Implementing AI Based Comprehensive Web Framework for Tourism

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Abstract. In current societies, the movement of all business activities is for effective participation among the market contenders, in addition not just withstanding their physical presence but also challenging their virtual presence. The Smart Tour recommender is a web-based framework for facilitating tourists through tour planning. Unlike other similar web-based systems our system is unique as it streamlines all the processes required for travel planning making it easy and convenient to use. It provides a plethora of features like providing information about tourist attractions, recommending tours based on the user's interests, searching hotels or restaurants based on the user's budget, booking accommodation, and providing users with a personalized itinerary. It focuses on making e-tourism easier and convenient as more and more people use such travel websites to plan their trips.

Keywords: Virtual Presence, Travel Planner, Recommending Tours, User's Interests, Personalized Itinerary, e-tourism.

1 Introduction

The focus of this research is to create an AI-based tour recommender system. The recommendation framework is a web-based system that may deliver a customized rundown of vacation sites, eateries, and accommodations relying upon the traveler's inclinations. Conventional recommendation techniques like content-based filtering and synergistic sifting are known to be advantageous in the tourism industry. Moreover, in light of the information gained from user's interests and inclinations, recommendations are made utilizing content-based suggestions. Data dependent on comparable profiles is suggested when the client utilizes the service more using community-oriented recommendations. Furthermore, a design of a chatbot is provided which gives a genuine and precise response for any question using Artificial Intelligence, which permits individuals to textually communicate with the objective of organizing visits and requesting fascinating spots worth visiting. The Flask development framework is utilized to construct the system since it accentuates rapid development and simple, pragmatic design.

The system methodology is discussed comprehensively with the aim of explaining the functionalities of the system.

2 Literature Review

In relation to the tourism industry and recommendation, the context can be defined as the characteristic information of an entity such as users or an object. The contextual information can be helpful to personalized recommendations when the available information about the item or person is not sufficient. This method is beneficial in producing recommendations on tours, travels, and places as suggested by Thomas and John [1]. This is also useful for recommending tourist sites according to the user's location, moods, the climate of the user's environment, etc. According to Adomavicius and Tuzhilin[2], the proper application of algorithms in recommendation systems is critical to delivering improved results. The dependability factor of various recommendation algorithms is determined by their data qualities. In some circumstances, an algorithm may generate superior results when working on one data set but fail to produce desirable results when working on another. A range of characteristics, such as the number of users, the number of items, the distribution of user ratings, and the influence of data sparsity, define an algorithm's applicability. [3].

Yoke Cheng and Noor Raihan also describe the understanding of the web surfer's behavior and preferences to allow the travel and tourism service providers to strategize their businesses effectively. To investigate and inspect the correlations and contrasts as far as web browsing inclinations among the people and worldwide web users. The authors propose the utilization of a mixed hybrid recommendation technique including demographic, content-based recommendations, preference-based filtering to travel and tourism service providers [5]. Regardless of how valuable these functionalities are, all of these applications lack the following: the ability to create user profiles (e.g., makeMytrip.com), view places of interest near the user's destination or current location (e.g., makemytrip.com Expedia, Trivago.in), calculate routes, or track the user's travel history (e.g., Tripadvisor.in). Furthermore, none of these have the option of restricting personal periods in the trip plan.

3 Proposed System

3.1 Technology Stack

Flask Dashboard. We introduce, Flask Dashboard, a Python library which is an extension for Flask-based Python applications functionalities that help developers to monitor the performance and utilization. The dashboard and the web application are created in python using Flask to bind the application's web services and adding extra routes to the service for making interaction quite efficient.

JavaScript Object Notation (JSON). JSON is an appropriate information trading language since it is used for serializing and transferring structured data over a network for all cutting-edge languages. It is used to evaluate the results of all models and choose

the best-performing model for chatbot on our dataset. It is used to pre-process and alter data before it is passed to the model. We need to pass the natural language representation that we need to perform. JSON is the language utilized in this application for making the information base.

TensorFlow using Python. TensorFlow is an open-sourced software library for jobs that require a large amount of numerical processing. As compared to other machine learning libraries, TensorFlow has a faster compile time. It is compatible with CPUs, GPUs, and distributed processing. Python API is simpler to use than C++ API. TensorFlow has a faster compile time than other machine learning libraries.

Google Positioning System (GPS). The GPS in our system keeps track of the tourist location in real-time. The web application keeps on updating location as the tourist changes location. Using GPS, the system is location-aware. The GPS receiver sends position and time data to any device by utilizing navigation satellites, 24 of which are operational and three of which serve as backups [21]. Trilateration is then used to estimate the user's precise position which then is fed to the system for a further recommendation of a nearby location to visit.

