SENTIMENT ANALYSIS FOR MARKETING

PHASE 3

Project : Sentient Analysis For Marketing

DATA VISUALIZATION:

Data visualization in sentiment analysis is the combination of these two processes, where the results of sentiment analysis are displayed in a visual form that can facilitate analysis and decision making. For example, data visualization in sentiment analysis can help to

- Compare the overall sentiment (positive, negative, or neutral) of different groups of customers, products, topics, or time periods.
- Identify the most common words or phrases that are associated with positive or negative sentiment.
- Explore the distribution and variation of sentiment scores across different categories or dimensions.
- Track the changes and trends of sentiment over time

PROGRAM:

SENTIMENTAL ANALSIS FOR MARKETING

Importing Libraries:

```
import pandas as pd
import seaborn as sns
import re, nltk
nltk.download('punkt')
import matplotlib.pyplot as plt
from sklearn import model_selection, naive_bayes, svm
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import GridSearchCV
from matplotlib import pyplot
import string
from nltk.corpus import stopwords
```

```
nltk.download('stopwords')
import numpy as np
from lime import lime_tabular
from tensorflow.keras.layers import Embedding
from tensorflow.keras.layers import LSTM, Bidirectional
from tensorflow.keras.layers import Dense, Dropout

import warnings
warnings.filterwarnings('ignore')
```

```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\ELCOT\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\ELCOT\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

```
#DATA LOADING

tweets_df =pd.read_csv('Tweets.csv')
tweets= tweets_df.copy()
tweets_df.head()
```

	tweet_id	airline_sentiment	airline_sentiment_confidence	\
0	570306133677760513	neutral	1.0000	
1	570301130888122368	positive	0.3486	
2	570301083672813571	neutral	0.6837	
3	570301031407624196	negative	1.0000	
4	570300817074462722	negative	1.0000	

	negativereason	negativereason_confidence	airline	\
0	NaN	NaN	Virgin America	
1	NaN	0.0000	Virgin America	
2	NaN	NaN	Virgin America	
3	Bad Flight	0.7033	Virgin America	
4	Can't Tell	1.0000	Virgin America	

	airline_sentiment_gold	name	negativereason_gold	retweet_count	\
0	NaN	cairdin	NaN	0	
1	NaN	jnardino	NaN	0	
2	NaN	yvonnalynn	NaN	0	
3	NaN	jnardino	NaN	0	
4	NaN	jnardino	NaN	0	

```
                                                text tweet_coord   \
0                    @VirginAmerica What @dhepburn said.         NaN
1  @VirginAmerica plus you've added commercials t...         NaN
2  @VirginAmerica I didn't today... Must mean I n...         NaN
3  @VirginAmerica it's really aggressive to blast...         NaN
4  @VirginAmerica and it's a really big bad thing...         NaN

              tweet_created tweet_location               user_timezone
0  2015-02-24 11:35:52 -0800            NaN  Eastern Time (US & Canada)
1  2015-02-24 11:15:59 -0800            NaN  Pacific Time (US & Canada)
2  2015-02-24 11:15:48 -0800      Lets Play  Central Time (US & Canada)
3  2015-02-24 11:15:36 -0800            NaN  Pacific Time (US & Canada)
4  2015-02-24 11:14:45 -0800            NaN  Pacific Time (US & Canada)
```

```
#Data columns

tweets_df.columns
```

```
Index(['tweet_id', 'airline_sentiment', 'airline_sentiment_confidence',
       'negativereason', 'negativereason_confidence', 'airline',
       'airline_sentiment_gold', 'name', 'negativereason_gold',
       'retweet_count', 'text', 'tweet_coord', 'tweet_created',
       'tweet_location', 'user_timezone'],
      dtype='object')
```

```
tweets_df['airline_sentiment'].unique()
```

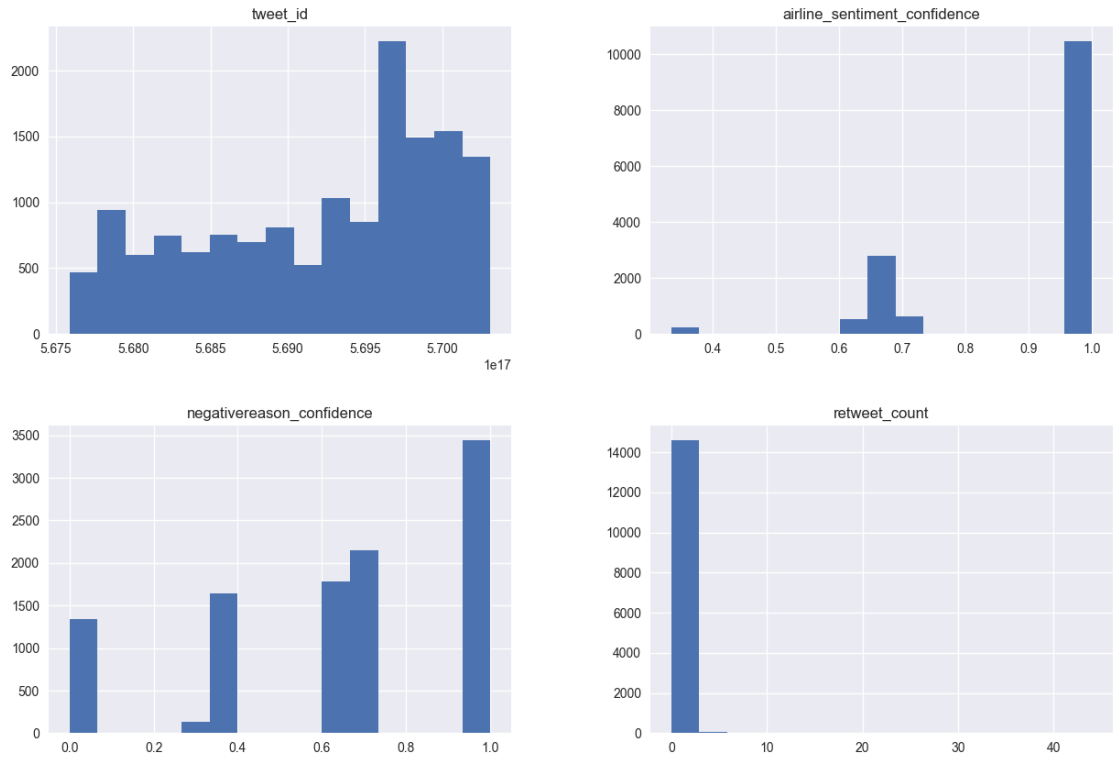
```
array(['neutral', 'positive', 'negative'], dtype=object)
```

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

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

