# CAPSTONE PROJECT

## Coronavirus Tweet Sentiment Analysis

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# POINTS FOR DISCUSSION

- Problem statement
- Data Summary
- Importing libraries
- Text-Preprocessing
- EDA
- Model preprocessing (CV & TF/IFD)
- Model Training
- Confusion matrix and performance metrics
- Conclusion
- Challenges

# Problem Description

This challenge asks us to build a classification model to predict the sentiment of COVID-19  tweets. The tweets have been pulled from Twitter and manual tagging has been done then.

The names and usernames have been given codes to avoid any privacy concerns.

We are given the following information:

1. Location
2. Tweet At
3. Original Tweet
4. Label

# Data Summary

We are given the dataset having 6 columns –

- UserName
- Screenname
- Location
- TweetAt
- OriginalTweet
- Sentiment

# Importing Libraries & Data Inspection

- Pandas – Manipulation of tabular data in Dataframes
- Numpy – Mathematical operations on arrays
- Matplotlib – Visualization
- Seaborn – Visualization
- Sklearn – Data Modeling
- Nltk – Pre Processing / Feature Engineering
- WordCloud – Visualization

# Text Pre-processing

Step 1 : Converted all characters to lowercase.

Step 2 : Removed Punctuation.

Step 3 : Removed stop words.

Step 4: Stemming

Step 5: Lemmatizing

## STEMMING

```
[26] from nltk.stem.porter import *
     stemmer = PorterStemmer()
```

```
[27] #function for stemming
     def stemming(text):
         text = [stemmer.stem(word) for word in text]
         return (" ".join(text))
```

```
[28] df['stemmed'] = df['clean_tweets'].apply(lambda x: stemming(x))
```

## Lemmatizing

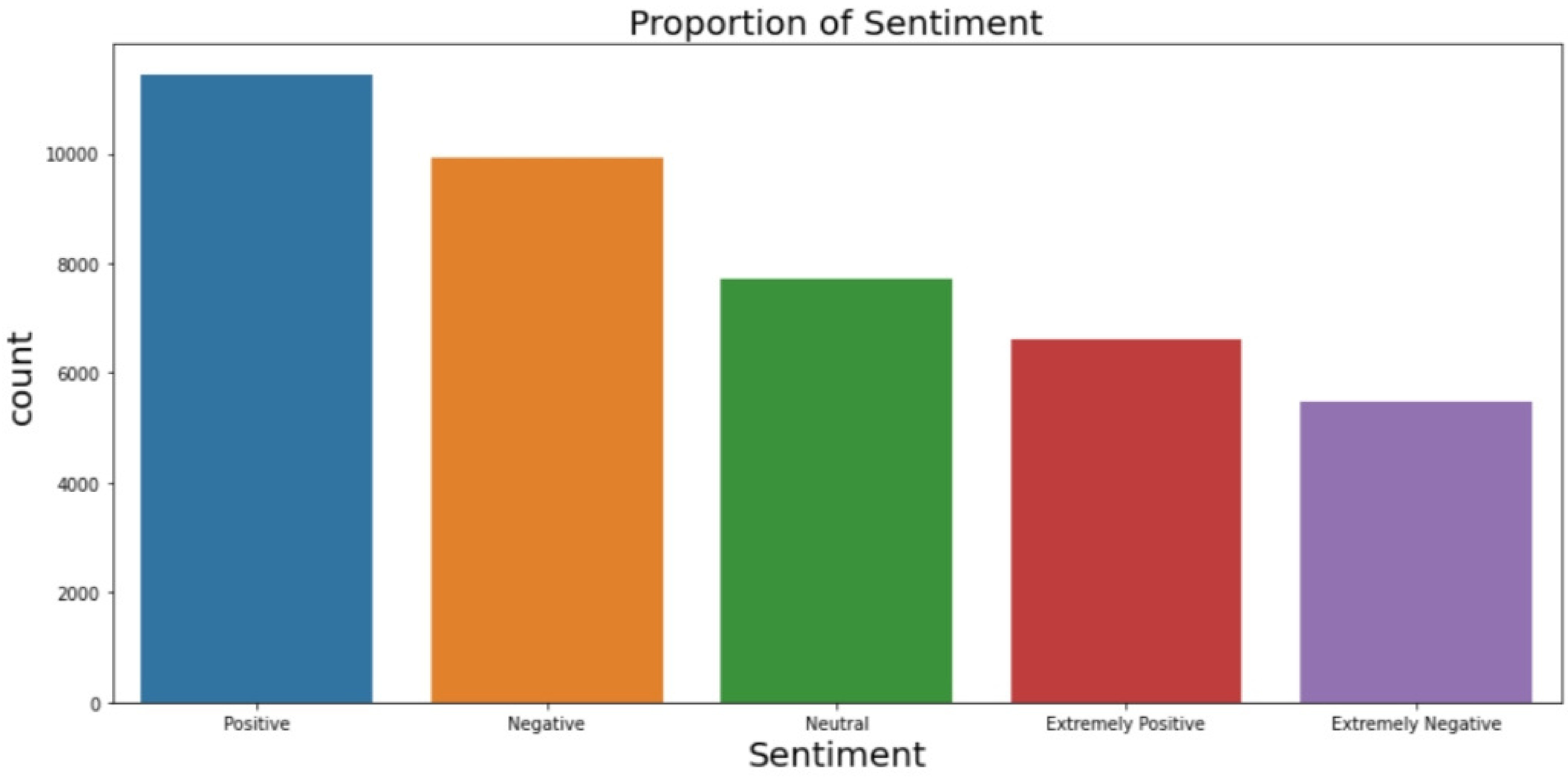
```
[30] # Lemmatizing
     from nltk.stem import WordNetLemmatizer
     lemmatizer=WordNetLemmatizer()
     df['lemmed'] = df['clean_tweets'].apply(lambda x: [lemmatizer.lemmatize(y) for y in x])
```

```
[31] df.head()
```

| | OriginalTweet | Sentiment | clean_tweets | stemmed | lemmed |
|---|---|---|---|---|---|
| 0 | @menyrbie @phil_gahan @chrisitv and and | Neutral | [menyrbie, philgahan, chrisitv] | menyrbi philgahan chrisitv | [menyrbie, philgahan, chrisitv] |
| 1 | advice talk to your neighbours family to excha... | Positive | [advice, talk, neighbours, family, exchange, p... | advic talk neighbour famili exchang phone numb... | [advice, talk, neighbour, family, exchange, ph... |
| 2 | coronavirus australia: woolworths to give elde... | Positive | [coronavirus, australia, woolworths, give, eld... | coronaviru australia woolworth give elderli di... | [coronavirus, australia, woolworth, give, elde... |
| 3 | my food stock is not the only one which is emp... | Positive | [food, stock, one, empty, please, dont, panic,... | food stock one empti pleas dont panic enough f... | [food, stock, one, empty, please, dont, panic,... |
| 4 | me, ready to go at supermarket during the #cov... | Extremely Negative | [ready, go, supermarket, covid, outbreak, im, ... | readi go supermarket covid outbreak im paranoi... | [ready, go, supermarket, covid, outbreak, im, ... |

