

Research Article

E-Learning Recommender Systems Based on Goal-Based Hybrid Filtering

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Received 28 March 2014; Accepted 24 April 2014; Published 8 July 2014

Academic Editor: Chong-Gun Kim

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This research work is based on the thesis contribution by proposing the goal-based hybrid filtering approach in e-learning recommender systems (eLearningRecSys). The proposed work has been used to analyze the personalized similarities between learner's profile preferences collaboratively. The proposed work consists of two hybridizations: the first hybridization has been made with content-based filtering and collaborative features to overcome the new-learners zero-rated profile recommendations issue; the second hybridization has been done with collaborative filtering and k-neighborhood scheme features to improve the average-learner's low-rated profile recommendations issue. Therefore, the proposed goal-based hybrid filtering approach that hybridized content-based filtering, collaborative filtering and k-neighborhood features simultaneously works on both types of learner's profiles recommendation issues in e-learning environments. The experiments in the proposed work are done using the famous "MovieLens" dataset, while the evaluation of experimental results has been performed with mean of precision 83.44% and mean of recall 85.22%, respectively. *t*-test result shows the probability difference value of 0.29 between the proposed hybrid approach and the evaluated literature work. The results demonstrate the effectiveness of the proposed hybrid recommender systems in e-learning scenarios.

1. Introduction

The intensification of web increased the difficulties to find the relevant learning contents quickly and efficiently, but electronic learning or e-learning scenarios provide many benefits to learners. They have some drawbacks too, for example, big data mismanagement [1] by increasing the number of pages, which have not been considered as an effective and good data management strategy [2] for e-learning. The reason for discouraging this strategy is that the learner's spend a huge time in visiting every page for retrieving their required learning content, which increases the leaning content's retrieving time and cuts the learner's interest. However, recommender systems in e-learning know as e-learning recommender systems [3], offer more flexibility for learner's to decrease the learning content searching time, increase the learner's interest, and provide the recommendations relevant to learner's goals or interests [4, 5].

Recommendation or recommender system (RS) is a branch of information retrieval; gradually it filters the learning content in three ways, namely, content-based filtering (CBF), collaborative filtering (CF), and hybrid filtering (HF) [6]. In content-based filtering (CBF), it recommends only relevant learning contents to learners that are similar to the ones they preferred themselves in the past [7], while in the collaborative filtering (CF), the learners recommend relevant learning contents that other learners with similar interest and preferences liked in the past [8]. The hybrid filtering (HF) is a third way to tackle the filtering results [9] that plays a controversial role to tackle the learner's required goals. Gradually, the hybrid filtering hybridized the features of content-based filtering and collaborative filtering. Somehow, the encouraged researchers combine some adopted machine learning techniques or approaches [7] with content-based filtering or collaborative filtering to emerge the artificial intelligent (AI) aspects in it. These adaptations construct

the intelligent hybrid approaches that drive the way of knowledge and management in an automotive intellectual era; perhaps they depend upon the controversial issues and domain requirements.

2. Problem Background

The major challenge in e-learning that affects the performance of recommender systems is learner-based cold-start problem [8] or new-starter problem that moderated against the learners' profile preferences in all types of recommender systems [15]. This problem endorses the learner-based profile recommendations issue and encompasses in two conditions.

(a) *New-Learner Zero-Rated Profile Recommendations Issue.* When the learner is new in the system, the system is unable to extract sufficient information from the learner profile that is required for the starter recommendations [19, 20]. In other words, the recommender systems generally work with the learners' own historical or rated profile preferences. Therefore, the new learner in the system does not visit and rate any learning content, so the system does not acclaim the learners required goals and is unable to filter the starter or new recommendations.

(b) *Average-Learners Low-Rated Profile Recommendations Issue.* The contemporary literature induced that the learners, which are not new in the system, are also facing the forecasting recommendation issues. In other words, the traditional e-learning recommender systems are unable to forecast the recommendations for low-rated learners [21, 22]. Critically, it has occurred when the learner is not regular in the system or learner has not rated and visited much learning contents. In both of the cases, the system is not able to recommend the learners required learning content, which loses the learner's interest.

2.1. Research Contribution towards E-Learning Recommender Systems. Salient aspects of our research work, which would contribute towards the recommender systems in e-learning, are as follows:

- (i) improve the traditional dataset driven method with f -fold cross validation and normalization for eLearningRecSys;
- (ii) drive a goal-based hybrid filtering approach that hybridized content-based filtering, collaborative filtering, and k -neighborhood scheme features to improve the content filtering feature of eLearningRecSys;
- (iii) overcome the new-learner zero-rated profile recommendation issue with the hybridization of content-based filtering and collaborative feature;
- (iv) improve the average-learner low-rated profile recommendation issue with the hybridization of collaborative filtering and k -neighborhood scheme features;
- (v) the proposed work is easily implemented for all sort of web-based learning recommender systems and implies the simplest way to improve the problem background.

2.2. Research Flexibility. The proposed goal-based hybrid approach interworks with learner's personalized profile preferences such as age, gender, and occupation, instead of metakeywords or historical informational aspects to overcome the learner-based cold-start problem that encompasses in two conditions: (i) overcome the new-learner zero-rated profile recommendations issue, and (ii) improve the average-learner low-rated profile recommendations issue. In other words, the proposed hybrid approach decreases the e-learning recommender systems dependency on learner's historical or past preferences. The proposed hybrid approach may affect the learner's profile flexibility to make the e-learning recommender system (eLearningRecSys) more appropriate than the other traditional recommendation scenarios working in e-learning domain. In terms of the flexibility, the proposed approach has worked in all types of e-learning scenarios; for example, some scenarios need long profile details and some need short. In that case, the proposed work just needs the three personalized profile preferences such as age, gender, and occupation to filter the recommendations for learners in the eLearningRecSys collaboratively.

3. Literature Background

The learning goals provide a sense of direction and purpose to guide the learner for next learning step and promote clarity to achieve learners required learning content accurately [23, 24]. Arguably, the learning goals are only effective if learners use them to pinpoint and process goal-relevant information. The abusement of learning goals will lay down the learner's interest and learner could not retrieve the learning contents as per their required goal or need. The importance of learning goals attract e-learning researchers to adopt this term in e-learning environment [25]. E-Learning enhanced the individual's problem-solving skills and enticed learner's to focus full attention on a task through the vividness of the learning concepts, intriguing or fascinating learning behavioral activities [26–31]. Some research studies define e-learning as an effective way for enhancing the individual's problem-solving skills [6, 32, 33]. The studies reported that collaborative learning reflects the interaction with other learners in the formal knowledge-retrieving environment, such as recommender technology, to know their learning goals and support them to be involved in practical work placements [34].

Recommender technology is a part of information retrieval [35]. It has been popular in the 1990s when researchers used this technology the first time to overcome the information overloading or big data mismanagement issue [35]. The working criterion of this system is far from page-to-page knowledge explorer scenario, which is also useful to enhance the knowledge management efficiency and increase the learner's interests. It helps the target individuals navigate through a complex information retrieval by making suggestions of which the bit of information that target individual should consume, that is, read, watch, learn, and so forth. This recommendations are based on numeric form of data such as the like, dislike or ratings of learning

content by the learners are operated numerically from 1 to 5 [36]. Such systems efficiently deal with any big length of data, evaluate the learner's interests, and automatically generate relevant materialistic learning content suggestions or recommendations [19].

The emerging term of recommender systems in e-learning is known as e-learning recommender systems [3]. In e-learning, the recommender systems work as instructor to acclaim the learner's goals, increase their interests, reduce boredom, and promote clarity to achieve learning requirements accurately [2]. Generally, "a goal in e-learning recommender systems is to specify the objectives that a learner may have when learners consult learning web services [37]." Goal, in e-learning recommender systems, is an identification of requirements and achievements of relevant learning content that are required by the learner. To do so, recommender systems are implied on three famous filtering approaches that help to tackle the learning content most relevant to learner's goals. These approaches are content-based filtering, collaborative filtering, and hybrid filtering. Every approach has its great benefits and little drawbacks [8], that is why most of researchers like to work with hybrid filtering approaches in which they peer different filtering approach with respect to domain and relevant issue [7–9, 38–40].

Recommendation or recommender system (RS) is a branch of information retrieval; gradually it filters the learning content in three ways, namely, content-based filtering (CBF), collaborative filtering (CF), and hybrid filtering (HF) [6]. In content-based filtering (CBF), it recommends only relevant learning contents to learners who are similar to the ones they preferred themselves in the past [1, 7, 13]. Typically, this technique has less effectiveness on zero-rated cold-start problem [8] which is one of the major weaknesses of this approach. In these systems the recognition of learner's interest in a particular learning content has been derived on the base of vector similarities such as cosine similarity measurement [16]. By using this type of filtering approach, the recommender systems fully rely on the learners and learning contents profile past preferences; pendor.com is an example of it.

In the collaborative filtering (CF), the learners recommend relevant learning contents that other learners with similar interest and preferences liked in the past [7, 8]. This approach depends on the collaborative learner's profile preferences more than learner's own profile and past preferences and tackles the learner's interest by using weight, distance, or correlation between two learners such as euclidean distance. The filtration process works collaboratively or on multiusers network with similar interests. Progressively, this technique works fine to overcome the zero-rated cold-start problem [16] in some domains, but this technique has less effectiveness on low-rated cold-start problem which is one of the major weaknesses of this approach. Its recommendations are based on numeric data, means the learners likes, dislikes or ratings for learning content which calculated as 1 to 5 and the number of clicks per learning content collaboration, and so forth; newsweeder.com is an example of it.

Gradually, the hybrid filtering hybridized the features of content-based filtering and collaborative filtering [3]. Somehow, the encouraged researchers combine some adopted machine learning techniques or approaches [7] with content-based filtering or collaborative filtering to emerge the artificial intelligent (AI) aspects in it [38, 41–45]. For example, [11] proposed user-oriented content-based recommender system (UCB-RS) [11] with two stages. In the first stage, the author in [11] used fuzzy theoretic content-based filtering to generate the initial population of users' preferences by interactive genetic algorithm (IGA) using recursive methods (RMs). In second stage, the author in [11] used k-mean algorithm for clustering the item in order to handle time complexity of interactive genetic algorithm (IGA). Usually, the traditional k-mean is unable to handle time computational complexity with genetic algorithm if "k" is small [46]. Mostly with large set of data, the traditional k-mean does not give sufficient performance.

3.1. Literature Gap Analysis. With the deep analysis on the existing literature, this study's results show that the three approaches that are famous in the study domain are content-based filtering CBF, collaborative filtering CF, and hybrid filtering HF, which are generally the combination of content-based filtering and collaborative filtering. The study also sees that researches adopted machine-learning technique KNN to become hybrid. These hybridizations depend upon the domain requirement. The deep and comprehensive eye of this study tackles that most of researches have done their work to solve the issue called cold-start. Table 1 shows the analyzed results of this literature review.

From a critical and a deep analysis, Table 1 shows that the cold-start problem is one of a common problems in recommender systems. The issue cause that is described in Table 1 is divided into four different types of learner-based profile issues, in which causes are elaborated in Table 2.

