Arab J Sci Eng (2017) 42:607–617
DOI 10.1007/s13369-016-2292-2

RESEARCH ARTICLE - COMPUTER ENGINEERING AND COMPUTER SCIENCE

A Recommender Model in E-learning Environment

Outmane Bourkoukou[1] · Essaid El Bachari[1] · Mohamed El Adnani[1]

Received: 12 January 2016 / Accepted: 17 August 2016 / Published online: 27 August 2016

Abstract Various researches in E-learning mainly focused on improving learner achievements based on learner profile. Explosive growth of distance learning has caused difficulty of locating appropriate learning objects for learner in this environment, and it becomes relatively widespread learning method for learner. In this paper, an innovative learning approach is proposed by using recommender system to address this challenge. Based on this tool, a learning model is designed to achieve personalized learning experiences by selecting and sequencing the most appropriate learning objects. Moreover, some experiments were conducted to evaluate the performance of our approach. The result reveals suitability of using recommender system in order to support online learning activities to enhance learning.

Keywords E-learning · Recommender system · Data sets · Collaborative filtering · Learning objects

1 Introduction

Nowadays, E-learning is increasingly gaining popularity in organizational and institutional learning for its several benefits to learn anywhere, anytime, and anyplace. Therefore, explosive growth of E-learning has caused difficulty of locating the most appropriate learning objects (LOs) to achieve positive educational experiences that fits the needs, goals, and interests of their learners. A learning object is defined in the literature as a type of digital content component that allows flexibility, independence, and reuse of content in order to deliver a high degree of control to instructors and students [1]. The success of E-learning has created huge amounts of LOs which makes locating suitable ones a real big challenge. Another advantage of E-learning is that the learning experience can be personalized in opposition to traditional learning situations. In fact, traditional learning based on one size fits all approach and tends to support only one educational experience, because in a typical classroom situation, a teacher often has to deal with several students at the same time in the same place. Such situation forces each student to receive the same course materials, disregarding their personal needs, characteristics, or preferences. Moreover, it is extremely difficult for a teacher to determine the best learning strategy for each learner and to apply it in a real classroom [2,3]. One way to address this issue is to use recommender system (RS) techniques to personalize learning process according to the interests and goals of each learner.

An appropriate LO must be chosen according to the learner's preferences and also to pedagogical goals. These interests and goals are derived from specific of lifelong [4]. Therefore, it is extremely important to provide a personalized learning system which can automatically adapt to these preferences and intelligently recommend suitable learning activities that would favor and improve learning process. Many researches using recommender systems have been done in E-learning environment [5–7]. As a result of the great success of RSs in many areas especially in online business, a variety of tools and techniques for developing recommendation have been done, including content-based filtering (CBF) [8–11], collaborative filtering (CF) [12–14], association pattern analysis (APA) [15–17], and hybrid methods combining these approaches [18–22]. According to many research works, combining several recommendation strategies can be expected to provide better results than each strategy alone [23]. Hybrid recommendation services attempt to deal with some limitation and overcome drawbacks of

✉ Outmane Bourkoukou
outmane.bourkoukou@ced.uca.ma

1 Cadi Ayyad University, Marrakesh, Morocco

each recommendation approach. For example, CF, the widely used technique since it is very useful for implementing, has a critical limitation because it requires the implicit rating information which is generally unobvious [20]. This limitation could be increased especially in E-learning context, making the information extraction of that latter very difficult in terms of learning interests and preferences. Furthermore, APA technique has also a limitation since it makes users unhappy most of the time by ignoring their explicit rating.

The proposed approach is taking into account both CF and APA techniques to build an innovative recommender model in E-learning environment, to achieve a personalized learning experience by selecting and sequencing the most appropriate learning objects. Thus, experiments were conducted using two real-world data sets publicly available to evaluate the performance of our proposed approach.

The originalities of our approach are twofold: (1) We define a new score function to weight learning objects taking into account the learners' explicit feedbacks and implicit preferences by mining web log files. Indeed, the most existing technology-enhanced learning recommender systems (TELRSs) used APA to compute the implicit ratings which could affect in our opinion the efficiency of predictions. (2) Firstly, we used CF for selecting from learning object repositories (LOR) a list of the most appropriate learning objects based on the learners' preferences obtained using our score function; secondly, APA tools are adapted to sequence and structure a personalized learning scenario.

This paper is structured as follows: Sect. 2 reviews related works regarding recommendation system in E-learning environments. Section 3 describes the proposed method which includes the recommender model used for recommending process. In Sect. 4, results and evaluations of our research are presented. Finally, the conclusion section provides the concluding remarks along with suggestions for future works.

