



An Association Rule Mining Based Model to Predict Learning Performance of a student with e-Learning Activity Log Data

S. Arumugam, A.Kovalan, A.E. Narayanan

Abstract: *There is a wider scope in research on log data of computed aided learning and interactive learning. We have an enormous collection of log data of students' activities during their learning process. Data Mining(DM) algorithms help us to discover knowledge and information from a huge and complex data sets. In a time-series log data, it is very complicated to verify the DM algorithms to mine the dataset. e-Learning activity log data is taken and converted into categorical data to predict the learning behavior of the students to implement the algorithms. The excavated knowledge can be used to modify the e-learning system. It is very easy from the result to note the slow learners and advanced learners well in advance before conducting an examination. Time series data is a numeric data that measures in a time period in successive order. The dataset used in this work is a UCI EPM dataset. It is a Non-Linear Time-Series Data. The converted dataset is used to apply a rule mining algorithm to predict the performance of a student. The measurements support and confidence will help us to predict the students' performance. The results also have been compared with other classification mining algorithms. It assists to improve and to build an educational model on e-Learning. In turn it supports students, teachers, and educational system as well Learning Management System.*

Keywords: *E-learning, Learning Analytics, Educational Data Mining, Educational Process Mining, Association Rule Mining.*

I. INTRODUCTION

E-Learning is an educational method using computers and with some electronic gadgets and away from a classroom[4]. Learning Management System (LMS) is a software application which helps us to prepare, to deliver to manage the course document of an e-learning program. It has a wider scope of research interest because the LMS makes huge data during the development and conduction of it. An LMS low level of granularity [5]. It also stores all students' activities and interactions. In our previous work[1], instead of treating it as time-series data, we proposed a model to convert it as simple multidimensional numerical data to make it suitable to check with clustering and classification. In our previous works [1],[2],[3], we examined the dataset using J48, MLPNN, RBFNN algorithms and compared the precision, recall and f-measures.

A. About Learning Analytics(La) And Educational Data Mining (Edm)

In any e-learning program, the learners and their contexts have many data that to gather, to gauge, to investigate and to report which helps to take any finding on it. It is called Learning Analytics(LA). Educational Data Mining (EDM) is used to study and analyze educational dataset.

In [6], the authors distinguished LA and EDM by their approaches namely top-down and bottom-up approaches respectively. In general, LA is analyzed manually and EDM is analyzed by software and tools. They are helpful to evaluate the learning content.

In e-learning, students are using educational software. It helps to collect enormous information about keystrokes, answering the questions, session details, students' activities, contextual level and so on. These data can be mined and retrieve meaningful information[7].

In [8], the authors discussed the role complexity in a programming course and performance of a student. The complexity of a software program in a linear autonomous path is cyclomatic complexity. That measures the quantitative paths in it. The various levels of complexity of the code are compared with the grades awarded to the students. The authors accomplished that this study was applied to correlate the students' performance.

Neural Networks are one of the best techniques to analyze the EDM dataset. Supervised learning, Multilayer Perceptron Neural Network (MLPNN) is used to predict the results. MLPNN uses training and target sets such that X and Y. It predicts Y based on given X. [9]

An RBFNN works based on the classification of the input likeness from the training set. The neuron stores the information of the training set as a prototype. The distance between the input and its prototype is calculated and classified from the target set[10].

According to [11], a diagrammatic representation of a learning process in a period of time is a Learnogram. Creating a learnogram from the available data is a challenging task. These learnograms are used to conclude the students' performance using the basic and high-level variables.

The association rule mining algorithm is used to predict a student's performance. The authors of [12] created a student model and the collected data are mined using association rule mining which helps to improve the course, learning style, methodologies, etc.,

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An Association Rule Mining Based Model to Predict Learning Performance of a student with e-Learning Activity Log Data

In [13], the authors rightly pointed out that to predict the students' performance before the examinations which would be useful to improve in their next examination. To analyze this, the authors used association rule mining. This examination helps us to make the student well and to implement any required changes in teacher or teaching methodologies in the required courses.

But in [14], it was discussed according to the variables grades, student population, institutional environments, financial supports, and other interactions. The authors compared with various data mining algorithms like Naive Bayes, Neural Networks, decision trees. Finally concluded that the Naive Bayes' analyze produced the highest accuracy.

