A Novel User Behavior Prediction Algorithm in Mobile Social Environment

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Abstract

According to the group, interactive and real-time characteristics of mobile social environment, a novel user behavior prediction algorithm in mobile social environment is proposed in this paper. First, a coding based two-dimensional Apriori method is presented to improve the efficiency of user behavior analysis. Furthermore, in order to comprehensively analyze user behaviors, on one hand, the correlation analysis based on behavior history of a target user is performed; on the other hand, an effectiveness factor is formulated to obtain the optimal correlation set of target user from its friend circle, and then the correlation analysis between the target user and each correlated user from its optimal correlation set is performed. Finally, for integrating the above correlation analysis results, an improved optimal weighted fusion method based on effectiveness factors is presented, so as to achieve accurate prediction of user service behaviors. Extensive simulations results show that the proposed algorithm outperforms several related algorithms in terms of prediction efficiency and accuracy.

Keywords: Mobile social environment, Two-dimensional Apriori, User service behaviors, Joint service recommendations

1 Introduction

With the rapid development of mobile Internet and social software, more and more attention has been focused on mobile social networks. In mobile social environment (MSE) [1-2], by using various social applications for mobile terminals such as Twitter, Facebook, and Instragram, a user shares thoughts, activities, photos, and other information with its friends anytime and anywhere. As a new social platform, MSE has group, interactive and real-time characteristics, where users may have similar interests or mutual impacts. Hence, there is a close correlation between service behaviors of users in friend circle.

On the other hand, user service behavior prediction [3-4], which can solve the information overloading problem effectively, has become a hot research field. In this field, joint behavior prediction algorithm [5] based on multi-user historical information has superior performance in terms of prediction accuracy. Obviously, MSE can provide extensive correlated users and correlated samples for each target user to improve its behavior prediction capability.

Therefore, the user service behavior prediction problem in MSE is investigated in this paper, which is organized as follows. Section 2 reviews the related work. Section 3 describes a novel user behavior prediction algorithm in MSE, and gives its algorithm flow as well as complexity analysis. Section 4 presents simulation results and performance analyses. Finally, conclusions are drawn in Section 5.

2 Related Work

At present, in the area of user behavior analysis in MSE, researches on group behaviors acquire a lot of attentions. For instance, user behaviors of contents sharing in friend circle are analyzed in [1]. In order to make new friends and expand user's friend circle based on the common interests, the building of model-based friend recommendation in location-based MSE is presented in [2]. In addition, some researchers connect users with services to analyze user access behaviors from several aspects [6]. An improved division method of MSE based on user communication behaviors is presented in [7]. In [8], the MSE user behaviors are analyzed from the perspective of ISP networks. Privacy-preserving distributed profile is used to realize user behavior analysis [9]. Besides, user behavior study of using packet-trace data technology is a hot research topic [10].

On the basis of user behavior analysis, researches on user behavior prediction in MSE have emerged. For example, a novel demand prediction engine is proposed in [11] to extract local demand depending on social content and estimate what content will be requested there. An idea with machine learning is presented in [12] to predict the forwarding behaviors of users, and pattern classification methods are used to solve the prediction problem. Additionally, in order to

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provide good intercommunication over nodes in MSE, scholars have paid much regard on user delivery behaviors [13].

However, there is very limited work in joint behavior prediction based on the association relationship of users. As a classical correlation analysis method, Apriori provides an effective tool for mining the behavior relationship between users [14-15]. In this paper, based on an improved Apriori method, a novel user behavior prediction algorithm in MSE is proposed. In order to comprehensively analyze user behaviors, *n+1* correlation analyses of a target user and the most correlated *n+1* users including itself are performed respectively; and then an improved optimal weighted fusion method is presented to integrate the above correlation analysis results. Finally, extensive simulations results verify that the proposed algorithm performs better than several related algorithms in efficiency and accuracy.

