US AIRLINE

SENTIMENT ANALYSIS

CSC 6850 Final Project Report

BY

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PROBLEM DESCRIPTION

Sentiment analysis is the computational examination of people's opinions, attitudes, and sentiments about a topic. One of the key topics among travelers has been the topic of airline service satisfaction. A company naturally strives to completely meet the expectations of its customers, but this isn't always the case and can occasionally put the passengers in challenging situations, such being stranded. If an airline firm can accurately evaluate, foresee, and respond to the complaints of its consumers, will popularity and revenue increase? This project aims to provide an answer to that question as well as a tool to help travelers make wise choices before making a reservation with an airline.

Dataset

The dataset used in this project was sourced from Kaggle.com. Below is a list of all the features in the dataset, as well as a brief description of each feature:

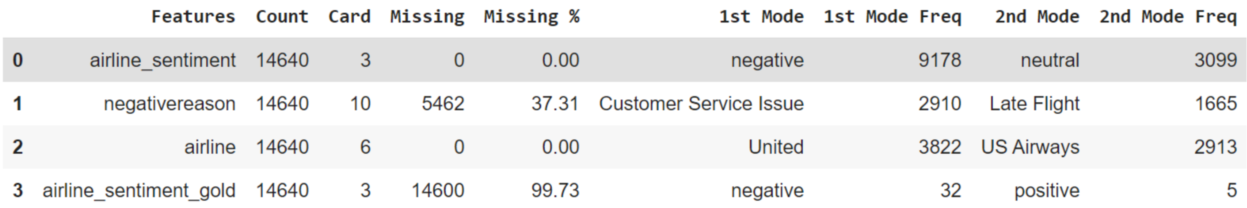
Feature	***Description***
Tweet_id	A unique identification number for each tweet
Airline_sentiment	Feedback sentiments {-1: negative, 0: neutral, 1: positive}
Airline_sentiment_confidence	Confidence of annotation for each tweet
Negativereason	Main negative reason why feedback was given
Negativereason_confidence	Confidence of negative reason
Airline	Name of all (6) airlines in the dataset
Airline_sentiment_gold	Annotation of a tweet {negative, neutral, positive}
Name	Tweeter account (username) providing the feedback
Negativereason_gold	Main negative reason why feedback was given
Retweet_count	Number of times feedback was retweeted
Text	Main content of feedback
Tweet_coord	Coordinate (location) of account providing the feedback
Tweet_created	Full date time feedback was created or posted
Tweet_location	Location of the feedback provider
User_timezone	User time zone

Proposed Analytics Solution

The goal of this project is to develop a machine learning model that will help airline companies identify services that need to be improved to satisfy their customers and better understand the needs and complaints of their customers through analysis of their feedback. By incorporating these insights, airline firms will have the resources they need to enhance customer satisfaction, increase brand recognition, and ultimately increase revenues.

DATA PREPROCESSING AND EXPLORATION

The dataset has one target feature and 14 features overall, as can be seen above. However, the majority of the characteristics are deemed unnecessary for my project, thus before starting the data exploration process, I took into consideration features with fewer than 11 unique entries. As a result, our features—excluding the target feature—dropped from 14 to 4. I initially take a look at the data quality report for the four chosen features before I start my preprocessing and exploratory analysis.

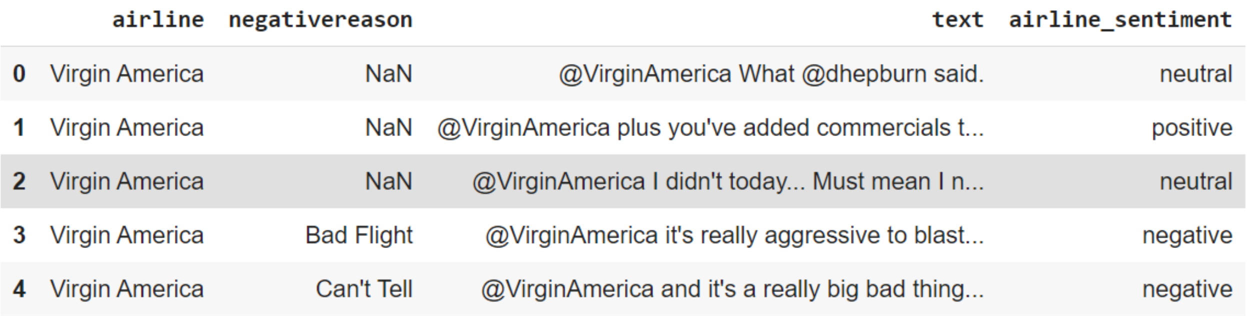


	Features	Count	Card	Missing	Missing %	1st Mode	1st Mode Freq	2nd Mode	2nd Mode Freq
0	airline_sentiment	14640	3	0	0.00	negative	9178	neutral	3099
1	negativereason	14640	10	5462	37.31	Customer Service Issue	2910	Late Flight	1665
2	airline	14640	6	0	0.00	United	3822	US Airways	2913
3	airline_sentiment_gold	14640	3	14600	99.73	negative	32	positive	5

