



Department of Computer Science and Engineering
SRM University, AP.

TOURISM RECOMMENDATION SYSTEM

Group:

Anjana Nallanagula - AP19110010340

Lasya Nagamlla - AP19110010365

Hema Sai Kota - AP19110010454

Bhavana Tondupalli - AP19110010482

1. INTRODUCTION:

Recommendation systems are very popularly used nowadays for enhancing user experience. It filters the information given by the user and predicts the preference a user might give to the system. Many recommendation algorithms are used in traditional product recommendations, such as collaborative filtering algorithms, content-based recommendation algorithms, and hybrid recommendation algorithms.

In this project, we have shown our interest in tourism recommendation systems using a content-based recommendation algorithm. With the rise of more tourist websites, it is easy to get online data that explains users' preferences and interests. This recommendation system takes on the user's origin country and destination interests and provides a list of similar destinations. For this we can use location API, to determine distances between places.

1.a Places API:

The main objective of applying places API is to discover different places in the selected range of the user, following their preferences according to their criteria. Hence, we can display the places with the URLs.

urllib module in python can access the user's current location based on his or her IP address. This module is very useful as it shows up-to-date coordinates of the user to recommend places efficiently.

Place search - It returns a list of places based on a user's location or search string.

Place details - It returns more detailed information about a specific place.

Place photos - It provides access to millions of place-related photos stored in Google's Place database.

Place Autocomplete - It automatically fills in the name and/or address of a place as users type.

Query Autocomplete - provides query prediction service for text-based geographic searches, returning suggested queries as users type.

2. Problem Statement:

The tourism recommendation system offers users to find destination places using places API. It is mainly developed for people who are busy and couldn't find time to learn about new places. Tourists will get proper information about places and they can visit based on their current location and the information extracted from the places API which gives the accurate distance between places.

2.a Problem Statement (Mathematical):

The main aspect of recommending places to the user is the computation of the distance between the user and the potential places belonging to the same category. Since the places are represented using coordinates the distance between them should be computed using the Haversine formula.

The Haversine formula calculates the shortest distance between two points that are represented on a sphere using their coordinate points along the sphere's surface. This formula is used in navigation systems. The trigonometric representation of the haversine formula is:

$$\text{haversine}(\theta) = \sin^2(\theta / 2)$$

The haversine of the central angle is calculated using:

$$(d / r) = \text{haversine}(\Phi_2 - \Phi_1) + \cos(\Phi_1) \cos(\Phi_2) \text{haversine}(\lambda_2 - \lambda_1)$$

Where r is the radius of the earth (6371 km), d is the distance between two points, Φ_1 , Φ_2 is the latitude of the two points, and λ_1 , λ_2 is the longitude of the two points respectively.

Solving d by applying the inverse haversine or by using the inverse sine function, we obtain :

$$d = 2r \sin^{-1}(\sqrt{\sin^2(\Phi_2 - \Phi_1 / 2) + \cos(\Phi_1) \cos(\Phi_2) \sin^2(\lambda_2 - \lambda_1 / 2)})$$

The distance computed using this formula is not completely accurate as it assumes the earth to be a perfect sphere, but the earth is an oblate spheroid.

2.b Diagrammatic representation:

