

Twitter US Airline Sentiment

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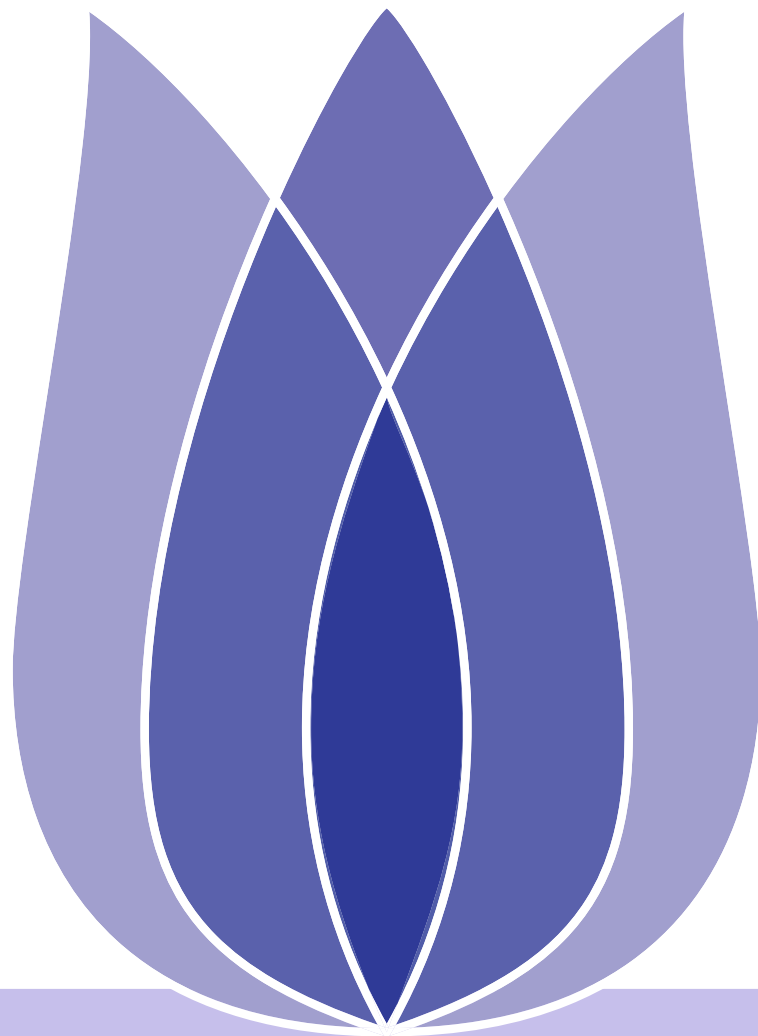




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Airline Attitude

Airline Attitude

Airline Attitude

negative Word Cloud

Positive Word Cloud

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Negative Reason

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Description

Sentiment analysis work on the issues of each major US airline. Twitter counted the tweets related to airlines since February 2015, and analyzed whether the sentiments contained in these tweets were positive, neutral or negative.

- Analyze how travelers in February 2015 expressed their feelings on Twitter.



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Table 1: Train

Attribute	Explanation
airline_sentiment	About the attitude of airlines.
text	The text content of the tweet.
airline	The name of the airline.
retweet_count	The number of reposts of the tweet.
tweet_created	The time the tweet was generated.

It also includes attributes such as tweet_id, airline_sentiment_confidence, negativereason, negativereason_confidence, airline_sentiment_gold, name, negativereason_gold, tweet_coord, tweet_location, user_timezone, etc.



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Date Analysis



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- Positive, negative and neutral emotions accounted for the number and proportion of the total number of people respectively. Among them, the number of negative attitudes is the largest and the number of positive attitudes is the least.

