 2008; Moreno et al. 2013; Vansteenwegen et al. 2011; Rodriguez-Sanchez et al. 2013; Sebastia et al. 2009; Chen et al. 2014; Bhowmick et al. 2012; Zhu et al. 2012). Gavalas et al. (Gavalas et al. 2014) provided a comprehensive survey of the research landscape in Tourist Trip Design Problems (TTDPs). They defined TTDP as the route-planning problem for tourists interested in visiting multiple POIs while accounting for constraints. The survey highlighted that TTDPs are often solved using classical optimization approaches or stochastic local search techniques. These methods aim to

generate personalized and efficient travel plans catering to users’ specific preferences and constraints.

To further enhance the user experience, recent works have focused on incorporating personalization techniques by harnessing crowdsourcing and social networks (Manikonda et al. 2014; Lucas et al. 2012; Cenamor et al. 2017; Chen et al. 2014; Brilhante et al. 2015; Majid et al. 2014), as well as case-based reasoning (Ricci et al. 2006). These methods leverage the collective knowledge and experiences of other travelers to provide more tailored and relevant itinerary recommendations. In addition, Tenemaza et al. (Tenemaza et al. 2020) employed genetic algorithms to refine and improve proposed travel plans.

A common limitation of the aforementioned approaches is the need for manual formulation of the optimization or planning problem. More recent works use deep learning techniques for POIs and travel recommendations (Halder et al. 2024), lifting the requirement for manual formulation of the planning problem. However, these deep learning models do not account for optimality from a planning perspective. In contrast, our work addresses this challenge by utilizing LLMs to automatically parse user travel queries into planning problems. By adopting the method proposed by Keyder et al. (Keyder and Geffner 2009) for compiling away soft goals, we can effectively solve the oversubscription problem and find the optimal travel plan without requiring manual problem formulation.

Travel Planning with LLMs

In recent years, a few works have explored the use of LLMs for travel planning. An early probe of LLMs such as ChatGPT on automatic travel decision-making (Wong, Lian, and Sun 2023) showed LLMs’ capability to improve tourists’ experience in the pre-trip, en-route, and post-trip stages. However, when quantitatively benchmarked LLM agents on travel planning, it revealed that the problem is still too difficult for LLM agents, with even GPT-4 achieving only a low success rate (Xie et al. 2024). To address this issue, Gundawar et al. (2024) adopted the LLM-Modulo framework (Kambhampati 2024) in travel planning, which iteratively improves the generated travel plan through interactions between a travel plan generation LLM and a suite of external verifiers. However, this approach does not involve formal planning or optimization tools, thus providing no guarantee of meeting all travel constraints, especially as the constraints increase (Zheng et al. 2024). To provide guarantees, Hao et al. (2024) proposed to use LLMs to formulate the travel planning problem as a satisfiability modulo theory (SMT) problem, followed by using an SMT solver. Their methodology led to promising travel planning results where user constraints are satisfied. However, their method assumes visiting all given POIs, rather than automatically trading-off, which is the most realistic scenario, and selecting the optimal subset of POIs as in the oversubscription setting. Additionally, TRIP-PAL maximizes the user’s utility on top of satisfying constraints. To accommodate both constraint satisfaction and utility maximization which was not included in (Xie et al. 2024), we created a new benchmark dataset as discussed in our experiments.

¹We can easily see that this number is already a lower bound of all relevant places to visit in Paris.

LLMs could be a valuable source of POI recommendations given their extensive knowledge, providing results similar to those acquired from public sources (Brilhante et al. 2015; Majid et al. 2014) such as Flickr and Wikipedia. However, for numeric information, such as commute time or distances between places, especially for less populated areas (Roberts et al. 2023), web services like Google Places API (Google 2023) are a more accurate source.

