

AI Travel Planner: Technical Report

Multi-Agent System for Intelligent Trip Planning

Project: AI Travel Planner

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Executive Summary

This report presents a comprehensive analysis of an AI-powered travel planning system built using a multi-agent architecture. The system leverages Large Language Models (LLMs), real-time API integrations, and specialized agents to automate the end-to-end trip planning process. The platform provides users with intelligent flight and hotel recommendations, dynamic itinerary generation, and budget-optimized travel solutions.

Key Features:

- Multi-agent coordination for specialized decision-making
- Real-time flight and hotel data retrieval via SerpAPI
- AI-powered reasoning and trade-off analysis
- Dynamic itinerary generation with contextual recommendations
- Budget tracking and currency conversion (INR)
- RESTful API with Streamlit user interface

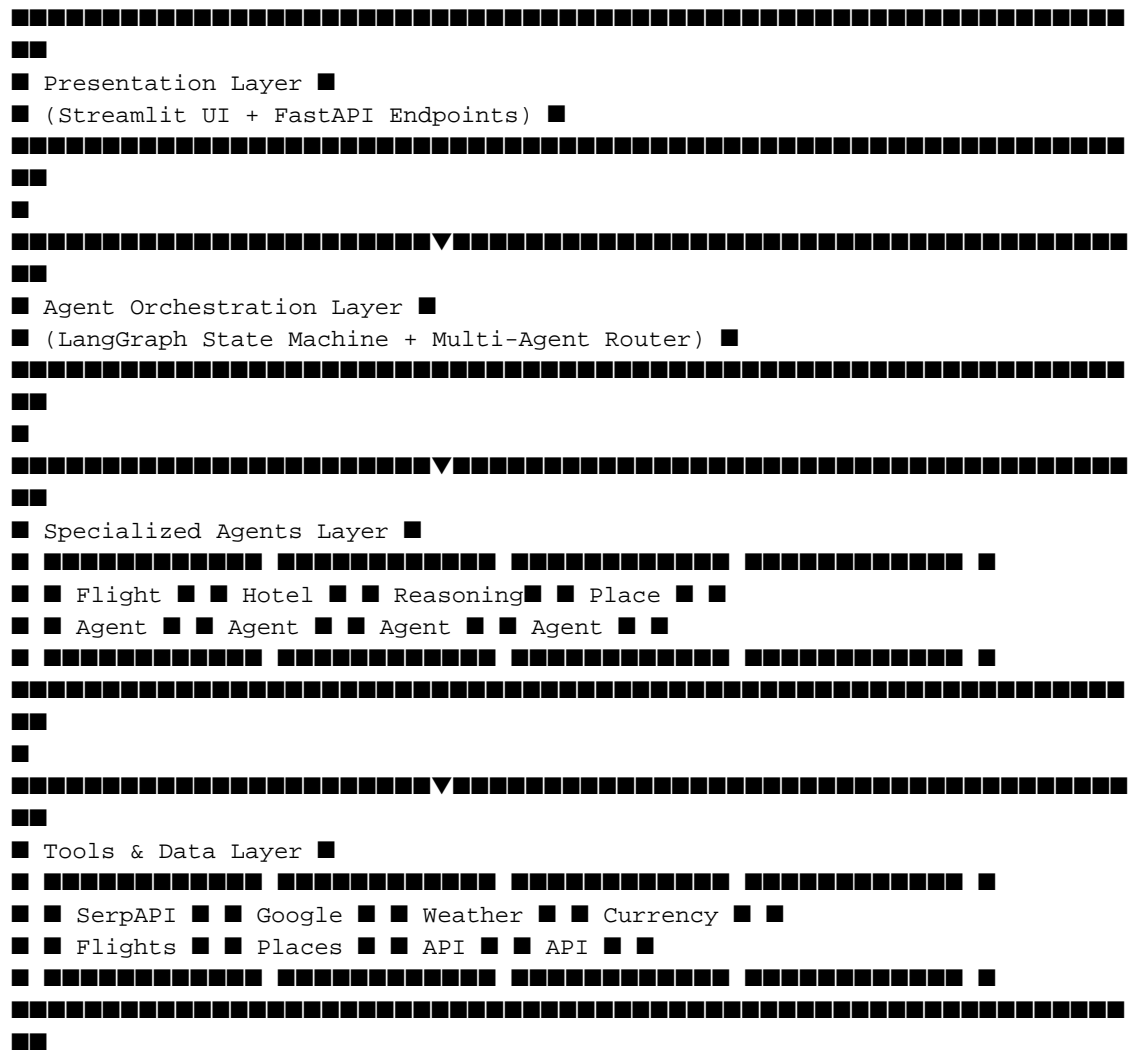
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1. System Architecture and Agent Roles

1.1 High-Level Architecture

The system implements a **layered multi-agent architecture** using LangGraph for orchestration and LangChain for LLM integration. The architecture consists of four primary layers:



