• SUPERVISED ML CLASSFICATION CAPSTONE PROJECT

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PREDICTING SENTIMENT OF COVID-19 TWEETS

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- Data Analysis
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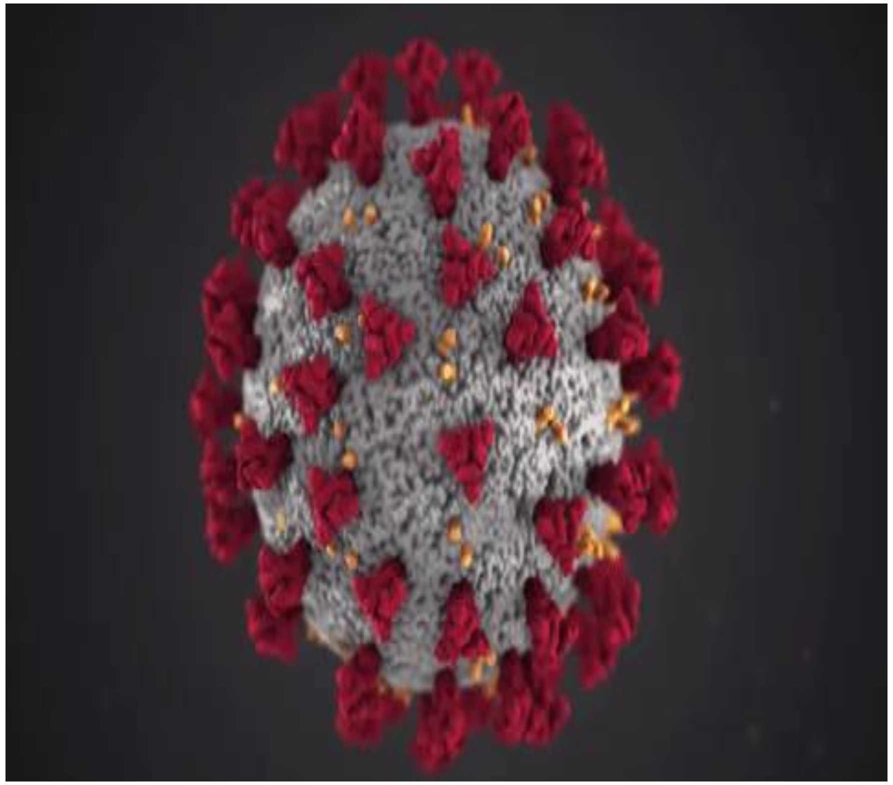
Introduction:

- The respiratory infections caused by human respiratory viruses are among the most prevalent viral illnesses that affect people (RVs) The influenza virus, also known as the "flu," is the most well-known type of respiratory viral infection and accounts for between 250,000 and 500,000 fatalities annually globally. The H1N1 virus is its most well-known variety. The corona virus is one of the virus families that cause respiratory illnesses. It infects the epithelial cells of the respiratory tract in humans, frequently going undetected but occasionally being fatal. The Middle East Respiratory Syndrome (MERS), Severe Acute Respiratory Syndrome (SARS), and currently Corona virus Disease are the most well-known corona virus varieties (COVID-19)..



Problem Statement:

The pandemic illnesses that are currently plaguing the world, in particular, pose major issues for the population on all fronts: economic, emotional, status, planning, and politics, in addition to the complexity of customs, ethics, personal psychology, and interpersonal behaviours. Therefore, when difficult situations happen, it is essential and required to analyse people's views. Observing how people respond to this threat can reveal crucial details about how society behaves and responds to unforeseen events, whether positively or negatively. At the moment, the internet and social media have evolved into potent tools for gathering people's opinions and comments on a variety of subjects. The major goal is to create a prediction model that could aid in anticipating a tweet's sentiment.

Data Analysis Steps:

Imported Libraries

In this part, we imported the required libraries NumPy, Pandas, matplotlib, and seaborn, to perform Exploratory Data Analysis and for prediction, we imported the Scikit learn library.

Descriptive Statistics

In this part, we start by looking at descriptive statistic parameters for the dataset. We will use describe() this told mean, median, standard deviation

Missing Value Imputation

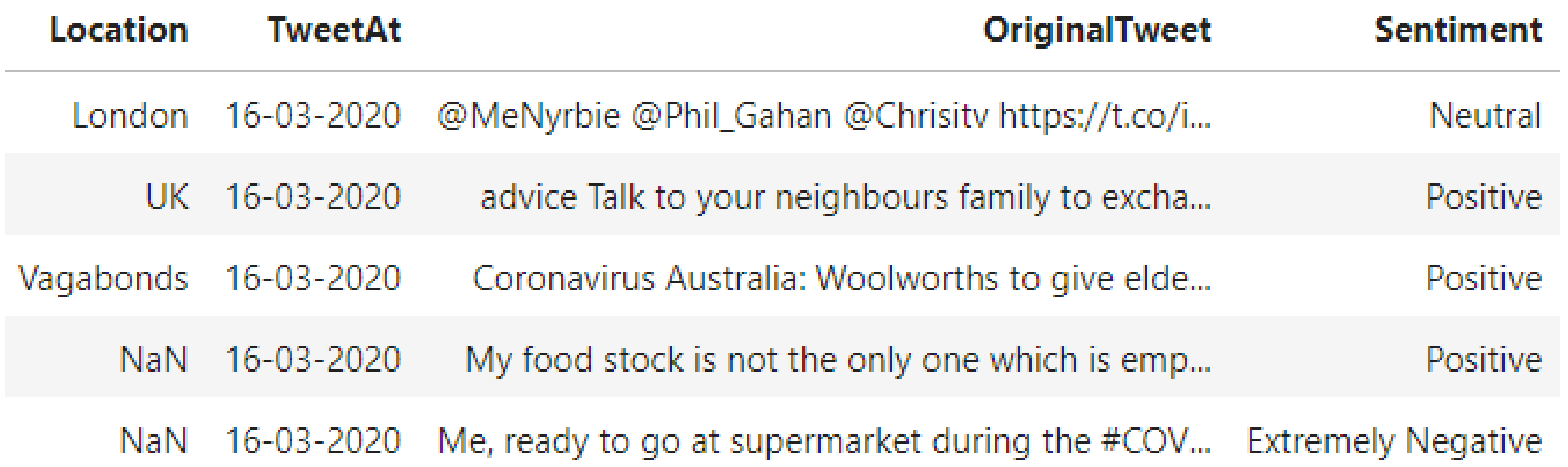
We will now check for missing values in our dataset. after checking not existed any missing values, In case there are any missing entries, we will impute them with appropriate values.

Graphical Representation

We will start with Univariate Analysis, bivariate Analysis and conclude with various prediction models helps us predict the Risk.

Attribute Information

Location - location of country
Tweet At – timestamp of tweets
Original Tweet – textual content of tweets
Label – Sentiment of the tweets

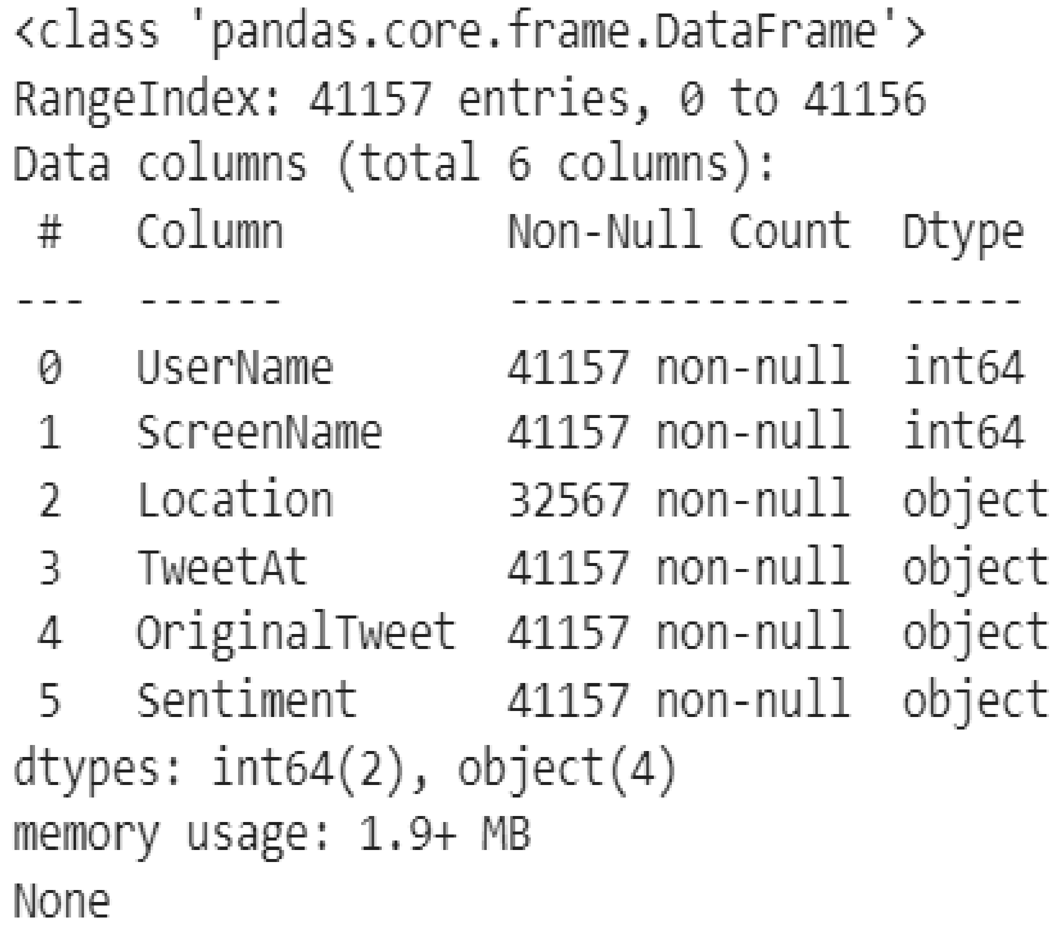


Location	TweetAt	OriginalTweet	Sentiment
London	16-03-2020	@MeNyrbie @Phil_Gahan @Chrisitv https://t.co/i...	Neutral
UK	16-03-2020	advice Talk to your neighbours family to excha...	Positive
Vagabonds	16-03-2020	Coronavirus Australia: Woolworths to give elde...	Positive
NaN	16-03-2020	My food stock is not the only one which is emp...	Positive
NaN	16-03-2020	Me, ready to go at supermarket during the #COV...	Extremely Negative

Data Inspection:

- This Dataset has contains 41157 rows and 6 columns.

