ASSOCIATION RULE MINING IN EDUCATIONAL RECOMMENDER SYSTEMS

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ABSTRACT

Higher learning institutions and learners experience the need for recommendations in various academic processes. Educational Recommender System helps learners to identify the most interesting and relevant academic objects from a large number of objects. Data mining process is used to discover new, interesting and useful knowledge from huge and complex data sets. This study focuses on relevance of Data Mining techniques with special reference to Association Rule Mining in Educational Recommender Systems. An application of Association Rule Mining to understand the effectiveness of Internal Assessments in educational institutions is also given here.

Keywords*: Association Rule Mining, Data Mining, Educational Recommender System*

I.   INTRODUCTION

In Higher Education System, learner selects course offered by Institution/ University and the institution selects learners in the admission process which determines the success of both institution and the learner to achieve better academic outcomes. Higher learning institutions experience the need for effective academic analysis, recommendations and educational research tools to assist in various academic processes. The increasing implementation of ICT in higher learning institutions and Universities has led to the storage of large amounts of data. The database systems in supporting applications with interactive query based reporting are important services of this technology. An enormous amount of learning resources in both traditional education and e-learning systems has led to the difficulty of locating suitable academic resources, creating the need for recommendation tools.

1.1. Recommender Systems in Education

Recommender Systems are software tools and techniques providing suggestions for items to be of use to a user [1]. Recommender System (RS) helps users to identify the most interesting and relevant objects from a large number of objects. RS are widely used in e-commerce field [2]. Most of E-Commerce and knowledge management systems use RS as a tool to identify a set of elements that will be of interest to a particular user. Recently, they are applied in e-learning tasks such as recommending resources to the learners which include papers, books, web links [3] etc. Learners and academic administrators may ask for recommendations or the system may auto recommend. Based on the students' major subjects, preferences, interests and market trends the system will produce suitable recommendations. RSs have been a useful tool to recommend different objects in many online systems, including e-learning. RSs are useful to analyse learner data and to obtain predictions.

Different RS techniques for performing recommendation in education are – Content-Based filtering, Collaborative filtering, Demographic Filtering, Knowledge-Based Filtering and Hybrid Filtering.

1) Content-Based Filtering - the learners are recommended related learning contents and objects that are similar to the ones they preferred in the past.

2) Collaborative Filtering - learners are recommended related objects and learning contents that other learners with the similar interest and preferences liked earlier. For example, a collaborative recommender system can be used to recommend university optional courses to students based on similarities and dissimilarities among learner's preferences.

3) Demographic Filtering - Demographic attributes such as gender, age, place etc. can be used to generate personalized recommendations. The idea is that learners with common demographic attributes may have common preferences.

4) Knowledge-Based Filtering - prefer to generate a relevant recommendation based on matching learner's needs, interests and preferences. Knowledge-based recommendation attempts to suggest objects based on logical inferences about a user's needs and preferences.

5) Hybrid Filtering - generally combines the content-based, collaborative filtering and other methods. These combined methods borrow both content-based and collaborative features to get the learners' interest and recommend them required related learning elements more closely related to learner need, interest and preferences.

1.2. Data Mining and Educational Recommendations

Data Mining (DM) is the important step of the Knowledge Discovery in Databases (KDD) [4] process which is automatic, exploratory analysis and modeling of large data repositories for identifying novel, useful and hidden patterns from large data sets. DM is increasingly being used in banking, retailing, insurance, medicine and fraud detection purposes in different fields. Key areas of data mining applications in education are: i) improving student models, models that provide detailed information about a student's characteristics or states, such as knowledge, motivation, metacognition, and attitudes ii) discovering or improving models of the knowledge structure of the domain iii) studying the pedagogical support provided by learning software and iv) scientific discovery about learning and learners [5]. DM is well suited to provide decision support in the education environments, presenting relevant information and knowledge to sustain evaluation and choices for performance. DM based systems provide decision support in the higher education environments by generating and presenting relevant information and knowledge towards quality improvement of education processes [6]. The patterns discovered through DM are valuable to gain a competitive advantage and it assists in the decision-making processes in Higher Education System. Presently, Educational Data Mining (EDM) [7] [8] is a new and growing research community. DM uses a variety of techniques such as prediction, classification, clustering, Association Rule Mining (ARM) and other techniques. DM techniques helps in getting recommendations concerned with academic activities, institutional planning, curriculum improvements, faculty support suggestions and administrative decision making.