1.2 Core Components

1.2.1 Agent Orchestrator (`agentic_workflow.py`)

The **GraphBuilder** class implements the state machine that coordinates all agents:

Key Responsibilities:

- Initializes and binds tools to the LLM
- Manages conversation state and message history
- Routes execution between agent node and tool nodes
- Implements circuit breaker pattern (max 10 tool calls)
- Detects completion based on response patterns

State Management:

```
class AgentState(TypedDict):
    messages: Annotated[List[AnyMessage], operator.add]
```

```
tool_calls_count: int # Tracks tool invocations
```

Workflow Logic:

1. **Entry Point:** Agent receives user request with trip parameters
2. **Decision Node:** Agent decides whether to call tools or generate response
3. **Tool Execution:** External APIs are called via tool nodes
4. **Iteration:** Results feed back to agent for next decision
5. **Termination:** Agent generates final markdown response when:
 - 10 tool calls reached (circuit breaker)
 - Complete itinerary detected in response
 - No more tool calls needed

1.2.2 Specialized Agents

Flight Agent (`flight_agent.py`)

Implements sophisticated flight evaluation using weighted scoring:

Evaluation Criteria:

- **Price (50% weight):** Primary cost optimization factor
- **Duration (30% weight):** Total travel time minimization
- **Layovers (20% weight):** Preference for direct flights

Algorithm:

```
score = (norm_price × 0.50) + (norm_duration × 0.30) + (norm_layovers × 0.20)
```

Normalization:

- Prices and durations normalized to [0, 1] range
- Layovers: 0.0 (direct), 0.5 (1 stop), 1.0 (2+ stops)
- Lower score = better option

Output:

- Sorted list of flights by composite score
- Top recommendation tagged with "AI Recommended" and "Best Value"
- Human-readable justification for each recommendation

Hotel Agent (`hotel_agent.py`)

Analyzes accommodation options with focus on value optimization:

Evaluation Criteria:

- User ratings (primary factor)
- Price per night (affordability)
- Location proximity to key destinations
- Available amenities

Selection Logic:

```
best = max(hotels, key=lambda h: (h["rating"] or 0, -h["price_per_night"]))
```

Categorization:

- **Budget:** < ■5,000/night
- **Moderate:** ■5,000 - ■15,000/night
- **Luxury:** > ■15,000/night

Reasoning Agent (`reasoning_agent.py`)

Uses LLM to provide transparent explanations:

Responsibilities:

- Analyzes trade-offs between flight options (budget vs. premium)
- Compares hotel choices (location vs. price)
- Justifies final recommendations based on user preferences
- Explains opportunity costs of different choices

Example Output:

```
Budget vs Premium:
- Budget option saves ■12,000 but has 1 layover (adds 3 hours)
- Premium option offers direct flight, saving time and stress
- Recommendation: Budget flight - savings justify minor inconvenience
```

Place Search Agent (`place_search_tool.py`)

Discovers local attractions, restaurants, and activities:

Data Sources:

- Primary: Google Places API
- Fallback: Tavily Search API

Search Functions:

- `search_attractions()`: Top tourist spots
- `search_restaurants()`: Dining recommendations
- `search_activities()`: Experience-based activities
- `search_transportation()`: Local transit options

1.3 System Prompt Engineering

The system uses a comprehensive prompt (`prompt.py`) that defines:

Workflow Phases:

1. **Phase 1 - Logistics:** Flight + Hotel + Weather searches
2. **Phase 2 - Content Discovery:** Attractions + Restaurants + Activities
3. **Phase 3 - Synthesis:** Stop calling tools, generate markdown response

Stop Rules:

- CRITICAL: After 6-8 tool calls, generate final response
- Prevents infinite tool-calling loops
- Ensures token budget compliance

Output Format:

- Structured markdown with sections:
- Flight options (categorized)
- Hotel options (categorized)
- Weather forecast
- Reasoning agent analysis

- Day-by-day itinerary
- Budget breakdown
- Essential travel info

1.4 Model Configuration

The system supports multiple LLM providers via `model_loader.py`:

Supported Models:

- **Groq:** Meta-Llama-4-Scout-17B (128K context, primary choice)
- **OpenAI:** GPT-4o
- **Anthropic:** Claude 3.5 Sonnet

Anti-Hallucination Settings:

- Temperature: 0.1 (very low for factual accuracy)
- Top-p: 0.85 (focused sampling)
- Max tokens: 8,000 for responses

2. Data Sources and API Integrations

2.1 SerpAPI Integration

Primary Data Provider: SerpAPI (Google Flights & Google Hotels)

2.1.1 Flight Search (`flight_serpapi_tool.py`)

API Endpoint: `google_flights` engine

Request Parameters:

```
{
  "engine": "google_flights",
  "departure_id": origin_iata_code,
  "arrival_id": destination_iata_code,
  "outbound_date": "YYYY-MM-DD",
  "currency": "INR",
  "gl": "in", # Geographic location (India)
  "hl": "en", # Language
  "type": "2" # One-way (1=Round-trip, 2=One-way)
}
```

