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An Architecture for a Personalized Learning Recommendation on Knowledge Level of Learner

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Abstract— E-Learning is considered as one of the most popular research areas in distance and web-based education. Nowadays, most of the educational institutions such as universities, colleges, and vocational training centers are adapted e-Learning environment to give quality and efficient service to learners. This paper presents a novel approach, a framework for building an architecture for personalized learning recommendation system by considering learner's knowledge. The knowledge, skill, preferences and learning style of each learner is different. Therefore, we should understand different needs of learners and provide a better recommendation to motivate them. A set of students who are following web application development course was selected to determine knowledge levels and performances. The proposed recommendation system consists of four components, Learning model, Domain model, E-assessment model and Recommendation model. In the E-Assessment model, the learner takes assessments in different levels such as initial, final, practice and assignment. While learner attempts, the system generates recommendations based on the level of knowledge. Through the system, each learner's progress can be identified and compared with other e-learners' results. Then learner motivates to learn more learning objects and stick to self-learning style. During this research, content-based filtering is used as filtering approach for making recommendations. However, cold start problem has been minimized by using an initial test at the start point of each learning module. Furthermore, the impact of introducing the e-assessment model to support and improve the learning process is evaluated by using two main activities: system testing and validation. Finally, the system generates right resources to learners in a personalized manner and shows the progress of each learner to motivate them to improve their learning process.

Index Terms— e-assessment, E-Learning, diagnostic assessment, recommendation system

1 Introduction

E-Learning is a form of electronic teaching that enables people to learn anytime and anywhere [6][9]. Nowadays, most of the universities, colleges, and vocational training centers are adapted e-Learning environment to give quality and efficient service to learners. The objective of an online personalization system is to provide users with the information they require, without asking them explicitly [6][9]. Therefore, personalization plays a significant role in the e-Learning system. This needs learner profile due to different preferences, learning styles, knowledge, and performances among learners. Due to the huge amount of learning resources on the web, it is hard to find learning resources related to learner request.

Recommended learning resources to learners based on their personal characteristics has been an area of research for many researchers. Predicting learner's performance timely can help them to improve their learning process, consequently improving student's academic performance. Therefore, a web mining technique such as regression algorithm has been used to implement result [11].

This paper presents an approach, an architecture for a personalized learning recommendation system by considering learner's knowledge. To identify the level of knowledge of the learner, e-assessment or Technology Enhanced Assessment (TEA) can be integrated with e-Learning environment.

The Bachelor of Information Technology (BIT) degree program is offered by the University of Colombo School of Computing (UCSC) as an external degree that allows students with an interest in Information Technology [IT] to study for a degree over a period of three years[22][24]. At the first year of BIT program, there are approximately 3000 registered learners including repeaters.

At the beginning of the BIT in the year 2000, UCSC offered it as an external degree where the university conducted only testing based on the published curriculum and teaching was carried out by third party institutes who had never trained candidates for degree level program. After a few years of its commencement, students' performance at the semester exams was decreasing gradually, together with the number of new students (registration). A learning management system (LMS) was introduced as an alternative way to guide the learners using the supplementary Multiple Choice Question (MCQ) based online assignments. This had some effects on reducing the failure rate and dropout rate of the program but the curriculum based testing was not enough to make a significant effect on the learners' performance as we observed while conducting the program. At the same time, the web-based LMS was an effective environment that can be used to create self-assessments of the learning process, in addition to collaborative learning activities. Both formative and summative assessments are used with respect to the curriculum of the courses.

The summative assessment is designed considering the overall outcome (learning objectives) defined in the curriculum and the teachers select a set of aspects to designing the summative assessment within the limited time allocated. The formative assessment is conducted as a continuous learning activity during the learning process of. The results and feedback of formative assessment must be made available as soon as possible to make it effective for the learning process. Generally, the percentage of an overall mark is decided based on the formative assessment to give the recognition for the active participation in the course. At the same time, the formative assessment prepares the learner to face the summative assessment with more confidence [17][18].

