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 public 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 a large 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*—Article submission, IEEE, IEEEtran, journal, LaTeX, paper, template, typesetting.**

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I. Introduction

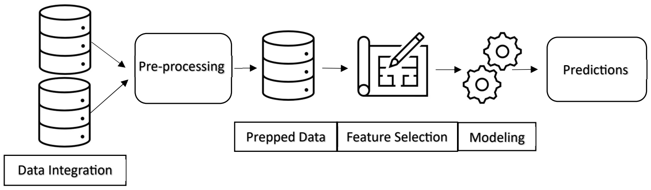
COVID-19 also had an impact on teacher preparation [1]. A study indicates how COVID-19 has led many veteran teachers to retire early and novice teachers to consider alternative professions [2]. The COVID-19 pandemic also forced many schools to close across the world [2]. According to the latest UNESCO statistics, there are 43 million students affected by school closures and nationwide closures [3]. Even in high-income countries, such as 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 of 5 months could generate learning losses with a present value of $10 trillion [3]. For the U.S. context, 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]. There is well-documented evidence that learning loss is not uniform across states such as Virginia, Maryland, Ohio, and Connecticut [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 aforementioned states, 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 pre-, during, and post-COVID-19 pandemic. We have collected data from eight public websites and processed data 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

In the introduction, we reviewed the related work from qualitative and reporting perspectives. 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.

Fig. 1: Machine Learning Pipeline



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

In this section, we propose 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. To evaluate these techniques, several algorithms for automated feature selection are tested, and a set of interpretable 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 tend to have a lot of overlapping information mixed with numerical and categorical data. With this filter method distilling correlated features mutually, our goal is 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 first have expanded several categorical features to multiple binary features as we found that multiple 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:

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

where $\text{cov}(X, Y)$ represents the covariance between variables X and Y, while σ_X and σ_Y are the standard deviations of X and Y respectively. The 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:

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

Here, $\bar{x}$ 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 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 decide to combine all binary dummy-coded variables from related categories as a set in variable selection. This approach thus reduces an attribute dimension that is providing better interpret-ability 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 approach of selecting minimum redundancy and maximum relevancy feature set yields either a set of features selected or a score of feature importance so that we can 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 important 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 50^{th} 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 evaluating 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.

Algorithm 1: Fusion Scoring Algorithm

```
Input  : Feature Selection Importance Scores(binary,
         numerical)
Output: Final Fusion Importance Ranking
Initialize BinarySumRankings;
Initialize AbsoluteScoreRankings;
foreach result in Results do
    if result is binary then
        Apply filtering mechanism to extract relevant
          features;
        Calculate the binary sum output for these
          features;
        Rank the features based on the binary sum
          outputs;
        Append the ranked features to
          BinarySumRankings;
    else
        Apply methods to provide scores for all
          features;
        Calculate the absolute scores for each feature;
        Rank the attribute importance based on the sum
          of absolute scores;
        Append the ranked attribute importance to
          AbsoluteScoreRankings;
    end
end
Transform the scores from BinarySumRankings and
  AbsoluteScoreRankings into rankings;
Combine the rankings derived from both
  methodologies;
Merge the filtering and ranking methods to generate
  the FinalFeatureImportanceRanking;
return FinalRanking;
```

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 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 access in this real example the predictive power of these nine machine learning models. 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. 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 tests for grades 3-8. These data also include the numbers and average scores for students 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] 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.

