RANKING RESILIENCE ATTRIBUTES FOR TEXAS PUBLIC SCHOOL DISTRICTS

by

Daniel Payan

HONORS CAPSTONE

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Supervisor:

Jelena Tešić

Second reader:

Li Feng

DEDICATION

This thesis is dedicated to the family and friends that have always been in my corner and supported me through thick and thin. I appreciate all you have done for me, and this thesis is an achievement for us all to celebrate.

Thank you, Nicole, for keeping me motivated and helping me through the long nights where I felt myself wavering. You've pushed me and kept me striving for greater heights, and you did all this with love and by leading through example. I'm grateful that we've experienced this college journey together and I'm so excited for our future together.

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ABSTRACT

Student learning, as measured by the State of Texas Assessment of Academic Readiness (STAAR) in public school systems in the US, plummeted during the COVID-19 pandemic, erasing years of improvements. In this body of research, we collect, integrate and analyze all available public data in the data science pipeline to see if public data can explain what factors contribute to learning loss recovery and inform public policy. This is a unique study of public data to address the post-COVID educational policy crisis from a data science perspective. To this end, we have developed an end-to-end large-scale educational data modeling pipeline that (i) integrates, cleans, and analyzes educational data; (ii) visualizes this data utilizing a free, open-source Python Panel dashboard; and (iii) implements automated attribute importance analysis to draw meaningful conclusions. We demonstrate a novel data-driven approach to discover insights from an extensive collection of disparate public data sources. We offer actionable insights to policymakers to identify the most affected areas to help policymakers' direct resources to those areas and schools.

Chapter 1: Introduction

1.1 The Impact of COVID-19

On January 21, 2020, the first confirmed coronavirus case on U.S. soil was recorded [1]. By March 25, all U.S. public school buildings were closed due to the COVID-19 pandemic. Teachers and students alike were forced to adapt to a new learning environment as teaching would continue through virtual classrooms [2]. This interruption in the classroom had a devastating effect, with standardized test scores seeing losses across all subjects as students and teachers struggled with unprecedented challenges. Policymakers at the federal, state, county, and district levels were also amidst this crowd in disarray as no consensus could be reached on the impact of reopening schools during this pandemic [3]. This inability to get a unanimous decision resulted in variegated levels of learning loss as different areas adopted vastly different approaches, i.e., virtual, hybrid, and in-person schooling, based on their resources and beliefs about COVID and its potentially harmful impacts on students and teachers [4].

This research aims to demonstrate an applied data science pipeline that can aid policymakers in understanding the features that have had the most influence on learning recovery so that, in the future, they are better prepared and equipped to develop effective solutions. These features were identified by collecting data from six public sources, creating a fully open-source Panel Python dashboard, and utilizing nine machine-learning models.

1.2 Learning Recovery Analysis

Learning loss is "any specific or general loss of knowledge and skills or to reversals in academic progress, most commonly due to extended gaps or discontinuities in a student's education" [5]. However, learning loss recovery occurs as learning loss is either mitigated or reversed through a school or district's actions. It will be called learning (loss) recovery for simplicity. In this work, learning recovery is measured through the change in STAAR (State of Texas Assessments of Academic Readiness) exam scores from 2019 to 2022. This delta reflects the shift from right before COVID-19 to the most recent year of scores, with negative changes labeled a loss and favorable changes marked a gain (recovery). The STAAR exam was chosen as the metric for learning recovery as it is a standardized test administered to all public-school students (grades 3-12) in Texas. STAAR tests students in reading, writing, mathematics, science, and social studies. This project focuses on math and reading in grades 3-8.

1.3 What Is Feature Selection?

In data science, "feature selection reduces the number of input variables when developing a predictive model" [6].

Figure 1: Demonstration of the feature selection process in which the original dataset is run through a machine learning model, which results in a new dataset.

The feature selection process is significant in machine learning, as it can improve a model's performance, decrease computational complexity, and allow users to identify the most influential features of a target value. These features will also be accompanied by a matter of importance calculated by each machine learning model, which will serve as a ranking system that identifies and develops a descending list of influential features.

Chapter 2: Methodology

This chapter will cover multiple areas of the work, including the utilities used, the development of labels, exploratory data analysis, the machine learning feature selection pipeline, and the score evaluation system.