1.3. Association Rule Mining

ARM is a data mining method for discovering interesting relationships between attributes. It is used to find frequent patterns, associations or correlations among sets of elements or items in data repositories. Based on the principles of Agarwal et al. [9] an association rule is an implication X⇒Y, where X and Y are separate itemsets. When X appears, Y is also likely to appear. Association rules are evaluated using measures of support and confidence. The confidence of an association rule X⇒Y is the proportion of the transactions containing X which also contain Y. Support of the rule is the percent of the transactions that contains both X and Y. ARM finds the association rules with the condition of minimum support and minimum confidence. First, it is required to discover frequently occurring itemsets and then generate association rules from the frequent itemsets. In some data mining applications infrequent associations are also considered as interesting patterns.

Apriori algorithm is simple and common algorithm of ARM [4] [9] [10] given in Fig. 1. Apriori Algorithm is used for finding frequent k-itemsets. k-itemsets is an itemset having k items in it. Support is number of transactions that contain a particular itemset. Frequent Itemset is an itemset that satisfies minimum support. (L_k is frequent k-itemset). All non-empty subsets of a frequent itemset are frequent. C_k, the set of candidate k-itemsets is generated by self-joining L_{k-1} (L_1: frequent 1-itemset, L_k: frequent k-itemset). L_k, the set of frequent k-itemsets is extracted from C_k by pruning non-frequent k-itemsets in C_k. In the Iterative process, k-itemsets used to explore (k+1)-itemsets. In each iteration C_k generated (candidate k-itemsets from C_k-1) and L_k (frequent k-itemsets). Frequent k-itemsets is used for generating association rules.

```
L₁= {large 1-itemsets};
for ( k = 2; Lₖ₋₁≠ Ø; k++ ) do begin
Cₖ= apriori-gen(Lₖ₋₁);  //New candidates
forall transactions t ∈D do begin
Cₜ= subset(Cₖ, t);      //Candidates contained in t
forall candidates c ∈Cₜ do
c.count++;
end
Lₖ= { c ∈ Cₖ | c.count ≥ minsup }
end
Answer = ∪ₖ Lₖ;
```

Figure 1. The Apriori algorithm [9]

II. ARM AND OTHER DM TECHNIQUES IN EDUCATIONAL RS

University students require suitable recommendations about educational resources based on preferences, past performance, social background, economic level, experience, project works, seminars and workshops, job market area, availability of learning resources, activities, knowledge and skills, curriculum contents, journal papers, citations, etc. In recommender applications ARM and other DM techniques are used to build recommendation models from large data sets. RS that incorporate these techniques make their recommendations using knowledge learned from the activities and attributes of users. Educational Recommender systems can use

DM techniques such as classification techniques, clustering, generation of association rules, to get recommendation rules from huge amount of data to create their recommendations using information learned from the academic actions and attributes of learners and learning system.

