

Data Driven Analysis of Intervention Effectiveness for COVID-19 Learning Loss in Texas Public Schools

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Abstract—Student learning gain rates in public school systems in the U.S. 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 inform and impact learning loss factors. The general data sources were collected from the Census Bureau 2010, USAFACTS, Texas Department of State Health Services (DSHS), National Center for Education Statistics (CCD), U.S. Bureau of Labor Statistics (LAUS), and three sources from the Texas Education Agency (STAAR, TEA, ADA, ESSER). This is the first known 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) implements automated attribute importance analysis to draw meaningful conclusions, and iii). develops a suite of interpretable learning loss prediction models utilizing all data points and features. We demonstrate a novel data-driven approach to discover insights from an extensive collection of heterogeneous public data sources and offer an actionable understanding to policymakers to identify learning-loss tendencies and prevent them in public schools.

Index Terms—Algorithms, Boosting, Data augmentation, Dimensionality reduction, Random Forest

I. INTRODUCTION

COVID-19 also had an impact on teacher preparation [1]. A study indicates how COVID-19 has led many veteran teachers to retire early and novice teachers to consider alternative professions [2]. The COVID-19 pandemic also forced many schools to close across the world [2]. According to the latest UNESCO statistics, there are 43 million students affected by school closures and nationwide closures [3]. Even in high-income countries like the Netherlands and Belgium, learning loss ranged from 0.08 to 0.29 [4], [5]. In a recent article, the global impact of a 5-month school shutdown could generate learning losses with a value of <10 trillion dollars [3].

In a recent paper, the global impact of a school shutdown for five months generated learning losses with a present value of \$10 trillion [3]. In the U.S., school district reopening decisions are difficult for policymakers since there is no consensus on the impact of school reopening on the spread of COVID-19 [6]. The learning loss was not uniform across states, as documented for Virginia, Maryland, Ohio, and Connecticut in [7]. Recently, two states, Rhode Island and North Carolina, published two reports estimating the learning losses in these states ([8], [9]). Texas Education Agency also published a report documenting the loss of learning [10]. There is no clear conclusion on what specifically led to the learning recovery

in the states above, and how to recover these learning losses will be the mounting policy and research questions for the next few years and even decades. In the U.S., researchers have disagreed on the impact of school reopening during the spread of COVID-19 [1], [6]. This made it difficult for policymakers to decide when to reopen the school, and these varied between states, counties, and school districts [11]. The learning losses have not been uniform across the board [7], [8]. The Texas Education Agency published a report documenting the 4% loss in Reading and 15% loss in math on the STAAR exam and how the negative impact of COVID-19 erased years of improvement in Reading and math [12]. This paper proposes a novel data-driven approach for public data integration and analysis on a scale, automated attribute importance analysis, and robust prediction modeling. As a proof-of-concept, we fuse and analyze multiple open sources of information on public education in Texas before, during, and after the COVID-19 pandemic. We have collected and processed data from eight public websites to find what specific factors were most important for the schools to experience a large learning loss. We looked into consensus information, public school district population makeup, mode of instruction, income, urban/rural settings, student attendance, county infection rates, and unemployment rates, among hundreds of other factors in 2019, 2021, and 2022. The data-driven findings show that the most resilient factor of influence for learning loss in the district is how early or late the students went back to in-person learning. 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.

II. RELATED WORK

We reviewed the related work from qualitative and reporting perspectives in the introduction. In this section, we will focus on (1) quantitative research and machine learning tools to gain insight from the data on the relationship with the outcome without overfitting the features to the data or (2) the directions for selecting machine learning models for predicting learning loss with tabular data.

The most popular machine learning (ML) techniques (logistic regression, support vector machines, Bayesian belief network, decision trees, and neural network) for data in the

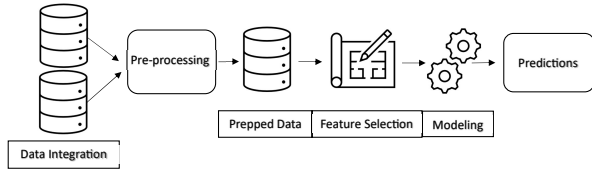


Fig. 1: The proposed noisy tabular data analysis pipeline.

wild generally offer an excellent classification accuracy above 70% for simple classification tasks [13]. From a data science perspective, the modeling approaches evaluated must be narrower in scope, and feature engineering almost guarantees poor domain/data translation results. A more elaborate evaluation of 30 selected articles revealed deep neural networks (DNN), decision trees, support vector machine (SVM), and nearest neighbor k (k -NN) as preferential methods to predict student academic performance [14]. Demographic, academic, family/personal, and internal assessments were the most frequently used features to predict student performance in class, at grade levels, on standardized tests, etc. [15]. A large-scale data science study correlated the Big Fish Little Pond Effect (BFLPE) in 56 countries in fourth-grade math and 46 countries in eighth-grade math using extensive data from the Trends in International Mathematics and Science Study (TIMSS) and a simple statistical analysis [16]. Recent findings show that the state of the art in machine learning in tabular data outperforms existing approaches and is not as sensitive to input bias and noise as DNN [17].

State-of-the-art gradient-boosted decision trees (GBDT) models such as XGBoost [18], LightGBM [19], and CatBoost [20] are the most popular models of choice when it comes to tabular data. In recent years, deep learning models have emerged as state-of-the-art techniques on heterogeneous tabular data: TabNet [21], DNF-Net [22], Neural Oblivious Decision Ensembles (NODE) [23], and TabNN [24]. Although papers have proposed that these deep learning algorithms outperform the GBDT models, there is no consensus that deep learning exceeds GBDT on tabular data because standard benchmarks have been absent. Open-source implementations, libraries, and their APIs are lacking [25], [26]. Recent studies provide competitive benchmarks comparing GBDT and deep learning models on multiple tabular data sets [25], [27], [28], [29]; however, all of these benchmarks indicate that there is no dominant winner, and GBDT models still outperform deep learning in general. The studies suggest developing tabular-specific deep learning models such that tabular data modalities, spatial and irregular data due to high-cardinality categorical features, missing values, and uninformative features cannot guarantee the same prediction power as deep learning obtains from homogeneous data, including images, audio, or text [27], [29].

III. PROPOSED METHODOLOGY

The work introduces a unified data science pipeline for handling tabular data. It validates the channel from the data science application to educational data by predicting learning loss in math and reading scores in Texas public schools.

A. Attribute Importance Scoring

This section proposes a novel way to select essential features from the hundreds of features considered. The work compares three different techniques for selecting features in data: filter methods, embedded methods, and wrapper methods. Several algorithms for automated feature selection are tested to evaluate these techniques, and a set of interpretative methods for analyzing feature importance are also provided to avoid the problems of "Garbage In, Garbage Out (GIGO)" and Trivial Modeling.

Attribute Filtering by Mutual Correlations Heterogeneous data tends to have much overlapping information mixed with numerical and categorical data. With this filter method distilling correlated features mutually, we aim to build a quasi-orthonormal attribute space to observe any correlation between two features or a feature and our label. We wanted to avoid artificial weighting of the features in the modeling step, so we utilized this correlation filtering in this section to aggregate linearly related features in our data set into one attribute. To this end, we have expanded several categorical features to multiple binary features as we found that numerous separate categories capture highly overlapping data. The Pearson correlation coefficient ρ measures the linear relationship between two normally distributed variables and is defined in Equation 1:

$$\rho = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y} \quad (1)$$

The $\text{cov}(X, Y)$ represents the covariance between variables X and Y , while σ_X and σ_Y are the standard deviations of X and Y respectively. Pearson's correlation coefficient estimate r , also known as a "correlation coefficient," for attribute feature vectors $x = (x_1, \dots, x_n)$ with mean \bar{x} and $y = (y_1, \dots, y_n)$ with mean \bar{y} , is obtained via a Least-Squares fit, as defined in Equation 2.

