MACHINE LEARNING

(Twitter Sentiment Analysis)

Summer Internship Report Submitted in partial fulfillment

of the requirement for undergraduate degree of

Bachelor of Technology

In

Computer Science Engineering

By

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Under the Guidance of

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July 2020

DECLARATION

I submit this industrial training work entitled **“TWITTER SENTIMENT ANALYSIS**” to GITAM (Deemed To Be University), Hyderabad in partial fulfillment of the requirements for the award of the degree of “**Bachelor of Technology**” in “**Computer Science Engineering**”. I declare that it was carried out independently by me under the guidance of ,Asst. Professor, GITAM (Deemed To Be University), Hyderabad, India.

The results embodied in this report have not been submitted to any other University or Institute for the award of any degree or diploma.

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Dated:

CERTIFICATE

This is to certify that the Industrial Training Report entitled **“TWITTER SENTIMENT ANALYSIS”** is being submitted by **Vishnu Pulipaka (221710302064)** in partial fulfillment of the requirement for the award of **Bachelor of Technology in Computer Science Engineering** at GITAM (Deemed To Be University), Hyderabad during the academic year 2019-20.

It is faithful record work carried out by him at the Computer Science Engineering,GITAM University Hyderabad Campus under my guidance and supervision.

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Department of CSE

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Vishnu Pulipaka

221710302064

ABSTRACT

Classification algorithms in supervised machine learning are used to predict the label of a given “tweet” as positive or negative based on it’s content. The text data is converted from the perception of a mode of expression to semantically equivalent numeric format so as to be used for training,testing and as input for the machine learning model developed.The client’s requirement of understanding sentiment among twitter users who may be consumers, viewers or any service receivers from the client’s entity is the key objective of this case study.

To understand the necessity of sentiment analysis, I have put myself in the perspective of the client aiming to explore the scope of advertisement of my services and consumer mentality pertaining to a product,service,business or a social movement. In general, this case study can be used to predict sentiment among buyers,commuters and even sports fans.etc. by searching the relevant topics. There is a scope of expansion to study the variation of sentiment with time,location and user etc.

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CHAPTER 1

MACHINE LEARNING

1.1 INTRODUCTION:

Machine Learning(ML) is the scientific study of algorithms and statistical models that computer systems use in order to perform a specific task effectively without using explicit instructions, relying on patterns and inference instead. It is seen as a subset of Artificial Intelligence(AI).

1.2 IMPORTANCE OF MACHINE LEARNING:

Consider some of the instances where machine learning is applied: the self-driving Google car, cyber fraud detection, online recommendation engines—like friend suggestions on Facebook, Netflix showcasing the movies and shows you might like, and "more items to consider" and "get yourself a little something" on Amazon—are all examples of applied machine learning. All these examples echo the vital role machine learning has begun to take in today's data-rich world.

Machines can aid in filtering useful pieces of information that help in major advancements, and we are already seeing how this technology is being implemented in a wide variety of industries.

With the constant evolution of the field, there has been a subsequent rise in the uses, demands, and importance of machine learning. Big data has become quite a buzzword in the last few years; that's in part due to increased sophistication of machine learning, which helps analyze those big chunks of big data. Machine learning has also changed the way data extraction, and interpretation is done by involving automatic sets of generic methods that have replaced traditional statistical techniques.

The process flow depicted here represents how machine learning works

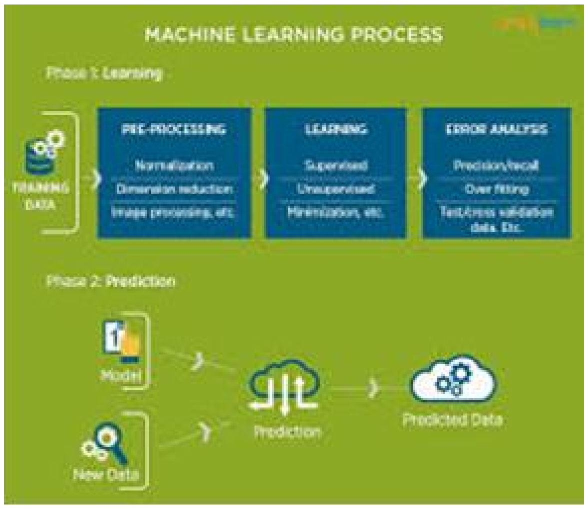


Figure 1.2.1 : The Process Flow

1.3 USES OF MACHINE LEARNING:

Earlier in this article, we mentioned some applications of machine learning. To understand the concept of machine learning better, let’s consider some more examples: web search results, real-time ads on web pages and mobile devices, email spam filtering, network intrusion detection, and pattern and image recognition. All these are by-products of applying machine learning to analyze huge volumes of data

Traditionally, data analysis was always being characterized by trial and error, an approach that becomes impossible when data sets are large and heterogeneous. Machine learning comes as the solution to all this chaos by proposing clever alternatives to analyzing huge volumes of data.

By developing fast and efficient algorithms and data-driven models for real-time processing of data, machine learning can produce accurate results and analysis.

1.4 TYPES OF LEARNING ALGORITHMS:

The types of machine learning algorithms differ in their approach, the type of data they input and output, and the type of task or problem that they are intended to solve.

1.4.1 Supervised Learning :

When an algorithm learns from example data and associated target responses that can consist of numeric values or string labels, such as classes or tags, in order to later predict the correct response when posed with new examples comes under the category of supervised learning.

Supervised machine learning algorithms uncover insights, patterns, and relationships from a labelled training dataset – that is, a dataset that already contains a known value for the target variable for each record. Because you provide the machine learning algorithm with the correct answers for a problem during training, it is able to “learn” how the rest of the features relate to the target, enabling you to uncover insights and make predictions about future outcomes based on historical data.

Examples of Supervised Machine Learning Techniques are Regression, in which the algorithm returns a numerical target for each example, such as how much revenue will be generated from a new marketing campaign.

Classification, in which the algorithm attempts to label each example by choosing between two or more different classes. Choosing between two classes is called binary classification, such as determining whether or not someone will default on a loan. Choosing between more than two classes is referred to as multiclass classification.

1.4.2 Unsupervised Learning:

When an algorithm learns from plain examples without any associated response, leaving to the algorithm to determine the data patterns on its own. This type of algorithm tends to restructure the data into something else, such as new features that may represent a class or a new series of uncorrelated values. They are quite useful in providing humans with insights into the meaning of data and new useful inputs to supervised machine learning algorithms.

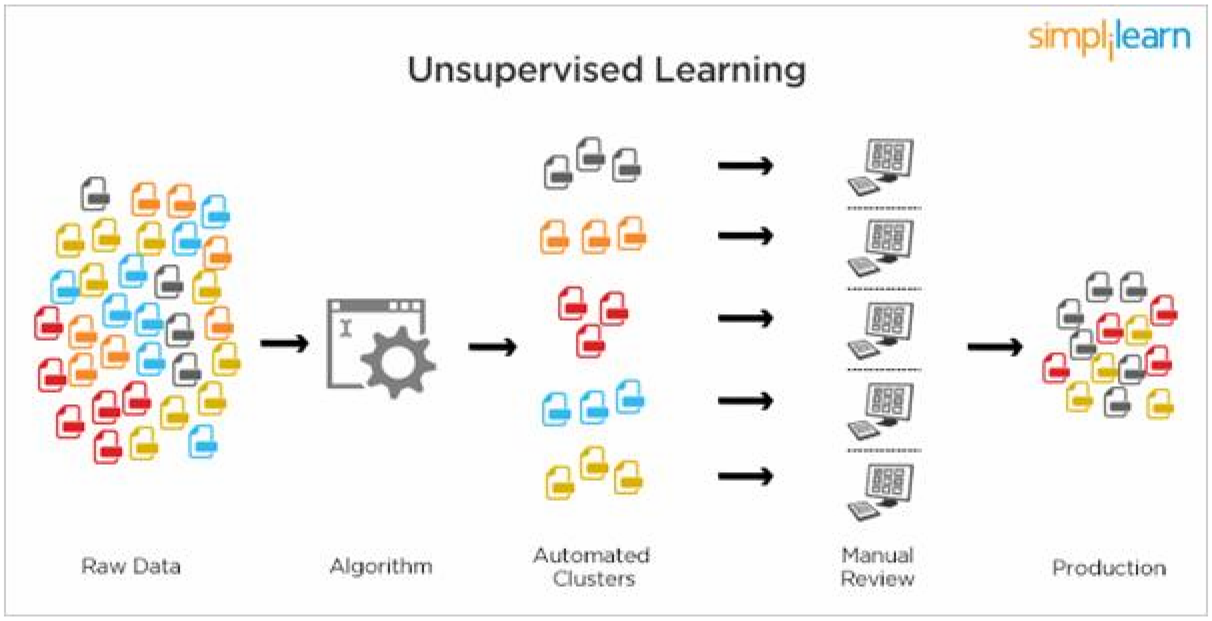


Figure 1.4.2 Unsupervised Learning

Popular techniques where unsupervised learning is used also include self-organizing maps, nearest neighbor mapping, singular value decomposition, and k-means clustering. Basically, online recommendations, identification of data outliers, and segment text topics are all examples of unsupervised learning.

1.4.3 Semi Supervised Learning:

As the name suggests, semi-supervised learning is a bit of both supervised and unsupervised learning and uses both labeled and unlabeled data for training. In a typical scenario, the algorithm would use a small amount of labeled data with a large amount of unlabeled data.

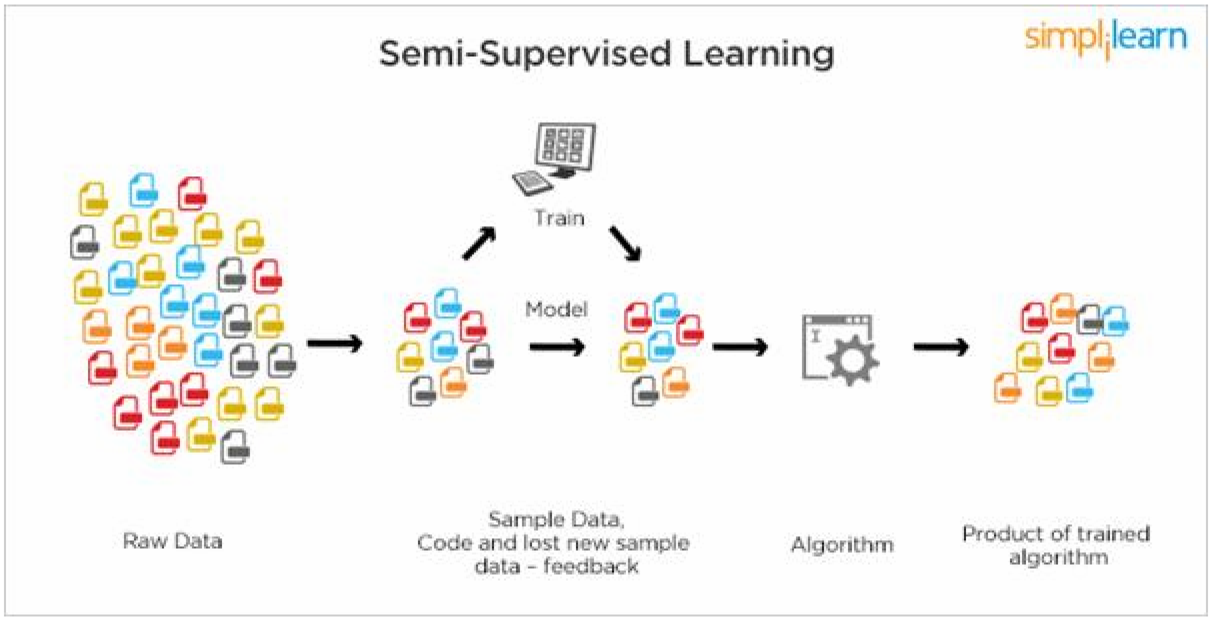

Semi-Supervised Learning
simplilearn
Train
Model
Raw Data
Sample Data, Code and lost new sample data - feedback
Algorithm
Product of trained algorithm

Figure 1.4.3 : Semi Supervised Learning

1.5 RELATION BETWEEN DATA MINING,MACHINE LEARNING AND DEEP LEARNING:

Machine learning and data mining use the same algorithms and techniques as data mining, except the kinds of predictions vary. While data mining discovered previously unknown patterns and knowledge, machine learning reproduces known patterns and knowledge—and further automatically applies that information to data, decision-making, and actions.Deep learning, on the other hand, uses advanced computing power and special types of neural networks and applies them to large amounts of data to learn, understand, and identify complicated patterns. Automatic language translation and medical diagnoses are examples of deep learning.

CHAPTER 2

PYTHON

Basic programming language used for machine learning is : PYTHON

2.1 INTRODUCTION TO PYTHON:

- Python is a high-level, interpreted, interactive and object-oriented scripting language.
- Python is a general purpose programming language that is often applied in scripting roles
- Python is Interpreted: Python is processed at runtime by the interpreter. You do not need to compile your program before executing it. This is like PERL and PHP.
- Python is Interactive: You can sit at a Python prompt and interact with the interpreter directly to write your programs.
- Python is Object-Oriented: Python supports the Object-Oriented style or technique of programming that encapsulates code within objects.

2.2 HISTORY OF PYTHON:

- Python was developed by GUIDO VAN ROSSUM in early 1990's
- Its latest version is 3.7 , it is generally called as python3

2.3 FEATURES OF PYTHON:

- Easy-to-learn: Python has few keywords, simple structure, and a clearly defined syntax, This allows the student to pick up the language quickly.
- Easy-to-read: Python code is more clearly defined and visible to the eyes.
- Easy-to-maintain: Python's source code is fairly easy-to-maintaining.
- A broad standard library: Python's bulk of the library is very portable and cross-platform compatible on UNIX, Windows, and Macintosh.
- Portable: Python can run on a wide variety of hardware platforms and has the same interface on all platforms.

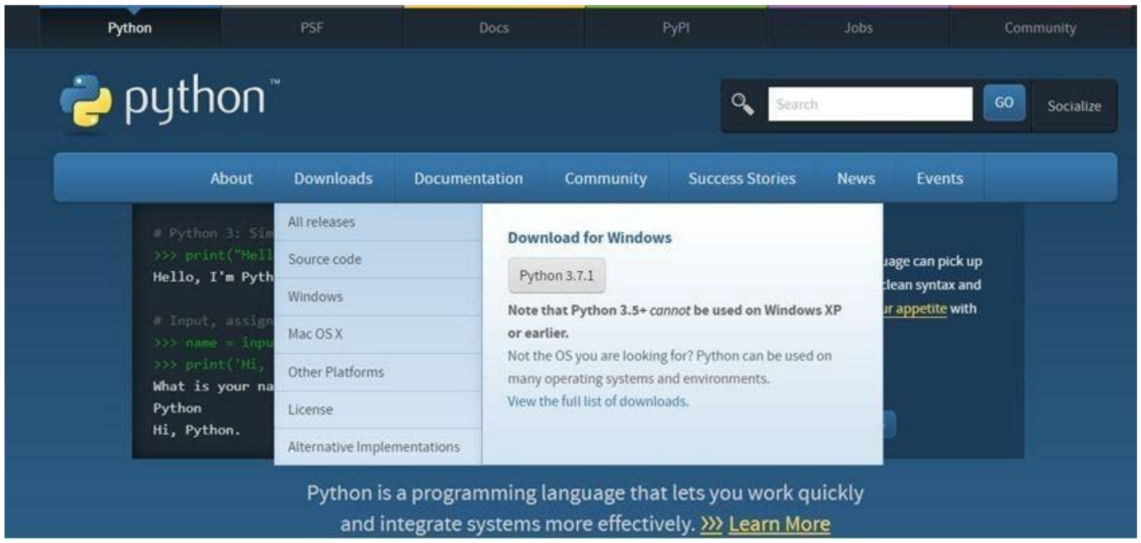
- Extendable: You can add low-level modules to the Python interpreter. These modules enable programmers to add to or customize their tools to be more efficient.
- Databases: Python provides interfaces to all major commercial databases.
- GUI Programming: Python supports GUI applications that can be created and ported to many system calls, libraries and windows systems, such as Windows MFC, Macintosh, and the X Window system of Unix.

2.4 HOW TO SETUP PYTHON:

- Python is available on a wide variety of platforms including Linux and Mac OS X. Let's understand how to set up our Python environment.
- The most up-to-date and current source code, binaries, documentation, news, etc., is available on the official website of Python.

2.4.1 Installation(using python IDLE):

- Installing python is generally easy, and nowadays many Linux and Mac OS distributions include a recent python.
- Download python from www.python.org
- When the download is completed, double click the file and follow the instructions to install it.
- When python is installed, a program called IDLE is also installed along with it. It provides a graphical user interface to work with python.



Download for Windows

Note that Python 3.5+ *cannot* be used on Windows XP or earlier.

Not the OS you are looking for? Python can be used on many operating systems and environments.

View the full list of downloads.

Python is a programming language that lets you work quickly and integrate systems more effectively. >>> Learn More

Figure 2.4.1 : Python download

2.4.2 Installation(using Anaconda):

- Python programs are also executed using Anaconda.
- Anaconda is a free open source distribution of python for large scale data processing, predictive analytics and scientific computing.
- Conda is a package manager that quickly installs and manages packages.

