Amazon Fine Food Reviews Analysis

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

EDA: 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

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
```

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 50
0000 data points
# you can change the number to any other number based on your computing
 power

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

```
filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score
 != 3 LIMIT 200000""", con)

# Give reviews with Score>3 a positive rating(1), and reviews with a sc
ore<3 a negative 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 (200000, 10)
```

Out[2]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomin
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	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	B005ZBZLT4	Breyton	1331510400	2	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ESG	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B005ZBZLT4	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ESG	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBEV0	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	B001ATMQK2	undertheshrine "undertheshrine"	1296691200	5	I bought this 6 pack because for the price tha...	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	HelpfulnessDenon

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenon
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	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"}, keep='first', inplace=False)
final.shape
```

Out[9]:
```
(160178, 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]:
```
80.089
```

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	HelpfulnessDenom
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	

In [12]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [13]:
```
#Before starting the next phase of preprocessing lets see the number of
 entries left
print(final.shape)

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

```
(160176, 10)
```

Out[13]:
```
1    134799
0     25377
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]:
```
# 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)
```

```
I remembered this book from my childhood and got it for my kids.  It's
just as good as I remembered and my kids love it too.  My older daughte
r now reads it to her sister.  Good rhymes and nice pictures.
```

```
==================================================
The qualitys not as good as the lamb and rice but it didn't seem to bot
her his stomach, you get 10 more pounds and it is cheaper wich is a plu
s for me. You can always ad your own rice and veggies. Its fresher that
way and better for him in my opinion. Plus if you you can get it delive
rd to your house for free its even better.  Gotta love pitbulls
==================================================
This is the Japanese version of breadcrumb (pan=bread, a Portuguese loa
n-word, and&quot;ko-&quot;  is &quot;child of&quot; or of &quot;derived
from&quot;.) Panko are used for katsudon, tonkatsu or cutlets served on
rice or in soups. The cutlets, pounded chicken or pork, are coated with
these light and crispy crumbs and fried. They are not gritty and dense
like regular crumbs. They are very nice on deep fried shrimps and decor
ative for a more gourmet touch.
==================================================
What can I say... If Douwe Egberts was good enough for my dutch grandmo
ther, it's perfect for me.  I like this flavor best with my Senseo... I
t has a nice dark full body flavor without the burt bean taste I tend s
ense with starbucks.  It's a shame most americans haven't bought into s
ingle serve coffe makers as our Dutch counter parts have.  Every cup is
fresh brewed and doesn't sit long enough on my desk to get that old tas
te either.
==================================================
```

In [15]:

```python
# remove urls from text python: https://stackoverflow.com/a/40823105/40
84039
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)
```

```
I remembered this book from my childhood and got it for my kids.  It's
just as good as I remembered and my kids love it too.  My older daughte
r now reads it to her sister.  Good rhymes and nice pictures.
```

In [16]:

```python
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how
-to-remove-all-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)
```

```
I remembered this book from my childhood and got it for my kids.  It's
just as good as I remembered and my kids love it too.  My older daughte
r now reads it to her sister.  Good rhymes and nice pictures.
==================================================
The qualitys not as good as the lamb and rice but it didn't seem to bot
her his stomach, you get 10 more pounds and it is cheaper wich is a plu
s for me. You can always ad your own rice and veggies. Its fresher that
way and better for him in my opinion. Plus if you you can get it delive
rd to your house for free its even better.  Gotta love pitbulls
==================================================
This is the Japanese version of breadcrumb (pan=bread, a Portuguese loa
n-word, and"ko-"  is "child of" or of "derived from".) Panko are used f
or katsudon, tonkatsu or cutlets served on rice or in soups. The cutlet
s, pounded chicken or pork, are coated with these light and crispy crum
bs and fried. They are not gritty and dense like regular crumbs. They a
re very nice on deep fried shrimps and decorative for a more gourmet to
uch.
==================================================
What can I say... If Douwe Egberts was good enough for my dutch grandmo
```

```
ther, it's perfect for me.  I like this flavor best with my Senseo... I
t has a nice dark full body flavor without the burt bean taste I tend s
ense with starbucks.  It's a shame most americans haven't bought into s
ingle serve coffe makers as our Dutch counter parts have.  Every cup is
fresh brewed and doesn't sit long enough on my desk to get that old tas
te either.
```

In [17]:

```
# 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 [18]:

```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
This is the Japanese version of breadcrumb (pan=bread, a Portuguese loa
n-word, and&quot;ko-&quot;  is &quot;child of&quot; or of &quot;derived
from&quot;.) Panko are used for katsudon, tonkatsu or cutlets served on
rice or in soups. The cutlets, pounded chicken or pork, are coated with
these light and crispy crumbs and fried. They are not gritty and dense
like regular crumbs. They are very nice on deep fried shrimps and decor
ative for a more gourmet touch.
==================================================
```

In [19]:

```
#remove words with numbers python: https://stackoverflow.com/a/1808237
0/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
I remembered this book from my childhood and got it for my kids.  It's
just as good as I remembered and my kids love it too.  My older daughte
r now reads it to her sister.  Good rhymes and nice pictures.
```

In [20]:

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

```
This is the Japanese version of breadcrumb pan bread a Portuguese loan
word and quot ko quot is quot child of quot or of quot derived from quo
t Panko are used for katsudon tonkatsu or cutlets served on rice or in
soups The cutlets pounded chicken or pork are coated with these light a
nd crispy crumbs and fried They are not gritty and dense like regular c
rumbs They are very nice on deep fried shrimps and decorative for a mor
e gourmet touch
```

In [21]:

```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'no
t'
# <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', 'o
urs', 'ourselves', 'you', "you're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselve
s', 'he', 'him', 'his', 'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'it
s', 'itself', 'they', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'th
is', 'that', "that'll", 'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'h
```

```
ave', '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', 'through', 'during', 'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out',
'on', 'off', 'over', 'under', 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'h
ow', 'all', 'any', 'both', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 's
o', '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', "is
n'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 [22]:

```
# Combining all the above stundents
from tqdm import tqdm
preprocessed_reviews = []
# 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 stopwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|██████████| 160176/160176 [01:14<00:00, 2157.79it/s]
```

In [23]:

```
preprocessed_reviews[1500]
```

Out[23]:
```
'japanese version breadcrumb pan bread portuguese loan word ko child de
rived panko used katsudon tonkatsu cutlets served rice soups cutlets po
unded chicken pork coated light crispy crumbs fried not gritty dense li
ke regular crumbs nice deep fried shrimps decorative gourmet touch'
```

Obtaining the Required DataFrame (W/O Feature Engineering) :

In [24]:
```
type(preprocessed_reviews)
```

Out[24]:
```
list
```

Basically after all the text preprocessing was carried out we obtained a list, whereas the dataset that we have is named 'final'. Initially I had a total of 200K datapoints to work upon which got reduced to approx. 160K datapoints after the entire deduplication as well as text preprocessing was carried out.

In [25]:
```
print(final.shape)
```

```
(160176, 10)
```

In [26]:
```
final.head(3)
```

Out[26]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessD
138695	150513	0006641040	ASH0DZQQF6AIZ	tessarat	0	

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessD
138707	150525	0006641040	A2QID6VCFTY51R	Rick	1	
138708	150526	0006641040	A3E9QZFE9KXH8J	R. Mitchell	11	

Basically, again, what we are concerned about is the Preprocessed text whereas in the dataframe named 'final' we only have the 'Text' as a feature. So first I will add the preprocessed text as a column to this dataframe before proceeding any further.

In [27]:
```
final['Preprocessed_Reviews'] = preprocessed_reviews
```

In [28]:
```
final.head()
```

Out[28]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessI
138695	150513	0006641040	ASH0DZQQF6AIZ	tessarat	0	
138707	150525	0006641040	A2QID6VCFTY51R	Rick	1	

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessI
138708	150526	0006641040	A3E9QZFE9KXH8J	R. Mitchell	11	
138686	150504	0006641040	AQEYF1AXARWJZ	Les Sinclair "book maven"	1	
138685	150503	0006641040	A3R5XMPFU8YZ4D	Her Royal Motherliness "Nana"	1	

Now I have a total of approx. 160K rows in the dataframe called 'final', of which I will consider only 100K rows to be applied to the Naive Bayes Classifier. Also here you have the Unix Timestamp in the data, which is basically the time when the review was posted.

This makes it possible to carry out Time Based Split of the data instead of random splitting of the data into Train, CV and Test Datasets. For Time Based Split I will take the oldest of the reviews as the Training Data, the intermediate reviews as the CV data and the latest reviews as the Test data.

Now to carry out the Time Based Split on the Unix Timestamp, first the reviews need to be sorted based on the 'Time' feature.

In [29]:
```
final_TBS = final.sort_values('Time')
```

In [30]:
```
final_TBS.head()
```

Out[30]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulnes
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	
138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	
70688	76882	B00002N8SM	A32DW342WBJ6BX	Buttersugar	0	
1146	1245	B00002Z754	A29Z5PI9BW2PU3	Robbie	7	
1145	1244	B00002Z754	A3B8RCEI0FXFI6	B G Chase	10	

Now the values have been sorted on the basis of Time and by default the rows (reviews) are sorted in ascending order of time.

Obtaining Train, CV and Test Data (W/O FE been carried out) :-

First I will remove all the useless columns from this dataframe of mine. The only columns that we are concerned about here are the 'Score' and the 'Preprocessed_reviews'. The remaining columns in the dataframe are of no use to us.

In [31]:
```
df = final_TBS[['Score','Preprocessed_Reviews']]
```

In [32]:
```
df.head()
```

Out[32]:

	Score	Preprocessed_Reviews
138706	1	witty little book makes son laugh loud recite ...
138683	1	remember seeing show aired television years ag...
70688	1	bought apartment infested fruit flies hours tr...
1146	1	really good idea final product outstanding use...
1145	1	received shipment could hardly wait try produc...

In [33]:
```
cleandf = df[:100000]
```

Basically we are taking a total of 100K reviews for the model. Since I am carrying out Time Based Splitting into Train, CV and Test datasets, I will split them in 70:10:20 ratio respectively.

```
So, # of Datapoints in Train data = 70,000
    # of Datapoints in CV data = 10,000
    # of Datapoints in Test data = 20,000
```

In [34]:
```
Tr_df = cleandf[:70000]
CV_df = cleandf[70000:80000]
Te_df = cleandf[80000:100000]
```

Validating the Shapes of the Train, CV and Test Datasets to ensure that everything is working as expected:

In [35]:
```
Tr_df.shape
```
Out[35]:
```
(70000, 2)
```

In [36]:
```
CV_df.shape
```
Out[36]:
```
(10000, 2)
```

In [37]:
```
Te_df.shape
```
Out[37]:
```
(20000, 2)
```

So yes, everything is fair as expected : 70K datapoints in Training data, 10K datapoints in CV data and 20K datapoints in Test data. Now we are good to proceed further.

Now we can split the datasets into their X and Y parts.

In [38]:
```
X_Train1 = Tr_df['Preprocessed_Reviews']
Y_Train1 = Tr_df['Score']

X_CV1 = CV_df['Preprocessed_Reviews']
Y_CV1 = CV_df['Score']

X_Test1 = Te_df['Preprocessed_Reviews']
Y_Test1 = Te_df['Score']
```

In [39]:
```
Y_Train1.value_counts()
```
Out[39]:
```
1    60269
0     9731
Name: Score, dtype: int64
```

In [40]:
```
Y_CV1.value_counts()
```
Out[40]:
```
1    8266
0    1734
```

```
Name: Score, dtype: int64
```

In [41]:
```
Y_Test1.value_counts()
```

Out[41]:
```
1    16635
0     3365
Name: Score, dtype: int64
```

Therefore, as expected this is an imbalanced real world dataset.

Applying Multinomial Naive Bayes :-

[5.1] Applying Naive Bayes on BOW (W/O FE) :-

SET 1: Review text, preprocessed one converted into vectors using (BOW)

In [42]:
```
count_vect = CountVectorizer()
count_vect.fit(X_Train1) # fit function is being applied only on the Tr
ain Data.