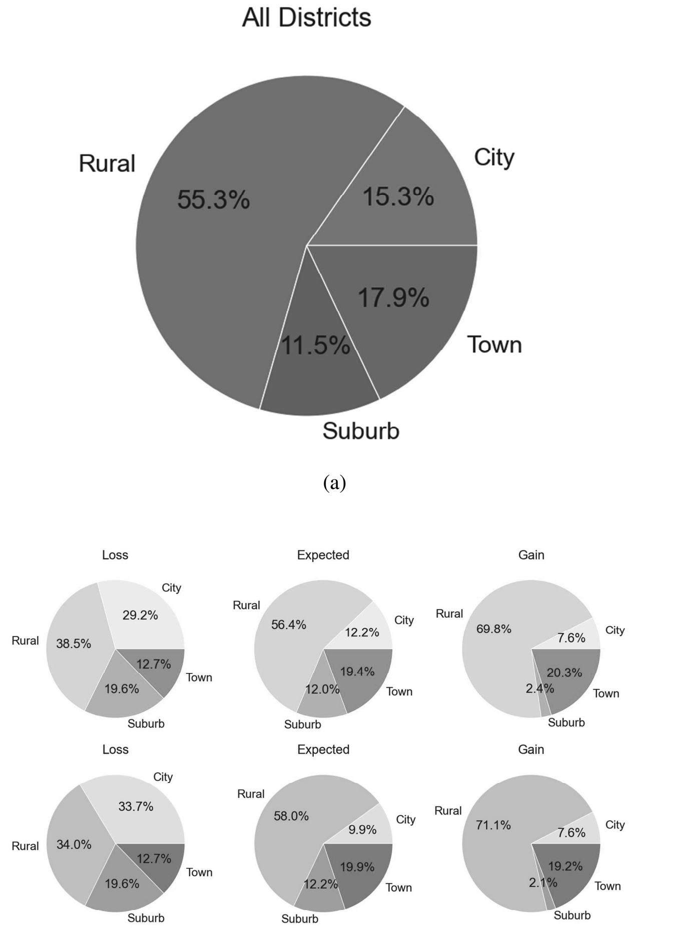
TABLE I: Data from eight different sources are integrated by matching school district I.D. and county FIPS code for 1,165 school districts with 506 features in 253 Texas counties.

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

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. The availability period is from March 13, 2020, to September 30, 2022. 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. The availability period is March 13, 2020, to September 30, 2023. 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 availability period is from March 13, 2020, to September 30, 2024. Our data have the allocation amount for the fiscal year of 2021. **ESSER-SUPP:** Authorized by the Texas Legislature to provide additional resources for unreimbursed costs to support students not performing well educationally. The availability period is March 13, 2020, to August 31, 2023. Our data have the allocation amount for the fiscal years 2022 and 2023.

B. Data Aggregation and Filtering

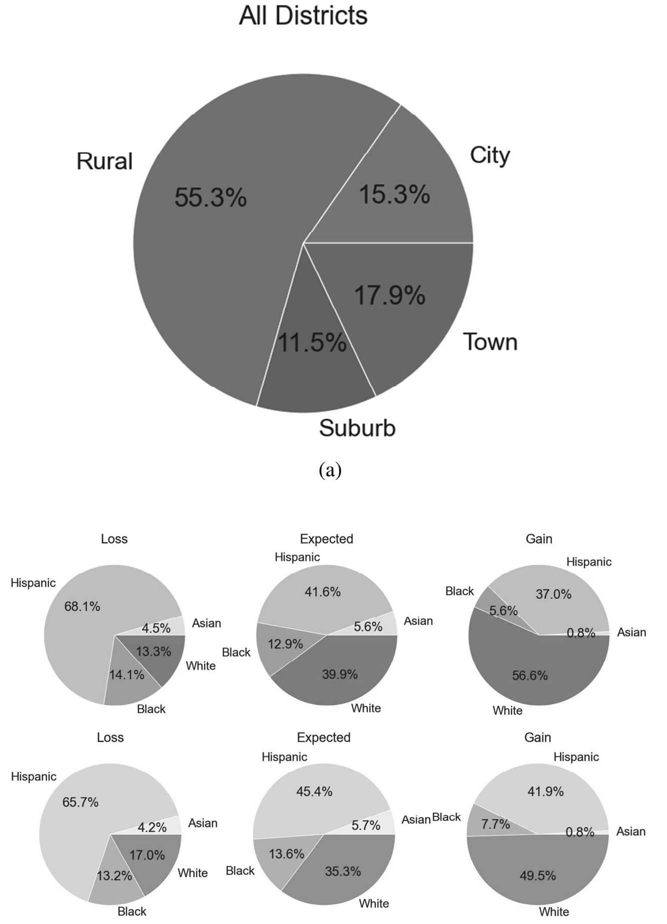
In order to help policymakers make more informative decisions on learning recovery with localized efforts in each school district, we collected data from eight different sources as described in Table I to answer our research questions: (i) Are students from low-income backgrounds and minority students 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, remote, in-person) related to learning loss? (v) Is school or district attendance negatively correlated with learning loss? (vi) Does the local or regional infection rate



(a)

(b)

Fig. 2: Exploratory Data Analysis - (a) All Locale (b) Math and Reading



(a)

(b)

Fig. 3: Exploratory Data Analysis - (a) All Race (b) Math and Reading

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 trials for grades 3-8. These data also include the numbers and average scores for students 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. Additionally, Census block group 2010 data [38] were 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

TABLE II: Example of **2019 and 2021** attribute aggregation

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

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 2 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 Fig. 6.

