International Journal of
Human Computations & Intelligence
Vol. 04, Issue. 03, 2025

RESEARCH ARTICLE OPEN ACCESS

Personalized Travel Direction Recommendation Using Social Media Photos

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DOI: **10.5281/zenodo.15267934**
Received: 27 January 2025 / Revised: 21 February 2025 / Accepted: 27 March 2025

Abstract – A travel recommendation system based on social media activity provides a customized place of interest to accommodate user-specific needs and preferences. In general, the user's inclination towards travel destinations is subject to change over time. In this project, we have analyzed users' twitter data, as well as their friends and followers in a timely fashion to understand recent travel interest. A machine learning classifier identifies tweets relevant to travel. The travel tweets are then used to obtain personalized travel recommendations. Unlike most of the personalized recommendation systems, our proposed model takes into account a user's most recent interest by incorporating time-sensitive recency weight into the model. Our proposed model has outperformed the existing personalized place of interest recommendation model, and the overall accuracy is 75.23%.

Index Terms – Travel recommendation; time sensitivity; effect; personalization; social media

I. INTRODUCTION

In the digital age, social media platforms have become an integral part of people's lives, influencing their choices, preferences, and decisions. One of the most significant impacts of social media is on the travel industry, where users frequently share their experiences through photos, videos, and location tags. These shared moments provide valuable insights into individual travel behaviors, interests, and preferences. Traditional travel recommendation systems rely on user reviews, ratings, or predefined interests to suggest destinations. However, these approaches may not fully capture a user's evolving travel preferences. On the other hand, analyzing social media photos provides a more dynamic and real-time understanding of user interests. Travel photos often contain metadata such as geotags, timestamps, and even visual elements like landscapes, cultural sites, and activities.

By applying artificial intelligence (AI) and deep learning techniques, these visual cues can be processed to generate personalized travel route suggestions.Recent advancements in computer vision,

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ISSN (Online): 2583-5696
Int. Jr. of Hum Comp. & Int.

machine learning, and natural language processing have made it possible to extract meaningful information from images. Features such as object detection, scene recognition, and facial expression analysis help understand whether a user prefers beaches, mountains, historical landmarks, or urban settings.

Motivation

According to the World Travel and Tourism Council (WTTC), approximately 1.4 billion travelers travel around the world with ranges of motivations staring from a pleasure trip to medical purpose, higher education to a business trip and so on. It is the second-fastest growing sector in the world. Traveling is a very personalize event and could be daunting with limited knowledge of the destination. To accommodate the user's unique places of visit preference, an individualistic study based on social media user profile can provide useful insights. Travelers with disabilities need facilities to fulfill their basic needs. Personalized information of a traveler's preference for places to visit plays a significant role in travel place selection. For example, for a tourist inclined to outdoor travel and interested in exploring new places, going to woods, hiking, biking, boating, etc., recommending an indoor bowling place may be less appropriate than a state park. Such personalized information can be easily extracted from a person's social media activity. To adequately accommodate the above-stated situation, a personalized travel place recommendation system seems a reasonable solution. Recommender systems are key to most online services.

II. RELATED WORK

Collaborative Filtering

As a research area, RS began to gain prominence in the 1990s both among academicians as well as industry. It also provided an early classification of RS which basically included content based RS, collaborative RS and hybrid systems, and the research being done in each of them. It is important to note that issues, like comprehensive understanding of users and items, the multidimensionality of recommendations, and non-intrusiveness, are aspects of RS that were considered important from early on. He introduced the concept of collaborative filtering based recommender systems and detailed the black box processes involved. It provided an exhaustive analysis of the user experience of recommender systems. They argued that "measuring algorithmic accuracy is an insufficient method to analyze the user experience of recommender systems". They introduced a "user-centric evaluation framework that explains how and why the user experience of an RS comes about". Another innovation in RS design is the dynamic generation of personalized hybrid recommender systems proposed in the media . User trust and trust-aware based RS are discussed in the recommendation. In particular, leveraged deep learning to determine the initialization in matrix factorization for trust-aware social recommendations and to differentiate the community effect in the user's trusted friendships.

