Enhanced Collaborative Filtering to Recommender Systems of Technology Enhanced Learning

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Abstract. Recommender Systems (RSs) are largely used nowadays in many areas to generate items of interest to users. Recently, they are applied in the Technology Enhanced Learning (TEL) field to let recommending relevant learning resources to support teachers or learners' need. In this paper we propose a novel recommendation technique that combines a fuzzy collaborative filtering algorithm with content based one to make better recommendation, using learners' preferences and importance of knowledge to recommend items with different context in order to alleviate the Stability vs. Plasticity problem of TEL Recommender Systems. Empirical evaluations show that the proposed technique is feasible and effective.

Keywords: Technology-Enhanced Learning, Recommender Systems, Collaborative Filtering, Content Based Filtering, Learner Profile, Fuzzy C-means, Matrix Factorization.

1 Introduction

Web development has created a need for new techniques to help users find what they want and also to know that information exists, these techniques are called Recommender Systems (RSs). These systems are built generally based on two different types of methods that are Content Based Filtering (CBF) and Collaborative Filtering (CF). RSs suffer from several problems defined in [1], where one of them is the problem of the system's stability compared to the user's profile dynamicity (Dynamicity vs. Plasticity Problem) [1]. This problem comes from the system's incapability to track the user's behavioral evolution, because in RSs once a user's profile has been established, it is difficult to change it. RSs are widely used in many areas, especially in e-commerce [2],[3]and[4]. Recently, they are applied in the e-learning field, more specifically in Technology Enhanced Learning (TEL) [5], in order to personalize learning content and connect suitable learners with each other according to their individual needs, preferences, and learning goals.

TEL can be differentiated into formal and non-formal learning settings. In non-formal learning, the learners are acting more self-directed and they are responsible for their own learning. The learning process is not designed by an institution or responsible teachers like in formal learning, but it depends on individual learners' preferences or choices, which is similar to consumers looking for products on the internet. So, lifelong learners are need to have an overview of the available learning activities and materials to decide which of them match better their personal needs, preferences, prior knowledge and current situation. Where the need to use Personalized Recommender Systems (PRS) that use efficiently the available resources in the network and propose learning resources and activities depending on individual needs, learning goals, context, and increase collaboration between learners. But the learner's need and preferences may change over period of time, also in the same time where he wants to learn from resources with different context. This creates the need of designing Adaptive RSs (ARS) capable of generating recommendations with different tastes depending on the learner's profile evolution. ARSs design is a great challenge because of the Stability vs. Plasticity problem of these systems.

Whereas recommendations in TEL field depend not only to learner's preferences but on the context as demonstrated in [6]; this makes more and more important the use of CBF in the recommendation process. To this end, we elaborate a hybrid technique that combines between a fuzzy-based CF algorithm and CBF using taxonomic information to generate multi-context recommendations with better performance.

The paper is organized as follows. Section two, presents the RSs field and the third section, contains some works deployed RSs in the TEL field. Then, we outline our proposed fuzzy hybrid technique to recommend learning resources with different tastes, in section four. Empirical results are presented in the fifth section. Finally, we give some conclusions and lines of future work.

2 Recommender Systems

RSs provide adequate information to people in need using a representation of the user called "User Profile". This profile is compared with different profiles available to determine those to which they correspond [7]. So, RSs intend to send from a large amount of information generated dynamically, the information judged relevant. Hence, filtering is interpreted as elimination of unwanted data on an incoming stream, rather than looking for specific data on this flow.

RSs are built generally based on two different types of methods that are Content Based Filtering (CBF) and Collaborative Filtering (CF). The CBF approach generates content recommendations based on the characteristics of users or items, while the CF method just use the evaluations made by users on the items to predict the unknown ratings of new user-item pair. Typical CF algorithms can be categorized into two classes: neighborhood methods and factorization methods. Generally factor-based algorithms are considered more effective than those based on neighborhood. But they are often complementary and the best performance is often obtained by blending them [8]. Hybridization between CF and CBF approaches has been the subject of interest in a lot of works on RSs, to enjoy their benefits.

