

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 ≥ 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}??" \\\n            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)

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

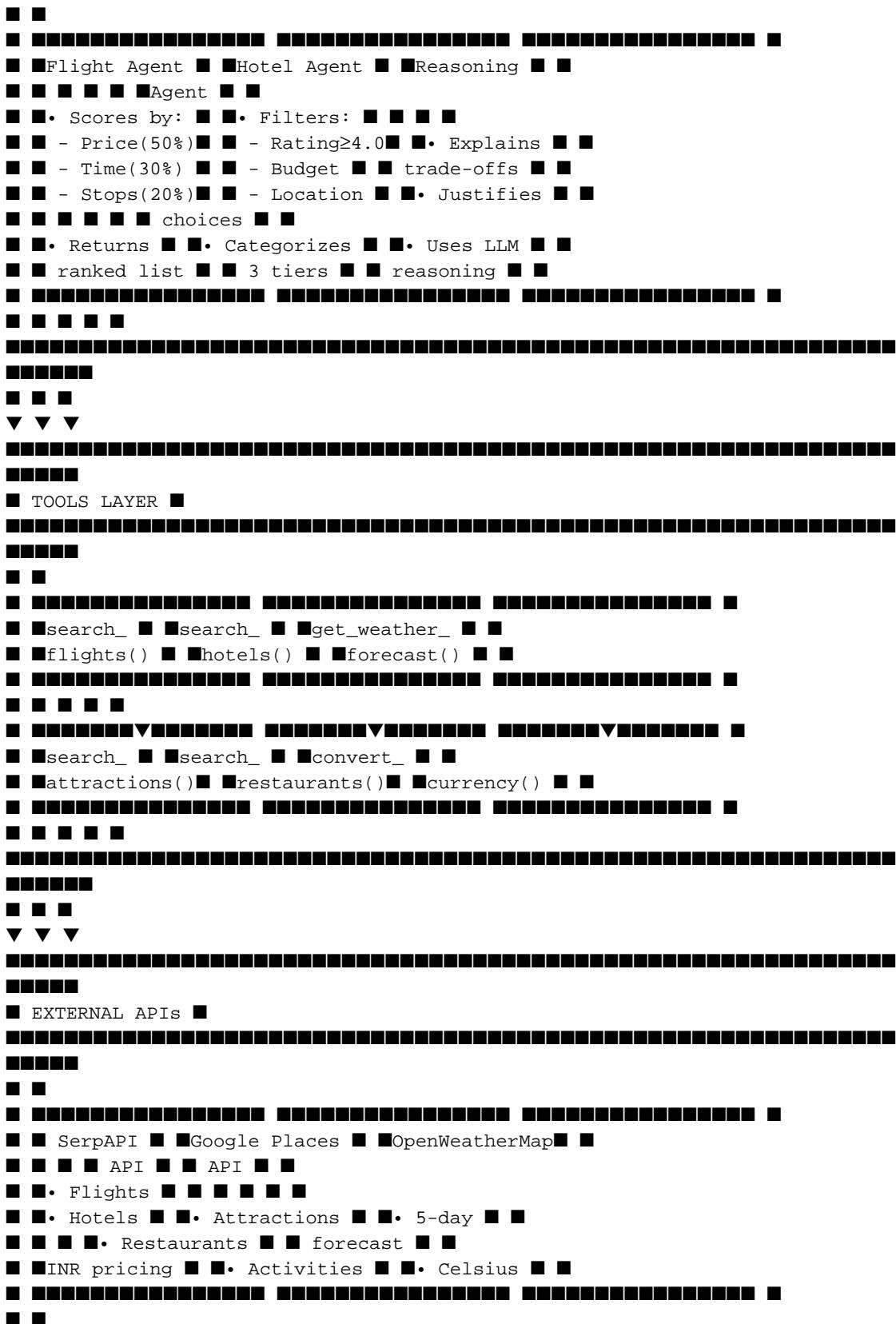
Phase 5 (Months 10-12): Advanced Features

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

Appendix: System Diagrams

A1. System Architecture Diagram





A2. Request Flow Diagram



```
graph TD; Start[Tool Node] --> SearchFlights[search_flights]; Start --> SearchHotels[search_hotels]; Start --> GetWeather[get_weather]; Start --> SearchPlaces[search_places]; SearchFlights --> ExecuteAPIs[6. Execute API calls<br/>(SerpAPI, Google, etc.)]; ExecuteAPIs --> ExternalAPIs[External APIs]; ExternalAPIs --> ReturnResults[Return Results]; ReturnResults --> AppendResults[7. Append results to messages]; AppendResults --> IncrementCalls[Increment tool_calls_count]; IncrementCalls --> LoopBack[8. Loop back to Agent Node<br/>(Repeat 5-7 until stop condition)]; LoopBack --> StopConditions[Stop Conditions:<br/>• tool_calls_count >= 10<br/>• Complete itinerary detected<br/>• No more tool calls needed]; StopConditions --> FinalPass[Agent Node<br/>(Final Pass)]; FinalPass --> GenerateResponse[9. Generate complete markdown response<br/>• Flight options (Budget/Moderate/Premium)<br/>• Hotel options (categorized)<br/>• Weather forecast<br/>• Reasoning analysis<br/>• Day-by-day itinerary<br/>• Budget breakdown]; GenerateResponse --> FastAPI[FastAPI]; FastAPI --> ReturnResponse[Return Response]; ReturnResponse --> JSONResponse[10. JSON response with markdown]
```

