Effective Trust-aware E-learning Recommender System based on Learning Styles and Knowledge Levels

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ABSTRACT

In the age of information explosion, e-learning recommender systems (ELRSs) have emerged as the most essential tool to deliver personalized learning resources to learners. Due to enormous amount of information on the web, learner faces problem in searching right information. ELRSs deal with the problem of information overload effectively and provide recommendations by taking into consideration the learners' preferences such as learning styles, goals, knowledge levels, learning paths etc. In this paper, we propose a weighted hybrid scheme to recommend right learning resources to a learner by incorporating both the learners' learning styles (LSs) and the knowledge levels (KLs). Further, by elicitation of trust values among learners, we develop a scheme such that for a given active learner, the trustworthy learners having greater knowledge and similar learning style patterns as that of the active learner have greater weightage in recommendation strategy. Experimental results are presented to demonstrate the effectiveness of the proposed scheme.

Keywords

E-learning, Recommender systems, Collaborative filtering, Learning styles, Knowledge levels, Trust

Introduction

Due to unprecedented proliferation of information and communication technologies in recent years, e-learning has become more and more popular in academics as well as in commercial environments (Zaiane, 2002). E-learning provides opportunities for learners not only to study courses or to learn professional knowledge without time and space constraints, but also to train themselves at their own pace through the asynchronous and synchronous learning network models (Chao and Chen, 2009). Due to enormous amount of learning resources in e-learning environment, learners face difficulties in searching appropriate resources according to their need (Ghauth & Abdullah, 2010). In this situation, recommender system (RS) seems a proficient solution for dealing with this resource overload in e-learning environment (Khribi et al., 2009).

Recommender systems (RSs) are one of the most promising technologies of web personalization to alleviate the problem of information and product overload. They provide personal, affordable and effective recommendations to users based on their preferences expressed, either explicitly or implicitly (Adomavicius & Tuzhilin, 2005; Al-shamri & Bharadwaj, 2008; Milicevic et al., 2010). E-learning recommender systems (ELRSs) deal with information about learners and their learning activities and recommend items such as articles, web pages, etc. (Nghe et al., 2010). Collaborative filtering provides recommendations to learner based on those learners who have similar preferences. Since CF is able to capture the particular preferences of a user so it has become most widely accepted technique in RSs for recommending web pages, music, books etc(Symeonidis et al., 2008). It has also been successfully employed in ELRSs (Manouselis et al., 2010; Bobadilla et al., 2009; Dwivedi & Bharadwaj, 2011).

RS is strongly context/domain dependent, so it is not feasible that recommendation strategy for one context/domain is transferable to others (Drachsler et al., 2007). The reason why the thriving application of movie or joke recommendation strategies has not had such an efficacy in e-learning because modeling accurate learner profile is a much harder task than in other application domains. Two important open research issues in ELRSs are as follows:

- **Learner's point of view:** Recommended resources should be interesting to learners, according to their needs as well as their characteristics.
- **Designer's point of view:** How to design learning materials considering learners' preferences and how to recommend these resources in a specified sequence so that learners' performance can be enhanced.

We designed our proposed ELRSs based on learner's point of view by taking into consideration learner's characteristics namely learning styles and knowledge levels etc.

In e-learning, learners are characterized on the basis of their learning styles, emotions, knowledge levels and goals etc. (Drachsler et al., 2007). Learning style of a learner can be considered as a valuable factor for enhancing the individual learning that would affect the recommendation task. Learning style (LS) indicates how a learner learns and likes to learn. It can be analyzed or collected from the learning behavior of learner during study (Chang et al., 2009; Garcia et al., 2008). Bobadilla et al. (2009) suggested that learners with greater knowledge should have greater weight in the computation of recommendation than the learners with less knowledge among all neighbors of an active learner in collaborative filtering framework. Therefore knowledge level of learners is an important factor in addition to LSs. Therefore, we are providing a hybrid ELRS which offers resource recommendations by acclimatizing automatically learners' learning styles and knowledge levels that would favor and improve the learning.

The following assumptions that motivated us for the adaptation of learning style and knowledge level in ELRS are:
- Learners with different learning style generate different perspectives on effective strategies for dynamic group interactivity (Kolb, 1976). As a consequence, learners can be grouped on the basis of learning styles to have an impact on recommendation task in our work.
- Researchers believe that learning style is a good predictor of an individual's preferred learning behavior (Bostrom et al., 1990).
- Milicevic et al. (2010) recognize the different patterns of LSs in PROTUS system which provides effective personalized recommendation of learning contents after processing the clusters based on different learning styles and mining frequent patterns for the habits and interest of learners. As a consequence, we generate effective clusters of learners' LSs by utilizing the GA K-means algorithm in our work and develop a collaborative framework (CF-LS) based on these clusters.
- Paechter et al. (2010) suggest that only few variables like exchange of knowledge with peer learners contribute to perceived learning achievements in a course.
- Bobadilla et al. (2009) have also showed that the incorporation of knowledge of other learners provided the better recommendations.

Besides LSs and KLs, we extend our hybrid system (CF-LS-KL) through the incorporation of trustworthiness of learners in recommendation task. The reason behind the incorporation of trustworthiness in recommendation task is that some similar learners may be malicious for the recommendations in collaborative filtering environment and the recommendation provided by them cannot be effective. The work presented in this paper, regarding to above aspects, is an effort towards developing a trust-aware ELRS utilizing both LSs and KLs of learners. The main contributions of this paper are three fold:
- First of all, a collaborative filtering using LSs (CF-LS) is designed utilizing clusters of different learning styles generated through Genetic K-means algorithm.
- Second, a collaborative filtering scheme based on KLs (CF-KL) is developed. Thereafter, a weighted hybrid scheme (CF-LS-KL) is presented to take possible advantages of learner preferences.
- Finally, in order to give weightage to trustworthiness of learners, a trust-aware weighted hybrid scheme (TRCF-LS-KL) is proposed.