# Exploratory Data Analysis

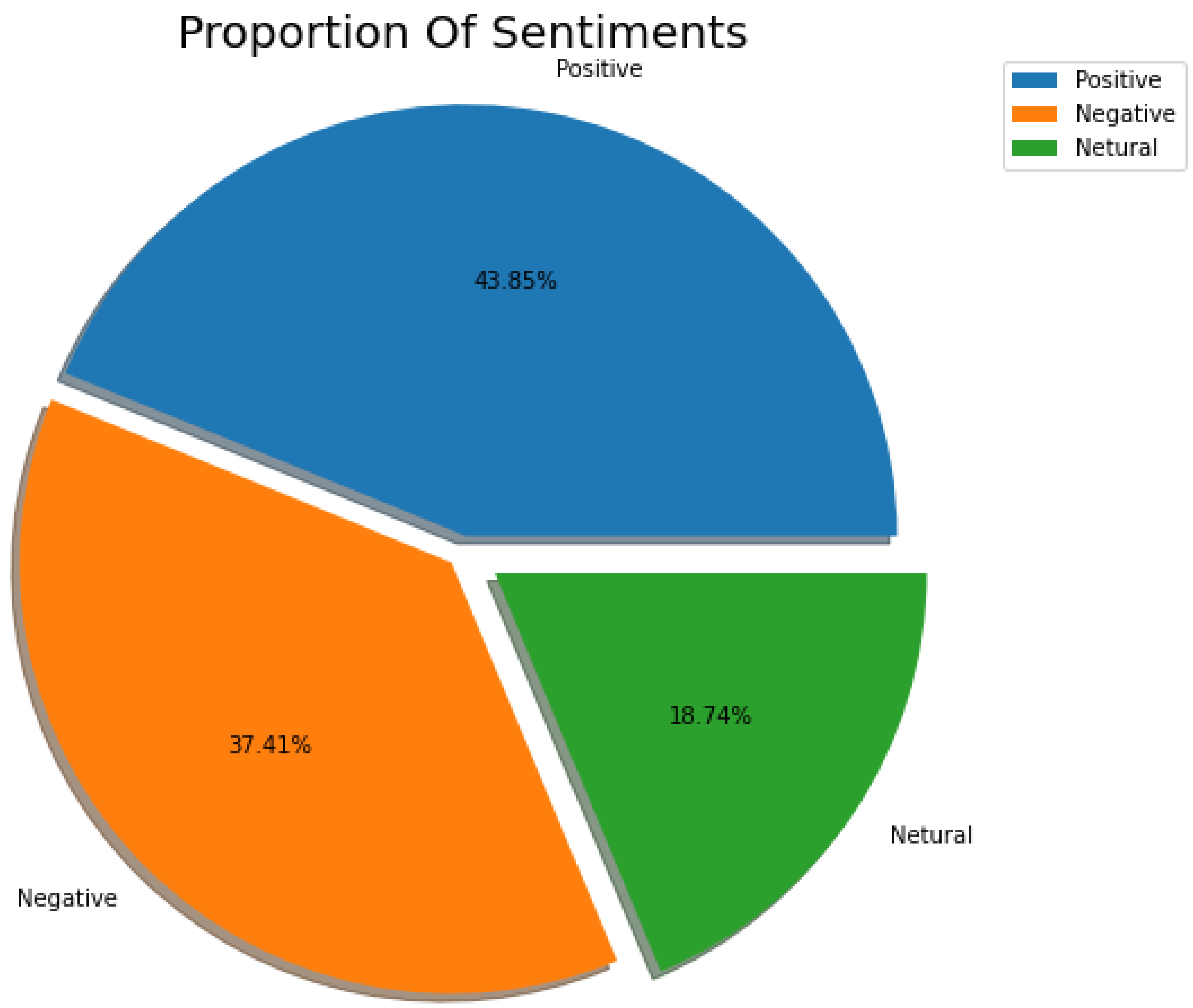
## Sentiments




There are five types of sentiments. The above graph shows count of each sentiment.

# EDA Continued…

## New Sentiments




As there was five types of sentiments – Positive Sentiment, Extremely Positive Sentiment, Negative Sentiment, Extremely Negative Sentiment and Neutral Sentiment. So, wehavereplaced Extremely Positive Sentiment byPositive Sentiment and Extremely Negative Sentiment by Negative Sentiment. Now we have three types of sentiments – Positive Sentiment, NegativeSentimentand NeutralSentiment.

ThePiChartshowstheproportionofeach sentiment.

Thereare 43.85% Positive Sentiments,37.41% NegativeSentimentsand18.74%NeutralSentiments.

Positive Sentiments arehaving higherproportion amongall.

