- Student name: Natalia Edelson
- Student pace: Flex
- Scheduled project review date/time: April 6, 2023
- Instructor name: Morgan Jones
- Blog: https://medium.com/p/f2eb4bd43db2

Table of Contents

Part 1

Importing Libraries

In [2]:
```
# Import Sklearn libraries to build models
from sklearn.feature_extraction.text import TfidfVectorizer #  TF-IDF to vectorize words
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
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

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
```

Importing the dataset

In [5]:

```
# Importing the dataset
DATASET_COLUMNS=["sentiment", "ids", "date", "flag", "user", "tweet"]
DATASET_ENCODING = "ISO-8859-1"
ta_df = pd.read_csv('training.1600000.processed.noemoticon.csv',
                    encoding=DATASET_ENCODING, names=DATASET_COLUMNS)

ta_df.head()
```

Out[5]:

	sentiment	ids	date	flag	user	tweet
0	0	1467810369	Mon Apr 06 22:19:45 PDT 2009	NO_QUERY	_TheSpecialOne_	@switchfoot http://twitpic.com/2y1zl - Awww, t...
1	0	1467810672	Mon Apr 06 22:19:49 PDT 2009	NO_QUERY	scotthamilton	is upset that he can't update his Facebook by ...
2	0	1467810917	Mon Apr 06 22:19:53 PDT 2009	NO_QUERY	mattycus	@Kenichan I dived many times for the ball. Man...

	sentiment	ids	date	flag	user	tweet
3	0	1467811184	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	ElleCTF	my whole body feels itchy and like its on fire
4	0	1467811193	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	Karoli	@nationwideclass no, it's not behaving at all....

In [6]:
```
# Sampling 30,000 tweets randomly
ta_df = ta_df.sample(30000,random_state=42)
```

In [7]:
```
# Checking the size of the data
ta_df.shape
```

Out[7]:
```
(30000, 6)
```

In [8]:
```
# 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'>
Int64Index: 30000 entries, 541200 to 1027373
Data columns (total 6 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   sentiment  30000 non-null  int64 
 1   ids        30000 non-null  int64 
 2   date       30000 non-null  object
 3   flag       30000 non-null  object
 4   user       30000 non-null  object
 5   tweet      30000 non-null  object
dtypes: int64(2), object(4)
memory usage: 1.6+ MB
```

In [9]:
```
# Checking the percentage of null values
ta_df.isna().mean()*100
```

Out[9]:
```
sentiment    0.0
ids          0.0
date         0.0
flag         0.0
user         0.0
tweet        0.0
dtype: float64
```

In [10]:
```
# Checking to see that 'flag' column only has one value 'NP_QUERY'
ta_df['flag'].unique()
```

Out[10]:
```
array(['NO_QUERY'], dtype=object)
```

In [11]:
```
# Dropping 'flag' and 'ids' columns
ta_df.drop(['flag','ids'], axis=1, inplace = True)
```

In [12]:
```
# Checking that the changes took place
ta_df.head()
```

Out[12]:

	sentiment	date	user	tweet
541200	0	Tue Jun 16 18:18:12 PDT 2009	LaLaLindsey0609	@chrishasboobs AHHH I HOPE YOUR OK!!!
750	0	Mon Apr 06 23:11:14 PDT 2009	sexygrneyes	@misstoriblack cool , i have no tweet apps fo...
766711	0	Tue Jun 23 13:40:11 PDT 2009	sammydearr	@TiannaChaos i know just family drama. its la...
285055	0	Mon Jun 01 10:26:07 PDT 2009	Lamb_Leanne	School email won't open and I have geography ...
705995	0	Sat Jun 20 12:56:51 PDT 2009	yogicerdito	upper airways problem

In [13]:
```
# Checking length
print('length of data is', len(ta_df))
```

```
length of data is 30000
```

Distribution of Data - Target

In [14]:
```
# Check unique values in the sentiment column
ta_df['sentiment'].unique()
```

Out[14]:
```
array([0, 4])
```

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 [16]:
```
# Checking distribution
ta_df['sentiment'].value_counts()
```

Out[16]:
```
4    15001
0    14999
Name: sentiment, dtype: int64
```

In [13]:
```
# Replacing the value 4 -->1 for ease of understanding.
# 0 = negative, 1 = positive
ta_df['sentiment'] = ta_df['sentiment'].replace(4,1)
ta_df.head()
```

Out[13]:

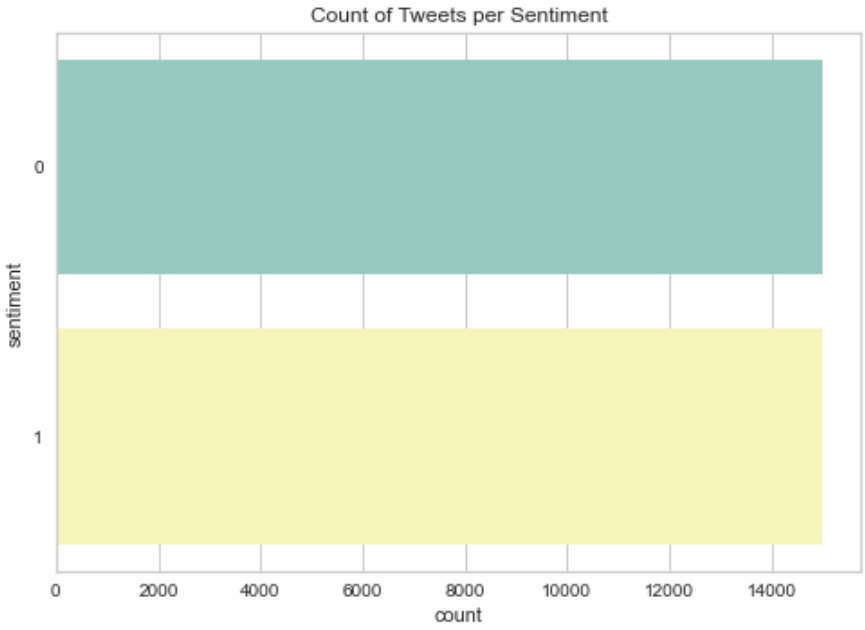
	sentiment	date	user	tweet
541200	0	Tue Jun 16 18:18:12 PDT 2009	LaLaLindsey0609	@chrishasboobs AHHH I HOPE YOUR OK!!!
750	0	Mon Apr 06 23:11:14 PDT 2009	sexygrneyes	@misstoriblack cool , i have no tweet apps fo...
766711	0	Tue Jun 23 13:40:11 PDT 2009	sammydearr	@TiannaChaos i know just family drama. its la...
285055	0	Mon Jun 01 10:26:07 PDT 2009	Lamb_Leanne	School email won't open and I have geography ...
705995	0	Sat Jun 20 12:56:51 PDT 2009	yogicerdito	upper airways problem

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:   4
Count of rows in the data is:   30000
```

Cleaning the data

- Checking and handling NaN values
- Drop duplicates

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

ta_df.dropna(inplace=True)
```

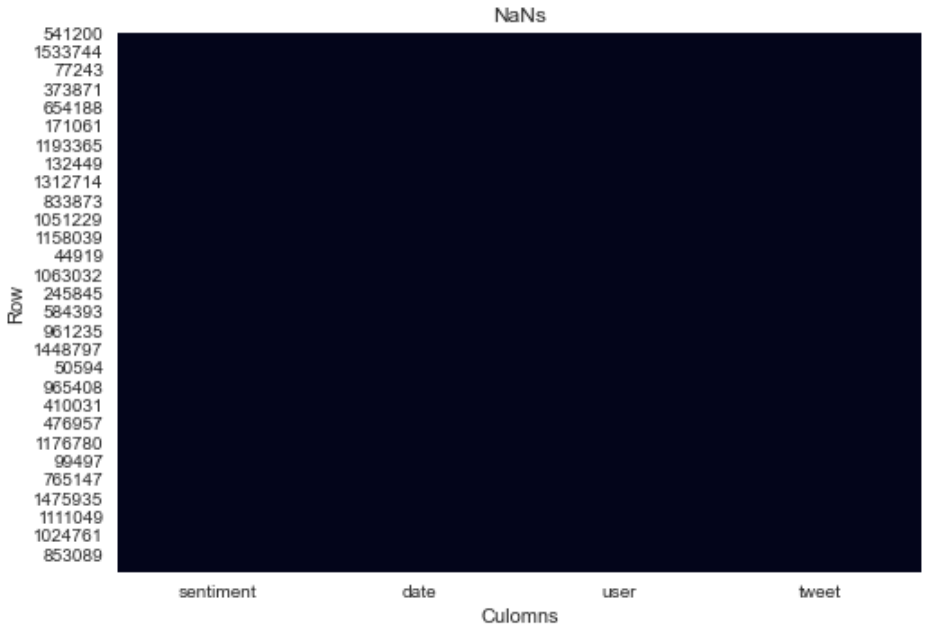
In [17]:
```
len(ta_df.duplicated(keep='last'))
```

Out[17]:
```
30000
```

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30000 entries, 541200 to 1027373
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   sentiment  30000 non-null  int64 
 1   date       30000 non-null  object
 2   user       30000 non-null  object
 3   tweet      30000 non-null  object
dtypes: int64(1), object(3)
memory usage: 1.1+ MB
```

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['tweet'].progress_apply(lambda x:preprocess(x,True))
)
```

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

Out[23]:
```
541200                                          ahh hope ok
750                                cool tweet app razr 2
766711    know famili drama lame hey next time u hang ki...
285055    school email open geographi stuff revis stupid...
705995                              upper airway problem
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['tweet']
    .progress_apply(lambda x: preprocess(x, False))
)
```

In [25]:
```
# ta_df.drop('clean_tweets',axis=1,inplace=True)
```

In [26]:
```
# Checking that the change has taken place.
ta_df.head()
```

Out[26]:

	sentiment	date	user	tweet	clean_tweet	clean_tweet_wt_stem
541200	0	Tue Jun 16 18:18:12 PDT 2009	LaLaLindsey0609	@chrishasboobs AHHH I HOPE YOUR OK!!!	ahh hope ok	ahh hope ok
750	0	Mon Apr 06 23:11:14 PDT 2009	sexygrneyes	@misstoriblack cool , i have no tweet apps fo...	cool tweet app razr 2	cool tweet apps razr 2
766711	0	Tue Jun 23 13:40:11 PDT 2009	sammydearr	@TiannaChaos i know just family drama. its la...	know famili drama lame hey next time u hang ki...	know family drama lame hey next time u hang ki...
285055	0	Mon Jun 01 10:26:07 PDT 2009	Lamb_Leanne	School email won't open and I have geography ...	school email open geographi stuff revis stupid...	school email open geography stuff revise stupi...
705995	0	Sat Jun 20 12:56:51 PDT 2009	yogicerdito	upper airways problem	upper airway problem	upper airways problem

In [27]:
```
ta_df['clean_tweet_wt_stem']
```

Out[27]:
```
541200                                          ahh hope ok
750                                cool tweet apps razr 2
766711    know family drama lame hey next time u hang ki...
```

```
285055     school email open geography stuff revise stupi...
705995                                 upper airways problem
                                  ...
263962     bout go eat eat sushi phoboy86 house hopefully...
1540392                    guess bus ride tour bus good job
1549636                                  hmm might go bed
706868     sounds suspiciously like year million dreams h...
1027373                                              problem
Name: clean_tweet_wt_stem, Length: 30000, 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 [28]:
```
def red_color_func(word, font_size, position, orientation,
                   random_state=None,**kwargs):
    return tuple(Reds_9.colors[random.randint(6,8)])
```

In [29]:
```
# Function to help us generate wordcloud
def red_color_func(word, font_size, position, orientation,
                   random_state=None,**kwargs):
    return tuple(Reds_9.colors[random.randint(6,8)])
```

In [30]:
```
# Storing clean tweets
tweets = ta_df['clean_tweet_wt_stem']
```

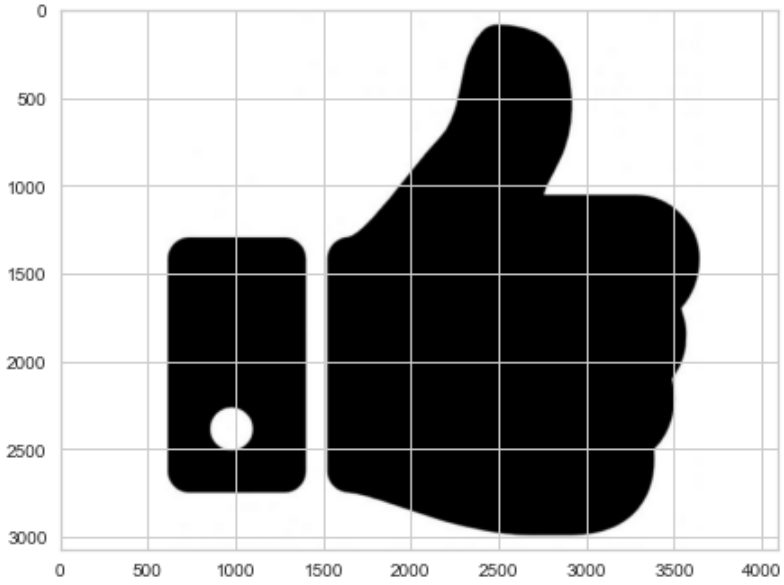
With these Series objects containing the preprocessed text, you can perform further analysis or visualization on the negative and positive tweets separately. We will be able to create separate word clouds for each sentiment group or calculate the most frequent words in each group.

In [31]:
```
# 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']==1]
```

In [32]:
```
# 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']
```

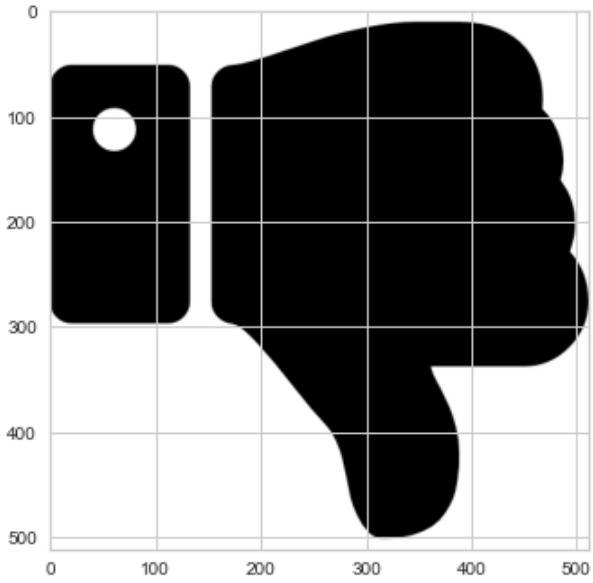
In [33]:
```
# Resizing  it to a 20x20 size using the Image.ANTIALIAS filter
img = Image.open('upvote.png')
img.resize((20, 20), Image.ANTIALIAS)
plt.imshow(img) # show output
```

Out[33]:
```
<matplotlib.image.AxesImage at 0x7fb256aff280>
```



In [34]:
```
# 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[34]: <matplotlib.image.AxesImage at 0x7fb255a0f2e0>



In [35]:
```
def wc(data, mask,fname):

    plt.figure(figsize = (50,50))

    wc = WordCloud(width = 300, height = 200,
                   background_color='white',
                   max_words = 50,  max_font_size =300,
                   colormap='rainbow',mask=mask)

    wc.generate(' '.join(data))

    plt.imshow(wc)
    plt.grid(visible=False)
```