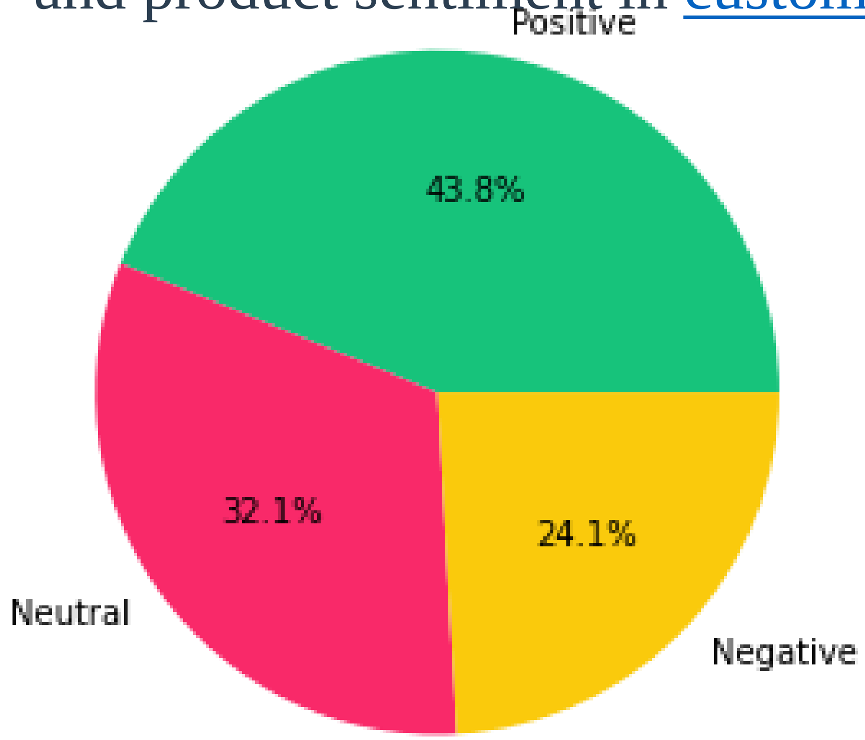
Location - location of country
Tweet At – timestamp of tweets
Original Tweet – textual content of tweets
Label – Sentiment of the tweets

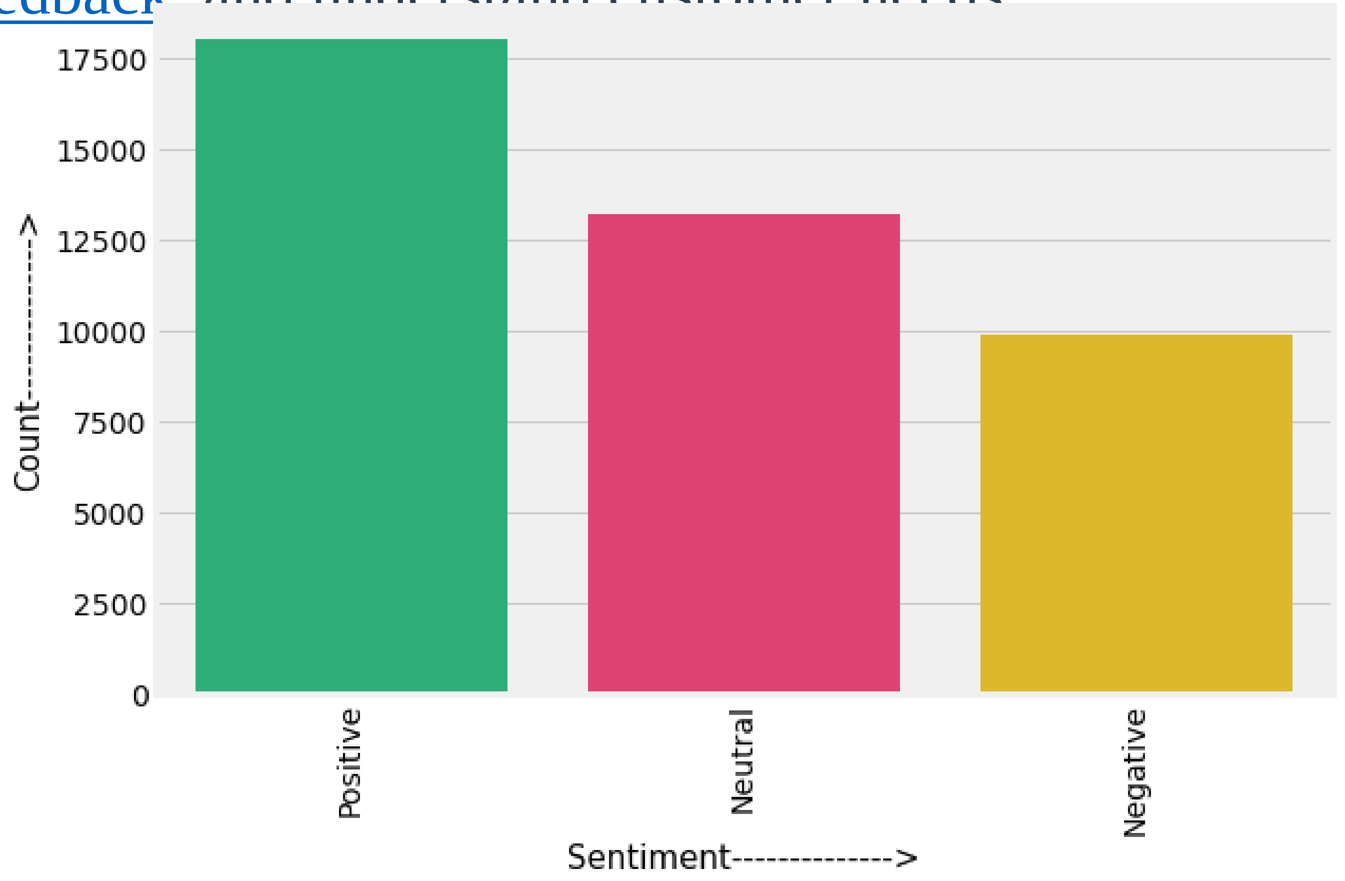


```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41157 entries, 0 to 41156
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   UserName       41157 non-null  int64 
 1   ScreenName     41157 non-null  int64 
 2   Location       32567 non-null  object
 3   TweetAt        41157 non-null  object
 4   OriginalTweet  41157 non-null  object
 5   Sentiment      41157 non-null  object
dtypes: int64(2), object(4)
memory usage: 1.9+ MB
None
```

Sentiment Analysis

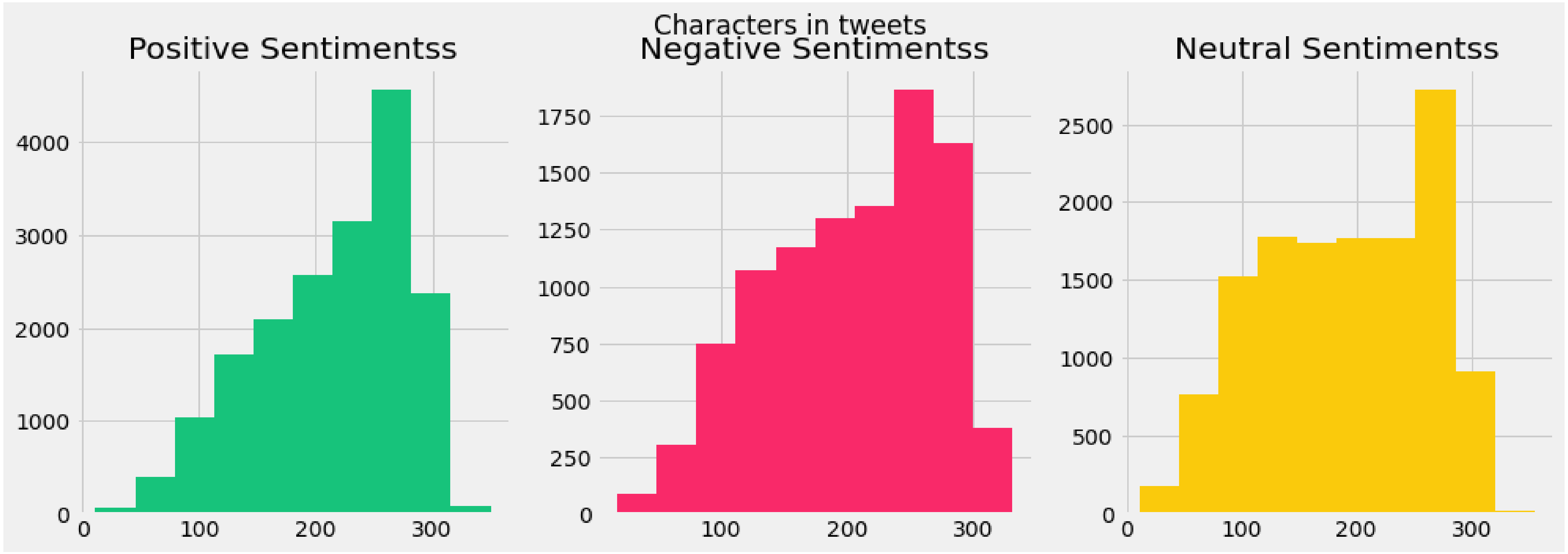
- Sentiment analysis (or opinion mining) is a natural language processing (NLP) technique used to determine whether data is positive, negative or neutral. Sentiment analysis is often performed on textual data to help businesses monitor brand and product sentiment in customer feedback, and understand customer needs