State Of The Art:

Van Canneyt et al. (2012) explored the use of social media to identify places of interest. Their study demonstrated how geographically tagged social media data can supplement existing place databases. Yin et al. introduced a novel three-way location-based rating system that integrates spatial user ratings for non-spatial items, non-spatial ratings for spatial items, and spatial ratings for spatial items, thereby considering both online and offline user activity. To enhance location prediction, the authors implemented

LALDA and ULA-LDA models.Another study proposed leveraging geotagged information—including location, time, tags, title, and weather—to generate personalized travel recommendations. This approach incorporated users' real-time activities to refine suggestions. Additionally, insights from social media were found to be useful for correcting errors in place databases and suggesting appropriate tags for users uploading photos. However, this work did not focus on personalizing recommendations based on social media content but rather provided a methodology for developing a comprehensive database of places of interest.

Martinkus and Madiraju demonstrated how Twitter data could be utilized to offer personalized place recommendations. Their approach involved creating a datastore using online resources such as Wikipedia and TripAdvisor. By analyzing user tweets and associated metadata, they identified categories of places of interest and used this information to generate recommendations when users queried the system. An improved version of this model incorporated additional tweet features such as URL count, media count, and preferences of friends and followers to enhance recommendation accuracy. The proposed model integrates collaborative filtering by analyzing tweets from users, friends, and followers to determine place-of-interest category scores. It also employs content-based filtering by assessing tweet sentiment and place-of-interest categories. Unlike traditional recommender systems that rely on public ratings, this model utilizes Google Services to compile a list of places to visit in a city. Trust concerns are minimal since the system only suggests options rather than making choices for users. A key advantage of this model is its ability to balance a user's transient interests with long-term travel preferences, accounting for both recent activity and consistent travel choices.

III. PROPOSED SOLUTION

The paper involves a service that recommends places of interest to a user based on historical data mined from their twitter account. The service takes the user's twitter handle, extracts the feed (of the user and their friends and followers), identifies travel tweets, segments them into time blocks from latest to oldest, analyzes for sentiment, and classifies based on the category of the places identified. The preferences are periodically updated with the user's latest tweets to reflect alteration in user's tastes and priorities. The prototype was developed in Python and R programming with the following packages: Tweepy (to access twitter data), BotoMeter (to identify bots), arules (association rule mining to boot up the bag of words), TextBlob (for sentiment analysis), SkLearn (for machine learning modules), and GoogleAPI (for accessing the list of tourist locations in a given place).

POIs refer to sites within a given town or city. For example, POIs in Milwaukee would include Milwaukee Public Museum, Discovery World, Milwaukee Art Museum, Basilica of St Josephat, Lakefront, Brady Street, Red Arrow Park, Washington Park, Milwaukee Zoo, etc. These POIs can be classified into categories such as museums, parks, restaurants, sports venues, historical buildings, shopping malls, etc. Sentiment analysis is a process that identifies the "mood" of the given tweet based on the words they contain. Sentiment may be positive, negative or neutral, and typical words that help in such analysis are happy, awesome, terrible, horrible, great, damper, etc. Users who want to use the service will provide the name of the place they want to visit. Based on their previously identified preferences, the service will list all places of interest around that location using a web service like Google API.Google API provides lists of locations based on a variety of location types like an amusement park, aquarium, art gallery, city hall, library, museum, park, shopping mall, stadium, zoo, etc.

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IV. SYSTEM ARCHITECTURE

The system architecture provides a high-level overview of how social media content is processed. Once a user grants access by providing credentials, the system's primary task is to filter and identify tweets related to travel from the user's feed. One method of classification involves detecting keywords such as "travel," "tour," "trip," and "museum." However, a more advanced approach is to utilize machine learning to distinguish travel-related tweets from non-travel tweets. In this study, we adopted the latter approach for improved accuracy.