Xavier Amatriain et al.[11] discussed on Preprocessing methods such as distance measures(e.g. Euclidean distance, Cosine similarity), Sampling, Reducing Dimensionality (Principal Component Analysis and Singular Value Decomposition), Classification techniques (k-Nearest Neighbor (kNN), Decision Trees, Rule, Bayesian Networks, SVM, ANN), Clustering (k-means, density-based, message passing and hierarchical clustering) and ARM used in the RS. One or more DM techniques or combination of techniques can be employed in the design and development of RS. Decision Tree (C4.5., ID3, CART) technique is easy to understand helpful to visualize differences of learners' information from the data. Decision Trees in a RS can be used as a tool for ranking of different learning elements. kNN can be used to cluster learners in a group and recommend similar contents to learners. Vector based approaches help to obtain high correlation between learning object and learner can be used for generating recommendations, monitor and predict learner performance. In data preprocessing sampling, distance measure and dimensionality reduction techniques are used. Clustering techniques work by identifying learner groups who have similar preferences. Once the clusters are generated, averaging the interests and preferences of the other learners in his/her cluster can be used to make predictions for individual learner. DM and Recommendation techniques and tools are used to improve web-based learning environments for the learner to have good learning experience and learning system to better evaluate the learning and navigation activities. DM techniques can be applied to get useful results from past communications of learners with the e-learning services and contents. The similarity of the learners could be recognized using learner profiles and previous access patterns. DM techniques (e.g. clustering or classification) can be applied to mine the appropriate values to use from past interactions of learners with the e-learning services. Computational models are used for assigning a category to an input known as classifiers. Classification techniques can be used for retrieval of the most appropriate tutors in online educational environments and assist learners to find the most suitable colleagues that are able to provide them help [12]. For example, in RS, classifier can be used to have information about an optional subject and a student data as the input, and to have the output category represent how well it recommends the optional subject to the student. Classifiers may be implemented using linear regression, neural networks, and Support Vector Machine regression and Bayesian networks [13] [14]. DM can be applied to get useful results from past communications of learners with the e-learning services and contents. DM techniques can be used to cluster learners in different groups regarding their involvement and motivation in the course and their learning levels (high, low, medium) to produce recommendations for educators. A semantic model was proposed supporting the teacher in describing recommendations for technology enhanced learning, presenting information to the user about the recommendations offered and providing semantic information to facilitate the reasoning by the algorithms [15]. Frameworks were developed for discovering new knowledge and predicting users' interests, based on collaboration of other users to build an efficient Recommender System [16]. An ontology based on the structure of a distance learning environment was proposed which enriches a recommendation system with rules generated by data mining techniques and tutors can use this recommendation system in order to predict learners' progress and their final performance [17]. In [18] Clustering technique was applied to the item content information to complement the user rating information, which improves the correctness of collaborative predication, and solves the cold start problem. In [19] ANN is used to classify the e-

Learner types and based on e-Learner groups, users can obtain course recommendation from the group's opinions. When groups of related interests can be established, DM will be used to elicit the rules of the best learning path which helps to stimulate learners' motivation and interest.

Technique of association rules can be used in order to discover correlations between the pages of a web application, based upon the analysis of the user's surfing sessions [20]. An automatic personalization approach was described aiming to provide online automatic recommendations for active learners without requiring their explicit feedback which employs offline mining of association rules from clustered learners sessions with other computations and an online module which uses these models to recognize the students' needs and goals, and predict a recommendation list [21].

Fig. 2 shows recommendation system architecture [22] in the context of enrollment to know how convenient for a student to take a specific course using results obtained by other students as basis. It uses data of historical database of students and their results. Rules were generated by Pattern Discovery Module. In this module C 4.5 sub module uses training data as input for generating Decision Tree. This is used by Production Rules to generate the rules and based on these rules system provides recommendations.
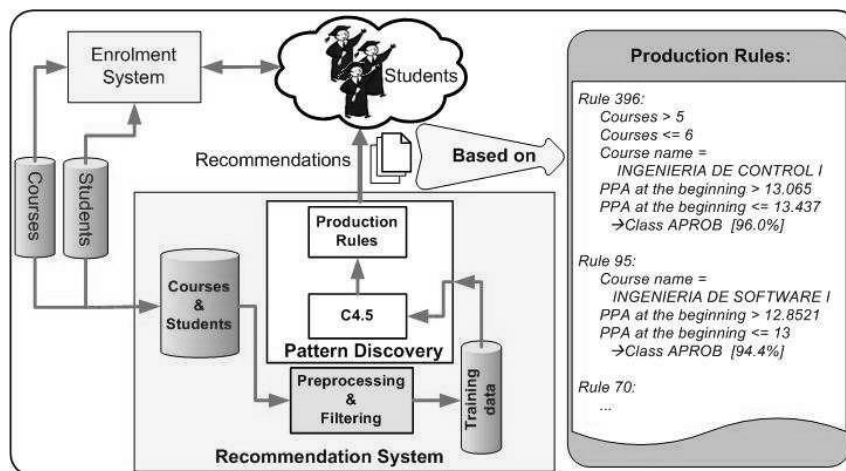

Figure 2. Recommendation System Architecture using Data Mining [22]

An online personalized English learning recommender system was developed which is capable of providing ESL students with reading lessons that suit their different interests and therefore increase the motivation to learn using content-based analysis, collaborative filtering, and DM techniques (Association rules, Clustering), analyzes real students' reading data and generates recommender scores, based on which to help select appropriate lessons for respective students [23].

