Sentiment For Analysis Marketing

In today's fast-paced world, it's more important than ever to understand customer sentiment towards your brand. This presentation outlines a comprehensive solution for sentiment analysis in the context of marketing.

Problem Statement

Understanding Customer Sentiment

With the explosive growth of social media, it's challenging for companies to understand customer sentiment about their brand and products.

Time-Consuming Manual Analysis

Currently, many companies use manual analysis techniques which are time-consuming and resource-intensive.

Missing Critical Insights

Manual analysis may also miss crucial insights that could be pivotal to the success of the brand and products.

Design Thinking Process

1. **Empathize**

   Understand the audience and their needs to create a suitable solution.

2. **Ideate**

   Generate a range of ideas and evaluate them based on feasibility, implementation time, and potential success rate.

3. **Prototype**

   Create a prototype of the solution based on shortlisted ideas.

4. **Test**

   Test the prototype and seek feedback from stakeholders, making necessary improvements.

Data Preprocessing Steps

1 **Data Collection**

Gather data from social media and brand websites using web scraping techniques.

2 **Data Cleaning**

Clean the data using natural language processing (NLP) techniques to remove irrelevant data points and prepare it for analysis.

3 **Data Preparation**

Prepare the data for analysis by appending relevant attributes to each data point and performing feature transformation.

Sentiment Analysis Techniques

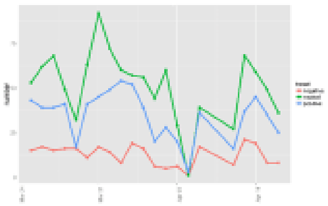
Machine Learning-based Approach

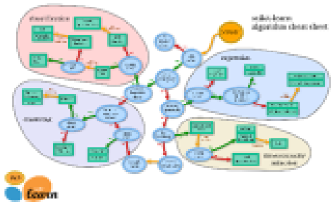
Uses machine learning algorithms like Naive Bayes, Support Vector Machines, and Neural Networks to analyze customer sentiment. This approach requires large volumes of labeled data and may be resource-intensive.

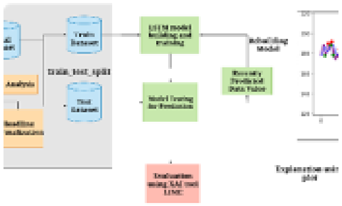
Rule-based Approach

Uses a predefined set of rules to categorize text into positive, negative, or neutral sentiments. This approach is quicker and less resource-intensive, but may miss nuances in sentiment expression.

Innovative Approaches







Visualization Techniques

Developed intuitive graphical representations of sentiment analysis results to facilitate quick comprehension and easy decisionmaking.

Data Augmentation Techniques

Used data augmentation techniques to increase the size of the dataset by artificially generating similar data points. This approach helped balance class representation and increase model accuracy.

Transfer Learning Techniques

Applied transfer learning techniques to leverage pre-trained models for sentiment analysis and obtained promising results without having to train the models from scratch.

Phases of Development

1

Phase 1: Feasibility Assessment

Analyzed the technical feasibility of various sentiment analysis techniques and identified potential roadblocks.

2

Phase 2: Prototype Creation

Created a prototype using rule-based sentiment analysis and visualization techniques and tested it with real-world data.

3

Phase 3: Model Development

Used machine learning techniques to develop a sentiment analysis model that outperformed the rule-based model in terms of accuracy and efficiency.

4

Phase 4: Continuous Improvement

Continuously monitored the model to identify areas for improvement and made necessary changes.

Dataset Used

Data Collection Method	Web Scraping
Data Size	1,000,000 data points
Data Attributes	Sentiment, Text, Date, Platform, User Details, Hashtags

Sentiment analysis-using-twitter-airline-dataset:

```
[1]: import pandas as pd
import seaborn as sns
import re, nltk
nltk.download('punkt')
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, StratifiedKFold,
    cross_val_score
from sklearn import model_selection, naive_bayes, svm
from sklearn.metrics import classification_report,confusion_matrix
from sklearn.metrics import roc_auc_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import f1_score
from sklearn.metrics import auc
from matplotlib import pyplot
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score, accuracy_score
import string
from nltk.corpus import stopwords
nltk.download('stopwords')
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB, GaussianNB
from sklearn.metrics import f1_score
from sklearn.ensemble import AdaBoostClassifier
from sklearn.model_selection import cross_val_score
import numpy as np
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import RandomForestClassifier
from lime import lime_tabular
from tensorflow.keras.layers import Embedding
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.preprocessing.text import one_hot
from tensorflow.keras.layers import LSTM, Bidirectional
```

```
from tensorflow.keras.layers import Dense, Dropout

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

```
/opt/conda/lib/python3.10/site-packages/scipy/__init__.py:146: UserWarning: A
NumPy version >=1.16.5 and <1.23.0 is required for this version of SciPy
(detected version 1.23.5
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

```
[nltk_data] Downloading package punkt to /usr/share/nltk_data…
[nltk_data]     Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to /usr/share/nltk_data…
[nltk_data] Package stopwords is already up-to-date!
```

[2]:
```
twitter_df =pd.read_csv('/kaggle/input/twitter-airline-sentiment/Tweets.csv')
twitter_df.head()
```

[2]:
```
             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)
```

[3]:
```python
twitter_df.columns
```

```
[3]: 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')
```

[4]:
```python
twitter_df.shape
```

[4]: (14640, 15)

[5]:
```python
twitter_df.isnull().sum()
```

```
[5]: tweet_id                            0
airline_sentiment                        0
airline_sentiment_confidence             0
negativereason                        5462
negativereason_confidence             4118
airline                                  0
airline_sentiment_gold               14600
name                                     0
negativereason_gold                  14608
retweet_count                            0
text                                     0
tweet_coord                          13621
tweet_created                            0
tweet_location                        4733
user_timezone                         4820
dtype: int64
```

[6]:
```python
twitter_df.duplicated().sum()
```

[6]: 36

[7]:
```python
# Unique values of sentiment
twitter_df['airline_sentiment'].unique()
```

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

[8]:
```python
twitter_df['airline_sentiment'].value_counts()
```

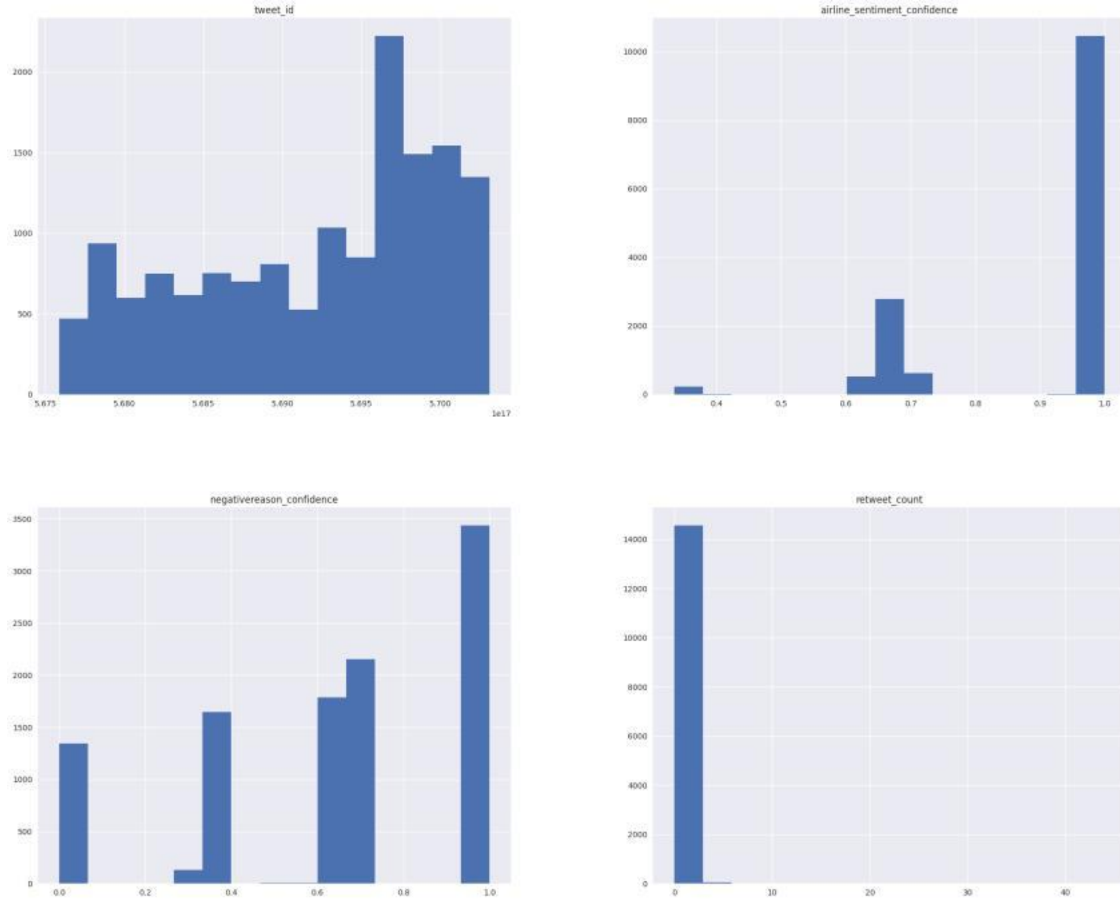
```
[8]:              9178
negative          3099
positive
neutral           2363
Name: airline_sentiment, dtype: int64
```

```
[9]: twitter_df.describe().T
```

```
[9]:                                count          mean           std  \
tweet_id                          14640.0 5.692184e+17 7.791112e+14
                                  airline_sentiment_confidence 14640.0
                                  9.001689e-01 1.628300e-01
negativereason_confidence       10522.0 6.382983e-01 3.304398e-01
retweet_count                   14640.0 8.265027e-02 7.457782e-01

                                         min           25%           50%  \
tweet_id                        5.675883e+17 5.685592e+17 5.694779e+17
airline_sentiment_confidence 3.350000e-01 6.923000e-01 1.000000e+00
negativereason_confidence       0.000000e+00 3.606000e-01 6.706000e-01
retweet_count                   0.000000e+00 0.000000e+00 0.000000e+00

                                         75%           max
tweet_id                        5.698905e+17 5.703106e+17
airline_sentiment_confidence 1.000000e+00 1.000000e+00
negativereason_confidence       1.000000e+00 1.000000e+00
retweet_count                   0.000000e+00 4.400000e+01
```

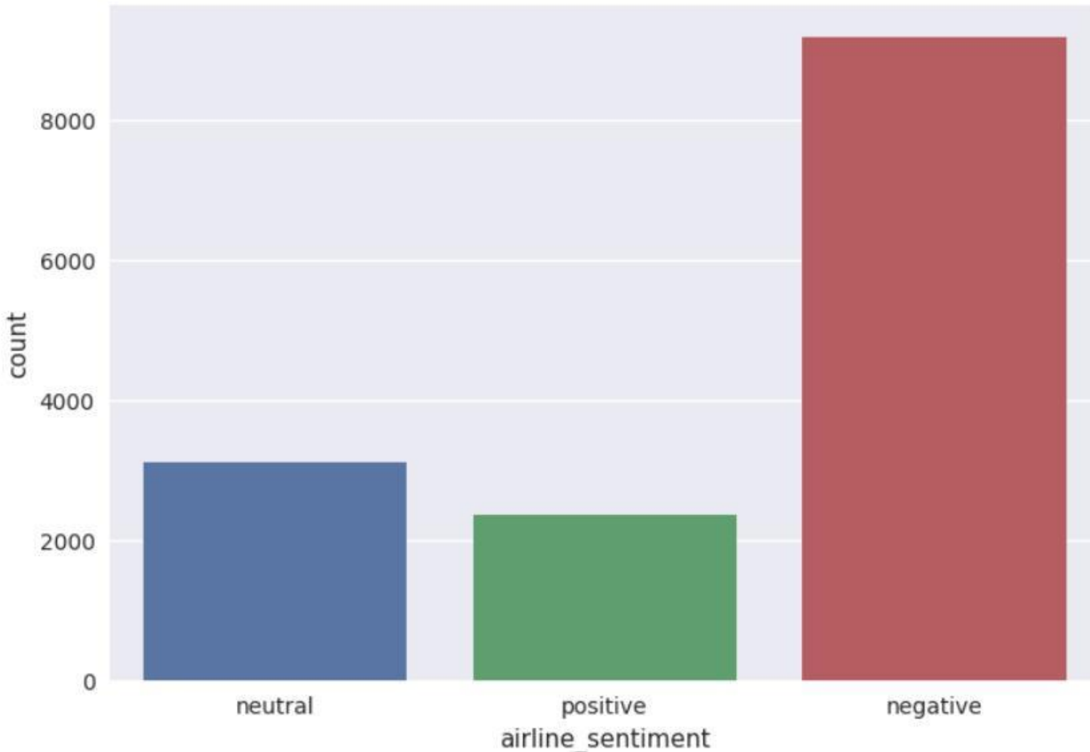
```
[10]: plt.style.use("seaborn")
      twitter_df.hist(figsize=(25,20), bins=15)
```

