Final Project Code

```
#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_report
from sklearn.ensemble import RandomForestClassifier
from sklearn import tree
from sklearn.model_selection import train_test_split, RandomizedSearchCV, GridSearchCV, cross_v
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, Dropout
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"
```

```
tweets_df = pd.read_csv('/content/tweets.csv')
```

EDA

EDA

```
# 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
```

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	n
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

	tweet_id	airline_sentiment_confidence	negativereason_confidence	retweet_cou
count	1.464000e+04	14640.000000	10522.000000	14640.0000
mean	5.692184e+17	0.900169	0.638298	0.0826
std	7.791112e+14	0.162830	0.330440	0.7457
min	5.675883e+17	0.335000	0.000000	0.0000
25%	5.685592e+17	0.692300	0.360600	0.0000

```
# Convert airline_sentiment classification to numeric: positive, neutral, negative = 1, 0, -1
tweets_df['numeric_sentiment'] = tweets_df.apply(lambda x: 1 if (x['airline_sentiment'] == 'p

# Create weighted_sentiment feature, the product of the sentiment and the confidence.
tweets_df['weighted_sentiment'] = tweets_df['numeric_sentiment'] * tweets_df['airline_sentime
```

```
     airline_sentiment                    0
```

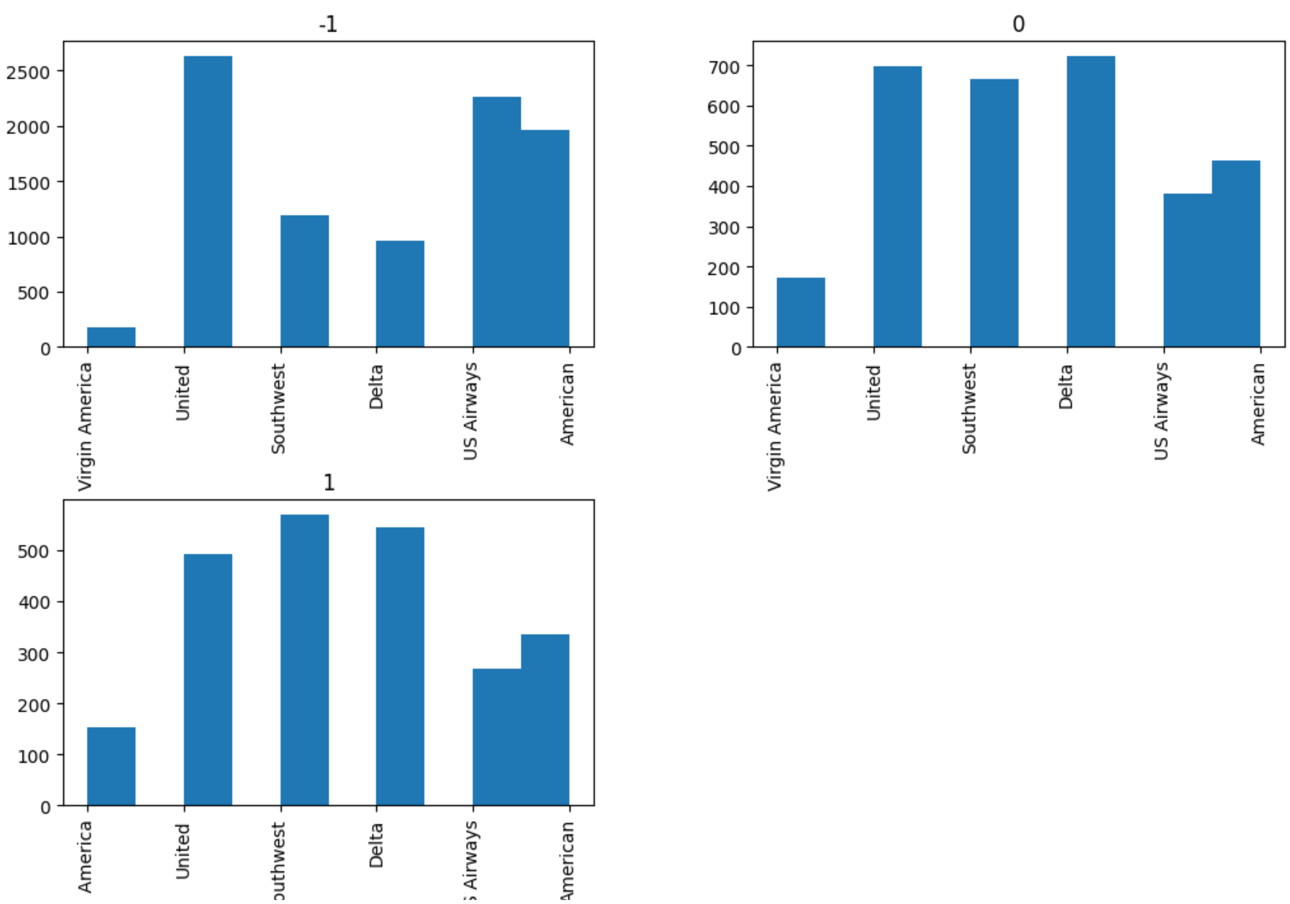
```
# Compute summary statistics for numeric_sentiment variable.

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 predominantly nega
```

