Discovering Mental Health In Micro Bloggers over tweets using sentiment analysis

Team Members
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Background:

The outbreak of Corona Virus pandemic is provoking havoc - explosion of viruses and its variants, millions of lost lives, economic depths of despair and restraints on human interaction causing perceptible disruption, all over the globe. One such undesirable outcome is on the psychological health of populace at large. Scientists & researchers, apprehend the deterioration of mental health caused by COVID isn’t temporary, and could persist long after the pandemic departs. Suddenly, innumerable people are suffering from stress, fear, anxiety, trepidation, hopelessness and ultimately depression. Closely monitoring mental health trends in real-time, can help people that are disproportionately affected and hence the study becomes extremely crucial. These trends can also be used to assess and compute the impact of policies and endeavors that address mental health status. Microblogging platforms like twitter have come to the fore as a space of trends. Tweets (twitter posts) are perspectives, views, comments on international, political, social trends, dispositions, and ongoing issues. They say, “You are what you Tweet”. Indeed, people are using this platform to unload the burdens of mental health. With this notion in mind, following is an analytical study of “Discovering Mental Health in micro bloggers”.

Problem Statement:

1. Has the mental health of populace in COVID deteriorated?
2. What is the proportion of people experiencing symptoms of anxiety and depression?
3. Are more people anxious than depressed or vice-versa?
4. With how much certainty can we predict the mental health of a person by using his history of tweets?

Pre-requsite modules

1. Code below contains all the required modules to run the code

In [1]:

```
pip install vaderSentiment
```

```
Collecting vaderSentiment
  Downloading https://files.pythonhosted.org/packages/76/fc/310e16254683c1ed
35eeb97386986d6c00bc29df17ce280aed64d55537e9/vaderSentiment-3.3.2-py2.py3-no
ne-any.whl (https://files.pythonhosted.org/packages/76/fc/310e16254683c1ed35
eeb97386986d6c00bc29df17ce280aed64d55537e9/vaderSentiment-3.3.2-py2.py3-none
-any.whl) (125kB)
     |████████████████████████████████| 133kB 7.7MB/s eta 0:00:01
Requirement already satisfied: requests in /usr/local/lib/python3.7/dist-pac
kages (from vaderSentiment) (2.23.0)
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.
7/dist-packages (from requests->vaderSentiment) (3.0.4)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.
7/dist-packages (from requests->vaderSentiment) (2020.12.5)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /u
sr/local/lib/python3.7/dist-packages (from requests->vaderSentiment) (1.24.
3)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist
-packages (from requests->vaderSentiment) (2.10)
Installing collected packages: vaderSentiment
Successfully installed vaderSentiment-3.3.2
```

In [58]:

```
import pandas as pd
from pandas import DataFrame
from wordcloud import WordCloud, STOPWORDS
import numpy as np
from numpy import percentile
import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib
import re # for regular expressions
import pandas as pd
pd.set_option("display.max_colwidth", 200)
import string
import nltk # for text manipulation
from nltk.stem.porter import *
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from tqdm import tqdm
from gensim.models.doc2vec import LabeledSentence
import gensim
from sklearn.linear_model import LogisticRegression
from scipy import stats
from sklearn import metrics
from sklearn.metrics import mean_squared_error,mean_absolute_error, make_scorer,classificat
from sklearn.model_selection import train_test_split,cross_val_score,KFold
from sklearn.model_selection import train_test_split
from sklearn.metrics import f1_score
from sklearn.naive_bayes import BernoulliNB
from sklearn import svm
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
import xgboost as xgb
import warnings
import tweepy as tw
warnings.filterwarnings("ignore")
import numpy as np
import matplotlib.pyplot as plt
from wordcloud import WordCloud
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

In [3]:

```
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
import pandas as pd
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.decomposition import TruncatedSVD
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import GridSearchCV
from sklearn import svm
import numpy as np
from sklearn import preprocessing
from mlxtend.plotting import plot_decision_regions
```

In [4]:

```
import nltk
import os
import re
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer

nltk.download('all')
lemmatizer = WordNetLemmatizer()
stopword_list = stopwords.words("english")
```

```
[nltk_data] Downloading collection 'all'
[nltk_data]    |
[nltk_data]    | Downloading package abc to /root/nltk_data...
[nltk_data]    |   Unzipping corpora/abc.zip.
[nltk_data]    | Downloading package alpino to /root/nltk_data...
[nltk_data]    |   Unzipping corpora/alpino.zip.
[nltk_data]    | Downloading package biocreative_ppi to
[nltk_data]    |     /root/nltk_data...
[nltk_data]    |   Unzipping corpora/biocreative_ppi.zip.
[nltk_data]    | Downloading package brown to /root/nltk_data...
[nltk_data]    |   Unzipping corpora/brown.zip.
[nltk_data]    | Downloading package brown_tei to /root/nltk_data...
[nltk_data]    |   Unzipping corpora/brown_tei.zip.
[nltk_data]    | Downloading package cess_cat to /root/nltk_data...
[nltk_data]    |   Unzipping corpora/cess_cat.zip.
[nltk_data]    | Downloading package cess_esp to /root/nltk_data...
[nltk_data]    |   Unzipping corpora/cess_esp.zip.
[nltk_data]    | Downloading package chat80 to /root/nltk_data...
[nltk_data]    |   Unzipping corpora/chat80.zip.
```

1. Data Collection :

For performing sentiment analysis we need training dataset to tune our model and test data to predict the emotional state of a person from his tweets.

1. Training data : We have collected the tweets (dataset) from twitter api from 2019 - 2021. Saved the data into csv and use it.
2. Testing data : We have split the training data set into two - one to train the model the other to test.

In [5]:

```
## Following code was used to create tweet dataset
def get_tweets(date_since,search_words):
  '''
    Input: list of dates from which you need tweets and List of search words
    Output: Dataframe of tweets
  '''
  # We need to have the below credentials from an active developer twitter account

  consumer_key =  # <INSERT YOUR CONSUMER KEY HERE>
  consumer_secret = # <INSERT CONSUMER_SECRET>
  access_token = # <INSERT ACCESS_TOKEN>
  access_token_secret = # <INSERT ACCESS_TOKEN_SECRET>


  auth = tw.OAuthHandler(consumer_key, consumer_secret)
  auth.set_access_token(access_token, access_token_secret)
  api = tw.API(auth, wait_on_rate_limit=True)

  tweets_list = []
  for date in date_since:
    # print(keyword,date)
    for keyword in search_words:
      search_key = keyword+' -filter:retweets'
      tweets = tw.Cursor(api.search,q= search_key,count=1000,lang="en",since=date).items(50
      # users_locs = [[tweet.user.screen_name, tweet.user.location] for tweet in tweets]
      for tweet in tweets:
        tweets_list.append([tweet.id,tweet.created_at,tweet.user.location,tweet.text] )

  return DataFrame(tweets_list)
```

In [137]:

```
## Following got calls the above tweet collection function as it takes lot of time to run t

# train_tweets_dates= ["2020-01-01","2020-02-01","2020-03-01","2020-04-01","2020-04-01","20
# train_tweets_search_words = ["Depression","hope","Hopeless","Joy","Quarantine","covid-19"
# train_tweet_data = get_tweets(train_tweets_dates,train_tweets_search_words)
# DataFrame(train_tweet_data).to_csv("Final_twitter.csv")
# train_tweet_data.columns = ["tweet.id","tweet.created_at","tweet.user.location","tweet.te
```

In [7]:

```
## Function into import the  dataset
def import_data(file_path):
  '''
    Input: File path of data set
    Output: Dataframe of csv data
  '''
  train_data = pd.read_csv(file_path)
  return train_data
```

In [74]:

```
url = "https://raw.githubusercontent.com/Shreya2012/data_bootcamp_final_project/main/Final_
train_tweet_data = import_data(url).drop(columns=['Unnamed: 0'])
train_tweet_data = train_tweet_data.drop(columns=['index'])
train_tweet_data
```

Out[74]:

	tweet.id	tweet.created_at	tweet.user.location	tweet.text
0	48751	16-03-2020	London	@MeNyrbie @Phil_Gahan @Chrisitv https://t.co/iFz9FAn2Pa and https://t.co/xX6ghGFzCC and https://t.co/I2NlzdxNo8
1	48752	16-03-2020	UK	advice Talk to your neighbours family to exchange phone numbers create contact list with phone numbers of neighbours schools employer chemist GP set up online shopping accounts if poss adequate su...
2	48753	16-03-2020	Vagabonds	Coronavirus Australia: Woolworths to give elderly, disabled dedicated shopping hours amid COVID-19 outbreak https://t.co/bInCA9Vp8P
3	48754	16-03-2020	NaN	My food stock is not the only one which is empty...\n\n\n\nPLEASE, don't panic, THERE WILL BE ENOUGH FOOD FOR EVERYONE if you do not take more than you need. \n\nStay calm, stay safe.\n\n\n\n#COVI...
4	48755	16-03-2020	NaN	Me, ready to go at supermarket during the #COVID19 outbreak.\n\n\n\nNot because I'm paranoid, but because my food stock is litteraly empty. The #coronavirus is a serious thing, but please, don't p...
...	...	...	...	...
44950	48746	16-03-2019	Israel ??	RT @aliahmed_ppp: Happy birthday to the poet of the east 🤍\n#IqbalDay2020 https://t.co/7WPDiGtx9x
44951	48747	16-03-2019	Farmington, NM	RT @sanditonlovebot: @MariannS18 Happy birthday!! 🎉 🤍 #Sanditon #SaveSanditon #SanditonPBS
44952	48748	16-03-2019	Haverford, PA	YOOOO ITS CORYS BIRTHDAY HAPPY BIRTHDAY TO THE ANKLE BREAKER HIMSELF
44953	48749	16-03-2019	NaN	RT @CoryxKenshin: Thank you all for all the birthday wishes, really made ya boy feel loved today 🎉 https://t.co/ns5V3ZEZHb
44954	48750	16-03-2019	Arlington, Virginia	@charlieINTEL Happy birthday BO1

44955 rows × 4 columns

2. Data Analysis (EDA):

Research

The approach for this study includes the use of twitter as the principal source of information for thoughts, comments, and views in the form of tweets. The python library, Tweepy has been employed for data extraction from twitter API. Vader algorithm is applicable to further classify tweets under sentiment polarity and intensity. Regex and NLP techniques have been used for text and data analysis including removal of https/urls/punctuations/numbers from tweets and tokenization and stemming procedures for maximum results. Decision Tree, Random Forest, Support Vector Machine and Logistic regression are the attempted machine learning models.

Agenda of this section is to understand the data distribution and variety. This analysis will help us in next step of data cleaning for accurate predictions.

1. Non-visual analysis
   A. Getting dimensions,data types and null values of the dataset
   B. Getting data types and null values
   C. Understanding the data distribution and outliners of float columns
   D. Categorial variables
2. Visual analysis
   A. Word cloud of unprocessed tweets.
   B. Heat map of null values in each column

In [75]:

```
## Getting dimensions of the dataset
def get_dimensions(df):
  print("-"*50,"\n")
  print("No of rows and columns: ", df.shape)
  print("-"*50,"\n")

## Getting data types of columns oin the dataset
def get_data_types(df):
  print("-"*50,"\n")
  print("Data types of columns: ", df.info())
  print("-"*50,"\n")

## Understanding the data distribution nad outliners of float columns
def get_describe(df):
  print("-"*50,"\n")
  print("Data distribution: ",df.describe())
  print("-"*50,"\n")

## Count of null rows in each column
def check_null(df):
  print("-"*50,"\n")
  print("Null values:\n",df.isnull().sum(axis = 0))
  print("-"*50,"\n")