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, 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.

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 Fig. 5, Step 1. Step 2 averaged these normalized scores for each year and subject, and Step 3 calculated the loss as the difference between the scores between 2019 and 2021 for the perspective of 2019.

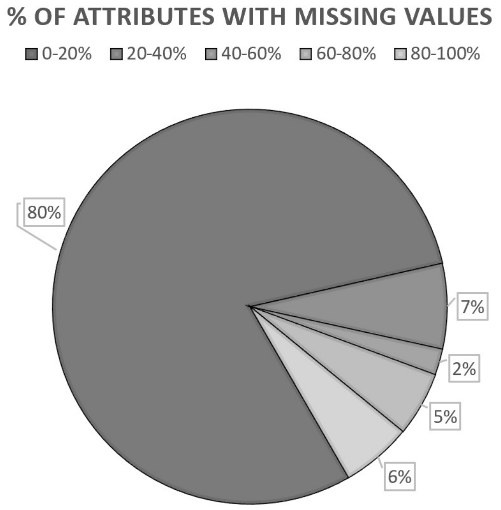


Fig. 4: Percentage of missing values for 416 features in the aggregated data.

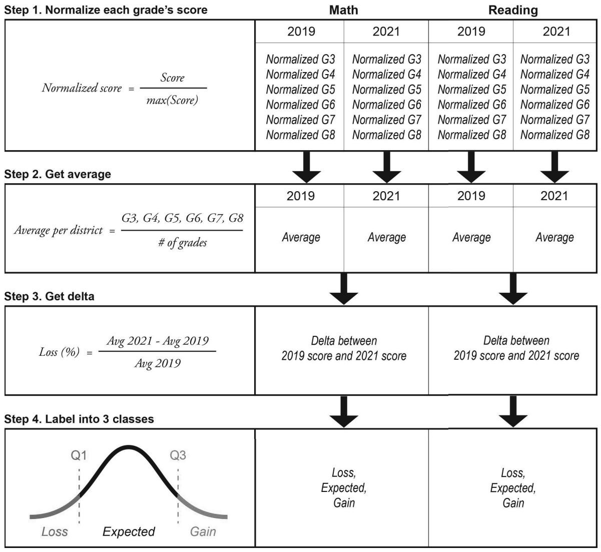

Step 1. Normalize each grade's score
Math
Reading
2019
2021
2019
2021
Normalized score = Score / max(Score)
Normalized G3
Normalized G4
Normalized G5
Normalized G6
Normalized G7
Normalized G8
Step 2. Get average
Average per district = G3, G4, G5, G6, G7, G8 / # of grades
Average
Step 3. Get delta
Loss (%) = Avg 2021 - Avg 2019 / Avg 2019
Delta between 2019 score and 2021 score
Step 4. Label into 3 classes
Q1
Q3
Loss
Expected
Gain
Loss, Expected, Gain

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

Consequently, our label – learning loss – is decided depending on the loss value: if it is positive, there is learning gain, but a negative value corresponds to learning loss.

The Distribution of the loss values in Fig. 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 Fig. 5 describes creating three label classes; the middle 50% of school districts is labeled as "Expected," and the loss values below the 25th percentile are set to be "Loss," and the loss values above 75th percentile become "Gain."

