Cleburne ISD
5th Grade Math STAAR Categorization

Jonathan Armstrong
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Problem Statement: How can Cleburne ISD distribute math resources over the next academic year to promote optimum student growth and achievement?

Context

Given 2020-2021 academic data, the district wants to better utilize resources

Scope

- 1 Academic Year
- General improvement based on generic “resource”
- Not connected to district RTI

Constraints

- Sample size
- Approximation for current distribution
- Approximation of resource effectiveness

Data Acquisition and Cleaning

The data for this project was delivered by Cleburne ISD. Campus and student identifiers were masked for legal and privacy reasons.

Legend

-Dropped due to lack of data

-Dropped (other)

-Dummy variables created

-Scaled

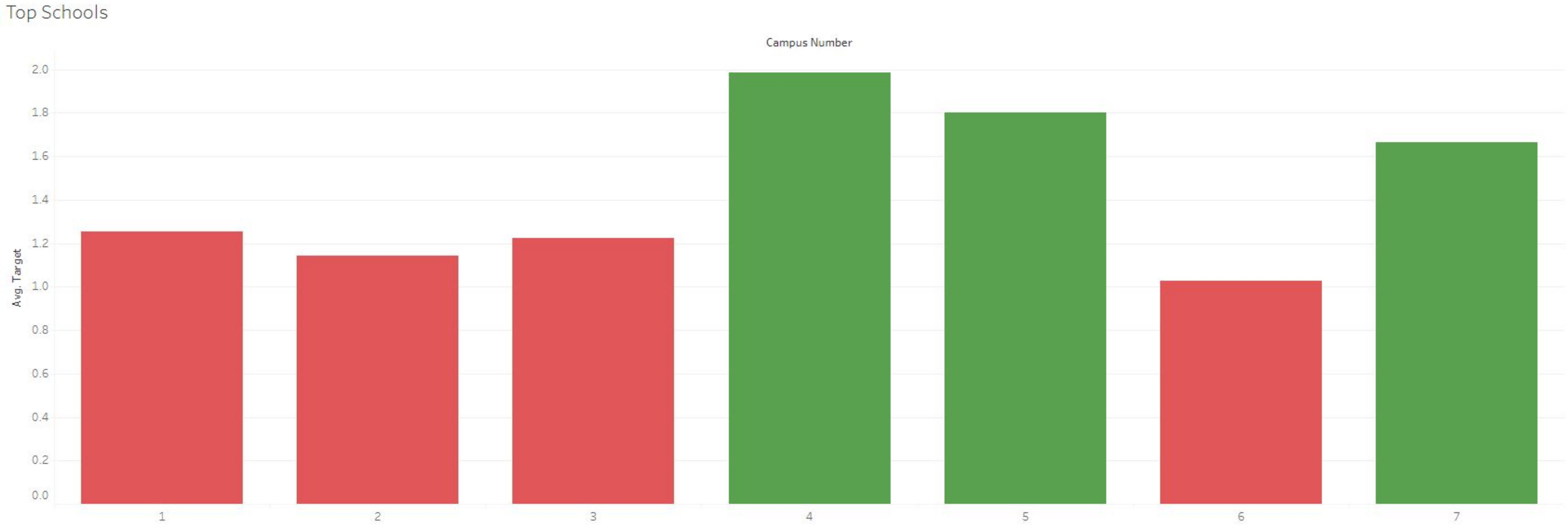
-Transformed other

Student Number
Grade Level
Campus Number
Gender
EthnicityRace
Economic Disadvantage
Economic Disadvantage Category
At Risk
Special Ed
LEP
ESL
Bilingual