One of the major problems of RSs is the Stability problem of these systems compared to the dynamic profile of the user (Stability vs. Plasticity Problem) [2]. To overcome this problem, we proposed a hybrid approach that combines between the CB approach that uses taxonomic information to represent the item's content and collaborative approach that uses preferences of similar learners (neighbors) to predict the active learner's preferences, then, generating diversified recommendations that meet their needs according to his membership degrees to different clusters. These membership values can be obtained in the CF phase by applying the Fuzzy Logic [9], or by applying the Fuzzy C-means algorithm (FCM) [10].

In order to offer all needs of the active learner that fit their different tastes, we propose a fuzzy based clustering algorithm to regroup learners including the active learner, and that guarantees a multi-affectation of learners to nearest clusters allowing them to receive partial recommendations generated in each cluster according to their membership degrees. Due to the two major challenges for the CF based systems, which are the Scalability and Sparcity Problems, the application of traditional FCM algorithm can confront some difficulties. From this point, our goal was to design an efficient CF algorithm that guarantee a multiple assignment of a user to different clusters, by modifying the FCM objective function to a Matrix Factorization (MF) one[11].

3 Background

Many RSs have been deployed in TEL, as surveyed in Manouselis and al.[5], for recommending learning materials and resources to the learners in both formal and informal learning environment[12]. Concretely, Garc'ıa and al.[13] uses association rule in the form of IF-THEN rules to discover information of interest through student performance data, then generating the recommendation based on those rules; Bobadilla and al.[14] had using a CF scheme where they incorporated learners' test score into the item prediction function; Soonthornphisaj and al.[15] applied CF to predict the most suitable learning objects to the learners; Ge and al.[16] have combined between CBF and CF to make personalized recommendation for a courseware selection module. Finally, Thay-Nghe and al.[17]applied the MF technique in the educational context, for predicting student performances. A critical study of recommender techniques regarding to their applicability and usefulness in TEL has presented in [12], providing an overview of advantages and disadvantages of each technique, and report the envisaged usefulness of each one for TEL recommenders. For more details on TEL Recommender Systems please refer to [5].

Generally RSs in e-learning deal with information about the learners and learning activities and would be able to track the evolution of the learner profile (behavior) during his different learning levels. For this aim, we propose a new hybrid technique that combines CF (using MF) with CBF to better predict the learner's need. The proposed technique allows generating learning resources recommendations to lifelong learners that correspond to their different interests, tracking their profiles evolution.

4 Contribution

To improve the recommendation quality, we are conducted toward hybridization between CF and a CBF to enhance the CF accuracy in TEL Recommender Systems in order to deal with the sparcity and scalability problems.

Our proposed approach can be divided into two main phases; the first one contains the description of the fuzzy-based CF algorithm and the CBF one, with their messing scores predictions. Then, it presents the hybrid scheme that blends the two predictions in order to obtain a full learner-course matrix. The second phase contains the recommendation algorithm adapted to TEL field by incorporating the learner's performances in order to generate effective recommendations.

4.1 Environment description

The universe of discourse considered in our system is based on pair-wise relationships between two types of entities u and t, which we call "*user*" and "*item*", or "*learner*" and "*course*", respectively. We envision a world with:

- A set of learners U = $\{u_1, u_2, \ldots\ldots u_N\}$; - A set of courses C = $\{c_1, c_2, \ldots, c_M\}$.
- Each item is described by a set of descriptors D(t)= $\{d_1, d_2, .., d_n\}$ such that $|D(t)| \geq 1$. A taxonomic descriptor d is an ordered sequence of topics p denoted by d = $\{p_0, p_1, \ldots p_q\}$ where $d \subseteq D(c)$, $c \subseteq C$. The topics within a descriptor are sequenced so that the former topics are super topics of the latter topics, when the super topic covers the general term of the domain and sub-topic covers a more specific term.
- $r_{u,c}$ The evaluation of course c made by learner u. All evaluations made by the learner u form a vector r_u, that represents his profile. The evaluation matrix is R.
- $z_{u,k}$The probability that learner u belongs to cluster k; Z= $(z_{u,k})$ is the probability matrix $U \times K$, where U, K are number of learners and clusters, respectively.
- $c_{k,t}$ The average of evaluations made by members of cluster k to item t, and C = $(c_{k,t})$ is the matrix of centroïds $K \times T$, where T is the number of items.

4.2 The Fuzzy-based Collaborative Filtering algorithm

As mentioned above, this part contains our novel CF algorithm description. From the literature survey on the CF algorithms, we have the main steps of our algorithm:

- First, the automatic construction of groups in the system from the evaluation matrix using the Non-Negative Matrix Factorization (NNMF) method. The reason behind this choice and use of this method, is the reduction of the scalability problem that occurs when adding a new user or a new item
- In addition, the resulting probability matrix can be used to process data to solve large-scale problems of CF more efficiently.
- Then, for the neighborhood selection, we propose to consider just the K-nearest neighbors belonging to the C-nearest clusters following the principle of [18], [8] but using the fuzzy extension of the algorithm.
- The prediction of learner's preferences.

4.2.1 Users clustering algorithm: Modified FCM to NNMF (MFCMtoNNMF).

In this step we will factorize the evaluation matrix R into two matrices Z and C. where Z is the probability matrix and C is the matrix of cluster centers.

We will use a modified version of *FCM* into *NNMF* following the same principle of WU and LI [11], with adding the non-negativity constraint on the elements of the matrix *C*. Since *C* is the matrix of cluster centers where each element is the evaluations' average made by members of a cluster *c* to a given course *c*, so its components must be ≥ 0. The problem with new constrained to be solved is

$$\mathrm{H(Z, C)} = \frac{1}{2}\sum_{(u,c)\in P}\left(r_{u,c} - \frac{1}{\sum_{\mathrm{k=1}}^{\mathrm{K}} \mathrm{e}^{\mathrm{z_{u,k}}}}\sum_{k=1}^{K} \mathrm{e}^{\mathrm{z_{u,k}}} c_{k,c}\right)^2 + \lambda_c\, ||c_c||_2^2 + \lambda_z ||z_u||_2^2 \qquad (1)$$

St. $Z_1 = 1$; Z ≥ 0 ; C ≥0.

To resolve this problem, we have used the ACLS algorithm (Alternating Constrained Least Squares Algorithm) proposed in [19]. And to initialize the ACLS algorithm, we proposed a modified version of the *random Acol initialization* method cited in [19] by initializing each row of the matrix *C* by averaging *p* random rows of the evaluation matrix *R*. we called this method *random Rows initiatization* method.

4.2.2 Neighbors Pre-selection and Selection

An important step in the CF algorithm is the search for neighbors of the current learner. Traditional methods generally need to search the entire database, which definitely suffer from the scalability problem. We proposed an adjusted version of the fuzzy neighborhood algorithm following the same principle as in [8], [18] as follows:

- Calculate similarity between the active learner and all clusters to select the Fuzzy *C*-Nearest Prototypes (*FCNP*) [20]. We have considered only the *FCNP* because it's uninteresting to assign the learner to dissimilar clusters.
- Calculate similarity between the active learner and members of the *FCNP* to select the Fuzzy *K*-Nearest Neighbors (*FKNN*) [20] using the learner membership degrees to clusters in order to minimize the calculations.

We proposed to use the difference between membership degrees to the same cluster as a similarity measure between the active learner and members of *FCNP*. Where, the similarity between two learners increases when the difference between their degrees of belonging tends to 0.

