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E-LEARNING PERSONALIZATION BASED ON COLLABORATIVE FILTERING AND LEARNER'S PREFERENCE

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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 for each student. In fact from the knowledge of his or her learning style; it is easier to recommend a teaching strategy 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 environment based on collaborative filtering and learning styles. Using the learner profile, the device proposed a personalized teaching strategy by selecting and sequencing learning objects fitting with the learners' learning styles. Moreover, an experiment was conducted to evaluate the performance of our approach. The result reveals the system effectiveness for which it appears that the proposed approach may be promising.

Keywords: E-learning; Learning style; Teaching strategy; Recommender system; Collaborative filtering

1. Introduction

Today, e-learning presents a new way to teach and to learn than the conventional learning, in the classroom, called also face to face learning. This new approach can use many modern educational techniques in a rich and varied context and allows for students to learn at any-time and any-where. In order to individualize needs, personalization in education not only facilitates students to learn better by using different strategies to create various learning experiences, but also teachers' needs in preparing and designing varied teaching or instructional packages.

Nomenclatures

b_{ui}	Baseline predictor
d	Euclidian distance
MAE	Mean absolute error
$P_{u,j}$	Prediction for user u for learning object j
$r_{u,i}$	Rating for learning object i by user u
U	User preference
w	Pearson correlation coefficient

Greek Symbols

θ	Learning object rated by user.
μ	The overall average score

Abbreviations

CF	Collaborative Filtering
FSLS	Felder-Silverman Learning Styles
ILSQ	Index Learning Styles Questionnaire
K-NN	K-Nearest Neighbours
LO	Learning Object
LS	Learning Style
RS	Recommender System

Most authors point that considering the learner profile (personality, preferences, knowledge, etc.), is an essential and an important element in achieving an efficient and successful teaching in distance education [1-3]. Therefore, it is extremely delicate and difficult for a teacher to achieve a personalized learning strategy for each learner. Even he was able to design a teaching strategy per each student, he could not apply then in a real learning environment in the same classroom and at the same time. In recent time, this problem can be solved in the e-learning context that offers an expected alternative from the classical learning and where the personalization is possible. Moreover, this new way of teaching proposed 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 in teaching and learning in the e-learning context and, several adaptive systems were introduced, most are based on learner preferences [1, 4-6].

The goal of our work is to present a personalized e-learning system using collaborative filtering techniques and learning styles. The idea is to build an innovative approach to generate relevant recommendations and also to deal with the cold start problem which is a relevant challenge in recommender system. This recommendation is centered on the dynamic selecting, sequencing of learning objects into a coherent, focused organization for instruction in online distance education.

Once the learning style is identified using the Felder-Silverman Learning Styles model [7], the system proposes the initial teaching 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. 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.

Moreover, in this work we define a new score function taking in mind not only the explicit rating but also the implicit rating generated by the learner's interactions with the system. Thus many experiments are conducted to evaluate the performance of our approach using K-Means Clustering and K-Nearest Neighbors classifier adapted for e-learning context.

This paper is structured as follows: section 2 gives the related works cited in literature. In section 3, we present the design of our adaptive system. In section 4, presents the methodology using to build the recommender system. Results and evaluation of our research are presented in section 5, and the conclusion is given in the last section.

2. Related Work

This research originated from the recognition of the need of complete solution to the central question: how to automate the e-leaning personalization according to an appropriate strategy?

Majority of researches on adaptive learning systems are focused on the learner profile based on learning styles. Indeed, the learning style is defined as the set of mental processes used by the individual for perceive and process the information in learning experience [8-10].

Therefore, different models more or less extensive have been done to describe learning styles. These works showed that learner, tend to favor a particular teaching strategy enabling them to better assimilate the course. The Felder's Model [11], use three categories: auditory, visual and kinesthetic to define the learning style of a person [12].

A personalized e-learning environment allows to automatically adapting the content or the organization of a courseware to fit the learner's needs. Several personalized e-learning system have been reported in the literature using learners' characteristics like: level of knowledge, learning styles, learner motivation and media preferences.

