ChinaTravel: An Open-Ended Benchmark for Language Agents in Chinese Travel Planning

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Abstract

Recent advances in LLMs, particularly in language reasoning and tool integration, have rapidly sparked the *Language Agents* for real-world development. Among these, travel planning represents a prominent domain, combining complex multi-objective planning challenges with practical deployment demands. However, existing benchmarks often oversimplify real-world requirements by focusing on synthetic queries and limited constraints. We address the gap of evaluating language agents in multi-day, multi-POI travel planning scenarios with diverse and open human needs. Specifically, we introduce *ChinaTravel*, the first open-ended benchmark grounded in authentic Chinese travel requirements collected from 1,154 human participants. We design a compositionally generalizable domain-specific language (DSL) for scalable evaluation, covering feasibility, constraint satisfaction, and preference comparison. Empirical studies reveal the potential of neuro-symbolic agents in travel planning, achieving a 37.0% constraint satisfaction rate on human queries, a 10× improvement over purely neural models. These findings highlight ChinaTravel as a pivotal milestone for advancing language agents in complex, real-world planning scenarios.

1 Introduction

A long-standing goal in AI is to build planning agents that are reliable and general, capable of assisting humans in real-world tasks. Recently, LLMs [3, 19, 1] have demonstrated remarkable potential in achieving human-level understanding and reasoning capabilities. This has sparked the rapid development of *Language Agents*, which employ LLMs to perceive the surroundings, reason solutions, and take appropriate actions, ultimately building autonomous planning agents [22, 30, 26, 13]. Among numerous real-world planning tasks, travel planning stands out as a significant domain, presenting both academic challenges and practical value due to its inherent complexity and real-world relevance. Specifically, given a query, agents require information integration from various tools (e.g., searching for flights, restaurants, and hotels) to generate a feasible itinerary. This involves making interdependent decisions across multiple aspects such as spatial, temporal, and financial dimensions, all while meeting the user's requirements and preferences (e.g., budget, dining habits, etc).

To evaluate the existing language agents on real-world travel planning tasks, Xie et al. [27] first provide a pivotal benchmark TravelPlanner [27]. However, it exhibits two critical limitations: (1) Task bias (U.S.-centric intercity itineraries vs. common but more complex single-city multi-day trips). (2) Synthetic query construction (limited requirements and templated expressions vs. real human travel queries which are diverse and open-ended). Just a few months after the benchmark's release, Hao et al. [12] proposed a neural-symbolic solution that integrates formal verification tools into agents, achieving a 97% success rate. This underscores the oversimplification of the TravelPlanner.

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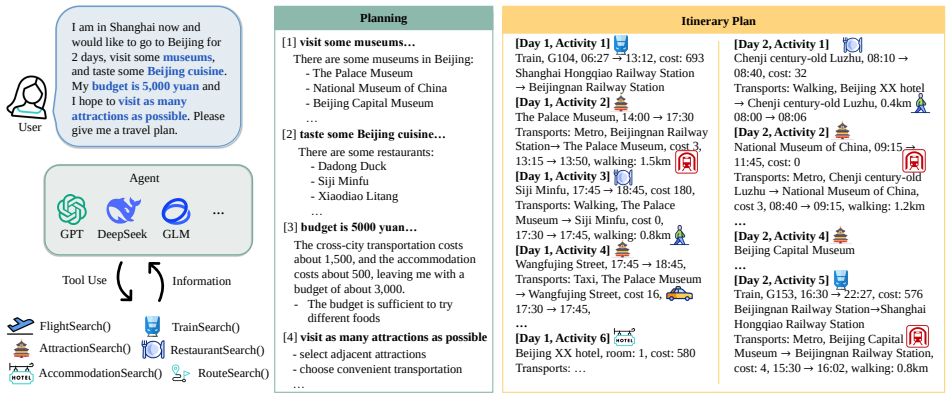


Figure 1: **Overview of ChinaTravel**. Given a query, language agents employ various tools to gather information and plan a multi-day multi-POI itinerary. The agents are expected to provide a feasible and reasonable plan while satisfying the **logical constraints** and **preference requirements**.

To address the gap, we introduce ChinaTravel, an open-ended travel planning benchmark. It concentrates on multi-point-of-interest (multi-POI) itineraries (as illustrated in Fig. 1) and supports the compositional constraints evaluation with authentic Chinese travel queries. It is more realistic and challenging, providing a new milestone for real-world travel planning. The main contributions are:

- **Comprehensive Evaluation Framework:** ChinaTravel provides a rich sandbox with authentic travel data, a domain-specific language for scalable requirements formulation and automated evaluation, and diverse metrics covering feasibility, constraint satisfaction, and preference ranking.
- **Integration of Synthetic and Human Data:** ChinaTravel integrates both LLM-generated and human-authored queries to create realistic evaluation scenarios. The validation set contains 154 human queries with combinatorial constraint requirements absent from synthetic data, while the test subset provides 1,000 open-scenario queries. This structure specifically assesses agents' generalization capabilities across unseen constraint composition.
- **Empirical Neuro-Symbolic Insights:** Extensive experiments are conducted and the results reveal that neuro-symbolic agents significantly outperform pure LLM-based solutions on constraints satisfaction, achieving a constraint satisfaction rate of 27.9% compared to 2.60% by purely neural methods, thus highlighting their promise for travel planning tasks.
- **Identified Challenges for Future Research:** We pinpoint key challenges of open-world requirements: open contextual reasoning, and unseen concept composition, providing a foundation for advancing agents toward real-world applicability.

Overall, ChinaTravel provides a multi-dimensional benchmark that rigorously assesses travel planning capacity, serving as a critical bridge between academic research and practical applications.

2 ChinaTravel Benchmark

Motivated by China's substantial travel demand, ChinaTravel provides a sandbox environment for generating multi-day itineraries with multiple POIs across specified cities. It is meticulously designed to provide a comprehensive and scalable evaluation framework in travel planning, encompassing three critical dimensions: environmental feasibility, constraint satisfaction, and preference comparison.

2.1 Environment Information

ChinaTravel provides a sandbox with real-world travel information. We collect information from 10 of the most popular cities in China. It includes 720 airplanes and 5,770 trains connecting these cities, with records detailing departure and arrival times, origins, destinations, and ticket prices. Additionally, the dataset contains 3,413 attractions, 4,655 restaurants, and 4,124 hotels, each annotated with name, location, opening hours, and per-person prices. Type annotations for these POIs are included to meet

Table 1: ChinaTravel's Domain-Specific Language (DSL) for logical constraints.

Name	Syntax	Description
variables	$x, y, z, \cdots$	Variables that refer to activities in the travel planning domain.
not	$not\ expr$	The negation of an Boolean-valued expression.
and,or	$expr_1\ and\ expr_2$	The conjunction/disjunction of an Boolean-valued expression.
$<, >, ==$	$expr_1 < expr_2$	Return an expression with built-in number comparison functions.
$+, -, *, /$	$expr_1 + expr_2$	Return an expression with built-in number calculation functions.
attributes	$cost(var)$	A function that takes activities as inputs and returns the attributes, such as cost, type or time.
relation	$dist(expr_1, expr_2)$	A function that takes locations as inputs and returns the distance.
effect	$var = expr$	An assignment affects a variable var with the expression $expr$.
union, inter, diff	$uni(\{var\}_1, \{var\}_2)$	Return a set with the built-in union/intersection/difference operations of given two sets.
enumerate	$for\ var\ in\ \{var\}$	Enumerate all variables in the collection $\{var\}$.
when	$if\ expr : effect$	The conditional effect takes a Boolean-valued condition of the expression $expr$, and the effect *effect*.

```
# Dining expenses <= 1000 CNY.
dining_cost = 0
for act_i in allactivities(plan):
  typ = activity_type(act_i)
  if typ=="breakfast" or typ=="lunch"
or typ=="dinner": dining_cost =
dining_cost + activity_cost(act_i)
return dining_cost <= 1000
```

(a) Dining expenses.

```
# Arriving in Shanghai should be before
6 PM on the second day.
return_time = 0
for act_i in day_activities(plan, 2):
  typ = activity_type(act_i)
  dest = transport_destination(act_i)
  if (typ=="train" or typ=="airplane")
and des=="Shanghai": return_time ==
activity_endtime(act_i)
return return_time < "18:00"
```

(b) Arrived Time.

```
# The number of attractions visited
count = 0
for act_i in all_activities(plan):
  if
activity_type(act_i)=="attraction":
count = count + 1
return count
# Compare the return during evaluation
of preference ranking
```

(c) Count of attraction visited.

Figure 2: Examples of DSL expressions for logical constraints and preference ranking.

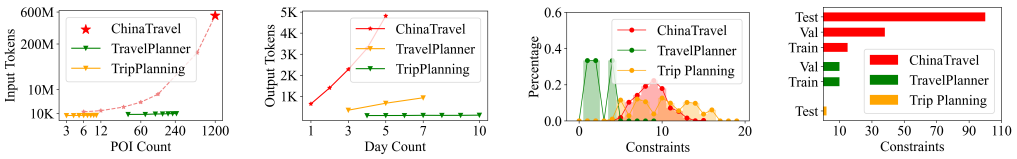
user needs. For a realistic interaction, we simulate the API interface of real market applications to query real-time information. We present 25 environmental constraints across six categories: Dietary, Accommodation, Transportation, Temporal, Spatial, and Attractions. The detailed designs of the sandbox are available in App. D.1. It acts as a feasibility metric, ensuring that the generated plans are both valid and effective. For example, POIs in the plan must exist in the designated city, transportation options must be viable, and time information must remain accurate.

2.2 Logical Constraint

A crucial ability for travel planning is to effectively satisfy personalized user needs. We extend the form of logical constraints from TravelPlanner [27] and present a Domain-Specific Language (DSL) to support general compositional reasoning in logical constraints. ChinaTravel's DSL is a general set of pre-defined concept functions with built-in implementations, as listed in Tab. 1. TravelPlanner relies on 5 pre-defined concepts {total budget, room rules, room types, cuisines, and transportation types}, to evaluate the logical constraints, where each concept is equivalent to a specific logical requirement. We find this design limits the ability to validate diverse logical needs in an open-world context. For example, it cannot express that the dining expenses should be within 1000 CNY or that arriving in Shanghai should be before 6 PM on the second day, despite the generated plan already including the expenses and time information of each activity. Each new logical requirement necessitates human intervention for incremental definition. To address this issue, our approach is grounded in a DSL-based solution that leverages basic concept functions and syntax to express and fulfill various logical requirements. Fig 2a and 2b present two examples, the DSL can represent varying requirements through concept composition in a Python format, and perform automated validation of plans using a Python compiler. This strategy maximizes the evaluation capability of the ChinaTravel. In App. D.2, we provide a detailed tutorial on DSL expression with more examples.

2.3 Preference Requirement

Travel requirements encompass not only hard logical constraints but also soft preferences. The term "soft" implies that these preferences cannot be addressed as boolean constraint satisfaction problems, instead, they involve quantitative comparisons based on continuous values. This distinction



(a) Token count across different benchmarks.

(b) Constraints across different benchmarks.

Figure 3: (a) ChinaTravel's fine-grained spatiotemporal planning demands extremely larger input/output text volumes than existing benchmarks, posing fundamental challenges to text-wise planning. (b) ChinaTravel's authentic requirements, with combinatorial scalable constraints formulation, systematically surpasses conventional closed-form benchmarks in diversity and openness.

highlights the unique nature of preference-based requirements compared to logical constraints. Common preferences identified through surveys include maximizing the number of attractions visited, minimizing transport time between POIs, and visiting positions near the specific POI, among others. In ChinaTravel, we formalize such preferences as minimization or maximization objectives via our DSL, thereby providing an automated evaluation. Fig. 2c provides a detailed case of DSL expression for maximizing the attractions visited.

2.4 Benchmark Construction

ChinaTravel provides user queries reflecting diverse requirements through a four-stage process:

Stage I: Manual design of database and APIs. We collect travel information for multi-day, multi-POI itineraries across attractions, accommodations, and transportation. We define essential POI features, such as cuisine types and hotel characteristics, to construct the database from public information. APIs are designed to support agent queries via regular expressions and modeled after commercial APIs to ensure realism. See App. D.1 for details.

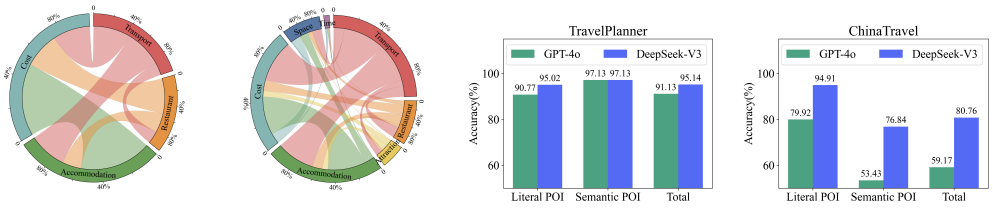
Stage II: Automatic data generation with LLMs. We model travel tasks with core parameters (origin, duration, etc.) and logical constraints. For scalable generation, we randomly construct query skeletons converted to natural language via DeepSeek-V2.5. Queries are stratified by complexity: *Easy* (1 extra constraint), with LLM-generated varying expressions (encouraging "Try local Beijing food"→"Taste Beijing cuisine"). See App. D.3 for synthesis details.

Stage III: Quality control and auto-validation. To ensure data quality, we manually check if the generated query conform to symbolic skeletons, and re-calibrate natural language description that contain ambiguities. Based on the symbolic skeletons, we verify if the plan can pass the required logical constraints by executing the DSL code via Python compiler. Building on this, we ensure that each query has at least one solution that satisfies the logical constraints via heuristic search.

Stage IV: Open requirements from humans. After the first round of closed-loop development with LLMs, including data generation and annotation, baseline development, and evaluation, we gathered over 250 human requirements via questionnaires. Rigorous quality control yielded 154 queries with novel constraints (e.g., departure time/dining cost), constructing the Human-154 validation set with DSL-annotated automated evaluation. Subsequent scaling through WJX (survey platform) yielded the *Human-1000* test set after analogous quality control and DSL annotation.

3 Benchmark Characteristics

Context-Rich Long-Horizon Planning. ChinaTravel poses unprecedented contextual complexity in travel planning compared to existing benchmarks, NaturalPlan [33] and TravelPlanner [27]. As quantified in Fig. 3a, (1) Processing over 1,200 candidate POIs per query (4× TravelPlanner's 244 max, 120× Trip Planning's 10) with detailed square order transportation. (2) Generating 540M contextual tokens from dense POI networks, surpassing both DeepSeek-V3 (64K) and GPT-4o (128K) capacities, even aggressive 6-POI downsampling retains 40K tokens (Fig. 3a). (3) Requiring 4.8K output tokens for 5-day plans, versus 0.9K (TravelPlanner's 7-day) and 0.5K (Trip Planning's 30-day) [31]. These findings necessitate a paradigm shift: the traditional single-pass text generation approach proves inadequate for such ultra-long-horizon planning tasks [31]. Effective solutions may



(a) TravelPlanner (b) ChinaTravel (c) POI Reasoning

Figure 4: Co-occurrence distribution of differnt constraints on TravelPlaner (a) and ChinaTravel's Human1000 (b). (c) The unsatisfactory performance of advanced LLMs on the auxiliary task, POI reasoning, reveals the challenges of open contextual reasoning in ChinaTravel's dataset.

require agents to adopt human-like hierarchical decomposition or symbolic planning techniques, iteratively executing subtasks to achieve final planning objectives through multi-step decisioning.

Diversity and Openness of Travel Requirements. ChinaTravel surpasses TravelPlanner and NaturalPlan in diverse requirement modeling. As Fig. 3b shown: (1) Constraint volume: ChinaTravel exhibits Gaussian-style distribution (6-12 constraints per query) versus TravelPlanner's simplicity bias ($\leq$5 constraints) and TripPlanning's limited diversity (16 max constraints but only 2 types). (2) Combinatorial capacity: TravelPlanner's atomic constraints yield merely 10 combinations, while ChinaTravel scales exponentially from 15 (synthetic) to 100 types (human1000 test), including 88 novel constraints formulated through Tab. 1's compositional system. We further investigate co-occurrence patterns of constraint types within individual queries, we categorize basic concepts in our DSL into seven clusters as visualized in Fig. 4b. The constraint co-occurrence distribution in ChinaTravel follows Zipf's law [2] with a characteristic long-tail pattern, contrasting sharply with TravelPlanner (Fig. 4a), whose synthetic data demonstrates relatively uniform frequencies. We could also find a strong correlation between cost-related constraints and transportation/accommodation requirements, which aligns with common sense, because transportation and accommodation typically constitute primary cost components. These characteristics stem from systematic user studies integrating open-ended travel requirements' evolving nature into our benchmark. Users continually raise novel composite constraints which are inexhaustible during developing, enhancing the challenges while ensuring verifiability through Section 3.2's verification framework, posing fundamental challenges for agents to achieve human-like composite reasoning.