Journey Tweets:

To build a reliable classifier, tweets were collected from the public Twitter stream and manually labeled as travel-related to create a training dataset. Additional travel-related tweets were sourced using relevant hashtags to expand the dataset. The classification process was implemented using three machine learning models from the Scikit-learn Python library: Naïve Bayes, Support Vector Classifier (SVC), and Stochastic Gradient Descent (SGD). The models were tested using two different feature extraction techniques: word count and Term Frequency-Inverse Document Frequency (TF-IDF). Word count represents the frequency of words within each tweet, while TF-IDF measures the importance of words by considering their occurrence in a tweet relative to their frequency across the dataset.

Before classification, tweets were preprocessed by converting text to lowercase, removing special characters, URLs, numerals, and usernames. Emoticons were converted into textual representations, and metadata such as tweet date, retweet count, and place mentions were preserved. After multiple evaluations, the SGD classifier with TF-IDF was found to provide the highest accuracy. This trained model was then applied to classify tweets for all participating users. The model can be updated periodically by incorporating new travel-related tweets into the dataset, further improving classification accuracy and adaptability. We must agree that any recommendation model has limitations and, using another dataset, the results could vary, but the overall results of our proposed recommendation model are promising.

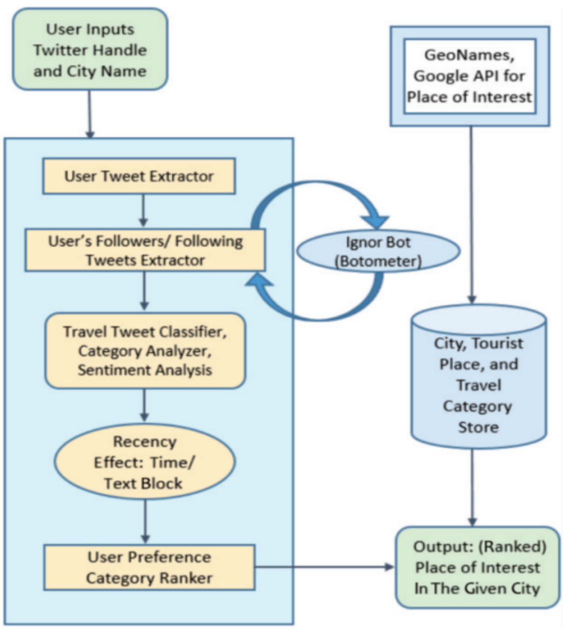

Fig. 1: System Architecture

Dataset used in model preparation:

Any recommendation model must be prepared and trained using historical data (in the model, is marked as Historical data). So, first, the Instagram users' profiles that have agreed to share their traveling photos have been web-scraped. The criteria for user selection were: 1) to have at least 10 photos taken during travel; 2) for at least half of the photos to define the country where the photo was taken (done by the user or by estimating photo metadata or text description); 3) user to participate in the research and define how he or she evaluates the recommendation. After that, object detection and metadata retrieval of each user photo were performed using the Microsoft Azure tool. The dataset has been filtered, and only the unique data items that had the full metadata have been included. The collected dataset is a set $X = \{x1, x2, \dots, xn\} \in R\,n$, $s = 1, \dots, N$, where $N = 12460$, $n = 4683$.

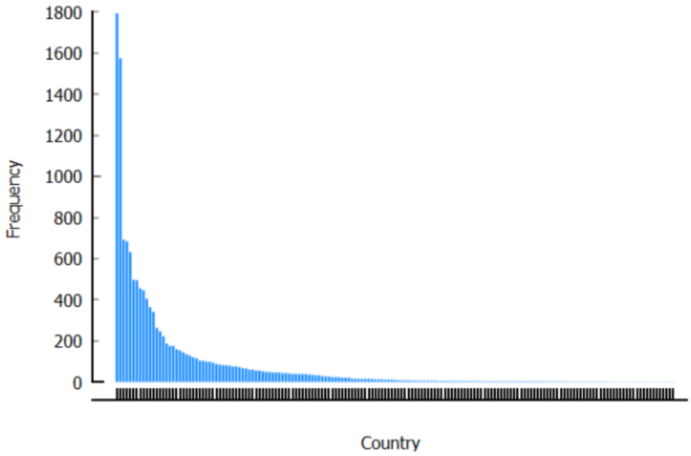

Fig. 2: country names distribution in the dataset

The each data item Xs has 4 metadata records: country name, full location address, latitude, and longitude. The remaining data item attributes (4679) are the probabilities of objects detected in the photos, such as landscape, outdoor, tree, human, sea, water, etc.

