**Boosted Reteach Planning: Optimizing Student Learning Outcomes**

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**Introduction**

Data science has evolved into an emerging field in recent history. With the increasing volume of data being generated, the complexity of the problems to be solved has grown, leading to a proliferation of studies in this domain. Data science plays a pivotal role in enabling individuals and organizations to refine their strategies, make data-driven decisions, and swiftly address contemporary challenges. Nearly every domain necessitates the collection, cleansing, analysis, and extraction of insights from data. Education is no exception. While statistics and data have always held a place in academia, they are now more profoundly integrated into the daily operations of educational institutions.

Data science contributes to education in various ways. For instance, learning analytics has a significant impact on educators and their ability to assess the results of their work. It makes educators' tasks more manageable by providing insights into students' areas of weakness, the influence of various resources on their performance, and their performance data.

The idea of using the data to enhance academic performance has always been an essential task. From students to the federal government, every party seeks insights from data to achieve better results. The federal government of the United States authorized the No Child Left Behind Act (NCLB) in 2001 to ensure that schools are held accountable for every student's performance and to provide more opportunities for students in need. Until 2015, local states were required to conduct yearly assessments to demonstrate their students' improvement. In 2015, the federal government signed Every Student Succeeds Act (ESSA), replacing the NCLB. ESSA grants more flexibility to states and, once again, requires every state to assess the performance of their students in reading, math, and science.

While these federal government-driven improvements were taking place, the state of Texas also made its own updates to yearly assessments. The assessment history in Texas dates to 1979, but this study focuses on the latest version of the STAAR assessment held annually by the Texas Education Agency (TEA). STAAR tests cover the yearly curriculum to measure students' performance and readiness for the next academic year's curriculum. Every year, students from the 3rd to the 12th grade take STAAR tests in core subjects, including Reading and Language Arts (RLA), math, science, and social studies.

In Texas, educators responsible for students from 3rd grade to 12th grade have the crucial task of preparing their students for the end-of-year state assessment known as STAAR. At Harmony Public Schools, a proactive approach is taken. They conduct two interim assessments before the STAAR test and monitor their students' performance. Additionally, teachers are required to develop reteaching plans based on the STAAR data and the provided resources. These plans are designed to enhance the performance of students who may need extra support in certain topics.

A study conducted on a small group of 3rd-grade students to examine the impact of pre-teaching and re-teaching math curriculum content on student performance (Lalley and Miller). The study resulted in a significant improvement in assessment scores and students’ self-concept. While re-teaching is a well-established strategy in the field, it also offers potential for further development, enabling the creation of more personalized and well-sourced reteach plans. These plans can leverage specific learning strategies tailored to individual students, with a statistical approach to improving reteach plans. In this research, I aim to enhance student performance through data-driven educational interventions, with the goal of achieving even better results.

**Objective**

The objectives of this research are twofold. First, the study aims to investigate the impact of various educational resources on student performance in interim assessments and to assess how the utilization of these resources affects learning outcomes. Secondly, the research seeks to provide valuable insights into the effectiveness of different strategies, focusing on their applicability within the context of Harmony DFW schools.

**Methodology**

Data Collection

Data will be collected in an anonymized manner by school administrators for legal compliance. The data sources will consist of reteaching plans created by 8th-grade math teachers in Harmony Public Schools DFW campuses during the 2021-2022 and 2022-2023 academic years. These reteach plans are designed to assist teachers in revisiting topics where students have demonstrated lower proficiency on interim assessments. In most cases, teachers create these plans individually, resulting in variations in formatting across different campuses.

The dataset will also include interim assessment scores for each student. To maintain anonymity, class data will be segregated by school administrators and can be paired with anonymized teacher identities if deemed necessary by the school.

Data Understanding

*Reteach Plans*

Reteaching plans that are individually created by teachers to reteach the targeted topics in between interim assessments held by the school. Reteach plans are in PDF or word format.

*Interim Assessment Data*

Interim assessment data is data exported from Harmony database and in CSV format.

Numerical features:

1. Student\_ID

Student ID numbers that are randomly distributed due to FERPA.

1. Percent Score

Percent score the student received on the assessment.

1. Scale Score

Scale scores the student received on the assessment.

1. Approach Probability

Probability of student approaching desired scale and percent score.

1. Meet Probability

Probability of student meeting desired scale and percent score.

1. Master Probability

Probability of student mastering the topics.

Categorical features:

1. Assessment

The type of assessment taken (‘Interim Fall’ or ‘Interim Spring’).

1. Course

The course student took during the semester (‘Math-8’ or ‘Algebra I’)

1. Teacher Name

Name of the teacher the student took class of.

1. Section

The section/class of the student.

1. Mastery Projection

The outcome prediction of the student on the actual STAAR test (‘Did Not Meet’, ‘Approach’, ‘Meet’ and ‘Master’)

1. Projected Tier

Data Preprocessing

*Handling Missing and Invalid Values*

There are no missing values in the dataset, but a few invalid percent scores exist. Since the distribution is right-skewed, median imputation technique will be applied. Any other inconsistency found will be addressed with domain knowledge and skills. Teachers’ commentary will be held in account.

*Outlier Detection and Treatment*

Outliers, if present, will be identified during the exploratory data analysis. It is imperative to retain outliers since they represent both high-performing and low-performing students, providing valuable insights into the effectiveness of the resources for these students, aligning with the project's goals.

Since the outliers will influence the modeling result. Modeling will be done with outliers and without outliers to determine if there is a huge difference. During the evaluation process, better performing technique will be kept.

*Single Variable and Multivariate Analysis*

Before performing feature engineering single variable and multivariate analyses will be performed on the numerical and categorical variables. This will give more insight into the raw interim assessment data and how clustering students can be done.

*Statistical Tests*

T-test and ANOVA tests will be performed to determine if there are significant differences between the means of groups.

Data Transformation

Transforming data is necessary because the skewed data distribution needs to be normalized. Also, to ensure that all features contribute to the result equally, transformation is a must.

*Feature Scaling*

The dataset contains ‘Scale Score’ variable which has a scale different than other numerical variables. To get all features in same scale of 0 to 1, robust scaling technique can be used. When modeling without outliers min-max scaling will be considered as the first option.

*Encoding Categorical Variables*

Categorical variables with ordinal data will be replaced with ordinal numbers. Other variables like ‘Course’, ‘Section’, and ‘Teacher Name’ will be label encoded. When the new features are created for resource types, one-hot encoding will be performed.

Feature Engineering

Given that reteach plan data is available in PDF or word format; a manual review process will be initiated. Each teacher's reteach plan will be carefully examined, and the resources they selected will be matched with the students in their respective classrooms. This process yields valuable features that enrich the master dataset. Key features that are named after the resource types will be created, enhancing the dataset's richness and analytical capabilities.

Another feature will be created as ‘Effectiveness’. This feature will show if there is an improvement in percentage and scale scores. Binary encoding will be used as a technique.

Modeling

After making sure the dataset is ready for modeling phase, 70% of the data will be split for training and the other 30% remaining will be used for testing.

*Model Selection*

Since many features in dataset are created later manually and there is high correlation between the variables expected, XGBoost is selected as a machine learning model for prediction task. Just to check the model differences Super Vector Machine might be trained too.

*Model Evaluation*

Many different metrics will be used to evaluate the model’s performance. Accuracy, precision, recall will be used along with the main metrics confusion matrix and AUC-ROC (Area Under the ROC Curve).

Outcome

The targeted outcome for this study is to provide data-driven insight to educational practices and more visual information about this specific dataset using learning analytics.