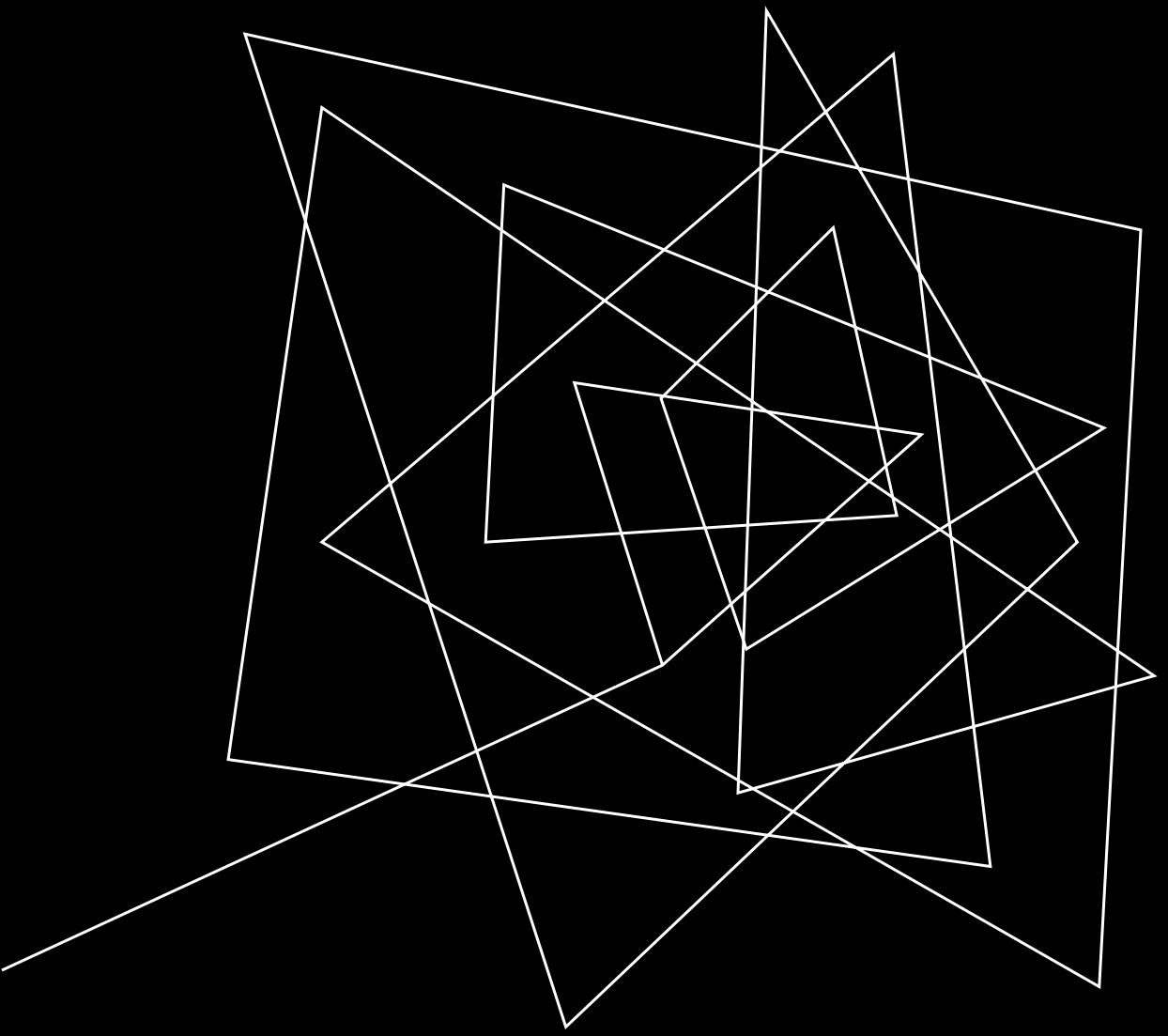

AIRLINE SENTIMENT ANALYSIS

By Yesim Cebeci

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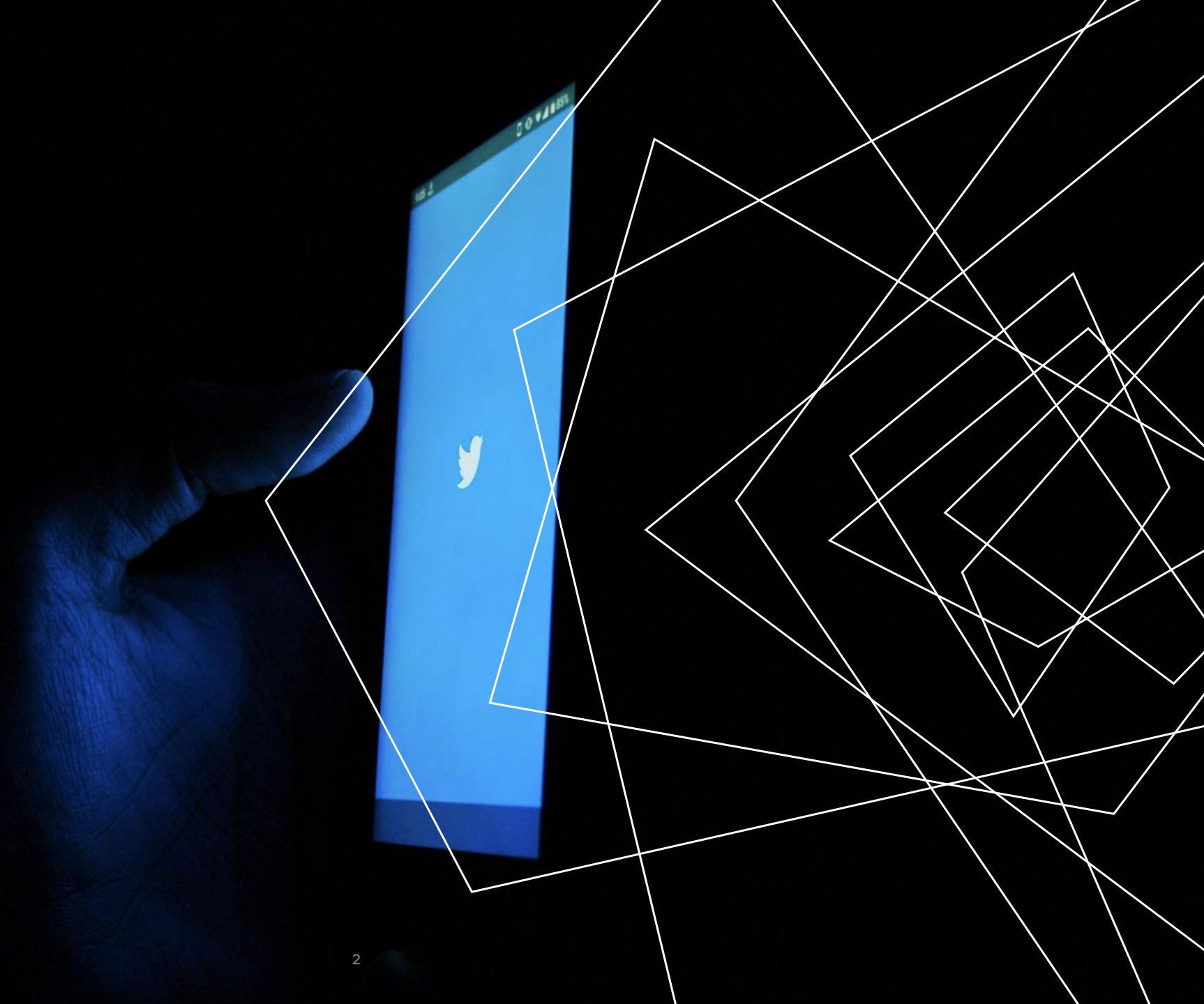

BUSINESS UNDERSTANDING

Airline companies aim to use a model to identify unhappy customers and direct negative tweets to the proper channel.

One way to do this negative tweets can be identified using sentiment analysis and redirected to customer service with a bot.

By implementing this system , Airline Companies can improve customer satisfaction, increase brand loyalty by addressing negative feedback.

