AN EMPIRICAL EVALUATION OF LEARNER PERFORMANCE IN E-LEARNING RECOMMENDER SYSTEMS AND AN ADAPTIVE HYPERMEDIA SYSTEM

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ABSTRACT

This paper introduces a novel architecture for an e-learning recommender system which is based on good learners' average ratings strategy and content-based filtering approach. The feasibility of the proposed system is conducted by comparing its performance against other recommender systems and an adaptive hypermedia system in order to measure the effectiveness of the proposed strategy in improving students' learning performance. Experimental result has shown that the recommender strategy can improve students' performance by at least 12.16%, as compared to other recommendation techniques. A performance evaluation with an adaptive hypermedia system that uses knowledge level as its adaptation feature also showed a positive increase of 14.99% in terms of students' performance.

Keywords: E-learning, Recommendation System, Adaptive Hypermedia System, Content-based Filtering, Collaborative Filtering

1.0 INTRODUCTION

World Wide Web has enabled users to gain access to almost any information at a click of a mouse. However, learners are often overwhelmed with a large amount of learning materials available on the Net. Despite having to spend time learning the materials, learners are lured into spending more time on browsing and filtering information that suits their needs better, either in terms of its knowledge value or preferences. Limited learning time can hinder learners in locating useful learning materials as they may usually end up getting irrelevant materials [17]. This problem has been addressed in both recommender systems and adaptive hypermedia systems researches, and several solutions have been proposed. Both technologies share a similar goal towards personalizing the delivery of learning materials based on users' profiles or preferences. While both technologies have been successfully implemented and tested, they are still lacking in terms of providing useful or good quality learning materials to the learners [12]. Perhaps, the existing research work focuses more on either personalizing the presentation of content, its navigation links or course sequencing according to a user model (e.g. users' preferences) [3, 13]. We are motivated to overcome these problems by proposing a new e-learning recommender system that uses a different approach based on two conceptual foundations – peer learning and social learning theory that is able to recommend quality learning materials to learners for improving student's performance.

Topping [23] defined peer learning as the acquisition of knowledge and skill through active helping and supporting among status equals or matched companions. It involves people from similar social groupings who are not professional teachers helping each other to learn while learning. Help and support between peers can be demonstrated in many ways such as teaching and/or sharing materials. Topping [23] uses the term "peer helper" for someone who is considered among the "best students" and acts as a surrogate teacher, in a linear model of the transmission of knowledge, from teacher to peer helpers to other learners. The idea of learning from the best students is also strongly supported by Social Learning Theory [2]. Social Learning Theory [2] states that people can learn by observing the behavior of others and the outcome of those behaviors. If the outcome is positive, other students will most likely exhibit the behavior, thus giving a positive impact to their learning performances. Despite its advantages, the idea of learning from the best students has not yet being implemented in any recommender system. Nonetheless, learning materials referred to by best students can be used as a viable indicator for locating useful materials from pools of learning materials available in the Web. Moreover, finding good quality learning materials from the Web has always been a common problem among e-learner [12].

This work is therefore aims to address this problem by incorporating good learners' rating strategy into an e-learning recommender system so that students can be guided into studying materials that are highly recommended by the best students in their attempt to boost their learning performances. Our proposed e-learning recommender also applied content-based filtering strategy in order to ensure that the recommended learning materials always remain within the current learning concept. In this work, a term good learners is used to represent the best students. We define good learners as students who scored more than 80% in a post-test conducted in this research experiment. Also note that the terms learning materials, items, and documents are used interchangeably throughout this work.

In this paper, we introduce our recommendation strategy and evaluate its feasibility in recommending useful learning materials to students. To accomplish the latter, a set of experiment was conducted against other recommender systems and adaptive hypermedia system in order to measure the effectiveness of the proposed strategy in improving students' learning performance. The rationale of including adaptive hypermedia system into the evaluation is because the system generally shares the same goal with the recommender system that is to personalize learning content or links to an individual learner.

The remaining part of this paper is organized as follows. Section 2.0 introduces the concept of e-learning recommender systems and adaptive hypermedia systems as well as discussing the current work. Section 3.0 elaborates the proposed recommender system in detail including the mathematical model to calculate the item's similarity and good learners' ratings. Section 4.0 discusses the data set, experiment setup, metrics used for measurement, and the result of the experiment. Finally, Section 5.0 provides the concluding remarks along with suggestions for future work.

2.0 LITERATURE REVIEW

We divide the related work into two sections. Section 2.1 discusses the current methods used for recommendation in e-learning and Section 2.2 describes the general idea of adaptive hypermedia systems and the related researches.

2.1 E-learning Recommender Systems

A recommender system is a tool that supports users in identifying interesting items especially among large numbers of items. Among the popular approaches used in recommender systems are collaborative filtering, content-based filtering, and hybrid filtering. Collaborative filtering identifies the interesting items from other similar users' opinions by calculating the nearest-neighbor from a rating matrix. New items that are of interest to the nearest-neighbor and that have not been rated by the users will be recommended to them. In contrast, content-based filtering uses features of items to infer recommendations. Hence, items with similar content to the current viewing item will be recommended to the active user [27]. Hybrid filtering on the other hand combines both content-based filtering and collaborative filtering technique to produce a recommendation [1]. Recommender systems in e-learning can differ in many ways depending on the kind of object to be recommended (i.e. course to enroll, learning materials, and etc.) and whether the context of learning is considered important [14, 20, 22].

