Analysis on the Survivability of NYC Restaurants During COVID-19

BIA660 final project

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Content

- Introduction
- Data collection & exploration
- Methodology & Results
  - Basic features classification
  - Word to Vector Embedding
  - Sentiment score & TextBlob
  - Negative reviews clustering / LDA topic model
- Discussion
- Conclusion
- Limitation & Recommendation

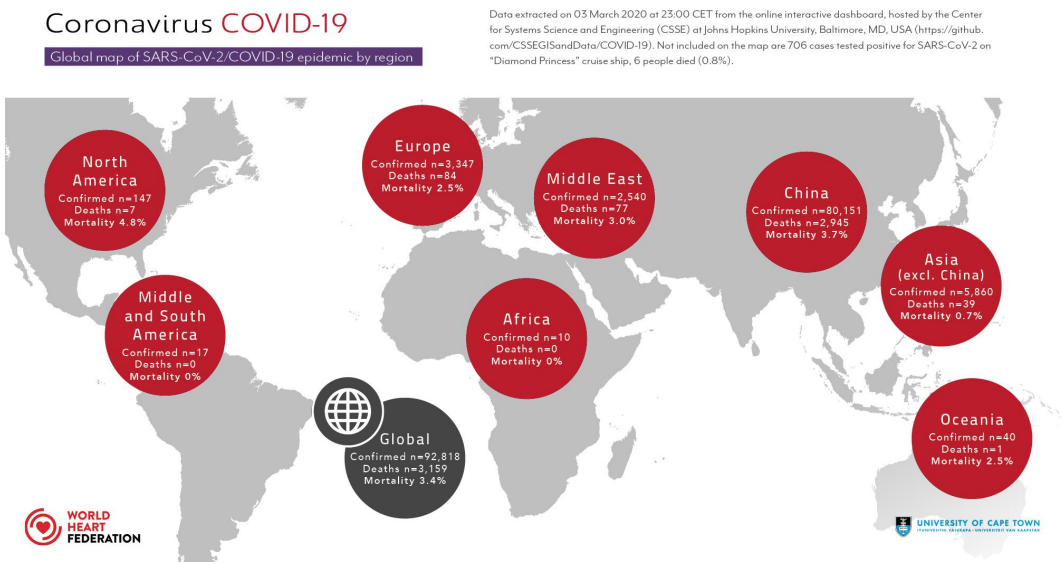
Introduction

Motivation

1. The COVID-19 pandemic has a profound influence on all countries and all the business over the world.

2. Food industry is one the businesses in the U.S. that got hit by the pandemic the hardest.

3. In this paper, we are going to explore the factors that correlate with the survivability of restaurants

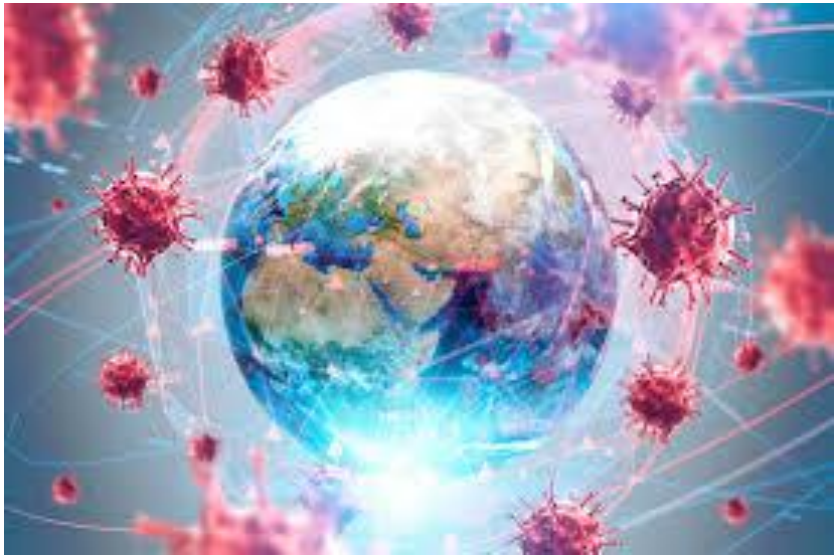


Introduction

Research questions:

Research questions 1: What features are most likely correlate with the survivability of restaurants located in New York City when facing pandemic like COVID-19?

Research question 2: Whether the extracted risk assessment features can be applied to restaurants located in other comparable areas and predict their survival state during 2020?