MongoDB. MongoDB is a JSON-formatted open-source document database that stores organized and unstructured data. Documents, which are groupings of fields with a dynamic design, are used to hold all individual records. MongoDB is a more versatile and user-friendly database than SQL. In modern programming language, the document data model is a powerful way to store and retrieve data.

Google Maps API. By utilizing Google Maps API, Maps can be added to any web application. The API helps to guide the system depending on Google Maps information. Google Maps servers handle all the reactions to the plan signal and to use the Google Maps API the developer has to register the project on the Google Developer Console and get a Google API key which can be used further on the site. Without the key Google Maps services cannot be accessed.

Google Places API. This API can be used to create a location-aware page. With the help of nearby local businesses and other places near the device as per place, the API can respond to the output. To implement Google Places API the developer must register the project on the Google Developer Console. Additionally, in order to access the google places API, the developer must include google play services in their development project [6].

3.2 Architecture

Users can make use of the website's features by checking in to the system after browsing the site. Users who have registered/signed up for the website are the only ones who can log in. New users can sign up for an account on the website and create a username, password, and other credentials, which are then recorded in the system database. After registering, a user may log in to the website using the username and password they used to sign up. The login is successful when the login information match those maintained in the database, and the user continues to the next page. After successfully logging in, the process of locating the optimal attraction location for the user begins with the user providing tour information. This procedure works by taking into account the interests

and preferences of the users. The category of tourist attraction site that the tourist chooses to visit, such as interior sites, outdoor activities, architectural heritage sites, environmental regions, and so on, is collected from users. The user must choose between two and three different categories of favorite interests. The Recommendation system uses AI/ML to provide recommendations based on the data (interests and preferences) provided by the user. The recommendation system's two main objectives are to provide users with generic travel plans and lodging options based on their preferences. The user is given a generic plan to which they may apply various filters to design the components of the tour that are most appropriate for them.

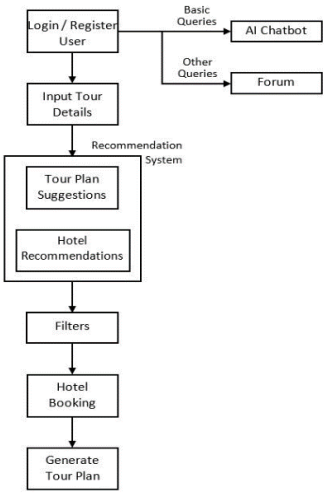

Fig. 1. Proposed system architecture

Filters by gross tour budget, area of stay, type of lodging, length of stay, hotel type, culinary preferences, and so forth. Following that, the customer may make a hotel reservation after deciding on a budget, length of stay, quality of stay, service, and food preference. It allows users to personalize their plans and is appropriate for people of all ages and interests. The consumers are given a wide variety of options that may be modified from one individual to the next. By selecting the cuisine that the user likes, the user may pick a restaurant with convenience and speed. Next, consumers may narrow down the best restaurants for them by picking a restaurant category, such as fast food, vegetarian, non-vegetarian, Jain, and so on. Users may also pick a financial range to spend at the restaurant, as well as the sort of restaurant they want to visit, such as Fine Dining, Casual Dining, Buffet, Café, Fast Casual, and so on. The processes for booking a hotel room are identical to those for booking a restaurant. To begin, customers can choose their desired budget for lodging. The user then chooses the sort of accommodation they want to stay in, such as Single, Double, Deluxe, Twin, or Suite. The customer must then choose depending on availability, budget, luxury, cleanliness, pool, and laundry facilities, among other factors. Following the customer is given with a one-of-a-

kind and tailored trip plan, complete with tourist information, nearby eateries, and an itinerary.

3.3 Principle Working of The System

AI-based Chatbot. A chatbot is an artificial intelligence (AI) program that can mimic a discussion with a user in genuine human language through informing mediums like websites, mobile applications, or messaging apps. This project incorporates the presence of an AI chatbot using TensorFlow which is a library of python. Thus, while operating the website the users can get a personalized automated support assistant to guide them through in and out of the system. The AI bot is trained using intents and entities to identify and understand the user and to provide suitably trained replies. However, the AI chatbot can only be used for basic user queries. Furthermore, other complex user queries can be posted on the forum. The forum is a community of travel agents and designated forum administrators that assist users by resolving their questions.

