Wuhan University Journal of Natural Sciences

2017, Vol.22 No.2, 149-156

Article ID 1007-1202(2017)02-0149-08

DOI 10.1007/s11859-017-1228-3

# Trust-Based Context-Aware Mobile Social Network Service Recommendation

□ XU Jun[1], ZHONG Yuansheng[2†], ZHU Wenqiang[2], SUN Feifei[3]

1. College of Modern Economics and Management, Jiangxi University of Finance and Economics, Nanchang 310013, Jiangxi, China;
2. College of Software and Communication Engineering, Jiangxi University of Finance and Economics, Nanchang 330031, Jiangxi, China;
3. College of Foreign Languages, Jiangxi University of Finance and Economics, Nanchang 330031, Jiangxi, China



**Abstract:** The service recommendation mechanism as a key enabling technology that provides users with more proactive and personalized service is one of the important research topics in mobile social network (MSN). Meanwhile, MSN is susceptible to various types of anonymous information or hacker actions. Trust can reduce the risk of interaction with unknown entities and prevent malicious attacks. In our paper, we present a trust-based service recommendation algorithm in MSN that considers users' similarity and friends' familiarity when computing trustworthy neighbors of target users. Firstly, we use the context information and the number of co-rated items to define users' similarity. Then, motivated by the theory of six degrees of space, the friend familiarity is derived by graph-based method. Thus the proposed methods are further enhanced by considering users' context in the recommendation phase. Finally, a set of simulations are conducted to evaluate the accuracy of the algorithm. The results show that the friend familiarity and user similarity can effectively improve the recommendation performance, and the friend familiarity contributes more than the user similarity.

**Key words:** trust; context-aware; mobile social network; recommendation

**CLC number:** TP 393

**Received date:** 2016-09-18

**Foundation item:** Supported by the National Natural Science Foundation of China (71662014 and 61602219), the Natural Science Foundation of Jiangxi Province of China (20132BAB201050) and the Science and Technology Project of Jiangxi Province Educational Department (GJJ151601)

**Biography:** XU Jun, male, Ph.D., research direction: fuzzy logic and trusted computing. E-mail: xujun1028@126.com

† To whom correspondence should be addressed. E-mail: zhong_ys@jxufe.edu.cn

## 0 Introduction

Online social networks (SNs) such as Facebook, Twitter and LinkedIn have experienced nearly explosive growth of users in the past years [1]. Simultaneously, with the mushroom development of mobile terminal devices and location-based services, SNs may have migrated from Web-based applications to mobile platforms. The convergence of mobile computing and SNs bring about a new class of applications called mobile social network (MSN) applications, which will be significantly important in the coming years. The top Web destinations on mobile phones are social networking sites (SNS), such as Facebook, MySpace and Twitter, and many SN applications are already available on popular mobile platforms [2]. Increasing services and contents are provided in MSN, as it is an emerging trend. However, the rapid growth of online service information imposes an increasing challenge for users who have to choose from the sheer volume of available data to satisfy their personalized needs. Choosing the service which is more trustworthy for a user's consumption has become a crucial issue. Moreover, mobile SNs offer several rich distinctive context awareness information regarding users' location, context (e.g., what terminal they use), situation context (i.e., current time or current activity), and preferences. Therefore, to meet the requirements of accessing quality, we need to make service information system with location-awareness, personalization, time-awareness and ubiquity.

A number of studies have been conducted to provide context-aware service recommendations [2-6] for mobile users as well as some methods for mining personal context-aware preferences. These methods can be roughly divided into three categories: content-based recommender method, collaborative filtering (CF) recommender method, and hybrid recommender method. Among above mentioned recommender methods, the CF recommender method has been applied to various online service applications successfully and widely. However, CF method usually suffers from some limitations [7] such as having a sparsely populated item-user matrix and being easily attacked by creating ad hoc user profiles and shifting the predicted ratings of a particular item. In addition, SNs may have millions of nodes that are quite sparse and that have low density of links among them. To overcome these limitations [8], we need to incorporate trust information among users.

Recently, a few trust-based recommendation methods that incorporate users' trust relations into CF techniques to enhance traditional recommender systems have been proposed [3-6, 9-12]. These methods [3-6, 9-12] employ the implicit or explicit trust information to improve the classical recommendation methods. These trust computation models can be divided into two main categories [13]: reputation-based trust models [3,4,6] and relationship-based trust models [5, 9-12].