MetaData Analysis:

The described dataset has been used in three parts of the proposed recommendation model: 1) the metadata used to train the classifier; 2) to calculate similarity distance between new data items fed to the model and historical data items, to determine the most similar TOP 10 countries names in the dataset; 3) to train the self-organizing maps. To determine which similarity distance measure and classifier are the most suitable, fits in the proposed recommendation model, the dataset has been split into 5 parts for the cross-validation method. The same parts of the data have been used in two stages: classification and similarity detection; training and evaluation.

To train the self-organizing maps, the entire dataset has been analyzed. Metadata have been omitted from the model, since the main purpose is to recommend travel destinations based solely on photos. Metadata is used to determine which country the consumer has already visited.The efficiency of eight classification algorithms has been investigated: AdaBoost, Decision trees, Random forest, a support vector machine (SVM), naive Bayes, multilayer perception (MLP), stochastic gradient descent (SGD), and k nearest neighbour (kNN). The related work analysis shows that these algorithms are suitable for fast upcoming data prediction and fast model retraining after historical data are updated.

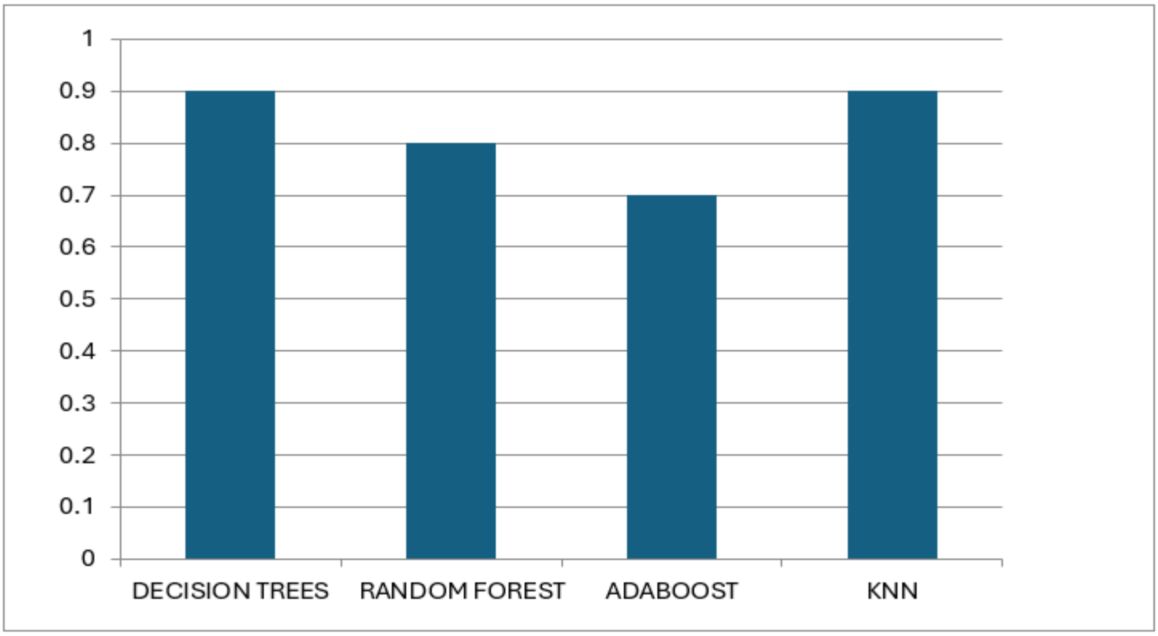

Fig 3: efficiency of classification algorithms to the country based on latitude and longitude

