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Learning Analytics: A Comprehensive Analysis of Methods for Student Performance Prediction

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Abstract: ***Data Mining plays an important role in the Business world and it helps the educational institution to predict and make decisions related to the students' academic status. From a large volume of data in educational databases it is difficult to predict student performance. In India currently the existing systems lack in monitoring and analyzing the students' performance. The main reason is that the existing system has insufficient capabilities for identification of performance of the student and it also not considered all factors that affect the achievements of a student's in the context of India. Therefore, a systematical literature review on predicting student performance by the proposed system is a web-based which makes use of the mining techniques for the extraction of useful information.***

This work is digging insight into the state-based and event-based approaches for predicting student performance. A Comparative analysis is conducted to suggest regression-based algorithms of state-based framework lack accuracy and correlation-based algorithms under the event-driven approach outperform classical regression algorithms. It is also concluded from pedagogical a point of view, higher engagement with social media leads to higher final grades.

Keywords: Performance Prediction, Learning Analytics, Regression algorithm, correlation algorithms, social media.

I. INTRODUCTION

Student performance analytics becomes important for predicting the performance of students in the course of study. Learning analytics in that regard is a growing research area that selects, analyze and report student data, find patterns from student behavior, display information in suggestive formats with the end goal to predict student performance, achieving optimization of prediction system and customization of personalized intervention.[1] Learning analytics is a framework that is used for measurement, analysis and reporting of data about learners for understanding and optimizing learning and the environment in which it is considered. Distinct educational tasks are supported by the use of learning analytics.[2] These tasks are broadly categorized into seven categories:

1.) Monitor and analysis
2.) Intervention and prediction
3.) Feedback
4.) Modification
5.) Customization
6.) Recommendation
7.) Reflection.

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Predicting the performance of the student is one of most important objectives of Learning Analytics. Learning Analytics not only predict future performance but also set performance indicators to improve the performance of the students. Data processing is a critical aspect of learning analytics as it is required for monitoring the learning progress of students, instructor can be advised to change study patterns for students who are in need of more assistance[3]. In addition individual the strategies for poor students with personalized intervention and feedback can be set for the guidance of students using the application of predictive modelling. The utilization framework for predictive modelling along with used metrics is elaborated in Figure 1.The primary component associated with LA is learning that could be distinguished as supervised and unsupervised mechanisms. These mechanisms form an effective part of the performance and monitoring module of LA. [4]The effectiveness of learning analytics is judged in terms of classification accuracy. The classification accuracy of learning analytics must be considered high otherwise wrong predictions could have an adverse effect on career the of students. [5]

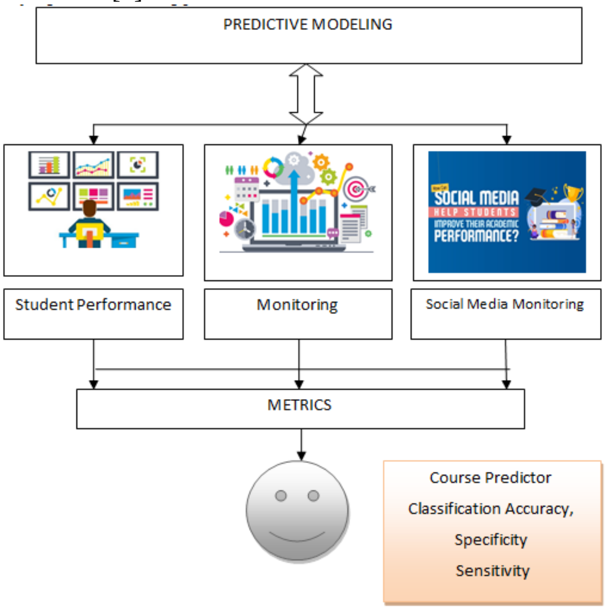

Figure 1: Framework for learning analytics

The rest of the paper is organized a follows. Section 2, presents the related work of the techniques used for performance monitoring, Section 3 gives the algorithm analysis corresponding to state and event-driven algorithm, Section 4, compares the state and event-driven algorithm. The last section concludes the paper.