Recent trends show that most of the researchers use data mining approach and information retrieval technique as the recommendation strategies [11, 14, 26]. Zaiane [26] proposed the use of web mining technique to build agents that could recommend online learning activities or shortcuts in a course website based on learners' access histories to improve course navigation as well as assisting with the online learning process. Khribi et al. [13] computed an online automatic recommendation based on learners' recent navigation histories as well as exploiting similarities and dissimilarities among user preferences and among the contents of the learning resources. They used web usage mining techniques together with content-based and collaborative filtering to compute relevant links to recommend to active users. Soonthornphisaj et al [20] applied the collaborative filtering approach to predict the most suitable documents for the learner. New learning materials are able to be recommended to learners with a high degree of similarity. They also proposed a new e-learning framework using web services that has the ability to aggregate recommended materials from other e-learning web sites and predicts more suitable materials for learners. Liu et al [15] designed a material recommendation system based on association rule mining and collaborative filtering. The system is implemented by integrating the techniques of LDAP (Lightweight Directory Access Protocol) and JAXB

(Java Architecture of XML Binding) to reduce the load of the development search engine and the complexity of the content parsing to improve the learning performance of learners. Liang et al [14] applied a knowledge discovery technique, and a combination of content-based filtering and collaborative filtering to generate personalized recommendations for a courseware selection module. Their experiment showed that the algorithm used is able to reflect users' interests with high efficiency. Tang et al. [22] proposed an evolving web-based learning system that is able to find relevant content on the web, personalize and adapt the content based on the system observation of its learners and the accumulated ratings given by the learners without the need for learners to directly interact with the open Web. They use a clustering technique to cluster learners into a subclass according to the learning interest before using collaborative filtering to calculate learners' similarities for content recommendation. Kerkiri et al. [11] proposed a framework that exploits both description and reputation metadata to recommend personalized learning resources. Their experiment proved that the use of reputation metadata augmented learner's satisfaction by retrieving those learning materials that were evaluated positively. Chen et al. [7] proposed a personalized e-learning system based on Item Repository Theory which estimates the abilities of online learners and recommends appropriate course materials for learners. The experiment showed that the system can precisely provide personalized course material recommendations based on learners' abilities and accelerate learners' learning efficiency and effectiveness. Otair et al. [18] proposed a framework for an expert personalized e-learning recommender system by using a rule-based expert system that can help learners find learning materials that best suit their needs. Tai et al. [21] proposed e-learning course recommendation based on artificial neural network (ANN) and data mining techniques. ANN is used to classify learners based on groups of similar interests and learners can obtain course recommendations from the group's opinion. They used a data mining technique to elicit the rules of the best learning path.

From the above literature, none of the recommender systems have attempted to use content-based filtering together with good learners' ratings as the method to recommend useful learning materials. Among the benefits of having this kind of recommendation strategy are that it can ensure the recommended items remain in the current learning context and thus quality materials are able to be recommended. We have chosen the method proposed by [20] to be compared with our proposed e-learning recommender system in terms of student's performance since they used a typical collaborative technique (without any combination with other techniques) and the output of the recommender system is similar to what our proposed system produced.

2.2 Adaptive Hypermedia Systems

Numerous researches on adaptive hypermedia systems have been reported in the last 10 years [9, 19, 24]. Adaptive hypermedia is a system that aims to personalize the delivery of the materials according to the user's needs. The basic idea of an adaptive hypermedia system is to personalize content (adaptive presentation) and link between Web pages (adaptive navigation) based on a user model (i.e. user knowledge level on a certain concept that is defined by a course instructor [5, 8]). Fig. 1 depicts the general idea of an adaptive hypermedia system.

