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Learning Recency and Inferring Associations in Location Based Social Network for Emotion Induced Point-of-Interest Recommendation

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The rapid research on the traditional recommender systems has proved the usefulness of the decision support tools on various real-time applications. In the recent years, hybrid recommendation models have become more popular due to its increased efficiency to manage the information overload problem. The context-aware location recommendations based on user's emotions improves the user satisfaction levels, but still the emotion based recommendation models are not explored completely due to the real-time issues in the acquisition of the user's emotions. This article presents an effective recommendation model for the location recommendation through exploiting the emotion of the user from online social media. In the proposed model, User, Point-of-Interest and User's Emotion during travel are the three main factors taken into consideration to generate recommendations. The proposed location recommendation models correlate the positive and negative impact of the user's emotions to generate the list of user relevant locations. The developed models are evaluated on the large-scale real world datasets and obtained results were compared with the existing baseline models. The presented results prove the improved efficiency and accuracy of the proposed location recommender system through validation by standard evaluation metrics.

Keywords: recommender systems, travel recommendation, location-based services, emotion analysis, emotion-aware, social networks, human-computer interaction

1. INTRODUCTION

The emergence of the location-based services has created a sophisticated living style of mankind in the recent years. The usage of the social media has extended to the Location Based Social Networks (LBSN). The familiar LBSNs include Facebook, Yelp and Foursquare. The LBSNs helps users to explore locations which are technically termed as Point-Of-Interests (POI) and these POIs are mostly, locations of people's interests such as restaurants, clubs and entertainment hubs. LBSN helps users to share their opinions and experience on the POIs they have visited, which will be helpful to the new visitor to the particular POI. LBSNs generally provides a check-in facility to the users during visit of POI, rating options to rate the POI and its services and finally reviewing facility to describe the likes and dislikes of the visited POI. This article considers the every POI as a business entity and compares the Quality-of-Service with the users' emotion after the visit at the POI. The LBSN data is exploited by Recommender Systems (RSs) and generation of personalized recommendations can benefit both users and POIs

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through enhanced satisfaction and better experience to the users and attract more relevant customers to the POIs. It is to be noted that users are interested to the POIs with higher check-ins and ratings. A half a point extra rating can make huge difference in the customer attraction and business turnover. Thus reputation of POIs and needs for personalized recommendations has became a hot research in the LBSN applications.

Conventionally, any POI recommender system developer can adopt traditional recommendation models by considering POIs as regular items [33]. Therefore, there are many existing base models are available such as model-based [9], neighborhood-based [20] and collaborative filtering based [16]. The existing models are based on the user-POI rating matrix, which is used to compute the similarity between the user and POIs. Rating score represents the preference score of user to particular POI. We argue that simple similarity calculation between user and POI through user's ratings and POI's ratings cannot give exact preference score on different changing contexts of the users. User's rating behavior and user's contextual information has not been investigated and modeled.

Generally, every user is different with their tastes on the locations/POIs through their context based preferences. Hence to be more personalized to the user preferences, the proposed recommendation model should be a context-aware to learn the behavior of the user based on his historical travel till the moment of recommendation. The different context information of the users comprises of time, activity, location, weather and emotion. Some existing recommendation models has employed hybrid context to generate suggestions. Since POI recommendation has direct association with the emotional context of the user, the emotional state of the user can be exploited to generate user specific list of POIs. User's emotion state is the secondary contextual information which cannot be directly measured but it can be derived from other contextual data of the user [1]. The collection and processing of the user's emotional state to make recommendations is a challenging task. To be specific, there is no existing work to demonstrate how user's emotional state makes an impact on the user's POI preferences and variation in performance of recommendations while incorporating user's emotion.

In this article, the emotional context of the user about the POI is extracted from the social media post and the user' review about the visited POI. The prevalence of the social media, LBSNs and smart phones has become a part of people's daily routine. People frequently share what they see, feel and think immediately to the social media world. With the assumption that social media can reflect the user's current emotion regarding the POI and location, we propose a context-aware location recommender system based on the user's emotions exploited from the LBSNs. To validate the performance of the proposed location recommender system, we conduct experiments on large-scale real-world data set from Yelp and TripAdvisor. The experimental results reveal that integration of user's emotions with recent timing improves the performance of recommendations appreciably. This work paves a new path to exploit the user emotion and time context to generate POIs as recommendations.

The remainder of the article is organized as follows. The next section discusses several existing POI recommender systems and other related works. In section 3, the problems taken into consideration for this article are explained. Section 4 introduces our proposed system. In sections 5, the proposed system is presented in detail and the experimental evaluation and obtained results with the discussion are presented in the section 6. Finally, section 7 concludes the article with summary and directions for the future work.

