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Personalized Travel Planner using Large Language Models : A Generative AI Approach

Dr. Amit K. Nerurkar
VIT, Mumbai

Dr. Monica G. Tolani
TSEC, Mumbai

Yash Khot
VIT, Mumbai

Prathamesh Kulkarni
VIT, Mumbai

Sameep Patrakar
VIT, Mumbai

***Abstract*— This paper introduces a personalized travel planning system leveraging the power of Generative Artificial Intelligence and Large Language Models. The system is designed to help prospective travel planners plan their travel with respect to the type of tour they want to endeavor like family, honeymoon, or friends for their desired destinations. The system uses real-time data fetched from various social media platforms and travel booking websites and generates a customized itinerary as per the users' requirements. The system offers dynamic recommendations based on user-defined criteria like their budget, number of days, and type of activities they want to experience. The system also utilizes the power of social media by analyzing location reviews and offering recommendations for the selected locations. This helps users cut down their planning time and plan their trips with just a few clicks.**

Keywords— Travel Management System, Generative AI, Personalized itinerary generation, Large Language Models, Vector Databases, Prompt Engineering.

I. Introduction

Over the years, there have been a series of rapid changes in the travel industry, planning as a part of travelling has become of utmost importance for a smooth travel experience to the dream destinations of the people. With the growth in the travel industry, the demand for sophisticated systems that offer a wide range of choices has increased drastically. Today, there are a bunch of platforms that allow travellers to schedule and plan their trips in advance, making it convenient for them. While offering convenience, the travellers may miss out on exploring lesser-known places and stringent schedules.[1]

The development of Technologies such as artificial intelligence (AI) and natural language processing have introduced a new era of travel planning. Lage Language Models (LLMs) in particular, are useful tools that can generate and understand text data in a contextual manner just like humans. The use of LLMs in tourism platforms would revolutionise the experience of travel planning.[2]

Prior to the development of LLMs, planning and making an itinerary for a vacation required a lot of effort to search for destinations, check destinations on various websites and blogs, and find the locations that suit you the best from a number of various options, which was a laborious process. Using AI-based trip planners can be convenient and would be adaptable as more personalised options could be explored. LLMs get their power from a thorough examination of large amounts of textual data. This enables them to obtain a deep insight on preferences, destinations, and logistics. LLMs can create itineraries and have smooth conversations with the user regarding choices and preferences.

The architecture, training procedure, and real-world uses of an LLM-based travel planner are covered in this paper along with its design and implementation. In the current world, we want to use LLMs to create new avenues for efficient, customised travel experiences. The travel sector is undergoing fast change due to the development of technologies like LLMs. This guarantees that LLMs will have more opportunities to make meaningful contributions.

II. Drawbacks Of Existing Travel Management System

The current Travel Management systems face several limitations:

- *Unavailability of Personalization and customisation:* Systems without artificial intelligence (AI) might have trouble providing personalised recommendations that take into account each traveller's tastes, which could result in generic recommendations that fall short of what travellers require.
- *Inefficient Planning*: Travellers looking for quick and easy travel arrangements could get discouraged by current systems' lengthier itinerary planning processes, which frequently rely on manual input and static databases.
- *Limited Adaptability*: Without artificial intelligence (AI), travel management systems would find it difficult to adjust to unanticipated events like weather shifts or airline cancellations, which could result in worse than ideal travel experiences and more anxiety for passengers.
- *Inaccurate Information:* Systems lacking AI-driven data analysis and real-time updates may provide outdated or incorrect information regarding travel options, accommodation availability, and local attractions, causing disappointment when their plans don't align with reality.
- *Reduced Competitive Advantage*: AI-powered systems offer competitive advantages in terms of efficiency, personalisation, and responsiveness in the current digital era. Traditional systems run the risk of losing market share and relevance if they can't keep up with the expectations of travellers and industry standards without artificial intelligence.
- *Higher Operational Costs*: Traditional systems with outdated technology and manual processes may have higher operating costs as a result of higher labour requirements, maintenance expenses, and lost opportunities for automation and optimisation.

III. Exploring The World Of Generative AI AND LLMs

We have utilized Generative AI technologies in our system to generate personalised travel plans. In this section, we shall see which technologies were used and how they were utilized in our system. We also discuss the prompting techniques which are a way to interact with the large language models.

