A Density-based Approach for Personalized Tourist Recommendations

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Abstract. The tourism sector has benefited from the easier access to digital technology and the influx of social media content with Geo-tagging. This study describes a novel approach to offering personalized travel recommendations using geo-tagged images as the basis to recommend specific places for tourism. Unlike traditional approaches that use user reviews or surveys, the system takes advantage of geographic metadata and image recognition. Geo-tagged images are used to identify tourist hotspots and subsequently, spatial patterns are analyzed using effective methods. To balance the popularity of tourist destinations and the density of people in those areas, the system employs min-max normalization and ranking using Haversine Distance to filter and rank tourist locations defined by the user through density preferences. The backend optimization is done on large datasets with time complexities targeted at $O(k)$ through the use of a Python-Flask stack. Results from the first exploratory phases reveal the system's ability to generate context-sensitive recommendations promptly, which is beneficial to Destination Marketing Organizations (DMO's) and travel businesses for increasing the precision of promotional campaigns. This study tackles issues of data noise, privacy, lacking temporal data among others, suggesting the incorporation of temporal patterns with real-time feedback to improve the recommendation algorithms. This not only increases the user's satisfaction by personalizing the experience, but also promotes environmentally sustainable tourism by shifting visitor concentration from popular places to less popular sites.

Keywords: Geo-tagged images, personalized tourist recommendations, density-based approach, Haversine distance, min-max normalization

1 Introduction

The tourism industry is changing dramatically due to the rapid pace of user adoption of digital technology and the sheer amount of content generated by users [1]. In this digital age, widespread adoption of smartphones and social networks has made it easier for people to travel, document their efforts, and post them online, thus producing location-specific content in the form of geo-tagged videos and photographs [2]. This phenomenon has created a new space for the creation of tourism market research as well as marketing information systems, thus greatly helping to understand tourist behavior patterns, their likes and dislikes, and even mobility patterns [3].

Travelers have strayed from conventional methods of documenting their journeys through journals and blogs. Social media platforms such as Instagram have enabled these travelers to post geo-tagged photos, videos and posts along with geo-coordinates, timestamping their real-time locations, thus demonstrating various ways of travel interactions with locations traversed to [4–6]. Unlike static and aggregated datasets, geo-tagged images offer real-time insights in tourist behaviour. Analysis of these datasets reveal great insight into emerging travel patterns, trends, and a myriad of other aspects, all based on an understanding of how and why people are influenced in choosing their travel destination [7].

Even though geo-tagged data prove to be very useful, standard methods used to analyze tourism and even recommendation systems suffer from a few drawbacks. Traditional approaches make use of user reviews and surveys that are too generalized and simply do not meet the individual needs of travelers [8]. In addition, these methods appear to be too simplistic as they do not take into account the increasing intricacies of travel behaviors in an interconnected world [9]. This study takes a step further, by integrating segmentation geo-information advanced image identification, in order to close these gaps and advance personalized travel recommendations [10–12]. The gap between the traditional methods and the unprecedented complexity of travel requirements can be solved by analyzing geographic metadata [13].

To perform the analysis of travel and tourism over time and space, geotagged data makes it easy to define tourist hotspots and determine spatial travel pattern [14–16]. These tools, when used in tandem with image recognition tools designed to interpret landscape, architectural and ethnological characteristics of a given region, create a complete picture of the attractiveness of the destination [17–19]. One way is to apply clustering methods to geo tagged photos so as to determine the location of tourists [20], as well as popular sites and thought routes. Moreover, the content of the tagged photos and videos can reveal the outstanding characteristics of these destinations, thereby assisting in determining traveler and tourist behavior [21, 22].

This study attempts to address both the technical issues facing the processing and analyzing of large datasets of geo-tagged images and their use for the enhancement of tourism marketing [23, 24]. The proposed system uses preference-score algorithm to provide recommendations based on density preference. Alongside, the analysis can help DMOs and travel companies create focused marketing campaigns and sustainable tourism development initiatives [25].