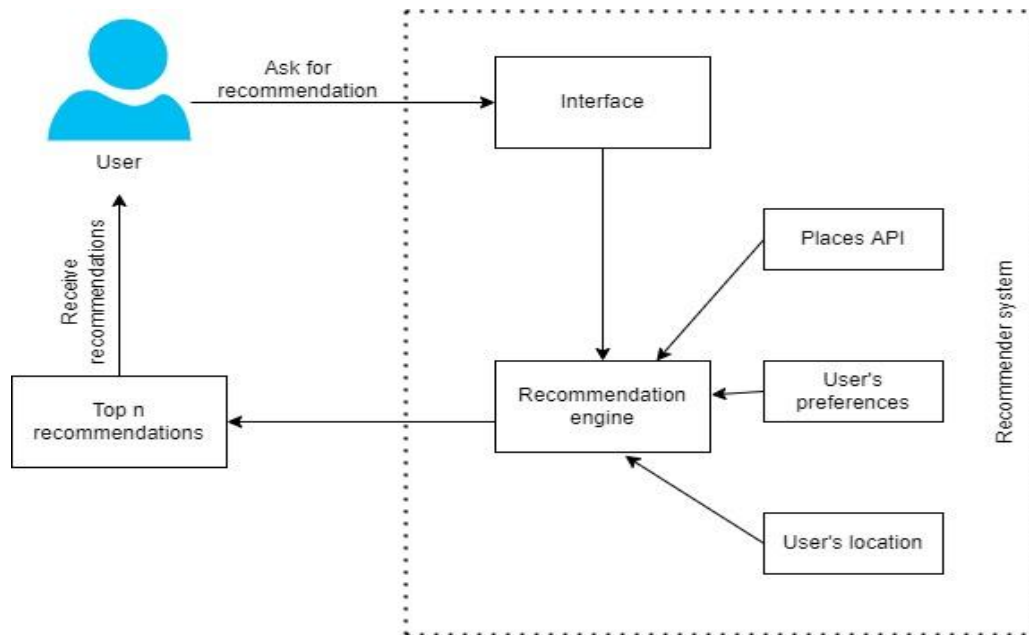


Fig. 1 Diagrammatic Representation of The System

The workflow of the system which includes the interaction of user interface, places API, and recommendation model is represented in Fig. 1.

3. Applications:

Through the internet nowadays we can find a lot of information which sometimes makes it hard and complex for users to search in which field they are interested. This recommendation system for tourists has many applications which are helpful for a happy vacation or a trip. The main agenda of this project is to help tourists who want to visit places hassle-free. Not only tourists but this will also help the tourism offices to boost the volume of tourists. It will also help people who want to visit other countries who have no idea about what kind of places they want to visit. This tourism recommendation system not only recommends tourist places but also helps in finding hospitals, restaurants, colleges, etc.

4. Motivation:

People frequently travel to satisfy their curiosity about the world, people, and life in general. People always tend to learn and know something unfamiliar when they travel. This makes tourism very important in everyone's life. In current scenarios of fraud and scams going on with tourism, the people are feeling difficult to double cross-check and make the correct decisions and adjust their money to complete their vacation. So to overcome this problem we decided to develop a recommendation system that guides the user to travel to their favorite tourist places. In many cases, we do not trust the results from such systems. But using places API, the Haversian distance is used to filter the places near to the user. Location API has large information which is accurate and can be utilized for travel recommendation systems. We can also explore different types of places easily. Users are given large amounts of information that are overwhelming, this new method and tools are beneficial to making decisions efficiently. Recommendations guide the users in the decision-making process through directions and suggestions.

5. Literature:

Abdul Majid et al.2012, developed a context-aware personalized travel recommendation system based on geotagged social media data mining with the features of collective wisdom, personalization, context awareness, etc.[1]. This is developed from multimedia data that has content generated by users like travel experiences having textual information, photos, tags, descriptions, temporal context which is the time at which the image was taken, and spatial context which is the location where the image is taken in terms of longitude and latitude in social media like Facebook, flicker, youtube, Gowalla, and etc. So, by considering the collection of tourist places that are often geotagged or photographed, assume a sequence of visited locations to create traveling histories of the community of users and recommend them to the other users in the same community. This travel recommendation system includes personalized tourist recommendations, trip deductions, geotags exploration, mapping to landmarks, etc.

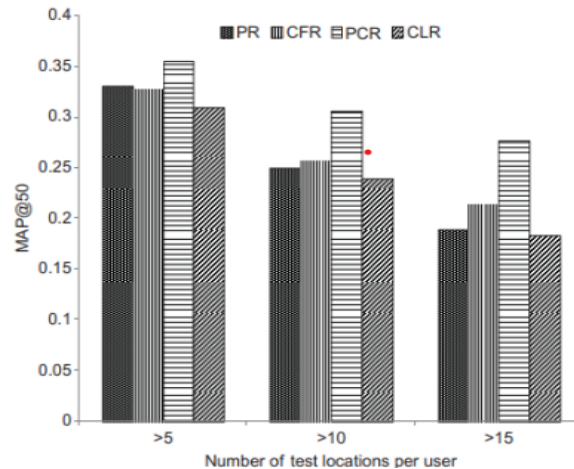


Fig.2

The rating ability of different methods in terms of mean average precision recommends 50 locations across different numbers of test locations per user as shown in Fig.2[1].