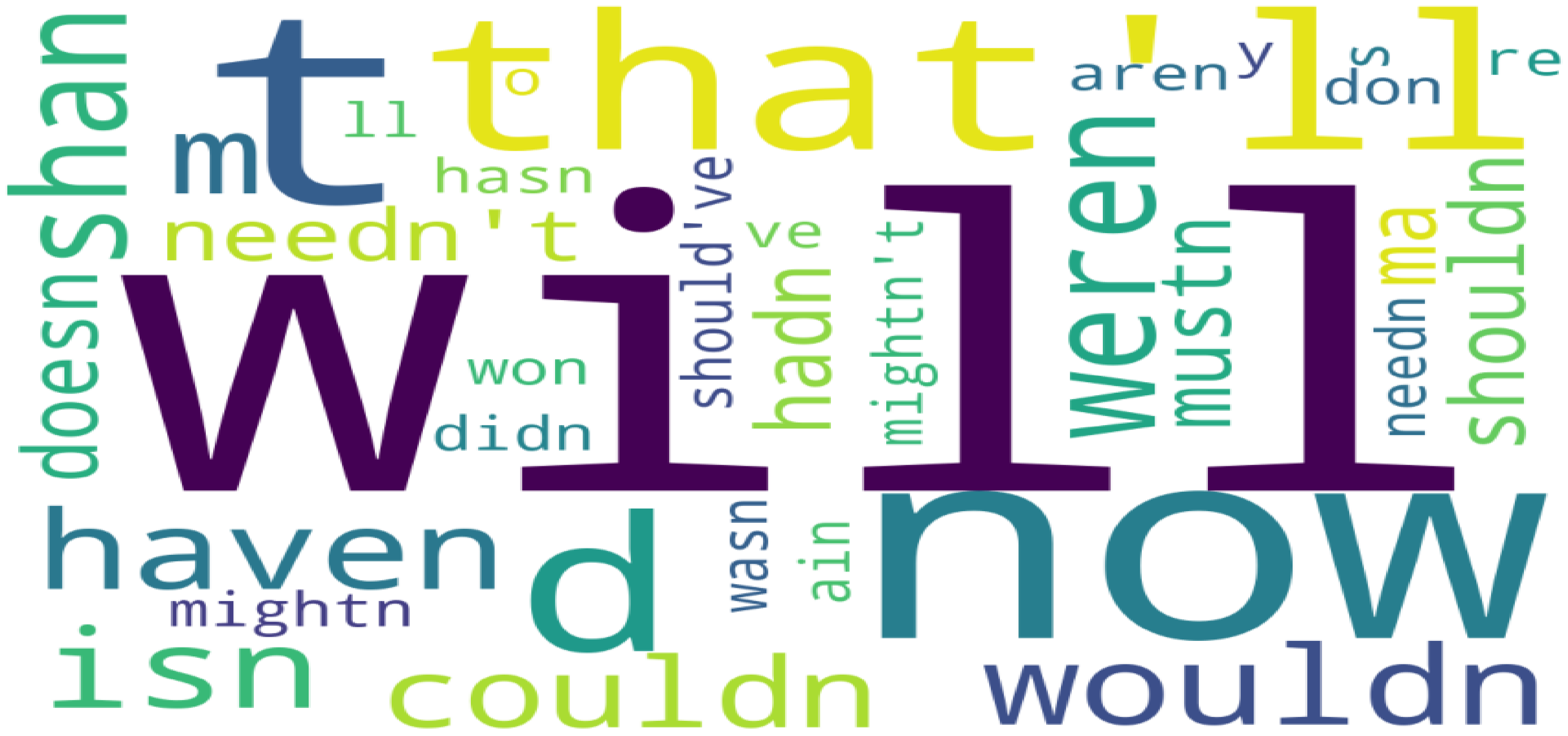
Number of characters in a Tweet

- As we can see the number of character used in positive sentiments is between 400-4000.on the other hand for negative sentiments its between 250-1750 and for neutral sentiments its between 200-2500



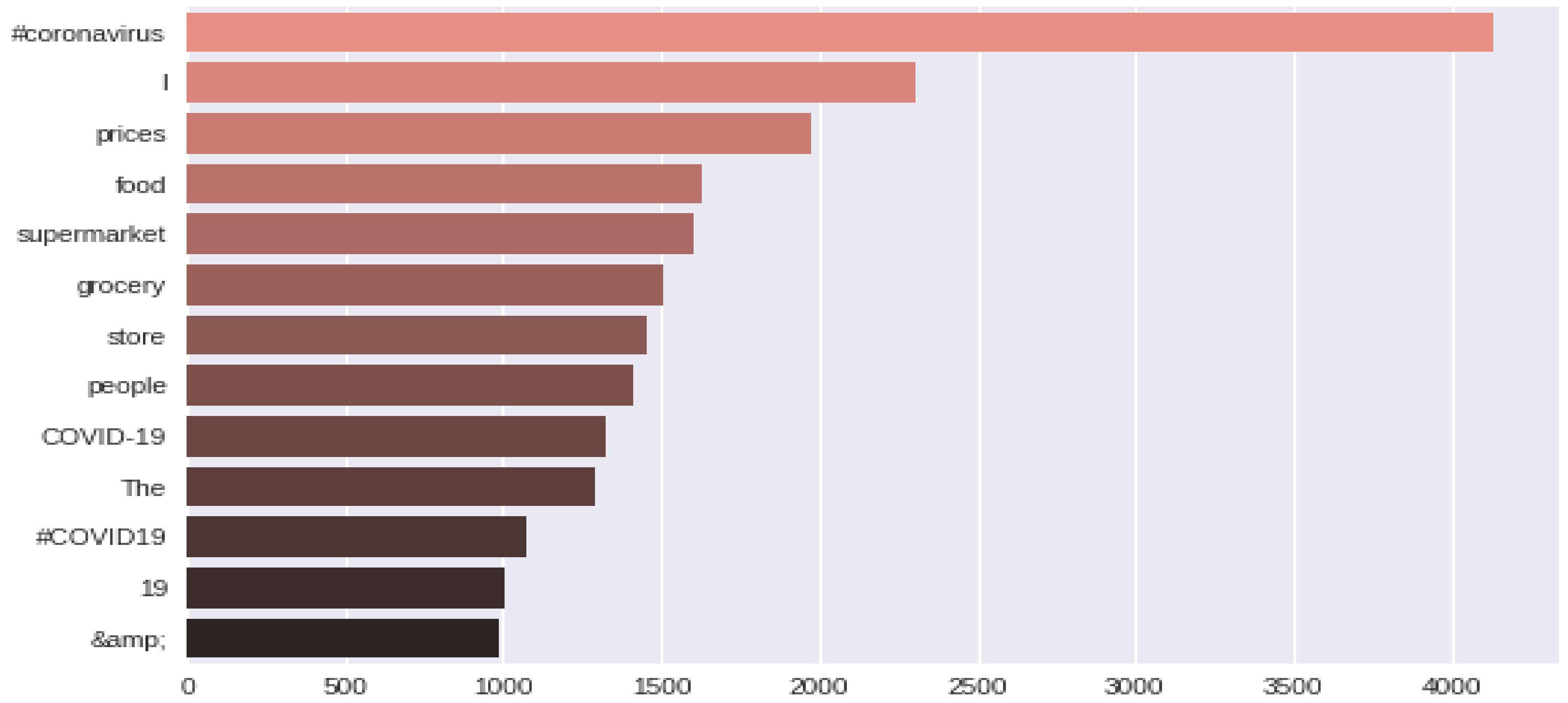
Common Stop words in the tweets

- Here we plot word cloud that shows the common stop words that a person used in a tweet whether its positive, negative or neutral sentiments.



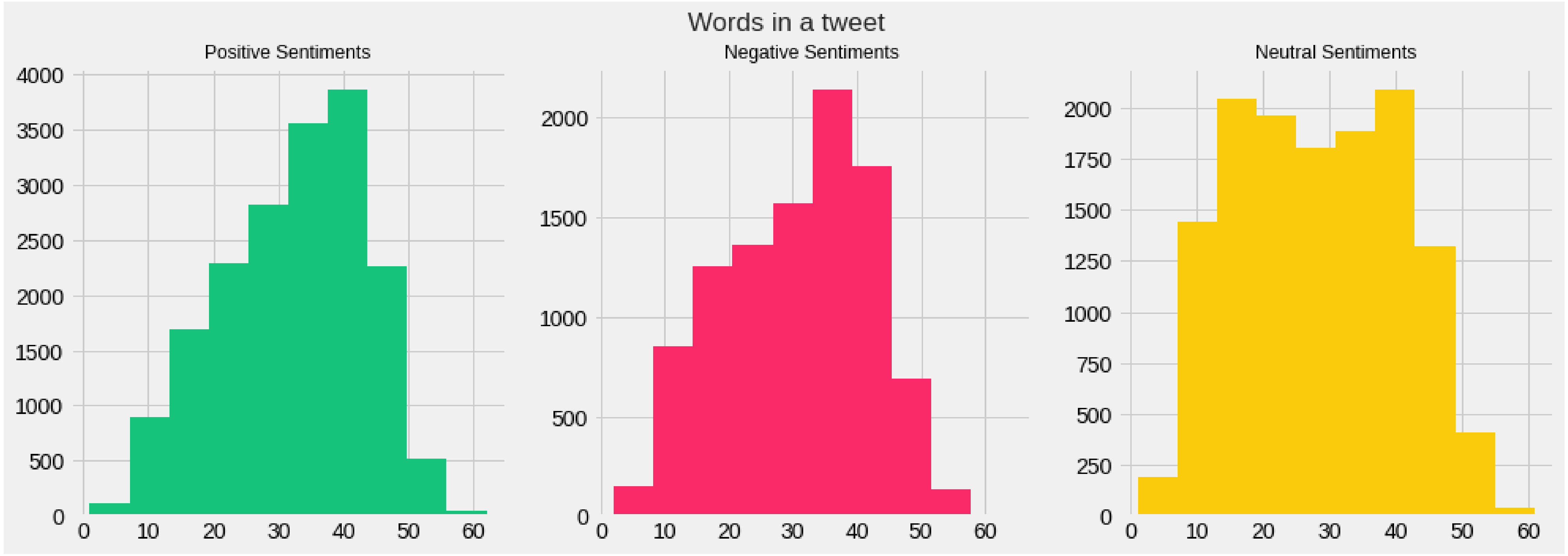
Common Stopwords in the tweets

- Here we use bar plot that shows the common words that a person used in a tweet whether its positive, negative or neutral sentiments.



Number of words in a Tweet

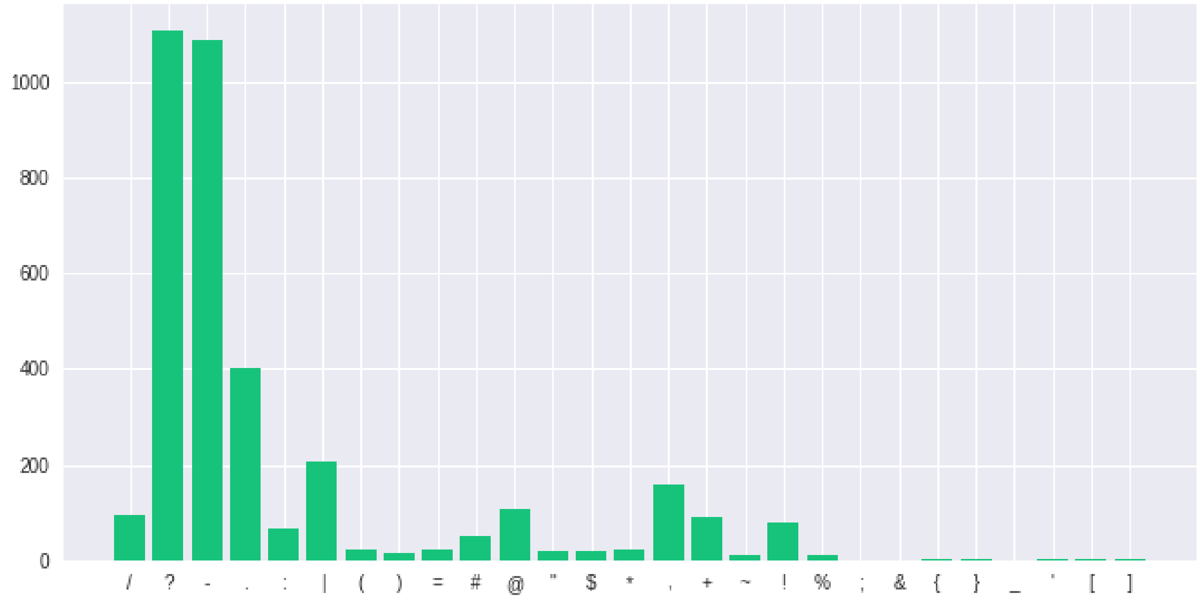
- As we can see the number of words used in positive sentiments is between 100-3800.on the other hand for negative sentiments its between 100-2100 and for neutral sentiments its between 200-2000.