After analyzing the dataset in existing e-Leaning Environment, it showed that learners are still scoring fewer marks for formative assessments and summative assessments. The objectives of the research are as follow.

- Integrating a suitable e-assessment mechanism to determine initial level of knowledge.
- Recommending right learning resources in a personalized manner.
- Motivating learners to follow learning process.
- Encourage learners to do more practices to accomplish the final task.
- Providing a descriptive feedback to identify the learners' success and failures.

2 Theoretical Consideration

2.1 E-Assessment

E-Assessment offers both teachers and students new possibilities for interacting in an immersive and responsive educational environment, moving beyond the static environment of the traditional pen and paper approach (Crisp, 2009). Alternative modes of presenting assessment tasks are now possible, ones that are more adapted to the diversity in learning styles displayed by students. E-assessment has the potential to offer new forms of assessment with immediate feedback to students and is, therefore, one of the major challenges for both schools and higher education institutions today. It is, therefore, becoming increasingly important to construct a pedagogically driven model for e-assessment that can incorporate assessment and feedback into a holistic dialogic learning framework, which recognizes the importance of students reflecting upon and taking control of their own learning [23].

E-Assessment can be categorized as diagnostic, formative and summative (see Fig. 1) based on, at which stage of the learning the assessment is carried out [7]. Diagnostic assessment task is carried-out before the beginning of the learning process and is used to identify the current knowledge level of students so that learning activities can match student requirements. Formative assessments are carried-out during learning, which provides practice for students on their learning in a course and possible development activities they could undertake in order to improve their level of understanding. Summative assessment is the final assessment which is used after the learning has been completed. This type of assessment tasks is designed to grade and judge a student's level of understanding and skill development of progression or certification [7][14].

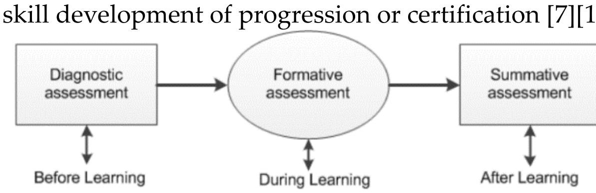

Fig. 1. The relationship between diagnostic, formative, summative assessment and learning

The formative e-assessment process explained in JISC [21] with respect to e-assessment and effective learning are described below. To provide an effective progress for the learner, learning and e-assessment have to be integrated together. Learning modules are provided either as e-learning or blended learning through a learning management system. After completion of the learning module, students are provided with assessments either as formative or summative depending on the course. After completion of the assessment, if they have successfully completed it, they will be provided with feedback or the final qualification. If they are not successful in the assessment, they will also be given a constructive feedback and a revision module which they can practice and take the assessment at a later stage. The relationship between e-assessment and effective learning is illustrated in Fig 2.

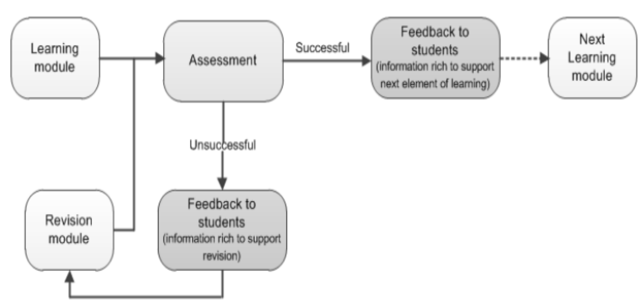

Fig. 2. The relationship between e-assessment and effective learning

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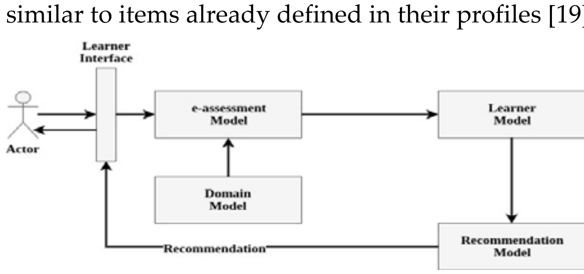
However, according to this model, students are provided with practice only if they are not successful in the assessment. As can be seen from the diagram, before moving to assessments, students are not provided with practice activities. Practice plays an important role in assessment as it provides students with the opportunity to act on the given feedback and improve their learning process [15].