Kevin Meehan et al.2013 developed context-aware intelligent recommendation systems for tourism using additional context data such as weather, time, social media sentiment, and user preferences that can provide an accurate model of the user's current context[2]. The contextual data used in this research are location, time, social media, weather, and personalization. GPS, GSM, and Wi-Fi are location sensing techniques used outdoors that use triangulation and proximity to detect the location and these provide users with directions and information to the users from their current location. More intelligence will be added to the application when time is combined with the other contexts. It calculates how much time a user is spending on each point of interest so that it will help in increasing those recommendations. Weather information like weather conditions is collected from WorldWeatherOnline API provides a textual format and recommends to users based on whether it is suitable outside or not outside. Sentiment analysis is performed on tweets to identify the current mood of tourist attractions resulting in a percentage of positive, negative, and neutral tweets about a point of interest.

Leila Etaati et al.2014 developed an adaptive tourism recommendation system that provides recommendations based on travelers' needs, interests, devices, and locations which can change their behavior to adapt to the new situation[3]. It gives personalized recommendations based on the information collected from different resources about travelers and travel products as shown in Fig.3. At first, this system collects the traveler's preferences about the travel place's recommendation order, and then it suggests the travel products based on the traveler's stage of travel. During the travel, the system follows the sequences, and finally, the admin of the system modifies the recommendation algorithm parameters. Modification of system information, modification of system stakeholders' interaction, modification of system process task scheduling, and modification of function allocation are done to alter the behavior of the system. This system collects information from other systems through collaboration techniques and employee integration to reach an acceptable level of adaptation. User profile, item profile, traveler, travel elements, and travel processes are the main services that are responsible for collaborating with external websites or applications.

The screenshot shows a web form titled "Traveller Profile" with the following sections:

- 1) Demographic Profile:** Includes fields for Age (32), Gender (female), Language (Persian/English), First Name (Leila), Last Name (Etaati), Country of Origin (Auckland, New Zealand), Current Address (Tehran, Iran), Education (College: The University), and Birthday (09/20/1982).
- 2) Previous Travel Information and interests:** A table with columns "Last Destination", "Last Visited Place", and "Last Restaurant/Book". It contains one row with a star icon in the first column. Below the table are "Confirm", "Change", and "ADD" buttons.
- 3) Health Profile:** Includes "Healthy Choice" (Gluten Free, Sugar Free, Dairy-free, Fat free, Halal), "Disability" (Physical Disability, Sensory Disability (Vision, Hearing), Emotional Disability), and "Illness" (Diabetic, Blood Pressure, Asthma).
- Purpose of travel:** A dropdown menu with options: Holiday, Business, MFR, Medical, and Miscellaneous. The "Business" option is selected.
- Duration:** A field with the value "0".
- Money:** A field with the value "2000".

At the bottom of the form are "Confirm" and "Get recommendation" buttons.

Fig. 3 Traveler Demographic Information which has been explicitly and implicitly extracted from his/her Facebook, Outlook account, and traveler inputs[3].

Rahim Ali Abbaspour et al.2017 developed a cold start context-aware recommender system for tour planning using artificial neural networks and case-based reasoning and added that the recommender systems can be defined as information filtering and decision support tools

that provide products and services that match user's preferences[5]. User needs a lot of time to search for suitable places on the web and sort from huge amounts of tourism information so, irrelevant information should be filtered and personalized options should be taken out according to user preferences and interests. Recommended systems with user preferences increase system usability limit information overload, and the content will be personalized user to user. In the case of a tourism recommender system, user preferences will be changed because of contextual factors like mobility, the timing of recommendation, history, etc, this context-aware recommender system for tour planning is developed in order to adapt to the changing contexts by incorporating contextual information to appropriate model and predict the user preference. To achieve accurate results, a case-based is used to take user preference as a query item that users like and each item case as a set of attributes therefore, the system retrieves system items that are similar to the user's query case. Ratings are taken from the user after every cycle in the selected recommendation tour as shown in Fig.4.