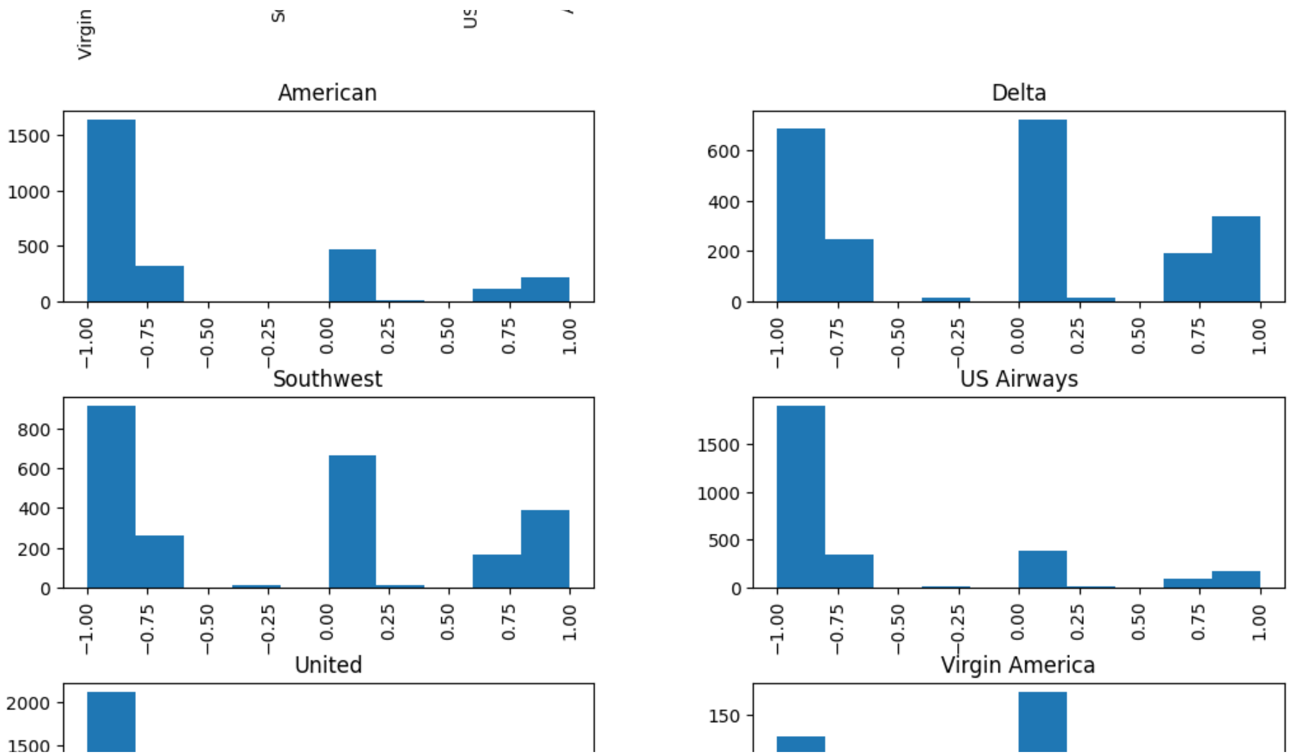
```
Summary stats for numeric_sentiment.
count    14640.000000
mean        -0.465505
std          0.756084
min         -1.000000
25%         -1.000000
50%         -1.000000
75%          0.000000
max          1.000000
Name: numeric_sentiment, dtype: float64
Median and mode for numeric_sentiment.
```

```
-1.0
-1
Summary stats for weighted_sentiment.
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.
-1.0
-1.0
```

```
# 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()
```