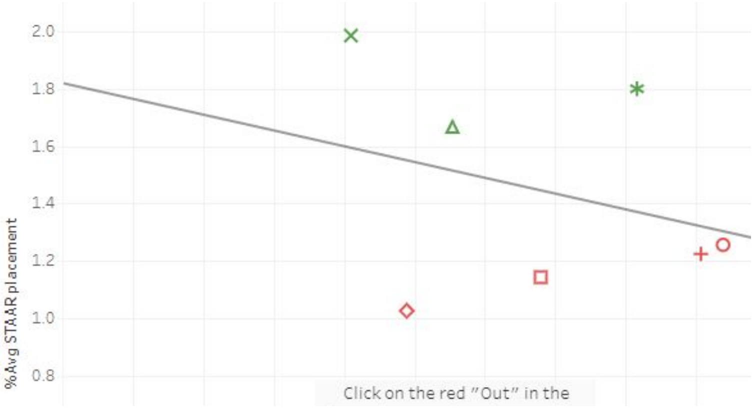
Gifted Talented
Tested Language
Military Connected Student
New To Texas
>=50.0% Remote SY 2020-21
Discipline Placement Incidents
Oral Administration
Test Admin Mode
Approaches
Meets
Masters
STAAR Progress from 2019

Exploratory Analysis

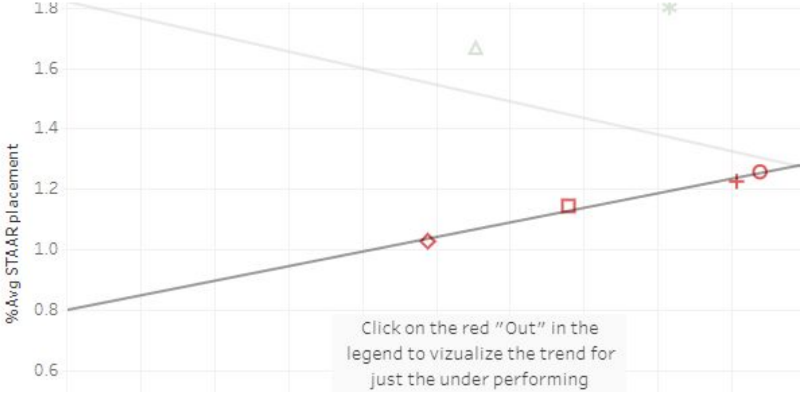
Overall trends matched statewide patterns. However, for many patterns the overall trends seemed to reverse when grouped within and without the top performing schools