II. REVIEW METHODOLOGY

The review process included the following steps:

1. Describing inclusion and exclusion criteria.
2. Defining the work analysis of student performance monitoring.
3. Explaining the existing techniques that are used for student performance monitoring.
4. Defining the problems with existing techniques and gives a comparative analysis.

A. Describing inclusion and exclusion criteria

After an initial selection of 24 papers, the relevant studies were determined following the inclusion/exclusion criteria as follows.

i. Inclusion Criteria

• Include the papers discussing the longitudinal analysis of the evolution of student performance systems' structure, and giving empirical evidence thereof;

• Include the research studies that combine the evolution of student performance monitoring software structure along with the evolution.

• Include studies which propose different strategies to analyze and/or predict student performance monitoring;

• Include studies on various techniques used for student performance evolution to complete the picture wherever need be. Though such studies were not part of the initial selection, they were included by following the references in the selected set of studies

ii. Exclusion Criteria

• Exclude research studies focusing only on the monitoring;

• Exclude the studies which don't report any empirical results;

• Exclude Review Studies.

B. WORK ANALYSIS OF STUDENT PERFORMANCE MONITORING

The significant part of learning analytics is predictive modeling for learning and teaching; the main motive of this is to the forecast success of the student in terms of achievement in academics[6][1]. Knowledge, score or grade, performance; can be the predicted values; classification approaches are basically used for values that are discrete/categorical, and approaches of regression for values that are numerical/continuous.

From the previous literature it is found that for predictive models two types of data are used that is (i) state-based data- e.g. Past performance, demographics, psychological traits; (ii) event–driven data:-it is based on the activity of student, it is derived from interaction of student with educational system and resources[7][2]. The latter can be in the form of structured(e.g., server logs) or unstructured(e.g., forum postings)[8][3].It can be derived from an educational system that is centralized(e.g., LMS) or learning environment that is distributed (e.g., formal and informal platforms, spread across space, media and time)[9][4]. The sources of data include MOOCs(massive open online courses), social media or wearable sensors, the integrity of these are directing to more accuracy of the models of learner[10][5].

An additional classification of the indicators of performance as, given in [11][6], includes three types:

I) Dispositional pointers (e.g., age, gender, past learning encounters);
II) Movement and execution markers (e.g., no. of logins, time depleted, number of talk posts);
III) Student ancient rarities (e.g., expositions, blog entries, gathering exchanges) [12] [7]. Around 200 pointers were perceived in a survey done in [13][8]; inside them, oftentimes utilized are: statistic qualities, earlier evaluations, portfolios, multimodal aptitudes, levels of sharing and duty, mind-set and full of feeling states [14][9].

So far as computational techniques are concerned, large no. of methodologies have been applied for predicting performance of students[15][10], such as linear regression[16][11], logistic regression [17][12], neural network models [18][13], support vector machines and k-nearest neighbours[19][14], Bayesian networks[20][15], decision trees[21][16] or genetic algorithms[22][17]. While provided that a whole review of literature is ahead of the scope of this paper, in what follows we express a few (recent) proposals in academic performance prediction, which are more narrowly connected to our work.

N. Hoic-Bozic, M. Holenko Dlab, and V. Mornar.[23] W. Feng, J. Tang, and T. X. Liu[18] 'explored students' usage data in Moodle LMS as a forecaster for their grade of exam. 438 students from seven engineering courses were included in the study.

Eight attributes related to learner action on quizzes, assignments, and forum messages were calculated for each and every student. For classifying students with similar grades, authors applied various data mining techniques . Performance comparisons were carried out, with various pre-processing techniques. On the whole, the accuracy obtained is not very high (around 65%), representing the complexity of the prediction task.