In WINDOWS:

- In windows
  - Step 1: Open Anaconda.com/downloads in a web browser.
  - Step 2: Download python 3.4 version for (32-bits graphic installer/64 -bit graphic installer)
  - Step 3: select installation type(all users)
  - Step 4: Select path(i.e. add anaconda to path & register anaconda as default python 3.4) next click install and next click finish
  - Step 5: Open jupyter notebook (it opens in default browser)

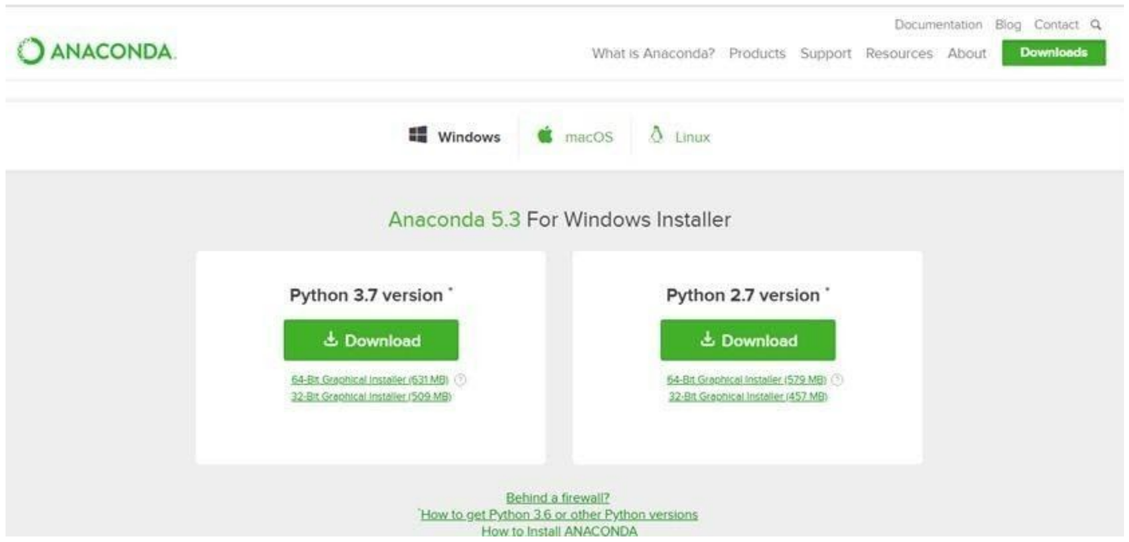

ANACONDA
Documentation Blog Contact
What is Anaconda? Products Support Resources About Downloads
Windows macOS Linux
Anaconda 5.3 For Windows Installer
Python 3.7 version
Download
64-Bit Graphical Installer (631 MB)
32-Bit Graphical Installer (509 MB)
Python 2.7 version
Download
64-Bit Graphical Installer (579 MB)
32-Bit Graphical Installer (457 MB)
Behind a firewall?
How to get Python 3.6 or other Python versions
How to Install ANACONDA

Figure 2.4.2.1 Anaconda download

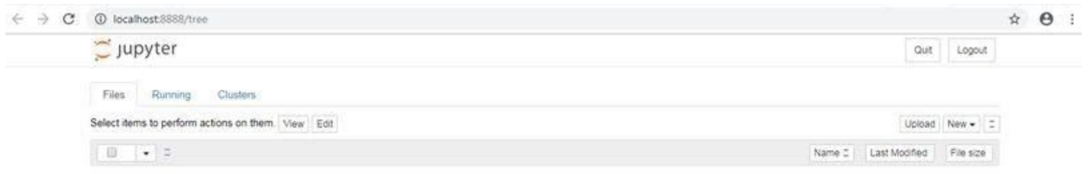

localhost:8888/tree
jupyter
Quit Logout
Files Running Clusters
Select items to perform actions on them. View Edit
Upload New
Name Last Modified File size

Figure 2.4.2.2 Jupyter notebook

2.5 PYTHON VARIABLE TYPES:

- Variables are nothing but reserved memory locations to store values. This means that when you create a variable you reserve some space in memory.
- Variables are nothing but reserved memory locations to store values.
- Based on the data type of a variable, the interpreter allocates memory and decides what can be stored in the reserved memory.
- Python variables do not need explicit declaration to reserve memory space. The declaration happens automatically when you assign a value to a variable.

- Python has various standard data types that are used to define the operations possible on them and the storage method for each of them.
- Python has five standard data types –
    - Numbers
    - Strings
    - Lists
    - Tuples
    - Dictionary

2.5.1 Python Numbers:

- Number data types store numeric values. Number objects are created when you assign a value to them.
- Python supports four different numerical types − int (signed integers) long (long integers, they can also be represented in octal and hexadecimal) float (floating point real values) complex (complex numbers).

2.5.2 Python Strings:

- Strings in Python are identified as a contiguous set of characters represented in the quotation marks.
- Python allows for either pairs of single or double quotes.
- Subsets of strings can be taken using the slice operator ([ ] and [:]) with indexes starting at 0 in the beginning of the string and working their way from -1 at the end.
- The plus (+) sign is the string concatenation operator and the asterisk (*) is the repetition operator.

2.5.3 Python Lists:

- Lists are the most versatile of Python's compound data types.
- A list contains items separated by commas and enclosed within square brackets-([]).
- To some extent, lists are similar to arrays in C. One difference between them is that all the items belonging to a list can be of different data type.
- The values stored in a list can be accessed using the slice operator ([ ] and [:]) with indexes starting at 0 in the beginning of the list and working their way to end -1.
- The plus (+) sign is the list concatenation operator, and the asterisk (*) is the repetition operator.

2.5.4 Python Tuples:

- A tuple is another sequence data type that is similar to the list.
- A tuple consists of a number of values separated by commas. Unlike lists, however, tuples are enclosed within parentheses.
- The main differences between lists and tuples are: Lists are enclosed in brackets ([ ]) and their elements and size can be changed, while tuples are enclosed in parentheses (( )) and cannot be updated.
- Tuples can be thought of as read-only lists.
- For example − Tuples are fixed size in nature whereas lists are dynamic. In other words, a tuple is immutable whereas a list is mutable. You can't add elements to a tuple. Tuples have no append or extend method. You can't remove elements from a tuple. Tuples have no remove or pop method.

2.5.5 Python Dictionary:

- Python's dictionaries are kind of hash table type. They work like associative arrays
- or hashes found in Perl and consist of key-value pairs. A dictionary key can be almost any Python type, but are usually numbers or strings. Values, on the other

hand, can be any arbitrary Python object.

- Dictionaries are enclosed by curly braces ({ }) and values can be assigned and accessed using square braces ([]).
- You can use numbers to "index" into a list, meaning you can use numbers to find out what's in lists. You should know this about lists by now, but make sure you understand that you can only use numbers to get items out of a list.
- What a dict does is let you use anything, not just numbers. Yes, a dict associates one thing to another, no matter what it is.

2.6 PYTHON FUNCTION:

2.6.1 Defining a Function:

You can define functions to provide the required functionality. Here are simple rules to define a function in Python. Function blocks begin with the keyword def followed by the function name and parentheses (i.e.()).

Any input parameters or arguments should be placed within these parentheses.
You can also define parameters inside these parentheses

The code block within every function starts with a colon (:) and is indented. The statement returns [expression] exits a function, optionally passing back an expression to the caller. A return statement with no arguments is the same as return None.

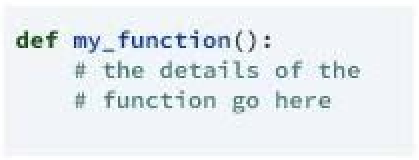
2.6.2 Calling a Function:

Defining a function only gives it a name, specifies the parameters that are to be included in the function and structures the blocks of code. Once the basic structure of a function is finalized, you can execute it by calling it from another function or directly from the Python prompt.

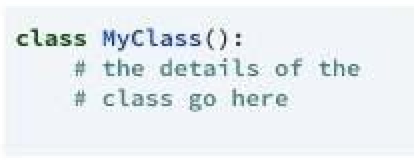
2.7 PYTHON USING OOPs CONCEPTS:

2.7.1 Class:

- Class: A user-defined prototype for an object that defines a set of attributes that characterize any object of the class. The attributes are data members (class variables and instance variables) and methods, accessed via dot notation.
- Class variable: A variable that is shared by all instances of a class. Class variables are defined within a class but outside any of the class's methods. Class variables are not used as frequently as instance variables are.
- Data member: A class variable or instance variable that holds data associated with a class and its objects.
- Instance variable: A variable that is defined inside a method and belongs only to the current instance of a class.
- Defining a Class:
    - o We define a class in a very similar way how we define a function.
    - o Just like a function ,we use parentheses and a colon after the class name(i.e. ():) when we define a class. Similarly, the body of our class is indented like a functions body is.



```
def my_function():
    # the details of the
    # function go here
```



```
class MyClass():
    # the details of the
    # class go here
```

Figure 2.7.1.1 : Defining a Class

2.7.2 init method in Class:

- The init method — also called a constructor — is a special method that runs when an instance is created so we can perform any tasks to set up the instance.
- The init method has a special name that starts and ends with two underscores: init ().

CHAPTER 3
CASE STUDY: TWITTER SENTIMENT ANALYSIS

3.1 PROBLEM STATEMENT:

“ To predict the sentiment of twitter data using machine learning algorithms - Decision Tree Classifier and Logistic Regression”.

3.2 DATA SET:

ID - tweet ID

Label - 0/1 (positive/negative)

Tweet - text data(tweets)

3.3 OBJECTIVE OF THE CASE STUDY:

Analysing sentiment of client’s domain related topic from twitter data using machine learning algorithms. Primary objective is to find the best suitable algorithm for the implementation of sentiment analysis and tune parameters for optimum accuracy.

Further helping the client to learn about the response of the consumer/public about a topic pertaining to their business domain.

CHAPTER 4

DATA PREPROCESSING

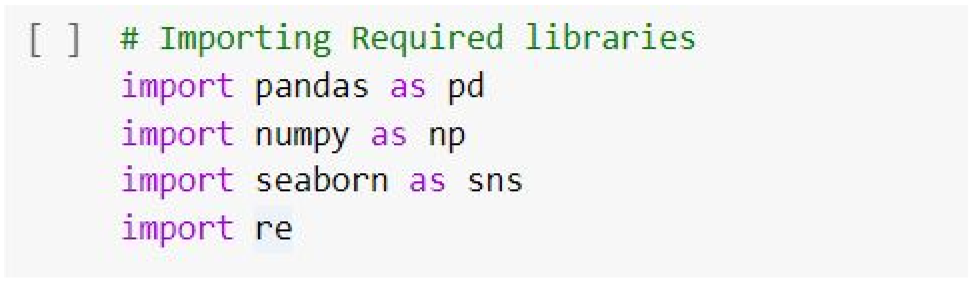
4.1 READING DATA AND LIBRARIES:

Preparing text using following steps:

4.1.1 Getting the dataset:

We can get the data set from twitter by scraping the web.

4.1.2 Importing the libraries:

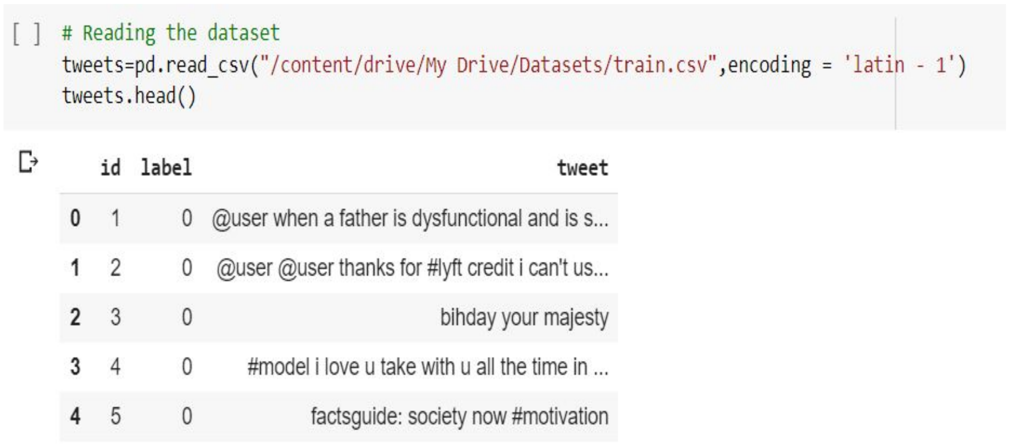


```
[ ]  # Importing Required libraries
     import pandas as pd
     import numpy as np
     import seaborn as sns
     import re
```

Figure 4.1.2: Importing libraries

4.1.3 Importing the data :

We read the training data and print the head.



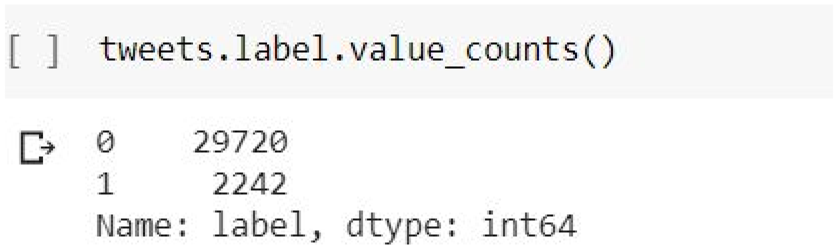
```
[ ]  # Reading the dataset
     tweets=pd.read_csv("/content/drive/My Drive/Datasets/train.csv",encoding = 'latin - 1')
     tweets.head()
```

	id	label	tweet
0	1	0	@user when a father is dysfunctional and is s...
1	2	0	@user @user thanks for #lyft credit i can't us...
2	3	0	bihday your majesty
3	4	0	#model i love u take with u all the time in ...
4	5	0	factsguide: society now #motivation

Figure 4.1.3: Reading the data and head of the data

4.2 STATISTICAL ANALYSIS :

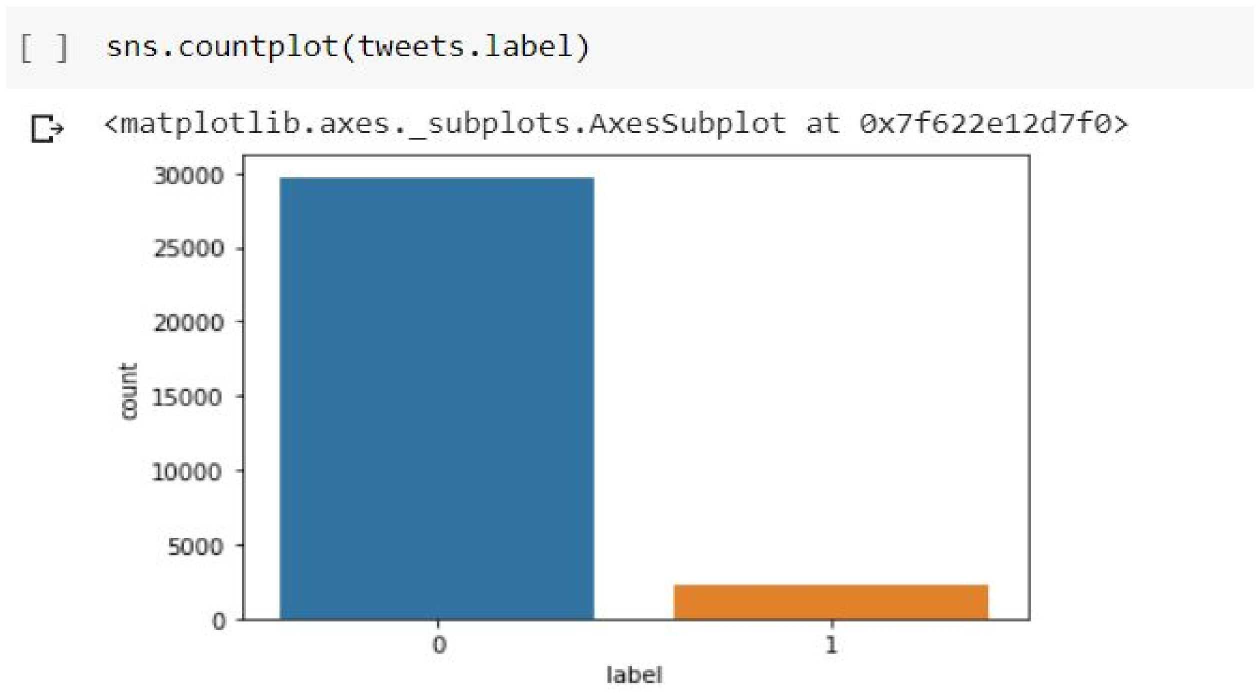
4.2.1 Checking the frequency of output data:



```
[ ]  tweets.label.value_counts()

     0    29720
     1     2242
     Name: label, dtype: int64
```

Figure 4.2.1: label counts

4.2.2 Visualising Output Column:

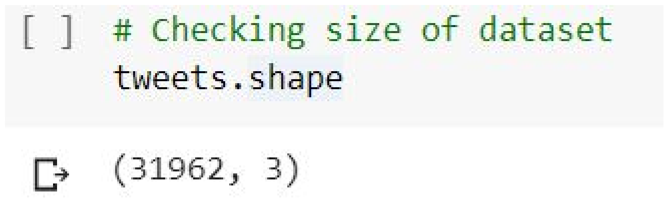


```
[ ]  sns.countplot(tweets.label)

     <matplotlib.axes._subplots.AxesSubplot at 0x7f622e12d7f0>
```

Figure 4.2.2 visualizing label counts

Observation : There is an imbalance in the data as label ‘0’ and label ‘1’ data are approximately in the ratio 15:1 . The data is imbalanced. Data is balanced in the upcoming section 5.5.