3 User Behavior Prediction Algorithm

3.1 Coding Based Two-dimensional Apriori Method

Association rule mining algorithm is used to find all frequent association rules in transaction database D. The frequent association rule refers to support degree and confidence degree larger than the minimum support degree (*min_sup*) and minimum confidence degree (*min_con*). $I=\{i_1,i_2,...,i_M\}$ is a collection of items; each transaction T of D is a combination of items from I. Assume X and Y are subsets of I. $X\bigcup Y$ means they appear simultaneously. $|\bullet|$ means the number of corresponding T. For association rule $X\Rightarrow Y$, its support degree and confidence degree can be calculated in (1) and (2).

$$support(X\Rightarrow Y)=\frac{|\{T{:}X\bigcup Y,X,Y\subseteq T,T\in D\}|}{|D|} \quad \textbf{(1)}$$

$$confidence(X\Rightarrow Y)=\frac{|\{T:X\bigcup Y,X,Y\subseteq T,T\in D\}|}{|\{T{:}\,X\subseteq T,T\in D\}|} \quad \textbf{(2)}$$

Apriori algorithm is a classical algorithm for mining association rules. However, there are two disadvantages in Apriori algorithm, which are producing a large number of candidate item sets and scanning the database D repeatedly. Therefore, a coding based two-dimensional Apriori method is presented to improve the algorithm efficiency. The baisc idea is: first, the sample table considering behavior sequence is mapped into the transaction table; then, the items of transaction table are encoded; finally, "*and*" encoding operation is used to obtain frequent association rules.

3.2 Correlation Analysis Based on Behavior History of Single User

Assume user *m* is the target user. User *m*'s service behaviors can be divided into *M* categories, such as news, video information, music, chat text, game, online shopping and so on. Table 1 gives service behaviors samples of user *m*, in which there are 7 transaction records with two dimensions.

Table 1. Service behaviors sample table of user *m*

TID	User service behaviors in the current moment	User service behaviors after t minutes
1	news	chat text
2	chat text	video information
3	game	music
4	video information	online shopping
5	news	chat text
6	chat text	video information
7	news	chat text

Table 1 can be mapped into Table 2 (transaction table). The transaction record T_i is composed of user service behavior in the current moment A_{I_j} and user service behavior after t minutes B_{I_k}. Here, I_j and I_k represent categories of user service behavior.

Table 2. Transaction table after mapping

TID	Current moment	After t minutes
T_1	A_{I_1}	B_{I_2}
T_2	A_{I_2}	B_{I_3}
T_3	A_{I_4}	B_{I_5}
T_4	A_{I_3}	B_{I_6}
T_5	A_{I_1}	B_{I_2}
T_6	A_{I_2}	B_{I_3}
T_7	A_{I_1}	B_{I_2}

Based on Table 2 and given that $min\_sup=20\%$, the improved Apriori method is used to generate frequent association rules. The generating process is as follows.

The first step. scan transaction table, all transaction items are encoded to form the item coding table, as shown in Table 3.

The second step. according to the coding count of each item, frequent 1 item sets L_1 can be obtained, as shown in Table 4.

The third step. generate frequent 2 item sets L_2 from L_1 by using "*and*" encoding operation, as shown in Table 5. Obviously, it is unnecessary to scan transaction table repeatedly.

Table 3. Item coding table

	T_1	T_2	T_3	T_4	T_5	T_6	T_7
A_{I_1}	1	0	0	0	1	0	1
A_{I_2}	0	1	0	0	0	1	0
A_{I_3}	0	0	0	1	0	0	0
A_{I_4}	0	0	1	0	0	0	0
L_2	1	0	0	0	1	0	1
B_{I_3}	0	1	0	0	0	1	0
B_{I_5}	0	0	1	0	0	0	0
B_{I_6}	0	0	0	1	0	0	0

Table 4. Generating frequent 1 item sets

Item	Coding	Support number	Frequent item sets
$\{A_{I_1}\}$	1000101	3	$\{A_{I_1}\}$
$\{A_{I_2}\}$	0100010	2	$\{A_{I_2}\}$
$\{A_{I_3}\}$	0001000	1	
$\{A_{I_4}\}$	0010000	1	
$\{B_{I_2}\}$	1000101	3	$\{B_{I_2}\}$
$\{B_{I_3}\}$	0100010	2	$\{B_{I_3}\}$
$\{B_{I_5}\}$	0010000	1	
$\{B_{I_6}\}$	0001000	1	
frequent 1 item sets: $\{A_{I_1}\}\{A_{I_2}\}\{B_{I_2}\}\{B_{I_3}\}$			

