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A Survey on Recommendation Systems in E-learning

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ABSTRACT

Currently new innovations and with rapid development of Internet, access to data have been made simpler, this gives raise to new difficulties to utilise educational resources. Gone are the days when conventional method of teaching was the only way where students could learn and practice. In current scenario, learning through MOOC's is on a rising trend. Massive Online Open Courses (MOOCs) sites, for example, EdX, Coursera and Udacity, are picking up force. In regards to this, students are able to learn through various online educational resources provided by different MOOC's platform. But it has been observed that is difficult to select the suitable learning material from the available massive educational resources online. Different recommendation systems have been developed to fulfill this need. Recommendation Systems try to assist the user by suggesting the objects that the user may be interested in, predicted on the basis of users known preferences or with similar features of the other users. In this paper we surveyed various recommendation systems and we provide comparative analysis of those systems.

1. Introduction

E-learning in reality is a progressive method to provide education, contrasting with the customary face-with face learning and teaching style. These days an ever increasing number of individuals have profited from different e-learning programs. Current educational platform, for example, Coursera, edX and Udacity, have turned out to be prevalent. Such platforms enable scale and distance teaching through the presentation of educational recourses as massive online courses (MOOC). In the educational technology environment, MOOCs are growing rapidly. MOOCs must move from their one- size-all mode [1]. Usually a course comprises of number of short videos, each focusing on a particular concept. To accomplish certain learning targets, teachers usually order the videos that are in the syllabus. The learners or students commonly expect to accomplish career growth as opposed to finish degrees or get certificates. It is important to give students with flexible access to a wider range of content from various courses [2-4]. MOOCs are equipped to provide access to online courses for a large number of students. MOOCs are allowing the people to get their learning resources. It offers novel learning method that is open and distributed. MOOCs have recently acquired a great deal of attention in top universities, currently it is also regarded as a very promising form of education. Many universities offer courses in the form of MOOC that offer students a wide range of options. Technology enhanced learning (TEL) is an academic area of research in which many disciplines are continually investigating learning processes and learning potential. Learners must find the most appropriate resources the enormous amounts of resources on the web. But finding suitable resources quickly isn't an easy task for any user [3-5-11]. Since the searching and retrieval of information for suitable learning resources is key activity in TEL, the development of recommendation systems for learning has received more attention [3]. Recommendation systems enable the learner to find the learning material that fits best to the learner.

The main purpose of the Recommendation Systems (RSs) is to select information which may be of interest to the user [6]. A recommendation system can be defined as is an application that can suggest an object to the user based on the user's earlier preferences and the preferences of other users having similar likes. Recommendation Systems assists us in reducing the information overloading, while simultaneously providing personalized access to resources for a particular domain.

Aditya Parameswaran et al [7] introduced two course requirement frameworks and considered the dual problems of monitoring requirements and making recommendations. Rel Guzman Apaza et al [8] introduced a new approach to recommend online courses combining the probabilistic Latent Dirichlet Allocation (LDA) model topic with content- based recommendation systems using machine learning approach where LDA allows, to extract feature descriptors from courses and prediction of rating is done by inferring user profile parameters using multi linear regression. Sunita B. Aher et al [9] shows how helpful data mining techniques for example, clustering and association rule algorithms are in the Course Recommendation System which suggests the course to students based on other students choice for specific Moodle courses. The new learner or student who recently registered for some course can be recommended other course based on the previous course. The methodology used combination of clustering techniques, such as Simple K-means, Association Rule Algorithm – Apriori Algorithm. Mohamed Koutheaïr Khribi et al [10] describes that the in the field of Technology Enhanced Learning (TEL) recommendation systems are gaining interest, especially as Big Data learning analytics and Data Mining are growing. TEL recommendation systems are generally used to help students locate relevant educational content based on their profiles. The authors analyze TEL recommendation systems which presently exist. D.F.O.Onah et al [11] proposed a framework, by using the learners' profile it provides the recommendation of instructional material. The system can provide a suggested learning path for the user to achieve the appropriate learning goals, further recommendations with appropriate resources can be made to enhance and develop the learner's understanding of previous topics. The MOOC Recommendation System depends on the idea of generating prediction as indicated by other students' encounters and experiences, but as the number of students expands it turns out to be computationally increasingly, more costly to compute the recommendation. Dr. Ritu Tiwari et al [12] proposes a hybrid approach to deal with this problem. Under this technique, just a small division of similar students or learners are taken in use to generate the prediction, instead of using a complete learning database. This division of similar students or learners is called the learner's neighborhood.