Trust value, which relies on co-rated items, is computed in these approaches. Two users having very few co-rated items will result in no direct trust relationship existing between them. Some studies have already used SN elements to make recommendations and enhance the performance of recommender systems [14-19]. Ziegler and Lausen [14] discovered that exploiting trust is not only useful for selecting small neighborhoods where collaborative filtering can be performed but also for the intelligent pre-filtering of relevant similar peers. Golbeck [15] proposed the FilmTrust system for movie recommendations and studied the utility of trust level in SNs. The trust value is calculated through user's opinion in SNs. Then the trust values of each rater are taken as the foundation for computing predictive ratings. Massa and Avesani [16] developed a new trust-aware recommendation model. This model presents a trust propagation algorithm over the trust network and calculates a trust weight that could be used to replace the similarity weight. It is verified that the performance of the trust-aware recommendations outperforms that of the classical CF. Therefore, trust-aware recommender systems are suitable for the situations where user can describe his/her trust for another user. Furthermore, in comparison with recommender systems, the recommendations from friends are accepted more likely [17], because recommendations derived from a network of friends and established on the basis of the explicit trust of the user. Although having social trust-based recommendations is certainly not the same as having recommendations coming directly from friends, it reflects a more detailed type of similarity than what is employed by classical recommender systems [18]. Deng *et al* [19] proposed the RelevantTrustWalker method, which combines the trust relationship in SNs with the random walk algorithm. Later, Deng *et al* [20] presented a service recommendation method based on the preferences, behaviors, and trust relationship of users. Although many trust computing methods have been proposed, few of them can be applied to mobile SNs. The current study presents a novel service recommendation for MSN based on user context, trust network of friendship, and collaborative filtering algorithm to enhance recommendation accuracy. Several experiments have been carried out to compare, in a simulation way, the developed method with the traditional CF method. As shown by our experiment results, the proposed trust model can improve the prediction accuracy effectively.

The rest of this paper is organized as follows: We present the related works in Section 1. We discuss the trust model in detail in Section 2. The results of the empirical analysis are presented in Section 3, and the conclusion and future work are given in Section 4.

# 1 Recommender Method

## 1.1 Collaborative Filter

Collaborative recommenders seek to find other users with tastes similar to those of the target user [21]. Generally, CF methods can be divided into two important classes of recommendation: item-based CF [22] and user-based CF [21]. Item-based CF makes recommendations based on items' associations. Conversely, user-based CF uses history records expressing preferences to obtain the $k$ nearest neighbors and to determine recommendations in accordance with the opinions of similar users. In our study, we focus on user-based CF.

To provide useful recommendations, the user-based CF mainly includes three steps [23]: 1) building a user profile, 2) neighborhood selection, and 3) generating a prediction. Given these three steps, the predicted rating score can be derived from the following equation:

$$\widehat{p}_{c,j} = \overline{r}_c + \frac{\sum_{p \in \mathrm{NS}} w_{c,p}(r_{p,j} - \overline{r}_p)}{\sum_{p \in \mathrm{NS}} | w_{c,p} |} \tag{1}$$

Where $r_{p,j}$ is recommender $p$'s rating of item $j$;

$\widehat{p}_{c,j}$ denotes the predicted rating with regard to target user $c$ to item $j$; $\overline{r}_p$ denotes average rating; $w_{c,p}$ denotes the similarity degree between target user $c$ and his/her neighbor $p$, which can be computed using the Pearson's correlation coefficient (Pcc); NS is the set of neighbors selected to provide their relative interests.

### 1.2 Context Similarity

In mobile SNS, the context situation and users' behavior are unsteady, and users' behavior is sensitive to context environment. Therefore, other users in a context similar to the active user's current situation can also affect the preference of the active user. As proposed by Chen [24], Pcc is suitable in measuring context similarity when the value is continuous. Given the nearly continuous value of the context, we apply the Pcc to calculate context similarity. We define the context set $C$, denoted by $C=(C_1,C_2,\cdots,C_n)$, where the component of vector $C_t(t=1,2,\cdots,n)$ is a context type (e.g., Air quality, Weather, or Location). Let $x$ and $y$ be two different context variables, their similarity weight for item $i$ is as follows:

$$\mathrm{rel}_t(x,y,t)=\frac{\sum_{u=1}^{n}(r_{u,i,x_t}-\overline{r}_i)\cdot(r_{u,i,y_t}-\overline{r}_i)}{\sigma_{x_t}\cdot\sigma_{y_t}} \tag{2}$$

Where $r_{u,i,x_t}$ and $r_{u,i,x_t}$ are the ratings given by the user $u$ on item $i$ in context $x$ and $y$; $\overline{r}_i$ is average rating; $\sigma_{x_t}$ and $\sigma_{y_t}$ are the standard deviation of $x$ and $y$.