Table 5. L_2 generated from L_1

Item	Coding	Support number	Frequent item sets
$\{A_{I_1}, B_{I_2}\}$	1000101	3	$\{A_{I_1}, B_{I_2}\}$
$\{A_{I_1}, B_{I_3}\}$	0000000	0	
$\{A_{I_2}, B_{I_2}\}$	0000000	0	
$\{A_{I_2}, B_{I_3}\}$	0100010	2	$\{A_{I_2}, B_{I_3}\}$
frequent 2 item sets: $\{A_{I_1}, B_{I_2}\}\{A_{I_2}, B_{I_3}\}$			

Due to the Markov characteristic of user behaviors, it is enough for user behavior prediction to use frequent 2 item sets L_2. Assume $min\_con = 75\%$, all the frequent association rules based on L_2 can be obtained. For example, the support degree of A_{I_1} is 3/7. According to frequent item set A_{I_1}, the confidence degree of association rule $A_{I_1} \Rightarrow B_{I_2}$ is 100%, which is larger than *min_con*. Hence, $A_{I_1} \Rightarrow B_{I_2}$ is a a frequent association rule. Naturally, if user *m*'s service behavior in the current moment is Γ_m, user *m's* service behavior after *t* minutes is likely to be A_{I_2}. There is a strong correlation between them. In addition, although the confidence degree of $B_{I_2} \Rightarrow A_{I_1}$ is also 100%, it is not a frequent association rule due to the consideration of behavior appearance sequence. This is the main difference between our improved Apriori method and Apriori method, which can increase our algorithm efficiency remarkably.

3.3 Correlation Analysis Based on Behavior History of Multi-user

Effectiveness factor. Service behaviors of user m in MSN are influenced not only by itself, but also by its correlated users. Therefore, it is necessary to perform correlation analysis between user m and its correlated users, so as to mine the corresponding frequent item sets. However, it is not economy nor accurate for user *m* to perform correlation analysis with all correlated users. An effectiveness factor is presented to select the most correlated *n* users of user *m*. Based on the statistics information of online time and interaction frequency of all users, the effectiveness factor is formulated in (3).

$$T_{(m,n_i)} = \alpha \times \log_2\left(\frac{SN_{(m,n_i)}}{SN_m} + 1\right) + \beta \times \log_2\left(\frac{IN_{(m,n_i)}}{IN_m} + 1\right) \quad \textbf{(3)}$$

$SN_{(m,n_i)}$ is the duration that user m and user n_i are simultaneously online; SN_m is the duration that user m is online; $IN(m,n_i)$ represents the interaction frequency between user *m* and user n_i; IN_m represents the total interaction frequency between user *m* and each correlated user. α, β are weighted parameter, and $\alpha + \beta = 1$. α, β can be obtained through experiment analysis. Obviously, $0 \le T_{(m,n_i)} \le 1$. Considering the actual situations, the effectiveness factor of user *m* influenced by itself $T_{(m,m)} = 1$.

According to (3), the effectiveness factor of user *m* influenced by each correlated user can be calculated. Then, by comparing the above calculated results, the most correlated *n* users of user *m* can be selected, which constitute its optimal correlation set Γ_m. In addition, the most correlated *n* users of user *m* may vary with time, and should be updated in each prediction process.

Correlation analysis between user *m* and each correlated user in Γ_m. According to the effectiveness factor mentioned above, Γ_m can be obtained. Then, the correlation analysis between user *m* and each correlated user in Γ_m is performed. Current service behavior of each correlated user in Γ_m is used to predict user *m*'s service behavior after *t* minutes. Table 6 gives the correlation samples of user *m* and user u_1, $u_1 \in \Gamma_m$. The process of mining frequent item sets is same as section 3.2.

Table 6. Correlation sample table of user *m* and user u_1

TID	User u_1's service behavior in the current moment	User *m*'s service behavior after t minutes
1	video information	game
2	chat text	video information
3	game	music
4	video information	news
5	news	online shopping
6	chat text	video information
7	news	online shopping

For example, the support degree of { A_{I_1} , B_{I_6} } is 2/7. The frequent association rule $A_{I_1} \Rightarrow B_{I_6}$ can be obtained by using the improved Apriori method. Namely, if user u_1's service behavior in the current moment is I_1, user *m's* service behavior after *t* minutes is likely to be I_6. There is a strong correlation between them. In order to facilitate the final result fusion, *n+1* correlation analyses of user m and the most correlated *n+1* users including itself should be performed in the same way (i.e. same method and same parameter settings).

