REAL ESTATE PRICING PREDICTIONS

Elio Aybar, Cristal Garcia, Sunny Li, and Matt Norgren

PROBLEM STATEMENT

GOAL: PREDICT MEDIAN HOUSE PRICES GIVEN CONVENTIONAL ATTRIBUTES AND PRESENCE OF A TARGET AND/OR STARBUCKS.

VALUE: TESTING NON-CONVENTIONAL FEATURES TO SEE IF WORTH EXPLORING IN THE FUTURE.

HYPOTHESIS: DIFFERENT TYPES OF NEIGHBORHOODS MAY ATTRACT SPECIFIC BUSINESSES.

PROJECT DEFINITION OF VARIABLES

- Zillow Real Estate: 4.3M X 75

- Starbucks location 25K X 7
- Target Locations: 1.8K X 47

- USA Public Schools data: 47K X 33
- Food Desert & Economic Data: 73K X 148
- Hospital Ratings: 4.8K X 28

FEATURES & TARGET VARIABLE

Zip code (Key)

Zillow

- NumberOfBedrooms
- Dwelling Type

School

- LEVEL_: Grade level
- Class_Teacher_RATIO:

Food Desert/Economic Data

- Urban Indicator
- Occupied Unit Housing Count (2010 Census)
- Low Income Indicator
- Median Family Income
- Food Desert Indicator

Hospital

- Hospital Rating
- Emergency Services Flag

Starbucks Locations

Target Locations

Pricing

LIMITATIONS AND DELIMITATIONS OF DATA

01

Hospital: hospital deserts (distance between hospital and home)

02

Public School Data: Creating Student-to-Teacher Ratio

03

Food Desert Data: converting CensusTract number to Zipcode

04

Starbucks and Target

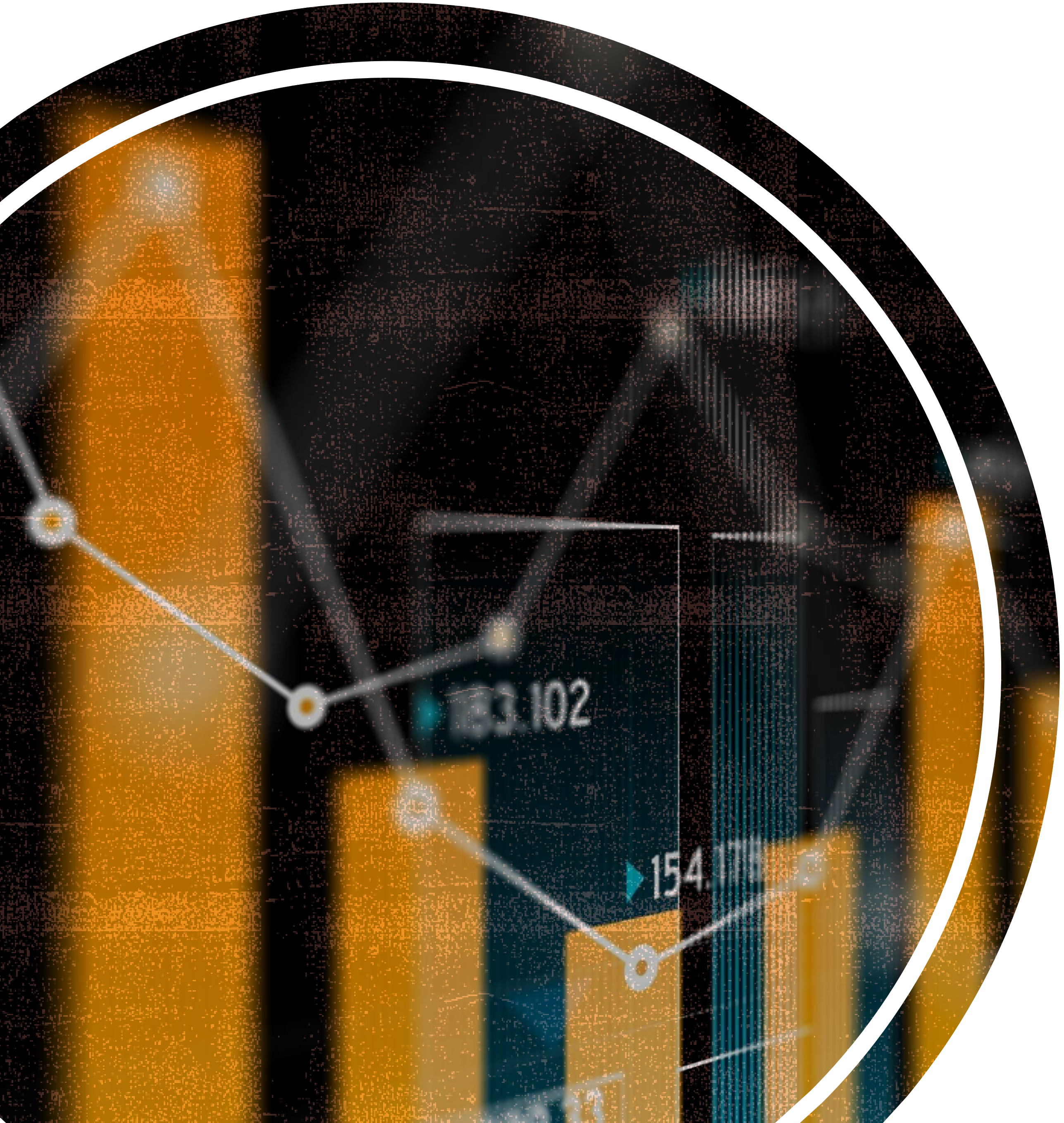
LIMITATIONS AND DELIMITATIONS OF DATA PART 2