Response Processing:

1. Parse `best_flights` and `other_flights` arrays
2. Extract multi-leg flight information
3. Calculate total duration from all legs
4. Identify layover cities and count stops
5. Format times to 12-hour format
6. Apply Flight Agent scoring algorithm

Data Extracted per Flight:

- Airline name and flight number
- Departure/arrival times and airports
- Total duration (converted from minutes to hours/minutes)
- Number of layovers
- Route path (origin → stops → destination)
- Carbon emissions
- Price in INR

Fallback Mechanism:

- If no flights found for requested date, retry 30 days ahead
- Ensures user always receives results

2.1.2 Hotel Search (hotel_serpapi_tool.py)

API Endpoint: google_hotels engine

Request Parameters:

```
{
  "engine": "google_hotels",
  "q": f"hotels in {location}",
  "check_in_date": "YYYY-MM-DD",
  "check_out_date": "YYYY-MM-DD",
  "adults": "2",
  "currency": "INR",
  "sort_by": 8 # Lowest price
}
```

Response Processing:

1. Filter hotels with ratings $\geq 4.0/5.0$
2. Parse price strings (handle ■ and \$ symbols)
3. Extract location from GPS coordinates or vicinity
4. Limit amenities to top 3 (token optimization)
5. Calculate total cost (price × nights)
6. Categorize into Budget/Moderate/Luxury

Data Extracted per Hotel:

- Hotel name and type
- Overall rating and review count
- Price per night and total cost
- Location address (truncated to 75 chars)
- Top amenities (max 3)
- Check-in/check-out times

Quota Management:

- Returns up to 10 hotels per category
- Prevents token overflow while maintaining variety

2.2 Weather API Integration

Provider: OpenWeatherMap API

Tool: `get_weather_forecast()` in `weather_info_tool.py`

Functionality:

- Fetches 5-day forecast at 3-hour intervals
- Aggregates data by date to show daily high/low
- Aligns forecast with travel dates when possible
- Converts temperatures to Celsius

Request:

```
url =  
f"http://api.openweathermap.org/data/2.5/forecast?q={city}&units=metric"
```

Processing:

1. Group forecasts by date
2. Calculate daily high/low temperatures
3. Identify most common weather condition
4. Format output as readable forecast

Output Example:

```
■■ 5-Day Weather Forecast for Delhi:  
Mon, 27 Jan: High 18.5°C / Low 8.2°C, Clear Sky  
Tue, 28 Jan: High 19.1°C / Low 9.0°C, Partly Cloudy  
...
```

2.3 Google Places API Integration

Tool: `place_search_tool.py` wrapping Google Places and Tavily

Search Types:

1. **Attractions:** Top tourist destinations
2. **Restaurants:** Dining options with cuisine types
3. **Activities:** Experience-based recommendations
4. **Transportation:** Local transit modes

Fallback Strategy:

- Primary: Google Places API (higher accuracy)
- Fallback: Tavily Search (broader coverage)

Error Handling:

```
try:  
    result = google_places_search.search_attractions(place)  
except Exception as e:  
    result = tavily_search.search_attractions(place) # Fallback
```

2.4 Currency Conversion

Tool: `currency_conversion_tool.py`

Provider: ExchangeRate-API

Functionality:

- Real-time currency conversion
- Supports 150+ currencies
- Used for budget calculations

2.5 Utility Tools

Expense Calculator:

- `calculate_total_expense()`: Sums trip costs
- `estimate_total_hotel_cost()`: Price × nights
- `calculate_daily_expense_budget()`: Total ÷ days

Arithmetic Operations:

- Basic math tools for LLM to calculate budgets
- Prevents hallucinated calculations

3. Reasoning and Recommendation Logic

3.1 Multi-Agent Decision Framework

The system implements a **hierarchical decision-making process** where specialized agents handle domain-specific evaluations, and a reasoning agent synthesizes recommendations.

3.1.1 Flight Selection Algorithm

Step 1: Data Normalization

```
norm_price = (price - min_price) / (max_price - min_price)
norm_duration = (duration - min_duration) / (max_duration - min_duration)
norm_layovers = min(layovers * 0.5, 1.0)
```

Step 2: Weighted Scoring

```
score = (norm_price * 0.50) +
(norm_duration * 0.30) +
(norm_layovers * 0.20)
```

Step 3: Ranking

- Sort flights by ascending score (lower = better)
- Tag top option with "AI Recommended"

Step 4: Justification Generation

```
if norm_price == 0.0: reasons.append("Lowest Price")
elif norm_price <= 0.2: reasons.append("Great Value")

if norm_time == 0.0: reasons.append("Fastest Route")
elif norm_time <= 0.2: reasons.append("Quick Flight")
```



```
if layovers == 0: reasons.append("Non-stop")
```