Similar Distance:

we have been analyzing the effectiveness of several commonly used similarity distances using our newly collected data. Most of the chosen similarity distances have been used and analyzed in overviewed related work recommendation systems, so it is important to investigate the performance of them in our proposed model, too. Suppose that we have two data items of the same dimensionality n: X = ($x1$,x2,…,xn) and Y = ($y1$,$y2$,…,yn). The calculation of similarity distances between these data items (X,) is presented. To determine which similarity distance measure and classifier are the most suitable, fits in the proposed recommendation model, the dataset has been split into 5 parts for the crossvalidation method. The same parts of the data have been used in two stages: classification and similarity detection; training and evaluation. To train the self-organizing maps, the entire dataset has been analyzed.

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Distance name	Equation	Comments
Euclidean	$d(X,Y) = \sqrt{\sum_{k=1}^{n}(x_k - y_k)^2}$	The Euclidean distance is a special case of the Minkowski distance, where $p = 2$.
City block	$d(X,Y) = \sum_{k=1}^{n}\lvert x_k - y_k\rvert$	The city block distance is a special case of the Minkowski distance, where $p = 1$.
Chebychev	$d(X,Y) = max_k\{\lvert x_k - y_k\rvert\}$	The Chebychev distance is a special case of the Minkowski distance, where $p = \infty$.
Minkowski	$d(X,Y) = \sqrt[p]{\sum_{k=1}^{n}\lvert x_k - y_k\rvert^p}$	-
Cosine	$d(X,Y) = \frac{\sum_{k=1}^{n} x_k y_k}{\sqrt{x_k^2} \times \sqrt{y_k^2}}$	-

As mentioned above, the dataset has been split into five folds. 80% of the dataset has been used as historical data, and the rest 20% to test whether the similarity distance can determine which country the test data item really belongs to. First, the distance between each test data item and all historical data has been calculated using all similarity distances presented in Table 1. In the next step, a calculation was performed to determine at which position the country name of the test data item is detected. We have calculated three variants: 1) The real country of the test data item has been recognized in the first place; 2) The real country of the test data item falls into TOP 5; 3) The real country of the test data item falls into TOP 10. Experiments have been carried out with each fold separately. The results of all the folds were averaged.

In the perfect case, the analyzed data items fed to the recommendation model consist of full data: 4 metadata attributes and 4679 object detection results. In this case, we have the list of countries where consumers have already been. Sometimes, the data cannot be retrieved fully data. e. There are many different classification algorithms that have their own advantages and disadvantages in different fields. Efficiency analyses of various classification algorithms have been performed in the past decade. The learning is repeated until the maximum number of iterations is reached. Many SOM visualization methods use coloring techniques to show the distance on the map. It shows how close the vectors of the neighbouring cells are in the dimensionality space of the analysed data.

The most popular visualization technique is based on the so-called unified distance matrix (u-matrix). The SOM is colored by the values of u-matrix elements. If grayscale is used, a dark color between neurons corresponds to a large distance. A light color between the neurons signifies that the codebook vectors are close to each other in the input space. Light areas can be thought of as clusters, and dark areas can be thought of as cluster separators. To recommend the list of travel countries, first of all, the self-organizing map has been trained using the Xs dataset. The proposed recommendation model is that it adopts different data (Instagram photos) for travel direction recommendation, defines a new combined method, integrates results of similarity measurement and SOM application results into one final recommendation, and estimates the parameter impact for different components of recommendation model.

