



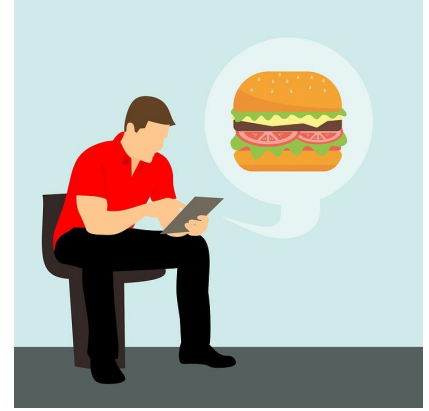
# **Yelp Reviews: Sentiment Analysis and Food Recommendation**

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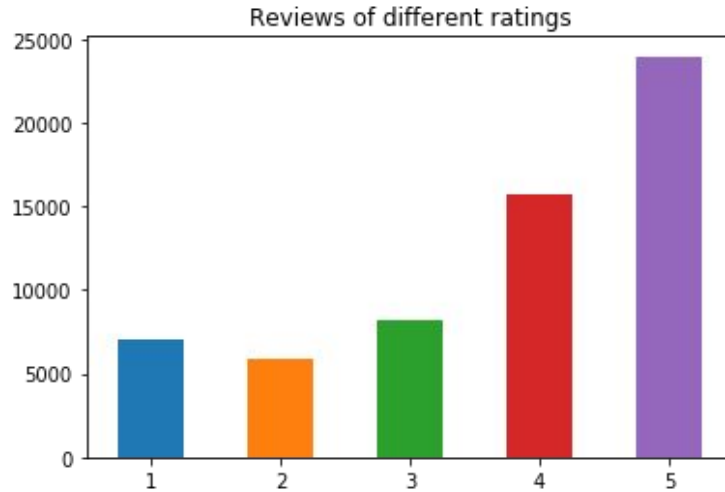
# Problem Statement

- People don't know what to order.
- A “popular dishes” feature will help customers with orders.
- Restaurants can promote their popular dishes and improve disliked ones.

Data Source: Yelp Open Dataset <https://www.yelp.com/dataset>

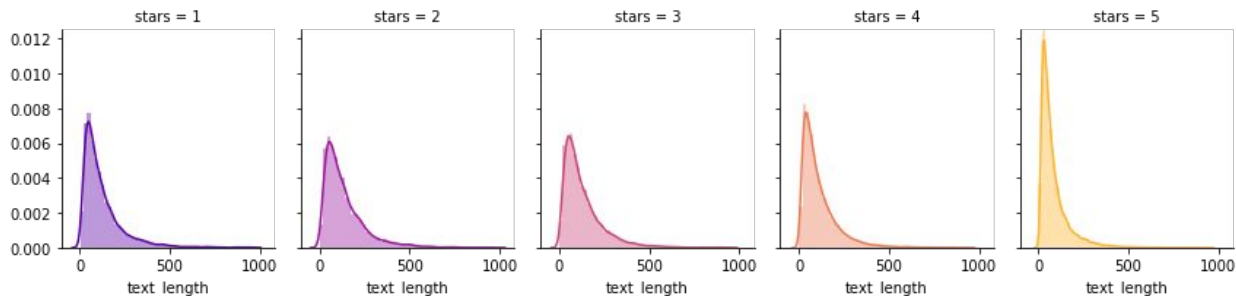


# Exploratory Data Analysis



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

# Review Lengths



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.

# Text Mining



Word Cloud of Reviews of 5 Stars



Word Cloud of Reviews of 4 Stars





## Prediction of Review Stars

Vectorizer	Supervised Learning Algorithm	Training Accuracy	Test Accuracy
CountVectorizer	MultinomialNB	0.677	0.596
TfidfVectorizer	MultinomialNB	0.611	0.549
2-gram CountVectorizer	MultinomialNB	0.727	0.609
CountVectorizer	Random Forest	0.999	0.560
CountVectorizer	Gradient Boosting Machine	0.611	0.558



# Strongly Predictive Features

Unigram: “Disrespectful”, “flawless”, “insulting”, “locked”, “magnificent”, “manny”, “prakash”, “redeeming”, “remembers”, and “sublime”.

Bigram: “best italian”, “give zero”, “instead 5”, “manager told”, “notch service”, “place rocks”, “recommend everyone”, “took great”, “worst customer”, and “worst place”.

Trigram: “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

polenta	delish	flavorless	poisoning
unique	perfection	unprofessional	aok
beautifully	gem	worst	tasteless
delightful	hearty	terrible	lacked
perfect	pumpkin	unacceptable	luke



# Food Recommendation for a Restaurant

- Test the function to recommend 10 most recommended food for a random restaurant:

```
['macaroni', 'pork', 'mango', 'avocado', 'plate', 'date', 'noodle', 'tuna', 'orange', 'guava']
```

- Test the function to list food items to avoid for five random restaurants:

```
['eggplant', 'chocolate', 'strawberry', 'green', 'coconut', 'beef', 'bread', 'mango', 'prawn', 'spinach'],  
['beef', 'raspberry', 'veau', 'bread', 'spaghetti', 'truffle', 'plate', 'tart', 'pumpkin', 'bacon'],  
['onion', 'mushroom', 'pepper', 'meat', 'buffalo', 'pineapple', 'ham', 'leftovers', 'shoulder', 'wiener'], ['chicken', 'bacon', 'fish', 'cheese',  
'pie', 'buffalo', 'lettuce', 'heart', 'pepperoni'],  
['loaf', 'collards', 'confit', 'beef', 'shoulder', 'pepper', 'butter', 'meatloaf', 'scone', 'gem']]
```