Granularity	
Time	(1996 – 2017)
Features	Sales Data Zillow Estimates
Complexity of combination	19K Unique Zip codes
Aggregation of Features	Number of Bedrooms Dwelling Type

IS IT ALL HERE?

- Scarcity of price
- Duplicative feature types
- Scaling & Aggregation
- Consolidated variable creation
  - Function creation
  - Factorization
- Melting and Reshaping

Zillow®

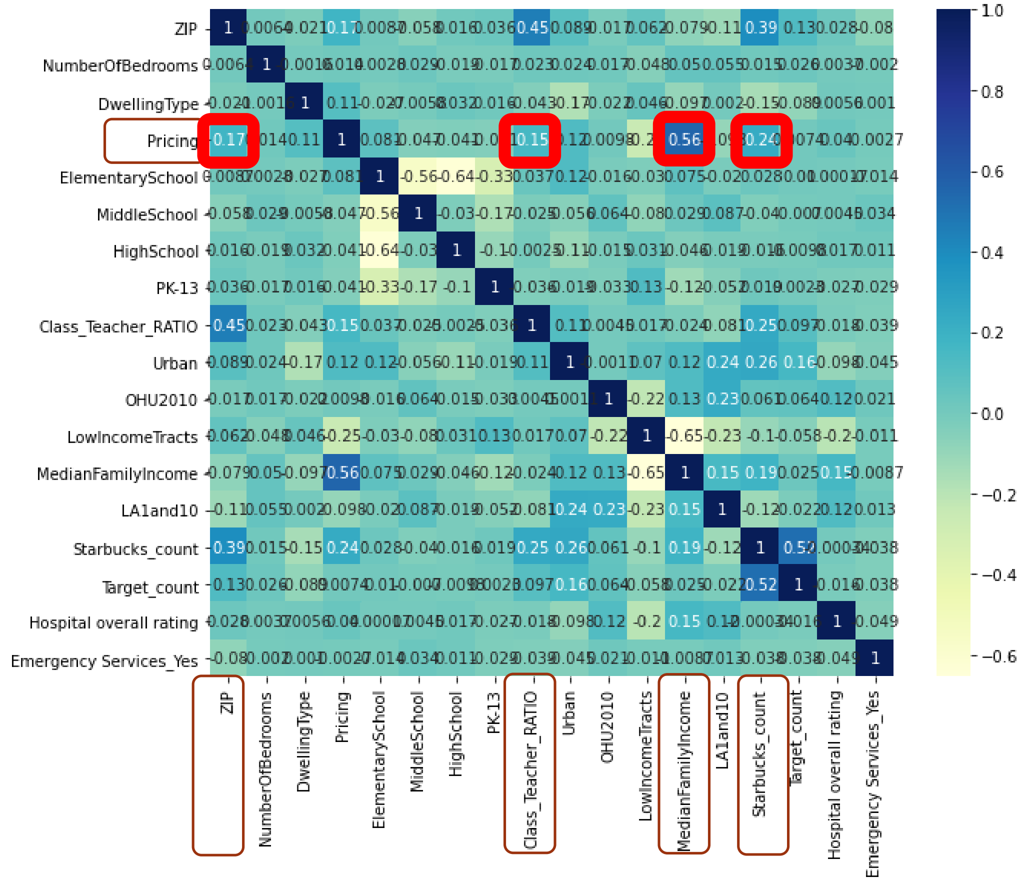


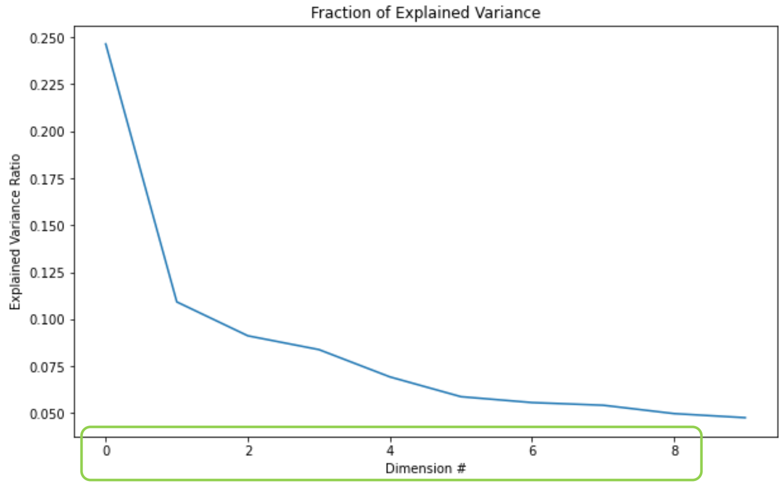
DATA EXPLORATION

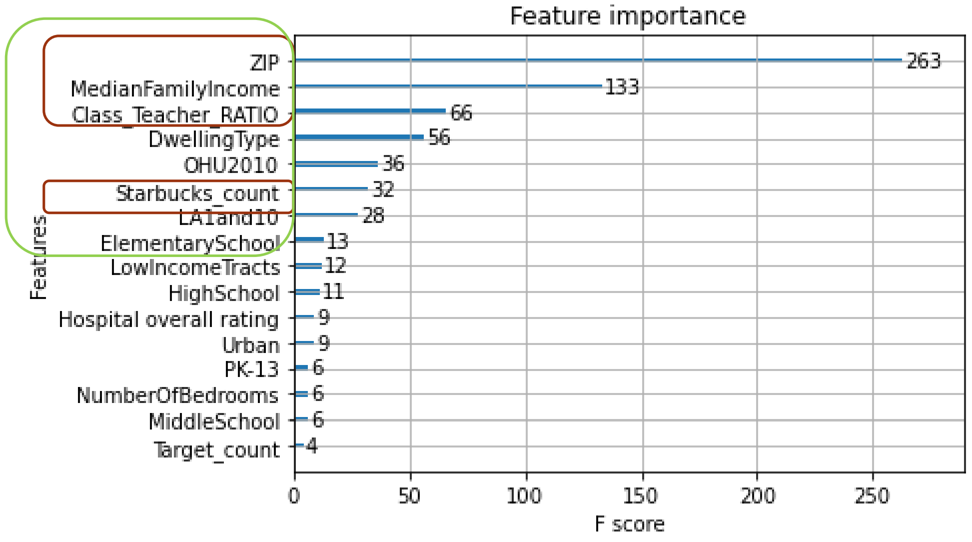
Featurization:

- 90%-time spent feature engineering (5.5 weeks)
- Individually worked on datasets separately:
  - Identified and removed features with high collinearity
  - Captured summary statistics
- Consolidated features and visualized relationship