In [24], a Hybrid Data Mining Model of neural network and decision tree classifier that serves as the core design for a system prototype called Recommender System of Admission to University (RSAU system) analyzes various sources of secondary school students' data, in order to predict their chances of admissions to universities and provides decision support about recommendations. A course recommender system known as RARE based on association rules (fig 3.) combines the benefits of both former students' experience and current students' ratings in order to recommend the most relevant courses to its users [25].
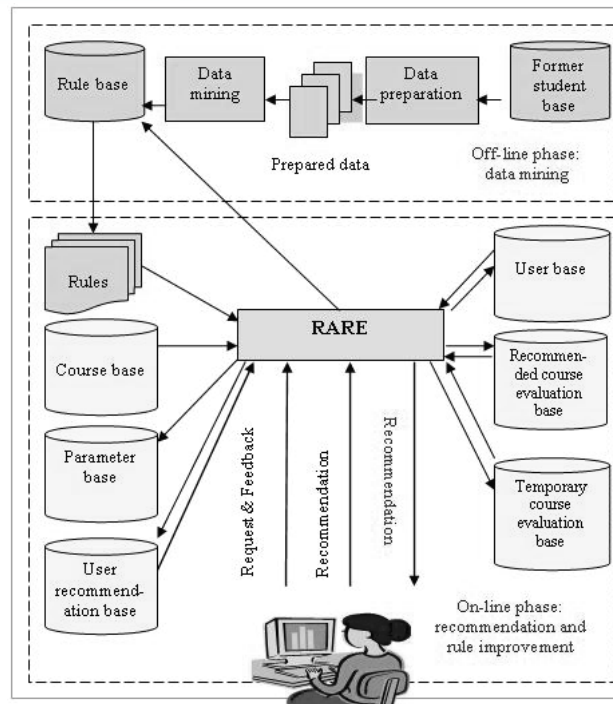
Figure 3. A course recommender system RARE [25]

Zaiane and Luo [26] have implemented a system that takes advantage of the latest DM techniques and pushes constraint specification at all stages of the web usage mining to help the educators control and guide the knowledge discovery, and effectively and efficiently understand the students' behaviours in e-learning sites. Zaiane and Osmar [27] have proposed an approach to build a software agent that uses ARM in order to build a model that represents on-line user behaviours, and use this model to suggest activities or shortcuts and these suggestions can help learners better navigate the on-line materials by finding relevant resources faster using the recommended shortcuts and assist the learner choose pertinent learning activities that should improve their performance based on on-line behaviour of successful learners.

Material recommender system framework based on sequential pattern mining and multidimensional attribute-based Collaborative Filtering (CF) was proposed in which the sequential pattern based approach, modified Apriori and PrefixSpan algorithms are implemented to discover latent patterns in accessing of materials and use them for recommendation [28]. A Literature recommendation system makes use of the web usage logs of a literature digital library with appropriate pre-processing of the Web usage log, discovery of article associations, and article recommendations [29].

Association rules have been used to analyse patterns of preference across different courses, subjects and contents, and to recommend course and subjects to learners based on other course and subjects they have selected. An association rule expresses the relationship that one course is often selected along with other course subjects. Discovery of association rules is the important application in recommender systems which use techniques to identify items frequently found in association with items in which the user has interest. A simple Strategy to obtain Course Recommendations using DM techniques is to apply clustering on course database to group similar students to the same cluster using clustering algorithm such as k-means. Distance measure techniques can be employed to compute the distance between each pair of courses to get similarity between courses and nearest

neighborhood technique to select the similar groups. On this similar groups generated, ARM can be applied to discover the patterns in courses association rules considering course and grade. The courses association rules obtained can be used for recommending optional courses.

