Towards an Adaptive Learning Framework for MOOCs

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Abstract. Massive Open Online Courses (MOOCs) are a new shaking development in higher education. They combine openness and scalability in a most energetic way. They have the capacity to broaden participation in higher education. In this way, they help to achieve social inclusion, the dissemination of knowledge and pedagogical innovation and also the internationalization of higher education institutions. However, one of the most essential elements for a massive open language learning experience to be efficient is to enhance learners and to facilitate networked learning experiences. In fact, MOOCs are meant to serve an undefined number of participants, thus serving a high heterogeneity of profiles, with various learning styles and schemata, and also contexts of contribution and diversity of online platforms. Personalization can play a primary role in this process. Accordingly, adaptive MOOCs use adaptive techniques so as to present personalized learning experiences, having as basis dynamic assessment and data collecting on the course. They count on networks of prerequisites and deal with learners according to their different personalized paths through the content. This has been described by the Gates Foundation as an essential novelty in the area for large-scale productivity in online courses. Analytics are also to be credited with bringing about change and improvement of the course in the future. This paper looks into the MOOCs system by reviewing the available literature, spotting the various limitations of traditional MOOC system and suggesting a proposed framework for adaptive MOOCs based on hybrid techniques. By so doing, we generate suggestions of learning paths adapted to the competences profile of each participant with a focus on objectives, such as reducing the rate of dropout and improving MOOCs quality.

Keywords: MOOCs · Big data · Adaptive learning · Student modeling · System recommender

1 Introduction

MOOCs or massive open online courses have become a fashionable theme of debate about online education. MOOCs can be defined as online courses that rely on open educational resources (OER), with a wide number of simultaneous participants, and including interaction among participants using social tools.

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According to Siemens, a key figure in the field, MOOCs are a continuation of the trend in innovation, experimentation and the use of technology initiated by distance and online learning in order to provide large numbers of learners with a variety of opportunities [1]. MOOCs have been subject to controversy. In fact, some supported them; others had doubt about them; whereas traditional academic community dealt with them cautiously. One of the credits of MOOCs is that they offered the chance for numerous people to take part in true "education for all". Up to December 2015 there have been more than 4,000 active MOOC courses worldwide, and the trend continues to enhance as new institutions start further courses in more languages [2]. The key elements of MOOCs stand for:

- Massive: unlimited attendance.
- Open: participants are not charge and access is possible to anyone with internet connection.
- Online: distance learning, delivered via the internet.
- Courses: streamlined around a set of goals in a specific area of study.

In the literature, we distinguish between two pedagogical forms of MOOCs; these are explained below and might be seen as 'process' or 'content-based' approaches [5]:

- cMOOCs: The early MOOCs were 'connectivist' [1], described as cMOOCs, it is based on a participatory approach, where each learner performs their own information research, exchange with other participants, and publishes their own conclusions. This goes hand in hand with the idea that learning occurs within a network, where learners use digital platforms such as blogs, wikis, social media platforms to make connections with content, learning communities and other learners to create and construct knowledge. It is worth mentioning that cMOOCs are usually not sponsored by higher education institutions, but are rather organized by individuals with passion for a specific subject. The time allotted by the organizers aims at creating a framework for learning, where students worldwide can connect, share, contribute and collaborate, while at the same time learn about a specific subject and enlarge their network of professional and personal contacts [3].
- xMOOCs: The most instructivist models have been labeled xMOOCs. These have a tendency to employ a knowledge transmission model, by dint of video recordings of classroom lectures or custom produced mini-lectures. Besides, xMOOCs are the most popular type of MOOCs, for higher education, last but not least, xMOOCs are the most widely known because they are closer to the traditional education.