### 1.3 Context-Aware Generating Prediction

Each rating has an associated context in the context-aware CF technology. The similarity of the context indicates the extent of the relevance of the rating in different contexts. Therefore, we need to extend this technology for weighting the ratings to the context.

Using context similarity as weights, we can obtain the weighted ratings $R_{u,i,c}$ of item $i$ in context $c$ given by user $u$.

$$R_{u,i,c}=k\sum_{x\in C}\sum_{t=1}^{z}r_{u,i,x}\cdot\mathrm{sim}_t(c,x) \tag{3}$$

where $k=1\Big/\sum_{x\in C}\sum_{t=1}^{z}|\mathrm{sim}_t(c,x)|$ denotes the linear regression coefficient. This expression has nested sums which contain inner loops and outer loops. The former indicates context attribute (e.g., City and Time) and the latter indicates the attribute value (e.g., Lushan, Huangshan and Wuyuan for the City context).

Subsequently, the rating without context $r_{p,j}$ in Eq. (1) is substituted for $R_{u,i,c}$. The predicted rating of the active user $a$ on service $i$ can be computed as

$$\widehat{p}_{a,i,c}=\overline{r}_a+\sum_{p\in \mathrm{NS}}w_{a,u}(R_{u,i,c}-\overline{r}_u)\Big/\sum_{p\in \mathrm{NS}}|w_{a,u}| \tag{4}$$

## 2 Trust Model

In consideration of the social properties of mobile SNS, the simplest way is to combine user similarity and friend familiarity to produce a trust value through the computation described in Definition 1.

**Definition 1** Let $u$ and $v$ be the target user and recommender in the mobile SNS, respectively. $\mathrm{TSim}_{u,v}$ returns the similarity of context profiles between $u$ and $v$, which is denoted by $A$. Function $\mathrm{TFam}_{u,v}$ returns the social relationship familiarity to target user $u$ with respect to recommender $v$, which is denoted by $B$. The trust-based weighting is defined as

$$W_{u,v}=\begin{cases}(2\times A\times B)/(A+B), & A>0 \text{ and } B>0\\ B, & A=0 \text{ and } B>0\\ 0, & B=0\end{cases} \tag{5}$$

From Eq.(5), it is easy to see that a large weight will only be obtained if both familiarity and similarity are large.

### 2.1 Trust Factor Based on User Similarity

In SN, people tend to trust others with the same experiences or interests. As proved in Ref. [14], trust and interest similarity have positive correlations. The more similar the two users are, the greater the trust between them.

The traditional similarity measures between two users (mean squared differences, Spearman rank, Pearson's correlation, cosine, etc.) are calculated considering only the ratings which are provided by these two users. In this paper, the similarity among users is measured by their profiles, which includes ratings of items and personal information and opinions of users. According to the significant weighting results, if only a few of items are co-rated items for the neighborhood, a higher similarity degree between users is derived likely. Therefore, compared with users who have rated few items, users who have rated a great deal of items will be assigned more neighborhoods. It is potentially risky to this situation with profile injection attacks. The significance trust weight of a target user $u$ for a neighbor $v$ is computed as

$$\mathrm{TSim}_{u,v}=\begin{cases}\mathrm{Sim}_{u,v}\times\dfrac{n}{k}, & n<k\\ \mathrm{Sim}_{u,v}, & \text{otherwise}\end{cases} \tag{6}$$

where $k$ is a global constant, $n$ is the number of co-rated items and $\mathrm{Sim}_{u,v}$ is the Pcc.

### 2.2 Trust Factor Based on Friend Familiarity

In the mobile SNSs, a user can register other users as friends and enjoy communication through renren (*http://3g.renren.com*). With the rapid growth of mobile SNs, users of MSNSs may easily become overwhelmed by the excessive volume of information. Friendship can significantly affect the quality of recommendations [25]. Therefore, the recommendation of a trustworthy friend is the essential factor in choosing SNS services. Most trust-based recommendation models consider accurate predictions derived from past rating records to infer the trust value. In this work, we extend the previously reported graph-based method [26] and propose graph-based trust models using friend familiarity to improve the recommendation quality.

According to theory of six degrees of space [27], two persons are acquainted with each other only through the most six-level intermediaries. Therefore, we consider five levels network, and used the target use as a root. An example is shown in Fig. 1. Friendship in SN has an asymmetric relation between two users, and it can be represented as an edge in a directed graph. We remove all one-way relationships, i.e., those that do not have an inverse relationship.

