# DETECTING AIRLINE TWITTER SENTIMENT

Mariya Graff

# CONTENTS

# 1. CONTEXT

Labeling a tweet as negative or positive is a pretty easy task when you're a human.
But unfortunately, that's hard to scale...

I set out to put Vader (along with other ML tools) to the test in identifying negative tweets
about 6 major US airlines.

I tested the results against human labels with a Logistic Regression,
and then mapped out the negative tweets to main topics.

# 2. METHODOLOGY

Data:

Twitter US Airline Sentiment

Kaggle dataset with over 14,000 tweets and 10 features scraped in February 2015

https://www.kaggle.com/crowdflower/twitter-airline-sentiment

Tools:

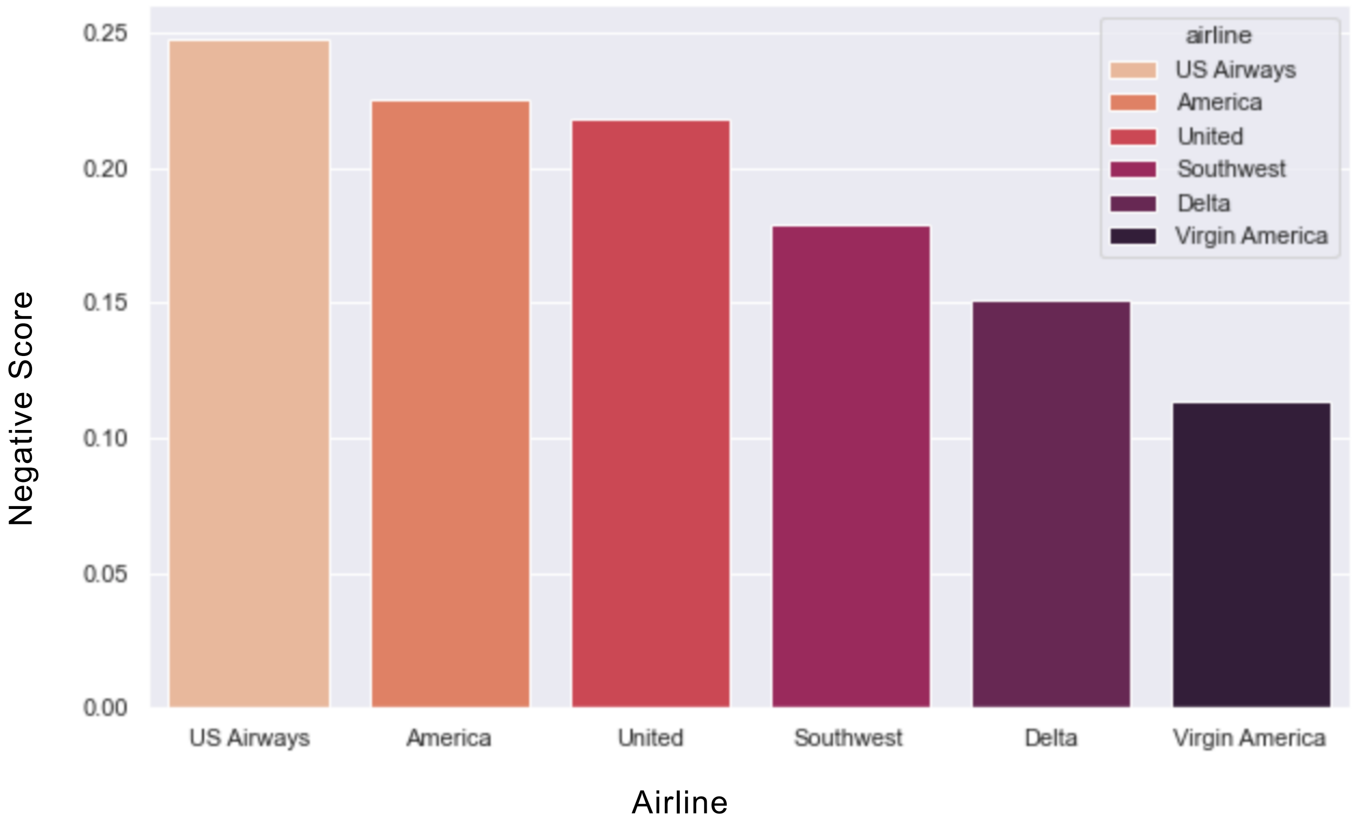
Text pre-processing and EDA: SQL, Pandas, Numpy, SQL, NLTK: stopwords, , MWETokenizer, WordNetLemmatizer, RegEx

