



iJRASET

International Journal For Research in
Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 11 Issue: V Month of publication: May 2023

DOI: <https://doi.org/10.22214/ijraset.2023.51527>

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A Real Time Tourism Recommender System using KNN and RBM Approach

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Abstract: *Tourism has become a significant contributor to both the industry and national economy. Over the years, the desire to travel and explore new places has led to a substantial increase in the number of tourists. This boom in tourism has resulted in many businesses, both global and local, as well as governments investing heavily in the industry. However, while governments invest in maintaining and promoting tourist attractions, there is often no emphasis on improving the overall experience of tourists. To address this issue, a real-time recommender system can be implemented. This system will provide tourists with recommendations based on their preferences, rather than just providing them with information. As the environment for recommender systems has become increasingly complex and dynamic, with diverse information available in real-time, it is necessary to develop an effective touring recommender system based on real-time characteristics. This system will provide tourists with real-time recommendations, thus enhancing their experience. To achieve this, a recommendation framework that provides comprehensive information for tourists is needed. This framework will guide tourists from the initial stage of exploring which country to visit, to providing a complete comprehensive guide for them once they arrive at their vacation destination. The goal of this solution is to give tourists the best possible experience, eliminating the need to depend on the help of others. Several features will be implemented in this application, such as comprehensive information on places to stay, dine, and visit, using the current location and budget, popularity, and other characteristics. The system will also create a timetable for tourists based on their duration of stay and provide real-time assistance. Overall, the system will provide a personalized and optimized touring experience for the tourist. With the implementation of this recommender system, tourists will be able to make more informed decisions about where to go, what to do, and where to stay. By using real-time data and personalized recommendations, tourists can enjoy a more engaging and satisfying vacation experience. This system will also benefit the tourism industry as a whole, by increasing customer satisfaction and promoting repeat visits.*

Keywords: *Recommender systems, Recommender systems for Tourism, Real-time Recommender systems, Hybrid Recommender systems, Collaborative filtering, Content based Filtering, Tourism.*

I. INTRODUCTION

Automated travel recommendation systems have become increasingly important in the travel industry due to the vast amount of information available on destinations, accommodations, and activities. These systems help travellers make more informed decisions about their travel plans by providing personalised recommendations based on their preferences, budget, and past travel experiences. One of the biggest benefits of automated travel recommendation systems is that they save time for both travellers and travel agents. These systems can quickly analyse large amounts of data and generate recommendations that are tailored to the individual traveler. This means that travellers can get the information they need quickly and efficiently, without having to spend hours researching different options themselves.[2][3] Moreover, automated travel recommendation systems can also help travellers discover new and exciting destinations or activities that they may not have considered otherwise. By analysing data from a variety of sources, these systems can identify hidden gems and unique experiences that may not be well-known.[8]

Overall, automated travel recommendation systems are a valuable tool for both travellers and the travel industry. They help travellers make more informed decisions, save time, and discover new destinations and experiences. As technology continues to advance, these systems will only become more sophisticated and helpful in planning memorable and enjoyable trips.[8]

Recommender systems are the systems that are designed to recommend things to the user based on many different factors. These systems predict the most likely product that the users are most likely to prefer. In a content-based recommendation system, keywords are and the recommendations are generated by the system based on the likes and dislikes of the user. Collaborative filtering is a method that is based on collection of information and analysing it based on the preferences, and determining whether they will prioritise the recommendation based on the similarity with other similar users.

[19] An advantage of collaborative filtering is that it does not rely on content and so, it is capable of recommending complex such as consumer products and movies without the knowledge and understanding of the item itself. A hybrid approach, combining collaborative filtering and content-based filtering could be more effective in some cases. Hybrid approaches can be implemented in several ways, by making content-based and collaborative-based predictions separately and then combining them, by adding content-based capabilities to a collaborative-based approach (and vice versa), or by unifying the approaches into one model.[2][3][9]

II. LITERATURE SURVEY

There are several algorithms that can be used for building a recommendation system, and some of the popular ones are:

- 1) *Matrix Factorisation*: Matrix Factorisation is a collaborative filtering method that decomposes the user- item interaction matrix into two lower dimensional matrices representing users and items. It then estimates the missing values in the matrix and generates recommendations based on the reconstructed matrix. Factorisation Machines: Factorisation Machines is a linear model that can capture the interactions between features. It can be used for both collaborative filtering and content-based recommendation systems. Neural Networks: Neural Networks are powerful models that can learn complex patterns in the data and can be used for both collaborative filtering and content-based recommendation systems. Variants like deep neural networks (DNNs) and convolutional neural networks (CNNs) are often used for recommender systems[4]. Association Rule Mining: Association Rule Mining is a rule-based approach that discovers interesting patterns in the data, such as which items are frequently purchased together. These patterns can then be used to generate recommendations.
- 2) *Content-Based Filtering*: Content-Based Filtering recommends items similar to those that a user has previously shown interest in. This approach typically requires item descriptions, features or tags to be extracted and used to represent items and users.[2] Each of these algorithms has its strengths and weaknesses, and the best choice will depend on the specifics of the problem being solved. It's important to evaluate the performance of each algorithm in the context of the use case and choose the one that works best for the data and business needs.

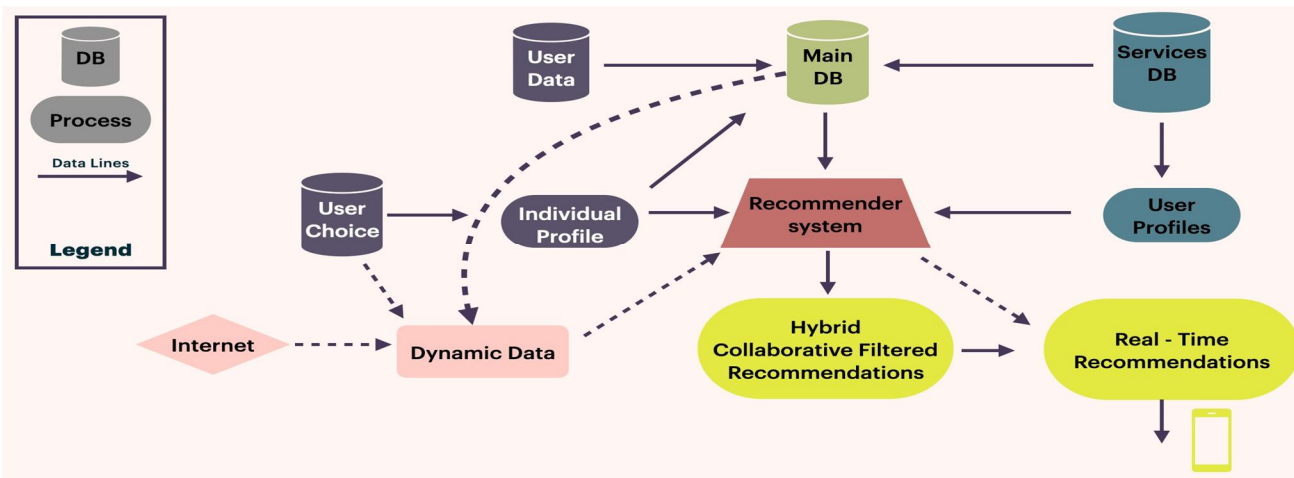


Figure 1. Architecture Diagram of the proposed system

While tourism apps have become an increasingly popular tool for travellers to plan and organise their trips, there are still some limitations in existing apps that can affect their usability and effectiveness.

One of the primary limitations is that many tourism apps rely on user-generated content, which can be unreliable and biased. For example, reviews and ratings of hotels or restaurants may be skewed by fake reviews or people with certain interests or agendas.

This can make it difficult for travellers to trust the recommendations provided by the app [6][14]. Another limitation of existing tourism apps is that they often lack integration with other travel services or platforms. For example, a traveler may use one app to book their flight, another to book their hotel, and yet another to find local attractions or activities. This can lead to a fragmented experience, and make it difficult to manage all aspects of the trip in one place.

