



# EduViz: Visualizing Statewide Assessment Data Final Presentation



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Visualization for Machine Learning

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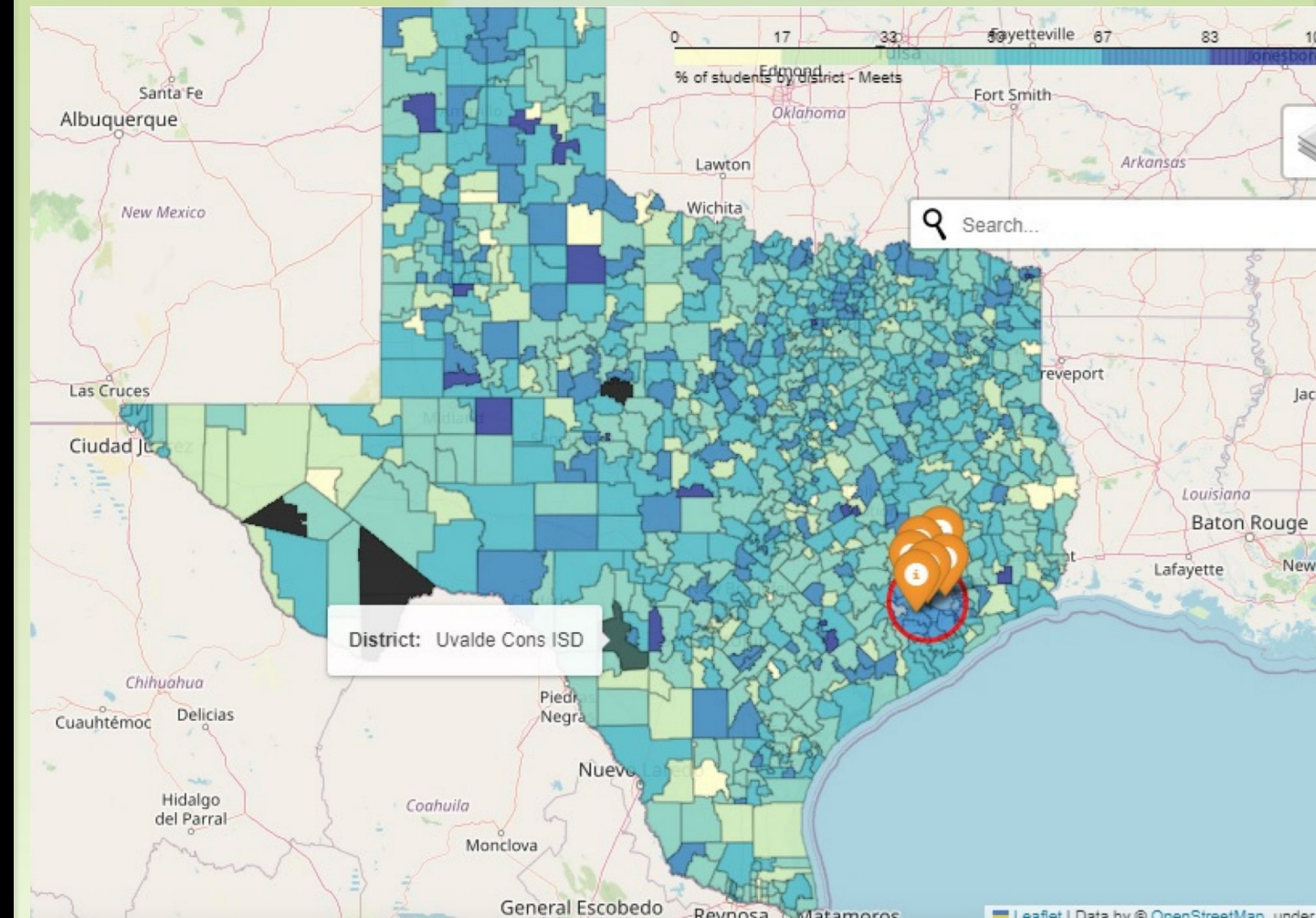
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# Introduction



- A lot of state-level End of Year assessment data gets gathered
- Individual districts struggle with doing in-house ML/data analysis
- Growing need for data-driven decision making
- District-level work results from state-level statistics! Can we use district results to predict state-wide changes?
- Debate between policy makers and teachers





# Prior Related Work

## Leveraging Visualization and Machine Learning Techniques in Education: A Case Study of K-12 State Assessment Data

by Loni Taylor<sup>1</sup> ✉, Vibhuti Gupta<sup>2,\*</sup> ✉  and Kwanghee Jung<sup>3</sup> ✉ 



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<sup>3</sup> Department of Educational Psychology and Leadership, Texas Tech University, Lubbock, TX 79409, USA

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## The timeless beauty of data: inventing educational pasts, presents and futures through data visualisation

Tatiana Mikhaylova ✉  & Daniel Pettersson 

Pages 142-158 | Received 11 Sep 2023, Accepted 18 Jan 2024, Published online: 30 Jan 2024

“Cite this article

<https://doi.org/10.1080/17508487.2024.2308689>

 Check for updates

## Application of Data Visualization and Machine Learning Algorithms for Better Decision Making

Olta Llaha<sup>1</sup>, Azir Aliu<sup>2</sup>

<sup>1,2</sup> South East European University, Tetovo, North Macedonia


## Digital education governance: data visualization, predictive analytics, and ‘real-time’ policy instruments

Ben Williamson ✉

Pages 123-141 | Received 30 Sep 2014, Accepted 23 Mar 2015, Published online: 29 Apr 2015

“Cite this article

<https://doi.org/10.1080/02680939.2015.1035758>

 Check for updates



# Data Used

TEA

Texas Education Agency

TEXAS ASSESSMENT

Research Portal

Support

Home / My Selections

1

Find Your Campus or District

Favorites

Search

Campus

District

Region

State

State

☐

★ TEXAS

Your Campuses, Districts, and Regions:

2

Select the Program

☒ STAAR 3-8

☐ STAAR Alternate 2 3-8

☐ STAAR Alternate 2 EOC

☐ STAAR Cumulative

☐ STAAR EOC

☐ TELPAS

☐ TELPAS Alternate

3

Select the Report

☐ Group Summary: Performance Levels & Reporting Categories

☐ Item Analysis Summary

☐ Score Codes Summary

☐ Standard Combined Summary

☐ Standard Constructed Response Summary

☒ Standard Summary

Organization	Administration	Tested Grade	STAAR - Mathematics				STAAR Spanish - Mathematics			
			Tests Taken	Average Scale Score	Performance Levels				Tests Taken	Average Scale Score
					Did Not Meet	Approaches and Above	Meets and Above	Masters		
ABBOTT ISD	Spring 2023	5	15	1731	13% 2 Tests	87% 13 Tests	67% 10 Tests	40% 6 Tests	0	
ABERNATHY ISD	Spring 2023	5	53	1672	13% 7 Tests	87% 46 Tests	64% 34 Tests	23% 12 Tests	0	
ABILENE ISD	Spring 2023	5	1,057	1598	28% 298 Tests	72% 759 Tests	37% 391 Tests	12% 127 Tests	19	15
ACADEMY ISD	Spring 2023	5	129	1658	12% 16 Tests	88% 113 Tests	55% 71 Tests	17% 22 Tests	0	

- No data reported for fewer than 5 students.

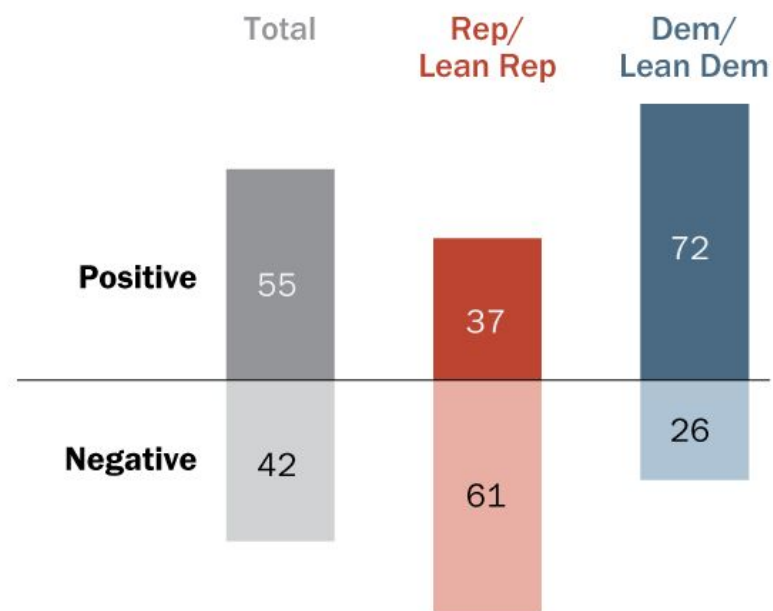
Total: over 1200 school districts  
2022-2024 train; 2025 test



# Why it matters?

**In 2022, a majority of Republicans said K-12 schools were having a negative effect on the U.S.**

*% saying K-12 public schools have a \_\_\_\_ effect on the way things are going in the country*

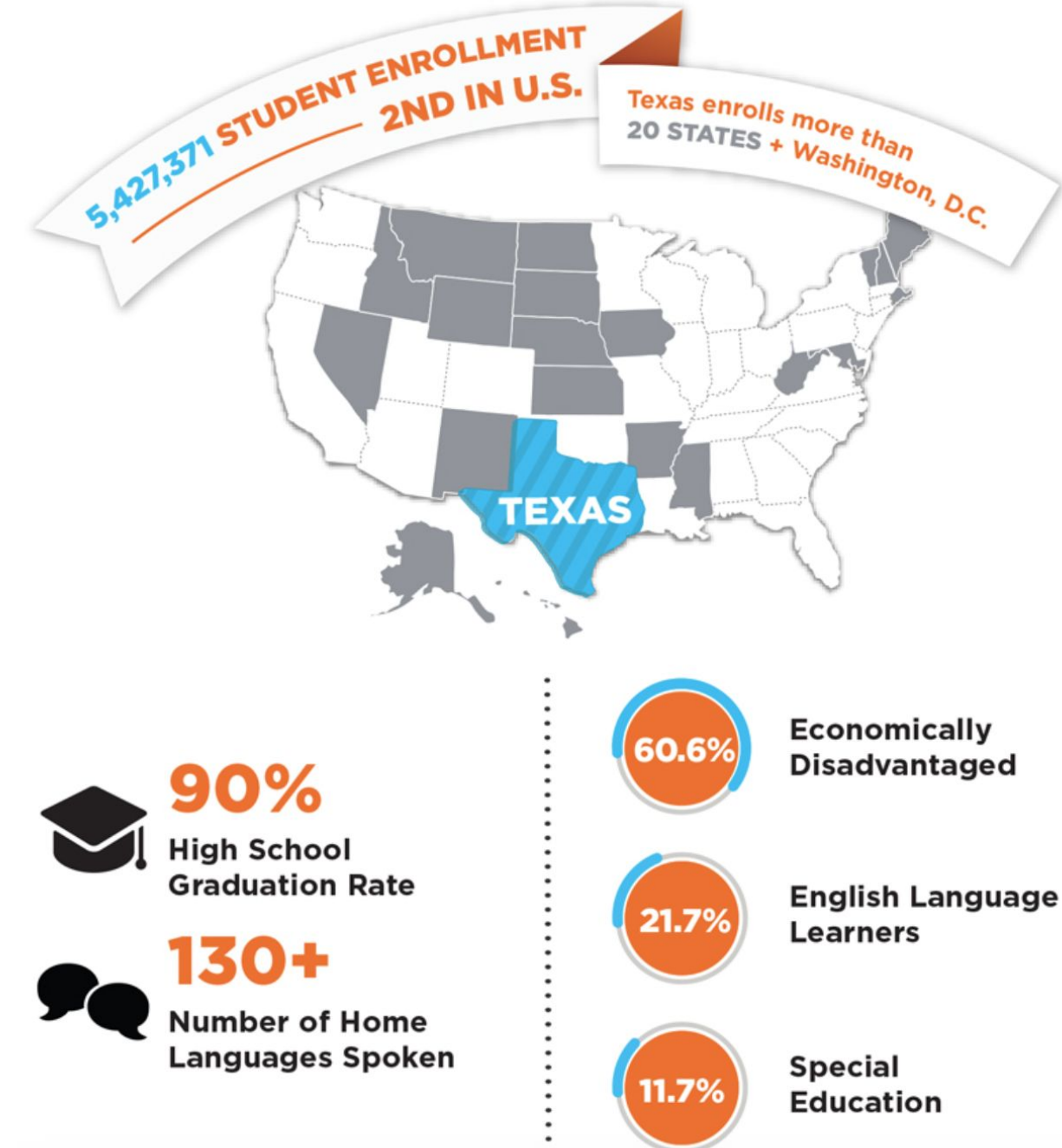


Note: Share of respondents who didn't offer an answer not shown.