LLMs and Planning

When we extend the scope from travel planning to general planning, there are many more recent papers leveraging LLMs in the general planning domain. Recent works have tried using LLMs to solve planning tasks directly through prompting (Valmeekam et al. 2022b; Silver et al. 2024). These works conducted extensive evaluations on standard planning benchmarks and showed that LLMs perform poorly at generating valid plans. This highlights the limitations of using LLMs alone for complex planning tasks and the need for more advanced approaches.

To address this issue, researchers have explored ways to bridge LLMs and planners, such that LLMs are responsible of formulating the planning problem in standard planning languages, such as Planning Domain Definition Language (PDDL) (Fox and Long 2003), while planners are in charge of solving the formulated planning problems (Guan et al. 2023; Liu et al. 2023). Specifically, LLMs have been shown to generate PDDL problems reasonably well (Oswald et al. 2024; Pallagani et al. 2024). By leveraging the strengths of both LLMs and planners, these hybrid approaches improved the overall performance and efficiency of planning systems.

However, the aforementioned works primarily evaluated LLMs in classical planning domains such as blocksworld, which may not have had sufficient relevant data during the training stage of these LLMs. In contrast, the travel planning domain is a domain that LLMs possess extensive knowledge of, as evident in (Wong, Lian, and Sun 2023). Therefore, it is crucial to benchmark how well GPT-4 readily addresses the travel planning problem from both constraints and utility perspectives. To the best of our knowledge, we are the first to 1) introduce the hybrid approach of LLMs and planners to the travel planning domain and benchmark its effectiveness; 2) solve oversubscription planning tasks using such hybrid approach; and 3) benchmark the suboptimality of the travel plans generated by GPT-4.

Method

In this section, we describe how we extract the travel information, and how that information is used to generate plans by GPT-4 and TRIP-PAL. The components used are illustrated in Figure 1.

Retrieval of Travel Information

The inputs to each planning episode are: the desired city, C ; the number of POIs to consider, N ; and the maximum number of hours the travel plan should take, H . The first step in our travel planning process is to extract the corresponding information to those requirements: a set of size N of POIs in

the city C with associated relevant information. TRIP-PAL uses a sequence of prompts to GPT-4, that return the data it requires to compose a travel plan (excerpts from these prompts are in Figure 1). The result of each prompt is included in the context of the next call. The summary of steps goes as follows:

- For a given city C , TRIP-PAL asks GPT-4 to return a set P of N tourist points of interest (POIs). Each POI $p \in P$ will become a goal of the planning problem as $\text{visit}(p)$.
- For each POI provided before, TRIP-PAL gets the rating or utility of the POI by asking GPT-4 for the popularity expressed in a utility value between 1 and 10, with 10 as the maximum utility. It uses this value as the POI’s utility, $\text{utility}(p, u)$. The sum of utilities of POIs in any plan will provide the total plan utility or plan value. Since we are dealing with oversubscription planning, not all POIs will necessarily be visited in the plans.
- Then, TRIP-PAL asks for the time one should spend in each location; this information is asked to be returned in units of 15 minutes, and will define the $\text{visit-time}(p, t)$ property.

With the set of POIs returned by GPT-4, TRIP-PAL can query a service to get the travel time between POIs such as the google places API (Google 2023). For this work we randomly assigned travel times between POIs to be between 15 and 60 minutes in units of 15-minutes. This gives us a travel-times graph. All the accumulated travel information described so far is then fed to a travel planner. The travel planning step can be a simple call to GPT-4 or alternatively (in TRIP-PAL) a call to an automated planner. In the latter, it called after all the information is translated to a formal planning task. This flow of information is shown in Figure 1.

