Twitter Sentiment Analysis

+ Code + Text

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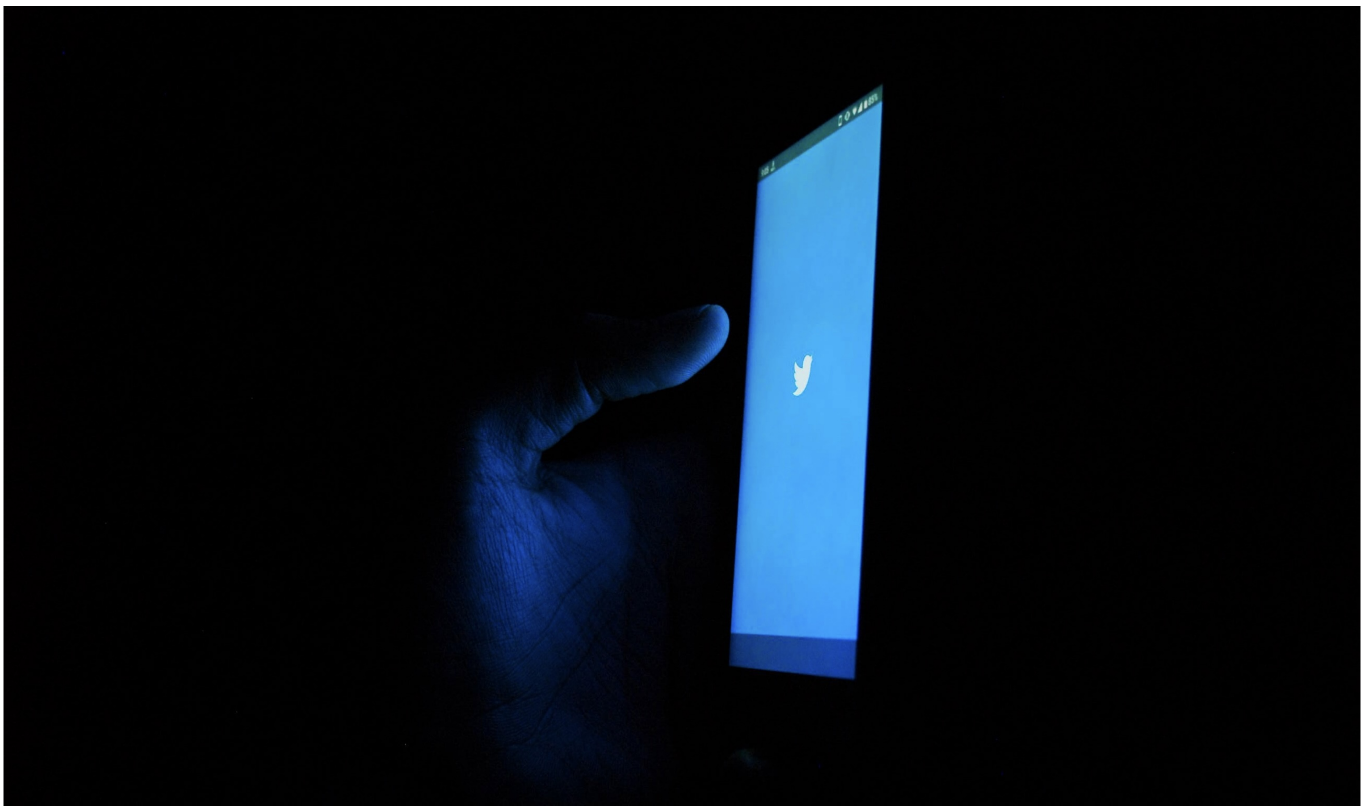
Overview

Sentiment Analysis is a type of data mining that measures the sentiment of a given text corpus, such as customer reviews or public opinion polls. It uses Natural Language Processing (NLP) algorithms to detect the sentiment of a text and assign it a polarity score, ranging from negative to positive. The polarity score helps an analyst understand which words, phrases, and topics have an impact on the sentiment of the overall text. With this information, an analyst can better understand the opinions and feelings of their readers, and target their communication strategies accordingly.



Business Understanding

Airline companies wants to use model to identify customers that are having a negative experience and direct tweets with negative sentiment towards the proper channel.

One way this might be accomplished would be to set up a bot that uses sentiment analysis to automatically identify tweets with negative sentiment, and then direct those tweets to the appropriate customer service representative or department for further assistance. This could include offering customers discounts or refunds, or providing additional support or information to help resolve any issues they may be experiencing.