2.2 Content-based filtering (CBF)

The content-based technique is a domain-dependent algorithm and it emphasizes more on the analysis of the attributes of items in order to generate predictions. When documents such as web pages, publications and news are to be recommended, the content-based filtering technique is the most successful. In content-based filtering technique, the recommendation is made based on the user profiles using features extracted from the content of the items the user has evaluated in the past [3][5][13]. Items that are mostly related to the positively rated items are recommended to the user. It could use Vector Space Model such as Term Frequency/Inverse Document Frequency (TF/IDF) or Probabilistic models such as Naïve Bayes Classifier [12]. Decision Trees [10] or Neural Networks [2] to model the relationship between different documents within a corpus. These techniques make recommendations by learning the underlying model with either statistical analysis or machine learning techniques. Content-based filtering technique does not need the profile of other users since they do not influence recommendation. The major disadvantage of this technique is the need to have an in-depth knowledge and description of the features of the items in the profile [19].

However, the techniques suffer from various problems. Content-based filtering techniques are dependent on items' Metadata. That is, they require the rich description of items and very well organized user profile before the recommendation can be made to users. This is called limited content analysis. So, the effectiveness of CBF depends on the availability of descriptive data. Content over-specialization (Zhang and Vijay, 2002) is another serious problem of CBF technique. Users are restricted to getting recommendations similar to items already defined in their profiles [19].



3 RESEARCH METHODOLOGY

The proposed recommendation system consists of four components, they are learning model, domain model, e-assessment model and recommendation model. Fig. 3 shows the architecture of the proposed recommendation system.

Fig. 3. The architecture of the proposed recommendation system

3.1 Domain Model

A domain model contains the knowledge about the curriculum structure. This model is split into three layers (course, learning module, learning object), the first represents the course and each course is divided into several learning modules, and each learning modules is presented by a set of learning objects [1]. A learning object holds one unit of knowledge and presents different aspects such as lecture notes, presentations, questions (multiple choice questions - MCQs, true/false, short answer and fill in the blanks questions), activities, examples, exercises etc.

Each course includes different levels of test to identify the learner level of knowledge. Each level of the test has a set of questions. Those questions have different types of difficulty levels. Table 1 describes the test structure.

TABLE 1. DIFFERENT LEVEL OF TEST

Test Name	**No of Questions per Test**	**No of Attempts**	**Type**
Initial Test(IT)	5	1	Diagnostic
practice Test(PT)	5	Any	Formative
Final Test(FT)	10	3	Formative
Assignment Test (AT)	nLM * nLo * 5	3	Formative

*No of Learning Modules per Course – nLM *No of Learning Objects per Learning Module – nLo

When a question contains more than one correct answer or when a question consists of multiple statements its difficulty level increases with respect to readability and

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reasoning. Although a MCQ generally has more than one correct answer, poor wording or phrasing in a question could make it a good or weak question [17].

- Difficulty Level 1 (Simple): A question could be read and answered within 30 Sec. to 1 Minute. These questions tests if students remember or understand concepts.
- Difficulty Level 2 (Intermediate): A question could be read and answered within 1 Minute – 2.5 Minutes. These questions tests if students can explain ideas and use if new ways.
- Difficulty Level 3 (Advanced): A question could be read and answered within 2.5 Minutes – 5 Minutes. These questions tests if students can distinguish between parts and solve problems.