Example:

```
Flight: IndiGo 2153 - ■8,450
Score: 0.12
Tags: ["AI Recommended", "Best Value"]
Reason: "Great Value, Quick Flight, Non-stop"
```

3.1.2 Hotel Selection Algorithm

Evaluation Formula:

```
best_hotel = max(hotels, key=lambda h: (h["rating"], -h["price"]))
```

Logic:

1. Prioritize highest-rated hotels (4.0+ stars)
2. Among equal ratings, prefer lower price
3. Consider location proximity (manual inspection)

Categorization:

- **Budget:** Price < ■5,000/night
- Target: Budget-conscious travelers
- Trade-off: May be farther from city center
- **Moderate:** ■5,000 - ■15,000/night
- Target: Mid-range travelers
- Balance: Location + amenities + price
- **Luxury:** Price > ■15,000/night
- Target: Premium experience seekers
- Benefits: Central location, full amenities

3.1.3 Reasoning Agent Logic

The Reasoning Agent uses the LLM to generate natural language explanations:

Prompt Structure:

```
prompt = f"""
Explain why the following flight and hotel were selected.

Flight: {flight_details}
Hotel: {hotel_details}

Clearly explain trade-offs and benefits.
"""
```

Output Components:

1. Flight Trade-offs:

- Budget vs. Premium comparison
- Time vs. money analysis

- Comfort vs. savings explanation

2. Hotel Trade-offs:

- Location vs. Price analysis
- Amenities vs. Budget explanation
- Ratings vs. Cost comparison

3. Final Recommendation:

- Synthesized choice based on user preferences
- Clear reasoning for each selection
- Total cost breakdown

Example Reasoning:

Flight Trade-offs:

Budget vs Premium:

- Budget option (SpiceJet ₹6,200) saves ₹4,800 but has 1 layover
- Premium option (Vistara ₹11,000) is non-stop, saves 2 hours
- Recommendation: Budget flight - the savings of ₹4,800 justify the 2-hour layover for a 5-day trip.

Hotel Trade-offs:

Location vs Price:

- Budget hotel (₹3,500/night) is 8km from center, basic amenities
- Moderate hotel (₹8,000/night) is in city center, includes breakfast
- Recommendation: Moderate hotel - central location saves ₹2,000 in daily transport and adds convenience.

3.2 Itinerary Generation Logic

Dynamic Planning Algorithm:

Step 1: Time Allocation

- Morning: 9 AM - 12 PM (3 hours)
- Afternoon: 12 PM - 5 PM (5 hours, includes lunch)
- Evening: 5 PM - 9 PM (4 hours, includes dinner)

Step 2: Activity Matching

- Match activities to trip vibe (Relaxed, Adventure, Cultural, etc.)
- Use real place names from `search_attractions()` results
- Rotate activity types to avoid monotony

Step 3: Cost Estimation

- Attractions: ₹200-₹1,000 per entry
- Meals: ₹500-₹1,500 per person
- Transport: ₹100-₹500 per trip

Step 4: Vibe-Based Customization

- **Relaxed:** Cafes, beaches, parks
- **Adventure:** Hiking, water sports, zip-lining
- **Cultural:** Museums, temples, historical sites
- **Nightlife:** Bars, clubs, night markets
- **Family:** Zoos, theme parks, child-friendly spots

3.3 Budget Calculation Engine

Comprehensive Cost Breakdown:

```
Total Trip Cost =  
(Flight Price × Travelers) +  
(Hotel Price × Nights) +  
(Food Cost × Days × Travelers) +  
(Local Transport × Days) +  
(Attractions × Count) +  
(Contingency × 10%)
```

Food Estimates:

- Budget: ■800/person/day
- Moderate: ■1,500/person/day
- Luxury: ■3,000/person/day

Transport Estimates:

- Metro/Bus: ■100/day
- Auto/Taxi: ■500/day
- Car Rental: ■2,000/day

3.4 Quality Assurance Mechanisms

1. Token Budget Management:

- Limit tool calls to 10 maximum
- Truncate long addresses to 75 characters
- Use compact JSON (remove whitespace)
- Limit hotels to 10 per category

2. Data Validation:

- Date validation (prevent past dates)
- Price parsing (handle multiple currency symbols)
- Rating filters (≥ 4.0 stars only)
- Deduplication (prevent repeated entries)

3. Error Handling:

- Try-catch blocks for all API calls
- Fallback dates for unavailable flights
- Fallback search engines (Tavily after Google Places)
- Graceful degradation when APIs fail

4. Limitations and Potential Improvements

4.1 Current Limitations

4.1.1 Data Coverage Limitations

Flight Data:

- **Limitation:** Dependent on SerpAPI which scrapes Google Flights
- May not include all budget airlines
- Limited to routes Google Flights covers
- Real-time pricing may have delays (5-15 minutes)