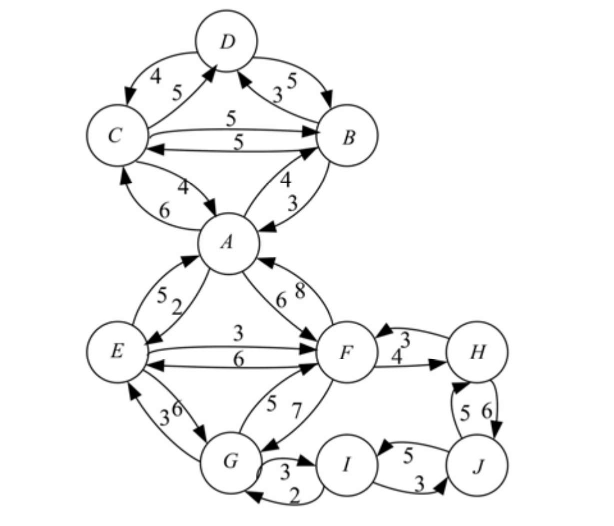

**Fig.1 Original interaction network**

The network with minimum-message is depicted in Fig.2. Then the unnecessary edges can be deleted since the interactive relationships between same level nodes are redundant. So the candidate network with minimum-message can be obtained, depicted in Fig.3.

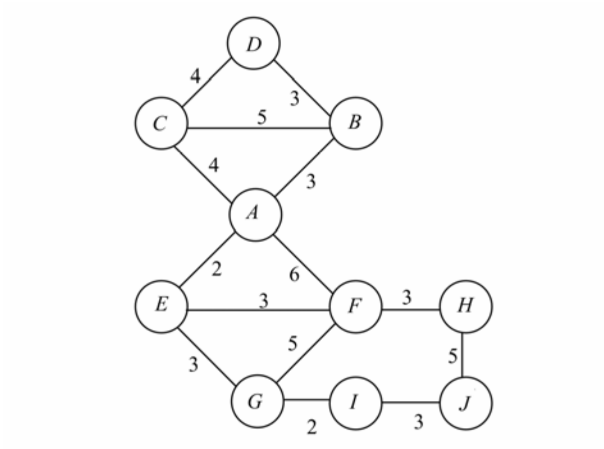

**Fig.2 Network with minimum message**

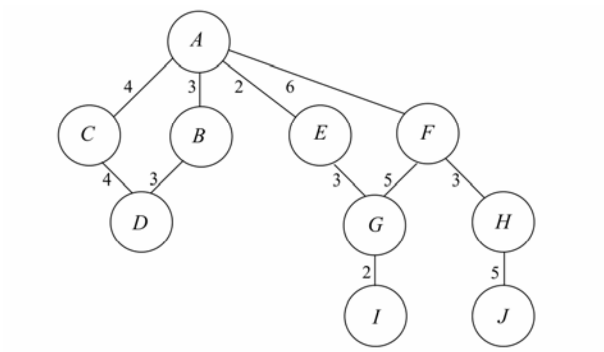

**Fig.3 Candidate network with minimum message**

We define a set of descriptive features as follows. Some simple examples are based on the network in Fig.3.

$N(G)$ : Total messages of all nodes.

$N_{ij}$ : Minimum messages between parent node $i$ and child node $j$, e.g., $N_{AB}$=3.

$L(h)$ : All the nodes belong to level $h$ in the candidate network, e.g., $L(1)=\{B,C,E,F\}$ .

$L(h)$.Sum : Total messages of $L(h)$ , e.g., $L(1)$ . Sum $= N_{AB}+N_{AC}+N_{AE}+N_{AF}$=15.

$\mathrm{Pth}(j)$.Sum : Minimum total messages of all the paths that start from the root (the target user) to any node $j$.

**Definition 2** Let $X$ and $Y$ be the two users in the mobile SN. The trust value of $X$ to $Y$ is defined as

$$\mathrm{TFam}_{X,Y}=\omega_Y\cdot\sum_{i=1}^{n}\Big[\prod_{j=1}^{m}N(S_{j-1},S_j)\Big] \tag{7}$$

where $N(i,j)$ returns the ratio of the minimum message $N_{ij}$ and the total messages of the level $h$ in which node $j \in L(h)$ and $i \in L(h-1)$; and $i$ is the parent node of node $j$, e.g., $N(A,B)$ = $N_{AB}/L(1)$. Sum =3/15=0.2. Weight $\omega_Y$ is the minimum total messages of all the paths that start from $A$ to $Y$ divided by the total messages of all nodes denoted by $\omega_Y = 1 - \text{Pth}(Y)$. Sum $/N(G)$. For example, $\text{Trust}(A,D)$ = (1 6/51)×{[3/(3+4+2+6)]×[3/(3+4+3+5+3)]+[4/(3+4+2+6)]×[4/(3+ 4+3+5+ 3)]}.

