Amazon Fine Food Reviews Analysis

Data Source: https://www.kaggle.com/snap/amazon-fine-food-reviews (https://www.kaggle.com/snap/amazon-fine-food-reviews)

EDA: https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/ (https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/)

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454
Number of users: 256,059
Number of products: 74,258
Timespan: Oct 1999 - Oct 2012
Number of Attributes/Columns in data: 10

Attribute Information:

1. Id
2. ProductId - unique identifier for the product
3. UserId - unqiue identifier for the user
4. ProfileName
5. HelpfulnessNumerator - number of users who found the review helpful
6. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
7. Score - rating between 1 and 5
8. Time - timestamp for the review
9. Summary - brief summary of the review
10. Text - text of the review

Objective:

Given a review, determine whether the review is positive (rating of 4 or 5) or negative (rating of 1 or 2).

[Q] How to determine if a review is positive or negative?

[Ans] We could use Score/Rating. A rating of 4 or 5 can be cosnidered as a positive review. A rating of 1 or 2 can be considered as negative one. A review of rating 3 is considered nuetral and such reviews are ignored from our analysis. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

[1]. Reading Data

[1.1] Loading the data

The dataset is available in two forms

1. .csv file
2. SQLite Database

In order to load the data, We have used the SQLITE dataset as it is easier to query the data and visualise the data efficiently.

Here as we only want to get the global sentiment of the recommendations (positive or negative), we will purposefully ignore all Scores equal to 3. If the score is above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

In [1]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer
from scipy import sparse
import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle

from tqdm import tqdm
import os

from sklearn.model_selection import GridSearchCV
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import cross_val_score
from sklearn.naive_bayes import BernoulliNB
from scipy.sparse import coo_matrix, hstack
```

In [2]:
```
# using SQLite Table to read data.
con = sqlite3.connect('database.sqlite')

# filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
# SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000, will give top 500000 data po
ints
# you can change the number to any other number based on your computing power

# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMI
T 500000""", con)
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 """, c
on)

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a nega
tive rating(0).
def partition(x):
    if x < 3:
        return 0
    return 1

#changing reviews with score less than 3 to be positive and vice-versa
actualScore = filtered_data['Score']
positiveNegative = actualScore.map(partition)
filtered_data['Score'] = positiveNegative
print("Number of data points in our data", filtered_data.shape)
filtered_data.head(3)
```

```
Number of data points in our data (525814, 10)
```

Out[2]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominat
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1

In [3]:
```
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
""", con)
```

In [4]:
```
print(display.shape)
display.head()
```

```
(80668, 7)
```

Out[4]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
0	#oc-R115TNMSPFT9I7	B007Y59HVM	Breyton	1331510400	2	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ET0	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B007Y59HVM	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ET0	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBE1U	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	2

In [5]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[5]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
80638	AZY10LLTJ71NX	B006P7E5ZI	undertheshrine "undertheshrine"	1334707200	5	I was recommended to try green tea extract to ...	5

In [6]:
```
display['COUNT(*)'].sum()
```

Out[6]: 393063

[2] Exploratory Data Analysis

[2.1] Data Cleaning: Deduplication

It is observed (as shown in the table below) that the reviews data had many duplicate entries. Hence it was necessary to remove duplicates in order to get unbiased results for the analysis of the data. Following is an example:

In [7]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[7]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomin
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	2
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	2
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	2
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	2
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	2

As it can be seen above that same user has multiple reviews with same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that

ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8)

ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

It was inferred after analysis that reviews with same parameters other than ProductId belonged to the same product just having different flavour or quantity. Hence in order to reduce redundancy it was decided to eliminate the rows having same parameters.

The method used for the same was that we first sort the data according to ProductId and then just keep the first similar product review and delelte the others. for eg. in the above just the review for ProductId=B000HDL1RQ remains. This method ensures that there is only one representative for each product and deduplication without sorting would lead to possibility of different representatives still existing for the same product.

In [8]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=
False, kind='quicksort', na_position='last')
```

In [9]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, ke
ep='first', inplace=False)
final.shape
```

Out[9]:
```
(364173, 10)
```

In [10]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[10]:
```
69.25890143662969
```

Observation:- It was also seen that in two rows given below the value of HelpfulnessNumerator is greater than HelpfulnessDenominator which is not practically possible hence these two rows too are removed from calcualtions

In [11]:

```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[11]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomin
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2

In [12]:

```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [13]:

```
#Before starting the next phase of preprocessing lets see the number of entries lef
t
print(final.shape)

#How many positive and negative reviews are present in our dataset?
final['Score'].value_counts()
```

```
(364171, 10)
```

Out[13]:

```
1    307061
0     57110
Name: Score, dtype: int64
```

[3] Preprocessing

[3.1]. Preprocessing Review Text

Now that we have finished deduplication our data requires some preprocessing before we go on further with analysis and making the prediction model.

Hence in the Preprocessing phase we do the following in the order below:-

1. Begin by removing the html tags
2. Remove any punctuations or limited set of special characters like , or . or # etc.
3. Check if the word is made up of english letters and is not alpha-numeric
4. Check to see if the length of the word is greater than 2 (as it was researched that there is no adjective in 2-letters)
5. Convert the word to lowercase
6. Remove Stopwords
7. Finally Snowball Stemming the word (it was obsereved to be better than Porter Stemming)

After which we collect the words used to describe positive and negative reviews

In [14]:
```
review_length=[]
for sent in final['Text'].values:

    review_length.append(len(sent))
```

In [15]:

```
# printing some random reviews
sent_0 = final['Text'].values[0]
print(sent_0)
print("="*50)

sent_1000 = final['Text'].values[1000]
print(sent_1000)
print("="*50)

sent_1500 = final['Text'].values[1500]
print(sent_1500)
print("="*50)

sent_4900 = final['Text'].values[4900]
print(sent_4900)
print("="*50)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as we'
re driving along and he always can sing the refrain. he's learned about whales,
India, drooping roses:  i love all the new words this book  introduces and the s
illiness of it all.  this is a classic book i am  willing to bet my son will STI
LL be able to recite from memory when he is  in college
==================================================
I was really looking forward to these pods based on the reviews.  Starbucks is g
ood, but I prefer bolder taste.... imagine my surprise when I ordered 2 boxes -
both were expired! One expired back in 2005 for gosh sakes.  I admit that Amazon
agreed to credit me for cost plus part of shipping, but geez, 2 years expired!!!
I'm hoping to find local San Diego area shoppe that carries pods so that I can t
ry something different than starbucks.
==================================================
Great ingredients although, chicken should have been 1st rather than chicken bro
th, the only thing I do not think belongs in it is Canola oil. Canola or rapesee
d is not someting a dog would ever find in nature and if it did find rapeseed in
nature and eat it, it would poison them. Today's Food industries have convinced
the masses that Canola oil is a safe and even better oil than olive or virgin co
conut, facts though say otherwise. Until the late 70's it was poisonous until th
ey figured out a way to fix that. I still like it but it could be better.
==================================================
Can't do sugar.  Have tried scores of SF Syrups.  NONE of them can touch the exc
ellence of this product.<br /><br />Thick, delicious.  Perfect.  3 ingredients:
Water, Maltitol, Natural Maple Flavor.  PERIOD.  No chemicals.  No garbage.<br /
><br />Have numerous friends & family members hooked on this stuff.  My husband
& son, who do NOT like "sugar free" prefer this over major label regular syrup.<
br /><br />I use this as my SWEETENER in baking: cheesecakes, white brownies, mu
ffins, pumpkin pies, etc... Unbelievably delicious...<br /><br />Can you tell I
like it? :)
==================================================
```

In [16]:

```
# remove urls from text python: https://stackoverflow.com/a/40823105/4084039
sent_0 = re.sub(r"http\S+", "", sent_0)
sent_1000 = re.sub(r"http\S+", "", sent_1000)
sent_150 = re.sub(r"http\S+", "", sent_1500)
sent_4900 = re.sub(r"http\S+", "", sent_4900)

print(sent_0)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as we'
re driving along and he always can sing the refrain. he's learned about whales,
India, drooping roses:  i love all the new words this book  introduces and the s
illiness of it all.  this is a classic book i am  willing to bet my son will STI
LL be able to recite from memory when he is  in college
```

In [17]:
```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-a
ll-tags-from-an-element
from bs4 import BeautifulSoup

soup = BeautifulSoup(sent_0, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1000, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1500, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_4900, 'lxml')
text = soup.get_text()
print(text)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as we'
re driving along and he always can sing the refrain. he's learned about whales,
India, drooping roses:  i love all the new words this book  introduces and the s
illiness of it all.  this is a classic book i am  willing to bet my son will STI
LL be able to recite from memory when he is  in college
==================================================
I was really looking forward to these pods based on the reviews.  Starbucks is g
ood, but I prefer bolder taste.... imagine my surprise when I ordered 2 boxes -
both were expired! One expired back in 2005 for gosh sakes.  I admit that Amazon
agreed to credit me for cost plus part of shipping, but geez, 2 years expired!!!
I'm hoping to find local San Diego area shoppe that carries pods so that I can t
ry something different than starbucks.
==================================================
Great ingredients although, chicken should have been 1st rather than chicken bro
th, the only thing I do not think belongs in it is Canola oil. Canola or rapesee
d is not someting a dog would ever find in nature and if it did find rapeseed in
nature and eat it, it would poison them. Today's Food industries have convinced
the masses that Canola oil is a safe and even better oil than olive or virgin co
conut, facts though say otherwise. Until the late 70's it was poisonous until th
ey figured out a way to fix that. I still like it but it could be better.
==================================================
Can't do sugar.  Have tried scores of SF Syrups.  NONE of them can touch the exc
ellence of this product.Thick, delicious.  Perfect.  3 ingredients: Water, Malti
tol, Natural Maple Flavor.  PERIOD.  No chemicals.  No garbage.Have numerous fri
ends & family members hooked on this stuff.  My husband & son, who do NOT like "
sugar free" prefer this over major label regular syrup.I use this as my SWEETENE
R in baking: cheesecakes, white brownies, muffins, pumpkin pies, etc... Unbeliev
ably delicious...Can you tell I like it? :)
```

In [18]:
```
# https://stackoverflow.com/a/47091490/4084039
import re

def decontracted(phrase):
    # specific
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)

    # general
    phrase = re.sub(r"n\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase
```

In [19]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
Great ingredients although, chicken should have been 1st rather than chicken bro
th, the only thing I do not think belongs in it is Canola oil. Canola or rapesee
d is not someting a dog would ever find in nature and if it did find rapeseed in
nature and eat it, it would poison them. Today is Food industries have convinced
the masses that Canola oil is a safe and even better oil than olive or virgin co
conut, facts though say otherwise. Until the late 70 is it was poisonous until t
hey figured out a way to fix that. I still like it but it could be better.
==================================================
```

In [20]:
```
#remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as we'
re driving along and he always can sing the refrain. he's learned about whales,
India, drooping roses:  i love all the new words this book  introduces and the s
illiness of it all.  this is a classic book i am  willing to bet my son will STI
LL be able to recite from memory when he is  in college
```

In [21]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
Great ingredients although chicken should have been 1st rather than chicken brot
h the only thing I do not think belongs in it is Canola oil Canola or rapeseed i
s not someting a dog would ever find in nature and if it did find rapeseed in na
ture and eat it it would poison them Today is Food industries have convinced the
masses that Canola oil is a safe and even better oil than olive or virgin coconu
t facts though say otherwise Until the late 70 is it was poisonous until they fi
gured out a way to fix that I still like it but it could be better
```

In [22]:
```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
# <br /><br /> ==> after the above steps, we are getting "br br"
# we are including them into stop words list
# instead of <br /> if we have <br/> these tags would have revmoved in the 1st step

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourse
lves', 'you', "you're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'hi
m', 'his', 'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself'
, 'they', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that',
"that'll", 'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has',
'had', 'having', 'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because',
'as', 'until', 'while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'thro
ugh', 'during', 'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off',
'over', 'under', 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all',
'any', 'both', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', '
too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've",
'now', 'd', 'll', 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn
't", 'doesn', "doesn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', '
mightn', "mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't"
, 'wasn', "wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

In [23]:
```
# Combining all the above stundents
from tqdm import tqdm
preprocessed_reviews = []
```

In [24]:
```
# tqdm is for printing the status bar
for sentance in tqdm(final['Text'].values):
    sentance = re.sub(r"http\S+", "", sentance)
    sentance = BeautifulSoup(sentance, 'lxml').get_text()
    sentance = decontracted(sentance)
    sentance = re.sub("\S*\d\S*", "", sentance).strip()
    sentance = re.sub('[^A-Za-z]+', ' ', sentance)
    # https://gist.github.com/sebleier/554280
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in sto
pwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|████████████████████████████████████████████████████████████████████████| 3
64171/364171 [05:20<00:00, 1137.53it/s]
```

In [25]:
```
import pickle
with open("preprocessed_reviews.txt", "wb") as fp:   #Pickling
    pickle.dump(preprocessed_reviews, fp)
```

In [26]:
```
preprocessed_reviews[1500]
```

Out[26]:
```
'great ingredients although chicken rather chicken broth thing not think belongs
canola oil canola rapeseed not someting dog would ever find nature find rapeseed
nature eat would poison today food industries convinced masses canola oil safe e
ven better oil olive virgin coconut facts though say otherwise late poisonous fi
gured way fix still like could better'
```

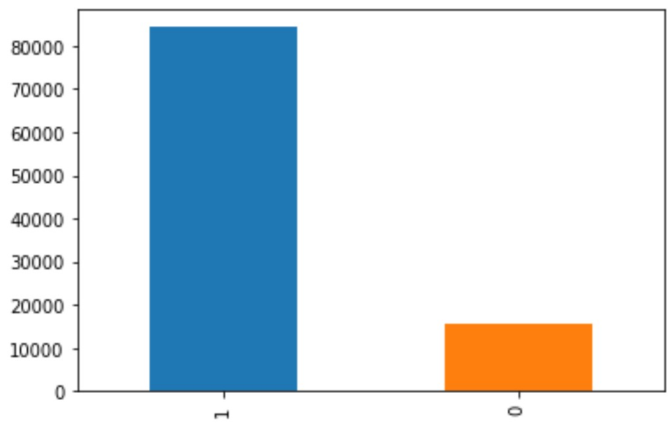
In [27]:
```
#https://www.kaggle.com/premvardhan/amazon-fine-food-review-tsne-visualization/note
book

final['CleanedText']=preprocessed_reviews #adding a column of CleanedText which dis
plays the data after pre-processing of the review
```

In [28]:
```
Sample_data=final.sample(n = 100000)
```

In [29]:
```
Sample_data["Score"].value_counts().plot(kind='bar')
```

Out[29]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1df3be25e48>
```



[3.2] Preprocessing Review Summary

In [30]:
```
## Similartly you can do preprocessing for review summary also.
```

In [31]:
```
#Function to Split the data into Test and Train
def Split_data(X,Y):
    # intermediate/test split (gives us test set)
    from sklearn.model_selection import train_test_split
    train_x, test_x, train_y, test_y = train_test_split(X, Y, shuffle=True,test_siz
e=0.30)
    print('train: {}% |  test {}%'.format(round(len(train_y)/len(Y),2),
                                              round(len(test_y)/len(Y),2))
)
    return train_x,train_y,test_x,test_y
```

In [32]:
```
#Instializing the input data and Output varibles
X = Sample_data["CleanedText"]
y = Sample_data["Score"]
print(X.shape, y.shape)
```

```
(100000,) (100000,)
```

In [33]:
```
#Split the data into test and train
X_train,y_train,x_test,y_test = Split_data(X,y)
```

```
train: 0.7% |  test 0.3%
```

In [34]:
```
#Split the data into test and CV
X_tr, y_tr, X_cv, y_cv =Split_data(X_train,y_train)
```

