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Utilizing Learners' Negative Ratings in Semantic Content-based Recommender System for e-Learning Forum

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ABSTRACT

Nowadays, most of e-learning systems embody online discussion forums as a medium for collaborative learning that supports knowledge sharing and information exchanging between learners. The exponential growth of the available shared information in e-learning online discussion forums has caused a difficulty for learners in discovering interesting information. This paper introduces a novel recommendation architecture that is able to recommend interesting post messages to the learners in an e-learning online discussion forum based on a semantic content-based filtering and learners' negative ratings. We evaluated the proposed e-learning recommender system against exiting e-learning recommender systems that use similar filtering techniques in terms of recommendation accuracy and learners' performance. The obtained experimental results show that the proposed e-learning recommender system outperforms other similar e-learning recommender systems that use non-semantic content-based filtering technique (CB), non-semantic content-based filtering technique with learners' negative ratings (CB-NR), semantic content-based filtering technique (SCB), with respect to system accuracy of about 57%, 28%, and 25%, respectively. Furthermore, the obtained results also show that the learning performance has been increased by at least 9.84% for the learners whom are supported by recommendations based on the proposed technique as compared to other similar recommendation techniques.

Keywords

E-learning recommender system, E-learning discussion forum, Content-based filtering, Learners' negative ratings, Latent semantic analysis

Introduction

The emergence of web 2.0 has led to a revolution in education industry where interactive e-learning systems show fast and significant growth world-wide. Nowadays, interactive e-learning environments utilize online discussion forums as a medium for collaborative learning that supports knowledge sharing and information exchanging between learners that have different knowledge levels. Shana (2009) asserted that using online discussion forums as an instructional tool improves the students' learning performance through providing better cognitive and exploratory learning. Furthermore, the idea of utilizing online discussion forums for learning is strongly supported by Social Learning Theory (Bandura, 1977). However, the exponential growth of the available shared information on e-learning discussion forums, as well as the learners' limited time for studying have caused a difficulty for learners in discovering interesting information that is relevant to their learning context. To overcome this problem, we propose a novel e-learning recommender system that recommends interesting information to the learners, thus save learners' time and improve their learning performance.

Recommender systems are utilized for personalizing information sources for users by guiding them in a personalized way to interesting items selected from myriad of available options (Lops et al., 2011). Basically, recommender systems are classified into several categories based on the adopted filtering approach (Adomavicius & Tuzhilin, 2005). Content-based, collaborative and hybrid filtering techniques are the most common filtering approaches used in recommender systems. In content-based recommender systems, recommended items are similar to the ones that the user preferred in the past. This approach is effective in filtering items of textual form where each item is represented as a set of keywords that describe it (Lops et al., 2011). Vector space model is considered as one of the widely used algorithms in content-based recommender systems where items in this model are represented as weighted vectors of keywords in the vector space (Turney & Pantel, 2010). The similarity values between items are obtained based on the cosine of the angle between their weighted vectors. In contrast, collaborative recommender systems recommend items based on item's profile, where the recommended items are similar to the ones that have been preferred by similar users. Nearest neighbor algorithm is one of the most popular methods used in collaborative filtering (Ekstrand et al., 2011). It was first proposed in GroupLens recommender system by Resnick et al. (1994) to filter news articles for users. On the other hand, hybrid recommender systems were emerged to overcome certain limitations in both of content-based and collaborative filtering techniques by combining them using several ways (Adomavicius & Tuzhilin, 2005).

One way to build a hybrid recommender system is by implementing both methods separately and combining their final predictions, while another way can be done by incorporating some characteristics from one filtering approach into another (Burke, 2002).

Unlike recommendations in other domains, recommender systems in e-learning domain should assist learners in constructing their knowledge in a contextualized progressive way rather than acquiring it. Constructivism Learning Theory states that learning is an active and contextualized process of constructing knowledge; thus, it emphasizes the importance of the active involvement of learners in constructing their knowledge in a contextualized progressive way (Fosnot & Perry, 1996). This theory strongly supports the idea of avoiding the information that is relevant to the learner's previous understandings (i.e., avoiding the negatively rated items), and keeping the recommendations relatively progressive to promote a contextualized and smooth learning process within a given framework or structure. Furthermore, traditional recommender systems usually rely only on users' positive ratings to suggest recommendations, while in contrast, users' negative ratings are rarely taken into consideration. Zeng et al. (2011) indicated that negative ratings may play a positive role in recommendation systems especially for very sparse data sets. Their experimental results show that when the user's positive ratings are insufficient to recommend relevant items, the negative ratings could indicate disfavor or relevance.

The aim of this study is to propose a novel semantic content-based recommender system utilizing learners' negative ratings in an e-learning discussion forum. The proposed recommender system utilizes learners' negative ratings to provide active learners with novel recommendations that in turn will increase their learning performance and save their time. Moreover, the proposed recommender system ensures that the recommendations will remain within the current learner's context. Therefore, we evaluated the proposed e-learning recommender system in terms of recommendation accuracy and learners' performance. The terms post messages, items, and learning materials are used interchangeably through this research paper.

The remainder of this paper is organized as follows: we first introduce "Related Work" section which discusses the existing works in e-learning recommender systems research. Section "E-learning Recommendation Framework Utilizing Learners' Negative Ratings" elaborates on a semantic content-based recommendation framework that utilizes learners' negative ratings in e-learning discussion forum. Next section "Experimentation and Results" presents the data sets used for evaluation, experiments setup, evaluation metrics, and the obtained results. Finally, the last section of this paper introduces the concluding remarks along with suggestions and extensions for future work.

Related work

Recommender systems in e-learning domain are assorted based on the filtering approach and the type of recommended items. A recent survey of recommender systems in e-learning domain has been conducted by Drachsler et al. (2015). It reported that the vast majority of recommender systems in this research field aim to suggest good learning content (i.e., learning materials, discussions, links) where recommender systems that aim to suggest people who can help with a learning activity (i.e., peer learners) are very limited. On the other hand, recent studies in e-learning recommender systems show that knowledge-based recommendation techniques are the most used recommendation techniques by researchers to recommend good learning items in e-learning systems (Wang, 2008; Santos et al., 2014; Capuano et al., 2014; Lu et al., 2015).