# 3 Experiments and Evaluations

We design an application scenario of recommendation for hotels, restaurants and tourist spots. For example, a tourist attraction recommender is usually on the basis of information such as influence of friends, friend familiarity, preferences of similar users and location-based context aware, etc.

## 3.1 Experiment Setup

In this section, we construct a MSN simulation experiment, in which the mobile device of each user had installed mobile client software of Renren to ensure the validity of simulations. Users were mobile and could keep in touch while on the move. We collect a data set from thirty graduate students friendship in 3g.renren.com, that is the most popular SNS in China, providing recommendation services for hotels, movies and scenic spots and user rating. Users employ a five-mark system to rate hotels, movies and scenic spots. Users also find their friends through the SNS. It means that great majority friends on Renren actually know each other offline. Therefore, Renen can be regarded as an ideal source for our study on MSN recommendation.

We crawled 30 graduate students in 3g.renren.com, and took these students as seeds in order to further crawl their social networks with their item ratings for a month. Finally, we got 1 394 users and 5 541 movies with 25 879 item ratings. This MSN data was composed of about 24 592 friend links between users.

The configuration of simulation computer system was as follows: Microsoft Windows 7, Mysql server 5.0, Ucinet 6 software package, Android 6.0 and Matlab 7.6 data analysis platform were used to establish the simulation environment.

## 3.2 Evaluation Measures

To evaluate the performance of the proposed recommendation methods, we use several accuracy metrics including the mean absolute error (MAE), recall, precision and $F_1$ measures [28, 29]. These four evaluation metrics are defined as follows.

1) The MAE is the average absolute deviation between predicted rating and true rating of users, which can be defined as:

$$\text{MAE} = \frac{\sum_{k=1}^{N} | \hat{p}_k - r_k |}{N} \tag{9}$$

where $r_k$ denotes the rating of item $k$, $\hat{p}_k$ denotes the corresponding rating predicted by the model, and $N$ is the number of testing data.

2) The recall is a completeness measurement which can be defined as:

$$\text{recall} = \frac{X}{Y} \tag{10}$$

where $Y$ is the number of all relevant items retrieved and not recommended, $X$ is the number of relevant items recommended.

3) The precision is an accuracy or exactness measurement, which can be defined as:

$$\text{precision} = \frac{X}{Z} \tag{11}$$

where $Z$ is the number of all items retrieved and recommended.

4) The $F_1$ measure is a combination of metrics recall and precision, which can be defined as:

$$F_1 = \frac{2 \times \text{recall} \times \text{precision}}{\text{recall} + \text{precision}} \tag{12}$$

## 3.3 Methods Compared in the Experiment

In order to evaluate the proposed trust model involving user similarity and friend familiarity, we built the following five recommendation strategies:

CF: The classical Resnick algorithm [19] in which the Pcc (Eq. (1)) is used for filtering and making predictions.

CCF: Incorporating context into CF [23].

User similarity CCF (US-CCF): Trust-based weighting using user similarity .

Friend familiarity CCF (FF-CCF): Trust-based weighting using friend familiarity.

User similarity and friend familiarity CCF (US-FF-CCF): Trust-based weighting considering both user similarity and friend familiarity.

## 3.4 Experiment Results

In this section, we compare the MAE, recall, precision and $F_1$ performances under different recommendation approaches and number of neighbors ($m$).

**1) The effect of user's similarity and friend familiarity**

Figures 4-7 report the results of the proposed hybrid trust methods, including US-CCF (user similarity), FF-CCF (friend familiarity) and US-FF-CCF, respectively over the MAE, recall, precision and $F_1$ measures. From Figs. 4-7, FF-CCF performs better than US-CCF on MAE, precision and $F_1$ measures. Though US-CCF obtains better results on the recall measure than FF-CCF, the FF-CCF have better results on comprehensive measure $F_1$ than US-CCF. Thus, the recommendation performance of FF-CCF is superior to US-CCF. This finding is mainly because the friend familiarity factor contributes more than the user similarity. Moreover, it is to see that US-FF-CCF performs slightly better than FF-CCF. That is to say, the trust weight based on the user similarity and friend familiarity synchronously can better optimize the recommendation quality than the trust weight based on friend familiarity factor only.