A. Introduction to Generative AI

Artificial intelligence with the capacity to produce new data samples is known as generative AI. These data samples could be text, picture, audio, or other types of content that are similar to the data used to train the models. They are able to generate new, original content by doing this by comprehending the underlying patterns and structures found in the training data. [4]

B. Introduction to Large Language Models

Large language models, or LLMs for short, are AI models created to comprehend and generate human-like writing. Large-scale text datasets from books, papers, the internet, and other textual sources are used to train these models so they can learn about the statistical patterns and structures present in human language. Natural language processing (NLP) jobs have become increasingly dependent on natural language machines (LLMs) as their capacity to produce and comprehend natural language has grown over time.[6]

All things considered, large language models are a revolutionary step forward in natural language processing that will transform how we interact with and comprehend text. But they also raise significant ethical issues. Among these issues are making sure they are impartial and fair, protecting people's privacy, and stopping the spread of misleading information.

Large language models (LLMs) like GPT (Generative Pre-trained Transformer), which are based on the Transformer architecture, work via pre-training and fine-tuning. LLMs perform the following tasks operationally:

Natural language models, or LLMs for short, are a class of machine learning models that anticipate absent words or tokens in a given context by utilising self-attention mechanisms. These mechanisms assist in the model's comprehension of the syntactic, semantic, and contextual relationships between words and phrases as well as the statistical patterns and structures found in human language.

LLMs employ the Transformer architecture, which consists of two parts: the encoder and the decoder. Both parts have multiple layers of self-attention mechanisms. After processing the input sequence, the encoder creates vector embeddings. Then, using these embeddings and token-by-token predictions, the decoder creates output sequences.

Tokenization, which divides input text into smaller sub-word units or tokens, is a fundamental stage in LLMs. After that, each token's semantic meaning is captured by embedding it into a higher-dimensional vector space. The model's self-attention mechanisms allow it to determine each token's relative importance to other tokens in the input sequence.

By channelling attention outputs through each layer after self-attention, feedforward neural networks (FFNs) make sure the model learns more detailed representations of the input data. A loss function that measures the difference between the number of predicted and actual tokens in the input sequence is what the training objective is to minimise.

The ability to fine-tune the model to perform specific downstream NLP tasks, such as text classification, language translation, or text generation, makes fine-tuning an essential step in LLMs. Task-specific loss functions and supervised learning techniques are frequently used in this.

Essentially, LLMs use self-supervised learning techniques and the Transformer architecture to generate comprehensive representations of textual data. This facilitates their comprehension and production of text that is human-like in a variety of natural language processing applications.

C. Introduction to Prompt Engineering and its techniques

In order to facilitate communication between users and AI systems, prompts in LLMs give a detailed explanation of the model's expected result. Prompt engineering is crucial to the creation of prompts because it enhances the effectiveness and dependability of AI models for specific tasks. Prompt engineering instructs the model to produce more accurate and desired responses in order to enhance performance across a variety of natural language processing tasks.

Prompt engineering is necessary for efficient communication with large language models. It requires creating precise questions or prompts in order to elicit the right responses while reducing the likelihood of generating false or irrelevant information—a condition known as hallucinations. Numerous frequently employed prompt engineering techniques consist of:

1. *Retrieval Augmented Generation (RAG):* RAG adds domain-specific information from knowledge bases or private databases to large language model responses. It consists of two parts: the retrieval part, which uses information from the database to contextualise responses, and the generation part, where the model creates responses based on the information retrieved. [7]
2. *Chain-of-Thought Prompting (COT):* COT breaks up complicated questions into a number of more manageable prompts. The model is guided by these smaller prompts in steps that ultimately produce the desired response. Through the process of decomposing the problem into smaller, more manageable chunks, COT improves the degree of accuracy and completeness of the model's output.
3. *ReAct (Retrieval and Action):* It is a few-shot prompting method that limits the model to knowledge specific to a particular domain. In order to improve the outputs even further, it also allows the model to retrieve any extra data that might be needed from outside public knowledge bases. It consists of three steps: identifying the task, initiating the action to obtain the required data, and observing the outcome.
4. *Directional Stimulus Prompting (DSP):* It provides the model with precise instructions on how to extract particular data. DSP allows the model to extract only a subset of particular details by adding directed hints or cues.

