

Twitter US Airline – Sentiment Analysis

Dataset from Twitter

- 14,640 thousand tweets
- 15 Features
- 6 US Airlines
- Positive | Neutral | Negative



Aligns with a business problem

- How to stop negative tweet trends before they go out of control?
- Identify the early tweets accurately -> Sentiment Analysis!

Presents an interesting ML/Data challenge

Data is messy (Twitter character limit, slang, emojis, @ and #)



Loading Data

Loading Data

- Available as CSV and SQL
- UTF-8 encoding to preserve emojis

Check for NULL Values

```
Column 'negativereason' has a few missing nulls, but they are null only if 'airline_sentiment' is positive or neutral.

df_tweets['negativereason'].isnull().sum()

5462

df_tweets['airline_sentiment'].loc[df_tweets['negativereason'].isnull()].unique()

array(['neutral', 'positive'], dtype=object)
```



Cleaning Data

- Twitter data notoriously unclean
 - Character limit forces non-standard English



- Remove noise for sentiment analysis
 - @ Mentions, RT re-tweets
- Retain value-adds
 - Emojis , hashtags #
 - Add important context and content







- Clean text itself
 - Remove HTML, translate slang, remove STOP words and grammar, lemmatize



Data Cleaning Challenges

- How to extract emojis?

```
emot 2.1

pip install emot
```

```
Name: emojis_flag, dtype: object
18  [♥, ⊕, ♣]
Name: emojis, dtype: object
18   I ♥ flying @VirginAmerica. ⊕♣
Name: text, dtype: object
18   I ♥ flying . ⊕♣
Name: text_cleaned, dtype: object
18   I flying .
Name: text_cleaned_without_emojis_emoticons, dtype: object
```



Data Cleaning Challenges

Extract Hashtags?

```
def extract_and_remove_hashtags(df_tweets):
    regex_to_replace= r'#(\w+)'
    replace_value= ''
    df_tweets['hashtags'] = ''
    df_tweets['text_cleaned_without_emojis_emoticons_hashtags'] = ''

    for i, row in df_tweets.iterrows():
        df_tweets.at[i, 'hashtags'] = re.findall(regex_to_replace, df_tweets.at[i, 'text_cleaned'])
        df_tweets.at[i, 'text_cleaned_without_emojis_emoticons_hashtags'] = re.sub(regex_to_replace, replace_value, df_tweets.at[i, 'text_cleaned'])
```

Text to lowercase

Convert Slang

Find and replace based on an existing dictionary





Text Cleaning

- Remove stop words
 - o "The", "and", "You", etc. -> noise
- Remove punctuation & numbers
- Lemmatize
- Tokenize





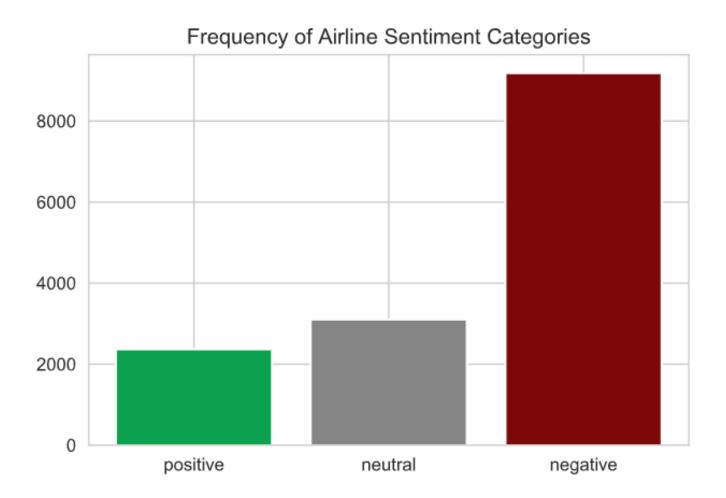
- 15 columns

- 6 main features that interest us
 - 1. airline_sentiment
 - 2. airline_sentiment confidence
 - 3. negativereason
 - 4. negativereason_confidence
 - 5. airline
 - 6. text

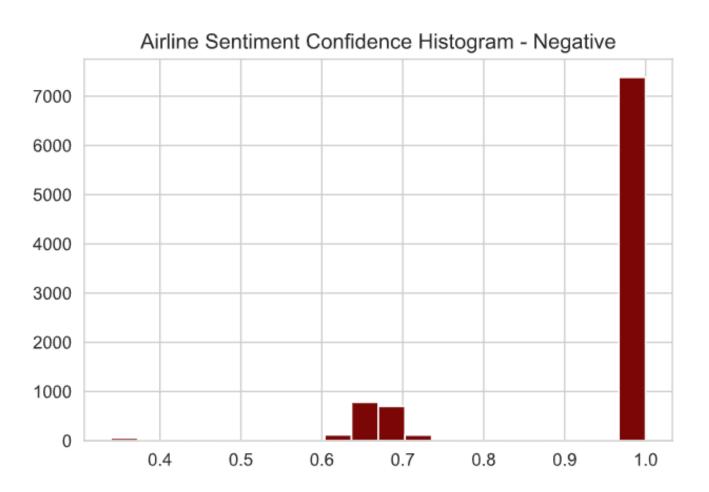
Engineered Features

- 1. emojis
- 2. emoticons
- 3. cleaned text (lemmas)