With the data labeled as learning loss, Expected, and Gain,

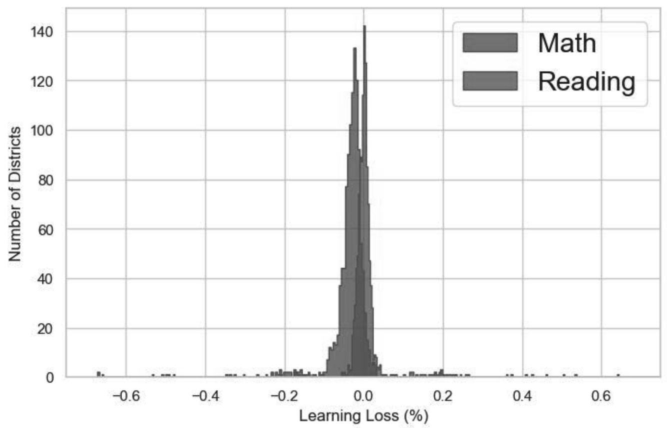


Fig. 6: Distribution of normalized STAAR scores between 2019 and 2021. More school districts in Texas faced learning loss in math than in the reading subject.

we analyzed each in-depth concerning a correlation between features and the label. Fig. 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 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 Fig. 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 in comparing the importance modeling of the two is illustrated in Section III-A.

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

TABLE III: Resilient factors for Top 15 (math) and 14 features (reading). Low income and Grade level are the most impactful resilient factors for both subjects.

Since our data set contains 506 attributes for 1,165 school districts, in this section, we engage in dimensionality reduction to obtain interpretability and identify the resilience factors for learning loss.

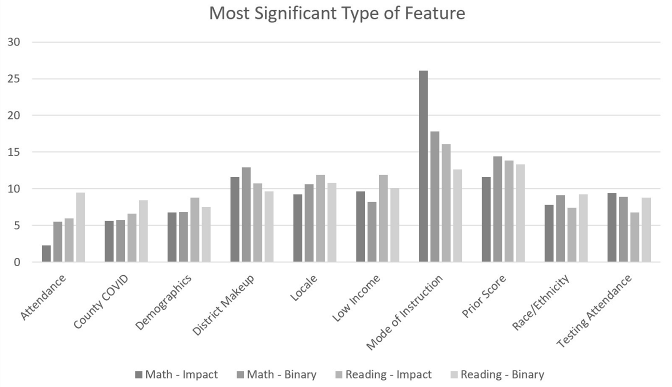


Fig. 7: Most Significant Type of Feature - Impact Score and Binary Score

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

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, both in terms of average daily attendance (ADA) and as a percentage of total students per district, undergo normalization. By grade, the standardization involves the percentage of students taking the STAAR Reading and Math tests, with average scores ratioed to the 100th percentile score 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 specific dates like 09/28/20, 10/30/20, and 01/29/21. Additionally, it involves the categorization of 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 with missing values for Gradient Boosting experiment.

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

Attribute	Math	Attribute	Reading
% On Campus 10/30/20	5	CARES ESSER I 20	5
% Black Diff	5	CRRSA ESSER II 21	5
CARES ESSER I 20	5	ARP ESSER III 21	5
% Tested Math G8 Diff	4	% Prek Diff	4
% Reduced-price Lunch Diff	4	Unemployed Level Diff	4
% Asian Diff	4	ESSER-SUPP 23	4
% Grades 1-8 Diff	4	% Black Diff	4
CRRSA ESSER II 21	4	% Reduced-price Lunch Diff	4
ARP ESSER III 21	4	% Tested Reading G7 Diff	4
% PreK Diff	4	# of Families 10	4
Median Age 10	4	% Tested Reading G4 Diff	4
% On Campus 09/28/20	4	Avg Household Size 10	4
% White Diff	4	ESSER-SUPP 22	4
Rural: Distant	4	Median Age Female 10	4
ESSER-SUPP 22	4	% Asian Diff	4
Unemployed Level Diff	4	% County Deaths 10/30/20	4
% ADA Diff	3	% Free Lunch Diff	3
% Grades 9-12 Diff	3	% Grades 1-8 Diff	3

TABLE IV: Top 18 features selected by ranking filtering outcomes of five approaches for math: 3 modes of instruction, 1 district attendance, 4 district race/ethnicity, 2 district poverty levels, two school populations, and three census locations.

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 been repeated for each subject separately. Variance Threshold, SFS Ridge, and SFS KNN provide a binary selection of features. ElastiNet 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. Table IV 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 ElastiNet Gain and ElastinNet Loss. Since all of them have importance ranking per feature (including the sign), first, we normalize the scores for each method, and then we sum them.