The rest of the paper is organized as follows: firstly literature review on recommendation techniques and recommendation systems. Secondly comparative table of recommender system and lastly we conclude the study.

2. Literature Review

The purpose of the recommendation relates to the utilization objective of the recommendation systems, its practical purpose is for a particular category of users, i.e teachers, learners, students, who may be one of these:

- Recommending the action of a learner: Proposing a user to take the next action after the recent click
- Location and suggestion of relevant links: To provide users with a set of associated and suitable educational objects such as learning activities and learning activities.
- Building appropriate learning mechanisms: To achieve some of the underlying objectives, propose appropriate paths for learning or instances for an online course.
- Location of users: To create an educational network, recommend a number of users with similar interests and profiles

It is vital to understand the characteristics of learners in order to create an efficient RS or E-learning systems.

- Characteristics of learner
- learning objective
- prior knowledge
- Pathways of learning
- learning in group
- Evaluation of learning activities (LAs)
- Strategies for learning in an RS.

E-learning systems ought to identify learners and use the characteristics of these learners as guidelines to design the frameworks and the implementation of platforms for good e-learning RS

- A good RS should be very customized: The selection and presentation of relevant learning materials to the students or researchers should be based on the learning style, current activities, interests, individual preferences.
- A good RS must suggest learning resources at the acceptable location and time: It should provide students with appropriate learning materials at the suitable location and time to assist the acquirement of knowledge and skills by the students.
- Good RS should be viewed without disruption: It must be non disruptive, that is students can either follow relevant materials or discount them on the basis of their learning needs.
- A good RS must be socially located: It should be able to identify the level of influence and trust, role models, social networks, of the learners and exploit them. RS should also help students recognize the process of acquiring knowledge in the group.
- The adoption phase should be included in good RS: A decent RS ought to examine, know the learner and model the different phases of learner adoption. It incorporates into specific the stages in which the new ideas are tried, inspected, disguised lastly connected.
- The process of continuous learning should be supported by a good RS: It should maintain just-in-time learning through a better analysis of its present and future activities. Motivational support and encouragement should also be provided.
- A good RS should offer high level interactivity level: A decent RS in the form of rich selection strategies of interaction should offer a very active, effective behavioural and diverse mode of communication with the students.
- A good RS should provide appropriate course materials in accordance with the students learning style: Every student learns completely in a different way and develop their own learning skills. Learners have different interests, weaknesses and strengths, aspirations, accountability, motivation levels and learning approaches.
- For instance, different students enjoy different forms of presentation, some incline towards multimedia contents like visuals, presentations and graphics material while others may lean towards conventional web pages like surveys, exercises, questionnaires, research methodology.

2.1 Recommendation Techniques

Content based filtering technique: This technique recommends items based on a comparison of the content of the items with a user profile. They offer similar items to those preferred by the user in the past.

Collaborative filtering technique: This technique is actually referred to as a similar learning pattern which is considered to be the similar rating behaviour of learners used to predict learning similarity recommendations among the participants [1]. It follows up on similar patterns of learning of figuring out how to recommend courses to the students so as to improve their learning background and experience. Fig.1 shows a flowchart of the learners rating concepts and contents recommendation

