

Capstone Project - 3 CoronaVirus Tweet Sentimental Analysis



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Aim of our project

This challenge asks you 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.



What is Sentimental Analysis?

Sentiment analysis (or **opinion mining**) is a natural language processing 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.



Data Summary

The following images gives basic detail about our data.

- Total Number of rows are 41156
- Data of type int64(2) and Object(4) are only present
- Location column has some null values.
- About 20.8% null values are present in location column, whereas all other columns are clean.

	Null Percentage
UserName	0.000000
ScreenName	0.000000
Location	20.871298
TweetAt	0.000000
OriginalTweet	0.000000
Sentiment	0.000000

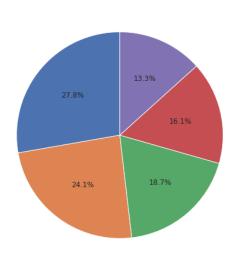
⊋	<pre><class 'pandas.core.frame.dataframe'=""> RangeIndex: 41157 entries, 0 to 41156</class></pre>								
	umns):								
	#	Column	Non-N	ull Count	Dtype				
	0	UserName	41157	non-null	int64				
	1	ScreenName	41157	non-null	int64				
	2	Location	32567	non-null	object				
	3	TweetAt	41157	non-null	object				
	4	OriginalTweet	41157	non-null	object				
	5	Sentiment	41157	non-null	object				
	dtyp	es: int64(2), o	bject(4	4)					
	memo	rv usane: 1.9+ l	MR						

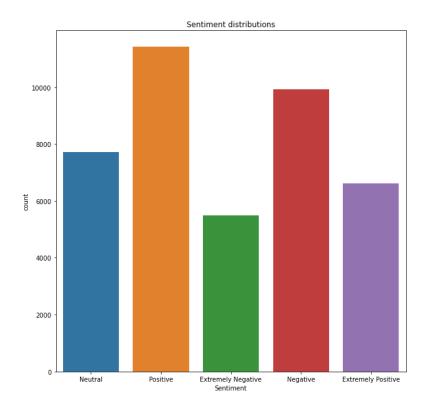


Exploratory Data Analysis



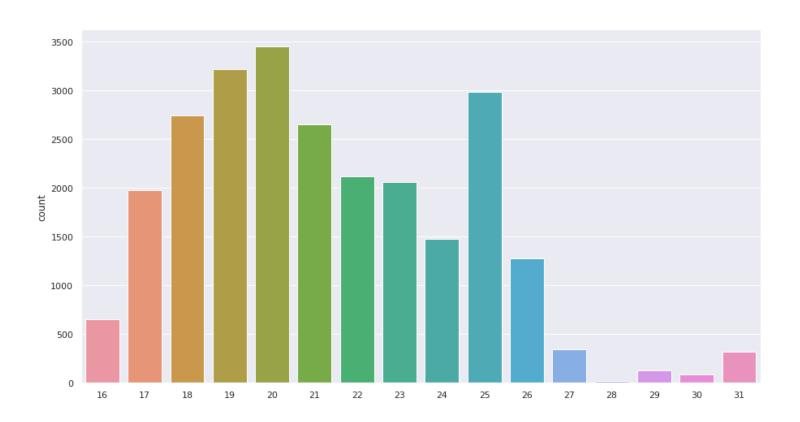
Sentimental Distribution





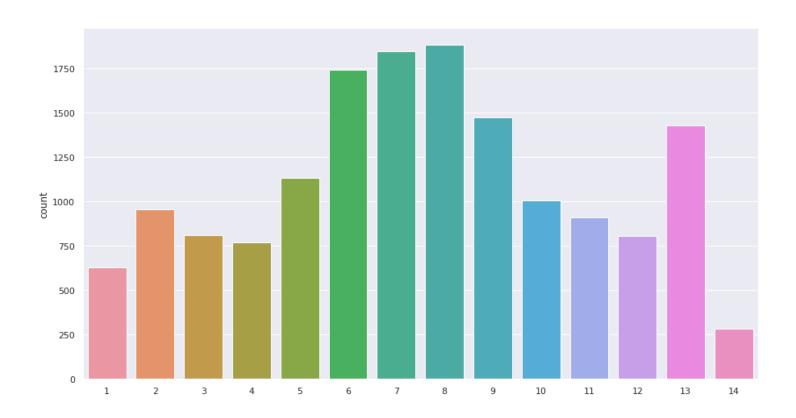


Tweet distribution in March





Tweet distribution in April



Top 10 locations which has most tweets from them.

	Location	Location_Count
0	London	9130
1	United States	528
2	London, England	520
3	New York, NY	395
4	Washington, DC	373
5	United Kingdom	337
6	Los Angeles, CA	281
7	India	268
8	UK	232
9	Australia	225

Top 10 dates on which maximums tweets have been made.

	Date	Count	of	Tweets
0	16-03-2020			3448
1	17-03-2020			3215
2	18-03-2020			2979
3	19-03-2020			2742
4	20-03-2020			2653
5	21-03-2020			2114
6	22-03-2020			2062
7	23-03-2020			1977
8	24-03-2020			1881
9	25-03-2020			1843



Insights from EDA

- 1) From sentimental distribution, it was clear that 24.1% people tweets something positive, which is help-full.
- 2) There are a total of 12220 uniques locations of tweets.
- 3) London has most active people who tweets related to covid-19.
- 4) India Ranks 7th in most active locations with an average of 4.4 tweets related to corona per day.
- 5) 16 MARCH 2020 had most number of tweets related to corona, with main as lockdown in most country had started on that day.
- 6)



Preprocessing of data

The preprocessing of the text data is an essential step as it makes the raw text ready for mining, i.e., it becomes easier to extract information from the text and apply machine learning algorithms to it. If we skip this step then there is a higher chance that you are working with noisy and inconsistent data.