2.1 Utilities

The research employed four essential tools: Python, Anaconda, Jupyter Notebook, and Panel. These tools were selected for their extensive support for machine learning libraries and packages and their open-source nature.

2.1.1 Python

Python is a versatile, open-source, high-level programming language widely used today. Its flexibility allows developers to create everything from simple scripts to complex machine-learning algorithms while maintaining a readable, human-like syntax. Furthermore, Python is free to use, which contributes to its popularity.

2.1.2 Anaconda

Anaconda is a distribution of the Python language which strives to streamline Python data science packages by providing an organized user interface that is simple to navigate. The Anaconda distribution includes "...over 8,000 open-source data science and machine learning packages, Anaconda-built and compiled for all major operating systems and architectures" [7].

2.1.3 Jupyter Notebook

Jupyter Notebook is a web-based development environment part of the Anaconda open-source package. Despite being a Python package, it is flexible and supports over 40 programming languages. This versatility enables the creation of complex machine-learning techniques, the manipulation of vast datasets, and the generation of top-notch dashboards.

2.1.4 Panel

Panel is an open-source Python library that enables the creation of interactive web applications and dashboards. The library is particularly robust since it supports a wide range of plotting libraries, making it possible to develop competitive dashboards with proprietary software.

2.2 Data Aggregation and Integration

The data was collected from six public sources described in Table 1.

Data Frame	Data Source	Level	RowXCol
Census	Census Bureau 2010	County	254, 37
Covid	USAFacts	County	253, 16
Covid	Texas Department of State Health Services	District	1216, 7
CCD	National Center for Education Statistics	District	994, 98
LAUS	U.S. Bureau of Labor Statistics	County	254, 13
STAAR 2019	Texas Education Agency	District	1184, 217
STAAR 2021	Texas Education Agency	District	1182, 217
STAAR 2022	Texas Education Agency	District	1185, 217
ADA	Texas Education Agency	District	1225, 4
ESSER	Texas Education Agency	District	1208, 6

Table 1: Data from six sources are integrated by matching school district ID and county FIPS code for 1,160 school districts with 750 attributes in 253 counties in Texas.

Ten separate data frames were generated from six publicly available sources, each with varying dimensions. The inclusion of 2010 Census Bureau data aimed to investigate whether a county's general population characteristics influenced learning recovery. Two different COVID-19 data frames were created using county and district-level data from USAFacts and the Texas Department of State Health Services (DSHS), which provided information on the pandemic's impact on student enrollment and campus attendance, infection and death rates, and other relevant features [8,9]. The Common Core of Data (CCD) data frame was obtained from the National Center for Education

Statistics (NCES) and contained detailed student demographic and teacher-related data [10]. The Local Area Unemployment Statistics (LAUS) data frame from the U.S. Bureau of Labor Statistics included employment and unemployment rates at the Texas County level. The Texas Education Agency (TEA) also provided three STAAR data frames containing district-level information on math and reading scores and the number of students tested grouped by different classifications, such as free lunch, special education, and race/ethnicity [11]. The Average Daily Attendance (ADA) data frame was extracted from the TEA, providing attendance information. In contrast, the Elementary and Secondary School Emergency Relief (ESSER) data frame contained information on federal distribution support programs for school districts from 2020 to 2023. All these data frames were merged based on school district ID numbers and county FIPS codes into a comprehensive dataset, which included information from 1,160 school districts in Texas, located in 253 counties, and containing 750 attributes [12,13].

2.3 Labeling Outcomes

The dataset includes information on the average math, reading, and overall STAAR scores for grades 3-8 in each district for academic years 2019 (2018-19), 2021 (2020-2021), and 2022 (2021-2022). Although the dataset contains 750 attributes, it is currently unlabeled, meaning a target must be established for the machine learning model to work correctly. However, for this study, only the fiscal years 2019 and 2022 are relevant as the overall change serves as the target.