Despite their common goal of providing open and free (or relatively cheap) education to the public, xMOOCs and cMOOCs have distinctly different structures and qualities. Each form of MOOC sets up a different type of learning environment and is suitable for distinct methods of knowledge acquisition. Generally speaking, on the one hand, cMOOCs reflect the new learning environments characterized by flexibility and openness. On the other hand, xMOOCs offer high quality content as compared to cMOOCs [4]. Ultimately, the purpose of MOOCs was to open up education and cater free access to university level education for as many students as possible. The development of MOOCs is rooted within the basic ideal of openness in education. In other words, knowledge should be shared freely, and the desire to learn should not be

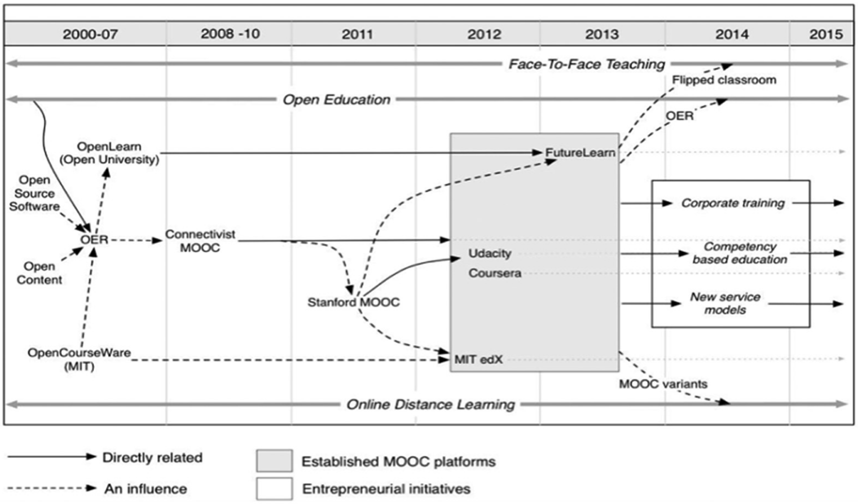

Fig. 1. Potential impact and trends of MOOC on education [5].

hampered by any demographic, economic, or geographical hindrances. As Fig. 1 shows [5], since 2000 the concept of openness in education has witnessed fast evolution. Accordingly, Massachusetts Institute of Technology (MIT) launched OpenCourseWare in 2002 followed by the Open University which started OpenLearn in 2006, representing a continuous evolution of the open education movement. As a result of this early development of MOOCs, various open learning platforms have been founded by leading institutions. MIT edX and OU's Futurelearn in 2012 can be given as an illustration.

Several types of MOOC platforms provide courses open to the public, either for free or for credit. The most lively ones these days are Coursera, Udacity, and edX. Table 1 is a good illustration of a sample and brief description of some features of the many MOOC Providers offering courses today. Table 1 is also an evidence that shows most platforms are made in such a way that they imitate the traditional features of pedagogy in electronic form [6], so the completion rate for most courses is below 13%. We believe that adaptive learning has the potential to take part in important key aspects of MOOCs and can overcome the current problems of high dropout rate in MOOCs.

In this research, we propose a framework based on a hybrid technique to provide students with an adapting content of MOOC according to the participant's competences, taking into account their prior knowledge. The proposed framework is based on two essential topics in personalization learning system such as student modeling and system recommender, having as an objective to provide adaptation mechanisms for MOOC platforms which integrates machine learning and soft computing. The paper is organized as follows: Sect. 2 for literature review on learning adaptivity, Sect. 3 describes our proposed system. Finally, in Sect. 4, we summarize our work and provide an outlook on the future related to this area of research.

Table 1. Summary of features supported by various MOOCs platforms [6]

	edX	Coursera	Udacity	Future-Learn	Canvas Network
1. Learning Methods					
Video with audio	✓	✓	✓	✓	✓
Audio only	×	×	×	✓	×
Articles	✓	✓	×	✓	✓
Projects	×	×	✓	×	×
Discussions	✓	✓	✓	✓	✓
2. Assignments	✓	✓	✓	✓	✓
3. Quiz tests	✓	✓	✓	✓	✓
4. Transcriptions	✓	x	✓	✓	×
5. Video with interactive transcription	✓	×	×	×	×
6. Certificate	✓	✓	✓	✓	✓
7. Peer Assessment	×	✓	×	×	×
8. Adaptive learning	×	×	×	×	✓
9. Course joining timings	Scheduled Anytime	Scheduled Anytime	Scheduled Anytime	Scheduled	Scheduled
10. Target Users	Anyone	Anyone	Professionals	Anyone	Anyone

2 Literature Review

Web systems generally suffer from their incapacity to meet the heterogeneous needs of many users. To tackle this challenge, a special trend of research that has been called adaptive web systems; Adaptive systems makes it easier for users to find appropriate items in a commonly large information space, by basically engaging three main adaptation technologies [7]: adaptive content selection, adaptive navigation support, and adaptive presentation.