R. R. Kabra and R. S. Bichkar[24] K. B. Eashwar and R. Venkatesan[19] also analyzed students' online activity in a LMS, in the framework of a blended medical course, aiming to show a relationship it with the learners' course performance. 133 students utilized LMS for about a month and a half and various information is gathered: logins, asset sees, discussion posts and peruses, time spent utilizing instructive materials, developmental assessment results. Five commitment markers were determined to rely upon students' follows. For evaluation expectation programmed straight demonstrating was utilized, prompting a 63.5% exactness. Moreover, double strategic relapse was utilized for foreseeing students at threat, with a precision of 80.8%.

A. Pinjuh[25] R. Bekele and W. Menzel [20] Focused on the utilization of students' commitment in a discussion gathering as a displayer of student execution. Information was taken from 114 students that are tried out an early on a software engineering course. They utilized the gathering that is incorporated into Moodle LMS for talking about the substance obviously , posing inquiries or giving assistance to peers and took a test at the remainder of the semester. The creators proposed to gauge whether students passed or bombed the course dependent on their gathering utilization, in states of quantitative, subjective and informal organization pointers.A contrast between traditional classification and clustering algorithms implemented in Weka was performed, together with various approaches for instance and attribute selection.

J. Chen, J. Feng, X. Sun, N. Wu, Z. Yang, and S. Chen [26] A. Rosenfeld, S. Sina, D. Sarne, O. Avidov, and S.

Kraus[21] investigated students' interaction patterns with digital textbooks as predictors of course grades. Data was collected from 233 students from 11 courses (such as Introduction to Accounting, American Judicial Process, Human Resource Management etc.) they take into account a digital textbook presented by Course Smart supplier. The authors performed linear regression analysis on textbook practice metrics and found out that time used up reading was a strong forecaster of course grade. The Engagement Index score (computed by Course Smart based on various usage metrics) was also a good display of the course result (better than prior academic achievement).

B. J. Carter [27], D. Q. G. Ix, J. Dojrulwkp, D. Dpvd, [22] used a mixed-effects analysis of variance (ANOVA) models to evaluate the impact of using Twitter on college student engagement and learning outcomes. The engagement was measured with a dedicated instrument called National Survey of Student Engagement. Results showed a significant increase in both engagement and grades for the experimental group, in which students used Twitter for various types of academic discussions.

E. Popescu and F. Leon [28], N. Hoic-Bozic, M. Holenko Dlab, and V. Mornar [23] investigated whether students' engagement with a collaborative wiki tool can forecast educational performance. Significant correlations were found between wiki activity indicators (number of page edits, number of different articles edited, number of days on which the student-edited the wiki) and the course grade. The originality of our existing work consists of the utilize of a novel algorithm, called Large Margin Nearest Neighbour Regression (rather than classic algorithms, available in a variety of data mining engines, as mentioned in the related works). An initial study depending on one student only cohort yielded hopeful results.

A. A. Amra [29], R. R. Kabra and R. S. Bichkar[24]; this paper extends the pilot study to a much-outsized number of students (six cohorts, over the course of six years), also providing a requirement of the LMNNR technique, as described next

III. BACKGROUND ANALYSIS OF ALGORITHMS

In this study, we have considered only state and event-driven algorithms for evaluation. The state-driven algorithms are dependent upon historical data and strictly static in nature.

The comparison of techniques using state and event-driven approaches is given in table 1.

The mechanism followed in state-driven approaches is generally historical data based and hence convergence rate is generally a problem but with event-driven approach data in real time in nature and convergence rate is also good. This is demonstrated in table 1 also.

Table 1:- Parametric comparison of state and event-based approach:-

Parameter	**State driven approach**	**Event driven approach**
Dataset	Historical	Real-time
Convergence Rate	Low	High
Specificity	Specificity measure degree of the false positive rate that is high in state-driven approaches	Low specificity indicates better performance
Sensitivity	Sensitivity indicating degree of true positive is low	High sensitivity is accomplished through this approach
Accuracy	Classification accuracy is hampered by noisy data	Classification accuracy is rectified using pre-processing mechanisms
Learning rate	Learning rate is about 60-70%	Learning rate is about 80-90%
Coupling	High coupling indicating high dependency on modules	Low coupling indicting modules can be changed without affecting other modules
Cohesion	Cohesion is high	Cohesion is low causing performance degradation in the changeable entity
Mobility	Modifiable data does not degrades accuracy	Modifiable data causes classification accuracy to decay considerably.