The first step of the labeling process is to normalize the STAAR scores by grade level. This is done by dividing a district's score value by the maximum score for that grade. Once the grade level scores are normalized, an average score is calculated by summing the grade level scores for grades 3-8 and then dividing by the number of stages. The third step is to then recalculate a delta between 2019 and 2022 as

$$\frac{2022\ Average\ Score - 2019\ Average\ Score}{2019\ Average\ Score}.$$

Finally, based on the value of these delta scores, a district would be classified with one of three created labels; the values below the 25th percentile would be labeled "Loss," the values within the middle two quartiles would be labeled as "Expected," and values above the 75th percentile would be labeled "Gain."

2.4 Exploratory Data Analysis

Before applying a machine learning model to the dataset, a fully open-source dashboard was developed using Panel, Python, and Jupyter Notebook. This interactive dashboard contains multiple tabs of information, including STAAR scores at both the county and district levels, student and staff counts, funding received by districts from each ESSER program, funding per student received by a district, and normalized differences in STAAR scores by demographic group and grade for three different year ranges. These year ranges are 2019-2021 (COVID-19 pandemic years), 2021-2022 (recovery year), and 2019-2022 (overall change). The dashboard also includes county-level maps of Texas, in which users can input student demographics, grade level, subject of the STAAR test, and the year range to visualize the potential influence on STAAR scores. Figures 2 and 3 display examples of such plots.

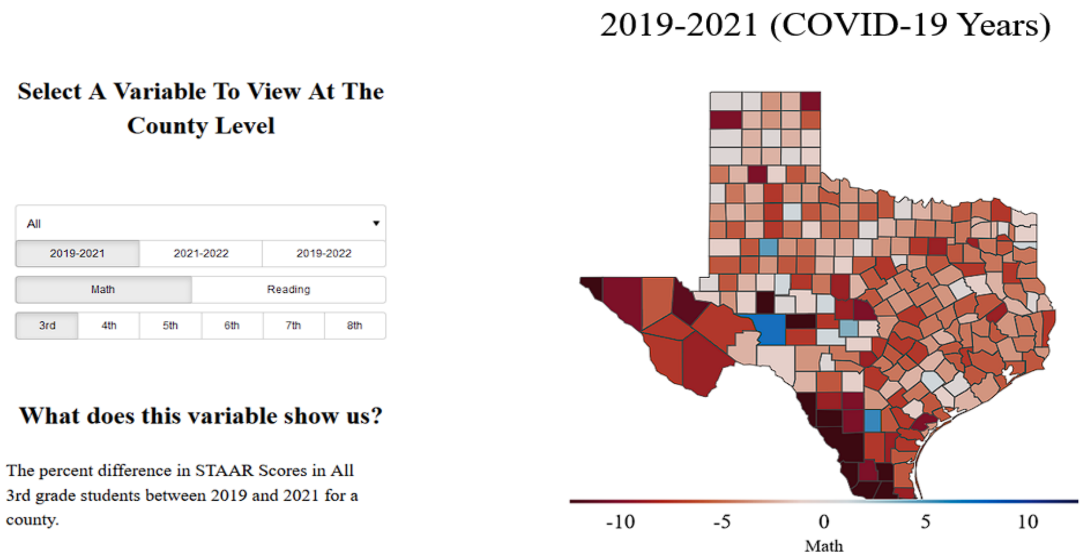

Figure 2: A county-level map of Texas displaying data for all 3rd-grade students in math for the year range 2019-2021. There is a drop-down menu to select a demographic variable as input and buttons for year range, subject, and grade level.

