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- Scheduled project review date/time: April 19, 2023
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- Blog: https://medium.com/@nataliagoncharov/analyzing-customer-sentiment-for-major-us-airlines-on-twitter-6656d23b1800

Table of Contents

In [1]:
```
# Import Sklearn libraries to build models
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import LinearSVC
# from sklearn.metrics import plot_confusion_matrix
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.model_selection import GridSearchCV
# Import Libraries to perform computation and do visualization.
import pandas as pd
import numpy as np
np.random.seed(0)
import seaborn as sns
import matplotlib.pyplot as plt
import string
import time
# Import nltk to check english lexicon.
import nltk
from nltk.tokenize import word_tokenize
nltk.download('stopwords')
from nltk.corpus import wordnet, stopwords
```

```
from nltk import word_tokenize, FreqDist
from nltk import pos_tag # for Parts of Speech tagging
from nltk.tokenize import RegexpTokenizer
from nltk.stem import WordNetLemmatizer
from nltk.stem import PorterStemmer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
# Generate wordcloud for word distribution visualization.
from wordcloud import WordCloud

# Generating random numbers.
import random

from xgboost import XGBClassifier

# Transforms text to a fixed-length vector of integers.
import warnings
warnings.filterwarnings(action='ignore', category=UserWarning,
                        module='gensim')
import gensim
import os

!pip install -q textdistance
import textdistance
#Efficient functions to search in strings.
import re as re

# Import images for world cloud.
from PIL import Image, ImageDraw, ImageFont



from yellowbrick.text import FreqDistVisualizer
from yellowbrick.datasets import load_hobbies

from tqdm.notebook import tqdm

from os import path
from os import environ
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

In [2]:

```
# # Importing the dataset
ta_df_full = pd.read_csv('Tweets.csv')

ta_df = ta_df_full[['airline_sentiment','text']]

ta_df.rename(columns={'airline_sentiment':'sentiment'},inplace=True)
ta_df.head()
```

```
<ipython-input-2-44819eb4c92b>:6: 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_guide/indexing.html#returning-a-view-versus-a-copy
  ta_df.rename(columns={'airline_sentiment':'sentiment'},inplace=True)
```

Out[2]:

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

In [3]:
```
ta_df_full.head()
```

Out[3]:

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	negativer
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	

In [4]:
```
# Looking into the type of data. Noting the data does not seem to have
# any missing values.

ta_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14640 entries, 0 to 14639
Data columns (total 2 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   sentiment  14640 non-null  object
 1   text       14640 non-null  object
dtypes: object(2)
memory usage: 228.9+ KB
```

In [5]:
```
ta_df.shape
```

Out[5]:
```
(14640, 2)
```

In [6]:
```
# Check unique values in the sentiment column
ta_df['sentiment'].unique()
```

Out[6]:
```
array(['neutral', 'positive', 'negative'], dtype=object)
```

In [7]:
```
# Checking distribution
ta_df['sentiment'].value_counts()
```

Out[7]:
```
negative    9178
neutral     3099
positive    2363
Name: sentiment, dtype: int64
```

In [8]:
```
ta_df['sentiment'] = ta_df['sentiment'] \
          .replace(['negative', 'neutral', 'positive'], [0, 1, 2])
```

```
<ipython-input-8-287330abf2f8>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  ta_df['sentiment'] = ta_df['sentiment'] \
```

In [9]:
```
# Balance the data; Smpling 2,363 tweets randomly

df_positive = ta_df[ta_df['sentiment']==2]
df_negative = ta_df[ta_df['sentiment']==0].sample(2363)
df_neutral = ta_df[ta_df['sentiment']==1].sample(2363)
```

In [10]:
```
# Merging back the three sentiments
ta_df = pd.concat([df_positive,df_negative,df_neutral])
```

In [11]:
```
# Checking the size of the data
ta_df.shape
```

Out[11]:
```
(7089, 2)
```

In [12]:
```
# Checking the percentage of null values
ta_df.isna().mean()*100
```

Out[12]:
```
sentiment    0.0
text         0.0
dtype: float64
```

In [13]:
```
ta_df['sentiment'].value_counts()
```

Out[13]:
```
2    2363
0    2363
```

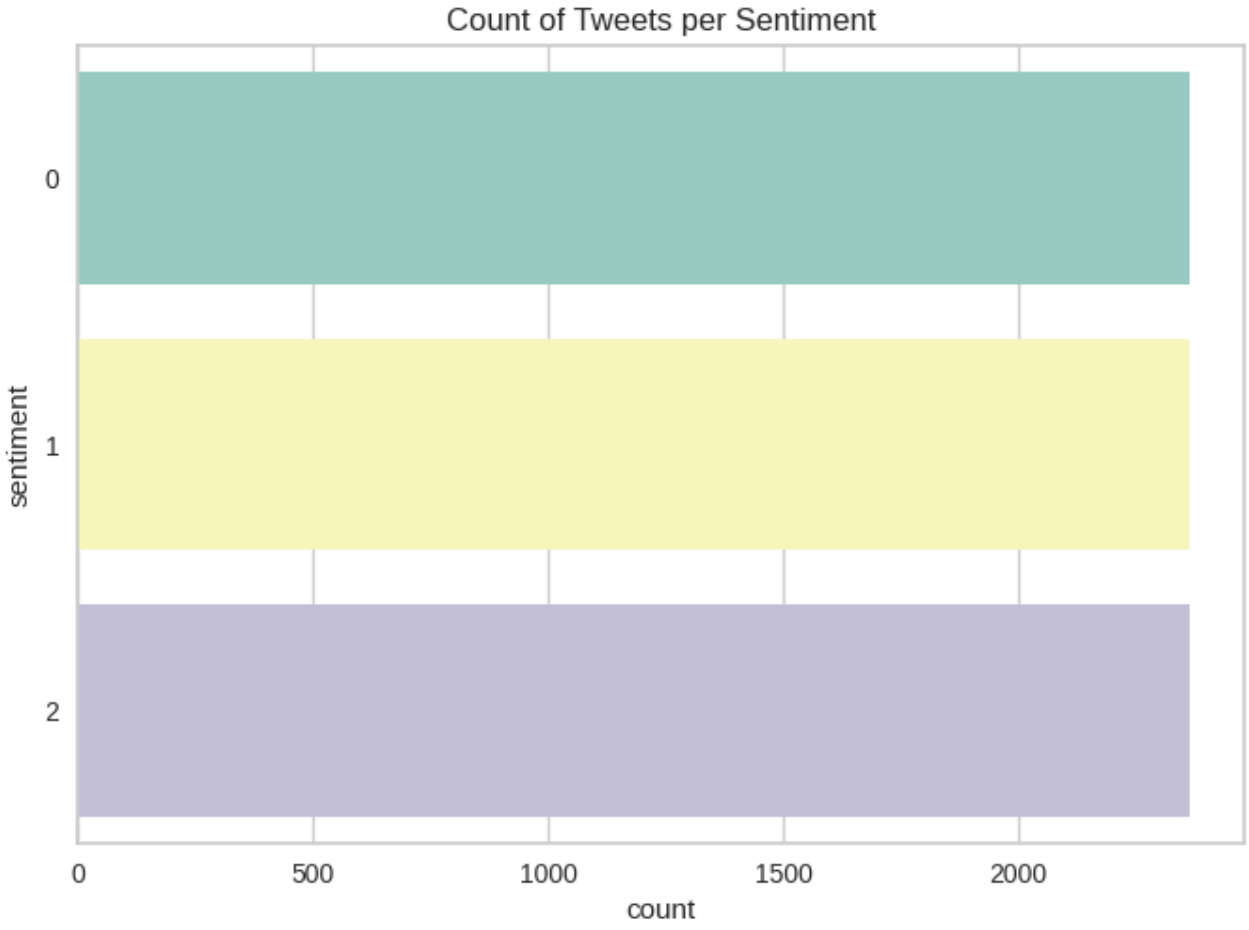
```
1    2363
Name: sentiment, dtype: int64
```

Distribution of Data - Target

The value_counts method is used to count the number of occurrences of each unique value in the sentiment column, and the "normalize=True" argument is used to calculate the percentages instead of the counts.

In [14]:
```
# Plot the count plot for the target labels.

# Setting p to plot of Emotion

p = sns.countplot(data = ta_df, y = 'sentiment', palette="Set3")
p.set(xlabel = 'count') #Labling X
p.set(ylabel = 'sentiment') #Labling Y
p.set(title = "Count of Tweets per Sentiment")
```

Out[14]:
```
[Text(0.5, 1.0, 'Count of Tweets per Sentiment')]
```



In [15]:
```
# Displays the count of columns and rows in the DataFrame.

print('Count of columns in the data is:  ', len(ta_df.columns))
print('Count of rows in the data is:  ', len(ta_df))
```

```
Count of columns in the data is:   2
Count of rows in the data is:   7089
```

CLEANING THE DATA

- Cleaning the data
- Checking and handling NaN values
- Drop duplicates

In [16]:
```
# Dropping NaN values

ta_df.dropna(inplace=True)
```

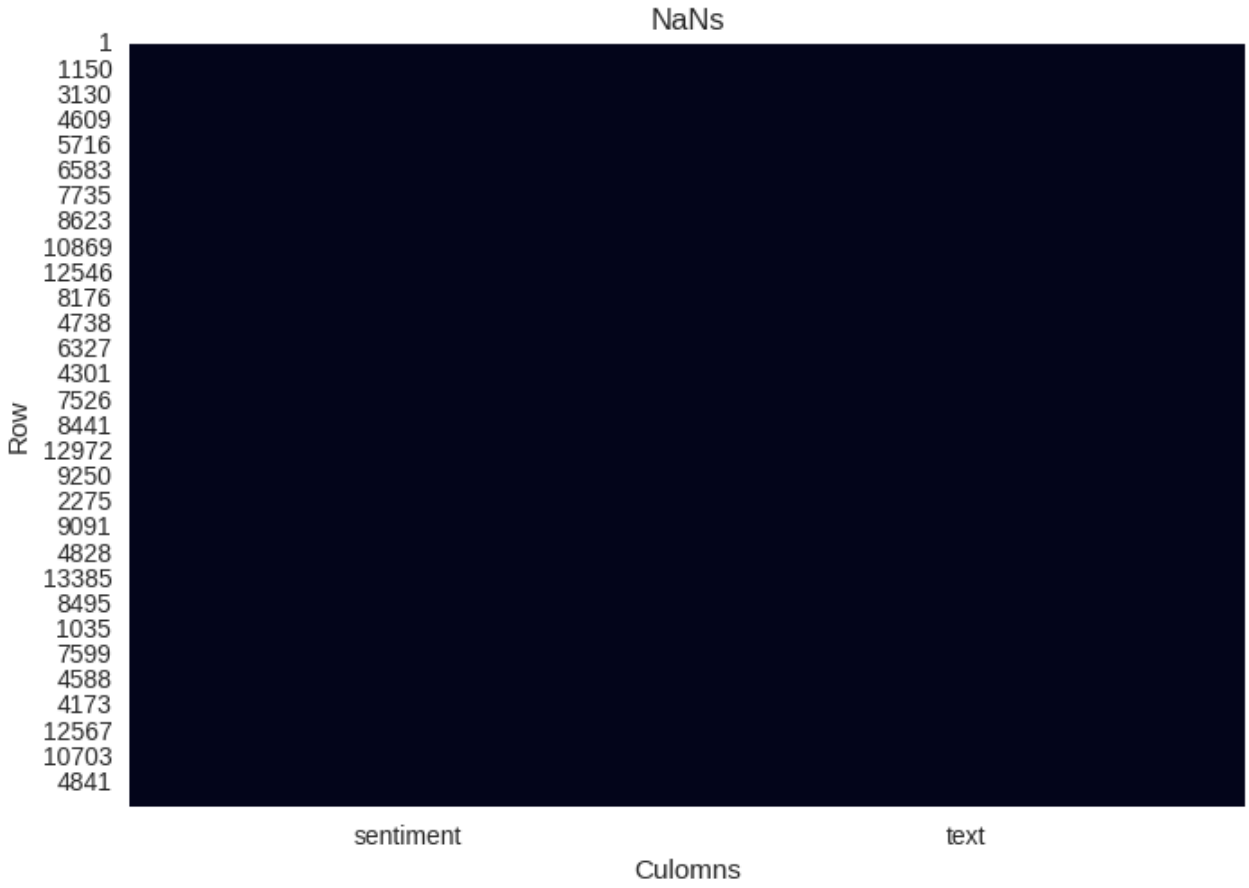
In [17]:
```
len(ta_df.duplicated(keep='last'))
```

Out[17]:
```
7089
```

In [18]:
```
# Dropping duplicates
ta_df.drop_duplicates()
ta_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7089 entries, 1 to 3378
Data columns (total 2 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   sentiment  7089 non-null   int64 
 1   text       7089 non-null   object
dtypes: int64(1), object(1)
memory usage: 166.1+ KB
```

In [19]:
```
# Checking for Null values.  We use the heatmap code which
# shows the contrast well.

sns.heatmap(ta_df.isnull(), cbar=False)
plt.title("NaNs")
plt.xlabel('Culomns')
plt.ylabel('Row')
plt.show()
```



Now that our data is clean and without duplicates, we can proceed to preprocess the tweets for our machine learning models.

In [20]:
```
# Creating an independent copy
ta_df_copy = ta_df.copy()
```

Pre-process Text We will use text processing to allow the data to be more digestible for model use later in this project. This is an integral step in Natural Language Processing (NLP).

The Preprocessing steps taken are:

Converting to lower case letters: Each text will be transferred to a lower case letter.

Removing stop words: Remove common words like "a", "an", "the", etc., which don't carry much meaning and can be safely removed without affecting the model's performance.

Removing Words with 2 letters: Words with length less than 2 are removed.

Replacing http with space: Links starting with "http" or "https" or "www" are replaced by " ".

Stemming to reduce words to their root form to remove any variations of the same word.

In [21]:
```
# Defining a preprocessing function for cleaning and preprocessing
# text data.

tqdm.pandas() # Adding the progress bar
ps = PorterStemmer() # Defining stemming words wiht ps
```

```
# Removes URLs and non-alphanumeric
TEXT_CLEANING_RE = "@\S+|https?:\S+|http?:\S|[^A-Za-z0-9]+"

# Replace 3 or more consecutive letters by 2 letter.
sequencePattern   = r"(.)\1\1+"
seqReplacePattern = r"\1\1"

stop_words = set(stopwords.words("english")) # Creating a set of
#English stopwords


# Defining  the preprocessing function

def preprocess(text,apply_stem=True):

# Remove link,user and special characters
    text = re.sub(TEXT_CLEANING_RE, ' ', str(text).lower()).strip()
    text = re.sub(sequencePattern, seqReplacePattern, text)

    tokens = []
    for token in text.split():
        if token not in stop_words:
        # Checking if the word is not a stopword
            if apply_stem:
        # Stemming to the word using the PorterStemmer if True
                tokens.append(ps.stem(token))
            else:
        # Adding the original word if stemming is not
        # applied (for wordcloud)
                tokens.append(token)
        # Joining and retuning the list of tokenized words
        # into a one string
    return " ".join(tokens)
```

In [22]:
```
# Creating a new column apply a function to each row

ta_df['clean_tweet'] = (
    ta_df['text'].progress_apply(lambda x:preprocess(x,True))
)
```

In [23]:
```
ta_df['clean_tweet'].head()
```

Out[23]:
```
1                           plu ad commerci experi tacki
6          ye nearli everi time fli vx ear worm go away
8                                                  well
9                            amaz arriv hour earli good
11    lt 3 pretti graphic much better minim iconographi
Name: clean_tweet, dtype: object
```

In [24]:
```
# Creating a new column apply a function to each row

