CAR-based Personalized Learning Activity Recommendations for Medical Interns

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ABSTRACT

Clinical education has a great impact on the health care quality. In a hospital, clinical teachers often devote much time to provide services for patients in the pressed health care environment. Clinicians have less or no time to teaching clinical courses, discussing clinical cases with medical interns. In this study, we setup an electronic learning (e-learning) platform, a learning management system (LMS) in a hospital as a complement to clinical education for internship. Interns could learn and discuss with their classmates any time. Despite LMS could assist clinical training and provide the collaborative environment, however, students only have the same user interfaces even though they have the different learning preferences on LMS. Typical LMS could not provide the personalized learning activities for students.

Recommender system could provide the personalized services to customers according to their interest, which are often used in electronic commerce (EC). In this study, we propose a cluster association rules (CAR) based method to recommend the personalized activities to students on LMS. First, students were clustered into two groups, active and inactive groups. In each group, student learning behavior pattern, i.e., activity association rules and most frequent activities were derived from LMS. Finally, the activities were recommended to the target student, which were sorted by the confidences of the association rules and the frequencies of the activities. The experiment results demonstrate that the proposed CAR-based method performs better than the typical collaborative filtering (CF) method over all top N recommendations. CAR-based method could provide the better personalized activities to students than the traditional CF method.

Categories and Subject Descriptors

J.3 **[Life and Medical Sciences],** K.3.1 **[Computer Uses in Education]**

General Terms

Design, Experimentation, Human Factors

Keywords

Clinical Education, Intern, e-Learning, Activity, Recommender System, Clustering, Association Rule, Collaborative Filtering

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1. INTRODUCTION

Electronic health (e-health) use information technology to deliver services such as electronic health record and electronic prescription (e-prescription) and electronic learning (e-learning) in modern health care environment [3, 7]. Health care quality is related to clinical training directly [5]. In a hospital, clinical teachers often devote much time to provide services for patients in the contemporary and pressed health care environment. Clinicians have less or no time to teaching clinical courses, discussing clinical cases for internship [18]. However, e-learning could be complement to clinical education for the internship to form a part of blended-learning [21]. Most medical students felt e-learning had a positive impact on their learning of clinical skill and acknowledged its integration in a blended approach [8]. Students used the e-learning platform as a complement to in-classroom education and obtained higher scores in the final examination [23]. Students perceived blogs to be useful during the internship in providing a way for knowledge construction, problem solving, reflection, and communicating emotions [6].

An e-learning platform could complement clinical education to form a part of blended-learning to solve the problem of lack of time in teaching clinical courses. In e-learning collaborative environment, interns could interact with their classmates any time to construct their own knowledge. However, students only have the same user interfaces even though they have the different learning preferences in e-learning platform. Typical platform such as learning management system (LMS) could not provide the personalized learning activities. Therefore, recommender system could provide the personalized services to recommend various items, such as movies and music, to customers according to their interests [9, 24]. Recommendation systems are often used in electronic commerce (EC), but few are used in e-learning. Generally, recommender systems are based on either collaborative or content-based filtering techniques. Collaborative filtering (CF), which utilizes preference ratings given by customers with similar interests to make recommendations to a target customer [20, 22]. In contrast, content-based filtering (CBF) derives recommendations by matching customer profiles with content features [11, 17]. Some studies have combined collaborative filtering and content-based filtering techniques as a hybrid recommendation method [2].

In this study, we propose a personalized learning activity recommendation method based on cluster association rules (CAR) to recommend on-line activities for students in an e-learning environment. Our approach is as follows. First, the method clusters students into two groups based on their activity preferences, i.e., active and inactive groups. Students in active group often view course, complete feedback, add post, update post and view discussion on forum. Second, we retrieve activity association rules and most frequent activities of two groups to find students' learning behavior patterns. For example, active group students often view teaching material videos for the learned lessons after viewing course and completing feedback. Inactive group students often pay attention to their personal information security to logout the system. Next, the target student then identified his group with the similar activity preferences. Finally, on-line activities could be sorted by the confidences of the association rules and the frequencies of the activities from student group, which were recommended to the target student.

The remainder of this study is organized as follows. In Section 2, we discuss the related work of our research. In Section 3, we describe our proposed method. In Section 4, we present the experiment results. In Section 5, we summarize our findings, and state the limitations and future research of the study.

