# A Personalized E-Learning Based on Recommender System

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***Abstract*—Personalized E-learning based on recommender system is recognized as one of the most interesting research field in the education and teaching in this last decade, since, the learning style is specific with each student. In fact from the knowledge his/her learning style; it is easier to recommend a learning scenario builds around a collection of the most adequate learning objects to give a better return on the educational level. This work focuses on the design of a personalized E-learning system based on a psychological model of Felder and Solomon and the collaborative filtering techniques. Using the learner profile, the device proposes a personalize learning scenario by selecting the most appropriate learning objects.**

***Index Terms*—E-learning, recommender system, collaborative filtering, learning styles, learning objects**

## I. Introduction

Today, E-learning presents a new way to teach and to learn than the conventional learning in classroom, called also face to face learning [1]-[3]. This new approach can use many modern educational techniques in a rich and varied context [1], [2] and allows for students to learn any-time and any-where.

Most authors point that consideration of the learner profile (personality, preferences, knowledge, etc), is an essential and an important element in achieving an efficient and successful teaching [4]. Therefore, it is extremely delicate and difficult to achieve a personalized learning scenario for each learner in the traditional closed classroom. This problem can be solved in the E-learning context that offers an expected alternative from the classical where the personalization is possible. Moreover, this new way of teaching proposes an ideal environment to individualize the learning term review and succeed the interactions between different actors (teachers, tutors and learners).

In this perspective, many works have been done in this last decade about personalization and adaptation of teaching and learning using E-learning system [1], [5], [6]. In fact, several adaptive system were introduced, most are based on learner preferences [1], [2], [5], [7].

The main of our work is to propose a Personalized E-learning Recommender System (PERS) design based on collaborative filtering methods. The idea is to build a novel approach to generate an adaptive curriculum using suitable learning scenarios to offer learner's personalized needs. This learning is centered on the dynamic selecting, sequencing and linking of learning resources into a coherent, focused organization for instruction.

Therefore, in this study we have adopted the collaborative filtering approach as one the well-known for recommender systems in distance learning context. The idea of this method is to build predictions about learner's preferences or tastes based on the preferences of a group of learners that are considered similar to this learner.

Recommender systems and collaborative filtering are a subclass of information filtering system that focus on tow tasks. The first is to predict the 'rating' or 'preference' that user would give to an item. The second is to recommend the list of items for user's needs.

Once the learning style is identified using the questionnaire developed by Felder and Soloman [8], the system proposes the first learning strategy on the cold start session. This happens in cases where there is a lack of data about learners and theirs preferences which makes it impossible to provide relevant recommendations.

This paper is structured as follows: Section 2 gives the related work cited in literature. In Section 3 we present the design of our proposed system. In Section 4, results and evaluation of our research are presented, and the conclusion is given in the last section.

## II. Related Work

The Personalized E-learning System allows to automatically adapting the content or the organization of courses to fit the learner's needs. The distinction between the terms "personalization," "adaptation" and "individualization" was not obvious. According to Graf and List [9], the term "adaptation" for E-learning environment, can be presented into four categories: flexibility: consists of all facility to customize the platform to the needs of the institution, personalization: possibility for the learner to customize interface, extensibility: possibility in the case of open source E-learning platform to modify or extend the code by plug-in (s), and finally, adaptivity: shows all kinds of automatic adaptation to the needs of each user. This adaptation can be done progressively depending on the learner in response to his behavior [10].

On the other hand, most of the researches on adaptive learning systems are focused on the learner profile based

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on their level of knowledge and/or learning styles [1], [2], [11]-[13]. This style is defined as the set of mental processes used by the individual for perceive and process to the information.

The relation between the Learning Style (LS) and Learning Strategy (LS) has attracted many researches in the last decade [1], [2]. In this regard, several studies have been conducted to see if this adaptation can improves the performance of the learning. The results seem to be mixed [14], [15], but most authors agree that taking into account the learning style could help learners to achieve an effective and efficient learning [5], [16].

Therefore, different models more or less extensive have been done to describe the learning style. These works showed that learner, tend to favor a particular teaching strategy enabling them to better assimilate the course. The Felder's Model [17], use three categories: auditory, visual and kinesthetic [18] to define the learning style of a person.