By implementing this system, the airline company can improve customer satisfaction by addressing negative experiences more quickly and efficiently, increase brand loyalty by showing that they value and take action on customer feedback.

Data Understanding

The dataset used in this project is provided on Kaggle and originally collected by Crowdflower's Data for Everyone library.

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**.

Dataset has **14,640** entries and **15** columns.

We have three different target categories as positive, neutral or negative depend on tweet.

Importing Libraries

```
# importing necessary libraries for EDA and Cleaning
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('whitegrid')

import warnings
warnings.filterwarnings('ignore')

# Plotting pretty figures and avoid blurry images
%config InlineBackend.figure_format = 'retina'
# Larger scale for plots in notebooks
sns.set_context('notebook')
```

Loading Dataset

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
path = "/content/drive/MyDrive/Sentiment Analysis/Tweets.csv"
df = pd.read_csv(path)
df.head()
```

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	negativereason_confidence	airline	air:
0	570306133677760513	neutral	1.0000	NaN	NaN	Virgin America	
1	570301130888122368	positive	0.3486	NaN	0.0000	Virgin America	
2	570301083672813571	neutral	0.6837	NaN	NaN	Virgin America	
3	570301031407624196	negative	1.0000	Bad Flight	0.7033	Virgin America	
4	570300817074462722	negative	1.0000	Can't Tell	1.0000	Virgin America	

Exploratory Data Analysis

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14640 entries, 0 to 14639
Data columns (total 15 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   tweet_id                      14640 non-null  int64  
 1   airline_sentiment             14640 non-null  object 
 2   airline_sentiment_confidence  14640 non-null  float64
 3   negativereason                9178 non-null   object 
 4   negativereason_confidence     10522 non-null  float64
 5   airline                       14640 non-null  object 
 6   airline_sentiment_gold        40 non-null     object 
 7   name                          14640 non-null  object 
 8   negativereason_gold           32 non-null     object 
 9   retweet_count                 14640 non-null  int64  
 10  text                          14640 non-null  object 
 11  tweet_coord                   1019 non-null   object 
 12  tweet_created                 14640 non-null  object 
 13  tweet_location                9907 non-null   object 
 14  user_timezone                 9820 non-null   object 
dtypes: float64(2), int64(2), object(11)
memory usage: 1.7+ MB
```

```
#Check for missing values
100*df.isna().sum()/len(df)
```

```
tweet_id                         0.000000
airline_sentiment                0.000000
airline_sentiment_confidence     0.000000
negativereason                  37.308743
negativereason_confidence       28.128415
airline                          0.000000
airline_sentiment_gold          99.726776
name                             0.000000
negativereason_gold             99.781421
retweet_count                    0.000000
text                             0.000000
tweet_coord                     93.039617
tweet_created                    0.000000
tweet_location                  32.329235
user_timezone                   32.923497
dtype: float64
```

As we can see there is a lot of null values. I will be mainly focusing on the following columns:

“airline”: Name of the airline company

“airline_sentiment”: A categorical feature contains labels for tweets, positive, negative or neutral.

“negativereason”: Categorical feature which represents the reason behind considering this tweet as negative.