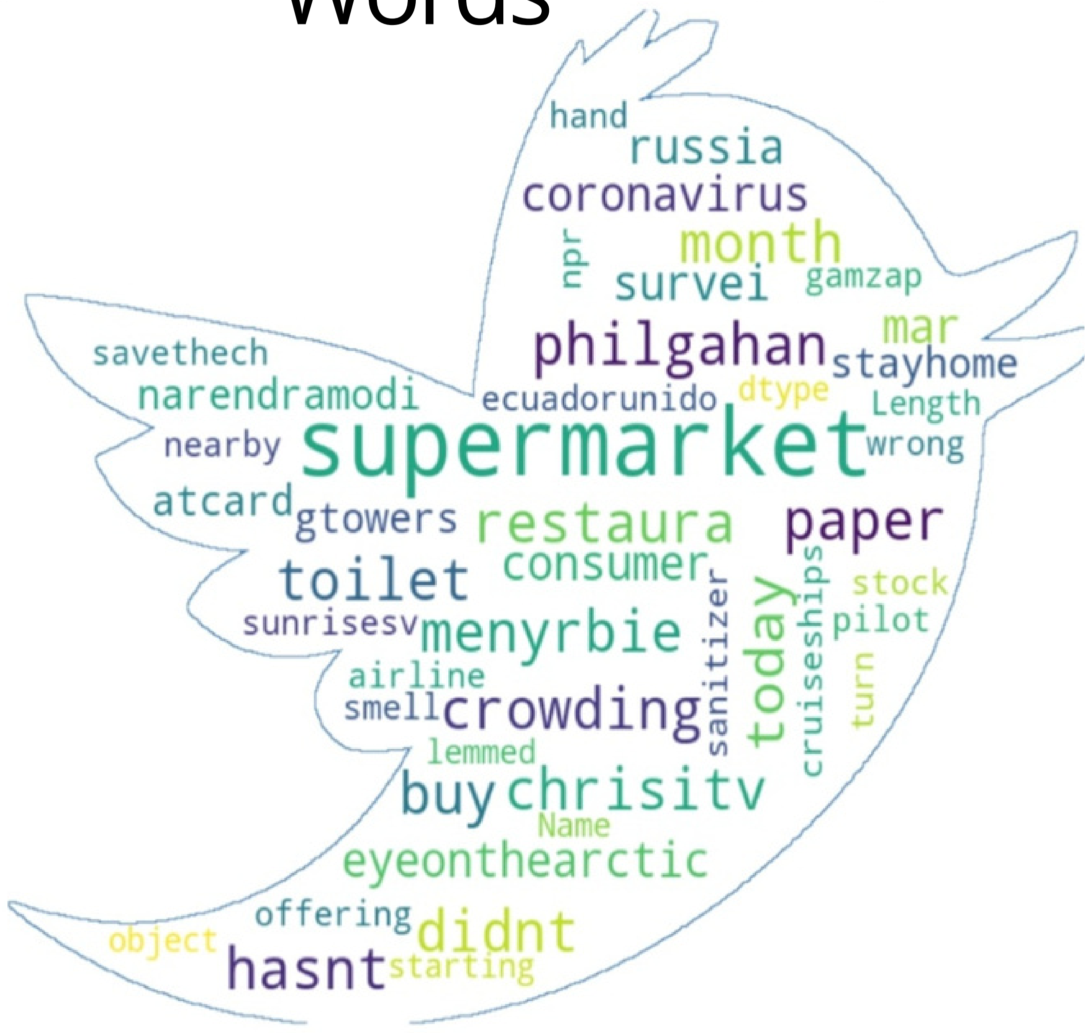
# EDA Continued…

## Word cloud

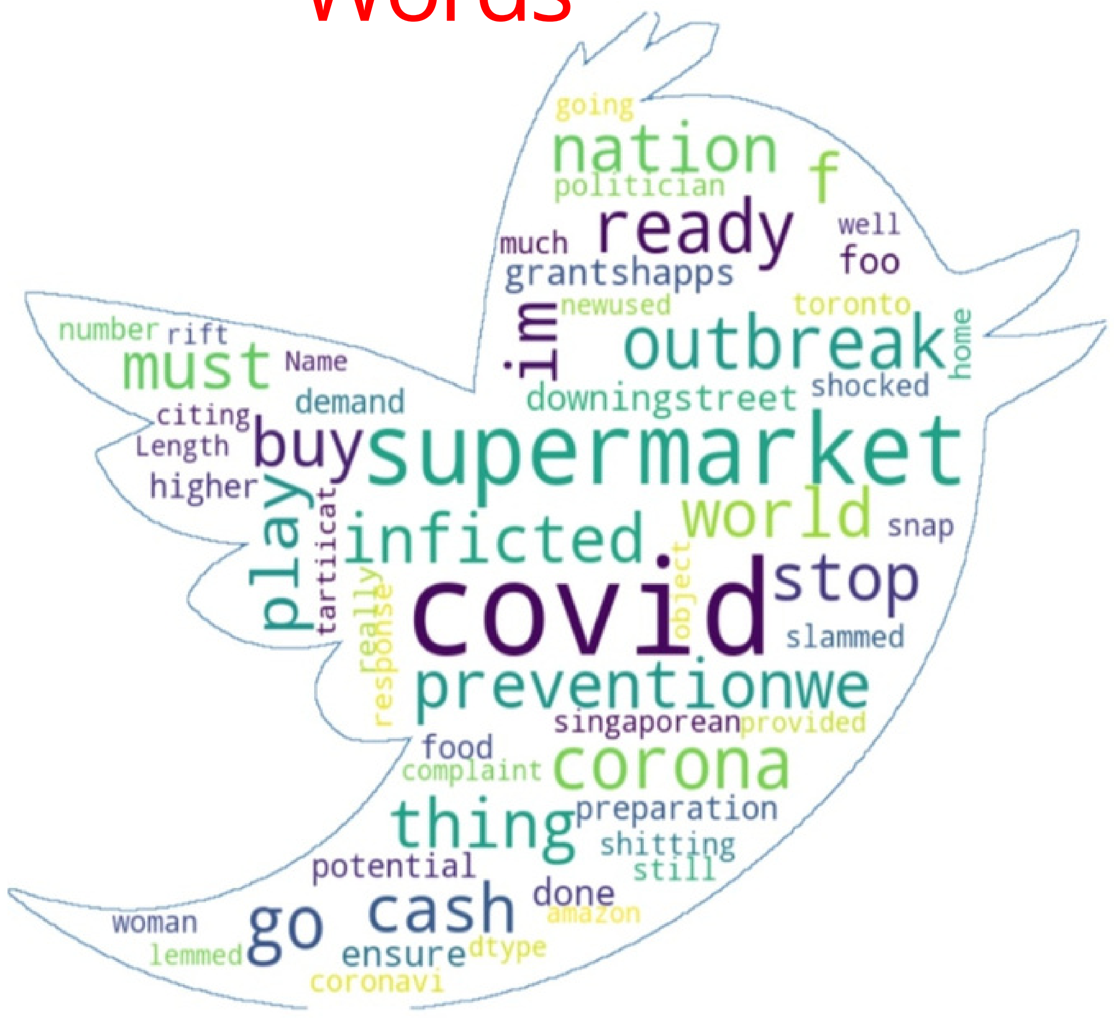
Word Clouds are **visual displays of text data – simple text analysis**. Word Clouds display the most prominent or frequent words in a body of text.

1. Positive Words


2. Neutral Words




3.Negative Words



# Model Preprocessing

## Extracting Features From Text

- **Count Vectorizer -** Count Vectorizer is a great tool provided by the scikit-learn library in Python. It is used to transform a given text into a vector on the basis of the frequency (count) of each word that occurs in the entire text.

```
Document-1: He is a smart boy. She is also smart.
Document-2: Chirag is a smart person.
```

he dictionary created contains the list of unique tokens(words) present in the corpus

```
Unique Words: ['He', 'She', 'smart', 'boy', 'Chirag', 'person']
```

lere, D=2, N=6

o, the count matrix M of size 2 X 6 will be represented as –

| | He | She | smart | boy | Chirag | person |
|---|---|---|---|---|---|---|
| )1 | 1 | 1 | 2 | 1 | 0 | 0 |
| )2 | 0 | 0 | 1 | 0 | 1 | 1 |

low, a column can also be understood as a word vector for the corresponding word in the matrix M.

# Model Preprocessing

## Extracting Features From Text

- **TF-IDF** Count Vectorizer method is simple and works well, but the problem with that is that it treats all words equally. As a result, it cannot distinguish very common words or rare words. So, to solve this problem, TF-IDF comes into the picture! Term frequency-inverse document frequency ( TF-IDF) gives a measure that takes the importance of a word into consideration depending on how frequently it occurs in a document and a corpus.

## TF Term Frequency

Term frequency denotes the frequency of a word in a document.
It is the percentage of the number of times a word (x) occurs in a particular document (y) divic
total number of words in that document

$$TF(\boldsymbol{term}) = \frac{Number\ of\ times\ \boldsymbol{term}\ appears\ in\ a\ document}{Total\ number\ of\ items\ in\ the\ document}$$

The formula for finding Term Frequency is given as:

```
tf ('word') = Frequency of a 'word' appears in document d / total number of words in the documen
```

**For Example,** Consider the following document

```
Document: Cat loves to play with a ball
```

# Model Preprocessing

## Extracting Features From Text

**Inverse Document Frequency -** It measures the importance of the word in the corpus. It measures how common a particular word is across all the documents in the corpus.
It is the logarithmic ratio of no. of total documents to no. of a document with a particular word.

The difference in the TF-IDF method is that each cell doesn't indicate the term frequency, but contains a weight value that signifies how important a word is for an individual text message or document

$\texttt{tf}(t, d)$

| | blue | bright | can | see | shining | sky | sun | today |
|---|---|---|---|---|---|---|---|---|
| 1 | 1/2 | 0 | 0 | 0 | 0 | 1/2 | 0 | 0 |
| 2 | 0 | 1/3 | 0 | 0 | 0 | 0 | 1/3 | 1/3 |
| 3 | 0 | 1/3 | 0 | 0 | 0 | 1/3 | 1/3 | 0 |
| 4 | 0 | 1/6 | 1/6 | 1/6 | 1/6 | 0 | 1/3 | 0 |

x

$\texttt{idf}(t, D)$

| | blue | bright | can | see | shining | sky | sun | today |
|---|---|---|---|---|---|---|---|---|
| | 0.602 | 0.125 | 0.602 | 0.602 | 0.602 | 0.301 | 0.125 | 0.602 |

$\texttt{tfidf}(t, d, D) = \texttt{tf}(t, d) \cdot \texttt{idf}(t, D)$

| | blue | bright | can | see | shining | sky | sun | today |
|---|---|---|---|---|---|---|---|---|
| 1 | **0.301** | 0 | 0 | 0 | 0 | 0.151 | 0 | 0 |
| 2 | 0 | 0.0417 | 0 | 0 | 0 | 0 | 0.0417 | **0.201** |
| 3 | 0 | 0.0417 | 0 | 0 | 0 | **0.100** | 0.0417 | 0 |
| 4 | 0 | 0.0209 | **0.100** | **0.100** | **0.100** | 0 | 0.0417 | 0 |

- TF-IDF: Multiply TF and IDF scores, use to rank importance of words within documents
  - Most important word for each document is highlighted

