A Density-Based Approach for Personalized Tourist Recommendations

Pratyay Dhond
Dept. of Computer Science and Engg.
COEP Technological University
Pune, India 411005

Chinmay Sheth
Dept. of Computer Science and Engg.
COEP Technological University
Pune, India 411005

Soma Ghosh
Dept. of Computer Science and Engg.
COEP Technological University
Pune, India 411005

Amit Joshi
Dept. of Computer Science and Engg.
COEP Technological University
Pune, India 411005

Suraj Sawant
Dept. of Computer Science and Engg.
COEP Technological University
Pune, India 411005

I. 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 [3]. 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 [1]. 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 [8].

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 [2]. These digital artifacts nurture the nuanced and dynamic preferences of the traveler. Unlike static and aggregated datasets, articulated images have far greater storytelling power. Analysis of these stunning 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 [13].

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 tend to make use of user reviews and surveys that are too generalized and simply do not meet the individual needs of travelers. 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. This work takes a step further, by integrating segmentation geo-information advanced image identification, in order to close these gaps and advance personalized travel recommendations [27]. Still, the gap between the traditional methods and the unprecedented complexity of travel requirements can be solved by analyzing geographic metadata.

To perform the analysis of travel and tourism over time and space, information on latitude and longitude makes it easy to define tourist hotspots and determine spatial travel patterns [32]. These tools, when used in tandem with image recognition tools designed to interpret landscape, architectural, and ethnological features of a certain region, create a complete picture of the attractiveness of the destination. One way is to apply clustering methods to geo tagged photos so as to determine the location of tourists [30], 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.

This study attempts to address both the technical issues facing the processing and analyzing of extensive datasets of geo-tagged images and its use for the enhancement of tourism marketing. The proposed system uses sophisticated algorithms to provide recommendations based on personal preferences which makes the travel more interesting and enjoyable. Alongside, the analysis can help Destination Marketing Organizations (DMOs) and travel companies create focused marketing campaigns and sustainable tourism development initiatives.

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. This research helps achieve that goal by providing actionable insights on tourist behavior. There is always a fine line between economic development and environmental and cultural conservation. DMOs can use this information to enhance tourism in specific underdeveloped regions 'off the beaten path' as well as reduce overcrowding of well-known sites.

The research also focuses on the geo-tagged image qualitative analysis issues dealing with data noise, bias, and privacy issues. 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.

This research 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 paper 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

II. Literature Review

The academic and industry sectors have been experimenting with the utilization of geotagged images in tourism, which points to their potential in the growth of destination marketing and management strategies [9]. 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.

A. 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 [10]. The very first studies that have been carried out in this field were primarily focused on using geographic matter tools like GIS in order to show and decode the spatial information [26]. 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 analyses of traveler behavior and preferences, lies in the possibilities of granular GPS data.

Some researchers, one of whom is Xiang, who in 2010, pointed out the role of user-contributed content in travel decisions, indicating the location-based absorbing of the information into tourism management sector, which is a result of higher integration [43]. The articles of Zhuang et al. (2016) [45] and Majid et al.(2012) [44] revealed that the combination of geo-tagged data with much improved image recognition Travel recommendation systems. By analyzing visual content, such as landmarks, landscapes, and activities, these systems offer highly personalized suggestions that align with user interests.

B. 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. (2006) [35] investigated the use of spatial data to disclose hot tourist destinations and predict travel patterns. Their conclusions emphasize the potential of geo-tagged data in providing the actionable insights that Destination Marketing Organizations (DMOs) and tour operators can use [30]. Also, Zhou et al. (2015) provided the example of location-based insights in connecting the dots of travel trends and designing the perfect targeted marketing campaigns [48]. 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 preferences. Park et al. (2016) [49] laid stress on the fact that the tourism sector should make use of these platforms to conduct marketing that is data-driven. With the help of analyzing geotagged 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.