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

Table V indicates the dimension reduced to the various numbers by each approach. 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 importance ranking of the features resulting from the ten approaches is shown in Fig. V, (a) Top 15 for math, and (b) Top 14 for reading selected by six or more feature selection methods.

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). Based on the characteristics of the top 15 (math) and 18 (reading) important features selected by six or more selection methods in Fig. V, we analyzed the resilient factors for seeking the most impactful factor among them. Low income and Grade level are the most influential resilient factors to predict learning loss for math and reading, as shown in Fig. 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, in math and reading, we analyzed positive or negative correlations between

Method Index	Full name	Output	*Math*	*Reading*
LR Lasso	Logistic Regression with L1 Reg.	score	51	51
LR ElasticNet	Logistic Regression with L1+L2 Reg. score	score	41	45
PFI LR	Permutation Feature importance for LR L2 model	score	28	82
PFI RF	Permutation Feature importance for Random Forest model	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 model	rank	36	36

TABLE V: Feature dimension is X. After method Y is applied, the feature dimension is Z.

TABLE VI: Top 18 2019-2021

Math				
Attribute	**Impact**	**Binary**	**ElasticNet Gain**	**ElasticNet Loss**
Median Household Income	6.621	5	0	0.265
Total Students 2018-2019	6.227	7	0	0
Total Students 2019-2020	6.142	6	0	0
Total Students 2020-2021	6.109	7	0	0
Rural: Distant	6.052	3	0.075	0.071
# of Families 10	5.841	4	0	0
Avg Annual Pay	5.825	2	0	0.066
ARP ESSER III 21	5.761	3	0	0
CARES ESSER I 20	5.759	4	0	0
Rural: Remote	5.741	3	0	0
# of Housing Units 10	5.704	3	-0.018	0
# of Households 10	5.700	3	-0.015	0
Per Capita Income	5.697	3	0	0
% Pop Under 18 in Poverty	5.684	3	0	-0.048
Median Age Male 10	5.683	3	0	0
County Population	5.679	2	0	0
% of Population in Poverty	5.674	2	0	0
CRRSA ESSER II 21	5.670	2	0	0
Reading				
Feature	**Impact**	**Binary**	**ElasticNet Gain**	**ElasticNet Loss**
Avg Annual Pay	6.405	3	0.037	0.179
Per Capita Income	6.266	4	-0.149	0
County Population	5.921	5	-0.013	0
# of Families 10	5.914	6	0	0
Total Students 2018-2019	5.893	5	-0.005	-0.002
Total Students 2020-2021	5.871	5	-3.9E-05	-0.014
# of Households 10	5.836	5	-0.015	0
% Pop Under 18 in Poverty	5.805	4	-0.020	0
CRRSA ESSER II 21	5.810	4	0	0
Median Household Income	5.782	5	0	0.015
# of Housing Units 10	5.785	4	-0.031	0
Median Age Female 10	5.761	3	0	0
% Pop in Poverty	5.767	4	0	0
42-Rural: Distant	5.704	3	0.008	0
CARES ESSER I 20	5.713	4	0	0
ARP ESSER III 21	5.695	4	0	0
Median Age Male 10	5.659	3	0	0
Median Age 10	5.585	2	0	0

the most critical features and our label, Loss, Expected, or Gain.

Fig. 8 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. This means that the ESSER amounts 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].

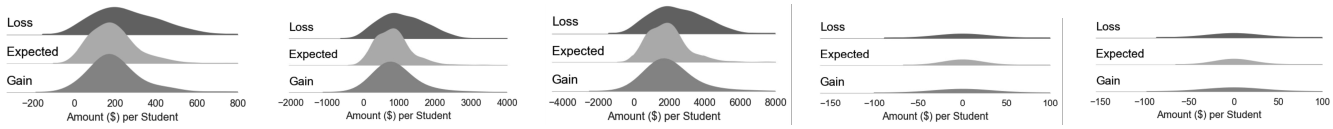
Fig. 9 indicates that *% of Campus 10/30/20* is positively correlated with Gain as the Distribution of school districts with the highest proportion of students on a campus populated more for Gain and Expected in math; however, the students experienced Loss are inhabited the most where the enrollment is 0%. It is clear that in-person classes, the mode of instruction, were the key to avoiding Loss in math.

