Final Project Code

In [ ]:
```
#load libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import missingno
from mpl_toolkits.mplot3d import Axes3D
from sklearn.feature_extraction.text import CountVectorizer
import nltk
from nltk.corpus import stopwords
from nltk.stem.porter import PorterStemmer
import collections
from collections import Counter
import string
import re
from wordcloud import WordCloud
from nltk.tokenize import word_tokenize
from nltk.probability import FreqDist
from nltk import bigrams
from pprint import pprint
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import confusion_matrix, accuracy_score, classification_re
from sklearn.ensemble import RandomForestClassifier
from sklearn import tree
from sklearn.model_selection import train_test_split, RandomizedSearchCV, GridS
from sklearn.preprocessing import PowerTransformer, OneHotEncoder
from sklearn.compose import ColumnTransformer
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
from keras.models import Sequential
from keras.layers import Dense, Embedding, LSTM, SpatialDropout1D, GRU, Dropou
from tensorflow.keras.utils import to_categorical
from keras.callbacks import EarlyStopping, ModelCheckpoint

# View all columns and rows
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', 90) # set to fit 90 column descriptions

# Set up notebook to display multiple outputs in one cell
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

In [ ]:
```
tweets_df = pd.read_csv('/content/tweets.csv')
```

EDA

In [ ]:
```
# Inspect dataset

## Inspect columns and variable types
tweets_df.info()
```

```
## View dataframe rows
tweets_df.head()

## View summary statistics
tweets_df.describe()

## View missing values
tweets_df.isnull().sum()

## Plot missing values
missingno.matrix(tweets_df)
```

```
<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
```

Out[ ]:

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	negati
0	570306133677760513	neutral	1.0000	NaN	
1	570301130888122368	positive	0.3486	NaN	
2	570301083672813571	neutral	0.6837	NaN	
3	570301031407624196	negative	1.0000	Bad Flight	
4	570300817074462722	negative	1.0000	Can't Tell	

Out[ ]:

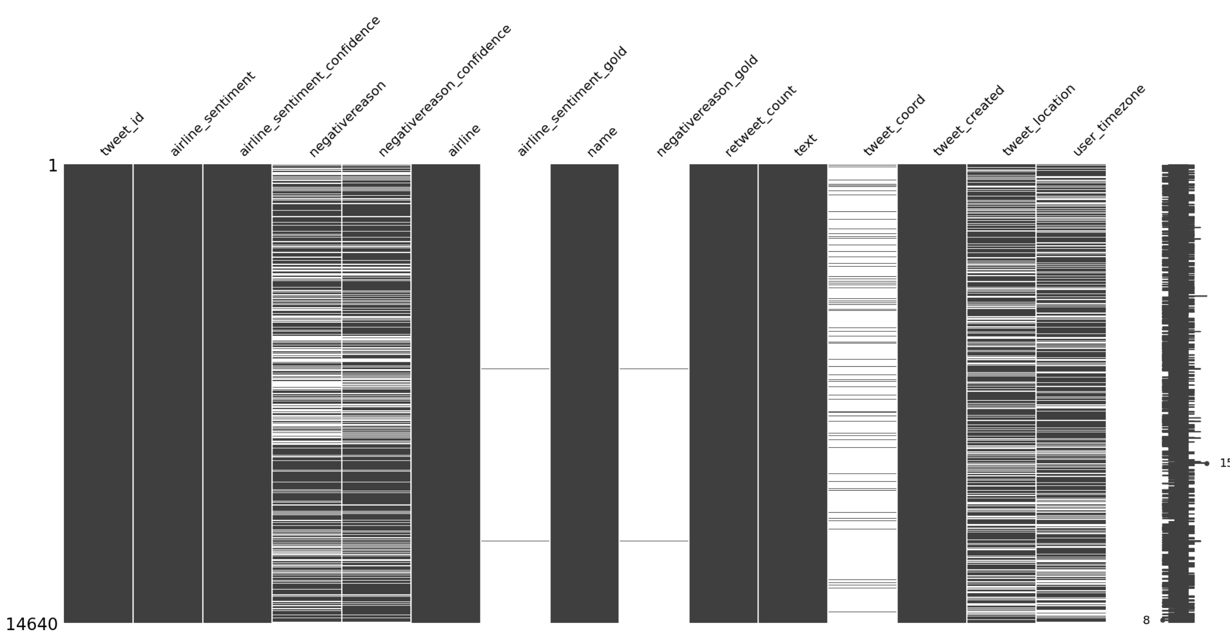
	tweet_id	airline_sentiment_confidence	negativereason_confidence	retweet_count
count	1.464000e+04	14640.000000	10522.000000	14640.000000
mean	5.692184e+17	0.900169	0.638298	0.082650
std	7.791112e+14	0.162830	0.330440	0.745778
min	5.675883e+17	0.335000	0.000000	0.000000
25%	5.685592e+17	0.692300	0.360600	0.000000
50%	5.694779e+17	1.000000	0.670600	0.000000
75%	5.698905e+17	1.000000	1.000000	0.000000
max	5.703106e+17	1.000000	1.000000	44.000000

Out[ ]:

```
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
```

Out[ ]:

```
<Axes: >
```



In [ ]:

```
# Convert airline_sentiment classification to numeric: positive, neutral, nega
tweets_df['numeric_sentiment'] = tweets_df.apply(lambda x: 1 if (x['airline_se

# Create weighted_sentiment feature, the product of the sentiment and the conf
tweets_df['weighted_sentiment'] = tweets_df['numeric_sentiment'] * tweets_df['a
```

In [ ]:
```python
# Compute summary statistics for numeric_sentiment variable.

print("Summary stats for numeric_sentiment.")
tweets_df['numeric_sentiment'].describe()

print("Median and mode for numeric_sentiment.")
tweets_df['numeric_sentiment'].median()
tweets_df['numeric_sentiment'].mode().iloc[0] # Taking first mode if multiple.

print("Summary stats for weighted_sentiment.")
tweets_df['weighted_sentiment'].describe()

print("Median and mode for weighted_sentiment.")
tweets_df['weighted_sentiment'].median()
tweets_df['weighted_sentiment'].mode().iloc[0] # Taking first mode if multiple

## Noting that the 'numeric_sentiment' and 'weighted_sentiment' columns are pre
```

```
Summary stats for numeric_sentiment.
```

Out[ ]:
```
count    14640.000000
mean        -0.465505
std          0.756084
min         -1.000000
25%         -1.000000
50%         -1.000000
75%          0.000000
max          1.000000
Name: numeric_sentiment, dtype: float64
Median and mode for numeric_sentiment.
```

Out[ ]:
```
-1.0
```

Out[ ]:
```
-1
```

```
Summary stats for weighted_sentiment.
```

Out[ ]:
```
count    14640.000000
mean        -0.444385
std          0.698999
min         -1.000000
25%         -1.000000
50%         -1.000000
75%          0.000000
max          1.000000
Name: weighted_sentiment, dtype: float64
Median and mode for weighted_sentiment.
```

Out[ ]:
```
-1.0
```

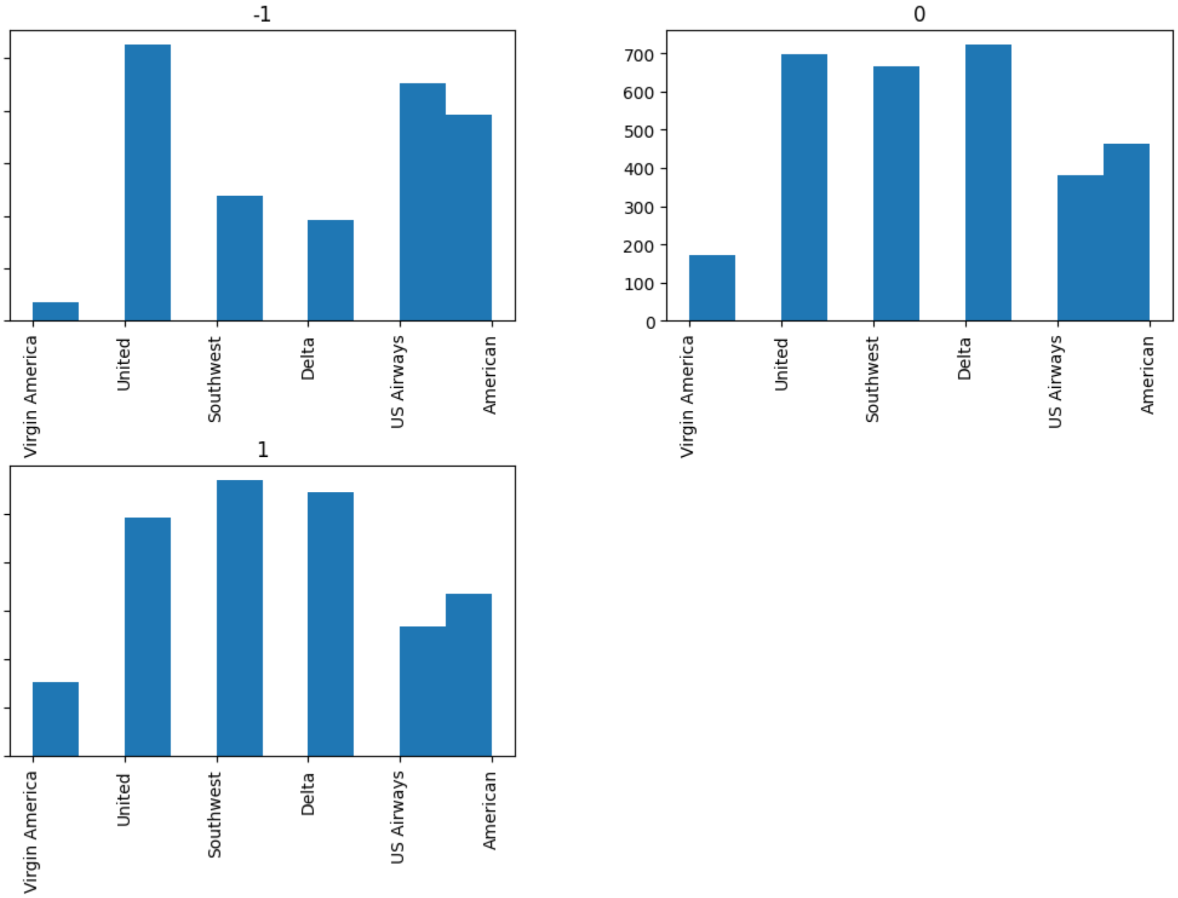
Out[ ]:
```
-1.0
```

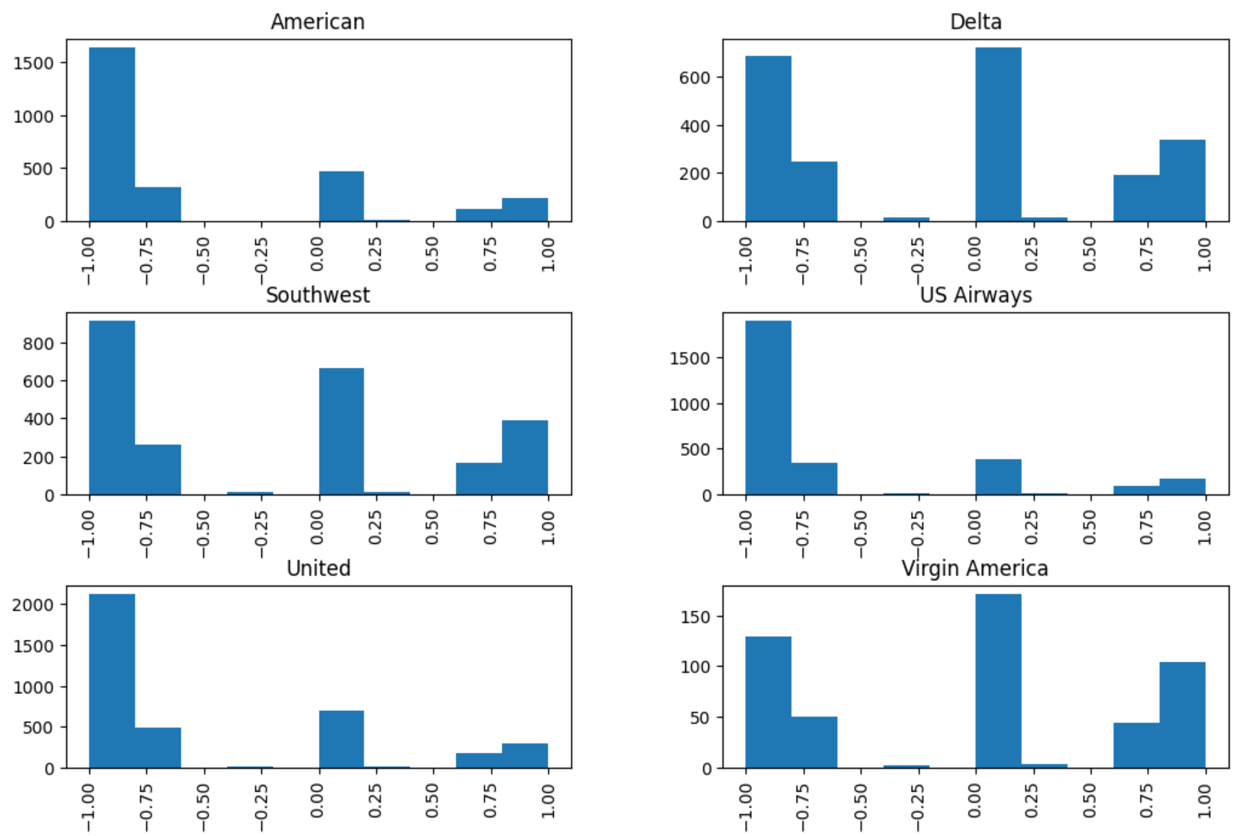
In [ ]:
```python
# look at Airline Sentiment distribution
tweets_df.hist(column ='airline', by='numeric_sentiment',figsize=(12,8))
tweets_df.hist(column ='weighted_sentiment', by='airline',figsize=(12,8))
#sns.histplot(data_df,x = 'airline',hue = 'num_sentiment')
#plt.show()
```

Out[ ]:
```
array([[<Axes: title={'center': '-1'}>, <Axes: title={'center': '0'}>],
       [<Axes: title={'center': '1'}>, <Axes: >]], dtype=object)
```

Out[ ]:

```
array([[<Axes: title={'center': 'American'}>,
        <Axes: title={'center': 'Delta'}>],
       [<Axes: title={'center': 'Southwest'}>,
        <Axes: title={'center': 'US Airways'}>],
       [<Axes: title={'center': 'United'}>,
        <Axes: title={'center': 'Virgin America'}>]], dtype=object)
```





In [ ]:

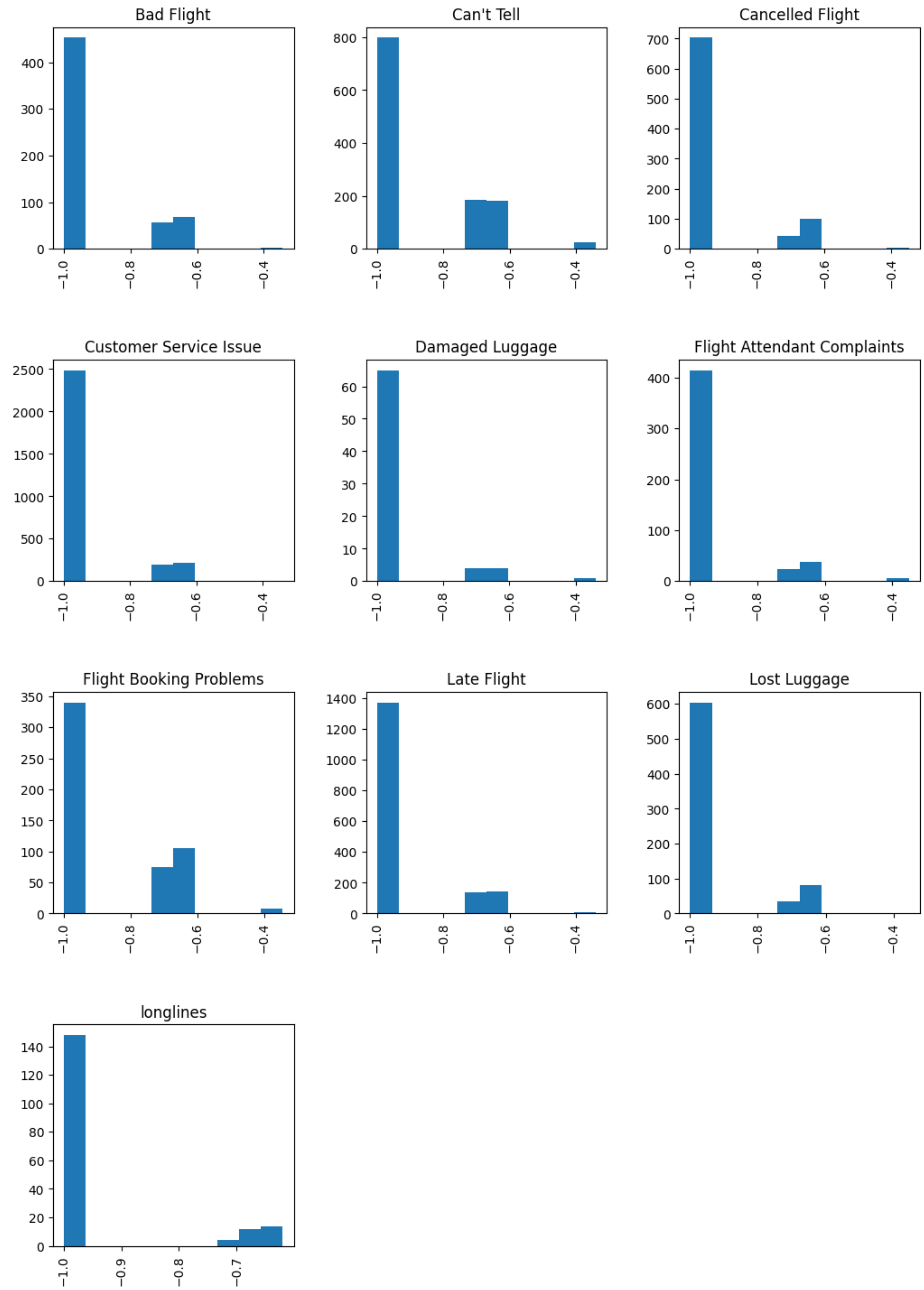
```
# look at Negative Reason distribution
data_neg = tweets_df[tweets_df['numeric_sentiment'] < 0]
data_neg.hist(column ='weighted_sentiment', by='negativereason',figsize=(12,18
data_neg.hist(column ='airline', by='negativereason',figsize=(12,18))
```

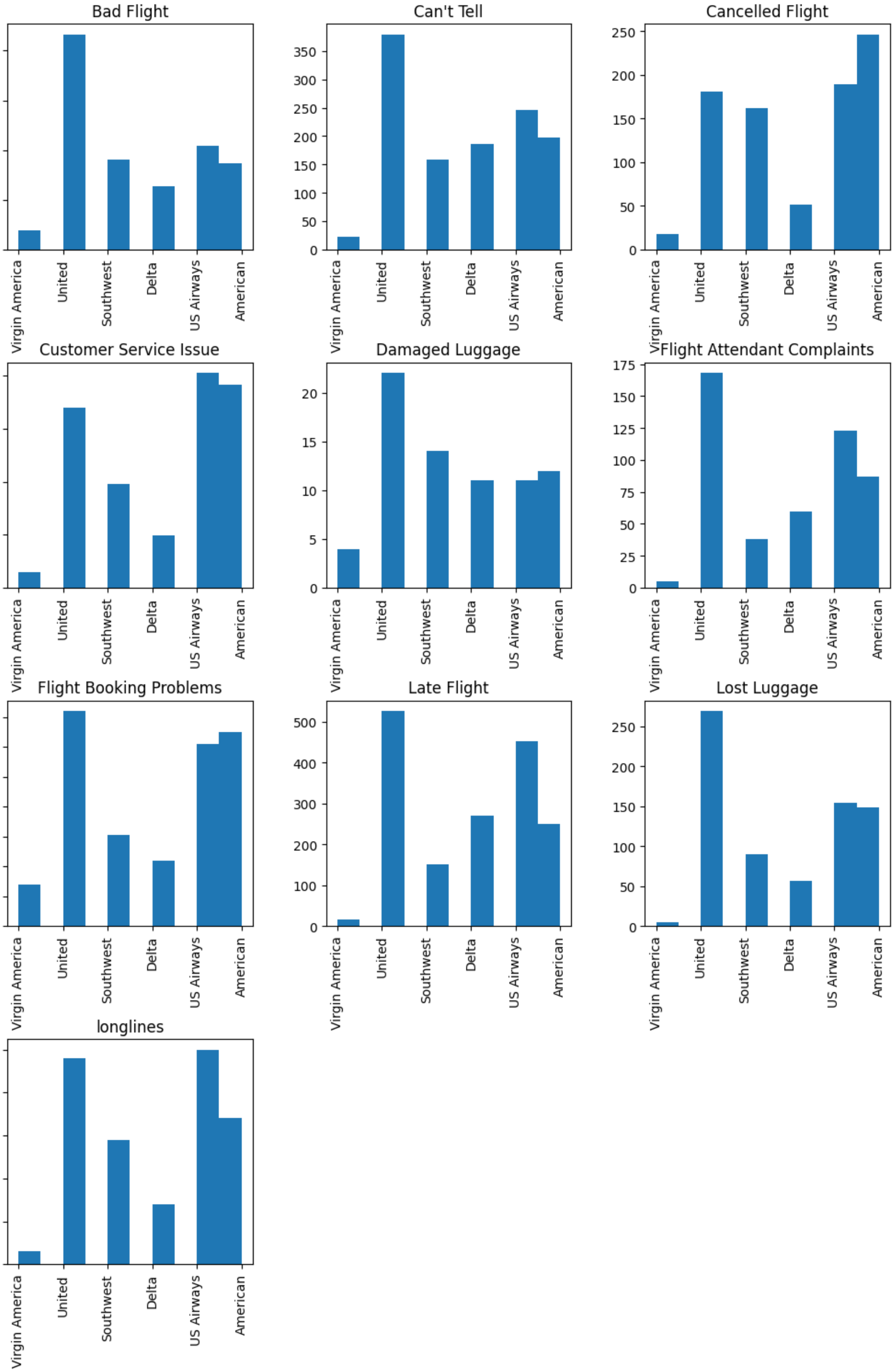
Out[ ]:

```
array([[<Axes: title={'center': 'Bad Flight'}>,
        <Axes: title={'center': "Can't Tell"}>,
        <Axes: title={'center': 'Cancelled Flight'}>],
       [<Axes: title={'center': 'Customer Service Issue'}>,
        <Axes: title={'center': 'Damaged Luggage'}>,
        <Axes: title={'center': 'Flight Attendant Complaints'}>],
       [<Axes: title={'center': 'Flight Booking Problems'}>,
        <Axes: title={'center': 'Late Flight'}>,
        <Axes: title={'center': 'Lost Luggage'}>],
       [<Axes: title={'center': 'longlines'}>, <Axes: >, <Axes: >]],
      dtype=object)
```

Out[ ]:

```
array([[<Axes: title={'center': 'Bad Flight'}>,
        <Axes: title={'center': "Can't Tell"}>,
        <Axes: title={'center': 'Cancelled Flight'}>],
       [<Axes: title={'center': 'Customer Service Issue'}>,
        <Axes: title={'center': 'Damaged Luggage'}>,
        <Axes: title={'center': 'Flight Attendant Complaints'}>],
       [<Axes: title={'center': 'Flight Booking Problems'}>,
        <Axes: title={'center': 'Late Flight'}>,
        <Axes: title={'center': 'Lost Luggage'}>],
       [<Axes: title={'center': 'longlines'}>, <Axes: >, <Axes: >]],
      dtype=object)
```


Bad Flight
0 100 200 300 400
−1.0 −0.8 −0.6 −0.4
Can't Tell
0 200 400 600 800
−1.0 −0.8 −0.6 −0.4
Cancelled Flight
0 100 200 300 400 500 600 700
−1.0 −0.8 −0.6 −0.4
Customer Service Issue
0 500 1000 1500 2000 2500
−1.0 −0.8 −0.6 −0.4
Damaged Luggage
0 10 20 30 40 50 60
−1.0 −0.8 −0.6 −0.4
Flight Attendant Complaints
0 100 200 300 400
−1.0 −0.8 −0.6 −0.4
Flight Booking Problems
0 50 100 150 200 250 300 350
−1.0 −0.8 −0.6 −0.4
Late Flight
0 200 400 600 800 1000 1200 1400
−1.0 −0.8 −0.6 −0.4
Lost Luggage
0 100 200 300 400 500 600
−1.0 −0.8 −0.6 −0.4
longlines
0 20 40 60 80 100 120 140
−1.0 −0.9 −0.8 −0.7




```
In [ ]: #create visuals
```

```
nltk.download('stopwords')
nltk.download('punkt')

# Check for missing values
print(tweets_df.isnull().sum())

# Explore sentiment distribution
sns.countplot(x='airline_sentiment', data=tweets_df, order=tweets_df['airline_s
plt.title('Sentiment Distribution')
plt.show()

# Explore sentiment distribution for each airline
sns.countplot(x='airline', hue='airline_sentiment', data=tweets_df)
plt.title('Sentiment Distribution by Airline')
plt.show()

# Word cloud for positive, negative, and neutral sentiments
company_names = ['Virgin America', 'United', 'Southwest', 'Delta', 'US Airways
                'Southwest Air', 'SouthwestAir', 'VirginAmerica', 'AmericanAir
stop_words = set(stopwords.words('english') + company_names)

def plot_wordcloud(sentiment):
    words = ' '.join(tweets_df[tweets_df['airline_sentiment'] == sentiment]['te
    wordcloud = WordCloud(width=800, height=400, stopwords = stop_words, randon
    plt.figure(figsize=(10, 7))
    plt.imshow(wordcloud, interpolation="bilinear")
    plt.axis('off')
    plt.title(f'Word Cloud for {sentiment} Sentiment')
    plt.show()

plot_wordcloud('positive')
plot_wordcloud('negative')
plot_wordcloud('neutral')

# Tokenize and analyze word frequencies

def process_text(text):
    words = word_tokenize(text)
    words = [word.lower() for word in words if word.isalpha() and word.lower()
    return words

tweets_df['processed_text'] = tweets_df['text'].apply(process_text)

# Calculate and plot word frequencies
all_words = [word for sublist in tweets_df['processed_text'] for word in sublis
freq_dist = FreqDist(all_words)
freq_dist.plot(30, cumulative=False)
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

Out[ ]:

```
True
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
```

Out[ ]:

```
True
```

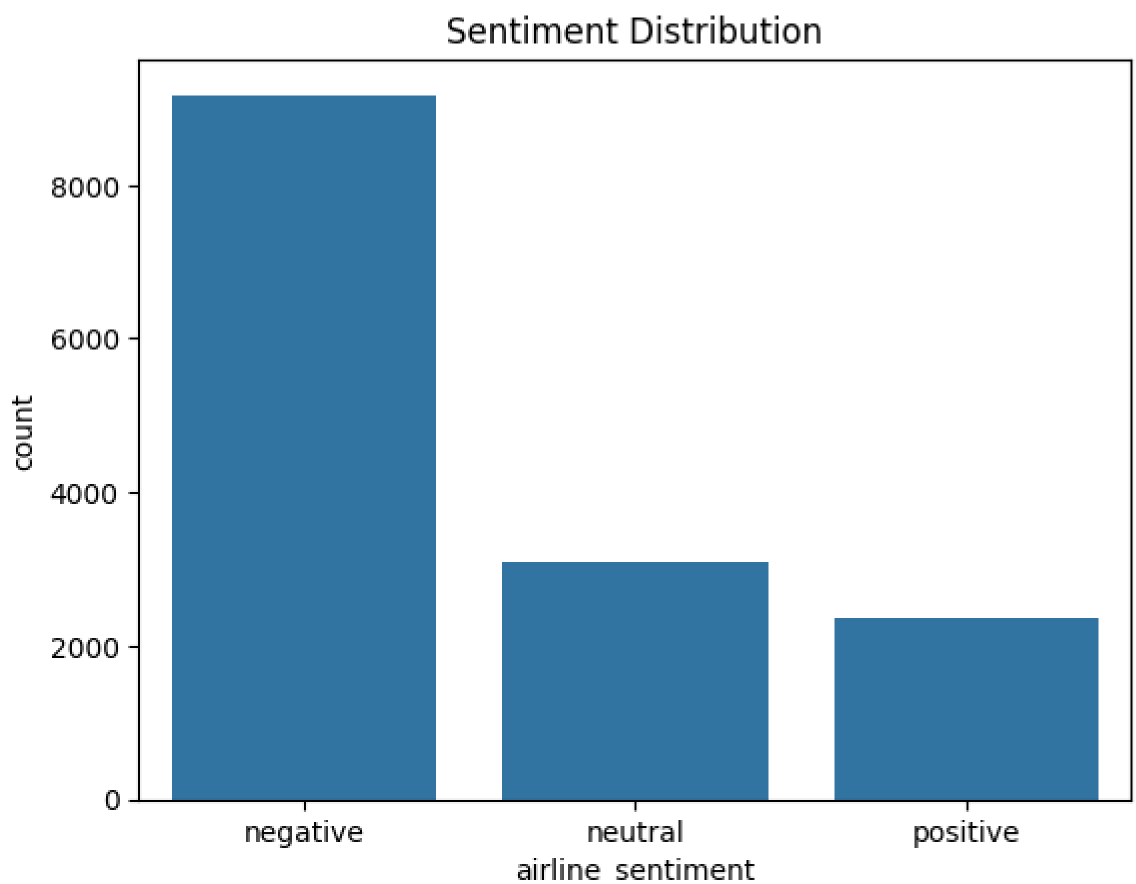
```
tweet_id                            0
airline_sentiment                   0
airline_sentiment_confidence        0
negativereason                   5462
negativereason_confidence        4118
airline                             0
airline_sentiment_gold          14600
name                          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

Out[ ]:

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

Out[ ]:

```
Text(0.5, 1.0, 'Sentiment Distribution')
```

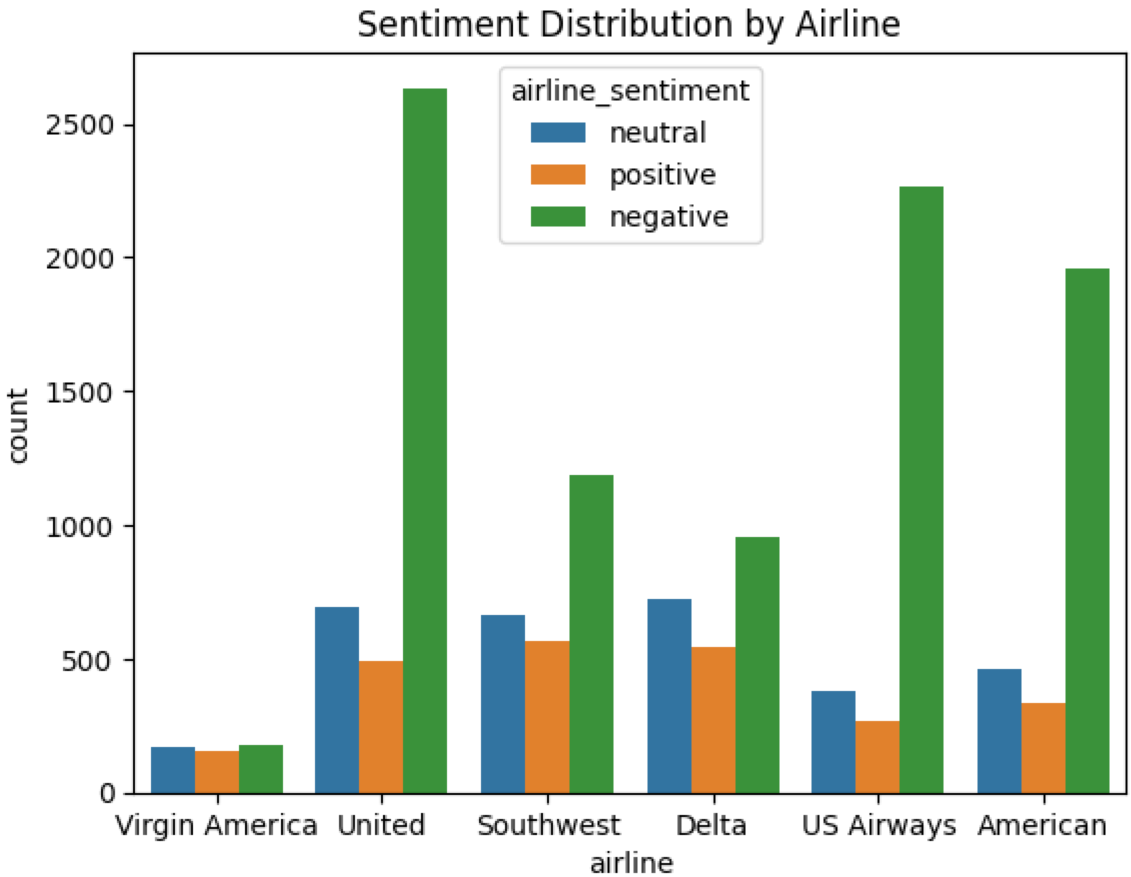


Out[ ]:

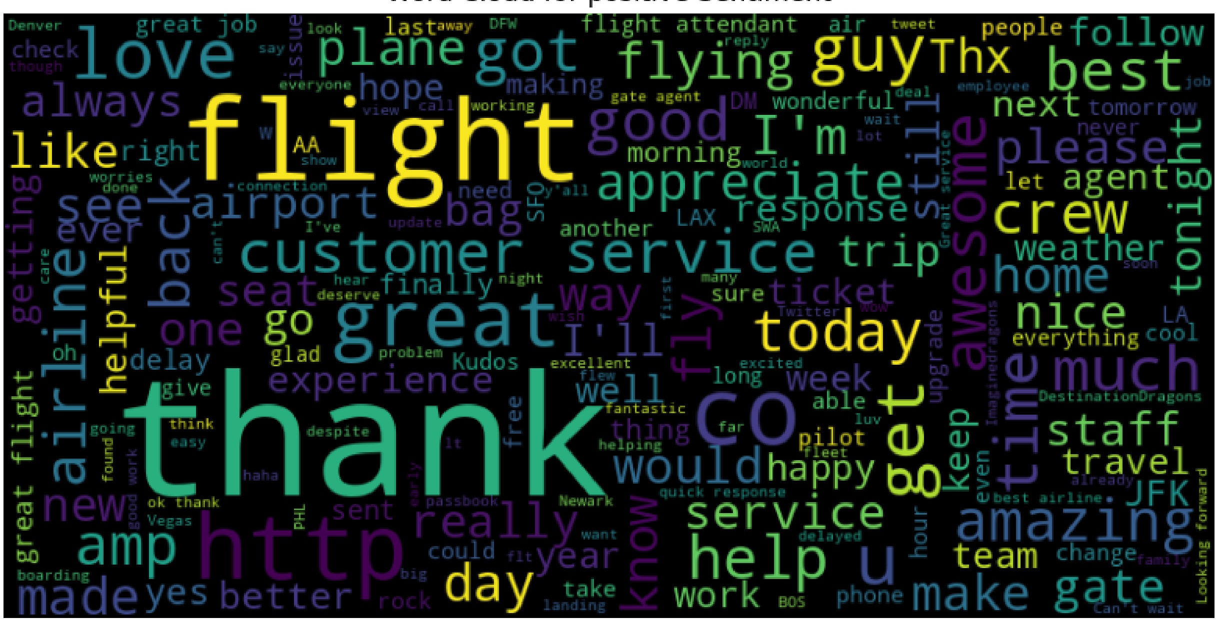
```
<Axes: xlabel='airline', ylabel='count'>
```

Out[ ]:

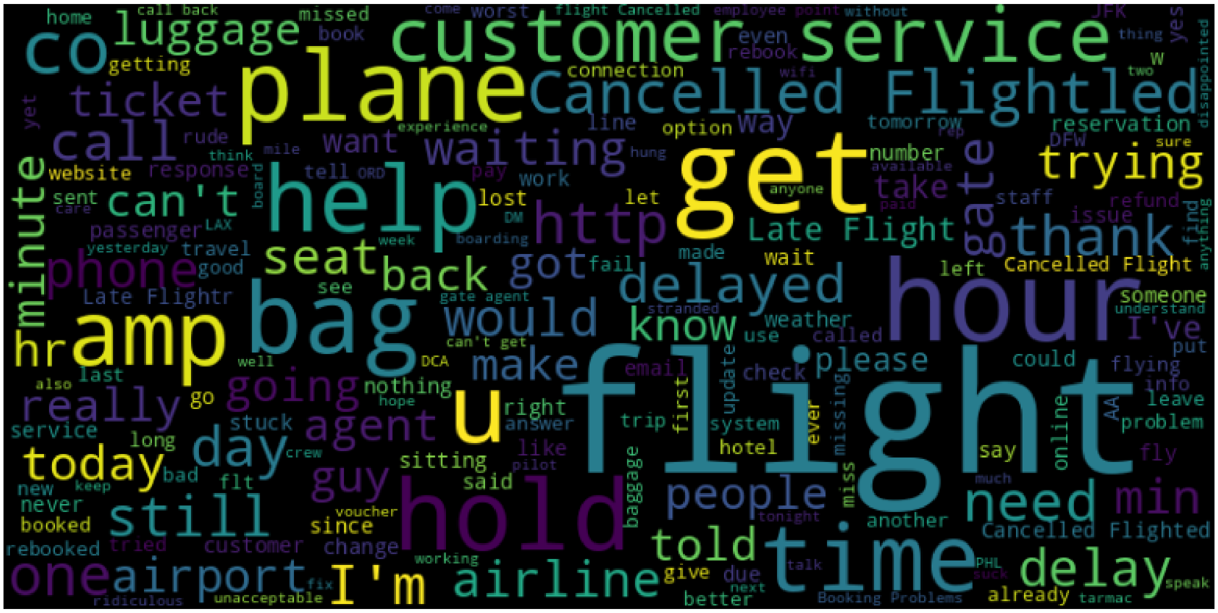
```
Text(0.5, 1.0, 'Sentiment Distribution by Airline')
```



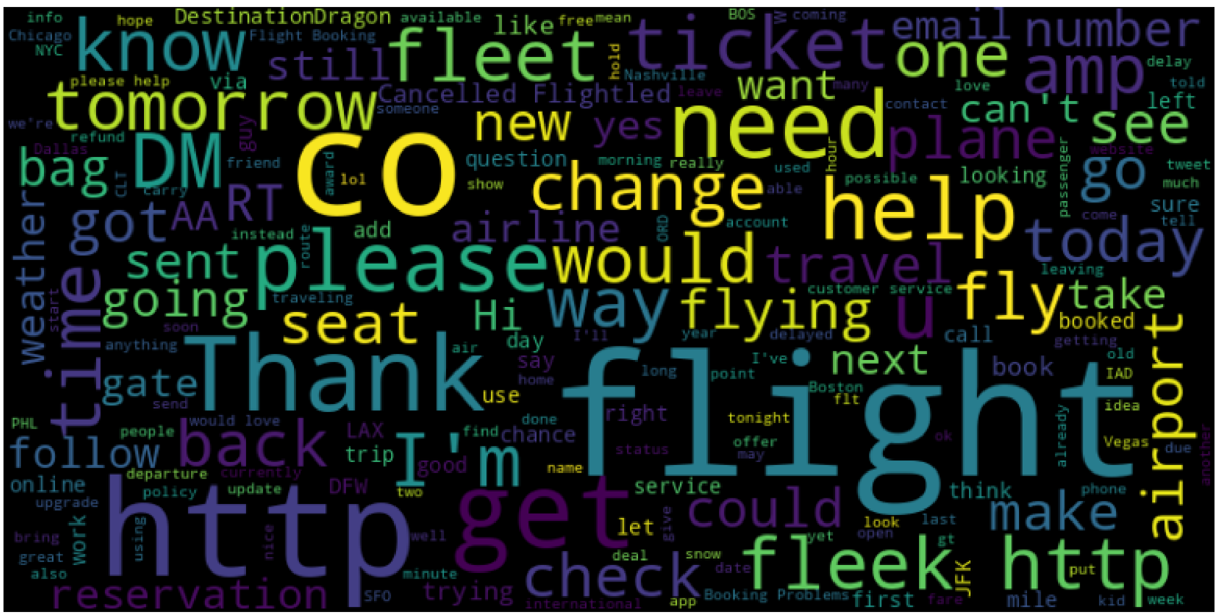
Word Cloud for positive Sentiment

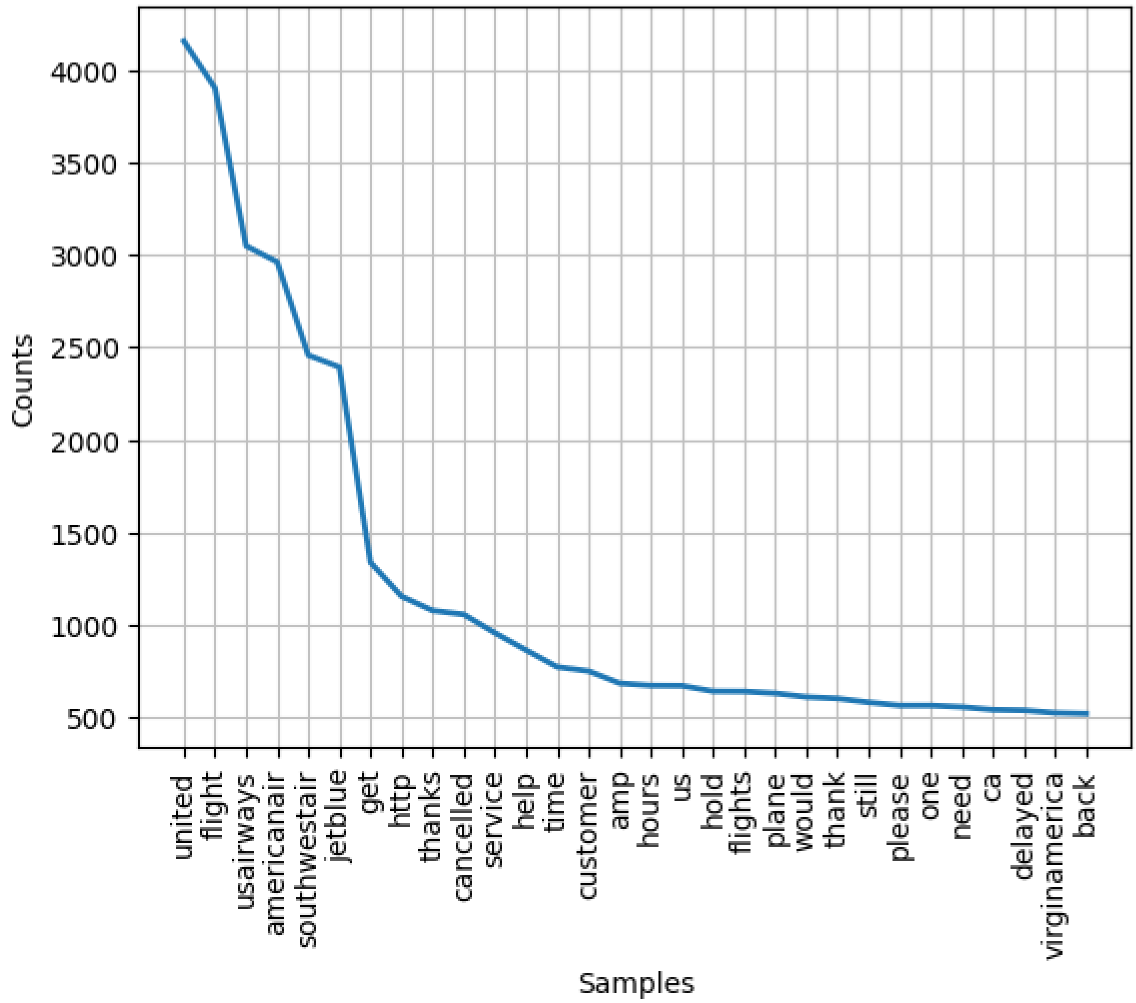


Word Cloud for negative Sentiment



Word Cloud for neutral Sentiment





Out[ ]: <Axes: xlabel='Samples', ylabel='Counts'>

Cleaning the Data

In [ ]:
```
# We note that the majority of airline_sentiment_gold is empty. However, non-nu

diffs = tweets_df[tweets_df['airline_sentiment_gold'].notnull()]
diffs = (diffs['airline_sentiment'] != diffs['airline_sentiment_gold']).any()

print(diffs)

## There are no differences between airline_sentiment and airline_sentiment_go
tweets_df.drop(columns=['airline_sentiment_gold'], inplace=True)
```

False

In [ ]:
```
# However, there are differences between those of negativereason and negativere

# If confidence level in airline_sentiment_confidence is higher on average we'c
sentiment_mean = tweets_df.groupby('negativereason')['airline_sentiment_confide
gold_sent_mean = tweets_df.groupby('negativereason_gold')['airline_sentiment_cc

print(f"Mean of confidence for negativereason:\n{sentiment_mean}")
print(f"\nMean of confidence for negativereason_gold:\n{gold_sent_mean}")

## Since negativereason_gold has a higher mean confidence level in the value of
```

```python
tweets_df['imputed_neg_reason'] = tweets_df['negativereason_gold'].fillna(twee

check_df = tweets_df[(tweets_df['negativereason_gold'].notnull()) & (tweets_df
check_df = check_df[['negativereason', 'negativereason_gold', 'text']]
check_df

## A spot check confirms negativereason_gold offers more adequate information
```

```
Mean of confidence for negativereason:
negativereason
Bad Flight                        0.925816
Can't Tell                        0.885067
Cancelled Flight                  0.941773
Customer Service Issue            0.951616
Damaged Luggage                   0.955727
Flight Attendant Complaints       0.951697
Flight Booking Problems           0.876460
Late Flight                       0.940308
Lost Luggage                      0.944268
longlines                         0.943487
Name: airline_sentiment_confidence, dtype: float64

