Journal of Education and Praxis Research. Volume 1, Issue 1, (2015) 8-18
http://www.cayley-nielson.com/jepr

Enhancing E-Learning Personalized Recommender Systems with Implicit Rating and Social Information

Kate Kelvin
Courant Institute of Mathematical Sciences, New York University, Bursar 105 East 17th street, 3rd Floor New York, NY 10003, USA
E-mail: kk2001@nyu.edu

Abstract

With the emergence of Web 2.0 and virtual learning system, a huge and increasing amount of e-learning resources have been generated in a varity of formats, which can be selected by users with their own freedom. It is very difficult for users who are lack of sufficient background knowledge to choose suitable resources in their current learning processes without proper guidance. On the other hand, in the e-learning scenario, users' behaviors are more social and coherent. It is very necessary to derive implicit rating information from users' behaviors for improving the precision of e-learning recommendation. In this paper, a hybrid recommender method is proposed to recommend learning items in users' learning processes. Our method is composed of two phases: sequential pattern analysis phase and social network analysis phase. The two approaches are combined to recommend potentially useful learning items to guide users in their current learning processes. Experiments on a real-world datasets are carried out to evaluate the performance of our method. The results show that the proposed method outperforms other methods and improves e-learning recommendation quality effectively.

Keywords: E-learning; Collaborative filtering; Personalized recommendation; Sequential pattern mining; Social network analysis.

1. Introduction

In the last decade, electronic learning (e-learning) systems have undergone rapid development with the growth of Internet, information and educational technologies. Many e-learning applications have been developed, which enable people to learn in anywhere and anytime [1]. In contrast, traditional face-to-face teaching methods are so time consuming that learner have to spend losts of time and effort for finding the desired topic while the probability of reaching the goal and finding the appropriate resources is not clear [2]. Meanwhile, a lot of conventional learning resources have been digitalized and stored on the Web by individuals and educational organizations all over the world. Thus, Those digital learning materials are usually heterogeneous and dynamic [3]. Besides, from the e-learning systems users' point of view, e-learning is very different from conventional learning where teachers are responsible for the guidance of students' learning processes. While on the Internet, users have their own freedom to select courses and learning resources. However, it can be very difficult for users who are lack of sufficient background knowledge to choose suitable resources in their current learning processes without proper guidance. As the rapid growth of e-learning systems on the Internet, these proplems have made personalized recommendation in e-learning environments a challenging issue and therefore an important direction of research [4].

March, 2015

Recently, recommender systems are developed to provide personalized recommendations to users in e-commerce, such as Amazon, Netflix and YahooMusic [5]. The core of recommender systems depends on two popular methods: content-based filtering (CBF) and collaborative filtering (CF) [6,7]. Compared with CBF, CF only depends on historical information about whether or not a given target user who has previously preferred an item, and does not necessarily required any analysis on the actual content of an item [7]. In the scenario of e-learning, learning resources on the Internet are in many kinds of formats, e.g. text, video, audio, slides and so on. The nature of multimedia files makes it difficult to calculate content similarity of two items [8]. In this case, the preference information of users is a good indication for recommendation. Therefore, CF has an advantage over CBF in e-learning systems since it is not necessary to analyze the underlying content of the candidate items [5]. But, CF has a critical limitation that it cannot be adopted by recommendation systems for e-learning since explicit rating on items is not available. Meanwhile, compared with in e-commerce, users' behaviors are more consistent, coherent and social in e-learning, and learning resources usually have certain intrinsic orders in learning processes of users [9]. However, traditional CF methods can not reflect these characteristics that could severely affect the recommendation quality in e-learning envirement. Therefore, it is necessary to derive implicit rating information from users' behaviors, such as browsing and retrieval, which can be utilized to along with explicit rating information to improve the precision of CF recommendation.

In this paper, a hybrid recommending method with sequential pattern analysis and social network analysis is proposed to enhance the effectiveness of CF recommendation in e-learning envirement. First, we use SPA to capture users' implicit preference information and cluster the users in e-learning systems into different groups with related preferences. Then, the SNA will be employed for the analysis of the patterns of social interaction between the various e-learners. This hybrid approach is ideal for e-learning system to stimulate e-learners' motivation and interest and can be acted as a reference when e-learners choose resources or classes.