2 Recommender Systems in TEL

Technology-enhanced learning (TEL) aims to design, to develop, and to test socio-technical innovations that will support and enhance learning practices of both individuals and organizations. Recently, recommender systems have been researched extensively and applied to technology-enhanced learning in order to identify suitable learning objects and to deliver a variety of learning activities to the learners [24–26]. Therefore, according to [27], learning object is being regularly produced, organized, and published in different types of TEL environments such as:

– Learning object repositories (LOR) is a kind of digital library which enables to share, to manage, and to use learning object like GEM, CLOE, and MITOCW.
– A massive open online course (MOOC) is a kind of free open and available digital publication of high-quality educational materials like Udemy free courses, MIT free courses, and ITunesU free courses.
– Learning management systems (LMS) is a software application or Web-based technology used to plan, to implement, and to assess a specific learning process like Moodle, Edmode, and Blackboard.

This excessive amount of LOs merges various opportunities but also causes difficulties for learner to locate appropriate learning objects. Such situation is known in the literature as the cyberspace syndrome.

In the last decade, a number of technology-enhanced learning recommender systems (TELRSs) based on data mining techniques have been introduced in order to support learners to achieve specific learning needs since it is very useful to design and to implement especially in informal learning [28].

One of the first attempts to develop a collaborative filtering system for digital learning objects has been the altered vista system [29–31]. This system supports discovery and automatic filtering for relevant learning resources that addresses needs of learners and educators. Another system that has been proposed for the recommendation of audio learning objects is the RACOFI system (rule applying collaborative filtering) [32]. Dorca et al. [33] presented in their work a recommender system based on CBF. Their approach is based on an expert system that implements a set of rules which classifies learning objects according to their teaching style, and then automatically filters learning objects according to students' learning styles. Zaiane [34] proposed an approach to build a software agent that uses data mining techniques such as association rules mining in order to build a model that represents online user behaviors, and uses this model to suggest activities or shortcuts. Imran et al. [35] proposed PLORS system supports learners by providing them recommendations about which learning objects within the course are more useful for them. The recommendation mechanism uses association rule mining to find the association between LOs. Avancini and Straccia [36] developed CYCLADES system for users and communities search to share and to organize their information space according to their own view and to evaluate learning resources. The system is able to give recommendations based on user and community profiles using several collaborative filtering techniques. Bobadilla et al. [37] defined an equation which incorporates the learners score obtained from a test into the calculations of collaborative filtering for resources prediction.

In the last few years, many researchers suggest that recommender system should combine more than one technique in order to provide a better analysis of student's behavior as well as selection, and sequencing of recommendation list of

Table 1 List of existing TELRSs with hybrid approaches

Refs.	Score function		Techniques			Comments
	Explicit	Implicit	CF	CBF	APA	
[40]	×	–	×	–	–	Clustering learners by K-means based on their learning interests. CF works by making recommendations based on explicit ratings
[38]	–	–	×	–	×	Clustering data courses using K-means. Applying APA on clustered data to find the sequence adequate courses
[41]	×	–	×	–	×	APA tool is used to uncover interesting relationships found in student usage. CF is used to make recommendations for instructors about how to improve E-learning courses
[42]	–	×	×	×	×	APA is adopted to extract behavioral of patterns from log files of learners. Recommending learning activities based on CF using as input the learner's knowledge degree for each unit
[5]	–	×	×	×	×	Extracting user preferences from server logs using APA and weighting visited learning objects by Binary 0 or 1. Recommendation strategies based mainly on CBF and CF
[7]	×	×	×	–	×	Extracting user's explicit rating and implicit ratings using APA tool. Recommendation learning based on CF and APA techniques

learning objects to fit the specific learner's needs and interests [38,39].

As examples, an evolving learning management system has been developed by Tang and McCalla [40] to store and to share digital learning resources. This system used a hybrid recommendation process based on data clustering and collaborative filtering approaches to classify students with similar interests and tastes by using the explicit ratings. Aher and Lobo [38] apply data mining techniques such as K-means clustering and association rule algorithm in TELRS to recommend the course to a student based on choices of other students for particular set of courses collected. Garcia et al. [41] proposed a collaborative TELRS based on association rule mining and collaborative filtering for the continuous improvement of E-learning courses and allowing educators with similar course profiles to share and to score the discovered learning activities. In his work, Klasnja-Milicevicet et al. [42] have developed a system called PROTUS which can recommend relevant links and activities for learners, based on hybrid recommendation using the collaborative filtering as input the learner's knowledge degree and the sequential pattern mining to extract the behavior of patterns from log files of learners. Khribi et al. [5] proposed a framework to build automatic recommendations of learning objects with combining CBF and memory-based CF techniques. The system uses the learners' navigation histories, similarities, and dissimilarities among the content of the learning resources for online personalized recommendations. Salehi [7] proposed an E-learning system that can recommend learning resources based on implicit and explicit ratings using collaborative filtering and sequential pattern mining combination. Table 1 summarizes the existing TELRSs using the hybrid approaches.

