Naive bayes implementation over Amazon fine food reviews dataset

In [13]:
```
#IMPORTING RELEVANT LIBRARIES

%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
import itertools

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics

from sklearn.cross_validation import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.cross_validation import cross_val_score
from collections import Counter

from sklearn import cross_validation
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import KFold
from sklearn.naive_bayes import BernoulliNB
from imblearn.over_sampling import SMOTE
from prettytable import PrettyTable
from sklearn.model_selection import cross_validate
from random import *
```

In [2]:
```
#Connecting to the SQL table
con = sqlite3.connect('final.sqlite')

#Reading data from the database

Data = pd.read_sql_query("""
SELECT *
FROM Reviews """,con)
Data.shape
```

Out[2]:
```
(364171, 12)
```

In [3]:
```
# Drop index column
Data.drop(columns=['index'],inplace=True)
```

In [4]:
```
Data["Time"]=pd.to_datetime(Data.Time)
Data.head(5)
```

Out[4]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	
0	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0	positive	1970- 00:00:00.9393
1	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1	1	positive	1970- 00:00:01.1947
2	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1	1	positive	1970- 00:00:01.1914
3	150508	0006641040	AZGXZ2UUK6X	Catherine Hallberg " (Kate)"	1	1	positive	1970- 00:00:01.0760
4	150509	0006641040	A3CMRKGE0P909G	Teresa	3	4	positive	1970- 00:00:01.0183

In [5]:

```
#Setting Time column as index of the dataframe
Data.set_index("Time",inplace=True)

#Sampling the above data
Sorted=Data.sort_index()
```

In [6]:

```
Sorted.head()
```

Out[6]:

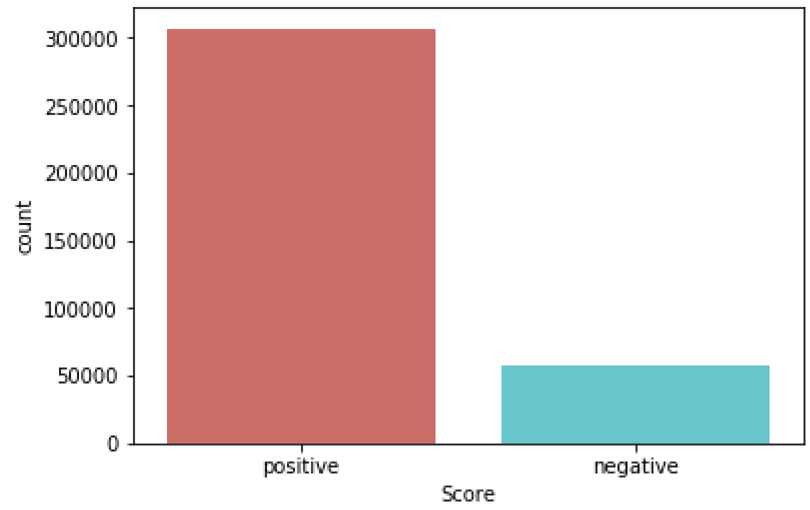
Time	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Sc
1970-01-01 00:00:00.939340800	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0	posit
1970-01-01 00:00:00.940809600	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	2	posit
1970-01-01 00:00:00.944092800	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0	0	posit
1970-01-01 00:00:00.944438400	374359	B00004CI84	A344SMIA5JECGM	Vincent P. Ross	1	2	posit
1970-01-01 00:00:00.946857600	451855	B00004CXX9	AJH6LUC1UT1ON	The Phantom of the Opera	0	0	posit

In [7]:

```
#Sampling the above data

Sampled_data=Sorted.sample(n=50000,replace='False')
Sample_sort=Sampled_data.sort_index()
Sample_sort.shape
```

Out[7]: (50000, 10)

In [8]:
```
Class=Sorted["Score"]
label=Sample_sort["Score"]
sns.countplot(x="Score",data=Sorted,palette="hls")
plt.show()
plt.savefig("count_plot")
```




```
<Figure size 432x288 with 0 Axes>
```

