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GEOGRAPHICHAL LOCATIONS POINTED THROUGH SOCIAL NETWORKS PREDICTED BY RATING ALGORITHM

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ABSTRACT:Rapid growth of web and its applications has created a colossal importance for recommender systems. Intelligent mobile device and positioning techniques have fundamentally enhanced social networks, which allow users to share their experiences, reviews, ratings, photos, check-ins, etc. The geographical information located by smart phone bridges the gap between physical and digital worlds. Location data functions as the connection between user's physical behaviors and virtual social networks structured by the smart phone or web services. We refer to these social networks involving geographical information as location-based social networks (LBSNs). Such information brings opportunities and challenges for recommender systems to solve the cold start, sparsity problem of datasets and rating prediction. This paper, we make full use of the mobile users' location sensitive characteristics to carry out rating predication. Moreover, three factors: user-item geographical connection, user-user geographical connection, and interpersonal interest similarity, are fused into a unified rating prediction model. Later, we have enhanced the LBRP model for group of users recommendations. The results obtained from the experiments have been presented.

1. INTRODUCTION

The enormous growth of web and its user base has become source for large amount of information available online. This information may be helpful for users, to suggest items or services as per their preferences. Recommender system plays the role of generating suggestions by collecting user information such as preferences, interests, and locations.However, users do not always have a clear idea about where they want to go, especially for tourists who are not familiar with local placesor prefer a casual walk to famous attractions. In location-based social networks (LBSNs) as shown in Figure 1,users establish social links with others, check in some interesting locations, known as *points-of-interest* (POIs), e.g., restaurants, stores and museums, and post tips to express their opinions about various aspects of POIs, e.g., atmosphere, price and service. With the rapid growth of LBSNs, e.g., Foursquare and Yelp, it is preva-
lent and important to recommend users with their preferred POIs. Recent studies have argued that social friends tend to share common interests and thus can be used in the process of collaborative filtering for making recommendations While the ideas above aim to explore the essential information available in LBSNs, i.e., the user-location interactivities and user-user social links. Recommender system uses information from many sources to make predictions and to suggest an item for a user. Factors such as novelty, stability, and accuracy are

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balanced in the generated recommendations. Filtering mechanisms play an important role in the recommendation process [7].

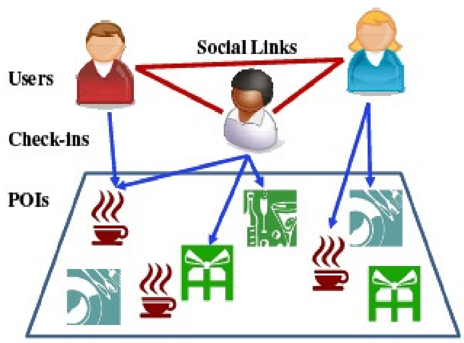

Figure 1: A location-based social network

The most commonly used filtering techniques are collaborative filtering, content-based filtering, knowledge-based filtering, and social filtering [8].Already many researches had contributed to the development of various recommender systems such as movie,music, books ,shopping malls, atm, restaurants, colleges. When users take a long journey, they may keep a good emotion and try their best to have a nice trip. Most of the services they consume are the local featured things. They will give high ratings more easily than the local. This can help us to constrain rating prediction. In addition, when users take a long distance travelling afar away new city as strangers. They may depend more on their local friends. Therefore, users' and their local friends' ratings may be similar. It helps us to constrain rating prediction. Furthermore, if the geographical location factor is ignored, when we search the Internet for a travel, recommender systems may recommend us a new scenic spot without considering whether there are local friends to help us to plan the trip or not. But if recommender systems consider geographical location factor, the recommendations may be more humanized and thoughtful. These are the motivations why we utilize geographical location information to make rating prediction. With the above motivations, the goals of this paper are:

1) To mine the relevance between user's ratings and user item geographical location distances, called as user-item

Geographical connection, 2) to mine the relevance between users' rating differences and user-user geographical location distances, called as user-user geographical connection, and 3) to find the people whose interest is similar to users. In this paper, three factors are taken into consideration for rating prediction: user-item geographical connection, user-user geographical connection, and interpersonal interest similarity. These factors are fused

Into a location based rating prediction model. The main aim of using personalization techniques is to generate customized recommendation according to the user preferences and interests.The recommender system has an objective to filter unwanted information and to provide specific results for the particular user . Proposed model learns the user preferences and of users to make a decision regarding the recommended products or services. By using community-contributed data, such as blogs, social networks, Geographic Positioning Systems (GPS) logs, and geotagged photos, recommender systems tend to help the users by generating personalized recommendations, which will be more useful for the users in their decision making process.generates places of attractions according to the user interests.

