A New Adaptive Hybrid Recommender Framework for Learning Material Recommendation

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Abstract—**Recommender system is a promising technology in online learning environments to present personalized offers for supporting activity of users. According to difficulty of locating appropriate learning materials to learners, this paper proposes an adaptive hybrid recommender framework that considers dynamic interests of learners and multi-attribute of materials in the unified model. Since learners express their preference based on some specific attributes of materials, learner preference matrix (LPM) is introduced that can model the interest of learners based on attributes of materials using historical rating of accessed materials by learners. Then, the approach uses collaborative filtering and content based filtering to generate hybrid recommendation. In addition, a new adaptive strategy is used to model dynamic preference of learners. The experiments show that our proposed method outperforms the previous algorithms on precision, recall and intra-list similarity measure and also can alleviate the sparsity problem.**

I. INTRODUCTION

The Internet is one communication tool that has the potential to radically change society in the 21st century. In the recent years, with advances in wireless networking and mobile broadband Internet access technologies, and also the maturing of portable mobile devices, online e-learning has become a relatively widespread learning method. But one of the most important problems in e-learning is recommendation of appropriate learning material for each learner.

By increasing learning materials available on the e-learning systems, the delivery of appropriate learning materials to learners is difficult using keyword searching method. Hence, locating the suitable learning materials has become a big challenge. One way to address this challenge is the use of recommender systems [1]. In addition, up to the very recent years, several researches have addressed the need for personalization in the e-learning environment. In fact, one of the new forms of personalization in e-learning environment is to give recommendations to learners in order to support and help them through the

e-learning process [2]. The task of delivering personalized learning material is often framed in terms of a recommendation task in which a system recommends items to an active user [3].

Recommender systems that have been deployed usually in e-commerce entities for expressing customer's interests use three strategies for recommendation including content-based, collaborative, and hybrid recommendation [4]. Content-based recommendation algorithm identifies and extracts features of items and user and then builds matching model for them. User profiles including information about their preferences are collected as well. Recommendations are made based on comparison of user's preference and item's features. Collaborative filtering assumes that users who had similar choices before will make same selection in the future. Collaborative recommender systems give users suggestion by observing the neighbor of the user. Hybrid recommendation mechanisms attempt to deal with some of limitations and overcome drawbacks of pure content-based approach and pure collaborative approach by combining the two approaches.

One of the most important drawbacks of existing recommendation systems is that they usually use only rating matrix as useful information and not fully consider contextual information for improving recommendation. On the other hand, the learners' preferences will be changing dynamically. However, most of existing recommendation algorithms do not use a dynamical approach for recommendation and thus they cannot make good recommendation in time when learners' current interests are changing. Therefore, it will lead to a great difference between recommended materials and learners' actual preferences. By implementing an adaptive hybrid approach for recommendation, this paper can take into account contextual information including multi-attribute of materials, dynamic preferences of learner simultaneously. Therefore, in this paper, to address the drawbacks of existing material recommendation algorithms, a new material recommender system framework and relevant recommendation algorithms for e-learning environments are proposed.

In order to reflect learner's complete spectrum of interests, learner matrix preference (LMP) is introduced to consider multi-dimensional attributes of materials. Truly, preference matrix is built based on target learner's historical rating and multi-dimensional attributes of materials. In addition, an updating approach for preference matrix is introduced to consider the dynamic preference of learner. Finally, for improving of recommendation a hybrid approach is proposed that uses content based and collaborative filtering. Experiments are being formulated to illustrate the system's capability.

The rest of this paper is organized as follows. In Literature survey section, the previous related works on e-learning material recommender systems are discussed. Methodology section introduces the overall system framework and describes the proposed algorithms step by step. Result and discussion section describes some experiments for evaluation of the proposed approach. Finally, Conclusion section provides the concluding remarks.

II. LITERATURE SURVEY

The recommender systems were developed in the mid of 1990s [5]. Recommendation systems most are implemented in various fields such as movies, music, news, commerce and medicine but few are implemented in education field [6]. With the rapid growth of learning resources, either offline or online in educational organizations at recent years, it is quite difficult to find suitable learning resources based on learner's preference. Therefore, recommender systems have been used for e-learning environments to recommend useful resources to users. These systems address information overload and make a personal learning environment (PLE) for users. The motivation for any recommender system is to assure an efficient use of available resources. Using this approach, we can improve a personal learning path according to pedagogical issues and available resources.

