

Improvising Personalized Travel Recommendation System with Recency Effects

Paromita Nitu*, Joseph Coelho, and Praveen Madiraju

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%.

Key words: travel recommendation; time sensitivity; recency effect; personalization; social media

1 Introduction

The extensive amount of information accessibility on electronic platforms (such as social media), urges the rapid development of the system that filters out irrelevant information and provides effective content that meets user-specific needs and expectations. In general, online services can grant an enormous number of options and the act of choosing can become an overwhelming activity for a target user. Recommendation systems (RS) are algorithms that predict users' likes and dislikes based on previous consumer activity (online) and recommend relevant items to resolve the aforementioned crisis. The recommendation system is one of the principal underlying software technologies of most online services from shopping to newscasting to educational sites and so on. In the present state of information overflow, RS has

become remarkably powerful and immensely popular in e-commerce and evolved considerably over the last decade^[1]. In all existing states of art recommendation system filtering techniques, collaborative filtering (CF) and content-based filtering (CBF) are most trendy in terms of generating mainstream recommendations as well as moderately treating a cold start for a brand-new user. In CF, the recommendations are made based on user similarity on previous preference and CBF discretizes the matching attributes of a selected item. The closer the similarity, the higher the likelihood of the items to be recommended by these basic filtering techniques. The effectiveness of these contemporary recommendation techniques is evaluated based on the prediction accuracy. Most of the online stores, starting from Amazon to Rakuten, Netflix to Rotten Tomatoes and so on, customize the initial recommendation list based on users' filter specification such as price, product description, availability, etc. and relevant accessories have been looked up by preceding shopper's search/purchase history. However, the "filter bubble" syndrome can lead to niche objects not being presented to the user thereby limiting the horizon for widening user tastes. Factoring diversity into the algorithm ensures that niche objects will not be overlooked, and the user will be made aware of items that might otherwise be missed^[2]. Thus, an

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explicit study on individualized human behavior is a resourceful solution to address user-specific attention and it helps solidify knowledge gathered and provides better understanding of a user's personalized taste.

Personalized RS requires information regarding the user's perception towards products/services. In that regard, one can explicitly state their preferences in a given domain. Otherwise, users' preferences can be inferred from the choices they make or do not make while using various web services. Some web services allow for the integration of social media content that further strengthens the validity of the recommendations being made by correlating users' information with information gleaned from choices that other similar users have made. One of the vastly desired areas of personalized recommendation is in the travel/tourism sector. Planning a vacation to an unfamiliar place can be daunting with little or no in-site information especially for the tourists with physical limitations as well as the language barrier. Websites like TripAdvisor.com and Expedia.com provide information about places of interest (POI) based on ratings provided by other users of the website. This may not match every person's taste. Therefore, personalized place of interest recommendation that caters user specifications in a timely manner is not only desirable but also immensely useful. Martinkus and Madiraju^[3] proposed a model that uses twitter activities, extracts travel information, and categorizes place of interest based on tweet attributes such as favorite-count, retweet count, and similar user count score. These scores are used to compute the rank value of each category. A successive research project by Coelho et al.^[4] has carried the aforementioned fundamental ideas forward by including other relevant tweet attributes, such as URL count, number of hash-tags, number of user mentions, number of media attachments, length of the tweet, and followers' and friends' preferences to boost up more precise personalization. Since then, the modern tourist has exhibited a rapid change in travel preference that is influenced not only by their traditional environments such as society, culture, friends, family and so on, but also shaped significantly by social media induced advertisements, brands, social networks, time-based occasions, and programs, etc.^[5] Thus, to accommodate the traveler's choice of POI more precisely, it is crucial to study the user's social media activity in a temporal fashion.

In this paper, we endeavor to provide personalized

travel recommendation (PTR) using social media (twitter profile) information of an individual to obtain travel relevant tweet attributes such as URL count, number of hashtags, number of users mentions, the emotion of emoticons, number of media attachments (photos/video), length of tweets, and followers and friends' preferences to provide user-oriented recommendation. In particular, our PTR system is modeled with users' social profile based collaborative filtering with augmented user profile matrix and comprehends recency effect to ensure the more appropriate and recent choice of POI. A prototype system for this model has been developed and evaluated.

Main contributions: Social media analysis for personalization of travel recommendations.

- Travel tweet classifier using machine learning and diversified list of recommended places based on predicted scores.
- Incorporating the recency effect of social media for relevance and freshness on the POI recommendation.

The rest of paper is organized as follows: Sections 2 and 3 present the motivation and theoretical background required for the place of interest recommendation system. Section 4 describes related work. Section 5 discusses the recommendation modeling and features of this travel recommendation system architecture. Section 6 presents the results and validation of this recommendation modeling. Section 7 points out the strength and weakness of this recommendation engine and discusses the boarder impact of this endeavor. The definitions of notations are shown in Table 1.

Table 1 Definitions of notations.

Notation	Definition
t	Term
d	Document
D	Total number of documents
$n(t,d)$	Term counts in d document
T_{ij}	Number of tweets containing the j -th term
p	Number of topics in a document
c	Place of interest category
s	Tweet sentiment
U	Twitter user
β_U	User's tweet score weight
β_F	Friend's tweet score weight
β_L	Follower's tweet score weight
w_1	Count normalizer
w_2	Tweet length normalizer
t_{post}	Time to post travel tweet
t_{search}	Time to search POI
G_i	Gradient at the i -th time block

2 Motivation

According to the World Travel and Tourism Council (WTTC), approximately 1.4 billion travelers travel around the world with ranges of motivations starting from a pleasure trip to medical purpose, higher education to a business trip and so on^[6]. It is the second-fastest growing sector in the world. Traveling is a very personalized 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. The headlines displayed on a news website are generally filtered based on the user's browsing history supported by implicit recommendations. Apart from browsing history, recommendations may be made based on how a user navigates through the website thus providing implicit feedback. A user's social media content is another rich resource for making recommendations. Smartinsights.com in its latest report states that over 2.3 billion people are active social media users. Over 1.9 billion are on Facebook, 900 million are on WhatsApp, and 320 million are on Twitter. All these users post content on these platforms. If this content can be mined to understand the user's likings and disliking, it may compile immense value in making recommendations to the user.

Twitter is a service, which allows users to post 280 characters long text called tweets. These tweets may include hashtags that enable tweets to be clustered into topics. Hashtags allow Twitter to discover trending topics or users to search for tweets related to a topic. Tweets by one user can be viewed by any other user (unless the tweets are marked private). Thus, even if a user is not another user's friend or follower, their tweets can be viewed, commented upon, and re-tweeted. Tweets

can also include media like photos. Users follow other users and in return have a following. This relationship provides for user-user collaborative filtering based on the topics they tweet about. When users tweet, they are expressing an opinion on a topic. Using sentiment analysis score, we can classify tweets into positive, negative or neutral categories and thereby understand the nature of the opinion. This score can then be used to rank the topic for a given user. Further, this provides the required data to develop a content-based filtering model.