In [9]:
```
#Dropping the Score column which are the actual class labels of the dataset
Sorted.drop(columns=['Score'],inplace=True)
Sorted.shape
```

Out[9]:
```
(364171, 9)
```

In [10]:
```
#Dropping the Score column from the sampled_set which are the actual class labels of the dataset
Sample_sort.drop(columns=['Score'],inplace=True)
Sample_sort.shape
```

Out[10]:
```
(50000, 9)
```

Observations

- Here after all the text-preprocesing and the data-cleaning only 364k datapoints remained.
- I have taken a sample size of 50k and also the whole data out of the total population for the purpose of analyzing and studying the behaviour of the data by applying the Naive bayes algorithm.
- First I took the "TIME" column and set as the index of the new sampled dataframe and then sorted accordingly in ascending order since the data has a temporal nature.
- By setting the "SCORE" column as a class label for classifying the reviews as a positive and negative.
- By observing the above bar plot it is clear that the above dataset is highly imbalanced and this may cause problems in the future analysis.

Function for Spltting the dataset into Train,CV and Test sets (70:30)

In [11]:
```
def data_split(x,y):
    #Splitting the model into 70:30 split of Training and Cross_validate split
    X_1, X_test, y_1, y_test = train_test_split(X, Y, test_size=0.3,shuffle=False,random_state=None)

# split the train data set into cross validation train and cross validation test
    X_tr, X_cv, y_tr, y_cv = train_test_split(X_1, y_1, test_size=0.3,shuffle=False,random_state=None)

    return X_tr,y_tr,X_cv,y_cv,X_test,y_test
```

Preparing and printing the Train,cv and test sets

In [12]:
```
X=Sorted
Y=Class

X_tr,y_tr,X_cv,y_cv,X_test,y_test=data_split(X,Y)

print("The shape of x_train is:",X_tr.shape)
print("the shape of y_train is:",y_tr.shape)
print("the shape of x_cv is:",X_cv.shape)
print("the shape of y_cv is:",y_cv.shape)
print("the shape of x_test is:",X_test.shape)
print("the shape of y_test is:",y_test.shape)
```

```
The shape of x_train is: (178443, 9)
the shape of y_train is: (178443,)
the shape of x_cv is: (76476, 9)
the shape of y_cv is: (76476,)
the shape of x_test is: (109252, 9)
the shape of y_test is: (109252,)
```

Utility function for training and calculating the missclassification error of the model

In [14]:
```
#function for training the model
def train(X_tr,Y_tr,X_cv,y_cv):

    clf = MultinomialNB()
    clf.fit(X_tr, y_tr)

    pred= clf.predict(X_cv)

    acc = accuracy_score(y_cv, pred, normalize=True) * float(100)

    print('\n The train accuracy by using default alpha over cv set is =  %f%% ' % ( acc))
    return pred,acc

def test(X_tr,y_tr,X_test,y_test):
    Nb = MultinomialNB()
    Nb.fit(X_tr,y_tr)
    pred = Nb.predict(X_test)
    acc = accuracy_score(y_test, pred, normalize=True)*float(100)
    print('\n**** The Test accuracy by using default alpha is %d%%' % (acc))


def optimal_test(optimal_a,X_tr,y_tr,X_cv,y_cv,X_test,y_test):
    # instantiate learning model a = optimal_alpha
    B_optimal =MultinomialNB(alpha=optimal_a)

# fitting the model
    B_optimal.fit(X_tr, y_tr)

# predict the response
    pred = B_optimal.predict(X_test)

    Y_pred=B_optimal.predict(X_cv)

    TRAIN_acc = accuracy_score(y_cv, Y_pred, normalize=True) * float(100)
    print("\n The train accuracy of the NB classifier for the best alpha=%f%% is %f%% "%(optimal_a,TRA
IN_acc))

    print("*"*100)

# evaluate accuracy
    Acc = accuracy_score(y_test, pred,normalize=True) * float(100)
    print('\nThe Test accuracy of the NB classifier by using the best alpha = %f%% is %f%%' % (optimal
_a, Acc))

    return pred, Acc

def cross_validation(X_cv,y_cv):
    a=[0.001, 0.0001, 0.12, 0.42,0.25,0.50,0.33,0.0065,0.72, 1]
    multinom= a
    cv_Scores=[]
    for a in multinom:
        clf =MultinomialNB(a)
        scores = cross_val_score(clf, X_cv, y_cv, cv=10,scoring='accuracy')
        cv_Scores.append(scores.mean())
    #printing the 10 Cross-Validation scores
    print(cv_Scores)
    return cv_Scores,multinom
```

