Personalized recommender system for e-Learning environment based on student's preferences

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Summary
Nowadays, new technologies and the fast increase of the Internet have made access to information easier for all kind of people, building new challenges for education when utilizing the Internet as a tool. One of the best examples is how to personalize an e-learning system according to the learner's requirements and knowledge level in a learning process. This system should adapt the learning experience according to the goals of the individual learner. In this paper, we present a recommender e-learning approach which utilizes recommendation techniques for educational data mining specifically for identifying e-Learners' learning preferences. The proposed approach is based on three modules, a domain module which contains all the knowledge for a particular area, a learner module which uses to identify learners' learning preferences and activities and a recommendation module which pre-processes data to create a suitable recommendation list and predicting performances. Recommended resources are obtained by using level of knowledge of learners in different steps and the range of recommendation techniques based on content-based filtering and collaborative approaches. Several techniques such as classification, clustering and association rules are used to improve personalization with filtering techniques to provide a recommendation and assist learners to improve their performance.

Key words:
E-learning, recommender system, educational data mining, collaborative filtering, learning objects.

1. Introduction

Technology Enhanced learning is the application of information and communication technologies for teaching and learning [1]. Recommendation Systems (RS) are software tools based on machine learning and information retrieval techniques [2] that provide recommendations for potential useful items to someone's interest. Most of the modern e-Learning systems are still producing the same educational resources in the same way to learners with various profiles [3]. In general, to enable personalization, existing systems use one or more type of knowledge (learning process knowledge, learners' knowledge, learning materials knowledge, etc.) and personalization in e-Learning systems involve adaptive course delivery, adaptive collaboration support, adaptive interaction and content discovery [12]. The category of adaptive course delivery presents the most common and generally used collection of adaptation techniques implemented in e-Learning systems today [3].Therefore, personalization represents an important role in an adaptive e-Learning system. This needs learner profile due to different preferences, learning activities between learners.

Due to a large amount of learning resources on the web, it is difficult to find learning resources associated to learner request [4].E-learning recommender systems intend to recommend a sequence of items to learners, that is, to recommend the most efficient or effective paths within a large among of learning resources to achieve a specific competence [3, 4]. Moreover, it is very challenging for a teacher to decide the best learning strategy for each learner and to apply it in a real classroom and also the current e-Learning systems are not providing a better facility to track the learner's progress. It leads learners to interact less with the e-Learning system or keep out from e-Learning. One way to address this problem is to use recommender system techniques which can help e-learning by automatically recommending the most suitable learning resources to the learners according to their personalized preferences and profile.

This paper presents a recommender system for e-Leaning personalization based on learners learning activities and performance. It means personalization approach for giving learning resources for active learners in the e-Learning system. This system recommends some learning resources based on learner's profile, level of knowledge, and some other learner's activities. Also, the system provides the ability to track learner achievement based on practical tests and exercises and observe the learner's performance in order to supervise and support the learners.

The remaining part of this paper is organized as follows. The existing work on e-learning recommender systems is presented in Section 2. Section 3 presents the proposed model introduces the overall system architecture and describes the proposed method which includes the recommendation framework. The conclusion is given in Section 4.

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2. Related Work

The increasing number of publications on recommender systems for Technology Enhanced Learning (TEL) indication a growing interest in their development and deployment. In order to support learning, recommender systems for TEL need to consider particular requirements, which differ from the requirements for recommender systems in other domains like e-commerce. Consequently, these special requirements drive the establishment of specific objects and methods in the evaluation process for TEL recommender systems.

The article [5] propose an investigation on diverse evaluation methods that have been applied to evaluate TEL recommender systems. A total of 235 articles are selected over conferences, journals, workshops and books where important work have been published between 2000 and 2014. These articles are quantitatively analyzed and classified according to the following criteria: the subject of evaluation, type of evaluation methodology, and effects measured by the evaluation. Results from the survey suggest that there is a growing awareness in the research community of the necessity for more elaborate evaluations. Same time, still substantial potential for more improvements. This survey highlights trends and discusses the strengths and shortcomings of the evaluation of TEL recommender systems so far.