2. Related work

2.1. E-learning

Generally, e-learning is defined as a the use of Internet, information and communication technologies to provide a varity of solutions of distance learning for the acquisition or improvement knowledge and practical applicability [3]. It is one of the main innovations that is increasingly diffusing in corporate settings. Moreover, e-learning systems attract considerable attention worldwide since they bare the potential to improve the quality of e-learning applications, and the use of recommending technologies in e-learning systems can overcome the main shortcoming of commom e-learning by facilitating personalized learning experiences [4].

According to the International Data Corporation (IDC), the size of the e-learning market in Europe was reported to be over \$358 million in 2003, and it grew to \$994 million in 2007. In 2009, Western Europe was the 2nd largest market for e-learning in the world and the global market for e-learning reached \$29.1 billion. Furthermore, the global market for e-learning is forecast to reach \$46.9 billion by 2014. North America will continue to be the largest market right through to 2014 and Asia will surpass Western Europe for 2nd place. These reveal that the number of e-learning initiatives in corporate training settings is steadily increasing.

Despite its advances, e-learning suffers from several problems, such as "information overload", the lack of ability to stimulate students' interactions and the short of high-quality recommending systems specifically designed to the needs of both teachers and students [10]. These facts are the main reason why current forms of e-learning are more oriented towards communication and collaboration between students and teachers in the learning process [11]. With the advent of Web 2.0, the new learning envirement on the Internet has great potential to improve the existing e-learning services. Thus, it is very necessery that recommendation mechanisms are adapted to make e-learning systems more effective [12]. However, most e-learning systems have not been personalized in recent years and researchers attempted to develop personalized e-learning systems to improve online learning [1]. These systems recommend courses or learning materials to learners regardless of recommended learning resources consistence with the e-learners' interests or preferences [13]. Most of them are still delivering the same resources to e-learners who have different preferences. Meanwhile, social interactions often affect the effectiveness of the learning activities interactions directly or indirectly [14]. E-learning systems needs not only personalized recommendation but also social information to facilitate e-learners learn more efficiently [1].

2.2. Collaborative filtering

To provide recommendations, CF tries first to search for users who have rated the same or similar items. After the users sharing similar interests are found, CF will recommend the items highly rated by those users. Generally, the more items that users have rated, the more similar the users are. The procedure of CF can be stated as follows.

Assumed that $U=\{u_i|i=1,2,\ldots,m\}$ is a set of m users and $I=\{I_j|j=1,2,\ldots,n\}$ is a set of n distinct items. The set of user ratings is denoted by $R=\{(u_i, I_j)|\ u_i\in U, I_j\in \mathrm{I}\ \}$ which is a $m\times n$ matrix, which indicates the user's preference for different items.

Once the data preparation is finished, CF needs to select a similarity function to measure how similar two users are. Two of the most well-known similarity measures are Cosine-based similarity and Pearson correlation coefficient [7] defined in Eq.(1) and Eq.(2).

$$Sim\left(u_i,u_j\right)=\frac{\sum_{i\in I(u_i,u_j)} r_{u_i,I}\cdot r_{u_j,I}}{\sqrt{\sum_{i\in I(u_i,u_j)} {r_{u_i,I}}^2}\cdot\sqrt{\sum_{i\in I(u_i,u_j)} {r_{u_j,I}}^2}} \tag{1}$$

$$Sim\left(u_i,u_j\right)=\frac{\sum_{i\in I(u_i,u_j)} (r_{u_i,I}-\overline{r}_{u_i})(r_{u_j,I}-\overline{r}_{u_j})}{\sqrt{\sum_{i\in I(u_i,u_j)} (r_{u_i,I}-\overline{r}_{u_i})^2}\sqrt{\sum_{i\in I(u_i,u_j)} (r_{u_j,I}-\overline{r}_{u_j})^2}} \tag{2}$$

where $\overline{r}_u$ is mean rating of user u, and $I(u_i\ ,u_j)$ represents the items co-rated by users u_i and u_j.

