The Effectiveness of Implementing Prescriptive Analytics in Addressing Student Academic Needs and Behavioral Challenges

M.S.Sassirekha

Department of Applied Mathematics and Computational Science, Thiagarajar College of Engineering, Madurai-15

Abstract - The challenge of students struggling to pass exams on their first attempt is a pressing issue in higher education institutions. Such difficulties not only undermine the academic progress of individual students but also compromise the overall pass rate and reputation of the institution. To address this problem, researchers have proposed the implementation of an early warning system, which could leverage data analytics and machine learning techniques to proactively identify students at risk of academic failure and provide them with timely interventions and support to improve their performance. In this research paper, the key aspects of developing and deploying such an early warning system is explored. First, descriptive analytics was conducted to analyse and filter the relevant data, identifying the critical features that influence student performance and then employed various machine learning models to generate predictions and determine the best-performing model using a sample of 500 students from a pool of 4,000. Based on the insights gained from the predictive analytics, we designed a set of interventions and support measures to be offered to the students identified as being at risk of academic failure. To evaluate the effectiveness of these interventions, we divided the student sample into a control group and an experimental group, with the latter receiving the targeted support.

Keywords- Prescriptive Analytics, Student Academic Needs, Behavioural Challenges, Machine learning, Data Analytics

1. INTRODUCTION

Business analytics has become an increasingly important tool for organizations seeking to gain a competitive edge and make more informed strategic decisions. The process of business analytics involves analyzing historical data using statistical methods and technologies to uncover new insights and patterns that can inform decision-making. (Bayrak, 2015). There are three primary components of business analytics: descriptive, predictive, and prescriptive. Descriptive analytics focuses on understanding the current state of the business by analyzing past and real-time data, providing insights into what has happened. (Bayrak, 2015) Predictive analytics, on the other hand, uses mathematical models to forecast future behavior and potential outcomes based on existing data. Prescriptive analytics takes this a step further by recommending specific courses of action or strategies based on the analysis of potential scenarios, available resources, and past performance. (Bayrak, 2015). In the realm of analytics, prescriptive analytics stands out as a powerful tool for organizations seeking to optimize their decision-making and achieve the best possible outcomes. Prescriptive analytics goes beyond the realm of descriptive and predictive analytics by not only understanding what has happened in the past and what is likely to happen in the future, but by providing recommendations on the optimal actions to take (Katerina Lepenioti, 2020). Optimization and heuristics are two key components of prescriptive analytics.

Control and Experiment group: A control group is one that is kept distinct from the rest of the experiment so that the independent variable being examined has no bearing on the outcome. This helps rule out alternate explanations for the experimental results by isolating the impact of the independent variable on the experiment. A test sample or group that receives an experimental method is referred to as the experimental

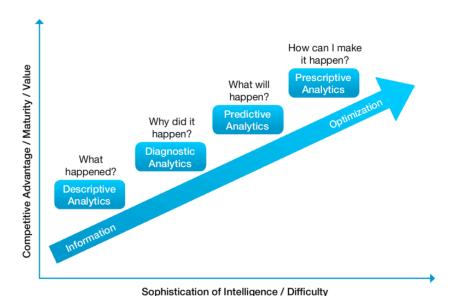


Figure 1 Gartner Framework of Data Analytics

group. Changes in the independent variables tested were presented to this group. The values of the independent variables and their impact on the dependent variable were recorded. At any given time, an experiment may comprise of many experimental groups. Although each experiment had an experimental group, not every experiment required a control group. When the experimental circumstances are complex and difficult to isolate, controls are particularly beneficial. Control experiments included control groups. The control and experimental groups were pitted against one another. The only difference between the two groups was that the independent variable in the experimental group was altered. In the control group, the independent variable is "controlled" or kept constant. A single experiment can contain many experimental groups, all of which can be compared with the control group. The objective of having control was to rule out other factors that could affect the outcomes of the experiment. Control groups are not included in all trials, but those that do are referred to as "controlled experiments."

2. LITERATURE REVIEW

The Education domain can make extensive use of prescriptive analysis to

- Find the best factors influencing students' performance in various portfolios such as academics, careers, and other skills (Obeid, 2018).
- First, determine the best possible techniques in a particular portfolio (Ezz, 2020).
- Improve performance rate by training machine learning models to recognize the most beneficial factors [2]
- Optimize procedures to eliminate unsuccessful attempts (Khanal, A systematic review: machine learning based recommendation systems for e-learning., 2020).