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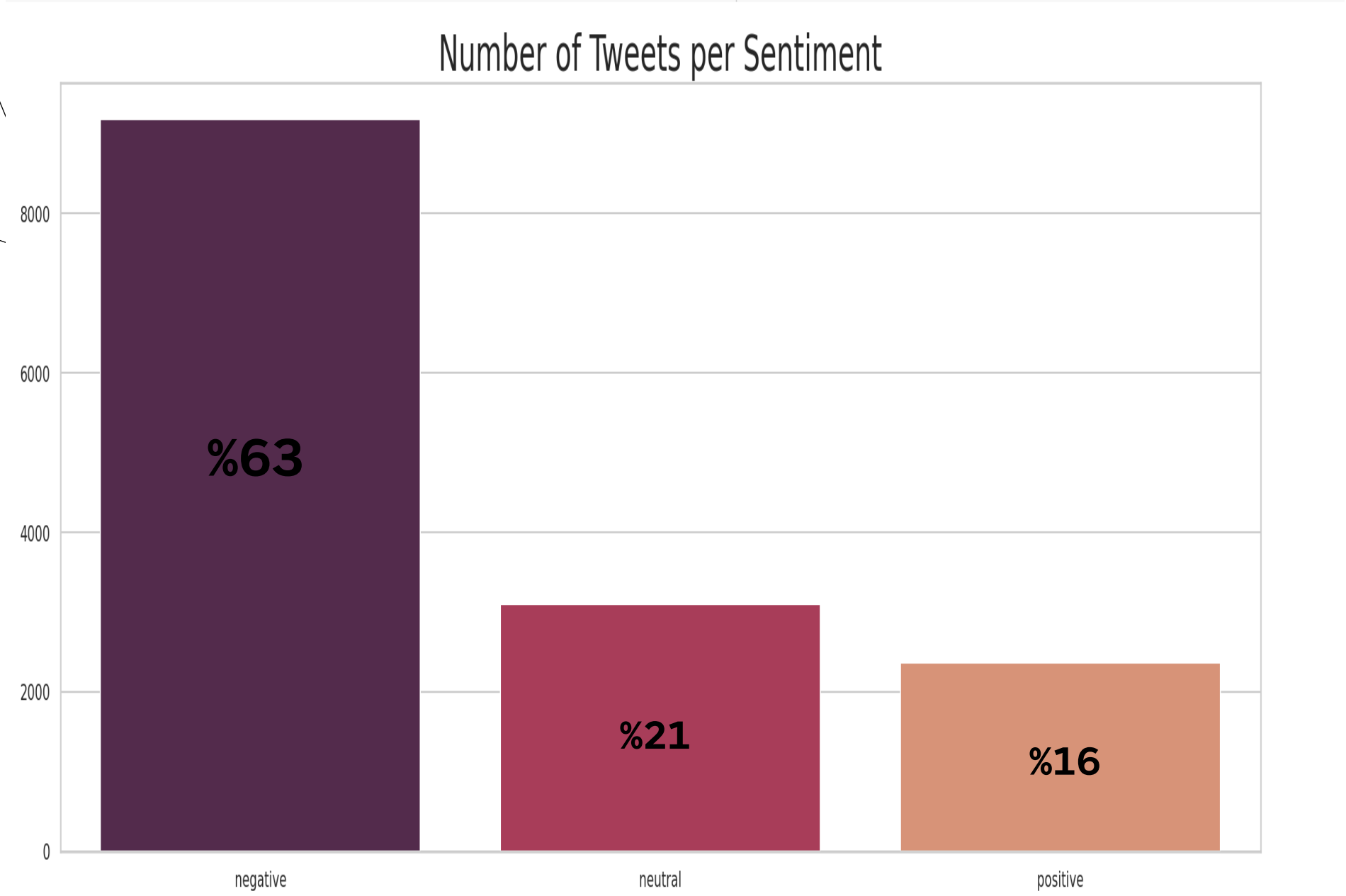
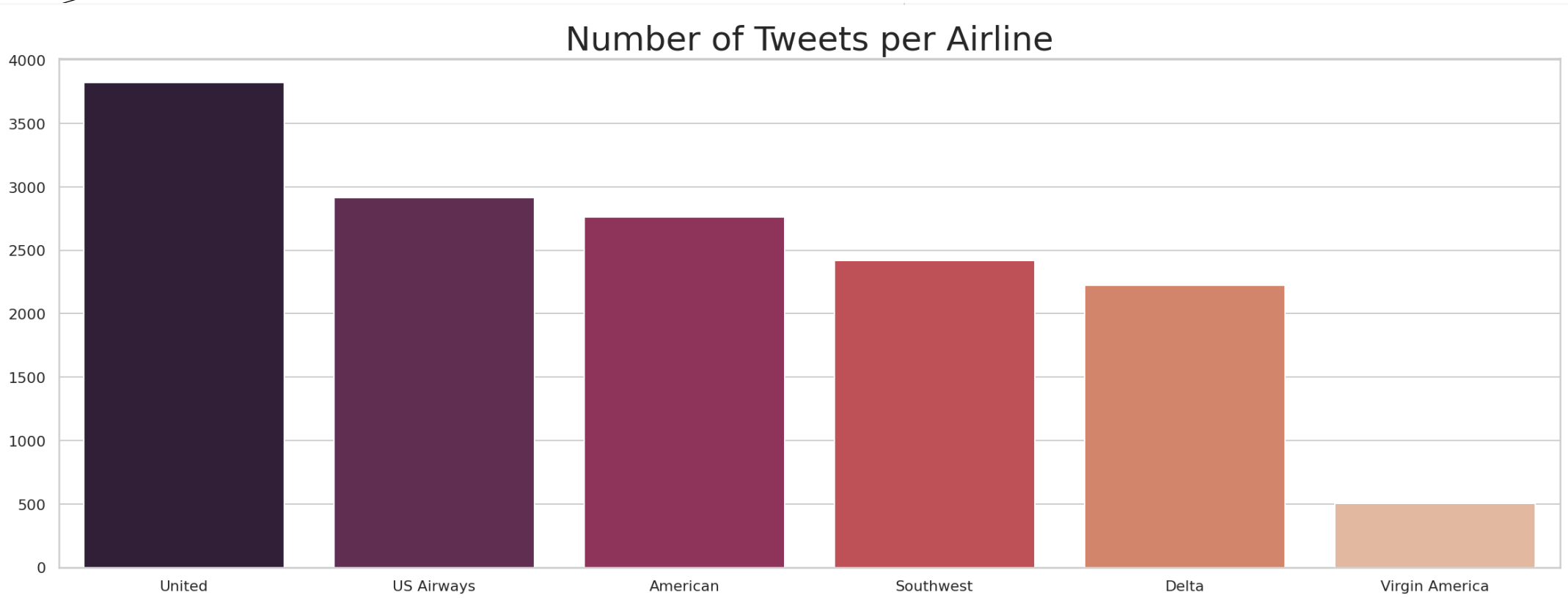
DATA UNDERSTANDING

