IBM HACKCHALLENGE 2020

SENTIMENTAL ANALYSIS OF COVID-19 TWEETS – VISUALISATION DASH-BOARD

Challenge Title : IBM Hack Challenge 2020
Project ID : SPS_PRO_302
Project Title : Sentimental Analysis of Covid-19 Tweets
Duration : 32 Days
Application ID : SPS_CH_APL_20200001593

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CONTENT

1. INTRODUCTION:

The main of the project is to do the sentiment analysis on the tweets about the COVID-19 in the Twitter.The API is used to connect the communication between the Node-red application and the Twitter.The Twitter Node that is found in the Node-red application is used as the source to give the tweets about the COVID-19 .The Important node that is used to give the sentiment score is the sentiment node that is found in the Node-red application.The tweets are given as the input to the Sentiment node the sentiment node separates the tweets as POSITIVE,NEUTRAL AND NEGATIVE.If the value is positive then there was positive thing going on the twitter, if the sentiment score is negative then there was negative action going on the twitter .If the value is neutral then there was a neutral action going in the twitter.It will be very helpful to known about the public opinion.

1.1 OVERVIEW:

The overview of the IBM HACK CHALLENGE 2020 Problem for COVID-19 sentiment analysis is to do the sentiment analysis for the tweets that were tweeted by the public and the social media about the corona virus .

1.2 PURPOSE:

- The usefulness is that it creates the awareness of the COVID-19 among the public.
- The website contains the sentiment of the covid-19 based on the tweets in the twitter by the people.
- The sentiment gives the information among the people about the seriousness of the COVID-19 among the public.
- The website also gives the sentiment data about the COVID-19 .
- The website also gives the tips and Ayurvedic medicine tips to protect against the COVID-19.
- The website also gives the information about the wearing of the mask and the handwashing.

- This also helps the government to extract the data about the COVID-19 among the public.

2. LITERATURE SURVEY:

2.1 EXISTING PROBLEM:

The Existing problem is that the news some times obtained is not understood by the people whether it is a Negative or it is the positive.

2.2 PROPOSED SOLUTION:

This is will help to divide the news into three sentiments namely:

1.POSITIVE(sentiment value>=1)
2. NEGATIVE(sentiment value<0)

3. NEUTRAL(sentiment value=0)

Example:

Let us take the existing situation about the COVID-19
People do not known the current situation is positive or negative about the corona .

The idea is made in the form of the website where it gives the exact current situation about the covid-19.
if(sentiment_value==0):

    then output is NEUTRAL

else if(sentiment_value>0):

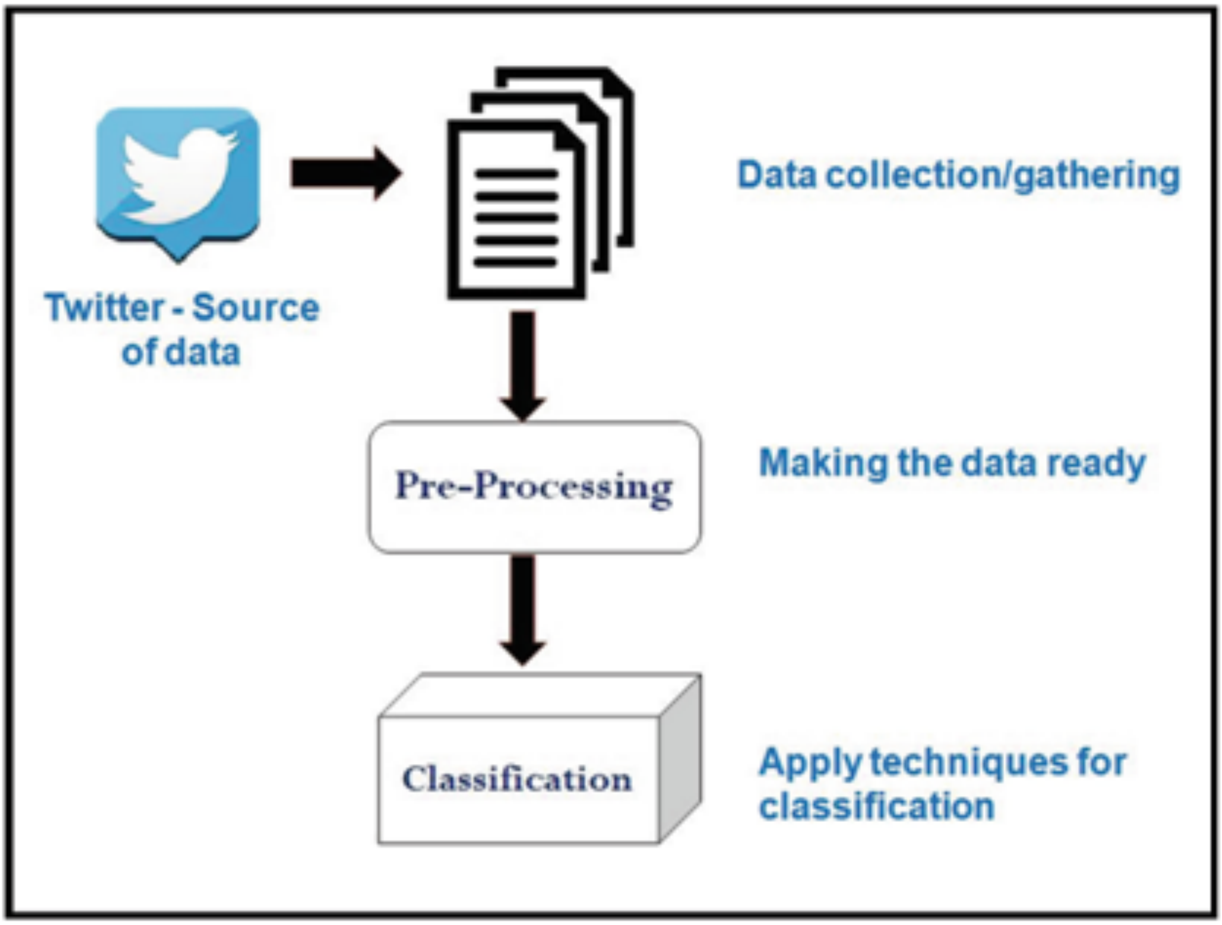
    then output POSITIVE

else:

   the output NEGATIVE

3. THEORITICAL ANALYSIS:

3.1 BLOCK DIAGRAM:



3.2 SOFTWARE DESIGNING:

The Software is designed with the help of services provided by the IBM CLOUD SERVICES.

IBM Cloud provides a full-stack, public **cloud** platform with a variety of offerings in the catalog, including compute, **storage**, and networking options, end-to-end developer solutions for app development, testing and deployment, security management **services**, traditional and open-source databases, and **cloud**-native .

- **Project Requirements**: Python, IBM Cloud, IBM Watson,
- **Functional Requirements**: IBM cloud
- **Technical Requirements**: Machine Learning, Deep Learning, NLP, WATSON Services, Python, Watson Dashboard, Twitter API
- **Software Requirements**: Python,Watson Studio

4. EXPERIMENTAL ANALYSIS:

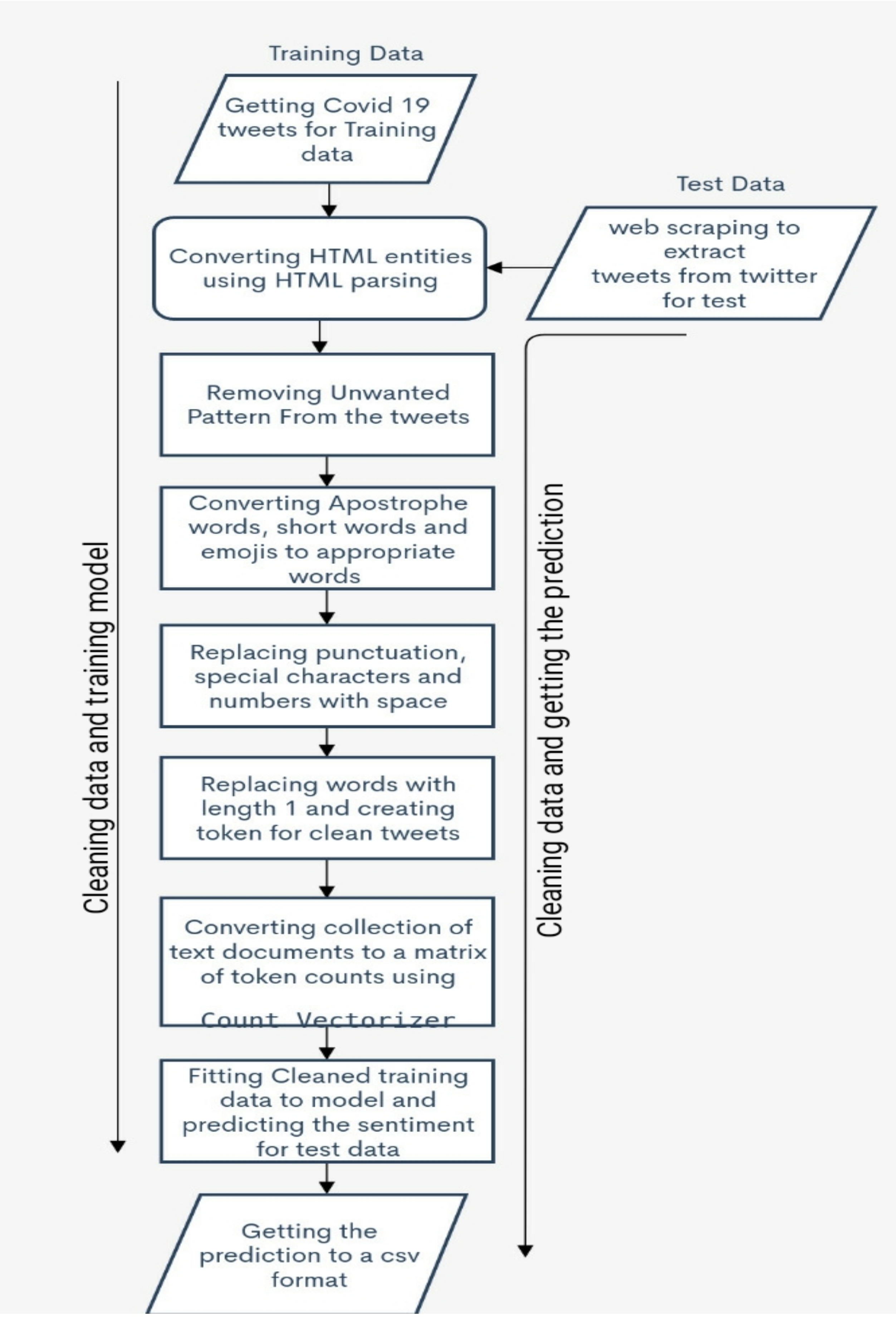
I have done Various Experiment Analysis on this Covid-19 Sentiment Analysis. OBSERVED that is gives:

POSITIVE: >1

NEGATIVE: <1

NEUTRAL: =0

5. FLOW CHART:

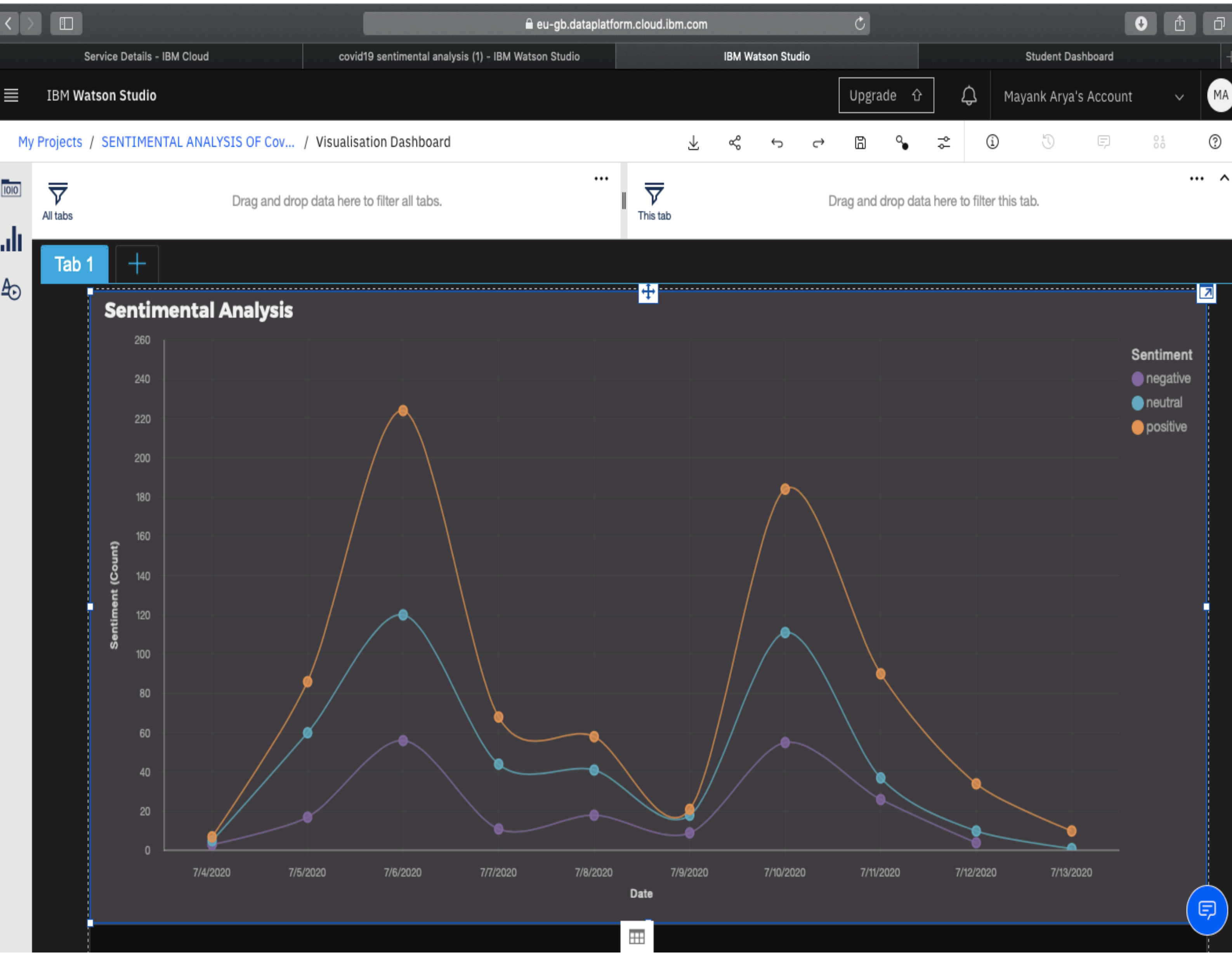


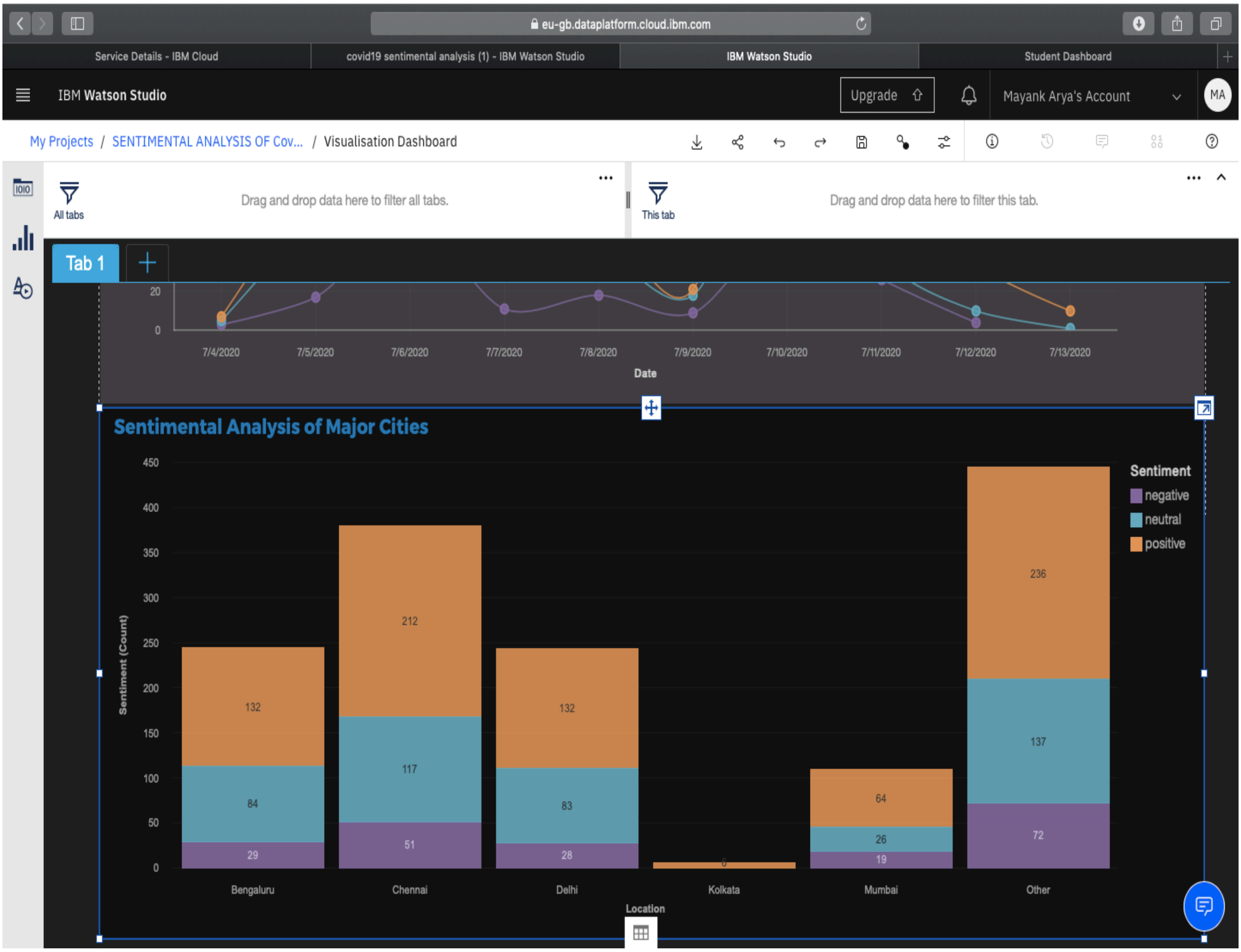
Training Data
Getting Covid 19 tweets for Training data
Test Data
web scraping to extract tweets from twitter for test
Converting HTML entities using HTML parsing
Removing Unwanted Pattern From the tweets
Converting Apostrophe words, short words and emojis to appropriate words
Replacing punctuation, special characters and numbers with space
Replacing words with length 1 and creating token for clean tweets
Converting collection of text documents to a matrix of token counts using Count Vectorizer
Fitting Cleaned training data to model and predicting the sentiment for test data
Getting the prediction to a csv format
Cleaning data and training model
Cleaning data and getting the prediction

6. RESULTS:

	Text	Date	Location	Sentiment
0	rt @yogendrapal72: 8,80,603 and counting... co...	2020-07-13	Other	positive
2	8,80,603 and counting... corona virus india up...	2020-07-13	Other	positive
3	@vishaldadlani @aamaadmiparty amidst all, only...	2020-07-12	Delhi	positive
4	total confirmed #covid-19 cases in #delhi, #in...	2020-07-12	Delhi	neutral
5	rt @orfonline: .@oommen: with ramped-up testin...	2020-07-12	Delhi	positive
6	#delhi #covid19 recovery rate is better than o...	2020-07-11	Delhi	negative
7	total confirmed #covid-19 cases in #delhi, #in...	2020-07-11	Delhi	positive
8	rt @thedailypioneer: #covid19: prime minister ...	2020-07-11	Other	positive