We have incorporated the RAG prompting technique into our system to give the itinerary generation model a domain-specific knowledge base. Data that has been scraped from numerous social media and itinerary websites is included in this knowledge base. This improves the accuracy and relevance of the LLM's responses by ensuring that they are specific to the tourism domain. Our goal is to solve the quality issues related to generative AI in personalised travel by utilising the RAG pipeline.[8]

IV. Applications of LLMs in the Travel Industry

Large Language Models (LLMs) have the potential to revolutionise the tourism sector by enhancing customer experiences, engagement strategies, and service delivery. The most fascinating task for these LLMs is understanding user preferences, which enables personalised client recommendations and dynamic itinerary planning. LLMs have the ability to automate customer support with chatbots that can provide multilingual assistance and real-time information updates—both of which are critical for disaster management. Their changing role in reshaping the tourism scene indicates the necessity of continued study and funding for this game-changing technology. Among the ways that LLMs are used in the travel industry are [9]

- *Personalized Trip Planning*: LLMs can analyse user given preferences and constraints, and historical travel data on which they are trained on, to generate personalised travel itineraries. LLMs can recommend specific destinations, activities, accommodations, and attractions updated with the individual's interests and budget by understanding the data of the user's trip.[5]

- *Natural Language Understanding (NLU) for Customer Service*: Chatbots or virtual assistants that understand natural language queries from travellers can be developed by LLMs. These assistants can provide users with multiple services at the same time which includes booking flights, hotels, rental cars, and other travel services. Also these assistants provide users, information about destinations, travel restrictions, and other necessary guidelines.

- *Translation Services*: LLMs can be used for real-time text or speech translation services, allowing explorers to communicate with locals in foreign countries. By supporting multiple languages, LLMs help overcome the language barrier and enhance the travel experience for international tourists and explorers from various locations as well.[3]

- *Content Generation for Travel Guides and Blogs*: LLMs can generate various travel content which includes destination guides, and itinerary suggestions. This content can be used to be included in travel websites, apps, and marketing materials, providing a valuable source of information and inspiration to new aspiring tourists.

- *Sentiment Analysis and Reputation Management*: Travel companies may monitor their reputation, identify areas of improvement, and respond to customer concerns speedily. Online reviews, social media posts, and customer feedback can be analysed by LLMs to assess the sentiment towards hotels, restaurants, attractions, and tour operators.

- *Market Research and Trend Analysis*: To identify upcoming travel trends, destinations, and preferences, LLMs can be used to analyse social media trends, search queries, and online discussions. This data can inform marketing strategies, product development, and pricing decisions for various travel companies for market research.

V. Proposed System of Personalised Travel Planner

Headings, or heads, are organizational devices that guide the reader through your paper. There are two types: component heads and text heads.

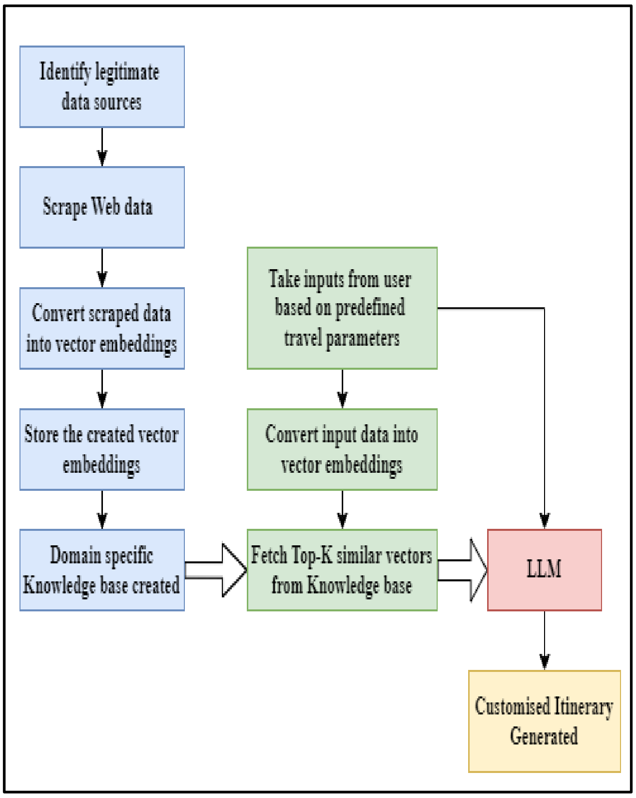

Fig. 1. Flowchart of Proposed System for Personalised Itinerary Generation

A. Data Collection and Storage

For an Artificial Intelligence model, data is the most important aspect, hence we need to assure that the data is accurate, complete, consistent, timely updated, relevant, valid and has a high degree of granularity and accessibility. Our system comprises of varied dataset of locations, reviews, ratings, and prices which acts as the backbone of the model. This data is gathered from various social media platforms, and touring and itinerary websites.

This data is stored in a vector database, which is specifically designed for efficient storage and retrieval of similar vectors. Each part of the scraped data is encoded into a vector embedding and stored in the database.

As seen in Fig. 2., 1000 vectors from the vector database are randomly fetched and they are visualized. These vectors are divided into clusters based on their similarities as seen in the Fig. 2.