Table 2 defines the four issues and their causes in learner-based cold-start problem. In the first issue, the new-learner or user cold-start occurs when the learner is new in the system and learner or user has zero past preferences. In the second issue, the new-item or content cold-start occurs when the item or content is new in the system and no learners have browsed it and rated or voted it before [7]. The third issue is low-rated user or learner cold-start; it occurs when the collaborative users or learners could not have high rated learning contents in the past preferences. And the fourth issue is low-rated item or content cold-start; it occurs when the item or content profile is unable to clarify the high rating by collaborative learners [38]. In these four issues, the domain systems are unable to suggest the recommendations [15].

In recommender system approaches, if the content-based systems could not find the required information in the learning contents profile [13] or new or other learners did not have any past learning preferences, so the approach is unable to filter any recommendation for the learners. This cause generated an issue called cold-start in content-based filtering systems [7, 14]. The low-rated learner's profiles in cold-start are the main problem in collaborative filtering [38]. In both cases, the recommender system is unable to filter

TABLE 1: Current and existing literature analysis results.

Author(s)	Year	Problem	Issue
Kant and Bharadwaj [11]	2013	Cold-start	New learner or user
Shinde and Kulkarni [12]	2012	Cold-start	Low-rated learner or user
Souali et al. [13]	2011	Cold-start	New-learner or user
Ghani et al. [14]	2010	Cold-start	New-learner or user
Lécué [15]	2010	Cold-start	Low-rated learner or user
Ahn [16]	2008	Cold-start	New-learner or user
Wang et al. [17]	2008	Cold-start	New-learner or user
Adomavicius and Tuzhilin [7]	2005	Cold-start	Low-rated learner or user
Schein et al. [18]	2002	Cold-start	New-learner or user

TABLE 2: Two issues in learner-based cold-start problem and their causes.

	Issue	Cause
1	New-learner or user cold-start	Zero rating to the item or learning content or no past preferences
2	Low-rated learner or user cold-start	No high rated item or learning contents in past preferences

the recommendations [18]. Instead of this, hybrid filtering systems delightedly help to improve the learner low-rated profile cold-start issue but it still may have zero-rated profiles cold-start issue. Due to these aspects, the study identified that cold-start is an important limitation of recommender systems that need more intention and integration from future researchers.

4. A Brief Introduction of Research Methodology

Gradually, the research methodology has been envisioned to meet the research study objectives and serves to provide subsequent processes. Table 3 defines the objectives of each research methodological phase that includes each phase objective, its activities that are involved in this research work, its processes, and the possible outcomes.

4.1. Phase-I: Dataset Cross Validation. Since there is no well-known dataset publically accessible of e-learning recommender system, perhaps based on the literature [21, 47–51], this research examines that most of previous researchers mapped “MovieLens” dataset for e-learning recommender systems [52–56]. Therefore, this research work considered the “MovieLens” [57] dataset for tackling the experiments on proposed research work. The specialty of “MovieLens” is that it is a real-time dataset [57] and is famous for experimenting the constructed hybrid recommendation systems [49–51]. The dataset “MovieLens” [21, 48] generally comes with validated data, which are defined in Table 4.

The density of the learners and learning contents matrix with respect to the ratings to the learning contents by the learners, created from the “MovieLens” dataset, is

$$\text{Density} = \frac{\text{total ratings } (R_{u,i})}{(\text{total users } | u \in U) \times (\text{total items } | i \in I)}. \quad (1a)$$

Equation (1a) is formulated as

$$\begin{aligned} \text{Density} &= \frac{\sum R_{u,i}}{(\sum u \in U) \times (\sum i \in I)} \\ &= \frac{100000}{(943) \times (1682)} = 15.86\%. \end{aligned} \quad (1b)$$

Here, (1b) shows the results of the percentage of 15.86 density in “MovieLens” dataset “D” that can be considered as appropriate enough in terms of sparsity for the evaluation of the dataset. Perhaps we see that the general validated dataset is not quite sufficient for the implementation of the proposed work. Alternatively, as per this study requirement, we operate f -fold cross-validation [10] method for revalidation of “MovieLens” dataset “D”, which is shown in Figure 1.

In Figure 1, the individual dataset sample ($D \in [d_1, \dots, d_N]$) was used to obtain the random generation of subdataset samples, where D_1, \dots, D_f ($f = N$) are equal in size [10, 58]. The normalized estimation of each subdataset, E_1, \dots, E_f | $E \in$ rating of each learner against the learning content is the overall number of correct identification. The identifications have been helpful for the classification of the learners personalized profiles as zero-rated, low-rated, and high-rated learners dataset class from individual “MovieLens” “D” dataset sample. Each looping has been averaged and produced the actual normalization of the learners personalized profile dataset. Finally, the learners personalized profile classification is used to categorize the number of training and testing sets. The revalidated dataset key points are defined in Table 5.

In Table 5, the revalidated key points of “MovieLens” dataset “D” are mentioned in detail. The study found only 10 learner’s “U”, which have the lowest ratings from 943 learner’s “U”; therefore, the study sees them as new-learner profiles. In the rest of 843 profiles, only 61 learner’s “U” profiles have high ratings “R” and 872 have average ratings “R”. Therefore, the system counts the 872 average ratings “R” of learner’s “U” profiles as average-learner profiles and

TABLE 3: Overview of research activities involved and its possible outcomes.

Action	Activities Involved	Possible Outcome
Phase-I: Dataset validation	Validation of dataset “ D ”, and classifies it into subsequent training “ T_R ” and testing “ T_S ” sets for the further experimental process on problem domain.	(i) Categorize the zero-rated new-learners and low-rated average-learners profile. (ii) Classify training-set training set and testing set for the zero-rated new-learner cold-start recommendation experimental process.
Phase-II: Propose approach	Content-based filtering hybridized with collaborative features. Collaborative filtering inherited with k -neighborhood scheme features.	(i) Categorize the low-rated average-learners and high-rated super-learners profile. (ii) Classify training-set training set and testing set for the low-rated average-learner cold-start recommendation experimental process. Overcome new-learner zero-rated profile recommendations issue. Overcome average-learner low-rated profile recommendations issue.

TABLE 4: “MovieLens” dataset D key points.

Key point 1:	The strength of learner’s “ U ” is 943
Key point 2:	The strength of learning contents “ I ” is 1682
Key point 3:	Each learner “ U ” vote or rate “ R ” at least 20 learning contents “ I ” from 1682
Key point 4:	The rating scores from 1 to 5
Key point 5:	The rating strength of 943 learners “ $u \in U$ ” against 1682 learning contents “ $i \in I$ ” is around 100,000

the 61 high ratings “ R ” of learner’s “ U ” profiles as super-learner profiles. The classification of zero-rated, low-rated and high-rated learner profiles have been done from database “ D ”.

4.2. Phase-II: Proposed Approach. In second phase, the research work accommodates proposed approach in two eras. First, it overcomes the new-learner zero-rated profile recommendations [19, 20] with the hybridization of content-based filtering and collaborative features. Secondly, it improves the average-user low-rated profile recommendations [21, 22] with the hybridization of collaborative filtering and k -neighborhood scheme features. Figure 2 demonstrates the working flow of proposed approach, its working features and dimensions of learner’s profile recommendations to encompass the learner-based cold-start problem in the above two eras simultaneously. The description of Figure 2 parameters is mentioned in Table 6.

Figure 2 demonstrates the proposed approach recommendation model, its working features, and dimensions of learner’s profile recommendations that encompass the learner-based cold-start problem in two ways simultaneously: the first is new-learner zero-rated profile recommendations and the second is average-learner low-rated profile recommendations. The description of Figure 2 parameters is mentioned in Table 6.

In Table 6, T_R represents the training set and T_S represents the testing sets from “MovieLens” dataset. For fulfilling the objectives of this proposed work, the proposed goal-based hybrid filtering approach works with (i) content-based

filtering with collaborative features that helps to overcome the new-user profiling issue and show the usefulness of user-to-user personalized profile similarities; and (ii) collaborative filtering with k -neighborhood scheme features that helps to overcome the new-user profiling issue and show the usefulness of user-to-user personalized profile neighborhood similarities. In both of the above approaches, (a) and (b) performed their work simultaneously in the proposed goal-based hybrid approach to overcome the learner-based cold-start recommendation challenges. The system attempt the learner’s profile “ U ” personalized preferences similarity with learner’s profile “ V ” and recommends the relevant learning content “ I ” to the target learner. In the proposed approach, the system generates relevant learning contents to overcome two types of learner’s cold-start profile recommendation issues, which are as follows: (a) new-learner zero-rated profile recommendations [19, 20] and (b) average-learner low-rated profile recommendations [21, 22].

5. Goal-Based Hybrid Filtering

This research proposed a goal-based hybrid filtering approach in e-learning recommender systems, defined as eLearningRecSys to provide a sense of learning direction and purpose to guide the learner for the next learning step. This research may promote the clarity to achieve required learning contents, enhancing the learning interest and personal satisfaction that help to build the learner interest. Usually, recommender systems in e-learning are based on the learner’s profile extra information, such as past history,

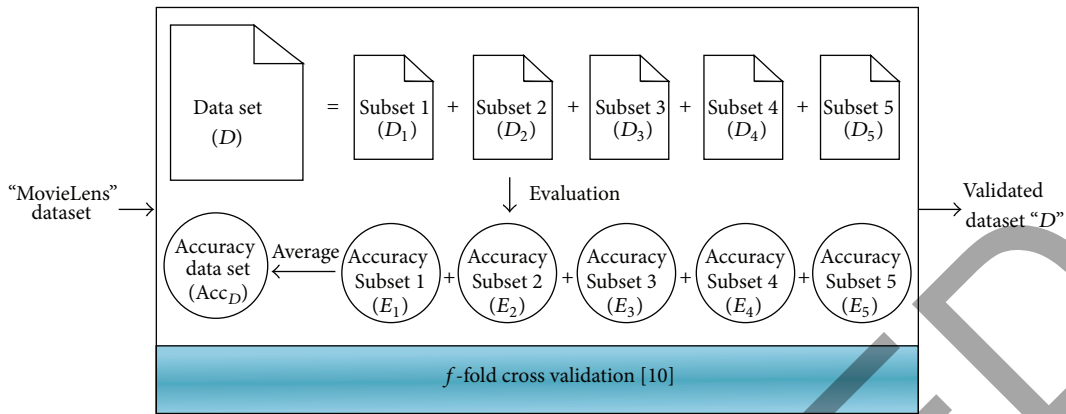


FIGURE 1: Process in f -fold cross validation [10].

TABLE 5: “MovieLens” dataset D revalidated key points.