Mean of confidence for negativereason_gold:
negativereason_gold
Bad Flight                                     0.965800
Can't Tell                                     0.913100
Cancelled Flight                               1.000000
Cancelled Flight\nCustomer Service Issue       0.924850
Customer Service Issue                         0.990667
Customer Service Issue\nCan't Tell             0.799100
Customer Service Issue\nLost Luggage           1.000000
Flight Attendant Complaints                    0.955300
Late Flight                                    0.927025
Late Flight\nCancelled Flight                  1.000000
Late Flight\nFlight Attendant Complaints       1.000000
Late Flight\nLost Luggage                      1.000000
Lost Luggage\nDamaged Luggage                  1.000000
Name: airline_sentiment_confidence, dtype: float64
```

Out[ ]:

	negativereason	negativereason_gold	text
1286	Late Flight	Late Flight\nFlight Attendant Complaints	@united I'm aware of the flight details, thank...
2017	Late Flight	Late Flight\nLost Luggage	@united flighted delayed for hours. 10pm arriv...
3149	Customer Service Issue	Cancelled Flight\nCustomer Service Issue	@united rebooked 24 hours after original fligh...
6530	Customer Service Issue	Cancelled Flight\nCustomer Service Issue	@SouthwestAir I never got a Cancelled Flightla...
8536	Lost Luggage	Lost Luggage\nDamaged Luggage	@JetBlue I am heading to JFK now just on princ...
12025	Cancelled Flight	Late Flight\nCancelled Flight	@AmericanAir over the last year 50% of my flig...
12034	Lost Luggage	Customer Service Issue\nLost Luggage	@AmericanAir you need to work harder on the di...
12038	longlines	Customer Service Issue	@DeltaAssist now at 57 minutes waiting on Silv...
12039	Can't Tell	Customer Service Issue\nCan't Tell	@DeltaAssist what I have to say is more than 1...

Feature Engineering

In [ ]:

```
# Cleaning user_timezone values in stages. tweet_location not as useful (e.g.,

# Clean timezone column
tweets_df['clean_timezone'] = tweets_df['user_timezone'].where(tweets_df['user_

# Fill NaN values in the original column
tweets_df['user_timezone'].fillna('N/A', inplace=True)

# Unclean timezone column
tweets_df['unclean_timezone'] = tweets_df['user_timezone'].where(~tweets_df['c

## Code leaves in unclean_timezone column. We could delete the above line and s
```

In [ ]:

```
# Convert 'tweet_created' column to datetime dtype
tweets_df['tweet_created'] = pd.to_datetime(tweets_df['tweet_created'])

# Extract day of the month
tweets_df['tweet_day'] = tweets_df['tweet_created'].dt.day

# Extract time of day
tweets_df['time_of_day'] = pd.cut(
    tweets_df['tweet_created'].dt.hour,
    bins=[0, 6, 12, 18, 24],
    labels=['Night', 'Morning', 'Afternoon', 'Evening'],
    include_lowest=True
)
```

Pull Only Data Columns of Interest

In [ ]:
```
#clean up data set
data_pre_process=tweets_df[['text','numeric_sentiment', 'weighted_sentiment','a
```

Initial Cleaning of Text Column and Prepare Data for Thorough Cleaning

In [ ]:
```
#clean the text column for random forest modelling to identify key word counts
from bs4 import BeautifulSoup
import re
import nltk
# nltk.download()
from nltk.corpus import stopwords # Import the stop word list
nltk.download('stopwords')

data_size = (data_pre_process['text'].size)
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

Out[ ]:
```
True
```

Cleaning the Data Using Beautiful Soup

In [ ]:
```
#function to clean text usint Beautiful Soup
def clean_text_data(data_point, data_size):
    review_soup = BeautifulSoup(data_point)
    review_text = review_soup.get_text()
    review_letters_only = re.sub("[^a-zA-Z]", " ", review_text)
    review_lower_case = review_letters_only.lower()
    review_words = review_lower_case.split()
    stop_words = stopwords.words("english")
    meaningful_words = [x for x in review_words if x not in stop_words]

    if( (i)%2000 == 0 ):
        print("Cleaned %d of %d data (%d %%)." % ( i, data_size, ((i)/data_size

    return( " ".join( meaningful_words))

for i in range(data_size):
    data_pre_process["text"][i] = clean_text_data(data_pre_process["text"][i],
print("Cleaning training completed!")
```

```
<ipython-input-15-85e9262fa24a>:17: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/st
able/user_guide/indexing.html#returning-a-view-versus-a-copy
  data_pre_process["text"][i] = clean_text_data(data_pre_process["text"][i], d
ata_size)
<ipython-input-15-85e9262fa24a>:3: MarkupResemblesLocatorWarning: The input lo
oks more like a filename than markup. You may want to open this file and pass
the filehandle into Beautiful Soup.
  review_soup = BeautifulSoup(data_point)
```

```
Cleaned 0 of 14640 data (0 %).
Cleaned 2000 of 14640 data (13 %).
Cleaned 4000 of 14640 data (27 %).
Cleaned 6000 of 14640 data (40 %).
Cleaned 8000 of 14640 data (54 %).
Cleaned 10000 of 14640 data (68 %).
Cleaned 12000 of 14640 data (81 %).
Cleaned 14000 of 14640 data (95 %).
Cleaning training completed!
```

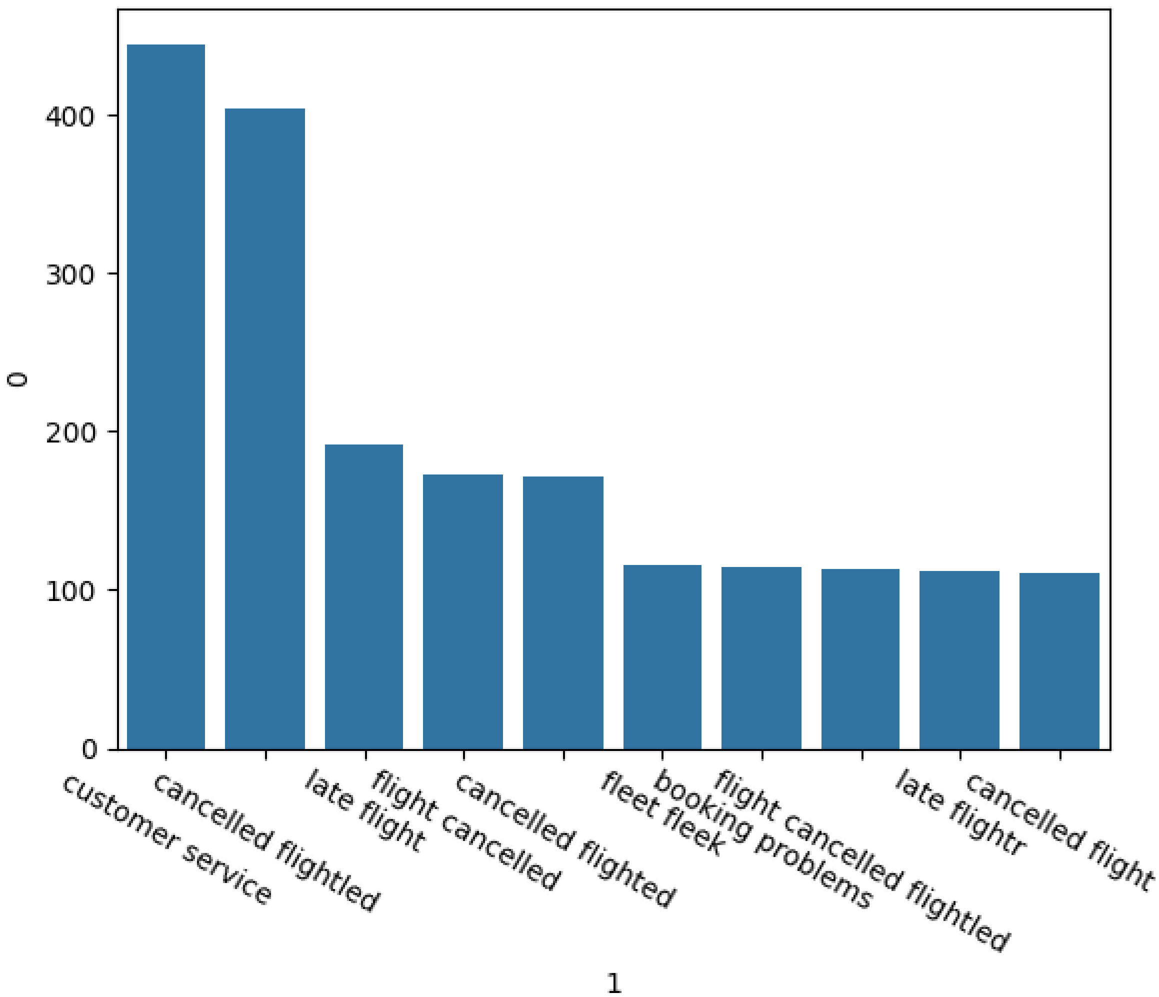
Executing a Random Forest Model Without Fitting to Learn Top Phrases and Number of Occurences for Each

In [ ]:
```python
vectorizer = CountVectorizer(analyzer = "word",   \
                             ngram_range= (2,3),   \
                             tokenizer = None,    \
                             preprocessor = None, \
                             stop_words = ['united','usairways','americanair',


X_train, X_cv, Y_train, Y_cv = train_test_split(data_pre_process["text"], data_

X_train = vectorizer.fit_transform(X_train)
X_train = X_train.toarray()
print(X_train.shape)

X_cv = vectorizer.transform(X_cv)
X_cv = X_cv.toarray()
print(X_cv.shape)

vocab = vectorizer.get_feature_names_out()
distribution = np.sum(X_train, axis=0)

#for tag, count in zip(distribution[:100],vocab[:100]):
#    print(count, tag)

zipped = zip (distribution,vocab)
zipped = list(zipped)
zipped.sort(reverse=True)
zip_top = zipped[:10]
zip_top_df = pd.DataFrame(zip_top)
#zip_top_df.head()
graph = sns.barplot(zip_top_df,x=zip_top_df[1],y=zip_top_df[0])
graph.set_xticklabels(
    labels=zip_top_df[1], rotation=-30)
plt.show()
```

```
(11712, 141166)
(2928, 141166)
```

```
<ipython-input-16-8eb1748bbf50>:31: UserWarning: FixedFormatter should only be
used together with FixedLocator
  graph.set_xticklabels(
```

Out[ ]:
```
[Text(0, 0, 'customer service'),
 Text(1, 0, 'cancelled flightled'),
 Text(2, 0, 'late flight'),
 Text(3, 0, 'flight cancelled'),
 Text(4, 0, 'cancelled flighted'),
 Text(5, 0, 'fleet fleek'),
 Text(6, 0, 'booking problems'),
 Text(7, 0, 'flight cancelled flightled'),
 Text(8, 0, 'late flightr'),
 Text(9, 0, 'cancelled flight')]
```



Bag of Words

In [ ]:
```
tweets_df1 = tweets_df.copy()
tweets_df1['text'] = tweets_df1['text'].astype(str)
```

In [ ]:
```
stop_words = set(stopwords.words('english'))
stop_words.remove('not') #need 'not' as a negative identifier in tweets

string.punctuation
```