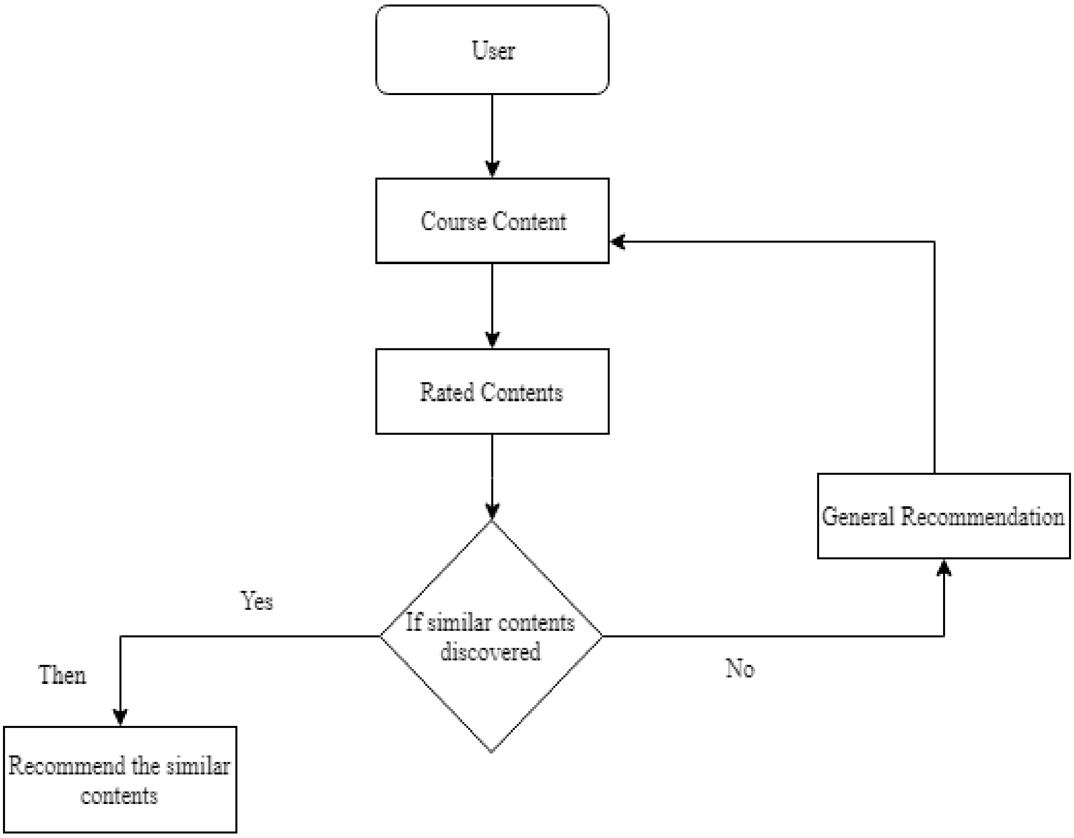

Fig. 1. Flowchart of learners rating concept and content recommendation [1]

2.2 Recommendation Systems

MOOCex Recommendation system

In [2], the author introduce the MOOCex recommendation system. MOOCex seeks to help students or learners access MOOC content effectively and efficiently, across courses and content platforms. They first combine this content into several courses and introduce the difficulty in linking videos wherein instructors cover up linked topics from various perspectives. In addition, users must also select their information needs from these related videos. A content based recommendation and interactive visualization are presented to assist course navigation.

MOOCex is build using advance data mining techniques and takes into account video topics and sequential inter-topic relationships together to recommend lectures. In order to present additional depth about particular concepts and optimize learning, instead of individual videos MOOCex recommends short sub sequences of videos in courses.

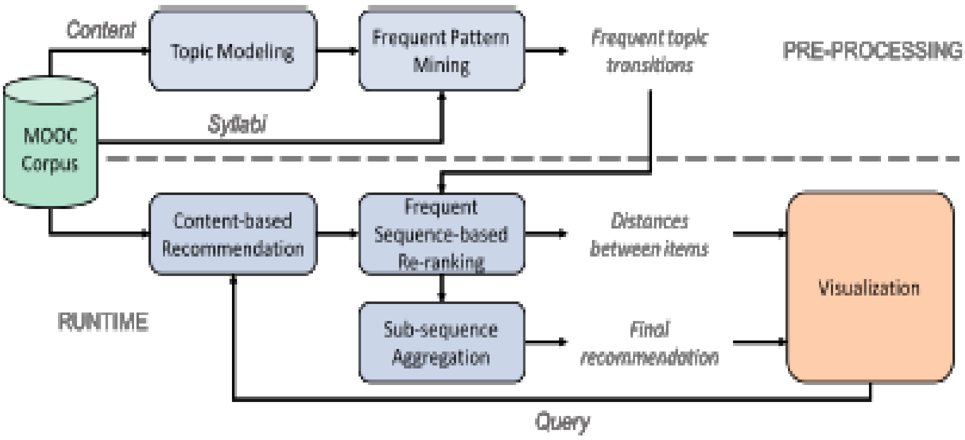

Fig.2. MOOCex System Architecture [2]

MOOCex is composed of two segments as shown in Fig.2 (i)Content-based recommendation engine (ii)A visual interface for video playback and semantic exploration. While the syllabi provide guidance to the learners in courses, recommendation is given to encourage investigation of multi-course corpus.