9	#covid19: prime minister @narendramodi on satu...	2020-07-11	Other	positive
11	rt @ridhimb: new zealnder youtuber @iamkarlro...	2020-07-11	Delhi	positive
12	.@oommen: with ramped-up testing, aggressive c...	2020-07-11	Delhi	positive
16	new zealnder youtuber @iamkarlrock has been i...	2020-07-11	Delhi	neutral
17	rt @themornstandard: as #delhi's #covid19 situ...	2020-07-11	Delhi	positive
18	rt @editorji: #pmmodi appreciated the efforts ...	2020-07-11	Delhi	neutral
19	#pmmodi appreciated the efforts of the centre,...	2020-07-11	Delhi	positive
20	rt @imfmoharkan: does anyone realise that #ben...	2020-07-11	Mumbai	negative
21	rt @sonimishra20: #delhi govt cancels all upco...	2020-07-11	Delhi	positive
22	rt @oaadhunik: #delhi #examscancelled\n#cancel...	2020-07-11	Delhi	negative
23	#delhi #examscancelled\n#cancelallexams #covid...	2020-07-11	Delhi	neutral

7. OUTPUT OF SENTIMENTAL ANALYSIS & DASHBOARD:





8. ADVANTAGES :

- Helps to make awareness among the public Gives the sentiment values
- Simple to handle
- Simple to get any statistical data
- Easy for Government to analysis the people view over their policies.

DISADVANTAGES:

Some times the dashboard lost s its connection due to the server problem.

9. APPLICATION:

The Application of the COVID-19 Sentiment is that it spread the awareness among the public and the statistical data can derived using the COVID-19 Sentiment Analysis in the Simple Way.