Out[ ]:
```
'!"#$%&\'()*+,-./:;<=>?@[\\]^_`{|}~'
```

In [ ]:
```
#clean Tweet text
ps = PorterStemmer()
```

```python
tweet_list = []

for i in range(0, 14640):
    tweet = re.sub('@[^\s]+','', tweets_df1['text'][i])
    tweet = re.sub('http[^\s]+','', tweet)
    tweet = re.sub('['+string.punctuation+']', '', tweet)
    tweet = tweet.lower()
    tweet = tweet.split()
    tweet = [ps.stem(word) for word in tweet if not word in stop_words]
    tweet = ' '.join(tweet)
    tweet_list.append(tweet)
```

In [ ]:
```python
#remove emojis
def remove_emoji(text):
    emojis = re.compile("["
                           u"\U0001F600-\U0001F64F"  # emoticons
                           u"\U0001F300-\U0001F5FF"  # symbols & pictographs
                           u"\U0001F680-\U0001F6FF"  # transport & map symbols
                           u"\U0001F1E0-\U0001F1FF"  # flags (iOS)
                           u"\U00002702-\U000027B0"
                           u"\U000024C2-\U0001F251"
                           "]+", flags=re.UNICODE)

    text = re.sub(emojis,'',text)
    return text

tweet_list = list(map(remove_emoji, tweet_list))
```

In [ ]:
```python
len(tweet_list)
tweet_list[1:5]
```

Out[ ]:
```
14640
```

Out[ ]:
```
['plu youv ad commerci experi tacki',
 'didnt today must mean need take anoth trip',
 'realli aggress blast obnoxi entertain guest face amp littl recours',
 'realli big bad thing']
```

In [ ]:
```python
#find unique words for count vectorizor
text = ' '.join(tweet_list)
words = text.split()
unique_words = set(words)
print(len(unique_words))

#look at word counts
word_count = Counter(words)
sorted_word_count = sorted(word_count.items(), key = lambda x: x[1], reverse=Tr
for word, count in sorted_word_count:
    print(f'{word}: {count}')

#find all words that occur at least 5 times
count_mult_words = sum(1 for word, count in sorted_word_count if count >= 5)
print(count_mult_words)
```

Streaming output truncated to the last 5000 lines.
ridic: 1
paycheck: 1
thingunit: 1
crackersnabisco: 1
pepperidg: 1
farm: 1
2daysofhel: 1
exitrow: 1
rj145: 1
lta: 1
answerthi: 1
whack: 1
circul: 1
burningman: 1
mkwlkr: 1
b737900: 1
9may5sep: 1
ua6465: 1
lostyou: 1
63446373: 1
sfodfw: 1
1576: 1
sfoord: 1
disappointedunit: 1
waspaid: 1
ua6255: 1
winnipeg: 1
ua1059: 1
tightconnect: 1
coltsmissingbag: 1
lightyear: 1
frighten: 1
1person: 1
namesdalla: 1
borderlin: 1
letsworktogeth: 1
dope: 1
staffcust: 1
lgaord: 1
711: 1
unempathet: 1
fulldont: 1
pri: 1
opsec: 1
leisur: 1
master: 1
companyi: 1
4411: 1
aircargo: 1
bcn: 1
ltltltltlt: 1
whatsoev: 1
ltltltltltlt: 1
correspond: 1
2600: 1
anticonsum: 1
welfar: 1
turquois: 1
ua1121: 1

```
aa504: 1
aa200: 1
cst: 1
golden: 1
custi: 1
pvr: 1
duck: 1
robertsamps1: 1
stuffi: 1
296: 1
arbitrarili: 1
passengersdont: 1
retribut: 1
3078: 1
cxldprotect: 1
nocharg: 1
nycbueno: 1
john”: 1
delays: 1
blackberry10: 1
2450
```

Count Vectorizer

In [ ]:
```
cv = CountVectorizer(max_features = 2471)
cv.fit(tweet_list)
```

Out[ ]:
```
▾ CountVectorizer
CountVectorizer(max_features=2471)
```

In [ ]:
```
#create bag of words
bow = cv.transform(tweet_list)
bow.shape

#create bag of words dataframe
bow_df = pd.DataFrame(bow.toarray())
bow_df.columns = cv.get_feature_names_out()
bow_df.head()
```

Out[ ]: (14640, 2471)

Out[ ]:

	10	100	1000	10000	1024	1030	105	1051	10pm	11	1130	1130pm	12	1200	1230
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Join Dataframes

In [ ]:
```
tweets_df2 = pd.concat([tweets_df1, bow_df.set_axis(tweets_df1.index)], axis=1
tweets_df2.info()
tweets_df2.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14640 entries, 0 to 14639
Columns: 2493 entries, tweet_id to zone
dtypes: category(1), datetime64[ns, pytz.FixedOffset(-480)](1), float64(3), in
t64(2475), object(13)
memory usage: 278.4+ MB
```

Out[ ]:

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	negati
0	570306133677760513	neutral	1.0000	NaN	
1	570301130888122368	positive	0.3486	NaN	
2	570301083672813571	neutral	0.6837	NaN	
3	570301031407624196	negative	1.0000	Bad Flight	
4	570300817074462722	negative	1.0000	Can't Tell	

Drop Irrelevant Columns

In [ ]:
```
tweets_df3 = tweets_df2.copy()
```

In [ ]:
```
columns = ['airline_sentiment', 'airline_sentiment_confidence', 'negativereaso
           'negativereason_confidence', 'name', 'negativereason_gold', 'text',
           'tweet_created', 'tweet_location', 'user_timezone', 'weighted_senti
          'unclean_timezone']

tweets_df3 = tweets_df3.drop(columns, axis = 1)
tweets_df3.head()
```

Out[ ]:

	tweet_id	airline	retweet_count	numeric_sentiment	imputed_neg_reason	clea
0	570306133677760513	Virgin America	0	0	NaN	E (U
1	570301130888122368	Virgin America	0	1	NaN	Paci
2	570301083672813571	Virgin America	0	0	NaN	(U
3	570301031407624196	Virgin America	0	-1	Bad Flight	Paci
4	570300817074462722	Virgin America	0	-1	Can't Tell	Paci

Encoding

In [ ]:

```
#encode categorical variables

# Converting type of columns to category
tweets_df3['airline'] = tweets_df3['airline'].astype('category')
tweets_df3['imputed_neg_reason'] = tweets_df3['imputed_neg_reason'].astype('ca
tweets_df3['clean_timezone'] = tweets_df3['clean_timezone'].astype('category')
tweets_df3['time_of_day'] = tweets_df3['time_of_day'].astype('category')

# Assigning numerical values and storing it in another columns
tweets_df3['airline_new'] = tweets_df3['airline'].cat.codes
tweets_df3['imputed_neg_reason_new'] = tweets_df3['imputed_neg_reason'].cat.co
tweets_df3['clean_timezone_new'] = tweets_df3['clean_timezone'].cat.codes
tweets_df3['time_of_day_new'] = tweets_df3['time_of_day'].cat.codes

# one hot encoder
enc = OneHotEncoder()

# Passing encoded columns
enc_data = pd.DataFrame(enc.fit_transform(
    tweets_df3[['airline_new', 'imputed_neg_reason_new', 'clean_timezone_new',

# Merge with main
tweets_df4 = tweets_df3.join(enc_data)
tweets_df4.columns = tweets_df4.columns.astype(str)
tweets_df4 = tweets_df4.drop(['airline', 'imputed_neg_reason', 'clean_timezone

tweets_df4.head()
tweets_df4.info()
```

Out[ ]:

	tweet_id	retweet_count	numeric_sentiment	tweet_day	10	100	1000	10000
0	570306133677760513	0	0	24	0	0	0	0
1	570301130888122368	0	1	24	0	0	0	0
2	570301083672813571	0	0	24	0	0	0	0
3	570301031407624196	0	-1	24	0	0	0	0
4	570300817074462722	0	-1	24	0	0	0	0

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14640 entries, 0 to 14639
Columns: 2511 entries, tweet_id to 33
dtypes: float64(34), int64(2473), int8(4)
memory usage: 280.1 MB
```

Create Models

In [ ]:

```
#split train and test datasets 80/20 split
train_df, rest_df = train_test_split(tweets_df4, train_size=0.8, shuffle=False

#split validation and test data 10/10 split
val_df, test_df = train_test_split(rest_df, test_size = 0.5, shuffle = False)
```

In [ ]:

```
#get targets
train_target = train_df['numeric_sentiment']
train_tweet_ids = train_df['tweet_id']
train_df = train_df.drop(['numeric_sentiment', 'tweet_id'], axis = 1)

val_target = val_df['numeric_sentiment']
val_tweet_ids = val_df['tweet_id']
val_df = val_df.drop(['numeric_sentiment', 'tweet_id'], axis = 1)

test_target = test_df['numeric_sentiment']
test_tweet_ids = test_df['tweet_id']
test_df = test_df.drop(['numeric_sentiment', 'tweet_id'], axis = 1)
```

In [ ]:

```
train_df.head()
```

Out[ ]:

	retweet_count	tweet_day	10	100	1000	10000	1024	1030	105	1051	10pm	11	1130
0	0	24	0	0	0	0	0	0	0	0	0	0	0
1	0	24	0	0	0	0	0	0	0	0	0	0	0
2	0	24	0	0	0	0	0	0	0	0	0	0	0
3	0	24	0	0	0	0	0	0	0	0	0	0	0
4	0	24	0	0	0	0	0	0	0	0	0	0	0

Naive Bayes

In [ ]:

```
X = train_df
y = train_target

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, ra
```

In [ ]:

```
nb = GaussianNB()
print('Current Parameters:\n')
pprint(nb.get_params())
```

```
Current Parameters:

{'priors': None, 'var_smoothing': 1e-09}
```

In [ ]:
```
classifier = GaussianNB()
classifier.fit(X_train, y_train)

cv_scores = cross_val_score(classifier, X, y, cv=5)

print(classifier, ' mean accuracy: ', round(cv_scores.mean()*100, 3), '% std:
```

Out[ ]:

```
▾ GaussianNB
GaussianNB()
```

```
GaussianNB()  mean accuracy:  82.608 % std:  0.019 %
```

Tune Hyperparameters

In [ ]:
```
np.logspace(0,-9, num=10)

cv_method = RepeatedStratifiedKFold(n_splits=5,
                                    n_repeats=3,
                                    random_state=999)
```

Out[ ]:
```
array([1.e+00, 1.e-01, 1.e-02, 1.e-03, 1.e-04, 1.e-05, 1.e-06, 1.e-07,
       1.e-08, 1.e-09])
```

In [ ]:
```
params_nb = {'var_smoothing': np.logspace(0,-9, num = 100)}

gcv_nb = GridSearchCV(estimator = classifier,
                      param_grid = params_nb,
                      cv = cv_method,
                      verbose = 1,
                      scoring = 'accuracy')

df_transformed = PowerTransformer().fit_transform(X_test)

gcv_nb.fit(df_transformed, y_test)

model_nb = gcv_nb
```

```
Fitting 15 folds for each of 100 candidates, totalling 1500 fits
```

Out[ ]:

```
▸ GridSearchCV
▸ estimator: GaussianNB
    ▸ GaussianNB
```

In [ ]:
```
gcv_nb.best_score_

gcv_nb.best_params_
```

Out[ ]:
```
0.6975443296338818
```

Out[ ]:
```
{'var_smoothing': 0.0012328467394420659}
```

Fit Model

In [ ]:
```
y_pred = model_nb.predict(X_test)

cm = confusion_matrix(y_test, y_pred)
print(cm)

accuracy_score(y_test, y_pred)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:486: UserWarning: X ha
s feature names, but GaussianNB was fitted without feature names
  warnings.warn(
[[1391    6   24]
 [   0  295  206]
 [   0    0  421]]
```

Out[ ]:
```
0.8992744344857021
```

Fit Test Data

In [ ]:
```
nb_pred = model_nb.predict(test_df)

cm = confusion_matrix(test_target, nb_pred)
print(cm)

accuracy_score(test_target, nb_pred)
```

```
[[1114    6    7]
 [   0   75  125]
 [   0   25  112]]
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:486: UserWarning: X ha
s feature names, but GaussianNB was fitted without feature names
  warnings.warn(
```

Out[ ]:
```
0.8886612021857924
```

Random Forest Classifier

In [ ]:
```
rf = RandomForestClassifier(random_state = 12)
print('Current Parameters:\n')
pprint(nb.get_params())
```