This paper focuses on the recommender systems and their application in location. To make this paper useful to all, including new readers of recommender systems, it covers topics from evolution to applications along with the challenges in it. Since more research is required to improve the effectiveness and efficiency of recommender systems, this paper will be more useful to the upcoming

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researchers to develop a user specific recommender system. we explore users' rating behaviors through their geographical location distances. The main contributions of this paper are summarized as follows:

- we mine the relevance between ratings and user item

Geographical location distances. It is discovered that users usually give high scores to the Items (or services) which are very far away from their activity centers. It can help us to understand users' rating behaviors for recommendation.

- we integrate three factors: user-item geographical

Connection, user-user geographical connection,

and interpersonal interest similarity, into a Location

Based Rating Prediction (LBRP) model.

2. SIGNIFIGANCE OF RECOMMENDER SYSTEM

Recommender systems (RSs)were generally defined as expert systems which are used to recommend products or services to the users. Figure 1 portrays the working of a traditional recommender system. Various factors influence the interests. of users to make a decision regarding the recommended products or services. By using community-contributed data,such as blogs, social networks, Geographic Positioning Systems (GPS) logs, and geotagged photos, recommender systems tend to help the users by generating personalized recommendations, which will be more useful for the users in their decision making process.

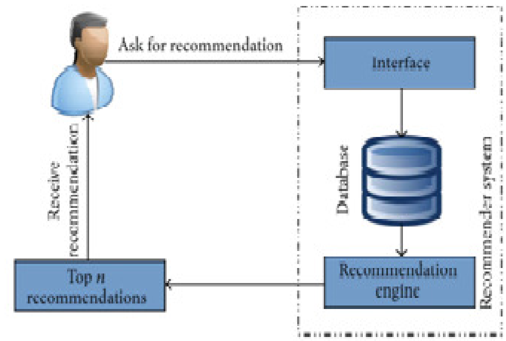

Figure 2.Traditional recommendar system

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.1. Foundations of Recommender Systems. Traditionally, recommender systems are based on their building blocks such as algorithms, filtering methodologies, taxonomies, and databases. When the recommender systems have only small amount of data for generating suggestions, collaborative models face issues with them. Such problem is called cold start problem and it is described below. The usage of similarity and differences between users' interests is mostly used by many recommendation models. Finally, by comparing the users or items, different similarity measures were described.

2.1.1. Fundamentals. In the recommender systems, process of generating recommendations depends on various factors, such as the following:

(i) Available user data in the database (such as user information, interests, ratings, locations, and social relationships);

(ii) Filtering mechanism/algorithm used (like, contentbased, hybrid, collaborative, etc.);

(iii) Techniques used to enhance the results (such as Bayesian networks, singular value decomposition,

and fuzzy models);

(iv) Sparsity level and scalability of database;

(v) System performance (such as memory and time consumption);

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(vi) Considered objectives of the system (such as top recommendations and predictions);
(vii) Quality and its metrics used for the result and analysis
(such as precision, recall, F-measure, and novelty).

2.1.2. Cold Start Problem. The problem of generating no reliable Recommendations due to lack of initial ratings is known as cold start problem. New user, new item, and new Community are the three types of cold start problems. During Recommender systems' operations, new user problem is a great difficulty in producing personalized recommendations.

Since there are no user ratings provided by these new users, memory-based content filtering cannot help in
the recommendations. New users may reject unreliable, no personalized Recommendations and the recommendation Services too. Adding additional information to the new user Database, such as references, tackles the new user problem. Similarly, new item problem arises due to addition of new items in the recommender systems. Since there is no initial rating for these new items added to the recommender systems, it gets unnoticed by most of the users and large group of users may be unaware of such items. Developing a set of motivational users to rate the new items will help in solving new items problem. New community problem occurs during the initialization of recommender systems due to insufficient ratings. Collaborative filtering based recommendations and encouraging users to rate items can easily solve the new community problem.

