LLM-Augmented Optimization for Singapore Travel Itinerary Planning

Daniel James[a,*], **Leonardo**[a,**], **Jing Shen Tai**[a,***], **Valerian Yap**[a,****] **and Hoong Chuin Lau**[a,*****]

[a]School of Computing and Information Systems, Singapore Management University
ORCID (Daniel James): https://orcid.org/....-....-....-...., ORCID (Leonardo): https://orcid.org/....-....-....-...., ORCID (Jing Shen Tai): https://orcid.org/....-....-....-...., ORCID (Valerian Yap): https://orcid.org/....-....-....-...., ORCID (Hoong Chuin Lau): https://orcid.org/....-....-....-....

Abstract. This paper presents a combined approach of Large Language Model (LLM) and Operation Research (OR) to develop an optimized travel planner for tourists visiting Singapore. Recognizing that traveler preferences vary significantly across demographics, we aim to generate customized itineraries that balance cost, travel time and personal satisfaction. We apply LLM agents to convert traveler's preferences in text format into a structured format that can be used for optimization. For optimization, we apply Adaptive Large Neighborhood Search (ALNS) with data enrichment techniques such as route matrix from Google Maps API to find out duration and price from point A to point B. Our contribution is the ability to make more-realistic itineraries, putting distance and cost into perspective, while focusing on traveler's best interest to minimize expenses and maximize satisfaction. We benchmarked against ... . Our approach ..., demonstrating the power of leveraging strengths of both LLM and ALNS in solving this problem.

1 Introduction

The objective of this project is to develop a personalized travel itinerary planner for tourists visiting Singapore, capable of allowing natural language inputs and input fields into the demo product and generating a feasible yet personalized itinerary by minimizing travel cost, minimizing total transit time between locations, and maximizing satisfaction that aligns with Persona-specific preferences.

Our commercial inspiration was primarily drawn from Pelago by Singapore Airlines, an AI-powered trip planner platform that covers over 2,000 destinations. While Pelago appears to be employing an LLM-based recommendation engine, our work diverges by introducing a multi-agent LLM system that is combined with Operation Research (OR) optimization techniques.

Our goal in this paper includes answering the following questions:

1. Recognising the hallucination in LLM, to what extent can LLM alone generate realistic and feasible travel itineraries? Is Agentic AI needed to be used in our project?
2. Assuming we have an LLM agent (e.g. a domain-expert in Singapore Attractions, equipped with memory, knowledge base and tools), can it handle reasoning consistency and personalisation without hallucinating? What is the trade-off for having multiple domain experts in our system?
3. What are the quantitative and qualitative trade-offs between optimization-only, LLM-only, multi-agent, and hybrid optimization itinerary planning pipelines?

This study is geographically and thematically scoped to the context of Singapore considering our familiarity of our local culture. Specifically, we focus on two categories of points of interest (POIs): (i) attractions, and hawker centres. In total, our curated dataset includes over 85 unique POIs.

2 Related Work

Recent research highlights the growing synergy between LLMs and traditional optimization methods in itinerary planning.

For example, *TRIP-PAL: Trip Planning with Guarantees by Combining LLMs and Automated Planners* (JP Morgan AI Research, 2024) explores how LLMs can be integrated with formal planning algorithms such as A* to produce reliable trip plans. This study shows that LLMs are capable of translating natural language inputs into structured formats compatible with optimization algorithms commonly used in operations research.

Similarly, *Optimizing Travel Itineraries with AI Algorithms in a Microservices Architecture: Balancing Cost, Time, Preferences, and Sustainability* (Barua & Kaiser, 2024) demonstrates how LLMs can support personalization within a modular microservices framework, enabling the coordination of multiple optimization objectives such as budget, travel time, user preferences, and sustainability.

