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Weighting Based Approach for Learning Resources Recommendations

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Abstract— **Personalized e-learning systems based on recommender systems refines enormous amount of data and provides suggestions on learning resources which is appealing to the learner. Although, the recommender systems depends on content based approach or collaborative filtering technique to make recommendations, these methods suffers from cold start and data sparsity problems. To overcome the limitations of the aforementioned problems, a weight based approach is proposed for better performance. The main criterion for building a personalized recommender system is to exploit useful content and provide better recommendations with minimal processing time. The proposed system is a web based client side application which uses user profiles to form neighborhoods and calculates predictions using weights. For newcomers a profile is constructed based on learning styles. The resources which might be of interest to the user are predicted from calculated predictions.**

Keywords— **E-learning, Recommender system, Data sets, Collaborative filtering.**

I. INTRODUCTION

Nowadays, development of searching technology provides learners a new way to break free with the more traditional educational models by exploring ways in which Web-based could adapt their behaviour to the goals, tasks, interests, and other characteristics of users [5]. In response to individual needs, personalization in education facilitates students to learn better by using different strategies to create various learning experiences [18, 12]. In recent years, one of the new form of learning personalization that has been expressed as a need by several studies is to give recommendations for learners in order to support and to help them through the learning process [13].

An appropriate LO must be chosen according to learner's preferences and also to pedagogical goals. These goals and interests are derived from specific of lifelong [8]. Thereby, 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 favour and improve learning process. Many researches using recommender systems have been done in e-learning environment [2]. As a result of the great success of RSs in many areas specially in online business, a variety of tools and techniques for developing recommendation have been done, including Content-Based Filtering (CBF), Collaborative Filtering (CF), and hybrid methods combining these approaches [9, 13, 22, 25].

- Content-based recommendation selects items based on the correlation between the content of the items (products, services or contents) and user profile most time by using Physiological models.
- Collaborative–based recommendation also known as "people-to-people correlation." recommends to the active user the items that other users with similar tastes liked in the past. The similarity in taste of two users is calculated based on the similarity in the rating history of users. Collaborative filtering is considered to be the most popular and widely implemented techniques in RS.
- Hybrid–based recommendation combines these two techniques to improve the "quality" of recommendations and to eliminate drawbacks of each one.

The objective of this work is to present a recommender system for e-learning context using new score function for identifying learners' preferences. The idea is to build an innovative approach to generate relevant recommendations and also to deal with the cold start and data sparsity problems which are a relevant challenge in recommender system.

The rest of this paper is organized as follows. Section 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 section 4, results and evaluations of our research are presented. Finally, the conclusion section provides the concluding remarks along with suggestions for future works.

II. LITTERATURE REVEIW

In last decade, a number of Learning Recommender Systems (LRSs) based on collaborative filtering have been introduced in order to support learners to achieve specific learning needs. Nevertheless, considering the various existing digital learning objects, such frameworks, could potentially play an important educational role [15, 19, 3].

Recommender systems based on approaches such as collaborative filtering (CF) techniques have been shown to be very useful to design and to implement specially in informal learning [17, 23, 24].

One of the first attempts to develop a collaborative filtering system for digital learning objects has been the Altered Vista system [20]. 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 learning objects is the RACOFI system (Rule Applying Collaborative Filtering) [1]. The RACOFI system assists and recommends online users audio learning objects. [10] 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. The CYCLADES system has proposed by Avancini and Straccia [2] for allowing users and communities search, share and organize their information space according to their own view and evaluate learning resources available in Open Archives Initiative (OAI). The system is able to give recommendations of several types based on user and community profiles. [6] use recommender agents for recommending online learning activities or shortcuts in a course web site based on a learner's web logs using association rule algorithm.

However, in last few years, many researchers suggest that recommender system should combine more than technique in order to provide a better selecting, and sequencing recommendation list of learning objects to fit the specific learner's needs and interests [12]. As examples, an evolving learning management system has been developed by Tang and McCalla [21] to store, and to share digital learning resources using a hybrid recommendation process based on a clustering and collaborative filtering approach to classify students with similar interests and tastes. In his work Klasnja-Milicevic et al. [14] have developed a system called PROTUS (PRogramming TUtoring System) which can recommend relevant links and activities for learners, by considering the Felder-Silverman Learning styles Model and the learner's level of knowledge. This system has been designed based on hybrid recommendation using the collaborative filtering and the sequential pattern mining.

Tarus et al. [22] propose a hybrid knowledge-based recommender system based on ontology and sequential pattern mining (SPM) for recommendation of E-learning resources to learners. In the proposed recommendation approach, ontology is used to model and represent the domain knowledge about the learner and learning resources whereas SPM algorithm discovers the learners' sequential learning patterns. Li et al. [16] present a general architecture of learning recommender system for the smart learning environment. By constructing learner models and resource models, the proposed recommender system aims to recommend learning resources by using the clustering and association rule mining and to recommend peers via social interaction computing.