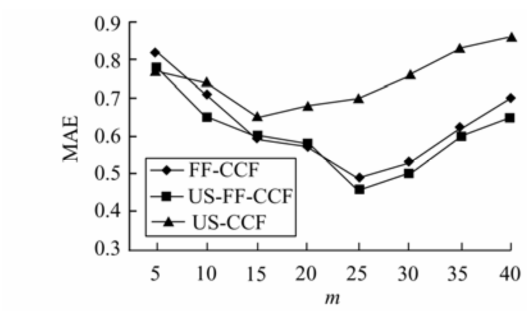


**Fig. 4 Results of MAE for US-CCF, FF-CCF and US-FF-CCF**

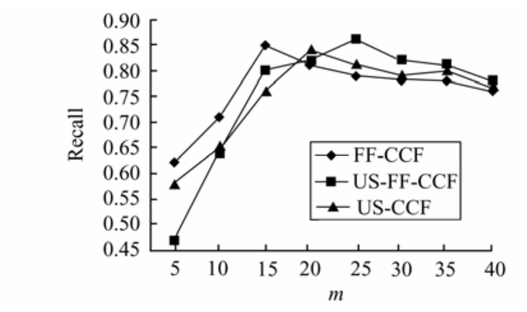


**Fig. 5 Results of recall for US-CCF, FF-CCF and US-FF-CCF**

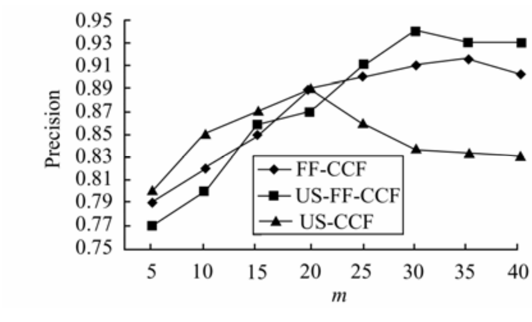


**Fig. 6 Results of precision for US-CCF, FF-CCF and US-FF-CCF**

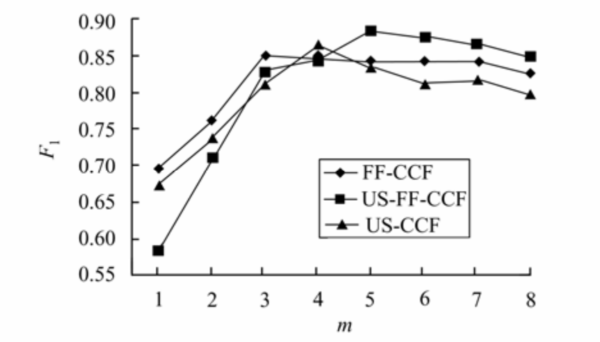


**Fig. 7 Results of $F_1$ for US-CCF, FF-CCF and US-FF-CCF**

**2) Comparative study with other methods**

We compare trust-based methods proposed in this paper with the CF method and CCF method in terms of MAE, recall, precision and $F_1$ measures under different sizes of neighbors. As shown in Figs.8-11, the trust-based method combined with user similarity and friend familiarity performs better than CF method and CCF method on MAE, recall, precision and $F_1$ measures. The prediction is more accurate when the weight is derived by combining the context based trust with friend

