

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

Mirna Elizondo *Student Member, IEEE*, June Yu, Daniel Payan, Li Feng and Jelena Tešić *Member, IEEE*

**Abstract**—Student learning gain rates in public school systems in the US plummeted during the COVID-19 pandemic, erasing years of improvements. In this body of research, we collect, integrate, and analyze all available public data in the data science pipeline to see if public data can inform and impact learning loss factors. *Missing: specific data name?* 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 attributes. 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.

## I. INTRODUCTION

COVID-19 also had an impact on teacher preparation [Choate et al.(2021)]. A study indicates how COVID-19 has led many veteran teachers to retire early and novice teachers to consider alternative professions [Zamarro et al.(2022)]. The COVID-19 pandemic also forced many schools to close across the world [Zamarro et al.(2022)]. According to the latest UNESCO statistics, there are 43 million students affected by school closures and nationwide closures [OECD(2021)]. Even in high-income countries, such as the Netherlands and Belgium, learning loss ranged from 0.08 to 0.29 [Engzell et al.(2021)], [Maldonado and De Witte(2022)]. In a recent article, the global impact of a 5-month school shutdown could generate learning losses with a value of <10 trillion dollars [OECD(2021)].

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. *Missing: citation* For the US 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 [Courtemanche et al.(2021)]. There is well-documented evidence that learning loss is not uniform across states such as Virginia, Maryland, Ohio, and Connecticut [Halloran et al.(2021)]. *Missing: add TEA 2021 and 2022 and 2023 report findings from the other states.* 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 US, researchers have disagreed on the

impact of school reopening during the spread of COVID-19 [Choate et al.(2021)], [Courtemanche et al.(2021)]. This made it difficult for policymakers to decide when to reopen the school, and these varied between states, counties, and school districts [Rebai et al.(2020)]. The learning losses have not been uniform across the board [Halloran et al.(2021)], [Betebenner et al.(2021)]. 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 [Agency([n.d.))]. *Missing: Add TEA report on 2022 STAAR here* 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. *Missing: add 2022 findings for resilience*

## 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.

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 [Cardona et al.(2020)]. From a data science perspective, the modeling approaches evaluated must be narrower in scope, and feature engineering almost guarantees poor domain/data translation results. State-of-the-art gradient-boosted decision trees (GBDT) models such as XGBoost [Chen and Guestrin(2016)], LightGBM

[Guolin Ke(2017)], and CatBoost [Dorogush et al.(2018)] 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 [Arik and Pfister(2021)], DNF-Net [Abutbul et al.(2020)], Neural Oblivious Decision Ensembles (NODE) [Popov et al.(2019)], and TabNN [Ke et al.(2019)]. 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 [Shwartz-Ziv and Armon(2022)], [Joseph(2021)]. Recent studies provide competitive benchmarks comparing GBDT and deep learning models on multiple tabular data sets [Shwartz-Ziv and Armon(2022)], [Borisov et al.(2021)], [Gorishniy et al.(2021)], [Grinsztajn et al.(2022)]; 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 [Borisov et al.(2021)], [Grinsztajn et al.(2022)].

*Missing: Make sure we are not missing an analysis of educational data at scale*

### III. PROPOSED METHODOLOGY

*Comment: add figure –Jelena* We propose

#### A. Attribute Importance Scoring

In this section, we propose a novel way to select important attributes from the hundreds of attributes 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. **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 [Hooker and Mentch(2019)]. In this work, the 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 attributes. **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 attributes [Abe(2005)]. **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<sup>th</sup> 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 attributes with low variance in the training data set [Ghojogh et al.(2019)]. In this work, the threshold used is  $0.8 \times (1 - 0.8)$ , meaning that features with 80% similar values in the training data set are removed. The final set of features consists of the k attributes 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, some rank scores. In Alg. *Comment: add algorithm –Jelena* 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 approaches that provide scores for all attributes 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 predict school district performance during COVID-19 years in terms of the 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 [Shwartz-Ziv and Armon(2022)], our goal is to access on 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 approaches handle tricky observations well and are optimized in terms of faster

and efficient fitting using data sparsity aware histogram-based algorithm. In contrast to the pointwise split of the traditional Gradient Boosting that is 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 [Chen and Guestrin(2016)]. Also, LightGBM provides the Gradient-Based One-Side Sampling technique, which is filtering data instances with 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 [Guolin Ke(2017)].