Association Rules and Neural Network techniques have been used in a Hybrid Recommendation System Framework (Fig. 4) to Support Student Relationship Management to find the structures and relationships within the data for helping the counselors in recommending the appropriate courses for students thereby increasing their chances of success [30].
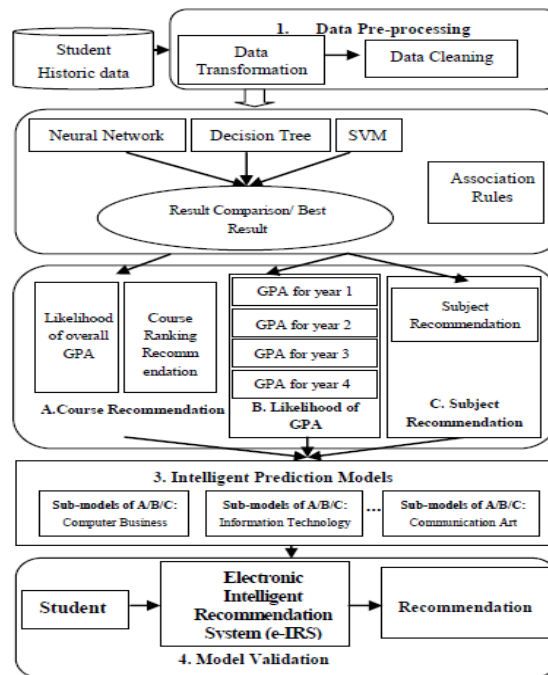

Figure 4. Hybrid Recommendation System Framework to Support Student Relationship Management [30]

Client-Server architecture of distributed data mining system (fig. 5) with Collaborative Recommender technique was developed by E.Garcia et al. which uses iterative and interactive association rule algorithm to help the teacher to improve the web-based adaptive courses & learning performance [31].
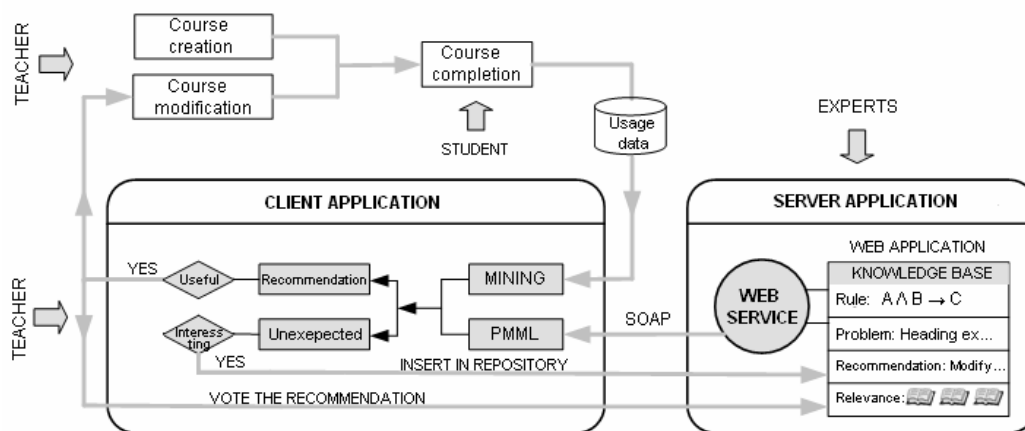

Figure 5. System architecture [31]

Architecture of a recommender system using web mining techniques for recommending a student which (next) links to visit within an adaptive web-based educational system was described by Cristobal Romero et al. [32]. In its basic architecture student's information stored in web log files and system uses sequential mining algorithm. Advanced architecture uses additional student's information such as profiles and several mining algorithms for example, clustering and sequential pattern mining. It helps to discover clusters of students showing common behavior and/or knowledge and then the sequential patterns of each cluster can be discovered. This type of RS can personalize the recommendations which have a specific mining tool and a recommender engine that are integrated in the Adaptive Hypermedia Architecture (AHA!) system [32].