Wang (2008) proposed a new method that uses association mining and statistical techniques to contextualize learners' browsing events based on several contextual factors (i.e., learner's group relevance, performance relevance, support and confidence). This method was implemented in an e-learning system to recommend learning content based on learner's browsing history which in turn supports learners in making decisions on what to study next. Capuano et al. (2014) developed a hybrid recommender system prototype and integrated it into a commercial adaptive e-learning system called IWT (Intelligent Web Teacher) to recommend learning goals and generate learning experiences for learners. This hybrid recommendation technique involves three main phases: concept mapping, concept utility estimation and upper level learning goals utility estimation (ULLGs). The ULLGs with the greater utility are recommended to the active learner. Ghauth and Abdullah (2011) proposed a recommendation method that uses good learners' ratings with content-based filtering techniques to recommend good learning materials to learners in a web-based learning system. The learners that scored more than 80% in the post-test were considered as good learners and their ratings were used to rate recommendations to other learners. Dwivedi and Bharadwaj (2013) introduced a trust-aware recommendation framework that recommends trusted learning resources to learners in an e-learning environment. They utilized both the learners' learning styles and the knowledge levels to elicit trust values among learners and incorporate them with collaborative filtering techniques to suggest trusted learning resources. Distante et al. (2014) introduced a technique that enhances the navigation of learning content in online forums. They applied information retrieval techniques (i.e., topic models and formal concept analysis) to semi-automatically extract topics and hierarchical relations between them from the learning forum to associate them to posts and discussion threads based on similarity score basis. Abel et al. (2010) proposed a general-purpose semantic web service based recommendation framework that encapsulates generic personalization algorithms. This rule-based recommendation framework can be integrated with discussion forums in e-learning environments to suggest appropriate recommendations to learners by selecting different recommendation techniques in a flexible rule-based manner. Li et al. (2009) proposed an e-learning semantic forum based on domain ontology and text mining technologies to facilitate active collaborative learning in e-learning discussion forums. The semantic forum automatically processes posted messages for structural modeling with semantic association to discover special interest groups for topic-centric social context measurement. The proposed approach achieved several distinctive functionalities in the semantic forum (i.e., semantic search, relational navigation and recommendation). Khribi et al. (2009) proposed an automatic personalization approach that recommends learning resources in e-learning platforms based on learner's recent navigation history. The proposed approach exploits similarities and dissimilarities among user preferences and the content of learning resources by using a range of filtering strategies that based mainly on content-based filtering and collaborative filtering techniques. Dascalu et al. (2015) developed an educational recommender agent that produces two types of recommendations (i.e., suggestions and shortcuts for learning materials) based on collaborative filtering techniques and integrated learning style finder. They introduced shortcuts for learning materials by computing the similarity values based on current user's profile, while suggestions are computed based on the similarity values among learning materials and other learners with similar learning style. Muñoz et al. (2015) combined users' context information and expert knowledge to build a semantic intelligent system that provides recommendation services and user profiling features in learning management systems. They created an ontology model called OntoSakai to represent users' context information. This ontology model consists of four ontologies that represent several areas of the learning process. Their experimental results show that this combination of users' context information and expert knowledge is able to recommend learning resources that help learners to improve their experiences as well as their academic results.

This review of related research works in e-learning recommender systems domain aims to provide more understanding of the different aspects posed by e-learning recommender systems research to enhance the learning experience. It is obvious from the reviewed research that utilizing recommender systems for learning is very important nowadays due to its efficacy in assisting learners in reaching to interesting information from a huge amount of available options. However, the vast majority of these research works lack the exploitation of the learners' negative ratings to predict better recommendations. Hence, we propose an e-learning recommendation framework by utilizing the learners' negative ratings to recommend relevant learning content and to keep the recommendations in the learner's current learning context.

E-learning recommendation framework utilizing learners' negative ratings

In this section, we introduce our e-learning recommendation framework, then we present its phases and the processes involved in each phase. However, this section extends our previous work proposed in (Albatayneh et al., 2014) by exploiting and modeling learners' negative ratings to optimize the quality of recommendations, and to personalize e-learning discussion forums in a way that supports constructive learning.

The framework of the proposed e-learning recommender system involves four phases, as Figure 1 depicts. The recommendation process starts by automatically retrieving all the post messages along with learners' ratings from the database. Post messages can hold discussions about different topics, answers, articles, or any useful information of textual form that can be considered as learning material. However, the retrieved data enter pre-processing phase which involves two processes: removing stop-words and word stemming. These two processes are performed to prepare the input data which will reduce the processing time needed in next phases. Then, the processed data enter the semantic indexing phase to capture the latent semantics into post messages as well as to reduce the dimensionality in the vector space by performing three main processes. Subsequently, the system models the latent semantics along with learners' negative ratings to build learner's profile in the next phase. The learner profile builder process builds the learner's profile by integrating the semantic-based and the negative rating-based profiles. The recommendation prediction phase uses the learner profile to compute the recommendations. More thorough discussions on the processes in each phase are given in the next subsections.