All these studies claim to be innovative, but unfortunately they are still in application area and concentrated on small-scale experiments [5,39,43,44]. Due to the lack of publicly available data sets for E-learning, some researchers have been tested their RSs using external data sets from movies and books in order to evaluate educational recommendation algorithms [7,37,43,44]. Publicly available data sets for the specific E-learning context become a necessity need to evaluate the quality and accuracy of TELRSs. Several challenges

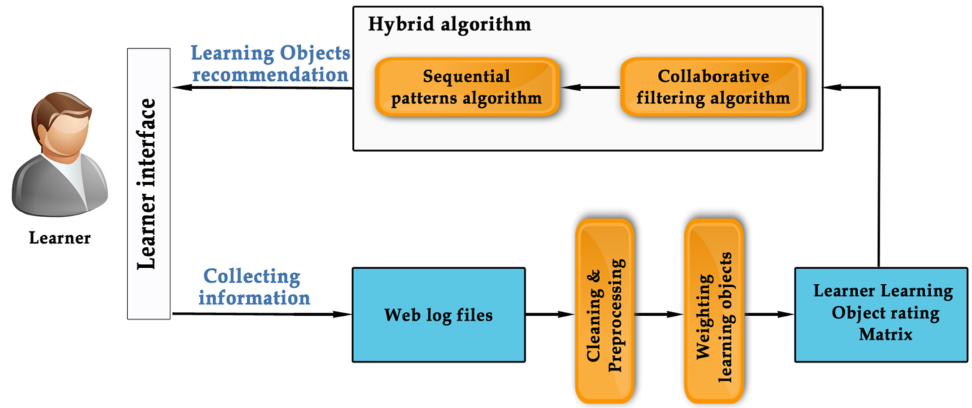

Fig. 1 Recommender process

to collect and to share the data about interactions of learners with tools and learning activities were launched by RecSys-TEL workshop [44–47] and Pittsburgh science of learning center (PSLC) DataShop [48]. In the next section, we present our proposed recommender model based on a hybrid collaborative filtering and sequential pattern tools.

3 Proposed Recommender Model

The recommender model for E-learning context is depicted in Fig. 1. The learner profile can be revisited dynamically using the learner's interactions with the system by extracting their interests and preferences from web log files that are generated, in order to recommend the most appropriate list of learning objects. The data mining techniques use the collected information about learner interactions, such as navigation history and bookmarks, to build the learner profile and thereafter to build recommendations. In the following of this section, we present this approach step by step.

3.1 Cleaning and Preprocessing

In E-learning experience, several information about learners is collected from their active session, explicitly or implicitly by observing learner's behaviors and interactions with the system. The first step consists to clean and to preprocess the information. In fact, in data mining area, the cleaning and preprocessing data are the most important tasks to prevent data anomalies such as missing or noising data [49,50].

3.2 Weighting Learning Objects

After cleaning and preprocessing the web logs, data are transformed or consolidated into appropriate forms for recommended purpose.

In this paper, the attribute data are normalized so as to fall between small ranges, such as 0–10 using a score function based on Chan's works, implicit rate for web pages [51]. We adopted this formula in E-learning context to weight learning objects by defining the score function S:

Table 2 A LLOR matrix example

Learners	j_1	j_2	j_3	j_4
l_1	0	5	3	9
l_2	6	4	0	1
l_3	8	3	8	4
l_4	3	0	0	4

$$S(\theta) = \frac{1}{2}\left(E(\theta) + I(\theta)\right) \tag{1}$$

where E is the explicit score given by the learner for each learning object $E(\theta)$, and I is the implicit score defined by:

$$\begin{cases} I(\theta) = A(\theta) + 2B(\theta) + 2C(\theta)E \\ B(\theta) = \mathrm{e}^{-t} \end{cases} \tag{2}$$

where A equals 1, θ when is stored in the bookmarks, 0 otherwise. The function B computes the duration t spent by the learner to use the selected learning object. C is the selection's frequency of the learning object θ. The functions A, B, and C must be normalized so the maximum of each one can be equal to number 1.

After weighting learning resources, we obtained a learner learning object rating (LLOR) matrix with n rows, where n denotes the number of learners $L = \{l_1, l_2, \ldots, l_n\}$, and m columns, where m denotes the number of learning objects $J = \{j_1, j_2, \ldots, j_m\}$. Table 2 shows a LLOR matrix example.