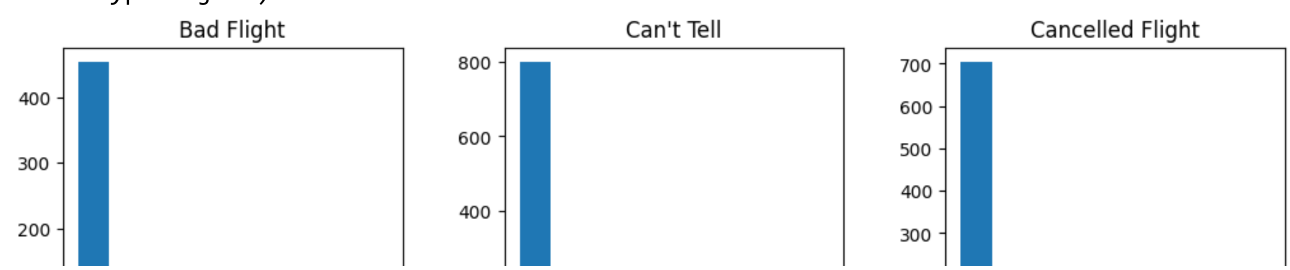
```
array([[<Axes: title={'center': '-1'}>, <Axes: title={'center': '0'}>],
       [<Axes: title={'center': '1'}>, <Axes: >]], dtype=object)
array([[<Axes: title={'center': 'American'}>,
        <Axes: title={'center': 'Delta'}>],
       [<Axes: title={'center': 'Southwest'}>,
        <Axes: title={'center': 'US Airways'}>],
       [<Axes: title={'center': 'United'}>,
        <Axes: title={'center': 'Virgin America'}>]], dtype=object)
```

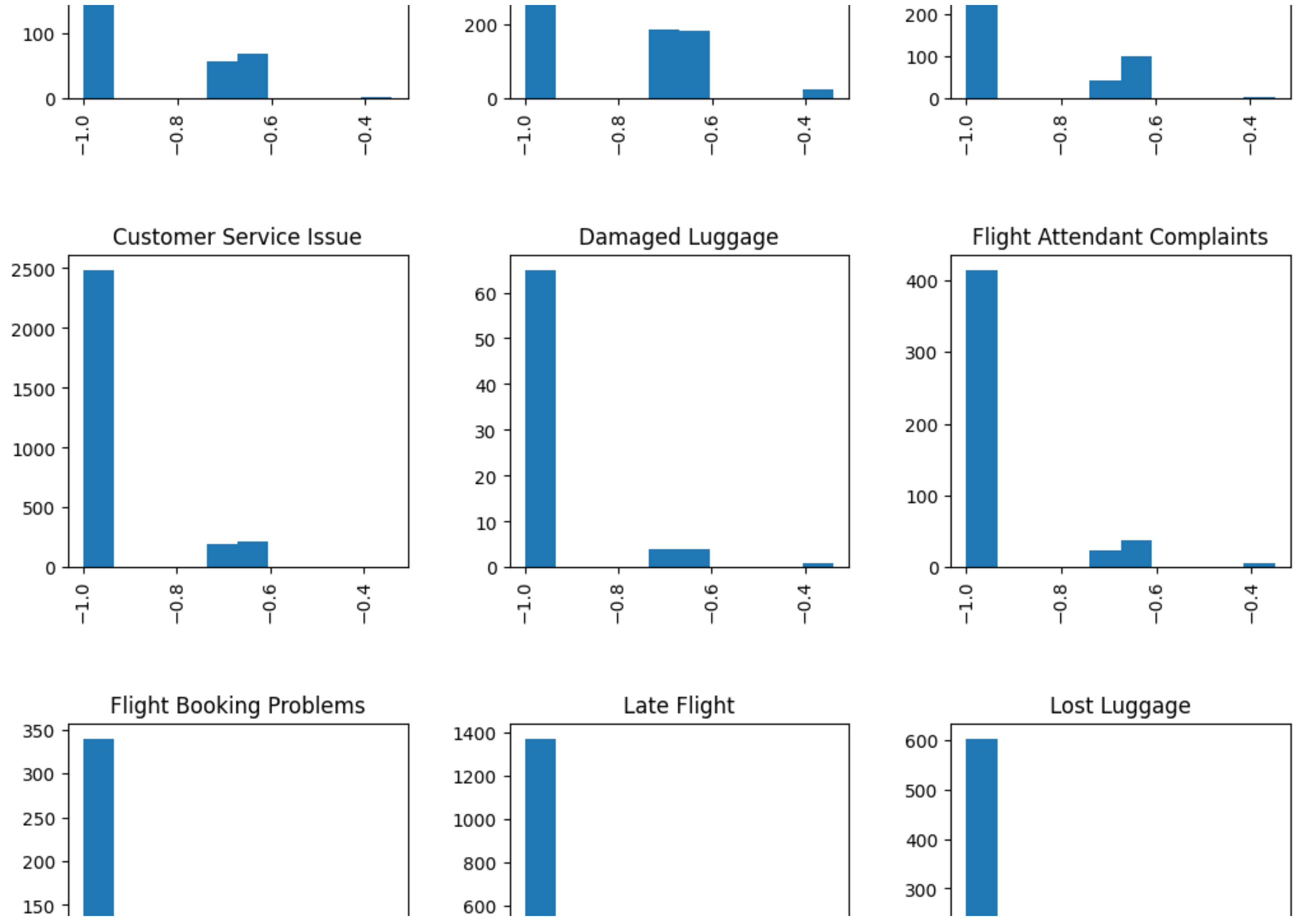





```
# look at Negative Reason distribution
data_neg = tweets_df[tweets_df['numeric_sentiment'] < 0]
data_neg.hist(column ='weighted_sentiment', by='negativereason',figsize=(12,18))
data_neg.hist(column ='airline', by='negativereason',figsize=(12,18))
```

```
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)
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)
```