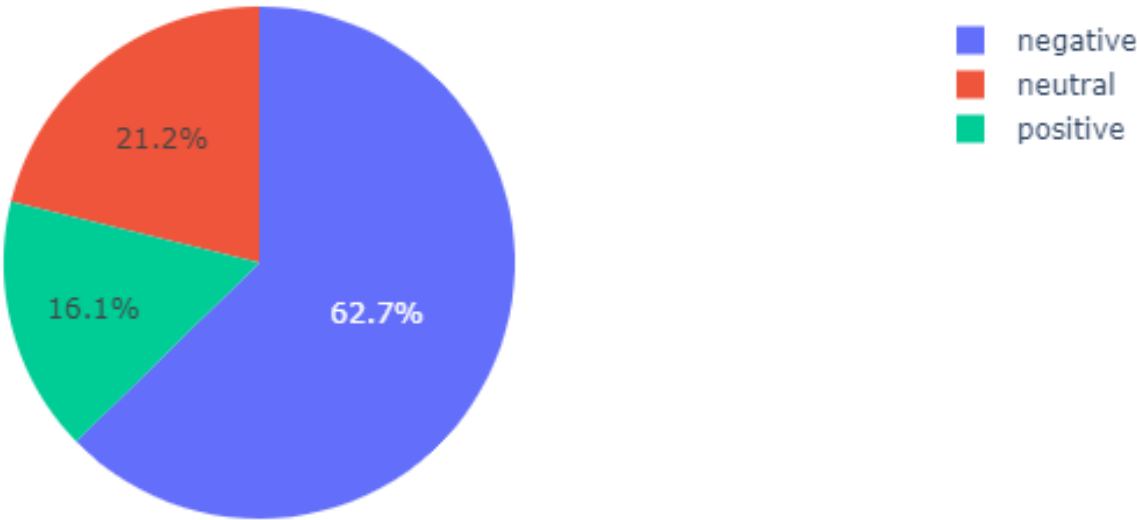


Figure 1: Sentiment Map

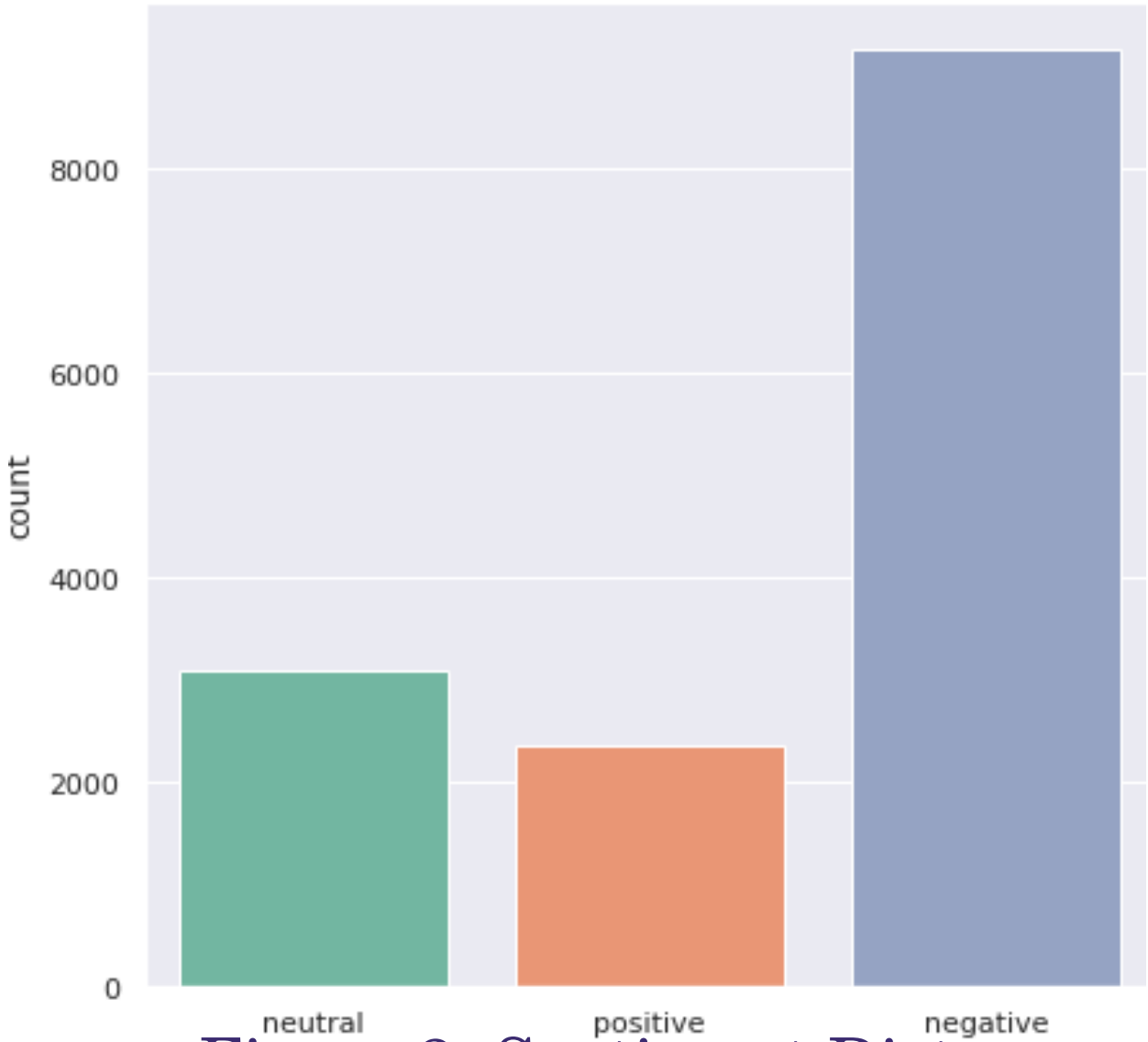


Figure 2: Sentiment Dist



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- The percentage of each airline in all airlines.