Open Contextual Reasoning. From human queries, we could find that travel requirements often exhibit contextual ambiguity not directly aligned with predefined database attributes. For instance, when users express requirement for "local cuisine", which contextually maps to Benbang cuisine in Shanghai versus Beijing cuisine in Beijing. Another representative case involves users specifying "traveling with children who cannot eat spicy food",requiring agents to logically exclude Sichuan and Chongqing cuisines from restaurant selections, beacuse both of them are well-known as the spaicy style. These observations arise the necessity for real-world travel agents to conduct open contextual reasoning that bridges arbitrary user expressions with verifiable symbolic semantics in databases, a evaluation capability inadequately supported by existing synthetic benchmarks like TravelPlanner. To systematically investigate this challenge, we designed a auxiliary task, POI reasoning, within ChinaTravel. It involves replacing all Chinese POIs in DSL-defined constraints with a <placeholder> tags, requiring LLMs to complete masked-DSL sentences through contextual reasoning. This simplified formulation isolates POI inference from full DSL generation. We further categorize POIs as Literal (explicitly mentioned in user queries) or Semantic (requiring cultural/contextual inference). Quantitative analysis shows 78.4% of DSL statements from Human1000 contain Semantic POIs needing implicit reasoning, contrasting sharply with TravelPlanner's 5.4% rate that predominantly requires literal mapping. Experimental results from DeepSeek-V3 and GPT-4o are shown in Fig. 4c. Both models achieve the accuracy over 90% on TravelPlanner, where semantic POIs follow simplistic synthetic patterns. However, on ChinaTravel's authentic Semantic POIs, performance significantly declines (DS: 94% $\rightarrow$ 76%, GPT: 79% $\rightarrow$ 53%). This performance gap underscores the benchmark's crucial open contextual understanding challenges for real-world travel planning.

4 Empirical Study

LLMs. We evaluate the state-of-the-art LLMs, DeepSeek-V3, OpenAI GPT-4o, recognized for their world-leading performance. We also examine the open-source LLMs, Qwen3-8B, Llama3.1-8B, and Mistral-7B, selected based on their computationally efficient 7B/8B architectures, which enables practical deployment in resource-constrained academic computing environments.

Metrics. We examine the Delivery Rate (DR), Environmental Pass Rate (EPR), Logical Pass Rate (LPR), and Final Pass Rate (FPR) from TravelPlanner [27]. To address potential evaluation biases caused by unrealistic constraint prioritization, e.g., misreporting costs to satisfy budget requirements, we design a novel metric, **Conditional Logical Pass Rate (C-LPR)**. It assesses the success rate of travel plans that ***first satisfy environmental constraints*** before meeting logical requirements, thereby ensuring logical validity within realistic contextual boundaries. The introduction of C-LPR provides a more rigorous viewpoint for quantifying meaningful constraint satisfaction in travel planning.

$$C\text{-}LPR = \frac{\sum_{p \in P} \mathbb{1}_{passed(Env,p)} \cdot \sum_{c \in C_p} \mathbb{1}_{passed(c,p)}}{\sum_{p \in P} |C_p|}$$

P is the plan set, C_p is the constraints set for plan p, and passed(c, p) indicates whether p satisfies c.

Methods. In this work, we mianly focus on the training-free methods with both pure-LLM-based and neuro-symbolic solutions on the ChinaTravel benchmark. For the former category, we implement ReAct [30], a widely-adopted reasoning-and-acting framework, along with its Act-only ablation variant. We exclude Reflexion [22] due to its performance being similar to ReAct on the TravelPlanner [27] and the high economic overhead associated with the larger input token size. For neuro-symbolic methods, we assess three frameworks: (1) TTG [14], which converts natural language requirements into mixed-integer linear programming formulations for solver-based optimization. We adapt their formulation into ChinaTravel. The rapied growth of transformed constraints in TTG becomes computationally prohibitive. To address this, we employ LLMs to extract the most relevant POIs for constraint reduction, with detailed linear constraint formulations and experimental configurations provided in App. K. (2) LLM-modulo [15, 9], employing ground-truth symbolic verification to guide iterative LLM self-refinement, which could be regrad as an enhanced variant of Reflexction. To ensure compatibility with mainstream LLMs, we perform POI subsampling within a 64K context window. (3) NeSy Planning, extending prior NeSy pipelines [12, 20, 29, 28] through our DSL enhancements to address complex multi-day, multi-POI itineraries.

4.1 Neuro-Symbolic Planning

This subsection presents a NeSy solution as a preliminary baseline for ChinaTravel. This solution consists of two stages. **(I) NL2DSL translation** transforms natural language queries into logic and preference DSL requirements. We use Reflexion [22] and a DSL syntax checker to iteratively assist the LLMs (5 rounds in experiments). **(II) Interactive search** uses a neuro-symbolic solver to sequentially arrange activities, guided by a symbolic sketch and LLM-driven POI recommendations, generating a multi-day itinerary with DSL validation. If constraints are violated, the process backtracks until a feasible solution is found. To ensure fairness, the symbolic sketch search is limited to 5 minutes per query, excluding LLM inference time. To observe the performance across the two stages, we also evaluated the planning results based on the Oracle DSL. In App. F, we provide the search algorithm's pseudo-code and LLM prompts to enhance reproducibility and support future research.

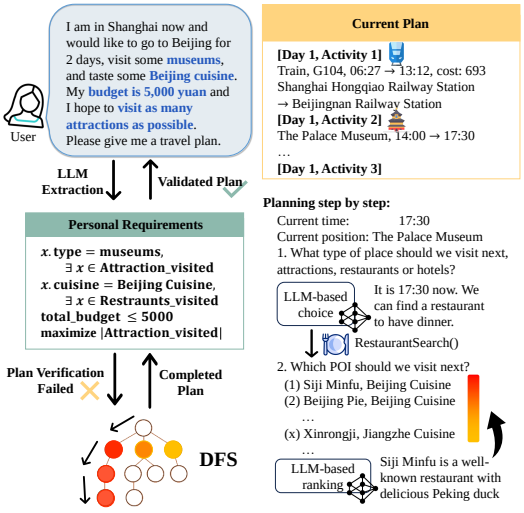


Figure 5: NeSy Planning with search-based solver.

Table 3: Main results of different LLMs and planning strategies on the ChinaTravel benchmark.

		DR	EPR		LPR		C-LPR	FPR	DR	EPR		LPR		C-LPR	FPR
			Mic.	Mac.	Mic.	Mac.				Mic.	Mac.	Mic.	Mac.		
		Easy (#300)							**Human-Val (#154)**						
Act		70.4	49.9	0	64.6	30.8	0	0				-			
		97.5	70.8	0	86.8	68.8	0	0				-			
ReAct (zero-shot)		43.3	40.8	0	41.9	19.6	0	0	36.4	29.5	0.65	35.2	16.2	0.38	0
		95.4	48.2	0	71.3	32.9	0	0	**96.1**	50.5	0	**72.4**	32.5	0	0
ReAct (one-shot)		77.5	68.3	6.25	74.1	52.5	5.77	5.42	55.2	**57.3**	2.60	64.6	44.2	1.71	2.60
		94.2	68.1	0	**89.4**	**70.8**	0	0	69.5	46.3	0	63.6	46.8	0	0
NeSy Planning		75.3	**75.3**	75.3	70.4	52.6	70.4	52.6	51.9	53.2	52.5	47.0	**37.6**	46.5	**37.0**
		75.0	73.6	**64.0**	73.5	63.3	**61.7**	**60.6**	45.4	50.1	45.4	40.9	29.8	**38.5**	27.9
		72.3	67.0	34.0	70.4	49.6	32.6	28.3	42.8	47.4	42.2	36.2	27.2	34.4	25.3
		32.0	31.9	31.3	29.1	21.0	28.3	21.0	25.9	25.8	24.0	22.3	12.3	20.5	11.0
		30.3	30.3	30.3	27.6	19.6	27.6	19.6	37.6	38.2	37.6	32.7	18.8	32.2	18.8
TTG (oracle)		18.3	21.5	8.66	17.2	15.0	8.23	8.66	9.09	12.8	2.59	7.65	5.19	2.39	1.29
LLM-Modulo* (Oracle Verifier)		48.3	94.5	4.33	58.4	43.6	4.11	4.33	61.6	90.2	2.59	75.9	51.2	2.75	2.59
		91.6	88.2	7.66	**95.5**	**84.6**	7.66	7.00	91.5	87.2	3.24	**92.9**	**66.2**	2.87	3.24
		30.0	80.5	0.0	62.7	25.0	0.0	0.0	35.0	75.3	0.0	61.6	19.4	0.0	0.0
		28.6	69.4	0.0	55.2	8.33	0.0	0.0	19.4	74.1	0.0	43.4	5.19	0.0	0.0
		10.3	90.5	0.0	39.1	9.0	0.0	0.0	3.24	**92.2**	0.0	31.4	4.54	0.0	0.0
NeSy Planning* (Oracle Translation)		**82.6**	**81.7**	**75.0**	**82.2**	75.3	**75.0**	**74.0**	**58.4**	59.6	**57.7**	53.8	46.1	**52.0**	**45.4**
		66.6	66.7	66.0	64.6	63.6	64.6	62.6	52.6	46.9	42.9	47.6	40.9	43.9	40.9
		69.3	69.3	59.3	70.2	59.6	59.3	57.9	53.2	55.1	54.5	48.0	42.8	47.6	40.9
		52.6	52.6	52.6	50.4	45.3	50.4	45.6	40.9	42.8	42.8	37.7	28.5	37.7	27.9
		33.3	33.2	32.6	32.1	32.0	31.4	32.3	29.2	29.1	26.6	25.4	20.1	23.4	19.4
		Human-Test (#1000)							NeSy Planning* (Oracle Translation)						
NeSy Planning		**44.6**	**44.5**	**42.6**	**38.7**	**23.3**	**37.6**	**23.3**	**60.6**	**60.3**	**59.0**	**53.6**	**32.0**	**52.5**	**31.6**
		37.3	37.2	35.0	30.7	11.3	29.2	11.3	27.8	27.8	27.1	24.8	12.8	24.4	12.8
		36.6	36.5	34.6	29.6	6.43	28.5	6.43	41.1	41.1	40.6	34.6	13.8	34.2	13.8

4.2 Main Results

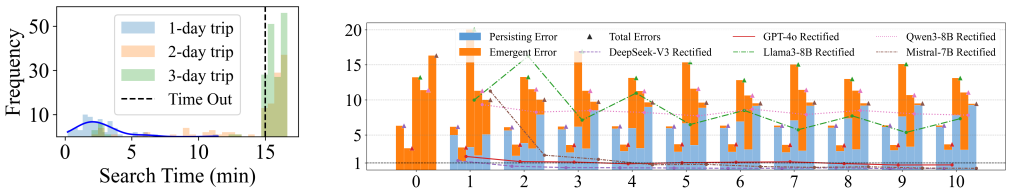
Table 2: Cost per query across different methods.

Method	#Input	#Output	($)	($)
Act	88K	2K	007	.219
ReAct (0-shot)	206K	3K	.021	.638
ReAct (1-shot)	1058K	4K	.081	2.43
LLM-modulo	362K	11K	.025	1.12
NeSy Planning	467K	3K	.003	.306

Based on the results presented in Table 3 and 2, we have the following finding and analyses:

Pure LLMs struggle in ChinaTravel. The DR evaluates agents' capability to generate valid JSON travel plans (see Fig. 1). While high DR values indicate that state-of-the-art LLMs can produce structurally correct outputs, the near-zero EPR reveals their fundamental limitations in acquiring and strictly adhering to required constraints. The sole exception is the DeepSeek model, which achieves the 6% EPR and 5% FPR at easy level, likely due to its strong capability to follow Chinese requirements. ReAct (one-shot, GPT-4o) excels in Macro LPR but achieves no FPR, suggesting it circumvents constraints via shortcuts. Our proposed C-LPR metric offers a more reliable measure of logical constraints, serving as a supplement to FPR. As shown in Table 2, pure neural methods incur prohibitively high computational costs due to excessive token consumption. When powered by GPT-4o, each query incurs $2.4 on average, yet these approaches fail to produce any constraint-satisfying plans.

The Inadequacies of Existing NeSy Approaches. The fundamental limitation of TTG arises from its computational complexity, where the constraint count scales as $O(N^3T)$ with N POIs and T time



(a) Solution Time of TTG.

(b) Refinement of LLM-modulo.

Figure 6: (a) The high computational complexity of TTG renders it infeasible for real-world multi-day itineraries. (b) LLM-modulo's error correction declines during iteration, causing emergent errors.

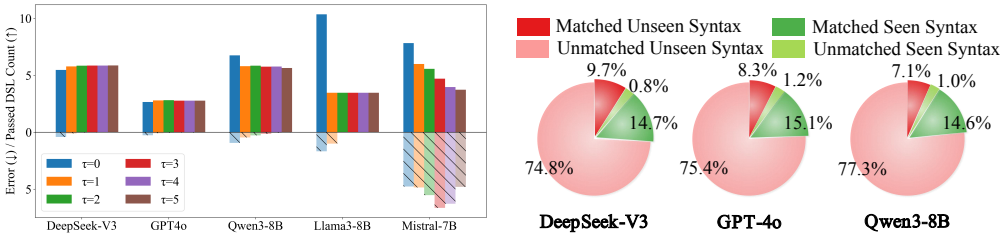
windows. Even when subsampling to 22 POIs and discretizing time into 1-hour slots ($T = 24$), the system generates approximately 600,000 constraints for 2-day itinerary. In our main experiments using the SCIP solver from the PuLP package, TTG was allocated a relaxed 15-minute search limitation. However, this configuration yielded only 18% valid solutions on easy-subet instances, with the FPR further reduced to 8% due to the solver's pruning heuristics. Fig. 6a illustrates the solution time of TTG on 1-3 day itinerary. Within the time limit, solutions were found for merely 23% for two-day and 6% for three-day itineraries.

LLM-modulo introduces a oracle symbolic verifier and feedback the error to LLM to refine the plan. As illustrated in Fig. 6b, which depicts the error dynamics across 10 refinement iterations, GPT-4o maintains the lowest cumulative error count ($\mu = 3.2 \pm 0.8$), followed by DeepSeek ($\mu = 5.1 \pm 1.2$). However, their rectification capacity, quantified by successfully rectified errors per iteration rapidly decays to ≤ 1 after 3-5 rounds, indicating diminishing returns in error correction. Notably, smaller models (Qwen3-8B and Llama3-8B) achieve higher rectification, but this comes at the cost of introducing substantial emergent errors. The error reduction remains statistically insignificant across these models. This pattern suggests that while LLM-modulo enables basic constraint feedback from previous travel benchmarks [33, 27], its effectiveness diminishes for complex multi-day itineraries.

Nesy Planning provides a promising solution. Our NeSy Planning framework integrates symbolic programs to orchestrate travel planning and tool management while utilizing LLMs to extract language-based requirements and prioritize POIs. By separating understanding (flexible natural language handling), planning (DSL-guided backtrack) and grounding (precise execution), the framework enhances adaptability and ensures compliance with constraints during context-rich long-horizon planning. Across all data subsets, it outperforms previous TTG and LLM-modulo mthods, even without the help of oracle translation. Among the evaluated LLMs, DeepSeek-V3 achieves state-of-the-art performance across three subsets. With DeepSeek-V3 as the backend, it achieves FPRs of 52.6%, 37.0% and 23.3% on three subsets, highlighting the effectiveness of NeSy solutions for travel planning with complex constraints. Moreover, this superior performance demonstrates its enhanced capability for inter-constraint generalization in compositionally novel situations. Another potential explanation is that the model is developed by a Chinese company. As a result, it has been trained on a vast amount of Chinese-language data. This extensive exposure to Chinese text has enabled it to perform exceptionally well in our Chinese travel planning scenarios, giving it advantages over others.

Challenges Persist for Nesy Planning. The performance gap between standard and oracle modes underscores the importance of DSL translation in NeSy planning. Inadequate translations may result in plan searches failing to meet user requirements, while incorrect translations can misguide the search, making feasible solutions unattainable.

We conclude with three challenges and provide the corresponding cases in the Fig. 7. **(1) DSL Syntax Compliance**: As evidenced in Fig. 7a, while the reflexion process with syntactic validation effectively reduces surface-level errors, it inadvertently triggers constraint deletion behaviors across multiple LLMs. Specifically, Qwen3-8B, Llama3-8B, and Mistral-7B exhibit progressive reduction in extracted DSL constraints during iterative refinement. Notably, GPT-4o generates approximately two fewer constraints per iteration than DeepSeek-V3 on average. Although this conservative strategy enables rapid error convergence (achieving zero detected errors within limited iterations), it risks oversimplifying constraint specifications, critical dependencies may be prematurely discarded, ultimately yielding solutions that fail to satisfy complex requirements. This observed conservatism



(a) Syntax error of DSL translation.

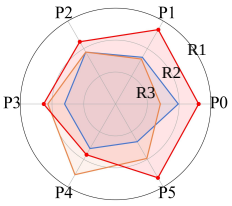
(b) Syntax generalization of DSL translation.