In the recommendation engine, sequential pattern mining is then used to incorporate sequential information. In a sequence database, sequential pattern mining (SPM) algorithms identify significant sequences. Firstly the recommendation engine issues a query to the currently watched video in the content based recommendation system. Currently it uses standard tf/idf vector space recovery based on video transcript with a cosine similarity ranking.In order to emphasize with results, which the users are much more probale to watch next, a method is introduced namely Re-ranking method which incorporates scores and emphasize results that are consistent with the conceptual transition undertaken in global analysis of corpus.

The MOOCex visualization interface is composed of three parts, Video panel, Recommendation Panel and Configuration Panel. The video panel is a media player for watching a video which is selected. A learner can explore recommend videos in recommendation panel and evaluate their relationships to notify their descision to watch the next video. This allows basic configuration panel parameters to be manipulated to control the presentation of recommendations of specific videos and courses.

MOOC-Rec Recommendation System

In [3], the authors introduce the MOOC-Rec RS. The system presents that in reply to a particular student request, the MOOC-Rec system recommends appropriate MOOCs. Using Case Base Reasoning (CBR) techniques, the MOOC-Rec system responds to the students request with the most appropriate MOOCs from different providers.

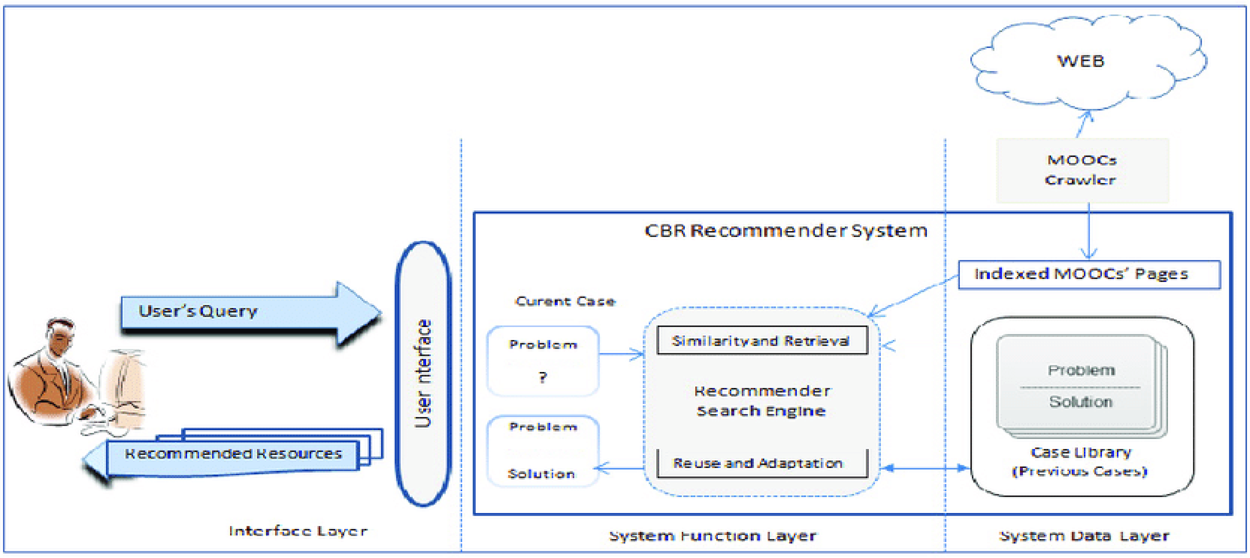

Fig.3. MOOC-Rec System Architecture [3]

The MOOC-Rec's architecture is shown in fig.3 MOOC-Rec consists of three layers (i) User interface layer (ii) System function layer (iii) System data layer. The layer of user interface is the MOOC-Rec system interface; the primary function is to receive requests from the user interface. The system layer handles the processing and construction of case search, case recovery and case adaptation, also the recommender's reasoning function. System data layer is composed of three parts (i) Case base (ii) The user case and (iii) Similar user case.

The CBR recommender system in MOOC-Rec is very much alike the generic CBR problem solving system, involving the conventional four steps of the CBR method which is recovery, reuse, adaptation and retention. This begins with a new problem, from the case base it finds related cases suggesting the solutions found to the user or adapting the solutions to considerably better solve the new problem and ending the procedure by retaining the new case.