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (2)$$

The \bar{x} and \bar{y} represent the means of vectors x and y respectively. A value of 1 represents a perfect positive relationship, -1 is a perfect negative relationship, and 0 indicates the absence of a relationship between variables. We use features with high correlation coefficients to aggregate them into one attribute, as they are linearly dependent on each other. Eventually, we could keep one attribute, the most highly correlated to our label, of those overlapping features in our analysis. Then, we can combine all binary dummy-coded variables from related categories as a set in variable selection. This approach thus reduces an attribute dimension that provides better interpretability of our attribute set and its importance.

Multi-View Relevancy of the Attribute To select and have a glimpse of the features that affect our prediction models, we compare and contrast ten different approaches from the three methods mentioned above—filter methods, embedded methods, and wrapper methods—to evaluate the importance of features. Every technique of selecting minimum redundancy and maximum relevancy feature sets yields either a set of features chosen or a score of feature importance to reduce the dimensionality of feature space.

Permutation Feature Importance (PFI) is a technique that replaces the values of a feature with noise and measures the change in performance metrics (such as accuracy) between the baseline and permuted data set. This method overcomes some limitations of impurity-based feature importance but can also be biased by the correlation between features[30]. Our final set of features includes any feature with positive mean importance, as the PFI method returns positive values for essential features. We use Random Forests **PFI RF** and Logistic Regression with Ridge Regularization **PFI LR**. All these approaches provide the non-zero scores for all features. **Recursive Feature Elimination (RFE)** is a method training a model on the full set of features in the data set. It then eliminates the features with the smallest coefficients. It continues this process until the 10-fold cross-validation score of the models with Random Forest **RFE RF** and Logistic Regression with Ridge Regularization **RFE LR** on the training data decreases. The final scores are attribute rankings where 1 indicates the most relevant features [31]. **Logistic Regression with Filtering and Regularization** is a technique that uses L1 **LR Lasso** or L1 and L2 **ElasticNet** penalty terms to shrink the coefficients during training. This reduces the coefficients of some features to zero for both, and the remaining non-zero coefficients are considered useful information for prediction. **Feature Importance Random Forest (FI RF)** is a method that leverages the Random Forests machine learning algorithm to determine the importance of each feature. This importance is measured using either the Gini or the mean decrease impurity. A threshold of the 50th percentile of feature importance is used to determine which features should be included in the final set. **Variance Threshold** is a straightforward method to eliminate features by removing features with low variance in the training data set[32]. In this work, the threshold used is $0.8*(1-0.8)$, meaning that features with 80% similar values in the training data set are removed. The final set of features consists of the k features with the highest variance. Variance Threshold, SFS LR, and SFS KNN provide a binary selection of features.

Sequential Feature Selection (SFS) searches for the optimal set of features by greedily evaluating all possible combinations of features. The method works by adding one feature at a time and assessing each subset based on the 5-fold cross-validation score of logistic regression with ridge regression **SFS RR** and **SFS KNN** models. Overall, we have ten different results: some binary, some numerical, and some rank scores in Alg. 1. We propose several fusion scoring mechanisms for the end user to consider. First, we look into five approaches that filter out features and rank the features by the binary sum outputs. Next, we take five methods that provide scores for all features and rank the attribute importance based on the sum of absolute scores. We transform the scores into rankings and combine them with the filtering and ranking methods to develop the final feature importance ranking.

B. Prediction Modeling

The second question we are answering in this research is if the public data we mined from the web is enough to robustly

Algorithm 1: Fusion Scoring Algorithm

Input : Feature Selection Importance Scores(binary, numerical)
Output: Final Fusion Importance Ranking

- 1 Initialize BinarySumRankings;
- 2 Initialize AbsoluteScoreRankings;
- 3 **foreach** *result* in *Results* **do**
- 4 **if** *result* is binary **then**
- 5 Apply filtering mechanism to extract relevant features;
- 6 Calculate the binary sum output for these features;
- 7 Rank the features based on the binary sum outputs;
- 8 Append the ranked features to BinarySumRankings;
- 9 **else**
- 10 Apply methods to provide scores for all features;
- 11 Calculate the absolute scores for each feature;
- 12 Rank the attribute importance based on the sum of absolute scores;
- 13 Append the ranked attribute importance to AbsoluteScoreRankings;
- 14 **end**
- 15 **end**
- 16 Transform the scores from BinarySumRankings and AbsoluteScoreRankings into rankings;
- 17 Combine the rankings derived from both methodologies;
- 18 Merge the filtering and ranking methods to generate the FinalFeatureImportanceRanking;
- 19 **return** *FinalRanking*;

predict school district performance during COVID-19 years in terms of learning performance.

To this end, we establish five simple baseline models: logistic regression with ridge regularization, Support vector machines (SVM) and K-nearest neighbor (KNN) for nonlinear and non-separable data, random forests, and gradient boosting; and four advanced gradient boosting algorithms: XGBoost, LightGBM, CatBoost, and HistGradientBoosting. Our data fit the description of tabular data. Since gradient boosting approaches showed the most robustness when dealing with heterogeneous tabular data [25], our goal is to assess the predictive power of these nine machine learning models in this real example. Gradient Boosting assembles many weak decision trees, and unlike the random forests, the approach grows trees sequentially and iteratively based on the residuals from the previous trees. Gradient boosting methods handle tricky observations well and are optimized for faster and more efficient fitting using data sparsity-aware histogram-based algorithm.

In contrast to the pointwise split of the traditional Gradient Boosting prone to overfitting, the algorithm's approximate gradient creates estimates by creating a histogram for tree splits.

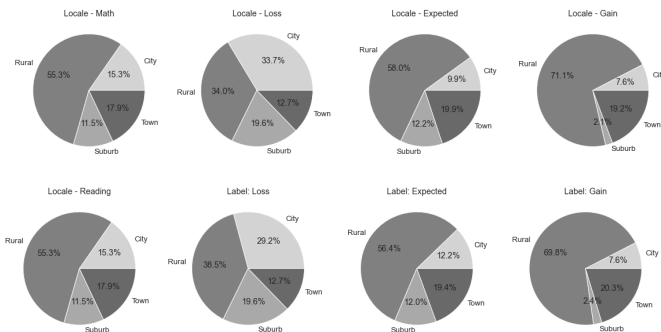


Fig. 2: Exploratory Data Analysis - Locale (top) Math (bottom) Reading

As this histogram algorithm does not handle the sparsity of the data, especially for tabular data with missing values and one-hot encoded categorical features, these algorithms improved tree splits. For example, XGBoost uses Sparsity-aware Split Finding, defining a default direction of tree split in each tree node [18]. Also, LightGBM provides the Gradient-Based One-Side Sampling technique, which filters data instances with a large gradient to adjust the influence of the sparsity, and Exclusive Feature Bundling combining features with non-zero values to reduce the number of columns [19].