Adaptation is a key topic in traditional e-learning systems and different concepts have been used for this purpose. George Siemens, the authority of the MOOC, was quoted in The New York Times in December 2013 saying, “the next challenge will be scaling creativity, and finding a way that even in a class of 100,000, adaptive learning can give each student a personal experience.” [1]. Adaptive learning develops a model of a learner’s understanding of topics and concepts, permitting detailed feedback on progress and supplying personalized pathways to attain learning outcomes. Nevertheless, adaptation is not very developed in MOOCs, where it has gained even more ground as they commonly have more participants whose profiles are more varied. Moreover, many frameworks have also been suggested, Daradoumis et al. [8] use software agents to ameliorate and personalize management, delivery and evaluation of massive online courses on an individual level basis. This framework takes into account the participants schemata which is very important because most MOOCs incorporate lectures formatted as short videos. Bassi et al. [9] propose an agent-based framework for MOOCs. Agents gather data and analyze them based on different perspectives including educational objective, time management, pedagogical preferences, etc. The analyzed data is used by other agents for content personalization, teaching feedback; the authors contend that intelligent agents could also be used for cutting down cheating and fraud during quizz and online tests. Lerís et al. [10] propose a construct of adaptivity for MOOCs to detect some specific personalizing indicators. These indicators are selected as a consequence of previous work done and are based on two aspects of learning: self-regulation and cooperation. Sonwalkar [11] suggests an adaptive system with web services and computer architecture, which counts on diagnostic assessment adapted to five learning styles. In addition, Onah [12] recommends systems by which users create their own learning paths, making choices based on their own objectives and preferences. Teixeira et al. [13] add to the pedagogical model for MOOCs, with content adaptation aiming at making compatible initial knowledge and the device used. Adaptive MOOCs can be defined as an intelligent system that allows personalization for each individual user, its content and its presentation according to user preferences and characteristics. The process of personalization of MOOCs is implemented through a decision making and personalization engine which adapts the contents according to a user model. In this context, it is clear that the key element of an adaptive e-learning system is the user model.

2.1 Student Modeling

Building of the student model and following related cognitive processes are important aspects in providing personalization. The student model is a representation of information about an individual learner that is essential for an adaptive system. The system uses that information from student model so as to predict the learner's behavior, and there by adapt to his/her individual needs. Data from student model is classified along three layers that are suggested in [14]:

- Objective information, which incorporate data provided directly by the learner like: personal data, previous knowledge, preferences, etc. The learner edits this data during his/her registration on the system.
- Learner's performance, which includes data about level of knowledge of the subject domain, his/her misconceptions, progress and the general performance for particular learner.
- Learning history, which includes information about lessons and tests learner has already studied, his/her interaction with system, the assessments he/she went through, etc.

2.2 Student Modeling Techniques and Methods

Machine Learning Techniques. The concept of machine learning (ML) has been around for decades. What's new is that it can now be applied to huge quantities of complex data. Less expensive data storage, distributed processing, more powerful computers, and the analytical opportunities available have dramatically increased interest in machine learning systems. There is no denying that learning is the process of acquiring knowledge. On the one hand, humans naturally learn from experience by dint of their ability to reason. On the other hand, computers do not learn by reasoning, but learn with algorithms. Today, there are a large number of ML algorithms found in the literature. The main machine learning methods which are used in MOOC data analysis enable us to do prediction, clustering, relationship mining, discovery with models and data distillation for human judgment.

Two main branches of machine learning can be identified: on the one hand, supervised learning and unsupervised learning. Supervised learning is used when the algorithms are provided on the basis of training data and correct answers. The task of the ML algorithm is to learn on the training data and apply the knowledge acquired in the real data; the goal was to identify patterns within independent variables to explain a dependent variable. The key example here is the linear regression and logistic regression, known from classical statistics. Recent techniques such as support vector machines, random forests, and generalized boosted regression are gaining popularity due to their robustness, computational feasibility, and effectiveness [15]. On the other hand, in unsupervised learning, ML algorithms have not a training set. They are used with some data about the real world and have to learn from that data on their own. Unsupervised learning algorithms are mainly axed on finding hidden patterns in data, there is no dependent variable and we want to investigate patterns in the data, most commonly clusters similar observations. Clustering is realized by the simple k-means or k-medoid.

