Large Language Models Can Plan Your Travels Rigorously with Formal Verification Tools

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Abstract

In Xie et al. (2024), the authors proposed TravelPlanner, a U.S. domestic travel planning benchmark, and showed that LLMs themselves cannot make travel plans that satisfy user requirements with a best success rate of 0.6%. The state-of-the-art methods that combine LLMs with external critics, verifiers, and humans can only improve the success rate to 20% (Kambhampati et al.). In this work, we propose a framework that enables LLMs to formally formulate and solve combinatorial search problems such as the travel planning problem as a satisfiability modulo theory (SMT) problem, and use SMT solvers to automatically and interactively solve them. The SMT solvers guarantee to find a plan when input constraints are satisfiable. When the input constraints cannot be satisfiable, our LLM-based framework can interactively and adaptively offer modification suggestions to users using SMT solvers' capability of identifying the unsatisfiable core. We evaluate our framework with TravelPlanner and achieve a success rate of 97% for satisfiable queries. We also create a separate dataset that contains international travel benchmarks and show that when initial user queries are unsatisfiable, our interactive planning framework can generate valid plans with an average success rate of 78.6% for the international travel benchmark and 85.0% for TravelPlanner according to diverse humans preferences. We show that our framework could achieve zero-shot generalization to unseen constraints in travel planning problems. In addition, we introduce four new combinatorial optimization tasks and show that our framework could generalize well to new domains in a zero-shot manner.

1 Introduction

Recent work has demonstrated that large language models (LLMs) (Brown et al., 2020; Ouyang et al., 2022; Achiam et al., 2023), with abundant world knowledge, abilities to collect information via tools, and capabilities of reasoning, have significant potential in solving planning problems (Huang et al., 2022a; Ahn et al., 2022; Yao et al., 2022; Song et al., 2023). However, the planning scenarios of the existing LLM planning works are still limited to simple tasks such as household cleaning in which the agents only consider one or few constraints. Modern LLMs are not well-suited for directly solving highly complex combinatorial optimization problems with multiple levels of constraints as they generate responses based on token probabilities derived from their training data and do not inherently possess the ability to perform rigorous logical or mathematical reasoning. Imagine you have a one-week vacation, a $3000 budget, and are longing for somewhere with a beautiful beach and delicious seafood restaurants. To make a detailed plan, you need to utilize various tools to search for flights, cities with famous sea attractions, seafood restaurants, accommodations, and may need to repeat this process iteratively to ensure the total price is within your budget. Even for humans, it is a complex and time-consuming undertaking to accomplish. Are LLM agents capable of handling complex and realistic planning problems like this? To investigate this problem, Xie et al. (2024) proposed a U.S. domestic travel planning benchmark, TravelPlanner, and showed that LLMs are not capable of handling this task and even strongest LLM GPT-4 can only achieve a pass rate of 0.6% by itself without access to pre-collected information. LLM-Modulo Framework (Kambhampati et al.), a recent work that combines LLMs with external critics, verifiers, and humans, raises the pass rate to 20%, which is the best performance on TravelPlanner as of now.

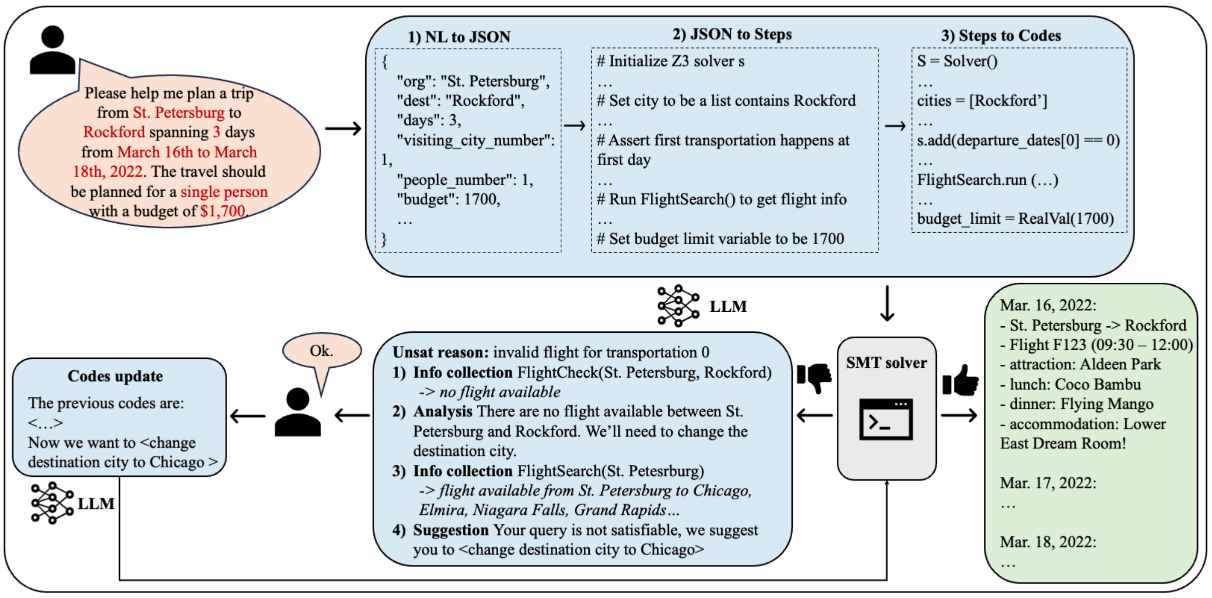
The travel planning problem contains diverse constraints including time, budget, destinations, etc., making it extremely challenging for LLM agents to search for a feasible plan considering all constraints. To tackle this problem, an alternative way is through constraint-based planning to formalize the problem as a constraint satisfaction problem (CSP) (Dechter, 2003; Lozano-Pérez and Kaelbling, 2014), boolean satisfiability problem (SAT) (Kautz and Selman, 1999; Rintanen, 2012), or satisfiability modulo theory (SMT) (Barrett et al., 2010; De Moura and Bjørner, 2011; Dantam et al., 2016) and solve it with existing algorithm-based solvers (Dutertre and De Moura, 2006; De Moura and Bjørner, 2008; Barrett et al., 2011). However, algorithm-based solvers usually have steep learning curves. And as human natural language queries have no fixed format, planners need to extract key information from input queries accurately to model the problem. Crucially, even if the extracted key information is correct, if the proposed query is unsatisfiable itself, the users have to modify inputs by themselves and query the tools multiple times.

LLMs are good at parsing human input and interactions but hard to rigorously consider all constraints, while SMT solvers are sound and complete in solving multi-constraint satisfiability problems but unable to handle dynamic, general, and sometimes ambiguous natural language requirements. In this work, we propose a framework that combines the advantages of both methods by enabling LLM to utilize SMT solver as a tool to formally formulate, solve, and reason over the travel planning problem. In our framework, the LLM first translates natural language input to a fixed JSON format. Then, with instruction steps and corresponding codes of using SMT solver to solve the example travel planning problem, LLM learns the pattern and generalizes to new inputs. Executing LLM-generated codes encodes the query and calls the solver, which guarantees to generate a plan if it exists. If the input query is not satisfiable, SMT solvers can identify the exact unsatisfiable constraints, using which LLM can propose suggestions to modify the query by analyzing the unsatisfiable reasons until it becomes satisfiable. LLM can even interactively communicate with humans to incorporate their unique preferences.

We evaluate our framework over different LLMs using TravelPlanner Xie et al. (2024), which contains 180 satisfiable queries in their validation set and 1000 satisfiable queries in their test set. Our framework achieves a best final pass rate of 98.9% in the validation set and 97.0% in the test set. To evaluate the plan repair capability for unsatisfiable queries, we modify 12 constraints from TravelPlanner's training set to be unsatisfiable, and also build another international travel dataset that contains 39 unsatisfiable queries with different types of constraints from TravelPlanner. We evaluate on both datasets and show our framework's capability of interactively making satisfiable travel plans for users with different preferences for modifying their constraints. We verify with ablation studies the positive effects of key components of our framework. We test the generalization capability of our framework by encoding unseen constraints of travel planning problems with existing instruction step examples. We also introduce four new combinatorial tasks and generalize with existing step and code examples to solve them in a zero-shot manner. All experiments demonstrate that our framework could reliably handle diverse human inputs, deliver formally verified plans, interactively modify unsatisfiable queries considering human preferences, could be effectively adapted to different LLMs, and generalize to new constraints and new domains well.

2 Related Work

LLM Planning. LLMs have shown significant intelligence in reasoning (Wei et al., 2022; Kojima et al., 2022; Yao et al., 2022) and tool-use (Qin et al., 2023; Schick et al., 2024), offering the potential of promising planning capability. Previous works tackle planning problems with various ways: 1) decomposing the task into sub-tasks and plan sequentially (Wei et al., 2022; Yao et al., 2022; Shen et al., 2024); 2) generating multiple plans with methods like tree and graph search and selecting the optimal solution (Wang et al., 2022; Yao et al., 2024; Zhao et al., 2024; Besta et al., 2024; Hao et al., 2023); 3) reflecting on experiences and refining plan based on feedback (Shinn et al., 2024; Madaan et al., 2024; Chen et al., 2023b); 4) formalizing tasks and aiding the planning with external planner (Liu et al., 2023; Guan et al., 2023; Chen et al., 2023a). These methods are summarized in Huang et al. (2024) with details. While these planning algorithms have shown promising result, their planning scenarios are limited to simple tasks with single objective function. Xie et al. (2024) proposes a realistic and complex travel planning benchmark and tests on various LLM planning algorithms to show that LLMs are not capable of handling multi-constraint tasks. While Liu et al. (2023); Guan et al. (2023) utilize LLM to process information and formulate problems into PDDL (Aeronautiques et al., 1998; Haslum et al., 2019) to account for multiple objectives, as far as


Please help me plan a trip from St. Petersburg to Rockford spanning 3 days from March 16th to March 18th, 2022. The travel should be planned for a single person with a budget of $1,700.
1) NL to JSON
2) JSON to Steps
3) Steps to Codes
LLM
SMT solver
Ok.
Codes update
LLM

```
{
    "org": "St. Petersburg",
    "dest": "Rockford",
    "days": 3,
    "visiting_city_number": 1,
    "people_number": 1,
    "budget": 1700,
    …
}
```

```
# Initialize Z3 solver s
…
# Set city to be a list contains Rockford
…
# Assert first transportation happens at first day
…
# Run FlightSearch() to get flight info
…
# Set budget limit variable to be 1700
```

```
S = Solver()
…
cities = [Rockford']
…
s.add(departure_dates[0] == 0)
…
FlightSearch.run (…)
…
budget_limit = RealVal(1700)
```

Unsat reason: invalid flight for transportation 0
1) **Info collection** FlightCheck(St. Petersburg, Rockford)
   -> *no flight available*
2) **Analysis** There are no flight available between St. Petersburg and Rockford. We'll need to change the destination city.
3) **Info collection** FlightSearch(St. Petesrburg)
   -> *flight available from St. Petersburg to Chicago, Elmira, Niagara Falls, Grand Rapids…*
4) **Suggestion** Your query is not satisfiable, we suggest you to <change destination city to Chicago>

The previous codes are: <…>
Now we want to <change destination city to Chicago >

Mar. 16, 2022:
- St. Petersburg -> Rockford
- Flight F123 (09:30 – 12:00)
- attraction: Aldeen Park
- lunch: Coco Bambu
- dinner: Flying Mango
- accommodation: Lower East Dream Room!

Mar. 17, 2022:
…

Mar. 18, 2022:
…

Figure 1: An overview of the framework. The pink region represents human, blue region represents LLM, gray region represents SMT solver, and the green region is the generated plan. Given a natural language query, LLM 1) translates it into JSON format, 2) generates steps to formulate it as a SMT problem, 3) generates corresponding codes that encode the problem and call the solver. If the solver is not able to find the solution, LLM receives unsatisfiable reasons from solver, collects information, analyzes current situation, and offer suggestions to modify query interactively. LLM then update the code based on suggestions and call the solver again to find a feasible plan.

we know, there is no *complete* PDDL-based approach that can identify travel planning problems.

Algorithm-based Planning. Another way to tackle the travel planning problem is through algorithm-based planning such as heuristic search (Hoffmann and Nebel, 2001; Helmert, 2006; Vidal, 2014) and constraint-based methods (Kautz and Selman, 1999; Rintanen, 2012, 2014; Lozano-Pérez and Kaelbling, 2014; Dantam et al., 2016). However, heuristic search is not able to guarantee to find the plan, and pure constraint-based planning is not able to generalize to diverse natural language inputs. Our framework enables LLM to utilize the constraint-based planning method by translating and formalizing diverse human queries into a SMT problem. Since SMT solvers are sound and complete, the generated plan is guaranteed to be correct. If SMT solver fails to find a solution, the problem is verified to be unsatisfiable and the solver can output unsatisfiable reasons for future usage.

LLM Tool-use. Tool-using allows LLMs to utilize powerful external tools to increase reliability. Recent works explore how LLMs could utilize external tools such as search engines, operating environments, and code generators (Press et al., 2022; Yao et al., 2022; Schick et al., 2024; Liang et al., 2023; Singh et al., 2023; Peng et al., 2023; Song et al., 2023; Huang et al., 2022b) to provide feedback or extra information. In our framework, LLMs generate codes to formulate the travel planning problem as a SMT problem and calls the SMT solver. This overcomes LLM's failure to consider all constraints by encoding and solving all constraints rigorously.

3 Approach

We propose a framework that equips the LLM with tools to formulate and solve the travel planning problem as an SMT problem, shown in Fig. 1. In our framework, we call LLM multiple times to accomplish a number of distinct functionalities: translating natural language query into a JSON format description, generating steps to formulate the problem, and generating codes based on steps. In addition, when the input query is not satisfiable, LLM reasons about current situation to give suggestion and modifies existing codes based on suggestion. See Appendix F for all prompts we use.