Source: Survey of U.S. adults conducted Oct. 10-16, 2022.

PEW RESEARCH CENTER

Increasing political impacts on education

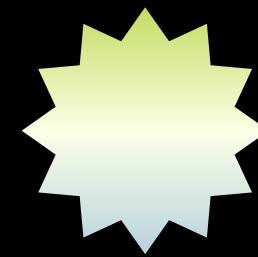


Huge education system with diverse student body

# Tools and Methodology

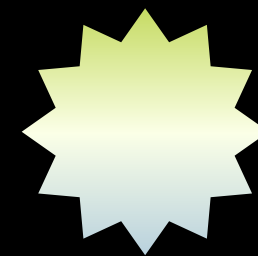
Build and train predictive ML models to forecast student performance (both continuous scores and pass/fail outcomes) across diverse Texas educational systems.

Break down to specific districts for regression models and set 70% meeting expectations as threshold for binary classification models.



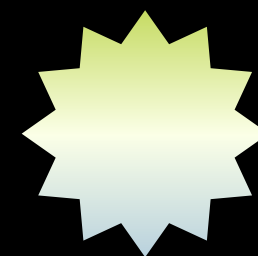
## Regression Models

Generative Additive Model (GAM), Gradient Boosting Regressor (RBG), Logistic Regression



## Classification Models

Logistic Regression, Decision Tree, Simple Neural Network/MLP (70% threshold)



## Creating Visualizations

Confusion Matrices, Heatmaps, ROC curves, etc.

# Findings and Results



<<

Dashboard Filters & Navigation

Select View

Overview & Model Comparison

Regression Deep-Dive

Classification Deep-Dive

Trend Analysis

Explainability (Lime)

Filter by District

All

Filter by Grade

All

Rows after filtering: 449 / 449

# Texas Statewide Assessment Data Visualization Dashboard

This dashboard visualizes and analyzes Texas Statewide Assessment data from 2022–2025. Machine learning models were trained on 2022–2024 data and predict 2025 outcomes across all Texas districts. Compare multiple models across **regression** (continuous score prediction) and **classification** (pass/fail) paradigms.

## Model Performance Overview

Compare all models side-by-side across regression and classification metrics.