Figure 7: Challenges in NL2DSL translation.

toward unseen constraints likely contributes to GPT-4o's relative performance gap on the Human-154 and Human-1000 benchmarks compared to DeepSeek-V3. **(2) Open Contextual Reasoning**: In the Section 3 we have provided a quantitative analysis. In App. D.2, more examples are provied for this challenges. **(3) Unseen Concept Composition**: Real-world requirements are inherently diverse and complex, making expecting models to encounter all possible needs during development impractical. A more feasible way is to emulate human reasoning by generalizing existing knowledge to novel problems. Fig. 7b compares three LLMs on seen vs unseen DSL structures under POI-anonymized evaluation with syntax-level pattern matching. Results reveal critical gaps: 84% novel DSLs show only 12% alignment (9% overall), vs 93% accuracy on 16% known patterns. GPT-4o and Qwen3 also demonstrate this limitation, excelling on same concepts but failing on novel compositions.

In summary, ChinaTravel poses significant challenges for current agents. Neuro-symbolic agents outperform pure-LLM approaches in constraint satisfaction, showing strong potential for real-world travel planning. With realistic queries and a versatile DSL for constraint validation, we highlight the critical challenges while providing a foundation for advancing neuro-symbolic systems in practice.

4.3 Ablation Study with Preference



NeSy Planning	BQ	PEQ	PDS
Daily attractions ↑	0.75	0.79	**1.63**
Transport time ↓	27.0	26.9	**24.8**
Transport time to rest. ↓	**22.2**	26.8	22.8
Food cost ratio ↑	0.19	0.29	**0.32**
Hotel cost ↓	1350	559	**519**
Distance to POI ↓	30.9	30.6	**26.1**

Figure 8: Ablation on preference ranking.

The comparison of preferences should be conducted under the premise that both environmental and logical constraints are satisfied. Given the limited FPR achieved by existing methods, we perform a separate analysis of preference optimization here. Specifically, we sampled 50 queries from the easy subset that NeSy-DeepSeek-Oracle successfully passed as seed samples. Based on these, six subsets were created by introducing common preferences identified from user surveys. Three comparative scenarios were designed to explore the roles of LLMs and symbolic search in optimizing preferences during NeSy Planning: (1) BQ: Baseline solutions without preference consideration. (2) PEQ: LLM-enhanced recommendations with natural language preferences. (3) PDS: Hybrid symbolic search optimizing preference objectives under 5-min constraints. The results are provided in Fig. 8 (where ↑ /↓ indicate maximization/minimization). We cound find that: (1) PEQ outperforms BQ in 5/6 preference scenarios, confirming LLMs' capacity to interpret natural language preferences during POI ranking. (2) PEQ underperforms on P2 (transport time minimization), likely from LLMs' misinterpretation of complex spatiotemporal constraints. These results support the scalability of DSL in preference optimization but also highlights the pressing need for more efficient algorithms.

5 Conclusion

We present ChinaTravel, a benchmark for multi-day multi-POI travel planning focused on authentic Chinese needs. We address the limitations of previous benchmarks by incorporating open-ended and diverse human queries, capturing real-world user needs. Additionally, we propose a scalable evaluation framework based on DSL, enabling comprehensive assessments of feasibility, constraint satisfaction, and preference comparison. These advancements provide a foundation for developing language agents capable of meeting diverse user requirements and delivering reliable travel solutions.

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Contents

A Limitations

Our research represents a significant step forward in evaluating the travel planning capabilities of language agents, but it is not without challenges. One limitation lies in its focus on Chinese travel planning. Due to the inherent differences in natural language, the translated versions of queries may fail to fully capture the challenges of understanding requirements in Chinese queries, potentially limiting its applicability in a global context. However, given the substantial demand within China's travel market, we believe a benchmark tailored to Chinese travel planning is both necessary and socially valuable. Although our benchmark is comprehensive, it may not encompass the full range of requirements encountered in real-world scenarios. The high cost of collecting authentic data has limited the number of human queries in our study. To address this, future work will focus on combining LLMs with real user queries to automate the generation of a wider variety of human-like queries. Continuous refinement and expansion of our benchmark are crucial for more accurately reflecting the realistic travel planning needs.

B Broader impacts

The ChinaTravel benchmark primarily serves as a foundational research tool to evaluate language agents in complex, real-world travel planning scenarios. By providing an open-ended benchmark grounded in authentic Chinese travel requirements, this work aims to advance the development of reliable and generalizable AI systems for practical planning tasks. Its positive societal impacts include: (1) Improved Travel Planning Efficiency: By rigorously testing agents' ability to handle multi-day itineraries and combinatorial constraints, this benchmark encourages the creation of more robust AI assistants, potentially reducing the time and effort users spend on organizing trips. (2) Validation for Real-World Applications: The benchmark establishes a critical foundation for deploying language agents in practical travel planning settings, where multi-objective planning and constraint satisfaction are essential. (3) Promotion of Open Research: The release of this benchmark bridges cutting-edge LLMs with classical neuro-symbolic AI paradigms, fostering cross-disciplinary collaboration between academia and industry. It promotes the reliable, constraint-aware AI systems, while accelerating innovation in both foundational planning capabilities and real-world deployment scenarios.

Potential negative impacts largely depend on how future systems built upon this benchmark are deployed. For instance: (1) Bias and Fairness: If agents inherit biases from training data or misalign with diverse user preferences, they might disproportionately recommend certain POIs or services. Mitigation requires ongoing fairness audits and inclusive data practices. (2) Misuse Risks: Malicious actors could exploit highly capable planning agents to generate deceptive itineraries or manipulate travel services. Such risks underscore the need for ethical guidelines and safeguards in downstream applications. As a benchmark, ChinaTravel itself does not directly deploy agents but focuses on evaluation. Its design emphasizes transparency, verifiability, and scalability, aligning with broader efforts to ensure AI systems are both effective and controllable. Future work should prioritize responsible use, including robust validation of real-world systems and addressing socio-technical challenges like bias mitigation and user privacy.

C Discussion with Related Work

LLM-based Agents have demonstrated significant capability in understanding complex instructions and employing domain-specific tools to complete tasks, showcasing their potential in fields such as visual reasoning [10], healthcare [32] and robotics [16]. This reduces the reliance of previous agents on domain-specific efforts, that is, either mainly following domain-specific rules to plan (rule-based agents, such as DeepBlue [4] and Eliza [21]) or mainly learning from domain-specific data to plan (reinforcement-learning-based agents, such as AlphaGo [23] and Atari DQN [18]). While the language agents have shown promising results in some domains, most of their planning scenarios are limited to simple tasks with single objective function and fail in the travel planning benchmark with complex logical constraints.

Neuro-Symbolic Learning explores to combine traditional symbolic reasoning with learning to enhance the reliability [17, 25, 6]. In the era of large language models, Pan et al. [20] presents the LogicLM integrates LLMs with separate symbolic solvers for various logical reasoning tasks. They first utilize LLMs to translate a natural language problem into a symbolic formulation. Afterward, a deterministic symbolic solver performs inference on the formulated problem to ensure the correctness of the results. Deng et al. [7] supplement LogicLM with a Self-Refinement Module to enhance the reliability of LLM translation. In the travel planning domain, Hao et al. [12] presents a framework with a similar pipeline. It first extracts the logical constraints from natural language queries and then formalizes them into SMT code. Thanks to SMT solvers being sound and complete, this neuro-symbolic solution guarantees the generated plans are correct and has basically solved the TravelPlanner benchmark with a 97% pass rate.

Travel Planning is a time-consuming task even for humans, encompassing travel-related information gathering, POI selection, route mapping, and customization to meet diverse user needs [11]. Natural languages are one of the most common ways for users to express their travel requirements. However, the ambiguity and complexity of travel requirements make it still challenging for LLMs to generate accurate and reliable travel plans. Xie et al. [27] presents the TravelPlanner benchmark for cross-city travel planning and reveals the inadequacies of pure-LLM-driven agents. TravelPlanner generates user queries through LLMs and provides a rigorous evaluation mechanism to verify whether the provided plans can meet the logical constraints in the queries. It has become a pivotal benchmark for language agents in real-world travel planning. Tang et al. [24] study the open-domain urban itinerary planning where a single-day multi-POI plan is required. They integrates spatial optimization with large language models and present a system ITTNERA, to provide customized urban itineraries based on user needs. A concurrent work, TravelAgent [5], also considers a multi-day multi-POI travel planning problem for the specified city. It constructs an LLM-powered system to provide personalized plans. However, due to the high cost of collecting and annotating real travel needs, they evaluate the proposed TravelAgent in only 20 queries. This also demonstrates the necessity of introducing a new benchmark for travel planning.

D Detailed Design of ChinaTravel

D.1 Sandbox Information

We started collecting travel information with the motivation of planning a multi-day, multi-POI itinerary in four aspects: attractions, accommodation, activities, and transportation. Developers first determine the POI description information that needs to be obtained from the user's perspective, such as cuisine and hotel features. Based on this feature set, we collect public information to construct the database. For the design of APIs, we directly support queries based on the regular expressions from agents. At the same time, we expect the design of APIs to have similar features and characteristics to existing commercial APIs, enabling our dataset to be applicable to more realistic scenarios. The information our database contains is shown in Table 4 and the APIs we offer is in Table 5. Table 6 shows the information of environment constraints in ChinaTravel.

D.2 Tutorial of DSL Expression

Here is a tutorial, that provides a step-by-step guide to utilizing ChinaTravel's Domain-Specific Language (DSL) with predefined concept functions for expressing logical constraints and preferences.

Tool	Information
Attractions	Name, Type, Latitude, Longitude, Opentime, Endtime, Price, Recommendmintime, Recommendmaxtime
Accommodations	Name, Name_en, Featurehoteltype, Latitude, Longitude, Price, Numbed
Restaurants	Name, Latitude, Longitude, Price, Cuisinetype, Opentime, Endtime, Recommendedfood
Transportation	Transportation in specific city including walk, metro and taxi
IntercityTransport	Flight: FlightID, From, To, BeginTime, EndTime, Duration, Cost Train: TrainID, TrainType, From, To, BeginTime, EndTime, Duration, Cost
Poi	Names of POIs(including intercity transportation hub) and their coordinates

Table 4: Sandbox Information

DSL Overview In the main body of this paper, we have detailed the basics of our DSL in the Table 1. The DSL is a Python-like language designed to formalize travel planning requirements into executable code. It enables automated validation of itineraries against user constraints and preferences. Key components include: 1) *Concept Functions*: Predefined functions (e.g., activity_cost, poi_distance) that extract attributes from travel plans. 2) *Operators*: Logical (and, or, not), arithmetic (+, -, *, /), and comparison operators (<, >, ==). 3) *Control Structures*: Loops (for), conditionals (if), and set operations (union, intersection). More examples are provided in Fig. 9.

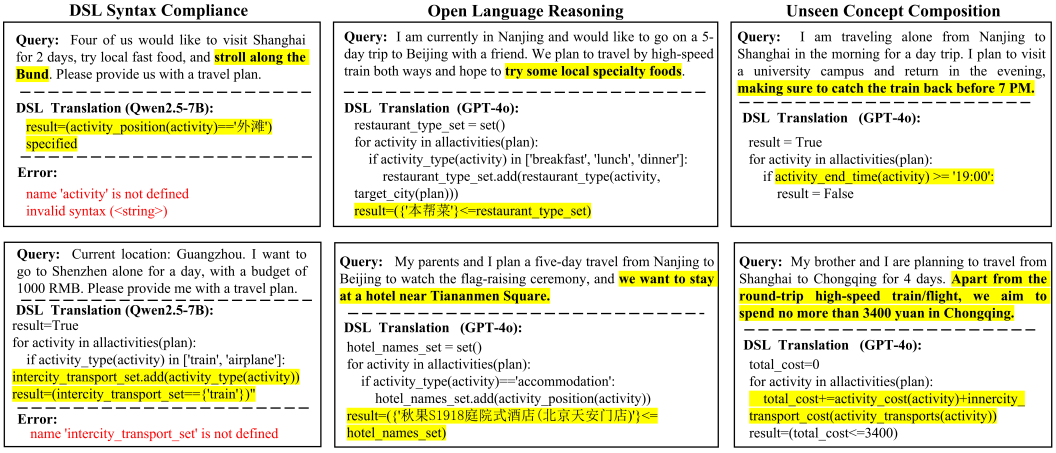

Figure 9: Challenges in the Neuro-Symbolic Planning.

Core Concept Functions We have defined 35 concept functions. Their definition and implementation is in Table 10, 11, 12 and 13. Below are common use cases:

Example: Budget Constraint User Query: "Total expenses must not exceed 5000 CNY."

```
total_cost = 0
for act in all_activities(plan):
    total_cost += activity_cost(act)
    total_cost += innercity_transport_cost(activity_transports(act))
return total_cost <= 5000
```

The function all_activities(plan) iterates through all activities in the itinerary. The function activity_cost retrieves the cost of each activity. The function innercity_transport_cost sums transportation expenses. Based on Python syntax, combining these concept functions can calculate the cost of the entire plan, thereby determining whether the budget constraints are met.

Debugging Tips (1) Syntax Validation: Use the python compiler to check for syntax errors (e.g., missing colons, undefined variables). (2) Unit Testing: Test individual concept functions (e.g.,

Tool	API	Docs
Attractions	attractions_keys(city)	Return a list of (key, type) pairs of the attractions data.
	attractions_select(city, key, func)	Return a DataFrame with data filtered by the specified key with the specified function.
	attractions_id_is_open(city, id, time)	Return whether the attraction with the specified ID is open at the specified time.
	attractions_nearby(city, point, topk, dist)	Return the top K attractions within the specified distance of the location.
	attractions_types	Return a list of unique attraction types.
Accommodations	accommodations_keys(city)	Return a list of (key, type) pairs of the accommodations data.
	accommodations_select(city, key, func)	Return a DataFrame with data filtered by the specified key with the specified function.
	accommodations_nearby(city, point, topk, dist)	Return the top K accommodations within the specified distance of the location.
Restaurants	restaurants_keys(city)	Return a list of (key, type) pairs of the restaurants data.
	restaurants_select(city, key, func)	Return a DataFrame with data filtered by the specified key with the specified function.
	restaurants_id_is_open(city, id, time)	Return whether the restaurant with the specified ID is open at the specified time.
	restaurants_nearby(city, point, topk, dist)	Return the top K restaurants within the specified distance of the location.
	restaurants_with_recommended_food(city, food)	Return all restaurants with the specified food in their recommended dishes.
	restaurants_cuisine(city)	Return a list of unique restaurant cuisines.
Transportation	goto(city, start, end, start_time, transport_type)	Return a list of transportation options between two locations with the specified departure time and transportation mode.
IntercityTransport	intercity_transport_select(start_city, end_city, intercity_type, earliest_leave_time)	Return the intercity transportation information between two cities.
Others	notedown(description, content)	Write the specified content to the notebook
	plan(query)	Generates a plan based on the notebook content and query and report the plan is done.
	next_page()	Get the next page of the latest Result history if it exists. Because of the length limited, all returned DataFrame information is split into 10 rows per page.

Table 5: APIs

Category	Environment Constraints	Semantics
Cross-city Transportation	Intercity transportation events must occur.	The first event and last event must be cross-city transports.
	Available Trains or Airplanes across cities.	The provided TrainID/FlightID, origin and destination should be valid in the travel sandbox.
	Correct information of price, duration.	The price and duration information should match the travel sandbox.
	Detailed cost on inter-city transportation	Provide number of tickets and cost of each inter-city activity. $cost = price \times tickets$
Inner-city Transportation	Available Metro, Taxi or Walking between different positions.	The provided routes should be valid in the travel sandbox.
	Correct information of price, distance, and duration.	These details should match the travel sandbox.
	Detailed cost on inner-city transportation	Provide number of tickets/cars and cost. Taxi: 4 people per car. $cost = price \times tickets$, $cost = price \times cars$
Attractions	Available attractions in the target city	The provided attractions should be valid in the travel sandbox.
	Visiting during opening hours.	Activities must respect the attraction's opening time.
	Correct price information.	Must match the sandbox.
	Detailed cost of attraction activity.	Provide ticket number and total cost. $cost = price \times tickets$
	No repeated attractions.	Attractions should not repeat across the trip.
Restaurants	Available restaurants in the target city	Must be valid in the travel sandbox.
	Visiting during opening hours.	Same as above.
	Correct price information.	Must match the sandbox.
	Detailed cost of restaurant activity.	$cost = price \times tickets$
	No repeated restaurants.	Same restaurant should not be visited more than once.
	Meals served in proper time slots.	Breakfast: 06:00–09:00; Lunch: 11:00–14:00; Dinner: 17:00–20:00.
Accommodation	Available accommodations in target city.	Must be valid in the travel sandbox.
	Correct price and room type.	Must match the sandbox.
	Detailed accommodation cost.	$cost = price \times rooms$
	Required for trips over one day.	A hotel is necessary for multi-day trips.
Time	Activity duration details.	Must include start and end time; end time must be after start.
	Activities in chronological order.	Events listed in order, respecting preceding transport arrivals.
Space	Transport info for changing positions.	If positions differ, the transport route must be included.