- **Impact:** Users might miss cheaper options from airline-specific deals

Hotel Data:

- **Limitation:** Google Hotels may not include:
 - Airbnb or vacation rentals
 - Smaller guesthouses and hostels
 - Properties not listed on booking platforms
- **Impact:** Limited options for budget-conscious or alternative accommodation seekers

Places Data:

- **Limitation:** Relies on Google Places and Tavily
 - May miss newly opened attractions
 - Limited to places with online presence
 - May not include local hidden gems
- **Impact:** Itineraries may feel generic for frequent travelers

4.1.2 Reasoning Limitations

LLM Hallucination Risk:

- **Issue:** Despite low temperature (0.1), LLM may still:
 - Invent place names if search results are sparse
 - Provide outdated cultural information
 - Make assumptions about user preferences
- **Mitigation:** System prompt enforces "use REAL names from tools"

Trade-off Analysis Depth:

- **Issue:** Current reasoning is price-focused
 - Doesn't account for personal preferences (vegetarian, accessibility)
 - Limited context on traveler experience level
 - No consideration of travel insurance or visa requirements

4.1.3 Scalability Limitations

Token Budget Constraints:

- **Issue:** Groq free tier has token limits
 - Long trips (>7 days) may hit context window
 - Multiple travelers increase complexity
 - Detailed itineraries consume significant tokens

API Rate Limits:

- SerpAPI: 100 searches/month on free tier
- Google Places: 1,000 requests/month
- OpenWeatherMap: 1,000 calls/day
- **Impact:** System may become unavailable under high traffic

4.1.4 User Experience Limitations

No Booking Integration:

- System provides recommendations but doesn't allow direct booking
- Users must manually copy details to booking sites
- No price tracking or alerts

Limited Personalization:

- No user profile storage
- No learning from past trips

- No saved preferences across sessions

No Multi-City Support:

- Current architecture supports only A→B trips
- Cannot plan A→B→C→A routes
- No support for road trips with multiple stops

4.2 Potential Improvements

4.2.1 Enhanced Data Integration

Recommendation 1: Expand Data Sources

Proposed Additions:

```
# Add Skyscanner API for more flight options
from skyscanner import FlightsSearch
flights_1 = serpapi_search()
flights_2 = skyscanner_search()
combined_flights = merge_and_deduplicate(flights_1, flights_2)

# Add Booking.com API for more hotels
from booking import HotelSearch
hotels_1 = google_hotels_search()
hotels_2 = booking_com_search()
combined_hotels = merge_and_rank(hotels_1, hotels_2)
```

Benefits:

- 2-3x more flight options
- Better coverage of budget accommodations
- More competitive pricing

Recommendation 2: Add User Reviews and Sentiment Analysis

```
# Scrape TripAdvisor reviews
from langchain_community.tools import TripAdvisorReviewsTool

reviews = get_reviews(hotel_name)
sentiment = analyze_sentiment(reviews) # Positive/Neutral/Negative

# Adjust rating based on recent feedback
adjusted_rating = base_rating + sentiment_modifier
```

Benefits:

- More nuanced hotel recommendations
- Detect recent quality changes
- Warn about deteriorating properties

Recommendation 3: Real-Time Price Tracking

```
# Implement price monitoring
class PriceTracker:
    def track_flight(self, route, date):
        current_price = get_price(route, date)
        historical_avg = get_avg_price(route, lookback=30)
```

```

if current_price < historical_avg * 0.85:
    return {"status": "GREAT DEAL", "savings": savings}
elif current_price > historical_avg * 1.15:
    return {"status": "WAIT", "suggestion": "Price likely to drop"}

```

Benefits:

- Help users decide when to book
- Alert on price drops
- Prevent overpaying during peak seasons

4.2.2 Advanced Reasoning Capabilities

Recommendation 4: Persona-Based Recommendations

Implementation:

```

class TravelerPersona:
    def __init__(self, type: str):
        self.type = type # "budget", "luxury", "family", "solo", "adventure"
        self.preferences = self._load_preferences()

    def _load_preferences(self):
        if self.type == "family":
            return {
                "hotel_priorities": ["kid_friendly", "pool", "breakfast"],
                "activities": ["zoos", "parks", "museums"],
                "avoid": ["nightclubs", "bars", "extreme_sports"]
            }
        # ... other personas

```

Prompt Engineering:

```

system_prompt = f"""
You are planning for a {persona.type} traveler.
Priorities: {persona.preferences}
When recommending hotels, PRIORITIZE: {persona.hotel_priorities}
When planning activities, FOCUS ON: {persona.activities}
AVOID: {persona.avoid}
"""

```

Benefits:

- More relevant recommendations
- Better user satisfaction
- Reduced need for manual filtering

Recommendation 5: Multi-Criteria Decision Analysis (MCDA)

