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EASY GO VENTURE: A Multi-Agent AI System for Destination Insights Using Modular Taskflow AI Pipelines

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Abstract - *The emergence of intelligent travel solutions has increased the demand for comprehensive and real-time trip planning systems. TripPlanner, a production-ready, modular system driven by Multi-AI Agents utilizing the Taskflow AI framework, is presented in this paper. Web Research, Travel, and Reporter Agents are specialist agents that use external technologies such as SerperSearch, Wikipedia APIs, Amadeus Flights API, and Weather.com to collect and aggregate data in order to process a single question. GPT-3.5 Turbo balances memory and API limitations while enabling reasoning. The system employs Retrieval-Augmented Generation (RAG) to boost accuracy and real-time awareness. Analysis reveals that TripPlanner provides incredibly pertinent and eye-catching trip information. It opens the door for more extensive uses outside of travel by showcasing the usefulness and scalability of agent coordination.*

Key Words: Multi-Agent Systems, Trip Planning, Retrieval-Augmented Generation, Taskflow AI, GPT-3.5, Real-Time Insights, Modular AI, Travel Itinerary

1.INTRODUCTION

Artificial intelligence (AI) has changed how people use digital platforms in recent years, particularly in areas like research, travel, and tailored suggestions. Conventional travel planning is looking through numerous websites, evaluating flight alternatives, examining weather predictions, and reading a tonne of blogs or articles. In addition to being time-consuming, this procedure lacks a cohesive, intelligent interface that can accommodate a wide range of changing user preferences.

In order to overcome these constraints, this paper presents TripPlanner, an intelligent itinerary creation system that uses several independent AI agents and is based on the Taskflow AI framework. The TripPlanner system uses a modular and multi-agent strategy that breaks down user enquiries into smaller tasks that are performed by specialised agents, in contrast to monolithic AI models that try to answer general questions in isolation. Every agent is made to concentrate on a particular task, such gathering travel data, assessing the weather, or summarising content.

The coordination amongst agents—each driven by language and supplemented by external tools and APIs—is the fundamental breakthrough. For instance, the Travel Agent retrieves real-time flight information from the Amadeus API, while the Web Research Agent uses Wikipedia and SerperSearch to collect contextual data. After that, a Reporter Agent compiles the results into an approachable format. Additionally, the architecture adheres to the concepts of Retrieval-Augmented Generation (RAG), which enables agents to make informed judgements beyond the static knowledge of the model by referencing real-time data.

The following are the contributions made by this work:

• A scalable and modular architecture that uses AI agents to generate itineraries.

• The incorporation of external tools and APIs for pertinent, real-time data.

• The Taskflow framework facilitates effective task decomposition and agent collaboration.

• An economical implementation that takes memory and API limitations into account.

This paper's remaining sections are arranged as follows: Related work is discussed in Section II. The system architecture is shown in Section III, and the roles and toolchains of each agent are explained in Section IV. Use cases and implementation are described in Section V. Evaluation and results are presented in Section VI, and the paper's conclusion with recommendations for the future is covered in Section VII.

2. RELATED WORK

Intelligent trip planning research has progressed from early rule-based systems to contemporary designs that integrate multi-agent coordination and retrieval-augmented generation (RAG). The main goal of early travel recommender systems was to tailor suggestions based on static databases and past user information. Recent studies on recommender systems for sustainable tourism have pointed out that these systems frequently failed to incorporate broader sustainability measures and provide current information [1].

Large language model creation can now incorporate external, real-time data thanks to developments in RAG. The accuracy and contextual relevance of the outputs are much enhanced by this integration, which also lessens model hallucinations [2]. Applications like travel planning, where details like operating hours, current affairs, and seasonal patterns are vital, particularly require these features.

Simultaneously, studies on multi-agent systems have shown that breaking down difficult tasks (such composite travel planning) into smaller, more manageable jobs can result in more reliable and effective solutions. When used to learn dialogue policies for complicated tasks, hierarchical deep reinforcement learning techniques have demonstrated significant gains in handling multi-step planning difficulties [3]. In order to tackle real-world trip sharing issues, other research has investigated strategic multiagent planning, highlighting the efficiency and environmental advantages of group decision-making [4].

