THE STARBUCKS DATA HUNT

PREDICTING STARBUCKS YELP SCORES TO FIND THE ISSUES THAT MATTER

CHRISTOPHER JOSE, 1/2017

MOTIVATION

- Executive, VIP Starbucks connoisseur who often clocks more hours at his local coffee bean hangout than even the baristas themselves
- Just like how a neighbor longs to improve their neighborhood, a coffee addict naturally wants the best for his coffee kingdom (aka caffeine drug dealer)

ISSUES AT STARBUCKS

- Lingering homeless people who smell horribly and talk to themselves
- Unclean bathrooms and overflowing garbage cans
- The “barista from hell”
- Inconsistent drink quality

OBJECTIVE

- Figure out which issues customers care more about using Yelp
- Do this by making models to predict Starbucks Yelp star scores, and then examining predictors that contribute the most to these models

YELP

- Yelp is a website that lets customers give public feedback to businesses.
- Feedback consists of written reviews and “star” scores ranging from 1 - 5
- 5=coffee nirvana, 1 = like going to a coffee slave camp

YELP DATA

- Yelp has freely provided *some* of its data as part of its "Yelp Dataset Challenge"
- The data consists of json files, two of which I import and convert to pandas DataFrames in Python

YELP DATA THAT I ACTUALLY USE

- I make two tables – *business* and *reviews*
- *business* contains a row for each store, which includes store id, review count, location, and star score
- *reviews* contains a row for each review, which includes store id, date, review text content, and star score

