

A Framework for Adaptive Personalized E-learning Recommender Systems

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Abstract: With the undergoing technological revolution in education, adapting recommender systems to the personalized e-learning is an emerging topic in the education sector. Detecting the student model offers a potential to recommend a learning material that is adequate to the student progress. Accordingly, the learning objects and hypermedia can be adapted to each individual student to meet the personalized learning needs. This paper proposes a framework for applying recommender systems in personalized e-learning domain. Furthermore, the recommender system previous examples, opportunities, and associated challenges are discussed.

Keywords: E-Learning, Recommender, Personalized

1. Introduction

Education is considered as an important factor in the economic growth. The economic growth can be achieved by education that increases labor productivity and increase knowledge on new technologies, products, and processes that promote welfare. E-learning is a new trend to teach and learn better than the traditional class room and allows everywhere anytime learning [32].

The idea of the adaptive personalized e-learning is emerged from products recommendation and personalized goods advice and guidance in the e-commerce using software modules for recommending relevant products to the customers based on their experiences. This effective idea is then migrated to e-learning domain [16].

In 1984, Benjamin Bloom proposed the "two sigma problem" which indicates the one-to-one instruction is better than traditional classroom by two standard deviations. Traditional educational systems disregard differences among students and capabilities among teachers. Bloom emphasizes teaching style would be continuously differing to match the student learning style and advancing rate of each student separately. The teaching would fit the student while advancing with the course. The advanced student needs the class to advance more quickly than the struggling student.

The advanced student may sense bored with the class. The too fast class advancing with the class may make the struggling student feel unable to follow and give up.

Personalized learning is the solution for one teacher per each student learning methodology. The real class may not be able to provide one teacher per each student. However, the advance in the e-learning is offering a good candidate for implementation of one teacher per each student in the class and adapting the course material, learning styles, and the quizzes to the learner preferences. Personalized E-learning offers learning solutions for large classes of diverse backgrounds, attitudes, and learning needs [46].

Firstly, the proposed architecture of the personalized e-learning recommender system is explained and then sample works of the holistic recommender personalized e-learning systems are discussed. Later, the future works and opportunities after implementation of the proposed architecture are studied. In the end of the paper, the main opportunities and highlights of the proposed framework are summarized.

2. E-Learning Recommender System Architecture

The proposed platform for the general e-learning

recommender system contains the following layers:

- i. Cold start mechanism.
- ii. Data Cleaning and Pre-Processing
- iii. Recommendation model
- iv. Learner Model
- v. Domain Model
- vi. Supplementary data like web logs.

2.1. Cold Start Problem Mitigation

The first learning object recommendation of the recommender system cannot depend on previous user preferences. To solve this problem, a static questionnaire can be used at initialization or new user registration. As a starting point, learning style and accordingly a learning strategy can be deduced from the questionnaire. The questionnaire should be filled carefully by the student. If it is filled within a short period of time, it can be requested by the framework to repeat it to assure recommender system quality.

2.2. Data Cleaning and Pre-Processing

The raw data collected are cleaned to remove low quality or faulty data. Also, pre-processing operations are done. For example, data format is adjusted to be processed using next layer.

3. Adaptive E-Learning Model

The adaptation module algorithm and some literature examples of the module are discussed.

3.1. Adaptation Module

The recommender system links the best fit materials to the user. The following tasks are considered before processing in the adaptive model:

- i. Normalization: Data coming from different sources need to be normalized to same range for mining purposes.
- ii. Grouping Step: in the recommendation algorithm, continuously clustering the student is used for dynamically fitting the student into a group for recommending materials accordingly. K-NN is a popular method for clustering the student into the nearest group for the student to fit in.
- iii. Recommending: predicting the learning object that is the most suitable for the student.

The proposed platform will gather the data from high number of users to overcome sparsity problem and will recommend with techniques not completely based on high ratings to overcome overspecialization problem.

Adaptive hypermedia recommendation process depends on a recommendation algorithm through collaborative recommendation, content-based recommendation, experience based, or hybrid recommender system.

3.1.1. Collaborative Recommendation

The technique is based on the previous experience of

learners and analyzing the current student interaction and records to find similarity between the current learner and the previous learners in order to assign the current student to a student group. It compares behavior patterns and find a group for the current learner. The drawback of the collaborative recommendation is that it requires user interaction and feedback while some users resist the forms of feedback or ignore them. One other drawback is the cold start problem. Moreover, the method fails to classify the users with unique demands who are not good match to any other groups. In addition, the collaboration filtering technique cannot solve the sparsity problem as the technique needs to have knowledge about high number of user ratings [40]. Also, the technique is not coping with the possible preference change of the student. A wide range of student models through previous recommender framework can mitigate this problem. Examples of recommender systems include collaborative recommendation like MEMOIR [36].