3 Problem Definition

In this paper, we propose My Travel Itinerary Buddy – Automatic Itinerary (MITB – AI), where the goal is to generate multi-day travel itinerary for a tourist visiting Singapore, consisting of a sequence of POIs – including both attractions and hawker centres. This is also subjected to user-defined constraints (e.g. budget, number of days and person types) while optimizing for the following objectives: (1) minimize costs, (2) minimize travel time, and (3) maximize traveler's satisfaction from online ratings. This problem can be classified as a multi-objective combinatorial optimization task, where the system

* Corresponding Author. Email: danieljames.2023@mitb.smu.edu.sg.
** Corresponding Author. Email: leonardo.2023@mitb.smu.edu.sg.
*** Corresponding Author. Email: js.tai.2023@mitb.smu.edu.sg.
**** Corresponding Author. Email: valerianyap.2023@mitb.smu.edu.sg.
***** Corresponding Author. Email: hclau@smu.edu.sg.

must select and order POIs over multiple days while satisfying both hard and soft constraints (Fan, et al., 2024).

3.1 Assumptions

The assumptions that we have incorporated in our itinerary planners includes:

- all POIs are open from 9:00 AM to 10:00 PM.
- travelers return to the same hotel by the end of the day.

3.2 Route Matrix Generation using Google Maps API

To support accurate travel time estimation between POIs, we constructed a route matrix using Google Maps API.

4 Contribution

!!! HELP THIS SECTION. Not to rely on outdated city census data Domain expert view (pre-selection) not possible for large scale comparison and large n since it is continuous, it is not possible to find by manual methods (scalable) and need a smart way of approximation many applications

5 Case Study

TBA

6 Proposed Approach

6.1 LLM and Multi-Agent Framework

!!! SHORTEN Although LLMs are highly capable at interpreting and generating human-like text, they are passive systems—limited to single-turn type of interaction without persistent memory. This presents clear limitations when applied to travel itinerary planning, a task that requires structured decision-making, retrieval of external data (e.g., Google ratings, Cost of Attraction Entrance Fees), and context tracking across multiple steps. A passive LLM may generate a generic itinerary but lacks the capability to provide personalization such as “I prefer scenic routes” or “maximize shopping time within budget.”

To bridge this gap, we extend LLMs into autonomous agents by integrating three key capabilities: tool-calling (e.g., invoking Google Maps APIs), memory (to retain user goals and prior decisions), and Retrieval Augmented Generation (RAG) for incorporating external data into the reasoning process. This turns the LLM from a reactive text generator into a goal-driven planner capable of making informed decisions. Our system adopts this Agentic RAG architecture to retrieve attraction details, estimating hawker visit durations, and enrich itinerary planning with contextual knowledge beyond the LLM’s static knowledge from pre-training.

While a single agent can technically handle the entire itinerary pipeline, research has also shown that such monolithic setups often struggle with domain specialization. To address the limitation, we extend our architecture into a multi-agent framework where each agent focuses on a well-scoped domain task.

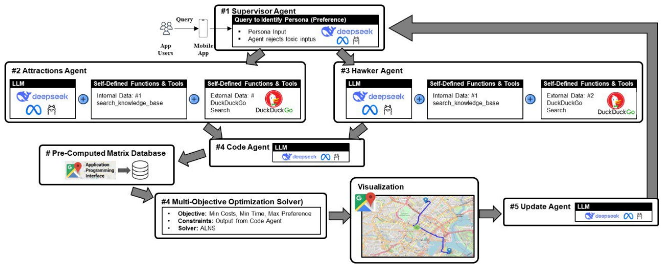

Figure 1. Multi-Agent Architecture

6.2 Adaptive Large Neighborhood Search (ALNS)

!!! REPHRASE ALNS is designed to solve optimization problems by iteratively destroying and repairing solutions. While traditional methods offer precise formulations, they struggle with scaling and flexibility in real-world data scenarios. In our project, ALNS was found to deal with our optimization problem better.

7 Experimental Result

TBA

!!! try to use https://arxiv.org/pdf/2402.01622 for the benchmark narratives: 1. agentic + alns is better than alns only and llm only 2. for feedback, compare 2B 2C 2D. - ideally: 2d is best, but slowest

8 Conclusion

TBA