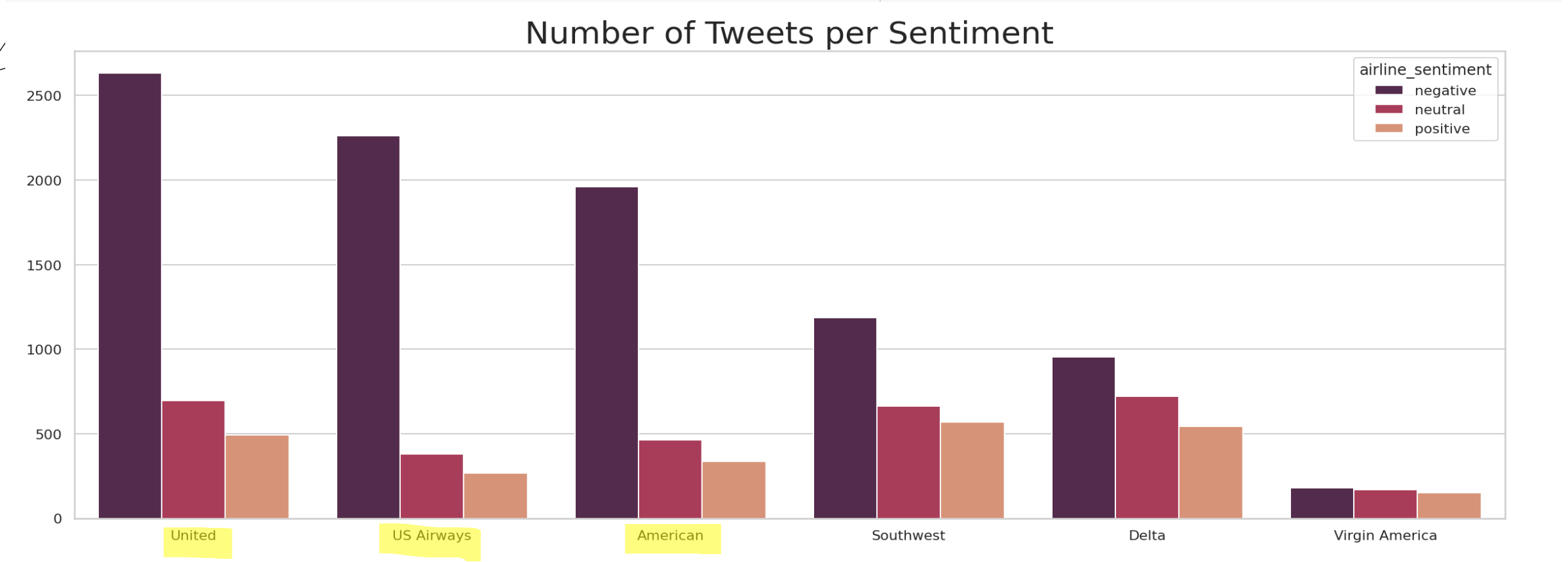
- The dataset used in this project is provided on Kaggle.
- This Twitter data was scraped on **February 2015**
- It contains tweets on six major United States (US) airlines: **United, Us Airways, American, Soutwest, Delta** and **Virgin America.**
- Mainly focusing on "**airlines" , "airline_sentiment"** and **"text"** columns

- Tweets are overwhelmingly **negative**.
- This is an imbalanced dataset.