2. RELATED WORK

Among various research domains of recommender systems, tourism and travel planning is considered to be very interesting and become increasingly popular due to its commercial value [3]. The real-time problems of the tourism domain are unique and it has its own characteristics to be considered as novel problems while developing a travel recommender system [23]. Ricci has already affirmed the needs and requirements of the recommender systems in the travel and tourism domain [27]. Ricci gave a clear idea that knowledge-based and content-based systems are considerably apt to recommend travel destinations. The knowledge on the previous travel of the users is exploited by the case-based reasoning model to offer travel recommendations to the users [28]. Personalization is a unique challenge of travel recommender systems as every user has personal preferences along with specific limitations on distance of travel and budget for their needs towards recommendations [6].

The recent popularity of smart mobile devices has attracted many researches to the development of POI recommendation applications. A location and POI is similar in our research context and we use it interchangeably. Traditional Collaborative Filtering (CF) models have been deployed to POI recommender systems by considering POI as a normal item [33]. Further, emergence of LBSN has explored fresh opportunities of utilizing social connection [5, 21], geographical location [4, 22, 34], POI description [19, 35] and temporal information [11, 32, 36] of the users to make recommendations list. Ye *et al.* observed an availability of strong social and geographical attachments between users and their preferred locations through a conventional neighborhood based CF model for computing similarity between social and geographical information of the user [33]. Ye *et al.* has proposed a combinational POI recommendation model by integrating the geographical and social information through naïve Bayesian and modeling of geographical influence is done by power law distribution [34]. The probability of user's historical check-ins is modeled by multi-center Gaussian model and later combined into MF to generate POI recommendation [4]. The location preference of the users in LBSN is explored by geographical probabilistic factor and LDA embedded Topic-Location PMF models developed by Liu [21, 22]. LDA model is further extended as LCA-LDA to consider local preference along with user's interests for POI recommendation [35].

Integrating the crucial information from LBSN has considerable importance in making personalized POI recommendations. Yuan *et al.* proposed a location recommendation model that incorporates temporal data from LBSN as contextual information with the user-based CF [36]. Gao employed MF to model user's time preference based on consecutiveness and non-uniformness properties [11]. The modeled changing temporal preferences of users are integrated with the traditional CF for recommendation [14, 17]. Yang *et al.* exploited utility theory to explore user behavior with the generated recommendations [31].

There are several existing studies to exploit sentiments from the reviews to enhance ratings in CF recommender systems [2, 9]. Ganu *et al.* developed an enhanced model through influencing the sentiment and topic information at sentence level [10]. The estimation of ratings is computed from the text comments of the users in a multi-point rating scale. A probabilistic sentiment inference based recommendation framework is presented by Leung [18]. To compute orientation of sentiment in reviews, they had applied natural language processing techniques and they inferred ratings using Naïve Bayes classifier. The inferred ratings from reviews are integrated along with the sentimental knowledge to enhance the quality of recommendations [24, 30]. The work of Peleja *et al.* has employed Bernoulli classification algorithm to calculate ratings from the reviews and to generate recommendations, matrix factorization has been applied. Garcia *et al.* exploited microblogging posts of the users to generate recommendations [12]. In their work, the user's posts are indexed to create a user-item profile and the built profile is used to retrieve pertinent items to the user. Similar study is done by He and Tan by presenting a personalized recommendation model for blogs [15].

Similar to sentiment, there are existing studies to demonstrate the significance of emotions in the generation of recommendations [7]. The current emotion of user can be a supporting vector to generate personalized recommendations. Han *et al.* presented a context-aware recommendation framework which utilizes the current emotional state of the user to generate recommendations [13]. To differ from other work, we consider temporal and emotional context to represent user's short-term information which can portray a better user preferences. Based on the comparison of the proposed study with the existing works, the user's changing preferences are also considered along with the complete rating vectors. The abundant information available in the LBSN helps in modeling the user preferences and we incorporate user's current emotional context to the user preference model to generate recommendations. To the best of our knowledge, there is no existing works on temporal and emotion based user preference model to generate POI recommendations.

3. RESEARCH PRELIMINARIES AND EXPLANATIONS

POIs and Check-ins are basic building blocks of LBSNs. POIs are particularly known as location of user's interests by which it is described using location and content labels. The geographical location of the POI is described using location label and where as other characteristic features of POI is described by content label. During the check-in of a user at particular POI, the feedback such as rating and reviews from user is obtained with respect to visited POI. The information tagged by content label may be further used by RSs to make recommendations for new visitors of the particular zone. The LBSN induced recommendations will be almost personalized due to enhanced similarity between user and POI. The location information can be efficiently used to rank the POIs based on geographical details. In this section, we deeply explain the preliminaries required to understand the remainder sections of this article.