Modeling the Uncertainty of Learning. One of the most important problems encountered when constructing a student model is uncertainty [16]. The processes of learning and student's diagnosis are complex. They are defined by many factors and depend on tasks and facts that are uncertain and, usually, unmeasured. The determination of the student's knowledge, mental state and behavior is not a straightforward task, it is rather based on uncertain observations, measurements, assumptions and inferences. The presence of uncertainty in student's diagnosis is increased in an adaptive/personalized tutoring system due to either the indirect interaction between the learner and the teacher or the technical difficulties [16].

The limitations of traditional machine learning techniques for modeling human behavior led to the introduction of Soft Computing (SC) for User Modeling (UM). The most common used techniques to face this kind of uncertainty are fuzzy logic (FL), Bayesian Networks and neural network. FL is not a machine learning technique; nevertheless due to its ability to handle uncertainty it is used in combination with other machine learning techniques in order to produce behavior models that are able to capture and to manage the uncertainty of human behavior [17].

The knowledge domain representation in an adaptive and/or personalized tutoring system is a key factor for providing adaptivity. The most usual used techniques of knowledge domain representation are hierarchies and networks of concepts. The knowledge representation approach enables the system to identify the domain concepts that are already partly or completely known for a learner, or the domain concepts that the student has forgotten, while taking into consideration the learner's knowledge level of the related concepts. Therefore, the representation of dependencies between the domain concepts of the learning material comprises uncertain and imprecise information. Consequently, an effective solution for dealing with this uncertainty is to use fuzzy logic techniques in the representation of the knowledge domain. In fact, Fuzzy Cognitive Maps (FCMs) is a way to represent real-world dynamic systems (Fig. 2); in a form that corresponds tightly to the way humans think of it [18]. A FCM is a network of nodes (N_1, N_2, … N_n) which represent the important concepts of the mapped system and oriented arcs representing the causal relationships between two nodes (N_i, N_j). The directed arcs are marked with fuzzy values (f_{ij}) in the interval [−1, 1] that show the "strength of impact" of node N_i on node N_j.

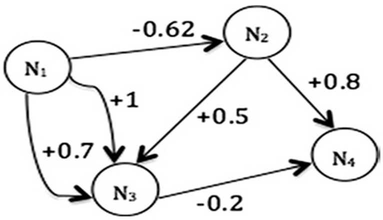

Fig. 2. Fuzzy cognitive maps [18]

Ontology-Based Student Modeling. Recently, a lot of research has been done around the modeling of users and web ontologies. Due to the fact that adaptive and/or customized teaching systems try to model learning processes in the real world and as they are web applications, so they can be combined with Web ontologies. These allow the representation of abstract properties and concepts and make them expanded and reusable in different applications [18]. These characteristics of ontologies can participate in the modeling of students, find a solution to describe the learning preferences of the learners and are also used for searching and indexing various educational resources. The main advantages of ontological models are: formal semantics, reuse of domain knowledge, domain knowledge from the operational knowledge.

2.3 Recommendation System

The main goal of recommender systems in web-based learning system, such as MOOC is to assist users by providing personalized recommendations related to content and services. Recommender systems are increasingly being adopted in E-commerce for recommending movies, books, music, TV shows or different types of items. Such successful implementation of recommender systems in the e-commerce domain has encouraged researchers to explore similar benefits in the e-learning domain since the implementation of recommender systems in e-learning has high potential for achieving advanced personalization. Recommendation system is the most popular application for personalization and recommendation techniques. In this regard, there are several techniques used in the learning system [19]. The following section will discuss the most used techniques and their efficiencies to improve learners' experiences.

Collaborative Filtering (CF). Collaborative filtering focuses on identifying of learners with similar learning patterns and uses their learning methods to recommend contents to others [20]. The CF technique can be divided into user-based and item-based CF approaches [21]. In the user-based CF approach, a user will receive recommendations of items liked by similar users. In the item-based CF approach, a user will receive recommendations of items that are similar to those they have loved in the past. The similarity between users or items can be calculated by Pearson correlation-based similarity [19], constrained Pearson correlation (CPC)-based similarity, cosine-based similarity, or adjusted cosine-based measures.