For example, Abrahamian et al. [13] designed an interface for computer learners appropriate to their personality types using MBTI model. Using learner's personality Maldonado et al. [14], and Fatahi et al. [15], proposed an Expert system for virtual Classmate Agent. PERSO (PERSOnalizing e-learning system) uses Case Based Reasoning (CBR) approach to determine which course to propose to the students based on their levels of knowledge, and their media interests [16]. INSPIRE adopts the learning style model of Honey and Mumford as the basis for determining the presentation of the learning resources on each of the performance levels [17]. Klasnja-Milicevic et al. [18] 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. Dwivedi and Bharadwaj [19] proposed a weighted hybrid scheme to recommend right learning resources to a learner by incorporating both the learners' learning styles and the knowledge levels.

Milosevic et al. [20], used Kolb's learning cycle for tailoring lessons. Their work uses the personalization based on the learner motivation, which is used to determine the complexity and the semantic quantity of learning objects. El Bachari et al. [21], have developed a personalized e-learning system LearnFit with an adaptive learning framework based on the learner's personality using Myers-Briggs Indicator tool.

Many works on learning styles gave multiple methods and instruments to categorize students according to their difference's, Kolb's model [22], Felder-Silverman Learning Styles (FSLS) Model [7], and Myers-Briggs's model [23]. Most of these researches are been done in the context of the classroom training. However, in the specific context of e-learning, works carried still appear in the preliminary and exploratory phase.

In this paper, we adopted the Felder-Silverman Learning Styles Model for two major reasons [7]. Firstly, it is the most widely used in the design of adaptation learning systems and secondly it is easy to implement.

This model stands a learner preference in four dimensions: Information processing, information perception, information reception and information understanding. Each dimension has two scales as shown in Table 1, which means that each leaner has four and only four categories.

Table 1. Characteristics of learner based on FSLSM.

Scales	Learning style	Characteristics
Information processing	Active(A)	-Works in groups - Prefers to try new material instantly - Handles practical stuff
	Reflective(R)	-Works alone - Prefers for taking the time to think about a problem
Information perception	Sensing(S)	-Is patient with details -Prefers senses, facts and experimentation
	Intuitive(I)	-Interested in overviews and a broad knowledge -Interested in innovations and accept complications -Preferring principles and theories
Information reception	Visual(L)	-Prefers to perceive materials as images, diagrams and films
	Verbal(B)	-Prefers to perceive materials as text
Information understanding	Global(G)	-Prefers to get the big picture first -Assimilates and understands information in a linear and incremental step,
	Sequential(Q)	-Preferring to process information sequentially

Felder-Silverman model proposes the Index of Learning styles Questionnaire, with 44 questions for assessing preferences [24]. The questions are provide four values, between +11 and -11, representing the learner's learning style preferences of each dimension.

In our approach, we have used ILSQ to get the learning of students to deal with the cold start problem since it has been well proved to be reliable and are considered credible. The combination of these preferences result a total of sixteen personality types and are typically be noted by four letters to represent a person's tendencies on the four scales as shown in Table 2.

Table 2. Learner's personality types.

RSLQ	RSBQ	ASLG	ASBG
RIBQ	RILQ	AIBG	AILG
RSBG	RIBG	ASBQ	AIBQ
RSLG	RILG	ASLQ	AILQ

For example, *RSLQ* stands the personality type of learner who is Reflective, Sensor, Visual, and Sequential. That's mean, this learner doesn't like to work in group, he prefers facts and experimentation to learn. This learner likes also visual learning materials like diagrams, images, videos and he prefers more the sequential scenarios.

Many studies use FSLS to select the most suitable and appropriate learning objects for each learning style [18, 25, 26]. Properties learner's preference, pertaining to education and learning, were collected from the literature [25, 26] as shown in Table 3.

Table 3. Recommendation strategy and learning style identification.

Learners' group	Learning object	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

3. System Architect and Design

The main purpose of our system is to recommend useful and interesting learning resources to learners based on their preferences in e-learning context. The system was organized using three basic components: Learner Model, Domain Model and Pedagogical Model. These three components interact to adapt with learner to achieve a relevant instructional process.

Figure 1 illustrates the system architecture. The following subsections will briefly explain the framework.