2. RELATED WORK

2.1 Recommendation Systems for E-learning

First, there are some recommendation systems to recommend course material or learning resources based on collaborative filtering in an e-learning environment. Manouselis et al. [16] use multi-attribute collaborative filtering to recommend learning resources for teachers. Bobadilla et al. [4] propose that the users with greater knowledge have greater weight in the calculation of the recommendations than the users with less knowledge. They design new equations in the nucleus of the memory-based collaborative filtering. Second, some recommendation systems combine collaborative filtering and data mining technologies, i.e., clustering and sequential pattern, to recommend leaning contents to learners. Tang and McCalla [25] use clustering and collaborative filtering technologies to recommend papers to learners. Klašnja-Milićević et al. [10] cluster users into groups based on their learning style, find the sequential pattern by AprioriAll algorithm, and recommend learning contents based on collaborative filtering. Third, some recommender systems combine collaborative filtering and content-based filtering technologies as hybrid recommender systems. Liang et al. [13] make courseware recommendations by a hybrid recommendation method which combines collaborative filtering and content-based filtering. Finally, there are some other systems considering on-line/off-line modules and learner ability to make personalized recommendation. Li and Zaïane [12] combine on-line and off-line modules to recommend website shortcut or page resources based on user's navigation pattern, which includes usage, content, and structure data. In this study, we propose a learning activity recommendation method based on collaborative filtering, clustering and association rules. The recommendation systems for e-learning are shown in Table 1 as follows.

Table 1. Recommendation systems for e-learning

Techniques
• Collaborative filtering: e.g. [4] • Collaborative filtering and clustering: e.g. [25] • Collaborative filtering and sequential pattern: e.g. [10] • Collaborative and content-based filtering: e.g. [13] • Collaborative filtering, clustering and association rules: (The approach proposed in this study)
Applications
• Course material and learning resources: e.g. [10, 13, 16] • Web pages, links and shortcut : e.g. [12]; Papers: e.g. [25] • Learning activities: e.g. (The approach proposed in this study)

2.2 Clustering Method

Clustering techniques, which are usually used to segment markets [19], seek to maximize the variance among groups while minimizing the variance within groups. K-means clustering [15] is a widely used similarity grouping method that partitions a dataset into k groups. The K-means algorithm assigns instances to clusters based on the minimum distance principle. An instance is assigned to a cluster based on the minimum distance to the center of the cluster over all k clusters.

2.3 Association Rule Mining

Association rule mining tries to find the associations between two sets of activities in a transaction database. Agrawal et al. [1] formalized the problem of finding association rules that satisfy the minimum support and the minimum confidence requirements. For example, assume that a set of purchase transactions includes a set of product items I. An association rule is an implication of the form $X \Rightarrow Y$, where $X \subset I$, $Y \subset I$, and $X \cap Y = \Phi$. X is the antecedent (body) and Y is the consequent (head) of the rule. Two measures, support and confidence, are used to indicate the quality of an association rule. The support of a rule is the percentage of transactions that contain both X and Y, whereas the confidence of a rule is, among all transactions that contain X, the fraction that also contains Y.

2.4 Association Rule-based Recommendation Method

Sarwar et al. [22] described the association rule-based recommendation method as follows. For each customer, a customer transaction is created to record all the products that he or she purchased previously. An association rule mining algorithm is then applied to find all the recommendation rules that satisfy the given minimum support and minimum confidence. The top N products to be recommended to a customer, u, are then determined as follows. Let Xu be the set of products purchased by u previously. The method first finds all the recommendation rules $X \Rightarrow Y$ in the rule set. If $X \subseteq Xu$ then all products in Y–Xu are deemed to be candidate products for recommendation to the customer u. The candidate products are then sorted and ranked according to the associated confidence of the recommendation rules, and the top N candidate products are selected as the top N recommended products.

2.5 Most Frequent Item-based Recommendation Method

The most frequent item-based recommendation method [22] counts the purchase frequency of each product by scanning the products purchased by the users in a cluster. Next, all the products are sorted by the purchase frequency in descending order. Finally, the method recommends the top N products that have not been purchased by the target customer.