```
#Data Visualization
plt.style.use("seaborn")
tweets_df.hist(figsize=(15, 10), bins=15)
```

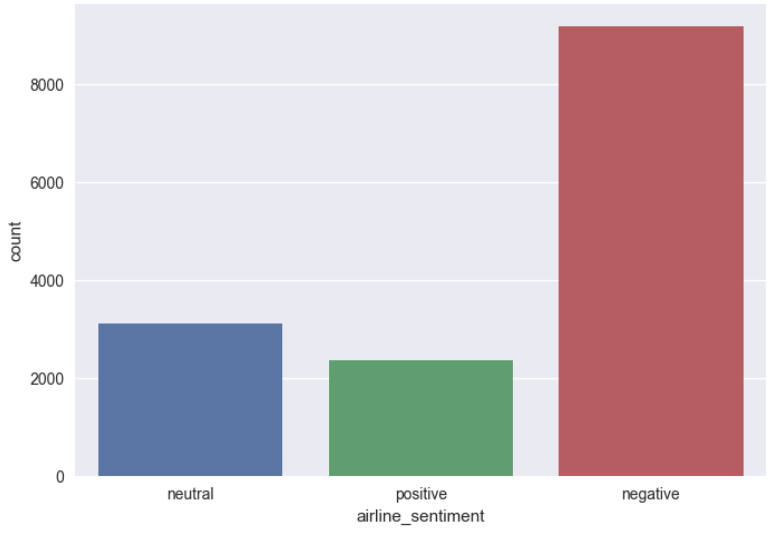
```
array([[<AxesSubplot: title={'center': 'tweet_id'}>,
        <AxesSubplot: title={'center': 'airline_sentiment_confidence'}>],
       [<AxesSubplot: title={'center': 'negativereason_confidence'}>,
        <AxesSubplot: title={'center': 'retweet_count'}>]], dtype=object)
```



#COUNT PLOT

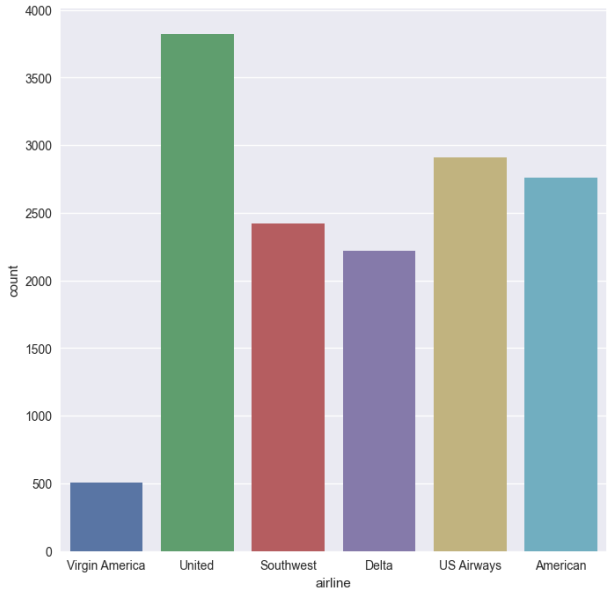
```
sns.countplot(x="airline_sentiment", data=tweets_df)
```