This matrix uses a 0–10 rating scale where 10 means that the learner is strongly satisfied with the selected learning object, 5 indicates that the learner is moderately satisfied, 1 indicates that the learner is not at all satisfied with the learner object, and finally the score 0 indicates that the learning object is not yet explicitly rated or used at all.

3.3 Collaborative Filtering

Collaborative filtering techniques are based on the simple idea that users who share similar past choices will be interested in similar items in the future. In this paper, we use CF to predict the utility of learning objects for a particular learner based on the learning objects previously rated by other learners.

After weighting learning objects using the first step, we apply a method based on CF in order to build virtual community of learners sharing the same interests and preferences. In fact, we have to make predictions for all learning object weighted 0 which indicates in the LLOR matrix the unknown value. For example, in Table 2, l_4 is an active learner for whom we want to make predictions on learning objects j_2 and j_3. This step is carried out by adapting the most known classifier algorithm K-nearest neighbors (K-NN) on E-learning scenario [43,52]. This technique allows finding predictions by using the following steps:

3.3.1 Computing Similarities Between Learners

The critical step in memory-based CF methods is to define similarity and dissimilarity between users or items [53]. Indeed, various approaches are proposed to compute similarities and dissimilarities, the most used are as follows: Pearson's correlation, Cosine similarity, and Tanimoto–Jaccard coefficient [44,53]. The Pearson's correlation between two learners' u and v is calculated as follows:

$$S_1(u, v) = \frac{\sum_j^n \left(r_{u,j} - \bar{r_u}\right)\left(r_{v,j} - \bar{r_v}\right)}{\sqrt{\sum_j^n \left(r_{u,j} - \bar{r_u}\right)^2 \sum_j^n \left(r_{v,j} - \bar{r_v}\right)^2}} \tag{3}$$

In the above equation, $\bar{r_u}$ and $\bar{r_v}$ are the average rating of learner u and v, respectively; $r_{u,j}$ and $r_{v,j}$ are the rating of learner u and v for learning object j. The similarity between two learners' u and v with Cosine similarity method can be calculated as follows:

$$S_2(u, v) = \frac{\sum_j^n r_{u,j} X r_{v,j}}{\sqrt{\sum_j^n r_{u,j}^2}\sqrt{\sum_j^n r_{v,j}^2}} \tag{4}$$

The Tanimoto–Jaccard measures the overlap degree between two sets by dividing the numbers of learning objects selected by both learners and the number of different learning objects from both sets of rated learning objects. The similarity between two learners' u and v using this calculation measure is defined as:

$$S_3(u, v) = \frac{|J_u \bigcap J_v|}{|J_u| + |J_v| - |J_u \bigcap J_v|} \tag{5}$$

where J_u and J_v represent, respectively, the number of items that have been rated by learner u and v. This similarity metric considers only the number and not the values of learning objects. In addition, several studies have shown that this metric have advantageous in the case of sparse data sets [44,54].

The value of all defined metrics indicates how much learner u tends to agree or to disagree with learner v on the learning object that both learners have already rated; moreover, the higher the similarity is, the better the K-NN works.

3.3.2 Selecting K Learners Neighbors

After the similarity between two learners is calculated, an $N \times N$ similarity matrix is generated, where N is the number of learners. Then, to predict the unrated learning object j in the rating matrix by the active learner u, the K most similar learners will be selected and used as input to compute prediction for u on j.

3.3.3 Computing Predictions

To make a prediction for an active learner u on certain learning object j, we can take a weighted average of all the ratings on those learning objects according to the following formula:

$$p_{u,j} = \bar{r_u} + \frac{\sum_{v=1}^n S(u, v)\left(r_{v,j} - \bar{r_v}\right)}{\sum_{v=1}^n |S(u, v)|} \tag{6}$$

In Eq. (6), $r_{v,j}$ denotes the rating value given by the user v for the selected learning object j. After computing predictions, we obtained a learner learning object predicted (LLOP) matrix. The process of K-NN to classify learners and to give predictions for learning objects using Algorithm 1.

Algorithm 1 K-NN Algorithm

Input: LLOR_Matrix LM; K
Output: LLOP_Matrix P
Description:

```
for Rate r in the LM # 0 do
    for Learner u in the LM do
        for Learner v in the LM && u # v do
            computeS (u, v) according in (3, 4 & 5) formula
        end for
        selectNeighbors (u, k)
        computeP (u, j) according in (6) formula
    end for
end for
return p(u, j)
```

After LLOP matrix to predict unknown ratings using collaborative filtering step, we select for each learner all learning objects with rating score higher or equal than 3 as a list of the most appropriate learning objects based on the learners' preference. The result could be used in the next step which used APA technique in order to sequence and to structure a personalized learning scenario. Figure 2 depicts the different matrix transformations from an example of web log file.