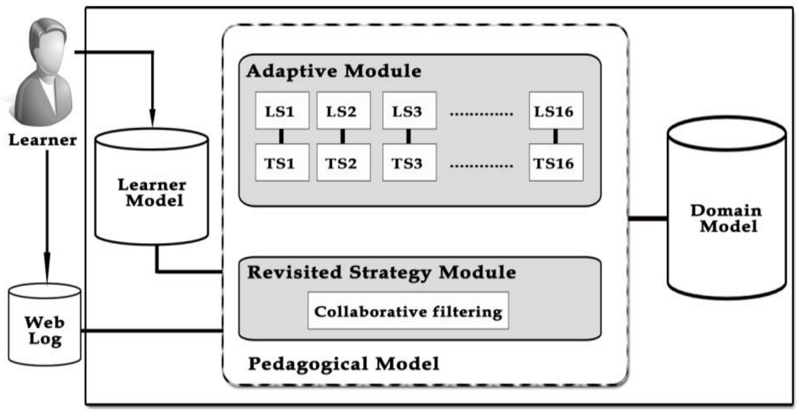

Fig. 1. System architecture.

2.1. Learner model

This model represents the various characteristics of the learners that can be used to generate an individualized learning experience. Indeed, the goal is to adapt the educational system with properties learner. In our approach, this model takes into account only the learning style of the learner determined by the ILSQ. Our model can be extended to take into account other characteristics, cognitive styles, motivational styles, etc. Figure 2 shows the structure of the learner's profile according to FSLS model.

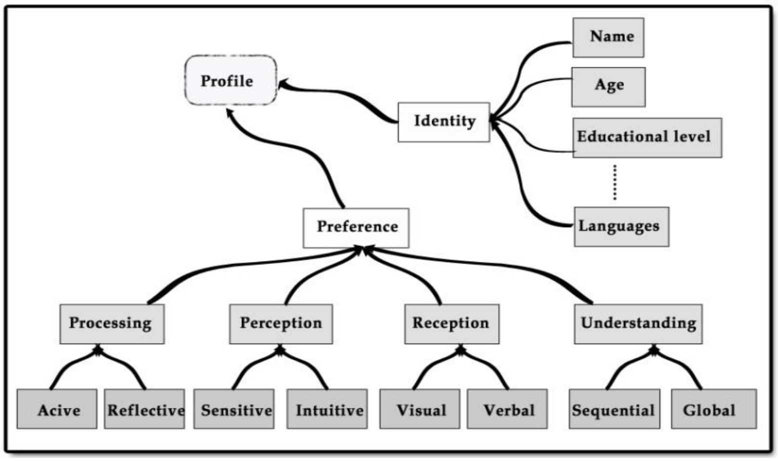

Fig. 2. Learner's profile.

The preference part describes the learning style according the ILSQ and which can be defined as followed:

$$U = \{u \in [0,1]^8 \ /u = (u_A, u_R, u_S, u_I, u_{VI}, u_{VE}, u_G, u_Q)\} \qquad (1)$$

Each component u_i of the vector u element of U represents the priori probability of preference at i^{th} ILSQ dimension and *A* represents Active, *R*-Reflexive, *S*-Sensitive, *I*-Intuitive, *Vi*-Visual, *Ve*-Verbal, *S*-Sequential and *G* represents Global. Using the ILSQ questionnaire, we may explicitly evaluate the *u* value for each learner on numerical values in an interval [0, 1] such that 0 indicates a minimal satisfaction and 1 indicates a maximal satisfaction.

2.2. Domain model

A domain model contains all the knowledge for a particular discipline. A chapter can be represented as a tree of learning units or concepts. A learning unit holds one unit of knowledge and presents different aspects of it with different types of learning object which constitutes multiple external representations such presentations, questions activities, examples, exercises, glossary [17, 21]. Figure 3 shows the structure of our suggested domain model.

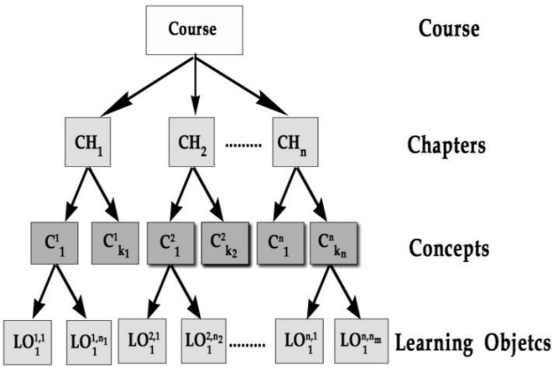

Fig. 3. Hierarchical organization of the knowledge concepts.