3.1.2. Content Based Recommendation

The recommendation results from the pages and the content which the learner visited with no consideration about what other learners did. Documents and lessons retrieval results in identification of user preferences and user model. The drawbacks of content-based recommendation are the cold start problem and the inability of wide recommendation after specializing too much in the user detailed preferences. It is also missing inspection of images and monitoring the viewing time of the document as it may be not a student preference. Examples of recommender systems include content-based recommendation like Personal WebWatcher [30] and Web-Mate [15].

3.1.3. Knowledge Based Recommendation

Knowledge based method is used for recommending when the user ratings are not ready or sufficient. The recommendation is based on some if-then rules that represents the knowledge of learner interests. The technique is suitable when the experts design significant rules that are not too much get affected by aging and still valid after time. It requires expert based rules, but it is sensitive to student preference changes and does not suffer from sparsity or cold start problems.

3.1.4. Hybrid Filtering Recommendation

The method is based on combining several techniques like machine learning with recommending algorithm to combine advantages of both techniques and minimize limitations for the integrated solution [19].

3.1.5. Examples of Recommender Systems

Kazanidis and Satratzemi [28] proposed AEHS system that is following SCORM standard. It is built to conduct courses which are adapted to the user and allow the mentors to track the progress and deliver feedback when necessary.

Al-Aubidy [2] designed a fuzzy logic model for the learner in order to feed the student with the educational data required for his level. It detects the student leaning level upon which it

suggests the corresponding way to enrich knowledge per each student. An introductory exam identifies the primary model of the student level. Then, it conducts continuous update of the learner model based on progress with the lessons. The change in the student model results in changing the content. It selects either to give a summary for the student in case of the student is high achiever or it teaches the normal class to the common students. For the student straggling with the course, it recommends the comprehensive explanation materials. Fuzzy rules are based on current knowledge level of the student, time spent on the lesson, and the outcome of the current lesson assessment to determine the content for the next lesson.

Almohammadi et al. [3, 4] proposed a scalable type-2 fuzzy logic recommender system for improving e-learning adaptability to the learner taking into consideration the student engagement level detection through the Kinect 3D Camera which identifies student engagement through the learner facing direction and emotions without wearable electronics. The proposed system can help in implementing adaptive teaching using type-2 fuzzy system that is interval-based which allows more freedom in dealing with extreme uncertainty conditions. The fuzzy rules recommend the most appropriate teaching approach like the PowerPoint explanation, questions and answers, examples, or the practical examples approach depending on the engagement and course difficulty. Also, this data empowers the system to recommend course modifications to teachers. The system is tested on learners in University of Essex and compared to Fuzzy Type-1 and non-personalized teaching approaches. Fuzzy Type-2 was found to have better recommendation than Type-1 and much better than the non-personalized approaches.

Combination of machine learning approaches proposed by Aher & Lobo [1] and combined algorithm (Clustering, Simple K-Means, and Apriori Association Rule Algorithm) are utilized to recommend particular MOODLE courses for learners based on enrolled classes. Aher & Lobo [1] proposed a data mining recommendation process based on historical data.

3.2. Learner Model

Learning style has no concrete definition in the literature. However, it can be defined as the set of attributes and behaviors that define the best student learning method [20, 22, 41]. Learning style has different models like Kolb's model [43], Felder's model [27], and Myers-Brigg's [13] presented below:

Felder-Silverman learning style (FSLSM): invented by Felder and Silverman in 1988 with focus on engineering students. Based on 44 questions, it categorizes the student learning style (sensory, intuitive, visual, verbal, active reflective, sequential, or global) according to four dimensions (perception, input, processing, and understanding) [24]. It is the most preferred in the literature because it provides more details and uses scales representing the strength of the student preferences rather than one concrete judgement [7].

Kolb's learning style model: invented by David Kolb. It starts from reflection till experimentation based on four stages (concrete experience through feeling, reflective observation through watching, conceptualization through thinking, and active experimentation through doing). The learning style can be accommodator who prefers practical problem approach, converger who prefer tasks and problems, diverger who prefer to watch, imagine, and gather information, and assimilator who prefer ideas and abstract concepts.

Learner model can be identified using several methods:

- i. Rule Based (KNN): through applying rules that map learning styles to the learner behavior. For example, applying KNN for learning style identification. Applying KNN, [37] achieved 95% precision.
- ii. Probability based techniques: Bayesian Knowledge Tracing can deduce skill proficiency level of the student through the past achievements and identify if each skill is learned or not [17]. Spaulding and Brezeal [42] extended other variables like taking into consideration the student connection to the material presented. This extends the Bayesian model through adding new nodes to the old Bayesian system like nodes for student ambiguity and happiness level. Actions to repeat lessons may be taken if it is deduced that the student cannot follow the class. [5] applied the combined algorithm for performance prediction on Gaza secondary school student with 93.6% precision.
- iii. Markov Chain Model: Student model and progress is prone to stochastic characteristics. [11] developed a Markov model for Slovenian student's performance for monitoring and estimation based on student logs and records.
- iv. Decision Tree: can identify the output learning style from input behaviors. [35, 14] used decision tree and hidden Markov for student model identification.
- v. Artificial Neural Networks: LSID-ANN [7] proposed a system that contains four networks (one network per each learning style) and three perception layers. The system applied on 75 students. [25] proposed learning style identification in MOOCs. Identification process is based on interaction behavior of learner and questionnaires (example ILS questionnaire).
- vi. Optimization techniques like Particle Swarm Optimization: [8] provided automatic identification of Felder-Silverman learning style model and evaluated on 75 students.
- vii. Fuzzy logic: Fuzzy logic is an attractive solution for representations of human uncertainties, experience, knowledge, student assessment and people differences. Nolan [33] proposed a fuzzy logic system that is responsible for grade estimation of students' writing activities. The system could achieve the student grades faster and with similar ratings of the real class teacher. The traditional teacher rating is facing difficulties like the challenge that the student is not receiving the same rating by two different