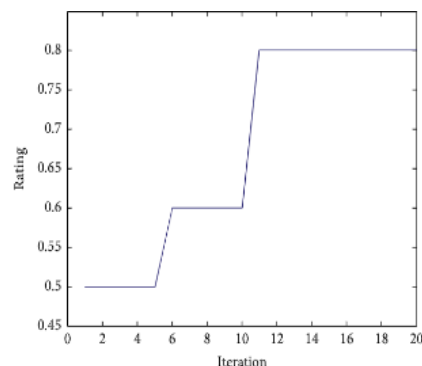


Fig. 4 The rating that the user assigns to a selected tour at each cycle[5].

Logesh Ravi et al.2016 developed a collaborative location-based travel recommendation through enhanced rating prediction for the group of users[4]. The location-based social network contains a user's location formed from tags and activities like photos, videos, and text in their social structure to share information by location embedded and the new structure will be formed when an individual user is connected to the location on the social network. From the information, location-based network shows graphs are built as a

location-location graph, user-location graphs, and user-user graphs based on geotagged media-based services, point location-based services, and trajectory-based services. This recommendation system is developed using a social pertinent trust walker algorithm in which locations recommended to the user are predicted from location-based social networks. This algorithm determines a location rating score based on existing scores rated for similar location categories. After calculating the rating score for the location category, the user is recommended a list of more relevant locations. In the group recommendation, point of interest plays a key role so, after gathering a set of points of interest-based on the location category that has to be recommended to the group of users, sptw based group recommendation model calculates the ranking for point of interest-based on the popularity of POI and consideration score for POI that are combined to form top-POIs as a recommendation.

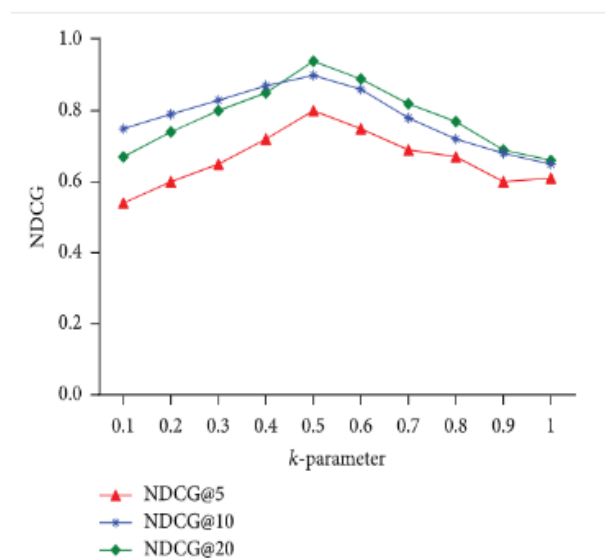


Fig.5.1. Comparison of normalized discounted error for cumulative Gain for all users[4].

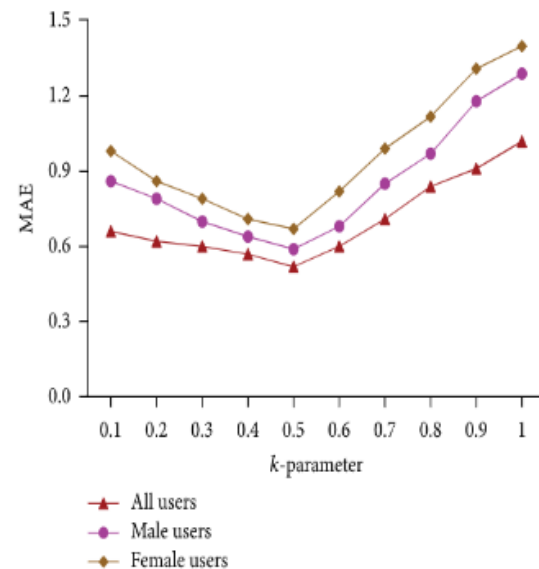


Fig.5.2. Comparison of mean absolute error for male, female, and all users[4].