The classification of state and event-driven approach is presented in figure 2

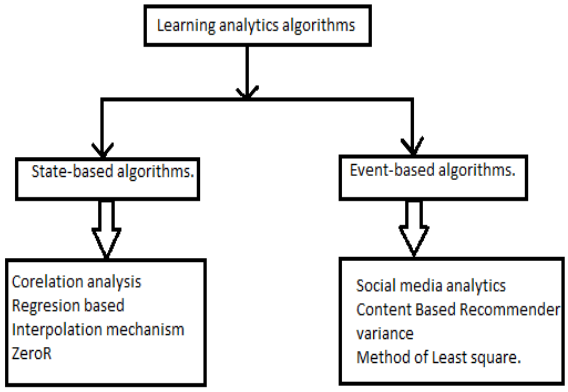

Figure 2: Algorithms for performance prediction

The various algorithms that are used for performance prediction are given below:

A. State -Based Algorithm

This is the one that is based on the previous data analysis. In this the data that are stored utilized for further analysis.

I. Correlation Analysis

It is a widely used technique that is used to identify relationships in data that helps in predicting the target classes. This measures how the variable is predicted using another set of values. It measures the relationships between two variables and the result shows the effect of one variable change to another variable. The comparison of two variables correlation is to be done and the changes are seen. It analysis the dependent variable and independent variables that help in predicting the values.

[30]It decides the quality of a relationship between two sets, which can be a dependent and a free factor or even two autonomous factors. In such a case, the quality can be distinguished dependending on the bearing, structure, and scattering quality. Numerically, this relationship is normally a dictated by a decimal esteem, known as the correlation coefficient. The correlation coefficient has a resolved under a certain predefined run (contingent upon the calculation). In light of the estimation of the coefficient in the given range, its quality and course can be resolved. The coefficient having positive sign shows that the two factors are decidedly related, though negative sign demonstrates a negative relationship. A higher number of coefficient demonstrates that the two factors have solid connection and lower esteem shows generally. For instance, Lift is one relationship measure with a coefficient going around one. However that the esteem is more prominent than one, at that point the two factors are decidedly associated; else, they are contrarily connected. On account of the esteem being 1, there is no relationship. This relationship encourages us to distinguish the independent and dependent variables.

Consider two variables A and B. Then the Pearson's correlation coefficient can be calculated using the following formula

$$C_{A,B} = \frac{Covariance(A,B)}{\sigma_A \sigma_B}$$

II. Regression Analysis

Regression analysis is a statistical-based technique that is used to establish a relationship between dependent variables and the predictors set. It is a data mining technique that utilizes supervised learning for prediction. In supervised learning the database is divided into validation and training data that are used in regression analysis[31]. Regression Analysis is a measurable apparatus that uses the connection between at least two quantitative factors with the goal that one variable (subordinate variable) can be anticipated from the other(s) (autonomous factors).

In any case, regardless of how solid the factual relations are between the factors, no circumstances and logical results example are fundamentally suggested by the regression model. Regression analysis comes in numerous flavors, including direct, different direct, curvilinear, and various curvilinear regression models, just as strategic regression. Strategic Regression is utilized when the reaction variable is a twofold or subjective result. Also it calculated regression finds a "best fitting" condition similarly as direct regression does, the standards on which it does as such are somewhat unique.

III. Interpolation Model

The way through which the unknown values are found from known values is known as interpolation. In this the knowledge of two points is required and also the rate of change must be constant. The tabulated functions are expensive in order to store a large set of values so the arbitrary values of the arguments are calculated. [32]

For example: the value of (X_i, Y_i) is calculated using function Y=f(x). where i =0,1,2,3………. N. the value of y is estimated using the intermediate values of x . this process is known as interpolation.