Both type of systems including content-based filtering and collaborative have inherent strengths and weaknesses. In addition, to produce the accurate and effective recommendations and ensure the real-time requirement of the system, researchers proposed several different algorithms. Table 1 presents an overview of the recommendation strategies. We briefly explain some of important researches:

A. Content based filtering

This approach that is mainly used to recommend documents, Web pages, publications, jokes or news finds similarity between items using similar their features.

As an example for e-learning application, Khribi et al. [2] used learners' recent navigation histories and similarities and dissimilarities among the contents of the learning materials for online automatic recommendations. Clustering was proposed by Hammouda and Kamel [7] to group learning documents based on their topics and similarities. In fact, the existing metrics in content based filtering only detect similarity between items that share the same attributes. Indeed, the basic process performed by a content-based recommender consists in matching up the attributes of a user profile in which preferences and interests are stored, with the attributes of a content object (item), in order to recommend to the user new interesting items [8]. This causes overspecialized recommendations that only include items very similar to those the user already knows. To avoid the overspecialization of content-based methods, researchers proposed new personalization strategies, such as collaborativefi ltering and hybrid approaches mixing both techniques.

B. Collaborative filtering

Majority of researchers used collaborative filtering (CF) based recommendation system. This approach can be divided in to three categories that have been shown in Table 1. The collaborative e-learning field is strongly growing [9-11], converting this area in an important receiver of applications and generating

TABLE 1. OVERVIEW OF THE RECOMMENDATION STRATEGIES

Techniques	Process	Usefulness for Material Recommendation
Collaborative Strategy		
Neighbor-based CF(Item-based/user-based);	Finds similar item or user based on rating data and predicts rating using weighted average of similar user or item.	**No content analysis, Domain-independent**
latent semantic analysis; Markov decision processes; Data mining (Regression, Bayesian classifier, clustering,..)	Predicts rating of a user by learning of complex patterns based on the training data (rating matrix)	**No content analysis, Domain-independent**
Demographics	User with similar attributes are matched, then recommends items that are preferred by similar users	**No cold-start problem, No sparsity problem Domain independent**
Content Based Strategy		
Case-based reasoning	Assumes that if a user likes a certain item, s/he will probably also like similar items, recommends new but similar items.	**No content analysis, Domain independent No sparsity problem, Useful for hybrid RS Keeps learner informed about learning goal**
Data mining (Bayesian classifier, clustering, association rules, …)	Recommends items based on the matching of their attributes to the user profile. Attributes could be weighted for their importance to the user	**No cold start problem, No sparsity problem Sensitive to change of preference Can include non-item related features Useful for hybrid RS**
Hybrid		
weighted, cascade, metal-level, mixed, switching, feature combination, feature augmentation	**Combines rating of user and attributes of item and user for learner's rating prediction and recommendation**	**Based on hybrid approach differs (try to cover the weakness of other approaches)**

numerous research papers. CF was used by Soonthornphisaj et al. [12] for prediction the most suitable materials for the learner. At first, the weight between all users and the active learner is calculated by Pearson correlation. Then, the *n* users that have the highest similarity to the active learner are selected as the neighborhoods. Finally, using the weight combination obtained from the neighborhood, the rating prediction is calculated. Bobadilla et al. [13] used a new equation for incorporating the learners score obtained from a test into the calculations in collaborative filtering for materials prediction. Their experiment showed that the method obtained high item-prediction accuracy.