ta_df['clean_tweet_wt_stem'] = (
    ta_df['text']
    .progress_apply(lambda x: preprocess(x, False))
)
```

In [25]:
```
# Checking that the change has taken place.
ta_df.head(50)
```

Out[25]:

	sentiment	text	clean_tweet	clean_tweet_wt_stem
1	2	@VirginAmerica plus you've added commercials t...	plu ad commerci experi tacki	plus added commercials experience tacky
6	2	@VirginAmerica yes, nearly every time I fly VX...	ye nearli everi time fli vx ear worm go away	yes nearly every time fly vx ear worm go away
8	2	@virginamerica Well, I didn't...but NOW I DO! :-D	well	well
9	2	@VirginAmerica it was amazing, and arrived an ...	amaz arriv hour earli good	amazing arrived hour early good
11	2	@VirginAmerica I <3 pretty graphics. so muc...	lt 3 pretti graphic much better minim iconographi	lt 3 pretty graphics much better minimal icono...
12	2	@VirginAmerica This is such a great deal! Alre...	great deal alreadi think 2nd trip australia am...	great deal already thinking 2nd trip australia...
13	2	@VirginAmerica @virginmedia I'm flying your #f...	virginmedia fli fabul seduct sky u take stress...	virginmedia flying fabulous seductive skies u ...
14	2	@VirginAmerica Thanks!	thank	thanks
16	2	@VirginAmerica So excited for my first cross c...	excit first cross countri flight lax mco heard...	excited first cross country flight lax mco hea...
18	2	I❤️ flying @VirginAmerica. ☺👍	fli virginamerica	flying virginamerica
19	2	@VirginAmerica you know what would be amazingl...	know would amazingli awesom bo fll pleas want fli	know would amazingly awesome bos fll please wa...
21	2	@VirginAmerica I love this graphic. http://t.c...	love graphic	love graphic
22	2	@VirginAmerica I love the hipster innovation. ...	love hipster innov feel good brand	love hipster innovation feel good brand
34	2	@VirginAmerica this is great news! America co...	great news america could start flight hawaii e...	great news america could start flights hawaii ...
36	2	@VirginAmerica Moodlighting is the only way to...	moodlight way fli best experi ever cool calm m...	moodlighting way fly best experience ever cool...
37	2	@VirginAmerica @freddieawards Done and done! B...	freddieaward done done best airlin around hand	freddieawards done done best airline around hands
40	2	@VirginAmerica View of downtown Los Angeles, t...	view downtown lo angel hollywood sign beyond r...	view downtown los angeles hollywood sign beyon...
45	2	@VirginAmerica I'm #elevategold for a good	elevategold good reason rock	elevategold good reason rock

	sentiment	text	clean_tweet	clean_tweet_wt_stem
		rea...		
47	2	@VirginAmerica wow this just blew my mind	wow blew mind	wow blew mind
51	2	@VirginAmerica @ladygaga @carrieunderwood Juli...	ladygaga carrieunderwood juli andrew way thoug...	ladygaga carrieunderwood julie andrews way tho...
56	2	@VirginAmerica you know it. Need it on my spot...	know need spotifi stat guiltypleasur	know need spotify stat guiltypleasures
57	2	@VirginAmerica @ladygaga @carrieunderwood I'm...	ladygaga carrieunderwood ladi gaga amaz	ladygaga carrieunderwood lady gaga amazing
64	2	@VirginAmerica @ladygaga @carrieunderwood lov...	ladygaga carrieunderwood love three realli bea...	ladygaga carrieunderwood love three really bea...
68	2	@VirginAmerica Congrats on winning the @Travel...	congrat win travelzoo award best deal airlin us	congrats winning travelzoo award best deals ai...
74	2	@VirginAmerica not worried, it's been a great ...	worri great ride new plane great crew airlin like	worried great ride new plane great crew airlin...
75	2	@VirginAmerica awesome. I flew yall Sat mornin...	awesom flew yall sat morn way correct bill	awesome flew yall sat morning way correct bill
81	2	@VirginAmerica I've applied more then once to ...	appli member inflight crew team im 100 interes...	applied member inflight crew team im 100 inter...
105	2	@VirginAmerica - amazing customer service, ag...	amaz custom servic raeann sf best customerserv...	amazing customer service raeann sf best custom...
109	2	@VirginAmerica has getaway deals through May, ...	getaway deal may 59 one way lot cool citi chea...	getaway deals may 59 one way lots cool cities ...
111	2	@VirginAmerica has getaway deals through May, ...	getaway deal may 59 one way lot cool citi chea...	getaway deals may 59 one way lots cool cities ...
113	2	@VirginAmerica Have a great week 🌞✈	great week	great week
114	2	@VirginAmerica come back to #PHL already. We n...	come back phl alreadi need take us horribl col...	come back phl already need take us horrible co...
116	2	@VirginAmerica is the best airline I have flow...	best airlin flown easi chang reserv help repre...	best airline flown easy change reservation hel...
117	2	@VirginAmerica and again! Another rep kicked b...	anoth rep kick butt naelah repres team beauti ...	another rep kicked butt naelah represents team...
118	2	@VirginAmerica your beautiful front-end design...	beauti front end design right cool still book ...	beautiful front end design right cool still bo...
119	2	@VirginAmerica Love the team running Gate E9 a...	love team run gate e9 la tonight wait delay fl...	love team running gate e9 las tonight waited d...

	sentiment	text	clean_tweet	clean_tweet_wt_stem
123	2	@VirginAmerica thanks to your outstanding NYC-...	thank outstand nyc jfk crew move mountain get ...	thanks outstanding nyc jfk crew moved mountain...
124	2	@VirginAmerica you have the absolute best team...	absolut best team custom servic ever everi tim...	absolute best team customer service ever every...
127	2	@VirginAmerica completely awesome experience l...	complet awesom experi last month bo la nonstop...	completely awesome experience last month bos l...
136	2	@virginamerica you ROCK for making it so I can...	rock make watch oscar flight redcarpet oscar o...	rock making watch oscars flight redcarpet osca...
138	2	@VirginAmerica always!!! Xoxo	alway xoxo	always xoxo
141	2	@VirginAmerica best customer service rep in th...	best custom servic rep world irmafromdalla tak...	best customer service rep world irmafromdallas...
144	2	@VirginAmerica you have amazing staff & su...	amaz staff amp super help ran waltdisneyworld ...	amazing staff amp super helpful ran waltdisney...
147	2	Always have it together!!! You're welcome! RT ...	alway togeth welcom rt virginamerica jessicaja...	always together welcome rt virginamerica jessi...
148	2	@virginamerica #flight home to #dc #sunset #gl...	flight home dc sunset globe backtowint back wo...	flight home dc sunset globe backtowinter back ...
152	2	@VirginAmerica thank you for checking in. tick...	thank check ticket purchas custom happi	thank checking tickets purchased customer happy
176	2	@VirginAmerica Thank you for the follow	thank follow	thank follow
183	2	😎 RT @VirginAmerica: You've met your match. Go...	rt virginamerica met match got statu anoth air...	rt virginamerica met match got status another ...
184	2	@VirginAmerica Only way to fly! #Elevate #Gold	way fli elev gold	way fly elevate gold
189	2	@VirginAmerica you will match my #AmericanAirl...	match americanairlin statu cool	match americanairlines status cool

In [26]:
```
ta_df['clean_tweet_wt_stem']
```

Out[26]:
```
1                  plus added commercials experience tacky
6              yes nearly every time fly vx ear worm go away
8                                                      well
9                          amazing arrived hour early good
11         lt 3 pretty graphics much better minimal icono...
                                 ...
11264      noticed believe saw confirmation flight bought...
1505                   tell jet airways award availability
8194                                     look capture uvf
12486      already reply sorry believe fair journalist wr...
```

```
3378                                                dm conf receive
Name: clean_tweet_wt_stem, Length: 7089, dtype: object
```

Word Cloud

We are creating a wordcloud with masking which allows us to visualize words in a specific shape of thumbs up and down.

In [27]:
```
# Storing clean tweets
tweets = ta_df['clean_tweet_wt_stem']
```

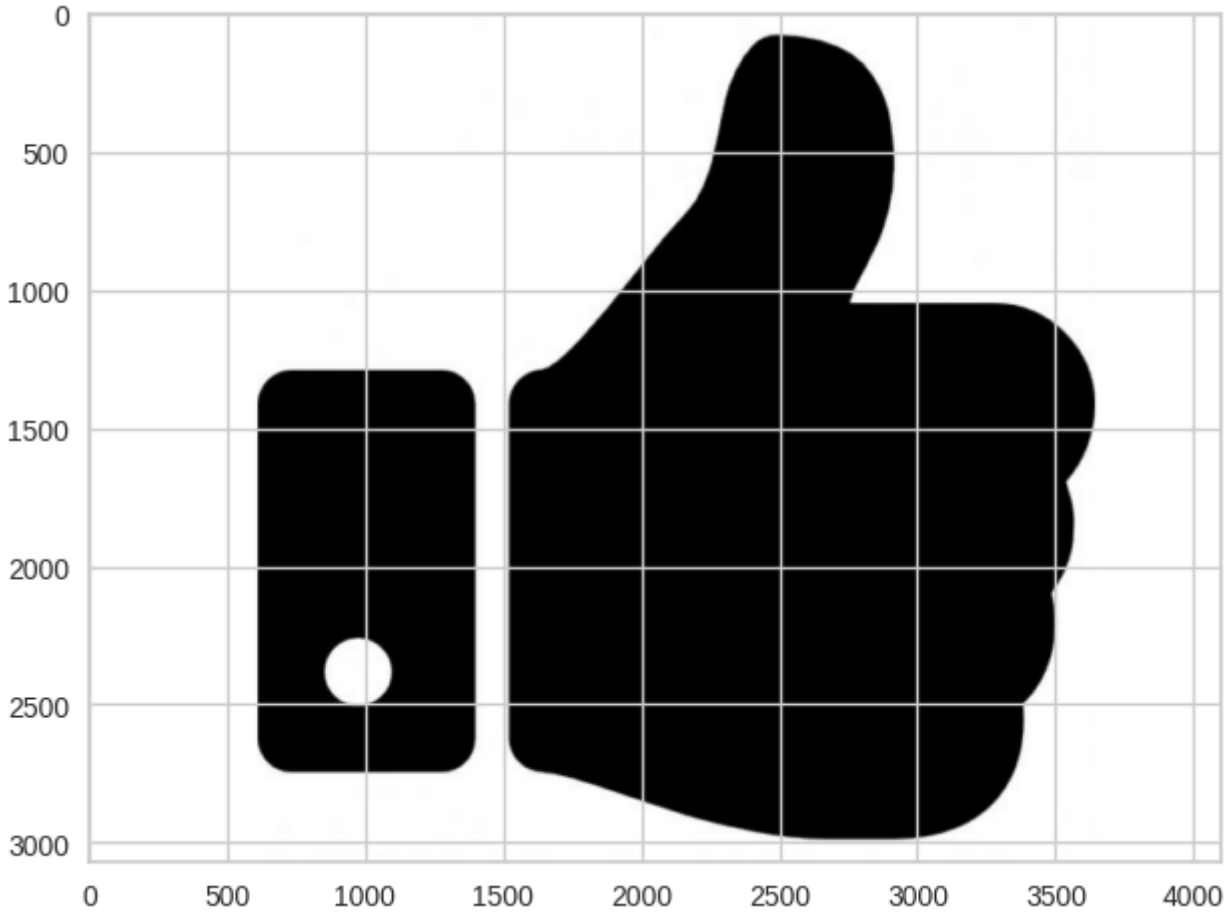
With these Series objects containing the preprocessed text, you can perform further analysis or visualization on the negative and positive tweets separately. We will be able to create separate word clouds for each sentiment group or calculate the most frequent words in each group.

In [28]:
```
# Storing the rows with a sentiment value of 0,
# which represents negative sentiment.
tweet_negative = ta_df[ta_df['sentiment']==0]

# Storing the rows with a sentiment value of 1,
# which represents positive sentiment.
tweet_positive = ta_df[ta_df['sentiment']==2]
```

In [29]:
```
# Storing the preprocessed text of the tweets with negative sentiment
tweet_negative = tweet_negative['clean_tweet_wt_stem']
# Storing the preprocessed text of the tweets with positive sentiment
tweet_positive = tweet_positive['clean_tweet_wt_stem']
```

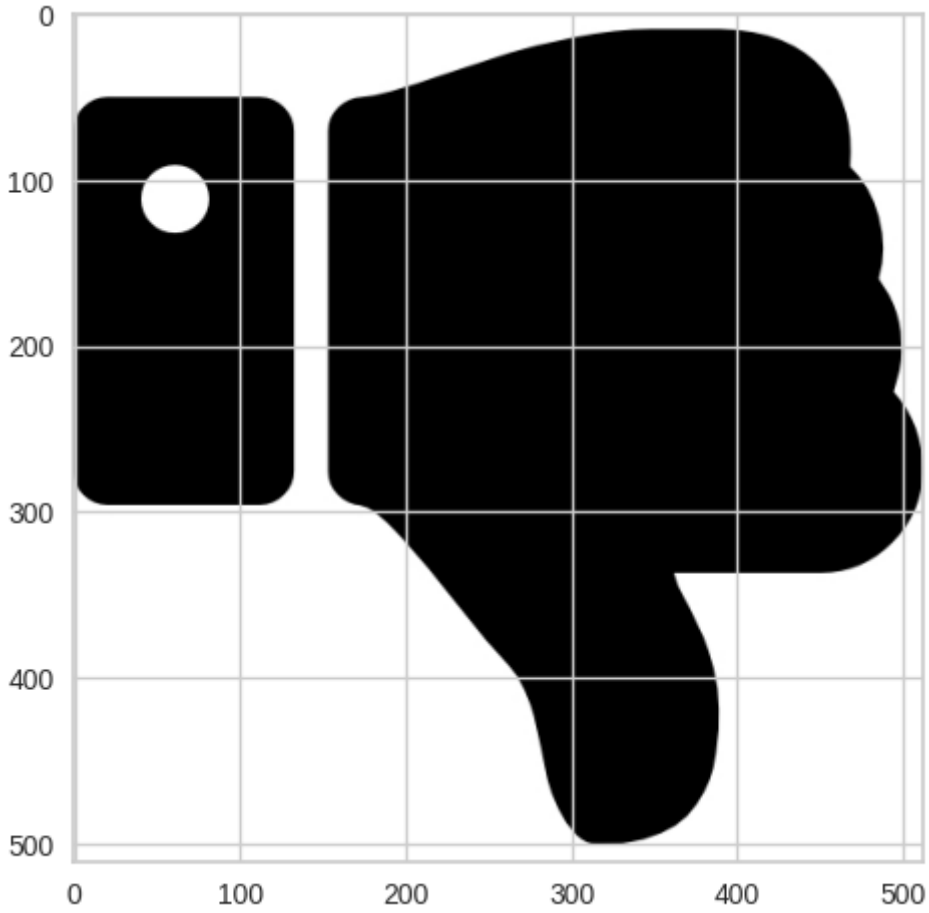
In [30]:
```
# Resizing  it to a 20x20 size using the Image.ANTIALIAS filter
img = Image.open('upvote.png')
img.resize((20, 20), Image.ANTIALIAS)
plt.imshow(img) # show output
```

Out[30]:
```
<matplotlib.image.AxesImage at 0x7fa8c469f100>
```



In [31]:
```
# Resizing  it to a 20x20 size using the Image.ANTIALIAS filter
mask_d = Image.open('final.png')
mask_d.resize((20, 20), Image.ANTIALIAS)
plt.imshow(mask_d) # show output
```

Out[31]: <matplotlib.image.AxesImage at 0x7fa8c3b6dd30>



In [32]:
```
# Gerenrating wordcloud
def wc(data, mask, fname):

    plt.figure(figsize=(50,50))  # Set the size of the plot

    wc = WordCloud(width=300, height=200, background_color='white',
                   max_words=50, max_font_size=300, colormap='rainbow',
                   mask=mask)
    # Create a new WordCloud object with the specified parameters

    wc.generate(' '.join(data))  # Generate the WordCloud from the text data

    plt.imshow(wc)  # Display the WordCloud on the plot
    plt.grid(visible=False)  # Remove the grid from the plot
    plt.savefig(f'{fname}.png', dpi=200) # Save the  image as a PNG file
    # plt.axis('off') # Optionally, remove the axes from the plot
```

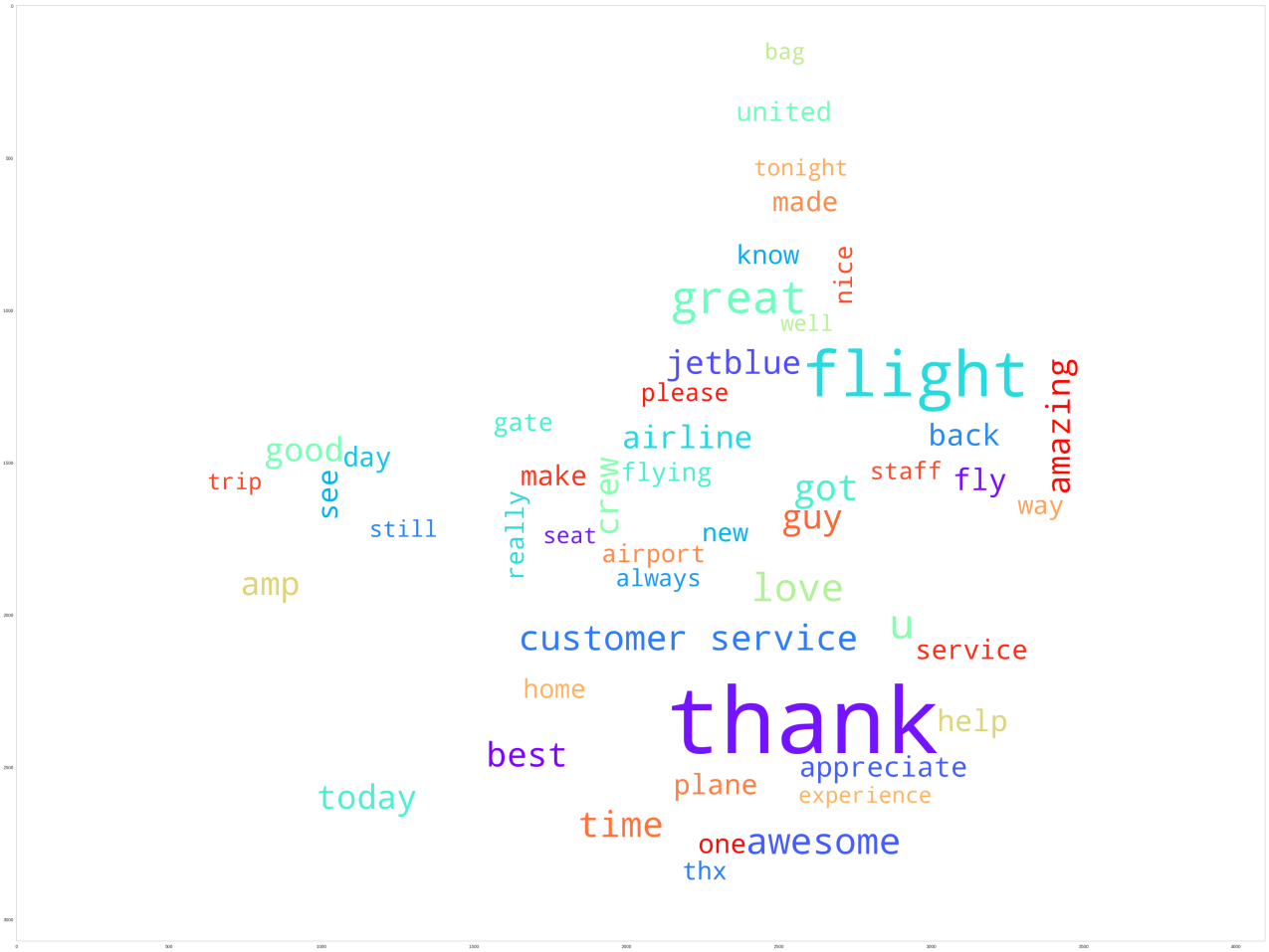
In [33]:
```
# Open image
mask_pos = np.array(Image.open('upvote.png'))
```

In [34]:
```
# Open image
mask_neg = np.array(Image.open('final.png'))
#wc(tweet_negative, mask_neg, 'negative')
```

In [35]:
```
# Run function for wordcloud
wc(tweet_negative, mask_neg,'negative')
```

Based on the top keywords generated from the positive topic, it seems that the topic is related to positive feedback or comments regarding flights. The top keywords "flight", "thank", "seat", "please", and "fleet" suggest that customers are expressing gratitude and appreciation for their flights or for the service provided by airline staff, including comfortable seating. This topic could represent a cluster of tweets that express positive sentiment or satisfaction with airline travel.

In [36]:
```
# Run function for wordcloud
wc(tweet_positive, mask_pos,'positive')
```



Based on the top keywords generated from the negative topic, it seems that the topic is related to complaints or negative feedback regarding flight cancellations, customer service, and delays. The top keywords "flight", "canceled", "help", "waiting", "customer service", "agent", and "delay" suggest that customers are expressing frustration and dissatisfaction with airline travel due to cancellations, long wait times, poor customer service, and delays caused by airline staff.

In [37]:
```
pos_df = (
    ta_df['clean_tweet_wt_stem']
    .loc[ta_df['sentiment'] == 2]
    .progress_apply(lambda line: line.split())
)
```

In [38]:
```
neg_df = ta_df['clean_tweet_wt_stem'].loc[ta_df['sentiment'] == 0]\
    .progress_apply(lambda line: line.split())
```

In [39]:
```
tokens = [] # Instantiating total token list
tokens_pos = [] #Instantiating positive token list
tokens_neg = [] #Instantiating negative token list


for row in pos_df:
    tokens.extend(row) #Populating token list from dataframe
```

```
for row in pos_df:
    tokens_pos.extend(row) #Populating token list from dataframe
for row in neg_df:
    tokens_neg.extend(row) #Populating token list from dataframe

print(f'Total Corpus Tokens: {len(tokens)}')
# Print total number of tokens
print(f'Number of Positive Tokens: {len(tokens_pos)}')
# Print number of positive tokens
print(f'Number of Negative Tokens: {len(tokens_neg)}')
# Print number of negative tokens
```

