Adaptive Learning System (ALS) using Fuzzy Logic and K-means

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Abstract

E-learning is increasing in popularity due to its accessibility and reduction in spatial and/or temporal boundaries. Notwithstanding these benefits, e-learning platforms must consider the student's level of commitment, the delivery and assessment of course materials, along with the underlying pedagogical approach. It is of paramount importance to use this information in order to evaluate the quality of teaching and modify the way that the information is presented to the students. To tackle these challenges, an automated adaptive learning system is proposed according to the selection concepts of a customised learning path using integrated the Fuzzy Logic based classifier and the K-means clustering algorithm. This paper presents the architecture for an integrated Fuzzy Logic and K-means clustering adaptive learning system which allows learning paths to be adapted to the learner, according to the evaluation criteria set by the teacher.

1. Introduction

On March 11th, 2020, the WHO declared a global pandemic [1]. In an effort to reduce the spread of COVID-19, schools, colleges, childcare centers and non-essential services were closed. More than 180 countries globally rapidly transitioned to 100% online delivery, impacting more than 150 billion learners [9]. The advantages of accessing course content via the Internet include flexibility, remote access and cost effectiveness [4]. A significant drawback is that course content and feedback are typically not tailored to the learner [4]. To address this limitation and meet the learner's specific learning requirements, adaptive learning systems (ALSs) have evolved [2]. An ALS provides the learner with a customised interactive learning system based on personal behavioural data and the learner's level of understanding [8]. Within the context of adaptation, two terms have emerged, adaptability and additivity. Adaptability refers to lesson materials changing in response to the learner's behaviour in the learning system. Meanwhile, additivity is the personalisation of the learning system to suit the learner's learning process [5]. This study focuses on the relatively newer approach of using a combination of different algorithms. What makes this approach distinctive is that it incorporates both the absolute approach (based on predefined rules) and the relative approach (based on peer performance). The proposed integrated adaptive learning approach integrates the Fuzzy Logic algorithm with the K- means clustering algorithm using the learners' input data. The aim of this approach therefore is to adapt the learners' learning path according to their personalised data i.e., score and time etc. Consequently, the research question for this paper is: "Can an adaptive learning system using integrated Fuzzy Logic and K-means clustering algorithms be used effectively to generate domain models and improve learning outcomes through the creation of adaptive learning approaches for learners according to data from personalised / adaptive learning features?"

2. Related Work

Adaptive learning can be characterised as a learning system that employs teaching with networked information and processing of correspondence. By virtue of automation and personalised learning, adaptive learning goes beyond traditional web-based learning, interactive teaching, disseminated teaching and networked and/or web-based teaching [10]. In traditional learning systems, it is not common to focus on the learning preferences and needs of each student, and therefore, all students are treated in the same way, regardless of their specific needs [14]. If a learning environment is able to: monitor the activities of its users; deduce user requirements and preferences from the interpreted activities; and finally, act upon the knowledge that is available for its users and the subject matter at hand, to dynamically facilitate the learning process, it is considered adaptive [11]. There have been many adaptive learning systems developed over the years. An example of this would be User-Centric Adaptive Learning and Personalized Learning Systems as well as Two Source Adaptive Learning.

2.1. User-Centric Adaptive Learning

The User-centric Adaptive Learning System (UALS) [12] uses sequential pattern mining and the pooled intellect of the learners to build adaptive learning paths. The ability of students to recommend adaptive resources is estimated by using Item Response Theory (IRT) and collaborative voting. Figure 1 explains the working architecture of the UALS. Assessment and pedagogical models are not specified in the UALS platform although the learner creates the complete learner path model.