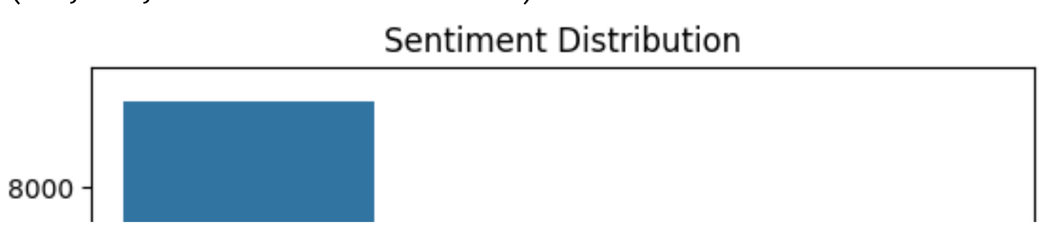


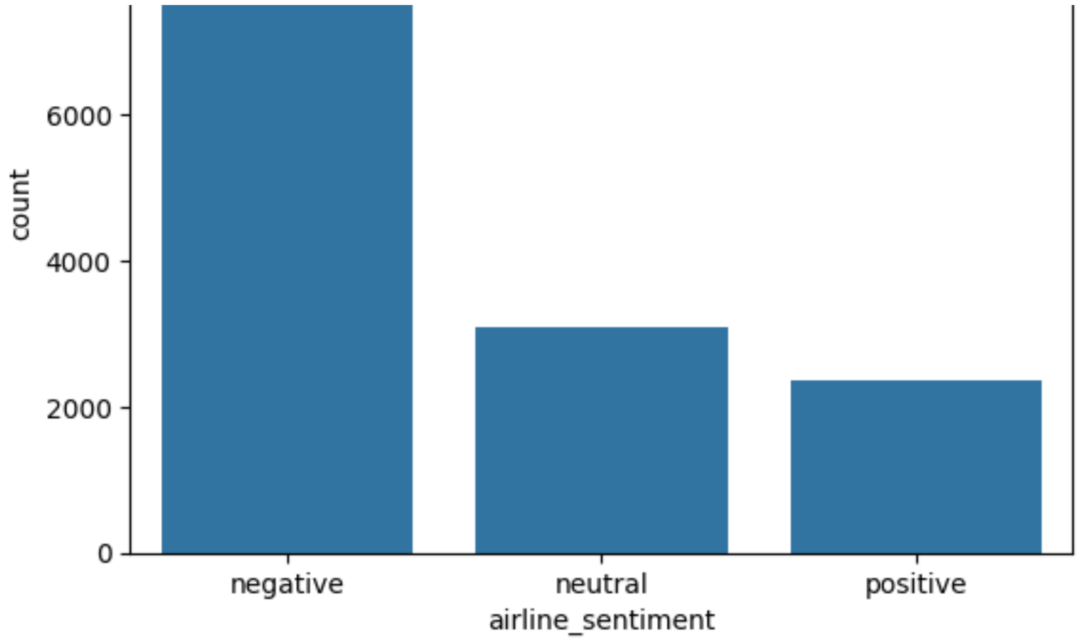



```
#create visuals

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_sentiment'].valu
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', 'American',
                'Southwest Air', 'SouthwestAir', 'VirginAmerica', 'AmericanAir', 'USAir', 'US/
stop_words = set(stopwords.words('english') + company_names)

def plot_wordcloud(sentiment):
    words = ' '.join(tweets_df[tweets_df['airline_sentiment'] == sentiment]['text'])
    wordcloud = WordCloud(width=800, height=400, stopwords = stop_words, random_state=21, max_
    plt.figure(figsize=(10, 7))
    plt.imshow(wordcloud, interpolation="bilinear")
```