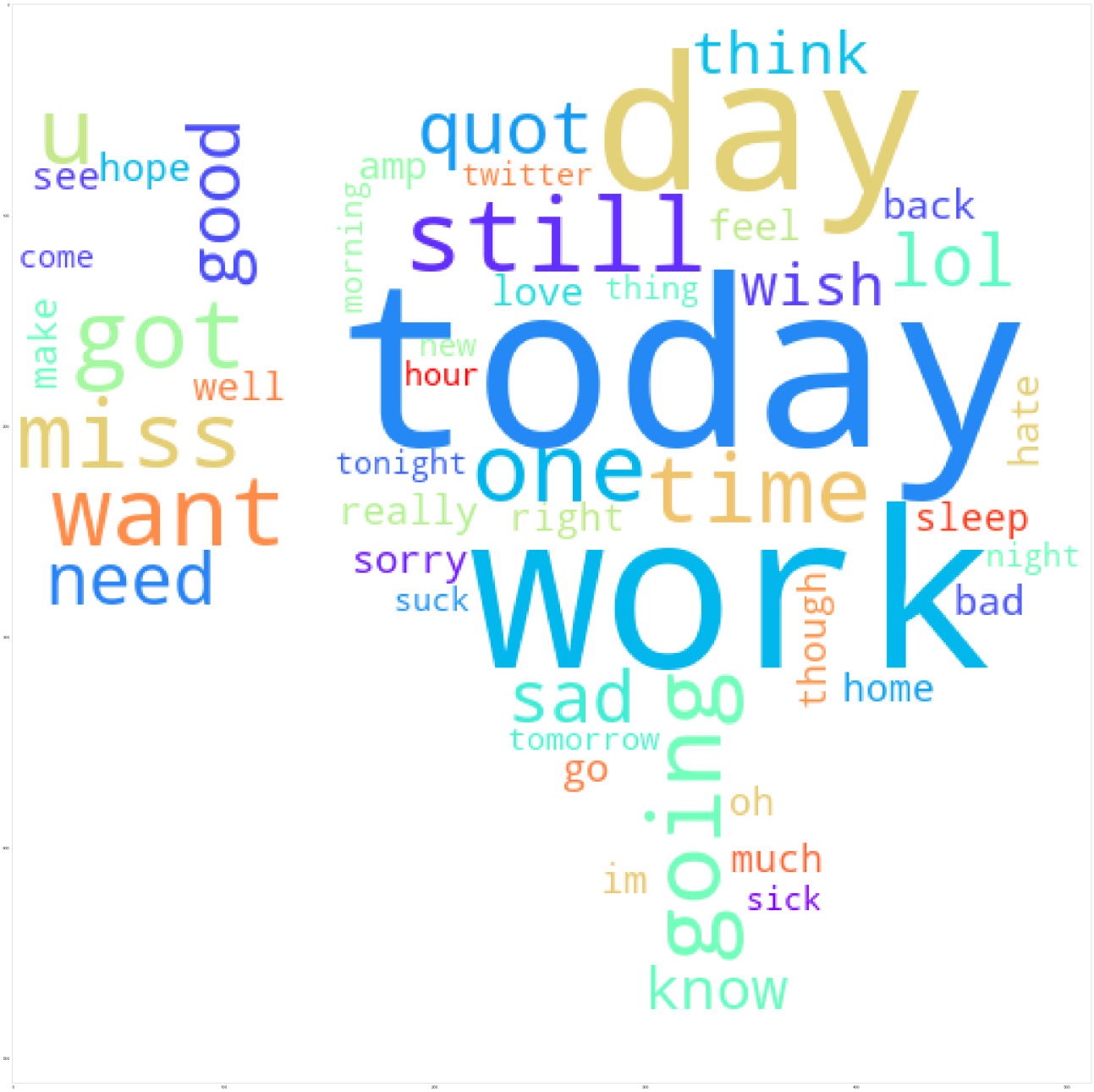
```
    plt.savefig(f'{fname}.png',dpi=200)
#   plt.axis('off')
```

In [36]:

```
mask_pos = np.array(Image.open('upvote.png'))

wc(tweet_positive, mask_pos,'positive')
```

In [37]:

```
mask_neg = np.array(Image.open('final.png'))
wc(tweet_negative, mask_neg, 'negative')
```



Words appear most frequently in a positive tweet:

“Thank,” “Haha, “Love ,” “Good,” and “lol”

This might suggest that many of the positive tweets e]s on feelings of appreciation, laughter and love. On the other hand, in negative tweets, these are the most common words:

“Miss,” “Today,” “Time,” “Still,” and “Wish”

These words possibly express frustration and dissatisfaction.

In [38]:
```
pos_df = (
    ta_df['clean_tweet']
    .loc[ta_df['sentiment'] == 1]
    .progress_apply(lambda line: line.split())
)
```

In [39]:
```
    ta_df['clean_tweet']
    .loc[ta_df['sentiment'] == 0]
    .progress_apply(lambda line: line.split())
)
```

In [40]:
```
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
```

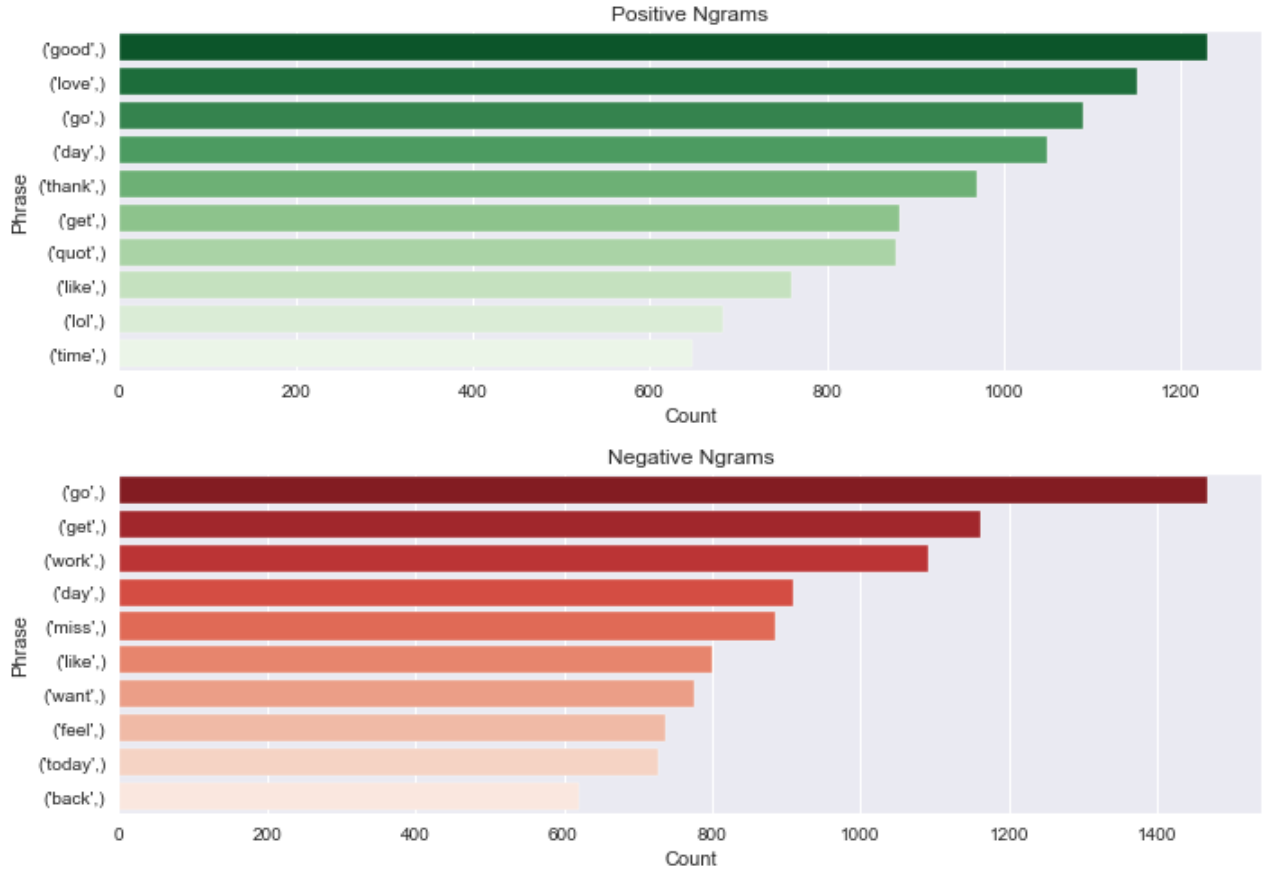
```
Total Corpus Tokens: 106790
Number of Positive Tokens: 106790
Number of Negative Tokens: 109861
```

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).

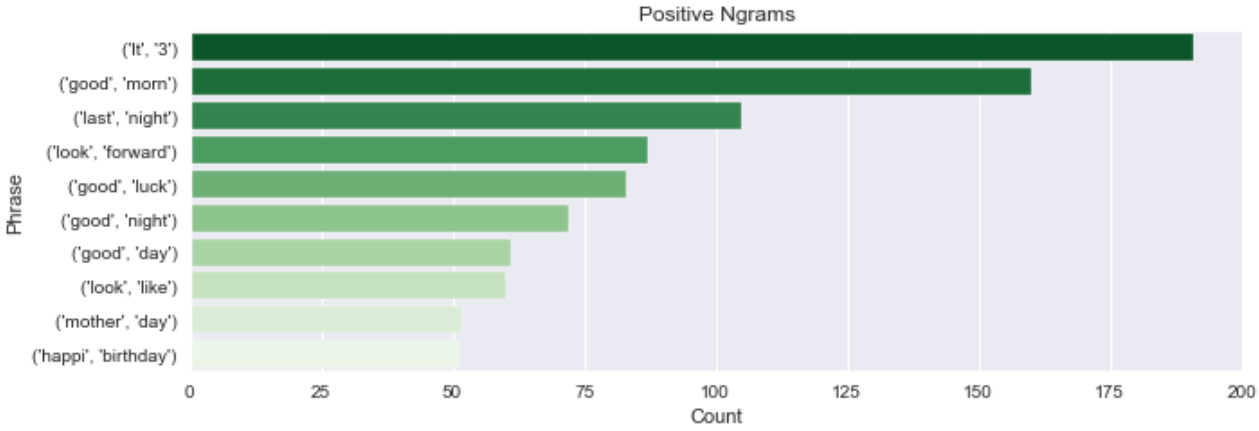
In [42]:
```
# Defining function

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,
```

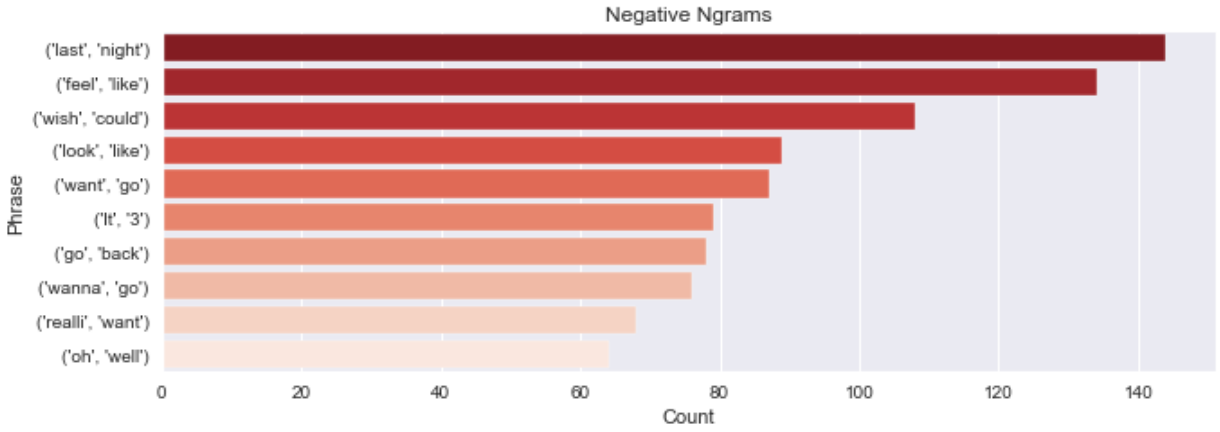
```
                    # Assigning barplot to positive ngrams
                    palette = 'Greens_r').set(title = 'Positive Ngrams')
        sns.barplot(ax = ax2, x = 'Count', y = 'Phrase', data = n_gram_df_neg,
                    # Assigning barplot to negative ngrams
                   palette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


    plt.tight_layout() #Make plot layouts tight

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



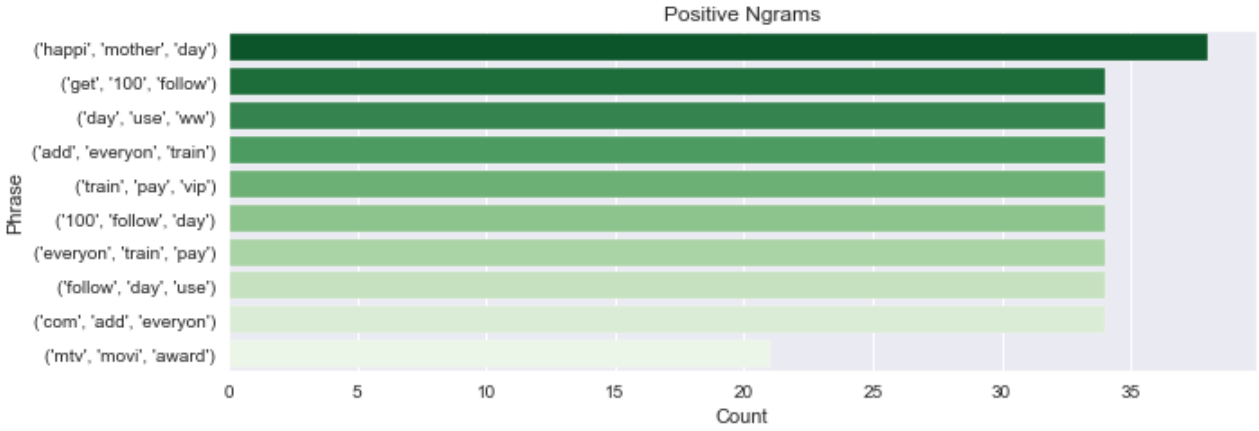
In [43]:

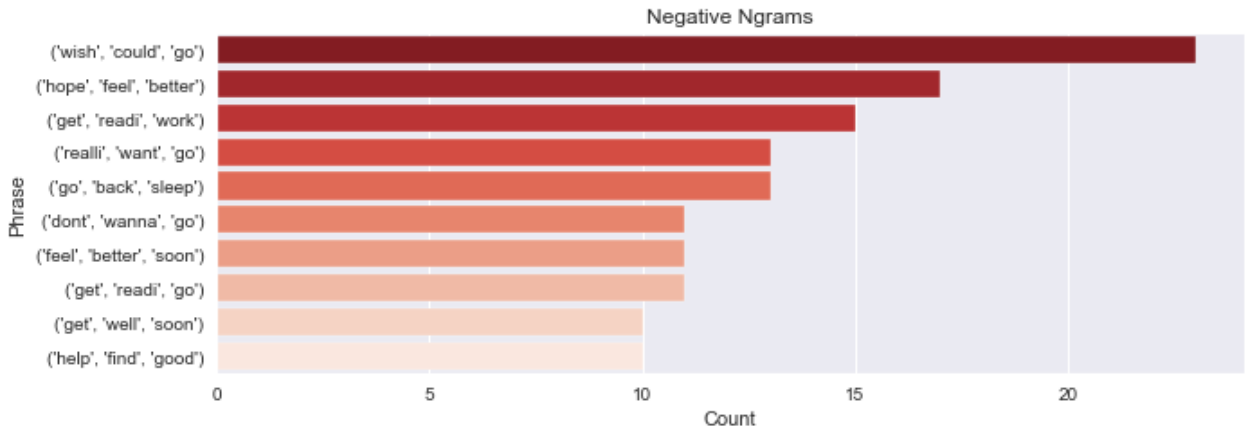
```
make_ngram(2) #Plot 2 word ngrams
```





In [44]:
```
make_ngram(3) #Plot 3 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.