Introduction

Background : Yelp

- Crowd-sourcing websites to help customers to target local business
- Million of customers rely Yelp for food hunting
- Review data in yelp is reliable and up-to-date and has wide coverage of all businesses

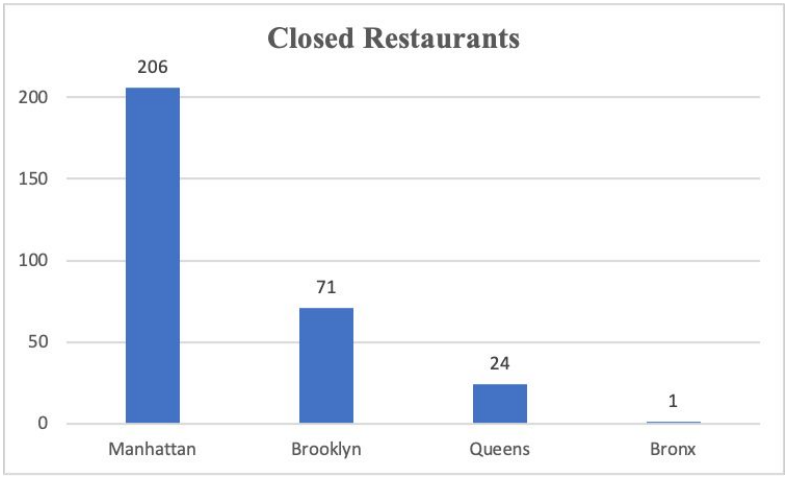
Data Collection

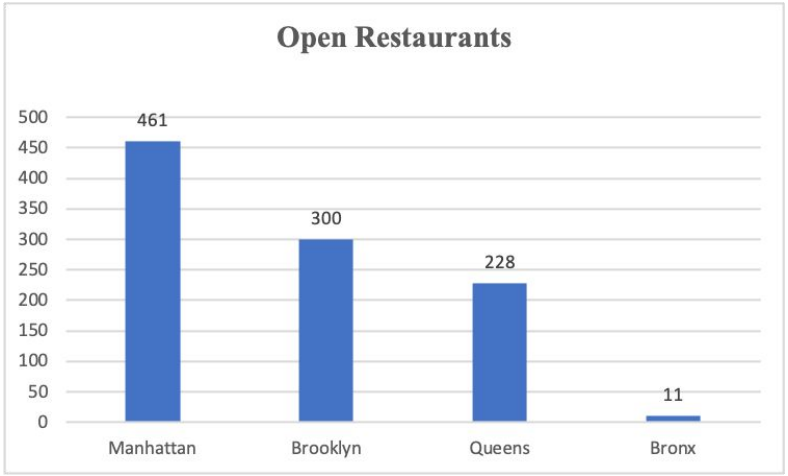
- Permanent close restaurants due to COVID-19
- May 8th to October 31st, 2020
- Total 302 restaurants