2.6 Collaborative Filtering

Collaborative filtering (CF) [20, 24] utilizes the nearest-neighbor principle to recommend products to a target audience. The neighbors are identified by computing the similarity between customers' purchase behavior patterns or tastes. The similarity is measured by Pearson's correlation coefficient, which is defined as follows:

$$corr_p(c_i, c_j) = \frac{\sum_{s \in I}(r_{c_i,s} - \overline{r_{c_i}})(r_{c_j,s} - \overline{r_{c_j}})}{\sqrt{\sum_{s \in I}\left(r_{c_i,s} - \overline{r_{c_i}}\right)^2 \sum_{s \in I}\left(r_{c_j,s} - \overline{r_{c_j}}\right)^2}} \quad , \tag{1}$$

where $\overline{r_{C_i}}$ and $\overline{r_{C_j}}$ denote the average number of products purchased by customers C_i and C_j respectively; the variable I denotes the mix of the set of products; and $r_{c_i,S}$ and $r_{c_j,S}$ indicate, respectively, that customers C_i and C_j purchased product item S.

The kNN-based CF method utilizes k-nearest neighbors (k-NN) to recommend N products to a target user [22]. The k-nearest neighbors are identified by computing the similarity between customers' purchase behavior or tastes. The similarity is measured by Pearson's coefficient, as shown in Eq. (1). After the neighborhood has been formed, the N recommended products are determined by the k-nearest neighbors as follows. The frequency count of products is calculated by scanning the data about the products purchased or browsed by the k-nearest neighbors. The products are then sorted based on the frequency count, and the N most frequently occurring products that have not been purchased by the target customers are selected as the top-N recommendations.

3. METHODOLOGY

In this section, we propose a personalized learning activity recommendation schemes for students, which is shown in Figure 1. The proposed methods would be compared to the typical CF method which is described in Section 2.6. First, we calculated each activity usage count of each student on LMS. Hence, we filled the missing values with proper data preprocessing. Because there are some activities few or no students used, feature selection is applied to some activities and these activities would not be taken into account. Next, the continuous values of activity usage count were transformed into the discrete preference score to form a student-activity preference score matrix. With the preference score matrix, cluster association rule-based (CAR-based) recommendation method was applied to generate activities for the target student.

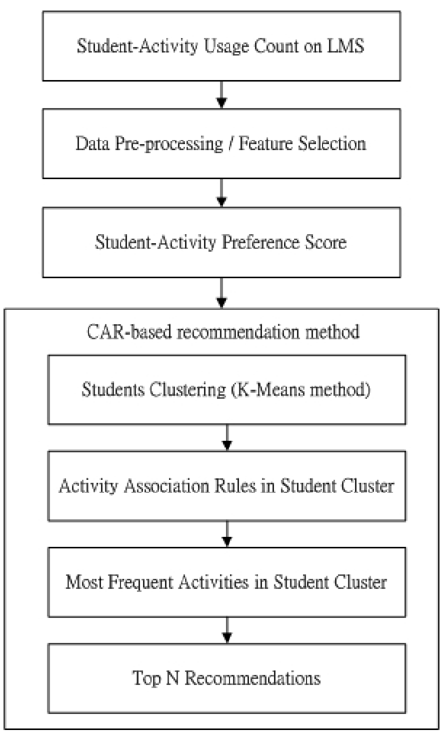

Figure 1. Overview of the proposed personalized recommendation method

In CAR-based recommendation method, we use the K-means clustering method to cluster students into activity preference groups based on the similarity between students' activity preferences, which were measured by Pearson's correlation coefficient of students' activity preference scores. In each student group, the learning behavior pattern, i.e., the association rules and frequent items were derived from the transaction data of the learning management system (LMS). Students in the same group have the similar learning behaviors. On-line activities could be recommended to students based on activity association rules and most frequent activities in their group.

For each target student, similar students are selected by aligning to each student group based on their activity preference scores. Once the similar student group was determined, the system then finds the association rules of activities and the most frequent activities of the similar users based on their transactions data on LMS. Finally, the activities were recommended to the target student, which were sorted by the confidences of the activity association rules and the frequencies of the activities from the aligned cluster.

3.1 Data Preprocessing and Feature Selection

First, we pre-process students and activities transaction data on a learning management system (LMS). We use the linear method to fill the missing value. Second, feature selection is applied. Despite there are many learning activities on LMS, some activities students never used. Furthermore, some activities few students used. We finally selected 18 activities which is shown as Table 2. M_a and σ_a are the mean value and the standard deviation of activity a's usage count of all students.