Since in the e-learning environment learning resources are in a variety of multimedia formats including text, hypertext, image, video, audio and slides, it is difficult to calculate content similarity of two items [14]. In this sense, users' preference information is a good indication for recommendation. Therefore, CF is more suitable in e-learning systems since it is completely independent of the intrinsic properties of the items being rated or recommended [15]. However, it has a serious drawback. Its applicability and quality is limited by the so-called sparsity problem, which occurs when the available data are insufficient for identifying similar users [16]. Therefore, many researches were run to alleviate the sparsity problem using data mining techniques. In e-learning environments, the data mining techniques use the gathered information about the learner behavior,

such as navigation history, to produce recommendations. For example, Romero et al. [17] developed a specific Web mining tool for discovering suitable rules in recommender engine. Their objective was to recommend to a student the most appropriate links/WebPages to visit next. Lobo and Sunita [18] used a classification algorithm for the data selected from Moodle database to classify the data, then they used Apriori Association Rules algorithm for recommender.

C. Hybrid approach

To overcome drawbacks of these strategies, most of researchers used hybrid approach for material recommendation. Most hybrids work by combining several input data sources or several recommendation strategies. Table 1 lists some techniques that are used for hybrid recommendation. Khribi [2] used learners' recent navigation histories and similarities and dissimilarities among user preferences and among the contents of the learning materials for online automatic recommendations. They implemented web usage mining techniques with content-based and collaborative filtering for computing relevant links to recommend to active learners. García et al. [19] applied association rule mining to discover interesting information through student's usage data in the form of IF-THEN recommendation rules and then used a collaborative recommender system to share and score the recommendation rules obtained by teachers with similar profiles along with other experts in education. García et al. [20] described a collaborative educational

data mining tool based on association rule mining for the ongoing improvement of e-learning courses and allowing teachers with similar course profiles to share and score the discovered information.

In material recommendation for learning environment, we must consider pedagogical reasons. These pedagogical reasons are derived from specific demands of lifelong learning [21]. One way to implement pedagogical decisions into a recommender system is to use a variety of recommendation techniques in a recommendation strategy. This paper uses two recommendation techniques based on attributes of resources and also considers a dynamic approach. By combining content based and collaborative filtering approaches, we alleviate sparsity and overspecialized recommendation problems that are the drawbacks of collaborative and content based recommendation approaches respectively.

In this research, we integrate the contextual information including multi-dimensional attributes of resources; learner's rating information and also access order of learning materials in the unified model. Our proposed framework can use this information simultaneously to model adaptive multi-preference of learners. According to the property of this technique, system can alleviate the sparsity and however increase the diversity of recommendation list.

III. METHODOLOGY

In this section, the overall system framework is presented and the proposed algorithms are described step by step. Figure 1 shows the recommender architecture of our system. In the proposed architecture, at first the learner model and material model are build. Materials are modeled according to material modeling approach that will be explained in the next section. LPM is formed for each user based on the user's historical rating. Finally, the generated recommendations by two methods including weighted attribute based content based recommendation and weighted attribute based collaborative filtering recommendation are combined with each other.

A. Material profiling

$$s_{ikj} = AW_k . r_{ij} \qquad (1)$$

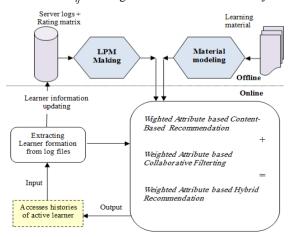Where r_{ij} is rating of user i for the material j

Figure 1. Overall architecture of the proposed material recommender system

	r_{i1}	r_{i2}	r_{i3}	....	r_{iT}
A_1	s_{i11}	s_{i12}	s_{i13}	....	s_{i1T}
A_2	s_{i21}	s_{i22}	s_{i23}	....	s_{i2T}
A_3	s_{i31}	s_{i32}	s_{i33}	....	s_{i3T}
A_4	s_{i41}	s_{i42}	s_{i43}	....	s_{i4T}
...	.....	.....	.....	....	.....
AK	s_{iK1}	s_{iK2}	s_{iK3}	....	s_{iKT}

Figure 2. Personal preference matrix

B. Wighted Attribute based Content-based Recommendation (WACB)

In this work, the similarity between leaner behavior i and material m is calculated using the following equation:

$$sim(u_i, m) = \frac{\sum_{j=1}^{T} w_{ij} . \sum_{k=1}^{K} s_{ikj} . M_k(m, m_{ij})}{\sum_{j=1}^{T} w_{ij} . r_{ij}} \qquad (2)$$

