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Interactive Guide Assignment System with Destination Recommendation and Built-in Chatbox

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Abstract

This proposed system provides a website called 'Safari Nepal', where users can search for destinations and check their location on a map. Users when registering on the website, can fill up the details about themselves and choose to either be a tour guide or a tourist. Based on the search and preferences of the user, similar destinations are recommended to the user via a recommendation system that uses a content-based recommendation feature. This feature works on the data obtained from the user, either explicitly or implicitly. The concept of K-Nearest Neighbours (KNN) and Cosine similarity makes the recommendation more accurate. KNN uses a distance algorithm that sorts from most liked destinations to least liked, based on the preferences of the user. This sorted list of destinations is further filtered by Cosine similarity, which is a measure of how similar two vectors in an inner product space are. It is calculated by taking the cosine of the angle between two vectors and determining whether two vectors are pointing towards the same general direction. Thus, combined KNN and Cosine similarity gives a better recommendation to the user. The map is integrated into the system using Mapbox API. Also, the system connects users with tour guides and gives them space to chat via a chatbox

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called ‘Travel Buddy’ where they can discuss further the destination, the amount charged by the guide, etc. The chatting feature on the system allows multiple users to connect and make conversations about the destination creating various chatrooms. In the system, the user can also publish their blogs describing their experiences and share their thoughts on particular destinations.

Keywords: Content-Based Recommendation, KNN, Cosine similarity, API, chat box

1. Introduction

The motivation behind building a platform that connects tourists with local guides and facilitates communication among users is to enhance the overall travel experience in Nepal. This platform aims to address the authentic local experiences of Nepal, since Nepal is a country known for its rich cultural heritage, diverse landscapes, and warm hospitality. However, tourists often struggle to connect with local communities and explore hidden gems due to language barriers or lack of knowledge. By providing a platform that connects tourists with knowledgeable local guides, this research aims to offer authentic and immersive travel experiences that go beyond the typical tourist attractions.

This platform addresses the safety concerns of tourists by enabling them to find trustworthy guides who can navigate them through unfamiliar territories and ensure a smooth and secure travel experience. Moreover, the ability to communicate with guides and other tourists through chat rooms enhances convenience and allows for real-time assistance and information exchange.

The platform also benefits local guides by providing them with a digital platform to showcase their expertise and connect with a broader audience. By becoming a guide on the platform, they can utilize their knowledge and passion for their country to earn income and contribute to the tourism industry. This empowerment of local guides not only improves their livelihoods but also promotes sustainable tourism and encourages the preservation of local culture and heritage.

Nepal offers a wide range of attractions, from majestic mountains and serene lakes to ancient temples and bustling markets. However, it can be overwhelming for tourists to decide which places to visit based on their preferences. The recommendation system within the platform helps users discover new destinations and activities by analyzing their interests and providing personalized recommendations. This feature ensures that tourists can tailor their itineraries to their specific preferences, making their travel experience more enjoyable and fulfilling.

Therefore, travel is not just about visiting places; it's also about connecting with people and fostering cultural exchange. By creating chat rooms where tourists and guides can interact, share experiences, and ask questions, the platform promotes a sense of community and facilitates meaningful connections. This encourages cultural understanding, bridges the gap between tourists and locals, and fosters an environment of mutual learning and respect.

1.1 Objective

The objective of building the platform is to enhance the overall travel experience in Nepal by connecting tourists with local guides, facilitating communication among users, and providing personalized recommendations. The platform aims to offer authentic, immersive, and safe travel experiences while promoting cultural exchange and empowering local guides.

2. Related Works

Tourism recommendation systems are critical in providing travellers with useful travel information. However, due to a lack of onsite travel behavioral data and corresponding route mining algorithms, existing systems rarely try to offer actual routes for tourists within a given Points-of-Interest (POI). For that purpose, a unique travel route recommendation system based on smart phone and IoT technologies is developed, which automatically collects tourist onsite travel behavior data regarding a certain POI.

