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A DUAL-PERSPECTIVE EVENT AND USER RECOMMENDATION SYSTEM BASED ON SOCIAL NETWORKS

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ABSTRACT

Social Media platforms have become an important source of real-life information resource and host huge amount of user created content. The users can use this platform to report real-life events which spread quickly and widely across the entire social networks. Due to the richness of available events, selecting the most interesting events and deciding who to invite for attending these events becomes increasingly difficult. Recent works are limited to event classification and personalized user interest discovery. This approach introduces a solution for event and user recommendations based on the user's personal interest. A dual perspective method is used to provide recommendations for both user and the person who host the event. Event classification is performed by analyzing the posts extracted from microblogging sites. The user's interest is identified from their posts. The dataset collected from twitter are used for demonstration. This method facilitates personalized recommendation of events and provide list of interested users to the event.

Keywords: User Recommendations, Event Detection

1. INTRODUCTION

The increase in the availability of information in online can confuse the users when they try to find their desired information, services or products on the internet. This leads to the need for recommendation system. The recommendation system aims to find the items that are of user's preferences. The event recommendation system is different from traditional recommendation system such as product recommendations [13]. In item recommendations, the users have already rated the items to be recommended. But the event has characteristics such as time and location. That is events vary with respect to time and location. It makes it difficult to apply the traditional recommendations on the events. Social events are created continuously and are valid only for a short time span. This property of event cause the difficulty in event recommendation as recommending the event that has already occurred is meaningless.

An important accept of events is that they are created by people, used by people and displayed by people. Social Media have become an important means of communication for humans during the recent years Micro blogging is a type of social media where a user shares opinions and status updates that occurred in their daily life in the form of short messages. They popularity of these social network made it a main source of these events. The people found social networks as a most convenient way to provide event related information's as it reaches a large number of users. This provides a large amount of event related details available to the users. Thus make it difficult for the users in searching events that match their preferences from a large number of events details about the upcoming events. The existence of a system that can help users to find the events that are relevant to them in a personalized way is essential. Recommendation system appears to provide a personalized recommendation for a user to discover the preferred events. The main aim of a recommender system is guide users to their interested items mostly in a personalized way. Due to the large number of events available it also becomes difficult for the person who creates new events to identify its potential users.

2. RELATED WORKS

This section reviews studies on the existing work on event classification, user interest discovery, and event recommendation and user recommendation.

A. Event Classification

An event can be described as a public assembly for the purpose of celebration, marketing, reunion etc. Events can be classified on the basics of their types, contexts and size. Events play a prominent role in our lives, such that many social media documents describe or are related to some event. Organizing social media contents with respect to the events thus seems to be a promising approach to better manage and organize the ever increasing amount of content in social media applications. Many solutions have been proposed to classify social events by exploiting the information over content, temporal, and social dimensions.

Tseng et.al [3] has proposed an approach to classify twitter data using Naïve Bayes Classifier. The information classification starts when user entering a search keyword. That keyword is then taken as an input and generates a file of tweets. The information of tweets is then passed and was saved to a persistent medium. This information is then served as an input to the classifier model. The baseline classifier used in this approach is Naïve Bayes Classifier. It classifies the tweet data into different classes that are present in the training dataset. The classifier is then used to classify unstructured data. The Naïve Bayes Classifier is used in this method because of its ease of use, simple design and ability to solve complex problems [3].

Dilrukshi [4] have proposed a method to classify news tweets into different groups so that the user could be able to identify the most popular news group in a given time. In this approach each short message was classified manually into 12 groups. Words of each short message were considered as features. Considering the features, feature vector was created using the bag of words approach in order to create instances. The data was trained using Support Vector Machine (SVM) machine learning technique [4]. The main reason for using SVM in this approach is that it supports high-dimensional data. When the data were far from linear and the datasets are inseparable, kernels are used to map the dataset into a high-dimensional space, where the new mapping is the linearly separable [4]. It creates the hyper plane between different data groups. The hyper plane is created by maximizing the margin. Margin describes the distance from the hyper plane to the closest data points.

SVM do not over generalize the problem, as it minimizes the complexity and the error. SVM do not address local minimum of the error rate. This caused an increase to the accuracy of SVM.