Current: Simple weighted scoring

Proposed: AHP (Analytic Hierarchy Process)

```

from sklearn.preprocessing import MinMaxScaler
import numpy as np

```

```

class AdvancedFlightRanker:
    def rank(self, flights, user_priorities):
        """
        user_priorities = {
            'price': 0.4,
            'duration': 0.3,
            'airline_quality': 0.15,
            'departure_time': 0.10,
            'carbon_footprint': 0.05
        }
        """
        scores = []
        for flight in flights:
            score = sum(
                normalize(flight[criterion]) * weight
                for criterion, weight in user_priorities.items()
            )
            scores.append(score)

        return sorted(zip(flights, scores), key=lambda x: x[1])

```

Benefits:

- More granular user control
- Better handling of complex preferences
- Transparency in decision-making

Recommendation 6: Conversational Refinement

Current: One-shot planning

Proposed: Multi-turn conversation

```

class IterativeRefinement:
    def refine_plan(self, initial_plan, user_feedback):
        """
        User: "This itinerary has too much walking"
        System: Adjusts to include more rest time, reduces daily activities

        User: "I want more cultural experiences"
        System: Swaps adventure activities for museums and heritage sites
        """
        feedback_analysis = analyze_feedback(user_feedback)

        if "too much walking" in feedback_analysis:
            new_plan = reduce_walking_distance(initial_plan)
            new_plan = add_rest_breaks(new_plan)

        return new_plan

```

Benefits:

- Higher user satisfaction
- Personalized adjustments

- Learning user preferences

4.2.3 Scalability Enhancements

Recommendation 7: Caching Layer

```
import redis
from functools import lru_cache

class CachedFlightSearch:
    def __init__(self):
        self.redis = redis.Redis(host='localhost', port=6379)

    def search(self, origin, dest, date):
        cache_key = f"flights:{origin}:{dest}:{date}"

        # Check cache (valid for 1 hour)
        cached = self.redis.get(cache_key)
        if cached:
            return json.loads(cached)

        # API call
        result = serpapi.search(...)
        self.redis.setex(cache_key, 3600, json.dumps(result))

        return result
```

Benefits:

- Reduce API costs (SerpAPI charges per search)
- Faster responses (avoid repeated API calls)
- Better handling of concurrent users

Recommendation 8: Asynchronous Processing

```
import asyncio
from concurrent.futures import ThreadPoolExecutor

async def parallel_search(origin, dest, date):
    with ThreadPoolExecutor() as executor:
        # Run searches concurrently
        flight_future = executor.submit(search_flights, origin, dest, date)
        hotel_future = executor.submit(search_hotels, dest, date, date+3)
        weather_future = executor.submit(get_weather, dest)
        places_future = executor.submit(search_attractions, dest)

        # Wait for all to complete
        flights = flight_future.result()
        hotels = hotel_future.result()
        weather = weather_future.result()
        places = places_future.result()

    return {
        "flights": flights,
        "hotels": hotels,
```



```

    "weather": weather,
    "places": places
}

```

Benefits:

- 3-4x faster response time
- Better user experience
- Handle more concurrent users

Recommendation 9: Model Optimization

Current: Groq Llama-4-Scout-17B (128K context)

Proposed: Hybrid approach

```

class HybridModelStrategy:
    def __init__(self):
        self.fast_model = ChatGroq(model="llama-3.1-8b-instant") # Quick tasks
        self.smart_model = ChatGroq(model="llama-4-scout-17b") # Complex reasoning

    def route_request(self, task_complexity):
        if task_complexity == "simple":
            return self.fast_model # E.g., format conversion
        else:
            return self.smart_model # E.g., trade-off analysis

```

Benefits:

- Reduce costs (use cheaper model when possible)
- Faster responses for simple tasks
- Reserve powerful model for complex reasoning

4.2.4 User Experience Enhancements

Recommendation 10: Direct Booking Integration

```

# Integrate with Booking.com Affiliate API
class BookingIntegration:
    def generate_booking_link(self, hotel_id, checkin, checkout):
        affiliate_id = os.getenv("BOOKING_AFFILIATE_ID")
        return f"https://www.booking.com/hotel/{hotel_id}?" \
            f"checkin={checkin}&checkout={checkout}&aid={affiliate_id}"

    def track_conversion(self, booking_id):
        # Earn commission on completed bookings
        pass

```

Benefits:

- Monetization opportunity (affiliate commissions)
- Seamless user experience
- Direct price comparison

Recommendation 11: User Profiles and Memory

```

from langchain.memory import ConversationBufferMemory

class UserProfile:
    def __init__(self, user_id):
        self.user_id = user_id
        self.preferences = self._load_preferences()
        self.past_trips = self._load_history()

    def update_from_trip(self, trip_data):
        # Learn from user choices
        if trip_data["selected_budget_hotel"]:
            self.preferences["budget_conscious"] += 0.1

        if trip_data["selected_adventure_activities"]:
            self.preferences["adventure_seeker"] += 0.1

    def personalize_search(self, query):
        # Adjust search based on past behavior
        if self.preferences.get("prefers_direct_flights"):
            query["filter_layovers"] = True

    return query