The rest of the paper is organized as follows: We first give a brief summary of related work and literature survey on LSs, KLs and clustering technique in Section 2. Section 3 elaborates collaborative filtering framework utilizing LSs and KLs in trust aware e-learning recommendation environment. Section 4 describes the experimental setup, evaluation metrics and results of the evaluation followed by the discussion in Section 5. Finally, Section 6 provides concluding remarks and suggests some future research directions.

Related work and literature survey

In the age of large information space, adaptive hypermedia educational systems try to reduce the size of information space through several techniques and provide effective resources for learners using recommendation techniques. AHA!, the "Adaptive Hypermedia Architecture", has been developed for providing online course recommendations

(De Bra et al., 2003). Generally e–learning recommendation strategies are based on data mining techniques by adapting learner's characteristics and preferences such as learning styles, knowledge levels, goals etc.

Several researchers have shown that the incorporation of LSs, an important factor in e-learning environment, can lead to enhance learning performance of a learner (Graf & Kinshuk, 2007; Milicevic et al., 2010). Al-Hamad et al. (2008) presented a user expert personalized ELRS that integrates learning styles information in e-learning environment to enhance learner efficiency and productivity. Milicevic et al. (2010) proposed PROTUS system that automatically adapts to the interest and knowledge level of learners and recommends the learning contents. They applied clustering technique on learning styles and analyze the habits and interest through frequent sequence patterns by aprori-all algorithm. Bobadilla et al. (2009) also propose that users with greater knowledge have greater weights in recommendation task. They designed new metric in the collaborative filtering framework.

Khiribi et al. (2009) recommends the learning resources that are based on current learner navigational history and exploiting similarities among learner preferences and educational contents. The proposed framework is composed of two module, offline module in which learner and content model are built and another is online module, where recommendation list is provided by recognizing learners' needs, goal. Bitonto et al. (2010) proposed a recommendation strategy that combines two knowledge based techniques which can consider learning goal, cognitive features, learning styles into account in the recommendation process. Lu (2004) proposed a framework of personalized learning RS which aims to provide the learning material according to learners' need. Here, two technologies are developed, one is multi attribute evaluation method to justify a learner need and second one is fuzzy matching method to find suitable learning material to the best match for learners' needs. Gauth and Abdullah (2011) introduce a novel architecture for an ELRS that is based on content-based filtering and good learners' ratings. They also compared the proposed ELRS with exiting ELRSs that use both collaborative filtering and content-based filtering techniques in terms of system accuracy and student's performance. Carchiolo et al. (2010) proposed a model for searching personalized and useful learning path suggested by trusted peers. They exploit the issue of trusted resources. They performed some simulation on real dataset to evaluate the efficiency and effectiveness of proposed model.

In the previous work related to ELRSs, none of theRSs have attempted to use trust in collaborative filtering framework utilizing both learning styles and knowledge levels. Our work in this paper is an attempt towards developing a hybrid trust-aware ELRSs based on both LSs and KLs. The benefits of incorporating trust in proposed scheme are that it will ensure that recommended resources are suggested by trustworthy learners.

Felder Silverman LSs model (FSLSM)

In this work, we adapt the FSLSM model proposed by Felder and Silverman. According to FSLSM, LSs are measured in the following four dimensions in two scales:

Perception
- *Sensing:* sensing learners tend to be patient with details.
- *Intuitive:* intuitive learners prefer principles and theories.

Input
- *Visual:* visual learners prefer to perceive material as pictures, diagrams and flowcharts.
- *Verbal:* verbal learners prefer to perceive materials as text.

Processing
- *Active*: active learners work well in groups.
- *Reflective:* reflective learners prefer to learn alone.

Understanding
- *Sequential:* sequential learners like to learn step wise process.
- *Global:* global learners like to learn in large jumps.

The Felder–Silverman model was chosen among the existing learning style models because it has been successfully used in previous works for individual adaptation of e-learning material (Graf et al., 2010, Milicevic et al., 2010). One of the advantages of this model is that the sliding scales support a classification of student's style more flexible than bipolar models (Alfonseca et al., 2006).

Clustering

Clustering is a widely implemented methodology in various application fields such as image processing, data mining etc (Alfonseca et al., 2006; Milicevic et al., 2010; Kim & Ahn, 2008). The simplest and most popular clustering algorithm is the K-means clustering algorithm. However, K-means has two shortcomings: dependency on the initial seeds or centers and tendency to converge towards local optima. In order to overcome these shortcomings, Krishna & Murty (1999) proposed a Genetic K-means approach that converges to the best known optimum seeds. The main steps involved in GA K-means algorithm are as follows:

GA K-means algorithm **(Kim& Ahn, 2008)**

1. Firstly, system generates the initial population randomly for finding global optimum initial seeds. Before the search process, chromosome is designed in the form of binary strings.
2. In the second step, system performs the process of K-means clustering. The value of fitness function is updated after the process of K-means algorithm.
3. Finally, GA performs genetic operations such as crossover, mutation and selection on the current population. Update the current population for better initial seeds. After that, Step 2 and 3 are repeated until the stopping conditions are satisfied.

In our work, we have designed a GA K-means scheme for clustering learners based on their learning styles as discussed in the next Section.

Trust-aware CF framework utilizing learning styles and knowledge levels

In this Section, we discuss the hybrid scheme CF-LS-KL based on LSs as well as KLs and also describe the trust enhanced hybrid scheme, TRCF-LS-KL. Firstly we discuss collaborative filtering than we start by presenting two innovative filtering approaches namely; learning styles based collaborative filtering (CF-LS) and collaborative filtering using knowledge levels (CF-KL) which are the major components of our proposed schemes.