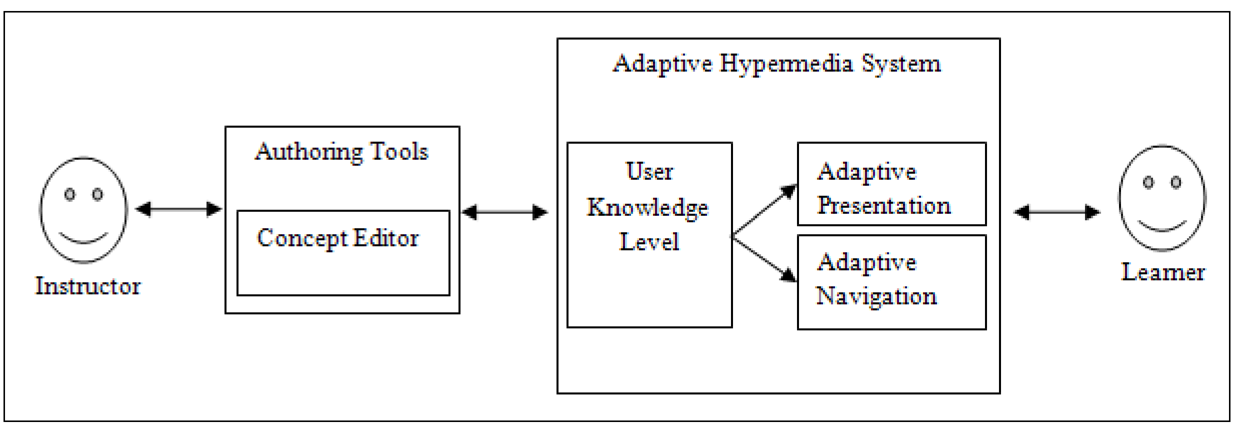

Fig 1: The general architecture of Adaptive Hypermedia System

Adaptive presentation can be applied to either a text-based or a multimedia content. Three techniques [3] can be used on the text-based content that includes: i) page variant: several versions of pages exist for the same content ii) fragment variant: several versions of fragments exist in a page, and iii) frame based techniques: a page is assembled by a combination of words and/or sentences that is based on natural language processing techniques. In the case of multimedia contents, the current implementation is only limited to the media selection, rather than the content itself.

Adaptive navigation, on the other hand, helps to personalize links of the pages (hyperlink) according to a user model (e.g. user's knowledge level). Several methods [3] that have been used include: i) direct guidance: a set of links that direct users to the next appropriate content, ii) adaptive sorting of links: links are sorted according to the relevancy, iii) link hiding: links are hidden from the user by making the link anchor indistinguishable from normal text, iv) link removal: links are completely removed from a page, v) link disabling: label of a link remains within a page but its functionality is removed to disable navigation (to other pages/fragments) through the link, and vi) link annotation: links are annotated with different color to indicate the relevancy of the link.

Adaptive content and adaptive navigation work based on a user model. In a case of modeling user's knowledge level on certain concepts, the following techniques are often used. The techniques are [3]: i) boolean: the concepts are determined by two values (e.g. true or false, known or not known), ii) discrete: the concepts are determined by several values (e.g. not known or known or learned or well learned), and iii) continuous: the concepts are determined from a range of values (e.g. percentage of known knowledge).

Some of the adaptive techniques (adaptive content and adaptive link) mentioned above have been implemented by many researches in educational field [3]. Among the notable adaptive hypermedia systems are AHA! [8], InterBook [4] and ELM-ART [25]. InterBook is a tool for authoring and delivering adaptive electronic textbooks on World Wide Web. InterBook server maintains an individual model of a user's knowledge and applies this model to provide adaptive guidance, adaptive navigation support, and adaptive help. ELM-ART is an intelligent interactive educational system to support learning programming in LISP. It provides adaptive navigation support, course sequencing, individualized diagnosis of student solutions, and example-based problem-solving support. AHA! is an adaptive hypermedia software that can be used in all kinds of applications including education. AHA! consists of an engine which maintains a user-model based on knowledge about concepts and knowledge is generated by reading pages and taking tests. AHA! provides adaptive links and adaptive content by means of link hiding, link annotation, and fragment variants. The implementation of AHA! covers most of the aspects of adaptive hypermedia system. Due to this, we have chosen AHA! to be compared with e-learning recommender systems including our proposed system in term of student's performance.