### Regression Models

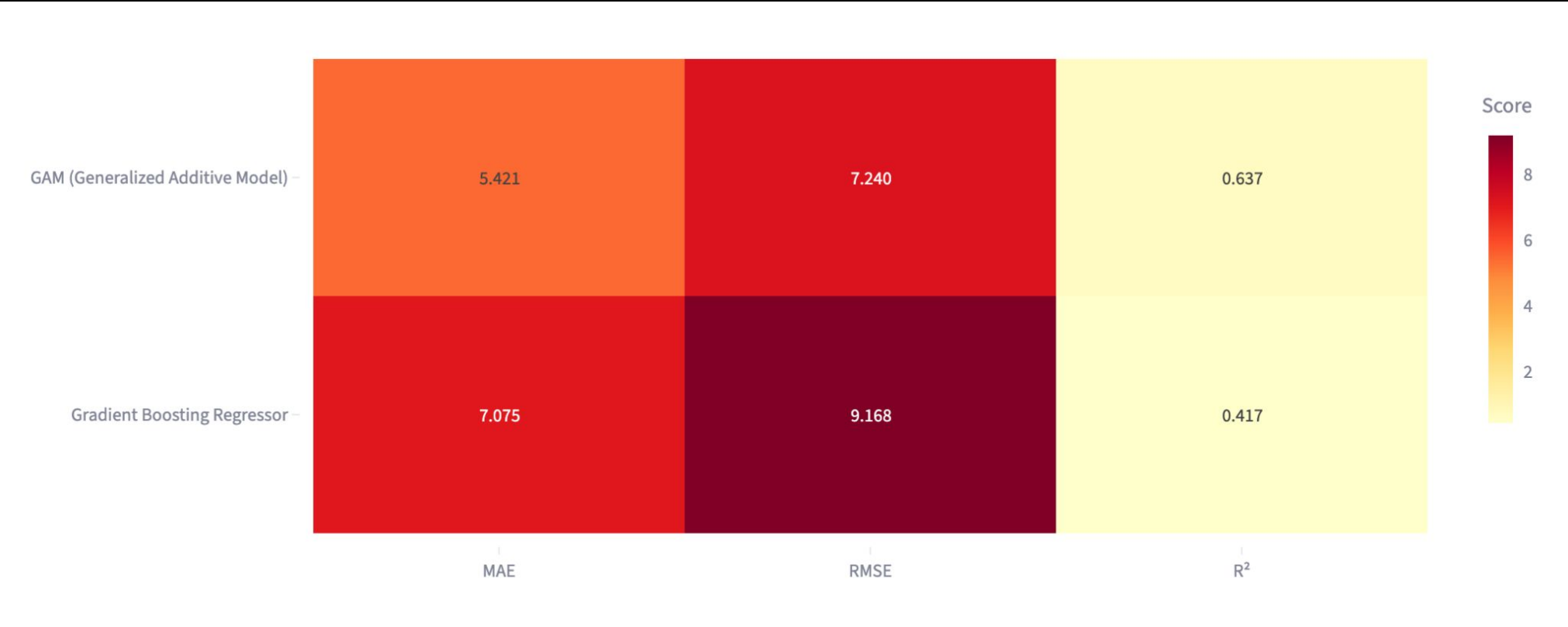
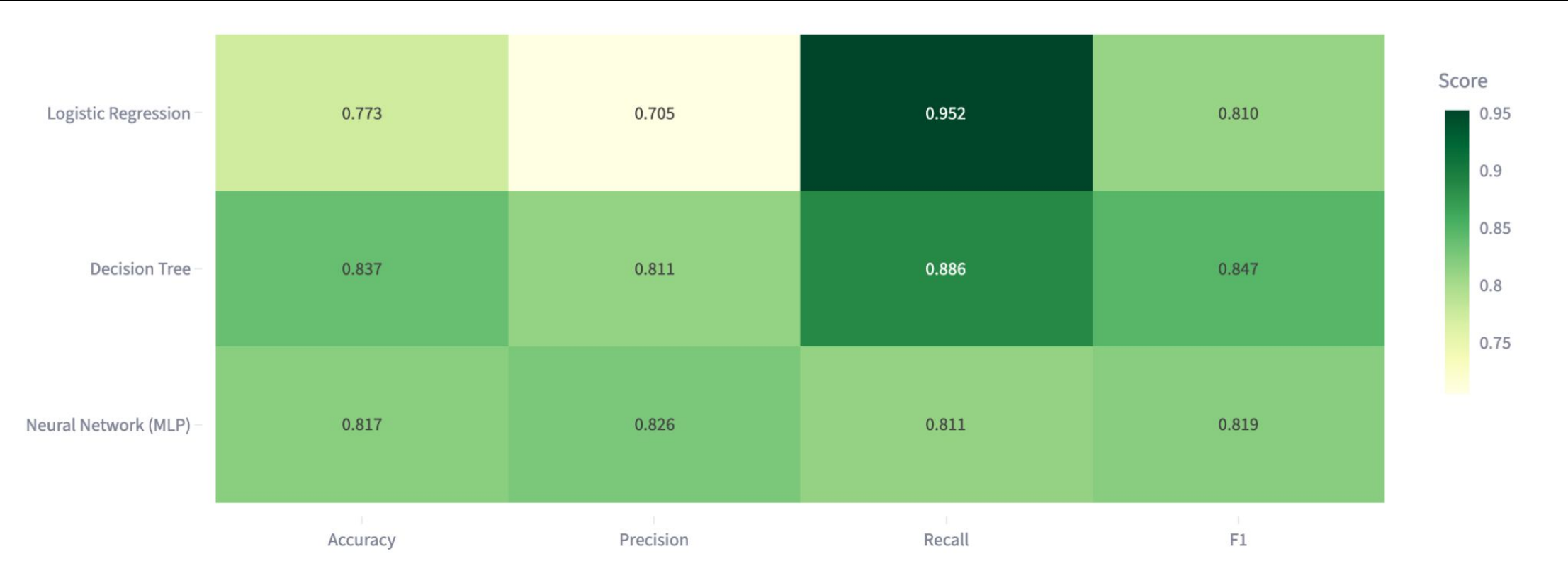
	MAE	RMSE	R <sup>2</sup>
GAM (Generalized Additive Model)	5.420890	7.239998	0.636682
Gradient Boosting Regressor	7.075204	9.167659	0.417458

### Classification Models

	Accuracy	Precision	Recall	F1
Logistic Regression	0.772829	0.704545	0.951754	0.809701
Decision Tree	0.837416	0.811245	0.885965	0.846960
Neural Network (MLP)	0.817372	0.825893	0.811404	0.818584

