Capstone Project
Predicting Inspection Results at Food Establishments

Introduction

As a destination that attracts millions of tourists every year, Southern Nevada, and particularly Las Vegas, offers many possibilities when it comes to dining options. With food offerings that range from family owned locales to Michelin star restaurants, the choices may seem endless. Although this can result in a great experience for visitors, it can become a challenging task for the Southern Nevada Health District, who must inspect every food establishment to ensure that it meets the food and safety requirements to protect public's health.

Since these are unannounced inspections that happen at least once a year, it's vital to prioritize visits to restaurants that are most likely to have food and safety violations to avoid foodborne outbreaks and maximize the effectiveness of inspections.

Hence, the goal of this project is to use publicly available data on restaurant inspection and social media to predict non-compliant results and optimize and prioritize inspection visits.

The hypothesis is that inspection results vary across food establishments based on the type, date, and time of the inspection, establishment's cuisine type, business ratings, and the number of reviews it has received.

Approach

Using publicly available data from restaurant inspection results from the Southern Nevada Health District and Yelp's data on businesses and consumers' ratings, the goal is to identify the factors that contribute to downgrades and noncompliance results, using the inspection outcome as the predictor variable. This is accomplished by identifying patterns between business attributes, consumer ratings, and historic data on inspection results.

The results from the analysis can provide actionable insights to local officials to decide when to adjust the rank and frequency of inspections based on the factors that are most likely to influence low compliance rates.

Open Data

Inspections Data

The Southern Nevada Health District Restaurant Inspections is a publicly available dataset that provides inspection results of food establishments. Each record represents the outcome of an inspection, with the following details:

Serial Number
Permit Number
Restaurant Name
Location Name
Category Name
Address
City
State
Zip Code
Current Demerits
Current Grade
Date Current
Inspection Date
Inspection Time
Employee ID
Inspection Type
Inspection Demerits
Inspection Grade
Permit Status
Inspection Result
Violations
Record Updated

Target variable:

A separate binary variable was created as the target variable (‘*is_compliant*’) by grouping the inspections results into complaint and non-compliant.
Once an inspection is conducted, the establishment receives an inspection grade based on the number and type of violations. Each violation is assigned a value, called demerit, that results in a grade. A-grades are given to establishments that are compliant (0 – 10 demerits), while ‘B’ (11 – 20) and ‘C’ (21-40) are downgrades and indicate critical or major violations. Hence, inspections results with a B, C, and

other conventions denoting a downgrade were categorized as non-compliant and all A-grades or conventions denoting a passing grade were categorized as compliant

Yelp Data

The Yelp Academic Dataset includes two files, the businesses description and the customer reviews. Each file is a JSON object file per line file. The business description contains the following details:

business_id
name
neighborhood
address
city
state
postal_code
latitude
longitude
stars
review_count
is_open
attributes
categories
hours

The reviews file contains customers' reviews including:

review_id
user_id
business_id
stars
date
text
useful
funny
cool

How to Improve Decision Making

After obtaining the restaurant inspections results and the Yelp data, the datasets are merged to provide greater depth to the analysis and create new attributes that could give additional information. The idea is to give health inspectors a tool to schedule visits more efficiently, by looking at the factors considered when scheduling visits and focusing on establishments that have a higher probability to have critical violations.

Data Wrangling

The inspections results were obtained from the Nevada Health District Restaurant Inspections webpage using their API and the Yelp academic files were downloaded directly from Yelp. All the JSON files were normalized to manipulate them using Pandas and some initial processing was done before merging.

For the **restaurant inspections results**, which had over 160,000 records and 24 attributes, a subset was taken to include:
Address, category_name, city, current_demeritis[1], current_grade, inspection_date, inspection_time, inspection_demerits, inspection_grade, inspection_result, violations, inspection_type, location_coordiantes, location_name, permit_status, restaurant_name and zip code.
The main data cleaning steps included:

- removing trailing and leading spaces from column names and values in the category name and restaurant name attributes.
- removing special characters from the restaurant names to merge with the Yelp data.
- splitting zip codes to leave only the first five digits (e.g. 89103-4004 became 89103)
- splitting the date into year and month to merge with Yelp data.
- creating a binary target variable, ‘is_compliant’, with 1, if the inspections results were ‘compliant’, ‘A grade’, ‘approved’, or ’no further action’ and 0 otherwise.

[1] As noted in previous report (‘Predicting Critical Health and Safety Violations at Food Establishments – Proposal'), each violation is assigned a value, demerit, that results in a grade. ‘A’s are given to establishments that are compliant (0 – 10 demerits). ‘B’s (11 – 20) and ‘C’s (21-40) are downgrades indicating critical or major violations.

For the Yelp data, only two files were used, the business data and reviews data. For the **business data file**, which had over 180,000 records, the main data cleaning steps included:

- filtering the data to include only records for the state of Nevada
- selecting business id, name, location, review count, categories, attributes, and zip code.
- performing the same first four steps done to the inspection results dataset.

For the **Yelp reviews data file,** which had over 5 million records, the main cleaning steps included:

- selecting only the date, rating, and business id attributes. The review text was not included for this analysis.
- grouping the data by date and business id and get the daily rating average for each business before merging it with the business data. This was done to mitigate 'unnecessary’ data duplication when merging the Yelp file with the inspections file, since the text was not considered.

After the pre-processing, the datasets were merged to include only values that were present in both data sets. Since the inspection results didn’t include a business id to match the business id from Yelp, the datasets had to be merged using a combination of restaurant name, zip code, year, and month. Using the year and month ensured the ratings and business attributes were still relevant.

Feature engineering

- Three new attributes were derived from the inspection date: season, day of the week and inspection shift.
- similar levels of the ‘category_names’ and the ‘categories’ attributes were combined to later create separate binary attributes to identify cuisine type

(Latin, American, Fast food, etc.) and type of establishment (food truck, restaurants, etc.)