Exploratory Analysis

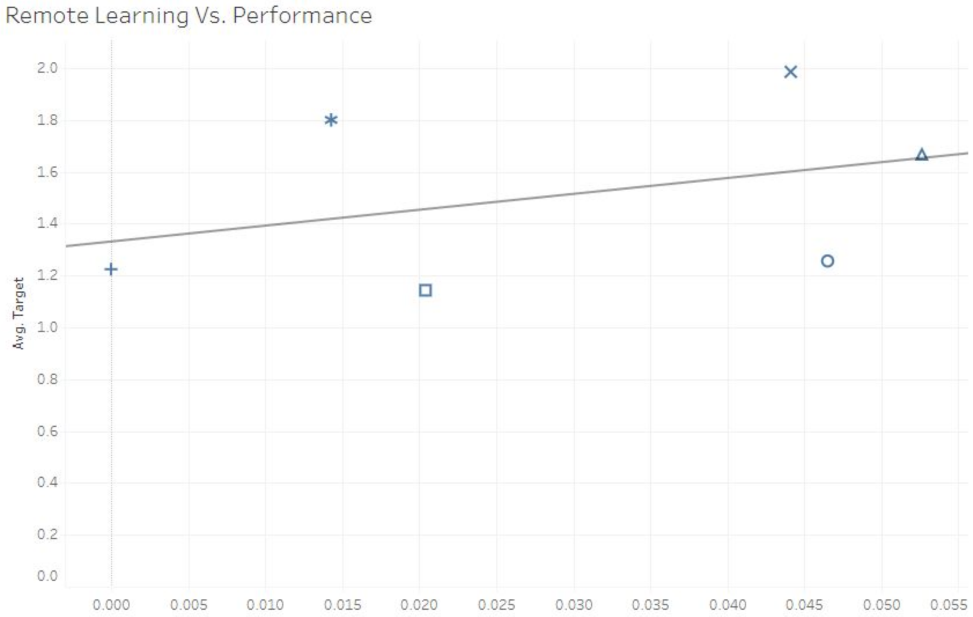


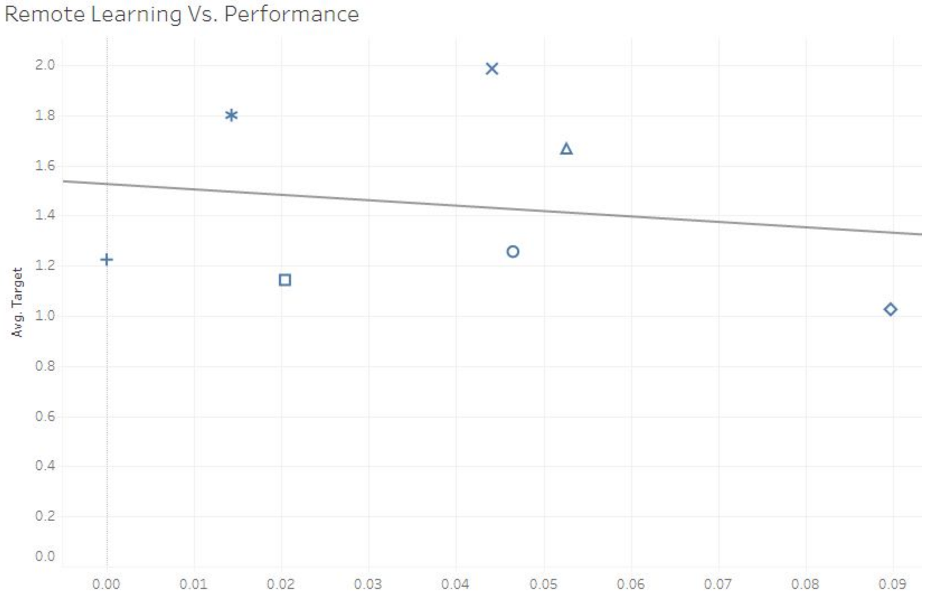
Econ dis2



Exploratory Analysis

More exploration revealed that this was due to the influence of individual campuses rather than proportionality of various demographic groupings. Notice the impact campus 6 has on the trend of remote learning vs performance.



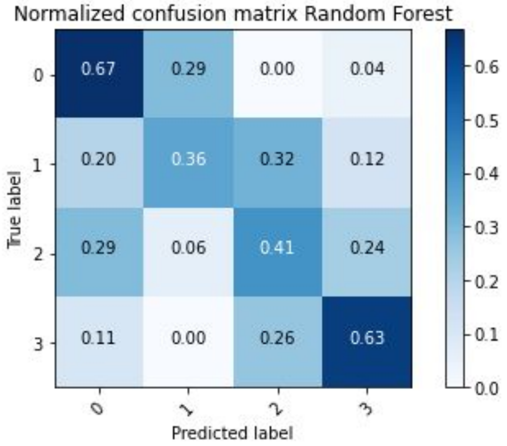


Explore for yourself

Choosing a model

Logistic Regression Classification - Base

Name	Accuracy	f1-score
LogisticRegression	0.494	0.488
RandomForest	0.518	0.513
KNN	0.506	0.507



Accuracy and f1 equally valid because of proportionality of the data.

