Studies and Analysis of Performance Evaluation of Different Student Models with Data Mining Techniques

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Abstract -- The education environment mostly concerns the outcome based education rather than the physical activity they engage in the learning activity. The outcome of any system is depending on the model of the system. In the present paper various models of EDM are presented and discussed their advantages and disadvantages retrieved from various literatures. A wide variety of EDM models traditional and other advanced models are presented in this paper. Several metrics are available to evaluate the performance of different student models. Different metrics are discussed here to support the suitable metric for the student models. In this paper the merits and demerits of mostly used metrics are explored and stated the suitable metric.

Keywords -- Student models, Metrics, Educational Data Mining, Performance evaluation.

I. INTRODUCTION

Student performance evaluation is one of the biggest challenges in the present education scenario. Improper student performance evaluation may affect the university ranking, may affect the proposed analysis report prepared for lag students. This report will help the student to take the right decision for their future performance optimization. Based on this report a supervisor can guide the students to enhance their performance in their academic curriculum. The performance evaluation depends on many factors. The factors may influence the performance evaluation process directly or indirectly. Some of inter and intra mutual dynamics influences the performance evaluation. In this context several methods are effectively involved in evaluation process to avoid deviations from the actual requirements. Due to large databases many of the existing techniques failed to analyse the huge student related data. To evaluate large databases an efficient datamining techniques are mandatory to assess a student speculative track perfectly. There are various data mining techniques available to search appropriate record and information from large databases. In the present work various methods are implemented to assess student performance for analysing student achievement and future performance track. Educational Data Mining (EDM) techniques are used to analyse large student data sets. EDM techniques will boost the searching process speed and analysis. In the present work the existing techniques are discussed and presented the defects in various contemporary techniques.

The aim of this research is to show the potential of (Educational Data Mining) EDM in enlightening the criteria or measures of effective student performance as perceived by the instructor. The EDM is the branch of soft computing which deals with the concerned data obtained by exploring various education evaluation methodologies to make the students better accustom the current system and to understand the students in the given environment. The EDM is a branch of combination of psychology and learning analytics which are frequently used in analysing student data and reconfiguring the learning model [1][2]. In recent trends of educational data mining approaches the various algorithms and tools to reach the appropriate student evaluation statistics. The EDM uses various algorithms like machine learning algorithms, data mining techniques and statistical analysis to collect information at various educational and learning schemes. The EDM is a recent research area combination of or mainly concentrated on topics machine learning, data mining, and statistics [3][4]. New opportunities such as graphics, games, simulations, and tutorials have built in emerging EDM technology to collect student information easily. The data will help the educators to meet their requirements discussed in the above paragraphs. The goals [5] of EDM are classified as predicting students' future learning behaviour, discovering or improving domain models, studying the effects of educational support, and advancing scientific knowledge about learning and learners. For the benefit of reader the merits are presented concisely here.

1. The student performance can be predictable in the given environment.
2. Able to design and modify the student learning methodologies by integrating information such as student knowledge, attitude, motivation etc., obtained from EDM tools
3. Estimation of consequences can be calculated after applying every modification of learning methodologies.
4. It allows reconfiguring advanced Information Communication Technologies (ICT) by building learning and computational model and incorporating knowledge database.

Levels of Educational Data Mining
As the research area growing day by day variety of data mining techniques came into picture with respect to the context of education environment. After applying each technique the researchers must see that ultimately reach the above goals and benefits. To satisfy the above goals and benefits the EDM is divided into four different levels [1][6].

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Level 1: In the first level of EDM identify the meaning full relationship between data. This process mainly involves the mining of data in educational environment. Various techniques are effectively involved in identifying the relationships to reach the specified goal. Some of the algorithms are classification, associate rule mining, regression, factor analysis, Clustering, sequential pattern mining, and social network analysis.

Level 2: Validate the relationship identified in level 1. This is done after pre-processing to avoid overfitting.

Level 3: Apply the validated relationships to predict the future planning in learning methodologies.

Level 4: Finally the decision making process is applied based on predictions obtained in level 3.

Various applications of EDM System
With the advancement of EDM technology the applications of EDM is widely spread in to many areas, some of them are present here.

- Designing Innovative Student modelling
- Provides effective feedback which helps the instructors to decide the plan of action
- Predicting performance of student in education environment
- Identifying the student attitude
- Studying student Psychology
- Analysis of Social Networks
- Developing Course Plan

Limitations of EDM
Although the vast growing of EDM enriches the experience of both students and instructors, on the other side it is facing some challenges as described below.