3.2 Leaner Model

The learner model represents the various characteristics of the learner such as personal information, preferences, navigational patterns, accessed contents, level of knowledge, etc. which can be used to generate an individualized learning experience [4]. In our research, a learner who enrolls in a particular course is going to take tests to determine the level of knowledge and build the learner profile. Apart from that, learner preferences are used to present the learner profile as well [1].

3.3 E-assessment Model

In the e-assessment model, when the learner enrolls in a course and first time he/she is going to access the learning module, there is an initial test. After completion of initial test then the learner can access learning module. It consists of a set of learning objects. Each learning objects has learning materials and a practice test. The learner is provided an unlimited number of attempts in practice test. Once the completion of practice tests, the learner is provided a final test to check the knowledge level again about a particular module. Once it is successfully finished then the learner can move to next learning module. During this learning process, the learner has to take assignment tests to get the pass or fail with the grade. The main purpose of introducing this model was to provide more benefits for the learner to improve his/her e-Learning process. When introducing practice, feedback plays an important role. Feedback should be provided in a way that encourages the students to actively change their ideas and ways of organizing their answers and discourse within a given subject domain. This was taken into consideration while defining the formative e-assessment model to make it generally used for any subject [18]. Fig. 4 shows the proposed model for e-assessment.

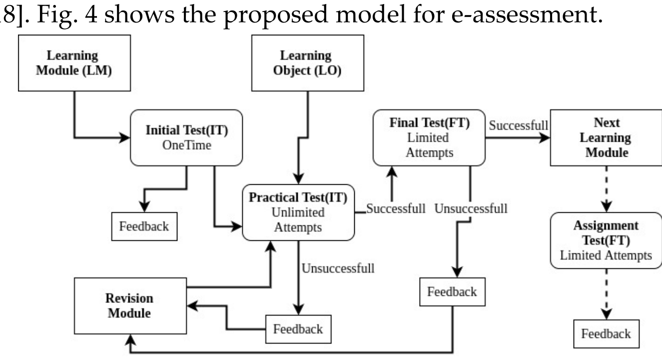

Fig. 4. The proposed model for e-assessment

3.4 Recommendation Model

In the proposed recommendation model, if there is a new learner, the proposed system invites the learner to take the initial test in order to build learner profile. Once the learner completes the initial test, the result is stored in learner model and the system generates the recommendation list for specific learner based on the result. Then the learning process can be started, we can overcome the cold-start problem in recommendation system. A common problem in recommendation systems is the cold start problem. It occurs when the new user is logged into the system. Due to lack of ratings of the new user, it is impossible to calculate the similarity between her/him and other users and thus the system cannot make accurate recommendations.

The recommendation module helps to generate the suitable recommendation to learners based on the level of knowledge. This module uses content-based filtering to do that. We apply the content-based filtering approach, the term vector is submitted in order to compute recommendation list. Results are ranked according to the cosine similarity of their content (vector of TF-IDF weighted terms) with submitted term vector [20].

4 Result and Discussion

The impact of introducing the e-assessment model to support and improve the learning process is evaluated following the action research methodology and comprised two main activities: system testing and validation, in a real scenario, a programming course in Bachelor of Information Technology at University of Colombo School of Computing.

For testing, a methodology is deployed in parallel with the system design and development process to evaluate the system. The testing methodology is comprised of three main tests, such as unit, integration and system testing. Under system testing, usability testing is also carried out to observe people using the system to discover errors and areas of improvement. During testing methodology, the errors found are iteratively corrected under each test.

The validation methodology is defined with respect to a validation plan to verify the quality, performance of the system and the model, and whether it satisfies expected educational requirements and learner needs. In other words, the objective of validation is to show 'proof of demonstration' in real life and show that the system and the overall process fulfill its intended purpose. For validation methodology, a mixed-mode evaluation technique comprising both quantitative and qualitative techniques is used. This is carried out through a pilot study in the real online environment. For evaluation, conducting a pilot study is important as it allows one to identify whether there is a positive impact with respect to introducing the proposed model, then carry out necessary modifications and introduce it into the actual classroom [18].