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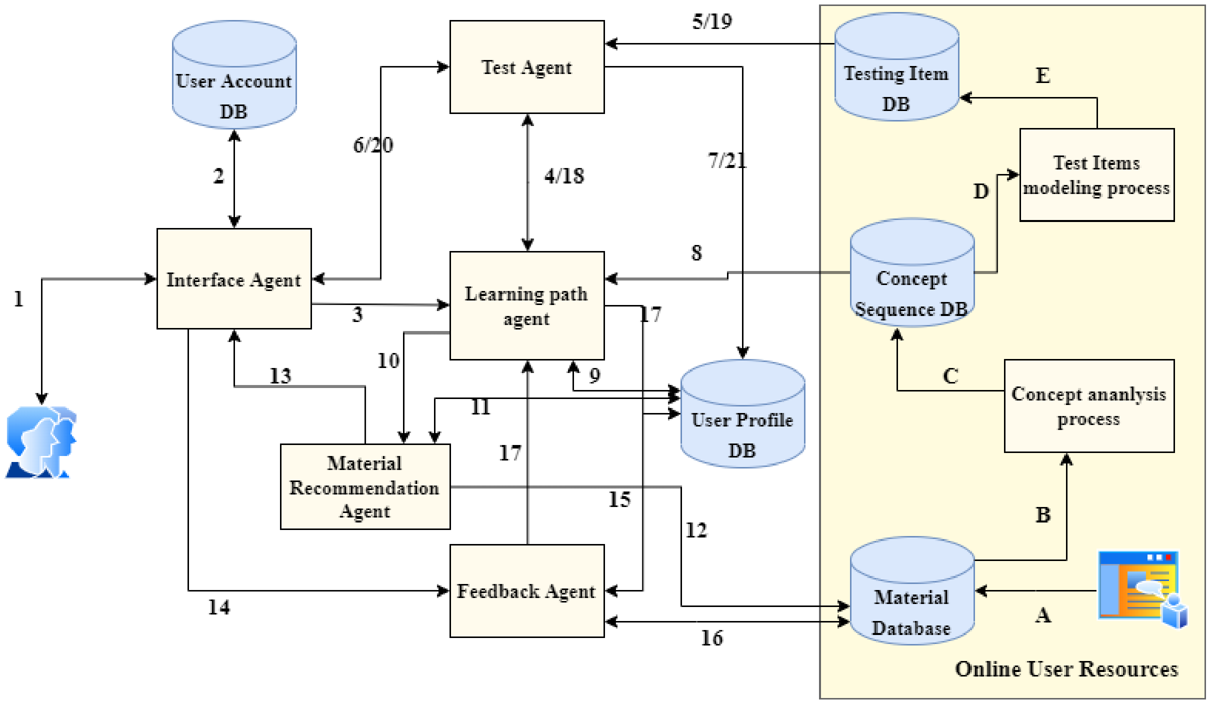

Figure 1. Flowchart of the User-Centric Adaptive Learning System [12]

The strengths of the UALS system are that users are allowed to create learning services and automatically organise learning services immediately. The main limitations of the UALS platform are that it only accounts only for prior knowledge, comprehension and ability. A case study was undertaken on a group of 79 students by way of using collective intelligence to create adaptive learning pathways and select material, making it comparable to an educational expert.

2.2. Personalized Learning Systems

The Personalized Learning System (PLS) model is described as shown in Figure 2 and taken from [13]:

- Elaboration theory and e-learning standards support the design of learning objects.
- In the student ability test, we use item response theory (IRT).
- A Dynamic Conceptual Network (DCN) to organise course materials.
- In order to comprehend the learner's behavior, it is necessary to adopt a user profile.

The strengths of a PLS include a reduction in the integration costs and the number of operations in the learning systems and the requirement for a redirection of scarce resources to support academics and enhance research. The key limitations are that a PLS does not take into account the learner’s prior knowledge of the learner, and it has limited flexibility.

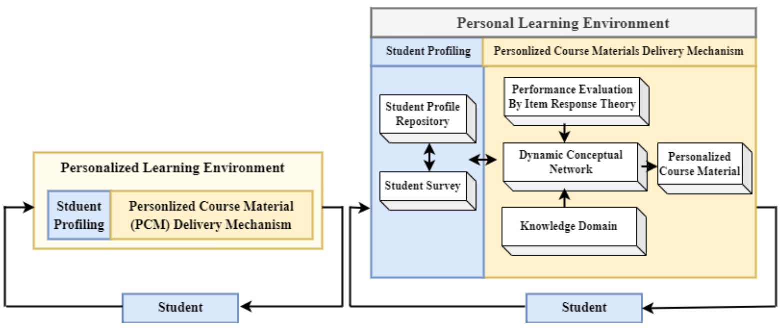

Figure 2. PLS System Architecture [13]

In this paper we presents the results of a case study conducted on a group of 55 students to present the adoption of Personalized Course Materials (PCM) as a delivery model for an existing e-learning course, along with specific ideas for future research on the topic.

2.3. Two Source Adaptive Learning

Whilst User-Centric Adaptive Learning and Personalized Learning Systems are primarily focused on a single source of personalized information, such as learning behaviour or learning style, the Two-Source Adaptive Learning (TSAL) system focuses on two main sources of student personalized information: learning behaviour (i.e., concentration, achievement, effectiveness) and learning skills (i.e., analytical, processing and semantic skills). Figure 3 illustrates the working architecture of the TALS system.