4.2.3 The CF-Based prediction of the learner preferences

Similar to the idea presented in [21], we propose a framework that can effectively improve the performance, by combining linearly the prediction results of user based and item based algorithms, respectively as a CF Based prediction.

$$CFB\_pred(ua, c) = \delta\, \widehat{ur}_{ua,c} + (1 - \delta)\widehat{ir}_{ua,c} \qquad (2)$$

Where $\widehat{ur}_{ua,c}$ and $\widehat{ir}_{ua,c}$ are user-based and item-based predictions.

After the application of CF-based prediction methods, values in the cells of learner-course matrix are recalculated and updated. So, the sparseness of the matrix is therefore reduced. However, there may still be some empty cells due to the inadequate number of nearest neighbors for that learner. For this reason, it is necessary to use content information to make prediction for each learner-course pair. Then, merging the two predictions types to make full evaluation matrix.

4.3 Content-Based Filtering

To predict messing values based on content, we must have a set of features to describe the items' content in order to correlate similar items. In our system, items are courses and features are topics (information used to describe the courses' content).

We propose to calculate the occurrence frequency of each topic in all evaluated items by the active learner ua. Then, we will give a score to each topic to promote courses according to the topics' appearance and evaluations made by learner ua to each course. The reason is that two topics p_1 and p_2 belong to two courses c_1 and c_2, respectively, can have the same occurrence frequency in the set of items evaluated by ua, but the course c_1 had a better evaluation against the course c_2. Hence, the learner's preferences should promote $p_1 \in c_1$ over $p_2 \in c_2$ through their scores in the preferences' vector. So, the score assigned to the topic p_n in the preferences' vector of the learner ua is computed as follows

$$score\ (p_n, \vec{\mathrm{V}}_{\mathrm{ua}}) = \frac{\sum_{p_n \in c(ua)} (rating(ua,c)\ .\ Occur(p_n))}{|c(ua)|} \quad (3)$$

Such that $|c(ua)|$ is the number of items rated by u_a. $rating(ua,c)$ is the evaluation made by ua to the course c containing topic p_{n}, and $Occur(p_n)$ represents the occurrence frequency of the topic p_n in the set of items evaluated by ua.

After have given a score for each topic, we calculate the similarity between the test course and the set of courses assessed by the active learner to select the *T*-nearest courses to the test course. We propose to use the cosine similarity measure to calculate the similarity between two course vectors.

4.3.1 Content-Based prediction

Finally, we make the content-based prediction of the messing values. The rating prediction for an unseen course is formulated as follows

$$B\_pred(ua,c) = \frac{\sum_{m \in TNI(c)} rating(ua,m)\ .\ \mathrm{sim}(c,m)}{\sum_{m \in TNI(c)} sim(c,m)} \quad (4)$$

Where $\mathrm{rating}(\mathrm{u_a}, \mathrm{m})$ represents the evaluation made by the learner ua to course $m \in TNI(c)$ and *sim(c,m)* is the similarity calculated in the previous section.

This type of prediction use topics to predict messing ratings. So, it needs predictive features to achieve a good prediction which limit the effectiveness use of this prediction lonely. To address limitations of the CF-based and Content-based predictions, we are conducted toward hybridization between them.

4.4 Hybrid prediction

In this section, we will present our hybrid prediction scheme that combines between the CF-based prediction and the Content-based prediction in order to obtain a full user-item matrix. Our proposed hybrid prediction scheme is defined as follows

$$Final\_pred = \alpha \times CFB\_pred(ua,c) + (1-\alpha) \times CB\_pred(ua,c) \quad (5)$$

Where α is used to control the weight between the two predictions.

4.5 *The Top-K* Recommendation

After applying the hybrid algorithm cited above, we obtain predictions of the unviewed items by the active learner. Then, we apply the procedure for generating the recommendation. The first step is to calculate the scores of items based on clusters' preferences and the learner preferences' prediction, to select the Top-N items in each group. Then, generating a list of Top-K items selected from the Top-N items.