In addition, some tourism apps may be limited in the range of information they provide. For example, they may only focus on popular tourist destinations, and not provide information on lesser-known or off-the-beaten-path attractions. This can limit the traveler's options and prevent them from discovering new and unique experiences. Finally, tourism apps may not always take into account the specific needs and preferences of the traveler.

For example, a traveler with mobility issues may need information on accessible attractions or accommodations, but the app may not provide this information. Similarly, a traveler with specific dietary needs may require information on restaurants that cater to those needs, but the app may not have that information available.

Overall, while tourism apps can be a useful tool for travellers, it's important to be aware of their limitations and to use them in conjunction with other sources of information and services to ensure a well-rounded and enjoyable travel experience. Automated tourism apps have been the subject of numerous research studies in recent years, covering a wide range of topics, including user behaviour, usability, and the impact of technology on travel experiences. Here are a few examples: A study evaluates the effectiveness of a mobile travel recommendation system that uses collaborative filtering and data mining techniques to provide personalised travel recommendations to users. The study found that the system significantly improved users' travel planning experiences and satisfaction. [15]. Also, another study examines the development and implementation of a mobile-based automated tourist guide application that provides real-time location-based information to users. The study found that the application was effective in enhancing the tourist experience and facilitating navigation in unfamiliar areas. [16] This study explores the impact of technology on the tourist experience, focusing on the use of mobile apps for travel planning and navigation. The study found that technology has a positive impact on the tourist experience, enhancing convenience, information access, and decision-making. [17]. Another study investigates the usability and user acceptance of mobile travel applications, examining factors such as user interface design, functionality, and content. The study found that user acceptance is influenced by a combination of factors, including usability, usefulness, and user experience. These are just a few examples of the research studies related to automated tourism apps, and as technology continues to evolve, we can expect to see even more research and innovation in this area. [18]

III. METHODOLOGIES

A. Real Time Data Collection

Collecting real-time data for a recommender system involves the process of continuously gathering data on user behaviour, preferences, and interactions with the system. Here are some steps to consider:

Identify the data needed: Identification of the types of data that are relevant to the recommender system. This may include user behaviour data (e.g., clicks, purchases, ratings), user profile data (e.g., demographics, interests), and item data (e.g., product features, category, price).

Table 1. Dataset used for the recommender system

```
In [4]: hotels.head()
```

Out [4]:	HID	HOTEL	PRICE_RUPEES	NUMBER_OF_REVIEWS	Lng	Lat	Grade	District	AGA Division	PS/MC/UC
0	HID1	CINNAMON GRAND HOTEL	898.92	1305	79.849235	6.918034	FIVE	Colombo	Colombo	Colombo Divisional Secretariat
1	HID2	CINNAMON LAKESIDE COLOMBO	2771.67	4358	79.849414	6.929273	FIVE	Colombo	Colombo	Colombo Divisional Secretariat
2	HID3	CINNAMON LODGE	4120.05	499	80.748810	8.034584	FIVE	Anuradhapura	Anuradhapura	Anuradhapura East
3	HID4	GALADARI HOTEL	2172.39	278	79.843155	6.931679	THREE	Colombo	Colombo	Colombo Divisional Secretariat
4	HID5	EDEN RESORTS AND SPA	3221.13	6189	79.990213	6.444585	FIVE	Kalutara	Kalutara Pradeshiya Sabha	Kalmunai Divisional Secretariat

Set up data collection: To collect real-time data, there will be the need to set up data collection tools that can track user behaviour and interactions with the system. This can be done through various methods such as web analytics, tracking user clicks or movements, or monitoring user search queries. For storing the data, there will be a need to store the collected data in a database or data warehouse. This can be done through a variety of technologies like Apache Cassandra, Apache H-Base, or Apache Kafka. Process the data: Once having collected the data, there is the need to preprocess it to remove any noise or irrelevant data. This can involve filtering out any data that is not useful for the recommender system. To train the recommender system, after collecting the data, need to train the recommender system using the collected data. This can involve developing machine learning models or using a recommendation engine.