3.4 An Improved Optimal Weighted Fusion Method Based on Effectiveness Factors

Naturally, it is necessary to integrate the above *n+1* correlation analysis results according to their relative importance for user m's behavior prediction. Hence, An improved optimal weighted fusion method based on effectiveness factors is presented. There are various frequent association rules and *K* support degree samples for the same frequent association rule in each correlation analysis. So, the support degree of each frequent association rule in each correlation analysis can be considered as a random variable. For a frequent association rule, there are *n+1* random variables of support degree, whose variance are denoted as $\sigma_1^2, \sigma_2^2, ..., \sigma_{n+1}^2$, and mean are denoted as $x_1, x_2, ..., x_{n+1}$ respectively. Obviously, the *n+1* random variables are independent from each other and the mean x_i, $1 \le i \le n+1$. is exactly the corresponding support degree result of frequent association rule in i_{th} correlation analysis. Assume the weighted coefficient of x_i is ω_i, $1 \le i \le n+1$. Then, the basic fusion method can be described as (4).

$$x = \sum_{i=1}^{n+1} \omega_i x_i \quad \textbf{(4)}$$

ω_i must satisfy: $\sum_{i=1}^{n+1} \omega_i = 1$, and x denotes the basic fusion result.

First, the case that *n+1=2* is analyzed. Namely, there are 2 correlation analyses. Based on the above description and given the frequent association rule, the corresponding estimated values of support degree results are respectively denoted as:

$$\hat{x}_1 = x + v_1, \hat{x}_2 = x + v_2 \quad \textbf{(5)}$$

v_1 and v_2 are random estimated errors. Moreover, $v_1 \sim N(0, \sigma_1^2)$ and $v_2 \sim N(0, \sigma_2^2)$. So, the estimated value of fusion result $\hat{x}$ is described in (6).

$$\hat{x} = \omega_1 x_1 + \omega_2 x_2 \quad \textbf{(6)}$$

ω_1, ω_2 are the corresponding weighted coefficients. Then, the estimated error is given in (7).

$$\tilde{x} = x - \hat{x} \quad \textbf{(7)}$$

Naturally, the cost function is defined as the mean square error of $\hat{x}$, which is calculated in (8).

$$J = E(\tilde{x}^2) = E\{[x - \omega_1(x + v_1) - \omega_2(x + v_2)]^2\} \quad \textbf{(8)}$$

Because $\hat{x}_1$ and $\hat{x}_2$ are independent from each other, it can be assumed that $\hat{x}$ is the unbiased estimation of x. So,

$$E(\tilde{x}) = E[x - \omega_1(x + v_1) - \omega_2(x + v_2)] = 0 \quad \textbf{(9)}$$

Furthermore, $E(v_1) = E(v_2) = 0$. So,

$$\omega_2 = 1\text{-}\omega_1 \quad \textbf{(10)}$$

The cost function J can be rewritten in (11).

$$J = E[\omega_1^2 v_1^2 + (1 - \omega_1)^2 v_2^2 + 2\omega_1(1 - \omega_1)v_1 v_2] \quad \textbf{(11)}$$

Furthermore, $E(v_1^2) = \sigma_1^2$, $E(v_2^2) = \sigma_2^2$ and $E(v_1 v_2) = 0$. So,

$$J = E(\tilde{x}^2) = \omega_1^2 \sigma_1^2 + (1 - \omega_1)^2 \sigma_2^2 \quad \textbf{(12)}$$

In order to obtain the minimum of J , ω_1 has to satisfy (13).

$$\frac{\partial J}{\partial \omega_1} = 0 \quad \textbf{(13)}$$

Thus, the optimal weighted values are calculated in (14)

$$\omega_1^* = \frac{\sigma_2^2}{\sigma_2^2 + \sigma_1^2}, \omega_2^* = \frac{\sigma_1^2}{\sigma_2^2 + \sigma_1^2} \quad \textbf{(14)}$$