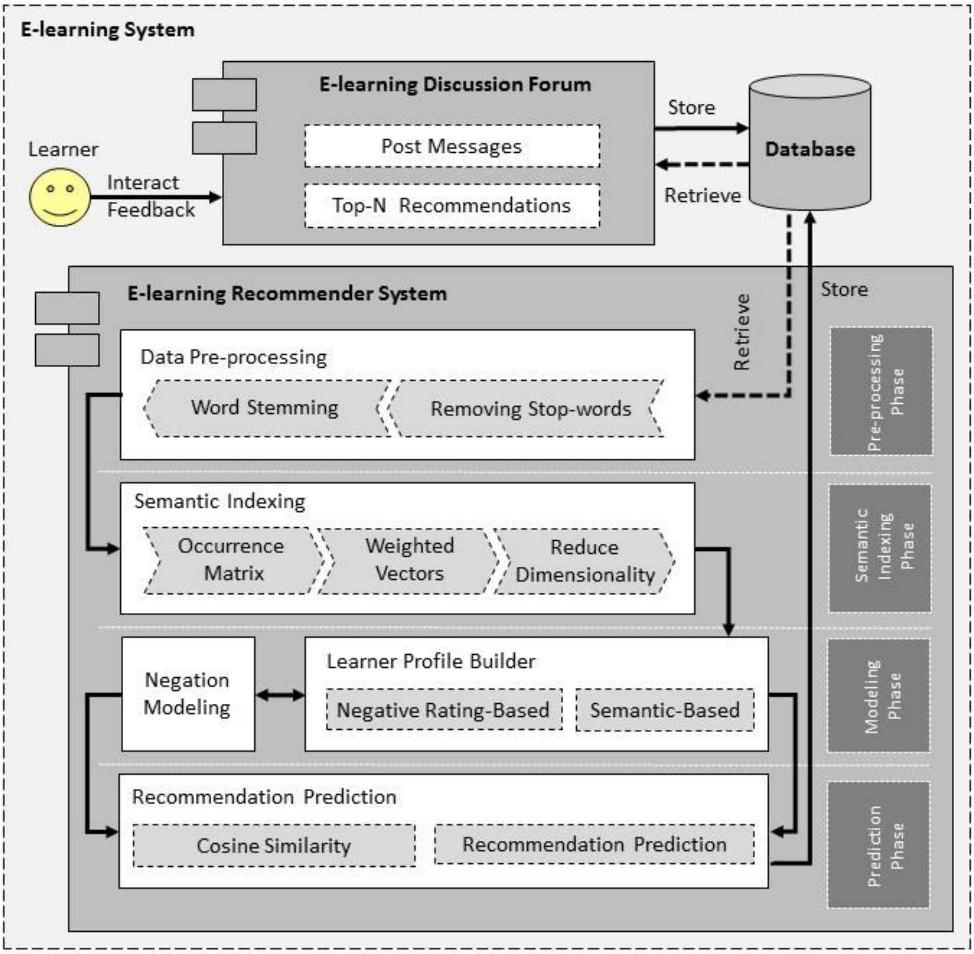


Figure 1. The overall framework of the proposed recommendation system

Data pre-processing phase

In this phase, the input data (i.e., post messages, learners' ratings and other contextual data) is retrieved from the database to prepare it for the next phase. This phase involves removing stop-words and word stemming processes. In order to remove stop-words, each post message is parsed and every stop-word (i.e., the words that do not influence the overall meaning of the text, such as: the, is, at, which, he, and etc.), special characters and numbers are removed from each post message. Next process is performed by converting each word in each post message to its root (e.g., "learner" and "learning" will be converted to their root which is "learn"). Among the most popular word stemming algorithms is the one proposed by Porter (1980). The aim of applying these two processes on the input data is to prepare it for the next phases.

Semantic indexing phase

We use Vector Space Model (Salton et al., 1975) to represent post messages, where each post message is represented as an m-dimensional vector, in which each dimension corresponds to a distinct term and m is the total number of terms occurred in a collection of post messages. As the number of distinct terms increase, the dimensionality of the vector space increases too. Therefore, the representation of the post messages becomes more complicated. Moreover, representing post messages by the terms that occur in them could lead to a shortcoming in identifying similar post messages if they happen to use different sets of keywords. Thus, representing post messages based on the latent semantics would enhance the quality of filtering. In this regard, we exploit the Latent Semantic Analysis (LSA) technique to capture the latent semantic structure into post messages. LSA assumes that terms that have similar meanings occur in similar contexts.

However, this phase begins by creating the occurrence matrix which is a huge rectangular matrix where each column represents the terms frequencies vector of a particular post message. Consider a rectangular matrix A =

[A_1, A_2, …, A_n] with each column vector A_i represents the terms frequencies vector of post message *i*. If there is a total of *m* terms that occur in *n* post messages, then we will have an $m \times n$ rectangular matrix *A*, and an *m*-dimensional vector space. Matrix *A* is a sparse matrix since every term does not normally occur in every post message.

Once the occurrence matrix is constructed, we normalize its elements using Term Frequency/Inverse Document Frequency (TF-IDF) weighting algorithm (Salton & Buckley, 1988), where the terms that rarely occur in the post messages are given high weight to reflect their relative importance as shown in equation (1).

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

Where $w_{i,j}$ is the weighted frequency value of term *i* that occurs in post message *j*, $f_{i,j}$ denotes the frequency value of term *i* occurring in post message *j*, $max_z\, f_{z,j}$ is the maximum frequency among all the *z* terms that occur in post message *j*, *D* is the total number of post messages, and d_i is the number of post messages that term *i* occurs in them.

Next step is to find a low-rank approximation to the occurrence matrix *A* by using a mathematical technique called Singular Value Decomposition (SVD). Given an $m \times n$ rectangular matrix *A*, where without loss of generality $m \geq n$, matrix *A* can be decomposed into a product of three other matrices using SVD as defined in equation (2).

$$A = U\,\Sigma\,V^T \quad (2)$$

Where *U* is an $m \times n$ column-orthonormal matrix whose columns are called left singular vectors, Σ is an $n \times n$ diagonal matrix whose diagonal elements (i.e., σ_1, σ_2,…, σ_n) are non-negative singular values sorted in descending order, and *V* is an $n \times n$ orthonormal matrix whose rows are called right singular vectors.

By applying truncated SVD, that is, keeping only the *k* column vectors of *U* and *k* row vectors of V^T corresponding to the *k* largest singular values in Σ, and discarding the rest of the matrices as figure 2 depicts, the number of rows is reduced while preserving the similarity structure among columns in the approximate matrix $\hat{A}$. Consequently, the terms (i.e., dimensions in the vector space) that occur in similar contexts are merged and treated as one component (i.e., semantic concept) in a low-rank semantic vector space, thus mitigate the problems of synonymy and polysemy which in turn enhances the quality of filtering. On the other hand, the factorization process became quicker and more economical in processing time and memory allocation. Equation (3) defines the truncated SVD.

$$\hat{A} = U_k \Sigma_k V_k^T \quad (3)$$

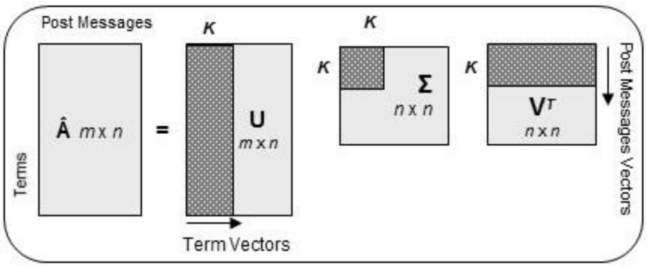


Figure 2. Matrix decomposition using truncated SVD

In our proposed system, we set the value of *k* to 100, which means reducing the dimensionality of the vector space to 100 dimensions. Thus, the post messages are represented as vectors of semantic concepts in a 100-dimensional semantic space. These semantic vectors are used in the next phases to model the learners' profiles and then to calculate the similarity values.

Modeling phase

This phase involves modeling the negation in the post messages based on the learners' negative ratings, and creating the learner's profile which is a conjunction of the negative rating-based profile and the semantic-based profile. The semantic-based profile is created by combining the vectors of the post messages that a learner has rated positively. These vectors are obtained from the approximate matrix $\hat{A}$ as defined in equation (3). Meanwhile, the negative rating-based profile is created by combining the vectors of the negated post messages (i.e., the post messages that have been rated negatively by a learner).

We define negation in term of vectors orthogonality in the vector space, where the scalar product of two orthogonal normalized vectors (i.e., the cosine of the angle between two orthogonal normalized vectors) equals to zero as shown in Figure 3. Thus, if the normalized vectors of two post messages are orthogonal in the vector space, then they are entirely dissimilar (i.e., they have no features in common). Equations (4 and 5) define the learner's semantic-based profile vector and negative rating-based profile vector, respectively.

$$qS_r = \sum_{i=1}^{|P^+|} P_i^+ \quad (4)$$

$$qN_r = \sum_{i=1}^{|P^-|} P_i^- \quad (5)$$

Where qS_r denotes the semantic-based profile vector for learner r, P^+ denotes the weighted vectors of the post messages that have been rated positively by learner r, $|P^+|$ indicates the total number of the weighted vectors of the post messages that have been rated positively by learner r, qN_r denotes the negative rating-based profile vector for learner r, P^- denotes the weighted vectors of the post messages that have been rated negatively by learner r, $|P^-|$ indicates the total number of the weighted vectors of the post messages that have been rated negatively by learner r.