IV. Regression-based analysis ZeroR

This procedure utilizes examination to fabricate classifiers and after that characterization is finished. In the arrangement information is anticipated by utilizing class names. These dataset are additionally partitioned into test set and preparing sets. Further investigation is finished utilizing this test set and it haphazardly inspected dataset. The tuples remaining that are not used to build classifiers are independent of the training set and dataset. The classifiers accuracy is estimated using the test set. It will give the test tuples that are classified correctly. It uses cross-validation to predict higher accuracy.[33]

Event-based Analysis

These analyses are based on real time data set values. It is also used to predict the values. The various techniques that are used are as given below:

I. Social media analytics

Social media analytics (SMA) consists of the methodology of gathering information from social media destinations and writes and assessing that information to settle on business choices. This procedure goes past the typical observing or an essential investigation of re-tweets or "preferences" to build up a top to bottom thought of the social purchaser. [34]This is viewed as the essential establishment for empowering ventures to:

• Execute centered commitment like balanced and one-to-numerous.

• Enhance social joint effort over an assortment of business capacities, for example, client administration, promoting, support, and so on.

• Maximize the client experience.

Social media is a decent medium to see continuous buyer decisions, aims and opinions.

The most pervasive utilization of social media analytics is to become acquainted with the client base on a progressively enthusiastic dimension to help better target client administration and promoting.

II. Content Based Recommender

The recommender system is based on the data that is provided by the users using implicit or explicit methodology. On the basis of this data, the profile of the user is generated that which is further used for making suggestions. According to these suggestions users, take action and the recommendation becomes more or more accurate[35]. It utilizes the terms term frequency and inverse document filtering that are used to find the importance of documents within the system.

III. Variance

It is used to measure the spread between the numbers in the dataset. In this first of all mean value is calculated by taking the difference of each number in set and then mean of squaring of values are taken after that sum of all values in the set is done. [36]

3.10 Variance

$$\sigma^2 = \frac{\sum_{i=1}^{n}(x_i - mean(x))^2}{n}$$

where:

xi=the ith data point

$\bar{x}$=the mean of all data points

n=the number of data points

IV. Method of least square

It is a statistical technique that is used to find a line of best fits for the set of values. This provides the visual representation of the relationships between various data points. It describes the relationship between the dependent and independent variables using each point in the variable. [37]

The least-squares method gives the general justification to the situation of the line of best fit among the information focuses being examined. The most widely recognized use of the least-squares method, which is alluded to as direct or standard, expects to make a straight line that limits the aggregate of the squares of the mistakes created by the aftereffects of the related conditions, for example, the squared residuals coming about because of contrasts in the watched esteem and the esteem foreseen dependent on the model.

IV. PROBLEM DEFINITION

The existing SVM technique is used prediction rate that is used for predicting the performance of the student. But it does not handle misleading data properly and the classification accuracy is less. The state-based approaches use previous data set for prediction but the current values ignored so the prediction rate is not good. The event-driven approaches utilizes real-time values and give relationships among these values so that predict rate accuracy improved but it does not consider. Therefore, historical data therefore the performance of student cannot be accurate.

The comparative analysis of these techniques is given in below table 2:-

Technique	Advantages	Disadvantage
State-driven approaches	It is used to handle any problem with the extracted values from the dataset and also predict relationships among these values	Missing values causes the problem and classification accuracy is a problem
Event driven approaches	Useful educational data are extracted for predicting the student evaluation at an early stage using real-time data.	There is no mechanism present that group both real-time and historical data to accomplish greater classification accuracy.

V. CONCLUSION

In this paper we analyzed the various techniques that are used to predict student performance. It gives a detailed review of state-driven and event-driven algorithms that are used for prediction. Also, the comparative study is done that elaborates on the limitation of existing techniques. It explained that regression-based algorithms of state-based framework lack accuracy and correlation-based algorithms under the event-driven approach outperforms classical-regression algorithms. It is also concluded from a pedagogical point of view, higher engagement with social media leads to higher final grades. For resolving this problem we proposed a least square method that has more accuracy in predicting the performance of students.

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