“text”: Original tweet posted by the user.

```
df['airline_sentiment'].value_counts()
```

```
negative    9178
neutral     3099
positive    2363
Name: airline_sentiment, dtype: int64
```

```
df['airline_sentiment'].value_counts(normalize = True)
```

```
negative    0.626913
neutral     0.211680
positive    0.161407
Name: airline_sentiment, dtype: float64
```

```
df['airline'].value_counts()
```

```
United            3822
US Airways        2913
American          2759
Southwest         2420
Delta             2222
```

```
Virgin America     504
Name: airline, dtype: int64
```

```
df['negativereason'].value_counts()
```

```
Customer Service Issue         2910
Late Flight                    1665
Can't Tell                     1190
Cancelled Flight                847
Lost Luggage                    724
Bad Flight                      580
Flight Booking Problems         529
Flight Attendant Complaints     481
longlines                       178
Damaged Luggage                  74
Name: negativereason, dtype: int64
```

```
df['negativereason_gold'].value_counts()
```

```
Customer Service Issue                        12
Late Flight                                    4
Can't Tell                                     3
Cancelled Flight                               3
Cancelled Flight\nCustomer Service Issue       2
Late Flight\nFlight Attendant Complaints       1
Late Flight\nLost Luggage                      1
Bad Flight                                     1
Lost Luggage\nDamaged Luggage                  1
Late Flight\nCancelled Flight                  1
Flight Attendant Complaints                    1
Customer Service Issue\nLost Luggage           1
Customer Service Issue\nCan't Tell             1
Name: negativereason_gold, dtype: int64
```

```
df['airline_sentiment_gold'].value_counts()
```

```
negative    32
positive     5
neutral      3
Name: airline_sentiment_gold, dtype: int64
```

```
df['retweet_count'].value_counts()
```

```
0     13873
1       640
2        66
3        22
4        17
5         5
7         3
6         3
22        2
8         1
32        1
28        1
9         1
18        1
11        1
31        1
15        1
44        1
Name: retweet_count, dtype: int64
```

```
df['tweet_coord'].value_counts()
```

```
[0.0, 0.0]                        164
[40.64656067, -73.78334045]         6
[32.91792297, -97.00367737]         3
[40.64646912, -73.79133606]         3
[35.22643463, -80.93879965]         2
                                 ...
[40.69429232, -74.17208436]         1
[37.61833841, -122.38389799]        1
[37.61859126, -122.38385699]        1
[45.58931882, -122.5959928]         1
[40.64946781, -73.76624703]         1
Name: tweet_coord, Length: 832, dtype: int64
```

- According to percentage of null values in dataset, there are three columns that are not very useful, **negativereason_gold (%99,7)** , **airline_sentiment_gold (%99,7)** , **tweet_coord(%93)**
- Eventhough **'retweet_count'** doesnt have any null values ,13873 rows out of 14640 rows have a value 0.
- Therefore, we can remove these columns in order to keep our dataset clean, so we can develop our analysis more clearly based on the information given.
- I have also dropped **tweet_location**, **tweet_created**,**user_timezone** and name as these pieces of data will not contribute to our analysis.

- According to my Exploratory Data Analysis, I will be mainly focusing on the following columns:

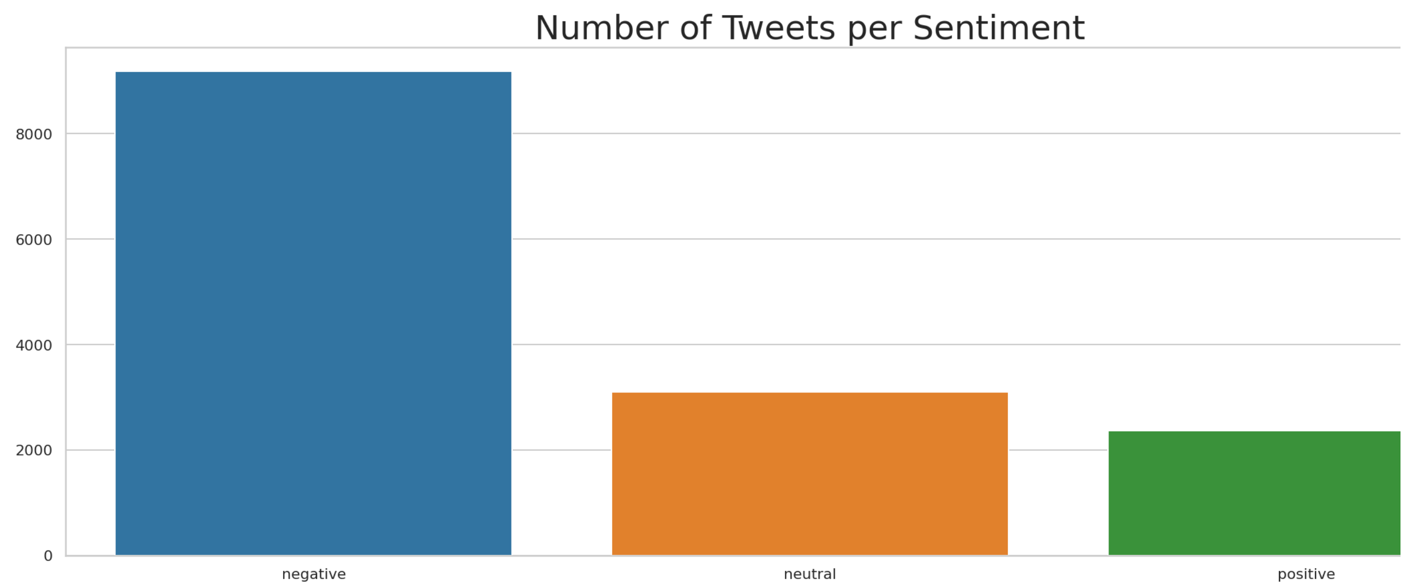
  “airline”: Name of the airline company

  “text”: Original tweet posted by the user.

