Capstone 3:
Customer Feedback With Natural Language Processing

Problem Statement

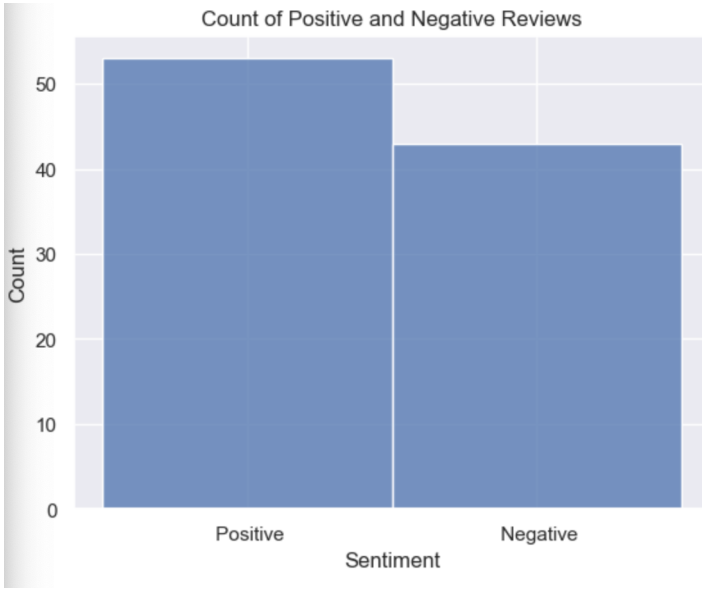
Customer feedback is an important tool for many companies and currently there are many different platforms and ways to receive that information. Analyzing text data can be very challenging due to the qualitative nature of the data. In order to analyze feedback, natural language processing (NLP) combined with machine learning can be used on such data to determine the sentiment. Utilizing NLP allows for efficient processing of text without human intervention and can determine if the sentiment of the text is positive, negative, or neutral.