```
<AxesSubplot: xlabel='airline_sentiment', ylabel='count'>
```



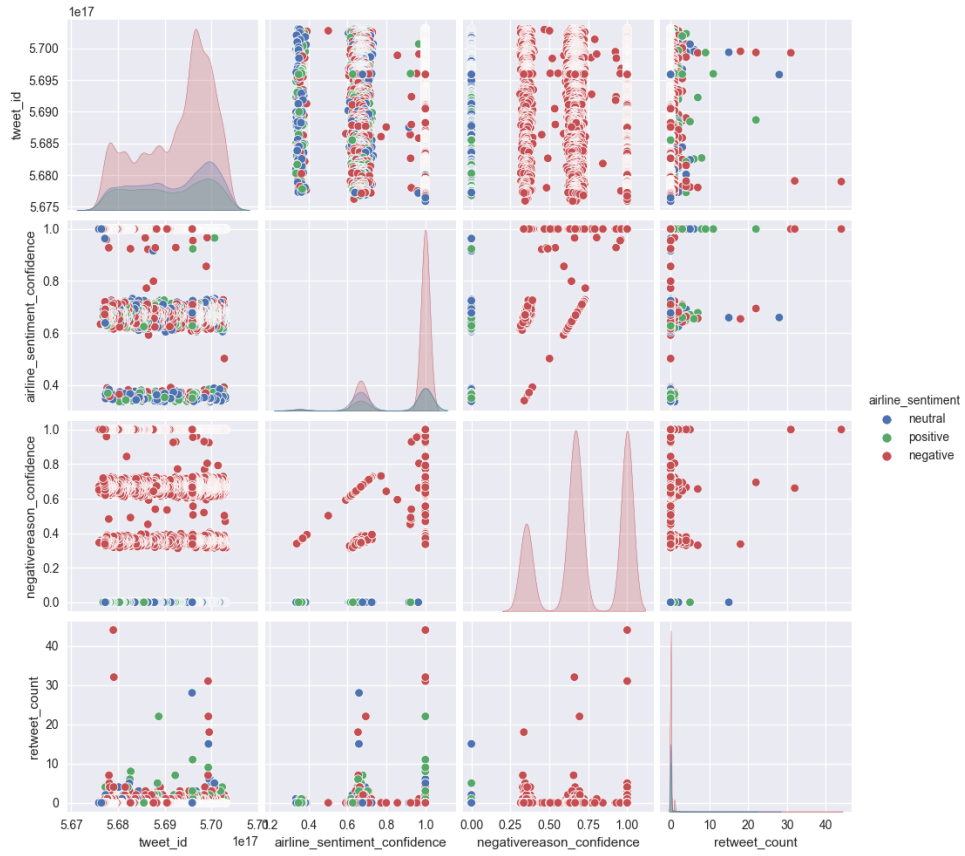