DATA WRANGLING

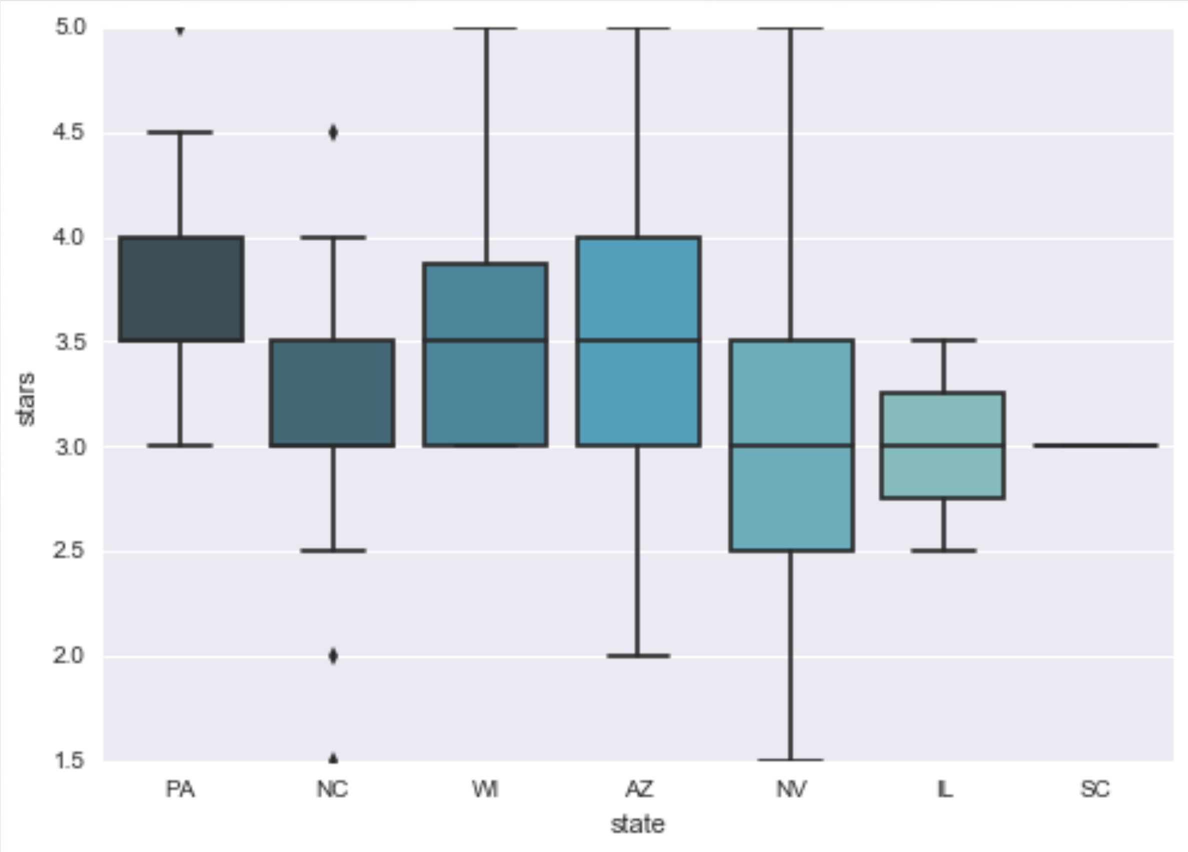
I make the following variables

- Average year in which a store is reviewed
- Dummy variables - clean vs unclean, homelessness problems yay/nay, unfriendly baristas yay/nay, a dummy for each state (all values =0 represents AZ)

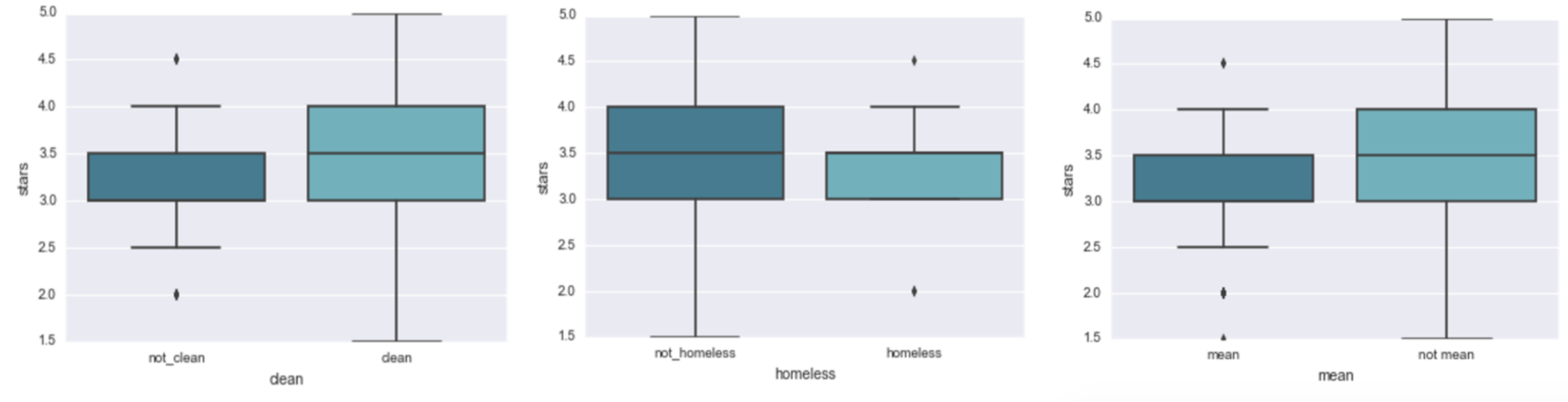
EXPLORATORY DATA ANALYSIS

- 494 stores – 201 in AZ, 161 in NV
- 18 reviews per store on average
- Data is provided for only 7 states, and Canada
- Examine relationship between potential predictors and star score using statistical graphics