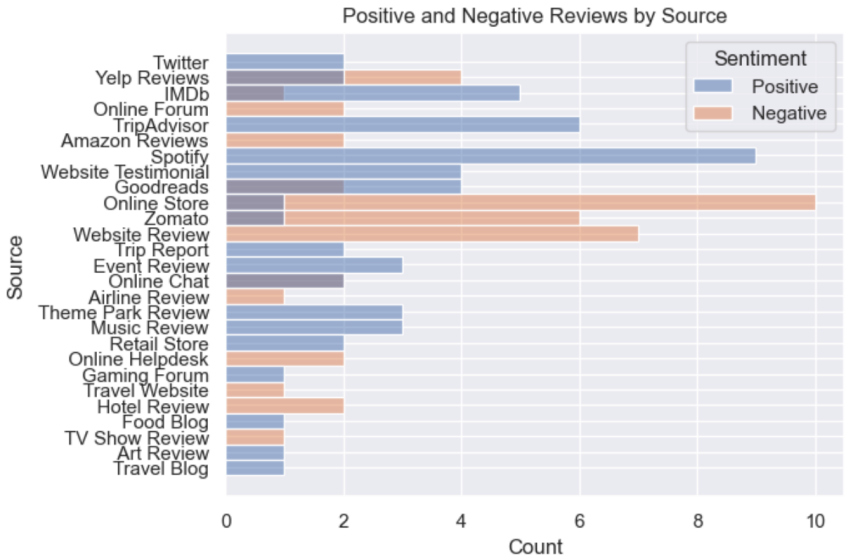
Data Wrangling

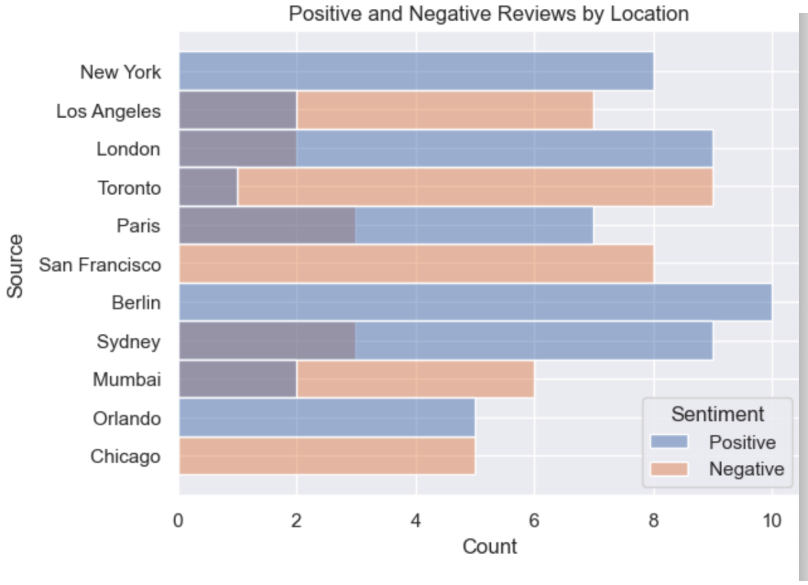
The data used for this project was obtained from kaggle. The dataset contains a collection of customer sentiments from various sources and platforms. A few examples of where the data was collected is Twitter, Facebook, and review platforms. The source code can be reviewed for a more detailed view of all of the exploratory data analysis and modeling. The data came with 98 rows and 9 columns. The data includes text, sentiment (positive or negative), source of the text, time/date of when the text was published, user ID, location, and confidence score. There were a couple rows with missing data that were dropped and the time column was split into additional features to separate out month, day, and hour for each row. New features including, total words, total characters, and total words after transformation were created for visual analysis.

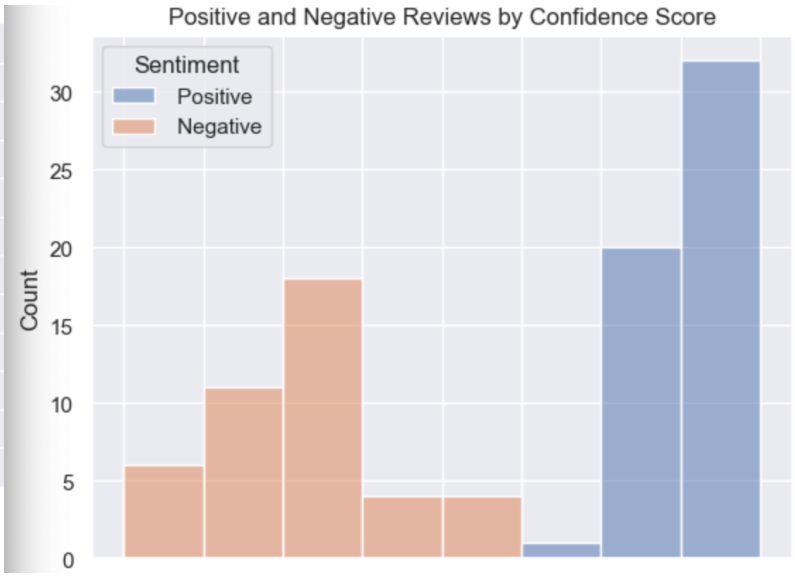
Exploratory Data Analysis

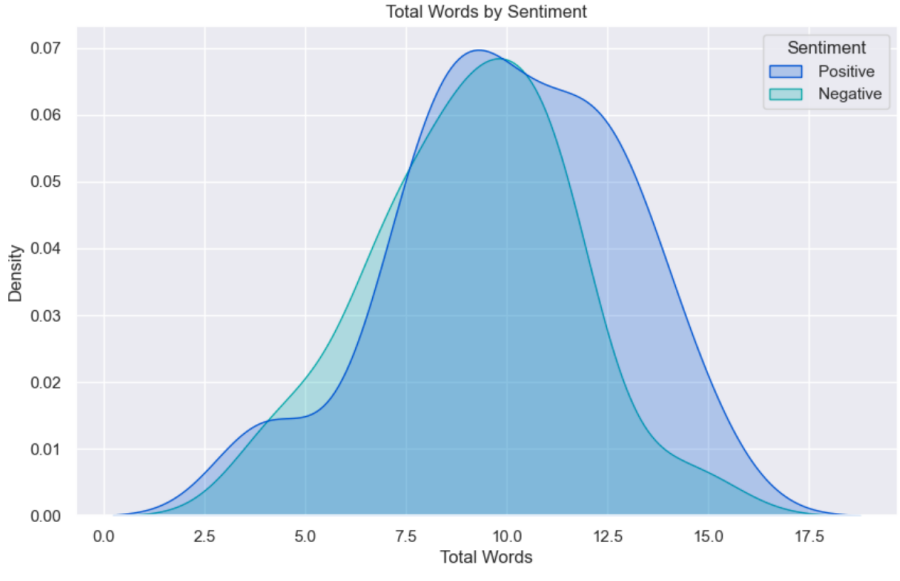
The features of the dataset were visualized with histograms to see if there were any correlations related to the sentiment outcome. Sentiment was observed by, source, location, comfidence score, month, day, and hour. Of the 96 rows, 53 of the responses were recorded as positive and 43 as negative. A density plot of total words and total characters were observed by sentiment, and most common positive and negative words were identified. Overall there was a large discrepency between sentiment amoung all features. This may be attributed to the size of the dataset and the diversity of the source of the sentiment.