Let V be a vector space. qS_r, $qN_r \in V$. Then, for the negative rating-based profile vector subspace $\langle qN_r \rangle \subseteq V$, the orthogonal vector subspace is defined as follows:

$$\langle \neg qN_r \rangle \equiv \langle qN_r \rangle^{\perp} \equiv \{v \in V : \forall\, qN_r \in \langle qN_r \rangle, qN_r \cdot v = 0\} \quad (6)$$

Consequently, we can integrate the negative rating-based profile vector qN_r and the semantic-based profile vector qS_r by projecting the semantic-based profile vector onto the orthogonal subspace of the negative rating-based profile vector $\langle qN_r \rangle^{\perp}$ to create a single profile that have those features of the semantic-based profile, in which the features of the negative rating-based profile are irrelevant, as defined in equation (7).

$$q_r = qS_r \neg qN_r \quad (7)$$

Where q_r is the profile of learner r that integrates the features of qS_r in which the features of qN_r are irrelevant. This profile is used in the next phase to calculate the similarity values between it and the post messages.

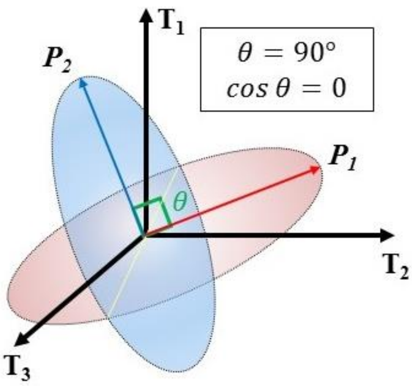


Figure 3. Orthogonal vectors in 3-dimensional vector space

Recommendation prediction phase

The recommendation prediction phase involves calculating the similarity values between the learner's profile and the post messages using cosine similarity measure, and recommending top-N interesting post messages to the learner. Cosine similarity measures the cosine of the angle between the vector of the learner's profile and the vector of the post message in the vector space. Similarity values ranges from 0 to 1, where the value of 1 indicates the highest similarity between the features of the learner's profile and the features of the post message. In contrast, the value of 0 indicates that there are no similarities between the features of the learner's profile and the features of the post message. Equation (8) defines the cosine similarity measure.

$$S = \cos(q_r, P_i) = \frac{q_r \cdot P_i}{\|q_r\| \, \|P_i\|} \quad (8)$$

Where q_r indicates the weighted vector of learner's profile for learner r, P_i indicates the weighted vector of the post message i, $\| q_r \|$ and $\| P_i \|$ are the magnitudes of the vectors q_r and P_i, respectively.

Once the similarity values between the learner's profile and all unviewed post messages are obtained using equation (8), top-N similar post messages will be recommended to the learner.

Experimentation and results

In order to conduct this experiment, we implemented an online discussion forum and integrated it with an e-learning system to enable the learners of different knowledge levels and backgrounds share their knowledge with other learners by making discussions about several topics. Five groups of a total number of 125 bachelor students who were enrolled in computer science program and undertaking operating systems course had participated in this experiment. Each group consists of 25 students from a different section of operating systems course. The first group (G1) comprises the students that used the e-learning system without recommendations. The second group (G2) comprises the students that used the e-learning system with recommendations based on traditional content-based filtering (CB). The third group (G3) comprises the students that used the e-learning system with recommendations based on content-based filtering with learners' negative ratings (CB-NR). The fourth group (G4) comprises the students that used the e-learning system with recommendations based on semantic content-based filtering (SCB). The fifth group (G5) comprises the students that used the e-learning system with recommendations based on semantic content-based filtering with learner' negative ratings (SCB-NR).

In order to evaluate the knowledge level of the students from all groups before they start using the e-learning system, they were required to sit for the same pre-test. Then, all the students from all groups were enabled to use the e-learning system, make discussions over the discussion forum and rate the posted messages for three months. When the operating systems course ended (i.e., after three months of using the e-learning system), the students from all groups were required to sit for the same post-test. In order to obtain as reliable results as possible, all the classes (i.e., groups) were taught by the same professor. Furthermore, each of the pre-test and the post-test was conducted online and simultaneously in five different classrooms under a well-monitored condition to rule out the possibility of collaborating between the students from different groups. Each of the two tests contained a set of 50 instructor-made and objective multiple-choice questions, where each question is accompanied by five possible answers in which only one of these answers is correct. Both the questions and their answers were arranged randomly in each student's test screen, and a button for submitting the answer must be clicked to enable the student to proceed to the next question. The purpose beyond such procedures is to rule out any possibility of cheating between the students, and to make the correct answers hard to be guessed unless the student truly knows them.

However, the obtained results from pre-test and post-test were used to evaluate the students' learning performance during the course. The students from all groups have posted a total of 10021 messages under 347 different threads on the discussion forum during the course. A total of 100107 ratings were received on all the messages posted by the students from all groups. Figure 4 shows the user interface of the e-learning discussion forum, where the learners can make discussions. Figure 5 shows a screenshot of the top-N recommendations list.

In our experiments, we benchmarked the accuracy of the proposed e-learning recommender system against other similar systems in terms of rating deviation by using Mean Absolute Error (MAE). MAE can be defined as a quantity used to measure how close the predicted ratings are to the actual ratings given by the user (Shani & Gunawardana, 2011). The small value of MAE denotes that the predicted ratings by the recommender system are close to the actual ratings given by the user, thus the accuracy of the recommender system is considered high. MAE is defined in equation (9):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{r}_i - r_i| \quad (9)$$

Where $\hat{r}_i$ is the predicted rating for item i, r_i is the actual rating for item i, and n is the total number of items.