C. Challenges and Opportunities

Despite the promising applications of geo-tagged image analysis, several challenges remain. The scale of the crowd-sourced content makes it indispensable to improving the data processing techniques. 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 [11]. 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 avenues the researchers can explore aiming at these problems being solved for the implementation of advanced machine learning algorithms and the use of strong data preprocessing frameworks [30].

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 [27]. 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. In conclusion, the accumulated literature makes it clear that the groundbreaking nature of the method for geo-tagged image analysis in the tourism sector can be validated through the use of it. The purpose of this research is to build a congruent concept for using geographic metadata and visual content to boost travel. Attraction recommendations and strategic decision-making support for better destination management.

III. Proposed Methodology

Tourist recommendation systems play a crucial role in enhancing travel experiences by suggesting destinations based on user preferences and real-time conditions. 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.

A. Overview of Previously Proposed Methods

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 geotagged regions that match the input are returned [37] uses a cluster of around 1.1 million images. Clustering and representative image identification effectively support relevant tourism recommendations. 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 our 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 [38]. 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.

B. Our Proposed Solution Against Previous Methods

Our Recommendation System relies solely on spatial data, with future scope for including temporal data as a factor for recommendation. The recommendation system takes user preference for minimum and maximum density preference (between a range of 0 to 100) normalized using min-max normalization [39]. The application does not depend on past history of the user, but uses a pre-computed 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 geotagged locations and calculating desnity distributions to identify tourist regions and their respective densities. The density for each region is then normalised via min-max normalization with range of 0 to 100 [39]. This normalization ensures that our model doesn't require collaborative filtering, and efficiently analyzes spatial data without significant preprocessing. Once the normalisation 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 normalised range of density of tourist places. This filtered list of places is then sorted by using the Haversine distance [40] by calculating distance from user's current co-ordinates to nearby location that fall in the acceptable density ranges.

This filtered list is then returned to the user according to the number of specified results requested by the user. The return data consist of a List of JSON objects consisting of following fields:

1) Tourist Place name
2) Latitude Data
3) Longitude Data
4) density
5) normalised Density (Min-Max Normalised)

The front-end of the application now 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 the 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.

While our current implementation does not incorporate temporal trends such as seasonal variabtions or peak tourist hours, it provides a robust foundation for real-time, scalable, and computationally efficient tourist recommendations. Future improvements may explore integrating temporal data to refine results further.

Thus, we decided to propose a solution where we would be using a combination of an altered min-max normalization technique [39], haversine distance formula [40], 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 geotagged data. We also provide a novel dataset of consisting of 5612 images with embedded geotag data. This dataset has been constructed by adding images from multiple sources including Historical Places dataset of Pune [41], Images from Google Maps API, and Personally captured pictures.

C. Algorithm's Runtime Details

Terminologies

1) n – No. of Images in the dataset

2) k – No. of Tourist places

Our 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 $O(n)$.

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

Calculating the co-ordinates 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, we move on to 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 be serve the requesting client.
When the user makes a request for a recommendation with parameters consisting of:

1) $user\_latitude$
2) $user\_longitude$
3) $min\_density\_preference$
4) $max\_density\_preference$
5) $num\_of\_recommendations$

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.