In [15], the authors employed the techniques named Honeybee Colony Optimization and Particle Swarm Optimization to predict the performance of the students. They have pointed out that the swarm-based algorithm was performed well as compared to the other algorithms.

Association rule mining techniques are the most constructive methods in EDM. This technique pulls out the associations between various data items in the dataset. It was explained in [16], the authors made clear that the association between the data by both matching and error associations helped to predict the students' performance.

In [17], the authors compared various association rule mining algorithms such as Apriori, MagnumOpus, Closet, and FP-Growth. Further, they clarified that the association rule mining algorithms to fix the lower support and lower confidence. They have discussed the drawbacks of the association rule mining too.

Incremental Relational Association Rule Mining (IRARM) was brought up as a data mining tool to analyze the relational association rules especially for the dynamic data set[18]. The authors expressed that this method was very useful in EDM data investigation and prediction of the students' performance.

In [19], the authors explained that the Apriori algorithm is an important association rule mining algorithm for the recurrent type of the dataset. In this algorithm candidate and frequency in a dataset is established with the least amount of support.

The authors of [20], also expressed on the powerfulness of the Apriori algorithm for association rule mining. It is very useful in Boolean association rule mining. Here n datasets are employed to examine $(n+1)$ -dataset.

In [21], the authors took 159 students with 25 courses and they have applied the Apriori algorithm to predict the probability of getting awarded in that examination.

Finally, it was explained that how to use mathematic formulae to find support and confidence. Here X and Y are the set of grades the set of awards gained by the students respectively. And they are calculated as follows:

$$\text{Support}(X \Rightarrow Y) = P(XUY)$$

$$\text{Confidence}(X \Rightarrow Y) = P(Y|X)$$

This paper contains Introduction in section I. Section II gives detail of the algorithm used and the source of the dataset. Apriori algorithm is explained and implemented in section III. In section IV it is discussed the implementation and results. V Section concludes the work and discusses the scope of the future work.

II. DATASET AND ALGORITHMS USED IN THIS ASSOCIATION RULE MINING TASK

UC Irvine (UCI) is a machine learning repository; it holds a non-linear complex time series dataset of the department of Industrial Design, Eindhoven University, Netherlands. The data items available in the dataset can not be analyzed directly using any data mining techniques. Hence, it is converted into multidimensional data using data transformation techniques [1].

The UCI dataset has a time-series of activities of six laboratory sessions of a course of 115 students. This dataset has 13 attributes such as session, student_id, exercise, activity, etc., These educational datasets are taken for process mining to pull out the knowledge in it[1]. The students' intermediate and final grades are available in two separate excel files. In our previous works [2],[3], the converted multi-dimensional text data are taken into training and testing the grades available in the excel file. Then it was analyzed using a J48 classifier and random tree classifier, neural network algorithms like MLPNN and RBFNN. The measured precision, recall, and f-measure of association rule mining algorithms were compared with J48 and random tree classifier algorithm results. And it is interpreted with previous works.

III. THE PROPOSED MODEL OF EDM SYSTEM

In our Matlab implementation, we used only two categorical values 0 and 1 to represent "low" and "high" activities as well as "low" and, "high" marks. Further, we have imported that numerically coded categorical data into an MS Excel Spreadsheet and converted all the labels 0 and 1 as "low" and, "high" for better understanding while applying rule mining.

It is taken that only a few selected columns from our converted EPM dataset to apply the association rule mining algorithm. The reason is, with 31 categories and few hundred transactions, a typical "shopping cart analysis" kind of association rule mining process will take lot of memory and time and it will make it impractical run the rule mining algorithm on a typical hardware with limited resources and it will end up with "memory-related errors". To avoid this, after doing some preliminary experiments with a dataset with the different numbers of column/attribute we decide to use only 10 specific columns (including the grade/mark attribute) to get more understandable results from the mined rules.

In this work, we propose an association rule mining algorithm to mine the facts and knowledge that are available in the converted dataset, after that it can be used to improve any e-Learning, Intelligent Tutoring Systems and, Adaptive Educational Models. Further, we calculated the common metrics clustering and classification such as precision, confidence, etc., as a metric for measuring the complexity of a learning session design as well as the metric for measuring student learning performance and try to correlate with the results of precious metric, Cyclomatic Complexity.

