ISBN: 978-981-94-4198-3
2025 the 15th International Workshop on Computer Science and Engineering (WCSE 2025)
doi: 10.18178/wcse.2025.06.005

PATH: Personalized Assistance Tool for Holidays — An Initial Prototype for Smart Tourism Recommendations

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Abstract. Given the wide variety of destination options available, travel planning has become a complex and time-consuming task. Recommendation systems offer practical solutions to aid in the selection process by categorizing and ranking the options. In this paper, we present a prototype of an intelligent recommendation system to assist travelers. Our system relies on user preferences, inputs including budget, number of people, type of transportation, etc., and contextual factors to generate suggestions for suitable destinations.

The system is designed modularly and combines filter-based selection and user interaction to produce personalized recommendations. We noticed that there is a gap between user needs and preference, and digital travel planning therefore we aimed at bridging this gap by providing a tourist recommender system that is user-friendly, simple, responsive and adaptable. The system was tested using various scenarios and demonstrated its ability to provide recommendations based on users' budget and preferences. While we are still in the early stages of developing an application that is scalable and requires real-time data integration, our contribution is a prototype of a functioning personalized assistant for travel planning.

Keywords: Tourism Recommender Systems, Context based, Personalized recommendations.

1. Introduction

Tourism is an important sector of the economy seen as a financial source by an increasing number of countries. According to [17], international arrivals, referred to as overnight visitors, stood at 97% in the first quarter of 2024; this is almost a similar level to that which was recorded before the outbreak of the pandemic in 2019. Revenue from tourism is about USD 1.7 Trillion, which represents about 96% of the pre-COVID 19 figures. The COVID-19 pandemic affected tourism industry adversely; however, in its recovery phase, recommender systems gained much importance by offering carefully designed safe and green journeys tailored for individual tastes.

The effect of tourism is not just its direct expenditures, but it has its important influence on job creation, countries' infrastructure as well as cultural diffusion and development. However, with the huge number of touristic sites and attractions available, potential tourists become overwhelmed with options making it very difficult to decide on which destination they should opt for. To aid tourists, recommender systems can play a crucial role in the selection process. Such systems apply artificial intelligence AI and machine learning ML algorithms that analyse users' preferences, historical data as well as contextual information to offer personalized travel options [3][8]. Effective recommender systems are capable of significantly improving planning behaviour for trips and encouraging bookings [18]. They provide services that include accommodation and tourist attractions options in addition to making personalized itineraries. Despite their potential, they still face challenges in development and implementation. The cold start problem is a main challenge whereby systems face difficulties providing acceptable recommendations for new customers or items with limited historical data [12]. This problem concerns travellers who are usually looking for new experiences and destinations. Additionally, the dynamic nature of tourist preferences, which are seasonally affected, tend to be influenced and determined by personal circumstances, makes it difficult for systems to maintain current and meaningful recommendations [6].

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Generally, tourism experience is context dependent, so reference factors such as weather conditions, local events or travel companions should be considered. Integrating contextual information into recommendation algorithms and incorporating contextual aspects into recommender systems proved to be very difficult [1]. Moreover, the issue with data sparsity within tourism datasets reduces the accuracy of recommendations made [11]. Contextual filtering suffers from sparsity as the low number of ratings rends the recommendation ineffective.

Context-aware systems adapt recommendations to the user's current situation and environment and thus enhance the user experience. For instance, an application for context aware tourism may suggest going out to eat at some restaurant when it is time for lunch, or it may recommend a visit to the museums indoors on a rainy day [4]. These systems have been known to enhance the quality of recommendations thus satisfying and engaging varying customers. They also help adapt to unforeseen changes based on real-time events, which is very important for travel and tourism that are always changing dynamically. They enable users to make informed decisions with less cognitive effort through filtering prioritized information based on its contextual relevance [10]. In addition, they increase safety and comfort by giving timely notifications and alerts regarding local events or circumstances that may disturb travellers' plans. Considering how tourism industry is changing in the digital era, context-aware systems will play a key role in making more efficient and enjoyable people's travel experiences [15]. In this paper we present an initial prototype of an application for personalized travel recommender system. The rest of the paper is organized as follows: the second section contains a brief literature review; in the third section we present our system architecture and in section 4. We conclude the paper and give plans for improving the system in the fifth section.

2. Related Work

To improve the precision and applicability of recommender systems, an increasing amount of research has investigated different methods ranging from collaborative filtering to context-aware approaches. Several recommender systems for tourism has been developed based on the different approaches with emphasis now on using AI based recommendations.