Split Data

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 [45]:
```
# Splitting data target and clean tweets

X = ta_df['clean_tweet'] # 30,000

y = ta_df['sentiment'] # 30,000
```

In [46]:
```
# List of unique sentiment values

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

Out[46]:
```
[0, 1]
```

In [47]:
```
# View independent

y.head()
```

Out[47]:
```
541200    0
750       0
766711    0
285055    0
705995    0
Name: sentiment, dtype: int64
```

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

Out[48]:
```
1    15001
0    14999
Name: sentiment, dtype: int64
```

In [49]:
```
# 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)
```

In [50]:
```
# Checking shape of train and test data

print(X_train.shape, y_train.shape)
print(X_test.shape , y_test.shape)
```

```
(22500,) (22500,)
(7500,) (7500,)
```

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 [75]:
```
# Initializing TFIDF
vectoriser_tfidf = TfidfVectorizer()
```

In [76]:
```
# Fit the data
vectoriser_tfidf.fit(X_train)

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

```
Number of feature words: 18078
```

In [77]:
```
# 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 [78]:
```
# Initializing countvector
vectorizer_vc = CountVectorizer()
# Fitting countvector
vectorizer_vc.fit(X_train)
```

Out[78]:
```
▾ CountVectorizer
CountVectorizer()
```

In [79]:
```
# 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 [58]:
```
# Initializing corpus using funciton progress_apply
# to go though each row and tokenize
corpus = X.progress_apply(lambda line:line.split())
```

In [59]:
```
# View corpus
corpus
```

Out[59]:
```
541200                                        [ahh, hope, ok]
750                                 [cool, tweet, app, razr, 2]
766711     [know, famili, drama, lame, hey, next, time, u...
285055     [school, email, open, geographi, stuff, revis,...
705995                               [upper, airway, problem]
                                  ...
263962     [bout, go, eat, eat, sushi, phoboy86, hous, ho...
1540392               [guess, bu, ride, tour, bu, good, job]
1549636                                [hmm, might, go, bed]
706868     [sound, suspici, like, year, million, dream, h...
1027373                                            [problem]
Name: clean_tweet, Length: 30000, dtype: object
```

In [60]:
```
# Train Word2Vec Model on corpus
import warnings

warnings.filterwarnings(action = 'ignore')


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 [62]:
```
# Creating a new column of tokenized tweets
ta_df['tokens'] = (
    ta_df['clean_tweet']
    .progress_apply(lambda line: line.split())
)
```

In [63]:
```
# Checking that change took place
ta_df.head()
```

Out[63]:

	sentiment	date	user	tweet	clean_tweet	clean_tweet_wt_stem	tokens
541200	0	Tue Jun 16 18:18:12	LaLaLindsey0609	@chrishasboobs AHHH I HOPE YOUR OK!!!	ahh hope ok	ahh hope ok	[ahh, hope, ok]

	sentiment	date	user	tweet	clean_tweet	clean_tweet_wt_stem	tokens
		PDT 2009					
750	0	Mon Apr 06 23:11:14 PDT 2009	sexygrneyes	@misstoriblack cool , i have no tweet apps fo...	cool tweet app razr 2	cool tweet apps razr 2	[cool, tweet, app, razr, 2]
766711	0	Tue Jun 23 13:40:11 PDT 2009	sammydearr	@TiannaChaos i know just family drama. its la...	know famili drama lame hey next time u hang ki...	know family drama lame hey next time u hang ki...	[know, famili, drama, lame, hey, next, time, u...
285055	0	Mon Jun 01 10:26:07 PDT 2009	Lamb_Leanne	School email won't open and I have geography ...	school email open geographi stuff revis stupid...	school email open geography stuff revise stupi...	[school, email, open, geographi, stuff, revis,...
705995	0	Sat Jun 20 12:56:51 PDT 2009	yogicerdito	upper airways problem	upper airway problem	upper airways problem	[upper, airway, problem]

In [64]:
```
# 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 [66]:
```
# View tokens
ta_df['tokens']
```

Out[66]:
```
541200                                      [ahh, hope, ok]
750                                [cool, tweet, app, razr, 2]
766711     [know, famili, drama, lame, hey, next, time, u...
285055     [school, email, open, geographi, stuff, revis,...
705995                                [upper, airway, problem]
                                  ...
263962     [bout, go, eat, eat, sushi, phoboy86, hous, ho...
1540392               [guess, bu, ride, tour, bu, good, job]
1549636                                  [hmm, might, go, bed]
706868     [sound, suspici, like, year, million, dream, h...
1027373                                             [problem]
Name: tokens, Length: 29855, dtype: object
```

In [68]:
```
# Storing the tokenized text data and corresponding sentiment labels
X_w2v = ta_df['tokens']
y_w2v = ta_df['sentiment']
```

In [69]:
```
# Length of the embedding
len(X_w2v)
```

Out[69]:
```
29855
```

In [70]:
```
# model.wv.get_vector('there')
```

In [71]:
```
# Creating a set of all words in the vocabulary of a trained Word2Vec model
all_word2vec_vocab = set(model.wv.key_to_index)
```

In [81]:
```
# 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 + model.wv.get_vector(token)

    else: # if not  in the vocabulary of Word2Vec
            # Using levenshtein distance between the token and takes 2nd element
            temp = sorted([(textdistance.levenshtein.normalized_distance(e, token),
                            e) for e in all_word2vec_vocab],reverse=False)[0][1]
            embed = embed + model.wv.get_vector(temp) #  Adding the selected word
    return embed/n # Averaging of the word embeddings

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

In [82]:
```
# Applying the function to each row  (200 dimensional embedding)
X_w2v_embed = X_w2v.progress_apply(get_embed)
```

In [83]:
```
# View embedding
X_w2v_embed
```

Out[83]:
```
541200     [0.06851391276965539, -0.09154102951288223, -0...
750        [0.034500939678400754, -0.0822992317378521, -0...
766711     [0.06930903100261562, -0.07717739801706844, -0...
285055     [0.018783764928230084, -0.12192256841808558, -...
705995     [0.01074135295736293, -0.06879128531242411, 0....
                                ...
263962     [0.02220468013204963, -0.1353233720668975, -0....
1540392    [0.07094248304409641, -0.08008804558111089, -0...
1549636    [0.04116647597402334, -0.10027825180441141, -0...
706868     [0.027969976741587743, -0.08249159273691475, -...
1027373    [0.0009594860021024942, -0.1414019614458084, -...
Name: tokens, Length: 29855, dtype: object
```

In [85]:
```
# Creating a dataframe
df_new = pd.DataFrame(X_w2v_embed)
```

In [86]:
```
# Reseting index
df_new.reset_index(drop=True,inplace=True)
```

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

In [88]:
```
#  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 [89]:
```
# Dropping tokens
df_new.drop('tokens',axis=1,inplace=True)
```

In [90]:
```
# View data frame
df_new.head()
```

Out[90]:

	0	1	2	3	4	5	6	7	8	
0	0.068514	-0.091541	-0.103803	0.324743	0.097741	-0.216004	0.068874	0.436102	-0.065999	0.2
1	0.034501	-0.082299	-0.048294	0.174695	0.182607	-0.286788	0.030019	0.316800	-0.020411	0.0
2	0.069309	-0.077177	-0.095453	0.218893	0.107716	-0.263946	0.037270	0.386705	-0.013344	0.1
3	0.018784	-0.121923	-0.020300	0.237091	0.148512	-0.247636	0.019359	0.403607	-0.119163	0.2
4	0.010741	-0.068791	0.008459	0.073478	0.079290	-0.127433	0.000541	0.197276	-0.069902	0.05
...	...	...	...	...	...	...	...	...	...	
29850	0.022205	-0.135323	-0.011604	0.220139	0.107597	-0.204771	-0.014877	0.404414	-0.143336	0.1
29851	0.070942	-0.080088	-0.034401	0.194365	0.149497	-0.248896	0.053803	0.404973	-0.093688	0.1
29852	0.041166	-0.100278	-0.016394	0.245068	0.108878	-0.250209	0.065530	0.470274	-0.164613	0.2
29853	0.027970	-0.082492	-0.038959	0.136888	0.159569	-0.186139	-0.029539	0.321192	-0.009501	0.07
29854	0.000959	-0.141402	-0.001341	0.146052	0.151828	-0.251664	0.022471	0.382959	-0.117100	0.0

29855 rows × 200 columns

In [91]:
```
# 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 [80]:
```
# Building a function that will fit the model and
# then fit it to produce predicted values.

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)
    recall = recall_score(y_test,y_preds)
    f1 = f1_score(y_test,y_preds)

    # 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
```

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 [92]:

```
%%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 = []
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.toarray()
        x_test_temp = X_test_w2v.toarray()

    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)

    #     x_probs.append(x_prob)
    #     pipe_models.append(pipe_model)
        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 [08:56, 536.25s/it]
RandomForestClassifier(n_jobs=-1)
2it [17:02, 507.05s/it]
XGBClassifier(base_score=None, booster=None, colsample_bylevel=None,
              colsample_bynode=None, colsample_bytree=None, gamma=None,
              gpu_id=None, importance_type='gain', interaction_constraints=None,
              learning_rate=None, max_delta_step=None, max_depth=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=-1, num_parallel_tree=None,
              random_state=None, reg_alpha=None, reg_lambda=None,
              scale_pos_weight=None, subsample=None, tree_method=None,
              validate_parameters=None, verbosity=None)
[16:35:30] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6691-43e9a6c0910
f/volume/xgboost-split_1619728204606/work/src/learner.cc:1061: Starting in XGBoost 1.3.0, t
he default evaluation metric used with the objective 'binary:logistic' was changed from 'er
ror' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
3it [1:51:06, 2222.06s/it]
CountVector
0it [00:00, ?it/s]
GaussianNB()
1it [02:47, 167.58s/it]
RandomForestClassifier(n_jobs=-1)
2it [47:03, 1631.06s/it]
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.300000012, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=-1, num_parallel_tree=1, random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=None)
[18:11:28] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6691-43e9a6c0910
f/volume/xgboost-split_1619728204606/work/src/learner.cc:1061: Starting in XGBoost 1.3.0, t
he default evaluation metric used with the objective 'binary:logistic' was changed from 'er
ror' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
3it [1:08:16, 1365.50s/it]
0it [00:00, ?it/s]
Word2Vec
GaussianNB()
1it [00:41, 41.56s/it]
RandomForestClassifier(n_jobs=-1)
2it [02:27, 79.16s/it]
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.300000012, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=-1, num_parallel_tree=1, random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=None)
[18:49:39] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6691-43e9a6c0910
f/volume/xgboost-split_1619728204606/work/src/learner.cc:1061: Starting in XGBoost 1.3.0, t
he default evaluation metric used with the objective 'binary:logistic' was changed from 'er
ror' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
3it [38:10, 763.66s/it]
CPU times: user 2h 38min 6s, sys: 4h 45min 57s, total: 7h 24min 3s
Wall time: 3h 37min 35s
```

In [93]:
```
models_DataFrame
```

Out[93]:

	Vectorizer	Model	Train_Accuracy	Test_Accuracy	Precision	Recall	F1_score
0	TF-IDF	GaussianNB	0.754800	0.534400	0.587083	0.216774	0.316634

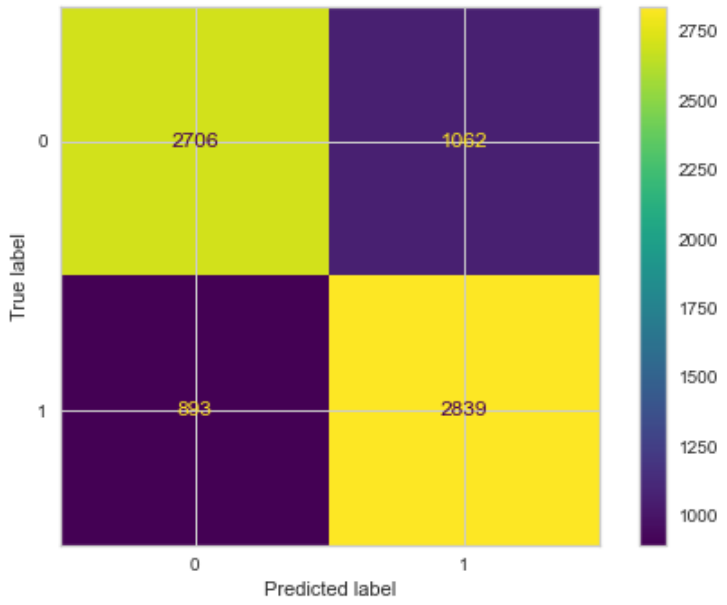
	Vectorizer	Model	Train_Accuracy	Test_Accuracy	Precision	Recall	F1_score
1	TF-IDF	RandomForest	0.994978	0.738400	0.727040	0.759378	0.742857
2	TF-IDF	XGboost	0.782800	0.722000	0.687799	0.808146	0.743132
3	CountVector	GaussianNB	0.733111	0.527733	0.587477	0.170954	0.264840
4	CountVector	RandomForest	0.995111	0.735867	0.732413	0.739282	0.735831
5	CountVector	XGboost	0.765022	0.730533	0.693159	0.822615	0.752359
6	Word2Vec	GaussianNB	0.733111	0.527733	0.587477	0.170954	0.264840
7	Word2Vec	RandomForest	0.995111	0.735600	0.729950	0.743837	0.736828
8	Word2Vec	XGboost	0.765022	0.730533	0.693159	0.822615	0.752359

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 [97]:
```
Train_Test_Scores(RandomForestClassifier(n_jobs=-1),X_train_tfidf,y_train,
                  X_test_tfidf,y_test,True)
```

```
Training_Accuracy: 0.9949777777777777
Test_Accuracy: 0.7393333333333333
Precision: 0.7277621122789029
Recall: 0.7607181136120043
F1_Score: 0.7438752783964365
```



Out[97]:
```
(0.9949777777777777,
 0.7393333333333333,
 0.7277621122789029,
 0.7607181136120043,
 0.7438752783964365)
```

In [106…
```
# Define classifier and fit it
clf = RandomForestClassifier(n_jobs=-1)
clf.fit(X_train_tfidf, y_train)
```

Out[106…

```
RandomForestClassifier
RandomForestClassifier(n_jobs=-1)
```

In [118…

```
# Get predictors from Random Forest using TF-IDF
y_pred = clf.predict(X_test_tfidf)
```

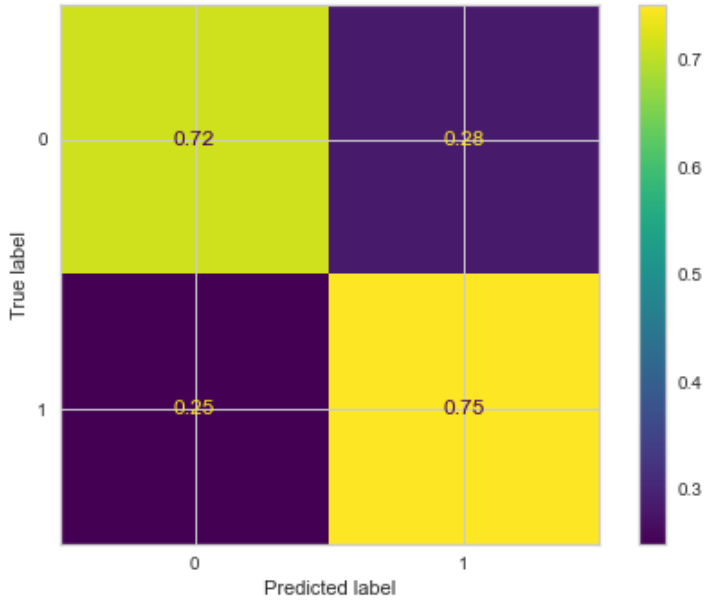
In [119…

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

```
              precision    recall  f1-score   support

    Negative       0.74      0.72      0.73      3768
    Positive       0.72      0.75      0.74      3732

    accuracy                           0.73      7500
   macro avg       0.73      0.73      0.73      7500
weighted avg       0.73      0.73      0.73      7500
```

In [120…

```
#cm = confusion_matrix(y_test,y_pred)
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])
#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.

Please see part 2 (deep learning) in the colab notebook on GitHub.