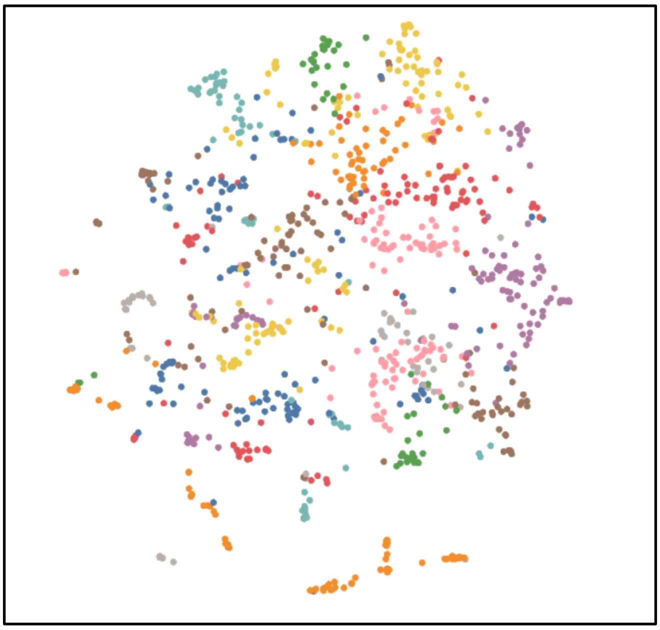

Fig. 2. Visualization of 1000 embedded vectors in the database

B. *Embedding User-defined parameters*

When a user submits a prompt to our system, it preprocesses the query and embeds relevant travel parameters such as destination, dates, budget, preferences like activities, accommodations, transportation, and other relevant details.

These parameters are converted into a vector representation using the same techniques used for embedding the scraped data stored in the vector database.

C. *Retrieval of similar vectors from vector database*

The system retrieves the top-k vectors from the Vector Database that are most closely related or similar to the embedded user prompt and travel parameters. This can be achieved using similarity search algorithms such as cosine similarity or nearest neighbor search. We have used cosine similarity in our vector database.

The retrieved vectors represent contexts or snippets of travel-related information that match the user query and preferences.

D. *Prompt Engineering for Optimal Solution*

Prompt Engineering is a developing field in natural language processing (NLP) that uses strategies to optimize the output given to the user.
In the backend, prompt engineering is carried out to guarantee pertinent outputs that meet and fulfil the user's requirements. Depending on how quickly prompt engineering is completed, the results may differ.

For prompt-based retrieval and generation, the system makes use of the sophisticated natural language processing model GPT (Generative Pre-trained Transformer). We have made use of the Retrieval Augmented Generation (RAG) prompt engineering technique.

E. *Personalised Itinerary Generation*

The system creates an extensive travel schedule for the user based on the appropriately retrieved contexts. To do this, data from the retrieved vectors must be combined and synthesized to produce a cohesive plan that takes the user's interests, preferences, and limitations into account.

The itinerary is formatted in an actionable and human-readable manner using methods like template-based generation and natural language generation (NLG).

VI. Implementation and Results

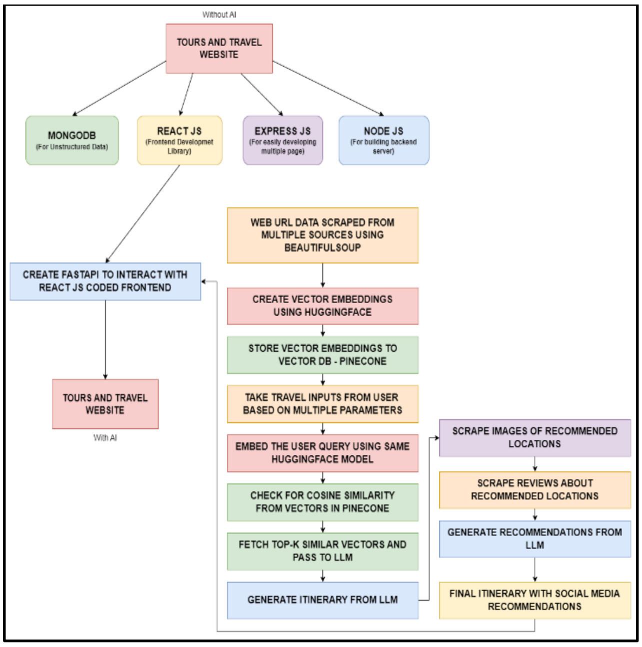

Fig. 3. Implementation Flowchart

In our project implementation we utilized the MERN stack, MongoDB was used as the database management system , Express.js was the backend server, which manages incoming requests from the browser, executing database or file system read/write operations, and communicates with the server. The Express.Js layer also deals with setting and passing variables from the browser to the web server. Also, we utilized React.js as the frontend , which is a JavaScript library for building user interfaces. It handled the view layer for the web application. Finally, Node.js as the JavaScript runtime was utilized on server side, making it possible for the browser-based front end and the server-based backend to communicate seamlessly.