2.3. The pedagogical model

Represents the way used by a teacher to present concept of some domain of knowledge. In that way a teacher can use multiple TSs for each concept. Teaching Strategies are the way a teacher select and sequence LOs to facilitate a deeper understanding of information.

Our pedagogical model has two main intelligent modules: adaptation module and strategy revisited module. In the following sub-sections, these parts will be thoroughly described.

2.3.1. Adaptation module

This module is the most important part in the learning process and constitutes the core of our proposed system. This is the decision body allowing associating the most appropriate teaching strategies matching with learner's preferences. The process of this adaptation is depicted in Fig. 4.

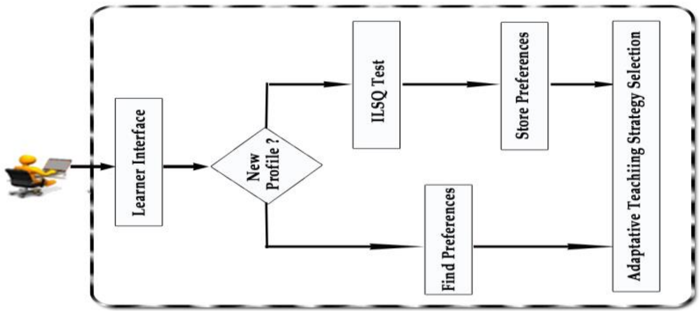

Fig. 4. Process of selecting the adaptive teaching strategies.

At first, the system tries to find the learner profile. If this profile has been recognized, the learning process can start using the recommender system. Otherwise, the system invites the student to fill the ILSQ. Once he completes this task, the framework builds the learner's profile and stored it in the database, and then the learning process can be started by selecting the most appropriate learning strategies fitting with the learner's preferences to deal with the cold start problem the difficulty in providing recommendations. It's happened when there is no data available to base it on [27].

2.3.2. Strategy revisited module

The revisited strategy module helps to determine whether a given teaching strategy is appropriate for a specific learning style or not. This module uses the collaborative filtering to classify a teaching strategy as "appropriate" or "not appropriate" for the learner [21]. For an instructional strategy used by a teacher for a given concept, our proposed approach is composed of three phases: an On-line phase which uses to collect the user interests from the log files, and Off-line phase, consist to preprocess and to clean the collected information in order to build a learner profile, finally, Recommender phase which uses to predict a recommendation list from the filtered data of learning content and generate the recommendation list most suitable. The recommendation list is sent to learner within a new session. The recommendation process occurs in two general steps as shown in Fig. 5.

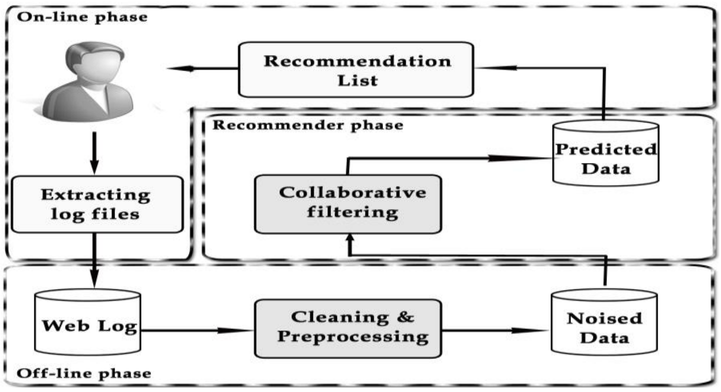

Fig. 5. Recommendation process.

Cleaning and Preprocessing

Data preprocessing or preparation is an important element for all techniques used in data mining. The data preprocessing is a recommender task for reducing the size of the dataset in order to improve the quality of the data for mining. The data are transformed or consolidated into appropriate forms 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 [28]. We adopted this formula in e-learning context, in such way we can rate all learning objects by defining the score function *S* in Eq. (2):

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

Where $\mathrm{E}(\theta)$ is the explicit score given by the learner for each learning object θ and *I* is the implicit score that we defined by:

$$I(\theta) = \mathrm{A}(\theta) + 2\mathrm{B}(\theta) + 2\mathrm{C}(\theta) \tag{3}$$

Where *A* equals 1, when θ is stored in the bookmarks, 0 otherwise. The function $\mathrm{B}(\theta) = 1 - \mathrm{e}^{-\mathrm{t}}$ is the duration *t* spending with the learning object . *C* is the selection's frequency of θ . The function A, B and C must be normalized so the maximum of each one is 1.