```
Total Corpus Tokens: 17779
Number of Positive Tokens: 17779
Number of Negative Tokens: 24246
```

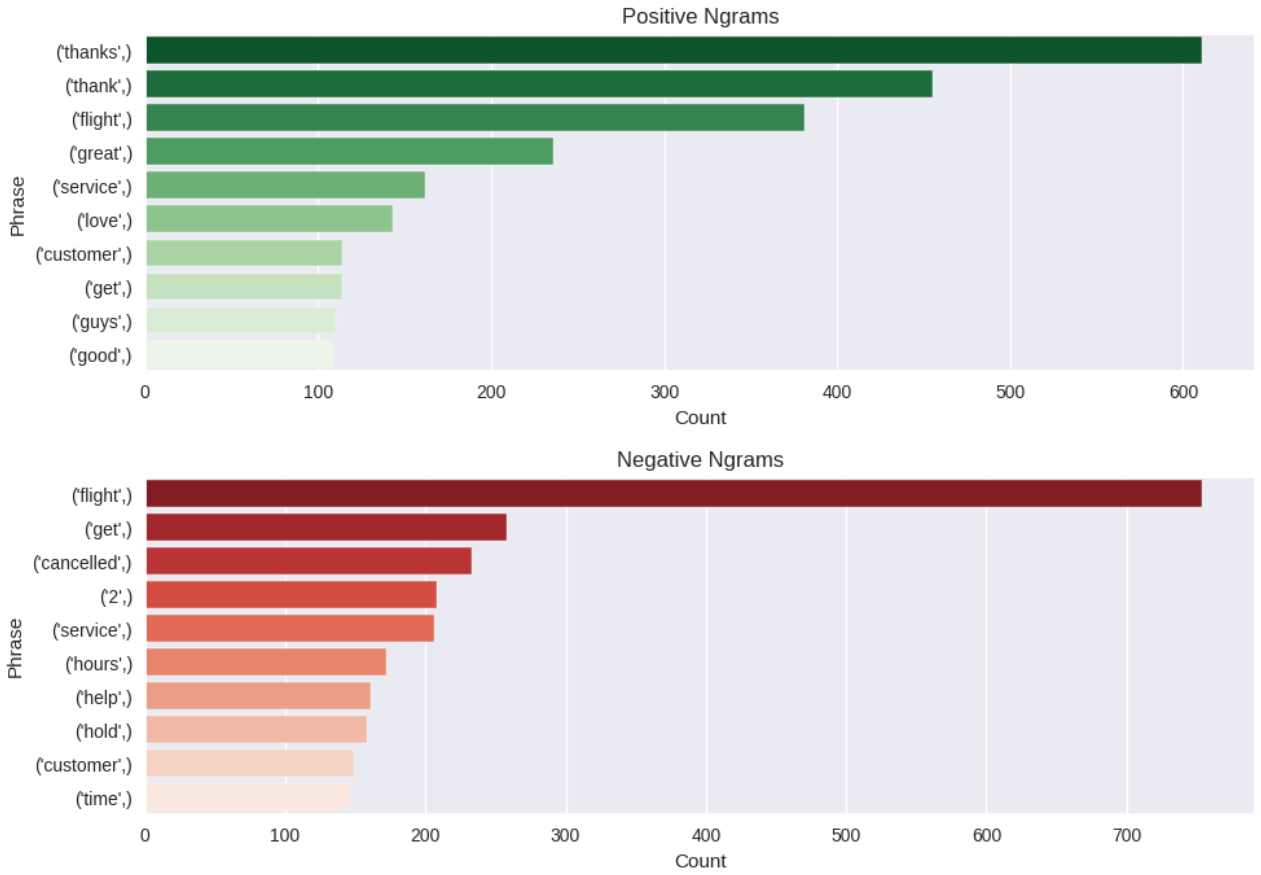
The function creates two bar plots. The first plot shows the top 10 most frequent positive n-grams, and the second plot shows the top 10 most frequent negative n-grams.

This will create and display the bar plots for unigrams (1-grams) of positive and negative tokens. You can change the input integer to display n-grams of different sizes: bigrams (2-grams) or trigrams (3-grams).

In [40]:

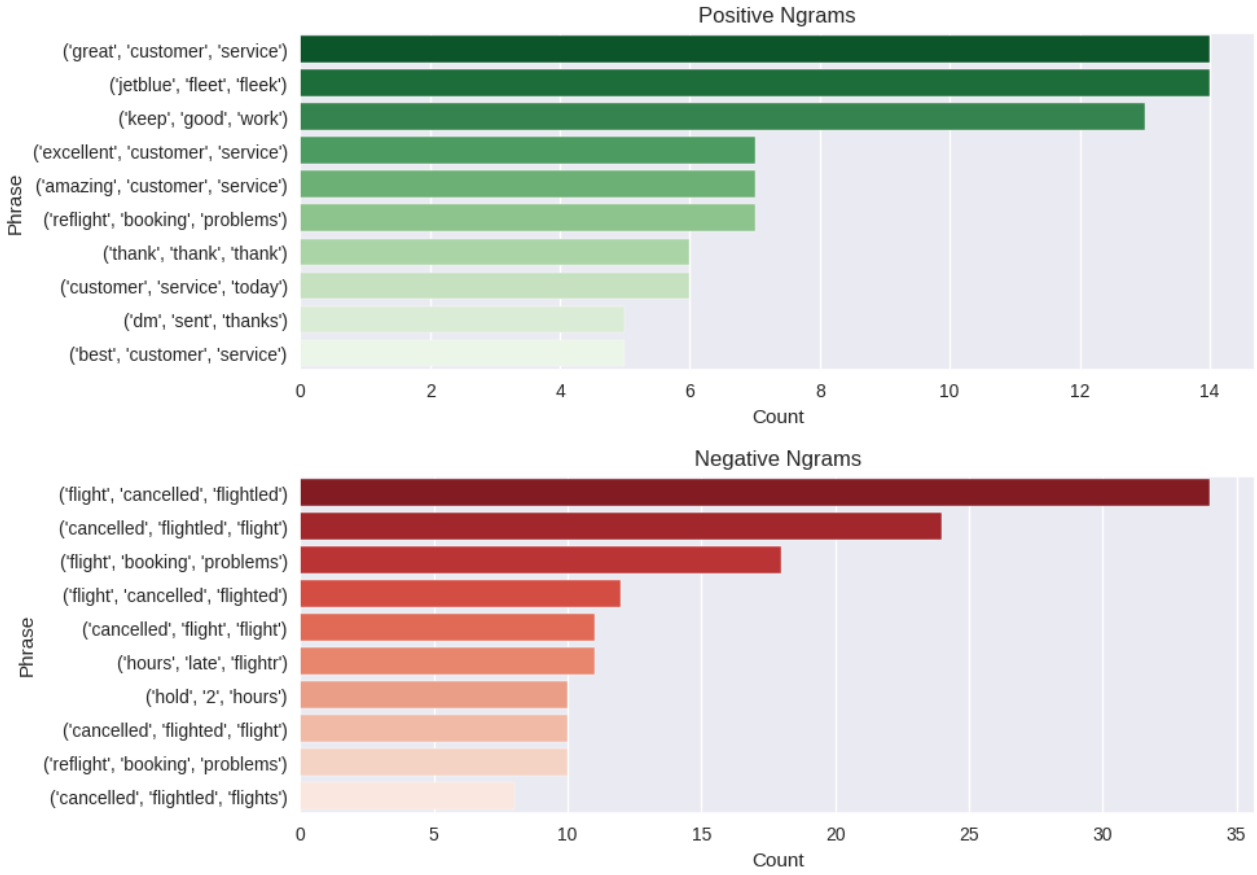
```
# Defining function

def make_ngram(i, tokens_pos = tokens_pos, tokens_neg = tokens_neg):
     #Setting up positive ngram
    n_gram_pos = (pd.Series(nltk.ngrams(tokens_pos, i)).value_counts())[:10]
    #Setting up negative ngram
    n_gram_neg = (pd.Series(nltk.ngrams(tokens_neg, i)).value_counts())[:10]

    n_gram_df_pos = pd.DataFrame(n_gram_pos) #Creating positive ngram dataframe
    n_gram_df_neg = pd.DataFrame(n_gram_neg) #Creating negative ngram dataframe

    n_gram_df_pos = n_gram_df_pos.reset_index() #Resetting index
    n_gram_df_neg = n_gram_df_neg.reset_index() #Resetting index

    #Renaming positive plot
    n_gram_df_pos = n_gram_df_pos.rename(columns = {'index': 'Phrase',
                                                    0: 'Count'})
    #Renaming negative plot
    n_gram_df_neg = n_gram_df_neg.rename(columns = {'index': 'Phrase',
                                                    0: 'Count'})

    with sns.axes_style('darkgrid'): #Setting seaborn to darkgrid style

        fig = plt.figure(figsize = (10, 10)) #Setting figsize
        ax1 = fig.add_subplot(311) #Stacking first figure
        ax2 = fig.add_subplot(312) #Stacking second figure

        sns.barplot(ax = ax1, x = 'Count', y = 'Phrase', data = n_gram_df_pos,
                    # Assigning barplot to positive ngrams
                    palette = 'Greens_r').set(title = 'Positive Ngrams')
        sns.barplot(ax = ax2, x = 'Count', y = 'Phrase', data = n_gram_df_neg,
                    # Assigning barplot to negative ngrams
                   palette = 'Reds_r').set(title = 'Negative Ngrams')


    plt.tight_layout() #Make plot layouts tight
```

```
make_ngram(1) #Plot 1 word ngrams
```



In [41]:

```
make_ngram(3) #Plot 2 word ngrams
```



*Positive tweets 3-ngrams

"happy mother day" - This 3-ngram likely indicates that people are tweeting positive messages about Mother's Day, expressing happiness and joy on this occasion.

The ngram "get 100 followers" suggests that someone may be offering advice or tips on how to gain more followers.

*Negative tweets 3-ngrams

The phrase "wish we could" implies a sense of regret or disappointment about not being able to go.

"hope feel better" sending to someone who may be feeling unwell or going through a tough time.

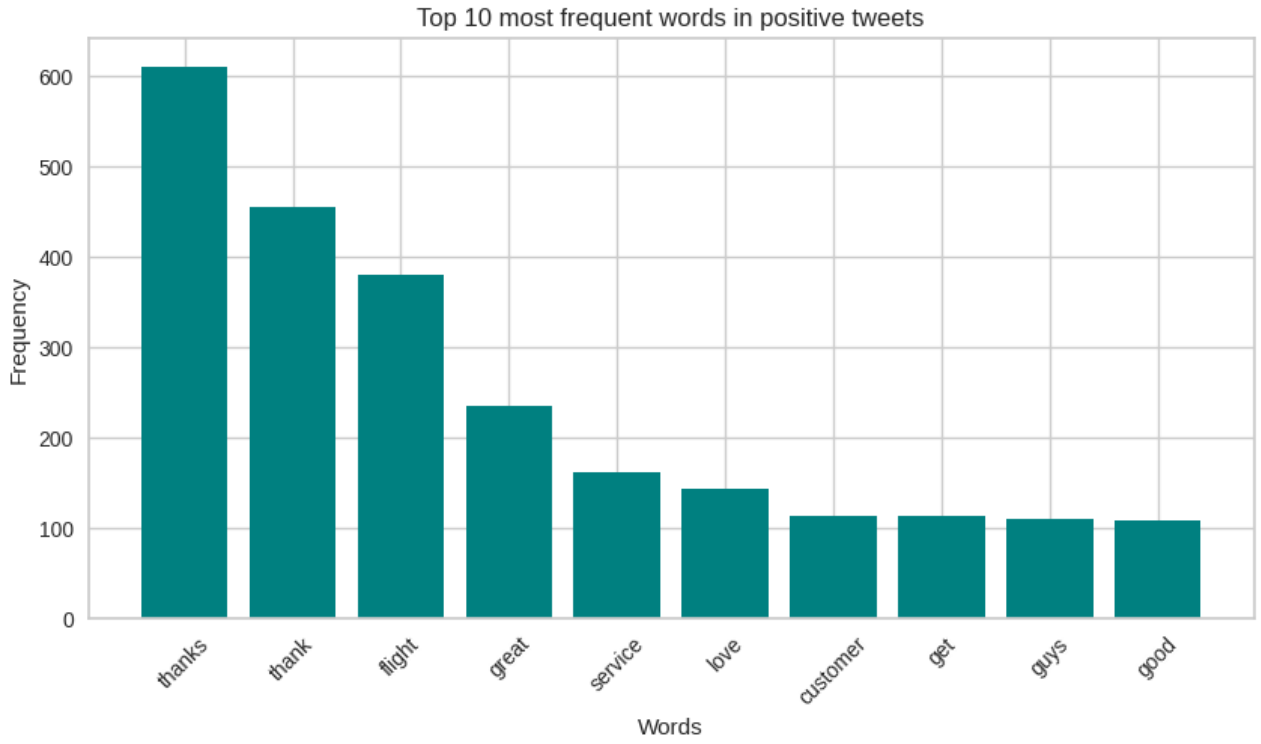
In [42]:

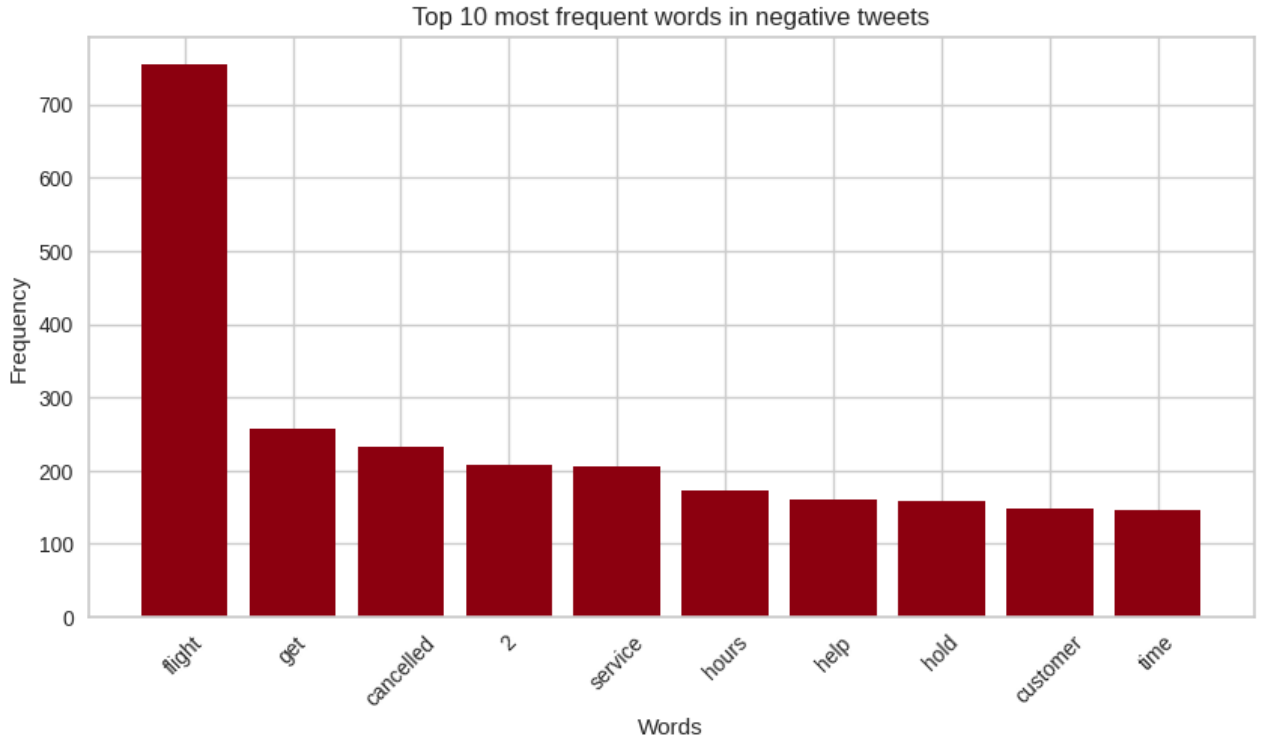
```
import nltk
from nltk.tokenize import word_tokenize
from nltk.probability import FreqDist
import matplotlib.pyplot as plt
import numpy as np
nltk.download('punkt')

positive_color = '#008080' # dark green
negative_color = '#8C000F' # dark red


def plot_word_frequency(positive_tweets, negative_tweets, num_words):
```

```
## Join the positive tokens back into a string
positive_tweet_string = ' '.join(positive_tweets)
# Tokenize the positive tweets
positive_tokens = word_tokenize(positive_tweet_string)

# Join the negative tokens back into a string
negative_tweet_string = ' '.join(negative_tweets)
# Tokenize the negative tweets
negative_tokens = word_tokenize(negative_tweet_string)


# Calculate the frequency distribution of the positive tokens
positive_fdist = FreqDist(positive_tokens)
# Calculate the frequency distribution of the negative tokens
negative_fdist = FreqDist(negative_tokens)

# Get the `num_words` most common words and their frequency for
# each category
positive_top_words = positive_fdist.most_common(num_words)
positive_words, positive_frequencies = zip(*positive_top_words)

negative_top_words = negative_fdist.most_common(num_words)
negative_words, negative_frequencies = zip(*negative_top_words)

# Set colors for the bars
colors = [positive_color, negative_color]

# Create a bar chart of the word frequencies for positive tweets
fig, ax = plt.subplots(figsize=(10,5))
ax.bar(np.arange(num_words), positive_frequencies, color=colors[0])

# Add titles and labels to the chart
ax.set_title(f"Top {num_words} most frequent words in positive tweets")
ax.set_xlabel("Words")
ax.set_ylabel("Frequency")

# Set the x-axis tick labels to the most common words
ax.set_xticks(np.arange(num_words))
ax.set_xticklabels(positive_words)

# Rotate the x-axis labels to make them more readable
plt.xticks(rotation=45)

# Display the chart
plt.show()

# Create a bar chart of the word frequencies for negative tweets
fig, ax = plt.subplots(figsize=(10,5))
ax.bar(np.arange(num_words), negative_frequencies, color=colors[1])

# Add titles and labels to the chart
ax.set_title(f"Top {num_words} most frequent words in negative tweets")
ax.set_xlabel("Words")
ax.set_ylabel("Frequency")

# Set the x-axis tick labels to the most common words
ax.set_xticks(np.arange(num_words))
ax.set_xticklabels(negative_words)

# Rotate the x-axis labels to make them more readable
```

```
    plt.xticks(rotation=45)