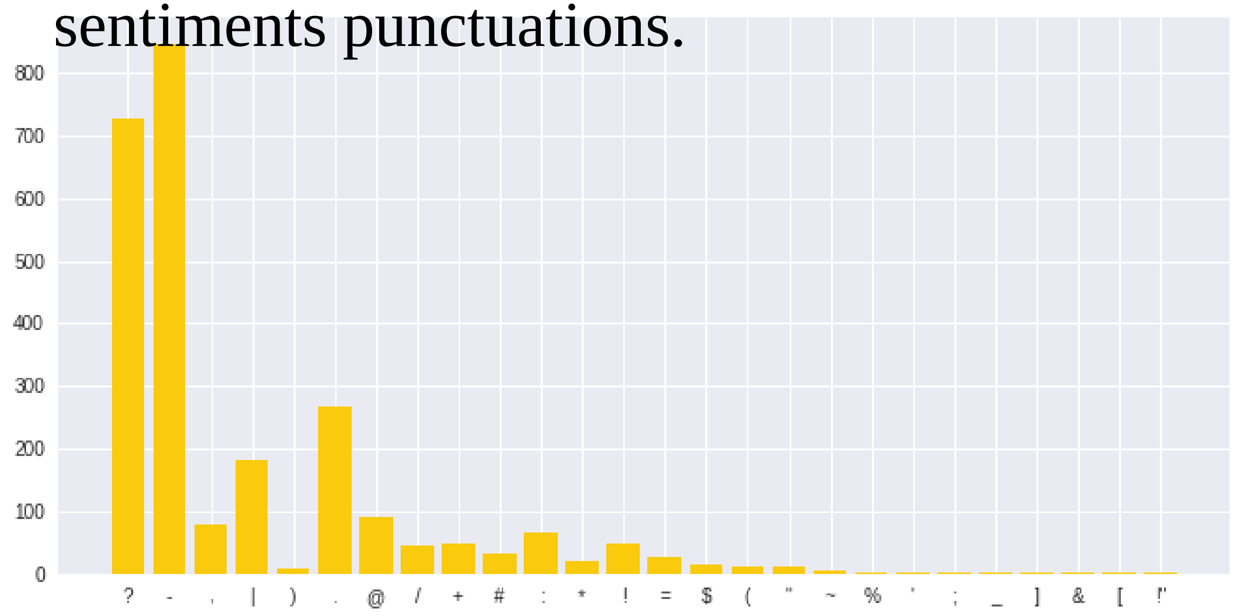


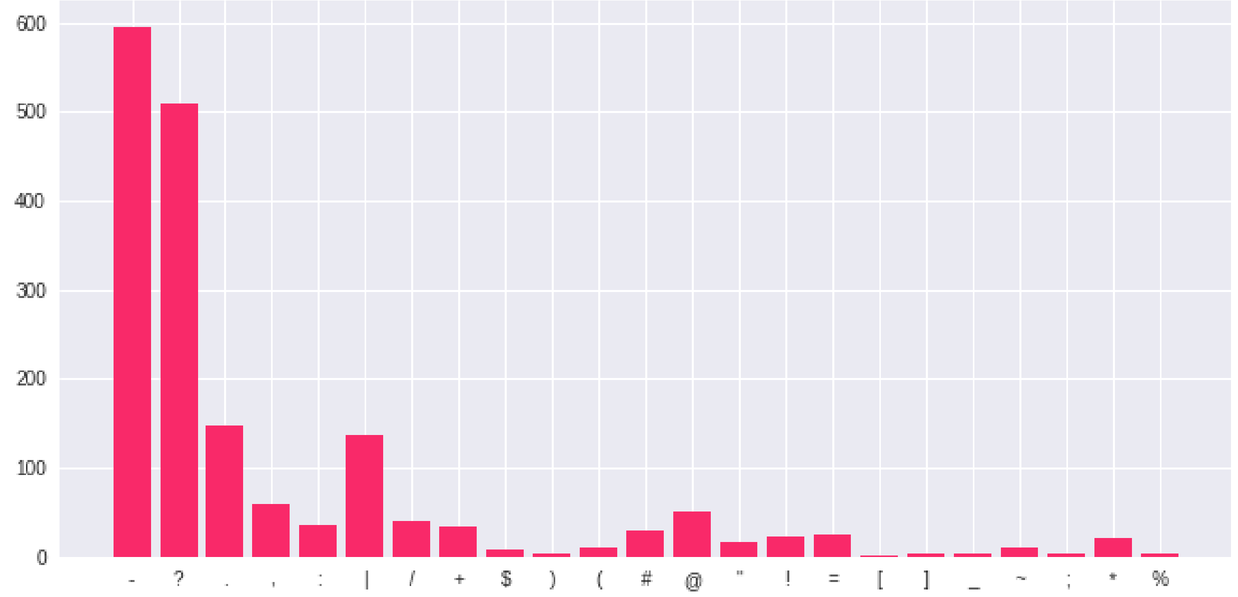
Number of Punctuations

Punctuations used by a person in a tweet.

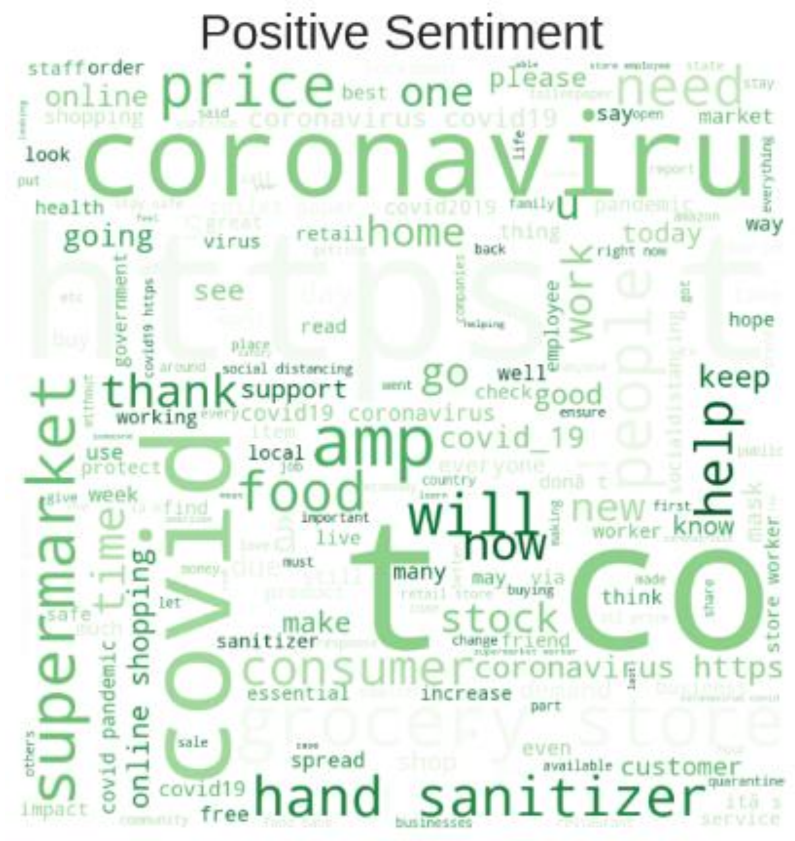
Green color histogram represent positive sentiments punctuations.
Pink color histogram represent Negative sentiments punctuations.
Yellow color histogram represent Neutral sentiments punctuations.