Extending the above conclusion, if there are $n+1 \ge 2$ correlation analyses, the optimal weighted values can be calculated by solving the corresponding minimum of mean square error. That is,

$$\omega_i^* = \frac{1/\sigma_i^2}{\sum_{i=1}^{n+1} 1/\sigma_i^2} \quad \textbf{(15)}$$

According to section 3.3.1, the impacts on user *m's* service behaviors from different correlated users (including itself) are quite different. Therefore, it is necessary to utilize effectiveness factors to modify (15). So,

$$\omega_i^\bullet = \frac{\ln(e^{\omega_i^*} \times T_{(m,n_i)})}{1+\ln(\prod T_{(m,n_i)})} \quad \textbf{(16)}$$

Obviously, $\sum_{i=1}^{n+1} \omega_i^\bullet = 1$. The final fusion result can be calculated in (17).

$$x^\bullet = \sum_{i=1}^{n+1} \omega_i^\bullet x_i \quad \textbf{(17)}$$

The larger $x^\bullet$ is, the more possibly the corresponding frequent association rule appears. By computing and comparing the $x^\bullet$ s of all possible association rules, the frequent association rule can be obtained.

3.5 Algorithm Flow and Complexity Analysis

First, a coding based two-dimensional Apriori method is used to perform *n+1* correlation analyses. Second, an improved optimal weighted fusion method based on effectiveness factors is used to integrate the above correlation analysis results. Finally, user m's service behavior after *t* minutes can be predicted accurately. The flow chart of proposed algorithm is shown in Figure 1.

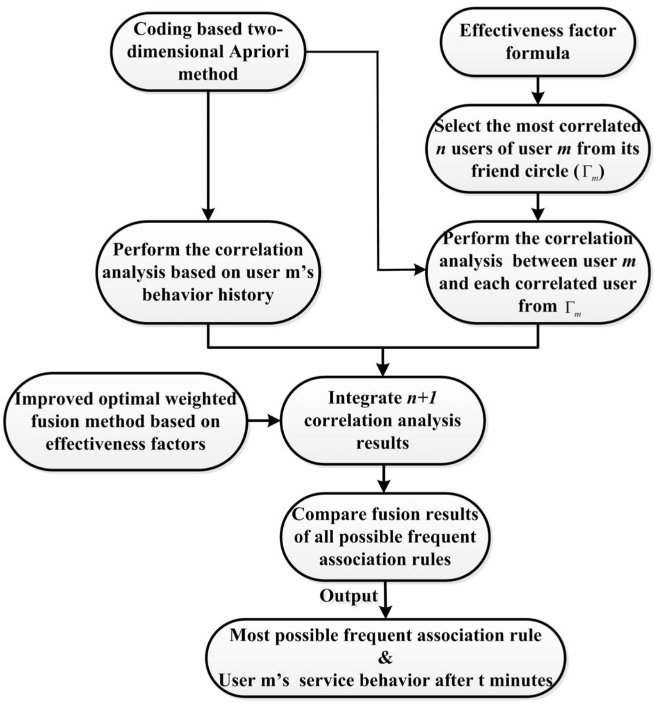

Figure 1. Flow chart of proposed algorithm

Due to the adoption of our improved Apriori method, one-time correlation analysis has quite small time complexity and space complexity. However, the above complexities cannot evaluated explicitly because of depending on the practical behavior samples. Hence, the time and space taken by one-time correlation analysis are assumed as *basic time unit* (BTU) and *basic space unit* (BSU). Hence, for the process of *n+1* correlation analyses of proposed algorithm, the time complexity is $O(nK)$ in BTU; the space complexity is $O(nK)$ in BSU. Furthermore, for the process of Γ_m selection of proposed algorithm, the time complexity is $O(nW)$ and the space complexity is $O(n+W)$; for the process of result fusion of proposed algorithm, the time complexity is $O(nM)$ and the space complexity is $O(n+M)$. Here, *W* denotes the total number of correlated users from user *m*'s friend circle. For the processes of Γ_m selection and result fusion, the corresponding complexity units are the time taken by a basic operation and the space taken by a local variable, which are smaller than BTU and BSU respectively. On the other hand, according to the definitions of *K* (see section 3.4), *W* and *M* (see section 3.2), they can be expressed as the linear function of *n*. Therefore, the time complexity of proposed algorithm is $O(n^2)$ in BTU and the space complexity of proposed algorithm is $O(n^2)$ in BSU approximately.