10. FUTURE SCOPE:

Sentiment analysis is a uniquely powerful tool for government that are looking to measure attitudes, feelings and emotions regarding their policies of COVID-19. To date, the majority of sentiment analysis projects have been conducted almost exclusively by companies and brands through the use of social media data, survey responses and other hubs of user-generated content. By investigating and analysing people sentiments, these policies are able to get an inside look at peoples behaviours and, ultimately, better serve their audiences with theÂ Â services and experiences they offer.

The future of sentiment analysis is going to continue to dig deeper, far past the surface of the number of likes, comments and shares, and aim to reach, and truly understand, the significance of social media interactions and what they tell us about the consumers behind the screens. This forecast also predicts broader applications for sentiment analysis â€“ brands will continue to leverage this tool, but so will individuals in the public eye, governments, nonprofits, education centres and many other organisations.

11. BIBLOGRAPHY:

- SmartBridge Bootcamps
- Google
- Twitter

- Mentor support

12. Source Code:

```
# # Importing Required Libraries


import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import re




import types
import pandas as pd
from botocore.client import Config
import ibm_boto3

def __iter__(self): return 0

# @hidden_cell
# The following code accesses a file in your IBM Cloud Object
Storage. It includes your credentials.
# You might want to remove those credentials before you share the
notebook.
client_ebbb4a33aa644527a29c121fe811d861 = ibm_boto3.client(ser-
vice_name='s3',
    ibm_api_key_id='CATeNJuWTcb5iuplHUzr71UNMP3TOofUtoYLNXei6xUh',
    ibm_auth_endpoint="https://iam.cloud.ibm.com/oidc/token",
    config=Config(signature_version='oauth'),
    endpoint_url='https://s3.eu-geo.objectstorage.service.network-
layer.com')

body =
client_ebbb4a33aa644527a29c121fe811d861.get_object(Bucket='senti-
mentalanalysisofcovid19tweet-donotdelete-pr-
ye1lk5o4jj2gzb',Key='Data.csv')['Body']
# add missing __iter__ method, so pandas accepts body as file-like
object
if not hasattr(body, "__iter__"): body.__iter__ = types.Method-
Type( __iter__, body )
```

```
data= pd.read_csv(body)
data.head()
```

```
data=data.drop(columns='retweet_count')
data.shape
```

```
# #### checking for all null values
```

```
data.isnull().sum()
```

```
# #### Dropping null value
```

```
data=data.dropna()
data.isnull().sum()
```

```
# #### Changing all the tweets into lowercase¶
#
```

```
data['clean_tweet'] = data['full_text'].apply(lambda x: x.lower())
data.head(5)
```

```
# #### Removing words whom length is 1 And Replacing Numbers (in-
tegers) with space¶
```

```
data['clean_tweet'] = data['clean_tweet'].apply(lambda x: '
'.join([w for w in x.split() if len(w)>1]))
data['clean_tweet'] = data['clean_tweet'].apply(lambda x:
re.sub(r'[^a-zA-Z]',' ',x))
data.head()
```

```
import nltk
```

```
nltk.download("punkt")


# #### Creating token for the clean tweets



data['tweet_token'] = data['clean_tweet'].apply(lambda x:nltk.-
word_tokenize(x))
data.head()




from nltk.corpus import stopwords
nltk.download('stopwords')


# #### Importing stop words from NLTK corpus for english language



stop_words = set(stopwords.words('english'))
data['tweet_token_filtered'] = data['tweet_token'].apply(lambda x:
[word for word in x if not word in stop_words])
data.head()




nltk.download('wordnet')


# #### Lemmatization - Lemmatization is the process of converting
a word to its base form.¶
#



# Importing library for lemmatizing
from nltk.stem.wordnet import WordNetLemmatizer
lemmatizing = WordNetLemmatizer()

# Created one more columns tweet_lemmatized it shows tweets' lem-
matized version
data['tweet_lemmatized'] =
data['tweet_token_filtered'].apply(lambda x: ' '.join([lemmatiz-
ing.lemmatize(i) for i in x]))
data['tweet_lemmatized'].head(10)
```

```
get_ipython().system('pip install wordcloud')


# #### Will see the most commonly used words in the column i.e. "
"tweet_lematized"



#visualizing all the words in column "tweet_lemmatized" in our
data using the wordcloud plot.
all_words = ' '.join([text for text in data['tweet_lemmatized']])
from wordcloud import WordCloud
wordcloud = WordCloud(width=800, height=500, random_state=21,
max_font_size=110).generate(all_words)

plt.figure(figsize=(10, 7))
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis('off')
plt.title("Most Common words in column Tweet Lemmatized")
plt.show()


# ####  Most common words in Positive tweets



positive_words =' '.join([text for text in
data['tweet_lemmatized'][data['Sentiment'] == "positive"]])

wordcloud = WordCloud(width=800, height=500, random_state=21,
max_font_size=110).generate(positive_words)
plt.figure(figsize=(10, 7))
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis('off')