In which w_{ij} is a weighting value for observation of material j by user i. Since user's recent accessed material preference plays an important role to the future interests, the relative importance of each observation pre-determined as follows:

$$w_{ij} = e^{-\lambda(T - t(m_{ij}))} \qquad (3)$$

Where $t(m_{ij})$ is the order of material j in the recent observation by user i and λ is an adjustable parameter used to describe the change rate of user's preference. This formula gives more weight to recent visited materials. $M_k(m, m_{ij})$ is a matching function between k-th attribute of material m and m_{ij} that is calculated as follows for non-numeric attributes:

$$M_k(m, m_{ij}) = \begin{cases} 1 & if \ value(A_k, m) = value(A_k, m_{ij}) \\ 0 & otherwise \end{cases} \qquad (4)$$

Therefore, for non-numeric attributes if the value of k-th attribute for m and m_{ij} be same $M_k(m, m_{ij})$ gets 1 otherwise 0. For numeric attributes, matching function is as follows:

$$M_k(m, m_{ij}) = 1 - \frac{|value(A_k, m) - value(A_k, m_{ij})|}{\max value(A_k) - \min value(A_k)} \qquad (5)$$

Where $\max value(A_k)$ and $\min value(A_k)$ indicate maximum and minimum value for attribute A_k respectively. Materials are ranked according to the similarity score between the preference matrix made up of weighted behavior attribute sets and materials. Highly ranked materials are then recommended to the user. It must be noted, to increase the scalability of our system, we can categorize materials. The material set in

each category is not large and therefore similarity computation time between users and materials is not very high.

C. Adaptive strategy

The preference of a user may change and therefore, it is necessary to set w_{ij} adaptively based on changing of user's preferences. When a user selects a material of his/her interest from the recommended rank list, the weight w_{ij} must be changed according to the attribute weights of selected material. This feedback process is performed in the following steps.

Step-1: From the recommended rank list, a user selects the material m which s/he is interested in.

Step-2: In order to detect the influential behavior that strongly affects the similarity score between m_{ij} and m, the following similarity measure is used:

$$Sim(m,m_{ij}) = \frac{\sum_{k=1}^{K} M_k(m,m_{ij})}{K} \qquad (6)$$

Step-3: The weight of the observation j (i.e. m_{ij}) whose score in (6) is greater than 0 is increased:

$$w_{ij}^{new} = w_{ij} + Sim(m,m_{ij}) \qquad (7)$$

Where w_{ij}^{new} is the new weight for the observation j (i.e. m_{ij}).Using the new weights, the weight adapting process is performed again. The materials with the top-N similarity scores are recommended to the user. This feedback is an iterative process so that even if a particular user changes his/her information preference over time, appropriate recommendation can still be made with the adaptive capability of our system. It must be noted when we use adaptive strategy, w_{ij} changes gradually and after that we don't use equation (3) to compute w_{ij}. In other words, we use equation (3) only in the first recommendations of each user.

D. Weighted Attribute based Collaborative Filterting (WACF)

This research uses CF also as follows:

Step 1: For reflecting the similarity between the preferences of two users, the similarity $sim(u_i,u_j)$ is calculated as follows:

$$sim(u_i,u_j) = \frac{\sum_{h=1}^{T}\sum_{f=1}^{T} w_{ih}w_{jf}.\sum_{k=1}^{K} s_{ikh}.s_{jkf}.M_k(m_{ih},m_{jf})}{\sum_{h=1}^{T}\sum_{f=1}^{T} w_{ih}w_{jf}.r_{ih}.r_{jf}} \qquad (8)$$

Step 2: In this step, system determines attribute-based neighborhoods of user i, $N(u_i)$ according the calculated similarity in Step 1.

Step 3: Rating predication of material j by using attribute based method for active user u_i is p_{ij} that is gained by the rating of u_i neighborhood, $N(u_i)$, that have rated j before. The computation formula is as the follows:

$$p_{ij} = \bar{r}_i + \frac{\sum_{x \in N(u_i)} sim(u_i,u_x) \times (r_{xj} - \bar{r}_x)}{\sum_{x \in N(u_i)} sim(u_i,u_x)} \qquad (9)$$

Where $\bar{r}_i$ and $\bar{r}_x$ is rating average of items rated by active user u_i and u_x respectively and $sim(u_i,u_x)$ is the similarity between active user u_i and u_x that is a member of $N(u_i)$.