Table of Contents

Table of Contents

Part 2 Deep Learning

To upload data to Google Colab, follow these steps:

In [1]:
```
# Create a  new folder
!mkdir .kaggle
## upload.json
# ! chmod 600 .kaggle/kaggle.json
```

In [2]:
```
# Changing the permissions of the kaggle.json
! chmod 600 .kaggle/kaggle.json
```

In [4]:
```
# Move to the root path
!mv .kaggle /root/
```

In [6]:
```
# download data from kaggle
!kaggle datasets download -d kazanova/sentiment140
!kaggle datasets download -d crowdflower/twitter-airline-sentiment
```

```
sentiment140.zip: Skipping, found more recently modified local copy (use --force to force d
ownload)
```

```
twitter-airline-sentiment.zip: Skipping, found more recently modified local copy (use --for
ce to force download)
```

In [7]:
```
! unzip sentiment140.zip
! unzip twitter-airline-sentiment.zip
```

```
Archive:  sentiment140.zip
  inflating: training.1600000.processed.noemoticon.csv
Archive:  twitter-airline-sentiment.zip
  inflating: Tweets.csv
  inflating: database.sqlite
```

In [8]:
```
# remove all zip file
!rm product-tweets-dataset.zip
!rm sentiment140.zip
!rm twitter-airline-sentiment.zip
```

```
rm: cannot remove 'product-tweets-dataset.zip': No such file or directory
```

In [9]:
```
# Import Sklearn libraries to build models
from sklearn.feature_extraction.text import TfidfVectorizer # vectorize words
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 ConfusionMatrixDisplay
# from sklearn.metrics import plot_confusion_matrix
from sklearn.naive_bayes import GaussianNB

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 nltk to check english lexicon.
import nltk
from nltk.tokenize import word_tokenize
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 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.
from gensim.models import Word2Vec

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 tqdm.notebook import tqdm

from os import path
from os import environ
```

In [10]:
```
import tensorflow as tf
```

In [11]:
```
# !pip install tensorflow
```

In [12]:
```
# Uploading data
DATASET_COLUMNS=["sentiment", "ids", "date", "flag", "user", "tweet"]
DATASET_ENCODING = "ISO-8859-1"
ta_df = pd.read_csv('training.1600000.processed.noemoticon.csv',
                    encoding=DATASET_ENCODING, names=DATASET_COLUMNS)

ta_df.head() #View Tweets Data Frame
```

Out[12]:

	sentiment	ids	date	flag	user	tweet
0	0	1467810369	Mon Apr 06 22:19:45 PDT 2009	NO_QUERY	_TheSpecialOne_	@switchfoot http://twitpic.com/2y1zl - Awww, t...
1	0	1467810672	Mon Apr 06 22:19:49 PDT 2009	NO_QUERY	scotthamilton	is upset that he can't update his Facebook by ...
2	0	1467810917	Mon Apr 06 22:19:53 PDT 2009	NO_QUERY	mattycus	@Kenichan I dived many times for the ball. Man...
3	0	1467811184	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	ElleCTF	my whole body feels itchy and like its on fire
4	0	1467811193	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	Karoli	@nationwideclass no, it's not behaving at all....

In [13]:
```
# Genarating a random sample of 1,000,000 tweets from a 1.6 million database
ta_df = ta_df.sample(1000000,random_state=42)
```

In [14]:
```
# Checking shape
ta_df.shape
```

Out[14]:
```
(1000000, 6)
```

In [15]:
```
# Dropping 'flag' and 'ids'
ta_df.drop(['flag','ids'], axis=1, inplace = True)
```

In [16]:
```
# Checking tha the data is balanced
ta_df['sentiment'].value_counts()
```

Out[16]:
```
0    500167
4    499833
Name: sentiment, dtype: int64
```

In [17]:
```
# The variable target labeling in the data set is binary: 0 and 4,
# where 0 represents the tweets that
# are negative and 4 represents the tweets that are positive.
ta_df['sentiment'] = ta_df['sentiment'].replace(4,1)
ta_df.head()
```

Out[17]:

	sentiment	date	user	tweet
541200	0	Tue Jun 16 18:18:12 PDT 2009	LaLaLindsey0609	@chrishasboobs AHHH I HOPE YOUR OK!!!
750	0	Mon Apr 06 23:11:14 PDT 2009	sexygrneyes	@misstoriblack cool , i have no tweet apps fo...
766711	0	Tue Jun 23 13:40:11 PDT 2009	sammydearr	@TiannaChaos i know just family drama. its la...
285055	0	Mon Jun 01 10:26:07 PDT 2009	Lamb_Leanne	School email won't open and I have geography ...
705995	0	Sat Jun 20 12:56:51 PDT 2009	yogicerdito	upper airways problem

CLEANING THE DATA

We repeat from Part 1 the preprocessing and cleaning the tweets data using the preprocess() function.

In [18]:
```
tqdm.pandas() # Monitor completion
ps = PorterStemmer() # defining and applying stemming to words in the text.

# text patterns that we want to remove from the text
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"
nltk.download('stopwords')
# Listst of common words we will removed from text.

stop_words = set(stopwords.words("english"))

# The preprocess() function takes in the tweet and
# applies various text cleaning techniques to it.

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 = [] # Initializing an empty list to store tokenized words.
    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.
```

```
                tokens.append(token)
    # Joining and retuning the list of tokenized words into a single string
    return " ".join(tokens)
```

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

In [19]:
```
# Creating a new column in the DataFrame
# Using lambda function aplying the 'preprocess()'
# function to each row in the 'tweet' column.
ta_df['clean_tweet'] = ta_df['tweet'].progress_apply(lambda x:preprocess(x,True))
```

In [20]:
```
# Creating a new column in the DataFrame without stemming  for wordcloud.
# Using lambda aplying the 'preprocess()' function to each row in the 'tweet'
# column but adding 'false'.
ta_df['clean_tweet_wt_stem'] = ta_df['tweet'].progress_apply(lambda
                                                    x:preprocess(x, False))
```

In [21]:
```
# Splitting data target and clean tweets

X = ta_df['clean_tweet']#[:1000000]
y = ta_df['sentiment']#[:1000000]
```

In [22]:
```
# 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)
```

In [23]:
```
# Apllying tokenizing to the corpus using lambda
corpus = X.progress_apply(lambda line:line.split())
```

In [24]:
```
# View corpus
corpus
```

Out[24]:
```
541200                                      [ahh, hope, ok]
750                                 [cool, tweet, app, razr, 2]
766711     [know, famili, drama, lame, hey, next, time, u...
285055     [school, email, open, geographi, stuff, revis,...
705995                                [upper, airway, problem]
                                 ...
21340      [bad, time, lap, top, broken, good, time, foun...
80620                                 [yeah, fun, think, movi]
411912     [ministri, agricultur, forest, keep, take, cat...
798815               [sad, news, farrah, fawcett, pass, away]
1406049    [indo, pro, shop, trocar, meu, celular, quando...
Name: clean_tweet, Length: 1000000, dtype: object
```

In [25]:
```
# Train Word2Vec Model on corpus
WORD2VEC_MODEL = Word2Vec(corpus,
                 min_count=1,          # word frequency
                 vector_size =300,      # dimention of word embeddings
                 workers=os.cpu_count(),            # Number of processors
                 sg=0 # default, 1 for skipgram and 0 for cbow
                )
```

In [26]:
```
# help(Word2Vec)
```

In [27]:
```
# Adding a new column and applying token to each row.
ta_df['tokens'] = (
    ta_df['clean_tweet']
    .progress_apply(lambda line: line.split())
)
```

When the DataFrame is filtered using this True if len(line) else False, only the rows with at least one token in the 'tokens' column will be retained.

In [28]:
```
# Removing rows from ta_df if the 'tokens' column contains an empty list
ta_df = ta_df[
    ta_df['tokens']
    .apply(lambda line: True if len(line) else False)
]
```

In [29]:
```
# all_word2vec_vocab = model.wv.vocab.keys()
```

In [31]:
```
# Max charecter size for a tweet
W2V_SIZE = 300 # its vector dimention
```

Preparing to model the data

Given that the results were not great from our machine learning models, we will implement the Long Short-Term Memory ("LSTM") model, which works better with a larger data set. Therefore we increased our data to 1,000,000 tweets.

We are utilizing the deep model LSTM to achieve better results. LSTM is a type of Recurrent Neural Network (RNN) a type of artificial neural network that is used to process sequential data.

In [34]:
```
# 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
# from keras.preprocessing.sequence import pad_sequences
```

In [35]:
```
# from keras_preprocessing.sequence import pad_sequences
# Downloading tensorflow library
from tensorflow.keras.preprocessing.sequence import pad_sequences
```

In [36]:
```
%%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 162955
CPU times: user 8.64 s, sys: 55.1 ms, total: 8.7 s
Wall time: 8.67 s
```

In [37]:
```
# tokenizer.word_index
```

In [38]:
```
# KERAS
# Maximum length of the tweet.
SEQUENCE_LENGTH = 300

#Number of times it passes through the training data.
EPOCHS = 10

# Number of training examples/samples to process at once during each iteration.
BATCH_SIZE = 1024

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

In [39]:
```
max(X_train.apply(lambda x: len(x))) # the maximum length of the text
```

Out[39]: 174

Converting the tweets in training and testing to sequences of word indices using the tokenizer then padding them to have a fixed length of 300.

In [40]:
```
# 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)
```

Word2Vec

Embedding matrix using a pre-trained Word2Vec model for words in the tweet learned by the tokenizer. The embedding matrix will be used to establish the weights of an embedding layer in a neural network.

In [41]:
```
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 WORD2VEC_MODEL.wv: # Checksing if the word is in Word2Vec model
    embedding_matrix[i] = WORD2VEC_MODEL.wv[word] # If yes, it assigns a vector
print(embedding_matrix.shape) # Printing shape
```

```
(162955, 300)
```

In [42]:
```
# embedding_matrix[95]
```

Creating an embedding layer using the Embedding class from Keras.

In [43]:
```
# Initializing embedding layers for our model
embedding_layer = Embedding(vocab_size, W2V_SIZE, weights=[embedding_matrix],
                            input_length=SEQUENCE_LENGTH, trainable=False)
```

Layers to LSTM model

In [44]:
```
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='sigmoid'))

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 the criteri
a. It will use a generic GPU kernel as fallback when running on GPU.
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 300, 300)          48886500

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

 lstm (LSTM)                 (None, 100)               160400

 dense (Dense)               (None, 1)                 101

=================================================================
Total params: 49,047,001
Trainable params: 160,501
Non-trainable params: 48,886,500
_________________________________________________________________
```

Compilying the model, specifying the binary cross-entropy loss function, the Adam optimizer, and the accuracy metric.

In [45]:
```
# Compilying the model

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

Learning the rate when the validation loss stops improving, and EarlyStopping stops training when the validation accuracy stops improving.

In [46]:
```
# Initializing callback
callbacks = [ ReduceLROnPlateau(monitor='val_loss', patience=5, cooldown=0),
              EarlyStopping(monitor='val_accuracy', min_delta=1e-4, patience=5)]
```

In [47]:
```
x_train.shape
```

Out[47]:
```
(750000, 300)
```

In [48]:
```
y_train.shape
```

Out[48]:
```
(750000,)
```

In [49]:
```
history = KERAS_MODEL.fit(x_train, y_train,
                    batch_size=BATCH_SIZE,
                    epochs=EPOCHS,
                    validation_split=0.1,
                    verbose=1,
                    callbacks=callbacks)
```

```
Epoch 1/10
660/660 [==============================] - 591s 884ms/step - loss: 0.5105 - accuracy: 0.745
5 - val_loss: 0.4719 - val_accuracy: 0.7728 - lr: 0.0010
Epoch 2/10
660/660 [==============================] - 572s 866ms/step - loss: 0.4881 - accuracy: 0.761
4 - val_loss: 0.4689 - val_accuracy: 0.7754 - lr: 0.0010
Epoch 3/10
660/660 [==============================] - 571s 865ms/step - loss: 0.4800 - accuracy: 0.766
8 - val_loss: 0.4583 - val_accuracy: 0.7797 - lr: 0.0010
Epoch 4/10
660/660 [==============================] - 569s 862ms/step - loss: 0.4746 - accuracy: 0.770
1 - val_loss: 0.4535 - val_accuracy: 0.7829 - lr: 0.0010
Epoch 5/10
660/660 [==============================] - 584s 885ms/step - loss: 0.4706 - accuracy: 0.773
1 - val_loss: 0.4527 - val_accuracy: 0.7838 - lr: 0.0010
Epoch 6/10
660/660 [==============================] - 574s 869ms/step - loss: 0.4686 - accuracy: 0.774
2 - val_loss: 0.4535 - val_accuracy: 0.7850 - lr: 0.0010
Epoch 7/10
660/660 [==============================] - 574s 870ms/step - loss: 0.4661 - accuracy: 0.775
6 - val_loss: 0.4492 - val_accuracy: 0.7866 - lr: 0.0010
Epoch 8/10
660/660 [==============================] - 576s 873ms/step - loss: 0.4649 - accuracy: 0.776
3 - val_loss: 0.4493 - val_accuracy: 0.7876 - lr: 0.0010
Epoch 9/10
660/660 [==============================] - 574s 870ms/step - loss: 0.4632 - accuracy: 0.777
5 - val_loss: 0.4479 - val_accuracy: 0.7873 - lr: 0.0010
Epoch 10/10
660/660 [==============================] - 574s 870ms/step - loss: 0.4621 - accuracy: 0.778
2 - val_loss: 0.4464 - val_accuracy: 0.7884 - lr: 0.0010
```

Saving the model

In [50]:
```
# Saving the model so that we don't need to keep training it.
KERAS_MODEL.save('keras_model.h5') # Saving LTSM
WORD2VEC_MODEL.save("model.w2v") # Saving Word2Vec
```

Loading the model

In [51]:
```
from tensorflow.keras.models import load_model # Import to load the model
# Loading  model
keras_model = load_model('keras_model.h5')

# summarize model.
# keras_model.summary()
```

```
WARNING:tensorflow:Layer lstm will not use cuDNN kernels since it doesn't meet the criteri
a. It will use a generic GPU kernel as fallback when running on GPU.
```