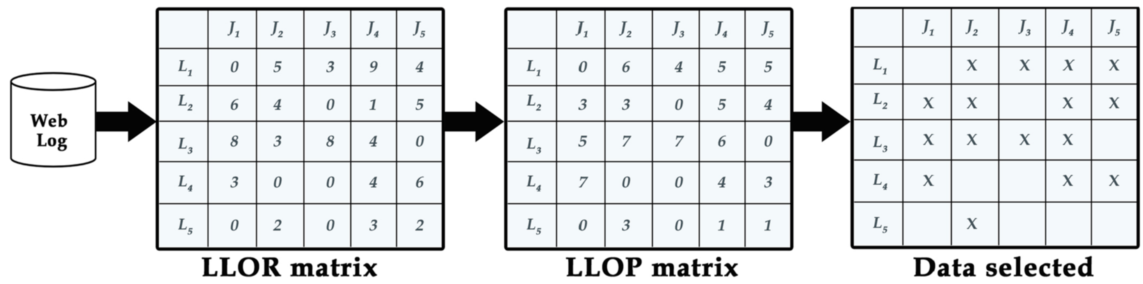

Fig. 2 Matrix transformations

3.4 Sequential Pattern Mining

Sequential pattern mining (SPM) is a large data mining technique used by researchers in this last decade with broad applications in several domains, which is an efficient technique to mine frequent patterns in database and maintaining their order [7,25,38].

After generating a learner learning object predicted (LLOP) matrix and selecting the most appropriate learning objects using collaborative filtering step detailed in the previous section, we use a SPM algorithm to retrieve the most frequent sequence of learning objects in this matrix.

Consequently, using the SPM analysis, those sequences of learning objects could be selected as the most appropriate learning scenario to achieve an optimal learning experience.

Indeed, a learning scenario is defined as the manner an instructor or tutor could present and sequence a list of learning objects to conduct instructional activities. This scenario is designed in a way that the learner is encouraged to observe, to analyze, and to learn efficiently [3]. For example, a learning scenario can be achieved by the sequence of learning objects composed with a lecture, a video presentation, read text, questions and answers, and assessment.

For example, Fig. 3 depicts the way this learning experience could be structured and sequenced as a personalized learning scenario. In a typical traditional E-learning experience, learners use a linear path $\{j_1, j_2, \ldots, j_{12}\}$ to learn without putting in mind their own preferences or interests.

However, a personalized E-learning experience could be designed and presented in a nonlinear manner in order to build for each learner the optimal sequence of learning objects. We defined an optimal sequence, the best learning scenario can be recommended for a given learner. In this personalized scenario, some learning objects like j_5 or j_8 can be ignored or isolated by the system since they are not fitting with the learner profile.

In our recommender process, we used the generalized sequential pattern (GSP) algorithm to generate recommendation list, the main procedures can be described as follows [50]:

- First pass: determines the support for each item (learning object) and find the frequent 1-sequence that has the minimum support.
- Candidate generation: generates new candidate sequence (next level) from the previous frequent set of all candidates.
- Prune candidates: deletes candidate sequences, the support of which is less than the minimal support threshold.

The generalized sequential pattern mining algorithm is given by:

Algorithm 2 Generalized sequential pattern

Input: SelectedData D; Min_sup
Output: frequent Learning objects
Description:

```
F_1 ← {1-LOsets}
k ← 1
while (F_k != null) do
    C_{k+1} ← Generate(F_k)
    for each candidate c ∈ C_{k+1} do
        for each row r in the D do
            count[c] ← count[c] + 1
        end for
    end for
    F_k ← {c ∈ F_k | count[c] ≥ Min_Sup}
    k ← k + 1
end while
return ⋃_k F_k
```

4 Experimentation and Results

In order to verify the effectiveness of the proposed approach, we conduct several experiments in real data sets in E-learning context. In this section, we describe data sets used; experimental methodology and performance improvement of our approach is compared with several classical algorithms. Experiments are conducted on HP Computer with CORE i5 processors using MATLAB 7.10.