IV. WEB DATA COLLECTION AND PROCESSING

A. Data Sources and Collection

We have collected data from eight different public sources as described in Table I. **Common Core of Data (CCD)** [33] is the primary database on public elementary and secondary education supplied by the National Center for Education Statistics (NCES) in the United States. The CCD provided us with public school characteristics, student demographics by grade, and faculty information at the school district in Texas for the fiscal years 2019 and 2021. **State of Texas Assessments of Academic Readiness (STAAR)** data was obtained from the Texas Education Agency (TEA) for the fiscal year 2019 and 2021 for each school district [34]. The STAAR data we collected are the average scores for math and reading tests and the number of students who participated in the grades 3-8 tests. These data also include students' numbers and average scores under various classifications, such as Title 1 participants, economically disadvantaged, free lunch, special education, Hispanic, Black, White, and Asian. **Texas School COVID-19** campus data was provided by the Texas Department of State Health Services (DSHS) [35], including the self-reported student enrollment and on-campus enrollment numbers of the dates September 28, 2020, October 30, 2020, and January 29, 2021, at each school district in Texas. **County COVID-19** data on infection and death cases due to Coronavirus for each Texas County was parsed from USAFacts source[36]. **The average daily attendance (ADA)** is a sum of attendance counts divided by days of instruction per school district and provided by TEA. **Elementary and Secondary School Emergency Relief (ESSER) Grant** data provided by TEA summarizes COVID-19 federal distribution by TEA to school districts for the fiscal years 2020, 2021, 2022, and 2023. **The Local Area Unemployment Statistics (LAUS)** data [37]

TABLE I: Data from eight different sources are integrated by matching school district I.D. and county FIPS code for 1,165 school districts with 506 features in 253 Texas counties

Data Frame	Data Source	Level	RowXCol
CCD	National Center for Education Stat [33]	District	1189X66
STAAR	Texas Education Agency [34]	District	1184x217
TEA	Texas Education Agency [10]	District	1182x217
ADA	Texas Education Agency [39]	District	1226X3
ESSER	Texas Education Agency [40]	District	1208X6
census	Census Bureau 2010 [38]	County	254, 37
Covid	USAFacts [36]	County	254X8
LAUS	U.S. Bureau of Labor Statistics [37]	County	254X13
Covid	DSHS [35]	District	1216X7

was parsed from the U.S. Bureau of Labor Statistics (BLS) for the years 2019 and 2021 to examine the workforce impact on learning loss in the counties. **Census block group 2010** data [38] were included to see if the county's general population characteristics make a difference in learning loss. At the end of the initial data integration merging data from eight sources by matching school district I.D. and county FIPS code, the data set represents 1,165 school districts of Texas located in 253 counties with 506 features, consisting of 1 categorical and 505 numerical.

The data was collected from March 13, 2020, to September 30, 2022. **CARES ESSER I 20, ARP ESSER III 21** features are part of the Elementary and Secondary School Emergency Relief (ESSER) grant programs, which are federal funds granted to State education agencies (SEAs) providing Local education agencies (LEAs) to address the impact due to COVID-19 on elementary and secondary schools across the nation; thus, the funds have been administered by Texas Education Agency (TEA) and allocated in each school district in Texas [40], [41]. **CARES ESSER I:** Authorized on March 27, 2020, as the Coronavirus Aid Relief and Economic Security (CARES) Act with \$13.2 billion. Our data have the allocation amount for the fiscal year of 2020. **CRRSA ESSER II:** Authorized on December 27, 2020, as the Coronavirus Response and Relief Supplemental Appropriations (CRRSA) Act with \$54.3 billion. Our data have the allocation amount for the fiscal year of 2021. **ARP ESSER III:** Authorized on March 11, 2021, as the American Rescue Plan (ARP) Act with \$122 billion. The data show the allocation amount for the fiscal year 2021. **ESSER-SUPP:** Authorized by the Texas Legislature to provide additional resources for not reimbursed costs to support students not performing well educationally. The data have the allocation amount for the fiscal years 2022 and 2023.

B. Data Aggregation and Filtering

To help policymakers make more informative decisions on learning recovery with localized efforts in each school district, we collected data from eight different sources as described in Table I to answer our research questions: i) Are students from low-income backgrounds and minority students experiencing more learning loss? ii) Do students of different grade levels experience learning loss differently? iii) Does the school or school district reopening decision influence learning loss experienced by students? iv) Is the mode of instruction (hybrid,

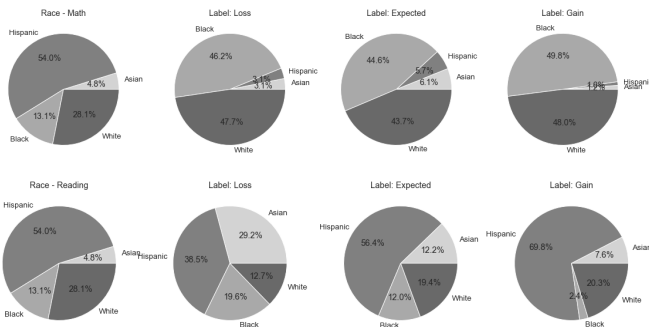


Fig. 3: Math (top) and Reading (bottom) scores broken by race

remote, in-person) related to learning loss? v) Is the school or district attendance negatively correlated with learning loss? vi) Does the local or regional infection rate lead to more learning loss? vii), Does the local unemployment rate negatively affect learning losses? If we can answer these questions with our approach, we can also identify resilient factors in learning recovery for Texas public schools.

Primarily, we gathered the Common Core of Data (CCD) [33], which is the primary database on public elementary and secondary education supplied by the National Center for Education Statistics (NCES) in the United States. The CCD provided us with public school characteristics, student demographics by grade, and faculty information at the school district in Texas for the fiscal years 2019 and 2021. Then, we merged the CCD data with the State of Texas Assessments of Academic Readiness (STAAR) data [34] from the Texas Education Agency (TEA) for fiscal years 2019 and 2021 at each school district. The STAAR data we collected are the average scores for math and reading tests and the number of students who participated in the grades 3-8 trials. These data also include students' numbers and average scores under various classifications, such as Title 1 participants, economically disadvantaged, free lunch, special education, Hispanic, Black, White, and Asian. Next, our data merged with COVID-19 campus data from the Texas Department of State Health Services (DSHS) [35], including the self-reported student enrollment and on-campus enrollment numbers of the dates September 28, 2020, October 30, 2020, and January 29, 2021, at each school district in Texas. Additional COVID-19 data involved confirmed infection and death cases [36] due to Coronavirus at each county from USAFacts. Also, the average daily attendance (ADA) [39], which consists of the sum of attendance counts divided by days of instruction, and data from the Elementary and Secondary School Emergency Relief (ESSER) Grant Programs [40] – COVID-19 relief funding – were collected from TEA for school district level. The ADA data for fiscal years 2019 and 2021 were added to our data to see the impact of district attendance, and the ESSER data reflect the localized efforts of TEA allocating the grant amount at each school district in the fiscal years of 2020, 2021, 2022 and 2023. Also, we combined the Local Area Unemployment Statistics (LAUS) data [37] from the U.S. Bureau of Labor Statistics (BLS) for the years 2019 and 2021 to examine the negative impact of the unemployment rate on learning loss at the county level. The census block group 2010 data [38] were

TABLE II: Example of 2019 and 2021 attribute aggregates

Attribute	Aggregated Attribute	Data
Total Schools 2020-2021	Total Schools Diff	CCD, NCES
Total Schools 2018-2019		
% Title 1 Eligible 2020-2021	% Title 1 Eligible Diff	CCD, NCES
% Title 1 Eligible 2018-2019		
% Hispanic 2020-2021	% Hispanic Diff	CCD, NCES
% Hispanic 2018-2019		
% Grades 1-8 2020-2021	% Grades 1-8 Diff	CCD, NCES
% Grades 1-8 2018-2019		
% Tested Reading G3 2020-2021	% Tested Reading G3 Diff	STAAR, TEA
% Tested Reading G3 2018-2019		
Unemployed Rate 2021	Unemployed Rate Diff	LAUS, BLS
Unemployed Rate 2019		
% ADA 2020-2021	% ADA Diff	ADA, TEA
% ADA 2018-2019		

included to grasp demographic characteristics at a county for the general population. At the end of the initial data integration merging data from eight sources by matching school district I.D. and county FIPS code, the data set represents 1,165 school districts of Texas located in 253 counties with 506 features, consisting of 1 categorical and 505 numerical. All eight sources were integrated by the district I.D. and county FIPS code, and the aggregated dataset covers 1,165 school districts of Texas located in 253 counties with 506 features, one categorical and 505 numerical.