Bourkoukou et al. [3] propose a recommender model for e-learning environment to achieve personalized learning experiences by selecting and sequencing the most appropriate learning objects. By using a hybrid recommender system based on collaborative filtering techniques and association rule mining algorithm.

III. MATERIALS AND METHODS

The proposed approach aims to recommend learning resources to the learner by considiring the learner's preferences and previous browsing history extracted from the log files. This approach combines learning styles and collaborative filtering techniques to enhance the quality of suggestions.

Firstly, by using the model of learning style of Felder-and Silverman [7], the learning style of learners is identified; secondly, the system proposes the initial teaching strategy on the cold start session in order to deal with the cold start problem. This happens in cases where there is a lack of data about learners and theirs preferences which makes it impossible to provide relevant recommendations. Therefore, we have also adopted the collaborative filtering approach to revisit these first recommendations. The idea of this technique is to build predictions about learner's preferences based on the preferences of others who are similar with the active learner. Indeed, the groupe of learners whose preference matches with the current learner is identified by considiring the learners profile. The profile of the ccurrent learner is then compared with different groups of learners that were classified previously and the most appropriate neighborhood is identified. Moreover, to update this profile we defined new score function for weighting learning resoucres, in order to extract learner's preference from the log files. Also, this function allows boosting up the performance and normalizing the ratings to avoid data sparsity problem. The architecture for recommending the resources using the based technique is given in Fig. 1.
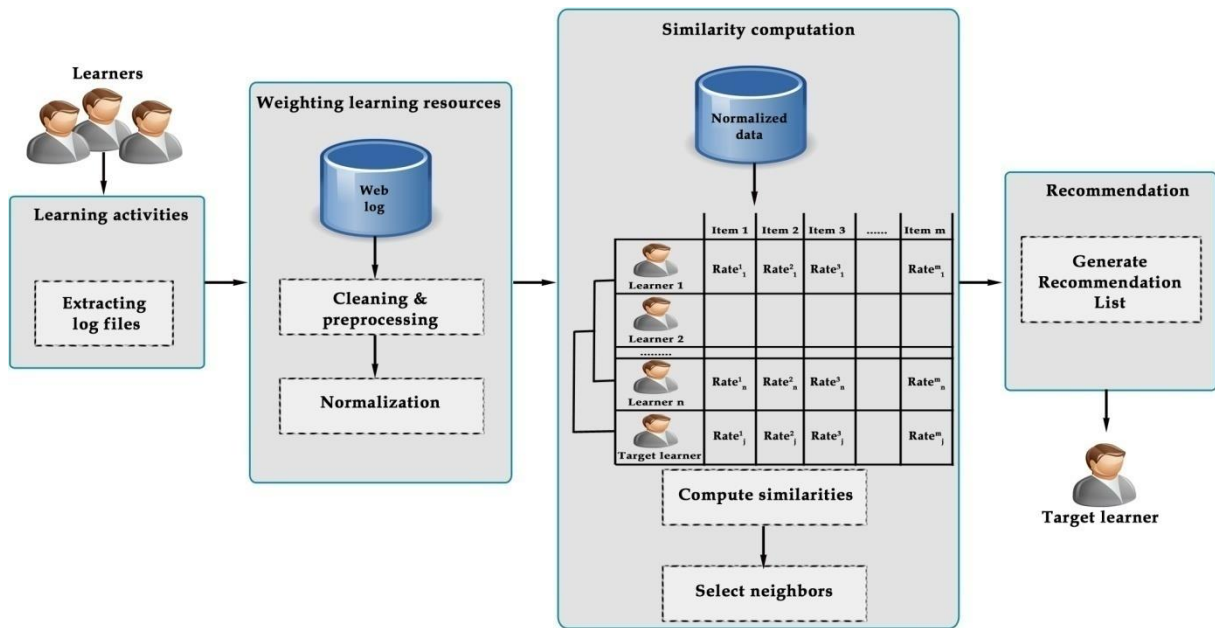
Fig. 1 Recommendation Process

Implementation: Our general purpose framework may be viewed as being comprised of at least the following three elements.

- Domain Model: Consist of concepts and the relations that exist between them. Typically the domain model gives a domain expert's view of domain.
- Learner Model: Consists of relevant information about the user that is pertinent to the personalization of the learning style.
- Represents the way used by a teacher to present concept of some domain of knowledge. In that way a teacher can use multiple teaching strategies for each concept. Teaching strategies are the way a teacher select and sequence learning objects to facilitate a deeper understanding of information.

These three elements are described in detail in [3]. The system designed is used for recommending learning resources to the learner. It is implemented using Symphony framework and bootstrap (Wikipedia.org).