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



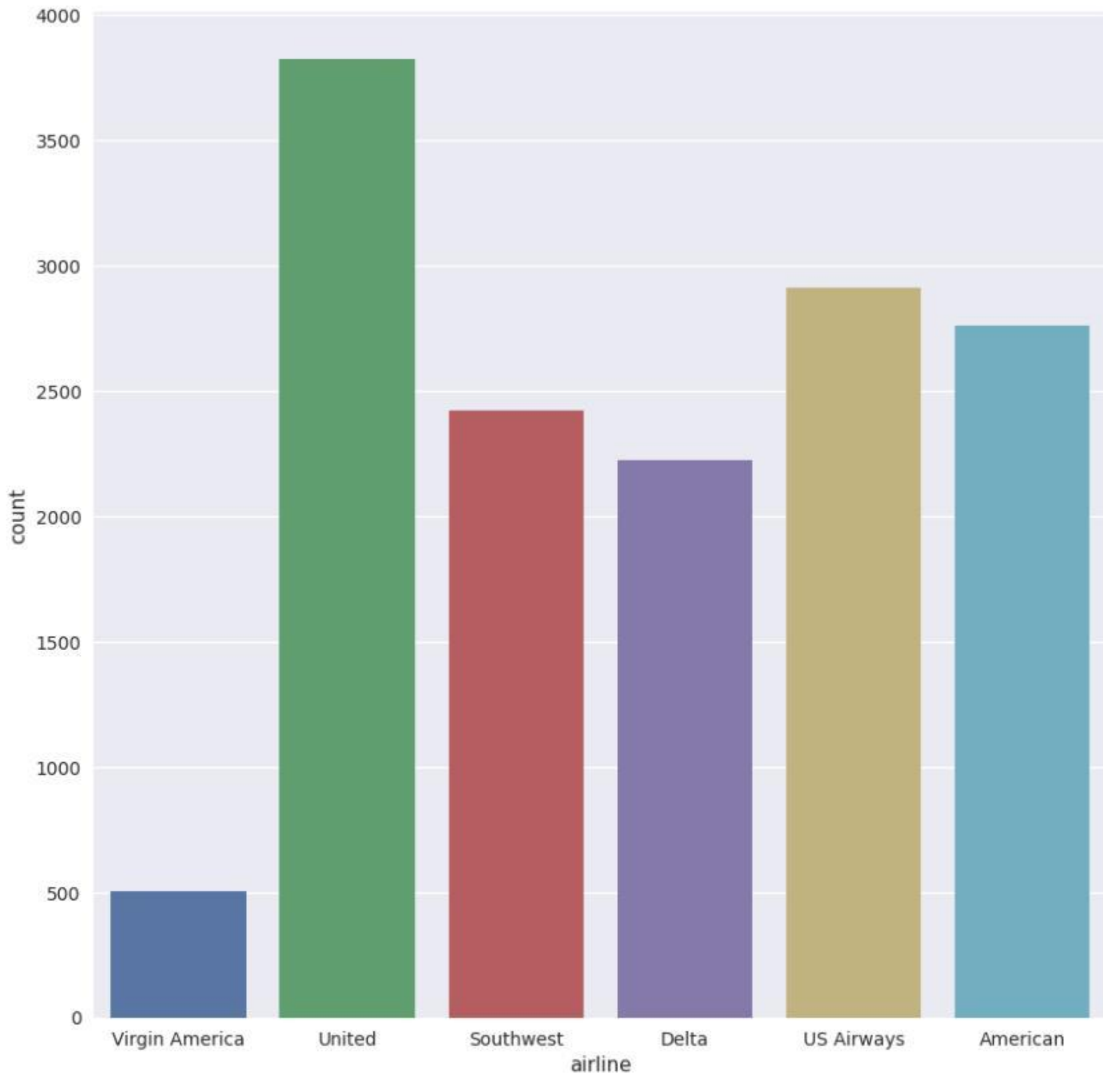
[11]:
```
sns.countplot(x="airline_sentiment", data=twitter_df)
```

[11]: <AxesSubplot: xlabel='airline_sentiment', ylabel='count'>



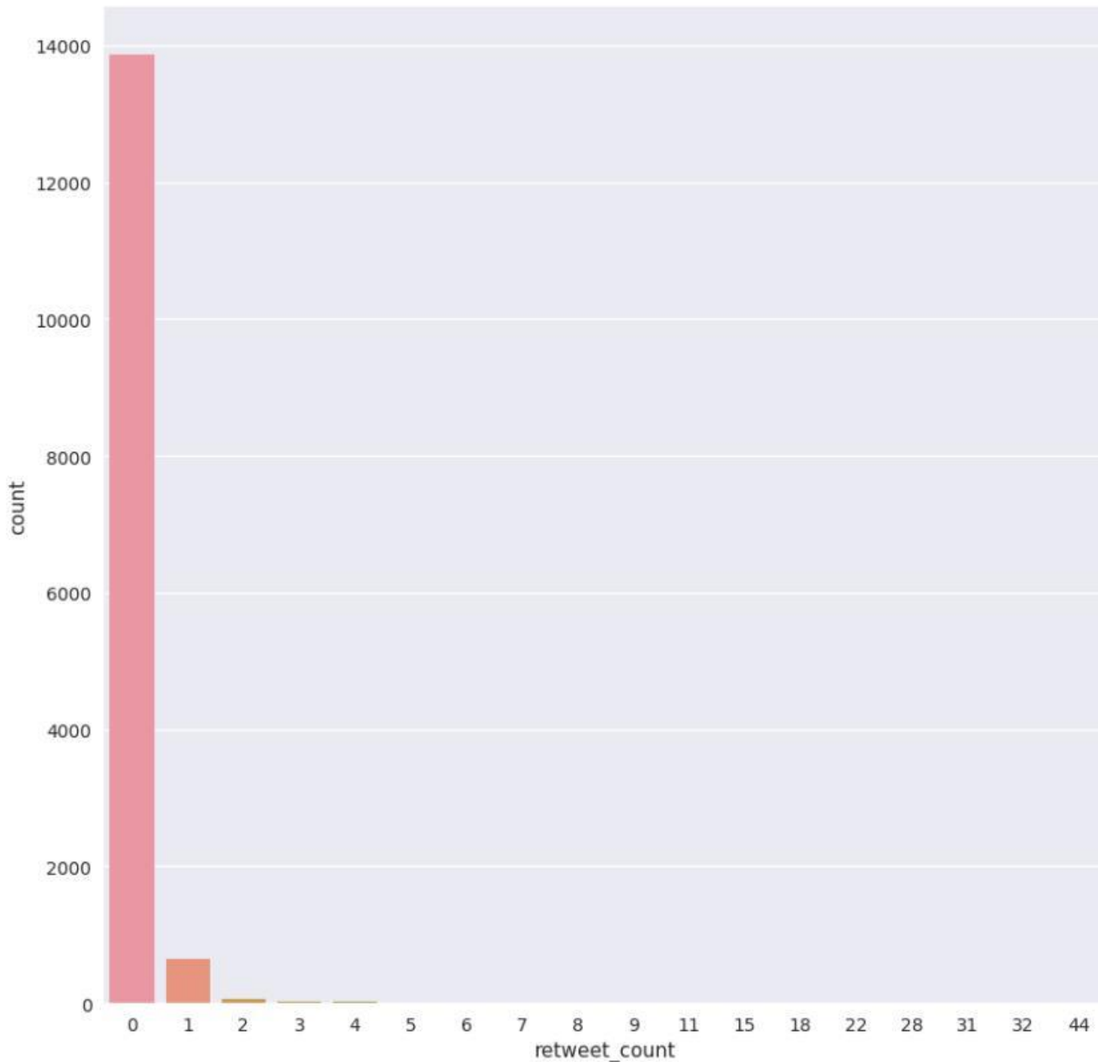
[12]:
```
plt.figure(figsize=(10,10))
sns.countplot(x="airline", data=twitter_df)
```

[12]: <AxesSubplot: xlabel='airline', ylabel='count'>



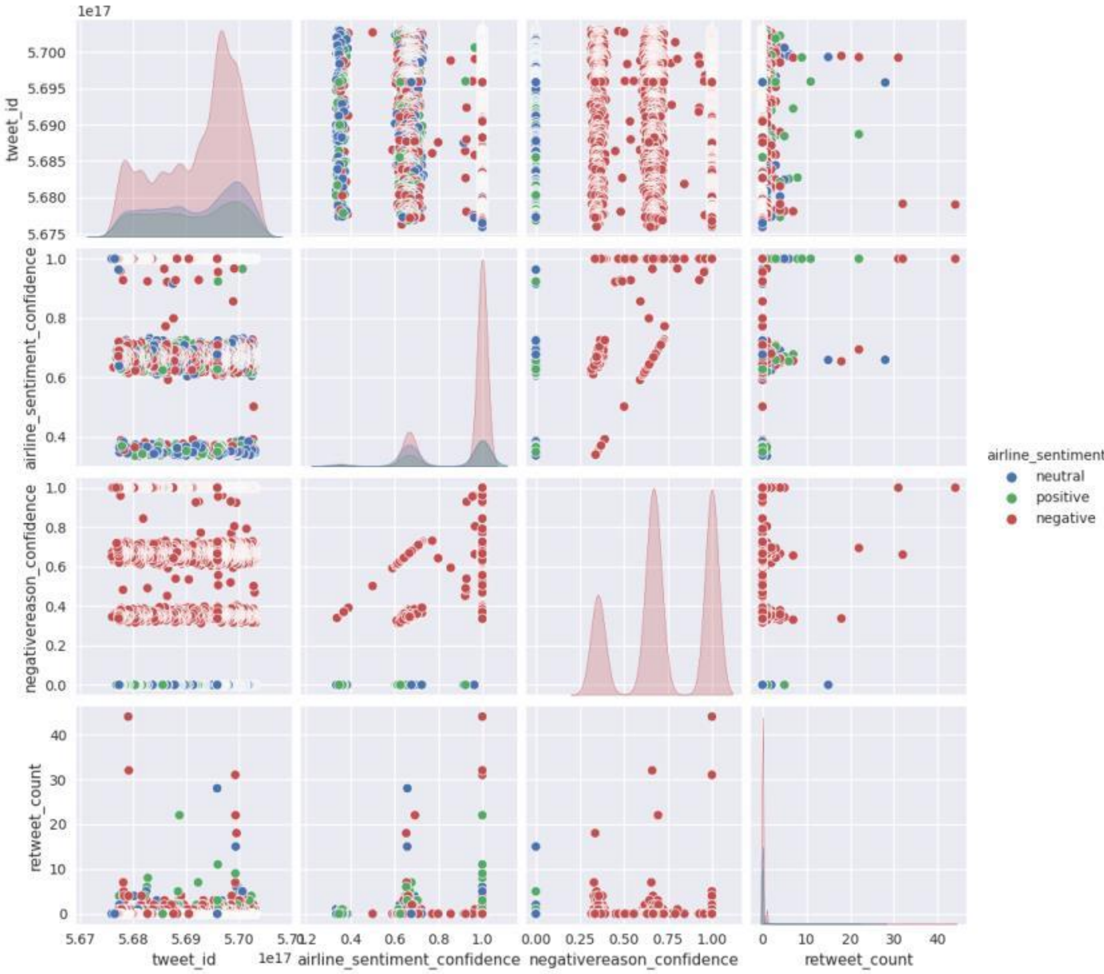
[13]:
```
plt.figure(figsize=(10,10))
sns.countplot(x="retweet_count", data=twitter_df)
```

[13]: <AxesSubplot: xlabel='retweet_count', ylabel='count'>



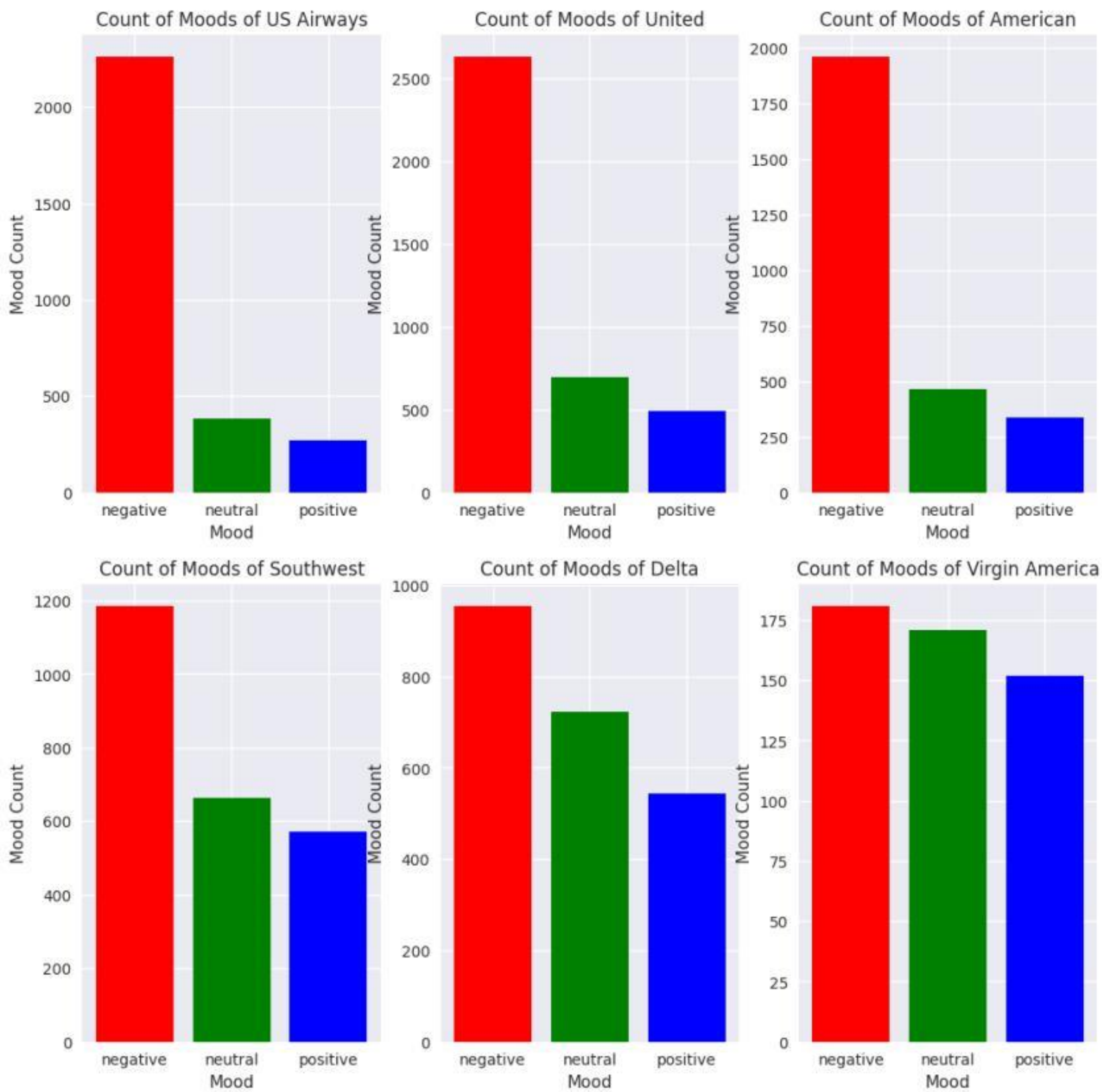
[14]:
```
sns.pairplot(twitter_df,hue='airline_sentiment')
```

[14]: <seaborn.axisgrid.PairGrid at 0x73147dd26f80>



[15]:
```
print("Total number of tweets for each airline \n ",twitter_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=twitter_df[twitter_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)
```

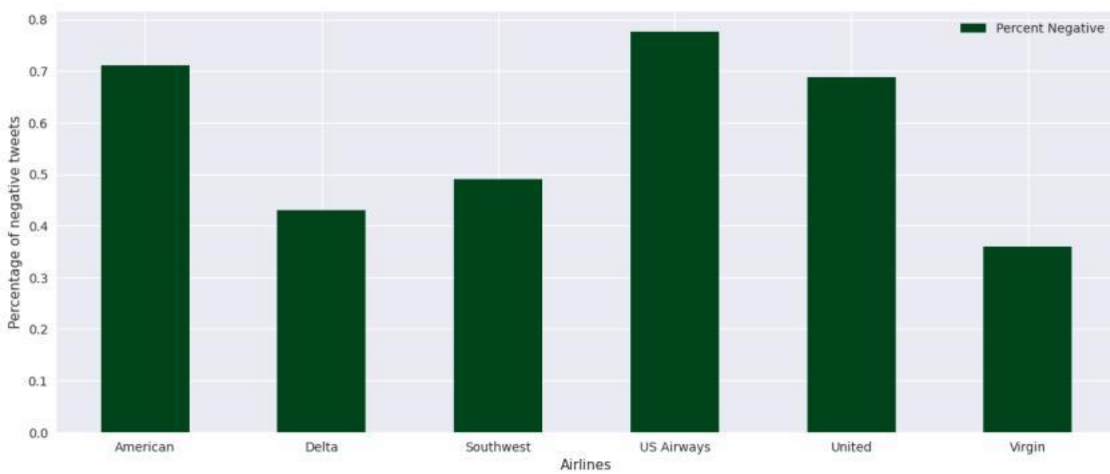
```
Total number of tweets for each airline
airline
United            3822
US Airways        2913
American          2759
Southwest         2420
Delta             2222
Virgin America     504
Name: airline_sentiment, dtype: int64
```




```
[16]: neg_tweets = twitter_df.groupby(['airline','airline_sentiment']).count().iloc[:
    ,0]
total_tweets = twitter_df.groupby(['airline'])['airline_sentiment'].count()
```