Although CF is a very successful recommending technology, there are still some potential problems. The traditional CF approaches predict the rating of items for target users only based on the useritem rating matrix. With the development of mobile e-commerce, the magnitudes of users and commodities grow rapidly, while users' rating information is of insufficiency. This resulted in extreme sparsity of user rating data, i.e. the sparsity problem [8]. To solve the sparsity problem, Anand and Bharadwaj [15] proposed various sparsity measure schemes based on local and global similarities for achieving quality predictions. Shinde and Kulkarni [16] introduced a clustering based CF algorithm (CBBCCF) to overcome sparsity problem for a better rating prediction. Due to the extreme situation of data sparsity, i.e. cold start problem, Leung et al [17] utilized association rules to integrate domain items information into traditional CF, and introduced a preference model to comprise user-item relationships and item-item relationships. Ahn [18] applied a heuristic similarity measure method that focuses on improving the recommendation performance under the cold-start conditions. Lee et al [19] presented a CF recommendation methodology based on both implicit ratings and less ambitious ordinal scales to enhance the quality of collaborative recommendation.

These previous researches have made several improvements on traditional CF algorithms, and they partially reduced the effect of data sparsity on the rating prediction. However, it is assumed in most existing CF approaches that all users have the same weight to rating data when measuring similarity [20]. In the other word, it is assumed that there is no relationship between users. Actually, it is a common knowledge that differences exist between users with different rating behaviors [21]. This problem will lead to the fact that recommending results do not meet the actual demands of users to a certain extent,i.e. this results in a lower accuracy of prediction results, so the quality recommendation is reduced. Therefore, this important factor has to be considered to effectively improve the prediction accuracy, and thereby enhance the quality of collaborative recommendation.

3. Our hybrid recommending method

This paper proposes a hybrid recommendation method, named SPSNAR, to address the problems mentioned in section 2. This method integrates CF-based recommendation using implicit rating and social information. SPSNAR is composed of two phases: sequential pattern analysis (SPA) phase and social network analysis (SNA) phase, as shown in Fig.1.

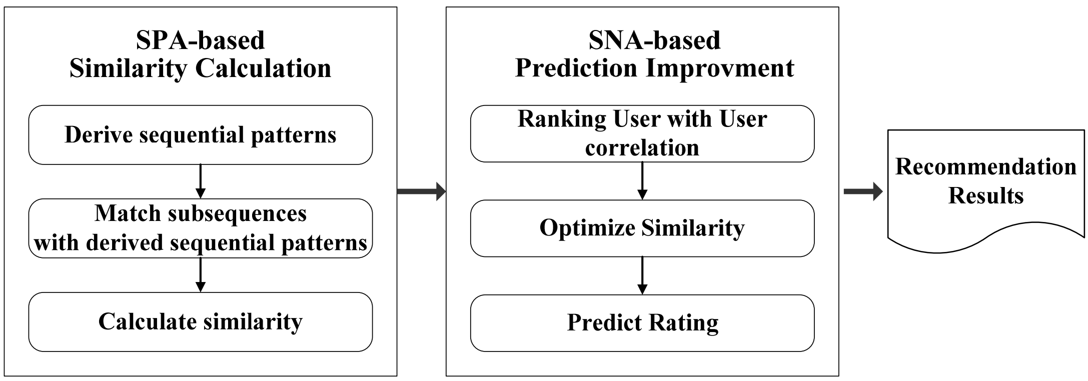

Fig. 1. Comparisons of three algorithms' results on MAE.

The first phase stated in section 3.1, implicit ratings information is collected and the similarity between a target e-learner and every other e-learner is calculated based on implicit ratings. The second phase describe in section 3.2 constructs a user ranking model by using social network analysis and user ranking model is employed to optimize the similarity score obtained in section 3.1 for improving the prediction accuracy. At last, the recommendations are made by computing the weighted average of the rating of items.

3.1. SPA-based similarity calculation

SPA is based on the assumption that two products are similar in human mentality when they share similar access sequences among multiple users. For example, user access sequences on seven different items by five users are shown in Table 1.

Table.1 An example of user access sequences

	I_1	I_2	I_3	I_4	I_5	I_6	I_7
u_1	1	1	1	0	0	0	0
u_2	1	0	0	0	1	1	1
u_3	1	0	0	1	1	1	0
u_4	1	1	1	0	0	0	1
u_5	1	0	0	0	1	1	0

In Table 1, number 1 represents the item is accessed by corresponding users while number 0 means not. It is clear that i_1, i_2 and i_3 are similar from the views of u_1 and u_4. Also, i_1, i_5 and i_6 are similar because they are accessed by u_2, u_3 and u_5.