```
train: 0.7% |  test 0.3%
```

[4] Featurization

In [35]:
```
#function to add a new feature lenght of each review
def Add_new_feature(data,Feature):
    #array to capture the length of each review
    review_length=[]
    #Loop runs through the data and captures the length of each review
    for sent in data.values:
        review_length.append(len(sent))
    #As this is a List we convert to matrix to append the feature with the BOW/tfid
f features which will be in matrix
    review_length=sparse.csr_matrix(review_length)
    #Transpose will help to convert all row s to colums to fit the resultent matrix
to the feature matrix
    review_length=sparse.csr_matrix.transpose(review_length)
    print("the type of new feature ",type(review_length))
    print("the shape of new feature ",review_length.get_shape())
    #Append the new feature to the existing feature matrix this function will outpu
t an arry so we convert it to orginal matrix form again
    Feature_new = hstack([review_length,Feature])
    Feature_new =sparse.csr_matrix(Feature_new)
    print("the type of new count vectorizer ",type(Feature_new))
    print("the shape of out text new BOW vectorizer ",Feature_new.get_shape())
    print("the number of unique words ", Feature_new.get_shape()[1])
    return Feature_new
```

[4.1] BAG OF WORDS

In [36]:
```
from sklearn import preprocessing
#BoW for train data
count_vect = CountVectorizer() #in scikit-learn
BOW_train = count_vect.fit_transform(X_tr)
#Normalize Data
BOW_train = preprocessing.normalize(BOW_train)
print("the type of count vectorizer ",type(BOW_train))
print("the shape of out text BOW vectorizer ",BOW_train.get_shape())
print("the number of unique words ", BOW_train.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (49000, 42908)
the number of unique words  42908
```

In [37]:
```
#Adding new feature to the train BOW feature matrix
BOW_train_new=Add_new_feature(X_tr,BOW_train)
```

```
the type of new feature  <class 'scipy.sparse.csc.csc_matrix'>
the shape of new feature  (49000, 1)
the type of new count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text new BOW vectorizer  (49000, 42909)
the number of unique words  42909
```

In [38]:
```
#BoW for test data
BOW_c_test = count_vect.transform(X_cv)
#Normalize Data
BOW_c_test = preprocessing.normalize(BOW_c_test)
print("the type of count vectorizer ",type(BOW_c_test))
print("the shape of out text BOW vectorizer ",BOW_c_test.get_shape())
print("the number of unique words ", BOW_c_test.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (21000, 42908)
the number of unique words  42908
```

In [39]:
```
#Adding new feature to the CV BOW feature matrix
BOW_c_test_new=Add_new_feature(X_cv,BOW_c_test)
```

```
the type of new feature  <class 'scipy.sparse.csc.csc_matrix'>
the shape of new feature  (21000, 1)
the type of new count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text new BOW vectorizer  (21000, 42909)
the number of unique words  42909
```

In [40]:
```
#BoW for test data
BOW_test = count_vect.transform(x_test)
#Normalize Data
BOW_test = preprocessing.normalize(BOW_test)
print("the type of count vectorizer ",type(BOW_test))
print("the shape of out text BOW vectorizer ",BOW_test.get_shape())
print("the number of unique words ", BOW_test.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (30000, 42908)
the number of unique words  42908
```

In [41]:
```
#Adding new feature to the test BOW feature matrix
BOW_test_new=Add_new_feature(x_test,BOW_test)
```

```
the type of new feature  <class 'scipy.sparse.csc.csc_matrix'>
the shape of new feature  (30000, 1)
the type of new count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text new BOW vectorizer  (30000, 42909)
the number of unique words  42909
```

[4.2] TF-IDF

In [42]:
```
#Instilize the function to calculate the TF-IDF
tf_idf_vect= TfidfVectorizer(ngram_range=(1,2), min_df=10)

Train_tf_idf = tf_idf_vect.fit_transform(X_tr)
#Normalize the data
Train_tf_idf = preprocessing.normalize(Train_tf_idf)
print("the type of count vectorizer ",type(Train_tf_idf))
print("the shape of out text TFIDF vectorizer ",Train_tf_idf.get_shape())
print("the number of unique words including both unigrams and bigrams ", Train_tf_i
df.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (49000, 28649)
the number of unique words including both unigrams and bigrams  28649
```

In [43]:
```
#Adding new feature to the test tfidffeature matrix
Train_tf_idf_new=Add_new_feature(X_tr,Train_tf_idf)
```

```
the type of new feature  <class 'scipy.sparse.csc.csc_matrix'>
the shape of new feature  (49000, 1)
the type of new count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text new BOW vectorizer  (49000, 28650)
the number of unique words  28650
```

In [44]:
```
Train_c_tf_idf = tf_idf_vect.transform(X_cv)
Train_c_tf_idf = preprocessing.normalize(Train_c_tf_idf)
print("the type of count vectorizer ",type(Train_c_tf_idf))
print("the shape of out text TFIDF vectorizer ",Train_c_tf_idf.get_shape())
print("the number of unique words including both unigrams and bigrams ", Train_c_tf
_idf.get_shape()[1])

#minimizing the the features
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (21000, 28649)
the number of unique words including both unigrams and bigrams  28649
```

In [45]:
```
#Adding new feature to the test tfidf feature matrix
Train_c_tf_idf_new=Add_new_feature(X_cv,Train_c_tf_idf)
```

```
the type of new feature  <class 'scipy.sparse.csc.csc_matrix'>
the shape of new feature  (21000, 1)
the type of new count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text new BOW vectorizer  (21000, 28650)
the number of unique words  28650
```

In [46]:
```
Test_tf_idf = tf_idf_vect.transform(x_test)
Test_tf_idf = preprocessing.normalize(Test_tf_idf)
print("the type of count vectorizer ",type(Test_tf_idf))
print("the shape of out text TFIDF vectorizer ",Test_tf_idf.get_shape())
print("the number of unique words including both unigrams and bigrams ", Test_tf_id
f.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (30000, 28649)
the number of unique words including both unigrams and bigrams  28649
```

In [47]:
```
#Adding new feature to the test tfidf feature matrix
Test_tf_idf_new=Add_new_feature(x_test,Test_tf_idf)
```

```
the type of new feature  <class 'scipy.sparse.csc.csc_matrix'>
the shape of new feature  (30000, 1)
the type of new count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text new BOW vectorizer  (30000, 28650)
the number of unique words  28650
```

[5] Assignment 4: Apply Naive Bayes

1. **Apply Multinomial NaiveBayes on these feature sets**
    - SET 1:Review text, preprocessed one converted into vectors using (BOW)
    - SET 2:Review text, preprocessed one converted into vectors using (TFIDF)

2. **The hyper paramter tuning(find best Alpha)**
    - Find the best hyper parameter which will give the maximum AUC (https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/receiver-operating-characteristic-curve-roc-curve-and-auc-1/) value
    - Consider a wide range of alpha values for hyperparameter tuning, start as low as 0.00001
    - Find the best hyper paramter using k-fold cross validation or simple cross validation data
    - Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this task of hyperparameter tuning

3. **Feature importance**
    - Find the top 10 features of positive class and top 10 features of negative class for both feature sets Set 1 and Set 2 using values of `feature_log_prob_` parameter of MultinomialNB (https://scikit-learn.org/stable/modules/generated/sklearn.naive_bayes.MultinomialNB.html) and print their corresponding feature names

4. **Feature engineering**
    - To increase the performance of your model, you can also experiment with with feature engineering like :
        - Taking length of reviews as another feature.
        - Considering some features from review summary as well.

5. **Representation of results**
    - You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure. Here on X-axis you will have alpha values, since they have a wide range, just to represent those alpha values on the graph, apply log function on those alpha values.
    - Once after you found the best hyper parameter, you need to train your model with it, and find the AUC on test data and plot the ROC curve on both train and test.

Note: Data Leakage

1. There will be an issue of data-leakage if you vectorize the entire data and then split it into train/cv/test.
2. To avoid the issue of data-leakag, make sure to split your data first and then vectorize it.
3. While vectorizing your data, apply the method fit_transform() on you train data, and apply the method transform() on cv/test data.
4. For more details please go through this [link. (https://soundcloud.com/applied-ai-course/leakage-bow-and-tfidf)](https://soundcloud.com/applied-ai-course/leakage-bow-and-tfidf)

Applying Multinomial Naive Bayes

In [48]:

```
#Save the processed tfidf w2v to local for future referance
```

In [49]:

```
#function to perform the Hyper-Perameter Tunning
def Hyper_PM_tunning(KDX_train,KDY_train):
    #GridSearchCV
    param_grid = {'alpha':neighbors}
    MNavie=MultinomialNB(class_prior = [0.5, 0.5])
    MNavie_CV= GridSearchCV(MNavie,param_grid,cv=10,verbose=1,scoring='roc_auc')
    MNavie_CV.fit(KDX_train,KDY_train)
    #save the file to local for future referance
    with open("MNavie_CV.txt", "wb") as fp:   #Pickling
        pickle.dump(MNavie_CV, fp)
    print("Best HyperParameter: ",MNavie_CV.best_params_)
    print("Best Accuracy: %.2f%%"%(MNavie_CV.best_score_*100))
```

In [50]:

```
#Function to Plot the AUC values for each alpha

def Plot_AUC(Train_auc,cv_auc):
    #plt AUC for Test and the Validation
    plt.title('AUC Varying for different Alpha')
    plt.plot(neighbors, Train_auc, label='Testing AUC')
    plt.plot(neighbors, cv_auc, label='Validation AUC')
    High_test_AUC = neighbors[Train_auc.index(max(Train_auc))]
    print('\nThe highest AUC for test data is for  alpha  %.3f.' % High_test_AUC)
    High_CV_AUC  = neighbors[cv_auc.index(max(cv_auc))]
    print('\nThe highest AUC for CV data is for  alpha %.3f.' % High_CV_AUC)
    plt.legend()
    plt.xlabel('Alpha values ')
    plt.ylabel('AUC Values')
    plt.show()
```

In [51]:

```
# Function to find the optimal Alpha value
def find_OPT_K(KDX_train,KDY_train,KDX_test,KDY_test):

    Train_auc= []
    cv_auc= []
    cv_scores = []
    for i,k in enumerate(neighbors):
        #Setup a MultinomialNB classifier with k alpha value
        model = MultinomialNB(alpha = k,class_prior = [0.5, 0.5])


        #Fit the model
        model.fit(KDX_train, KDY_train)



        #Acu values for the Train data
        probs_train = model.predict_proba(KDX_train)
        preds_train = probs_train[:,1]
        fpr_train, tpr_train, threshold_train = metrics.roc_curve(KDY_train, preds_
train)
        Train_auc.append(metrics.auc(fpr_train, tpr_train)*100)

        #Acu values for the Test data
        probs = model.predict_proba(KDX_test)
        preds = probs[:,1]
        fpr, tpr, threshold = metrics.roc_curve(KDY_test, preds)

        cv_auc.append(metrics.auc(fpr, tpr)*100)

        # perform simple  cross validation on train
        scores = cross_val_score(model, KDX_train, KDY_train, cv=10, scoring='roc_a
uc')
        cv_scores.append(scores.mean())

    optimal_alpha = neighbors[cv_scores.index(max(cv_scores))]
    print('\nThe optimal value of alpha is %.3f.' % optimal_alpha)
    Plot_AUC(Train_auc,cv_auc)
    return optimal_alpha
```

In [52]:
```
#function to plot the ROC curve for train and the Test Data
def plot_roc(KDX_train,KDY_train,X_test,Y_test):
    # calculate the fpr and tpr for all thresholds of the classification
    probs = model.predict_proba(KDX_train)
    preds = probs[:,1]
    fpr_train, tpr_train, threshold = metrics.roc_curve(KDY_train, preds)
    roc_auc_train = metrics.auc(fpr_train, tpr_train)*float(100)
    probs_test = model.predict_proba(X_test)
    preds_test = probs_test[:,1]
    fpr_test, tpr_test, threshold = metrics.roc_curve(Y_test, preds_test)
    roc_auc_test = metrics.auc(fpr_test, tpr_test)*float(100)

    plt.title('Receiver Operating Characteristic')
    plt.plot(fpr_train, tpr_train, label = 'Train AUC = %0.2f' % roc_auc_train)
    plt.plot(fpr_test, tpr_test, label = 'Test AUC = %0.2f' % roc_auc_test)
    plt.legend(loc = 'lower right')
    plt.plot([0, 1], [0, 1],'r--')
    plt.xlim([0, 1])
    plt.ylim([0, 1])
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
    plt.show()
    return roc_auc_train,roc_auc_test
```

In [53]:
```
#Function to print the Confusion matrix

def Confusion_Matrix(X_test,Y_test):

    pred = model.predict(X_test)
    cm = confusion_matrix(Y_test, pred)
    class_label = ["positive","negative"]
    df_cm = pd.DataFrame(cm, index = class_label, columns = class_label)
    sns.heatmap(df_cm, annot = True, fmt = "d")
    plt.title("Confusiion Matrix")
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.show()
```

In [54]:
```
#Function to Print the top n feature
def important_features(vectorizer,classifier,n,labele):

    if(labele == "negative"):
        i=0
    elif(labele == "positive"):
        i=1
    else:
        print("provide negative/positive lable %s is nt valied" %labele)
    class_labels = classifier.classes_

    feature_names =vectorizer.get_feature_names()

    topn_class = sorted(zip(classifier.feature_count_[i], feature_names),reverse=Tr
ue)[:n]

    print("Important words in %s reviews" %labele)

    for coef, feat in topn_class:

        print(class_labels[0], coef, feat)
```

[5.1] Applying Naive Bayes on BOW, SET 1

In [55]:
```
# Please write all the code with proper documentation
```

In [56]:
```
MX_train=BOW_train
MX_test=BOW_c_test
MY_train=y_tr
MY_test=y_cv
```

In [57]:
```
#taking a wide range of alpha values from 10^-5 to 10^5
neighbors = []
i =  0.000001
while(i<=100000):
    neighbors.append(np.round(i,8))
    i *= 3

bnb = MultinomialNB(class_prior = [0.5, 0.5])
```

In [58]:
```
print(neighbors)
```

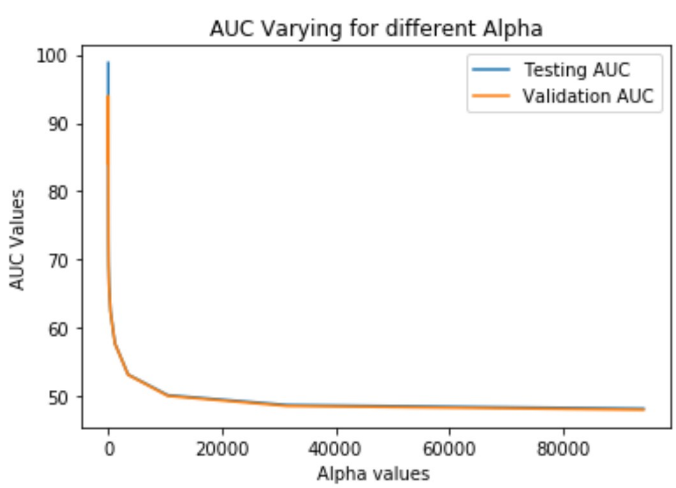
```
[1e-06, 3e-06, 9e-06, 2.7e-05, 8.1e-05, 0.000243, 0.000729, 0.002187, 0.006561,
0.019683, 0.059049, 0.177147, 0.531441, 1.594323, 4.782969, 14.348907, 43.046721
, 129.140163, 387.420489, 1162.261467, 3486.784401, 10460.353203, 31381.059609,
94143.178827]
```

In [59]:
```
#find the optimal alpha for the MultinomialNB
optimal_alpha=find_OPT_K(MX_train,MY_train,MX_test,MY_test)
```

```
The optimal value of alpha is 0.059.

The highest AUC for test data is for  alpha  0.000.

