HYBRID RECOMMENDER SYSTEM FOR E-LEARNING APPLICATIONS

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Abstract:

Recommender systems are regularly used in e-commerce applications. These Systemscombine ideas from machine learning and user profiling to provide users with an information retrieval applications. They can be also used in e-learning and web-based educational systems like LMS. Nowadays, E-learning arewidely adopted in educational organisation. The advances in e-learning has changed the traditional way of learning and has provided a positive environment for both learners and teachers. Educators are finding it difficult to select the suitable learning materials for the learners from vast collection of materials available.This paper provides a novel approach to implement arecommender system for e-learning using association rule mining.Thissytemmakes recommendations based on learners' current knowledge.

Keywords—**Recommender system,Association rule mining, E-learning.**

I INTRODUCTION

Over the past years, Recommender systems are used in various applications to satisfy the needs of the different users in different circumstances. They have been successfully implemented in various domains from e-commece to search engines.

Differntapproaches can be used to implement recommender systems.Content-based and case-based recommender systemsrelyon feature-based descriptions of items as the basis for recommendation. A typical content-based recommender suggests items for user on the ground of past history ,whichare similar to items that the user has bought inthe past.

Collaborative filtering recommender systems are the most commonly used systems. They use the information provided by other similar users to make recommendations to a particular user. This can be compared to when an item is bought based on the suggestion made by a friend. Thus, these systems use the information provided by othersin order to tie it to the profile available about specific user to make a prediction.

Colloborative recommender systems commonly use association rules. Though they were originally developed for retail industry, the same idea can be applied to any domain particularly in e-learning.Due to the inherent nature of scalablility and interpretablility, they provide an excellent basis for a recommender Systems. The scalability of this algorithm has also been well recorded in literature [1].

The application of recommender in e-learning,particularly the learner-centred approach aimed at improving the efficiency of learning ,has series ofhurdles that need to be addressed [2].The foremost hurdle is the that these tools are too complex for educators to use and their features do not cover the scope ofwhat an educator might.

II RELATED WORK

For more than a decade, researches have been carried out on the application of recommender systems in e-learning and aslo recommender system based on associationrule mining.

In [3],the researchers hasproposed mining contrast rules that are of interest for web-basededucational systems. Contrast rules help them to identify attributes that characterize patterns of performancedisparity between different groups of students.

In [4], recommender system for e-learning is implemented based on agent technology.This system which use association rule mining to show associations between user's action and URL.Based on a learner's accesshistory,agents recommend online learning materials/activitiesin a on line course web-site.

In [5],association fuzzy rules is used in a personalized e-learning recommendersystem. Authorimplemented the system using fuzzy matching rules. These rules discover associations between a learners's requirements and a listof learning objects.

In [6], reseachersused association rule, symbolic data analysis and SQL queries to minestudent data. These data are captured from a web-based tutoring tool. Using these rule, the system find mistakes that occurtogether.

Freyberger et al. [7] use association rules to guide a search for the best fitting transfer model of student learning in intelligent tutoring systems. The association rules determine the operation thatneeds to be performed on the transfer model to predict a student's possibility of success.

Chang et al. [8] proposed (ew Fast UpdateMethod (NFUP),anApriori-based algorithm. To mine new frequent patterns in updated database,NFUP partitions the database logicallytime interval (month oryear). For each item, the ending period ofexhibition interval is similar. It scans eachpartition backward and can reveal new frequentitemsets at the latest time periods.It does not even require scanning ofthe original databaseeverytime. The NFUP implements incremental algorithm requiring scanning of newly added items only.

Leung et al. [9] proposed a canonical-order tree named CanTree, which is an extension of the rule mining algorithm FPtree.It scans database once in the canonical order to acquire the items of the database. Hence,it does not need to search and discover mergeabletrails likeCATS tree. After the construction Tree,original FP-growth is applied to mine frequent patterns [10].

III PROPOSED ARCHITECTURE

This section introduces the proposed architecture for developing an efficient recommender systems using association rule mining. It aims to design and develop a framework that may efficiently assist the learning management systems.The overall system architecture is shown in Fig. 1.