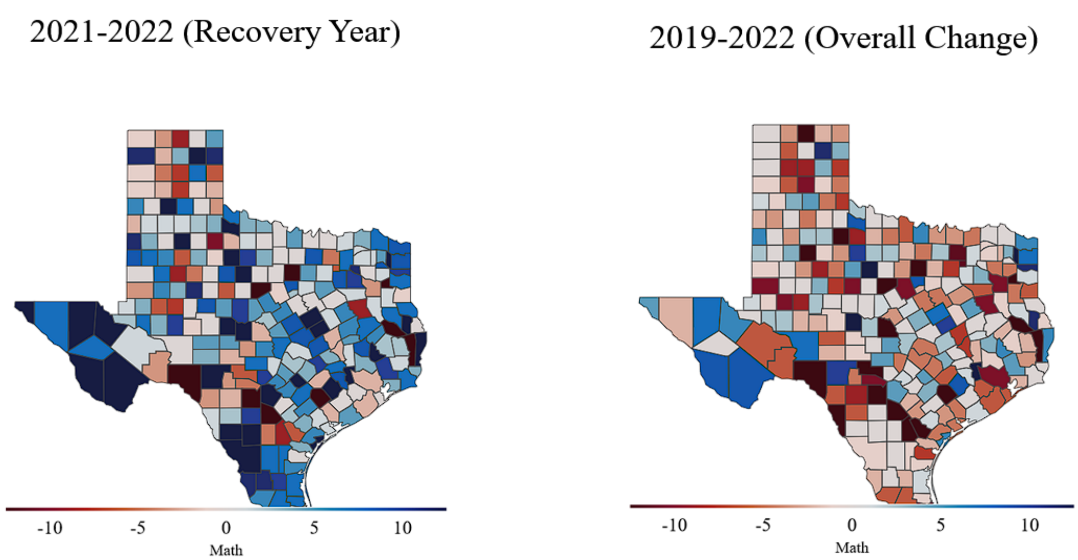

Figure 3: Two county-level maps of Texas displaying data for all 3rd-grade students in math for two different year ranges. The left map shows 2021-2022 (Recovery Year) data and the right one displays 2019-2022 (Overall Change) data.

Figure 2 and Figure 3 display three instances of information from a single tab in the dashboard, third-grade math scores for all students for the 2019-2021, 2021-2022, and 2019-2022 school years. The red shading indicates learning loss in a county, and the blue shading indicates learning recovery. These figures allow us to visualize a wave of learning loss impacting Texas during the 2019-2021 period, and despite the recovery seen in the 2021-2022 map, the overall change from 2019-2022 still leans towards the red shades indicating that the state has not fully recovered from the learning loss experienced. Overall, this dashboard includes several tabs, each displaying different variable sets and capable of displaying more than one hundred different variable combinations. This versatility made the dashboard a valuable tool for conducting exploratory data analysis.

2.5 Feature Selection

The work utilizes nine different machine learning methods to perform feature selection on the data, as seen in Figure 4.