The highest AUC for CV data is for  alpha 0.059.
```



In [60]:
```
#Fit the model with optimal alpha value
model = MultinomialNB(alpha =0.059,class_prior = [0.5, 0.5])
#Fit the model
model.fit(MX_train, MY_train)
```

Out[60]:
```
MultinomialNB(alpha=0.059, class_prior=[0.5, 0.5], fit_prior=True)
```

In [61]:
```
print("Training Score for optimal alpha is : ",model.score(MX_train, MY_train)*100)
print("CV Score for optimal alpha is : ",model.score(MX_test, MY_test)*100)
print("Test Score for optimal alpha is : ",model.score(BOW_test, y_test)*100)
```

```
Training Score for optimal alpha is :  91.71020408163265
CV Score for optimal alpha is :  88.92380952380952
Test Score for optimal alpha is :  88.86666666666667
```

In [62]:
```
#Hyperperameter Tuning for Best  alpha for the MultinomialNB
Best_alpha=Hyper_PM_tunning(MX_train,MY_train)
```

```
Fitting 10 folds for each of 24 candidates, totalling 240 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 240 out of 240 | elapsed:   35.8s finished

Best HyperParameter:  {'alpha': 0.059049}
Best Accuracy: 93.21%
```

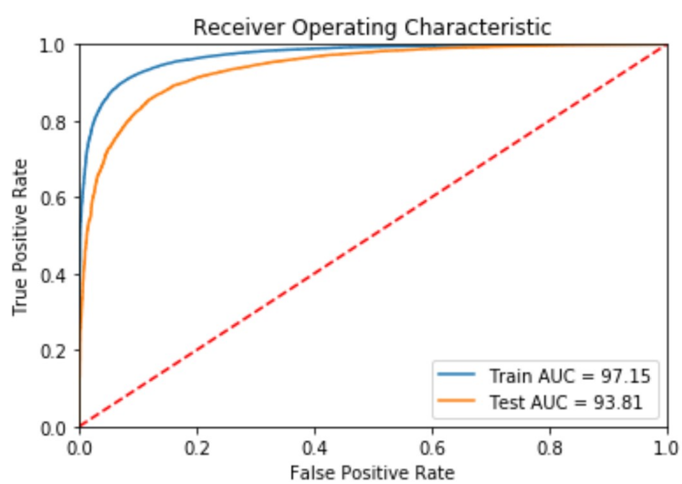
In [63]:
```
#Fit the model with Best alpha value
model = MultinomialNB(alpha =0.059,class_prior = [0.5, 0.5])
#Fit the model
model.fit(MX_train, MY_train)
```

Out[63]:
```
MultinomialNB(alpha=0.059, class_prior=[0.5, 0.5], fit_prior=True)
```

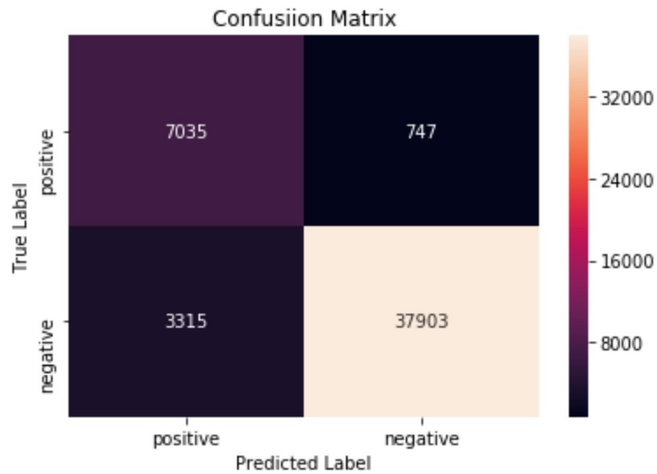
In [64]:
```
print("Training Score for Best alpha is : ",model.score(MX_train, MY_train)*100)
print("CV Score for Best alpha is : ",model.score(MX_test, MY_test)*100)
print("Test Score for Best alpha is : ",model.score(BOW_test, y_test)*100)
```

```
Training Score for Best alpha is :  91.71020408163265
CV Score for Best alpha is :  88.92380952380952
Test Score for Best alpha is :  88.86666666666667
```

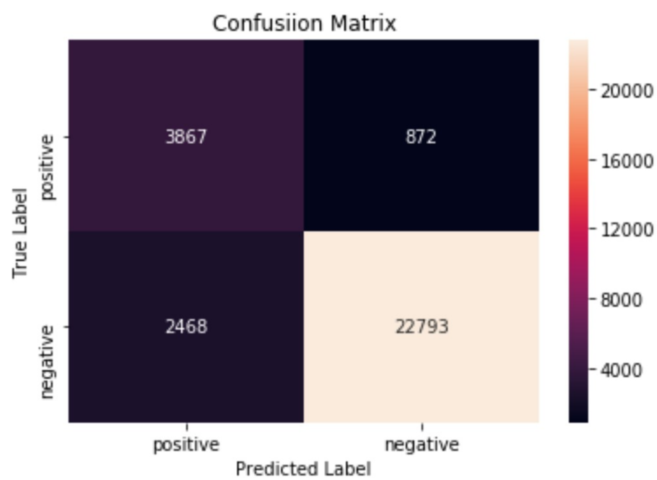
In [65]:
```
#Print the ROC curve for the test and training data
BOW_Train_AUC,BOW_Test_AUC=plot_roc(MX_train,MY_train,BOW_test,y_test)
```



In [66]:
```
#Confusion Matrix for Train Data
Confusion_Matrix(MX_train,MY_train)
```



In [67]:
```
#Confusion Matrix for Test Data
Confusion_Matrix(BOW_test,y_test)
```



In [68]:
```
BOW_Model=model
```

Adding a New Feature review length and verifing the Model Perfomance

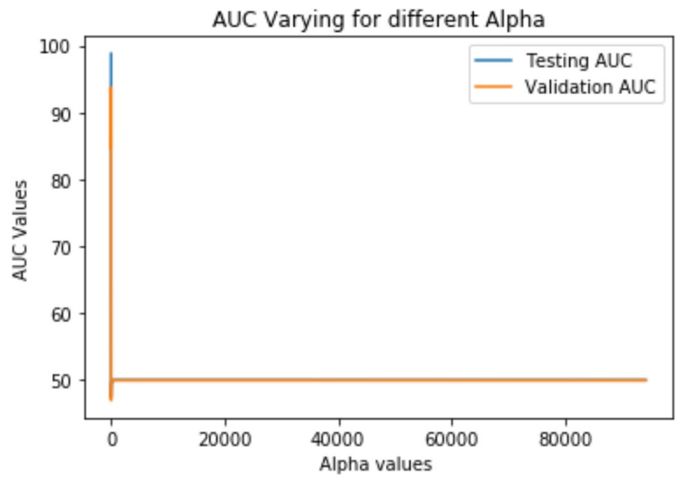
In [69]:
```
#Load the data with new feature Data set
MX_train=BOW_train_new
MX_test=BOW_c_test_new
MY_train=y_tr
MY_test=y_cv
```

In [70]:
```
#find the optimal alpha for the MultinomialNB
optimal_alpha=find_OPT_K(MX_train,MY_train,MX_test,MY_test)
```

```
The optimal value of alpha is 0.059.

The highest AUC for test data is for  alpha  0.000.

The highest AUC for CV data is for  alpha 0.059.
```



In [71]:
```
model = MultinomialNB(alpha =0.059,class_prior = [0.5, 0.5])
#Fit the model
model.fit(MX_train, MY_train)
```

Out[71]: `MultinomialNB(alpha=0.059, class_prior=[0.5, 0.5], fit_prior=True)`

In [72]:
```
print("Training Score for optimal alpha is : ",model.score(MX_train, MY_train)*100)
print("CV Score for optimal alpha is : ",model.score(MX_test, MY_test)*100)
print("Test Score for optimal alpha is : ",model.score(BOW_test_new, y_test)*100)
```

```
Training Score for optimal alpha is :  91.31428571428572
CV Score for optimal alpha is :  88.61904761904762
Test Score for optimal alpha is :  88.57333333333334
```

In [73]:
```
#find the Best alpha for the MultinomialNB with hyperperameter tunning
Best_alpha=Hyper_PM_tunning(MX_train,MY_train)
```

```
Fitting 10 folds for each of 24 candidates, totalling 240 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 240 out of 240 | elapsed:   40.7s finished