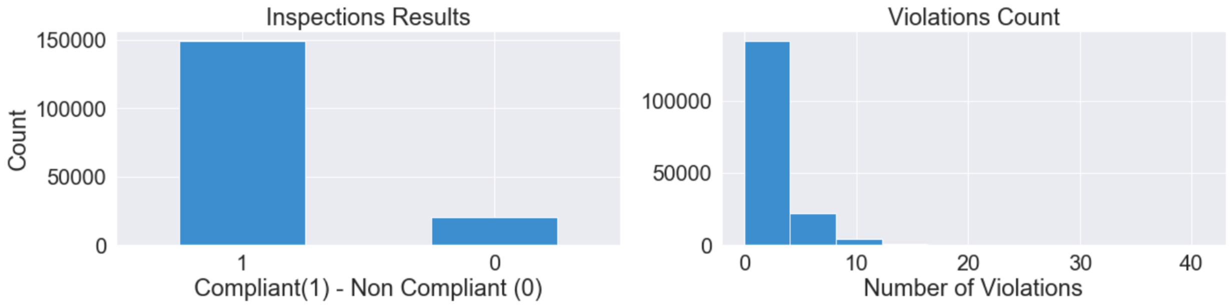
- A new variable with the number of days between inspection and customer star ratings.
- A new weighted star rating variable was created using time weighting for star ratings that happened before the inspection date, with ratings closer to the inspection having higher weights.

EDA and Statistical Inference

Inspection Results Distribution

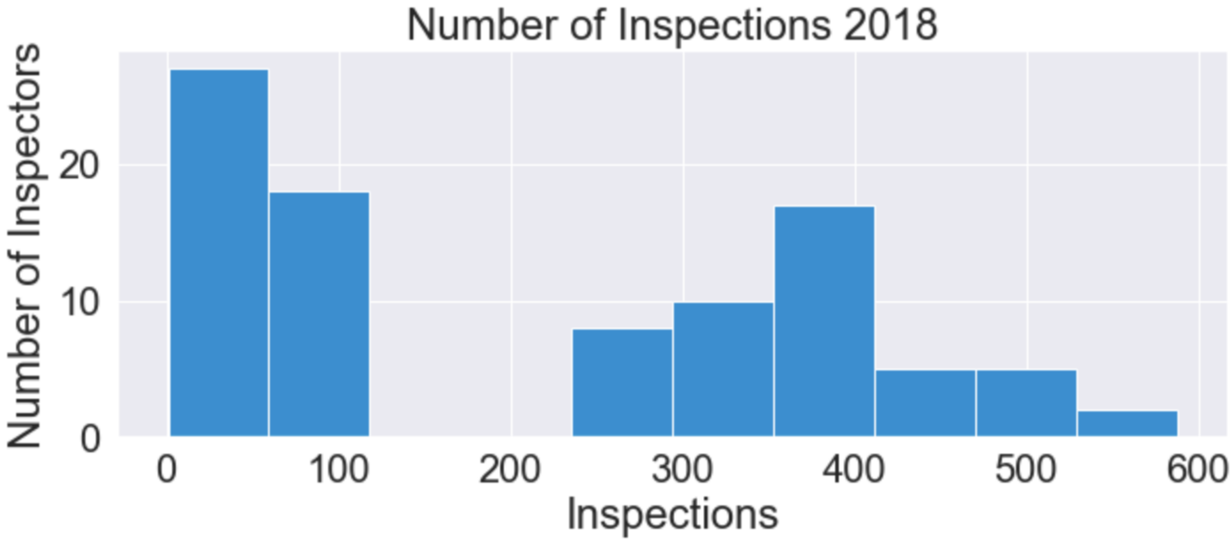
The first step was to look at the distribution of inspection results from the original data to compare the proportion of compliant vs. non-complaint establishments and see how well food establishments performed when it comes to safety and hygiene.

A visualization of the number of inspections by inspection results, shows that over 80% of inspections resulted in a passing grade. In fact, a histogram of the total number of violations, shows that most inspections have less than 10 violations.



Inspectors and Inspections

Next, a close analysis of the number of visits done by employee ID, showed that in 2018, a small number of inspectors performed a large number of visits, with a single employee having over 550 recorded visits. This shows that inspections in 2018 were not evenly distributed among inspectors and the large number of visits for a single inspector may even impact the inspection results due to the large workload.

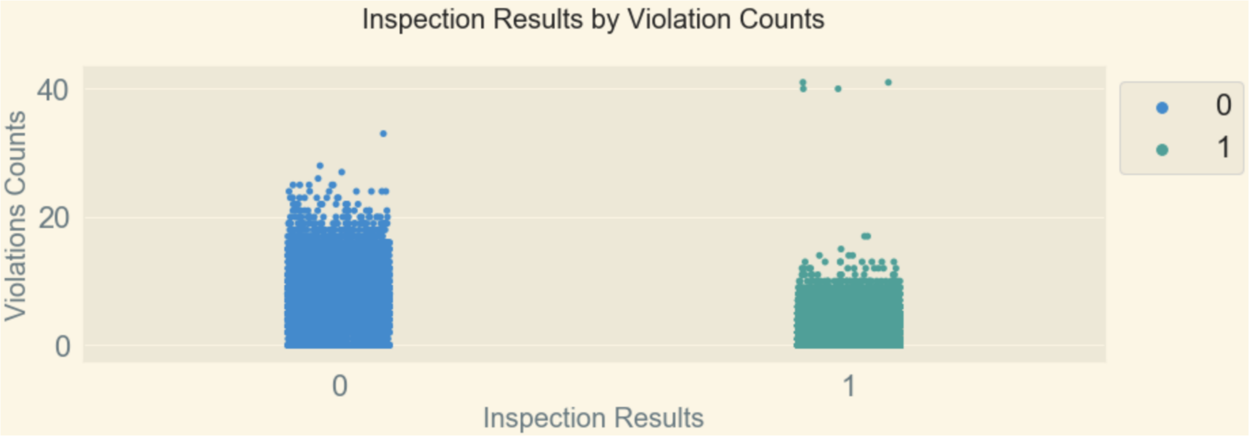


Inspection Results by Violation Counts

The Southern Nevada Health District manages 90 different violation codes for restaurant inspections with each violation having a value that results in a grade. An analysis of the violation counts by inspection, shows that some restaurants with less than 17 violations can in fact received a non-compliance result.