Utility function for visualizing the model scores and CV error of the model

In [15]:

```
from sklearn.metrics import confusion_matrix
def Confusion_metric(y_test,y_pred,acc):
    print(metrics.confusion_matrix(y_test,y_pred))
    confusion=metrics.confusion_matrix(y_test,y_pred)

    plt.figure(figsize=(9,9))
    sns.heatmap(confusion, annot=True, fmt=".3f", linewidths=.5, square = True, cmap = 'Blues_r');
    plt.ylabel('Predicted label');
    plt.xlabel('Actual label');
    all_sample_title = 'Accuracy Score: {0}'.format( acc)
    plt.title(all_sample_title, size = 15);
    plt.show()

#Storing the values of the confusion matrix
    TN=confusion[0,0]
    FP=confusion[0,1]
    FN=confusion[1,0]
    TP=confusion[1,1]

# use float to perform true division, not integer division
    Class_acc=((TP + TN) / float(TP + TN + FP + FN))*100

#Code for classification error

    classification_error = ((FP + FN) / float(TP + TN + FP + FN))*100


#Code for finding the TPR,FPR,TNR,FNR

    TPR = (TP / float(FN + TP))*100

    FNR = (FN / float(FN + TP))*100

    TNR=(TN / float(TN + FP))*100

    FPR=(FP / float(TN + FP))*100

#Code for finding the Precision,Recall & F1_score

    precision = (TP/float(TP+FP))*100

    recall= (TP / float(FN + TP))*100

    F1_s= ((float(precision*recall)/float(precision+recall))*2)

    print()

    ptable=PrettyTable()
    ptable.title="The performance metrics of the above model are as follows: "
    ptable.field_names=["Metrics","Scores"]
    ptable.add_row(["Classification_accuracy",Class_acc])
    ptable.add_row(["Classification_error",classification_error])
    ptable.add_row(["True positive",TP])
    ptable.add_row(["False positive",FP])
    ptable.add_row(["True negative",TN])
    ptable.add_row(["False negative",FN])
    ptable.add_row(["True positive rate",TPR])
    ptable.add_row(["False negative rate",FNR])
    ptable.add_row(["True negative rate",TNR])
    ptable.add_row(["False positive rate",FPR])
    ptable.add_row(["Precision value",precision])
    ptable.add_row(["Recall value",recall])
    ptable.add_row(["f1_score value",F1_s])

    print(ptable)

#Function for plotting the missclassification errors

def MSE_plot(CV_scores,multinom):
#Calculating the minimum Missclassification error of the above model

    MSE = [1 - x for x in CV_scores]

# determining best a
    optimal_a =multinom[MSE.index(min(MSE))]
    print('\nThe optimal number of alpha value is %f%%.' % optimal_a)

# plot misclassification error vs a
    plt.plot(multinom, MSE)

    for xy in zip(multinom, np.round(MSE,3)):
        plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')

    plt.xlabel('Number of alpha')
    plt.ylabel('Misclassification Error')
    plt.show()
```

```
    print("the misclassification error for  alpha value is : ", np.round(MSE,3))
    return optimal_a
```