Best HyperParameter:  {'alpha': 0.059049}
Best Accuracy: 93.07%
```

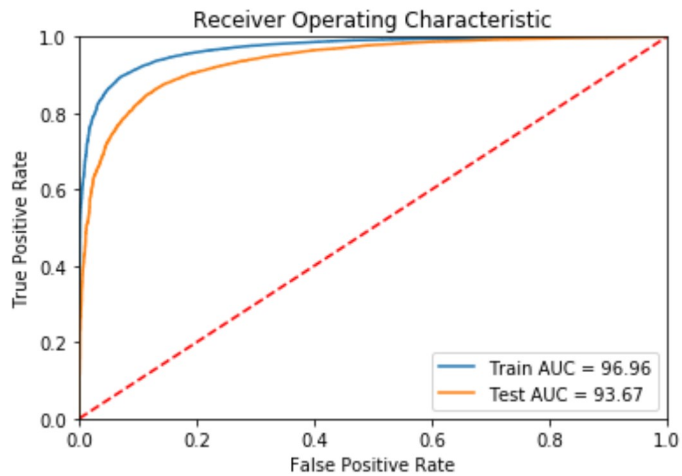
In [74]:
```
model = MultinomialNB(alpha =0.059,class_prior = [0.5, 0.5])
#Fit the model
model.fit(MX_train, MY_train)
```

Out[74]: `MultinomialNB(alpha=0.059, class_prior=[0.5, 0.5], fit_prior=True)`

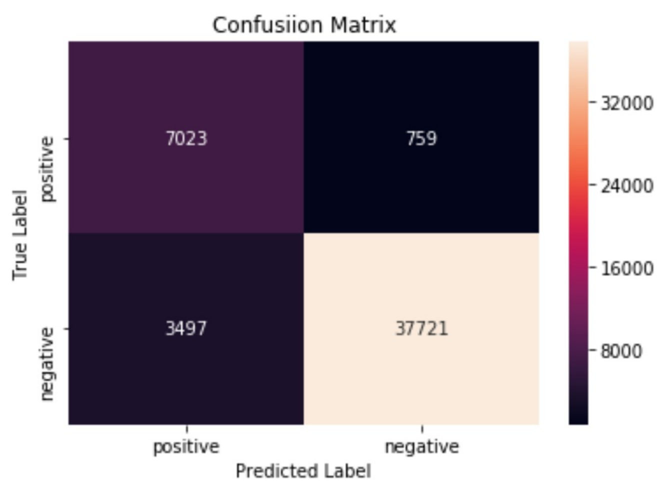
In [75]:
```
print("Training Score for Best alpha is : ",model.score(MX_train, MY_train)*100)
print("CV Score for Best alpha is : ",model.score(MX_test, MY_test)*100)
print("Test Score for Best alpha is : ",model.score(BOW_test_new, y_test)*100)
```

```
Training Score for Best alpha is :  91.31428571428572
CV Score for Best alpha is :  88.61904761904762
Test Score for Best alpha is :  88.57333333333334
```

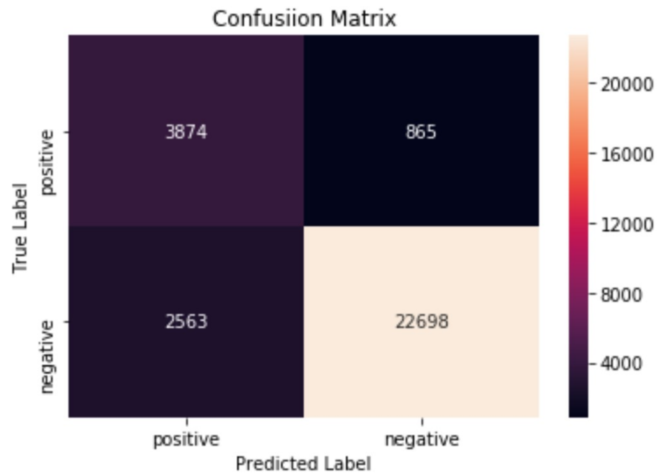
In [76]:
```
BOW_Train_AUC_New,BOW_Test_AUC_New=plot_roc(MX_train,MY_train,BOW_test_new,y_test)
```



In [77]:
```
#Confusion Matrix with train dataset
Confusion_Matrix(MX_train,MY_train)
```



In [78]:
```
#Confusion Matrix with test dataset
Confusion_Matrix(BOW_test_new,y_test)
```



In [79]:
```
BOW_Model_new=model
```

[5.1.1] Top 10 important features of positive class from SET 1

In [80]:
```
#Top 10 Features of Postive class
important_features(count_vect,BOW_Model,10,"positive")
```

```
Important words in positive reviews
0 4877.220857518181 not
0 2350.634632086267 great
0 2245.116704588181 good
0 2137.9861703224615 like
0 1638.7762719747554 love
0 1581.344034607647 product
0 1526.9644016539257 taste
0 1515.0835620480182 one
0 1383.8645861786995 coffee
0 1382.840575117228 flavor
```

In [81]:
```
#Top 10 Features of Postive class with new feature
important_features(count_vect,BOW_Model_new,10,"positive")
```

```
Important words in positive reviews
0 10342115.0 aa
0 4877.220857518181 notable
0 2350.634632086267 greatcoffee
0 2245.116704588181 goodbar
0 2137.9861703224615 likeability
0 1638.7762719747554 loveable
0 1581.344034607647 productand
0 1526.9644016539257 tasteand
0 1515.0835620480182 oneat
0 1383.8645861786995 coffeeam
```

[5.1.2] Top 10 important features of negative class from SET 1

In [82]:
```
#Top 10 Features of Negative class
important_features(count_vect,BOW_Model,10,"negative")
```

```
Important words in negative reviews
0 1644.6864047936936 not
0 534.9987145943688 like
0 427.74105041239886 product
0 416.1793337763289 taste
0 396.8854561440918 would
0 308.99635525191076 one
0 263.4653964321093 good
0 243.56273371938167 no
0 237.99169227804433 flavor
0 236.23632888092828 coffee
```

In [83]:
```
#Top 10 Features of Negative class with new feature
important_features(count_vect,BOW_Model_new,10,"negative")
```

```
Important words in negative reviews
0 2178484.0 aa
0 1644.6864047936936 notable
0 534.9987145943688 likeability
0 427.74105041239886 productand
0 416.1793337763289 tasteand
0 396.8854561440918 woulda
0 308.99635525191076 oneat
0 263.4653964321093 goodbar
0 243.56273371938167 noah
0 237.99169227804433 flavorable
```

[5.2] Applying Naive Bayes on TFIDF, SET 2

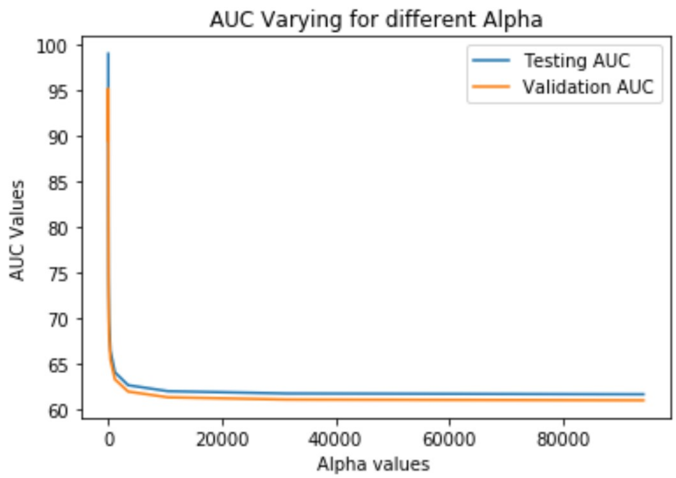
In [84]:
```
MX_train=Train_tf_idf
MX_test=Train_c_tf_idf
MY_train=y_tr
MY_test=y_cv
```

In [85]:
```
#find the Optimal alpha for the MultinomialNB
optimal_alpha=find_OPT_K(MX_train,MY_train,MX_test,MY_test)
```

```
The optimal value of alpha is 0.177.

The highest AUC for test data is for  alpha  0.000.