The process starts by scraping web data from various sources using Beautiful Soup. The collected data includes information on travel gathered from different websites. The vector embeddings are created using the Hugging Face Embedding Model based on the scraped data. The embeddings are then stored in a vector database, which is Pinecone.

After receiving the user-defined parameters for designing the travel itinerary, the system embeds the user-defined parameter quesry using the same Hugging Face embedding model. After converting the query to vector embedding, similar vectors to the query are searched in the Pinecone vector database using Cosine Similarity. The top-k similar vectors are fetched and passed to the large language model as the context for itinerary generation.

The LLM generates an itinerary based on the input vectors, considering factors such as destination preferences, travel duration, and activities. Additionally, the system scrapes images and recommendations from reviews of recommended locations to enhance the itinerary. Utilizing the LLM once more, personalized recommendations are generated about the recommended place, from the reviews of social media platforms. The final itinerary, enriched with social media recommendations, is then presented to the user.

Following the flowchart's itinerary generation process, we developed a FastAPI to streamline the generation of travel itineraries based on user inputs and AI recommendations. This involved integrating the FastAPI into our existing website infrastructure, ensuring seamless communication between the frontend and backend components. The FastAPI facilitated the efficient processing of user queries and AI-generated recommendations, enabling the generation of personalized travel itineraries in real-time.

To provide a demonstration of our implemented project, we captured a screenshot of the website showcasing its functionality. The screenshot includes demo inputs simulating user queries and preferences, along with the generated travel itinerary displayed on the interface. This visual demonstration offers a tangible representation of the project's capabilities and serves as a reference for illustrating its functionality in the research paper.

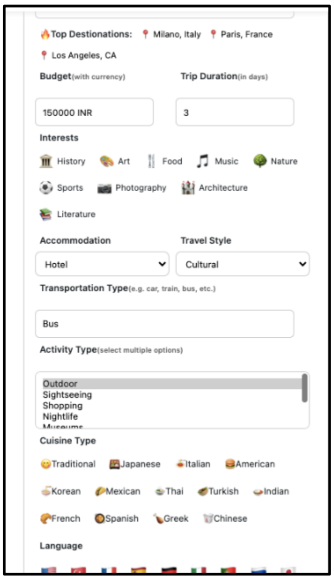

Fig. 4. User interface for user-defined parameters

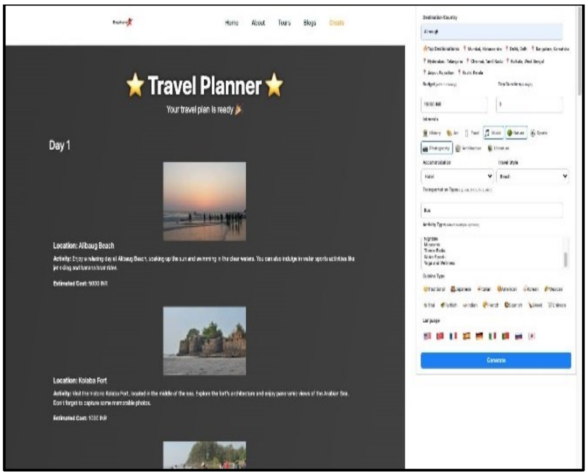

Fig. 5. Itinerary generated based on custom user parameters

VII. Conclusion

In conclusion, Generative AI when introduced to personalized travel planning represents a paradigm shift in the way individuals plan travel. By harnessing the power of machine learning and data-driven insights, the personalized travel planner offers a transformative approach to trip planning, enriching the travel experience for users and driving innovation within the travel industry as a whole. As technology and Artificial Intelligence continue to evolve, the potential for personalized travel planning to further enhance the way we explore the world is never-ending.

By implementing our design, the existing Travel Management Systems can easily integrate personalized travel by making efficient use of their proprietary data and data from social media platforms. We have proposed a basic representation of a large-scale system. On a large scale, they shall have to train their custom domain-specific LLMs on their data which should be continuously evaluated. They may even have to develop LLMs with NLP-specific tasks for Travel such as Sentiment Analysis, Question Answering, providing Multilingual support and personalized itinerary generation LLMs.

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