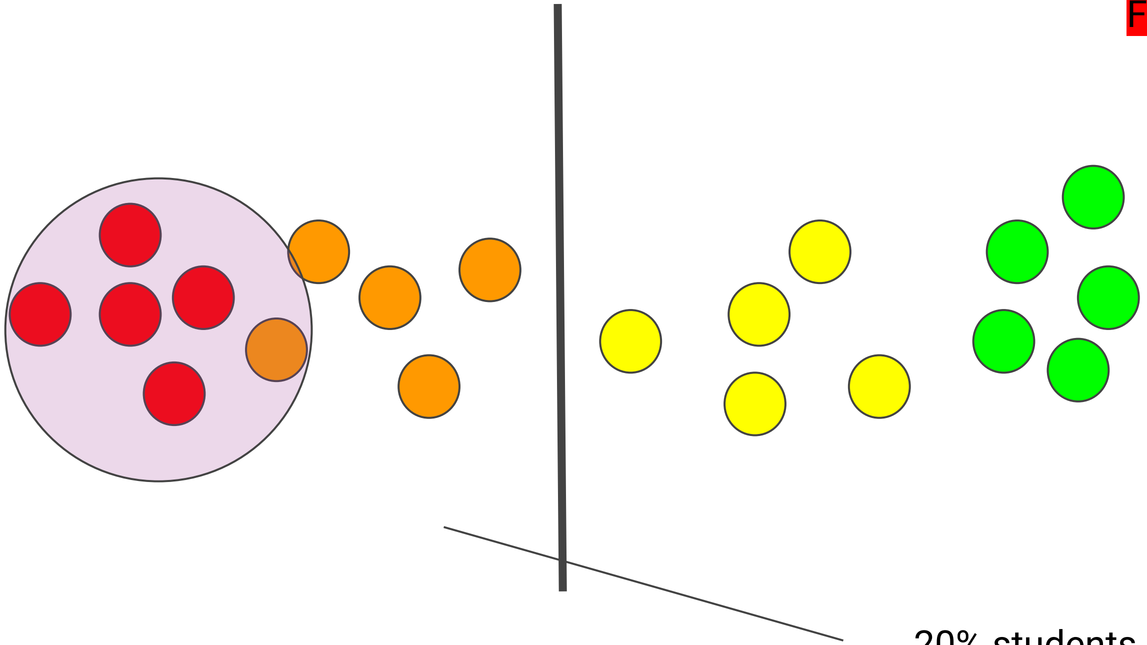
Most important metric was accuracy of level 1 prediction

Employed Feature Reduction
Feature Importances aligned with EDA
Functionality reduction increased accuracy but hindered business application