plt.title("positive Tweet Lemmatized")
plt.show()


# ####  Most common words in neutral tweets



neutral_words =' '.join([text for text in data['tweet_lemmatized']
[data['Sentiment'] == "neutral"]])

wordcloud = WordCloud(width=800, height=500, random_state=21,
max_font_size=110).generate(neutral_words)
plt.figure(figsize=(10, 7))
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis('off')
plt.title("neutral Tweet Lemmatized")
```

```
plt.show()


# ####  Most common words in negative tweets



negative_words =' '.join([text for text in
data['tweet_lemmatized'][data['Sentiment'] == "negative"]])

wordcloud = WordCloud(width=800, height=500, random_state=21,
max_font_size=110).generate(negative_words)
plt.figure(figsize=(10, 7))
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis('off')
plt.title("negative Tweet Lemmatized")
plt.show()


# #### Bag-of-Words Features



## Importing library
from sklearn.feature_extraction.text import CountVectorizer
bow_vectorizer = CountVectorizer(max_df=0.90, min_df=2, max_fea-
tures=1000, stop_words='english')

# Bag-Of-Words feature matrix - For columns "combine_df['tweet-
_lemmatized']"
bow_lemm =
bow_vectorizer.fit_transform(data['tweet_lemmatized']).toarray()
bow_lemm


# #### mapping the Sentiment column (Dependent column) with 1, 0
and -1

x=bow_lemm
y=data['Sentiment']
y.replace(['neutral','positive','negative'],[0,1,-1],inplace=True)
y.head()


# #### Splitting data into train and test

from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(x, y, test_-
size = 0.25, random_state = 42)
```

```python
# #### Scaling the training and testing data

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()

x_train = sc.fit_transform(x_train)
x_test = sc.transform(x_test)



# #### Using Decision Tree Classifier for training and testing

from sklearn.tree import DecisionTreeClassifier

model = DecisionTreeClassifier()
model.fit(x_train, y_train)

y_pred = model.predict(x_test)

print("Training Accuracy :", model.score(x_train, y_train))
print("test Accuracy :", model.score(x_test, y_test))




y_pred=pd.Series(y_pred)
y_pred.replace([0,1,-1],
['neutral','positive','negative'],inplace=True)
y_pred.head()


# ### Scrapping twitter data with the help of Tweepy Library and
saving it in a csv file



get_ipython().system('pip install tweepy')




import tweepy
import pandas as pd

consumer_key = "rm2bLDjA2BzljoA0GomL5o6W7"
consumer_secret = "xiFBG4VKWPuQts1v3uqAesllpDp36y44YkFnzBtezSbSY-
W9dBV"
access_token = "935519854064418816-sOBxmFMaDygAx3FQXRBjH0drp-
Z2OXpB"
access_token_secret = "GbOTefzapdet9vpmR3H9OBRuJNJNs1cI4Adh5Hrk-
IYPJz"
```

```
# Creating the authentication object
auth = tweepy.OAuthHandler(consumer_key, consumer_secret)
# Setting your access token and secret
auth.set_access_token(access_token, access_token_secret)
# Creating the API object while passing in auth information
api = tweepy.API(auth)
number_of_items=500

searchword="#COVID and #DELHI "
tweets=tweepy.Cursor(api.search,q=searchword,lang='en').items(num-
ber_of_items)
names_text=[[tweet.user.screen_name,tweet.text.lower(),tweet.cre-
ated_at,tweet.user.location.lower()]for tweet in tweets]
df=pd.DataFrame(data=names_text,columns=['Name','Text',"Date","Lo-
cation"])


searchword="#COVID and #Chennai"
tweets=tweepy.Cursor(api.search,q=searchword,lang='en').items(num-
ber_of_items)
names_text=[[tweet.user.screen_name,tweet.text.lower(),tweet.cre-
ated_at,tweet.user.location.lower()]for tweet in tweets]
df1=pd.DataFrame(data=names_text,columns=['Name','Text',"Date","Lo
cation"])

searchword="#COVID and #Mumbai"
tweets=tweepy.Cursor(api.search,q=searchword,lang='en').items(num-
ber_of_items)
names_text=[[tweet.user.screen_name,tweet.text.lower(),tweet.cre-
ated_at,tweet.user.location.lower()]for tweet in tweets]
df2=pd.DataFrame(data=names_text,columns=['Name','Text',"Date","Lo
cation"])

searchword="#COVID and #Bengaluru"
tweets=tweepy.Cursor(api.search,q=searchword,lang='en').items(num-
ber_of_items)
names_text=[[tweet.user.screen_name,tweet.text.lower(),tweet.cre-
ated_at,tweet.user.location.lower()]for tweet in tweets]
df3=pd.DataFrame(data=names_text,columns=['Name','Text',"Date","Lo
cation"])

searchword="#COVID and #Kolkata"
tweets=tweepy.Cursor(api.search,q=searchword,lang='en').items(num-
ber_of_items)
names_text=[[tweet.user.screen_name,tweet.text.lower(),tweet.cre-
ated_at,tweet.user.location.lower()]for tweet in tweets]
df4=pd.DataFrame(data=names_text,columns=['Name','Text',"Date","Lo
cation"])

frames=[df,df1,df2,df3,df4]
result = pd.concat(frames)
print(result)
```

```
for i in range(len(result)) :
    if "delhi" in result.iloc[i, 3] or "delhi" in result.iloc[i, 
1]:
        result.iloc[i, 3]="Delhi"
    elif "mumbai" in result.iloc[i, 3] or "mumbai" in 
result.iloc[i, 1]:
        result.iloc[i, 3]="Mumbai"
    elif "chennai" in result.iloc[i, 3] or "chennai" in re-
sult.iloc[i, 1]:
        result.iloc[i, 3]="Chennai"
    elif "bengaluru" in result.iloc[i, 3] or "bengaluru" in re-
sult.iloc[i, 1]:
        result.iloc[i, 3]="Bengaluru"
    elif "kolkata" in result.iloc[i, 3] or "kolkata" in re-
sult.iloc[i, 1]:
        result.iloc[i, 3] = "Kolkata"
    else:
        result.iloc[i, 3] = "Other"

result.to_csv('tweets.csv', index=True)
df=result


# ###  Viewing the scapped tweets csv file

df["Location"].value_counts()

df.head()

df.shape



# ### Converting HTML entities and saving clean tweets to new 
clean tweet column
import html
from html.parser import HTMLParser
html_parser = HTMLParser()
df['clean_tweet'] = df['Text'].apply(lambda x: html.unescape(x))



# ### Removing twitter handles from all tweets in clean tweet col-
umn
def remove_pattern(input_txt, pattern):
    r = re.findall(pattern, input_txt)
    for i in r:
        input_txt = re.sub(i, '', input_txt)
    return input_txt
```

```python
df['clean_tweet'] = np.vectorize(remove_pattern)
(df['clean_tweet'], "@[\w]*")


# ### converting tweets to lowercase
df['clean_tweet'] = df['clean_tweet'].apply(lambda x: x.lower())


# ### Apostrophe lookup in tweets

apostrophe_dict = {
"ain't": "am not / are not",
"aren't": "are not / am not",
"can't": "cannot",
"can't've": "cannot have",
"'cause": "because",
"could've": "could have",
"couldn't": "could not",
"couldn't've": "could not have",
"didn't": "did not",
"doesn't": "does not",
"don't": "do not",
"hadn't": "had not",
"hadn't've": "had not have",
"hasn't": "has not",
"haven't": "have not",
"he'd": "he had / he would",
"he'd've": "he would have",
"he'll": "he shall / he will",
"he'll've": "he shall have / he will have",
"he's": "he has / he is",
"how'd": "how did",
"how'd'y": "how do you",
"how'll": "how will",
"how's": "how has / how is",
"i'd": "I had / I would",
"i'd've": "I would have",
"i'll": "I shall / I will",
"i'll've": "I shall have / I will have",
"i'm": "I am",
"i've": "I have",
"isn't": "is not",
"it'd": "it had / it would",
"it'd've": "it would have",
"it'll": "it shall / it will",
"it'll've": "it shall have / it will have",
"it's": "it has / it is",
"let's": "let us",
"ma'am": "madam",
"mayn't": "may not",
"might've": "might have",
"mightn't": "might not",
```

```
"mightn't've": "might not have",
"must've": "must have",
"mustn't": "must not",
"mustn't've": "must not have",
"needn't": "need not",
"needn't've": "need not have",
"o'clock": "of the clock",
"oughtn't": "ought not",
"oughtn't've": "ought not have",
"shan't": "shall not",
"sha'n't": "shall not",
"shan't've": "shall not have",
"she'd": "she had / she would",
"she'd've": "she would have",
"she'll": "she shall / she will",
"she'll've": "she shall have / she will have",
"she's": "she has / she is",
"should've": "should have",
"shouldn't": "should not",
"shouldn't've": "should not have",
"so've": "so have",
"so's": "so as / so is",
"that'd": "that would / that had",
"that'd've": "that would have",
"that's": "that has / that is",
"there'd": "there had / there would",
"there'd've": "there would have",
"there's": "there has / there is",
"they'd": "they had / they would",
"they'd've": "they would have",
"they'll": "they shall / they will",
"they'll've": "they shall have / they will have",
"they're": "they are",
"they've": "they have",
"to've": "to have",
"wasn't": "was not",
"we'd": "we had / we would",
"we'd've": "we would have",
"we'll": "we will",
"we'll've": "we will have",
"we're": "we are",
"we've": "we have",
"weren't": "were not",
"what'll": "what shall / what will",
"what'll've": "what shall have / what will have",
"what're": "what are",
"what's": "what has / what is",
"what've": "what have",
"when's": "when has / when is",
"when've": "when have",
"where'd": "where did",
"where's": "where has / where is",
```

```
"where've": "where have",
"who'll": "who shall / who will",
"who'll've": "who shall have / who will have",
"who's": "who has / who is",
"who've": "who have",
"why's": "why has / why is",
"why've": "why have",
"will've": "will have",
"won't": "will not",
"won't've": "will not have",
"would've": "would have",
"wouldn't": "would not",
"wouldn't've": "would not have",
"y'all": "you all",
"y'all'd": "you all would",
"y'all'd've": "you all would have",
"y'all're": "you all are",
"y'all've": "you all have",
"you'd": "you had / you would",
"you'd've": "you would have",
"you'll": "you shall / you will",
"you'll've": "you shall have / you will have",
"you're": "you are",
"you've": "you have"
}
def lookup_dict(text, dictionary):
    for word in text.split():
        if word.lower() in dictionary:
            if word.lower() in text.split():
                text = text.replace(word,
dictionary[word.lower()])
    return text
df['clean_tweet'] = df['clean_tweet'].apply(lambda x:
lookup_dict(x,apostrophe_dict))


# ### Short words lookup


short_word_dict = {
"121": "one to one",
"a/s/l": "age, sex, location",
"adn": "any day now",