    # Display the chart
    plt.show()

# Example usage
positive_tweets = tokens_pos
negative_tweets = tokens_neg
plot_word_frequency(positive_tweets, negative_tweets, 10)
```

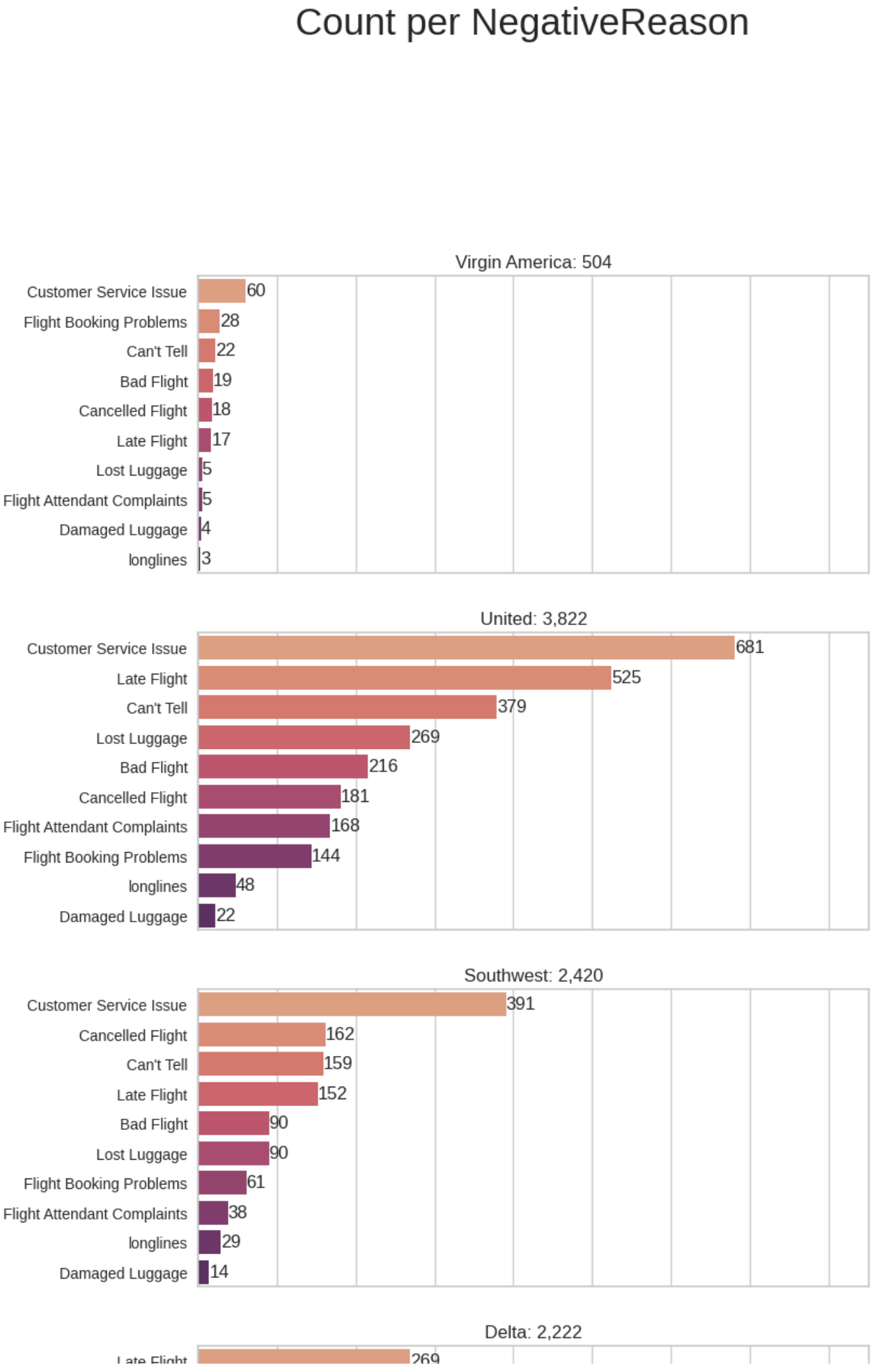
```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
```

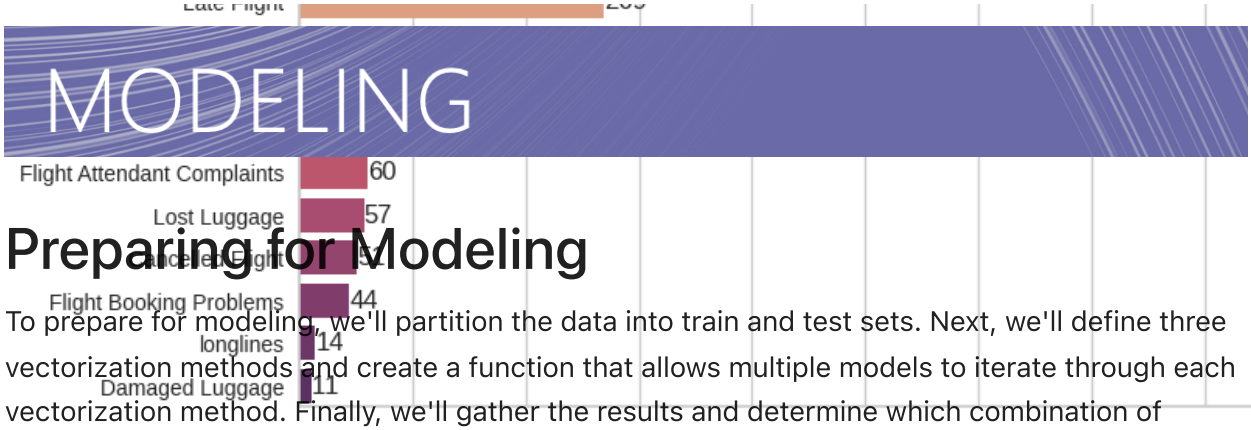




In [43]:
```
df_neg = ta_df_full[['airline','negativereason']]
```

In [44]:
```
# Create a figure with 6 subplots for each airline and set the size and sharing
fig, axes = plt.subplots(6, 1, figsize=(8, 25), sharex=True)

# Flatten the axes array for easier iteration
axes = axes.flatten()

# Get the unique airline names from the negative dataframe
names = df_neg['airline'].unique()

# Iterate over each airline name and its corresponding subplot
for name, n in zip(names, axes):

    # Create a countplot for the negative reasons for the current airline,
    # with a specific color palette and order of values
    ax = sns.countplot(data=df_neg[df_neg.airline==name], y='negativereason',
                       palette='flare',
                       order=df_neg[df_neg.airline==name].negativereason. \
                       value_counts().index, ax=n)

    # Add labels to the bars with their respective counts
    ax.bar_label(ax.containers[0])

    # Set the title of the subplot to include the airline name and the
    # total count of negative reviews for that airline
    ax.set_title(f"{name}: {format(len(df_neg[df_neg.airline==name]),',')}")

    # Remove the x-label to prevent overlapping with the shared x-axis
    ax.set_xlabel('')

    # Set the y-label to indicate the negative reasons
    ax.set_ylabel('')

# Add a title to the entire figure
plt.suptitle("Count per NegativeReason", fontsize=25)

# Show the plot
plt.show()
```


Count per NegativeReason
Virgin America: 504
Customer Service Issue 60
Flight Booking Problems 28
Can't Tell 22
Bad Flight 19
Cancelled Flight 18
Late Flight 17
Lost Luggage 5
Flight Attendant Complaints 5
Damaged Luggage 4
longlines 3
United: 3,822
Customer Service Issue 681
Late Flight 525
Can't Tell 379
Lost Luggage 269
Bad Flight 216
Cancelled Flight 181
Flight Attendant Complaints 168
Flight Booking Problems 144
longlines 48
Damaged Luggage 22
Southwest: 2,420
Customer Service Issue 391
Cancelled Flight 162
Can't Tell 159
Late Flight 152
Bad Flight 90
Lost Luggage 90
Flight Booking Problems 61
Flight Attendant Complaints 38
longlines 29
Damaged Luggage 14
Delta: 2,222
Late Flight 269



Preparing for Modeling

To prepare for modeling, we'll partition the data into train and test sets. Next, we'll define three vectorization methods and create a function that allows multiple models to iterate through each vectorization method. Finally, we'll gather the results and determine which combination of method and model worked best.

In [46]:
```
# Filter out tweets with no content (i.e., no words) after cleaning.
ta_df = ta_df[ta_df['clean_tweet'].apply(lambda x: len(x.split())!=0)]
```

In [47]:
```
# List of unique sentiment values

list(set(ta_df['sentiment']))
```

Out[47]:
```
[0, 1, 2]
```

In [48]:
```
# Count values
ta_df['sentiment'].value_counts()
```

Out[48]:
```
2    2360
0    2359
1    2358
Name: sentiment, dtype: int64
```

In [49]:
```
ta_df['sentiment'].value_counts()
```

Out[49]:
```
2    2360
0    2359
1    2358
Name: sentiment, dtype: int64
```

In [50]:
```
X = ta_df['clean_tweet']

y = ta_df['sentiment']
```

In [51]:
```
# Spliting your dataset into training and testing sets.

X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size = 0.25,
                                                    random_state = 43)
```

Vectorization

We will utilize three different vectorization approaches: TF-IDF, Vector Count, and Word2Vec. We will examine which vector approach has worked best among the machine learning models.

TF-IDF

TF-IDF (Term Frequency-Inverse Document Frequency) is a numerical statistic that reflects the importance of a word to a document in a corpus. It assigns more weight to words that are less frequent in the entire corpus and less weight to words that are more common. The calculation involves both: Term Frequency (TF) and Inverse Document Frequency (IDF).

IDF: IDF = log((count of documents) / (count of documents containing the word))

TF: TF = (count of the frequency of a word in a document) / (count of words in a document)
https://www.geeksforgeeks.org/understanding-tf-idf-term-frequency-inverse-document-frequency/

In [52]:
```
# Initializing TFIDF
vectoriser_tfidf = TfidfVectorizer()
```

In [53]:
```
# Fit the data
vectoriser_tfidf.fit(X_train)

print('Number of feature words:',
      len(vectoriser_tfidf.get_feature_names_out()))
```

```
Number of feature words: 6295
```

In [54]:
```
# Converting the tweets in train and test data into TFIDF features
X_train_tfidf = vectoriser_tfidf.transform(X_train)
X_test_tfidf  = vectoriser_tfidf.transform(X_test)
```

CountVectorizer

Count vectorization is a simple technique to vectorize words by counting their frequency in a document. It creates a matrix in which each word is represented by its count in the corpus.

In [55]:
```
# Initializing countvector
vectorizer_vc = CountVectorizer()
# Fitting countvector
vectorizer_vc.fit(X_train)
```

Out[55]:
```
▾ CountVectorizer
CountVectorizer()
```

In [56]:
```
# Converting tweets in train and test data into countvector features

X_train_vc = vectorizer_vc.transform(X_train)
X_test_vc  = vectorizer_vc.transform(X_test)
```

Word Embedding using Word2Vec

Word2Vec is a neural network-based technique that learns a vector representations of words from large amounts of text data. It represents each word as a vector in a multi dimensional space - and the distance between vectors(words) reflects the semantic similarity between words.

In [57]:
```
# Initializing corpus using funciton progress_apply
# to go though each row and tokenize
corpus = X.progress_apply(lambda line:line.split())
```

In [58]:
```
# View corpus
corpus
```

Out[58]:
```
1                        [plu, ad, commerci, experi, tacki]
6          [ye, nearli, everi, time, fli, vx, ear, worm, ...
8                                                   [well]
9                           [amaz, arriv, hour, earli, good]
11         [lt, 3, pretti, graphic, much, better, minim, ...
                                ...
11264      [notic, believ, saw, confirm, flight, bought, ...
1505                       [tell, jet, airway, award, avail]
8194                                     [look, captur, uvf]
12486      [alreadi, repli, sorri, believ, fair, journali...
3378                                      [dm, conf, receiv]
Name: clean_tweet, Length: 7077, dtype: object
```

In [59]:
```
# Train Word2Vec Model on corpus
import warnings
warnings.filterwarnings(action = 'ignore')
from gensim.models import Word2Vec

w2v_model = Word2Vec(corpus,
                     min_count=1,  # Minimum frequency count of words
                     vector_size=200,  # Dimensionality of the word vectors
                     workers=os.cpu_count(), # Number of processors
                     sg=1                  # 1 for skip-gram
                    )
```

In [60]:
```
# Creating a new column of tokenized tweets
ta_df['tokens'] = (
    ta_df['clean_tweet']
    .progress_apply(lambda line: line.split())
)
```

In [61]:
```
# Checking that change took place
ta_df.head()
```

Out[61]:

	sentiment	text	clean_tweet	clean_tweet_wt_stem	tokens
1	2	@VirginAmerica plus you've added	plu ad commerci experi tacki	plus added commercials experience tacky	[plu, ad, commerci,

	sentiment	text	clean_tweet	clean_tweet_wt_stem	tokens
		commercials t...			experi, tacki]
6	2	@VirginAmerica yes, nearly every time I fly VX...	ye nearli everi time fli vx ear worm go away	yes nearly every time fly vx ear worm go away	[ye, nearli, everi, time, fli, vx, ear, worm, ...
8	2	@virginamerica Well, I didn't...but NOW I DO! :-D	well	well	[well]
9	2	@VirginAmerica it was amazing, and arrived an ...	amaz arriv hour earli good	amazing arrived hour early good	[amaz, arriv, hour, earli, good]
11	2	@VirginAmerica I <3 pretty graphics. so muc...	lt 3 pretti graphic much better minim iconographi	lt 3 pretty graphics much better minimal icono...	[lt, 3, pretti, graphic, much, better, minim, ...

In [62]:
```
# Filtering out any rows where the tokens column is an empty list.
ta_df = ta_df[
    ta_df['tokens']
    .apply(lambda line: True if len(line) else False)
]
```

In [63]:
```
# View tokens
ta_df['tokens']
```

Out[63]:
```
1                       [plu, ad, commerci, experi, tacki]
6          [ye, nearli, everi, time, fli, vx, ear, worm, ...
8                                                   [well]
9                            [amaz, arriv, hour, earli, good]
11         [lt, 3, pretti, graphic, much, better, minim, ...
                                 ...
11264      [notic, believ, saw, confirm, flight, bought, ...
1505                      [tell, jet, airway, award, avail]
8194                                   [look, captur, uvf]
12486      [alreadi, repli, sorri, believ, fair, journali...
3378                                    [dm, conf, receiv]
Name: tokens, Length: 7077, dtype: object
```

In [64]:
```
# Storing the tokenized text data and corresponding sentiment labels
X_w2v = ta_df['tokens']
y_w2v = ta_df['sentiment']
```

In [65]:
```
# Length of the embedding
len(X_w2v)
```

Out[65]:
```
7077
```

In [66]:
```
# Creating a set of all words in the vocabulary of a trained Word2Vec model
all_word2vec_vocab = set(w2v_model.wv.key_to_index)
```

In [1]:
```
# Averaging the embedding of a list of tokens
def get_embed(token_list):
    n = len(token_list)  # Calculating the length
    embed = np.zeros((200)) # Initializing array of zeros with length 200
    for token in token_list: # Iterating over each token
        # Checking if the token is present in the Word2Vec
        if token in all_word2vec_vocab:
            # If so, embedding vector is added
            embed = embed + w2v_model.wv.get_vector(token)
    return embed/n # Averaging of the word embeddings

# https://radimrehurek.com/gensim/models/keyedvectors.html
```

In [68]:
```
# Applying the function to each row  (200 dimensional embedding)
X_w2v_embed = X_w2v.progress_apply(get_embed)
```

In [69]:
```
# View embedding
X_w2v_embed
```

Out[69]:
```
1        [0.060171250440180304, -0.08320541307330132, -...
6        [0.05605091182515025, -0.07544947899878025, -0...
8        [0.06284672021865845, -0.09401337057352066, -0...
9        [0.07140630334615708, -0.10013464242219924, -0...
11       [0.04759641701821238, -0.0748624544357881, -0....
                              ...
11264    [0.06312447557082543, -0.08740132173093465, -0...
1505     [0.07314498424530029, -0.09500521272420884, -0...
8194     [0.039811063945914306, -0.05072377032289902, -...
12486    [0.05765734929591417, -0.0841545706614852, -0....
3378     [0.08229405184586842, -0.1708636631568273, -0....
Name: tokens, Length: 7077, dtype: object
```

In [70]:
```
# Creating a dataframe
df_new = pd.DataFrame(X_w2v_embed)
```

In [71]:
```
# Reseting index
df_new.reset_index(drop=True,inplace=True)
```

In [72]:
```
# View Dataframe
df_new.head()
```

Out[72]:

	tokens
0	[0.060171250440180304, -0.08320541307330132, -...
1	[0.05605091182515025, -0.07544947899878025, -0...
2	[0.06284672021865845, -0.09401337057352066, -0...
3	[0.07140630334615708, -0.10013464242219924, -0...
4	[0.04759641701821238, -0.0748624544357881, -0....

In [73]:
```
#  Adding column numbers corresponding to the integers in the list
#(converted from array)
df_new[list(range(200))] = pd.DataFrame(df_new.tokens.tolist(),
                                        index= df_new.index)
```

In [74]:
```
# Dropping tokens
df_new.drop('tokens',axis=1,inplace=True)
```

In [75]:
```
# View data frame
df_new.head()
```

Out[75]:

	0	1	2	3	4	5	6	7	8
0	0.060171	-0.083205	-0.076482	0.126554	0.030360	-0.133420	-0.019955	0.169237	-0.11186
1	0.056051	-0.075449	-0.077855	0.126850	0.026221	-0.145113	-0.007246	0.167682	-0.09561
2	0.062847	-0.094013	-0.106180	0.167686	0.045378	-0.176704	-0.025085	0.231679	-0.16017
3	0.071406	-0.100135	-0.130546	0.177310	0.046599	-0.210892	-0.000395	0.231823	-0.10842
4	0.047596	-0.074862	-0.073810	0.112042	0.017829	-0.116183	-0.010500	0.144747	-0.09383

5 rows × 200 columns

In [76]:
```
# Splitting the embedding data innto training and testing sets
X_train_w2v, X_test_w2v, y_train_w2v, y_test_w2v = train_test_split(
    df_new, y_w2v, test_size=0.25, random_state=43
)
```

Modeling

The 'Train_Test_Scores' function returns the evaluation metrics (train_acc, test_acc, precision, recall, f1) as output. We will use these metrics can to evaluate and compare different machine learning models.

In [77]:
```
# Building a function that will fit the model and
# then fit it to produce predicted values.

from sklearn.metrics import precision_score,recall_score,f1_score

def Train_Test_Scores(model,X_train,y_train,X_test,y_test,display=False):

    model.fit(X_train,y_train)
    y_preds = model.predict(X_test)

    # Store the score for later evaluation of the model.

    train_acc = model.score(X_train,y_train)
    test_acc = model.score(X_test,y_test)
    precision = precision_score(y_test,y_preds,average='weighted')
    recall = recall_score(y_test,y_preds,average='weighted')
```

```
    f1 = f1_score(y_test,y_preds,average='weighted')

    # Allowing the display to switch off for later on when
    # I just need to function to run
    # for other purposes like creating a data frame of the scoring.

    cm = confusion_matrix(y_test,y_preds)
    if display:
        print('Training_Accuracy:',  train_acc)
        print('Test_Accuracy:', test_acc)

        print('Precision:', precision)
        print('Recall:', recall)
        print('F1_Score:', f1)

        disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                                      display_labels=model.classes_)
        disp.plot()
        plt.show()


    return train_acc,test_acc,precision,recall,f1
```

In [78]:
```
# Testing
def check_dataset_size(X_train, X_test):

    print("Training data shape:", X_train.shape)
    print("Number of training examples:", len(X_train))