3.1 Location Based Social Networks

Location Based Social Networks are the extension of Online Social Networks (OSNs) with hybrid capabilities to virtually represent the physical world or real world and Fig. 1 depicts the associations in LBSN. With entry of Google in to the play as Google+, the grounds are busy with other familiar players such as Facebook and Foursquare. Among all LBSNs, Facebook as more number of user base and check-ins and Foursquare has its own set of users and it has more POIs with its service extensions. LBSNs are mostly dependent of smart mobiles which capable of sharing user's current

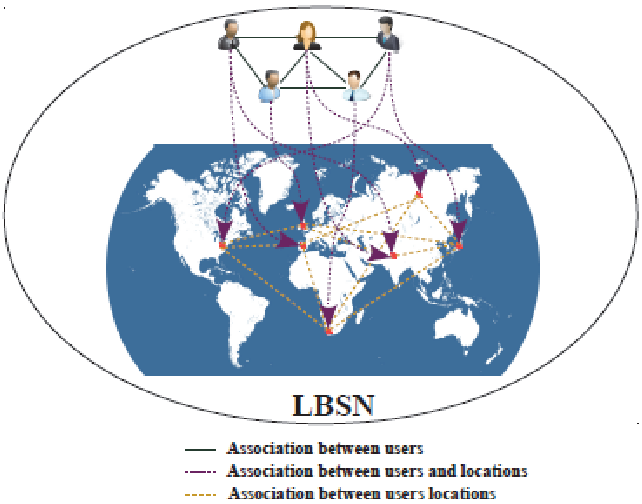

Fig. 1. Various associations in LBSN.

location using built-in GPS module. With the help of GPS and internet connectivity, a user can record their presence at a particular POI is familiarly known as check-in and this activity is shared between the friends and connected circles of OSNs. Though a check-in is combination of geographical co-ordinates, it is shared as a semantic entity to the friends circle. The semantic representation of the location is identified with the name of the venue which nothing but the name of the POI. The data available of the LBSNs with combination of other features can be developed as third party applications. Uber is the best successful third party application based on LBSN data.

3.2 Behavior in Location Based Social Networks

Identifying the behavior in the LBSN can help the analyzing application to investigate the power of available information. The information available on the LBSN can be classified into four major sets of attributes, such as, user, venue, social and content attributes. The user attributes is characteristic set of user behavior in the LBSN which consists of list of venues, reviews, ratings *etc.* The venue attributes is relevant to POI/location with the properties set containing the total number of check-ins, ratings for the venue, reviews, likes and dislikes. The social attributes generally represents the connections of the user in the social network. Finally, content attributes represent the properties of the review and other text available in the LBSN. The organization of the content is done based on the analysis of the text for supportive or offensive words. Content attributes of LBSN data includes the number of views, number of responses, likes and dislikes. These sets of characteristic attributes of LBSN can help decision support systems to make personalized recommendations with more relevancies to the user.

3.3 Sentiment Analysis for Recommendation

Computational models are becoming more powerful to generate personalized recommendations through incorporating the social interactions of the users. Sensing user emotions for better assessment of feelings to understand and predict behavior has attained significant importance in the affective recommender systems. Contextual information is very mandatory for any computational system to understand the needs of the user and to provide quality recommendations. The combinational research on connectivity between human science and social studies using computers and its resources has become more popular. The user data available on OSNs and LBSNs are very large in volume and more rewarding in nature. The affective content from the social networks can be mined using sentiment analysis techniques which can be further used to make recommendations to the users. Generally, the sentimental analysis techniques classify the content into polarity categories (*i.e.* positive and negative) based on the classifier used. Lately, based on the results obtained from the classifier, the recommendations are generated to the users. The recommendations of the Sentiment-Aware recommender systems have better performance over traditional models. It is to be noted that the information from the social networks may be affective but the classification of the sentiments from binary state should be extended. Additional classifications other than positive and negative can improve the granularity of sentimental analysis.

4. PROPOSED EMOTION-AWARE LOCATION RECOMMENDATION MODEL

Our proposed emotion-aware location recommendation model comprises of three major segments namely, pre-processing, prediction and recommendation. The clear organization of proposed model is depicted in the Fig. 2. In the first segment the complete visited venues of all users and the OSN posts within a time lime analyzed for the extraction of emotional context. In the second segment, the current emotional context of the user is obtained and makes a list of POIs relevant to the user. Finally the recommendation segment, organize the predicted list of POIs and generates list of most appropriate list of POIs to the user based on user's historical behavior.

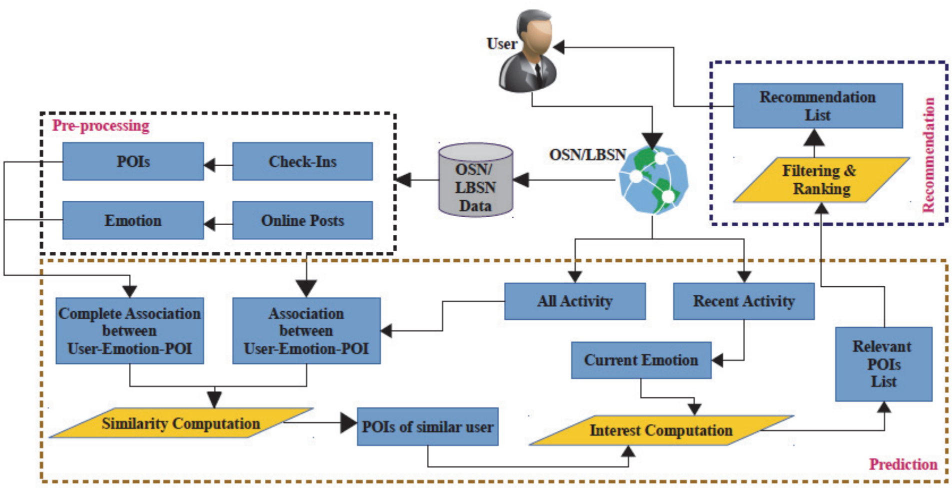

Fig. 2. Proposed emotion-aware location recommendation model.