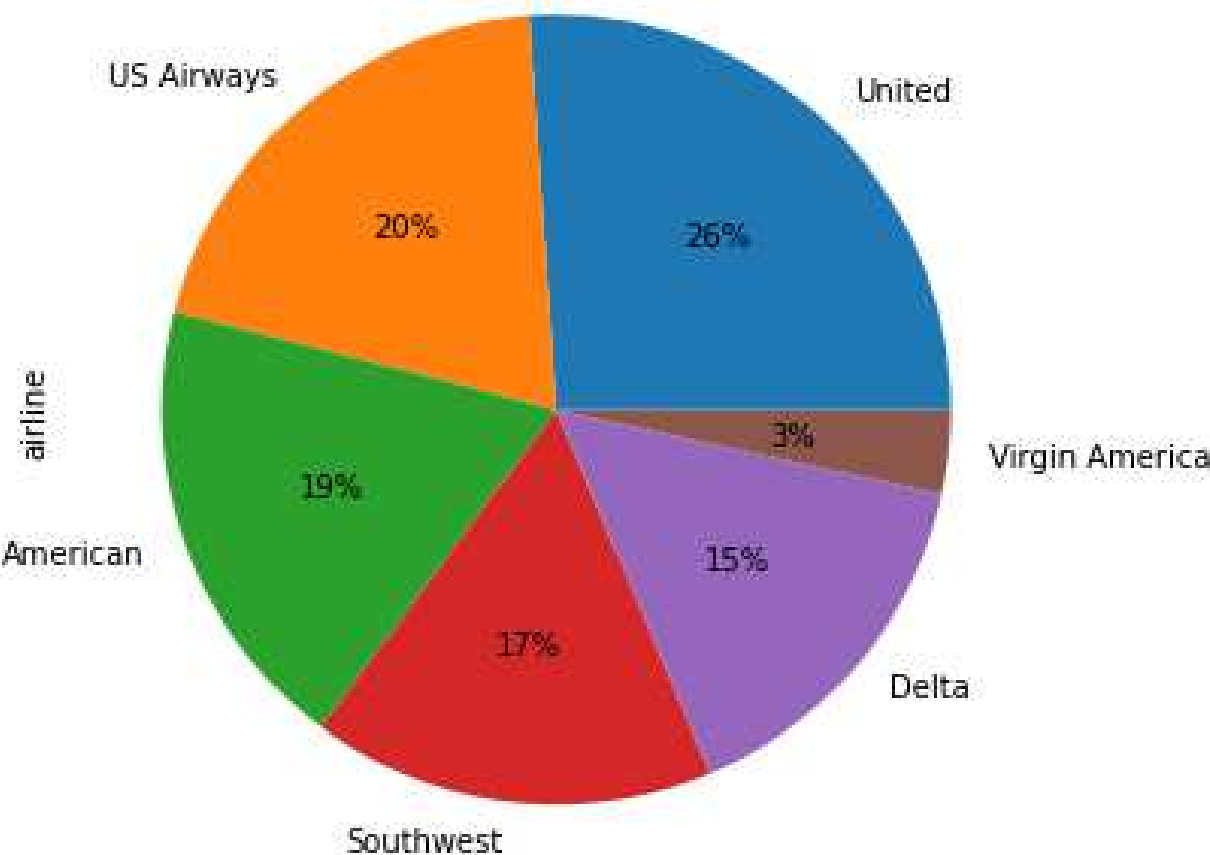


Figure 3: Airline Map

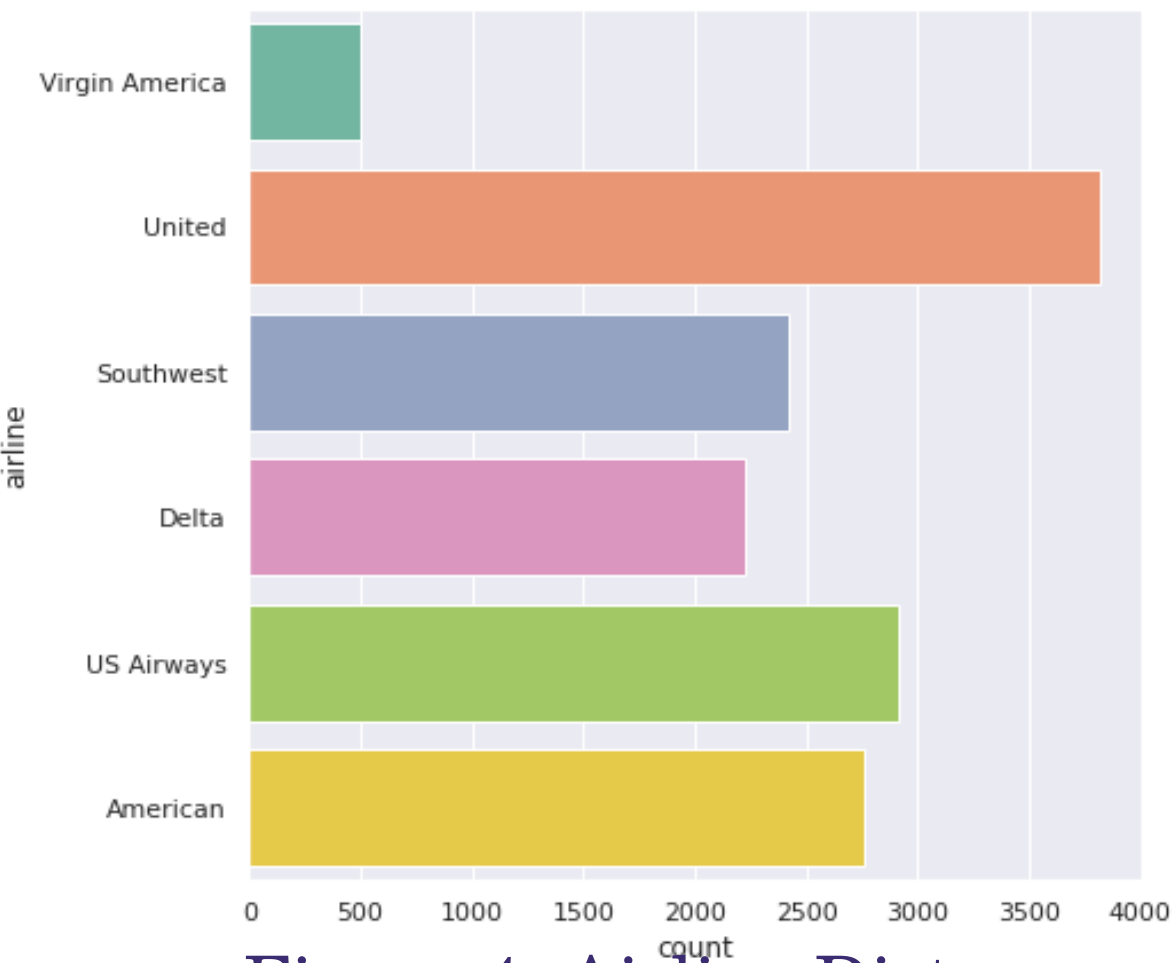


Figure 4: Airline Dist



Airline Attitude

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■ Distribution of attitudes of different airlines.

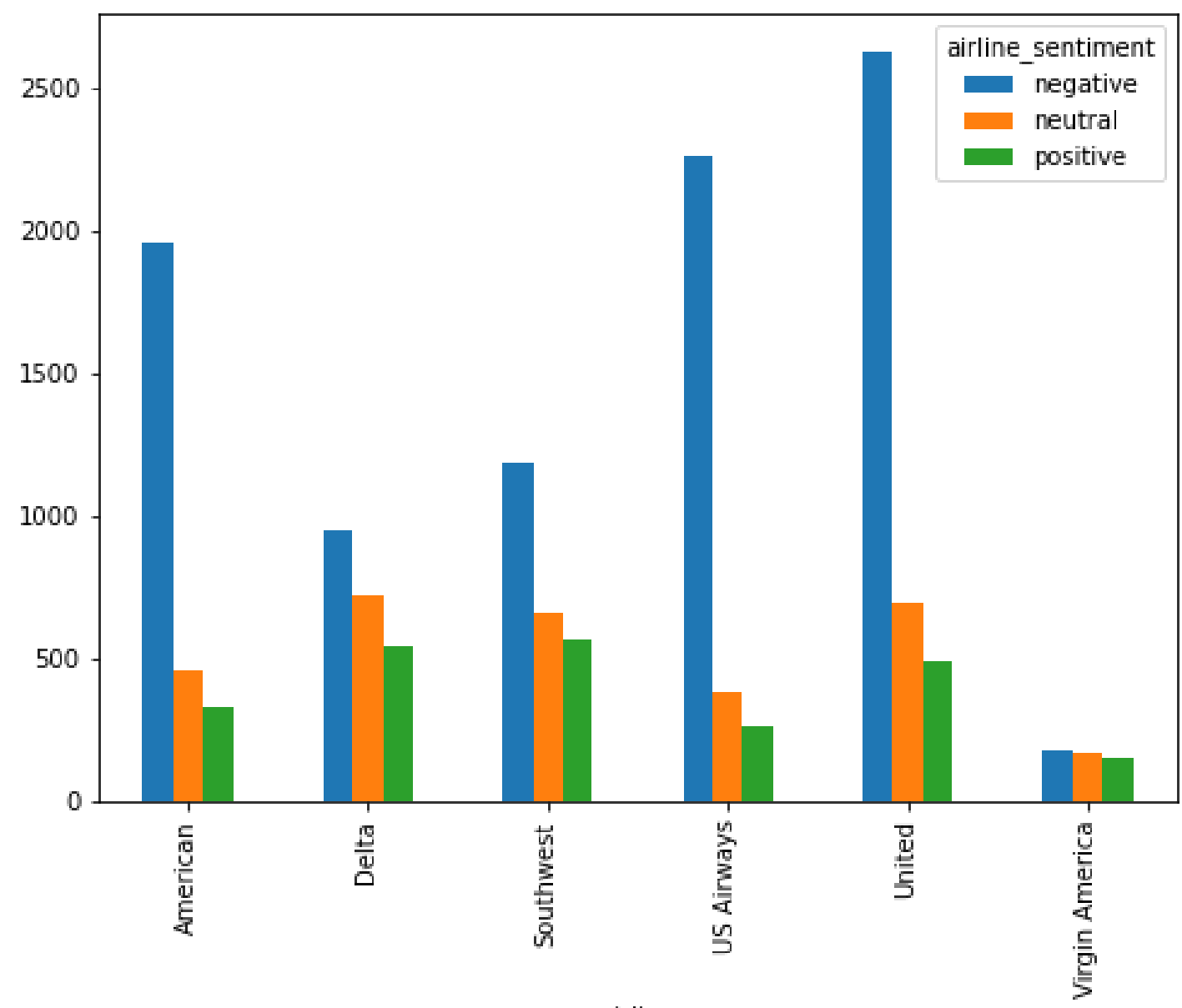


Figure 5: Airline Attitude



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- The individual attitude distribution of each airline.