Content-Based. The system learns to recommend items that are similar to the ones that the user liked in the past taking into account the object content analysis that the user has evaluated in the past. The similarity of items is calculated based on the features associated with the compared items. Clustering was proposed by [22] to group learning documents based on their topics and similarities. In fact, the existing metrics in content based filtering only detect similarity between items that share the same attributes. Indeed, the basic process performed by a content-based recommender consists in matching up the attributes of a user profile in which preferences and interests are stored with the attributes of a content object (item). The objective is to recommend to the user new interesting items. In CB recommender systems, two techniques have been used to generate recommendations. One technique generates recommendations heuristically using traditional information retrieval methods, such as cosine similarity measure. The other technique generates recommendations using statistical learning and machine learning methods, largely building models that are capable of learning users' interests from the historical data (training data) of users.

Knowledge-Based Recommendation System. This system recommends contents based on specific domain knowledge on the usefulness of the contents to the learners needs and preferences [23]. The knowledge-based systems are case-based systems which use a similarity function to access the needs of the learners and provide recommendations. Another example of knowledge-based system is a constraint-based system, which collect learners' requirement and re-adjust the preferences for consistency, and also automatically suggest recommendation if none is offered originally. While case-based recommenders offer recommendation based on similarity matrices, constraints-based recommenders exploit predefined knowledge bases with explicit rules to suggest contents to learners suitable to their learning needs. However, in [23] authors, argue that knowledge-based systems tend to be more efficient as compared to the others at the early stages or phases of their application, but there exists some criticisms, which they argue that if knowledge-based systems are not properly "equipped with learning components", they certainly can be overshadowed by other methods such as collaborative filtering which can exploit both human and computer interactions.

In this section, we have presented a review of principal techniques for adaptation in e-learning, such as system student model and recommendation technique. We believe that many combined powerful techniques can improve adaptation for MOOCs. We have also showed that machine learning and fuzzy logic technique can provide a robust user model which can be useful to recommender system so as to provide dynamic feedback and suggest the suitable resources to the MOOC learner.

3 Proposed Framework

MOOC user behaviors are also a big part of massive MOOC data. User behavior real-time data (study process, assignment achievement, test score, etc.) mean the effect of MOOC learning. Therefore, identifying the learning problems during the course as early as possible enables educators to apply the intervention or the suitable measures to achieve improvement in online learning. In this respect, there are a wide variety of current techniques popular within educational big data analytics. Most used techniques are statistics and machine learning. Figure 3 shows the classical learning workflow in the MOOC environment. The course material is made of lecture videos, exercises, assignments etc., which is generally split on a week basis. At the start of the week, the learner has access to the above mentioned material during the current week. In other words, the learner watches video lectures, does exercises, debates in the provided

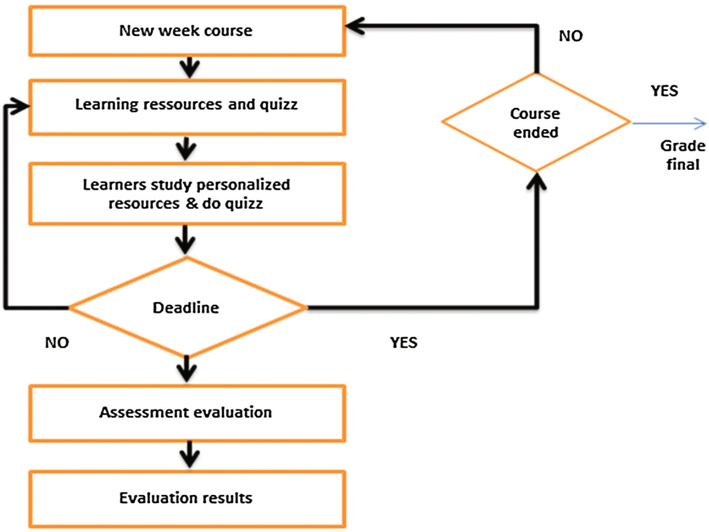

Fig. 3. Classical MOOC system flow diagram.

discussion forum, completes assignments etc. Once the deadline is reached, the learners' assignments are subjected to an evaluation procedure, which is mostly peer evaluation. The same procedure is repeated for the next week as long as the course is not completed.