    # Check the size of the test data
    print("Test data shape:", X_test.shape)
    print("Number of test examples:", len(X_test))
```

In [79]:
```
check_dataset_size(X_train_w2v, X_test_w2v)
```

```
Training data shape: (5307, 200)
Number of training examples: 5307
Test data shape: (1770, 200)
Number of test examples: 1770
```

In [80]:
```
X_train_tfidf.toarray()
```

Out[80]:
```
array([[0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.]])
```

In [81]:
```
check_dataset_size(X_train_tfidf.toarray(), X_test_tfidf.toarray())
```

```
Training data shape: (5307, 6295)
Number of training examples: 5307
Test data shape: (1770, 6295)
Number of test examples: 1770
```

In [82]:
```
check_dataset_size(X_train_w2v, X_test_w2v)
```

```
Training data shape: (5307, 200)
Number of training examples: 5307
Test data shape: (1770, 200)
Number of test examples: 1770
```

We built a loop we store the results of three machine learning models (GaussianNB RandomForest XGboost) applied to three vectorization techniques (TF-IDF, CountVector, and Word2Vec). WE create a new DataFrame that has columns for the Vectorizer used, the Model used, and various evaluation metrics such as Train Accuracy, Test Accuracy, Precision, Recall, and F1 Score.

In [83]:
```
X_train_w2v
```

Out[83]:

	0	1	2	3	4	5	6	7	
5053	0.050317	-0.060673	-0.105911	0.163311	0.029515	-0.181474	0.036251	0.207229	-0.05
496	0.068982	-0.110297	-0.099458	0.167354	0.036573	-0.164335	-0.009597	0.214891	-0.1
3939	0.074087	-0.103294	-0.102641	0.168240	0.041788	-0.179122	-0.006817	0.213991	-0.10
5429	0.043408	-0.039706	-0.081030	0.106482	0.032017	-0.132706	0.016302	0.135138	-0.05
4097	0.069581	-0.103467	-0.122234	0.163653	0.032699	-0.184795	-0.000610	0.216410	-0.08
...	...	...	...	...	...	...	...	...	
6202	0.054148	-0.080871	-0.076827	0.132117	0.024347	-0.129609	0.010292	0.156864	-0.06
2325	0.086110	-0.135906	-0.079304	0.196568	0.039700	-0.131563	-0.002522	0.212690	-0.15
2303	0.054227	-0.070372	-0.078096	0.135238	0.035277	-0.149558	0.005006	0.177543	-0.0
3392	0.057740	-0.092157	-0.070637	0.143862	0.044738	-0.141290	-0.018523	0.183438	-0.12
5956	0.078131	-0.104163	-0.101887	0.181249	0.040535	-0.173720	0.007942	0.228033	-0.10

5307 rows × 200 columns

In [84]:
```
X_train_w2v.shape
```

Out[84]: (5307, 200)

In [85]:
```
y_train.shape
```

Out[85]: (5307,)

In [86]:
```
check_dataset_size(X_train_tfidf.toarray(), X_test_tfidf.toarray())
```

```
Training data shape: (5307, 6295)
Number of training examples: 5307
Test data shape: (1770, 6295)
Number of test examples: 1770
```

In [87]:

```
%%time
# Creating a data frame to collect all the results
# and evaluate them

models_DataFrame = pd.DataFrame(columns=['Vectorizer','Model','Train_Accuracy',
                                         'Test_Accuracy',
                                         'Precision',
                                         'Recall',
                                         'F1_score'])
list_models = [GaussianNB(),
               RandomForestClassifier(n_jobs=-1),
                XGBClassifier(n_jobs=-1)
               ]

model_names = 'GaussianNB RandomForest XGboost'.split()

from tqdm import tqdm
x_probs  = []
predictions = []

# Looping through all vector methods
for vector in ['TF-IDF', 'CountVector', 'Word2Vec']:
    print(vector)
    if vector == "TF-IDF":
        x_train_temp = X_train_tfidf.toarray()
        x_test_temp = X_test_tfidf.toarray()

    elif vector == 'CountVector':
        x_train_temp = X_train_vc.toarray()
        x_test_temp = X_test_vc.toarray()

    elif vector == 'Word2Vec':
        x_train_temp = X_train_w2v
        x_test_temp = X_test_w2v

        y_train = y_train_w2v
        y_test = y_test_w2v

    for model, model_name in tqdm(zip(list_models, model_names)):
        print(model)
        train_acc, test_acc, precision, recall, f1 = Train_Test_Scores(
        model, x_train_temp, y_train, x_test_temp, y_test)


        models_DataFrame.loc[len(models_DataFrame)] = [vector,model_name,
                                                       train_acc,
                                                       test_acc,precision,
                                                       recall,f1]
```

```
TF-IDF
0it [00:00, ?it/s]
GaussianNB()
1it [00:01,  1.54s/it]
RandomForestClassifier(n_jobs=-1)
2it [00:09,  5.39s/it]
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
```

```
                colsample_bytree=None, early_stopping_rounds=None,
                enable_categorical=False, eval_metric=None, feature_types=None,
                gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
                interaction_constraints=None, learning_rate=None, max_bin=None,
                max_cat_threshold=None, max_cat_to_onehot=None,
                max_delta_step=None, max_depth=None, max_leaves=None,
                min_child_weight=None, missing=nan, monotone_constraints=None,
                n_estimators=100, n_jobs=-1, num_parallel_tree=None,
                predictor=None, random_state=None, ...)
3it [02:36, 52.16s/it]
CountVector
0it [00:00, ?it/s]
GaussianNB()
1it [00:01,  1.84s/it]
RandomForestClassifier(n_jobs=-1)
2it [00:09,  5.33s/it]
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=-1, num_parallel_tree=None,
              objective='multi:softprob', predictor=None, ...)
3it [02:36, 52.14s/it]
Word2Vec
0it [00:00, ?it/s]
GaussianNB()
RandomForestClassifier(n_jobs=-1)
2it [00:02,  1.22s/it]
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=-1, num_parallel_tree=None,
              objective='multi:softprob', predictor=None, ...)
3it [00:33, 11.16s/it]
CPU times: user 21min 39s, sys: 3.22 s, total: 21min 42s
Wall time: 5min 46s
```

In [88]:
```
models_DataFrame
```

Out[88]:

	Vectorizer	Model	Train_Accuracy	Test_Accuracy	Precision	Recall	F1_score
0	TF-IDF	GaussianNB	0.816092	0.488701	0.522790	0.488701	0.476424
1	TF-IDF	RandomForest	0.994347	0.710734	0.712875	0.710734	0.711428
2	TF-IDF	XGboost	0.866026	0.718079	0.722925	0.718079	0.719500
3	CountVector	GaussianNB	0.794988	0.490960	0.549069	0.490960	0.474426
4	CountVector	RandomForest	0.994347	0.705650	0.706566	0.705650	0.706047

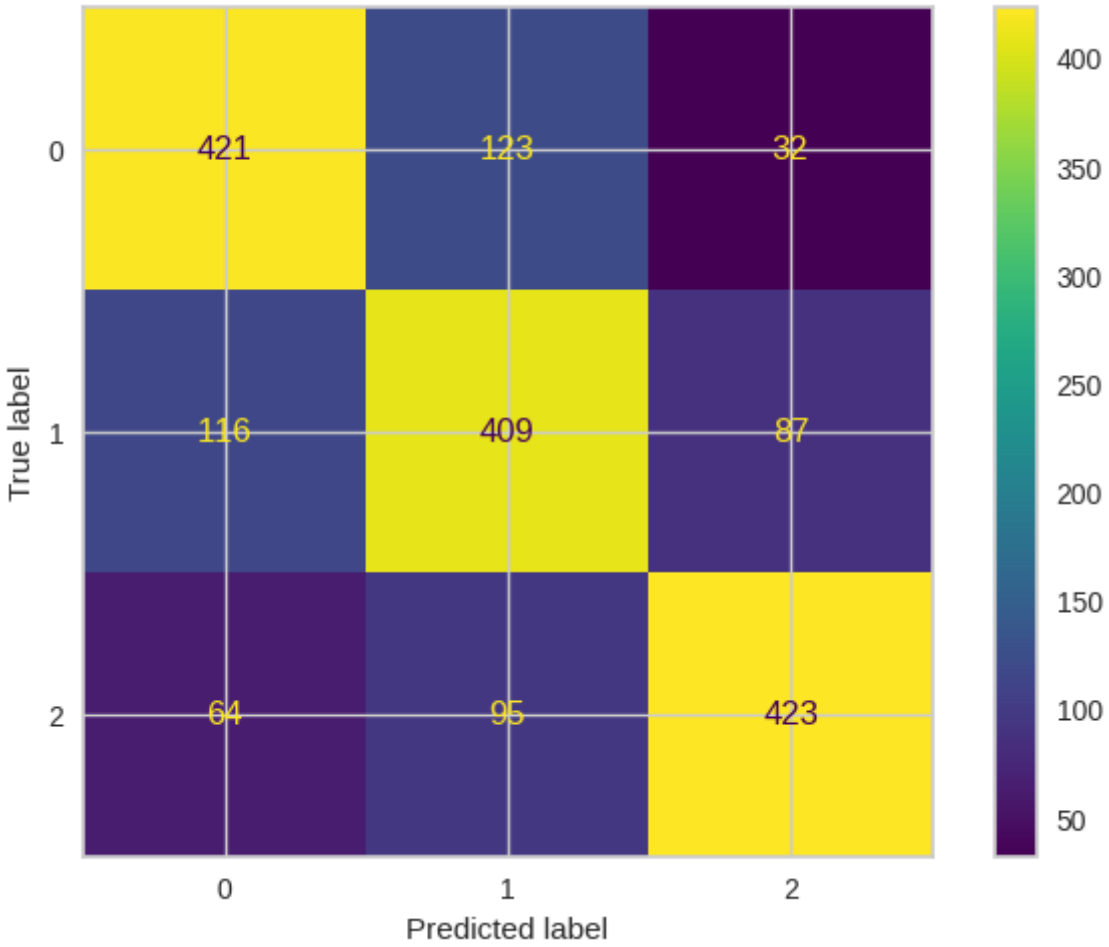
	Vectorizer	Model	Train_Accuracy	Test_Accuracy	Precision	Recall	F1_score
5	CountVector	XGboost	0.832297	0.718644	0.723014	0.718644	0.720004
6	Word2Vec	GaussianNB	0.501225	0.516949	0.539352	0.516949	0.480632
7	Word2Vec	RandomForest	0.994536	0.615819	0.616656	0.615819	0.615080
8	Word2Vec	XGboost	0.994536	0.619774	0.618659	0.619774	0.618505

Interpreting results of the best performing model

The models in general performed well on the training data and did not do as well on the testing data. They mostly were all overfitting. It is possible that the if we increase the data the model will do better or if we use a more advanced deep learning approach which we will attempt both in the part 2. In the meantime, the top performer is Random Forest using the TF-IDF method for vectorization.

In [89]:
```
Train_Test_Scores(RandomForestClassifier(n_jobs=-1),X_train_tfidf,y_train,
                  X_test_tfidf,y_test,True)
```

```
Training_Accuracy: 0.9943470887507067
Test_Accuracy: 0.707909604519774
Precision: 0.7101246011189691
Recall: 0.707909604519774
F1_Score: 0.7085647349913776
```



Out[89]:
```
(0.9943470887507067,
 0.707909604519774,
 0.7101246011189691,
 0.707909604519774,
 0.7085647349913776)
```

In [90]:
```
# Define classifier and fit it
clf = RandomForestClassifier(n_jobs=-1)
clf.fit(X_train_tfidf, y_train)
```

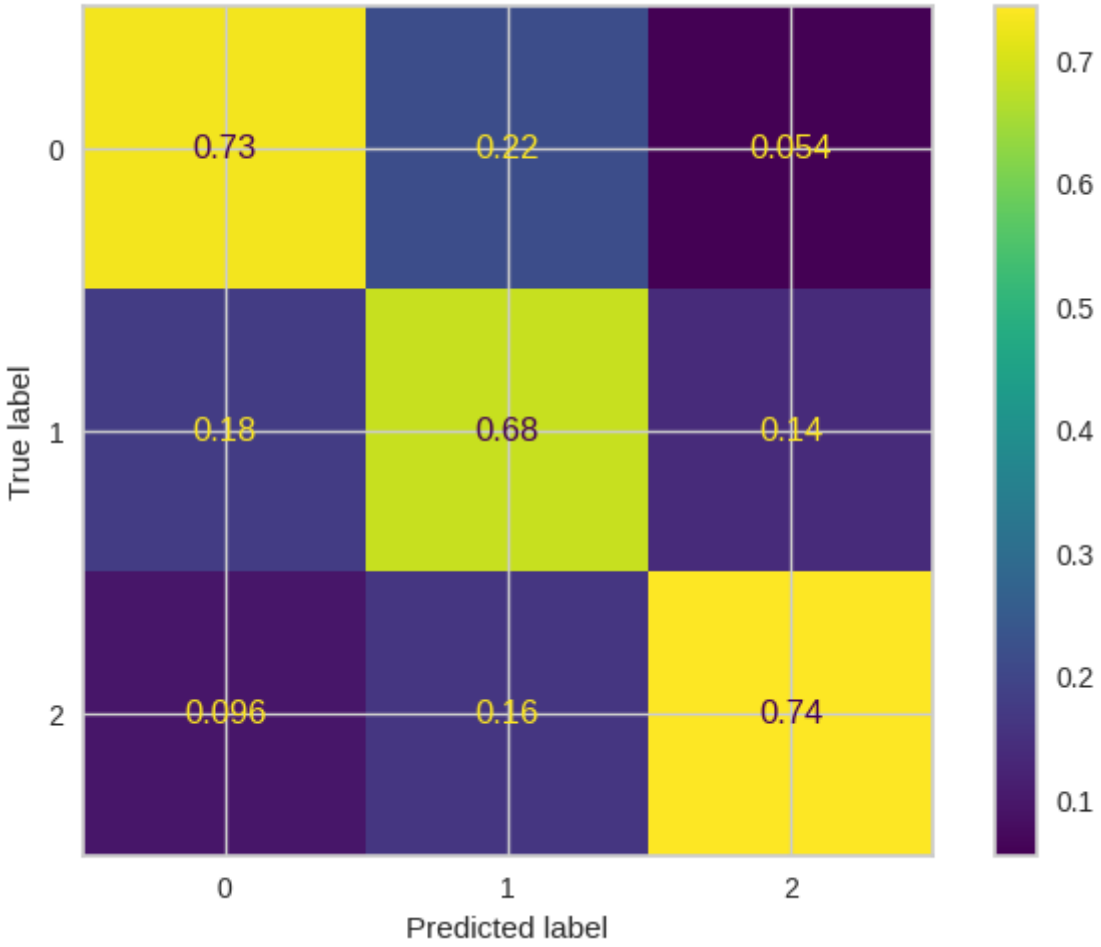
Out[90]:
```
RandomForestClassifier(n_jobs=-1)
```

In [91]:
```
# Get predictors from Random Forest using TF-IDF
y_pred = clf.predict(X_test_tfidf)
```

In [92]:
```
# Classification report
target_names = ['Negative', 'Positive','Nuetural']
print(classification_report(y_test, y_pred, target_names = target_names))
```

```
              precision    recall  f1-score   support

    Negative       0.72      0.73      0.73       576
    Positive       0.66      0.68      0.67       612
    Nuetural       0.79      0.74      0.76       582

    accuracy                           0.72      1770
   macro avg       0.72      0.72      0.72      1770
weighted avg       0.72      0.72      0.72      1770
```

In [93]:
```
cm1 = confusion_matrix(y_test,y_pred,normalize='true')

#disp = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=[0,1])
disp1 = ConfusionMatrixDisplay(confusion_matrix=cm1,display_labels=[0,1,2])
#disp.plot()
disp1.plot()
plt.show()

# https://scikit-learn.org/stable/modules/generated/sklearn.
# metrics.ConfusionMatrixDisplay.html
```



Random Forest shows accuracy of 73%, which means that it correctly classified 73% of the samples in the test set both negative and positive tweets correctly.

LSTM

LSTM (Long Short-Term Memory) is a type of neural network model that is structred to work with sequences of data, like text.

- It has a unique architecture that includes both gates and memory cells, which allow it to learn and remember information over long periods of time.
- There are three types of gates in an LSTM: the input gate, the forget gate, and the output gate. These gates control the flow of information into and out of the memory cells.
  - The **input gate** determines how much new information is added to the memory cell at each time step.
  - The **forget gate** decides which information to discard from the memory cell, based on the current input
    and the previous hidden state.
  - The **memory cell** stores and updates information over time, and is the key component that allows LSTM to handle long-term dependencies.
  - Finally, the **output gate** determines how much information is passed from the memory cell to the output at each time step.

In [94]:
```
# Importing Keras libraries
from keras.preprocessing.text import Tokenizer
# from keras.preprocessing.sequence import pad_sequences
from keras.models import Sequential
from keras.layers import Activation, Dense, Dropout, Embedding, Flatten
from keras.layers import Conv1D, MaxPooling1D, LSTM
from keras import utils
from keras.callbacks import ReduceLROnPlateau, EarlyStopping
# from keras_preprocessing.sequence import pad_sequences

# Downloading tensorflow library
from tensorflow.keras.preprocessing.sequence import pad_sequences
```

In [95]:
```
%%time
tokenizer = Tokenizer() # Initializing a new object
tokenizer.fit_on_texts(X_train) # Tokenizer will learn the
# vocabulary of the text data and assign a unique index to each word

# Vocabulary size (tokenizer reserves index 0)
vocab_size = len(tokenizer.word_index) + 1
print("Total words", vocab_size)
```

```
Total words 6323
CPU times: user 70.9 ms, sys: 2 ms, total: 72.9 ms
Wall time: 72.3 ms
```

In [96]:
```
# KERAS
# Maximum length of the tweet.
SEQUENCE_LENGTH = 300

#Number of times it passes through the training data.
EPOCHS = 3

# Size of matric for word2vec embeddings
W2V_SIZE = 200
# Number of training examples/samples to process at once during each iteration.
BATCH_SIZE = 16

# https://medium.com/@dclengacher/keras-lstm-recurrent-
#neural-networks-c1f5febde03d
```

In [97]:
```
# Converting training and testing data to sequences of word
# indices to prepare for the model.
x_train = pad_sequences(tokenizer.texts_to_sequences(X_train),
                        maxlen=SEQUENCE_LENGTH)
x_test = pad_sequences(tokenizer.texts_to_sequences(X_test),
                       maxlen=SEQUENCE_LENGTH)
```

In [98]:
```
# Check ditribution
y_train.value_counts()
```

Out[98]:
```
0    1783
2    1778
```

```
1    1746
Name: sentiment, dtype: int64
```

In [99]:
```
x_train.shape
```

Out[99]:
```
(5307, 300)
```

In [100…
```
# Prepring word2vec for LSTM/Keras
embedding_matrix = np.zeros((vocab_size, W2V_SIZE)) # Initializing an empty
# embedding matrix with the shape
for word, i in tokenizer.word_index.items(): # Looping over each word in  tweet
  if word in w2v_model.wv: # Checksing if the word is in Word2Vec model
    embedding_matrix[i] = w2v_model.wv[word] # If yes, it assigns a vector
print(embedding_matrix.shape) # Printing shape
```

```
(6323, 200)
```

In [101…
```
# Initializing embedding layers for our model
embedding_layer = Embedding(vocab_size, W2V_SIZE, weights=[embedding_matrix],
                            input_length=SEQUENCE_LENGTH, trainable=False)
```

In [102…
```
KERAS_MODEL = Sequential() # Creating a new sequential model
KERAS_MODEL.add(embedding_layer) # Adding embedding layer to the model.