Lee et.al [5] has proposed a method to classify the twitter trending topics into 18 general categories such as sports, politics, technology etc. In this approach a well-known Bag-of-words approach was used for text classification. They construct word vectors with the trending topic definition and tweets. The commonly used tf-idf weights were used to classify the topics using a Naïve Bayes Multinomial Classifier (NBM). NBM considers frequency of words and can be denoted as:

$$P(c \vee d) \propto P(c) \prod 1 \leq k \leq nd\ P(tk \vee c) \qquad (2.1)$$

where P(c|d) describes the probability of a document d being in the class c, P(c) describes the prior probability of a document occurring in class c and P(tk|c) depicts the conditional probability of term tk occurring in a document of class c. A document d is trend definition or tweets related to each trending topic identified. Considering Naive Bayes Multinomial (NBM), Naive Bayes (NB), and Support Vector Machines (SVM-L) with linear kernels classifiers, the accuracy of classification is a function of number of tweets and frequent terms, the NBM has higher accuracy for snippet documents [5]. NB model always provides lower accuracy over NBM model because it models the word counts and adjusts the underlying calculations. SVM-L performs better than NB but has slightly lower accuracy compared to NBM.

B. User Interest Discovery

User interest discovery refers to the process of discovering the interest of individual users. In recent year's user interest have become an important area of research. Kywe et. al [6] has proposed an explicit user profile based collaborative filtering method, called Explicit User Profile Based Collaborative Filtering (EUCF). In this method each user is represented then by a vector. The weight of the vector is calculated by a Term Frequency – Inverse Document Frequency (TF-IDF) schema, where the TF denotes the frequency of key word in user u's user profile and IDF denotes the number of users who have used the key words. This method recommends the topics after calculating the weights of users. Although EUCF performs well, it has a significant functional limitation: as EUCF finds similar users based TF-IDF schema, the results tend to be local [1].

Lei et.al [1] has proposed a user interest discovery method based on collaborative filtering, named User Interest Discovery- Latent Dirichlet Allocation (UID-LDA). This method contains latent user profile based collaborative filtering and explicit user profile based collaborative filtering. It also considers the importance of topic key words on user interest generation. In UID-LDA, first the latent factors in the whole dataset were found and then each user is represented by a feature vector. The vectors are then considered as the user-interest distributions. The UID-LDA mines the latent relationships between users, interest and words, thus the similar users found by this method tend to be global. Moreover, UID-LDA also takes full advantage of the importance of key words when mining the latent relationships. It is identified that user interest may be varied over time. In EUCF the variation of the interest over time is not considered whereas in UID-LDA this variation is considered.

The UID-LDA model has more accuracy than EUCF model [1].

C. Event Recommendation

Event recommendation is the process of recommending events. With the advent of EBSN (Event based Social Network) event recommendation system have recently gain prevalence. Yogesh and Fang [2] has proposed a dual-perspective latent factor model for group aware event recommendation. In this system two types of latent factors are used to model the dual effect of groups: one from the user- oriented perspective (e.g., topics of interest) and another from the event-oriented perspective (e.g., event planning and organization) [12]. Logistic and Probit functions are used to model the probability of pairwise preferences that consist of observed and unobserved user feedback. The proposed model is flexible to incorporate additional contextual information including event venue, event popularity, temporal influence and geographical distance [12]. These latent group factors reduce the cold start problems, which are common in event recommendation because events published in EBSNs are always in the future and they have little or no trace of historical attendance. Additional contextual information such as event venue, temporal influence, popularity and geographical distance can be readily incorporated into the model.

Qiao et al [7] has proposed a standard matrix factorization approach, which jointly models events, location, and social relation. It present a Bayesian latent factor model that combines these data for event recommendation. Bayesian personalized ranking (BPR) is used for rating. It uses a social regularization term. This term is used based on the assumption that preference of a user is close to the average weighted preference of his friends. This approach ignores the content and organizer information of events. Cold start problem occurs in this system as new user does not have any friend.

Macedo et.al [8] proposed a context-aware approach by exploiting various information including social signals based on group memberships, location signals based on the users' geographical preferences, and temporal preferences derived from the users' time preferences. In this approach a personalized recommendation is proposed by combining these signals for learning to rank the event for recommendation. This system was proposed to use a Multi-Relational Factorization with Bayesian Personalized Ranking (MRBPR), which is a state of art recommendation system that solves the top-n

recommendation task by optimizing the personalized ranking function.

From the previously mentioned works on event recommendation, the dual perspective latent factor model provides better recommendation of events to the users than the other works. This is because, latent factors are considered in this model. This model considers pair-wise ranking instead of point-wise ranking to rank the events based on the user's interest.

D. User Recommendation

User recommendation refers to the process of recommendation of user. Xing Xie [9] has proposed a framework for potential friend recommendations which have two main key inventions:(i) the user interest is characterized in two dimensions i.e. context (location, time) and content interest, which makes the friend recommendation more real and more precise; (ii) domain knowledge can be included to enhance content interest design. Advantage: Characterizes user interest in two dimensions context and content. Disadvantage: Accuracy in acceptance of recommended friend degrades for high user base.