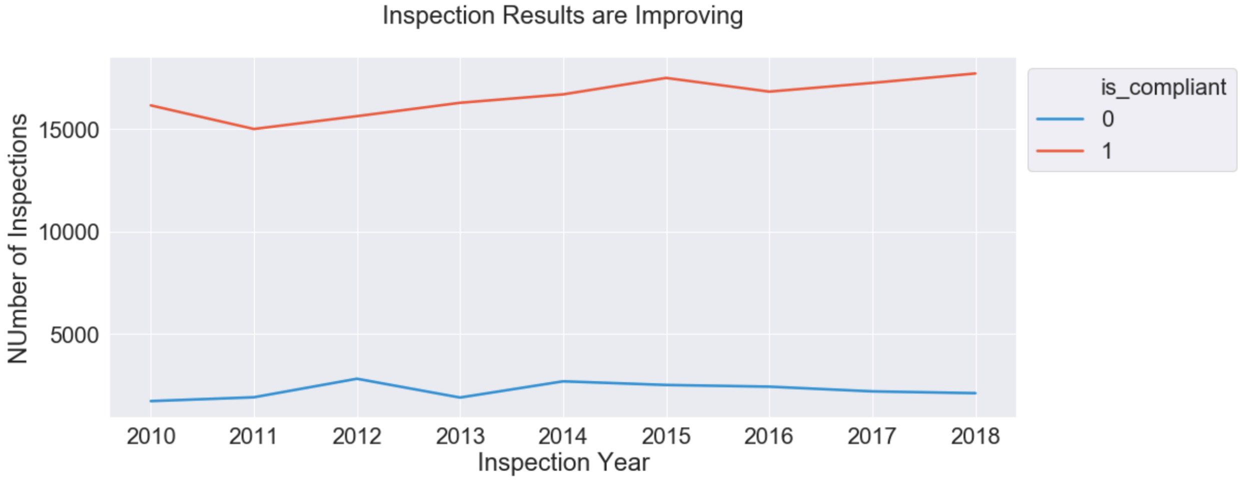
The graph below shows that not all violations carry the same weight and even a restaurant with a single violation can be found non-compliant, if the violation is an imminent public hazard.

The same can be said for a few restaurants that had multiple violations, but received passing grades.



Grades are Improving

Looking at compliance rate overtime, it shows that in general, grades have been improving. Since 2011 compliance rate has gone up, with only a slight decline between 2015 and 2016 when grades were consolidated and inspectors started using A grades for compliance.



Compliance by Seasons

The general assumption for this project is that inspection results and passing rates are different across months, food categories, establishment's star ratings, business ratings, and review count.

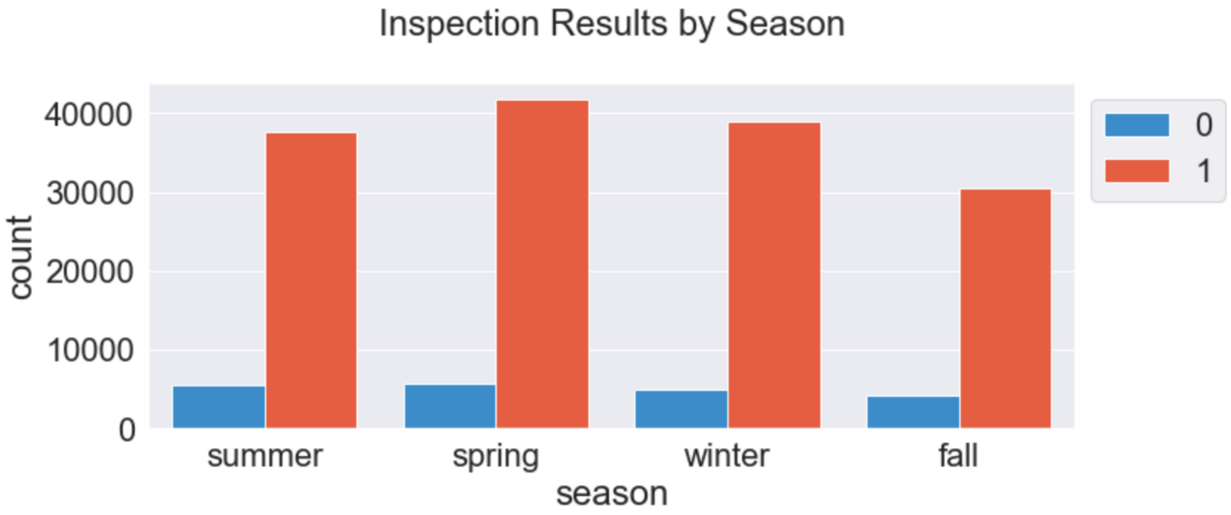
Thus, one of the hypotheses is that seasonal changes in weather may affect food handling and preparation, increasing the likelihood of food violations. The assumption is that higher temperatures during the summer months may increase the growth of bacteria if food is not prepared and consumed promptly. A detailed analysis of inspection results by season, showed that although there are less inspections during the summer months, the number of non-compliance results is slightly higher, particularly when compared to winter inspection results.

$H0$: Compliance rate in cooler months = Compliance rate in warmer months

HA: Compliance rate in warmer months $\neq\neq$ compliance rate in cooler months

$\alpha = 0.05$

Based on all the inspection results, compliance in winter is 88.7 %, compared to is 87.93% in Spring, 87.89 % in the Fall and 87.4% in summer. Since the Summer months tend to be especially busy with a growing number of tourists visiting the city, being able to predict and focus on establishments that are estimated to have critical health violations, can minimize the risks of foodborne illness outbreaks.