[6] In this research, a personalized web content recommendation system is proposed to encourage the learners to pro-actively interest in an e-learning environment to improve their education. This system used web mining techniques such as web content and usage mining. Web content mining was applied to identify important web contents and specifically web usage mining was used to identify e-Learners navigational patterns, which could help to identify interests and weaknesses of e-Learners and frequently visited web contents and to predict performances of e-Learners. Then the recommendation system could give an efficient, effective and personalized web contents. The authors used content and collaborative filtering techniques to cluster Learner groups and web content groups to give personalized recommendations. Here, the course facilitators could identify the virtual structure of web contents based on relationship and they could successfully create an interactive site topology.

The authors in this paper [7] introduced a personalized recommendation approach joins the user clustering technology and item clustering technology. Users are clustered based on users' ratings on items, and each users cluster has a cluster center. Based on the similarity between target user and cluster centers, the nearest neighbors of target user can be found and smooth the prediction where necessary. Then, the proposed approach uses the object clustering collaborative filtering to generate the recommendations. In the paper [8], the authors proposed a novel approach which uses recommender system techniques for educational data mining, especially in predicting student performance. They also proposed how to link the educational data to user/item in recommender systems. To validate this approach, they compared recommender system techniques with traditional regression methods such as logistic regression by using educational data. Experimental results showed that the proposed approach can improve the prediction results. For the paper [10], The proposed system supports learners by providing them recommendations about which learning objects within the course is more beneficial for them, considering the learning object they are visiting as well as the learning objects visited by other learners with similar profiles. This kind of personalization can help in improving the overall quality of learning by giving recommendations of learning objects that are useful but were ignored or intentionally skipped by learners. Such recommendations can improve learners' performance and satisfaction during the course.

3. The proposed recommender system

The aim of our recommender system is to recommend useful and interesting learning resources to learners based on their preferences in the e-learning context. The system was organized using three basic components: Learner Model, Domain Model, and Recommender Model. Fig 1 illustrates functional models of the proposed system. The following subsections will briefly explain the approach.

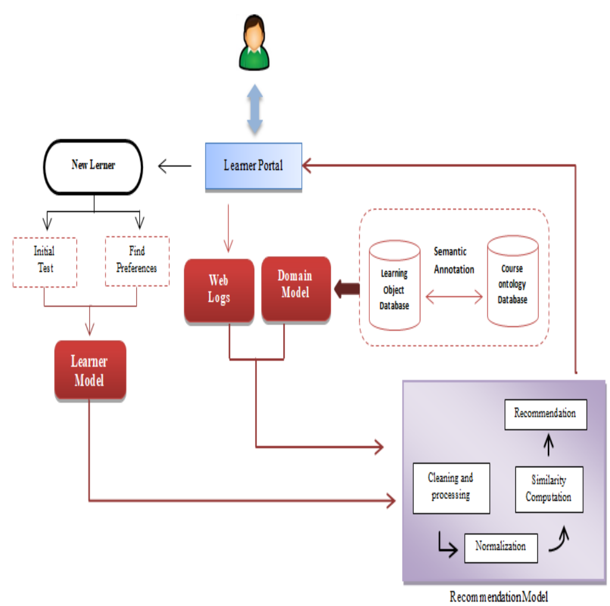

Fig. 1 Functional Models for the proposed system

3.1 Domain Model

A domain model contains all the information for a particular curriculum. Curriculum conceptualizes the knowledge of curricula concepts such as program of study, course contained in the program, key concepts, goals of program, and body of knowledge that should be obtained in that program [12]. Course content model involves three layers, the first each course is divided into many topics, and each topic is presented by a set of Lessons. Finally, each Lesson is associated with different learning objects. A learning object holds one unit of knowledge and presents various characters such as lecture notes, activities, presentations, questions, examples, exercises etc. [9]. Each course combines the different level of the tests to identify the learner level of knowledge. The course organization is shown in fig 2.