Personalization in the travel-domain can take into account various aspects of an individual like economic status, occupation, marital status and family size, hobbies, ethnic background, location of current residence, education level, community engagement, etc. All these aspects in some way may determine the interests of the individual as well as the kinds of places they might want to visit. However, such information is not readily available in a user's Twitter profile. Obtaining such details may involve scraping information from other platforms like LinkedIn or Facebook. With increased scrutiny over privacy issues, such data gathering might be difficult as well as unethical. To offset this deficit of information, a voluntary one-time input indicating preferences could be got from the user as a way to cold-start the recommendation process. This one-time input has not been implemented in the current model.

We have used Twitter data in our project since Facebook does not allow public access to user posts. If Facebook posts can be accessed for data mining, it will prove to be an immense trove of great value for personalization in recommender systems. The goal of this project is to develop a hybrid RS that mines a user's tweets for topics related to places of interest and then makes recommendations for places of interest when the user wants to visit a new place. The model was tested with 22 users who validated the recommendations. The project can be carried further to any area of recommendation and the social media platform can be grown to include other platforms like Facebook, Google+, Instagram, etc., provided data on those platforms are accessible. Twitter generally does not provide personal information of the user apart from the profile, location, and language. The profile in many cases does not reflect the true identity of the individual. Many users also turn off the location setting. Hence in the current study, we have not taken into account any of the user's profile attributes, such as age, sex, occupation,

relationship status, family size and so on, to enhance the personalization.

3 State-of-the-Art Recommendation Techniques

The Recommender Systems Handbook^[1] provides a detailed classification of RS based on the techniques used: data mining methods based RS, content-based RS, neighborhood-based RS, and content-aware RS. Incorporating additional features, like constraints and trust-level into the basic recommendation techniques, improves the recommendation accuracy. The typical recommendation process takes a user's evaluation of observed items as input. This evaluation is usually expressed in the form of a rating collected either implicitly (e.g., system monitors browsing behavior) or explicitly when users are asked to provide their ratings, e.g., on a one-to-five scale. Ratings are then used by a recommendation approach in combination with other users' ratings and item features in order to produce recommendations that match the users' interests. To produce recommendations using collaborative filtering, the active users (the users that prediction refers to) similarities with the remaining of the users are calculated using a correlation measure (typically Pearson correlation coefficient). Then the group (neighborhood) of the users that are the most similar to the active user is selected and their ratings are combined to produce predictions. Rating predictions may typically lead to the presentation of a ranked or a top- n list of the most relevant (to the active user) items. In order to produce content-based recommendations, items have to be described by some features. For example, in the book recommendation domain, the author, the genre, and the most frequently used words could serve as features. Metrics, such as TF-IDF and information gain (IG), are commonly used to extract these features. The items that the active user has rated are used to create a user profile. All the unrated items are compared with this profile, and the most similar ones are presented to the active user.

However, accuracy alone is not the measure of a good RS. Diversity needs to be factored in the recommendations being made to ensure that "niche" objects are not blinded by the desire for accuracy. Therefore, in this model, while considering the users' interests, all categories of places are displayed with " n " number of places for each category depending on the level of user interest in that category.

The application domain determines the kind of RS to be used^[1]. Domains include entertainment, content (newspapers, research papers, e-learning applications, email filters, etc.), e-commerce, and services (travel, consultation, housing, matchmaking, etc.). In each case, the items available for recommendation will have different attributes and factors, like "types of users", "required trust level", etc., that need to be considered. Thus, RS needs to be tweaked for the particular application domain for effective performance. Social media enables better personalization of the RS.

4 Related Work

4.1 Recommendation filtering techniques

The roots of RS can be traced back to the extensive work in cognitive science, approximation theory, information retrieval, forecasting theories, and management and marketing science^[7]. As a research area, RS began to gain prominence in the 1990s both among academicians as well as industry. Reference [7] 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. Herlocker et al.^[8] introduced the concept of collaborative filtering based recommender systems and detailed the black box processes involved. They also indicated how an automated collaborative filtering (ACF) system had significant advantages over traditional CBF, while acknowledging that ACF worked best when used along with CDF in a hybrid model. Celdrán et al.^[9] proposed a recommender system based on users' behavior and collaborative location and tracking. They combined CF, CBF, and context-aware filtering (CAF) to identify items that can be recommended. CAF provides for location and tracking of elements close to the user in terms of relevance and meaning. Their system does not make use of social media content. Reference [10] proposed a genetic algorithm solution for collaborative filtering. The weights of implicit attributes of the items become the genes, and using rating history, the system aims to reach the optimum weights for the item. Reference [11] developed a user-based collaborative filtering model using fuzzy clustering means as opposed to k-means. Reference [12] provided a rich survey of

RS and discussed two relevant issues: social filtering and content-based filtering. Most RS are ensemble hybrid models. Reference [13] provided a survey of hybrid RS and discussed various hybrid models: weighted, mixed, switching, feature combination, cascade, feature augmented, and meta-level-based hybrids. Reference [14] detailed the process of hybrid collaborative filtering while Ref. [15] provided a method for missing value prediction using co-clustering and radial basis function networks for collaborative filtering. The RS should also be immune to attacks from malicious users who can affect the ratings of weights of item attributes. Reference [16] detailed a provably manipulation-resistant RS using an influence limiter strategy. Reference [17] discussed efforts in serendipity in RS. Serendipitous items are interesting, unexpected, and novel to a user. Reference [18] proposed a technique for topic diversification which generated improved recommendation lists. Reference [19] described RS in the context of automatically building research reading lists. It concludes that “collaborative filtering outperforms content-based approaches for generating introductory reading lists”. Zhou et al.^[2] dealed with the issue of diversity when making recommendations thereby avoiding the pitfall of narrowing the pool from

which recommendations may be made. They proposed a hybrid system which comprises of two models: one which ensures similarity and the other which factors in diversity. Knijnenburg et al.^[20] 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 Ref. [21]. User trust and trust-aware based RS are discussed in Refs. [22, 23]. In particular, Ref. [22] 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. Reference [23] proposed trust SVD, a trust-based matrix factorization technique for recommendations that integrates multiple information sources into the recommendation model in order to reduce data sparsity and cold start problems. A comparison table (Table 2) provides a complete overview of the aforementioned state-of-art recommendation systems. Zhang et al.^[24] introduced the idea of text mining to nullify potential

Table 2 Comparison for different recommendation filtering techniques.

Area of research	Research objective	Research methodology	Uniqueness	Limitation
Recommendation filtering technique	User-based collaborative filtering	Generate a classifier that fits users’ rating behavior and uses it on items.	Domain knowledge not needed. Adaptive: quality improves over time.	Quality dependent on large historical dataset.
	Content-based collaborative filtering	Generate a classifier that fits users’ rating behavior and uses it on items.	Domain knowledge not needed. Adaptive: quality improves over time. Implicit feedback sufficient.	Quality dependent on large historical dataset.
	Demographic filtering	Identify users that are demographically similar to users, and extrapolate from their ratings of items.	It can identify cross-genre niches. Domain knowledge not needed.	Computationally expensive.
	Knowledge-based filtering	Infer a match between items and users’ need.	No ramp-up required. Sensitive to changes of preference. It can include non-product.	Computationally expensive.
	Mixed-hybrid collaborative filtering	Recommendations from several different recommenders are presented at the same time.	Consider a significant number of information to recommend places of interest.	Requires a significant amount of data to implement.
	Feature augmentation filtering	Features from different recommendation data sources are thrown together into a single recommendation algorithm.	Different important information regarding the blogger and the places to visit improve the accuracy.	Computationally expensive.
	Meta-level filtering	The model learned by one recommender is used as input to another.	It offers refined recommendation.	Computationally expensive. Hard to implement.

cold starts of personalized recommendation systems. Sentiment analysis on user reviews better expresses any hidden sentiment of user personal test.