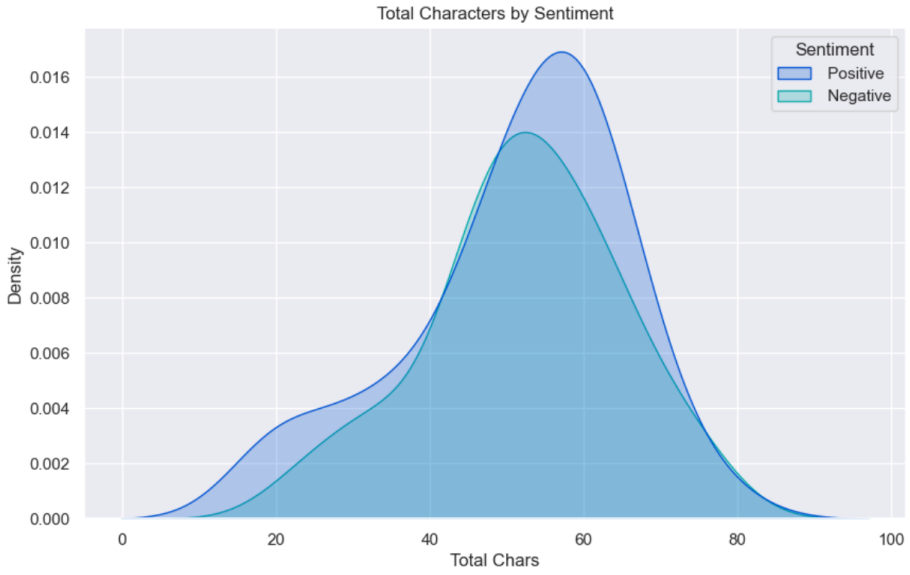

Count of Positive and Negative Reviews
Count
Sentiment
Positive
Negative
0
10
20
30
40
50

