Capstone Project 2 - Milestone Report 2

Sentiment Analysis of Yelp Restaurant Reviews

Shirley Zhu

Problem Statement

When people go to a new restaurant, they usually don't know what to order. Yelp reviews can usually provide some ideas about what they might like, but there are often too many reviews and it takes a long time to read the reviews and make a decision. This project leverages machine learning to figure out what everyone prefers to eat based on the restaurant"s reviews.

My client will be Yelp and the users of this feature will be the restaurants that list their business on Yelp and the customers who go to eat in these restaurants. Yelp can build this feature because users would love using Yelp to figure out what to order. Yelp can help restaurants to roll out its "popular dishes feature" to help the customers in deciding what to order from the restaurant with whom they aren't familiar. Good rated restaurants can have bad dishes and ok restaurants can have really good dishes. The restaurants can use this information to advertise their popular dishes and improve their not so good dishes, so the customers will be more satisfied after eating there. This will boost the business of the restaurants. Yelp can charge the restaurants for this feature, and Yelp takeout business will grow too.

The first part of this project is the prediction of review stars using Natural Language Processing. The second part is the recommendation of highly rated food items for a restaurant.

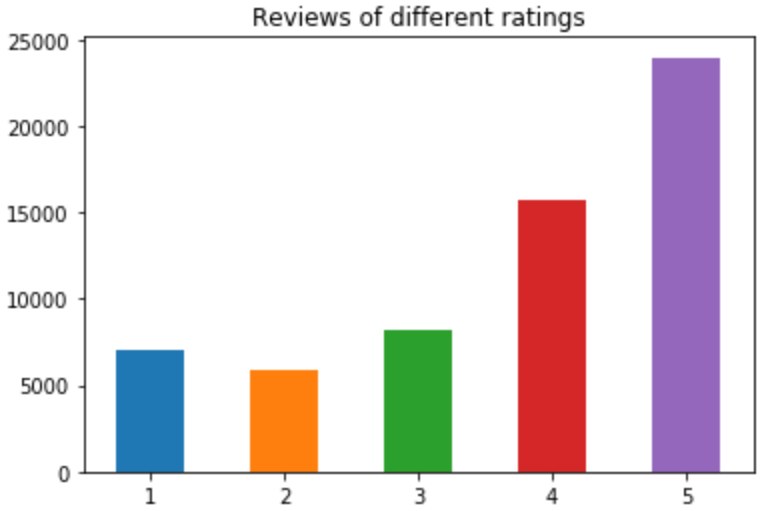
The data source is from the Yelp Open Dataset https://www.yelp.com/dataset. The dataset is in the json format. Business.json and review.json were used in this project.

Data Wrangling

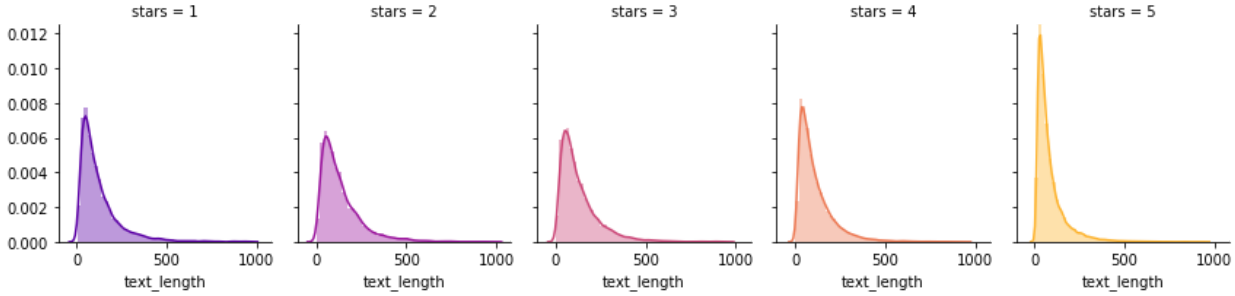
- Read the json file into a pandas dataframe. Because the size of the json is too big, the json was read by data chunks.
- Plot the distribution of review counts for businesses.

- Load the business json. Filter out the businesses that have “Restaurants” in their categories. Sample 2000 restaurants because the original dataset is too big.
- Create a dataframe that contains only restaurants and these restaurants have reviews in the review dataframe.
- There are 188593 businesses in the yelp_academic_dataset_review dataset. There are 57173 businesses that are restaurants. In order to extract the restaurants from the review dataset, merge the restaurants dataframe with the reviews dataframe on business_id.
- A sample size of 30000 was taken to make it faster.

Exploratory Data Analysis



The 5 star reviews have the most counts, followed by 4, 3, 1 and 2.



It shows that people who tend to review a business as good (4 or 5 stars) have shorter reviews (86 or 113 words), and the reviews that have poorer ratings tend to be longer words.