Table 2. Selected activities which students used

No.	Activity		M_a	σ_a
1	recent	course	3	2
2	view	course	399	264
3	complete	feedback	9	4
4	view	folder	10	7
5	add discussion	forum	2	0
6	add post	forum	53	29
7	delete post	forum	1	0
8	update post	forum	3	2
9	view discussion	forum	402	231
10	view forum	forum	295	321
11	write	message	5	4
12	view	resource	18	16
13	view	url	2	1
14	login	user	126	82
15	logout	user	25	37
16	update	user	2	1
17	view	user	9	8
18	view all	user	6	6

3.2 Activity Preference Scores of Students

The usage count of the selected 18 activities are continuous value, we use Eq. (2) [14] to transform the continuous value to the discrete value, i.e., -1, 0, or 1.

$$Z_{i,a} = \frac{U_{i,a} - M_a}{\sigma_a} \tag{2}$$

where $U_{i,a}$ is activity a's usage count of student i. M_a and σ_a are the mean value and the standard deviation of activity a's usage count of all students. $Z_{i,a}$ is the semantic variable for student i and activity a.

We tried various semantic variable $Z_{i,a}$ and found that students can be clustered into appropriate groups when $Z_{i,a}$ is set to 0.3. Therefore, we set all $Z_{i,a}$ to 0.3 for all students and activities to normalize the continuous value to the discrete value by Eq. (2), with $Z_{i,a} < -0.3$, $-0.3 \leqq Z_{i,a} \leqq 0.3$, and $Z_{i,a} > 0.3$, representing inactive, neutral, and active preferences. Preference score $PS_{i,a}$ demonstrate activity a's preference degree of student i, which is defined as the following Eq. (3). For example, preference score $PS_{i,a}$ is 1 to represent the active preference if $U_{i,a} > M_a + 0.3\sigma_a$, and preference score $PS_{i,a}$ is -1 to represent the inactive preference if $U_{i,a} < M_a - 0.3\sigma_a$, the other preference scores are 0 to represent the neutral preference.

$$\text{Preferece Score } PS_{i,a} = \begin{cases} 1, \text{ when } U_{i,a} > M_a + 0.3\sigma_a \\ -1, \text{ when } U_{i,a} < M_a - 0.3\sigma_a \\ 0, \text{ otherwise} \end{cases} \tag{3}$$

With Eq (3), student-activity preference score matrix could be calculated, which is shown as the following Table 3.

Table 3. Student–activity preference score matrix

Student ID	View Course	Complete Feedback	Add post on Forum	Update Post	View Discussion	…
1	-1	0	1	0	1	…
2	0	-1	0	-1	1	…
3	1	0	-1	1	0	…
4	0	1	0	1	-1	…
⋮	⋮	⋮	⋮	⋮	⋮	…

3.3 CAR-based Recommendation Method

First, cluster association rules (CAR) based method use student-activity preference score matrix described in Section 3.2 to cluster students into groups by the K-means clustering method based on students' similarity, which is measured with Pearson's correlation coefficient of their preference scores on activities. CAR-based recommendation method is shown as the following Figure 2.

Second, after clustering students into groups, the method then derives activity association rules in each group when these rules' support and confidence are both larger than the thresholds of support and confidence set in experiment. Let X_u represent the set of activities previously browsed by a student *u*. For each association rule $X^k \rightarrow Y^k$, if $X^k \subseteq X_u$ then all activities in $Y^k - X_u$, denoted by Y^k_u, are regarded as candidate activities for recommendation to the student *u*. Let Y_u^{AR} be the set of all candidate activities generated from all association rules that satisfy $X^k \subseteq X_u$. The activities in Y_u^{AR} are ranked according to $c(Y_u^k)$, i.e., the associated confidence of the association rule (AR) $X^k \rightarrow Y^k$.

Finally, we compare the number of candidate activities $|Y_u^{AR}|$ and the top-N recommendations. If the former is greater than the latter, the system recommends the top-N activities among the activities in Y_u^{AR}. On the other hand, if the number of candidate activities $|Y_u^{AR}|$ is less than the number of top N recommendations ($|Y_u^{AR}| < N$), the remaining $N - |Y_u^{AR}|$ activities for recommendation are selected from Y_u^{MF}. The selected activities are the most frequent items ranked according to the frequency count of activities browsed by students in the target student's cluster. Then, activities in Y_u^{MF} that have not been browsed by the student *u* and have not been included in Y_u^{AR} are added to the recommended activity list so that the number of top-N recommendations is sufficient.