In modern tourism, sustainability is an important aspect. Famous attractions are becoming overwhelmed by tourists and being able to redistribute their flows to the hidden gems is a must [26]. This study helps achieve that goal by providing actionable insights on tourist behavior.

The study also focuses on the geo-tagged image qualitative analysis issues dealing with data noise, bias, and privacy issues [27]. Pre-filtering techniques are critical to the reliability and relevance of the extracted information as well as the insights drawn from it. Ethical considerations such as user privacy and data protection laws also form a part of this framework and its implementation [28].

This study has both types of contributions: practical and theoretical. For example, the integration of geographic metadata and the visual content to study tourist impressions to destination attractiveness is a new dimension theoretically.

This study is organized in the following way: section 2 addresses the concept and foundation of geo-tagged data and image recognition as well as attempt to review related work. Section 3 describes the research design covering data collection, preprocessing, and analytical framework. Section 4 presents the main experimental findings, especially the efficiency of the system to user feedback and future outcomes while concluding in brief points.

2 Literature Review

The academic and industry sectors have been experimenting with the utilization of geo-tagged images in tourism, which points to their potential in the growth of destination marketing and management strategies [11]. This section provides a comprehensive review of existing literature, focusing on the evolution of geo-tagged data analysis, the integration of image recognition technologies, and their applications in the tourism industry.

2.1 Evolution of Geo-Tagged Data Analysis

The Age of Geo-Tagged Data Analysis, Geo-tagged data, the collection of latitude and longitude coordinates which are inserted into digital content, have been a very important option to analyze spatial patterns and trends [1, 2, 7]. The very first studies that have been carried out in this field were primarily focused on using geographic matter tools like GIS (Geographic information system) in order to show and decode the spatial information [17, 30]. Apart from the idea of social media platforms and smart devices that got even more accessible due to simplification of language users can input, the other reason for the increased availability of geo-tagged content that now allows for more precise analysis of traveler's behavior and preferences, lies in the possibilities of granular GPS (Global Positioning System) data [5, 31].

Xiang et al. have highlighted the significant role of user-generated content in influencing travel decision-making processes, indicating the location-based absorbing of the information into tourism management sector, which is a result of higher integration [32]. The research by Zhuang et al. and Majid et al. revealed the combination of geo-tagged data with much improved image recognition Travel recommendation systems [33, 34]. By analyzing visual content, such as landmarks, landscapes, and activities, these systems offer highly personalized suggestions that align with user interests [18].

2.2 Applications in Tourism

The utilization of geo-tagged image analysis in tourism is diverse; it includes fields such as destination marketing, visitor behavior analysis, as well as sustainable tourism planning. Wong et al. investigated the use of spatial data to disclose hot tourist destinations and predict travel patterns [25]. Their conclusions emphasize the potential of geo-tagged data in providing the actionable insights that DMOs and tour operators can use [8]. Also, Zhou et al. provided the example of location-based insights in connecting the dots of travel trends and designing the perfect targeted marketing campaigns [35]. Social media platforms, for example, Flickr and Instagram, function as one of the most comprehensive repositories of geo-tagged images, thus allowing real-time data to be collected on traveler activities and references [5, 43]. Park et al. laid stress on the fact that the tourism sector should make use of these platforms to conduct marketing that is data-driven [36]. With the help of analyzing geo-tagged photos, DMOs can take note of those destinations that do not get enough visitors and for those places target different consumer groups, thus broadening the tourist population and balancing out the visitor crowds [37].

2.3 Overview of Existing Models

Previously various methods for Tourist Recommendation have been proposed. A tourist recommendation model that requires a user query describing the tourist place and/or giving image input for which corresponding geo-tagged regions that match the input are returned uses a cluster of around 1.1 million images [11]. Clustering and representative image identification effectively support relevant tourism recommendations [38, 39, 41]. This application still has a requirement for refinement of accuracy and handling of outliers to be used in real-time applications.