The steps for recommending learning resources to the learner are explained as:

Step 1: Weighting learning resources

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

For this purpose we defined the weight of rating for each learning activity by using the following score function :

$$P(\theta) = EXP(\theta) + \alpha * IMP(\theta) + \beta * S(\theta) \qquad (1)$$

Where Exp is the explicit score given by the learner for each learning object θ. Imp is the implicit score and S is the social dimension score. Parameters α and β are chosen to normalize the functions Impl and S to unity 5. The implicit score is given by:

$$IMP(\theta) = A(\theta) + B(\theta) + C(\theta) \qquad (2)$$

Where A equals 1, when   is stored in the bookmarks, 0 otherwise. The function $B(\theta) = 1 - e^{-t}$ where t is the duration spending by learner during the learning object C is the access frequency of the learning activity.

Finally the function S which is the social rating dimension is defined by:

$$S(\theta) = c * e^{t'} \qquad (3)$$

Where t' is the duration spending during all synchronous or asynchronous communications by using associated tools, c number of contributions and interactions with these tools.

After weighting learning resources, we obtained a preference model for each learner defined as a Learner Learning Object Rating (LLOR) matrix with n rows, where n denotes the number of learners L ={l1, l2, ...ln},and m columns, where m denotes the number of learning objects J={j1, j2,…., jm}.

The following Table 1 shows an example of Learner Learning Object Rating (LLOR) matrix.

TABLE 1.A LLOR MATRIX EXAMPLE

Learners	j_1	j_2	j_3	j_4	J_5
l_1	0	5	3	9	5
l_2	6	4	0	1	3
l_3	8	3	8	4	4
l_4	3	0	0	4	8

This matrix use a 0-to-10 rating scale where: 10 means that the learner is strongly satisfied with the selected learning object, 5 indicates that the learner is not 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.

Step 2: Similarity computation

The critical step in memory based CF methods is to defined similarity and dissimilarity between users or items (Feng et al., 2014). The measurement for the weight for similarity between two learners u, v is the Pearson correlation coefficient calculated as follows:

$$SC(u,v) = \frac{\sum_j^m (r_{u,j} - \bar{r}_u)(r_{v,j} - \bar{r}_v)}{\sqrt{\sum_j^m (r_{u,j} - \bar{r}_u)^2 (r_{v,j} - \bar{r}_v)^2}} \quad (4)$$

In the above equation: and are the average rating of learner u and v, respectively; ru,j and rv,j are the rating of learner u and v for learning object j.

After the similarity between two learners is calculated, an N x 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.

Step 3: Generate recommendations

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

$$P_{u,j} = \bar{r}_u + \frac{\sum_{v=1}^k SC(u,v)(r_{v,j} - \bar{r}_v)}{\sum_{v=1}^k |SC(u,v)|} \quad (5)$$

In equation (5), rv,j denotes the rating value given by the user v for the selected learning object j.

IV. RESULTS AND DISCUSSIONS

To evaluate our system, we have conducted a research on LearnFitII's (http://learnfitproject.com/) effectiveness in learning "Java programming". We selected 163 participants of Computer Information Systems Bachelor's degree students at Cadi Ayyad University Marrakesh Morocco in four months of 2016. Indeed, students had to study the four learning chapters in LearnFitII environment. Chapter 1"Java introduction", Chapter 2 "Java language fundamentals", Chapter 3 " Java Classes and methods" Chapter 4 "Framework Collection". The dataset collected contains 163 learners and 400 learning objects.

In order to verify the effectiveness of our recommender system, we conduct several experiments in the collected data set. Experiments are conducted on HP Computer with CORE i5 processors using MatLab 7.10.

The data set contain the explicit, implicit and social information about interactions between learners with the LearnFitII 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 2.

TABLE I
EXPERIMENTAL DATASET

Learners	Learning objects	Transactions	Sparsity (Explicit score)	Sparsity (Exp+ Imp)	Sparsity (Exp+ imp+ S)	Total Student Hours
163	400	21462	88,20%	80%	63,52%	2306,99

The rating sparsity is computed by:

$$Sparsity = (1 - \frac{\sum Ratings}{\sum Learners * \sum LOs} \times 100 \quad (6)$$

The explicit, implicit and social learning ratings are represented as numeric values from 0 to 5 using our formula (1) for weighting learning objects. In the experiments, we have used KNN algorithm using formula (4) in order to find the best value of K-neighbors in incremental data set.

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

$$MAE = \frac{\sum_{u,j} |P_{u,j} -}{m}$$

$$MAE = \frac{\sum_{u,j} |P_{u,j} - r_{u,j}|}{m} \quad (7)$$

Where m is the total number of ratings over all users; Pu,j is the predicted rating for learner u using the learning object j, and ru,j is the learner rating. Obviously, the smaller MAE is the better performance of the algorithm will be.