Modeling: vaderSentiment, sklearn: CountVectorizer, TfidfVectorizer, NMF; Logistic Regression, CorEx, gensim: Word2Vec

Visualizations: Matplotlib, Seaborn

# 3. SENTIMENT ANALYSIS

```
Delta:  {'neg': 0.151, 'neu': 0.643, 'pos': 0.206, 'compound': 1.0}
United:  {'neg': 0.218, 'neu': 0.614, 'pos': 0.168, 'compound': -1.0}
Southwest:  {'neg': 0.179, 'neu': 0.616, 'pos': 0.205, 'compound': 1.0}
US Airways:  {'neg': 0.248, 'neu': 0.608, 'pos': 0.144, 'compound': -1.0}
Virgin America:  {'neg': 0.114, 'neu': 0.695, 'pos': 0.191, 'compound': 0.9999}
American:  {'neg': 0.225, 'neu': 0.619, 'pos': 0.156, 'compound': -1.0}
```




United, US Airways and American have an <u>overall</u> sentiment score of -1, or negative.

Delta, Southwest, Virgin America have an <u>overall</u> sentiment score of 1, or positive.

# 4. LOGISTIC REGRESSION

A multinomial logistic regression to compare Vader's results to human labels

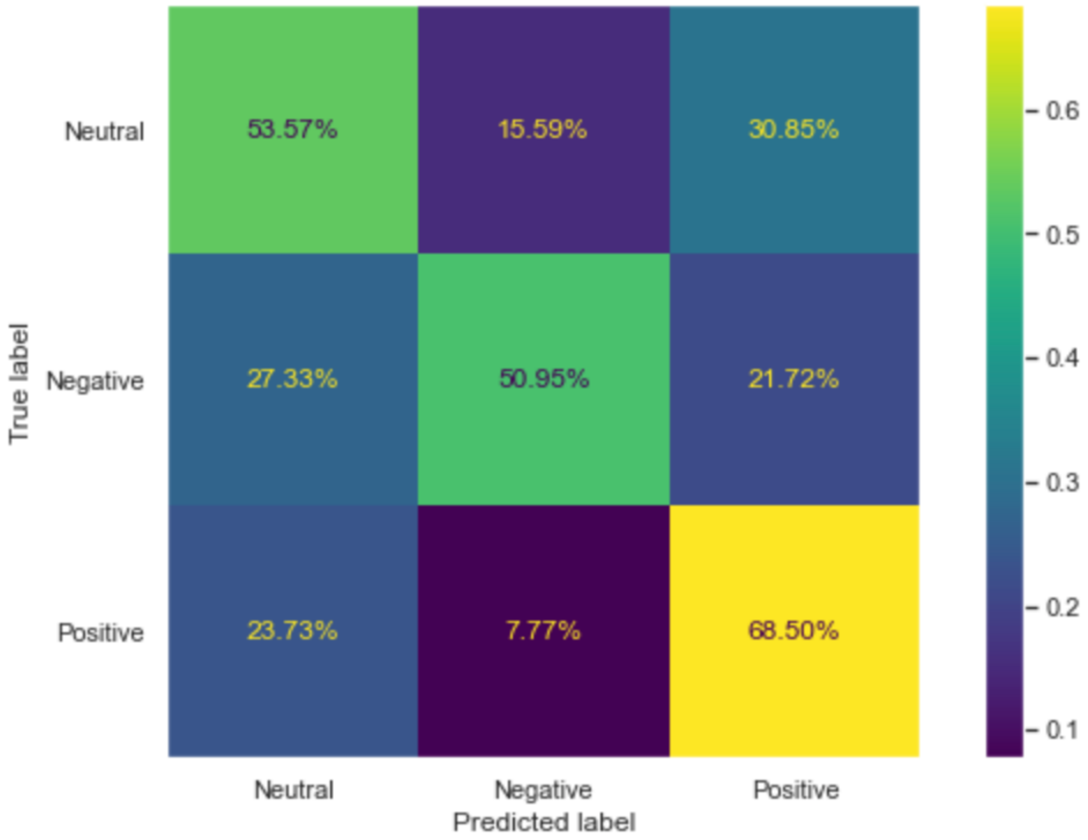
Accuracy: 0.54

Negative Class precision: 88%

# 4. LOGISTIC REGRESSION

C=10

## CountVectorizer




| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.35 | 0.54 | 0.42 | 911 |
| 1 | 0.88 | 0.51 | 0.64 | 2726 |
| 2 | 0.36 | 0.69 | 0.47 | 708 |
| accuracy | | | 0.54 | 4345 |