The analysis of user access sequence is stated as follows. It is assumed that m users are denoted by set $U=\{u_i|i=1,2,\ldots,m\}$, n distinct items are denoted by set $I=\{I_j|j=1,2,\ldots,n\}$ and user access sequence is marked as set $S(u)$, whose lengths is denoted by $|S(u)|$ as shown in Eq.(3).

$$S(u)=\left\langle u_i,\left\{I^{u_i}\left|I_j^k\in I\right.\right\}\right\rangle,\ \left|S(u)\right|=k \tag{3}$$

where I^{u_i} denotes the items accessed by u_i and u_j.

User access sequence is a unidirectional growing sequence, and it can be decomposed into a plurality of different lengths which is called sub-sequence. The sub-sequence is denoted by $S(u^k)$, defined in Eq.(4).

$$S\left(u^k\right)=I_j^1\rightarrow\cdots\rightarrow I_n^k\ ,\ 1\le k\le n \tag{4}$$

where k indicates the length of sub-sequence, and j is the order number of a item in I. When k=1, $S(u^1)$ represents a certain item accessed by u; when $k=n$, $S(u^n)$ is the user access sequence of u, $S(u)$.

For instant, the user access sequence of u_2 in Table 1 is $S\left(u^2\right)=I_1^1\rightarrow I_5^2\rightarrow I_6^3\rightarrow I_7^4$, and all sub-sequences of $S(u^2)$ are shown in Table 2.

Table 2. All sub-sequences of user access sequence S(u2)

$S(u^1)$	$S(u^2)$	$S(u^3)$	$S(u^4)$
I_1^1	$I_1^1\rightarrow I_5^2$	$I_1^1\rightarrow I_5^2\rightarrow I_6^3$	$I_1^1\rightarrow I_5^2\rightarrow I_6^3\rightarrow I_7^4$
I_5^2	$I_5^2\rightarrow I_6^3$	$I_5^2\rightarrow I_6^3\rightarrow I_7^4$	
I_6^3	$I_6^3\rightarrow I_7^4$		
I_7^4			

When users' access sequences and corresponding sub-sequences are obtain, SPA is employed to measure user similarity, which is described as follows.

For two different users u_i and u_j, their access sequences are denoted by $S(u_i)$ and $S(u_j)$, and the length of $S(u_i)$ is usually not equal to that of $S(u_j)$, i.e. $|S(u_i)| \neq |S(u_j)|$. However, traditional similarity measurement method such as Manhattan and Euclidean distance can not be used to calculate the similarity between $S(u_i)$ and $S(u_j)$. In this paper, the Levenahtein distance widely applied in the field of natural language processing is introduced for the measuring similarity between $S(u_i)$ and $S(u_j)$. The similarity measuring procedure is described as follows.

Let vector $\overrightarrow{S_u}$ denote the user access sequence $S(u)$; let S_u^I denote a certain item in $\overrightarrow{S_u}$; and let $Sim\left(u_i,u_j\right)_{S(u_i),S(u_j)}$ denote the similarity measurement between $S(u_i)$ and $S(u_j)$. Then, a $(m+1)\times(n+1)$-dimentional matrix P is constructed to store the Levenahtein distances, as defined in Eq.(5) .

$$P=\left(P_{ij}\right)_{(m+1)\times(n+1)}=\min\begin{Bmatrix} m_{i-1,j}+1 \\ m_{i,j-1}+1 \\ m_{i-1,j-1}+d \end{Bmatrix} \tag{5}$$

where d is an integer variable; If $S_{u_i}^I=S_{u_j}^I$, d=0; else, d=1.

When P is estiblished, it can be found that the value of $P_{m+1,n+1}$ is equal to the Levenahtein distance between $\overrightarrow{S_{u_i}}$ and $\overrightarrow{S_{u_j}}$. Thus, the similarity measurement of user access sequence can be calculated by Eq.(6).

$$Sim\left(u_i,u_j\right)_{S(u_i),S(u_j)}=\left|\frac{P_{m,n}}{\max\left(m,n\right)}-1\right| \tag{6}$$

3.2. SNA-based prediction improvment

User interactions in e-learning system or website can be described in the scenario of the social network [20,21], and these interactions will probably affect the purchasing behaviors of users directly or indirectly [21]. Thus, we introduce SNA to analyze the user correlations and construct user ranking model to improve the performance of similarity.