Key point 1:	Total learner’s “ U ” profiles are 943
Key point 2:	New-learner’s zero-rated profiles are 10
Key point 3:	Average-learners low-rated profiles are 872
Key point 4:	Super-learners high-rated profiles are 61
Key point 5:	The strength of learning contents “ I ” is 1682
Key point 6:	Each learner “ U ” profile has validated as per vote or rate “ R ” to each content “ I ” from 1682
Key point 7:	The rating scores from 1 to 5
Key point 8:	The rating strength ($R_{u,i}$) of 943 learners “ $u \in U$ ” against 1682 learning contents “ $i \in I$ ” is around 100,000

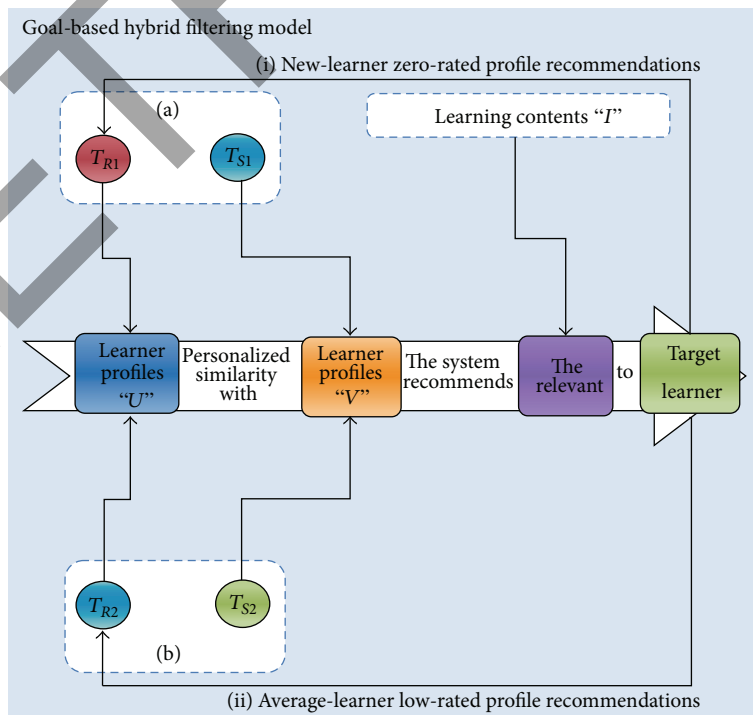


FIGURE 2: Proposed approach recommendation model, its features, and dimensions.

TABLE 6: Parameters description that has been used in Figure 2.

Parameters	Description
T_{R1}	First training set of learner's "U" profile with ratings "R" range ($0 \leq R \leq r \leq 60$).
T_{S1}	First testing set of learner's "U" profile with ratings "R" range ($60 < R \leq r \leq 1000$).
T_{R2}	Second training set of learner's "U" profile with ratings "R" range ($60 < R \leq r \leq 1000$).
T_{S2}	Second is testing set of learner's "U" profile with ratings "R" range ($R \leq r > 1000$).
(a)	Hybridization of content-based filtering with collaborative.
(b)	Hybridization of collaborative filtering with k -neighborhood features.
(i)	New-learner zero-rated profile recommendations.
(ii)	Average-learner low-rated profile recommendations.
"U"	Training class of learner's profiles ($U = u_1, u_2, u_3, \dots, u_n$).
"V"	Testing class of learner's profiles ($V = v_1, v_2, v_3, \dots, v_n$).

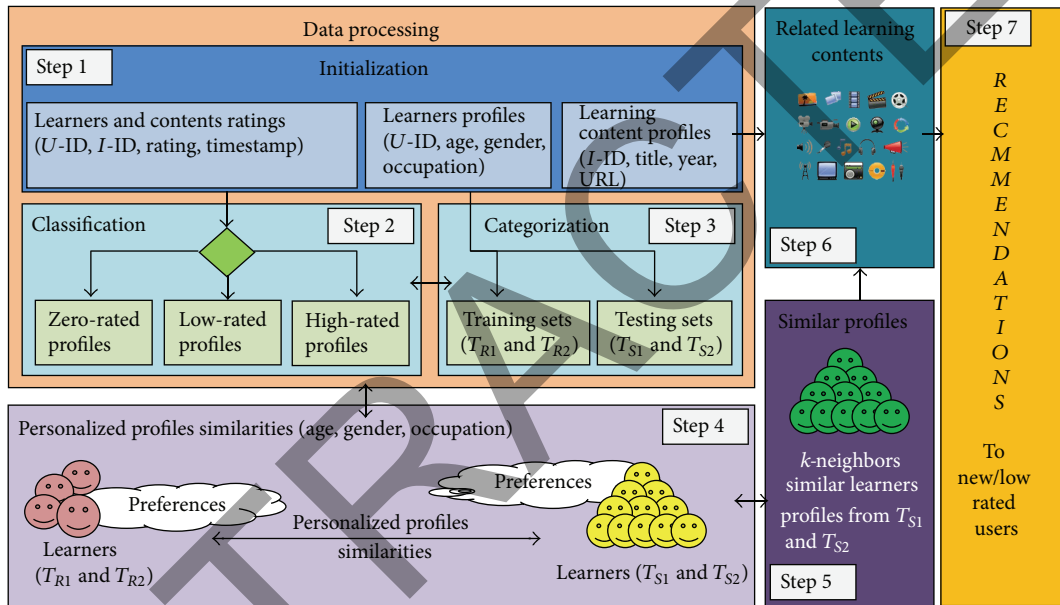


FIGURE 3: Framework of proposed goal-based hybrid filtering approach.

ratings, or likes and dislikes. Alternatively, the proposed hybrid approach does not require any extra information or historical data of the learner; it only requires the learner's personalized profile preferences, such as age, gender, and occupation that a recommender knows to produce the possible recommendation outcome for end learner in the focused domain of e-learning. The proposed hybrid filtering allows the system to simultaneously assist the learner of zero-rated and low-rated profile recommendations and retrieve their required goals. Figure 3 demonstrates the framework of the proposed goal-based hybrid filtering approach.

5.1. Step 1: Initialization. The first step is a part of data preprocessing; it has initialized the three dataset classes form "MovieLens" D as learner and content ratings, learner's profiles, and learning content profiles where learner profiles class "U" uses their ratings "R" information for each learning

content "I". The initialization of data is based on the users personalized profile preferences, for example, age, gender, occupation, and learning content for recommendation of the learner's rating information. The set of users, items, and ratings has been initialized as (2a), (2b), and (2c):

$$U = \{u_1, u_2, u_3, \dots, u_n \mid u \in U\}, \quad (2a)$$

$$I = \{i_1, i_2, i_3, \dots, i_m \mid i \in I\}, \quad (2b)$$

$$R = \{r_1, r_2, r_3, r_4, r_5 \mid r \in R\}. \quad (2c)$$

5.2. Step 2: Classification. The classification of learners' class "U" from "MovieLens" dataset has been tackled as per of their total ratings against each learning content. In this system, the recommendations are based on the k-neighbors similar

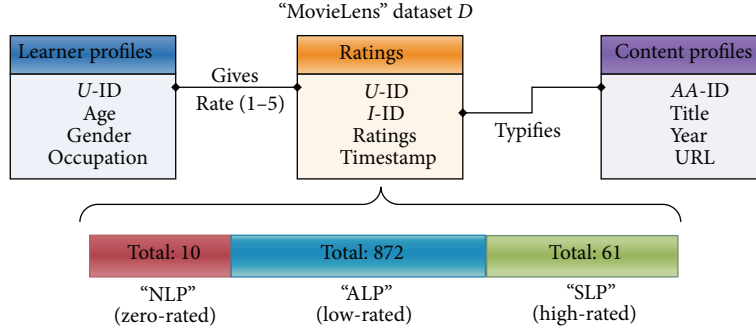


FIGURE 4: Classification of learners profiles class “ U_n ” using their ratings “ R_n ” information from “MovieLens” dataset “ D ”.

TABLE 7: Description of three classified learner’s profiles classes.

Classification	Rating range	Description
Zero-rated	0 to 60	New learner’s profiles class
Low-rated	61 to 1000	Average-learner’s profiles class
High-rated	Above 1000	Super-learner’s profiles class

learner profiles and their total ratings against the learning contents $R_{(u \rightarrow i)}$ which have been counted with the help of the following:

$$\frac{\text{count}(R_u) \times \text{avg}(R_u) + U_n \times I_n}{\text{count}(R_u) + R_{(u \rightarrow i)}} \quad (3)$$

Equation (3) is being used to analyze the new and other learners by their ratings against all learning contents. Here, R_u defines the total learner rating, U_n defines the total number of learner’s, and I_n defines total learning contents and range of rating from r_1 to r_5 to the learning contents I_n . Perhaps, we could not find any zero-rated user profile in “MovieLens” dataset. Alternatively, with the help of (3), this research work classified the learner’s profiles U_n class into three types of learner’s profiles classes described in Table 7.

Table 7 shows the classified classes as zero-rated from 0 to 60, low-rated from 61 to 1000, and super-rated from 1000 to onward rating profiles. Figure 4 demonstrates the classification method of “MovieLens” dataset D learner “ U_n ” profiles class into 3 subsequent learner profiles dataset classes for further operations. The classified classes names are set as new-learner zero-rated profiles “NLP” class, average-learner low-rated profiles “ALP” class, and super-learner’s high-rated profiles “SLP” class using the count of their total ratings “ R_n ” information for learning contents “ I_n ”.

Figure 4 demonstrates the classification of “MovieLens” dataset “ D ”. By referring to Figure 4, the classification of learner’s U class can be described as follows:

(a) *The New-Learner’s Zero-Rated Profiles.* The new-learner’s profile classification has been occurred from the “MovieLens” dataset learner’s “ U ” class. To handle the zero-rated profile situation, this study makes the strategy to classify those profiles as new-learner, in which count of ratings is in range of 0 to 60 against all the learning contents. The study

found only 10 learner profiles with less than 60 ratings “ $r \in R$ ” history preferences. Therefore, the new-learner’s zero-rated profiles “NLP” are settled in the range from $(0 \leq R \in r \leq 60)$ that are shown in Figure 4. By using the new-learner zero-rated strategy, which has been settled within the range of 0 to 60, the system automatically classifies the upcoming new-learner’s U as zero-rated category with the help of (4a) to go through the next process:

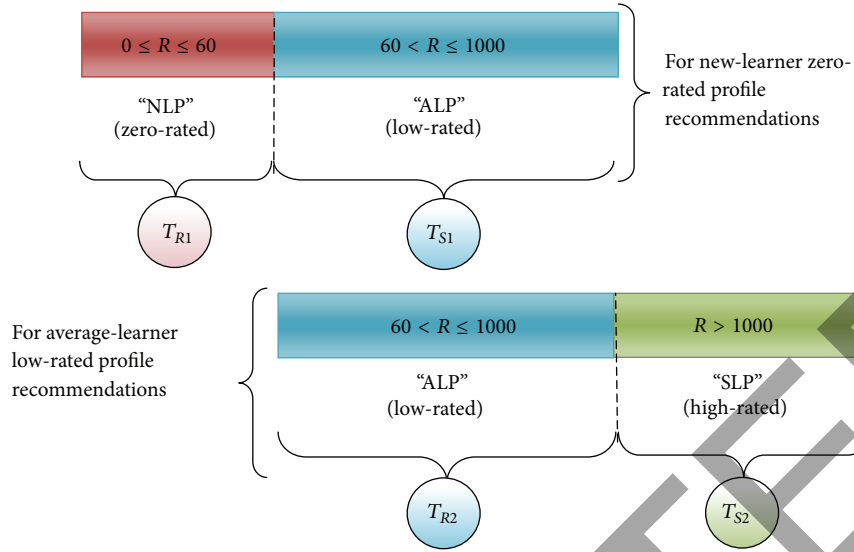
$$\text{NLP} = \max_{0 \leq R \in r \leq 60} \text{Count}(R_{(u \rightarrow i)}). \quad (4a)$$