```
plt.figure(figsize=(8, 8))
sns.countplot(x="airline", data=tweets_df)
```

```
<AxesSubplot: xlabel='airline', ylabel='count'>
```




```
sns.pairplot(tweets_df, hue='airline_sentiment')
```

```
<seaborn.axisgrid.PairGrid at 0x211c88598d0>
```




```
print("Total number of tweets for each airline \n
", tweets_df.groupby('airline')['airline_sentiment'].count().sort_values(ascending=False))
```

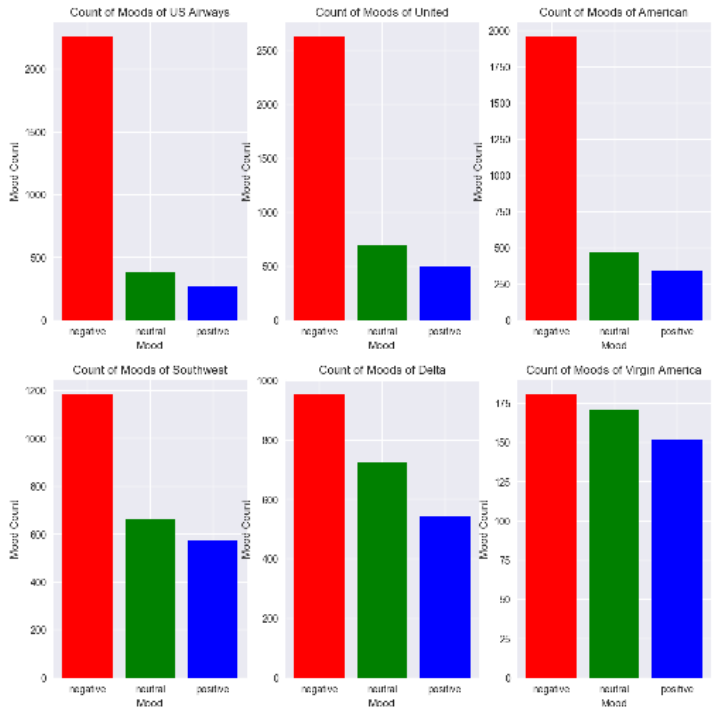
```
airlines= ['US Airways', 'United', 'American', 'Southwest', 'Delta', 'Virgin America']
plt. figure(1, figsize=(12,  12))
for i in airlines:
        indices= airlines. index(i)
        plt. subplot(2, 3, indices+1)
        new_df=tweets_df[tweets_df['airline']==i]
        count=new_df['airline_sentiment']. value_counts()
        Index = [1, 2, 3]
        plt. bar(Index, count,  color=['red',  'green',  'blue'])
        plt. xticks(Index, ['negative', 'neutral', 'positive'])
        plt. ylabel('Mood Count')
        plt. xlabel('Mood')
        plt. title('Count of Moods of '+i)
```

Out:

Total number of tweets for each airline

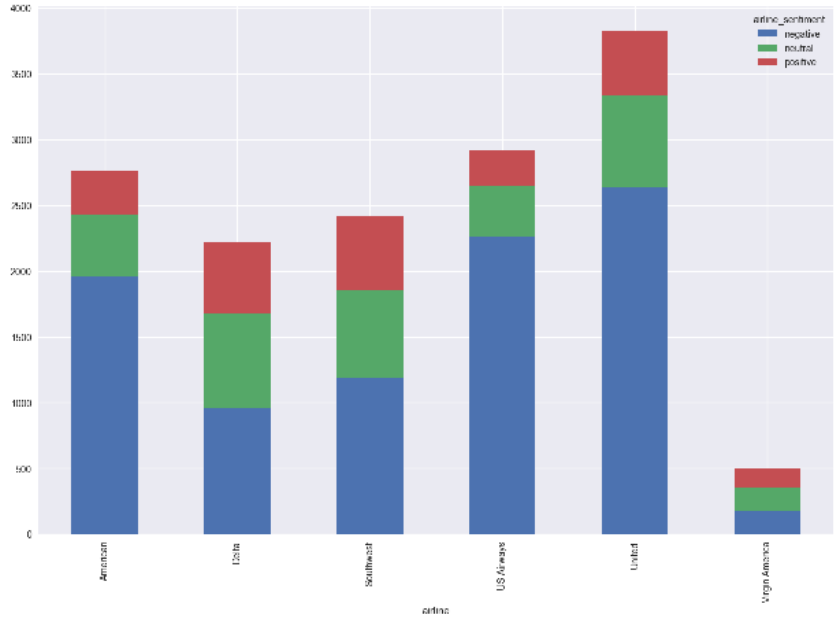
airline	
United	3822
US Airways	2913
American	2759
Southwest	2420
Delta	2222
Virgin America	504

Name: airline_sentiment, dtype: int64

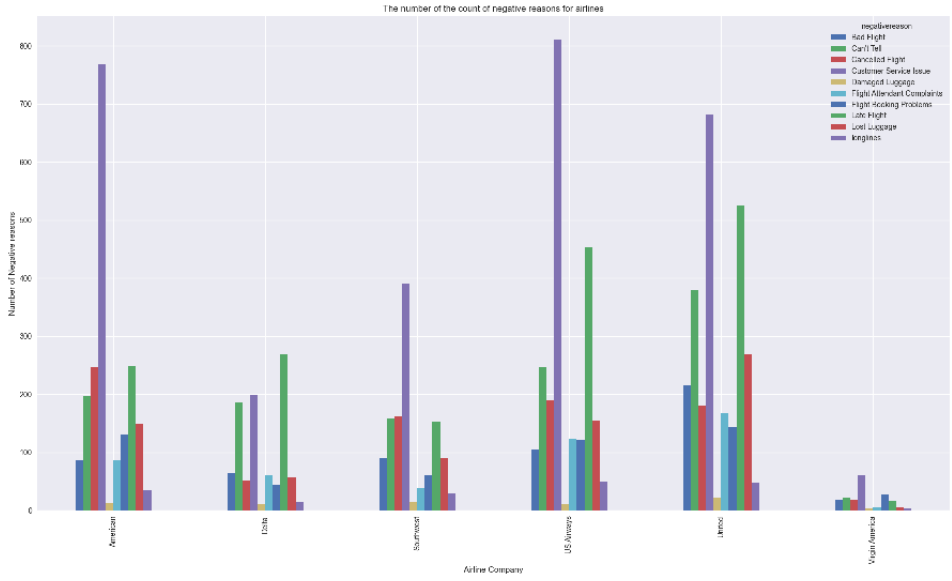


```
figure_2 = tweets_df.groupby(['airline', 'airline_sentiment']).size()
figure_2.unstack().plot(kind='bar', stacked=True, figsize=(15, 10))
```

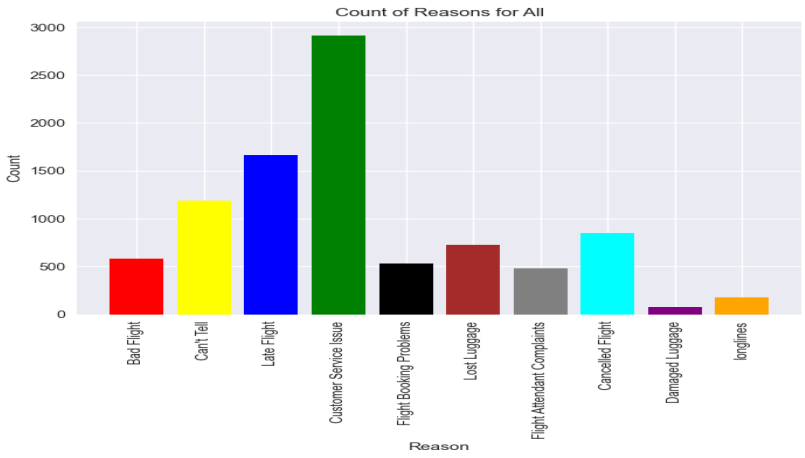
```
<AxesSubplot: xlabel='airline'>
```

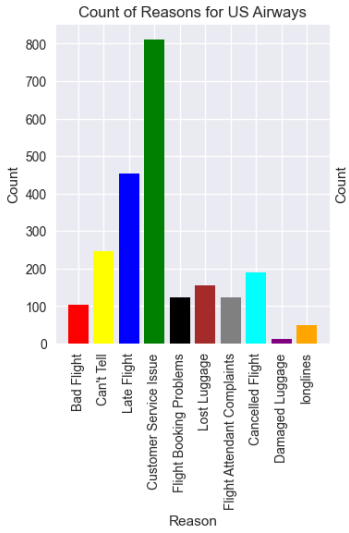


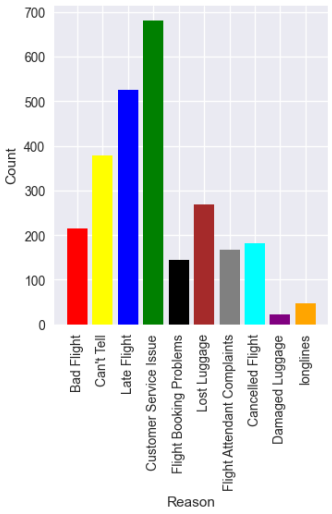