Nepal et al [12] have proposed social trust based model for friend recommendation which defines 'trust' between users to suggest friends. It captures the implicit trust members have towards each other as exhibited through their active as well as passive activities in the community. Social trust based model considers trust members have towards each other as shown through their behaviours in the online social community. Social Trust consists of two types of trust: popularity trust and engagement trust. Advantage: Good during boot strapping stage of the community. Disadvantage of approach is that the system gives good performance only when there are not mutual interactions in the community.

Tang et al [10] have proposed a friend recommendation tactic at micro-blog based on micro-blog user model. The main difference between micro-blog user model and traditional user model is that micro-blog user model not only covers the users' interest, but also covers the link relationship and interaction relationship between users [1]. The link relationship and interaction relationship can affect users' behaviour in online social network. The main idea of the proposed approach includes four stages: First, construction of the micro-blog user model by using the user profile, the link relationship between users, the topic membership which is calculated according to content user post and the interaction relationship between users. Second, calculation of user content similarity and link similarity based on the micro-blog user model constructed in the first stage. Third, combining the user similarity found in the second stage together in order to calculate the similarity of micro-blog user model. Finally, recommendation of friends to users by using the similarity. Friend recommendation based on micro-blog have more precision, running time and scalable [11].

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Our system aims to combine these modules to build an efficient event and user recommendation system. The existing event recommendation system considers only the interest parameters; it does not consider the date preferences of the user. This system is proposed by considering the interest preference and date preference for the event recommendation system. There are many researches carried out for recommending users to products but recommending possible users to event is less considered area. This system also aims to recommend the potential users who may attend the events to event handlers when the post the details of the event.

3. THE PROPOSED SYSTEM

Fig.1 represents the System Architecture of the event and user recommendation system. The event and user recommendation system is used to recommend the events and users. To recommend the events to users, the events and users preferences must be known. A synthetic dataset of event tweets are created. From the tweets the event details are identified. The user's preferences are retrieved from the tweets posted by the user. Then the events are recommended to the user by comparing event details and users interest preferences. This system also provides recommendation of users who may attend the events to the event handlers when he posts new events. For user recommendation, the event tweet posted by the event handler is extracted to find the event detail. Then the event details are matched with the interest preferences of the users of the system. The matched users are recommended to the event handler.

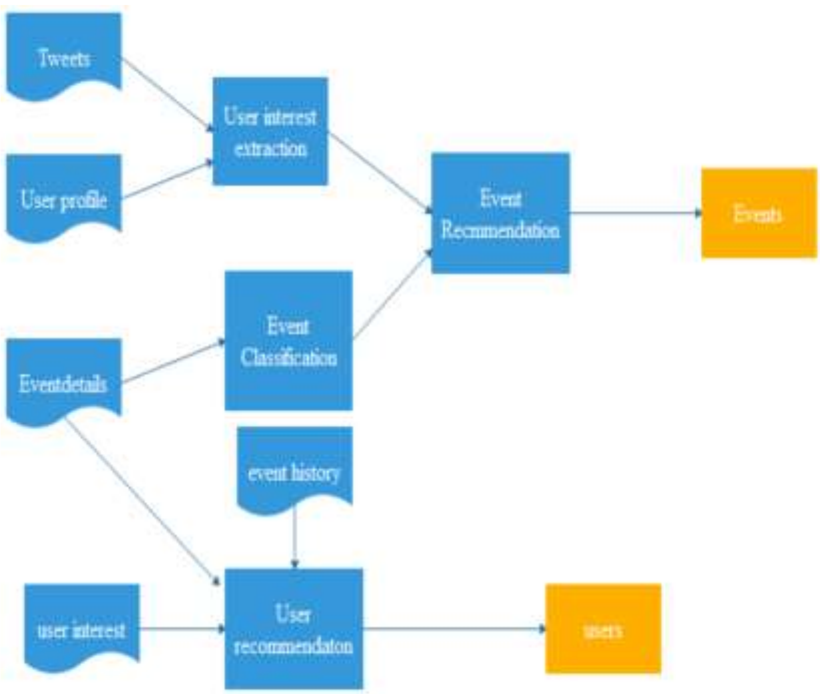

Fig.1: System Architecture

4. THE PROPOSED METHODOLOGY

This sub-section describes the procedures performed for the implementation of the event and user recommendation system. To perform the recommendation first the event tweets must be extracted. Then the user's interest must be identified. To retrieve this data we must have access to twitter. To retrieve data an app is created with twitter. After retrieving data from twitter, these data are pre-processed. From the pre-processed event tweets event category, location and date are identified. The user's interest and location preferences are identified from the tweets posted by that user. The event details and user preferences are compared to provide event recommendation. The users are can accept or reject the recommendation. The accepted results are stored by the system for future computations. For user recommendation, users are recommended to the event handlers who create events based on the event details.