Garcia et al. [33] 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. It supports teacher who is not an expert in data mining to take decisions about how to improve the e-learning course (Fig.6).
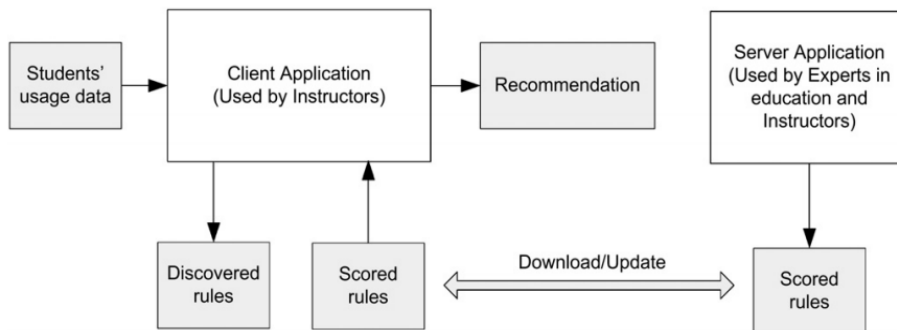
Figure 6- Collaborative Data Mining Tool [33]

RS based on an idea of adaptation model development using DM techniques (Fig.7) was proposed to provide knowledge needed to recommend concepts to students according to their characteristics and to assist the author of the course to improve the structure of the domain. It also incorporates the module for visualization of discovered knowledge helping the author of the course to prepare modification to the content [34].

Figure 7. Recommender System [34]

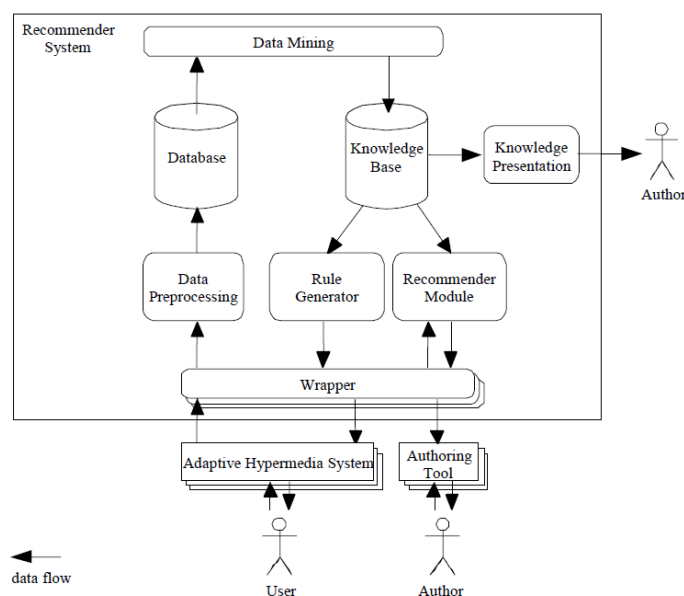Romero et al. [35] have shown how the rules discovered by RARM (Rare Association Rule Mining) algorithms can help the instructor to detect infrequent student behavior/activities in an e-learning environment such as Moodle. They have evaluated the relation/influence between the on-line activities and the final mark obtained by the students.

Relevant contextual information does matter in recommender systems and that it is important to take this information into account when providing recommendations [36]. Contextual information helps to increase the quality of recommendations in educational system. Some contextual information include a new responsibility, obtaining scholarship, present family problems, change in parent's financial status, change in curriculum, extension of work period, change in project/research area etc. which helps mining patterns relating to this particular context by concentrating only on the relevant data of learners.

Personalized learning system for web-based distance learning focusses on the web usage mining techniques aimed at personalized recommendation service [37] explained a web page classification method, which uses - i) attribute-oriented induction method according to related domain knowledge shown by a concept hierarchy tree, ii) an algorithm of mining association rules with one-support using Freq- Set-Tree and iii) based on their current access patterns, page classes at the home site, page integration from other sites, and the rules discovered in mining, recommendation pages are made and presented for the students.

[38] Presented a rule-based personalization framework for encapsulating and combining personalization algorithms known from adaptive hypermedia and recommender systems and showed how this personalization framework can be integrated into existing systems by example of the educational online board Comtella-D, which exploits the framework for recommending relevant discussions to the users.