*TF-IDF score computation. [Image Source]*

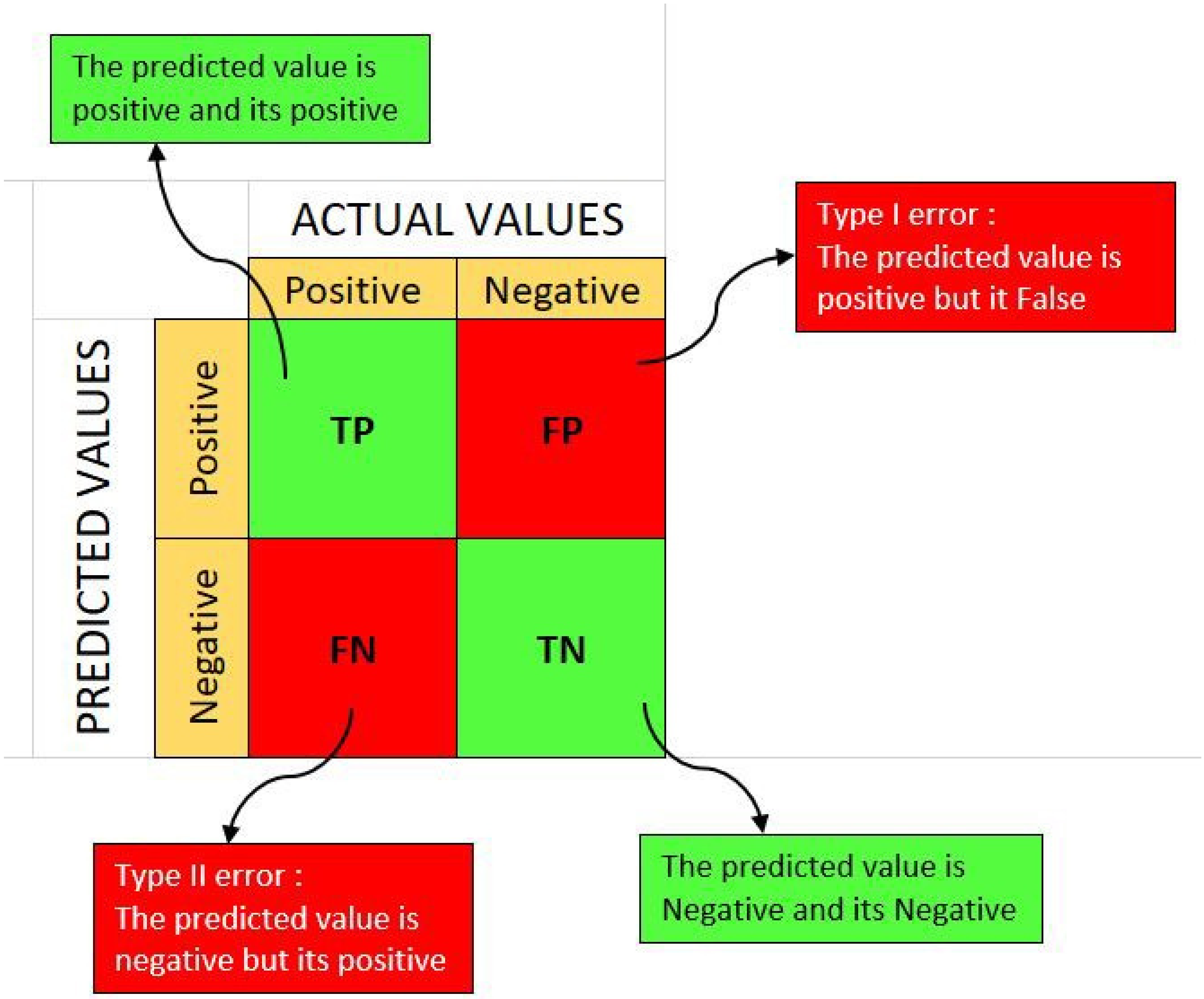
```
[ ] # Vectorization
    from sklearn.feature_extraction.text import CountVectorizer,TfidfVectorizer

[ ] # Bag of words
    cv=CountVectorizer(binary=False,max_df=1.0,min_df=5,ngram_range=(1,2))
    cv_X_train=cv.fit_transform(X_train.astype(str).str.strip())

[ ] # TF-IDF
    tv=TfidfVectorizer(use_idf=True,max_df=1.0,min_df=5,ngram_range=(1,2),sublinear_tf=True)
    tv_X_train=tv.fit_transform(X_train.astype(str).str.strip())

[ ] tv_X_train.shape

    (28809, 17189)

[ ] cv_X_test=cv.transform(X_test.astype(str).str.strip())
    tv_X_test=tv.transform(X_test.astype(str).str.strip())
```

# Model Training

## Model Used

- Logistic Regression with Grid Search CV
- Decision Tree Classifier
- XG Boost Classifier
- KNN Classifier
- SVM Classifier

# Performance metrics of classification models




$$precision = \frac{TP}{TP + FP}$$

$$recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 \times precision \times recall}{precision + recall}$$

$$accuracy = \frac{TP + TN}{TP + FN + TN + FP}$$

$$specificity = \frac{TN}{TN + FP}$$

# Precision Accuracy And Recall

## Precision

Precision is the proportion of correct predictions among all predictions of a certain class. In other words, it is the
proportion of true positives among all positive predictions.

$$Precision = \frac{TP}{FP + TP}$$

## Accuracy

Accuracy is the proportion of examples that were correctly classified. More precisely, it is sum of the number of true positives and true negatives, divided by the number of examples in the dataset.

$$Accuracy = \frac{TP + TN}{FP + FN + TP + TN}$$

# Precision Accuracy And Recall

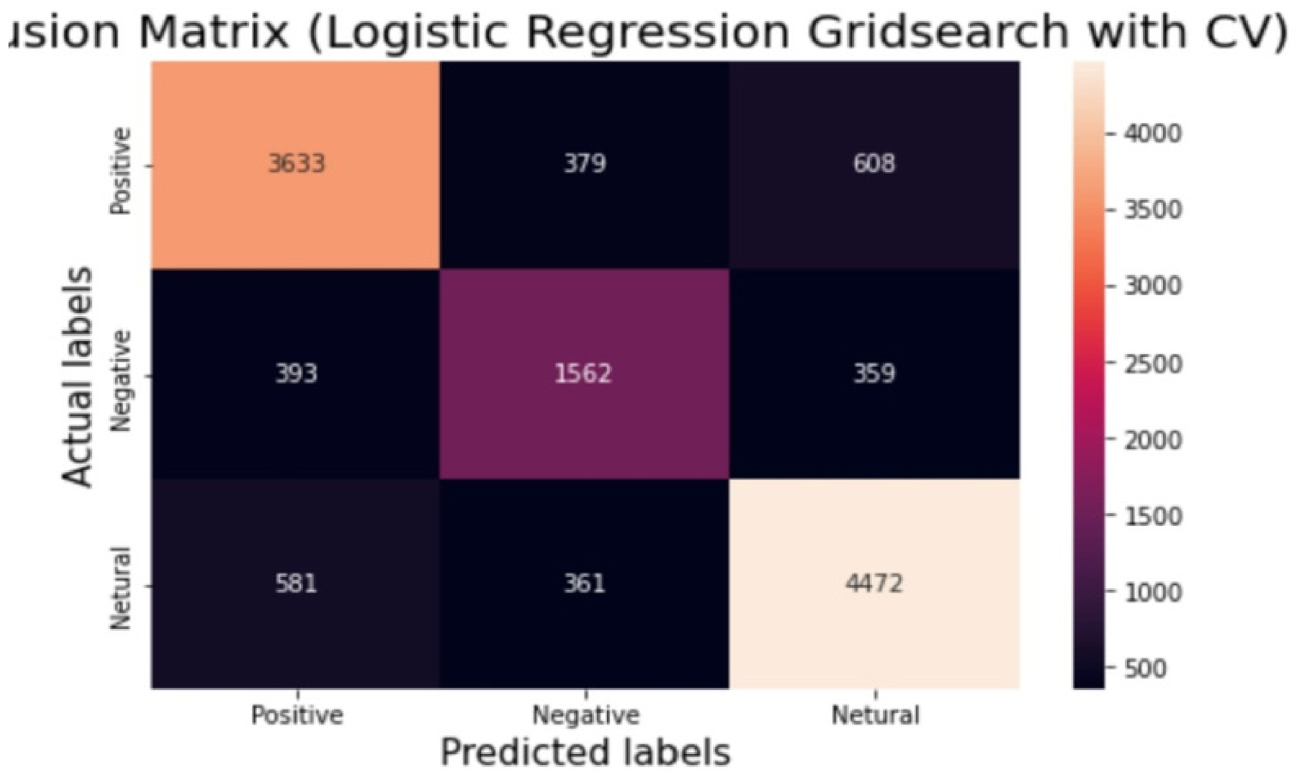
## Recall

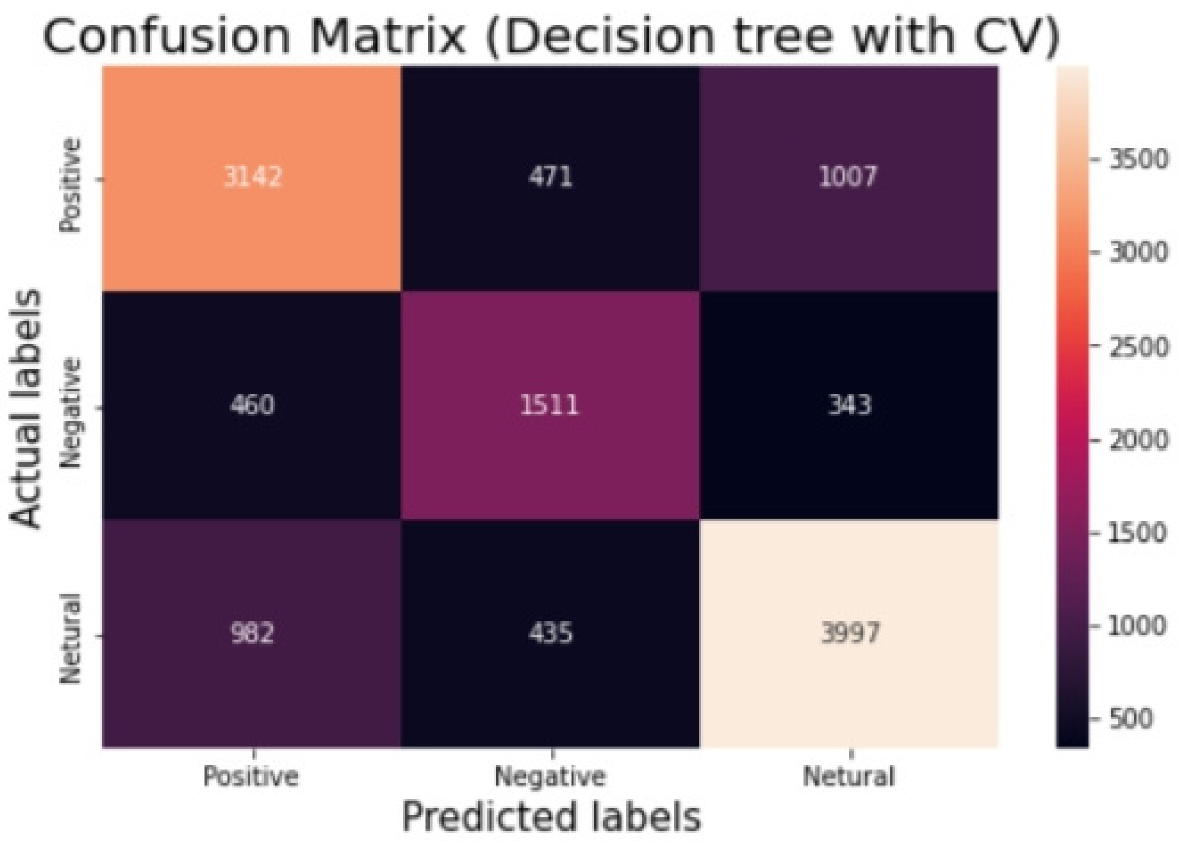
Recall is the proportion of examples of a certain class that have been predicted by the model as belonging to  that class. In other words, it is the proportion of true positives among all true examples.