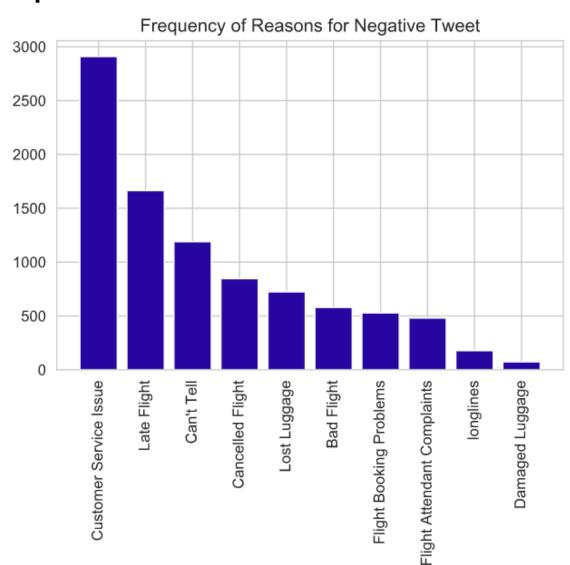




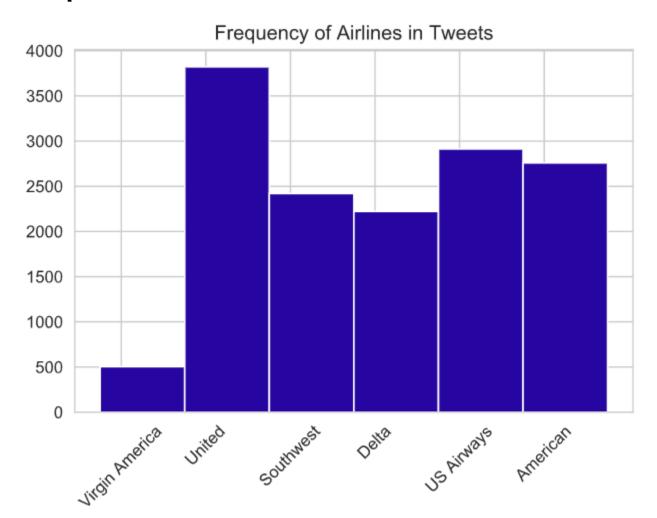














love

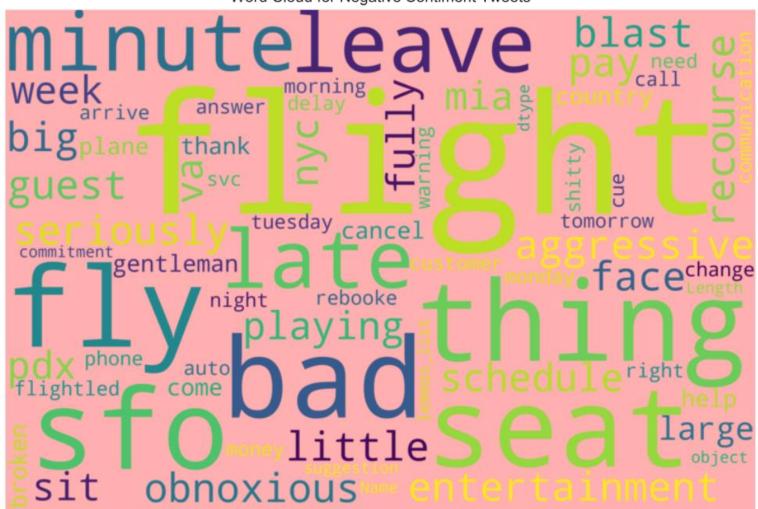
amazing minimal landing flywill time flywill day crew plane jfk