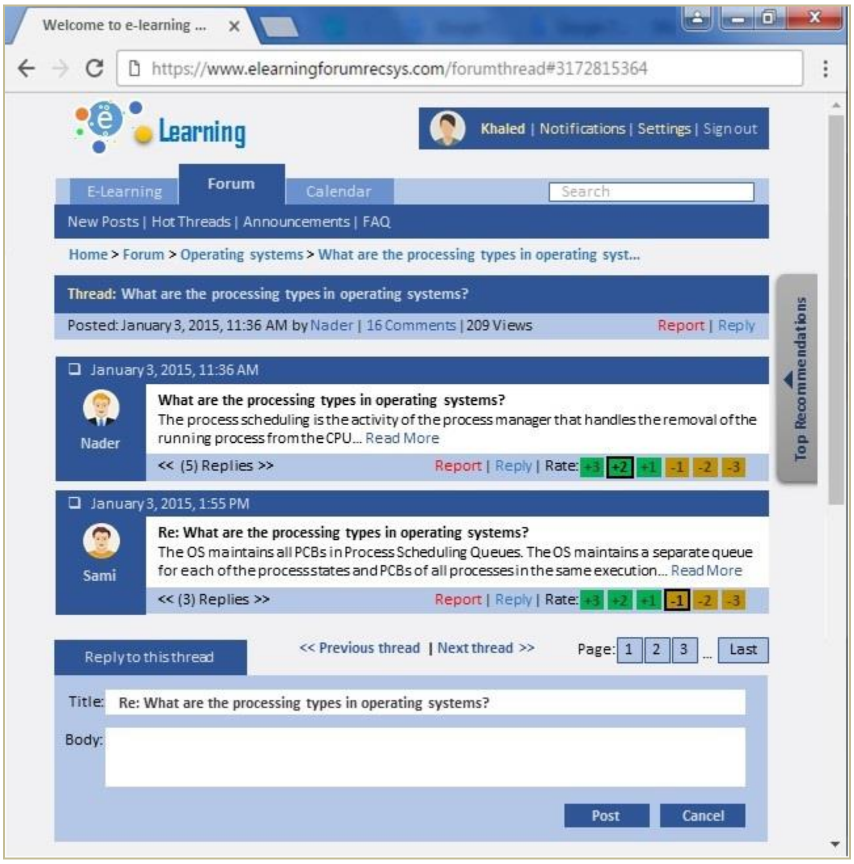


Figure 4. User interface of the e-learning discussion forum

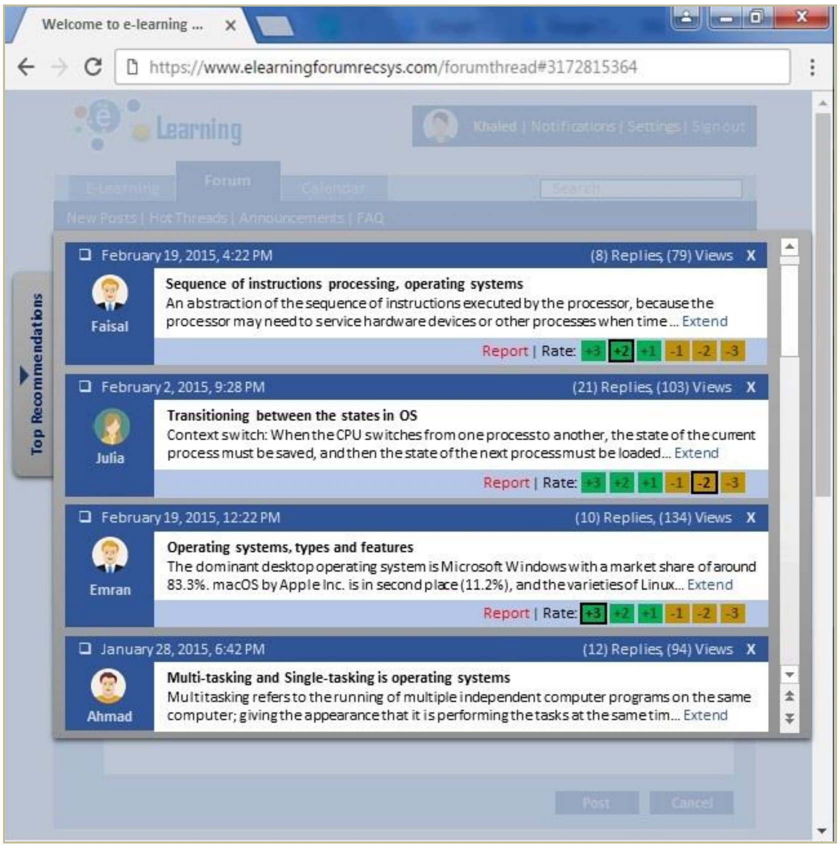
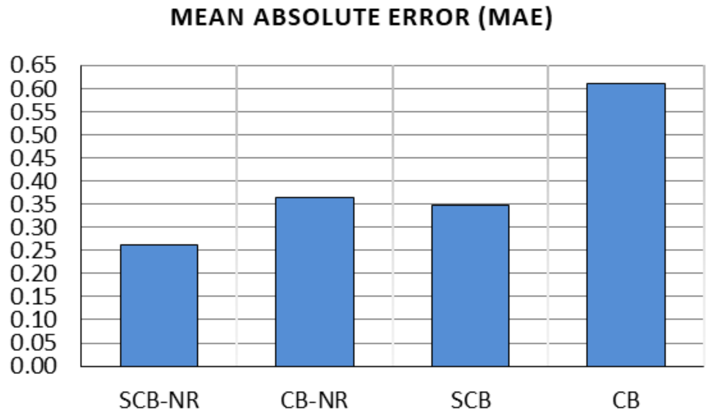


Figure 5. Screenshot of the top-N recommendations list



Note. SCB-NR (semantic content-based filtering technique with learners' negative ratings); CB-NR (traditional content-based filtering with learners' negative ratings); SCB (semantic content-based filtering technique); CB (traditional content-based filtering technique).

Figure 6. The values of MAE for all recommender systems

Figure 6 depicts the difference between the MAE value of the proposed e-learning recommender system (SCB-NR) and the MAE values of the other three similar systems. The proposed e-learning recommender system has obviously achieved the highest accuracy in term of rating deviation comparing to the other three similar systems, where it has the smallest MAE value that is about 0.26. In contrast to the proposed recommender system which uses semantic content-based filtering technique with learners' negative ratings (SCB-NR), the recommender system that uses a traditional content-based filtering technique (CB) has the lowest rating deviation accuracy with the highest MAE value which is about 0.61. On the other hand, the recommender system that uses a semantic content-based filtering technique (SCB) has a MAE value of about 0.35 which is close to the MAE value of the recommender system that uses a traditional content-based filtering technique with learners' negative ratings (CB-NR) where it is about 0.36.

Furthermore, we have evaluated the proposed e-learning recommender system in term of decision-support accuracy to measure its effectiveness in supporting the learners in the process of selecting interesting items from a huge set of available options. Thus, we used three other metrics for this purpose which are Precision, Recall, and F-measure. Equations 10, 11, and 12 define Precision, Recall, and F-measure, respectively.

$$Precision = \frac{|\{relevant\ items\} \cap \{retrieved\ items\}|}{|\{retrieved\ items\}|} \quad (10)$$

$$Recall = \frac{|\{relevant\ items\} \cap \{retrieved\ items\}|}{|\{relevant\ items\}|} \quad (11)$$

$$F - measure = \frac{2 * Precision * Recall}{Precision + Recall} \quad (12)$$

Where Precision is the fraction of retrieved items that are relevant, Recall is the fraction of relevant items that are retrieved. F-measure is the harmonic mean of Precision and Recall. The values of these three measurements range from 0 to 1, where 0 is the worst value and 1 is the best value.