- 1000 open restaurants
- Using Yelp API

Data Exploration

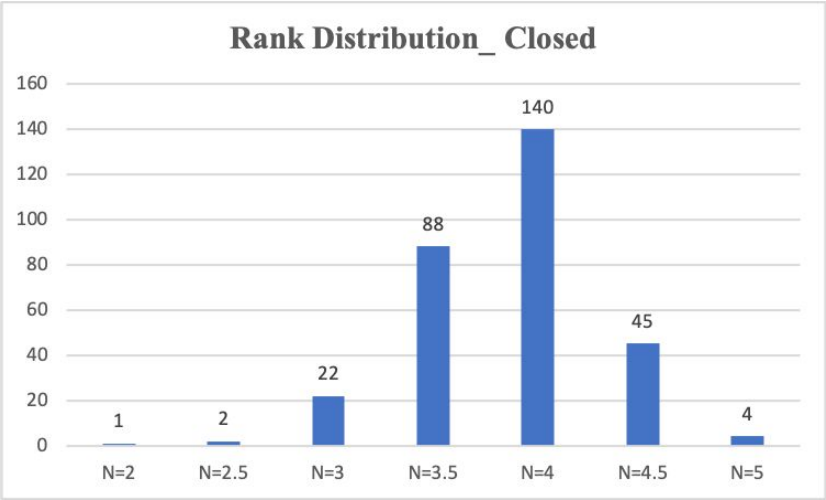
Area Distribution

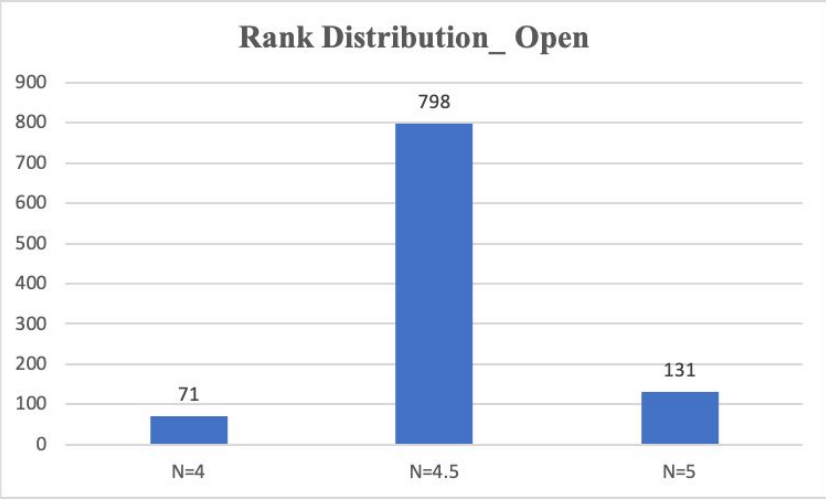




Data Exploration

Rank Distribution

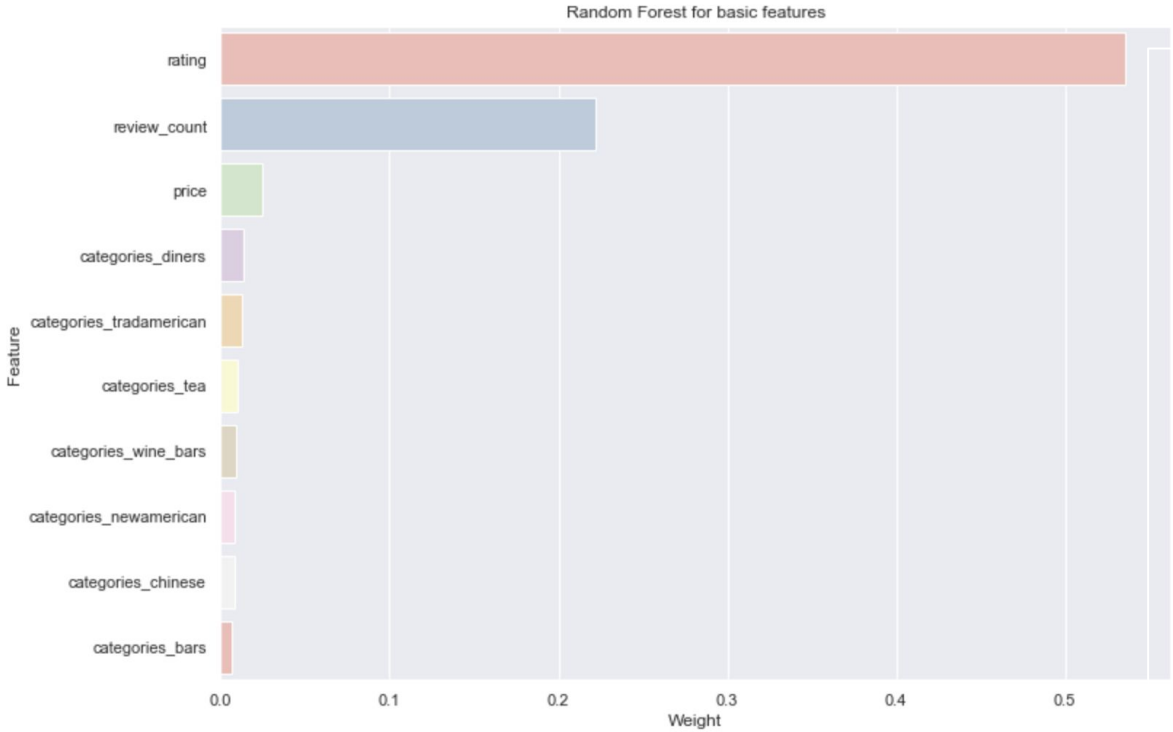




Data Exploration

Price	1 stands for $, 2 stands for $$, 3 stands for $$$, and 4 stands for $$$$.
Is_close	0 stands for closed and 1 stands for open
Review	10 reviews from the official website of the restaurant.