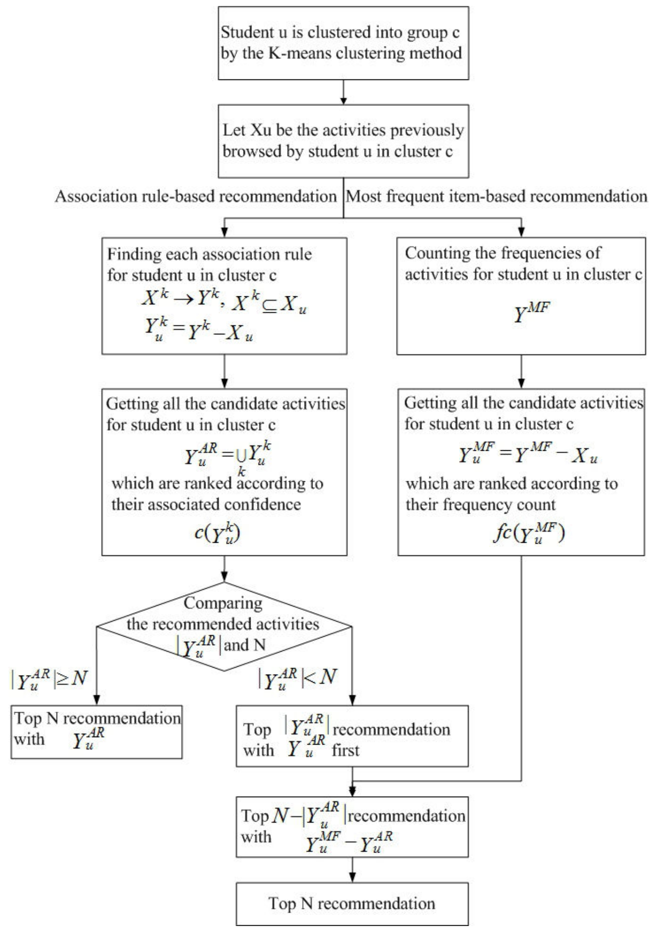

Figure 2. CAR-based recommendation method

4. EXPERIMENT EVALUATION

4.1 Experiment Setup and Dataset

We use a data set obtained from the learning management system (LMS) of a hospital to conduct our experiment evaluation. The hospital is a medical center in the northern Taiwan. Clinic teacher often add learning resources (course, teaching material videos, feedback) and activities (forum, chat room) on LMS, and students could view courses, talk in chat room, discuss on forums and complete feedback on LMS, which is shown as Figure 3.

The experiment dataset were extracted from the first semester of 2013. There are 10,637 student activity transaction data on LMS. The dependent variable, support and confidence threshold of the association rules are set to 0.5, 0.2 and 0.6. The most frequently browsed activities were to view course, complete feedback, add and update post, view discussion on forum.

Figure 3. Clinical cases discussed on the e-learning forum

4.2 Identification of Student Cluster

First, we need to identify the characteristics of each student cluster, i.e. the activity preference of each student cluster. Assume that M_a and σ_a are the mean value and the standard deviation of activity a's usage count of all students. $U_{c,a}$ is the mean value of activity a's usage count of students in cluster c, which compared to $M_a + 0.3\sigma_a$ and $M_a - 0.3\sigma_a$ to derive preference score PS of the cluster, which is shown in Eq. (4).

$$\text{Preferece Score } PS_{c,a} = \begin{cases} 1, & \text{when } U_{c,a} > M_a + 0.3\sigma_a \\ -1, & \text{when } U_{c,a} < M_a - 0.3\sigma_a \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

For example, $PS_{0,\text{view course}} = -1$ because the mean value of "view course" usage count of students in cluster 0 is 269.3, which is smaller than $M_a-0.3\sigma_a$ (319.8) of all students. $PS_{1,\text{view course}} = 1$ because the mean value of "view course" usage count of students in cluster 1 is 519.3, which is larger than $M_a+0.3\sigma_a$ (478.2) of all students. Preference scores of cluster0 and 1 are shown as Table 4.

From Table 4, we extracted the preference scores $PS_{c,a}$ of 5 popular activities, i.e., view course, complete feedback, add post, update post and view discussion on forum. In cluster 1, these activity preference scores $PS_{c,a}$ is (1, 1, 1, 1, 1), and the preference scores in cluster 0 is (-1, -1, -1, -1, -1), which is shown as Table 5. Two student clusters have the opposite preferences on these learning activities. Students in cluster 1 often view course, complete feedback, add post, update post and view discussion on forum, but students in cluster 0 seldom view course, complete feedback, add post, update post and view discussion on forum. Furthermore, the usage counts of these activities in cluster 1 are twice as large as the usage counts in cluster 0. We could identify cluster 0 is an inactive group and cluster 1 is an active group.