- The EDM techniques are implemented in a particular education environment and for specific time period. Hence the results may not be applicable to all educational institutes and at all time. The learning model developed for a particular size of student strength, may not be suitable for all types of institutions.
- The learning methods are developed based on their psychology, IQ level, and culture. Hence learning models may vary from country to country.
- The Education data mining tools are freely available in the market. The parents and students are enthusiastic in using those tools to assess the performance. But it leads privacy concern of individual personality.
- The EDM tools are widely spreading in educational institutions. Many institutions are adopting the EDM tolls in their teaching and learning tools. But there is no strategy of evaluation for whether it is accustom to the present state of instructors or all level of students.
- The plagiarism is one of the biggest challenges for the teachers facing in class rooms and online teaching methodologies. The learning models should concentrate on the individual student performance and avoiding duplication.
- In addition developing new learning models with traditional methods like computer assessment and in other environment is difficult. So, developers are expanding the EDM to new frontier like collaborative work and in informal learning environment.

II. TYPES OF EDUCATIONAL DATA MINING TECHNIQUES FOR DIFFERENT STUDENT MODELS
In this section some of mostly used student models are presented from literature survey. These student models are very much use full in analysing student performance. The model is developed with prediction, clustering, or with some human intelligence methods. This model can be used as component in another model analysis such as relationship mining.

In predicting analysis the predicted variables are used as components in predicting a new variable in another model. The knowledge component of a student in a particular domain of a model will help to assess the student knowledge. It is represented as mapping between current knowledge components and learning component [7][8].

In relationship mining the relationships are studied between model predictions variables and additional variables. This will allow the researchers to analyse wide variety of model predictions in wide complex context [9].

A. Traditional Modelling

Skill Modelling: The mostly used student models are student skills or skill modelling [10]. In Bayesian Knowledge tracing skill modelling technique the performance of students are predicted and compared with actual pragmatic performance. These performances are compared with suitable metric discussed in the later sections. Generally the performance measure is in binary and sometimes it is measured in multiple values.

The adaptive behaviour of the education model is directed by skill model particularly in student learning model. The prediction of model parameters such as degree of learning and problem difficulty, is also important along with model prediction [11][12]. The skill models are also used in other high level model predictions and analysis [13][14][15][16][17].

Affect Model and Motivation: Along with skill model the affect model also used at different state analysis like boredom, confusion, concentration, frustration, and student behaviour. In this model the estimated prediction parameters are compared with actual predicted values measured by human observation [18].
B. Other Existing Methods

There are variety of other methods used for EDM apart from skill model and affect model. The methods are classified into clustering, prediction, relationship mining, distillation of data for human judgement, and discovery with models.

Prediction: In prediction model the knowledge of predicted variable is produced from knowledge of other predicted variable. Predictions methods are very important because they are very useful in analysing features of the model which are used for prediction. These predicted values help to analyse the student outcomes [19]. There are three types of predictions; they are classification, density estimation, and regression. The classification methods include support vector machines, decision trees, and logistic regression. The logistic regression used for binary predictions and other two supports multiple predictions. The prediction variable is continuous in regression. The popular regression methods in EDM are linear regression, support vector machine, and neural network regression. The predicted parameter is a probability density function in density estimation model. They are based on kernel functions and Gaussian functions. The input variable is either definite or continuous.

Clustering: In clustering technique the data parameters are grouped together and partitioned the group into small units. The most common features of data set are classified into one group so that data set is known in advance. In this model the data point is similar to other data point in the cluster, and it is more similar when compared with other cluster data point. For example Institutions can be considered as one cluster, student behaviour is consider as one cluster, and students can be clustered separately to evaluate the similarities between individual data points in the specific cluster [20]. A clustering algorithm defines that a data point belongs to same cluster, or belongs to multiple clusters, or no cluster (Gaussian mixture model). The clusters usually assed with Bayesian Information or how well the data points fits in the cluster.

Relationship Mining: It compares the relationships between the variable of data set with the other variable in the dataset which are under same interest. The Relationship mining is classified into four types. They are correlation mining, causal data mining, associate rule mining, sequential pattern mining. In correlation mining positive and negative relationships are found between the variables. It is linear correlation between variables. In associate mining if the data set variables have some value and another variable in the same data set will have specific value. In sequential mining temporal relationship is evaluated between variables. The causal correlation mining evaluates whether one parameter or variable depends on or caused by another variable or by triggering information of one event in the data set. The relationship mining must satisfy two principles. One is statistical significance and the second one is interestingness. The first one generally assessed with standard statistical tests. The interestingness of each variable is assessed with relationship miner to reduce the rules and correlations. In the case of thousands of significant relationships are found the interestingness model find which points are more supportive to the data.

Discovery with Model: This model is established with clustering, prediction models and sometimes with knowledge engineering with deals mostly with human intervention instead of automation. This model can be used as variable in some other model analysis such as clustering, prediction, and Relationship mining.