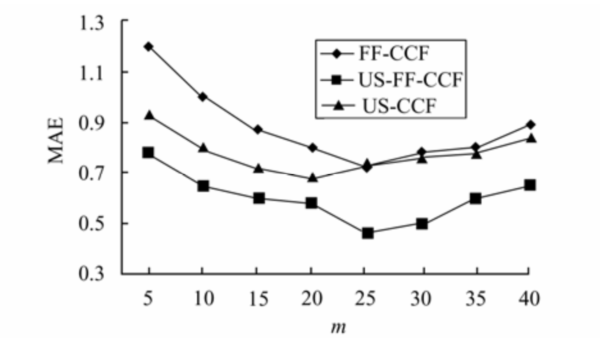


**Fig. 8 Results of MAE for CF, CCF and US-FF-CCF**

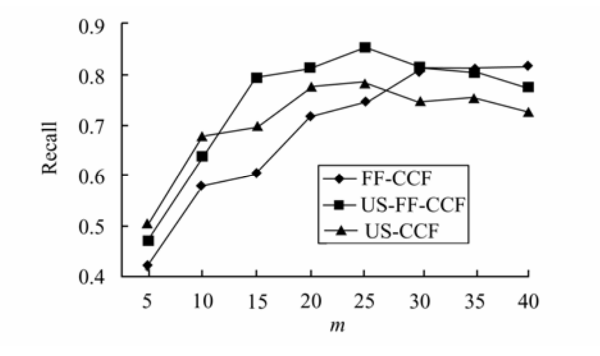


**Fig. 9 Results of recall for CF, CCF and US-FF-CCF**

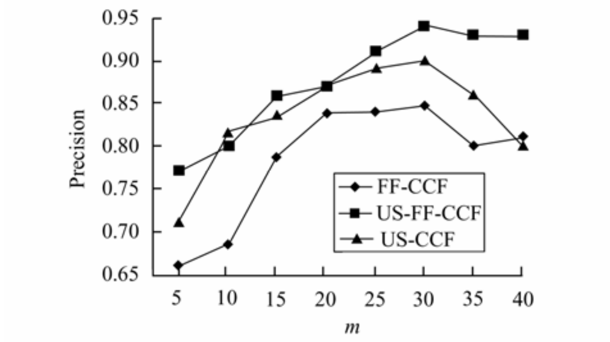


**Fig. 10 Results of precision for CF, CCF and US-FF-CCF**

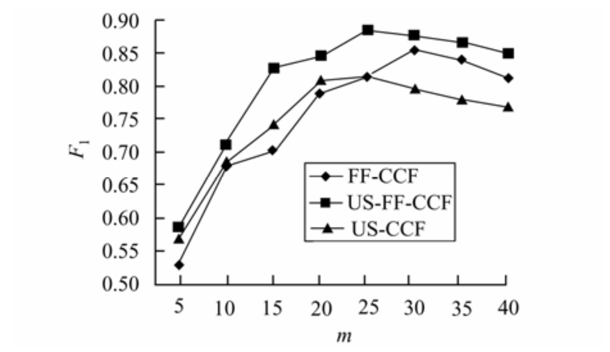


**Fig. 11 Results of $F_1$ for CF, CCF and US-FF-CCF**

familiarity factor and user similarity factor than the traditional CCF. This also indicates that the friend familiarity and user similarity can improve the recommendation performance in most cases.

## 4 Conclusion

This work proposes a novel service recommendation for MSN based on user context, trust network of friendship, and collaborative filtering algorithm. Our proposed methods consider user similarity and familiarity factors in computing trustworthy neighbors of the target user. Moreover, the proposed methods are further enhanced by considering user context and social relationship. Aside from the theoretical modeling and analysis, the simulations showed that the proposed method could effectively increase the recommendation accuracy. The practical application environment restricts the size and number of participants in the experiments, given the difficulty in obtaining a dataset that contains both user familiarity and ratings. In consideration of this limitation, our future work entails an evaluation of our method in other application domains referring to large-scale users and items.

## References

[1] Jiang W, Gao M D, Wang X X, *et al*. A new evaluation algorithm for the influence of user in social network [J]. *China Communications*, 2016, **13**(2): 200 -210.

[2] Bellavista P, Montanari R, Das S K. Mobile social networking middleware: A survey [J]. *Pervasive and Mobile Computing*, 2013, **9**(4): 437- 453.

[3] Moradi P, Ahmadian S. A reliability-based recommendation method to improve trust-aware recommender systems [J]. *Expert Systems with Applications*, 2015, **42**(21): 7386 -7398.

[4] Shambour Q, Lu J. An effective recommender system by unifying user and item trust information for B2B applications [J]. *Journal of Computer and System Sciences*, 2015, **81**(7): 1110 -1126.

[5] Yang X, Guo Y, Liu Y, *et al*. A survey of collaborative filtering based social recommender systems [J]. *Computer Communications*, 2014, **41**: 1-10.

[6] Lee W P, Kaoli C, Huang J Y. A smart TV system with body-gesture control, tag-based rating and context-aware recommendation [J]. *Knowledge-Based System*, 2014, **56**: 167-178.

[7] Chen C C, Wan Y H, Chung M C, *et al*. An effective recommendation method for cold start new users using trust and distrust networks [J]. *Information Sciences*, 2013, **224**: 19-36.

[8] Ruan Y, Durresi A. A survey of trust management systems for online social communities Trust modeling, trust inference and attacks [J]. *Knowledge-Based Systems*, 2016, **106**: 150 -163.