E. Final recommendation(WAH)

We proposed two recommendation approaches including content based recommendation and collaborative filtering based recommendation to generate final recommendation list for active learner using Weighted Attribute based Hybrid (WAH) recommendation, we used a weighted approach and combined the results of two methods as follows:

$$rec.sco.(u_i,m_j) = \alpha.Nor(sim(u_i,m_j)) + (1-\alpha).Nor(p_{ij}) \qquad (10)$$

Where $rec.sco.(u_i,m_j)$ means the recommendation score of m_j for u_i, $Nor(x)$ is the normalization function and α is a weight for combination of results of two methods.

IV. RESULT AND DISCUSSION

We have conducted a set of experiments to examine the effectiveness of our proposed recommender system in terms of sparsity and recommendation accuracy and quality.

A. Data set and Evaluation metrics

In order to check the performance of the proposed algorithm, a real-world dataset is applied in our simulations. Data is delivered by Education and Student Service Center (STU) of Eindhoven University of Technology (TU/e). The data is given the format of a Microsoft Access Database.

TABLE2. SELECTED ATTRIBUTES AND THEIR VALUES FOR LEARNING MATERIALS

Attribute	Weight	Values
Subject	0. 5	Mathematic, Information Technology,…
Sub subject	0.25	Neural network, e-learning,…
Education level	0.15	Bachelor, Master, PhD
Publisher	0.1	TU/e, UU, UA, …

In this research, to implement our approach, we consider four attributes including subject, secondary subject, education level and publisher. According to expert' opinion, we weight these attributes as Table 2 presents. In addition, the attribute value for each material was obtained using of the material information table of data. The attributes and some of their values are shown in Table 2.

TABLE 3. A COMPARISON OF PREDICTION ACCURACY

Method	MAE	RMS
AWCF	0.865	1.312
Collaborative filtering	0.937	1.635
Hybrid recommendation	0.863	1.327

User' rating on materials obtained from the preference rating table of data files. We used Matlab software to implement our framework for recommendation.

After preprocessing the data, the database, which contained 1,500 users and 13,000 rating on materials, was obtained. In experiments, the transaction data is ordered by user' access timestamp, and then is divided into a training set and a test set.

In this paper, the evaluation metrics of recommendation algorithms are divided into to three categories:

Decision support accuracy metrics assume the prediction process as a binary operation either items are predicted (good) or not (bad). The precision and recall are the most popular metrics in this category. For the evaluation of recommender system, they have been used by various researchers [22, 23]. When referring to recommender systems, the recall and precision can be defined as follows:

$$Recall = \frac{tp}{tp + fp} \tag{11}$$

$$\Pr ecision = \frac{tp}{tp + fn} \tag{12}$$

Where *tp* stands for true positive, *fp* stands for false positive, and *fn* stands for false negative. Since we rescale rating information of student between 0 to 5, the threshold for determining true positive is set to 3.5 meaning that if an item is rated 3.5 or higher, it is considered to be accepted by the user.

Since increasing the size of the recommendation set leads to an increase in recall but at the same time a decrease in precision, we can use F_1 measure [24] that is a well-known combination metric with the following formula:

$$F_1 = 2.\frac{\Pr ecision.\mathrm{Re} call}{\Pr ecision + \mathrm{Re} call} \tag{13}$$

The other metrics that we use are predictive accuracy metrics. These metrics measure how close the recommender system's predicted ratings are to the true user ratings. Mean Absolute Error [1] is used with following formulas:

$$MAE = \frac{\sum_{i=1}^{i=S}|r^i - p^i|}{S} \tag{14}$$

Where p^i is the predicted rating for resource *i*, r^i is the given rating for resource *i*, and *S* is the total number of the pair rating p^i and r^i.

Since most of recommendation algorithms have been developed based on accuracy measures, recommendation list produced by them contain similar items. Going to Amazon.com for a book by Isaac Asimov, for example, will give you a recommendation list full of all of his other books. In this case, the Item-Item collaborative filtering algorithm can trap users in a 'similarity hole', only giving exceptionally similar recommendations. Since accuracy metrics are designed to judge the accuracy of individual item predictions, they cannot see this problem.