Why choose level 1

Before Resource 50% passing targeting lowest students

Master
Meet
Approach
Fail

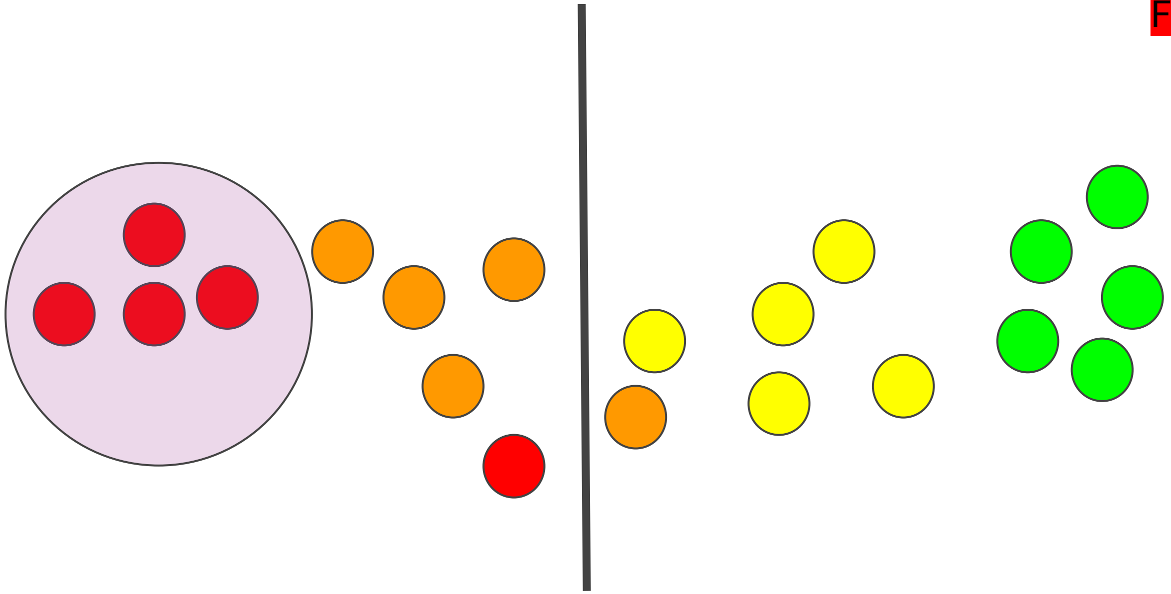


20% students move up a level

Why choose level 1

After Resource 55% passing targeting lowest students

Master
Meet
Approach
Fail