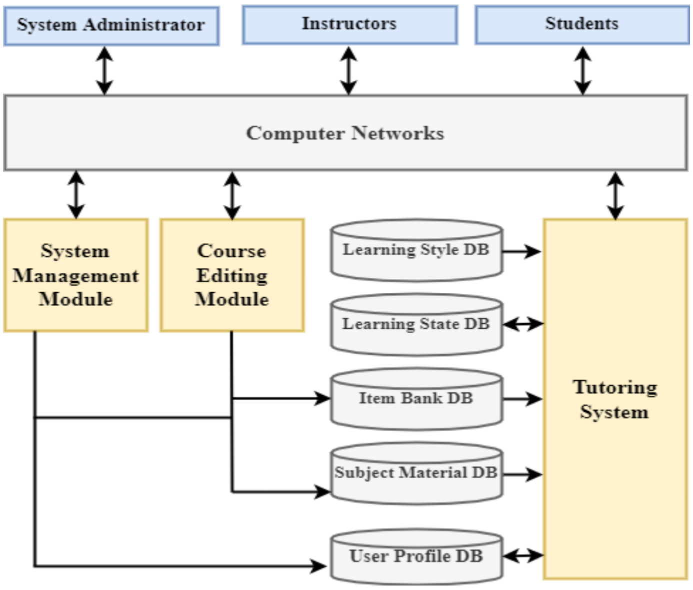

Figure 3. Architecture of Two Source Adaptive Learning (TSAL) [18]

subject based on the learning style and learning behaviour of the students involved in the course. The instructor considers the different learning behaviours and styles of the students in order to create customised subject material for the students based on their learning styles and behaviours. The TSAL system consists of eight modules: Course Editing Module, Tutoring System, System Management Module, User-Profile Database, Subject Material Database, Item Bank, Learning State Database and Learning Style Database. The TSAL system is typically implemented through PHP and SQL on Linux environments. The core strength of the TSAL approach is that it improves learning and the productivity of individual students. The main drawback is that it is difficult to plan because several types of material have to be produced so that it can be personalized.

A study conducted with on 91 students determined that adaptive subject material assisted students improve their academic performance as well as their learning productivity by helping them to increase their learning ability.

3. ALS using Fuzzy Logic and K-means

The fundamental challenges in the domain of adaptive learning systems include: how to make adaptive learning systems more scalable, how to improve usability and improve confidence, as well as how to integrate information adeptly.

Studies demonstrate the potential for Machine Learning (ML) approaches in overcoming obstacles related to upscaling and the integration of expert knowledge integration [16]. However, when determining whether or not to pursue the ML solution, there is commonly a substantial amount of scepticism among practitioners and at least two conflicting theories [17].

- Experts have valuable knowledge that may be able to improve and/or validate the learning system.
- It is difficult to believe in a black box.

The proposed ALS addresses the above conflict through its use of a combination of two different models. One is Fuzzy Logic (which is a knowledge-based model and satisfies the first theory) and K-means clustering (which despite being an ML model does not count as a black box because of its low complexity [15]).Fuzzy Logic is a supervised ML algorithm which is used to imitate human decision making [6]. As a result of fuzzy Logic, there are several characteristics that can be described as follows [19]:

- Based on real-life situations, it allows easy transitions by means of associated fuzzy sets in order to allow smooth transitions and overlaps between them.
- This system is driven by a number of pre-defined rules based on knowledge.
- As fuzzy sets overlap, they provide non-crisp behaviour. Thus, any minor changes in input will not have a significant impact on output.

A Fuzzy Logic algorithm is typically used when it is not possible to precisely define the boundaries or when the range of decisiveness is beyond a binary Yes or No answer [6]. As an example, the two options of Yes and No are not satisfactory when used to answer the question "Does one like music?” Meanwhile, K-means clustering is an unsupervised ML algorithm that initially attempts to discover similarities between different data points in a large data set and then mark multiple subsets / clusters of similar instances [7].The K-means clustering algorithm provides the clusters (i.e., the performance of each learner relative to the remainder of the learners) that enable the system to evolve overtime.