Collaborative filtering

The main motivation for collaborative filtering comes from the idea that people often get best recommendation from someone with similar tastes to themselves. This method explores techniques for matching people with similar interests and making recommendation on this basis [29-31].

Once the first step is achieved, we apply the method based collaborative filtering in order to build virtual communities of interests. This step is carried out by comparing the k-means clustering and k-nearest neighbor classifier described in the following section.

4. A collaborative Filtering Methods for E-learning Context

After preprocessing and weighting learning objects for each learner. We obtained the noised data (D) is a matrix with two dimension (*L)* learners and (*M)* learning objects. This section presents two useful and popular algorithms in collaborative filtering K-means and K-NN for e-learning context and learning objects to generate predictions.

Firstly, we present K-means clustering method for recommending learning objects. K-means is one of the simplest unsupervised learning algorithms and follows partitioning method for clustering. This technique creates *k* clusters each of which consists of learners who have similar preferences among themselves [32, 33]. In this method we first select randomly *k* learners as the initial centroids points of the *k* clusters, respectively. Next, each learner is assigned to one the cluster in such way the distance between the learner and the centre of cluster is minimized. The distance is calculated using Euclidian distance defined as:

$$d(u,v) = \sqrt{\sum_{i=1}^{n} (r_{u,i} - r_{v,i})^2} \tag{4}$$

In (4), $r_{u,i}$ and $r_{v,i}$ denote the rating for the learning object θ_i respectively by users u and v.

The proposed K-means clustering algorithm:

1. Initialize the value of K number of clusters.
2. Randomly choose k centroid from training data D
3. Assign learners to their closet cluster using the Euclidean distance according in (4).
4. Update the centroid by calculating the average value of the existing data on the cluster.
5. Repeat step 3 and 4 until the centroid no longer move.

Secondly, we present K-Nearest Neighbor (also known as user-user collaborative filtering) is a supervised learning algorithm, which is the most popular method used for classification, estimate, and prediction [34, 35]. Our purpose of this algorithm is to classify learners and give predictions for learning objects. The idea is to find other learners whose past ratings for learning objects are similar for the active learner and use their ratings to predict current learner's preference for a learning object he/she has not rated.

The measurement for the weight for similarity between two learners *u*, *v* is the Pearson correlation coefficient [29, 36, 37].

$$w(u,v) = \frac{\sum_{j}^{m} (r_{u,j} - \bar{r}_u)(r_{v,j} - \bar{r}_v)}{\sqrt{\sum_{j}^{m} (r_{u,j} - \bar{r}_u)^2} \sqrt{\sum_{j}^{m} (r_{v,j} - \bar{r}_v)^2}} \tag{5}$$

In the above equation: $\bar{r}_u$ and $\bar{r}_v$ are the averages of learner u's and v's ratings, respectively; $r_{u,j}$ and $r_{v,j}$ are learner u's ratings and learner v's ratings for the learning object *j*. 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, $w(u,v) = 0$, can be between -1 and 1.

And finally, compute the prediction for current learner *u* on learning object *j*. To generate predictions or recommendations for learner *u*, KNN uses similarity to select a neighborhood $N \in L$ of neighbors of u. Once *N* has been selected, the recommender system combines the ratings of learners in *N* to generate prediction for learner *u's* preference for a learning object *j*:

$$P_{u,j} = \bar{r}_u + \frac{\sum_{v=1}^{n} w(u,v)(r_{v,j} - \bar{r}_v)}{\sum_{v=1}^{n} |w(u,v)|} \tag{6}$$

In equation (6), $r_{u,j}$ denote the rating for the learning object *j* by users *u* and *v*.