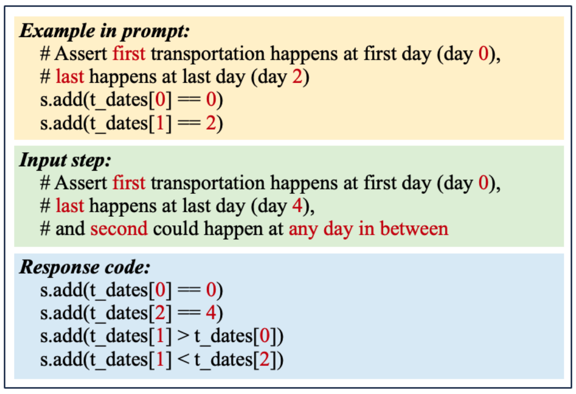
3.1 Satisfiable Plan Solving

3.1.1 Problem Statement

We define the travel planning problem as: given a natural language description of humans' constraints $\mathcal{C}$ of a travel plan, the system should output a plan that satisfies $\mathcal{C}$. The travel starts from city o, travels k destination cities, and returns to o. The travel spans n days. The travel takes $k + 1$ transportation

Constraint	Description
Destination cities	Destination cities should not be repeated
Transportation dates	First transportation happens at first day, last transportation happens at last day, and others happens in between non-repeatedly
Transportation methods	Every transportation uses flight, self-driving, or taxi Self-driving is not valid during the trip if taxi or flight is used No flight if “no flight" is mentioned, and no self-driving if “no self-driving" is mentioned
Flight	No flight if flights unavailable between two cities on certain dates All taken flights are non-stop if “non-stop" is mentioned All taken flights’ airlines are within the required airlines list
Driving	No driving if driving routes unavailable between two cities
Restaurant	Restaurant choices should not be repeated Restaurant for day must be located within that day’s city All specified cuisine types must be visited
Attraction	Attraction choices should not be repeated Attraction for day must be located within that day’s city All specified attraction types must be visited
Accommodation	Accommodation for day must be located within that day’s city All specified accommodations must satisfy specified Room Rule All specified accommodations must satisfy specified Room Type The number of consecutive days spent in an accommodation must meet the accommodation’s minimum number of nights’ stay.
Budget	Total spend is within specified budget

Table 1: Descriptions of constraints for two datasets. Constraints in teal are the constraints only in TravelPlanner. Constraints in brown are the constraints only in our dataset. Constraints in black are common constraints.


Example in prompt:

```
# Assert first transportation happens at first day (day 0),
# last happens at last day (day 2)
s.add(t_dates[0] == 0)
s.add(t_dates[1] == 2)
```

Input step:

```
# Assert first transportation happens at first day (day 0),
# last happens at last day (day 4),
# and second could happen at any day in between
```

Response code:

```
s.add(t_dates[0] == 0)
s.add(t_dates[2] == 4)
s.add(t_dates[1] > t_dates[0])
s.add(t_dates[1] < t_dates[2])
```

Figure 2: Step to Code translation example.

method for $k+1$ travels from city to city. The travel visits x attractions, dine in y restaurants, and live in accommodations for $n-1$ nights. By default, we set x=n, y=3n. However, this is not a fixed requirement. Users could specify their unique requirements by adding descriptions in prompts, for example, “Number of attractions to visit per day is 2". Table 1 summarizes the constraints $\mathcal{C}$ for the two datasets we used. The output plan should satisfy $\mathcal{C}$ and clearly specify the city to visit, transportation method, attraction, restaurant, and accommodation for each day. See Appendix D for example input query and output plan.

3.1.2 NL-JSON Translation

Travel planning problem is a real-world complex planning problem that contains various constraints including time, location, budget, etc. These information are contained in humans’ natural language queries in different forms. Our framework’s first step is to extract important information from the natural language input and translate it into a problem description of JSON format, as shown in Fig. 1 part 1). We provide LLM with descriptions of JSON’s required fields and three translation examples.

3.1.3 JSON-Step Generation

The steps to formulate travel plan problems differ with the change of constraints, e.g., number of destination cities, number of travel days, and special restaurant cuisine requirements. However, although the steps may be different, they have similar patterns. We provide LLM with the JSON problem description and three examples of JSON-Step generation in the prompt to enable it to generalize to different input queries. We separate the steps into subsections based on the type of constraints. For example, to specify the "travel spanning 3 days" constraint in the query in Fig. 1, the steps are:

```
1. Set 't_dates' variables for 2 transportation between cities
2. Assert first transportation happens at first day (day 0),
   and last happens at last day (day 2)
```

While for a new query that asks to travel 2 destination cities in 5 days, the steps become:

```
1. Set 't_dates' variables for 3 transportation between cities
2. Assert first transportation happens at first day (day 0),
   last happens at last day (day 4),
   and second could happen at any day in between
```

3.1.4 Step-Code Generation

Inspired by Liang et al. (2023), we directly prompt the LLM to generate language model programs in

Python by providing CitySearch, FlightSearch, AttractionSearch, DistanceSearch, AccommodationSearch, RestaurantSearch APIs and SMT solver, and demonstrating how to use each of these functions. With the generated steps of how to solve each constraint, we provide these steps as instructions to LLM, as shown in Fig. 1 part 3). Fig. 2 shows how LLM generalizes to new instruction steps to write corresponding codes given examples.

3.1.5 SMT Solver

After gathering the generated codes, our framework executes the codes to encode the problem and call the SMT solver. Since the SMT solver is sound and complete, it guarantees to find a solution if there exists one. Thus, if the constraints are satisfiable, the solver generates a formally verified plan. If the constraints are not satisfiable, the solver outputs the unsatisfiable reasons and LLM could, based on its commonsense and reasoning capabilities, analyze the reasons, actively collect more information, and provide humans with suggestions to modify the constraints. We extract the unsatisfiable reasons with Z3 solver's `get_unsat_core` function. When the framework proves the constraints to be unsatisfiable, it proceeds to interactive plan repair with the unsatisfiable reasons.

3.2 Interactive Plan Repair

When a proposed query is not satisfiable, LLM's reasoning capability and commonsense knowledge to analyze current situation and offer suggestions become vital. Furthermore, these capabilities enable an interactive setting, in which humans can agree, disagree, or provide feedback to LLM's proposed suggestions. LLM can deliver personalized plans built upon different human preferences.

Inspired by ReAct (Yao et al., 2022), in our framework, LLM could either take an action to collect information based on unsatisfiable reasons, analyze current situation based on collected information, or provide suggestions. We equip LLM with information collection APIs and descriptions of their usage. As shown in Fig. 1, the unsatisfiable reason is "invalid flight for transportation 0". With the reason, the LLM first takes action to collect flight information by calling FlightCheck API. Realizing no flight is available between St. Petersburg and Rockford, LLM analyzes and decides to change the destination city. Then, it runs FlightSearch API to search for all available destinations and eventually chooses one of them. LLM offers this as a suggestion to the user and waits for the user's feedback. The feedback could be yes, no, any natural language preference, or even modifications users proposed. If the user disagrees with the suggestion or provides their preferences, the framework starts another iteration and proposes new suggestions. If the users agree with the suggestion or propose their own modification, the framework continues by inputting this modification, together with original codes, to an LLM and prompting it to modify the codes. By running the modified codes, the framework generates a plan if the modified constraints are satisfiable. Otherwise, the framework gathers the unsatisfiable reasons and starts another round.

4 Dataset

To access our framework's ability to 1) generalize to unseen constraints and 2) interactive plan repair for unsatisfiable queries, we propose a dataset, UnsatChristmas, that introduces new constraints not included in TravelPlanner and contains 39 unsatisfiable queries under this setting. The queries in UnsatChristmas aim to create an international travel plan for Christmas week in 2023. We set cities in our dataset to be the top ten worldwide city destinations in 2019[1] and obtain attraction information from Metabase[2]. We utilize Google Flights[3] to collect flight information from 12-24-2023 to 12-30-2023 for these ten cities. Compared with TravelPlanner, we omit detailed information of transportation methods, restaurants, and accommodations but introduce detailed constraints regarding flights and attractions. As shown in Table 1, UnsatChristmas allows users to specify 1) whether they want to take non-stop flights only, 2) the list of airlines they prefer, and 3) the list of attraction categories they prefer. We collect 39 unsatisfiable queries with 4 possible reasons: non-stop flight rule not satisfied, flight airline requirement not satisfied, attraction category requirement not satisfied, budget not enough. Out of the 39 queries, 12 fail due to one reason, 18 fail due to two reasons, 8 fail due to three reasons, and 1 fails due to four reasons. There are 13 queries with a single destination city, 13 with two, and 13 with three. In addition, to test the interactive plan repair performance, we also modify 12 queries from the training

[1]https://go.euromonitor.com/white-paper-travel-2019-100-cities.html

[2]https://www.metabase.com/blog/data-guide-to-travel

[3]https://www.google.com/travel/flights

set of TravelPlanner to be unsatisfiable.

5 Experimental Results

We examine our framework on both TravelPlanner and UnsatChristmas. We use GPT-4 (Achiam et al., 2023) with temperature 0 as our LLM by default, and we also compare with Claude 3 Opus-20240229 (cla) and Mixtral-Large (mix) with temperature 0 for satisfiable plan solving evaluation. We use Z3 solver (De Moura and Bjørner, 2008) as our SMT solver for all experiments.

5.1 Satisfiable Plan Solving Evaluation

We examine how well our framework can create travel plans for satisfiable natural language queries on the TravelPlanner benchmark. We design our example instruction steps and corresponding codes using three queries from TravelPlanner's training set and tune the prompt with other queries in the training set. We evaluate our method on both the validation (180 queries) and test set (1000 queries) of TravelPlanner. Our framework evaluates validation and testing set identically, but we report the results separately for better comparison.

Evaluation Metric We adapted the evaluation metrics from Xie et al. (2024) and mainly look at two evaluation metrics: 1) Delivery Rate: measures whether a final plan is generated within a limited time; 2) Final Pass Rate: represents whether LLMs pass all constraints. Please refer to Appendix E for Commonsense Constraint Pass Rate, Hard Constraint Pass Rate, and detailed description of Micro and Macro evaluation modes.

Baselines We compare our framework with three strongest models using different strategies from Xie et al. (2024). Greedy Search uses a traditional search algorithm and heuristically sets total cost as the optimization objective. TwoStage (GPT-4), the most powerful model among two-stage tool-use frameworks, collects information with ReAct (Yao et al., 2022) and gives plans based on the collected information. Direct (GPT-4), the most powerful model among sole-planning frameworks, has access to all necessary pre-collected information and gives plans without tool-calling needs. To verify the effectiveness of our framework in varied LLMs, we also evaluate our framework with Claude 3 Opus and Mixtral-Large. We tune the prompt with the training set and include the prompt differences in Appendix F.1.4. Due to computational resources and cost considerations, we only evaluate two new LLMs on the validation set with 180 queries.

Results and Analysis Table 2 shows the performance comparison of satisfiable queries. Since TravelPlanner's database has 65 states, 312 cities, 3827361 flights, 17603 driving information, 5303 attractions, 9552 restaurants, and 5064 accommodations, the solution space is extremely large considering the combinatorial choices. In addition, a few queries are challenging in that they have few feasible plans. We limit SMT solver's maximum runtime for each query to 30 minutes and pause the program if this limit is reached. Please refer to Appendix A for detailed cost and runtime performance. The delivery rate of Ours (GPT-4) is 99.4% and 97.2% for validation and test set. From the results, both LLM planning methods, TwoStage (GPT-4) and Direct (GPT-4), struggle to take all constraints into consideration with a final pass rate of 0.6% and 4.4%. In addition, without formal specification, Greedy Search fails to pass any of the tasks. Ours (GPT-4), with the capability of formally encoding the problem as an SMT problem, achieves a high final pass rate of 98.9% and 97.0% for validation and test set. This demonstrates our framework's robustness in solving satisfiable queries of the travel planning problem. In addition, Ours (Mixtral-Large) achieves a delivery rate of 85.0% and final pass rate of 84.4%, and Ours (Claude-3) achieves a delivery rate and final pass rate of 98.3%. Ours (Claude-3) could reach comparable results as Ours (GPT-4). Although the delivery rate for Ours (Mixtral-Large) drops 14.4% compared to Ours (GPT-4), it still significantly outperforms TwoStage (GPT-4) and Direct (GPT-4), and 99.2% of its delivered plans are correct plans. See Appendix F.1.5 for major failure cases of Ours (Mixtral-Large). These results demonstrates the adaptability of our framework to other LLMs.

5.2 Interactive Plan Repair Evaluation

We examine our framework's interactive plan repair capability on both the modified queries from TravelPlanner and UnsatChristmas.

Evaluation Metric We evaluate our framework based on the success rate: whether LLM eventually modifies the constraints to successfully deliver a feasible plan within a limited number of iterations.

Implementation Details UnsatChristmas constraints have four unsatisfactory modes: 1) budget is not enough, 2) required non-stop flight does not exist, 3) required airline does not exist, 4) required attraction category does not exist. We test

Method	Delivery Rate	Commonsense Pass Rate		Hard Constraint Pass Rate		Final Pass Rate
		Micro	Macro	Micro	Macro	
***Validation** (#180)*						
Greedy Search	**100**	74.4	0	60.8	37.8	0
TwoStage (GPT-4)	89.4	61.1	2.8	15.2	10.6	0.6
Direct (GPT-4)	**100**	80.4	17.2	47.1	22.2	4.4
Ours (Mixtral-Large)	85.0	85.0	85.0	79.3	84.4	84.4
Ours (Claude-3)	98.3	98.3	98.3	98.6	98.3	98.3
Ours (GPT-4)	99.4	**99.4**	**99.4**	**99.5**	**98.9**	**98.9**
***Test** (#1000)*						
Greedy Search	**100**	72.0	0	52.4	31.8	0
TwoStage (GPT-4)	93.1	63.3	2.0	10.5	5.5	0.6
Direct (GPT-4)	**100**	80.6	15.2	44.3	23.1	4.4
Ours (GPT-4)	97.2	**97.2**	**97.2**	**96.2**	**97.0**	**97.0**

Table 2: Performance comparison of satisfiable queries for 180 queries in validation set and 1000 queries in test set. The results of Greedy Search, TwoStage, and Direct are from Xie et al. (2024)

Method	Always Agree	Budget	Non-stop	Airline	Attraction Category	Destination Cities	Average
No Reason	74.4	61.5	69.2	53.8	69.2	53.8	63.7
No Feedback	N/A	59.0	79.5	61.5	79.5	74.4	70.8
No Solver	25.6	20.5	28.2	20.5	23.1	33.3	25.2
Ours	89.7	59.0	84.6	64.1	89.7	84.6	78.6
Ours-20	92.3	61.5	87.2	66.7	89.7	92.3	81.6

Table 3: Performance of interactive plan repair for unsatisfiable queries on 39 queries from UnsatChristmas.

Method	Always Agree	Budget	Destination Cities	Transportation Methods	House Type	Average
No Reason	75	83.3	91.7	83.3	66.7	80
No Feedback	N/A	50	91.7	66.7	75	70.9
No Solver	16.7	16.7	50	25	16.7	25.0
Ours-Code	91.7	75	100	83.3	75	85.0
Ours-20	100	83.3	100	91.7	83.3	91.7

Table 4: Performance of interactive plan repair for unsatisfiable queries on 12 modified queries from TravelPlanner.

our framework with mimic users with different preferences. One mimic user agrees to all suggestions proposed by LLM, and five mimic users have hard constraints for budget, non-stop flight, airline, attraction category, and destination cities, respectively. They refuse any suggestion that changes their hard constraint, and provide feedback indicating they will not change this information.