Another research done prior to this research creates a tourist guide updated with fresh data from use's images and aims to offer precise information about locations and events in cities. The research was carried out with the aim of implementing a recommendation algorithm (similar to Amazon) based on user's past experiences, offering personalized suggestions for users to visit places [42]. The system uses collaborative filtering techniques to recommend places based on a user's past visits in other cities. The major challenge for this system was scalability and precision due to requirement of both high compute capacity/power and large dataset availability. This system is not yet suited for real-time applications due to high compute cost and thus the future work includes improving the accuracy through clustering algorithms and investigating in temporal and spatial variations of user activities to identify trends and tourist flows [43, 30].

2.4 Challenges and Opportunities

Despite the promising applications of geo-tagged image analysis there are some challenges like the captured data noise, biases, and the variation in image quality that can affect the accuracy of anaylsis as the authors of the work have pointed out [13]. Additionally, the moral issues of public use of data, such as privacy and the responsibility of data, also must be closely taken care of.

The merging of geo-tagged image analysis to novel technologies, namely augmented reality and the Internet of Things (IoT), offers diverse opportunities to enhance the tourist experience [22]. In addition, the team work composed of tourism experts, data scientists, and policymakers may be an effective strategy to successfully develop and implement the idea of adding new innovative projects to the industry refuge. The purpose of this study is to build a recommendation system using geographic metadata and visual content to boost tourism.

3 Proposed Methodology

Tourist recommendation systems play a crucial role in enhancing travel experiences by suggesting destinations based on user preferences and real-time conditions [38–40]. As tourism continues to grow, there is a need for a more efficient and scalable system that can process large datasets while improving the accuracy of the recommendations. This study focuses on optimizing a Flask-based tourist place recommendation system by refining how locations are suggested based on density heuristics and user preferences. This study uses a novel approach to the recommendation of tourist places based on a normalized density preference for tourists from their current location. The goal is to build an optimized tourist place recommendation system by improving the way locations are suggested based on user preferences and the density heuristics of the tourist place itself. The new system aims to process large datasets more efficiently while improving accuracy in recommending not only less crowded, popular places, but also more crowded tourist attractions. The proposed application aims to improve personalization, ensuring tourists receive better recommendations that balance popularity and crowd density, ultimately leading to a more seamless and satisfying travel experience.

3.1 Proposed Model

The Proposed Recommendation System relies solely on spatial data [44]. The recommendation system takes user preference for minimum and maximum density preference (range of 0-100) normalized using min-max normalization [27]. The application does not depend on past history of the user, but uses a precomputed cluster of geotags for tourist places clustered together as density of a tourist region.

This approach makes the application light-weight and enables users to discover tourist destinations that match their crowd tolerance without requiring high compute power usage in real-time application.

The recommendation process involves processing geo-tagged locations and calculating density distributions to identify tourist regions and their respective densities. The density for each region is then normalized via min-max normalization with range of 0 to 100 [27]. This normalization ensures that the model doesn't require collaborative filtering, and efficiently analyzes spatial data without significant preprocessing. Once the normalization is done, the recommendation model is ready to be used.

The user opens the front-end of the application, where they have to enter minimum density preference, maximum density preference and number of locations to recommended within the density range. Once the user enters the three details, an API call is made to the backend server hosted on top of a Python-Flask tech-stack. The API Call contains user's preferences according to their input and their current location's latitude and longitude values.
At the backend, a filtered list of places is calculated according to the normalized range of density of tourist places. This filtered list of places is then sorted by using the Haversine distance [28] by calculating distance from user's current coordinates to nearby location that fall in the acceptable density ranges [45].

This filtered list is then returned to the user according to the number of specified results requested by the user.

The front-end of the application uses the data to display user the nearby locations with their normalised density values. The user can then select any of these locations and start navigation to the chosen location. To ensure density doesn't shift too much over time, we have decided to add a factor of incrementing the density values for locations whenever user chooses to proceed to travelling on a suggested location. This will ensure an approximated accuracy of the recommendation system with live updation of data [8, 33, 46].