Figure 1: *A Data Quality Report on Selected Features.*

The data set comprises 14,640 instances, according to the data quality assessment; the majority of the feedback was *negative*, with a frequency of 9,178, or almost 63% of our dataset. Additionally, *customer service issues* were the most frequently reported or tweeted unfavorable issues for most people, as well as the most well-known airline, *United*, with 3,822 flights (or feedback), or around 26%.

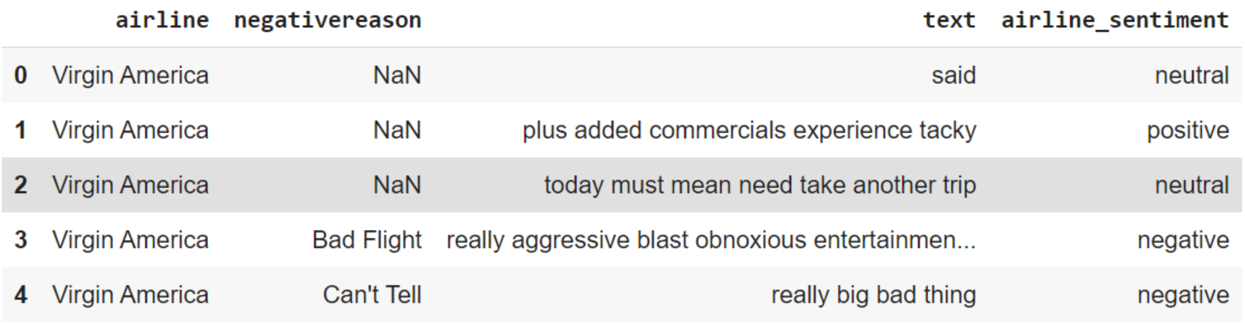
The *Airline_sentiment_gold* feature was also dropped before proceeding because it had *99.73%* of its data missing and it seemed to be copy of *Airline_sentiment* feature so I am assuming there's no information lost dropping this very sparse feature.



	airline	negativereason	text	airline_sentiment
0	Virgin America	NaN	@VirginAmerica What @dhepburn said.	neutral
1	Virgin America	NaN	@VirginAmerica plus you've added commercials t...	positive
2	Virgin America	NaN	@VirginAmerica I didn't today... Must mean I n...	neutral
3	Virgin America	Bad Flight	@VirginAmerica it's really aggressive to blast...	negative
4	Virgin America	Can't Tell	@VirginAmerica and it's a really big bad thing...	negative

Figure 2 (a): *Current Dataset After Dropping Irrelevant Features.*

Since this is a tweeter dataset, our main independent feature, *text*, contains symbols, emoji, regular expressions, extra spaces, and most crucially, worthless Twitter tags from other users. *Text* will be utilized to train our models. Thus, removing these characters was the first step in the data cleaning procedure. The next stage was to deal with words or expressions referred to as *"stopwords"* that are frequently employed in (English) sentence construction but have no meaningful bearing when identifying opinions as negative, neutral, or positive. *Sample stopwords: I, it's, didn't, you've, a, the, is, are, an, so, what, my, how,* etc.



	airline	negativereason	text	airline_sentiment
0	Virgin America	NaN	said	neutral
1	Virgin America	NaN	plus added commercials experience tacky	positive
2	Virgin America	NaN	today must mean need take another trip	neutral
3	Virgin America	Bad Flight	really aggressive blast obnoxious entertainmen...	negative
4	Virgin America	Can't Tell	really big bad thing	negative