#### 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)** [for Education Statistics (NCES)([n.d.])] 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 Texas Education Agency (TEA) for the fiscal year 2019 and 2021 for each school district [(TEA)([n.d.])b]. 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) [of State Health Services (DSHS)([n.d.])], 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[USAFacts([n.d.])]. **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 [of Labor Statistics (BLS)([n.d.])] 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 [Bureau([n.d.])] were included to see if the county's general population characteristics make a difference in learning loss.

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

TABLE I: Data from eight different sources are integrated by matching school district ID and county FIPS code for 1,165 school districts with 506 attributes in 253 Texas counties. *Comment: add web links –Jelena TODO: need help confirming Covid – Mirna*

**CARES ESSER I 20, ARP ESSER III 21** attributes 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 [(TEA)([n.d.])a], [of Elementary & Secondary Education([n.d.])]. **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.

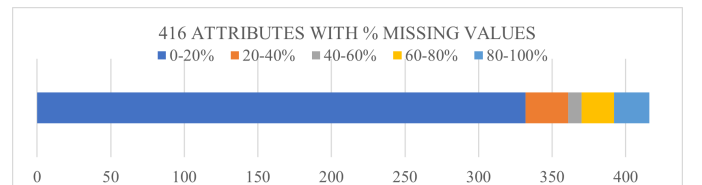


Fig. 1: Percentage of missing values for 416 attributes in the aggregated data. *Comment: add hiResimage –Jelena*

##### B. Data Aggregation and Filtering

All eight sources were integrated by the district ID and county FIPS code, and the aggregated dataset covers 1,165



school districts of Texas located in 253 counties with 506 attributes, 1 categorical and 505 numerical. The aggregated data set contains 506 attributes for 1,165 school districts in Texas. Among the 506 attributes, 416 attributes contain missing values from 3 data sources ranging from 1 to 88% in our data set: 408 attributes from STAAR, TEA, 6 attributes from CCD, NCES, and 2 attributes from COVID, DSHS data. Of these 416 attributes, 332 attributes have fewer than 20% missing values and 24 attributes have more than 80% of missing values, and the distribution is illustrated in Figure 1.

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		

TABLE II: Example of 2019 and 2021 attribute aggregation

The attributes 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 attributes 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 attributes with no missing values.

### C. Data Labeling

Our data set is unlabeled; thus we need to 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. This means that each school district has total of 24 attributes 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 2, 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. 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 Figure ?? 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 2 describes creating 3 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".

### D. Data Pre-Processing

*Comment: describe two different approaches here and compare –Jelena* In the dataset *LossA*, we aggregate aggregate the 58 attributes that duplicate the data for 2019 and 2021 in 29 differential attributes as illustrated in Table II. For example, the attributes *Total Schools 2020-2021* and *Total Schools 2018-2019* are aggregated into *Total Schools Diff*, and the total number of attributes is reduced to 90. In the dataset *LossB*, we treat them as independent attributes. The experiment in comparing importance modeling of the two is illustrated in Section III-A.

## V. RESULTS

### A. Setup

### B. Attribute Importance Analysis

Attribute	Math Filter	Attribute	Reading Filter
% On Campus 10/30/20	4		
CARES ESSER I 20	4		
% PreK Diff	4		
% Asian Diff	4		
% Black Diff	4		
City: Mid-size	4		
Rural: Distant	4		
% On Campus 01/29/21	3		
% On Campus 09/28/20	3		
% ADA Diff	3		
% Reduced-price Lunch Diff	3		
% Title 1 Diff	3		
% Grades 1-8 Diff	3		
% Hispanic Diff	3		
ARP ESSER III 21	3		
CRRSA ESSER II 21	3		
Town: Remote	3		
Teachers:Students Diff	3		

TABLE III: Top 18 attributes 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, 2 school population, and 3 census location. *Comment: finish –Jelena*

We executed the ten different feature selection approaches described in Section III-A to detect the resilient factors for learning loss due to COVID-10 using the data set with 90 attributes 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. RF feature importance, RF permutation, and Ridge permutation importance provide non-zero scores for all 90 attributes, and RFE ridge regression and RFE Random forest provide attribute ranking. Table III sums up the filtering results. The five methods ranked 18 features as top importance and agreed on excluding 33 descriptors, mostly 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 attributes using Random Forest feature Importance, Random Forest permutation, Ridge permutation importance, RFE Ridge