TODO: create figures once we decide on agg. of Loss - Most Significant Type of Feature - Loss Aggregation – Mirna

B. Modeling Learning Loss from Public Data

Primarily, 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. To find the best model, we use performance metrics suitable for prediction problems. First, we look at the accuracy score for both problems to get a big picture. Then, the F1 score is measured to reflect the precision and recall harmonically. Additionally, Matthews correlation coefficient (MCC) considers true negatives, class imbalance, and multi-class of data. Each model runs with a 10-fold cross-validation of GridSearch to find optimal hyperparameters, in the Appendix. As the boosting algorithm trains weak learners iteratively, early stopping is used to reduce training time and avoid 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. 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.

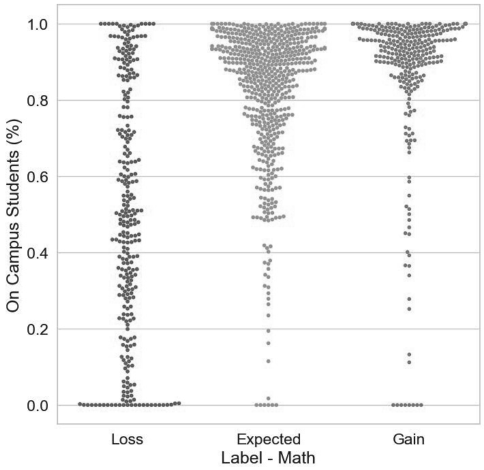
Five state-of-the-art machine learning models – ridge regression, SVM, KNN, random forests, and gradient boosting – fit our complete set of 90 features and another ten different groups of selected features from RFE with ridge regression and random forests, Variance Threshold, SFS with ridge regression and KNN, random forests feature importance, Lasso regularization, and PMI with ridge regression and random forests as shown in Fig. 10. The performance, accuracy, F1, and MCC of these models are plotted on bar graphs in Fig. 11(a) for math and in Fig. 11(b) for reading; predicting learning loss for reading shows weak performance compared to math generally. While no apparent differences between the performance of all models, except KNN, and the number of features observed for both subjects, gradient boosting for math and ridge regression for reading indicate the best accuracy, F1, and MCC on average.



(a) (b) (c) (d) (e)

Fig. 8: Analysis on the most important feature for predicting learning loss in reading: 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.

Fig. 9: Analysis on the most important feature for predicting learning loss in math: % On Campus 10/30/20. School districts in Gain and Expected label have more students who went to school on October 30, 2020.



For comparison purposes, four advanced gradient boost models, XGBoost, LightGBM, CatBoost, and HistGradientBoosting, train the same sets of features. To improve the gradient boosting models, we can penalize and regularize the algorithm by hyperparameter tuning so that we aim at increasing accuracy and avoiding overfitting, in the Appendix. 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 leave 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.

TABLE VII:

Math				
Attribute	**Impact**	**Binary**	**ElasticNet Gain**	**ElasticNet Loss**
Total Students 2018-2022	6.227	7	0	0
% On Campus 10/30/20	1.430	5	0	-0.406
% White Students 2020-2021	0.632	5	0	0
% Tested Math G3 2020-2021	0.736	5	0	0
Median Household Income	6.621	5	0	0.265
% On Campus 09/28/20	0.660	4	0.479	-0.214
% White Students 2018-2019	0.608	4	0	-0.014
% On Campus 01/29/21	0.689	4	0.203	-0.29
Total Staff 2020-2021	0.607	4	0	0
Total Teachers 2020-2021	1.207	4	0.079	0
# of Families 10	5.840	4	0	0
CARES ESSER I 20	5.759	4	0	0
% Tested Math G5 2018-2019	0.868	4	0.127	0
% Asian Students 2018-2019	0.524	4	-0.190	0
City: Small	0.413	4	0	-0.050
Suburb: Mid-size	0.397	4	-0.060	-0.011
% White Students 2021-2022	0.516	3	0	0
% Hispanic Pop 10	0.189	3	-0.015	0
Reading				
Feature	**Impact**	**Binary**	**ElasticNet Gain**	**ElasticNet Loss**
# of Families 10	5.914	5	0	0
Total Students 2021-2022	6.016	5	-0.033	-0.014
County Population	5.921	5	-0.014	0
# of Households 10	5.836	4	-0.030	0
Total Students 2018-2019	5.893	4	-0.002	-0.005
Total Students 2020-2021	5.870	4	-0.014	-3.87E-05
# of Housing Units 10	5.785	4	-0.031	0
CRRSA ESSER II 21	5.809	4	0	0
% Asian Pop 10	0.394	3	-0.010	0
% Prek 2018-2019	0.369	3	0	0.163
% Tested Reading G7 2021-2022	0.350	3	0.037	0
Median Household Income	5.782	3	0	0.015
Total Teachers 2020-2021	0.863	3	0.128	-0.020
% On Campus 10/30/20	0.477	3	0.402	-0.371
% Tested Reading G8 2018-2019	0.272	3	0	0
% White Students 2020-2021	0.528	3	0	0
% White Students 2021-2022	0.391	3	0	0
% Pop Under 18 in Poverty	5.805	3	-0.020	0