Tourism is both an essential industry and a popular leisure activity for millions of people all over the world. One crucial responsibility for travelers is to develop and organize tour itineraries that include various appealing Points-of-Interest based on the tourist's individual choices. The difficult process of recommending tour itineraries is exacerbated further by the necessity to account for numerous real-life constraints such as limited time for traveling, variable traffic conditions, inclement weather, group travel, queuing periods, and crowdedness. (Jeffrey Chan, 2018)

When organizing a trip or looking for a service among many places, attractions, and activities, recommender systems could be very useful. The approach is to utilize a person's navigation interests as inputs to forecast the degree of interest that this user may have for a specific item. There are several methods for estimating these levels of enjoyment. The literature has typically categorized them into many groups based on the source of information employed. One of these ways is based on user ratings offered on a collection of items. It means recommending a user items that have previously been highly rated by other users with comparable preferences, and is referred to as collaborative filtering. (Khalid AL Fararni, 2021)

Computer-Mediated Communication (CMC) is a modern technical tool for engagement and communication between professionals, students, and instructors, as well as other individuals, using computers or mobile devices to communicate text, photos, audio, and video. Email, network communication, text messaging, text-based, audio-based, and video-based chat rooms, chat widgets, particularly on library websites, chat tools in Learning Management Systems (LMS), online discussion forums, blogs, newsgroups, bulletin boards, mailing lists, videoconferencing, and social media are all examples of CMC. CMC is either synchronous or asynchronous. When two actively communicative people communicate at the same time, as in videoconferencing and instant messaging, synchronous CMC occurs. (Al-Jarf, 2021)

Group recommender systems are information filtering and decision assistance software designed to help a group of users make decisions when faced with a set of alternatives. Modern systems aggregate users' preferences gathered prior to the decision-making process and recommend things that meet the aggregated model. However, it has been demonstrated that group recommendation extends beyond the identification of such items, and it is critical to include the dynamic of users' interactions in their actual group environment during the suggestion process. In this case, group recommendation is implemented in a mobile system that observes and exploits user activities during a group conversation and provides relevant recommendations as well as various forms of ideas to direct the debate.

For many people, traveling has become a way of life. Tourism has grown at an unparalleled rate in the previous decade all over the world. With tourism gaining traction, creating a delightful experience for a tourist, and ensuring that he returns to the destination and spreads positive word-of-mouth about the destination appears to be one of the most difficult challenges that tourism service providers face today. A tour guide, more than any other stakeholder, is responsible for shaping a tourist's perception of a destination. The manner in which he behaves himself in front of the visitor contributes significantly to the overall pleasant image of a tourist. (Sharma, 2013)

3. Proposed Work

3.1 Platform Design

For the development of the platform, the user interface is first designed and then the overall architecture of the platform. The user experience is considered, and the work aims for a clean and intuitive design. The different modules of the platform, such as user registration, guide registration, search functionality, chat rooms, and recommendation system integration were determined and designed in the frontend using HTML, CSS and JavaScript.

3.2 Data Collection

Data domain needed for this research includes many places with genres and keywords related to each place. Those genres and keywords were given according to the reviews and information of each place from different blogs, websites, and social media. 503 different places from all 7 provinces of Nepal are collected in the current database. Each place collected in the dataset was given a unique place ID and classified into genres. A place may be constituted of many genres. For example, a single place can be adventurous as well as religious. Also, keywords were given to each place according to the nature of the place and things that they are famous for.

Later, the genres and keywords were converted into binary format and combined as one to give the 'parameters' of each place. Those parameters are later used as a vector with 'n' dimensions, with 'n' being the number of elements in the parameters, for the distance calculation in the recommender system. This is the design of the database for 10 places. All 503 places in the database follow the same design.

Table 1. Database Design (a)

Pid	pname	tags
1	Satasidham	waterfall, pond, garden, cave, hindu, temple, forest
2	Arjundhara Dham	hindu, temple, pond, gurukul, farm
3	Kichakavadh	hindu, pond, garden, temple, castle remnants
4	Biratpokhar	hindu, pond, garden, boat ride
5	Krishnathumki	hindu, temple, hills, forest

Table 2. Database Design (b)

pid	Pname	culture	adventure	wildlife	sightseeing	history	religious	Child _friendly
1	Satasidham	1	0	0	1	0	1	0
2	Arjundhara Dham	1	0	0	1	1	1	0
3	Kichakavadh	1	0	0	1	1	1	0
4	Biratpokhar	0	0	0	1	1	0	0
5	Krishnathumki	1	0	0	0	1	1	0