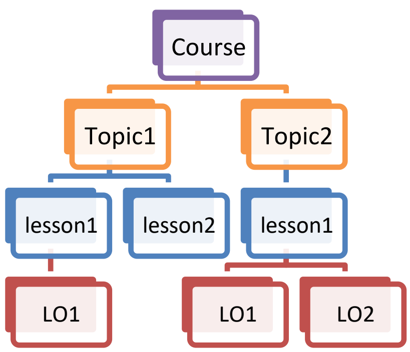

Fig. 2 Course organization

Each part of the given structure should be correctly indexed for a later goal of searching and reusing the learning material. For this purpose, all of the components in the designed structure can also include metadata, which is information about the element itself. This metadata can include the title, author, education level, level of difficulties, interactivity level and type, etc. By using metadata, learning material exploring and identifying becomes easier since it can contain different information which can be used as an identity for a certain learning object [13, 15]. In the context of the defined ontology mode, Table 1 summarizes metadata that can be used for each component represented in Fig 2.
Part of the well-defined structure within the course and concept ontology is to define the connection and the relationship between all components. This relationship is represented in three statuses: prerequisite, obligatory, and optional. Each concept, topic and learning object should have a specified achievement level and its prerequisites. Achievement level defines whether a learning object is obligatory or optional, while prerequisites define learning objects, topics or concepts that must be learned in order to gain the necessary prerequisite knowledge before studying that specific learning object.

Table 1: Metadata for course components

Component	Metadata
Course	name, author, version, grading policy, prerequisites, attainment goal
Concept	name, attainment goal, attainment level, prerequisite
Topic	name, attainment goal, attainment level, prerequisite
Learning Object (LO)	name, author, creation date, version, last modified, attainment level, keyword, prerequisite, level of interactivity, instruction method, difficulty level

Each learning object contains a group of tests; every test is represented by a type (assessment, final test, initial test…) and contains many questions. The question is defined by a type, level of difficulty (easy, medium and hard) and knowledge level which define if it is a basic level or advanced level.

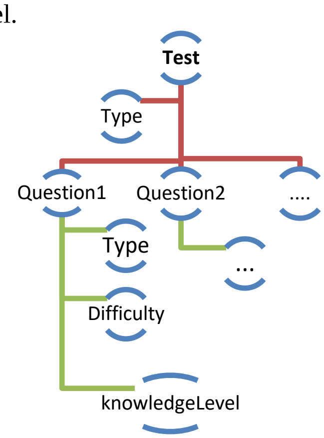

Fig. 3 Test model

Example of Test for learning object X (LOx):

Questions	Type	Difficulty	Knowledge Level
Q1	True/False	Easy	Basic
Q2	MultipleChoice	Medium	Basic
Q3	check boxes	Hard	Basic
Q4	One answer	Easy	Advanced
Q5	True/False	Medium	Advanced
Q6	check boxes	Hard	Advanced

3.2 Learner model

The profile is a general word that organizes the learner in several categories. This is a unique characteristic that plays an important role in the success of learning. Learner profile of a learner explains how the learner learns best. It is almost the normal representational of Learner's data that can be collected in two ways: from the student or by analyzing his behavior through a learning management system [14]. In our research, the learner who enrolls in a particular course is going to take an initial level test to determine the initial level of knowledge and build the learner profile. The questions in the initial level test are generated according to the level and the discipline of students and classified by orders of difficulty. The obtained results will be treated in an algorithm of classification wish allow us to know level of a student and affect him afterward to a class according to his level.