4.1 Create an App with Twitter

Twitter is a micro-blogging site which provides public data for developers and researchers. In order to provide streaming tweets we have to register an app at https:/twitter.com/devices. When we register our application it provides some credentials which are used for Open Authentication by twitter. Credential includes consumer key, consumer secret, oauth access token and oauth access token secret.

consumer_key = 'uQwTEXhQRSv9EGhBVNwSzIRnN'

consumer_secret='oJURM05jel8DXc7RTNagNv5P0caQY3IACDsepOZWsLFHyMnodj'

access_token = '924324552531886082-R3fhJECstB1ye7eF7gQaRSCnstQpy7n'

access_token_secret = 'cPVlGt6bIoA3C0VZFcaE8hC85fKOh7T5Rtp1qSN9z7n5I'

4.2 Data Collection

The event details are identified from the tweets related to those events. To identify the user's interest category and location preference, the tweets of that user is extracted from twitter using the twitter streaming API. The extracted tweet set contains the tweet posted by the user within duration of 60 seconds. Only the latest tweets are considered by the system. This helps us to identify the user's interest accurately as user's interest may vary over time. To classify the events into categories, tweets corresponding to different categories must also be collected. The dataset is used for training the event classifier.

4.3 Data Preprocessing

Preprocessing deals with the parsing of JSON file and extracting entities needed for the implementation. JSON stand for JavaScript Object Notation. It is a light weight data inter change format. It is easy for machines to parse and generate the data. But parsing JSON is very slow and therefore there is a need to convert the data extracted into another format. We use csv format to store the extracted entities. For each tweet in the csv the system does the following steps:

- Tweet tokenization
- Removal of stop words
- Removal of hyperlinks
- Removal of hashtags
- Removal of punctuation
- Clean list of words

4.4 Event Details Extraction

A synthetic dataset containing a list of future events is used since, it is not possible to get future event from twitter. From the event tweets the event details such as category, location and dates are identified. To identify the event details the preprocessed tweets about the events are considered as input. An event classification approach is used to classify the events into appropriate categories. Then the location where the event occurs are identified from the preprocessed tweets. The dates of the events are also extracted from the preprocessed tweets. The event category, location and date constitute the event details.

Event Classification

The event classification is performed to classify the events into different categories. For the purpose of classification of events a Multinomial Naive-Bayes Classifier is used. A training dataset is also used to train the classifier. The training dataset contains a set of tweets for each category such as sports, music etc. In the event classification module, first the training dataset and testing dataset are loaded to the system. Then the classifier is trained using the training dataset. The classifier creates pickles based on the training. Then while classifying the events, it compares the event tweets with the trained pickle and classify the events into categories. The classifier is imported from the nltk packages. The output of the event classification is that the testing dataset will be classified into an event category.

Event Location Extraction

This module is used to extract the location of the event from the event tweets. The location of the event is extracted from the tweet using ne_chunk. The ne_chunk function classifies tokens into different entities like ‘person’, ‘organisation’, ‘location’, etc. [13]. It uses a classifier based approach and are trained on parts of speech tagged data.

Event Date Identification

This module is used to extract the date specified on the event tweets. The date extraction is done using the regular expression and strip time. The event tweets contain the date in which the event occurs. The date is extracted from the tweet using datefinder. Datefinder is a python module for locating the dates inside a text [12]. Datefinder extract all types of date like strings from a text and turn them into datetime objects. This extracts the date specified in the event tweet.

4.5 User Interest Discovery

To perform the user interest discovery, the user's profile and user tweets are retrieved from the twitter. The user profile contains the user's description and location information. From the user description the user interest is identified. For the interest discovery, first the description is preprocessed. Then the preprocessed list is then compared with the list containing interest words. If it matches with any of the interest words, that will be the user's interest. The user's interest is also identified from the tweets extracted from the user's timeline. The extracted tweets are preprocessed. The preprocessed tweets are used for the topic modeling. From the preprocessed tweets the interests are identified using topic modeling. The preprocessed tweets are considered as a document. A term dictionary is created for the directory, where every unique term is assigned an index. The lists of documents are converted into Document Term Matrix using dictionary. Then LDA is used for topic modeling. The LDA produces the main topics addressed in the tweets of the user. The topics having frequency greater than the minimum frequency are extracted. These topics are then compared with the list containing interest types. The matched topics will be added as user's interest.