The process of K-NN algorithm is:

1. Initialize *N* number of nearest neighbors
2. Calculate the similarities between active learner *u* and all learners *(L)* of D according in (5).
3. Select *N* learners which have the highest similarities with *u*.
4. Calculate the prediction for each learning object *j* with the formula according in (6).
5. Calculate MAE according in (7).

In order to compare the deviation between predictions and the real user-specified values, we use the Mean Absolute Error (MAE) as one of the most widely used technique; we computed the average error between the predictions and the *t* ratings as shown in formula:

$$MAE = \frac{\sum_{u,j}^{t} |\tilde{P}_{u,j} - r_{u,j}|}{t} \tag{7}$$

where *t* the total number of ratings is over all learners; $\tilde{P}_{u,j}$ is the predicted rating for learner u for the learning object θ_j and $r_{u,j}$ is the learner as rating.

5. Results and Discussion

In e-learning context, all developed recommender system still in application area and concentrated on small-scale experiments [20, 30, 31]. The availability of open e-learning data sets is considered as key for developing new personalized e-learning systems. Several challenges to collect and to share the data about interactions of learners with tools and learning activities were launched by RecSysTEL workshop and Pittsburgh Science of Learning Center (PSLC) DataShop [38, 39]. These data sets are used as benchmarks to develop new algorithms and to compare them to other techniques [40]. Moreover, to evaluate the prediction accuracy of the proposal recommendation algorithms, we used in our experiments *AdaptErrEx* a publicly available dataset, which includes 537.302 transactions of real learners in e-learning environment [38].

Preprocessing of original dataset is necessary to make it as a suitable for mining purpose. 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 10. The matrix obtained after cleaning and processing step includes 400 learners and 790 learning objects. We split the dataset into training set (90%) and test set (10%) randomly. In order to measure the efficiency of our algorithm, we employ MAE (mean absolute error) as metric defined in (7). The smaller MAE value is the more accuracy the prediction is. All experiments were conducted on HP Computer with 2GHz core duo processors using MatLab 7.10. We design four experiments to test the accuracy and efficiency of the proposed algorithms. In the first experiment, we try to specify the number of clusters K since the performance may be affected by the K-value and the numbers of users. In Fig. 6, the MAE curve in terms of different K-values on the 10 training subsets is illustrated and allows us to choose a proper K-value to achieve reasonable estimation performance.

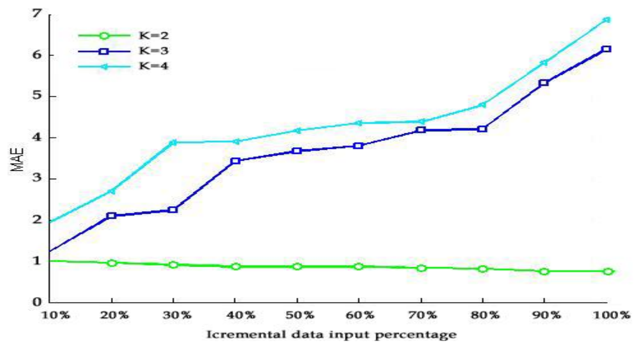

Fig. 6. Performance of K-Means by varying K.

Specially, we see that for all sizes of data, 2-Mearns performs better than 3-Mearns and 4-Means. Therefore, we fixed the k parameters at 2-Means to contribute the prediction in the rest of our experiments. In the second experiment, we have executed the simple K-NN algorithm in order to find the best values for *N* neighborhoods. This experiment was carried out for each of the following values: 40, 80, and 140. The results of our experiment are presented in Fig. 7, its shows a comparison of accuracy by increasing the learners' number for each value *N*.

In Fig. 7, with the increase of number of learners it can be seen how MAE of the *N* = 80 and *N*=140 are greater than the MAE of the *N* = 40 in all cases, we can conduct that *N* =40 is the best value for K-NN algorithm because MAE value corresponding is the smallest. Thus we fixed the *N* parameters at 40 neighbors to contribute the prediction in the rest of our experiments.