There are different degrees of correlation between users in a recommendation system of e-learning web sites, just as there are various user relationships in a certain social network. Thus, a user correlation matrix has to been constructed for the description of the relationship between users in the social networks by using user rating data. The user correlation matrix is the data foundation of the user rating model.

Assumed that m users are denoted by set $U=\{u_i|i=1,2,...,m\}$, n distinct items are denoted by set $I=\{I_j|j=1,2,...,n\}$ and user ratings matrix is marked as R. Accordingly, a $m\times n$ binary matrix $M_p=(p_{ij})_{m\times n}$ is constructed based on matrix R for the representation whether user u_i rated item I_j, as shown in Eq.(7).

$$M_p=\left(p_{ij}\right)_{m\times n},\ p_{ij}=\begin{cases}1 \text{ if } u_i \text{ rated } I_j \\ 0 \text{ if } u_i \text{ not rated } I_j\end{cases},\ i=1,2,...,m; j=1,2,...,n \tag{7}$$

where p_{ij}=1 represents that u_i has rated I_j, and p_{ij}=0 indicates the fact that u_i did not rated I_j.

Then, user correlation matrix M_c is constructed based on matrix M_p. Matrix M_p is used for the description of the numbers of the same items rated by different users, and M_p is a symmetric matrix, as shown in following equation.

$$M_c = M_p \cdot M_p{}' = \left(c_{ij}\right)_{m\times m},\ c_{ij} = \begin{cases} c_{ji} \neq 0 \text{ if } u_i \text{ and } u_j \text{ rated same } I \\ 0 \quad\quad \text{if } u_i \text{ not rated same } I \text{ with } u_j \end{cases} \tag{8}$$

where c_{ij} represents the number of items that are rated by users u_i and u_j at the same time. When $i \neq j$, $c_{ij} \neq 0$ indicated that item I_j is rated by both user u_i and user u_j, and $c_{ij}=0$ means that there is no common item rated by users u_i and u_j; when $i=j$, let $c_{ij}=0$, i.e. the number of item rated by the same user is not taken into account.

For example, participating rating matrix M_p and user correlation matrix M_c are constructed, shown in Table.3 and Table.4. In matrix M_c, $c_{14}=c_{41}=2$ means that user u_1 and user u_4 have rated both item I_1 and item I_7 (as shown in Table 3). The total number of items rated by u_1 is 3 (I_1, I_4 and I_7), while the total number of items rated by u_4 is 2 (I_1 and I_7), less than that of u_1. Thereby, the importance of u_1 and u_4 should be different, and the matrix M_c does not reflect the relationships between users.

Table. 3 Participating rating matrix M_p

	I_1	I_2	I_3	I_4	I_5	I_6	I_7
u_1	1	0	0	1	0	0	1
u_2	1	1	0	0	1	0	0
u_3	0	0	1	0	0	1	0
u_4	1	0	0	0	0	0	1
u_5	0	1	0	1	1	0	0
u_6	1	0	0	0	0	1	1

Table.4 User correlation matrix M_c

	u_1	u_2	u_3	u_4	u_5	u_6
u_1	0	1	0	2	1	2
u_2	1	0	0	1	2	1
u_3	0	0	0	0	0	1
u_4	2	1	0	0	0	2
u_5	1	2	0	0	0	0
u_6	2	1	1	2	0	0

Therefore, M_c has to be further processed in order to describe the common items rated by different users and reflect differences between users. In this paper, M_c is standardized and transformed to an unsymmetrical matrix M_w, shown in Eq.(9).

$$M_w = \left(w_{ij}\right)_{m\times m},\ w_{ij} = c_{ij} \Big/ \sum_{i=1}^{m} c_{ij} \text{ and } \sum_{j=1}^{m} w_{ij} = 1 \ ,\ i,j = 1,2,\ldots,m \tag{9}$$

where c_{ij} represents the number of items that are rated by users u_i and u_j at the same time in M_c; $\sum_{j=1}^{n} c_{ij}$ is the total number of common items rated by user u_i and other users.