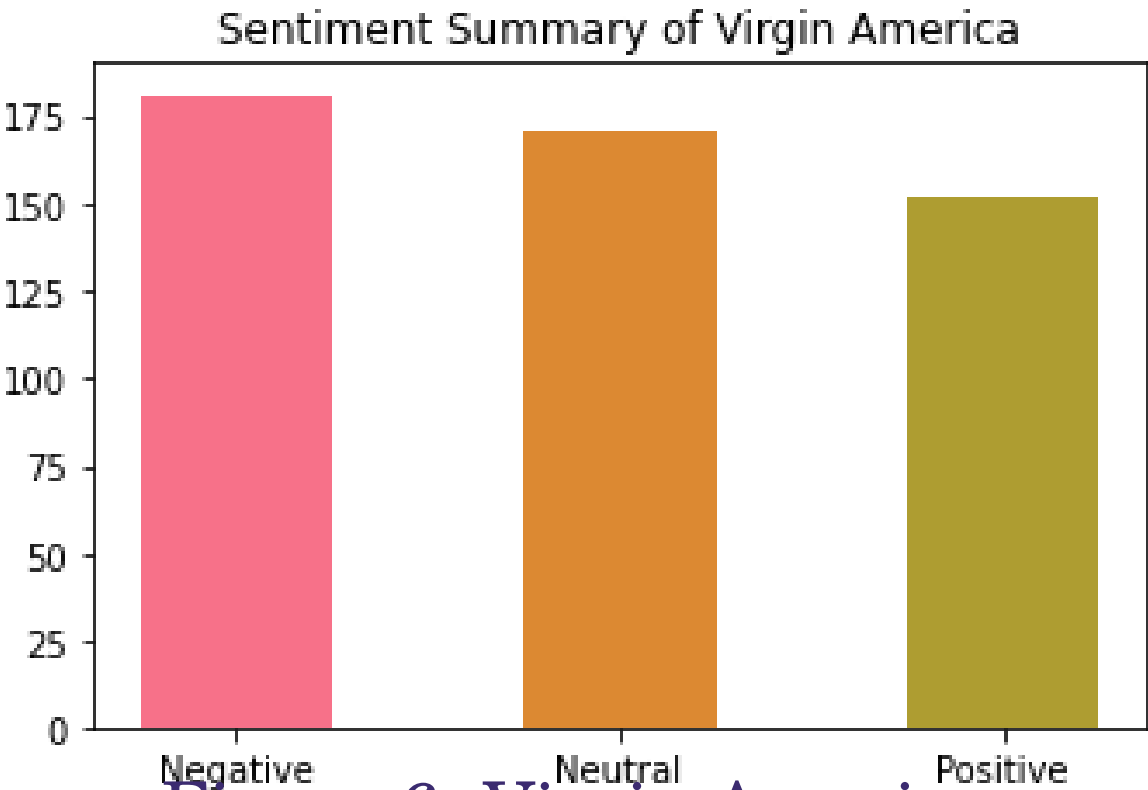


Figure 6: Virgin America

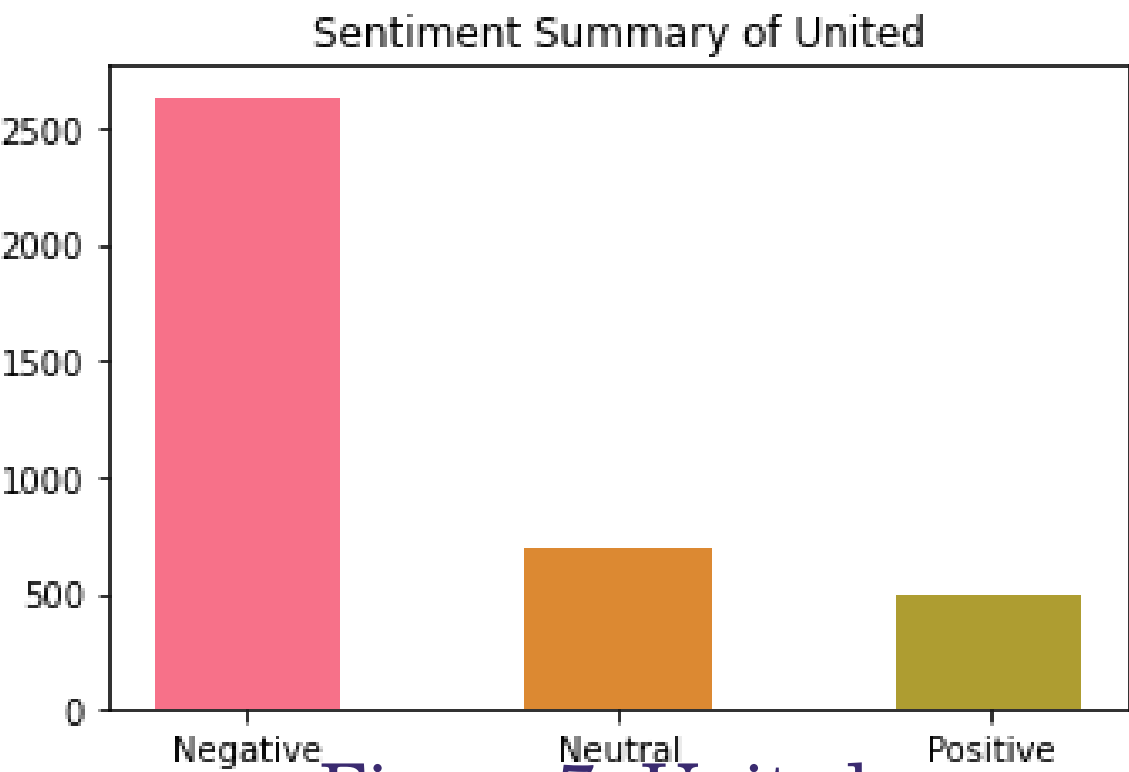


Figure 7: United



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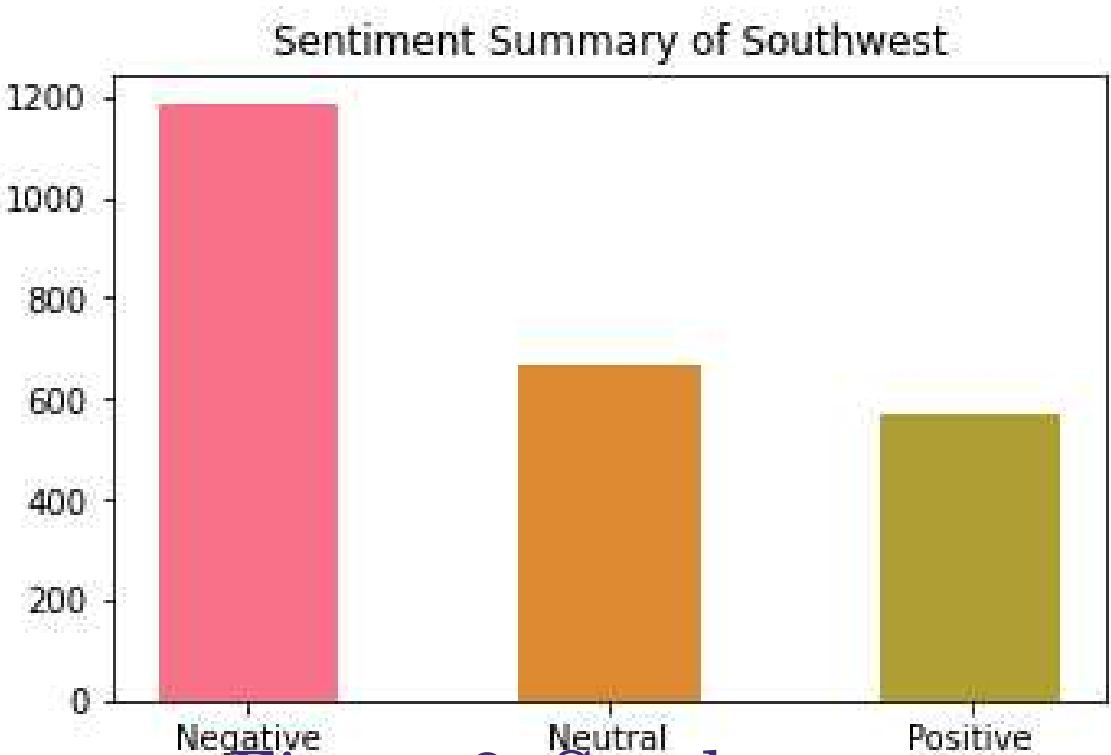