Utility function for vectorizing the given data & finding the top features

In [16]:
```
#Function for vectorizing the train data

from sklearn.preprocessing import StandardScaler
def vec_train(vect,X_tr):
    import warnings
    warnings.filterwarnings("ignore")

    count_vect = vect #in scikit-learn
    BOW = count_vect.fit_transform(X_tr.values)

    return count_vect,BOW


#Function for vectorizing the CV data

def vec_cv(count,X_cv):
    cv=count.transform(X_cv.values)
    cv.get_shape()

    return cv


#Function for vectorizing the test data

def vec_test(count,X_test):
    test=count.transform(X_test.values)
    test.get_shape()

    return test

#Funtion for printing the total number of top features
def top_tfidf_feats(name,row, features, top_n=25):
    ''' Get top n tfidf values in row and return them with their corresponding feature names.'''
    topn_ids = np.argsort(row)[::-1][:top_n]
    top_feats = [(features[i], row[i]) for i in topn_ids]
    df = pd.DataFrame(top_feats)
    df.columns = ['feature', name]
    return df
```

Bag of words vectorization technique

In [17]:
```
#Initializing the count vectorizer
Count_vect=CountVectorizer(binary=True)

#vectorizing the X_train set
count,x_tr=vec_train(Count_vect,X_tr["CleanedText"])

print("The shape of the X_train is: ",x_tr.shape)

#Vectgorizing the X_crossvalidation set
x_cv=vec_cv(count,X_cv["CleanedText"])
print("The shape of the X_cv is: ",x_cv.shape)

#Vectorizing the X_test set
x_test=vec_test(count,X_test["CleanedText"])
print("The shape of the X_test is: ",x_test.shape)


#Printing the total length of the features
print("\nTop 25 feaures acording to the Bow score are as follows")
features = Count_vect.get_feature_names()
len(features)


top_Bow = top_tfidf_feats("bow",x_tr[1,:].toarray()[0],features,25)
top_Bow
```

```
The shape of the X_train is:  (178443, 49468)
The shape of the X_cv is:  (76476, 49468)
The shape of the X_test is:  (109252, 49468)

Top 25 feaures acording to the Bow score are as follows
```

Out[17]:

	feature	bow
0	someth	1
1	teach	1
2	later	1
3	thirti	1
4	day	1
5	rememb	1
6	tradit	1
7	air	1
8	show	1
9	book	1
10	see	1
11	ago	1
12	preschool	1
13	whole	1
14	use	1
15	televis	1
16	student	1
17	turn	1
18	seri	1
19	school	1
20	song	1
21	purchas	1
22	children	1
23	child	1
24	bought	1