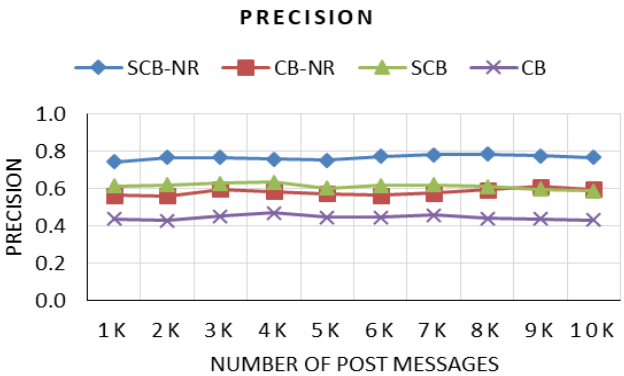


Figure 7. The values of Precision for all recommender systems

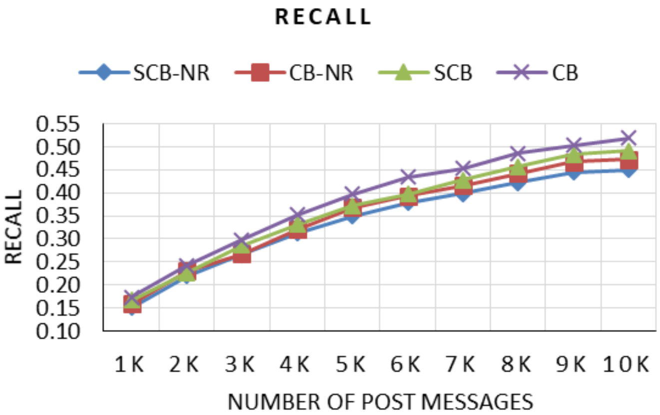


Figure 8. The values of Recall for all recommender systems

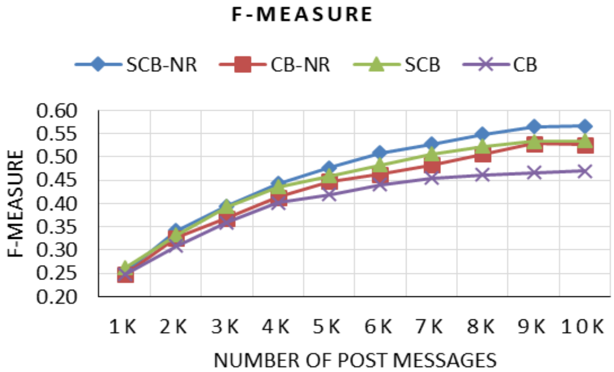


Figure 9. The values of F-measure for all recommender systems

Figures 7, 8, and 9 depict the obtained results of Precision, Recall, and F-measure of the proposed e-learning recommender system as compared with the other three similar recommender systems. The proposed e-learning recommender system (SCB-NR) has evidently achieved the highest precision with the expense of recall. In contrast to the proposed system, the recommender system that uses traditional content-based filtering technique (CB) has the highest recall as a consequence of the lowest precision. Furthermore, the recommender system that uses semantic content-based filtering technique (SCB) has achieved a slightly higher precision and recall than the recommender system that uses traditional content-based filtering with learners' negative ratings technique (CB-NR). However, the F-measure metric compares the harmonic mean of both Precision and Recall for all similar systems to reveal the best system accuracy in term of decision-support. It is obvious that the proposed e-learning recommender system (SCB-NR) has the highest F-measure value, while in contrast, the recommender system that uses traditional content-based filtering technique (CB) has the lowest F-measure value. On the other hand, the recommender system that uses semantic content-based filtering technique (SCB) still outperforms the other recommender system that uses traditional content-based filtering technique with learners' negative ratings (CB-NR) in term of F-measure. According to the obtained results, it is obvious that the proposed e-learning recommender system (SCB-NR) has achieved the best decision-support accuracy, while in contrast, the recommender system that uses traditional content-based filtering technique (CB) has the worst decision-support accuracy.

In order to study the impact of using different recommendation methods for learning on the learners' performance in five independent groups, we conducted a one-way Analysis of Covariance (ANCOVA) to determine whether or not there was a statistically significant difference between using these different recommendation methods for learning on the learners' achievements in the post-test in five independent groups, controlling for the learners' marks in the pre-test. In this analysis, the independent variable was the group of learners, while the learners' marks in the post-test was the dependent variable, and the learners' marks in the pre-test was the covariate.

We assumed the null hypothesis (H_0) for the post-test is that there is no significant difference between the means of marks for the five groups, while in contrast, we assumed the alternative hypothesis (H_1) is that there are at least two group means that are statistically significantly different from each other. The null hypothesis and the alternative hypothesis are defined as follows:

H_0: $\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$
H_1: There are at least two group means that are statistically significantly different from each other.

Furthermore, we calculated the average percentage of marks increments from the pre-test to the post-test for each group for further justification and understanding of the differences between groups in term of learners' performance. Figures 10, 11, and 12 depict the difference between the means of marks for the pre-test and the post-test, the standard deviations of the pre-test and the post-test for the five groups, and the average percentage of mark increments from the pre-test to the post-test for each group, respectively. Table 1 summarizes the means of the marks and the standard deviation for all groups.

Table 1. The means of marks and the standard deviations

Groups	Pre-test		Post-test	
	Mean	Standard deviation	Mean	Standard deviation
G1	37.24	11.78	56.64	14.21
G2	39.12	13.48	59.84	12.85
G3	38.96	13.88	59.20	12.03
G4	38.00	12.91	61.36	14.64
G5	37.52	13.81	72.04	12.80