The initial step in the data analytics process is to identify the necessary information and its organizational structure. Demographic data, such as age, income, and sex, can be used to categorize and classify the information. Both numerical and categorical data can be collected during this step. The second phase of data analytics is data collection (Alarape, 2022).

The initial step in the data analytics process involves determining the information required and organizing it appropriately (Alarape, 2022). This can be done by categorizing the data according to various factors such as age, gender, income, and demographics. The information can be either numerical or categorical in nature. The next step is to collect the data using a range of methods, such as computers, online resources, cameras, environmental sources, and individuals (Badugu, 2020). Once the data has been collected, it must be organized in a spreadsheet or other statistical data-gathering software before it can be analyzed. This involves cleaning the data to ensure that it is free from duplication or errors and is complete (Badugu, 2020). This step is crucial as it helps in repairing any inaccuracies before the data is given to a data analyst for processing. It is important to note that descriptive and predictive analytics have already been applied to the dataset, and the relevant features and the best-suited model for the situation are well understood.

The population of this study comprised students of mathematics teacher candidates residing in Cimahi City, and the sample consisted of 90 individuals from this group who were selected and divided into experimental and control groups through a purposeful and random process (Hidayat, 2018).

Based on the analysis and discussion of the results, it was concluded that:

- (1) students who received instruction in Argument-Driven Inquiry (ADI) demonstrated a greater improvement in their math abilities compared to those who received direct instruction; and
- (2) there was no discernible difference in the math abilities of students who received instruction in ADI versus those who received direct instruction. Moreover, there was no observable interaction between the variables.
- (3) The development of students' mathematical creative reasoning ability was influenced by learning elements and the type of Adversity Quotient (AQ), and there was no interaction impact between these factors.
- (4) The mathematics creative reasoning ability of students aspiring to be mathematics teachers was not fully realized in terms of originality.

Research Questions

- 1) How are the features found in feature selection techniques given a focus in practice?
- 2) How does the prediction of student performance help in selecting the decision through prescriptive analytics?
- 3) Is there any improvement based on the interventions applied?

Despite the abundance of studies on prediction, there is a dearth of appropriate prescriptive analytics in the education domain for improving students' academic performance. Only a few recommender systems can be chosen from (Urdaneta-Ponte, 2021) (Otero-Cano, 2021) (Khanal, 2020) (Permana, 2019). This could be a new way of expanding research in the field of education.

3. MATERIALS AND METHODS

Prescriptive analytics were initially broken down into four key components: data, setting goals, creating an outline, and testing. In this instance, the dataset utilized was a real-time dataset of postgraduate students from a renowned engineering college in Tamil Nadu, which had a student population of 4,000. The study analyzed 300 samples of Internet and Java programming topic marks and used them as input. Several input variables, such as name, register number, email ID, date of birth, gender, course name, course

code, high school score, higher secondary score, undergraduate specialization, undergraduate overall score, entrance exam score, continuous assessment test 1, and final grade, were collected and stored in a commaseparated value (csv) file. The educational strategy for a postgraduate course involved calculating marks based on the aggregate of three internal evaluations and assignments (50 percent) and one external test (50 percent). However, the current method of detecting slow students is done too late, at the end of the semester. If a student is predicted to be unqualified after the first internal assessment, proactive interventions and extra caution during subsequent internal and external examinations may be offered. All essential data were obtained and categorized, and students were randomly assigned to groups based on their prediction for CAT2 (continuous assessment test 2) with the lowest score.

The primary objective of the study was to enhance the academic performance of students by implementing five experimental groups and a control group. The control group received traditional instruction, and the progress of the students was assessed in comparison to the other experimental groups. The first experimental group was provided with frequent training and improvement was observed. The second group took daily tests, which helped to evaluate the students' improvement in results. The third group utilized daily class attention checks with questions. The fourth group utilized peer coaching for assessment. The fifth group conducted tests and discussions on the same topic. The goal was to increase students' academic performance based on the main elements identified during the descriptive analytics phase, which included the selection of critical role-playing aspects. The chosen group of students was divided into the control group and five experimental groups to address the problem and improve the solution.

The five interventions or supports provided gave an idea of the potential value of the selected feature. Outline: Defining a specific problem or crucial component during this phase is critical. A subset of the main goal, such as enhancing student performance while taking into account one or two elements discovered, to see if the analytics were moving in the correct way. Because the educational system is a large model, a proof of concept was conducted on a group of students to ensure that the numerous proposals were effective. Minor scenarios and tests aid in validating the complete model.