Table 6: Environment Constraints and Semantics in ChinaTravel Environment

poi_distance) with mock itineraries. (3) Iterative Refinement: For ambiguous requirements (e.g., "local cuisine"), map natural language to precise DSL concepts from sandbox information (e.g., restaurant_type(act, city) == "Beijing Cuisine").

Integration with Neuro-Symbolic Agents. (1) NL2DSL Translation: Convert user queries into DSL using LLMs (e.g., "Try local food" → restaurant_type(POI, city) == "Beijing Cuisine" when the destination city is Beijing). (2) Symbolic Validation: Execute DSL code to verify plans against logical constraints. (3) Search Optimization: Use DSL-defined preferences (e.g., minimize(transport_time)) to rank candidate itineraries.

Query in Chinese (from easy subset):当前位置成都。我和朋友两个人想去南京玩 2 天，住一间双床房，酒店要可以打牌，请给我一个旅行规划。
Current location: Chengdu. My friend and I want to go to Nanjing for 2 days. We need a twin room in a hotel where we can play cards. Please provide a travel plan for us.

```
accommodation_type_set=set()
for activity in allactivities(plan):
    if activity_type(activity) == 'accommodation': accommodation_type_set.add(accommodation_type(activity, target_city(plan)))
result=({'棋牌室'}<=accommodation_type_set)
```

Query in Chinese (from medium subset): 当前位置成都。我一个人想去重庆玩 2 天，预算 3000 人民币，坐火车往返，想吃火锅，想去洪崖洞。
Current location: Chengdu. I want to travel alone to Chongqing for 2 days with a budget of 3000 RMB. I plan to take the train, want to eat hotpot, and visit Hongya Cave.

```
total_cost=0
for activity in allactivities(plan):
        total_cost+=activity_cost(activity)
        total_cost += innercity_transport_cost(activity_transports(activity))
result=(total_cost<=3000)
intercity_transport_set=set()
for activity in allactivities(plan):
    if activity_type(activity) in ['train', 'airplane']: intercity_transport_set.add(intercity_transport_type(activity))
result=({'train'}==intercity_transport_set)"
restaurant_type_set=set()
for activity in allactivities(plan):
    if activity_type(activity) in ['breakfast', 'lunch', 'dinner']: restaurant_type_set.add(restaurant_type(activity, target_city(plan)))
result=({'火锅'}<=restaurant_type_set)
attraction_name_set=set()\nfor activity in allactivities(plan):
    if activity_type(activity)=='attraction': attraction_name_set.add(activity_position(activity))
result=({'洪崖洞'}<=attraction_name_set)
```

Query in Chinese (from human subset): [当前位置南京,目标位置武汉,旅行人数 2,旅行天数 3] 我们 2 人想去武汉玩 3 天，主要想体验武汉的一些有些历史的区域，同时还想尝一尝本地人常去吃的特色美食，怎么规划行程。
English translation: [Current location: Nanjing, Destination: Wuhan, Number of travelers: 2, Travel days: 3] The two of us want to visit Wuhan for 3 days. We mainly want to experience some of the historical areas in Wuhan and also try the local specialty foods that residents often eat. How should we plan our itinerary?

```
attraction_type_set=set()
        for activity in allactivities(plan):
            if activity_type(activity)=='attraction': attraction_type_set.add(attraction_type(activity, target_city(plan)))
result=({'历史古迹'}<=attraction_type_set)"
restaurant_type_set=set()\nfor activity in allactivities(plan):
        if activity_type(activity) in ['breakfast', 'lunch', 'dinner']: restaurant_type_set.add(restaurant_type(activity, target_city(plan)))
result=({'湖北菜'}<=restaurant_type_set)"
```

Query in Chinese (from human subset): [当前位置南京,目标位置杭州,旅行人数 2,旅行天数 3] 我们打算去杭州看西湖，预算 2000，给我一个旅游安排。
[Current location: Nanjing, Destination: Hangzhou, Number of travelers: 2, Number of travel days: 3] We plan to visit West Lake in Hangzhou with a budget of 2000. Please provide me with a travel itinerary.

```
attraction_name_set=set()
for activity in allactivities(plan):
    if activity_type(activity)=='attraction': attraction_name_set.add(activity_position(activity))
result=({'西湖风景名胜区'}<=attraction_name_set)
total_cost=0
for activity in allactivities(plan):
        total_cost+=activity_cost(activity)
            total_cost += innercity_transport_cost(activity_transports(activity))
result=(total_cost<=2000)"
```

Figure 10: Examples of travel requirements and their DSL expressions.

Logical Constraint	
Transportation	The required type of transportation.
Attraction	The required type or specified attractions.
Restruants	The required type or specified restruants.
Accommodation	The number of rooms and the room type must meet the requirements. The required features or specified hotels.
Budget	The total cost is within required budget.
Unseen Logical Constraints in Human data	
POIs	The negation/conjunction/disjunction of given POIs
Time	The duration of specific activities is within the limitation
Budget	The cost of specific activities is within the required budget

Table 7: Descriptions of **Logical Constraints** for two benchmarks. Constraints in black are common in both TravelPlanner and ChinaTravel. Metrics in brown are the metrics only in our benchmark.

Preference Requirements	
Daily attractions ↑	Visit as many attractions as possible
Transport time ↓	Minimize the travel time between POIs
Transport time to the restaurants ↓	Minimize the travel time to restaurants
Food cost ratio ↑	Maximize the proportion of dining expenses
Hotel cost ↓	Minimize accommodation costs
Distance to POI ↓	Visit places as close to {POI} as possible

Table 8: Descriptions of **Preference Requirements** in ChinaTravel benchmark.

D.3 Query Synthesis

We designed common travel information (origin, destination, days, number of people) and logical constraints based on the nature of travel tasks. To facilitate scalable queries for ChinaTravel, we randomly constructed query skeletons from the aforementioned information and used advanced LLMs to generate natural language queries from these skeletons. In practice, we provide the LLMs with more intuitive hard logic constraints to ensure the LLMs do not make mistakes and use a Python script to convert it after generating the query. The automatically generated data is categorized into two difficulty levels: In the *Easy* level, user inputs encompass a single logical requirement, sourced from categories such as transportation, restaurants, attractions, and accommodations. In the *Medium* level, user inputs involve 2 to 5 logical requirements, introducing more complex constraints. During the generation, we encourage the LLMs to provide varied and human-like expressions, necessitating a deeper understanding and processing to accurately interpret and fulfill the user's needs. For instance, the logical requirement "taste Beijing cuisine" could correspond to the natural language query: "Try local food in Beijing." We utilize prompt engineering to guide LLMs in refining natural language expressions to facilitate automated generation. One of the prompts is shown in Figure 11. Several examples of generated data is in Figure 12. As a result, we obtain the synthetic queries across diverse

Table 9: Results of different LLMs and planning strategies on the ChinaTravel *medium* subset.

		DR	EPR		LPR		C-LPR	FPR
			Mic.	Mac.	Mic.	Mac.		
Act		72.7	52.3	0	63.5	15.3	0	0
		97.4	70.5	0	89.3	55.3	0	0
ReAct (zero-shot)		41.3	35.2	0	37.6	4.0	0	0
		92.0	54.8	0	78.6	22.7	0	0
ReAct (one-shot)		82.7	77.1	3.33	82.6	48.7	2.95	1.33
		94.7	69.2	0.67	91.8	64.0	0.53	0

		DR	EPR		LPR		C-LPR	FPR
			Mic.	Mac.	Mic.	Mac.		
NSP		71.3	71.9	69.3	69.4	50.0	69.3	46.7
		68.0	68.0	68.0	64.1	46.6	64.1	46.7
		53.3	45.9	16.0	49.2	33.3	14.8	8.50
NSP oracle		68.6	65.4	54.0	66.2	61.3	52.5	54.0
		60.8	59.4	54.9	60.3	58.2	60.3	56.9
		53.3	51.3	36.6	51.9	43.3	34.8	34.6

Function Name	Meaning	Implementation
day_count	total days in the plan	`def day_count(plan):` `  return len(plan["itinerary"])`
people_count	number of people in the trip	`def people_count(plan):` `  return plan["people_number"]`
start_city	start city of the plan	`def start_city(plan):` `  return plan["start_city"]`
target_city	target city of the plan	`def target_city(plan):` `  return plan["target_city"]`

allactivities	all the activities in the plan	`def allactivities(plan):`
		`  activity_list = []`
		`  for day_activity in plan["itinerary"]:`
		`  for act in day_activity["activities"]:`
		`  activity_list.append(act)`
		`  return activity_list`

allactivities_count	the number of activities in the plan	`def allactivities_count(plan):`
		`  count = 0`
		`  for day_activity in plan["itinerary"]:`
		`  count += \`
		`  len(day_activity["activities"])`
		`  return count`

dayactivities	all the activities in the specific day [1, 2, 3, ...]	`def dayactivities(plan, day):`
		`  activity_list = []`
		`  for act in plan["itinerary"]\`
		`  [day - 1]["activities"]:`
		`  activity_list.append(act)`
		`  return activity_list`

activity_cost	the cost of specific activity without transport cost	`def activity_cost(activity):` `  return activity.get("cost", 0)`
activity_position	the position name of specific activity	`def activity_position(activity):` `  return activity.get("position", "")`
activity_price	the price of specific activity	`def activity_price(activity):` `  return activity.get("price", 0)`
activity_type	the type of specific activity	`def activity_type(activity):` `  return activity.get("type", "")`
activity_tickets	the number of tickets needed for specific activity	`def activity_tickets(activity):` `  return activity.get("tickets", 0)`
activity_transports	the transport information of specific activity	`def activity_transports(activity):` `  return activity.get("transports", [])`
activity_start_time	the start time of specific activity	`def activity_start_time(activity):` `  return activity.get("start_time")`
activity_end_time	the end time of specific activity	`def activity_end_time(activity):` `  return activity.get("end_time")`

Table 10: Concept Function

Function Name	Meaning	Implementation

activity_time	the duration of specific activity	`def activity_time(activity):`
		`  start_time = activity.get("start_time")`
		`  end_time = activity.get("end_time")`
		`  if start_time and end_time:`
		`  st_h, st_m = \`
		`  map(int, start_time.split(":"))`
		`  ed_h, ed_m = \`
		`  map(int, end_time.split(":"))`
		`  return \`
		`  (ed_m - st_m) + (ed_h - st_h) * 60`
		`  return -1`

poi_recommend_time	the recommend time of specific poi(attraction) in the city	`def poi_recommend_time(city, poi):`
		`  select = Attractions().select`
		`  attrction_info = \`
		`  select(city, key="name",`
		`  func=lambda x: x == poi).iloc[0]`
		`  recommend_time = \`
		`  (attrction_info["recommendmintime"]) \`
		`  * 60`
		`  return recommend_time`

poi_distance	the distance between two POIs in the city	`def poi_distance(city, poi1, poi2):`
		`  start_time="00:00"`
		`  transport_type="walk"`
		`  goto = Transportation().goto`
		`  return goto(city, poi1, poi2, start_time,`
		`  transport_type)[0]["distance"]`

innercity_transport_cost	the total cost of specific innercity transport	`def innercity_transport_cost(transports, mode):`
		`  cost = 0`
		`  for transport in transports:`
		`  if node is None or \`
		`  transport.get("type") == node:`
		`  cost += transport.get("cost", 0)`
		`  return cost`

innercity_transport_price	the price of innercity transport	`def innercity_transport_price(transports):`
		`  price = 0`
		`  for transport in transports:`
		`  price += transport["price"]`
		`  return price`

innercity_transport_distance	the distance of innercity transport	`def innercity_transport_distance\`
		`  (transports, mode=None):`
		`  distance = 0`
		`  for transport in transports:`
		`  if mode is None or \`
		`  transport.get("type") == mode:`
		`  distance += \`
		`  transport.get("distance", 0)`
		`  return distance`

innercity_transport_time	the duration of innercity transport	`def innercity_transport_time(transports):`
		`  def calc_time_delta(end_time, start_time):`
		`  hour1, minu1 = \`
		`  int(end_time.split(":")[0]), \`
		`  int(end_time.split(":")[1])`
		`  hour2, minu2 = \`
		`  int(start_time.split(":")[0]), \`
		`  int(start_time.split(":")[1])`
		`  return (hour1 - hour2) * 60\`
		`  + (minu1 - minu2)`

Table 11: Concept Function

Function Name	Meaning	Implementation
metro_tickets	the number of metro tickets if the type of transport is metro	`def metro_tickets(transports):` `  return transports[1]["tickets"]`
taxi_cars	the number of taxi cars if the type of transport is taxi	`def taxi_cars(transports):` `  return transports[0]["cars"]`
room_count	the number of rooms of accommodation	`def room_count(activity):` `  return activity.get("rooms", 0)`
room_count	the number of rooms of accommodation	`def room_count(activity):` `  return activity.get("rooms", 0)`
room_type	the type of room of accommodation	`def room_type(activity):` `  return activity.get("room_type", 0)`

restaurant_type	the type of restaurant's cuisine in the target city	`def restaurant_type(activity, target_city):`
		`  restaurants = Restaurants()`
		`  select_food_type = \`
		`  restaurants.select(`
		`  target_city, key="name",`
		`  func=lambda x: x == activity["position"]`
		`  )["cuisine"]`
		`  if not select_food_type.empty:`
		`  return select_food_type.iloc[0]`
		`  return ""`

attraction_type	the type of attraction in the target city	`def attraction_type(activity, target_city):`
		`  attractions = Attractions()`
		`  select_attr_type = \`
		`  attractions.select(`
		`  target_city, key="name",`
		`  func=lambda x: x == activity["position"]`
		`  )["type"]`
		`  if not select_attr_type.empty:`
		`  return select_attr_type.iloc[0]`
		`  return ""`

accommodation_type	the feature of accommodation in the target city	`def accommodation_type(activity, target_city):`
		`  accommodations = Accommodations()`
		`  select_hotel_type = \`
		`  accommodations.select(`
		`  target_city, key="name",`
		`  func=lambda x: x == activity["position"]`
		`  )["featurehoteltype"]`
		`  if not select_hotel_type.empty:`
		`  return select_hotel_type.iloc[0]`
		`  return ""`

innercity_transport_type	the type of innercity transport	`def innercity_transport_type(transports):`
		`  if len(transports) == 3:`
		`  return transports[1]["mode"]`
		`  elif len(transports) == 1:`
		`  return transports[0]["mode"]`
		`  return ""`

intercity_transport_type	the type of intercity transport	`def intercity_transport_type(activity):` `  return activity.get("type", "")`

Table 12: Concept Function

Function Name	Meaning	Implementation
innercity_-transport_-start_time	the start time of innercity transport	`def innercity_transport_start_time(transports):` `  return transports[0]["start_time"]`
innercity_-transport_-end_time	the end time of innercity transport	`def intercity_transport_end_time(transports):` `  return transports[-1]["end_time"]`

intercity_-transport_-origin	the origin city of intercity transport	`def intercity_transport_origin(activity):`
		`  if "start" in activity:`
		`  for city in city_list:`
		`  if city in activity["start"]:`
		`  return city`
		`  return ""`

intercity_-transport_-destination	tthe destination city of intercity transport	`def intercity_transport_destination(activity):`
		`  if "end" in activity:`
		`  for city in city_list:`
		`  if city in activity["end"]:`
		`  return city`
		`  return ""`

Table 13: Concept Function

travel requirements, including 28 restaurant types, 23 attraction types, 29 hotel features, and more than 130 specific POIs.

D.4 Data Diversity and Bias Mitigation

This subsection provides a detailed analysis of ChinaTravel's hybrid query design, addressing concerns about synthetic data limitations and real-world representativeness.

ChinaTravel integrates both synthetic and human-authored queries to balance scalability and realism. When synthesizing data, we randomly constructed constraints based on the types and specific visit requirements of POIs such as restaurants, accommodations, transports, and attractions, thereby ensuring the diversity of the dataset. The human query subset comprises 154 samples collected through structured questionnaires, which introduce complex real-world constraints such as time-bound returns (e.g., explicit requirements like "return before 7 PM") and activity-specific budget allocations. These queries also incorporate colloquial expressions that reflect native Chinese travel preferences, exemplified by phrases like local specialty foods frequented by residents. The synthetic queries are generated through LLM-based paraphrasing techniques and systematically categorized into two tiers: Easy-tier queries contain single logical constraints (e.g., specific cuisine requirements), while Medium-tier queries combine 3–5 interdependent constraints (e.g., compound conditions like "budget $\leq$ 3000 CNY + train transport + hotpot dining").

To mitigate synthetic data bias and enhance diversity, three primary strategies were implemented. First, constraint combinations were deliberately diversified across temporal, spatial, and cost dimensions, as detailed in Table 7. Second, a human validation layer filters out unrealistic LLM-generated queries, such as physically implausible itineraries like "visiting 10 attractions within one day." Third, the DSL framework enables compositional generalization of requirements, supporting open-ended constraint combinations through its formal syntax shown in Table 1.