# Dropout is a fraction of the neurons will drop in a layer during training.
KERAS_MODEL.add(Dropout(0.5)) # Adding a dropout layer
# Adding LSTM hidden layer with 100 neurons

KERAS_MODEL.add(LSTM(100, dropout=0.2, recurrent_dropout=0.2))


# Adding a dense output layer to the model with a one one output and
# a sigmoid activation function ( this layerreceives input from all
# the neurons in the previous layer.)

KERAS_MODEL.add(Dense(1, activation='softmax'))

KERAS_MODEL.summary() # Print summary

# https://heartbeat.comet.ml/using-a-keras-long-shortterm-memory-
# lstm-model-to-predict-stock-prices-a08c9f69aa74
```

```
WARNING:tensorflow:Layer lstm will not use cuDNN kernels since it doesn't meet t
he criteria. It will use a generic GPU kernel as fallback when running on GPU.
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 300, 200)          1264600

 dropout (Dropout)           (None, 300, 200)          0

 lstm (LSTM)                 (None, 100)               120400

 dense (Dense)               (None, 1)                 101

=================================================================
```

```
Total params: 1,385,101
Trainable params: 120,501
Non-trainable params: 1,264,600
_________________________________________________________________
```

In [103…

```
# Compilying the model

KERAS_MODEL.compile(loss='categorical_crossentropy',
              optimizer="adam",
              metrics=['accuracy'])
```

In [104…

```
# Initializing callback
callbacks = [ ReduceLROnPlateau(monitor='val_loss', patience=5, cooldown=0),
              EarlyStopping(monitor='val_accuracy', min_delta=1e-4, patience=5)]
```

In [105…

```
# Fitting the model
history = KERAS_MODEL.fit(x_train, y_train,
                    batch_size=BATCH_SIZE,
                    epochs=EPOCHS,
                    validation_split=0.1,
                    verbose=1,
                    callbacks=callbacks)
```

```
Epoch 1/3
299/299 [==============================] - 274s 891ms/step - loss: 0.0000e+00 -
accuracy: 0.3289 - val_loss: 0.0000e+00 - val_accuracy: 0.3296 - lr: 0.0010
Epoch 2/3
299/299 [==============================] - 263s 881ms/step - loss: 0.0000e+00 -
accuracy: 0.3289 - val_loss: 0.0000e+00 - val_accuracy: 0.3296 - lr: 0.0010
Epoch 3/3
299/299 [==============================] - 262s 876ms/step - loss: 0.0000e+00 -
accuracy: 0.3289 - val_loss: 0.0000e+00 - val_accuracy: 0.3296 - lr: 0.0010
```

In [106…

```
# Storing test and training
y_test_1d = list(y_test)
scores = KERAS_MODEL.predict(x_test, verbose=1, batch_size=16)
# Rounding to match a label
y_pred_test_1d = [0 if score[0]<0.5 else (1 if score[0]==0.5 else 2) for score i

y_train_1d = list(y_train)
scores = KERAS_MODEL.predict(x_train, verbose=1, batch_size=16)
# Rounding to match a label
y_pred_train_1d = [0 if score[0]<0.5 else (1 if score[0]==0.5 else 2) for score
```

```
111/111 [==============================] - 9s 81ms/step
332/332 [==============================] - 27s 80ms/step
```

In [107…

```
from sklearn.metrics import accuracy_score
```

In [108…

```
# Storing scores
train_acc = accuracy_score(y_train,y_pred_train_1d)
test_acc = accuracy_score(y_test,y_pred_test_1d)
precision = precision_score(y_test,y_pred_test_1d,average='weighted')
recall = recall_score(y_test,y_pred_test_1d,average='weighted')
f1 = f1_score(y_test,y_pred_test_1d,average='weighted')
```

In [109…
```
# Show dataframe
models_DataFrame
```

Out[109…

	Vectorizer	Model	Train_Accuracy	Test_Accuracy	Precision	Recall	F1_score
0	TF-IDF	GaussianNB	0.816092	0.488701	0.522790	0.488701	0.476424
1	TF-IDF	RandomForest	0.994347	0.710734	0.712875	0.710734	0.711428
2	TF-IDF	XGboost	0.866026	0.718079	0.722925	0.718079	0.719500
3	CountVector	GaussianNB	0.794988	0.490960	0.549069	0.490960	0.474426
4	CountVector	RandomForest	0.994347	0.705650	0.706566	0.705650	0.706047
5	CountVector	XGboost	0.832297	0.718644	0.723014	0.718644	0.720004
6	Word2Vec	GaussianNB	0.501225	0.516949	0.539352	0.516949	0.480632
7	Word2Vec	RandomForest	0.994536	0.615819	0.616656	0.615819	0.615080
8	Word2Vec	XGboost	0.994536	0.619774	0.618659	0.619774	0.618505

In [110…
```
# Adding word2vec and LTSM to dataframe
models_DataFrame.loc[len(models_DataFrame)] = ['Word2vec','LSTM',train_acc,
                                               test_acc,precision,recall
```

In [111…
```
# Show dataframe
models_DataFrame
```

Out[111…

	Vectorizer	Model	Train_Accuracy	Test_Accuracy	Precision	Recall	F1_score
0	TF-IDF	GaussianNB	0.816092	0.488701	0.522790	0.488701	0.476424
1	TF-IDF	RandomForest	0.994347	0.710734	0.712875	0.710734	0.711428
2	TF-IDF	XGboost	0.866026	0.718079	0.722925	0.718079	0.719500
3	CountVector	GaussianNB	0.794988	0.490960	0.549069	0.490960	0.474426
4	CountVector	RandomForest	0.994347	0.705650	0.706566	0.705650	0.706047
5	CountVector	XGboost	0.832297	0.718644	0.723014	0.718644	0.720004
6	Word2Vec	GaussianNB	0.501225	0.516949	0.539352	0.516949	0.480632
7	Word2Vec	RandomForest	0.994536	0.615819	0.616656	0.615819	0.615080
8	Word2Vec	XGboost	0.994536	0.619774	0.618659	0.619774	0.618505
9	Word2vec	LSTM	0.335029	0.328814	0.108118	0.328814	0.162729

In [112…
```
# Sorting by accracy
models_DataFrame.sort_values('Test_Accuracy',ascending=False,inplace=True)
```

In [113…
```
models_DataFrame
```

Out[113…

	Vectorizer	Model	Train_Accuracy	Test_Accuracy	Precision	Recall	F1_score
5	CountVector	XGboost	0.832297	0.718644	0.723014	0.718644	0.720004
2	TF-IDF	XGboost	0.866026	0.718079	0.722925	0.718079	0.719500
1	TF-IDF	RandomForest	0.994347	0.710734	0.712875	0.710734	0.711428
4	CountVector	RandomForest	0.994347	0.705650	0.706566	0.705650	0.706047
8	Word2Vec	XGboost	0.994536	0.619774	0.618659	0.619774	0.618505
7	Word2Vec	RandomForest	0.994536	0.615819	0.616656	0.615819	0.615080
6	Word2Vec	GaussianNB	0.501225	0.516949	0.539352	0.516949	0.480632
3	CountVector	GaussianNB	0.794988	0.490960	0.549069	0.490960	0.474426
0	TF-IDF	GaussianNB	0.816092	0.488701	0.522790	0.488701	0.476424
9	Word2vec	LSTM	0.335029	0.328814	0.108118	0.328814	0.162729

LSTM model using Word2Vec achieved low accuracy scores. The dataset might not have contained enough data to train the models well. Deep learning models like Word2Vec and LSTM typically require large amounts of data to learn complex patterns.

Huggingface Models

Hugging Face specializes in natural language processing (NLP) and provides a library called "Transformers" for building and using regirous NLP models. The Hugging Face Transformers library provides access to pre-trained models which can be fine-tuned. I will use the Pretrained BERT model - will use the weights of the pre-trained model and then adjust them for my airlines data.

https://huggingface.co/docs/transformers/training

BERT (Bidirectional Encoder Representations from Transformers) is a type of NLP model that is designed to understand the context and meaning of words in text. It is a pre-trained model that uses a technique called transformer architecture to process input text and create contextualized word embeddings, which represent the meaning of words based on their surrounding words in a sentence.

https://jalammar.github.io/illustrated-bert/

High-level steps for Hugging Face to fine-tune a pre-trained RoBERTa model:

```
1. Prepare the dataset: converting the data into a dictionary
format.
2. Define a function to compute performance - this will be passed
as an argument when using Trainer.
3. Define labeling for the classes.
4.Define a function to get the BERT pre-trained model by loading
the tokenizer from the pre-trained model
checkpoint, tokenizing the dataset, and preparing the training
arguments and trainer for fine-tuning.
```

5.Train the model for fine-tuning and save the model.
6.Define a function for inference/ (tokenizer,fine-tuned model, and the
text.)
7. Implementing/appling the fine-tuned model to new data and obtain predictions.

In [114…
```
#  Accessing and processing various natural language processing (NLP) dataset
!pip install -q datasets
# Library for working with various transformer-based models, such as BERT,
!pip install -q transformers
```

```
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 468.7/468.7 kB 20.6 MB/s eta 0:00:00
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     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.0/1.0 MB 62.7 MB/s eta 0:00:00
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     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 132.9/132.9 kB 12.2 MB/s eta 0:00:00
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 114.2/114.2 kB 13.9 MB/s eta 0:00:00
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 264.6/264.6 kB 28.8 MB/s eta 0:00:00
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 158.8/158.8 kB 19.5 MB/s eta 0:00:00
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 7.0/7.0 MB 38.2 MB/s eta 0:00:00
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 7.8/7.8 MB 107.3 MB/s eta 0:00:00
```

In [115…
```
# Viewing training data
X_train
```

Out[115…
```
2230            appear six flight calgari tomorrow correct
3293     well taken care thank alreadi sent survey requ...
9212     travel agenc said usairway accept refund money...
12655                late flightst usair4603 earlier 4591
14388    kid think done call dozen time amp tell call b...
                               ...
318      u help freyabevan fund need urgent treatment 2...
14292                                          thank see
14022                    dai presid good luck dfw even aa
9312                  airway joke never dealt wors servic
8936     ok great thank great flight fyi excit fli frus...
Name: clean_tweet, Length: 5307, dtype: object
```

In [116…
```
# Checking the shape
X_train.shape
```

Out[116…
```
(5307,)
```

Splitting a ta_df into three parts: 1.training data, 2.validation data, and 3.test data. This allows for the model to be trained on one subset of the data, validated on another subset, and then tested on a completely separate subset to assess its performance.

In [117…
```
# Spliitting dataset
df_train = pd.DataFrame({'text':X_train,'label':y_train})
df_val = df_train.sample(550) #sampling random 550 for validaiton set
df_train = df_train.drop(df_val.index) # Dropping it so there is no overlap
df_test = pd.DataFrame({'text':X_test,'label':y_test})
```

Now we beed to import libraries and create a data set dictionary for the training and validation sets.

In [118…
```
import datasets # Access to NLP
import os # Interact with numpy
import numpy as np

# Prepare dataset for finetuning by conveting the data into dict. format
train_dataset = datasets.Dataset.from_dict(df_train)
val_dataset = datasets.Dataset.from_dict(df_val) #Validation
my_dataset_dict = datasets.DatasetDict({"train":train_dataset,
                                        "val":val_dataset})
```

In [119…
```
# Check keys to prepare for dict. form.
print(my_dataset_dict.keys())
```

```
dict_keys(['train', 'val'])
```

In [120…
```
# Viewing dataset in doct. format
my_dataset_dict
```

Out[120…
```
DatasetDict({
    train: Dataset({
        features: ['text', 'label'],
        num_rows: 4757
    })
    val: Dataset({
        features: ['text', 'label'],
        num_rows: 550
    })
})
```

We use the transformers library to load a pre-trained tokenizer for the BERT model and tokenize the input data from the dict. format.

Importing from the transformers library to load the BERT model for sequence classification from the bert-base-uncased checkpoint.

In [121…
```
!pip install -q evaluate
```

```
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 81.4/81.4 kB 247.5 kB/s eta 0:00:00
```

In [122…
```
# Importl library functions for evaluating the performance
import evaluate

# obtain accuracy
metric = evaluate.load("accuracy")
```

In [123…
```
# function to compute performance while finetuning
def compute_metrics(eval_pred):
# logits: predicted probabilities for each class, while labels: true labels.
    logits, labels = eval_pred
    predictions = np.argmax(logits, axis=-1)
```

```
# Evaluating
    return metric.compute(predictions=predictions, references=labels)
# https://huggingface.co/docs/evaluate/transformers_integrations
```

Specifying the directory where the model checkpoints and training logs will be saved and how often to evaluate the model performance during training (5 times).

Function for finetuning

- This function builds a process for fine-tuning a BERT-based language model on an airline sentiment dataset.
- It takes a checkpoint as input and loads a tokenizer from it.
- The function tokenizes the dataset using the tokenizer, pads the data, and gets the weights from the checkpoint for a pre-trained BERT model.
- It then prepares necessary training arguments for the fine-tuning process.
- The model is trained for 3 epochs using a Trainer.
- After training, the function saves the fine-tuned model so it can be retrieved.

In [124…

```
from transformers import AutoModelForSequenceClassification
from transformers import AutoTokenizer
from transformers import TrainingArguments, Trainer

# Defining labling
class_names = ['negative','neutral','positive']

def get_finetuned_model(checkpoint):

    # Loading Tokenizer from twitter-roberta-base-sentiment checkpoint

    # checkpoint = chkpoint #"cardiffnlp/twitter-roberta-base-sentiment"
    tokenizer = AutoTokenizer.from_pretrained(checkpoint)

    # Getting tokenized dataset
    def tokenize_function(examples):

       # Padding and returning tokenizer
    #https://huggingface.co/transformers/v3.0.2/preprocessing.html
        return tokenizer(examples["text"], padding="max_length", max_length=20,
                         truncation=True)
      #  Creating a new tokenized dataset  - to fine tune BRET model
    tokenized_datasets = my_dataset_dict.map(tokenize_function, batched=True)

    # Loading classifier from twitter-roberta-base-sentiment - to get weights
    # is a generic model class that will be instantiated as one of the sequence
    # classification model classes.
    # https://huggingface.co/transformers/v3.0.2/model_doc/auto.html#
    # automodelforsequenceclassification
    model = AutoModelForSequenceClassification.from_pretrained(checkpoint,
            num_labels=len(class_names))

    # Preparing training Arguments
    # https://programtalk.com/python-more-examples/
```

```
    # transformers.TrainingArguments/
    training_args = TrainingArguments(output_dir="test_trainer",
                                      evaluation_strategy="epoch",
                                      num_train_epochs = 3,
                                      overwrite_output_dir=True)

    # Trainer for finetuning

    trainer = Trainer(
        model=model, # Pre trained BRET model
        args=training_args,
        train_dataset=tokenized_datasets["train"],
        eval_dataset=tokenized_datasets["val"],
        compute_metrics=compute_metrics,
    )

    # train the model for finetuning
    trainer.train()

    # save the model, its architecture and learned parameters
    trainer.save_model("finetuned_model")

    # Loading fientuned model
    model_tuned = AutoModelForSequenceClassification.from_pretrained("finetuned_
    return model_tuned,tokenizer
```

In [125…

```
# model_tuned1,tokenizer1 = get_finetuned_model('bert-base-uncased')
```

In [126…

```
model_tuned2,tokenizer2 = get_finetuned_model('cardiffnlp/twitter-roberta-base-s
```

[1785/1785 02:39, Epoch 3/3]

Epoch	Training Loss	Validation Loss	Accuracy
1	0.819000	0.726748	0.736364
2	0.603100	0.714538	0.749091
3	0.447600	0.958426	0.760000

The function below takes a tokenizer, a trained BERT model.

- It creates a dictionary of features that can be used as input to the BERT model, including tokenization and padding.
- The function computes the outcome of the model using the spesific features.
- The output from the model is converted to an array of scores.
- The scores are transformed into probabilities for each class using the softmax function.
- The function assigns labels to each class.
- Finally, the function returns the index of the class with the highest probability.

In [127…

```
# https://huggingface.co/cardiffnlp/
# twitter-roberta-base-sentiment-latest
# Maximum sequence length
max_seq_length = 100

# import library for multi class
from scipy.special import softmax

def inference(tokenizer,model_tuned,text):

  # Creating a dictionary of features that can be used as input to the BERT mode
    features = tokenizer.batch_encode_plus(
        [text],
        add_special_tokens=True,
        padding='max_length',
        max_length=max_seq_length,
        truncation=True,
        return_tensors='pt',
        return_attention_mask=True
    )
    # Compuing to get the outcome
    outputs = model_tuned(features['input_ids'], features['attention_mask'])

    # Converting the output into an array
    scores = outputs[0][0].detach().numpy()
    # Getting propabilities for each class.
    scores = softmax(scores)
    # Storiing Postive, Neutral and Negative
    labels = class_names
    # Returning the highest prop.
    return scores.argmax()
```

In [128…

```
# Inference function Example

textual_input = "your airline is awesome but your lax loft needs to step up its
predicted_class = inference(tokenizer2, model_tuned2, textual_input)
print("Predicted class:", predicted_class)
```

```
Predicted class: 0
```

In [129…

```
# Passing inference through each tweet
y_pred = df_test['text'].progress_apply(lambda x: inference(tokenizer2,
                                                            model_tuned2, x))
```

In [130…

```
# Gertting accuracy score
accuracy_score(y_test,y_pred)
```

Out[130…

```
0.7519774011299435
```

This function takes the predicted labels of a checkpoint as input.

- It calculates the scores of the predicted labels.
- It updates the dataframe and sorts the it by test accuracy and returns the dataframe.

In [131…

```
def add_entry_dataframe(y_pred,chk_name):
  # Getting all the other scores
  test_acc = accuracy_score(y_test,y_pred)
  precision = precision_score(y_test,y_pred,average='weighted')
  recall = recall_score(y_test,y_pred,average='weighted')
  f1 = f1_score(y_test,y_pred,average='weighted')

  # updating a DataFrame with the results of fine-tuning a BERT mode
  models_DataFrame.loc[len(models_DataFrame)] = ['',f'{chk_name}-Finetuned',
                                                 '',
                                                    test_acc,precision,recall,f1