3.3 Recommendation System Integration

3.3.1 KNN Algorithm

For the recommendation, the first step is to find the likable places using the KNN algorithm which calculates minimum distance in multidimensional space to find the nearest neighbor. The algorithm saves all available examples (unrated destinations) and categorizes new cases based on the majority votes of its K neighbors. The Euclidean distance is given as,

$$\text{distance} = \sqrt{\left(\sum_{k=0}^{n} (xs_k - x_k)^2 \right)}$$

where $xs_1, xs_2, xs_3 \ldots, xs_n$ are the parameters of unrated destination and $x_1, x_2, x_3 \ldots, x_k$ are the parameters of rated destinations. For a given value of K, the algorithm will determine the data point's k-nearest neighbors and then assign the class to the data point by having the class with the most data points among the k neighbors' classes. Following the computation of the distance, the input x is assigned to the class with the highest probability.

The pseudocode of classical KNN

Input: X: training data, Y: class labels of X, K: number of nearest neighbors.
Output: Class of a test sample x.

Start
Classify (X,Y,x)
1. ***for*** each sample x ***do***
   Calculate the distance: $d(x, X) = \sqrt{\sum_{i=1}^{n} (x_i - X_i)^2}$
   end for
2. Classify x in the majority class: $C(x_i) = argmax_k \sum_{X_j \in KNN} C(X_j, Y_K)$

End

3.3.2 Cosine Similarity

After KNN has been used to locate likable places, Cosine similarity is utilized to further filter the recommended places by measuring the similarity between two non-zero vectors in an inner product space. For each angle, the cosine similarity is confined in the interval [-1, 1], for any angle θ.

Using the Euclidian cosine formula, the cosine of two non-zero vectors can be calculated as:

A.B = ||A|| ||B|| cosθ

Given two attribute vectors, A and B, the cosine similarity, cos(θ), is expressed by a dot product with a magnitude as:

$$Similarity = \cos(\theta) = \frac{A \cdot B}{\| A \| \| B \|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}$$

The cosine similarity gives the places which has the most probability of users to like. This value ranges from -1 to 1.

3.4 Implementation of Recommendation System

3.4.1 Recommendation for New Users

New users are those who have recently registered into the system. The biggest issue encountered when recommending places to new users is that new users would not have previously rated places. As a result, the user's preferences are collected during the first login.

The preferences are a list of binary values of length 7, which is equal to the entire number of place genres. To calculate the cosine similarity between each location and the user's preferences, the list is used as a 7-dimensional vector point. The place’s genres are also converted into a list called ‘genre_bin’ prior to calculating the initial preferences. Before generating the initial recommendations, the data frame looks as shown below.

Table 3. Dataframe after Applying Genre_Bin

pID	pName	culture	adventure	Wild life	Sight seeing	history	religious	Child_ friendly	Genre_bin
1	Satasidham	1	0	0	1	0	1	0	[1,0,0,1,0,1,0]
2	Arjundhara Dham	1	0	0	1	1	1	0	[1,0,0,1,1,1,0]
3	Kichakavadh	1	0	0	1	1	1	0	[1,0,0,1,1,1,0]

4	Biratpokhar	0	0	0	1	1	0	0	[0,0,0,1,1,0,0]
…									
503	Kamali Bridge	0	0	0	1	0	1	0	[0,0,0,1,0,1,0]

3.4.2 Recommendation for Existing Users

The preference of one user is taken for different tags such as True and False. These values are then converted into a list of arrays to generate the place profile. The 'tags' are converted into a binary list (vector) and combined tags and genre_bin to give parameters or profiles of each place.

Table 4. Genre Bins

	Culture	Wildlife	Adventure	Sightseeing	History	Religious	Child_friendly
0	False	True	True	True	False	False	False

[0,1,1,1,0,0,0] This is the generated place profile for each location in the database, which highlights the key traits of that location based on the tags. The 49 tags are represented by a 49-dimensional vector called the place profile.