Some authors [2], [19] suggest an association between personality type, learning style and learning objects in E-learning context. Many works on learning style gave multiple methods and instruments to categorize students according to their difference's, Kolb's model [20], Felder's model, [21], and Myers-Briggs's model [22]. Most of these researches are been done in the context of the classroom training. In this work, we adopted the FSLSM's model [23], for two major reasons. Firstly, for its simplicity it is easy to implement. Secondly, it is the most widely used in the design of adaptive systems.

The Index of Learning Styles Questionnaire (ILSQ) is an online form composed of 44 questions used to identify preferences of students [8]. The ILSQ reports learner's preferences on four scales: information processing; perception of information; receiving information; and understand information. The combinations of these preferences result in total 16 personality types and are typically denoted by four letters to represent a person's tendencies on the four scales.

Many studies used the model of Felder to determine the learner's learning styles relative to distance learning, and using the learning objects [5], [24], [25]. Properties of each learner's preference, pertaining to education and learning, were collected from the literature [24], [25].

TABLE I. PREFERRED LEARNING CHARACTERISTICS MATCHING WITH ELECTRONIC MEDIAS

| Learning's group | Characteristics | Electronic Media |
|---|---|---|
| Active | Simulation, Solve Problem, Discussion group, Brainstorming, Experiment, Questions and Answers | Forum, Wiki, learning, weblog, Chat, e-mail |
| Reflective | Presentation, Case study | E-book, Written text |
| Sensing | Presentation, Read, Solve Problem, Simulation games, Questions and Answers | Forum, weblog, Wiki, Animation, Graphic, Picture |
| Intuitive | Discussion group, Simulation, Roles games, Case study, Read | Internet research engine , QCM, |
| Visual | Simulation, Presentation, Read | Forum, Wiki, Animation, Graphic, Picture, Simulation, Videos |
| Verbal | Discussion group, Brainstorming, Questions and Answers , Solve Problem | Audio Recording, Podcast |
| Sequential | Presentation, Questions and Answers | e-book, Audio |
| Global | Roles games, Brainstorming, Case study | Weblog, Wiki, Chat, e-mail |

## III. SYSTEM ARCHITECTURE

Generally, a personalized E-learning recommender system consists of three main components, Domain Model, Learner Model, and Recommender Model. Fig. 1 shows the overall architecture of our system:

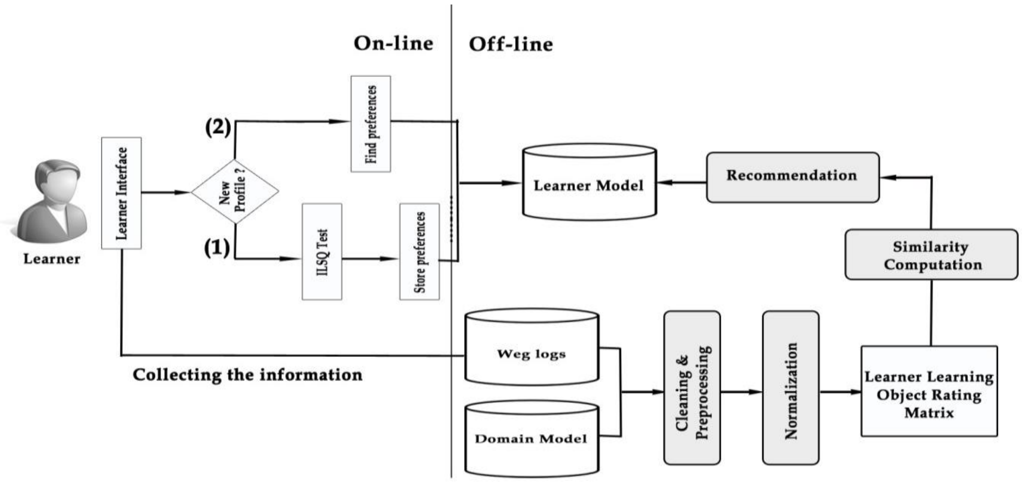


Figure 1. Overall system architecture of the proposed E-learning recommender system.

### A. Domain Model

A domain model contains all the knowledge for a particular discipline. This domain is splited in four layers, the first represents the category of courses and each category is divided on several courses, and each course is presented by a set of concepts. Finally each concept is associated with different learning objects.