3.0 PROPOSED E-LEARNING RECOMMENDER SYSTEM USING CONTENT-BASED FILTERING AND GOOD LEARNERS' RATINGS

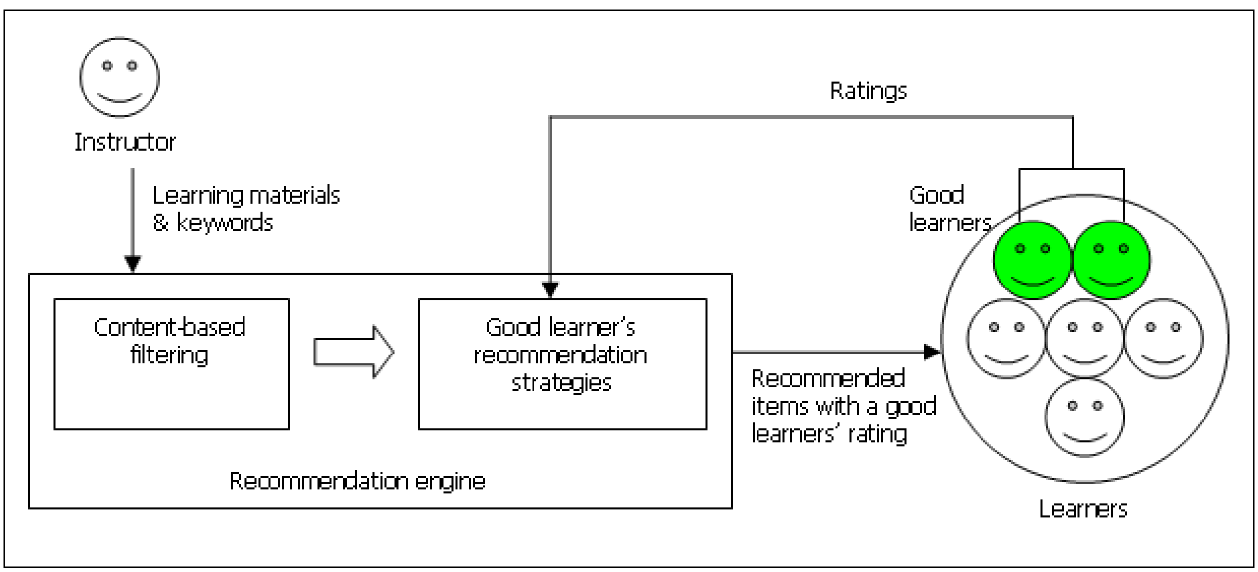

Fig. 2: The good learners' recommendation strategies framework

Fig. 2 shows the overall process in our recommendation strategy framework. The recommendation process begins after the annotated learning materials and the related keywords have been uploaded to a database by an instructor. The keywords are then retrieved by the recommendation engine for the document weight calculation. The document weight calculation calculates term (i.e. keyword) frequency in both local (i.e. frequency of the term in the document itself) and global documents (i.e. frequency of the term in the whole document stored in the database), and the product between the local and the global term frequency. The resulting weight becomes the input for the cosine similarity calculation. This calculation creates a vector that represents a document in an n-dimensional space. The relevancy rankings between the documents are determined by measuring the angle between the vectors. The smaller the angle is, the higher the similarity values between the two documents. The items' similarities are stored in the item-similarity database.

The good learners' rating calculation starts by gathering the initial rating from the good learners. This initial rating is important to avoid the cold-start problem (i.e. recommendation cannot be produced due to insufficient or no rating at all) faced by collaborative filtering technique [1]. If the ratings exist for a particular item, the good learners' average rating will be calculated by dividing the sum of all good learners' ratings by the number of good learners that have rated that particular item. The good learners' average rating is then stored in the rating database and will be used for rating recommendation and for the calculation of good learners' prediction rating. The good learners' rating prediction will be calculated when the good learners' ratings do not exist for a particular item. To calculate the prediction rating, the recommendation engine will retrieve both the items' similarity and its corresponding good learners' average rating, and divide the product between them with the sum of the items' similarity. The prediction ratings are then stored in the rating database. Note that, once the document has received ratings from good learners, the prediction rating will be overwritten and the good learners' average rating will be recommended.

The final stage in the recommendation process is to recommend the good learners' rating for the viewing item and to recommend top-N (items with the highest similarity) similar items. For this purpose, the recommendation engine will query the item's similarity from the item-similarity database and based on the item's similarities (that exceed a threshold value), the top-N documents will be retrieved from the database. Concurrently, the good learners' rating for the viewing item is retrieved from the rating database to be recommended to the learners.

Section 3.1 and Section 3.2 show the mathematical model involve for calculating the items' similarity and good learners' rating respectively.

3.1 Items' Similarity

The similarity between documents involving two phases of calculation: i) document weight calculation, and ii) cosine similarity. The document weight $w_{i,j}$ is calculated using the term frequency/inverse document frequency (TD-IDF) with normalized frequency as shown in equation (1). In TD-IDF, all the terms are treated as independent terms. The equation is defined as follows.

$$w_{i,j} = \frac{f_{i,j}}{max_z \, f_{z,j}} * \log\left(\frac{D}{d_i}\right) \quad (1)$$

where $f_{i,j}$ denotes the frequency a term *i* occurs in document *j*. The $max_z \, f_{z,j}$ is the maximum frequency among all the *z* keywords that appear in document *j*. The *D* is the total number of documents that can be recommended to the learners. The d_i is the number of documents that contain term ***i***. The normalized frequency ensures that the long documents with high occurrence terms will not have high impact on the weight thus it helps to reduce the possibility of keyword spamming [6]. The weight computed using equation (1) is used to calculate the similarity value between the two items. The cosine similarity value is defined as follows.

$$\cos(\overrightarrow{w_c}, \overrightarrow{w_s}) = \frac{\overrightarrow{w_c} . \overrightarrow{w_s}}{\| \overrightarrow{w_c} \| \| \overrightarrow{w_s} \|} \quad (2)$$

where $\overrightarrow{w_c}$ and $\overrightarrow{w_s}$ are treated as a vector for content based profile of user *c* and the content of document *s*. Both $\| \overrightarrow{w_c} \|$ and $\| \overrightarrow{w_s} \|$ are the magnitude of the vector $\overrightarrow{w_c}$ and $\overrightarrow{w_s}$. Similarities between the documents are measured by measuring the angle between the two vectors where a smaller angle indicates a higher similarity.

3.2 Good learners' rating

As mentioned earlier in the Introduction, the good learners' ratings serve as a guideline for the learners to focus on a particular learning material. If the good learners' ratings exist for a particular item, the good learners' average rating is calculated as follows.

$$R_{i,j} = \frac{\sum_{i=1}^{N} r_{i,j}}{N_j} \tag{3}$$

where $r_{i,j}$ is the rating of good learner *i* on item *j*. The N_j is the total number of good learners that rated item *j*. Note that the calculation for good learners' average rating on a particular item is solely based on good learners' ratings.

In the case where the item has not received any rating from the good learners, then the item will be recommended with good learners' prediction rating that is calculated as follows.

$$P_i = \sum_{n=1}^{N} \frac{sim(d_i, d_n) * R_n}{sim(d_i, d_n)} \tag{4}$$

where $sim(d_i, d_n)$ is the similarity between item *i* and item *n* [as calculated using equations (1) and (2)] and R_n is the good learners' average rating on item *n* [as calculated using equation (3)].