LLM-based Tourist Plan

All the acquired travel information (set of POIs, utility of each POI, visit time, and travel time) is concatenated and fed as text to GPT-4. GPT-4 is then asked to generate a travel plan for the time specified, and to optimize the travel plan based on the utilities of the points of interest passed in. We prompt GPT-4 to generate a day travel plan for a fixed amount of time indicated with start and end hours. To help GPT-4 generate valid plans in as many cases as possible, we asked it to output the travel plan using explicit time (e.g., *14:00*) which empirically worked better for us, for respecting the time constraint than using AM/PM or just asking to “*give a plan for x-hours*”. See an example in Figure 1. For GPT-4, the task of generating this plan with the previous information given in the prompt, involves selecting a subset of POIs that will fit in the schedule; this means considering the visiting time of POIs and the commute time between POIs, and then provide the best plan by utility to the user. Utility is the sum of the utilities of POIs in the plan.

Automated Planning Task

Automated Planning (AP) is the AI field that builds domain-independent solvers which produce sequence of actions (plans) to transform a given initial state into a state where

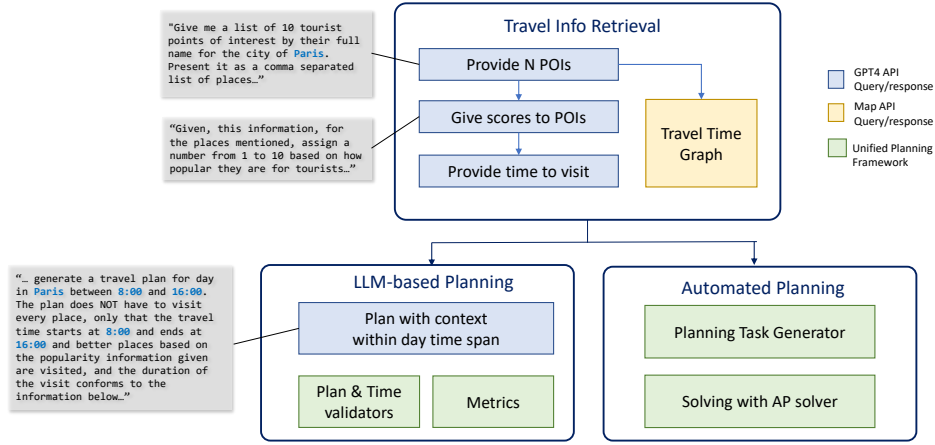


Figure 1: Components used in travel planning for GPT-4 and TRIP-PAL.

a set of goals have been achieved. A planning task in AP is specified in a declarative language (typically PDDL) comprising an action model (domain) and a problem description where the initial state, the goals and the metric to optimize are defined. Oversubscription planning focuses on the class of tasks where not all goals can be achieved because the availability of bounded resources. This is the case for travel planning, since a tourist may be willing to visit more POIs that one can handle in a day itinerary. In oversubscription planning, some, or even all goals, can be deemed as *soft-goals*, meaning that a plan is still valid if they are not reached in the final state. In PDDL3 this is represented with goal preferences (Gerevini and Long 2006). In this case, planners optimize for soft goals based on an utility function. Alternatively, soft goals can be represented with classic planning tasks where high-penalty artificial actions are included in the domain to skip the goals that are not achieved at the end of the real plan (Keyder and Geffner 2009). In this second case, planners optimize the cost function trying to avoid paying high penalties. In our setting, we set visiting all POIs as soft goals, encoding them with the latter approach.

In order to generate the planning task from the extracted information on a given travel (POIs, time constraints, driving times, ...), we used GPT-4 to convert the information on the POIs into dictionaries for the POI utility, travel-time and visit-time. TRIP-PAL then converts these dictionaries into a PDDL planning task using the UPF planning library in python (Micheli et al. 2022). The domain is fixed across all tasks and contains the following actions:

- Visit: the tourist spends time in a POI. For instance, visiting a park, taking a guided tour in a museum, etc.
- Move: A generic action representing the time spent in going from one point to another. This includes walking short distances or taking public transport.