  “airline_sentiment”: A categorical feature contains labels for tweets, positive, negative or neutral.

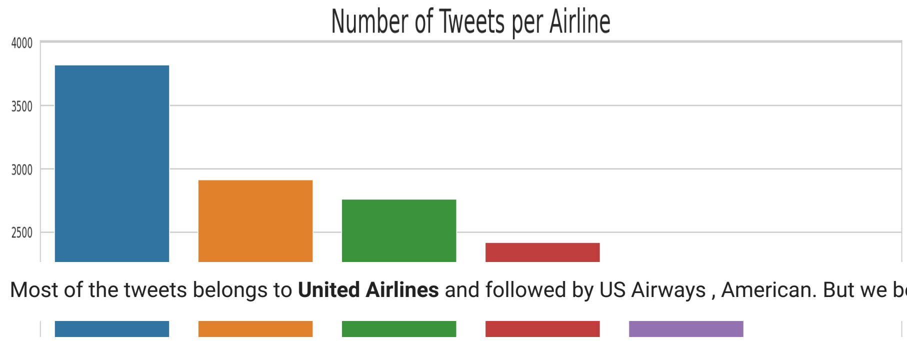
Data Visualization

```
plt.figure(figsize=(20,7));
sns.countplot(x= df.airline_sentiment, order = df.airline_sentiment.value_counts().index);
plt.xlabel('');
plt.ylabel('');
plt.title('Number of Tweets per Sentiment',fontsize = 25);
plt.show()
```



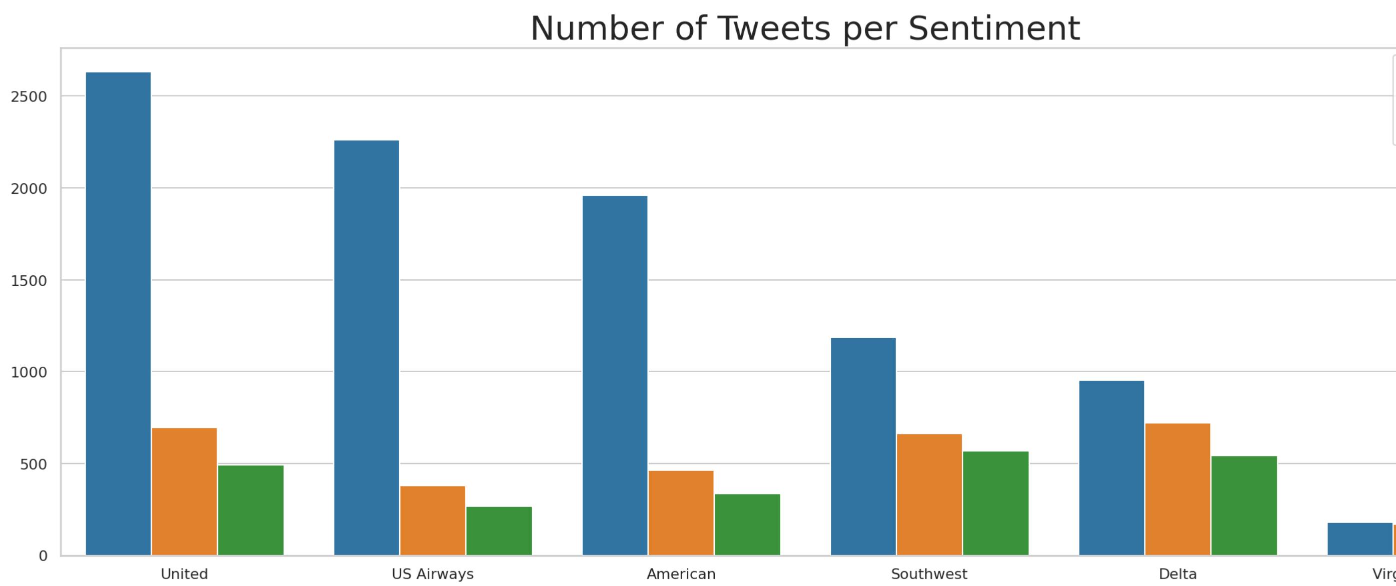
- Here, we can clearly see that these tweets are overwhelmingly **negative**.

```
plt.figure(figsize=(20,7));
sns.countplot(x= df.airline, order = df.airline.value_counts().index);
plt.xlabel('');
plt.ylabel('');
plt.title('Number of Tweets per Airline',fontsize = 25);
plt.show()
```