EDA – STARS BY STATE

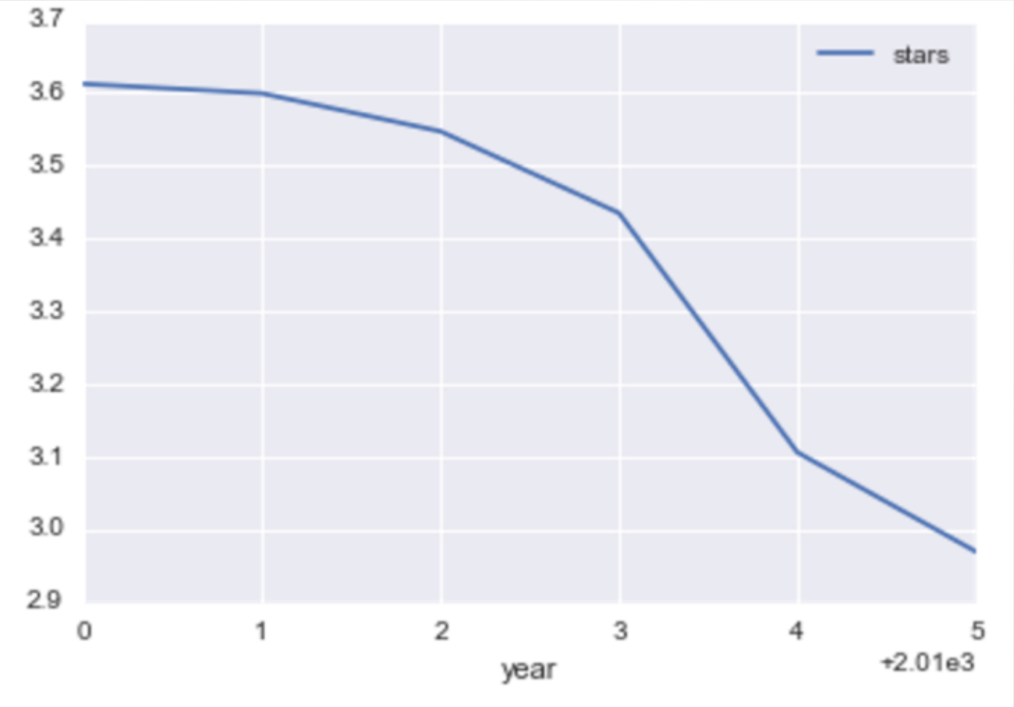


EDA – STARS BY DUMMY VARIABLES

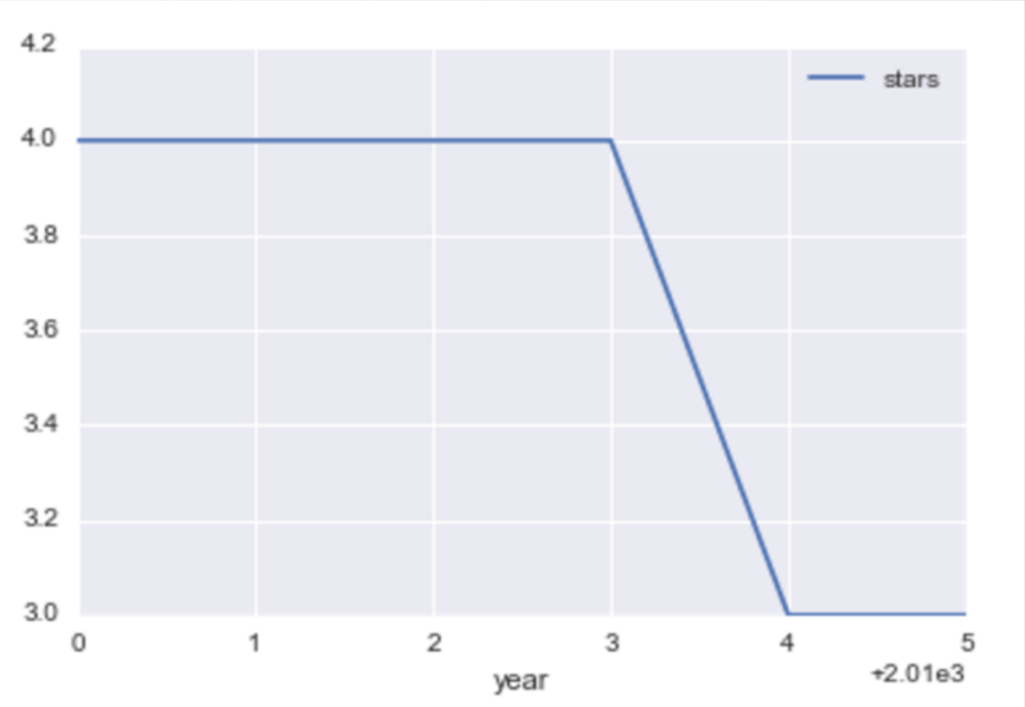


EDA – AVG AND MEDIAN STARS BY YEAR

Avg Star Score by Year



Median Star Score by Year



PREDICTORS TO USE

- mean review year, unclean, homeless, unfriendly, state dummy variables
- review count, since it is correlated with unfriendly and unclean variables (.78, .54 correlation coefficients)

THE MODELS

- Linear Regression (LR) , Principal Component Regression (PCR), Random Forests (RF), Gradient Boosted Trees (GBT)
- Models will be compared and ranked by their root mean square error (rmse), the typical amount by which a model's predictions deviate from the actual values.