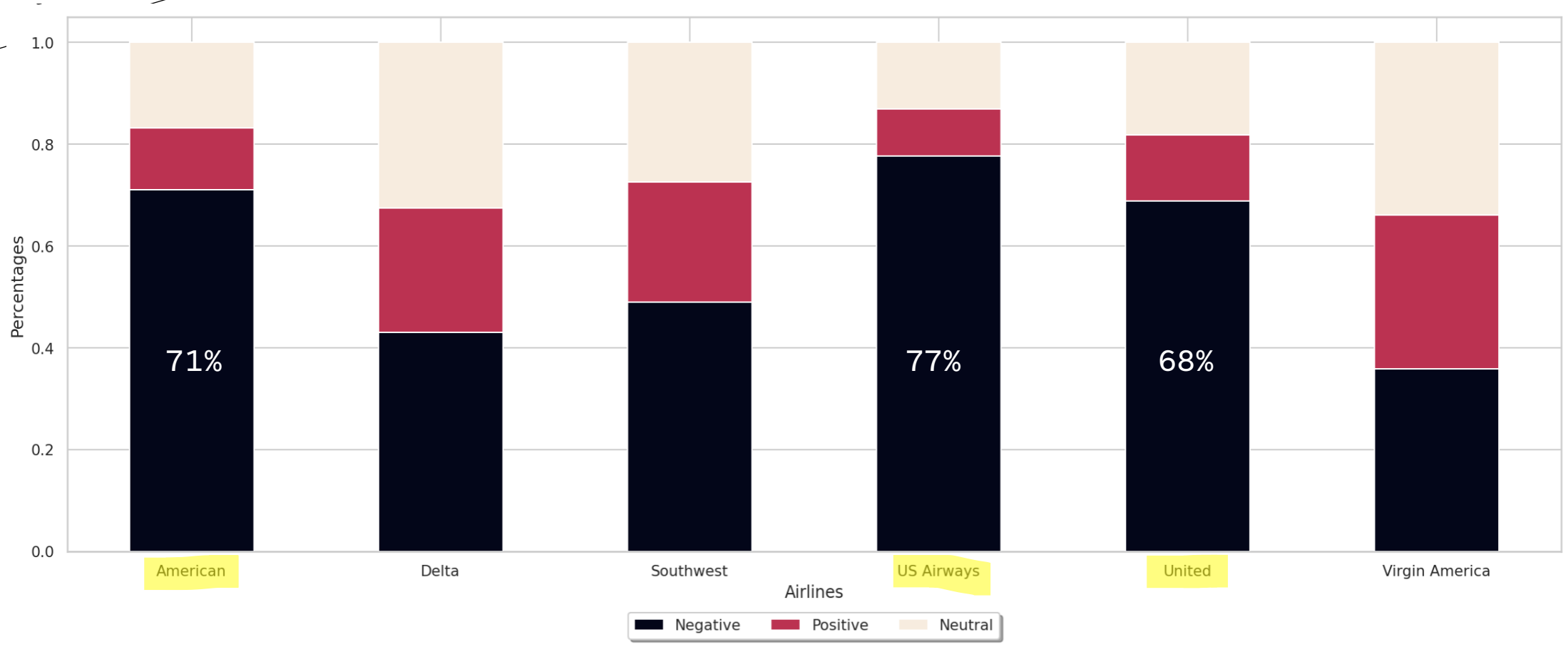


- Most of the tweets belongs to **United Airlines** and followed by **US Airways and American.**



- The number of negative sentiments, **United Airline** ranks the first, followed by **US Airways Airline** and **American Airline**