Collaborative filtering (CF)

CF systems measure the like mindedness of a pair of users by comparing their inclination for resources which they have evaluated. The process of recommending resources for an active learner l_a comprises of three main steps:
Similarity measure: The Similarity between learners l_x and l_y using the Pearson similarity is computed as.

$$sim(l_x , l_y) = \frac{\sum_{i \in S_{x,y}}(r_{l_x,i}-\bar{r}_{l_x})(r_{l_y,i}-\bar{r}_{l_y})}{\sqrt{\sum_{i \in S_{x,y}}(r_{l_x,i}-\bar{r}_{l_x})^2 \sum_{i \in S_{x,y}}(r_{l_y,i}-\bar{r}_{l_y})^2}} , \qquad (1)$$

where $r_{l_x,i}$ is the rating of learner l_x on resource i, $S_{x,y}$ is the set of all resource co-rated by both learners l_x and l_y. $\bar{r}_{l_x}$ is the average rating of learner l_x and $\bar{r}_{l_y}$ is the average rating of learner l_y.

Neighborhood formation: The most popular technique is the k-NN approach which selects the n most similar learners who have also rated the resource to take part in the recommendation process.

Generating recommendations: The most common approach to aggregate ratings as proposed by Resnick et al, 1994, for an resource i for active learner l_a.

$$pr_{l_a,i} = \bar{r}_{l_a} + \frac{\sum_{l=1}^{n} sim(l_a,l).(r_{l,i}-\bar{r}_l)}{\sum_{l=1}^{n} |sim(l_a,l)|}, \tag{2}$$

where $pr_{l_a,i}$ is the predicted rating for learner l_a for resource i, $\bar{r}_l$ is the mean rating for learner l, $sim(l_a,l)$ is the similarity between learners l_a and l.

CF-LS scheme

This approach utilizes the importance of LSs of learners for providing effective recommendations in collaborative filtering framework. For example, if learners X and Y have same LSs then recommendations can be provided to learner X on the basis of experienced resources of Y in e-learning environment. In order to take the importance of LSs in our proposed CF-LS scheme, we grouped learners on the basis of their LSs employing GA K-means algorithm discussed in phase 2 in this section. The following four phases are required to perform the recommendation task in CF-LS scheme as discussed below:

Phase 1. Learner model formation

Generally three types of data can be collected from learners, learning style detection through questionnaire based on index of learning styles (ILS) during registration process, explicit ratings for a subject of available teachers, books, subjects and implicit data from learners' online behavior. As discussed earlier, classification of learning styles of learners is considered according to FSLSM model (Felder & Silverman, 1988) and consequently classified into four dimensions within two scales according to the left handed or right handed scores in the results of questionnaire. So, every dimension is represented by binary value 1 or 0, where 1 bit is used for active, sensitive, visual and sequential dimension (Left handed scores) and 0 is used for reflective, intuitive, verbal and global dimension (Right handed scores). Therefore, four bits are required to represent a learner on the basis of learning styles. Sample data of learning styles of learners is shown in Table1.

Table 1. Sample data for learning styles

Learners	Learning Styles			
	Perception	Input	Processing	Understanding
	Sensing:1/Intuitive:0	Visual:1/Verbal:0	Active:1/Reflective:0	Sequential:1/Global:0
Learner1	0	0	1	1
Learner2	1	1	1	1
Learner3	1	1	1	0

Phase 2. Clustering employing GA K-means

As discussed earlier, K-means does not provide any mechanism for choosing appropriate initial seeds. However, the choice of selecting different initial seeds may generate huge differences in recommendation quality. To handle this situation, we employ GA K-means algorithm for clustering process. The problem of differentiating learners based on LSs is addressed in this phase using GA K-means algorithm as discussed below:

Chromosome representation

Here, we suggest that each chromosome should be a sequence of binary numbers representing k cluster centers with length $4*k$ bits where the first four bits represent the four dimensions of the first cluster center, the next four bits represent second cluster center and so on. Here, we considered each learner as a cluster center in our chromosome representation. Chromosome representation for three clusters associated with three learners (k =3) is shown in Figure 1.

Learner1				Learner 2				Learner 3			
0	0	1	1	1	1	1	1	1	1	1	0

Figure 1. Representation of chromosome

This figure represents the three cluster centers (0 0 1 1), (1 1 1 1) and (1 1 1 0) corresponding to three learners with learning styles (Intuitive, verbal, Active, Sequential), (Sensing, Visual, Active, Sequential) and (Sensing, Visual, Active, Global) respectively.

Initialization of population

The initial population is selected randomly. It is the collection of chromosomes described as in previous steps.

Genetic operators

Genetic operators drive the search process in GA. Crossover and mutation are the two fundamental genetic operators.
Crossover: It allows each individual has a chance to interchange gene information from two parent chromosomes. Two-point crossover generates two random positions and interchanges the genes between the two positions from the parent chromosomes, as Figure 2 depicts.
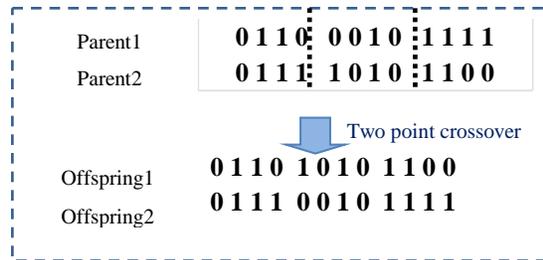
Parent1   **0 1 1 0 0 0 1 0 1 1 1 1**
Parent2   **0 1 1 1 1 0 1 0 1 1 0 0**

Two point crossover

Offspring1   **0 1 1 0 1 0 1 0 1 1 0 0**
Offspring2   **0 1 1 1 0 0 1 0 1 1 1 1**

Figure 2. Two point crossover

Mutation: It randomly alters one or more genes of a selected chromosome. Figure 3 illustrates mutations operation that alters three randomly chosen genes.
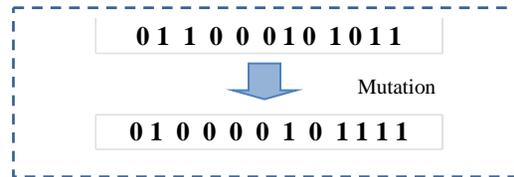
0 1 1 0 0 0 1 0 1 0 1 1

Mutation

0 1 0 0 0 0 1 0 1 1 1 1

Figure 3. Mutation

Fitness function

Fitness function is a factor which drives the GA process towards convergence to the optimal solution. Here fitness function is evaluated to find out the compactness of clusters. We computed the fitness of chromosome to find the optimal initial seed for K-means algorithm using the following fitness function.

$$F = \sum_{i=1}^{k} \sum_{p \in C_i} |p - m_i|^2, \qquad (3)$$

where p is the point in space representing given learner, m_i is the mean of cluster C_i and k is the number of clusters.