Some examples of associations that support various recommendations in education are-

- Associate learners demographic data with final academic outcomes
- Associate student assignment score, attendance with final result
- Associate learner with different academic subjects
- Associate learner attitude with their results
- Associate teaching faculty with learners examination score
- Associate lecturer performance with their personal data
- Associate course work, subject, curriculum related to different students
- Associate students behaviour with performance in assessments
- Associate difficulty level of assessments with student grade
- Associate learners' skills with present industry requirement
- Associate student or group with a particular project or activity

DM techniques including ARM in RS is helpful for following applications.

- Classification, clustering and association of learners' attributes for targeted recommendations for institutional advancements, marketing and placement opportunities.

- DM algorithms in RS can be used to extract pedagogically related knowledge which supports design and improvement of educational contents.

- To suggest short courses, subjects, books, resource persons, tutorials, webpages, videos, presentations, discussion forums, projects, groups, technicians, consultants, social networks, blogs, etc. to improve learning outcomes based on historical and present learning status.

- Design and development of hybrid RS based on the advantages of ARM and other DM techniques.

- Multidimensional view & analysis of subjects, students, materials, community, region and time.

- To learn the effectiveness of enrolments, assessments, educational projects and operations based on recommendations.

- Recommendations to institutions related to learner retention possibilities.

- Detection of outliers and pattern analysis in the recommendation process

- Association and sequential patterns analysis with multidimensional view of academic database.

- Indexing, similarity search, comparative analysis and associations in learner and institutional activities.

- Discovery of useful patterns and analysis of different academic models.

- Association and analysis of learning directions for recommendations

- To suggest combinations of learning materials required for a particular analysis and research.

- Development of RS with data mining algorithm detecting unusual behaviours in leaner and institutional data.

- Analyse learner satisfaction based on content, teaching quality, learning environment to obtain recommendations for improvements in related issues.

- Employ ARM and correlation analysis, aggregation to help select and build discerning attributes.

- To produce recommendations concerned with socio-economic status of learners at University and Government level using distributed data mining approaches.

- Analysis and estimate of skills acquired by a particular student.

- Intelligent analysis and quick feedback based on learner interactions to support improvements in interactions and performance of learners.

- Recommending persons based on academic knowledge.

- To support academic process and improve quality of education.

- Recommendations help institutions and learners to customize learning needs.

- To develop predictive model for the estimation risk factors based in historic observations and recommendations which helps to know the risks associated with future decisions such as starting a new course, new infrastructure, affiliations etc.

III. AN APPLICATION OF ASSOCIATION RULES

This simple work is given as an illustration of part of design & development process of an Educational Recommendation System. This is an application of ARM to learn more on effectiveness of Internal Assessment (IA) marks of students related to undergraduate course in commerce and business administration.

3.1. Subject and Objective

Clear understanding of academic subject concepts and good performance in internal tests, assignments and/or skill development works will enable students to attain better academic outcomes. The excellent teaching assessment will effectively guide the teaching work, promote education development, encourage the teachers, gully exploit working potential ability and strength education control and the establishment of assessment standard should base on the common basic of teaching activity that represent in the aspects teaching attitude, teaching content, teaching method and teaching effect [39]. A sample data set related to subject computer applications course of commerce (B.Com.) and business administration (BBA) is used. For every subject IA component includes two internal tests, course assignments and/or skill development works/practical works. IA weightage is 20% in the subject Computer Applications in Business (CAB) and 25% in in the subject Computer Applications (CA) which includes practical part. IA includes class attendance marks. In this work those records of students who are regular to the classes and maintained more than 75% attendance in the concerned subject are considered. IA will be given and evaluated by concerned teaching faculty. The objective of this work is to study the effectiveness of IA on students' final performance level.

3.2. Steps Followed

An application of selected DM techniques on sample data set of 75 records is given here. ARM, an unsupervised learning method, is used to search for hidden facts in data. Statistical techniques can be employed to identify the relationship and significance of different IA types. Here marks of students' assignments and/or skill development works, average assignment, internal test marks, final scores are considered as input.

