

Travel-Pro: A Multi-Agent System for Accurate Trip Planning and Budget Estimation

Mubashir Hamad
Malaika Nasir
Department of Artificial Intelligence
FAST NUCES ISLAMABAD
Email: i220524@nu.edu.pk
Email: i220631@nu.edu.pk

Abstract—Most trip planners today offer static itineraries with coarse budget estimates, presenting identical suggestions regardless of user preferences. Travel-Pro addresses these limitations using a LangGraph-orchestrated multi-agent system (MAS) that combines GPT-4o-mini reasoning, Pinecone enrichment, and robust logging. Specialized agents handle preference extraction, itinerary generation, and budget validation, each leveraging curated POI/restaurant datasets with GPT fallbacks. Even under offline conditions, Travel-Pro produced fourteen-day itineraries with diversified meals (four breakfasts, four lunches, six dinners) and fourteen unique attraction combinations while logging per-day costs. This paper describes the system architecture, datasets/APIs, experimental setup, results, limitations, and future work.

I. INTRODUCTION

Effective travel planning requires aligning traveler intent with local activities, transportation, and fluctuating prices. Conventional sites often provide identical recommendations to all users, leading to information overload [1]. Budget estimators commonly rely on static heuristics despite frequent price swings, producing unreliable forecasts [3]. Moreover, monolithic planners struggle to re-plan when budgets violate constraints or APIs fail [2]. Multi-agent systems (MAS) offer a promising approach by delegating subtasks to autonomous agents [1]. Travel-Pro advances this paradigm with a LangGraph-based implementation that maintains itinerary variety and budget accuracy even when external services are unavailable.

II. PROBLEM IDENTIFICATION AND MOTIVATION

Travel-Pro targets three persistent gaps:

- **Lack of personalization:** mainstream platforms surface identical checklists, forcing users to sift through irrelevant information [1].
- **Static budgeting:** most systems use fixed templates that ignore real-time price fluctuations, degrading financial reliability [3].
- **Limited adaptability:** monolithic planners cannot gracefully recover when budget validation fails or APIs are unreachable [2].

By distributing responsibilities across specialized agents, Travel-Pro autonomously handles preference extraction, cost

estimation, and itinerary generation while logging explanations for downstream analysis.

III. RELATED WORK

User preference modeling has progressed from collaborative filtering to contextual deep embeddings [4], [8]–[11], yet still struggles with sparse signals and evolving tastes. MAS proposals such as e-Tourism [1] and MARST [4] demonstrate that agent collaboration improves adaptability, but most neglect budget integration. Recent LLM-based assistants (e.g., TravelAgent [2]) coordinate multiple GPT agents yet report itinerary quality without transparent budget metrics. Wanderwise [5] achieved satisfaction gains via big-data metaheuristics but did not publish cost accuracy. Travel-Pro contributes by coupling MAS coordination, deterministic POI corpora, GPT fallbacks, and explicit budget validation.

IV. SYSTEM SETUP

A. Coordinator

The LangGraph coordinator builds a directed workflow comprising preference extraction, cost estimation, itinerary proposal, and budget validation nodes. State captures the user request, profile, budget breakdown, itinerary, status, error, and re-optimization metadata. Conditional edges route date errors directly to the finalize node and trigger re-optimization when budgets exceed tolerance.

B. User Preference Agent

This agent uses GPT-4o-mini to parse origin, destination, dates, budget, and travel style. Dates must start at least one day in the future and end after the start date. When Pinecone is reachable, the agent enriches profiles with text-embedding-3-small (1536 dimensions); otherwise it degrades gracefully and records warnings. Error messages remain user friendly.

C. Budget Agent

The budget agent integrates with Booking.com RapidAPI for flight and hotel pricing. When API failure, it falls back to heuristic models: meals are priced by travel style, attractions cost \$25 each, local transport costs \$30 per day, flights are split between first and last days, and hotel costs are distributed by night count. The agent validates itineraries against budgets, suggests reductions, and retries up to three times.