Constraints modified from TravelPlanner have three unsatisfactory modes: 1) budget is not enough, 2) required transportation method does not exist, 3) required house type does not exist. Mimic users have hard constraints for budget, destination cities, transportation methods, and house type.

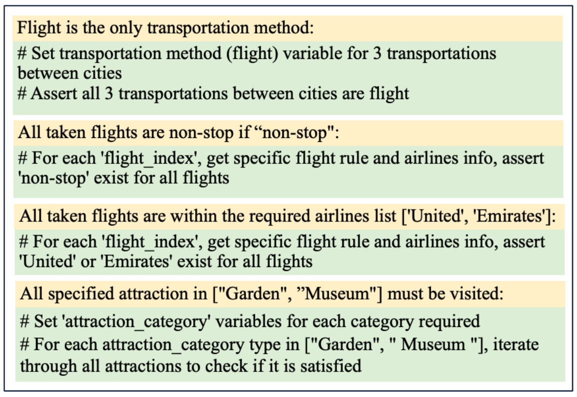
The maximal number of iterations is ten.

Ablation Studies Key components in our framework are 1) LLM receives unsatisfiable reasons from the solver; 2) LLM collects information based on the reasons, analyzes, and offers suggestions; 3) LLM receives human preferences regarding offered suggestions; 4) LLM modifies codes; 5) SMT solver gives satisfiability verification. We perform ablation studies to examine these key components. We compare the following: 1) **No Reason**: evaluates the need of unsatisfiable reasons by asking LLM to resolve unsatisfiable queries without providing unsatisfiable reasons; 2) **No Feedback**: tests how well the framework can incorporate human natural language preference by asking the human to only provide binary "agree" or "disagree" feedback without explaining why; 3) **No Solver**: examines the importance of tool-using by removing the SMT solver. The LLM collects information and gives a list of suggestions for only one iteration because it is not able to call the solver to verify the updated query; 4) **Ours**: our approach as described in 3.2; 5) **Ours-20**: a variant of our approach that changes the maximum number of iterations to be 20.

Results and Analysis Table 3 and 4 show the interactive plan repair performance. Our framework

Method	Block Picking		Task Allocation		TSP		Warehouse	
	Delivery	Optimal	Delivery	Optimal	Delivery	Optimal	Delivery	Optimal
TwoStage(GPT-4o)	80	4	84	0	100	0	72	0
Ours(GPT-4o)	100	92	92	92	100	100	84	72

Table 5: Performance of zero-shot generalization to four other combinatorial optimization tasks.


Flight is the only transportation method:
Set transportation method (flight) variable for 3 transportations between cities
Assert all 3 transportations between cities are flight

All taken flights are non-stop if "non-stop":
For each 'flight_index', get specific flight rule and airlines info, assert 'non-stop' exist for all flights

All taken flights are within the required airlines list ['United', 'Emirates']:
For each 'flight_index', get specific flight rule and airlines info, assert 'United' or 'Emirates' exist for all flights

All specified attraction in ["Garden", "Museum"] must be visited:
Set 'attraction_category' variables for each category required
For each attraction_category type in ["Garden", " Museum "], iterate through all attractions to check if it is satisfied

Figure 3: Example of how JSON-Step prompt generalize to unseen constraints. Texts with yellow background are the unseen constraint types, and texts with green background are corresponding generated steps.

could address diverse human preferences with an average of 78.6% and 85.0% across all types of mimic humans. **Ours-20** raises the success rate to 81.6% and 91.7%, showing the potential of increasing the iteration limit to achieve better results. We include detailed figures and analysis of how number of iterations affects performance in Appendix B. For queries from both datasets, **Ours** significantly outperforms **No Solver** by an average of 53.4% and 60.0% across all types of mimic humans. This suggests that LLM's capability to utilize SMT solver to verify the modified query largely benefits the interactive plan repair process. **Ours** also outperforms **No Reason** by an average of 14.9% and 5.0% and outperforms **No Feedback** by an average of 7.8% and 14.1%. These results validate the effectiveness of our key components.

5.3 Generalization Capability Analysis

5.3.1 New Travel Plan Constraints

Since the travel planning problem involves various constraints of different types, our example instruction steps may not be comprehensive enough to cover all possible constraints. Here we examine our framework's robustness by testing whether it could generalize to the constraint types not shown in prompt examples in a zero-shot manner. As shown in Table 1, UnsatChristmas has different constraints than TravelPlanner. We show that by adding several lines of constraint description in the JSON-Step prompt, LLM could generate steps for new constraints without the need to add new examples. Figure 3 shows how our framework encodes unseen constraints in UnsatChristmas. Please see Appendix F.3 for the added constraint description and see Appendix G for full generated steps.

5.3.2 New Combinatorial Optimization Tasks

To show the capability of our framework to generalize to other domains, we conduct experiments in four new tasks: **Block Picking**, **Task Allocation**, **Travelling Salesman Problem (TSP)**, **Warehouse**. For each task, we create 25 different scenarios. See Appendix C.1 for problem setup descriptions. For both JSON-Step and Step-Code generation, we include one example from travel planning and a few lines of new problem description in the prompt to test the zero-shot generalization capability. See Appendix C.2 for the added task descriptions in the prompts. We implement TwoStage, the two-stage tool-use framework, for four tasks as the baselines. We use GPT-4o (gpt) as the LLM to account for long code generation. We use both delivery rate and optimal rate as the evaluation metrics. The results in Table 5 show that LLMs themselves fail to directly solve combinatorial optimization problems that have large solution spaces, but our framework, with its knowledge of encoding and solving travel planning problems as SMT problems, could be adapted to other combinatorial optimization problems in a zero-shot manner with good optimal rate: 92%, 92%, 100%, and 72% respectively. Please refer to Appendix C.3 for failure cases analysis.

6 Conclusion

In this work, we propose a framework that enables LLM to utilize a SMT solver to formally formulate and solve a complex travel planning problem as an SMT problem. Our framework can generalize to natural language query inputs, almost guarantee to deliver plans if the query is satisfiable with a pass rate of 97%, and interactively work with humans to modify the input query if it is not satisfiable. Finally, we show that our framework can generalize to unseen constraint types and new domains without the need to add new examples to the prompt.

7 Limitation

The limitations and potential risks of the work are as follows:

Prompt Designing We need a careful and specific design of instruction steps and corresponding codes to encode the problem. It is time-consuming to formulate the problem from scratch. However, the potential of our framework to generalize to the unseen constraints and unseen tasks eases the future efforts needed to incorporate more constraints into the framework and to solve more different combinatorial optimization problems. In addition, as the designers of the framework, we design offline prompts to enable full model autonomy for end users. Thus, after these prompts are designed, the effort needed for any end user to utilize our framework is a simple natural language query. With our framework, end users can utilize powerful solvers to solve their problems without having any knowledge about the solvers.

Solver Runtime For a massive database with more destination city choices, various constraint types, and queries that only have a few feasible plans, our framework could take a long runtime to find the plan. To relieve this limitation, a potential way is to introduce some heuristics and prioritize a portion of choices to be verified first.

Risky Data Since all information sources of our framework is from the database we use, it currently does not have the capability to distinguish unsafe or incorrect information. One potential risk of our framework is that it could generate risky plans based on unsafe information from the database.

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A Runtime and cost analysis

In this section, we include the detail runtime and cost analysis of both satisfiable plan solving and interactive plan repair of our framework.

A.1 Satisfiable Plan Solving

For the satisfiable plan solving part, we recorded the runtime and cost for 180 queries in TravelPlanner's validation set. Over the 180 queries, the average cost is $0.74 per query using GPT-4. Over the 179 queries with delivered plans, the average time spent for different stages in our framework are shown in Table 6. The average total time spent for all stages is 245.66 seconds (4.09 minutes) per query. The Step-Code generation contains multiple LLM calls for various types of constraints, thus takes most of the time.

LLM NL-JSON	LLM JSON-Step	LLM Step-Code	SMT Solver	Total
5.45	35.16	166.66	38.39	245.66

Table 6: Runtime (seconds) of each stage of our framework for satisfiable plan solving.

Out of the 180 queries, there is one query with no delivered plan since its runtime exceeds 30 minutes. For queries with heavy computational costs, introducing some heuristics that prioritize a portion of all possible solutions could help to reduce the computational overhead of SMT solvers. Our framework introduces a simple heuristic: for queries that ask to visit multiple cities in a state, we will prioritize the cities with available transportations between the origin. This heuristic helps to reduce the runtime, especially for a big state with 20 cities. In addition to this simple heuristic, some other heuristics may help, which we plan to explore more in the future: pre-calculate estimated money spent and prioritize the cheaper solutions, prioritize the cities with a larger number of transportation methods/ restaurants/ accommodations, etc.

A.2 Interactive Plan Repair

For the interactive plan solving part, we recorded the runtime and cost for queries in UnsatChristmas for mimic-human with hard budget constraints. Over the 23 (out of 39) successful queries, the average cost is $0.65 per iteration using GPT-4. The average time spent for different stages in our framework are shown in Table 7. The average total time spent for both stages is 33.68 seconds per iteration. Note that for mimic-human with hard budget constraints, the average number of iterations that successfully modify the queries is 2.22 per query.

LLM interactive suggestion	Code Update	Total
10.35	23.33	33.68

Table 7: Runtime (seconds per iteration) of each stage of our framework for interactive plan repair.

B Interactive Plan Repair: Iteration versus Performance

Figure 4 shows the performance (success rate %) of interactive plan repair over different numbers of iterations for both datasets.
For the 39 queries in UnsatChristmas, 63.7% of the queries could be successfully modified to be satisfiable within 3 iterations, 74.8% within 5 iterations, 78.6% within 10 iterations, and 81.6% within 20 iterations. The performance increases quickly during the first 5 iterations, and the framework solves a limited number of more difficult queries with more iterations.
Similarly, for the 12 modified queries in TravelPlanner, 65.0% of the queries could be successfully modified to be satisfiable within 3 iterations, 73.3% within 5 iterations, 85.0% within 10 iterations, and 91.7% within 20 iterations.
The results suggest that we do not need extensive iterations to fully capture a major portion of the human queries.

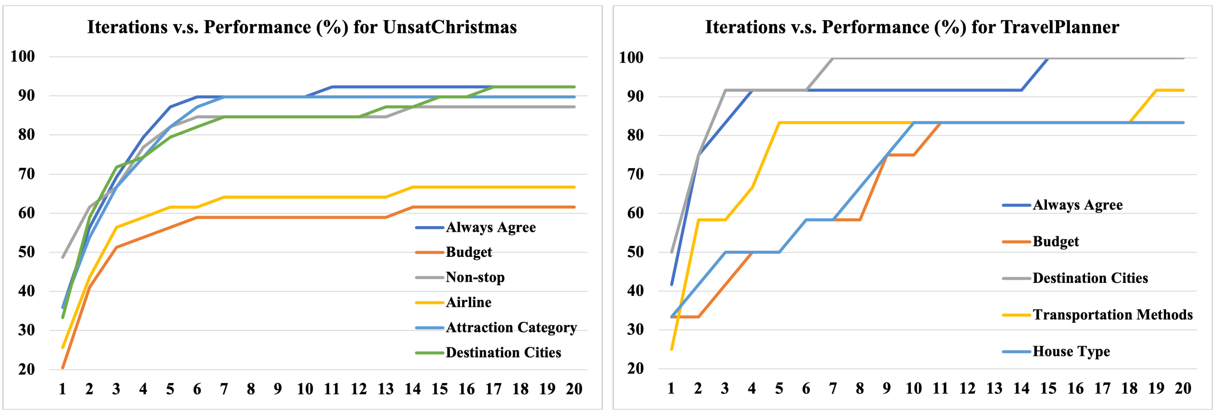

Figure 4: Performance (success rate %) of interactive plan repair over different numbers of iterations for two datasets

C New Combinatorial Optimization Tasks details

C.1 Task Setup

C.1.1 Block Picking

There are blocks of different colors and scores in the scene. The goal is to select required number of unique blocks with required color, while maximizing the score. All possible block colors are red, yellow, black, pink, and blue. For 25 different scenarios, we set the total number of blocks to be a random number between 50 to 200, each with a random score between 1 to 20 and a random color. For the query, we will randomly choose 1 to 3 colors from all colors to be the required color, and 10 to be the required number of blocks to pick.

C.1.2 Task Allocation

Given a list of three tasks A, B and C, and three heterogeneous robots that are skilled at different tasks, the goal is to find the way to assign different tasks to different robots and finish the tasks with minimized finish time. The three robots could work in parallel, but the finish time counts the time when the last robot stops working. For 25 different scenarios, we set number of task A, B and C to be random numbers between 10 to 100. For each robot, we set its work time to finish each task to be a random number between 10 to 100.

C.1.3 TSP

Given a list of ten cities, the goal is to visit each city exactly once with minimized distance travelled. For 25 different scenarios, we set the coordinates of each city to be a random tuple between 0 and 1.

C.1.4 Warehouse

The robot has a task list of length N that needs to be finished one by one. In the warehouse, there are 50 stations, where the robots can visit stations to finish different tasks. The robot starts at station 0, travel n stations to finish n tasks, and then travel back to station 0. The robot needs to finish n tasks while minimizing the total distance travelled. For 25 different scenarios, we set the total task number to be 50, and the total station number to be 50, and each station can be used to accomplish 3 random tasks. We set the number of tasks the robot need to finish to be a random number from 3 to 10, and the tasks to be random numbers within 50. We set the coordinates of each station to be a random tuple between 0 and 1.

C.2 Added task description in prompt

Block Picking
Now, you are given a JSON constraint of a block stacking problem.
There are blocks of different colors and scores in the scene. You need to select "block_number" non-repeat blocks with color in "color" list, while maximizing the score.
You have access to a BlockSearch API.
BlockSearch.run(color:list) gives 1.all possible block ids of color in "color" list and 2.corresponding score info. You should assert chosen blocks index does not exceed block id list length.
BlockSearch.get_info(score_info, block_index) gives the score of certain block.

Task Allocation
Now, you are given a JSON constraint of a task allocation problem.
Given a list of tasks and three heterogeneous robots that are skilled at different tasks, the goal is to find the way to assign different number of tasks to different robots and finish the tasks with minimized finish time. The three robots could work in parallel, but the finish time counts the time when the last robot stops working.
You have access to a TimeSearch() API.
TimeSearch.run() searches robots' accomplishing time info.
TimeSearch.get_info(time_info, robot: str, task: str) gives the accomplishing time of certain block for certain task. An example of robot and task string is: 'robotA', 'taskA'.