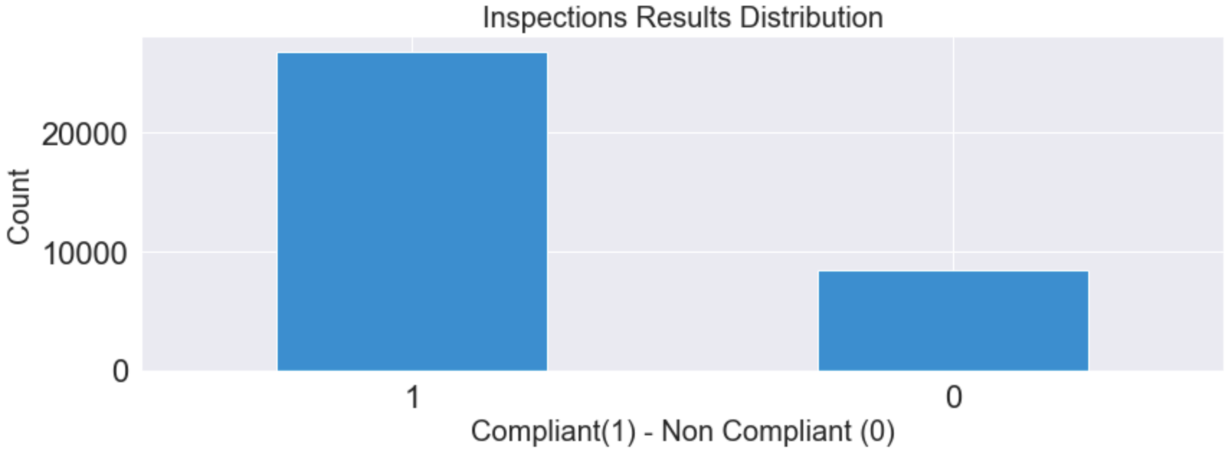


In order to see the likelihood of getting these inspection results again, the data for winter and summer were randomly sampled, ignoring the season ‘labels’ to see if there was a statistically significant difference between the compliance results obtained during each season. Using a t-test, the results show that after 10000 simulations, the difference is statistically significant at the 0.05 level, as none of the simulations reached a difference at least as high as the observed difference of 1.3%.

Merged Data

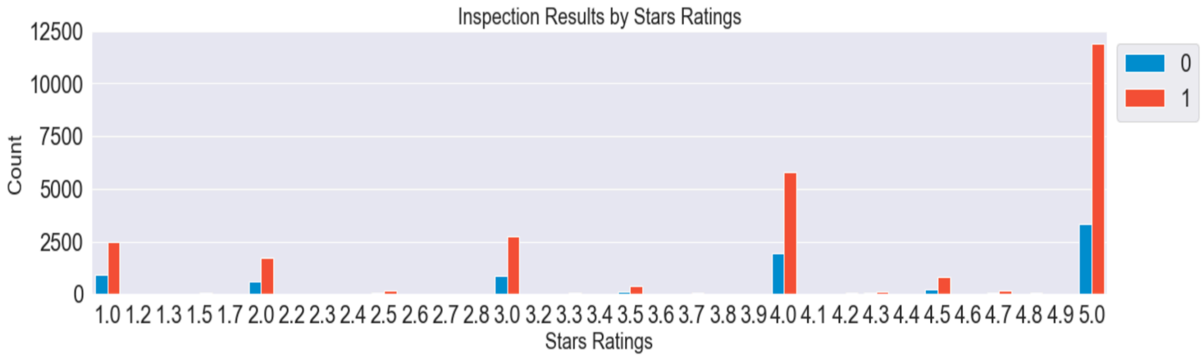
Distribution of Target Variable

Once the inspections and Yelp datasets were merged, the first step was to review the distribution of the target variable to see if it was unbalanced. The plot showed that the proportion of passing grades is 76%, which is a fairly balanced distribution.



Start Ratings and Inspection Results

One of the assumptions prior to the analysis was that the average daily star ratings were positively correlated with inspection results. Hence, five-star ratings would be highly correlated with passing grades. The analysis showed that the typical star ratings of most of the establishments with passing grades were 4 and 5 stars with very few establishments with a 5-star rating and non-compliance results..



Feature Engineering Merged Data

Since the data were very sparse across business attributes, similar business and food type categories were grouped, rename, and changed into binary features. Thus, there were 41 attributes for food and business types.

Food Type and Compliance

Another general assumption was that the establishment type and the food type may impact inspection results. For instance, establishments with buffet options and/or raw food menus may have higher food violations due to stricter standards of temperature and food handling.

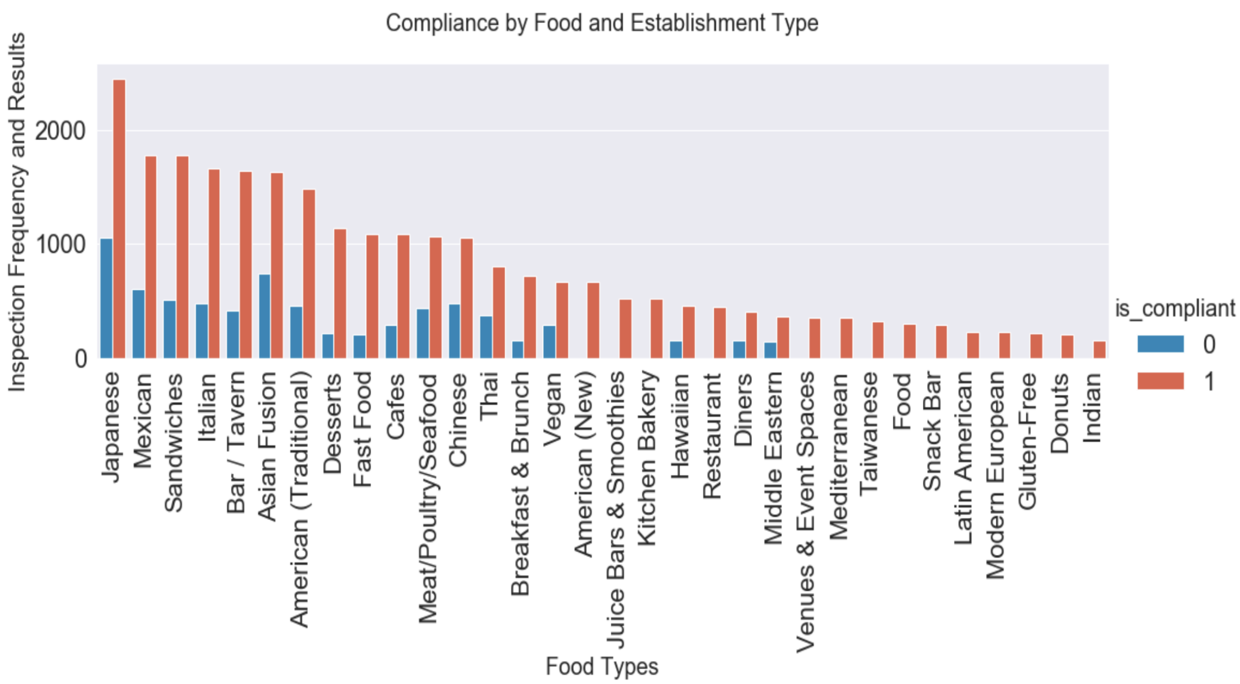
The hypotheses were:

H_0: There is no significant difference in compliance rates by food type.

H_A: compliance rate among establishments varies between food type.

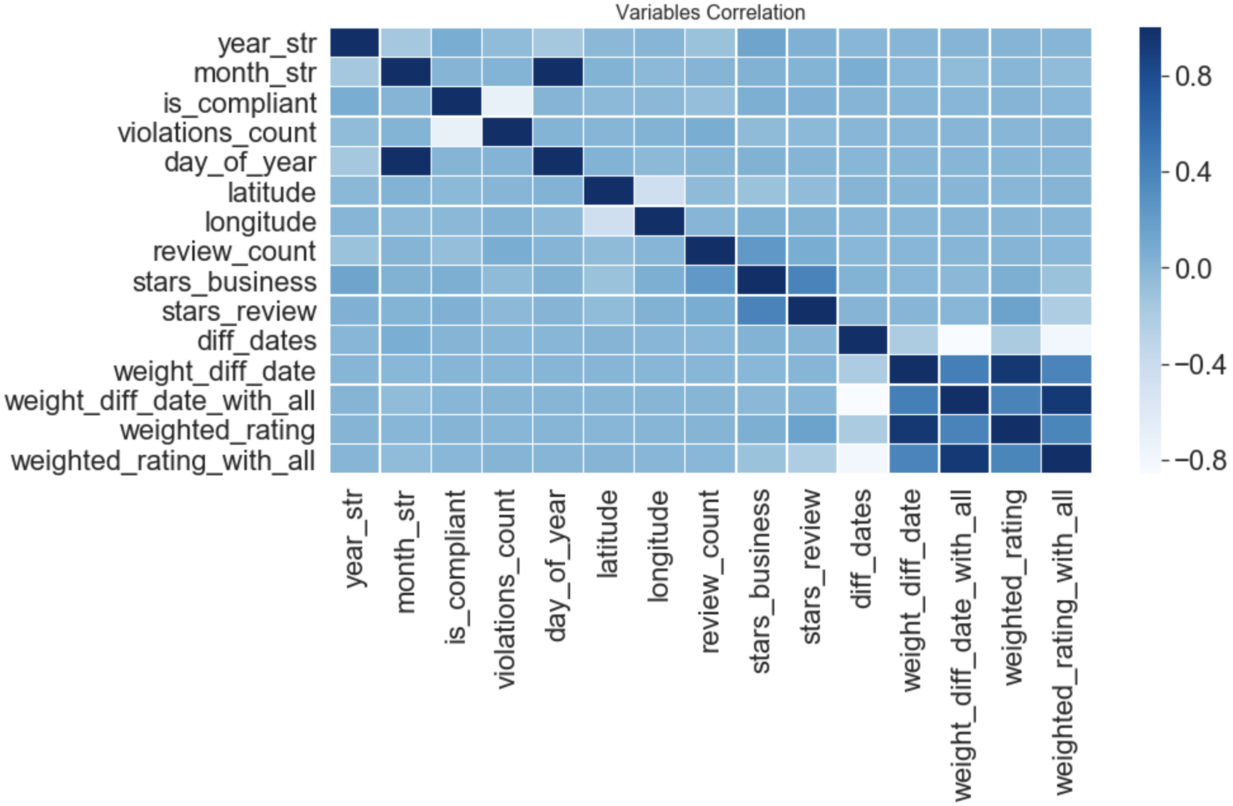
$$\boldsymbol{\alpha} = 0.05$$

Looking at the distribution of compliance rates across different establishment types, the data showed that establishments categorized as ‘Japanese’ by Yelp had a higher number of ‘non-compliant’ results followed by Asian Fusion, Mexican, Sandwiches, and Italian. At the same time, Japanese restaurants had also the highest compliance rate as many more Japanese restaurants were inspected.



Correlations

A heatmap of the correlation coefficients showed that violation counts are highly correlated to the inspection results, which makes sense, since the inspection grades are directly based on the violation points received. Other variables that were highly correlated with each other were those derived from the same attribute, such as the weighted star ranking and the days difference between inspection results and star rating. Some of these variables were removed since they were highly correlated and did not provide new information.



Machine Learning

The majority of the predictive stage was spent feature engineering and converting categorical variables into binary attributes since the data were very sparse.

One of the variables that was derived from the Yelp data was the weighted star rating. Since the same establishment could have multiple and different ratings each day, the first step was to get the average daily rating.

Then a new feature was created based on the inspection date and the rating date to find the number of days between rating and inspections to give more weight to ratings that happened shortly before an inspection. Hence, the same rating would have a different value based on the difference in dates.

The time weighting was calculated as follows:

$$Weight = 1/\sigma(star\ ratings)$$

$$Weighted\ difference = -1/(Weight * (inspection\ date - inspection\ review))$$

$$Weighted\ rating = Weighted\ difference * star\ rating$$

Modeling

The final dataset had 35,242 records and 92 attributes. Since this is a classification problem with a binary target variable, two different classification algorithms were tried, Logistic regression and Random Forest models, with slightly different predictors to compare the predictive power of each model.

Features

The target variable, ‘is_complaint’, indicates whether an establishment received a passing grade or not.