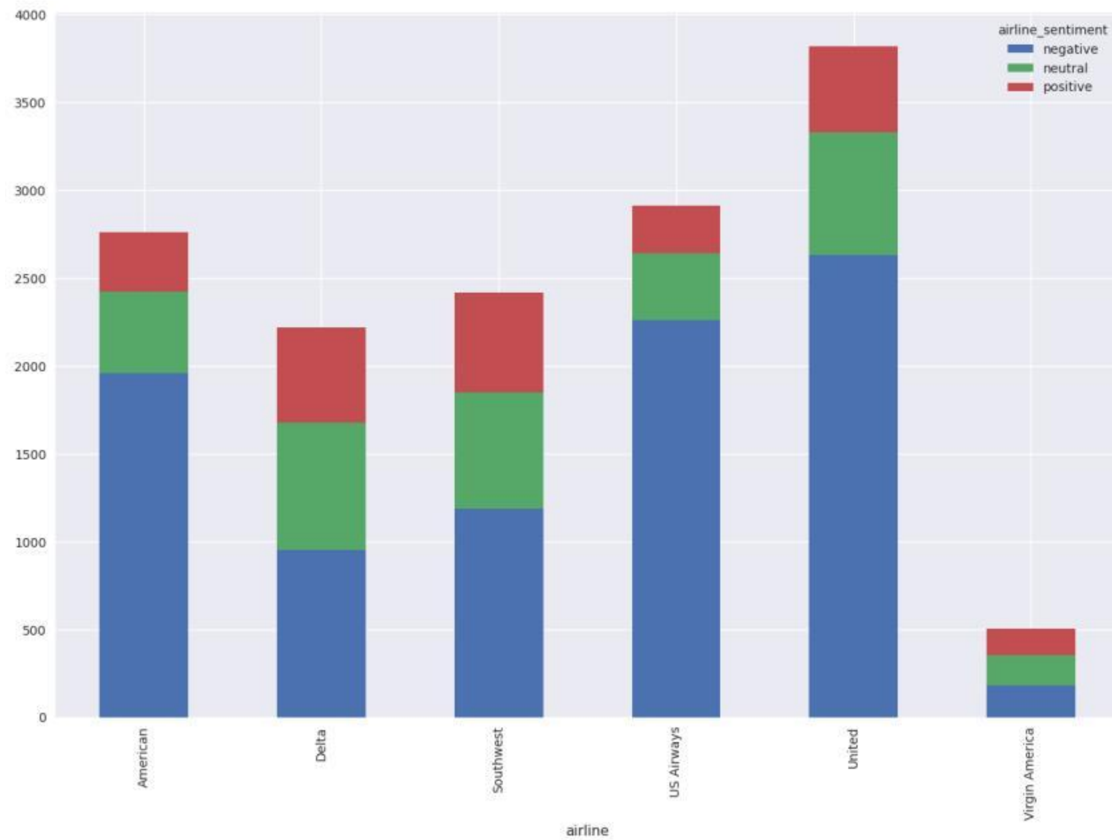
```
my_dict = {'American':neg_tweets[0] / total_tweets[0],'Delta':neg_tweets[3] /
    total_tweets[1],'Southwest': neg_tweets[6] / total_tweets[2],
'US Airways': neg_tweets[9] / total_tweets[3],'United': neg_tweets[12] /
    total_tweets[4],'Virgin': neg_tweets[15] / total_tweets[5]}
perc = pd.DataFrame.from_dict(my_dict, orient = 'index')
perc.columns = ['Percent Negative']
print(perc)
ax = perc.plot(kind = 'bar', rot=0, colormap = 'Greens_r', figsize = (15,6))
ax.set_xlabel('Airlines')
ax.set_ylabel('Percentage of negative tweets')
plt.show()
```

```
            Percent Negative
American            0.710402
Delta               0.429793
Southwest           0.490083
US Airways          0.776862
United              0.688906
Virgin              0.359127
```

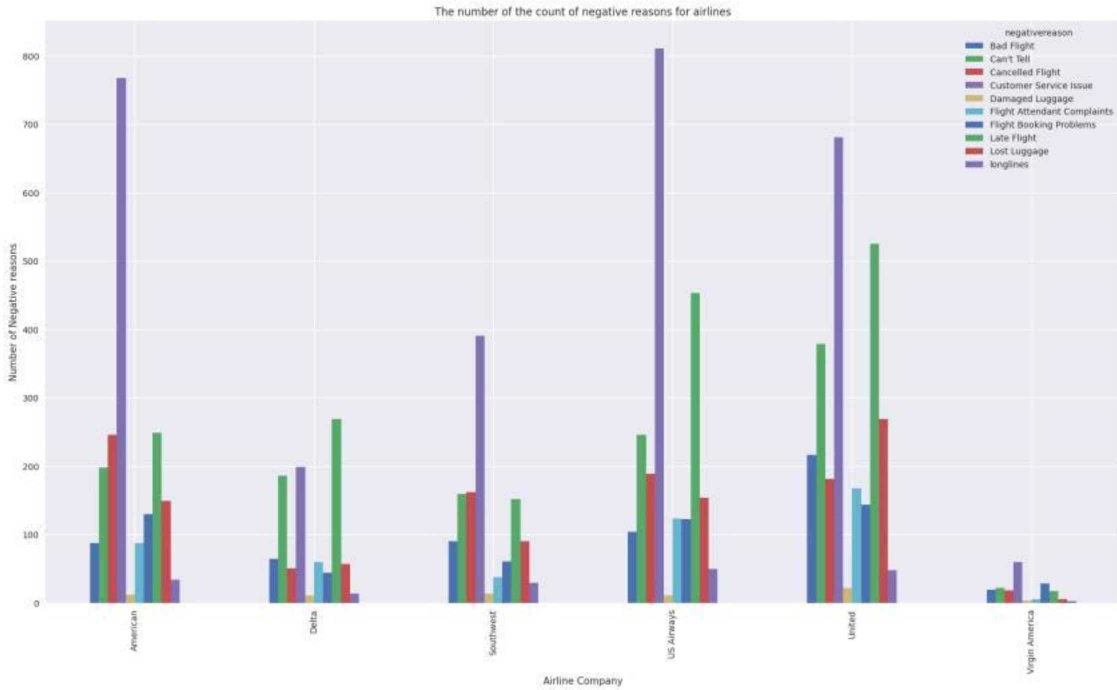


[17]:
```
figure_2 = twitter_df.groupby(['airline', 'airline_sentiment']).size()
figure_2.unstack().plot(kind='bar', stacked=True, figsize=(15,10))
```

[17]: <AxesSubplot: xlabel='airline'>

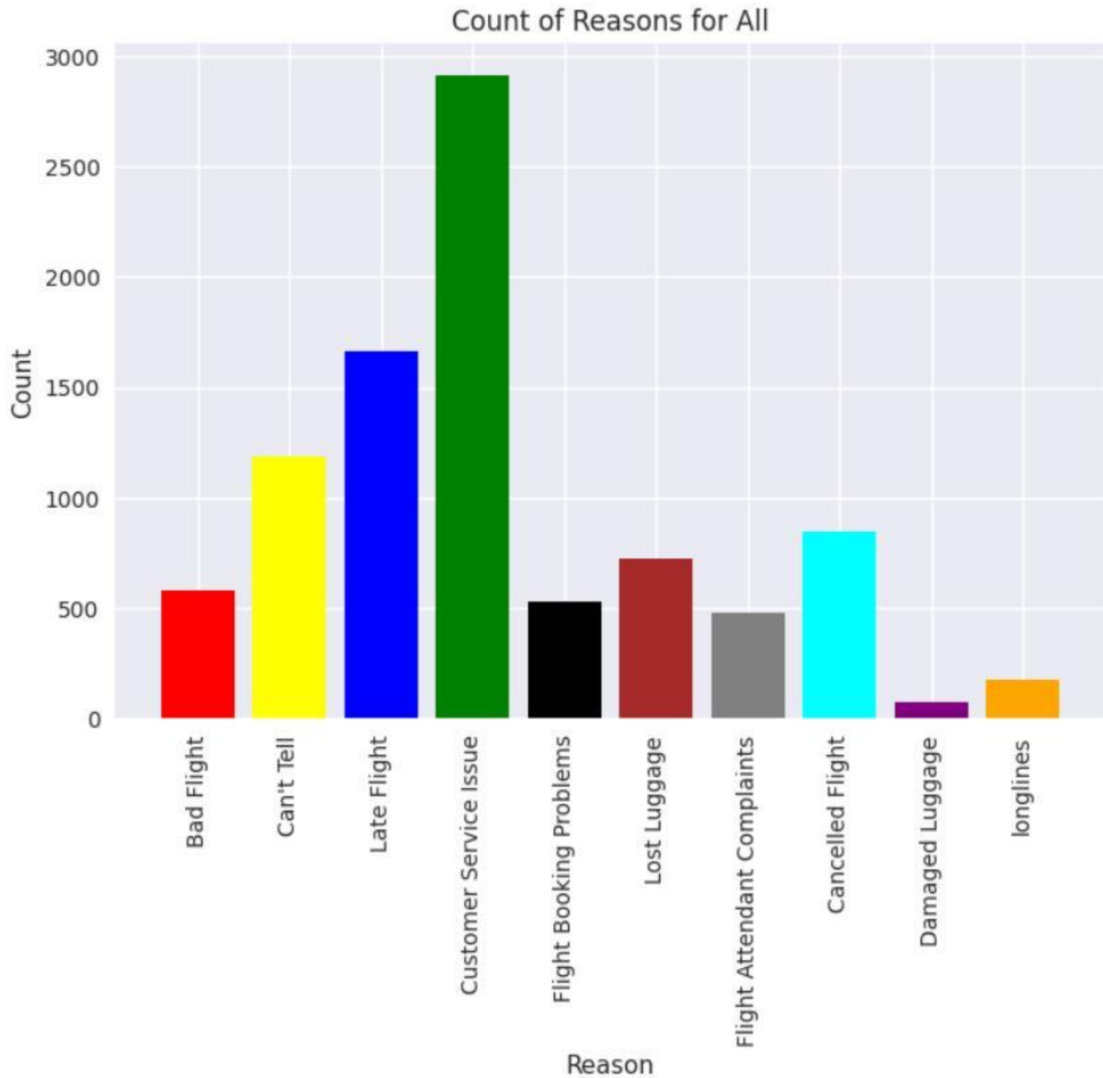


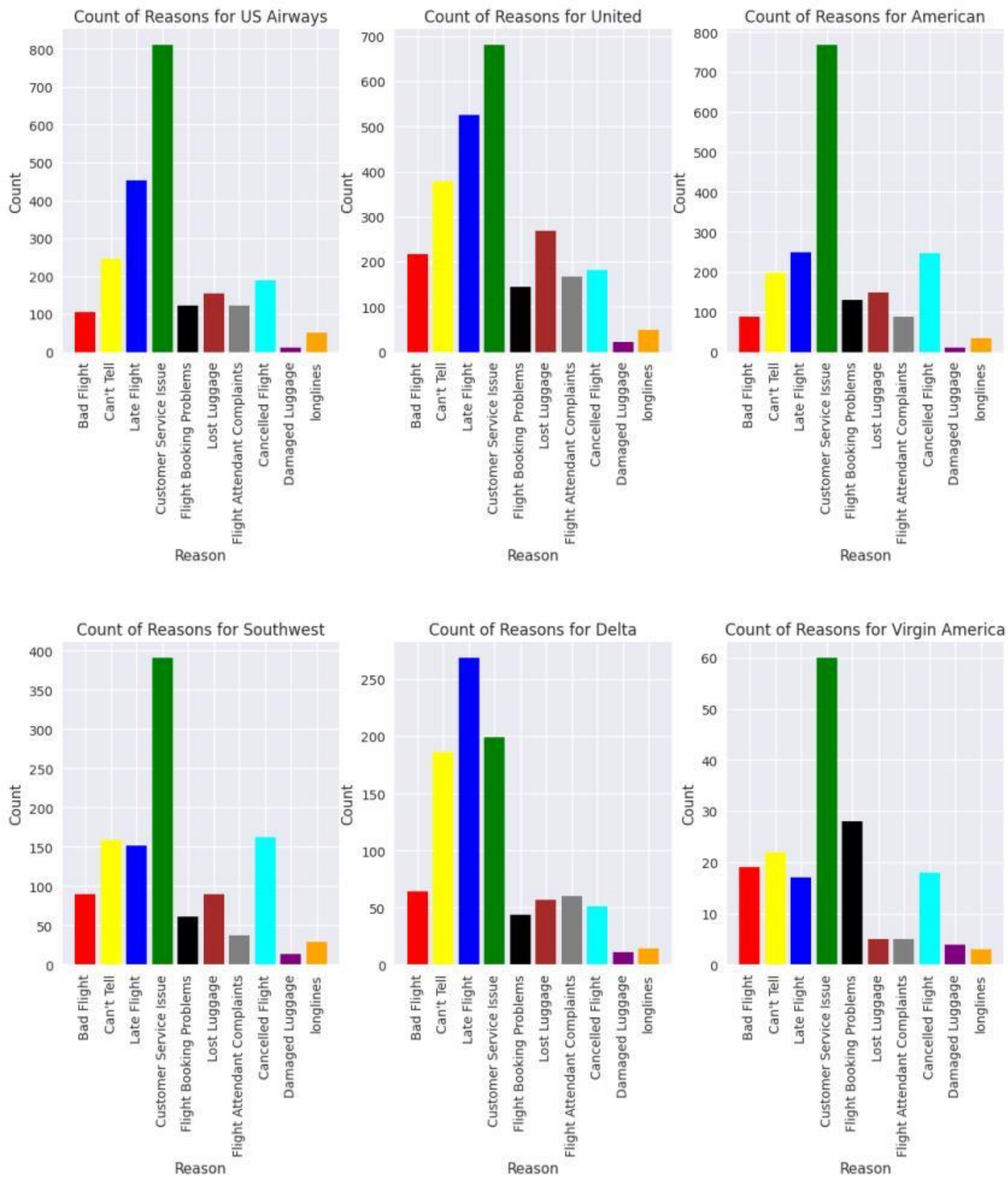
[18]:
```
negative_reasons = twitter_df.groupby('airline')['negativereason'].
    value_counts(ascending=True)
negative_reasons.groupby(['airline','negativereason']).sum().unstack().
    plot(kind='bar',figsize=(22,12))
plt.xlabel('Airline Company')
plt.ylabel('Number of Negative reasons')
plt.title("The number of the count of negative reasons for airlines")
plt.show()
```




```
[19]: twitter_df['negativereason'].nunique()

NR_Count=dict(twitter_df['negativereason'].value_counts(sort=False))
def NR_Count(Airline):
    if Airline=='All':
        a=twitter_df
    else:
        a=twitter_df[twitter_df['airline']==Airline]
        count=dict(a['negativereason'].value_counts())
        Unique_reason=list(twitter_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)
```