Note that for each robot R and each task T, the number of task T robot R is allocated needs to be non-negative and within the total number of T.
You have access to a Max(variable_list) function that outputs the max of a list of variables.

TSP
Now, you are given a JSON constraint of a travelling salesman problem (TSP) problem.
Given 10 cities, you need to non-repeatly visit each city exactly once with minimized distance travelled.
You have access to a DistanceSearch() API.
DistanceSearch.run() takes no argument and gives the distance info between cities, and DistanceSerarch.get_info(distance_info, city_1, city_2) gives the distance(a real number) between two cities.
You should explicitly assert city index does not exceed total number of cities.
You do not need to count the distance to go back to the first city, so the total number of distances you need to consider is 9.

Warehouse
Now, you are given a JSON constraint of a warehouse robot routing problem.
The robot are given a task list "task_id" of length n and needs to finish them one by one. In the warehouse, there are "total_station_number" stations, where the robots can visit stations to finish different tasks.
The robot needs to finish n tasks while minimizing the total distance travelled. When calculating total travel distance, make sure to include 1.the distance to travel from origin (0) to first station; 2.distance between n stations (so this is n-1 values); 3.distance to travel from last station back to origin(0).
You have access to a StationSearch() API.
StationSearch.run_task(tasks) takes a list of tasks that the robot needs to accomplish, and gives a list of stations_id_list. For each task, you should assert robot choose one station id from corresponding stations_list, which is all possible stations.
StationSearch.run_distance() takes no argument and gives the distance info between stations, and StationSearch.get_info(distance_info, station_1_id, station_2_id) takes gives the distance (a real number) between two stations.

C.3 Failure case analysis

For Block Picking, Task Allocation, and Warehouse, there are failure cases.

Block Picking For Block Picking, LLM fails to give the optimal plan for 2 out of 25 delivered plans. The failure reasons are same for these two plans. In the block picking task, all picked blocks need to be distinct. Thus, in the codes LLM writes, it needs to explicitly check all block indexes it chooses are different. In these two plans, the LLM fails to take this into account, thus repeatedly choose same blocks with high scores to maximize the score.

Task Allocation For Task Allocation, LLM fails to deliver the plan for 2 out of 25 scenarios. The failure reasons are same. The LLMs are provided a Max(variable_list) function, which takes in a list of variables and return the max. However, in the codes written by LLM, they fail to input a list of variables, but input the variables themselves one by one. This gives runtime errors thus fails to deliver the plan.

Warehouse For Warehouse, LLM fails to deliver the plan for 4 out of 25 scenarios, and fails to give the optimal plan for 3 out of the 21 delivered plan.
Note that Warehouse is a more challenging task in that it needs to select stations to visit while calculate

the minimum travel distance between them at the same time. Thus, the codes are more complex to write. The delivery failure reasons for the 4 scenarios are same. Since the task requires the robot to travel from origin, visit n stations, and back to origin at the end. LLM could choose to set n station variables to represent n stations needs to visit or set n+2 station variables and make the first and last one to equal to 0. However, in the failure cases, the LLM set n variables to represent n stations, but at the same time assert first and last one to equal to 0. This brings conflicts because the it could assert one variable to equal to two values at the same time.

The non-optimal reasons for the 3 delivered plan are same: since the StationSearch.run_task(tasks) outputs a station_id_list, the contents are IDs of stations. LLM needs to create station variables and assert it to equal to *value* from the ID lists. However, in the codes, LLM assert the station variables to equal to *index* from zero to length of station_id_list. This makes it to calculate incorrect distance thus outputting non-optimal solutions.

D Example input queries and output plans

In an query, the user can specify 1) length of travel (3, 5, or 7 days), 2) the destination city or state (for 5/7 days travel, the destination cities would be 2/3 cities from a state), 3) travel dates, 4) budget, 5) preferences regarding transportation methods, 6) preferences regarding restaurant cuisine types, 7) preferences regarding accommodation type and rules.
We list an example input query and the corresponding output plans.

Input query:
Can you create a 5-day travel itinerary for a group of 3, departing from Atlanta and visiting 2 cities in Minnesota from March 3rd to March 7th, 2022? We have a budget of $7,900. We require accommodations that allow parties and should ideally be entire rooms. Although we don't plan to self-drive, we would like the flexibility to host parties.
Corresponding output plan:

```
{
"days": 1,
"current_city": "from Atlanta to Minneapolis(Minnesota)",
"transportation": "Taxi, from Atlanta to Minneapolis(Minnesota), duration: 16 hours 26 mins, distance: 1,821 km, cost: 1821",
"breakfast": "-",
"attraction": "Minneapolis Sculpture Garden, Minneapolis(Minnesota)",
"lunch": "-",
"dinner": "Bawa Chicken, Minneapolis(Minnesota)",
"accommodation": "Light-filled Apartment in great area, close 2 all!, Minneapolis(Minnesota)"
},
{
"days": 2,
"current_city": "from Minneapolis(Minnesota) to St. Cloud(Minnesota)",
"transportation": "Taxi, from Minneapolis(Minnesota) to St. Cloud(Minnesota), duration: 1 hour 6 mins, distance: 105 km, cost: 105",
"breakfast": "Friends Restaurant, St. Cloud(Minnesota)",
"attraction": "Blacklight Adventures, St. Cloud(Minnesota)",
"lunch": "Madras Cafe, St. Cloud(Minnesota)",
"dinner": "Aggarwal's Sweets Paradise, St. Cloud(Minnesota)",
"accommodation": "The Gramercy East, St. Cloud(Minnesota)"
},
{
"days": 3,
"current_city": "St. Cloud(Minnesota)",
"transportation": "-",
"breakfast": "Mocha, St. Cloud(Minnesota)",
"attraction": "AirMaxx Trampoline Park & Warrior Course, St. Cloud(Minnesota)",
"lunch": "House of Commons, St. Cloud(Minnesota)",
"dinner": "Cakewalk - Park Plaza, St. Cloud(Minnesota)",
"accommodation": "The Gramercy East, St. Cloud(Minnesota)"
},
{
"days": 4,
"current_city": "St. Cloud(Minnesota)",
"transportation": "-",
"breakfast": "Pa Pa Ya, St. Cloud(Minnesota)",
"attraction": "Beaver Island Trail South, St. Cloud(Minnesota)",
"lunch": "Grecian Key Restaurant, St. Cloud(Minnesota)",
"dinner": "Food Care, St. Cloud(Minnesota)",
"accommodation": "The Gramercy East, St. Cloud(Minnesota)"
},
{
"days": 5,
"current_city": "from St. Cloud(Minnesota) to Atlanta",
"transportation": "Taxi, from St. Cloud(Minnesota) to Atlanta, duration: 17 hours 19 mins, distance:
1,919 km, cost: 1919",
"breakfast": "Annapurna Sweets, St. Cloud(Minnesota)",
"attraction": "-",
"lunch": "Republic of Chicken, St. Cloud(Minnesota)",
"dinner": "-",
"accommodation": "-"
}
```

E Satisfiable Plan Solving Evaluation Details

Commonsense constraints defined in (Xie et al., 2024) include: all information in the plan is within closed sandbox, the plan is complete without any left out part, all activities should be conducted in current city, travel route is reasonable, restaurant and attractions should not be repeated, transportation is reasonable (no self-driving if taxi or flight is taken during the travel), the nunmber of consecutive days spent in a specific accommodation must meet its required minimum number of nights' stay.

Hard constraints include: the total spend of the trip is within budget, the specified room rule does not exist ("No parties", "No smoking", "No children under 10", "No pets", and "No visitors"), the specified room type exists ("Entire Room", "Private Room", "Shared Room", and "No Shared Room"), the specified cuisine types are fulfilled during the trip ("Chinese", "American", "Italian", "Mexican", "Indian", "Mediterranean", and "French"), the specified transportation method is satisfied ("No flight" and "No self-driving".).

For Commonsense Constraint Pass Rate and Hard Constraint Pass Rate, two evaluation modes, micro and macro, are used to test the agent's capability to follow single constraint and follow constraints holistically. Micro calculates the ratio of passed constraints to the total number of constraints, while Macro calculates the ratio of plans that pass all commonsense or hard constraints among all tested plans.

F Prompts

F.1 Prompts for Satisfiable Plan Solving

F.1.1 NL-JSON prompt

The instruction prompt for natural language to JSON translation prompt is provided as follows:

> Please assist me in extracting valid information from a given natural language text and reconstructing it in JSON format, as demonstrated in the following example.
> In the JSON, "org" denotes the departure city. "dest" denotes the destination city. "days" denotes the total number of travel days. When "days" exceeds 3, "visiting_city_number" specifies the number of cities to be covered in the destination state. "date" includes the detailed date to visit. In addition, "local_constraint" contains four possible constraints. Possible options of "house rule" includes ["parties", "smoking", "children under 10", "pets", "visitors"]. Possible options of "cuisine" includes ["Chinese", "American", "Italian", "Mexican", "Indian", "Mediterranean", "French"]. Possible options of "house type" includes ["entire room", "private room", "shared room", "not shared room"]. Possible options of "transportation" includes ["no flight", "no self-driving"]. If neither are mentioned in the text, make the value to be null.
> Here are three examples:
> —–EXAMPLE 1—–
> Text: Please help me plan a trip from St. Petersburg to Rockford spanning 3 days from March 16th to March 18th, 2022. The travel should be planned for a single person with a budget of $1,700.
> JSON:
> {
> "org": "St. Petersburg",
> "dest": "Rockford",
> "days": 3,
> "visiting_city_number": 1,
> "date": ["2022-03-16", "2022-03-17", "2022-03-18"],
> "people_number": 1,
> "local_constraint": {
> "house rule": null,
> "cuisine": null,
> "room type": null,
> "transportation": null
> },
> "budget": 1700
> }
> —–EXAMPLE 2—–
> Text: {Please create a 3-day travel itinerary for 2 people beginning in Fort Lauderdale and ending in Milwaukee from the 8th to the 10th of March, 2022. Our travel budget is set at $1,100. We'd love to experience both American and Chinese cuisines during our journey.}
> JSON:
> {
> "org": "Fort Lauderdale",
> "dest": "Milwaukee",
> "days": 3,
> "visiting_city_number": 1,
> "date": ["2022-03-08", "2022-03-09", "2022-03-10"],
> "people_number": 2,
> "local_constraint": {
> "house rule": null,

```
"cuisine": ["American", "Chinese"],
"room type": null,
"transportation": null
},
"budget": 1100
}
—–EXAMPLE 3—–
Text: {Can you create a 5-day travel itinerary for a group of 3, departing from Atlanta and visiting 2 cities in Minnesota from March 3rd to March 7th, 2022? We have a budget of $7,900. We require accommodations that allow parties and should ideally be entire rooms. Although we don't plan to self-drive, we would like the flexibility to host parties.}
JSON:
{
"org": "Atlanta",
"dest": "Minnesota",
"days": 5,
"visiting_city_number": 2,
"date": ["2022-03-03", "2022-03-04", "2022-03-05", "2022-03-06", "2022-03-07"],
"people_number": 3,
"local_constraint": {
"house rule": "parties",
"cuisine": null,
"room type": "entire room",
"transportation": "no self-driving"
},
"budget": 7900
}
—–EXAMPLES END—–
Text: {query}
JSON:
```