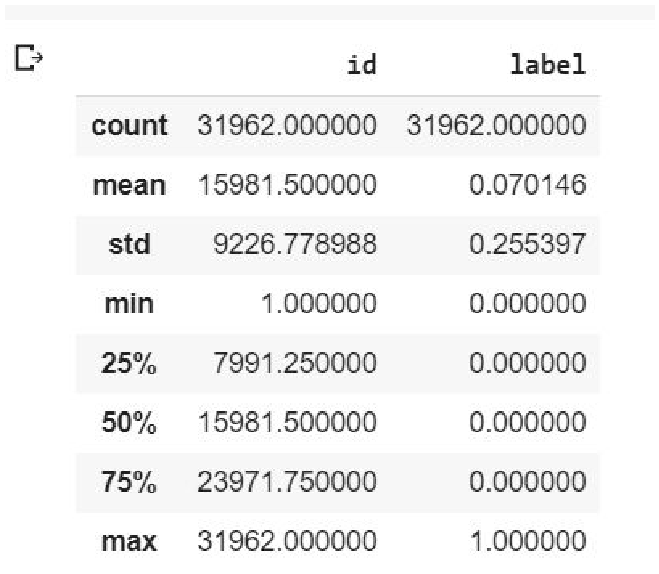
4.2.3 Checking Shape Of Data Set:



```
[ ] # Checking size of dataset
    tweets.shape

(31962, 3)
```

Figure 4.2.3: Shape of dataset

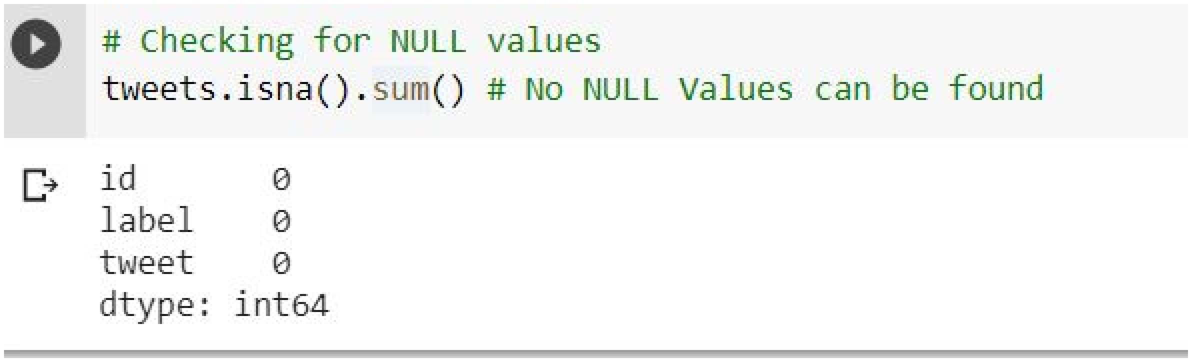
4.2.4 Checking Statistical Description:



	id	label
count	31962.000000	31962.000000
mean	15981.500000	0.070146
std	9226.778988	0.255397
min	1.000000	0.000000
25%	7991.250000	0.000000
50%	15981.500000	0.000000
75%	23971.750000	0.000000
max	31962.000000	1.000000

Figure 4.2.4: Statistical Description

4.3 HANDLING MISSING VALUES :



```
# Checking for NULL values
tweets.isna().sum() # No NULL Values can be found
```

```
id       0
label    0
tweet    0
dtype: int64
```

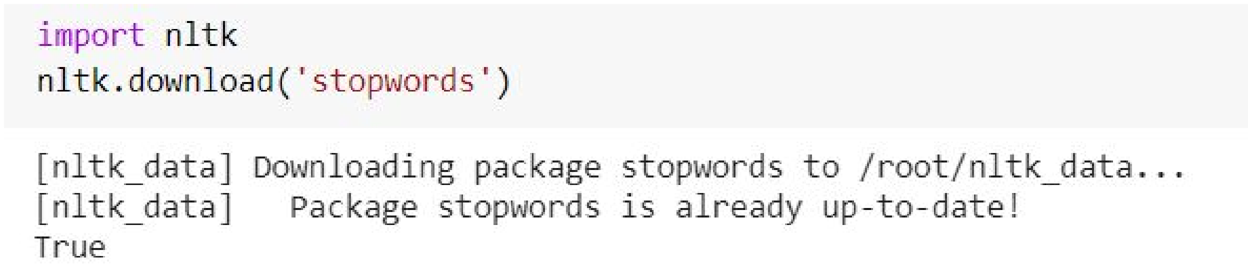
Figure 4.3.1: Checking missing values

- No missing values found in the dataset .
- Hence, no need for imputation .

4.4 CLEANING TEXT DATA WITH NLTK:

4.4.1 Downloading Resources And Nltk Library:

- List of stopwords

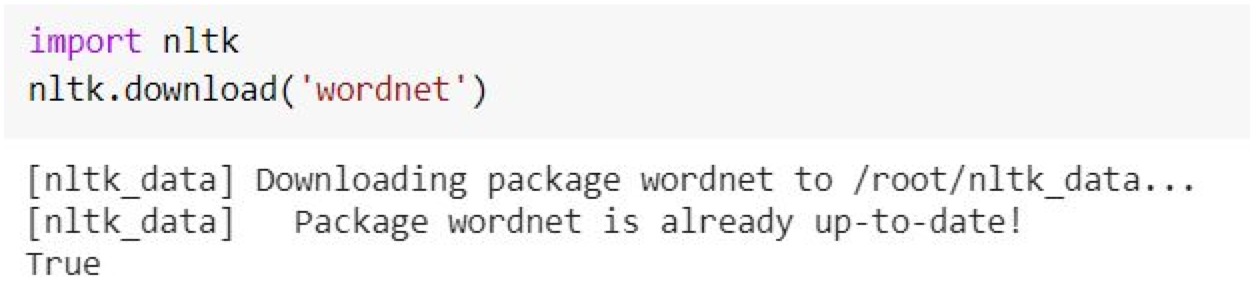


```
import nltk
nltk.download('stopwords')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
True
```

Figure 4.4.1.1: nltk stopwords download

- WordNet



```
import nltk
nltk.download('wordnet')
```

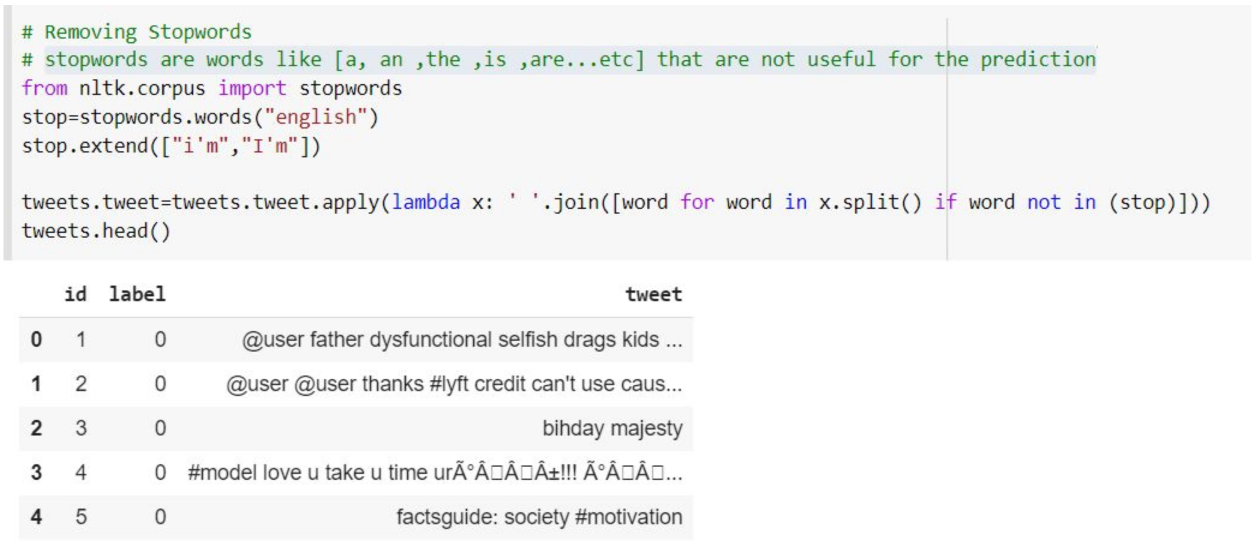
```
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
True
```

Figure 4.4.1.2: nltk wordnet download

4.4.2 Removing Stop Words:

Stopwords:

stopwords are words like [a, an ,the ,is ,are...etc] that are not useful for the prediction.



```
# Removing Stopwords
# stopwords are words like [a, an ,the ,is ,are...etc] that are not useful for the prediction
from nltk.corpus import stopwords
stop=stopwords.words("english")
stop.extend(["i'm","I'm"])

tweets.tweet=tweets.tweet.apply(lambda x: ' '.join([word for word in x.split() if word not in (stop)]))
tweets.head()
```

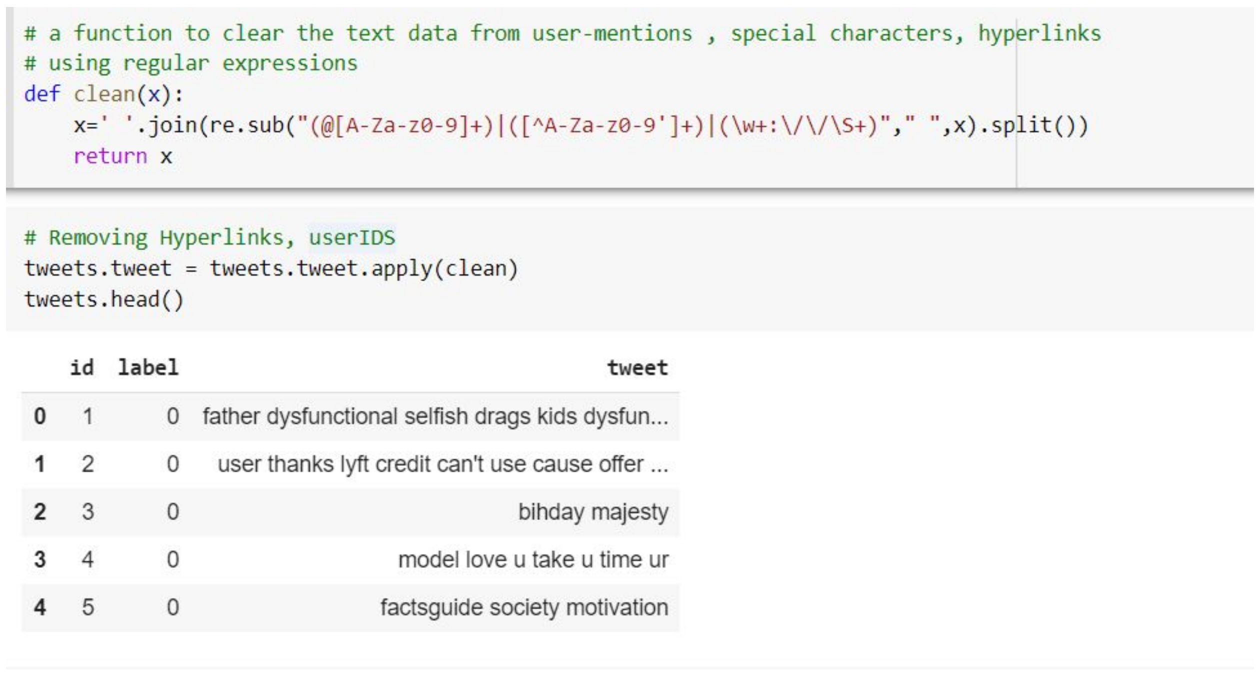
	id	label	tweet
0	1	0	@user father dysfunctional selfish drags kids ...
1	2	0	@user @user thanks #lyft credit can't use caus...
2	3	0	bihday majesty
3	4	0	#model love u take u time urÃ°Â□Â□Â±!!! Ã°Â□Â□...
4	5	0	factsguide: society #motivation

Figure 4.4.2.1 Removing stopwords

Example : “I am having a bad day” becomes “ having bad day”

- am,I,a are removed as they are the stopwords

4.4.3 Removing Hyperlinks,Mentions And Special Characters:



```python
# a function to clear the text data from user-mentions , special characters, hyperlinks
# using regular expressions
def clean(x):
    x=' '.join(re.sub("(@[A-Za-z0-9]+)|([^A-Za-z0-9']+)|(\w+:\/\/\S+)"," ",x).split())
    return x
```

```python
# Removing Hyperlinks, userIDS
tweets.tweet = tweets.tweet.apply(clean)
tweets.head()
```

	id	label	tweet
0	1	0	father dysfunctional selfish drags kids dysfun...
1	2	0	user thanks lyft credit can't use cause offer ...
2	3	0	bihday majesty
3	4	0	model love u take u time ur
4	5	0	factsguide society motivation

Figure 4.4.3 Removing Hyperlinks

For example:

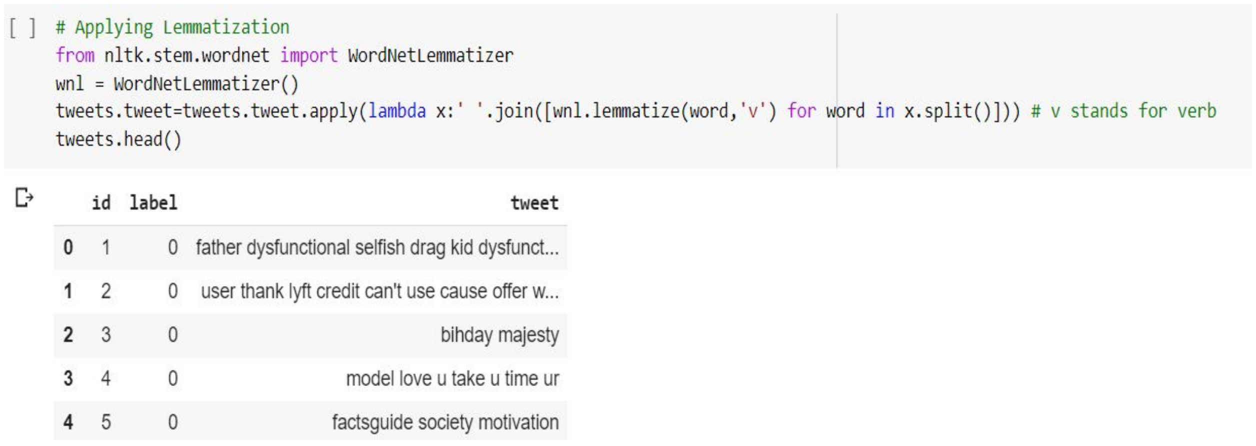
(@[A-Za-z0-9]+) -	@peter	removed
([^A-Za-z0-9']+) -	#Macy	Macy
(\w+:\/\/\S+)	http://bit.ly//WjdiW4	removed

"@peter I really don't love that shirt at #Macy. http://bit.ly//WjdiW4" becomes ,

“I really don't love that shirt at Macy”

4.4.4 Lemmatization:

"Lemma" is a group of words and their inflections. When a word is encountered in any inflected form, lemmatizer converts the word into its base form or root by referring to its Lemma. WordNet provides a database of Lemma which is used. An alternative processing called stemming is also available. As lemmatization uses a reference in the database,hence returns a meaningful root. While stemming uses a series of steps,like suffix elimination to arrive at a root. This may or may not result in semantically correct words. Hence in this case,we prefer lemmatization even though stemming is faster.



```
# Applying Lemmatization
from nltk.stem.wordnet import WordNetLemmatizer
wnl = WordNetLemmatizer()
tweets.tweet=tweets.tweet.apply(lambda x:' '.join([wnl.lemmatize(word,'v') for word in x.split()])) # v stands for verb
tweets.head()
```

	id	label	tweet
0	1	0	father dysfunctional selfish drag kid dysfunct...
1	2	0	user thank lyft credit can't use cause offer w...
2	3	0	bihday majesty
3	4	0	model love u take u time ur
4	5	0	factsguide society motivation

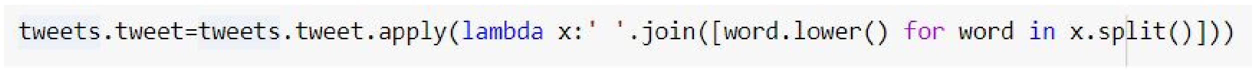
Figure 4.4.4 Lemmatization

Example:

"Playing" is converted to the root word "Play".

4.4.5 Converting To Lowercase:

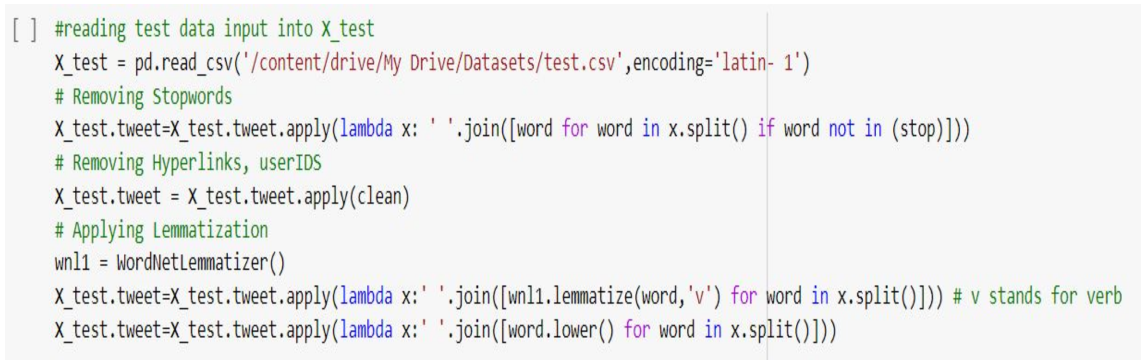
- Converting all words to lowercase for convenience.



```
tweets.tweet=tweets.tweet.apply(lambda x:' '.join([word.lower() for word in x.split()]))
```

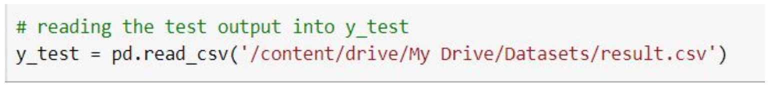
Figure 4.4.5 Lowercase conversion

4.4.6 Applying The Above Techniques To Test Data



```
[ ] #reading test data input into X_test
    X_test = pd.read_csv('/content/drive/My Drive/Datasets/test.csv',encoding='latin- 1')
    # Removing Stopwords
    X_test.tweet=X_test.tweet.apply(lambda x: ' '.join([word for word in x.split() if word not in (stop)]))
    # Removing Hyperlinks, userIDS
    X_test.tweet = X_test.tweet.apply(clean)
    # Applying Lemmatization
    wnl1 = WordNetLemmatizer()
    X_test.tweet=X_test.tweet.apply(lambda x:' '.join([wnl1.lemmatize(word,'v') for word in x.split()])) # v stands for verb
    X_test.tweet=X_test.tweet.apply(lambda x:' '.join([word.lower() for word in x.split()]))
```

Figure 4.4.6.1 Applying all cleaning techniques to test data



```
# reading the test output into y_test
y_test = pd.read_csv('/content/drive/My Drive/Datasets/result.csv')
```

Figure 4.4.6.2: Reading test data output

4.5 APPLYING TF-IDF VECTORIZER:

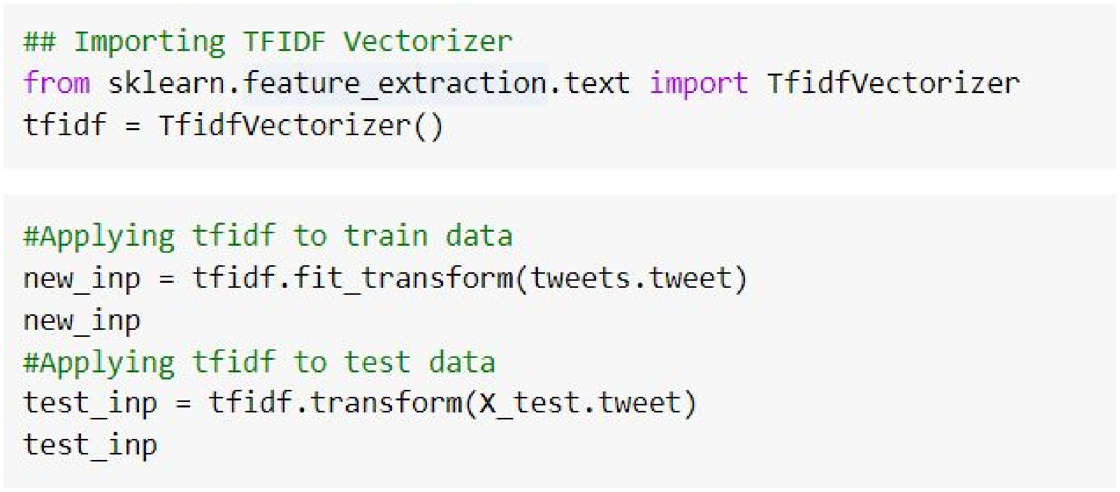
TF : Term Frequency, which measures how frequently a term occurs in a document. Since every document is different in length, it is possible that a termwould appear much more often in long documents than shorter ones .