```
negative_reasons = tweets_df.groupby('airline')['negativereason'].value_counts(ascending=True)
negative_reasons.groupby(['airline', 'negativereason']).sum().unstack().plot(kind='bar', figsize=(22, 12))
plt.xlabel('Airline Company')
plt.ylabel('Number of Negative reasons')
plt.title("The number of the count of negative reasons for airlines")
plt.show()
```

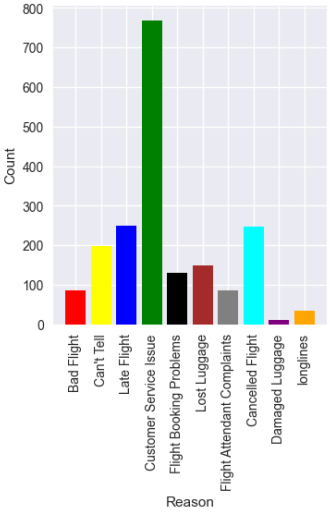


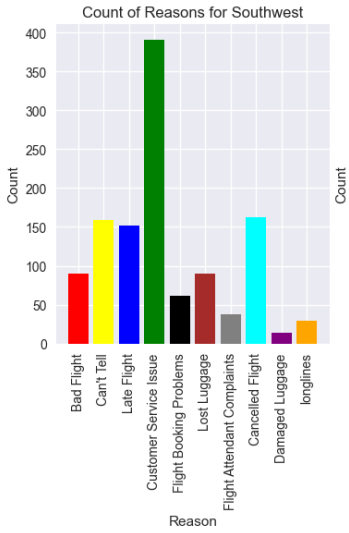
```
tweets_df['negativereason']. nunique()

NR_Count=dict(tweets_df['negativereason']. value_counts(sort=False))
def NR_Count(Airline):
    if Airline=='All':
        a=tweets_df
    else:
        a=tweets_df[tweets_df['airline']==Airline]
    count=dict(a['negativereason']. value_counts())
    Unique_reason=list(tweets_df['negativereason']. unique())
    Unique_reason=[x for x in Unique_reason if str(x) != 'nan']
    Reason_frame=pd. DataFrame({'Reasons':Unique_reason})
    Reason_frame['count']=Reason_frame['Reasons']. apply(lambda x: count[x])
    return Reason_frame
def plot_reason(Airline):

    a=NR_Count(Airline)
    count=a['count']
    Index = range(1, (len(a)+1))
    plt. bar(Index, count,  color=['red', 'yellow', 'blue', 'green', 'black', 'brown', 'gray', 'cyan', 'purple', 'orange'])
    plt. xticks(Index, a['Reasons'], rotation=90)
    plt. ylabel('Count')
    plt. xlabel('Reason')
    plt. title('Count of Reasons for '+Airline)