The aggregated data set contains 506 features for 1,165 school districts in Texas. Among the 506 features, 416 features include missing values from 3 data sources ranging from 1 to 88% in our data set: 408 features from STAAR, TEA, six features from CCD, NCES, and two features from COVID, DSHS data. Of these 416 features, 332 features have fewer than 20% missing values and 24 features have more than 80% of missing values, and the distribution is illustrated in Figure 4.

The features with over 20% missing values are predominantly from the STAAR data, related to average scores and participants in the STAAR tests, and we have removed those features from the STAAR data. We have also dropped the school districts that do not have the CCDE and COVID data and ended up with 955 public school districts in Texas to analyze and a total of 119 features with no missing values. Out of 119 features, we aggregate the 58 features that duplicate the data for 2019 and 2021 into 29 differential features as illustrated in Table II. For example, Total Schools 2020-2021 and Total Schools 2018-2019 features are aggregated into Total Schools Diff, and the total number of features is reduced to 90.

C. Data Labeling

Our data set is unlabeled; thus, we must create a ground truth label for further prediction processes. The data set contains average scale scores of the STARR for math and Reading between grades 3 and 8 for the fiscal years of 2019 and 2021. Each school district has 24 features indicating the scores for calculating learning loss. We first normalized each cell of the scores by the maximum score value of the attribute as described in Figure 5, Step 1. Step 2 averaged these normalized scores for each year and subject, and Step

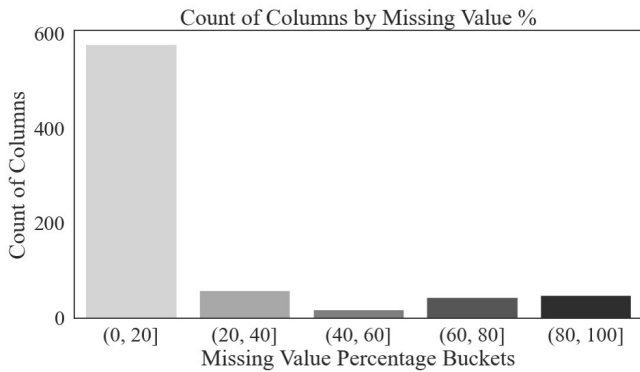


Fig. 4: Percentage of missing values for 416 features in the aggregated data. 2022-2023

3 calculated the loss as the difference between the scores between 2019 and 2021 for the perspective of 2019.

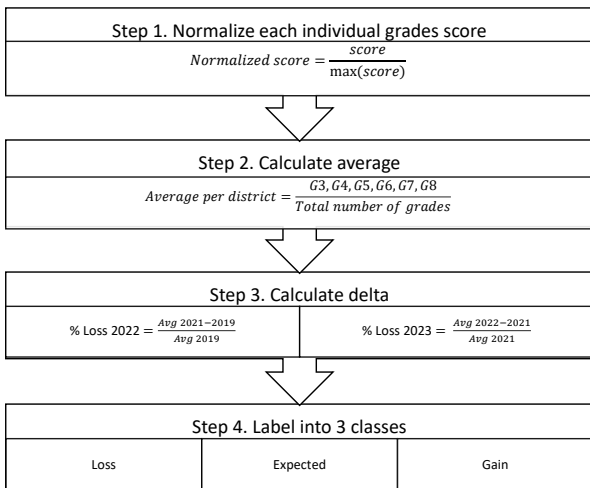


Fig. 5: Four steps to label learning loss with "Expected," "Loss," and "Gain" using the STAAR scores. First, normalize each score, then get averages and deltas of the scores between 2021 and 2019.

The *learning loss* label is decided depending on the loss value: if it is positive, there is learning gain, but a negative value corresponds to learning loss. *TODO: make sure the definition is consistent – Mirna*. The distribution of the loss values in Figure 6 informed us to set a threshold determining the loss and gain. The Distribution shows that more districts have experienced loss in math as the median for math (-0.03) is lower than for Reading (0). We proceeded with further analysis and prediction separately for math and Reading. Step 4 in Figure 5 describes creating three label classes; the middle 50% of school districts are labeled as "Expected," the loss values below the 25th percentile are set to be "Loss," and the loss values above 75th percentile become "Gain." *TODO: does this make sense – Mirna*

With the data labeled as learning loss, Expected, and Gain, we analyzed each in-depth concerning a correlation between features and the label. Figure 3 illustrates (a) White students are correlated to our label as they are the majority population for Gain and decreased towards Loss label; (b) Hispanic

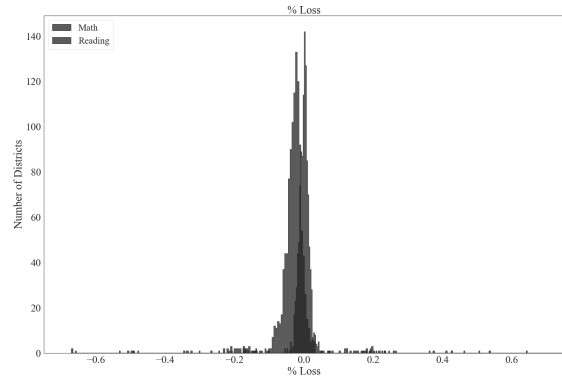


Fig. 6: Distribution of normalized STAAR scores between 2019-2023. More school districts in Texas faced learning loss in math than in reading

students are 2/3 of Loss students then reduced as for Expected and Gain labels for both math and Reading. Also, we realized that the locale of school districts is correlated to the label learning loss, as illustrated in Figure 2 (a), confirms that over half the schools are located in rural areas in Texas despite the positive correlation between rural areas and the label from Loss to Gain; however, Loss occurring in schools located in City and Suburb areas increasingly appeared in (b) and (c).

D. Data Pre-Processing

In the dataset *LossA*, we aggregate the 58 features that duplicate the data for 2019 and 2021 in 29 differential features as illustrated in Table II. For example, the features *Total Schools 2020-2021* and *Total Schools 2018-2019* are aggregated into *Total Schools Diff*, and the total number of features is reduced to 90. In the dataset *LossB*, we treat them as independent features. The experiment comparing the two's importance modeling is illustrated in Section III-A. The dataset contains 506 attributes for 1,165 school districts.