TF(t) = (Number of times term t appears in a document) / (Total number of terms in the document).

Inverse Document Frequency : This downscales words that appear a lot across documents , which measures how important a term is. While computing TF, all terms are considered equally important.

IDF(t) = log(Total number of documents / Number of documents with term t in it).

The TfidfVectorizer will tokenize documents, learn the vocabulary and inverse document frequency weightings, and allow you to encode new documents. Alternatively, if you already have a learned CountVectorizer, you can use it with a TfidfTransformer to just calculate the inverse document frequencies and start encoding documents.



```
## Importing TFIDF Vectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
tfidf = TfidfVectorizer()
```

```
#Applying tfidf to train data
new_inp = tfidf.fit_transform(tweets.tweet)
new_inp
#Applying tfidf to test data
test_inp = tfidf.transform(X_test.tweet)
test_inp
```

Figure 4.5: Tfidf Vectorizer

4.6 Balancing Dataset:

Imbalanced data typically refers to a classification problem where the number of observations per class is not equally distributed.

Since most Machine Learning algorithms are designed to achieve maximum accuracy, they tend to classify only the class with higher data population to achieve this accuracy. Since this accuracy is only biased, the accuracy cannot be considered as genuine.

As we have seen in sections 5.2.1 and 5.2.2, the data is imbalanced which may lead to falsely high metrics. To avoid this we use data balancing techniques.

The technique used in this case study is Synthetic sample generation.

It is a technique similar to upsampling where the sample count of the minority class is increased. Instead of repeated duplication of samples, here we use imblearn's SMOTE or Synthetic Minority Oversampling Technique. SMOTE uses a nearest neighbours algorithm to generate new and synthetic data we can use for training our model.

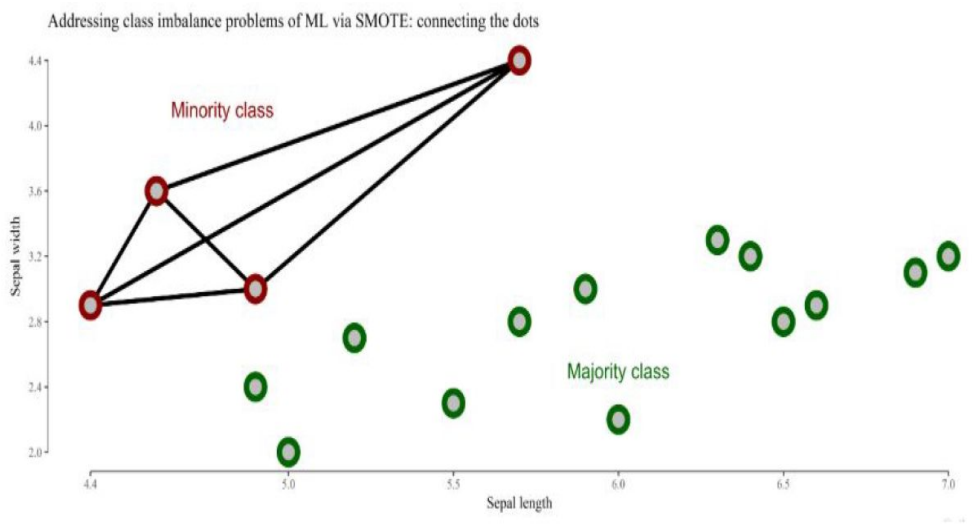


Figure 4.6.1: SMOTE Lines

In the above image, the minority classes represented in red, are clearly outnumbered. The SMOTE technique assumes more minority samples plotted on the SMOTE lines used to join the minority data points as seen below.

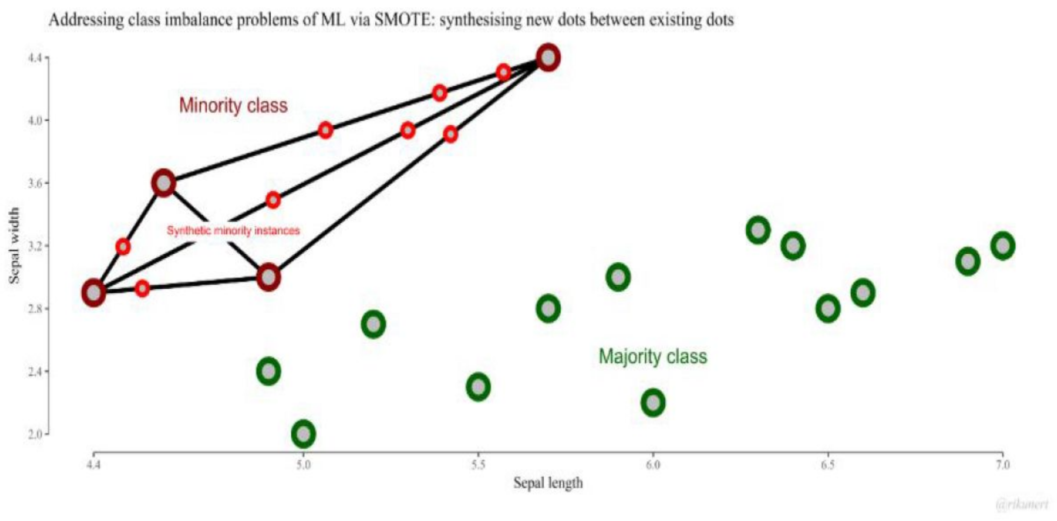
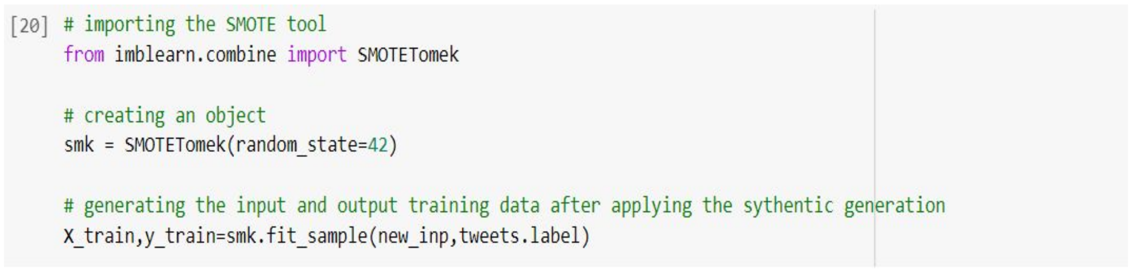


Figure 4.62. Synthetic data point for minority class

Applying SMOTE on our dataset:

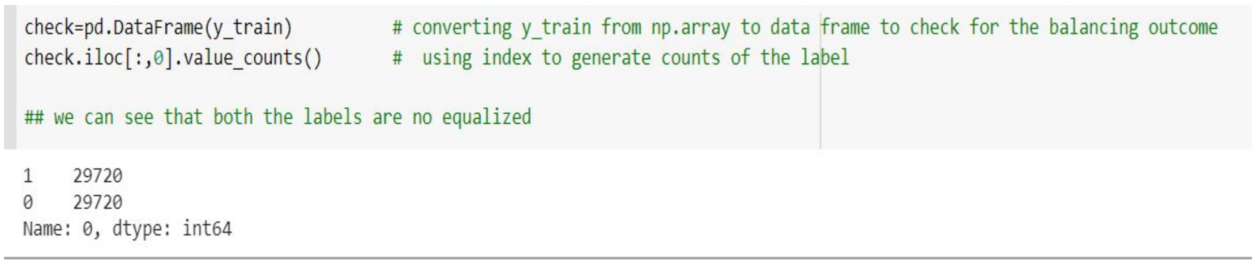


```
[20] # importing the SMOTE tool
     from imblearn.combine import SMOTETomek

     # creating an object
     smk = SMOTETomek(random_state=42)

     # generating the input and output training data after applying the sythentic generation
     X_train,y_train=smk.fit_sample(new_inp,tweets.label)
```

Figure 4.6.3 Applying smote to data

1. Importing the SMOTE library and SMOTETomek
2. Creating the object
3. Generating the train data - input(X_train) and output(y_train)

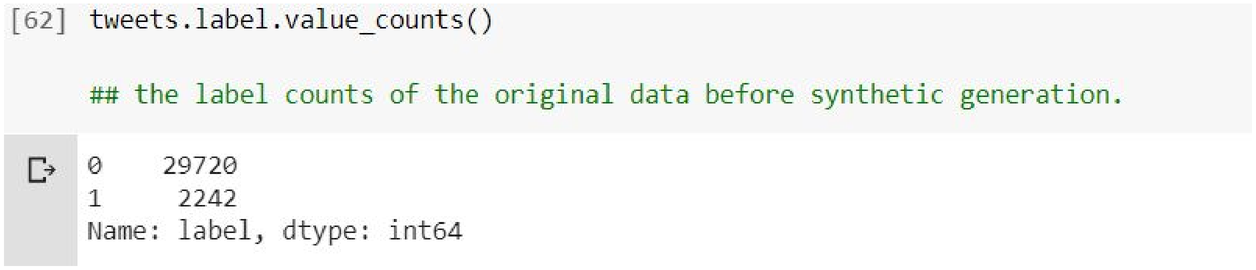
Checking if the synthetic generation has worked:



```
check=pd.DataFrame(y_train)          # converting y_train from np.array to data frame to check for the balancing outcome
check.iloc[:,0].value_counts()       #  using index to generate counts of the label

## we can see that both the labels are no equalized

1    29720
0    29720
Name: 0, dtype: int64
```

Figure 4.6.4: value counts for label

As we can see, both the labels (0/1) have the same frequency as compared to the original data shown below.



```
[62] tweets.label.value_counts()

     ## the label counts of the original data before synthetic generation.

     0    29720
     1     2242
     Name: label, dtype: int64
```

Figure 4.6.5 value counts before SMOTE

Final Outcome of the step:

The frequency count of the minority label(1) is sampled up from 2242 to 29720 samples by adding synthetically generated data ,in this case using K-means clustering algorithm.

CHAPTER 5
BUILDING MODEL AND EVALUATION

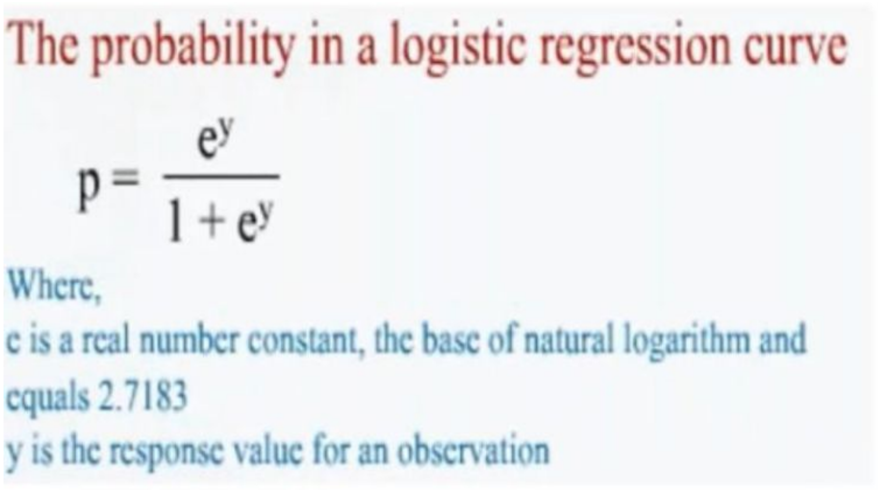
5.1 LOGISTIC REGRESSION

5.1.1 About The Algorithm

Logistic Regression is used when the dependent variable(target) is categorical.Logistic Regression is the appropriate regression analysis to conduct when the dependent variable is binary. Like all regression analyses, the logistic regression is a predictive analysis and it predicts the probability.

Also called a classification algorithm, because it classifies the data. It predicts the probability associated with each dependent variable category.

- The algorithm finds a linear relationship between independent variables and a link function of these probabilities which provides the best of goodness fit for the given data is chosen.
- The below formula is used to keep the probability in between 0 and 1.


The probability in a logistic regression curve

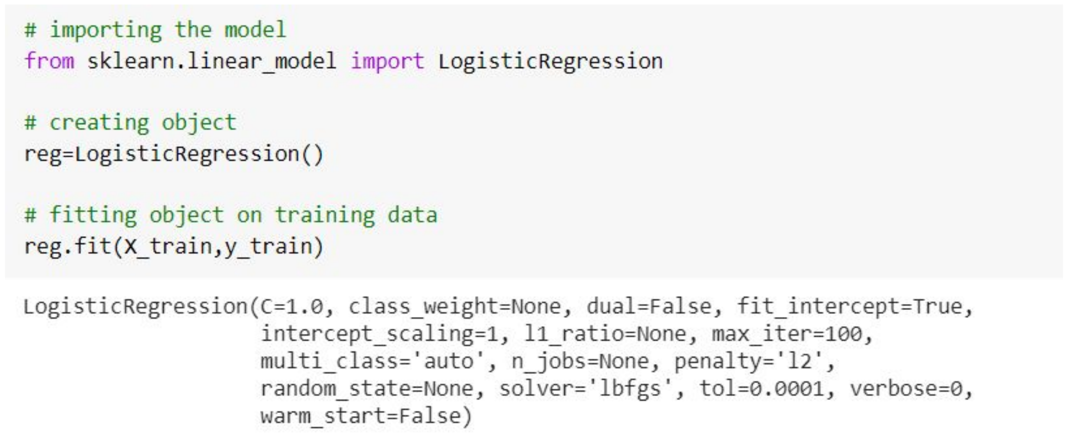
$$p = \frac{e^y}{1 + e^y}$$

Where,
e is a real number constant, the base of natural logarithm and equals 2.7183
y is the response value for an observation

Figure 5.1.1: Probability function for logistic regression

5.1.2 Train The Model

- In Machine Learning in order to access the performance of the classifier. You train the classifier using 'training set' and then test the performance of your classifier on unseen 'test set'. An important point to note is that during training the classifier only uses the training set . The test set must not be used during training the classifier. The test set will only be available during testing the classifier.
- training set - a subset to train a model.(Model learns patterns between Input and Output)
- Then we need to import the Logistic regression method from the linear_model package from scikit learn library.
- We need to train the model based on our train set.
    - Import the model
    - Creating an object
    - Fitting the object on training data.



```
# importing the model
from sklearn.linear_model import LogisticRegression

# creating object
reg=LogisticRegression()

# fitting object on training data
reg.fit(X_train,y_train)
```

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

●

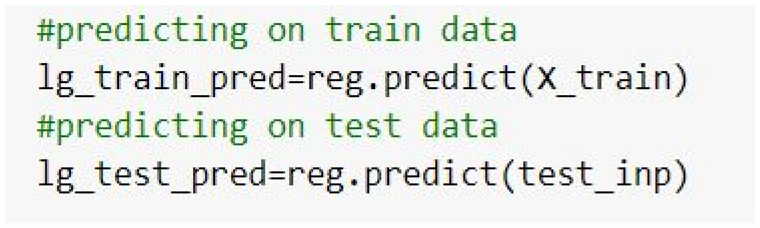
Figure 5.1.2 Importing,object creation and training

- Now we have a trained Logistic Regression model "reg".

5.1.3 Making Predictions And Testing

- Predict method of the object is used to make the predictions.
- It takes input data as an argument and returns a numpy array containing the predictions.

Predicting on training and testing data.



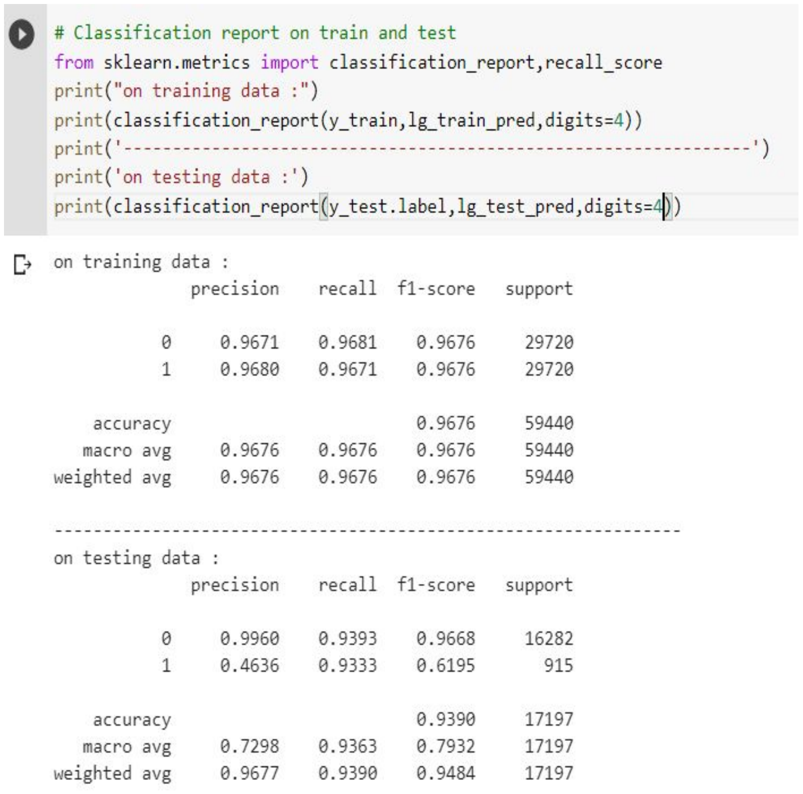
```
#predicting on train data
lg_train_pred=reg.predict(X_train)
#predicting on test data
lg_test_pred=reg.predict(test_inp)
```

Figure 5.1.3: Predicting on training and testing data

- We have the predicted output on both training and testing data.