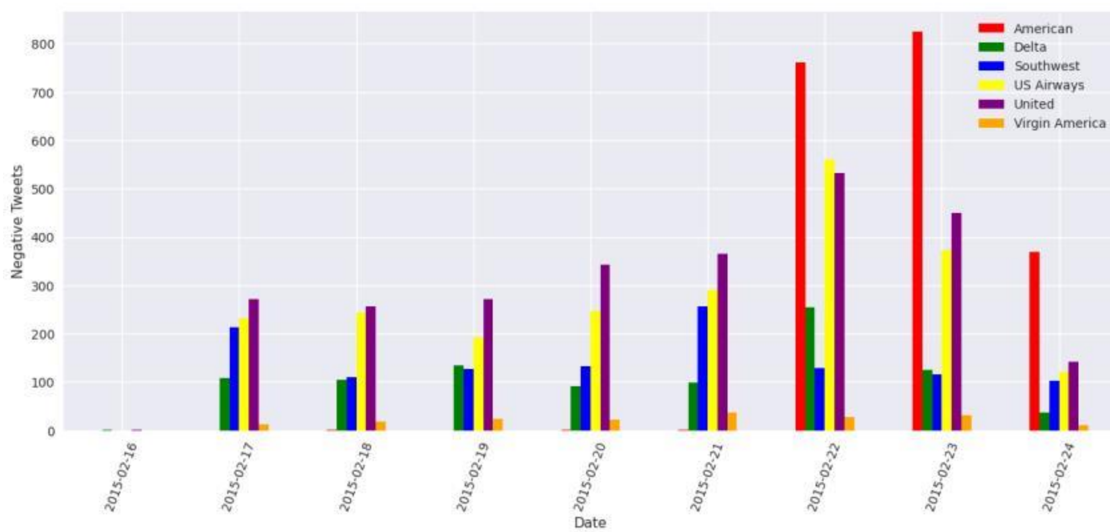


[20]:
```
date = twitter_df.reset_index()
#convert the Date column to pandas datetime
date.tweet_created = pd.to_datetime(date.tweet_created)
#Reduce the dates in the date column to only the date and no time stamp using the 'dt.date' method
date.tweet_created = date.tweet_created.dt.date
date.tweet_created.head()
df = date
```

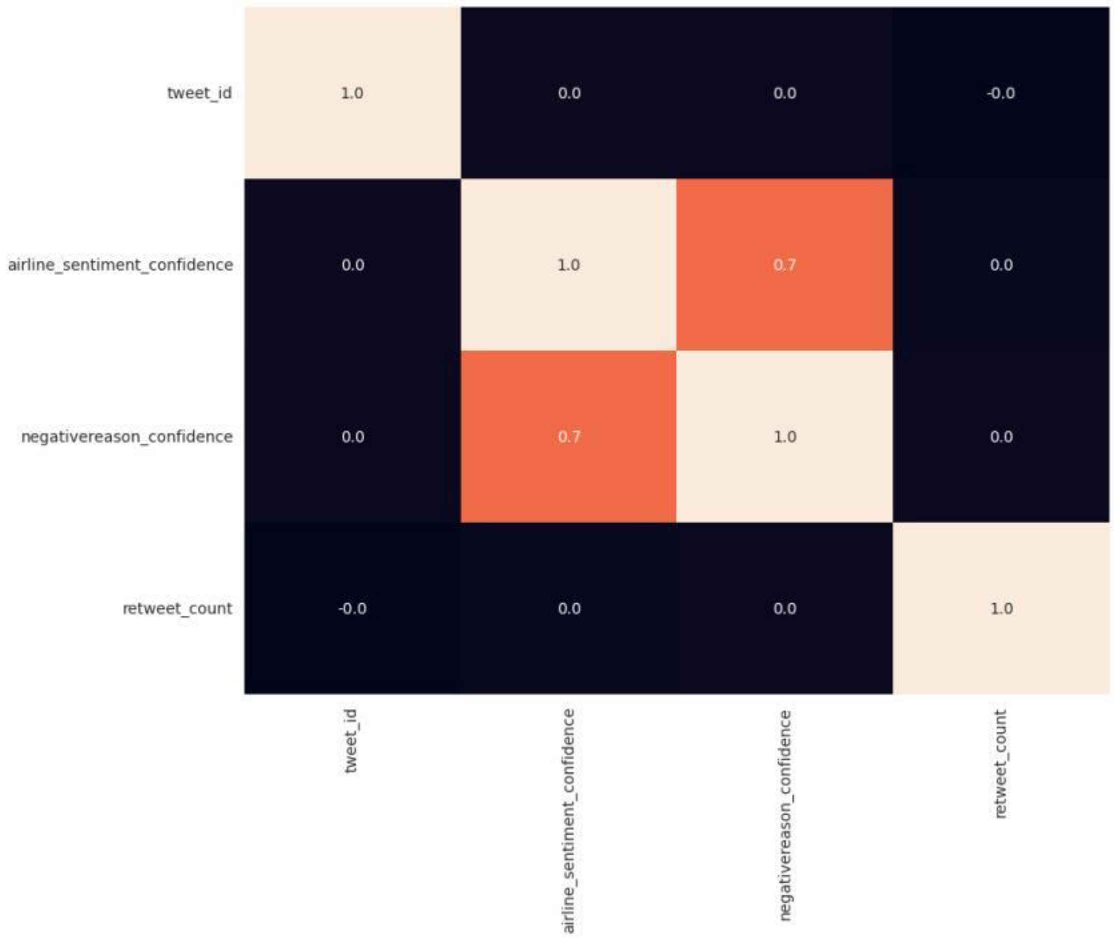
```
day_df = df.groupby(['tweet_created','airline','airline_sentiment']).size()
# day_df = day_df.reset_index()
day_df
```

```
[20]: 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             10
                                     America             6
                                     positive
                                     negative           13
      Length: 136, dtype: int64      neutral
```

```
[21]: 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 = 
    (15,6), 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()
```

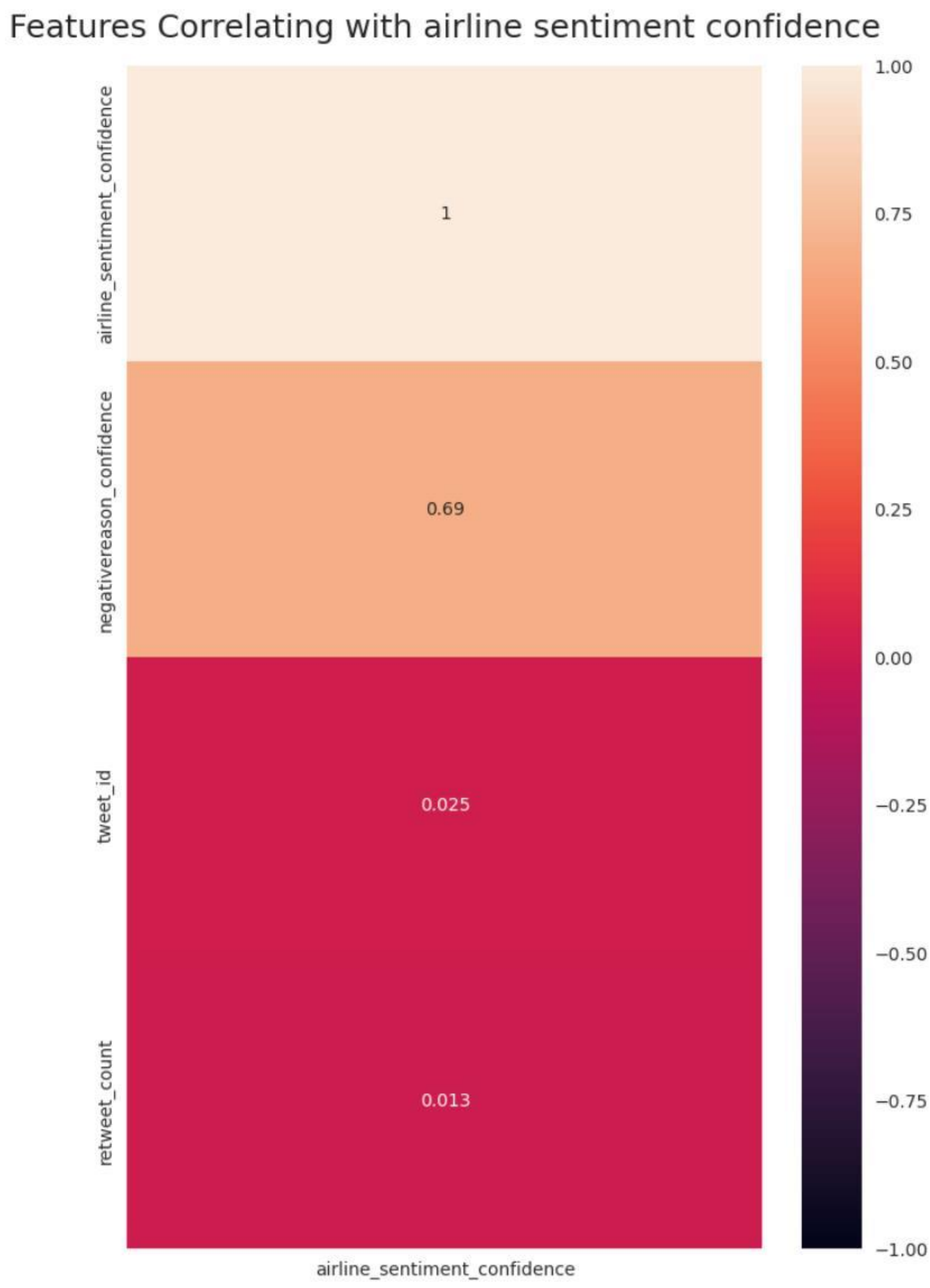


[22]:
```
plt.figure(figsize=(10,8))
sns.heatmap(twitter_df.corr(),annot=True,cbar=False,fmt='.1f')
plt.show()
```

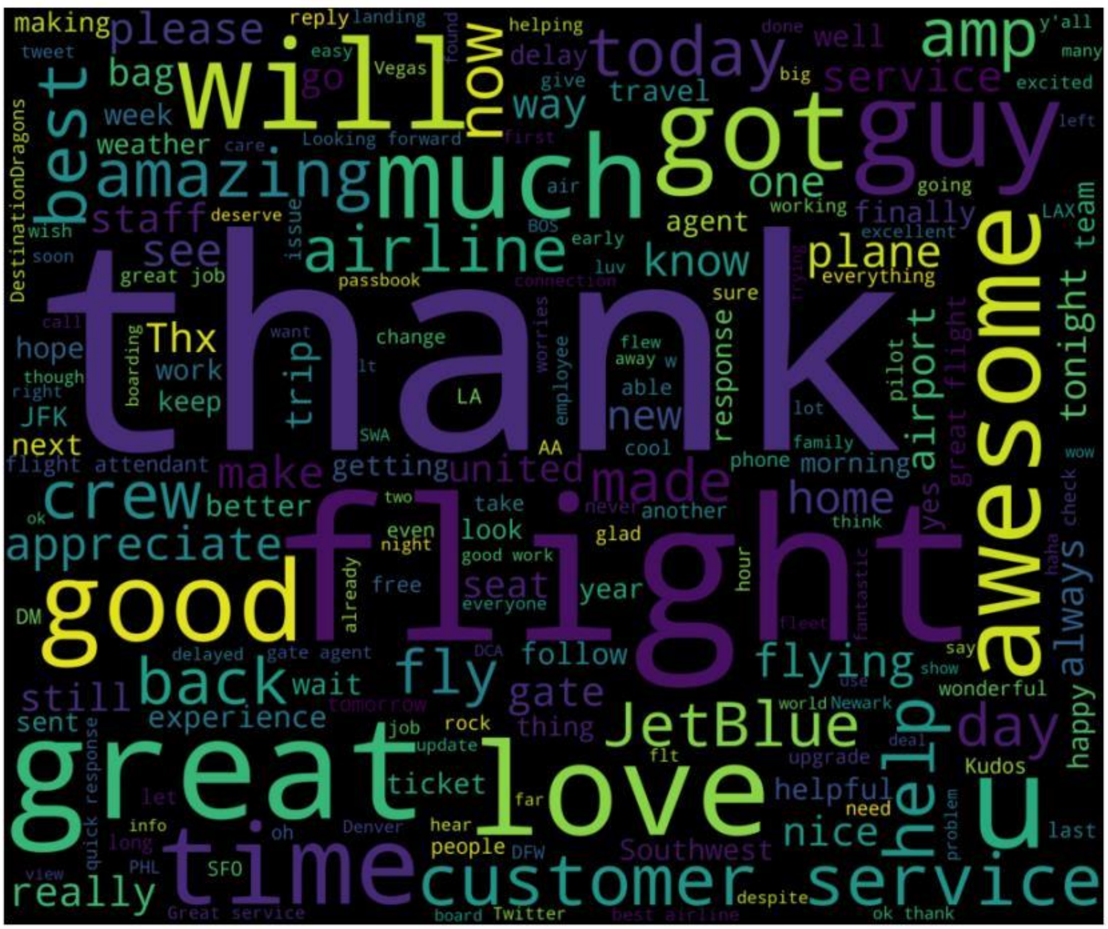


[23]:
```
plt.figure(figsize=(8, 12))
heatmap = sns.heatmap(twitter_df.corr()[['airline_sentiment_confidence']].
    sort_values(by='airline_sentiment_confidence', ascending=False), vmin=-1,
 ↪vmax=1, annot=True)
 ↪heatmap.set_title('Features Correlating with airline sentiment confidence',
    fontdict={'fontsize':18}, pad=16)
 ↪
```