Figure 2 shows the definition of the visit action in PDDL. Symbols preceded by a question mark represent variables. Preconditions define conditions that have to be true in the state in order to execute the action. Effects are literals that are expected to be true in the state after applying the action.

```
(:action visit
:parameters (?vloc - location
             ?vt0 - time
             ?vtvisit - time
             ?vtf - time)
:precondition
  (and (normal_mode)
        (current_time ?vt0)
        (visited_time ?vloc ?vtvisit)
        (user_at ?vloc)
        (logic_sum ?vt0 ?vtvisit ?vtf))
:effect
  (and (visited ?vloc)
        (not (current_time ?vt0))
        (current_time ?vtf)
        (increase (total-cost)
                  (visit_cost ?vloc))))
```

Figure 2: PDDL definition of the visit action.

Additionally, the model includes the artificial actions (*end_mode* and *no_visit*) needed to stop the real plan and then ignore unachieved goals (Keyder and Geffner 2009) and thus, handle the oversubscription problem in the same way as in previous work (Cenamora et al. 2017). The problem description incorporates as static facts the information collected in the information retrieval step regarding the time to spend at POIs and time to commute. Given that most current planners only optimize by minimizing a given function, the POIs' utility is reversed ($MaxUtility - POI_Utility + 1$), to translate it to cost. Time is discretized to 15-minutes slots, so the task can be represented without numeric preconditions. Each day slot is represented as an object. Thus, domain actions include parameters for the current slot, the time slot at action termination, and delta between the two. The logic of how to assign each parameter is encoded through pre-computed static facts of the initial state. See for instance in Figure 2 the *logic_sum* precondition, which requires the current time (*vt0*) is changed to the final time slot (*vtf*) when the time-to-visit slot (*vtvisit*) has passed.

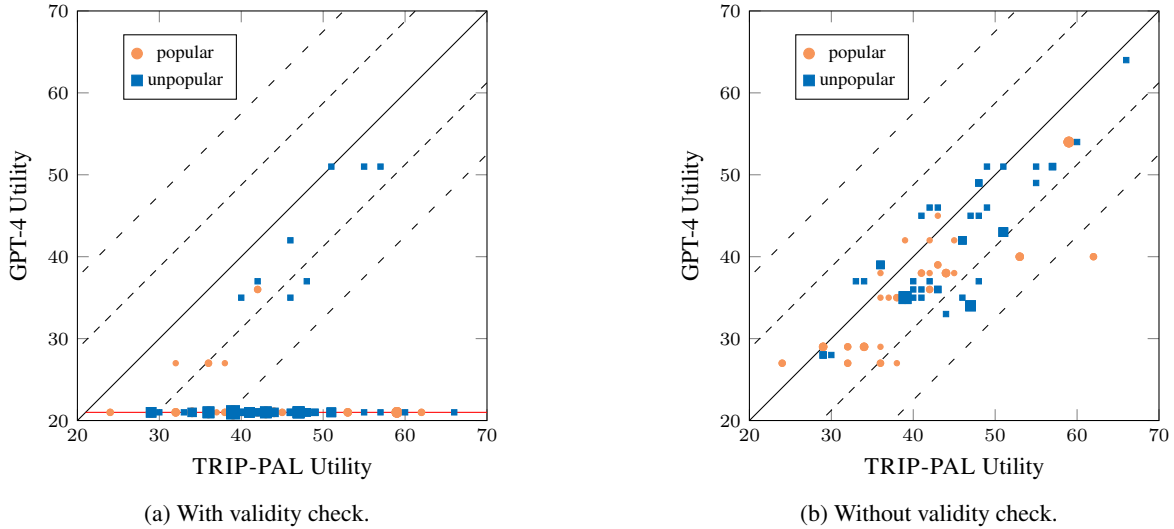


Figure 3: Utility of the plans returned by TRIP-PAL and GPT-4. Points below the solid diagonal indicate that TRIP-PAL generated a higher quality plan than GPT-4 for the given travel planning task. Points at the horizontal red line indicate that GPT-4 generated an invalid plan.