TABLE III: Resilient factors for Top 15 (math) and 14 features (Reading) Low income and grade level are both subjects' most impactful resilience factors

Resilient Factor	Math	Reading
Low-income	4	5
Grade Level	4	4
Race/Ethnicity	3	1
Mode of instruction	2	3
Attendance	1	0
Census demographics	1	0
Unemployment	0	1

We propose dimensionality reduction to obtain interpretability and identify the resilience factors for learning loss as follows:

LossA We remove noise and missing values from the data and then aggregate attributes conveying the same information for 2019 and 2021. In turn, we successfully reduced the number of attributes to 90 to finally adopt the attribute selection methods Section III-A.

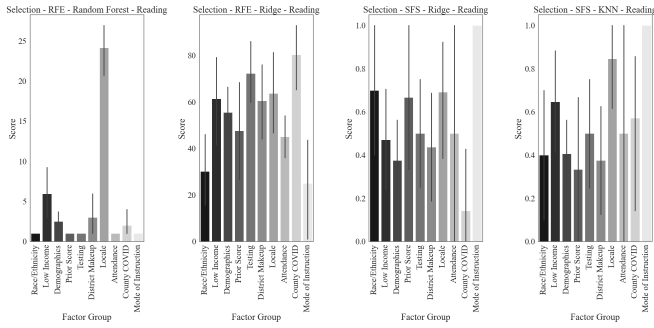


Fig. 7: Random Forest Recursive Feature Elimination, Ridge Recursive Feature Elimination, Sequential Feature Selection using Ridge, and K-Nearest Neighbors selecting the most reading significant resilient factors

When analyzed by year, the normalization process encompasses various facets of educational institutions, such as the count of operational public schools, identification of School-wide Title 1 designations, and Title 1 eligibility. Additionally, it includes insights into the educational workforce, encompassing FTE teachers and overall staff counts, along with lunch program statistics like free and reduced-price lunch participants. Race and ethnicity distributions among Asian, Hispanic, Black, and White demographics, delineated by grade groups from Prekindergarten to Grade 12, are normalized for accurate assessment. Attendance metrics undergo normalization in terms of average daily attendance (ADA) and as a percentage of total students per district. By grade, the standardization involves the percentage of students taking the STAAR Reading and Math tests, with average scores ratio-ed to the 100th percentile in each grade, regarding population metrics, normalization factors in confirmed COVID-19 cases, and deaths as percentages of the county population. It also encompasses race/ethnicity and age group distributions as a percentage of the county population in 2010. Lastly, when assessed by date, the normalization process considers the percentage of students on campus for dates like September 28, 2020, October 30, 2020, and January 29, 2021. Additionally, it categorizes different household types and housing units as percentages of the total number of households and housing units in 2010, respectively. This comprehensive standardization methodology ensures a consistent and comparable analysis across diverse data points and timeframes.

LossB Raw integrated data without normalization but missing values for the Gradient Boosting experiment. *TODO: add more ... this is awfully short compared to the LossB writeup – Mirna*

V. RESULTS

A. Attribute Importance Analysis

We executed the ten different feature selection approaches described in Section III-A to detect the resilient factors for learning loss due to COVID-19 using the data set with 90 features and 955 school districts in Texas as a baseline.

As we discriminate the subjects, math, and Reading, on predicting learning loss, the feature selection process has

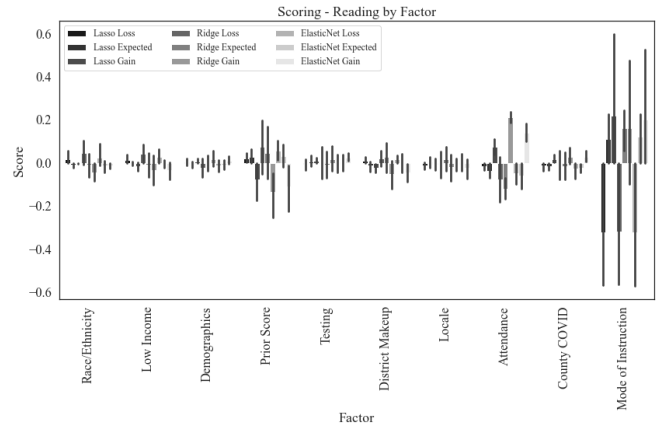


Fig. 8: Comparison of Feature Selection Techniques — Lasso Loss, Lasso Expected, Lasso Gain, Ridge Loss, Ridge Expected, Ridge Gain, ElasticNet Loss, ElasticNet Expected, and ElasticNet Gain — to identify the most significant reading resilient factors

been repeated for each subject separately. Variance Threshold, SFS Ridge, and SFS KNN provide a binary selection of features. ElasticNet Logistic Regression fit for the Gain and Loss provides scores for a subset of coefficients that are not zeroed out. R.F. feature importance, R.F. permutation, and Ridge permutation importance offer non-zero scores to all 90 features, and RFE ridge regression and RFE Random forest provide attribute ranking. Figure 7 sums up the filtering results. The five methods ranked 18 features as top importance and agreed on excluding 33 descriptors, mainly from the workforce, census, and COVID data sources. The difference between free lunch and the COVID deaths in the county had little impact on learning loss. Next, we sort the remaining 57 features using Random Forest feature Importance, Random Forest permutation, Ridge permutation importance, RFE Ridge and R.F. scores, and ElasticNet Gain and ElasticNet Loss. Since all of them have importance ranking per feature (including the sign), we first normalize the scores for each method and then sum them.

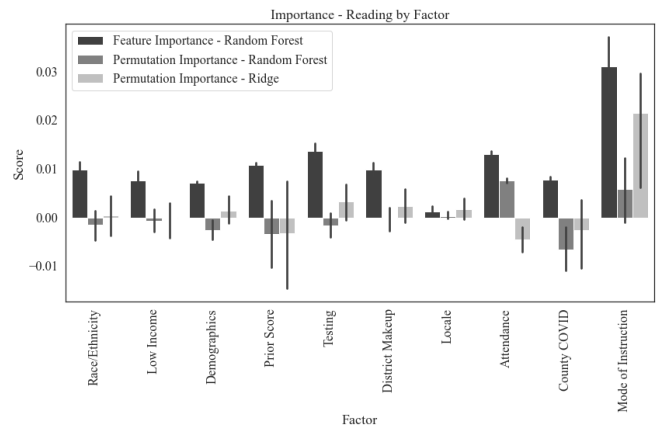


Fig. 9: *TODO: please rewrite the captions to reflect what is in the figure – Mirna*

First, we aggregate five filtering method outcomes for Reading and math: Variance Threshold, SFS KNN, SFS Ridge,

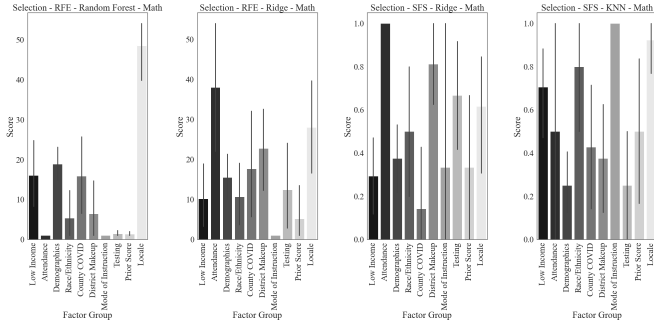


Fig. 10: Random Forest Recursive Feature Elimination, Ridge Recursive Feature Elimination, Sequential Feature Selection using Ridge, and K-Nearest Neighbors comparison to identify significant math resilient factors