3.LOCATION BASED SOCIAL NETWORKS

More than one number of individuals connected together
With more than one type of relations (e.g., friends, family Common interests, and groups) is known as social network. A real world social network service can be digitally represented. The social network not only mentions the users' network, but also enhances their activities. The activities of a user depend on their actual ideas and on sharing posts and events and making likes.

The user-location based social network data strengthens
the social network activities and also this location mentioned in the social network services.The location based social network comprises the people's Physical location in their social structure to share the information By location embedded system. The new structure is Created when an individual user is connected to a location on a social network. The location of user derived fromtheir location tagged media content and other activities (Such as their photos, video, and text). The user physical Location consists of individual location at current time and their location history with specific period of time. If one or more people has the same location and also similar location histories, it will not affect our social network structure. This Structure also contains individual behaviors, activities, and other information. The concept of locations based networks shows new locations and correlations in addition to the old one. From The new information, graphs build into three types of location Based social network, such as location-location graphs, user location graph, and user-user graph.

(i) Location-Location Graph. In this graph, users consecutively Visit the edge between two locations indicating the node location of the location-location graph. The correlation between strengths of two locations is represented by edge weight.

(ii) User-Location Graph. Users and locations are the two types of entities in user-location graph. The visited location of the users is indicated by the edge starting from the users

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and ending at a location and the number of visits calculated by weight of the edge.

(iii) User-User Graph. Basically a node is a user and edge between two nodes represents two relations. The two relations are existing social network between two users and a new location of the users.

3.1Challenges to Recommendations in LBSNs. The new LBSNs have three unique properties of locations. The unique properties of LBSN are location context awareness, the heterogeneous domain, and the rate of growth.

3.1.1. Location Context Awareness. What kind of recommendation system is needed for LBSNs to consider the users current location, users location history, and the influences of location histories to other users?

3.1.2. The Current Location of a User. Due to the following reasons, the current locations of users are more important parameter for generating recommendation system for LBSNs. The location granularity for different levels is represented by the current location of users. In recommendation system, it is very difficult to choose a proper granularity. If we choose hotel location of users that has a fine granularity, then a relative coarse granularity represents the town location of Users.

The most visited location is near to the users compared to
the location at far distance; this implies the distance property of locations. But also the quality of location is important for making recommendation system for LBSNs because of the ranking of recommendation system based on both the quality of locations and the location close to users. Another challenge is with respect to the collection of users' fine grain location, as it is frequently updated using mobile.

3.1.3. The Historical Locations of the User. The users' preference is indicated by the powerful histories of users' behaviors. The LBSNs mention the user's historical location and also reflect the user's preferences, experiences, and living patterns compared to the online behaviors of users. It is not easy to model a location history of users because the location History depends on distance, hierarchy, and sequential properties of users. Based on the location history of users We have to learn user's personal preferences. Due to the following reason, it is very challenging work in LBSNs.

(1)The challenging work is that we create users preference from sparse location data because a full set location history of users does not exist.

(2) The user's location preferences are not only limited to their hotel and shopping locations because user has multiple kinds of interests: cycling, sports, movies, arts, and so forth.

(3) Users preferences have granularity and also follow some hierarchical steps like snakes → food → pizza.

(4) The user's preferences always depend on their location.

3.1.4. The Location Histories of Other Users. Social opinion is one of the most important information bases for recommended system making up with location history generated by other users. From the location history we extract social opinions; it is not easy one because we are faced with the following challenges. (1) The continuous representation of user's changing location history is a complex task. (2) For each location, user has different knowledge. For example, local user has expert knowledge to find
high quality of hotel and shopping malls. It is easy to interface user's experiences
and knowledge to the social opinion. From this users preference, we created a massive users location data. But for all locations, the same users do not have this much knowledge and location data.

