# San Francisco Restaurant Health Scores

— A supervised learning capstone ——

### **Outline**

- 1. Research Question
- 2. Overview of Dataset
- 3. EDA and Feature Engineering
- 4. Models, results, and drawbacks
- 5. Who can use this model and for what purpose?

### What are we trying to learn?







Can a restaurant's consumer reviews help predict its health score?

Research Question



Overview of Dataset



EDA & Feature Engineering



Models, Results, & Drawbacks



### Why does this matter?

2011:

#### Source:

https://www.cdc.gov/foodborn eburden/estimates-overview.h tml CDC estimates 48 million people get sick, 128,000 are hospitalized, and 3,000 die from foodborne diseases each year in the United States.

Research Question



Overview of Dataset



EDA & Feature Engineering



Models, Results, & Drawbacks



### Not much to work with...

About 50,000 records from San Francisco Restaurants.

Pulled from the Kaggle open data set found here.

#### **Business Information**

Name

Latitude

Longitude

Phone Number

Postal Code

# Neighborhoods

# Polic Districs

# Fire Districts

#### **Inspection Information**

Inspection Score

Date

Earliest: 8/2/2016

Most Recent:: 8/1/2019

Violation Category Violation Description



Research Question



Overview of Dataset



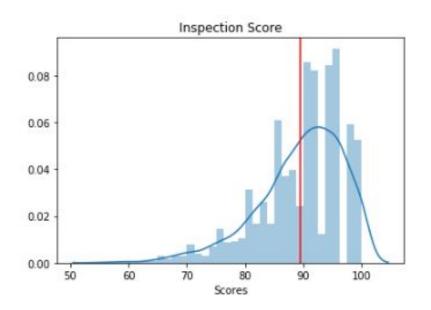
EDA & Feature Engineering



Models, Results, & Drawbacks



### What does our inspection score look like?



Mean: 89.53

**Standard Deviation**: 7.43

#### **Other Noticings:**

- Long tail
- High scores almost discreet

Research Question



Overview of Dataset



EDA & Feature Engineering



Models, Results, & Drawbacks



## **Duplicate Entries?**

business_name	business_postal_code	business_latitude	business_longitude	inspection_id	inspection_date	inspection_score	inspection_type
Parada 22	94117	37.769303	-122.451961	62051_20180514	2018-05- 14T00:00:00.000	86.0	Routine - Unscheduled
Parada 22	94117	37.769303	-122.451961	62051_20180514	2018-05- 14T00:00:00.000	86.0	Routine - Unscheduled
Parada 22	94117	37.769303	-122.451961	62051_20180514	2018-05- 14T00:00:00.000	86.0	Routine - Unscheduled
Parada 22	94117	37.769303	-122.451961	62051_20180514	2018-05- 14T00:00:00.000	86.0	Routine - Unscheduled
Parada 22	94117	<b>3</b> 7.769303	-122.451961	62051_20190509	2019-05- 09T00:00:00.000	88.0	Routine - Unscheduled
Parada 22	94117	37.769303	-122.451961	62051_20190509	2019-05- 09T00:00:00.000	88.0	Routine - Unscheduled
Parada 22	94117	37.769303	-122.451961	62051_20190509	2019-05- 09T00:00:00.000	88.0	Routine - Unscheduled

Research Question



Overview of Dataset



EDA & Feature Engineering



Models, Results, & Drawbacks



### Other noticings and changes?

- 1) Drop rows where there the scores and violations are incongruous
  - a) Scores with 100 but had violation ids/descriptions
  - b) Scores with less than 100 but no violations
- 2) Scores with 100 and null descriptions are changed from null to 'No Violation'
- 3) Filled null values of basic business information with the median
- 4) About 12,000 unique inspections

Research Question



Overview of Dataset



EDA & Feature Engineering



Models, Results, & Drawbacks



## Feature Engineering via Data Mining

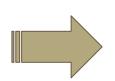
**Kaggle open Data** 

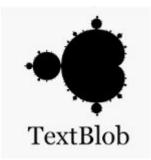


**Yelp Fusion API** 









Basic Business and Inspection Information Average Yelp Review

3 Most Recent Reviews

**Restaurant Price** 

Average Sentiment Analysis

Research Question



Overview of Dataset



EDA & Feature Engineering



Models, Results, & Drawbacks



### **Created Features - SF open Dataset**

#### **Kaggle open Data**



Basic Business and Inspection Information

- Total Number of Violations
- Counts of the different risk categories
  - No Violation
  - Low Risk
  - Medium Risk
  - High Risk
- This is a dynamic dataset