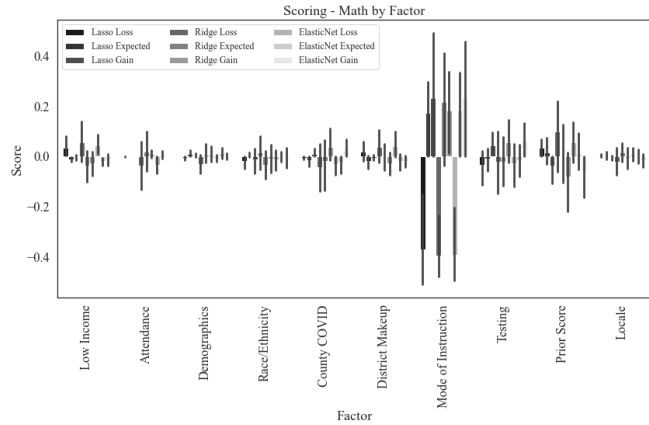


Fig. 11: Lasso Loss, Lasso Expected, Lasso Gain, Ridge Loss, Ridge Expected, Ridge Gain, ElasticNet Loss, ElasticNet Expected, and ElasticNet Gain *TODO: what is the point? Fix axis labels as it takes too much space. Mirna*

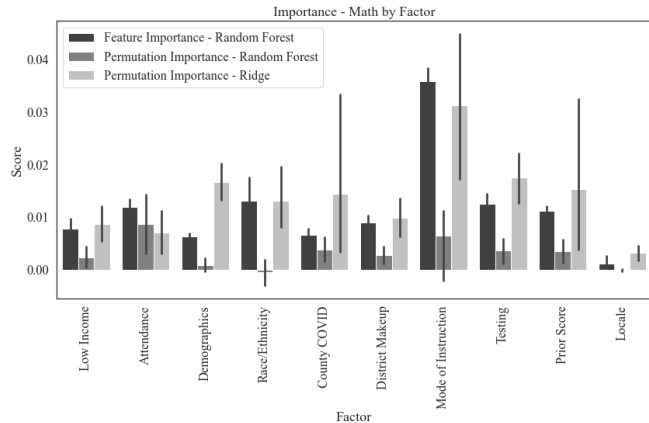


Fig. 12: Mirna rewrite to make sense

and ElastiNet Gain and ElastiNet Loss binarized coefficients. 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 output transformation, where we binarize all scores as SFS KNN, SFS RR, and Variance Threshold, which 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

TABLE IV: Method index and corresponding full name and output format. Feature dimensions after the method is applied are in the last two columns for Math and Reading

Index	Method	Output	Math	Reading
LR Lasso	Logistic Regression with L1 Reg.	score	51	51
LR ElasticNet	Logistic Regression with L1+L2 Reg.	score	41	45
PFI LR	Permutation Feature importance for LR L2	score	28	82
PFI RF	Permutation Feature importance for Random Forest	score	70	26
FI RF	Feature Importance Random Forest	score	45	45
VR	Variance Threshold	binary	20	20
SFS LR	Sequential Feature Search with Ridge Regression	binary	45	45
SFS KNN	Sequential Feature Search KNN	binary	45	45
RFE LR	Recursive Feature Elimination with Ridge Regression	rank	6	5
RFE RF	Recursive Feature Elimination Random Forest	rank	36	36

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 the importance of permutation features, 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.

Table IV indicates the dimension each approach reduces to the various numbers. RFE with random forests only selected 6 and 5 features for math and Reading, respectively; however, the PMI method selected the most significant number of features for both subjects: 70 features for math using random forests and 82 features for reading using ridge regression. The 2022 importance ranking of the features resulting from the ten approaches is shown in Table V, (a) Top 20 for math, and (b) Top 20 for reading selected by six or more feature selection methods, and the 2023 *TODO: 2022 or 2023? - Mirna* selection results are listed in Table VI.

The most significant feature predicting learning loss in math is % of Campus 10/30/20, the enrollment of students in the campus district on October 30, 2020, representing the mode of instruction. For reading subject, three critical features were selected, all of which were resilience factors related to the

Low-income backgrounds of students: *CARES ESSER I 20* (Coronavirus Aid, Relief and Economic Security (CARES) grant amount in 2020), *ARP ESSER III 21* (American Rescue Plan Act (ARP) grant amount in 2021), *% Reduced-price Lunch Diff* (Reduced-price Lunch Eligible Students Difference in percent between 2019 and 2021). The top 20 in math in Figure 10, and the top 20 in reading in Figure 7 were important features selected by six or more selection methods **TODO: check this please – Mirna**. Low income and Grade level are the most influential resilient factors to predict learning loss for Math and Reading, as shown in Table III. Race/Ethnicity and mode of instruction continued to be decisive, resilient factors for both subjects; on the other hand, Attendance and Census demographics are considered significant factors only in math, and Unemployment is essential only for Reading.

Although we now realize these essential features can identify the resilient factors for Loss or Gain in learning due to the COVID-19 pandemic, it is still unknown whether those features positively impact learning. For example, we analyzed positive or negative correlations between the most critical features and our label, Loss, Expected, or Gain, in math and Reading.

Figure 13 shows the Distribution of each ESSER fund amount converted to the amount per student. The students who experienced Loss in Reading received more significant funding for all funding programs on average than the students who participated, gained, or Expected in the same subject. The ESSER funds have been distributed to proper districts in need of financial help for adapting and preparing for learning Loss due to COVID-19 as the ESSER fund amounts are calculated by a formula based on Title I, Part A grant that is considered as a poverty proxy [40], [41].

Figure 14 indicates that *% of Campus 10/30/20* is positively correlated with Gain as the Distribution of school districts with the highest proportion of students on a campus populated more for Gain and Expected in math; however, the students experienced Loss are inhabited the most where the enrollment is 0%. It is clear that in-person classes, the mode of instruction, were the key to avoiding Loss in math.

B. Modeling Learning Loss from Public Data

The data sets have been randomly split into 80% of the training set and 20% of the test set with shuffling and stratification on the label. We use performance metrics suitable for prediction problems to find the best model. The accuracy score for both gain and loss is used to get a big picture, and the F1 score is used for an in-depth measure as it harmonically includes the precision and the recall scores. Matthews' correlation coefficient (MCC) considers true negatives, class imbalance, and multi-class data. Each model runs with a 10-fold cross-validation of GridSearch to find optimal hyperparameters. As the boosting algorithm trains weak learners iteratively, early stopping reduces training time and avoids overfitting. At every boost round, the model evaluates and decides whether to stop or continue the training when the model shows no more improvement for a certain number of consecutive rounds in terms of the evaluation metric specified as the fit parameter.