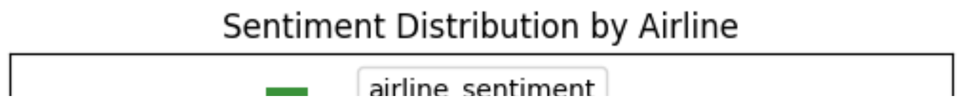
```
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis('off')
    plt.title(f'Word Cloud for {sentiment} Sentiment')
    plt.show()

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() not in stop_wo
    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 sublist]
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!
True
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
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
<Axes: xlabel='airline_sentiment', ylabel='count'>
Text(0.5, 1.0, 'Sentiment Distribution')
```






```
<Axes: xlabel='airline', ylabel='count'>
Text(0.5, 1.0, 'Sentiment Distribution by Airline')
```



Cleaning the Data

```
# We note that the majority of airline_sentiment_gold is empty. However, non-null values may l

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_gold. We remove tl
tweets_df.drop(columns=['airline_sentiment_gold'], inplace=True)
```

```
False
```

```
# However, there are differences between those of negativereason and negativereason_gold.

# If confidence level in airline_sentiment_confidence is higher on average we'd suspect that ı
sentiment_mean = tweets_df.groupby('negativereason')['airline_sentiment_confidence'].mean()
gold_sent_mean = tweets_df.groupby('negativereason_gold')['airline_sentiment_confidence'].meaı

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 the sentiment,
tweets_df['imputed_neg_reason'] = tweets_df['negativereason_gold'].fillna(tweets_df['negativeı

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

```
check_df

## A spot check confirms negativereason_gold offers more adequate information to the Tweet.
```

```
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
```

	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...

Feature Engineering

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

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

# 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['clean_timezone']

## Code leaves in unclean_timezone column. We could delete the above line and simply use clea

# 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

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

Initial Cleaning of Text Column and Prepare Data for Thorough Cleaning

```
#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!
True
```

Cleaning the Data Using Beautiful Soup

```
#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)*100))

    return( " ".join( meaningful_words))

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

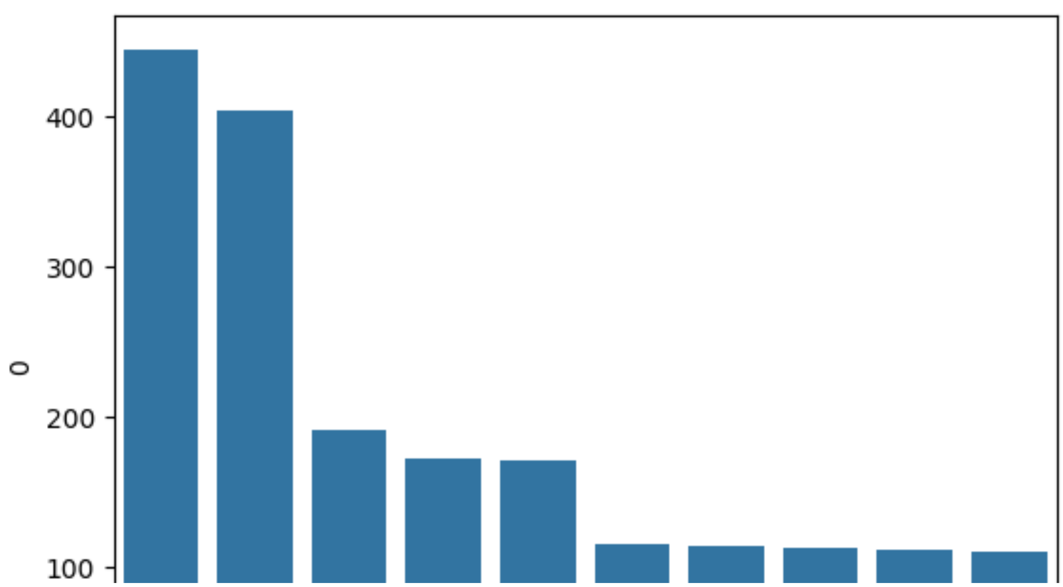
```
<ipython-input-15-85e9262fa24a>:17: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
  data_pre_process["text"][i] = clean_text_data(data_pre_process["text"][i], data_size)
<ipython-input-15-85e9262fa24a>:3: MarkupResemblesLocatorWarning: The input looks more li
  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!
```