#fit internally stores the parameters that will be used for transformin
g the data from the text to a numerical
#vector.
```

Out[42]:
```
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), preprocessor=None, stop_words=None,
        strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
        tokenizer=None, vocabulary=None)
```

In [43]:
```
X_Train_BOW = count_vect.transform(X_Train1)
X_CV_BOW = count_vect.transform(X_CV1)
X_Test_BOW = count_vect.transform(X_Test1)
```

In [44]:
```
print("Shapes before the BOW Vectorization was carried out:")

print(X_Train1.shape, Y_Train1.shape)
print(X_CV1.shape, Y_CV1.shape)
print(X_Test1.shape, Y_Test1.shape)

print("*"*100)

print("Shapes after the BOW Vectorization was carried out:")

print(X_Train_BOW.shape,Y_Train1.shape)
print(X_CV_BOW.shape,Y_CV1.shape)
print(X_Test_BOW.shape,Y_Test1.shape)
```

```
Shapes before the BOW Vectorization was carried out:
(70000,) (70000,)
(10000,) (10000,)
(20000,) (20000,)
**********************************************************************
******************************
Shapes after the BOW Vectorization was carried out:
(70000, 49871) (70000,)
(10000, 49871) (10000,)
(20000, 49871) (20000,)
```

Hyperparameter Tuning on the BOW Representation (W/O FE) :-

Here, I will take the values of alpha in the range from 10^-4 to 10^4 and apply the same on the CV dataset with AUC as the metric to obtain the best value of alpha.

In [45]:

```python
alpha_hyperparam=[]
#initializing an empty list

for a in range(-4,5):
    alpha_hyperparam.append(10**a)

#For the range() function if we need to consider the values from -4 to
 +4 in the exponent, the stop needs to be +5.
```

In [46]:

```python
print(alpha_hyperparam)
```

```
[0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]
```

In [47]:

```python
#Importing the Required Packages

from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
import matplotlib.pyplot as plt

from tqdm import tqdm
#tqdm is used to print the status bar
```

In [48]:

```python
Train_BOW_AUC =[]
CV_BOW_AUC=[]

for a in tqdm(alpha_hyperparam):
    naive = MultinomialNB(alpha=a)
    naive.fit(X_Train_BOW,Y_Train1)

    Y_Train_pred1 = naive.predict_proba(X_Train_BOW)[:,1]
    Y_CV_pred1 = naive.predict_proba(X_CV_BOW)[:,1]

    Train_BOW_AUC.append(roc_auc_score(Y_Train1,Y_Train_pred1))
    CV_BOW_AUC.append(roc_auc_score(Y_CV1,Y_CV_pred1))
```

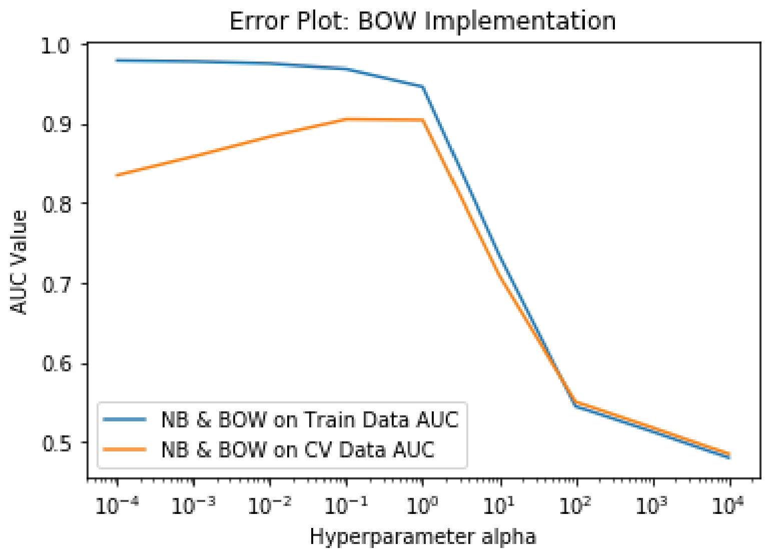
```
100%|██████████| 9/9 [00:01<00:00,  7.86it/s]
```

In [49]:
```
import matplotlib.pyplot as plt

plt.plot(alpha_hyperparam,Train_BOW_AUC, label = "NB & BOW on Train Dat
a AUC")
plt.plot(alpha_hyperparam,CV_BOW_AUC, label = "NB & BOW on CV Data AUC"
)
plt.xscale('log')

plt.legend()
plt.xlabel('Hyperparameter alpha')
plt.ylabel('AUC Value')
plt.title('Error Plot: BOW Implementation')

plt.grid(False)
plt.show()
```



From the curves plotted above we choose the Best value of alpha on the basis of AUC as a metric such that :

- The AUC value on the CV Dataset is the maximum.
- The gap between the Train and CV AUC Curves is low.

Therefore based on these 2 conditions, with the help of the curves above, I can choose the best value of alpha to be equal to :

In [50]:
```
#Best value of alpha = 10^0 ie 1
best_alpha = 1

#Since the AUC value in this scenario is approx. 0.90.
```

Obtaining the Top 10 Important Features:-

Now basically we can train our Naive Bayes Model on the best value of alpha that we obtained above in Cross Validation.

In [51]:
```
naive1 = MultinomialNB(alpha=best_alpha)
naive1.fit(X_Train_BOW,Y_Train1)
```

Out[51]:
```
MultinomialNB(alpha=1, class_prior=None, fit_prior=True)
```

In [52]:
```
Y_Train_pred1 = naive1.predict(X_Train_BOW)
```

In [53]:
```
print(naive1.classes_)
log_probabilities1 = naive1.feature_log_prob_

print(log_probabilities1)
```

```
[0 1]
[[-11.94968681 -13.0482991  -13.0482991  ... -12.35515192 -13.0482991
  -13.0482991 ]
 [-12.10292762 -13.05843907 -12.87611751 ... -14.66787698 -13.9747298
  -13.9747298 ]]
```

In [54]:
```
len(log_probabilities1[1])
```

Out[54]:
```
49871
```

First I have used the Naive Bayes attribute called "classes_" which basically returns the names of distinct classes in the dataset. Here in this scenario this is a Binary classification problem and hence we have 2 classes returned:

```
          class 0 :- Negative class,
      and,class 1 :- Positive class.
```

The order in which the 2 classes are returned is also important. This is because the nd array obtained by fetaure_log*prob* (present in the log_probabilities variable) also returns the log probabilities for each word in this order ie. :-

```
             Row 1 in the matrix :- Log Probabilities of the corre
    sponding word belonging to class "0" {Negative}
             Row 2 in the matrix :- Log Probabilities of the corre
    sponding word belonging to class "1" {Positive}
```

Also, since the model is fit on Train data, the length of each element in the array = No. of unique words in X_Train_BOW ie 49,871 in our case.

[5.1.1] Top 10 Important features of Positive Class from BOW (Set 1) :

In [55]:
```
positive_log_probabilities1 = log_probabilities1[1]

print(positive_log_probabilities1)
```

```
[-12.10292762 -13.05843907 -12.87611751 ... -14.66787698 -13.9747298
 -13.9747298 ]
```

In [56]:
```
feature_names1 = count_vect.get_feature_names()
type(feature_names1)
```

Out[56]: list

We have stored the feature names ie. basically each of the words in X_Train_BOW inside a variable called feature_names1 which is a list.

In [57]:
```
sorted_positiveprob1 = list(np.argsort(positive_log_probabilities1))
```

Now what I am doing is as follows:

```
* What argsort() does is it first sorts all the elements in the
 list and then returns the presorted indices
  of the elements. These presorted indices are important because
 the feature names will correspond to the
  presorted indices only.
* However, argsort() is used because at the same time we also wa
nt the features corresponding to the largest
  10 log probabilities. These largest 10 log probabilities can b
e obtained by considering the last 10 elements
  of the list (or by the first 10 elements after reversing the l
ist).
```

In [58]:
```
#I am reversing the list over here because I want the largest log of pr
obability value to be printed first followed by
#the values in descending order

sorted_positiveprob1.reverse()
```

In [59]:
```
print("The Top 10 Most Important Positive Features with BOW Representat
ion are as follows:")
print("="*100)

for i in sorted_positiveprob1[0:10]:
    print(feature_names1[i], "\t", round(positive_log_probabilities1[i
],3))
```

```
The Top 10 Most Important Positive Features with BOW Representation are
as follows:
================================================================================
==============================
not      -3.756
like     -4.586
good     -4.707
great    -4.764
one      -4.899
tea      -4.981
taste    -4.986
coffee   -5.085
flavor   -5.099
love     -5.13
```

[5.1.2] Top 10 Important features of Negative Class from BOW (Set 1) :

In [60]:

```
negative_log_probabilities1 = log_probabilities1[0]
print(negative_log_probabilities1)
```

```
[-11.94968681 -13.0482991  -13.0482991  ... -12.35515192 -13.0482991
 -13.0482991 ]
```

In [61]:

```
sorted_negativeprob1 = list(np.argsort(negative_log_probabilities1))
```

In [62]:

```
#I am reversing the list over here because I want the largest log of pr
obability value to be printed first followed by
#the values in descending order

sorted_negativeprob1.reverse()
```

In [63]:

```
print("The Top 10 Most Important Negative Features with BOW Representat
ion are as follows: ")
```

```
print("="*100)

for i in sorted_negativeprob1[0:10]:
    print(feature_names1[i],"\t", round(negative_log_probabilities1[i],
3))
```

```
The Top 10 Most Important Negative Features with BOW Representation are
as follows:
====================================================================================================
not	-3.405
like	-4.525
taste	-4.776
would	-4.776
product		-4.832
one	-4.97
good	-5.186
coffee	-5.242
flavor	-5.265
no	-5.299
```

Testing with the Test Data for BOW Representation (W/O FE) :-

I will use the Training data and the best value of alpha that we obtained from CV that will be used to train the model before we test the same on the test data.

In [64]:
```
naive1 = MultinomialNB(alpha=best_alpha)
naive1.fit(X_Train_BOW,Y_Train1)
```

Out[64]:
```
MultinomialNB(alpha=1, class_prior=None, fit_prior=True)
```

In [65]:
```
X_Train_BOW.shape
```

Out[65]:
```
(70000, 49871)
```

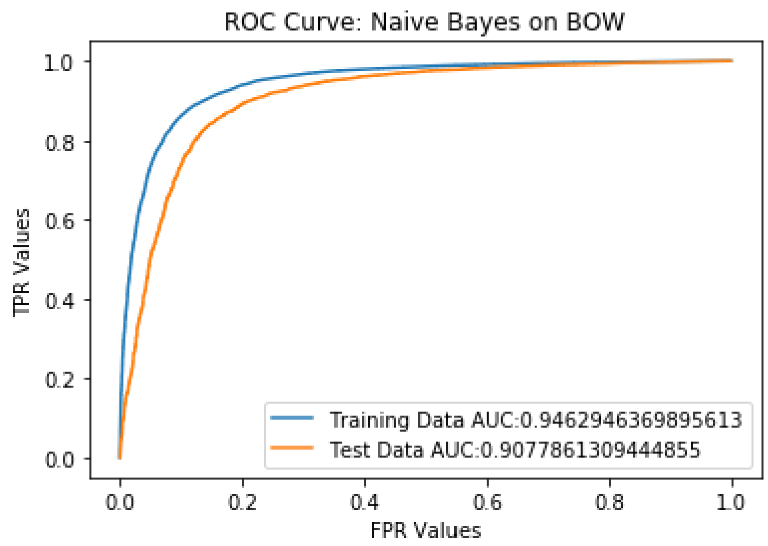
In [66]:
```
Y_Train1.shape
```
Out[66]:
```
(70000,)
```
In [67]:
```
X_Test_BOW.shape
```
Out[67]:
```
(20000, 49871)
```
In [68]:
```
Y_Test1.shape
```
Out[68]:
```
(20000,)
```
In [69]:
```
from sklearn.metrics import roc_curve,auc

train_fpr2,train_tpr2,thresholds = roc_curve(Y_Train1,naive1.predict_proba(X_Train_BOW)[:,1])
test_fpr2, test_tpr2, thresholds = roc_curve(Y_Test1,naive1.predict_proba(X_Test_BOW)[:,1])
```
In [70]:
```
import matplotlib.pyplot as plt

plt.plot(train_fpr2,train_tpr2, label = "Training Data AUC:" + str(auc(train_fpr2,train_tpr2)))
plt.plot(test_fpr2,test_tpr2, label = "Test Data AUC:" + str(auc(test_fpr2,test_tpr2)))
plt.legend()

plt.xlabel('FPR Values')
plt.ylabel('TPR Values')
plt.title('ROC Curve: Naive Bayes on BOW')

plt.grid(False)
plt.show()
```



User Defined Function to obtain the best value of Threshold with Best Tradeoff between TPR and FPR :-

In [71]:
```
def matrixpredict(data,thresholds,tpr,fpr):
    matrixpredict.best_tradeoff = tpr*(1-fpr)
    matrixpredict.ideal_threshold = thresholds[matrixpredict.best_trade
off.argmax()]

    predictions = []

    for i in data:
        if i>= matrixpredict.ideal_threshold:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions
```

User Defined Function to plot the Heatmap of The Confusion Matrix for the Training Data:

```
In [72]: import seaborn as sns

def plottrainmatrix (train_matrix):
    sns.set_style("whitegrid")

    labels = [0,1]

    print("-"*20, "Training Confusion Matrix", "-"*20)
    print(" ")
    print("The Training Data Confusion Matrix is as follows:")
    print(" ")
    print("The maximum value of tpr*(1-fpr) :", max(matrixpredict.best_
tradeoff))
    print("Threshold for Maximum Value of tpr*(1-fpr) :",round(matrixpr
edict.ideal_threshold,3))

    plt.figure(figsize=(10,7))


    sns.heatmap(train_matrix,
                annot=True, cmap="YlGnBu",fmt=".0f", xticklabels=labels
, yticklabels=labels,
                annot_kws={"size": 15})
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
```

User Defined Function to plot the HeatMap of The Confusion Matrix for the Test Data:

```
In [73]: import seaborn as sns

def plottestmatrix (test_matrix):
    labels = [0,1]

    print("-"*20, "Test Data Confusion Matrix", "-"*20)
    print(" ")
    print("The Test Data Confusion Matrix is as follows:")
    print(" ")
```

```
    print("The maximum value of tpr*(1-fpr) :", max(matrixpredict.best_
tradeoff))
    print("Threshold for Maximum Value of tpr*(1-fpr) :",round(matrixpr
edict.ideal_threshold,3))

    plt.figure(figsize=(10,7))

    sns.heatmap(test_matrix,annot=True, cmap="YlGnBu",fmt=".0f", xtickl
abels=labels,
                yticklabels=labels,annot_kws={"size": 15})
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
```

In [74]:
```
Y_Test_pred1 = naive1.predict_proba(X_Test_BOW)[:,1]
```

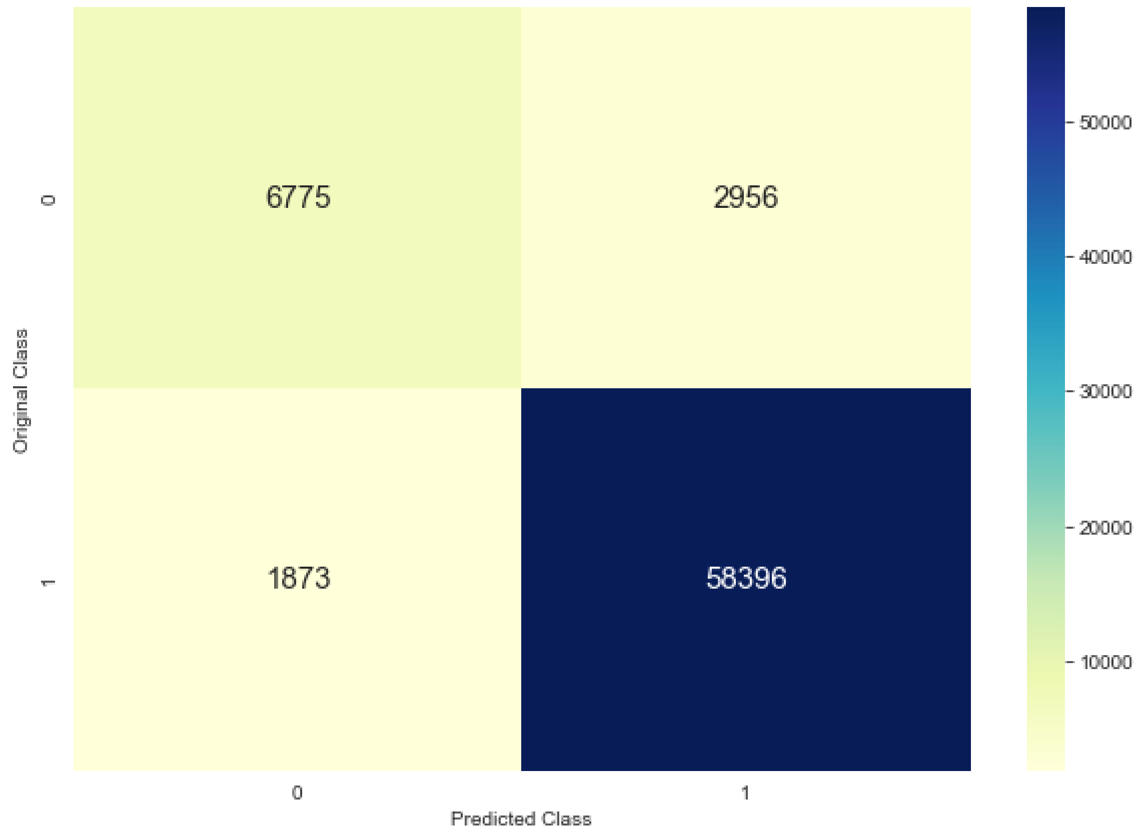
The Train Data Confusion Matrix looks as follows:-

In [75]:
```
BOW_Train = confusion_matrix(Y_Train1,matrixpredict(Y_Train_pred1,thres
holds,train_tpr2,train_fpr2))
plottrainmatrix(BOW_Train)
```

```
-------------------- Training Confusion Matrix --------------------

The Training Data Confusion Matrix is as follows:

The maximum value of tpr*(1-fpr) : 0.7807711147875495
Threshold for Maximum Value of tpr*(1-fpr) : 0.001
```



Accuracy on the Training Data = (58396+6775)/70000 => 93.10 %.

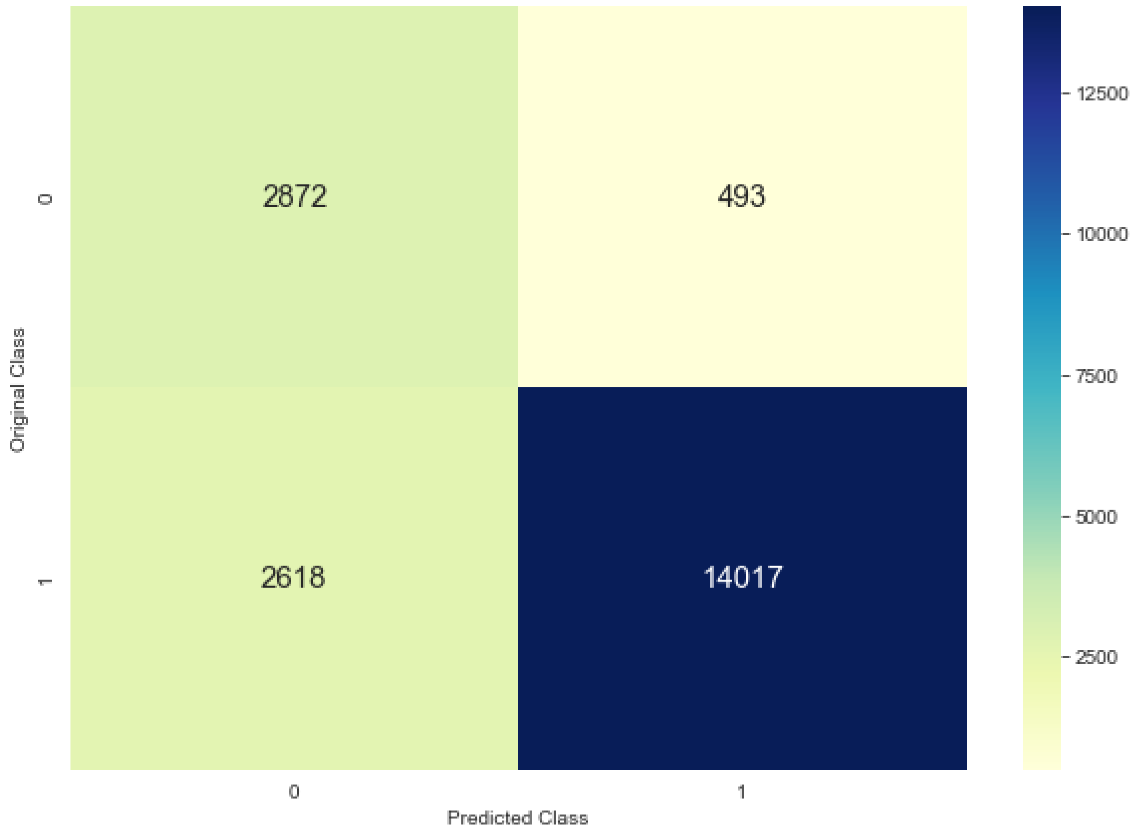
Similarly the Test Data Confusion Matrix is as follows:-

In [76]:
```
BOW_Test = confusion_matrix(Y_Test1,matrixpredict(Y_Test_pred1,threshol
ds,test_tpr2,test_fpr2))
plottestmatrix(BOW_Test)
```

```
-------------------- Test Data Confusion Matrix --------------------

The Test Data Confusion Matrix is as follows:
```

```
The maximum value of tpr*(1-fpr) : 0.7191701201078483
Threshold for Maximum Value of tpr*(1-fpr) : 0.982
```



Accuracy on the Test data = 84.44 %

[5.2] Applying Naive Bayes on TFIDF (W/O FE) :-

SET 2: Review text, preprocessed one converted

into vectors using (TFIDF)

In [77]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tf_idf_vect.fit(X_Train1)
```

Out[77]:
```
TfidfVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.float64'>, encoding='utf-8', input='conten
t',
        lowercase=True, max_df=1.0, max_features=None, min_df=10,
        ngram_range=(1, 2), norm='l2', preprocessor=None, smooth_idf=Tr
ue,
        stop_words=None, strip_accents=None, sublinear_tf=False,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, use_idf=Tru
e,
        vocabulary=None)
```

In [78]:
```
X_Train_TFIDF = tf_idf_vect.transform(X_Train1)
X_CV_TFIDF = tf_idf_vect.transform(X_CV1)
X_Test_TFIDF = tf_idf_vect.transform(X_Test1)
```

In [79]:
```
print("Shapes of the vectors before TFIDF Representation was carried ou
t:")

print(X_Train1.shape,Y_Train1.shape)
print(X_CV1.shape,Y_CV1.shape)
print(X_Test1.shape,Y_Test1.shape)

print("="*100)

print("Shapes of the vectors after TFIDF Representation was carried ou
t:")

print(X_Train_TFIDF.shape,Y_Train1.shape)
print(X_CV_TFIDF.shape,Y_CV1.shape)
print(X_Test_TFIDF.shape,Y_Test1.shape)
```

```
Shapes of the vectors before TFIDF Representation was carried out:
(70000,) (70000,)
(10000,) (10000,)
```

```
(10000,) (10000,)
(20000,) (20000,)

===========================================================================
==============================
Shapes of the vectors after TFIDF Representation was carried out:
(70000, 40652) (70000,)
(10000, 40652) (10000,)
(20000, 40652) (20000,)
```

Hyperparameter Tuning on the TFIDF Representation:

In [80]:

```
print(alpha_hyperparam)
```

```
[0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]
```

In [81]:

```
Train_TFIDF_AUC=[]
CV_TFIDF_AUC=[]

for a in alpha_hyperparam:
    naive = MultinomialNB(alpha=a)
    naive.fit(X_Train_TFIDF,Y_Train1)

    Y_Train_pred2 = naive.predict_proba(X_Train_TFIDF)[:,1]
    Y_CV_pred2 = naive.predict_proba(X_CV_TFIDF)[:,1]

    Train_TFIDF_AUC.append(roc_auc_score(Y_Train1,Y_Train_pred2))
    CV_TFIDF_AUC.append(roc_auc_score(Y_CV1,Y_CV_pred2))
```

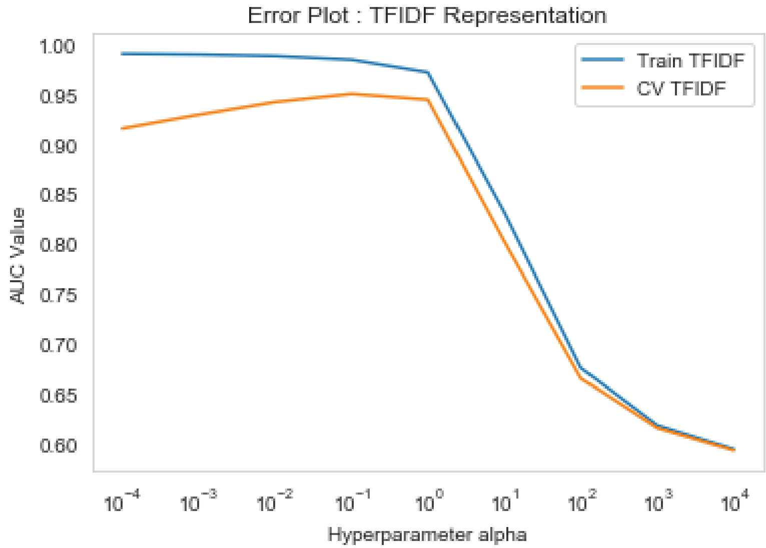
In [82]:

```
import matplotlib.pyplot as plt

plt.plot(alpha_hyperparam,Train_TFIDF_AUC, label = "Train TFIDF")
plt.plot(alpha_hyperparam,CV_TFIDF_AUC,label="CV TFIDF")
plt.xscale('log')
plt.legend()
```

```
plt.xlabel('Hyperparameter alpha')
plt.ylabel('AUC Value')
plt.title('Error Plot : TFIDF Representation')

plt.grid(False)
plt.show()
```



Again, based on the criteria in choosing the best value of alpha, we need to look for 2 things:

```
1. Largest value of AUC score for the CV Plot for a particular v
alue of alpha.
2. Smallest gap in the 2 plots of TFIDF and AUC for the chosen v
alue of alpha.
```

Based on these 2 conditions, the Best Value of alpha in this scenario would be as follows:

In [83]:
```
best_alpha = 1
#10^0 is the best value of alpha.
```

Obtaining the Top 10 Important Features with TFIDF Implementation:-

Now we can work on the Training dataset basis the best value of alpha obtained after Cross Validation.

In [84]:
```
naive2 = MultinomialNB(alpha=best_alpha)
naive2.fit(X_Train_TFIDF,Y_Train1)
```

Out[84]:
```
MultinomialNB(alpha=1, class_prior=None, fit_prior=True)
```

In [85]:
```
Y_Train_pred2 = naive2.predict(X_Train_TFIDF)
```

In [86]:
```
print(naive2.classes_)

log_probabilities2 = naive2.feature_log_prob_
print(log_probabilities2)
```

```
[0 1]
[[-11.04935408 -11.1061419  -11.49257509 ... -10.8931964  -11.39692889
  -11.11683862]
 [-11.69459725 -11.8854597  -11.81442195 ... -10.45415607 -11.80994774
  -10.99385424]]
```

In [87]:
```
len(log_probabilities2[0])
len(log_probabilities2[1])
```

Out[87]:
```
40652
```

First I have used the Naive Bayes attribute called "classes_" which basically returns the names of distinct classes in the dataset. Here in this scenario this is a Binary classification problem and hence we have 2 classes returned:

```
     class 0 :- Negative class,
and,class 1 :- Positive class.
```

The order in which the 2 classes are returned is also important. This is because the nd array obtained by fetaure_log*prob* (present in the log_probabilities variable) also returns the log probabilities for each word in this order ie. :-

```
            Row 1 in the matrix :- Log Probabilities of the corre
sponding word belonging to class "0" {Negative}
            Row 2 in the matrix :- Log Probabilities of the corre
sponding word belonging to class "1" {Positive}
```

Also, since the model is fit on Train data, the length of each element in the array = No. of unique words in X_Train_TFIDF ie 40,652 in our case.

Top 10 Important Features of the Positive Class for TFIDF (Set 2) :

In [88]:
```
positive_log_probabilities2 = log_probabilities2[1]

print(positive_log_probabilities2)
```

```
[-11.69459725 -11.8854597  -11.81442195 ... -10.45415607 -11.80994774
 -10.99385424]
```

In [89]:
```
feature_names2 = count_vect.get_feature_names()
type(feature_names2)
```

Out[89]:
```
list
```

In [90]:
```
sorted_positiveprob2 = list(np.argsort(positive_log_probabilities2))
```

In [91]:
```
#I am reversing the list over here because I want the largest log of pr
obability value to be printed first followed by
```

```
#the values in descending order

sorted_positiveprob2.reverse()
```

In [92]:
```
print("The Top 10 Most Important Positive Features with TFIDF Represent
ation are as follows:")
print("="*100)

for i in sorted_positiveprob2[0:10]:
    print(feature_names2[i], "\t", round(positive_log_probabilities2[i
],3))
```

```
The Top 10 Most Important Positive Features with TFIDF Representation a
re as follows:
========================================================================
============================
kelly	-5.419
faithfulness	-5.777
event	-5.843
grooms	-5.898
reactive		-5.9
capilary		-5.988
highlands		-6.03
likelihood		-6.123
quanities		-6.132
monitored		-6.134
```

Top 10 Important Features of the Negative Class for TFIDF (Set 2) :

In [93]:
```
negative_log_probabilities2  = log_probabilities2[0]

print(negative_log_probabilities2)
```

```
[-11.04935408 -11.1061419  -11.49257509 ... -10.8931964  -11.39692889
 -11.11683862]
```

In [94]:
```
sorted_negativeprob2 = list(np.argsort(negative_log_probabilities2))
```

In [95]:
```
#I am reversing the list over here because I want the largest log of pr
obability value to be printed first followed by
#the values in descending order

sorted_negativeprob2.reverse()
```

In [233]:
```
print("The Top 10 Most Important Negative Features with TFIDF Represent
ation are as follows:")
print("="*100)

for i in sorted_negativeprob2[0:10]:
    print(feature_names2[i], "\t", round(negative_log_probabilities2[i
],3))
```

```
The Top 10 Most Important Negative Features with TFIDF Representation a
re as follows:
========================================================================
============================
kelly    -5.27
grooms   -6.078
quanities        -6.174
monitored        -6.195
smacking         -6.198
capilary         -6.435
likelihood       -6.473
discredit        -6.618
jujubee          -6.64
event    -6.68
```

Testing with the Test Data for TFIDF Representation (W/O FE) :-

I will use the Training data and the best value of alpha that we obtained from CV that will be used to train the model before we test the same on the test data.

In [97]:
```
naive2 = MultinomialNB(alpha=best_alpha)
naive2.fit(X_Train_TFIDF,Y_Train1)
```

Out[97]: MultinomialNB(alpha=1, class_prior=None, fit_prior=True)

In [98]:
```
X_Train_TFIDF.shape
```

Out[98]: (70000, 40652)

In [99]:
```
Y_Train1.shape
```

Out[99]: (70000,)

In [100]:
```
X_Test_TFIDF.shape
```

Out[100]: (20000, 40652)

In [101]:
```
Y_Test1.shape
```

Out[101]: (20000,)

In [102]:
```
from sklearn.metrics import roc_curve, auc

train_fpr3,train_tpr3,thresholds = roc_curve(Y_Train1,naive2.predict_pr
oba(X_Train_TFIDF)[:,1])
test_fpr3,test_tpr3,thresholds = roc_curve(Y_Test1,naive2.predict_proba
(X_Test_TFIDF)[:,1])
```

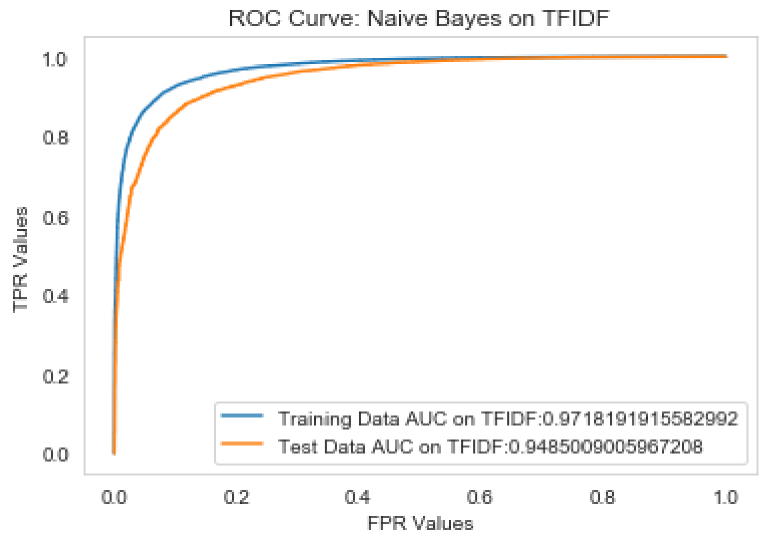
In [103]:
```
import matplotlib.pyplot as plt

plt.plot(train_fpr3,train_tpr3, label = "Training Data AUC on TFIDF:" +
 str(auc(train_fpr3,train_tpr3)))
plt.plot(test_fpr3,test_tpr3, label="Test Data AUC on TFIDF:" + str(auc
(test_fpr3,test_tpr3)))
```

```
plt.legend()

plt.xlabel("FPR Values")
plt.ylabel("TPR Values")
plt.title('ROC Curve: Naive Bayes on TFIDF')

plt.grid(False)
plt.show()
```



Plotting the Confusion Matrices for the TFIDF Train Data & Test Data for the Ideal Value of the Threshold:-