F.1.2 JSON-Step prompt

The instruction prompt for JSON description to steps translation prompt is provided as follows:

```
You are given a constraint to satisfy for a travel plan problem in JSON format.
In the JSON, "org" denotes the departure city. When total travel days is 5 or 7, "dest" denotes the destination state; when total travel day is 3, "dest" denotes the destination city. "days" denotes the total number of travel days. When "days" equals 5 or 7, "visiting_city_number" specifies the number of cities to be covered in the destination state. "date" includes the specific date to visit. In addition, "local_constraint" contains four possible constraints. Possible options of "house rule" includes ["parties", "smoking", "children under 10", "pets", "visitors"]. Possible options of "cuisine" includes ["Chinese", "American", "Italian", "Mexican", "Indian", "Mediterranean", "French"]. Possible options of "house type" includes ["entire room", "private room", "shared room", "not shared room"]. Possible options of "transportation" includes ["no flight", "no self-driving"]. If the field value is null in JSON, this specific hard constraint is not included.
Your job is to give a detailed step by step instuction to encode this constraint as code.
Here are some example steps for different constraint:
—–EXAMPLE 1—–
JSON Constraint:
{
```

```
"org": "Atlanta",
"dest": "Minnesota",
"days": 5,
"visiting_city_number": 2,
"date": ["2022-03-03", "2022-03-04", "2022-03-05", "2022-03-06", "2022-03-07"],
"people_number": 3,
"local_constraint": {
"house rule": "parties",
"cuisine": null,
"room type": "entire room",
"transportation": "no self-driving"
},
"budget": 7900
}
Steps:
# Destination cities #
# Run CitySearch to get all possible destination cities in Minnesota State from origin 'Atlanta', remove origin 'Atlanta' if it is in list
# Loop through cities for 2 destination cities
# Initialize Z3 solver s
# Set 'city' variable to be indexes of 2 destination cities
# If city_0_index and city_1_index are not same, assert 2 'city' variables equal to city index

# Departure dates #
# Set 'departure_dates' variables for 3 transportations between cities
# Assert first transportation happens at first day (day 0), last transportation happens at last day (day 4), and second transportation could happen at any day in between

# Transportation methods #
# Set transportation method (flight, self-driving, taxi) variable for 3 transportations between cities
# Assert only one of flight, self-driving, or taxi is used for 3 transportations between cities, self-driving is not valid if taxi or flight is used for any transportation
# Assert all 3 transportations between cities are not self-driving

# Flight information #
# Run FlightSearch to get flight info for Atlanta as origin, list of cities, city_0 and city_1, and dates
# Get specific flight price info with Atlanta as origin and final destination, specific city variable, and departure date for 3 transportations
# Set 'flight_index' variable for 3 transportations
# Assert 3 'flight_index' variables are within valid range if taking flight, assert flight index to be -1 if not taking flight
# Calculate flight price for 3 people for 3 transportations based on flight index variable
# Get specific flight arrival time info with Atlanta as origin and final destination, specific city, and departure date for 3 transportations
# Calculate flight arrival time for 3 transportations based on flight index variable

# Driving information #
# Run DistanceSearch to get driving info for Atlanta as origin and city_0 and city_1
# Get specific driving distance info with Atlanta as origin and final destination, specific city, and departure date for 3 transportations
# Assert driving info is not empty if driving
# Calculate self-driving and taxi price for 3 people and 3 transportations based on driving distance
# Get driving arrival time with Atlanta as origin and final destination, specific city, and departure date for 3 transportations

# Restaurant information #
# Get arrivals and city list for each day based on 3 transportations, 5 total travel day, and departure dates variables
# Run RestaurantSearch to get restaurant price info and cuisine info for city_0 and city_1
# Set 'restaurant_in_which_city' variables for 15 (3 meals per day, 5 days) meals
# For each 'restaurant_in_which_city' variable, assert it to be either current city or next city based on transportation arrivals time
# Set 'restaurant_index' variables for 15 (3 meals per day, 5 days) meals
# For each 'restaurant_index', get specific price info based on 'restaurant_in_which_city' variable, assert index are within valid range, assert restaurants in same city are not repeated, and calculate restaurant price for 3 people
# Calculate restaurant price based on restaurant index

# Attraction information #
# Run AttractionSearch to get attraction info for city_0 and city_1
# Set 'attraction_in_which_city' variables for 5 (1 per day) attractions
# For each 'attraction_in_which_city' variable, assert it to be either current city or next city based on transportation arrivals time
# Set 'attraction_index' variables for 5 (1 per day) attractions
# For each 'attraction_index', get specific length info based on attraction in which city variable, assert index are within valid range, and attrations in same city are not repeated

# Accommodation information #
# Run AccommodationSearch to get accommodation info and accommodation constraints for city_0 and city_1
# Set 'accommodation_index' variables for 2 (1 per city) accommodations
# For each 'accommodation_index', get specific price info based on accommodation in which city variable, assert 'accommodation_index' variable are within valid range, calculate number of room need for 3 people and accommodation price
# For each city, get accommodation minimum night info and assert it to be less than the days stay in this city
# For each 'accommodation_index', get specific room type and house rules info, assert 'Entire home/apt' exist for all accommodations, assert 'No parties' does not exist for all accommodations

# Budget #
# Set budget limit variable to be 7900
# Add 3 transportation price to spent, according to whether transportation method is flight, self-driving, or taxi
# Add restaurant price to spent
# Add accommodation price to spent
# Assert current spent is within budget

—–EXAMPLE 2—–
JSON Constraint:
{
```

```
'org': 'Indianapolis',
'dest': 'Colorado',
'days': 7,
'visiting_city_number': 3,
'date': ['2022-03-11', '2022-03-12', '2022-03-13', '2022-03-14', '2022-03-15', '2022-03-16',
'2022-03-17'],
'people_number': 5,
'local_constraint': {
'house rule': 'pets',
'cuisine': ['Mexican', 'Italian', 'Mediterranean', 'Indian'],
'room type': 'entire room',
'transportation': None
},
'budget': 15100
}
Steps:
# Destination cities #
# Run CitySearch to get all possible destination cities in Colorado State from origin 'Indianapolis',
remove origin 'Indianapolis' if it is in list
# Loop through cities for 3 destination cities
# Initialize Z3 solver s
# Set 'city' variable to be indexes of 3 destination cities
# If city_0_index, city_1_index, city_2_index are not same, assert 3 'city' variables equal to city
index

# Departure dates #
# Set 'departure_dates' variables for 4 transportations between cities
# Assert first transportation happens at first day (day 0), last transportation happens at last day (day
6), second and third transportation happen in between but not at the same day

# Transportation methods #
# Set transportation method (flight, self-driving, taxi) variable for 4 transportations between cities
# Assert only one of flight, self-driving, or taxi is used for 4 transportations between cities,
self-driving is not valid if taxi or flight is used for any transportation

# Flight information #
# Run FlightSearch to get flight info for Indianapolis as origin, list of cities, city_0, city_1 and
city_2, and dates
# Get specific flight price info with Indianapolis as origin and final destination, specific city
variable, and departure date for 4 transportations
# Set 'flight_index' variable for 4 transportations
# Assert 4 'flight_index' variables are within valid range if taking flight, assert flight index to be -1
if not taking flight
# Calculate flight price for 5 people for 4 transportations based on flight index variable
# Get specific flight arrival time info with Indianapolis as origin and final destination, specific city,
and departure date for 4 transportations
# Calculate flight arrival time for 4 transportations based on flight index variable

# Driving information #
# Run DistanceSearch to get driving info for Indianapolis as origin and city_0, city_1 and city_2
# Get specific driving distance info with Indianapolis as origin and final destination, specific city, and departure date for 4 transportations
# Assert driving info is not empty if driving
# Calculate self-driving and taxi price for 5 people and 4 transportations based on driving distance
# Get driving arrival time with Indianapolis as origin and final destination, specific city, and departure date for 4 transportations

# Restaurant information #
# Get arrivals and city list for each day based on 4 transportations, 7 total travel day, and departure dates variables
# Run RestaurantSearch to get restaurant price info and cuisine info for city_0, city_1 and city_2
# Set 'restaurant_in_which_city' variables for 21 (3 meals per day, 7 days) meals
# For each 'restaurant_in_which_city' variable, assert it to be either current city or next city based on transportation arrivals time
# Set 'restaurant_index' variables for 21 (3 meals per day, 7 days) meals
# For each 'restaurant_index', get specific price info based on 'restaurant_in_which_city' variable, assert index are within valid range, assert restaurants in same city are not repeated, and calculate restaurant price for 5 people
# Set 'cuisine_type' variables for each cuisine type required
# For each cuisine type, iterate through all restaurant to check if it is satisfied

# Attraction information #
# Run AttractionSearch to get attraction info for city_0, city_1 and city_2
# Set 'attraction_in_which_city' variables for 7 (1 per day) attractions
# For each 'attraction_in_which_city' variable, assert it to be either current city or next city based on transportation arrivals time
# Set 'attraction_index' variables for 7 (1 per day) attractions
# For each 'attraction_index', get specific length info based on attraction in which city variable, assert index are within valid range, and attrations in same city are not repeated

# Accommodation information #
# Run AccommodationSearch to get accommodation info and accommodation constraints for city_0, city_1 and city_2
# Set 'accommodation_index' variables for 3 (1 per city) accommodations
# For each 'accommodation_index', get specific price info based on accommodation in which city variable, assert 'accommodation_index' variable are within valid range, calculate number of room need for 5 people and accommodation price
# For each city, get accommodation minimum night info and assert it to be less than the days stay in this city
# For each 'accommodation_index', get specific room type and house rules info, assert 'Entire home/apt' exist for all accommodations, assert 'No pets' does not exist for all accommodations

# Budget #
# Set budget limit variable to be 15100
# Add 4 transportation price to spent, according to whether transportation method is flight, self-driving, or taxi
# Add restaurant price to spent
# Add accommodation price to spent
# Assert current spent is within budget
——EXAMPLES 3——
```

```
JSON Constraint:
{
"org": "Fort Lauderdale",
"dest": "Milwaukee",
"days": 3,
"visiting_city_number": 1,
"date": ["2022-03-08", "2022-03-09", "2022-03-10"],
"people_number": 2,
"local_constraint": {
"house rule": null,
"cuisine": ["American", "Chinese"],
"room type": null,
"transportation": "no flight"
},
"budget": 1100
}
Steps:
# Destination cities #
# Set cities to be a list includes Milwaukee only
# Loop through cities for 1 destination cities
# Initialize Z3 solver s
# Set 'city' variable to be indexes of 1 destination cities
# Assert 'city' variable equal to city index

# Departure dates #
# Set 'departure_dates' variables for 2 transportations between cities
# Assert first transportation happens at first day (day 0), last transportation happens at last day (day 2)

# Transportation methods #
# Set transportation method (flight, self-driving, taxi) variable for 2 transportations between cities
# Assert only one of flight, self-driving, or taxi is used for 2 transportations between cities,
self-driving is not valid if taxi or flight is used for any transportation
# Assert all 2 transportations between cities are not flight

# Flight information #
# Run FlightSearch to get flight info for Fort Lauderdale as origin, list of cities, city_0, and dates
# Get specific flight price info with Fort Lauderdale as origin and final destination, specific city,
and departure date for 2 transportations
# Set 'flight_index' variable for 2 transportations
# Assert 2 'flight_index' variables are within valid range if taking flight, assert flight index to be -1
if not taking flight
# Calculate flight price for 2 people for 2 transportations based on flight index variable
# Get specific flight arrival time info with Fort Lauderdale as origin and final destination, specific
city, and departure date for 2 transportations
# Calculate flight arrival time for 2 transportations based on flight index variable

# Driving information #
# Run DistanceSearch to get driving info for Fort Lauderdale as origin and city_0
# Get specific driving distance info with Fort Lauderdale as origin and final destination, specific
city, and departure date for 2 transportations
```

```
# Assert driving info is not empty if driving
# Calculate self-driving and taxi price for 2 people and 2 transportations based on driving distance
# Get driving arrival time with Fort Lauderdale as origin and final destination, specific city, and departure date for 2 transportations

# Restaurant information #
# Get arrivals and city list for each day based on 2 transportations, 3 total travel day, and departure dates variables
# Run RestaurantSearch to get restaurant price info and cuisine info for city_0
# Set 'restaurant_in_which_city' variables for 9 (3 meals per day, 3 days) meals
# For each 'restaurant_in_which_city' variable, assert it to be either current city or next city based on transportation arrivals time
# Set 'restaurant_index' variables for 9 (3 meals per day, 3 days) meals
# For each 'restaurant_index', get specific price info based on 'restaurant_in_which_city' variable, assert index are within valid range, assert restaurants in same city are not repeated, and calculate restaurant price for 2 people
# Set 'cuisine_type' variables for each cuisine type required
# For each cuisine type, iterate through all restaurant to check if it is satisfied

# Attraction information #
# Run AttractionSearch to get attraction info for city0
# Set 'attractioninwhichcity' variables for 3 (1 per day) attractions
# For each 'attractioninwhichcity' variable, assert it to be either current city or next city based on transportation arrivals time
# Set 'attractionindex' variables for 3 (1 per day) attractions
# For each 'attractionindex', get specific length info based on attraction in which city variable, assert index are within valid range, and attrations in same city are not repeated

# Accommodation information #
# Run AccommodationSearch to get accommodation info and accommodation constraints for city0
# Set 'accommodationindex' variables for 1 (1 per city) accommodations
# For each 'accommodationindex', get specific price info based on accommodation in which city variable, assert 'accommodationindex' variable are within valid range, calculate number of room need for 2 people and accommodation price
# For each city, get accommodation minimum night info and assert it to be less than the days stay in this city

# Budget #
# Set budget limit variable to be 1100
# Add 2 transportation price to spent, according to whether transportation method is flight, self-driving, or taxi
# Add restaurant price to spent
# Add accommodation price to spent
# Assert current spent is within budget
—–EXAMPLES END—–
Based on the examples above, give the steps for following JSON constraint.
Note to keep the format in examples and start each line containing steps with '#'
JSON Constraint: {JSON}
Steps:
```

F.1.3 Step-Code prompt

The step to code example prompt for each constraint type is provided as follows:
Destination cities:

```
# Python script for testing satisfiability of the destination cities constraint of a travel plan problem.

# Run CitySearch to get all possible destination cities in Minnesota State from origin 'Atlanta', remove origin 'Atlanta' if it is
# in list
cities = CitySearch.run('Minnesota', 'Atlanta', query_json['date'])
if 'Atlanta' in cities:
        cities.remove('Atlanta')
# Set cities to be a list includes Milwaukee only
cities = ['Milwaukee']
# Loop through cities for 2 destination cities
for city_0_index, city_0 in enumerate(cities):
    for city_1_index, city_1 in enumerate(cities):
        # Initialize Z3 solver s
        s = Optimize()
        # Set 'city' variable to be indexes of 2 destination cities
        variables['city'] = [Int('city_' + str(i)) for i in range(2)]
        # If city_0_index and city_1_index are not same, assert 2 'city' variables equal to city index
        if city_0_index != city_1_index:
        s.assert_and_track(variables['city'][0] == city_0_index,  'visit city in cities list')
        s.assert_and_track(variables['city'][1] == city_1_index,  'visit city in cities list')
# Loop through cities for 1 destination cities
for city_0_index, city_0 in enumerate(cities):
    # Initialize Z3 solver s
    s = Optimize()
    # Set 'city' variable to be indexes of 1 destination cities
    variables['city'] = [Int('city_' + str(i)) for i in range(1)]
    # Assert 'city' variable equal to city index
    s.assert_and_track(variables['city'][0] == city_0_index,  'visit city in cities list')

# Based on the examples above, in which the lines start with '#' is the instuction, where the line/lines below it before the
# next '#' is the corresponding code.
# For this below instruction, write corresponding code and respond instruction with code only. Start with ########## Destination
# cities response########## and end with ########## Destination cities response ends##########.
```

Departure Dates:

```
# Python script for testing satisfiability of the departure dates constraint of a travel plan problem.

# Set 'departure_dates' variables for 3 transportations between cities
variables['departure_dates'] = [Int('departure_dates_transportation_' + str(i)) for i in range(3)]
# Assert first transportation happens at first day (day 0), last transportation happens at last day (day 6), second and third
# transportation happen in between but not at the same day
s.assert_and_track(variables['departure_dates'][0] == 0,  'travel start date')
s.assert_and_track(And(variables['departure_dates'][1] > 0, variables['departure_dates'][1] < variables['departure_dates'][2]),
↪  'valid travel date')
s.assert_and_track(And(variables['departure_dates'][2] > variables['departure_dates'][1], variables['departure_dates'][1] < 6),
↪  'valid travel date')
s.assert_and_track(variables['departure_dates'][3] == 6,  'travel end date')
# Assert first transportation happens at first day (day 0), last transportation happens at last day (day 2)
s.assert_and_track(variables['departure_dates'][0] == 0,  'travel start date')
s.assert_and_track(variables['departure_dates'][2] == 2,  'travel end date')

# Based on the examples above, in which the lines start with '#' is the instuction, where the line/lines below it before the next
# '#' is the corresponding code.
# For this below instruction, write corresponding code and respond instruction with code only. Start with ########## Departure
# dates response########## and end with ########## Departure dates response ends##########.
```