4.1 Pre-Processing

The main aim of this segment is to mine the association between user, POI and emotion. As the initial step, an absolute emotional context lexicon is constructed through utilizing the existing resources. Then, the OSN/LBSN posts with the emotion words are represented with emotional vectors. Finally, the relationship between the user, POI and emotion is formed and represented as a three element tuple within a time window. Emotions are of different granularities and act as an intermediate element between user and POI in the three element tuple.

4.2 Prediction

The prediction segment of the proposed emotion-aware location recommender system is used to organize the relevant list of POIs to be recommended to the user. The prediction process is based on the historical bonds between user emotion and POIs along with the OSN/LBSN posts. To make recommendations for the particular user, the proposed model will study their recent online posts and extract the current emotion as a context. Then the users with the similar location preferences based on similarity with the target user are sorted. The sorting of the users is based on both user similarity and emotional context similarity. Then a list of most relevant POIs based on sorted list of users is created as a result of this segment.

4.3 Recommendation

The recommendation section manages to make list of locations/POIs as recommendations to the target user. An appropriate list of POI is generated based on the user's historical behavior. Normally, in the recommended list of locations, the POIs of the similar users with the similar emotional context were highly ranked and given more preferences. Finally, location context is also considered to sort out the POIs which are out of threshold distance of travel. The organization of the recommendation list is more personalized to the user and capable of having more successful check-ins with enhanced satisfaction levels.

5. LOCATION RECOMMENDATION ENGINE

The location recommendation engine based on emotional context is introduced in the former section and this section gives detailed information on the working of proposed model.

5.1 Pre-Processing Segment

This segment of the location recommendation engine mines the emotion of the user from the OSN and LBSN posts and computes the connection between the user and POIs based on the emotional context.

(A) Classification of user emotion

OSNs and LBSNs has become more prevalent in people's life and sharing of information such as opinions, news, current status and other resources has happen to be the part of their activities. This results in the utilization of user's contextual information from social network to infer user's interests. In specific to this domain of research work, users make their check-in at POIs and share their feelings about the location as a status posts with in a threshold time of their visit. The proposed model exploits the association between the users, status posts and POIs to make a strong indication of user's current context as preference for recommendations.

Generally, the user's social network posts including status can be classified into ordinary and location sharing type. Ordinary posts are the generic information about user's feelings and opinions with a time stamp, where as location sharing posts include the location information along with them. There is a correlation between the user's location and their posts on the social networks. To be in clear, user's current location can make an impact over behavior of user while making a social network posts. Classification of user's emotion mined from social network post is a most significant task. Our emotion classification system is based on the classical psychological research by Ekman and Davidson [7, 8]. According to their research, emotions can be classified into different granularities such as 2d, 7d and 21d as shown in the Fig. 3. We have also pre-classified Bag of Words to make a fine extraction of emotion from the social network posts of the users. Based on the created emotion lexicon, the words with emotional context are counted for its occurrence in the post's text.

(B) Algorithm for Lexicon based Emotion Analysis and Classification

```
Input: Social network post p, Emotion Lexicon EL, Negative mood words set NEG
Output: emotion score E_Score of p
Initialize NEGA=−1;
Split p into sen;
For every sen in p do,
    Segment sen into w;
        For every sen in p do,
            if w∈EL then,
                E_Score=E_Score+Rank_Score(w);
            if w∈NEG then,
                NEGA=NEGA+2;
        end For
        If NEGA is ODD then,
          E_Score=−E_Score/2;
end For
return sum of E_Score;
```

We introduce a lexicon based emotion classification algorithm for social network post, which analyses the positive and negative words of the posts based on the lexicon constructed. In the above algorithm, the social network post p is split into sentences s with respect to punctuations used. Every sentence is analyzed for the emotional context and emotion score *E_Score* is computed with the help of created emotion Lexicon *EL*. When the negative words count *NEGA* in the sentence turn to *ODD*, the *E_Score* is reduced to −*E_Score/*2 to mark the negative mood of the user. From the sum of *E_Score* the social network post can be classified. When the sum *E_Score* is above 0, the post is tagged as positive and when sum *E_Score* is less than 0, post is termed as negative. The emotion classification algorithm is power with the psychological emotion lexicons.