- Most of the tweets belongs to **United Airlines** and followed by US Airways , American. But we better check the sentiments of these tweets

```
plt.figure(figsize=(20,7));
sns.countplot(x= df.airline , order = df.airline.value_counts().index ,hue= df.airline_sentiment ,
              hue_order = df.airline_sentiment.value_counts().index);
plt.xlabel('');
plt.ylabel('');
plt.title('Number of Tweets per Sentiment',fontsize = 25);
plt.show()
```



- Looking at 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.
- For all airlines, negative sentiments outnumber positive and neutral sentiments.
- But this isn't normalizing the data. We can see that Virgin America isn't really talked about all that much. So we need to consider percentage of negative tweets for all tweets

```
# Negative Sentiment by Airlines Company
grouped_tweets =df.groupby(['airline','airline_sentiment']).count().iloc[:,0]
grouped_tweets
```

```
airline         airline_sentiment
American        negative            1960
                neutral              463
                positive             336
Delta           negative             955
                neutral              723
                positive             544
Southwest       negative            1186
                neutral              664
                positive             570
US Airways      negative            2263
                neutral              381
                positive             269
United          negative            2633
                neutral              697
                positive             492
Virgin America  negative             181
                neutral              171
```

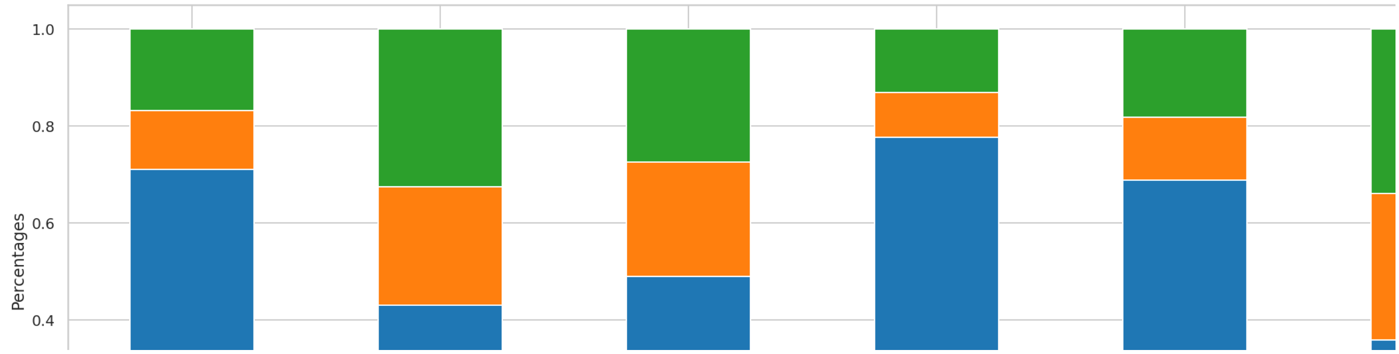
```
                positive          152
    Name: tweet_id, dtype: int64
```

```
# Total Sentiment by Airlines Company
total_tweets =df.groupby('airline')['airline_sentiment'].count()
total_tweets
```

```
    airline
    American          2759
    Delta             2222
    Southwest         2420
    US Airways        2913
    United            3822
    Virgin America     504
    Name: airline_sentiment, dtype: int64
```

```
negative_perc = {'American':grouped_tweets[0] / total_tweets[0],
                 'Delta':grouped_tweets[3] / total_tweets[1],
                 'Southwest': grouped_tweets[6] / total_tweets[2],
                 'US Airways': grouped_tweets[9] / total_tweets[3],
                 'United': grouped_tweets[12] / total_tweets[4],
                 'Virgin America': grouped_tweets[15] / total_tweets[5]}

positive_perc = {'American':grouped_tweets[2] / total_tweets[0],
                 'Delta':grouped_tweets[5] / total_tweets[1],
                 'Southwest': grouped_tweets[8] / total_tweets[2],
                 'US Airways': grouped_tweets[11] / total_tweets[3],
                 'United': grouped_tweets[14] / total_tweets[4],
                 'Virgin America': grouped_tweets[17] / total_tweets[5]}

neutral_perc =  {'American':grouped_tweets[1] / total_tweets[0],
                 'Delta':grouped_tweets[4] / total_tweets[1],
                 'Southwest': grouped_tweets[7] / total_tweets[2],
                 'US Airways': grouped_tweets[10] / total_tweets[3],
                 'United': grouped_tweets[13] / total_tweets[4],
                 'Virgin America': grouped_tweets[16] / total_tweets[5]}


#make a dataframe from the dictionary
df_neg_perc = pd.DataFrame.from_dict(negative_perc, orient = 'index')
df_pos_perc = pd.DataFrame.from_dict(positive_perc, orient = 'index')
df_neu_perc = pd.DataFrame.from_dict(neutral_perc, orient = 'index')

#have to manually set column name when using .from_dict() method
df_neg_perc.columns = ['Negative']
df_pos_perc.columns = ['Positive']
df_neu_perc.columns = ['Neutral']

# Merge all percentage dataframes
# percentage = merge_dfs(df_neg_perc, df_pos_perc, df_neu_perc)
df_list = [df_neg_perc, df_pos_perc, df_neu_perc]
percentage =pd.concat(df_list, axis = 1)
print(percentage)

#graph all of our data
ax = percentage.plot(kind = 'bar', stacked = True, rot = 0, figsize = (20,7))
#set x label
ax.set_xlabel('Airlines')
#set y label
ax.set_ylabel('Percentages')
#move the legend to the bottom of the graph since it wants to sit over all of our data and block it - stupid legend
ax.legend(loc='upper center', bbox_to_anchor=(0.5, -0.1),
          fancybox=True, shadow=True, ncol=5)

plt.show()
```