A pseudo-code for GA K-Means algorithm is depicted in Figure 4.

GENETIC K-means Algorithm

Input: Database=D, Number of clusters=k, maximum number of generations= MAX_GEN
Output: Optimal cluster centers C^*

Step 1: Initialization
   $g \leftarrow 0;$
   $P_g \leftarrow$ Initial random population of size, N;
Step 2:
  for g = 1: MAX_GEN
    for each $C_i^g \in P_g$ /* C_i^g is the ith chromosome of population P_g*/
      C_i^* =K-means (C_i);
      $F(C_i) = \sum_{j=1}^{k} \sum_{p \in C_j} |p - m_j|^2$; /* Computing fitness of chromosome*/
    end
    if Stopping criteria is not satisfied
      $P_g \leftarrow GenerateNewPopulation(P_{g-1});$ /* By applying Crossover and Mutation*/
    else
       Stop;
       Return (C^*);
    end
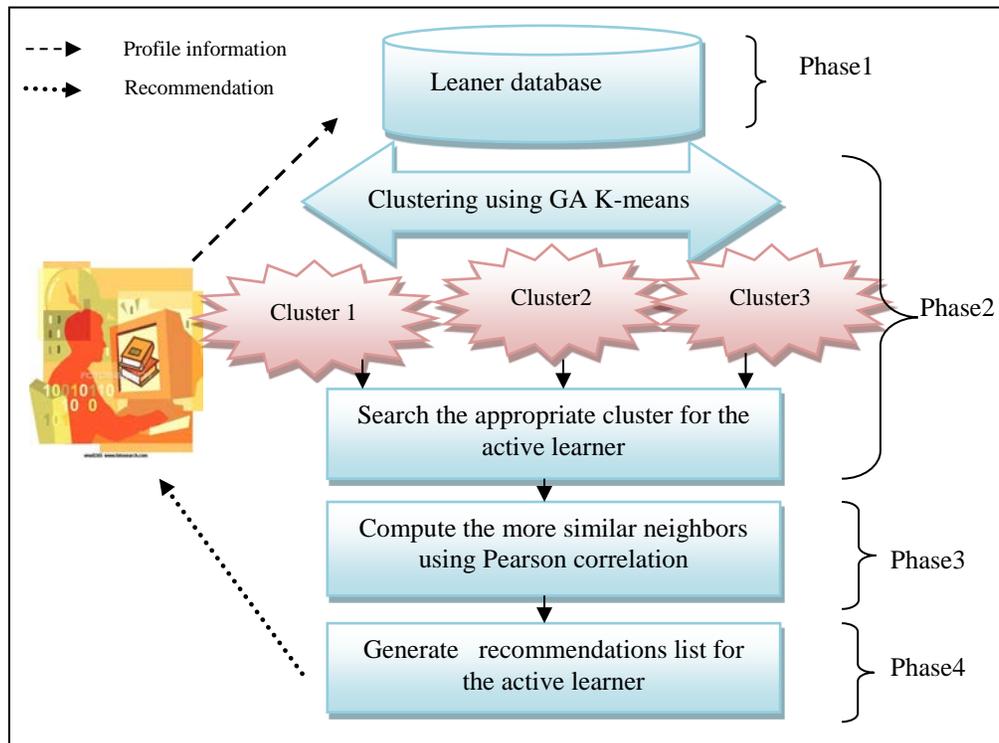 **end**

Figure 4. Pseudo code of GA K-means

Figure 5. CF-LS architecture

Phase3. Neighborhood set generation

Once the process of clustering using GA K-means has been completed, the system matches the active learner to the available clusters and generates a set of top-n neighbors for him. We used the most popular Pearson similarity function (Eq.1) for generating more similar neighbors.

Phase4. Making predictions

CF-LS system assigns predicted rating to all the resources experienced by the neighborhood set and unseen by the active learner. The predicted rating can be computed for an active learner l_a to an unseen resource i using Eq. (2). A pictorial representation of the CF-LS scheme is given in Figure 5.

CF-KL scheme

Knowledge level of a learner is an important factor for recommending the valuable resources in collaborative e-learning environment and Bobadilla et al. (2009) designed a new metric which capture the importance of knowledgeable learners in recommendation task. In our work, a two level filtering methodology is presented by incorporating knowledge level in recommendation task. Firstly, the set of neighbors is generated using Pearson similarity and thereafter the knowledge levels are used to refine the set of recommenders who are more knowledgeable than the active learner. The recommendation task using CF-KL would require the following three phases.

Phase 1. Learner model formation

Along with the learner model for CF-LS scheme, knowledge level for each learner is also included for the formation of learner model in CF-KL scheme. Importance of knowledge level in recommendations for each learner is computed through the Eq. (4) (Bobadilla et al., 2009).

$$f(x) = \begin{cases} K_x - K_y, & K_x > K_y \\ 0, & K_x \leq K_y \end{cases}$$
(4)

where K_x is the knowledge of learner l_x and K_y is the knowledge of learner l_y.