(b) *The Average-Learner Low-Rated Profiles.* In this, the classification of learner profile has been done on behalf of ratings of each learner as like new-learner profiles. Although, the scenario slightly changed with average-learner profiles, here the system collects those learners’ profiles, which are not new in the system nor visit or rate “ $r \in R$ ” much learning contents. Therefore, the learners have less or average level of rated profiles and system recorded those profiles as average-learner low-rated profiles “ALP.” The study examined that “MovieLens” dataset D learners “ U ” class has only 872 learner’s profiles, in which count of rating has been higher than 60 but lower than 1000, as shown in Figure 5. Therefore, the strategy automatically settled the learner profiles, in which range of ratings is from $(60 < R \in r \leq 1000)$ and classifies them as average-learner low-rated profiles with the help of (4b) to go through the next process:

$$\text{ALP} = \max_{60 < R \in r \leq 1000} \text{Count}(R_{(u \rightarrow i)}). \quad (4b)$$

(c) *The Super-Learner High-Rated Profiles.* The classification of super-learner profiles also has been made on behalf of ratings of each learner as like average-learner and new-learner profiles. The super-learners are so called super because they visit the learning content more than average learner. In the super-learner’s scenario, the system examined “MovieLens” dataset and found that in the 61 learners’ profiles the ratings range has been above 1000 as shown in Figure 5. In the high-rated learner’s profiles, strategy settles the range from $(R \in r > 1000)$, so the system automatically classifies super-learner’s with the help of (4c) as high-rated category and is represented as “SLP”:

$$\text{SLP} = \max_{R \in r > 1000} \text{Count}(R_{(u \rightarrow i)}). \quad (4c)$$

FIGURE 5: The categorization of "MovieLens" dataset D in subsequent training T_R and testing T_S sets.TABLE 8: The definitions and purposes of derived training set (T_R) and testing set (T_S).

	Definition	Ratings " $r \in R$ " range	Objective
T_{R1}	First training set of new learner's profiles "NLP" with ratings " R " to item " I ."	$0 \leq R \leq r \leq 60$ (3)	(i) To overcome the new-learner zero-rated profile recommendations
T_{S1}	First testing set of average learner's profiles "ALP" with ratings " R " to item " I ."	$60 < R \leq r \leq 1000$ (5)	
T_{R2}	Second training set of average learner's profiles "ALP" with ratings " R " to item " I ."	$61 < R \leq r \leq 1000$ (6)	(ii) To improve the average-learner low-rated profile recommendations
T_{S2}	Second testing set of super learner's profiles "SLP" with ratings " R " to item " I ."	$R \in r > 1000$ (6)	

5.3. Step 3: Categorization. In this step, the proposed work categorizes the learner's profiles into the training set T_R and testing set T_S . These training and testing sets have been used to in the personalized profile similarities computation. Gradually, the categorization of dataset has been done as 50 percent of training and rest of dataset for testing [11] or as 70 percent of training and rest of dataset for testing [18] and vice versa. Alternatively, this research work classifies and uses the training set T_R and testing set T_S in a slighter different way, which are defined in Figure 5.

To handle the training and testing sets strategy, the zero-rated learner's profiles with ratings range from $0 \leq R \leq r \leq 60$ profiles have been set as first training set T_{R1} and average-rated learner's profiles with ratings range from $60 < R \leq r \leq 1000$ are as first testing set T_{S1} which were discussed earlier. The first training set T_{R1} and first testing set T_{S1} are being used in the proposed hybrid approach to overcome the new-learner zero-rated profile recommendations issue. Afterwards, for the low-rated profile recommendation issue, T_{R2} and T_{S2} are being used in the proposed hybrid approach to improve the average-learner low-rate profile recommendations issue. With this being settled, the second training set T_{R2} has been set with the average-learner's low-rated profiles with rating range from

$60 < R \leq r \leq 1000$ and the second testing set T_{S2} is set with the super-learner's high-rated profiles with the ratings range as $R \in r > 1000$. The detailed description on new-learner, average-learner, and super-learner profiles with respect to their learning content ratings is presented. The definitions of these training T_R and testing T_S sets that are shown in Table 8.

This research study categorized the training T_R and testing T_S sets in a slighter different way from the previous literature [11, 18]. This research study system categorizes two training sets, such as T_{R1} and T_{R2} , and two types of testing sets, such as T_{S1} and T_{S2} , for the further experiments. Methodologically, the first training set T_{R1} and first testing set T_{S1} have been used to overcome the new-learner zero-rated profile recommendations issue with the help of content-based filtering and collaborative features in the proposed hybrid filtering approach. Simultaneously, the second training set T_{R2} and second testing set T_{S2} have been used to improve the average-learner low-rated profile recommendations issue with the help of collaborative filtering and k-neighborhood scheme features in hybrid filtering approach.

5.4. Step 4: Personalized Profile Similarities. After the categorization of dataset into training and testing sets in step 3, step 4 collects the personalized profile preferences, such

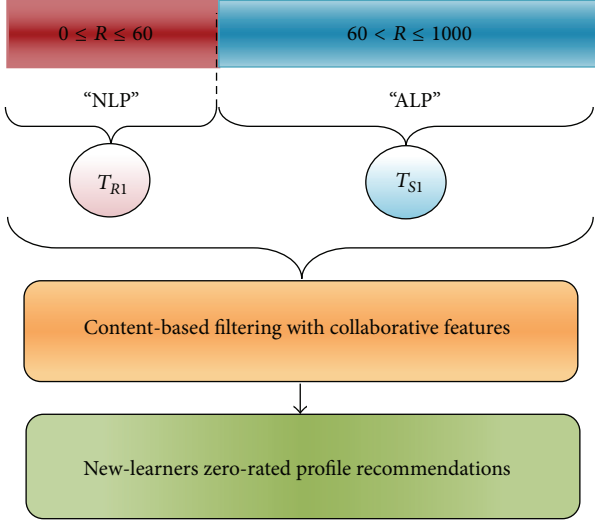


FIGURE 6: Workflow of content-based filtering with collaborative features for new-learner's zero-rated profile recommendations.

as age, gender, and occupation with respect to the training sets T_{R1}, T_{R2} and testing sets T_{S1}, T_{S2} . These personalized profile preferences are tackled to perform the learner's personalized profile comparisons with each other. The profile comparisons help to compute the similarities between the learner's goals or interests in collaborative network with the hybridization of content-based filtering, collaborative filtering, and k-neighborhood features, which are described as follows.

(a) *Content-Based Filtering with Collaborative Features.* In traditional content-based recommender systems, the recommendation is being predicted through the learner's own historical profile activities which means that the system produces recommendations using only those clusters which belong to the learner historical activities. Figure 6 shows the workflow of content-based filtering with collaborative features to overcome the new-learner zero-rated profile recommendations issue, and it shows the usefulness of collaborative personalized profile similarities scheme.

Figure 6 shows the operational workflow of content-based filtering with collaborative filtering features to overcome the new-learner zero-rated profile "NLP" recommendations issue. The conventional, content-based approach [13, 43, 59] recommends relevant items, if and only if the learners have their own background profile history of rated or visited learning contents. In the other way, the traditional content-based approach worked on learner's U_n own historical details or rating details R_n . Alternatively, the proposed hybridization of content-based filtering with collaborative features worked in a slightly different way from the traditional content-based filtering approach. In this, foremost the total rating R_n of each learner U is being used to classify the new-learner's zero-rated profiles "NLP" and average-learner's low-rated profiles "ALP" for the further process. The personalized profile similarities between collaborative learner's profile preferences such as age, gender, and occupation in content-based filtering with

collaborative features method have been measured to overcome the new-learner zero-rated profile recommendation. The following similarities are being measured by using cosine similarity method with the help of (5), as follows:

$$\text{Sim}(T_{R1}, T_{S1}) = \sum \frac{\text{dot}(T_{R1}, T_{S1})}{(\text{norm}_{T_{R1}})_2 \times (\text{norm}_{T_{S1}})_2}. \quad (5)$$

With the help of (5), the personalized similarities have been measured between new-learner's zero-rated profiles "NLP" which are considered as first training set T_{R1} and average-learner's low-rated profiles "ALP" which are considered as first testing set T_{S1} . Both of training T_{R1} and testing T_{S1} sets have worked as cosine vector and the similarities computational results are represented as $\text{Sim}(T_{R1}, T_{S1})$. The similarity results are demonstrated further in this paper.

(b) *Collaborative Filtering with k-Neighborhood Features.* Generally, in the collaborative filtering approaches [22, 50, 60], the system recommends those learning contents as relevant learning contents to the target learner's, which are highly rated or sequently visited by the other learner's. For example, if one learner highly rated or visited any learning content of category 1 and the second learner may highly rate or visit other learning contents of the same category 1, so the traditional collaborative system recommends the first learner rated learning content to second learner and the visited or rated learning content of second learner has been recommended to the first learner. This means that the traditional collaborative approaches did not work efficiently if the learners have low rated or less sequently visited learning contents or have minimum rated or visited historical profile.

Alternatively, the collaborative filtering with k-neighborhood scheme features foremost worked with total rating R_n of per learner U in a slightly different way. The proposed work used the total ratings R_n of each learner to classify the average-learner low-rated profiles "ALP" and super-learner's high-rated profiles "SLP" to overcome the average-learner low-rated profile recommendations issue and show the usefulness of user-to-user personalized profile similarities using k-neighborhood scheme features. Figure 7 shows the workflow of famous machine learning k-neighborhood scheme features with collaborative filtering approach.