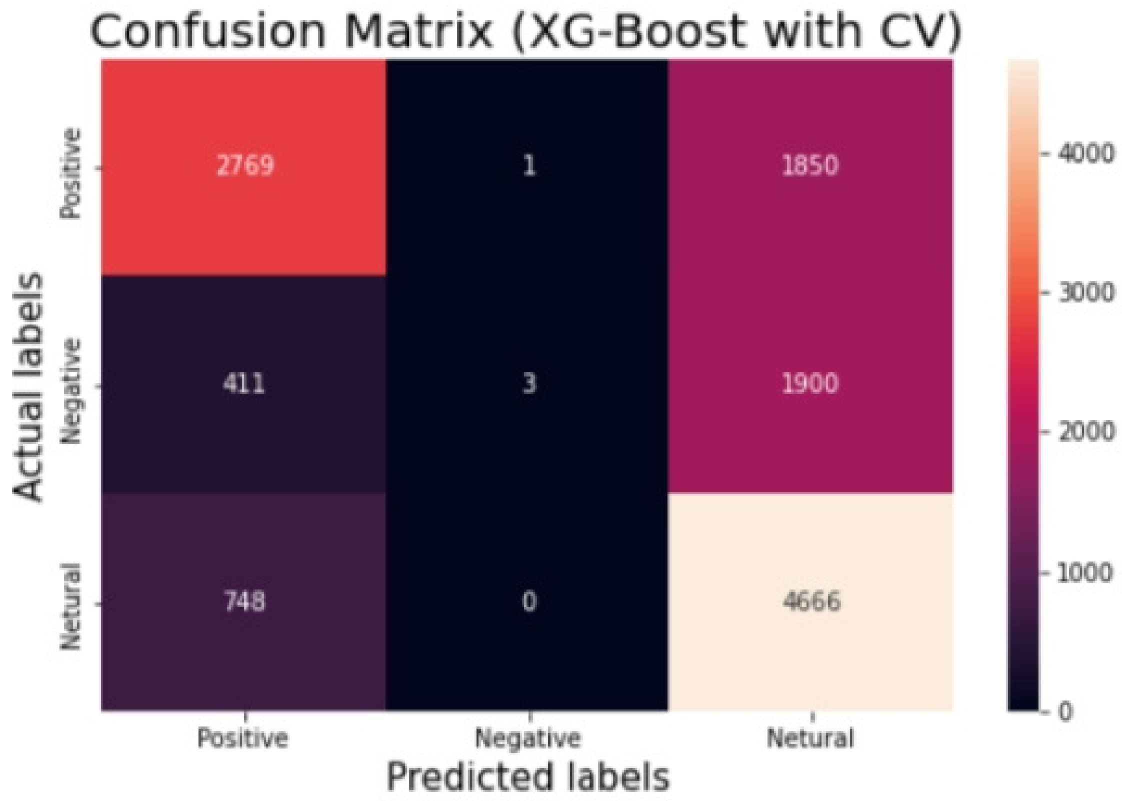
$$Recall = \frac{TP}{FN + TP}$$

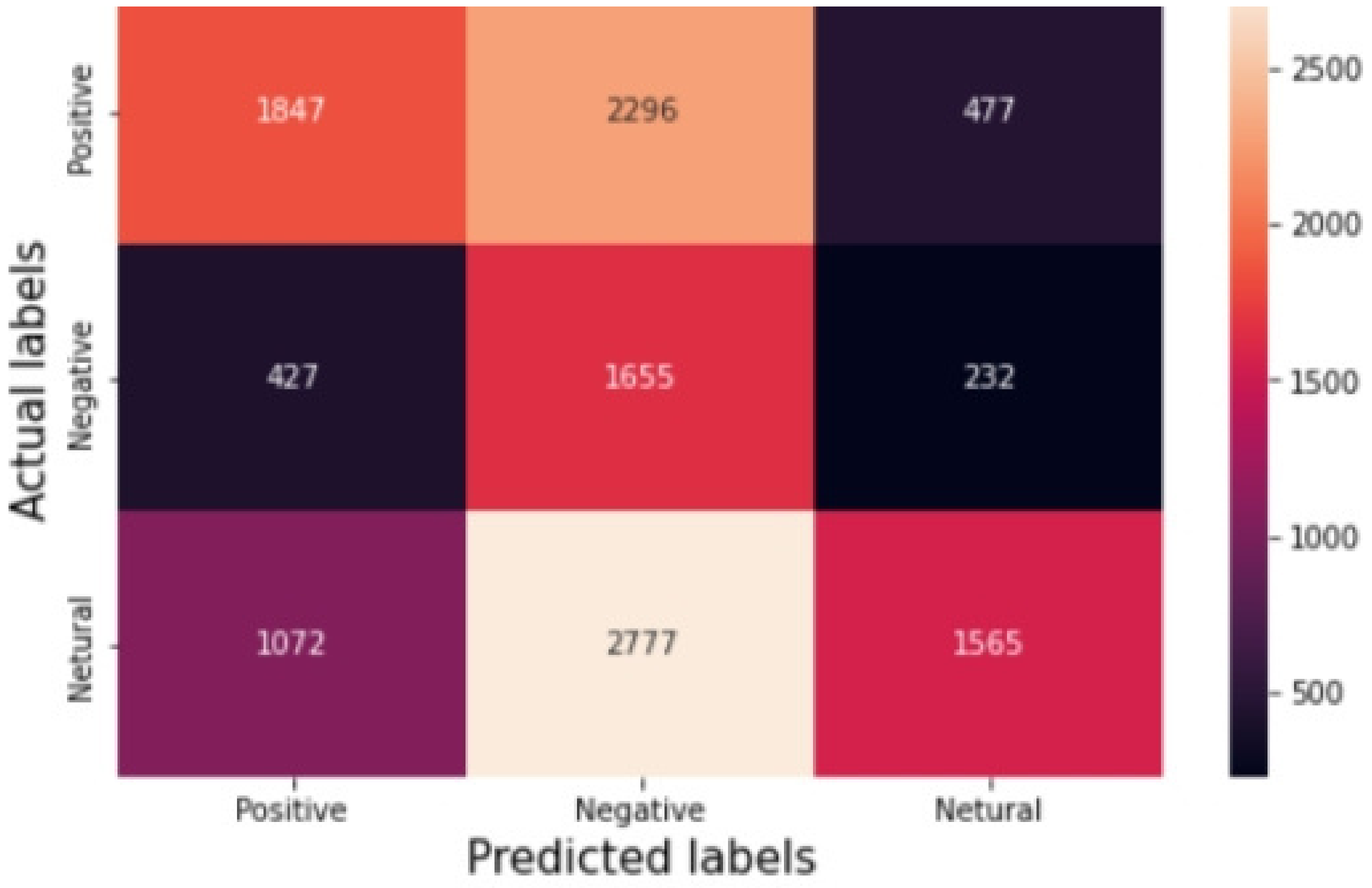
# Confusion Matrix (count vector)