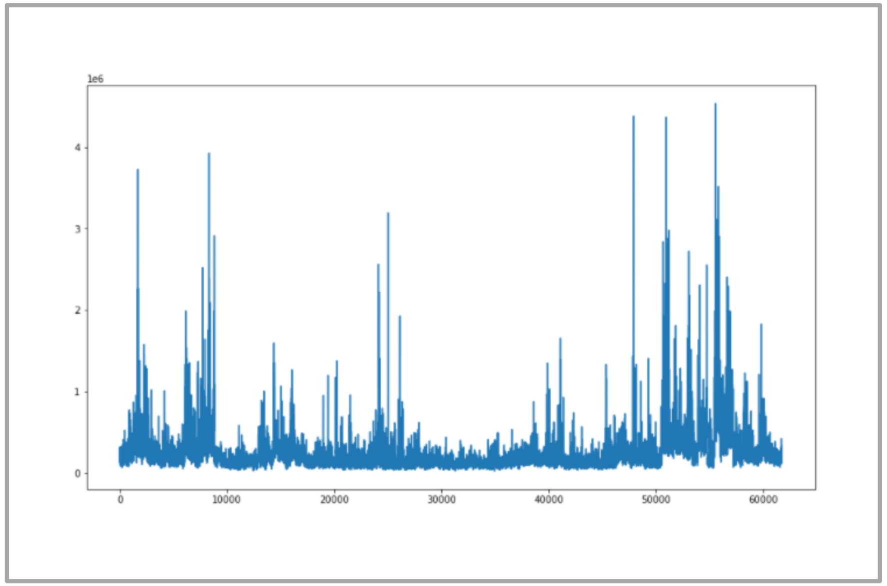
HEATMAP, PCA & FEATURE IMPORTANCE

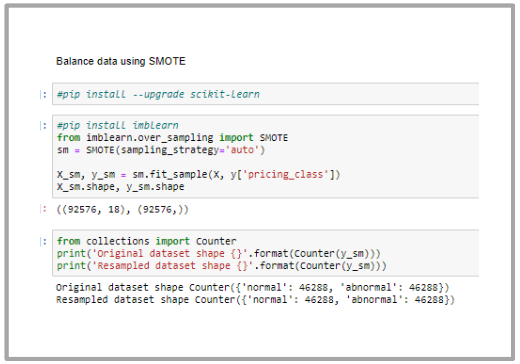


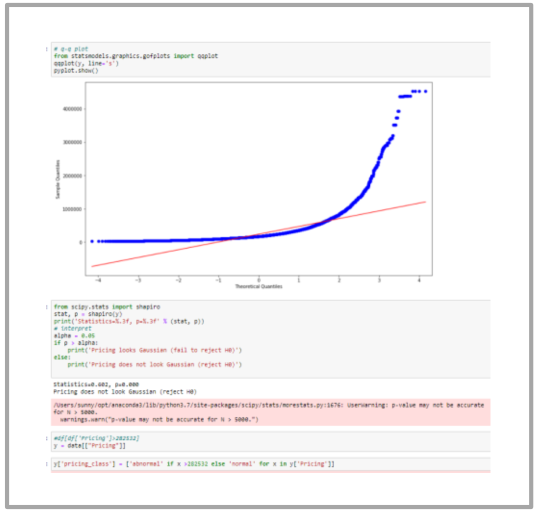




TARGET VARIABLE EXPLORATION







METHODOLOGY

- Models
  - Linear Regression
  - Decision Tree
  - Random Forest
  - Support Vector Regression
  - Gradient Boosting
  - KNN for Regression
  - XGBoost

FRAMEWORK

1

Validation Methodology

- Compare Desired Errors with Training and Cross Validation errors

2

Descriptions

- Choose top 3 models

3

Model Selection Justification

- Best performing RMSE

RESULTS

MODELING RESULTS

- Linear Regression
  - Desired Error: 279471.46
  - Training Error: 0.78
  - Cross Validation Error: 0.78
- Support Vector Regression (SVR)
  - RMSE score: 0.65
- Decision Tree
  - Hyperparameter Tuning: max depth = 4, min_samples_leaf = 0.1
  - Desired Error: 210381.81
  - Training Error: 194304.60
  - Cross Validation Error: 195936.04
- Random Forest
  - Hyperparameter Tuning: max depth = 4, min_samples_leaf = 0.1
  - Desired Error: 204785.74
  - Training Error: 201373.10
- Gradient Boosting
  - RMSE: 131471.88186
- KNN for Regression
  - N_neighbors = 2, RMSE value for k = 2 of 325245.033
- XGBoost
  - RMSE = 108618

MODELING RESULTS DIFFERENT FEATURES

- Linear Regression
  - Desired Error: 294214.72
  - Training Error: 0.84
  - Cross Validation Error: 0.84
- Support Vector Regression (SVR)
  - RMSE score: 0.79
- Decision Tree
  - Hyperparameter Tuning: max depth = 4, min_samples_leaf = 0.1
  - Desired Error: 204245.67
  - Training Error: 200400.99
  - Cross Validation Error: 200487.57
- Random Forest
  - Hyperparameter Tuning: max depth = 4, min_samples_leaf = 0.1
  - Desired Error: 208813.27
  - Training Error: 205483.11
- Gradient Boosting
  - RMSE: 173276.42
- KNN for Regression
  - N_neighbors = 2, RMSE value for k = 2 of 327642.71
- XGBoost
  - RMSE = 112413