In [104]:
```
Y_Test_pred2 = naive2.predict_proba(X_Test_TFIDF)[:,1]
```

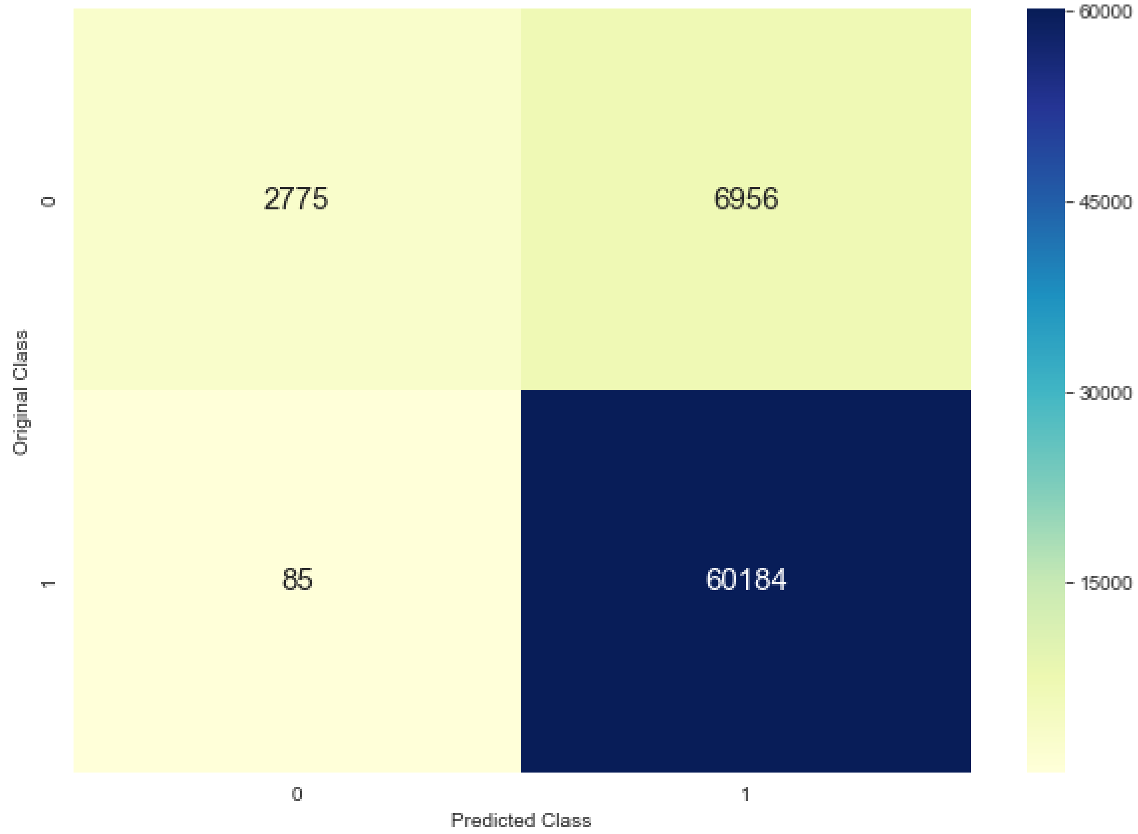
The Training Data Confusion Matrix will look as follows by calling the user defined functions matrixpredict() and plottrainmatrix() that were defined previously:

In [105]:
```
TFIDF_Train = confusion_matrix(Y_Train1,matrixpredict(Y_Train_pred2,thr
esholds,train_tpr3,train_fpr3))
plottrainmatrix(TFIDF_Train)
```

```
------------------- Training Confusion Matrix -------------------

The Training Data Confusion Matrix is as follows:

The maximum value of tpr*(1-fpr) : 0.8364827017727098
Threshold for Maximum Value of tpr*(1-fpr) : 0.822
```



Accuracy on the Train Data :- (60184+2775)/70000 => 89.94 %

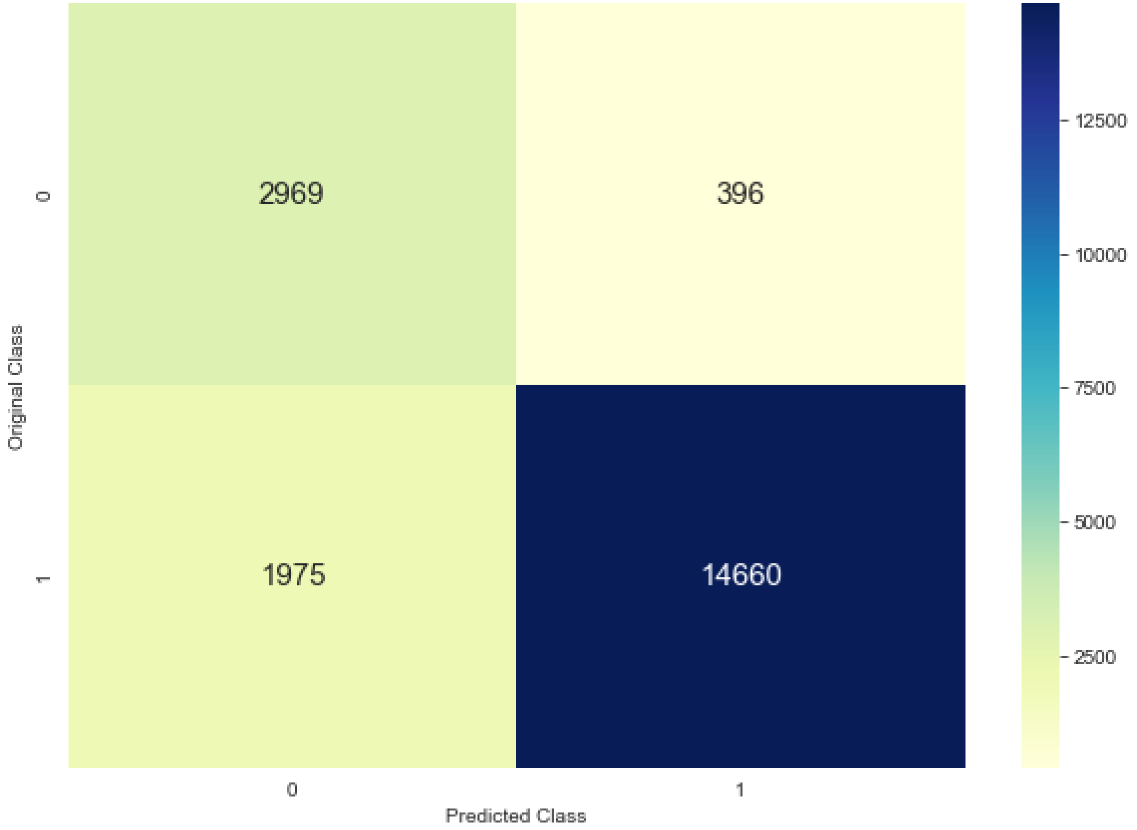
The Test Data Confusion Matrix will look as follows by calling the user defined functions matrixpredict() and plottrainmatrix() that were defined previously:

In [106]:
```
TFIDF_Test = confusion_matrix(Y_Test1,matrixpredict(Y_Test_pred2,thresh
olds,test_tpr3,test_fpr3))
plottestmatrix(TFIDF_Test)
```

```
------------------- Test Data Confusion Matrix -------------------

The Test Data Confusion Matrix is as follows:

The maximum value of tpr*(1-fpr) : 0.7775642666087855
Threshold for Maximum Value of tpr*(1-fpr) : 0.906
```



Accuracy on the Test Data = (14660+2969)/20000 => 88.14 %

[**] Preprocessing Review Summary

In [107]:

```
# printing some random reviews
summary_0 = final_TBS['Summary'].values[0]
print(summary_0)
print("="*50)

summary_1000 = final_TBS['Summary'].values[1000]
print(summary_1000)
print("="*50)

summary_1700 = final_TBS['Summary'].values[1700]
print(summary_1700)
print("="*50)

summary_4900 = final_TBS['Summary'].values[4900]
print(summary_4900)
print("="*50)
```

```
EVERY book is educational
==================================================
Somebody better check their specifications
==================================================
Treat yourself with a great breakfast.
==================================================
Great Gluten-Free Bread
==================================================
```

In [108]:

```
import warnings
warnings.filterwarnings('ignore')

preprocessed_summary = []

for title in final_TBS['Summary'].values:
    title = re.sub(r"http\S+", "", title)
    title = BeautifulSoup(title, 'lxml').get_text()
    title = decontracted(title)
    title = re.sub("\S*\d\S*", "", title).strip()
```

```
    title = re.sub('[^A-Za-z]+', ' ', title)

    title = ' '.join(e.lower() for e in title.split() if e.lower() not
in stopwords)
    preprocessed_summary.append(title.strip())
```

In [109]:
```
preprocessed_summary[1700]
```

Out[109]: 'treat great breakfast'

Feature Engineering to Increase the Model Performance:

We obtained a dataframe called "final" which had all the columns, out of which we considered only a single column of "Preprocessed_Reviews" in our final DataFrame, whereas we can try with additional features as our Xis to try and improve the model even further.

In [110]:
```
final_TBS.head(3)
```

Out[110]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulnes
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	
138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulnes
70688	76882	B00002N8SM	A32DW342WBJ6BX	Buttersugar	0	

Adding the Preprocessed Summary as another column to this dataframe:

In [111]:
```
final_TBS['Preprocessed_Summary'] = preprocessed_summary
```

In [112]:
```
Review_Length =[]
for i in final_TBS['Preprocessed_Reviews']:
    Review_Length.append(len(i))
```

Here, basically I am calculating the length of the 'Preprocessed_Reviews', which is : The number of characters in the review after the entire text preprocessing has been carried out.

Now I am adding this particular calculated feature as another column :'Review_Length' in my dataset.

In [113]:
```
final_TBS['Review_Length'] = Review_Length
```

In [114]:
```
final_TBS.head(3)
```

Out[114]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulnes
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulness
138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	
70688	76882	B00002N8SM	A32DW342WBJ6BX	Buttersugar	0	

Obtaining the Required Train,CV and Test Datasets (With FE) :-

First I will remove all the useless columns from this dataframe of mine. Now I will try Feature Engineering: The only columns that we are concerned about now are the 'Score','Preprocessed_Reviews','Review_Length' & 'Preprocessed_Summary'. The remaining columns in the dataframe are of no use to us.

In [115]:
```
df2 = final_TBS[['Preprocessed_Summary','Preprocessed_Reviews','Review_
Length','Score']]
```

In [116]:
```
df2.head()
```

Out[116]:

	Preprocessed_Summary	Preprocessed_Reviews	Review_Length	Score
138706	every book educational	witty little book makes son laugh loud recite ...	222	1
138683	whole series great way spend time child	remember seeing show aired television years ag...	222	1

	Preprocessed_Summary	Preprocessed_Reviews	Review_Length	Score
70688	sure death flies	bought apartment infested fruit flies hours tr...	207	1
1146	great product	really good idea final product outstanding use...	109	1
1145	wow make islickers	received shipment could hardly wait try produc...	277	1

In [117]:
```
cleandf2 = df2[:100000]
```

Again, just as in the previous case, I am taking a total of 100K reviews. Again the splitting of the data that I will carry out will be in the 70:10:20 ratio.

In [118]:
```
Tr_df2 = cleandf2[:70000]
CV_df2 = cleandf2[70000:80000]
Te_df2 = cleandf2[80000:100000]
```

In [119]:
```
Tr_df2.shape
```

Out[119]:
```
(70000, 4)
```

In [120]:
```
CV_df2.shape
```

Out[120]:
```
(10000, 4)
```

In [121]:
```
Te_df2.shape
```

Out[121]:
```
(20000, 4)
```

In [122]:
```
X_Train2 = Tr_df2[['Preprocessed_Summary','Preprocessed_Reviews','Revie
w_Length']]
Y_Train2 = Tr_df2['Score']

X_CV2 = CV_df2[['Preprocessed_Summary','Preprocessed_Reviews','Review_L
ength']]
```

```
Y_CV2 = CV_df2['Score']

X_Test2 = Te_df2[['Preprocessed_Summary','Preprocessed_Reviews','Review
_Length']]
Y_Test2 = Te_df2['Score']
```

In [123]:
```
type(X_Train2)
type(X_CV2)
type(X_Test2)
```

Out[123]:
```
pandas.core.frame.DataFrame
```

Basically, previously when we considered only a single column in our X_Train (Preprocessed_Reviews) we obtained a Series whereas in this case we obtain a DataFrame because we are considering multiple columns in our X_Train,X_CV and X_Test.

Applying Multinomial Naive Bayes on BOW (With FE) :-

Previously, we had only 1 feature : Preprocessed_Reviews to be concerned about. However in this scenario we have a total of 3 features : Preprocessed_Reviews,Preprocessed_Summary as well as the Review_Length to be concerned about.

So, what I will do is as follows:

- We should only fit() on the training data {to understand the vocabulary of the Training Dataset}, however we carry out the transformation on all datasets to convert the text data into numeric vectors.
- Hence, first I will fit and transform the 'Preprocessed_Reviews' feature in my Text dataset and store the same in a variable called 'X_Train_Reviews': This has 70K datapoints and 49871 features.
- Next I will fit and transform the 'Preprocessed_Summary' feature from my Text Dataset and store the same in a variable called 'X_Train_Summary' : This has 70k datapoints and 13358

features.