plot_reason('All')
plt. figure(2, figsize=(13,  13))
for i in airlines:
    indices= airlines. index(i)
    plt. subplot(2, 3, indices+1)
    plt. subplots_adjust(hspace=0. 9)
    plot_reason(i)
```

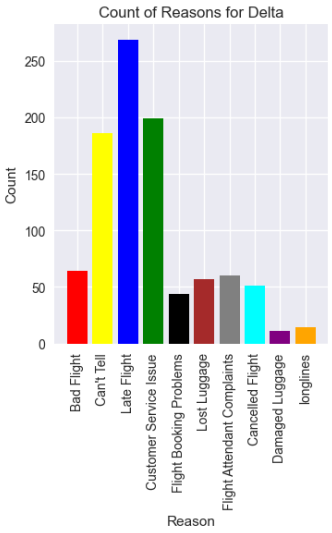


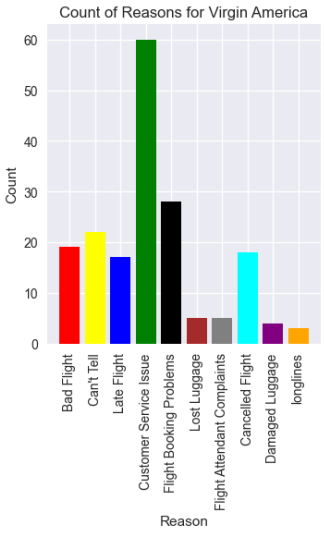










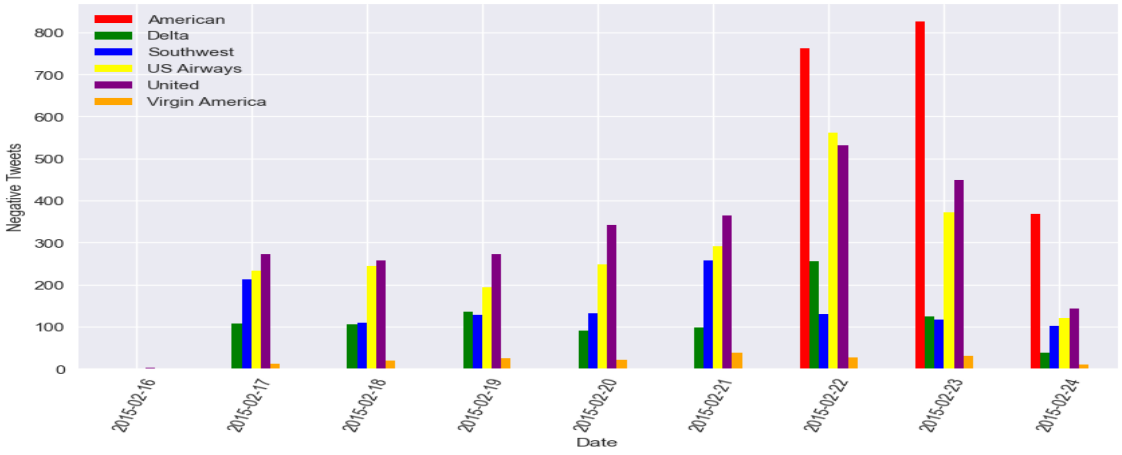



```
date = tweets_df.reset_index()
#convert the Date column to pandas datetime
```

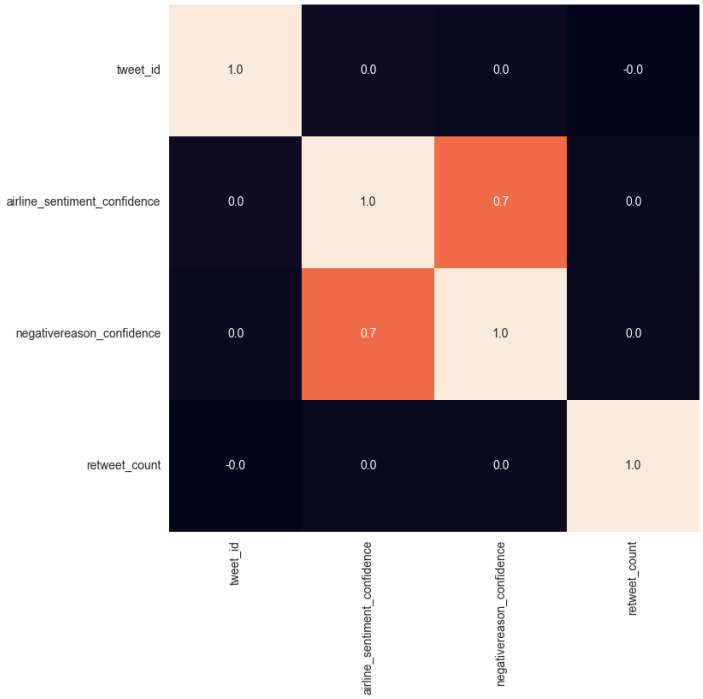
```
date.tweet_created = pd.to_datetime(date.tweet_created)
#Reduce the dates in the date column to only the date and no time stamp using the 'dt.date' method
date.tweet_created = date.tweet_created.dt.date
date.tweet_created.head()
df = date
day_df = df.groupby(['tweet_created', 'airline', 'airline_sentiment']).size()
day_df
```

```
tweet_created  airline         airline_sentiment
2015-02-16     Delta           negative            1
                               neutral             1
               United          negative            2
2015-02-17     Delta           negative          108
                               neutral            86
                                                  ...
2015-02-24     United          neutral            49
                               positive           25
               Virgin America  negative           10
                               neutral             6
                               positive           13
Length: 136, dtype: int64
```

```
day_df = day_df.loc(axis=0)[:, :, 'negative']