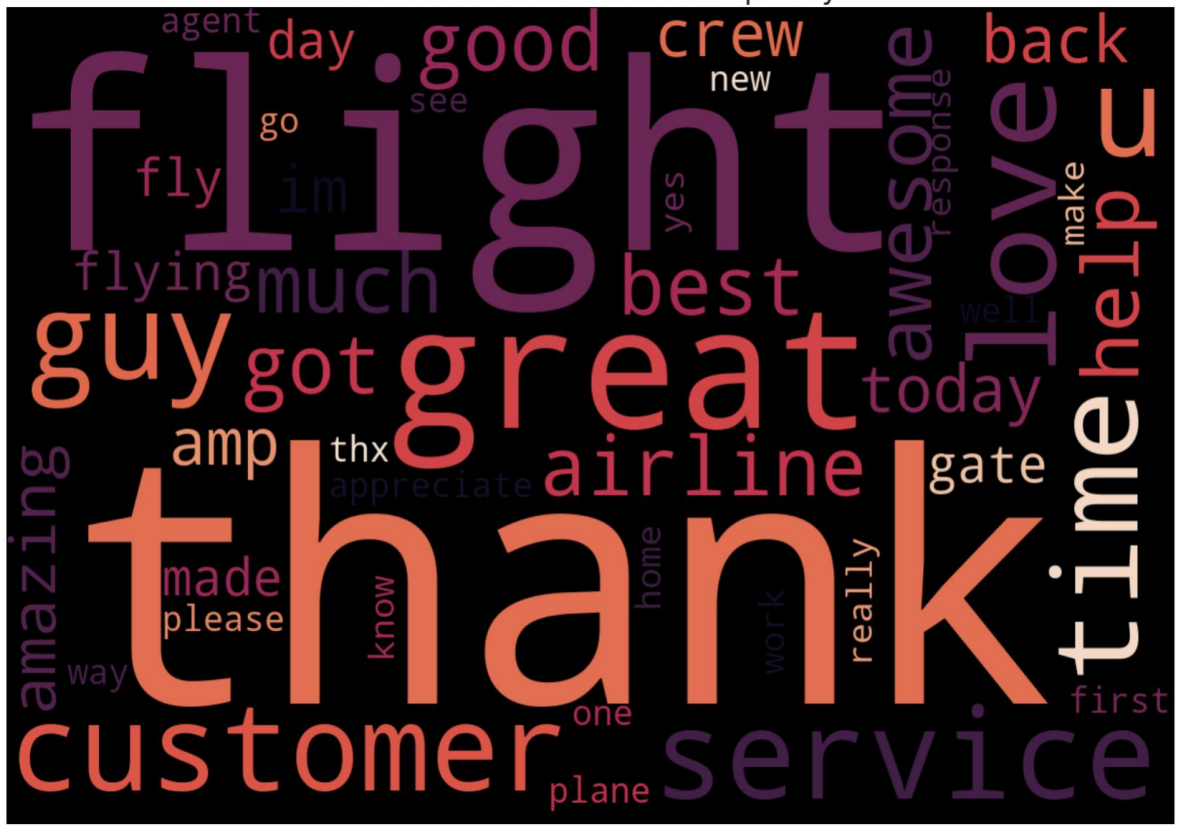
- The numbers of negative, neutral and positive sentiments for **Virgin America Airline** is fairly balanced.



- **US Airways** has the highest proportion of negative sentiments at **77%,** followed by **American Airlines** at **71%**.

- **Virgin America** has highest percentage positive tweets.