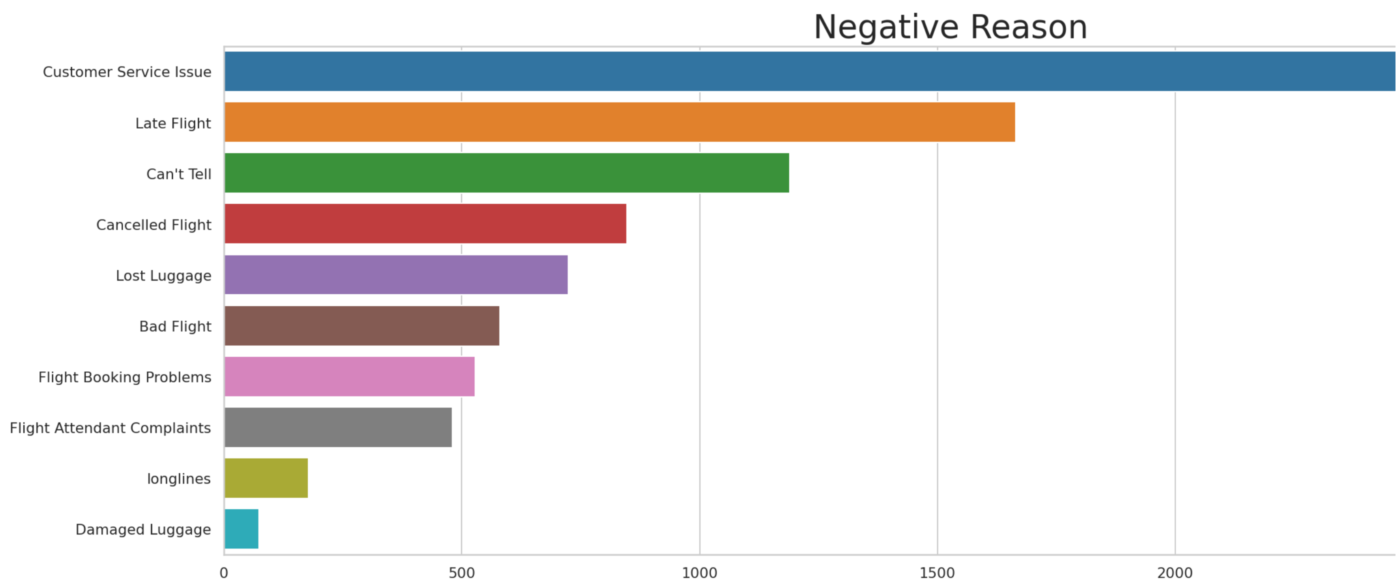
	Negative	Positive	Neutral
American	0.710402	0.121783	0.167814
Delta	0.429793	0.244824	0.325383
Southwest	0.490083	0.235537	0.274380
US Airways	0.776862	0.092345	0.130793
United	0.688906	0.128728	0.182365
Virgin America	0.359127	0.301587	0.339286