4.0 EXPERIMENTATION AND RESULTS

In this work, several sets of experiment were conducted to achieve two main goals: 1) To evaluate the performance of the proposed strategy against the existing recommendation strategies which are mainly based on content-based and collaborative-based filtering; 2) To evaluate the performance of the proposed strategy against an adaptive hypermedia system that uses knowledge level as its adaptation feature. The focus of both evaluations is to measure the impact of each system on students' learning performances.

Until now, there is no standard datasets being used in testing the performance of e-learning recommender system or adaptive hypermedia system (8, 13, 25). The commonly used datasets for a recommender system is at MovieLens [16] which are based on movie data, thus less suitable for e-learning purpose. This experiment therefore uses a collection of 131 Power Point slides which are prepared by a course author for the teaching and learning of the basic of eXtensible Markup Language (XML). This collection of slides comprises the mandatory learning materials for different topics of XML, as well as the supplementary materials that serve as the additional references for each of the taught topics. Each of the slides is manually annotated by the course author using a set of predefined keywords which are related to the course domain and its instructional value. The slides are then converted into images before they are embedded into HTML pages. The conversion is necessary in order to preserve the fidelity of the original slides. Fig. 3 shows the screenshot of the e-learning system with the proposed recommender system. A set of similar items (as shown in Fig. 3 label A) are recommended at the bottom of the current viewing slide and they are arranged according to the highest rated item by the good learners. The good learners' rating for the current viewing slide is shown at the top of the slide (refer to Fig. 3 label B). During the experiment, we used a similar interface for all types of recommender systems except for the good learners' rating (refer to Fig. 3 label B) which is set to be hidden and the recommended items (refer to Fig. 3 label A) are displayed according to the most relevant to the current viewing slide.