Figure 2 (b): *Dataset after Text Preprocessing*

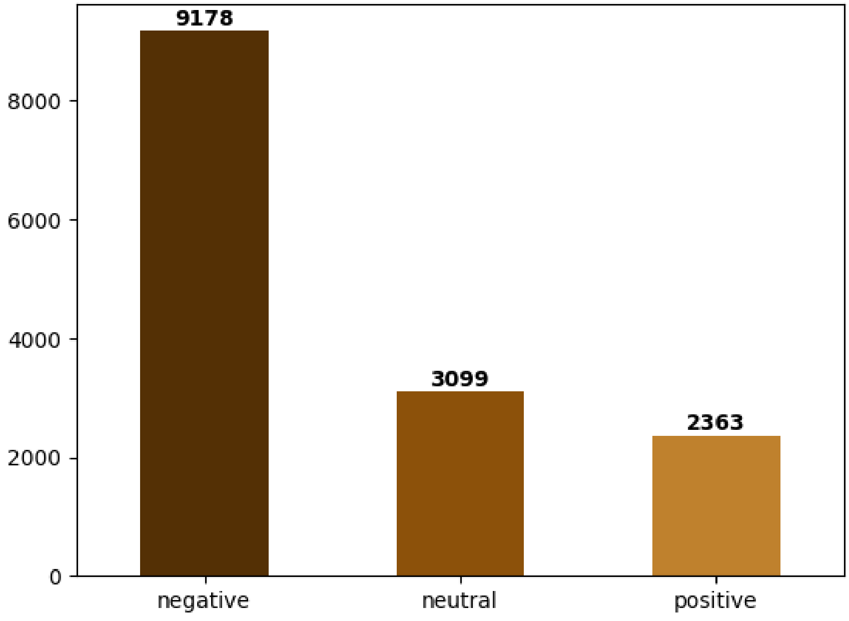


Figure 3: *Frequency of Sentiments.*

The frequency of sentiment expressed in the dataset is depicted in this graph. With around *63%* of the feedback expressing a complaint, the dataset is dominated by *negative* feedback. The least amount of tweets came from the *positive* category (2,363 tweets, or around *16%* of the responses).

The frequency of sentiment for each airline in the sample is examined in **Figure 4**. *United* appears to be the most well-liked airline in our dataset with sentiments totaling 3,822. It does, however, have some negatives, though, as it receives the most unfavorable reviews out of the six carriers. Also, since *Virgin America* only accounts for *4%* of our dataset's total flights, having the fewest bad reviews (181) does not necessarily suggest it is the most reliable airline. *US Airways* and *American* Airlines, which account up *20%* and *19%* of the dataset respectively, are not far behind in terms of popularity.

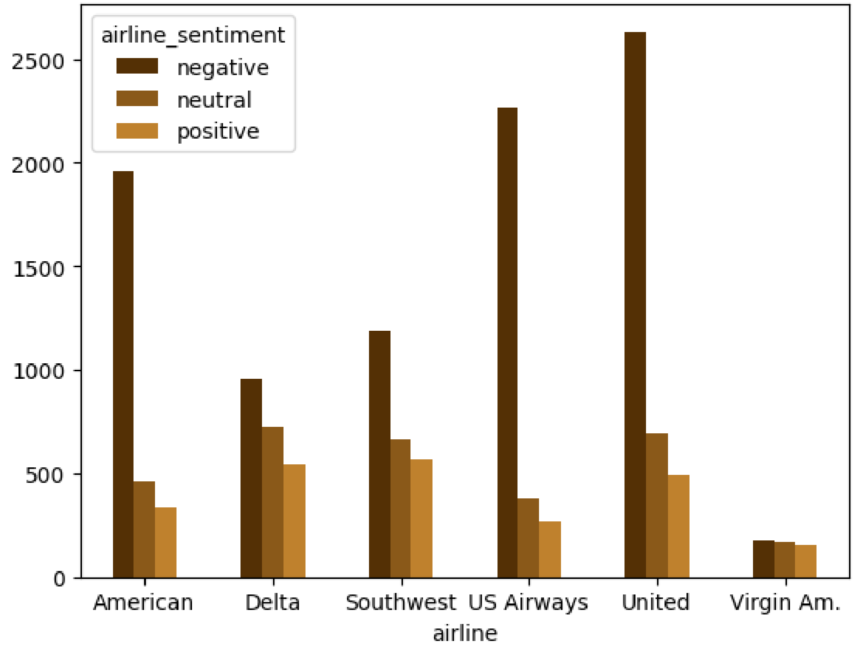


***Figure 4:** Frequency of Airline Sentiments.*

I represented the frequency of the *negative* explanations in **Figure 5.** This demonstrates that the majority of comments expressed worry about or dissatisfaction with the *customer service* received prior to or following their flights. The second unsettling problem for customers was *delayed flights*, which received 1,665 comments and accounts for *18%* of the *negative* feedback. Additionally, it is obvious that all airlines are doing a fantastic job of securing and delivering luggage because this reason receives the fewest bad comments (only 74), or around *1%* of all negative comments. **Figure 6** depicts the information shown in **Figure 5** for each airline. All airlines are doing their utmost to transport luggage, as is evident. It is also important to note that many *American Airlines'* critics expressed their dissatisfaction with *delayed flights*, with poor *customer service* a close second.