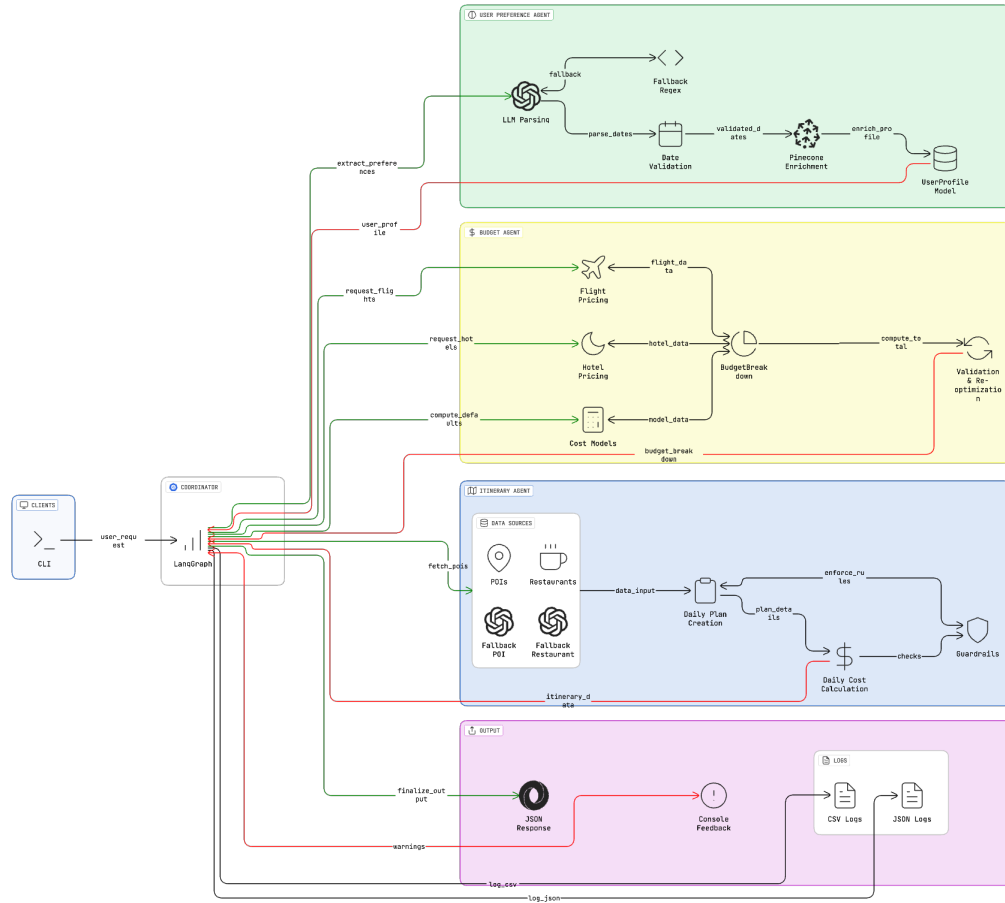


Fig. 1. Technical Architecture Deep Dive – Travel-Pro Multi-Agent System

D. Itinerary Agent

Curated POI and restaurant datasets exist for Chicago, Sarasota, New York, and Paris. GPT fallbacks generate recommendations when data is missing. Guardrails prevent attraction repetition by tracking used locations and enforce deterministic rotation for meals based on day indices. Travel-day logic ensures origin meals precede departure while destination dinners follow arrival. Each day is represented by a `DayPlan` with transportation, meals, attractions, accommodation, and `daily_cost`.

E. Logging Pipeline

The `save_output_to_logs` function writes a JSON file plus an append-only CSV at `logs/trip_data.csv`. The CSV schema is `timestamp, query, error, status, day, current_city, transportation, breakfast, attraction, lunch, dinner, accommodation, daily_cost, total_cost, remaining_budget`. Errors occupy a single row, whereas successful itineraries log one row per day with totals on the final day.