4.2 Related work to travel recommendation

Van Canneyt et al.^[25] in 2012 proposed using social media to find places of interest. They showed how geographically annotated social media data could be used to complement existing place databases. Yin et al.^[26] incorporated a unique feature of a three-way location-based rating, spatial user rating for non-spatial items, and non-spatial rating for spatial items, and spatial rating for the spatial item takes care of both the online and offline user activity. To predict the location, the authors implemented LALDA and ULA-LDA for the location prediction of the user^[26]. The authors in Ref. [6] introduced the use of geotagging including all the information on location, time, tags, title, and weather to predict personalized recommendation. The brand-new method in Ref. [6] proposed to use travel locations incorporating the user's real-time activity. In addition, such information from social media could help correct errors in place databases and recommend tags to users who are uploading photos. Reference [6] did not focus on personalizing the recommender system using social media content. However, Ref. [6] did provide a methodology for creating a comprehensive database of places of interest. Martinkus and Madiraju^[3] explained how twitter data can be used to personalize places of interest recommendations. A data-store is created using online resources like Wikipedia and TripAdvisor. A user's tweets are mined to identify categories of places of interest from tweet text and meta-data. This information is used to recommend places of interest when a user queries the system. Reference [4] enhanced the model using additional tweet features like URL count, media count, friends/followers' tastes, etc. to generate better recommendations.

The proposed model involves collaborative filtering since user-friends-follower tweets are mined to identify places of interest category scores. It also involves content-based filtering since tweets are mined to identify their sentiment and places of interest categories. While the model does not depend on public ratings to generate a list of places, it does use Google Services to obtain a list of places to visit in a given city. Trust issues related to the recommender system are minimal since the model only provides a list and does not make any decisions for the user. The unique aspects are that the proposed

model considers the transient and temporal nature of users in the recency bias and accommodates users' place of interest by balancing the current as well as steady choices of travel places.

5 Proposed Solution

In this project, a prototype solution was implemented that provides users with travel recommendations based on their social media, in particular to twitter profile, contents that were measured temporally. The primary assumption of this study is that every user or the user's followers/friends have tweets related to travel. Any participant with no travel tweet is a subject to a cold start. The project 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^[27]. 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.

5.1 System architecture

Figure 1 provides a high-level view of the system architecture. Once the user provides the credentials for accessing social media content, the first task involves identifying “travel” tweets from among all the tweets in the user feed. One way of classifying tweets is based on keywords like [“travel”, “tour”, “trip”, “museum” ...] that may appear in a tweet. A more impactful method involves classifying tweets as travel vs. non-travel tweets using machine learning. Here, we have implemented the later method as explained below.

5.1.1 Travel tweet classifier

Tweets were gleaned from the public twitter stream and manually identified as travel-related topics to create a travel tweets training dataset for the machine language classifier. To boost up the training set, a range of tweets with travel-related hash-tags were extracted and combined. We tried out three classification methods from the sklearn Python library using two different input data formats: word count and TF-IDF. Word count refers to a dictionary of words with the count of their occurrences in each item of the dataset. TF-IDF stands for Term Frequency-Inverse Document Frequency and is a way of scoring words based on their relative importance in the document in relation to its occurrence across all documents. In other words, it is a statistical

measure to evaluate how important a word is to a document in a collection or corpus. The importance increases proportionately to the number of times the word appears in the document but is offset by the frequency of the word in the corpus. The common equations for calculating TF and IDF are as follows:

$$TF(t, d) = \frac{n(t, d)}{\sum_k n(t, d)} \quad (1)$$

where t and d refer to the term and document. $n(t, d)$ is the count of t in d and \sum_k is the number of terms in d .

$$IDF(t, D) = \log \frac{D}{(d \in D : t \in d)} \quad (2)$$

where D refers to the total number of documents. $(d \in D : t \in d)$ is the number of documents where t occurs.

In both cases, the tweets were first converted to lower case and special characters, numerals, URLs, and user-names were stripped, emoticons were converted to word forms, date of tweet and retweet has recorded, and place and name mentions in tweets were saved up. The tweets were then tagged manually to create a travel tweet dataset. We have performed classification using Naive-Bayes classifier, Support Vector classifier, and Stochastic Gradient classifier using word-count and TF-IDF scores. The performance evaluation is indicated in Table 3. We used the SGD Classifier with TF-IDF data since it gave the best accuracy scores. This one-time generated model is used for all users who participated in this study. The model can be regenerated if and when the travel tweet dataset is extended with more tweets to enhance the quality of the training data thereby improving the model accuracy.

5.1.2 User tweet extraction

Up to 3200 recent tweets of the user are collected. This can be a limitation to a frequent twitter user due to inaccessibility of previous tweets exceeding tweet extraction limit. To understand the user preference with the time relevance, we have collected the data over six months of the time period to initially test out this prototype. Once the system is set up, the service will

Table 3 Accuracy achieved in various classification algorithms.

Algorithm	Data format	Accuracy (%)	F1-score
Multinomial NB	Word count	54.09	0.46
Linear SVC	Word count	53.27	0.43
SGD Classifier	Word count	54.91	0.39
Multinomial NB	TF-IDF	60.10	0.49
Linear SVC	TF-IDF	76.77	0.76
SGD Classifier	TF-IDF	79.23	0.79

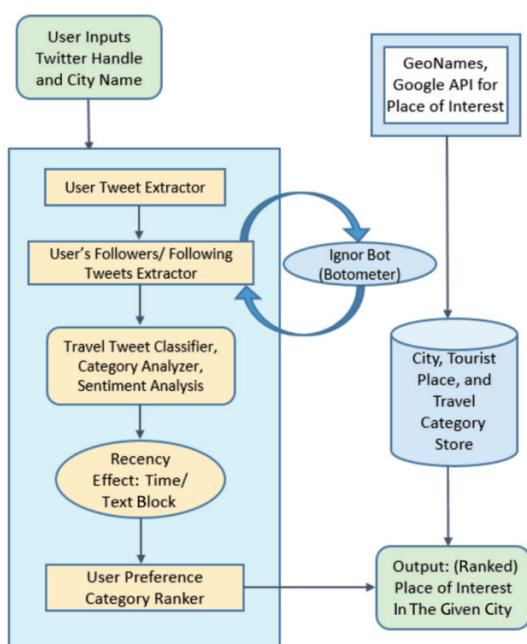


Fig. 1 System architecture.

collect tweets periodically and perform the analysis, updating the preferences for the user each time. This takes care of the recency bias issue. While updating the user preference scores, lesser weight will be given to older scores and higher weight to the latest tweet scores. The collected tweets are passed on to the travel tweet classifier and tweets related to travel are identified.