Why choose level 1

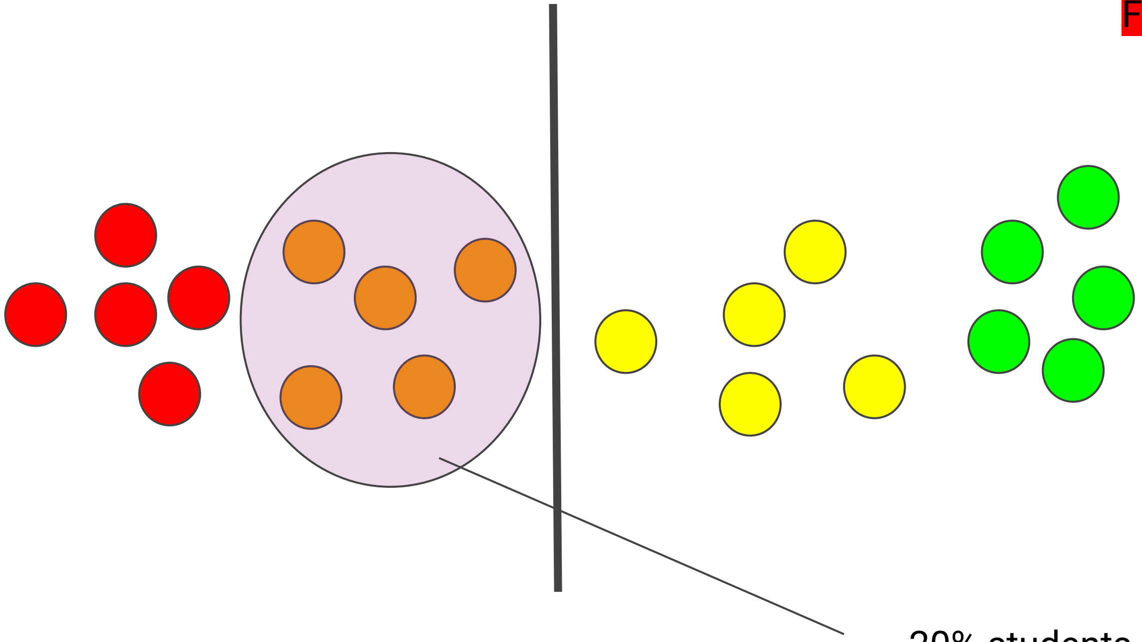
Before Resource 50% passing targeting highest failing students

Master

Meet

Approach

Fail



Why choose level 1

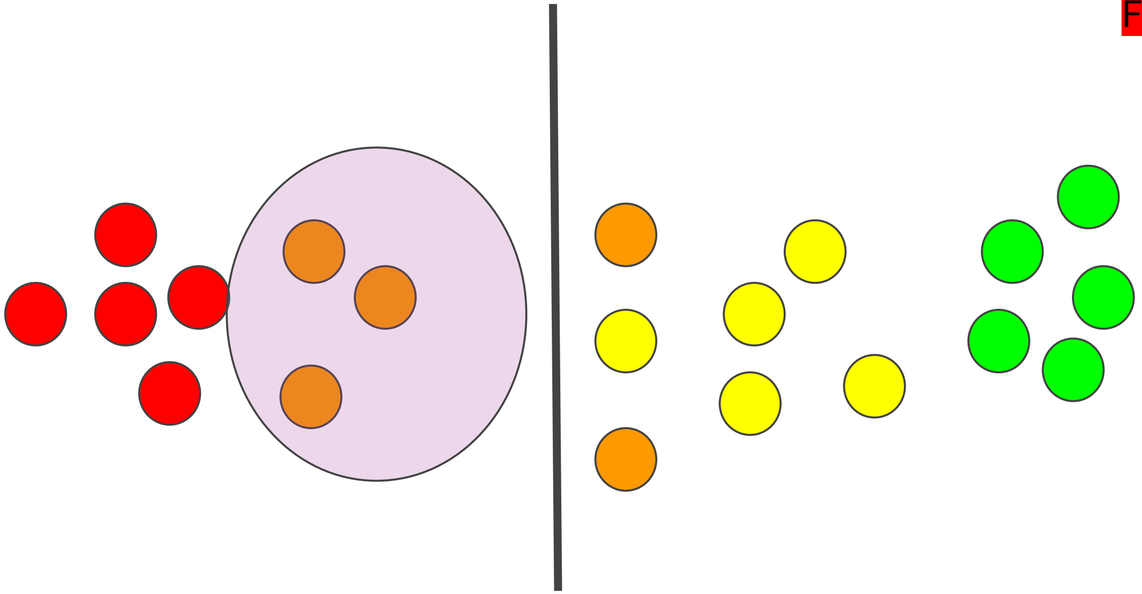
After Resource 60% passing targeting highest failing students