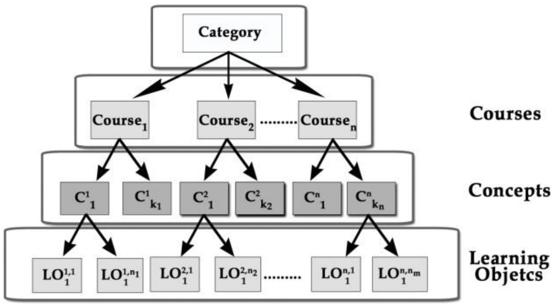


Figure 2. Hierarchical organization of the knowledge concepts.

### B. Learner Model

This model represents the various characteristics of the learner that can be used to generate an individualized learning experience. Indeed, the goal is to adapt the educational system with learner's preferences. In our approach, this model takes into account only the learning style of the learner defined by the FSLSM [y]. Our model can be extended to take into account other characteristics, cognitive styles, motivational styles, etc.

### C. Recommender Model

Fig. 1 shows the process of the proposed recommender model. The proposed recommender model has two recommender approaches dump and intelligent recommender modules, respectively: 1) At first we explain recommendations produces for new student, the system invites the learner to fill the registration form and Index Learning Style Questionnaire (ILSQ) in order to create an initial student profile based on learning style. Once learner is registered the framework builds the learner's preferences and stored it in the Leaner Model, and then the learning process can be started. Using the learning style recommender system give initial decision of recommendations list for a specific learner's preference, by this first approach, we can overcome the Cold-Start Problem [26]. 2) 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 his/her current preferences, and produce a recommendations list most suitable. The data mining techniques use the collected information about learner's interactions, such as navigation history and bookmarks, to build learner profile and to produce intelligent recommendations. In the following of this section, the intelligent recommender system is presented step by step.

The intelligent recommender module helps to determine whether a given learning scenario is appropriate for a specific learning style or not. This module uses the collaborative filtering to classify a learning strategy as "appropriate" or "not appropriate" for the learner. The learning scenario is fulfilled by the following steps: Cleaning and preprocessing, Normalization, Similarity computation, and Recommendation, which is shown in Fig. 1.

Step 1. **Cleaning and preprocessing:** Data preparation is an important issue for all methods used in data mining, as real-world data tends to be missing (lacking attribute values or certain attributes of interest), noisy(containing errors, or outlier values which deviate from the expected data).

Step 2. **Normalization:** The data are transformed or consolidated into forms appropriate for mining. For example, attribute data may be normalized so as to fall between a small ranges, such as 0 to 10 using a score function based on CHAN works, implicit rate for web pages [27]. We adopted this formula in E-learning context, in such way we can rate all learning objects we define the score function in (1):

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

where $E$ is the explicit score given by the learner for each learning object $\vartheta$ and $I$ is the implicit score that we defined by:

$$I(\vartheta) = A(\vartheta) + 2B(\vartheta) + 2C(\vartheta) \tag{2}$$

where $A$ equals 1, when $\vartheta$ is stored in the bookmarks, otherwise. The function $B$ is the duration spending to deal with learning object. $C$ Is the selection's frequency of $\vartheta$. The function $A$,$B$ and $C$ must be normalized so the maximum of each one is 1.

After weighting learning resources, we obtained a preference model for each learner defined as a Learner-Learning Object Rating(LLOR) matrix with $N$ rows in which $N$ denotes the number of learners L={$l_1$, $l_2$,….. $l_n$},and $M$ columns denotes the number of learning objects J={$j_1$, $j_2$,…., $j_m$}.

TABLE II. 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 |

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 3. **Similarity computation**: Once learner's model is recognized, we apply the method based collaborative filtering in order to build virtual communities of interests. This step is carried out by improving the most known classifier algorithm K-Nearest-Neighborhood (K-NN) in several domains [28].

The critical step in collaborative filtering algorithms is the similarity computation between users or items. There are various approaches to compute the similarity, the most commonly used measurement of similarities is Cosine Similarity. The similarity between two learners' $u$ and $v$ with Cosine similarity is calculated as follows:

$$w(u,v) = \frac{\sum_j^m r_{u,j} \times r_{v,j}}{\sqrt{\sum_j^m r_{u,j}^{\;2}}\sqrt{\sum_j^m r_{v,j}^{\;2}}} \tag{3}$$

In the above equation: $r_{u,j}$ and $r_{v,j}$ are learner u's ratings and learner v's ratings for the learning object.