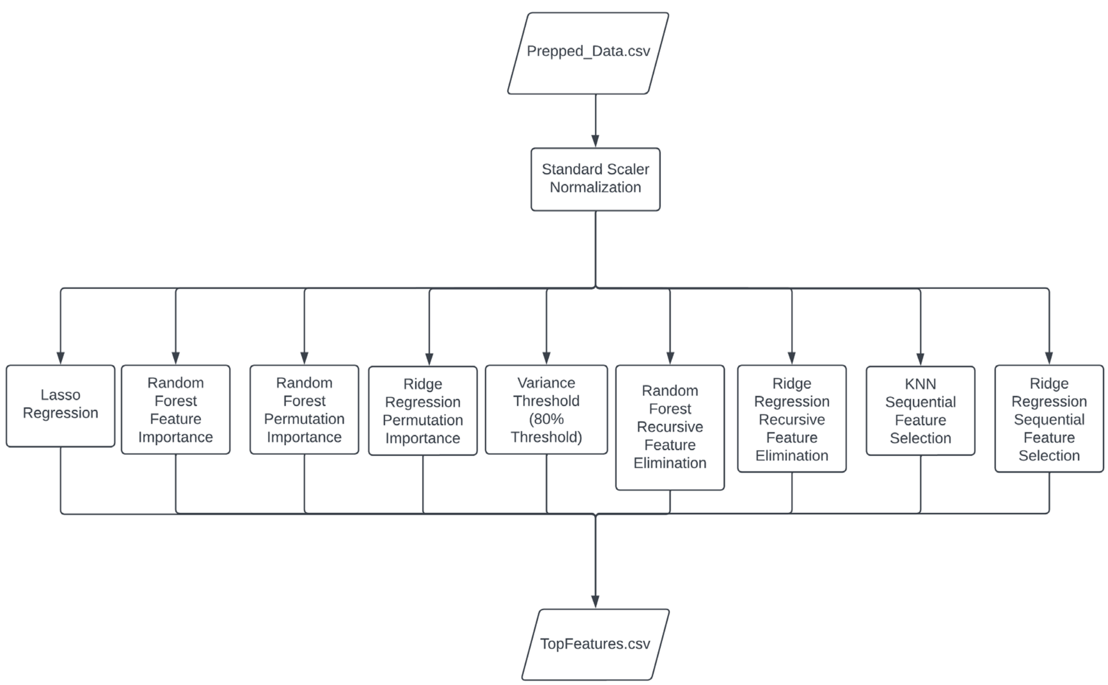

Figure 4: The feature selection pipeline begins with the prepped dataset and then is normalized using the sklearn Standard Scaler class. Nine different feature selection methods then process the dataset. The feature importance values are saved into a comma-separated (CSV) file.

The first method is **Logistic Regression with Lasso Regularization** which utilizes a penalty value "L1," which shrinks the coefficients of the features towards zero, potentially causing some coefficients to become precisely zero. When this occurs, the corresponding feature is removed from the model as it no longer contributes to the predictions. The remaining features with non-zero coefficients are considered significant and used in the model for making predictions. The following method is **Random Forest Feature Importance** which determines if a feature is essential through a 50^{th} percentile threshold placed on the Gini importance or the mean decrease impurity. If a feature's importance score exceeds this threshold, it is considered significant and retained for use in the model. **The Variance Threshold** method eliminates low variance features in a dataset utilized in this work at a threshold of 0.8*(1-0.8), eliminating any feature with 80% of the same values in the training set. **Recursive Feature Elimination (RFE)** is a feature selection method that starts with the entire list of features in the dataset. It then recursively removes the features with the smallest coefficients until the optimal set of features is identified. The process involves training a model using Logistic Regression with Ridge Regularization or the Random Forests on the complete set of features and then ranking the importance of each feature based on its coefficient value. The feature with the smallest coefficient is then eliminated from the list, and the model is retrained on the reduced feature set. This process is repeated until the model's performance, measured by 10-fold cross-validation scores, decreases. **Permutation Importance** is a technique that involves permuting the values of a feature in the dataset and observing the impact on the model's performance metric, such as accuracy or R-squared. This is done by randomly shuffling the feature values while keeping the target variable unchanged, thus breaking the relationship between the feature and the target. By comparing the original model's performance metric with the metric obtained after permuting a feature, we can determine how important the feature is in predicting the target variable. If permuting a feature significantly decreases the model's performance metric, then that feature is considered necessary. **Sequential feature selection (SFS)** is a method used in machine learning to select a subset of features from a more extensive set of features. Unlike RFE, which starts with all features and removes one feature at a time, SFS begins with an empty set of features and adds one feature until all possible combinations of features have been evaluated. In this method, the initial set of features is empty. At each step, a feature is added to the set based on its performance evaluated by a wrapped model (in this case, Logistic Regression with Ridge Regularization and K-Nearest Neighbors) using a 5-fold cross-validation technique. The evaluation is done based on the performance metric (such as accuracy or R-squared) obtained by the model after adding the feature. The final set of features is selected based on the best cross-validation score obtained during the sequential addition of features. In this work, the final set of features is restricted to half of the total provided list, which can help reduce the model's complexity while maintaining its predictive power.

After processing all the feature selection methods, the obtained importance values are saved into a file in comma-separated values (CSV) format. However, the importance values generated by each method are not standardized, as each technique follows a unique selection process. For instance, the Variance Threshold, Sequential Feature Selection (SFS) Ridge Regression, and SFS K-Nearest Neighbors methods produce binary values indicating whether a feature was selected or eliminated in the final feature set, with 1 representing a selected feature and 0 showing an eliminated feature. RFE Ridge Regression and RFE Random Forest produce a ranking score for each feature based on their final selection order. In contrast, Random Forest Feature Importance, Random Forest Feature Importance, and Ridge Regression Permutation Importance all generate non-zero importance scores. However, these scores are not directly comparable due to differences in their scales and normalization techniques, so a method was developed to create a composite ranking system which will be discussed in the next section.