Once M_w is established, we employ social network analysis to analyze the user correlation and build the user ranking model. Then, the user ranking model is utilized to enhance the traditional similarity measure.

The standardized user correlation matrix M_w is regarded as a weighted connection matrix of a certain social network. A weighted directed graph denoted by $G=(U,E)$ is created based on M_w, where users nodes are denoted by U and user nodes are connected with weighted directed links marked as E, shown in Eq.(10). G is called user correlation graph, which is used for the description of the relationship between different users in the social network [16].

$$G\left(u_i,u_j\right)=\begin{cases} w_{ij}\neq 0 & \text{if } u_i \text{ and } u_j \text{ are connected} \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

where w_{ij} is the elements of M_w. If $w_{ij}\neq 0$, it means that there is a connection between u_i and u_j; otherwise, there is no correlation between u_i and u_j.

In the scenario of social network, the correlations of different users with different ranking are spread in the social network [20]. The propagation and attenuation rules of user ranking are similar to those of PageRank algorithm [22]. Meanwhile, the PageRank algorithm has been used to analyze user relationship in social network [23]. Therefore, the advantage of PageRank algorithm is taken to measure the importance of user for calculating user ranking.

It is assumed that $U=\{u_i|i=1,2,\ldots,m\}$ is a set of m user nodes, user relationship graph is denoted by $G=(U,E)$ and users(U) are connected with a set of directed links, marked as E. The value of PR for each node can be calculated by using PageRank model, as shown in Eq.(11).

$$PR\left(u_i\right)=\left(1-\alpha\right)\cdot\gamma+\alpha\cdot\sum_{u_j\in inLink\{u_i\}}\frac{PR\left(u_j\right)}{outLink\left(u_j\right)} \tag{11}$$

where α is the attenuation factor andγ is the transfer probability. Node u_j denotes a neighbour node of u_i; $inLink\{u_i\}$ represents the nodes connecting to node u_i; and $outLink(u_j)$ is the sum of the out-degrees of u_j.

Each of the directed link connecting two user nodes has their own weight. Assumed that $M_w=(w_{ij})$ is the matrix of connection weights, and let w_{ij} be the weight value of the directed link (u_i, u_j) that connects user nodes u_i and u_j. According to PageRank algorithm, the user ranking model is defined by $UR(u_i)$, as shown in Eq.(12).

$$UR\left(u_i\right)=\left(1-\alpha\right)\cdot\gamma\cdot UR_0\left(u_i\right)+\alpha\cdot w_{jk}\cdot\sum_{u_j\in inLink\{u_i\}}\frac{UR}{outLink(u_j)} \tag{12}$$

where $UR_0(u_i)$ is the initial ranking of user u_i, and it is the number of items that u_i has rated.

According to the definition of M_w in Eq.(12), $outL(u_j)$ = 1. Thus, Eq.(10) can be transformed to another equation as shown in Eq.(13).

$$UR\left(u_i\right)=\left(1-\alpha\right)\cdot\gamma\cdot UR_0\left(u_i\right)+\alpha\cdot w_{jk}\cdot\sum_{u_j\in inLink\left(u_i\right)}UR\left(u_j\right) \tag{13}$$

Once user ranking model is finished, user ranking $UR(u_i)$ is regarded as the rating weight of user u_i, and incorporated into the similarity measure obtained from Eq.(6) to facilitate rating prediction.

4. Experiments and Results

In this section, a numerical experiment is designed to test and evaluate our method. The dataset, performance metrics and benchmark algorithms are introduced. Then, the experimental results are analyzed to evaluate the effectiveness of the hybrid model.

4. 1. Experiments design

The experiments are carried out on a real-world dataset, MACE dataset, which is Pan-European initiative to interconnect and disseminate digital information about architecture. This dataset is issued from MACE project that is done from From Aug. 2009 to Sept. 2012, and it contains more than 1200 learners and 150000 learning objects.