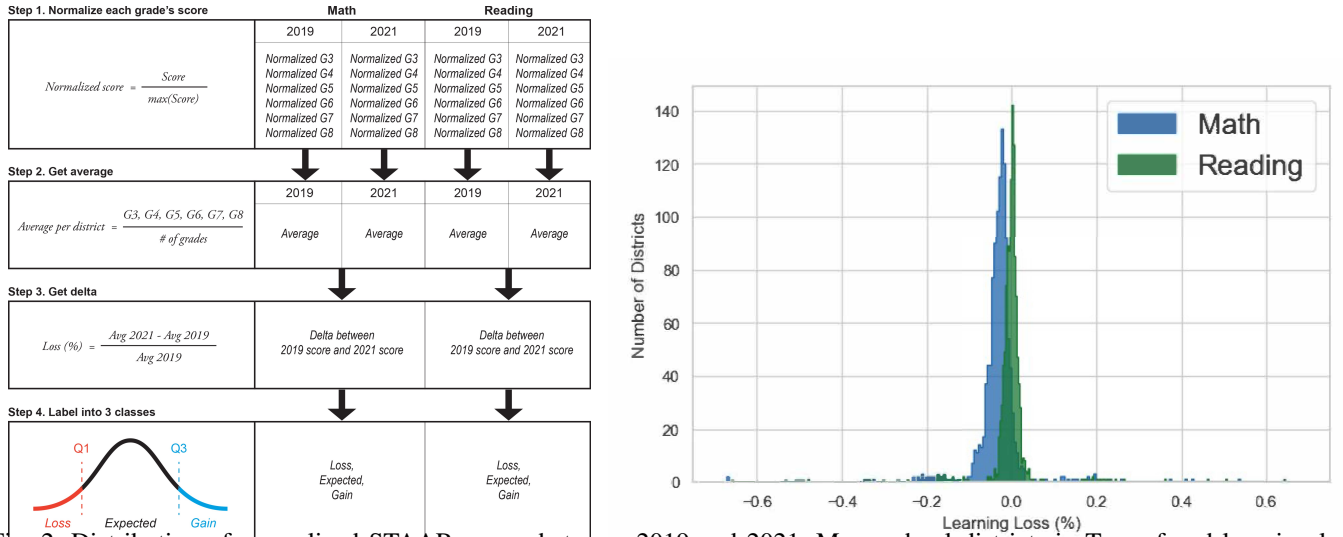


Fig. 2: Distribution of normalized STAAR scores between 2019 and 2021. More school districts in Texas faced learning loss in math than in the reading subject. Four steps to label learning loss with "Expected", "Loss", and "Gain" using the STAAR scores. First, normalizing each score, then getting averages and delta of the scores between 2021 and 2019.

and RF scores, and ElastiNet Gain and ElastiNet 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.

Table IV 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 Figure IV, (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 14 (reading) important features selected by six or more selection methods in Figure IV, we analyzed the resilient factors for seeking the most impactful factor among them. Low-income and Grade level is the most influential resilient factors to predict learning loss for math and reading, as shown in Figure VI. 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 iden-

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

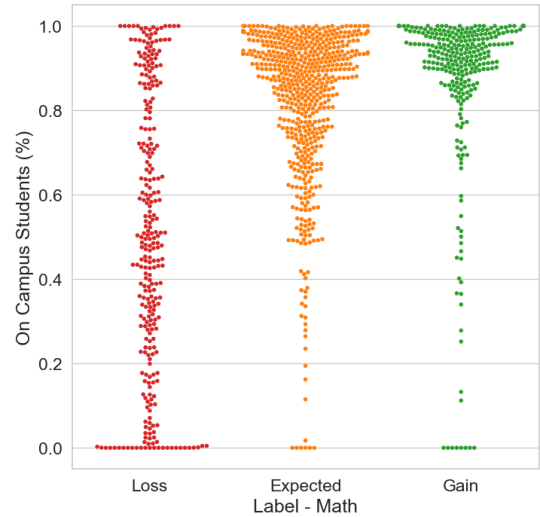


Fig. 3: Analysis on the most important feature for predicting learning loss in math: *% On Campus 10/30/20*. School districts in Gain and Expected label have more students who went to school on October 30, 2020. *TODO: Keeper. – Mirna*

Figure 3 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 populated 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.