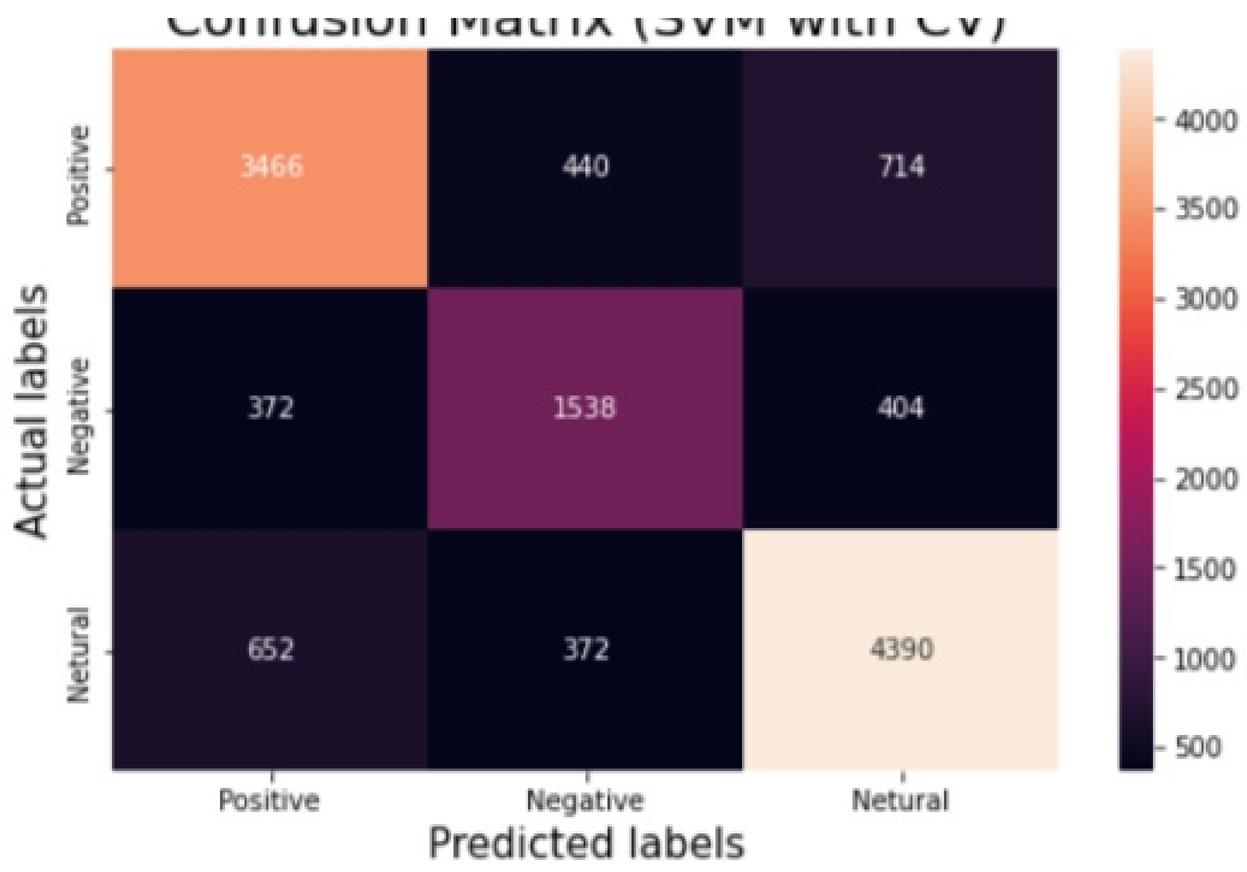
A **Confusion matrix** is an N x N matrix **used for** evaluating the performance of a classification model, where N is the number of target classes.