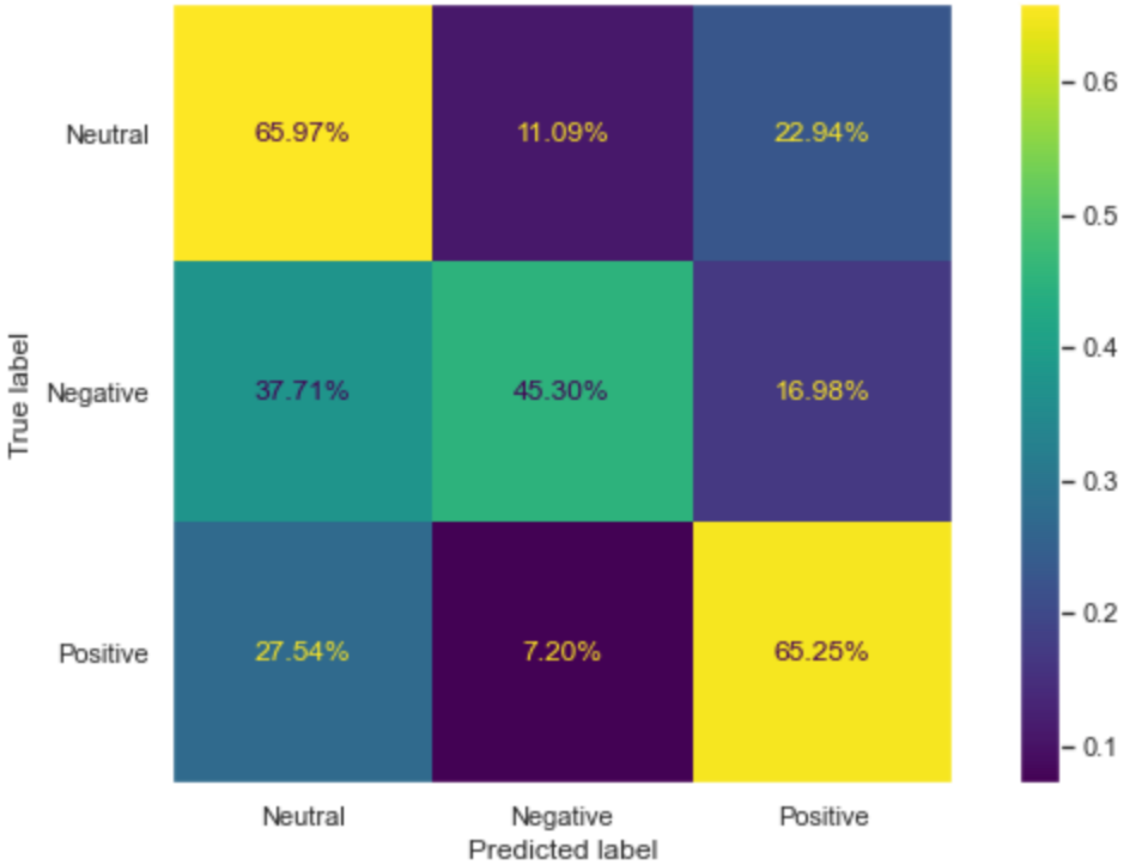
Accuracy: 0.53

Negative Class precision: 89%

# 4. LOGISTIC REGRESSION

C=1, class_weight='balanced'

## TfidfVectorizer




| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.33 | 0.66 | 0.44 | 911 |
| 1 | 0.89 | 0.45 | 0.60 | 2726 |
| 2 | 0.41 | 0.65 | 0.50 | 708 |
| accuracy | | | 0.53 | 4345 |

# 5. TOPIC MODELING OF NEGATIVE TWEETS (COREX)

1: problems, booking, online, number, change, plane, phone, website, reservation, sitting

2: airport, going, pay, people, seat, stuck

3: leave, line, service, tell, terrible, thanks, told, wrong

4: disappointed, getting, passenger, poor, refund, sorry, travel, weather, work

5: agent, answer, bad, baggage, boarding, day, flt, horrible, hour, know

6: experience, got, issue, like, new, really, ridiculous, right, said, seriously

7: check, email, fail, finally, let, luggage, make, pm, trip

8: ago, jfk, morning, pilot, response, voucher, way

9: called, guy, missed, stop, today, unacceptable, update

10: customer, dfw, flying, home, hotel, left, minute, problem, rebook, rude

1. Issues with booking, changing flights/reservations
2. Being stuck in the airport or on the plane
3. Wrong information, lack of clarity from support
4. Refunds for weather delays/flight cancelation
5. Gate agents, waiting at the gate
6. Technical issues on flight/with plane
7. Late arrivals/luggage claim
8. Flight delays at the airport, hotel/food vouchers
9. Problems reaching customer support
10. Issues with connecting flights when flying home