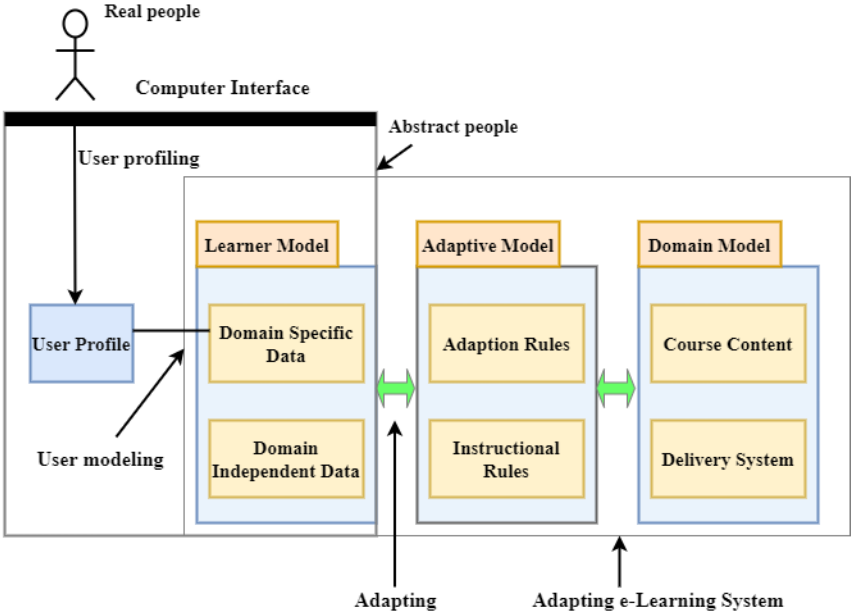

Figure 4. ALS architecture

The proposed Fuzzy Logic and K-means clustering ALS is presented in Figure 4 above and briefly detail below:

- Learner Model (LM) describes the learner's profile (i.e., their knowledge, characteristics, and preferences). The ALS sets up the LM by calculating each learner’s performance metrics which comprise the learner's score and the average time taken to attempt questions.
- Domain Model (DM) is composed of a set of domain knowledge elements (DKEs) (note: each DKE represents an elementary fragment of knowledge for the given domain). K-means clustering is employed to generate the DM by unearthing similarities between the domain elements / learning content.
- Adaptation Model (AM) defines the content selection, and the concept selection rules that are used to select appropriate content from the media space and concepts from the domain model. The AM is created using the Fuzzy Logic algorithm that defines the content selection rules that are applied to select appropriate content from the DM for each learner from the LM.

4. Dataset

In order to test the integration of the Fuzzy Logic and the K-means clustering algorithms, the authors used the EdNet dataset which comprises the student-system interactions of more than 780,000 Korean students on a multi-platform AI tutoring service, captured over two years (April 2017 – April 2019). Based on these interactions, EdNet provides academics with access to massive amounts of data from the actual world. The data points that make up EdNet are organised in a hierarchical fashion, so as to provide a variety of different actions in a dependable and well-organised way. Based on the number of students enrolling online and the number of students interfacing with the learning content, the type of interaction between the students that is in the EdNet dataset is among the largest educational datasets [20]. The EdNet dataset consists of students' question-solving logs in question-response sequence format and is accessible via iOS, Android and the web. The fact that the questions are presented in bundles, specifically a collection of questions that are based on the same reading passage, picture or audio material, is one of the most notable characteristics of the EdNet dataset. For instance, if two different questions refer to the same reading passage, these questions form a bundle. Subsequently, that bundle will be provided to the learner along with the corresponding shared learning content. A student who has access to a bundle also has access to all of the problems and questions associated with that content in that bundle. In order to complete the bundle, the student must provide answers to all of the associated questions. The EdNet dataset is comprised of the following features:

- **timestamp -** indicates the point in time at which the inquiry was posed and is formatted as a Unix timestamp in milliseconds.
- **solving_id -** is an integer that represents the learning session that corresponds to each bundle. This identifies the problem being solved.
- **question_id -** is an integer that represents the ID of the question that is provided to the student. This ID is a unique identifier for the question.
- **user_answer -** is the answer that was provided by the student. It is recorded as a character between ‘a’ and ‘d’, inclusively, in the range.
- **elapsed_time –** is the total amount of time, measured in milliseconds, that the student spent working through each question.

5. Approach

In the proposed ALS approach integrating Fuzzy Logic and K-means clustering algorithms, the learner model and the domain model are created based on the dataset, whilst the adaptation model recommends the most suitable learning material for the learner. As the goal of the ALS is to provide a suitable learning path and automated personalised content for each learner, the ALS model will automate the learning process and make appropriate recommendations regarding subsequent elements of the pre-specified content. For example, if the learner is performing well, the ALS will suggest advanced level learning material. However, if the learner is struggling with their performance, the ALS will suggest easier topics. The ALS continually monitors the performance of the learner and adjusts and changes the suggested content accordingly as a result of monitoring the performance of the learner.

6. Conclusion

The concept of adaptive learning has emerged as one of the most important paradigms in the field of educational technology research in recent years [3]. In this paper, a Fuzzy Logic and K-means clustering-integrated adaptive learning system (ALS) is proposed. This integrated adaptive learning system includes multiple learning paths for learners according to their responses based on their understanding of the learning material. This paper discusses the proposed ALS architecture and approach of generating multiple learning paths established upon the learner’s responses to the presented material.

7. References

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