Predicting GeoSpatial Affluence For Disaster Recovery With yelp

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Problem Statement & Key Objectives

Problem Statement

- Traditional methods estimate geospatial wealth via income or unemployment rates
- These data sources may not provide sufficient granular data for the agile needs of disaster response agencies

Key Objective

- **Build a model that will take zip codes or location as input and will leverage frequently updated commercial data to estimate geospatial affluence with high accuracy**

Executive Summary

- Yelp Dollar sign ($) data alone is not a strong predictor of geospatial affluence
    - Correlation of Yelp Dollar Sign to Median Income is 0.09
- Challenges observed: limited venue/business/service representation in low affluence or low population areas, non-residents providing yelp reviews
- Augmenting Yelp Dollar Sign data with feature engineering improved scores
- Ultimately our model is able to accept a location as input and estimate the affluence category with 65.5% accuracy
- We do not recommend using Yelp price level data alone to predict affluence

Process & Model Overview

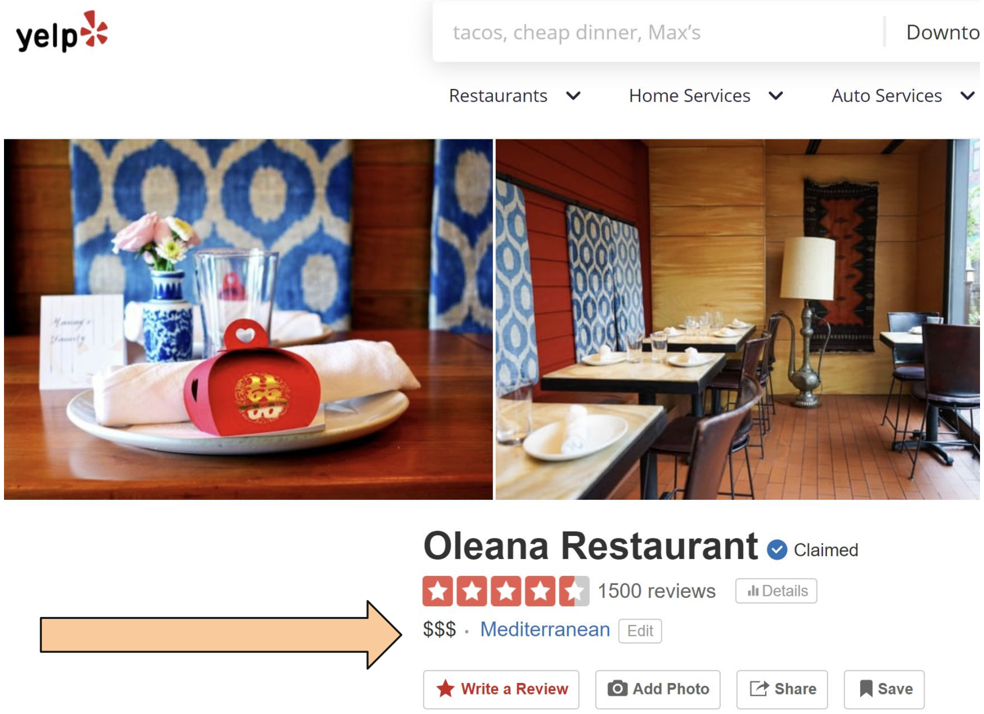
1. Data Gathering
   - Yelp API
   - ASC data