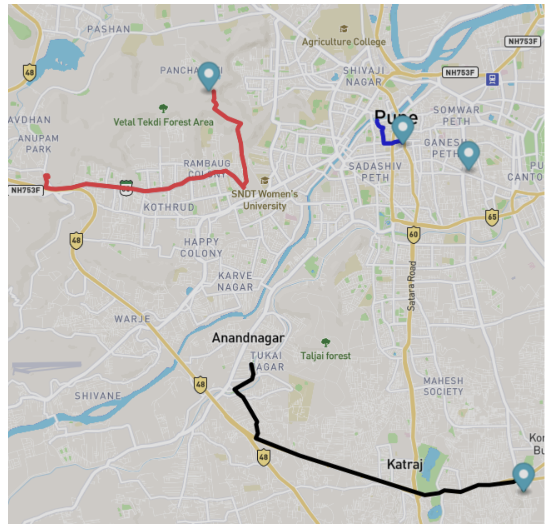

Fig. 1. Density range: 10-65

D. How Our Proposed Solution Will Enhance Previous Solutions:

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. Our system would help users go to places with fewer crowds and the polar opposite as well, according to their preference. Even though the current version has only spatial data, in the future with a spatio-temporal dataset we could increase the accuracy multiple times by predicting user according to their location, timestamp and density parameters.

Our solution can be integrated with other tourist recommended solutions, such as the recommendation based on a query [37] enhanced with density preference along with the query. The density-based recommendation system can also be used with the recommendation algorithm based on user's past experiences [38] with density preference as an additional parameter.

E. Advantages and Limitations of our implementation

The major advantage would be the reduce in the raw time-taken to calculate and recommend nearby tourist-place, landmark in the nearby 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.

F. Detailed structure of our implementation

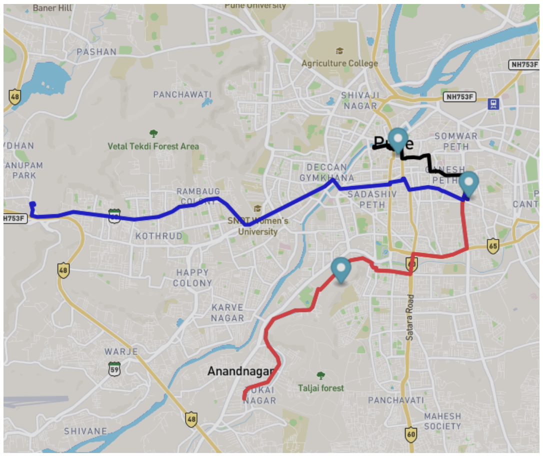

Fig. 2. Density Range: 20-80

1) Recommendation Output: The above figures Figure 1 and Figure 2 show the output of the density-based tourist recommendation system for specific density ranges on our dataset.
Figure 1 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 will vary based on the weighted density-distance preference for users from different locations. Figure 2 shows the recommendation for density range of 20-80 from the same three lat-lon pairs. In this output a single tourist location falls near the preferred location for weighted density-distance preference.
The other map markers (location pins) indicate the other locations that fall in the same range but didn't qualify as the highest preference due to density/distance algorithmic calculations. These are still available for users to select from and visit by simply clicking on them.

2) Flow-charts: The above figures, Fig. 3, Fig. 4, display the overall flow of the backend server's intialization process and the flow for API Usage and User Interaction with the Recommendation System respectively.
Figure 3, walks you through the process of backend server initialisation, which consists of the following:

1) processing of Geo-tagged images
2) GIS metadata extraction to JSON for portability
3) Density Calculation for each tourist location
4) Density Normalisation
5) Backend server checks and API tests
6) Backend server is up and ready for serving users.