The association rule mining can be defined as follows

Let $A = \{A_1, A_2, \dots, A_n\}$ be a set that contains n distinct features. Let DB be a database, in each row T has a unique variable and holds a set of items such that $T \subseteq A$. An association rule is an implication of the form $X \Rightarrow Y$, where $X, Y \subseteq A$, are the sets of items called item sets. If $X \cap Y = \emptyset$ then, X is called antecedent, and Y consequent.

Two metrics in association rule mining are, support (s) and confidence (α), which are described as follows.

The support (s) of an association rule is the percentage of the ratio of the records that contain $X \cup Y$ to the total number of records available in the database. While high support is often desirable for association rules, this is not always the case.

The confidence (α) is a statistical matrix that holds the percentage of the ratio of the number of records that contain $X \cup Y$ to the number of records available in X .

The confidence of a rule points out the degree of correlation in the dataset between X and Y . Large confidence is good for association rules. User-specified threshold for support and confidence are identified the rules from this algorithm.

Algorithm Basic:

Step 1: Input I, D, s, α

Step 2: Apply rule mining

To calculate a frequency that is greater than or equal to the user-specified threshold support, s .

To prepare the best rules with the item sets, that have user-specified threshold confidence, α

Step3 : Output : Association rules satisfying s and α

A. The Proposed Model Of The Epm System

The following diagram shows the proposed model of the EPM system[3].

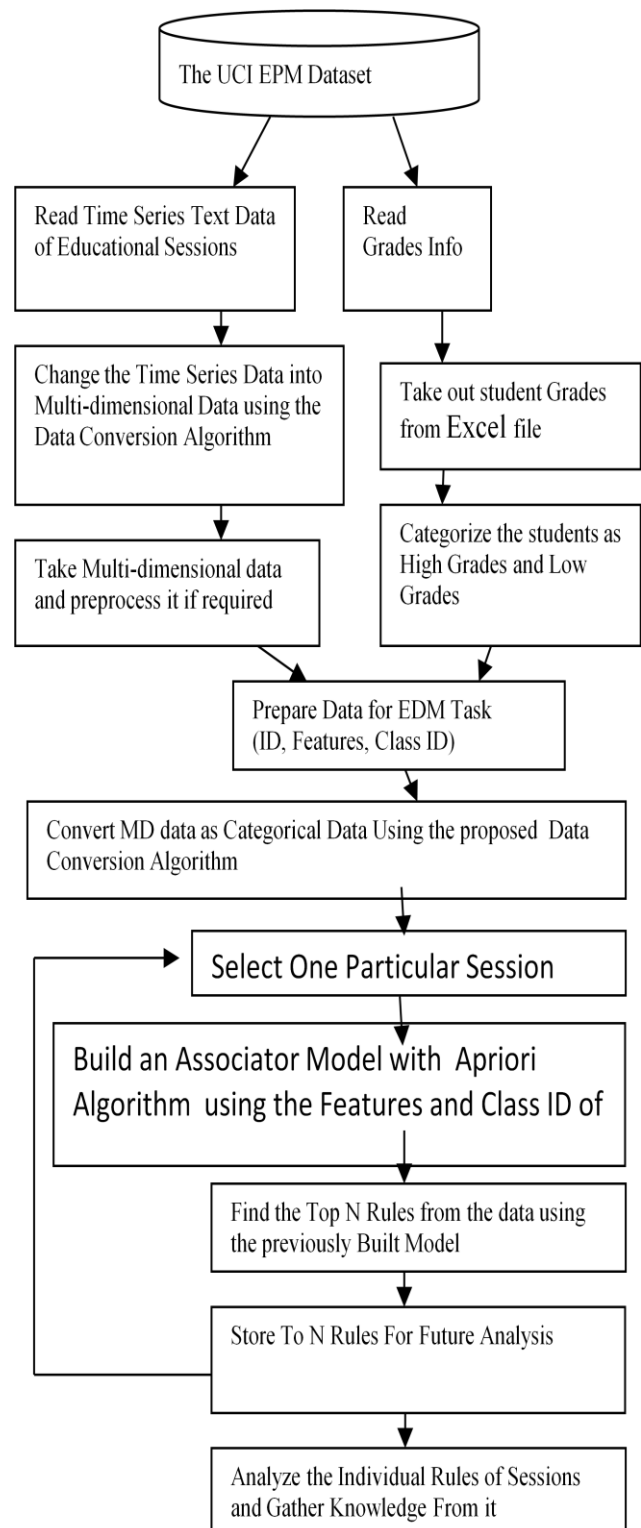


Figure 1. Proposed model of the EPM system

IV. THE IMPLEMENTATION RESULTS AND DISCUSSION

To test the converted data, we used the Apriori association rule mining algorithm as a tool. The performance of the proposed rule mining model will be tested with the database called "UCI EPM Dataset".