Figure ?? shows the distribution of each ESSER fund amount converted to the amount per student, the students

Method Index	Full name	Output	DistrictA	DistrictB
LR Lasso	Logistic Rereession with L1 Reg.	score	Z	Z
LR ElasticNet	Logistic Regression with L1+L2 Reg. score	Z	Z	
PFI LR	Permutation Feature importance for LR L2 model	score	Z	Z
PFI RF	Permutation Feature importance for Random Forest model	score	Z	Z
FI RF	Feature Importance Random Forest	score	Z	Z
VR	Variance Threshold	binary	Z	Z
SFS LR	Sequential Feature Search with Ridge Regression	binary	Z	Z
SFS KNN	Sequential Feature Search KNN	binary	Z	Z
RFE LR	Recursive Feature Elimination ?	rank	Z	Z
RFE RF	Recursive Feature Elimination Random Forest model	rank	Z	Z

TABLE IV: Feature dimension is X. After method Y is applied the feature dimension is Z. *Comment: finish –Jelena*

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

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 VI: *TODO: Here we will introduce another level of aggregation and present the aggregated impact score that way. We also need to determine if the overall impact was positive or negative. Please update the approximate labels in the Excel sheet, column A – Mirna*  
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. Meaning 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 [(TEA)([n.d.])a], [of Elementary & Secondary Education([n.d.])].

### C. 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, 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. As the boost algorithm trains weak learners iteratively, early stopping is used to reduce training time and avoid overfitting. At every round of the boost, 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 is set to 10% of the maximum number of boosting iterations are provided.

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. To begin with, constraining tree structures reduces the growth of complex and longer 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, normally 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 [Chen and Guestrin(2016)]. 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 search 100 distributions of the parameters; the number of iterations for RandomizedSearch is 20 times.

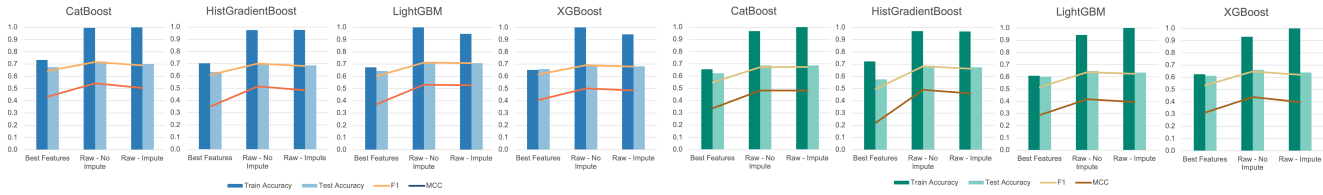
The various dimensions of the selected features were experimented with to examine the effects of dimensionality reduction methods and the best set of the features by predicting learning loss with the machine learning models introduced in Section III-B. Then, our initial data set was also experimented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

DistrictA Math 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	<b>0.675</b>	<b>0.645</b>	<b>0.434</b>
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

DistrictA Reading Model	Best Set	(a) Math 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	<b>0.553</b>	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	<b>0.623</b>	0.548	<b>0.338</b>
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

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



(a) Train & Test Accuracy, MCC for Math; (b) Train & Test Accuracy, MCC for 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 VII. *Comment: address this experiment. –Jelena*

## VI. CONCLUSION AND FUTURE WORK

The intentional data science pipeline can automatically uncover important attributes 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 attributes of the learning loss data sets contain missing values. Reproducible experiments and datasets are published on [Yu and Tešić([n.d.])]. 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.