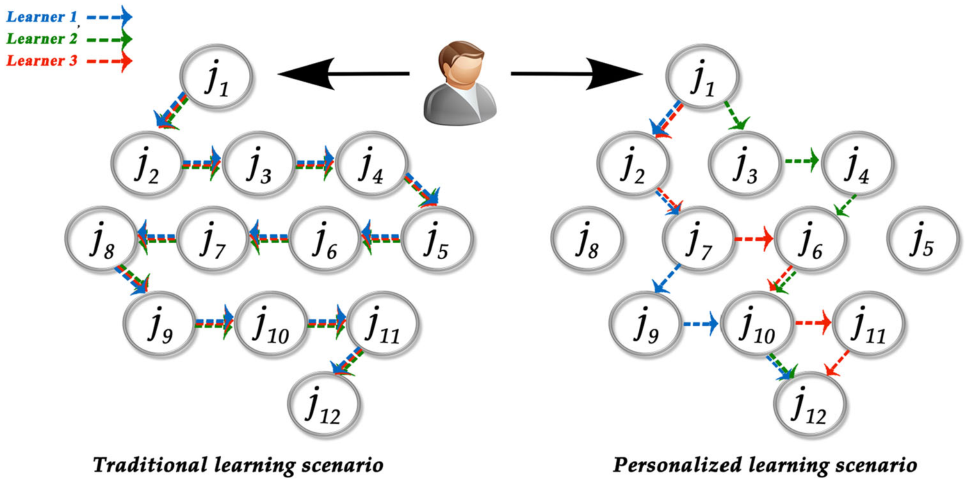

Fig. 3 Comparison between traditional and personalized learning strategy

4.1 Data Sets

Two real-world data sets are used in our experiments, namely Algebra 2005–2006 (Alg) and Geometry 2006–2007 (Geo) which are extracted from the Cognitive Tutor System and published by PSLC DataShop [48]. These available data sets contain the implicit information about interactions between learners with the tutoring system and learning resources. To evaluate the performance of our algorithm, the data set needs to be partitioned into two sections: training set (80 %) and testing set (20 %). The specifications of the data sets are summarized in Table 3.

The rating sparsity is computed by:

$$\text{Sparsity} = \left(1 - \frac{\sum \text{Ratings}}{\sum \text{Users} \times \sum \text{Items}}\right) \times 100 \tag{7}$$

In the previous section, cleaning and preprocessing step of the original data sets are necessary to make data suitable for mining purpose and recommender decision. This task had been achieved by using the first step of the recommendation process previously explained. The implicit learning ratings are represented as numeric values from 0 to 5.

4.2 Evaluation Metric

We mainly focus on testing the prediction accuracy of our proposed method, and we used the mean absolute error (MAE), which is the most widely used technique to compare the deviation between predictions and the real user-specified values. MAE can be defined as:

$$\text{MAE} = \frac{\sum_{(u,j)} |\tilde{p}_{u,j} - r_{u,j}|}{m} \tag{8}$$

where m is the total number of ratings over all learners, $p_{u,j}$ is the predicted rating for learner u on learning object j, and $r_{u,j}$ is the actual rating. Obviously, the smaller MAE is the better performance of the algorithm will be.

4.3 Experiment Process

The experiments are conducted specifically to find out the following questions: (1) How parameters like similarity metrics, number of neighborhood and data sets size could influence results? (2) How the performance of our CF can be achieved in comparison with other CF techniques in different data sets?

4.4 Results

In the first experiments, we have used K-NN algorithm with different similarity metrics using formula (6) in order to find the best value of K-neighbors in static data set and in incremental data set, respectively, depicted in Figs. 4 and 5.

In Fig. 4, to determine the optimal K-value of neighbors for KNN method on Alg and Geo data sets, the number of neighbors is chosen between 10 and 200. By increasing the number of neighbors, the performance of the KNN algorithms using different similarity metrics obtains a better prediction accuracy. In Fig. 4a on Alg data set, the MAE values using KNN-Pearson and KNN-Cosine metrics are almost adjacent in all cases, when the number of K value is less than 100 using KNN-Tanimoto metric performs better than any other algorithms, and when K is more than 100, KNN-

Table 3 Experimental databases

Data set	Learners	LOs	Transactins	Sparsity (%)	Total student hours
Alg	576	1216	2,146,238	81.67	8306.99
Geo	567	5181	2,441,583	93.01	6565.94