Continuously update the recommender system: Finally, to ensure the recommender system stays accurate, the system should be regularly updated with new data that is collected in real-time. A batch processing approach or a stream processing approach to continuously update the system. Overall, collecting real-time data for a recommender system requires careful planning and setup. The key is to ensuring that collecting relevant data is ensured, storing it in a reliable and scalable manner, and continuously training and updating the system with new data.

B. Real Time Data Updation Of The Proposed System

In a K-Nearest Neighbours (KNN) recommender system, updating the data involves retraining the model with new data. Here are some steps to automatically update data in a KNN recommender system:

First, need to collect the new data that is needed to use to update the model. This could be new user interactions, ratings, or other relevant data. Once having collected the new data, preprocess it so that it is in the correct format to be used by the KNN algorithm. This could involve transforming the data into a sparse matrix or converting it to a standardised format.

To update the existing model, simply retraining the KNN algorithm with the new data is possible. This involves calculating the distances between the new data and the existing data and updating the model's recommendations accordingly.

It's important to choose an appropriate update frequency that balances the need for up-to-date recommendations with the computational cost of retraining the model. Depending on the size of the dataset, there might be a need to update the model daily, weekly, or monthly.

After updating the model, the system should monitor its performance to ensure that it is still producing accurate recommendations. This can involve calculating metrics such as precision, recall, and RMSE.

Updating the data in a KNN recommender system provides an opportunity to improve the model's accuracy. This can be experimented with different K values or distance metrics to see if they improve the model's performance.

Overall, updating data in a KNN recommender system involves retraining the model with new data and choosing an appropriate update frequency. By monitoring and evaluating the updated model and considering model improvement, it can be ensured that the KNN recommender system continues to produce accurate recommendations over time.

C. Real Time Data Recommendation Of The Proposed System

KNN (K-Nearest Neighbours) and RBM (Restricted Boltzmann Machines) are popular algorithms used in recommendation systems, but whether they are the "best" depends on the specific problem and context. KNN is a simple and intuitive algorithm that is easy to understand and implement.

It works by finding the K nearest neighbours to a user or item and making recommendations based on the preferences of those neighbours. KNN is particularly useful when the data is sparse or when users have similar preferences. It is also a memory-based algorithm, which means that it does not require a training phase and can make predictions in real-time. However, KNN can struggle with scalability and can be computationally expensive as the dataset grows.

RBM is a type of unsupervised neural network that can be used for both collaborative filtering and content-based filtering. RBMs can model complex patterns in the data and are particularly effective at capturing non-linear relationships between items and users. They can also be used to learn latent features that can be used for content-based recommendations.

Table 2 - Real time data recommendation

df.describe()															
	PID	POIs	Address	Grade	Type	District	AGA Division	PS/MC/UC	IN-TIME1	IN-TIME2	OUT-TIME1	OUT-TIME2	PRIORITY_1	PRIORITY_2	PRIORITY_3
count	670	670	670	670	670	670	670	670	670	670	670	670	670	670	670
unique	670	654	668	4	5	22	89	105	17	9	19	9	5	4	3
top	PID1	INFINITY SPA	PINNAWALA, RAMBUKKANA	A	Dining	Colombo	Colombo	Colombo Divisional Secretariat	0:00	-	17:00	-	Dining	-	-
freq	1	3	2	470	476	298	213	176	102	565	162	565	476	616	476

RBM's are trained using a contrastive divergence algorithm, which can be computationally expensive and time-consuming, but there are fast approximate techniques that can be used to speed up training. Both KNN and RBM have their strengths and weaknesses, and the choice between them will depend on the specifics of the problem being solved. Other factors that may influence the choice of algorithm include the size of the dataset, the available computational resources, and the business needs.

Ultimately, the "best" algorithm is the one that works best for the given problem and context, and it may require experimentation and evaluation to determine which algorithm is most effective.