In [5], a recommendation system for context-aware personalized hotels (CAPH) was created. The user-feature matrix is built by representative preference results to generate the neighbourhood-based CF models. The researchers used data from TripAdvisor.com on hotels in the USA to assess the proposed CAPH framework. Based on contributions of users have authored at least 20 reviews. The original dataset includes 2092 ratings and reviews, 8257 hotels, and 279 people. The experimental outcomes have shown that the proposed strategy successfully enhances the sparse matrices of the baseline. To recommend hotels to customers, [9] studied the Expedia online hotel booking system. Expedia made the dataset available as a Kaggle competition. The aim was eliminating the typical rabbit hole from hotel searches by offering users customized hotel recommendations. The information gathered contained a variety of variables that could give important insights into the procedure users go through when selecting hotels. There are 2,528,243 entries in the test set and 37,670,293 items in the training set. Even though most of the data was anonymized, which limited the amount of feature engineering that could have been performed, a hotel recommendation system using Expedia's dataset was developed. A context-aware smart tourism recommender system (STRS) for the city of Tangier in Morocco is presented in [2]. The authors propose a context metamodel that defines context as an aggregation of channel, location and time, system activity and user profile. The architecture is composed of 3 components (context, tourism content repository and recommender system). The output of the system is illustrated using two case studies with different scenarios of different tourists.

In [13], the authors used machine learning to produce accurate suggestions for potential customers. They studied an intelligent method for handling diverse and large-sized data using machine learning. They have put forth a novel Collaborative Filtering CF recommendation approach in which opinion-based sentiment analysis is applied to generate a hotel feature matrix using polarity identification. Their method integrates lexical, syntactic, and semantic analysis to comprehend perceptions of hotel amenities and the profiling of diverse types of guests (solo, family, couple etc.). The information is typically provided as text and quantitative (such as votes, ranks, and the number of views for videos). The proposed recommender approach offers promising results in terms of time and accuracy improvement, helping consumers to get

recommendations that are related to their choice and type. The work in [7] examines numerous reviews of tourist attractions and generates a list of suggestions. The system makes a custom trip plan for the user after considering their interests. The user can look up information about various tourist destinations and explore relevant websites. Different machine learning and deep learning techniques have been discussed to assess the reviews of the Amazon Reviews dataset to generate the suggestion list. In [16], the authors propose a novel approach labelled Model-Drive Engineering MDE that aims at simplifying and accelerating the development of recommended systems for smart tourism. MDE uses a Domain Specific Language DSL and code generation tools to minimize the need for extensive programming or machine language experience. An in-depth evaluation of AI-based tourism recommendation system with focus on real world performance metrics is presented in [19]. The metrics include recommendation accuracy, user satisfaction and system efficiency. The showed the potential that AI can have in tourism recommendation, continuous model optimization. A thorough review of recommendation systems in tourism was conducted in [14]. The study concentrated on the systems' methodologies and strengths and the challenges faced by the different recommendation system types: collaborative, content based, context aware, hybrid and social network-driven approaches. While stressing the significance of ethical concerns like privacy and algorithmic fairness, the study also emphasizes the growing significance of personalization, contextual awareness, and the utilization of multimodal data to enhance the user experience. Future developments in this area include explainable AI, large scale personalization, and the integration of sustainability into smart tourist solutions.

3. Our System

The tourist recommendation system is a valuable tool that leverages sophisticated algorithms to offer tailored travel suggestions. By considering various factors such trip type, budget, and group size, we present developed a system that assists individuals in selecting suitable travel destinations based on their preferences. To enrich users' travel experiences by providing personalized recommendations, we used Python and incorporated NLP techniques to implement this content-based recommendation system prototype.

3.1. System Implementation

The system used a client-server architecture with a web browser, and a server running MySQL, PHP, and Apache interact as part of the client/server paradigm. The client in this paradigm is the web browser, and the backend is the server.

This system heavily relied on Python. We first created a module that uses web scrapping and read websites to add the nationalities into the database table nationality automatically. We then created another module to obtain the Google map location using the name. We used Selenium driver to connect with Chrome and searched Uniform Resource Locator (URL) for Google Maps with the links. The links are inserted it into the CSV file created by Bing AI and then added them to the database. Similarity functions were created to calculate the similarity between the different categories based on their description. The aim was to display the recommendation based on the user's information, and other similar categories. The function calculates the similarity and saves the top 6 similar categories CSV file, Figure1. The recommendation function is then used to get the different attractions to be used in the flask.