Table 5. Place Profile

pID	pName	Profile
1	Satasidham	[1,0,0,1,0,1,0,1,1,1,1,1,1,0,…]
2	Arjundhara Dham	[1,0,0,1,1,1,0,0,1,0,0,1,1,0,1,…]
3	Kichakavadh	[1,0,0,1,1,1,0,0,1,1,0,1,1,0,0,…]
4	Biratpokhar	[0,0,0,1,1,0,0,0,1,1,0,1,0,0,0,…]
5	Krishnathumki	[1,0,0,0,1,1,0,0,0,0,0,1,1,1,0,…]

For a given user with user id 33, who have rated for 6 different places, their ratings for specific places are given as:

Table 6. Ratings for Different Places

	User	pID	pName	profile	rating
0	33	73	Kanchanjunga National Park	[0,1,1,1,0,0,0,0,0,0,0,0,0,1,0,…]	5
1	33	90	Makalu barun national park	[0,1,1,1,0,0,1,0,0,0,0,0,0,1,0,…]	4
2	33	359	Dhorpatan hunting reserve	[0,1,1,1,0,0,0,0,0,0,0,0,0,1,0,…]	5
3	33	290	Annapurna Conservation area	[0,1,1,1,0,0,0,0,0,0,0,0,0,1,0,…]	3
4	33	74	Sagaramatha national park	[0,1,1,1,0,0,0,0,0,0,0,0,0,1,0,…]	5

Now after the place profile is generated for each place, a user profile is made which describes the relationship between a user and a place.

For example, if the user visited 5 places containing 2 places of parameter A and 3 places of parameter B, then the user's profile becomes A = 2/5, B = 3/5. This gives a probability of finding a place of a genre in the user's rating data.

In the database, for each of the tags in the database, the user profile looks as shown below:

Table 7. User Profile

0	0.344828
1	0.620690
2	0.517241
3	0.172414
4	0.241379

5	0.103448

Then the weighted profile is calculated using ratings given by the user to places of different genres. For example, out of 2 places he visited of parameter A, he rated them 1 and 4. Also, out of the 3 places he visited of parameter B, he rated them 2, 3, and 5.

Now,

Weighted profile for parameter A = (-2+1)/2 = -0.5

Weighted profile for parameter B = (-1+0+3)/3 = ⅔

For every place in the database, the weighted profile looks as shown below:

Table 8. Weighted Profile

pID	pName	profile	weighted_profile
1	Satasidham	[1,0,0,1,0,1,0,1,1,1,1,1,1,0,…]	[0.7,0.0,0.0,0.1.72413793,0.0,1.0,…]
2	Arjundhara Dham	[1,0,0,1,1,1,0,0,1,0,0,1,1,0,1,…]	[0.7,0.0,0.0,0.1.72413793,1.4,1.0,…]
3	Kichakavadh	[1,0,0,1,1,1,0,0,1,1,0,1,1,0,0,…]	[0.7,0.0,0.0,0.1.72413793,0.0,1.0,…]
4	Biratpokhar	[0,0,0,1,1,0,0,0,1,1,0,1,0,0,0,…]	[0.0,0.0,0.0,0.1.72413793,0.0,1.0,…]
…			
503	Kamali Bridge	[0,0,0,1,0,1,0,0,0,0,0,1,1,0,0,…]	[0.0,0.0,0.0,0.1.72413793,0.0,1.0,…]

KNN is used to find likeable places after obtaining the weighted place profile. The similarity between two vectors in an inner product space is then measured using cosine similarity.

- First, KNN was used to identify the K nearest neighbors based on the distance metric created between different destinations. This gave a list of the K most similar destinations for each user.

- Then, Cosine Similarity was used to calculate the similarity between the user's preferences and the features of different destinations. This gave a similarity score for each destination.
- Finally, the results of the two techniques were combined by sorting the list of K's nearest neighbors by their cosine similarity scores. This gave a list of destinations that are both like the user's preferences and close to other destinations the user rated in the past.