One of the shortcomings of MOOC implementation system is the fact that learners attend the same course, without taking in consideration the features and behavior of each learner. In order to cope with this pitfall in the traditional MOOC system, there is a need for an adaptive system that takes into account the specificities of each learner before the beginning of each week. This adaptation should take the form of some suggestive tasks or readings to be performed based on the interaction with the system. Figure 4 is an illustration of the adaptive MOOC system. This adaptive MOOC system is to be credited with two fold advantages. Firstly, it is personalized as it takes into consideration the particularities of each learner. Secondly, the learner is aware of his weaknesses and thus provided with recommended tasks to overcome them. This adaptive MOOC system manages to achieve this by analyzing the behavior and characteristics of each learner at the beginning of each week which enables it to suggest the suitable and efficient tasks to be performed. More importantly, this behavior analysis is done continuously and recurrently throughout the week while the learner is interacting with the system which makes it possible to renew and revise the recommended tasks to fit the learner's individual needs.

For more details, this section describes the adaptive learning framework that could cater for improved and personalized recommendations for MOOCs. Our framework structured in four layers (Fig. 5).

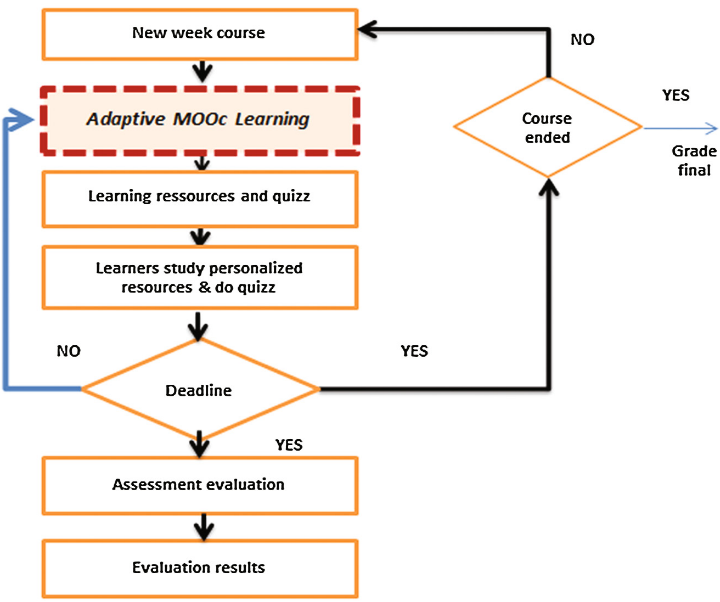

Fig. 4. Proposed adaptive MOOC flow diagram

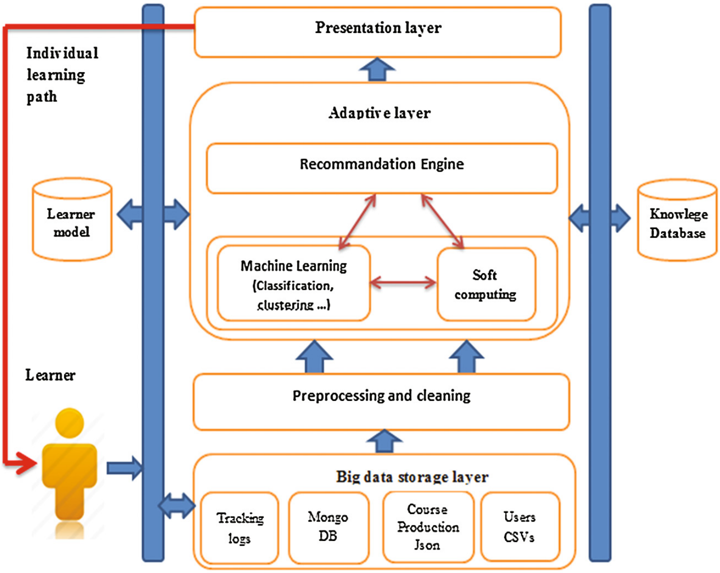

Fig. 5. The proposed framework for an adaptive learning of MOOCs.