Transportation Methods:

```
# Python script for testing satisfiability of the transportation methods constraint of a travel plan problem.

# Set transportation method variable (flight, self-driving, taxi) for 3 transportations between cities
variables['flight'] = [Bool('flight_travel_' + str(i)) for i in range(3)]
variables['self-driving'] = [Bool('self-driving_travel_' + str(i)) for i in range(3)]
variables['taxi'] = [Bool('taxi_travel_' + str(i)) for i in range(3)]
# Assert only one of flight, self-driving, or taxi is used for 3 transportations between cities, self-driving is not valid if taxi
# or flight is used for any transportation
s.assert_and_track(Or(variables['flight'][0], variables['self-driving'][0], variables['taxi'][0]),  'either flight, self-driving,
↪  or taxi for first transportation')
s.assert_and_track(Or(variables['flight'][1], variables['self-driving'][1], variables['taxi'][1]),  'either flight, self-driving,
↪  or taxi for second transportation')
s.assert_and_track(Or(variables['flight'][2], variables['self-driving'][2], variables['taxi'][2]),  'either flight, self-driving,
↪  or taxi for third transportation')
s.assert_and_track(Not(Or(And(variables['flight'][0], variables['self-driving'][0]), And(variables['flight'][0],
↪  variables['taxi'][0]), And(variables['taxi'][0], variables['self-driving'][0]))),  'flight, self-driving, and taxi not
↪  simutaneously for first transportation')
```

```
s.assert_and_track(Not(Or(And(variables['flight'][1], variables['self-driving'][1]), And(variables['flight'][1],
↪  variables['taxi'][1]), And(variables['taxi'][1], variables['self-driving'][1]))),  'flight, self-driving, and taxi not
↪  simutaneously for second transportation')
s.assert_and_track(Not(Or(And(variables['flight'][2], variables['self-driving'][2]), And(variables['flight'][2],
↪  variables['taxi'][2]), And(variables['taxi'][2], variables['self-driving'][2]))),  'flight, self-driving, and taxi not
↪  simutaneously for third transportation')
s.assert_and_track(Implies(Or(variables['flight'][0], variables['flight'][1], variables['flight'][2]),
↪  Not(Or(variables['self-driving'][0], variables['self-driving'][1], variables['self-driving'][2]))), 'no self-driving if taken
↪  flight for any transportation')
s.assert_and_track(Implies(Or(variables['taxi'][0], variables['taxi'][1], variables['taxi'][2]),
↪  Not(Or(variables['self-driving'][0], variables['self-driving'][1], variables['self-driving'][2]))), 'no self-driving if taken
↪  taxi for any transportation')
# Assert all 3 transportations between cities are not self-driving
s.assert_and_track(Not(variables['self-driving'][0]), 'no self-driving for first transportation')
s.assert_and_track(Not(variables['self-driving'][1]), 'no self-driving for second transportation')
s.assert_and_track(Not(variables['self-driving'][2]), 'no self-driving for third transportation')

# Based on the examples above, in which the lines start with '#' is the instuction, where the line/lines below it before the next
# '#' is the corresponding code.
# For this below instruction, write corresponding code and respond instruction with code only. Start with ########## Transportation
# response########## and end with ########## Transportation response ends##########.
```

Flight Information:

```
# Python script for testing satisfiability of the flight constraint constraint of a travel plan problem.

# Run FlightSearch to get flight info for Atlanta as origin, list of cities, city_0 and city_1, and dates
flight_info = FlightSearch.run_for_all_cities_and_dates('Atlanta', cities, [city_0, city_1], query_json['date'])
# Get specific flight price info with Atlanta as origin and final destination, specific city variable, and departure date for 3
# transportations
flight_0_price_list, flight_0_price_list_length = FlightSearch.get_info(flight_info, 'Atlanta', variables['city'][0],
↪  variables['departure_dates'][0], 'Price')
flight_1_price_list, flight_1_price_list_length = FlightSearch.get_info(flight_info, variables['city'][0], variables['city'][1],
↪  variables['departure_dates'][1], 'Price')
flight_2_price_list, flight_2_price_list_length = FlightSearch.get_info(flight_info, variables['city'][1], 'Atlanta',
↪  variables['departure_dates'][2], 'Price')
# Set 'flight_index' variable for 3 transportations
variables['flight_index'] = [Int('flight_{}_index'.format(i)) for i in range(3)]
# Assert 3 'flight_index' variables are within valid range if taking flight, assert flight index to be -1 if not taking flight
s.assert_and_track(Implies(variables['flight'][0], And(variables['flight_index'][0] >= 0,variables['flight_index'][0] <
↪  flight_0_price_list_length)), 'valid flight index for flight 0')
s.assert_and_track(Implies(variables['flight'][1], And(variables['flight_index'][1] >= 0,variables['flight_index'][1] <
↪  flight_1_price_list_length)), 'valid flight index for flight 1')
s.assert_and_track(Implies(variables['flight'][2], And(variables['flight_index'][2] >= 0,variables['flight_index'][2] <
↪  flight_2_price_list_length)), 'valid flight index for flight 2')
s.assert_and_track(Implies(Not(variables['flight'][0]), variables['flight_index'][0] == -1), 'valid flight index for flight 0')
s.assert_and_track(Implies(Not(variables['flight'][1]), variables['flight_index'][1] == -1), 'valid flight index for flight 1')
s.assert_and_track(Implies(Not(variables['flight'][2]), variables['flight_index'][2] == -1), 'valid flight index for flight 2')
# Calculate flight price for 2 people for 3 transportations based on flight index variable
flight_0_price = 2 * FlightSearch.get_info_for_index(flight_0_price_list, variables['flight_index'][0])
flight_1_price = 2 * FlightSearch.get_info_for_index(flight_1_price_list, variables['flight_index'][1])
flight_2_price = 2 * FlightSearch.get_info_for_index(flight_2_price_list, variables['flight_index'][2])
# Get specific flight arrival time info with Atlanta as origin and final destination, specific city, and departure date for 3
# transportations
flight_0_arrtime_list, _ = FlightSearch.get_info(flight_info, 'Atlanta', variables['city'][0], variables['departure_dates'][0],
↪  'ArrTime')
flight_1_arrtime_list, _ = FlightSearch.get_info(flight_info, variables['city'][0], variables['city'][1],
↪  variables['departure_dates'][1], 'ArrTime')
flight_2_arrtime_list, _ = FlightSearch.get_info(flight_info, variables['city'][1], 'Atlanta', variables['departure_dates'][2],
↪  'ArrTime')
# Calculate flight arrival time for 3 transportations based on flight index variable
flight_0_arrtime = FlightSearch.get_info_for_index(flight_0_arrtime_list, variables['flight_index'][0])
flight_1_arrtime = FlightSearch.get_info_for_index(flight_1_arrtime_list, variables['flight_index'][1])
flight_2_arrtime = FlightSearch.get_info_for_index(flight_2_arrtime_list, variables['flight_index'][2])

# Based on the examples above, in which the lines start with '#' is the instuction, where the line/lines below it before the next
# '#' is the corresponding code.
# For this below instruction, write corresponding code and respond instruction with code only. Start with ########## Flight
# response########## and end with ########## Flight response ends##########.
```

Driving Information:

```
# Python script for testing satisfiability of the driving constraint of a travel plan problem.

# Run DistanceSearch to get driving info for Atlanta as origin and city_0 and city_1
driving_info = DistanceSearch.run_for_all_cities('Atlanta', cities, [city_0, city_1])
# Get specific driving distance info with Atlanta as origin and final destination, specific city, and departure date for 3
# transportations
driving_0_distance, driving_0_length = DistanceSearch.get_info(driving_info, 'Atlanta', variables['city'][0], 'Distance')
driving_1_distance, driving_1_length = DistanceSearch.get_info(driving_info, variables['city'][0], variables['city'][1],
↪  'Distance')
driving_2_distance, driving_2_length = DistanceSearch.get_info(driving_info, variables['city'][1],'Atlanta', 'Distance')
```

```
# Assert driving info is not empty if driving
s.assert_and_track(Implies(Or(variables['self-driving'][0], variables['taxi'][0]), driving_0_length > 0), 'driving is possible for
↪  transportation 0')
s.assert_and_track(Implies(Or(variables['self-driving'][1], variables['taxi'][1]), driving_1_length > 0), 'driving is possible for
↪  transportation 1')
s.assert_and_track(Implies(Or(variables['self-driving'][2], variables['taxi'][2]), driving_2_length > 0), 'driving is possible for
↪  transportation 2')
# Calculate self-driving and taxi price for 3 people and 3 transportations based on driving distance
self_driving_0_price = 0.05 * driving_0_distance * math.ceil(3 / 5)
self_driving_1_price = 0.05 * driving_1_distance * math.ceil(3 / 5)
self_driving_2_price = 0.05 * driving_2_distance * math.ceil(3 / 5)
taxi_0_price = driving_0_distance * math.ceil(3 / 4)
taxi_1_price = driving_1_distance * math.ceil(3 / 4)
taxi_2_price = driving_2_distance * math.ceil(3 / 4)
# Get driving arrival time with Atlanta as origin and final destination, specific city, and departure date for 3 transportations
driving_0_arrtime, _ = DistanceSearch.get_info(driving_info, 'Atlanta', variables['city'][0], 'Duration')
driving_1_arrtime, _ = DistanceSearch.get_info(driving_info, variables['city'][0], variables['city'][1], 'Duration')
driving_2_arrtime, _ = DistanceSearch.get_info(driving_info, variables['city'][1], 'Atlanta', 'Duration')

# Based on the examples above, in which the lines start with '#' is the instuction, where the line/lines below it before the next
# '#' is the corresponding code.
# Follow the variable names in examples.
# For this below instruction, write corresponding code and respond instruction with code only. Start with ########## Driving
# response########## and end with ########## Driving response ends##########.
```

Restaurant Information:

```
# Python script for testing satisfiability of the restaurant constraint of a travel plan problem.

# Get arrivals and city list for each day based on 3 transportations, 5 total travel day, and departure dates variables
transportation_0_arrtime = If(variables['flight'][0], flight_0_arrtime, driving_0_arrtime)
transportation_1_arrtime = If(variables['flight'][1], flight_1_arrtime, driving_1_arrtime)
transportation_2_arrtime = If(variables['flight'][2], flight_2_arrtime, driving_2_arrtime)
arrives = get_arrivals_list([transportation_0_arrtime, transportation_1_arrtime, transportation_2_arrtime], 5,
↪  variables['departure_dates'])
city_list = get_city_list(variables['city'], 5, variables['departure_dates'])
# Run RestaurantSearch to get restaurant price info and cuisine info for city_0 and city_1
restaurant_price, restaurant_cuisines = RestaurantSearch.run_for_all_cities(cities, [city_0, city_1])
# Run RestaurantSearch to get restaurant price info and cuisine info for city_0
restaurant_price, restaurant_cuisines = RestaurantSearch.run_for_all_cities(cities, [city_0])
# Set 'restaurant_in_which_city' variables for 15 (3 meals per day, 5 days) meals
variables['restaurant_in_which_city'] = [Int('restaurant_' + str(i)) for i in range(3*5)]
# For each 'restaurant_in_which_city' variable, assert it to be either current city or next city based on transportation arrivals
# time
for i, variable in enumerate(variables['restaurant_in_which_city']):
    date_index = i // 3
    meal_index = i % 3
    if meal_index == 0: # breakfast
        s.assert_and_track(Or(variable == city_list[date_index], variable == city_list[date_index+1]),  'eat in which city b')
        s.assert_and_track(Implies(arrives[date_index]> 10, variable == city_list[date_index]),'eat in which city b')
        s.assert_and_track(Implies(arrives[date_index]< 5, variable == city_list[date_index+1]),'eat in which city b')
    if meal_index == 1: # lunch
        s.assert_and_track(Or(variable == city_list[date_index], variable == city_list[date_index+1]),  'eat in which city l')
        s.assert_and_track(Implies(arrives[date_index]> 15, variable == city_list[date_index]),'eat in which city l')
        s.assert_and_track(Implies(arrives[date_index]< 10, variable == city_list[date_index+1]),'eat in which city l')
    if meal_index == 2: # dinner
        s.assert_and_track(Or(variable == city_list[date_index], variable == city_list[date_index+1]),  'eat in which city d')
        s.assert_and_track(Implies(arrives[date_index]> 22, variable == city_list[date_index]),'eat in which city d')
        s.assert_and_track(Implies(arrives[date_index]< 17, variable == city_list[date_index+1]),'eat in which city d')
# Set 'restaurant_index' variables for 15 (3 meals per day, 5 days) meals
variables['restaurant_index'] = [Int('restaurant_{}_index'.format(i)) for i in range(3*5)]
# For each 'restaurant_index', get specific price info based on 'restaurant_in_which_city' variable, assert index are within valid
# range, assert restaurants in same city are not repeated, and calculate restaurant price for 2 people
all_restaurant_price = 0
for i, variable in enumerate(variables['restaurant_index']):
    restaurant_price_list, restaurant_list_length = RestaurantSearch.get_info(restaurant_price,
    ↪  variables['restaurant_in_which_city'][i], 'Price')
    s.assert_and_track(Implies(variables['restaurant_in_which_city'][i] != -1, And(variable >= 0, variable <
    ↪  restaurant_list_length)), 'valid restaurant index')
    s.assert_and_track(Implies(variables['restaurant_in_which_city'][i] == -1, variable == -1), 'valid restaurant index')
    for j in range(i-1, -1, -1):
        s.assert_and_track(Implies(And(variables['restaurant_in_which_city'][i] != -1, variables['restaurant_in_which_city'][i] ==
        ↪  variables['restaurant_in_which_city'][j]), variable != variables['restaurant_index'][j]), 'non repeating restaurant
        ↪  index')
    Calculate restaurant price based on restaurant index
    all_restaurant_price += 2 * If(variables['restaurant_in_which_city'][i] != -1,
    ↪  RestaurantSearch.get_info_for_index(restaurant_price_list, variable), 0)
# Set 'cuisine_type' variables for each cuisine type required
variables['cuisines_type'] = [Int('cuisines_' + i) for i in query_json['local_constraint']['cuisine']]
# For each cuisine type, iterate through all restaurant to check if it is satisfied
for index, cuisine in enumerate(query_json['local_constraint']['cuisine']):
    count = 0
    for i, variable in enumerate(variables['restaurant_index']):
        restaurant_cuisines_list, _ = RestaurantSearch.get_info(restaurant_cuisines, variables['restaurant_in_which_city'][i],
        ↪  'Cuisines')
        count += If(RestaurantSearch.check_exists(cuisine, restaurant_cuisines_list, variable), 1, 0)
    s.assert_and_track(variables['cuisines_type'][index] == count,  cuisine + 'type restaurant')
    s.assert_and_track(variables['cuisines_type'][index] > 0,  cuisine + 'type restaurant is visited')

# Based on the examples above, in which the lines start with '#' is the instuction, where the line/lines below it before the next
# '#' is the corresponding code.
# For this below instruction, write corresponding code and respond instruction with code only. Start with ########## Restaurant
# response########## and end with ########## Restaurant response ends##########.
```