Master

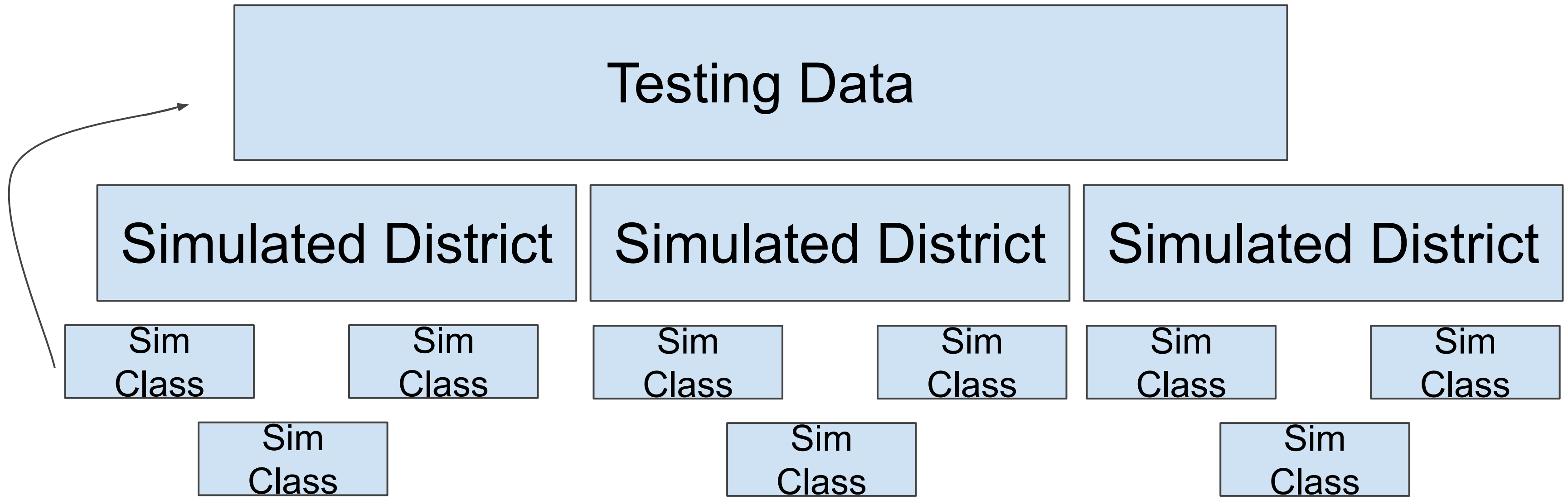
Meet

Approach

Fail



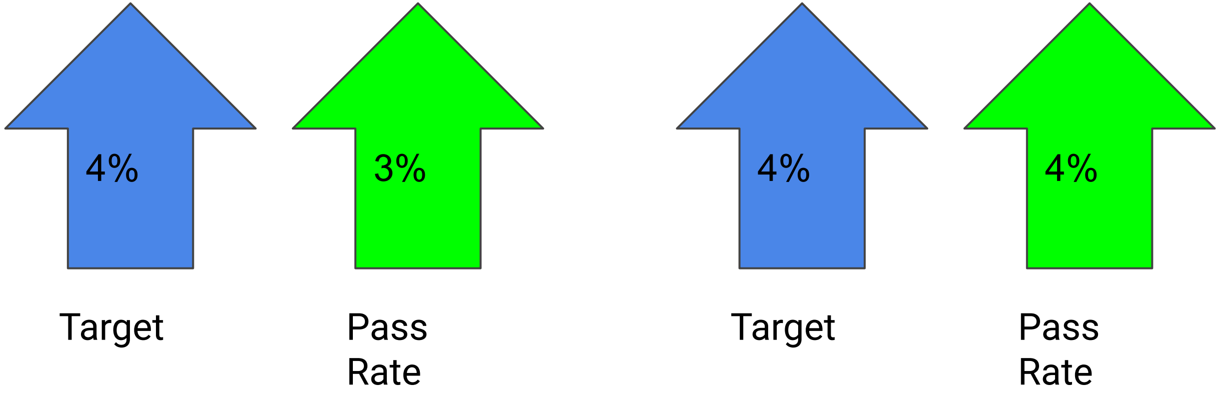
Efficacy of ML selection vs Traditional Methods
Simulating traditional resource distribution



How were resources delivered? What were the outcomes?

Traditional Method:
Classes sorted by handicap
Handicap = econ + sped
5 classes with highest handicap
20% random students gain level

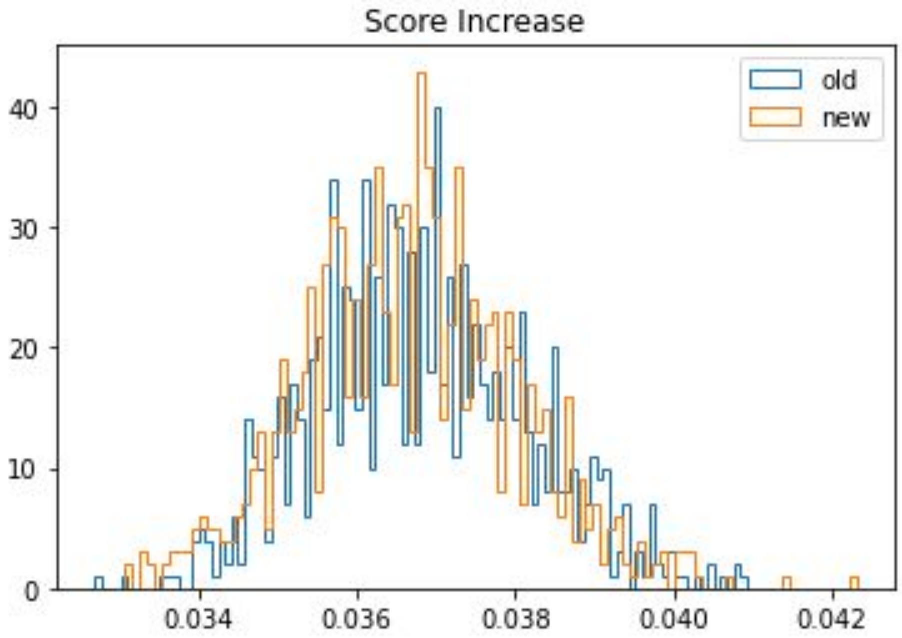
Machine Learning Method:
Classes sorted by approach
Prediction not actual result
5 classes with highest approach
20% random students gain level