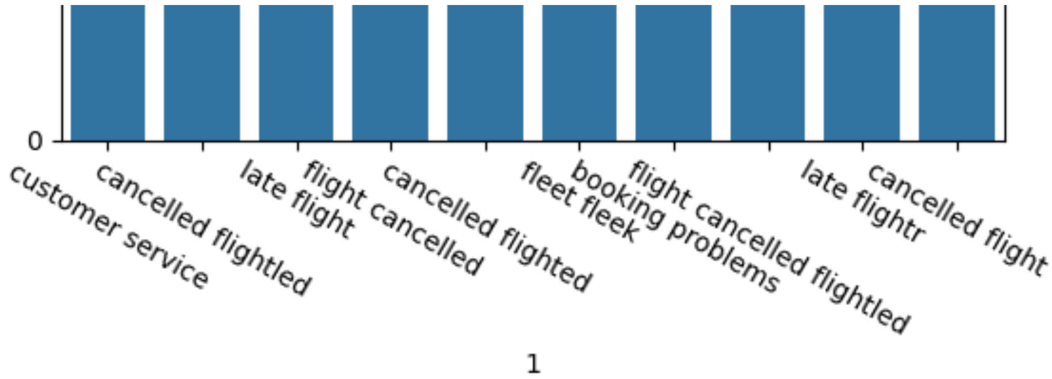
Executing a Random Forest Model Without Fitting to Learn Top Phrases and Number of Occurences for Each

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


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

X_train = vectorizer.fit_transform(X_train)
```

```
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 togetl
  graph.set_xticklabels(
[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

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

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

string.punctuation
```

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

```
#clean Tweet text
ps = PorterStemmer()

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)

#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))


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

```
14640
['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']
```

```
#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=True)
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
```

Count Vectorizer

```
cv = CountVectorizer(max_features = 2471)
cv.fit(tweet_list)
```

```
▾ CountVectorizer
CountVectorizer(max_features=2471)
```

```
#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()
```

```
(14640, 2471)
```

	10	100	1000	10000	1024	1030	105	1051	10pm	11	1130	1130pm	12	1200	1230	13
0	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	0
2	0	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	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Join Dataframes

```
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), int64(2475), (
memory usage: 278.4+ MB
```

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	n
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

```
tweets_df3 = tweets_df2.copy()
```

```
columns = ['airline_sentiment', 'airline_sentiment_confidence', 'negativereason',
           'negativereason_confidence', 'name', 'negativereason_gold', 'text', 'tweet_coord',
           'tweet_created', 'tweet_location', 'user_timezone', 'weighted_sentiment', 'process
          'unclean_timezone']

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

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

Encoding

```
#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('category')
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.codes
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', 'time_of_day_n

# 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', 'time_of_day

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

	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

```
#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)

#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)

train_df.head()
```

	retweet_count	tweet_day	10	100	1000	10000	1024	1030	105	1051	10pm	11	1130	1
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

```
X = train_df
y = train_target

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state = 12

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

```
Current Parameters:

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

```
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: ', round(cv_scor
```

```
▾ GaussianNB i ?
GaussianNB()
```

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

Tune Hyperparameters

```
np.logspace(0,-9, num=10)

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

```
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])
```

```
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
▸ GridSearchCV i ?
▸ estimator: GaussianNB
  ▸ GaussianNB ?
```

```
gcv_nb.best_score_

gcv_nb.best_params_
```

```
0.6975443296338818
{'var_smoothing': 0.0012328467394420659}
```

Fit Model

```
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 has feature n
  warnings.warn(
[[1391    6   24]
 [   0  295  206]
 [   0    0  421]]
0.8992744344857021
```

Fit Test Data

```
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 has feature n
  warnings.warn(
0.8886612021857924
```

Random Forest Classifier

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

```
Current Parameters:

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

```
classifier = RandomForestClassifier(n_estimators = 400, criterion = 'entropy', random_state =
classifier.fit(X_train, y_train)
```

```
▾                         RandomForestClassifier                    i ?
RandomForestClassifier(criterion='entropy', n_estimators=400, random_state=12)
```

```
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]]
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