5.1.3 Computing travel tweet score

The travel tweets' attributes favorite count (fc), re-tweet count (rc), hash-tags count (hc), URL count (urlc), count of user mentions (umc), count of media (mc), and length of tweet (tlen) are collected and used to compute a tweet score. The inclusion criteria of the tweet features are primarily obtained through extensive literature review and some of those are highlighted in Table 4. The rational for social media feature inclusion, such as media count or URL count, is to obtain user interest towards the tweet. The more elements including emoji, retweet count, hash tags count and so on contain more information about the user. Thus, we have included the aforementioned tweet attributes to compute the tweet score. Each of those attributes carries a certain weight as indicated below:

$$\text{Score} = w_1(\text{fc}) + w_1(\text{rc}) + \text{hc} \times 0.3 + \text{urlc} \times 0.4 + \text{umc} \times 0.3 + \text{mc} \times 0.6 + w_2(\text{tlen}) \quad (3)$$

The retweet and favorite counts assigned weights are given in Table 5. w_2 is a function that normalizes the value for the length of the tweet based on the fact that a tweet can be no longer than 280 characters. The weights assigned to each of these features are based on the generally accepted notion that hashtags, media, and links add to the “value” of a tweet. In the next iteration of the model, we propose that these weights can be further tweaked based on the semantics of the hashtags or content of the media and links.

5.2 Travel tweet categorization

In this prototype, travel tweets are classified into four categories of interest: historical buildings, museums,

Table 5 Weights for re-tweet/favorite count.

Re-tweet/favorite count	Weight
< 1	0
1 – 10	0.2
11 – 30	0.5
31 – 100	0.8
> 100	1.0

parks/outdoors, and restaurants. Words in each tweet are matched with collections of words that identify the category. A word can have multiple forms and listing all the forms of a word in each category can be tedious. To enable words with the same stem to be classified correctly, we used the NLTK's WordNetLemmatizer method. An example of the word-set for the 'Museums' category is shown below:

[“museum”, “history”, “learning”, “exhibit”, “gallery”, “archive”, “art”, “science”, “collection”, “visit”, “curator”, “painting”, “curio”, “statuary”, “artwork”, “dinosaur”, “showcase”, “fresco”, “display”, “statue”, “Smithsonian”, “space”, “history”]

To boost up the bag-of-words model, we have implemented a data-driven lift measure based Apriori on travel tweet category-oriented hash tagged data to acquire frequently appeared words in each category. Figure 2 depicts a list of most frequent words with hash tags gallery and restaurants. A tweet is classified based on the category that has the maximum matches.

5.3 Sentiment analysis

Texts that appear in social media generally convey sentiment which may be positive or negative. Some text merely mentions a fact or observation, and these can be marked as neutral in sentiment. Performing sentiment analysis on tweet text helps to gauge the mood of the user in reference to the text. We used TextBlob^[33], an open-source text processing library based on the NLTK Python library, to perform sentiment analysis. TextBlob returns two values indicating the polarity and subjectivity of the input text. The polarity score is a float value in the range -1.0 to +1.0 while the subjectivity score ranges from

Table 4 Personalized recommendation based on social media profile.

Research paper	Sentiment analysis	Topic modeling	Social media	Friend, follower & collaborator	Tag & hyper link	Demographic filtering	Scientific weight	Recency effect
Proposed model	✓	✗	✓	✓	✗	✗	✓	✗
Majid et al., 2013 ^[28]	✗	✓	✓	✓	✓	✗	✗	✗
Guy et al., 2010 ^[29]	✗	✓	✓	✓	✓	✓	✗	✓
Parul and Daleep, 2013 ^[30]	✓	✗	✓	✗	✗	✗	✓	✓
Pennacchiotti and Gurumurthy, 2011 ^[31]	✗	✓	✓	✓	✗	✗	✓	✗
Ajantha et al., 2017 ^[32]	✗	✓	✓	✓	✓	✗	✓	✗

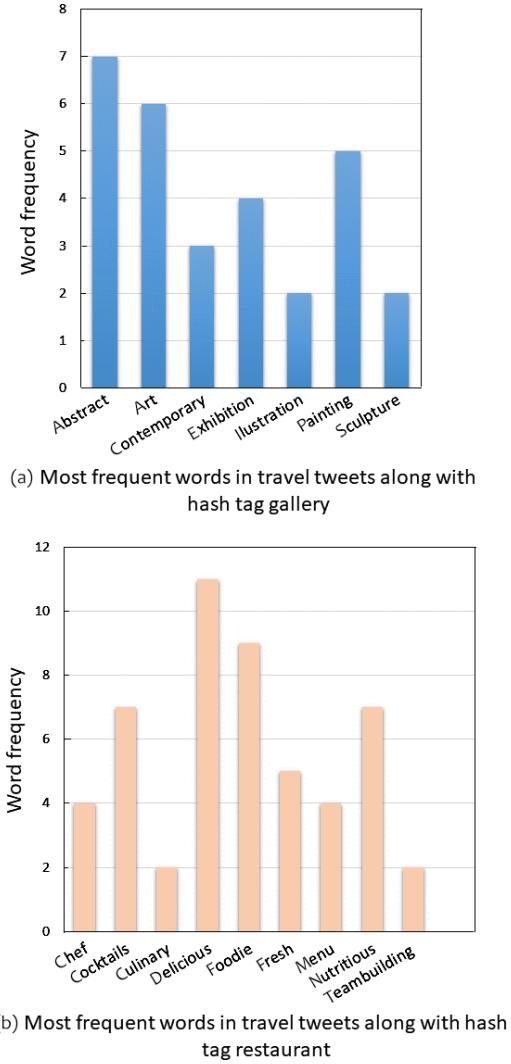


Fig. 2 Mining relevant words by place of interest category.

0.0 (objective) to 1.0 (subjective). For this prototype, we consider three sentiments: positive ($\text{polarity} > 0$), neutral ($\text{polarity} = 0$), and negative ($\text{polarity} < 0$). The scores of all tweets for the given category and sentiment are summed and then normalized. Table 6 shows an example sentiment score for different places of interest categories. This provides scores that indicate preferences for the given user $U_{c,s}$, where c is the category, s refers to sentiment, and $\max(c, s)$ refers to the maximum score in the given category.

$$U_{c,s} = \frac{\sum_{c,s} \text{score}(\text{user})}{\max(c, s)} \quad (4)$$

5.4 User collaboration model

Identifying travel tweets is a problem related to deriving topics in twitter feeds. Reference [15] proposed a method that takes into account the interactions among tweets such as liking in terms of favorite count

and retweeting. We have adopted a similar idea for identifying friends and followers based on the most recent interactions of the user. The second stage of the user-user collaboration is identifying friends (following) of the given user who might have similar interests. A list of 100 recent friends is drawn up. If the user has re-tweeted any of the friends' tweets that friend is added as a prospective collaborator. Here, the collaborator group is defined as user group with mutual interest and interaction. To determine that any user or a friend is a real person, the open-source BotoMeterPython library is invoked. BotoMeter provides a score and we have assumed a threshold level of < 0.60 to determine that the friend is not a Bot^[34]. If collaborators are fewer than 10, then friends starting with the most recent are added to get 10 sources from which tweets are mined and scores are obtained as indicated in the previous subsection. Only friends with at least 15 travel tweets were accepted. The scores of all ten friends are summed up based on category and sentiment and then normalized using the same process as before to obtain $F_{c,s}$. For each friend, we have

$$F_{c,s} = \frac{\sum_{c,s} \text{score}(\text{friend})}{\max(c, s)} \quad (5)$$

The third stage involves identifying the followers of the user and again the 100 most recent followers are taken into account. If the given user has re-tweeted any of the follower's tweets, that follower is considered as a collaborator. Tweets of ten such collaborators, and if they are fewer, then other followers are added who have at least 15 travel tweets. These are mined as before and scores are obtained for the given categories and sentiments $L_{c,s}$. For each of those followers we have,

$$L_{c,s} = \frac{\sum_{c,s} \text{score}(\text{followers})}{\max(c, s)} \quad (6)$$

5.5 Scientific weight with recency effect

For a personalized recommendation, machine learning is used across all industries to track consumer behavior. It allows algorithms to make person specified recommendations based on past history respond quickly to requests, and ultimately ensure consumer satisfaction.