Figure 7 shows the operational workflow of collaborative filtering with k-nearest neighbor's scheme features for the improvement of average-learner's low-rated profiles "ALP" recommendations issue. The personalized similarities have been computed between average-learner low-rated collaborative profiles and super-learner's high-rated collaborative profiles by using their personalized profile preferences such as age, gender, and occupation. The average-learner low-rated profiles "ALP" are considered as second training set T_{R2} and super-learner's high-rated profiles "SLP" are considered as

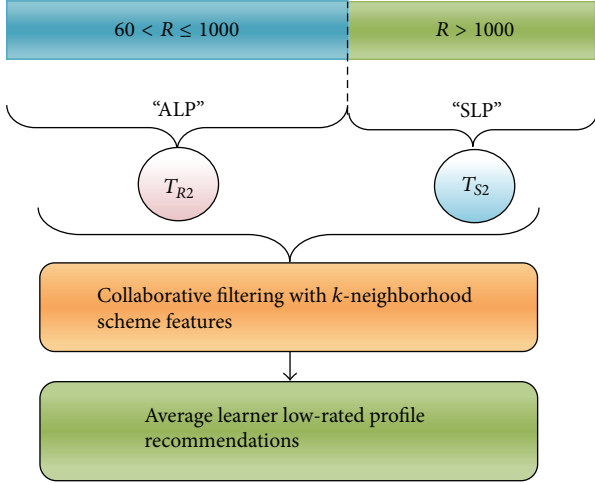


FIGURE 7: Workflow of collaborative filtering with k-neighbor features for average-learner's low-rated profile "ALP" recommendations.

second testing set T_{S2} for the personalized similarities measurement by using the euclidean cosine similarity method as follows:

$$\begin{aligned} \text{Sim}(T_{R2}, T_{S2}) &= \sum(T_{R2}, T_{S2}) \times \left(\sum T_{R2} \sum T_{S2} \right) \\ &\times \left(\sqrt{\left(\left(\sum T_{R2} \right)^2 \times \left(\sum T_{R2} \right)^2 \right)} \right) \\ &\times \left(\sqrt{\left(\left(\sum T_{S2} \right)^2 \times \left(\sum T_{S2} \right)^2 \right)} \right)^{-1}. \end{aligned} \quad (6)$$

With the help of (6), the personalized similarities have been measured between the average-learner's low-rated profiles "ALP" as first vector class which is represented as second training set T_{R2} and super-learner's high-rated profiles "SLP" as second vector class which is represented as second testing set T_{S2} by using their personalized profile preferences such as age, gender, and occupation. The similarities results of "ALP" vector class as training set $2T_{R2}$ and "SLP" vector class as testing set $2T_{S2}$ are represented as $\text{Sim}(T_{R2}, T_{S2})$ and are demonstrated further in this paper.

5.5. Step 5: Similar Profiles. As discussed earlier, the new-learner zero-rated profiles "NLP" are set to as first training set T_{R1} and average-learner low-rated profiles "ALP" as first testing set (T_{S1}) to overcome the new-learner zero-rated profile recommendations. Similarly, to improve the average-learner low-rated profile recommendations, the system categorized average-learner low-rated profiles "ALP" as second training set T_{R2} and super-learner's high-rated profile "SLP" as second testing set T_{S2} . Step 5 collects the similar learner's profile results as $\text{Sim}(T_{R1}, T_{S1})$ and $\text{Sim}(T_{R2}, T_{S2})$ from step 4 for the next process. With respect to the similarities between both training and testing sets, this step chooses only k-neighbors similar learner's profile results as $\text{Sim}(T_{R1}, T_{S1})$ and $\text{Sim}(T_{R2}, T_{S2})$ in which profiles personalized preferences such as age, gender, and occupation are very similar to other

learner's profiles in the collaborative network. Afterwards, this step selects the similar k-neighborhood learner's profiles of T_{S1} and T_{S2} and forwards them to step 6 for further process.

5.6. Step 6: Related Learning Contents. This step collects the similar k-neighborhood learner's profiles of T_{S1} and T_{S2} from step 5 and selects the learning contents which have been visited or rated "R" in the past by the k-neighborhood learner's of T_{S1} and T_{S2} . The selected learning contents "I" have been sent to step 7 for recommendations to the target learner's, denoted as $I_{(T_{S1}, T_{S2}) \rightarrow \hat{R}}$.

5.7. Step 7: Recommendations. Step 7 is the last step of operational framework of the proposed hybrid approach and plays its part of work between the system and the relevant learners. This step receives the recommendation learning-contents "I" from step 6 and recommends them to the new-learner zero-rated profiles "NLP" and average-learner low-rated profiles "ALP". The recommendations in both cases are denoted as "rm."

6. Hybrid Results and Discussion

This section shows the proposed work experiments and results. With respect to the problem background, the experimental work is partitioned into two portions. The first is new-learner zero-rated profile recommendation experimental results and the second is average-learner low-rated profile recommendation experimental results, which are as follows.

6.1. New-Learner Zero-Rated Profile Recommendations. As per reconsideration of (5), the experimental operations are based on the cosine vector-based similarity measurement. Experimental results are structured as per the availability of dataset. For new-learner's zero-rated profile "NLP" recommendations issue, this research work has used T_{R1} as training set 1 and T_{S1} as testing set 1 in the experimental setup of the proposed hybrid approach for this issue. Here, we considered T_{R1} as training set 1 as U_n and T_{S1} as testing set 1 as V_n . The similarity between the U_n and V_n has been used as $[U_n \times V_n]$ factorization matrix as $0 \leq U_n \sim V_n \leq 1$. Therefore, the U_n is set to be as target learner's profile class; perhaps, V_n is set as other learner's profile classes. This study conducts three similarity experiments using different lengths of training sets $U_n = (u_1, u_2, \dots, u_n)$ and operates the personalized profile preferences such as age, gender, and occupation similarity measurement with the total range of testing set $V_n = (v_1, v_2, \dots, v_n)$. The three experiments are discussed as follows.

(a) **Experiment 1.** In the first experiment of new-learner's profile recommendation issue, the system randomly selects 2 learner's profiles in which count of ratings against learning contents or items is between 0 and 60 as new-learner's $U_n = (u_1, u_2)$ as a training set T_{R1} and operates the similarity with the total number of learner's $V_n = (v_1, v_2, \dots, v_{872})$ profiles with ratings 61 to 1000 identifies as other or average learner's and considered as testing set T_{S1} . Table 9(a) shows

TABLE 9: (a) Similarity matrix of training-set T_{R1} and testing-set T_{S1} as $U_{n=2} \times V_{n=872}$. (b) Similarity matrix of training-set T_{R1} and testing-set T_{S1} as $U_{n=5} \times V_{n=872}$. (c) Similarity matrix of training-set T_{R1} and testing-set T_{S1} as $U_{n=10} \times V_{n=872}$.

(a)										
	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	...	V_{872}
U_1	0.878	0.957	0.752	0.957	0.986	0.715	0.842	0.757	...	0.701
U_2	0.934	0.788	0.957	0.913	0.957	0.817	0.899	0.621	...	0.697
(b)										
	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	...	V_{872}
U_1	0.938	0.957	0.498	0.499	0.492	0.499	0.938	0.914	...	0.411
U_2	0.899	0.621	0.957	0.948	0.947	0.925	0.899	0.935	...	0.499
U_3	0.788	0.878	0.752	0.957	0.986	0.715	0.878	0.752	...	0.701
U_4	0.934	0.584	0.621	0.913	0.957	0.819	0.899	0.621	...	0.697
U_5	0.948	0.912	0.842	0.949	0.748	0.957	0.948	0.878	...	0.752
(c)										
	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	...	V_{872}
U_1	0.957	0.938	0.911	0.944	0.938	0.729	0.952	0.944	...	0.949
U_2	0.938	0.957	0.954	0.956	0.892	0.788	0.878	0.752	...	0.948
U_3	0.947	0.982	0.957	0.955	0.934	0.584	0.621	0.913	...	0.499
U_4	0.788	0.878	0.752	0.957	0.956	0.715	0.842	0.949	...	0.701
U_5	0.819	0.899	0.621	0.697	0.957	0.934	0.584	0.621	...	0.913
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\ddots	\vdots
U_{10}	0.911	0.897	0.893	0.944	0.899	0.621	0.697	0.952	...	0.957

the resulting matrix of experiment 1, which is conducted with $U_n = (u_1, u_2)$ training and $V_n = (v_1, v_2, \dots, v_{872})$ testing set.

Table 9(a) shows the similarity measurement results between the $[U_n \times V_n]$ similarity matrix, where $U_n = (u_1, u_2)$ and used as training set T_{R1} ; perhaps $V_n = (v_1, v_2, \dots, v_{872})$

and set to be defined as testing set T_{S1} . The results are discussed further in this paper. The similarities in Table 9 have been computed with parameters that work between 0.1 and 1.0 with the help of (7) as follows.

$$\text{Similarity}_{[U_n \times V_n]} = \begin{cases} 0.9 \text{ to } 1.0 & \text{if there is perfect similarity between learner } u \text{ and learner } v \text{ profiles} \\ \geq 0.1 \text{ and } < 0.9 & \text{if there is mature similarity between learner } u \text{ and learner } v \text{ profiles} \\ 0 & \text{if there is no similarity between learner } u \text{ and learner } v \text{ profiles.} \end{cases} \quad (7)$$

(b) *Experiment 2.* In the second experiment, the system randomly selected 5 learner's profiles, which total learning contents rating is between 0 to 60 and considered them as a new-learner. The learners have total ratings above then 60 and less than 1000 are considered as average-learners. The range of new-learner class profiles $U_n = (u_1, u_2, u_3, u_4, u_5)$ are set to be as training set T_{R1} and the range of average-learner class profiles $V_n = (v_1, v_2, v_3, \dots, v_{872})$ are set to be as testing set T_{S1} . Table 9(b) shows the resulting matrix of experiment 1, which is conducted with $U_n = (u_1, u_2, u_3, u_4, u_5)$ training and $V_n = (v_1, v_2, \dots, v_{872})$ testing set. Table 9(b) represents the similarity results of $[U_5 \times V_{872}]$ learner's profile similarity matrix. The learner's class "U" is set to be as training set 1 T_{R1} and users class "V" is set to be as testing set 1 T_{S1} . The similarity results of Table 9(b) have been computed with the parameters from higher 1.0 to lower 0.1 score. The scores

are helpful to identify the high, average and less similar learner's profiles. The parameters have been defined with the help of (9). Each score of the similarity matrix contains a measure of similarity between the elements of T_{S1} and T_{R1} learner's profiles. The similarities in Table 9(b) have been computed with the parameters that work from higher score 1.0 to lower score 0.1. The higher scores are given to accurate similar learner's profiles; lower scores are given to less similar learner's profiles and in between the score are given to average similar learner's profiles. The parameters have been defined with the help of (9) as follows:

(c) *Experiment 3.* In the third experiment, the system select all the new-learners profiles, which total learning contents rating is between 0 to 60 and the range of new-learner's class $U_n = (u_1, u_2, u_3, u_4, u_5, u_6, u_7, u_8, u_9, u_{10})$ is set

TABLE 10: Similarity matrix of training-set T_{R2} and testing-set T_{S2} as $U_{n=872} \times V_{n=61}$.

	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	...	V_{61}
U_1	0.975	0.938	0.911	0.944	0.938	0.729	0.952	0.944	...	0.949
U_2	0.938	0.975	0.954	0.956	0.892	0.788	0.878	0.752	...	0.948
U_3	0.947	0.982	0.975	0.955	0.934	0.584	0.621	0.913	...	0.499
U_4	0.788	0.878	0.752	0.975	0.956	0.715	0.842	0.949	...	0.701
U_5	0.819	0.899	0.621	0.697	0.975	0.934	0.584	0.621	...	0.913
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots
U_{872}	0.946	0.715	0.842	0.949	0.701	0.752	0.788	0.878	...	0.973

to be as training set 1 as T_{R1} . The average-learners with total ratings above then 60 and less than 1000 with the range of class $V_n = (v_1, v_2, \dots, v_{872})$ is set to be as testing set 1 as T_{S1} . Table 9(c) represents the similarity results of $[U_n \times V_n]$ learner's profile similarity matrix. The results of similarity matrix have been computed with the parameters from higher 1.0 to lower 0.1 score. The higher scores are given to accurate the learner's profiles similarity; lower scores shows less similarity of learner's profiles and in between the score are given to average similar learner's profiles of $[U_n \times V_n]$. The parameters have been defined with the help of (9).