## REFERENCES

- [Abe(2005)] Shigeo Abe. 2005. Modified backward feature selection by cross validation.. In *ESANN*. Citeseer, 163–168.
- [Abutbul et al.(2020)] Ami Abutbul, Gal Elidan, Liran Katzir, and Ran El-Yaniv. 2020. DNF-Net: A Neural Architecture for Tabular Data. *CoRR* abs/2006.06465 (2020). arXiv:2006.06465 <https://arxiv.org/abs/2006.06465>
- [Agency([n.d.])] Texas Educational Agency. [n.d.]. Impacts of COVID-19 and Accountability Updates for 2022 and Beyond. <https://tea.texas.gov/sites/default/files/2021-tac-accountability-presentation-final.pdf>.
- [Arik and Pfister(2021)] Sercan Arik and Tomas Pfister. 2021. TabNet: Attentive Interpretable Tabular Learning. *Proceedings of the AAAI Conference on Artificial Intelligence* 35, 8 (May 2021), 6679–6687. <https://doi.org/10.1609/aaai.v35i8.16826>
- [Betebenner et al.(2021)] Damian Betebenner, A Van Iwaarden, A Cooperman, M Boyer, and N Dadey. 2021. Assessing the academic impact of COVID-19 in summer 2021. *Center for Assessment* (2021).
- [Borisov et al.(2021)] Vadim Borisov, Tobias Leemann, Kathrin Seßler, Johannes Haug, Martin Pawelczyk, and Gjergji Kasneci. 2021. Deep Neural Networks and Tabular Data: A Survey. <https://doi.org/10.48550/ARXIV.2110.01889>
- [Bureau([n.d.])] Census Bureau. [n.d.]. Census Block Group 2010. <https://schoolsdata2-93b5c-tea-texas.opendata.arcgis.com/datasets/census-block-group-2010-tx/>.
- [Cardona et al.(2020)] Tatiana Cardona, Elizabeth A Cudney, Roger Hoerl, and Jennifer Snyder. 2020. Data Mining and Machine Learning Retention Models in Higher Education. *Journal of College Student Retention: Research, Theory & Practice* (2020), 1521025120964920.
- [Chen and Guestrin(2016)] Tianqi Chen and Carlos Guestrin. 2016. XG-Boost: A Scalable Tree Boosting System. *Information Fusion* (2016), 785–794. <https://doi.org/abs/1603.02754>
- [Choate et al.(2021)] Kathryn Choate, Dan Goldhaber, and Roddy Theobald. 2021. The effects of COVID-19 on teacher preparation. *Phi Delta Kappan* 102, 7 (2021), 52–57.
- [Courtemanche et al.(2021)] Charles J Courtemanche, Anh H Le, Aaron Yelowitz, and Ron Zimmer. 2021. *School reopenings, mobility, and COVID-19 spread: Evidence from Texas*. Technical Report. National Bureau of Economic Research.
- [Dorogush et al.(2018)] Anna Veronika Dorogush, Vasily Ershov, and Andrey Gulin. 2018. CatBoost: gradient boosting with categorical features support. *arXiv preprint arXiv:1810.11363* (2018).
- [Engzell et al.(2021)] Per Engzell, Arun Frey, and Mark D Verhagen. 2021. Learning loss due to school closures during the COVID-19 pandemic. *Proceedings of the National Academy of Sciences* 118, 17 (2021).
- [for Education Statistics (NCES)([n.d.])] National Center for Education Statistics (NCES). [n.d.]. Common Core of Data (CCD). <https://nces.ed.gov/ccd/elsi/tableGenerator.aspx>.
- [Ghojogh et al.(2019)] Benyamin Ghojogh, Maria N Samad, Sayema Asif Mashhadi, Tania Kapoor, Wahab Ali, Fakhri Karay, and Mark Crowley. 2019. Feature selection and feature extraction in pattern analysis: A literature review. *arXiv preprint arXiv:1905.02845* (2019).
- [Gorishniy et al.(2021)] Yury Gorishniy, Ivan Rubachev, Valentin Khulikov, and Artem Babenko. 2021. Revisiting Deep Learning Models for Tabular Data. In *Advances in Neural Information Processing Systems*, M. Ranzato, A. Beygelzimer, Y. Dauphin, P.S. Liang, and J. Wortman Vaughan (Eds.), Vol. 34. Curran Associates, Inc., 18932–18943. <https://proceedings.neurips.cc/paper/2021/file/9d86d83f925f2149e9edb0ac3b49229c-Paper.pdf>
- [Grinsztajn et al.(2022)] Léo Grinsztajn, Edouard Oyallon, and Gaël Varoquaux. 2022. Why do tree-based models still outperform deep learning on tabular data? <https://doi.org/10.48550/ARXIV.2207.08815>
- [Guolin Ke(2017)] Thomas Finley et al. Guolin Ke, Qi Meng. 2017. LightGBM: A Highly Efficient Gradient Boosting Decision Tree. *NIPS'17: Proceedings of the 31st International Conference on Neural Information Processing Systems* (2017), 3149–3157. <https://doi.org/doi/10.5555/3294996.3295074>
- [Halloran et al.(2021)] Clare Halloran, Rebecca Jack, James C Okun, and Emily Oster. 2021. *Pandemic schooling mode and student test scores: Evidence from us states*. Technical Report. National Bureau of Economic Research.
- [Hooker and Mentch(2019)] Giles Hooker and Lucas Mentch. 2019. Please stop permuting features: An explanation and alternatives. *arXiv e-prints* (2019), arXiv:1905.
- [Joseph(2021)] Manu Joseph. 2021. PyTorch Tabular: A Framework for Deep Learning with Tabular Data. <https://doi.org/10.48550/ARXIV.2104.13638>
- [Ke et al.(2019)] Guolin Ke, Jia Zhang, Zhenhui Xu, Jiang Bian, and Tie-Yan Liu. 2019. TabNN: A Universal Neural Network Solution for Tabular Data. <https://openreview.net/forum?id=r1eJssCqY7>
- [Maldonado and De Witte(2022)] Joana Elisa Maldonado and Kristof De Witte. 2022. The effect of school closures on standardised student test outcomes. *British Educational Research Journal* 48, 1 (2022), 49–94.
- [OECD(2021)] OECD. 2021. *Education at a Glance 2021*. Organisation for Economic Co-operation and Development. 474 pages. <https://doi.org/10.1787/b35a14e5-en>
- [of Elementary & Secondary Education([n.d.])] OFFICE of Elementary & Secondary Education. [n.d.]. Elementary and Secondary School Emergency Relief Fund. <https://oese.ed.gov/offices/education-stabilization-fund/elementary-secondary-school-emergency-relief-fund/>.
- [of Labor Statistics (BLS)([n.d.])] U.S. Bureau of Labor Statistics (BLS). [n.d.]. Local Area Unemployment Statistics (LAUS). <https://www.bls.gov/lau>.