In the context of information extraction from social

Table 6 Sample of user's sentiment scores.

Category	Positive	Neutral	Negative
Museum	1.000	0.962	0.731
Park	0.520	1.000	0.707
Food	0.624	0.631	1.000
Building	0.200	0.159	0.121

media profile, a common tendency is to emphasize more on the recent events than events of distant past, leading a bias towards decision making. In performance review studies, recency bias is a tendency of overemphasizing on most recent arrivals. Recency bias has a two-fold impact on the final ranking of the user's preference category. Most of the traditional machine-learned ranking algorithms are trained in batch mode assuming static relevance. Thus, having a long-term investigation plan is one of the best defenses against recency bias. Therefore, the place of interest recommendation needs to be conducted with attention to recency sensitive queries where the user expects the documents to be both topic-wise relevant and as well as fresh^[35].

5.5.1 Recency feature

The relevance aspect of recency effect can be adequately treated with travel tweet classifier. Let tweets with w_i words contain topics/places of interest and T be the $t \times w$ matrix with T_{ij} 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 $t \times p$ matrix that represents the occurrence of p topic in a tweet. So, the term vector for the j -th place of interest is

$$TP_j^T = \sum_{i=0}^n T_{ij} \times p_i \quad (7)$$

To address proper weight to freshness component, a batch mode model approach has congenial impact. Nzeko'O et al.^[6] 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. Intuitively, the recency of a block of tweets can be represented by elapsed time $\Delta t'$ ^[36] and defined as

$$\Delta t' = t'_{\text{search}} - t'_{\text{post}} \quad (8)$$

where t'_{search} is the time to search POI with the proposed personalized model and t'_{post} is the time to post travel relevant tweets. Steps for extracting time stamp features are as following:

Step 1: Detect the time stamp of a given tweet.

Step 2: Aggregate tweets within a time block.

Step 3: Compute block freshness component.

5.5.2 Recency modeling

The recency model is the time sensitive weighted model with the scores generated by the regular model. To acquire freshness component, social media profile with reasonable amount of information at each time block can be discounted with recency weight normalized

discounted cumulative gain NDCG_i , which is defined as

$$\text{NDCG}_i = Z_n \sum_{i=0}^n \frac{G_i}{\log_2(i+1)} \quad (9)$$

where Z_n is the normalization factor. G_i is the gradient at the i -th time block $\Delta t'_i$ using gradient boosted decision tree (GBDT). To accommodate uneven information abundance at each time block, the proposed model uses text block with approximately equal amount of tweets. In cases of less active social media appearance, the proposed model incorporates the i -th text block with lower weight.

5.6 Personalized travel recommendation model

To predict the user's comprehensive travel interest, a sentiment analysis was performed and the positive, neutral, and negative scores of extracted social media activity of the user, the friends, and the followers are separately summed for each place of interest category. To emphasize user's recent interest, we have imparted social media contents into time blocks represented by suffix i , and more weights have been assigned to contemporary activities. However, the scores for the user, friends, and followers cannot be considered on par. Different weights need to be assigned for each of them, indicating their level of importance, while computing the final scores for each category. From the survey conducted, we got the actual user preference scores of 22 users for each category (S_b, S_m, S_p, S_r) and from the model we have tweet scores and categories for each tweet. We obtained the coefficients ($\beta_b, \beta_m, \beta_p, \beta_r$) for each of the categories using logistic regression. The highest β for each category was summed across all users to obtain β_U which is the weight to be assigned to the users' tweet scores. These weights would be updated periodically to reflect the changing data.

$$\begin{bmatrix} S_b \\ S_m \\ S_p \\ S_r \end{bmatrix} = \beta_b \begin{bmatrix} t_{b1} \\ t_{b2} \\ \dots \\ t_{bn} \end{bmatrix} + \beta_m \begin{bmatrix} t_{m1} \\ t_{m2} \\ \dots \\ t_{mn} \end{bmatrix} + \beta_p \begin{bmatrix} t_{p1} \\ t_{p2} \\ \dots \\ t_{pn} \end{bmatrix} + \beta_r \begin{bmatrix} t_{r1} \\ t_{r2} \\ \dots \\ t_{rn} \end{bmatrix}.$$

This process is repeated with all the tweets of the user's friends to obtain β_F which is the weight assigned to the friends' tweet scores; and with the tweets of the user's followers to obtain β_L which is the weight

assigned to the followers' tweet scores. β_U , β_F , and β_L are normalized using the above method and approximated at $\beta_U = 4$, $\beta_F = 3.25$, and $\beta_L = 2.75$. The tweet scores for each category for the user, the friends, and the followers are summed based on sentiment. The scores for positive sentiment have a weight of 1.0, for neutral sentiment, 0.65; and for negative sentiment, 0.35. The final scores are sorted to obtain the preferred list of categories.

$$U_c = \sum_{i=0}^n \text{NDCG}_i \{(U_{ci+}) \times \beta_U + (F_{ci+}) \times \beta_F + (L_{ci+}) \times \beta_L + (U_{cin} \times \beta_U + F_{cin} \times \beta_F + L_{cin} \times \beta_L) \times 0.65 + (U_{ci-} \times \beta_U + F_{ci-} \times \beta_F + L_{ci-} \times \beta_L) \times 0.31\} \quad (10)$$

where i refers to the time of the event in terms of time block, and NDCG_i is the recency weights for the i -th time block defined as normalized discounted cumulative gain. Here, the signs $+, -, -$ refer to the sentiment of the tweet. U refers to the user, F refers to the friends, and L refers to the followers. U_c refers to the final score for category c for the user U .

The above section details the user-user collaboration in identifying friends and followers who share similar interests with the given user and drawing up a ranked score for the specified categories. The result will be a list of scores as shown in the following example for a particular user (Table 7). The developed prototype provides up to fifteen recommendations to the user and the recommendations are proportionately drawn based on the computed scores. Thus, the proposed framework has recommended 6 POIs for parks, 4 for museums, 3 for restaurants, and 2 for historical buildings in the recommendation list provided to the user based on the scores in Table 7. If this user wants to visit Milwaukee, WI, the RS will list the following sites:

Parks

- Pere Marquette Park 900 N Plankinton Ave, Milwaukee, WI 53203, United States
- Kern Park 3614 N Humboldt Blvd, Milwaukee, WI 53212, United States
- Veterans Park 1010 N Lincoln Memorial Dr,

Table 7 Travel place category scores.