5.1.4 Generating Classification Report

- We generate the classification report for both training and testing data.



```
# Classification report on train and test
from sklearn.metrics import classification_report,recall_score
print("on training data :")
print(classification_report(y_train,lg_train_pred,digits=4))
print('------------------------------------------------------------')
print('on testing data :')
print(classification_report(y_test.label,lg_test_pred,digits=4))
```

```
on training data :
              precision    recall  f1-score   support

           0     0.9671    0.9681    0.9676     29720
           1     0.9680    0.9671    0.9676     29720

    accuracy                         0.9676     59440
   macro avg     0.9676    0.9676    0.9676     59440
weighted avg     0.9676    0.9676    0.9676     59440

------------------------------------------------------------
on testing data :
              precision    recall  f1-score   support

           0     0.9960    0.9393    0.9668     16282
           1     0.4636    0.9333    0.6195       915

    accuracy                         0.9390     17197
   macro avg     0.7298    0.9363    0.7932     17197
weighted avg     0.9677    0.9390    0.9484     17197
```

Figure 5.1.4: Logistic Regression classification report

- Since we perform synthetic sample generation to balance the data, we can consider the accuracy score as an evaluation metric.
- We observe that the accuracy score for :

  Training data : 0.9676

  Testing data : 0.9390

Which implies correct predictions are made for 93.9 % of the time on test data.

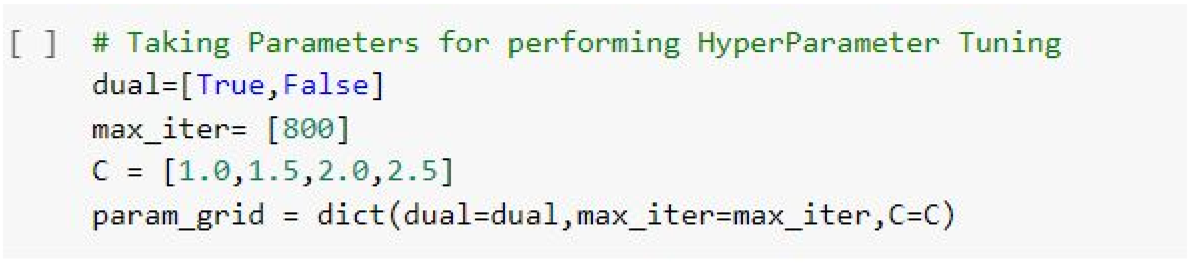
5.1.5 Hyperparameter Tuning For Logistic Regression

- A hyperparameter is a parameter whose value is set before the learning process begins.
- Hyperparameter value will reduce the loss of the model,hence,increasing the evaluation metric
- Hyperparameters are taken by specifying the range of possible values for the parameters of that model and understand how they are affecting the model architecture and performance.

Grid Search CV:

- It is a traditional way to perform hyperparameter optimization,it works by searching exhaustively through a specified set of hyperparameters.
- Using sklearn's GridSearchCV, we first define our grid of parameters to search over and then run the grid search.

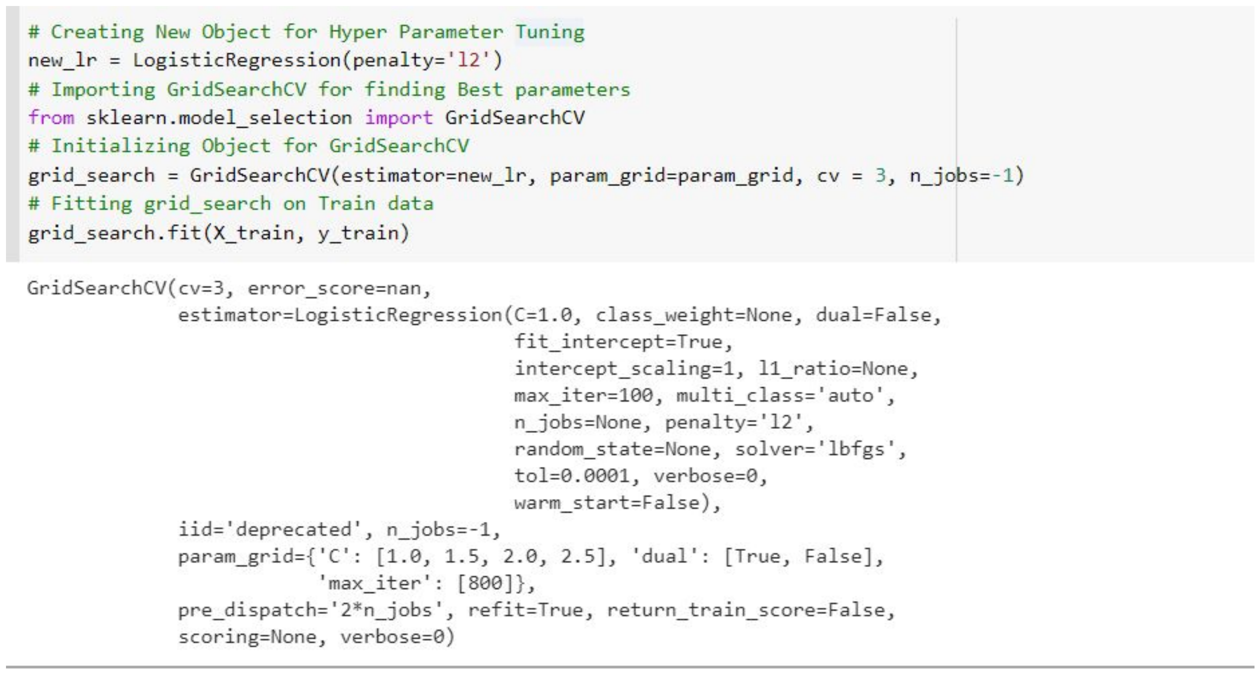
Considering the range of parameters



```
# Taking Parameters for performing HyperParameter Tuning
dual=[True,False]
max_iter= [800]
C = [1.0,1.5,2.0,2.5]
param_grid = dict(dual=dual,max_iter=max_iter,C=C)
```

Figure 5.1.5.1: Setting range of parameters of hyper parameter tuning

Performing the GridSearchCV

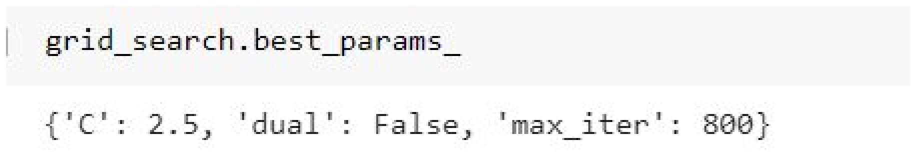


```
# Creating New Object for Hyper Parameter Tuning
new_lr = LogisticRegression(penalty='l2')
# Importing GridSearchCV for finding Best parameters
from sklearn.model_selection import GridSearchCV
# Initializing Object for GridSearchCV
grid_search = GridSearchCV(estimator=new_lr, param_grid=param_grid, cv = 3, n_jobs=-1)
# Fitting grid_search on Train data
grid_search.fit(X_train, y_train)
```

```
GridSearchCV(cv=3, error_score=nan,
             estimator=LogisticRegression(C=1.0, class_weight=None, dual=False,
                                          fit_intercept=True,
                                          intercept_scaling=1, l1_ratio=None,
                                          max_iter=100, multi_class='auto',
                                          n_jobs=None, penalty='l2',
                                          random_state=None, solver='lbfgs',
                                          tol=0.0001, verbose=0,
                                          warm_start=False),
             iid='deprecated', n_jobs=-1,
             param_grid={'C': [1.0, 1.5, 2.0, 2.5], 'dual': [True, False],
                         'max_iter': [800]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

Figure 5.1.5.2: Performing the GridSearchCV

Generating best parameters

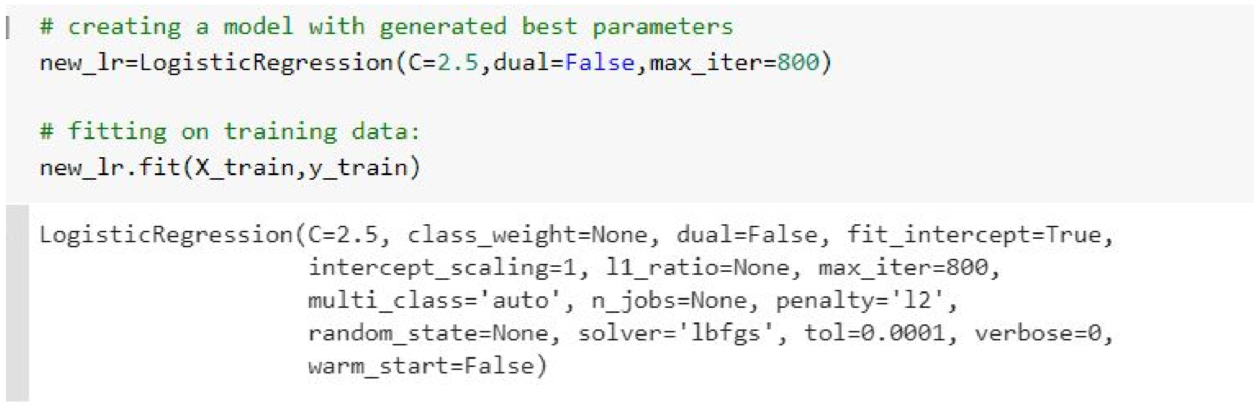


```
grid_search.best_params_
```

```
{'C': 2.5, 'dual': False, 'max_iter': 800}
```

Figure 5.1.5.3: Extracting best parameters

Creating a new model and fitting best parameters

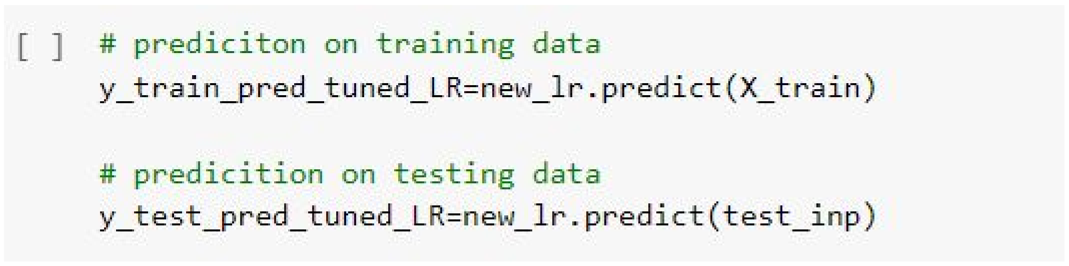


```
# creating a model with generated best parameters
new_lr=LogisticRegression(C=2.5,dual=False,max_iter=800)

# fitting on training data:
new_lr.fit(X_train,y_train)
```

```
LogisticRegression(C=2.5, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=800,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

Figure 5.1.5.4 fitting the new model with best parameters

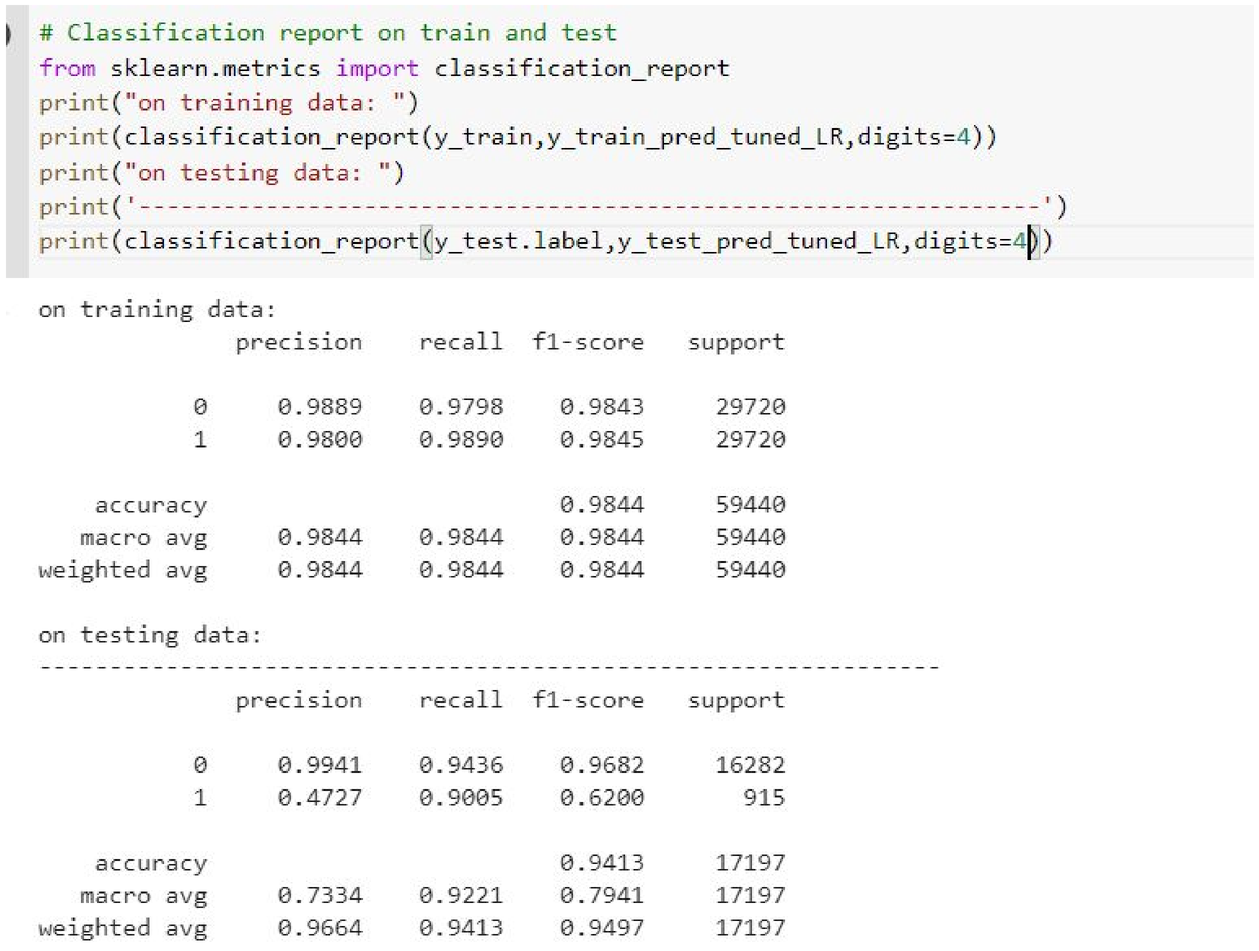
Predicting training and testing data



```
[ ]  # prediciton on training data
     y_train_pred_tuned_LR=new_lr.predict(X_train)

     # predicition on testing data
     y_test_pred_tuned_LR=new_lr.predict(test_inp)
```

Figure 5.1.5.5 Making predictions on train and test data

New classification report



```
# Classification report on train and test
from sklearn.metrics import classification_report
print("on training data: ")
print(classification_report(y_train,y_train_pred_tuned_LR,digits=4))
print("on testing data: ")
print('----------------------------------------------------------------')
print(classification_report(y_test.label,y_test_pred_tuned_LR,digits=4))
```

```
on training data:
              precision    recall  f1-score   support

           0     0.9889    0.9798    0.9843     29720
           1     0.9800    0.9890    0.9845     29720

    accuracy                         0.9844     59440
   macro avg     0.9844    0.9844    0.9844     59440
weighted avg     0.9844    0.9844    0.9844     59440

on testing data:
----------------------------------------------------------------
              precision    recall  f1-score   support

           0     0.9941    0.9436    0.9682     16282
           1     0.4727    0.9005    0.6200       915

    accuracy                         0.9413     17197
   macro avg     0.7334    0.9221    0.7941     17197
weighted avg     0.9664    0.9413    0.9497     17197
```

Figure 5.1.5.6: New classification report for Logistic Regression with best parameters

Observation:

The accuracy increases from 0.9390 to 0.9413 after hyper parameter tuning.

5.2 DECISION TREE CLASSIFIER

5.2.1 About The Algorithm

Decision tree is one of the predictive modelling approaches used in statistics, data mining and machine learning.Decision trees are constructed via an algorithmic approach that identifies ways to split a data set based on different conditions. It is one of the most widely used and practical methods for supervised learning. Decision Trees are a non-parametric supervised learning method used for both classification and regression tasks.

- Decision trees are generated by splitting an attribute as a node.
- The attribute to be split is selected such that it has highest information gain and lowest entropy.

Entropy

Entropy is an indicator of how messy your data is.Entropy is the measure of randomness or unpredictability in the dataset. In other terms, it controls how a decision tree decides to split the data. Entropy is the measure of homogeneity in the data. Its value ranges from 0 to 1.It measures the impurity of the split. Gini index is also used instead of entropy.

$$Info(D) = -\sum_{i=1}^{m} p_i \log_2(p_i)$$

Figure 5.2.1.1: entropy

Information gain

Information gain (IG) measures how much “information” a feature gives us about the class.

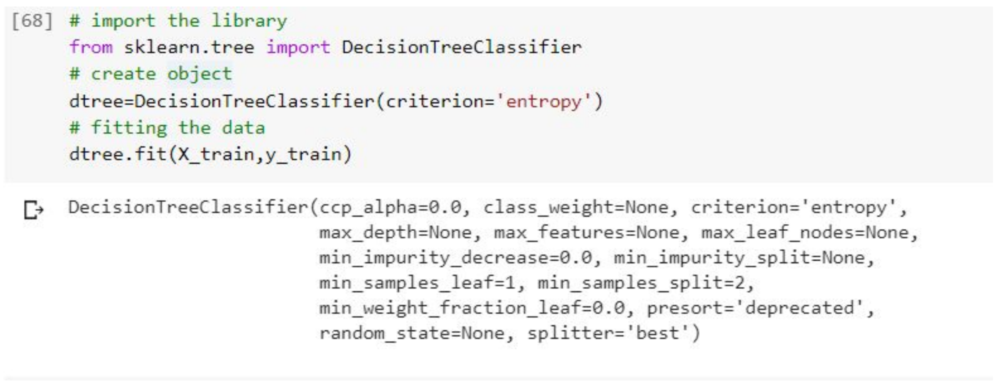
$$\text{Information gain} = \text{base entropy} - \text{new entropy}$$

$$Information\ Gain\ =\ Entropy(before) - \sum_{j=1}^{K} Entropy(j,\ after)$$

Figure 5.2.1.2: information gain

5.2.2 Train The Model

- In Machine Learning in order to access the performance of the classifier. You train the classifier using 'training set' and then test the performance of your classifier on unseen 'test set'. An important point to note is that during training the classifier only uses the training set . The test set must not be used during training the classifier. The test set will only be available during testing the classifier.
- training set - a subset to train a model.(Model learns patterns between Input and Output)
- Then we need to import the Decision tree classifier method from the tree package from scikit learn library.
- We need to train the model based on our train set.
    1. Import the model
    2. Creating an object
    3. Fitting the object on training data.



```
[68] # import the library
     from sklearn.tree import DecisionTreeClassifier
     # create object
     dtree=DecisionTreeClassifier(criterion='entropy')
     # fitting the data
     dtree.fit(X_train,y_train)
```

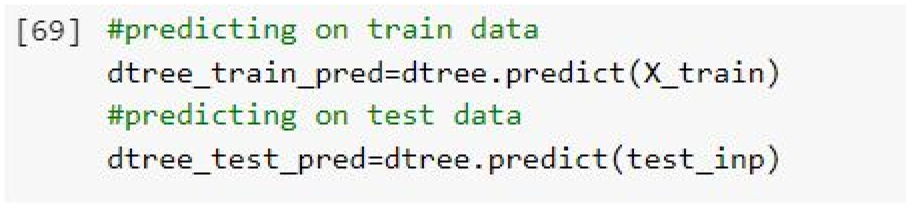
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='entropy',
                       max_depth=None, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

Figure 5.2.2: importing,training and fitting decision tree classifier

5.2.3 Making Predictions And Testing

- Predict method of the object is used to make the predictions.
- It takes input data as an argument and returns a numpy array containing the predictions.