The current human query subset remains limited by annotation costs, as discussed in the limitation section. In future work, we will advance data collection by integrating LLMs with real user queries to automate and diversify the generation of human-like queries. Additionally, all human queries and automated synthesis tools will be publicly released to support community-driven benchmark extensions.

D.5 Data with Preference

We introduce six common preferences from user surveys to construct the preference sub-datasets. Table 8 provides a summary of these preferences.

The corresponding DSL could be formulated as follows.

```
# The number of attractions visited
count = 0
for act_i in all_activities(plan):
  if activity_type(act_i)=="attraction": count = count + 1
return count
```

```
# The average travel time between POIs
time_cost = 0
transport_count = 0
for activity in allactivities(plan):       transports =
    activity_transports(activity)
    transport_count += 1        time_cost += innercity_transport_time(
        transports)
average_time_cost = time_cost / transport_count if transport_count > 0
     else -1
return average_time_cost
```

```
# The average travel time to restaurants
restaurant_count = 0
time_cost = 0
for activity in allactivities(plan):
    if activity_type(activity) in ['breakfast', 'lunch', 'dinner']:
        restaurant_count += 1
        time_cost += innercity_transport_time(activity_transports(
            activity))
```

```
if restaurant_count == 0:
    average_time_cost = -1
else:
    average_time_cost = time_cost / restaurant_count
return average_time_cost
```

```
# The ratio of food cost
food_cost = 0
total_cost = 0
for activity in allactivities(plan):
    total_cost += activity_cost(activity)
    total_cost +=innercity_transport_cost(activity_transports(activity
        ))
    if activity_type(activity) in ['breakfast', 'lunch', 'dinner']:
        food_cost += activity_cost(activity)
food_cost_ratio = food_cost / total_cost if total_cost > 0 else -1
return food_cost_ratio
```

```
# The cost of accommodations
accommodation_cost = 0
for activity in allactivities(plan):
    if activity_type(activity) == 'accommodation':
        accommodation_cost += activity_cost(activity)"
return accommodation_cost
```

```
# The average distance to poi (e.g. xxx)
target_poi = 'xxx'
poi_list = list()
total_distance = 0
poi_count=0
city = target_city(plan)
for activity in allactivities(plan):
    if activity_type(activity) in ['breakfast', 'lunch', 'dinner', '
        accommodation', 'attraction']:
        poi_list.append(activity_position(activity))
for poi in poi_list:
    total_distance += poi_distance(city, target_poi, poi)
    poi_count += 1
average_dist_cost = total_distance / poi_count if poi_count > 0 else
    -1
return average_dist_cost
```

D.6 Benchmark Difficulty and Applicability

While the Human subset presents significant challenges, the baseline NeSy solution has achieved 60.6% and 46.7% FPR on Easy and Medium subsets, respectively, providing developers with actionable validation points for initial testing and refinement. Additionally, the Human subset's extreme difficulty arises from open language reasoning and unseen concept composition, key challenges absent in prior benchmarks but unavoidable in practice. By explicitly formalizing these challenges, ChinaTravel has provided a roadmap for advancing agents toward real-world robustness. Despite current LLMs' limitations in handling unseen combinations, their success in code generation suggests that post-training with DSL may enhance their understanding of diverse travel needs, moving toward real-world applications.

E Discussion with TravelPlanner

TravelPlanner's logical constraints contain the total cost, 15 cuisines, 5 house rules, 3 room types, and 3 intercity transports. ChinaTravel's logical constraints contain the total cost, 42 cuisines, 15 attraction types, 78 hotel features, 2 room types, 2 intercity-transports types, 3 inner-city-transports types, and specific POI names (attractions, restaurants, hotels). Crucially, our benchmark introduces

compositional constraints derived from human queries (e.g., "return before 7 PM", "cost of intercity transports"), reflecting real-world complexity. The key advancement lies in addressing open-language reasoning and unseen concept composition, which represent significant challenges beyond TravelPlanner's scope. Our Domain-Specific Language (DSL) enables automated validation of these combinatorial requirements, bridging the gap between synthetic and real-world needs.

We also provide some example queries and corresponding examples from the TravelPlanner at each level in Figure 18, 19, and 20.

As shown in Figure 18, in the "easy level", TravelPlanner only includes constraints on cost. In contrast, ChinaTravel demonstrates significant advantages over TravelPlanner, particularly in terms of personalized support for specific Points of Interest (POIs) and more realistic transportation and time management. These advantages are crucial for developing and evaluating language agents that can handle real-world travel planning scenarios effectively. ChinaTravel allows users to directly specify POI names, such as "Nanjing DaPaXiang" or "HuQiu Mountain Scenic Area," requiring the agent to precisely match the entity information from the travel sandbox.

As shown in Figure 19, in the medium set, TravelPlanner includes queries with two types of constraints: cost and cuisine, or cost and accommodation. In contrast, ChinaTravel includes queries with 2 to 5 types of constraints, reflecting more complex and diverse multi-constraint requirements. This difference highlights the ability of ChinaTravel to handle more realistic and varied travel planning scenarios.

As shown in Figure 20, TravelPlanner includes queries with multiple constraints, such as cost, accommodation type, and cuisine preferences. However, ChinaTravel goes a step further by including queries with unseen logical constraints and more colloquial expressions. These unseen logical constraints and colloquial expressions are essential for travel planning agents to handle real-world users effectively. They reflect the complexity and diversity of real-world travel planning scenarios, where users may have diverse requirements that need to be understood and addressed. By incorporating these elements, ChinaTravel bridges the gap between current academic research benchmarks and real-world application demands, making it a more comprehensive and realistic benchmark for evaluating the capabilities of travel planning agents.

F NeSy Planning

Since the Z3 solver from [12] would restructure the tool API to return travel information expressed in specific Z3 variables, which may not be feasible given that APIs in the real world are typically black boxes that agents can only call. Following their two-stage solution, we first extract logical constraints from natural language. Based on these constraints, we implement a step-by-step plan generation process using depth-first search, mimicking how humans plan to travel by arranging activities one by one. As shown in Fig. 5, we first translate the natural languages to logical constraints through prompting. generate the next activity type based on the current plan, and then recursively generate the next activity until the goal is reached. The generated plan is then used to solve the problem. In the second step, we define the rule-based activity selection and score function. For example, if the current time is in the [10:30, 12:30] and there is no scheduled lunch in the current plan, then the agent should find a restaurant to have lunch at this time. If the current time is after 22:00 and there are no open-time attractions nearby, the agent should choose to return to the hotel. For the score function, we select the restaurants that satisfy the required cuisine and sort the candidates by the price if there a budget constraints in the constraints C. These ranking functions will help us to find a feasible solution as soon as possible. In ChinaTravel, the duration arrangement of activities is continuous and difficult to enumerate and search. We pre-define a meal or a visit to an attraction as 90 minutes, and when there are less than 90 minutes until closing time, the event continues until the closing time. Given these designs, we adapt the neural-symbolic solution into a multi-POI planning problem and evaluate it in the ChinaTravel benchmark.

Given that some queries are particularly challenging due to the limited number of feasible plans, we set the maximum runtime for the symbolic sketch from interactive search to 5 minutes per query, excluding the LLM inference time, to ensure a fair comparison across different models. If a plan satisfying the generated DSL validation is found within the time limit, it is returned directly. Otherwise, the program halts when the time limit is reached, and the plan that satisfies environmental constraints while achieving the highest number of validation code successes among all intermediate

Algorithm 1 Depth-First Greedy Search

Require: Constraints C, current plan p,
  if the least activity is an intercity-transport from destination to origin **then**
    return ConstraintValidation(p, C), p ▷ The plan p is finished, return the validation result.
  end if
  type = GetNextActivityType(p) ▷ Select the next type of activities, e.g. lunch, attraction.
  candidates = ToolUse(type) ▷ Collect the corresponding information for the activity type
  scores = LLMScore(candidates, p, C) ▷ Score candidates through constraints C.
  for activity in candidates **do**
    p.push(activity) ▷ Perform a greedy search with priority ranking.
    flag, p = Depth-FirstGreedySearch(C, p)
    if flag **then**
      return True, p ▷ Return the solution p if the validation is passed.
    end if
    p.pop(activity)
  end for
  return False, p ▷ Fail to find a solution with the given conditions.

results is returned. In cases where no environment-compliant plan is identified, the partially completed plan generated up to that point is returned.

In the Figure 21, 22 and 23, we provide the prompts of the LLM POI-ranking phases.

G Evaluation Metric in Competition

The Delivery Rate (DR), Environmental Pass Rate (EPR), Logical Pass Rate (LPR), and Final Pass Rate (FPR) have been detailed in TravelPlanner [27]. To make the paper more self-contained, we also provide the corresponding definition here.

Delivery Rate: This metric assesses whether agents can successfully deliver a formatted plan. For the Nesy planning, if a solution that satisfies the logical constraints has not been found by the time out, the search is terminated, and the current solution that satisfies the environmental constraints is returned. If no solution that satisfies the environmental constraints is obtained, an empty plan is returned. Therefore, unlike the pure LLM method, which primarily assesses the Delivery Rate based on whether the output meets the formatting requirements, the nesy planning method, which uses depth-first-search to arrange POIs one by one, shows differences in the Delivery Rate. These differences mainly reflect the proportion of effective solutions obtained within a limited time based on the LLM's POI recommendation. This proportion demonstrates the degree to which the LLM prioritizes POI arrangements from a natural language perspective and meets formalized logical requirements. The more accurately the LLM can arrange POIs that are beneficial for long-horizon planning, the more likely it is to obtain effective solutions and improve the Delivery Rate.

Environmental Pass Rate Comprising the environmental dimensions (as detailed in Tab. 6), this metric evaluates whether a language agent can accurately incorporate sandbox information into their generated plans.

$$EPR - micro = \frac{\sum_{p \in P} \sum_{c \in Env} \mathbb{1}_{passed(c,p)}}{|P| * |Env|}$$

$$EPR - macro = \frac{\sum_{p \in P} \prod_{c \in Env} \mathbb{1}_{passed(c,p)}}{|P|}$$

Logical Pass Rate Comprising the logical dimensions (as detailed in Tab. 7), this metric evaluates whether a language agent can accurately meet the personalized requirements of the queries.

$$LPR - micro = \frac{\sum_{p \in P} \sum_{c \in C_p} \mathbb{1}_{passed(C_p,p)}}{\sum_{p \in P} |C_p|}$$

$$LPR - macro = \frac{\sum_{p \in P} \prod_{c \in C_p} \mathbb{1}_{passed(C_p, p)}}{|P|}$$

Final Pass Rate This metric represents the proportion of feasible plans that meet all aforementioned constraints among all tested plans. It serves as an indicator of agents' proficiency in producing plans that meet a practical standard.

$$FPR = \frac{\sum_{p \in P} \mathbb{1}_{passed(Env, p)} \cdot \mathbb{1}_{passed(C_p, p)}}{|P|}$$

Preference Ranking To systematically evaluate the satisfaction of soft user preferences in travel planning, we introduce a Preference Ranking metric that quantifies the alignment of generated itineraries with diverse user requirements. Each preference (e.g., "maximize attraction visits" or "minimize transportation time") is formalized into a Domain-Specific Language (DSL)-based concept, enabling automated numerical extraction from plans. For instance, the preference for "visiting more attractions" is translated into a DSL function that counts the total attraction-type activities in a plan, while "minimizing dining costs" is operationalized via cumulative expense calculations for meal-related activities.

The Preference Ranking metric operates in two steps: 1) Quantification: Execute DSL code to compute concept-specific scores (e.g., attraction count, transport time) for each generated plan. 2) Ranking: Compare methods (e.g., BQ vs. PEQ vs. PDS) by ranking their concept values, prioritizing higher values for maximization goals (↑) and lower values for minimization goals (↓). 3) Aggregation: Calculate the average ranking on the given samples.

H Additional Experimental Results

H.1 Multi-Preference Comparison

For multi-preference scenarios (e.g., balancing "attraction visits ↑" and "transport time ↓"), we adopt an averaged aggregation approach, where rankings reflect the combined performance across all preferences. This framework ensures scalability and objectivity.

To rigorously evaluate the ability of language agents to balance multiple soft constraints, we constructed 15 test subsets by pairing six user preferences (P0–P5) into all possible combinations (e.g., "P0 + P1"). Each subset contains queries with two preference requirements. We compared two methods, Baseline Query (BQ) and Preference-Enhanced Query (PEQ), by quantifying their performance through our DSL-based Preference Ranking metric. For each subset, we extracted numerical scores for both preferences (Value-1 and Value-2), computed individual rankings (Rank-1, Rank-2), and derived an aggregated ranking (Agg. Rank.) to reflect overall performance. The results are provided in the Table 14.

From these results, we could find that: (1) **PEQ Outperforms BQ in Most Scenarios**: In 10/15 combinations, PEQ achieves superior aggregated rankings (Aggregated Ranking = 1.43 vs. BQ's 1.56). Notably, PEQ demonstrates stable improvements on preferences P3 (e.g., maximizing dining quality↑) and P4 (e.g., minimizing accommodation costs↓). For instance: In "P0↑ + P4↓", PEQ reduces accommodation costs by 64% (Value-2: 441 vs. BQ's 1221) while maintaining high attraction counts (Value-1: 0.97 vs. 0.79). For "P3↑ + P4↓", PEQ simultaneously improves dining quality (Value-1: 0.26 vs. BQ's 0.18) and lowers costs (Value-2: 531 vs. 1229). This stability likely stems from the direct impact of POI selection on these preferences. LLMs in PEQ effectively prioritize low-cost hotels or high-quality restaurants through natural language hints (e.g., "reduce the cost on accommodations"), enabling explicit alignment with P3 and P4 requirements. (2) **Challenges in Balancing Multiple Preferences**: The results also reveal inherent difficulties in harmonizing conflicting preferences, particularly when optimizing one requirement necessitates sacrificing another. Notably, in the P0↑ + P1↓ scenario, PEQ underperforms BQ on both preferences, highlighting the inherent difficulty in resolving conflicting objectives. While PEQ marginally improves attraction counts (Value-1: 0.83 vs. BQ's 0.79), it incurs a 5.7% increase in transport time (Value-2: 29.7 vs. BQ's 28.0). This trade-off results in a worse aggregated ranking for PEQ (1.55 vs. BQ's 1.44), indicating that the combined effect of conflicting preferences negates the benefits of natural language

Preference Combination	Vaule-1		Vaule-2		Rank-1		Rank-2		Agg. Rank.	
	BQ	PEQ	BQ	PEQ	BQ	PEQ	BQ	PEQ	BQ	PEQ
P0 ↑, P1 ↓	0.79	**0.83**	**28.0**	29.7	**1.44**	1.55	**1.44**	1.55	**1.44**	1.55
P0 ↑, P2 ↓	0.82	**1.26**	**29.0**	31.9	1.56	**1.43**	**1.43**	1.56	1.5	1.5
P0 ↑, P3 ↑	0.81	**0.94**	0.18	**0.20**	**1.42**	1.57	1.59	**1.40**	1.51	**1.48**
P0 ↑, P4 ↓	0.79	**0.97**	1221	**441**	1.46	**1.53**	1.73	**1.26**	1.59	**1.40**
P0 ↑, P5 ↓	0.78	**0.91**	**33.6**	34.0	**1.37**	1.62	1.70	**1.29**	1.54	**1.45**
P1 ↓, P2 ↓	28.2	**27.8**	**26.6**	30.1	1.62	**1.37**	**1.48**	1.51	1.55	**1.44**
P1 ↓, P3 ↑	**28.2**	36.2	0.20	**0.27**	**1.31**	1.68	1.6	**1.4**	**1.45**	1.54
P1 ↓, P4 ↓	**30.3**	44.8	1440	**585**	**1.14**	1.85	1.77	**1.22**	**1.45**	1.54
P1 ↓, P5 ↓	**30.1**	38.3	30.7	**30.2**	**1.27**	1.72	1.69	**1.30**	**1.48**	1.51
P2 ↓, P3 ↑	24.7	**23.3**	0.27	0.27	**1.43**	1.56	1.60	**1.39**	1.52	**1.47**
P2 ↓, P4 ↓	24.1	**21.1**	1687	**719**	1.51	**1.48**	1.89	**1.10**	1.70	**1.29**
P2 ↓, P5 ↓	**28.0**	30.8	29.4	**26.0**	1.51	**1.48**	1.89	**1.10**	1.70	**1.29**
P3 ↑, P4 ↓	0.18	**0.26**	1229	**531**	1.64	**1.35**	1.69	**1.30**	1.66	**1.33**
P3 ↑, P5 ↓	0.22	0.22	33.3	**29.0**	1.51	**1.48**	1.84	**1.15**	1.68	**1.31**
P4 ↓, P5 ↓	1366	**767**	33.1	**31.6**	1.67	**1.32**	**1.45**	1.54	1.56	**1.43**
Aggregated Ranking									1.56	**1.43**

Table 14: Multi-Preference Comparison of BQ and PEQ.

guidance. In 9/15 combinations, PEQ improves one preference at the expense of the other. For example: P1↓ + P4↓: PEQ reduces accommodation costs by 59% (Value-2: 585 vs. BQ's 1440) but increases transport time by 48% (Value-1: 44.8 vs. 30.3). The inability to concurrently satisfy both preferences underscores the limitations of current LLM-driven prioritization in handling trade-offs.