## Metric Heatmap: Regression Models

# Overview of Models

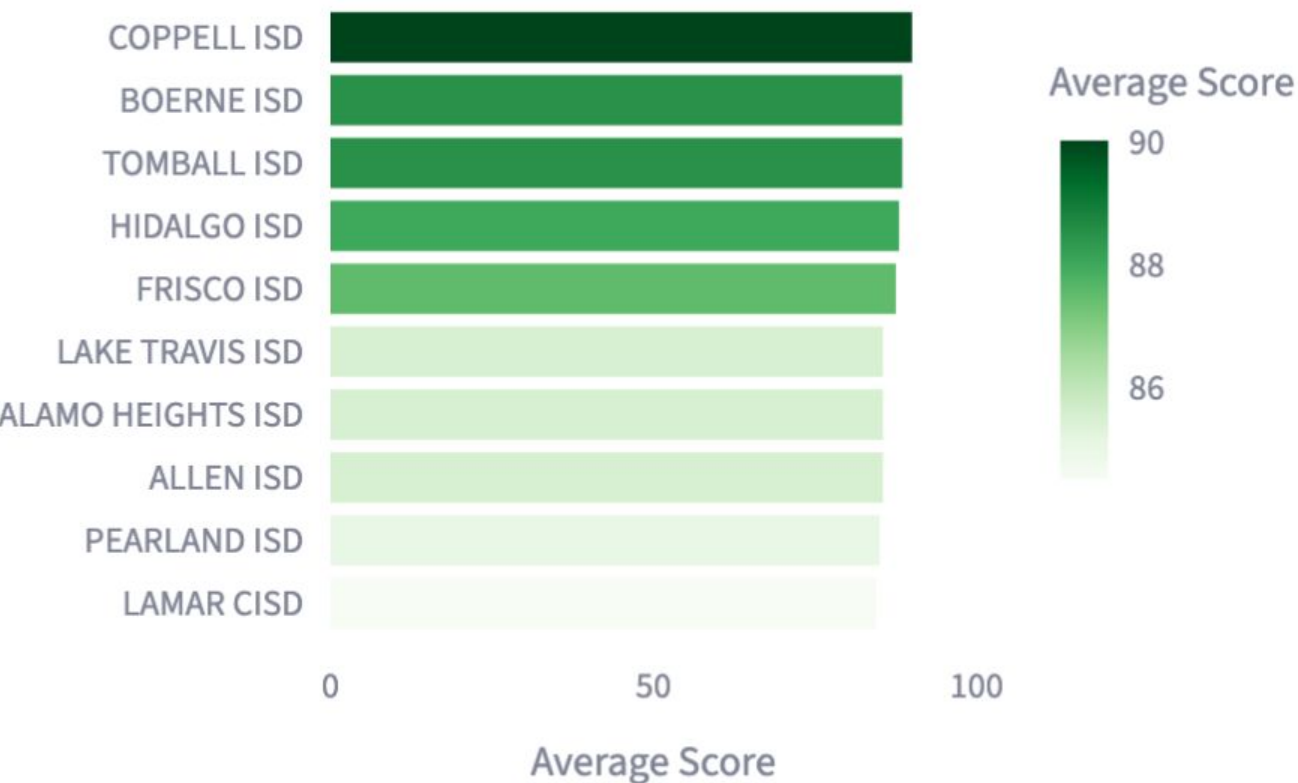


# General Predictions

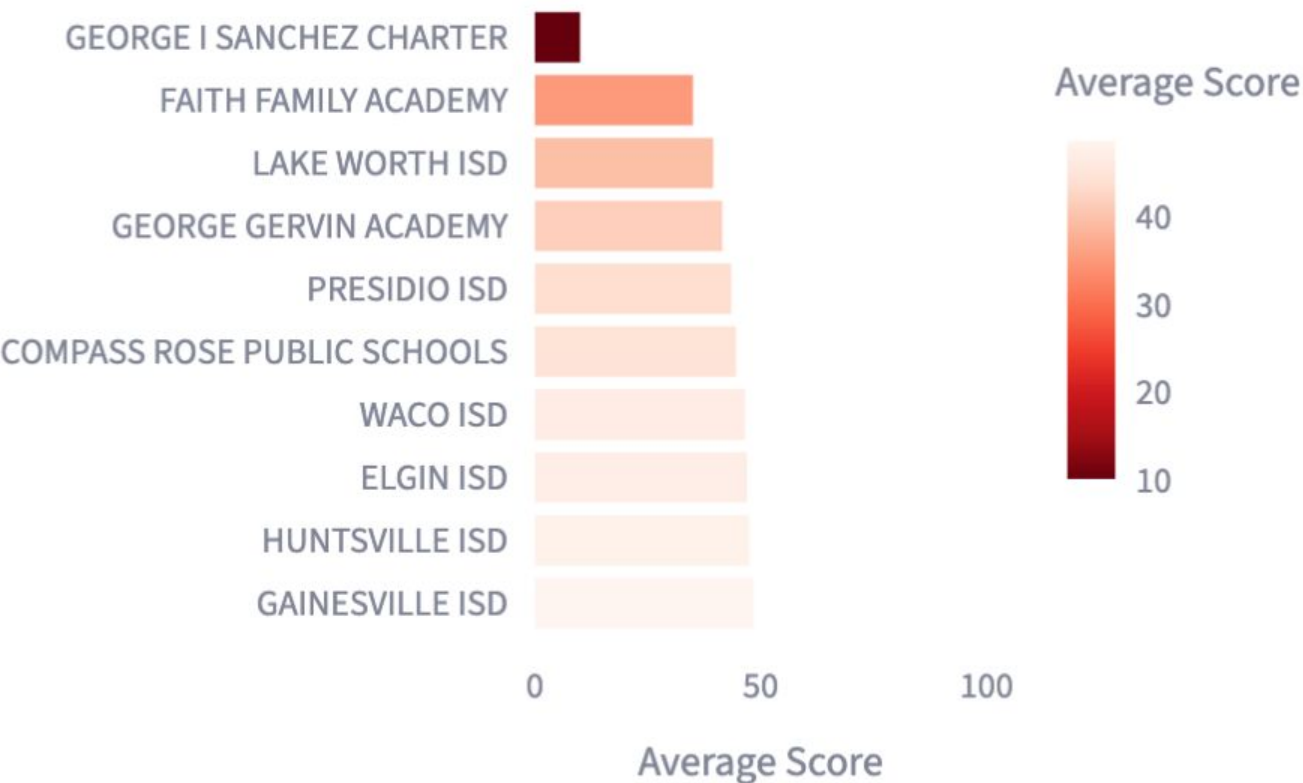
## Geographic Performance Disparities

Examine performance variation across Texas school districts.

### Top 10 Highest-Performing Districts



### Bottom 10 Lowest-Performing Districts





Choose classification model

Logistic Regression (w/ probability) ▼

Accuracy ?

0.773

Precision ?

0.705

Recall ?

0.952

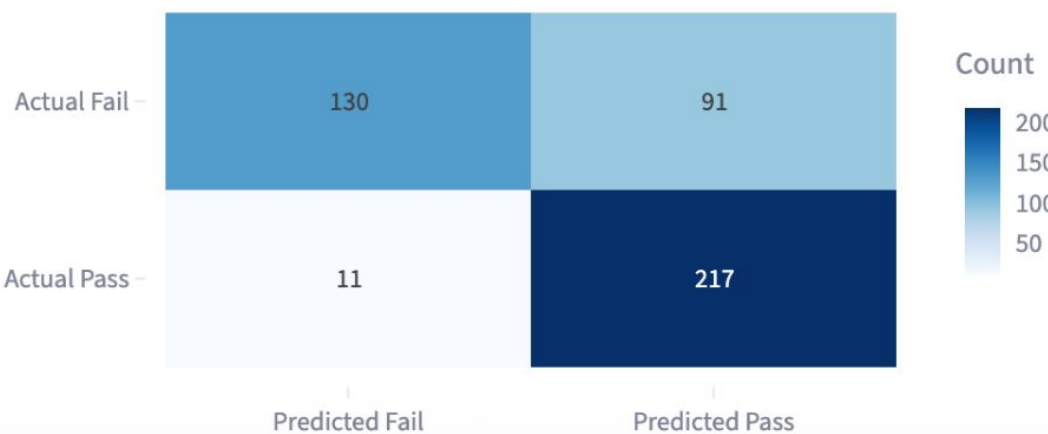
F1-Score ?