Figure 8: Southwest

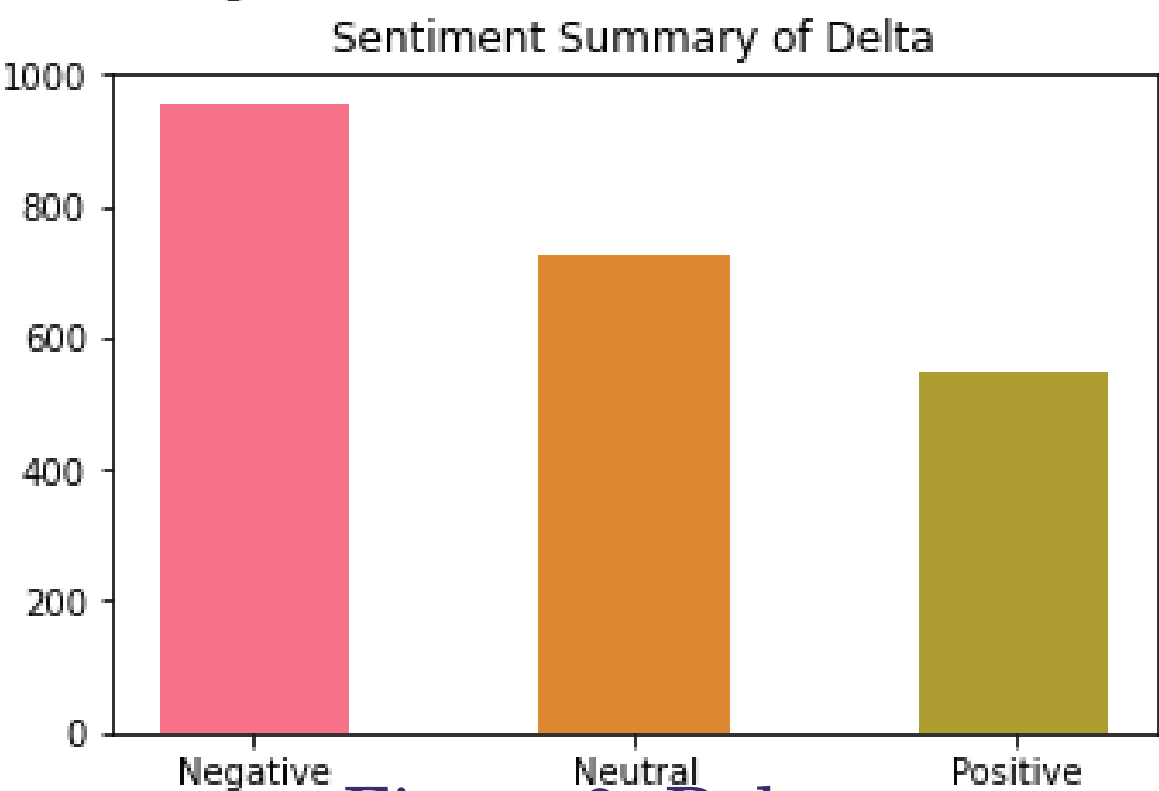


Figure 9: Delta



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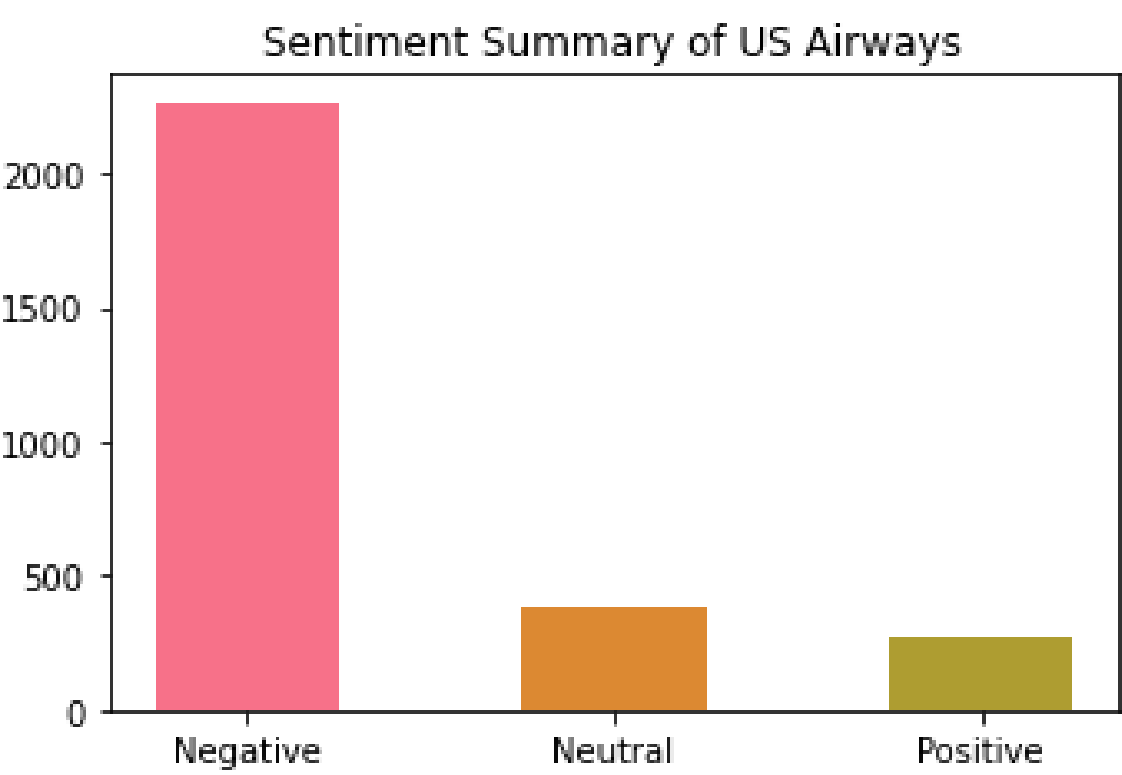