4.6 Event Recommendation

The event recommendation module is used to recommend the events to the user. The events are recommended based on the user's interest, user location and the event type and the event location. In this module the pair wise learning is used over the point wise learning approach. That is the users' interest and location preferences are compared with the event type and the location of events. In the point wise learning approach only the point preference will be considered. The point wise approach will rank only the events where the event which matches the both user preferences. The pair wise approach considers the interest and location pairs. The pair wise ranking is used because it is not possible to say that a user will not attend the event whose location is not matched with the user location. There may be chances that user will travel to that location to attend the event. Thus recommending the events which matches both the user preference will not be adequate. In this approach a priority will be set for considering the user preferences. The user preferences are prioritized based on the user's interest and user location preference. That is, the events whose type and location are matched with the user's interest and location will be scored high. Then the events with only user location is mismatched are considered later. The users may attend the event occurring in the nearby location. Thus the distance between the user location and event location is identified. The events nearer to the user are also located to the user. The users may attend the events which are in the user location. Thus, the events in the user location are also considered. The user history is also considered to provide more accuracy in the scoring. The users are provided with a provision to either accept or reject the recommendations. The accepted events are stored in the user's history. These histories are also used for further scoring. The event venue score is calculated from the event related history. The number of users accepting the events on that venue is identified to compute the event venue score. After the scoring of all the events is done the system performs the pair wise ranking between the events to rank the event.

The system then fetches the current date. It then identifies the next k days. The dates of the ranked events are then compared with the extracted dates. The events whose dates matched with the dates extracted are only recommended to the user.

Pair-wise ranking

The pair-wise ranking approach to learn the preferences of the users on events. Formally, given a user u, if item is preferred over item j, we have a preference instance (u, i, j) = Ds where is whole set of preference instances [2]. s(u, i) represent the ranking score of event i of user u and denote:

$$x(u, i, j) = s(u, i) - s(u, j) \tag{4.1}$$

4.7 User Recommendation

In the user recommendation module an event handler provides an event to the system. It then recommends the interested users to the event handlers. The event handlers can use this recommendation identify users who are interested in attending the event. This will help the event handlers ensure the participation of the users in that event. To perform this operation the type of the event category and the location of the event are identified. The event category and the location are compared with the user's interest and location preferences. The users whose interest preferences matched with the event category and location are recommended to the event handler. The event handler is provided with the provision to either accept or reject the recommended users.

Event Category identification

The system first preprocesses the event specified by the event. The preprocessed event is then compared with the set of existing event types and identifies in which type the event it belongs to. The words represented in the event details can be used to compare with the list containing the words and the event type. From this the event category is identified.

Event Location identification

In the user provided event details the location of the event will be specified by a hashtag. The hash tagged elements are extracted from the event details. The extracted elements are then compared with the list containing the locations. This then identifies the location of the event.

Recommendation

The event category and the location are compared with the user's interest and location and then provide the recommendations. In this process also a pair wise ranking approach is used to rank the users. The events rank score on each user will be based on the user interest and user location. The users whose interest and location that matched with those events will have the highest score. The users whose interest is matched will have the next high score. The user's whose location is matched is also considered. After that score of each event is calculated. The recommendation is done in the pair-wise ranking approach. In which the score of each user is compared with the score of each other users. The top n ranked users are recommended to the event handlers. The event handlers can either accept the given recommendation or reject the recommendation. The accepted recommendations are stored in the history for the future computation.

5. EXPERIMENTAL RESULTS

The Event and User Recommendation system provides two types of recommendations. First one is the event recommendation which recommends the list of interested events to the user. Second one is user recommendation which recommends the users who may attend the events provided by the event handler.

5.1 Event Recommendation

In event recommendation system, it recommends the events to the users based on their interest parameters. The system allows users to accept or reject the recommendations. The accepted recommendations are stored in the history along with its location. This history is also used for further recommendations to provide better recommendation. When a user is logged into the system it computes the user’s interest and location preference from twitter data. For providing the recommendation, the system first computes the current date. The system then identifies the next 7 dates. It then retrieves the events occurring on these days. Based on the user’s interest and location preferences events occurring on these days are recommended to the user. The system computes the recommendation by providing scores to the events based on the user’s preferences. The events listed will be in the ascending order of score. Table 1 shows the recommended events for a user whose interest is ‘digital marketing’ and location is ‘ernakulam’.

Recommended Events
'AIMA LMA SUMMIT & NATIONAL MANAGEMENT CONVENTION –digital marketing -business -entrepreneurship #Kochi 12 Apr 2018 - 13 Apr 2018 10:00 AM onwards'
' National Digital Marketing submit on 12 Apr 2018- 16 Apr 2018 Venue #Trivandrum'
'Boot Camp on Digital Marketing April 16 2018 - April 27 2018 AVIV DIGITAL #Ernakulam'
' NLP SALES Mastery Time Fri Apr 20 2018 at 04:00 pm Venue #Ernakulam'

Table 1: Recommended events for the user whose interest is “digital marketing” and location is “ernakulam”