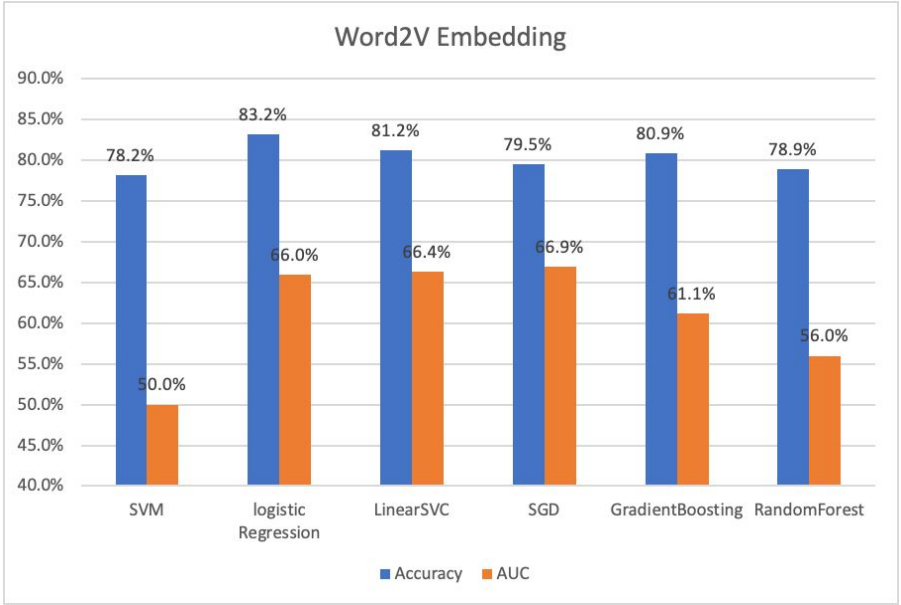
Method_Basic features classification



- Use original features on Yelp to build a classification model
- Use Random Forest Model to fit and find feature importance
- The model performance is good, AUC: 0.906; F1 macro: 0.8573
- Traditional American, tea, wine bars, bars, New American, and Chinese seem to be the top survival features

Method_Word to Vector Embedding

Embedding Method	Model	Accuracy	AUC
Word to Vector	SVM	78.19%	50.00%
Word to Vector	logistic Regression	83.22%	65.98%
Word to Vector	LinearSVC	81.21%	66.35%
Word to Vector	SGD	79.53%	66.94%
Word to Vector	GradientBoosting	80.87%	61.15%
Word to Vector	RandomForest	78.86%	55.98%

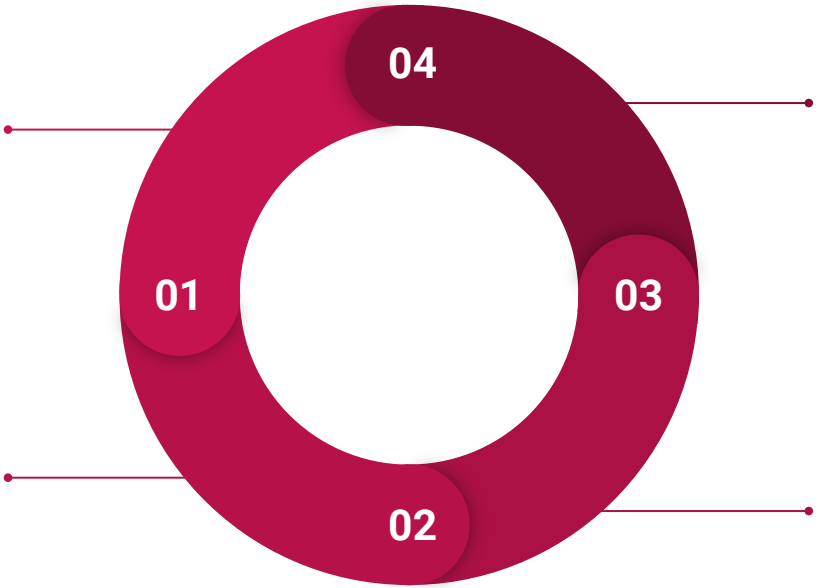


Method_Text analytics

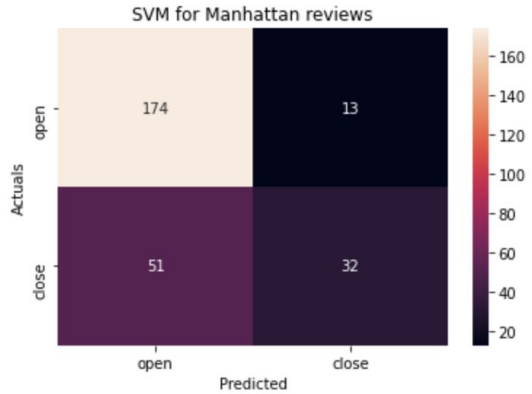
Use tf-idf, doc2vec in five classification model

logistic regression, linear SVC, SGD, Gradient Boosting, and random forest

Linear SVC has the highest test accuracy: 0.7379



The test accuracy slightly increased to 0.7629



Second adding: sentiment scores (pos, neg, neu, com)