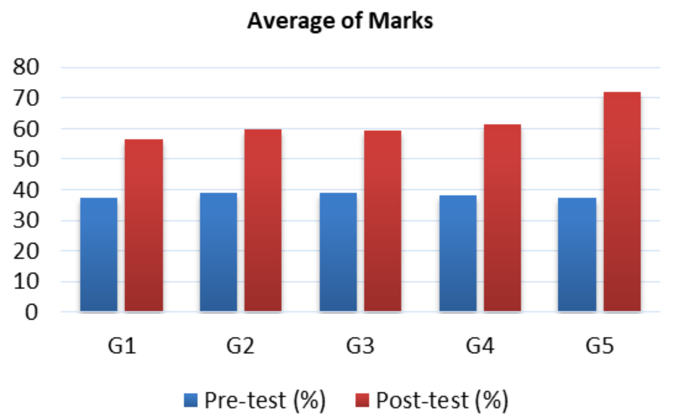


Figure 10. The mean of marks for the pre-test and the post-test

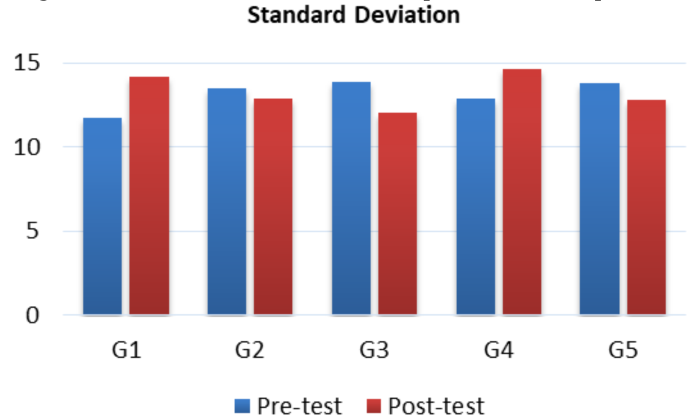


Figure 11. The standard deviation for the pre-test and the post-test

Table 2. One-way ANCOVA test results (Dependent variable: post-test, covariate: pre-test)

Source	Type III sum of squares	*df*	Mean square	*F*	*Sig.*	Partial eta squared
Corrected Model	14897.493[a]	5	2979.499	35.381	.000	.598
Intercept	14609.526	1	14609.526	173.484	.000	.593
Pre-test	11340.565	1	11340.565	134.666	.000	.531
Group	3803.593	4	950.898	11.292	.000	.275
Error	10021.275	119	84.212			
Total	502571.000	125				
Corrected Total	24918.768	124				

Note. ([a]) Indicates that R Squared = .598 (Adjusted R Squared = .581).

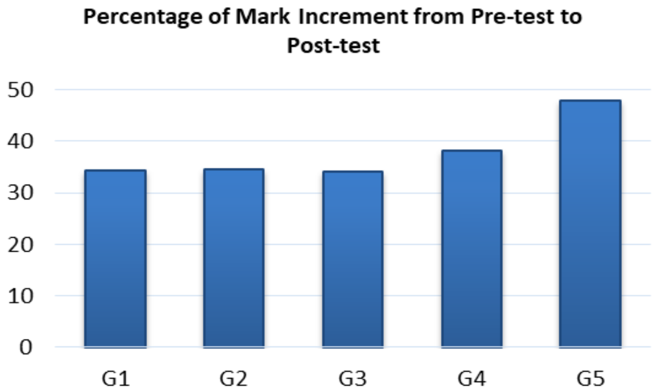


Figure 12. The percentage of marks increment from pre-test to post-test

The results shown in Table 2 reveal that there was a statistically significant difference at $p < .05$ between the mean scores of the post-test marks for all groups controlling for pre-test marks as determined by one-way ANCOVA ($F(4,119) = 11.292$, $p = .000$), therefore we rejected the null hypothesis (H_0) for the means of the post-test marks. Table 3 summarizes the results obtained from Bonferroni post hoc test, it obviously reveals that there was a statistically significant difference between the mean scores of the post-test marks between each of G5 and G1 (p =.000), G5 and G2 (p =.000), G5 and G3 (p =.000), G5 and G4 (p =.000). Furthermore, Figure 12 depicts that G5 has achieved a value of 47.91% as the highest percentage of marks increment from the pre-test to the post-test, while in contrast, G1 and G3 has achieved the lowest percentage of marks increment which is about 34.20%.

Table 3. Pairwise comparisons of the estimated marginal means using Bonferroni post hoc test

(I) Group	(J) Group	Mean difference (I-J)	Std. error	*Sig.*[b]	95% Confidence interval for difference[b]	
					Lower bound	Upper bound
G1	G2	-1.815	2.598	1.000	-9.247	5.617
	G3	-1.293	2.598	1.000	-8.724	6.138
	G4	-4.160	2.596	1.000	-11.586	3.265
	G5	-15.194*	2.596	.000	-22.618	-7.769
G2	G1	1.815	2.598	1.000	-5.617	9.247
	G3	.522	2.596	1.000	-6.902	7.946
	G4	-2.345	2.597	1.000	-9.772	5.082
	G5	-13.379*	2.598	.000	-20.809	-5.949
G3	G1	1.293	2.598	1.000	-6.138	8.724
	G2	-.522	2.596	1.000	-7.946	6.902
	G4	-2.867	2.596	1.000	-10.293	4.559
	G5	-13.901*	2.597	.000	-21.330	-6.472
G4	G1	4.160	2.596	1.000	-3.265	11.586
	G2	2.345	2.597	1.000	-5.082	9.772
	G3	2.867	2.596	1.000	-4.559	10.293
	G5	-11.034*	2.596	.000	-18.458	-3.609
G5	G1	15.194*	2.596	.000	7.769	22.618
	G2	13.379*	2.598	.000	5.949	20.809
	G3	13.901*	2.597	.000	6.472	21.330
	G4	11.034*	2.596	.000	3.609	18.458

Note. (*) Indicates that the mean difference is significant at .05 level, and (b) indicates that the adjustment for multiple comparisons is done using Bonferroni post hoc test.

Conclusion and future work

In this paper, we have proposed a new recommendation framework to achieve learning personalization in e-learning environments based on content-based filtering techniques and learners' negative ratings. The proposed recommender system exploits learners' negative ratings to fulfill a crucial step in e-learning recommendation strategies which is ensuring that the recommended items are in the learner's current learning context, thus increasing the system accuracy and improving the learners' performance. A comparative study has been conducted to benchmark the performance of the proposed recommender system against other similar e-learning recommender systems. The obtained experimental results show that the proposed e-learning recommender system (SCB-NR) outperforms other similar e-learning recommender systems that use non-semantic content-based filtering technique (CB), non-semantic content-based filtering technique with learners' negative ratings (CB-NR), semantic content-based filtering technique (SCB), with respect to system accuracy of about 57%, 28%, and 25%, respectively. On the other hand, the learners' performance has been increased by 9.84% as a consequence of utilizing learners' negative ratings in the proposed e-learning recommendation framework. Thus, exploiting learners' negative ratings into e-learning recommender systems has a positive effect on both improving the recommendations accuracy and increasing the learning performance of the students in e-learning environments.