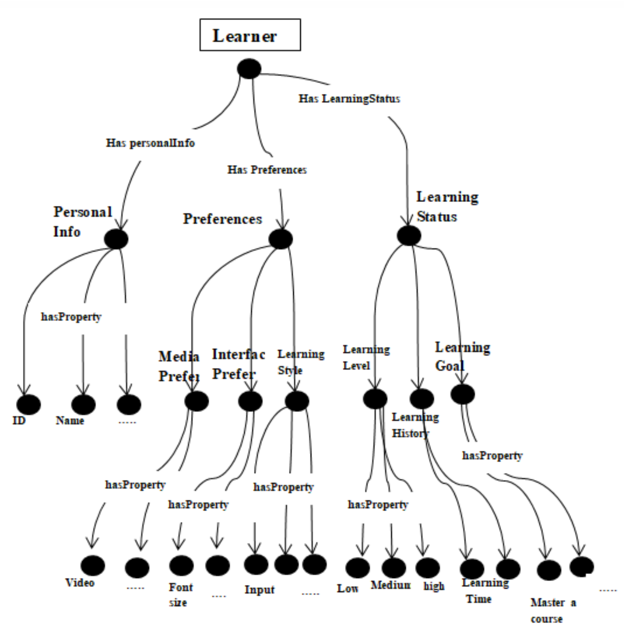

Fig. 4 Learner ontology Model

The learner ontology embodies the knowledge of a learner, and it consists of:

- Personal general information, such as name, age, gender and so on, it usually keeps static throughout;
- Personal preference information.
- Personal learning status information, it is presented by learning level, learning goal, and current learning knowledge point and so on. This kind of information will be updated constantly during the learning. The learner ontology can be represented as fig 4.

3.3 Recommendation Model

The proposed recommender model, as shown in figure 1, based on two approaches. The first one concern the first student's interaction with the system, the system requests the learner to fill the registration form and to take the initial level test in order to build learner profile based on learning activities [14, 16]. After completing the initial test, the results is used to classify the students' in homogenous subclasses according to their knowledge level and then saved in the learner model. Then, the student can start learning. The recommender module helps to produce suitable recommendations to learners based on learning preferences and activities. The learner model can be revisited dynamically using the student's interactions with the system by extracting user interests from log files in order to revisited students' current preferences, and produce a recommendations list most suitable. The data mining techniques utilize the collected information about learner's interactions, such as navigation history and bookmarks, to build learner profile and to produce recommendations.

- Students' classification Algorithm

Our algorithm for student's classification is based on educational data mining to predict the homogeneous sub-classes of students according to their previous results in several assessments that are designed in a relevant and simple educational approach. Figure 5 shows the detailed schema to illustrate our implemented solution to perform the students classifier based on decision tree.

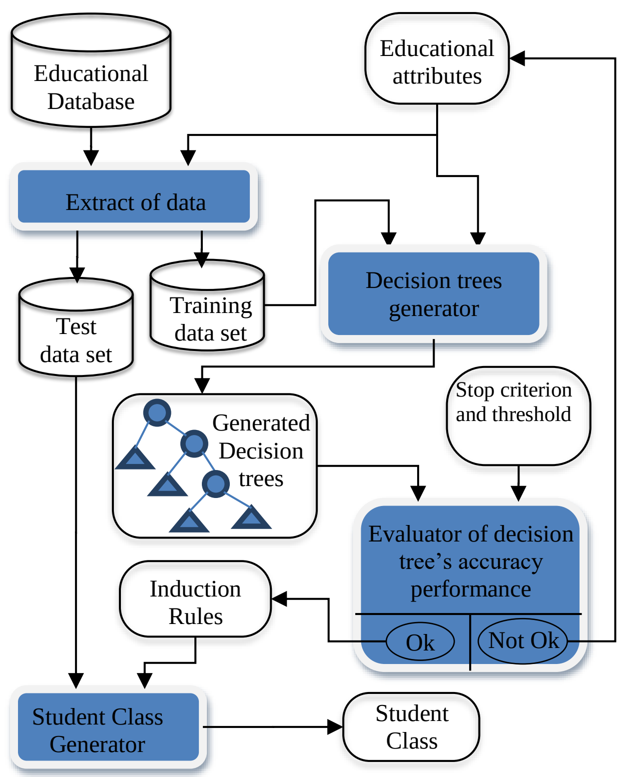

Fig. 5 schema of student classification algorithm based on decision trees

Attribute values are defined based on the range of total scores obtained by a student in assessments in relation to each factor as indicated in the following table:

Table 2: attribute values based on the range of total scores

Range in [0..20]	Attribute value
>=18	Excellent
>=16	Very Good
>=13	Good
>=10	Average
>=5	Poor
<5	Very Poor

- Recommendation Model

The recommender module helps to decide whether a given learning scenario is suitable for specific learner preferences or not. This module utilizes the collaborative filtering to classify a learning strategy as "suitable" or "not suitable" for the learner. The learning scenario is achieved by the four steps. The First step is the "Cleaning and preprocessing", the data preparation is an important issue for all methods utilized in data mining, as real-world data tends to be missing or containing errors, or outlier values which deviate from the expected data. The second step is the "Normalization" in which the data is transformed or combined into forms appropriate for mining.