Table 5. Comparison of two clusters' preference scores (PS)

Cluster	View Course	Complete Feedback	Add Post on Forum	Update Post	View Discussion
0	-1	-1	-1	-1	-1
1	1	1	1	1	1

Especially, most of activities' average usage count in cluster 1 are larger than cluster 0, only "recent course" activity's average usage count (3.0) in cluster 0 is larger than the usage count (2.5) in cluster 1. "Recent course" is a service provided by LMS, and students could check the latest course information by clicking the web links. Students in inactive group were more afraid of missing the latest course notices than the students in active group.

4.3 Evaluation Metrics

Two metrics, precision and recall, are commonly used to measure the quality of a recommendation. They are also used in the field of information retrieval [26]. Activities can be classified into activities that students are interested in browsing and those that are of no interest. The recommendation method then suggests activities of interest to the students accordingly. The recall metric indicates the effectiveness of a method in locating activities of interest, while the precision metric represents students' levels of interest in the recommended activities.

Recall is the fraction of interesting activities located:

$$\text{Recall} = \frac{\text{number of correctly recommended activities}}{\text{number of interesting activities}} \quad (5)$$

Precision is the fraction of the recommended activities that students find interesting:

$$\text{Precision} = \frac{\text{number of correctly recommended activities}}{\text{number of recommended activities}} \quad (6)$$

Table 4. Preference scores of activities in student clusters

No.	Activity		All students		Students in cluster 0		Students in cluster 1	
			$M_a - 0.3\sigma_a$	$M_a + 0.3\sigma_a$	$U_{c,a}$	$PS_{c,a}$	$U_{c,a}$	$PS_{c,a}$
1	recent	course	2.4	3.6	3.0	0	2.5	0
2	view	course	319.8	478.2	269.3	-1	519.3	1
3	complete	feedback	7.8	10.2	7.0	-1	14.7	1
4	view	folder	7.9	12.1	12.0	0	13.3	1
5	add discussion	forum	2.0	2.0	2.0	0	3.0	1
6	add post	forum	44.3	61.7	38.3	-1	78.5	1
7	delete post	forum	1.0	1.0	1.0	0	1.5	1
8	update post	forum	2.4	3.6	1.0	-1	5.5	1
9	view discussion	forum	332.7	471.3	294.3	-1	531.3	1

The activities deemed interesting to students are the activities that the students browsed in the test set. Correctly recommended activities are those that match the interesting activities. Because increasing the number of recommended activities tends to reduce the precision and increase the recall, the F1 metric is used to balance the tradeoff between precision and recall [26]. The F1 metric, which assigns equal weights to precision and recall, is calculated as follows:

$$\mathrm{F1} = \frac{2\times\mathrm{recall}\times\mathrm{precision}}{\mathrm{recall}+\mathrm{precision}} \tag{7}$$

The three metrics are computed for each student, and the overall average (i.e., of all students) is calculated to measure the quality of the recommendations.

4.4 Evaluation of the CAR-based Method

Table 6 shows the evaluation results of the two recommendation methods. We compare the proposed cluster association rule-based (CAR-based) recommendation method with the typical CF method, which includes precision, recall and F1-metric with top N recommendations. The CAR-based method recommends learning activities to students based on the association rules of their cluster, inactive or active group, which described in Section 3. The typical CF method recommends activities which are ranked by the frequency counts of the frequent activities of the similar users as described in Section 2.6. The CAR-based method performs better than the typical CF method over all top N recommendations. The average precision, recall and F1-metric of CAR-based method are larger than the average precision, recall and F1-metric of the typical CF method.

Table 6. Comparison of CAR-based and typical CF method

Method	CAR-based			Typical CF		
Top N	Precision	Recall	F1-Metric	Precision	Recall	F1-Metric
0	0.000	0.000	0.000	0.000	0.000	0.000
1	1.000	0.111	0.200	0.000	0.000	0.000
2	1.000	0.222	0.364	0.000	0.000	0.000
3	1.000	0.333	0.500	0.000	0.000	0.000
4	1.000	0.444	0.615	0.125	0.071	0.091
5	1.000	0.556	0.714	0.200	0.143	0.167
6	1.000	0.667	0.800	0.250	0.214	0.231
7	0.929	0.722	0.813	0.214	0.214	0.214
8	0.813	0.722	0.765	0.188	0.214	0.200
9	0.722	0.722	0.722	0.222	0.286	0.250
10	0.650	0.722	0.684	0.250	0.536	0.319
Average	0.828	0.475	0.562	0.132	0.153	0.134

The experiment results demonstrate that the proposed cluster association rules-based (CAR-based) method performs better than the typical collaborative filtering (CF) method for all top-N recommendations, which are shown in the following Figure 4.