teachers. Moreover, the same writing task may have different ratings by the same teacher due to different psychological factors like nervous conditions. The trained fuzzy model ended with 21 classification variable and 200 rules based on writing rating principles used for inference like understanding, new ideas presented, etc. The model presented 97% coincidence with the expert teachers with 1-degree tolerance.

- viii. Hybrid methods: Ogwoka et al [34] presented a J48 decision tree and Simple K-means based model to evaluate the student model based on data like the attendance, lesson tests, student enrolment status (full-time, part-time), etc.

3.3. Content Model

It represents representation of all learning materials like the courses while each course contains a set of concepts. The concepts are linked to different learning objects. Learning management systems (LMS) materials are abided by standards like SCORM (Sharable Content Object Reference Model) [9, 39] to simplify its re-usability in the recommender system.

Traditional static hypermedia expresses same content for all students while content adaptation through dynamic adaptive hypermedia representation supports the adaptation models [6] that include designing a representation for the goals, preferences and the knowledge per every student for matching the individual needs [12]. [12] provided a taxonomy to classify adaptive hypermedia technologies to include:

- i. Adaptive presentation: content concepts are changing according to the student's needs. The concepts represent the atomic information amount. Examples are AHA! [18] and HYPADAPTER [26].
 - 1. Adaptive Multimedia presentation: information can be presented as text, audio, or videos according to learner preferences.
 - 2. Adaptive text presentation:
 - (a) Natural Language adaptation.
 - (b) Canned text adaptation: include fragment processing, changing, inserting, removal, and dimming.
 - 3. Presentation modality.
- ii. Adaptive navigation support: modifies hyperlinks the user can see.
 - 1. Direct guidance: through the shown buttons like "next" or "continue".
 - 2. Adaptive link sorting: best sorting based to the most relevant to the user. The method used extensively in INTERBOOK [21] and HYPADAPTER.
 - 3. Adaptive link hiding: non-relevant information links are handled by:
 - (a) Hiding.
 - (b) Disabling (can be done through color changes).
 - (c) Removal.

- (i) Adaptive link annotation: changes the link text and appearance style. The method is very popular in AHA!, INTERBOOK, ELM-ART [45], CHEOPS [23], and COOL [44].
- (ii) Adaptive link generation.
- (iii) Map adaptation.

4. Holistic Recommender Systems

[10] proposed a personalized e-learning recommender system, called PERS, based on collaborative filtering recommendation to propose adaptive class materials that match student's needs based on group preferences. The cold start problem is solved using a static questionnaire per each new student base on Index Learning Style Questionnaire (ILSQ) to create initial model and initial recommendation. Learner model is continuously updated based on data mining of student interactions and preferences.

[16] presented a framework named personalized learning recommender systems (PLRS) applied on online learning to recommend new corresponding course material that fulfill the student needs. The proposed framework analyzes the learner data (static data like enrollment type whether full-time or part-time student, behavioral data and lessons visited before) and specifications (based on fuzzy multi-criteria decision problem as non-deterministic weights of factors vary per each learner) to find a corresponding list of learning materials recommended based on the fuzzy rules. The offline based PLRS system is experimentally applied on a database course for irrelevant background faculty learners such as engineering, business, and science to support each individual learner with the material required to follow the class.

5. Future Work

Most personalized systems are using collaborative filtering or content-based recommendation. Knowledge based recommendation is to be further investigated.

In the middle school mathematics, data sets are available like PSLC DataShop public available DataShop (n.d.).

Future work can be applying bigger and different datasets using the proposed framework to conduct larger training and testing test sets. Comparisons using different combining different AI methods in terms of time, cost, not only precision.

6. Conclusion

Recommender systems help the students to discover new learning objects. The one to one learning remains the main challenge for better education system. The personalized e-learning systems takes into consideration the learner style and personality for learning material recommendation per each student.

The study suggests a layered framework for personalized recommender system that solves the previous literature limitations like cold start problem, sparsity problem, and the

over specialization problem. Several insights about previous works for researchers and educators for improving the educational system are discussed and highlighting new opportunities with the implementation of the proposed framework using the available datasets.

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