0.810

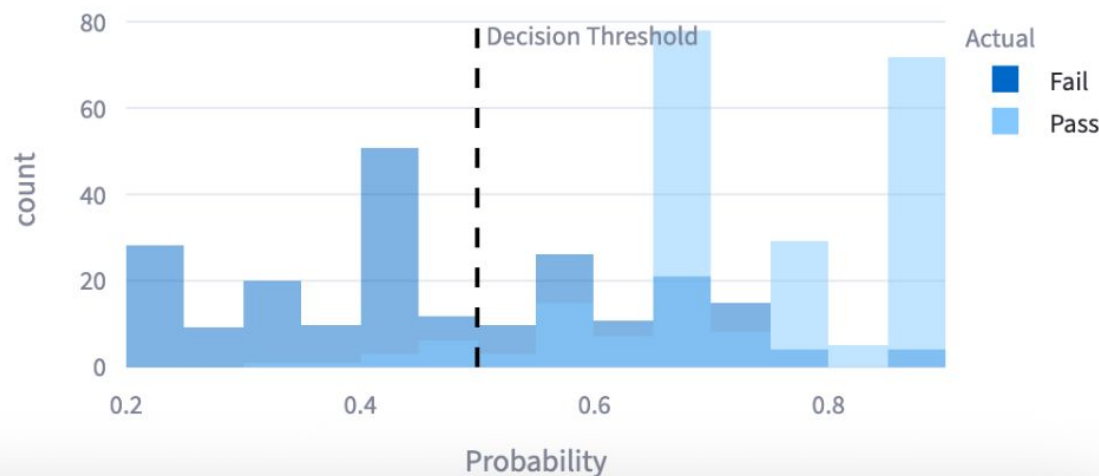
AUC-ROC ?

0.880

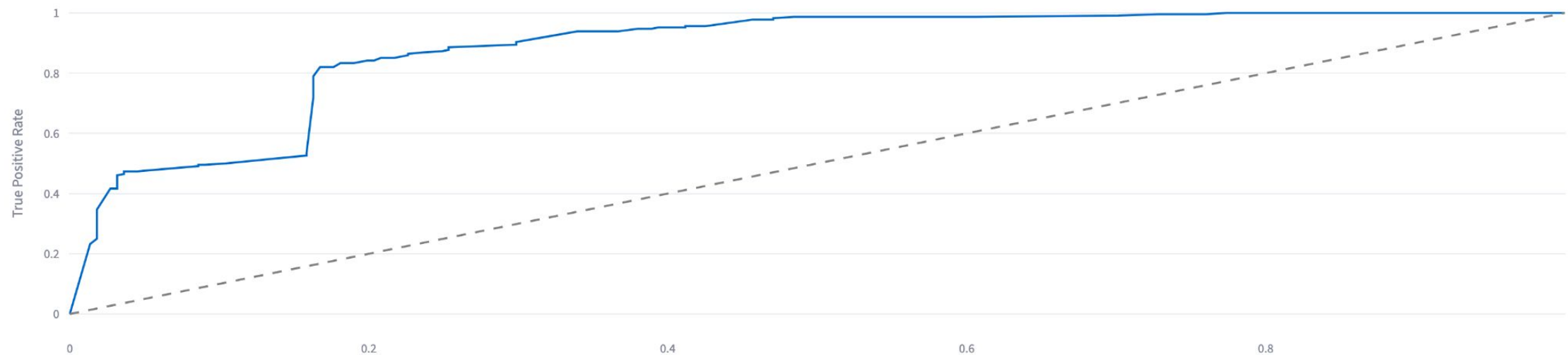
## Confusion Matrix



## Prediction Distribution



ROC Curve (AUC=0.880)



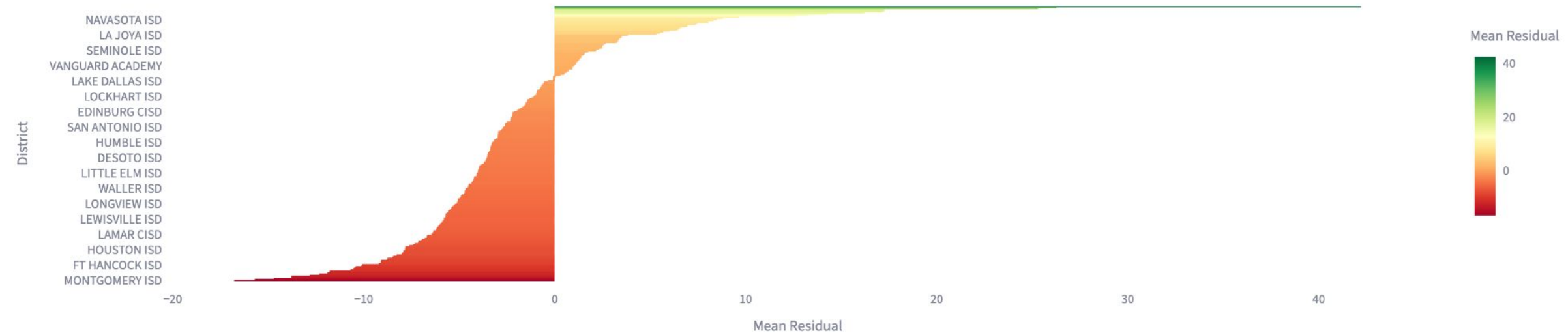
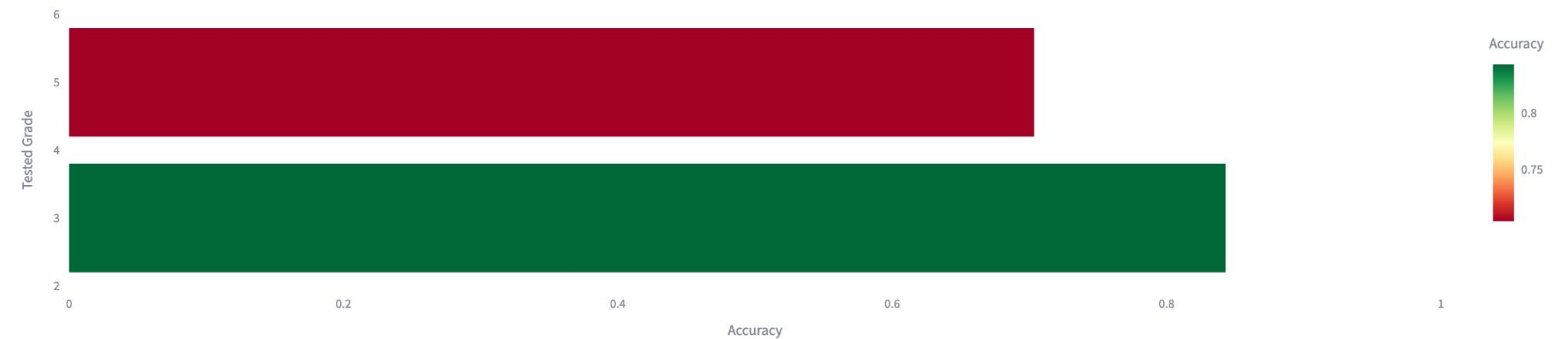
# Model Biases

In general, all **classification** models had a much easier time predicting 3rd grade performance than 5th grade performance.