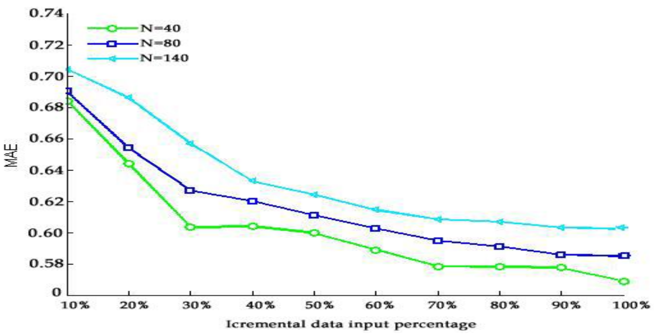

Fig. 7. Performance of K-NN by varying N.

In the third experiment, we aim to compare our proposal algorithms with a simple baseline predictor to estimate learning object ratings of each particular learner. In the baseline predictor, the unknown rating score is estimated as:

$$b_{ui} = \mu + b_u + b_i \quad (8)$$

where, μ is the overall average score, b_u and b_i are estimated using a decoupling method, which requires less complexity but less accurate [39]. Running these methods, we get the results depicted in Figs. 8 and 9, which shows that the classifier algorithm KNN outperforms than the others.

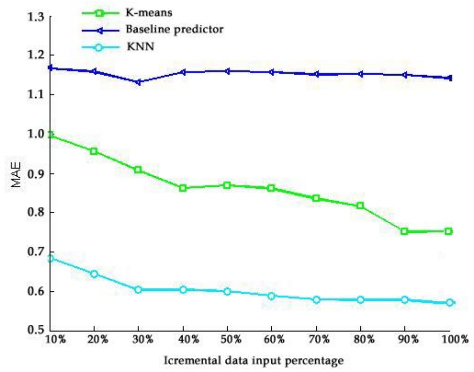

Fig. 8. The comparison of accuracy among all tested algorithms.

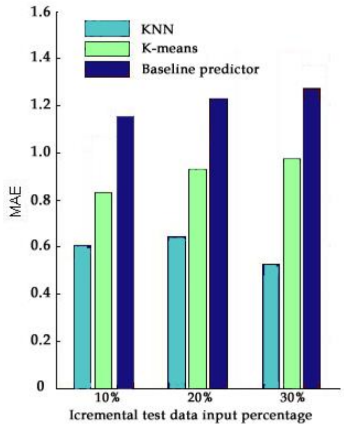

Fig. 9. Performance comparison.

In the fourth comparison, we recorded the computation time required to execute these algorithms in all training data (pre-processing time excluded). The execution time is compared by increasing the dataset; the results are shown in Fig. 10.

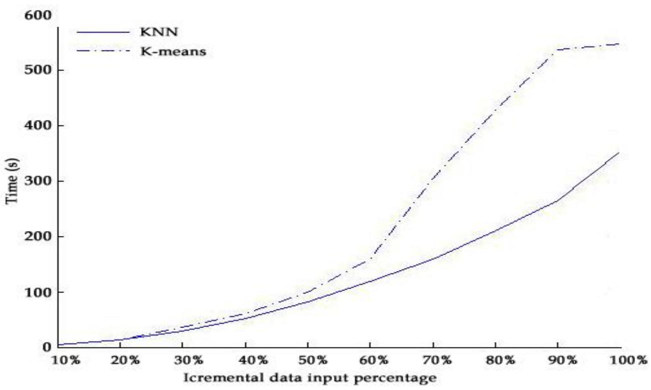

Fig. 10. Execution time among all tested algorithms.

In Fig. 10, during the change size of data, the execution time of each algorithm is increasing. By completing predictions for K-Means algorithm execution time takes 9 minutes 52 seconds. Processing time using K-NN classifier to complete predictions is reduced to 6 minutes 34 seconds. So, it can be seen that the K-NN algorithm can reduce the time complexity of using in recommender system for e-learning environment.

6. Conclusions

Nowadays, recommender systems are used to support individual learning in E-learning context. Indeed, personalized learning occurs when E-learning environments make deliberate efforts to design, to elaborate and to accomplish educational experiences that fit the needs, goals, talents, and interests of their learners. 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 E-learning environment 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.
- This teaching strategy will be adjusted by the decision body of the system using collaborative filtering method in order to achieve the desired fit.
- In order to evaluate the prediction accuracy of our proposed recommendation approach, we used an external data set of learners. The result reveals the system effectiveness for which it appears that the proposed approach may be promising.

In future, we plan 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 and can be enhanced by comparing various machine learning techniques.

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