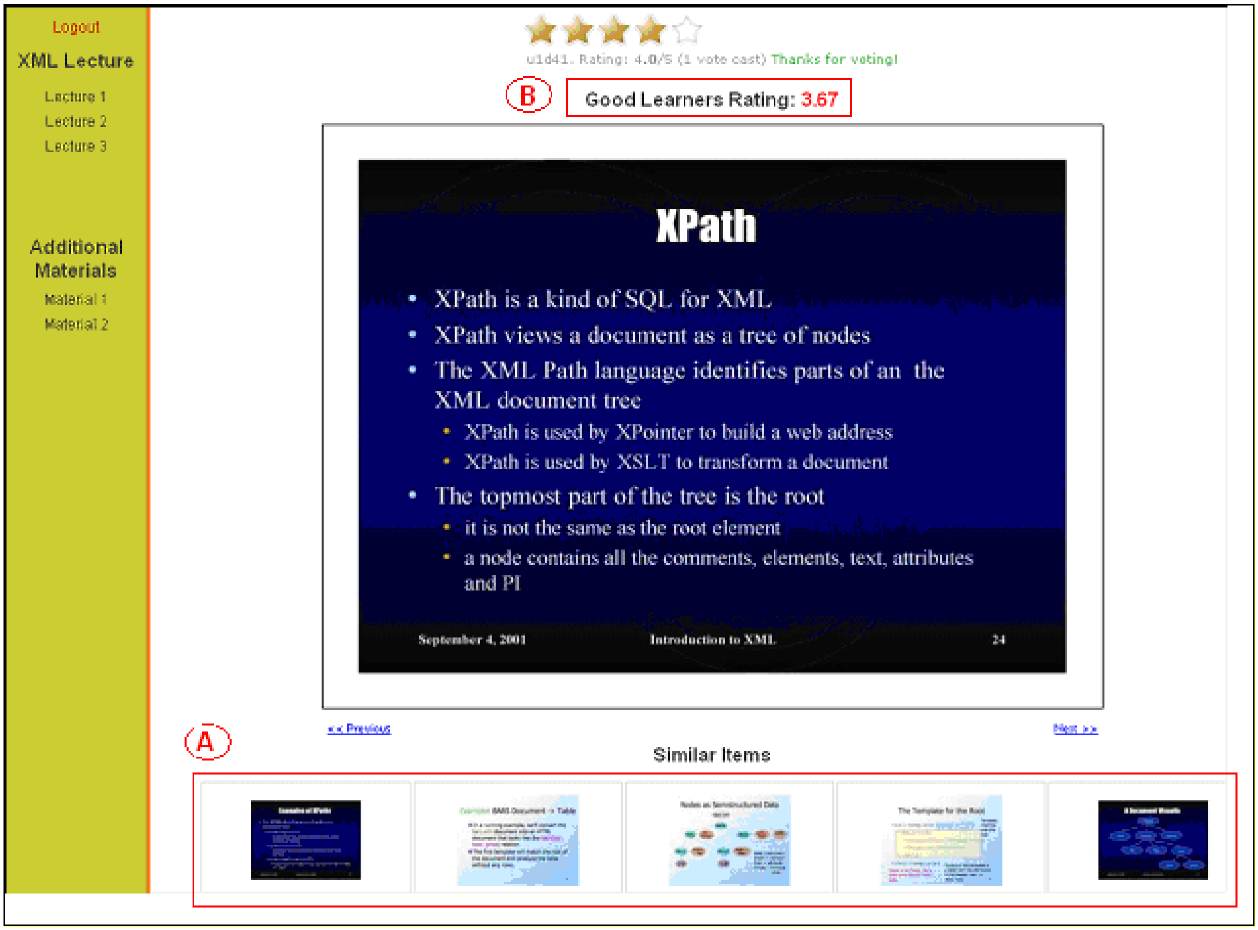

Fig. 3: A sample screenshot of the e-learning recommender system

For experimenting the adaptive hypermedia system, the same amount of slides was directly converted into HTML pages in order to control visibility of fragments and to execute link hiding and link annotation features. This feature is possible to be implemented since links to examples and other HTML pages can be easily included within HTML fragments. Fig. 4 shows the screenshot of the adaptive hypermedia system. Link annotation and link hiding are implemented by using different link text colors (as shown in Fig. 4 label A and label B). Blue color for example indicates an unvisited link while purple color indicates a visited link. For the link hiding, the link color is set to black to make it indistinguishable from the normal text. The adaptive system is also capable of showing fragments that are based on the learner's knowledge. Each time a learner has completed the reading of a fragment, the learner needs to click on a "I have read" button (as shown in Fig. 4 label C) in order to update the database about the learner's knowledge, and the system in turn will decide which fragment to be shown and update the link (link annotation) color accordingly.

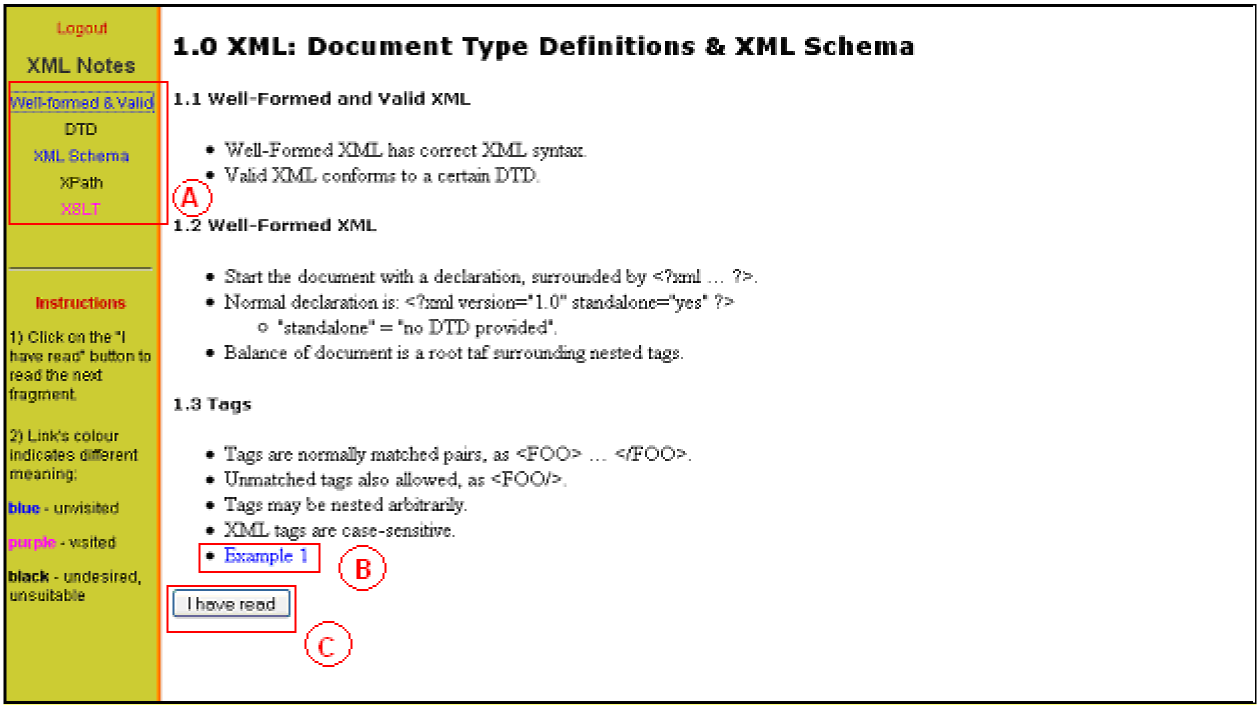

Fig. 4: A sample screenshot of the adaptive hypermedia system

The subjects for this experiment are second year Software Engineering undergraduate students. A total of 123 students are taken from five different classes. For the purpose of this experiment, each class represents a specific target group for the experiment as follows. The first group (G1) consists of 21 students and used an e-learning without a recommender system. The second group (G2) consists of 21 students and used an e-learning with a content-based recommender system (G2). The third group (G3) consists of 24 students and used an e-learning with the proposed recommender system. The fourth group (G4) consists of 29 students and used an e-learning with a collaborative filtering recommender system as proposed by [20]. The last group (G5) consists of 28 students and used an adaptive educational hypermedia system as proposed by [8].