Figure 10: US Airways

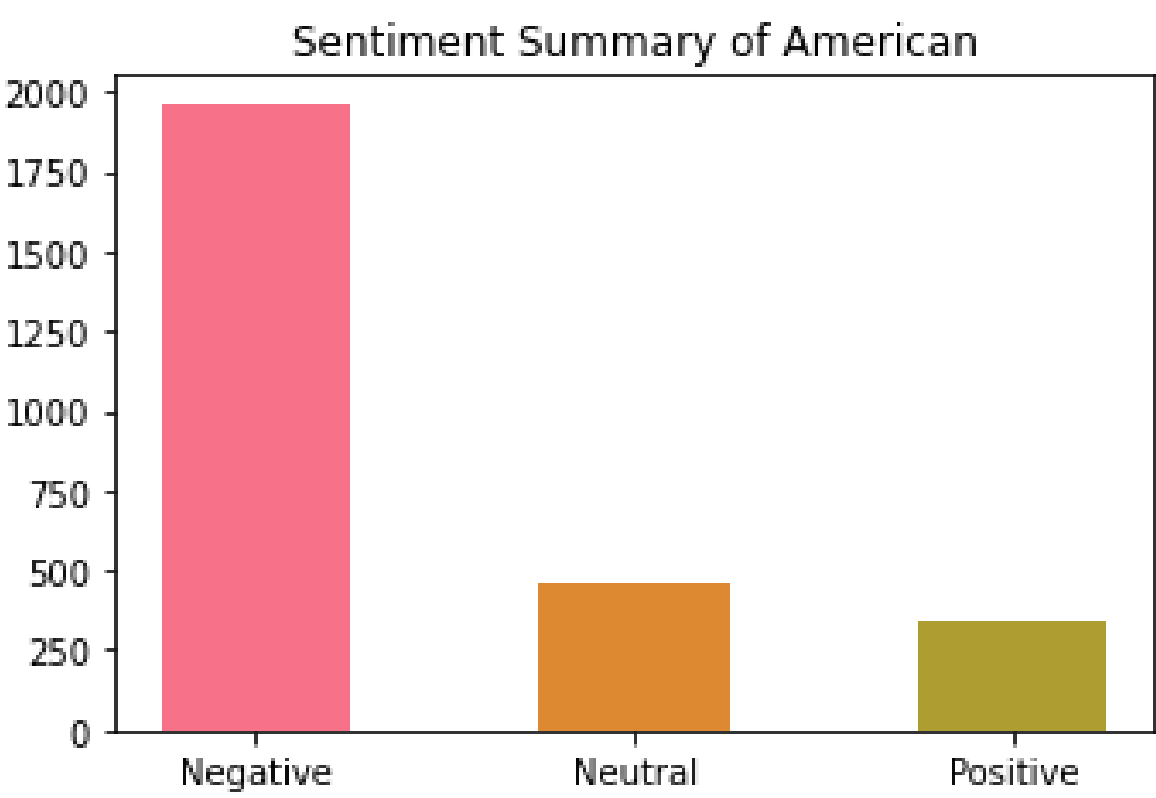


Figure 11: American

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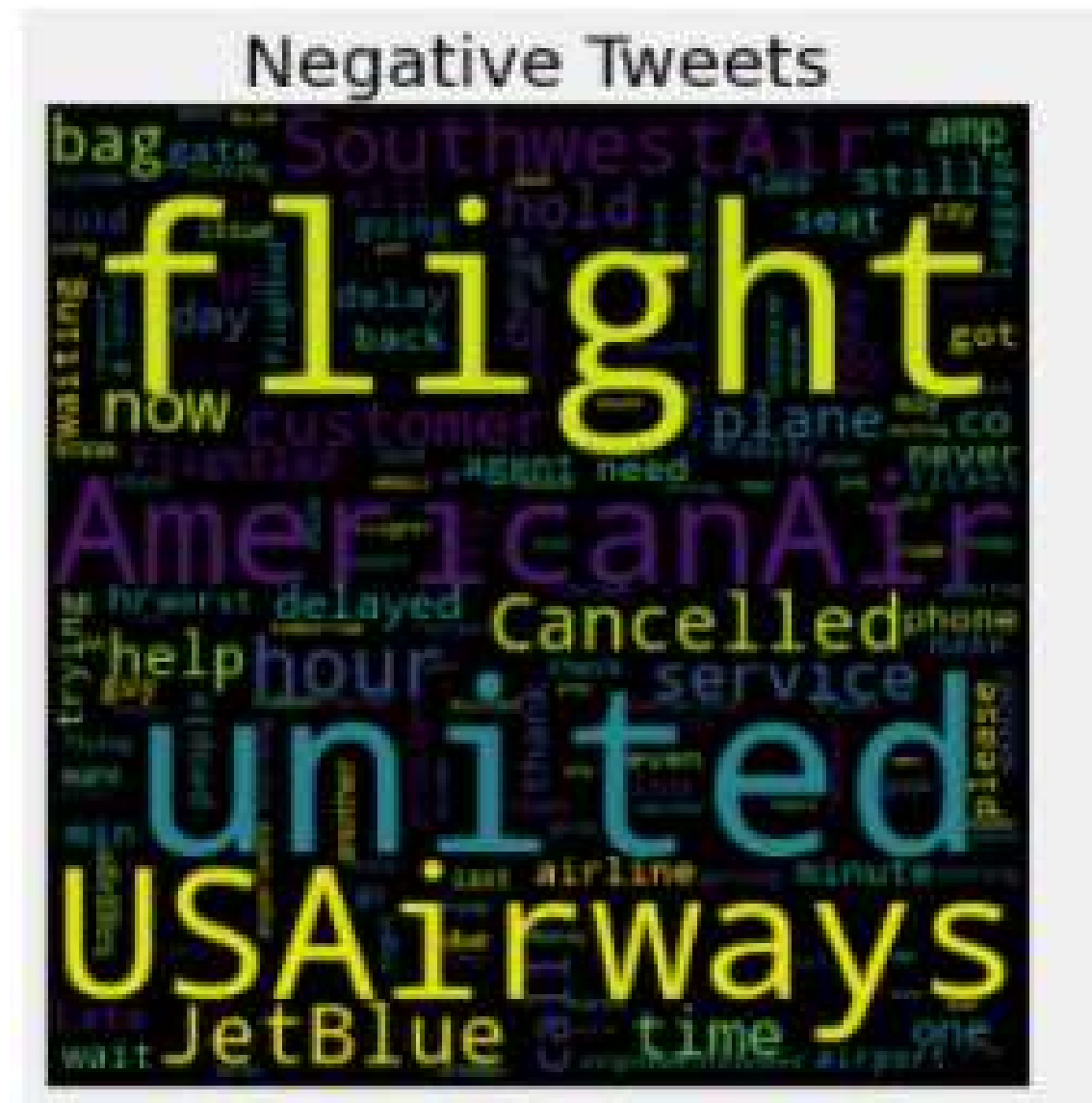