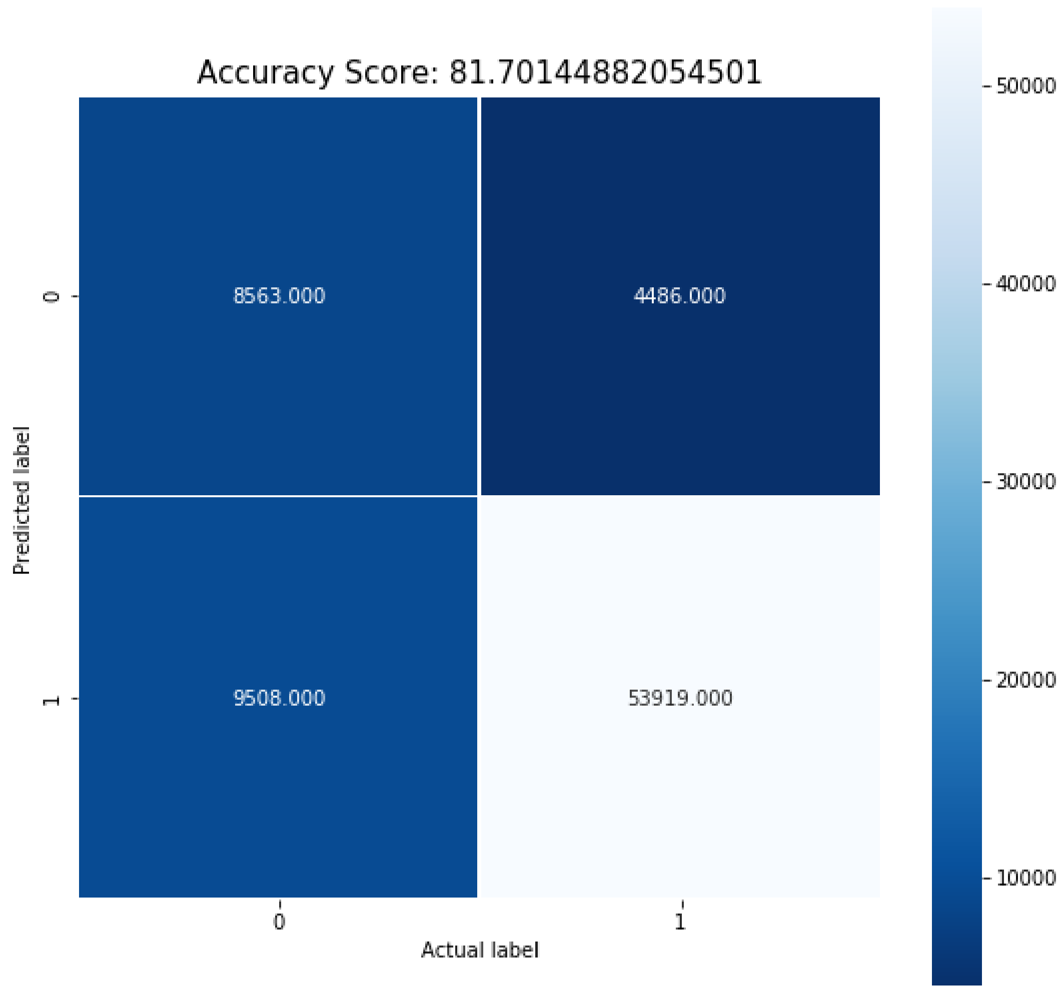
Training the NB model using the train set and testing over the CV set with default values

In [19]:
```
pred,acc=train(x_tr,y_tr,x_cv,y_cv)
```

```
The train accuracy by using default alpha over cv set is =  81.701449%
```

In [26]:
```
#Confusion metric of the above model:

Confusion_metric(y_cv,pred,acc)
```

```
[[ 8563  4486]
 [ 9508 53919]]
```



```
+-----------------------------------------------------------+
| The performance metrics of the above model are as follows: |
+------------------------------+----------------------------+
|           Metrics            |           Scores           |
+------------------------------+----------------------------+
|   Classification_accuracy    |      81.70144882054501     |
|     Classification_error     |     18.298551179454993     |
|        True positive         |           53919            |
|        False positive        |            4486            |
|        True negative         |            8563            |
|        False negative        |            9508            |
|      True positive rate      |      85.00953852460309     |
|     False negative rate      |     14.990461475396913     |
|      True negative rate      |      65.62188673461567     |
|     False positive rate      |      34.37811326538432     |
|       Precision value        |      92.31915075764061     |
|         Recall value         |      85.00953852460309     |
|        f1_score value        |      88.51369098430625     |
+------------------------------+----------------------------+
```

OBSERVATIONS

- The train accuracy usong default parameters of the model is 81.70% which is not that good for a classification model.
- Here the TP is dominating metric as compared to other metric which also results in high TPR value.
- Due to the low TN value the TNR value is very less (65.52%) which is not a good sign for aclassification model.
- The precision,recall and the f1_score cannot be trusted due to high TPR & low TNR values.