Experiments on G1 and G2 were conducted before G3. This is because initial values for good learners' ratings are required from participants in G1 and G2 prior to experiencing learning in the proposed recommender system. Also note that, experiment on G4 was carried out after the completion of experiment on G3 as G4 needs ratings from a large number of users (i.e. from G1 until G3) in order to calculate users' similarity (i.e. similarity in terms user's rating pattern) and to minimize the cold-start problem. Cold-start problem is a problem where the items cannot be recommended due to insufficient ratings received [10]. Initially, no items will be recommended to the users in G4 until the users have rated a few items and the similarity values between users have been updated. The system will periodically calculate the users' similarities as the similarity value will change each time the user provides a rating or re-rates a learning material.

The basic procedure for the experiment is as follows. The students were required to sit for a pre-test prior to using any system. The motive for the pre-test is to assess the pre-knowledge of the students before they can start their learning process using the assigned system. Basic questions about XML were asked during the pre-test such as the definition about valid and well-formed XML document. The students were then given a week to study all the learning materials using the assigned e-learning system before they were examined in a post-test. The post-test questions cover a deep knowledge in XML such as analyzing and correcting the XML syntax. The students were not aware of the experiment until they were given the URL address of the assigned e-learning system. The questions for both the pre-test and post-test were arranged in different orders. Both the pre-test and post-test assessments are conducted during formal teaching classes under a closely monitored environment. As each group in the experiment was from different classes, the possibility of collaborating between the students from different groups can therefore be minimized. These precautions were taken into account since the experiment on G3 was conducted after the tests on G1 and G2 were over, and the experiment on G4 was conducted after the experiments on G1, G2, and G3 were over.

The measurement for students' performances is done by calculating the average mark of each group and the t-score for the average mark among each pair of groups to determine the significance of the pre-test and post-test marks. A two-tailed test is used for the pre-test and a one-tailed test for the post-test. Our hypothesis is that there is no significant difference in the average mark among the groups in a pre-test. For the post-test hypothesis, we assume that students who use the proposed system will have a higher average mark compared to other groups. The average mark and standard deviation for all groups are summarized in Fig. 5 and Fig. 6 respectively. It is clear that (from Fig. 5) there is no large gap between the marks obtained by all the groups for the pre-test. In contrast, G3 obtained the highest post-test mark compared to other groups. The standard deviation (from Fig. 6) shows that all the groups consist of learners in a well distributed mark range. To further justify the result, we calculate the average percentage of mark increments from the pre-test to the post-test for each group.