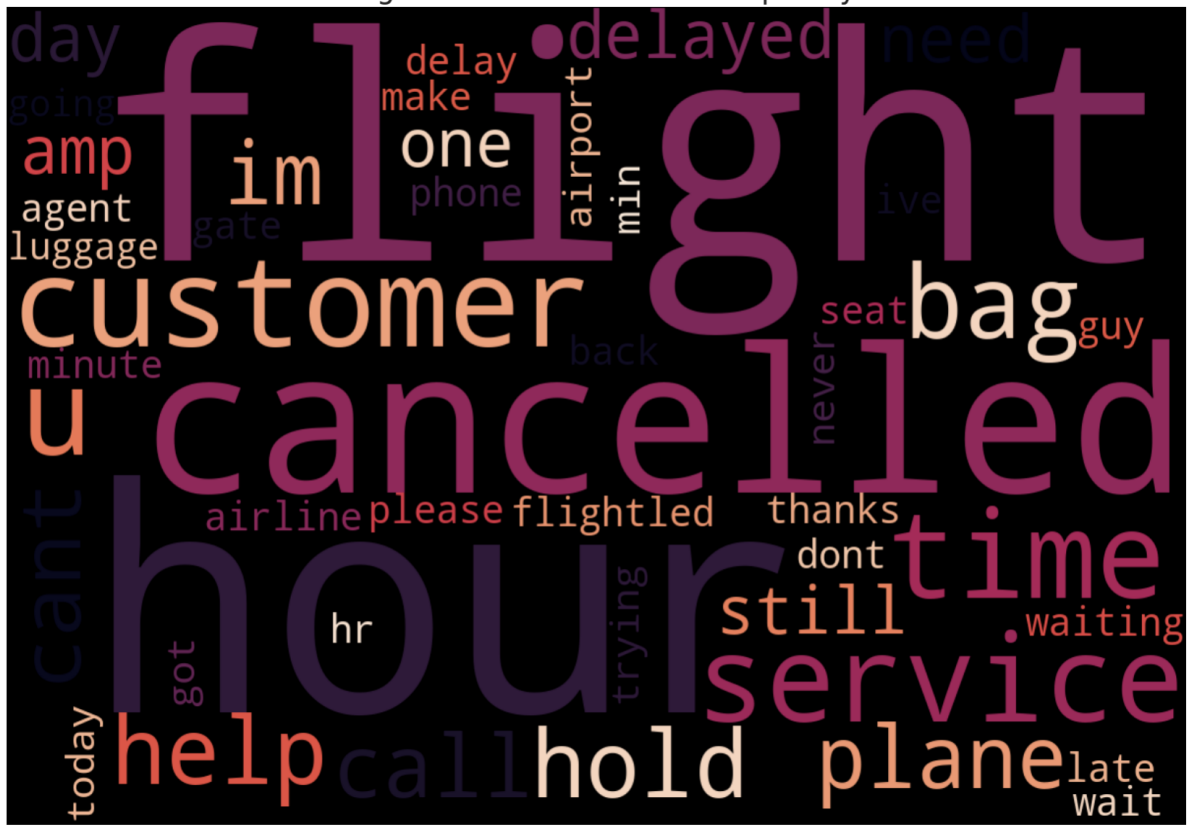
Positive Feedback Word Frequency



- Positive sentiments mostly consist of words such as **'thank,' 'flight,'** and **'great'**.
- This shows people tend to appreciate the airline on social media when they have positive flight experience

- Hey @united you've upgraded me on a 10 hour International flight. I forgive you :-) thank
- @JetBlue great flight on a brand new jet. Great seating. Beautiful plane. Big fan of this airline.

Negative Feedback Word Frequency



- Tweets related to **"flight"** and **"hour"** are causing the most negative tweets.
- **"canceled"**,**"delayed"**, **"customer"** and **"service"** have higher frequencies than other words

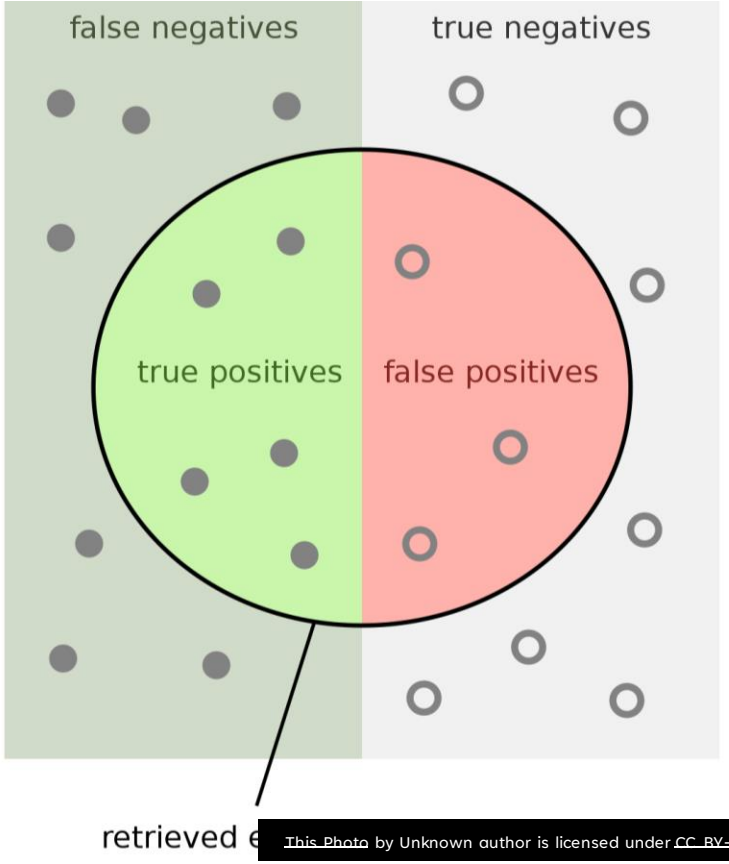
- @united 4840 WTF! Why can't you update your times in a timely manner? You've known the fight was more delayed! Ur service is awful!
- @united still no refund or word via DM. Please resolve this issue as your Cancelled Flightled flight was useless to my assistant's trip.

METRIC TO USE: F1-SCORE

- **False Positive:** Model predicts negative tweet but it's actually positive, leading to wrong customer service response and wasting company time/money.

- **False Negative:** Model predicts positive tweet but it's actually negative, leading to lack of proper customer service and potential loss of customer

- To balance the downsides of False Positive and False Negative, F1-Score is used to find maximum negative sentiment tweets while avoiding incorrect customer service actions.