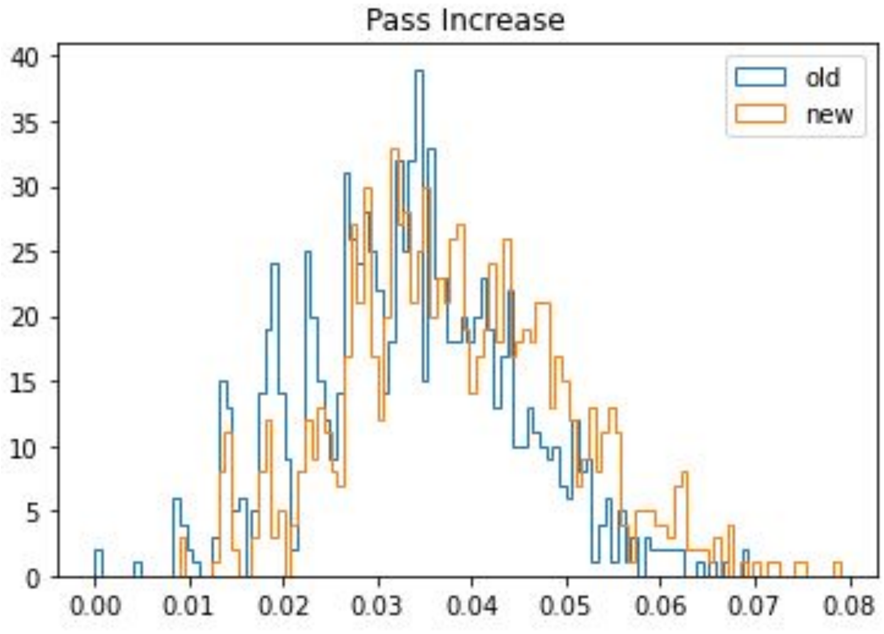


ML = 33% Increase

Verifying Results

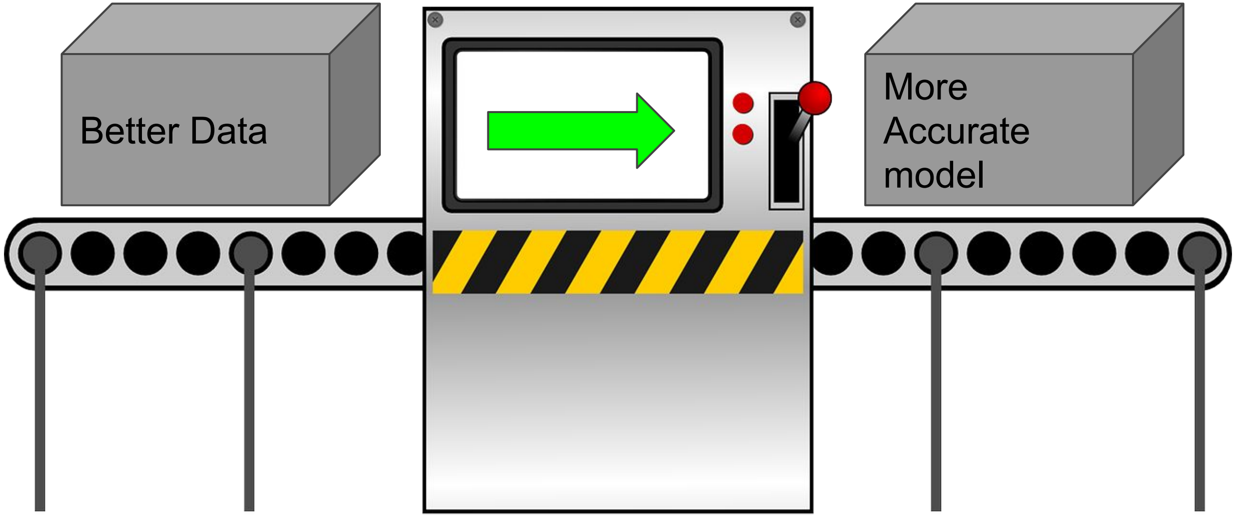
Z-Test indicated statistically significant p-value
Increases measured by taking avg per class
before and after resource was delivered





Future Work

-Modest results indicate proof of concept
-Model Constrained by size/quality of data



Potential Features

Historical Data could establish seasonal trends

Previous years' STAAR results could be added as a feature for the model to predict with

STAR/REN or CBA data could have the potential to greatly increase model accuracy

Future Improvements

Binary Classification or 2 level binary classification could be used to improve performance

SHAP could be employed to better understand feature importances