4 Simulation Analysis

By randomly selecting target users from the real world, we observe and record the service behaviors as well as interaction behaviors of each target user and its correlated users of friend circle within 10 days. Thus, the test data sets for our simulations can be obtained. In each correlation analysis, *K=10* support degree values are sampled for each possible frequent association rule, so as to calculate $x^\bullet$. In the simulation, our algorithm PUBPA (Proposed User Behavior Prediction Algorithm) is compared with PUBPAWEF (Proposed User Behavior Prediction Algorithm Without Effectiveness Factor), ABUBPA (Apriori Based User Behavior Prediction Algorithm) [15], UDUBPA (Uniform Distribution User Behavior Prediction Algorithm), AWUBPA (Average Weighted User Behavior Prediction Algorithm) and RWUBPA (Random Weighted User Behavior Prediction Algorithm) respectively. Here, PUBPAWEF uses (15) to integrate correlation analysis results without considering effectiveness factors; ABUBPA uses Apriori method to perform the corresponding correlation analyses; UDUBPA selects the most correlated *n* users of target user by means of uniform distribution; AWUBPA and RWUBPA uses average weighted method and random weighted method to integrate correlation analysis results respectively. Except the above differences, the rest of these algorithms are same with PUBPA. Matlab is used to realize the above algorithms. Running time and

Accuracy are adopted to evaluate prediction efficiency and accuracy of algorithms respectively. Each data point represents an average of 20 runs corresponding to 20 target users. In addition, $min\_con = 75\%$, $\alpha = 0.4$, $t = 30\,\text{min}$.

First, we change minimum support to compare running time values of PUBPA, PUBPAWEF and ABUBPA for a correlation analysis. As shown in Figure 2, the running time curves of three algorithms all decrease as min_sup increases. That is because the number of frequent item sets decreases as min_sup increases. Furthermore, PUBPA and PUBPAWEF have the same running time values because they have the same correlation analysis method; compared with ABUBPA, running time of PUBPA improves by 8.33% averagely; when min_sup is small, PUBPA performs much better. For obtaining the appropriate quantity of frequent item sets, we set $min\_sup = 40\%$ in the following simulations.

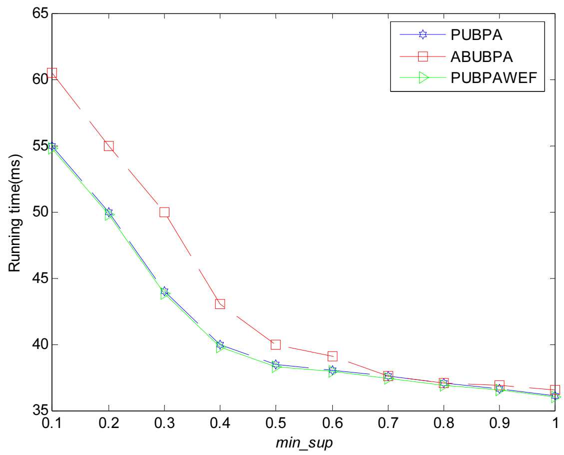

Figure 2. Running time comparison with min_sup

Then, we change *n* to compare accuracy values of PUBPA, PUBPAWEF and UDUBPA in two cases. In case I, the three algorithms perform *n+1* correlation analyses of a target user and the most correlated users including itself, and integrate *n+1* correlation analysis results for user behavior prediction. In case II, the three algorithms perform *n* correlation analyses of a target user and the most correlated users without including itself, and integrate *n* correlation analysis results for user behavior prediction. Here, *n* is the cardinal number of optimal correlation set Γ_m. As shown in Figure 3, the accuracy curves of three algorithms in two cases all increase with *n*, which indicates the necessity of considering correlated users' impacts. However, when *n* reaches a larger value, all accuracy curves begin to increase slowly. Thus, *n* should not take too large value. Furthermore, the accuracy values of each algorithm in case I are larger than those in case II correspondingly due to the consideration of impact on a target user from itself; for the same cases, PUBPA outperforms PUBPAWEF in prediction accuracy, indicating the importance of effectiveness factors for result fusion; for the same cases, PUBPA outperforms UDUBPA in prediction accuracy, indicating the importance of effectiveness factors for Γ_m selection.