- [of State Health Services (DSHS)([n.d.])] Texas Department of State Health Services (DSHS). [n.d.]. Texas Public Schools COVID-19 Data. <https://dshs.texas.gov/coronavirus/schools/texas-education-agency/>.
- [Popov et al.(2019)] Sergei Popov, Stanislav Morozov, and Artem Babenko. 2019. Neural Oblivious Decision Ensembles for Deep Learning on Tabular Data. *CoRR* abs/1909.06312 (2019). arXiv:1909.06312 <http://arxiv.org/abs/1909.06312>
- [Rebai et al.(2020)] Sonia Rebai, Fatma Ben Yahia, and Hédi Essid. 2020. A graphically based machine learning approach to predict secondary schools performance in Tunisia. *Socio-Economic Planning Sciences* 70 (2020), 100724.
- [Shwartz-Ziv and Armon(2022)] Ravid Shwartz-Ziv and Amitai Armon. 2022. Tabular data: Deep learning is not all you need. *Information Fusion* 81 (2022), 84–90. <https://doi.org/10.1016/j.inffus.2021.11.011>
- [(TEA)([n.d.]a)] Texas Education Agency (TEA). [n.d.]a. Elementary and Secondary School Emergency Relief (ESSER) Grant Programs. <https://tea.texas.gov/finance-and-grants/grants/elementary-and-secondary-school-emergency-relief-esser-grant-programs>.
- [(TEA)([n.d.]b)] Texas Education Agency (TEA). [n.d.]b. State of Texas Assessments of Academic Readiness (STAAR) for 2018-2019 and 2020-2021. <https://tea.texas.gov/student-assessment/testing/staar/staar-aggregate-data>.
- [USAFacts([n.d.])] USAFacts. [n.d.]. Texas Coronavirus Cases and Deaths. <https://usafacts.org/visualizations/coronavirus-covid-19-spread-map/state/texas>.
- [Yu and Tešić([n.d.])] June Yu and Jelena Tešić. [n.d.]. Tabular Data in the Wild: Gradient Boosting Modeling Improvement. <https://github.com/DataLab12/educationDataScience>.
- [Zamarro et al.(2022)] Gema Zamarro, Andrew Camp, Dillon Fuchsman, and Josh B McGee. 2022. Understanding how Covid-19 has changed teachers' chances of remaining in the classroom. *Sinquefield Center for Applied Economic Research Working Paper No. Forthcoming* (2022).