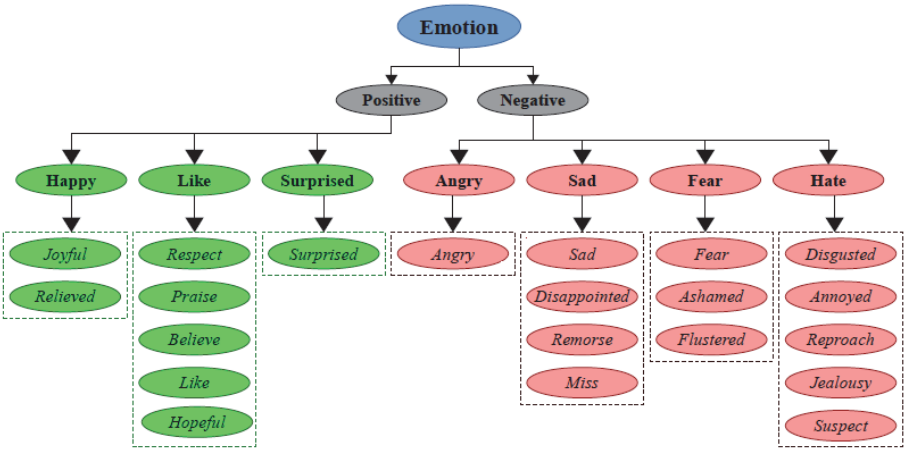

Fig. 3. Classification of user emotion into 2d, 7d and 21d.

(C) Relationship between user and location based on emotion

When user makes a check-in at a venue with a time stamp, it reflects user's connection with the location. To discover the emotion of the user, the social network posts before the check-in at a venue is taken into consideration to make a prediction. To make analysis of emotions, recency is a key factor to be considered. So, the time window for the posts has been set to collect the qualified recent posts of the users. After processing of the social network post, emotional context is identified and represented as emotion vectors of recent time. The associated data is represented by three element tuple of user, POI and emotion for further processing.

5.2 Prediction Segment

As the next segment in the proposed location recommendation mode, prediction segment deals with the process of mining user's current emotion, similarity computation, current interest computation for target user and forming relevant list of POIs. We propose three different models as the extension of traditional CF methods.

Our proposed models, user's social network activities as status sharing and check-ins are mined first to extract the current emotion of the user through proposed lexicon based emotion analysis and classification algorithm. Then similarity between target user and other users are computed based on their digital foot prints available. Then the similarity emotional contexts of the similar users are analyzed to compute enhanced similarity. It can be noted that users with similar emotion after visiting the venue are more similar than the users visiting a venue with different emotion. For an example, three users *x*, *y* and *z* visit a venue *ven*, after the visit *x* and *y* is very much satisfied at *ven*, where as *z* is unhappy with the same *ven*, then *x* and *y* are said to be with the same taste compared to *z*. Then based on the user similarity top-n similar users list is generated and these users are analyzed for similar emotional context to obtain similar POIs list. Based on the above depicted procedure, we introduce three emotion based location recommendation models.

(A) Emotion Induced User-based Collaborative Filtering (EIUCF)

The proposed EIUCF is the extension of traditional UCF model proposed by Resnick *et al.*, which computes the weights for users based on computed similarity [26]. Then similar users are formed as a subset of global users set and further treated as neighbors. The target user's interest prediction is done by considering the ratings of similar users (*i.e.*) neighbors. In order to incorporate emotion into the traditional model, modifications are made to obtain improved results. Initially, emotional context vectors are used in the computation of similarity between users. The computation of the user similarity is done as follows:

$$similarity(tu, au) = \frac{\sum_{poi \in POI_{tu} \cap POI_{au}} \cos(e_{tu\_poi}, e_{au\_poi})}{\sqrt{|POI_{tu}| \times |POI_{au}|}} \tag{1}$$

Here, *tu* and *av* are target and other similar users in the dataset. POI_{tu} and POI_{au} is the set of visited locations by *tu* and *au.* Emotional context of the user *tu* is represented by e_{tu_poi} during the visit of *poi* and e_{au_poi} is the emotional context of *au*. Cosine similarity is computed between the emotion vectors through $cos(e_{tu\_poi}, e_{au\_poi})$.

Then, the current emotion of the target user *tu* is taken into consideration during the prediction of recommendation. The predicted relevancy between the target user and particular poi of the set is computed as follows:

$$prediction(tu, poi) = \sum_{au \in U_{tu,n} \cap U_{poi}} similarity(tu, au) \times \cos(ce_{tu}, e_{au\_poi}) \times \omega \tag{2}$$

Here, *tu* is target user and *au* is other user in the similar users set $U_{tu,n}$. U_{poi} is the set of users visited *poi.* ce_{tu} is the current motional context of the target user *tu* and e_{au_poi} represents the emotional context of user *au* during the visit of *poi*. ω is the weight used as a tuning parameter based on *E_Score*. This emotion based location recommendation model predicts relevant lists of POIs visited by the similar users with similar emotional context of the target user.