#groupby and plot data
ax2 = day_df.groupby(['tweet_created', 'airline']).sum().unstack().plot(kind = 'bar', color=['red', 'green', 'blue', 'yellow', 'purple', 'orange'], figsize = (10, 6), rot = 70)
labels = ['American', 'Delta', 'Southwest', 'US Airways', 'United', 'Virgin America']
ax2.legend(labels = labels)
ax2.set_xlabel('Date')
ax2.set_ylabel('Negative Tweets')
plt.show()
```

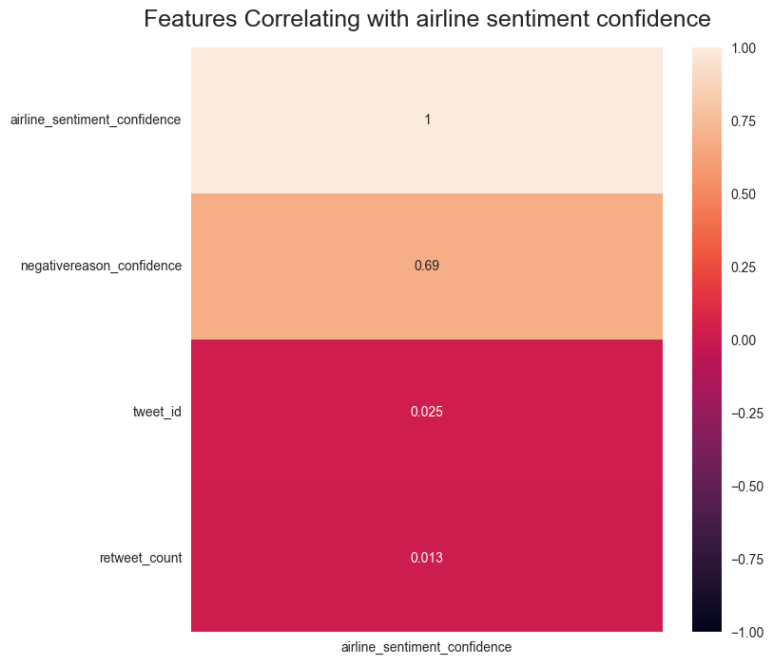


```
#Heatmap
plt. figure(figsize=(8, 8))
sns. heatmap(tweets_df. corr(), annot=True, cbar=False, fmt='. 1f')
plt. show()
```

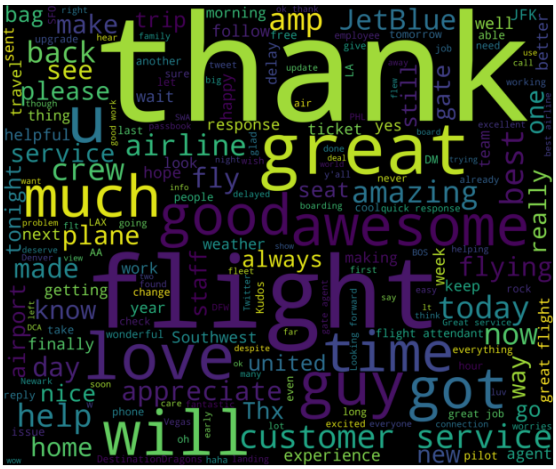



```
plt. figure(figsize=(8, 8))
heatmap =
sns. heatmap(tweets_df. corr()[['airline_sentiment_confidence']]. sort_values(by='airline_sentiment_confidence
', ascending=False), vmin=-1, vmax=1, annot=True)
heatmap. set_title('Features Correlating with airline sentiment confidence', fontdict={'fontsize':18}, pad=16)
```

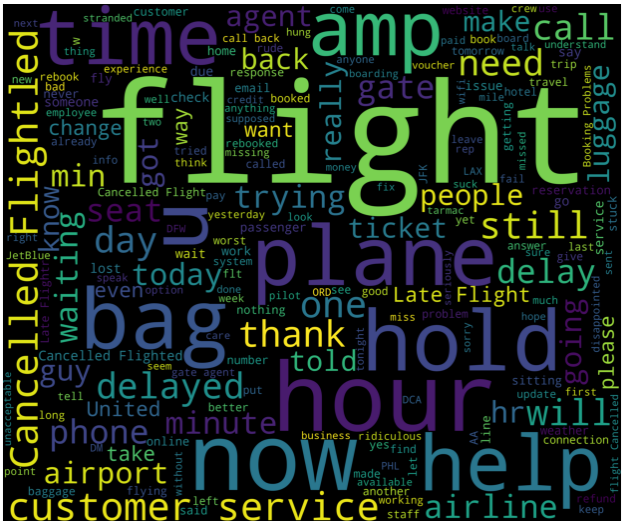
```
Text(0. 5, 1. 0, 'Features Correlating with airline sentiment confidence')
```




```
from wordcloud import WordCloud, STOPWORDS
new_df=tweets_df[tweets_df['airline_sentiment']=='positive']
words = ' '. join(new_df['text'])
cleaned_word = " ". join([word for word in words. split()
                                    if 'http' not in word
                                        and not word. startswith('@')
                                        and word ! = 'RT'
                                    ])
wordcloud = WordCloud(stopwords=STOPWORDS,
                    background_color='black',
width=3000, height=2500). generate(cleaned_word)
plt. figure(1, figsize=(8,  8))
plt. imshow(wordcloud)
plt. axis('off')
plt. show()
```

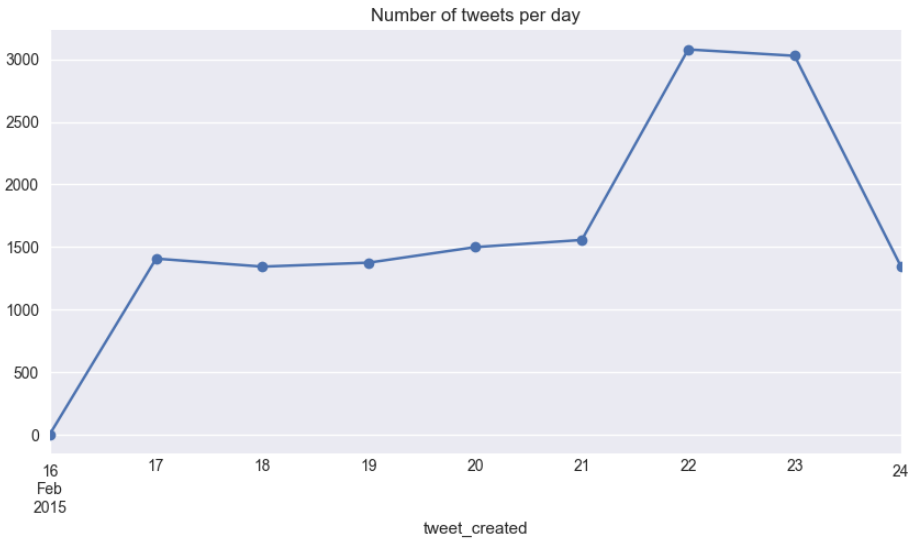