These scholarly findings are further supported by recent corporate initiatives. For instance, Aimpoint Digital has created an AI agent system that creates detailed travel routes almost instantly by utilising vector and RAG databases [5]. In addition to streamlining the planning process, these tools make it easier to include real-time data, allowing for more sustainable and customised travel suggestions.

3. METHODOLOGY

In order to dynamically create customised travel plans based on user preferences, real-time data, and contextual information, the suggested system uses a modular, agent-based architecture. Our methodology is based on retrieval-augmented generation (RAG), multi-agent collaboration, and Taskflow AI-enabled orchestrated task execution.

3.1 Multi-Agent Collaboration

The core of our approach is a collection of specialised agents created to carry out distinct subtasks that add up to the final itinerary. Among the primary agents are: Travel agents are responsible for creating suggested itineraries based on consumer preferences, such as place categories, budget, and duration.

• Reporter Agent: Arranges information gathered from multiple sources and creates summaries that are readable by humans.

• Web Research Agent: Conducts contextual research, including finding popular travel locations, regional happenings, or travel warnings.

With access to pertinent tools and knowledge sources, each agent works autonomously while reporting its findings to a centralised workflow orchestrator. By adhering to parallelism and separation of concerns, this architecture produces outputs more quickly and accurately.

3.2 Retrieval-Augmented Generation (RAG) Pipeline

Our solution adds current external knowledge to agent outputs via a lightweight RAG pipeline. The web research agent, for example, searches the internet for the most recent articles and updates when a user chooses a destination. These are then condensed and contextualised before being shown to the user. This system guarantees that the planner stays up to date on the latest events, travel circumstances, and logistical details.

Three steps make up the RAG flow:

1. Querying: Agents create dynamic queries according to the job aim and user input.

2. Retrieval: Web scraping and custom search APIs are used to retrieve pertinent results.

3. Generation: To improve readability and relevance, retrieved data is subjected to summarisation and categorisation processes.

3.3 Orchestration using Taskflow AI

We use Taskflow AI, which enables the execution of intricate, multi-step workflows using a declarative task-based design, to coordinate the aforementioned agents. Inputs, outputs, and dependencies are used to define tasks, allowing for conditional execution and modular debugging. When it comes to vacation planning, this coordinated flow replicates human decision-making processes, such as confirming visa requirements before advising overseas travel or checking the weather before offering outdoor activities.

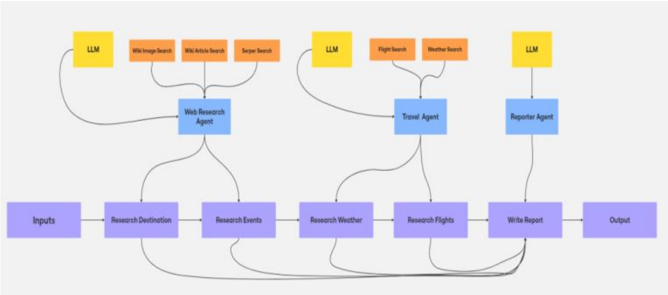
3.4 User Interaction and Feedback Loop

Users can set preferences via the front-end system, including budget, number of days, preferred climate, and destination kinds (such as beaches, temples, and hill stations). The orchestrator uses this information to initiate the proper agents, gather their answers, and create a logical multi-day plan. An interactive and customised experience is made possible by the planner's dynamic updating of its recommendations in response to user feedback (e.g., adding more adventure places or removing a destination).

3.5 Tool Integration and Automation

The system incorporates capabilities for flight and hotel searches, weather forecasting, and image-based destination previews.

To ensure security and adaptability across various deployment scenarios, environment variables are used to safely load all API keys and sensitive information. The planner's testing, deployment, and upgrades are streamlined via automation scripts and CI/CD pipelines.



4. CONCLUSIONS:

TripPlanner proves that modular multi-agent systems can simplify complex tasks like travel planning. Our implementation, using Python and Taskflow AI, generates interactive, context-aware itineraries. Future plans include expanding to international locations, real-time booking, enhanced agent interactions, and reinforcement learning for adaptation to user feedback.

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