Test: With the structure in place, the students in the experimental group received the interventions and assistance they needed, and their performance was evaluated and compared with that of the control group. The control and experimental groups knew what information was required and could handle all the technical aspects of a predictive model. Finally, the preliminary findings partially or completely resolved the issue and boosted students' academic performance.

Roll out: Interventions that have a high impact on the specified goal can now be rolled out as a practice for a larger population, resulting in a positive outcome.

The study was set up as a series of trials with a pretest-posttest control group design, with the goal of determining the function of factor continuous assessment test 2 in increasing student academic performance. The population of this study was postgraduate students, and the sample size was 600 students from purposively selected candidates, who were then randomly assigned to the experimental and control groups. In this study, data were analyzed using a one-way ANOVA statistical test to examine whether there was a difference and if there was an interaction effect between the factor and the target variable in terms of improving student academic performance.

To determine the degree of improvement in students' academic performance before and after the activity, a normalized gain score analysis was performed using the following formula:

$$g = \frac{\text{postest score} - \text{pretest score}}{\text{maximum ideal score} - \text{pretest score}}$$

as such in normalized gain score levels are grouped into three categories are 0.70 < (g): High, $0.30 \le (g) \le 0.70$: Medium and (g) < 0.30: Low [11].

4. RESULTS AND DISCUSSIONS

Findings on student's academic performance prediction based on Continuous Assessment Test 2 and the target variable are presented in Figure 2.

Various Groups			Group 1	Group 2	Group 3	Group 4	Group 5
The increase	Control Group(n=50)	Mean	0.63	0.72	0.68	0.75	0.79
in student's		SD	0.12	0.15	0.15	0.13	0.11
academic	Experiment Group(n=50)	Mean	0.67	0.8	0.69	0.79	0.81
performance		SD	0.07	0.09	0.09	0.15	0.09

Figure 2 Gain factor of selected features and target variable

There were five experiment groups here: 1,2,3,4, and 5, which were used in the ANOVA analysis. Treatments are an independent variable known as a factor. The experimental factor has five levels because there are five different types of experiments. The X-axis represents the factor or independent variable to evaluate, while the Y-axis represents the control and other experimental groups indicated previously; therefore, the one-way ANOVA approach was used for analysis.

Based on the previous description, it is clear that the features chosen to improve students' academic performance through the experimental group were superior to those learned through the control group, whether considered as a whole or when compared to other groups, as shown in figure 3. In addition, if the components that affect the rise are examined, the learning factors and groups have an impact on the improvement of a student's academic performance, as shown in Figure 1. To back up the preceding description of the students' academic performance improvement, test data analysis was performed using the statistical test of average difference. The data on students' academic performance was found to be normally distributed following a normality test. The above-average difference test was performed using pairwise t-test Analysis of Variance (ANOVA), based on these findings. One-way ANOVA was used to establish simultaneous confidence intervals.

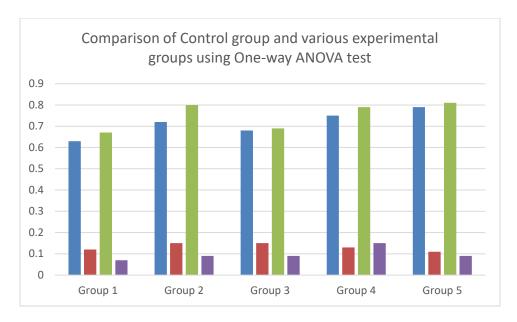


Figure 3 Comparison of Control group and various experimental groups using

One-way ANOVA test

5. CONCLUSION AND FUTURE WORKS

Key properties were determined using descriptive analytics. One of these aspects was chosen and the task of repairing it was undertaken. The feature of continuous assessment exam 2 was chosen as the focus, and 600 students were randomly assigned to one of five experimental groups: 1,2,3,4, or 5. The use of prescriptive analytics to forecast student performance aided in the selection of a decision, and improvement was discovered based on the interventions used and demonstrated using the ANOVA technique. Other advantages include instructions on what to do and how to do it correctly for the first time. Decision makers would be able to see both real-time and forecasted data at the same time to make decisions that would support long-term growth and success. This simplifies decision-making by providing specific suggestions. Data analytics and outcome prediction were completed in real time, indicating that less time was spent repairing problems, and more time was spent devising flawless solutions. It also lowers the chance of human error or bias. Predictive analytics provides a more extensive and accurate type of data collection and analysis than descriptive analytics, predictive analytics, or even individuals, owing to more complex algorithms and machine learning techniques.

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