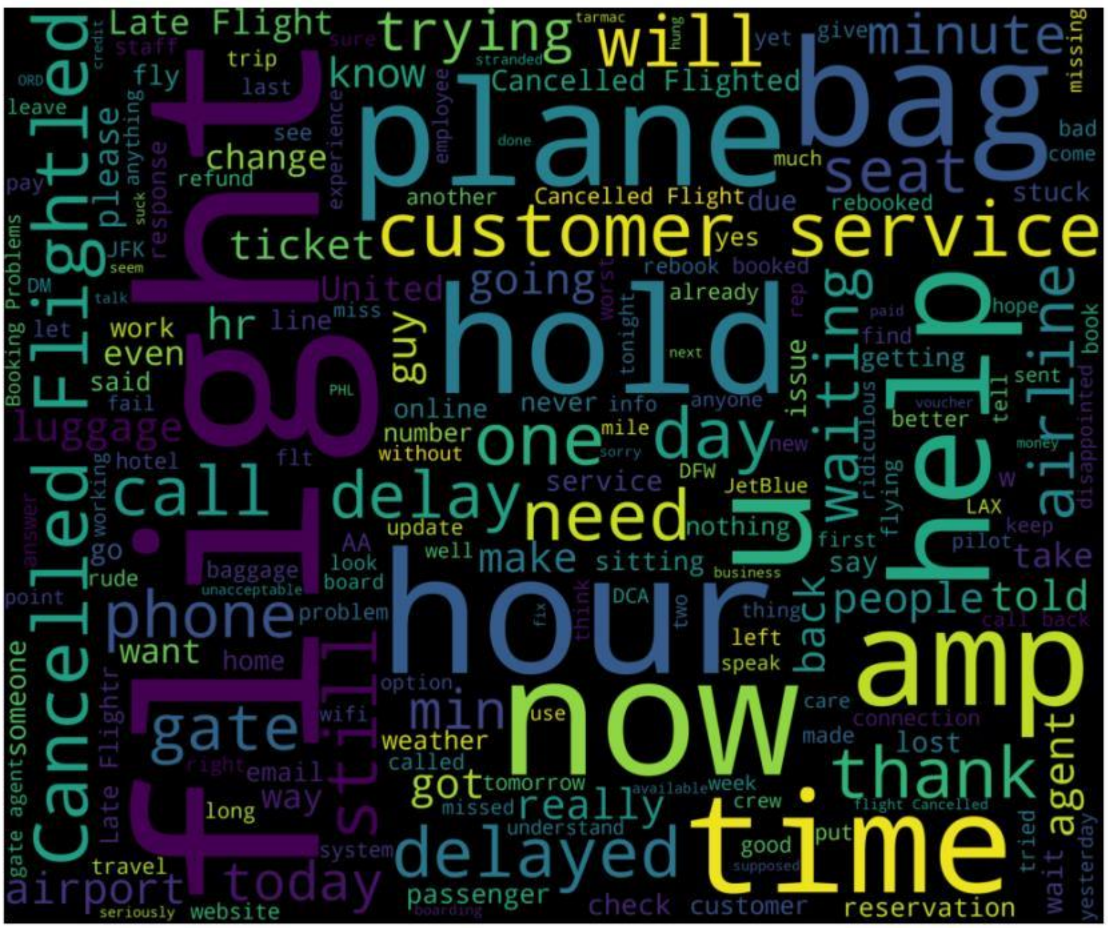
[23]: Text(0.5, 1.0, 'Features Correlating with airline sentiment confidence')


Features Correlating with airline sentiment confidence
airline_sentiment_confidence
negativereason_confidence
tweet_id
retweet_count
1
0.69
0.025
0.013
airline_sentiment_confidence
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

```
[24]: from wordcloud import WordCloud,STOPWORDS
new_df=twitter_df[twitter_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=STOP
                            WORDS,
                            background_color='black',
                            width=3000,
                            height=2500
                            ).generate(cleaned_word)
plt.axis('off')             plt.figure(1,figsize=(12, 12))
plt.show()                  plt.imshow(wordcloud)
```



```
[25]: new_df=twitter_df[twitter_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',
height=2500,
width=3000
).generate(cleaned_word)
plt.figure(1,figsize=(12, 12))
plt.imshow(wordcloud)
plt.axis('off')
plt.show()
```



```
[26]: def clean_the_tweet(text):
    tokens= nltk.word_tokenize(re.sub("[^a-zA-Z]", " ",text))
    tokens = [token.lower() for token in tokens]
    return ' '.join(tokens[2:])



def text_process(msg):
    nopunc =[char for char in msg if char not in string.punctuation]
    nopunc=''.join(nopunc)
    return ' '.join([word for word in nopunc.split() if word.lower() not in␣
    ↪stopwords.words('english')])



def check_scores(clf,X_train, X_test, y_train, y_test):

    model=clf.fit(X_train, y_train)
    predicted_class=model.predict(X_test)
    predicted_class_train=model.predict(X_train)
    test_probs = model.predict_proba(X_test)
    test_probs = test_probs[:, 1]
    yhat = model.predict(X_test)
    lr_precision, lr_recall, _ = precision_recall_curve(y_test, test_probs)
    lr_f1, lr_auc = f1_score(y_test, yhat), auc(lr_recall, lr_precision)


    print('Train confusion matrix is: ',)
    print(confusion_matrix(y_train, predicted_class_train))

    print()
    print('Test confusion matrix is: ')
    print(confusion_matrix(y_test, predicted_class))
    print()
    print(classification_report(y_test,predicted_class))
    print()
    train_accuracy = accuracy_score(y_train,predicted_class_train)
    test_accuracy = accuracy_score(y_test,predicted_class)

    print("Train accuracy score: ", train_accuracy)
    print("Test accuracy score: ",test_accuracy )
    print()
    train_auc = roc_auc_score(y_train, clf.predict_proba(X_train)[:,1])
    test_auc = roc_auc_score(y_test, clf.predict_proba(X_test)[:,1])

    print("Train ROC-AUC score: ", train_auc)
    print("Test ROC-AUC score: ", test_auc)
```

```
fig, (ax1, ax2) = plt.subplots(1, 2)

ax1.plot(lr_recall, lr_precision)
ax1.set(xlabel="Recall", ylabel="Precision")

plt.subplots_adjust(left=0.5,
                    bottom=0.1,
                    right=1.5,
                    top=0.9,
                    wspace=0.4,
                    hspace=0.4)
                    print()
print('Are under Precision-Recall curve:', lr_f1)

fpr, tpr, _ = roc_curve(y_test, test_probs)


ax2.plot(fpr, tpr)
ax2.set(xlabel='False Positive Rate', ylabel='True Positive Rate')

print("Area under ROC-AUC:", lr_auc)
return train_accuracy, test_accuracy, train_auc, test_auc



def grid_search(model, parameters, X_train, Y_train):
#Doing a grid
                        grid = GridSearchCV(estimator=model,
                        param_grid = parameters,
                        cv = 2, verbose=2, scoring='roc_auc')
                        #F itting the grid
                        grid.fit(X_train,Y_train)
                        print()
                        print()
                        # Best model found using grid search
                        optimal_model = grid.best_estimator_
                        print('Best parameters are: ')
                        print( grid.best_params_)

return optimal_model
```

1 Text Preparation

[27]:
```python
df = df[df['airline_sentiment']!='neutral']
df['cleaned_tweet'] = df['text'].apply(clean_the_tweet)

df.head()
df['airline_sentiment'] = df['airline_sentiment'].apply(lambda x: 1 if x␣
    =='positive' else 0)
↪df.head()
```

[27]:
```
       index             tweet_id airline_sentiment airline_sentiment_confidence  \
1          1   570301130888122368                 1                       0.3486
3          3   570301031407624196                 0                       1.0000
4          4   570300817074462722                 0                       1.0000
5          5   570300767074181121                 0                       1.0000
6          6   570300616901320704                 1                       0.6745

  negativereason negativereason_confidence         airline  \
1            NaN                    0.0000  Virgin America
3            Bad                    0.7033  Virgin America
4         Flight                    1.0000  Virgin America
5          Can't                    0.6842  Virgin America
6           Tell                    0.0000  Virgin America
           Can't
  airline_sentiment_gold          name negativereason_gold retweet_count  \
1            Tell NaN      jnardino                 NaN             0
3            NaN NaN      jnardino                 NaN             0
4                NaN      jnardino                 NaN             0
5                NaN      jnardino                 NaN             0
6                NaN cjmcginnis                     NaN             0

                                               text tweet_coord  \
1  @VirginAmerica plus you've added commercials t…         NaN
3  @VirginAmerica it's really aggressive to blast…         NaN
4  @VirginAmerica and it's a really big bad thing…         NaN
5  @VirginAmerica seriously would pay $30 a fligh…         NaN
6  @VirginAmerica yes, nearly every time I fly VX…         NaN

  tweet_created   tweet_location               user_timezone  \
1    2015-02-24              NaN Pacific Time (US & Canada)
3    2015-02-24              NaN Pacific Time (US & Canada)
4    2015-02-24              NaN Pacific Time (US & Canada)
5    2015-02-24              NaN Pacific Time (US & Canada)
6    2015-02-24 San Francisco CA Pacific Time (US & Canada)

                                   cleaned_tweet
1                                     you ve added
                                    commercials to
                                    the experience
                                             tacky
```

```
3                    s really aggressive to blast obnoxious
4                    enterta…
5                    it s a really big bad thing about it
6                    would pay a flight for seats that didn t have
                     …
                     nearly every time i fly vx this ear worm won
                     t…
```

[28]:
```python
df['cleaned_tweet'] = df['cleaned_tweet'].apply(text_process)
df.reset_index(drop=True, inplace = True)
df.head()
```

[28]:
```
   index             tweet_id airline_sentiment airline_sentiment_confidence  \
0      1  570301130888122368                 1                       0.3486
1      3  570301031407624196                 0                       1.0000
2      4  570300817074462722                 0                       1.0000
3      5  570300767074181121                 0                       1.0000
4      6  570300616901320704                 1                       0.6745

  negativereason negativereason_confidence          airline  \
0            NaN                    0.0000  Virgin America
1            Bad                    0.7033  Virgin America
2         Flight                    1.0000  Virgin America
3          Can't                    0.6842  Virgin America
4           Tell                    0.0000  Virgin America
           Can't
           Tell
           NaN

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

                                                text tweet_coord  \
0  @VirginAmerica plus you've added commercials t…         NaN
1  @VirginAmerica it's really aggressive to blast…         NaN
2  @VirginAmerica and it's a really big bad thing…         NaN
3  @VirginAmerica seriously would pay $30 a fligh…         NaN
4  @VirginAmerica yes, nearly every time I fly VX…         NaN

  tweet_created  tweet_location               user_timezone  \
0  2015-02-24                NaN Pacific Time (US & Canada)
1  2015-02-24                NaN Pacific Time (US & Canada)
2  2015-02-24                NaN Pacific Time (US & Canada)
3  2015-02-24                NaN Pacific Time (US & Canada)
4  2015-02-24 San Francisco CA Pacific Time (US & Canada)

                                      cleaned_tweet
0                                             added
1                                       commercials
                                  experience tacky
                                 really aggressive
                                  blast obnoxious
                                   entertainmen…
```

2	really big bad thing
3	would pay flight seats
4	playing really bad thin…
	nearly every time fly vx
	ear worm go away

[29]:
```
df['airline_sentiment'].unique()
```

[29]: array([1, 0])

2 Base SVM model with TF-IDF

[30]:
```
# Creating object of TF -IDF vectorizer
vectorizer = TfidfVectorizer(use_idf=True, lowercase=True)
X_tf_idf= vectorizer.fit_transform(df.cleaned_tweet)
x_train, x_test, y_train, y_test = train_test_split(X_tf_idf, ␣
    ↪df['airline_sentiment'], random_state=42)
```

[31]:
```
SVM = svm.SVC( probability=True)
s_train_accuracy, s_test_accuracy, s_train_auc, s_test_auc = ␣
    ↪check_scores(SVM,x_train, x_test, y_train, y_test)
```

Train confusion matrix is:
[[6824 31]
[151 1649]]

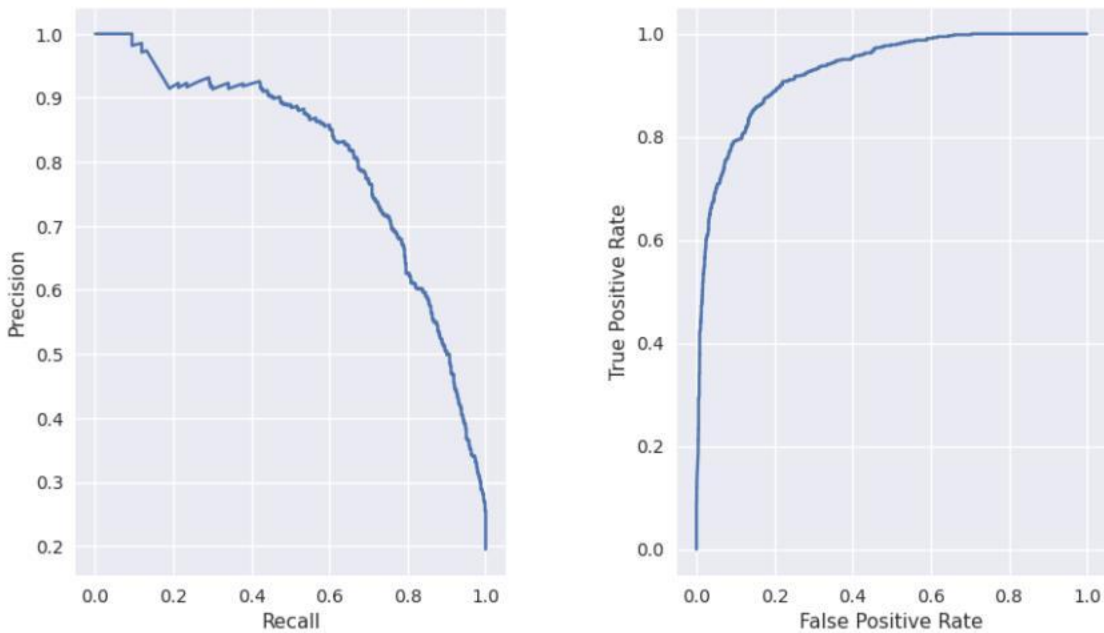
Test confusion matrix is:
[[2291 32]
[296 267]]

	precision	recall	f1-score	support
0	0.89	0.99	0.93	2323
1	0.89	0.47	0.62	563
accuracy			0.89	2886
macro avg	0.89	0.73	0.78	2886
weighted avg	0.89	0.89	0.87	2886

Train accuracy score: 0.9789716926632005
Test accuracy score: 0.8863478863478863

Train ROC-AUC score: 0.9969059080962801
Test ROC-AUC score: 0.9291699576938928

Are under Precision-Recall curve: 0.6194895591647333
Area under ROC-AUC: 0.8049981076642363