The preferred items (courses) will be determined by the number of nearest learners who evaluated the course (popularity) and their mean explicit evaluations by:

$$C\_pref(uc, c) = \beta * moy(uc, c) + (1-\beta) * pop(uc, c) \quad (6)$$

This formula is based only on the explicit evaluations. To apply this formula in the TEL field, we introduce the importance of knowledge proposed in [14]. So the average will be replaced by an evaluation estimation e_i of a course taking into consideration the importance of knowledge of learners who evaluated the course *c*;

$$e(uc, c) = \frac{1}{\sum_{u=1}^{FKNN} \bar{s}_u} \sum_{u=1}^{FKNN} \bar{s}_u \, r_{u,c} \quad (7)$$

Such as $\bar{s}_u$ is calculated as $\bar{s}_u = \frac{1}{t} \sum_{t=1}^{T} s_{u,t}$ (8)

Where $c_{u,t}$ is the score obtained by the learner *u* in the test *t*. $r_{u,c}$ is the explicit evaluation of the learner *u* the course *c*. Thus, the *C_pref* formula becomes as follows;

$$C\_pref(uc, c) = \beta * e(uc, c) + (1-\beta) * pop(uc, c) \quad (8)$$

Then, a score (rank) is assigned to each item (course) in order to ranging items according to the cluster preferences and the predicted learner preferences. As

$$Rank_{u,c} = \alpha C\_pref(uc, c) + (1-\alpha)\, \hat{r}(u, c) \quad (9)$$

The list of recommendations to be generated in the cluster *uc* is chosen by selecting the *TOP-N* items with the highest scores and the *TOP-K* items will be set as follow

$$K = z_{u,uc} * N \quad (10)$$

Where *N* is the number of items selected from cluster *uc* and $z_{u,uc}$ is the membership degree of the learner *u* to cluster *uc*. The final recommendation is formally represented as

$$\sum_{\mathrm{uc} \in \mathrm{C-FNP(u)}} \mathrm{TOP-K\,(uc, c)} \quad (11)$$

5 Application: Experiment and Results

5.1 Moodle Dataset

Moodle[1] is a free source e-learning software platform. Due to the lack of no data sets have been made publicly available for formal and non-formal learning, we used a database very known in RSs, BX-Book-Rating[2] and we consider that each book is a learning resource or a course. We restricted our validation to a subset of this base by selecting just 21 learners, 20 courses and we have added information about the knowledge level of the learner, which are his test scores. And we integrated it with our technique in the Moodle platform. As showed in Fig.1.

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[1] www.moodle.org
[2] www.informatik.uni-freiburg.de/~cziegler/BX/

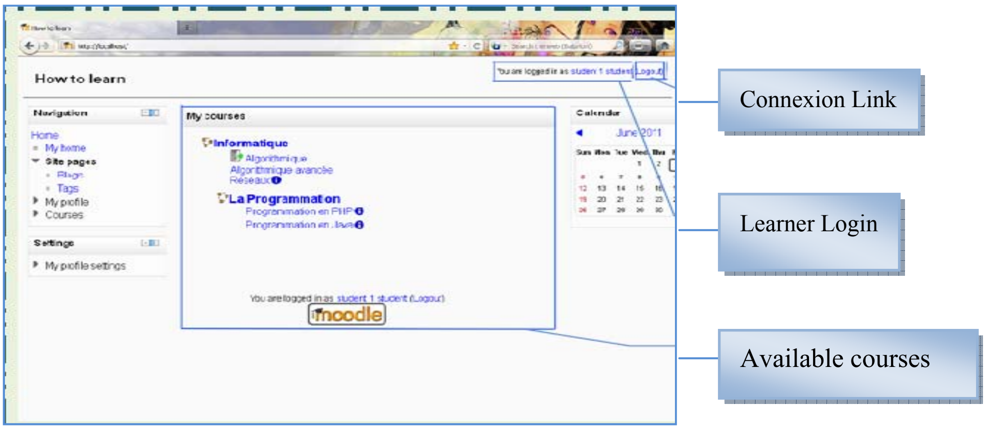

Fig. 1. Moodle Platform with our dataset

5.2 Mean Absolute Error (MAE)

We choose the Mean Absolute Error (MAE) as the evaluation metric to calculate the performance of our CF scheme.