The recommendation list should be judged for its usefulness as a complete entity, not just as a collection of individual items. Therefore, in this research we introduced a new measure to compute similarity between recommended items in the recommendation list. Less similarity between items in the recommendation list, more diversity between them. An Intra-List Similarity Metric (ISM) [25] is defined as follows:

$$ISM(List) = \frac{\sum_{R_i \in list} \sum_{R_j \in list, i \neq j} f(m_i, m_j)}{\binom{\#List}{2}} \tag{15}$$

Where

$$f(m_i, m_j) = \frac{mat(m_i, m_j)}{K} \tag{16}$$

Where *mat* function indicates number of matched attributes (similar attributes) between material m_i and m_j and as it was said before *K* is number of attributes for resources. Higher similarity denotes lower diversity. This measure is used to evaluate the quality of recommendation.

B. Performance evaluation

In this section, the proposed recommendation approaches are compared with content-based recommendation algorithm [1], collaborative-based recommendation algorithm [26] and hybrid recommendation algorithm [27]. In relevant input parameters, *l* denotes the number of recommendation resources; *p* denotes the number of participated users which are selected from the dataset to build simulation dataset. We select only users that have rated at least 40 items in the dataset. *N* denotes number of neighborhoods of active learner.

1) Parameters setting

Firstly, we will analyze how some parameters affect the recommendation performance of the proposed algorithms. Goal of the following experiments is to determine the values of these parameters (as different dataset may correspond to different optimal value of these parameters). We examine the impacts of various values for T, λ and α on the F_1 measure of proposed

approaches. According to our experiments, λ =0.6, T=5 and α = 0.7 give good results for our problem.

Impact of λ : Figure 3 shows the impacts of λ on the F_1 of content based method while N =15, p =200, T=5 and l=20. It indicates that giving a more weight for user's recent accessed material can improve the recommendation accuracy and the best accuracy can be obtained with λ = 0.6.
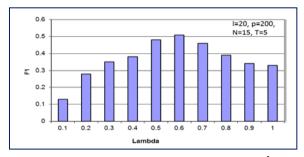

Figure 3. The F_1 of AWCB method with respect to λ

Impact of T: To consider the impact of T on the content based algorithm, we vary T from 2 to 6 while N=15, p=200 and λ = 0.6. Fig. 4 shows the impact of different window sizes on F_1 of recommendations against varying numbers of recommendations from 4 to 40. A large sliding window provides more information to the system while on the other hand makes a more computation time. As Figure shows a window of size 2 cannot hold enough information for the recommendation. Therefore, the accuracy improves with increasing the window size. But the difference of accuracy between window size 5 and 6 is not very much. In this research, we consider T=5.
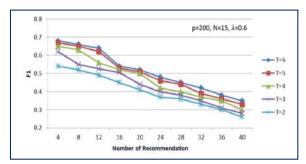

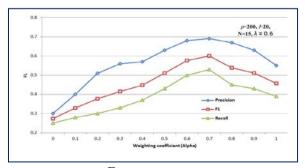Figure 4.The F_1 of AWCB method with respect to T

Figure 5. The F_1 of WAH method with respect to α

Impact of α : Figure 5 shows the impacts of α on the precision, recall and F_1 of proposed hybrid

recommendation. It indicates that taking into consideration a combination of AWCB and AWCF to produce recommendation will play a positive role in recommendation process, but α does not acknowledge 'the larger the better' rule: the best precision can be obtained with α = 0.7. The reason is that using two types of information including attribute based preference similarity between two users or between user and materials can give more accuracy than one type alone.

C. Performance comparison

After setting parameters, we used the best values of them for comparative study with other algorithms. Experiments must implement to validate the premise that our adaptive recommender can improve recommendation results by exploiting the connection between a user's information preference and his/her behavior via adaptive strategy.