3 optimizing the hyperparameters with TF-IDF

[32]:
```
parameters ={
        "C":[0.1,1,10],
        "kernel":['linear', 'rbf', 'sigmoid'],
        "gamma":['scale', 'auto']
}



svm_optimal = grid_search(svm.SVC(probability=True), parameters,x_train,
    y_train)
```

```
Fitting 2 folds for each of 18 candidates, totalling 36 fits
[CV] END …C=0.1, gamma=scale, kernel=linear; total time=   6.0s
[CV] END …C=0.1, gamma=scale, kernel=linear; total time=   5.8s
[CV] END …C=0.1, gamma=scale, kernel=rbf; total time=   9.6s
[CV] END …C=0.1, gamma=scale, kernel=rbf; total time=   9.4s
[CV] END …C=0.1, gamma=scale, kernel=sigmoid; total time=   5.9s
[CV] END …C=0.1, gamma=scale, kernel=sigmoid; total time=   5.8s
[CV] END …C=0.1, gamma=auto, kernel=linear; total time=   6.0s
[CV] END …C=0.1, gamma=auto, kernel=linear; total time=   5.9s
[CV] END …C=0.1, gamma=auto, kernel=rbf; total time=   4.7s
[CV] END …C=0.1, gamma=auto, kernel=rbf; total time=   4.7s
[CV] END …C=0.1, gamma=auto, kernel=sigmoid; total time=   4.4s
```

```
[CV] END …C=0.1, gamma=auto, kernel=sigmoid; total time=   4.4s
[CV] END …C=1, gamma=scale, kernel=linear; total time=   5.9s
[CV] END …C=1, gamma=scale, kernel=linear; total time=   5.7s
[CV] END …C=1, gamma=scale, kernel=rbf; total time= 10.6s
[CV] END …C=1, gamma=scale, kernel=rbf; total time= 10.5s
[CV] END …C=1, gamma=scale, kernel=sigmoid; total time=   5.6s
[CV] END …C=1, gamma=scale, kernel=sigmoid; total time=   5.4s
[CV] END …C=1, gamma=auto, kernel=linear; total time=   5.9s
[CV] END …C=1, gamma=auto, kernel=linear; total time=   5.7s
[CV] END …C=1, gamma=auto, kernel=rbf; total time=   4.9s
[CV] END …C=1, gamma=auto, kernel=rbf; total time=   4.9s
[CV] END …C=1, gamma=auto, kernel=sigmoid; total time=   4.5s
[CV] END …C=1, gamma=auto, kernel=sigmoid; total time=   4.4s
[CV] END …C=10, gamma=scale, kernel=linear; total time=   6.3s
[CV] END …C=10, gamma=scale, kernel=linear; total time=   6.3s
[CV] END …C=10, gamma=scale, kernel=rbf; total time= 11.6s
[CV] END …C=10, gamma=scale, kernel=rbf; total time= 11.5s
[CV] END …C=10, gamma=scale, kernel=sigmoid; total time=   8.8s
[CV] END …C=10, gamma=scale, kernel=sigmoid; total time=   7.6s
[CV] END …C=10, gamma=auto, kernel=linear; total time=   6.3s
[CV] END …C=10, gamma=auto, kernel=linear; total time=   6.2s
[CV] END …C=10, gamma=auto, kernel=rbf; total time=   6.2s
[CV] END …C=10, gamma=auto, kernel=rbf; total time=   6.1s
[CV] END …C=10, gamma=auto, kernel=sigmoid; total time=   5.3s
[CV] END …C=10, gamma=auto, kernel=sigmoid; total time=   5.3s


Best parameters are:
{'C': 10, 'gamma': 'scale', 'kernel': 'rbf'}
```

[33]:
```
so_train_accuracy, so_test_accuracy, so_train_auc, so_test_auc = 
    check_scores(svm_optimal,x_train, x_test, y_train, y_test)
```

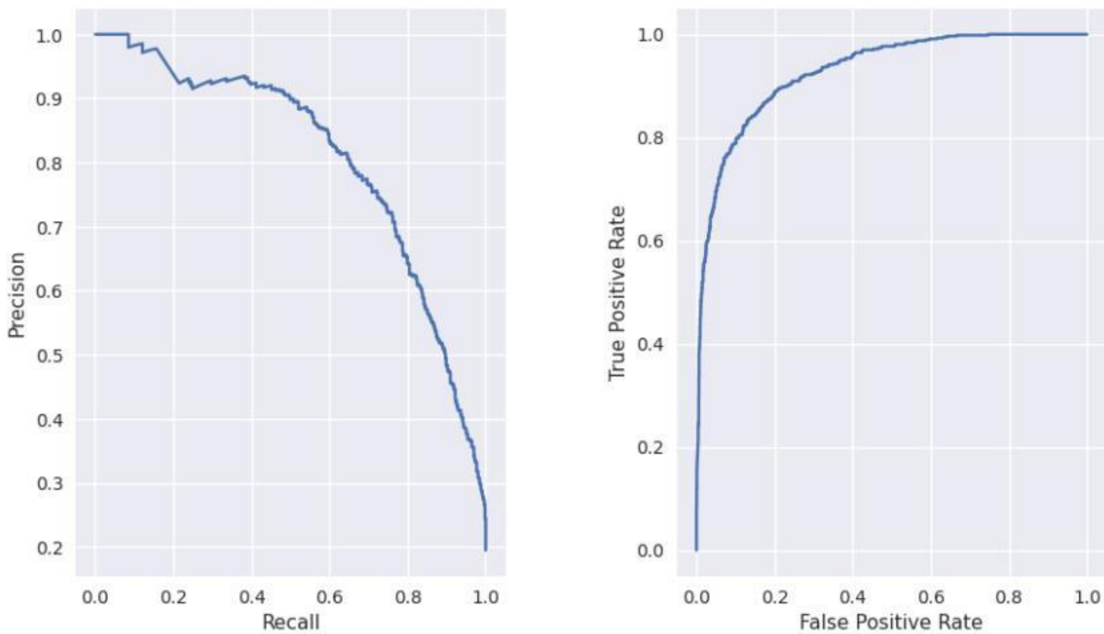
```
Train confusion matrix is:
[[6829   26]
 [   5 1795]]

Test confusion matrix is:
[[2272   51]
 [ 245  318]]

              precision    recall  f1-score   support

           0       0.90      0.98      0.94      2323
           1       0.86      0.56      0.68       563

    accuracy                           0.90      2886
   macro avg       0.88      0.77      0.81      2886
```

weighted avg	0.89	0.90	0.89	2886

Train accuracy score: 0.996418255343732
Test accuracy score: 0.8974358974358975

Train ROC-AUC score: 0.9987310154793744
Test ROC-AUC score: 0.928759359834354

Are under Precision-Recall curve: 0.6824034334763949
Area under ROC-AUC: 0.80756377046123



4 Multinomial Naive Bayes

[34]:
```
m_train_accuracy, m_test_accuracy, m_train_auc, m_test_auc = 
    check_scores(MultinomialNB(),x_train, x_test, y_train, y_test)
```

Train confusion matrix is:
 [[6853   2]
 [1296 504]]

Test confusion matrix is:
 [[2318   5]
 [474   89]]

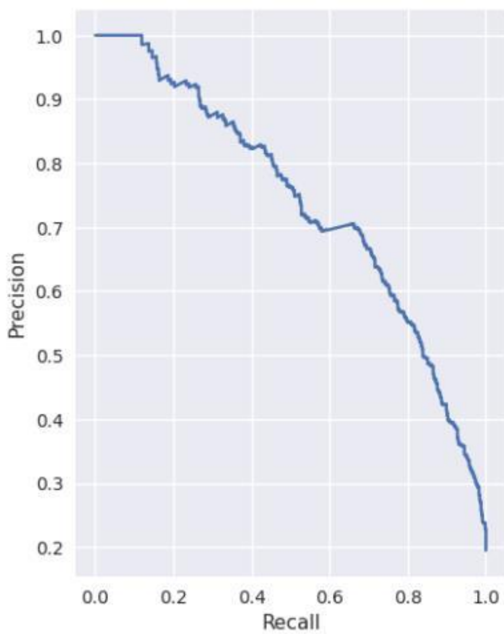
	precision	recall	f1-score	support

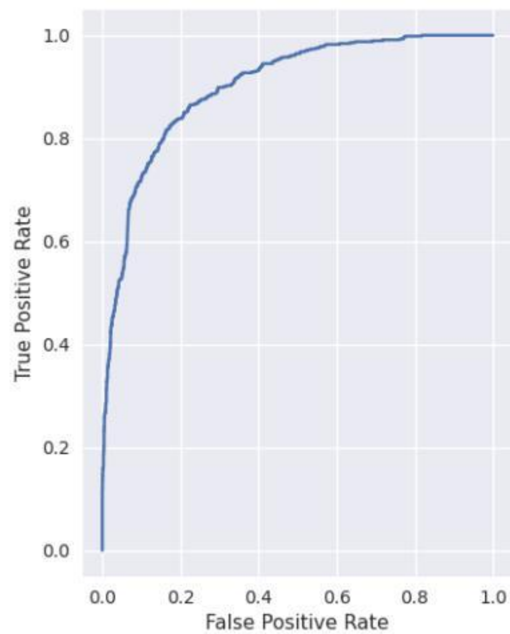
0	0.83	1.00	0.91	2323
1	0.95	0.16	0.27	563
accuracy			0.83	2886
macro avg	0.89	0.58	0.59	2886
weighted avg	0.85	0.83	0.78	2886

Train accuracy score: 0.8500288850375506
Test accuracy score: 0.834026334026334

Train ROC-AUC score: 0.9561105438041981
Test ROC-AUC score: 0.9013005324009118

Are under Precision-Recall curve: 0.27092846270928466
Area under ROC-AUC: 0.7374839454006489





5 Gaussian Naive Bayes

[35]:
```
g_train_accuracy, g_test_accuracy, g_train_auc,
    g_test_auc=check_scores(GaussianNB(),x_train.toarray(), x_test.toarray(),
    y_train, y_test)
```

Train confusion matrix is:
[[5543 1312]

[0 1800]]

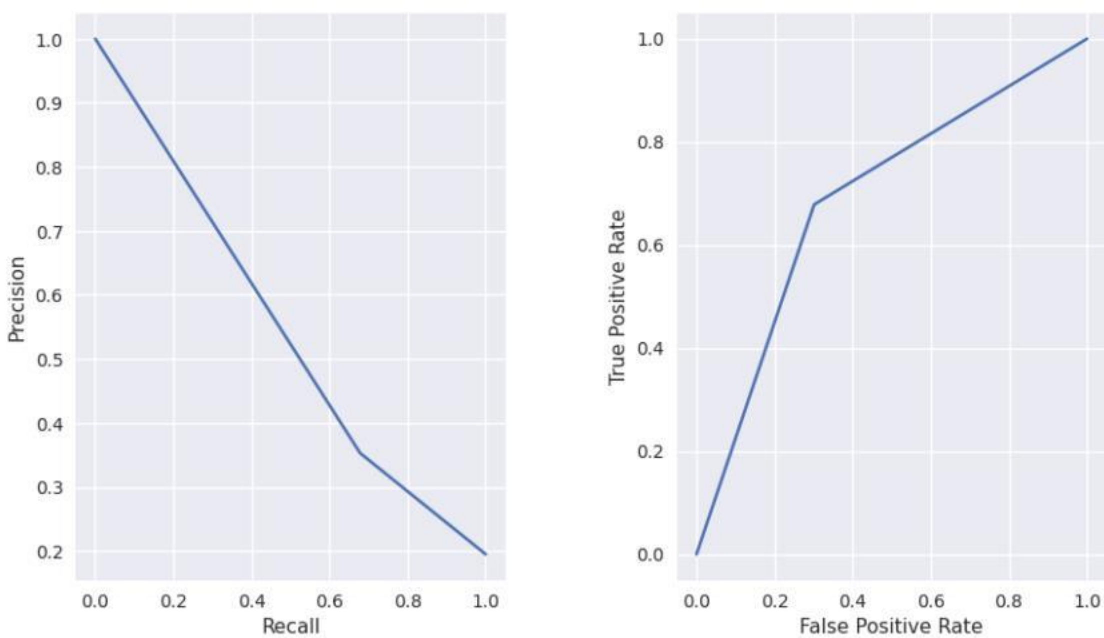
Test confusion matrix is:
[[1623 700]
[181 382]]

	precision	recall	f1-score	support
0	0.90	0.70	0.79	2323
1	0.35	0.68	0.46	563
accuracy			0.69	2886
macro avg	0.63	0.69	0.63	2886
weighted avg	0.79	0.69	0.72	2886

Train accuracy score: 0.8484113229347198
Test accuracy score: 0.6947331947331947

Train ROC-AUC score: 0.9043034281546316
Test ROC-AUC score: 0.688586755810495

Are under Precision-Recall curve: 0.4644376899696049
Area under ROC-AUC: 0.5471372315951626

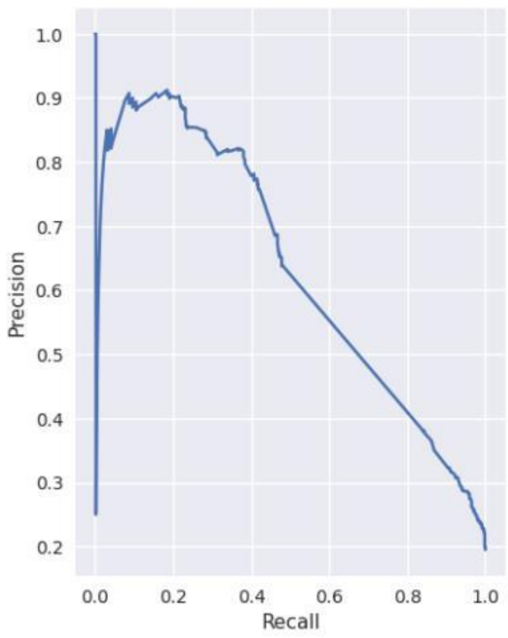


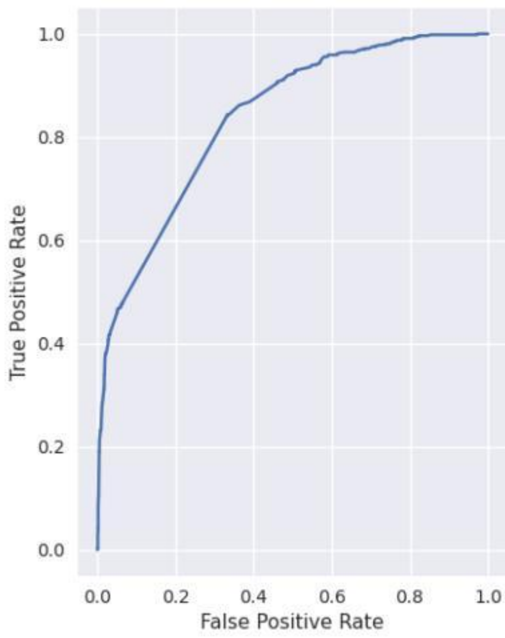
It is interesting to see in Naive Bayes, we are getting linear relationship.