5.2 User Recommendation

The user recommendation system is used to recommend the list of users who may attend the event specified by the event handler. When an event handler provides an event to the system, it recommends the list of users who may attend the events. The event handler has the provision to accept or reject the users. The accepted users are stored in the history for future computations. That is, when an event handler is again logged into the recommendation system, he has the provision to provide an event details. The system then identifies in which category the event belongs to. It also finds the location where the event occurs. It then identifies the users whose interest matches with the event category and also whose location preference matches with the event location. The previous history can also be used to identify the users who may attend the event. The users whose interest and location matched with the event category and location have the highest score. The users whose interest only matched with that of the event category have the next score. The users whose location only matched with that of the event location have the next score. All the ranked users are considered and users with highest rank are recommended. Table 2 shows the recommended users for a event handler who posted an event “AIMA LMA SUMMIT & NATIONAL MANAGEMENT CONVENTION –digital marketing –business -entrepreneurship #Kochi 12 Apr 2018 - 13 Apr 2018 10:00 AM onwards”

Recommended Users
vishnum
Sabuakpachu
Shijualex
Rahulmanthattil
j0banj0hn

Table 2: Recommended Users to event handler

5.3 Result Analysis

This section shows the various analyses performed for the Event and User Recommendation System. First the accuracy of the event recommendation system is computed by using the implicit and explicit feedbacks obtained from 50 users of the system. Then the MAP of 10 users is calculated for 3 time interval to identify for which time interval the events should be recommended. That is, we consider 7 days, 14 days and 30 days as time interval. The number of users to be recommended to the event handlers in user recommendation is evaluated using precision. The analysis is done by evaluating the dataset of recommended events with respect to that of the accepted events. The recommended dataset constitute the recommended list to the user and the accepted dataset contains the accepted list by the user.

5.3.1 Comparison: Implicit vs Explicit feedbacks of users for event recommendation

The overall system performances are evaluated using the implicit and explicit feedbacks of 50 users. These 50 users are different in some attributes like age, job, gender, location and interest. Implicit feedbacks are collected from the system itself and the explicit feedbacks are collected manually. Fig.2 shows the implicit feedbacks obtained by the event recommendation system.

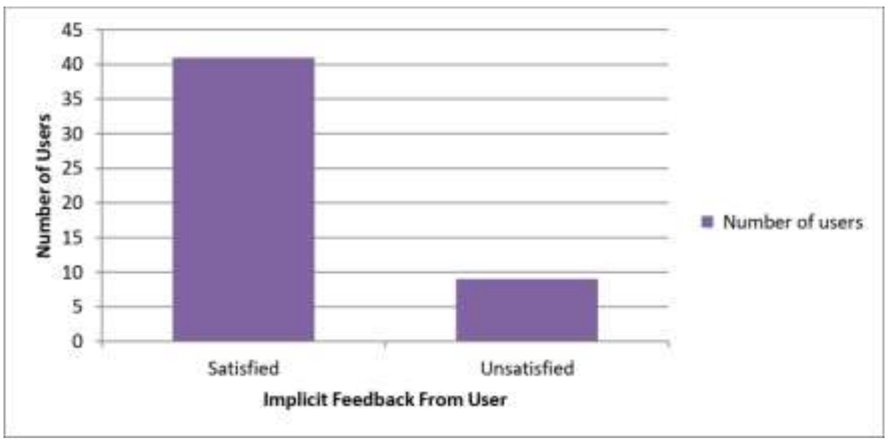

Fig.2: Implicit Feedbacks from Users of Event Recommendation System

Fig.3 explicit feedbacks collected from 50 users of the system. The accuracy of the system is obtained by evaluating both the implicit and explicit feedbacks, which is shown in Fig.4.