Guangli Li et al. 2019 developed a novel recommendation system for tourist spots based on hierarchical sampling statistics and SVD++ by creating a new dataset named “Smart Travel” initially and a hierarchical sampling statistics model is utilized to acquire the user implicit preference for different population attributes, SVD++ algorithm is designed to complete the final recommendation[6]. SVD++ algorithm is used to predict the user ratings and the

predicted rating comparison is shown in fig.6. This system has several components like user data collection, a collaborative filtering model, and a hybrid recommendation list. From the recommendation lists generated by the HSS and SVD++ algorithm, a novel recommendation system is formed. The dataset has 5000 user ratings on 60 tourist spots that are classified into 8 categories, 4000 ratings are taken for training and 1000 ratings are taken for testing. The user preferences and details have been collected that help in giving a better recommendation. In this system, travel interest, travel season, and travel method are chosen as user preferences. To find the accuracy of recommendation, Root means square error and mean absolute error is performed. Less RMSE and MAE means more accuracy.

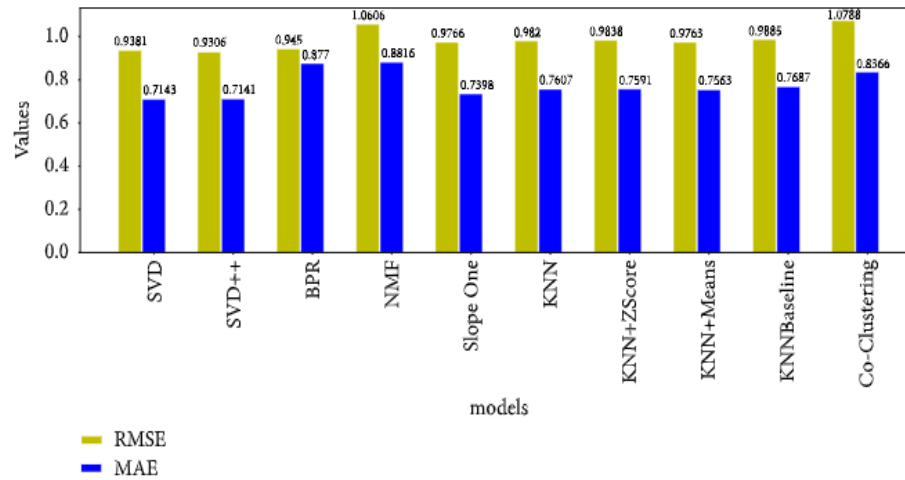


Fig.6.The prediction rating comparisons with baselines[6].

Zihao Pu et al.2020 developed an Improved Tourism Recommendation System using Classification, Collaborative Filtering, Linear regression, and Feature Selection[7]. This system used collaborative filtering on the basis of historic data for calculating similarities between items and the evaluation of the target user's history to predict the preferences of target users for specific items which the system recommends based on this preference. Feature selection is used in order to reflect the cities in the perception of tourists and it improves the effectiveness of the model by taking factors like sample size, subject, and object. Before implementation, the feedback information is collected from tourists through questionnaires after traveling considered image perception. The questionnaire is based on the comprehensive score of the respondent on

the city the user has visited, the city the respondent wants to go to and etc. Data cleaning is performed on the collected feedback information to get accurate results. In this, each feature is weighed using the coefficient of the regression model and calculated the similarity which is the main core of the collaborative filtering system. Using Bayesian statistics, the user-city score is predicted and the three cities with the highest scores are recommended for users.

Xi Cheng et al.2021 developed a travel route recommendation algorithm based on interest theme and distance matching, the optimal travel route calculation method is designed under the given travel time limit, starting point, and end point[8]. This algorithm is said to have a higher accuracy rate and recall rate than the traditional algorithm which considers interest theme and distance matching in separate implementations by Flicker social network analysis. The data used in this paper is the webserver log of tourism enterprises, which contains rich tourism product information and a large number of user behavior click records. The fundamental idea behind this approach is to take each user's travel history data to determine the user's preferred topic and acceptable distance, then apply those weights to the recommendation model to create a new personalized travel path. This algorithm implementation is divided into the point of interest association graph construction, learning the user's interest, and route recommendation. The most essential metric of the evaluation method is the accuracy of recommendations and to know that precision and recall are used, the higher the accuracy and recall, the recommendation is better. The proposed algorithm has higher accuracy than the traditional algorithm only considering user interests and poi topics as shown in Fig.7.