## Value count of unique values in tweets - location and id
def get_value_count(df):
  print("-"*50,"\n")
  print("\n","Value count of unique location", df['tweet.user.location'].value_counts())
  print("-"*50,"\n")
  print("-"*50,"\n")
  print("Value count of unique id:", df['tweet.id'].value_counts())
  print("-"*50,"\n")
```

In [76]:

```
def word_frequency_chart(data):
  '''
    Input : Tweet data
    Ouput : None
    Console output - bar chart
  '''
  # Frequently used words
  unique_words = []
  words_list = []
  for tweet in data:
    word_list = tweet.split(" ")
    unique_words = unique_words + word_list
    words_list = words_list + word_list
    unique_words = list(set(unique_words))

  unique_word_count = []
  for word in unique_words:
    unique_word_count.append([word, words_list.count(word)])
  unique_word_count = unique_word_count[3:]
  unique_word_count = pd.DataFrame(unique_word_count, columns = ['word', 'count'])
  unique_word_count = unique_word_count.sort_values(by =["count"],ascending= False)
  print(unique_word_count.head(10))
```

Call the Functions

In [77]:

```
get_dimensions(train_tweet_data)
```

```
--------------------------------------------------

No of rows and columns:  (44955, 4)
--------------------------------------------------
```

In [78]:

```
get_data_types(train_tweet_data)
```

```
--------------------------------------------------

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 44955 entries, 0 to 44954
Data columns (total 4 columns):
 #   Column               Non-Null Count  Dtype 
---  ------               --------------  ----- 
 0   tweet.id             44955 non-null  int64 
 1   tweet.created_at     44955 non-null  object
 2   tweet.user.location  35526 non-null  object
 3   tweet.text           44955 non-null  object
dtypes: int64(1), object(3)
memory usage: 1.4+ MB
Data types of columns:  None
--------------------------------------------------
```

In [79]:

```
get_describe(train_tweet_data)
```

```
--------------------------------------------------

Data distribution:              tweet.id
count  44955.000000
mean   67430.000000
std    12977.535012
min    44953.000000
25%    56191.500000
50%    67430.000000
75%    78668.500000
max    89907.000000
--------------------------------------------------
```

In [80]:

```
check_null(train_tweet_data)
```

```
--------------------------------------------------

Null values:
 tweet.id                  0
tweet.created_at          0
tweet.user.location    9429
tweet.text                0
dtype: int64
--------------------------------------------------
```

In [81]:

```
get_value_count(train_tweet_data)
```

```
--------------------------------------------------


 Value count of unique location United States              605
London                     581
London, England            568
New York, NY               429
Washington, DC             411
                          ...
Probably in the kitchen      1
Clermont, FL                 1
Brooklyn, NY, USA            1
Crawley, South East          1
the Interwebz                1
Name: tweet.user.location, Length: 12881, dtype: int64
--------------------------------------------------

--------------------------------------------------

Value count of unique id: 67583    1
73033    1
56657    1
54608    1
77135    1
        ..
86687    1
88734    1
82589    1
84636    1
65536    1
Name: tweet.id, Length: 44955, dtype: int64
--------------------------------------------------
```

Observation of Non visual EDA:

1. Only User id is a numeric value in the dataset. Hence the we can skip trying to find the outliers in the column as id is unique and represents individual persons.
2. Created at, user location and tweet are objects - this information was used to dig deep into the value of location and user id. This can give us a greater picture of infering the demographic statistics after completing the analysis.
3. We saw location column had multiple null values, but we have decided not to clean that as we may lose the user tweet data which in our case plays cruical role.
4. Frequecy of top 10 words show the most used words. From the result we see most of them are atop words which needs to be removed as part of cleaning for precise prediction.

In [82]:

```
def create_cloud(df):
    '''
      Input : Tweet data set
      Output : None
      Console output - word cloud
    '''

    all_words = ' '.join([text for text in df])
    wordcloud = WordCloud(width=800, height=500, random_state=21, max_font_size=110).generate
    plt.figure(figsize=(10, 7))
    plt.imshow(wordcloud, interpolation="bilinear")
    plt.axis('off')
    plt.show()
```

In [83]:

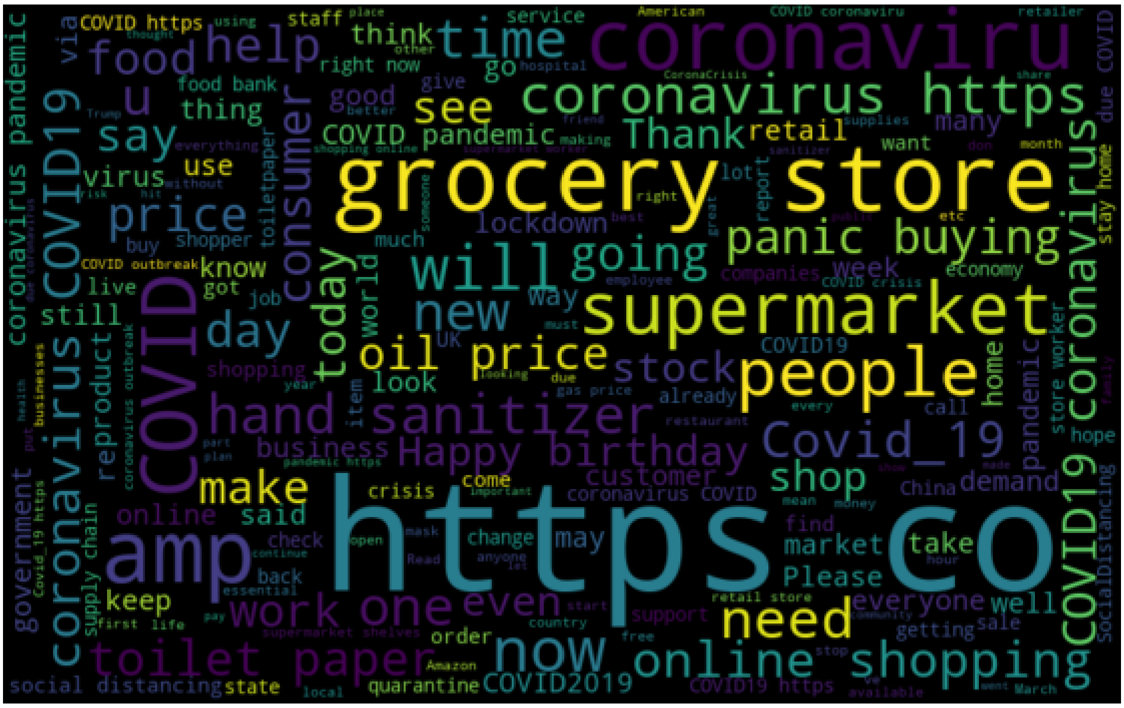
```
def heat_map_null_values(data):
    '''
      Input : tweet data set
      Output : None
      Console output - heat map
    '''
    # Heat Map for missing values
    plt.figure(figsize=(17, 5))
    sns.heatmap(data.isnull(), cbar=True, yticklabels=False)
    plt.xlabel("Column_Name", size=14, weight="bold")
    plt.title("Places of missing values in column",fontweight="bold",size=17)
    plt.show()
```

In [84]:

```
def unique_word_count_chart(data):
    '''
      Input : tweet data
      Ouput : None
      Console output - bar graph of unique words
    '''
    # Unique Values In Each Feature Coulmn
    unique_df = pd.DataFrame()
    unique_df['Features'] = data.columns
    unique=[]
    for i in data.columns:
        unique.append(data[i].nunique())
    unique_df['Uniques'] = unique

    f, ax = plt.subplots(1,1, figsize=(15,7))

    splot = sns.barplot(x=unique_df['Features'], y=unique_df['Uniques'], alpha=0.8)
    for p in splot.patches:
        splot.annotate(format(p.get_height(), '.0f'), (p.get_x() + p.get_width() / 2., p.get_
                       va = 'center', xytext = (0, 9), textcoords = 'offset points')
    plt.title('Bar plot for number of unique values in each column',weight='bold', size=15)
    plt.ylabel('#Unique values', size=12, weight='bold')
    plt.xlabel('Features', size=12, weight='bold')
    plt.xticks(rotation=90)
    plt.show()
```

In [85]:

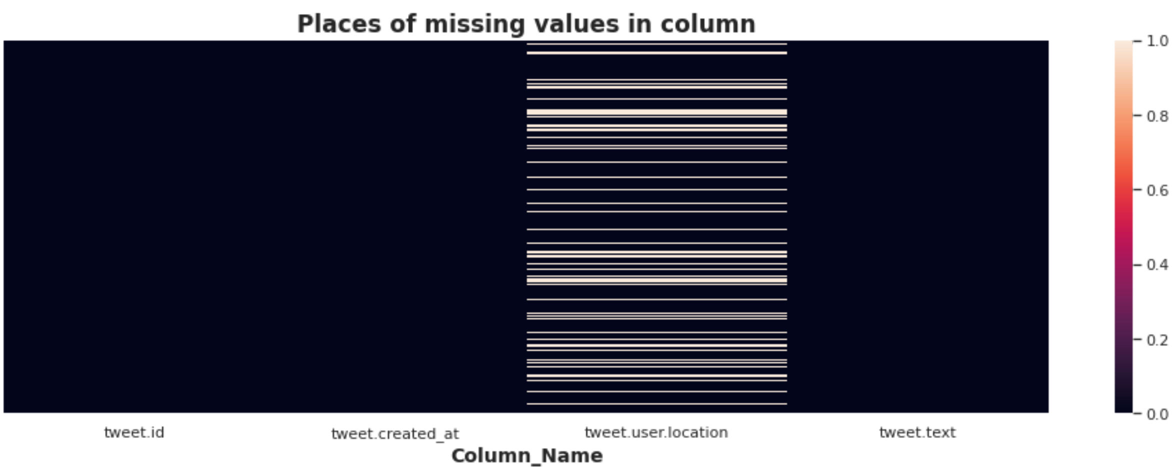
```
# Word Cloud of uncleaned tweets
create_cloud(train_tweet_data["tweet.text"])
```



The word cloud clearly captures the social disorder by the pandemic. The words like social distancing, grocery store, toilet paper and hand sanitizer were trending not only during 2020 but even in 2021.

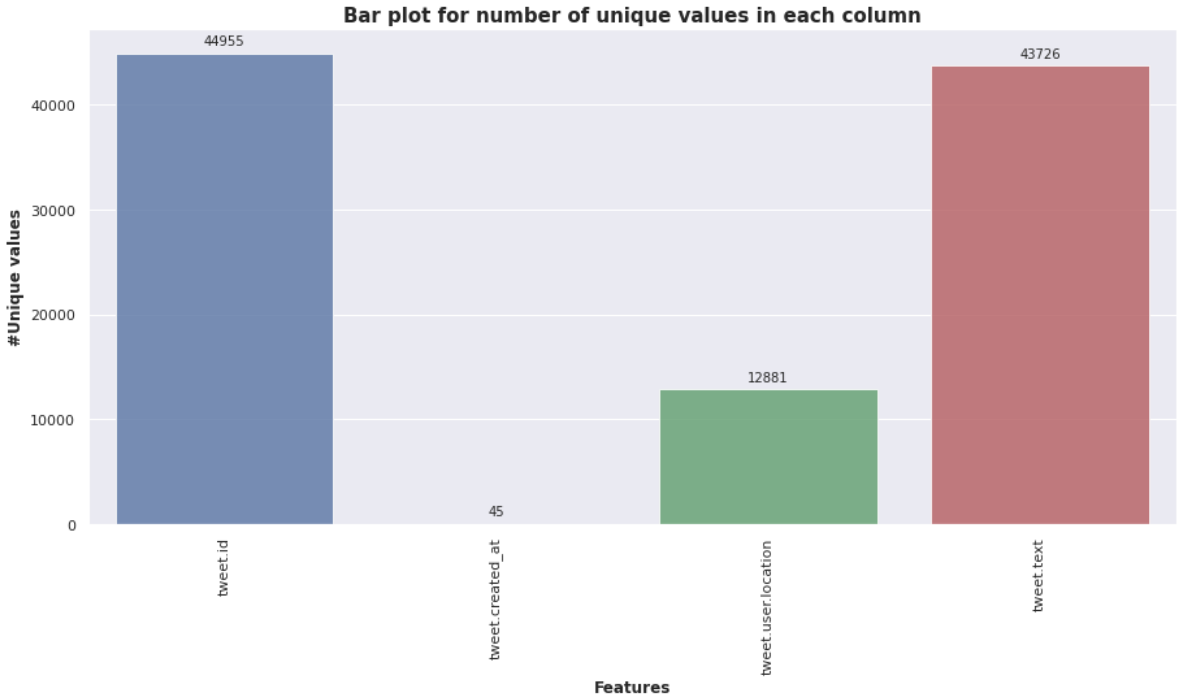
In [86]:

```
# Null value Heat map
heat_map_null_values(train_tweet_data)
```



In [87]:

```
unique_word_count_chart(train_tweet_data)
```



Observation of visual EDA:

1. From word cloud we can see that there are many words like https, CO, US which doesnt convey any emotion - This leads us to remove the stop words for deducing the relavent words.
2. From the heat map we can see there are no null values in any other column other than location.

3. Data Cleaning and Processing:

1. Clean the tweets - remove punctations, stop words, URL and special characters.
2. Lemmetization & Stemming

In [23]:

```
def clean_tweet(tweet):
    '''
    Utility function to clean tweet text by removing links, special characters
    using simple regex statements.
    '''
    return(' '.join(re.sub("(@[A-Za-z0-9]+)|([^0-9A-Za-z \t])|(\w+:\/\/\S+)", " ", tweet).s


def clean_post(post):
    '''
      Input : text
      Ouput : lemmatized text with removed stop words
    '''
    global stopword_list, lemmatizer
    post_tokens = word_tokenize(post)
    filtered_tokens = [token for token in post_tokens if token not in stopword_list]
    lemmas = [lemmatizer.lemmatize(token, pos='v') for token in filtered_tokens]
    return " ".join(lemmas)


def cleantweets(tweets_list):
  '''
    Input : tweet list
    Ouput : cleaned tweets
  '''
  # Clean the tweets - remove punctations, stop words, URL and special characters.
  cleaned_tweet = []
  for tweet in tweets_list:
    cleaned_tweet.append(clean_tweet(tweet))

  # Lemmetization & Stemming of tweets
  clean_post_tweet = []
  for tweet in cleaned_tweet:
    clean_post_tweet.append(clean_post(tweet))

  return clean_post_tweet
```

In [24]:

```
# getting cleaned tweets and saving the data into csv as DataFrame
train_tweet_data["Cleaned_Tweets"] = cleantweets(train_tweet_data["tweet.text"])
train_tweet_data.drop_duplicates(subset ="Cleaned_Tweets",keep = False, inplace = True)
tweets_cleaned = pd.DataFrame(train_tweet_data)
tweets_cleaned
```

Out[24]:

	tweet.id	tweet.created_at	tweet.user.location	tweet.text	Cleaned_Twee
0	48751	16-03-2020	London	@MeNyrbie @Phil_Gahan @Chrisitv https://t.co/iFz9FAn2Pa and https://t.co/xX6ghGFzCC and https://t.co/I2NlzdxNo8	gah
1	48752	16-03-2020	UK	advice Talk to your neighbours family to exchange phone numbers create contact list with phone numbers of neighbours schools employer chemist GP set up online shopping accounts if poss adequate su...	advice ta neighbour fam exchange phon number crea contact list phon number neighbo school employ chemist gp s online sh account po adequate supp regular meds ord
2	48753	16-03-2020	Vagabonds	Coronavirus Australia: Woolworths to give elderly, disabled dedicated shopping hours amid COVID-19 outbreak https://t.co/bInCA9Vp8P	coronavir austra woolworths gi elderly disab dedicate sh hours amid cov 19 outbre
3	48754	16-03-2020	NaN	My food stock is not the only one which is empty...\n\n\n\nPLEASE, don't panic, THERE WILL BE ENOUGH FOOD FOR EVERYONE if you do not take more than you need. \n\nStay calm, stay safe.\n\n\n\n#COVI...	food stock o empty please pa enough fo everyone take ne stay calm stay sa covid19fran covid 19 covid coronavir confineme confinemento confinementgene
4	48755	16-03-2020	NaN	Me, ready to go at supermarket during the #COVID19 outbreak.\n\n\n\nNot because I'm paranoid, but because my food stock is litteraly empty. The #coronavirus is a serious thing, but please, don't p...	ready supermark covid19 outbre paranoid food sto litteraly emp coronavirus serio thing please pa cause shorta coronavirusfran restezchezvo stayathon confineme
...	...	...	...	...	

	tweet.id	tweet.created_at	tweet.user.location	tweet.text	Cleaned_Twee
44947	48743	16-03-2019	Cincinnati, Ohio	Awwee Heysh making me feel so appreciated 😍 she really going all out for me to make sure I have a good birthday 😩 ♡	awwee heysh mal feel apprecia really go make su good birthd
44949	48745	16-03-2019	Washington D.C.	RT @BazookaJoeDJ: Remembering American film and theatre actress, singer, and dancer Dorothy Dandridge on her birthday (November 9, 1922 – S…	rt rememb american fi theatre actre singer danc dorothy dandrid birthday novemb 9 19
44950	48746	16-03-2019	Israel ??	RT @aliahmed_ppp: Happy birthday to the poet of the east ♡ \n#IqbalDay2020 https://t.co/7WPDiGtx9x	rt ppp hap birthday poet ea iqbalday20
44952	48748	16-03-2019	Haverford, PA	YOOOO ITS CORYS BIRTHDAY HAPPY BIRTHDAY TO THE ANKLE BREAKER HIMSELF	yoooo cor birthday hap birthday ank break
44954	48750	16-03-2019	Arlington, Virginia	@charlieINTEL Happy birthday BO1	happy birthday b

42790 rows × 5 columns

Performing basic EDA to see the effect of cleaning an processing

In [25]:

```
get_dimensions(tweets_cleaned)
```

```
-----------------------------------------------

No of rows and columns:  (42790, 5)
-----------------------------------------------
```

In [26]:

```
get_data_types(tweets_cleaned)
```

```
--------------------------------------------------

<class 'pandas.core.frame.DataFrame'>
Int64Index: 42790 entries, 0 to 44954
Data columns (total 5 columns):
 #   Column               Non-Null Count  Dtype 
---  ------               --------------  ----- 
 0   tweet.id             42790 non-null  int64 
 1   tweet.created_at     42790 non-null  object
 2   tweet.user.location  33843 non-null  object
 3   tweet.text           42790 non-null  object
 4   Cleaned_Tweets       42790 non-null  object
dtypes: int64(1), object(4)
memory usage: 2.0+ MB
Data types of columns:  None
--------------------------------------------------
```

In [27]:

```
get_describe(tweets_cleaned)
```

```
--------------------------------------------------

Data distribution:                tweet.id
count  42790.000000
mean   68256.474457
std    12527.908438
min    44953.000000
25%    57506.250000
50%    68272.500000
75%    79074.750000
max    89907.000000
--------------------------------------------------
```

In [28]:

```
check_null(tweets_cleaned)
```

```
--------------------------------------------------

Null values:
 tweet.id                  0
tweet.created_at          0
tweet.user.location    8947
tweet.text                0
Cleaned_Tweets            0
dtype: int64
--------------------------------------------------
```

In [136]:

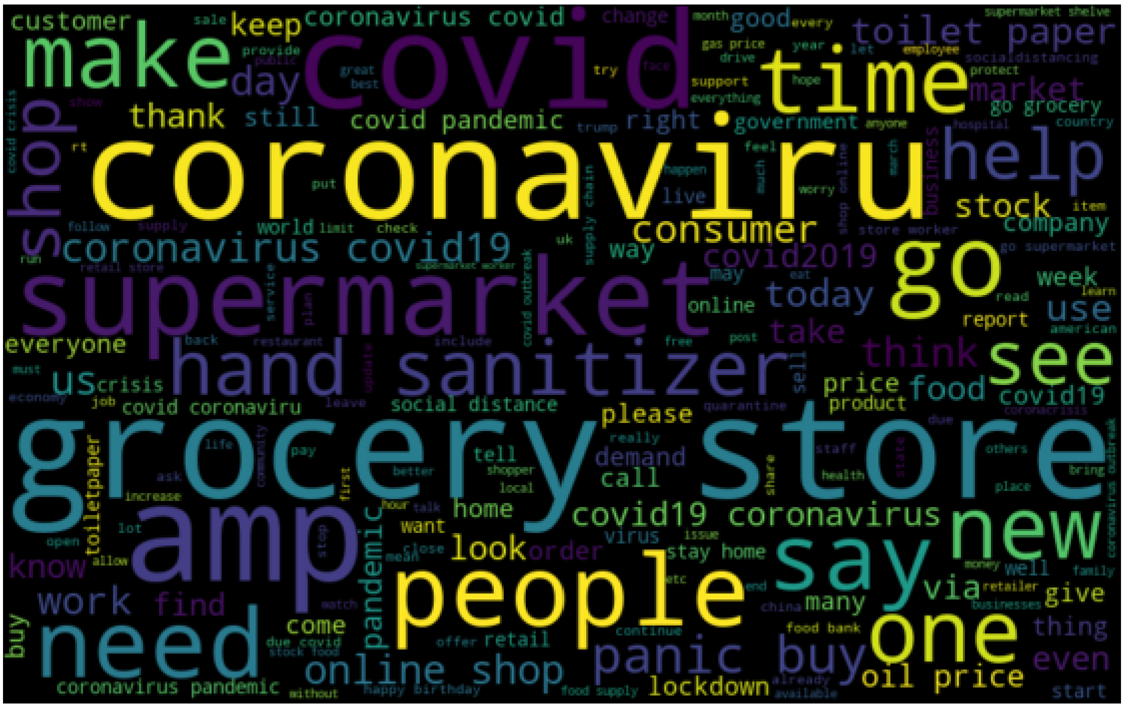
```
get_value_count(tweets_cleaned)
```

```
--------------------------------------------------



 Value count of unique location London                  566
United States           555
London, England         543
New York, NY            412
Washington, DC          397
                       ...
Front Range, CO           1
Flintshire, UK            1
Amritsar, India           1
Allen, Texas              1
Valencia, California      1
Name: tweet.user.location, Length: 12423, dtype: int64
--------------------------------------------------

--------------------------------------------------

Value count of unique id: 67583    1
75086    1
79180    1
68939    1
66890    1
        ..
64138    1
57993    1
60040    1
86655    1
65536    1
Name: tweet.id, Length: 42790, dtype: int64
--------------------------------------------------
```

Performing visual EDA

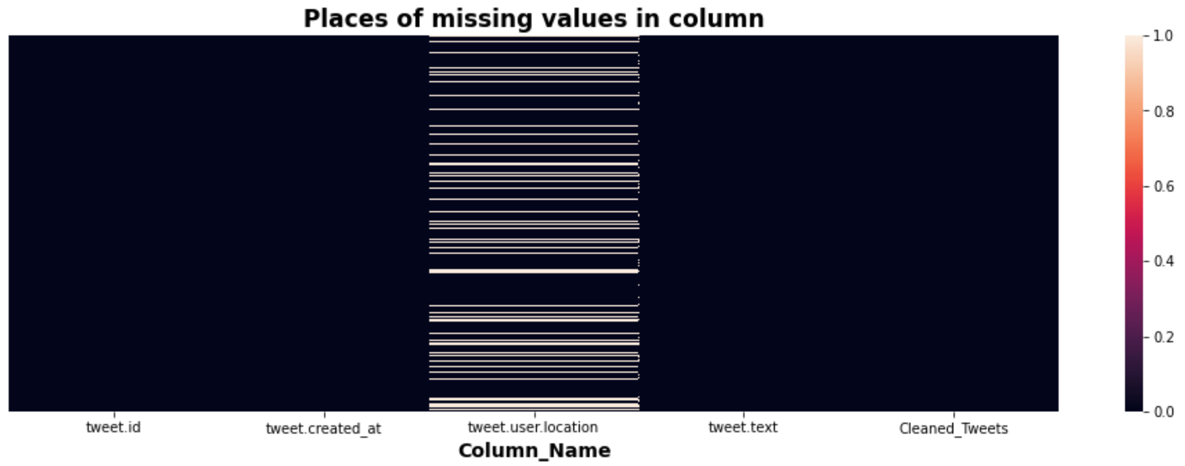
In [30]:

```
create_cloud(tweets_cleaned["Cleaned_Tweets"])
```



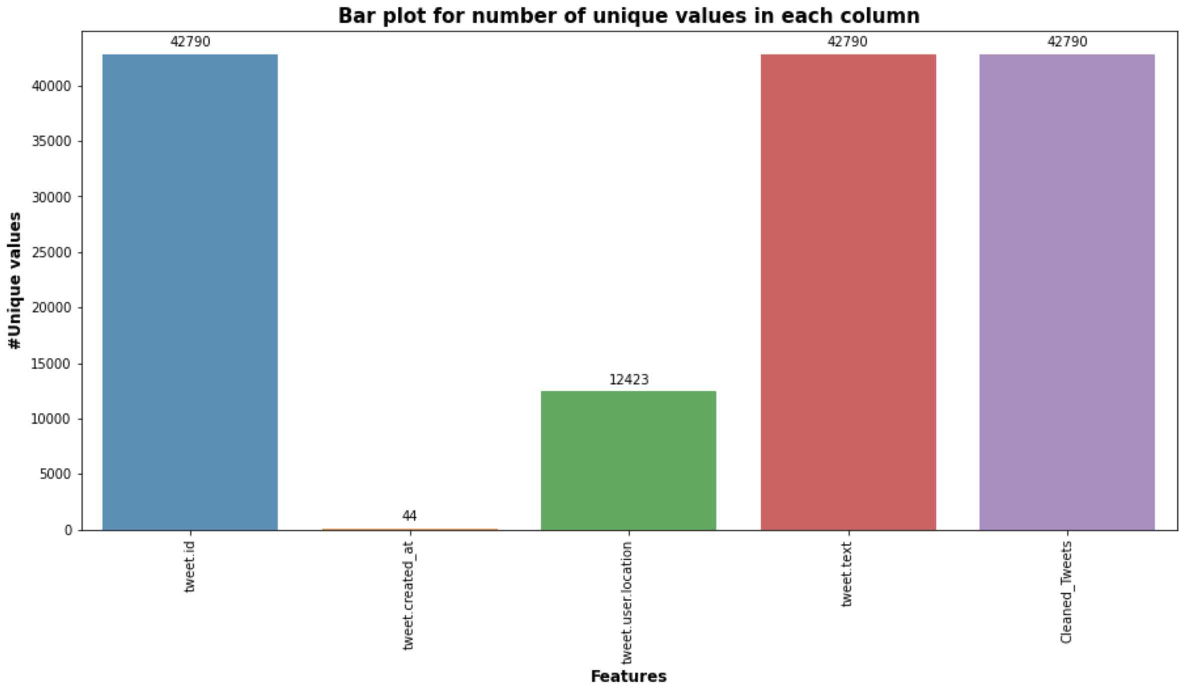
In [31]:

```
heat_map_null_values(tweets_cleaned)
```



In [32]:

```
unique_word_count_chart(tweets_cleaned)
```



4. Vader sentiment:

VADER (Valence Aware Dictionary and sEntiment Reasoner) is a lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media, and works well on texts from other domains

1. Assign vader score and classify them into a bucket

In [33]:

```
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
analyzer = SentimentIntensityAnalyzer()

def get_vader_score(data,tweet_column_name):
  '''
    Input : tweet data set , tweet text column name
    Ouput : None
    Function will add a column- vader_score in the data set
  '''
  data['vader_score'] = data[tweet_column_name].apply(lambda x: analyzer.polarity_scores(x)

def bucket_vader_score(data,vader_score_column_name):
  '''
    Input : tweet data set , tweet text column name
    Ouput : None
    Function will add a column-vader sentiment boolean value in the data set
  '''
  data['vader_sentiment_label']= data[vader_score_column_name].map(lambda x:int(1) if x>=0.

## Function call
get_vader_score(tweets_cleaned,'Cleaned_Tweets')
bucket_vader_score(tweets_cleaned,"vader_score")
```

In [34]:

```
#Vader Scores appended to our DataFrame
tweets_cleaned
```

Out[34]:

	tweet.id	tweet.created_at	tweet.user.location	tweet.text	Cleaned_Tweets
0	48751	16-03-2020	London	@MeNyrbie @Phil_Gahan @Chrisitv https://t.co/iFz9FAn2Pa and https://t.co/xX6ghGFzCC and https://t.co/I2NlzdxNo8	gahan
1	48752	16-03-2020	UK	advice Talk to your neighbours family to exchange phone numbers create contact list with phone numbers of neighbours schools employer chemist GP set up online shopping accounts if poss adequate su...	advice talk neighbour family exchange phone number create contact list phone number neighbour school employer chemist gp set online shop account poss adequate supply regular meds order
2	48753	16-03-2020	Vagabonds	Coronavirus Australia: Woolworths to give elderly, disabled dedicated shopping hours amid COVID-19 outbreak https://t.co/bInCA9Vp8P	coronavirus australia woolworths give elderly disable dedicate shop hours amid covid 19 outbreak
3	48754	16-03-2020	NaN	My food stock is not the only one which is empty...\n\n\n\nPLEASE, don't panic, THERE WILL BE ENOUGH FOOD FOR EVERYONE if you do not take more than you need. \n\nStay calm, stay safe.\n\n\n\n#COVI...	food stock one empty please panic enough food everyone take need stay calm stay safe covid19france covid 19 covid19 coronavirus confinement confinementotal confinementgeneral
4	48755	16-03-2020	NaN	Me, ready to go at supermarket during the #COVID19 outbreak.\n\n\n\nNot because I'm paranoid, but because my food stock is litteraly empty. The #coronavirus is a serious thing, but please, don't p...	ready go supermarket covid19 outbreak paranoid food stock litteraly empty coronavirus serious thing please panic cause shortage coronavirusfrance restezchezvous stayathome confinement
...	...	...	...	...	...
44947	48743	16-03-2019	Cincinnati, Ohio	Awwee Heysh making me feel so appreciated 🥺 she really going all out for me to make sure I have a good birthday 😩 ♡	awwee heysh make feel appreciate really go make sure good birthday

	tweet.id	tweet.created_at	tweet.user.location	tweet.text	Cleaned_Tweets
44949	48745	16-03-2019	Washington D.C.	RT @BazookaJoeDJ: Remembering American film and theatre actress, singer, and dancer Dorothy Dandridge on her birthday (November 9, 1922 – S...	rt remember american film theatre actress singer dancer dorothy dandridge birthday november 9 1922
44950	48746	16-03-2019	Israel ??	RT @aliahmed_ppp: Happy birthday to the poet of the east ♡ \n#IqbalDay2020 https://t.co/7WPDiGtx9x	rt ppp happy birthday poet east iqbalday2020
44952	48748	16-03-2019	Haverford, PA	YOOOO ITS CORYS BIRTHDAY HAPPY BIRTHDAY TO THE ANKLE BREAKER HIMSELF	yoooo corys birthday happy birthday ankle breaker
44954	48750	16-03-2019	Arlington, Virginia	@charlieINTEL Happy birthday BO1	happy birthday bo1

42790 rows × 7 columns

4.1 A step furthur, we want determine does negative sentiment tweets show signs of depression and anxiety.

1. For that purpose we got bag of words related to depression and anxiety and check tweet text against that to flag if tweet showed any signs.

In [35]:

```
def has_depression(tweets_cleaned):
  '''
    Input : tweet data set
    Output : None
    Function will add a column- has_depression boolean value in the data set
  '''
  dep_list = ['hopeless', 'discouraged','lost interest', 'lonely', 'unhappy', 'sad', 'dissa
  global dep_dict
  dep_dict = dict()

  for i,val in tweets_cleaned.iterrows():
    has_dep = 0
    if(val[5] < 0.0):
      for dep in dep_list:
        if dep in val[4]:
          if dep in dep_dict.keys():
            dep_dict[dep] += 1
          else:
            dep_dict[dep]=1
          has_dep = 1
      tweets_cleaned.at[i,'has_depression'] = has_dep
  tweets_cleaned['has_depression'] = tweets_cleaned['has_depression'].replace(np.nan, 0)
```

In [36]:

```
def has_anxiety(tweets_cleaned):
  '''
    Input : tweet data set
    Output : None
    Function will add a column- has_depression boolean value in the data set
  '''
  anx_list = ['fear','nervous','anxiety','lonely','tightness','faint','breath','hear racing
  global anx_dict
  anx_dict = dict()

  for i,val in tweets_cleaned.iterrows():
    has_anx = 0
    if(val[5] < 0.0):
      for anx in anx_list:
        if anx in val[4]:
          if anx in anx_dict.keys():
            anx_dict[anx] += 1
          else:
            anx_dict[anx] = 1
          has_anx = 1
      tweets_cleaned.at[i,'has_anxiety'] = has_anx
  tweets_cleaned['has_anxiety'] = tweets_cleaned['has_anxiety'].replace(np.nan, 0)
```

In [37]:

```
# Function calling
has_depression(tweets_cleaned)
has_anxiety(tweets_cleaned)
```

In [38]:

```
# Adding has_depression and has_anxiety classification columns
tweets_cleaned
```

Out[38]:

	tweet.id	tweet.created_at	tweet.user.location	tweet.text	Cleaned_Tweets
0	48751	16-03-2020	London	@MeNyrbie @Phil_Gahan @Chrisitv https://t.co/iFz9FAn2Pa and https://t.co/xX6ghGFzCC and https://t.co/I2NlzdxNo8	gahan
1	48752	16-03-2020	UK	advice Talk to your neighbours family to exchange phone numbers create contact list with phone numbers of neighbours schools employer chemist GP set up online shopping accounts if poss adequate su...	advice talk neighbour family exchange phone number create contact list phone number neighbour school employer chemist gp set online shop account poss adequate supply regular meds order
2	48753	16-03-2020	Vagabonds	Coronavirus Australia: Woolworths to give elderly, disabled dedicated shopping hours amid COVID-19 outbreak https://t.co/bInCA9Vp8P	coronavirus australia woolworths give elderly disable dedicate shop hours amid covid 19 outbreak
3	48754	16-03-2020	NaN	My food stock is not the only one which is empty...\n\n\n\nPLEASE, don't panic, THERE WILL BE ENOUGH FOOD FOR EVERYONE if you do not take more than you need. \n\nStay calm, stay safe.\n\n\n\n#COVI...	food stock one empty please panic enough food everyone take need stay calm stay safe covid19france covid 19 covid19 coronavirus confinement confinementotal confinementgeneral
4	48755	16-03-2020	NaN	Me, ready to go at supermarket during the #COVID19 outbreak.\n\n\n\nNot because I'm paranoid, but because my food stock is litteraly empty. The #coronavirus is a serious thing, but please, don't p...	ready go supermarket covid19 outbreak paranoid food stock litteraly empty coronavirus serious thing please panic cause shortage coronavirusfrance restezchezvous stayathome confinement
...	...	...	...	...	...
44947	48743	16-03-2019	Cincinnati, Ohio	Awwee Heysh making me feel so appreciated 🥺 she really going all out for me to make sure I have a good birthday 😩 ♡	awwee heysh make feel appreciate really go make sure good birthday

	tweet.id	tweet.created_at	tweet.user.location	tweet.text	Cleaned_Tweets
44949	48745	16-03-2019	Washington D.C.	RT @BazookaJoeDJ: Remembering American film and theatre actress, singer, and dancer Dorothy Dandridge on her birthday (November 9, 1922 – S…	rt remember american film theatre actress singer dancer dorothy dandridge birthday november 9 1922
44950	48746	16-03-2019	Israel ??	RT @aliahmed_ppp: Happy birthday to the poet of the east ♡ \n#IqbalDay2020 https://t.co/7WPDiGtx9x	rt ppp happy birthday poet east iqbalday2020
44952	48748	16-03-2019	Haverford, PA	YOOOO ITS CORYS BIRTHDAY HAPPY BIRTHDAY TO THE ANKLE BREAKER HIMSELF	yoooo corys birthday happy birthday ankle breaker
44954	48750	16-03-2019	Arlington, Virginia	@charlieINTEL Happy birthday BO1	happy birthday bo1

42790 rows × 9 columns

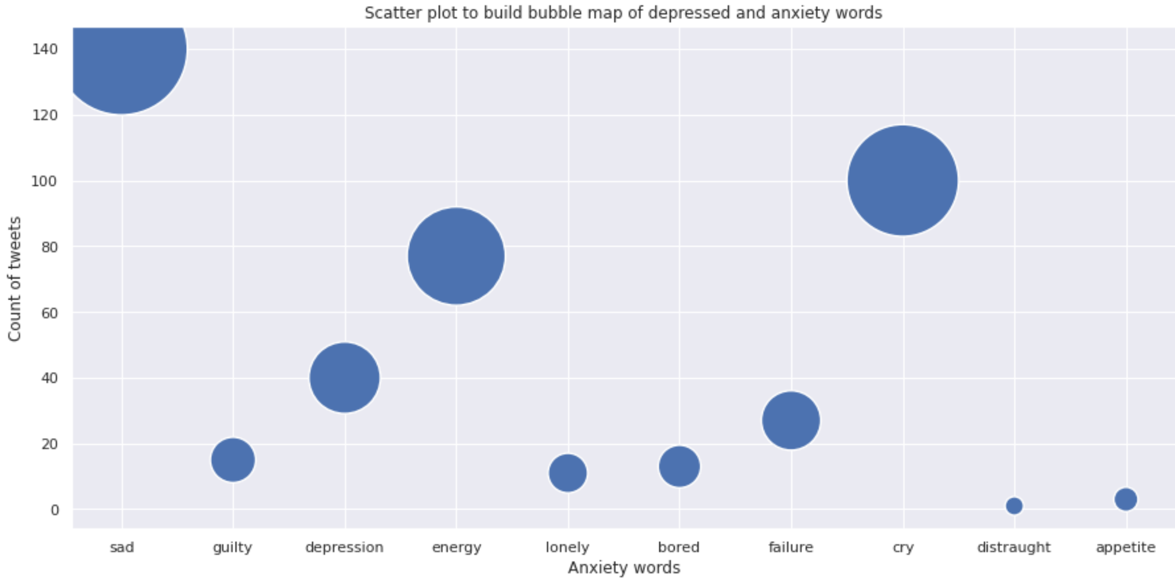
4.1.1 Visual analysis of vader sentiment, depression and anxiety score.

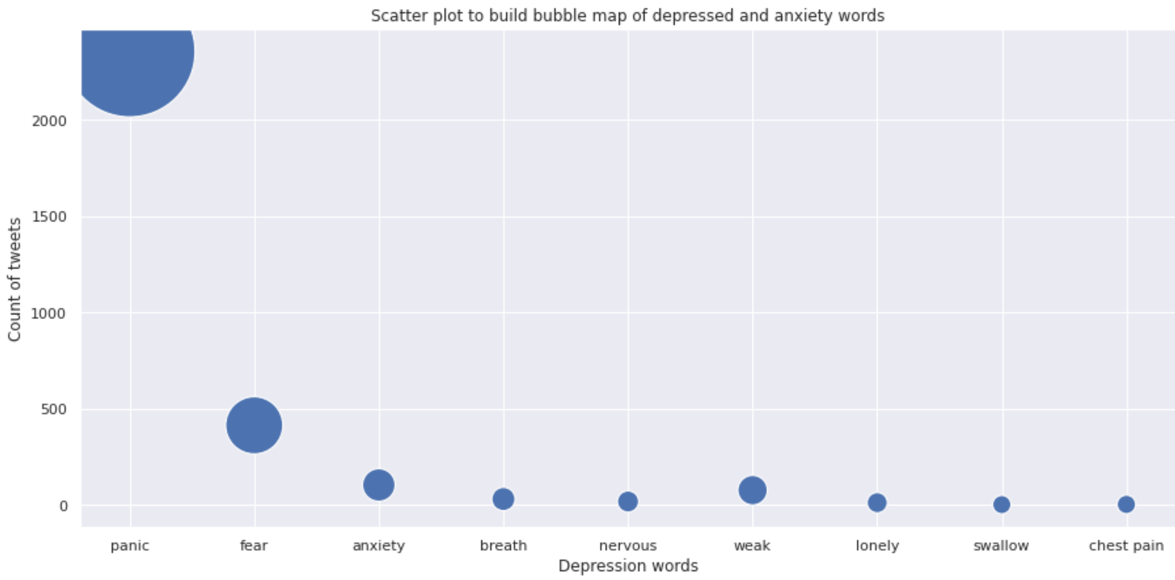
1. Change in number of negative tweets before and after covid.
2. Vader score distribution
3. Negative tweet distribution over time
4. Propotion of negative tweets related to covid during 2020-2021

Visualizing negative test scores

In [99]:

```
# Scatter plot to build bubble map of depressed and anxiety words
def count_Depression_anxiety_words(dep_dict, anx_dict):
  f, ax = plt.subplots(1,1, figsize=(15,7))

  df1 = pd.DataFrame(dep_dict.items(), columns=['word', 'count'])
  sns.scatterplot(data=df1, x="word", y="count",size="count", legend=False, sizes=(200, 100
  plt.xlabel("Anxiety words")
  plt.ylabel("Count of tweets")
  plt.title("Scatter plot to build bubble map of depressed and anxiety words")
  plt.show()

  f, ax = plt.subplots(1,1, figsize=(15,7))
  df2 = pd.DataFrame(anx_dict.items(), columns=['word', 'count'])
  sns.scatterplot(data=df2, x="word", y="count",size="count", legend=False, sizes=(200, 100

  plt.xlabel("Depression words")
  plt.ylabel("Count of tweets")
  plt.title("Scatter plot to build bubble map of depressed and anxiety words")
  plt.show()

count_Depression_anxiety_words(dep_dict, anx_dict)
```

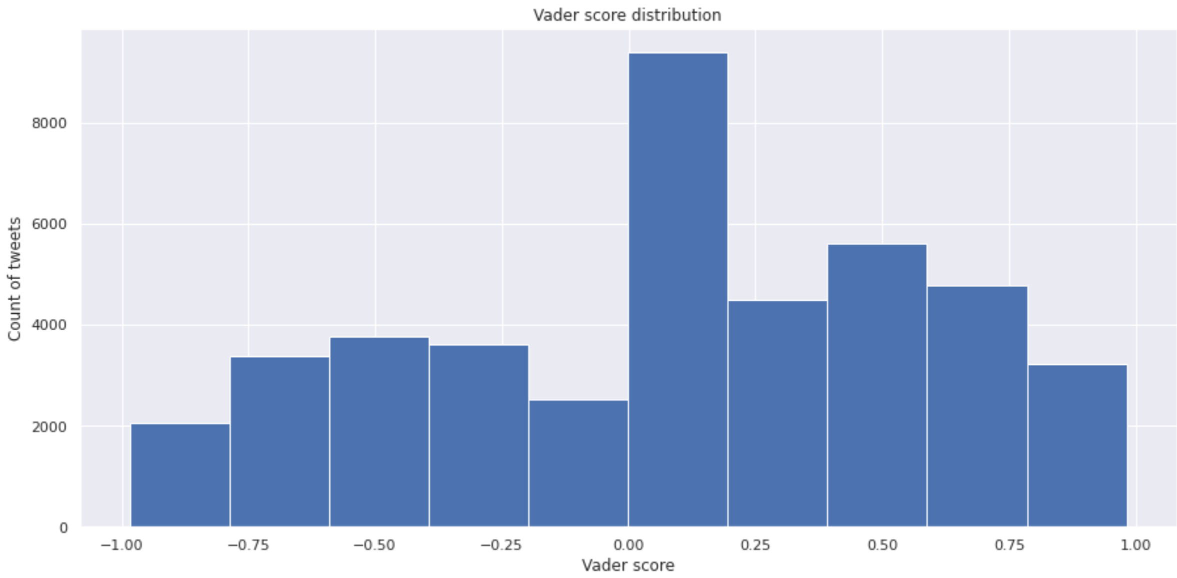




The above scatter plot of anxiety and depression words versus the count of tweets clearly shows the intensity of burning words like panic, sad, cry, fear etc.

In [106]:

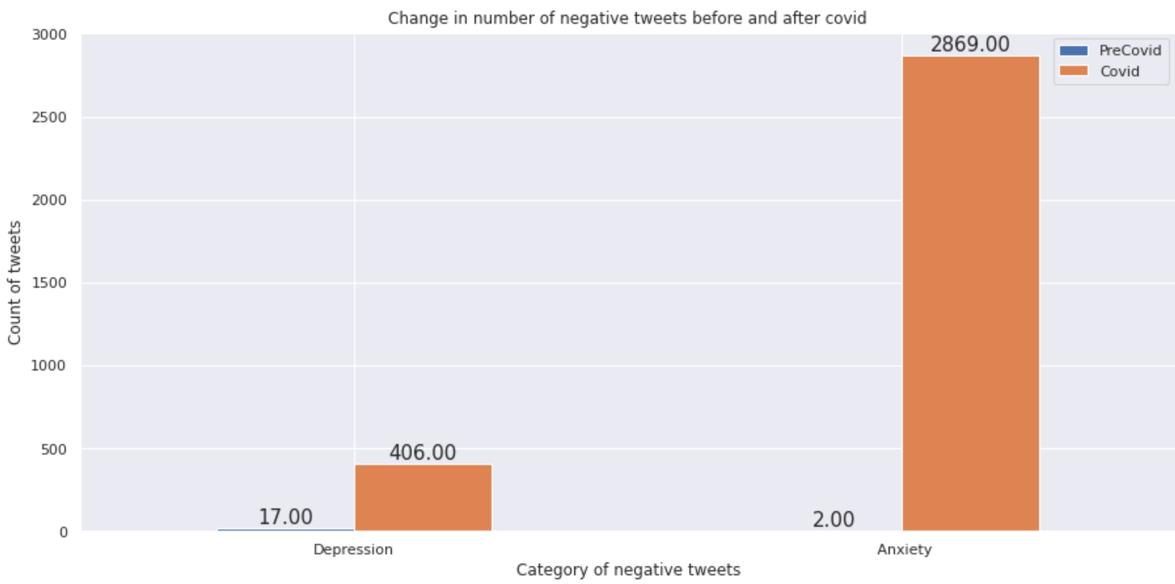
```
# Vader score distribution
def vader_score_distribution(df):
  fig, ax = plt.subplots(figsize=(15, 7))
  df['vader_score'].hist(ax=ax)
  plt.xlabel("Vader score")
  plt.ylabel("Count of tweets")
  plt.title("Vader score distribution")
  plt.show()