To evaluate the performance of our approach, the following metrics are selected: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) that used by various researchers to evaluate recommender systems [5], as shown in equations (14) and (15). In order to compare the performance of our algorithm, two other CF algorithms are implemented: kNN [1] and CoFoSIM [19]. Our SPSNAR is evaluated in comparison with those benchmark algorithms.

$$MAE = \frac{\sum_{i=1}^{N} \left| P_i - Q_i \right|}{N} \tag{14}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \left(P_i - Q_i \right)^2}{N}} \tag{15}$$

4.2. Experimental results

In the experiment, predictive recommendations are generated through three approaches using a series of parameters of the number of nearest neighbors. The number of nearest neighbors is set to be 10, 20, 30, 40, 50, 60, 70, 80. The experimental results of three algorithms on MACE dataset are shown in Fig.2 and Fig.3, respectively.

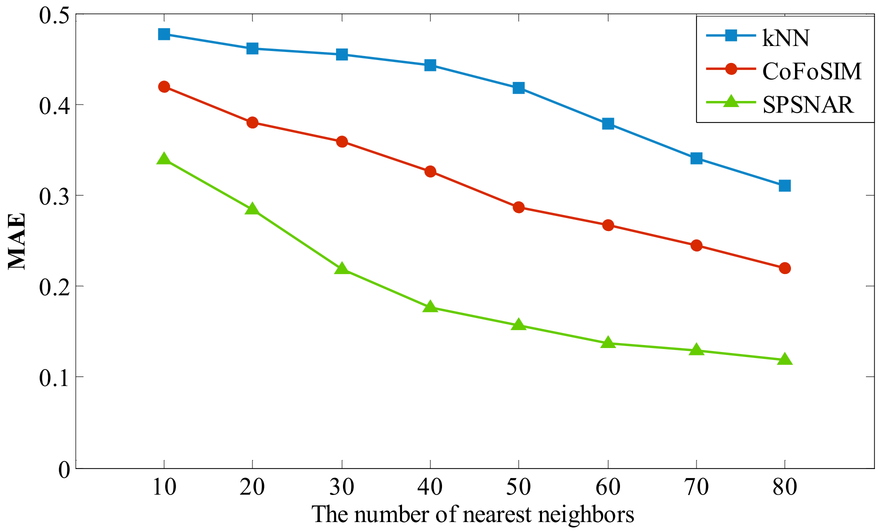

Fig. 2. Comparisons of three algorithms' results on MAE.

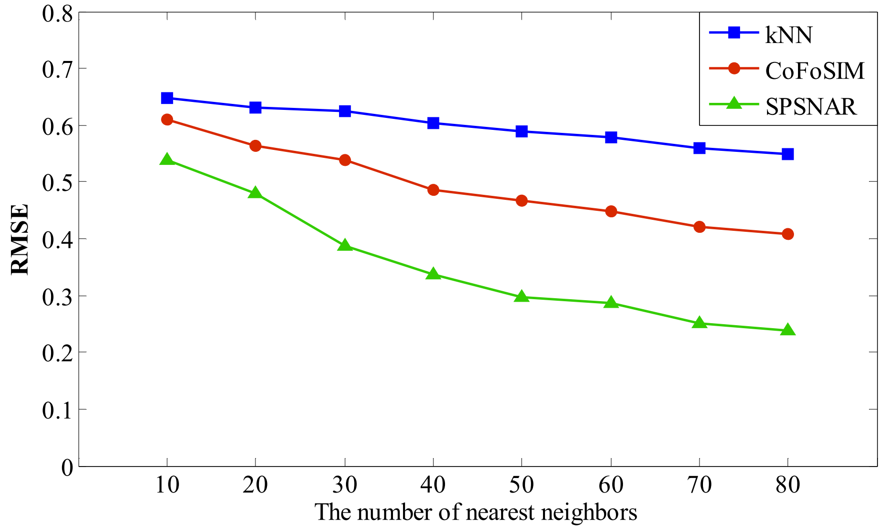

Fig. 3. Comparisons of three algorithms' results on RMSE.

From Fig.2 and Fig.3, it is clear that SPSNAR outperforms the other three typical CF models, and it can effectively improve the quality of collaborative recommendation.

5. Conclusions

This paper presents a hybrid method SPSNAR to enhance the prediction quality of recommendation in e-learning envirement. SPSNAR integrates CF-based recommendation method with SPA and SNA-based model for improving the prediction results.