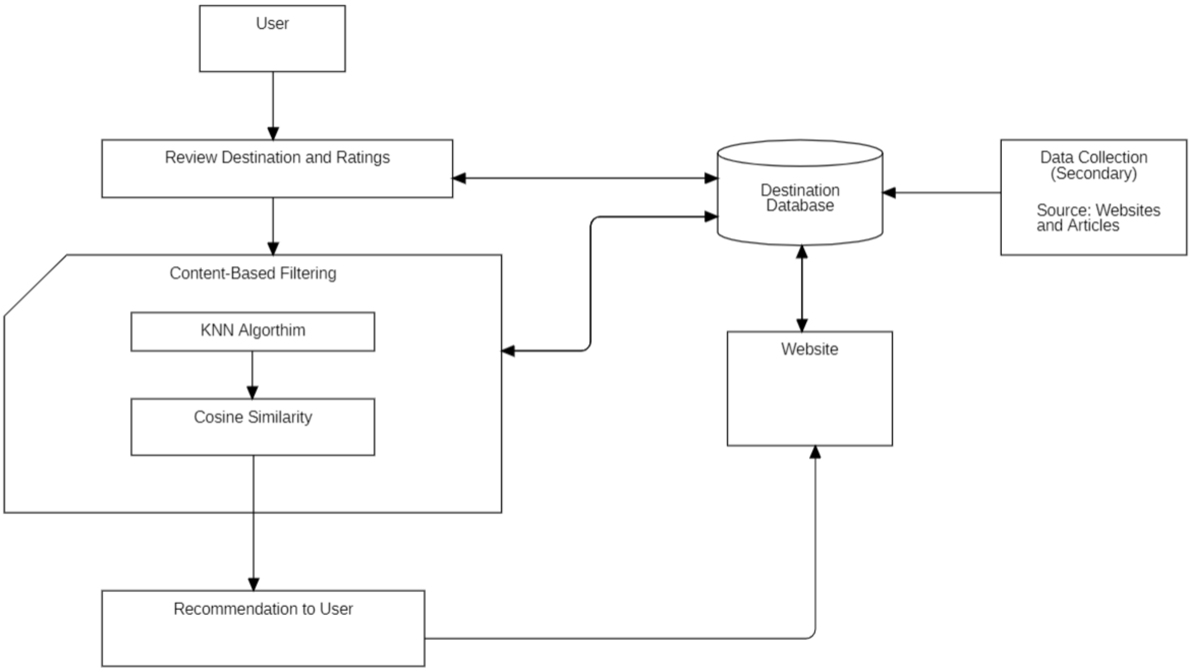

Figure 1. Content Based Recommendation System

3.5 User-Guide Interaction System

With the aid of a chat application made with Django, the tourists are able to communicate with the guides. The users can interact with other group members by joining one that corresponds to their tastes. The users can choose their preferred guide from the variety of guides offered by contacting them using this chat box. Implementing a chatting platform using Django involves several steps. The following key implementation details were followed:

- Django Project Setup and App Creation: A Django project was created using the 'django-admin' command and new Django app within the project using the 'python manage.py startapp app_name' command. This app handled the implementation of the chatting functionality.

- Database Configuration: SQLite database was configured in the project's settings.py file.
- Define necessary models: Models for users, messages, chatrooms, activity components for the chatting platform were defined in the app's models.py file.
- Migrations: Migrations were generated and applied to create the corresponding database tables using 'python manage.py makemigrations' command and then applied using ‘python manage.py migrate’.
- Views and URL mapping: The created views handle the logic for chat functionality with functions-based views in app's views.py file which was mapped to appropriate URL patterns configured in app's urls.py file.
- Templates: Templates were designed to display chat rooms, messages, user profiles, and overall chat interface with HTML.
- Forms: Forms for user input, such as sending messages or creating new chat rooms which was defined in app's forms.py file, were implemented.
- User Authentication: The user authentication and authorization was finally implemented using Django's built-in authentication system which ensures that only authenticated users can access the chat functionality.

4. Results and Discussion

4.1 Recommendation System

4.1.1 Selection of KNN algorithm for Recommendation

K-nearest neighbours algorithm is used in recommendation systems for several reasons.

- By identifying the nearest neighbours, or users with similar tastes, KNN can suggest items liked by those neighbours to a target user.

- Additionally, KNN is effective in addressing the cold start problem, where a new user or item has limited data for personalized recommendations.
- By relying on the item or user similarity, KNN can provide reasonable recommendations even with sparse or limited data.
- Moreover, KNN offers interpretability as it makes recommendations based on the actual neighbours or similar items, enhancing transparency and user trust.