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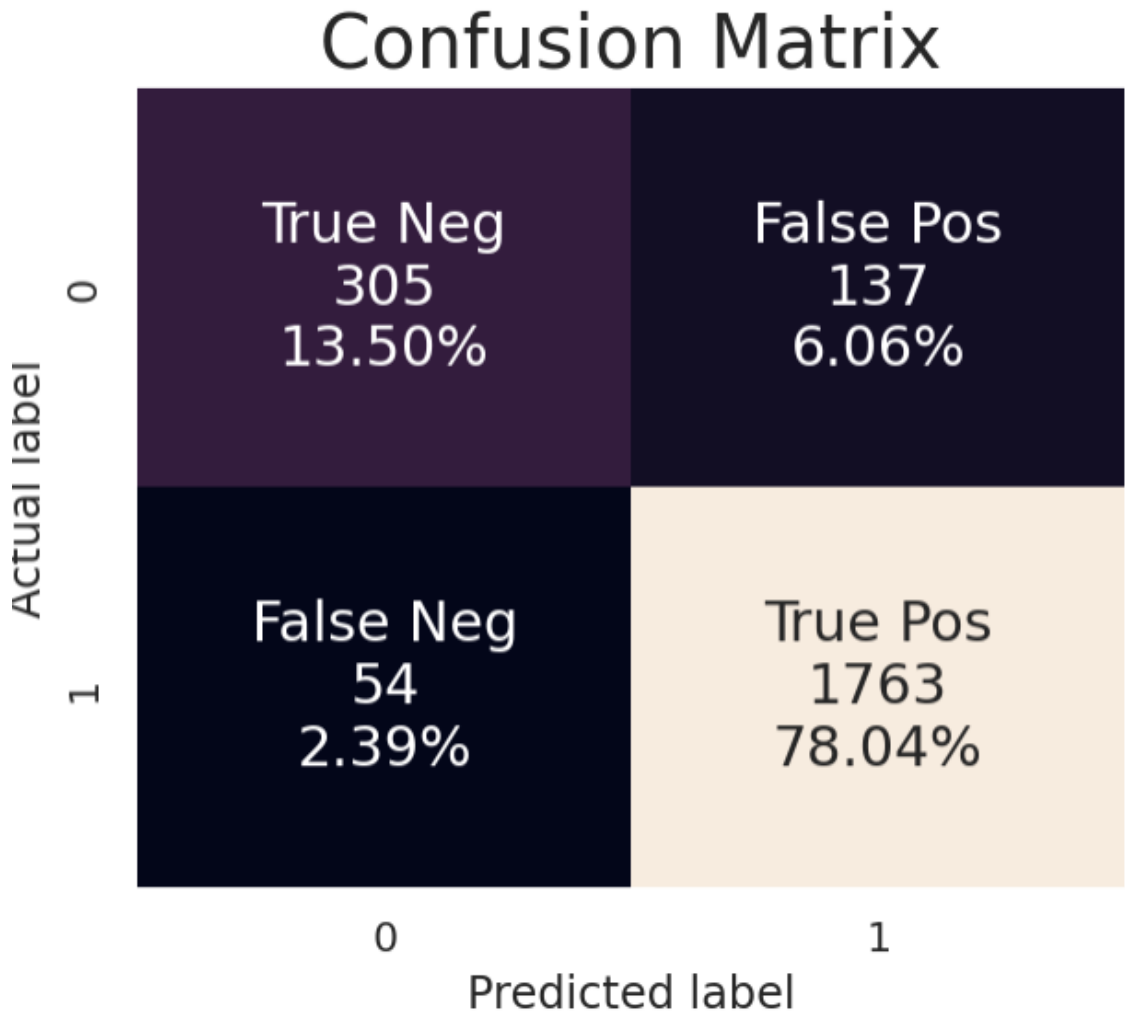
BEST PERFORMING MODEL

- Throughout the project ,Our goal was reducing False Negatives and False Positives
- Best F1 score were achieved through parameter tuning with GridSearch on Support Vector Classifier



CONCLUSION

- The model appears to be working effectively and making accurate predictions in general
- Interpreting sentiment in text can be difficult due to factors like sarcasm and irony

Tweets	Predicted Sentiment
"@united that's cool - now what?"	Positive
"counter agents at RDU deserve a medal. #thankyou"	Positive
" I'm rebooked now, but the line was 300 people deep. "	Negative
"@united @retailbagholder hahaha. At least they gave u a refund."	Negative

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RECOMMENDATION

- We would need a cost analysis of the false positives and compare them to the false negatives to determine the next best step for the airlines.
- The bot might offer personalized solutions based on the negative sentiment reason. For example, if a customer is dissatisfied with flight delays, we might offer alternatives such as offering a discount or refund.
- This model can be used for airlines based on specific business needs

NEXT STEP

- The data was limited to tweets from February 2015, it is probable that collecting data for the entire year would result in a more robust and generalizable model.
- According to the analysis the data set contains way more negative tweets than positive ones. Future works may focus on obtaining a more balanced and larger dataset for better classifier model performance.
- A tweet can have positive language, but the user can be using sarcasm which can throw the model off. With more time, we should look deeper into this.

THANK YOU

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