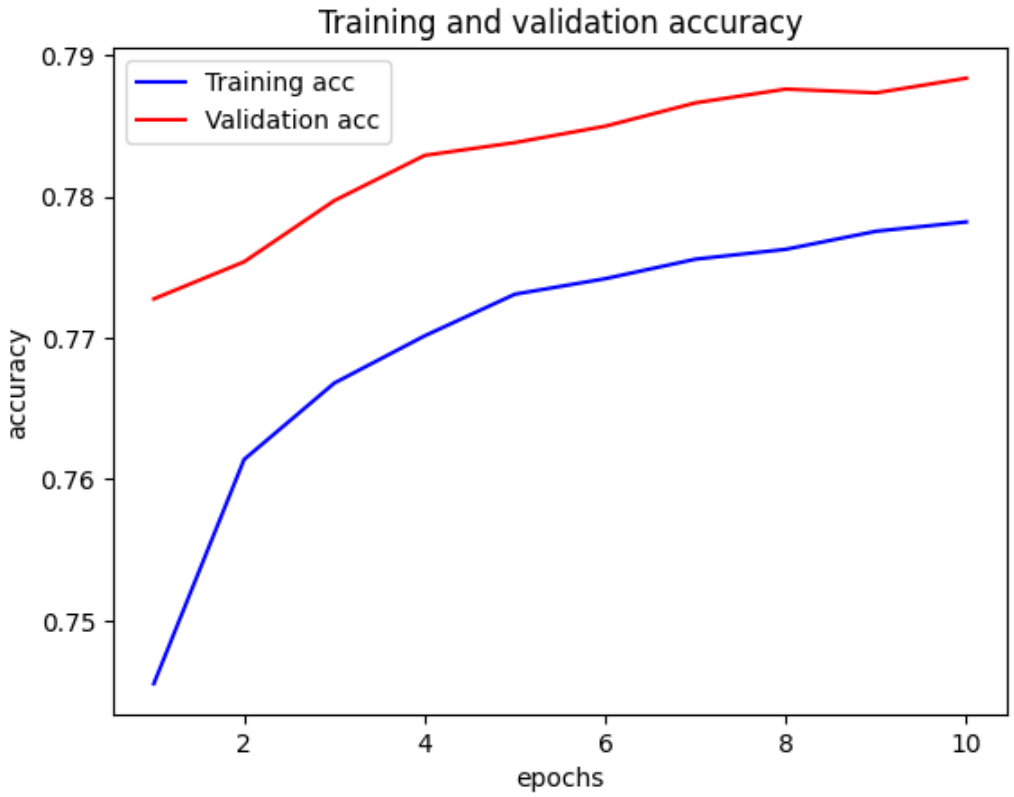
Results

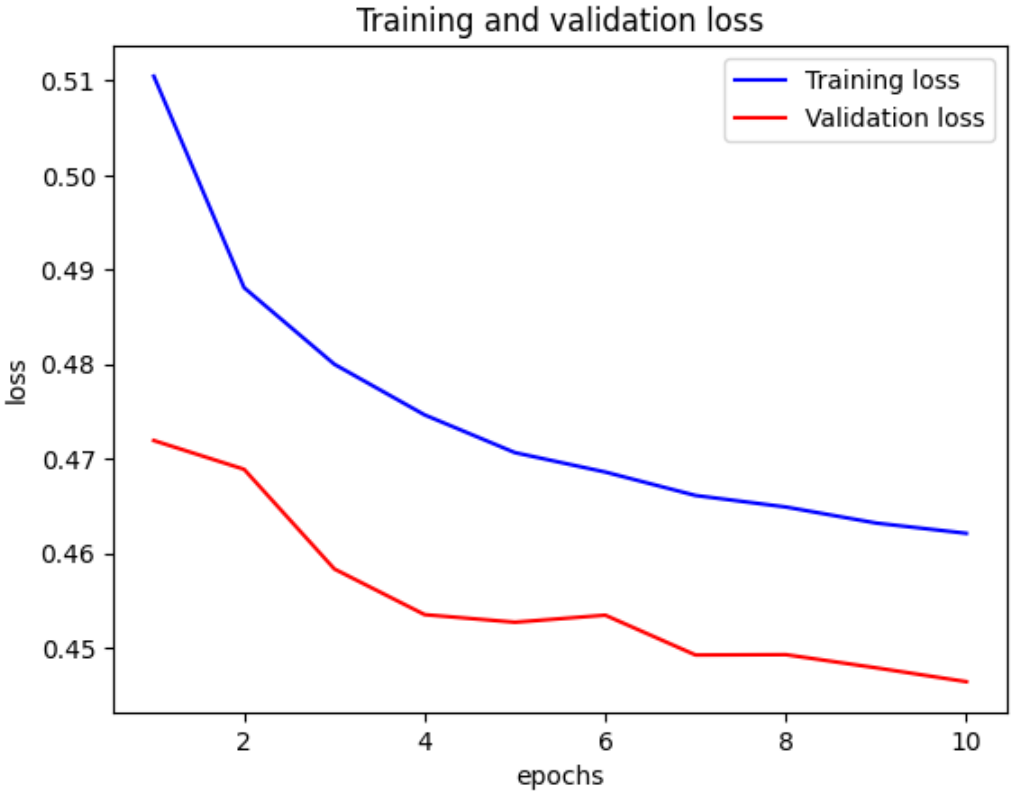
In [52]:
```
# Showing Accuracy and Loss
score = keras_model.evaluate(x_test, y_test, batch_size=BATCH_SIZE)
print()
print("ACCURACY:",score[1])
print("LOSS:",score[0])
```

```
245/245 [==============================] - 26s 104ms/step - loss: 0.4517 - accuracy: 0.7864

ACCURACY: 0.7863839864730835
LOSS: 0.45171108841896057
```

We are plotting the accuracy and loss values over the epochs of the model training, so we can get an idea of how the model is performing over time of the itteration in the neural network setting.

In [53]:
```
# Defining variables

# Returning when calling the fit() method on a Keras LSTM model.
val_acc = history.history['val_accuracy']
acc = history.history['accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']

# it will give the epoch it stopped at after training or
# 0 if it didn't early stop.
n = callbacks[1].stopped_epoch

# get X axis range
n = range(1,EPOCHS+1) if n==0 else range(1,n+2)

# epochs = range(EPOCHS) # range object 10

# Ploting training accuracy over the epochs in blue.
plt.plot(n, acc, 'b', label='Training acc')
plt.plot(n, val_acc, 'r', label='Validation acc')
plt.title('Training and validation accuracy')
plt.xlabel("epochs") # Labelng
plt.ylabel("accuracy") # Labelng
plt.legend()

plt.figure()

# Ploting training loss over the epochs in red.
plt.plot(n, loss, 'b', label='Training loss')
plt.plot(n, val_loss, 'r', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel("epochs") # Labelng
plt.ylabel("loss") # Labeling
plt.legend()

plt.show()


# https://stackoverflow.com/questions/41908379/keras-plot-training-
#validation-and-test-set-accuracy
```



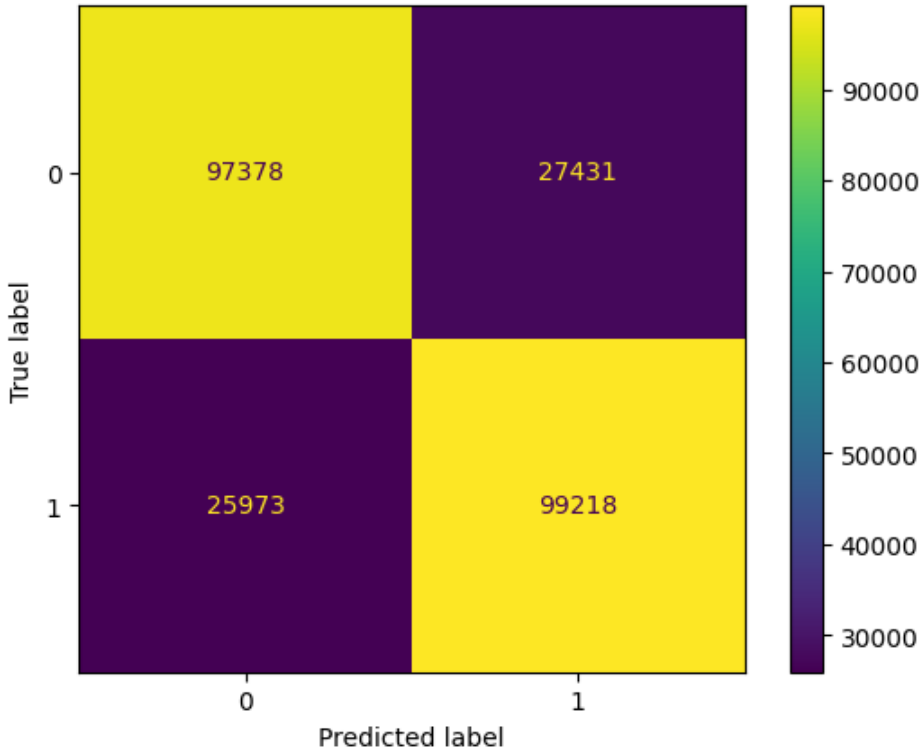


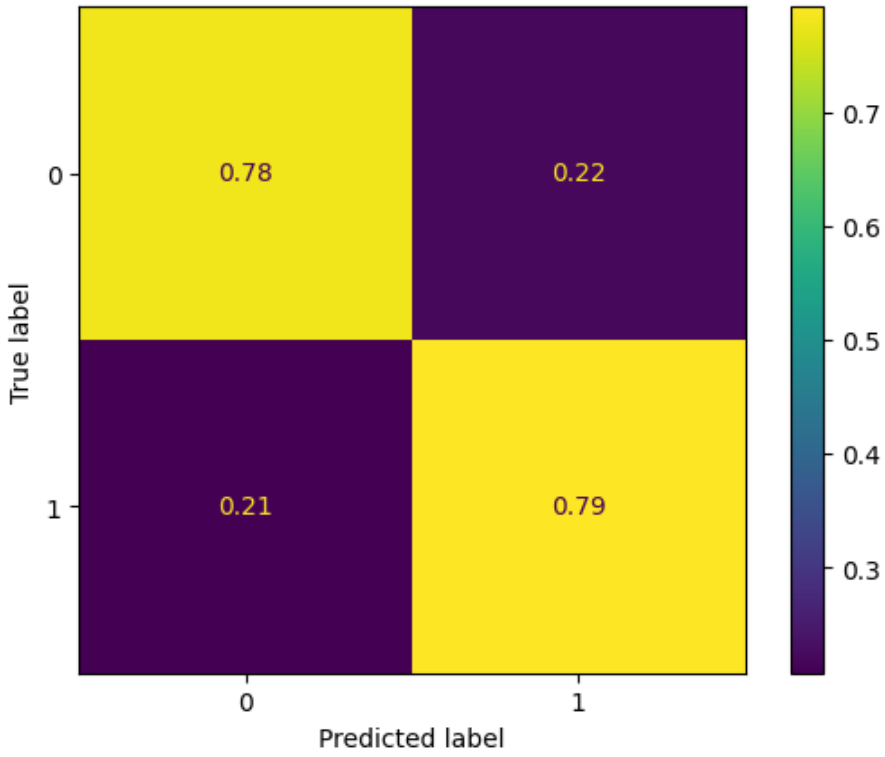
The training accuracy is increasing, and the validation accuracy is also increasing. We are seeing the same patteren with the training loss graph. Loss is decreasing, and the validation loss as well. This suggests that the model is learning the patterns in the data and generalizing well to new data. In both graphs, when the epochs pass 6, the training and the vaidation are starting to get a little closer to one another. With higher than 10 epochs the model might be overfitting to the training data and not teaching the new data.

In [54]:
```
y_test_1d = list(y_test)
scores = keras_model.predict(x_test, verbose=1, batch_size=1000)
y_pred_1d = [0 if score[0]<0.5 else 1 for score in scores ]
```

```
250/250 [==============================] - 25s 100ms/step
```

In [55]:
```
cm = confusion_matrix(y_test_1d,y_pred_1d)
cm1 = confusion_matrix(y_test_1d,y_pred_1d,normalize='true')

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





In [56]:
```
print(classification_report(y_test_1d,y_pred_1d))
```

```
              precision    recall  f1-score   support

           0       0.79      0.78      0.78    124809
           1       0.78      0.79      0.79    125191

    accuracy                           0.79    250000
   macro avg       0.79      0.79      0.79    250000
weighted avg       0.79      0.79      0.79    250000
```

Accuracy: The accuracy is the proportion of correctly labled class as negative or positive tweet. In this case, the accuracy is 79%. the LSTM model correctly classified 79% of the time both negative and positive tweets.

LIME

LIME (Local Interpretable Model-agnostic Explanations) provides an explanation for the prediction made by our LSTM on a specific tweet from the testing data.

In [57]:
```
!pip install -q lime
```

```
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 275.7/275.7 KB 5.8 MB/s eta 0:00:00a 0:00:01
  Preparing metadata (setup.py) ... done
  Building wheel for lime (setup.py) ... done
```

We define a predict_proba function that takes a list of tweet texts as input, preprocesses and tokenizes the texts, and then returns the predicted probabilities for each class (negative and positive) using the LSTM model.

In [58]:
```
# Import to explain text classifiers.
from lime.lime_text import LimeTextExplainer
class_names=[0,1]

def predict_proba(tweet_text):
  example = pad_sequences(tokenizer.texts_to_sequences(list(tweet_text)),
```

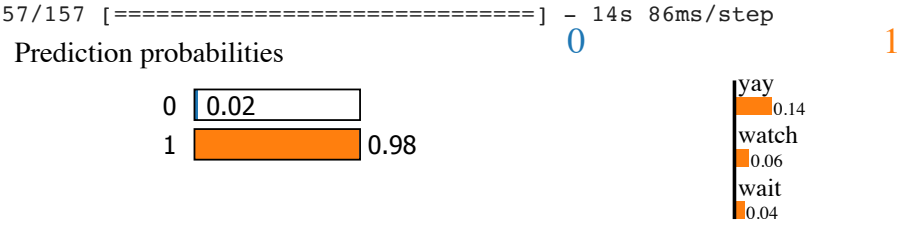
```
                        maxlen=SEQUENCE_LENGTH) # Tokenizes the tweets then pads
  # Training LSTM predict sentiment probbilities
  pred=keras_model.predict(example)
  returnable=[] # initializing list to store predicted probabilities.
  for i in pred:
    temp=i[0]
     # Predictes for each class in all tweets
    returnable.append(np.array([1-temp,temp]))
  return np.array(returnable)
# https://towardsdatascience.com/interpreting-an-lstm-through-lime-e294e6ed3a03
  # print(pred)
  # temp = pred[0][0]
  # return np.array([1-temp,temp]).reshape(1,2)
```

In [59]:
```
# View test date
X_test
```

Out[59]:
```
956610                                          spongebob isnt
483432                                                   rain
1523842                                       yay wait watch
48041      morn mother natur left monthli present fun fun...
366878                                             mess huh
                                ...
560578                                          ack happen
916703                            happi mother day everyon
631662     sick cough fever bodi ach headach runni nose g...
549361                           hold anymor act like fine
283913     lt got call earli work b c dude work call mill...
Name: clean_tweet, Length: 250000, dtype: object
```

In [60]:
```
print("Actual sentiment",y_test[1523842])
#  positive (orange), Negative (blue)

# Initializing a LimeTextExplainer object to explain the tweet.
explainer= LimeTextExplainer(class_names=class_names)
# Returning the predicted probabilities for each class.
exp = explainer.explain_instance(X_test[1523842],
                                 predict_proba).show_in_notebook(text=True)
```

```
Actual sentiment 1
157/157 [==============================] - 14s 86ms/step
```



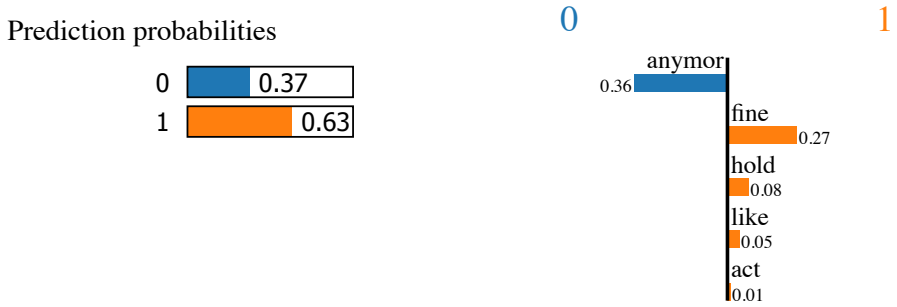
Text with highlighted words

yay wait watch

The model predicts probabilities of 65% for the negative class and 35% for a positive class. This means that the model is more confident that the tweet is labeled as negative.

In [61]:
```
print("Actual sentiment",y_test[549361])
#  positive (orange), Negative (blue)
# Initializing a LimeTextExplainer object to explain the tweet.
explainer= LimeTextExplainer(class_names=class_names)
exp = explainer.explain_instance(X_test[549361],
                                 predict_proba).show_in_notebook(text=True)
```