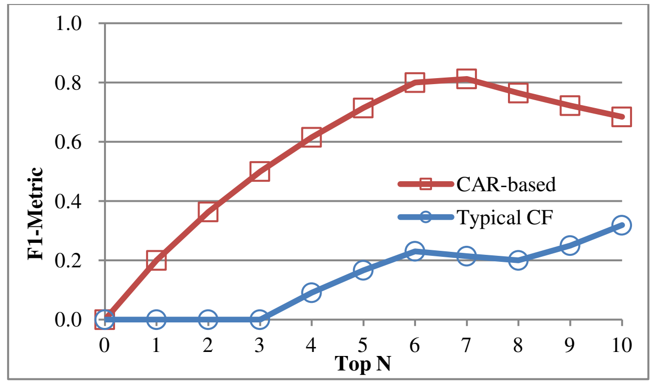

Figure 4. Evaluation of CAR-based and the typical CF method

5. CONCLUSION

In a hospital, clinical teachers are often busy and have no time to teaching clinical courses and discussing clinical cases for internship. An e-learning platform could complement clinical education to form a part of blended-learning to solve the problem of lack of time in teaching clinical courses. However, students only have the same learning activity interfaces even though they have the different learning preferences in e-learning environment. Typical platform such as learning management system (LMS) could not provide the personalized learning activities for students. Therefore, recommender systems could provide the personalized service to recommend various items, such as courses and activities, to students according to their interests. In this study, we tried to propose a cluster association rules-based (CAR-based) method to recommend the personalized activities to student on LMS. The experiment results demonstrate that the average precision, recall and F1-metric of the proposed CAR-based method are larger than the metrics of the traditional CF recommendation method. The proposed CAR-based method performs better than the typical CF method over all top N recommendations. CAR-based method could recommend the better personalized activities to students than the traditional CF method.

Our study has some limitation. For example, it's better to have more student activity transaction data to be analyzed at the beginning of the internship. Some students seldom use the e-learning platform because they were not familiar to the platform. In the future, we will introduce the e-learning platform before the internship.

6. ACKNOWLEDGMENTS

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7. REFERENCES

[1] AGRAWAL, R., IMIELINSKI, T., and SWAMI, A., 1993. Mining association rules between sets of items in large databases. In *Proceedings of the Proceedings of the 1993 ACM SIGMOD International Conference on Management of Data.* (Washington, D.C., United States1993), ACM, 207-216.

[2] BALABANOVIĆ, M. and SHOHAM, Y., 1997. Fab: content-based, collaborative recommendation. *Communications of the ACM 40*, 3, 66-72.

[3] BLACK, A.D., CAR, J., PAGLIARI, C., ANANDAN, C., CRESSWELL, K., BOKUN, T., MCKINSTRY, B., PROCTER, R., MAJEED, A., and SHEIKH, A., 2011. The impact of eHealth on the quality and safety of health care: a systematic overview. *PLoS medicine 8*, 1, e1000387.

[4] BOBADILLA, J., SERRADILLA, F., and HERNANDO, A., 2009. Collaborative filtering adapted to recommender systems of e-learning. *Knowledge-Based Systems 22*, 4, 261-265.

[5] CHASSIN, M.R. and GALVIN, R.W., 1998. The urgent need to improve health care quality: Institute of Medicine National Roundtable on Health Care Quality. *Jama 280*, 11, 1000-1005.

[6] CHU, S.K., CHAN, C.K., and TIWARI, A.F., 2012. Using blogs to support learning during internship. *Computers & Education 58*, 3, 989-1000.

[7] EYSENBACH, G., 2001. What is e-health? *J Med Internet Res 3*, 2, e20.

[8] GORMLEY, G.J., COLLINS, K., BOOHAN, M., BICKLE, I.C., and STEVENSON, M., 2009. Is there a place for e-learning in clinical skills? A survey of undergraduate medical students' experiences and attitudes. *Medical teacher 31*, 1, e6-e12.

[9] HILL, W., STEAD, L., ROSENSTEIN, M., and FURNAS, G., 1995. Recommending and evaluating choices in a virtual community of use. In *Proceedings of the Proceedings of the SIGCHI Conference on Human factors in Computing Systems* (Denver, Colorado, USA1995), ACM Press/Addison-Wesley Publishing, 194-201.