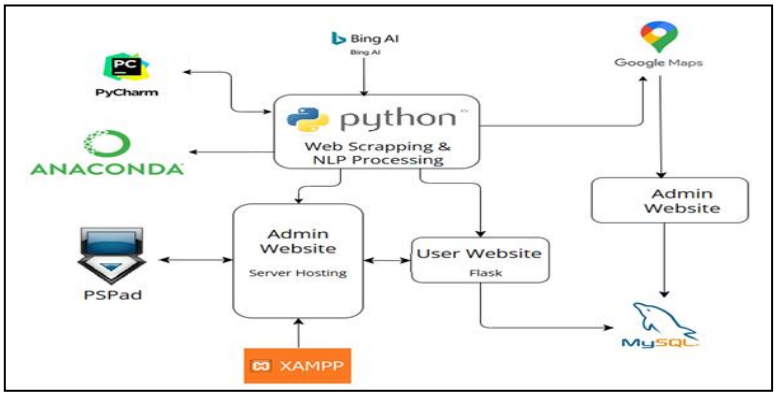

Fig. 1: Tools and Packages used in the system.

In Python flask, we created the entirety of the user logic to display the system functionality. The login page acts as the index, it is connected to the register function, admin dashboard and user dashboard. In the login, we store the user id in the session.

3.2. Tools and Packages Used

As mentioned earlier, the system relies heavily on Python, and we used a variety of tools as coding environment or to accomplish the different tasks. Figure 1 shows the communication and interaction between the different tools used.

The PyCharm integrated development environment (IDE) provided tools and features to facilitate Python development, including code editing, debugging, version control integration, and project management. PyCharm was used as the primary development environment for writing, developing and testing the Python code. Scientific programming and data science tools provided by Anaconda™ were manage the Python environment and install libraries and packages required for web development and data analysis. PSPad was used a text editor for PHP, CSS and HTML scripts. We used XAMPP to set up a local server environment to host and test the PHP-based admin website and MySQL database. To search for tourist attractions, museums, shops, restaurants… etc, we use Bing AI. The results are stored in a comma separated values (CSV) file along with the link to Google Maps location for the attraction.

Based on the intended trip information provided by the user like number of days, budget and number of people, … etc, the system calculates 6 recommendations of different destinations for each day of the trip. The system also recommends hotels, shops, restaurants, activities, mode of transportation and so on. The functions use the number of people, budget and number of days to calculate the user cost category. All the recommendations and searches are stored in the session using JavaScript/Python functions.

3.3. Testing and Performance

The system prototype was tested on a large set of possible factors that could affect the recommendation, and the results were as expected. The actual results for this project aligned with the expected outcomes. The system provides personalized recommendations and successfully incorporates the similarity functions to calculate the similarity between categories and generate recommendations based on user preferences and trip information. The techniques used, such as vectorization and cosine similarity calculation, successfully captured the similarities between categories and provided meaningful recommendations.

However, it is important to note that the accuracy and relevance of the recommendations can be influenced by a variety of factors. The quality and availability of data from external sources can impact the effectiveness of the similarity functions. Inaccurate or incomplete data may lead to less precise recommendations. Furthermore, the complexity of the similarity functions and the choice of features used for comparison can also impact the results. Fine-tuning the parameters and optimizing the algorithms may be necessary to improve the accuracy of the similarity calculations and enhance the relevance of the recommendations.

Overall, while the actual results of the similarity functions and recommendation generation aligned with the expected outcome, continuous refinement and improvement are essential to enhance the accuracy and relevance of the recommendations. Addressing data quality issues and optimizing the algorithms will contribute to the ongoing enhancement of the system's recommendation capabilities.

4. Conclusion and Future Work

We presented in this paper a very brief description of a recommendation system prototype aimed at improving the experience of selecting a tourist destination (path). The system aims to provide personalized recommendations aligned with the user's unique needs by integrating user preferences with contextual factors such as time and location. Based on our initial experiments, the system demonstrated performance that reduced the gap between user requests and expectations and the tourist destinations that match these requests, providing a simplified, user-centric approach.

There are undoubtedly several paths to expand the system's capabilities, such as incorporating real-time contextual data such as weather conditions, traffic congestion, or local events at the tourist destination, as in

[18]. We have not addressed challenges such as the cold start problem, and we plan to address them using a hybrid recommendation approach, as demonstrated by recent research. We also look forward to deploying the system on various platforms as a mobile application to increase system accessibility and enhance user engagement.

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