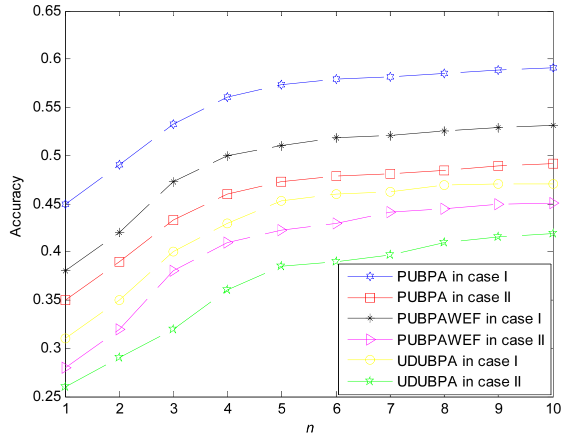

Figure 3. Accuracy comparison of PUBPA, PUBPAWEF and UDUBPA with *n*

For further verifying the effectiveness of our weighted fusion method, we change *n* to compare accuracy values of PUBPA, AWUBPA and RWUBPA. In Figure 4, the accuracy curves of three algorithms all increase with *n*. Furthermore, PUBPA performs much better than the other two algorithms in prediction accuracy, which indicates that our weighted fusion method can improve PUBPA's performance remarkably.

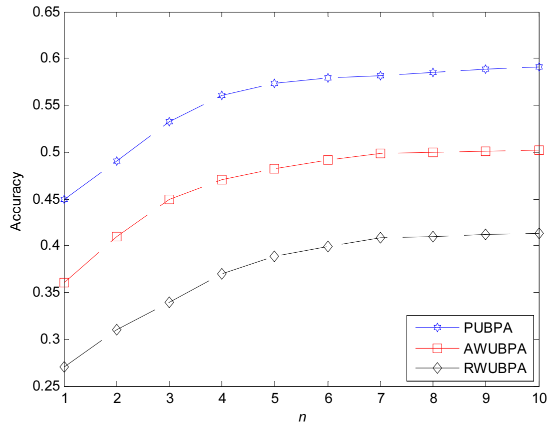

Figure 4. Accuracy comparison of PUBPA, AWUBPA and RWUBPA with *n*

Because the parameter α influences the validity of effectiveness factors directly. In order to acquire the best value of α, we change *n* to compare accuracy values of PUBPA for different α. As can be seen from Figure 5, when $\alpha = 0.4$, PUBPA performs optimally. Thus, 0.4 can be considered as the best value of α approximately.

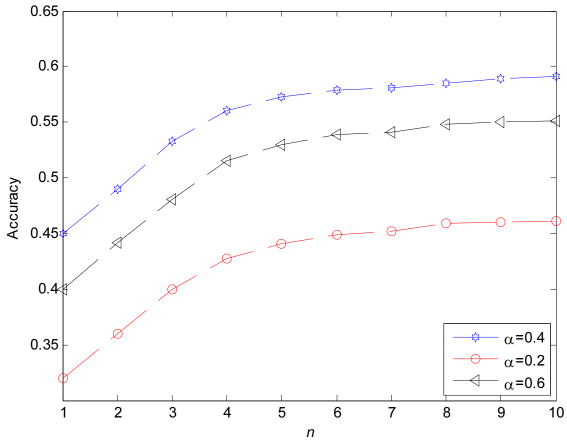

Figure 5. Accuracy comparison of PUBPA for different α with n

5 Conclusion

A novel user behavior prediction algorithm in mobile social environment is proposed in this paper. In order to improve the prediction efficiency, a coding based two-dimensional Apriori method is presented. Furthermore, in order to improve the prediction accuracy, $n+1$ correlation analyses of a target user and the most correlated $n+1$ users including itself are performed respectively, and then an improved optimal weighted fusion method is presented to integrate the above correlation analysis results. Finally, comparative simulations of the proposed algorithm against several related algorithms are conducted. The results show that the proposed algorithm can predict user service behaviors more efficiently and accurately.