Experiment process. The experiments are conducted specifically to find out the following question: 1) How parameters like number of neighborhood and datasets size could influence predications? 2) How the performance of our recommender system can be achieved by comparing our algorithm in different data sets?

Results. In the experiments, we have used KNN algorithm by considering, firstly, only the explicit ratings, secondly, by considering both the explicit and the implicit ratings and finally, by improving our dataset by adding the social preferences. The experiment was carried for each of the following values 15, 30, 60 and 90.
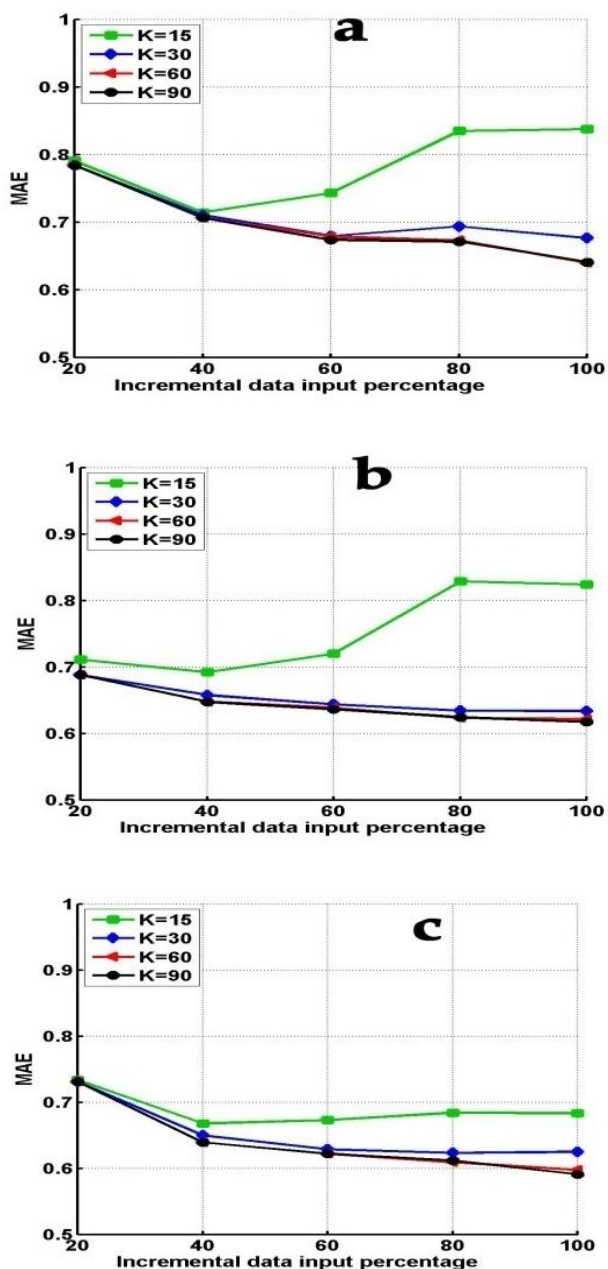
Fig.1 The comparison of accuracy among all tested cases

In Fig. 7 (a), the dataset contain only the explicit ratings. 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. The value K=90 can be considered the best value for KNN algorithm since the corresponding MAE value is the smallest one. However, by varying K-value it can be seen that KNN algorithm outperforms better when the dataset contains both explicit and implicit ratings (Fig. 7(b)). We can also observe that when the incremental data input contains the explicit, implicit and learners' social preferences our algorithm performs better than any other cases (Fig. 7(b)).

V. CONCLUSION

Nowadays, recommender systems are one of the recent and important technologies used to improve individual and social learning in E-learning area. Furthermore, the issues concerning personalization in learning process have been widely discussed in the past decades and remain the focus of attention of many researchers to day. However, there are several limitations when applying the existing recommendations algorithms. To address these limitations in this paper, we propose a personalized recommender system based on learning identification and collaborative filtering approach. The main idea is to deliver a personalized teaching strategy for each learner by selecting and sequencing the most appropriate learning objects into a coherent, focused organization in online distance education. These following conclusions can be arrived.

• To deal with the absence of data about learner and his/her preferences during the first connection, the framework offers a "lacking teaching" based only on the learning style.

• These preferences will be adjusted by the decision body of the system using new functions' predictions and collaborative filtering method in order to achieve the desired fit.

• In order to evaluate the prediction accuracy of our proposed recommendation approach, we used a data set of learners. The result reveals the system effectiveness for which it appears that the proposed approach may be promising.

In the future, we plan to refine the recommender model to deal with several inherent issues such as data sparsity and data correlation. 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, knowledge level, and apply other intelligent artificial techniques.

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