6 AdaBoost

[36]:
```
a_train_accuracy, a_test_accuracy, a_train_auc,␣
↪a_test_auc=check_scores(AdaBoostClassifier(),x_train,x_test, y_train, y_test)
```

```
Train confusion matrix is:
[[6655 200]
[1012 788]]

Test confusion matrix is:
[[2251   72]
 [ 328 235]]

              precision    recall  f1-score   support

           0       0.87      0.97      0.92      2323
           1       0.77      0.42      0.54       563

    accuracy                           0.86      2886
   macro avg       0.82      0.69      0.73      2886
weighted avg       0.85      0.86      0.84      2886

Train accuracy score: 0.8599653379549393
Test accuracy score: 0.8613998613998614

Train ROC-AUC score: 0.8689482940270687
Test ROC-AUC score: 0.8373803091947158

Are under Precision-Recall curve: 0.5402298850574713
Area under ROC-AUC: 0.6298876361965743
```





7 AdaBoost with hyperparameters

```
[37]: params = {'n_estimators': [10, 50, 100, 500],
 'learning_rate': [0.0001, 0.001, 0.01, 0.1, 1.0],
 'algorithm': ['SAMME', 'SAMME.R']}

ada_optimal_model = grid_search(AdaBoostClassifier(), params,x_train, y_train)
```

Fitting 2 folds for each of 40 candidates, totalling 80 fits
[CV] END algorithm=SAMME, learning_rate=0.0001, n_estimators=10; total time=
0.4s
[CV] END algorithm=SAMME, learning_rate=0.0001, n_estimators=10; total time=
0.4s
[CV] END algorithm=SAMME, learning_rate=0.0001, n_estimators=50; total time=
1.8s
[CV] END algorithm=SAMME, learning_rate=0.0001, n_estimators=50; total time=
1.7s
[CV] END algorithm=SAMME, learning_rate=0.0001, n_estimators=100; total time=
3.5s
[CV] END algorithm=SAMME, learning_rate=0.0001, n_estimators=100; total time=
3.5s
[CV] END algorithm=SAMME, learning_rate=0.0001, n_estimators=500; total time=
17.6s
[CV] END algorithm=SAMME, learning_rate=0.0001, n_estimators=500; total time=
17.5s

[CV] END algorithm=SAMME, learning_rate=0.001, n_estimators=10; total time=
0.4s
[CV] END algorithm=SAMME, learning_rate=0.001, n_estimators=10; total time=
0.4s
[CV] END algorithm=SAMME, learning_rate=0.001, n_estimators=50; total time=
1.7s
[CV] END algorithm=SAMME, learning_rate=0.001, n_estimators=50; total time=
1.7s
[CV] END algorithm=SAMME, learning_rate=0.001, n_estimators=100; total time=
3.5s
[CV] END algorithm=SAMME, learning_rate=0.001, n_estimators=100; total time=
3.5s
[CV] END algorithm=SAMME, learning_rate=0.001, n_estimators=500; total time=
17.6s
[CV] END algorithm=SAMME, learning_rate=0.001, n_estimators=500; total time=
17.4s
[CV] END algorithm=SAMME, learning_rate=0.01, n_estimators=10; total time=
0.4s
[CV] END algorithm=SAMME, learning_rate=0.01, n_estimators=10; total time=
0.4s
[CV] END algorithm=SAMME, learning_rate=0.01, n_estimators=50; total time=
1.8s
[CV] END algorithm=SAMME, learning_rate=0.01, n_estimators=50; total time=
1.7s
[CV] END algorithm=SAMME, learning_rate=0.01, n_estimators=100; total time=
3.5s
[CV] END algorithm=SAMME, learning_rate=0.01, n_estimators=100; total time=
3.5s
[CV] END algorithm=SAMME, learning_rate=0.01, n_estimators=500; total time=
17.6s
[CV] END algorithm=SAMME, learning_rate=0.01, n_estimators=500; total time=
17.5s
[CV] END algorithm=SAMME, learning_rate=0.1, n_estimators=10; total time= 0.4s
[CV] END algorithm=SAMME, learning_rate=0.1, n_estimators=10; total time= 0.4s
[CV] END algorithm=SAMME, learning_rate=0.1, n_estimators=50; total time= 1.7s
[CV] END algorithm=SAMME, learning_rate=0.1, n_estimators=50; total time= 1.8s
[CV] END algorithm=SAMME, learning_rate=0.1, n_estimators=100; total time=
3.5s
[CV] END algorithm=SAMME, learning_rate=0.1, n_estimators=100; total time=
3.5s
[CV] END algorithm=SAMME, learning_rate=0.1, n_estimators=500; total time=
17.6s
[CV] END algorithm=SAMME, learning_rate=0.1, n_estimators=500; total time=
17.5s
[CV] END algorithm=SAMME, learning_rate=1.0, n_estimators=10; total time= 0.4s
[CV] END algorithm=SAMME, learning_rate=1.0, n_estimators=10; total time= 0.4s
[CV] END algorithm=SAMME, learning_rate=1.0, n_estimators=50; total time= 1.8s
[CV] END algorithm=SAMME, learning_rate=1.0, n_estimators=50; total time= 1.7s

[CV] END algorithm=SAMME, learning_rate=1.0, n_estimators=100; total time=
3.5s
[CV] END algorithm=SAMME, learning_rate=1.0, n_estimators=100; total time=
3.5s
[CV] END algorithm=SAMME, learning_rate=1.0, n_estimators=500; total time=
17.6s
[CV] END algorithm=SAMME, learning_rate=1.0, n_estimators=500; total time=
17.5s
[CV] END algorithm=SAMME.R, learning_rate=0.0001, n_estimators=10; total time=
0.4s
[CV] END algorithm=SAMME.R, learning_rate=0.0001, n_estimators=10; total time=
0.4s
[CV] END algorithm=SAMME.R, learning_rate=0.0001, n_estimators=50; total time=
1.8s
[CV] END algorithm=SAMME.R, learning_rate=0.0001, n_estimators=50; total time=
1.8s
[CV] END algorithm=SAMME.R, learning_rate=0.0001, n_estimators=100; total time=
3.6s
[CV] END algorithm=SAMME.R, learning_rate=0.0001, n_estimators=100; total time=
3.6s
[CV] END algorithm=SAMME.R, learning_rate=0.0001, n_estimators=500; total time=
17.9s
[CV] END algorithm=SAMME.R, learning_rate=0.0001, n_estimators=500; total time=
17.9s
[CV] END algorithm=SAMME.R, learning_rate=0.001, n_estimators=10; total time=
0.4s
[CV] END algorithm=SAMME.R, learning_rate=0.001, n_estimators=10; total time=
0.4s
[CV] END algorithm=SAMME.R, learning_rate=0.001, n_estimators=50; total time=
1.8s
[CV] END algorithm=SAMME.R, learning_rate=0.001, n_estimators=50; total time=
1.8s
[CV] END algorithm=SAMME.R, learning_rate=0.001, n_estimators=100; total time=
3.6s
[CV] END algorithm=SAMME.R, learning_rate=0.001, n_estimators=100; total time=
3.6s
[CV] END algorithm=SAMME.R, learning_rate=0.001, n_estimators=500; total time=
18.0s
[CV] END algorithm=SAMME.R, learning_rate=0.001, n_estimators=500; total time=
17.9s
[CV] END algorithm=SAMME.R, learning_rate=0.01, n_estimators=10; total time=
0.4s
[CV] END algorithm=SAMME.R, learning_rate=0.01, n_estimators=10; total time=
0.4s
[CV] END algorithm=SAMME.R, learning_rate=0.01, n_estimators=50; total time=
1.8s
[CV] END algorithm=SAMME.R, learning_rate=0.01, n_estimators=50; total time=
1.8s

```
[CV] END algorithm=SAMME.R, learning_rate=0.01, n_estimators=100; total time=
3.6s
[CV] END algorithm=SAMME.R, learning_rate=0.01, n_estimators=100; total time=
3.6s
[CV] END algorithm=SAMME.R, learning_rate=0.01, n_estimators=500; total time=
17.9s
[CV] END algorithm=SAMME.R, learning_rate=0.01, n_estimators=500; total time=
17.9s
[CV] END algorithm=SAMME.R, learning_rate=0.1, n_estimators=10; total time=
0.4s
[CV] END algorithm=SAMME.R, learning_rate=0.1, n_estimators=10; total time=
0.4s
[CV] END algorithm=SAMME.R, learning_rate=0.1, n_estimators=50; total time=
1.8s
[CV] END algorithm=SAMME.R, learning_rate=0.1, n_estimators=50; total time=
1.8s
[CV] END algorithm=SAMME.R, learning_rate=0.1, n_estimators=100; total time=
3.6s
[CV] END algorithm=SAMME.R, learning_rate=0.1, n_estimators=100; total time=
3.6s
[CV] END algorithm=SAMME.R, learning_rate=0.1, n_estimators=500; total time=
18.0s
[CV] END algorithm=SAMME.R, learning_rate=0.1, n_estimators=500; total time=
17.9s
[CV] END algorithm=SAMME.R, learning_rate=1.0, n_estimators=10; total time=
0.4s
[CV] END algorithm=SAMME.R, learning_rate=1.0, n_estimators=10; total time=
0.4s
[CV] END algorithm=SAMME.R, learning_rate=1.0, n_estimators=50; total time=
1.8s
[CV] END algorithm=SAMME.R, learning_rate=1.0, n_estimators=50; total time=
1.8s
[CV] END algorithm=SAMME.R, learning_rate=1.0, n_estimators=100; total time=
3.6s
[CV] END algorithm=SAMME.R, learning_rate=1.0, n_estimators=100; total time=
3.5s
[CV] END algorithm=SAMME.R, learning_rate=1.0, n_estimators=500; total time=
17.9s
[CV] END algorithm=SAMME.R, learning_rate=1.0, n_estimators=500; total time=
17.9s


Best parameters are:
{'algorithm': 'SAMME.R', 'learning_rate': 0.1, 'n_estimators': 500}
```

[38]:
```
ao_train_accuracy, ao_test_accuracy, ao_train_auc,
    ao_test_auc=check_scores(ada_optimal_model,x_train,x_test, y_train, y_test)
```

Train confusion matrix is:
[[6761 94]
[1043 757]]

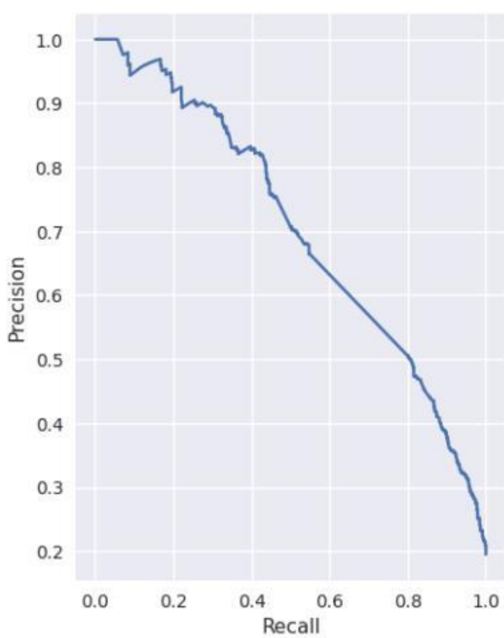
Test confusion matrix is:
[[2278 45]
[340 223]]

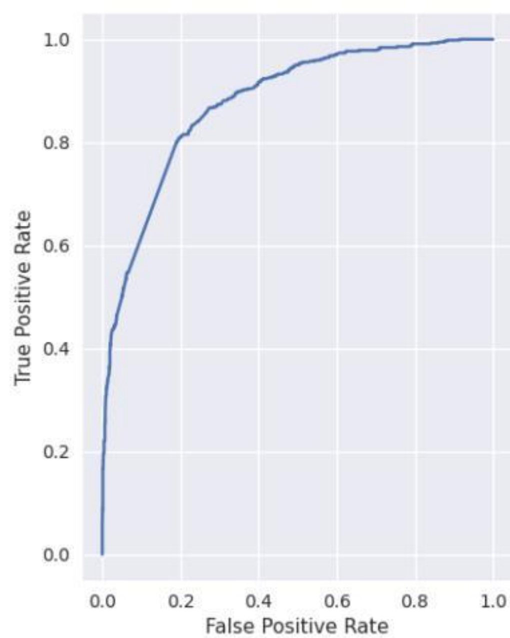
	precision	recall	f1-score	support
0	0.87	0.98	0.92	2323
1	0.83	0.40	0.54	563
accuracy			0.87	2886
macro avg	0.85	0.69	0.73	2886
weighted avg	0.86	0.87	0.85	2886

Train accuracy score: 0.868630849220104
Test accuracy score: 0.8665973665973666

Train ROC-AUC score: 0.9218550936056407
Test ROC-AUC score: 0.8779339205061136

Are under Precision-Recall curve: 0.5367027677496993
Area under ROC-AUC: 0.7021179688268547

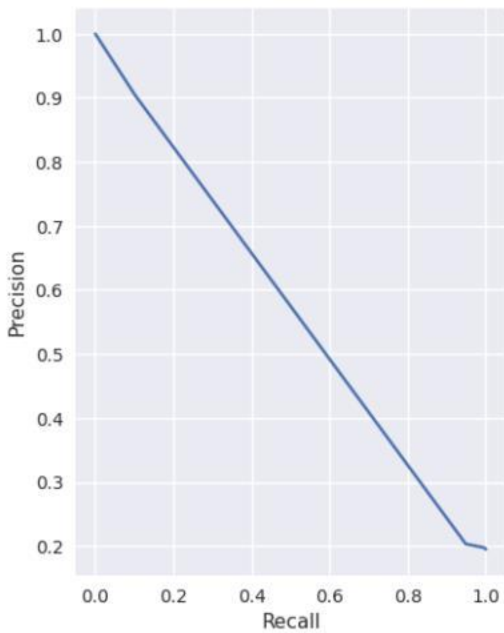


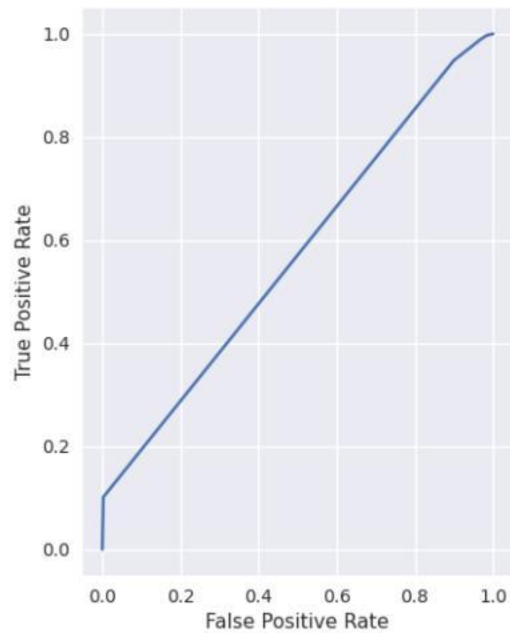


8 KNeighbors

[39]:
```
from sklearn.neighbors import KNeighborsClassifier
knn_train_accuracy, knn_test_accuracy, knn_train_auc, knn_test_auc=
    check_scores(KNeighborsClassifier().fit(x_train, y_train),
    x_train,x_test,y_train,y_test)
```

```
Train confusion matrix is:
[[ 661 6194]
 [   20 1780]]

Test confusion matrix is:
[[ 73 2250]
 [    6   557]]

              precision    recall  f1-score   support

           0       0.92      0.03      0.06      2323
           1       0.20      0.99      0.33       563

    accuracy                           0.22      2886
   macro avg       0.56      0.51      0.20      2886
weighted avg       0.78      0.22      0.11      2886


Train accuracy score: 0.28203350664355864
Test accuracy score: 0.2182952182952183

Train ROC-AUC score: 0.9672222222222223
Test ROC-AUC score: 0.5688336344639173

Are under Precision-Recall curve: 0.3305637982195846
Area under ROC-AUC: 0.5761885418599553
```