The following screen-shot explains that simple GUI form to run the algorithms repeatedly during the evaluation[3].

An Association Rule Mining Based Model to Predict Learning Performance of a student with e-Learning Activity Log Data

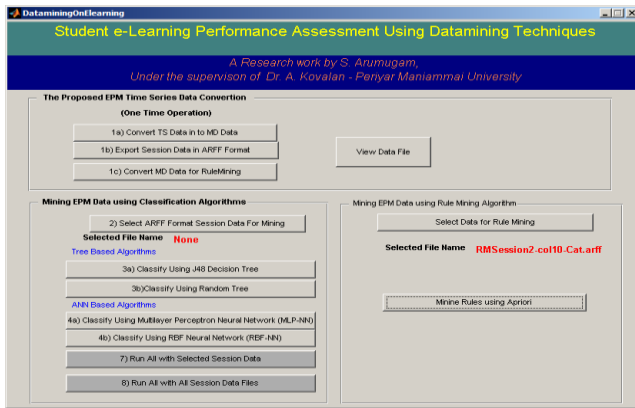


Figure 2. The GUI of proposed the EPM System.

The following screen is a sample output screen. In this example, it shows the rules mined from our categorical version of session-I EPM data derive from UCI EPM Dataset.

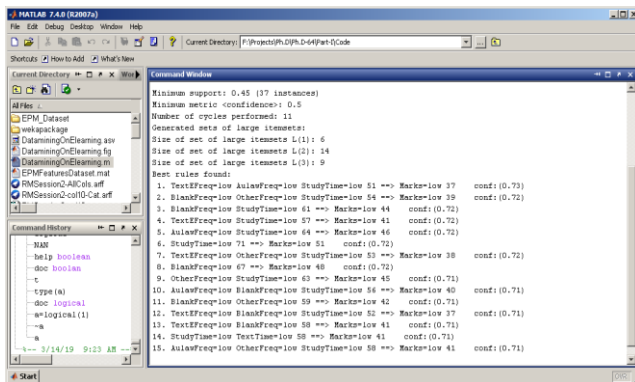


Figure 3. An Example of EPM output.

The Results

=== Run information ===

Scheme: weka.associations.Apriori -N 15 -T 0 -C 0.5
-D 0.05 -U 1.0 -M 0.1 -S -1.0 -A -c 10

Relation: RMSession2-col10

Instances: 82

Relation: RMSession3-col10

Instances:

Relation: RMSession4-col10

Instances:

Relation: RMSession6-col10

Instances:

Relation: RMSession6-col10

Instances:

Attributes: 10

StudyFreq

DeedsFreq

TextEFreq

AulawFreq

BlankFreq

OtherFreq

StudyTime

DeedsTime

TextTime

Marks

=== Associator model (full training set) ===

Apriori

Minimum metric <confidence>: 0.5

CM	Rules
Session-2 105	<ol style="list-style-type: none"> 1. TextEFreq=low AulawFreq=low StudyTime=low 51 ==> Marks=low 37 conf:(0.73) 2. BlankFreq=low OtherFreq=low StudyTime=low 54 ==> Marks=low 39 conf:(0.72) 3. BlankFreq=low StudyTime=low 61 ==> Marks=low 44 conf:(0.72) 4. TextEFreq=low StudyTime=low 57 ==> Marks=low 41 conf:(0.72) 5. AulawFreq=low StudyTime=low 64 ==> Marks=low 46 conf:(0.72) 6. StudyTime=low 71 ==> Marks=low 51 conf:(0.72) 7. TextEFreq=low OtherFreq=low StudyTime=low 53 ==> Marks=low 38 conf:(0.72) 8. BlankFreq=low 67 ==> Marks=low 48 conf:(0.72) 9. OtherFreq=low StudyTime=low 63 ==> Marks=low 45 conf:(0.71) 10. AulawFreq=low BlankFreq=low StudyTime=low 56 ==> Marks=low 40 conf:(0.71) 11. BlankFreq=low OtherFreq=low 59 ==> Marks=low 42 conf:(0.71) 12. TextEFreq=low BlankFreq=low StudyTime=low 52 ==> Marks=low 37 conf:(0.71) 13. TextEFreq=low BlankFreq=low 58 ==> Marks=low 41 conf:(0.71) 14. StudyTime=low TextTime=low 58 ==> Marks=low 41 conf:(0.71) 15. AulawFreq=low OtherFreq=low StudyTime=low 58 ==> Marks=low 41 conf:(0.71)

Session-3 63	1. StudyFreq=low DeedsFreq=low OtherFreq=low 76 ==> Marks=low 44 conf:(0.58) 2. StudyFreq=low OtherFreq=low 82 ==> Marks=low 47 conf:(0.57) 3. StudyFreq=low DeedsFreq=low StudyTime=low 77 ==> Marks=low 44 conf:(0.57) 4. StudyFreq=low StudyTime=low TextTime=high 77 ==> Marks=low 44 conf:(0.57) 5. StudyFreq=low DeedsFreq=low 79 ==> Marks=low 45 conf:(0.57) 6. StudyFreq=low OtherFreq=low StudyTime=low 81 ==> Marks=low 46 conf:(0.57) 7. StudyFreq=low StudyTime=low 83 ==> Marks=low 47 conf:(0.57) 8. StudyFreq=low 85 ==> Marks=low 48 conf:(0.56) 9. StudyFreq=low TextTime=high 78 ==> Marks=low 44 conf:(0.56) 10. DeedsFreq=low OtherFreq=low 78 ==> Marks=low 44 conf:(0.56) 11. OtherFreq=low 84 ==> Marks=low 47 conf:(0.56) 12. DeedsFreq=low StudyTime=low 79 ==> Marks=low 44 conf:(0.56) 13. StudyTime=low TextTime=high 79 ==> Marks=low 44 conf:(0.56) 14. StudyFreq=low AulawFreq=low OtherFreq=low 79 ==> Marks=low 44 conf:(0.56) 15. DeedsFreq=low 81 ==> Marks=low 45 conf:(0.56)
Session-4 74	1. StudyFreq=low 97 ==> Marks=high 70 conf:(0.72) 2. StudyFreq=low TextEFreq=low 97 ==> Marks=high 70 conf:(0.72) 3. StudyFreq=low StudyTime=low 97 ==> Marks=high 70 conf:(0.72) 4. StudyFreq=low DeedsTime=low 97 ==> Marks=high 70 conf:(0.72) 5. StudyFreq=low TextEFreq=low StudyTime=low 97 ==> Marks=high 70 conf:(0.72) 6. StudyFreq=low TextEFreq=low DeedsTime=low 97 ==> Marks=high 70 conf:(0.72) 7. StudyFreq=low StudyTime=low DeedsTime=low 97 ==> Marks=high 70 conf:(0.72) 8. StudyFreq=low TextEFreq=low StudyTime=low DeedsTime=low 97 ==> Marks=high 70 conf:(0.72) 9. TextEFreq=low 99 ==> Marks=high 71 conf:(0.72) 10. StudyTime=low 99 ==> Marks=high 71 conf:(0.72) 11. DeedsTime=low 99 ==> Marks=high 71 conf:(0.72) 12. TextEFreq=low StudyTime=low 99 ==> Marks=high 71 conf:(0.72) 13. TextEFreq=low DeedsTime=low 99 ==> Marks=high 71 conf:(0.72) 14. StudyTime=low DeedsTime=low 99 ==> Marks=high 71 conf:(0.72) 15. TextEFreq=low StudyTime=low DeedsTime=low 99 ==> Marks=high 71 conf:(0.72)
Session-5 76	1. StudyTime=low TextTime=low 86 ==> Marks=high 78 conf:(0.91) 2. StudyTime=low DeedsTime=low TextTime=low 86 ==> Marks=high 78 conf:(0.91) 3. OtherFreq=low StudyTime=low TextTime=low 84 ==> Marks=high 76 conf:(0.9) 4. OtherFreq=low StudyTime=low DeedsTime=low TextTime=low 84 ==> Marks=high 76 conf:(0.9) 5. AulawFreq=low StudyTime=low TextTime=low 83 ==> Marks=high 75 conf:(0.9) 6. AulawFreq=low StudyTime=low DeedsTime=low TextTime=low 83 ==> Marks=high 75 conf:(0.9) 7. TextEFreq=low StudyTime=low TextTime=low 82 ==> Marks=high 74 conf:(0.9) 8. TextEFreq=low StudyTime=low DeedsTime=low TextTime=low 82 ==> Marks=high 74 conf:(0.9) 9. AulawFreq=low OtherFreq=low StudyTime=low TextTime=low 82 ==> Marks=high 74 conf:(0.9) 10. AulawFreq=low OtherFreq=low StudyTime=low DeedsTime=low TextTime=low 82 ==> Marks=high 74 conf:(0.9) 11. TextEFreq=low OtherFreq=low StudyTime=low TextTime=low 81 ==> Marks=high 73 conf:(0.9) 12. TextEFreq=low OtherFreq=low StudyTime=low DeedsTime=low TextTime=low 81 ==> Marks=high 73 conf:(0.9) 13. StudyTime=low 88 ==> Marks=high 79 conf:(0.9) 14. StudyTime=low DeedsTime=low 88 ==> Marks=high 79 conf:(0.9) 15. OtherFreq=low StudyTime=low 86 ==> Marks=high 77 conf:(0.9)