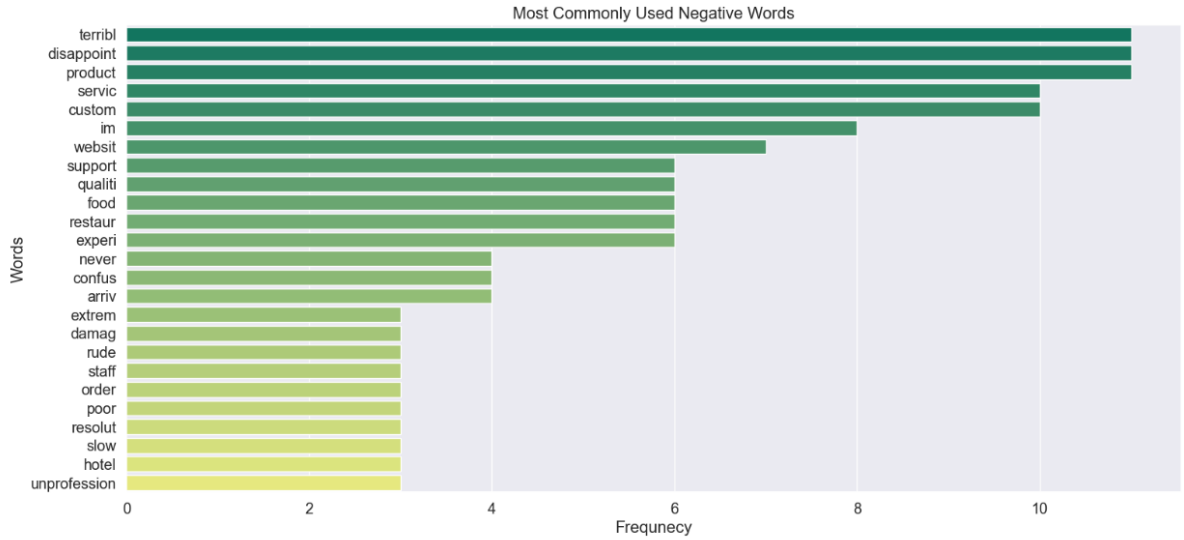

Positive and Negative Reviews by Source
Source
Count
Sentiment
Positive
Negative
Twitter
Yelp Reviews
IMDb
Online Forum
TripAdvisor
Amazon Reviews
Spotify
Website Testimonial
Goodreads
Online Store
Zomato
Website Review
Trip Report
Event Review
Online Chat
Airline Review
Theme Park Review
Music Review
Retail Store
Online Helpdesk
Gaming Forum
Travel Website
Hotel Review
Food Blog
TV Show Review
Art Review
Travel Blog
0
2
4
6
8
10

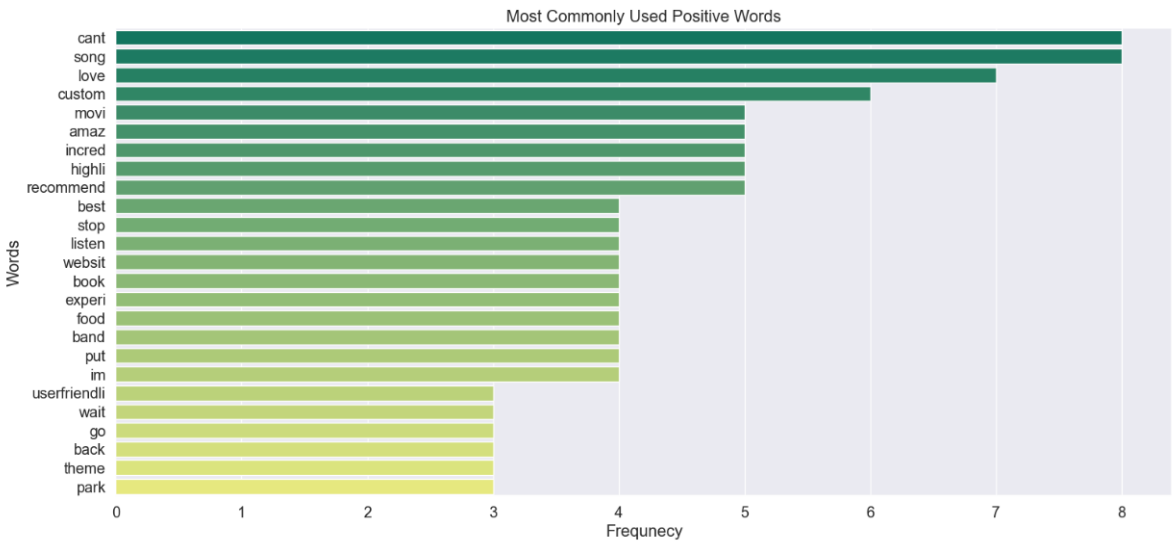

Positive and Negative Reviews by Location
Source
Count
Sentiment
Positive
Negative
New York
Los Angeles
London
Toronto
Paris
San Francisco
Berlin
Sydney
Mumbai
Orlando
Chicago
0
2
4
6
8
10


Positive and Negative Reviews by Confidence Score
Count
Sentiment
Positive
Negative
0
5
10
15
20
25
30
0.80
0.85
0.90
0.95
e Score


Total Words by Sentiment
Density
Total Words
Sentiment
Positive
Negative
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5


Total Characters by Sentiment
Sentiment
Positive
Negative
Density
0.016
0.014
0.012
0.010
0.008
0.006
0.004
0.002
0.000
0
20
40
60
80
100
Total Chars