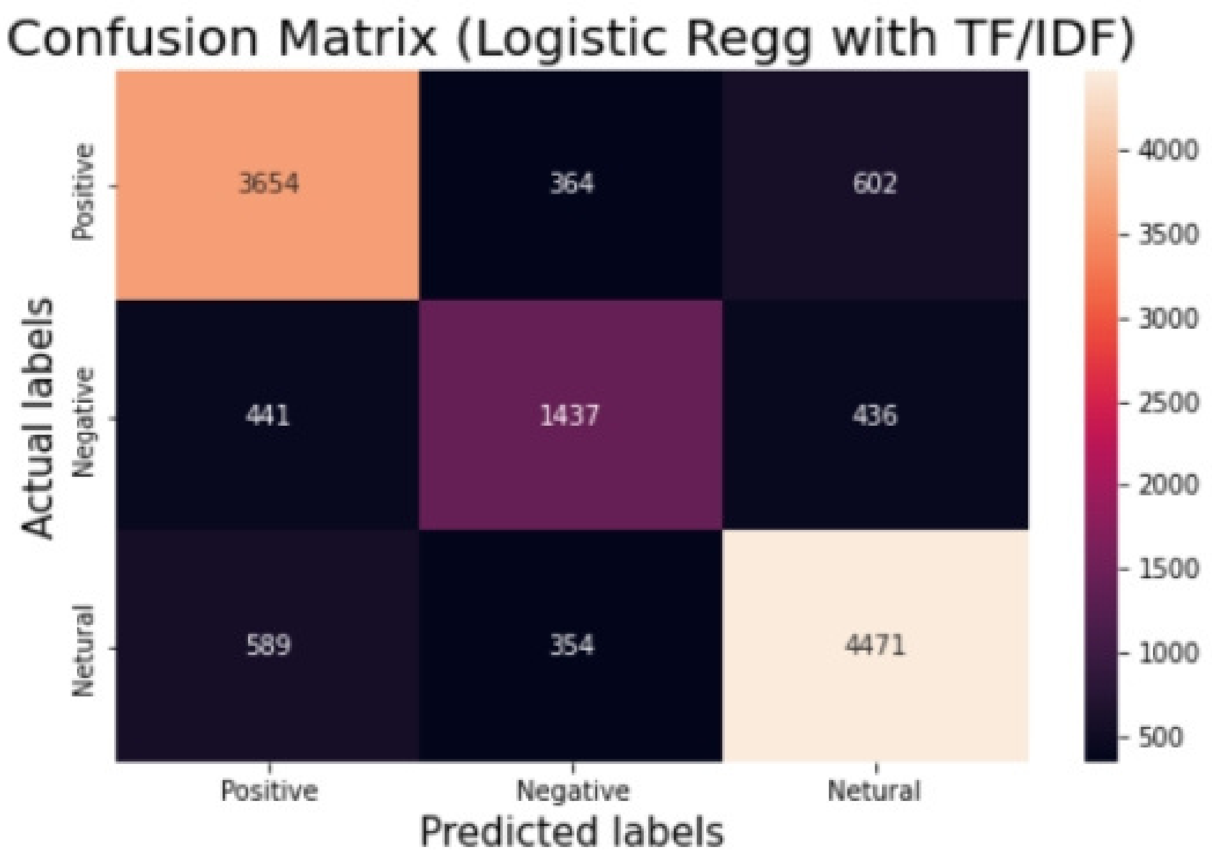



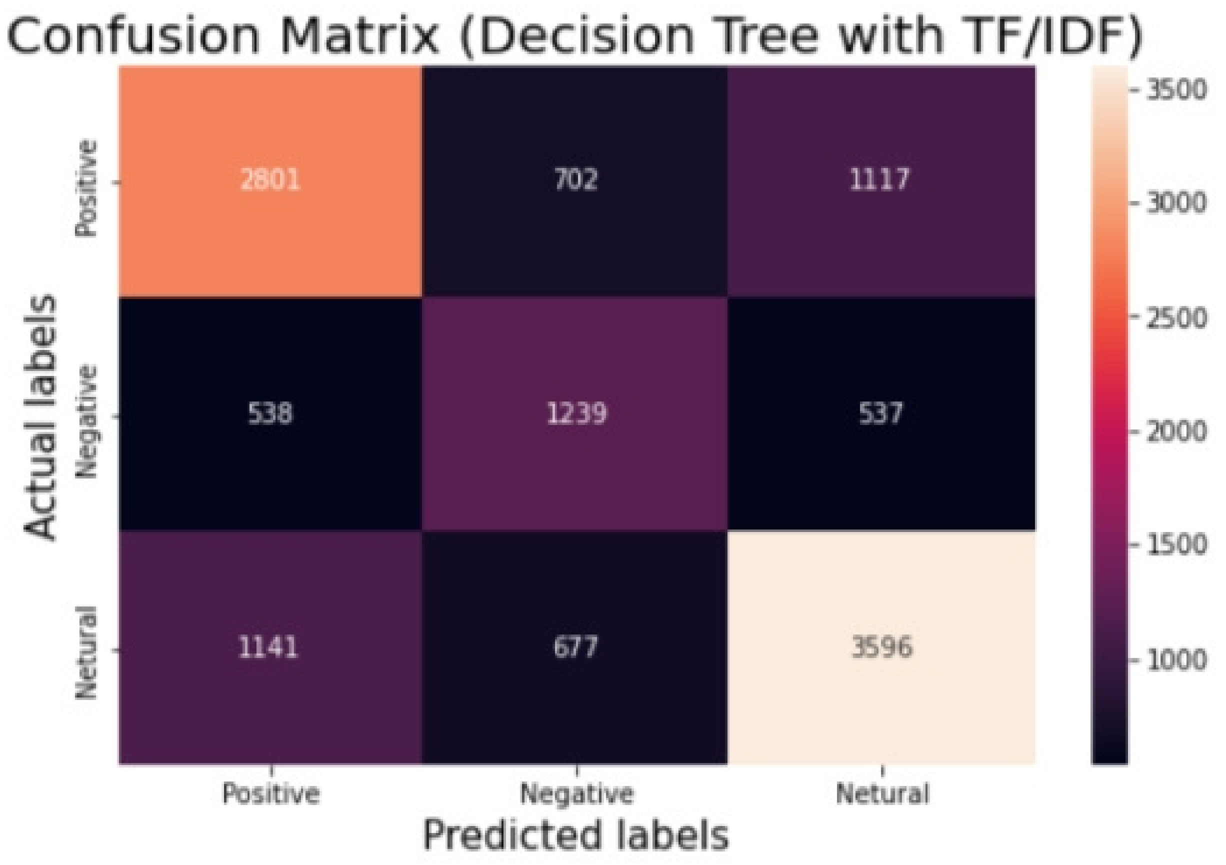



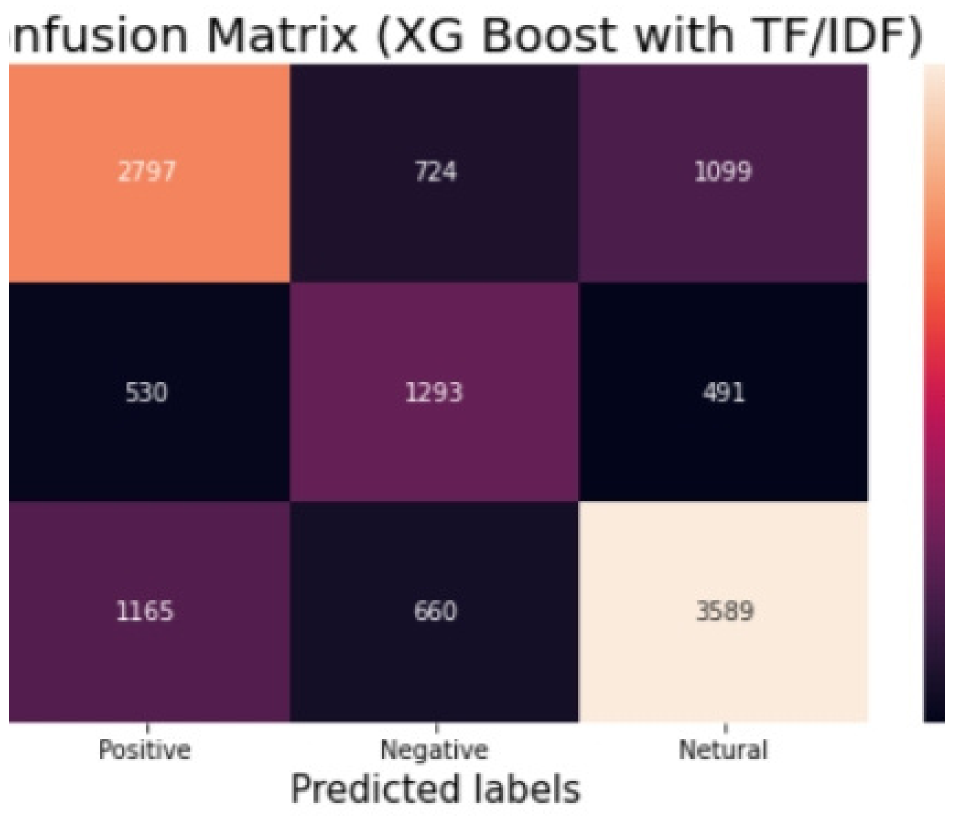



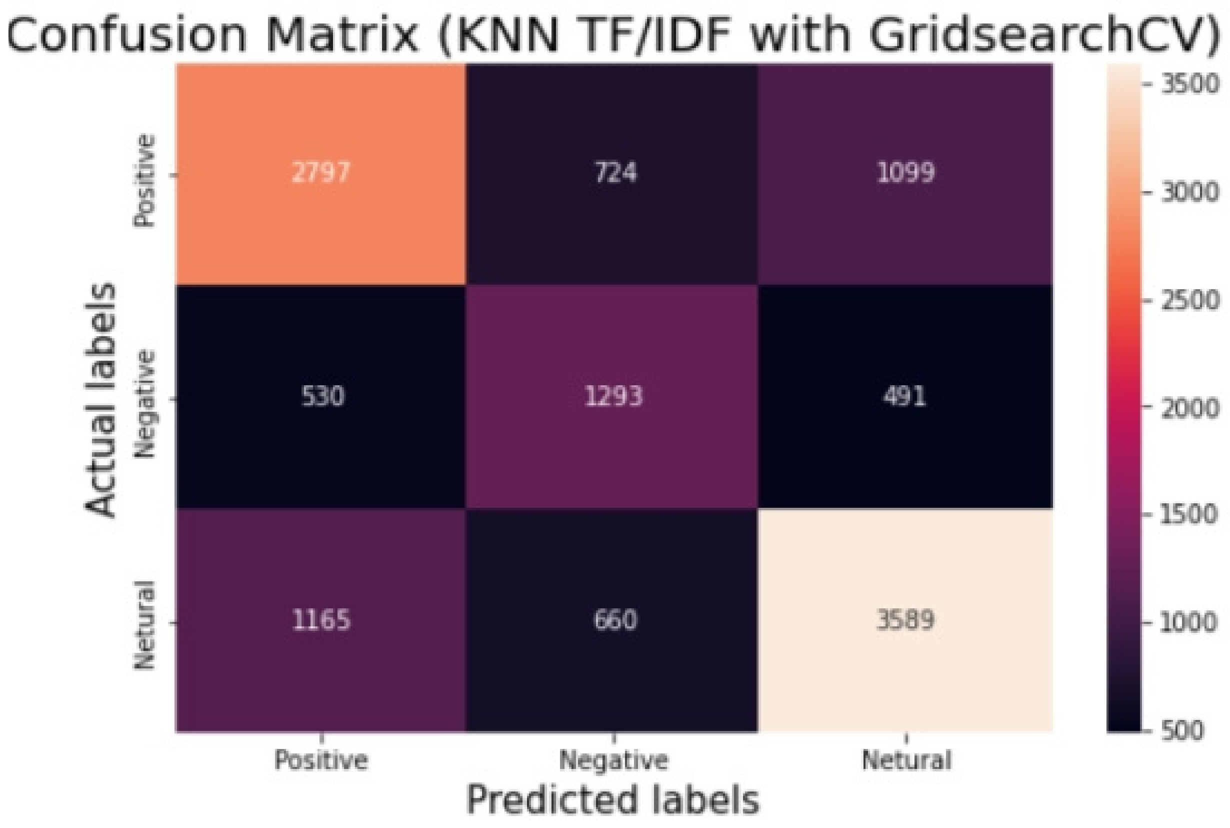



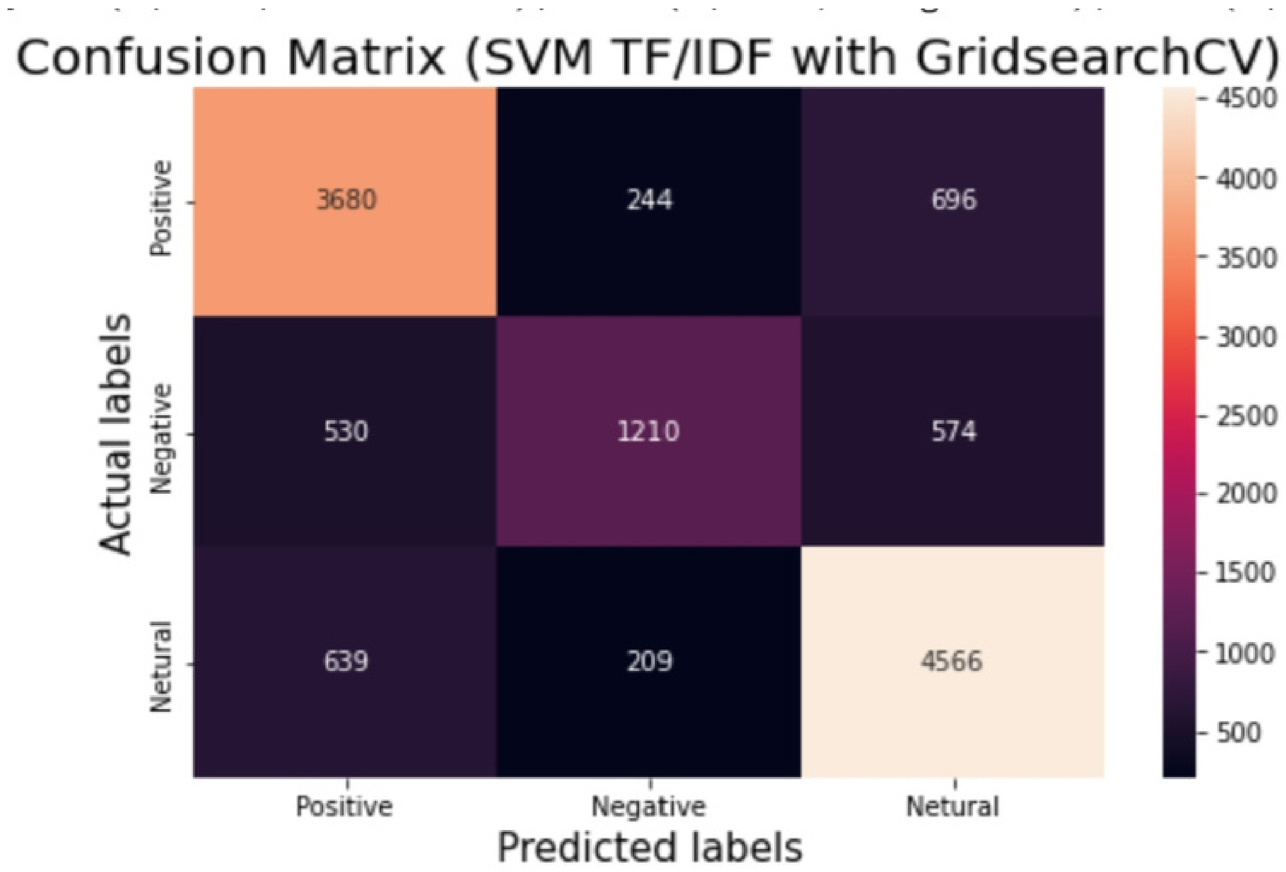
# Confusion Matrix (TF-IDF Vector)



# Performance Metrics and Accuracy (count vector)

## Performance of Logistic Regression Model

| | Precision | Recall | F1-score |
|---|---|---|---|
| Negative | 0.79 | 0.79 | 0.79 |
| Neutral | 0.68 | 0.68 | 0.68 |
| Positive | 0.82 | 0.83 | 0.82 |
| Accuracy | | | 0.78 |

## Performance of KNN Classifier

| | Precision | Recall | F1-score |
|---|---|---|---|
| Negative | 0.55 | 0.40 | 0.46 |
| Neutral | 0.25 | 0.72 | 0.37 |
| Positive | 0.69 | 0.29 | 0.41 |
| Accuracy | | | 0.41 |

## Performance of Decision Tree Classifier

| | Precision | Recall | F1-score |
|---|---|---|---|
| Negative | 0.69 | 0.68 | 0.68 |
| Neutral | 0.62 | 0.67 | 0.64 |
| Positive | 0.75 | 0.74 | 0.75 |
| Accuracy | | | 0.70 |

## Performance of SVM Classifier

| | Precision | Recall | F1-score |
|---|---|---|---|
| Negative | 0.77 | 0.75 | 0.76 |
| Neutral | 0.65 | 0.66 | 0.66 |
| Positive | 0.80 | 0.81 | 0.80 |
| Accuracy | | | 0.76 |

## Performance of XG Boost Classifier

| | Precision | Recall | F1-score |
|---|---|---|---|
| Negative | 0.70 | 0.60 | 0.79 |
| Neutral | 0.75 | 0.00 | 0.68 |
| Positive | 0.55 | 0.86 | 0.67 |
| Accuracy | | | 0.60 |

# Performance Metrics and Accuracy (TF/IDF Vector)

## Performance of Logistic Regression Model

| | Precision | Recall | F1-score |
|---|---|---|---|
| Negative | 0.78 | 0.79 | 0.79 |
| Neutral | 0.66 | 0.62 | 0.64 |
| Positive | 0.81 | 0.82 | 0.82 |
| Accuracy | | | 0.77 |

## Performance of KNN Classifier

| | Precision | Recall | F1-score |
|---|---|---|---|
| Negative | 0.37 | 1.00 | 0.55 |
| Neutral | 0.93 | 0.01 | 0.01 |
| Positive | 0.33 | 0.00 | 0.00 |
| Accuracy | | | 0.38 |

## Performance of Decision Tree Classifier

| | Precision | Recall | F1-score |
|---|---|---|---|
| Negative | 0.62 | 0.60 | 0.61 |
| Neutral | 0.48 | 0.55 | 0.51 |
| Positive | 0.68 | 0.66 | 0.67 |
| Accuracy | | | 0.62 |

## Performance of SVM Classifier

| | Precision | Recall | F1-score |
|---|---|---|---|
| Negative | 0.76 | 0.80 | 0.78 |
| Neutral | 0.73 | 0.52 | 0.61 |