TABLE V: Top 20 Attributes for 2022 data

Math		
Feature	Impact Score	Binary Score
Median Household Income	6.6214	5
Total Students 2018-2019	6.2266	7
Total Students 2020-2021	6.1418	6
Total Students 2021-2022	6.1089	7
Rural: Distant	6.0521	3
# of Families 10	5.8406	4
Average Annual Pay	5.8252	2
ARP ESSER III 21 NORM	5.7606	3
CARES ESSER I 20 NORM	5.7590	4
Rural: Remote	5.7405	3
# of Housing Units 10	5.7040	3
# of Households 10	5.7005	3
Per Capita Income	5.6966	3
% of Pop Under 18 in Poverty	5.6840	3
Median Age Male 10	5.6834	3
County Population	5.6794	2
% of Pop in Poverty	5.6740	2
CRRSA ESSER II 21 NORM	5.6704	2
Median Age 10	5.6540	2
Median Age Female 10	5.5848	1
Reading		
Feature	Impact Score	Binary Score
Average Annual Pay	6.4049	3
Per Capita Income	6.2658	4
Total Students 2021-2022	6.0159	6
County Population	5.9212	5
# of Families 10	5.9140	6
Total Students 2018-2019	5.8932	5
Total Students 2020-2021	5.8707	5
# of Households 10	5.8357	5
% of Pop Under 18 in Poverty	5.8048	4
CRRSA ESSER II 21 NORM	5.8094	4
Median Household Income	5.7823	5
# of Housing Units 10	5.7847	4
Median Age Female 10	5.7612	3
% of Pop in Poverty	5.7661	4
Rural: Distant	5.7042	3
CARES ESSER I 20 NORM	5.7132	4
ARP ESSER III 21 NORM	5.6947	4
Median Age Male 10	5.6591	3
Median Age 10	5.5855	2
Rural: Remote	5.5603	2

For early stopping, a validation set, the split test set at the beginning of the modeling process, and the number of early stopping rounds that are set to 10% of the maximum number of boosting iterations are provided.

Five state-of-the-art machine learning models – ridge regression, SVM, KNN, **TODO: make sure all abbreviations are defined in every section and consistent – Mirna** random forests and gradient boosting – fit our complete set of 90 features and another ten different groups of selected features from RFE with ridge regression and random forests, Variance Threshold, SFS with ridge regression and KNN, random forests feature importance, Lasso regularization, and PMI with ridge regression and random forests as shown in Figure 15. The performance, accuracy, F1, and MCC of these models are plotted on bar graphs in Figure 16(top) for math and in Figure 16(bottom) for Reading; predicting learning loss for Reading shows weak performance compared to math generally. While there are no apparent differences between the performance of all models, except KNN, and the number of features observed for both subjects, gradient boosting for math

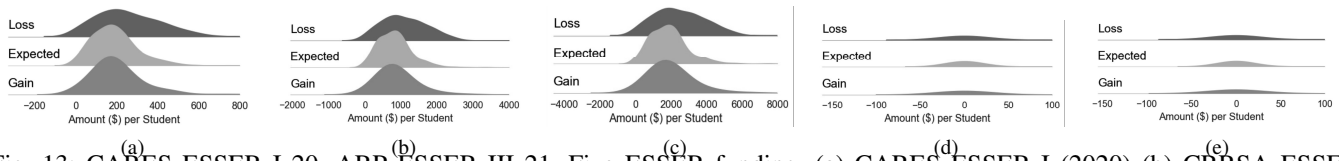


Fig. 13: CARES ESSER I 20, ARP ESSER III 21. Five ESSER funding, (a) CARES ESSER I (2020) (b) CRRSA ESSER II (2021) (c) ARP ESSER III (2021) (d) ESSER-SUPP (2022) (e) ESSER-SUPP (2023), allocation for school district per student confirms that the funds have been distributed to the districts needing help as those districts have more students who experienced learning loss in reading *TODO: not sure if we should keep this one. – Mirna*

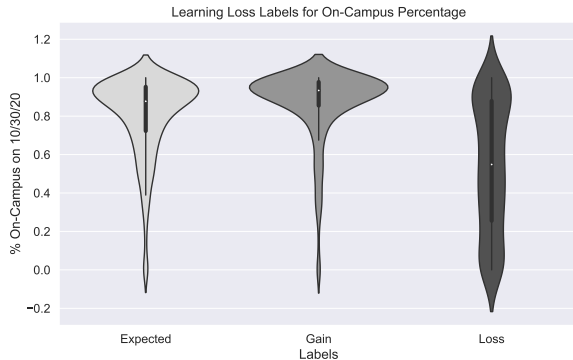


Fig. 14: Analysis on the most important feature for predicting learning loss: % On Campus 10/30/20. Gain and Expected label school districts have more students who went to school on October 30, 2020,

and ridge regression for Reading indicates the best accuracy, F1, and MCC on average.

Four advanced gradient boost models, XGBoost, LightGBM, CatBoost, and HistGradientBoosting, train the same sets of features for comparison purposes. To improve the gradient boosting models, we can penalize and regularize the algorithm by hyperparameter tuning so that we aim to increase accuracy and avoid overfitting. These hyperparameters are searched with a 5-fold cross-validation RandomizedSearch with the number of iterations that is 20% of parameter distributions of each model. For example, XGBoost is supposed to explore 100 distributions of the parameters; the number of iterations for RandomizedSearch is 20 times.

To begin with, constraining tree structures reduces the growth of complex and more extended trees by optimizing parameters such as the number of trees, the depth of trees, and the number of leaves per tree. In addition, setting a smaller learning rate, usually less than 0.5, allows weighting trees to slow the learning by a small amount at each iteration to reduce errors. Furthermore, setting the optimal L1 and L2 regularization terms penalizing the sum of the leaf weights improves the models by simplifying the complexity and size of the model [18]. The gradient boosting algorithms also show higher prediction power for math than reading and indicate no significant model exceeding other models, including the best state-of-the-art models, in terms of performance.

The various dimensions of the selected features were experimented with to examine the effects of dimensionality reduction methods and the best set of the features by predicting learning loss with the machine learning models introduced in Section III-B. Then, our initial data set was also experimented

TABLE VI: Top 20 Attributes - 2023

Math		
Feature	Impact Score	Binary Score
Total Students 2018-2022	6.2266	7
% On Campus 10/30/20	1.4300	5
% White Students 2020-2021	0.6324	5
% Tested Math - G3 2020-2021	0.7360	5
Median Household Income	6.6214	5
% On Campus 09/28/20	0.6603	4
% White Students 2018-2019	0.6082	4
% On Campus 01/29/21	0.6892	4
Total Staff 2020-2021	0.6071	4
Total Teachers 2020-2021	1.2075	4
# of Families 10	5.8406	4
CARES ESSER I 20 NORM	5.7590	4
% Tested Math - G5 2018-2019	0.8683	4
% Asian Students 2018-2019	0.5235	4
City: Small	0.4131	4
Suburb: Mid-size	0.3970	4
% White Students 2021-2022	0.5163	3
% Hispanic Pop 10	0.1885	3
% Tested Math - G5 2020-2021	1.0852	3
% Tested Math - G6 2020-2021	0.2561	3
Reading		
Feature	Impact Score	Binary Score
# of Families 10	5.9140	5
Total Students 2021-2022	6.0159	5
County Population	5.9212	5
# of Households 10	5.8357	4
Total Students 2018-2019	5.8932	4
Total Students 2020-2021	5.8707	4
# of Housing Units 10	5.7847	4
CRRSA ESSER II 21 NORM	5.8094	4
% Asian Pop 10	0.3936	3
% Prek 2018-2019	0.3689	3
% Tested Reading - G7 2021-2022	0.3498	3
Median Household Income	5.7823	3
Total Teachers 2020-2021	0.8628	3
% On Campus 10/30/20	0.4773	3
% Tested Reading - G8 2018-2019	0.2727	3
% White Students 2020-2021	0.5280	3
% White Students 2021-2022	0.3913	3
% of Pop Under 18 in Poverty	5.8048	3
% of Pop in Poverty	5.7661	3
City: Small	0.1889	3

with gradient boosting models in terms of missing values and their imputation.

For the ten models, the best set of features for each model is described in Table VII (a) for math and (b) for Reading; both subjects suggest CatBoost as the most robust models: 36 features selected by RFE with random forests with precision (68%), F1 (65%) and MCC (43%) for math and 82 features selected by PMI with ridge regression with precision (62%), F1 (55%) and MCC (34%) for Reading.