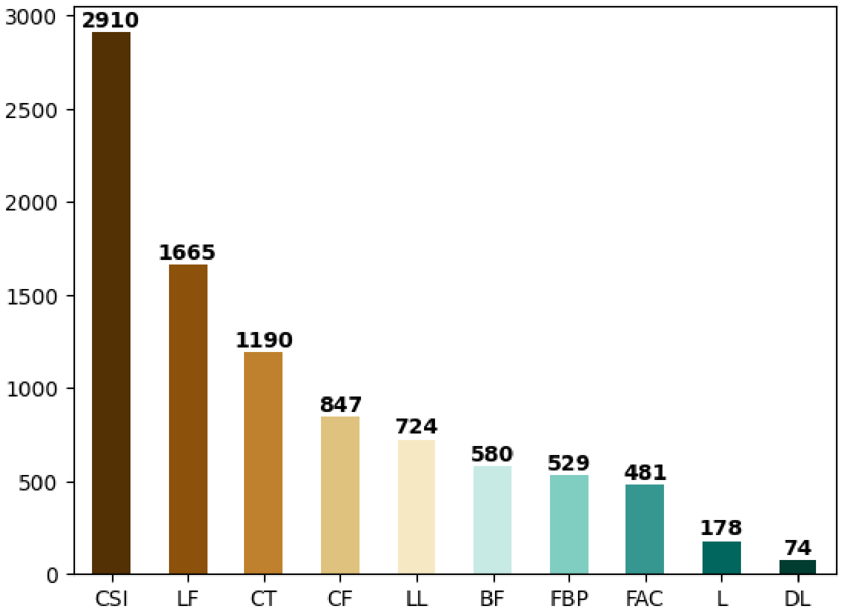


Figure 5: *Frequency of Negative Feedback Reasons.*

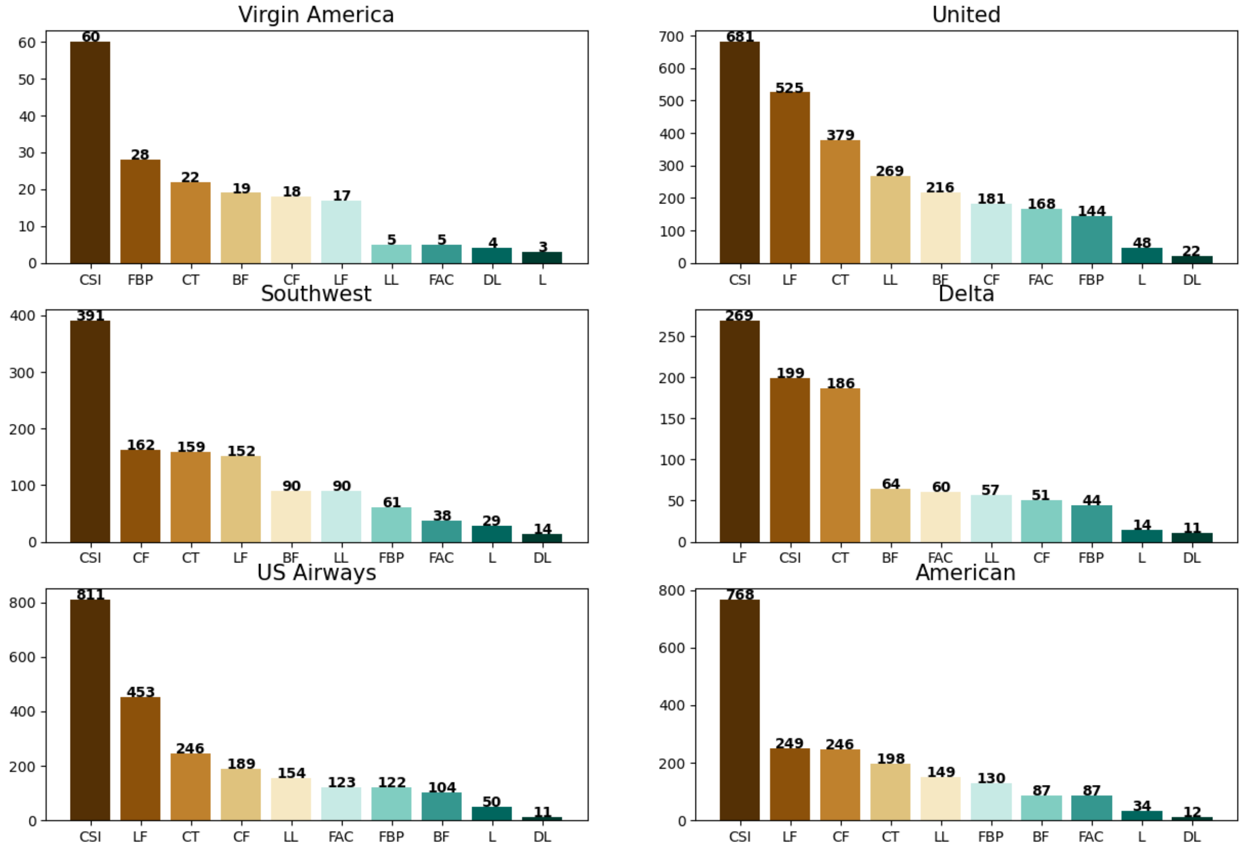


Figure 6: *Frequency of Negative Feedback Reasons for each Airline.*

Next, I represented in **Figure 7** the words that are frequently used to categorize tweets or feedback as *positive, neutral, or negative*. As this is a flight data set, which very probably contains the word *"flight(s)"* in at least 50% of the data set, it is crucial to highlight that all occurrences of the word *"flight(s)"* were deleted before making this graphic. This omission made it simple to identify the words that best captured the emotions of the airline passengers.