Our experiments demonstrate that the neuro-symbolic agent (PEQ), enhanced by LLM-driven POI recommendation, outperforms baseline methods in multi-preference travel planning. By integrating natural language hints to guide POI selection, PEQ effectively translates user requirements into actionable itineraries, demonstrating its capability to handle synergistic preferences. However, balancing inherently conflicting objectives remains challenging. This highlights the need for future advancements, such as domain-specific fine-tuned LLMs to better resolve preference conflicts or multi-objective optimization techniques to systematically navigate trade-offs.

H.2 Open Reasoning with Chinese Context

In this section, we quantitatively compare the reasoning capabilities of LLMs in the context of Chinese travel requirements. Given that many leading LLMs, such as GPT-4, are primarily trained in English corpora, it is essential to evaluate their performance in a Chinese travel planning context to better understand their reasoning abilities. We focus on three LLMs: GPT-4o, DeepSeek-V2.5, and Qwen2.5-7B, which are employed in the main experiments.

Specifically, we analyze the POI matching in the NL2DSL process with varying travel requirements from the synthesized quires and further provide the distribution of the results in Figure 13. The comparative analysis reveals significant disparities in reasoning capabilities across the three LLMs when handling Chinese travel-related queries. DeepSeek-V2.5 demonstrates robust performance in most categories, achieving high accuracy (Correct $\geq$ 93%) for attraction-names, attraction-types, restaurant-names, and hotel-features. However, its performance sharply declines in hotel-names (Correct: 67%, Missing: 33%), suggesting limited familiarity with Chinese hotel nomenclature or insufficient contextual grounding in this domain. This contrasts with GPT-4o, which excels in hotel-names (Correct: 93%) and achieves perfect accuracy (Correct: 100%) for attraction-types,

highlighting its superior cross-lingual transfer capabilities despite being primarily English-trained. Notably, GPT-4o maintains consistent performance across all categories (Correct ≥ 93%), underscoring its balanced reasoning proficiency in Chinese contexts. In stark contrast, Qwen2.5-7B exhibits critical weaknesses, particularly in attraction-names (Correct: 13%, Error: 43%), indicating severe limitations in entity recognition and syntactic coherence for Chinese proper nouns. The pronounced missing rates observed in Qwen2.5-7B (e.g., 43% for attraction-names and 23% for hotel-names) align with its constrained parameter size (7B), which likely impedes its ability to internalize diverse travel requirements or align them with sandbox's POI information.

We further conduct the analysis and provide the results on human queries in Figure 14. The evaluation of human queries reveals critical limitations in LLMs' practical reasoning capabilities that synthetic data fails to expose. DeepSeek-V2.5's accuracy plummets in hotel-feature (Correct: 40% vs. 93% in synthetic data), indicating severe degradation when handling ambiguous or culturally nuanced requirements (e.g., interpreting subjective descriptors like "luxury" or "traditional courtyard-style" in Chinese contexts). GPT-4o similarly exhibits instability, with significant declines in restaurant-types (Correct: 37% vs. 97% in synthetic data) and attractions-type (Correct: 69% vs. 100%), suggesting that its cross-lingual transfer mechanisms falter when confronted with real-world linguistic variability (e.g., colloquial phrasing or dialect influences). This analysis underscores the necessity of introducing human queries into benchmarks when evaluating travel planning, as they reveal critical gaps in open language reasoning for deploying LLMs in real-world travel assistants.

H.3 Analysis of Pure-LLM Methods

Pure LLM-based methods have demonstrated significant shortcomings in constraint satisfaction, as evidenced by their near-zero success rates in benchmarks like TravelPlanner. We also attempt the multi-round refinement methods like Reflexion. While theoretically promising, it is still impractical in our context. In preliminary evaluations, Reflexion not only failed to achieve improvements in constraint satisfaction (consistent 0% FPR) but also incurred prohibitive computational costs due to its reliance on iterative token-heavy interactions. This rendered large-scale evaluation infeasible given our resource constraints. In light of their current limitations in constraint satisfaction, NeSy frameworks remain the effective pathway for real-world travel planning. Therefore, in the main body of this work, we mainly analyze the Nesy method.

In this section, we further summarize the key failure modes of pure-LLM-based methods observed in our experiments:

(1) **Incorrect API Calls:** LLMs frequently generate invalid or hallucinated API calls, leading to cascading errors in downstream planning. For instance, models may query non-existent APIs (e.g., city_transport_select instead of inter_city_transport_select) or misuse parameters (e.g., filtering attractions by an unsupported feature like "bus"). Such errors exhaust API call limits and prevent agents from retrieving essential information.

(2) **Repetitive Output Loops** In iterative planning frameworks like ReAct, LLMs often enter infinite loops when resolving constraints. For example, an agent might repeatedly query transportation details for all candidate attractions, even after selecting one, due to a failure to update its internal state. This behavior mimics the "hallucination loops" reported in TravelPlanner paper.

(3) **Reasoning-Action Inconsistency.** In ReAct framework, the model first reasons and then takes an action. However, the reasoning and the action are not always consistent. For example, the model may reason that the user wants to book a flight, but then take an action to check the information of trains. Another example is that the model may detect that the expenses exceed the budget but does not respond to this and ultimately generates a plan that exceeds the budget.

(4) **Critical Information Missing.** Even when intermediate steps (e.g., API responses) are logged in a "notebook," LLMs frequently omit essential details when synthesizing final plans. A recurring failure is neglecting return transportation (e.g., omitting the train from Shanghai back to Beijing), which violates feasibility constraints.

Figure 15 provides the fail examples of ReAct (one-shot) with DeepSeek, which outperforms other pure-LLM-based methods in the main experiments.

These limitations underscore the inadequacy of pure-LLM-based approaches for deployment in long-horizon and constraint-rich domains like travel planning.

I Statements about Scientific Artifacts

The ChinaTravel benchmark is designed to facilitate research in natural language processing and artificial intelligence, specifically for travel planning tasks. ChinaTravel includes a travel sandbox, user queries, and an evaluation framework intended for non-commercial, academic research purposes.

Availability. We will publicly release the ChinaTravel benchmark upon publication to facilitate community research. We look forward to broader adoption and extension of this benchmark.

Licenses. The ChinaTravel benchmark and its associated datasets are licensed under the Creative Commons Attribution-NonCommercial 4.0 International (CC-BY-NC 4.0) license. This license allows for the free use, distribution, and reproduction of the benchmark in any medium, provided that appropriate credit is given to the original authors and the source of the data is acknowledged, and that the use is for non-commercial purposes only.

Data anonymization and offensive content. We anonymized the human queries during collection and instructed participants to avoid including sensitive information. We removed queries containing offensive content during the data cleaning process.

J Statements about Human Participants

We recruited over 250 volunteers through a structured questionnaire to collect authentic Chinese travel requirements. Participants were informed about the public use of their data and instructed to avoid including sensitive personal information. During data cleaning, offensive content and identifiable details were removed. While no explicit ethics board approval is mentioned, we ensured compliance with anonymization practices and obtained participant consent for data inclusion. The final dataset contains 154 human-derived queries reflecting diverse real-world travel needs.

J.1 Instructions Given To Participants

To gather the authentic travel requirements, we collected data through a carefully designed questionnaire. We provided the following instruction information to the participants:

1. The specific constraints the agent can handle and the corresponding details, including the types and specific names of attractions, restaurants, and hotels; requirements for intercity transportation (airplane or train) and urban transportation (walk, taxi or subway); as well as budget limitations for overall expenses or specific activities (such as accommodation and intercity transportation).
2. The necessary information should be provided in the query, including the departure and destination cities of the trip, the number of travel days and constraint information.
3. A detailed example with the query and travel planning response.

Fig. 16 and Fig. 17 respectively show the questionnaire and its translated version.

J.2 Recruitment And Payment

For the collection of Human-154, we recruited a total of 250 student volunteers to provide authentic Chinese travel requirements. The participants included 121 undergraduate students, 86 master's students, and 43 doctoral students. The task of understanding the query background and providing travel requirements was estimated to take 1-2 minutes per participant. Given the simplicity of the task and the fact that it did not require extensive professional background or expertise, we compensated each participant with 1 yuan. This compensation was deemed adequate considering the nature of the task and the time required to complete it. The payment was determined based on the estimated time and the straightforward nature of the natural language requirements, ensuring a fair and reasonable reward for the participants.

For Human-1000, we partnered with WJX (a professional survey platform) to scale data collection. Each valid query was incentivized with 6 CNY. After WJX's initial screening, our team rigorously

annotated responses, filtering invalid entries (e.g., nonsensical inputs). It finally yielded 1,000 high-quality queries meeting DSL annotation standards, ensuring both diversity and alignment with real-world planning scenarios.

J.3 Data Consent

When collecting the data, we clearly informed the participants about the usage of the data and the potential irreversible risks of it becoming part of a public dataset. We did not track the ID information of the questionnaire respondents. Additionally, we reminded participants not to include any sensitive personal information in the questionnaire responses. During the data cleaning process, we directly removed queries containing offensive content and filtered out sensitive identity information.

J.4 Characteristics of Annotators

Our data collection process solely involved travel requirements and did not include any protected information, such as sexual orientation or political views as defined under the General Data Protection Regulation (GDPR). All data were collected from native Chinese speakers to ensure that the travel requirements fully align with the context and nuances of the Chinese language. This approach was taken to accurately capture the needs and preferences of the target population, which is primarily composed of Chinese-speaking individuals. The annotators were recruited from a diverse range of academic backgrounds, including undergraduate, master's, and doctoral students, to provide a broad and representative set of travel requirements.

J.5 DSL Annotation for Human Data

The annotation process for the human data involved four stages to ensure the accuracy and validity of the Domain-Specific Language (DSL) annotations: (1) Initial DSL Version Generation: GPT-4o was utilized to provide the initial version of the DSL annotations for the human data. This step aimed to leverage the language model's capabilities to generate a baseline for further refinement. (2) Data Annotation Team Revision: A team of five data annotators was responsible for reviewing and revising the DSL annotations. The team members divided the workload and made necessary corrections to the DSL annotations to ensure their accuracy and relevance to the travel requirements. (3) Primary Developer Verification and Correction: Three of the main developers of the benchmark conducted a thorough review of all the DSL annotations. They verified the correctness of the annotations and made revisions as needed. This stage also involved the exclusion of any invalid queries that could not be verified within the sandbox environment. (4) Final Verification by Primary Developers: The same three main developers performed a final check on all the DSL annotations. This step ensured that the annotations were accurate, consistent, and met the required standards for the benchmark.

Throughout the annotation process, the focus was on ensuring that the DSL annotations accurately captured the travel requirements and were valid within the context of the ChinaTravel benchmark's sandbox environment. The annotation process for human data required a deep understanding of the ChinaTravel DSL and involved joint debugging and verification with the sandbox information. This significantly limited the size of the annotation team, as only a limited number of annotators had the necessary expertise and familiarity with both the DSL and the sandbox environment. Additionally, the process was time-consuming and required meticulous attention to detail, further constraining the rate at which the human dataset could grow. Despite these challenges, the rigorous annotation process ensured the quality and reliability of the human data, which is crucial for the evaluation and development of language agents in real-world travel planning.

K TTG

K.1 Constraints Formulation

TTG [14] models the travel planning problem as a MILP (Mixed-Integer Linear Programming) problem. We adapt their formulation into ChinaTravel for solver-based optimization and the specific parameters, variable and constraint settings can be found in Tab. 151617.

K.2 Experiment

Although TTG performs very well on Travelplanner, the solver takes slightly more than 1 second on average to complete the computation. On the ChinaTravel benchmark, the rapid growth of constraints in TTG becomes computationally prohibitive. If we use the full sandbox, the average number of constraints will exceed **10B** (For detailed calculations of variable sizes and the number of constraints, please refer to Tab. 1819). Therefore, we only include 22 POIs (2 hotels, 10 attractions, 5 restaurants, 5 stations, 100 intercity transports each for arrivals and departures) and use one hour as a time step. We use LLMs to select them from sandbox to ensure sufficient flexibility in handling different queries. Nonetheless, its constraint scale still reaches $320k \times$ days and the number of variables also reaches $36k \times$ days. In comparison, the commonly used benchmark for evaluating MILP solvers, MIPLIB 2017 [8], contains only 10 instances with more than 320k constraints and about 60 instances with over 36k variables (out of a total of 1065 instances).

In our main experiments, using the SCIP solver from the PuLP package, TTG was allocated a relaxed 15-minute search limitation. However, this configuration yielded only 18% valid solutions on easy-subset instances, with the false positive rate (FPR) further reduced to 8% due to the solver's pruning heuristics. Fig. 6(a) illustrates the solution time of TTG on 1- to 3-day itineraries. Within the time limit, solutions were found for merely 23% of two-day and 6% of three-day itineraries.

Parameter	**Meaning**
hotelNum	Number of hotels
attrNum	Number of attractions
restNum	Number of restaurants
transNum	Number of transport modes
stationNum	Number of stations
goNum	Number of arriving trains/buses
backNum	Number of departing trains/buses
timeStep	Number of time steps
$locNum = hotelNum + attrNum + restNum$	Total number of POI locations except stations
$totalNum = locNum + stationNum$	Total number of all locations including stations

Table 15: Definition of parameters used in TTG

Variable	**Meaning**
$u[\text{idx}][t]$	The traveler is at location `idx` at time t
$\text{event}[t]$	The traveler's location changes at time t
$\text{hotel}[\text{idx}][d]$	Number of times the traveler visits hotel `idx` on day $(d+1)$
$\text{attr}[\text{idx}]$	Number of times the traveler visits attraction `idx`
$\text{rest}[\text{idx}][\text{meal}]$	Number of times the traveler visits restaurant `idx` at meal `meal`
$z_{\text{hotel}}, z_{\text{attr}}, z_{\text{rest}}, \delta$	Auxiliary variables
$\text{needEat}[m]$	Whether the traveler needs to eat meal m (during intercity travel)
check[idx][t]	Whether the attraction idx is open at time t
y[(i, j, tr,t)]	The solution, a matrix of shape $totalNum \times totalNum \times transNum \times timeStep$

Table 16: Variables used in TTG

Constraint Type	Mathematical Formulation
Spatio-temporal Constraints	$\delta[\text{idx}][t] \geq u[\text{idx}][t+1] - u[\text{idx}][t]$
	$\delta[\text{idx}][t] \geq u[\text{idx}][t] - u[\text{idx}][t+1]$
	$\text{event}[t] = 0 \Rightarrow u[\text{idx}][t] = u[\text{idx}][t+1]$
	$\text{event}[t] = 1 \Rightarrow \sum_{\text{idx}} \delta[\text{idx}][t] = 2$
	$\sum_i u[i][t] = 1$
Hotel Constraints	$z_{\text{hotel}}[\text{idx}][t] = u[\text{idx}][t] \wedge \text{event}[t]$
	$\text{hotel}[\text{idx}][d] = \sum_{t=d\cdot\text{stepPerDay}}^{(d+1)\cdot\text{stepPerDay}} z_{\text{hotel}}[\text{idx}][t]$
	$\sum_{\text{idx}} \text{hotel}[\text{idx}][d] = 1$
Attraction Constraints	$z_{\text{attr}}[\text{idx}][t] = u[\text{idx}][t] \wedge \text{event}[t]$
	$\text{attr}[\text{idx}] = \sum_t z_{\text{attr}}[\text{idx}][t]$
	$\sum_{\text{idx}} \text{attr}[\text{idx}] \geq \text{min\_attr}$
	$\text{check}[\text{idx}][t] = \text{False} \Rightarrow u[\text{idx}][t] = 0$
Meal Necessity	$\text{needEat}[m] = 1 \Rightarrow a[m] < T_{\text{dep}}$
	$\text{needEat}[m] = 1 \Rightarrow b[m] > T_{\text{arr}}$
Innercity Transport Constraints	$y[(i,j,\text{tran},t)] \leq u[i][t]$
	$y[(i,j,\text{tran},t)] \leq \text{event}[t]$
	$y[(i,j,\text{tran},t)] \leq u[\text{tran}][t+1]$
	$y[(i,j,\text{tran},t)] \leq u[\text{tran}][t+\delta]$
	$y[(i,j,\text{tran},t)] \leq \text{event}[t+\delta]$
	$y[(i,j,\text{tran},t)] \leq u[j][t+\delta+1]$
Restaurant Constraints	$z_{\text{rest}}[\text{idx}][t] = u[\text{idx}][t] \wedge \text{event}[t]$
	$\text{rest}[\text{idx}][m] = \sum_{t=a[m]}^{b[m]} z_{\text{rest}}[\text{idx}][t]$
	$\sum_{\text{idx}} \text{rest}[\text{idx}][m] \leq \text{needEat}[m]$
	$\text{check}[\text{idx}][t] = \text{False} \Rightarrow u[\text{idx}][t] = 0$
Intercity Travel Constraints	$\sum_i \text{interGo}[i] = 1$
	$\sum_i \text{interBack}[i] = 1$
	$\text{interGo}[i] = 1 \Rightarrow u[\text{goStation}[i]][t] = 1$
	$\text{interBack}[i] = 1 \Rightarrow u[\text{backStation}[i]][t] = 1$

Table 17: Constraints used in TTG

An Example of Prompts for Data Generation

```
# You are a user who wants to ask an AI agent to help you
   plan a trip. Please construct some natural language
   inquiries based on the following example and provide
   the corresponding logical constraint expressions. Note
    that "tickets" and "people_number" are the same.
# Example:
# JSON:
# {}
# Use the following restaurants.
# Restaurant name: {}
# This means that "restaurant_names" should include this
   restaurant.
# The dining options may not always be exactly as
   described by the provided features; synonyms can be
   used. For example, if the hotel's feature is a pool,
   you could ask naturally in language like "I want to
   swim in the hotel pool."
# Now, your departure location is {}, and your destination
    is {}. The number of people is {}, and the number of
   days is {}.
# Now please provide a JSON inquiry.
# JSON:
```

Figure 11: An example of prompts for data generation. This example is about restaurant_name. By replacing this with other constraints or combining multiple constraints, we can generate data with different levels of difficulty based on different constraints.