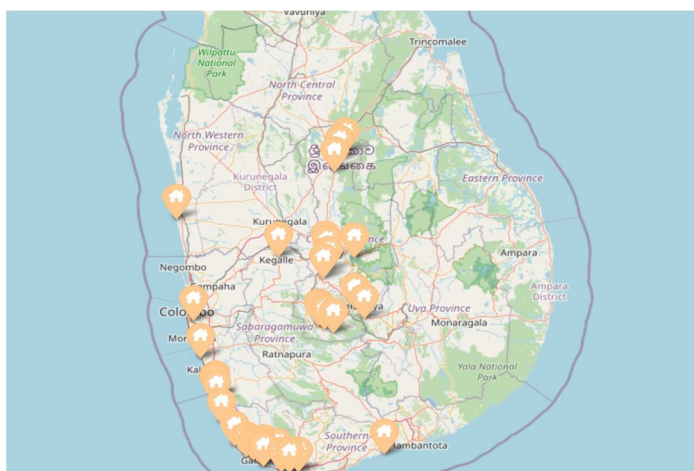


Fig 2. The proposed system generating real time recommendation for hotel stays based on budget

Tourism apps have evolved significantly in recent years, but there is still room for advancement and improvement. Here are some potential advancements in the proposed recommender system

Personalisation: Advances in artificial intelligence and machine learning can be used to create more personalised travel recommendations based on the traveler's preferences, past travel behaviour, and other data points. **Augmented reality:** Augmented reality technology can be used to enhance the traveler's experience by providing real-time information and interactive experiences, such as virtual tours of tourist attractions.

Seamless integration: Future tourism apps can be designed to integrate seamlessly with other travel-related services, such as transportation, accommodation, and activity bookings, to provide a more streamlined and integrated travel experience. **Real-time information:** Real-time information on traffic, weather, and other factors can be integrated into tourism apps, allowing travellers to make more informed decisions and plan their trips more effectively.[6]

These are just a few potential advancements and as technology continues to evolve, we are expected to see even more innovative features and capabilities in the future.

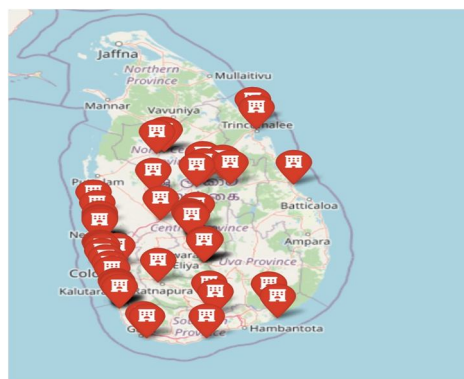


Fig 3. The proposed system generating real time recommendation for hotel stays based on popularity

Creating a real-time recommender system involves a few key steps. Here is a high-level overview of the process:

Define the problem and choose a recommendation approach. For this, Before starting the development process, define the problem that is to be solved and choose a recommendation approach that suits the problem domain. There are several recommendation approaches available, such as collaborative filtering, content-based filtering, and hybrid approaches.

Collect and preprocessing of data is the next step. The next step is to collect data from various sources such as user interactions, website clicks, product purchases, and user feedback.

Once having collected the data, preprocess it to remove any irrelevant data and transform it into a format that is suitable for the recommendation algorithm. In order to choose a real-time data processing framework to create a real-time recommender system, there is a need for a framework that can process incoming data in real-time.

Popular frameworks for this task include Apache Kafka, Apache Flink, and Apache Spark Streaming. To Train the model using the processed data. This typically involves building a recommendation algorithm using machine learning techniques.

After training the model, there arises the need to deploy it to a production environment where it can be used to generate recommendations in real-time. This can be done by creating an API that takes in user inputs and returns personalised recommendations. To continuously evaluate and improve the model, evaluate the performance of the real-time recommender system and improve it over time. This can involve collecting feedback from users, monitoring the performance of the recommendation algorithm, and tweaking the system based on the results. [6][14]

IV. CONCLUSION AND FUTURE WORKS

The features we try to implement in the future include: Implementing voice recognition and computer vision modules to further increase the user experience and tourism experience of the traveller and additional preferences to choose among sustainable travel choices etc and also blockchain technology for improved security measures. It can also be scaled by adding accurate datasets of different countries and providing accurate recommendations based on the user logs and feedback provided during his travel in different countries using the application.

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