International Journal of Informatics and Applied Mathematics
e-ISSN:2667-6990 Vol. 6, No. 1, 1-10

Recommendation of Pedagogical Resources Based on Learners' Profiles

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Abstract. To help the learner mind in his selection process, several recommender systems have attracted researchers in e-learning systems. The recommendation system solves the problem of overload information due to the multitude of resources and interactions. How select the appropriate pedagogical resources and providing suitable ones for learners is the main objective of this work. Thus, in order to help these learners, we take into account their social relationships, the course they follow and their evaluation according to their levels. These factors are extracted to define three types of recommendations: the recommendation of the most visited resources, the recommendation of the most evaluated resources and the recommendation of the useful resources. All these propositions are used by an approach that is solid, new and solves the cold start problem. It is adopted by a system called RR-LEARNER (Resources Recommendation for LEARNER) where its use gives good results.

Keywords: Learning· CSCL· Recommendation System · Learner Profile · Educational Resources.

1 Introduction and motivation

There is no doubt, now more than ever due to the changes in education caused by COVID-19, education through technology has established itself globally in higher education. Collaboration is a distinctive and necessary activity for learning in any modality, and, in particular, for learning processes in virtual environments. In fact, Computer-supported Collaborative Learning facilitates the creation of learning communities aligned with the education paradigm. The utilization of this system every day can cause a problem from information overload due to the multitude of resources and interactions [1]. Therefore, the recommender system is the best way to help users easily access their resources in different areas.

The recommendation has been studied in many fields: information retrieval, E-Learning, Web, E-commerce, etc. In the literature, we found that different forms of recommendation depending on the data to be recommended, the information available and the goal [2]. According to Erdt et al. [3], the main objective of recommender systems in e-learning is to support learners during their learning process to achieve their educational goals. The same researchers explain that recommender systems can have positive effects on learning, such as learning performance and motivation.Basically there are six types of recommender systems: Collaborative Recommender system, Content-based recommender system, Demographic-based recommender system, Utility-based recommender system, Knowledge-based recommender system and Hybrid recommender system [4]. These techniques have their characteristics and suitable application scenarios.

In our work, we focused on the relationship among learners in CSCL in order to recommend the relevant pedagogical resources. In our previous work, our central focus was on the research area of collaboration among learners [9]. In this work, several research questions motivated our contribution:

1. How to define the appropriate factors to recommend the relevant resource?
2. How to recommend the relevant resources for each learner?

To answer these questions, a system was implemented called RR-LEARNER (i.e. Resources Recommendation for LEARNER). This platform allows learners to upload, to share and evaluate educational resources. All of this information will helps us to recommend the most appropriate resources. Using these factors, we have categorized the recommendation into three different types: The recommendation of the most visited resources, the recommendation of the most evaluated resources and the recommendation of the useful resources. The structure of the current work is as follows: Introduction in Section 1. Section 2 deals with some works related to the recommendation system. Section 3 describes the structure of the proposed approach. In Section 4 presents the implementation of a system that adopted the proposed approach. Finally, section 5, we present the conclusion and some future works.

2 Related Work

With the fast pace of modern life, E-learning systems use new computer technologies to improve the quality of education and also to ensure proper monitoring of the learner's learning activity. The COVID-19 pandemic has resulted in the widespread deployment of these systems in educational settings. Sometimes learners need advice from their teachers to guide them during their learning to choose, for example, courses, exercises, or tutorials. In order to encounter this need, many different information and recommendation strategies have been developed. Recommender systems have been applied in several areas; in this section, we try to synthesize some works that use recommender systems in distance education.

There are different types of recommendations: items, courses, etc. The type of recommendation differs according to the objectives of the work, The authors ([10]; [11])presented the recommender system using aspect analysis for the extraction of material resources to improve online learning. Wan and Niu [11] proposed to apply learner influence model (LIM), self-organization-based approach and sequential pattern mining (SPM) in the hybrid system to recommend personalized learning objects. The first model helps to collect information about the learner. The self-organizing approach helps to analyze the influence between the active learners with the target learner. The last model (i.e. sequential) is applied to decide the final learning objects to recommend. Madani et al [6] proposed a method to recommend courses. This method is based on a social collaborative filtering approach that uses the social content of learners such as tweets, Facebook posts, likes and comments for grouping them into clusters, and also it is based on the knowledge of learners for finding K-nearest neighbors of the learner to generate recommendation of courses to the target learners.Mehenaoui [5] proposed a system for recommending relevant collaborators based on several criteria. These criteria were used as an input to the mathematical formulas to model the appropriate criteria and recommendation rules.