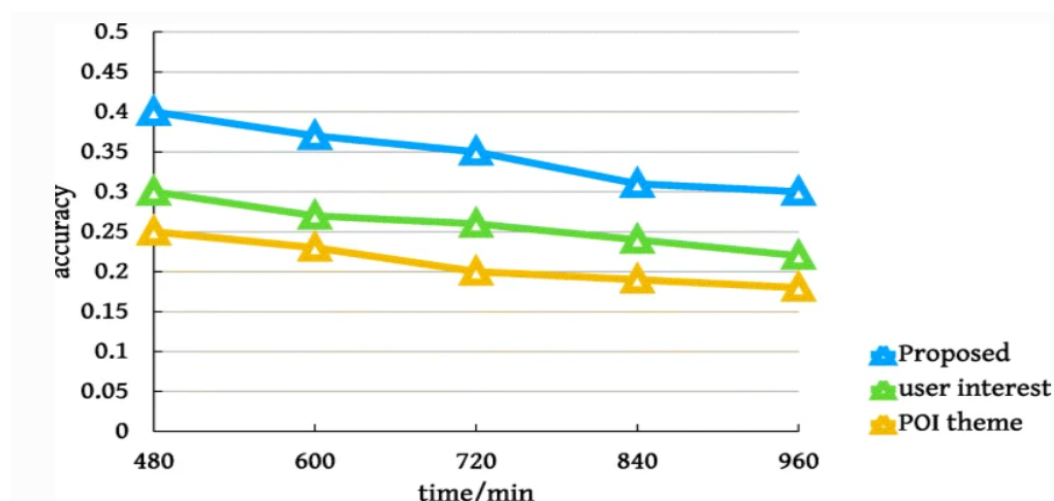


Fig.7.Results of Accuracy[8].

Table 1. Literature Summary

S.No	Citation	Year	Contribution
1	Abdul Majid et al.[1]	2012	developed a context-aware personalized travel recommendation system based on geotagged social media data mining.
2	Kevin Meehan et al.[2]	2013	developed context-aware intelligent recommendation systems for tourism.
3	Leila Etaati et al.[3]	2014	developed an adaptive tourism recommendation system.
4	Logesh Ravi et al.[4]	2016	developed a collaborative location-based travel recommendation through enhanced rating prediction for the group of users.
5	Rahim Ali Abbaspour et al.[5]	2017	developed a cold start context-aware recommender system for tour planning using artificial neural networks and case-based reasoning.
6	Guangli Li et al.[6]	2019	developed a novel recommendation system for tourist spots based on hierarchical sampling statistics and SVD++.
7	Zihao Pu et al.[7]	2020	developed an Improved Tourism Recommendation System.
8	Xi Cheng et al.[8]	2021	developed a travel route recommendation algorithm based on interest theme and distance matching.

6. Approach:

The fundamental blocks of this project are the urllib module, folium module, places API, and Python. This project highlights an efficient way of utilizing the places API to extract places near to the user based on applied filters. The process begins with accessing the user's current location. The coordinates of the user's system are accessed using the request sub-module from the urllib module which is available in python. This function gets a response in HTTP format. From this response object, the JSON data is loaded which contains the required information.