4. PROPOSED LBRP APPROACH

The proposed personalized location based rating prediction model (LBRP) has three main steps: 1) obtain three geo-social factors,

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interpersonal interest similarity, useruser geographical connection, and user-item geographical connection, through smart phone with the Wi-Fi technology and Global Positioning System (GPS); 2) build up personalized rating prediction model combining with the three factors in the cloud; 3) train the model in the cloud to learn user and item latent feature matrices for rating prediction to recommend suitable items of user's interest. In this paper, we focus on the algorithm part: step 2 and step 3. User and item latent feature matrices can be calculated by machine learning methods for rating prediction. Once the ratings are predicted, the items can be ranked by the ratings and provided as TopN recommendation list.

4.1 Geographical Social Factors

Geographical social factors include interpersonal interest similarity, user-item geographical connection and user-user geographical connection. The user-item and user-user geographical connections are measured by ratings through diverse geographical distances. Interpersonal interest similarity is measured by the similarity between user's interest vector and friend's interest vector [13]. Note that, the geographical distance between two latitude/longitude coordinates is calculated by using the Haversine geodesic distance equation proposed.

4.1.1 User-Item Geographical Connection

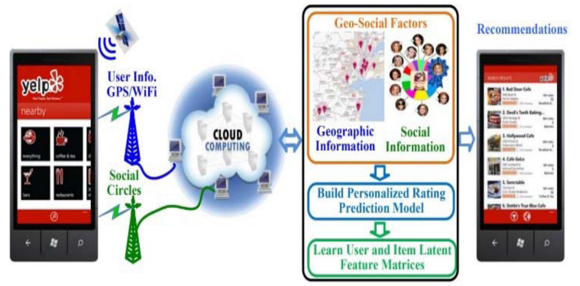
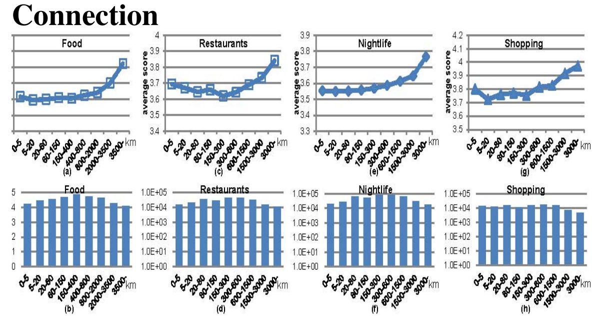


Fig. 3. System overview

4.1.1 User-Item Geographical Connection



distributions of the average scores with different user-item geographical distances (km) based on Yelp Food, Yelp Restaurants,Yelp Nightlife, and Yelp Shopping of data of Foursquare, users tend to activities in nearby areas. radiusof 45% users is no more than 10 miles, and the activity radius of 75% users is no more than 50 miles. Moreover,the same conclusion is drawn in [23].
It is reasonable that people's activity centers are close to their residences or companies.

$$Lui_{u,i} = \sum_i a_i \times exp\left(-\left(\left(d_{u,i} - b_i\right)/c_i\right)^2\right)$$

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4.1.1 User-Item Geographical Connection

It can be used to solve the cold start problem, especially when users travel to a new city. In this paper, we conduct curve fitting by ordinary least squares techniques based on Gaussian model as follows:

$$y = \sum_i a_i \times exp(-((x - b_i)/c_i)^2)$$

where y denotes the average rating, i.e. the ordinate value
in Fig. 3. x denotes the abscissa value and the coefficients need to be learned by curve fitting.
The impact of different curve fitting approaches on performance is discussed. Once the coefficients are learned, the proposed user tem geographical connection is expressed as follows:
The geographical location distance between user u and item i. and the coefficients learned by curve fitting. Then user's ratings can be constrained according to user-item geographical connection with considering diverse user-item distances.
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4.1.2 User-user Geographical Connection

the user-user geographical connection can be learned in the same way. The personalized recommendation via geographical social networking, including smart phone user of mobile social network services,cloud computing, rating prediction, and the recommendation lists. In this section, we analyze the relevance between users rating differences and user-user geographical distances. For each user, the difference between his/her rating and his/her friends' to the same item is calculated. Meanwhile, we compute the geographical distance between them. In Fig. 5 (a), (c), (e), and (g), the value of y-axis could be expressed by:

$$y = |R_{u,i} - R_{f,i}|$$

where $R_{u,i}$ denotes the rating user u to item i, and $R_{f,i}$ denotes the rating user's friend f to item i. The corresponding value on x-axis could be expressed by:

$$x = Distance(u, f)$$

where Distance(u ,f) denotes the geographical distance
between user u and his/her friend f.
Then the propose user-user geographical connection is expressed as follows:

$$Luu_{u,v} = \sum_i a'_i \times exp\left(-\left((d_{u,v} - b'_i)/c'_i\right)^2\right)$$

Where $d_{u,v}$ denotes the geographical location distance
between user u and his/her friend v. a'_i, b'_i, and c'_i are
the coefficients learned by curve fitting.