Following steps are required to get association rules from IA database.

1. Read student marks prepare and clean the marks. Cleaning, preparation and preprocessing of marks were done by eliminating missing marks and replacing them by 0. Records with null values of marks were not selected. Attributes which are not affecting this study statistically were not considered.

2. Input data set is transformed into a set of elements shown in Table I with considered attributes. Student marks are converted into rules of elements such as [T2, T6, T10] etc. More number of rules can be considered depending on the further assessment requirements. Sample rules necessary to study the effectiveness of assessments are considered here. Averages of marks scored by student were used. For example, if student scores [68, 72, 76] respectively in assignment, final exam and Total marks. These marks are transformed into items [T3, T6, T10]. In this illustration, transformation is done based on the rules defined shown in Table I.

3. Apply Apriori algorithm [9] with data elements to get association rules. Interpret and learn the effectiveness of the association rules using confidence and support values.

Table I. Rules used for data transformation

Attribute Name	Meaning	Rule consideration	Rule_Id
ASG_Score	Assignment Score	> =90	T1
		>=70 and <90	T2
		>=50 and <70	T3
		<50	T4
Test1_Score	First Internal Test Score	> =90	T5
		>=70 and <90	T6
		>=50 and <70	T7
		<50	T8
Test2_Score	Second Internal Test Score	> =90	T9
		>=70 and <=90	T10
		>=50 and <70	T11
		<50	T12
SEE_Score	Semester End Exam Score	> =90	T13
		>=70 and <90	T14
		>=50 and <70	T15
		<50	T16

3.3. Results and Knowledge Obtained

Association rules for the input dataset is generated and it helps to predict learners' level of performance. Student who scores more than 90% in IA will obtain more than 70% in final examinations. In this work, two internal tests have highest effect on final outcomes with 100% chance of passing the subject in the final examination. CA subject with 25% IA weightage produced better final results showing that student who scores in the range 70 to 90 will attain similar final result. Some other sample rules obtained with support and confidence values (rounded off) are shown in Table II.

Table II. Sample rules obtained

Antecedent	Consequent	Support	Confidence
Asg_Score<50	SEE_Marks<50	13	96
Asg_Score<50	Test2_Score<50	31	89
SEE_Score>=70and <90	Test1_Score>90	27	74

IV. CONCLUSIONS AND DISCUSSIONS

RS can use Association Rules and other DM techniques for generating recommendations using knowledge learnt from the activity and attributes of learners and learning environment. The approach to personalization uses social, economic, family, learning behavior, skills, online learning and other information about learners and learning system for the creation of learner models and to use these models for revision and improvement of contents. Some of the uses of ARM with other DM techniques in Educational Recommender System were discussed. DM based RS helps to find academic information quickly and recommends new items of interest to the active learner based on their preferences. ARM and other DM algorithms used in RS in higher learning institutions recommend next task to a learner based on the tasks already done by the learner and based on tasks

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made by other learners with similar preferences. Implementations of Hybrid Recommender Systems using DM techniques are recommended towards the improvement of quality and standards of education for Indian Higher Education System where merit, social, economic, family, personal and region aspects related to learners are influential factors. Use of DM helps to know recommendation on learning content and when to learn/use that content. In addition to suggestion, learner can get information on future implications of a course/content.

ARM Techniques can be applied successfully in Education System and it is useful for academic and administrative processes for improving analysis and decision making. This study offers useful suggestions to academic faculty members to decide on the IA related facts such as number of assignments and/or skill development works, how much weight should be given to each category of IA of the students. Teaching faculty can take suitable remedial measures in concerned course topics to improve the performance of the students placed below expected level even though they are regular to the classes. The work shows application of ARM that can be used in RS to extract hidden factors related to different IA types such as internal tests, assignments etc. Professors can take measures on improving assessment types, difficulty levels of assessments and curriculum as we observe in this study that IA marks have the direct influence over final academic outcomes. This example is useful to have quick identification of leaners' performance based on IA marks in different subjects especially in large classes. This method can be incorporated in RS considering attributes of learning activities in e-learning systems. For future works, learners' cognitive and pedagogical factors will be considered.

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