Variable	Dimension
$u[\text{idx}][t]$	$(totalNum + transNum) \times timeStep$
$\delta[\text{idx}][t]$	$(totalNum + transNum) \times (timeStep - 1)$
$\text{event}[t]$	$timeStep$
$\text{hotel}[\text{idx}][d]$	$hotelNum \times days$
$z_{\text{hotel}}[\text{idx}][t]$	$hotelNum \times timeStep$
$\text{attr}[\text{idx}]$	$attrNum$
$z_{\text{attr}}[\text{idx}][t]$	$attrNum \times timeStep$
$\text{rest}[\text{idx}][\text{meal}]$	$restNum \times 3 \times days$
$z_{\text{rest}}[\text{idx}][t]$	$restNum \times timeStep$
$y[(i, j, \text{tr}, t)]$	$totalNum \times totalNum \times transNum \times timeStep$
total	$days \times stepPerHour \times 36k$

Table 18: Variable sizes in TTG

Examples of Generated Data

Example 1

{
”start_city”: ”杭州”,
”target_city”: ”上海”,
”hard_logic”: [
”days==2”,
”people_number==1”,
”tickets==1”,
”{’本帮菜’} ¡= food_type”
],
”nature_language”: ”当前位置杭州。我一个人想去上海玩2天，想尝试当地的特色菜，请给我一个旅行规划。”
}

Example 2

{
”start_city”: ”深圳”,
”target_city”: ”北京”,
”hard_logic”: [
”days==2”,
”people_number==3”,
”intercity_transport=={’airplane’}”,
”tickets==3”,
”rooms==3”,
”room_type==1”
],
”nature_language”: ”当前位置深圳。我们三个人计划去北京玩两天，选择飞机出行，开三间大床房。请给我一个旅行规划。”
}

Example 3

{
”start_city”: ”重庆”,
”target_city”: ”苏州”,
”hard_logic”: [
”days==3”,
”people_number==3”,
”cost¡=7300”,
”{’日本料理’} ¡= food_type”,
”intercity_transport=={’train’}”,
”tickets==3”,
”rooms==2”,
”room_type==2”
],
”nature_language”: ”当前位置重庆。我们三个人计划去苏州玩三天，选择火车出行，想吃日本料理，预算7300元，开两间双床房。请给我一个旅行规划。”
}

Figure 12: Examples of Generated Data

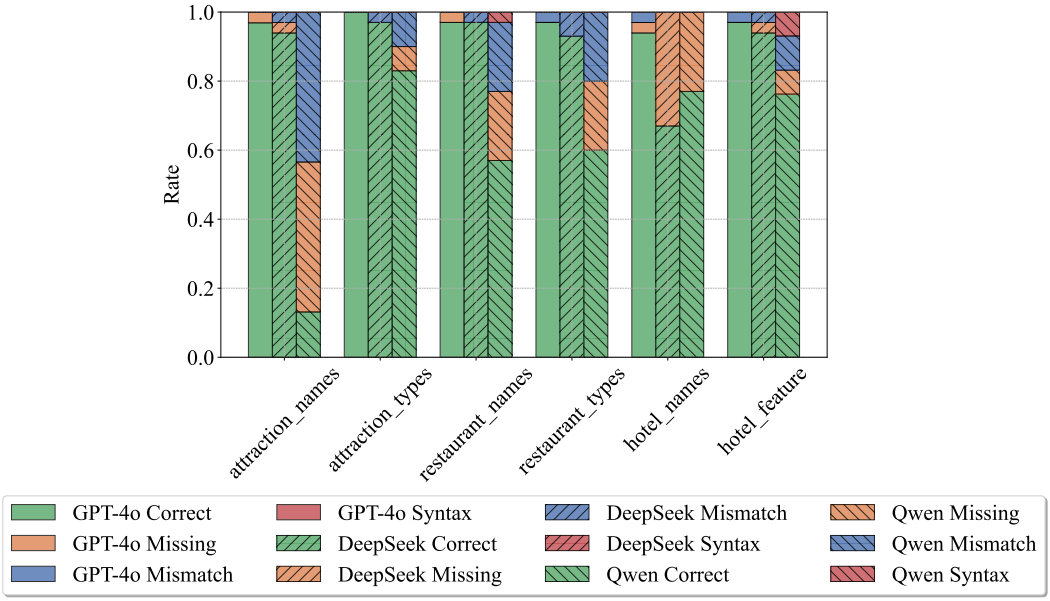

Figure 13: Results Distribution on Synthesized Quires

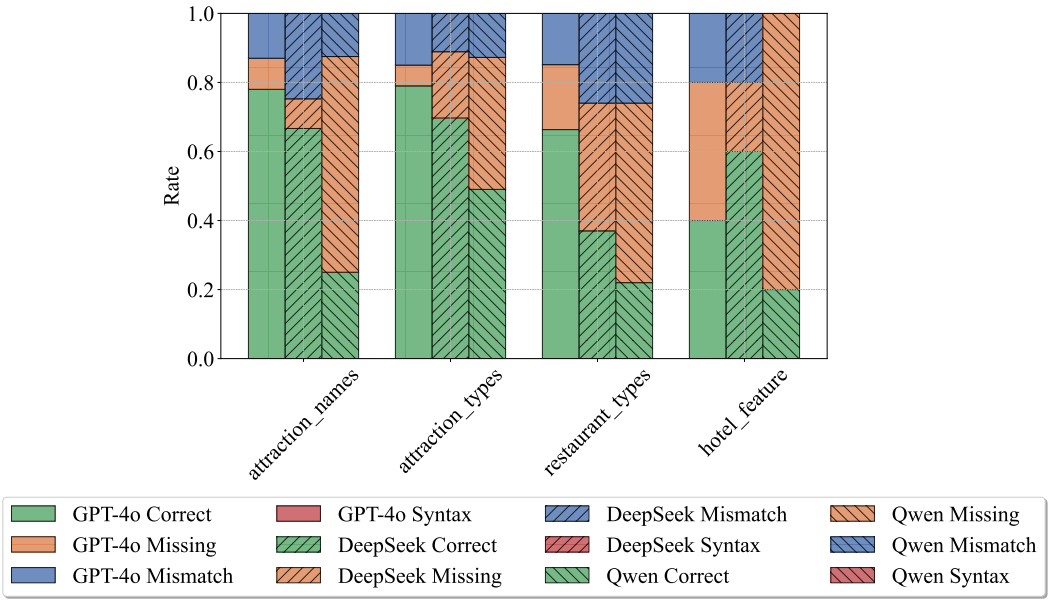

Figure 14: Results Distribution on Human Quires

Category	**Estimated Size**
Spatio-temporal constraints	$(totalNum + transNum) \times (4 \times timeStep + 3)$
Hotel constraints	$hotelNum \times (3 \times timeStep + days)$
Attraction constraints	$4 \times attrNum \times timeStep$
Restaurant constraints	$restNum \times (4 \times timeStep + days)$
Urban transport constraints	$7 \times totalNum^2 \times transNum \times timeStep + 4 \times totalNum \times timeStep$
Intercity transport constraints	$(goNum + backNum) \times timeStep$

Table 19: Number of constraints sizes in TTG

Incorrect API Calls

Action[20]: goto(city="深圳", start="深圳北站", end="大鹏所城", start_time="19:00", method="bus")
Observation[20]: Invalid method. Only support ['metro', 'walk', 'taxi']
…
Action[25]: goto(city="深圳", start="深圳北站", end="大鹏所城", start_time="19:00", method="bus")
Observation[25]: Invalid method. Only support ['metro', 'walk', 'taxi']
…
Action[30]: goto(city="深圳", start="深圳北站", end="大鹏所城", start_time="19:00", method="bus")
Observation[30]: Invalid method. Only support ['metro', 'walk', 'taxi']

Action[3]: city_transport_select(start_city="成都", end_city="武汉", intercity_type="train", earliest_leave_time="19:00")
Observation[3]: 调用失败，错误信息：name 'city_transport_select' is not defined请思考错误原因以及如何修改.
Thought[4]": 函数名错误，应该是intercity_transport_select。重新调用正确的函数。

Repetitive Output Loops

Thought[12]: 我们可以选择黄鹤楼和东湖磨山景区作为主要景点。接下来我们需要查找这两个景点的详细信息。
Action[12]: attractions_select(city="武汉", key="name", func=lambda x: "黄鹤楼" in x or "东湖磨山景区" in x)
…
Thought[13]: 我们可以选择黄鹤楼和东湖磨山景区作为主要景点。接下来我们需要查找这两个景点的详细信息。
Action[13]: attractions_select(city="武汉", key="name", func=lambda x: "黄鹤楼" in x or "东湖磨山景区" in x)
…
Thought[14]: 我们可以选择黄鹤楼和东湖磨山景区作为主要景点。接下来我们需要查找这两个景点的详细信息。
Action[14]: attractions_select(city="武汉", key="name", func=lambda x: "黄鹤楼" in x or "东湖磨山景区" in x)
…
Thought[15]: 我们可以选择黄鹤楼和东湖磨山景区作为主要景点。接下来我们需要查找这两个景点的详细信息。
Action[15]: attractions_select(city="武汉", key="name", func=lambda x: "黄鹤楼" in x or "东湖磨山景区" in x)
…

Reasoning-Action Inconsistency

Thought[2]: "根据我们的经验判断，高铁可能比较快且舒适，可以查看一下高铁的航班。
Action[2]": "intercity_transport_select(start_city="深圳", end_city="南京", intercity_type="airplane")
Observation[2]: ['FlightID' 'From' 'To' 'BeginTime' 'EndTime' 'Duration' 'Cost']\n['FL240' '深圳宝安国际机场' '南京禄口国际机场'…

Thought[14]: 预算超支，我们需要重新规划。我们可以考虑减少一些开销，比如选择更便宜的餐馆或者减少一些景点的游览时间。
Action[14]: planner(query="当前位置广州。我和我朋友想去上海玩一天，预算3100人民币，请给我一个旅行规划。")
Observation[14]: Task finished. The answer is: {"people_number": 2, "start_city": "广州", "target_city": "上海", "itinerary": [{"day": 1, "activities": [{"start_time": "08:00", "end_time": "14:48", "start": "广州南站", "end": "上海虹桥站", "cost": 787.73, "FlightID": "G818", "type": "train", "tickets": 2, "transports": []}, {"position": "外滩", "type": "attraction", "transports": [{"start": "上海虹桥站", "end": "虹桥火车站-地铁站", "mode": "walk" …

Critical Information Missing

Action[15]: planner(query="当前位置广州。我一个人想去武汉玩一天，预算3000人民币，请给我一个旅行规划。")
Observation[15]: Task finished. The answer is: {"people_number": 1, "start_city": "广州", "target_city": "武汉", "itinerary": [{"day": 1, "activities … {"start_time": "18:00", "end_time": "22:39", "start": "武汉站", "end": "广州南站", "cost": 543.6, "TrainID": "G877", "type": "train", "tickets": 1, "transports": []}]}]}"

Action[23]: planner(query="当前位置深圳。我一个人想去苏州玩一天，预算1600人民币，请给我一个旅行规划。")"
Observation[23]: Task finished. The answer is: {"people_number": 1, "start_city": "深圳", "target_city": "苏州", "itinerary": [{"day": 1, "activities": [{"type": "train", "start_time": "06:33", "end_time": "15:46", "cost": 759.35, "tickets": 1, "start": "深圳站", "end": "苏州站", "TrainID": "G2787", "transports": []}, …., "start": "虎丘山风景名胜区", "end": "苏州站", "transports": []}, {"type": "train", "start_time": "22:33", "end_time": "07:00", "cost": 759.35, "tickets": 1, "start": "苏州站", "end": "深圳站", "TrainID": "G2788", "transports": []}]}]}"

Figure 15: Fail case studies of React-one-shot DeepSeek Method.

开放旅行规划问题搜集

本问卷旨在构建一个开放环境下的旅行规划数据集，以便于相关研究的开展。由于填写的问题将作为公开数据集的一部分，存在无法撤销的风险；请勿在填写内容中包含任何敏感的个人信息，感谢大家的参与！

1. 出发城市：_____（从北京、南京、上海、杭州、深圳、武汉、广州、成都、重庆、苏州中选择）
2. 目标旅游城市：_____（从北京、南京、上海、杭州、深圳、武汉、广州、成都、重庆、苏州中选择）
3. 旅行人数：_____（1-5）
4. 旅行天数：_____（1-5）

您作为用户可以向智能代理发起查询请求。查询内容可以包括对景点、餐饮、住宿、跨城交通(如火车、飞机)以及城内交通(如地铁、步行、出租车)的具体要求。同时，您也可以提供个人偏好。请确保查询中包含以下三个信息:目标城市、人数和天数，并确保这些信息相互匹配。智能代理将根据您的请求提供一个旅行规划结果，包括这几天的交通安排、住宿地点、推荐的景点及餐饮建议。

用户问题的例子:

当前位置苏州。我一个人想去南京玩 2 天，预算 3000 人民币，往返都坐高铁，请给我一个旅行规划。

智能代理回复的例子:

起点:苏州
目的地:南京
交通:苏州北站 -> 南京南站
列车:G4，07:24->08:15
费用:122.9 元
车票:1 张
游览:玄武湖景区
交通:地铁(南京南站 ->南京林业大学·新庄)，步行 3 分钟 +地铁 23 分钟+步行 8 分钟
费用:4 元
游览时间:08:50->10:00
门票:0 元
……
午餐:南京金鹰国际酒店·满园春中餐厅
费用:188 元
时间:12:10 ->13:10
住宿:桔子水晶南京玄武湖酒店
房型:大床房，1 间
费用:370 元
返回:南京南站 > 苏州站
列车:G7220，20:09->21:23
费用:122.9 元
车票:1 张

我们将用户问题分为不同难度级别进行分类，以下是每个级别的描述

低级:涉及一般性问题，不包含个性化需求。
中级:包含一定程度的个性化需求，通常涉及到食宿交通等方面。
高级:涉及更复杂、更具体的需求，如时间要求、特定地点或活动的安排等。

以下是不同难度级别下的用户问题示例:

低级:我想知道去上海玩 2 天的行程规划，从杭州出发。
中级:我想独自一人前往南京穷游，计划在那里待 3 天左右。我对历史文化很感兴趣，希望能深度游览一些古迹。
高级:我们三人后天需要前往北京玩 2 天。第二天晚上十点前需要从北京站返回。想在第一天去故宫，第二天去天坛，请给一个旅行规划

5. 请给出用户问题：_____

Figure 16: Questionnaire

Open Travel Planning Data Collection Questionnaire

This questionnaire aims to construct a dataset for travel planning in an open environment to facilitate relevant research. Since the responses will be part of a public dataset and cannot be revoked, please do not include any sensitive personal information in your responses. Thank you for your participation!

1. Departure City:_____ (Choose from Beijing, Nanjing, Shanghai, Hangzhou, Shenzhen, Wuhan, Guangzhou, Chengdu, Chongqing, Suzhou)
2. Destination City: _____ (Choose from Beijing, Nanjing, Shanghai, Hangzhou, Shenzhen, Wuhan, Guangzhou, Chengdu, Chongqing, Suzhou)
3. Number of Travelers:_____ (1-5)
4. Number of Travel Days:_____ (1-5)

As a user, you can submit queries to the intelligent agent. Your query may include specific requirements for attractions, dining, accommodation, intercity transportation (e.g., train, plane), and intra-city transportation (e.g., subway, walking, taxi). You may also provide personal preferences. Please ensure that your query includes the following three pieces of information: the destination city, the number of travelers, and the number of travel days, and make sure they are consistent. The intelligent agent will generate a travel plan based on your request, covering transportation arrangements, accommodation, recommended attractions, and dining suggestions.

Example User Query:
"My current location is Suzhou. I want to travel alone to Nanjing for 2 days with a budget of 3,000 RMB, taking the high-speed train for both departure and return. Please provide a travel plan."