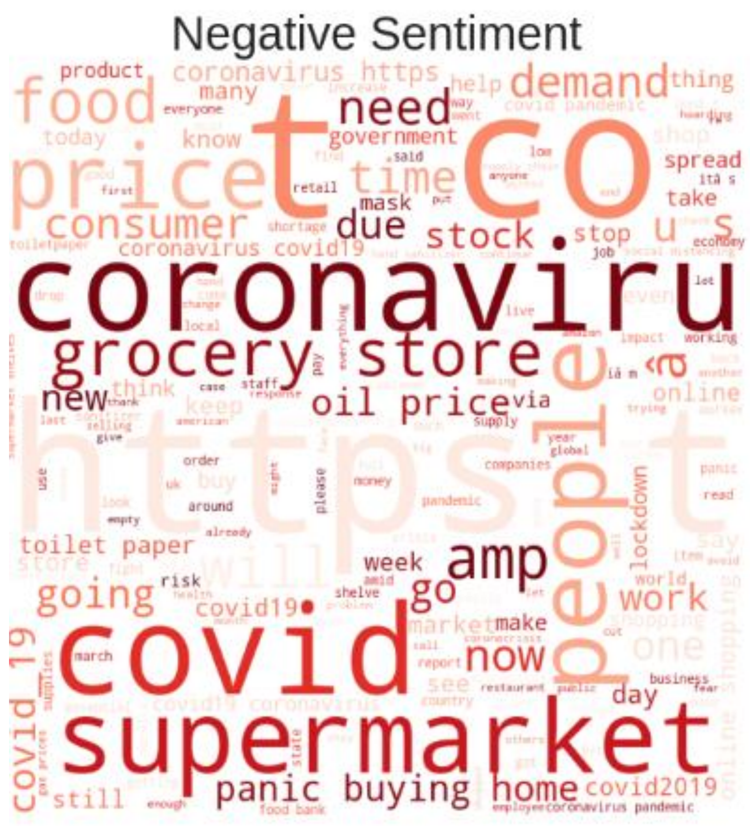


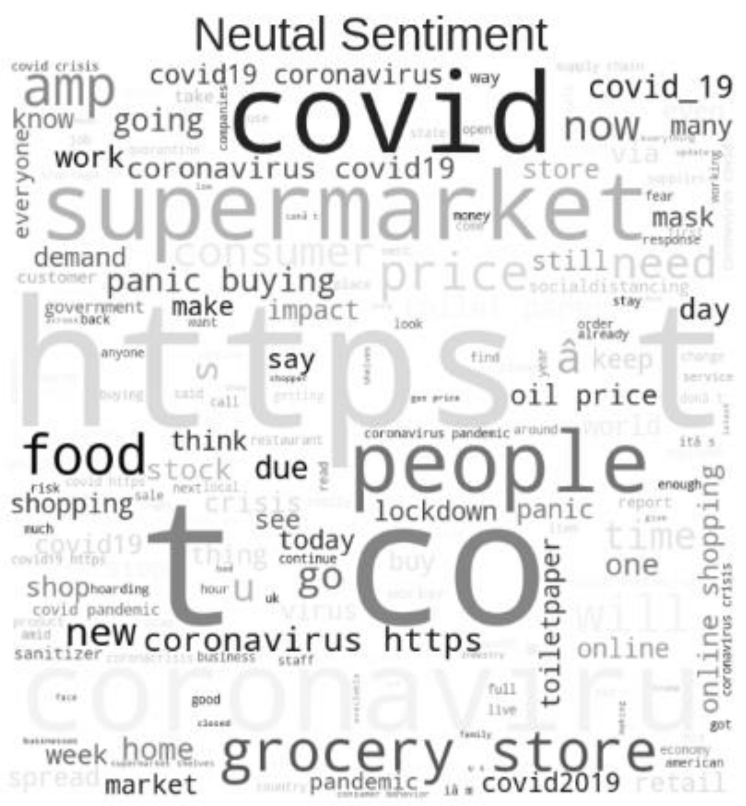




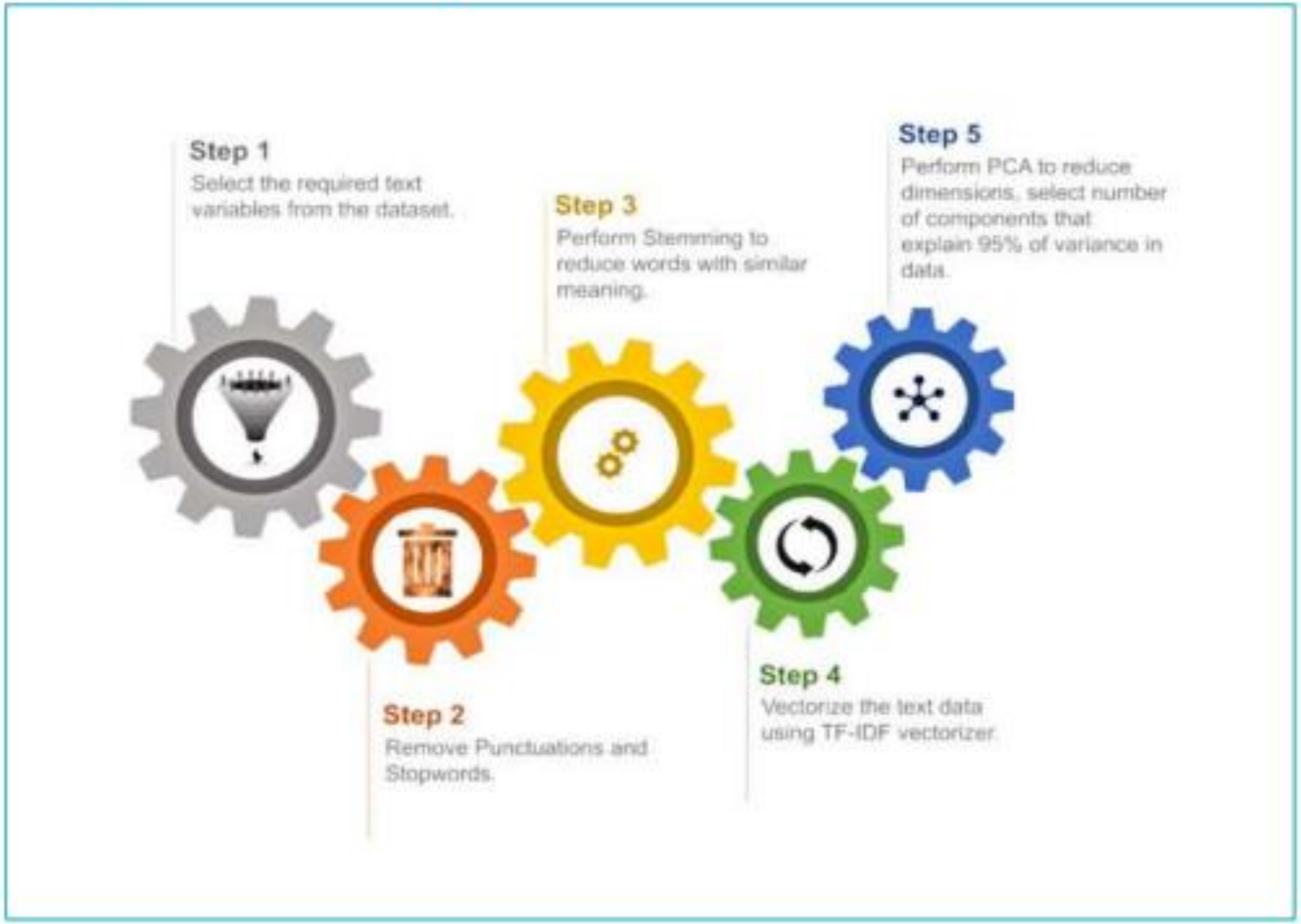
Mentions used in a Tweet



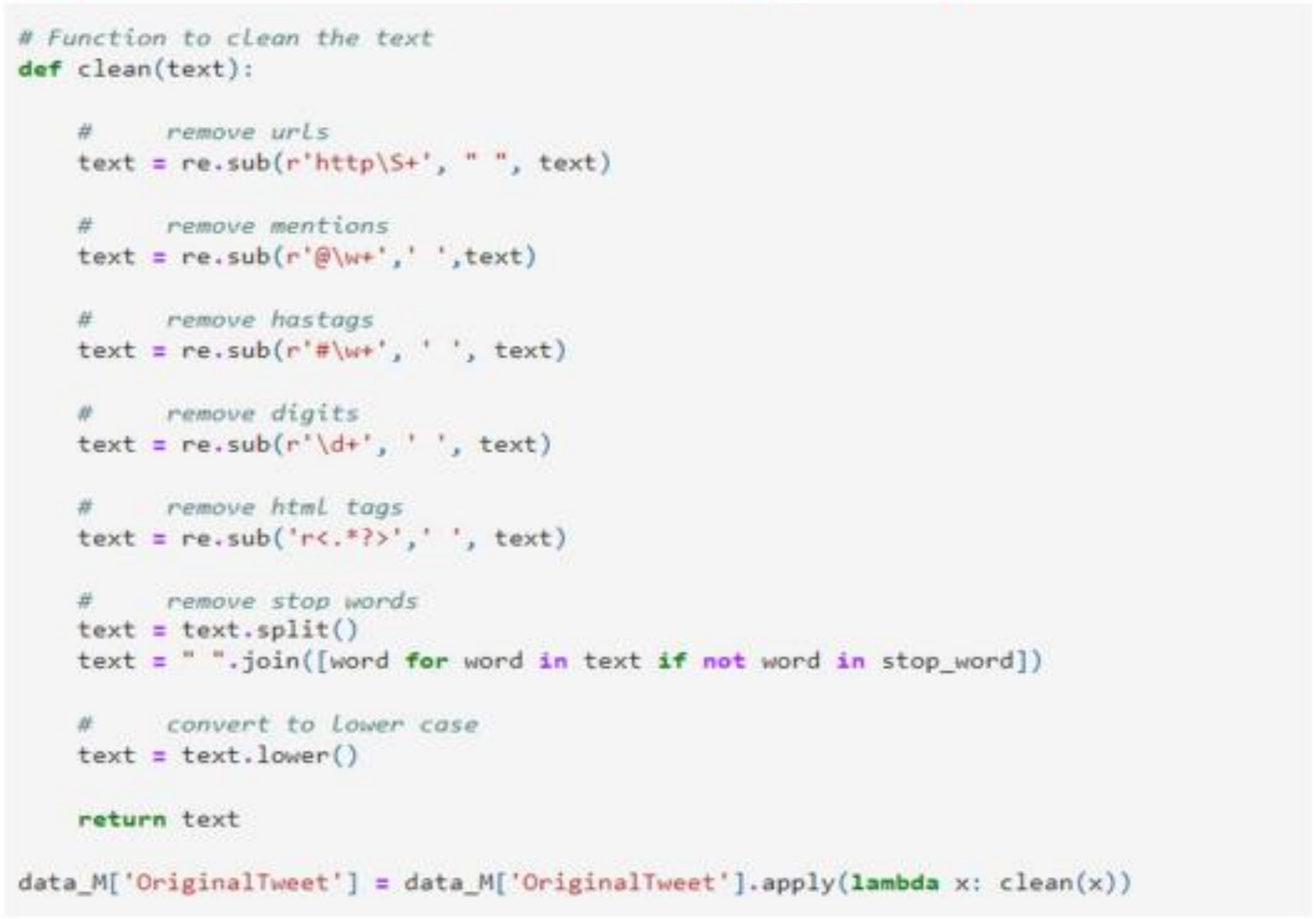




Data Pre-processing:

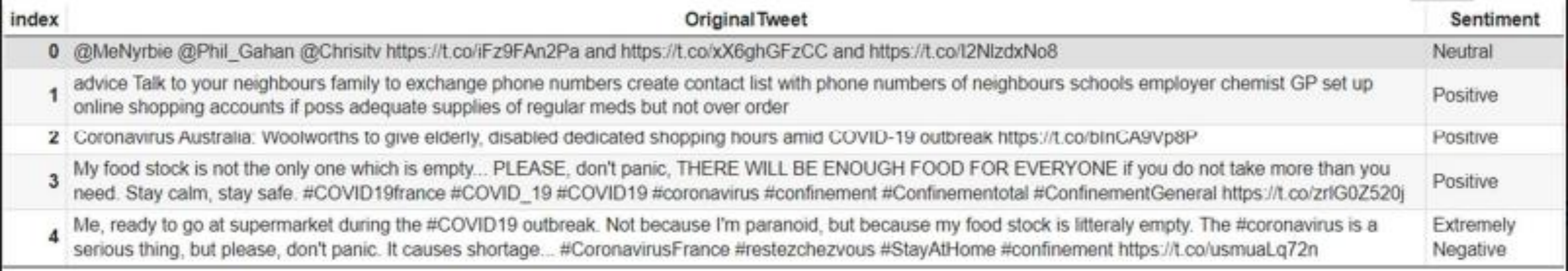

Step 1
Select the required text variables from the dataset.
Step 2
Remove Punctuations and Stopwords.
Step 3
Perform Stemming to reduce words with similar meaning.
Step 4
Vectorize the text data using TF-IDF vectorizer.
Step 5
Perform PCA to reduce dimensions, select number of components that explain 95% of variance in data.

Removing Punctuations, Hashtags, StopWords



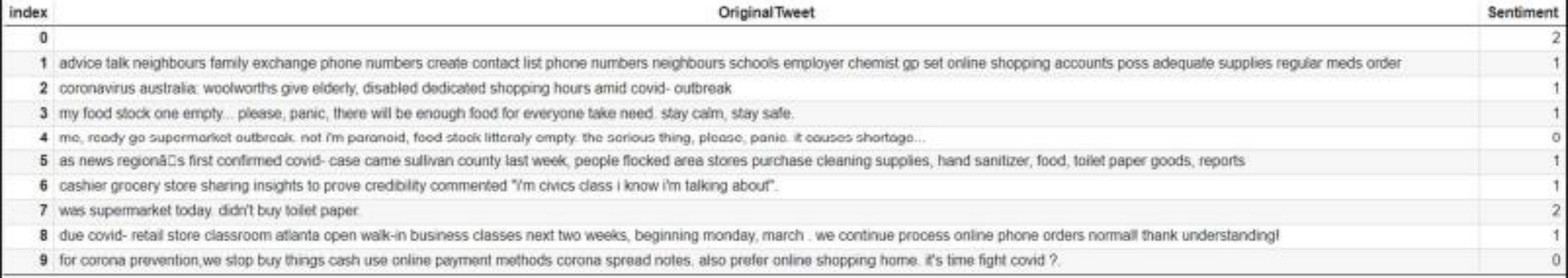
```
# Function to clean the text
def clean(text):

    #     remove urls
    text = re.sub(r'http\S+', " ", text)

    #     remove mentions
    text = re.sub(r'@\w+',' ',text)

    #     remove hastags
    text = re.sub(r'#\w+', ' ', text)

    #     remove digits
    text = re.sub(r'\d+', ' ', text)

    #     remove html tags
    text = re.sub('r<.*?>',' ', text)

    #     remove stop words
    text = text.split()
    text = " ".join([word for word in text if not word in stop_word])

    #     convert to lower case
    text = text.lower()

    return text

data_M['OriginalTweet'] = data_M['OriginalTweet'].apply(lambda x: clean(x))
```