2.6 Ranking Experiment

Initial Importance Values										
Feature	**FI RF**	**PFI RF**	**PFI RR**	**RFE RF**	**RFE RR**	**Regularization - Lasso**	**SFS - KNN**	**SFS - Ridge**	**Variance Threshold**	-
# of Families 10	0.002	-0.001	0.000	9	327	0	0	1	1	-
# of Households 10	0.004	0.005	0.002	40	324	0	0	1	1	-
# of Housing Units 10	0.003	-0.003	0.002	18	319	0	0	1	1	-
% ADA 2018-2019	0.002	0.006	0.014	103	126	0	0	0	0	-
% ADA 2020-2021	0.003	0.006	0.003	55	18	0	0	1	0	-
% ADA 2021-2022	0.002	0.001	0.000	242	237	0	0	0	0	-
% Age 0-4 Pop 10	0.003	0.005	0.000	239	148	0	0	0	0	-
Binary Selection Values										
Feature	**FI RF**	**PFI RF**	**PFI RR**	**RFE RF**	**RFE RR**	**Regularization - Lasso**	**SFS - KNN**	**SFS - Ridge**	**Variance Threshold**	**SUM**
# of Families 10	0	0	0	0	0	0	0	1	1	2
# of Households 10	1	1	1	0	0	0	0	1	1	5
# of Housing Units 10	1	0	1	0	0	0	0	1	1	4
% ADA 2018-2019	0	1	1	0	0	0	0	0	0	2
% ADA 2020-2021	1	1	1	0	0	0	0	1	0	4
% ADA 2021-2022	0	1	0	0	0	0	0	0	0	1
% Age 0-4 Pop 10	1	1	1	0	0	0	0	0	0	3
Impact Score Values										
Feature	**FI RF**	**PFI RF**	**PFI RR**	**RFE RF**	**RFE RR**	**Regularization - Lasso**	**SFS - KNN**	**SFS - Ridge**	**Variance Threshold**	**IMPACT SCORE**
# of Families 10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.92
# of Households 10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	2.14
# of Housing Units 10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.88
% ADA 2018-2019	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.33
% ADA 2020-2021	0.00	0.01	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.32
% ADA 2021-2022	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06

We used the three sets of values in the experiments to identify the most significant features. These sets are Initial Importance Values, Binary Selection Values, and Impact Score Values, as shown in Table 2.

Table 2: Displays three different score levels: initial importance, binary selection, and impact score.

The **Initial Importance Values** are the raw scores from the machine learning methods and are initially tricky to compare due to their non-uniformity. The **Binary Selection Values** are the first transformation of the output, where we binarize all of the scores as SFS KNN, SFS RR, and Variance Threshold are already binary. To transform the features into a binary format, we use the following approach: For RFE methods, we retain only the rank of one feature and assign a value of 1 to it while the others get a value of 0. For logistic regression, we give a +1 score to features with a positive coefficient and -1 to those with a negative coefficient, while the coefficients with a value of 0 are ignored. For feature importance, we select the top 50% of features with positive scores and assign a value of 1 to them, while the others get a value of 0. For permutation feature importance, we give 1 to features with positive scores and 0 to those with negative or zero scores. Finally, we sum the scores and sort the feature importance for each subject out of 9. The **Impact Score Values** are the second transformation of the output. They are obtained by normalizing the scores of each method by dividing them by their sum of overall features. This normalization ensures that each feature contributes equally to the final ranking. Next, we calculate the absolute value of the normalized score for each attribute and sum them up to create a feature ranking. The top 20 features with the highest scores are selected for math and reading by prioritizing the impact score, as it combines both binary and non-zero scores. In contrast, the binary score is used as a secondary measure to understand the importance. The number of features selected is based on a drop in impact score after the top 20 features, labeled the cutoff point. Secondary labels were also applied to the features to understand what "type" of the feature was most significant. Overall, this approach allows us to compare the relative importance of each feature and identify the most important ones.