```
Actual sentiment 0
157/157 [==============================] - 14s 89ms/step
```



Text with highlighted words

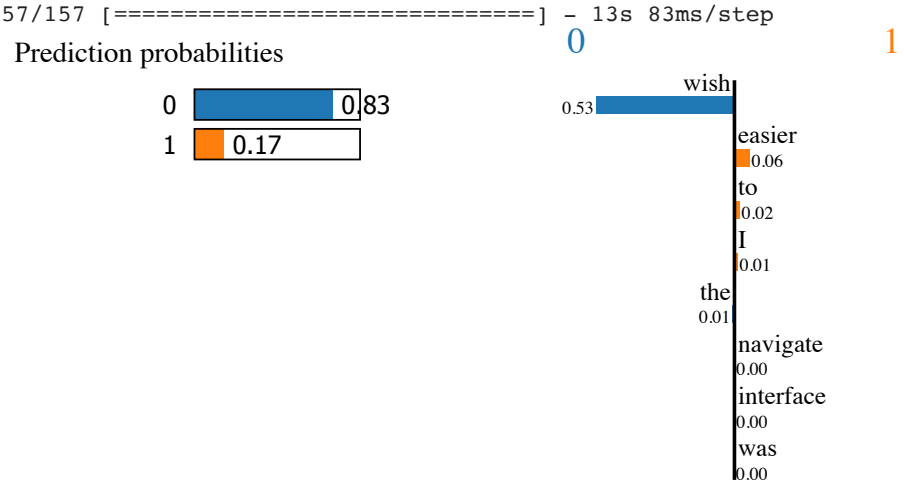
hold anymor act like fine

The model is very confident that the tweet belongs to the positive class, as the probability is 100%.

Testing a Review with LIME

In [62]:
```
# print("Actual sentiment",y_test[339425])
#  positive (orange), Negative (blue)
# explainer= LimeTextExplainer(class_names=class_names)
# Returning the predicted probabilities for each class.
exp = explainer.explain_instance("I wish the interface was easier to navigate.",
                                 predict_proba).show_in_notebook(text=True)
```

```
157/157 [==============================] - 13s 83ms/step
```



Text with highlighted words

I wish the interface was easier to navigate.

In [63]:
```
# https://www.reviews.io/company-reviews/store/tshirtfella
```

Testing on Product Reviews

https://www.kaggle.com/datasets/crowdflower/twitter-airline-sentiment

Airline Reviews on Twetter

For the business presentation, we will be conducting an analysis on a dataset containing actual customer feedback on a specific airline. This exercise primarily aims to demonstrate the potential insights that can be gained through data-driven approaches in enhancing our understanding of customer feedback.

In [64]:
```
# https://www.kaggle.com/datasets/crowdflower/
# twitter-airline-sentiment?select=Tweets.csv

# Reading and viewing data set (feedback tweets on arilines)
df_airline =  pd.read_csv('Tweets.csv')
df_airline.head()
```

Out[64]:

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

We are gathering equal amount of positive and negative tweets, resulting in a balanced dataset. Each sentiment category will have 2,363 tweets.

In [65]:
```
# Store only positive emotions
neg_al = df_airline[df_airline['airline_sentiment'].isin
                (['negative'])].sample(2363,random_state=42)
```

In [66]:
```
# Store only positive emotions
pos_al = df_airline[df_airline['airline_sentiment'].isin
                (['positive'])]
```

In [67]:
```
 #Merging the postive and negative tweets
 df_airline = pd.concat([pos_al, neg_al])
```

In [68]:
```
# View dataframe
df_airline.head()
```

Out[68]:

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	negativereason_confi
1	570301130888122368	positive	0.3486	NaN	
6	570300616901320704	positive	0.6745	NaN	

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	negativereason_confi
8	570299953286942721	positive	0.6559	NaN	
9	570295459631263746	positive	1.0000	NaN	
11	570289724453216256	positive	1.0000	NaN	

In [69]:
```
# View the tweets
df_airline['text']
```

Out[69]:
```
1        @VirginAmerica plus you've added commercials t...
6        @VirginAmerica yes, nearly every time I fly VX...
8          @virginamerica Well, I didn't…but NOW I DO! :-D
9        @VirginAmerica it was amazing, and arrived an ...
11       @VirginAmerica I &lt;3 pretty graphics. so muc...
                               ...
894                          @united where's my damn bag??
9875     @USAirways 5 hours on the phone waiting for a ...
10003    @USAirways flight 838 now leaving after 6 hour...
11674    @USAirways flt 5302 CLT to DAY supposed to dep...
9786     @USAirways over two hours on hold to talk to a...
Name: text, Length: 4726, dtype: object
```

In [70]:
```
# Downloading Spacy

!python -m spacy download en_core_web_lg
```

```
2023-04-03 15:39:39.988248: W tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] TF-TRT
Warning: Could not find TensorRT
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/
simple/
Collecting en-core-web-lg==3.5.0
  Downloading https://github.com/explosion/spacy-models/releases/download/en_core_web_lg-3.
5.0/en_core_web_lg-3.5.0-py3-none-any.whl (587.7 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 587.7/587.7 MB 2.6 MB/s eta 0:00:00
Requirement already satisfied: spacy<3.6.0,>=3.5.0 in /usr/local/lib/python3.9/dist-package
s (from en-core-web-lg==3.5.0) (3.5.1)
Requirement already satisfied: smart-open<7.0.0,>=5.2.1 in /usr/local/lib/python3.9/dist-pa
ckages (from spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (6.3.0)
Requirement already satisfied: typer<0.8.0,>=0.3.0 in /usr/local/lib/python3.9/dist-package
s (from spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (0.7.0)
Requirement already satisfied: requests<3.0.0,>=2.13.0 in /usr/local/lib/python3.9/dist-pac
kages (from spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (2.27.1)
Requirement already satisfied: murmurhash<1.1.0,>=0.28.0 in /usr/local/lib/python3.9/dist-p
ackages (from spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (1.0.9)
Requirement already satisfied: catalogue<2.1.0,>=2.0.6 in /usr/local/lib/python3.9/dist-pac
kages (from spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (2.0.8)
Requirement already satisfied: cymem<2.1.0,>=2.0.2 in /usr/local/lib/python3.9/dist-package
s (from spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (2.0.7)
Requirement already satisfied: preshed<3.1.0,>=3.0.2 in /usr/local/lib/python3.9/dist-packa
ges (from spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (3.0.8)
Requirement already satisfied: thinc<8.2.0,>=8.1.8 in /usr/local/lib/python3.9/dist-package
s (from spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (8.1.9)
Requirement already satisfied: srsly<3.0.0,>=2.4.3 in /usr/local/lib/python3.9/dist-package
s (from spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (2.4.6)
Requirement already satisfied: setuptools in /usr/local/lib/python3.9/dist-packages (from s
```

```
pacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (67.6.1)
Requirement already satisfied: pydantic!=1.8,!=1.8.1,<1.11.0,>=1.7.4 in /usr/local/lib/pyth
on3.9/dist-packages (from spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (1.10.7)
Requirement already satisfied: numpy>=1.15.0 in /usr/local/lib/python3.9/dist-packages (fro
m spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (1.22.4)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.9/dist-packages (from spacy
<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (3.1.2)
Requirement already satisfied: pathy>=0.10.0 in /usr/local/lib/python3.9/dist-packages (fro
m spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (0.10.1)
Requirement already satisfied: spacy-loggers<2.0.0,>=1.0.0 in /usr/local/lib/python3.9/dist
-packages (from spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (1.0.4)
Requirement already satisfied: langcodes<4.0.0,>=3.2.0 in /usr/local/lib/python3.9/dist-pac
kages (from spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (3.3.0)
Requirement already satisfied: spacy-legacy<3.1.0,>=3.0.11 in /usr/local/lib/python3.9/dist
-packages (from spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (3.0.12)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.9/dist-packages (f
rom spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (23.0)
Requirement already satisfied: tqdm<5.0.0,>=4.38.0 in /usr/local/lib/python3.9/dist-package
s (from spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (4.65.0)
Requirement already satisfied: wasabi<1.2.0,>=0.9.1 in /usr/local/lib/python3.9/dist-packag
es (from spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (1.1.1)
Requirement already satisfied: typing-extensions>=4.2.0 in /usr/local/lib/python3.9/dist-pa
ckages (from pydantic!=1.8,!=1.8.1,<1.11.0,>=1.7.4->spacy<3.6.0,>=3.5.0->en-core-web-lg==3.
5.0) (4.5.0)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.9/dist-packages
(from requests<3.0.0,>=2.13.0->spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (2022.12.7)
Requirement already satisfied: charset-normalizer~=2.0.0 in /usr/local/lib/python3.9/dist-p
ackages (from requests<3.0.0,>=2.13.0->spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (2.0.12)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.9/dist-packages (from
requests<3.0.0,>=2.13.0->spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (3.4)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /usr/local/lib/python3.9/dist-packa
ges (from requests<3.0.0,>=2.13.0->spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (1.26.15)
Requirement already satisfied: blis<0.8.0,>=0.7.8 in /usr/local/lib/python3.9/dist-packages
(from thinc<8.2.0,>=8.1.8->spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (0.7.9)
Requirement already satisfied: confection<1.0.0,>=0.0.1 in /usr/local/lib/python3.9/dist-pa
ckages (from thinc<8.2.0,>=8.1.8->spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (0.0.4)
Requirement already satisfied: click<9.0.0,>=7.1.1 in /usr/local/lib/python3.9/dist-package
s (from typer<0.8.0,>=0.3.0->spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (8.1.3)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.9/dist-packages (f
rom jinja2->spacy<3.6.0,>=3.5.0->en-core-web-lg==3.5.0) (2.1.2)
Installing collected packages: en-core-web-lg
Successfully installed en-core-web-lg-3.5.0
✔ Download and installation successful
You can now load the package via spacy.load('en_core_web_lg')
```

Topic Modeling

Filtering through only the negative tweets and look for problems that people might be experiencing,

In [133…

```
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
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')
# result = pd.DataFrame([],columns=['Corpus','No_of_Comments','No_of_Tokens'])
```

In [79]:
```
# loads the  language model of the spaCy library.
nlp = spacy.load('en_core_web_lg')
```

In [139…
```
# Creating doc using nlp language model named entitie
#doc = nlp(text)
```

In [78]:
```
# Creating a new column in the DataFrame called 'clean_tweet',
# Which stores the cleaned tweets ,using'preprocess()' function without steming.
df_airline['clean_tweet'] = (
    df_airline['text']
    .progress_apply(lambda x: preprocess(x, False))
)
```

We need to convert the cleaned tweets (x_test) into padded sequences of fixed length (SEQUENCE_LENGTH :300) using the tokenizer that we have previously defined. This step is essential for preparing the input data for a deep learning model, LTSM.

In [ ]:
```
# Importing the Spacy library
```

We will be deploying topic modeling, which allow us to identfy the topics presented in a the tweets reviews.

The function returns the matrix as well as the tfidf_featurizer object, which can be used later to transform new text data into the same format as the training data.

- max_df = threshold for ignoring words that appear too frequently
- min_df = parameter specifies the threshold for ignoring words that appear too infrequently.

In [81]:
```
def analysis(docs,vocab_size):

    # Sets up features for TF-IDF
    tfidf_featurizer = TfidfVectorizer(max_features=vocab_size,
                                       max_df=0.95, stop_words='english')

    # count_text_vectors = count_text_vectorizer.fit_transform(docs)

    X_tfidf = tfidf_featurizer.fit_transform(docs) # Transform to TF-IDF

    # feature_names = tfidf_featurizer.get_feature_names_out()
    # X = X_tfidf.toarray()

    # return X,feature_names
    return X_tfidf,tfidf_featurizer

    # https://python.hotexamples.com/examples/sklearn.
    # feature_extraction.text/TfidfVectorizer/get_feature_names/
    # python-tfidfvectorizer-get_feature_names-method-examples.html
```

This function "plot_top_words" can be used to visualize the top words for each topic in a topic model and help interpret the results of the model.

- k_topic: number of topics
- model: LDA Model
- n_top_words: top words to plot for each topic

In [111…

```
# Plotting the top words/topics
def plot_top_words(k_topic,model, feature_names, n_top_words,title=''):
    plt.clf()
    cols = 3
    rows = int(np.ceil(k_topic/cols))
    fig, axes = plt.subplots(rows, cols, figsize=(4 * cols, 4 * rows),
                             sharex=True)
    axes = axes.flatten()

    # Looping to iterate over the topics in a trained topic
    # model and creates a horizontal bar chart for each topic.

    # Iterate through the topics extracted by the model

    for topic_idx, topic in enumerate(model.components_):

         # Sort the indices of the features (words) in
        # descending order of their importance in the current topic,
        # and select the top 'n_top_words' features

        top_features_ind = topic.argsort()[::-1][:n_top_words]

       # Getting the actual words names corresponding to the indices

        top_features = [feature_names[i] for i in top_features_ind]

        # Getting the weights/importance scores of the top features in the topic
        weights = topic[top_features_ind]

        # Getting the Axes object for the current topic from the 'axes'
        ax = axes[topic_idx]

        # Create a horizontal bar chart of the top features
        ax.barh(top_features, weights, height=0.7)
        # Set the title
        ax.set_title(f'Topic {topic_idx + 1}',
                     fontdict={'fontsize': 15})

        # Invert the y-axis
        ax.invert_yaxis()

        # Set the tick parameters for both axes,
        ax.tick_params(axis='both', which='major', labelsize=20)

        # Formatting  and display the plot created in the plot_top_function


        # Iterate through the list of spine locations
        for i in 'top right left'.split():
            # Hide the spines (borders)
            ax.spines[i].set_visible(False)

         # Set the title of the entire figure
        fig.suptitle(title, fontsize=15)

    # Adjust the spacing between the subplots:
    plt.subplots_adjust(top=0.90, bottom=0.05, wspace=0.90, hspace=0.3)

    # Adjust the spacing

    fig.tight_layout()

    # fig.savefig(f'figure\{fname}.png')

    plt.show()
```

```
# https://github.com/scikit-learn/scikit-learn/blob/main/examples/
# applications/plot_topics_extraction_with_nmf_lda.py
```

wordcloud_topics creating a wordcloud for each topic in the model by first iterating over the topics in the model. For each topic, it calculates the top no_top_words features based on the topic model coefficients and builds a dictionary that maps each feature to its respective weight.

In [112…

```
# Wordcloud funciton
def wordcloud_topics(model, features, no_top_words=50):

    # Iterating through the list of topics
    for topic, words in enumerate(model.components_):

         # Initialize an empty dictionary
        size = {}

        # Sort the indices of the words in descending order
        largest = words.argsort()[::-1] # invert sort order

        # Iterating through the top 'no_top_words'
        # words and add them to the 'size' dictionary with
        # their importance scores
        for i in range(0, no_top_words):
            size[features[largest[i]]] = abs(words[largest[i]])

        # Initializing a WordCloud
        wc = WordCloud(background_color="white", stopwords = stopwords,
                       max_words=100,
                       width=960, height=540)

        # Generate the word cloud from the 'size'
        wc.generate_from_frequencies(size)

        # Create a new figure
        plt.figure(figsize=(7,7))

    # Displaying the word cloud image
    plt.imshow(wc, interpolation='bilinear')

    # Setting the title of the figure to display the topic number
    # and the number of top words
        plt.title(f'TOPIC - {topic}: top {no_top_words} words')
```

This function can be used to perform topic modeling on a collection of text documents and visualize the results in a meaningful way.

In [113…

```
# Topic modeling function
def get_topic_plot(data):
    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(" ")))

    # Store outcome of the analysis funciton
    X_tfidf,tfidf_vectorizer =  analysis(docs,vocab_size)

    X = X_tfidf.toarray() # Converting into a matrix for the model

    # Storing a list of the most important words for each topic.
    feature_names = tfidf_vectorizer.get_feature_names_out()
```

```
    # Convertinginto 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)


    #  Creating an LDA model with the selected number of topics
    # ('k_topic') and a fixed random state for reproducibility

    lda_model = LatentDirichletAllocation(n_components=k_topic,
                                          random_state=42)
    lda_model.fit(X)
    plot_top_words(k_topic,lda_model, feature_names, 10)
    wordcloud_topics(lda_model, feature_names)

# https://www.machinelearningplus.com/nlp/
# topic-modeling-gensim-python/#13viewthetopicsinldamodel
```

In [132…

```
# import locale
# locale.getpreferredencoding = lambda: "UTF-8"
```

We built a function arguments passing x_test and y_test, converting the test data into padded sequences using tokenizer and sequence length.

The function then generates predictions on the x_test which is the independent variables taked from the US airline data set - using a pre-trained LSTM model.

The predicted scores are thresholded at 0.5 to obtain predictions (0 = negative 1 = positive). We obtain the results using a confusion matrix and classification report. Finally, the function returns the binary predictions as a list for positive and negative tweets.

In [115…
```
# Building funciton to predict
def get_sentiment_prediction(x_test,y_test):
  x_test = pad_sequences(tokenizer.texts_to_sequences(x_test), maxlen=SEQUENCE_LENGTH)
  # Converting into list
  y_test_1d  = list(y_test)
  # Generating predictions on the x_test
  scores = keras_model.predict(x_test, verbose=1, batch_size=50)