Input variables:

- Binary variables for food type attributes. Whether the restaurant served Japanese, Asian, Mexican, Mediterranean, among others types of foods.
- Business review counts, weighted star rating, business rating.
- Binary variables for business attributes. Food truck, restaurant, venue, or other.
- Binary variables for month of inspection (Logistic Regression and one Random Forest)
- Binary variables for seasons
- Binary variables for weekdays
- Binary variable for inspection shift (morning and afternoon)
- Binary variables for establishment’s grade at the time of inspection
- Demerits at the time of the inspections

- Type of inspections (routine, re-inspection, survey)

Models

Logistic Regression

Two logistic regression models were trained after randomly splitting the data into training and testing sets with 75% of the data to fit the model and 25% to test the model’s accuracy on unseen data.

Using 76 attributes (see Appendix) to train the model, the accuracy of the model to predict inspection results on the test set was 76%. However, the model failed at classifying non-compliance results, with a zero precision and recall for non-compliant results.

The following classification report provides the results of the logistic model.

	precision	recall	f1-score	support
0	0.00	0.00	0.00	2125
1	0.76	1	0.86	6686
micro avg	0.76	0.76	0.76	8811
macro avg	0.38	0.5	0.43	8811
weighted avg	0.58	0.76	0.65	8811

Logistic Regression 2

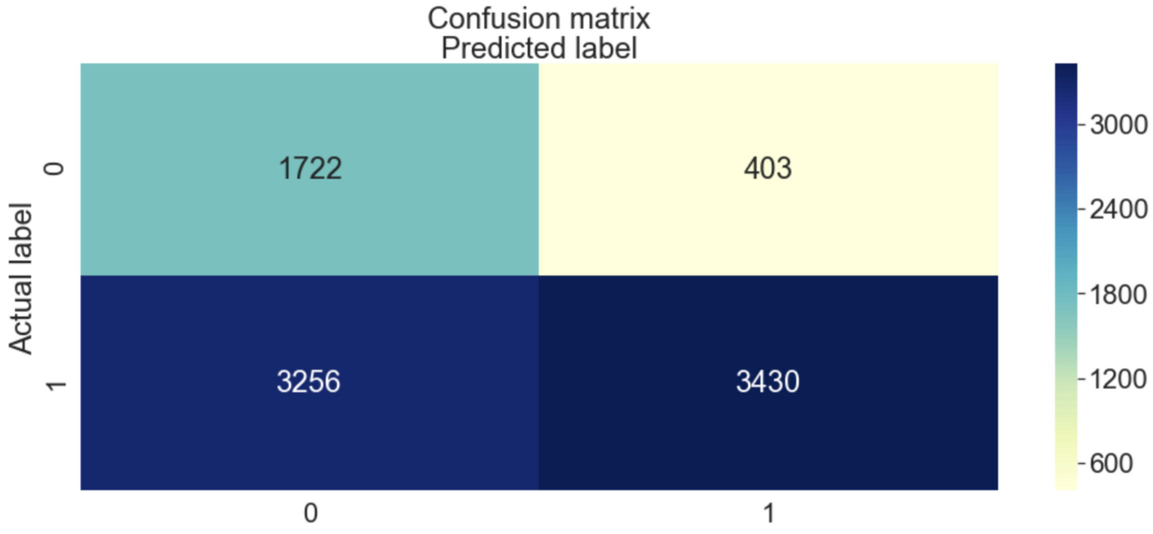
A second logistic regression model was tried setting the class_weight parameter to 'balanced', to see if the model will improve. Based on the documentation of the LogisticRegression function:

“The "balanced" mode uses the values of y to automatically adjust weights inversely proportional to class frequencies in the input data as n_samples / (n_classes * np.bincount(y)).”

The overall performance of the model decreased to 58.2%, however, the model was able to accurately identify 81% of non-compliance results, but it did not perform well with passing grades, identifying only 51% of true passing results.

Accuracy score Linear Regression Model:0.582				
Best parameter: {'C': 0.01}				
Classification Report Logistic Regression				
	precision	recall	f1-score	support
0	0.35	0.81	0.48	2125
1	0.9	0.51	0.65	6686
micro avg	0.58	0.58	0.58	8811
macro avg	0.62	0.66	0.57	8811
weighted avg	0.76	0.58	0.61	8811

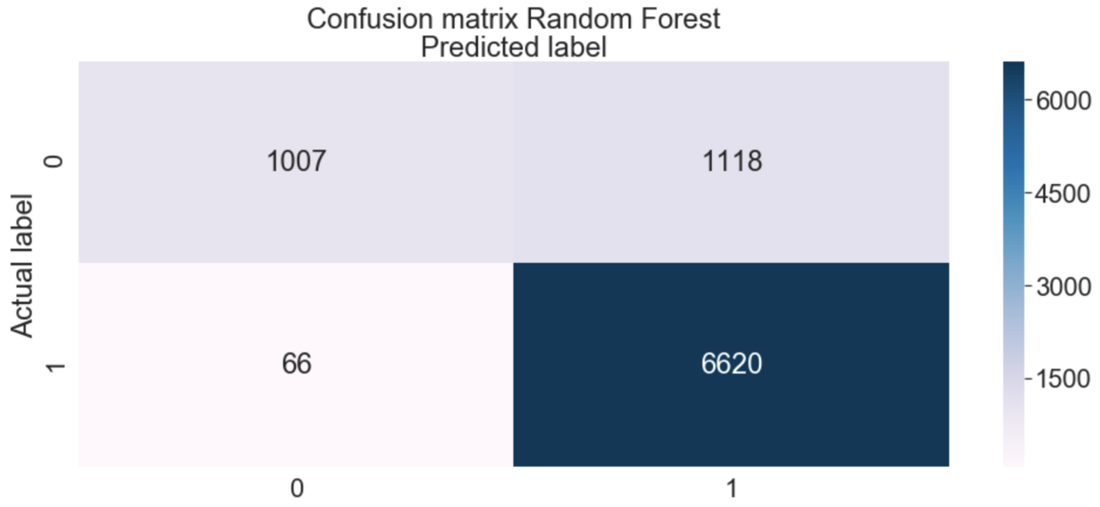
The confusion matrix shows the number of records that were accurately classified as well as the misclassifications.