Research Question



Overview of Dataset



EDA & Feature Engineering



Models, Results, & Drawbacks



## Created Features - GET Requests with Yelp's API

**Yelp Fusion API** 



Average Yelp Review

3 Most Recent Reviews

**Restaurant Price** 

#### Steps to take:

- 1) Pull in each businesses' unique yelp id
- 2) Get requests to pull in certain features:
  - a) Restaurants average yelp review
  - b) 3 most recent reviews
  - The restaurant's price (converted from '\$' to numeric 1-4
  - d) The average rating of the 3 reviews

Research Question



Overview of Dataset



EDA & Feature Engineering

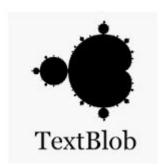


Models, Results, & Drawbacks



### **Created Features - Textblob and Sentiment**

#### **TextBlob API**



Average Sentiment Analysis

Information and how-to pulled from this site.

"TextBlob stands on the giant shoulders of NLTK and pattern, and plays nicely with both."

#### From the Yelp API:

- Get the sentiment from the 3 reviews and average them
- Scale from -1 to 1

Research Question



Overview of Dataset



EDA & Feature Engineering



Models, Results, & Drawbacks



### What does our dataframe look like?

Step	Number of Records	Number of Columns		
Original	53,732	20		
Remove duplicates - add & remove features	12,020	22		
Merge Yelp Data	3,876	26		
Used Features	3,876	1,202		

Research Question



Overview of Dataset



EDA & Feature Engineering



Models, Results, & Drawbacks



### How do certain features compare to our target

feature	r_squared	p_value
num_violations	0.714909	0.000000e+00
high_risk_count	0.629531	0.000000e+00
medium_risk_count	0.483993	7.941033e-227
no_risk_count	0.351163	7.068552e-113
low_risk_count	0.277726	1.375526e-69
yelp_rating	0.101012	2.922536e-10
review_sentiment	0.084302	1.471651e-07
review_rating	0.070498	1.117630e-05
price	0.046187	4.026364e-03

None are great, but the yelp data is near the top.

Research Question



Overview of Dataset



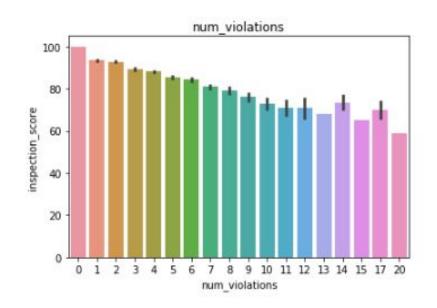
EDA & Feature Engineering

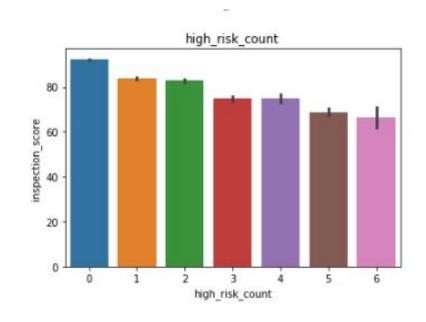


Models, Results, & Drawbacks



### **Number of Violations**





Research Question



Overview of Dataset



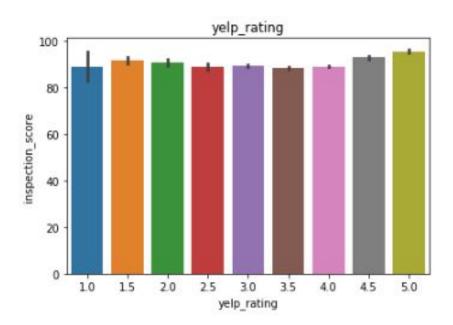
EDA & Feature Engineering

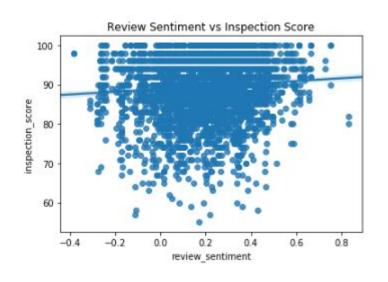


Models, Results, & Drawbacks



## **Yelp Data**





Research Question



Overview of Dataset



EDA & Feature Engineering



Models, Results, & Drawbacks



### **Feature Selection**

- 1) All names (as dummies)
- 2) Calendar Information (as dummies)
  - a) Date
  - b) Day
  - c) Year
  - d) Month
- 3) Numerical Features
  - a) SF Data Neighborhoods, Fire Prevention Districts, Police Districts, etc.
  - b) Yelp Data review sentiment, review rating, price, overall rating
- 4) Does not include violation information