- Finally we have good looking visualization of airlines sentiment, when we normalized sentiments something changed, We can see that even though **United** had the most negative tweets from initial anlaysis, they made up **68%** of all their tweets. And **US Airways** and **American** have highest negative percentages at **77%** and **71%** respectively.
- It looks like **Virgin America** has highest percentage positive tweets.

American Delta Southwest US Airways United Vi

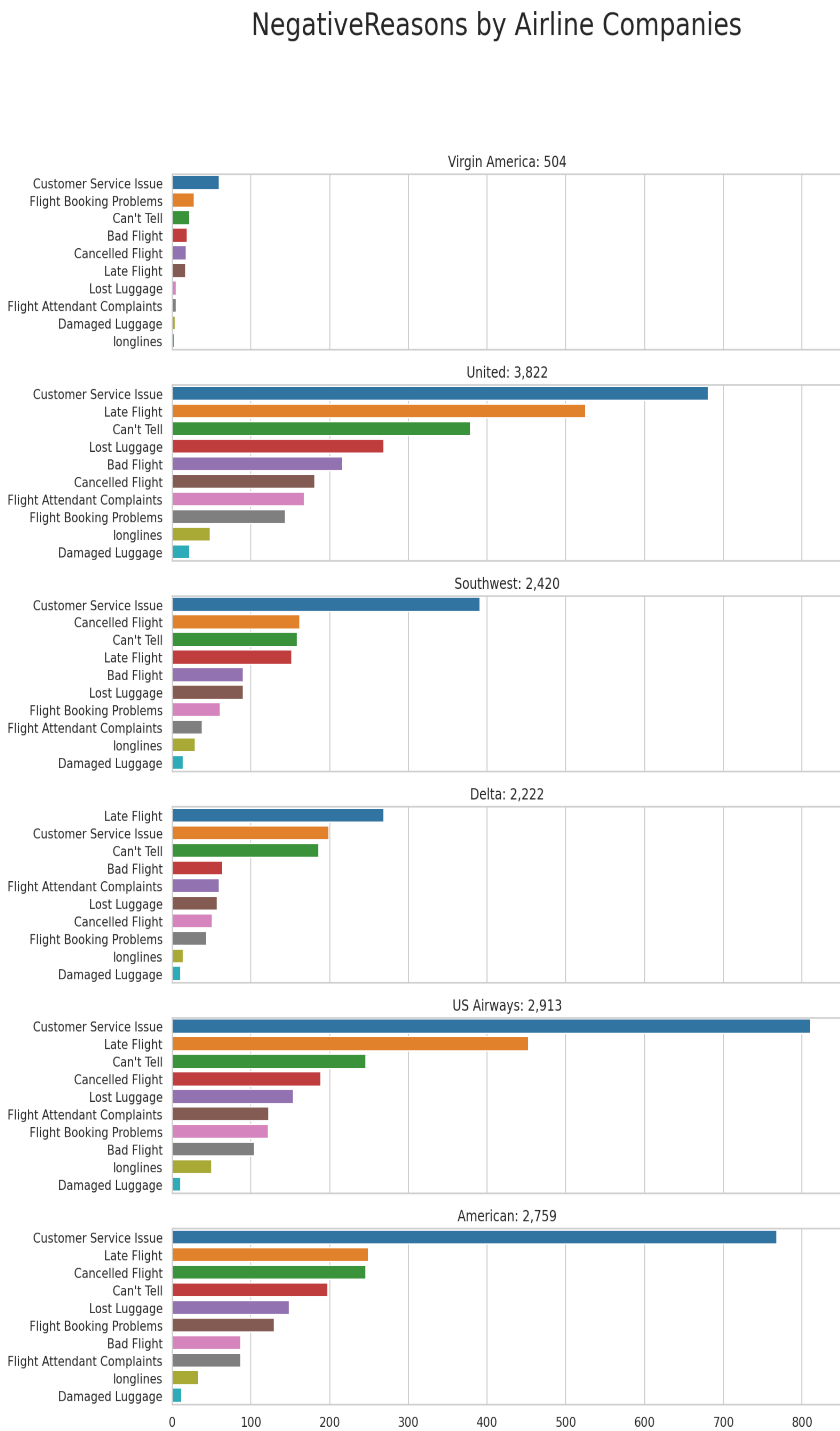
```
plt.figure(figsize=(20,7));
sns.countplot(y= df.negativereason , order = df.negativereason.value_counts().index);
plt.xlabel('');
plt.ylabel('');
plt.title('Negative Reason',fontsize = 25);
plt.show()
```