Contact away hour tacky prettyrun old conography featily arrive

concern



Word Cloud for Negative Sentiment Tweets



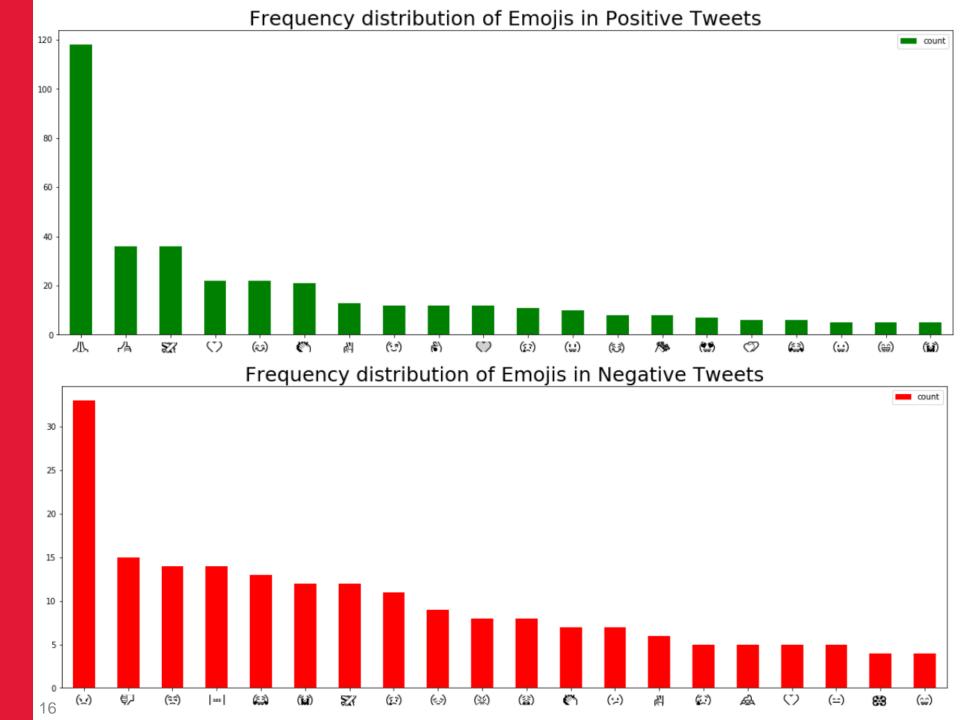


Is there value in the extracted emojis and hashtags?

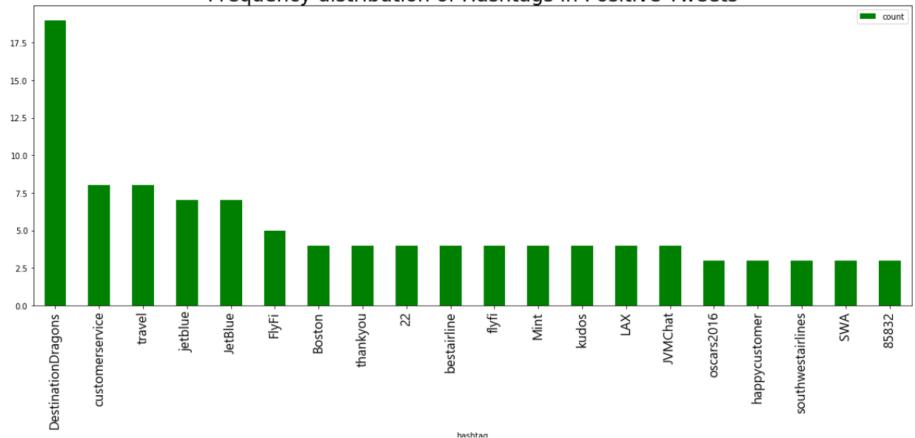
– Method:

- Plot frequency by sentiment class (positive, neutral, negative)
- If there is a clear difference emojis & hashtags are differentiators -> add context



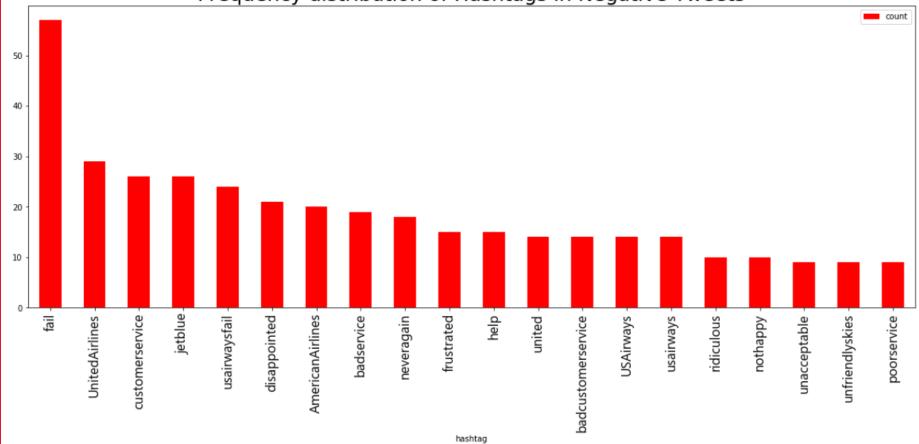








Frequency distribution of Hashtags in Negative Tweets





- Issues with our emoji, emoticon and hashtag extraction
 - Extraction process confuses non-emoticon string of characters for an emoticon
 - o E.g. time of day, airport codes
 - Hashtags could be cleaned further
 - Reduce to lowercase, remove stop words, lemmatize
 - Challenging as hashtags are not pure English