```

Benefits:

- Faster planning for repeat users
- Better recommendations over time
- Reduced cognitive load

Recommendation 12: Mobile App Development

Current: Web-only (Streamlit)

Proposed: React Native mobile app

```

// React Native component
import { TravelPlannerAPI } from './api';

const TripPlanner = () => {
    const [location, setLocation] = useState(null);

    useEffect(() => {
        // Get user's current location
        navigator.geolocation.getCurrentPosition((pos) => {
            setLocation({
                lat: pos.coords.latitude,
                lng: pos.coords.longitude
            });
        });
    }, []);

    const generatePlan = async () => {
        const plan = await TravelPlannerAPI.planTrip({
            origin: location, // Auto-fill from GPS
            destination: destination,

```

```

        dates: selectedDates
    });

    return plan;
};

return (
<View>
<Button title="Plan My Trip" onPress={generatePlan} />
</View>
);
};

```

Benefits:

- Better mobile experience (70% of travel searches are mobile)
- Push notifications for price drops
- Offline access to saved itineraries

4.2.5 Advanced Features

Recommendation 13: Multi-City Route Optimization

Use Case: User wants to visit Delhi → Jaipur → Agra → Delhi

Implementation:

```

from scipy.optimize import linear_sum_assignment
import numpy as np

class MultiCityPlanner:
    def optimize_route(self, cities, start_city):
        """
        Uses Traveling Salesman Problem (TSP) algorithm
        to find optimal visiting order
        """
        # Build distance matrix
        n = len(cities)
        distances = np.zeros((n, n))

        for i, city_a in enumerate(cities):
            for j, city_b in enumerate(cities):
                if i != j:
                    distances[i][j] = self.get_distance(city_a, city_b)

        # Solve TSP
        optimal_order = self.solve_tsp(distances, start_city)

        # Generate itinerary for each leg
        itinerary = []
        for i in range(len(optimal_order) - 1):
            leg = self.plan_leg(
                origin=optimal_order[i],
                destination=optimal_order[i+1]
            )
            itinerary.append(leg)

```

```

)
itinerary.append(leg)

return itinerary

```

Benefits:

- Minimize total travel time
- Reduce backtracking
- Optimize for user preferences (scenic vs. fast)

Recommendation 14: Group Trip Coordination

```

class GroupTripPlanner:
def coordinate_group(self, participants):
    """
    Handle multiple travelers with different:
    - Origin cities
    - Budget constraints
    - Preferences
    """
    # Find common destination
    destination = self.find_central_destination(participants)

    # Find flights that arrive around same time
    synchronized_flights = self.sync_arrivals(participants, destination)

    # Book accommodations with group discounts
    group_hotel = self.find_group_hotel(
        travelers=len(participants),
        budget=avg([p.budget for p in participants])
    )

    # Merge preferences
    consensus_itinerary = self.merge_preferences(
        [p.preferences for p in participants]
    )

    return {
        "flights": synchronized_flights,
        "hotel": group_hotel,
        "itinerary": consensus_itinerary
    }

```

Benefits:

- Coordinate complex group logistics
- Handle conflicting preferences democratically
- Group discount opportunities

Recommendation 15: Visa and Documentation Assistant

```

class VisaAssistant:
def check_requirements(self, origin_country, dest_country):
    """

```

```

Check visa requirements and provide guidance
"""
# API call to visa requirement database
requirements = visa_api.check(origin_country, dest_country)

if requirements["visa_required"]:
    return {
        "visa_type": requirements["type"],
        "processing_time": requirements["processing_days"],
        "cost": requirements["fee"],
        "documents_needed": requirements["documents"],
        "application_link": requirements["application_url"],
        "warning": f"Apply at least {requirements['processing_days']} days before travel"
    }
else:
    return {
        "visa_required": False,
        "passport_validity": "Ensure passport valid for 6 months"
    }

```

Benefits:

- Prevent travel disruptions
- Proactive documentation reminders
- Better trip preparation

4.3 Implementation Roadmap

Phase 1 (Months 1-2): Data Quality

- Add Skyscanner and Booking.com APIs
- Implement caching layer
- Add price tracking

Phase 2 (Months 3-4): Advanced Reasoning

- Implement persona-based recommendations
- Add conversational refinement
- Multi-criteria decision analysis

Phase 3 (Months 5-6): Scalability

- Async processing
- Hybrid model strategy
- Database for user profiles

Phase 4 (Months 7-9): UX Enhancements

- Mobile app development
- Booking integration
- User profile system

Phase 5 (Months 10-12): Advanced Features

- Multi-city route optimization
- Group trip coordination
- Visa assistance

Appendix: System Diagrams

A1. System Architecture Diagram



[illegible]