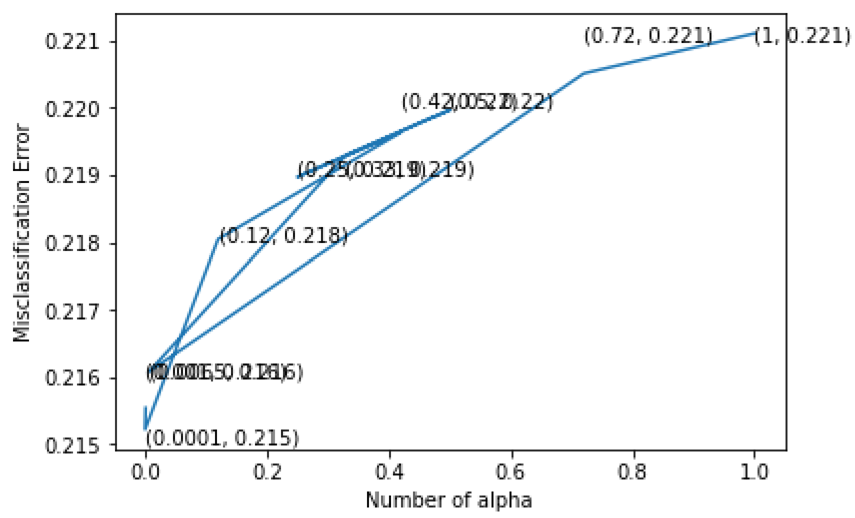
Hyperparameter tuning the alpha value by using 10-fold Cross-validation technique

In [27]:
```python
Score,mutinom =cross_validation(x_tr,y_tr)
```

```
[0.7844576677081012, 0.7847770971595364, 0.7819526695323858, 0.7803667330368377, 0.781028009694429, 0.780030493409807, 0.7807029745481355, 0.7839196792801396, 0.7794869039976551, 0.7788928809182714]
```

In [28]:
```python
optimal_a=MSE_plot(Score,mutinom) #CODE FOR PLOTTING THE ERROR PLOT
```

```
The optimal number of alpha value is 0.000100%.
```




```
the misclassification error for  alpha value is :  [0.216 0.215 0.218 0.22  0.219 0.22  0.219 0.216 0.221 0.221]
```

Testing the model by using the optimal alpha over the test set

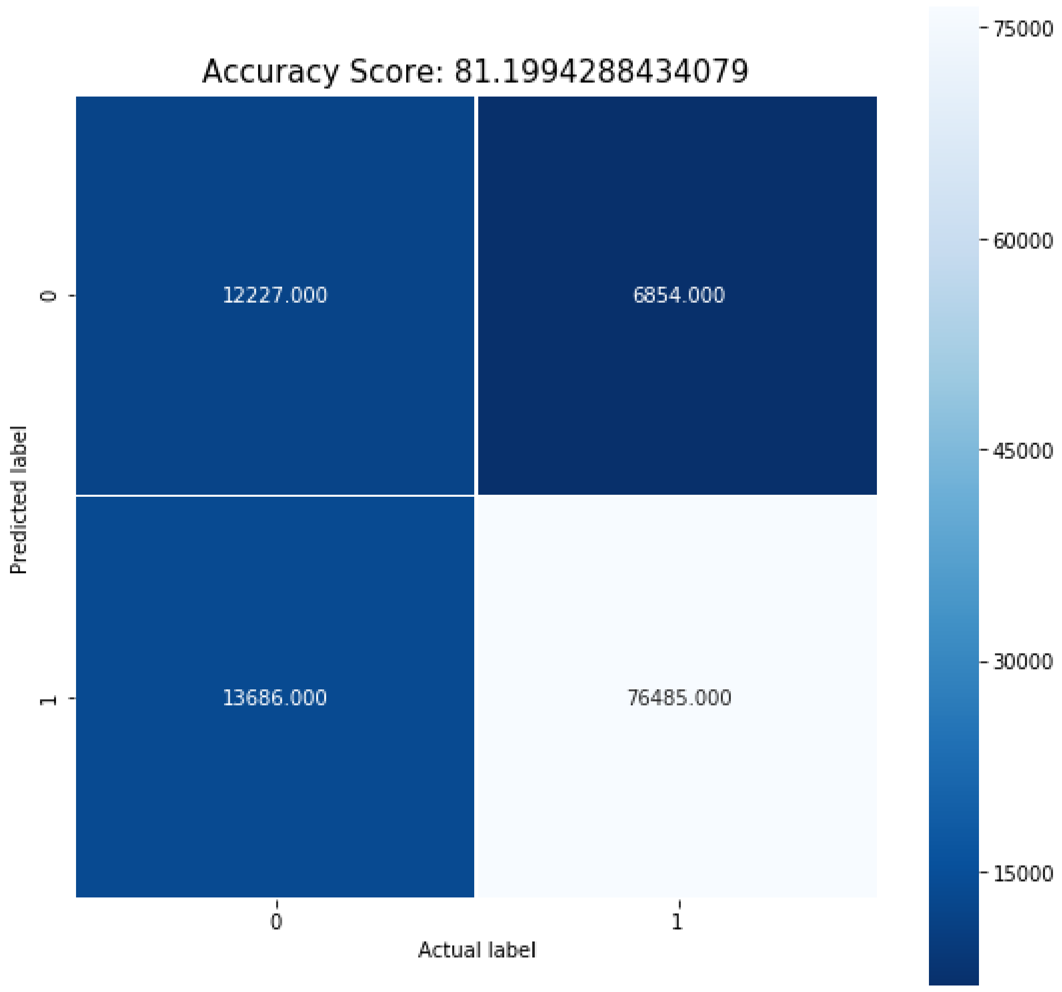
In [29]:
```python
#Testing the model with default value of alpha over the Test data
test(x_tr,y_tr,x_test,y_test)

print("*"*100)

#Testing the model with optimal alpha value over the test data
y_pred,Test_acc,=optimal_test(optimal_a,x_tr,y_tr,x_cv,y_cv,x_test,y_test)
```

```
**** The Test accuracy by using default alpha is 81%
****************************************************************************************************

 The train accuracy of the NB classifier for the best alpha=0.000100% is 81.633454%
****************************************************************************************************

The Test accuracy of the NB classifier by using the best alpha = 0.000100% is 81.199429%
```