Attraction Information:

```
# Python script for testing satisfiability of the attraction constraint of a travel plan problem.

# Run AttractionSearch to get attraction info for city_0 and city_1
attraction_info = AttractionSearch.run_for_all_cities(cities, [city_0, city_1])
# Run AttractionSearch to get attraction info for city_0
attraction_info = AttractionSearch.run_for_all_cities(cities, [city_0])
# Set 'attraction_in_which_city' variables for 5 (1 per day) attractions
variables['attraction_in_which_city'] = [Int('attraction_' + str(i)) for i in range(1*5)]
# For each 'attraction_in_which_city' variable, assert it to be either current city or next city based on transportation arrivals
# time
for i, variable in enumerate(variables['attraction_in_which_city']):
    s.assert_and_track(variable == If(arrives[i]> 18, city_list[i], city_list[i+1]),  'attraction in which city')
# Set 'attraction_index' variables for 5 (1 per day) attractions
variables['attraction_index'] = [Int('attraction_{}_index'.format(i)) for i in range(1*5)]
# For each 'attraction_index', get specific length info based on attraction in which city variable, assert index are within valid
# range, and attrations in same city are not repeated
for i, variable in enumerate(variables['attraction_index']):
    attraction_list_length = AttractionSearch.get_info(attraction_info, variables['attraction_in_which_city'][i])
    s.assert_and_track(Implies(variables['attraction_in_which_city'][i] != -1, And(variable >= 0, variable <
    ↪  attraction_list_length)), 'valid attraction index')
    s.assert_and_track(Implies(variables['attraction_in_which_city'][i] == -1, variable == -1), 'valid attraction index')
    for j in range(i-1, -1, -1):
        s.assert_and_track(Implies(And(variables['attraction_in_which_city'][i] != -1, variables['attraction_in_which_city'][i] ==
        ↪  variables['attraction_in_which_city'][j]), variable != variables['attraction_index'][j]), 'non repeating attraction
        ↪  index')

# Based on the examples above, in which the lines start with '#' is the instuction, where the line/lines below it before the next
# '#' is the corresponding code.
# For this below instruction, write corresponding code and respond instruction with code only. Start with ########## Attraction
# response########## and end with ########## Attraction response ends##########.
```

Accommodation Information:

```
# Python script for testing satisfiability of the accommodation constraint of a travel plan problem.

# Run AccommodationSearch to get accommodation info and accommodation constraints for city_0 and city_1
accommodation_info, accommodation_constraints = AccommodationSearch.run_for_all_cities(cities, [city_0, city_1])
# Run AccommodationSearch to get accommodation info and accommodation constraints for city_0
accommodation_info, accommodation_constraints = AccommodationSearch.run_for_all_cities(cities, [city_0])
# Set 'accommodation_index' variables for 2 (1 per city) accommodations
variables['accommodation_index'] = [Int('accommodation_{}_index'.format(i)) for i in range(2)]
# For each 'accommodation_index', get specific price info based on accommodation in which city variable, assert
# 'accommodation_index' variable are within valid range, calculate number of room need for 2 people and accommodation price
all_accommodation_price = 0
for i, variable in enumerate(variables['accommodation_index']):
    accommodation_price_list, accommodation_list_length = AccommodationSearch.get_info(accommodation_info, variables['city'][i],
    ↪  'Price')
    s.assert_and_track(And(variable >= 0, variable < accommodation_list_length), 'valid accomodation index')
    accommodation_maximum_occupancy_list, _ = AccommodationSearch.get_info(accommodation_info, variables['city'][i],
    ↪  'Maximum_occupancy')
    num_room = convert_to_int(RealVal(2) / AccommodationSearch.get_info_for_index(accommodation_maximum_occupancy_list, variable))
    all_accommodation_price += (variables['departure_dates'][i+1] - variables['departure_dates'][i]) * num_room *
    ↪  AccommodationSearch.get_info_for_index(accommodation_price_list, variable)
# For each city, get accommodation minimum night info and assert it to be less than the days stay in this city
for index, city in enumerate(variables['city']):
    accommodation_minimum_nights_list, _ = AccommodationSearch.get_info(accommodation_info, city, 'Minimum_nights')
    minimum_night = AccommodationSearch.get_info_for_index(accommodation_minimum_nights_list,
    ↪  variables['accommodation_index'][index])
    s.assert_and_track(minimum_night <= variables['departure_dates'][index+1]- variables['departure_dates'][index], 'minimum
    ↪  nights satisfied')
# For each 'accommodation_index', get specific room type and house rules info, assert 'Entire home/apt' exist for all
# accommodations, assert 'No parties' does not exist for all accommodations
for i, variable in enumerate(variables['accommodation_index']):
        accommodation_room_types_list, _ = AccommodationSearch.get_info(accommodation_constraints, variables['city'][i],
        ↪  'Room_types')
        accommodation_house_rules_list, _ = AccommodationSearch.get_info(accommodation_constraints, variables['city'][i],
        ↪  'House_rules')
        s.assert_and_track(AccommodationSearch.check_exists('Entire home/apt', accommodation_room_types_list, variable) == True,
        ↪  'Entire home/apt' + 'types accomadation visited')
        s.assert_and_track(AccommodationSearch.check_exists('No parties', accommodation_house_rules_list, variable) == False,  'No
        ↪  parties' + 'rules accomadation not visited')
```

```
# Based on the examples above, in which the lines start with '#' is the instuction, where the line/lines below it before the next
# '#' is the corresponding code.
# For this below instruction, write corresponding code and respond instruction with code only. Start with ########## Accommodation
# response########## and end with ########## Accommodation response ends##########.
```

Budget:

```
# Python script for testing satisfiability of the budget constraint of a travel plan problem.

# Set budget limit variable to be 7900
variables['budget_limit'] = RealVal(7900)
# Add 3 transportation price to spent, according to whether transportation method is flight, self-driving, or taxi
spent = 0
spent += If(variables['flight'][0], flight_0_price, If(variables['self-driving'][0], self_driving_0_price,
↪  If(variables['taxi'][0], taxi_0_price, 10000)))
spent += If(variables['flight'][1], flight_1_price, If(variables['self-driving'][1], self_driving_1_price,
↪  If(variables['taxi'][1], taxi_1_price, 10000)))
spent += If(variables['flight'][2], flight_2_price, If(variables['self-driving'][2], self_driving_2_price,
↪  If(variables['taxi'][2], taxi_2_price, 10000)))
# Add restaurant price to spent
spent += all_restaurant_price
# Add accommodation price to spent
spent += all_accommodation_price
# Assert current spent is within budget
s.assert_and_track(spent <= variables['budget_limit'], 'budget enough')

# Based on the examples above, in which the lines start with '#' is the instuction, where the line/lines below it before the next
# '#' is the corresponding code.
# For this below instruction, write corresponding code and respond instruction with code only. Start with ########## Budget
# response########## and end with ########## Budget response ends##########.
```

F.1.4 Prompt difference of GPT-4, Claude 3, and Mixtral-Large

With the prompt we have for GPT-4 as the starting point, we adjust the prompts (add more explainations or examples) for Claude-3 and Mixtral-Large using the training set in TravelPlanner.

Claude-3 almost has the same prompt as GPT-4, except for the JSON-Step prompt. Since in training set, a failure case for Claude-3 is it is not able to handle the "house rule" properly. When the JSON specifies "house rule" to be "children under 10" it means the travellers have children under 10 and would like to stay in accommodations without "No children under 10" rule. While Claude-3 sometimes is not able to give "No children under 10" in the step, instead, it gives steps with "children under 10 not allowed". To enable it to handle this, we add one sentence explanation **"if house rule 'xxx' is mentioned, then 'No xxx' should not exist for all accomadations."** in JSON-Step prompt.

Compared to Claude-3, Mixtral-Large needs more prompt adjustment:

- We add **"You can only assign null to local constraints if it is needed. Other fields must have values."** to NL-JSON prompt because Mixtral-Large sometimes misses some information in JSON translation.
- Claude-3 uses the same JSON-Step prompt as Mixtral-Large.
- We add a 3-city loop-through-cities example in Destination Cities Step-Code prompt; We add a 2-city travel-date-assertion example in Departure Dates prompt; We add a 1-city transportation-method assertion-example to Transportation Methods; We add instructions that ask LLM to not use for-loops and name variable with "i" as when it tries to iteratively create or access variables with i it fails to write the correct code.

From the amount of changes we need to make, we can observe that Mixtral-Large in general produces more code generation errors compared to GPT-4 and Claude-3, thus needing more examples and explanations provided in prompts.

F.1.5 Failure cases of Mixtral-Large

Although we tune our prompt with training set, there are still some failure cases that do not appear in training set and thus negatively affect Mixtral-Large's delivery rate.
The major failure mode is: "room type" takes the value "no shared room". This room type is special in

that when other room types such as "private room" is specified, the generated instruction steps should be "private room exists for all accommodations". However, only when "no shared room" is mentioned, the steps should be "shared room does not exist for all accommodations." Since "no shared room" does not appear in training set or examples, and Mixtral-Large is not able to generalize to it, it fails by producing "not shard room exists for all accommodations", thus fails to search for home with type "not shared room". This is the major failure mode and is responsible for 7.8% of failed delivered plans (15.0% in total). Other than this, the failures are induced by runtime issue or some occasional code generation errors.

F.2 Prompts for Interactive Plan Repair

F.2.1 Suggestion prompt

The instruction prompt that guides LLM to collect information, analyze current situation, and offer suggestions for unsatisfiable queries is provided as follows:
Suggestion prompt for UnsatChristmas:

```
As a travel planner, you have some constraints in JSON format to satisfy for a round trip travel plan problem.
The trip spans "date", goes from "org", travels "dest" cities in a row in between, and then goes back to "org"
For example, if "org" is city_0, and "dest" is [city_1, city_2], then the flights could be [city_0->city_1,city_1->city_2,city_2->city_0] or [city_0->city_2,city_2-> city_1,city_1->city_0]
In addition, "local_constraint" contains three possible constraints. "flight rule" specifies whether "nonstop" is required or not. "airlines" specifies a list of a airlines user can accept. Possible options of "attraction_category" specifies a list of categories of attractions want to visit. If the field value is null in JSON, this specific hard constraint is not included.
The specified "flight rule" needs to be satisfied by all flights. All flights need to be one of the accepted "airlines". All categories in "attraction_category" needs to be satisfied, and a category could be satisfied if it exists for one attraction.
After anaylzed these constraints, you found they are not satisfiable under current setting. You will be giving unsatisfiable reasons.
Collect information based on the reasons or, based on the information you collect, analyze current situation or give a suggested modification to the constraints.
Info collecting can take 4 different actions:
(1) FlightSearch[Departure City, Destination City]: Description: A flight information retrieval tool.
Parameters:
Departure City: The city you'll be flying out from.
Destination City: The city you aim to reach.
Example: FlightSearch[New York City, London] would fetch flights from New York City to London.

(2) AirlineSearch[Airline]:
Description: Find flights of input airline.
Parameter: Airline - The airline name you want to take.
Example: AirlineSearch[United] would return all flights of United airline.

(3) AttractionSearch[City]:
Description: Find attractions categories in a city of your choice.
Parameter: City - The name of the city where you're seeking attractions.
Example: AttractionSearch[London] would return attraction categories in London.

(4) CategorySearch[Category]:
Description: Find cities contain attractions of input category.
Parameter: Category - The attraction category where you want to visit.
```

Example: CategorySearch[Park] would return all cities where attractions of category Park exist.

You need to take an action analyze current situation and plan your future steps after each FlightSearch, AirlineSearch, AttractionSearch, or CategorySearch.
Example: Analyze[your analysis of current situation and plan for future]

You can suggest to remove the non-stop constraint, suggest to change required airlines, suggest to change destination cities(but keep number of destination cities unchanged), suggest to change attraction categories, or suggest to raise budget. Do not give other suggestions that change other fields in JSON input, such as origin, number of visit cities, etc.
Please give a reasonable suggestion to modify the constraint only when you think you've collected enough information and the suggestion has high chance to be satisfiable. For example, if destination city does not have required attraction category, you should suggest to change destination city if info shows the new city has the required category
Please try to keep original constraint and make minimal change to original constraint only when it is necessary.
Examples:
Suggest[raise budget to 5000]
Suggest[change destination cities to be Istanbul and Macau]
Suggest[remove the non-stop constraint]
Suggest[change airlines to be United, Air France, or JetBlue]
Suggest[change attraction categories to be Garden and Museum]

A list of possible cities is ['Bangkok', 'Dubai', 'Hong Kong', 'Istanbul', 'Kuala Lumpur', 'London', 'Macau', 'New York City', 'Paris', 'Singapore']
Now, based on the input query, unsatisfiable reasons, and collected information, please give the next action(only one action) you want to take only with no explainations, you need to give a suggestion within 15 iterations:
Input query: {query}
Unsatisfiable reasons: {reasons}
Collected information: {info}

Suggestion prompt for TravelPlanner:

As a travel planner, you have some constraints in JSON format to satisfy for a round trip travel plan problem.
The trip spans "date", goes from "org", travels "dest" city, and then goes back to "org" For example, if "org" is city_0, and "dest" is city_1, then the transportations would be [city_0->city_1,city_1->city_0]
In addition, "local_constraint" contains four possible constraints. Possible options of "house rule" includes ["parties", "smoking", "children under 10", "pets", "visitors"]. Possible options of "cuisine" includes ["Chinese", "American", "Italian", "Mexican", "Indian", "Mediterranean", "French"]. Possible options of "house type" includes ["entire room", "private room", "shared room", "not shared room"]. Possible options of "transportation" includes ["no flight", "no self-driving"]. If the field value is null in JSON, this specific hard constraint is not included.
The specified "house rule" and "house type" needs to be satisfied by all accommodations. The specified "transportation" needs to be satisfied by all transportations. All cuisines in "cuisine" needs to be satisfied, and a cuisine could be satisfied if it exists for one restaurant.
After anaylzed these constraints, you found they are not satisfiable under current setting. You will be giving unsatisfiable reasons.

Collect information based on the reasons or, based on the information you collect, analyze current situation or give a suggested modification to the constraints.
Info collecting can take 6 different actions:
(1) DrivingCheck[Departure City, Destination City]: Description: A driving information checking tool that checks if driving is feasible.
Parameters:
Departure City: The city you'll be driving out from.
Destination City: The city you aim to reach.
Example: DrivingCheck[Grand Forks, Minneapolis] would check if driving is feasible from Grand Forks to Minneapolis.

(2) DrivingSearch[Departure City]:
Description: A driving information retrieval tool that returns all reachable cities.
Parameters:
Departure City: The city you'll be driving out from.
Example: DrivingSearch[Grand Forks] would return all reachable cities from Grand Forks through driving.

(3) FlightCheck[Departure City, Destination City, Date]:
Description: A flight information checking tool that checks if flight is feasible.
Parameters:
Departure City: The city you'll be flying out from.
Destination City: The city you aim to reach.
Date: The date you take the flight.
Example: FlightCheck[Grand Forks, Minneapolis, 2022-06-05] would check if flight is feasible from Grand Forks to Minneapolis on 2022-06-05.