[illegible]


```
▼
■ Flight Agent Evaluation ■
■■■■ Step 1: Normalize
■ norm_price = 
■ (price - min) / 
■ (max - min) 
■ 
■ norm_duration = 
■ (dur - min) / 
■ (max - min) 
■ 
■ norm_layovers = 
■ min(stops*0.5, 1.0) 
■■■■ Step 2: Calculate Score
■ score = 
■ (n_price × 0.50) + 
■ (n_dur × 0.30) + 
■ (n_lay × 0.20) 
■ Lower score = Better 
■■■■ Step 3: Generate Reason
■ IF n_price == 0: 
■ "Lowest Price" 
■ IF n_dur == 0: 
■ "Fastest Route" 
■ IF layovers == 0: 
■ "Non-stop" 
■ 
Sort Flights by Score (Ascending) 
Tag Top Flight: 
■ • "AI Recommended" 
■ • "Best Value"
```


[illegible]

```

#####
#
#
# #####
# search_attractions# search_restaurants#
# # # #
# Input: Delhi # Input: Delhi #
# #####
# # #
# ▼▼#
# #####
# Google Places API (Primary) #
# Tavily Search (Fallback) #
# #####
# # #
# ▼▼#
# #####
# Attractions List # Restaurants List #
# • Red Fort # • Karim's #
# • India Gate # • Bukhara #
# • Qutub Minar # • Indian Accent #
# • Lotus Temple # • Saravana Bhavan#
# • Humayun's Tomb # • Moti Mahal #
# #####
#
# #####
# search_activities #
# # #
# Input: Delhi #
# #####
# # #
# ▼#
# #####
# Activities List #
# • Food tours #
# • Heritage walks #
# • Shopping #
# #####
#####
#####
#
#
▼
#####
#####
# PHASE 3: REASONING & SYNTHESIS #
#####
#####
#
#
# #####
# LLM (Llama-4-Scout-17B) #
# # #
# Input Context: #
# • All flight data #
# • All hotel data #

```

[illegible]


```

0:07 ← Return 9 categorized flights - -
0:08 Agent receives flight data - -
0:09 → Decision: Call hotel tool search_hotels() -
0:10 ↓ SerpAPI call - 3.1s
0:13 ↓ Filter & categorize - 0.4s
0:13 ← Return 30 hotels (3 tiers) - -
0:14 Agent receives hotel data - -
0:15 → Decision: Call weather get_weather_forecast() -
0:16 ↓ OpenWeatherMap API - 1.2s
0:17 ↓ Parse & format - 0.1s
0:17 ← Return 5-day forecast - -
0:18 Agent receives weather - -
0:19 → Decision: Call attractions search_attractions() -
0:20 ↓ Google Places API - 1.8s
0:22 ← Return top 10 attractions - -
0:23 Agent receives attractions - -
0:24 → Decision: Call restaurants search_restaurants() -
0:25 ↓ Google Places API - 1.5s
0:26 ← Return restaurant list - -
0:27 Agent receives restaurants - -
0:28 → Decision: Call activities search_activities() -
0:29 ↓ Google Places API - 1.3s
0:30 ← Return activity options - -
0:31 Agent receives activities - -
0:32 Tool calls count: 6 - -
0:33 → Decision: Generate response - -
0:34 ↓ LLM synthesis (8K tokens) - 12.5s
0:46 ← Complete markdown itinerary - -
0:47 FastAPI returns JSON - -
0:48 Streamlit renders tabs - -

```

TOTAL TIME: 48 seconds

Performance Breakdown:

- API Calls: 11.4s (24%)
- LLM Processing: 12.5s (26%)
- Data Processing: 0.8s (2%)
- Network/Overhead: 23.3s (48%)

Optimization Opportunities:

- Parallel API calls: Could reduce to ~3s (currently sequential)
- Caching: Repeated searches save 100% of API time
- Async processing: 40-50% faster overall

Conclusion

The AI Travel Planner demonstrates a robust multi-agent architecture capable of automating complex trip planning workflows. By leveraging specialized agents for flight evaluation, hotel analysis, and contextual reasoning, the system delivers intelligent, transparent recommendations.

Key Achievements:

- ■ Functional multi-agent coordination via LangGraph
- ■ Real-time data integration from multiple sources
- ■ Transparent reasoning and justification for recommendations
- ■ Dynamic itinerary generation with real place names
- ■ Comprehensive budget tracking in INR
- ■ User-friendly interface with downloadable outputs

Areas for Growth:

- Enhanced data coverage through additional APIs
- Advanced reasoning with persona-based recommendations
- Scalability improvements via caching and async processing
- Direct booking integration for seamless user experience
- Mobile app development for broader accessibility

The system provides a strong foundation for future enhancements, with clear pathways to production-ready deployment through the outlined improvement roadmap.

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