- Most of the customers complaning about **Customer Service**
- Another big reason they state negative reason is **late flights**.
- Over 1000 people preffer to not state what was the reason
- Now, Let's go detail and see negative reasons by the airlines

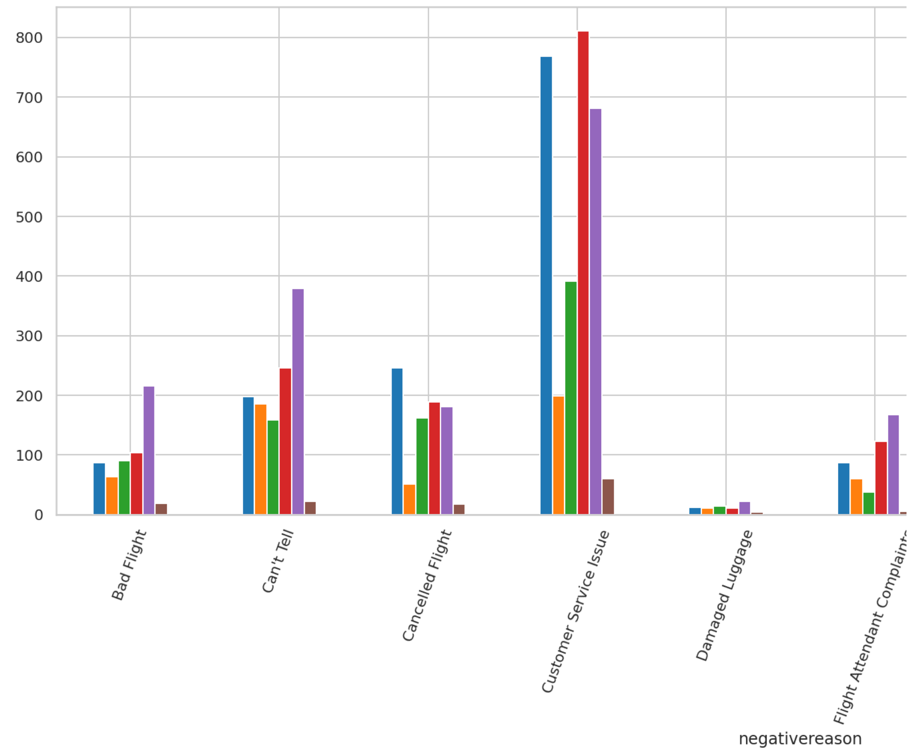
```
# Negative reasons per airline companies.
fig, axes = plt.subplots(6,1, figsize=(12,18), sharex=True)
axes = axes.flatten()
airlines = df['airline'].unique()

for airline, ax in zip(airlines, axes.flatten()):
    ax = sns.countplot(data = df[df.airline==airline], y = 'negativereason',
                       order = df[df.airline==airline].negativereason.value_counts().index,
                       hue_order =df.negativereason.value_counts().index,ax = ax
                       )
```

```
        ax.set_title(f"{airline}: {format(len(df[df.airline==airline]),',')}")
        ax.set_xlabel('')
        ax.set_ylabel('')

    plt.suptitle("NegativeReasons by Airline Companies", fontsize = 25)
    plt.show()
```



- Most of the passengers give negative reviews because they do not satisfy to the quality of **customer services**.
- Second major unsatisfaction is bad experience in the **flights' delay**
- And other negative reason provided by the airlines without providing any solid reason.
- The issue of **damaged luggage** is the least

```
#function that reduces the dataframe to only the airline and the negative reasons, then extract the reasons and the frequency
#each reason was referenced to an airline
def reason(df):
    df = df.reset_index().loc[:,['airline','negativereason']].dropna().groupby(['airline','negativereason']).size()
    return df

#call the function and plot the results
ax = reason(df).unstack(0).plot(kind = 'bar', figsize = (20,7), rot = 70)

plt.show()
```



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