In [124]:
```
count_vect2 = CountVectorizer()
X_Train_Reviews = count_vect2.fit_transform(X_Train2['Preprocessed_Revi
ews'])
```

In [125]:
```
X_Train_Reviews.shape
```

Out[125]: (70000, 49871)

Also I am performing 2 Vcetorizations separately for the 2 features : 'Preprocessed_Reviews' and 'Preprocessed_Summary', because we want the transformations for the CV and Test Datasets to be carried out separately.

In [126]:
```
count_vect3 = CountVectorizer()
X_Train_Summary = count_vect3.fit_transform(X_Train2['Preprocessed_Summ
ary'])
```

In [127]:
```
X_Train_Summary.shape
```

Out[127]: (70000, 13358)

In [128]:
```
type(X_Train_Reviews)
```

Out[128]: scipy.sparse.csr.csr_matrix

In [129]:
```
type(X_Train_Summary)
```

Out[129]: scipy.sparse.csr.csr_matrix

I have looked at the types of both of these variables that I have obtained : Both of them are sparse matrices and hence they can be easily horizontally stacked using hstack in scipy.sparse, that I have imported below:

In [130]:
```
from scipy.sparse import hstack

temp_train = hstack([X_Train_Reviews,X_Train_Summary])
```

In [131]:
```
temp_train.shape
```

Out[131]: (70000, 63229)

In [132]:
```
type(temp_train)
```

Out[132]: scipy.sparse.coo.coo_matrix

As expected, temp_train has a total of 63229 features : 49871 features from Preprocessed_Reviews as a feature and 13358 features from Preprocessed_Summary. Now I also want to add Review_Length from X_Train2 into the BOW representation of the dataset.

We know that Review_Length is a single column and hence it is a pandas series type, which first needs to be converted into a sparse matrix in order to be again stacked on top of temp_train.

In [133]:
```
import scipy as sp

A = X_Train2['Review_Length'].as_matrix()
B = sp.sparse.csr_matrix(A)

#Source : https://stackoverflow.com/questions/20459536/convert-pandas-d
ataframe-to-sparse-numpy-matrix-directly
```

Now the variable B is the Review_Length converted into a sparse matrix, which can now be horizontally stacked. B obtained is a row vector which needs to be transposed in order to be stacked horizontally.

In [134]:
```
X_Train_BOW2 = hstack([temp_train,B.T])
```

In [135]:
```
X_Train_BOW2.shape
```

Out[135]: (70000, 63230)

Therefore, as expected, X_Train_BOW2 is a sparse matrix obtained that we needed which has 70K datapoints (as required) in the Training Data and a total of 63230 features.

Now we can carry out the same approach for CV and Test datasets as well:

Carrying out the same approach for CV Dataset:-

In [136]:
```
X_CV_Reviews = count_vect2.transform(X_CV2['Preprocessed_Reviews'])
```

In [137]:
```
X_CV_Reviews.shape
```

Out[137]: (10000, 49871)

In [138]:
```
X_CV_Summary = count_vect3.transform(X_CV2['Preprocessed_Summary'])
```

In [139]:
```
X_CV_Summary.shape
```

Out[139]: (10000, 13358)

In [140]:
```
type(X_CV_Reviews)
type(X_CV_Summary)
```

Out[140]: scipy.sparse.csr.csr_matrix

In [141]:
```
cv_temp = hstack([X_CV_Reviews,X_CV_Summary])
```

In [142]:
```
cv_temp.shape
```

Out[142]: (10000, 63229)

In [143]:
```
import scipy as sp
```

```
C = X_CV2['Review_Length'].as_matrix()
D = sp.sparse.csr_matrix(C)
```

In [144]:
```
X_CV_BOW2 = hstack([cv_temp,D.T])
```

In [145]:
```
X_CV_BOW2.shape
```

Out[145]: (10000, 63230)

Carrying out the same approach for Test Dataset:-

In [146]:
```
X_Test_Reviews = count_vect2.transform(X_Test2['Preprocessed_Reviews'])
```

In [147]:
```
X_Test_Reviews.shape
```

Out[147]: (20000, 49871)

In [148]:
```
X_Test_Summary = count_vect3.transform(X_Test2['Preprocessed_Summary'])
```

In [149]:
```
X_Test_Summary.shape
```

Out[149]: (20000, 13358)

In [150]:
```
type(X_Test_Reviews)
type(X_Test_Summary)
```

Out[150]: scipy.sparse.csr.csr_matrix

In [151]:
```
test_temp = hstack([X_Test_Reviews,X_Test_Summary])
```

In [152]:
```
test_temp.shape
```

Out[152]: (20000, 63229)

In [153]:
```
import scipy as sp
```

```
E = X_Test2['Review_Length'].as_matrix()
F = sp.sparse.csr_matrix(E)
```

In [154]:
```
X_Test_BOW2 = hstack([test_temp,F.T])
```

In [155]:
```
X_Test_BOW2.shape
```

Out[155]:
```
(20000, 63230)
```

Overall Summary:-

In [156]:
```
print("The final dimensionalities across all datasets after BOW Represe
ntation (With FE):")

print(X_Train_BOW2.shape,Y_Train1.shape)
print(X_CV_BOW2.shape,Y_CV1.shape)
print(X_Test_BOW2.shape,Y_Test1.shape)
```

```
The final dimensionalities across all datasets after BOW Representation
(With FE):
(70000, 63230) (70000,)
(10000, 63230) (10000,)
(20000, 63230) (20000,)
```

Hyperparameter Tuning on the BOW Representation (With FE) :-

In [157]:
```
print(alpha_hyperparam)
```

```
[0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]
```

In [158]:
```
Train_BOW2_AUC =[]
CV_BOW2_AUC=[]
```

```
for a in alpha_hyperparam:
    naive = MultinomialNB(alpha=a)
    naive.fit(X_Train_BOW2,Y_Train1)

    Y_Train_pred3 = naive.predict_proba(X_Train_BOW2)[:,1]
    Y_CV_pred3 = naive.predict_proba(X_CV_BOW2)[:,1]

    Train_BOW2_AUC.append(roc_auc_score(Y_Train1,Y_Train_pred3))
    CV_BOW2_AUC.append(roc_auc_score(Y_CV1,Y_CV_pred3))
```

In [159]:

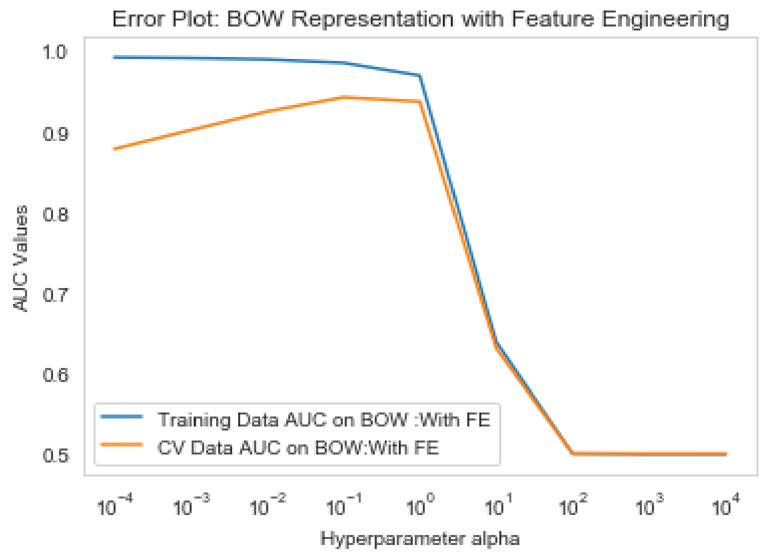
```
import matplotlib.pyplot as plt

plt.plot(alpha_hyperparam,Train_BOW2_AUC, label="Training Data AUC on B
OW :With FE")
plt.plot(alpha_hyperparam,CV_BOW2_AUC, label="CV Data AUC on BOW:With F
E")
plt.legend()

plt.xscale('log')

plt.xlabel('Hyperparameter alpha')
plt.ylabel('AUC Values')
plt.title('Error Plot: BOW Representation with Feature Engineering')

plt.grid(False)
plt.show()
```



Again, on the parameter basis which we choose the best value of alpha :

In [160]:
```
best_alpha= 1
```

Testing with the Test Data for BOW Implementation (With FE) :

In [161]:
```
naive3 = MultinomialNB(alpha=best_alpha)
naive3.fit(X_Train_BOW2,Y_Train1)
```

Out[161]:
```
MultinomialNB(alpha=1, class_prior=None, fit_prior=True)
```

In [162]:
```
X_Train_BOW2.shape
```

Out[162]:
```
(70000, 63230)
```

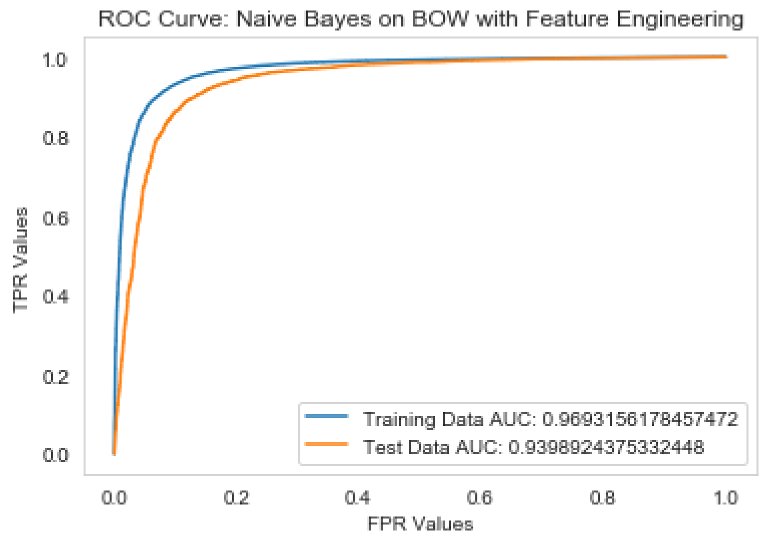
In [163]:
```
Y_Train1.shape
```
Out[163]:
```
(70000,)
```
In [164]:
```
X_Test_BOW2.shape
```
Out[164]:
```
(20000, 63230)
```
In [165]:
```
Y_Test1.shape
```
Out[165]:
```
(20000,)
```
In [166]:
```
from sklearn.metrics import roc_curve,auc

train_fpr4,train_tpr4,thresholds = roc_curve(Y_Train1,naive3.predict_pr
oba(X_Train_BOW2)[:,1])
test_fpr4,test_tpr4,thresholds = roc_curve(Y_Test1,naive3.predict_proba
(X_Test_BOW2)[:,1])
```
In [167]:
```
import matplotlib.pyplot as plt

plt.plot(train_fpr4,train_tpr4, label = "Training Data AUC: " + str(auc
(train_fpr4,train_tpr4)))
plt.plot(test_fpr4,test_tpr4, label = "Test Data AUC: " + str(auc(test_
fpr4,test_tpr4)))
plt.legend()

plt.xlabel('FPR Values')
plt.ylabel('TPR Values')
plt.title('ROC Curve: Naive Bayes on BOW with Feature Engineering')

plt.grid(False)
plt.show()
```



Plotting the Confusion Matrices for the BOW Test Data (with FE) for the Ideal Value of the Threshold:-