"afaik": "as far as I know",
"afk": "away from keyboard",
"aight": "alright",
"alol": "actually laughing out loud",
"b4": "before",
"b4n": "bye for now",
"bak": "back at the keyboard",
"bf": "boyfriend",
"bff": "best friends forever",
```

```
"bfn": "bye for now",
"bg": "big grin",
"bta": "but then again",
"btw": "by the way",
"cid": "crying in disgrace",
"cnp": "continued in my next post",
"cp": "chat post",
"cu": "see you",
"cul": "see you later",
"cul8r": "see you later",
"cya": "bye",
"cyo": "see you online",
"dbau": "doing business as usual",
"fud": "fear, uncertainty, and doubt",
"fwiw": "for what it's worth",
"fyi": "for your information",
"g": "grin",
"g2g": "got to go",
"ga": "go ahead",
"gal": "get a life",
"gf": "girlfriend",
"gfn": "gone for now",
"gmbo": "giggling my butt off",
"gmta": "great minds think alike",
"h8": "hate",
"hagn": "have a good night",
"hdop": "help delete online predators",
"hhis": "hanging head in shame",
"iac": "in any case",
"ianal": "I am not a lawyer",
"ic": "I see",
"idk": "I don't know",
"imao": "in my arrogant opinion",
"imnsho": "in my not so humble opinion",
"imo": "in my opinion",
"iow": "in other words",
"ipn": "I’m posting naked",
"irl": "in real life",
"jk": "just kidding",
"l8r": "later",
"ld": "later, dude",
"ldr": "long distance relationship",
"llta": "lots and lots of thunderous applause",
"lmao": "laugh my ass off",
"lmirl": "let's meet in real life",
"lol": "laugh out loud",
"ltr": "longterm relationship",
"lulab": "love you like a brother",
"lulas": "love you like a sister",
"luv": "love",
"m/f": "male or female",
```

```
"m8": "mate",
"milf": "mother I would like to fuck",
"oll": "online love",
"omg": "oh my god",
"otoh": "on the other hand",
"pir": "parent in room",
"ppl": "people",
"r": "are",
"rofl": "roll on the floor laughing",
"rpg": "role playing games",
"ru": "are you",
"shid": "slaps head in disgust",
"somy": "sick of me yet",
"sot": "short of time",
"thanx": "thanks",
"thx": "thanks",
"ttyl": "talk to you later",
"u": "you",
"ur": "you are",
"uw": "you’re welcome",
"wb": "welcome back",
"wfm": "works for me",
"wibni": "wouldn't it be nice if",
"wtf": "what the fuck",
"wtg": "way to go",
"wtgp": "want to go private",
"ym": "young man",
"gr8": "great"
}
df['clean_tweet'] = df['clean_tweet'].apply(lambda x:
lookup_dict(x,short_word_dict))



# ### Emoticon Lookup

emoticon_dict = {
":)": "happy",
":‑)": "happy",
":-]": "happy",
":-3": "happy",
":->": "happy",
"8-)": "happy",
":-}": "happy",
":o)": "happy",
":c)": "happy",
":^)": "happy",
"=]": "happy",
"=)": "happy",
"<3": "happy",
":-(": "sad",
```

```
":(": "sad",
":c": "sad",
":<": "sad",
":[": "sad",
">:[": "sad",
":{": "sad",
">:(": "sad",
":-c": "sad",
":-< ": "sad",
":-[": "sad",
":-||": "sad"
}
df['clean_tweet'] = df['clean_tweet'].apply(lambda x:
lookup_dict(x,emoticon_dict))


# ### Replacing punctuations with spaces
df['clean_tweet'] = df['clean_tweet'].apply(lambda x:
re.sub(r'[^\w\s]',' ',x))


# ### Replacing special characters with spaces
df['clean_tweet'] = df['clean_tweet'].apply(lambda x:
re.sub(r'[^a-zA-Z0-9]',' ',x))


# ### Replacing numbers with spaces
df['clean_tweet'] = df['clean_tweet'].apply(lambda x:
re.sub(r'[^a-zA-Z]',' ',x))


# ### Removing words with length 1
df['clean_tweet'] = df['clean_tweet'].apply(lambda x: ' '.join([w
for w in x.split() if len(w)>1]))


# ### Tokenizing the clean_tweet column and removing stop words
from new tweet_token column
from nltk import word_tokenize

df['tweet_token'] = df['clean_tweet'].apply(lambda x: word_tok-
enize(x))
df['tweet_token_filtered'] = df['tweet_token'].apply(lambda x:
[word for word in x if not word in stop_words])


# ### Lemmatization - Lemmatization is the process of converting a
word to its base form.
df['tweet_lemmatized'] = df['tweet_token_filtered'].apply(lambda
x: ' '.join([lemmatizing.lemmatize(i) for i in x]))
df.head()
```

```
# ### Extracting features from lemmatied tweets with the help of
Bag of words Feature
bow_vectorizer = CountVectorizer(max_df=0.90, min_df=2, max_fea-
tures=1000, stop_words='english')
bow_main=
bow_vectorizer.fit_transform(data['tweet_lemmatized']).toarray()
bow_main


# ### Prediction of sentiments with the help of our trained model
bow_main = sc.fit_transform(bow_main)
main_pred=model.predict(bow_main)



main_pred=pd.Series(main_pred)
main_pred.replace([0,1,-1],['neutral','positive','negative'],in-
place=True)
main_pred.head()


final=pd.concat([df["Text"],df["Date"],df["Location"]],axis=1)
final["Sentiment"]=main_pred
final.head(15)



final['Date'] = final['Date'].dt.date
final.drop_duplicates(subset='Text', keep='first', inplace=False)


final.drop(['Text'], axis=1)
final



from project_lib import Project
project = Project(sc,"b1b16b09-e8e8-4dad-9443-7329983c8856","p-
bb1cb98712cd7b785cb10f7bad5b2fda9de95b90")
project.save_data(file_name = "final.csv",data = final.to_csv(in-
dex=False))


final
```