vader_score_distribution(tweets_cleaned)
```



The inference from above vader score distribution is that more and more tweets near 0.00 giving them a neutral sentiment.

In [113]:

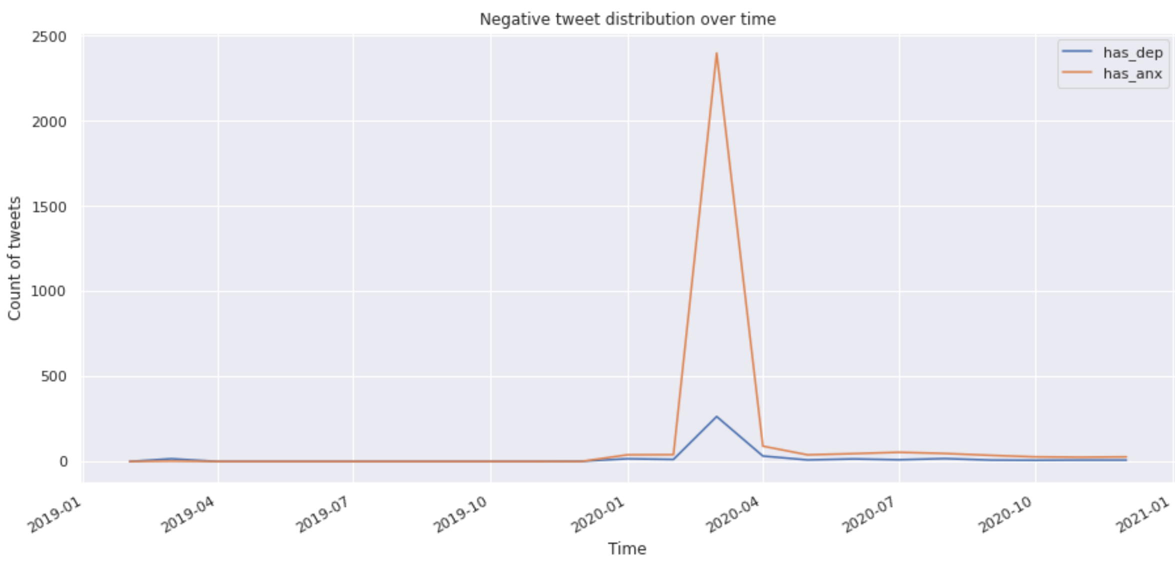
```
# Change in number of negative tweets before and after covid
def pre_post_covid(df):
  df['tweet.created_at'] =  pd.to_datetime(df['tweet.created_at'])
  has_dep_no_covid = 0
  has_dep_yes_covid = 0
  has_anx_no_covid = 0
  has_anx_yes_covid = 0
  for i,val in df.iterrows():
    if val[1].year < 2020:
      has_dep_no_covid += val[7]
      has_anx_no_covid += val[8]
    else:
      has_dep_yes_covid += val[7]
      has_anx_yes_covid += val[8]
  PreCovid = [has_dep_no_covid,has_anx_no_covid]
  Covid = [has_dep_yes_covid,has_anx_yes_covid]
  index = ['Depression', ' Anxiety']
  df1 = pd.DataFrame({'PreCovid': PreCovid,'Covid': Covid}, index = index)
  ax = df1.plot.bar(rot=0,figsize=(15, 7))
  for bar in ax.patches:
    ax.annotate(format(bar.get_height(), '.2f'),
                (bar.get_x() + bar.get_width() / 2,
                  bar.get_height()), ha='center', va='center',
                size=15, xytext=(0, 8),
                textcoords='offset points')

  plt.xlabel("Category of negative tweets")
  plt.ylabel("Count of tweets")
  plt.title("Change in number of negative tweets before and after covid")
  plt.legend()

pre_post_covid(tweets_cleaned)
```



Explicitly, depression and anxiety in the above comparison has increased in the humanoid population as a consequence of covid virus.

In [115]:

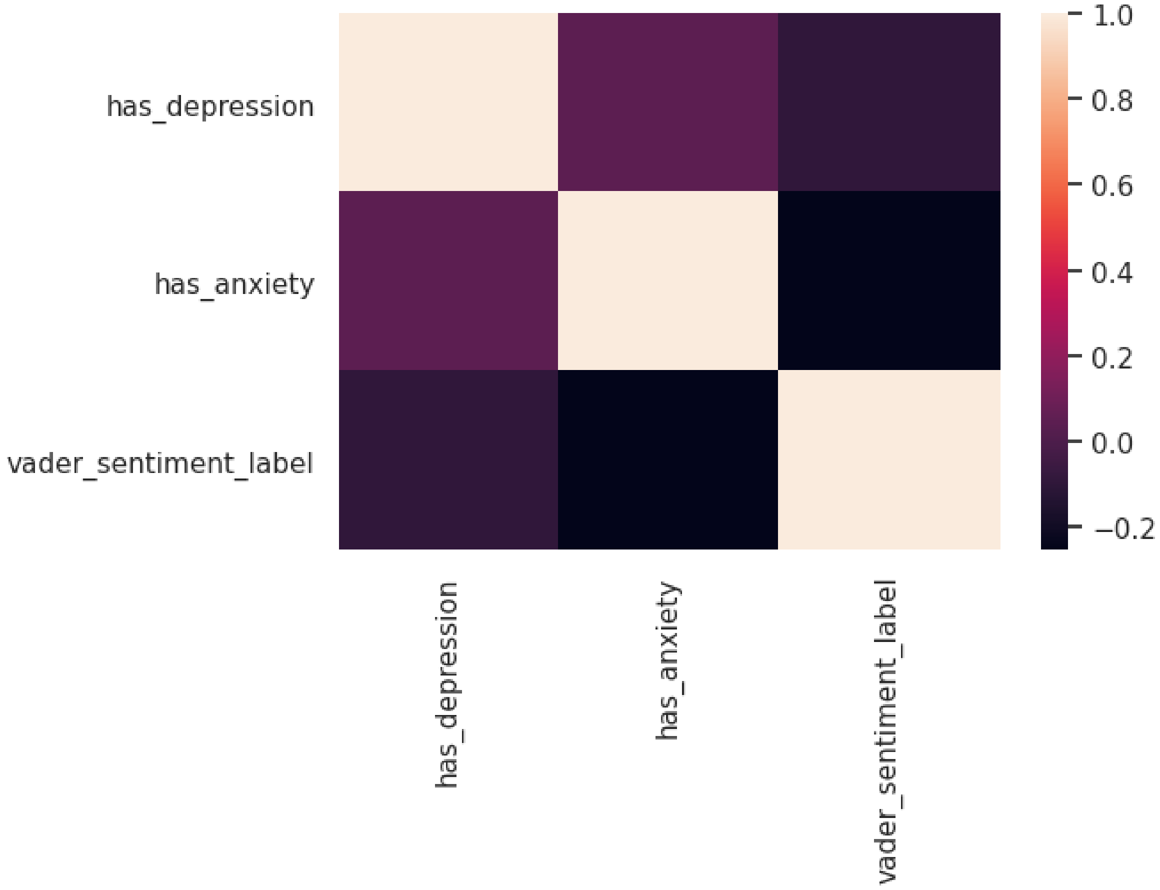
```
# Negative tweet distribution over time
def time_spent(tweets_cleaned):
  df = pd.DataFrame()
  for i,val in tweets_cleaned.iterrows():
    month = val[1].month
    year =  val[1].year
    df.at[i,'Time'] = str(year)+'-'+str(month)
    df.at[i,'has_dep'] = val[7]
    df.at[i,'has_anx'] = val[8]

  df['Time'] =  pd.to_datetime(df['Time'],format = '%Y-%m')
  ax = df.groupby(by=['Time'])['has_dep','has_anx'].sum()
  ax.plot(figsize=(15, 7))
  plt.xlabel("Time")
  plt.ylabel("Count of tweets")
  plt.title("Negative tweet distribution over time")
  plt.legend()

time_spent(tweets_cleaned)
```



The above time series chart demonstrates that during the months of March and April in 2020, people panicked (from scatter plot, panic word was used more than 2000 times in tweets) and slowly people started settling down and have accepted the new norm of life with social distancing, masks, hand sanitizing etc.

In [57]:

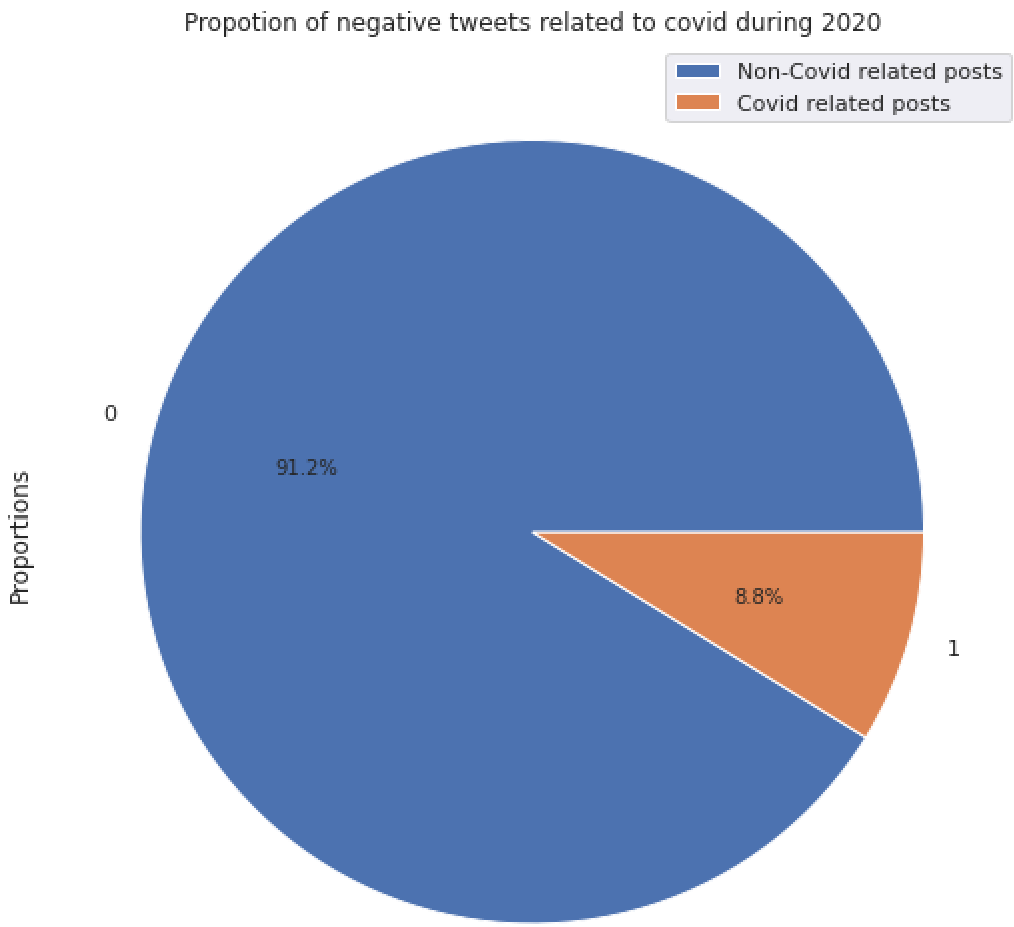
```
# Heatmap for categorical variables
def heatmap_depression_anxiety(df):
  sns.set_theme()
  ax = sns.heatmap(df.corr())

heatmap_depression_anxiety(tweets_cleaned[['has_depression','has_anxiety','vader_sentiment_
```



From the above correlation graph, depression tweets are more correlated with vader sentiments than the anxiety ones. Overall, there doesn’t seem to be a high correlation between these factors.

In [132]:

```
# Propotion of negative tweets related to covid during 2020
def check_covid_words(df):
  covid_words = {"COVID2019","COVID19","pandemic","Coronavirus","Social distancing","Flatte
  cov_count = 0
  temp = df[df["vader_score"] < 0 ]
  for i,val in temp.iterrows():
    for cov in covid_words:
      if cov in val[4]:
        cov_count += 1
        break

  non_cov_count = len(temp) - cov_count
  df1 = pd.DataFrame({'Post Counts':['Non-Covid related posts', 'Covid related posts'], 'Pr
  ax = df1.plot.pie(x='Post Counts', y='Proportions',figsize=(17, 9), autopct='%1.1f%%')
  plt.title("Propotion of negative tweets related to covid during 2020")
  plt.legend(['Non-Covid related posts', 'Covid related posts'],loc = "upper right")

check_covid_words(tweets_cleaned)
```



Even during COVID times, only 8.8% tweets were covid related out of the entire tweets. That certainly tells us that although covid became an integral part of peoples lives, people were focusing on other areas of living like NBA, politics etc

5. Classification Models:

1. Decision Tree
2. SVM
3. Logistic regression
4. Random forest

In [48]:

```
def get_svd(X_train_vectorized,X_test_vectorized):
  svd = TruncatedSVD(n_components=300, random_state=42)
    #normalization
  X_train_vectorized = preprocessing.normalize(X_train_vectorized, norm='l2')
  X_test_vectorized = preprocessing.normalize(X_test_vectorized, norm='l2')
    #svd
  X_train_vectorized_svd = svd.fit_transform(X_train_vectorized.toarray())
  X_test_vectorized_svd = svd.transform(X_test_vectorized.toarray())
  return X_train_vectorized_svd,X_test_vectorized_svd

def hyperpara_optim(parameters, clf):
    grid = GridSearchCV(clf,param_grid=parameters,cv=6)
    grid.fit(X_train_vectorized,y_train)
    print('Best parameters:',grid.best_params_,'Best scores:', grid.best_score_)
    return grid.best_params_

def split_data(df):
    X_train, X_test, y_train, y_test = train_test_split(df['Cleaned_Tweets'],df['vader_sent
    vect = TfidfVectorizer(max_features=1000).fit(X_train)
    X_train_vectorized = vect.transform(X_train)
    X_test_vectorized = vect.transform(X_test)
    X_train_vectorized_svd,X_test_vectorized_svd = get_svd(X_train_vectorized,X_test_vector
    return X_train_vectorized_svd,X_test_vectorized_svd,y_train,y_test

def get_confusion_matrix(y_test,y_pred):
  labels = ['Negative', 'Positive']
  cm = pd.DataFrame(metrics.confusion_matrix(y_test, y_pred),columns=["Predicted Negative",
  cm_df = pd.DataFrame(cm)
  ax= plt.subplot()
  sns.heatmap(cm, annot=True, ax = ax,fmt='g')
  ax.set_xlabel('Predicted labels')
  ax.set_ylabel('True labels')
  ax.set_title('Confusion Matrix')
  ax.xaxis.set_ticklabels(labels)
  ax.yaxis.set_ticklabels(labels)
  return cm_df

def get_cls_cm(y_test, y_pred,X_test_vectorized,model):
    #check accuracy
  target_names=['0','1']
  print("-----------Classification Report----------")
  cls_report = classification_report(y_test, y_pred, target_names=target_names,output_dict=
  cls_report_df = pd.DataFrame(cls_report).transpose()
  print(cls_report_df)
  # make the confusion matrix
  print("-----------Confusion Matrix----------")
  cm_df = get_confusion_matrix(y_test,y_pred)
  return cls_report_df,cm_df


def get_decision_tree(best_params_dt,X_train_vectorized,X_test_vectorized,y_train,y_test):

    clf_dt = DecisionTreeClassifier(max_depth=best_params_dt['max_depth'],min_samples_leaf=
    clf_dt.fit(X_train_vectorized,y_train)
    y_pred = clf_dt.predict(X_test_vectorized)
    print('Train score: ', clf_dt.score(X_train_vectorized,y_train),'Test score',clf_dt.sco
    cls_report,cm = get_cls_cm(y_test, y_pred,X_test_vectorized,clf_dt)
    return cls_report,cm,clf_dt
```

```
def get_random_forest(best_params_rf,X_train_vectorized,X_test_vectorized,y_train,y_test):

    clf_rf = RandomForestClassifier(max_depth=best_params_rf['max_depth'],min_samples_leaf=
    clf_rf.fit(X_train_vectorized,y_train)
    y_pred = clf_rf.predict(X_test_vectorized)
    print('Train score: ', clf_rf.score(X_train_vectorized,y_train),'Test score',clf_rf.sco
    cls_report,cm = get_cls_cm(y_test, y_pred,X_test_vectorized,clf_rf)
    return cls_report,cm,clf_rf

def get_svm(best_params_svm,X_train_vectorized,X_test_vectorized,y_train,y_test):

    clfrSVM = make_pipeline(StandardScaler(), SVC(gamma='auto',probability=True))
    clf_svm = make_pipeline(StandardScaler(), SVC(C=best_params_svm['C'], gamma=best_params
    clf_svm.fit(X_train_vectorized,y_train)
    y_pred = clf_svm.predict(X_test_vectorized)
    print('Train score: ', clf_svm.score(X_train_vectorized,y_train),'Test score',clf_svm.s
    cls_report,cm = get_cls_cm(y_test, y_pred,X_test_vectorized,clf_svm)
    return cls_report,cm,clf_svm

def get_logistic_regression(best_params_lr,X_train_vectorized,X_test_vectorized,y_train,y_t
  clf_lr = LogisticRegression(C=best_params_lr['C']).fit(X_train_vectorized, y_train)
    # predicting test set results
  y_pred = clf_lr.predict(X_test_vectorized)
  print('Train score: ', clf_lr.score(X_train_vectorized,y_train),'Test score',clf_lr.score
  cls_report,cm = get_cls_cm(y_test, y_pred,X_test_vectorized,clf_lr)
  return cls_report,cm,clf_lr
```

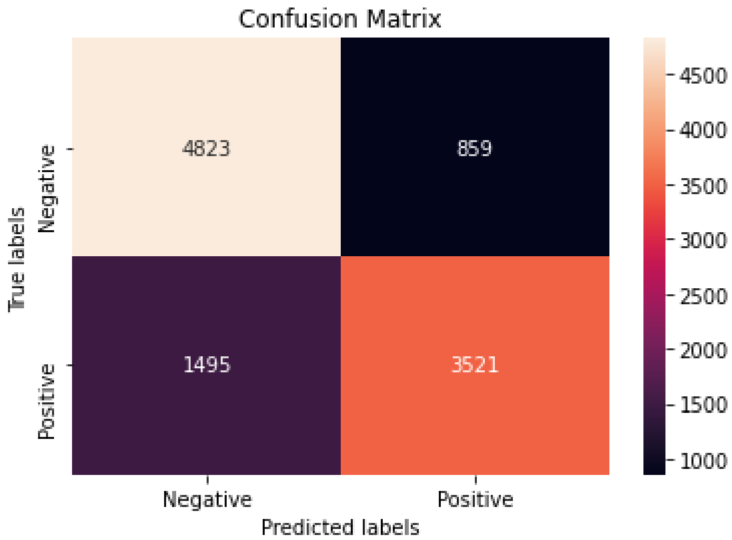
In [47]:

```
#get input value for models
X_train_vectorized,X_test_vectorized,y_train,y_test = split_data(tweets_cleaned)
```

In [52]:

```
"""Logistic Regression"""
print('Start processing Logistic Regression')
parameters_lr = {'C': [0.1, 1]}
best_params_lr = hyperpara_optim(parameters_lr,LogisticRegression())

cls_report_lr,cm_lr,clf_lr = get_logistic_regression(best_params_lr,X_train_vectorized,X_te
```

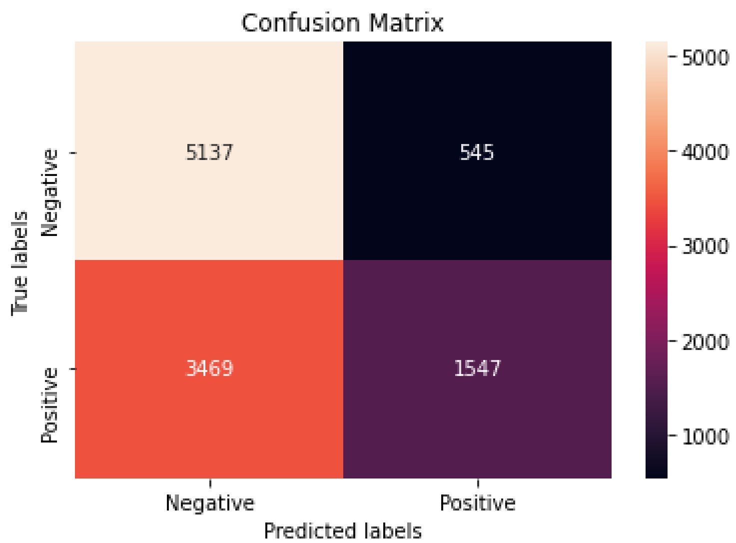
```
Start processing Logistic Regression
Best parameters: {'C': 1} Best scores: 0.7782623129914888
Train score:  0.7849931447089618 Test score 0.7799588708169751
-----------Classification Report----------
              precision    recall  f1-score       support
0              0.763374  0.848821  0.803833   5682.000000
1              0.803881  0.701954  0.749468   5016.000000
accuracy       0.779959  0.779959  0.779959      0.779959
macro avg      0.783628  0.775387  0.776651  10698.000000
weighted avg   0.782367  0.779959  0.778343  10698.000000
-----------Confusion Matrix----------
```



In [53]:

```
#get input value for models

"""Decision Tree"""
print('Start processing Decision Tree')
parameters_dt = { 'max_depth': [2, 5], 'min_samples_leaf': [1, 5]}
best_params_dt = hyperpara_optim(parameters_dt,DecisionTreeClassifier())

cls_report_dt,cm_dt,clf_dt = get_decision_tree(best_params_dt,X_train_vectorized,X_test_vec
```

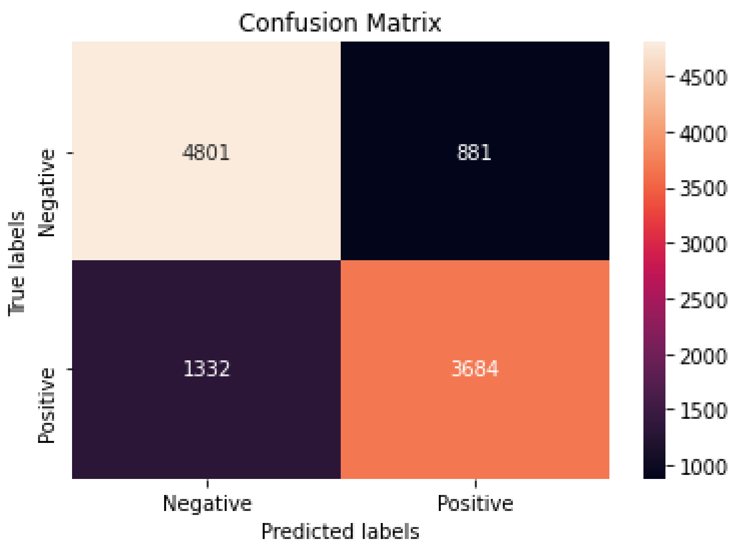
```
Start processing Decision Tree
Best parameters: {'max_depth': 5, 'min_samples_leaf': 1} Best scores: 0.6259
198274571066
Train score:  0.6301570484856039 Test score 0.6247896803140774
-----------Classification Report----------
              precision    recall  f1-score      support
0              0.596909  0.904083  0.719065   5682.00000
1              0.739484  0.308413  0.435284   5016.00000
accuracy       0.624790  0.624790  0.624790      0.62479
macro avg      0.668196  0.606248  0.577175  10698.00000
weighted avg   0.663758  0.624790  0.586008  10698.00000
-----------Confusion Matrix----------
```



In [51]:

```
#get input value for models

"""SVM"""
print('Start processing SVM')
parameters_svm = {'C': [10], 'gamma': [0.001], 'kernel': ['rbf']}
svc = svm.SVC()
best_params_svm = hyperpara_optim(parameters_svm,svc)

cls_report_svm,cm_svm,clf_svm = get_svm(best_params_svm,X_train_vectorized,X_test_vectorize
```

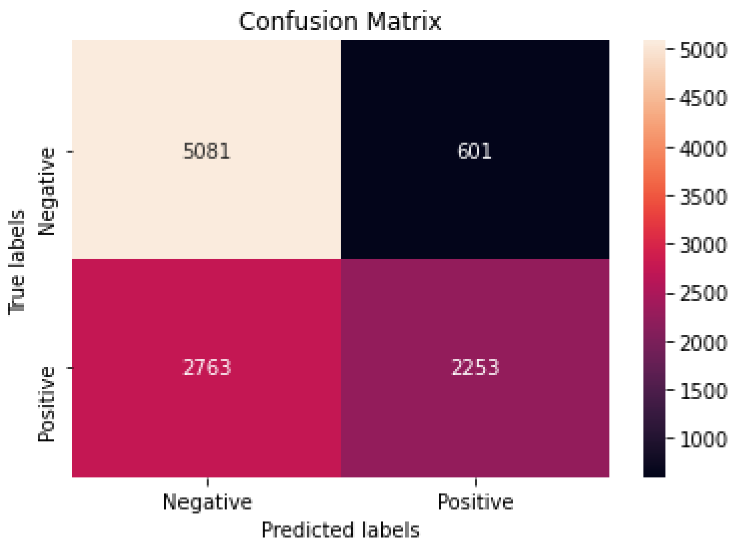
```
Start processing SVM
Best parameters: {'C': 10, 'gamma': 0.001, 'kernel': 'rbf'} Best scores: 0.7
059390424696267
Train score:  0.9382088994141842 Test score 0.7931389044681249
-----------Classification Report----------
              precision    recall  f1-score       support
0              0.782814  0.844949  0.812696   5682.000000
1              0.807010  0.734450  0.769022   5016.000000
accuracy       0.793139  0.793139  0.793139      0.793139
macro avg      0.794912  0.789699  0.790859  10698.000000
weighted avg   0.794159  0.793139  0.792218  10698.000000
-----------Confusion Matrix----------
```



In [50]:

```
#get input value for models

"""Random Forest"""
print('Start processing Random Forest')
parameters_rf = { 'max_depth': [2, 5], 'min_samples_leaf': [1, 5]}
best_params_rf = hyperpara_optim(parameters_rf,RandomForestClassifier())

cls_report_rf,cm_rf,clf_rf= get_random_forest(best_params_rf,X_train_vectorized,X_test_vect
```

```
Start processing Random Forest
Best parameters: {'max_depth': 5, 'min_samples_leaf': 1} Best scores: 0.6860
275728473191
Train score:  0.7024492085254892 Test score 0.685548700691718
-----------Classification Report----------
              precision    recall  f1-score       support
0              0.647756  0.894227  0.751294   5682.000000
1              0.789418  0.449163  0.572554   5016.000000
accuracy       0.685549  0.685549  0.685549      0.685549
macro avg      0.718587  0.671695  0.661924  10698.000000
weighted avg   0.714178  0.685549  0.667488  10698.000000
-----------Confusion Matrix----------
```



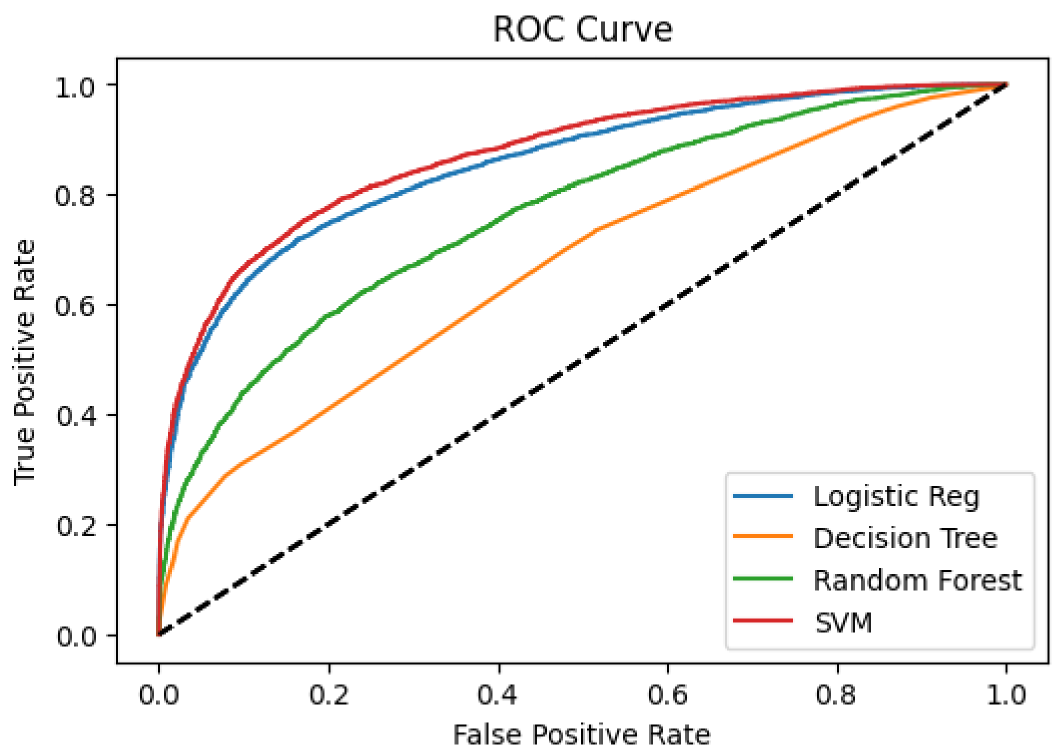
7. Model analysis :

1. AUC curve comparision.

In [54]:

```
def get_model_roc(models, Xs_test, names, Y_test):
    plt.rcParams['figure.dpi'] = 100
    for i in range(len(models)):
        model = models[i]
        X_test = Xs_test[i]
        name = names[i]
        if i == 3 :
          probs = clf_svm.decision_function(X_test_vectorized)
        else:
          probs = model.predict_proba(X_test)[:,1]
        fpr, tpr, thresholds = metrics.roc_curve(Y_test, probs)
        plt.plot(fpr, tpr, label=name)
        plt.plot([0, 1], [0, 1], linestyle='dashed', color='black')
        plt.xlabel("False Positive Rate")
        plt.ylabel("True Positive Rate")
        plt.title("ROC Curve")
        print ("AUC for {0} = {1:.3f}".format(name, metrics.roc_auc_score(Y_test, probs)))
    plt.legend()
    plt.show()

get_model_roc([clf_lr,clf_dt,clf_rf,clf_svm], [X_test_vectorized,X_test_vectorized,X_test_v
```

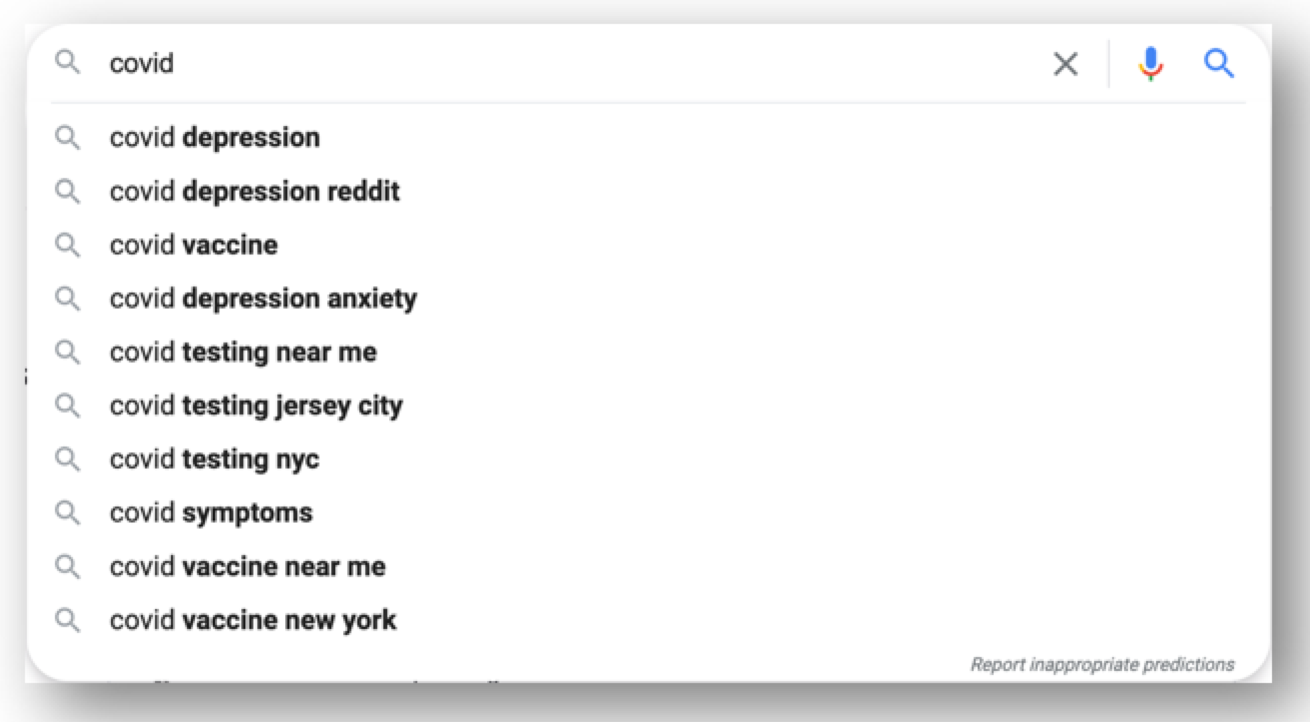
```
AUC for Logistic Reg = 0.854
AUC for Decision Tree = 0.667
AUC for Random Forest = 0.762
AUC for SVM = 0.871
```



Out of Logistic regression, decision tree, random forest and SVM the winner model has shown itself to be Support Vector Machines. Hence we can conclude that this dataset has a clear margin of separation in high dimension spaces.

Insights and Conclusion:

Let us do a quick exercise, type “COVID (and a space)” on google.



This quick internet search for COVID confirms our hypothesis. 3 out of top 5 search results are based on depression and anxiety due to the pandemic.

Similar trends in mental health analysis from tweets by different users during 2019-2020 can be seen as well.

Responding to the debrief of our problem statements:

1. Yes, with certainty and reliance, there is a rise in mental health issues among large inhabitant of this world.
2. 7.7% percent users from our dataset might be suffering from depression and anxiety, this can be calculated from the bar graph, “Change in number of tweets before and after COVID” (Calculation: Depression & Anxiety tweets: 3294, Total number of tweets: 42790, Calculated percent = 7.7%)
3. Yes, more people are anxious than depressed as we saw a large number of populace using the hashtag panic in their tweets.
4. From our model analysis, using SVM as the machine learning algorithm we can best predict whether the person is depressed, anxious or neither with an approximately 80% chance.

Note: This project operates on unsupervised learning algorithm. Vader score has been calculated to categorize the tweet as negative, positive or neutral.

Challenges

1. Data extraction from twitter is arduous and complicated.
2. The location feature from the dataset was of little to no importance in data analysis or visualization because of lack of consistency. Tweets are located as state/country/city/area, example this becomes difficult to manage or group areas of a country.
3. Due to Hyperparameter optimization, the code takes considerable amount of time to run.
4. Although SVM is our winner model, it took the longest to run with respect to other simpler models like logistic regression and decision tree.
5. The data cleaning part was intense as we were dealing with textual data which had a lot of punctuations, abbreviations and stop words.