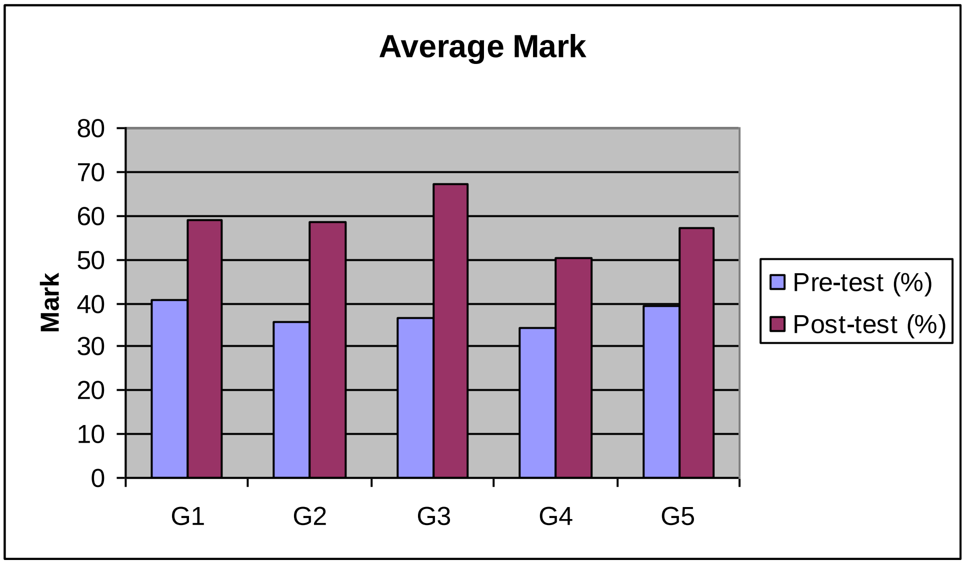

Fig. 5: The pre-test and post-test average mark for all groups

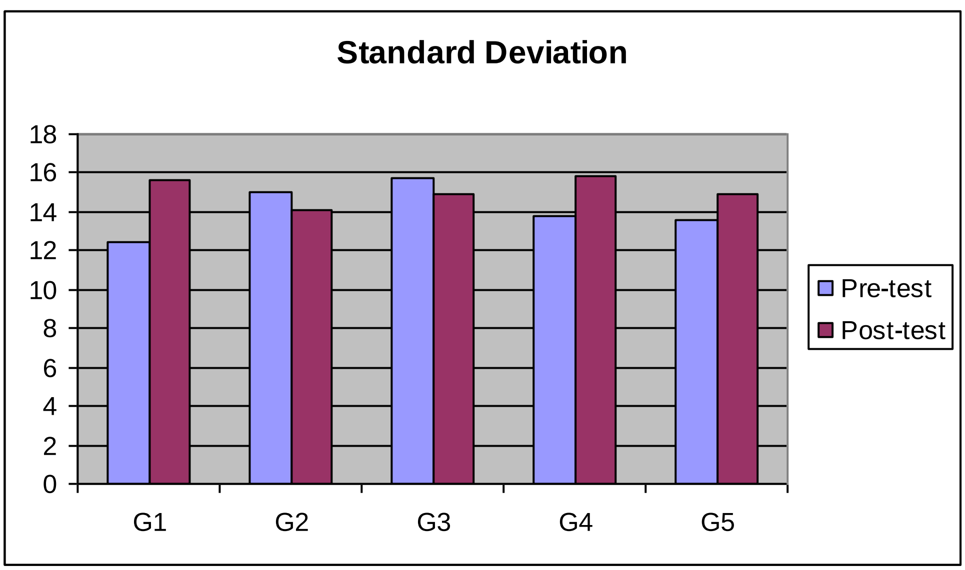

Fig. 6: The pre-test and post-test standard deviation for all groups

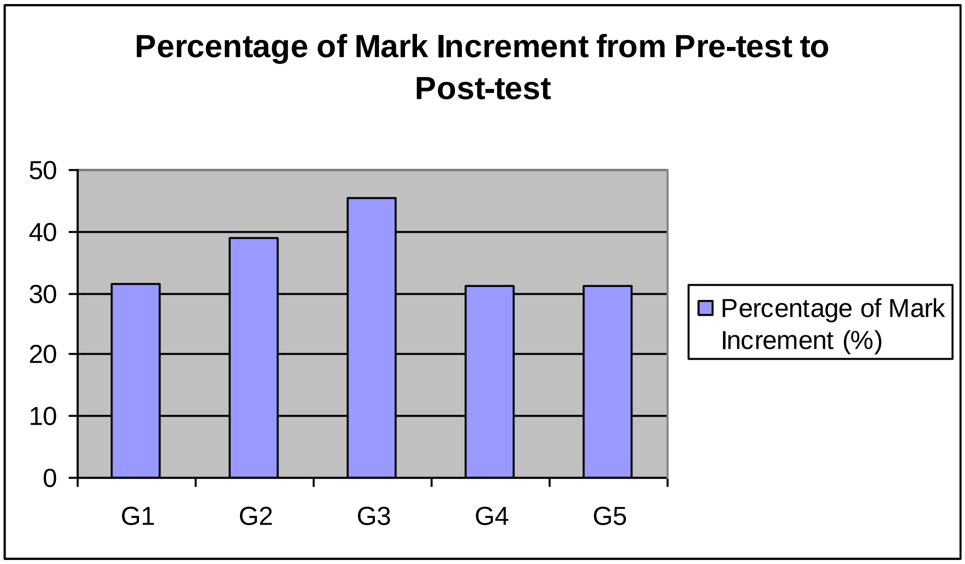

Fig. 7: The percentage of mark increment from pre-test to post-test for all groups

Table 1: A t-test result between each different pair of groups

	Pre-test (two-tailed test)		Post-test (one-tailed test)	
Group	t	df	t	df
G1-G2	1.118732	40	0.137881	40
G1-G3	0.904059	43	1.782697	43
G1-G4	1.606527	48	1.982239	48
G1-G5	0.318574	47	0.429926	47
G2-G3	0.207163	43	2.030145	43
G2-G4	0.296118	48	1.949840	48
G2-G5	0.857584	47	0.304143	47
G3-G4	0.530695	51	4.039761	51
G3-G5	0.635559	50	2.426511	50
G4-G5	1.324823	55	1.728338	55

Table 1 summarizes the t-score (t) and the degree of freedom (df) between each group pairs for the pre-test and the post-test average marks. The result shows that there is no significant difference at $p < 0.05$ between each group for the pre-test average mark. On the other hand, the post-test average mark obtained by G3 has a significant difference compared to G1, G2, G4, and G5 with a t-score value of 1.782697 (significant at $p < 0.05$), 2.030145 (significant at $p < 0.025$), 4.039761 (significant at $p < 0.0005$), and 2.426511 (significant at $p < 0.01$) respectively. Furthermore, G3 has the highest percentage of mark increment from the pre-test to the post-test which is about 45% as shown in Fig. 7. In contrast, G4 obtained the lowest percentage of mark increment from the pre-test to the post-test which is slightly above 30%.

The positive evaluation result acquired from these experiments gives an indication that the proposed recommendation strategy is indeed feasible in recommending useful learning materials to students.

5.0 CONCLUSION AND FUTURE WORKS

In this paper, we have discussed various techniques of e-learning recommender systems and adaptive hypermedia systems. We have proposed a new e-learning recommender system framework based on the content-based filtering and good learners' ratings that can help to increase student's performance. A comparative study among other e-learning recommender systems with an adaptive hypermedia system has been conducted for a performance benchmarking.

The experimental results show that students' performance has increased by at least 12.16%. The implementation of content-based filtering ensures that the related items are in the learning context and the average good learners' rating strategy is proven able to guide learners in selecting useful learning materials, hence allowing learners to concentrate more on the content of the materials rather than the process of getting them. In this study, the proposed e-learning recommender system is implemented together with a learning management system. In the future, it is of our interest to make the proposed e-learning recommender system as a lightweight program module that can be integrated into any web-based learning management system.

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