Random Forest (min. Sample split = 50)

A random forest was run using the same random split for the training and the testing sets, 75% - 25%, and the same input variables. The minimum number of samples for each split was set to 50 and the number of decision trees classifiers was set to 200.

The accuracy of the model on unseen data was 86.65%, however, the recall for non-compliant results was only 47%. This means that the model was able to identify only 47% of non-compliance results.



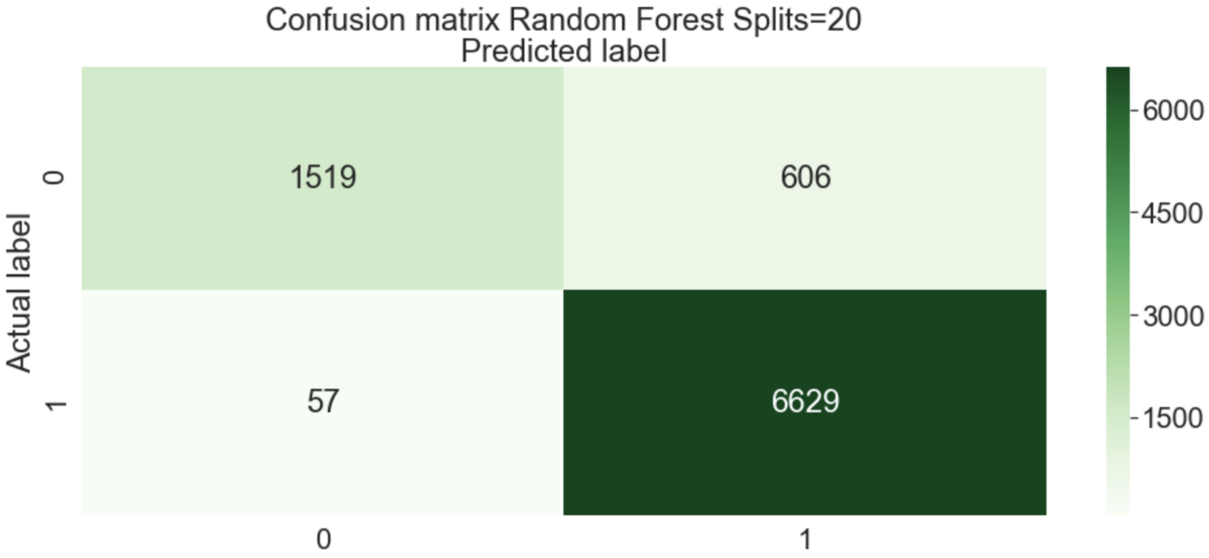
Accuracy score Random Forest (splits=50): 0.8665304732720464

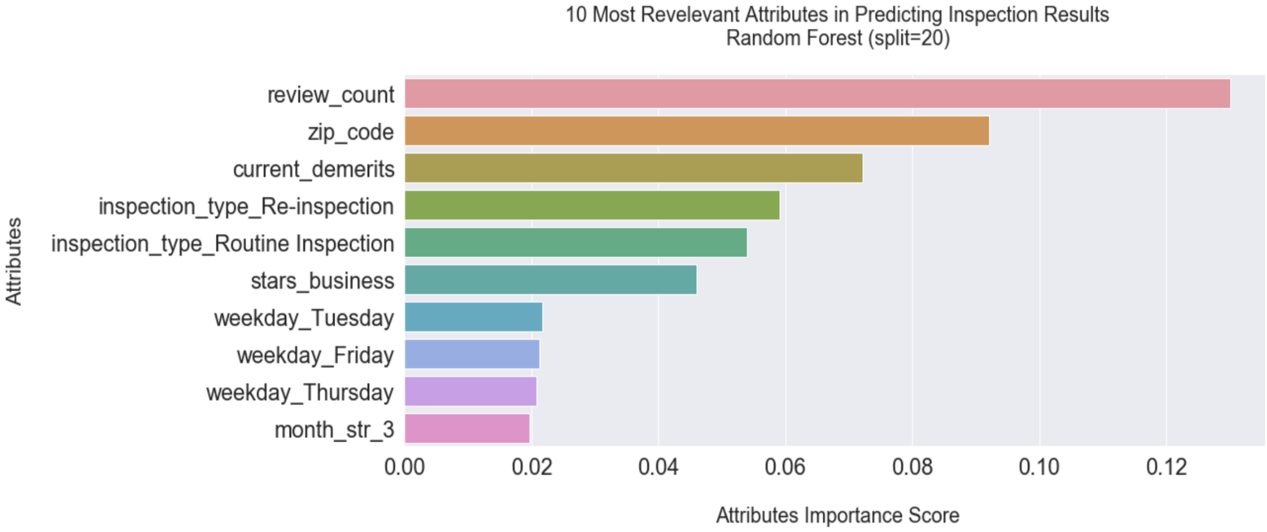
Classification Report Random Forest				
	precision	recall	f1-score	support
0	0.95	0.47	0.63	2125
1	0.86	0.99	0.92	6686
micro avg	0.87	0.87	0.87	8811
macro avg	0.9	0.73	0.77	8811
weighted avg	0.88	0.87	0.85	8811

Random Forest (min. Sample split = 20)

Since the random forest model performed better than the logistic regression, one more random forest was run, using 80% of the data to train the model, 80 input variables (see Appendix), and 100 decision trees classifiers. Using these parameters, the predictive accuracy of the model went up to 92.5% on unseen data with a 0.72 recall and 0.97 precision on non-compliance results. Thus, this model was able to accurately predict 72% of non-compliance results, and became the ‘best performer’.

The following graphs show the classification matrix and the 10 most relevant features for predicting inspection results based on the random forests results.