(B) Emotion Induced Item-based Collaborative Filtering (EIICF)

The proposed EIICF is the extension of traditional ICF model proposed by Sarwar *et al.*, which computes the similarity between POIs similar to EIUCF [29]. Then similar POIs of visited locations of target user is recommended. In order to include emotion into the traditional ICF model, modifications are made to obtain improved results. Initially, emotional context vectors are used in the computation of similarity between POIs. The computation of the user similarity is done as follows:

$$similarity(Xpoi, Ypoi) = \frac{\sum_{user \in USER_{Xpoi} \cap USER_{Ypoi}} \cos(e_{user\_Xpoi}, e_{user\_Ypoi})}{\sqrt{|USER_{Xpoi}| \times |USER_{Ypoi}|}} \tag{3}$$

Here, *Xpoi* and *Ypoi* are Point of Interests. $USER_{Xpoi}$ are the set of users who visited

Xpoi and $USER_{Ypoi}$ are the set of users who visited *Ypoi*. e_{user_Xpoi} is the emotional context of the *user* while visiting the *Xpoi* and e_{user_Ypoi} is the emotional context of the *user* while visiting the *Ypoi*. Cosine similarity is computed between the emotion vectors through $\cos(e_{user\_Xpoi}, e_{user\_Ypoi})$.

Then, the current emotion of the target user *tu* is taken into consideration during the prediction of recommendation. The predicted interest of the target user with respect to the particular *poi* of the set is computed as follows:

$$prediction(user, Xpoi) = \sum_{Ypoi \in POI_{Xpoi,n} \cap POI_{user}} similarity(Xpoi, Ypoi) \times \cos(ce_{user}, e_{user\_Ypoi}) \times \omega \quad (4)$$

Here, *user* is target user and $POI_{Xpoi,n}$ is top *n* similar *poi* to *Xpoi*. POI_{user} is the set of *poi* visited by *user*. ce_{tu} is the current motional context of the target user *user* and e_{user_Ypoi} represents the emotional context of *user* during the visit of *Ypoi*. ω is the weight used as a tuning parameter based on *E_Score*. This emotion based location recommendation model predicts and recommends list of POIs similar to the visited POIs of the target user.

(C) Hybrid Collaborative Filtering

To attain maximum efficiency of the proposed models, we tried to combine the EIUCF and EIICF as a separate model. This hybrid approach uses the predicted interests from EIUCF and EIICF which is based on user's current emotional context. The predicted interest of the target user with respect to the particular *poi* of the set is computed as follows:

$$prediction(user, poi) = \alpha \times prediction_{EIUCF}(user, poi) + \beta \times prediction_{EIICF}(user, poi) \quad (5)$$

Here, $prediction_{EIUCF}(user, poi)$ is the *user* interest computed for poi by EIUCF and α is its corresponding weight. The user interest computed for *poi* by EIICF is represented by $prediction_{EIICF}(user, poi)$ and β is its corresponding weight.

The combinational principle of this hybrid model has highest probabilities of user acceptance ratio and the recommendations have more correlations to the target user and their current emotional content.

5.3 Recommendation Segment

The recommendation section manages to organize most relevant locations/POIs as recommendations to the target user. An appropriate list of POI is generated based on the user's historical behavior.

Normally, the POIs predicted based on the interests of the similar users with the similar emotional context were highly ranked and given more preferences. But accessibility of the POI may be barrier due to user's current location and distance between current location and POI. The proposed algorithm solves the problem through considering the location context and removes the POIs which are out of threshold distance of travel. This organization of the recommendation list is more personalized to the user and capable of having more successful check-in with enhanced satisfaction levels.

(A) Algorithm for the generation of location recommendation list

Input: Predicted POIs generated based on user interest *PPOI*,

User's Current location *CL*
Output: top *n* list of POIs as recommendations
Initialize *R_List=empty*;
For every *poi* in *ppoi* do,
    if *poi* matches *user_travel_attributes then*,
        x_dist=*distance*(*poi*, *CL*);
    if *x_dist*<=δ then,
        append *poi* to *R_List*;
    reset *x_dist*;
End For
return *R_list*;

6. EXPERIMENTAL EVALUATION AND ANALYSIS

In this section, the proposed models are experimentally evaluated for the analysis of effectiveness, performance and efficiency with existing methods over user's emotional context. Experiments were conducted on a PC running on 64-bit Windows 7 operating system with Intel core i7-5500U clocked at 3.00 GHz and 16 GB of memory. The obtained results are compared with existing approaches and the results analyses are presented neatly.

6.1 Datasets

The proposed emotion-aware models are evaluated on two large-scale real-time datasets of Yelp and TripAdvisor. Yelp is a famous location reviewing website and it plays as an absolute source to make our experimental evaluation. The preprocessing of the dataset removes the users with fewer ratings on venues and results with 39104 venues, 20166 unique users and overall 586274 ratings. The TripAdvisor is the travel recommendation website comprises of reviews and feedbacks of the locations. Similar to the preprocessing of the Yelp dataset, TripAdvisor dataset is also preprocessed and users with fewer ratings are removed. The filtered TripAdvisor dataset includes 9149 venues, 13410 unique users and overall152721ratings. The statistical comparison of both dataset is portrayed in Table 1.

Table 1. Statistical comparison of Yelp and TripAdvisor.