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

After calculate the similarity between learners, 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 which have highest similarities with the current learner will be selected and use these as the input to compute prediction for $u$ on $j$.

Step 4. **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 $u$ on certain learning object $j$, we can take a weighted average of all the ratings on those learning objects according to the following formula:

$$P_{u,j} = \bar{r}_u + \frac{\sum_{v=1}^{n} w(u,v)(r_{v,j} - \bar{r}_v)}{\sum_{v=1}^{n} |w(u,v)|} \quad (4)$$

In equation (4), $r_{v,j}$ denote the rating for the learning object $j$ by user v.

## IV. Experimentation and Results

In order to evaluate the prediction accuracy of our proposed recommendation algorithm, we used the variation of publicly available dataset AdaptErrEx for real E-learning environment in our experiments. This was collected by PSLC DataShop[1.] The AdaptErrEx dataset consist of 537,302 transactions of real learners in E-learning context [29].

For our experiment we are limited for 61542 transactions, in fact, we consider a matrix which consists of 400 learners and 790 learning objects. This matrix has established using the first step of our recommendation process by cleaning and preprocessing web log of the selected dataset. In fact, the learner ratings are represented as numeric values from 0 to 10.

In the first experiment, we have executed the simple K-NN algorithm in order to find the best value for K-neighbors. This experiment was carried out for each of the following values: 20, 80, 140 and 200. The results of this experiment are presented in Fig. 3, which shows a comparison of accuracy by increasing the users' number for each selected value of K.

In Fig. 3, it can be seen that by increasing the number of learners with varying the K-value we can obtain an optimal prediction. The value K=20 can be considered the best value for K-NN algorithm since the corresponding MAE value is the smallest one.

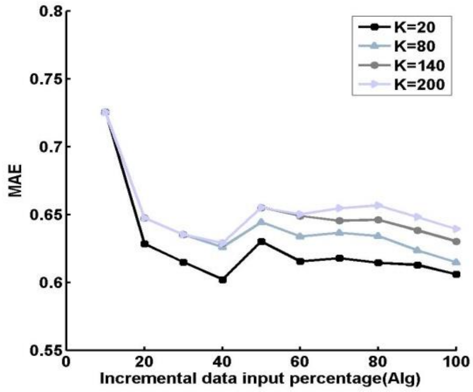


Figure 3. Comparison of MAE and BP by increasing number of learners (N)

In the second experiment, we aim to compare our proposal algorithms with a simple K-Means and baseline predictor to estimate learning object ratings of each particular learner.

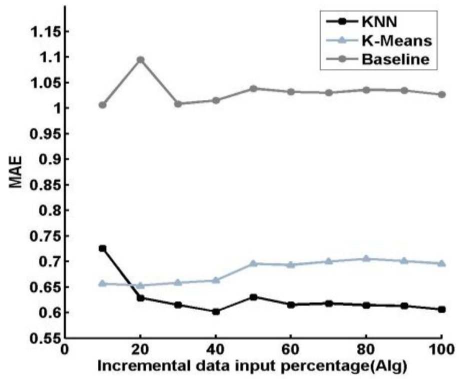


Figure 4. The comparison of accuracy among all tested algorithms

Running these methods, we get the results depicted in Fig. 4, which shows that the classifier algorithm KNN outperforms than the others technique in all case except in data size <20 %.

## V. Conclusion

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. In this paper, we propose a personalized E-learning system, which takes the learner's personality into account and uses collaborative filtering method for the recommender system. In this model some modules for personality recognition and selecting an appropriate learning scenario for learner's personality are presented.

In order to evaluate the prediction accuracy of our proposed recommender model, we used external data sets for real E-learning environment. Results show that using the proposed approach could improve the performance of predictions. Additionally, we are going to experiment our approach in real E-learning context on a large amount of learners widespread use during a long period to test the effectiveness of our proposed approach.

[1] https://pslcdatashop.web.cmu.edu/

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