Category	Score
Park	0.44
Museum	0.22
Restaurant	0.19
Historical building	0.15

- Milwaukee, WI 53202, United States
- Lake Park 2975 N Lake Park Rd, Milwaukee, WI 53211, United States
- Mitchell Park Horticultural Conservatory 524 S Layton Blvd, Milwaukee, WI 53215, United States
- South Shore Park 2900 S Shore Dr, Milwaukee, WI 53207, United States
- Museums
- Milwaukee Public Museum 800 W Wells St, Milwaukee, WI 53233, United States
- Milwaukee Art Museum 700 N Art Museum Dr, Milwaukee, WI 53202, United States
- Harley-Davidson Museum 400 W Canal St, Milwaukee, WI 53201, United States
- Charles Allis Art Museum 1801 N Prospect Ave, Milwaukee, WI 53202, United States
- Restaurants
- Mader's Restaurant 1041 N Old World 3rd St, Milwaukee, WI 53203, United States
- The Capital Grille 310 W Wisconsin Ave, Milwaukee, WI 53203, United States
- Rock Bottom 740 N Plankinton Ave, Milwaukee, WI 53203, United States
- Historical buildings
- Iron Block Building 205 E Wisconsin Ave, Milwaukee, WI 53202, United States
- Mitchell Building 207 E Michigan St, Milwaukee, WI 53202, United States

6 Result and Evaluation

The evaluation methodology for the proposed personalized travel recommendation system concerns conducting a double blinded short survey and the survey takers are chosen randomly in both in-person and online survey. 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", "roadtrip" and so on. However, the responses were not forthcoming, and hence we decided to contact local twitter users to fill out a paper survey^[26] indicating

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 (Fig. 3a). Because the minimum age required to open a social media profile on twitter platform is 13 years old, the initial age group categories start at 13 years and the age distribution is presented in Fig. 3b. The age group distribution is relatively even for most of the categories, however, the 16 years to 18 years age group has the highest percentage of participants at 32% (Fig. 3b). This skew on age distribution was expected^[37].

The POI recommendations are based on the social media profile activity with the primary assumption that user's preferences reflect on their social media

activity. Figure 4 displays the social media profile usage distribution of the survey participants. Three volunteers went through the twitter profile activities individually and provided a ranking of interest for travel categories based on their subjective judgement of the tweets for each user. 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. Figure 6 shows response vs. prediction accuracy at each travel

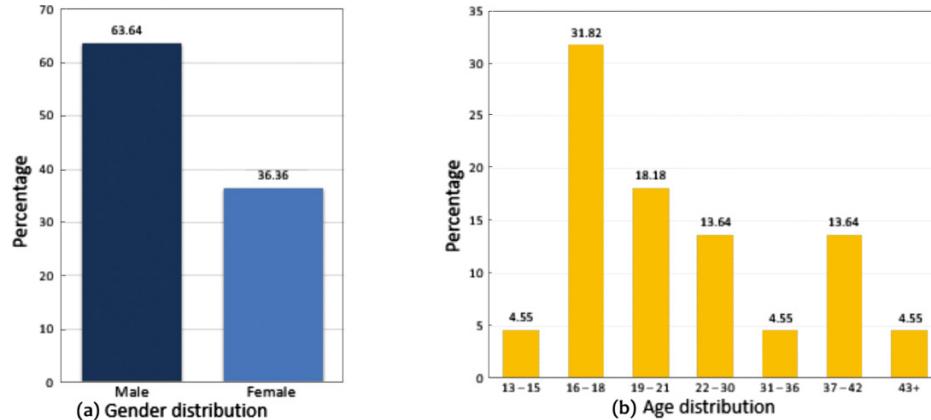


Fig. 3 Demographic distribution of study participants.

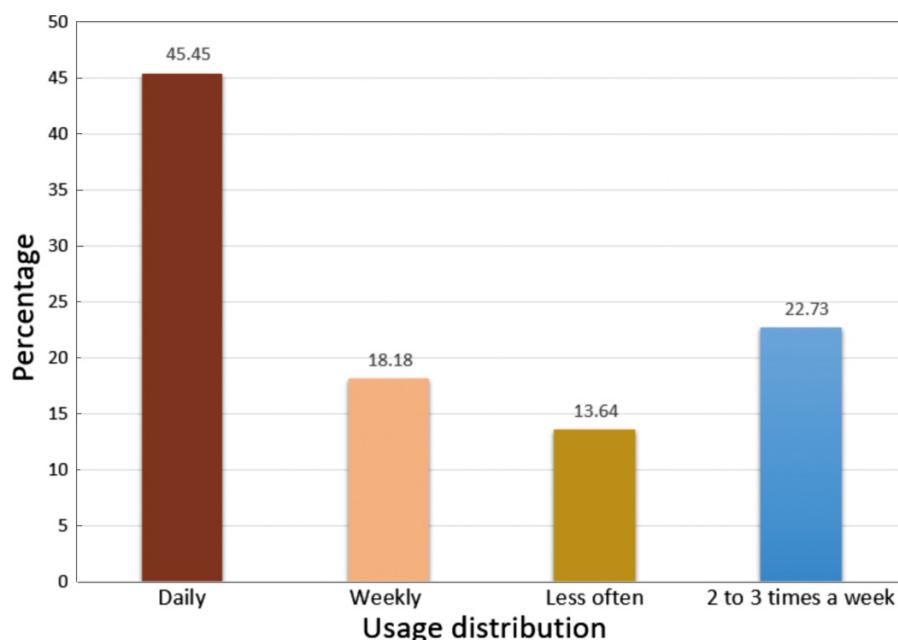


Fig. 4 Social media profile usage distribution of survey participants.

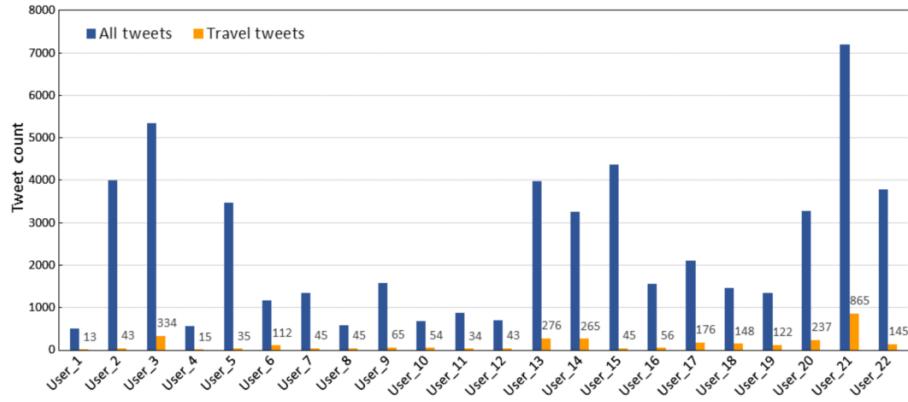


Fig. 5 User specific tweet count: All tweets vs. travel tweets.