An Association Rule Mining Based Model to Predict Learning Performance of a student with e-Learning Activity Log Data

Session-6	1. DeedsFreq=low 84 ==> Marks=low 76 conf:(0.9)
	2. TextEFreq=low 84 ==> Marks=low 76 conf:(0.9)
112	3. DeedsTime=low 84 ==> Marks=low 76 conf:(0.9)
	4. TextTime=low 84 ==> Marks=low 76 conf:(0.9)
	5. DeedsFreq=low TextEFreq=low 84 ==> Marks=low 76 conf:(0.9)
	6. DeedsFreq=low DeedsTime=low 84 ==> Marks=low 76 conf:(0.9)
	7. DeedsFreq=low TextTime=low 84 ==> Marks=low 76 conf:(0.9)
	8. TextEFreq=low DeedsTime=low 84 ==> Marks=low 76 conf:(0.9)
	9. TextEFreq=low TextTime=low 84 ==> Marks=low 76 conf:(0.9)
	10. DeedsTime=low TextTime=low 84 ==> Marks=low 76 conf:(0.9)
	11. DeedsFreq=low TextEFreq=low DeedsTime=low 84 ==> Marks=low 76 conf:(0.9)
	12. DeedsFreq=low TextEFreq=low TextTime=low 84 ==> Marks=low 76 conf:(0.9)
	13. DeedsFreq=low DeedsTime=low TextTime=low 84 ==> Marks=low 76 conf:(0.9)
	14. TextEFreq=low DeedsTime=low TextTime=low 84 ==> Marks=low 76 conf:(0.9)
	15. DeedsFreq=low TextEFreq=low DeedsTime=low TextTime=low 84 ==> Marks=low 76 conf:(0.9)

Table 1 – The Comparison with Cyclomatic Complexity of Sessions [5] and Previous results[3]

(The confidence of getting a high or a low mark is assumed as mid-value of 0.5 if it is unknown)

	Session 2	Session 3	Session 4	Session 5	Session 6
CM[5]	105	63	74	76	112
Normalized CM (CM/maxCM)	0.94	0.58	0.66	0.67	1
Apriori-Confidence Of Low Mark	0.73	0.58	0.72	0.91	0.9
Apriori-Confidence Of High Mark	0.5	0.5	0.77	0.78	0.5
Precision of MLP-NN in finding Low Grades	0.695	0.596	0.385	0.1	0.893
Precision of MLP-NN in finding High Grades	0.304	0.5	0.753	0.877	0
Precision of RBF-NN in finding Low Grades	0.667	0.534	0.136	0	0.915
Precision of RBF-NN in finding High Grades	0.188	0.414	0.675	0.871	0.5

As shown in the following graphs, the confidence of getting high or low marks in a session is very much coping with the Cyclomatic Complexity of Sessions calculated in the previous study[5].