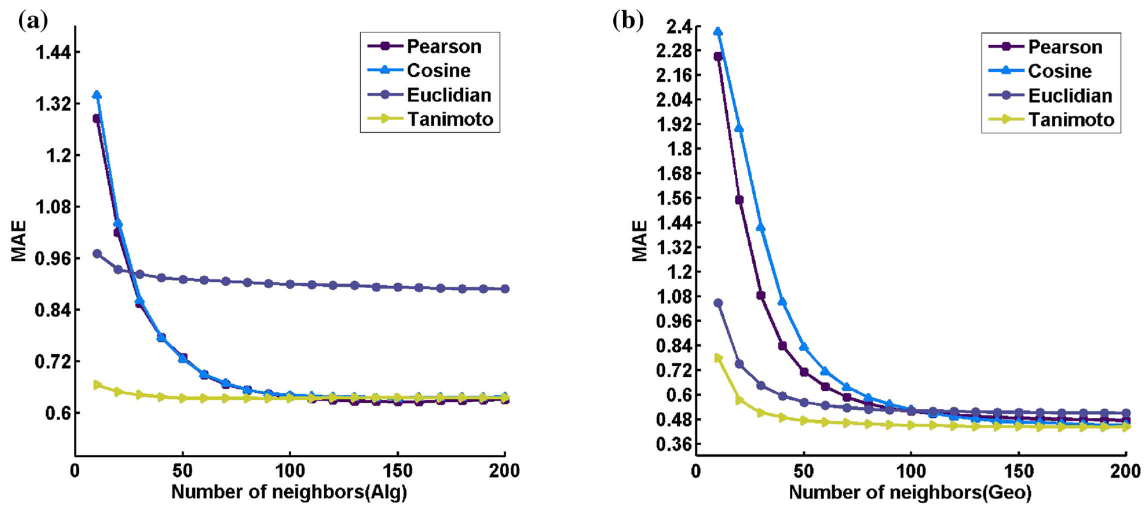

Fig. 4 Comparison between traditional and personalized learning strategy

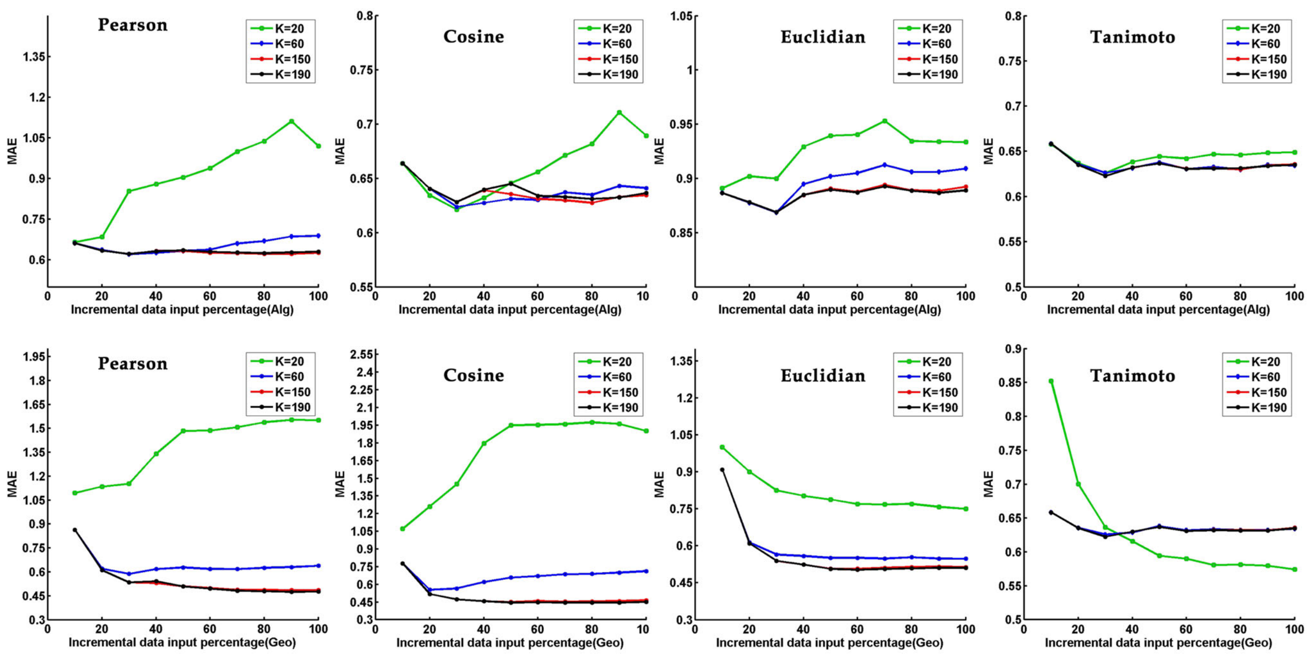

Fig. 5 Comparison between traditional and personalized learning strategy

Pearson performs better than KNN-Tanimoto. In Fig. 4b by varying K-value, it can be seen that KNN-Tanimoto outperforms better than other KNN metrics for both Alg and Geo data sets. This result is consistent with several experiments which show that the use of Tanimoto similarity measure performs much in the case of data set with sparsity like Geo [52,54]. The optimal performance is achieved when K is approximately equal to 190 for Geo data set and 150 for Alg data set.