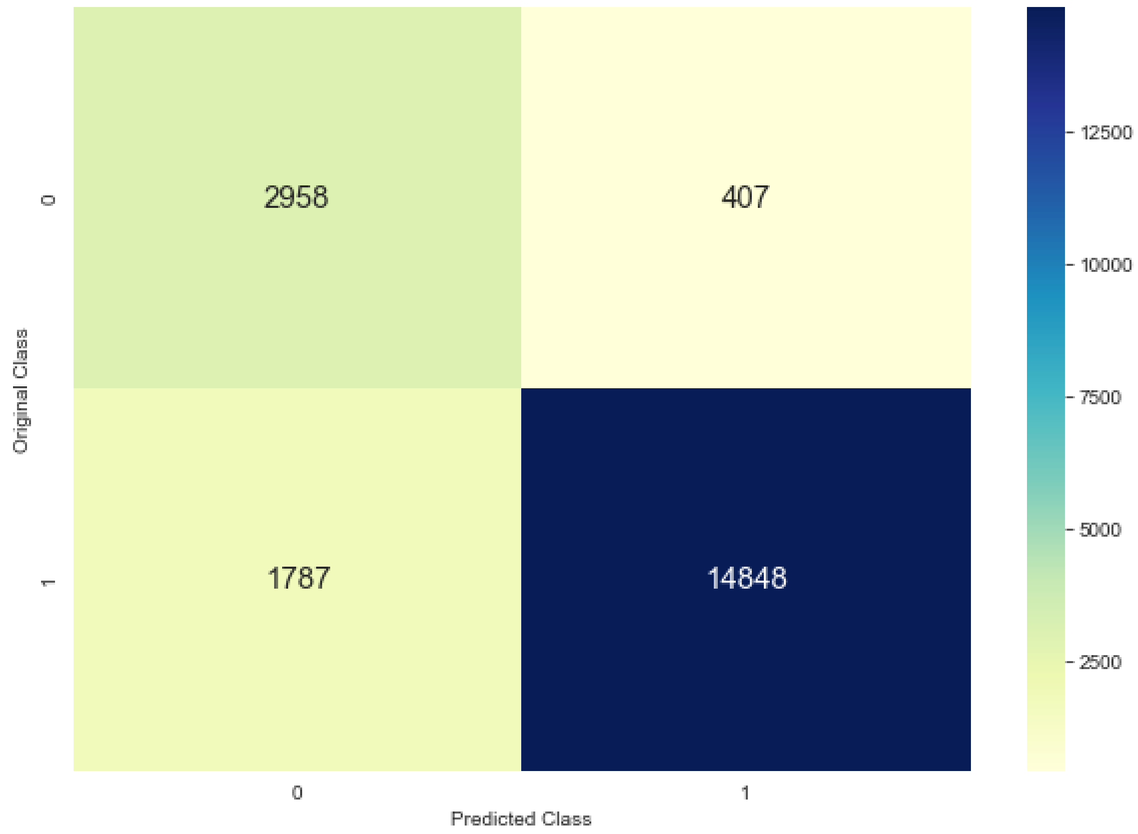
In [168]:
```
#To plot the confusion matrix
Y_Test_pred3 = naive3.predict_proba(X_Test_BOW2)[:,1]
```

In [169]:
```
BOW2_Test = confusion_matrix(Y_Test1,matrixpredict(Y_Test_pred3,thresho
lds,test_tpr4,test_fpr4))
plottestmatrix(BOW2_Test)
```

```
-------------------- Test Data Confusion Matrix --------------------

The Test Data Confusion Matrix is as follows:

The maximum value of tpr*(1-fpr) : 0.784617977723797
Threshold for Maximum Value of tpr*(1-fpr) : 0.987
```



Accuracy on the Test Data = (14848+2958)/20000 => 89.03 %

Applying Multinomial Naive Bayes on TFIDF (With FE) :-

Carrying out the same approach as the one followed above for Train Dataset with TFIDF Vectorization:-

In [170]:
```
tf_idf_vect2 = TfidfVectorizer(ngram_range=(1,2), min_df=10)
```

```
X_Train_TFIDF_Reviews = tf_idf_vect2.fit_transform(X_Train2['Preprocess
ed_Reviews'])
```

In [171]:
```
X_Train_TFIDF_Reviews.shape
```

Out[171]: (70000, 40652)

In [172]:
```
tf_idf_vect3 = TfidfVectorizer(ngram_range=(1,2), min_df=10)
X_Train_TFIDF_Summary = tf_idf_vect3.fit_transform(X_Train2['Preprocess
ed_Summary'])
```

In [173]:
```
X_Train_TFIDF_Summary.shape
```

Out[173]: (70000, 3541)

In [174]:
```
type(X_Train_TFIDF_Reviews)
type(X_Train_TFIDF_Summary)
```

Out[174]: scipy.sparse.csr.csr_matrix

In [175]:
```
from scipy.sparse import hstack

temp_train_tfidf = hstack([X_Train_TFIDF_Reviews,X_Train_TFIDF_Summary
])
```

In [176]:
```
temp_train_tfidf.shape
```

Out[176]: (70000, 44193)

In [177]:
```
import scipy as sp

G = X_Train2['Review_Length'].as_matrix()
H = sp.sparse.csr_matrix(G)

#Source : https://stackoverflow.com/questions/20459536/convert-pandas-d
ataframe-to-sparse-numpy-matrix-directly
```

In [178]:
```
X_Train_TFIDF2 = hstack([temp_train_tfidf,H.T])
```

In [179]:
```
X_Train_TFIDF2.shape
```

Out[179]: (70000, 44194)

Applying the same for CV Dataset:-

In [180]:
```
X_CV_TFIDF_Reviews = tf_idf_vect2.transform(X_CV2['Preprocessed_Review
s'])
```

In [181]:
```
X_CV_TFIDF_Reviews.shape
```

Out[181]: (10000, 40652)

In [182]:
```
X_CV_TFIDF_Summary = tf_idf_vect3.transform(X_CV2['Preprocessed_Summar
y'])
```

In [183]:
```
X_CV_TFIDF_Summary.shape
```

Out[183]: (10000, 3541)

In [184]:
```
type(X_CV_TFIDF_Reviews)
type(X_CV_TFIDF_Summary)
```

Out[184]: scipy.sparse.csr.csr_matrix

In [185]:
```
CV_TFIDF_Temp = hstack([X_CV_TFIDF_Reviews,X_CV_TFIDF_Summary])
```

In [186]:
```
CV_TFIDF_Temp.shape
```

Out[186]: (10000, 44193)

In [187]:
```
type(CV_TFIDF_Temp)
```

Out[187]: scipy.sparse.coo.coo_matrix

In [188]:
```
import scipy as sp
I = X_CV2['Review_Length'].as_matrix()
J = sp.sparse.csr_matrix(I)
```

In [189]:
```
X_CV_TFIDF2 = hstack([CV_TFIDF_Temp,J.T])
```

In [190]:
```
X_CV_TFIDF2.shape
```

Out[190]:
```
(10000, 44194)
```

Applying the same for Test Dataset:-

In [191]:
```
X_Test_TFIDF_Reviews = tf_idf_vect2.transform(X_Test2['Preprocessed_Rev
iews'])
```

In [192]:
```
X_Test_TFIDF_Reviews.shape
```

Out[192]:
```
(20000, 40652)
```

In [193]:
```
X_Test_TFIDF_Summary = tf_idf_vect3.transform(X_Test2['Preprocessed_Sum
mary'])
```

In [194]:
```
X_Test_TFIDF_Summary.shape
```

Out[194]:
```
(20000, 3541)
```

In [195]:
```
type(X_Test_TFIDF_Reviews)
type(X_Test_TFIDF_Summary)
```

Out[195]:
```
scipy.sparse.csr.csr_matrix
```

In [196]:
```
Test_TFIDF_Temp = hstack([X_Test_TFIDF_Reviews,X_Test_TFIDF_Summary])
```

In [197]:
```
Test_TFIDF_Temp.shape
```

Out[197]: (20000, 44193)

In [198]:
```
type(Test_TFIDF_Temp)
```

Out[198]: scipy.sparse.coo.coo_matrix

In [199]:
```
import scipy as sp
K = X_Test2['Review_Length'].as_matrix()
L = sp.sparse.csr_matrix(K)
```

In [200]:
```
X_Test_TFIDF2 = hstack([Test_TFIDF_Temp,L.T])
```

In [201]:
```
X_Test_TFIDF2.shape
```

Out[201]: (20000, 44194)

Overall Summary:-

In [202]:
```
print("The final dimensionalities across all datasets after TFIDF Repre
sentation (With FE):")

print(X_Train_TFIDF2.shape,Y_Train1.shape)
print(X_CV_TFIDF2.shape,Y_CV1.shape)
print(X_Test_TFIDF2.shape,Y_Test1.shape)
```

```
The final dimensionalities across all datasets after TFIDF Representati
on (With FE):
(70000, 44194) (70000,)
(10000, 44194) (10000,)
(20000, 44194) (20000,)
```

Hyperparameter Tuning on the TFIDF Representation (With FE) :-

In [203]:
```
print(alpha_hyperparam)
```

```
[0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]
```

In [204]:
```
Train_TFIDF2_AUC=[]
CV_TFIDF2_AUC=[]

for a in alpha_hyperparam:
    naive = MultinomialNB(alpha=a)
    naive.fit(X_Train_TFIDF2,Y_Train1)

    Y_Train_pred4 = naive.predict_proba(X_Train_TFIDF2)[:,1]
    Y_CV_pred4 = naive.predict_proba(X_CV_TFIDF2)[:,1]

    Train_TFIDF2_AUC.append(roc_auc_score(Y_Train1,Y_Train_pred4))
    CV_TFIDF2_AUC.append(roc_auc_score(Y_CV1,Y_CV_pred4))
```

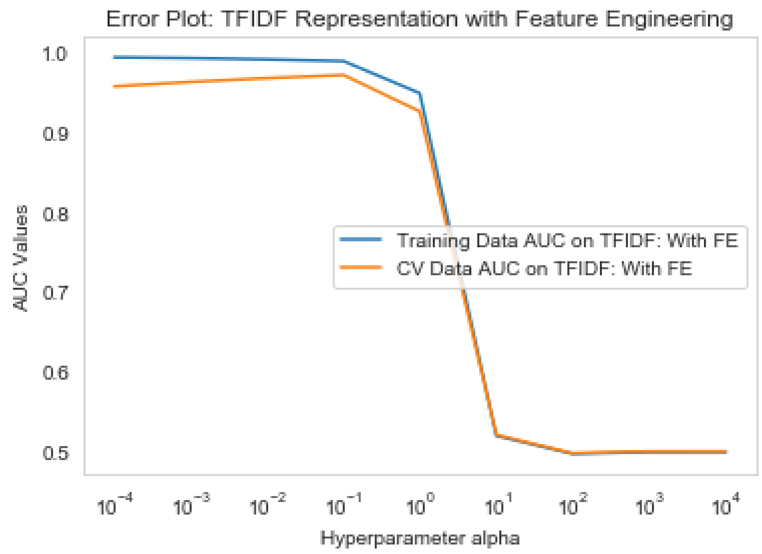
In [205]:
```
import matplotlib.pyplot as plt

plt.plot(alpha_hyperparam,Train_TFIDF2_AUC, label="Training Data AUC on
 TFIDF: With FE")
plt.plot(alpha_hyperparam,CV_TFIDF2_AUC, label="CV Data AUC on TFIDF: W
ith FE")
plt.legend()

plt.xscale('log')

plt.xlabel('Hyperparameter alpha')
plt.ylabel('AUC Values')
plt.title('Error Plot: TFIDF Representation with Feature Engineering')

plt.grid(False)
plt.show()
```



Again, based on the criteria on choosing the Best value of alpha based on the curve above:

In [206]:
```
Best_alpha = 1
#10^0 = 1
```

Testing with the Test Data for TFIDF Implementation (With FE) :-

In [207]:
```
naive4 = MultinomialNB(alpha=best_alpha)
naive4.fit(X_Train_TFIDF2,Y_Train1)
```