Evaluation

Experimental Setting

Approaches. We compare TRIP-PAL against an LLM-based baseline, GPT-4. TRIP-PAL uses Fast Downward (Helmert 2006) as the AI planner, as provided in the Unified Planning Framework (Micheli et al. 2022). We use the SEQ-OPT-LMCUT configuration of Fast Downward, which runs A* with the admissible LMCUT heuristic to compute plans that are guaranteed to be valid and optimal. Experiments were run on a EC2 T3-medium instance with 4Gb of RAM.

Benchmark. We sampled 20 cities for our experiments by asking GPT-4 to generate 10 popular destinations and 10 less popular ones. This selection ensures a comprehensive comparison across various travel contexts. For each city, we considered N POIs located within or near the city limits. These POIs serve as potential destinations for the travel plans. We ask both approaches, GPT-4 and TRIP-PAL for one day travel plans involving at most H tourism hours.

Metrics. We evaluate the generated travel plans using a set of metrics that assess their feasibility and quality. These metrics include:

- *Plan Validity.* TRIP-PAL plans will be valid by definition, since the planner we use is sound. However, this is not the case for the plans generated by GPT-4. We check whether LLM-based plans are valid or not in terms of action applicability and time constraints. For the applicability check, we translate each GPT-4 plan into PDDL output format and use the UPF validator (Micheli et al. 2022) that returns true if the plan is valid, or false otherwise. For the time constraints, we developed a validation function that checks if (1) the plan fits within H tourism hours, and (2) each action lasts at least the time collected

in the retrieval phase, i.e., travel and visit times are respected. This check is performed separately from the validator call because we verify that the time spend in each POI is at least the time required, and not the exact time. This is not directly achievable with the object representation we use for time slots. If any of these constraints is violated, the GPT-4-based plan is considered invalid.

- *Plan Utility.* We define the utility of a travel plan as the sum of the utility of the POIs it visits.
- *Runtime.* Time in seconds needed to generate a travel plan. This time comprises all the steps in each approach’s pipeline.

Results

Standard Day Travel Planning. Our first experiment aims to analyze the performance of both approaches when doing *standard* day travel planning. We define this as deciding the POIs to visit (and in which order) in $H = 8$ hours of tourism (leaving meals aside) among a set of $N = 10$ candidate POIs. We believe this is a standard travel planning setting faced by people when preparing for visiting a city.

We generate 5 different problems –each problem is a set of POIs with their associated utilities and visiting times, and travel times between POIs– for each of the 20 cities comprising our benchmark, thus having 100 travel planning tasks where we can compare TRIP-PAL and GPT-4. Figure 3a shows this comparison by plotting the utility of the plan computed by TRIP-PAL (x axis) and GPT-4 (y axis) for each task. Points below the solid diagonal indicate that TRIP-PAL generated a higher quality plan than GPT-4 for the given travel planning task. When GPT-4 generates an invalid plan, we associate it a utility value lower than the utility obtained by TRIP-PAL in any task. We used a value of 21 so that it can be easily visualized. These are the points