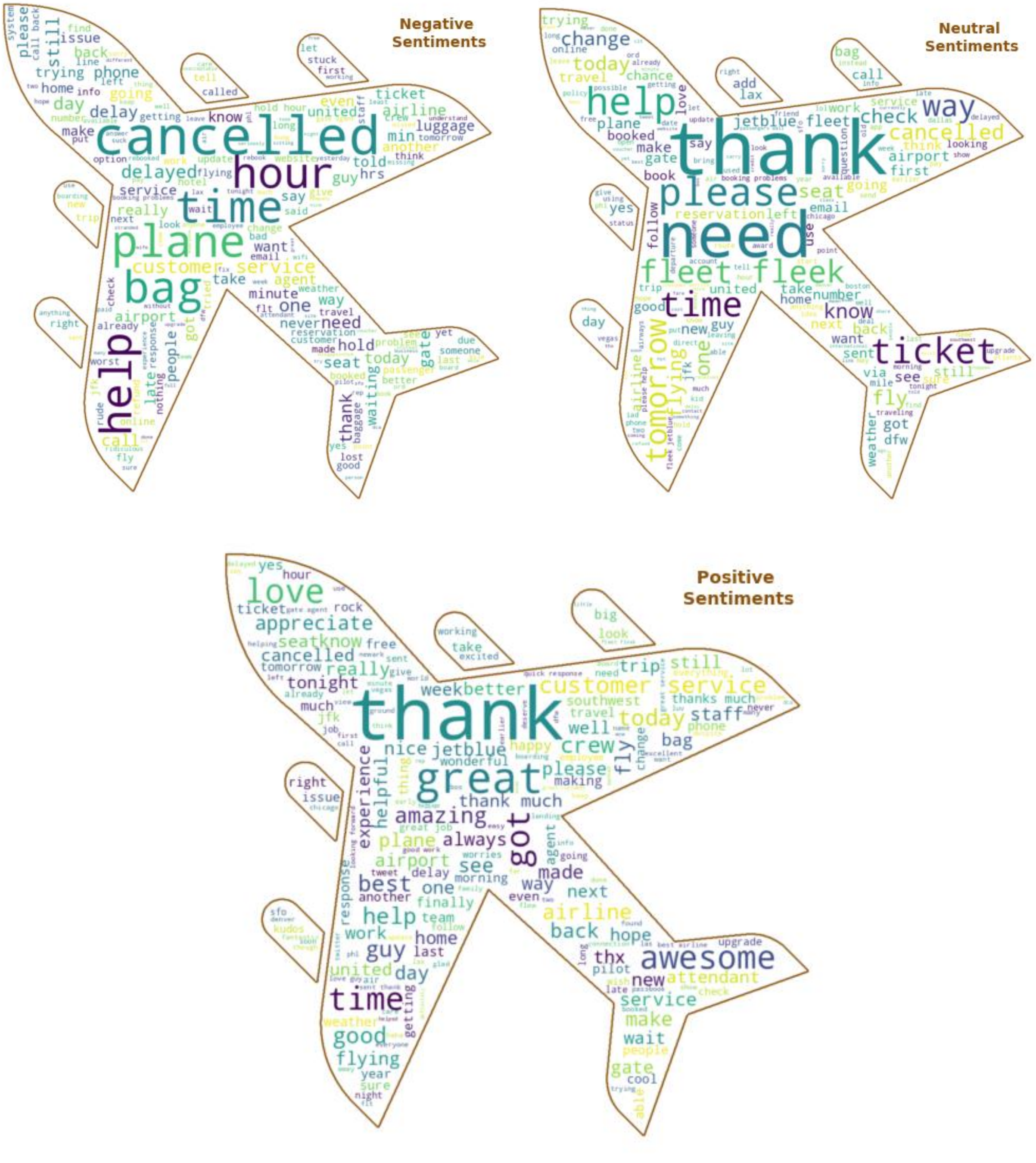
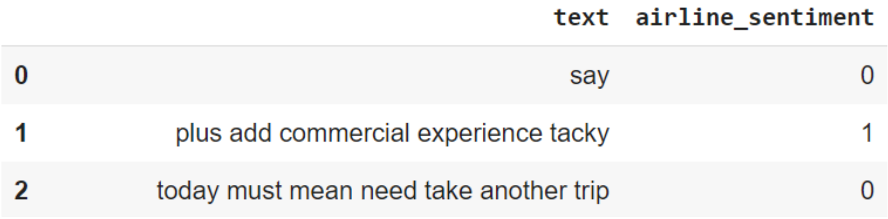