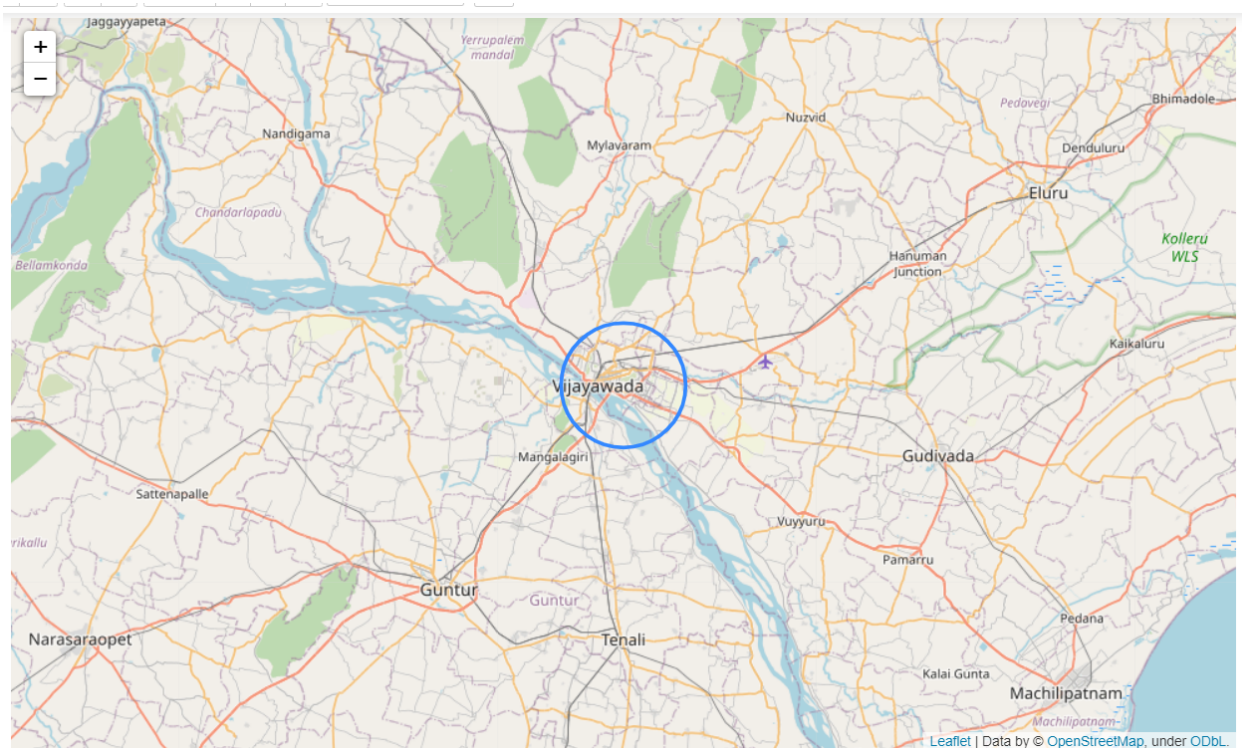


Fig. 8 User Location Representation

The folium module in python is used to visualize the user's location on the map with a predefined zoom value. The representation of the user's current location is depicted in Fig. 8. It plots the location on the map using the latitude and longitude data of the user's current location.

As a part of the next step, the user can specify the type of places he or she wants to go to. A few examples of the type of places that can be mentioned are commercial, education, health, accommodation, etc. The information about all these places is extracted using the places API provided by Geoapify. This API contains information about a wide variety of places all over the

world from which users can obtain a subset based on their requirements. The boundaries from which the data can be returned can be specified using rectangular coordinates, circular coordinates, or using the geometry of a region. In this project the boundaries are defined using the circular coordinates, all the values lying within a predefined radius from the user are extracted from the Places API. The data returned can be limited using the limit attribute which can be mentioned before searching for places. The request gives an HTTP response which is used to extract JSON data. The JSON data contains all the filtered places based on the user's request. Each element in this data contains the attributes of a place like a name, street, village, county, latitude, longitude, and category which can be used to gain more information about the place.

The recommendation part of the project begins with computing the distance between the user and the filtered place coordinates. The distance between two points on Earth can be computed using the Haversine distance formula -

$$Distance(d) = 3963.0 * \arccos[(\sin(lat1) * \sin(lat2)) + \cos(lat1) * \cos(lat2) * \cos(long2 - long1)]$$

d (in kilometers) = 1.609344 * d (in miles), The values of latitude and longitude are in radians.

This computation of distances is carried out for all the filtered places with the user's coordinates. The distance values are then sorted in ascending using an efficient sorting algorithm like merge sort and sorted in a list. Each of the resultant list items consists of the distance from the user, and their attributes like name, state, and address if available. These individual list items are printed in a tabular format to enable the user to access them in an easy format.

If the filtered list of places data is empty, It implies that there are no places around the user with the mentioned requirements. In this case, a message is provided saying "There are no places with the mentioned requirements".

The places in the resultant list can be plotted on the map along with the user's location to provide a more detailed view of the information. The map in Fig. 3 represents the places belonging to the education category near the user's current location. This project can be utilized

to identify a wide range of places around the user. It also allows the user to provide sub-categories like education-medical, accommodation-resorts, commercial-clothing, etc. to obtain more specific results. Given the constant speed of the user, the program can also return the estimated time to reach the place without considering any constraints.