$$MAE = \frac{\sum_{ua,t} |x_{ua,t} - \tilde{x}_{ua,t}|}{|N|} \quad (13)$$

N is the number of test evaluations. More MAE is lower, the performance is better.

As we are in the TEL field, we will apply the novel MAE metric proposed by [14], and adapted to the e-learning domain, in order to take in consideration the knowledge importance of the learner (his different test scores). The novel metric is as follow

$$MAE = \frac{1}{|k|} \sum_{k=1}^{|k|} r_{u,i} - [(1-\alpha)]e_i + \alpha r_{u,i}]; \quad 0 < \alpha < 1 \quad (14)$$

5.3 F1 metric

To evaluate the performance of *Top-K* recommendation, we used the F_1 metric,

$$F_1 = \frac{2PR}{P+R} \quad (15)$$

Where P and R are the precision and recall respectively. They are calculated as

$$P = \frac{N_t}{N} \ , \ R = \frac{N_t}{N_p} \quad (16)$$

N: The total number of items; N_t : Number of relevant items found and N_p : Total number of relevant items

5.4 Performance Evaluation of the CF technique

As the data sample on which we applied our algorithm is smaller the used by [14], therefore we cannot compare them. Such as [14] used four clusters of variant size between 15 and 90, we used only three groups with size between 5 and 10.We evaluate the performance using the novel MAE metric adapted to the e-learning field. Results are showed in Fig.2.

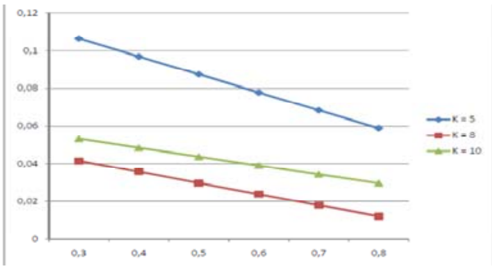

Fig. 2. MAE performance, less value means better performance

From Fig.2. We observe that the MAE has an inverse relationship with the clusters size K, and the different values of α (0.3+0.8), ie. Most K and α are large; most the value of MAE is small. We can notice that the new MAE in almost all cases is smaller than usual MAE, which is due to the subtraction of both products of the values on the y-axis and we know that the levels of RS accuracy are better when the new metric is applied, this is due to the favorable weighting of the users knowledge.

5.5 Performance Evaluation of the Top-K Recommendation

The figure below shows the evolution of the F1metric with number of recommended courses. We observe from Fig.3 that the F1 metric increase until 15 courses evaluated. The F1 values are varied depending on the number of relevant items. It can be seen also that the recommendation performance of the system is good.

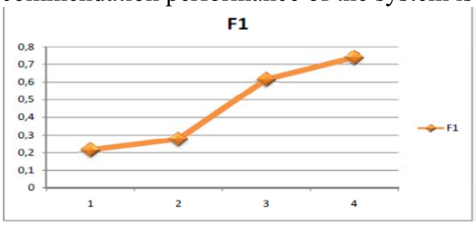

Fig. 3. F1metric

6 Conclusion and future works

Recommender Systems are widely used recently in Technology Enhanced Learning which creates the need to adapt these systems to e-learning. For this and we proposed, in this paper, a novel approach which uses an adapted RS to TEL field. Especially when recommending learning objects that belong to different contexts. Experimental results show that the proposed approach can improve the recommendation accuracy. In the future work, we will elaborate this technique to generate multi-context recommendations taking in the account the temporal dynamics effect.

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