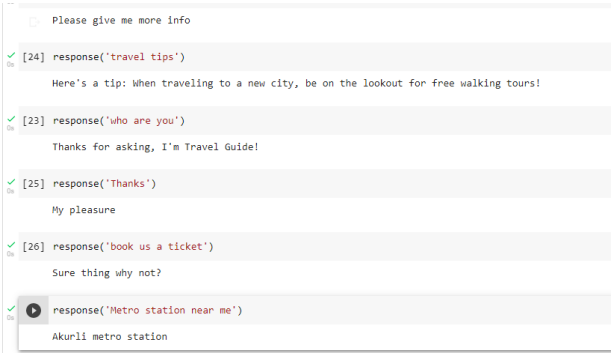

Fig. 2. Output generated from trained AI Chatbot using TensorFlow

Sign up Process. On the off chance that a client is new to the website, the client would need to initially join and register themselves on the website. In this cycle, the client is approached to enter essential data. The client is additionally approached to give a username and a password for signing into the website later on. The information taken from the client is shipped off the server data set where it is put away for future references. The password will be put away in the data set while carrying out a hash secret key for the client's information security. After completion of the registration process, the message will displayed “Sign up successful”.

Login Process. Users can use the website's features by signing in to the system after browsing through it. Users who have registered or signed up for the website can log in. Once a user has been registered, they can log in to the website using the input username and password used during sign-up. The login and password data entered by the user are taken in the system and compared to the data saved on the database. Once the login

details match the details saved on the database the login is successful and the user moves to the next page.

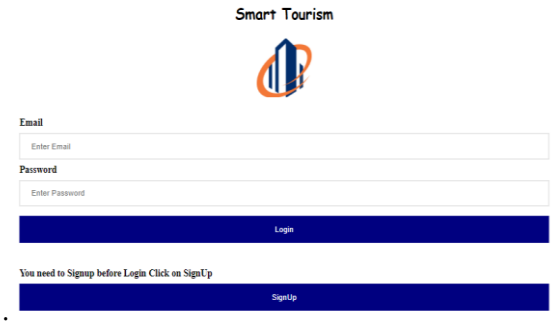

Fig. 3. Login Process

Client Data Input Process. On logging in successfully, the process to find the best attraction place for the user begins with collecting details of the tour from the user. It considers users' interests and choices for hotels, Restaurants, and Attraction sites. Data taken from users include the type of tourist attraction site the user wishes to tour, e.g., Outdoor activities, indoor sites, architectural heritage sites, environmental locations, etc. The user must select up to 2 or more types of preferred interests.

Fig. 4. Client Data Input Process

Recommendation System. In the content-based filtering technique, recommendations are made according to the analysis of the item's attributes. It makes use of the algorithms that are domain-dependent. The recommendations are derived from user profiles based on the characteristics of the users' interactions with the system. To provide recommendations, content-based filtering algorithms apply various models, such as vector space models. Furthermore, the models such as Neural networks and Decision trees are also used to produce the similarities or the relationships between different items. Later, the user profiles are set up similarly according to the terms related to the users' interests obtained from the different types of feedback. These terms are then classified into two

classes named positive and negative class. Only the positive class is relevant to the users for a recommendation, and the negative class is irrelevant [9].

The two principal functions performed by the recommendation system are to recommend users with generalized tour plans and hotels suggestions based on their inclination. The Recommendation system operates using Artificial Intelligence / Machine Learning calculations utilizes historical data as a contribution to predict new yield esteems. The recommendation system provides a unique output by using the data (interest and preferences) given as input by the user. Hence based on different data collected from the user's preferences a wide range of suggestions is generated by the recommendation system.

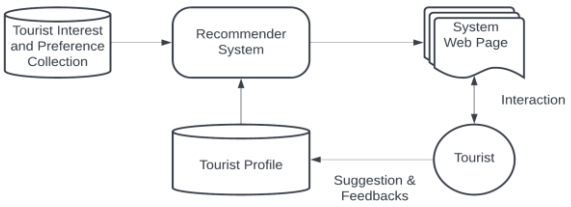

Fig. 5. Content-based filtering recommender system [9]

Data dynamic Updating. It is an important function to adapt to changing information so that the data in the system is updated in a timely and accurate manner to interact with the data model. Dynamic Data has functionalities that can assist in developing a data-driven application to perform CRUD functions. It has the ability to change how users see and modify data fields. Data maintenance is regulated to maintain the integrity and authenticity of the system. So, in order to improve the quality of the system, proper implementation for dynamic data collection and maintenance is crucial.