Learning object recommendation sequence is based on learners rating. LO's sequence take into consideration the evaluation on the content, the number of stars voted for this content, learner reputation and the number of likes and dislikes in order to evaluate the content.

$$Rating\ LO = \sum(L) + \sum(O) \quad (1)$$

Where $\sum(L)$ represents, the total number of evaluations of a learner and $\sum(O)$ represents the total number of evaluations of the contents of this learner. After weighting learning resources, the reference model for each learner is defined as a Learner-Learning Object Rating matrix with N rows in which N denotes the number of learners L={l1, l2,….. ln} and M columns denote the number of learning objects O={O1, O2,…., Om}.This matrix uses a 0-to-5 rating scale where: 5 means that the learner is strongly satisfied with the selected learning object, 1 means 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. The third step is the "Similarity computation": Once learner's model is identified, we apply the method based collaborative filtering in order to create virtual communities of interests. This step is carried out by improving the most known classifier algorithm K-Nearest-Neighborhood (K-NN) in several domains. The critical step in collaborative filtering algorithms is the similarity computation between users or items. There are various approaches to calculate the similarity, the most commonly employed measurement of similarities is Cosine Similarity. The similarity between two learners' x and y with Cosine similarity is calculated as follows:

$$w(x,y): \frac{\sum_j^m R_{x,j} \times R_{y,j}}{\sqrt{\sum_j^m R_{x,j}}^{\,2} \sqrt{\sum_j^m R_{y,j}}^{\,2}} \quad (2)$$

In the above equation: Rx,j and Ry,j are learner x's ratings and learner y's ratings for the learning object.

If the learner x and y have a similar rating for a learning object, w(x, y) > 0. |w(x, y)| indicates how much learner x tends to match with learner y on the learning object that both learners have previously rated. If they have different ratings for learning object w(x, y) < 0. |w(x, y)| Indicates how much they tend to disagree on the learning object that both again have already rated. Hence, if they don't agree each other, w(x, y) can be between -1 and 1.

After calculating the similarity between learners, an NxN 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 x, the K most similar learners which have highest similarities with the current learner will be selected and use these as the input to compute the prediction for x on j. The last step is the "Recommendation" In this step we compute prediction for each learning object unselected by the target learner. Finally, the learning objects with high ratings are used to compute learning resources in descending order. To make a prediction for the active learner x on certain learning object j, we can take a weighted average of all the ratings on those learning objects according to the following formula:

$$P_{x,j} = \bar{R}_x + \frac{\sum_{y=1}^n w(x,y)(R_{y,j} - \bar{R}_y)}{\sum_{y=1}^n |w(x,y)|} \quad (3)$$

In equation (3), Ry,j denote the rating for the learning object j by user y.

4. Conclusion

E-Learning environment represents a significant role in today's education. With the expansion of available learning resources, giving personalized resource recommendation is an important functionality for today's e-Learning systems. Hence, the recommendation systems are one of the best tools to deal with the problem of overload information which will assist users to find optimal interested items.

We proposed recommendations for e-Learning personalization system, which takes the learner's learning activities into account and applies content-based filtering, collaborative filtering, and educational data mining methods for recommendations. Here, we try to defeat the cold-start problem by introducing the initial level test to define the initial profile of new learner. In this research, the system evaluates learner's level of knowledge,

learner's learning activities and leaner's performances. Then, the system presents the recommendation list according to the results of learner's evaluation and profile.
In the same context and in order to develop the learning process our future work will be oriented to a new approach about adapting the recommendation process with student learning styles. Additionally, we are going to experiment our approach in real E-learning context on a large amount of learners to test the effectiveness of our proposed approach.

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