| Positive | 0.78 | 0.82 | 0.81 |
| Accuracy | | | 0.77 |

## Performance of XG Boost Classifier

| | Precision | Recall | F1-score |
|---|---|---|---|
| Negative | 0.63 | 0.61 | 0.62 |
| Neutral | 0.48 | 0.55 | 0.51 |
| Positive | 0.68 | 0.66 | 0.67 |
| Accuracy | | | 0.62 |

# Conclusion

- We applied 5 models namely, Logistic Regression with Grid Search CV, Decision Tree Classifier, XG Boost, KNN, and SVM Classifier for both Count Vector And TF ID Vectorization techniques.
- We conclude that the machine is generating the best results for the Logistic Regression with Grid Search CV (count vectorizer) model with an Accuracy of 78.28% followed by the Logistic Regression with Grid Search CV (TF/ID vectorizer) model with an Accuracy of 77.43%.
- Also, we observed that no overfitting is seen for the data, and we can deploy this model.
- The sentiments of future tweets can be easily predicted using this model.
- Even being in the unprecedented situation of CoVid-19, people's positive sentiments outnumbered negative sentiments. However, negative sentiments also has a significant chunk which various Government agencies, NGOs, etc. can use to help boost the morale of the people and then in future repeat the analysis and comparing it with the present sentimental analysis to gauge the impact of the initiatives on the ground.

```
# Model's acurracy Score Comparision

acurracy = {'Model':  ['Logistic Regression with GridserachCV', 'Decision Tree Classifier','XG-Boost 
        'CountVector':  [accuracy_lr_cv,np.mean(cv_score_dt_cv),np.mean(cv_score_xgb_cv),accuracy_KNN
        'TfidfVector': [accuracy_lr_Gcv,np.mean(cv_score_dt_tv),np.mean(cv_score_xgb_tv),accuracy_KNN

cv_score_table= pd.DataFrame (acurracy, columns = ['Model','CountVector','TfidfVector'])

cv_score_table
```

| | Model | CountVector | TfidfVector |
|---|---|---|---|
| 0 | Logistic Regression with GridserachCV | 0.782880 | 0.774376 |
| 1 | Decision Tree Classifier | 0.690479 | 0.604291 |
| 2 | XG-Boost Classifier | 0.607796 | 0.603006 |
| 3 | K-Nearest-Neighbours Classifier | 0.410350 | 0.375364 |
| 4 | Support-Vector-Machine Classifier | 0.760771 | 0.765792 |

# CHALLENGES FACED

- Text preprocessing.
- Vectorization.
- Model Training and performance improvement.

Thank you