Research Question



Overview of Dataset



EDA & Feature Engineering



Models, Results, & Drawbacks



## How did our models perform?

Model	Test R^2	Train R^2	RMSE	MA % Error
Random Forest Regression	41.43%	91.42%	5.47	4.71%
Bagging Regressor	41.37%	91.24%	5.48	4.67%
SVR w/stand	36.70%	65.46%	5.64	4.91%
Ridge	36.08%	68.09%	5.72	5.11%
Gradient Boosting Regressor	34.02%	61.68%	5.81	5.15%
KNN w/ Standard - Weights	15.73%	99.98%	6.57	5.45%
SVR w/PCA	25.30%	39.74%	6.18	5.45%
LRM w/PCA	21.97%	46.41%	6.32	5.60%
KNN w/ Standard - Uniform	19.47%	79.67%	6.42	5.28%
AdaBoost	6.43%	5.34%	6.92	6.31%

Research Question



Overview of Dataset



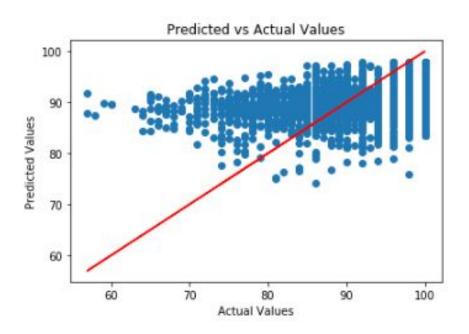
EDA & Feature Engineering



Models, Results, & Drawbacks



### **Random Forest**



#### Noticings:

- 1) Overvaluing small values
- 2) Almost all predictions between 80 90

Research Question



Overview of Dataset



EDA & Feature Engineering



Models, Results, & Drawbacks



## How important are the yelp features?

columns	importance
review_sentiment	0.055099
yelp_rating	0.042255
review_rating	0.037749
Neighborhoods	0.028515
Analysis Neighborhoods	0.027998

Research Question



Overview of Dataset



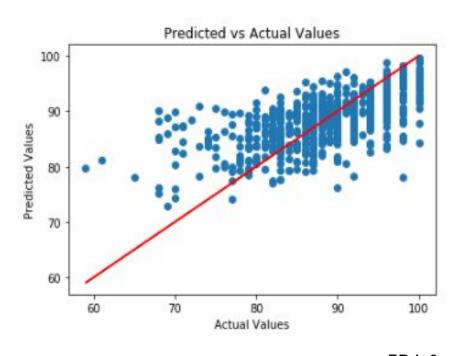
EDA & Feature Engineering



Models, Results, & Drawbacks



## **Bagging Regressor**



#### Noticings:

- 1) Overvaluing small values
- 2) Almost all predictions between 80 90

Research Question



Overview of Dataset



EDA & Feature Engineering



Models, Results, & Drawbacks



## How did our models perform without the Yelp data

Model	Test R^2	Train R^2	RMSE	MA % Error
Ridge	28.91%	78.06%	6.57	5.73%
Bagging Regressor	16.57%	84.24%	7.11	6.46%
Random Forest Regression	14.52%	88.24%	7.2	6.51%
KNN w/ Standard - Weights	-0.55%	55.45%	7.88	6.90%

### **Comparison**

Model	Test R^2	Train R^2	RMSE % Change	MA % Error - Percent Change
Ridge	7.17%	-9.97%	14.86013986	12.13307241
Bagging Regressor	24.80%	7.00%	22.37521515	25.4368932
Random Forest Regression	26.91%	3.18%	9.589041096	19.44954128
KNN w/ Standard - Weights	16.28%	44.53%	27.50809061	26.60550459
Averages:	18.79%	11.19%	18.58312168	20.90625287

Research Question



Overview of Dataset



EDA & Feature Engineering



Models, Results, & Drawbacks



### Where can this model improve?

- Reviews are 3 most recent reviews but health scores are from much earlier
  - <u>Possible Solution</u>: This is a living dataset continue to gather data that matches until many features
- Not many records after pulling in yelp information
  - Possible Solution: See above or integrate a different dataset google reviews?
- Does poorly predicting low scores
  - <u>Possible Solution</u>: Integrate some unsupervised clustering to discern target groups or work with potential stakeholders to determine

Research Question



Overview of Dataset



EDA & Feature Engineering



Models, Results, & Drawbacks



### Who could benefit from this model?

- 1) Restaurant patrons
- 2) Restaurant management/owners
- 3) Health inspectors
- 4) CDC potentially gather more foodborne illnesss data

Research Question



Overview of Dataset



EDA & Feature Engineering



Models, Results, & Drawbacks



### What did we learn/gain?

Can a restaurant's consumer reviews help predict its health score?







There's potential, but more research and time would be needed to improve model's accuracy

Research Question



Overview of Dataset



EDA & Feature Engineering



Models, Results, & Drawbacks