2. Data Cleaning/Wrangling
   - Aggregation by zip code
   - Identifying & addressing null/missing data

3. Analysis & Feature Engineering
   - Affluence Score Creation
   - Yelp features

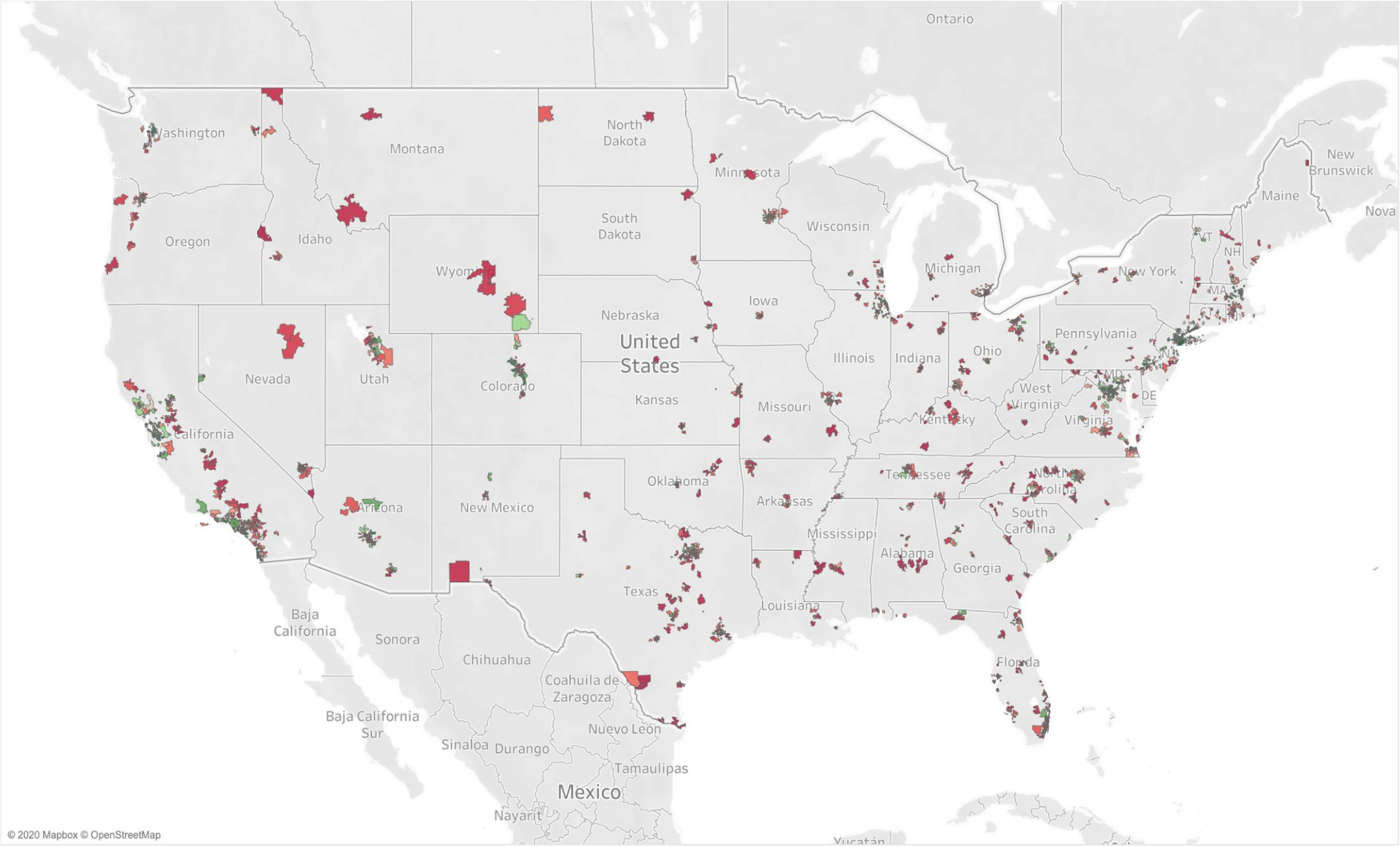
4. Conclusions & Recommendations

Gathering & Cleaning Data



- Yelp records with $ values were extracted for over **300** cities:
    - **Richest** cities in every U.S. state (median household income)
    - **Poorest** cities in every U.S. state
    - **200** most populous U.S. cities
- Over **100K** unique records were obtained, providing representation for the entire nation
- Data Extraction Tools and Approach:
    - **Webscraping** with BeautifulSoup for City Lists
    - Custom Python code leveraging **YelpAPI** used to pull Yelp JSON files spanning multiple hours
    - Python code used to parse, clean and merge datasets
- Data from American Fact Service (census data) downloaded for **income**, **median home value**, etc.

Zipcodes Scraped by Affluence Score



AVG(Affluence)

1.00 64.00

Key Challenges

- Correlation between price and income: 0.09
- There are more $$ establishments than the rest of the price categories combined
- Tried smaller dataframe where each zip code had at least 250 observations, the results did not improve. Lack of data is not the problem.