Classification Report Random Forest				
	precision	recall	f1-score	support
0	0.97	0.71	0.82	2125
1	0.92	0.99	0.95	6686
micro avg	0.93	0.93	0.93	8811
macro avg	0.94	0.85	0.89	8811
weighted avg	0.93	0.93	0.92	8811

Machine Learning Results

Several combinations of features were tried before selecting the ‘best model’ as it wasn’t clear what features would improve or decrease performance. For the last Random Forest, which provided the best performance, removing star ratings, along with season, year of inspection, and violation counts since these are not available until the inspection is completed, provided the highest accuracy when predicting inspection results.

The Random Forest found that the most relevant set of predictors of compliance are related to inspection details, such as the type, day, time, and location of the inspection and less with the type of cuisine or the specific rating given by users on a given day, but instead the overall number of reviews and the business rating.

Conclusions

The previous analysis used publicly available data on inspection results and social media data on business attributes and customer ratings, to help predict food and safety violations and improve inspection visits by prioritizing establishments that are likely to have a non-compliance result.

Since the hypothesis was that details such as type, date, and time of inspection, along with business’ attributes such as cuisine type, star rating, and number of reviews would have an impact on inspection results, feature engineering was a key component to the analysis. The derived features such as inspection shift, season, and weighted star ratings, provided relevant information to the analysis and to the predictive models.

The results of the analysis and the predictive model can be used to help prioritize inspections to food establishments by comparing current scheduled visits with the parameters that are most likely to result in a non-compliance result.

Further Analysis

Two of the variables used in early models that were considered very relevant by the logistic regression and random forest algorithms were the violation counts and the year of the inspection. Since these features are based on the actual inspection, they were omitted as they are obtained once the inspection is done. However, future analysis could consider the year when the establishment was opened and the number of violations found during the last inspection. The former could provide information on whether compliance is significantly different between established and new businesses, and the latter could indicate the areas where businesses continuously struggle.

Additional feature engineering, different tuning parameters, and combination of features could also provide more relevant variables that can help explain inspection results.

Appendix

Features used for Models

Models **Features**	**Logistic Regressions** *Test size=0.25*	**Random Forest** (splits = 50) *Test size=0.25*	**Random Forest** (splits=20) *Test size=0.25*
is_compliant'	TARGET	TARGET	TARGET
current_demerits'	✓	✓	✓
year_str'			
zip_code'	✓	✓	✓
inspection_demerits'			
violations_count'			
day_of_year'			
latitude'			
longitude'			
review_count'	✓	✓	✓
stars_business'	✓	✓	✓
stars_review'			
diff_dates'			
weight_diff_date'			
weight_diff_date_with_all'			
weighted_rating'			
weighted_rating_with_all'			
inspection_type_Epidemiological Investigation'	✓	✓	✓
inspection_type_Re-inspection'	✓	✓	✓

inspection_type_Routine Inspection'	✓	✓	✓
inspection_type_Survey'	✓	✓	✓
food_type_American (New)'	✓	✓	✓
food_type_American (Traditional)'	✓	✓	✓
food_type_Asian Fusion'	✓	✓	✓
food_type_Bar / Tavern'	✓	✓	✓
food_type_Breakfast & Brunch'	✓	✓	✓
food_type_Buffet'	✓	✓	✓
food_type_Cafes'	✓	✓	✓
food_type_Caterer'			✓
food_type_Chinese'	✓	✓	✓
food_type_Delis'	✓	✓	✓
food_type_Desserts'	✓	✓	✓
food_type_Diners'	✓	✓	✓
food_type_Donuts'	✓	✓	✓
food_type_Ethnic Food'	✓	✓	✓
food_type_Fast Food'	✓	✓	✓
food_type_Food'	✓	✓	✓
food_type_Food Trucks / Mobile Vendor'	✓	✓	✓
food_type_Gluten-Free'	✓	✓	✓

food_type_Hawaiian'	✔	✔	✔
food_type_Health Markets'	✔	✔	✔
food_type_Indian'	✔	✔	✔
food_type_Italian'	✔	✔	✔
food_type_Japanese'	✔	✔	✔
food_type_Juice Bars & Smoothies'	✔	✔	✔
food_type_Kitchen Bakery'	✔	✔	✔
food_type_Latin American'	✔	✔	✔
food_type_Meat/Poultry/Seafood	✔	✔	✔
food_type_Mediterranean'	✔	✔	✔
food_type_Mexican'	✔	✔	✔
food_type_Middle Eastern'	✔	✔	✔
food_type_Modern European'	✔	✔	✔
food_type_Public Services & Government'			
food_type_Restaurant'	✔	✔	✔
food_type_Sandwiches'	✔	✔	✔
food_type_Snack Bar'	✔	✔	✔
food_type_Spanish'	✔	✔	✔
food_type_Special Kitchen'	✔	✔	✔
food_type_Steakhouses'	✔	✔	✔

food_type_Taiwanese'	✓	✓	✓
food_type_Thai'	✓	✓	✓
food_type_Vegan'	✓	✓	✓
food_type_Venues & Event Spaces'	✓	✓	✓
season_fall'			✓
season_spring'			✓
season_summer'			✓
season_winter'			✓
month_str_1'	✓	✓	✓
month_str_2'	✓	✓	✓
month_str_3'	✓	✓	✓
month_str_4'	✓	✓	✓
month_str_5'	✓	✓	✓
month_str_6'	✓	✓	✓
month_str_7'	✓	✓	✓
month_str_8'	✓	✓	✓
month_str_9'	✓	✓	✓
month_str_10'	✓	✓	✓
month_str_11'	✓	✓	✓
month_str_12'	✓	✓	✓

weekday_Friday'	✓	✓	✓
weekday_Monday'	✓	✓	✓
weekday_Saturday'	✓	✓	✓
weekday_Sunday'	✓	✓	✓
weekday_Thursday'	✓	✓	✓
weekday_Tuesday'	✓	✓	✓
weekday_Wednesday'	✓	✓	✓
inspection_shift_afternoon'	✓	✓	✓
inspection_shift_morning'	✓	✓	✓
current_grade_A'	✓	✓	✓
current_grade_B'	✓	✓	✓
current_grade_C'	✓	✓	✓
current_grade_O'	✓	✓	✓
current_grade_X'	✓	✓	✓