The highest AUC for CV data is for  alpha 0.177.
```



In [86]:
```
        model = MultinomialNB(alpha =0.177,class_prior = [0.5, 0.5])
    #Fit the model
        model.fit(MX_train, MY_train)
```

Out[86]: `MultinomialNB(alpha=0.177, class_prior=[0.5, 0.5], fit_prior=True)`

In [87]:
```
print("Training Score for Best alpha is : ",model.score(MX_train, MY_train)*100)
print("CV Score for Best alpha is : ",model.score(MX_test, MY_test)*100)
print("Test Score for Best alpha is : ",model.score(Test_tf_idf, y_test)*100)
```

```
Training Score for Best alpha is :  91.82857142857142
CV Score for Best alpha is :  89.0
Test Score for Best alpha is :  89.07333333333334
```

In [88]:
```
#find the Best alpha for the MultinomialNB with hyperperameter tunning
Best_alpha=Hyper_PM_tunning(MX_train,MY_train)
```

```
Fitting 10 folds for each of 24 candidates, totalling 240 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 240 out of 240 | elapsed:   46.4s finished

Best HyperParameter:  {'alpha': 0.177147}
Best Accuracy: 95.33%
```

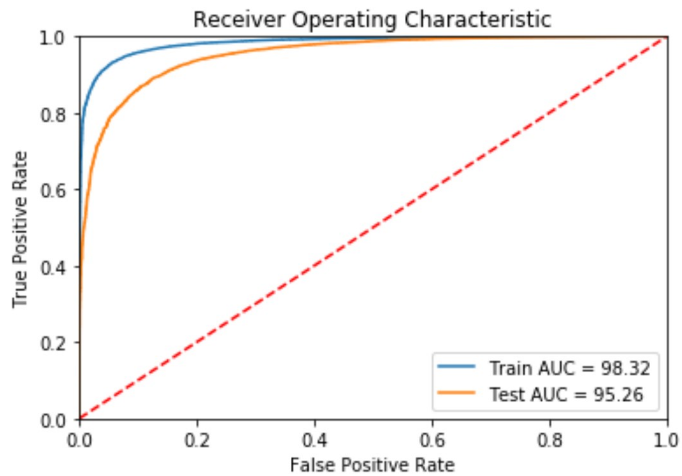
In [89]:
```
        model = MultinomialNB(alpha =0.117,class_prior = [0.5, 0.5])
    #Fit the model
        model.fit(MX_train, MY_train)
```

Out[89]: `MultinomialNB(alpha=0.117, class_prior=[0.5, 0.5], fit_prior=True)`

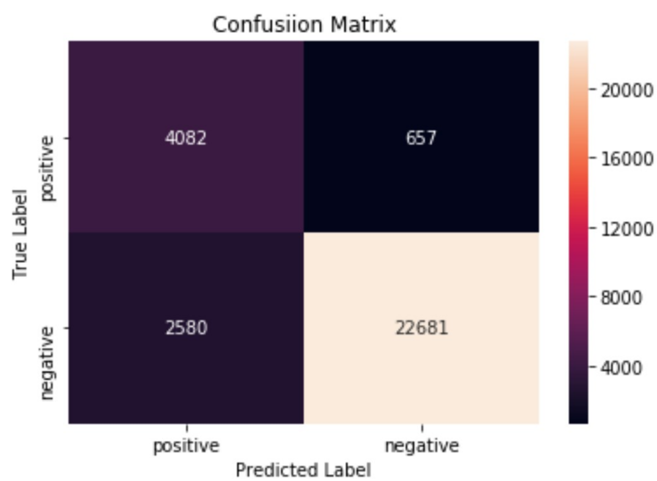
In [90]:
```
print("Training Score for Best alpha is : ",model.score(MX_train, MY_train)*100)
print("CV Score for Best alpha is : ",model.score(MX_test, MY_test)*100)
print("Test Score for Best alpha is : ",model.score(Test_tf_idf, y_test)*100)
```

```
Training Score for Best alpha is :  92.22857142857143
CV Score for Best alpha is :  89.16666666666667
Test Score for Best alpha is :  89.21
```

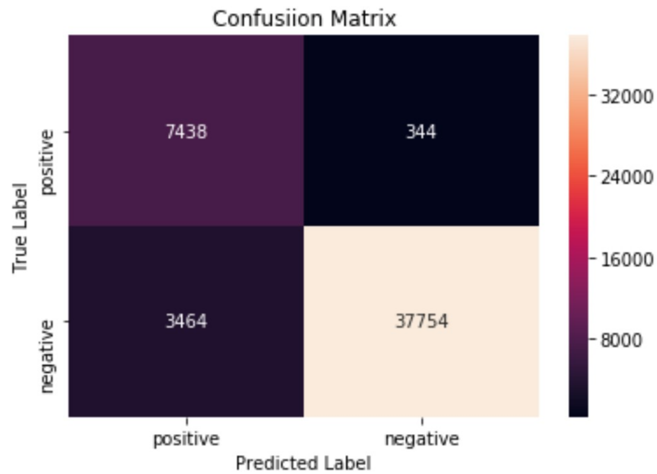
In [91]:
```
#Plot the ROC curve for test and Train data
tfidf_Train_AUC,tfidf_Test_AUC = plot_roc(MX_train,MY_train,Test_tf_idf,y_test)
```



In [92]:
```
#Confusion Matrix for Test data
Confusion_Matrix(Test_tf_idf,y_test)
```



In [93]:
```
#Confusion Matrix for Train data
Confusion_Matrix(MX_train,MY_train)
```



In [94]:
```
tf_idf_Model=model
```

Adding a New Feature review length and verifing the Model Perfomance

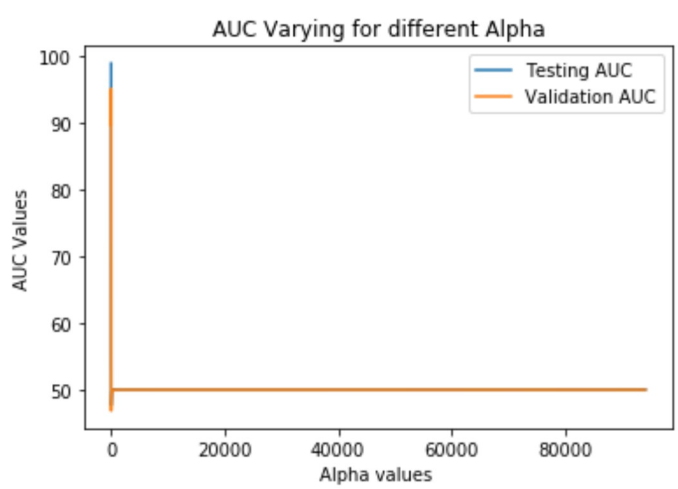
In [95]:
```
MX_train=Train_tf_idf_new
MX_test=Train_c_tf_idf_new
MY_train=y_tr
MY_test=y_cv
```

In [96]:
```
#find the Optimal alpha for the MultinomialNB
optimal_alpha=find_OPT_K(MX_train,MY_train,MX_test,MY_test)
```

```
The optimal value of alpha is 0.177.

The highest AUC for test data is for  alpha  0.000.

The highest AUC for CV data is for  alpha 0.177.
```



In [97]:
```
model = MultinomialNB(alpha =0.117,class_prior = [0.5, 0.5])
#Fit the model
model.fit(MX_train, MY_train)
```

Out[97]:
```
MultinomialNB(alpha=0.117, class_prior=[0.5, 0.5], fit_prior=True)
```

In [98]:
```
print("Training Score for Best alpha is : ",model.score(MX_train, MY_train)*100)
print("CV Score for Best alpha is : ",model.score(MX_test, MY_test)*100)
print("Test Score for Best alpha is : ",model.score(Test_tf_idf_new, y_test)*100)
```

```
Training Score for Best alpha is :  92.03673469387755
CV Score for Best alpha is :  88.96190476190476
Test Score for Best alpha is :  88.97
```

In [99]:
```
#find the Best alpha for the MultinomialNB with hyperperameter tunning
Best_alpha=Hyper_PM_tunning(MX_train,MY_train)
```

```
Fitting 10 folds for each of 24 candidates, totalling 240 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 240 out of 240 | elapsed:   36.1s finished