Databases stores all the information about the user and learning objects. Database layer includes the learners' current knowledge library, learners' assessment score, the learning resources' object database and the rules mined using association rule mining algorithm. The learners' current knowledge library has every learner's learning behavior and related properties, including the currently learning knowledge ID, learning level and learning time, etc.; The learners' assessment score library contains a learner's current state of study, assessment score etc.; The library of learning re-sources' object is used for the storage of learning objects.
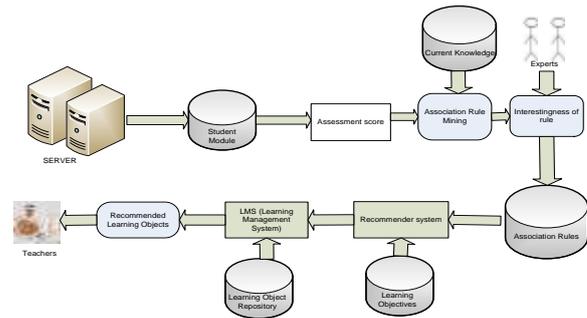

Figure 1: System Architecture

The proposed framework consists of two phases. The first phase is to generate a setof association rules usingApriori algorithm. The second phase is to use the generated association rules on learning object repository to recommend learning objects to a user.

3.1 Phase 1- Association Rule Generation

First step is to generate associaltion rules using Apriori algorithm.Number of rules generated depends on the minimum support, and minimum confidence. If they are high, there will be few rules. If they are low, there is a danger of many rules which increases the run time. Considering these facts, the minimum support, and minimum confidenceare set at 60% and 80% respectively.

3.2 Phase 1 - Evaluation Of Generated Rules

The second part of the first phase implements evaluation of the rule subjectively. It aims to determinethe interestingness of the rules obtained by Apriori algorithm. Interestingness of the rule is measured by the following parameters:

1) Usefulness of the generated rule   according to teachers
2) Interestingness of the rule according   to experts.

Let $T1, T2..., Tm$, be m different teachers, $Ri$the set of expected associationrules found by Ti (i=1,2,…m), $R = \{R1, R2,..., Rm\}$; and let $EX1, EX2...,$ EXk, be k experts. Let $R = \{R1, R2..., Rn\}$ represent all the rules in R, then the weight of Rican be defined as:

$$Wteachers_{Ri} = \frac{NumVotesTeachers(R_i)}{\sum_{j=1}^{m} NumVotesTeachers(R_j)}$$

where$i$=1,2,…,n and $NumVotesTeachers(Ri)$ is the number of teachers voted for rule Riin R.

By applying the same to the experts',

$$Wexperts_{Ri} = \frac{NumVotesExperts(R_i)}{\sum_{j=1}^{k} NumVotesExperts(R_j)}$$

where $i=1,2,\ldots,n$ and *NumVotesExperts(Ri)* is the number of experts voted for rule *Ri* in *R*. Therefore, the weight of rule *Ri* can be expressed as a weighted measurement of the votes registered by teachers and experts, so that:

$$W_{Ri} = Wteachers_{Ri} * C_u + Wexperts_{Ri} * C_e : C_u + C_e = 1$$

where *Cu* and *Ce* are the weighted coefficients denoting the opinions of the teachers and experts respectively.

Once the weight of each rule has been measured, an interestingness calculation can be devised, which is weighted accuracy (*WAcc*).

WAcc for rule *Ri* as:

$$WAcc_{R_i} = W_{R_i} * \frac{\sum_{j=1}^{m} accR_{ij}}{m}$$

where *WRi* is the weight of the rule .

3.3 phase 2 – Recommendation based on   rules

The second part is to apply the subjectively selected rules to recommend learning objects. Specifically, the proposed algorithm addresses the recommendation of appropriate learning objects by applying the generated association rules to offer recommendations for the user;