```
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_)
```

```
▸ GridSearchCV i ?
▸ estimator: RandomForestClassifier
  ▸ RandomForestClassifier ?
```

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

Fit Model

```
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))
```

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

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

```
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]]
0.950136612021858
```

LSTM Model

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

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	n
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

```
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

```
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', metrics = ['accuracy'
print(model_lstm.summary())

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, random_state = 42
print(X_train.shape,Y_train.shape)
print(X_test.shape,Y_test.shape)
```

Fit Model

```
batch_size = 32
model_lstm.fit(X_train, Y_train, epochs = 15, batch_size = batch_size, verbose = 2)
```

```
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
<keras.src.callbacks.History at 0x7fa05cc55cc0>
```

```
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 = batch_size)
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

```
# 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, random_state=4
```

Build Model

```
# Build GRU model
model_gru = Sequential()
model_gru.add(Embedding(vocab_size, 100, input_length=max_length))
```

```
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=['accuracy'])
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

```
batch_size = 64
model_gru.fit(X_train, y_train, epochs=15, batch_size=batch_size, validation_data=(X_test, y_
```

```
Epoch 1/15
206/206 [==============================] - 11s 40ms/step - loss: 0.8922 - accuracy: 0.633
Epoch 2/15
206/206 [==============================] - 7s 36ms/step - loss: 0.5903 - accuracy: 0.7516
Epoch 3/15
206/206 [==============================] - 7s 35ms/step - loss: 0.4488 - accuracy: 0.8290
Epoch 4/15
206/206 [==============================] - 10s 50ms/step - loss: 0.3294 - accuracy: 0.885
Epoch 5/15
206/206 [==============================] - 10s 48ms/step - loss: 0.2436 - accuracy: 0.914
Epoch 6/15
206/206 [==============================] - 7s 33ms/step - loss: 0.1858 - accuracy: 0.9409
Epoch 7/15
206/206 [==============================] - 8s 38ms/step - loss: 0.1534 - accuracy: 0.9533
Epoch 8/15
206/206 [==============================] - 9s 42ms/step - loss: 0.1312 - accuracy: 0.9583
Epoch 9/15
206/206 [==============================] - 7s 36ms/step - loss: 0.1093 - accuracy: 0.9676
Epoch 10/15
206/206 [==============================] - 8s 39ms/step - loss: 0.1008 - accuracy: 0.9693
Epoch 11/15
206/206 [==============================] - 7s 34ms/step - loss: 0.0864 - accuracy: 0.9760
Epoch 12/15
206/206 [==============================] - 8s 38ms/step - loss: 0.0779 - accuracy: 0.9767
Epoch 13/15
206/206 [==============================] - 7s 36ms/step - loss: 0.0748 - accuracy: 0.9772
```

```
Epoch 14/15
206/206 [==============================] - 7s 35ms/step - loss: 0.0673 - accuracy: 0.9800
Epoch 15/15
206/206 [==============================] - 8s 37ms/step - loss: 0.0579 - accuracy: 0.9841
<keras.src.callbacks.History at 0x7823c706dff0>
```