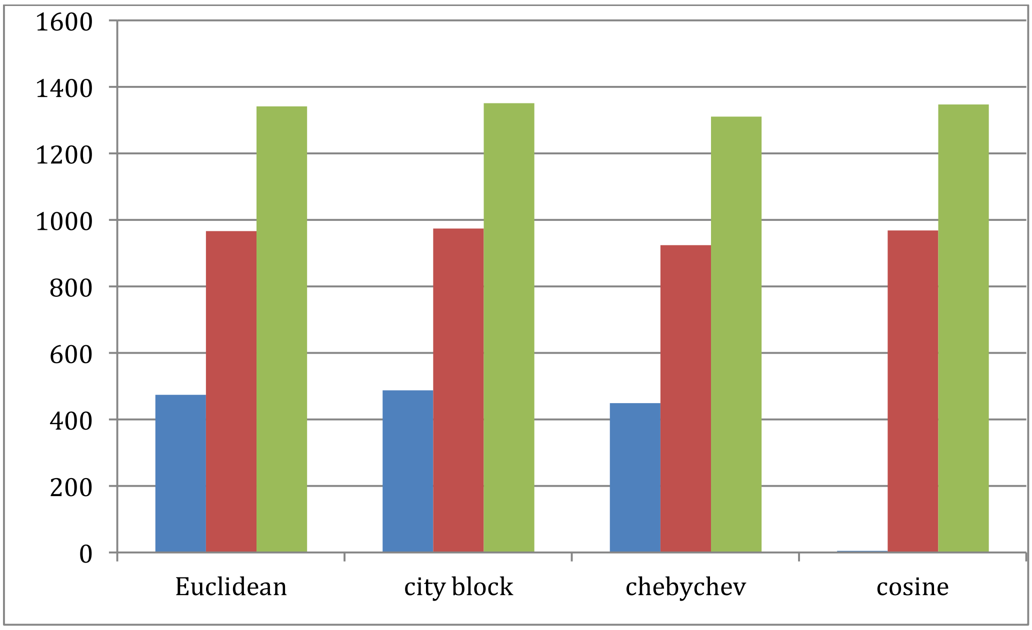

Fig 4: TOP most similar countries and evaluate is the country in the photo is present in the TOP similar photos.

Recency feature:

The relevance aspect of recency effect can be adequately treated with travel tweet classifier. Let tweets with wi words contain topics/places of interest and T be the t w matrix with Tij representing the number of tweets containing the j -th term. A search/query q can be represented as a w vector as a term of occurrence to obtain the cosine similarity. Let P be the t p matrix that represents the occurrence of p topic in a tweet. So, the term vector for the j -th place of interest

$$TP_j^{\mathrm{T}} = \sum_{i=0}^{n} T_{ij} \times p_i$$

To address proper weight to freshness component, a batch mode model approach has congenial impact. Nzeko'O et al. Introduced a unique idea to take care all the ground of personalized recommendation starting from short time-long time preference of potential users by proposed session-based temporal algorithm.

$$\Delta t' = t'_{\text{search}} - t'_{\text{post}}$$

V. RESULT AND DISCUSSION

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The primary selection of participants are the twitter users, with both frequent and non-frequent user activity, to serve all possible situations and evaluate the performance of the proposed framework. Participants with no or very less activity have been treated as cold start group and our model will recommend travel places based on trend. Over 100 twitter users were contacted randomly to obtain their actual travel preferences. Here, to select the survey takers online, we have performed a sequential block technique at a timely manner with the hash tagged travel key words such as “travel”, “tourism”, “vacation”, “adventure”, “hiking”, “road trip” and so on. However, the responses were not forthcoming, and hence we decided to contact local twitter users to fill out a paper survey indica 150 Big Data Mining and Analytics, September 2021, 4(3): 139–154 categories of most interest and least interest. 15 responses were obtained in this way. These survey takers are self-identified frequent twitter users. We have also collected travel tweets of 7 other twitter users. Approximately, 65% of these survey participants were male.