  # Sorting the dataframe by test accuracy
  models_DataFrame.sort_values('Test_Accuracy',ascending=False,inplace=True)

  return models_DataFrame
```

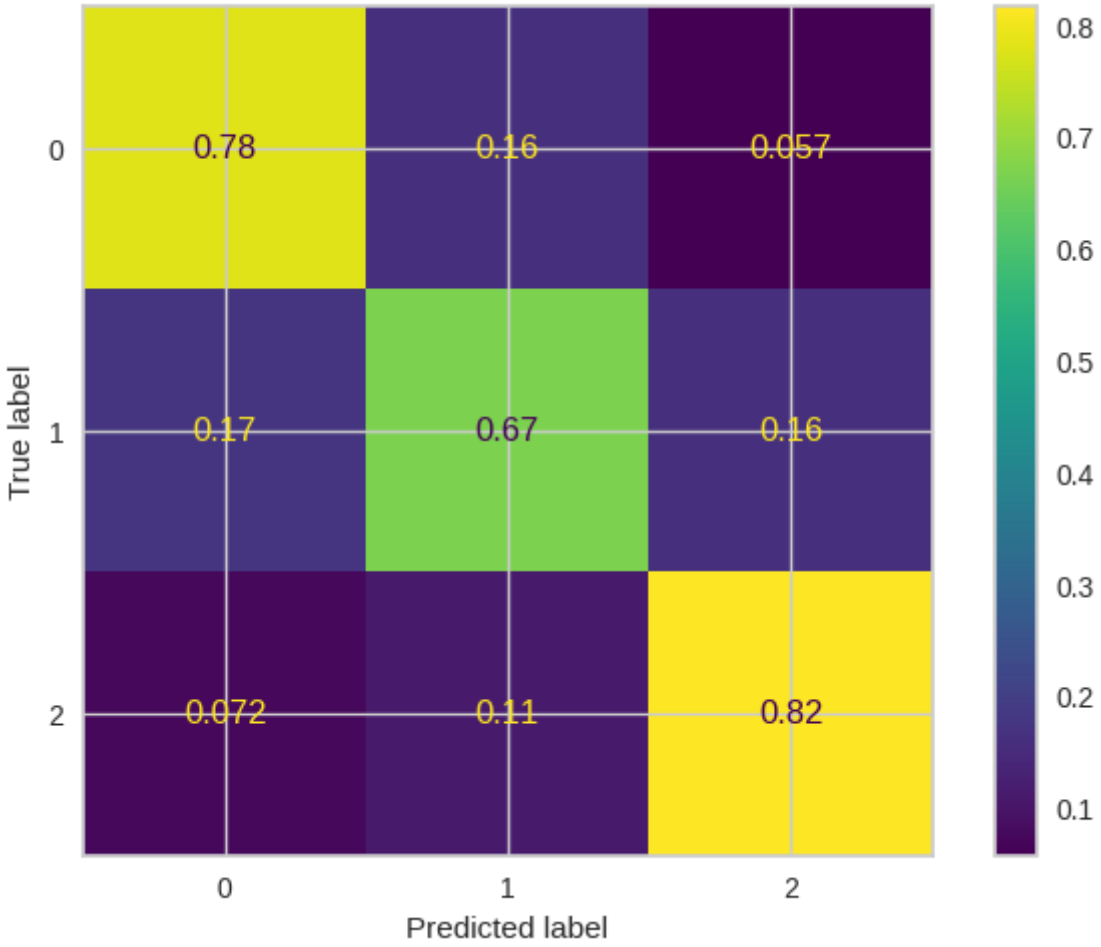
In [132…

```
 # Classification report for BERT
target_names = ['Negative', 'Positive','Nuetural']
print(classification_report(y_test, y_pred, target_names = target_names))
```

```
              precision    recall  f1-score   support

    Negative       0.75      0.78      0.77       576
    Positive       0.72      0.67      0.69       612
    Nuetural       0.78      0.82      0.80       582

    accuracy                           0.75      1770
   macro avg       0.75      0.75      0.75      1770
weighted avg       0.75      0.75      0.75      1770
```

In [133…

```
cm1 = confusion_matrix(y_test,y_pred,normalize='true')

#disp = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=[0,1])
disp = ConfusionMatrixDisplay(confusion_matrix=cm1,display_labels=[0,1,2])
#disp.plot()
disp.plot()
plt.show()

# https://scikit-learn.org/stable/modules/generated/sklearn.
# metrics.ConfusionMatrixDisplay.html
```



In [134…
```
# Interpreting resutls of the model
```

Accuracy: This measures the overall proportion of instances that the model correctly classified, regardless of class. In this case, the model achieved an accuracy of 0.75, which means that it correctly classified 75% of the instances in the dataset.

In [135…
```
add_entry_dataframe(y_pred,'bert-base-uncased') # change checkpoint name here
```

Out[135…

	Vectorizer	Model	Train_Accuracy	Test_Accuracy	Precision	Recall	F1_score
10		bert-base-uncased-Finetuned		0.751977	0.750689	0.751977	0.750772
5	CountVector	XGboost	0.832297	0.718644	0.723014	0.718644	0.720004
2	TF-IDF	XGboost	0.866026	0.718079	0.722925	0.718079	0.719500
1	TF-IDF	RandomForest	0.994347	0.710734	0.712875	0.710734	0.711428
4	CountVector	RandomForest	0.994347	0.705650	0.706566	0.705650	0.706047
8	Word2Vec	XGboost	0.994536	0.619774	0.618659	0.619774	0.618505
7	Word2Vec	RandomForest	0.994536	0.615819	0.616656	0.615819	0.615080
6	Word2Vec	GaussianNB	0.501225	0.516949	0.539352	0.516949	0.480632
3	CountVector	GaussianNB	0.794988	0.490960	0.549069	0.490960	0.474426

	Vectorizer	Model	Train_Accuracy	Test_Accuracy	Precision	Recall	F1_score
0	TF-IDF	GaussianNB	0.816092	0.488701	0.522790	0.488701	0.476424
9	Word2vec	LSTM	0.335029	0.328814	0.108118	0.328814	0.162729

Prepare data for topic modelling

For topic modeling, I will be using the PyLDAvis library. However, I have encountered issues between PyLDAvis and Google Colab. The visualizations can be seen in a separate Jupyter notebook.

In [136…
```
# Topic Modeling
from google.colab import files
```

In [137…
```
# negative tweets index
neg_index = df_test[df_test['label']==0].index
data = ta_df.loc[neg_index]

data.to_csv('data_for_topic_m.csv',index=False)
files.download('data_for_topic_m.csv')

# use this csv and use the topic modelling notebook
```

SHAP

https://shap.readthedocs.io/en/latest/example_notebooks/text_examples/sentiment_analysis/Emotic

SHAP (SHapley Additive exPlanations) helps interpret the predictions of a machine learning model. It does this by determining the importance of each input feature to the output prediction.

In this section, we will use shap to see how the model works for positive and negative tweets.

In [138…
```
# Intall shap library
!pip install -q shap
```

```
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 572.4/572.4 kB 22.8 MB/s eta 0:00:00
```

In [139…
```
# Importing snap and 'ignore' for removal of warning msg.

import shap
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
```

In [140…
```
import transformers

# Loading the model and tokenizer
tokenizer = tokenizer2
```

```
model = model_tuned2

# Building a pipeline object to do predictions
pred = transformers.pipeline("text-classification",
                             model=model, tokenizer=tokenizer, device=0,
                             return_all_scores=True)
```

In [141…

```
# Explainer object generates explanations for individual predictions
explainer = shap.Explainer(pred)
```

In [142…

```
data.head()
```

Out[142…

	sentiment	text	clean_tweet	clean_tweet_wt_stem	tokens
2136	0	@United Can you increase the legroom? : How ai...	increas legroom airlin compar via cnnmoney	increase legroom airlines compare via cnnmoney	[increas, legroom, airlin, compar, via, cnnmoney]
7416	0	@JetBlue Third straight time that my flight ha...	third straight time flight delay fli guy last ...	third straight time flight delayed flying guys...	[third, straight, time, flight, delay, fli, gu...
11985	0	@AmericanAir I'm not sure what happened to my ...	sure happen usairway statu merger took place	sure happened usairways status merger took place	[sure, happen, usairway, statu, merger, took, ...
2350	0	@united is probably the least satisfactory air...	probabl least satisfactori airlin ever never f...	probably least satisfactory airline ever never...	[probabl, least, satisfactori, airlin, ever, n...
14620	0	@AmericanAir I wait 2+ hrs for CS to call me b...	wait 2 hr cs call back flt cxld protect amp ha...	wait 2 hrs cs call back flt cxld protection am...	[wait, 2, hr, cs, call, back, flt, cxld, prote...

In [143…

```
data['y_pred']= y_pred
data.head()
```

Out[143…

	sentiment	text	clean_tweet	clean_tweet_wt_stem	tokens	y_pred
2136	0	@United Can you increase the legroom? : How ai...	increas legroom airlin compar via cnnmoney	increase legroom airlines compare via cnnmoney	[increas, legroom, airlin, compar, via, cnnmoney]	1
7416	0	@JetBlue Third straight time that my flight ha...	third straight time flight delay fli guy last ...	third straight time flight delayed flying guys...	[third, straight, time, flight, delay, fli, gu...	0
11985	0	@AmericanAir I'm not sure what happened to my ...	sure happen usairway statu merger took place	sure happened usairways status merger took place	[sure, happen, usairway, statu,	1

	sentiment	text	clean_tweet	clean_tweet_wt_stem	tokens	y_pred
					merger, took, ...	
2350	0	@united is probably the least satisfactory air...	probabl least satisfactori airlin ever never f...	probably least satisfactory airline ever never...	[probabl, least, satisfactori, airlin, ever, n...	0
14620	0	@AmericanAir I wait 2+ hrs for CS to call me b...	wait 2 hr cs call back flt cxld protect amp ha...	wait 2 hrs cs call back flt cxld protection am...	[wait, 2, hr, cs, call, back, flt, cxld, prote...	0

In [144…
```
# Extracting negative tweets
df_neg = data[data['y_pred']==0]['clean_tweet_wt_stem']
df_neg.head()
```

Out[144…
```
7416     third straight time flight delayed flying guys...
2350     probably least satisfactory airline ever never...
14620    wait 2 hrs cs call back flt cxld protection am...
9965     yesterday delayed six hours w lil explanation ...
6911     ok cancelled flight flight 1274 tmrw weather a...
Name: clean_tweet_wt_stem, dtype: object
```

In [145…
```
# Viewing first 5 tweets
df_neg[:3]
```

Out[145…
```
7416     third straight time flight delayed flying guys...
2350     probably least satisfactory airline ever never...
14620    wait 2 hrs cs call back flt cxld protection am...
Name: clean_tweet_wt_stem, dtype: object
```

In [146…
```
# Extracting negative tweets
df_pos = data[data['y_pred']==2]['clean_tweet_wt_stem']
df_pos.head()
```

Out[146…
```
1404     belabor point able put laptop bag seat announc...
4317                                 still waiting reply
10149    family friends colleagues never fly usair bad ...
9970     suggest failures make huge donation uso charlo...
8723     shout crew flight 89 headed back big apple kep...
Name: clean_tweet_wt_stem, dtype: object
```

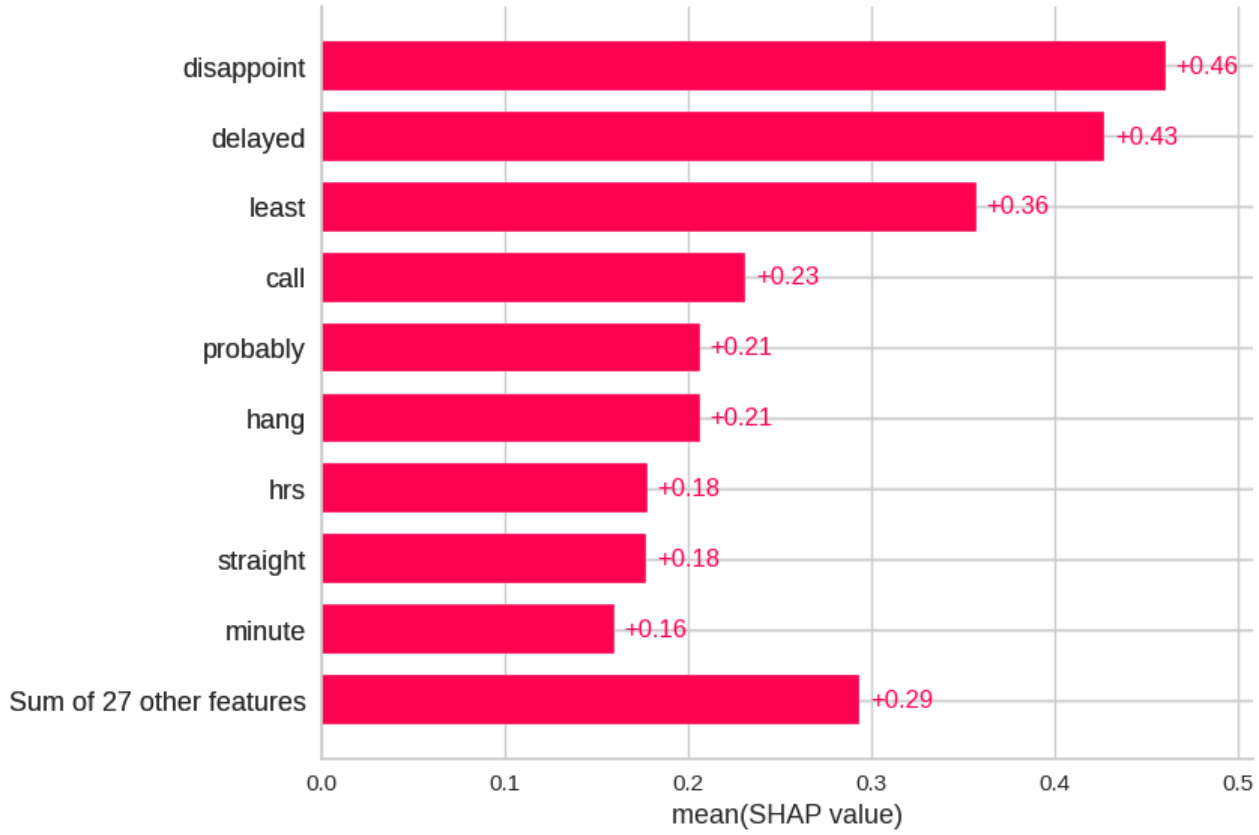
In [147…
```
df_pos[:6]
```

Out[147…
```
1404     belabor point able put laptop bag seat announc...
4317                                 still waiting reply
10149    family friends colleagues never fly usair bad ...
9970     suggest failures make huge donation uso charlo...
8723     shout crew flight 89 headed back big apple kep...
9186     yay glitchy tracking system bags made destinat...
Name: clean_tweet_wt_stem, dtype: object
```

Plotting Negative Tweets

In [148…
```
# Get the shap_values for the 3 rows
shap_values_neg = explainer(df_neg[:3])
```

In [149…
```
shap.plots.bar(shap_values_neg[:, :, 0].mean(0))
```



Plotting Positive Tweets

In [150…
```
# Extracting negative tweets
df_pos = data[data['y_pred']==2]['clean_tweet_wt_stem']
df_pos.head()
```

Out[150…
```
1404     belabor point able put laptop bag seat announc...
4317                                  still waiting reply
10149    family friends colleagues never fly usair bad ...
9970     suggest failures make huge donation uso charlo...
8723     shout crew flight 89 headed back big apple kep...
Name: clean_tweet_wt_stem, dtype: object
```

In [151…
```
# Obtaining 15 first positive tweets.
shap_values_pos = explainer(df_pos[:15])
```