MODELING SPECIFICS

- LR and PCR built by splitting the data randomly into a 70% train split and 30% test split
- RF and GBT built using 5-fold cross validation and grid search to tune certain model parameters

LINEAR REGRESSION

- Significant coefficients at 5% level for :

unclean, unfriendly, mean review year, NC, NV, and QC

- Unfriendly/Unclean stores see their predicted stars drop by .28 and .23, respectively
- rmse .6544
- Adj. R-Squared 13.7%,

PRINCIPAL COMPONENT REGRESSION

- Select 10 principal components (PCs) - 79% of variance is retained, eigenvalues close to zero are excluded
- Difficulty in interpreting resultant PCs and finding the most important variables
- rmse decreases to .645 (from .654)
- Adj. R-squared goes down to 10.8% (from 13.7%)

RANDOM FORESTS

- Grid search tunes the size of the random subset of features (max_features) used at each split to be .10
- Most important features are mean review year and review count, which does not seem interesting
- rmse is .6495 (PCR<RF<LR)

GRADIENT BOOSTED TREES

- Grid search optimizes: learning rate, tree depth, % of rows to sample while fitting model, max_features
- Most important features are again mean review year and review count
- rmse decreases to .622!

RESULTS – IMPORTANT FEATURES

- unclean, unfriendly, and state are important in LR
- mean review year and review count are important in RF and GBT
- In LR model, store cleanliness and barista friendliness are more important than homeless problems (though this model deserves further improvement)

RESULTS – PREDICTABILITY OF MODELS

RMSE

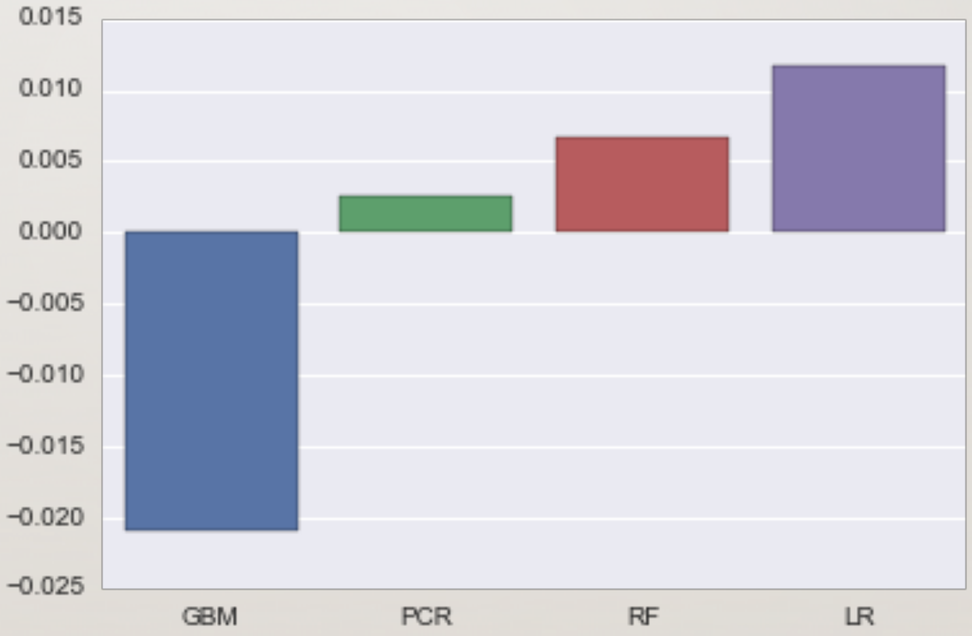
GBT .622

PCR .645

RF .649

LR .654

RMSE centered around the mean value



NEXT STEPS
FURTHER RESEARCH AND RECOMMENDATIONS

- Perform more sophisticated text analysis or sentiment analysis in making existing dummy variables
- Include more variables using Yelp's text review content
- Include more variables from data outside Yelp's data
- Use internal Starbucks data

NEXT STEPS (CONT'D)
FURTHER RESEARCH AND RECOMMENDATIONS

- Make models for subgroups of Yelp data, like a model for each state
- Make decisions from results of updated models. If drink quality is an issue, retrain baristas at stores with low star scores.
- Use predicted star score as a predictor in models that predict a metric that is correlated with star score. This would be needed for new stores or stores with little Yelp data. Use internal data as a proxy for Yelp data.

FINAL REMARKS

- Starbucks is a hub of community activity
- By improving the customer experience, we improve our communities
- Doing this also makes Starbucks more competitive and profitable. This is a win for everyone!