(4) FlightSearch[Departure City, Date]: Description: A flight information retrieval tool that returns all reachable cities.
Parameters:
Departure City: The city you'll be flying out from.
Date: The date you take the flight.
Example: FlightSearch[Grand Forks, 2022-06-05] would return all reachable cities from Grand Forks through flight on 2022-06-05.

(5) AccommodationSearch[City]:
Description: Find accommodations types in a city of your choice.
Parameter: City - The name of the city where you're seeking accommodations.
Example: AccommodationSearch[Grand Forks] would return accommodation categories in Grand Forks.

(6) TypeSearch[Type]:
Description: Find cities contain accommodations of input type.
Parameter: Type - The accommodation type where you want to visit.
Example: TypeSearch[entire room] would return all cities where entire room type accommodation exist.

You need to take an action analyze current situation and plan your future steps after each DrivingCheck, DrivingSearch, FlightCheck, FlightSearch, AccommodationSearch, or TypeSearch.
Example: Analyze[your analysis of current situation and plan for future]

```
You can suggest to remove the "house type" constraint, suggest to remove the "transportation" constraint, suggest to change destination cities(but keep number of destination cities unchanged), or suggest to raise budget. Do not give other suggestions that change other fields in JSON input, such as origin, number of visit cities, etc.
Please give a reasonable suggestion to modify the constraint only when you think you've collected enough information and the suggestion has high chance to be satisfiable. For example, if destination city does not have required accomadation type, you should suggest to change destination city if info shows the new city has the required type.
Please try to keep original constraint and make minimal change to original constraint only when it is necessary.
Examples:
Suggest[raise budget to 5000]
Suggest[change destination cities to be Minneapolis]
Suggest[remove the house type constraint]
Suggest[remove the flight/no flight/ no self-driving assertion for transportations]

Now, based on the input query, unsatisfiable reasons, and collected information, please give the next action(only one action) you want to take only with no explainations, you need to give a suggestion within 15 iterations:
Input query: {query}
Unsatisfiable reasons: {reasons}
Collected information: {info}
```

F.2.2 Suggestion-No Reason prompt

The Suggestion-No Reason prompt is basically modified from the Suggestion prompt by removing all descriptions about reasons.

F.2.3 Suggestion-No Sovler prompt

The instruction suggestion prompt that remove the iterative solver calling and directly guide LLM to offer a list of suggestions is provided as follows:
Suggestion-No Sovler prompt for UnsatChristmas:

```
As a travel planner, you have some constraints in JSON format to satisfy for a round trip travel plan problem.
The trip spans "date", goes from "org", travels "dest" cities in a row in between, and then goes back to "org" For example, if "org" is city_0, and "dest" is [city_1, city_2], then the flights could be [city_0->city_1,city_1->city_2,city_2->city_0] or [city_0->city_2,city_2-> city_1,city_1->city_0]
In addition, "local_constraint" contains three possible constraints. "flight rule" specifies whether "non-stop" is required or not. "airlines" specifies a list of a airlines user can accept. Possible options of "attraction_category" specifies a list of categories of attractions want to visit. If the field value is null in JSON, this specific hard constraint is not included.
The specified "flight rule" needs to be satisfied by all flights. All flights need to be one of the accepted "airlines". All categories in "attraction_category" needs to be satisfied, and a category could be satisfied if it exists for one attraction.
After anaylzed these constraints, you found they are not satisfiable under current setting.
Collect information or, based on the information you collect, analyze current situation or give a suggested modification to the constraints.
Info collecting can take 4 different actions:
(1) FlightSearch[Departure City, Destination City]:
Description: A flight information retrieval tool. Parameters:
Departure City: The city you'll be flying out from.
```

Destination City: The city you aim to reach.
Example: FlightSearch[New York City, London] would fetch flights from New York City to London.

(2) AirlineSearch[Airline]:
Description: Find flights of input airline.
Parameter: Airline - The airline name you want to take.
Example: AirlineSearch[United] would return all flights of United airline.

(3) AttractionSearch[City]:
Description: Find attractions categories in a city of your choice.
Parameter: City - The name of the city where you're seeking attractions.
Example: AttractionSearch[London] would return attraction categories in London.

(4) CategorySearch[Category]:
Description: Find cities contain attractions of input category.
Parameter: Category - The attraction category where you want to visit.
Example: CategorySearch[Park] would return all cities where attractions of category Park exist.

You need to take an action analyze current situation and plan your future steps after each FlightSearch, AirlineSearch, AttractionSearch, or CategorySearch.
Example: Analyze[your analysis of current situation and plan for future]

You can suggest to remove the non-stop constraint, suggest to change required airlines, suggest to change destination cities(but keep number of destination cities unchanged), suggest to change attraction categories, or suggest to raise budget. Do not give other suggestions that change other fields in JSON input, such as origin, number of visit cities, etc.
Please give reasonable suggestions to modify the constraint only when you think you've collected enough information and the suggestion has high chance to be satisfiable. For example, if destination city does not have required attraction category, you should suggest to change destination city if info shows the new city has the required category
Please try to keep original constraint and make minimal change to original constraint only when it is necessary.
You can give one or more suggestions if you think one is not enough. Please separate the suggestions with ;
Examples:
Suggest[raise budget to 5000]
Suggest[change destination cities to be Istanbul and Macau]
Suggest[remove the non-stop constraint]
Suggest[change airlines to be United, Air France, or JetBlue]
Suggest[change attraction categories to be Garden and Museum]
Suggest[raise budget to 3000; change destination cities to be London]

A list of possible cities is ['Bangkok', 'Dubai', 'Hong Kong', 'Istanbul', 'Kuala Lumpur', 'London', 'Macau', 'New York City', 'Paris', 'Singapore'] Now, based on the input query and collected information, please give the next action(only one action) you want to take only with no explainations, you need to give suggestions within 15 iterations:
Input query: {query}
Collected information: {info}

Suggestion-No Sovler prompt for UnsatChristmas:

As a travel planner, you have some constraints in JSON format to satisfy for a round trip travel plan problem.
The trip spans "date", goes from "org", travels "dest" city, and then goes back to "org" For example, if "org" is city_0, and "dest" is city_1, then the transportations would be [city_0->city_1,city_1->city_0]
In addition, "local_constraint" contains four possible constraints. Possible options of "house rule" includes ["parties", "smoking", "children under 10", "pets", "visitors"]. Possible options of "cuisine" includes ["Chinese", "American", "Italian", "Mexican", "Indian", "Mediterranean", "French"]. Possible options of "house type" includes ["entire room", "private room", "shared room", "not shared room"]. Possible options of "transportation" includes ["no flight", "no self-driving"]. If the field value is null in JSON, this specific hard constraint is not included. The specified "house rule" and "house type" needs to be satisfied by all accommodations. The specified "transportation" needs to be satisfied by all transportations. All cuisines in "cuisine" needs to be satisfied, and a cuisine could be satisfied if it exists for one restaurant.
After anaylzed these constraints, you found they are not satisfiable under current setting.
Collect information or, based on the information you collect, analyze current situation or give a suggested modification to the constraints.
Info collecting can take 6 different actions:
(1) DrivingCheck[Departure City, Destination City]: Description: A driving information checking tool that checks if driving is feasible.
Parameters:
Departure City: The city you'll be driving out from.
Destination City: The city you aim to reach.
Example: DrivingCheck[Grand Forks, Minneapolis]
would check if driving is feasible from Grand Forks to Minneapolis.

(2) DrivingSearch[Departure City]:
Description: A driving information retrieval tool that returns all reachable cities.
Parameters:
Departure City: The city you'll be driving out from.
Example: DrivingSearch[Grand Forks] would return all reachable cities from Grand Forks through driving.

(3) FlightCheck[Departure City, Destination City, Date]:
Description: A flight information checking tool that checks if flight is feasible.
Parameters:
Departure City: The city you'll be flying out from.
Destination City: The city you aim to reach. Date: The date you take the flight.
Example: FlightCheck[Grand Forks, Minneapolis, 2022-06-05] would check if flight is feasible from Grand Forks to Minneapolis on 2022-06-05.

(4) FlightSearch[Departure City, Date]:
Description: A flight information retrieval tool that returns all reachable cities.
Parameters:
Departure City: The city you'll be flying out from.
Date: The date you take the flight.
Example: FlightSearch[Grand Forks, 2022-06-05] would return all reachable cities from Grand Forks through flight on 2022-06-05.

(5) AccommodationSearch[City]:

Description: Find accommodations types in a city of your choice.
Parameter: City - The name of the city where you're seeking accommodations.
Example: AccommodationSearch[Grand Forks] would return accommodation categories in Grand Forks.

(6) TypeSearch[Type]:
Description: Find cities contain accommodations of input type.
Parameter: Type - The accommodation type where you want to visit.
Example: TypeSearch[entire room] would return all cities where entire room type accommodation exist.
You need to take an action analyze current situation and plan your future steps after each DrivingCheck, DrivingSearch, FlightCheck, FlightSearch, AccommodationSearch, or TypeSearch.
Example: Analyze[your analysis of current situation and plan for future]

You can suggest to remove the "house type" constraint, suggest to remove the "transportation" constraint, suggest to change destination cities(but keep number of destination cities unchanged), or suggest to raise budget. Do not give other suggestions that change other fields in JSON input, such as origin, number of visit cities, etc.
Please give a reasonable suggestion to modify the constraint only when you think you've collected enough information and the suggestion has high chance to be satisfiable. For example, if destination city does not have required accomadation type, you should suggest to change destination city if info shows the new city has the required type.
Please try to keep original constraint and make minimal change to original constraint only when it is necessary.
You can give one or more suggestions if you think one is not enough. Please separate the suggestions with ;
Examples:
Suggest[raise budget to 5000]
Suggest[change destination cities to be Minneapolis]
Suggest[remove the house type constraint]
Suggest[remove the flight/no flight/ no self-driving assertion for transportations]
Suggest[raise budget to 2000, change destination cities to be Chicago]

Now, based on the input query and collected information, please give the next action(only one action) you want to take only with no explainations, you need to give a suggestion within 15 iterations:
Input query: {query}
Collected information: {info}

F.2.4 Code modify prompt

As a travel planner, you have some python codes that tests the satisfiability of a travel plan problem. While now some of the constraints are changed, your task is to change the python codes according to the changed constraints.
Only change the part of code that needs to be modified, and do not add any new parts.
Please respond with codes only, and be sure to include full codes instead of lines of updated codes.
Start with ########## response ########## and end with ########## response ends ##########.

Original Codes: {codes}
Modified Constraints: {constraints}

F.3 Prompts for Generalization Evaluation

To test the capability of our framework to generalize to unseen constraint types, we add this task description and append at the end of Step-Code prompt:

> Based on the examples above, can you give the steps for following JSON constraint with different fields. In the input JSON, "org" denotes the departure city. "dest" denotes the destination city/cities. "days" denotes the total number of travel days. When "days" equals 5 or 7. "date" includes the specific date to visit.
> In addition, "local_constraint" contains three possible constraints. "flight rule" specifies the whether "non-stop" is required or not. "airlines" specifies a list of a airlines you can accept. Possible options of "attraction_category" specifies a list of categories of attractions want to visit. "transportation" is always 'flight'. If the field value is null in JSON, this specific hard constraint is not included.
> The specified "flight rule" needs to be satisfied by all flights. All flights need to be one of the accepted "airlines". All categories in "attraction_category" needs to be satisfied, and a category could be satisfied if it exists for one attraction.
> We do not consider restaurant information or accommodation information, instead, we fix each restaurant price to be 30 per person and accommodation to be 100 per person.

G Example input JSON and output step for generalization evaluation

We include the full example of JSON-Step generation for unseen constraint types here:

Input JSON query {
"org": "Hong Kong",
"dest": ["New York City", "Bangkok"],
"days": 5,
"visiting_city_number": 2,
"date": ["2023-12-22", "2023-12-23", "2023-12-24", "2023-12-25", "2023-12-26"],
"people_number": 3,
"local_constraint": {
"flight rule": "non-stop",
"airlines": ["United", "Emirates"],
"attraction_category": ["Garden", "Historical Landmarks"],
"transportation": "flight"
},
"budget": 5000
}

Corresponding output step # Destination cities #
# Set cities to be a list includes 'New York City' and 'Bangkok'
# Loop through cities for 2 destination cities
# Initialize Z3 solver s
# Set 'city' variable to be indexes of 2 destination cities
# If city_0_index and city_1_index are not same, assert 2 'city' variables equal to city index

# Departure dates #
# Set 'departure_dates' variables for 3 transportations between cities
# Assert first transportation happens at first day (day 0), last transportation happens at last day (day 4), and second transportation could happen at any day in between

```
# Transportation methods #
# Set transportation method (flight) variable for 3 transportations between cities
# Assert all 3 transportations between cities are flight

# Flight information #
# Run FlightSearch to get flight info for Hong Kong as origin, city_0 and city_1, and dates
# Get specific flight price info with Hong Kong as origin and final destination, specific city variable,
and departure date for 3 transportations
# Set ’flight_index’ variable for 3 transportations
# Assert 3 ’flight_index’ variables are within valid range if taking flight, assert flight index to be -1
if not taking flight
# Calculate flight price for 3 people for 3 transportations based on flight index variable
# Get specific flight arrival time info with Hong Kong as origin and final destination, specific city,
and departure date for 3 transportations
# Calculate flight arrival time for 3 transportations based on flight index variable
# For each ’flight_index’, get specific flight rule and airlines info, assert ’non-stop’ exist for all
flights, assert ’United’ or ’Emirates’ exist for all flights

# Attraction information #
# Get arrivals and city list for each day based on 3 transportations, 5 total travel day, and departure
dates variables
# Run AttractionSearch to get attraction info for city_0 and city_1
# Set ’attraction_in_which_city’ variables for 5 (1 per day) attractions
# For each ’attraction_in_which_city’ variable, assert it to be either current city or next city based
on transportation arrivals time
# Set ’attraction_index’ variables for 5 (1 per day) attractions
# For each ’attraction_index’, get specific length info based on attraction in which city variable,
assert index are within valid range, and attrations in same city are not repeated
# Set ’attraction_category’ variables for each category required
# For each category, iterate through all attraction to check if it is satisfied

# Restaurant information #
# Set restaurant price to be 30 per person per meal, calculate total restaurant price for 3 people for
5 days

# Accommodation information #
# Set accommodation price to be 100 per person per night, calculate total accommodation price for
3 people for 4 nights

# Budget #
# Set budget limit variable to be 5000
# Add 3 transportation price to spent, according to whether transportation method is flight
# Add restaurant price to spent
# Add accommodation price to spent
# Assert current spent is within budget
```

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