Most Commonly Used Negative Words
terribl
disappoint
product
servic
custom
im
websit
support
qualiti
food
restaur
experi
never
confus
arriv
extrem
damag
rude
staff
order
poor
resolut
slow
hotel
unprofession
Words
0
2
4
6
8
10
Frequnecy


Most Commonly Used Positive Words
cant
song
love
custom
movi
amaz
incred
highli
recommend
best
stop
listen
websit
book
experi
food
band
put
im
userfriendli
wait
go
back
theme
park
Words
0
1
2
3
4
5
6
7
8
Frequnecy

Modeling

The data was prepared for modeling by converting the positive and negative sentiment responses to integers. Naive Bayes, Random Forest, and LSTM models were chosen for this dataset, and were conducted on both sentiment with and without text. For sentiment classification with text, Naive Bayes performed the best with an accuracy score of 0.95.

```
Accuracy of the model: 0.95
Precision Score of the model: 1.0
Recall Score of the model: 0.909
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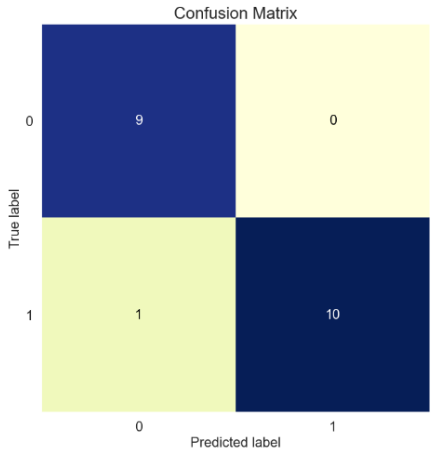
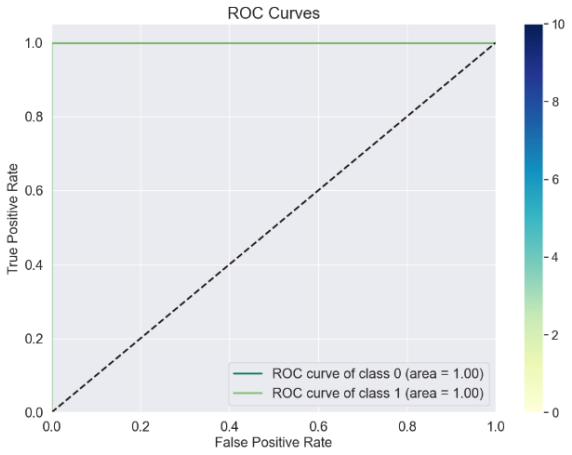
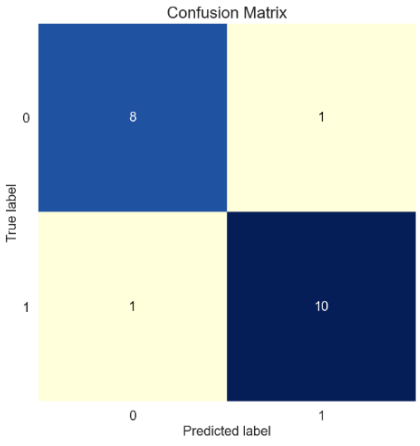
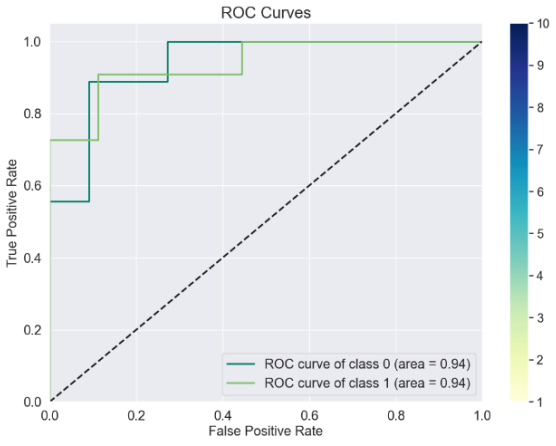




The data was then transformed to create dummy features for classification of sentiment without text. Naive Bayes performed the best with an accuracy score of 0.9.

```
Accuracy of the model: 0.9
Precision Score of the model: 0.909
Recall Score of the model: 0.909
```





Future work with a larger dataset could be explored to compare performance of the models.