Thus, the work attempts to propose a solution that uses a combination of an altered min-max normalization technique, haversine distance formula, and density ranges to implement tourist place recommendation system using Python, Flask along with various python libraries such as PIL, PIL.ExifTags to process images and extract geo-tagged data [46, 27, 28].

3.2 Algorithm's Runtime Details

Terminologies

1. n – No. of Images in the dataset

2. k – No. of Tourist places

This recommendation system builds its clusters of tourist places with their specific ranges over the dataset of size n taking a total time of $O(n)$ to read the images and convert geotags data to a JSON array $O(n)$ and processing the JSON Array $O(n)$ [48].

$$calculation\ time\ per\ pair < lat, lon >= O(n * k) \tag{1}$$

Calculating the coordinates that fall within a particular tourist place takes $O(k)$ time per $pair < latitude, longitude >$ and thus the total time taken for m such images is $O(n * k)$.

After the densities for each tourist place cluster is calculated, The system carries on with the calculation of *normalized_density* which is calculated in $O(1)$ time for each tourist place and done for k locations, thus a total time complexity of $O(k)$.

$$recommendation\ time\ = O(k) \tag{2}$$

At this point, the model is ready to serve the requesting clients.
When the user makes a request for a recommendation with parameters like $user\_latitude$, $user\ \_longitude$, $min\_density\_preference$, $max\_density\_preference$, $num\_of\_recommendations$

The tourist places falling in the acceptable density range are calculated in $O(k)$ time and m nearest results are returned as specified in $num\_of\_recommendations$ parameter.

3.3 Enhanced Features

The Previous solutions were not considering user preferences for population density on a specific tourist place. With an increase in tourism activities, it has become harder to find places where one can connect with nature in isolation. The system would help users go to places with fewer crowds and the polar opposite as well, according to their preference.

Figure 1 illustrates the process of backend server initialisation, which consists of states like processing of Geo-tagged images, GIS metadata extraction to JSON for portability, Density Calculation for each tourist location, Density Normalisation, Backend server checks and API tests, Backend server is up and ready for serving users.

Figure 2, illustrates the process of Client-side data flow of the system consisting of states like Frontend (User Interface), API Middleware layer, Backend Server, Geo-tagged images, MapBox API.

The above two defined processes give out a high level overview to the client for the working of the system and the data flow from the point of client request to getting the recommendation.

This solution can be integrated with other tourist recommendation systems, such as the recommendation based on a query enhanced with density preference along with the query [49]. The density-based recommendation system can also be used with the recommendation algorithm based on user's past experiences with density preference as an additional parameter [42].

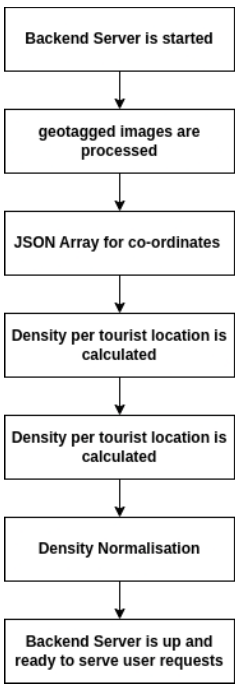

Fig. 1. Backend Server Initialization Data Flow

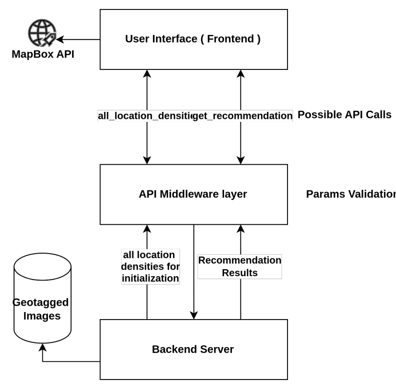

Fig. 2. Client-side Recommendation Flow

3.4 Advantages and Limitations

The major advantage would be the reduce in the raw time-taken to calculate and recommend nearby tourist-place in the user's region according to their preference.
One possible limitation would be the unavailability of temporal data in the current version and changing densities of places over time in real-life scenarios. This could be solved by integrating real-time user's feedback and inputs in the recommendation system. Another approach to mitigate real-time changes would be to choose an approximation parameter and increase density of places in real-time based on the user-queries and preferences of traveling to a tourist place.