Filter and Reservation Process. Users can proceed with the generated tour itinerary by merely using the system's tour, restaurant, and hotel recommendations; Or else they can add filters to the recommended itinerary to perfectly tailor the tour plan, as suitable to the user. The generalized itinerary is generated upon which the user can add various filters to plan the aspects of the tour suitable to the user. Filters based on gross tour budget, Area of stay, type of accommodation, period of stay, type of hotel, food preference, etc. Subsequently, the user can proceed with a hotel reservation after determining the budget, time of stay, quality of stay, service, and choice of cuisine.

3.4 Obstacles

The origins of tour recommendations traced back to the Orienteering Problem and related variations, do not include customization for specific users. As a consequence, given the identical starting/ending interest points and time budget as inputs, the same tour route is recommended to all users [18].

Orienteering Problem. in which participants visit checkpoints with pre-determined scores that attempt to maximize their overall score within a certain time limit. Numerous research in recent years have used the OP and its many versions to predict tour suggestions. Similarly, several online applications [17] have been built based on the OP. We begin by describing the original OP [19, 10] and how it has applied to the domain of tour recommendation. Numerous systems concentrate on specific cities, each has its own set of prime point. A visitor visiting a specific city will have concerns of a specific time or distance budget, and have to choose starting and ending preferred interest point. A tourist's budget often signifies the amount of time tourist is willing to spend on a tour or the distance that the tourist is willing to travel. Similarly, the starting and ending destination indicate the tourist's preference to begin the trip near a specific spot (e.g., the tourist's hotel) and complete the tour at a different point (e.g., near a restaurant). Thus, given a set of criteria such as a budget, a starting interest point, and a destination, our major goal is to recommend a tour itinerary that maximizes a certain score while sticking to the budget, starting, and destination POI limitations.

Problem for Itinerary Mining. The Itinerary Mining Problem (IMP) was introduced based on OP [8], which tries to discover an itinerary that optimizes tourist prime point popularity while keeping touring time within a predetermined budget. The model is based on the number of visits by unique visitors, transit times between tourist interest points based on the median transit time by all tourists, and interest point visit times based on visit time by all tourists. To solve the IMP, a recursive greedy algorithm [20] is implemented, which attempts to determine the itinerary's middle node.

4 Technical Methodology

4.1 Bias Removal method by Joshua C. [14].

We'll begin by attempting to change the ratings, into a more normalized distribution using three forms of bias removal. The first method of bias elimination computes the average rating across all users and goods. The second and third types of bias elimination repeat the same process. Due to the possibility of small sample sizes for the user and/or item ratings, Laplace smoothing is used to reduce the influence of outliers.

The first model, Base Bias, is a simple system that employs the current mean rating, as the anticipated rating. This is a straightforward model, but it may be a starting point for more sophisticated models and a benchmark against which future advances can be assessed. The next model is the User Bias which attempts to reduce our baseline model's prediction error by recognizing that users may have intrinsic biases reflected in their ratings. Starting with the baseline mean, we calculate the individual user's bias to enhance our model. Alternatively, the third model that is the Item bias(trips), understands that, just as each user has biases, each object(trips) may likewise have a general bias associated with it. To improve our model, we start with the baseline mean and then calculate the individual item's bias to improve our model. The nature of the fourth model is the User to Item Bias, and the fifth model is the Item to User Bias, which is quite identical. The models begin by computing the residual bias from either user bias or item bias. The projected ratings for the models' User to Item Bias and Item to User

Bias are then determined. These five models serve as baseline predictors that our subsequent models will employ as a stepping stone to better performance.

5 Conclusion

In this project we have created an e-tourism website that allows users to plan their trip entirely by themselves from researching places, to know about restaurants and hotels suited to the user's budget and preference, booking hotels, generating unique personalized tour plans etc. The system provides a streamlined approach through the entire tour planning process. This project helps users connect better with the tourism community and support when users have any tour related queries. This project thereby improves efficiency, simplifies the process, and consumes less time to plan a tour.

6 Future Scope

As AI/ML is employed for analysis and solution generation, the framework will become quicker and more efficient. Once used and managed domestically, the system may be used for an international tour all over the world. It will allow customers to reserve trains, automobiles, planes, and other kinds of transportation. A system can collaborate with hotels, restaurants, and other eateries to promote and highlight them on the site. If a recommendation system can be developed based solely on considering the visual content of the video, it would become the most accurate recommender system. A more realistic step towards achieving this can be to develop a model that could make recommendations according to the visual content of the video shorts instead of the whole video. This could also ensure that the recommended list varies according to the latest trends in video content.

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