However, MCQs, true/false, short answer and fill in the blanks questions were selected as quizzes, these types of questions are good for assessing knowledge levels of learners when it comes to assessing skill levels, it is needed to go beyond these types of questions to provide rich feedback. Cognitive skills and the application of methods cannot be assessed via multiple choice tests and equivalent forms of basic assessment items [18].

The quality of a recommendation algorithm can be evaluated using different types of measurement which can be accuracy or coverage. In this research, Decision support accuracy metrics were used for evaluating recommendation algorithm.

Decision support accuracy metrics that are popularly used are Reversal rate, weighted errors, Receiver Operating Characteristics (ROC) and Precision Recall Curve (PRC), Precision, Recall and F-measure. These metrics help users in selecting items that are of very high quality out of the available set of items. The metrics view prediction procedure as a binary operation which distinguishes good items from those items that are not good. ROC curves are very successful when performing comprehensive assessments of the performance of some specific algorithms. Precision is the fraction of recommended items that are actually relevant to the user, while recall can be defined as the fraction of relevant items that are also part of the set of recommended items [19].

They are computed as

$$\text{Precision} = \frac{\text{Correctly recommended items}}{\text{Total recommended items}}$$

$$\text{Recall} = \frac{\text{Correctly recommended items}}{\text{Total useful recommended items}}$$

F-measure defined below helps to simplify precision and recall into a single metric. The resulting value makes a comparison between algorithms and across data sets very simple and straightforward [19].

$$F\text{-measure} = \frac{2PR}{P+R} \tag{2}$$

In order to implement and evaluate the proposed recommendation system, we used "Web Application Development 2 – WAD2" (Semester 3 in BIT) course as a prototype. We selected a set of students who are following BIT at UCSC in private institute to determine knowledge levels and performances. Those students had a little or lack of knowledge about PHP programming and other web technologies.

The result shows that students' performance significantly as progress in the above-mentioned course and also their learning activities were high during the studies. The following figures show the relevant evidence such as learner's individual performance and result prediction of the learner. It shows the comparison with other learners as well as.

Fig. 5. Learner's progress

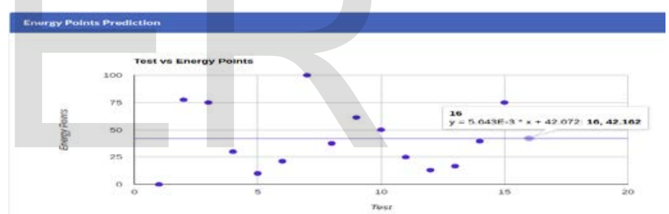

Fig. 6. Result prediction of the learners

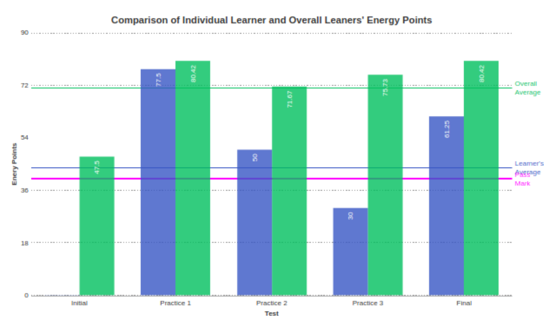

Fig. 7. Comparison of individual learner with other learners

5 Conclusion

The main goal of this research is to introduce recommendation system based on the level of knowledge for students to support and improve their learning process. Here, we proposed an e-assessment model that offers the different type of tests such as initial, practice, final and assignment to the learners. Based on the performance of the tests, we proposed a recommendation model to recommend suitable learning resources. The evaluation described using a course called “Web Application Development 2” in semester 3 BIT at UCSC and a set of students who are following BIT in the private institute. Here, we used CBF as recommendation technique to give right resources to students in a personalized manner. Web data mining was used to show the progress of each learner to motivate them to improve their learning process.

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