6.2. Average-Learner Low-Rated Profile Recommendations. In this section, the experimental result has been detailed with the help of (6); the experimental operations are based on the Euclidean distance similarity measurement. The similarity matrix factorization has been adjusted as $[U_n \times V_n]$. This study selects all the low-rated learner's profiles "ALP" with ratings between 61 and 1000 as $U_n = (u_1, u_2, u_3, u_4, u_5, u_6, u_7, u_8, u_9, u_{10}, \dots, u_{872})$ and the total number of learner V_{61} profiles with high ratings above 1000 are identified as other or super-learner's profiles "SLP". The low-rated learners have been considered as second training set T_{R2} and high-rated learner's profiles are considered as second testing set T_{S2} .

Table 10 shows the computational similarity results of $[U_{872} \times V_{61}]$ learner's profile similarity matrix, which is conducted with $(U_1, U_2, \dots, U_{n=872})$ training and $(V_1, V_2, \dots, V_{61})$ testing set. The similarity measurement results between the $[U_n \times V_n]$ similarity matrix to improve the low-rated average learner's profiles "ALP" recommendations. Here, $U_n = (u_1, u_2, u_3, u_4, u_5, u_6, u_7, u_8, u_9, u_{10}, \dots, u_{872})$ and is used as training set T_{R2} ; perhaps $V_n = (v_1, v_2, \dots, v_{61})$ and is set to be defined as testing set T_{S2} . The results are discussed further in this paper. The similarities in Table 10 have been computed with parameters that work between 0.1 and 1.0 with the help of (7).

6.3. Experimental Results Analysis. After collecting the experimental data, this section helps to analyze the experimental results. Mostly, researchers utilize statistics to determine if the results are statistically significant or not. This research work used the famous statistical methods precision and recall to analyze the results efficiency of proposed

filtering approach. The formulation structure of precision Pr and recall Re is as follows:

$$\begin{aligned} \text{Precision (Pr)} &= \frac{T_{rm}}{T_i} = \frac{\text{Total size of recommended learning contents}}{\text{Total size of learning contents}}, \end{aligned} \quad (8)$$

$$\begin{aligned} \text{Recall (Re)} &= \frac{T_{rm}}{T_{I_{(u,v) \rightarrow \bar{r}}}} = \frac{\text{Total size of recommended learning contents}}{\text{Total size of relevant learning contents}}. \end{aligned} \quad (9)$$

The results analysis has been done with the help of precision equation (8) and recall equation (9), respectively. In (8) and (9), T_{rm} embodies the total number of recommended contents, T_i represents total contents stored in the system, and $T_{I_{(u,v) \rightarrow \bar{r}}}$ is considered as total relevant contents with respect to ratings.

6.4. Hybrid Results Analysis. This research has been construct the personalized similarities between new-learner's, average-learner's and super-learner's profiles. The results analysis has been shown with the help of famous precision and recall methods. Table 11(a) shows the analyzed precision and recall scores for new-learner zero-rated profile "NLP" recommendations and average-learner low-rated profile "ALP" recommendations matrices are shown in Tables 9(a), 9(b), 9(c), and 10 and demonstrated in Figure 8(a) using bar graph diagram.

Table 11(b) shows the mean of precision and mean of recall scores for new-learner zero-rated profile "NLP" and average-learner low-rated profile "ALP" recommendations matrices in Table 11(a). Figure 8(b) shows the resultant values in Table 11(b) using bar graph diagram. With the help of the above parameters of precision Pr and recall Re, Figure 8(a) stated that new-learner zero-rated profiles "NLP" resultant matrices from Tables 9(a), 9(b), 9(c), and average-learner low-rated profiles "ALP" resultant matrices from Table 10 exhibit almost identical efficiency of proposed work that

TABLE 11: (a) Precision Pr and recall Re of Tables 9(a)–9(c) and Table 10 resultant matrices. (b) Mean of precision Pr and mean of recall Re of Table 11(a) measurements.

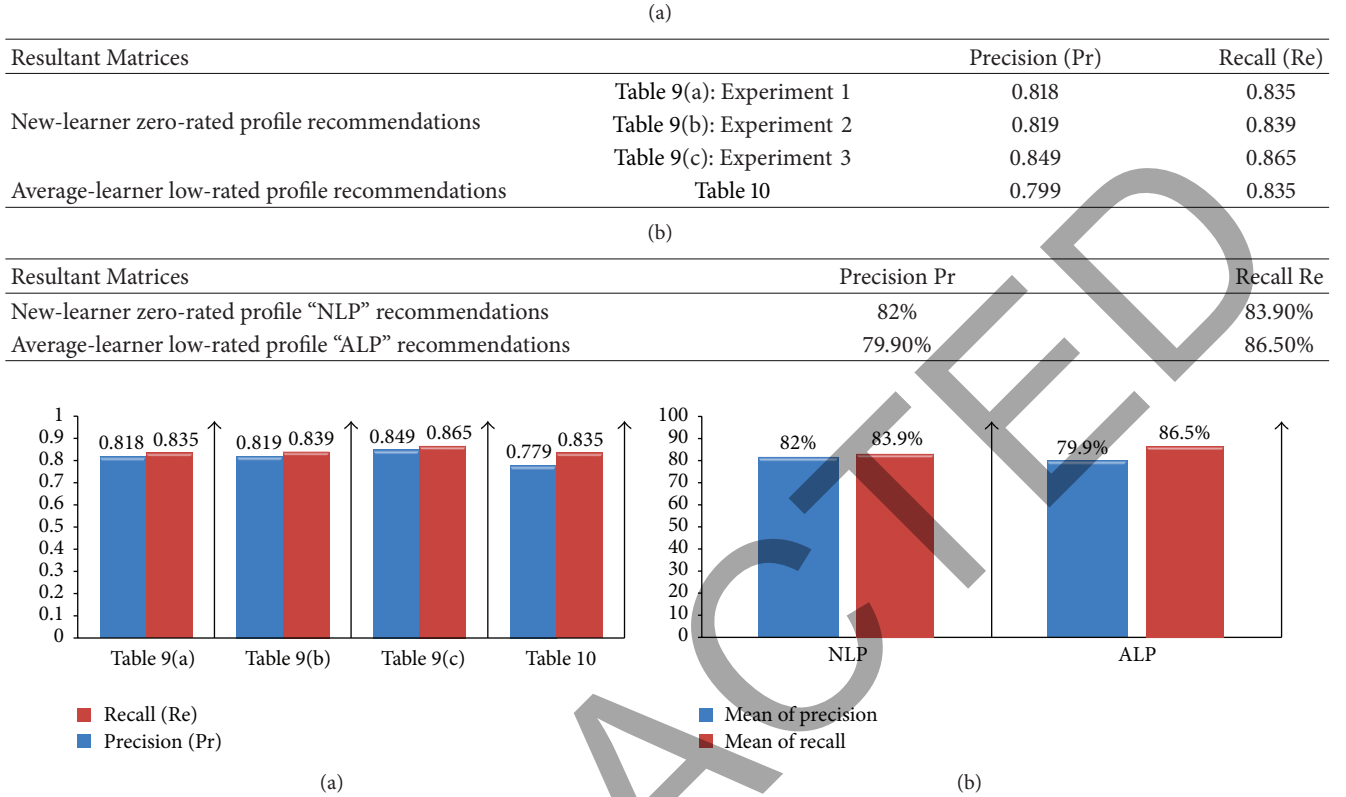


FIGURE 8: (a) Graph representation of Tables 9(a), 9(b), 9(c), and 10 by precision Pr and recall Re resultant matrices. (b) Graph representation of Table 11(b) using mean of precision Pr and mean of recall Re resultant matrices of new-learner’s profile “NLP” recommendations and average-learner’s profile “ALP” recommendations in the proposed hybrid filtering approach.

would be indicated by precision Pr values. Their recall Re values differ considerably, hinting at similar behavior with respect to the types of learner’s scored personalized profiles similarities. While the mean of precision Pr and mean of recall Re resultant values defined in Table 11(b) and graphically represented as Figure 8(b), respectively.

6.5. Results Evaluation and Discussion. For the evaluation of proposed Goal-based hybrid filtering, the recommendation results are compared with related literature work [11] results scheme. In [11], the author used machine learning to improve content-based filtering and proposed user-oriented content-based recommender system (UCB-RS) with two stages as like our proposed work. In the first stage, the authors [11] used fuzzy theoretic content-based filtering to generate the initial population of users’ preferences by interactive genetic algorithm using reclusive methods to improve the traditional content-based filtering for new cold-start users. Perhaps, in proposed goal-based hybrid filtering approach, the new-learner zero-rated profile recommendations issue has been improved with the hybridization of content-based filtering and collaborative features. In second stage, the authors [11] used k-mean algorithm for clustering the item in order to handle time complexity of interactive genetic algorithm to

TABLE 12: Overall results and evaluation of proposed goal-based hybrid filtering, measured by mean of precision Pr and mean of Recall Re.

Measures	Related literature work [11]	Proposed goal-based hybrid filtering approach
Mean of (8)	66.43%	83.44%
Mean of (9)	78.53%	85.22%

improve the collaborative recommendations. Perhaps, in proposed goal-based hybrid filtering, the average-learner low-rated profile recommendations have been overcome with the hybridization of collaborative filtering and k-neighborhood features.

The results evaluation helps to indicate that the proposed goal-based approach performance has improved the hybrid filtering recommender systems for new-learner and average-learner recommendations in e-learning scenarios. The evaluation of proposed approach has been compared with related literature work [11] results to see how much the proposed work contributes to increase the recommendations in hybrid recommender systems in e-learning scenarios. The evaluation results of related literature work [11] and the proposed goal-based hybrid filtering are given in Table 12.

TABLE 13: t -test result by using Table 12 mean of precision Pr and mean of recall Re values.