9 Random Forest

[40]:
```
r_train_accuracy, r_test_accuracy, r_train_auc, r_test_auc= check_scores(RandomForestClassifier(random_state=0).fit(x_train, y_train), x_train,x_test,y_train,y_test)
```

```
Train confusion matrix is:
[[6829   26]
 [   5 1795]]

Test confusion matrix is:
[[2215  108]
 [ 238  325]]
```

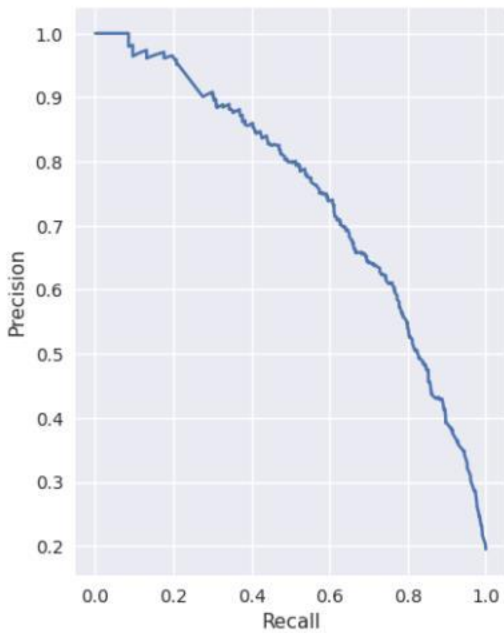
	precision	recall	f1-score	support
0	0.90	0.95	0.93	2323
1	0.75	0.58	0.65	563
accuracy			0.88	2886
macro avg	0.83	0.77	0.79	2886
weighted avg	0.87	0.88	0.87	2886

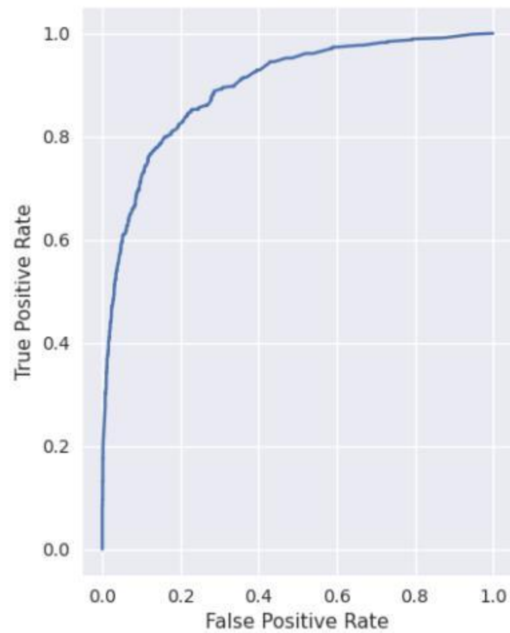
Train accuracy score: 0.996418255343732

Test accuracy score: 0.8801108801108801

Train ROC-AUC score: 0.9982442661479861
Test ROC-AUC score: 0.8956867344777572

Are under Precision-Recall curve: 0.6526104417670683
Area under ROC-AUC: 0.7441899264879837





10 Decision Tree

[41]:
```
from sklearn.tree import DecisionTreeClassifier
dt_train_accuracy, dt_test_accuracy, dt_train_auc, dt_test_auc= 
    check_scores(DecisionTreeClassifier(random_state=0).fit(x_train, y_train), 
    x_train,x_test,y_train,y_test)
```

Train confusion matrix is:
[[6829 26]
[5 1795]]

Test confusion matrix is:
[[2039 284]
[199 364]]

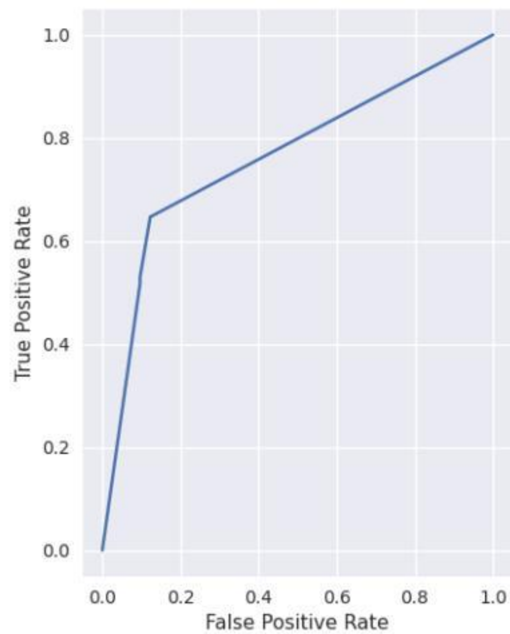
	precision	recall	f1-score	support
0	0.91	0.88	0.89	2323

1	0.56	0.65	0.60	563
accuracy			0.83	2886
macro avg	0.74	0.76	0.75	2886
weighted avg	0.84	0.83	0.84	2886

Train accuracy score: 0.996418255343732
Test accuracy score: 0.8326403326403327

Train ROC-AUC score: 0.9998750303914418
Test ROC-AUC score: 0.7627015809929127

Are under Precision-Recall curve: 0.6011560693641619
Area under ROC-AUC: 0.6116197326239008



11 Neural Network

[42]:
```
from sklearn.neural_network import MLPClassifier
mlp_train_accuracy, mlp_test_accuracy, mlp_train_auc, mlp_test_auc=
    check_scores(MLPClassifier(max_iter=500, random_state=42).fit(x_train,
    y_train), x_train,x_test,y_train,y_test)
```

Train confusion matrix is:
[[6825 30]
[5 1795]]

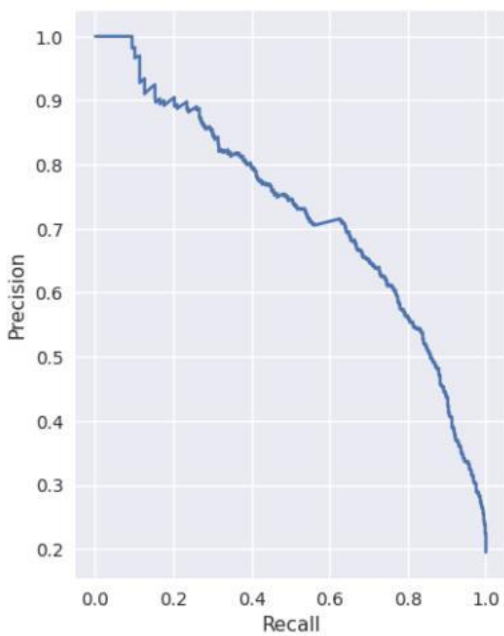
Test confusion matrix is:
[[2125 198]
[178 385]]

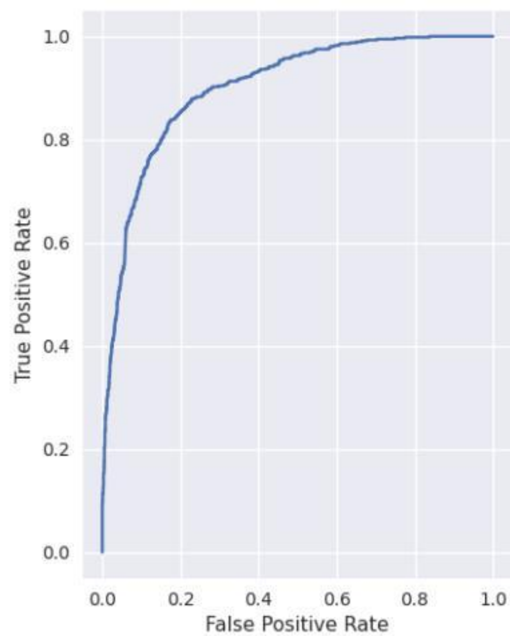
	precision	recall	f1-score	support
0	0.92	0.91	0.92	2323
1	0.66	0.68	0.67	563
accuracy			0.87	2886
macro avg	0.79	0.80	0.80	2886
weighted avg	0.87	0.87	0.87	2886

Train accuracy score: 0.9959560947429231
Test accuracy score: 0.8697158697158697

Train ROC-AUC score: 0.9998520139395413
Test ROC-AUC score: 0.9014878628954872

Are under Precision-Recall curve: 0.6719022687609075
Area under ROC-AUC: 0.724167033127511





12 LSTM

[43]:
```
corpus = [df['cleaned_tweet'][i] for i in range( len(df))]

voc_size=5000

onehot_=[one_hot(words,voc_size)for words in corpus]

max_sent_length=max([len(i) for i in corpus])

embedded_docs=pad_sequences(onehot_,padding='pre',maxlen=max_sent_length)

embedding_vector_features=40
model=Sequential()
model.
    add(Embedding(voc_size,embedding_vector_features,input_length=max_sent_length))
    model.add(Dropout(0.3))
    model.add(LSTM(100))
model.add(Dropout(0.3))
model.add(Dense(1,activation='sigmoid'))
model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])

X_final=np.array(embedded_docs)
y_final=np.array(df['airline_sentiment'])
X_final.shape,y_final.shape
```

[43]: ((11541, 124), (11541,))

[44]:
```
X_train, X_test, y_train, y_test = train_test_split(X_final, y_final,
    test_size=0.33, random_state=42)
model.
    fit(X_train,y_train,validation_data=(X_test,y_test),epochs=10,batch_size=64)
```

```
Epoch 1/10
121/121 [==============================] - 26s 192ms/step - loss: 0.4484 -
accuracy: 0.8100 - val_loss: 0.3276 - val_accuracy: 0.8645
Epoch 2/10
121/121 [==============================] - 21s 175ms/step - loss: 0.2641 -
accuracy: 0.8927 - val_loss: 0.2858 - val_accuracy: 0.8777
Epoch 3/10
121/121 [==============================] - 21s 175ms/step - loss: 0.1913 -
accuracy: 0.9245 - val_loss: 0.2932 - val_accuracy: 0.8777
Epoch 4/10
121/121 [==============================] - 22s 178ms/step - loss: 0.1558 -
accuracy: 0.9419 - val_loss: 0.3312 - val_accuracy: 0.8719
Epoch 5/10
121/121 [==============================] - 21s 176ms/step - loss: 0.1291 -
```

```
accuracy: 0.9531 - val_loss: 0.3519 - val_accuracy: 0.8727
Epoch 6/10
121/121 [==============================] - 21s 173ms/step - loss: 0.1073 -
accuracy: 0.9613 - val_loss: 0.4079 - val_accuracy: 0.8819
Epoch 7/10
121/121 [==============================] - 21s 176ms/step - loss: 0.0920 -
accuracy: 0.9659 - val_loss: 0.4288 - val_accuracy: 0.8784
Epoch 8/10
121/121 [==============================] - 21s 176ms/step - loss: 0.0791 -
accuracy: 0.9718 - val_loss: 0.4780 - val_accuracy: 0.8748
Epoch 9/10
121/121 [==============================] - 21s 175ms/step - loss: 0.0669 -
accuracy: 0.9766 - val_loss: 0.5347 - val_accuracy: 0.8669
Epoch 10/10
121/121 [==============================] - 21s 174ms/step - loss: 0.0622 -
accuracy: 0.9784 - val_loss: 0.5220 - val_accuracy: 0.8677
```

[44]: <keras.callbacks.History at 0x731470a4bdf0>

[45]:
```
y_test_pred=np.argmax(model.predict(X_test),axis=1)
y_train_pred=np.argmax(model.predict(X_train),axis=1)
```

```
120/120 [==============================] - 4s 26ms/step
242/242 [==============================] - 7s 27ms/step
```

[46]:
```
test_acc_lstm = accuracy_score(y_test,y_test_pred)
train_acc_lstm = accuracy_score(y_train,y_train_pred)
test_roc_lstm = roc_auc_score(y_test,y_test_pred)
train_roc_lstm = roc_auc_score(y_train,y_train_pred)
```

[47]:
```
data = [('Random Forest', r_train_accuracy, r_test_accuracy, r_train_auc, r_test_auc),
  ('MultinomialNB',m_train_accuracy, m_test_accuracy, m_train_auc, m_test_auc ),
  ('KNeighbors',knn_train_accuracy, knn_test_accuracy, knn_train_auc, knn_test_auc ),
  ('AdaBoost',a_train_accuracy, a_test_accuracy, a_train_auc, a_test_auc ),
  ('AdaBoost Optimized',ao_train_accuracy, ao_test_accuracy, ao_train_auc, ao_test_auc),
('Decision Tree ',dt_train_accuracy, dt_test_accuracy, dt_train_auc, dt_test_auc),
('Gaussian Naive Bayes',g_train_accuracy, g_test_accuracy, g_train_auc, g_test_auc),
('SVM', s_train_accuracy, s_test_accuracy, s_train_auc, s_test_auc),
('SVM Optimized', so_train_accuracy, so_test_accuracy, so_train_auc, so_test_auc),
('Neural Network',mlp_train_accuracy, mlp_test_accuracy, mlp_train_auc, mlp_test_auc),
```

```
('LSTM',train_acc_lstm, test_acc_lstm, train_roc_lstm, test_roc_lstm )]


Scores_ =pd.DataFrame(data = data, columns=['Model Name','Train Accuracy',␣
    'Test Accuracy', 'Train ROC', 'Test ROC'])
↪Scores_.set_index('Model Name', inplace = True)

Scores_
```

[47]:

Model Name	Train Accuracy	Test Accuracy	Train ROC	Test ROC
Random Forest	0.996418	0.880111	0.998244	0.895687
MultinomialNB	0.850029	0.834026	0.956111	0.901301
KNeighbors	0.282034	0.218295	0.967222	0.568834
AdaBoost	0.859965	0.861400	0.868948	0.837380
AdaBoost Optimized	0.868631	0.866597	0.921855	0.877934
Decision Tree	0.996418	0.832640	0.999875	0.762702
Gaussian Naive Bayes	0.848411	0.694733	0.904303	0.688587
SVM	0.978972	0.886348	0.996906	0.929170
SVM Optimized	0.996418	0.897436	0.998731	0.928759
Neural Network	0.995956	0.869716	0.999852	0.901488
LSTM	0.794232	0.797322	0.500000	0.500000

Conclusion

1 **Improved Analysis Accuracy**

The developed sentiment analysis model significantly improves accuracy compared to traditional manual analysis.

2 **Efficient Solution**

The model is efficient and scalable, reducing resource requirements and improving decision-making speed.

3 **Further Improvements Possible**

Although the model offers significant improvements, further tweaks and improvements are possible to achieve even better accuracy and efficiency.