1: problems, booking, online, number, change, plane, phone, website, reservation, sitting

2: airport, going, pay, people, seat, stuck

3: leave, line, service, tell, terrible, thanks, told, wrong

4: disappointed, getting, passenger, poor, refund, sorry, travel, weather, work

5: agent, answer, bad, baggage, boarding, day, flt, horrible, hour, know

6: experience, got, issue, like, new, really, ridiculous, right, said, seriously

7: check, email, fail, finally, let, luggage, make, pm, trip

8: ago, jfk, morning, pilot, response, voucher, way

9: called, guy, missed, stop, today, unacceptable, update

10: customer, dfw, flying, home, hotel, left, minute, problem, rebook, rude

# 6. SIMILAR BY SENTIMENT

A few key words with a list of similar sentiment words from the tweet body.

| LATE: | CONNECTION: | REFUND: |
| --- | --- | --- |
| plane, | departure, | booked, |
| sitting, | pm, | tried, |
| delayed, | JFK, | can't, |
| still, | stuck, | system, |
| tarmac, | miss, | error |
| gate | CLT | |

# 7. SUGGESTIONS AND NEXT STEPS

To reduce negative public sentiment, airlines should:

- Improve real-time updates sent directly to customers via text/app alerts
- Improve online self-service for changing/updating flights, seats, etc to eliminate intermediares
- Provide extra support to connection flight hubs like JFK or DFW
- Incentivize loyalty by providing concessions, however small, for inconveniences

# 9. SUGGESTIONS AND NEXT STEPS

- Model change in sentiment over time
- Test the model on current tweets
- Train other predictive models like Random Forest and Naïve Bayes

THANK YOU!