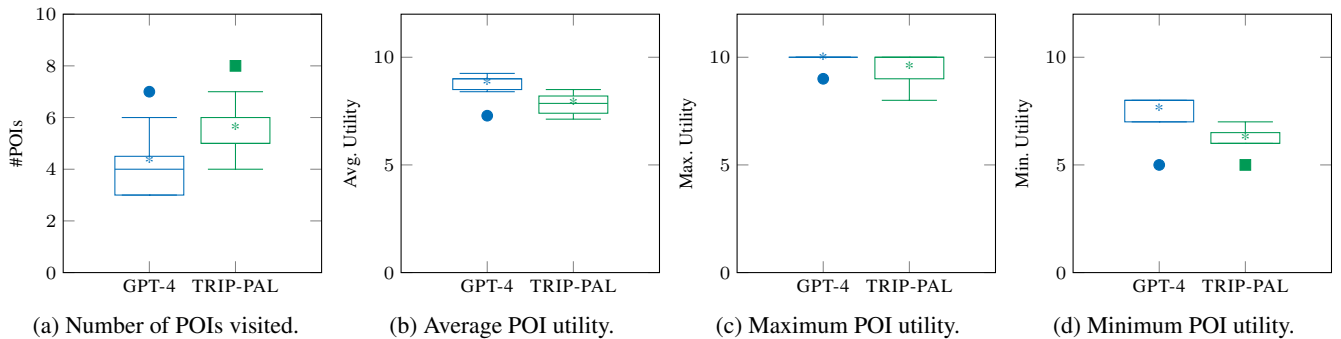


Figure 4: Distribution of the number of POIs visited by each plan, as well as their average, maximum, and minimum utility.

falling at the horizontal red line.

As we can see, TRIP-PAL generated higher utility plans than GPT-4 for all the tasks. GPT-4 returned 14 valid plans out of the 100 tasks, clearly indicating that it struggles to generate travel plans that satisfy hard constraints.

Taking a closer look to the sources of invalidity, they are distributed as follows. Across the 86 invalid plans, GPT-4 did not respect a visiting time in 81, a traveling time in 27, and the maximum number of hours devoted to tourism in 12 of the plans. In 25 out of the 86 cases, GPT-4 generated plans with more than one invalidity source, with a maximum of 6 invalid actions in some itineraries. The suggested time to visit POIs and travel between them in these invalid plans was on average 0.48 ± 0.22 of the time required to visit/travel, with extreme cases where this time deviation went as low as 0.08. This was the case of a GPT-4 plan that suggested to spend just 15 minutes to visit the Toronto Islands, while it was asked to allow at least 3 hours.

This is a blatant case where GPT-4 plan is clearly not executable in practice. However, in some cases the plan is invalid due to small visiting/traveling time differences. For example, one GPT-4 trip is invalid due to visiting the Tower of London for 1.5 hours rather than 2. Even if incorrect from a hard constraints point of view, that plan would arguably be realistic and executable in practice, so we decided to treat GPT-4 favourably by removing the hard constraint checks, and report the utility of the resulting plans. These results are shown in Figure 3b. In this setting, TRIP-PAL is still generating plans with higher utility than GPT-4 in 79 of the 100 problems. This highlights that, even when we do not constrain GPT-4 to follow some guidelines, it is still generating worse travel itineraries than TRIP-PAL, whose plans are guaranteed to be sound and optimal.

Focusing back on the 14 tasks for which GPT-4 generated a valid travel plan, TRIP-PAL’s plans have on average of 1.19 ± 0.12 times more utility.

Figure 4 shows the distribution of the number of POIs visited by the plans suggested by both approaches, as well as their average, maximum and minimum utility. As we can see, while GPT-4 suggests visiting an average of 4.2 POIs, TRIP-PAL suggests 5.5, with trips in which it manages to fit 8 POIs in small cities such as Colonia del Sacramento, Uruguay. By inspection, the GPT-4 solutions tend to involve

visiting 3 to 5 of the highest utility places, which allows it to obtain a higher average utility of the visited POIs in a plan (see Figure 4b). On the other hand, TRIP-PAL also considers POIs with slightly lower utility (see Figure 4d) if they can be visited within the given tourism hours, resulting into optimal travel plans that maximize utility.

Scalability. Next, we evaluate how both approaches scale in terms of execution time and validity/quality of the returned travel plans as we increase the number of POIs and the tourism hours. We perform this analysis in two popular cities, Paris and Rome, and as before, we do 5 runs for each $(\text{city}, \#POIs, H)$. We first fix the tourism hours to 8 and increase the number of POIs from 8 to 18 in steps of 2. Then, we fix the number of POIs to 10, and increase the tourism hours from 6 to 10. The results of this evaluation are shown in Figure 5. As a reminder, all travel plans generated by TRIP-PAL are guaranteed to be valid and optimal, so we will solely focus on GPT-4’s performance when referring to these two metrics.