The flowchart illustrates the process of generating a travel itinerary. It begins with a 'Tool Node' which performs four initial searches: 'search_flights', 'search_hotels', 'get_weather', and 'search_places'. The results from these searches are then used to execute external APIs (SerpAPI, Google, etc.). The responses from these APIs are appended to messages and the count of tool calls is incremented. This loop (steps 5-7) continues until a stop condition is met, which can be when the tool calls count reaches 10, the itinerary is complete, or no more tool calls are needed. Once the stop condition is reached, the process moves to the 'Agent Node' for a 'Final Pass'. During this pass, a complete markdown response is generated, including flight options (Budget/Moderate/Premium), hotel options (categorized), weather forecast, reasoning analysis, day-by-day itinerary, and budget breakdown. Finally, the response is returned via FastAPI as a JSON object containing markdown.

- Streamlit UI ■
- Display Tabs: ■
 - • Overview ■
 - • Flights ■
 - • Hotels ■
 - • Itinerary ■
 - • Budget ■
-
-
- 11. Rendered trip plan
- ▼
-
- USER ■
- Downloads ■
- MD/PDF ■

A3. Flight Agent Decision Flow

- search_flights() Tool Called ■
- Input: origin, destination, date ■
 -
 - ▼
- SerpAPI: google_flights Engine ■
- Request Parameters: ■
 - • departure_id: IATA code ■
 - • arrival_id: IATA code ■
 - • outbound_date: YYYY-MM-DD ■
 - • currency: INR ■
 -
 - ▼
- Parse Response ■
 - • best_flights[] ■
 - • other_flights[] ■
 -
 - ▼
- Extract Flight Data (per flight): ■
 - • Airline, Flight Number ■
 - • Departure/Arrival Times & Airports ■
 - • Total Duration (minutes) ■
 - • Layover Count ■
 - • Price (INR) ■
 - • Carbon Emissions ■
 -


```
■ Categorize All Flights: ■  
■ • Budget: Bottom 1/3 by price ■  
■ • Moderate: Middle 1/3 ■  
■ • Premium: Top 1/3 ■  
■  
■ ▼  
■  
■ Return JSON: ■  
■ { ■  
■   "route": "DEL → BOM", ■  
■   "flights": [ ■  
■     { ■  
■       "Airline": "IndiGo", ■  
■       "Price": 6200, ■  
■       "Score": 0.12, ■  
■       "Tags": ["AI Recommended"], ■  
■       "Category": "Budget", ■  
■       "Reason": "Great Value, ■  
■       "Non-stop": ■  
■     }, ■  
■     ... ■  
■   ], ■  
■   "count": 9, ■  
■   "currency": "INR" ■  
■ } ■
```

A4. Data Flow Diagram

- Weather forecast
- Attractions list
- Restaurants list
- Activities list
- User preferences (budget, vibe)

Processing:

1. Analyze flight trade-offs
2. Compare hotel options
3. Match activities to "Cultural" vibe
4. Generate 5-day itinerary
5. Calculate comprehensive budget

FINAL MARKDOWN RESPONSE

✈ 5-Day Trip: Dubai → Delhi

Flight Options

Budget Flights

Air India AI915 - ₹18,500

Departs: 09:15 AM from DXB

Arrives: 02:30 PM at DEL

Duration: 3h 15m

Non-stop

Flight Agent Recommendation:

Best Value: Air India AI915

Reason: Non-stop, Great timing, Budget-friendly

Hotels in Delhi

Moderate Hotels

The Leela Ambience 4.5/5

₹8,500/night × 5 nights = ₹42,500

Connaught Place (City Center)

Pool, Spa, Free Breakfast

Reasoning Agent Analysis

For a Moderate Cultural trip, I recommend:

Flight: Air India AI915 (₹18,500)

Direct flight, no layover hassle

Hotel: The Leela Ambience (₹8,500/night)

Central location saves transport costs

Total Core Cost: ₹79,500

DETAILED DAY-BY-DAY ITINERARY

Day 1: Arrival & Mughal Heritage

* Morning: Red Fort visit (₹600)

* Afternoon: Lunch at Karim's (₹800/person)

* Evening: India Gate & Rashtrapati Bhavan

A5. Tool Execution Timeline

Time	Agent	Action	Tool	Called API	Response Time
0:00	User	submits trip request	- -		
0:01	GraphBuilder	initializes	- -		
0:02	Agent	analyzes prompt	- -		
0:03	→ Decision:	Call flight tool search_flights()	-		
0:04	↓ SerpAPI	call	- 2.5s		
0:06	↓ Flight Agent	processes	- 0.3s		

```

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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