	Mean of precision Pr	Mean of recall Re	t -test results
Related literature work [11]	66.43%	78.53%	0.29
Proposed goal-based hybrid filtering approach for eLearningRecSys	83.44%	85.22%	

In the proposed approach, the mean of (8) precision Pr has been used for calculating all the recommendations that were useful to learners, while the mean of (9) has been used to measure the desired learning contents appearing among the recommendations. The results in Table 12 show improvements in proposed goal-based hybrid filtering approach results with the comparison of related literature work [11]. Now this work test the statistical significance to determine the probability difference of improvement between proposed hybrid approach and the literature work [11]. To do this, the t -test has been used to compute the comparison differences with the help of (10a), defined as follows:

$$\begin{aligned}
 t\text{-test} &= \frac{\text{difference between mean of set}_1 \text{ and set}_2}{\sqrt{\text{variance of set}_1 \text{ and set}_2 / \text{size of set}_1 \text{ and set}_2}} \\
 &= \frac{\text{mean (Pr)} - \text{mean (Re)}}{\sqrt{(S_1^2/n_1) + (S_2^2/n_2)}}.
 \end{aligned}
 \tag{10a}$$

Equation (10a) is used to compute the difference between evaluated literature work and proposed research work. The difference has been tackled between the mean of set₁ and set₂. In the case of this research work, the set₁ of t -test has been set as the value of mean of precision (Pr) and the set₂ of t -test has been set as the value of mean of recall (Re). The S_1^2 shows the population variance standard deviation of precision set and S_2^2 shows the population variance standard deviation of recall set. The variance of precision and recall sets is calculated by (10b) and (10c) as follows:

$$S_1^2 = \frac{\sum (\text{Pr} - \text{mean (Pr)})^2}{n_1}, \tag{10b}$$

$$S_2^2 = \frac{\sum (\text{Re} - \text{mean (Re)})^2}{n_2}. \tag{10c}$$

n_1 represents the total subjects values in precision set, while n_2 shows the subjects values in recall set. By calculating the t -test between the precision and recall sets of proposed approach and evaluation literature work [11], the process gets the precision and recall value sets from Table 12 and computes the t -test by using famous statistical software [61]. The results of t -test are shown in Table 13.

Table 13 shows the t -test result that shows the probability difference between the proposed approach and evaluation literature work [11]. The t -test result shows the difference value 0.29, which comes in the medium effect category [62]. Figure 9 shows the results of Tables 12 and 13 by using bar graph diagram.

In Figure 9, the results show clear improvement of our proposed goal-based hybrid filtering for e-learning

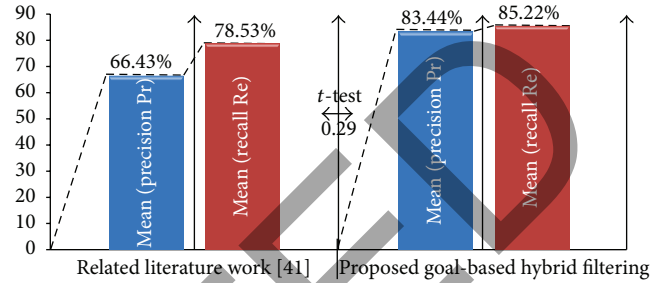


FIGURE 9: Overall results and evaluation of proposed goal-based hybrid filtering by mean of (8) precision Pr and mean of (9) recall Re and t -test probability difference between related literature work and the proposed approach.

recommender systems, defined as eLearningRecSys. The proposed hybrid approach enhanced the learning content recommendations as revealed in the result mean of precision Pr, 82.97%, mean of recall Re, 84.68%. The results demonstrate the controversial combination of content-based filtering, collaborative filtering, and k-neighborhood features that helps to overcome the new-learner zero-rated profile “NLP” recommendations and improve the average-learner low-rated profile “ALP” recommendations simultaneously. In the evaluation stage compared with the research work of [11], the authors work is based on reclusive traditional content-based recommendation methods aimed at dealing with content-based recommendations to the new-users. This approach contains precision mean 66.43% and recall mean 78.53% as mentioned in [11]. In the comparison evaluation of proposed goal-based hybrid filtering with [11], it is examined that one machine learning technique is enough to enhance the performance of recommender system if the hybridization sequence is controversially accurate. However, the traditional k-mean in [11] is unable to handle time computational complexity with genetic algorithm. Mostly with large set of content, the traditional k-mean does not give sufficient performance if k is small [46].

7. Conclusion

The e-learning applies to all the web-based styles and web-based fields of learning scenarios. Generally, these days, all the e-learning styles and fields work with the information retrieval crawlers. The information retrievals are gradually being used for retrieving the web-based learning content electronically over the Internet. The information retrieval systems take some initial keyword from the end user to retrieve the learning content. Due to the large size of e-learning content on web [63], the end user or learner failed to find their required content in sort time. For this,

the recommender systems are proposed in e-learning web-based scenarios. Recommender system is the branch of information retrieval that suggests the recommendations to end user that help to find the related learning content in a less time as compared to traditional e-learning web-based content retrieval systems. Recommender system is a very active research field. A number of works have already been mentioned in the literature background. This work proposed the goal-based hybrid filtering for personalized similarities between collaborative users profile preferences in e-learning recommender systems, defined as eLearningRecSys.

This paper discussed the research challenge learner-based cold-start problem; it occurs in eLearningRecSys when the system tackles the recommendation based on learner's past profile preferences, such as voting or like and dislike, to the specific learning contents by the learner. Previous literature taught that the learner-based cold-start problem is well known in recommendation systems. Bundle of literature has found the improvement of learner-based cold-start problem with the help of collaborative filtering and other approaches. However, none of them considered the learner's own personalized preferences such as age, gender, and occupation similarities and none of them overcome the both zero-rated and low-rated learner's recommendation issues simultaneously in one system. Alternatively, the goal-based hybrid filtering approach divides the learner-based cold-start problem into two issues, called new-learner zero-rated profile "NLP" recommendations and average-learner low-rated profile "ALP" recommendations with aim to help the learner's on both recommendation issues simultaneously in one system.

This research has used the famous "MovieLens" dataset "D" for experiments and proposed a work to overcome the new-learner zero-rated profile "NLP" recommendations and overcome the average-learner low-rated profile "ALP" recommendations using the learner's personalized profile preferences similarity with super-learner's high-rated profiles "SLP" collaboratively. The proposed research work has intended to introduce a goal-based hybrid filtering approach for e-learning recommender systems that hybridized the content-based filtering, collaborative filtering, and k-neighborhood scheme features. The results of proposed work demonstrate that the goal-based hybrid filtering plays its role to improve the new-learner zero-rated profile recommendation issue and overcome the average-learner low-rated profile recommendations issue simultaneously at the mean time. Nevertheless, the average mean of precision Pr scored 83.44% and mean of recall Re scored 85.22% and have been evaluated with related literature work [11]. The *t*-test probability difference of mean(Pr) and mean(Re) with evaluated literature work is 0.29 that seems the proposed hybrid approach have been made the medium level of improvement in the problem background of the relevant research domain.

The contribution of this research work has intend to propose a goal-based hybrid filtering approach that work with the learners personalized profile preferences such as age, gender and occupation to compute the similarity with other learner or group of learners profile in the collaborative network. These personalized similarities in collaborative

learner's network are helpful to get the similar goals of different learner's to overcome the zero-rated learner's recommendations and improve the low-rated learner's profile recommendations simultaneously in one proposed system. The results show that the proposed goal-based hybrid filtering has a flexibility to generate good similarities with minimum learner's profile preferences such as age, gender, and occupation without using any extra profile information. Perhaps, it may work with the maximum learner's profile personalized preferences too, if it is applicable in the future.

8. Research Limitation and Future Work

The limitation of proposed hybrid approach is intended to facilitate and respond to the recommendations to registered learners only who have their personalized profiles in the system. The nonregistered learners or guest is unable to receive the recommendations by the system.

The learner's requirements are increasing with the passage of time; for this, more research is required to be applicable in real-world situations in the field of e-learning recommender systems [59]. The future work will enhance the learner-profile based similarity results for the significance improvement of proposed goal-based hybrid filtering for learner-based cold-start problem using multiagent-based personalized similarities in different formal and informal e-learning scenarios with other machine learning approaches to check the content-filtering accuracy, time deficiency, and stability of other normalized datasets too. It may help in the multilearner's personalized similarities, recommendation timeline, and recommendation contents filtration accuracy.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

The Ministry of Higher Education Malaysia (MOHE), Universiti Teknologi Malaysia (UTM) under Research University Grant 03H02, and Ministry of Science, Technology & Innovations, Malaysia, under research Grant 4S062 are hereby acknowledged for some of the facilities utilized during the course of this research work.

References

- [1] G. Salmon, *E-Moderating: The Key to Teaching and Learning Online*, Softcover, Taylor & Francis, London, UK, 2nd edition, 2003.
- [2] S. Shishehchi, S. Y. Banihashem, N. A. M. Zin, and S. A. Mohd Noah, "Review of personalized recommendation techniques for learners in e-learning systems," in *Proceedings of the International Conference on Semantic Technology and Information Retrieval (STAIR '11)*, pp. 277–281, June 2011.
- [3] K. I. Ghauth and N. A. Abdullah, "Measuring learner's performance in e-learning recommender systems," *Australasian*