Phase 2. Neighborhood set generation

In this phase, a proposed two level filtering scheme is used to generate more effective neighborhood set. At the first level, top-n neighbors are selected using Pearson similarity Eq. (1). Thereafter, knowledge level is used as a means for filtering neighbors prior to recommendation. So that only the neighbors, who are more knowledgeable than the active learner participate in recommendation process.

Phase 3. Making predictions

CF-KL system assigns predicted ratings to all the resources experienced by learners in the neighborhood set and unseen by the active learner. The predicted rating can be computed for an active learner l_a to an unseen resource i using Eq. (2). CF-KL architecture is represented in Figure 6.
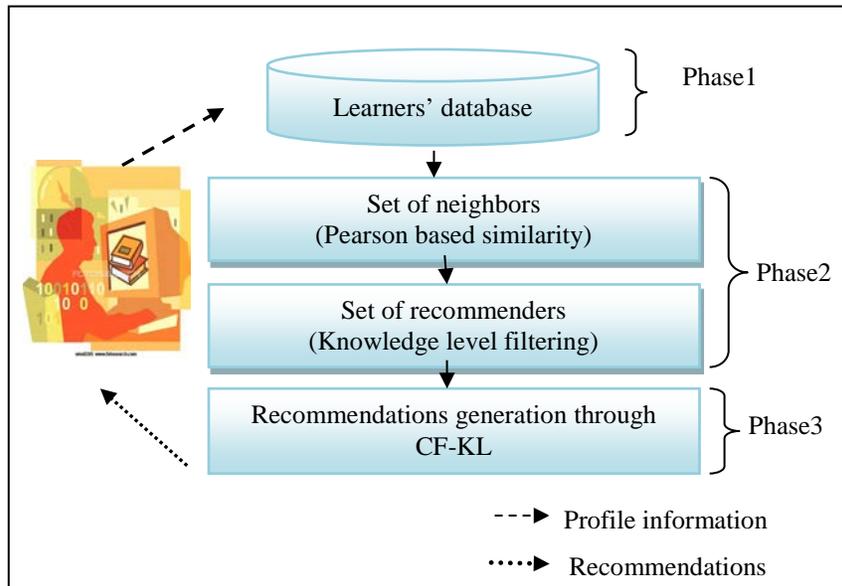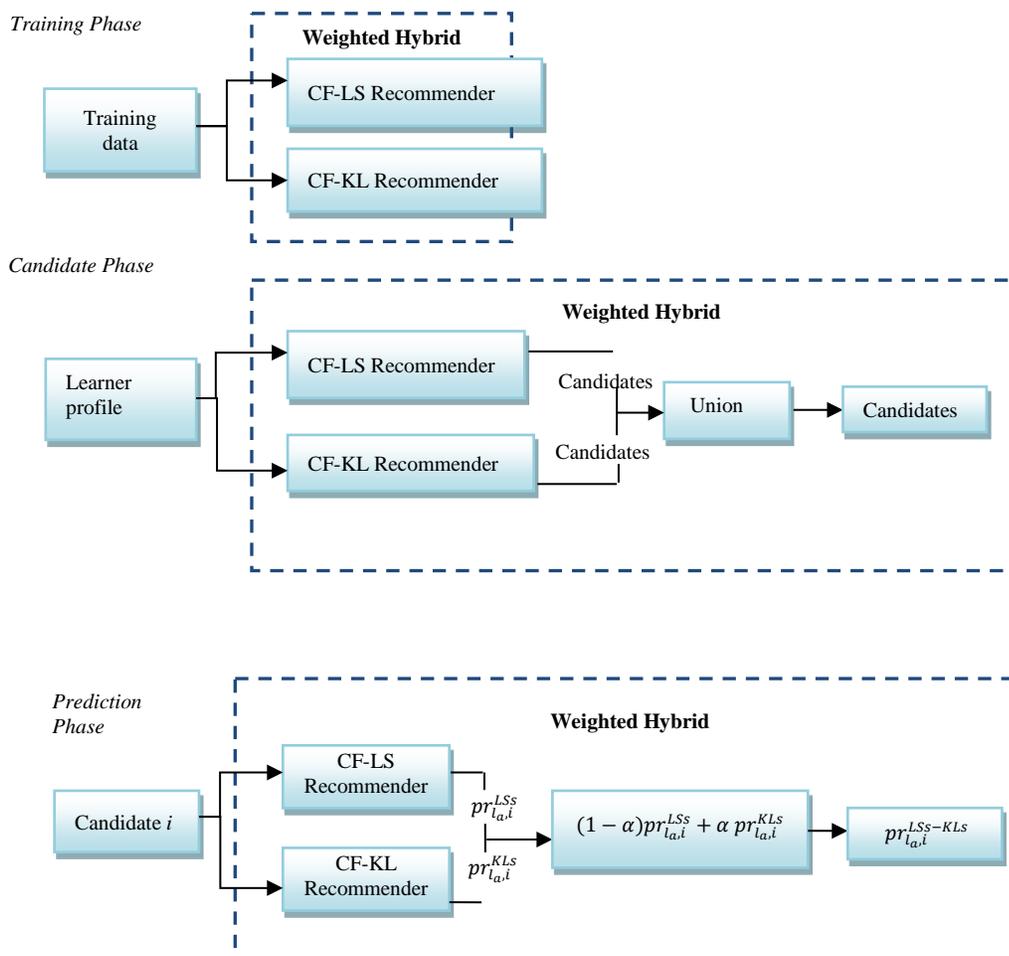
Figure 6. CF-KL Architecture

Figure 7. Architecture of hybrid CF-LS-KL scheme

CF-LS-KL scheme

The proposed ELRS has two components: Prediction based on CF-LS scheme and prediction generated through CF-KL scheme. Output of these two components is hybridized using linear weighting scheme shown in Figure 7.