As we can see in Figures 5a and 5d, GPT-4 is not able to consistently generate valid plans even in the simpler settings where it only needs to generate itineraries to visit 4 POIs (Figure 5a). While the 5 plans to visit Paris are valid, none of the itineraries satisfy the hard constraints in the case of Rome. The ratio of valid plans decreases even more as GPT-4 needs to consider more POIs, and we can observe the same behavior when we fix the number of POIs to 10 and increase the travel hours (Figure 5d).

Switching the focus to the quality of the returned plans (second column of Figure 5), we can observe a clear decrease in the quality of the travel plans generated by GPT-4 as we increase the number of POIs to be considered, even when we remove the hard constraints checks. GPT-4 is able to return the optimal solution in problems with only 4 POIs, as the optimal travel plan in these cases simply involves visiting them all. With 5 and 6 POIs, GPT-4 returns few plans with higher quality than TRIP-PAL (suboptimality ratio < 1). In these cases, it is not properly reasoning about the hard constraints, and it is just fitting more POIs into the plan, at the price of generating plans that are not actually executable in practice. However, the moment the problems start being oversubscribed, i.e., not all POIs can be visited within the given tourism hours, GPT-4 starts generating worse so-

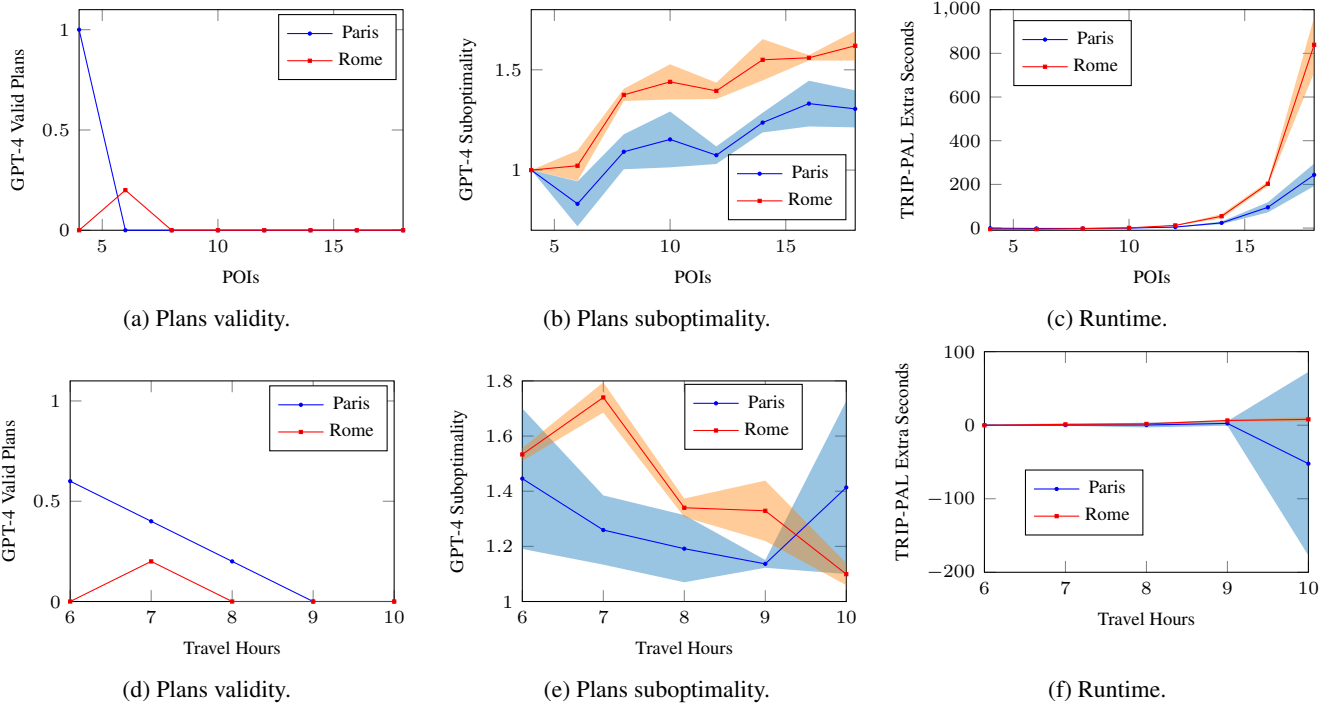


Figure 5: GPT-4 ratio of invalid plans (first column), GPT-4 suboptimality ratio (second column) and TRIP-PAL extra seconds compared to GPT-4 (third column) as we increase the number of POIs (first row) and the travel hours H (second row).

lutions that are up to 1.6 times as bad as the optimal plan returned by TRIP-PAL, which also offers the validity guarantees GPT-4 lacks. The suboptimality trend is not that clear when we increase the travel hours (Figure 5e), as this allows GPT-4 to fit more POIs in a plan, thus increasing its quality.

Finally, the third column of Figure 5 shows the extra seconds required by TRIP-PAL to generate a travel plan compared to GPT-4. As we can see in Figure 5c, both approaches running time is almost the same up to around 10 POIs. The resulting planning problems in these cases are small, and the planner can solve them in < 1 second, so the main runtime driver is the interaction with the LLM. As we increase the number of POIs, optimally solving the resulting tasks becomes more challenging, and TRIP-PAL requires from few seconds to up to 800 seconds more than GPT-4 to generate an optimal itinerary in Rome with 18 POIs. We do not observe this extra overhead when we fix the number of POIs and increase the travel hours (Figure 5f), as the planning tasks remain simple for the planner. There was one anomalous data point for travel planning in Paris for 10 hours, in which the LLM approach took 285 seconds. This was due to network issues and delays, as the other 9 out of 10 tries for the same experimental setting took no more than 11 seconds.