[9] Li J, Zhang Z, Zhang W. Mobitrust: Trust management system in mobile social computing [C]//*Proceedings of the* 10*th International Conference on Computer and Information Technology*. San Jose: IEEE Press, 2010: 954 - 959.

[10] Qureshi B, Min G, Kouvatsos D. Trusted information exchange in peer-to-peer mobile social networks [J]. *Concurrency and Computation*: *Practice and Experience*, 2012, **24**(17): 2055 - 2068.

[11] Li Z, Bi J. An adaptive trusted request and authorization model for mobile peer-to-peer networks [C]// *Proc High Performance Computing and Communications &* 2013 *IEEE International Conference on Embedded and Ubiquitous Computing*. San Jose: IEEE Press, 2013: 1274 - 1280.

[12] Li M, Xiang Y, Zhang B, *et al*. A trust evaluation scheme for complex links in a social network: a link strength perspective [J]. *Applied Intelligence*, 2016, **44**(4): 969-987.

[13] Kwan M, Ramachandran D. Trust and online reputation systems[C] // *Computing with Social Trust* . London: Springer-Verlag, 2009: 287 - 311.

[14] Ziegler C N, Lausen G. Analyzing correlation between trust and user similarity in online communities [C] // *Trust Management*. Berlin, Heidelberg: Springer-Verlag, 2004: 251-265.

[15] Golbeck J. Generating predictive movie recommendations from trust in social networks [C] // *Lecture Notes in Computer Science*. Berlin: Springer-Verlag, 2006, **3986**: 93-104.

[16] Massa P, Avesani P. Trust-aware recommender systems [C] // *Proc ACM Conf on Recommender Systems*. New York: ACM Press, 2007:17-24.

[17] Ankolekar A, Szabo G, Luon Y, *et al*. Friendlee: a mobile application for your social life [C] // *Proc* 11*th International Conf on Human-Computer Interaction with Mobile Devices and Services*. Berlin, Heidelberg: Springer-Verlag, 2010: 331-334.

[18] Golbeck J. Trust and nuanced profile similarity in online social networks [J]. *ACM Transactions on the Web* (*TWEB*), 2009, **3**(4): 1-30.

[19] Deng S G, Huang L T, Xu G D. Social network-based service recommendation with trust enhancement [J]. *Expert Systems with Applications*, 2014, **41**: 8075 - 8084.

[20] Deng S G, Huang L T, Yin Y Y, *et al*. Trust-based service recommendation in social network [J]. *Applied Mathematics & Information Sciences*, 2015, **9**(3): 1567-1574.

[21] Resnick P, Iacovou N, Suchak M, *et al*. GroupLens: an open architecture for collaborative filtering of netnews [C] //*Proc ACM Conf on Computer Supported Cooperative Work*. New York: ACM Press, 1994: 175 -186.

[22] Sarwar B M, Karypis G, Riedl J. Item-based collaborative filtering recommendation algorithms [C]// *Proc International Conf on World Wide Web*. New York: ACM Press, 2001: 285 - 295.

[23] Donovan J O, Smyth B. Trust in recommender systems [C]// *Proc International Conf on Intelligent User Interfaces*. New York: ACM Press, 2005: 167-174.

[24] Chen A. Context-aware collaborative filtering system: Predicting the user's preference in the ubiquitous computing environment [C] // *Lecture Notes in Computer Science*. Berlin, Heidelberg: Springer-Verlag, 2005, **3479**: 244-253.

[25] Gitelson R, Kerstetter D. The influence of friends and relatives in travel decision making [J]. *Journal of Travel & Tourism Marketing*, 1995, **3**(3): 59 - 68.

[26] Lo S, Lin C. Wmr a graph-based algorithm for friend recommendation [C]// *Proc IEEE/WIC/ACM International Conf on Web Intelligence*, *IEEE Computer Society*. New York: ACM Press, 2006: 121-128.

[27] Milgram S. The small world problem [J]. *Psychology Today*, 1967, **2** (1): 60 - 67.

[28] Beach A, Gartrell M, Xing X Y, *et al*. Fusing mobile, sensor, and social data to fully enable context-aware computing [C]// *Proc Eleventh Workshop on Mobile Computing Systems & Applications*. New York: ACM Press, 2010: 60 - 65.

[29] Moradi P, Ahmadian S, Akhlaghian F. An effective trust-based recommendation method using a novel graph clustering algorithm [J]. *Physica A*: *Statistical Mechanics and Its Applications*, 2015, **436**: 462 - 481.

□