For evolving the more knowledgeable recommenders who have similar LSs pattern, we combined both preferences LSs and KLs together as hybrid CF-LS-KL scheme using appropriate α value. The main steps involved in CF-LS-KL scheme are as follows:

Step1: Predict the rating of resource i to active learner l_a, $pr_{l_a,i}^{LSs}$, using CF-LS scheme.

Step2: Predict the rating of resource i to active learner l_a, $pr_{l_a,i}^{KLS}$, using CF-KL scheme.

Step3: Merge the ratings predicted by both CF-LS and CF-KL schemes to compute rating predicted by, $pr_{l_a,i}^{LSs-KLs}$, of CF-LS-KL scheme:

$$pr_{l_a,i}^{LSs-KLs} = (1-\alpha)pr_{l_a,i}^{LSs} + \alpha\, pr_{l_a,i}^{KLs}, \tag{5}$$

As in Eq. (5), we employed parameter α to balance the prediction based on CF-LS scheme and prediction based on CFKL Scheme. Here α can be set empirically in the range of [0, 1] for capturing various possibilities of hybridization. For example

α = 0:   prediction completely based on CF-LS scheme
α = 0.2: more weightage given to CF-LS scheme.
α = 0.5: equal weightage given to both CF-LS and CF-KL scheme.
α = 0.8: more weightage given to CF-KL scheme.
α = 1:   prediction completely based on CF-KL scheme

TRCF-LS-KL scheme

This scheme is an extended version of proposed hybrid scheme CF-LS-KL scheme by utilizing the trustworthiness of learners in recommendation process. The motivation behind it from real life situation where people would like to take suggestions from those on which they trust highly, whether suggestions related to careers, subjects, books or other items. In order to find out most similar as well as trustworthy neighbors, we design the following new similarity metric $TrustSim(l_x, l_y)$ for any two learner l_x and l_y :

$$TrustSim(l_x, l_y) = Trust(l_x, l_y) * Sim(l_x, l_y), \tag{6}$$

where term $Trust(l_x, l_y)$ represents the importance of trustworthy learners that is computed by the following formula (Lathia et al., 2008):

$$Trust(l_x, l_y) = 1 - \frac{\sum_{i=1}^{n}|r_{l_x,i} - r_{l_y,i}|}{r_{max}.n}, \tag{7}$$

and $Sim(l_x, l_y)$ refers to the similarity between learners according to Pearson formula (Eq.1).

Trust between two learners l_x and l_y can be computed using the following formula (Eq.7)
where n is the number of common resources between l_x and l_y, r_{max} is the maximum rating, $r_{l_x,i}$ is the rating of learner l_x on resource i and $r_{l_y,i}$ is the rating of learner l_y on resource i.
It is to be noted that the Eq.6 involving product of Trust and *Sim* ensures that *TrustSim* is using only when both trust and similarity are high.

For the proposed TRCF-LS-KL scheme, we have incorporated the metric $TrustSim(l_x, l_y)$, that obtained the top n neighbors of active learner who are trustworthy as well as more similar, into CF-LS-KL scheme instead of $Sim(l_x, l_y)$.

An illustrative Example

We now present an example that demonstrates the effectiveness of proposed metric in recommendation task. Table 2 is an example of rating matrix in which five learners have reported ratings on seven resources. Some entries are empty because learners do not rate every resource. Here, system would make the prediction for resource R7 for active learner, (Bob).

Table 1. Example of Learner ratings matrix

Learners	Resources						
	R1	R2	R3	R4	R5	R6	R7
Bob	5	2		5	3		4 ?
Alice		2	4		4		3
Jacob		5		5	5		3
Liu	3		3	5		1	1
John	4	2	4		4	2	4

Traditional similarity based CF

Similarity (Eq.1) between Active learner Bob with other learners are:
sim (Bob, Alice) = 0.5855, *sim* (Bob, Jacob) =0.2425, *sim* (Bob, Liu) =1, and
sim (Bob, John) = 0.9864
Here neighbor Liu has the highest similarity. Employing CF through Pearson similarity (Eq.1 & 2), the predicted rating and MAE for resource R7 for the active learner are 2.75 and 1.25 respectively.

Proposed TrustSim based CF

1. First we compute trust between Bob and remaining learners using Eq.(7)
   Computation of trust between Bob and Alice:
   For n=2 and r_{max}=5.
   Trust (Bob, Alice) = 1- $\frac{|2-2|+|3-4|}{5*2}$ = 0.9
   Similarly, we can compute Trust (Bob, Jacob) =.8, Trust (Bob, Liu) =.6 and Trust (Bob, John) =0.9
2. Similarity computation is again based on Eq. (1).
3. *TrustSim* using Eq.(6) between Bob with other learners are:
   TrustSim (Bob, Alice) = *Trust* (Bob, Alice)* *sim* (Bob, Alice) = 0.9*0.5855 = 0.5269
   Similarly, *TrustSim* (Bob, Jacob) = 0.1940, *TrustSim* (Bob, Liu) = 0.6, and *TrustSim* (Bob, John) = 0.8878

Here, neighbor with the highest *TrustSim* value is John. Because *TrustSim* is able to identify neighbors who have high values for similarity as well as trust in comparison to Jacob who has high trust value(0.8) but less similarity(0.2425) and Liu who has low trust value(0.6) but high similarity(1.0) .

The predicted rating and MAE for resource R7 for the active learner Bob, utilizing proposed metric (Eq. 6) are 3.75 and 0.25 respectively.

Hence MAE results show that similar learners who are also trustworthy are better recommenders.
All the schemes proposed in this work are listed in Table 3.