Math

Factor	Feature	Impact Score	Binary Score	ElasticNet Gain	ElasticNet Loss
Demographics	Median Household Income	6.62	5	0	0.2647
District Makeup	Total Students 2018-2019	6.23	7	0	0
District Makeup	Total Students 2020-2021	6.14	6	0	0
District Makeup	Total Students 2021-2022	6.11	7	0	0
Locale	42-Rural: Distant	6.05	3	0.0749	0.0713
Low Income	# of Families 10	5.84	4	0	0
Demographics	Average Annual Pay	5.83	2	0	0.0655
Low Income	ARP ESSER III 21 NORM	5.76	3	0	0
Low Income	CARES ESSER I 20 NORM	5.76	4	0	0
Locale	43-Rural: Remote	5.74	3	0	0
Low Income	# of Housing Units 10	5.70	3	-0.0179	0
Low Income	# of Households 10	5.70	3	-0.0147	0
Demographics	Per Capita Income	5.70	3	0	0
Low Income	% of the Population Under 18 in Poverty	5.68	3	0	-0.0483
Demographics	Median Age Male 10	5.68	3	0	0
County COVID	County Population	5.68	2	0	0
Low Income	% of Population in Poverty	5.67	2	0	0
Low Income	CRRSA ESSER II 21 NORM	5.67	2	0	0
Demographics	Median Age 10	5.65	2	0	0
Demographics	Median Age Female 10	5.58	1	0	0

Table 3: Top 20 most significant features for learning recovery in Math STAAR.

Reading

Factor	Feature	Impact Score	Binary Score	ElasticNet Gain	ElasticNet Loss
Demographics	Average Annual Pay	6.40	3	0.0365	0.1785
Demographics	Per Capita Income	6.27	4	-0.1492	0
District Makeup	Total Students 2021-2022	6.02	6	-0.0325	-0.0142
County COVID	County Population	5.92	5	-0.0136	0
Low Income	# of Families 10	5.91	6	0	0
District Makeup	Total Students 2018-2019	5.89	5	-0.0047	-0.0024
District Makeup	Total Students 2020-2021	5.87	5	0.0000	-0.0136
Low Income	# of Households 10	5.84	5	-0.0147	0
Low Income	% of the Population Under 18 in Poverty	5.80	4	-0.0204	0
Low Income	CRRSA ESSER II 21 NORM	5.81	4	0	0
Demographics	Median Household Income	5.78	5	0	0.0153
Low Income	# of Housing Units 10	5.78	4	-0.0318	0
Demographics	Median Age Female 10	5.76	3	0	0
Low Income	% of the Population in Poverty	5.77	4	0	0
Locale	42-Rural: Distant	5.70	3	0.0083	0
Low Income	CARES ESSER I 20 NORM	5.71	4	0	0
Low Income	ARP ESSER III 21 NORM	5.69	4	0	0
Demographics	Median Age Male 10	5.66	3	0	0
Demographics	Median Age 10	5.59	2	0	0
Locale	43-Rural: Remote	5.56	2	0	0

Table 4: Top 20 most significant features for learning recovery in Reading STAAR.

Chapter 3: Results

3.1 Most Influential Features

The ranking experiment has enabled us to identify the top 20 most significant features influencing learning recovery. These features are presented in Table 3 and Table 4, along with their scores for impact, binary selection, and ElasticNet Gain/Loss.

The size and location of a district play a critical role in the recovery process, along with the amount of money in the area and the Elementary and Secondary School Emergency Relief Fund received. The results identify the significance of various factors in promoting learning recovery in math and reading, highlighting the importance of considering a district's economic status, size, locale, demographics, and funding. In Figure 5, we also see how vital the mode of instruction for a classroom is, along with the factor types seen in Table 3 and Table 4.