Group Recommender System for Online Course Study (GRS-OCS)

In GRS-OCS recommender system [5] content-based filtering and collaborative filtering is integrated, to enhance the learning efficiency of online learners.

GRS-OCS makes broad utilization of recorded data about previous understudies and evaluations of courses, to suggest appropriate courses to the students. The GRS-OCS system consists of three segments (i) Categorization of course information (ii) clustering the learners and courses into groups (iii) Top-N recommendation.

Categorization of Course Information: Initially, every course information is by existing category. The system uses a multinomial text model wherein all information of course is modeled as an ordered sequence of word events taken from similar vocabulary.

Clustering the Learners and Courses into Groups: The student or learners and the courses can be partition into different classes in the field of online course study. The student or learners with the comparable ratings or learning preferences on the present courses can be separated into same cluster. Moreover courses can likewise be partitioned by remarks, class, and so forth into various clusters. For multiple classes clustering, a soft clustering method fuzzy c-means is used in GRS_OCS.

Top-N Recommendation: Students and courses may belong to different groups; the results of the prediction generated by these groups must be combined. In this step, these groups can be combined with conventional collaborative filtering methods. The best or the top- courses can be suggested or recommended by sorting the prediction scores in a decreasing order for each student. To enhance the recommendation results, the GRS-OCS system requires not more than three courses are from the same group.

Protus Recommendation System

The primary function of the Protus system [6] is to provide e-learners with significant and engaging materials depending on their diverse preferences, learner's backgrounds, learning purposes and other related attributes.

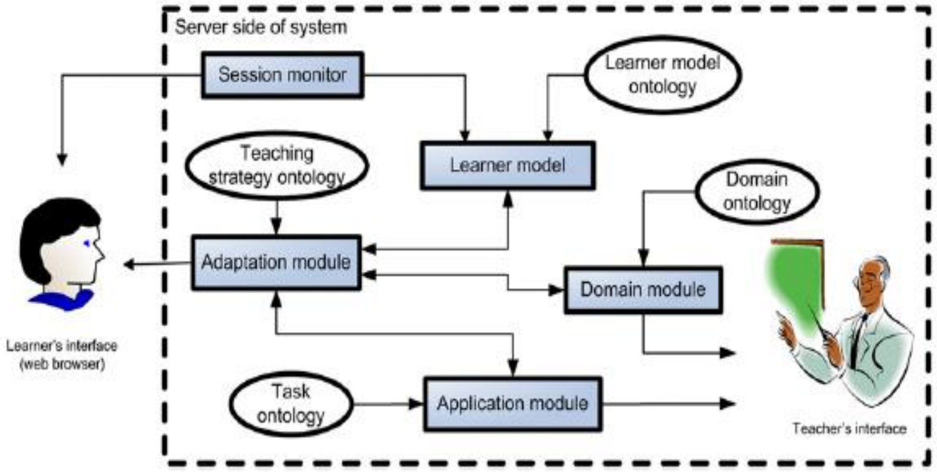

Fig.4. Protus System Architecture [6]

Fig 4. shows Protus system is composed of five practical modules to be specific namely domain module, learner model, application module, adaptation module and session monitor. The domain module provides storage for all the necessary learning material, tests and tutorials. The learner model is gathering learners static and dynamic information, the framework utilizes this data to foresee the conduct of the student and adjust it to his/her own needs. The adaptation is done by the application module, the adaptation module follows the instructions specified in the application module to be precise.

To facilitate the addition of new content clusters and adaptation functionalities, these two components are separated. The system gradually remakes the learner model amid the session within the session monitor component so as to monitor the students or learner's activity, action and progress, identify and correct the student's mistakes and potentially redirect the session accordingly. In the learner model all preferences of learners are recorded at the end of the session. By altering his/her favored learning style, the student can change this data whenever. In this way, if a student can't help contradicting the frameworks assumption about the user's preferences, user can analyze its model amid the learning session and make changes to it. The learner model is then used to instate the following session, for a similar student with other data and learning style.