```
Partition explainer:  87%|████████▋ | 13/15 [00:26<00:03,  1.65s/it]
```

```
Partition explainer: 16it [00:34,  3.13s/it]
```

In [152…
```
# Plotting the shap values
shap.plots.text(shap_values_pos)
```

[0]

outputs

LABEL_0 LABEL_1 LABEL_2

inputs

belabor point able put laptop bag seat announced leave rollers thx

[1]

outputs

LABEL_0 LABEL_1 LABEL_2

inputs

still waiting reply

[2]

outputs

LABEL_0 LABEL_1 LABEL_2

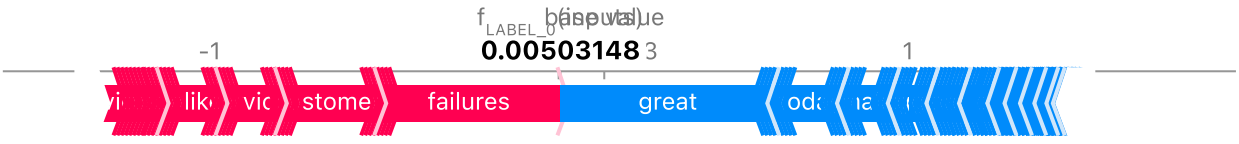
inputs

family friends colleagues never fly usair bad weather happens good airlines seem communicate better

[3]

outputs

LABEL_0 LABEL_1 LABEL_2



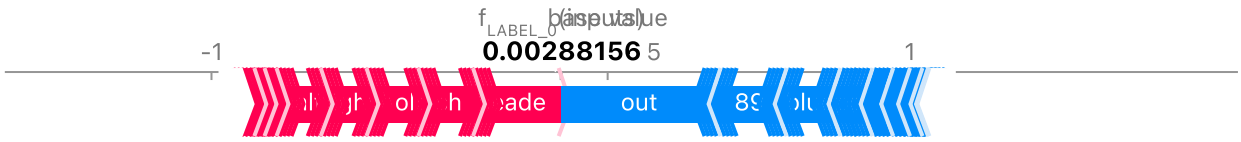
inputs

suggest failures make huge donation uso charlotte nc provided great customer service today unlike

[4]

outputs

LABEL_0 LABEL_1 LABEL_2



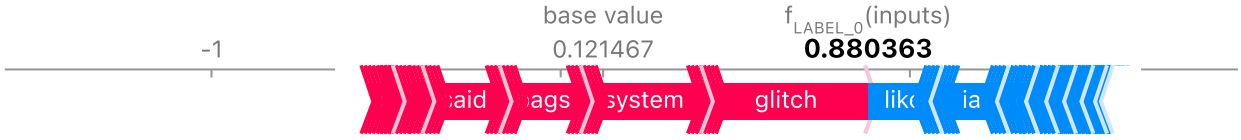
inputs

shout crew flight 89 headed back big apple kept glass half full whole flight jetbluejfk

[5]

outputs

LABEL_0 LABEL_1 LABEL_2



inputs

yay glitchy tracking system bags made destination laguardia like app said

[6]

outputs

LABEL_0 LABEL_1 LABEL_2

inputs

thank 7 hrs terminal dulles airport

[7]

outputs

LABEL_0 LABEL_1 LABEL_2

inputs

items sentimental value heartbroken missing

[8]

outputs

LABEL_0 LABEL_1 LABEL_2

inputs

tried ten times last night morning many times try meetings make tonight atx

[9]

outputs

LABEL_0 LABEL_1 LABEL_2

inputs

pretty hilarious want sweetingr finish awful experience something make right

[10]

outputs

LABEL_0 LABEL_1 LABEL_2

inputs

hey guys remembered lol bos flights delayed turn heat t5 feels hotter pr

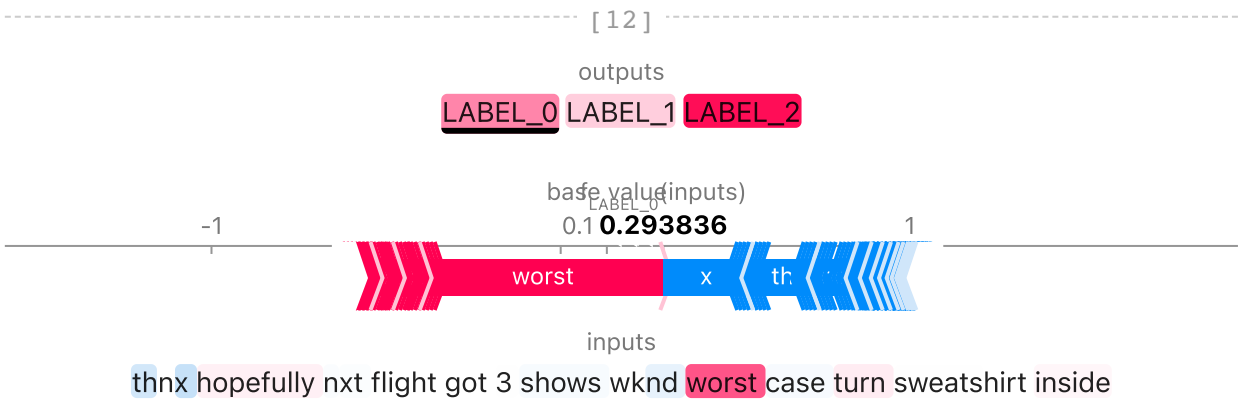
[11]

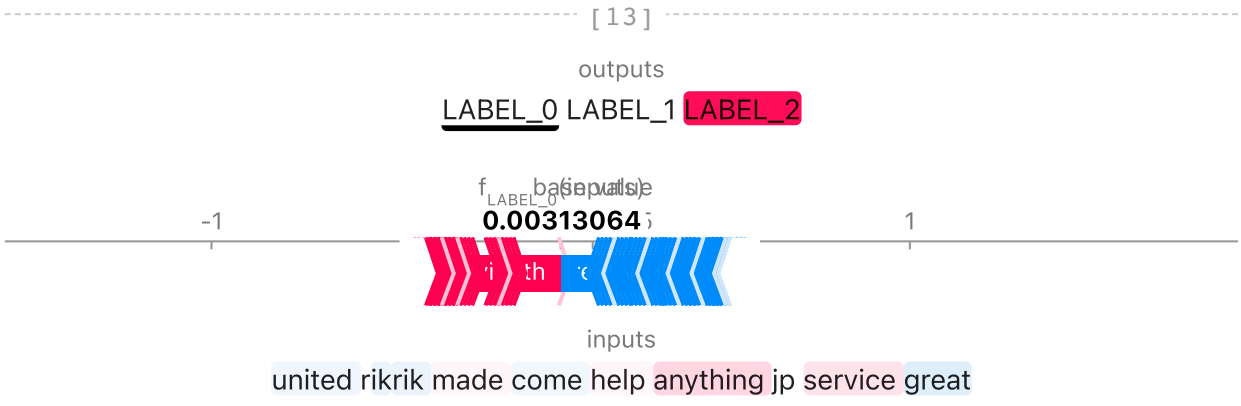
outputs

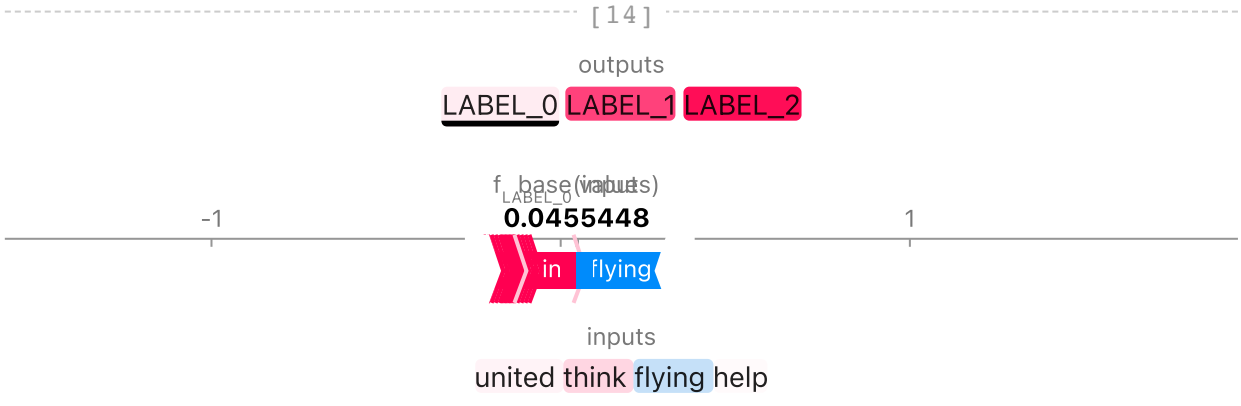
LABEL_0 LABEL_1 LABEL_2

inputs

good chance anyone else airport ever flight booking problems southwest



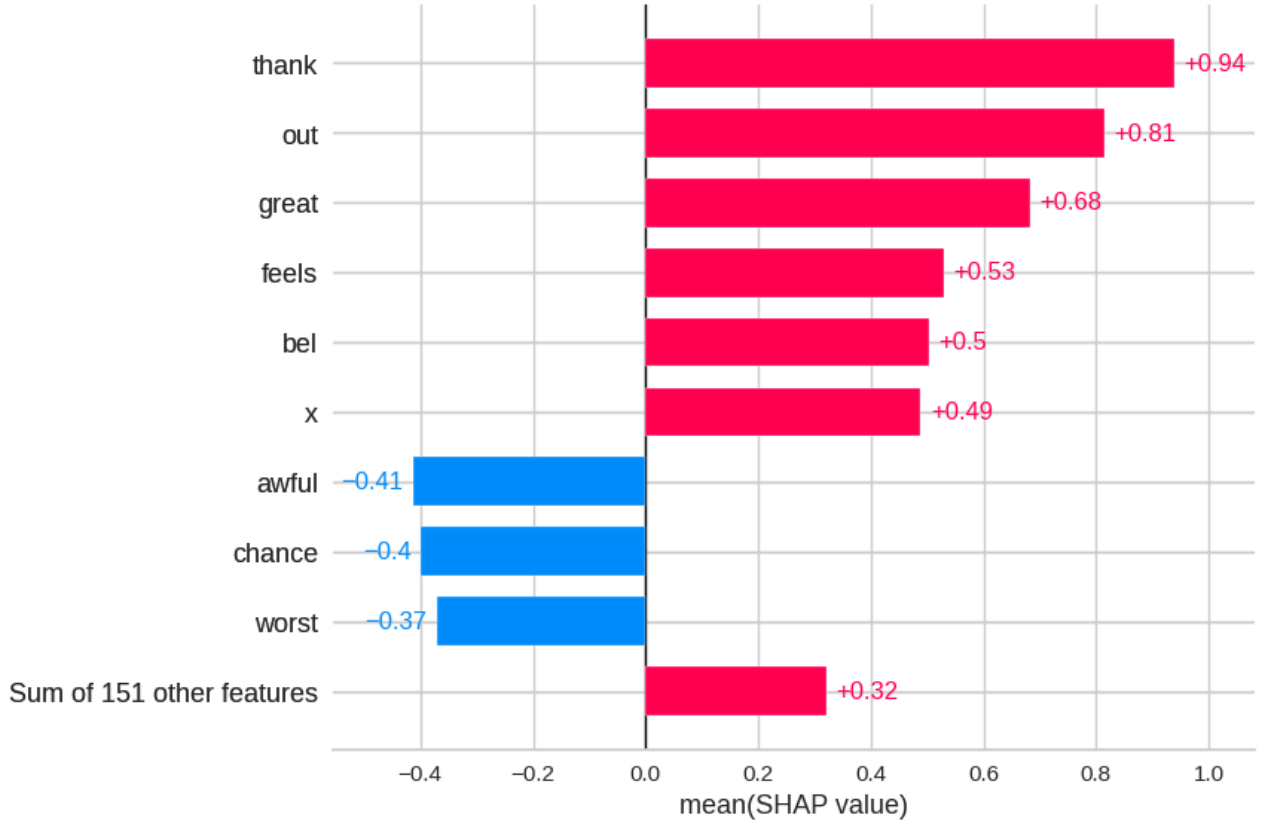




In [153…
```
print(shap_values_pos.shape)
```

```
(15, None, 3)
```

In [154…
```
# Create a bar plot of the SHAP values in the positive tweets.
shap.plots.bar(shap_values_pos[:, :, 2].mean(0))
```



Conclusion:

Given that customer service is a critical issue, here are few suggestions US airlines should implement comprehensive customer service training and rewards for exceptional service.

US airlines can improve flight delays by increasing efficiency in turnaround times and improving scheduling. We suggest that government agencies work with airlines to promote and incentivize these improvements.

US airlines should strive to do more of what customers appreciate, such as providing a positive and caring flight experience with attentive service and going above and beyond to help during flights. This can involve faster response times for customer issues and proactive inquiries about customer needs during flights.

Topic Modeling - US Airlines

- Student name: Natalia Edelson
- Student pace: Flex
- Scheduled project review date/time: April 19, 2023
- Instructor name: Morgan Jones
- Blog: https://medium.com/@nataliagoncharov/analyzing-customer-sentiment-for-major-us-airlines-on-twitter-6656d23b1800

```
!pip install -q scikit-learn==1.1.3
!pip install -q pyLDAvis==2.1.2
```

```
import pandas as pd
import os
from tqdm.notebook import tqdm
tqdm.pandas()
import re
import spacy
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from spacy.language import Language
from spacy import displacy
from gensim.models.ldamodel import LdaModel
from gensim.corpora.dictionary import Dictionary
from gensim.models.coherencemodel import CoherenceModel
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.decomposition import LatentDirichletAllocation

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

The LDA(Latent Dirichlet Allocation) model is an unsupervised machine learning technique used to identify the topics in a corpus. It achieves this by assigning a distribution of topics and then words to each topic. Specifically, each topic is a probability distribution over words.

The coherence score is a measure of how well the topics generated by the LDA model are meaningful and interpretable. A higher coherence score indicates better topic coherence and a higher degree of similarity between the words in a topic. The coherence score is calculated using the u_mass matrix, which is based on the co-occurrence of words within the corpus.

The function finds the optimal number of topics based on the highest coherence score, which is calculated using the co-occurrence of words within the corpus.

```
# Retrieving data to perform topic modeling
data = pd.read_csv('topic.csv')
```

```
# Only including the cleaned without stem column
data = data['clean_tweet_wt_stem'].loc[data['sentiment'] == 0]
```

```
# Dropping all hte null values
data.dropna(inplace=True)
```

```
data
```

```
0         increase legroom airlines compare via cnnmoney
1      third straight time flight delayed flying guys...
2       sure happened usairways status merger took place
3      probably least satisfactory airline ever never...
4      wait 2 hrs cs call back flt cxld protection am...
                            ...
571    son passenger flight 3710 chicago toronto plan...
572                                 inadequate accident
573    brothers baggage lost route 2015 panamerican c...
574      different airport way getting different airport
575    cancelled flightled none passengers notified c...
Name: clean_tweet_wt_stem, Length: 576, dtype: object
```

The bellow function performs topic modeling on a list of tweets using Latent Dirichlet Allocation (LDA) and selects the optimal number of topics based on coherence scores.

```
docs = [] # Initializing list
for tweet in tqdm(data): # loop through tweets
    docs.append(tweet)  # add to the list

# Merge the words into a single string
vocab_size = len(set(" ".join(docs).split(" ")))

# Converting into tokens
tokens = [text.split() for text in docs]

# Storing using class to map words to integers ids
id2word = Dictionary(tokens)

# Storing into corpus using method to generate
# no. of times word appears
corpus = [id2word.doc2bow(text) for text in tokens]

#Setting up LDA model

coh = []
for i in tqdm(range(5,30)):
    model = LdaModel(corpus, i, id2word,random_state=42)
    cm = CoherenceModel(model=model, corpus=corpus,
                        coherence='u_mass')
    coherence = cm.get_coherence()  # get coherence value
```

```
    coh.append(coherence)

# Setting up ploting details
plt.plot(range(5,30),coh)
plt.title('Coherence Score Vs Number of Topics (k)')
plt.xlabel('Number of Topics (k)')
plt.ylabel('Coherence Score')
plt.show()

# calculating for different numbers of topics
# 'np.array(coh).argmax()' finds the index of the maximum coherence score
# '+ 5' is added to the index, assuming the number of topics started from 5


k_topic = np.array(coh).argmax() + 5

print('No of Topic Selected by Coherence Score:',k_topic)
```

100% 576/576 [00:00<00:00, 32247.94it/s]

100% 25/25 [00:32<00:00, 1.11s/it]

```
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider i
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider i
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider i
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider i
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider i
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider i
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider i
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider i
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider i
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider i
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider i
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider i
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider i
```

```
# Creating a TfidfVectorizer object with vocab_size features,
# 0.95 max document frequency, and English stop words

tfidf_featurizer = TfidfVectorizer(max_features=vocab_size, 
                                       max_df=0.95, stop_words='english')

# Transforming the list of documents into a matrix of numerical features 
# using TfidfVectorizer fit_transform method
docs_tfidf = tfidf_featurizer.fit_transform(docs) 
```

```
import pyLDAvis.sklearn
```

```
pyLDAvis.enable_notebook() # To enable the visualization on the notebook
```

```
/usr/local/lib/python3.9/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `
  and should_run_async(code)
```

```
# Creating an LDA_model object with k_topic topics and a random state of 42
LDA_model = LatentDirichletAllocation(n_components=k_topic, random_state=42)

# Fitting the TF-IDF matrix (docs_tfidf) to the LDA model
LDA_model.fit(docs_tfidf)
```

```
/usr/local/lib/python3.9/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `
  and should_run_async(code)
```

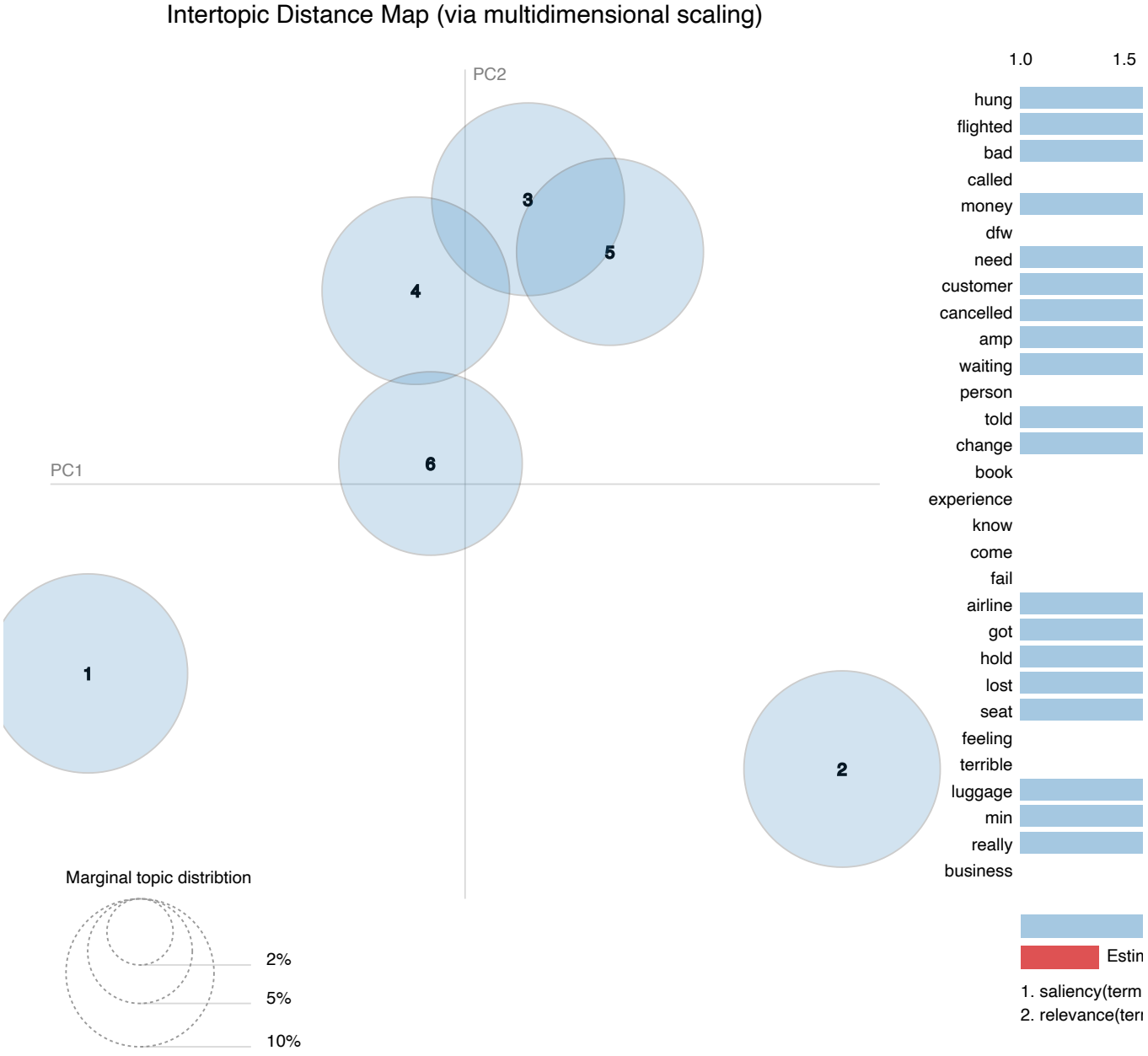
```
▾ LatentDirichletAllocation
LatentDirichletAllocation(n_components=6, random_state=42)
```

```
 # Creating a visualization panel for the LDA model using pyLDAvis
panel = pyLDAvis.sklearn.prepare(LDA_model, docs_tfidf, tfidf_featurizer)
panel
```

```
/usr/local/lib/python3.9/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `
  and should_run_async(code)
```

Selected Topic: 0 Previous Topic Next Topic Clear Topic

Slide to adju




```
pyLDAvis.save_html(panel, 'lda.html')
```

```
/usr/local/lib/python3.9/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `
  and should_run_async(code)
```

```
from google.colab import files
files.download('lda.html')
```

```
/usr/local/lib/python3.9/dist-packages/ipykernel/ipkernel.py:283: DeprecationWar
  and should_run_async(code)
```

Conclusion:

Based on the top keywords generated from the negative topic, it seems that the topic is related to complaints or negative feedback regarding flights. The top keywords "flighted", "bad", "called", "money", "need", "customer", "cancelled", "amp", "waiting", "person", "told", "change", "book", and "experience" suggest that customers are expressing frustration and dissatisfaction with airline travel due to a variety of issues, including flight cancellations, poor customer service, long wait times, and unhelpful staff.

This topic could represent a cluster of tweets that express negative sentiment or dissatisfaction with airline travel. It's important for airlines to monitor and address these types of complaints in order to improve the overall customer experience and reputation of their brand.