Figure 7: *Word Cloud of sentiments.*

MODEL SELECTION AND EVALUATION



	text	airline_sentiment
0	say	0
1	plus add commercial experience tacky	1
2	today must mean need take another trip	0

Figure 8: *Dataset state before modelling*

This project is a classification problem – predicting the class (*sentiment)* of a given tweet/feedback. The classes: *-1: negative, 0: neutral, 1: positive.*

Evaluation Metrics

The *accuracy score*, the *f1-score, the precision, recall*, and the *macro and weighted averages* generated by a classification report were the evaluation metrics employed for the classification models. The f1-score is used to determine the prediction skill of a model by focusing on its class-wise performance rather than an overall performance, as is done by the accuracy score. The accuracy score is equivalent to R^2 for a classification issue.

$$Accuracy\ \ score = \frac{TP+TN}{TP+TN+FP+FN} \qquad\qquad F1\ score = \frac{2TP}{2TP+FP+FN}$$

Where: TP = True Positive; FP = False Positive; TN = True Negative; FN = False Negative

Models

I chose three traditional classification models—Logistic Regression, Support Vector Machine, and Naïve Bayes classification—and put them into practice.

Sampling and Evaluation Settings

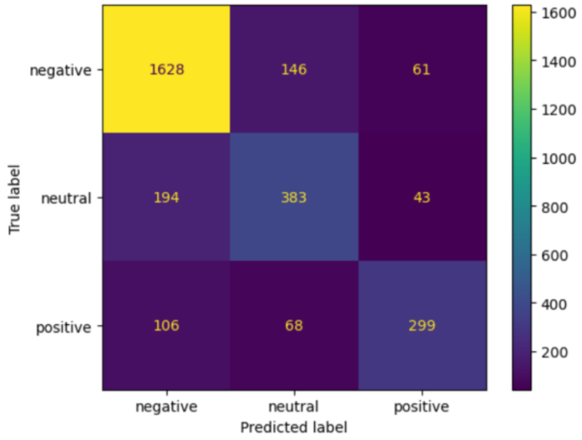
The models chosen above had the best assessment results when the train-test-split was 80% for the train data set and 20% for the test data set.

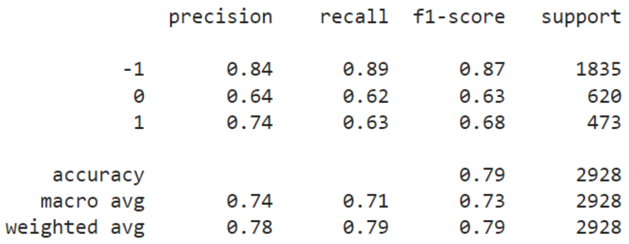
Hyper-Parameter Optimization

I discovered that all models had improved performance on both the train and test sets after implementing the lemmatization technique to change some words to their stem or basic forms (for example, walk and walking were both transformed to walk) and using unigram and bigram bag of words in an attempt to extract context from tweets.

RESULT, CONCLUSION, AND RECOMMENDATION

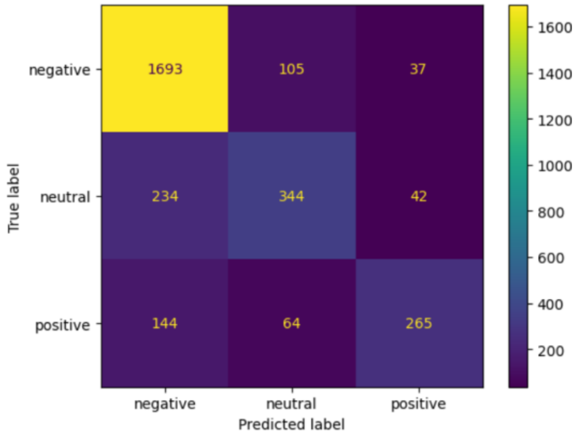
Model 1: Logistic Regression Train Accuracy: **92.18%** Test Accuracy: **78.89%**