In addition, recommendation systems have been applied in MOOCs (Massive Open Online Courses). For example, Jing and Tang [7] proposed a new course recommendation approach based on user interest, demographic profiles, and course prerequisites. This approach was used in XuetangX which is one of the largest MOOCs in China.

After analyzing the related works, the recommendation system can be applied in any area, it differs according to the objective and the data available. Generally, it is difficult to take a recommendation strategy from one area or particular context and apply it directly in another area. Our approach uses collaborative filtering that uses the evaluation of the learner. In table 1, we have analyzed some related works of the recommendation in e-learning system.

Author (s)	Recommendation method	Type of Recommendation	Recommendation factors	Platform	Dataset
[12]	Collaborative filtering	Resource recommendation	-Learning styles -Assessment - User history -Their feelings	N/A	N/A
[11]	Knowledge based approach	Learning objects recommendation	-Assessment data -Access time	N/A	2386 Learning objects
[7]	Collaborative filtering	Course recommendation	-Navigation history - Course content - Demographics	XuetangX https://xuetangx.com	114303 users
[13]	Collaborative filtering	Recommendation of activities	- Behaviors	N/A	10000 learners
[14]	Hybrid	learning resources	- Learner model - The resources - Interaction	N/A	66 learners
[6]	Collaborative filtering	Course recommendation	- Learners social network profiles - Assessment	N/A	N/A
[5]	Peer to Peer	relevant collaborators	-The cognitive profile -Learning style - His interests - and past collaborations	CRS	40 learners
[15]	Collaborative filtering	learning resources	Learners traces	Moodle	160 learners

Table 1. Analysis of work on recommender systems in e-learning..

3 Description of a new approach for recommending pedagogical resources in CSCL environments

In this section, we define the basic concepts for calculating scores for the recommendation of learning resources.

3.1 Recommendation criteria

Criterion 1: cognitive profile of learner The cognitive profile presents the knowledge level of each learner in the system. To carry out this assessment, each learner must answer some Multiple-Choice Questions proposed by their teacher according to their course. The score is calculated by applying formula 1. The result obtained represents the cognitive level of the learner in this subject [8].

$$CP(x)_j = (Number\ of\ correct\ answers\ j)/(Total\ number\ of\ questions\ j) * 100 \tag{1}$$

Where:
CP(x): the cognitive profile of learner x ,
j: is a subject to be taught.

Criterion 2: social relationship of learner In our work, we selected a set of indicators to select the sociable learners y with the current learner x in our collaborative learning system:

- The number of views done by the learner x on the other learners' profiles y, noted *V(x,y)*,
- The number of communication messages sent by the learner x to the other learners y, noted $Msg_sen(x, y)$
- The number of communication messages received by the learner x to the other learners y, noted $Msg_rec(x, y)$

This formula, which is denoted $Social_prof(x, y)$, represents the social relationship between the learner x and another learner of the system y. It is calculated as follows:

$$Social_prof(x, y) = (V(x, y) + Msg_sen(x, y) + Msg_rec(x, y))/3 \tag{2}$$

In the following, we will explain each indicator separately.