To compare the relative performance of WACB, WACF and WAH with traditional content based recommendation, collaborative filtering based recommendation and hybrid method in the recommendation generation, an experiment is performed. All parameters were set and then these methods were applied on the data. This comparison is based on number of recommendations for F_1 measure that is presented in Figure 6. As Figure 6 shows combination on WACF and WACB has the best performance. In addition, as you can see with increasing number of recommendation, the accuracy of all algorithm decreases. It is because that during the changing process, according to formula (13), the numerator and denominator of F_1 will increase synchronously, but denominator gets the higher increasing rate. In addition, as WAH method can make good use of the advantages of content-based and collaborative-based recommendation mechanism while integrate three kinds of information: multi-dimensional attributes of material, users 'rating and users' access order, hence the actual preference and interests of users can be reflected accurately.
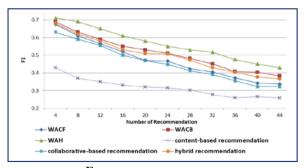

Figure 6. The F_1 of different recommendation algorithms with respect to number of recommendation

Table 3 presents a comparative study for rating prediction accuracy of different methods using mean absolute error (MAE) and root mean square (RMS).

Comparisons were produced for p=200, users with the average number of ratings about 50, l=15, N=15 and λ = 0.6. As can be seen, the proposed method

(WACH) generates better recommendations of other algorithms.

Performance evaluation for different sparsity levels: To evaluate our proposed approaches for sparsity data, we change the minimum number of rating required for test users, from 25 to 70 and compare the results of WAH with the traditional algorithms. As Figure 7 shows with increasing sparsity in the data or decreasing the value of minimum number of rating required for test users, the performance superiority of WAH increases. It is because; attributes of an item can still be used for finding similar items. Furthermore, this algorithm enriches item and user profiles with combining attributes information with rating information.
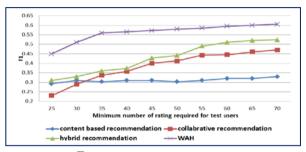

Figure 7. The F_1 of different algorithms with respect to minimum number of rating required for test users

Performance Evaluation for Intra-List Similarity: In the final experiment, to evaluate the quality of recommendation by proposed methods, they are compared with other algorithms based on defined Intra-List Similarity Metric. As shown in Figure 8, WAH method has lower ISM than any other algorithms that means higher diversity. WACF and traditional collaborative filtering have the lowest diversity and diversity in WACF and hybrid filtering is approximately equal. By increasing number of recommendations, diversity decreases for all algorithms.
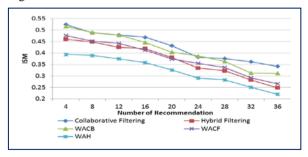

Figure 8. The ISM of algorithms with respect to l

V.   CONCLUSION

One of the most important applications of recommendation systems in e-learning environment is personalization and recommendation of learning resources. To address the sparsity problem and have a more diverse recommendation list for each learner, this paper presents a novel personalized recommendation framework that utilizes attributes of resources and rating information in the unified model. This research extracts the user's preference information based on

rating on different attributes and recommends suitable learning material. The adaptive recommender is capable of streamlining recommended material to a user's preference according to feedback.

In the proposed approach, preference matrix was introduced that can model the interest of learners based on attributes of materials using historical rating of materials by learners. Then, the approach uses two methods including collaborative filtering and content based filtering to generate recommendation.

However, there are some limitations that can determine some possible directions for further researches: (1) Many systems need to react immediately to online requirements and make recommendations for all users regardless of ratings history on visited resources, which demands a high scalability of a CF system. (2) There are some access rules of learners that this research doesn't use them. For example: The learning processes (resource access processes) usually have some time-dependency relationship and are repeatability and periodicity. Therefore, the time-dependency relationship between learning resources in a learning process can reflect learner's resource access latent pattern and preference.

Therefore, for further research, we can implement some techniques to increase the scalability of systems. For example clustering algorithms are good choices that can cluster users based on their behaviors and address the scalability problem by seeking users for recommendation within smaller and highly similar clusters instead of the entire database.

In addition, we can mine learner's historical access records for discovering the resource access sequential patterns. Then, using these sequential patterns, we can predict the most probable resource that a learner will access in near feature to further improve the quality of recommendations and solve the new user problem.

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