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for each target user m do
find the learning objects into two classes based     on the
   score of user m:
   Suitable Items Class (Score>= 65)
   Non- Suitable Items Class (Score<65)
   for each item n in the Suitable Items Class do
   if the item n is in the associated items then
   calculate interestigness of the item.
    For each interested item then
   recommend associated item u to the         user m
   end for
   end if
   end for
   end for
```

IV EXPERIMENTAL RESULTS

In this section, we evaluate the performance of the proposed framework. The experiment aims to evaluate

1) Does the recommended learning object satisfy the need of the learner?
2) Whether the contents of the recommended object are helpful for them?

4.1 Experimental setup

Two criteria selected for measurement are: Recall and Precision rate.

For the proposed model, *Relevant* is defined as the set of relevant learning objects for a given query and *Retrieved* is the learning objects retrieved by the system for the given query.

Recall and precicion is deined as follows:

$$Recall = \frac{number\ of\ retrieved\ relevant\ LOs}{number\ of\ all\ relevant\ LOs} = \frac{|\ Relevant\ LOs\ |\cap|\ Retrived\ LOs\ |}{|\ Relevant\ LOs\ |}$$

$$Precision = \frac{number\ of\ retrieved\ relevant\ LOs}{number\ of\ all\ retrieved\ LOs} = \frac{|\ Relevant\ LOs\ |\cap|\ Retrived\ LOs\ |}{|\ Retrieved\ LOs\ |}$$

Recommended results are evaluated using Mean Absolute Error (MAE). A feedback regarding the recommended learning object is collected from the user. The MAE is defined as the difference between the given feedback and the   prediction. It is given as follows:

$$MAE = \frac{\sum_{i=1}^{N} |p_i - q_i|}{N} ,$$

where, N represents the number of comparisons. Lower the MAE value, better the prediction accuracy.

4.2 Experimental Results

This experiment observes the variation of preference feedbacks for the learners with different weights, i.e w= 0.3 and 1-w=0.7, w= 0.5 and 1-w=0.5, and w= 0.7 and 1-w=0.3. The results are shown in Figure 1(a &b).

Figure 1(a) displays how soon the learners' preference patterns are formed. The x axis represents the number of learning objects studied. For example, (Y=2, X=5) means that the average score of preference feedbacks for the first 5 uses of learning objects is 2. The preference MAE has to be observed to understand the reasons that result in poor results of low preference feedback score.
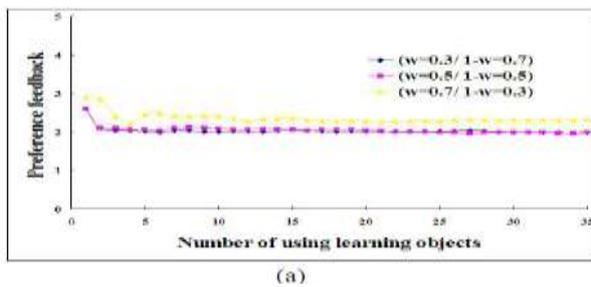
Figure 1.   Direct preference feedbacks

Figure 1(b)shows how the preference MAE varies against the number of learning objects studied. All three weight proportionshave their average MAEs lower than 1. This means in fact the system can infer learners' preferences accurately torecommend suitable learning objects. The reason behind the poor performance is probably that the feature values ofcandidate learning objects are not completely in accord with learners' preferences.
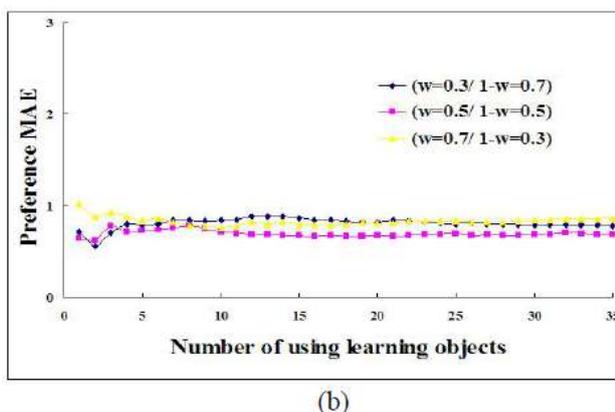
Preference MAE varies against the number of learning objects studied.

IV CONCLUSION AND FUTURE WORK

In the near future, E-learning will become more and more popular. Issues have to be solved before a learner can bereally benefited from the vast amount of E-learning object repositories on the Internet. This recommender system uses association rule mining and collaborative filtering in order to help the teacher maintain and continuously improve e-learning courses. It uses a weight-based evaluation measurement to rank the rules discovered, taking into accountthe opinion of both experts and teachers to produce more effective recommendations.

For the future work, the possibility of integrating educational preferences in thelearner's model such as learning styles, media types, etc are analysed. The learner's model shouldbe composed of three components: learner's profile, learner's knowledge and learner's educational preferences.All these components should be detected automatically within e-learning systems. We expect this enrichment ofthe learner's model to increase the quality of learning object

recommendations especially from an instructional pointof view.

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