Table 2. Representation of all proposed schemes

Schemes	e-learning recommender system
Traditional CF-PR	Traditional collaborative filtering approach based on Pearson correlation
CF-KL	Proposed two level filtering approach utilizing knowledge levels in collaborative filtering framework
CF-LS	Proposed learning styles based collaborative filtering approach
CF-LS-KL	Proposed hybrid approach based on both the learning styles and knowledge levels
TRCF-LS-KL	Proposed trust-aware hybrid approach incorporating trust in CF-LS-KL

Experiments and results

In order to evaluate the performance of proposed hybrid schemes, utilizing LSs and KLs in trust-aware ELRSs, we are conducting two experiments in the proposed collaborative filtering framework are as follows:
1. Evaluation of system's performance based on proposed scheme using MAE and Coverage measures
2. Effect of number of varying neighborhood size on system's performance

Experimental setup

Since there is no well known dataset publically accessible for research (Bobadilla et al., 2009) in the domain of ELRSs, we mapped well known datasets MovieLens and Jester from the RSs domain to ELRSs domain (here after referred as EL dataset) for our experimentation. MovieLens dataset consists of 100,000 ratings provided by 943 learners on 1682 movies. The rating scale follows the 1-bad, 2-average, 3-good, 4-very good and 5-excellent. Each user has rated at least 20 movies in this dataset. Jester dataset provides 4.1 million ratings by 73421 users on 100 jokes. The ratings are continuous and lie in range -10 to 10. MovieLens (ML) and Jester are different from each other, since the sparsity level of MovieLens is quite high whereas the jester dataset is dense. We mapped movies of ML dataset and jokes of jester dataset as teachers, books and subjects and the ratings to movies and jokes are considered as ratings provided by learners to teachers, books and subjects. Because of the requirement of learning styles and test scores in our proposed work, we assigned learning styles as well as test scores for each learner randomly. LSs are generated randomly using ILS questionnaire. For establishing correlation between LSs of learners and their ratings patterns, we generate LSs patterns for similar learners on the basis of the questionnaire and select pattern with high correlation.

To compare proposed schemes more thoroughly, we conducted the experiments under several configurations. We randomly selected subsets of 150-550 with increment of 100 learners called EL150, EL250, EL350, EL450 and EL550 from both of the datasets respectively. This is to illustrate the effectiveness of the proposed scheme under varying number of participating learners. Each of these sub datasets was randomly split into 60% training and 40% test data (Anand & Bharadwaj, 2011). The ratings of the items in the test set are treated as items unseen by the active learner while the ratings in the training set are used for neighborhood construction and for prediction of ratings. For each dataset, experiments were run 20 times to eliminate the effect of any bias in the data.

Performance evaluation

In order to test the performance of our schemes, we measure system's accuracy using two evaluation metrics, namely the mean absolute error (MAE) and the total coverage of system. The MAE measures the deviation of predictions generated by the RS from the true ratings specified by the learner. On the other hand, coverage measures the percentage of resource for which a RS can provide predictions

The MAE for the active learner l_a (Breese et al., 1998) is as follows:

$$MAE(l_a) = \frac{1}{|S_i|}\sum_{k=1}^{|S_i|}|pr_{i,k} - r_{i,k}| \; , \tag{8}$$

where i is the resource and S_i is the cardinality of the test ratings set of learner l_a ratings.
The total MAE over all the active learners N_A can be computed as:

$$MAE = \frac{1}{N_A}\sum_{a=1}^{N_A} MAE(l_a) \tag{9}$$

Coverage: It is measured as number of resources for which RS can generate prediction over the total number of unseen resources.

$$Coverage = \frac{\sum_{i}^{N_A} p_i}{\sum_{i}^{N_A} S_i} \tag{10}$$

here, p_i is the total number of predicted resources for active learner l_a. Low coverage value indicates that RS will not able to suggest the learner with many of resource he has not rated.

Experiment 1

In order to reveal the performance of system based on proposed schemes, we conduct experiments using datasets EL150, EL250, EL350, EL450 and EL550 mapped from MovieLens and Jester. By fixing the neighborhood size, we compare MAE and coverage. Using an appropriate value of α, we measured the effect of CF-PR, CF-KL, CF-LS, CF-LS-KL and TRCF-LS-KL.

Analysis of the results

Tables 4 and 5 show that TRCF-LS-KL outperforms CF-LS-KL, CF-LS, CF-KL and CF-PR for all the different configurations generated from MovieLens and Jester datasets respectively. The total MAE for TRCF-LS-KL is always smaller than CF-LS-KL, CF-LS, CF-KL and CF-PR schemes. Tables 6 and 7 show that TRCF-LS-KL outperforms CF-LS-KL, CF-LS, CF-KL and CF-PR generated from MovieLens and Jester datasets respectively. The coverage for TRCF-LS-KL is always greater than CF-LS-KL, CF-LS, CF-KL and CF-PR schemes.

Table 4. Comparison of MAE among CF-PR, CF-KL, CF-LS CF-LS-KL and TRCF-LS-KL on EL datasets mapped from MovieLens dataset

Datasets	CF-PR (MAE)	CF-KL (MAE)	CF-LS (MAE)	CF-LS-KL (MAE)	TRCF-LS-KL (MAE)
EL150	.8775	.8603	.8561	.8412	.8018
EL250	.9082	.8808	.8625	.8513	.8432
EL350	.9402	.9205	.8982	.8843	.8644
EL450	.9312	.9180	.8851	.8700	.8503
EL550	.9475	.9089	.9004	.8991	.8745

Table 5. Comparison of MAE among CF-PR, CF-KL, CF-LS, CF-LS-KL and TRCF-LS-KL on EL datasets mapped from Jester dataset

Datasets	CF-PR (MAE)	CF-KL (MAE)	CF-LS (MAE)	CF-LS-KL (MAE)	TRCF-LS-KL (MAE)
EL150	4.1509	3.7551	3.6743	3.6600	3.2214
EL250	4.3241	3.8132	3.7675	3.6645	3.4326
EL350	4.7062	3.9982	3.9648	3.8871	3.6652
EL450	3.8171	3.6167	3.5671	3.5000	3.4211
EL550	4.4507	3.9867	3.7111	3.6772	3.5286

Table 6. Comparison of coverage among CF-PR, CF-KL, CF-LS, CF-LS-KL and TRCF-LS-KL on EL datasets mapped from MovieLens dataset