The objective of this step is to clean noise those are less relevant to find the sentiment of tweets such as punctuation, special characters, numbers, and terms which don't carry much weightage in context to the text.



	OriginalTweet	Sentiment	Processed_text
0	@MeNyrbie @Phil_Gahan @Chrisitv https://t.co/i	Neutral	menyrbi philgahan chrisitv
1	advice Talk to your neighbours family to excha	Positive	advic talk neighbour famili exchang phone numb
2	Coronavirus Australia: Woolworths to give elde	Positive	coronaviru australia woolworth give elderli di
3	My food stock is not the only one which is emp	Positive	food stock one empti pleas dont panic enough f
4	Me, ready to go at supermarket during the #COV	Extremely Negative	readi go supermarket covid19 outbreak im paran



Model Training



A) Count Vectorizer Method

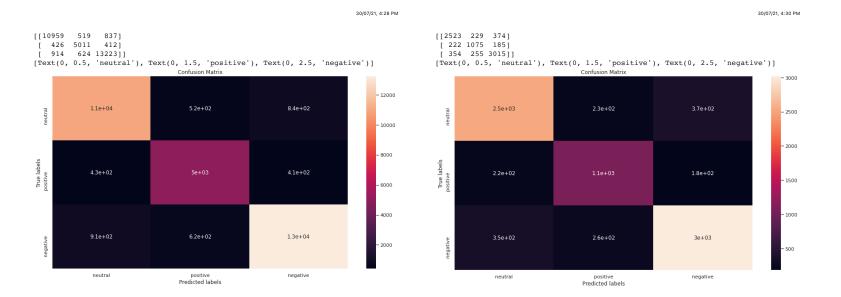
In order to use textual data for predictive modeling, the text must be parsed to remove certain words – this process is called **tokenization**. These words need to then be encoded as integers, or floating-point values, for use as inputs in machine learning algorithms.

Scikit-learn's CountVectorizer is used to convert a collection of text documents to a vector of term/token counts. It also enables the pre-processing of text data prior to generating the vector representation. This functionality makes it a highly flexible feature representation module for text



Confusion Matrix for train and Test set

Train Set Test Set





Classification Report of Train and Test Set

Train set report

	precision	recall	f1-score	support
-1 0 1	0.89 0.86 0.90	0.89 0.81 0.91	0.89 0.83 0.90	12299 6154 14472
accuracy macro avg weighted avg	0.88 0.89	0.87 0.89	0.89 0.88 0.89	32925 32925 32925

Test set report

	precision	recall	f1-score	support	
-1 0 1	0.81 0.73 0.83	0.81 0.69 0.84	0.81 0.71 0.84	3099 1559 3574	
accuracy macro avg weighted avg	0.79 0.80	0.78 0.80	0.80 0.79 0.80	8232 8232 8232	



B) Tf-IDF Method

This is another method which is based on the frequency method but it is different to the bag-of-words approach in the sense that it takes into account, not just the occurrence of a word in a single document (or tweet) but in the entire corpus.

TF-IDF works by penalizing the common words by assigning them lower weights while giving importance to words which are rare in the entire corpus but appear in good numbers in few documents.

Let's have a look at the important terms related to TF-IDF:

- TF = (Number of times term t appears in a document)/(Number of terms in the document)
- IDF = log(N/n), where, N is the number of documents and n is the number of documents a term t has appeared in.
- TF-IDF = TF*IDF



Confusion matrix for train and test data

30/07/21, 4:42 PM

Test Confusion Matrix

neutral

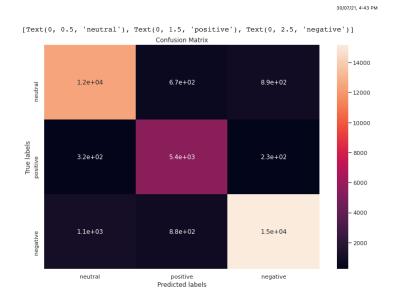
[Text(0, 0.5, 'neutral'), Text(0, 1.5, 'positive'), Text(0, 2.5, 'negative')] Confusion Matrix - 1400 1.3e+03 1.4e+02 1.8e+02 - 1200 - 1000 True labels - 800 4.8e+02 - 600 2.1e+02 1.8e+02 1.5e+03 - 200

positive

Predicted labels

negative

Train Confusion Matrix





Classification report for train and test data

Train set Test Set

	precision	recall	f1-score	support		precision	recall	f1-score	support
Negat	ive 0.89	0.90	0.89	13846	Negative	0.80	0.82	0.81	1552
Neut	ral 0.91	0.78	0.84	6910	Neutral	0.77	0.60	0.67	803
Posit	ive 0.89	0.93	0.91	16285	Positive	0.80	0.85	0.82	1761
accur	асу		0.89	37041	accuracy			0.79	4116
macro	avg 0.89	0.87	0.88	37041	macro avg	0.79	0.76	0.77	4116
weighted	avg 0.89	0.89	0.89	37041	weighted avg	0.79	0.79	0.79	4116