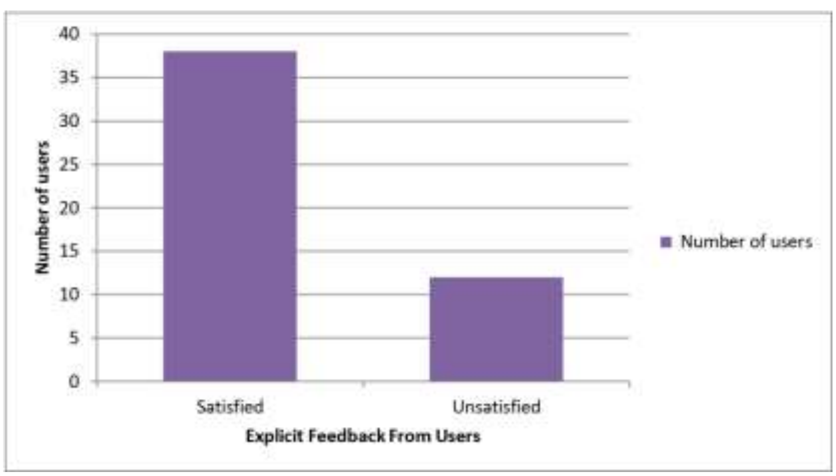

Fig.3: Explicit Feedback from Users of Event Recommendation System

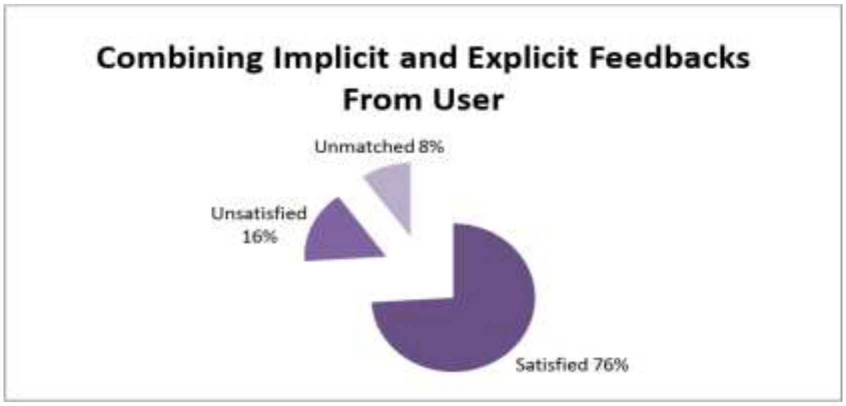

Fig.4: Accuracy of the event recommendation system based on Implicit and explicit Feedbacks

5.3.2 Analysis to compute the time interval for event recommendation

The event recommendations are done for a certain time interval. That is for a period of 7 days, 14 days, 30 days etc. In the 7 days interval the events occurring from the current date to the next 7 days are recommended. For the 14 days interval the events occurring from the current date to the next 14 days are recommended. For 30 days interval the events occurring from the current date to the next 30 days are recommended. Here MAP method is used to evaluate the precision for 10 users to identify which time interval is more preferred by the users. To calculate the MAP value of users for each time interval, the AP of each user for each time interval should be calculated. The table 5.3 shows the AP value of 10 users for the time intervals 7 days, 14 days and 30 days.

The MAP value for each time interval is the average of the AP values of all the users for each time interval. The Fig.5 shows the MAP for each time interval. From the figure it is identified that the MAP is higher for the time interval 7 days. As the users are surer to attend the events within an interval of 7 days, than the interval with higher days.

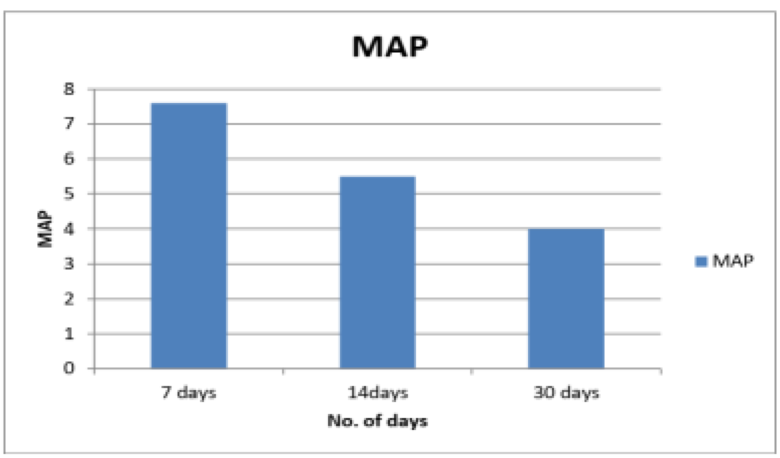

Fig.5: MAP value for users for different time interval

5.3.3 Comparison: Implicit vs Explicit feedbacks of event-handlers for user recommendation system

The overall system performances of user recommendation system are evaluated using the implicit and explicit feedbacks of 50 event-handlers. These 50 event-handlers have posted events in different categories. Implicit feedbacks are collected from the system itself and the explicit feedbacks are collected manually.