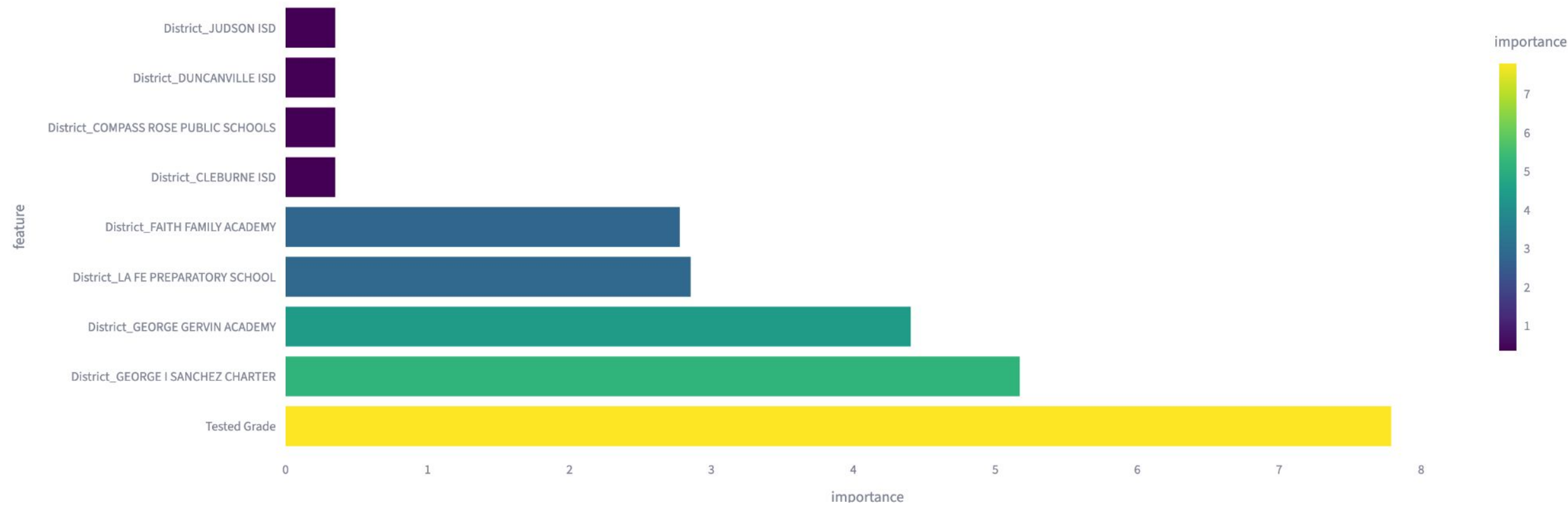
**Regression** models overestimated performance on larger districts and underestimated mostly on smaller, rural districts.

Classification Performance by Group

Group by:  
☒ Tested Grade  
☐ District



Combined Global (surrogate) importances



	feature	importance
8	Tested Grade	7.7897
5	District_GEORGE I SANCHEZ CHARTER	5.1723
4	District_GEORGE GERVIN ACADEMY	4.4045
7	District_LA FE PREPARATORY SCHOOL	2.8536
3	District_FAITH FAMILY ACADEMY	2.7769
0	District_CLEBURNE ISD	0.349
1	District_COMPASS ROSE PUBLIC SCHOOLS	0.349
2	District_DUNCANVILLE ISD	0.349
6	District_JUDSON ISD	0.349