- Journal of Educational Technology*, vol. 26, no. 6, pp. 764–774, 2010.
- [4] P. di Bitonto, M. Laterza, T. Roselli, and V. Rossano, “A recommendation method for e-learning environments: the rule-based technique,” *Journal of E-Learning and Knowledge Society*, vol. 6, no. 3, pp. 31–40, 2010.
 - [5] S. M. McNee, J. Riedl, and J. A. Konstan, “Being accurate is not enough: how accuracy metrics have hurt recommender systems,” in *CHI '06 Extended Abstracts on Human Factors in Computing Systems*, ACM, 2006.
 - [6] R. Lara, D. Olmedilla, S. Arroyo, H. Lausen, D. Roman, and P. Chirita, “A semantic web services framework for distributed e-learning environments,” Informe técnico L3S, Research Center, 2004.
 - [7] G. Adomavicius and A. Tuzhilin, “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*, vol. 17, no. 6, pp. 734–749, 2005.
 - [8] M. A. Ghazanfar and A. Prugel-Bennett, “A scalable, accurate hybrid recommender system,” in *Proceedings of the 3rd International Conference on Knowledge Discovery and Data Mining (WKDD '10)*, pp. 94–98, IEEE, January 2010.
 - [9] R. Burke, “Hybrid recommender systems: survey and experiments,” *User Modelling and User-Adapted Interaction*, vol. 12, no. 4, pp. 331–370, 2002.
 - [10] A. Selamat and C. C. Ng, “Arabic script web page language identifications using decision tree neural networks,” *Pattern Recognition*, vol. 44, no. 1, pp. 133–144, 2011.
 - [11] V. Kant and K. K. Bharadwaj, “A user-oriented content based recommender system based on reclusive methods and interactive genetic algorithm,” in *Proceedings of the 7th International Conference on Bio-Inspired Computing: Theories and Applications (BIC-TA '12)*, vol. 201, Springer, 2013.
 - [12] S. K. Shinde and U. Kulkarni, “Hybrid personalized recommender system using centering-bunching based clustering algorithm,” *Expert Systems with Applications*, vol. 39, no. 1, pp. 1381–1387, 2012.
 - [13] K. Souali, A. E. Afia, R. Faizi, and R. Chiheb, “A new recommender system for e-learning environments,” in *Proceedings of the International Conference on Multimedia Computing and Systems (ICMCS '11)*, April 2011.
 - [14] I. Ghani, Y. L. Choon, R. J. Seung, H. J. Sung, and A. Latiff, “A role-oriented content-based filtering approach: personalized enterprise architecture management perspective,” *International Journal of Computer Science and Information Security*, vol. 8, no. 7, 10 pages, 2010.
 - [15] F. Lécué, “Combining collaborative filtering and semantic content-based approaches to recommend web services,” in *Proceedings of the 4th IEEE International Conference on Semantic Computing (ICSC '10)*, pp. 200–205, IEEE, September 2010.
 - [16] H. J. Ahn, “A new similarity measure for collaborative filtering to alleviate the new user cold-starting problem,” *Information Sciences*, vol. 178, no. 1, pp. 37–51, 2008.
 - [17] Y. Wang, N. Stash, L. Aroyo, P. Gorgels, L. Rutledge, and G. Schreiber, “Recommendations based on semantically enriched museum collections,” *Web Semantics: Science, Services and Agents on the World Wide Web*, vol. 6, no. 4, pp. 283–290, 2008.
 - [18] A. I. Schein, A. Popescul, L. H. Ungar, and D. M. Pennock, “Methods and metrics for cold-start recommendations,” in *Proceedings of the 25th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, ACM, 2002.
 - [19] Y. Blanco-Fernández, M. López-Nores, A. Gil-Solla, M. Ramos-Cabrer, and J. J. Pazos-Arias, “Exploring synergies between content-based filtering and spreading activation techniques in knowledge-based recommender systems,” *Information Sciences*, vol. 181, no. 21, pp. 4823–4846, 2011.
 - [20] Y. Blanco-Fernández, J. J. Pazos-Arias, A. Gil-Solla, M. Ramos-Cabrer, and M. López-Nores, “Providing entertainment by content-based filtering and semantic reasoning in intelligent recommender systems,” *IEEE Transactions on Consumer Electronics*, vol. 54, no. 2, pp. 727–735, 2008.
 - [21] Z. Mi and C. Xu, “A recommendation algorithm combining clustering method and slope one scheme,” in *Bio-Inspired Computing and Applications*, vol. 6840, pp. 160–167, Springer, 2012.
 - [22] F. Ge, “A user-based collaborative filtering recommendation algorithm based on folksonomy smoothing,” in *Advances in Computer Science and Education Applications*, vol. 202, pp. 514–518, Springer, 2011.
 - [23] A. Grando, M. Peleg, and D. Glasspool, “Goal-based design pattern for delegation of work in health care teams,” in *Proceedings of the 13th World Congress on Medical and Health Informatics*, pp. 299–303, September 2010.
 - [24] L. Jiang and J. Elen, “Why do learning goals (not) work: a reexamination of the hypothesized effectiveness of learning goals based on students'behaviour and cognitive processes,” *Educational Technology Research and Development*, vol. 59, no. 4, pp. 553–573, 2011.
 - [25] F. Dinuzzo, G. Pillonetto, and G. de Nicolao, “Client-Server multitask learning from distributed datasets,” *IEEE Transactions on Neural Networks*, vol. 22, no. 2, pp. 290–303, 2011.
 - [26] P. Sharkey, “Running hard to stand still: communication and information technology within social work training,” *Social Work Education*, vol. 19, no. 5, pp. 513–520, 2000.
 - [27] O. Dysthe, “The learning potential of a web-mediated discussion in a university course,” *Studies in Higher Education*, vol. 27, no. 3, pp. 339–352, 2002.
 - [28] C. Johnston and N. Olekalns, “Enriching the learning experience: a CALM approach,” *Studies in Higher Education*, vol. 27, no. 1, pp. 103–119, 2002.
 - [29] R. Johns, “Application of Web-based learning in teaching social work law,” *Social Work Education*, vol. 22, no. 5, pp. 429–443, 2003.
 - [30] D. McConnell, *E-Learning Groups and Communities*, Open University Press, 2006.
 - [31] R. Kumar and V. Bansal, “Activity based learning new method of learning: a case study of teach-next,” *International Journal of Research in Economics and Social Sciences*, vol. 2, no. 2, pp. 414–428, 2012.
 - [32] A. T. Corbett and J. R. Anderson, *Knowledge Decomposition and Subgoal Reification in the ACT Programming Tutor*, Department of Psychology, Carnegie Mellon University, 2008.
 - [33] P. Makkonen, “Who benefits from WWW presentations in the basics of informatics,” in *Webbased Instructional Learning*, pp. 252–263, IGI, 2002.
 - [34] A. Quinney, “‘Placements online’: student experiences of a website to support learning in practice settings,” *Social Work Education*, vol. 24, no. 4, pp. 439–450, 2005.
 - [35] H. Werthner, H. R. Hansen, and F. Ricci, “Recommender systems,” in *Proceedings of the 40th Annual Hawaii International Conference on System Sciences (HICSS '07)*, 2007.

- [36] B. L. D. Bezerra and F. D. A. T. de Carvalho, "A symbolic approach for content-based information filtering," *Information Processing Letters*, vol. 92, no. 1, pp. 45–52, 2004.
- [37] D. Fensel and C. Bussler, "The web service modeling framework WSMF," *Electronic Commerce Research and Applications*, vol. 1, no. 2, pp. 113–137, 2002.
- [38] P. Pan, C. Wang, G. Horng, and S. Cheng, "The development of an ontology-based adaptive personalized recommender system," in *Proceedings of the International Conference on Electronics and Information Engineering (ICEIE '10)*, pp. V176–V180, August 2010.
- [39] Y. Liu, "A new mathematic model-based recommender system for e-commerce," in *Proceedings of the IADIS International Conference on e-Commerce 2010, Proceedings of the IADIS International Conference on e-Democracy, Equity and Social Justice 2010, Part of the (MCCSIS '10)*, Scopus, Beijing, China, July 2010.
- [40] E. Emadzadeh, A. Nikfarjam, K. I. Gauth, and N. G. Why, "Learning materials recommendation using a hybrid recommender system with automated keyword extraction," *World Applied Science Journal*, vol. 9, no. 11, pp. 1260–1271, 2010.
- [41] M. Jahrer, A. Töschler, and R. Legenstein, "Combining predictions for accurate recommender systems," in *Proceedings of the 16th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 693–701, ACM, July 2010.
- [42] M. Hsu, "A personalized English learning recommender system for ESL students," *Expert Systems with Applications*, vol. 34, no. 1, pp. 683–688, 2008.
- [43] K. I. B. Ghauth and N. A. Abdullah, "Building an e-learning recommender system using Vector Space Model and good learners average rating," in *Proceedings of the 9th IEEE International Conference on Advanced Learning Technologies (ICALT '09)*, pp. 194–196, IEEE, July 2009.
- [44] M. Lee, P. Choi, and Y. Woo, "A hybrid recommender system combining collaborative filtering with neural network," in *Adaptive Hypermedia and Adaptive Web-Based Systems*, Springer, 2006.
- [45] M. Reza Mashinchi and A. Selamat, "An improvement on genetic-based learning method for fuzzy artificial neural networks," *Applied Soft Computing Journal*, vol. 9, no. 4, pp. 1208–1216, 2009.
- [46] R. Dash, "Comparative analysis of k-means and genetic algorithm based data clustering," *International Journal of Advanced Computer and Mathematical Sciences*, vol. 3, no. 2, pp. 257–265, 2012.
- [47] J. J. Jung, "Attribute selection-based recommendation framework for short-head user group: an empirical study by MovieLens and IMDB," *Expert Systems with Applications*, vol. 39, no. 4, pp. 4049–4054, 2012.
- [48] K. Verbert, H. Drachsler, N. Manouselis, M. Wolpers, R. Vuorikari, and E. Duval, "Dataset-driven research for improving recommender systems for learning," in *Proceedings of the 1st International Conference on Learning Analytics and Knowledge (LAK '11)*, pp. 44–53, March 2011.
- [49] T. Qiu, G. Chen, Z. Zhang, and T. Zhou, "An item-oriented recommendation algorithm on cold-start problem," *Euro Physics Letters*, vol. 95, no. 5, Article ID 58003, 2011.
- [50] L. He and F. Wu, "A time-context-based collaborative filtering algorithm," in *Proceedings of the IEEE International Conference on Granular Computing (GRC '09)*, pp. 209–213, IEEE, Nanchang, China, August 2009.
- [51] P. Symeonidis, A. Nanopoulos, and Y. Manolopoulos, "Providing justifications in recommender systems," *IEEE Transactions on Systems, Man, and Cybernetics A: Systems and Humans*, vol. 38, no. 6, pp. 1262–1272, 2008.
- [52] J. Buncle, R. Anane, and M. Nakayama, "A recommendation cascade for e-learning," in *Proceedings of the IEEE 27th International Conference on Advanced Information Networking and Applications (AINA '13)*, IEEE, 2013.
- [53] J. Bobadilla, F. Serradilla, and A. Hernando, "Collaborative filtering adapted to recommender systems of e-learning," *Knowledge-Based Systems*, vol. 22, no. 4, pp. 261–265, 2009.
- [54] P. Dwivedi and K. K. Bharadwaj, "Effective resource recommendations for e-learning: a collaborative filtering framework based on experience and trust," in *Computational Intelligence and Information Technology*, pp. 166–170, Springer, 2011.
- [55] A. M. Rashid, G. Karypis, and J. Riedl, "Learning preferences of new users in recommender systems: an information theoretic approach," *ACM SIGKDD Explorations Newsletter*, vol. 10, no. 2, pp. 90–100, 2008.
- [56] M. W. Chughtai, I. Ghani, A. Semalat, and S. R. Jeong, "Goal-based Framework for cold-start problem using multi-user personalized similarities in e-Learning scenarios," in *Proceedings of the 2nd International Conference on e-Learning and e-Technologies in Education (ICEEE '13)*, IEEE, 2013.
- [57] G. Research, "MovieLens Dataset," 1997, <http://movielens.umn.edu/html/tour/index.html>.
- [58] A. Selamat and S. Omatu, "Web page feature selection and classification using neural networks," *Information Sciences*, vol. 158, pp. 69–88, 2004.
- [59] M. K. Khribi, M. Jemni, and O. Nasraoui, "Automatic recommendations for e-learning personalization based on Web usage mining techniques and information retrieval," in *Proceedings of the 8th IEEE International Conference on Advanced Learning Technologies (ICALT '08)*, pp. 241–245, July 2008.
- [60] M. López-Nores, Y. Blanco-Fernández, J. J. Pazos-Arias, and A. Gil-Solla, "Property-based collaborative filtering for health-aware recommender systems," *Expert Systems with Applications*, vol. 39, no. 8, pp. 7451–7457, 2012.
- [61] IBM Corporation, *IBM SPSS Statistics for Windows*, IBM, Armonk, NY, USA, 2010.
- [62] J. Cohen, *Statistical Power Analysis for the Behavioral Sciences*, Routledge, New York, NY, USA, 1988.
- [63] J. J. Jung, "Social grid platform for collaborative online learning on blogosphere: a case study of eLearning@BlogGrid," *Expert Systems with Applications*, vol. 36, no. 2, pp. 2177–2186, 2009.