Method_TextBlob

- Dependent variable: is_closed
- Independent variables :
  review_count, rating, price, reviews,
- Reviews: polarity and subjectivity

Model	Accuracy
RandomForest	93.18%
SVC	73.86%
LogisticRegression	84.85%
LinearSVC	77.27%
SGD	73.48%
GradientBoosting	93.56%

Method_Negative reviews clustering

- Use nltk vader to polarize if compound score < 0 then negative
- Nearly 10% of reviews are negative, we use reviews of closed restaurants only for clustering

Cluster 1	Cluster 2	Cluster 3	Cluster 4
20 minutes **understaffed** hasty delayed finally order **misunderstood** good lot finally swapped food **delayed** food excellent **hasty** order lot **miscommunication** server misunderstood food **rushing** understaffed lot rushing service **ignored** said definitely	food isn 30 minutes **left hungry** menu price lunch menu noodles known modify website gotten noodles noodles saw **terrible** fresh known **modify receipt** charged paid noticed regular price ordered noodles noodles **terrible website** picked noticed receipt website noodles price 17	sat bar probably **microwaved food lukewarm servers** said ignore took problem food right problem short ribs nearby got bother send **didn bother** proceeded **ignore** place quiet night place green curry sitting nearby lukewarm didn got special said hello asparagus cooked	mozzarella balls know place ricotta jalapeño mediterranean restaurant **assumes anorexic** toddler left choose eat **smallest portions** payed 10 left **nut** ordered obviously size portions imaginable size toddler **selfish places** places ordered place owner anorexic choose

Method_LDA topic model

- Use words at least showing five times and remove stop words and non-negative words

- The result shows that the generated topics are regarding place, table, food, and staff

Discussion_Algrorithms

- **Basic feature model**
  - Random Forest: 90.64% AUC
- **Word to Vector embedding:**
  - SGD model: AUC 66.94%; Accuracy: 79.53%
  - Logistic regression : Accuracy 83.22%; AUC:65.98%
- **Textblob approach**:
  - GradientBoosting model: Accuracy: 93.56%,
- **Sentiment score approach:**
  - LinearSVC model: Accuracy 76.29%.

Discussion_Findings

Based on the data of NYC restaurants:

- Categories belong to traditional American, bars, and tea are more likely affected by unpredictable changes
- Bars are more obvious because our model extracts the important keywords like bar and bartender

Textual data findings:

- Building effective communication is important
- Restaurants communicate about the COVID-19 crisis can create clarity, build resilience, and catalyze positive change during uncertainty

Our model predicts the Brooklyn area with AUC performance of 0.6477, decreased by the original of 0.7611. Currently, our indicators can continue to be optimized and refined. (research question 2)

Conclusion

- 2 Research questions
- 302 closed restaurants, 1000 open restaurants are used, and 10 reviews of each restaurant
- 4 different approaches
- Feature Importance : rating > review count > price > category
- This research can be used to predict the survivability of restaurants in other area models, but still can be enforced.

Limitation & Recommendation

Data size

- Only scripted 302 closed restaurants and 1000 open restaurants
- Increase the number of research restaurant and script more reviews,

Number of features

- Analyzed few features: rating, price, review count, category, reviews
- Adopt mores specific features, such as, delivery service, environment rating, service rating

Models

- Only used some baseline models
- Try more advanced feature engineering models, such as: LSTMs, BERT, Fine-turning BERT,

Reference

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EATER data source:

A Running List of NYC Restaurants That Have Permanently Closed, October 2020
https://ny.eater.com/2020/10/2/21459288/nyc-restaurant-closings-coronavirus-october-2020

A Running List of NYC Restaurants That Have Permanently Closed, September 2020
https://ny.eater.com/2020/9/3/21408479/nyc-restaurant-closings-coronavirus-september

A Running List of NYC Restaurants That Have Permanently Closed During the COVID-19 Crisis
https://ny.eater.com/2020/5/8/21248604/nyc-restaurant-closings-coronavirus

Thank you!