  # Setting up hreshold
  y_pred_1d = [0 if score[0]<0.5 else 1 for score in scores]

  # Producing Results
  cm = confusion_matrix(y_test_1d,y_pred_1d)
  disp = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=[0,1])
  print(classification_report(y_test_1d,y_pred_1d))

  # Plotting
  disp.plot()
  plt.show()

  return y_pred_1d
```

Deploying our pre-trained LTSM Keras model and then converting the predictions into a binary format.

In [116…
```
# Setting up variables
x_test_al  = df_airline['clean_tweet']
y_test_al = df_airline['airline_sentiment'] # Target variable
```

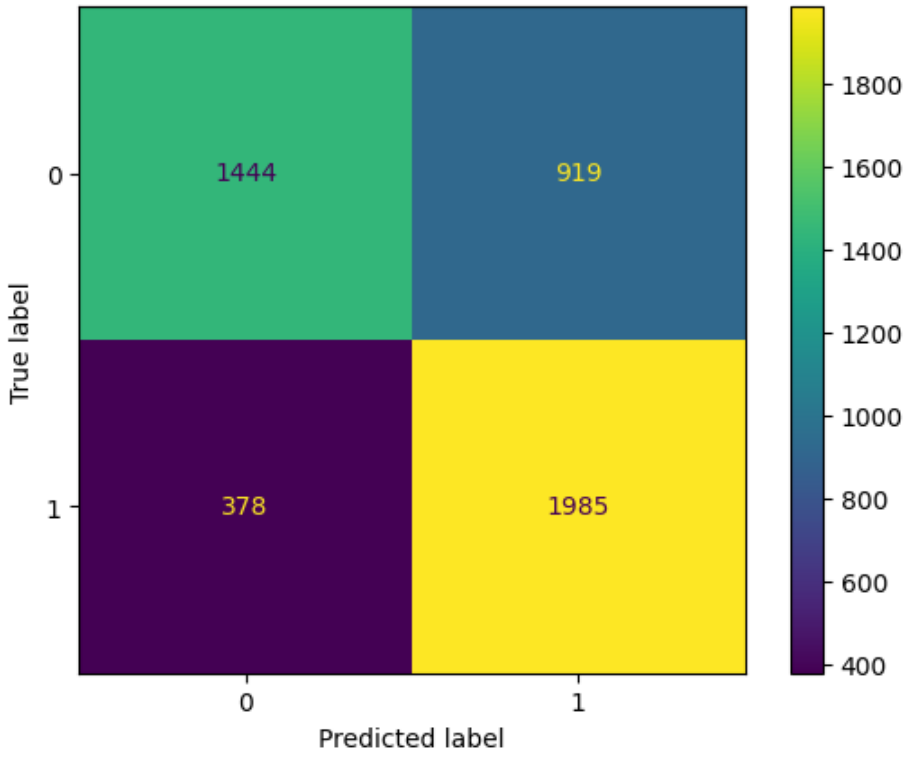
In [117…
```
# Replacing pos with 1 and neg with 0.
y_test_al = y_test_al.replace(['positive','negative'],[1,0])
```

In [118…
```
# Checking that sentiments classes are balanced
df_airline['airline_sentiment'].value_counts()
```

Out[118…
```
positive    2363
negative    2363
Name: airline_sentiment, dtype: int64
```

In [119…
```
# Viewing scores: classification report and classification report
y_pred_al = get_sentiment_prediction(x_test_al,y_test_al)
```

```
95/95 [==============================] - 8s 80ms/step
              precision    recall  f1-score   support

           0       0.79      0.61      0.69      2363
           1       0.68      0.84      0.75      2363

    accuracy                           0.73      4726
   macro avg       0.74      0.73      0.72      4726
weighted avg       0.74      0.73      0.72      4726
```



In [120…
```
# Storing the predicted values in a new column
df_airline['pred_sentiment'] = y_pred_al
```

In [121…
```
# Check upnique values
df_airline['airline'].unique()
```

Out[121…
```
array(['Virgin America', 'United', 'Southwest', 'Delta', 'US Airways',
       'American'], dtype=object)
```

In [122…
```
# Filtering only for US Airways airline to check for negative tweets
df_us_al = df_airline[df_airline["airline"].str.contains('US Airways',
                                                         case=False, na=False)]
```

In [123…
```
# Checking filter
df_us_al["airline"].unique()
```

Out[123…
```
array(['US Airways'], dtype=object)
```

In [124…
```
# Filtering negative tweets to obtain topic
df_us_al_neg = df_us_al[df_us_al['pred_sentiment']==0]['clean_tweet']
```

In [125…
```
# Checking the number of negative tweets
df_us_al_neg.shape
```

Out[125…
```
(408,)
```

In [126…
```
# View negative tweets
df_us_al_neg
```

Out[126…

```
8985     well miss gate agents rebooked boarding pass w...
9024     great job today team challenging weather delay...
9105                             waiting flight right thanks
9222                      worries flight attendant took care
9244     good work flight 1798 crew chairman recognitio...
                                                ...
10271    tough night two 90 minute calls hold delayed p...
9875     5 hours phone waiting call back find luggage s...
10003    flight 838 leaving 6 hour mechanical delay nee...
11674    flt 5302 clt day supposed depart 5 51 6 20 sti...
9786     two hours hold talk agent disconnects trying t...
Name: clean_tweet, Length: 408, dtype: object
```

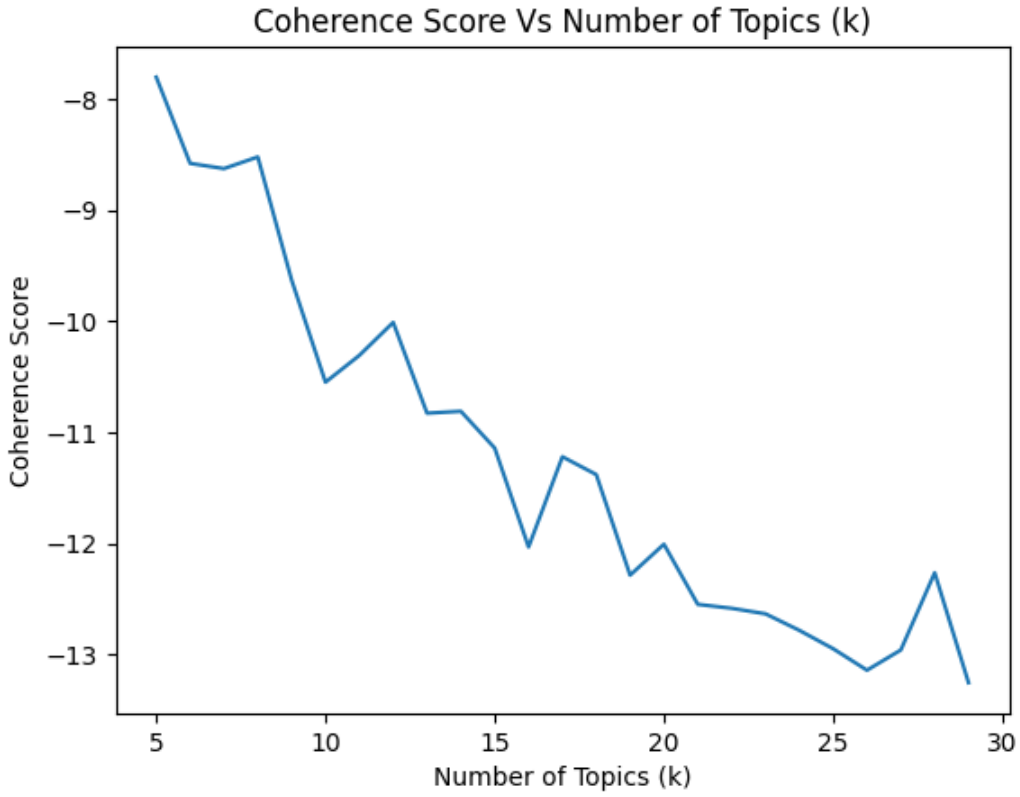
We are going to apply the LDA model to analyze which topics were discussed the most among the negative tweets concerning US airlines.

In [127…

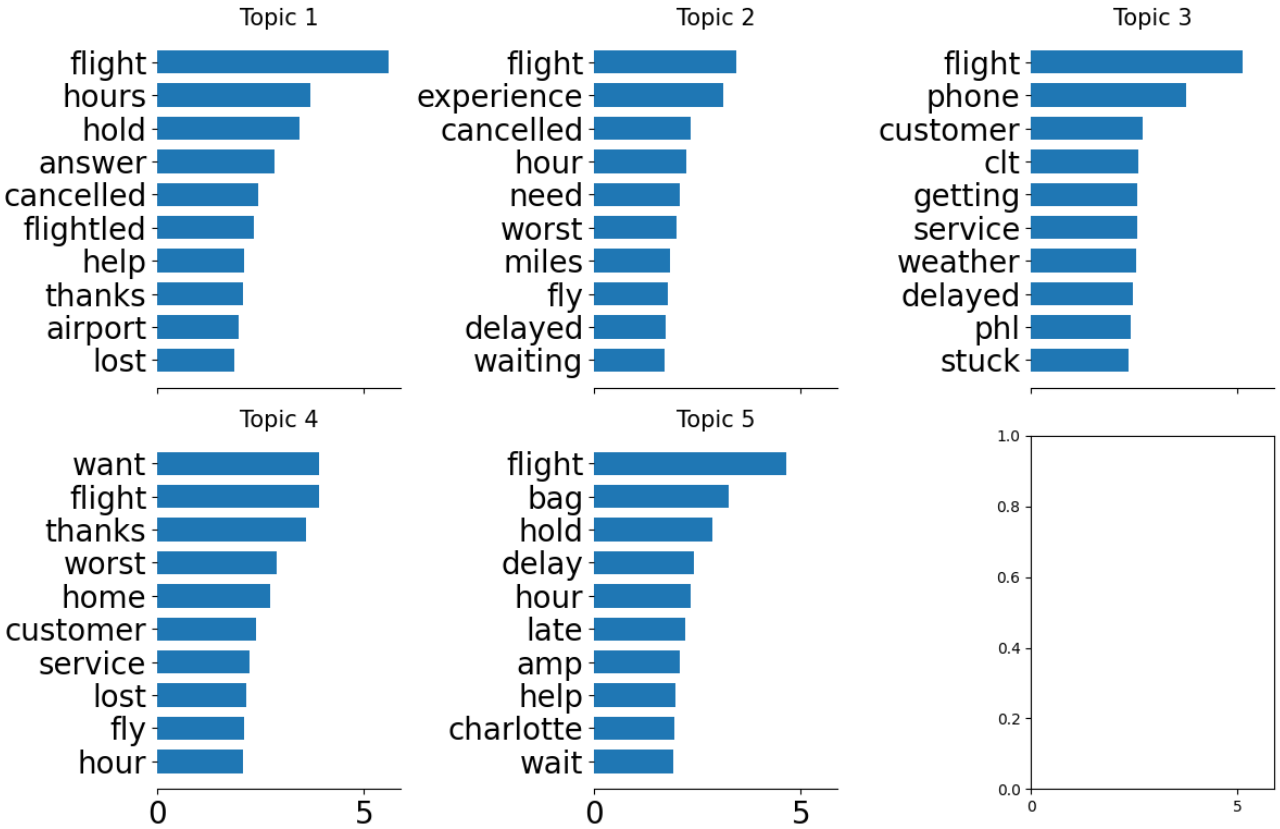
```python
# Running get_topic_plot function
get_topic_plot(df_us_al_neg)
```

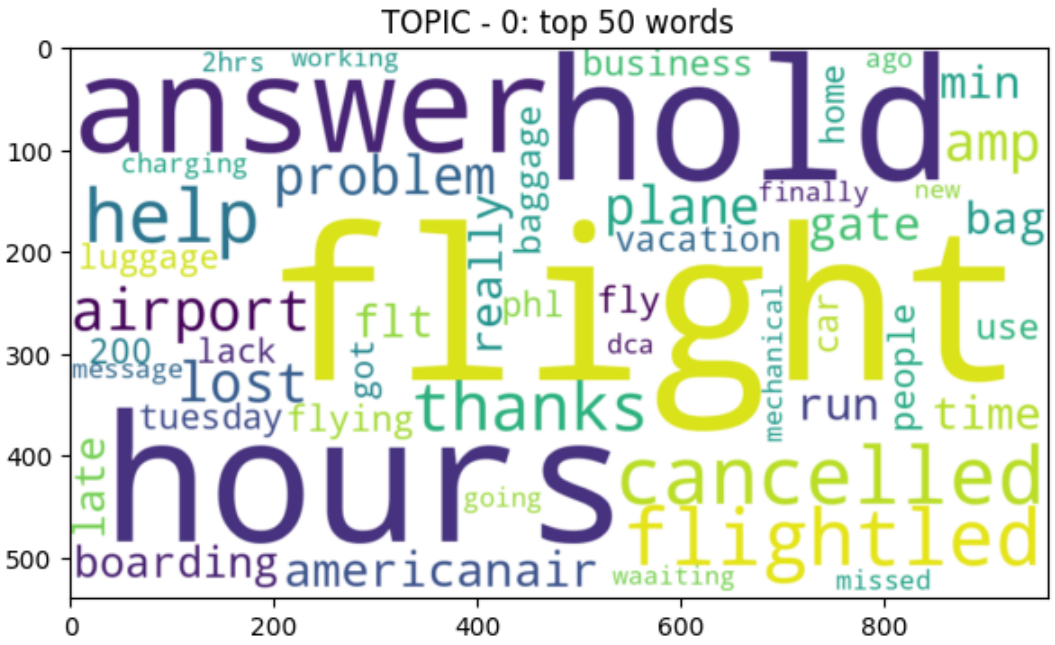
```
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
```

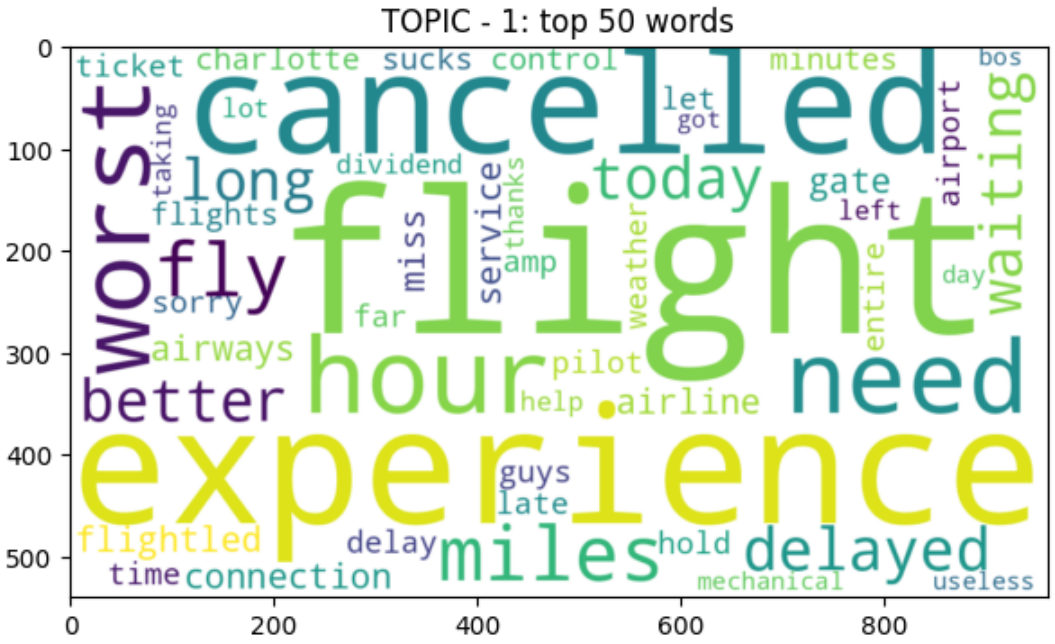
```
WARNING:gensim.models.ldamodel:too few updates, training might not converge; consider incre
asing the number of passes or iterations to improve accuracy
```

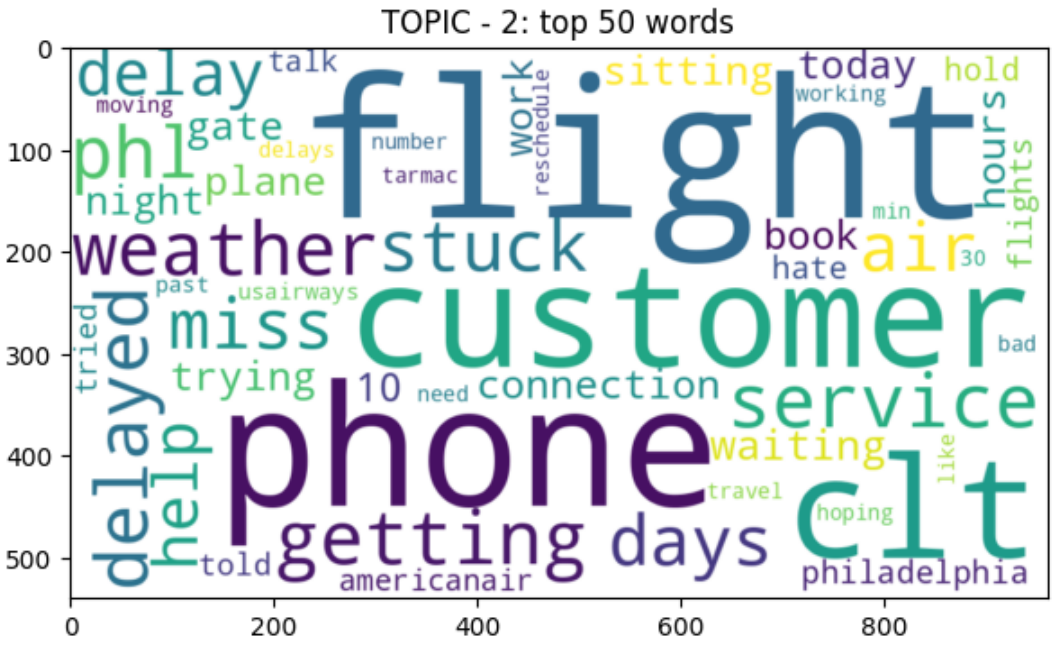


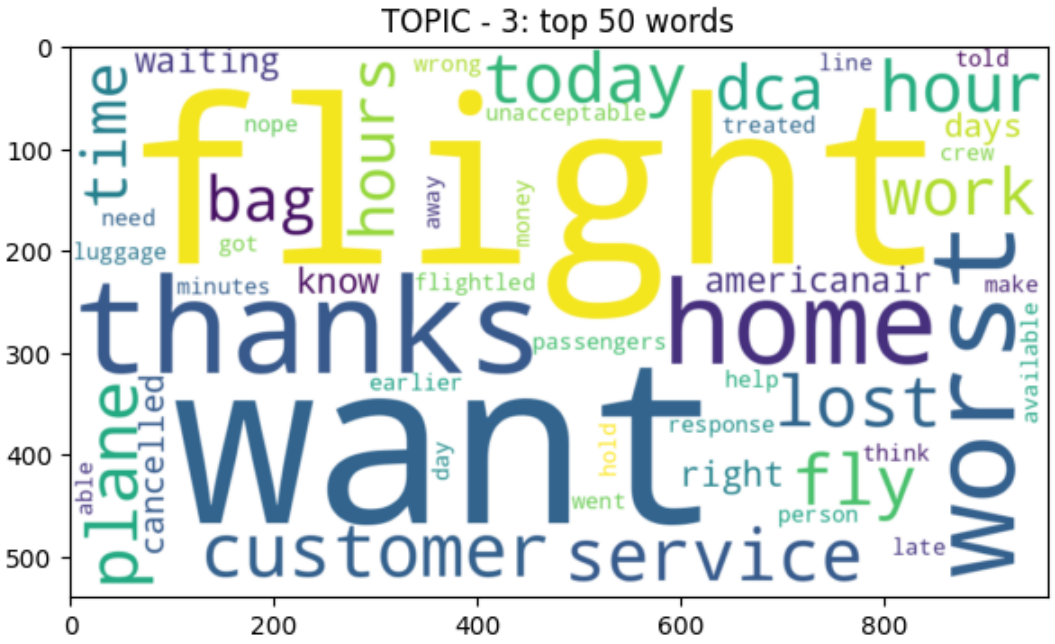