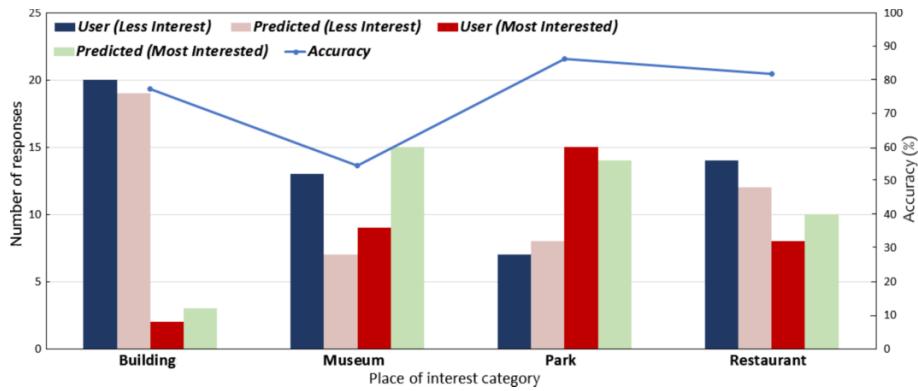


Fig. 6 Confusion matrix for recency effect model: User response vs. prediction accuracy.

category. The performance of our proposed personalized travel recommendation system has been evaluated and presented in a form of confusion matrix. The predictions made by the model were matched against the user preferences given in the survey (Table 8). The overall accuracy of the predictions with recency weight across all four categories was 69.2%. After observing that

most tweets that came from “friends” and “followers” rather than from the users themselves, we proposed to set $\beta_U = 1$, $\beta_F = 6$, and $\beta_L = 3$. The accuracy of travel interest categories including buildings, museums, parks, and restaurants are approximately 77%, 60%, 86%, and 82%, respectively. Inclusion of relevant social media features and weighting the content importance

Table 8 Confusion matrix.

		Model prediction	
		Interested in (ranked high)	Not interested (ranked low)
User specification	Interested in (ranked high)	0	2
	Not interested (ranked low)	3	17
		Model prediction	
		Interested in (ranked high)	Not interested (ranked low)
User specification	Interested in (ranked high)	7	2
	Not interested (ranked low)	8	5
		Model prediction	
		Interested in (ranked high)	Not interested (ranked low)
User specification	Interested in (ranked high)	13	2
	Not interested (ranked low)	1	6
		Model prediction	
		Interested in (ranked high)	Not interested (ranked low)
User specification	Interested in (ranked high)	7	1
	Not interested (ranked low)	3	11

with recency has improved the overall accuracy of our proposed framework to 75.23% from 68%^[4], which is a 10% increment than the previous framework.

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 Discussion and Conclusion

RS is an essential tool in the age of information overflow. Non-personalized RS may be useful in some contexts, but personalizing recommendation adds value in terms of saving time and effort to optimize opportunities. Social media provides a platform for mining data that can be used to make personalization's since users exhibit their positive, negative or even neutral opinions on various topics. This project mines data from twitter to personalize travel recommendations. The proposed model considers numerous tweet features like URL count, hash-tag count, favorite count, etc. that contribute

value to a tweet. This information can be used to separate general tweets from tweets that might be more informative. Numerous classification algorithms on two different data formats have been performed to obtain optimal travel tweet classifier. A combination of Stochastic Gradient classifier on TF-IDF data format has obtained approximately 80% accuracy. Tweets classified as travel tweets became the subject to further categorization. In this prototype, travel tweets are classified into four categories such as historical building, museums, parks/outdoors, and restaurants. To boost up the bag of words model for travel categorization, a lift measure based apriori has been implemented on travel category oriented hash tagged data. The sentiment of the travel tweet in a particular category has been obtained through TextBlob, an open source text processing library. Since the recent social media activity provides current status of a user's choice trend, this model gives relatively more weights to the recent posts but balances out the recency inclination with normalized discounted weight. This process involves computation of elapsed time. To implement time block and comprehend change in user's preference with time, the system needs data input over a period of time. At each iteration, up to 3200 tweets can be extracted. For a frequent twitter user, this prototype needs to reiterate and update the preference which is computationally expensive and requires data storage. This is one of the major limitations of this prototype. On the other hand, recency component accommodates change in preference and aids accuracy in final decision. In addition, connections between users and their friends and followers also provide useful information about the user. All these are factored in the proposed model. The overall accuracy of the model is 75.23% and further work may enhance the accuracy. Curating more travel tweets for the training dataset would enhance the ability of the model to classify travel tweets. Identifying categories of places could be transformed using machine learning to categorize the tweets. The model can also be improved by including reinforced learning whereby user feedback is obtained to fine-tune the model and enhance its predictive ability.

It was also observed that few people tweet about travel interests uniformly. Users were more likely to tweet about sporting events or restaurants rather than about visits to museums or historical sites. This skews the ability to predict user taste more precisely. One way to handle this, is by giving a lower rank to categories

that are commonly tweeted and a higher rank to tweets of categories that are generally less tweeted about. The proposed model also gives the user the ability to modify the rankings before actually presenting sites of interest in the given destination. While this prototype deals with only four categories of places, additional categories could be added. These could include sites specific to children, young adults, seniors, students on educational tours, etc. The proposed framework can also be used to accommodate situations like any pandemic when people are no longer traveling extensively. Thus, information that is obtained from social media, might not be adequate to achieve personalized place of interest. In that case, the proposed model can be fine-tuned at periodic level and adjust to access pre-crisis social media activity. On the other hand, for the user with actively showing concerns in their social media about a pandemic who also shows interest in relatively less crowded place to visit, our proposed framework can accommodate user's choice and recommend secluded places to cater user's personalized taste. The scope of the project could be extended to use social media content from Facebook, Instagram, etc. either independently or by aggregating all these feeds into one recommender system. We currently do not consider demographic information of the users as this may not be readily available from their social media profile. However, in the future when available, we plan on adding demographic information into our model.