```
new_df=tweets_df[tweets_df['airline_sentiment']=='negative']
words = ' '. join(new_df['text'])
cleaned_word = " ". join([word for word in words. split()
                                    if 'http' not in word
                                        and not word. startswith('@')
                                        and word ! = 'RT'
                                    ])
wordcloud = WordCloud(stopwords=STOPWORDS,
                                background_color='black',
width=3000, height=2500). generate(cleaned_word)
plt. figure(1, figsize=(8, 8))
plt. imshow(wordcloud)
plt. axis('off')
plt. show()
```



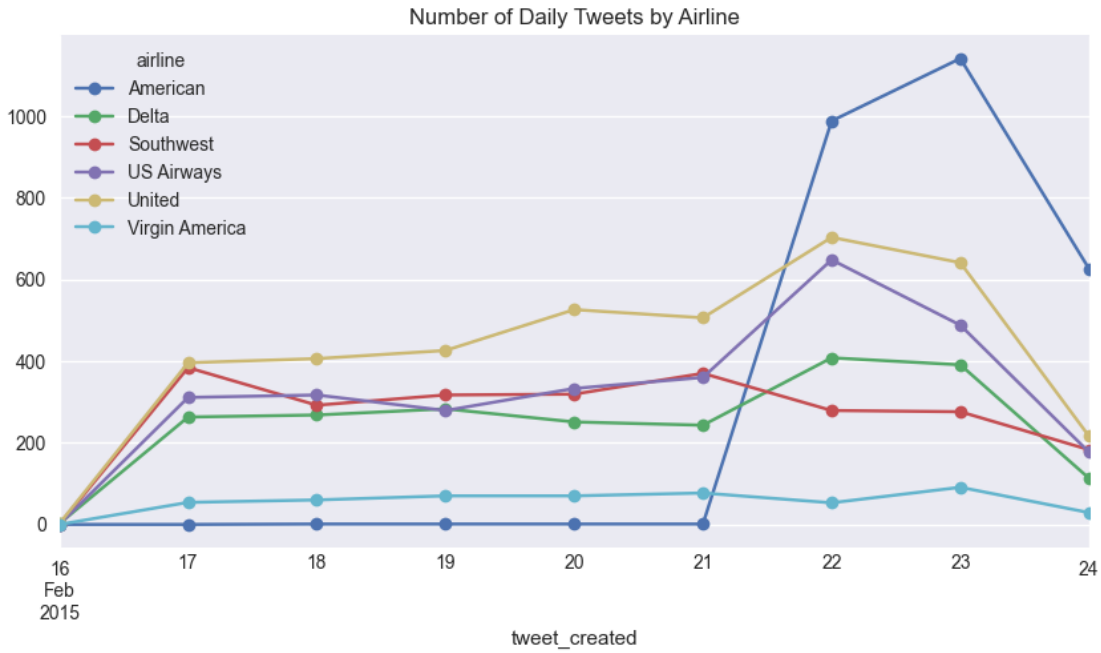
```
tweets['tweet_created'] = pd.to_datetime(tweets['tweet_created'])
tweets_time_index = tweets.copy()
tweets_time_index.set_index("tweet_created", inplace=True)

tweets_time_index.resample("D")['tweet_id'].count().plot(style="-o", figsize=(8, 5), title="Number of tweets per day")
```

```
<AxesSubplot: title={'center': 'Number of tweets per day'}, xlabel='tweet_created'>
```




```
tweets_time_index = tweets_time_index.pivot_table(index="tweet_created", columns="airline", values="tweet_id", aggfunc=np.count_nonzero, fill_value=0)
tweets_time_index.resample("D").sum().plot(style="-o", figsize=(10, 5), title="Number of Daily Tweets by Airline")
```

```
<AxesSubplot: title={'center': 'Number of Daily Tweets by Airline'}, xlabel='tweet_created'>
```



Conclusion:

In the quest to build a sentiment analysis for marketing, we have embarked on a critical journey that begins with loading and preprocessing the dataset. We have traversed through essential steps, starting with importing the necessary libraries to facilitate data manipulation and analysis.

Understanding the data's structure, characteristics, and any potential issues through exploratory data analysis (EDA) is essential for informed decision-making.

Data preprocessing emerged as a pivotal aspect of this process. It involves cleaning, transforming, and refining the dataset to ensure that it aligns with the requirements of machine learning algorithms.