XGBOOST

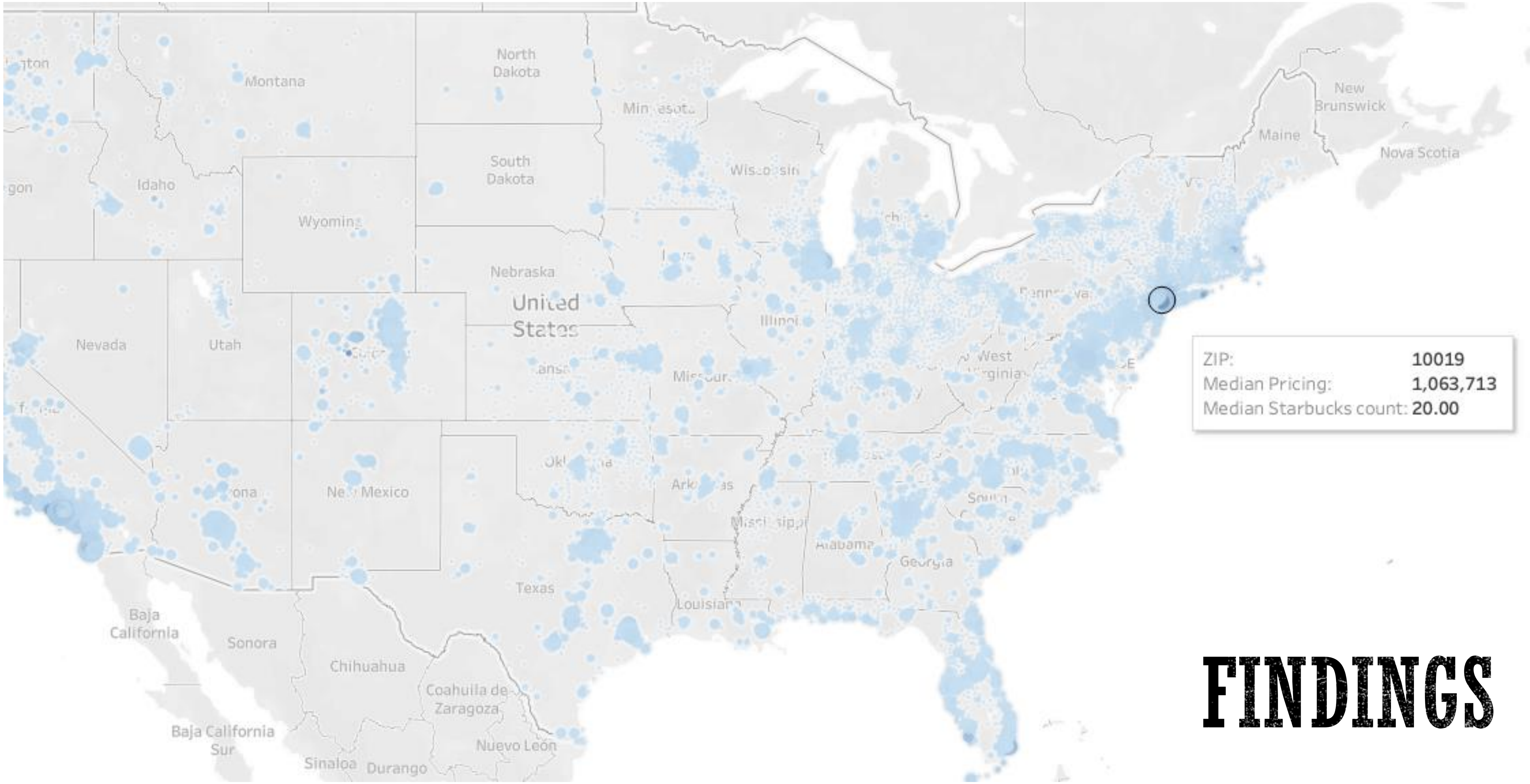
eXtreme Gradient Boosted trees

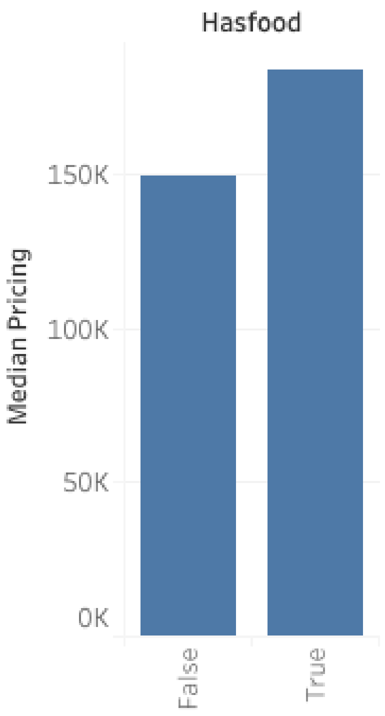
Most powerful machine learning algorithm up until today