Statistics	Yelp		TripAdvisor	
	User	POI	User	POI
Maximum number of Ratings	1234	1189	96	708
Average number of Ratings	29.1	15.0	11.4	16.7

6.2 Evaluation Metrics

The main aim of the conducted experiments is to evaluate the performance of the proposed emotion-aware models for its POIs recommendations. Experiments are conducted on both Yelp and TripAdvisor. The user's current emotional context and their historical check-ins are exploited to make POIs as recommendations. We use four evaluation metrics Hit-rate, precision, recall and *f*-measure to evaluate the generated recommendations.

(A) Hit-rate

Hit-rate is used to evaluate the satisfaction of the user with respect to generated emotion-aware recommended list. Hit-rate represents the fraction of hits in the recommended list of POIs which contains the user's interested POIs with respect to current emotional context. The hit-rate generally computed using the following definition.

$$Hit-rate=\frac{Number\ of\ Hits}{n} \tag{6}$$

Here, *Number of Hits* represents the total number of hits by user and the total times of recommendation are denoted by *n*.

(B) Precision

The commonly known positive predictive value is also known as precision. Precision is the percentage of recommended POIs relevant to the user and it is defined as follows:

$$Precision=\frac{|Reco\_POI(user)\bigcap Relevant\_POI(user)|}{|Reco\_POI(user)|}. \tag{7}$$

Here, *user* represents the target user in the test data, *Reco_POI*(*user*) is the list of recommended POIs and *Relevant_POI*(*user*) is the list of venues pertinent to the target user in the test set.

(C) Recall

The percentage relevant POIs that are recommended is known as recall. Recall is also known as sensitivity and it is defined as follows:

$$Recall=\frac{|Reco\_POI(user)\bigcap Relevant\_POI(user)|}{|Relevant\_POI(user)|}. \tag{8}$$

Here, *user* represents the target user in the test data, *Reco_POI*(*user*) is the list of recommended POIs and *Relevant_POI*(*user*) is the list of venues pertinent to the target user in the test set.

(D) F-Measure

The f-measure metric is the harmonic mean of recall and precision computed and is defined as:

$$F-Measure=2\times\frac{Precision\times Recall}{Precision+Recall}. \tag{9}$$

(E) AUC

The popular evaluation metric AUC (Area Under the ROC Curve) has been adopted to evaluate the prediction and performance of our proposed approaches. The AUC metric is defined as:

$$AUC = \frac{1}{|U|}\sum_{u}\frac{1}{|E(u)|}\sum_{(i,j)\in E(u)}\delta(Px_{ui} > Px_{uj}) \tag{10}$$

Here, Px_{ui} represents the preference value predicted for user u for the target POI i. Similarly, Px_{uj} represents the preference value predicted for user u for the target POI j. $E(u)$ is the set of evaluation POI pairs for the target user u and it is defined as:

$$E(u) = \{(i, j) \mid (u,i) \in DS_{test} \wedge (u, j) \notin (DS_{test} \cup DS_{train}).\tag{11}$$

Here, DS_{test} denotes the test dataset and DS_{train} represents the training dataset.

6.3 Comparison of Different Recommendation Models and Discussions

The experiments of the proposed models were conducted on the large-scale datasets and the obtained results were compared. The comparisons are also made with the baseline approaches which include, random recommendation, BPR (Bayesian Personalized Ranking) [25], User-based CF, Item-based CF, TBCF [14]. Figs. 4-9 portrays the results obtained from various methods and Table 2 tabulates the precision, recall, and F-measure achieved for the various approaches with respect to datasets. The obtained results depict that the approached induced by user emotion achieved better performance compared to other approached without emotions. This means that user's travel behavior is very much pertinent to the current emotional context, exploiting the emotion can provide better recommendations.

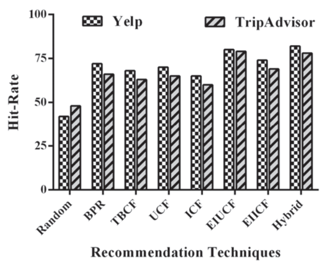

Fig. 4. Comparison of hit-rate.

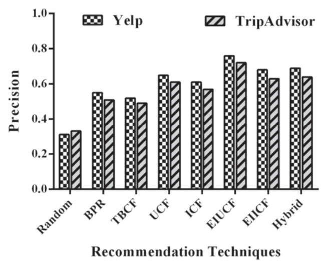

Fig. 5. Comparison of precision.

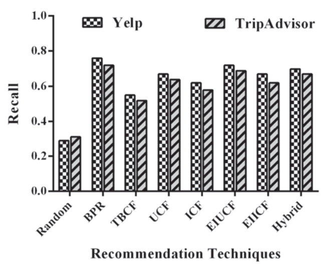

Fig. 6. Comparison of recall.

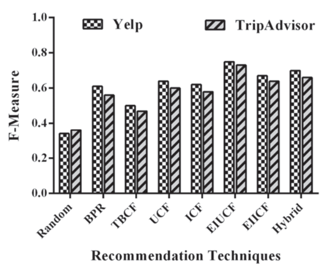

Fig. 7. Comparison of F-measure.