[10] KLAŠNJA-MILIĆEVIĆ, A., VESIN, B., IVANOVIĆ, M., and BUDIMAC, Z., 2011. E-Learning personalization based on hybrid recommendation strategy and learning style identification. *Computers & Education 56*, 3, 885-899.

[11] LANG, K., 1995. Newsweeder: Learning to Filter Netnews. In *Proc. 12th Int'l Conf. Machine Learning*.

[12] LI, J. and ZA ANE, O., 2004. Combining Usage, Content, and Structure Data to Improve Web Site Recommendation. In *E-Commerce and Web Technologies*, K. BAUKNECHT, M. BICHLER and B. PR LL Eds. Springer Berlin Heidelberg, 305-315. DOI= http://dx.doi.org/10.1007/978-3-540-30077-9_31.

[13] LIANG, G., WEINING, K., and JUNZHOU, L., 2006. Courseware Recommendation in E-Learning System. In *Advances in Web Based Learning – ICWL 2006*, W. LIU, Q. LI and R. W.H. LAU Eds. Springer Berlin Heidelberg, 10-24. DOI= http://dx.doi.org/10.1007/11925293_2.

[14] LIN, Q.-Y., CHEN, Y.-L., CHEN, J.-S., and CHEN, Y.-C., 2003. Mining inter-organizational retailing knowledge for an alliance formed by competitive firms. *Information & Management 40*, 5, 431-442.

[15] MACQUEEN, J., 1967. Some methods for classification and analysis of multivariate observations. In *Fifth Berkeley Symposium on Mathematical Statistics and Probability* University of California Press, Statistical Laboratory of the University of California, Berkeley, 281-297.

[16] MANOUSELIS, N., VUORIKARI, R., and VAN ASSCHE, F., 2010. Collaborative recommendation of e-learning resources: an experimental investigation. *Journal of Computer Assisted Learning 26*, 4, 227-242. DOI= http://dx.doi.org/10.1111/j.1365-2729.2010.00362.x.

[17] PENG, C.-C. and LIU, D.-R., 2010. Combining reputation and content-based filtering for blog article recommendation in social bookmarking websites. In *Proceedings of the 12th International Conference on Electronic Commerce: Roadmap for the Future of Electronic Business* ACM, 8-14.

[18] PRIDEAUX, D., ALEXANDER, H., BOWER, A., DACRE, J., HAIST, S., JOLLY, B., NORCINI, J., ROBERTS, T., ROTHMAN, A., and ROWE, R., 2000. Clinical teaching: maintaining an educational role for doctors in the new health care environment. *Medical education 34*, 10, 820-826.

[19] PUNJ, G. and STEWART, D.W., 1983. Cluster analysis in marketing research: review and suggestions for application. *Journal of Marketing Research 20*, 134-148.

[20] RESNICK, P., IACOVOU, N., SUCHAK, M., BERGSTROM, P., and RIEDL, J., 1994. GroupLens: an open architecture for collaborative filtering of netnews. In *Proceedings of the Proceedings of the 1994 ACM Conference on Computer Supported Cooperative Work* (Chapel Hill, North Carolina, USA1994), ACM, 175-186.

[21] RUIZ, J.G., MINTZER, M.J., and LEIPZIG, R.M., 2006. The impact of e-learning in medical education. *Academic medicine 81*, 3, 207-212.

[22] SARWAR, B., KARYPIS, G., KONSTAN, J., and RIEDL, J., 2000. Analysis of recommendation algorithms for e-commerce. In *Proceedings of the Proceedings of the Second ACM Conference on Electronic Commerce* (Minneapolis, Minnesota, USA2000), ACM, 158-167.

[23] SELUAKUMARAN, K., JUSOF, F.F., ISMAIL, R., and HUSAIN, R., 2011. Integrating an open-source course management system (Moodle) into the teaching of a first-year medical physiology course: a case study. *Advances in physiology education 35*, 4, 369-377.

[24] SHARDANAND, U. and MAES, P., 1995. Social information filtering: algorithms for automating "word of mouth". In *Proceedings of the Proceedings of the SIGCHI conference on Human factors in computing systems* (Denver, Colorado, USA1995), ACM/Addison-Wesley Publishing, 210-217.

[25] TANG, T. and MCCALLA, G., 2005. Smart Recommendation for an Evolving E-Learning System: Architecture and Experiment. *International Journal on E-Learning 4*, 1, 105-129.

[26] VAN RIJSBERGEN, C.J., 1979. *Information retrieval*. Butterworth-Heinemann Newton, MA, USA.