Datasets	CF-PR (Coverage%)	CF-KL (Coverage%)	CF-LS (Coverage%)	CF-LS-KL (Coverage%)	TRCF-LS-KL (Coverage%)
EL150	76.6848	79.7543	86.3468	88.3214	88.9987
EL250	70.5201	76.3456	82.2864	82.6548	82.6777
EL350	69.9815	70.3457	78.6143	80.1112	80.2345
EL450	63.3694	69.6634	75.6911	75.7436	76.1234
EL550	60.1599	64.3426	72.5489	72.9986	73.0067

Table 7. Comparison of coverage among CF-PR, CF-KL, CF-LS, CF-LS-KL and TRCF-LS-KL on EL datasets mapped from Jester dataset

Datasets	CF-PR (Coverage%)	CF-KL (Coverage%)	CF-LS (Coverage%)	CF-LS-KL (Coverage%)	TRCF-LS-KL (Coverage%)
EL150	96.7788	96.8622	97.9583	97.9622	98.9756

EL250	81.0811	87.6543	98.8225	98.9002	98.9407
EL350	85.7143	86.4532	87.5104	87.5421	89.7634
EL450	96.8322	97.4522	98.8707	98.8814	98.9123
EL550	94.7368	96.5342	98.7517	98.8345	98.8424

Experiment 2

In order to evaluate the effect of neighborhood size on performance of CF-PR, CF-KL, CF-LS, CF-LS-KL and TRCF-LS-KL, we conducted an experiment where we varied the number of nearest neighbors that were used and computed MAE for each scheme. We showed only the results for configuration EL250 and EL450 mapped from MovieLens and Jester datasets respectively. Results are shown in Figure 8(a) and Figure 8(b). We can observe that the size of neighborhood does affect the performance. All schemes improved the accuracy of prediction as neighborhoods size increases from 5 to 30 with increment 5.

Analysis of the results

Figure 8 (a) and Figure 8 (b) show that CF-KL performs better than CF-LS when the size of neighborhood lies in between 5 to 10. TRCF-LS-KL scheme is always better than other schemes. When the neighborhood size increases, MAE of all schemes decreases.
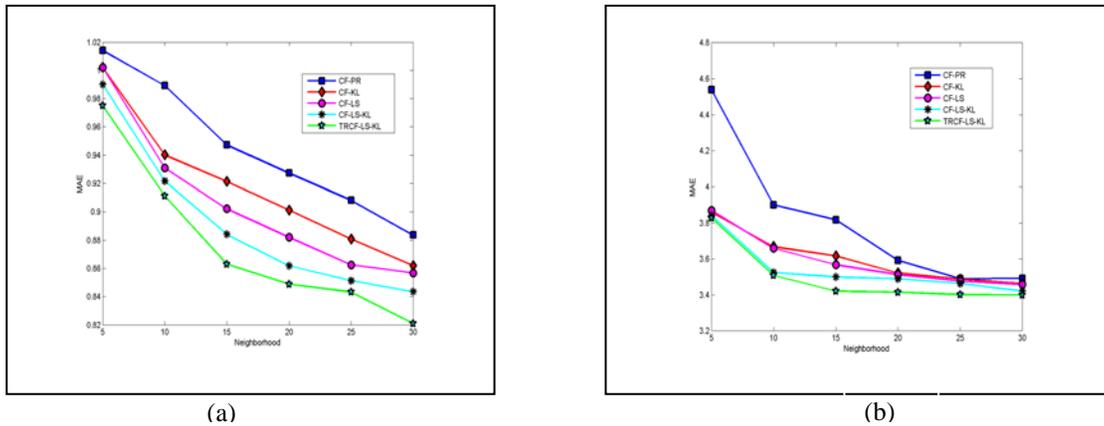

(a)   (b)

Figure 8. Sensitivity of neighborhood size on (a) EL250 mapped from MovieLens dataset (b) EL450 Mapped from Jester dataset

Discussion

The experimental results have clearly demonstrated that our proposed schemes namely, CF-KL, CF-LS, CF-LS-KL and TRCF-LS-KL have produced high predictive accuracy and better coverage on two different datasets (MovieLens and Jester) as compared to traditional collaborative filtering CF-PR. For TRCF-LS-KL, the mean MAE of all sample datasets of MovieLens decreases approximately by 8.5 % and the mean coverage increases by 18%. The improvement in accuracy via MAE and coverage is seen significantly for Jester dataset also. This improvement is possible because of the adaptation of trustworthy as well as similar learners in terms of their LSs and KLs in our proposed schemes. The proposed ELRS (TRCF-LS-KL) would be quite effective for providing resource recommendations to learners registered in online courses through e-learning systems.

Conclusion

E-learning recommender systems (ELRSs) need to consider specific demands and preferences of learners. Our proposed ELRS clearly demonstrates that trustworthy as well as similar learners generate effective resource

recommendations considering their learning styles (LSs) and knowledge levels (KLs). Experimental results reveal that the incorporation of trust in ELRS based on LSs and KLs has significantly outperformed other traditional schemes in terms of accuracy and coverage.

Even though the results reveal that the proposed scheme, TRCF-LS-KL has produced better accuracy and coverage, further studies are planned to extend the TRCF-LS-KL in the following two different directions:
Firstly, LS vector is fixed in our proposed system during learning process. It would be more promising by adapting the dynamic behavior of LSs and incorporating emotional states of learners such as sad, anger etc for further enhancing recommendation quality of our proposed system.

Further, our proposed system is error prone to the cold start and the sparsity problems. In future, we are planning to develop a hybrid ELRS for alleviating these problems by combining our system with content based filtering and incorporating trust propagation schemes into our system. The results presented in this study are still preliminary due to the lack of publically available datasets; it would be interesting to establish the effectiveness of our proposed system on future datasets with different data characteristics.

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