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

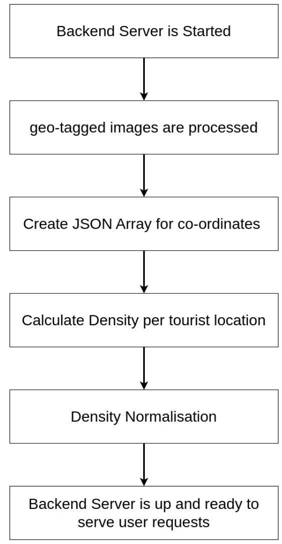

Fig. 3. Backend Server Initialization Data Flow

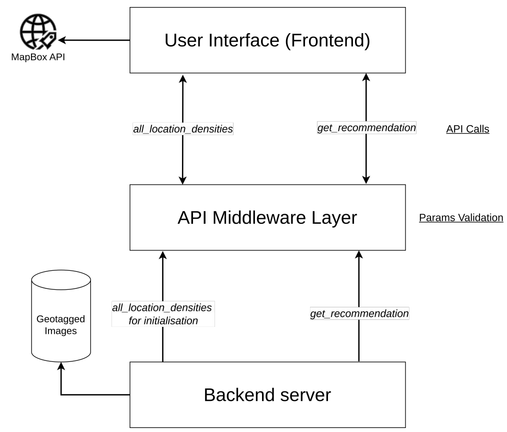

Fig. 4. User Interaction Recommendation Flow

G. Comparison of Implementations

Prior implementations such as [37] and [38] differ from our approach in terms of recommendation parameter: density and overall approach we have used towards recommendation based on spatial data along with user's current co-ordinates.
Our application is not a tourist trip planner, it is more of an impromptu getaway planner from your current spot to tourist location when the user is out of ideas.
As compared to our approach, Worldwide tourism recommendation system [37] uses a positive approach

IV. Result and Discussion

The accuracy / reproducibility and effectiveness of the recommendation system plays a critical role in ensuring relevant tourist place suggestions based on density preference of the users. Using data from geotagged images, it is indeed possible to generate heatmaps and locate tourist attractions to better aid in the recommendation for tourism.

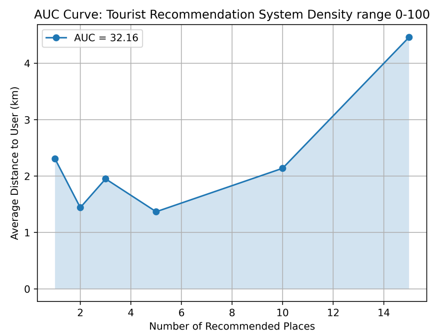

Fig. 5. Number of recommendations to Average distance curve

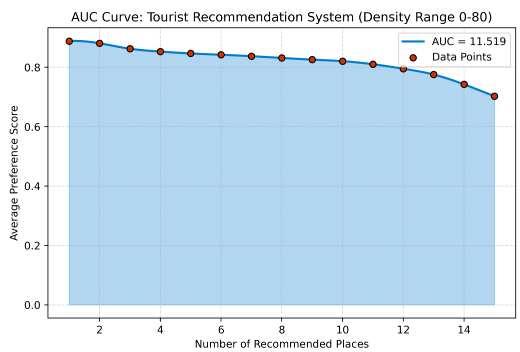

Fig. 6. Places Recommended to Average Preference Score graph

Our initial testing shows that recommendations align well with 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.

Our System has a major advantage that it gives the result in $O(k)$ as described in equation no 2. This k is extremely small as compared to the total dataset size n as k is the number of tourist places. The usage of Haversine distance gives the result in $O(1)$ for every co-ordinate pair, making our system capable of handling large datasets in the near future.

The usage of density heuristic in Tourism industry can be a revolutionary adaptation to improve recommendations in the tourism industry. Recommendations based on density preference will aid to users of different needs giving a more custom-tailored, personal vacation experience.

While solving this problem we faced a couple of problems:

- Geolocation accuracy issues for places with bad range and also geo-tags may have some vagueness associated with themselves as GPS data is not 100% accurate. To mitigate this we decided to go with dynamic latitude-longitude range pairs for every tourist place.
- Handling overlapping tourist areas could be an issue when there are multiple areas satisfying the density range. For such instances we have the fallback parameter of 'distance' to decide the top m locations that are to be recommended to the user.

V. Conclusion and Future Scope

For future implementations as addressed in the proposed methodology, there is the scope for using our implementation as an addon feature on the current tourist recommendation systems. Adding user feedback for recommended places and updating the density-map dynamically based on tourists requests would be another future improvement. Using temporal data along with spatial data would help in increasing the overall accuracy of the model and make it more suitable for real-time usage.

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