If all three judgments concurred, the ranking was accepted for the user in the given category. An MTurk (Amazon Mechanical Turk) survey has also been conducted to validate volunteers judgement. Tweets of each user, their friends, and followers were collected and then travel tweets were identified. The number of tweets collected for each user and the number of travel tweets identified are given in Fig. 5. The number of tweets ranges from 567 to 7200; while the count of travel tweets for the users ranges from 13 to 865. the analyzed data items fed to the recommendation model consist of full data: 4 metadata attributes and 4679 object detection results. In this case, we have the list of countries where consumers

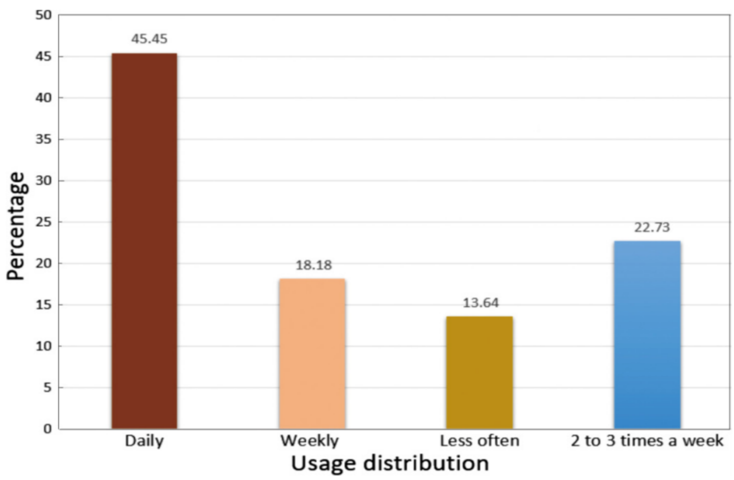

Fig 5: Social media profile usage distribution of survey participants

The confusion matrix further indicates the accuracy of the model. The matrix indicates significant false negatives for museums. One of the reasons for this performance could be the failure to adequately categorize travel tweets. At present, tweets are categorized based on words that are contained in the tweet. This could be improved by using machine learning to identify categories instead of a static classification method based on a set of words. Further, the model's inability to correctly identify categories could be due to the lack of category-specific tweets in the training dataset. The travel tweet identification was done using the machine learning model as explained in Section 5. The training dataset is relatively modest with about 2500 tweets. Improving the dataset will enable better identification of travel tweets. The survey done with volunteer twitter users might not have properly reflected their true preferences since they had to fill-out the form at a moment's notice. In the future, we plan to validate the predictions by generating a list of specific sites to visit and asking them to agree/disagree with the list. We can then compare the site-specific choices and the categories that the user picked. The project originally also included a category for "Sports Venues". However, this was not clear to the users and their response did not correspond to what they actually meant. For example, a user might be clearly interested in enjoying and watching sports, but they may not be interested in going to watch a local game or a sports venue when traveling. Therefore, this category was eliminated in this report.

7. CONCLUSION AND FURTURE WORK

Validation of the travel recommendation model has been performed using a small amount of data collected from real people and their travel experience data to simulate a real situation in the model. To validate the model, the artificially made dataset could be used instead of the real people's data, with a larger amount, but in that case it will distort the real situation. All parts of the model have been tested in the model development process, so there is no reason to test the final travel recommendation model proposed on the large dataset. This proposed model will be used in the real information system, and the collected user experience data will be taken into account in the future for a deeper analysis.

Comparison to other travel recommendation models is very limited. None of them use the same test cases or input data, Instagram photos. For example, Xiang Huang proposes a place of interest text description and user comment comparison based travel recommendation system. The model is able to achieve up to 88% recommendation accuracy and outperform existing analogue solutions. Considering text descriptions are more representative of user opinions than photos on Instagram, our results are in the same range - we achieved 66% accuracy for all user visited locations, and 96% accuracy for recommending countries not shown in the input photos.

In the context of the collected dataset, user photos can be analyzed and compared with the records in the dataset, calculating their similarity and membership of the cluster. By combining county data with similar photos, we can build a travel destination recommendation system. As a result of the experiments conducted, it can be concluded that different variation in the model is capable of improving accuracy. However, the most effective result is achieved by using a combination model, which is able to recommend ten countries, which corresponds to 63% of the countries the user visited. We found that accuracy was even higher, on average 96%, when we analyzed how many countries users travelled to in addition to those provided as input for the model. Based on only user photos, this is a promising result to predict travel directions more accurately.

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