Predicting on training and testing data



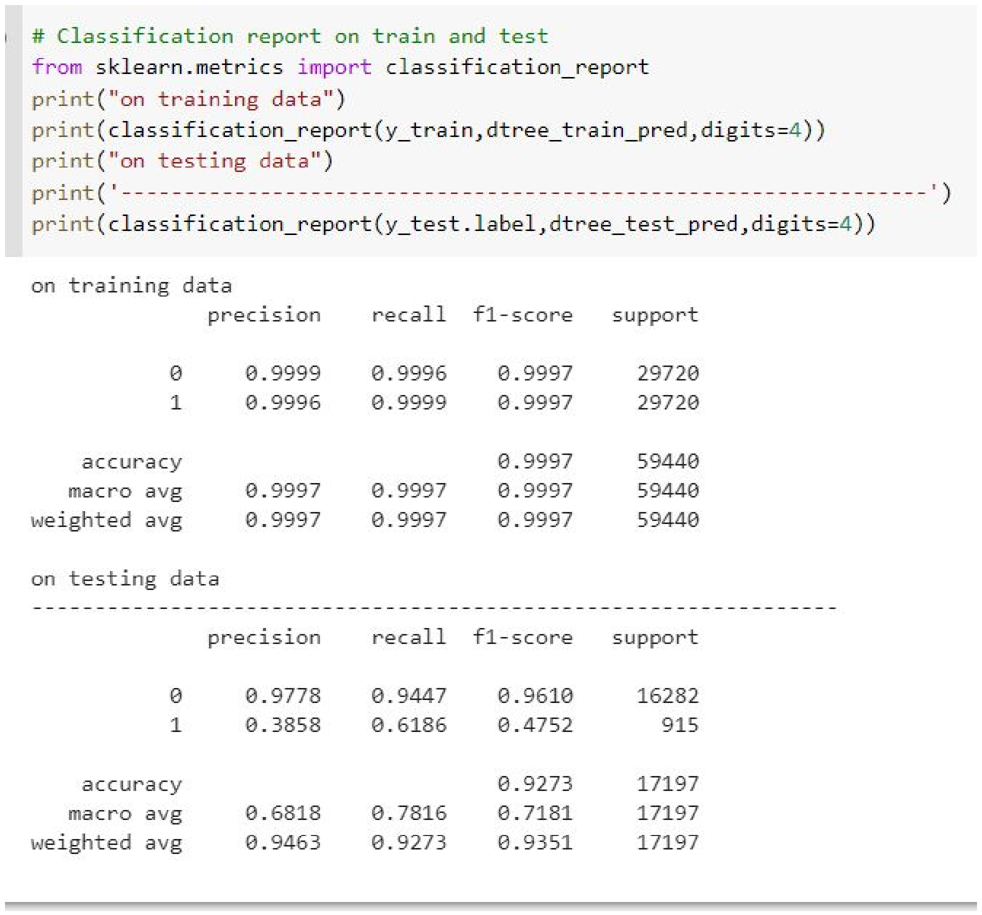
```
[69] #predicting on train data
     dtree_train_pred=dtree.predict(X_train)
     #predicting on test data
     dtree_test_pred=dtree.predict(test_inp)
```

Figure 5.2.3: predicting on training and testing data

- Now we have the predicted output for training and testing data

5.2.4 Generating Classification Report

- We generate the classification report for both training and testing data.



```
# Classification report on train and test
from sklearn.metrics import classification_report
print("on training data")
print(classification_report(y_train,dtree_train_pred,digits=4))
print("on testing data")
print('----------------------------------------------------------------')
print(classification_report(y_test.label,dtree_test_pred,digits=4))
```

```
on training data
              precision    recall  f1-score   support

           0     0.9999    0.9996    0.9997     29720
           1     0.9996    0.9999    0.9997     29720

    accuracy                         0.9997     59440
   macro avg     0.9997    0.9997    0.9997     59440
weighted avg     0.9997    0.9997    0.9997     59440

on testing data
----------------------------------------------------------------
              precision    recall  f1-score   support

           0     0.9778    0.9447    0.9610     16282
           1     0.3858    0.6186    0.4752       915

    accuracy                         0.9273     17197
   macro avg     0.6818    0.7816    0.7181     17197
weighted avg     0.9463    0.9273    0.9351     17197
```

Figure 5.2.4 Decision tree classifier classification report

Since we perform synthetic sample generation to balance the data, we can consider the accuracy score as an evaluation metric.

We observe that the accuracy score for

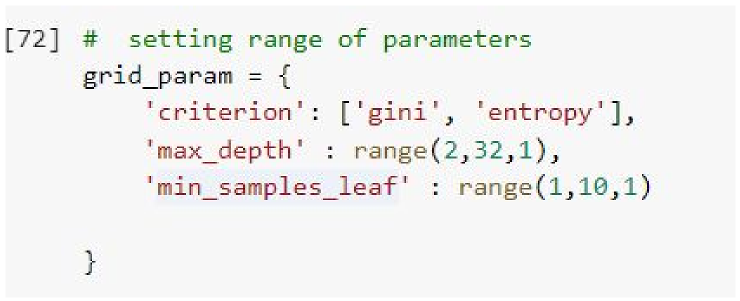
- Training data : 0.9991
- Testing data : 0.9273

Which implies correct predictions are made for 92.7 % of the time on test data.

5.2.5 Hyperparameter Tuning For Decision Tree Classifier:

Hyperparameter tuning explained in section 6.1.5

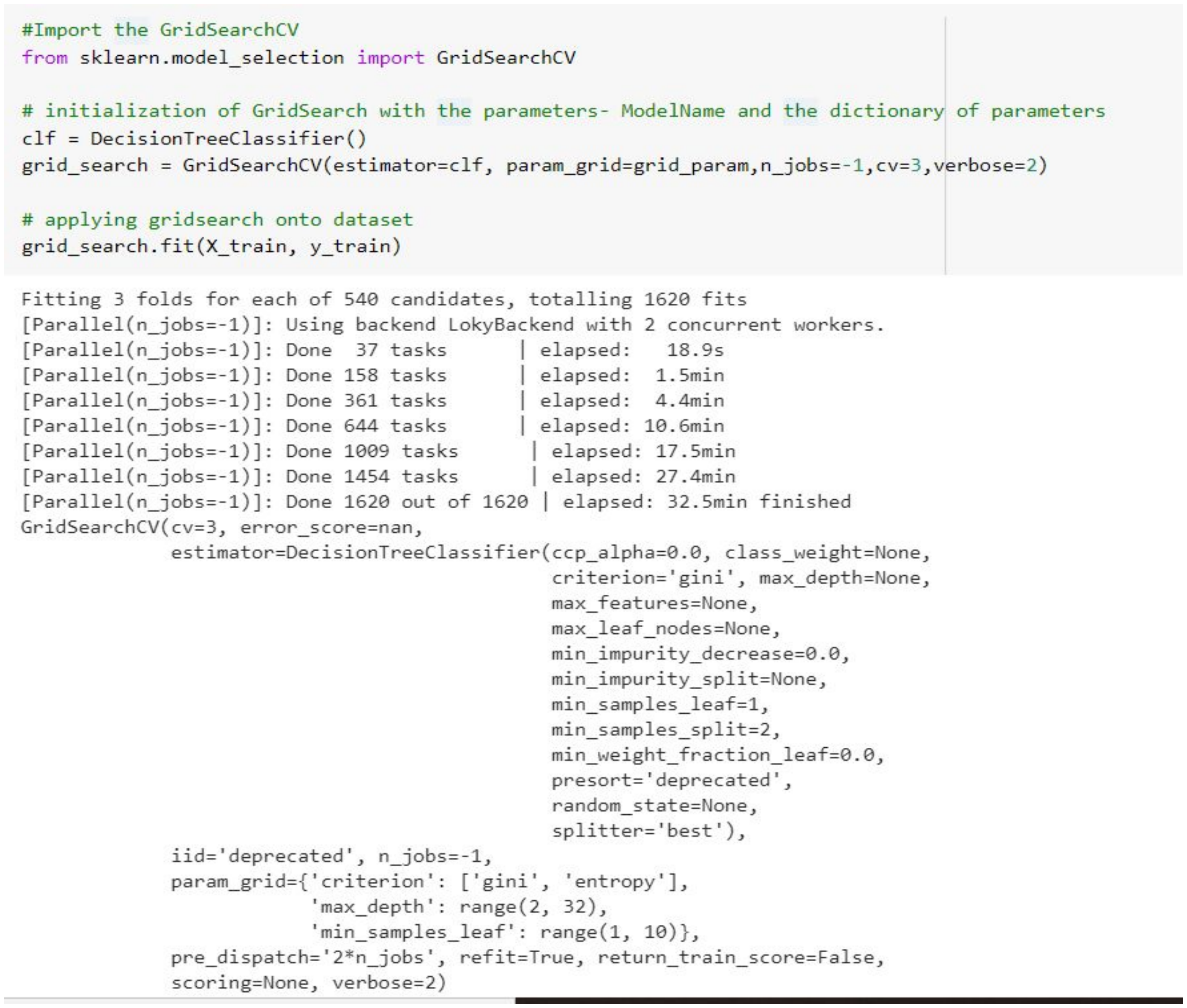
Considering the range of parameters:



```
[72] #  setting range of parameters
     grid_param = {
         'criterion': ['gini', 'entropy'],
         'max_depth' : range(2,32,1),
         'min_samples_leaf' : range(1,10,1)

     }
```

Figure 5.2.5.1: setting range of parameters for GridSearchCV

Performing the GridSearchCV

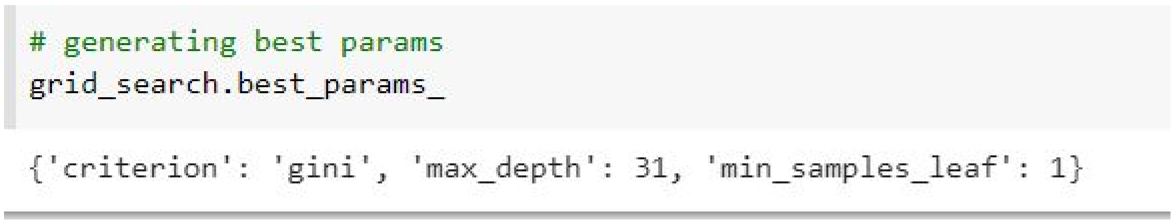


```
#Import the GridSearchCV
from sklearn.model_selection import GridSearchCV

# initialization of GridSearch with the parameters- ModelName and the dictionary of parameters
clf = DecisionTreeClassifier()
grid_search = GridSearchCV(estimator=clf, param_grid=grid_param,n_jobs=-1,cv=3,verbose=2)

# applying gridsearch onto dataset
grid_search.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 540 candidates, totalling 1620 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  37 tasks      | elapsed:   18.9s
[Parallel(n_jobs=-1)]: Done 158 tasks      | elapsed:  1.5min
[Parallel(n_jobs=-1)]: Done 361 tasks      | elapsed:  4.4min
[Parallel(n_jobs=-1)]: Done 644 tasks      | elapsed: 10.6min
[Parallel(n_jobs=-1)]: Done 1009 tasks      | elapsed: 17.5min
[Parallel(n_jobs=-1)]: Done 1454 tasks      | elapsed: 27.4min
[Parallel(n_jobs=-1)]: Done 1620 out of 1620 | elapsed: 32.5min finished
GridSearchCV(cv=3, error_score=nan,
             estimator=DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None,
                                              criterion='gini', max_depth=None,
                                              max_features=None,
                                              max_leaf_nodes=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
                                              presort='deprecated',
                                              random_state=None,
                                              splitter='best'),
             iid='deprecated', n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': range(2, 32),
                         'min_samples_leaf': range(1, 10)},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=2)
```

Figure 5.2.5.2: Performing the GridSearchCV

Generating best parameters

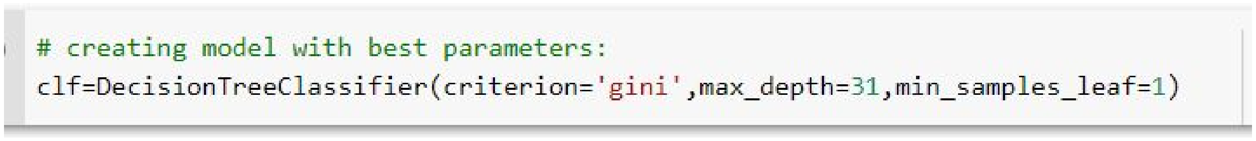


```
# generating best params
grid_search.best_params_
```

```
{'criterion': 'gini', 'max_depth': 31, 'min_samples_leaf': 1}
```

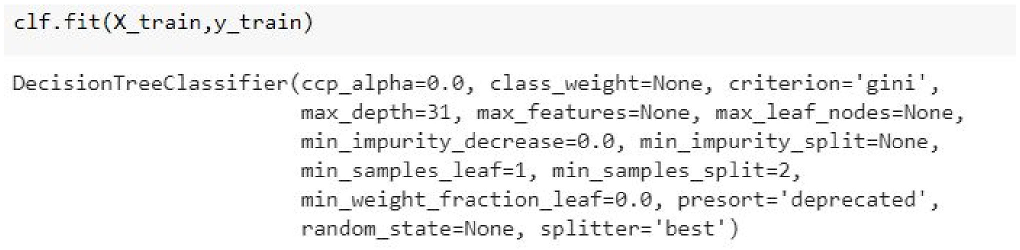
Figure 5.2.5.3: Extracting best parameters

Creating a new model and fitting best parameters



```
# creating model with best parameters:
clf=DecisionTreeClassifier(criterion='gini',max_depth=31,min_samples_leaf=1)
```

Figure 5.2.5.4: Building new model with best parameters

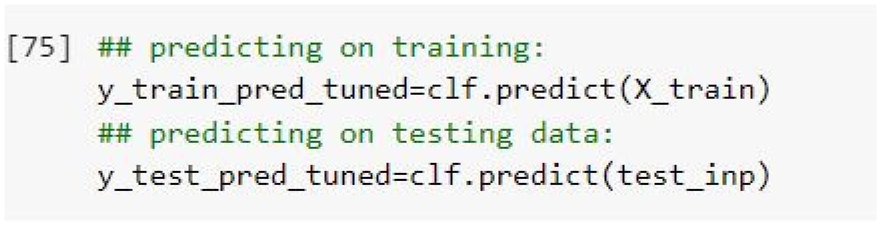


```
clf.fit(X_train,y_train)
```

```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                       max_depth=31, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

Figure 5.2.5.5: fitting the new model

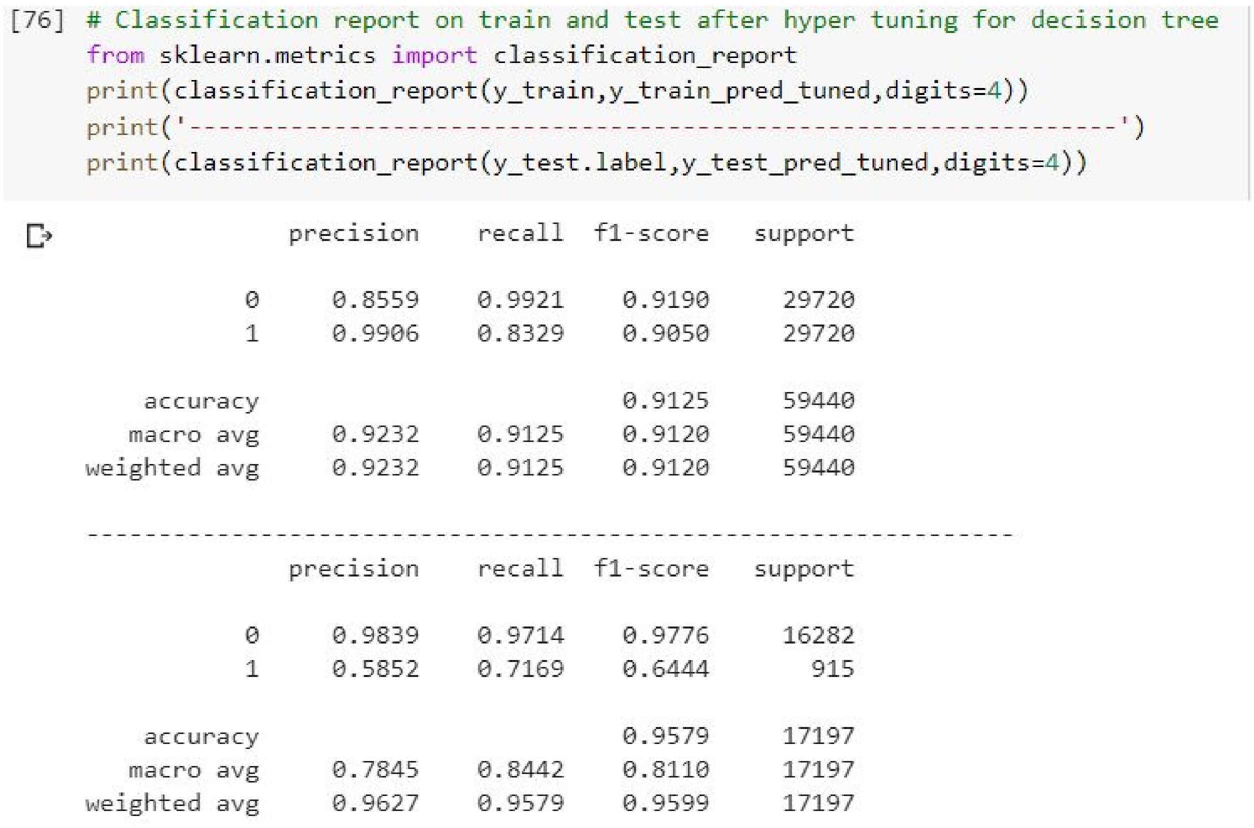
Predicting training and testing data