Data Cleaning and Wrangling

Cleaning

- Aggregating data by zip code
  - ~3400 unique zip codes
  - Mean and sum of particular features
- Removing the overpopulous zips
  - Consistent amounts of NaNs
  - Lack of reviews and restaurants per zip
- Binning appropriate features

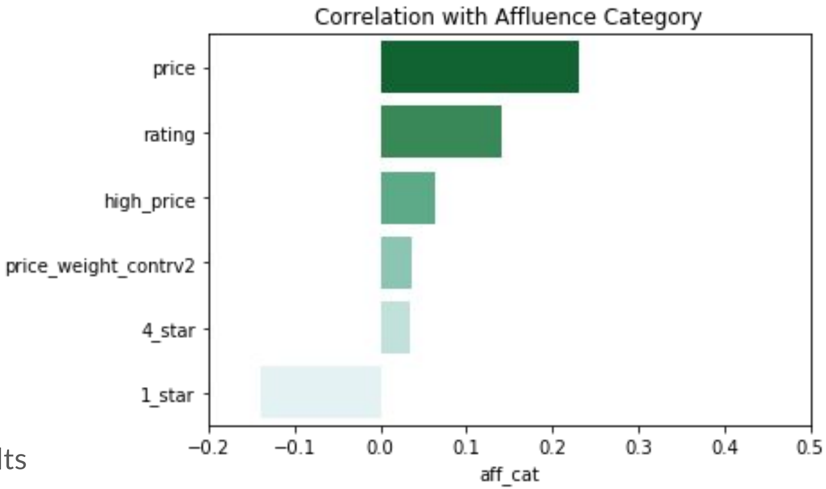
Wrangling

- Merging data from several data sources
  - Yelp scrape
  - Census data
- Normalization of Yelp Prices

Feature Engineering

We leveraged the price level data point and rating into additional valuable features:

- One star
- Four Star
- High Price
- Mean Price
- Price-weight-control



- Dummying establishment category provided no results
- Possibly because some types of establishments are far more likely to have price level than others

Affluence Score

- Income alone does not equate to “affluence”
- Combined several measures for better representation:
  - Median income
  - Percent with bachelor’s degree
  - Median home value

Model Performance

Pre- Feature Engineering Results

Model	Train/Test Scores
Logistic Regression	0.5441 / 0.5445
KNN Neighbors	0.5185 / 0.5445
Decision Tree	0.5446 / 0.548
Random Forest	0.5466/ 0.5482
AdaBoost	0.5426 / 0.5482
SVC	0.5466 / 0.5468

Feature Engineering Results

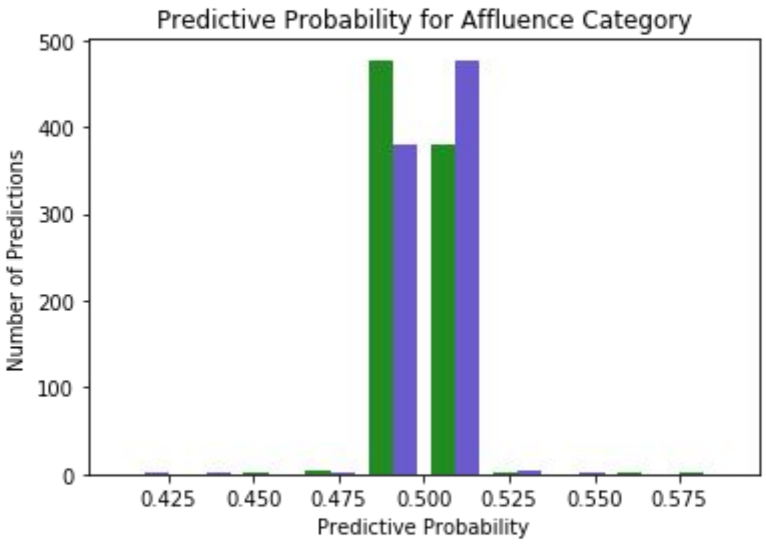
Model	Train/Test Scores
Logistic Regression	0.6416 / 0.6192
KNN Neighbors	0.7397 / 0.5752
Decision Tree	1.0000 / 0.5000
Random Forest	0.9722/ 0.5856
AdaBoost	0.6718 / 0.625
SVC	0.6745/ 0.617

Model Results

AdaBoost with 50 Decision Trees

65.5% accuracy

- Confidence of model generally low
- Mean price for high affluence: 1.88
- Mean price for low affluence: 1.67



Conclusion

- Yelp Dollar sign ($) data alone is not a strong predictor of geospatial affluence
    - Limited differentiation
- Turning the problem into two class classification problem made it more feasible
- Engineered features significantly improved performance
- Challenges observed: limited venue/business/service representation in low affluence or low population areas

Recommendations

- Do not heavily rely on Yelp price level data to predict affluence
- Continue building robustness of model with scheduled periodic Yelp Data updates to continue training model and improving accuracy
  - Consider using category data
- Consider purchase of Commercial Grade Yelp API access in order to streamline data extraction
- Expand functionality and improve user-experience by building front-end with Flask or similar tool