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4.1.3 Interpersonal Interest Similarity

User interest is a representative and prevalent factor in
recommender system. It is necessary to represent user
interest vector. In this paper, we replace topic distribution with category distribution as in previous works to represent user's interest vector.Based on the category distribution vector of the item, a
user's interest vector can be represented by summarizing
the topic vectors of his/her rated items as follows:

$$D_u = \frac{1}{|H_u|} \sum_{i \in H_u} D_i$$

where Hu is the set of items rated by user *u*. |Hu| is the
Corresponding item number.
The basic idea is that user latent feature vector should
be similar to his/her friends' latent feature vector based
on the similarity of their interest. The interest similarity
value between *u* and *v* is represented by *Wu,*

$$W_{u,v} = \frac{D_u \cdot D_v}{|D_u| \times |D_v|}$$

where D_u and D_v are the topic vectors of user *u* and *v* respectively

5 EXPERIMENTS

In this section, we conduct a series of experiments to evaluate the performance of our LBRP model, and compare with the existing approaches on our Yelp datasets.
The compared approaches include BaseMF [33], CircleCon [17], ContextMF [18], and PRM [13], and NCPD

5.1 Performance Measures

The data is split into 5 groups in order to perform 5-fold
cross-validation as our evaluation methodology. The
evaluation metrics we use in our experiments are Root
Mean Square Error (RMSE) and Mean Absolute Error
(MAE). They are the most popular accuracy measures in
the literature of recommender systems . RMSE and MAE are defined as:

$$RMSE = \sqrt{\sum_{(u,i) \in \Re_{test}} \left(R_{u,i} - \hat{R}_{u,i}\right)^2 / |\Re_{test}|}$$

$$MAE = \sum_{(u,i) \in \Re_{test}} \left|R_{u,i} - \hat{R}_{u,i}\right| / |\Re_{test}|$$

where $R_{u,i}$ is the real rating value user *u* to item *i*, $\hat{R}_{u,i}$ isthe corresponding predicted rating value. ffitest is the set of all user-item pairs in the test set. |ffitest| denotes the number of user-item pairs in the test set.

I. 5.2EVALUATION

5.2.1 Parameter Settings

Here we focus on parameter settings. First, the meaning of each parameter is explained as follows.

- ***k***: The dimension of the latent vector. If *k* is too small, it is difficult for the model to make a distinction among users or items. If *k* is too large, the complexity will considerably increase. Previous works

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[10], [33], [62] have investigated the changes of performance with different
k. But whatever the *k* is, it is fair for all compared algo- rithms when we set it as an invariant. Here we set *k* = 10 as in [13], [15] and [17].

- ***λ1*** and ***λ2***: The parameters of trading-off over-fitting factor in (11).
- ***β***: The weight of the inferred interest similarity in (11).
- ***δ***: The weight of user-user geographical connection in the third term of (11).
- ***η***: The weight of the user-item geographical connection
in the last term of (11).

These parameters play the roles of balancing factors. As in [18], to balance the components in each algorithm, these parameters are proportional as follows:

$$\lambda_1 : \lambda_2 : \beta : \delta : \eta = \frac{1}{\|U\|_F^2} : \frac{1}{\|P\|_F^2} : \frac{1}{\|U - \sum_v W^{*T} U\|_F^2} : \frac{2}{\|U - \sum_v Luu^{*T} U\|_F^2} : \frac{2}{\|Lui^{*} - U^T P\|_F^2}$$

In the performance comparison of different algorithms,
we set the same parameter to make sure of fairness. For
example, both CircleCon and ContextMF consider user
influence. The parameters are set to the same value.