Double-click (or enter) to edit

```
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_weights=True)
model_checkpoint = ModelCheckpoint('best_model_cv.h5', monitor='val_loss', save_best_only=Tru

# Perform K-fold cross-validation
for fold_index, (train_indices, val_indices) in enumerate(k_fold.split(X_pad, y)):
    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', metrics=['accurac

    # Train the model with callbacks
    history = model_gru_cv.fit(X_train_fold, y_train_fold, epochs=15, batch_size=batch_size,
                               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 - accuracy: 0.619
```

```
183/183 [==============================] - 14s 55ms/step - loss: 0.9364 - accuracy: 0.619
Epoch 2/15
  2/183 [..............................] - ETA: 9s - loss: 0.8669 - accuracy: 0.5859/usr/
  saving_api.save_model(
183/183 [==============================] - 7s 38ms/step - loss: 0.6474 - accuracy: 0.7228
Epoch 3/15
183/183 [==============================] - 7s 39ms/step - loss: 0.4621 - accuracy: 0.8233
Epoch 4/15
183/183 [==============================] - 6s 33ms/step - loss: 0.3428 - accuracy: 0.8774
Epoch 5/15
183/183 [==============================] - 6s 33ms/step - loss: 0.2488 - accuracy: 0.9166
Validation Score: [0.5552219152450562, 0.7790300250053406]
Fold 2/5
Epoch 1/15
183/183 [==============================] - 9s 38ms/step - loss: 0.9262 - accuracy: 0.6254
Epoch 2/15
183/183 [==============================] - 6s 31ms/step - loss: 0.6521 - accuracy: 0.7180
Epoch 3/15
183/183 [==============================] - 7s 36ms/step - loss: 0.4700 - accuracy: 0.8114
Epoch 4/15
183/183 [==============================] - 6s 32ms/step - loss: 0.3530 - accuracy: 0.8742
Epoch 5/15
183/183 [==============================] - 7s 36ms/step - loss: 0.2540 - accuracy: 0.9150
Epoch 6/15
183/183 [==============================] - 6s 32ms/step - loss: 0.1854 - accuracy: 0.9415
Validation Score: [0.5878012180328369, 0.7677595615386963]
Fold 3/5
Epoch 1/15
183/183 [==============================] - 10s 41ms/step - loss: 0.9252 - accuracy: 0.624
Epoch 2/15
183/183 [==============================] - 6s 34ms/step - loss: 0.6305 - accuracy: 0.7285
Epoch 3/15
183/183 [==============================] - 8s 44ms/step - loss: 0.4694 - accuracy: 0.8204
Epoch 4/15
183/183 [==============================] - 7s 37ms/step - loss: 0.3610 - accuracy: 0.8690
Epoch 5/15
183/183 [==============================] - 6s 33ms/step - loss: 0.2594 - accuracy: 0.9147
Validation Score: [0.5670248866081238, 0.7766393423080444]
Fold 4/5
Epoch 1/15
183/183 [==============================] - 10s 42ms/step - loss: 0.9033 - accuracy: 0.632
Epoch 2/15
183/183 [==============================] - 6s 34ms/step - loss: 0.6010 - accuracy: 0.7459
Epoch 3/15
183/183 [==============================] - 7s 36ms/step - loss: 0.4442 - accuracy: 0.8323
Epoch 4/15
183/183 [==============================] - 8s 41ms/step - loss: 0.3351 - accuracy: 0.8850
Epoch 5/15
183/183 [==============================] - 6s 35ms/step - loss: 0.2530 - accuracy: 0.9159
Epoch 6/15
183/183 [==============================] - 7s 38ms/step - loss: 0.1976 - accuracy: 0.9378
Validation Score: [0.5934033393859863, 0.7571721076965332]
Fold 5/5
Epoch 1/15
183/183 [==============================] - 10s 40ms/step - loss: 0.9287 - accuracy: 0.624
Epoch 2/15
```

```
history_final = model_gru.fit(X_pad, y, epochs=15, batch_size=batch_size, verbose=1)
```

```
Epoch 1/15
229/229 [==============================] - 17s 75ms/step - loss: 0.1504 - accuracy: 0.961
Epoch 2/15
229/229 [==============================] - 13s 56ms/step - loss: 0.0961 - accuracy: 0.973
Epoch 3/15
229/229 [==============================] - 13s 58ms/step - loss: 0.0720 - accuracy: 0.980
Epoch 4/15
229/229 [==============================] - 13s 59ms/step - loss: 0.0616 - accuracy: 0.982
Epoch 5/15
229/229 [==============================] - 11s 49ms/step - loss: 0.0587 - accuracy: 0.983
Epoch 6/15
229/229 [==============================] - 8s 36ms/step - loss: 0.0496 - accuracy: 0.9859
Epoch 7/15
229/229 [==============================] - 13s 58ms/step - loss: 0.0498 - accuracy: 0.985
Epoch 8/15
229/229 [==============================] - 13s 57ms/step - loss: 0.0476 - accuracy: 0.986
Epoch 9/15
229/229 [==============================] - 13s 57ms/step - loss: 0.0474 - accuracy: 0.985
Epoch 10/15
229/229 [==============================] - 8s 33ms/step - loss: 0.0485 - accuracy: 0.9850
Epoch 11/15
229/229 [==============================] - 9s 37ms/step - loss: 0.0445 - accuracy: 0.9859
Epoch 12/15
229/229 [==============================] - 8s 37ms/step - loss: 0.0409 - accuracy: 0.9874
Epoch 13/15
229/229 [==============================] - 7s 32ms/step - loss: 0.0394 - accuracy: 0.9876
Epoch 14/15
229/229 [==============================] - 8s 37ms/step - loss: 0.0361 - accuracy: 0.9885
Epoch 15/15
229/229 [==============================] - 8s 35ms/step - loss: 0.0331 - accuracy: 0.9896
```

```
# 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
```