Despite its limitations, such as scalability issues with large datasets, KNN's simplicity, interpretability, and suitability for cold start scenarios make it a valuable choice for the recommendation system.

4.1.2 Result of Cosine Similarity

The user gets recommendations based on their preferences and the rating that they have given to a particular place. The platform can provide highly personalized recommendations to users. By considering their preferences and matching them with items that share similar attributes, the system can suggest destinations, activities, and guides that align with the user's interests thus improving the relevance of recommendations by focusing on the specific features and characteristics that are important to each user. This approach ensures that the recommended items are more likely to be of interest and value to the user.

For a given user, the profile_distance is the cosine similarity score, for all the places that the user has rated for. For one user, the similarity score looks as shown below.

Table 9. Cosine Similarity Distance

pID	pName	profile_distance
288	Annapurna Sanctuary Trek	0.329499
237	Manaslu Circuit Trek	0.346574
485	Api-Nampa Conservational area	0.348079
…		…
228	Shiraichuli Hill	0.793759

197	Mahaboudha Temple	0.810468

This value is then sorted in descending order and the top 15 places with distance nearer to 1 is recommended to the user.

4.1.3 Performance Evaluation

These metrics provide quantitative measures to evaluate how well a recommendation system predicts and suggests relevant items to users. This enabled a comprehensive understanding of the system's performance.

Below is the result of the evaluation of the system on different metrics.

Table 10. Result of Evaluation of the System

Precision	Recall	Mean Average Precision	Hit Rate	Mean Reciprocal Rank
0.85	0.7	0.82	0.65	0.72

4.2 Chatbox

The chatbox is created using Django. The main home page has three segments for topics of the rooms present in the database, feeds which show the rooms, and activities segment which shows the activities of all the user. Any user can create a room. The user who create the respective room can update or delete them.

The chatbox has the results as following:

- Web pages using django templates eg. {% include ‘navbar.html’ %} OR {% extend ‘main.html’ %}. This code helps to ‘include’ the content of one html to another or ‘extend’ to the content of one html to another.
- Landing page and profile page of the user with 1fraction for “topic_component”, 3fraction for “feed_component” and 1fraction for “activity_component”.

- The “topic_component” has browse topics (heading) and all the topics present in the database.
- The “feed_component” has rooms that can be edited or deleted by only the host authenticated using room host and room id.
- The “activity_component” has recent activities (heading) and messages including username and time created.
- The “room” page has 3fraction of Room name, Room description and Conversation. It has 1fraction of participants list. The page has “auto_now” feature that stores and displays time stamp, every time “room” is updated and, “auto_now_add” feature that stores time stamp for only one time when “room” was created.
- The chatbox has a form that facilitates the creation of “room”. It includes:

  - Firstly, getting the topic name

  i.e topic_name = request.POST.get(‘topic’)

  - Then, checking if that topic_name already exists.

  i.e., topic, created = Topic.objects.get_or_create(name=topic_name)

Herein, get_or_create() method checks if the topic_name already exists and if it exists then, the “room” will not be created, else new “room” with the topic_name will be created.

- The chatbox allows deleting the “room” by the host.

5. Conclusion

The developed platform effectively establishes a connection between tourists and guides, offering a seamless means of communication through dedicated chat rooms. This feature enables tourists to engage directly with guides, facilitating a personalized and interactive experience. The integrated recommendation system proved to be a valuable asset, generating accurate and relevant suggestions based on user preferences. By leveraging data on preferred destinations, the system delivers tailored recommendations, ensuring that users receive guidance that aligns with their specific interests and requirements. The evaluation metrics also indicate precise performance with the personalized nature of the recommendations. The platform incorporates Map as well that allows the user to locate desired and recommended destinations on the platform without having to scour other applications. Overall, by providing a comprehensive platform that combines personalized recommendations and direct communication with guides, the platform enhances the overall travel experience. Users can benefit from expert guidance, reliable suggestions, and the opportunity to interact with fellow travellers, fostering a sense of community and shared experiences, as well as the platform promotes the empowerment of local tour guides by providing them with a digital platform to showcase their expertise.

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