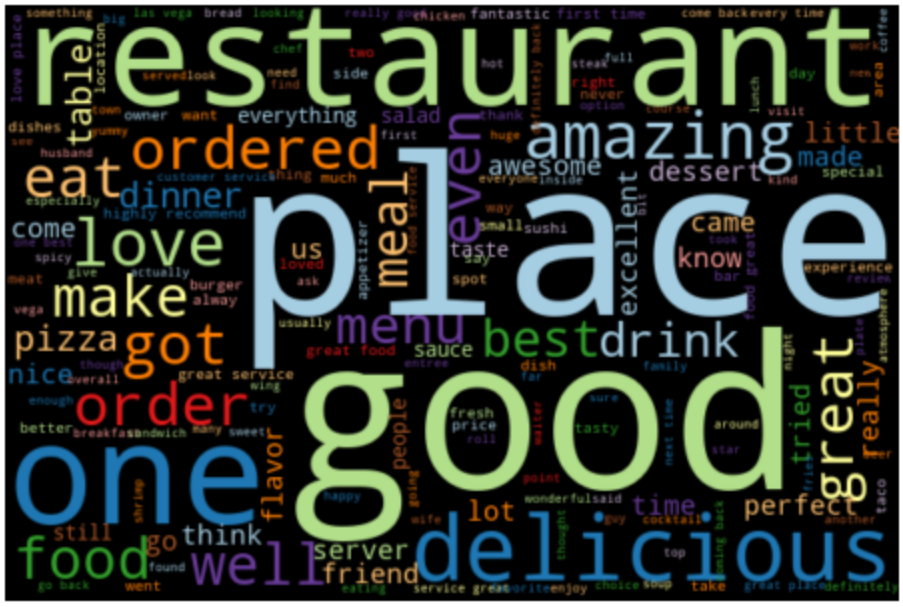
Inferential Statistics

One-way ANOVA was used to tests the null hypothesis that the distribution of the text lengths of all stars have the same mean length. The conclusion is the null hypothesis should be rejected because the p-value is 0, meaning the mean text lengths for different stars are significantly different.

Text Mining

Steps:

- Import the nltk, string, wordcloud libraries to do the text mining.
- Define a “cleaning” function to remove the punctuations, lowercase all case-based characters, and remove common English stopwords.
- Use the function “cleaning” to process the reviews.
- Create a bag of words by joining the words in cleaned text for each star.
- Generate the word clouds.



Word Cloud of Reviews of 5 Stars

Word Cloud of Reviews of 4 Stars

Word Cloud of Reviews of 1 Star

The 5 star reviews use positive words like good, great, love, delicious, amazing. The 4 star reviews have similar words as 5 stars, but not as many "love", "amazing", "best" as in 5 star reviews. The most frequent word for all reviews would be a neutral word "place". The most request words in 1 star reviews are neutral words such as place, food, time, said, total, table, order, service, never.

Prediction of the Review Stars

The code of the in-depth machine learning analysis to predict the review stars was in a jupyter notebook file “Sentiment Analysis of the Yelp Reviews”.

Steps:

- Create another column in the review dataframe called “clean_text” after removing the punctuations, lowercasing all case-based characters, and removing common English stop words.
- Use CountVectorizer to convert the “clean_text” to a matrix of token counts and convert this matrix to Compressed Sparse Column format by using .tocsc(). Use that as the feature variables.
- Specify the values of the stars as the target variables.
- Split the samples into train set (80%) and test set (20%).
- Apply supervised learning algorithms (Multinomial Naive Bayes, Gradient Boosting Machine, and Random Forest) to fit the training set and predict the labels of the test set.
- Apply different metrics to evaluate the models (accuracy scores, confusion matrix, classification report).

Summary of findings:

1) CountVectorizer() and MultinomialNB(): The accuracy scores for the train set and test set are 0.760 and 0.581 respectively. In multi-label classification, classifier.score is the subset accuracy which is a harsh metric since we require for each sample that each label set be correctly predicted. There are five categories for the classifier, so an accuracy score of 0.58 is not too bad.

   Confusion Matrix:

```
array([[ 476,   93,   54,   31,   38],
       [ 184,   91,  161,   99,   43],
       [  63,   40,  240,  369,   92],
       [  20,    9,   76,  705,  729],
       [  21,   10,   22,  360, 1974]])
```

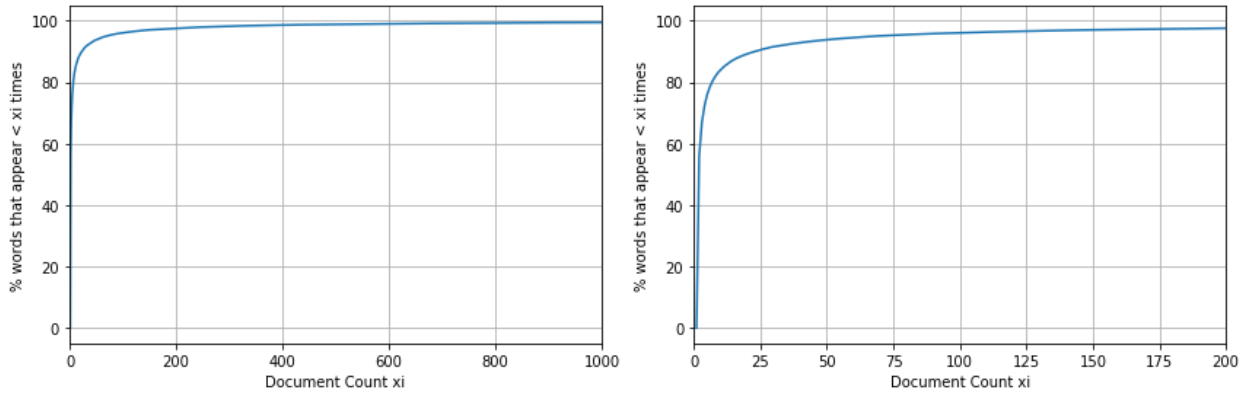
Classification Report:

	precision	recall	f1-score	support
1	0.62	0.69	0.65	692
2	0.37	0.16	0.22	578
3	0.43	0.30	0.35	804
4	0.45	0.46	0.45	1539
5	0.69	0.83	0.75	2387
micro avg	0.58	0.58	0.58	6000
macro avg	0.51	0.49	0.49	6000
weighted avg	0.55	0.58	0.56	6000

All metrics, precision, recall and f1-score are highest for 5 star reviews, followed by 1 star reviews. It shows that the naive bayes model works better for the extremely good or bad ratings. The recalls for class 2 and 3 are very low, because neutral customer experiences might not have distinct features to be labeled as neutral and also because the sample size are much smaller than 4 or 5 star reviews.

Hyperparameters tuning for CountVectorizer:

An elbow method was used to decide the min_df, and the max_df was set at 11000, because the frequency for the most common non-stopword “place” is 11767. The accuracy scores for the train set and test set are 0.677 and 0.596 respectively. The accuracy score for the test set after using min_df is slightly better than without min_df.



Hyperparameters tuning for Multinomial Naive Bayes:

The best hyperparameter alpha for the Multinomial Naive Bayes is 1.2.

When using the best alpha and specifying min_df and max_df, the accuracy score for the test set can improve slightly to 0.597.

2) TfidfVectorizer() and MultinomialNB()
The accuracy score for the train set is 0.611 and the accuracy score for the test set is 0.549, lower than using CountVectorizer.

3) n-grams CountVectorizer()
N-grams are phrases containing n words next to each other. This is useful because "not good" and "so good" mean very different things.
The accuracy score for the test set is 0.609 after adding 2-gram and 0.606 after further adding 3-gram.

The accuracy score after adding bigram to the unigram countvectorizer model is better than without it. The reason might be that many meaningful expressions are in 2 word phrases, and unigram does not consider these expressions that could make a difference in the meaning of a sentence. And the results showed that adding trigram does not add further value to the prediction. This is because as n increases, the model does not scale well since the feature set becomes more sparse.

4) CountVectorizer and Random Forest Classification
The accuracy score for the train set is 1.000 and the accuracy score for the test set is 0.560. The accuracy score for the test set shows there is overfitting for the train set. It took very long time to tune the hyperparameters for the random forest because the feature number is too large and my computer died every time if it was trying to tune the hyperparameters grid.

5) CountVectorizer and Random Forest Classification
The best parameters after using RandomizedSearchCV gave a best accuracy score for the test set of 0.550.

Among the algorithms that were tried, using the CountVectorizer of 2-gram and Multinomial Naive Bayes has got the best predictive power, the test accuracy score is 0.609. And the best alpha is 0.4.

As a baseline for the machine learning models, if I predict the most common class (5 stars) for every review, the accuracy would be 0.398, much lower than the accuracy of using the above algorithms.

Strongly Predictive Features:

By using sklearn feature ranking with recursive feature elimination, rfe(), we can get the then most important features of a model.

The ten most important features for the countvectorizer using unigram vectorizer and Naive Bayes are:
“Disrespectful”, “flawless”, “insulting”, “locked”, “magnificent”, “manny”, “prakash”, “redeeming”, “remembers”, and “sublime”.

The ten most important features for the countvectorizer using 1 and 2-gram vectorizer and Naive Bayes are:
“best italian”, “give zero”, “instead 5”, “manager told", "notch service", "place rocks", "recommend everyone", "took great", "worst customer", and "worst place".

The ten most important features for the countvectorizer using 1, 2 and 3-gram vectorizer and Naive Bayes are:
"give zero", "give zero stars", "great care us", "instead 5", "notch service", "reason didn’t give", "took great", "top notch service", "worst customer service", and "worst place".

Good Words and Bad Words:

Here we define the good words to be the words that have the highest probability in reviews with 5 stars and define the bad words to be words that have the highest probability in reviews with 1 stars, and get the probability by using the predict_log_proba() method of the MultinomialNB model.

Best words: "delish", "gem", "polenta", "unique", "beautifully", "perfect", "perfection", "delightful", "hearty", and "pumpkin".

Worst words: "flavorless", "poisoning", "unprofessional", "worst", "tasteless", "aok", "terrible", "unacceptable", "luke", and "lacked".