As concerns the first layer, while users work with the adaptive framework system, it logs and stores all their actions. When scheduled, the storage system retrieves usage data, preprocesses them and stores them into different types of files, namely log files, Json files and database (storage layer). As the systems generate daily due to learner's interaction with the system, the quantities of data get bigger which makes it hard to analyze them manually, especially that they are heterogeneous and need speed to manage. So as to reach deeper understanding of the outcomes, we can rely on the existing analytical techniques for big data and data mining techniques and use them in the teaching courses. This can help in a better understanding of the learner's behavior and interaction.

The second layer consists of preprocessing and cleaning. In fact, tracking logs provide a lot of useful information. However, the format of tracking logs is semi-structured. To understand the pattern and classify these logs based on their events, it is necessary to preprocess and clean them. The major benefit of processing the record of every user interaction in entire course is to gain more insights into learner behavior. Nevertheless, in relationship with the cleaning process, it is worth mentioning that finding meaningful interpretation from clickstream data is challenging task. This challenge lies in the difficulty to transform clickstream data into more understandable data. Data cleaning extracts valuable row data to draw meaningful interpretation thought it is not directly possible to apply these data for interpretation process. As result, we first need to identify the characteristics of the database and extract features out of it. By extracting each feature and applying data mining process, we get further valuable information from data.

As regards the third layer, the adaptive layer is responsible for building and updating learner's model characteristics and also for personalization of content to be given to the learner. Moreover, it treats changes of learner's characteristics in accordance with the learner's activities as well as providing ways to adapt visible aspects of the system with specific learner. Among its main tasks, we can find also storage and management of learning material, presenting that material to learners, generating of reports and test results etc. During each session, the system gradually re-builds the learner model in order to follow the learner's actions and his/her progress, identify and correct his/her errors and possibly redirect the session accordingly. As the session ends, all of learners' preferences are recorded in learner model.

Machine learning algorithms are executed on stored usage data and usage patterns are found out and saved in the knowledge base. With clustering algorithm, learners are grouped into recognizable and manageable clusters according to their common attributes and based on the privileged categories of content delivery. Parts of the instruction are then tailored to the groups and are carried out similarly to all members of a segmented group. That segmentation is accomplished by different surveys that the learner has to complete during the registration on the system and optionally after every sequence and by following the learner's actions, progress and general performance. Assessment techniques such as homework, quizzes, to name only a few can be used to evaluate concepts causing difficulties for learning.

The shortcomings of traditional machine learning techniques for modeling human behavior have led to the introduction of Soft Computing (SC) technologies that provide an approximate solution to wrongly defined problem and can create user models in an environment, such as a e-learning system, in which users are reluctant to give feedback on their actions and/or designers are not able to completely define all possible interactions. Human interaction is an essential component of MOOC system, which means that the data available will be usually inaccurate, incomplete and heterogeneous. In this context SC seems to be the convenient paradigm to deal with the uncertainty and fuzziness of the information available to create user models [15]. The elements that a user model captures, namely goals, plans, preferences, common characteristics of users can utilize the ability of SC of combining various behaviors and capturing human decision processes so as to carry out a system that is more flexible and sensible in relation to user interests.

Different techniques cater for different capacities. For example, Fuzzy Logic provides a mechanism to imitate human decision-making for the purpose of inferring goals and plans. Neural Networks is an adjustable mechanism for the representation of common characteristics of a learner and the definition of sophisticated stereotypes. Another technique is Fuzzy Clustering which is a mechanism in which a learner can be part of more than one stereotype at the same time and NeuroFuzzy systems is a mechanism to detect and tune expert knowledge which can be used to get assumptions about the learner. In this regard, Frías-Martínez et al. [17] draw a comparison of different SC techniques and allow to have guidelines to choose the most appropriate technique, and show that Fuzzy logic is best suited for the task of recommendations. Thus, we suggest selecting fuzzy clustering to categorize the learner of one or multiple group.

The task of recommending system in MOOC is to suggest for a learner a based individual learning path on the tasks already performed by the learner and based also on tasks done by other similar learners. These similar learners are incorporated in the profiles. The chief objective is to recommend a sequence of pertaining concepts for particular learner, based on the learner's current needs obtained from the system-user interactions. Accordingly, we propose a fuzzy-based system for MOOC learners to retrieve optimal resources.