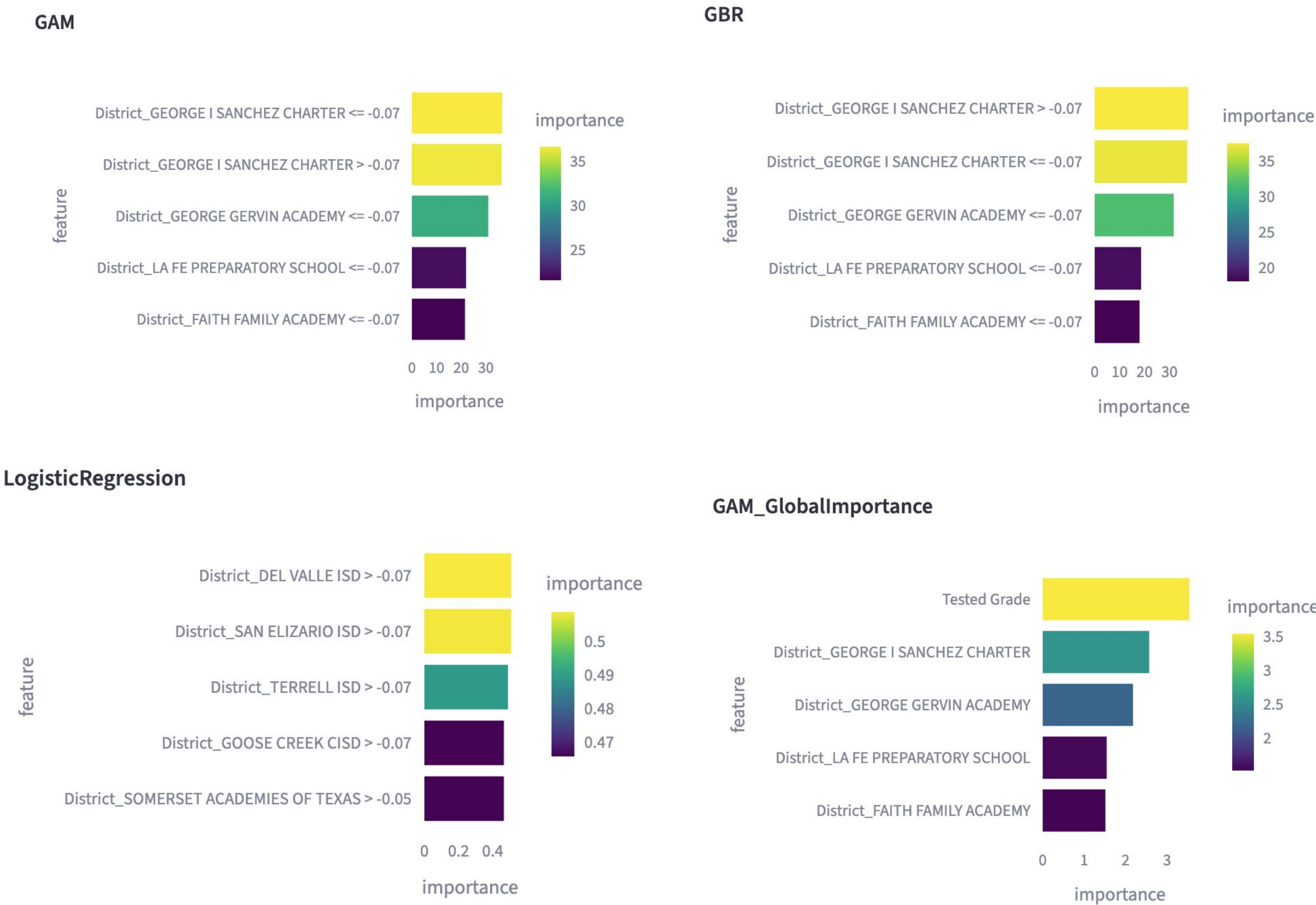


# LIME

## explanations

Models were able to find specific districts that need support.

Locally, smaller districts with more challenging students are the biggest explainers according to LIME



# LIME explainer matches reality

George I Sanchez Charter: 89.9% of students were considered at risk of dropping out of school. 68.1% of students were enrolled in bilingual and english language learning programs.

Charter schools receive less funding from the government compared to their public district counterparts, which are mainly funded by property tax in TX.

## Risk factors

A student is **identified as being at risk of dropping out of school** based on state-defined criteria. A student is defined as "economically disadvantaged" if he or she is eligible for free or reduced-price lunch or other public assistance.

At-risk students

89.9 %

Statewide: 53.2%

Economically disadvantaged

93.5 %

Statewide: 62.3%

Limited English proficiency

63.5 %

Statewide: 24.4%

At-risk students



89.9%

Econ. disadvantaged



93.5%

Limited Eng. proficiency



63.5%

## SAT

The average SAT score for students graduating in **2022-2023**, with critical reading, writing and mathematics results combined. The maximum score is 2400. For the small percentage of students who took the redesigned SAT with a maximum score of 1600, their scores were converted to the equivalent scores on the previous SAT using College Board concordance tables.

Avg. SAT score

938

Statewide: 978

## ACT

The average ACT composite score for students graduating in **2022-2023**. The maximum score is 36.

Avg. ACT score

15.8

Statewide: 19.2

## Chronic absenteeism

The chronic absenteeism rate for students during the **2022-2023** school year. It measures the number of students who were absent for at least ten percent of the school year.

All students

49.4 %

Statewide: 20.3%

African American

66.7 %

Statewide: 24.8%

American Indian

N/A

Statewide: 21.3%

Asian

N/A

Statewide: 7.6%

Hispanic

49.2 %

Pacific Islander

N/A

White

Masked

Two or more races

Masked

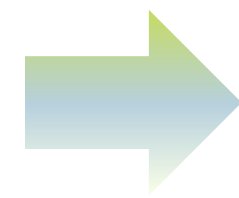


# Conclusion



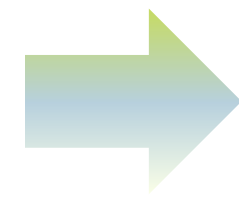


# Future Work



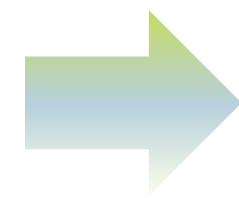
## Dimensionality Reduction

Applying PCA to identify underlying latent dimensions and reduce noise.



## Integrate geographic analysis

Using GeoJSON to create choropleth maps

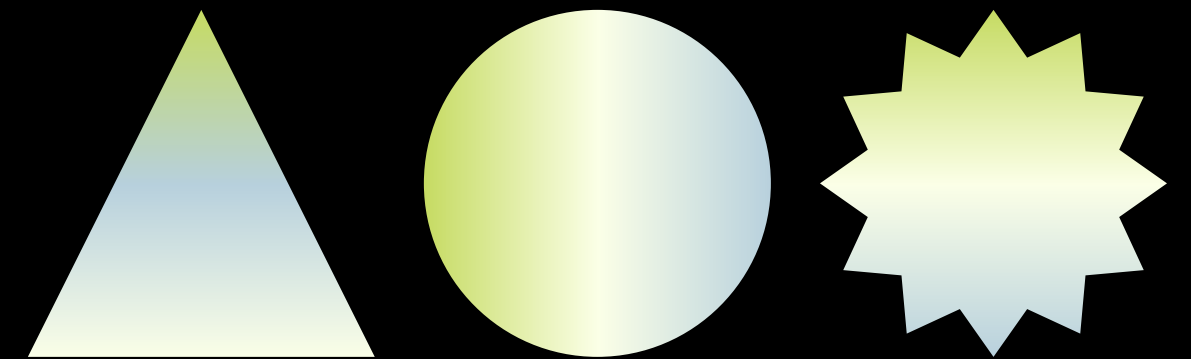


## Dig into funding amount and sources

A lot of political and economic reasons why schools fail. Would be cool to connect them to current data.



Thank  
You!



Any Questions?