The experimental results have shown that SPSNAR succeeds in advancing the quality of rating prediction. Compared with the other algorithms, SPSNAR has both the minimum values of MAE and the RSME. And SPSNAR outperforms the other two typical CF approaches in terms of prediction quality. This indicates that SPSNAR is more suitable for e-learning envirement.

Reference

[1] Barbera E, Gros B, Kirschner P. Temporal issues in e-learning research: A literature review. British Journal of Educational Technology, 2012; 43:53-55.

[2] Liu F, Shih B. Learning activity-based E-learning material recommendation system. Proceedings of 9th IEEE International Symposium on Multimedia - Workshops, 2007; 341-348.

[3] He D, Peng Y, Mao M and Wu D. Supporting information access in e-learning by integrating digital libraries and ontology. Online Information Review, 2010; 34:704-728.

[4] Rafaeli S, Dan-Gur Y, Barak M. Social recommender systems: Recommendations in support of E-learning. International Journal of Distance Education Technologies, 2005; 3:30-47.

[5] Adomavicius G. Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. IEEE Transactions on Knowledge and Data Engineering, 2005; 17:734-749.

[6] Sarwar B, Karypis G, Konstan J, Riedl J. Item based collaborative filtering recommendation algorithms. Proceeding of the 10th international conference on World Wide Web, Hong Kong, 2001; 285-295.

[7] Linden G, Smith B, York J. Amazon.com recommendations: item-to-item collaborative filtering. IEEE Internet Computing, 2003; 7:76-80.

[8] Su XY, Khoshgoftaar TM. A Survey of Collaborative Filtering Techniques. Advances in Artificial Intelligence, 2009; 2009:1-19.

[9] Graf S, Liu T-C and Kinshuk. Analysis of learners' navigational behavior and their learning styles in an online course. Journal of Computer Assisted Learning, 2010; 26:116-131.

[10] Gorucu A. Impact of multiple intelligence applications based on collaborative learning on primary school students' attitudes toward physical education course. Energ Educ Sci Tech-B, 2012; 4:43-50.

[11] Hoic-Bozic N, Mornar V, Boticki I. A blended learning approach to course design and implementation. IEEE Transactions on Education, 2009; 52:19-30.

[12] Yagci M. Designing a web-based learning environment and its effect on students' academic success and their attitudes. Energ Educ Sci Tech-B, 2013; 5:225-234.

[13] Khribi M, Jemni M, and Nasraoui O. Automatic recommendations for e-learning personalization based on Web usage mining techniques and information retrieval. Proceedings of the 8th IEEE International Conference on Advanced Learning Technologies, 2008; 241-245.

[14] Coklar AN. Analyzing the effects of use of facebook for educational purpose on academic success of the preservice teachers from their perspectives. Energ Educ Sci Tech-B, 2012; 4:617-626.

[15] Anand D, Bharadwaj KK. Utilizing various sparsity measures for enhancing accuracy of collaborative recommender systems based on local and global similarities. Expert Systems with Applications, 2011; 38:5101-5109.

[18] Shinde SK, Kulkarni U. Hybrid personalized recommender system using centering-bunching based clustering algorithm. Expert Systems with Applications, 2012; 39:1381-1387.

[19] Leung CW, Chan SC, Chung F. An empirical study of a cross-level association rule mining approach to cold-start recommendations. Knowledge-Based Systems, 2008; 21:515-529.

[18] Ahn HJ. A new similarity measure for collaborative filtering to alleviate the new user cold-starting problem. Information Sciences, 2008; 178:37-51.

[19] Lee SK, Cho YH, Kim SH. Collaborative filtering with ordinal scale-based implicit ratings for mobile music recommendations. Information Sciences, 2010; 180:2142-2155.

[20] Liu FK, Lee HJ. Use of social network information to enhance collaborative filtering performance. Expert Systems with Applications, 2010; 37:4772-4778.

[21] Meo PD, Nocera A, Terracina G, Ursino D. Recommendation of similar users, resources and social networks in a Social Internetworking Scenario. Information Sciences, 2011; 181:1285-1305.

[22] Page L, Brin S, Motwani R, Winograd T. The PageRank citation ranking: bringing order to the web. Stanford Digital Library Technologies Project, 1999; 31-75.

[23] Pedroche F. Competitivity groups on social network sites. Mathematical and Computer Modeling, 2010; 52:1052-1057.