Distillation of Data for human judgement: When the data is presented appropriately in EDM the human can infer about the data. When human inferences occur for the data in EDM system, data refinement is required to produce appropriate data. Generally data is distilled for two key reasons. The first one is distillation for identification, where a human being can easily identify the data patterns [21]. Secondly, the data is distilled for labelling. The labelling is done by human for further development of prediction model. In this model the data sets are given in the format of visual or text format, which are labelled by human coders. These labels are used for progress of predictors.

III. METRICS

There are many metrics available to evaluate the performance of above EDM techniques implemented for student models. In this section different metrics are discussed along with their merits and demerits. The most metrics evaluate the performance of the models in binary states. In continuous prediction the best choice for metric evaluation is root mean square error. The other metric models do not satisfy in acquiring required results after model comparisons [22]. The parametric estimation algorithms can improve the reliability of the prediction [23][24]. According to Ferri et al., the metrics are classified into three categories [25].

A. Probabilistic understanding of Errors

Assume set of data about with n cases, numbered \(i \in \{1,...,n\}\), then a student model offers predictions \(P_i \in [0,1]\) and the metric in binary value is \(O_i \in \{0,1\}\). The error in metric is defined by the difference between \(P_i\) and \(O_i\). The metric is mainly depends on probabilistic of identifying predictions and errors. In other models like decision analysis and weather forecasting the assessment of probability is called score rule [26]. The function \(S\) is derived as \(S(\hat{P},\hat{O})\), where \(\hat{P}\) is predictive distribution and \(\hat{O}\) is actual outcome. The scoring level is valid if \(S(\hat{O},\hat{P}) \geq S(\hat{P},\hat{O}) \forall \hat{P}\) and \(\hat{O}\). The table I is showing the most frequently used metrics Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Log-likelihood (LL) classified based on probabilistic understanding of errors.

MAE is represented by the absolute difference between predictions and answers. As the metric selects the prediction models which are mostly influenced by the majority results, the MAE metric is not suitable metric. As per the scoring rule it is also called as improper scoring rule [26] and there may be a chance of misleading the conclusion.
Table 1: Common Metrics used for Performance Evaluation

<table>
<thead>
<tr>
<th>Type of Metric</th>
<th>Expression</th>
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<tbody>
<tr>
<td>MAE (Mean Absolute Error)</td>
<td>$\frac{1}{n} \sum_{i=1}^{n}</td>
</tr>
<tr>
<td>RMSE (Root Mean Square Error)</td>
<td>$\sqrt{\frac{1}{n} \sum_{i=1}^{n} (O_i - P_i)^2}$</td>
</tr>
<tr>
<td>LL (Log-Likelihood)</td>
<td>$\sum_{i=1}^{n} O_i \log(P_i) + (1-O_i) \log(1-P_i)$</td>
</tr>
</tbody>
</table>

In the other metric, RMSE the error is obtained by square value instead absolute values. It is used to obtain the result with the same unit as actual measurements. Hence it is used to improve the interpretability of the resulting number. For achieving good interpretability users sometime used $R^2$ metric. In Logistic regression the interpretation does not hold and a new $R^2$ is used. But there is no idea of which type of $R^2$ is used. In Educational Data Mining, for evaluation skill models particularly RMSE is frequently selected [12][27][28][29]. In weather forecasting model the MSE without square root is called Brier score or quadratic score rule [26].

The LL metric is used in student model analysis but not more than RMSE [30][31]. The LL metric is interpreted from the theoretical view of a measure of data. It is frequently used in extension with Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC). The metric correct the model parameters to avoid overfitting. With respective student model overfitting can be avoided by cross-validation. The AIC and BIC may be used in heuristic algorithms as they are quicker than cross-validation [32][33].

In Future the performance can be optimized by implementing various software growth model techniques into the specified type of student models. Hence the metrics can further operate efficiently on different models. Different optimization techniques can be used to improve the reliability of performance evaluation of different student model. The reliability of extracting Prediction variable can be improved with different parametric estimation models. The comparison of prediction variable and actual variable can be enhanced with different software growth models [34][35].

IV. CONCLUSION

In the current paper different EDM student models and their performance evaluations are presented. The performance evaluations are discussed with standard metric type. There is a fundamental difference between MAE, RMSE and LL metrics. The MAE is an improper score and RMSE and LL are proper scores. The selection of metric is depends on student model. For predictions where the outcome is in binary format in the student modelling MAE metric should not be used as it may mislead the conclusions. The RMSE or LL metric are most suitable metrics for skill based models. The RMSE metric is most frequently used metric when compared with LL metric as it has connection with Brier score. The RMSE and LL metric have similar form and they require more attention in differentiating $R^2$.

REFERENCES


N. Suresh Kumar et al. / “Modern Computer Graphics Technologies Used at Educational Programs and Some Graphical output screens”, IJCSIS, Vol8no.3 jun 2010.