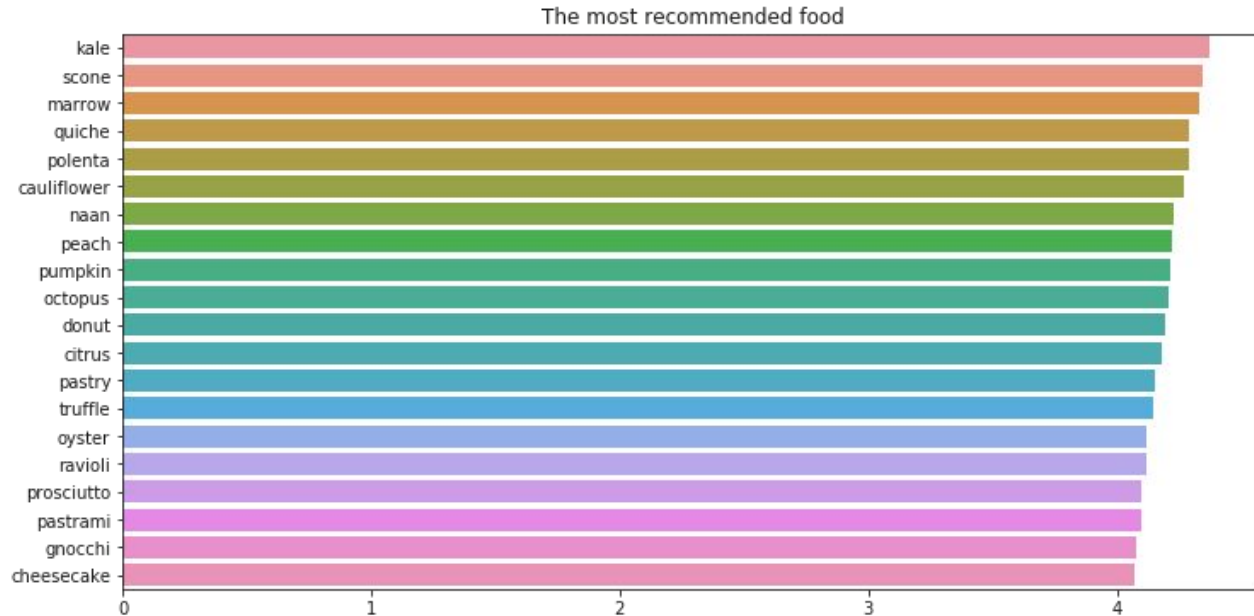


## 20 Most Common Food Items in the Sample Set

chicken shrimp meat cheese  
crab salmon beef side bacon  
green chips pasta bread fries  
roll pork fish plate steak cake

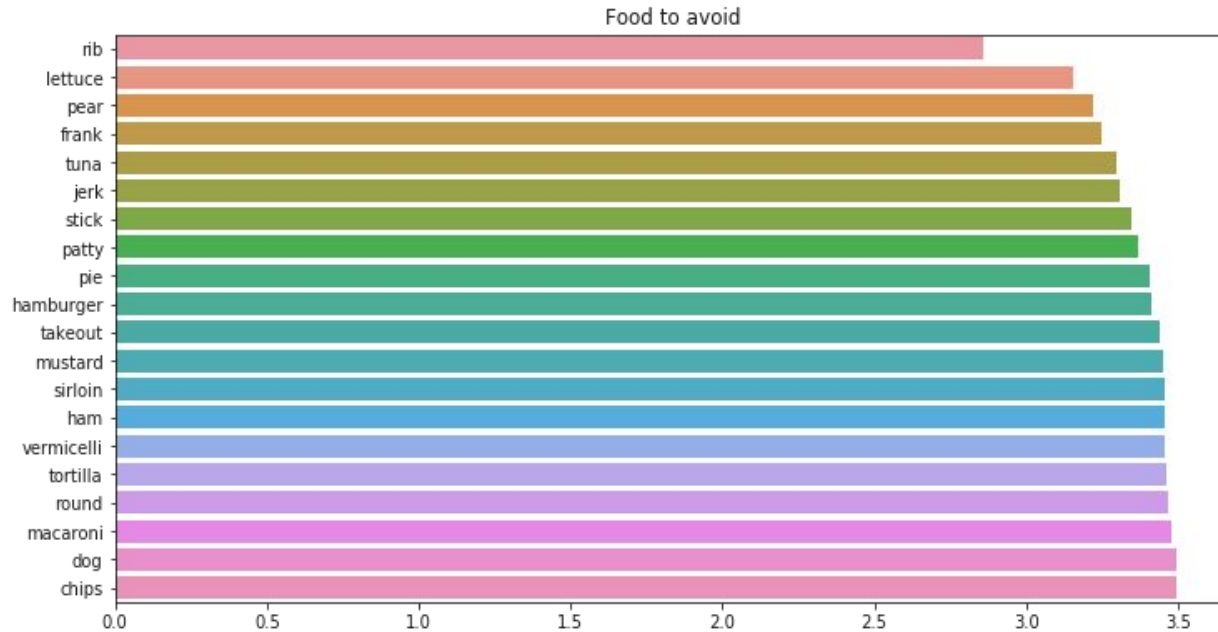


# The Most Recommended Food





# Food You Should Avoid





## Limitations

- I don't have the menu item names to begin with, so I used the a food list from `nltk.corpus wordnet`.
- Sometimes, there are several food items in one review. This model treats them as the same rating. More work could be done to analyze the reviews by sentence, and by the predicted score of that sentence in which the food item appears.



## Future Work

- Labeling the food items by phrases to create a list that is more similar to the real menu, for example, if "pork" and "rib" are together, the menu item might be "pork rib".
- The sentiment analysis of reviews by sentence, so a more accurate food recommendation model can be built.