In Fig. 5, the experiment was carried for each of the following values 20, 60, 150, and 190. It can be seen that by increasing the number of users with varying the K-value, we can obtain an optimal prediction except when $K = 20$ for the most similarity metrics. The value $K = 150$ can be considered the best value for KNN algorithm with different similarity metrics since the corresponding MAE value is the smallest one. According to these results, we employ value of K and carried out the validation for the accuracy of our approach in the next experiments. In the second experiment, to evaluate the performance of our proposed approach, we compare its performance with several methods. The results are depicted in Fig. 6.

Figure 6a shows that KNN with Pearson metric performs better in all cases in the Alg data set; in Fig. 6b,

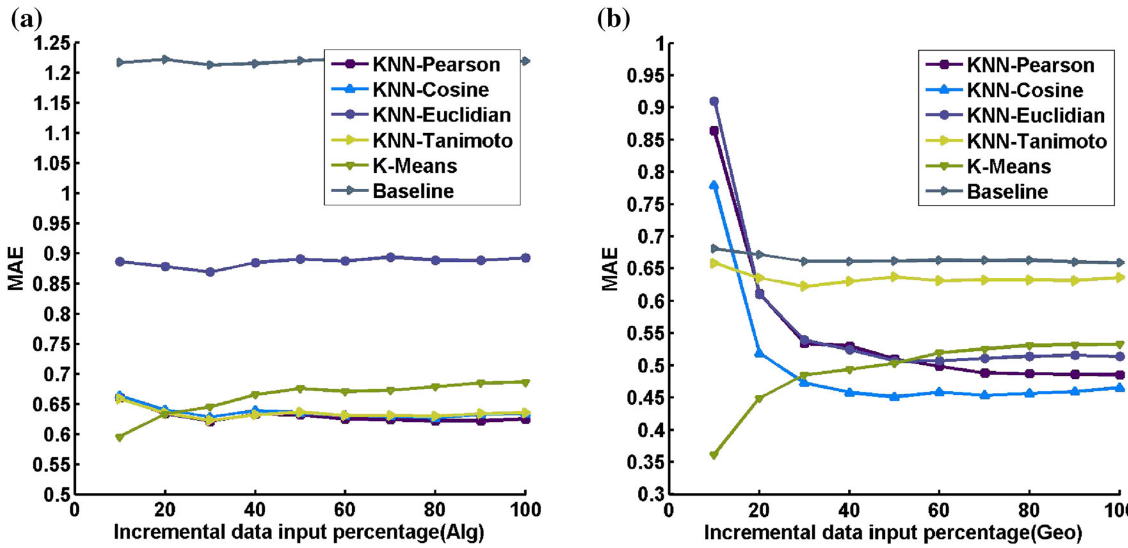

Fig. 6 Comparison between traditional and personalized learning strategy

we can also observe that when the incremental data input percentage of the training set is between 10 and 30 % the K-means performs better than any other methods. By varying the number of learners of the training set more than 30 %, it can be seen how the MAE of the KNN-cosine metric is the smallest than the MAE of any other techniques.

5 Conclusions

In this last decade, recommender systems are one of the recent and most important technologies used to improve individual and personalized learning in E-learning context. In this paper, an innovative recommender model for E-learning environment is proposed based on collaborative filtering and sequential pattern mining to improve recommendation system to achieve an efficient learning experience. Firstly, we defined a new score function to weight learning objects by both collecting the learner' feedbacks and extracting preferences from the existing web log files. Secondly, we used CF for selecting from learning object repositories (LOR) a list of the most appropriate learning objects based on the learners' preference obtained using our score function, and APA tools are adapted to sequence and structure a personalized learning scenario.

Moreover, the availability of open data sets in E-learning seems, until now, to be a real challenge since there are not enough experiences in real scenario using many learners and transactions. In order to evaluate the prediction accuracy of our proposed recommendation model, we used external data sets in E-learning environment. Results show that using the proposed approach could improve the performance of predictions.

We are currently testing this recommender system approach on an online course, and we will evaluate the recommendations by keeping track of learners' progress toward achieving their goals. Since in the cleaning and the preprocessing data step the precomputing of the learner' profiles is crucial, we should update profile at regular intervals frequently for more scalability of the system when a new learner or learning object is added.

In the future, we plan to refine the recommender model to deal with several inherent issues such as data sparsity and cold start. Since CF methods are known to be vulnerable to these problems in recommendation. In addition, we will consider more complex recommendation approaches, by including other factors such as learner motivation, learning styles, and apply other intelligent artificial techniques.

Acknowledgements We used the "Geometry 2006–2007" data set accessed via DataShop (www.pslcdatashop.org). We used the "Algebra I 2005–2006 (3 schools)" data set accessed via DataShop

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