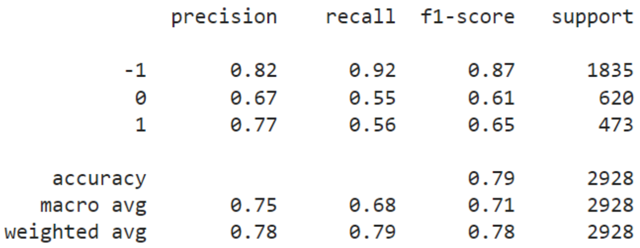




```
              precision    recall  f1-score   support

          -1       0.84      0.89      0.87      1835
           0       0.64      0.62      0.63       620
           1       0.74      0.63      0.68       473

    accuracy                           0.79      2928
   macro avg       0.74      0.71      0.73      2928
weighted avg       0.78      0.79      0.79      2928
```

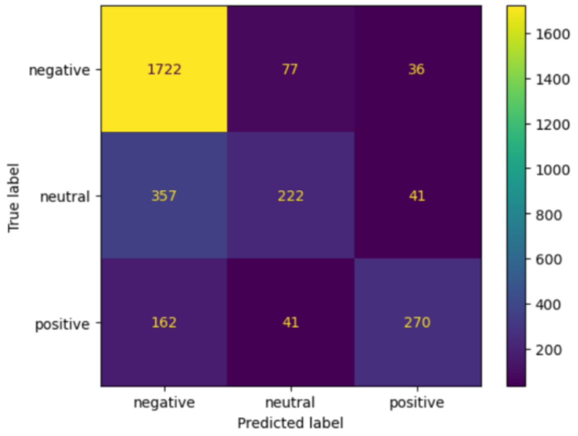
Model 2: Support Vector Machine *Train Accuracy: 91.69%* *Test Accuracy: 78.62%*

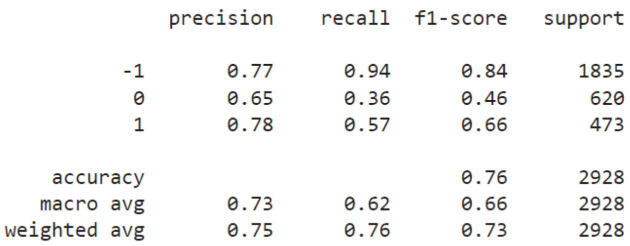




```
              precision    recall  f1-score   support

          -1       0.82      0.92      0.87      1835
           0       0.67      0.55      0.61       620
           1       0.77      0.56      0.65       473

    accuracy                           0.79      2928
   macro avg       0.75      0.68      0.71      2928
weighted avg       0.78      0.79      0.78      2928
```

Model 3: Naïve Bayes *Train Accuracy: 83.64%* *Test Accuracy: 75.61%*

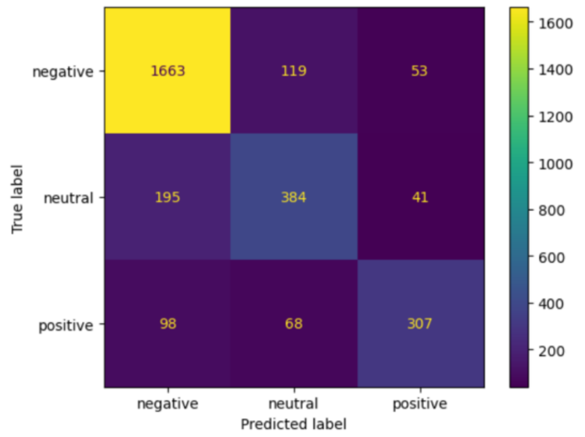


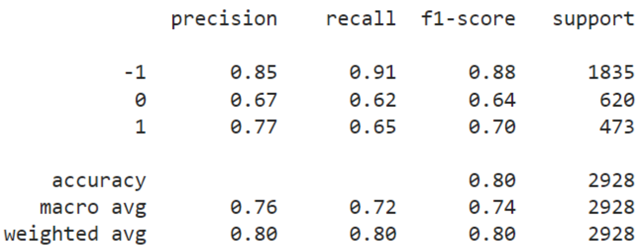


```
              precision    recall  f1-score   support

          -1       0.77      0.94      0.84      1835
           0       0.65      0.36      0.46       620
           1       0.78      0.57      0.66       473

    accuracy                           0.76      2928
   macro avg       0.73      0.62      0.66      2928
weighted avg       0.75      0.76      0.73      2928
```

Tunned Model: Lemmatization + (1,2) Ngram BOW

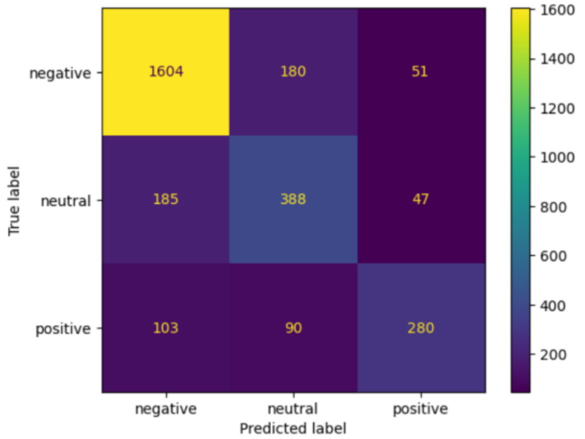
Model 1: Logistic Regression Train Accuracy: **98.39%** Test Accuracy: **80.40%**