Out[207]:
```
MultinomialNB(alpha=1, class_prior=None, fit_prior=True)
```

In [208]:
```
X_Train_TFIDF2.shape
```

Out[208]:
```
(70000, 44194)
```

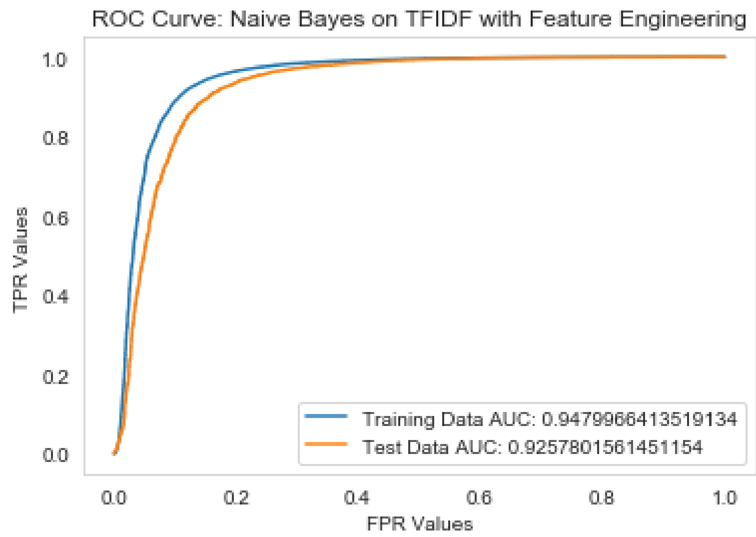
In [209]:
```
Y_Train1.shape
```
Out[209]:
```
(70000,)
```
In [210]:
```
X_Test_TFIDF2.shape
```
Out[210]:
```
(20000, 44194)
```
In [211]:
```
Y_Test1.shape
```
Out[211]:
```
(20000,)
```
In [212]:
```
from sklearn.metrics import roc_curve,auc

train_fpr5,train_tpr5,thresholds = roc_curve(Y_Train1,naive4.predict_pr
oba(X_Train_TFIDF2)[:,1])
test_fpr5,test_tpr5,thresholds = roc_curve(Y_Test1,naive4.predict_proba
(X_Test_TFIDF2)[:,1])
```
In [213]:
```
import matplotlib.pyplot as plt

plt.plot(train_fpr5,train_tpr5, label = "Training Data AUC: " + str(auc
(train_fpr5,train_tpr5)))
plt.plot(test_fpr5,test_tpr5, label = "Test Data AUC: " + str(auc(test_
fpr5,test_tpr5)))
plt.legend()

plt.xlabel('FPR Values')
plt.ylabel('TPR Values')
plt.title('ROC Curve: Naive Bayes on TFIDF with Feature Engineering')

plt.grid(False)
plt.show()
```



Plotting the Confusion Matrices for the TFIDF Test Data (with FE) for the Ideal Value of the Threshold:-

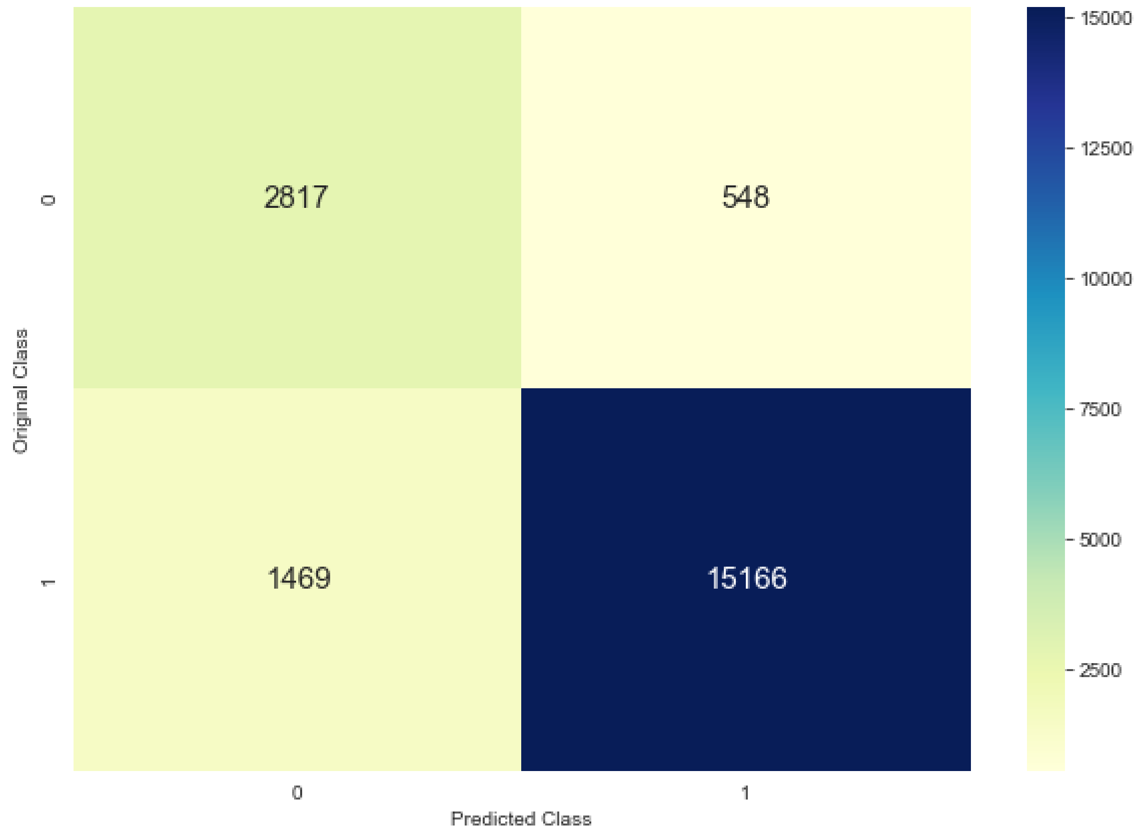
In [214]:
```
#To plot the confusion matrix
Y_Test_pred4 = naive4.predict_proba(X_Test_TFIDF2)[:,1]
```

In [215]:
```
TFIDF2_Test = confusion_matrix(Y_Test1,matrixpredict(Y_Test_pred4,thres
holds,test_tpr5,test_fpr5))
plottestmatrix(TFIDF2_Test)
```

```
-------------------- Test Data Confusion Matrix --------------------

The Test Data Confusion Matrix is as follows:

The maximum value of tpr*(1-fpr) : 0.7632204963576412
Threshold for Maximum Value of tpr*(1-fpr) : 0.924
```



Accuracy on the Test Data = (15166+2817)/20000 => 89.91 %

[6] Conclusions

In [228]:

```
from prettytable import PrettyTable
```

In [229]:

```
x=PrettyTable()
x.field_names=["S No.","Top 10 Positive Words","Log-Probability(+ve)",
"Top 10 Negative Words","Log-Probability(-ve)"]
```

In [230]:
```
print("Top 10 Positive and Negative Words with BOW Representation:")
print(" "*100)

x.add_row(["1","not","-3.756","not","-3.405"])
x.add_row(["2","like","-4.586","like","-4.525"])
x.add_row(["3","good","-4.707","taste","-4.776"])
x.add_row(["4","great","-4.764","would","-4.776"])
x.add_row(["5","one","-4.899","product","-4.832"])
x.add_row(["6","tea","-4.981","one","-4.97"])
x.add_row(["7","taste","-4.986","good","-5.186"])
x.add_row(["8","coffee","-5.085","coffee","-5.242"])
x.add_row(["9","flavor","-5.099","flavor","-5.265"])
x.add_row(["10","love","-5.13","no","-5.299"])

print(x)
```

```
Top 10 Positive and Negative Words with BOW Representation:


+-------+---------------------+--------------------+--------------
--------+---------------------+
| S No. | Top 10 Positive Words | Log-Probability(+ve) | Top 10 Negativ
e Words | Log-Probability(-ve) |
+-------+---------------------+--------------------+--------------
--------+---------------------+
|   1   |         not          |       -3.756       |          not
        |        -3.405        |
|   2   |         like         |       -4.586       |          like
        |        -4.525        |
|   3   |         good         |       -4.707       |         taste
        |        -4.776        |
|   4   |        great         |       -4.764       |         would
        |        -4.776        |
|   5   |         one          |       -4.899       |        product
        |        -4.832        |
|   6   |         tea          |       -4.981       |          one
        |        -4.97         |
|   7   |        taste         |       -4.986       |          good
        |        -5.186        |
|   8   |        coffee        |       -5.085       |         coffee
```

```
      |        -5.242        |
|   9   |         flavor        |        -5.099        |         flavor
      |        -5.265        |
|   10  |          love         |        -5.13         |           no
      |        -5.299        |
+-------+----------------------+----------------------+---------------
--------+---------------------+
```

In [231]:
```
y=PrettyTable()
y.field_names=["S No.","Top 10 Positive Words","Log-Probability(+ve)",
"Top 10 Negative Words","Log-Probability(-ve)"]
```

In [234]:
```
print("Top 10 Positive and Negative Words with TFIDF Representation:")
print(" "*100)

y.add_row(["1","kelly","-5.419","kelly","-5.27"])
y.add_row(["2","faithfulness","-5.777","grooms","-6.078"])
y.add_row(["3","event","-5.843","quanities","-6.174"])
y.add_row(["4","grooms","-5.898","monitored","-6.195"])
y.add_row(["5","reactive","-5.9","smacking","-6.198"])
y.add_row(["6","capilary","-5.988","capilary","-6.435"])
y.add_row(["7","highlands","-6.03","likelihood","-6.473"])
y.add_row(["8","likelihood","-6.123","discredit","-6.618"])
y.add_row(["9","quanities","-6.132","jujubee","-6.64"])
y.add_row(["10","monitored","-6.134","event","-6.68"])

print(y)
```

```
Top 10 Positive and Negative Words with TFIDF Representation:


+-------+----------------------+----------------------+---------------
--------+---------------------+
| S No. | Top 10 Positive Words | Log-Probability(+ve) | Top 10 Negativ
e Words | Log-Probability(-ve) |
+-------+----------------------+----------------------+---------------
--------+---------------------+
|   1   |         kelly         |        -5.419        |         kelly
      |        -5.27         |
```

```
|    2   |       faithfulness      |        -5.777        |         grooms
         |      -6.078          |
|    3   |         event          |        -5.843        |       quanitie
s        |      -6.174          |
|    4   |         grooms         |        -5.898        |       monitore
d        |      -6.195          |
|    5   |        reactive        |         -5.9         |        smackin
g        |      -6.198          |
|    6   |        capilary        |        -5.988        |        capilar
y        |      -6.435          |
|    7   |       highlands        |        -6.03         |       likeliho
od       |      -6.473          |
|    8   |       likelihood       |        -6.123        |       discredi
t        |      -6.618          |
|    9   |       quanities        |        -6.132        |        jujubee
         |      -6.64           |
|   10   |       monitored        |        -6.134        |         event
         |      -6.68           |
+--------+-----------------------+----------------------+---------------
--------+----------------------+
```

In [237]:
```python
z = PrettyTable()
z.field_names=["S No.","Model","Best Value of alpha","Test Accuracy on
 Ideal Threshold","Test AUC Score"]
```

In [238]:
```python
z.add_row(["1","BOW (Without FE)","1","84.44%","0.907"])
z.add_row(["2","TFIDF(Without FE)","1","88.14%","0.948"])
z.add_row(["3","BOW (With FE)","1","89.03%","0.939"])
z.add_row(["4","TFIDF(With FE)","1","89.91%","0.925"])

print(z)
```

```
+--------+--------------------+----------------------+-------------------
--------------+----------------+
| S No. |       Model       | Best Value of alpha | Test Accuracy on Id
eal Threshold | Test AUC Score |
+--------+--------------------+----------------------+-------------------
--------------+----------------+
|   1   |  BOW (Without FE) |          1           |             84.44%
```

```
             |     0.907      |
|   2   | TFIDF(Without FE) |          1          |                  88.14%
             |     0.948      |
|   3   |   BOW (With FE)   |          1          |                  89.03%
             |     0.939      |
|   4   |   TFIDF(With FE)  |          1          |                  89.91%
             |     0.925      |
+-------+-------------------+---------------------+-------------------
-------------+----------------+
```

Following are some Conclusions from the observations:-

- With the Feature Engineering (addition of BOW and TFIDF implementation) of the Preprocessed Summary as well as the Length of the Preprocessed Reviews there is a considerable increase in the accuracy for BOW and a slight increase in the case of TFIDF Representation.
- As far as AUC on the Test Dataset is considered there is an increase in AUC value after Feature Engineering with BOW and a slight decrease in AUC for TFIDF AUC with Feature Engineering.

  Finally, we can conclude that the Models in general are performing better after the Feature Engineering that has been carried out.