Example Response from the Intelligent Agent:

Departure: Suzhou
Destination: Nanjing
Transportation: Suzhou North Station → Nanjing South Station
Train: G4, 07:24 → 08:15
Cost: 122.9 RMB
Tickets: 1
Attraction: Xuanwu Lake Scenic Area
Transportation: Subway (Nanjing South Station → Nanjing Forestry University·Xinzhuang)
Route: Walk 3 minutes → Subway 23 minutes → Walk 8 minutes
Cost: 4 RMB
Visit Time: 08:50 → 10:00
Admission: 0 RMB
…
Lunch: Nanjing Jinling Hotel · Man Yuan Chun Chinese Restaurant
Cost: 188 RMB
Time: 12:10 → 13:10
Accommodation: Crystal Orange Hotel Nanjing Xuanwu Lake
Room Type: Queen Room, 1 room
Cost: 370 RMB
Return: Nanjing South Station → Suzhou Station
Train: G7220, 20:09 → 21:23
Cost: 122.9 RMB
Tickets: 1
Classification of User Queries by Difficulty Level
We categorize user queries into different difficulty levels as follows:

Easy Level: General inquiries without personalized requirements.
Medium Level: Includes some degree of personalization, usually involving food, lodging, or transportation.
Hard Level: Involves more complex and specific needs, such as time constraints, particular locations, or planned activities.
Examples of User Queries at Different Difficulty Levels:
Basic Level: "I want to know the itinerary for a 2-day trip to Shanghai from Hangzhou."
Intermediate Level: "I plan to travel alone to Nanjing on a budget and stay for about three days. I'm interested in history and culture and would like to explore historical sites in depth."
Advanced Level: "Three of us need to travel to Beijing the day after tomorrow for a 2-day trip. We need to return from Beijing Railway Station before 10 PM on the second day. We want to visit the Forbidden City on the first day and the Temple of Heaven on the second day. Please provide a travel plan."

5. Please provide a user query:_____

Figure 17: The translated version of the questionnaire

ChinaTravel	TravelPlanner
当前位置武汉。我一个人想去苏州玩一天，预算 1400 人民币，请给我一个旅行规划。 Current location: Wuhan. I want to visit Suzhou for a day by myself with a budget of 1,400 RMB. Please provide me with a travel plan.	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.
当前位置南京。我一个人想去重庆玩 3 天，喜欢吃甜食面包啥的，请给我一个旅行规划。 Current location: Nanjing. I want to travel to Chongqing alone for 3 days. I like sweet foods and bread. Please provide me with a travel plan.	Please design a travel plan departing from Las Vegas and heading to Stockton for 3 days, from March 3rd to March 5th, 2022, for one person, with a budget of $1,400.
当前位置重庆。我和朋友两个人想去武汉玩 3 天，想尝试当地菜，请给我们一个旅行规划。 Current location: Chongqing. My friend and I want to visit Wuhan for 3 days and try the local cuisine. Could you please provide us with a travel plan?	Craft a travel plan for me to depart from New Orleans and head to Louisville for 3 days, from March 12th to March 14th, 2022. I will be travelling alone with a budget of $1,900.
当前位置成都。我们三个人想去深圳玩 2 天，想去历史感比较重的景点，请给我们一个旅行规划。 Current location: Chengdu. The three of us want to visit Shenzhen for 2 days and are interested in historical sites. Could you please provide us with a travel itinerary?	Could you aid in curating a 5-day travel plan for one person beginning in Denver and planning to visit 2 cities in Washington from March 23rd to March 27th, 2022? The budget for this trip is now set at $4,200.
当前位置深圳。我和朋友两个人想去上海玩 3 天，想去海洋水族馆，请给我们一个旅行规划。 Current location: Shenzhen. My friend and I want to visit Shanghai for 3 days and we would like to go to the Ocean Aquarium. Could you please provide us with a travel plan?	Could you assist in crafting a travel itinerary for a 5-day, single-person trip departing from Orlando and touring 2 cities in Texas? The travel dates should range from March 10th to March 14th, 2022, and the entire travel budget is $3,100.
当前位置成都。我和朋友两个人想去上海玩 3 天，住一间双床房，期间可能要开会，酒店最好能提供个开会的地方，请给我一个旅行规划。 Current location: Chengdu. My friend and I want to visit Shanghai for 3 days. We need a twin room, and we might need a meeting space during our stay. Please provide me with a travel plan.	Could you help me arrange a 7-day solo travel itinerary from Kona to California with a budget of $5,800, intending to visit 3 distinct cities in California from March 7th to March 13th, 2022?
我目前在南京，计划和两个朋友一起去上海玩两天，选择原舍 • 在水一方度假酒店，请帮我们规划一个旅行方案。 I am currently in Nanjing and plan to travel to Shanghai with two friends for two days. We have chosen the YuanShe · Zai Shui Yi Fang Resort Hotel. Please help us plan a travel itinerary.	Please help me craft a 7-day travel plan. I'm planning on leaving from Punta Gorda and exploring 3 different cities in Wisconsin from March 16th to March 22nd, 2022. The budget for this trip is set at $5,700.
当前位置北京。我和三个朋友计划去成都玩两天，选择火车出行，市内交通方式为地铁。请给我一个旅行规划。 Current location: Beijing. My three friends and I are planning to visit Chengdu for two days. We have chosen to travel by train and use subway for city transportation. Please provide me with a travel itinerary.	Could you help me create a 7-day travel plan starting on March 18th, 2022, and ending on March 24th, 2022? The trip will start in Washington and I would like to visit 3 cities in Minnesota. This trip is for one person with a budget of $7,200.

Figure 18: Examples of easy-level queries from ChinaTravel and TravelPlanner.

ChinaTravel	TravelPlanner
当前位置武汉。我两个人想去苏州玩 2 天，预算 4000 人民币，坐火车去，住一间大床房，想去虎丘山风景名胜区这样的自然风光，请给我一个旅行规划。 Current location: Wuhan. Two of us want to visit Suzhou for 2 days with a budget of 4000 RMB. We plan to take the train and stay in a room with a king-size bed. We would like to visit natural attractions like Tiger Hill Scenic Area. Please provide a travel itinerary.	Could you please arrange a 3-day trip for two, starting in Sacramento and heading to Atlanta, from March 14th to March 16th, 2022. The budget for this trip is $4,700, and we require accommodations where parties are allowed.
当前位置广州。我两个人想去成都玩 3 天，预算 9000 人民币，坐火车往返，住一间大床房，麻烦给我一个旅行规划。 Current location: Guangzhou. Two of us want to visit Chengdu for 3 days with a budget of 9,000 RMB. We plan to travel round-trip by train and stay in a room with a double bed. Could you please provide a travel itinerary for us?	Could you please design a 3-day travel plan for a group of 5, departing from Manchester and heading to Charlotte, from March 29th to March 31st, 2022? Our budget is set at $4,800 and we would prefer to have entire rooms for our accommodations.
当前位置广州。我和我的两个朋友想去深圳玩两天，预算 2100 人民币，住两间双床房，坐地铁游玩，想吃海鲜，想去深圳欢乐谷玩。Current location: Guangzhou. My two friends and I want to go to Shenzhen for two days. Our budget is 2,100 RMB. We plan to stay in two twin-bed rooms, travel around by metro, eat seafood, and visit Shenzhen Happy Valley.	Could you tailor a 5-day travel plan for two people, departing from Knoxville and visiting 2 cities in Florida from March 20 to March 24, 2022? Our budget is set at $3,900. We'd love to explore local Chinese and Mediterranean cuisines during our stay.
当前位置武汉。我两个人想去杭州玩 3 天，预算 7000 人民币，坐飞机往返，住一间大床房，麻烦给我一个旅行规划。 Current location: Wuhan. Two of us want to visit Hangzhou for 3 days with a budget of 7,000 RMB. We plan to travel by plane round-trip and stay in a room with a large bed. Could you please provide a travel plan for us?	Could you help create a 7-day travel plan for a group of 3, departing from Greensboro and touring 3 different cities in Georgia from March 10th to March 16th, 2022? We have a new budget of $4,000 for this trip. We'd also appreciate if our accommodations have smoking areas.
当前位置杭州。我两个人想去苏州玩 2 天，预算 3500 人民币，住一间大床房，想去看看拙政园这样的园林景观，请给我一个旅行规划。 Current location: Hangzhou. Two of us want to visit Suzhou for 2 days with a budget of 3,500 RMB. We would like to stay in a room with a large bed and visit garden attractions like the Humble Administrator's Garden. Please provide a travel plan.	Could you help create a 5-day travel itinerary for a group of 4, starting from New York and visiting 2 cities in Louisiana from March 15th to March 19th, 2022? We have a budget of $12,300. Please note that we require accommodations where smoking is permissible.
当前位置北京。我两个人想去深圳玩 3 天，预算 7000 人民币，住一间大床房，坐飞机去，酒店最好有泳池，想去深圳欢乐谷看一下，请给我一个旅行规划。 Current location: Beijing. Two of us want to visit Shenzhen for 3 days with a budget of 7,000 RMB. We would like to stay in a hotel with a king-size bed and preferably a swimming pool. We plan to fly there and would like to visit Shenzhen Happy Valley. Please provide a travel itinerary.	Can you provide me with a 5-day travel plan for 2 people, starting from Asheville and exploring 2 cities in New York from March 13th to March 17th, 2022? Our budget is set at $4,700 and we would love to try local Mexican and Chinese cuisines during our trip.

Figure 19: Examples of medium-level queries from ChinaTravel and TravelPlanner.

ChinaTravel	TravelPlanner
[当前位置武汉,目标位置南京,旅行人数 2,旅行天数 4] 我和同学 2 人打算去南京玩 4 天，预算 1500 (不包括车票住宿)，只是玩和吃饭，请你帮忙规划。 [Current location: Wuhan, Destination: Nanjing, Number of travelers: 2, Duration of travel: 4 days] My classmate and I are planning to visit Nanjing for 4 days. Our budget is 1500 (excluding transportation and accommodation), just for activities and meals. Please help us plan.	Can you create a 5-day itinerary for a group of 7 people traveling from Richmond to two cities in Florida between March 9th and 13th, 2022? Our budget is $8,500. We require accommodations that allow visitors and should ideally be entire rooms. In regards to dining options, we prefer French, American, Mediterranean, and Italian cuisines.
[当前位置南京,目标位置成都,旅行人数 3,旅行天数 5] 我们一家三口想去成都旅游一周，主要想逛一些适合带小朋友的景点，预算 8000 元，然后品尝一些当地的美食。 [Current location: Nanjing, Destination: Chengdu, Number of travelers: 3, Travel days: 5] Our family of three wants to travel to Chengdu for a week. We mainly want to visit attractions suitable for children, with a budget of 8,000 yuan, and also taste some local delicacies.	Could you help design a travel plan for two people leaving from Houston to Pensacola for 3 days, from March 6th to March 8th, 2022? Our budget is set at $1,400 for this trip and we require our accommodations to be visitor-friendly. We would like to have options to dine at Indian, American, Chinese, and Italian restaurants. We also prefer not to self-drive during the trip.
[当前位置广州,目标位置深圳,旅行人数 3,旅行天数 2] 我们一行三人要从广州去到深圳玩两天，想去繁华的街区逛逛，尽可能减少麻烦的交通，总消费尽可能少。 [Current location: Guangzhou, Destination: Shenzhen, Number of travelers: 3, Number of travel days: 2] Our group of three plans to travel from Guangzhou to Shenzhen for two days. We want to explore bustling neighborhoods, minimize inconvenient transportation, and keep the total expenses as low as possible.	Could you help create a 3-day travel plan for two people? We're traveling from West Palm Beach to White Plains, visiting only one city from March 5th to March 7th, 2022. We have a budget of $2,600. For our accommodations, we'd like rooms that are not shared. We are not planning on self-driving and will be reliant on public transportation. Cuisines we are interested in trying include Mexican, Chinese, Mediterranean, and American.
[当前位置苏州,目标位置杭州,旅行人数 4,旅行天数 2] 我想 4 个人去杭州 2 天进行历史文化遗址的考察顺带玩一下。 [Current location: Suzhou, Destination: Hangzhou, Number of travelers: 4, Duration of travel: 2 days] I would like 4 people to go to Hangzhou for 2 days to explore historical and cultural sites and have some fun along the way.	Could you generate a 3-day travel plan for a group of 3 people, departing from Bangor and visiting Washington from March 21st to March 23rd, 2022? Our budget is set at $3,100. We require accommodations that are pet-friendly and we would prefer to have entire rooms to ourselves. We do not plan on self-driving for this trip
[当前位置上海,目标位置北京,旅行人数 1,旅行天数 3] 我要从上海出发，到北京玩三天，希望看一些名胜古迹，吃一些当地特色，预算充分。 [Current location: Shanghai, Destination: Beijing, Number of travelers: 1, Number of travel days: 3] I want to depart from Shanghai and spend three days in Beijing. I hope to see some famous landmarks and try some local specialties, with a sufficient budget.	Could you help with creating a 5-day travel plan for 2 people, originating from Evansville and covering 2 cities in Texas from March 17th to March 21st, 2022? Our preferred accommodations are private rooms, and they must permit children under 10 since we will have them with us. Transportation should not involve any flights. The budget for this trip is set at $2,800.
[当前位置北京,目标位置上海,旅行人数 2,旅行天数 3] 我和朋友计划用三天的时间从北京到上海玩，计划坐飞机来回，偏红色旅游线路。 [Current location: Beijing, Destination: Shanghai, Number of travelers: 2, Number of travel days: 3] My friend and I are planning to spend three days traveling from Beijing to Shanghai. We plan to fly round trip and prefer a red-themed travel route.	Can you assist in creating a travel itinerary for a group of 4, starting in Seattle and visiting 3 unique cities across Texas? This trip will span over 7 days from March 10th through March 16th, 2022. We have a budget of $11,000. Regarding our accommodations, we would like to rent entire rooms, and it's important that our lodgings allow parties. As for transportation, we do not plan to drive ourselves around.

Figure 20: Examples of human/hard level queries from ChinaTravel and TravelPlanner.

Prompts for POI recommendation

```
NEXT_POI_TYPE_INSTRUCTION = """
   You are a travel planning assistant.
   The user's requirements are: {}.
   Current travel plans are: {}.
   Today is {}, current time is {}, current location is
      {}, and POI_type_list is {}.
   Select the next POI type based on the user's needs and
      the current itinerary.
   Please answer in the following format.
   Thought: [Your reason]
   Type: [type in POI_type_list]
    """
```

Figure 21: Prompts for next-POI-type recommendation

Prompts for restaurants recommendation

```
RESTAURANT_RANKING_INSTRUCTION = """
    You are a travel planning assistant.
    The user's requirements are: {user_requirements}.
    The restaurant info is:
    {restaurant_info}
    The past cost for intercity transportation and hotel
       accommodations is: {past_cost}.

    Your task is to select and rank restaurants based on
       the user's needs and the provided restaurant
       information. Consider the following factors:
    1. Restaurant name
    2. Cuisine type
    3. Price range
    4. Recommended food

    Additionally, keep in mind that the user's budget is
       allocated across multiple expenses, including
       intercity transportation and hotel accommodations.
        Ensure that the restaurant recommendations fit
       within the remaining budget constraints after
       accounting for the past cost.
    Note that the price range provided for each restaurant
        is the average cost per person per meal, the
       remaining budget must cover the cost of three
       meals per day for {days} days.

    For each day, recommend at least 6 restaurants,
       combining restaurants for all days together.

    Your response should follow this format:

    Thought: [Your reasoning for ranking the restaurants]
    RestaurantNameList: [List of restaurant names ranked
       by preference, formatted as a Python list]
    """
```

Figure 22: Prompts for restaurant recommendation

Prompts for attractions recommendation

```
ATTRACTION_RANKING_INSTRUCTION = """
    You are a travel planning assistant.
    The user's requirements are: {user_requirements}.
    The attraction info is:
    {attraction_info}
    The past cost for intercity transportation and hotel
       accommodations is: {past_cost}.

    Your task is to select and rank attractions based on
       the user's needs and the provided attraction
       information. Consider the following factors:
    1. Attraction name
    2. Attraction type
    3. Location
    4. Recommended duration

    Additionally, keep in mind that the user's budget is
       allocated across multiple expenses, including
       intercity transportation and hotel accommodations.
        Ensure that the attraction recommendations fit
       within the remaining budget constraints after
       accounting for the past cost.

    For each day, recommend at least 8 attractions,
       combining attractions for all days together. To
       ensure a comprehensive list, consider a larger
       pool of candidates and prioritize diversity in
       attraction type and location.

    Your response should follow this format:

    Thought: [Your reasoning for ranking the attractions]
    AttractionNameList: [List of attraction names ranked
       by preference, formatted as a Python list]

    Example:
    Thought: Based on the user's preference for historical
        sites and natural attractions, the attractions
       are ranked as follows:
    AttractionNameList: ["Attraction1", "Attraction2",
       ...]
    """
```

Figure 23: Prompts for attraction recommendation