- The rate of views (*V(x,y)*)

Each learner viewing a profile must be marked as seen, so the rate of profile views is the number of views of the profile out of the total number of views:

$$V(x, y) = \frac{Number\ of\ view\ x\ for\ the\ profile\ y}{Total\ number\ of\ view\ x\ for\ the\ all\ learners\ profile} * 100 \tag{3}$$

– The rate of sent messages from learner x to another learners (*Msg_sen(x,y)*))

To calculate the sent messages from learner x to another learner y relative to all learners, we used the following formula:

$$Msg_sent(x,y) = \frac{Number\ of\ sent\ message\ from\ x\ to\ y}{Total\ number\ of\ sent\ message\ from\ x\ to\ all\ learners} * 100 \tag{4}$$

– The rate of received messages by learner x from other learners (*Msg_rec(x,y)*)

To calculate the received messages by learner x from learner y to all learners, we used the following formula:

$$Msg_rec(x,y) = \frac{number\ of\ received\ messages\ by\ xfrom\ y}{Total\ number\ of\ received\ messages\ by\ x\ from!\ all\ learners} *100 \tag{5}$$

3.2 Recommendation of educational resources

Our approach proposes three types of recommendations to meet the pedagogical needs of learners.

– Recommendation of the most visited resources $R_vis(x,i)$,
– Recommendation of the most evaluated resources $R_rat(x,i)$,
– Recommendation of the most useful resources $R_uti(x,i)$

In order to have applied each strategy, we have subsequently classified the resulting resources in ascending order.

a. Recommendation of the most visited resources: In this approach, we have recommended resources that have been widely visited and downloaded by system learners($Vis(y,i)$). Therefore, this recommendation helps the learner to consult the resources of the learners who are in contact with him ($Social_prof(x,y)$). This recommendation can be useful especially when the learner has no knowledge about the system so he can obtain the resource according to his relationship with learners. In addition, we have taken into consideration the teaching subject and the level of the current learner:

$$R_vis(x,i) = \sum_{i=1}^{n} Vis(y,i) * Social_prof(x,y) \tag{6}$$

Where : i: represents the resource that can be a course.

In the case where the learner x has not contacted any learner in the system in this case $Social_prof(x,y) = 0$, we have classified the resources according to ascending order and we recommend the resources most visited by the learners who have the same level.

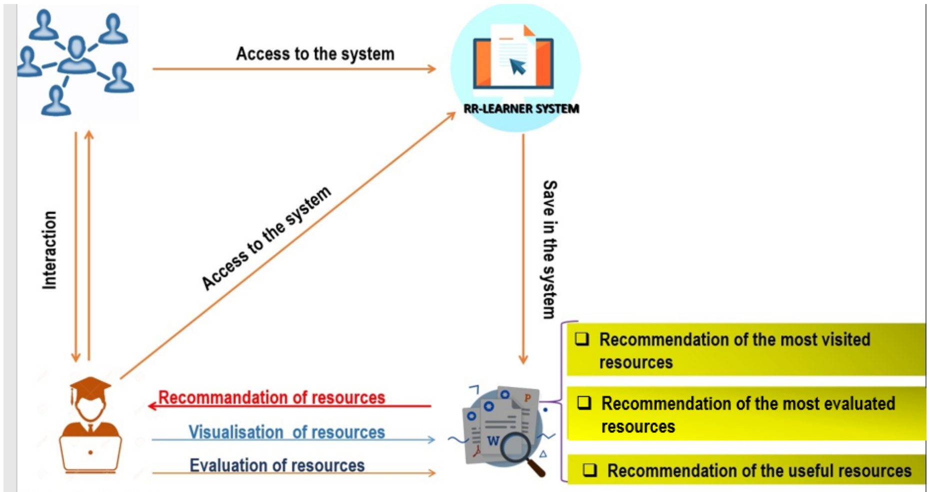

Fig. 1. The recommendation process.

b. Recommendation of the most evaluated resources: According to this type of recommendation, we proposed to recommend resources that have been evaluated by learners of the system $Rat(y, i)$where they used stars (rating) from 1 to 5. Only domains of interest of the user x which have been used to evaluate resource i by user y can be integrated in the calculation of this score. This learner y have a relationship with the current learner x. The formula used is the following:

$$R_rat(x, i) = \sum_{i=1}^{n} Rat(y, i) * Social_prof(x, y) \tag{7}$$

In the cold start case i.e. learner x has not contacted any learner in the system in this case, $Social_prof(x, y) = 0$, we have recommended the most rated resources by learners who have the same level.

c. Recommendation of the most useful resources: After the enrolment of a new learner, we recommend the resources of the teacher who registered in his teaching subject (R_ens). In addition, we recommend the rest the courses in the teaching subject which has already registered (R_mod) is recommended. According to the tests that the learner has passed in the system, we recommend the courses that had difficulties during their evaluation (R_dif).

$$R_uti(x) = \bigcup_{i=1}^{n} R_ens(x, i), R_mod(x, i), R_dif(x, i) \tag{8}$$

4 The Implementation of RR-LEARNER system

To validate the proposed approach, we implemented three different spaces: learner space, teacher space and administrator space. Figure 2 shows an interface from RR-LEARNER system, which presents an example of the recommendation of resources for a learner.