4 Result and Discussion

This section discusses about the experimental setup, dataset, performance measures and obtained results.

4.1 Experimental Setup

Figure 1 and Figure 2 showcase the high level flow of the recommendation system. The Backend server uses python-flask based environment and REST API to serve the client-side requests for recommendation. At initialization, the model sets the normalized density values for the places to be recommended and on client-requests uses pre-calculated values to calculate the preference score.

For implementation of the Tourist Recommendation System in real-time scenario a docker container with the Flask backend and dependencies included would be ideal for horizontal scaling and portability. For Load balancing, a third party load balancer could be used initially using leaky bucket algorithm or similar algorithm and as the system grows we could implement NGINX server with load balancing to distribute incoming traffic evenly among multiple hosted instances of recommendation system. Alternatively, we could deploy the application on cloud (e.g. AWS) and not have to worry about load balancing and other intricate details.

To make the recommendation system capable of being integrated and extended by other tourist recommendation systems, the APIs are written to be WSGI Compliant maximizing support and re-usability of the recommendation system across different platforms.

4.2 Dataset Description

Dataset Name : Geotagged Images for Tourist Locations near Pune
Total Number of Images: 5612
Types of Images: User-uploaded images, tourist spot images

The dataset was gathered from multiple different sources including Pawar et al., manually gathered images and from social media sites [47]. The dataset consists of the following attributes like image_name, Latitude, Longitude.

In order to remove noise and inconsistent values from the dataset a script is developed that uses the present geotag location in images to interpolate and fill in missing information in the relevant images of the dataset. The noise, in this context, refers to incomplete or erroneous data entries that could impair the accuracy of the recommendation system.

The recommendation system used this completed data set to perform operations on and ultimately give results.

4.3 Performance Metric - Preference Score

Weighted distance and density are added respectively in order to make the recommendations better for users based on their coordinates. This would ensure that every user had recommendations tailored to their density preference and based on their distance from list of tourist places.

$$\text{distance} = \frac{\text{haversine}(\text{user\_lat}, \text{user\_lon}, \text{place}_{\text{lat}}, \text{place}_{\text{lon}})}{\text{max\_distance}} \tag{3}$$

$$density \ = \frac{|\text{destination}_{\text{normalized\_density}} - \text{preferred\_density}|}{\text{max\_density\_diff}} \tag{4}$$

$$preference\_score \ = \ w_{\text{dist}} \times (distance) + w_{\text{den}} \times (density) \tag{5}$$

The filtered list was calculated using the *preference-score metric*. The top n results requested by the user are returned sorted according to the preference score by the recommendation system.
The preference score ranks tourist places by balancing distance and density similarity to the user's preference. It is computed as defined by Equations (3), (4), and (5). The density value shown in Equation (4) is the normalized density deviation. Normalized density deviation measures how closely the tourist place matches the user's density preference.

4.4 Recommendation System Output

The Figure 3 and Figure 4 show the output of the density-based tourist recommendation system for specific density ranges on the dataset. Figure 3 shows the system output for the density range of 10 to 65 from three different latitude-longitude pairs as follows: [18.528, 73.851, blue line], [18.473, 73.824, black line], [18.509, 73.783, red line].

This result shows how the recommendations vary based on the weighted density-distance preference for users from different locations.