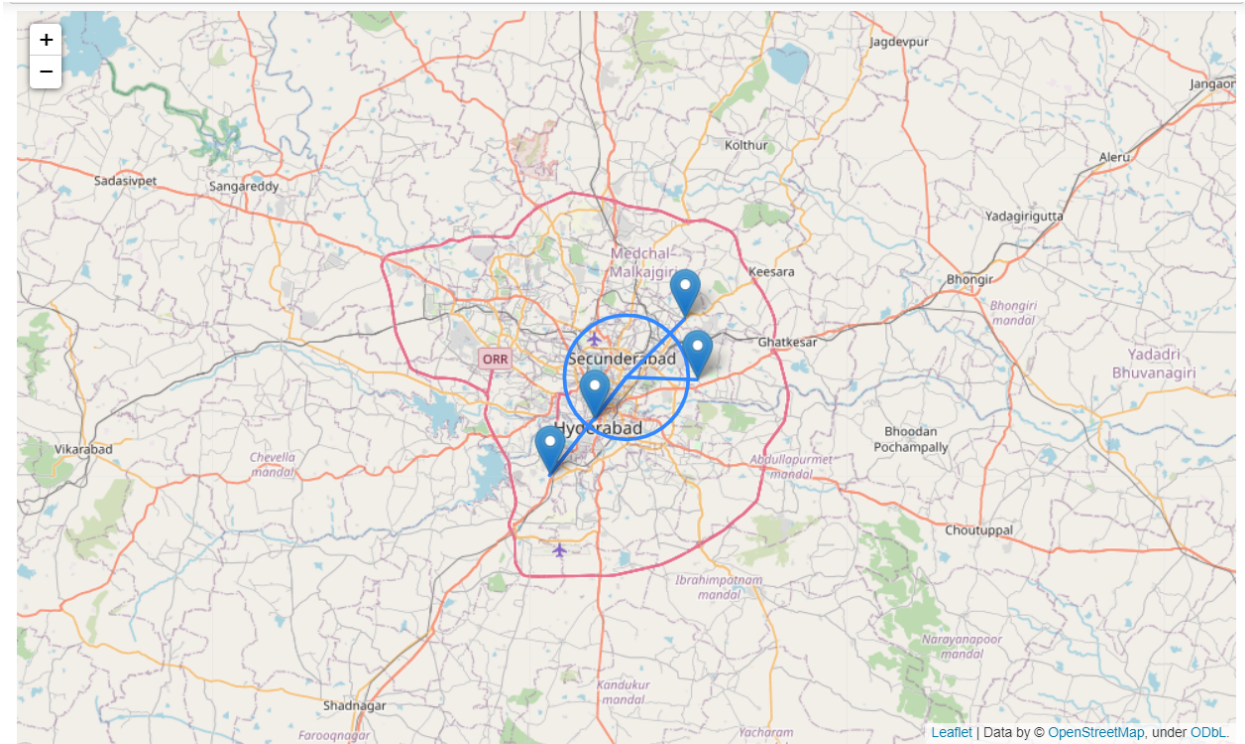


Fig. 9 Output Representing The Places Belonging to The Selected Category Near The User's Location

7. Conclusion:

In today's world, recommendation systems are an integral part of our lives including many shopping sites like amazon. In this tourism recommendation project, by the type of information integrated into the system, a content-based algorithm is used. By taking the user preferences, the system gives accurate results. The use of places API and different functionalities make this tourism recommendation system more user-friendly and hassle-free.

8. Future works:

This project can be expanded by adding many functionalities which will increase its application scope. This existing project can be implemented using web technologies like HTML, CSS, and Flask framework and can be deployed for easy and effective use. The preferences part of the project can include accepting multiple preferences from the user and can recommend places that combine the characteristics of all the user's preferences. The project can be modified to keep track of the user's current location and automatically recommend similar places based on the user's location. The project can be converted into a collaborative recommendation system where places can be recommended based on similar users' choices. The preferences part can be altered to allow the user to search for places based on the time they consider would be sufficient to reach the place of a given category. Example: Malls within 15 min of car.

9. References:

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