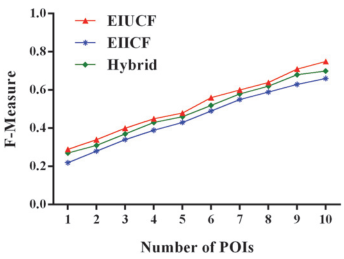

Fig. 8. F-Measure with respect to number of POIs recommended in Yelp dataset.

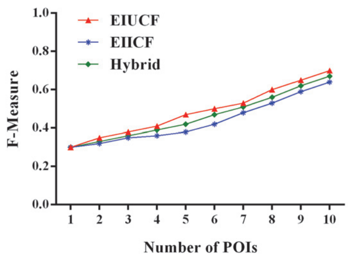

Fig. 9. F-Measure with respect to number of POIs recommended in TripAdvisor dataset.

Table 2. Precision, Recall and F-Measure of different approaches.

	Yelp			TripAdvisor		
	Precision	Recall	F-Measure	Precision	Recall	F-Measure
Random	0.3146	0.2989	0.3065	0.3364	0.3186	0.3273
BPR	0.5539	0.5253	0.5392	0.5193	0.7236	0.6047
TBCF	0.5276	0.5024	0.5147	0.4967	0.5243	0.5101
UCF	0.6554	0.6157	0.6349	0.6145	0.6447	0.6292
ICF	0.6273	0.5978	0.6122	0.5737	0.5884	0.5810
EIUCF	0.7653	0.6742	0.7169	0.7235	0.6928	0.7078
EIICF	0.6845	0.6177	0.6494	0.6354	0.6275	0.6314
Hybrid	0.6932	0.6561	0.6741	0.6423	0.6746	0.6581

EIUCF performed better than other models and it can be easily inferred from the results. EIICF recommends similar POIs of the visited locations of user and it lags with other two emotion aware models in the performance. In our opinion, hybrid model is not much better than EIUCF due to the similar recommendations which is more complex. For new users, $\beta > \alpha$ and β value plays a pivotal role in smoothing the sparsity issues of cold-start user. Emotion classification into 2d, 7d, 21d adds more value to the results. The emotion classification has resulted with better identification of user's current context and this improves the hit-rate of the recommendations. The mining of user emotion from within a smaller time window results with better performance. This indicates that, the emotional context of the user is variable and short-term emotions plays a key role in the visiting the locations. We have also evaluated the larger time windows for emotions extractions and it resulted with noise emotions which decreases the performance of the emotion-aware approaches.

The evaluation of prediction and performances of the proposed emotion-aware models are demonstrated in the Fig. 10 and 11 with respect to the ranging training set of fraction 1%, 5%, 10%, 20%, 40% and 60%. The models are validated and the results were compared with baselines on both Yelp and TripAdvisor datasets. The results prove efficiency of proposed emotion induced models over existing traditional baselines. The EIUCF and EIICF had attained nearly 90% (*i.e.* 0.9) on AUC on both datasets. Generally, the higher value of AUC indicates the better quality of performance of the model. The random model lags in the prediction and performance while comparing with other models. The performance of the proposed emotion-aware models gradually increases as the number of recommended POIs increases. The results obtained from the experiments clearly demonstrate that the proposed models are significantly effective to make personalized POI recommendations with recently mined user emotions.

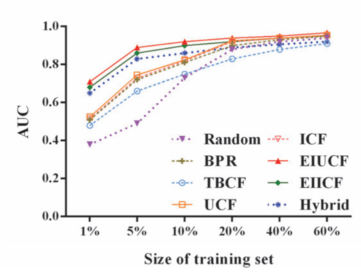

Fig. 10. AUC on Yelp dataset.

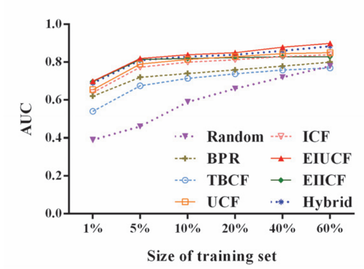

Fig. 11. AUC on TripAdvisor dataset.

7. CONCLUSIONS

This article focused on the location recommendation based on the contexts such as emotion, location and time. We attempt to develop a hybrid model to solve the personalization problems of the recommender systems and we have almost achieved our goals. In this work, user's online posts and check-ins were used to infer the current emotional context which is useful in relevant POI prediction. The Experiments are conducted on the large-scale real world datasets and the obtained results depict the performance of emotion induced recommendation models. The proposed models outperforms with accurate recommendations in terms of Precision, Recall, F-Measure, AUC and Hit-Rate. The limitations of the work include the sparsity and noise of the user's online posts, which is considered for emotion extraction. To improve recommendation, we plan to extend our emotion-aware models by exploiting user's EEG signals to mine current emotional context. We conclude the article with the inferred statement from the obtained results of this study. Prediction of user's preferences based on emotional context, enhances the user satisfaction and improves the acceptance ratio of generated personalized recommendations.

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