```
No of Topic Selected by Coherence Score: 5
<Figure size 640x480 with 0 Axes>
```

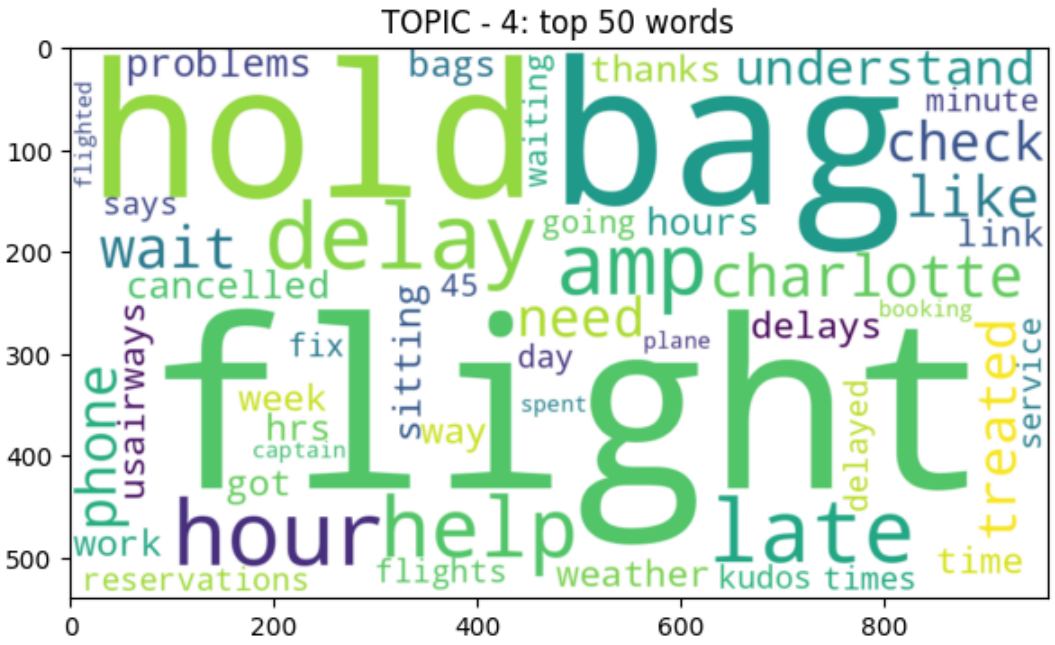



TOPIC - 0: top 50 words
answer
hold
flight
hours
cancelled
flightled
help
problem
airport
lost
thanks
boarding
americanair
2hrs
working
business
home
ago
min
amp
charging
plane
finally
new
gate
bag
luggage
vacation
really
baggage
flt
phl
fly
dca
car
mechanical
people
use
200
lack
message
got
tuesday
flying
run
time
late
going
waaiting
missed
0
100
200
300
400
500
0
200
400
600
800


TOPIC - 1: top 50 words
cancelled
worst
flight
experience
hour
need
fly
long
today
waiting
better
delayed
miles
ticket
charlotte
sucks
control
minutes
bos
lot
let
got
taking
dividend
service
thanks
gate
airport
flights
miss
amp
weather
left
sorry
far
entire
day
airways
pilot
help
airline
guys
late
flightled
delay
hold
time
connection
mechanical
useless
0
100
200
300
400
500
0
200
400
600
800


TOPIC - 2: top 50 words
flight
customer
phone
clt
weatherstuck
delay
talk
moving
gate
delays
number
tarmac
work
reschedule
sitting
today
working
hold
hours
flights
phl
plane
night
book
hate
air
30
min
past
usairways
miss
tried
delayed
trying
10
need
connection
service
bad
help
waiting
like
travel
hoping
getting
days
told
americanair
philadelphia
0
100
200
300
400
500
0
200
400
600
800


TOPIC - 3: top 50 words
flight
want
thanks
worst
home
customer
service
plane
waiting
time
hours
wrong
today
dca
hour
line
told
unacceptable
treated
days
crew
nope
bag
work
need
luggage
got
away
money
know
minutes
flightled
americanair
make
passengers
earlier
help
lost
response
available
cancelled
able
day
hold
went
right
fly
think
person
late
0
100
200
300
400
500
0
200
400
600
800



Using our model's tweet predictions, we filtered US Airlines' negative feedback and identified the main topics. Among them were customer service and flight delays. Based on these tweets, it seems that customers are dissatisfied with US Airlines' customer service and frequent delays. This valuable feedback can be used to address these issues.

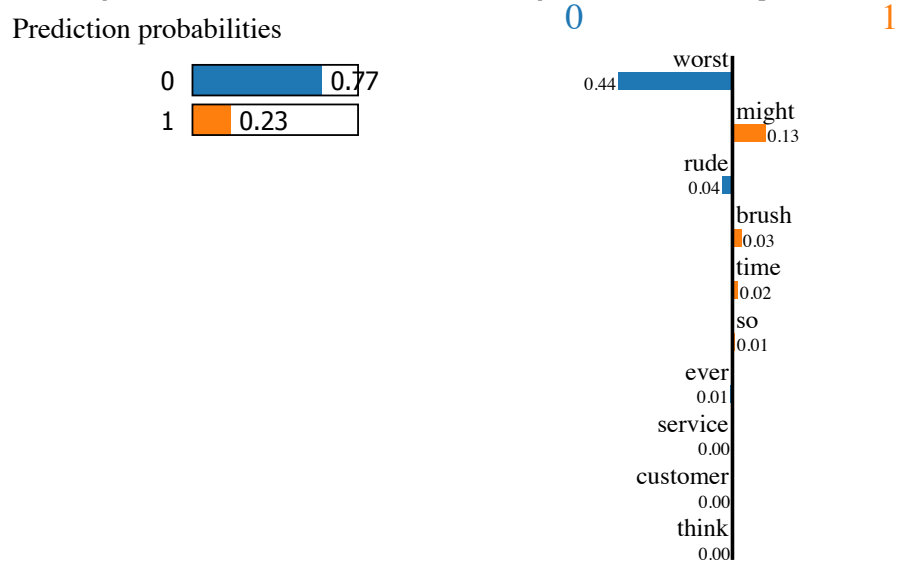
LIME

LIME interprates the model in a simpler way. This allows us to gain insights into the contribution of each feature to the prediction, making it easier to understand the model's behavior.

In [135…

```
# Generating explanations for a tweet
# 'predict_proba' is a function returns the predicted prob. for each class
exp = explainer.explain_instance(
    "might possibly worst airline ever think time brush customer service so rude.",
    predict_proba
).show_in_notebook(text=True)
```

```
157/157 [==============================] - 14s 87ms/step
```



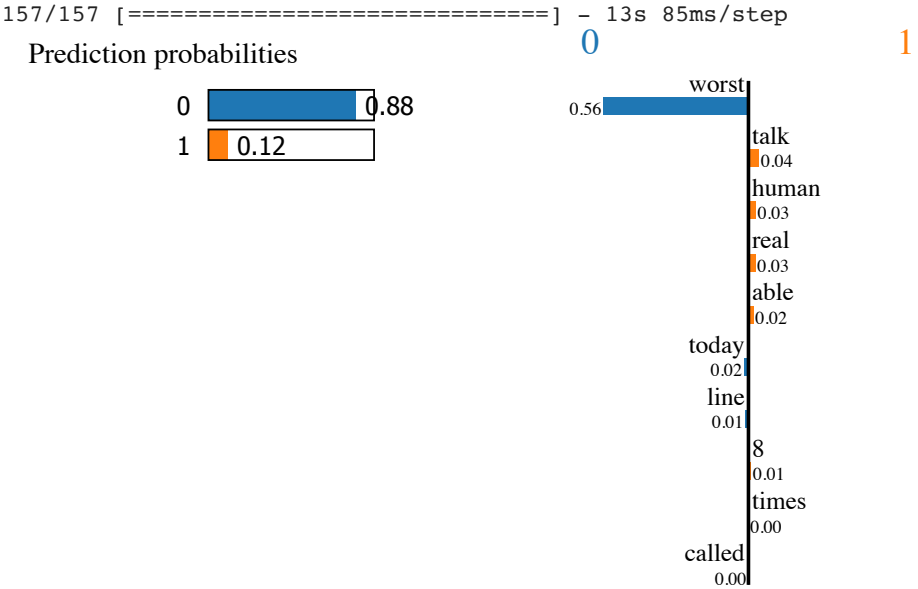
Text with highlighted words

might possibly worst airline ever think time brush customer service so rude.

In [136…

```
# Generating explanations for a tweet
# 'predict_proba' is a function returns the predicted prob. for each class
exp = explainer.explain_instance(
    "worst customer service line called 8 times today  able talk real human",
    predict_proba
).show_in_notebook(text=True)
```

```
157/157 [==============================] - 13s 85ms/step
```



Text with highlighted words

worst customer service line called 8 times today able talk real human

In [137…

```
# Generating explanations for a tweet
# 'predict_proba' is a function returns the predicted prob. for each class
exp = explainer.explain_instance(
    "impressed customer service everyone unhelpful incredibly rude",
    predict_proba
).show_in_notebook(text=True)
```

```
157/157 [==============================] - 12s 79ms/step
```

Text with highlighted words

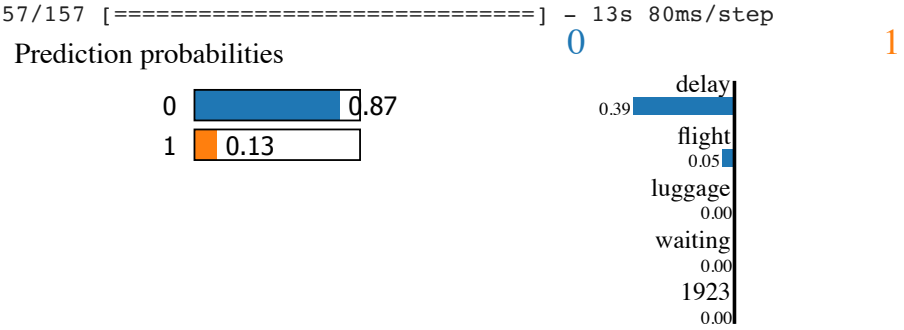
impressed customer service everyone unhelpful incredibly rude

In [138…

```
# Generating explanations for a tweet
# 'predict_proba' is a function returns the predicted prob. for each class
```

```
exp = explainer.explain_instance("waiting luggage flight 1923 delay",
                                 predict_proba).show_in_notebook(text=True)
```

```
157/157 [==============================] - 13s 80ms/step
```



Text with highlighted words

waiting luggage flight 1923 delay

Conclusion

In conclusion, we employed various models for sentiment analysis and found that the LSTM model outperformed the others. With training on one million tweets, the model achieved a prediction accuracy of 79%. To demonstrate its real-world application, we used the model to analyze airline feedback tweets, accurately predicting sentiments 71% of the time.

To gain further insights, we applied an LDA model for topic modeling, focusing specifically on negative tweets. The topics that emerged revealed that customers are predominantly dissatisfied with US Airlines' customer service and frequent delays. This valuable feedback can help airlines address these issues and make improvements in the areas that matter most to their customers. By continuously refining and applying such sentiment analysis models, businesses can gain actionable insights from customer feedback and enhance their products and services accordingly.