BEFORE CLEANING TEXT



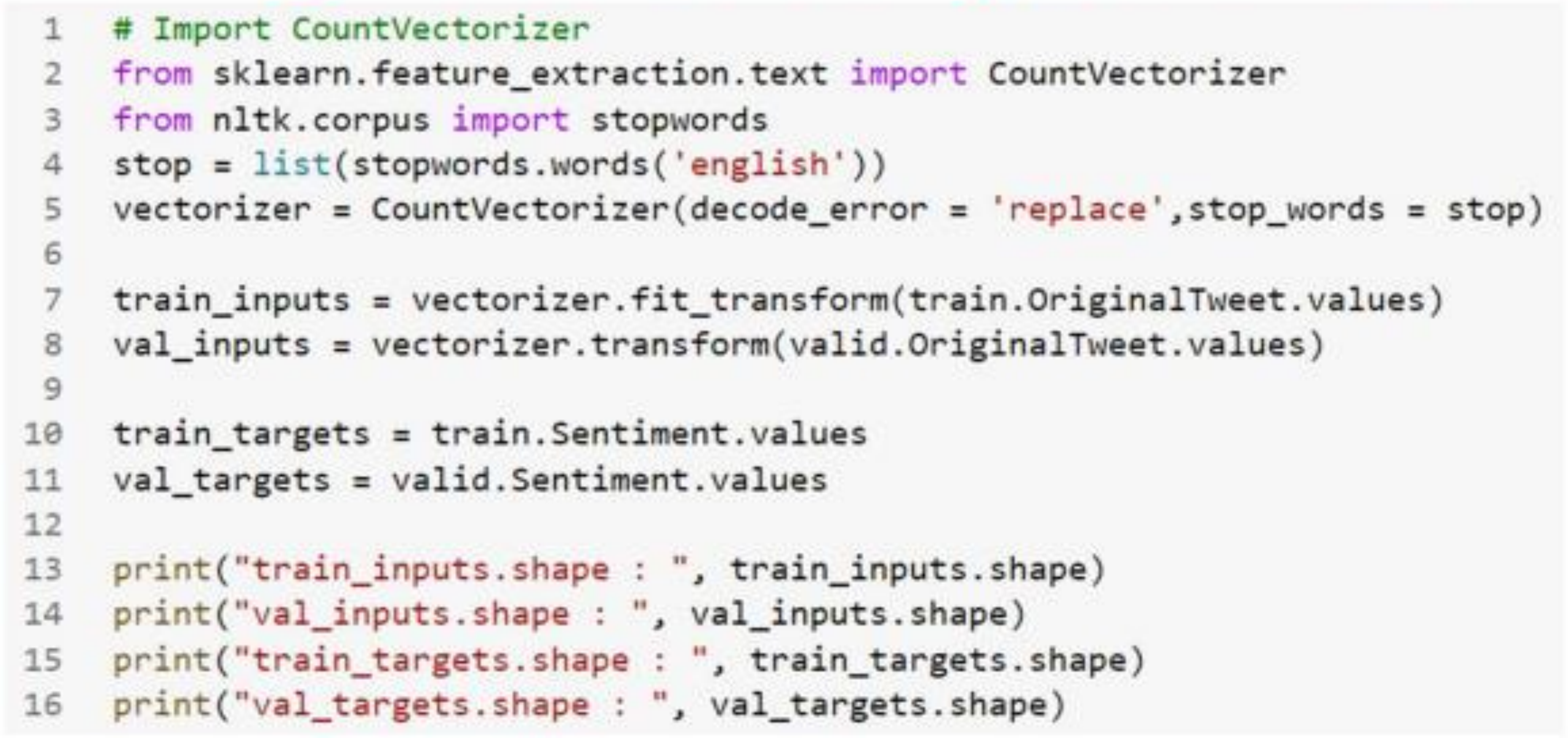
index	Original Tweet	Sentiment
0	@MeNyrbie @Phil_Gahan @Chrisitv https://t.co/iFz9FAn2Pa and https://t.co/xX6ghGFzCC and https://t.co/I2NlzdxNo8	Neutral
1	advice Talk to your neighbours family to exchange phone numbers create contact list with phone numbers of neighbours schools employer chemist GP set up online shopping accounts if poss adequate supplies of regular meds but not over order	Positive
2	Coronavirus Australia: Woolworths to give elderly, disabled dedicated shopping hours amid COVID-19 outbreak https://t.co/bInCA9Vp8P	Positive
3	My food stock is not the only one which is empty... PLEASE, don't panic, THERE WILL BE ENOUGH FOOD FOR EVERYONE if you do not take more than you need. Stay calm, stay safe. #COVID19france #COVID_19 #COVID19 #coronavirus #confinement #Confinementotal #ConfinementGeneral https://t.co/zrlG0Z520j	Positive
4	Me, ready to go at supermarket during the #COVID19 outbreak. Not because I'm paranoid, but because my food stock is litteraly empty. The #coronavirus is a serious thing, but please, don't panic. It causes shortage... #CoronavirusFrance #restezchezvous #StayAtHome #confinement https://t.co/usmuaLq72n	Extremely Negative

AFTER CLEANING TEXT



index	Original Tweet	Sentiment
0		2
1	advice talk neighbours family exchange phone numbers create contact list phone numbers neighbours schools employer chemist gp set online shopping accounts poss adequate supplies regular meds order	1
2	coronavirus australia: woolworths give elderly, disabled dedicated shopping hours amid covid- outbreak	1
3	my food stock one empty... please, panic, there will be enough food for everyone take need. stay calm, stay safe.	1
4	me, ready go supermarket outbreak. not i'm paranoid, food stock litteraly empty. the serious thing, please, panic. it causes shortage...	0
5	as news regionâs first confirmed covid- case came sullivan county last week, people flocked area stores purchase cleaning supplies, hand sanitizer, food, toilet paper goods, reports	1
6	cashier grocery store sharing insights to prove credibility commented "i'm civics class i know i'm talking about".	1
7	was supermarket today. didn't buy toilet paper.	2
8	due covid- retail store classroom atlanta open walk-in business classes next two weeks, beginning monday, march . we continue process online phone orders normall thank understanding!	1
9	for corona prevention,we stop buy things cash use online payment methods corona spread notes. also prefer online shopping home. it's time fight covid ?.	0

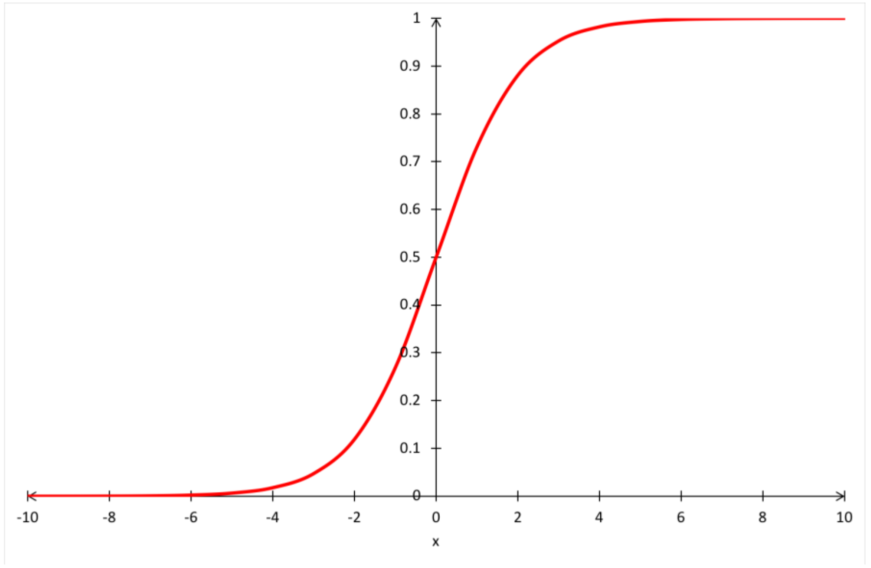
Vectorizing the text data using Count Vectorizer:



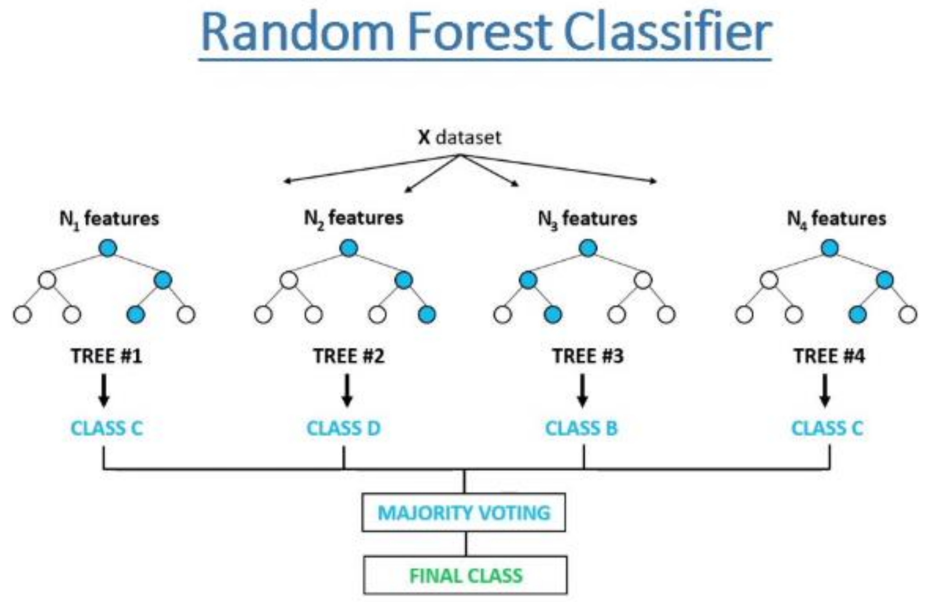
```python
# Import CountVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from nltk.corpus import stopwords
stop = list(stopwords.words('english'))
vectorizer = CountVectorizer(decode_error = 'replace',stop_words = stop)

train_inputs = vectorizer.fit_transform(train.OriginalTweet.values)
val_inputs = vectorizer.transform(valid.OriginalTweet.values)

train_targets = train.Sentiment.values
val_targets = valid.Sentiment.values

print("train_inputs.shape : ", train_inputs.shape)
print("val_inputs.shape : ", val_inputs.shape)
print("train_targets.shape : ", train_targets.shape)
print("val_targets.shape : ", val_targets.shape)
```