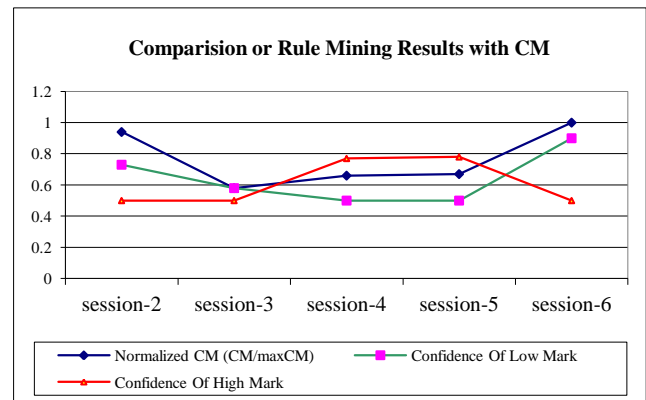


Figure 4. The Comparison with CM of Reference Paper[5]

As shown in the following graphs, the confidence of getting high marks in a session is very much coping with the results of our previous work [4]

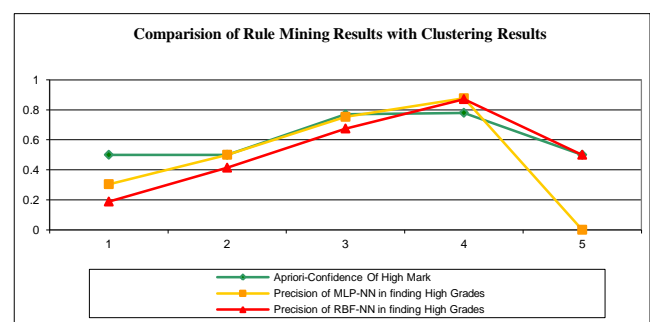


Figure 5. The Comparison with our Previous Results[4]

A. Interpretation Of The Discovered Rules

The above rules are discovered with the session-2 EPM data set. These rules signify “low” activity of students in almost all the category of activities on the online education platform.

The top rules show that there is much confidence of the result in which the students are getting poor marks because of this poor activity.

Further, it can be used as a metric for measuring the complexity of the online teaching session.

The results of this work are summarized with the following findings:

1. We propose an association rule mining model to mine the knowledge from the categorical dataset. So that it is to be used to refine an e-Learning System or an Educational Model.
2. We calculate the common metrics of clustering and classification such as precision, recall, f-score, accuracy, etc., to measure the complexity of a learning session design as well as metric for measuring student learning performance and proved that the measurements made with our proposed metrics correlate with the results of the precious metric, Cyclomatic Complexity.
3. We propose the application of common rule mining metric such as confidence and support to measure complexity of a learning session design and to measure student learning performance and proved that the measurements made with our proposed metrics correlate with the results of precious metric, Cyclomatic Complexity.
4. All the confidence of getting high or low marks in a session is very much coping with the Cyclomatic Complexity of Sessions calculated in the previous study[5] as well as our previous results with clustering algorithm based metrics.
5. It means the top rules mined from the data were able to explain the complexity of the educational sessions.

V. CONCLUSION

The altered time-series activity data set as multi-dimensional categorical data set is taken for the assessment. We verified a conventional Apriori association rule mining algorithm on this dataset. It helps to determine some meaningful results from the dataset. As our results show, we have achieved our goal. We proved that the top rules mined from the data were able to explain the complexity of the educational sessions. So the applied data transformation technique and the rule mining model can be used to understand and to improve any teaching or learning sessions. In this research, we proposed two kinds of data transformation techniques to transform the complex, time-series EPM data set to simple numerical and categorical datasets for easy data mining. The results have been summarized and compared with our previous Neural Network algorithms MLPNN and RBFNN. Further, we proposed classification based models to classify these data sets and we proposed the rule mining based model to mine rules from this complex data. Future work may use the clustering, classification and rule mining algorithms in combination to model a hybrid system for mining DPM data and try to discover more significant and much understandable knowledge from it. Further, one may address the possibilities of incorporating more advanced AI-based techniques along with the existing EPM design.

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