5.2.2 Performance Comparison

In this section, we compare the performance of LBRP algorithm with the existing models, including BaseMF [33], CircleCon [17], Context MF [18], PRM [13], [15], and NCPD [43] on our Yelp datasets. We implement performance comparison with performing 5-fold cross-validation. It can beseen that LBRP is better than other existing approaches on most of Yelp datasets.

5.3 Discussion

Five aspects are discussed in our experiments: the impact
of the amount of user information, the impact of the three
factors, the impact of geographical location distances, the
impact of different curve fitting methods, and the impact
of predicted integer ratings on performance.

Impact of three factors:

We compare the performance of the three independent factors in the proposed LBRP based on *Yelp Restaurants* dataset. Fig. 8 shows the corresponding RMSE of every approach. **NoN** denotes the approach that none of the three factors is taken into consider-

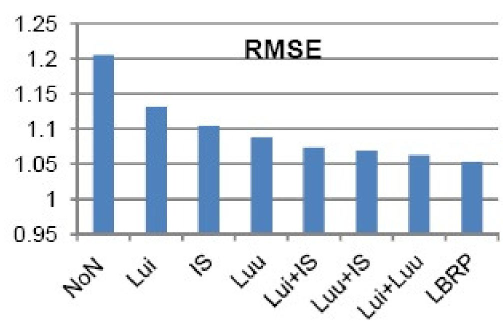

Fig. 8. Discussion on the three factors of LBRP.

-ation. **Lui** denotes the approach using the user-item geographical connection. **Luu** denotes the approach using the user-user geograph- ical connection. **IS** denotes the approach using interper- sonal interest similarity. **Lui+IS** denotes the approach integrating user-item geographical connection and inter- est similarity. **Luu+IS** denotes the approach integrating user-user geographical connection and interest similarity. **Lui+Luu** denotes the approach integrating suser-item and user-user geographical connections. **LBRP** denotes our approach that the three factors are all taken into account. It can be seen that all of the three factors have an effect on improving the accuracy of rating prediction model.

6.CONCLUSION:

This final section is the summary of the work presented in this paper, which describes the key points that should be taken into consideration by the researcher, who is aiming to develop a recommender system. This paper creates an impact through the outline of several future work challenges in the area of recommender systems design and development. Through the analysis of interfaces used by the recommender systems, it is very well noticed that the recent development of mobile platforms has been utilized very little. Clever xploitation of mobile platform with the personal data such as current location may help in providing precise recommendations to users in an improved manner. A personalized Location Based Rating Prediction (LBRP) model is proposed by combining three factors: user-item geographical zonnection, user-user geographical connection, and interpersonal interest similarity. In particular, the geographical location denotes user's real-time mobility, especially when users travel to new cities, and these factors are fused together to improve the accuracy and applicability of recommender systems. Every classical approach (such as collaborative, content based, and demographic) suffers from various problems in providing personalized recommendations to the individual user. Utilization of the social data such as check-in behaviour, ratings, social relationships, and recent area of work can help in the discovery of more accurate ecommendations, which fits better the tastes of the user. we presented an integrated analysis of the joint effect of multiple factors which influence the decision process of a user choosing a POI and proposed a general framework to learn geographical preferences for POI recommendation in LBSNs. Initially, recommender systems were focusing on filtering mechanisms to improve the accuracy of recommendations. Now, hybrid algorithms incorporated with the various factors influenced data have been taken into consideration in the development of efficient recommendation models. The rapid growth of social media sites created a wide opportunity to build social recommender systems. The clustering of users, according to their tastes as a similar metric, can generate good recommendation in more efficient manner. As a crucial conclusion, the success of recommender systems purely depends on the effective learning of user behavior and generation of user acceptable recommendations.

7.FUTURE WORK:

In our future work, check-in behaviors of users will be deeply explored by considering the factor of their multi-activity centers and the attribute of POIs. improved recommendations through utilizing the additional capacities of smart mobile phones. Group recommendation will be enhance for better rating prediction. For the future work, we plan to explore more efficient mobile commerce pattern mining algorithm, design more efficient similarity inference models, and develop profound prediction strategies to further enhance the Social Engine framework.

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