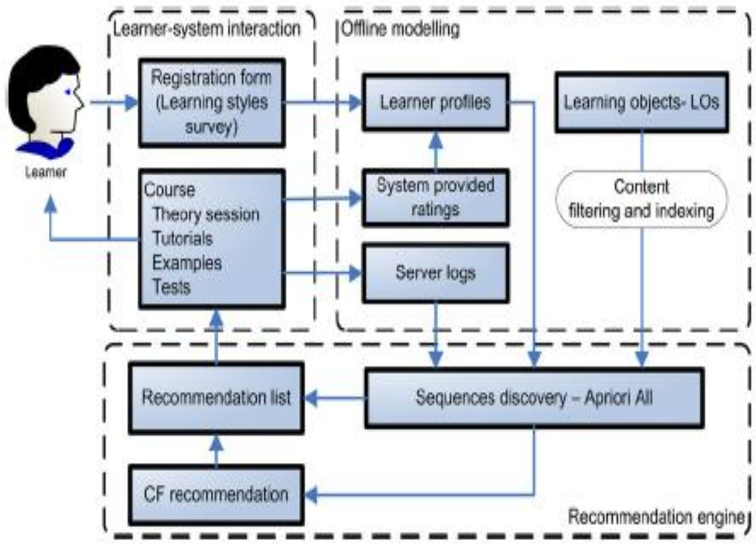

Fig.5. Protus system recommendation component [6]

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The Protus system, recommendation framework consists of three modules as shown in Fig.5: A learner-system interaction module: It pre-processes the data for building a learners module. This module collects data of learner's activities such as sequential patterns, results of visited pages and grades obtained. The student registration pages, theory sessions, tutorials, examples and tests are extended with the input background processing.

An offline module: It uses learner's model to recognize content profiles and learners goals. After each student has determined an appropriate learning style, the learning content is filtered on the basis of the initial survey, depending on the course's present, the student's association and the system ratings.

A recommendation engine: It delivers a suggestion list. The list of recommended actions and resources is sent from the filtered list of learning content and based on the discovered sequences to alter the interaction between learner and system in new session.

3. Conclusion

Recommendation systems are mainly used in the field of e-commerce and have been very successful. E-learning is relatively new area, considerable work has been done, but a lot of scope has not been discovered and therefore a lot could be contributed in the future. In essence, recommender systems analyse learner's requirements and needs, conclude the relevant learning content or items and recommend the most appropriate information content to the learner, which saves the user from overloading information and saves a lot of time and effort. This paper takes an overview on recommender system, providing the comparative analysis. From the study it is observed that Protus Recommendation System is better RS compared to other RS taking into account the pedagogical activity and also in terms of accuracy.

Table-1
Comparison of Existing Recommender Systems

Paper	Name of Recommendation System	Techniques/ Algorithm	Objectives	Observation
[2]	MOOCex RS	Content Based Technique	MOOCex is build using advance data mining techniques and recommendation of lectures is done by considering both video topics and sequential inter-topic relationships into account. In addition to individual videos, MOOCex alternatively recommends short sequences of videos in course to provide additional depth around specific concepts and simplify learning.	MOOCex promotes the semantic visualization of recommended videos in the current learning context of users by projecting videos in a 2D space annotated with tropical regions and key phases. This provides students with additional dimensions to explore related content effectively and to choose what to watch next.
[3]	MOOCRec RS	Case Base Reasoning Method	In response to a specific learners request, the system recommends appropriate MOOCs. Using CBR techniques, the system offers students the most suitable MOOCs from different providers to respond to their request.	CBR RSs do not have to store large amounts of data on the rating of items or specific users that the databases does not need to be too large as we only need sufficient features to look for similar cases.
[4]	Reciprocal RS	Ranking Algorithm	The reciprocal RS matches learners who are likely to communicate with each other based on their profile attributes like location, age, qualification, gender, interests, etc	The system enables students to reach other similar learners and communicate with them, thus facilitating intelligent discussions and encouraging peer learning.
[5]	GRS-OCS RS	Collaborative and Content based filtering Technique	GRS-OCS makes extensive use of historical information about former students and ratings of courses, which can recommend appropriate courses to students.	GRS-OCS has certain advantages compared to recommendation based on users and items. On the other hand it is found that the system can provide more diverse recommendation results.
[6]	Protus RS	Collaborative filtering Technique	The recommendation system for adaptive and intelligent web-based tutoring system Protus, which takes into account the learner pedagogical aspects and the need to recommend pedagogically effective sequence of learning activities.	The recommendation provided is expected to be more accurate in matching the learning material requirements of the students and thus a higher level of acceptance by the students.

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