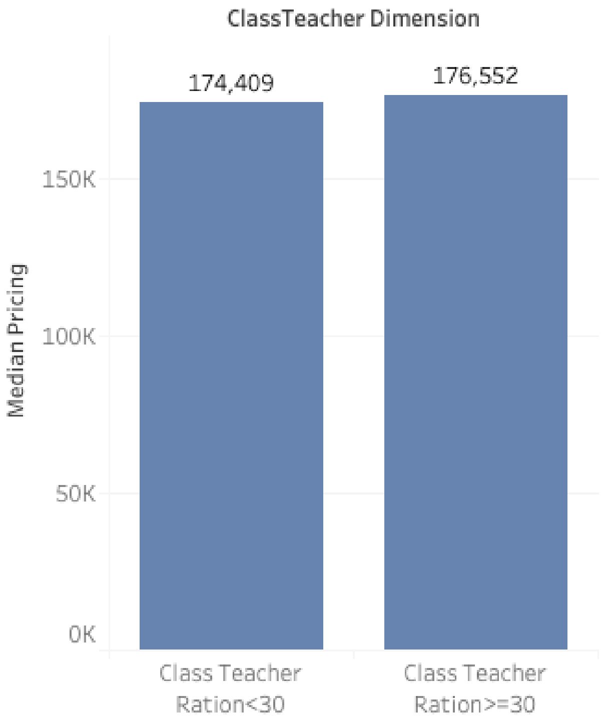
Features:

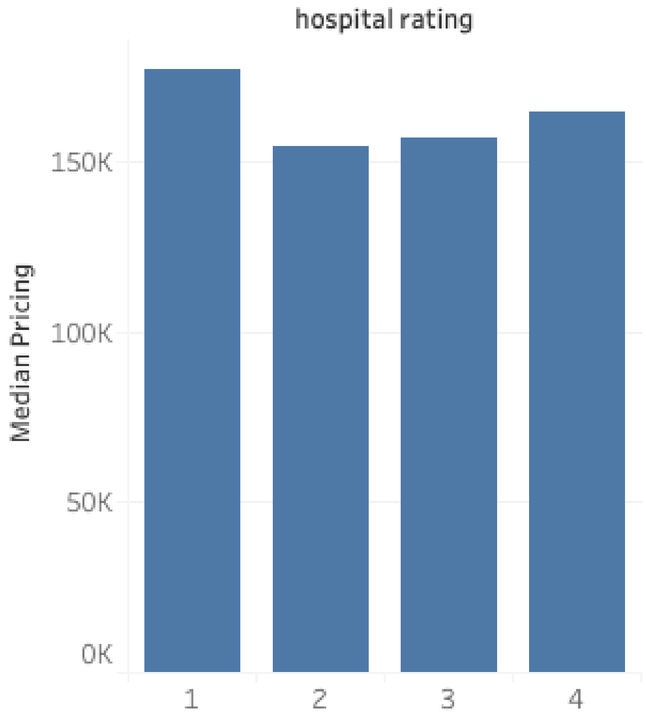
- Regularized boosting (prevent overfitting)
- Can handle missing values
- Parallel processing
- Can cross-validation at each iteration

FINDINGS


North Dakota
Montana
South Dakota
Idaho
Wyoming
Nebraska
United States
Nevada
Utah
New Mexico
Texas
Alabama
Georgia
New Brunswick
Maine
Nova Scotia
Baja California
Sonora
Chihuahua
Coahuila de Zaragoza
Baja California Sur
Sinaloa
Durango
Nuevo León
ZIP: 10019
Median Pricing: 1,063,713
Median Starbucks count: 20.00