Best HyperParameter:  {'alpha': 0.177147}
Best Accuracy: 95.33%
```

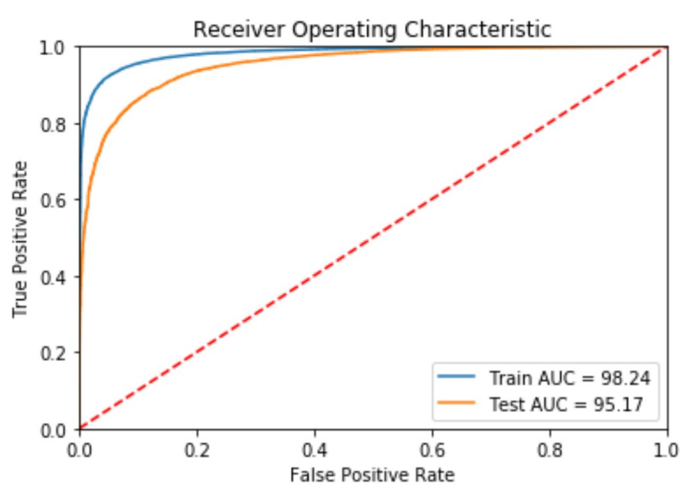
In [100]:
```
model = MultinomialNB(alpha =0.117,class_prior = [0.5, 0.5])
#Fit the model
model.fit(MX_train, MY_train)
```

Out[100]:
```
MultinomialNB(alpha=0.117, class_prior=[0.5, 0.5], fit_prior=True)
```

In [101]:
```
print("Training Score for Best alpha is : ",model.score(MX_train, MY_train)*100)
print("CV Score for Best alpha is : ",model.score(MX_test, MY_test)*100)
print("Test Score for Best alpha is : ",model.score(Test_tf_idf_new, y_test)*100)
```

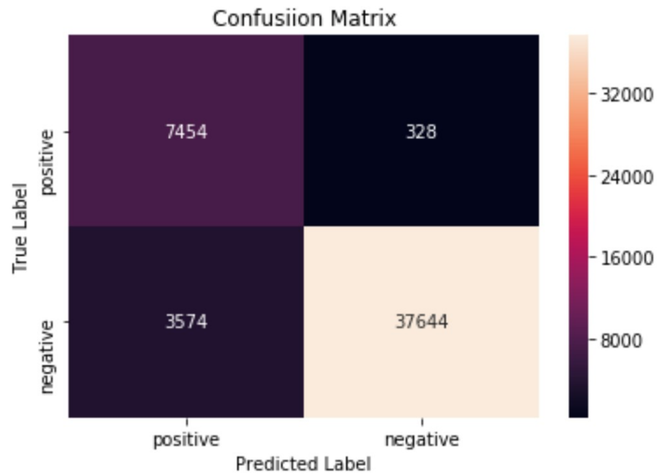
```
Training Score for Best alpha is :  92.03673469387755
CV Score for Best alpha is :  88.96190476190476
Test Score for Best alpha is :  88.97
```

In [102]:
```
#Plot the ROC curve for test and the train data
tfidf_Train_AUC_new,tfidf_Test_AUC_new=plot_roc(MX_train,MY_train,Test_tf_idf_new,
y_test)
```

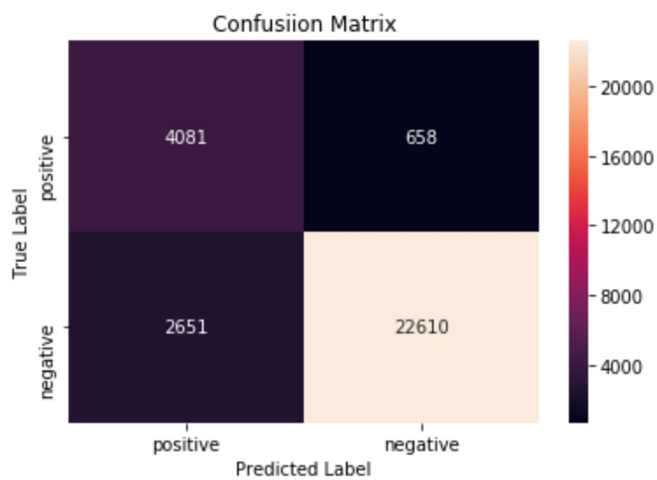


In [103]:
```
#Confusion Matrix for Test and Train data
print("Confusion Matrix for Train Data")
Confusion_Matrix(MX_train,MY_train)
print("Confusion Matrix for Test Data")
Confusion_Matrix(Test_tf_idf_new,y_test)
```

```
Confusion Matrix for Train Data
```




```
Confusion Matrix for Test Data
```



In [104]:
```
tf_idf_Model_new =model
```

[5.2.1] Top 10 important features of positive class from SET 2

In [105]:
```
#Top 10 Features of Postive classs
Tfidf_Pov_fev=important_features(tf_idf_vect,tf_idf_Model,10,"positive")
```

```
Important words in positive reviews
0 1235.3601512638593 not
0 871.7634134184359 great
0 810.3322447248672 good
0 750.9682361021412 like
0 696.4994954445472 coffee
0 694.0356582020069 tea
0 680.0286691808969 love
0 634.6918317395368 product
0 603.7866933303004 taste
0 598.1258113221047 one
```

In [106]:
```
#Top 10 Features of Postive class with new feature
Tfidf_Pov_fev_new=important_features(tf_idf_vect,tf_idf_Model_new,10,"positive")
```

```
Important words in positive reviews
0 10342115.0 abandoned
0 1235.3601512638593 not able
0 871.7634134184359 great able
0 810.3322447248672 good able
0 750.9682361021412 like able
0 696.4994954445472 coffee absolutely
0 694.0356582020069 tea absolutely
0 680.0286691808969 love able
0 634.6918317395368 product absolutely
0 603.7866933303004 taste absolutely
```

[5.2.2] Top 10 important features of negative class from SET 2

In [107]:
```
#Top 10 Features of negative class
Tfidf_Neg_fev=important_features(tf_idf_vect,tf_idf_Model,10,"negative")
```

```
Important words in negative reviews
0 427.07570799368864 not
0 192.957018668071 like
0 176.97312153321428 product
0 169.47376545346276 taste
0 165.8387591682988 would
0 124.91777540907407 one
0 122.22660263482877 coffee
0 113.86113719434596 no
0 102.80322544381264 flavor
0 97.63164137236411 good
```

In [108]:
```
#Top 10 Features of negative class with new feature
Tfidf_Neg_fev_new=important_features(tf_idf_vect,tf_idf_Model_new,10,"negative")
```

```
Important words in negative reviews
0 2178484.0 abandoned
0 427.07570799368864 not able
0 192.957018668071 like able
0 176.97312153321428 product absolutely
0 169.47376545346276 taste absolutely
0 165.8387591682988 would able
0 124.91777540907407 one absolutely
0 122.22660263482877 coffee absolutely
0 113.86113719434596 no added
0 102.80322544381264 flavor absolutely
```

[6] Conclusions

In [109]:
```
# Please compare all your models using Prettytable library
```

In [110]:
```
Best_Alpha_BOW=0.059
Best_Alpha_BOW_New=0.059
Best_Alpha_tfidf=0.177
Best_Alpha_tfidf_new=0.177
```

In [111]:
```
from prettytable import PrettyTable

names = ["Navie Bayes for BoW", "Navie Bayes for BoW with New Feature","Navie Baye
s for tfidf", "Navie Bayes for tfidf with New Feature"]

optimal_Alpha = [Best_Alpha_BOW,Best_Alpha_BOW_New,Best_Alpha_tfidf,Best_Alpha_tfi
df_new]

train_acc = [BOW_Train_AUC,BOW_Train_AUC_New,tfidf_Train_AUC,tfidf_Train_AUC_new]

test_acc = [BOW_Test_AUC,BOW_Test_AUC_New,tfidf_Test_AUC,tfidf_Test_AUC_new]

numbering = [1,2,3,4]

# Initializing prettytable
ptable = PrettyTable()

# Adding columns
ptable.add_column("S.NO.",numbering)
ptable.add_column("MODEL",names)
ptable.add_column("Best Alpha",optimal_Alpha)
ptable.add_column("Training Accuracy",train_acc)
ptable.add_column("Test Accuracy",test_acc)

# Printing the Table
print(ptable)
```

```
+-------+----------------------------------------+------------+-----------------
--+--------------------+
| S.NO. |                 MODEL                  | Best Alpha | Training Accurac
y |   Test Accuracy    |
+-------+----------------------------------------+------------+-----------------
--+--------------------+
|   1   |          Navie Bayes for BoW           |   0.059    | 97.1539883797178
3 | 93.81178579612805 |
|   2   |  Navie Bayes for BoW with New Feature  |   0.059    | 96.9578619958276
7 | 93.67195422602965 |
|   3   |          Navie Bayes for tfidf         |   0.177    |  98.318248182473
6 |  95.2560685310102 |
|   4   | Navie Bayes for tfidf with New Feature |   0.177    |  98.236011852107
7 | 95.16943928346492 |
+-------+----------------------------------------+------------+-----------------
--+--------------------+
```

Conclusions

```
Best Accuracy of 95.37% is achieved by Navie Bayes for tfidf Featurization
The Navie Bayes with New feature gives relatively similar results
Best alpha value is simmilar after adding new feature
```