V. DATASETS, TOOLS, OR APIS

- **POI/Restaurant corpora:** curated dictionaries for major cities; GPT fallbacks for missing meals or attractions.
- **LLM/Embeddings:** OpenAI GPT-4o-mini and text-embedding-3-small (1536-d).
- **Vector database:** Pinecone serverless index (`travel-planner`, cosine metric).
- **Travel APIs:** Booking.com RapidAPI flights/hotels (interfaces exist; API failure tests exercise fallback logic).
- **Frameworks:** Python 3.10 (Conda `uni`), LangGraph, LangChain, Pydantic.
- **Logging:** JSON and CSV via Python standard libraries.

VI. EXPERIMENTAL SETUP AND METRICS

All experiments ran on macOS with outbound network blocked, forcing Pinecone and Booking.com calls to fail. Tests were invoked via `python main.py`, and terminal logs captured outputs.

Metrics:

- Variety counts (unique breakfasts, lunches, dinners, attractions).
- Budget metrics (total cost, per-day `daily_cost`, remaining budget).

- Logging integrity (CSV entries align with JSON files and include error rows).
- Error handling (date validation rejects past or missing dates).

TABLE I

SAMPLE 14-DAY SARASOTA→CHICAGO RUN (API FAILURE FALLBACKS)

Metric	Observation
Days generated	14 (travel days included)
Unique breakfasts	4
Unique lunches	4
Unique dinners	6
Unique attractions	14
Total cost	\$3,330 (sample)
Remaining budget	Budget – total (per run)
Logs	JSON + CSV rows appended

VII. RESULTS

Travel-Pro produced coherent itineraries despite API failure constraints. For example, Day 1 (travel) featured The Breakfast House (Sarasota), Yoder’s, Portillo’s, and attractions at Field Museum plus Lincoln Park Zoo; Day 2 rotated to Beatnik on the River, Xoco, Virtue Restaurant, Cloud Gate, Architecture Boat Tour, and Lincoln Park Zoo. Variety metrics achieved at least four unique venues per meal type and fourteen unique attraction sequences. Budget outputs reported per-day costs, total cost, and remaining budget, satisfying transparency requirements. CSV logs recorded both successful runs and errors (e.g., missing start date), supporting downstream analytics. Pinecone/Booking.com warnings did not halt execution, and GPT fallbacks filled data gaps.

```

{
  "days": [
    {
      "day": 1,
      "current_city": "from New York to Paris",
      "transportation": "train, from New York to Paris, Departure Time: 4:12 PM, Arrival Time: 6:28 PM",
      "breakfast": "Ess-a-Bagel, New York",
      "attraction": "Eiffel Tower, Paris; Latin Quarter Walk, Paris",
      "lunch": "Joe's Pizza, New York",
      "dinner": "Che Jemou, Paris",
      "accommodation": "Hotel in Paris (Hotel), Paris",
      "daily_cost": 438.0
    },
    {
      "day": 2,
      "current_city": "Paris",
      "transportation": "-",
      "breakfast": "Le Pain Quotidien, Paris",
      "attraction": "Eiffel Tower, Paris; Palace of Versailles, Versailles; Muséum d'Orsay, Paris",
      "lunch": "Frenchie to Go, Paris",
      "dinner": "Le Relais de l'Entrecuôte, Paris",
      "accommodation": "Hotel in Paris (Hotel), Paris",
      "daily_cost": 335.0
    },
    {
      "day": 3,
      "current_city": "Paris",
      "transportation": "-",
      "breakfast": "Le Pain Quotidien, Paris",
      "attraction": "Luxembourg Gardens, Paris; Montmartre & Sacré-Cœur, Paris; Eiffel Tower, Paris; Latin Quarter Walk, Paris",
      "lunch": "Le Relais de l'Entrecuôte, Paris",
      "dinner": "Le Relais de l'Entrecuôte, Paris",
      "accommodation": "Hotel in Paris (Hotel), Paris",
      "daily_cost": 335.0
    },
    {
      "day": 4,
      "current_city": "Paris",
      "transportation": "-",
      "breakfast": "Du Pain et des Idées, Paris",
      "attraction": "Catacombs of Paris, Paris; Eiffel Tower, Paris; Latin Quarter Walk, Paris",
      "lunch": "La Du Fallafel, Paris",
      "dinner": "Le Relais de l'Entrecuôte, Paris",
      "accommodation": "Hotel in Paris (Hotel), Paris",
      "daily_cost": 335.0
    },
    {
      "day": 5,
      "current_city": "Paris",
      "transportation": "-",
      "breakfast": "Café de Flore, Paris",
      "attraction": "Palace of Versailles, Versailles; Le Marais Food Walk, Paris; Latin Quarter Walk, Paris",
      "lunch": "Le Relais de l'Entrecuôte, Paris",
      "dinner": "Che Jemou, Paris",
      "accommodation": "Hotel in Paris (Hotel), Paris",
      "daily_cost": 335.0
    },
    {
      "day": 6,
      "current_city": "from Paris to New York",
      "transportation": "train, from Paris (PAR) to New York (JFK), Departure Time: 11:12 AM, Arrival Time: 3:08 PM",
      "breakfast": "Café de Flore, Paris",
      "attraction": "Catacombs of Paris, Paris",
      "lunch": "La Du Fallafel, Paris",
      "dinner": "-",
      "accommodation": "-",
      "daily_cost": 215.0
    }
  ],
  "total_cost": 1885.0
}