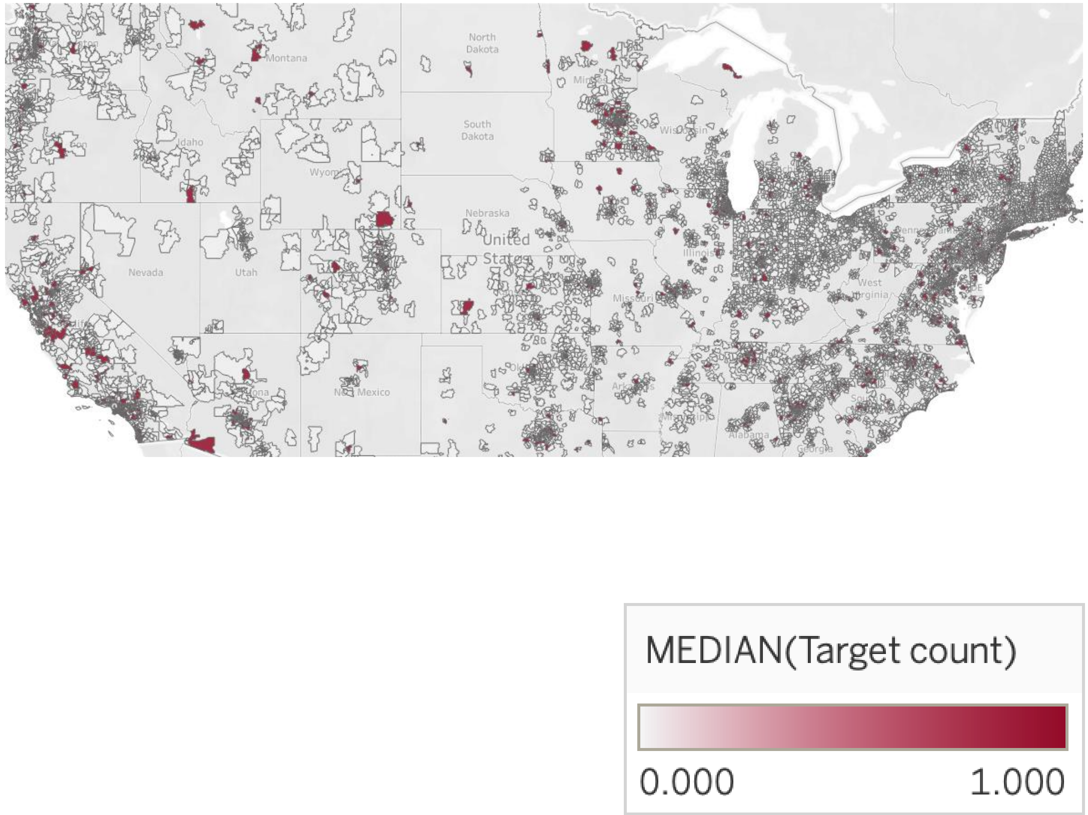




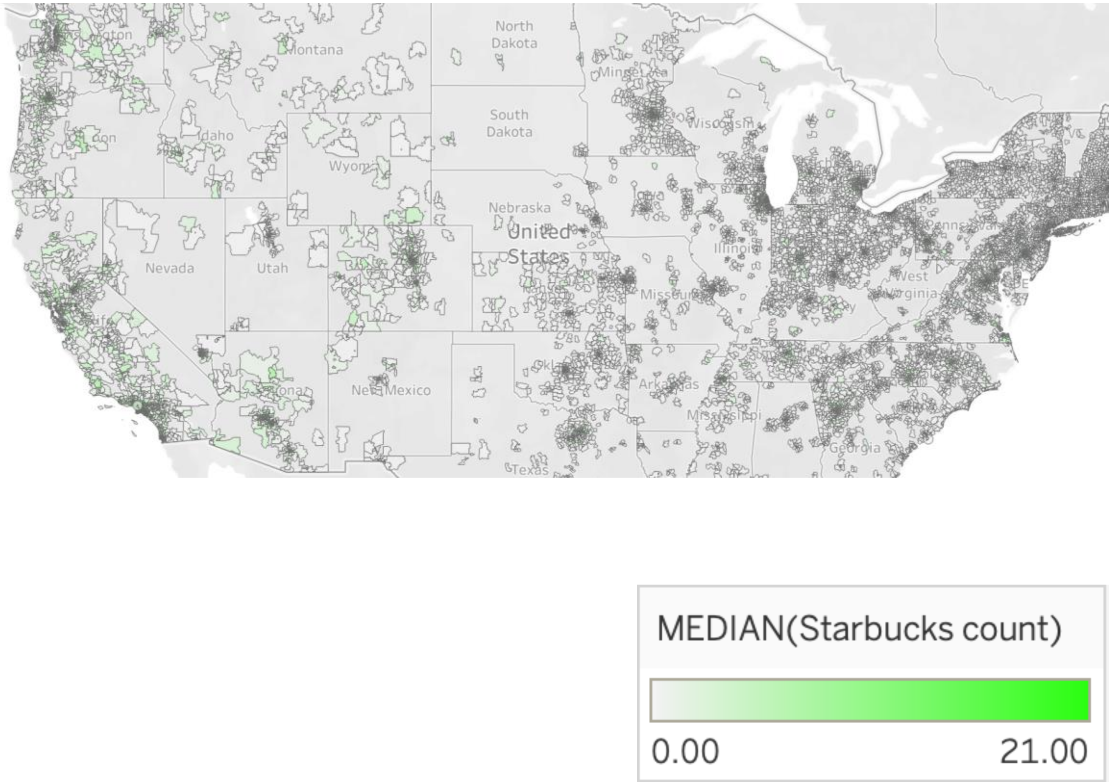


CONVENTIONAL FEATURES

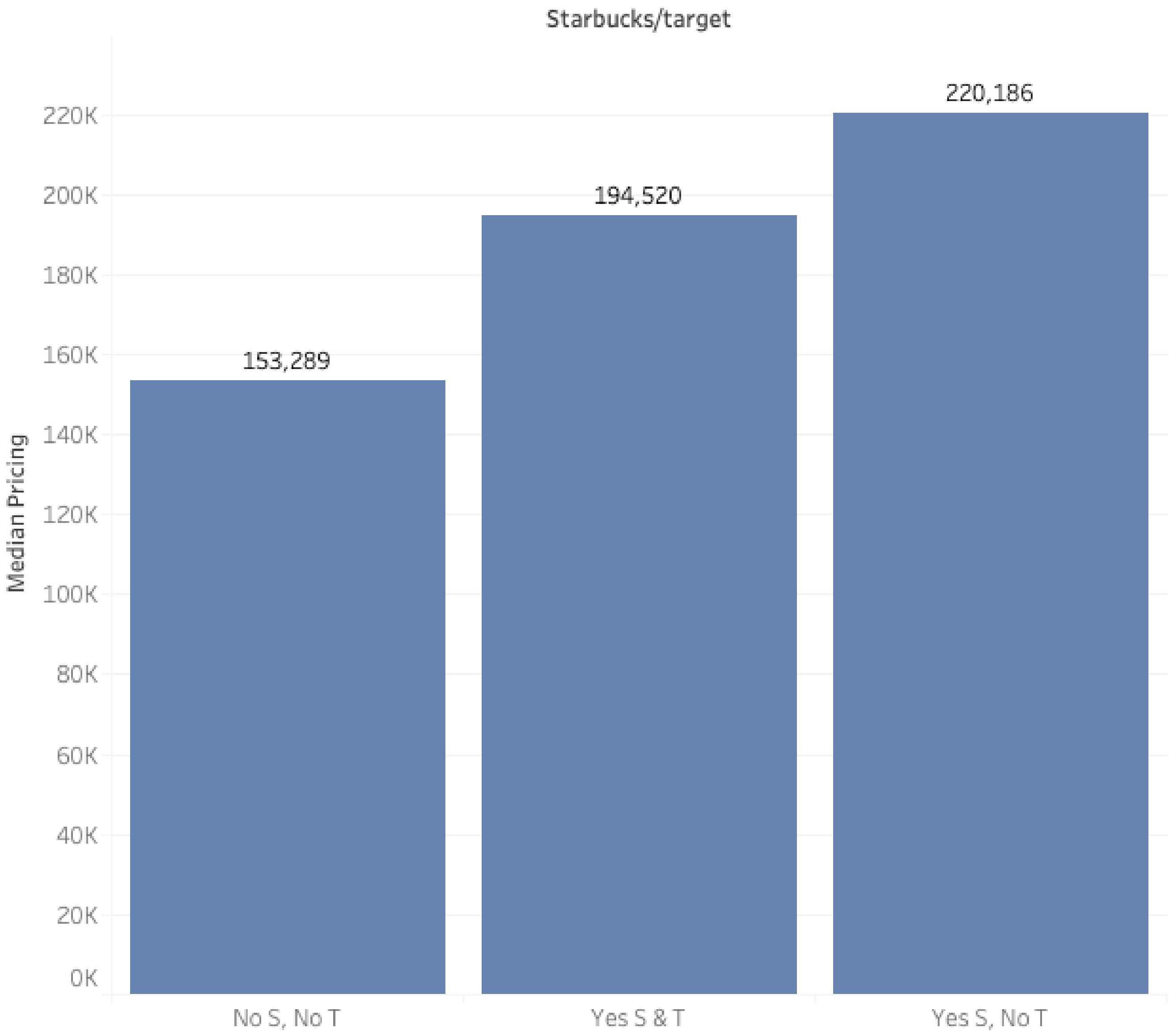
Target Density



Starbucks Density



STARBUCKS INFLUENCE



CONCLUSIONS

Non-conventional features may be economic indicators.

We spent 80% of time on addressing a number of issues around data quality, standards, access.

We have plans for model optimization but didn't have time to achieve it.

FUTURE CONSIDERATIONS

- New dataset or extension of features.
- Number of bathrooms, rent cost, Square footage, etc.
- Dollar trees stores, Dunkin donuts, pharmacies, supermarkets, etc
- Complex imputation methods

  - Focus on the hospital specifically, calculate the radii of hospitals, then use radii to weigh the hospital rating for each zip code.
- Robust test

  - Replacing zip code with county/city
- Include time series data to the analysis

QUESTIONS?

Thanks for Your attention