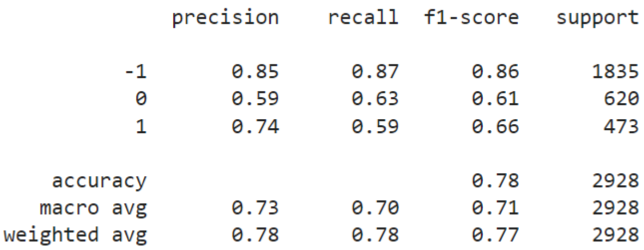




```
              precision    recall  f1-score   support

          -1       0.85      0.91      0.88      1835
           0       0.67      0.62      0.64       620
           1       0.77      0.65      0.70       473

    accuracy                           0.80      2928
   macro avg       0.76      0.72      0.74      2928
weighted avg       0.80      0.80      0.80      2928
```

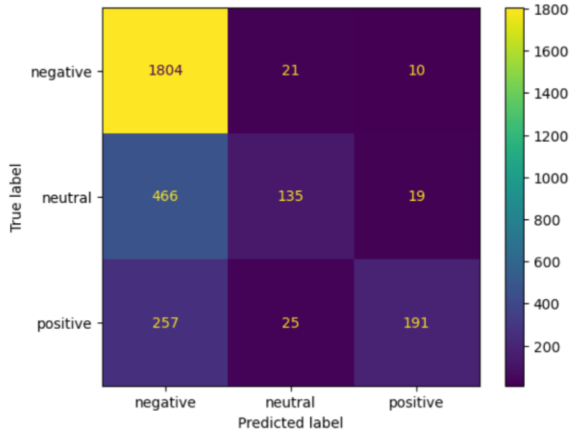
Model 2: Support Vector Machine *Train Accuracy: 93.16%* *Test Accuracy: 77.60%*

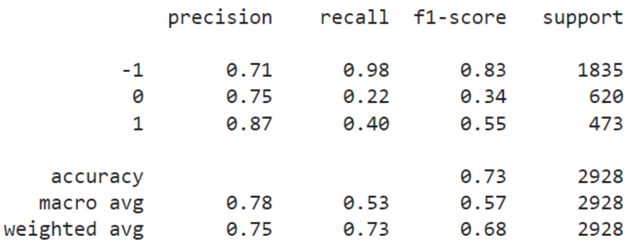




```
              precision    recall  f1-score   support

          -1       0.85      0.87      0.86      1835
           0       0.59      0.63      0.61       620
           1       0.74      0.59      0.66       473

    accuracy                           0.78      2928
   macro avg       0.73      0.70      0.71      2928
weighted avg       0.78      0.78      0.77      2928
```

Model 3: Naïve Bayes *Train Accuracy: 91.44%* *Test Accuracy: 72.75%*





```
              precision    recall  f1-score   support

          -1       0.71      0.98      0.83      1835
           0       0.75      0.22      0.34       620
           1       0.87      0.40      0.55       473

    accuracy                           0.73      2928
   macro avg       0.78      0.53      0.57      2928
weighted avg       0.75      0.73      0.68      2928
```

We conclude that *Logistic Regression is the best model* based on the evaluation metrics discussed above, and we advise airline businesses to employ the model to ascertain the tone of fresh comments. It is crucial to notice that while the Naïve Bayes has the best recall value for the negative class, its accuracy performance is comparably weak, which lowers its f1-score.

Additionally, by examining the *"support"* values in the classification report, we can see that there is a class imbalance that was already recognized *(page 4),* and as a result, we can see a small difference between the "macro avg" and the "weighted avg."

Furthermore, we saw an improvement in all three models after applying lemmatization and (1,2) Ngram BOW, which increased the dimensionality of our data set from 8,556 to 61,100. But I believe that all models of the train set have an overfitting problem.

In light of the fact that, sentiments containing words that are frequently found in both the negative and positive classes led to poor classification of the neutral classes, I advise one should consider developing models based solely on the positive and negative feedback. In addition, further research should explore sampling methods to address the problem of class imbalance.

Finally, because features like *Negativereason* were not considered by my model, future research should experiment with concatenating the *Negativereason* feature and the *text* feature. The feature has distinct reasons why something is unfavorable; thus, the model might do a better job of capturing those reasons than it now does.

CREDITS AND REFERENCES

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