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References

[1] H. Li, K. S. Bok, J. S. Yoo, An Efficient Mobile Social Network for Enhancing Contents Sharing over Mobile Ad-Hoc Networks, *International Conference on Parallel and Distributed Computing, Applications and Technologies*, Beijing, China, 2012, pp. 111-116.

[2] H.-L. Kim, J. G. Breslin, H.-C. Chao, L. Shu, Evolution of Social Networks based on Tagging Practices, *IEEE Transactions on Services Computing*, Vol. 6, No. 2, pp. 252-261, April-June, 2013.

[3] L.-B. Dong, T. He, L. Zhang, G.-Z. Sun, J.-Y. Shao, Qos Optimal Location-Based Services Architecture Based on Mobile Cloud Computing and Behavior Prediction, *Journal of Internet Technology*, Vol. 16, No. 5, pp. 895-904, September, 2015.

[4] S. Niu, W. Liu, X. Luo, User Behaviours Prediction in Microblog Based on Human Knowledge Cognitive Process, *International Conference on Semantics, Knowledge and Grids (SKG)*, Beijing, China, 2015, pp. 147-153.

[5] G. Neelima, S. Rodda, Predicting User Behavior through Sessions Using the Web Log Mining, *International Conference on Advances in Human Machine Interaction (HMI)*, Doddaballapur, India, 2016, pp. 1-5.

[6] G.-F. Zhao, W.-J. Lai, C. Xu, H. Tang, Analysis of User Behavior in Mobile Internet Using Bipartite Network, *International Conference on Mobile Ad-hoc and Sensor Networks*, Chendu, China, 2012, pp. 38-44.

[7] P.-K. Zhao, J.-J. Zhao, W. Wang, Division of Mobile Social Network based on User Behavior, *2013 International Conference on Wavelet Analysis and Pattern Recognition, Tianjin*, China, 2013, pp. 148-152.

[8] G. F. Zhao, D. Li, C. Xu, H. Tang, S. Yu, Network Dynamics of Mobile Social Networks, *International Conference on Communications*, Sydney, Australia, 2014, pp. 2478-2483.

[9] M. Li, S. Yu, N. Cao, W. Lou, Privacy-Preserving Distributed Profile Matching in Proximity-Based Mobile Social Networks, *IEEE Transactions on Wireless Communications*, Vol. 12, No. 5, pp. 2024-2033, May, 2013.

[10] F. Benevenuto, T. Rodrigues, M. Cha, V. Almeida, Characterizing User Behavior in Online Social Networks, *ACM Sigcomm Conference on Internet Measurement*, Chicago, IL, 2009, pp. 49-62.

[11] H. Kubo, R. Shinkuma, T. Takahashi, H. Kasai, K. Yamaguchi, R. Yates, Demand Prediction Based on Social Context for Mobile Content Services, *IEEE International Conference on Communications Workshops*, Kyoto, Japan, 2011, pp. 1-5.

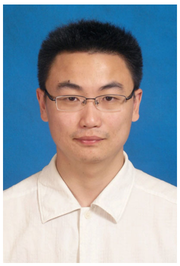
[12] G. H. Song, Z. T. Li, H. Tu, Forward or Ignore: User Behavior Analysis and Prediction on Microblogging, *International Conference on Computer Supported Cooperative Work in Design (CSCWD)*, Wuhan, China, 2012, pp. 678-684.

[13] E. Bulut, B. K. Szymanski, Friendship based Routing in Delay Tolerant Mobile Social Networks, *Global Telecommunications Conference*, Miami, FL, 2010, pp. 1-5.

[14] P.-J. Wang, L. Shi, J.-N. Bai, Y.-L. Zhao, Mining Association Rules Based on Apriori Algorithm and Application, *International Forum on Computer Science-Technology and Applications, IFCSTA'09, Chongqing*, China, 2009, pp. 141-143.

[15] T.-H. Hou, H.-Y. Houa, Data Mining the Factors of E-Learning Performance through Decision Trees and Apriori Association Rules, *Journal of Internet Technology*, Vol. 9, No. 4, pp. 411-419, October, 2008.

Biographies



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