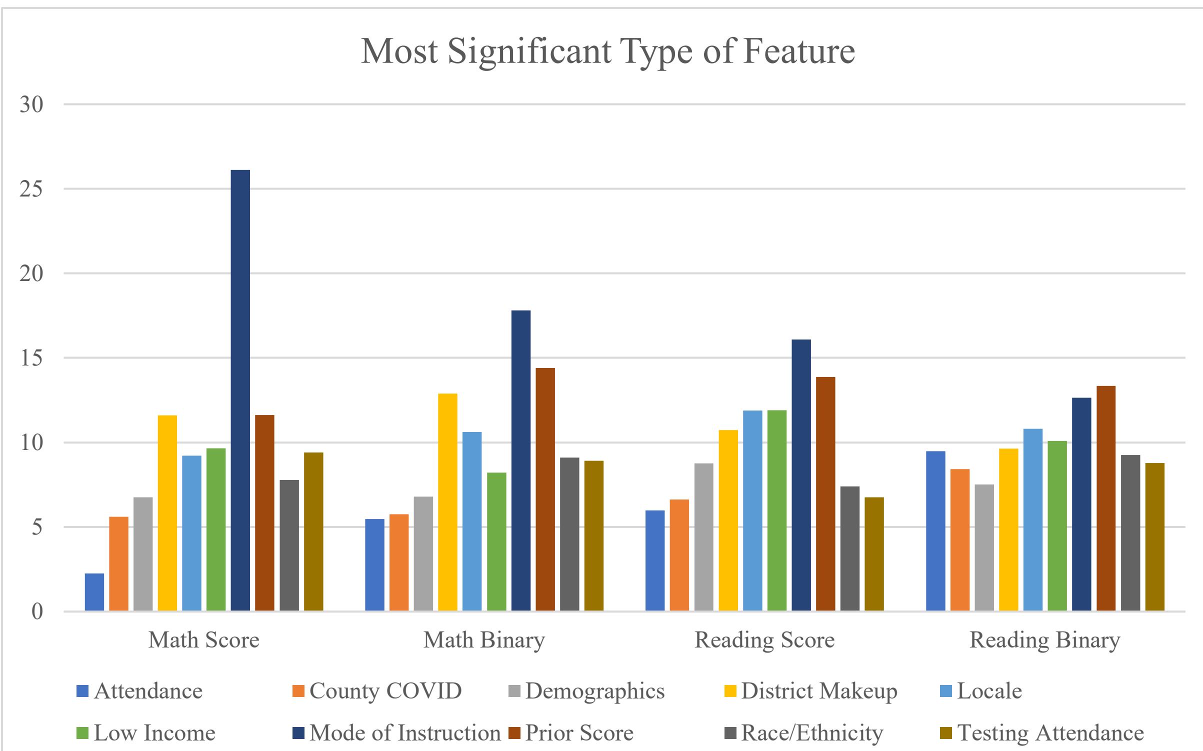

Figure 5: The normalized impact and binary scores based on the "type" of feature selected for ten different groups.

These findings suggest that larger districts with more financial resources and significant funding are better equipped to facilitate effective learning recovery in students and that the mode of instruction is crucial for student success.

The study's findings have important implications for policymakers and educators who design and implement policies promoting learning recovery. Policymakers must consider the factors highlighted in the research and work to ensure that resources are available to support learning recovery efforts. They must also provide targeted funding to districts with limited resources to help them support students in need. Educators will also need to work closely with policymakers and communities to design and implement effective recovery strategies that address the specific needs of their students. These strategies should incorporate evidence-based practices and be tailored to the district's and its students' unique characteristics. By working together and considering the factors highlighted in the study, policymakers and educators can help ensure that all students receive the support they need to recover from the deleterious impacts of the COVID-19 pandemic and succeed in school.

Chapter 4: Conclusion and Future Work

4.1 Conclusion and Future Work

In this work, we have designed a comprehensive pipeline that effectively handles data cleaning, manipulation, visualization, and feature selection using multiple sources' datasets. Our primary objective is to assist policymakers in identifying the most crucial factors influencing learning recovery efficiently. We have successfully placed the top 20 significant features for both math and reading based on STAAR scores from 2019 to 2022. Additionally, we have developed an open-source dashboard to provide policymakers with further insights into the areas that require greater attention, facilitating the efficient allocation of resources. Moving forward, we intend to conduct an in-depth analysis of the identified features and subject them to predictive modeling to ascertain any positive or negative correlations between them and learning recovery. Overall, this study contributes to the ongoing efforts to enhance the understanding of the critical factors that drive learning recovery and supports the development of data-driven policies to promote student success.

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[12] Agency, Texas Education. “Grant Compliance and Administration.” Tea.texas.gov, 9 Jan. 2023, tea.texas.gov/finance-and-grants/grants/. Accessed 30 Apr. 2023.

[13] github.com/DataLab12 – refer to both repositories in work, as they contain:

- STAAR Aggregate Level Data for 2021-2022;
- STAAR Aggregate Level Data for 2020-2021;
- STAAR Aggregate Level Data for 2018-2019