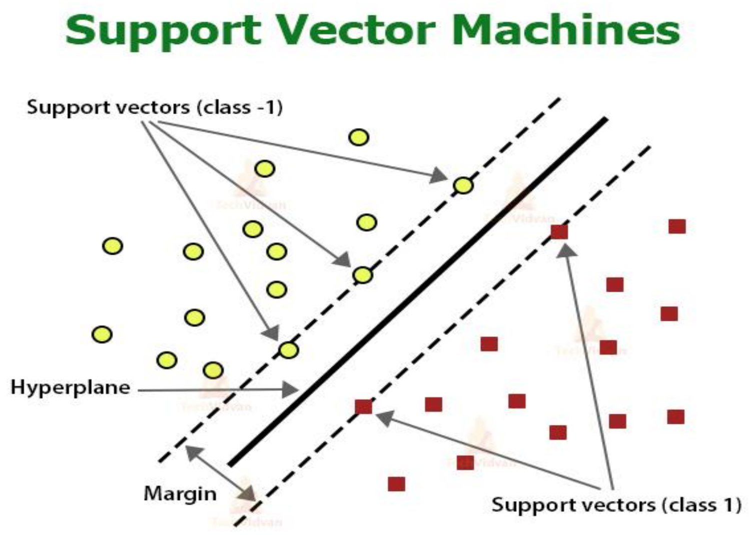
- Here we have textual data.
- Classification algorithms cannot understand textual data.
- So, we use vectorization technique to convert textual data to numerical vectors

Model Building:

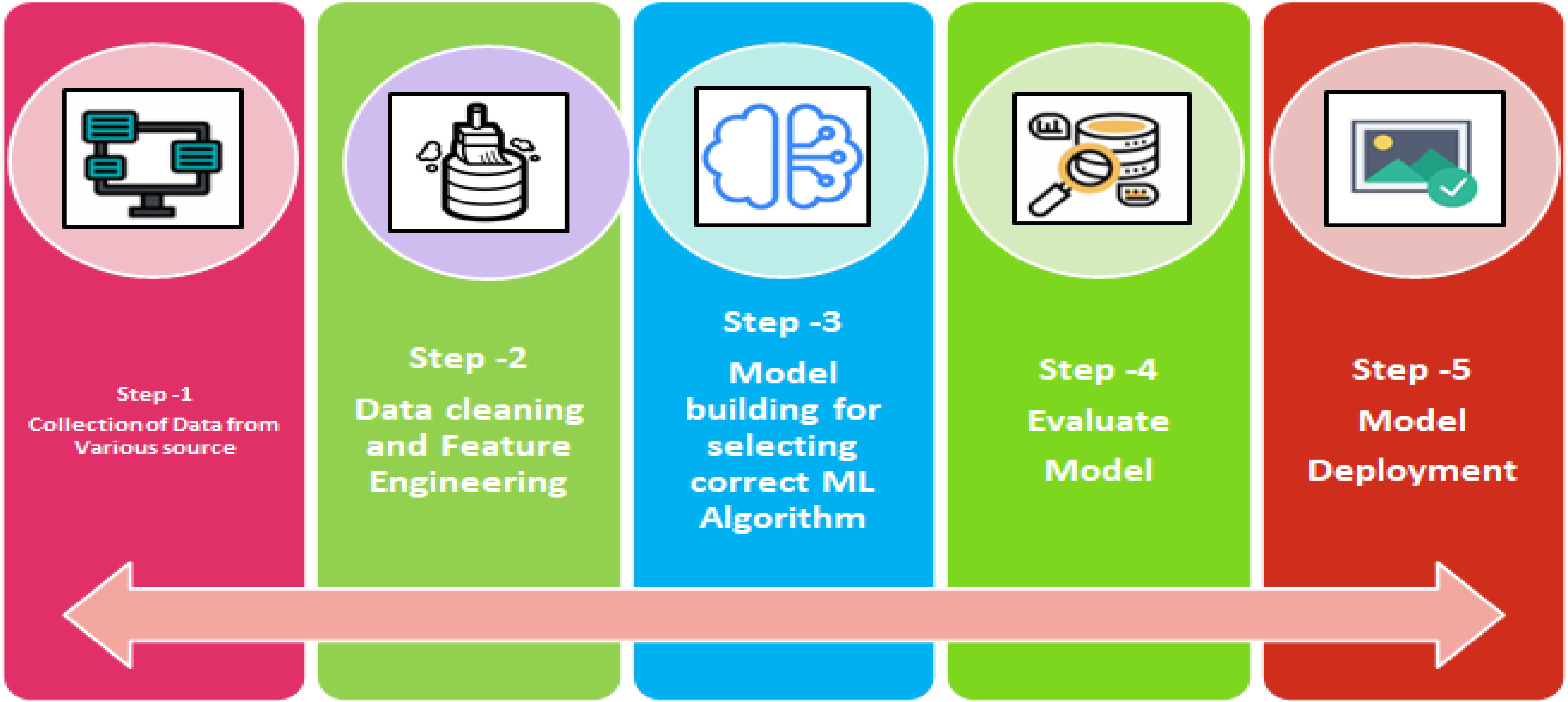


Logistic Regression

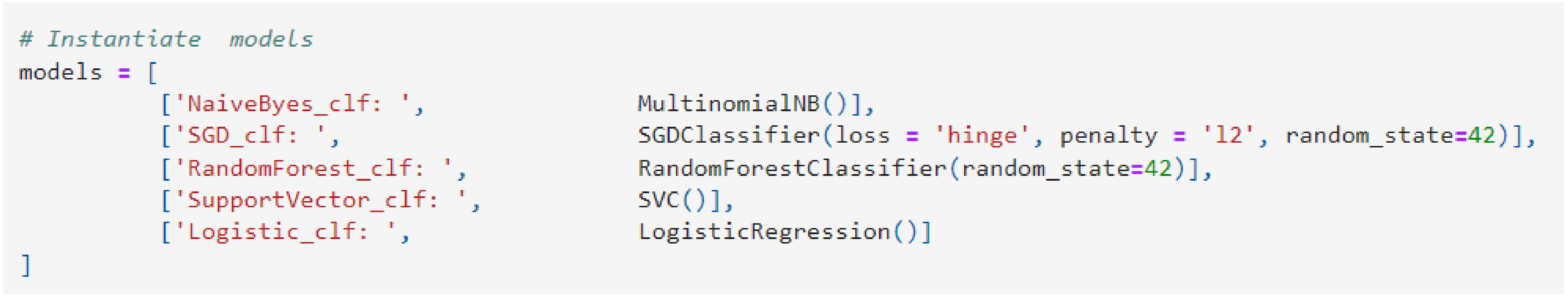




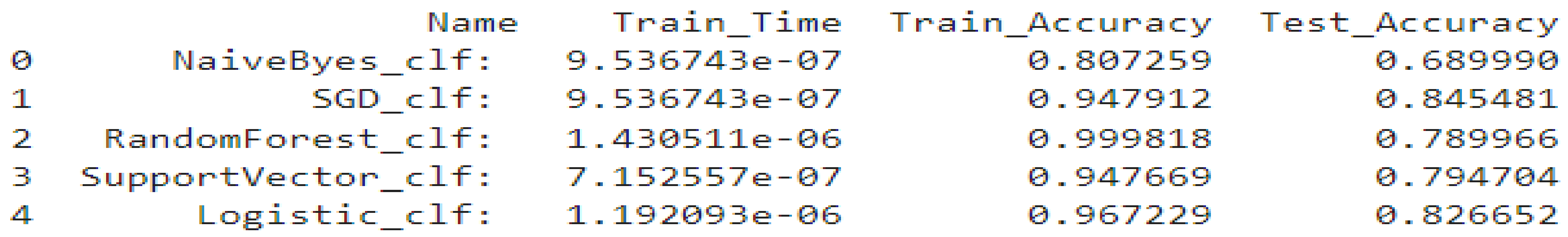
Machine Learning Process Flow:


Step -1
Collection of Data from Various source
Step -2
Data cleaning and Feature Engineering
Step -3
Model building for selecting correct ML Algorithm
Step -4
Evaluate Model
Step -5
Model Deployment

Comparing different Models for Multiclass Classification



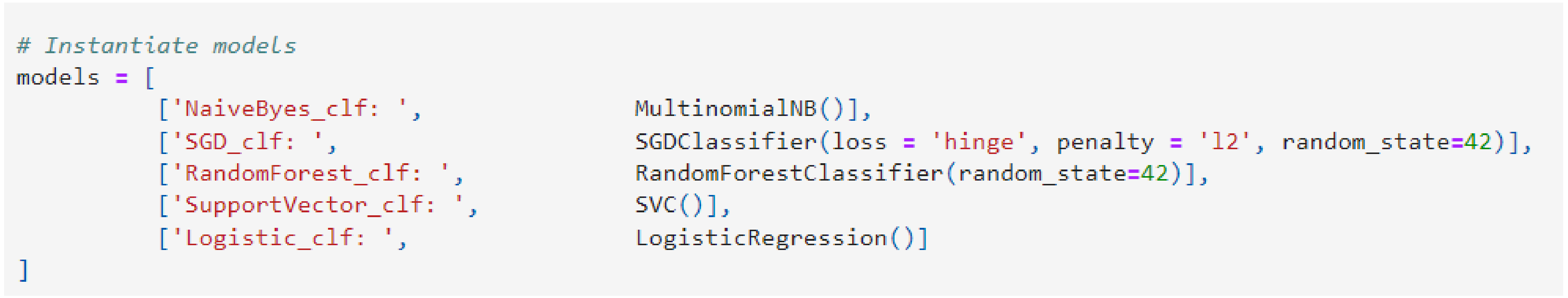
```
# Instantiate  models
models = [
          ['NaiveByes_clf: ',                MultinomialNB()],
          ['SGD_clf: ',                      SGDClassifier(loss = 'hinge', penalty = 'l2', random_state=42)],
          ['RandomForest_clf: ',             RandomForestClassifier(random_state=42)],
          ['SupportVector_clf: ',            SVC()],
          ['Logistic_clf: ',                 LogisticRegression()]
]
```



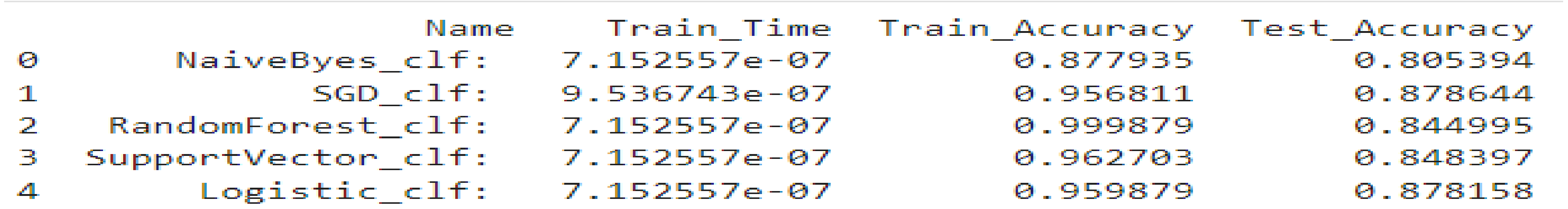
```
                 Name    Train_Time  Train_Accuracy  Test_Accuracy
0     NaiveByes_clf:   9.536743e-07        0.807259       0.689990
1           SGD_clf:   9.536743e-07        0.947912       0.845481
2  RandomForest_clf:   1.430511e-06        0.999818       0.789966
3 SupportVector_clf:   7.152557e-07        0.947669       0.794704
4      Logistic_clf:   1.192093e-06        0.967229       0.826652
```

- In the above Models Evaluation Table(Testing set) our accuracy score is less than 0.80 except Logistic Classifier and Stochastic gradient descent classifier.So we can say that our model predicted the classes in a good manner.
- SGD Classifier is performing well which has best Recall,Precision,F1-Score and Accuracy Score.