Discussion

As mentioned in the introduction, we are using the utilities of POIs provided by GPT-4 as a proxy for user satisfaction when visiting each POI. But, utility based on tourist

consensus (as retrieved by GPT-4) can be replaced by user preferences. The user could state their preference in natural language, and GPT-4 can be used to find and rate places according to the user input. For example, if the user said they like art museums, then The Louvre would be highly rated. Other scoring methods maybe employed as well, and these new utilities can be input to the planner.

In our work, we limited ourselves to day-planning and discretized time in 15 minute segments. One can extend this to continuous time and multi-day planning at the expense of higher planning time costs. The value of more granular time travel plans is left for future work. Additionally one can build multi-day travel plans by simply chaining single day travel plans and excluding the POI visited in previous days.

Conclusions and Future Work

In this paper, we presented a hybrid approach for travel planning that combines the strengths of LLMs and automated planners to generate travel plans that guarantee feasibility and maximize the satisfaction of user goals. We investigated the use of LLMs for oversubscription planning in the travel planning domain, considering real-world constraints. Experimental results across various travel scenarios demonstrate how we can greatly improve the performance of GPT-4-based approaches in this domain by embedding them with a hybrid approach.

This research opens up several exciting future directions. One avenue for exploration is integrating real-time infor-

mation, such as traffic conditions and weather forecasts, into the planning process to further enhance the practicality and adaptability of the generated plans. Moreover, extending the hybrid approach to other domains beyond travel planning, such as event scheduling and resource allocation, could broaden the impact of this research. As the field of AI continues to advance, we believe that the synergistic combination of LLMs and planners will play a crucial role in enabling intelligent and user-centric decision-making systems.

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