References

- [1] F. Ricci, L. Rokach, and B. Shapira, Introduction to recommender systems handbook, in *Recommender Systems Handbook*, F. Ricci, L. Rokach, B. Shapira, and P. B. Kantor, eds. Boston, MA, USA, 2011, pp. 1–35.
- [2] T. Zhou, Z. Kuscsik, J. G. Liu, M. Medo, J. R. Wakeling, and Y. C. Zhang, Solving the apparent diversity-accuracy dilemma of recommender systems, *Proc. Natl. Acad. Sci. USA*, vol. 107, no. 10, pp. 4511–4515, 2010.
- [3] P. Martinkus and P. Madiraju, Personalizing places of interest using social media analysis, Milwaukee, WI, USA, <https://ieeexplore.ieee.org/document/8457762>, 2015.
- [4] J. Coelho, P. Nitu, and P. Madiraju, A personalized travel recommendation system using social media analysis, in *Proc. 2018 IEEE Int. Congress on Big Data (Big Data Congress)*, San Francisco, CA, USA, 2018.
- [5] L. A. Caldito, F. Dimanche, and S. Ilkevich, Tourist behaviour and trends, in *Tourism in Russia: A Management Handbook*, F. Dimanche and L. A. Caldito, eds. Bingley, UK: Emerald Group Publishing Limited, 2015, pp. 1–30.
- [6] A. J. N. Nzeko’O, M. Tchuente, and M. Latapy, Time weight content-based extensions of temporal graphs for personalized recommendation, in *WEBIST 2017-Proc. 13th Int. Conf. Information Systems and Technologies*, Porto, Portugal, 2017, pp. 268–275.
- [7] A. Gediminas and T. Alexander, Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions, *IEEE Trans. Knowl. Data Eng.*, vol. 17, no. 6, pp. 734–749, 2005.
- [8] J. L. Herlocker, J. A. Konstan, and J. Riedl, Explaining collaborative filtering recommendations, in *Proc. ACM Conf. Computer Supported Cooperative Work*, Philadelphia, PA, USA, 2000, pp. 241–250.
- [9] A. H. Celadrán, M. G. Pérez, F. J. García Clemente, and G. M. Pérez, Design of a recommender system based on users' behavior and collaborative location and tracking, *J. Comput. Sci.*, vol. 12, pp. 83–94, 2016.
- [10] Y. Ar and E. Bostancı, A genetic algorithm solution to the collaborative filtering problem, *Expert Syst. Appl.*, vol. 61, pp. 122–128, 2016.
- [11] H. Koohi and K. Kiani, User based collaborative filtering using fuzzy C-means, *Measurement*, vol. 91, pp. 134–139, 2016.
- [12] J. Bobadilla, F. Ortega, A. Hernando, and A. Gutiérrez, Recommender systems survey, *Knowl.-Based Syst.*, vol. 46, pp. 109–132, 2013.
- [13] R. Burke, Hybrid recommender systems for electronic commerce, *User Model. User-Adapt. Interact.*, vol. 12, no. 4, pp. 331–370, 2000.
- [14] K. Kulkarni, K. Wagh, S. Badgjar, and J. Patil, A study of recommender systems with hybrid collaborative filtering, *Int. Res. J. Eng. Technol.*, vol. 3, no. 4, pp. 2216–2219, 2016.
- [15] R. Nugroho, J. Yang, Y. L. Zhong, C. Paris, and S. Nepal, Deriving topics in twitter by exploiting tweet interactions, in *Proc. 2015 IEEE Int. Congress Big Data*, New York, NY, USA, 2015, pp. 87–94.
- [16] P. Resnick and R. Sami, The influence limiter: Provably manipulation-resistant recommender systems, in *RecSys’07 Proc. 2007 ACM Conf. Recommender System*, Minneapolis, MN, USA, 2007, pp. 25–32.
- [17] D. Kotkov, S. Q. Wang, and J. Veijalainen, A survey of serendipity in recommender systems, *Knowl.-Based Syst.*, vol. 111, pp. 180–192, 2016.
- [18] F. G. Zhang, Improving recommendation lists through neighbor diversification, presented at 2009 IEEE Int. Conf. Intelligent Computing and Intelligent Systems, Shanghai, China, 2009, pp. 222–225.
- [19] M. D. Ekstrand, P. Kannan, J. A. Stemper, J. T. Butler, J. A. Konstan, and J. T. Riedl, Automatically building research reading lists, in *RecSys’10-Proc. 4th ACM Conf. Recommender Systems*, Barcelona, Spain, 2010, pp. 159–166.
- [20] B. P. Knijnenburg, M. C. Willemse, Z. Gantner, H. Soncu, and C. Newell, Explaining the user experience of recommender systems, *User Model. User-adapt. Interact.*, vol. 22, nos. 4 & 5, pp. 441–504, 2012.

- [21] S. Dooms, Dynamic generation of personalized hybrid recommender systems, in *RecSys 2013-Proc. 7th ACM Conf. Recommender Systems*, New York, NY, USA, 2013, pp. 443–446.
- [22] S. G. Deng, L. T. Huang, G. D. Xu, X. D. Wu, and Z. H. Wu, On deep learning for trust-aware recommendations in social networks, *IEEE Trans. Neural Networks Learn. Syst.*, vol. 28, no. 5, pp. 1164–1177, 2017.
- [23] G. B. Guo, J. Zhang, and N. Yorke-Smith, A novel recommendation model regularized with user trust and item ratings, *IEEE Trans. Knowl. Data Eng.*, vol. 28, no. 7, pp. 1607–1620, 2016.
- [24] H. Z. Yin, B. Cui, L. Chen, Z. T. Hu, and C. Q. Zhang, Modeling location-based user rating profiles for personalized recommendation, *ACM Trans. Knowl. Discov. Data*, vol. 9, no. 3, p.19, 2015.
- [25] S. Van Canneyt, O. Van Laere, S. Schockaert, and B. Dhoedt, Using social media to find places of interest: A case study, in *GEOCROWD 2012-Proc. 1st ACM SIGSPATIAL Int. Workshop on Crowdsourced Volunteered Geographic Information*, Redondo Beach, CA, USA, 2012, pp. 2–8.
- [26] M. Xie, H. Z. Yin, H. Wang, F. J. Xu, W. T. Chen, and S. Wang, Learning graph-based poi embedding for location-based recommendation, in *CIKM'16: Proc. 25th ACM Int. Conf. Information and Knowledge Management*, Indianapolis, IN, USA, 2016, pp. 15–24.
- [27] Google Places API, <https://developers.google.com/places/>, 2019.
- [28] A. Majid, L. Chen, G. Chen, H. T. Mirza, I. Hussain, and J. Woodward, A context-aware personalized travel recommendation system based on geotagged social media data mining, *Int. J. Geogr. Inf. Sci.*, vol. 27, no. 4, pp. 662–684, 2013.
- [29] I. Guy, N. Zwerdling, I. Ronen, D. Carmel, and E. Uziel, Social media recommendation based on people and tags, in *SIGIR 2010 Proc.-33rd Annu. Int. ACM SIGIR Conf. Res. Dev. Inf. Retr.*, no. Lc, Geneva, Switzerland, 2010, pp. 194–201.
- [30] M. Parul and K. Daleep, Career trends and worldwide employment growth in tourism, travel and hospitality industry, *An Int. Multidiscip. Res. J.*, vol. 3, no. 10, pp. 104–119, 2013.
- [31] M. Pennacchiotti and S. Gurumurthy, Investigating topic models for social media user recommendation, in *Proc. 20th Int. Conf. Companion World Wide Web*, Hyderabad, India, 2011, pp. 101–102.
- [32] D. Ajantha, J. Vijay, and R. Sridhar, A user-location vector based approach for personalised tourism and travel recommendation, in *Proc. 2017 Int. Conf. Big Data Anal. Comput. Intell. ICBDAI 2017*, Chirala, India, 2017, pp. 440–446.
- [33] TextBlob: Simplified text processing. <https://textblob.readthedocs.io/en/dev/>, 2019.
- [34] Botometer: An OSoMe project, <https://textblob.readthedocs.io/en/dev/>, 2019.
- [35] Y. Chang, A. L. Dong, P. Kolari, R. Q. Zhang, Y. Inagaki, F. Diaz, H. Y. Zha, and Y. Liu, Improving recency ranking using twitter data, *ACM Trans. Intell. Syst. Technol.*, vol. 4, no. 1, p. 4, 2013.
- [36] A. L. Dong, R. Q. Zhang, P. Kolari, J. Bai, F. Diaz, Y. Chang, Z. H. Zheng, and H. Y. Zha, Time is of the essence: Improving recency ranking using Twitter data, in *Proc. 19th Int. Conf. World Wide Web*, Raleigh, NC, USA, 2010, pp. 331–340, 2010.
- [37] A. Perrin, Social media usage: 2005–2015, in *Pew Internet & American Life Project*, Washington, DC, USA, 2015, pp. 2005–2015.



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