```
[75] ## predicting on training:
     y_train_pred_tuned=clf.predict(X_train)
     ## predicting on testing data:
     y_test_pred_tuned=clf.predict(test_inp)
```

Figure 5.2.5.6: predicting on training and testing data

New classification report



```
[76] # Classification report on train and test after hyper tuning for decision tree
     from sklearn.metrics import classification_report
     print(classification_report(y_train,y_train_pred_tuned,digits=4))
     print('--------------------------------------------------------------')
     print(classification_report(y_test.label,y_test_pred_tuned,digits=4))
```

```
              precision    recall  f1-score   support

           0     0.8559    0.9921    0.9190     29720
           1     0.9906    0.8329    0.9050     29720

    accuracy                         0.9125     59440
   macro avg     0.9232    0.9125    0.9120     59440
weighted avg     0.9232    0.9125    0.9120     59440

--------------------------------------------------------------
              precision    recall  f1-score   support

           0     0.9839    0.9714    0.9776     16282
           1     0.5852    0.7169    0.6444       915

    accuracy                         0.9579     17197
   macro avg     0.7845    0.8442    0.8110     17197
weighted avg     0.9627    0.9579    0.9599     17197
```

Figure 5.2.5.7: New classification report for decision tree classifier with best parameters

Observations

- Overfitting is balanced as train accuracy comes closer to test accuracy .
- The accuracy on the test data has increased from 0.92 to 0.9579.

5.3 MULTINOMIAL NAIVE BAYES

5.3.1 About The Algorithm

Naive Bayes classifier is a family of algorithms that uses conditional probability approach to solve classification problems. It is based on Bayes theorem and assumes the independence of the features. Even if the features show some interdependence ,the algorithm assumes independence,hence the term “Naive” .

Bayes Rule:

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(B|A)P(A)}{P(B)}$$

Figure 5.3.1.1 Bayes rule

In text classification, the probability of a word per class and logarithm is applied to avoid underflow.

Conditional Independence among variables given Classes!

$$P(C|X_1,X_2,\ldots,X_D) = \frac{P(C)P(X_1,X_2,\ldots,X_D|C)}{\sum_{C'} P(X_1,X_2,\ldots,X_D|C')} = \frac{P(C)\prod_{d=1}^{D} P(X_d|C)}{\sum_{C'}\prod_{d=1}^{D} P(X_d|C')}$$

$$\log\left(P(C|X_1,X_2,\ldots,X_D)\right) \propto \log\left(P(C)\right) + \sum_{d=1}^{D} \log\left(P(X_d|C)\right)$$

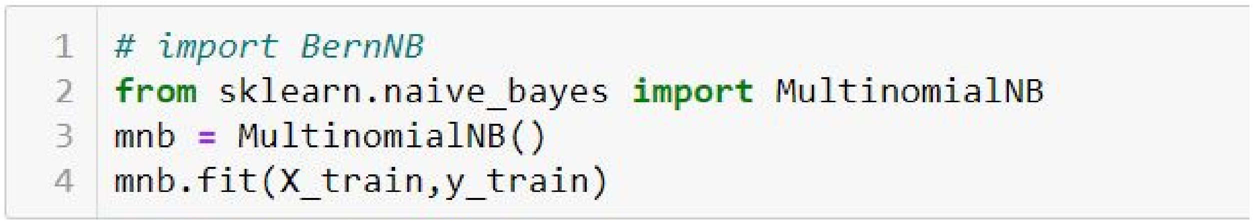
Figures 5.3.1.2 conditional independence **Figure 5.3.1.3 logarithm applied**

Naive Bayes classifier is a general term which refers to conditional independence of each of the features in the model, while Multinomial Naive Bayes classifier is a specific instance of a Naive Bayes classifier which uses a multinomial distribution for each of the features.

5.3.2 Train The Model

In Machine Learning in order to access the performance of the classifier. You train the classifier using 'training set' and then test the performance of your classifier on unseen 'test set'. An important point to note is that during training the classifier only uses the training set . The test set must not be used during training the classifier. The test set will only be available during testing the classifier.

- training set - a subset to train a model.(Model learns patterns between Input and Output)
- Then we need to import the MultinomialNB method from the naive_bayes package from scikit learn library.
- We need to train the model based on our train set.
    - Import the model
    - Creating an object
    - Fitting the object on training data.



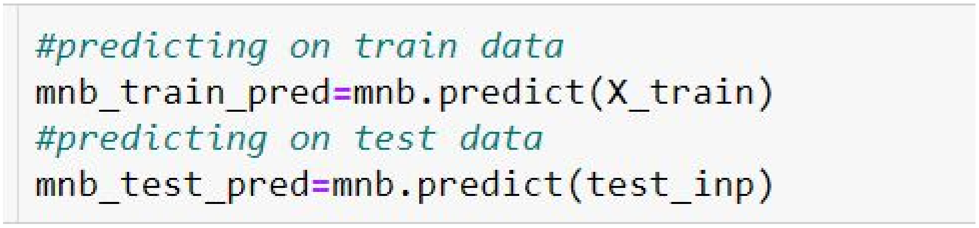
```python
# import BernNB
from sklearn.naive_bayes import MultinomialNB
mnb = MultinomialNB()
mnb.fit(X_train,y_train)
```

Figure 5.3.2 importing training and fitting model

5.3.3 Making Predictions And Testing

- Predict method of the object is used to make the predictions.
- It takes input data as an argument and returns a numpy array containing the predictions.

Predicting on training and testing data

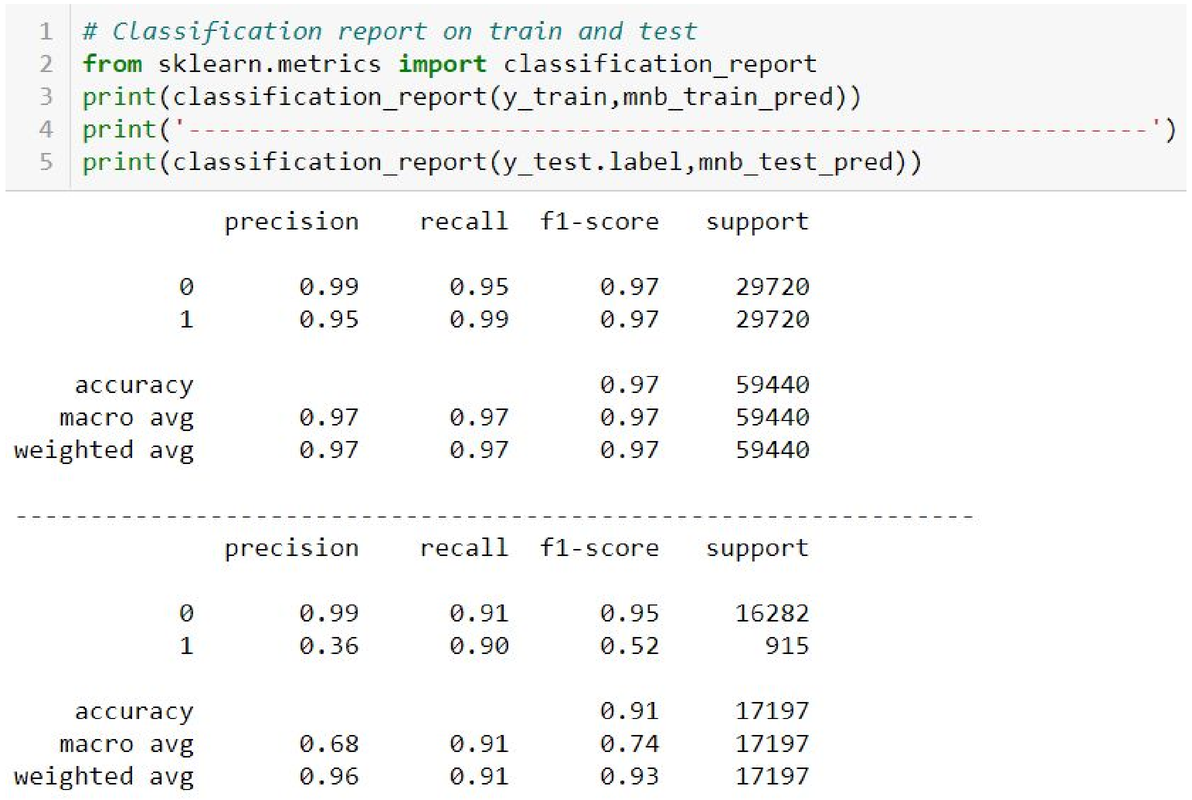


```
#predicting on train data
mnb_train_pred=mnb.predict(X_train)
#predicting on test data
mnb_test_pred=mnb.predict(test_inp)
```

Figure 5.3.3 Making predictions and testing

5.3.4 Generating Classification Report

We generate the classification report for both training and testing data.



```
# Classification report on train and test
from sklearn.metrics import classification_report
print(classification_report(y_train,mnb_train_pred))
print('----------------------------------------------------------------')
print(classification_report(y_test.label,mnb_test_pred))
```

```
              precision    recall  f1-score   support

           0       0.99      0.95      0.97     29720
           1       0.95      0.99      0.97     29720

    accuracy                           0.97     59440
   macro avg       0.97      0.97      0.97     59440
weighted avg       0.97      0.97      0.97     59440

----------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.99      0.91      0.95     16282
           1       0.36      0.90      0.52       915

    accuracy                           0.91     17197
   macro avg       0.68      0.91      0.74     17197
weighted avg       0.96      0.91      0.93     17197
```

Figure 5.3.4 Classification report for MultinomialNB

Comparing the accuracies

Multinomial Naive Bayes - 0.91 on test data

Decision Tree - 0.958 after parameter tuning.

Logistic Regression - 0.9390 after parameter tuning .

Since Multinomial Naive Bayes has the least accuracy among the three, it is eliminated. In the next section, the AUC-ROC scores are checked and the better algorithm out of Decision Tree and Logistic Regression can be found.

5.4 AUC-ROC

An **ROC curve** (**Receiver Operating Characteristic curve**) is a graph showing the performance of a classification model at all classification thresholds. This curve plots two parameters:

- True Positive Rate
- False Positive Rate

It is a probability curve that plots the **TPR** against **FPR** at various threshold values.

The **Area Under the Curve (AUC)** is the measure of the ability of a classifier to distinguish between classes and is used as a summary of the ROC curve.

The higher the AUC, the better the performance of the model at distinguishing between the positive and negative classes.

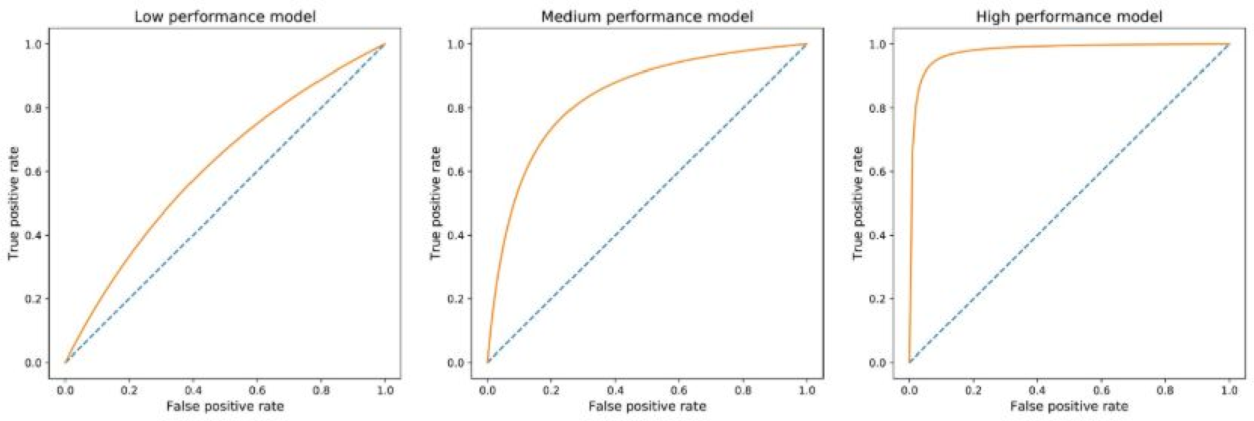
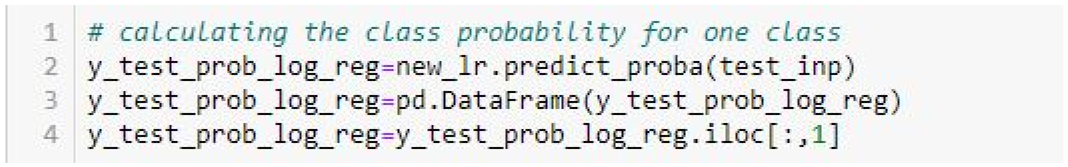


Figure 5.4 AUC-ROC performance comparison

5.4.1 AUC-ROC for Logistic Regression:

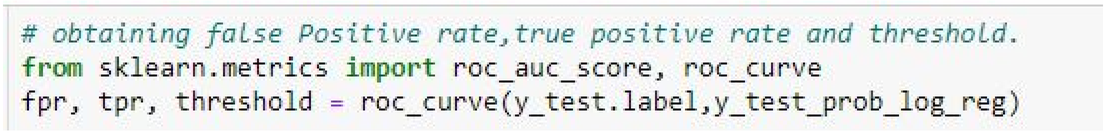
Calculating probability for one class:



```
# calculating the class probability for one class
y_test_prob_log_reg=new_lr.predict_proba(test_inp)
y_test_prob_log_reg=pd.DataFrame(y_test_prob_log_reg)
y_test_prob_log_reg=y_test_prob_log_reg.iloc[:,1]
```

Figure 5.4.1.1 calculating probability

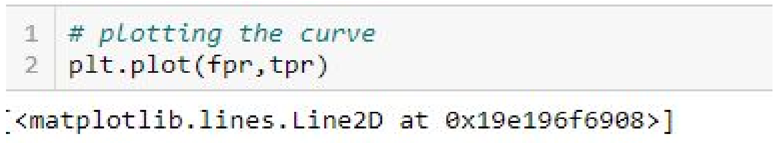
Obtaining objects for FPR,TPR and threshold:



```
# obtaining false Positive rate,true positive rate and threshold.
from sklearn.metrics import roc_auc_score, roc_curve
fpr, tpr, threshold = roc_curve(y_test.label,y_test_prob_log_reg)
```

Figure 5.4.1.2 getting AUC-ROC Objects

Plotting the curve:



```
# plotting the curve
plt.plot(fpr,tpr)
```

```
[<matplotlib.lines.Line2D at 0x19e196f6908>]
```

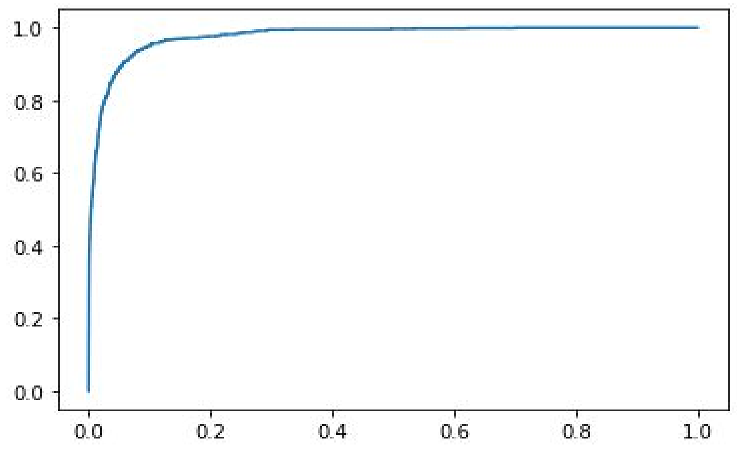
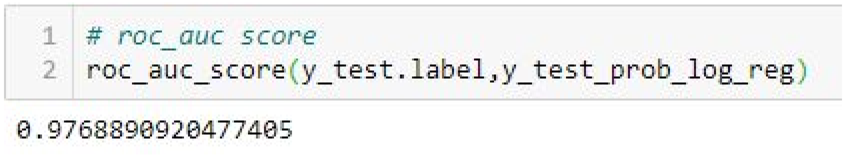


Figure 5.4.1.3 plotting the curve

Printing the AUC_ROC score:



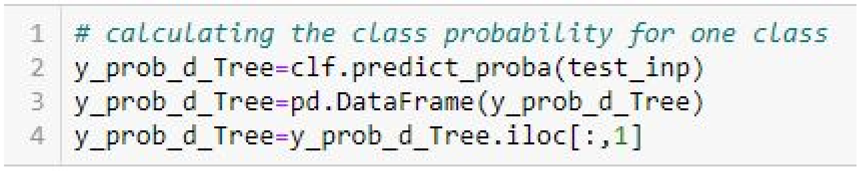
```
# roc_auc score
roc_auc_score(y_test.label,y_test_prob_log_reg)
```

```
0.9768890920477405
```

Figure 5.4.1.4 printing the AUC-ROC score

5.4.2 AUC-ROC for Decision Tree Classifier:

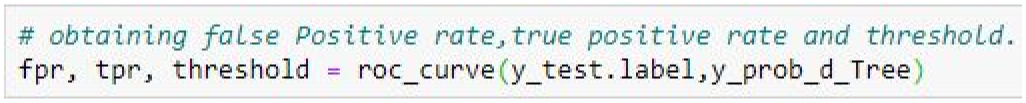
Calculating probability for one class:



```
# calculating the class probability for one class
y_prob_d_Tree=clf.predict_proba(test_inp)
y_prob_d_Tree=pd.DataFrame(y_prob_d_Tree)
y_prob_d_Tree=y_prob_d_Tree.iloc[:,1]
```

Figure 5.4.2.1 calculating probability

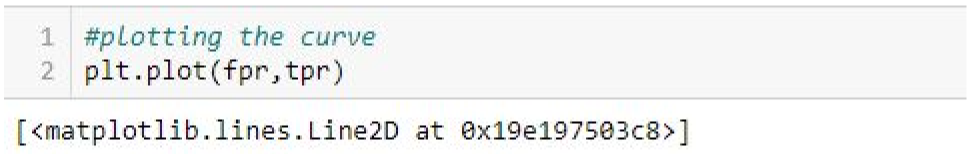
Obtaining objects for FPR,TPR and threshold:



```
# obtaining false Positive rate,true positive rate and threshold.
fpr, tpr, threshold = roc_curve(y_test.label,y_prob_d_Tree)
```

Figure 5.4.2.2 getting AUC-ROC Objects

Plotting the curve:



```
#plotting the curve
plt.plot(fpr,tpr)
```

```
[<matplotlib.lines.Line2D at 0x19e197503c8>]
```

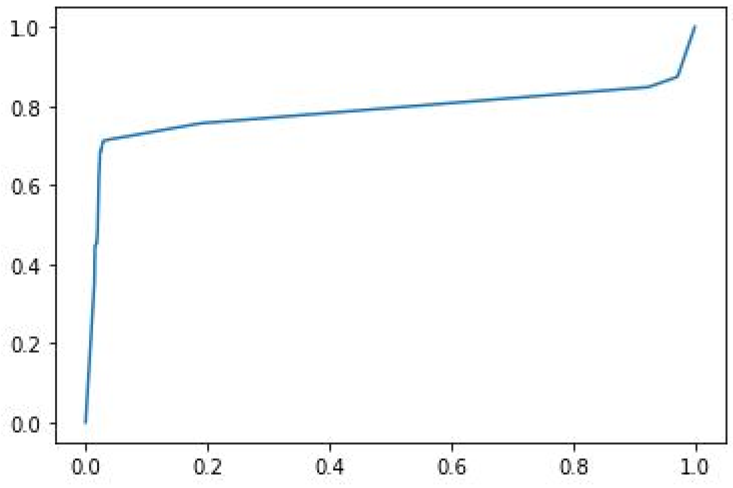
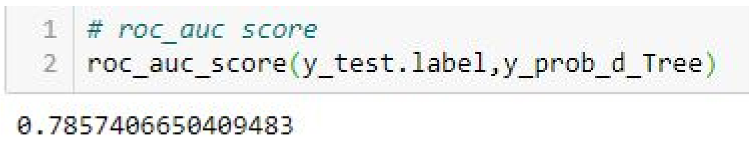


Figure 5.4.2.3 plotting the curve

Printing the AUC_ROC score:



```
# roc_auc score
roc_auc_score(y_test.label,y_prob_d_Tree)
```

```
0.7857406650409483
```

Figure 5.4.2.4 printing the AUC-ROC score

5.4.3 Final Selection of the algorithm:

As we can see in the above two cases , the Area Under The Curve is more for Logistic Regression . Since the distinguishing is clear, we finalize our algorithm as Logistic Regression.

OUTCOME OF THIS STEP:

After building,testing and evaluation of the three models Multinomial Naive Bayes classifier,Linear Regression and decision tree classifier, it is concluded that the logistic regression is the best suitable algorithm with higher efficiency on test data and resolved overfitting through hyper parameter tuning. Hence,this model is used in the following section to predict and visualize real-time data.

CHAPTER 6

SCRAPING REAL-TIME TWITTER DATA

6.1 GET OLD TWEETS 3 LIBRARY:

6.1.1 About the library

A project written in Python to get old tweets, it bypasses some limitations of Twitter Official API.

Advantages:

- It does not require a twitter developer account as the data used is public
- Unlike the twitter API ,tweets more than one week old can be extracted.
- The coding is relatively easy.

6.1.2 Python classes

Tweet: Model class that describes a specific tweet.

- id (str)
- username (str)
- to (str)
- text (str)
- date (datetime) in UTC

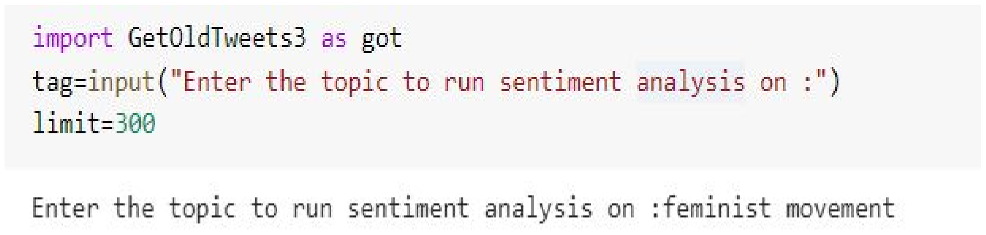
TweetManager: A manager class to help getting tweets in Tweet's model.

- getTweets (TwitterCriteria): Return the list of tweets retrieved by using an instance of TwitterCriteria.
- TwitterCriteria: A collection of search parameters to be used together with TweetManager.

- setUsername (str or iterable): An optional specific username(s) from a twitter account (with or without "@").
- setSince (str. "yyyy-mm-dd"): A lower bound date (UTC) to restrict search.
- setUntil (str. "yyyy-mm-dd"): An upper bound date not included to restrict search.
- setQuerySearch (str): A query text to be matched.
- setMaxTweets (int): The maximum number of tweets to be retrieved. If this number is unsettled or lower than 1 all possible tweets will be retrieved.

6.1.3 Applying the GetOldTweets:

Import the library :



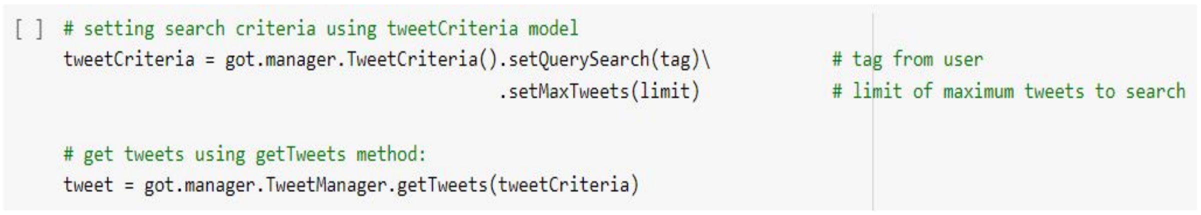
```
import GetOldTweets3 as got
tag=input("Enter the topic to run sentiment analysis on :")
limit=300
```

```
Enter the topic to run sentiment analysis on :feminist movement
```

Figure 6.1.3.1: import GetOldTweets, read input for topic

“Feminist movement” is the topic entered by the user.

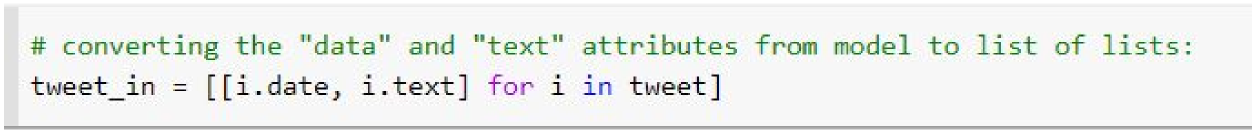
Setting criteria and extracting tweets:



```
[ ] # setting search criteria using tweetCriteria model
    tweetCriteria = got.manager.TweetCriteria().setQuerySearch(tag)\          # tag from user
                                              .setMaxTweets(limit)            # limit of maximum tweets to search

    # get tweets using getTweets method:
    tweet = got.manager.TweetManager.getTweets(tweetCriteria)
```

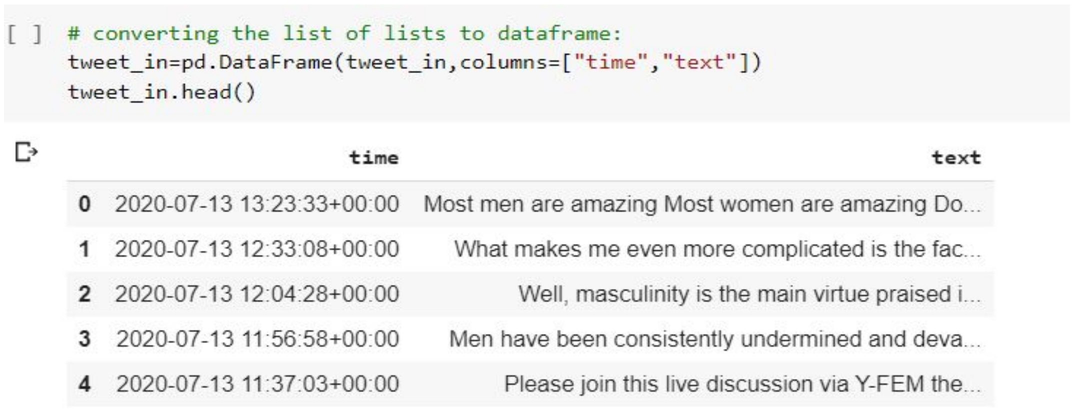
Figure 6.1.3.2: setting criteria and extracting tweets

Formatting to dataframe:



```
# converting the "data" and "text" attributes from model to list of lists:
tweet_in = [[i.date, i.text] for i in tweet]
```

Figure 6.1.3.3: formatting to data frame

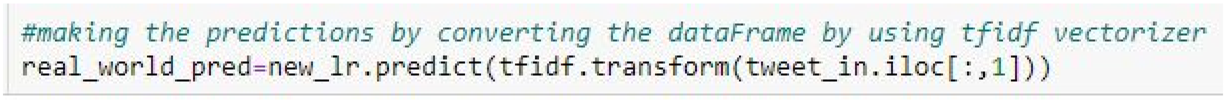


```
[ ] # converting the list of lists to dataframe:
    tweet_in=pd.DataFrame(tweet_in,columns=["time","text"])
    tweet_in.head()
```

```
                       time                                              text
0  2020-07-13 13:23:33+00:00  Most men are amazing Most women are amazing Do...
1  2020-07-13 12:33:08+00:00     What makes me even more complicated is the fac...
2  2020-07-13 12:04:28+00:00            Well, masculinity is the main virtue praised i...
3  2020-07-13 11:56:58+00:00      Men have been consistently undermined and deva...
4  2020-07-13 11:37:03+00:00          Please join this live discussion via Y-FEM the...
```

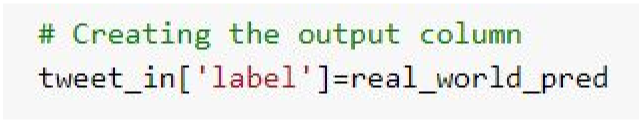
Figure 6.1.3.4: formatting to data frame

Making predictions:



```python
#making the predictions by converting the dataFrame by using tfidf vectorizer
real_world_pred=new_lr.predict(tfidf.transform(tweet_in.iloc[:,1]))
```

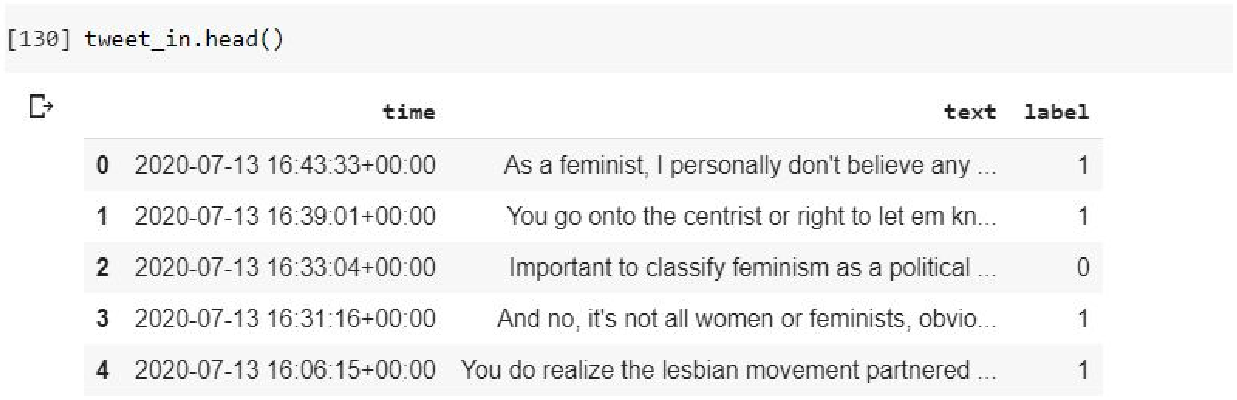
Figure 6.1.3.5: predicting on new unseen data



```python
# Creating the output column
tweet_in['label']=real_world_pred
```

Figure 6.1.3.6: appending output column

Final Predictions:



```
[130] tweet_in.head()
```

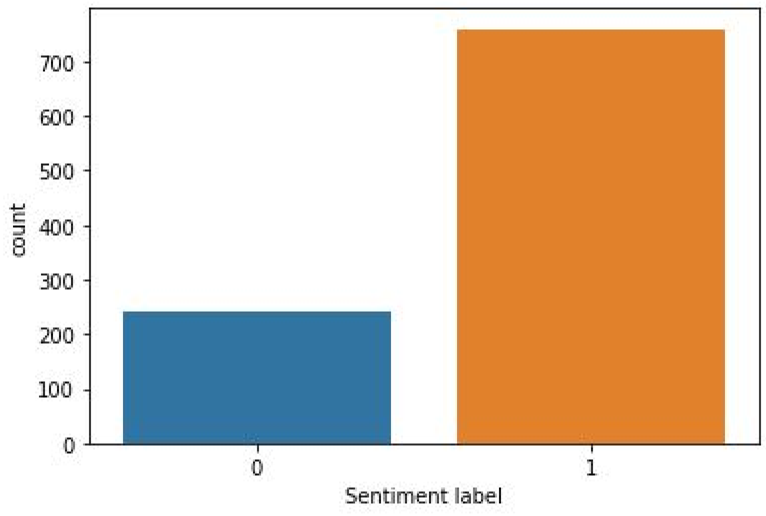
```
                        time                                               text  label
0  2020-07-13 16:43:33+00:00     As a feminist, I personally don't believe any ...      1
1  2020-07-13 16:39:01+00:00      You go onto the centrist or right to let em kn...      1
2  2020-07-13 16:33:04+00:00      Important to classify feminism as a political ...      0
3  2020-07-13 16:31:16+00:00   And no, it's not all women or feminists, obvio...      1
4  2020-07-13 16:06:15+00:00  You do realize the lesbian movement partnered ...      1
```

Figure 6.1.3.7: Final Predictions

6.1.4 Visualizing the predictions:

Using countplot:

```
import matplotlib.pyplot as plt
plt.xlabel("Sentiment label")
plt.ylabel("count")
sns.countplot(real_world_pred)
# 0- positive tweets
# 1- negative tweets
plt.show()
```



Observations :

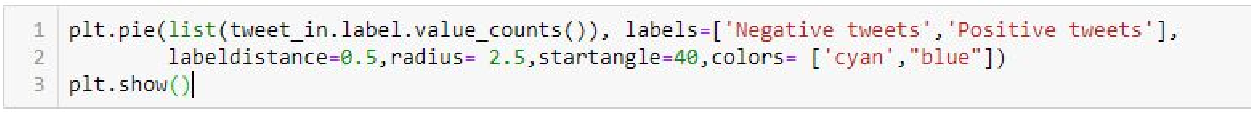
- The topic "feminist movement" have a 1:3 positive:negative sentiment

```
tweet_in.label.value_counts()
```

```
1    759
0    241
```

Figure 6.1.4.1: Countplot of positive and negative tweets

Using pie plots to see the distribution:



```python
plt.pie(list(tweet_in.label.value_counts()), labels=['Negative tweets','Positive tweets'],
        labeldistance=0.5,radius= 2.5,startangle=40,colors= ['cyan',"blue"])
plt.show()
```

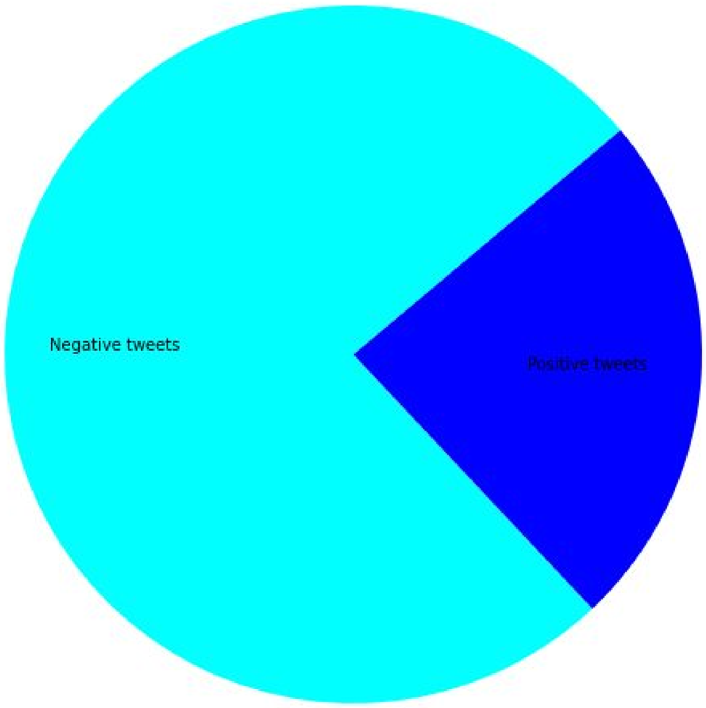


Figure 6.1.4.2: Pie chart for the distribution of tweets

Observations:

The topic "feminist movement" seems to have almost equally divided sentiment over twitter.

CONCLUSION

In conclusion of this case study, a machine learning model using Logistic Regression algorithm is built for a client whose purpose is to analyse the public response through sentiment analysis on a particular topic (on twitter platform). Sentiment analysis can be done by brands for market response on certain products, a film or book response, the sentiment around socialist movement etc, can be observed by the client successfully and the generated reports and predictions can be effectively tackled by taking their respective domain related measures accordingly.

Example:

Analysis performed on "feminist movement" in this case study can be used to understand the extent of debatability of the topic and plan news programs and panels accordingly.

REFERENCES

Code at: **https://github.com/VishnuPulipaka/TwitterSentimentAnalysis**

- **https://stackoverflow.com/questions/8376691/how-to-remove-hashtag-user-link-of-a-tweet-using-regular-expression**
- **https://medium.com/@SeoJaeDuk/basic-data-cleaning-engineering-session-twitter-sentiment-data-b9376a91109b**
- **https://stackoverflow.com/questions/29523254/python-remove-stop-words-from-pandas-dataframe**
- **https://stackoverflow.com/questions/771918/how-do-i-do-word-stemming-or-lemmatization**
- **https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html**
- **https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html**
- **https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html**
- **https://pypi.org/project/GetOldTweets3/**