Figure 4 shows the recommendation for density range of 20-80 from the same three latitude-longitude pairs. In this output a single tourist location falls near

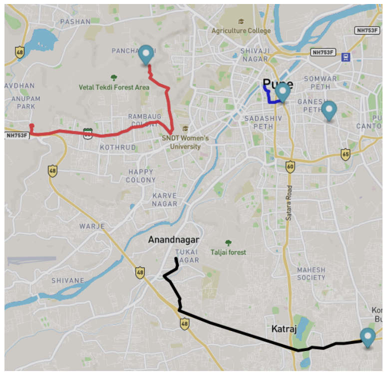

Fig. 3. Density Range: 10-65

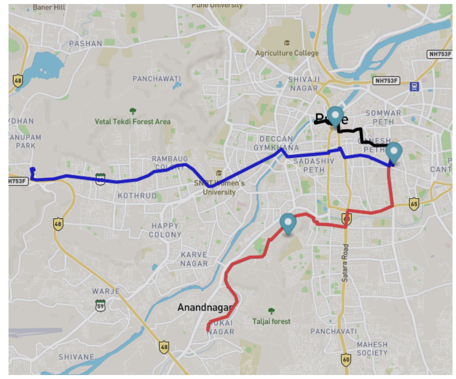

Fig. 4. Density Range: 20-80

the preferred location for weighted density-distance preference.
These are still available for users to select from and visit by simply clicking on them.

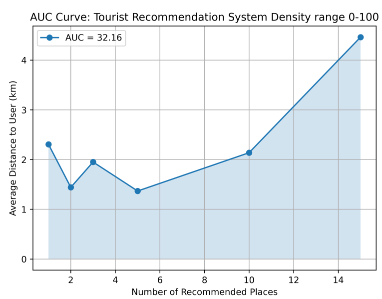

Fig. 5. Number of recommendations to Average distance curve

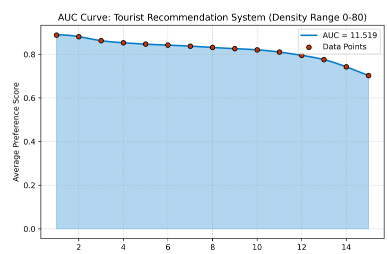

Fig. 6. Places Recommended to Average Preference Score graph

The graphs shown in Figure 5 and Figure 6 are the performance metrics of the recommendation system.
Figure 5 is the graph that depicts how average distance is affected as the number of recommended places is increased by the user. In the Figure the value dips after 3 recommendations and then the average distance keeps increasing for every extra recommendation. Figure 6 is the graph that depicts how average preference score (derived from Equation (5)) is affected as more recommendations are requested by the user.

The initial testing shows that recommendations align well with the expected results for well-known locations based on the data set. Variations in reproducibility may arise if the dataset is too sparse/dense for a single tourist spot.

4.5 Comparison

Existing implementations such as Mamei et al. and Cao et al. differ from the proposed method in terms of recommendation parameters like density and overall approach that has been used to perform recommendation based on spatial data along with user's current coordinates [42, 49].

This application is not a tourist trip planner, it is more of an spontaneous getaway planner from users current coordinates to tourist location when the user is out of ideas.

5 Conclusion and Future Scope

This study presents a novel tourist recommendation system that leverages geo-tagged images to provide personalized, density driven tourist recommendations. This system differentiates itself from the traditional system by utilizing GPS data to recommend tourist spots based on user's density preference. The use of density heuristic and Haversine distance drastically improves the quality of recommended tourist places and the computation speed for calculating distance respectively, making the recommendations faster, more specific to user's needs and their location. The system's backend is optimal for large datasets with $O(k)$ time complexity for calculating results. This system uses a novel preference-score metric in order to calculate and sort places to recommend to the users. This system can be integrated with pre-existing recommendations systems as an add-on and can even be used as a standalone alternative. The recommendation system is able to give recommendations with a preference scores of 0.888, 0.880 and 0.862 for 1,2 and 3 recommendations, respectively. The recommendation system successfully balances the popularity of tourist detinations with user-defined density preference offering a custom tailored tourism recommendation experience.

There is a scope for including temporal data as a factor for recommendations. With a spatio-temporal dataset we could increase the accuracy multiple times by predicting user-specific recommendation according to their location, timestamp and density preference parameters. Furthermore, enhancements can incorporate Deep learning for image classification, reinforcement learning for dynamic recommendations and real-time feedback loops to keep refining the suggestions continuously.

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