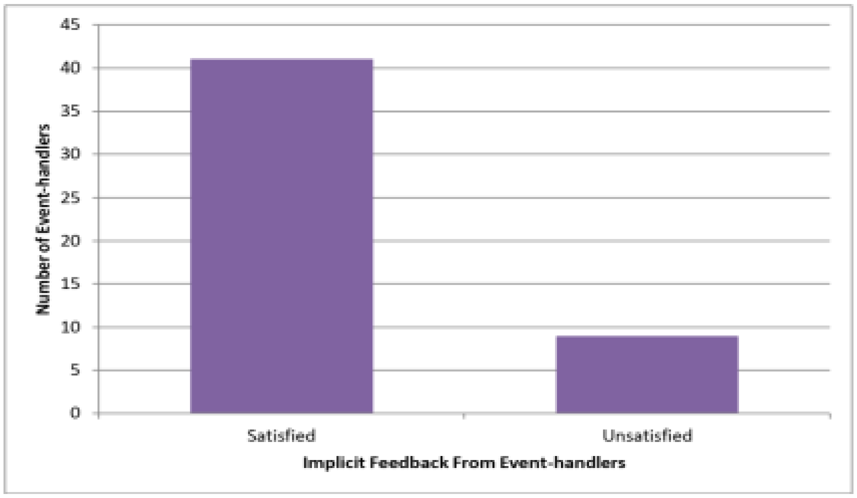

Fig.6: Implicit Feedbacks from Event-handlers of User Recommendation System

Fig.6 shows the implicit feedbacks obtained by the user recommendation system. Fig.7 explicit feedbacks collected from 50 event-handlers of the system. The accuracy of the system is obtained by evaluating both the implicit and explicit feedbacks, which is shown in Fig.8.

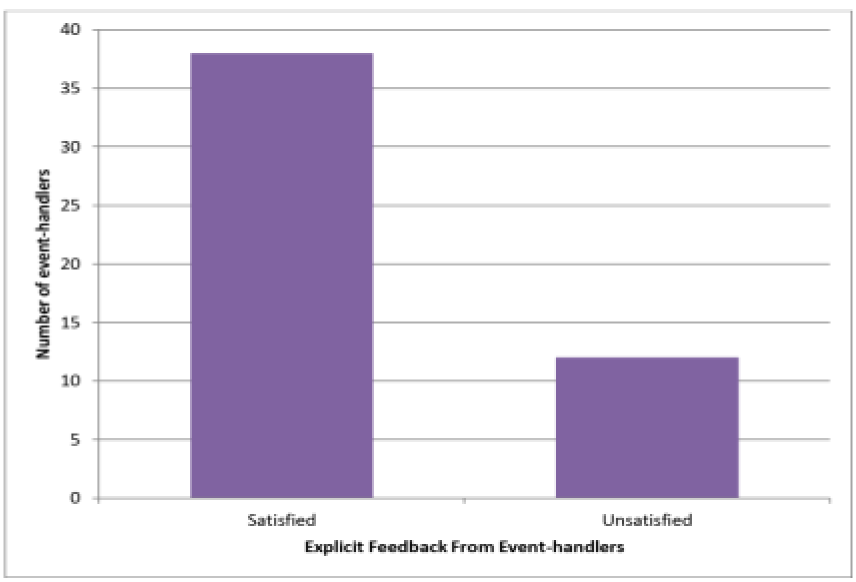

Fig.7: Explicit Feedback from Event-handlers of User Recommendation System

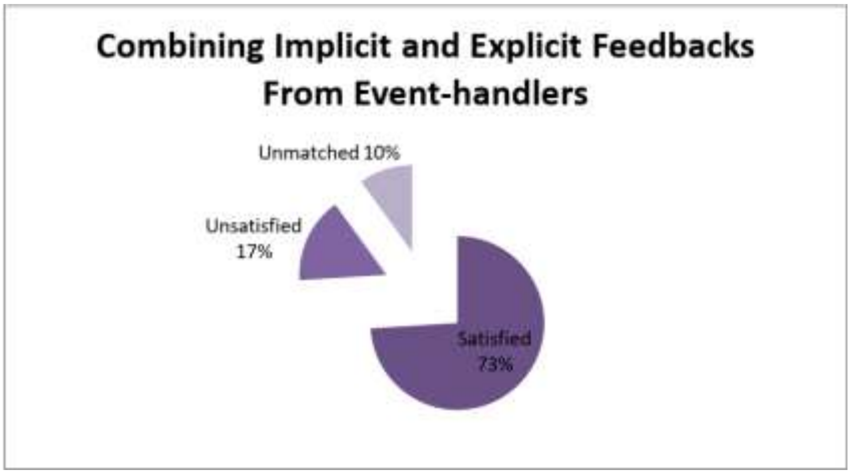

Fig.8: Accuracy of the user recommendation system based on Implicit and explicit feedbacks

6. CONCLUSION

A Dual perspective Event and User Recommendation System is developed to provide event recommendation to the users and user list recommendation to the event handlers. Initially a synthetic dataset containing future events are considered. A synthetic dataset is used because we cannot get the list of future events for a country like India. We cannot get data from twitter as twitter usually contains the details of events that occurred in the past. For a country like America we can get the dataset from the meetup. The user's interests and location preferences are obtained from the twitter to provide personalized recommendations. The user communities are also detected to group the similar users. Then the system recommends the events to the users based on their interest and similar users' interest. This system also recommends the list of interested users who are most likely to participate in that event. This system stores the recommendation, which is used for further recommendations.

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