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 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 VIII (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

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

TABLE VIII: 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.

(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 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 HistGrandientBoosing – 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 Fig. 11. In this experiment, we executed the pipeline of building the advanced gradient boosting models 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 the respective subjects, math and reading. 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 VIII from the performance results of the four gradient boosting models in Fig. VIII, (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 Fig. 11; 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 can automatically uncover important features using public-use data and the ten feature selection methods to model learning loss due to COVID-19 in this paper. While the reduction in the dimensionality of data plays no role in the prediction power, as the ten machine learning models training the feature sets selected by the feature selection method did not exhibit significant improvement for the performance, the gradient boosting algorithms are generally performing better in both projects. The gradient boosting models such as XGBoost and CatBoost are superior for handling missing values as we experimented with raw data for the project; over 2/3 of the features of the learning loss data sets contain missing values. Reproducible experiments and datasets are published on [42]. Policymakers can use our predictive models and analysis to focus resources on the public school system, including schools, students, and teachers, to mitigate and recover learning loss with possible interventions in public schools.

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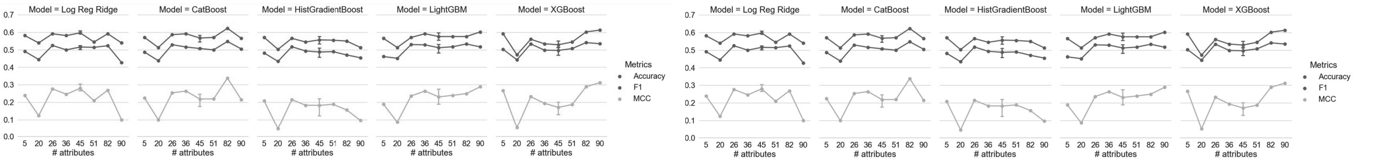
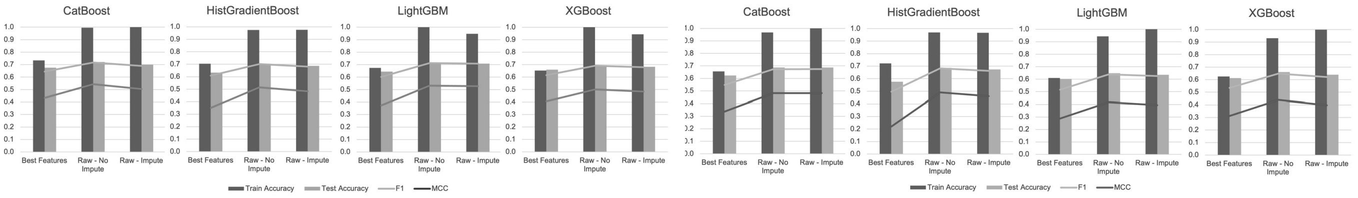


(a)

(b)

Fig. 10: 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, (a) gradient boosting for math and (b) ridge regression perform the best, while the rest, except KNN, also performs similarly.



(a)

(b)

Fig. 11: Train & Test Accuracy, MCC for (a) Math; (b) Reading. Four advanced gradient boosting models training Raw data, including missing values with or without imputation. MCC improved compared to the results using the data with the best features selected through feature engineering in Table VIII.

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