Despite the obtained results reveal that the proposed recommender system has outperformed other similar systems in terms of system accuracy and learners' performance, several further works are planned to be done in the future to further justify and extend our work in several directions. Firstly, our proposed e-learning recommendation framework uses semantic content-based filtering technique with learners' negative ratings to compute recommendations to learners, it would be promising if learner's contextual information (i.e., time and date, registered subjects in current semester, program enrolled in) are taken into consideration in the filtering process. This will enable the recommender system to recommend more accurate and novel recommendations. Verbert et al. (2012) conducted a survey on context-aware e-learning recommender systems. They stated that context information play a key factor in personalizing e-learning systems.

Furthermore, we are planning to extend our proposed recommender system in another direction to suggest to the learner a sorted sequence of recommendations based on the difficulty level of the learning content. This extension is expected to assist the learners in evolving from the beginning of learning a particular subject until they finish it successfully.

Lastly, we are planning to evaluate the proposed recommender system over time to ensure that the more the learner interact with the system, the more accurate recommendations will be suggested. For this purpose, we are planning to conduct an experiment on students of a particular class who use an e-learning system with the proposed recommender system for one complete semester. Then, we will evaluate the system accuracy and students' learning performance every three weeks.

References

Abel, F., Bittencourt, I. I., Costa, E., Henze, N., Krause, D., & Vassileva, J. (2010). Recommendations in online discussion forums for e-learning systems. *IEEE transactions on learning technologies, 3*(2), 165-176.

Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A Survey of the state-of-the-art and possible extensions. *IEEE transactions on knowledge and data engineering, 17*(6), 734-749.

Albatayneh, N. A., Ghauth, K. I., & Chua, F. F. (2014). A Semantic content-based forum recommender system architecture based on content-based filtering and latent semantic analysis. In *Recent Advances on Soft Computing and Data Mining* (pp. 369-378). Cham, Switzerland: Springer International Publishing. doi:10.1007/978-3-319-07692-8_35

Bandura, A. (1977). *Social learning theory*. Edgewood Cliffs, NJ: Prentice-Hall.

Burke, R. (2002). Hybrid recommender systems: Survey and experiments. *User modeling and user-adapted interaction, 12*(4), 331-370.

Capuano, N., Gaeta, M., Ritrovato, P., & Salerno, S. (2014). Elicitation of latent learning needs through learning goals recommendation. *Computers in Human Behavior, 30*, 663-673.

Dascalu, M. I., Bodea, C. N., Moldoveanu, A., Mohora, A., Lytras, M., & de Pablos, P. O. (2015). A Recommender agent based on learning styles for better virtual collaborative learning experiences. *Computers in Human Behavior, 45*, 243-253.

Distante, D., Fernandez, A., Cerulo, L., & Visaggio, A. (2014). Enhancing online discussion forums with topic-driven content search and assisted posting. In *International Joint Conference on Knowledge Discovery, Knowledge Engineering, and Knowledge Management* (pp. 161-180). Cham, Switzerland: Springer International Publishing.

Drachsler, H., Verbert, K., Santos, O. C., & Manouselis, N. (2015). Panorama of recommender systems to support learning. In *Recommender systems handbook* (pp. 421-451). Boston, MA: Springer US.

Dwivedi, P., & Bharadwaj, K. K. (2013). Effective trust-aware e-learning recommender system based on learning styles and knowledge levels. *Educational Technology & Society, 16*(4), 201-216.

Ekstrand, M. D., Riedl, J. T., & Konstan, J. A. (2011). Collaborative filtering recommender systems. *Foundations and Trends in Human-Computer Interaction*, *4*(2), 81-173.

Fosnot, C. T., & Perry, R. S. (1996). Constructivism: A Psychological theory of learning. *Constructivism: Theory, perspectives, and practice, 2*, 8-33.

Ghauth, K. I. B., & Abdullah, N. A. (2011). The Effect of incorporating good learners' ratings in e-learning content-based recommender system. *Educational Technology & Society, 14*(2), 248-257.

Khribi, M. K., Jemni, M., & Nasraoui, O. (2009). Automatic recommendations for e-learning personalization based on web usage mining techniques and information retrieval. *Educational Technology & Society, 12*(4), 30-42.

Li, Y., Dong, M., & Huang, R. (2009). Toward a semantic forum for active collaborative learning. *Educational Technology & Society, 12*(4), 71-86.

Lops, P., De Gemmis, M., & Semeraro, G. (2011). Content-based recommender systems: State of the art and trends. In *Recommender systems handbook* (pp. 73-105). Boston, MA: Springer US.

Lu, J., Wu, D., Mao, M., Wang, W., & Zhang, G. (2015). Recommender system application developments: A Survey. *Decision Support Systems, 74*, 12-32.

Muñoz, A., Lasheras, J., Capel, A., Cantabella, M., & Caballero, A. (2015). OntoSakai: On the optimization of a learning management system using semantics and user profiling. *Expert Systems with Applications, 42*(15), 5995-6007.

Porter, M. F. (1980). An Algorithm for suffix stripping. *Program*, *14*(3), 130-137.

Resnick, P., Iacovou, N., Suchak, M., Bergstrom, P., & Riedl, J. (1994). GroupLens: An Open architecture for collaborative filtering of netnews. In *Proceedings of the 1994 ACM conference on Computer supported cooperative work* (pp. 175-186). New York, NY: ACM.

Salton, G., & Buckley, C. (1988). Term-weighting approaches in automatic text retrieval. *Information processing & management, 24*(5), 513-523.

Salton, G., Wong, A., & Yang, C. S. (1975). A Vector space model for automatic indexing. *Communications of the ACM, 18*(11), 613-620.

Santos, O. C., Boticario, J. G., & Pérez-Marín, D. (2014). Extending web-based educational systems with personalised support through user centred designed recommendations along the e-learning life cycle. *Science of Computer Programming, 88*, 92-109.

Shana, Z. (2009). Learning with technology: Using discussion forums to augment a traditional-style class. *Educational Technology & Society, 12*(3), 214-228.

Shani, G., & Gunawardana, A. (2011). Evaluating recommendation systems. In *Recommender systems handbook* (pp. 257-297). Boston, MA: Springer US.

Turney, P. D., & Pantel, P. (2010). From frequency to meaning: Vector space models of semantics. *Journal of artificial intelligence research, 37*(1), 141-188.

Verbert, K., Manouselis, N., Ochoa, X., Wolpers, M., Drachsler, H., Bosnic, I., & Duval, E. (2012). Context-aware recommender systems for learning: a survey and future challenges. *IEEE Transactions on Learning Technologies, 5*(4), 318-335.

Wang, F. H. (2008). Content recommendation based on education-contextualized browsing events for web-based personalized learning. *Educational Technology & Society, 11*(4), 94-112.

Zeng, W., Zhu, Y. X., Lü, L., & Zhou, T. (2011). Negative ratings play a positive role in information filtering. *Physica A: Statistical Mechanics and its Applications, 390*(23), 4486-4493.