Figure 12: Negative Words



Positive Word Cloud

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- Words with negative emotions include thanks, great, etc.

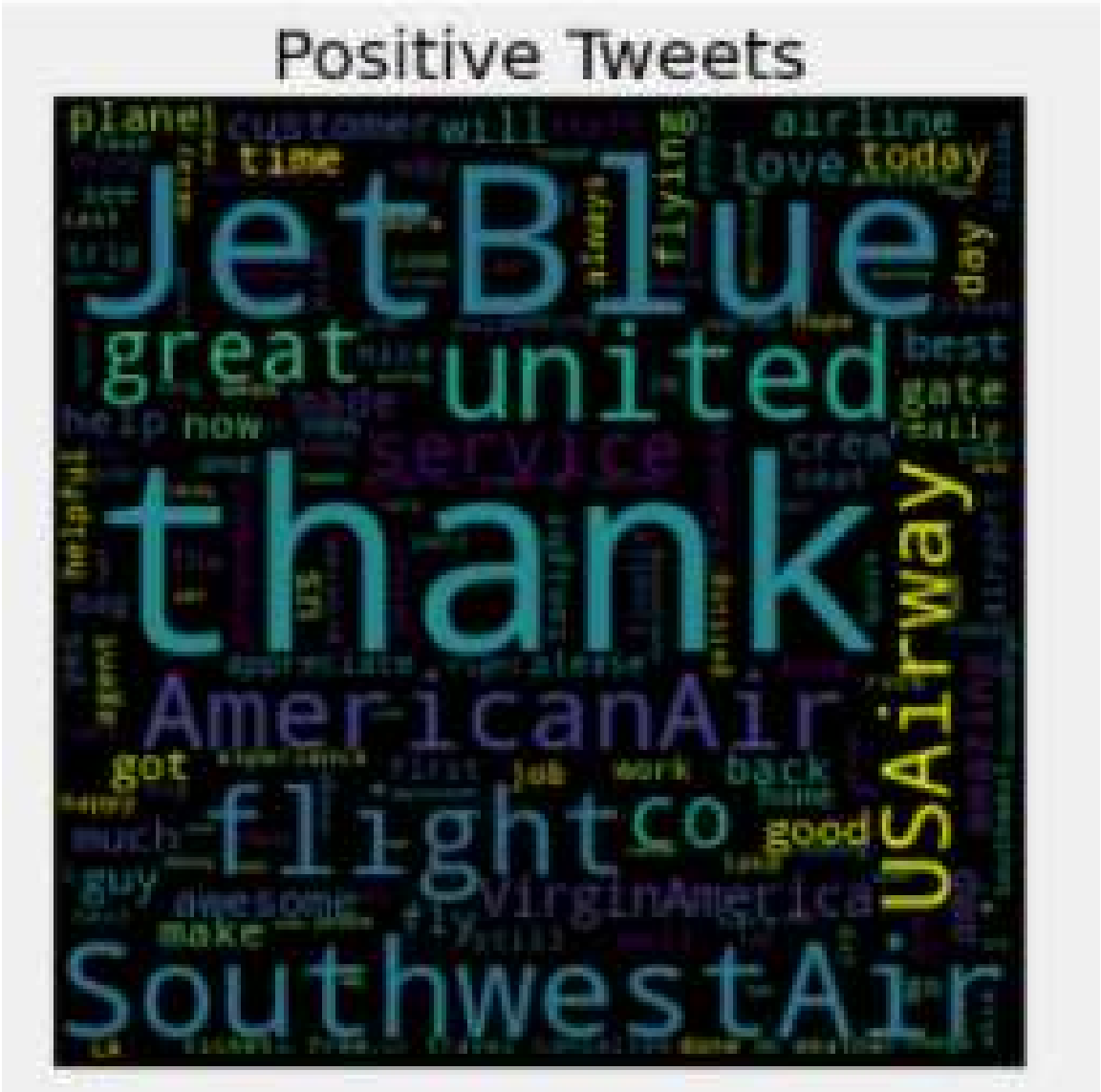


Figure 13: Positive Words

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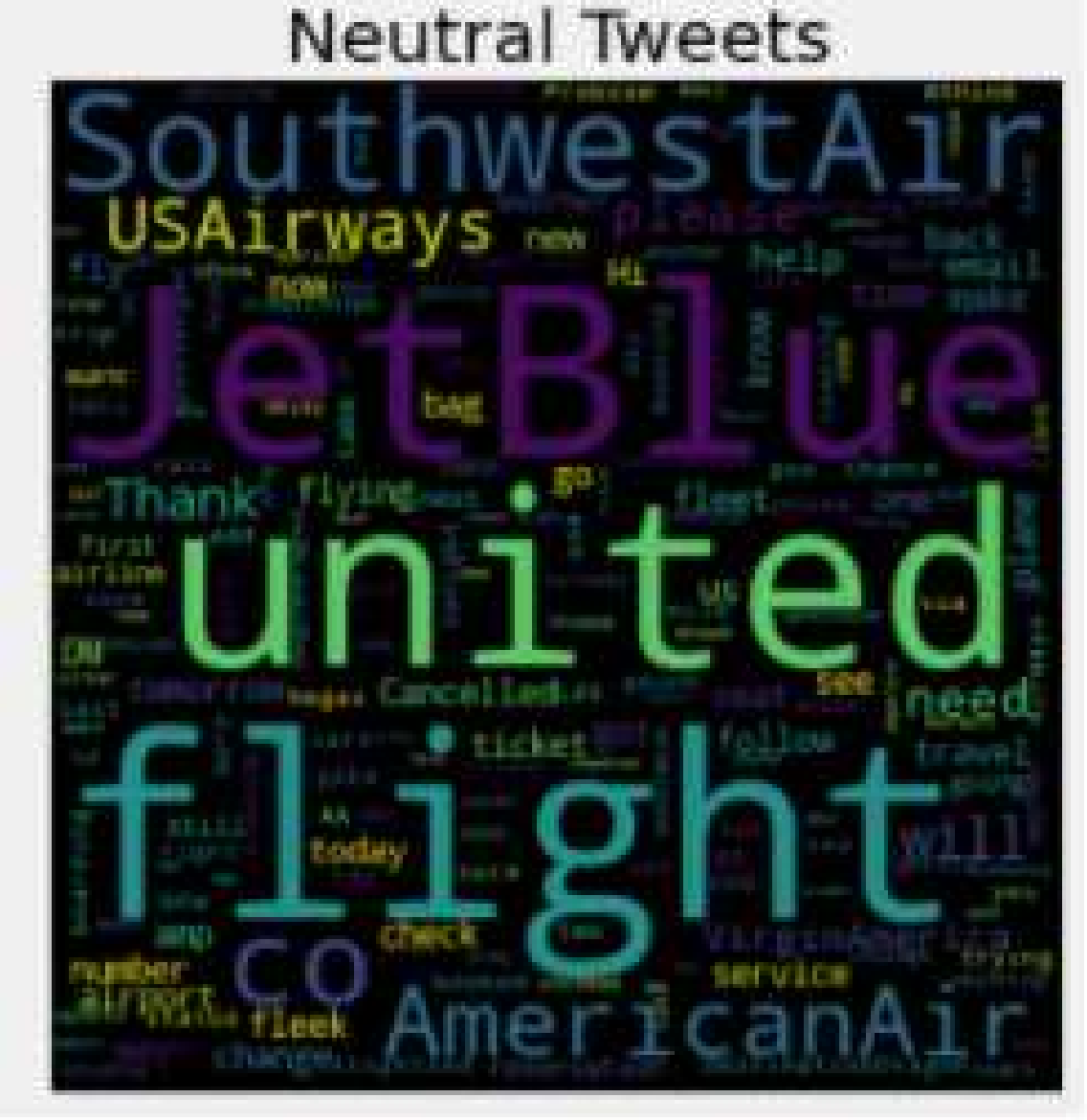


Figure 14: Neutral Words



Negative Reason

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- Perform statistical tactics on the causes of negative attitudes.

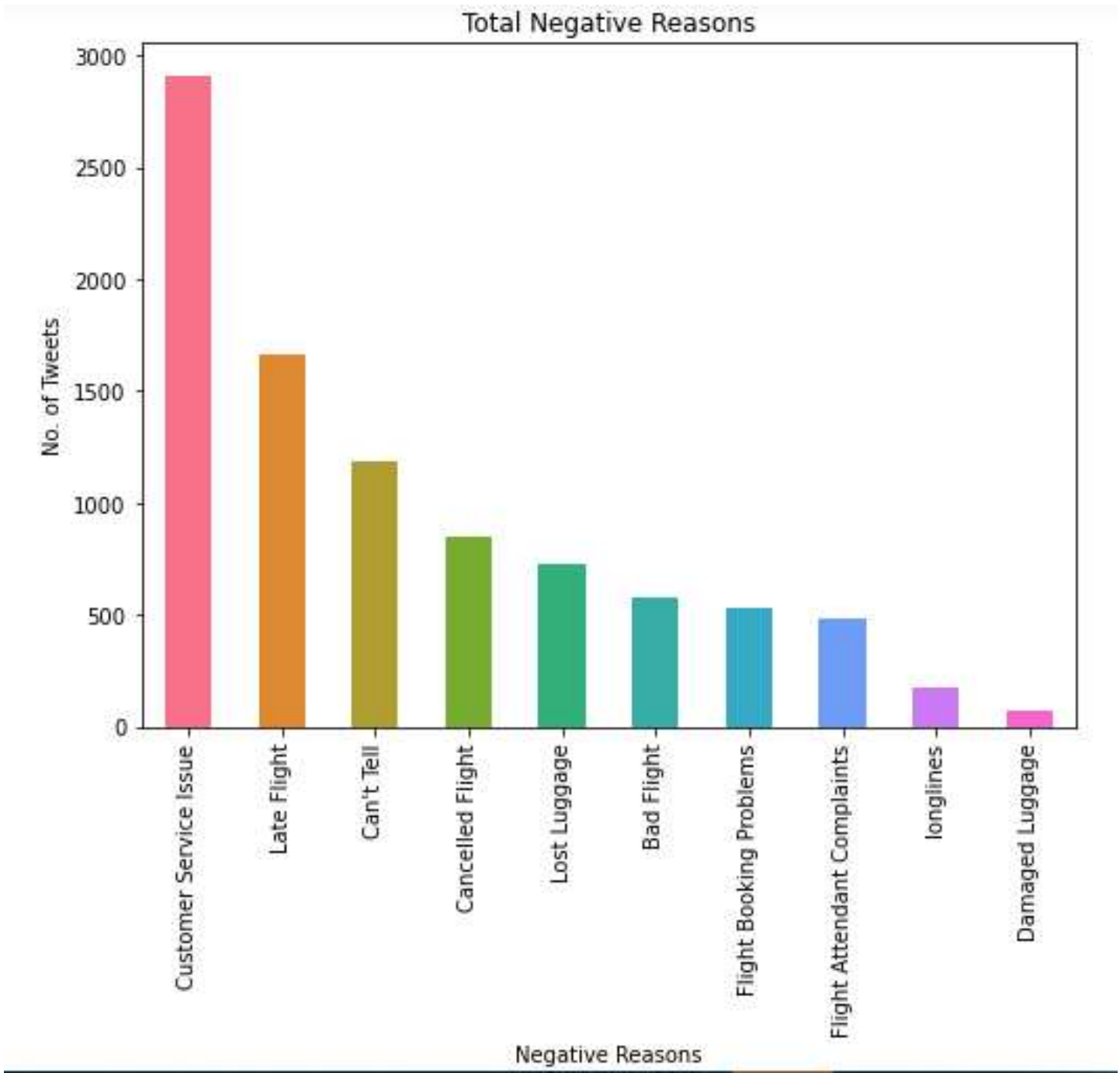


Figure 15: Total Negative Reasons



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Data Processing



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- Processing data independent of results.
 - ◆ For example:tweet_id,name,tweet_location,tweet_coord etc
- Normalization of training data and test data.
 - ◆ For example:airline_sentiment,airline etc
- Split train and test data.





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- Random Forest
- Gradient Boosting
- LSTM RNN

Table 2: Comparative Results

Model	Accuracy
Random Forest	0.8135245901639344
Gradient Boosting	0.8265027322404371
LSTM RNN	0.8865852952003479



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- On this issue, the new model is better than the traditional machine learning model.
- Pay attention to the adjustment of parameters when training the model.
- Other models can be used to further improve accuracy.