It is worth mentioning that the knowledge domain is responsible for the representation of the subject being dealt with that can take the shape of course modules, which involve domain concepts which include sub objectives. Figure 6 is an illustration of the course module components. The primary objective of knowledge representation is to display it in a way that makes reasoning an easy task. In an adaptive system, adaptation relies on the type of knowledge representation technique chosen. Thus Fuzzy Cognitive Mapping (FCM) is a way to represent knowledge of systems which are characterized by uncertainty and complex processes. FCM consists of concepts and relations among each other when it is used to present learning resource. Furthermore, FCM can represent not only causal relations between concepts but also knowledge of various granularity levels. However, learning resources should be organized in some semantic forms in order to back up high efficient searching and recommendation.

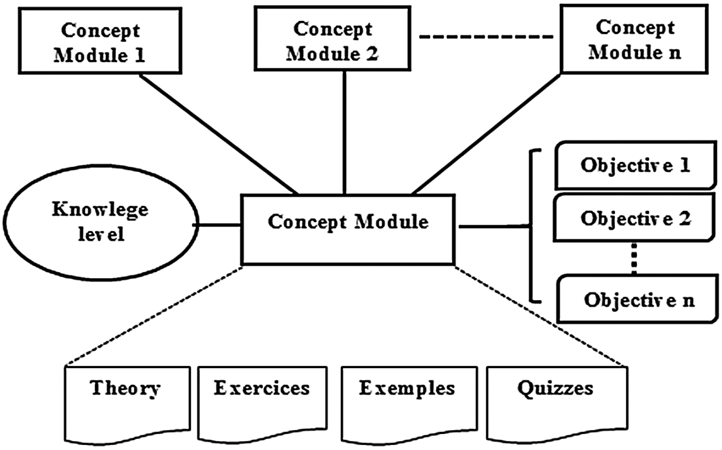

Fig. 6. Knowledge representation

Capturing initial data about the user occurs at the starting point of the system. This data includes user preferences, learning style, knowledge level about all the concepts taught in the week. At this initial stage the focus is on knowledge level of all the concepts previously taught in the week. This knowledge level can be captured by using exercises and quizzes of the week. The structure of the quizzes and exercises should be pre-defined and the structure in a way that each question must be mapped to a given objective of a given concept.

This system can use various recommendation techniques so as to propose online learning tasks or optimal browsing pathways to students. These systems use various machine learning algorithms, for example, clustering and sequential pattern mining combined with fuzzy logic. In this way, they can find out clusters of students showing common behavior and/or knowledge and then they are able to discover the sequential patterns of each cluster. This type of recommender system can personalize the recommendations. First, it categorizes the new students in one or more groups of students (fuzzy clusters). Then, it only uses the sequential patterns of the corresponding group to personalize the recommendations based on other similar students and his current navigation. The recommender module creates a sequence of recommended concepts based on the current session of a learner and the knowledge saved in the knowledge database. The concepts in the current user session are associated with the ones in patterns of the knowledge database. When corresponding (similar) patterns are found, the concept recommendation is implemented. The result is a sequence of recommended concepts and the evaluation of their appropriateness and relevance for the user. This sequence is generated as a response to MOOC system (each time the user shifts to another concept or fragment, or after some time period or at the beginning of each session). [24]

4 Conclusion and Future Work

In this paper, we have proposed an adaptive learning framework of massive open online courses (MOOCs), which is based on existing adaptive methodologies of adaptation model development using machine learning techniques, soft computing and recommender system. Therefore, the framework proposed is able to generate suggestions of learning paths adapted to the competences profile of each participant so as to allow for an increased personalization and contextualization of learning experiences. The framework is also flexible as it has the ability to adapt the content for MOOCs learners. In other words, we believe that the combination of these SC techniques among themselves and with other machine learning techniques will provide a useful framework to efficiently capture the natural complexity of human behavior and recommend useful personalized content for each student.

Future development of the recommender system will focus on enhancing the set of data mining algorithms, e.g., to use fuzzy clustering techniques in order to discover user clusters according to their learning styles. We also plan to evaluate quality of recommendations carried out by our recommender system using data produced by MOOCs provider. The evaluation will be based on a feedback from students as well as on results of the recommendation performed on a testing set of data.

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