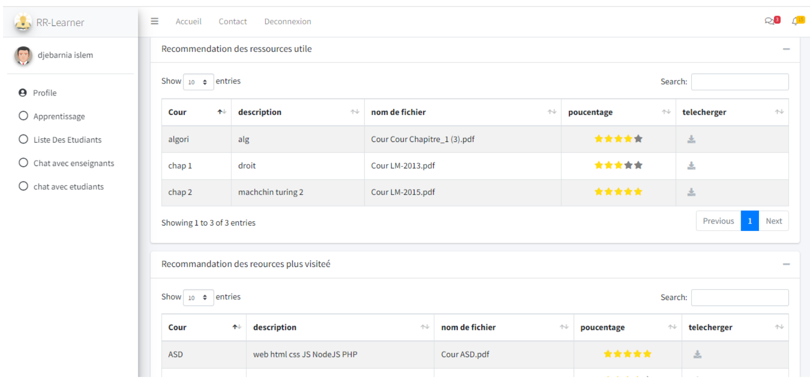

Fig. 2. The recommendation of pedagogical resources.

Figure 3 displays some interfaces from teacher space, how can he put the courses and he can also see the rating of each learning object.

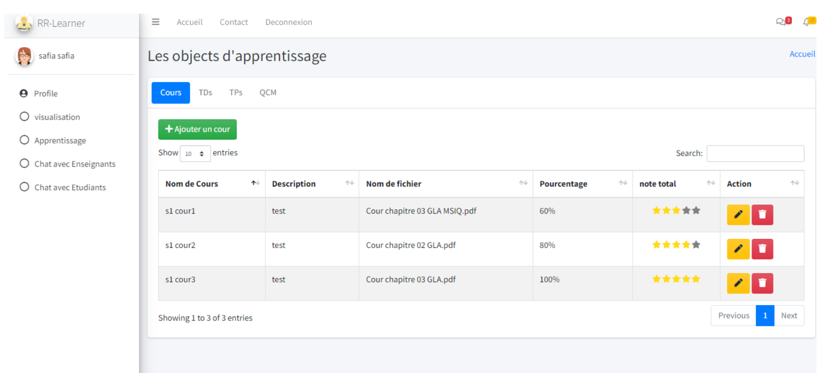

Fig. 3. The teacher space.

5 Conclusion and future work

In CSCL environment, learners can collaborate and communicate with each other in order to share different ideas. The good selection of pedagogical resources encourages learners to improve their levels of knowledge and also decreases the rate of abundance. Therefore, the central objective of this paper is to enhance resource recommendations. This recommendation is based not only on the learners interests but also on social profiles, ratings, level of knowledge, etc. In this work, we present a new approach for recommending pedagogical resources as well as the different formulas used. We have proposed three types of recommendations; each technique uses different data. The recommended system is based on collaborative filtering since we use items previously evaluated by other learners. This approach is new, and solves the cold start problem. After developing the proposed approach, we found that other social factors can enrich the database, which will be improved by the decision of the recommendation. In addition, this approach can be applied to even recommend activities to the learners. To answer the research questions mentioned at the beginning of the paper, we have found that the relevant resource is a resource in which the learner has some problems in his learning process. To do that, we identified a set of relevant criteria and a set of recommendation types, which are the first contribution of this research. The last contribution is the implementation of the proposed system that adopted the proposed ideas. In general, in this work we have solved the cold start problems and the problem with the learners who cant use platform, so we recommend the resource immediately.
As future work, we propose to:

- To add other data to improve the recommendation and also use another type of recommendation using the content of the pedagogical resource, and
- Test the system with real students.

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