Overall, the gradient boosting algorithms CatBoost and XGBoost are the best choices of all the machine learning

TABLE VII: Best Performance of the ten machine learning models that are trained for (a) Math and (b) Reading for *DistrictA* dataset. CatBoost is the overall winner

Model	Best Set	Feature Selection	Acc [0,1]	F1 [0,1]	MCC [-1,+1]
LR Ridge	45	FI RF	0.639	0.622	0.368
SVM	45	SFS LR	0.628	0.584	0.343
KNN	55	LR Lasso	0.618	0.591	0.318
Random Forests	45	SFS LR	0.639	0.582	0.363
Gradient Boost	36	RFE RF	0.644	0.622	0.375
CatBoost	36	RFE RF	0.675	0.645	0.434
HistGB	45	SFS KNN	0.634	0.609	0.35
LightGBM	70	PMI RF	0.644	0.601	0.372
XGBoost	21	VR	0.66	0.616	0.405

(a) Math

Model	Best Set	Feature Selection	Acc [0,1]	F1 [0,1]	MCC [-1,+1]
LR Ridge	45	SFS LR	0.607	0.522	0.303
SVM	45	SFS KNN	0.586	0.553	0.274
KNN	45	SFS KNN	0.571	0.536	0.232
Random Forests	45	SFS LR	0.592	0.513	0.26
Gradient Boost	45	SFS LR	0.56	0.542	0.231
CatBoost	82	PMI - Ridge	0.623	0.548	0.338
HistGB	45	SFS LR	0.576	0.495	0.219
LightGBM	90	All	0.602	0.516	0.288
XGBoost	90	All	0.613	0.535	0.312

(b) Reading

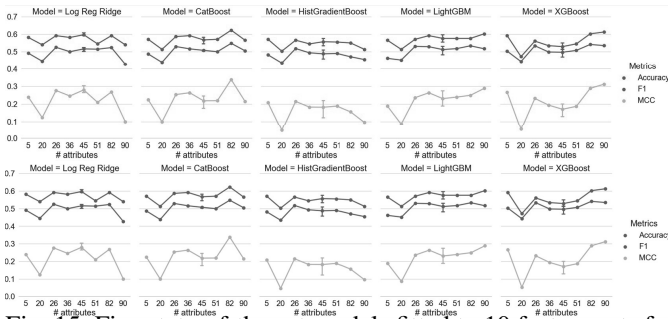


Fig. 15: Five state-of-the-art models fitted to 10 feature sets for predicting learning loss. With the train-test split, GridSearch, and 10-fold cross-validation, (top) gradient boosting for math and (bottom) ridge regression perform the best. *TODO: is this June’s figure or you redid it? – Mirna*

models we have experimented with to predict learning loss for both subjects. Although these models performed better in predicting failure in math rather than reading, in general, the performance gap between the four gradient boosting models and the five state-of-the-art models, except KNN, is negligible, as their difference in accuracy is around 3%. Furthermore, no clear indication of the best dimensionality reduction technique that performs across all models emerged.

C. Best Features vs. Raw Data for Gradient Boosting Models

All four gradient boosting models built – XGBoost, LightGBM, CatBoost, and HistGradientBoosting – are aware of the sparsity of data, such as missing values, by finding optimal tree split. Recall that the initial data set, also known as Raw data, containing 506 features (505 numerical and one categorical) for 1,165 school districts, includes 416 details with missing values as small as 1% and as large as 88% of each point, as shown in Figure 16. In this experiment, we executed the pipeline of building the advanced gradient boosting models

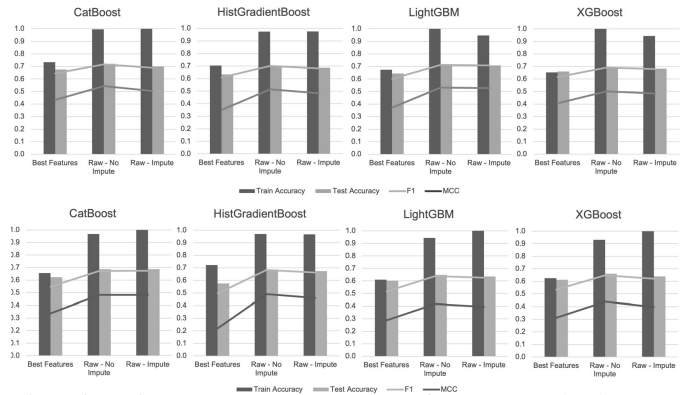


Fig. 16: Train & Test Accuracy, MCC for (top) Math; (bottom) Reading. MCC improved compared to the results using the data with the best features selected through feature engineering in Table VII

for raw data. We compared it with the models trained the data processed the feature engineering techniques regarding prediction power on learning loss. The classification task was completed for Math and Reading, respectively. All features with missing values except for eight details are subject-specific, e.g., the number of grade 3 students tested in math. After dropping the subject-specific math features for Reading and vice versa, 302 was the dimension of characteristics for this experiment for each subject. 212 of 302 details contain missing values. We have three data sets for comparison: (1) the best sets of features in Table VII from the performance results of the four gradient boosting models in Figure VII, (2) raw data without imputation for missing values, and (3) raw data impute missing values with mean values. Our data has only one categorical attribute, including no missing values, so the imputation method is limited to average. Regarding the performance of Best Features vs. Raw data, all models improved with Raw data throughout all performance metrics, especially MCC, for both subjects, as appeared in Figure 16; HistGradientBoost increased MCC the most by 47% following LightGBM (43%), CatBoost (25%) and XGBoost (24%) for math, and the improved MCC for Reading is even higher with 124% for HistGradientBoost and 45%, 43%, and 41% for LightGBM, CatBoost, and XGBoost, respectively. For a closer look, we also observed that the Raw data set without imputation performed slightly better compared to the Raw data set with imputation for all models and subjects; MCC for math rose the most, over 6%, in CatBoost and HistGradientBoost; on the contrary, XGBoost showed the most significant growth for MCC in reading with 10%.

VI. CONCLUSION AND FUTURE WORK

The intentional data science pipeline employed in this study automatically unearthed crucial features using publicly available data, leveraging ten distinct feature selection methods to model the impact of COVID-19 on learning loss. However, despite the reduction in data dimensionality facilitated by these methods, they exhibited limited influence on prediction accuracy. Surprisingly, the performance of the ten machine learning models trained on the feature-selected sets showcased negligible improvements. Notably, gradient-boosting algorithms, such

as XGBoost and CatBoost, emerged as consistently superior in both projects. These models demonstrated remarkable efficacy in managing missing values, a prevalent issue as more than two-thirds of the features in the learning loss datasets contained missing values. Our reproducible experiments and datasets are accessible at [42], offering valuable tools for policymakers.

Upon deeper analysis of the most influential features, it became evident that shifts in significance were predominantly observed at the individual feature level rather than through changes in resilience factor importance from 2022 to 2023. Notably, across this period, the mode of instruction and prior score stood out as the most significant resilience factors in the realm of education. This finding underscores the centrality of these factors in understanding and addressing learning loss dynamics. Policymakers can leverage our predictive models and analytical insights to strategically allocate resources and interventions within the public school system, targeting schools, students, and educators to mitigate and counteract the effects of learning loss.

Acknowledgments This research was partly supported by the Community Health and Economic Resilience Research at Translational Health Research Center at Texas State University.

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