```
Current Parameters:

{'priors': None, 'var_smoothing': 1e-09}
```

In [ ]:
```
classifier = RandomForestClassifier(n_estimators = 400, criterion = 'entropy',
classifier.fit(X_train, y_train)
```

Out[ ]:
```
▾ RandomForestClassifier

RandomForestClassifier(criterion='entropy', n_estimators=400, random_s
tate=12)
```

In [ ]:
```
y_pred = classifier.predict(X_test)

cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
accuracy_score(y_test, y_pred)

print(classification_report(y_pred, y_test))
```

```
[[1421    0    0]
 [   0  439   62]
 [   0  128  293]]
```

Out[ ]:

```
0.9189073836961161
```

```
              precision    recall  f1-score   support

          -1       1.00      1.00      1.00      1421
           0       0.88      0.77      0.82       567
           1       0.70      0.83      0.76       355

    accuracy                           0.92      2343
   macro avg       0.86      0.87      0.86      2343
weighted avg       0.92      0.92      0.92      2343
```

Tune Hyperparameters

In [ ]:

```
param_grid = {
    'n_estimators': [25, 50, 100, 150],
    'max_features': ['sqrt', 'log2', None],
    'max_depth': [3, 6, 9],
    'max_leaf_nodes': [3, 6, 9],
}


grid_search = GridSearchCV(RandomForestClassifier(),
                           param_grid=param_grid)

grid_search.fit(X_train, y_train)
print(grid_search.best_estimator_)
```

Out[ ]:

```
▸ GridSearchCV
▸ estimator: RandomForestClassifier
    ▸ RandomForestClassifier
```

```
RandomForestClassifier(max_depth=9, max_features=None, max_leaf_nodes=9)
```

Fit Model

In [ ]:

```
model_rf = RandomForestClassifier(max_depth = 9,
                                  max_features = None,
                                  max_leaf_nodes = 9,
                                  n_estimators = 25)

model_rf.fit(X_train, y_train)
y_pred_rf = model_rf.predict(X_test)

cm = confusion_matrix(y_test, y_pred)
print(cm)

accuracy_score(y_test, y_pred)
```

```
print(classification_report(y_pred, y_test))
```

Out[ ]:

```
RandomForestClassifier

RandomForestClassifier(max_depth=9, max_features=None, max_leaf_nodes=
9,
                       n_estimators=25)
```

```
[[1421    0    0]
 [   0  439   62]
 [   0  128  293]]
```

Out[ ]:

```
0.9189073836961161
              precision    recall  f1-score   support

          -1       1.00      1.00      1.00      1421
           0       0.88      0.77      0.82       567
           1       0.70      0.83      0.76       355

    accuracy                           0.92      2343
   macro avg       0.86      0.87      0.86      2343
weighted avg       0.92      0.92      0.92      2343
```

Fit Test Data

In [ ]:

```
rf_pred = model_rf.predict(test_df)

cm = confusion_matrix(test_target, rf_pred)
print(cm)

accuracy_score(test_target, rf_pred)
```

```
[[1127    0    0]
 [   0  171   29]
 [   0   44   93]]
```

Out[ ]:

```
0.950136612021858
```

LSTM Model

In [ ]:

```
tweets_df5 = tweets_df1.copy()
tweets_df5['clean_text'] = pd.Series(tweet_list)
tweets_df5.head()
```

Out[ ]:

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	negati
0	570306133677760513	neutral	1.0000	NaN	
1	570301130888122368	positive	0.3486	NaN	
2	570301083672813571	neutral	0.6837	NaN	
3	570301031407624196	negative	1.0000	Bad Flight	
4	570300817074462722	negative	1.0000	Can't Tell	

Tokenize

In [ ]:
```
max_fatures = 2471
tokenizer = Tokenizer(num_words=max_fatures, split=' ')
tokenizer.fit_on_texts(tweets_df5['clean_text'].values)
X = tokenizer.texts_to_sequences(tweets_df5['clean_text'].values)
X = pad_sequences(X)
```

Build Model

In [ ]:
```
embed_dim = 128
lstm_out = 196

model_lstm = Sequential()
model_lstm.add(Embedding(max_fatures, embed_dim,input_length = X.shape[1]))
model_lstm.add(SpatialDropout1D(0.2))
model_lstm.add(LSTM(lstm_out, dropout=0.2, recurrent_dropout=0.2))
model_lstm.add(Dense(3,activation='softmax'))
model_lstm.compile(loss = 'categorical_crossentropy', optimizer='adam', metric
print(model_lstm.summary())
```

In [ ]:
```
Y = pd.get_dummies(tweets_df5['numeric_sentiment']).values
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.33, ra
print(X_train.shape,Y_train.shape)
print(X_test.shape,Y_test.shape)
```

Fit Model

In [ ]:
```
batch_size = 32
model_lstm.fit(X_train, Y_train, epochs = 15, batch_size = batch_size, verbose
```

```
Epoch 1/15
307/307 - 42s - loss: 0.6740 - accuracy: 0.7210 - 42s/epoch - 137ms/step
Epoch 2/15
307/307 - 35s - loss: 0.4686 - accuracy: 0.8157 - 35s/epoch - 114ms/step
Epoch 3/15
307/307 - 38s - loss: 0.4006 - accuracy: 0.8427 - 38s/epoch - 124ms/step
Epoch 4/15
307/307 - 35s - loss: 0.3563 - accuracy: 0.8612 - 35s/epoch - 115ms/step
Epoch 5/15
307/307 - 34s - loss: 0.3165 - accuracy: 0.8774 - 34s/epoch - 112ms/step
Epoch 6/15
307/307 - 36s - loss: 0.2749 - accuracy: 0.8894 - 36s/epoch - 117ms/step
Epoch 7/15
307/307 - 34s - loss: 0.2418 - accuracy: 0.9083 - 34s/epoch - 112ms/step
Epoch 8/15
307/307 - 34s - loss: 0.2129 - accuracy: 0.9179 - 34s/epoch - 112ms/step
Epoch 9/15
307/307 - 35s - loss: 0.1930 - accuracy: 0.9275 - 35s/epoch - 114ms/step
Epoch 10/15
307/307 - 33s - loss: 0.1742 - accuracy: 0.9320 - 33s/epoch - 106ms/step
Epoch 11/15
307/307 - 34s - loss: 0.1535 - accuracy: 0.9389 - 34s/epoch - 112ms/step
Epoch 12/15
307/307 - 35s - loss: 0.1415 - accuracy: 0.9458 - 35s/epoch - 115ms/step
Epoch 13/15
307/307 - 36s - loss: 0.1261 - accuracy: 0.9528 - 36s/epoch - 116ms/step
Epoch 14/15
307/307 - 34s - loss: 0.1188 - accuracy: 0.9577 - 34s/epoch - 112ms/step
Epoch 15/15
307/307 - 34s - loss: 0.1112 - accuracy: 0.9587 - 34s/epoch - 112ms/step
```

Out[ ]:
```
<keras.src.callbacks.History at 0x7fa05cc55cc0>
```

In [ ]:
```
validation_size = 1500

X_validate = X_test[-validation_size:]
Y_validate = Y_test[-validation_size:]
X_test = X_test[:-validation_size]
Y_test = Y_test[:-validation_size]
score,acc = model_lstm.evaluate(X_test, Y_test, verbose = 2, batch_size = batcl
print("score: %.2f" % (score))
print("acc: %.2f" % (acc))
```

```
105/105 - 5s - loss: 1.3055 - accuracy: 0.7473 - 5s/epoch - 47ms/step
score: 1.31
acc: 0.75
```

GRU Model

Tokenize

In [ ]:
```
# Preprocessing
X = tweets_df5["clean_text"]
y = pd.get_dummies(tweets_df5['numeric_sentiment']).values

# Tokenization
```

```
tokenizer = Tokenizer()
tokenizer.fit_on_texts(X)
X_seq = tokenizer.texts_to_sequences(X)
vocab_size = len(tokenizer.word_index) + 1

# Padding sequences
max_length = max([len(seq) for seq in X_seq])
X_pad = pad_sequences(X_seq, maxlen=max_length, padding='post')

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X_pad, y, test_size = 0.1,
```

Build Model

In [ ]:
```
# Build GRU model
model_gru = Sequential()
model_gru.add(Embedding(vocab_size, 100, input_length=max_length))
model_gru.add(GRU(64))
model_gru.add(Dropout(0.5))
model_gru.add(Dense(3, activation='softmax'))
model_gru.compile(optimizer='adam', loss='categorical_crossentropy', metrics=[
print(model_gru.summary())
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 23, 100)           1200400

 gru (GRU)                   (None, 64)                31872

 dropout (Dropout)           (None, 64)                0

 dense (Dense)               (None, 3)                 195

=================================================================
Total params: 1232467 (4.70 MB)
Trainable params: 1232467 (4.70 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
None
```

Fit Model

In [ ]:
```
batch_size = 64
model_gru.fit(X_train, y_train, epochs=15, batch_size=batch_size, validation_da
```

```
Epoch 1/15
206/206 [==============================] - 11s 40ms/step - loss: 0.8922 - accu
racy: 0.6330 - val_loss: 0.6645 - val_accuracy: 0.6967
Epoch 2/15
206/206 [==============================] - 7s 36ms/step - loss: 0.5903 - accur
acy: 0.7516 - val_loss: 0.5615 - val_accuracy: 0.7760
Epoch 3/15
206/206 [==============================] - 7s 35ms/step - loss: 0.4488 - accur
acy: 0.8290 - val_loss: 0.5624 - val_accuracy: 0.7937
Epoch 4/15
206/206 [==============================] - 10s 50ms/step - loss: 0.3294 - accu
racy: 0.8854 - val_loss: 0.5608 - val_accuracy: 0.7951
Epoch 5/15
206/206 [==============================] - 10s 48ms/step - loss: 0.2436 - accu
racy: 0.9148 - val_loss: 0.5877 - val_accuracy: 0.7828
Epoch 6/15
206/206 [==============================] - 7s 33ms/step - loss: 0.1858 - accur
acy: 0.9409 - val_loss: 0.7654 - val_accuracy: 0.7746
Epoch 7/15
206/206 [==============================] - 8s 38ms/step - loss: 0.1534 - accur
acy: 0.9533 - val_loss: 0.8890 - val_accuracy: 0.7616
Epoch 8/15
206/206 [==============================] - 9s 42ms/step - loss: 0.1312 - accur
acy: 0.9583 - val_loss: 0.8267 - val_accuracy: 0.7657
Epoch 9/15
206/206 [==============================] - 7s 36ms/step - loss: 0.1093 - accur
acy: 0.9676 - val_loss: 0.9277 - val_accuracy: 0.7650
Epoch 10/15
206/206 [==============================] - 8s 39ms/step - loss: 0.1008 - accur
acy: 0.9693 - val_loss: 0.9182 - val_accuracy: 0.7555
Epoch 11/15
206/206 [==============================] - 7s 34ms/step - loss: 0.0864 - accur
acy: 0.9760 - val_loss: 0.9966 - val_accuracy: 0.7555
Epoch 12/15
206/206 [==============================] - 8s 38ms/step - loss: 0.0779 - accur
acy: 0.9767 - val_loss: 1.0102 - val_accuracy: 0.7589
Epoch 13/15
206/206 [==============================] - 7s 36ms/step - loss: 0.0748 - accur
acy: 0.9772 - val_loss: 1.0580 - val_accuracy: 0.7616
Epoch 14/15
206/206 [==============================] - 7s 35ms/step - loss: 0.0673 - accur
acy: 0.9800 - val_loss: 1.0818 - val_accuracy: 0.7548
Epoch 15/15
206/206 [==============================] - 8s 37ms/step - loss: 0.0579 - accur
acy: 0.9841 - val_loss: 1.2617 - val_accuracy: 0.7575
```

Out[ ]:

```
<keras.src.callbacks.History at 0x7823c706dff0>
```

In [ ]:

```python
k_fold = KFold(n_splits=5, shuffle=True, random_state=42)

# Initialize lists to store evaluation metrics
scores = []

# Define callbacks
early_stopping = EarlyStopping(monitor='val_loss', patience=3, restore_best_we
model_checkpoint = ModelCheckpoint('best_model_cv.h5', monitor='val_loss', save

# Perform K-fold cross-validation
for fold_index, (train_indices, val_indices) in enumerate(k_fold.split(X_pad, y
```

```python
    print(f"Fold {fold_index + 1}/{k_fold.n_splits}")

    # Split data into training and validation sets for this fold
    X_train_fold, X_val_fold = X_pad[train_indices], X_pad[val_indices]
    y_train_fold, y_val_fold = y[train_indices], y[val_indices]

    # Build GRU model
    model_gru_cv = Sequential()
    model_gru_cv.add(Embedding(vocab_size, 100, input_length=max_length))
    model_gru_cv.add(GRU(64))
    model_gru_cv.add(Dropout(0.5))
    model_gru_cv.add(Dense(3, activation='softmax'))
    model_gru_cv.compile(optimizer='adam', loss='categorical_crossentropy', met

    # Train the model with callbacks
    history = model_gru_cv.fit(X_train_fold, y_train_fold, epochs=15, batch_si
                               validation_data=(X_val_fold, y_val_fold),
                               callbacks=[early_stopping, model_checkpoint],
                               verbose=1)

    # Evaluate the model on the validation set
    score = model_gru_cv.evaluate(X_val_fold, y_val_fold, verbose=0)
    print("Validation Score:", score)
    scores.append(score)

# Calculate mean and standard deviation of validation scores
mean_score = np.mean(scores, axis=0)
std_score = np.std(scores, axis=0)
print("Mean Validation Score:", mean_score)
print("Standard Deviation of Validation Score:", std_score)
```

```
Fold 1/5
Epoch 1/15
183/183 [==============================] - 14s 55ms/step - loss: 0.9304 - accu
racy: 0.6195 - val_loss: 0.7839 - val_accuracy: 0.6452
Epoch 2/15
  2/183 [..............................] - ETA: 9s - loss: 0.8669 - accuracy:
0.5859
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3103: Use
rWarning: You are saving your model as an HDF5 file via `model.save()`. This f
ile format is considered legacy. We recommend using instead the native Keras f
ormat, e.g. `model.save('my_model.keras')`.
  saving_api.save_model(
```

```
183/183 [==============================] - 7s 38ms/step - loss: 0.6474 - accur
acy: 0.7228 - val_loss: 0.5552 - val_accuracy: 0.7790
Epoch 3/15
183/183 [==============================] - 7s 39ms/step - loss: 0.4621 - accur
acy: 0.8233 - val_loss: 0.5903 - val_accuracy: 0.7913
Epoch 4/15
183/183 [==============================] - 6s 33ms/step - loss: 0.3428 - accur
acy: 0.8774 - val_loss: 0.6059 - val_accuracy: 0.7753
Epoch 5/15
183/183 [==============================] - 6s 33ms/step - loss: 0.2488 - accur
acy: 0.9166 - val_loss: 0.6056 - val_accuracy: 0.7879
Validation Score: [0.5552219152450562, 0.7790300250053406]
Fold 2/5
Epoch 1/15
183/183 [==============================] - 9s 38ms/step - loss: 0.9262 - accur
acy: 0.6254 - val_loss: 0.8963 - val_accuracy: 0.6253
Epoch 2/15
183/183 [==============================] - 6s 31ms/step - loss: 0.6521 - accur
acy: 0.7180 - val_loss: 0.5901 - val_accuracy: 0.7599
Epoch 3/15
183/183 [==============================] - 7s 36ms/step - loss: 0.4700 - accur
acy: 0.8114 - val_loss: 0.5878 - val_accuracy: 0.7678
Epoch 4/15
183/183 [==============================] - 6s 32ms/step - loss: 0.3530 - accur
acy: 0.8742 - val_loss: 0.6337 - val_accuracy: 0.7637
Epoch 5/15
183/183 [==============================] - 7s 36ms/step - loss: 0.2540 - accur
acy: 0.9150 - val_loss: 0.6880 - val_accuracy: 0.7572
Epoch 6/15
183/183 [==============================] - 6s 32ms/step - loss: 0.1854 - accur
acy: 0.9415 - val_loss: 0.8130 - val_accuracy: 0.7374
Validation Score: [0.5878012180328369, 0.7677595615386963]
Fold 3/5
Epoch 1/15
183/183 [==============================] - 10s 41ms/step - loss: 0.9252 - accu
racy: 0.6249 - val_loss: 0.7838 - val_accuracy: 0.6332
Epoch 2/15
183/183 [==============================] - 6s 34ms/step - loss: 0.6305 - accur
acy: 0.7285 - val_loss: 0.5670 - val_accuracy: 0.7766
Epoch 3/15
183/183 [==============================] - 8s 44ms/step - loss: 0.4694 - accur
acy: 0.8204 - val_loss: 0.5755 - val_accuracy: 0.7715
Epoch 4/15
183/183 [==============================] - 7s 37ms/step - loss: 0.3610 - accur
acy: 0.8690 - val_loss: 0.5919 - val_accuracy: 0.7859
Epoch 5/15
183/183 [==============================] - 6s 33ms/step - loss: 0.2594 - accur
acy: 0.9147 - val_loss: 0.6682 - val_accuracy: 0.7773
Validation Score: [0.5670248866081238, 0.7766393423080444]
Fold 4/5
Epoch 1/15
183/183 [==============================] - 10s 42ms/step - loss: 0.9033 - accu
racy: 0.6323 - val_loss: 0.7586 - val_accuracy: 0.6643
Epoch 2/15
183/183 [==============================] - 6s 34ms/step - loss: 0.6010 - accur
acy: 0.7459 - val_loss: 0.6046 - val_accuracy: 0.7490
Epoch 3/15
183/183 [==============================] - 7s 36ms/step - loss: 0.4442 - accur
acy: 0.8323 - val_loss: 0.5934 - val_accuracy: 0.7572
Epoch 4/15
```

```
183/183 [==============================] - 8s 41ms/step - loss: 0.3351 - accur
acy: 0.8850 - val_loss: 0.6892 - val_accuracy: 0.7602
Epoch 5/15
183/183 [==============================] - 6s 35ms/step - loss: 0.2530 - accur
acy: 0.9159 - val_loss: 0.7233 - val_accuracy: 0.7520
Epoch 6/15
183/183 [==============================] - 7s 38ms/step - loss: 0.1976 - accur
acy: 0.9378 - val_loss: 0.8210 - val_accuracy: 0.7459
Validation Score: [0.5934033393859863, 0.7571721076965332]
Fold 5/5
Epoch 1/15
183/183 [==============================] - 10s 40ms/step - loss: 0.9287 - accu
racy: 0.6242 - val_loss: 0.8679 - val_accuracy: 0.6305
Epoch 2/15
183/183 [==============================] - 8s 42ms/step - loss: 0.6468 - accur
acy: 0.7183 - val_loss: 0.5907 - val_accuracy: 0.7579
Epoch 3/15
183/183 [==============================] - 6s 35ms/step - loss: 0.4668 - accur
acy: 0.8173 - val_loss: 0.5861 - val_accuracy: 0.7681
Epoch 4/15
183/183 [==============================] - 6s 35ms/step - loss: 0.3529 - accur
acy: 0.8691 - val_loss: 0.6392 - val_accuracy: 0.7824
Epoch 5/15
183/183 [==============================] - 6s 34ms/step - loss: 0.2570 - accur
acy: 0.9126 - val_loss: 0.6333 - val_accuracy: 0.7684
Epoch 6/15
183/183 [==============================] - 7s 36ms/step - loss: 0.1924 - accur
acy: 0.9388 - val_loss: 0.7228 - val_accuracy: 0.7674
Validation Score: [0.5861008167266846, 0.7681010961532593]
Mean Validation Score: [0.57791044 0.76974043]
Standard Deviation of Validation Score: [0.01440975 0.00772613]
```

In [ ]:

```
history_final = model_gru.fit(X_pad, y, epochs=15, batch_size=batch_size, verb
```

```
Epoch 1/15
229/229 [==============================] - 17s 75ms/step - loss: 0.1504 - accu
racy: 0.9616
Epoch 2/15
229/229 [==============================] - 13s 56ms/step - loss: 0.0961 - accu
racy: 0.9733
Epoch 3/15
229/229 [==============================] - 13s 58ms/step - loss: 0.0720 - accu
racy: 0.9803
Epoch 4/15
229/229 [==============================] - 13s 59ms/step - loss: 0.0616 - accu
racy: 0.9823
Epoch 5/15
229/229 [==============================] - 11s 49ms/step - loss: 0.0587 - accu
racy: 0.9838
Epoch 6/15
229/229 [==============================] - 8s 36ms/step - loss: 0.0496 - accur
acy: 0.9859
Epoch 7/15
229/229 [==============================] - 13s 58ms/step - loss: 0.0498 - accu
racy: 0.9857
Epoch 8/15
229/229 [==============================] - 13s 57ms/step - loss: 0.0476 - accu
racy: 0.9861
Epoch 9/15
229/229 [==============================] - 13s 57ms/step - loss: 0.0474 - accu
racy: 0.9859
Epoch 10/15
229/229 [==============================] - 8s 33ms/step - loss: 0.0485 - accur
acy: 0.9850
Epoch 11/15
229/229 [==============================] - 9s 37ms/step - loss: 0.0445 - accur
acy: 0.9859
Epoch 12/15
229/229 [==============================] - 8s 37ms/step - loss: 0.0409 - accur
acy: 0.9874
Epoch 13/15
229/229 [==============================] - 7s 32ms/step - loss: 0.0394 - accur
acy: 0.9876
Epoch 14/15
229/229 [==============================] - 8s 37ms/step - loss: 0.0361 - accur
acy: 0.9885
Epoch 15/15
229/229 [==============================] - 8s 35ms/step - loss: 0.0331 - accur
acy: 0.9896
```

In [ ]:

```
# Predict probabilities for each class on the entire dataset
probs = model_gru.predict(X_pad, verbose=2, batch_size=batch_size)

# Determine predicted classes based on the highest probability
y_pred = np.argmax(probs, axis=1)

# Convert one-hot encoded labels to single label for the entire dataset
y_true = np.argmax(y, axis=1)

# Generate classification report for the entire dataset
print("Classification Report:")
print(classification_report(y_true, y_pred))
```

```
229/229 - 2s - 2s/epoch - 10ms/step
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      9178
           1       0.98      0.98      0.98      3099
           2       0.98      0.99      0.98      2363

    accuracy                           0.99     14640
   macro avg       0.99      0.99      0.99     14640
weighted avg       0.99      0.99      0.99     14640
```