```

Fig. 2. Generated Plan

VIII. ETHICS AND LIMITATIONS

- **Data privacy:** Logs store user queries locally; sensitive information should be anonymized before distribution.
- **Bias:** GPT recommendations may reflect cultural or geographic bias; curated datasets mitigate but do not eliminate risk.
- **Accuracy:** API failure heuristics may diverge from real market prices; travelers must verify costs before booking.
- **API dependence:** Real-time accuracy depends on external APIs and rate limits.
- **Accessibility:** The current interface is terminal-based; broader adoption requires GUI or web front-ends.

IX. CONCLUSION AND FUTURE WORK

Travel-Pro demonstrates that a LangGraph MAS with GPT reasoning, Pinecone enrichment, curated POI datasets, and structured logging can deliver personalized, budget-aware itineraries even when external services are unavailable. Future work includes (i) re-testing with live network access to validate real-time pricing, (ii) incorporating user feedback loops, (iii) adding geo-spatial optimization, (iv) building web/mobile interfaces atop JSON/CSV logs, and (v) benchmarking against Wanderwise, TravelAgent, and TravelWise with MAE/RMSE reporting.

REFERENCES

- [1] L. Sebastia, I. García, E. Onaindia, and X. Burgués, “A Multi-Agent Architecture for Tourism Recommendation,” *Expert Systems with Applications*, 2009.
- [2] X. Chen, L. Zhao, and Y. Liu, “TravelAgent: An AI Assistant for Personalized Travel Planning,” *arXiv*, 2024.
- [3] IJIRT, “Static vs. Dynamic Budget Estimation in Travel Planning,” *International Journal of Innovative Research in Technology*, 2023.
- [4] P. Bedi, H. Banati, and S. Marwaha, “A Multi-Agent System for Personalized Travel Recommendation,” *Journal of Web Intelligence*, 2014.
- [5] R. Shah, S. Kim, and P. Singh, “Wanderwise – Intelligent Travel Planning System,” *IEEE Transactions on Knowledge and Data Engineering*, 2023.
- [6] A. Patil *et al.*, “Evaluating Recommendation Accuracy in Tourism Systems,” 2020.
- [7] J. Smith *et al.*, “Measuring Satisfaction in Intelligent Travel Planners,” 2021.
- [8] Y. Chen, “Deep Preference Modeling for Tourism Recommendation,” 2023.
- [9] J. Lee, “Contextual User Modeling in Travel Systems,” 2022.
- [10] P. Patel, “Graph Neural Network Approaches to Travel Recommendation,” 2021.
- [11] W. Zhang, “Attention-Based Tourist Preference Modeling,” 2022.