Comparing different Models for Binary Classification



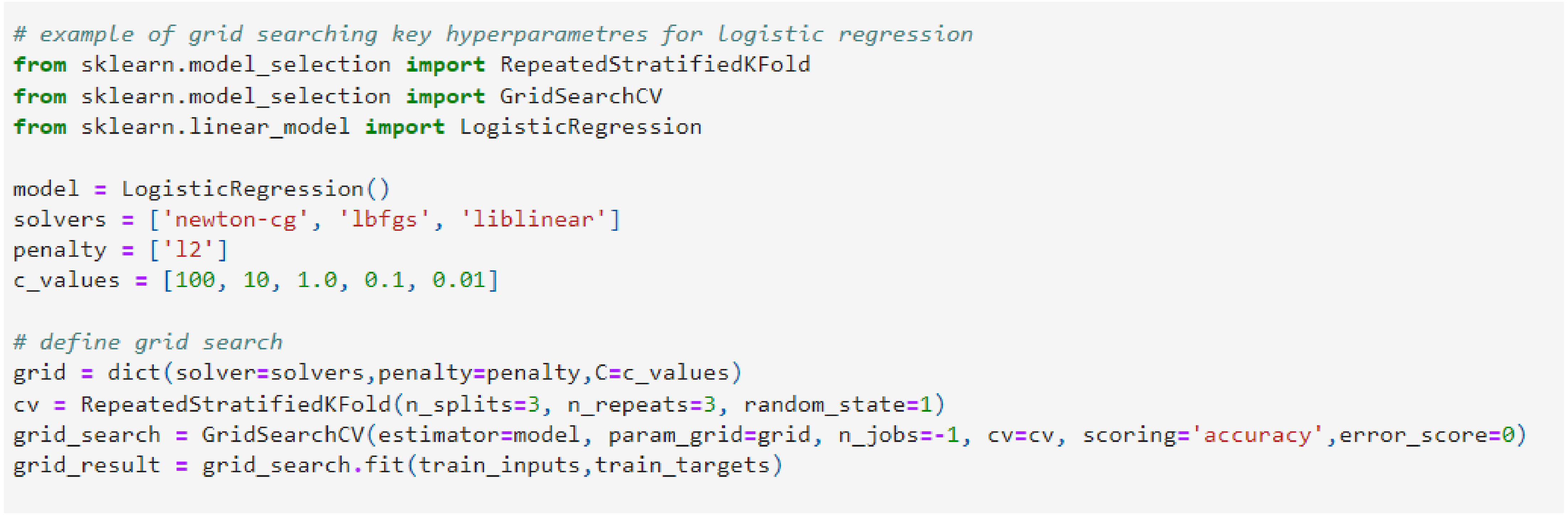
```
# Instantiate models
models = [
          ['NaiveByes_clf: ',               MultinomialNB()],
          ['SGD_clf: ',                     SGDClassifier(loss = 'hinge', penalty = 'l2', random_state=42)],
          ['RandomForest_clf: ',            RandomForestClassifier(random_state=42)],
          ['SupportVector_clf: ',           SVC()],
          ['Logistic_clf: ',                LogisticRegression()]
]
```



```
                  Name    Train_Time  Train_Accuracy  Test_Accuracy
0      NaiveByes_clf:   7.152557e-07        0.877935       0.805394
1            SGD_clf:   9.536743e-07        0.956811       0.878644
2   RandomForest_clf:   7.152557e-07        0.999879       0.844995
3  SupportVector_clf:   7.152557e-07        0.962703       0.848397
4       Logistic_clf:   7.152557e-07        0.959879       0.878158
```

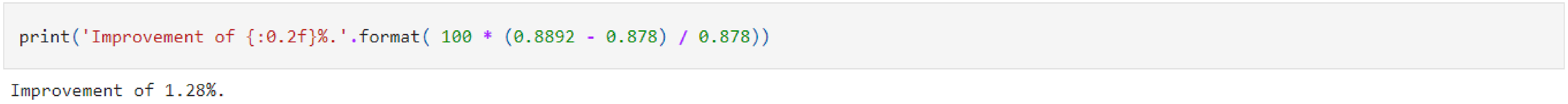
- In the above Models Evaluation Table(Testing set) our accuracy score is more than 0.80 except Logistic Classifier and Stochastic gradient descent classifier.So we can say that our model predicted the classes in a good manner.
- Logistic Regression Classifier is performing well which has best Recall,Precision,F1-Score and Accuracy Score.

Hyperparameter tuning for logistic regression classifier



```
# example of grid searching key hyperparametres for logistic regression
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression

model = LogisticRegression()
solvers = ['newton-cg', 'lbfgs', 'liblinear']
penalty = ['l2']
c_values = [100, 10, 1.0, 0.1, 0.01]

# define grid search
grid = dict(solver=solvers,penalty=penalty,C=c_values)
cv = RepeatedStratifiedKFold(n_splits=3, n_repeats=3, random_state=1)
grid_search = GridSearchCV(estimator=model, param_grid=grid, n_jobs=-1, cv=cv, scoring='accuracy',error_score=0)
grid_result = grid_search.fit(train_inputs,train_targets)
```

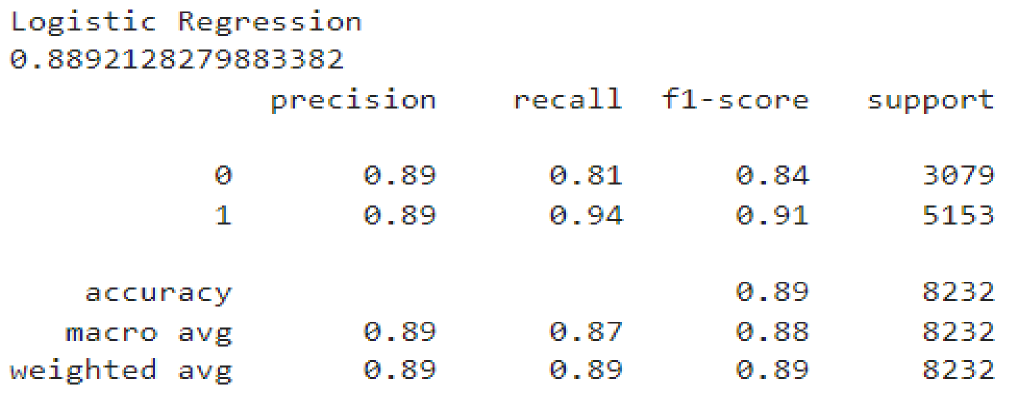
- In the above hyperparameter tunning we used grid search cv to find the best parameters to train our logistic regression classifier



```
print('Improvement of {:0.2f}%.'.format( 100 * (0.8892 - 0.878) / 0.878))
```

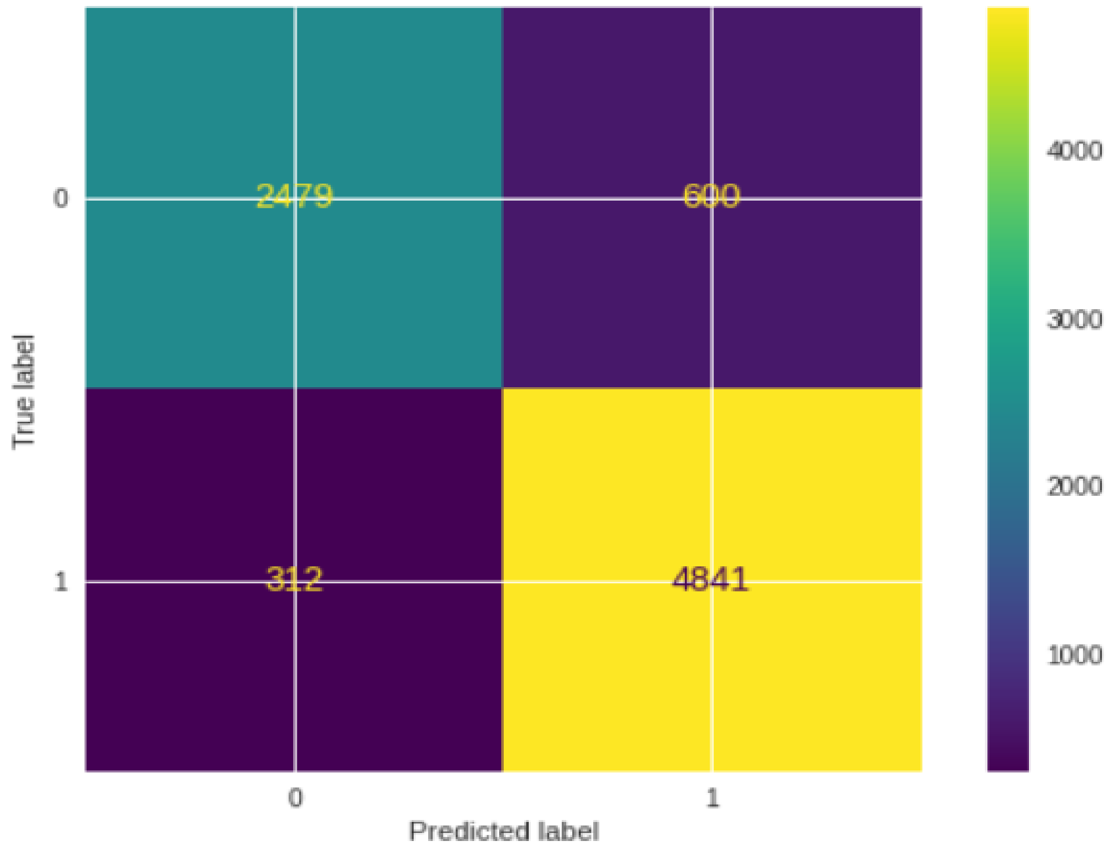
```
Improvement of 1.28%.
```

Performance metrics for Logistic classifier



```
Logistic Regression
0.8892128279883382
              precision    recall  f1-score   support

           0       0.89      0.81      0.84      3079
           1       0.89      0.94      0.91      5153

    accuracy                           0.89      8232
   macro avg       0.89      0.87      0.88      8232
weighted avg       0.89      0.89      0.89      8232
```

- Here 0 represent Negative Sentiments wherease 1 represent Positive Sentiments and Neutral Sentiments.
- Model Accuracy score is 89%



Conclusion

This model focuses on analyzing how individuals are responding to the pandemic, taking into account that the COVID-19 disease is a global health issue that has impacted most countries' economies. The model's major objective is to determine, using machine learning algorithms and NLP approaches, if the public's sentiment is favorable or negative. Although the analysis discovered a variety of opinions, it appears that people generally continue to have a positive attitude toward the pandemic. The only month in which negative thoughts predominated was January, and the month in which the COVID-19 disease was declared a pandemic and many countries began to implement care measures and safety protocols is March, which also happens to be the month in which positive thoughts began to increase.

THANK YOU
HEROES