Confusion metric of the above model.

In [30]:
```
Confusion_metric(y_test,y_pred,Test_acc)
```

```
[[12227  6854]
 [13686 76485]]
```




```
+-------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+---------------------------------+---------------------------+
|             Metrics             |           Scores          |
+---------------------------------+---------------------------+
|     Classification_accuracy     |      81.1994288434079     |
|      Classification_error       |      18.8005711565921     |
|          True positive          |           76485           |
|          False positive         |            6854           |
|          True negative          |           12227           |
|          False negative         |           13686           |
|        True positive rate       |     84.82217120803807     |
|       False negative rate       |     15.17782879196194     |
|        True negative rate       |     64.07945076253864     |
|       False positive rate       |     35.920549237461344    |
|         Precision value         |     91.77575924837112     |
|           Recall value          |     84.82217120803807     |
|          f1_score value         |     88.16206558699788     |
+---------------------------------+---------------------------+
```

OBSERVATION

- After training the model over optimal alpha value the model score decreased by 0.51% which is not good.
- This model scores are also similar to the previous model except there is slight decrease is seen on all the parameters.
- Since the model is trained over imbalanced dataset so the it is suffering from the high bias problem.
- So the performance can be increased if data balancing is performed over the dataset which can be done by using the oversampling technique.

Oversampling the data by using the SMOTE technique

In [31]:
```
#FUNCTION FOR IMPLEMENTING THE SYNTHETIC MINORITY OVERSAMPLING TECHNIQUE
from imblearn.over_sampling import SMOTE

def Bal_train (X_tr, y_tr,X_cv,y_cv,X_test,y_test):

    sm = SMOTE()
    X_Train_res, y_Train_res = sm.fit_sample(X_tr, y_tr)
    X_Cval_res,y_Cval_res=sm.fit_sample(X_cv,y_cv)
    X_Test_res,y_Test_res=sm.fit_sample(X_test,y_test)


    clf = MultinomialNB()
    clf.fit(X_Train_res, y_Train_res )

    pred= clf.predict(X_Cval_res)

    acc = accuracy_score(y_Cval_res, pred, normalize=True) * float(100)

    print('\n The TRAIN accuracy by using default alpha over CV set is =  %f%% ' % ( acc))

    return X_Train_res, y_Train_res,X_Cval_res,y_Cval_res,X_Test_res,y_Test_res,pred, acc
```

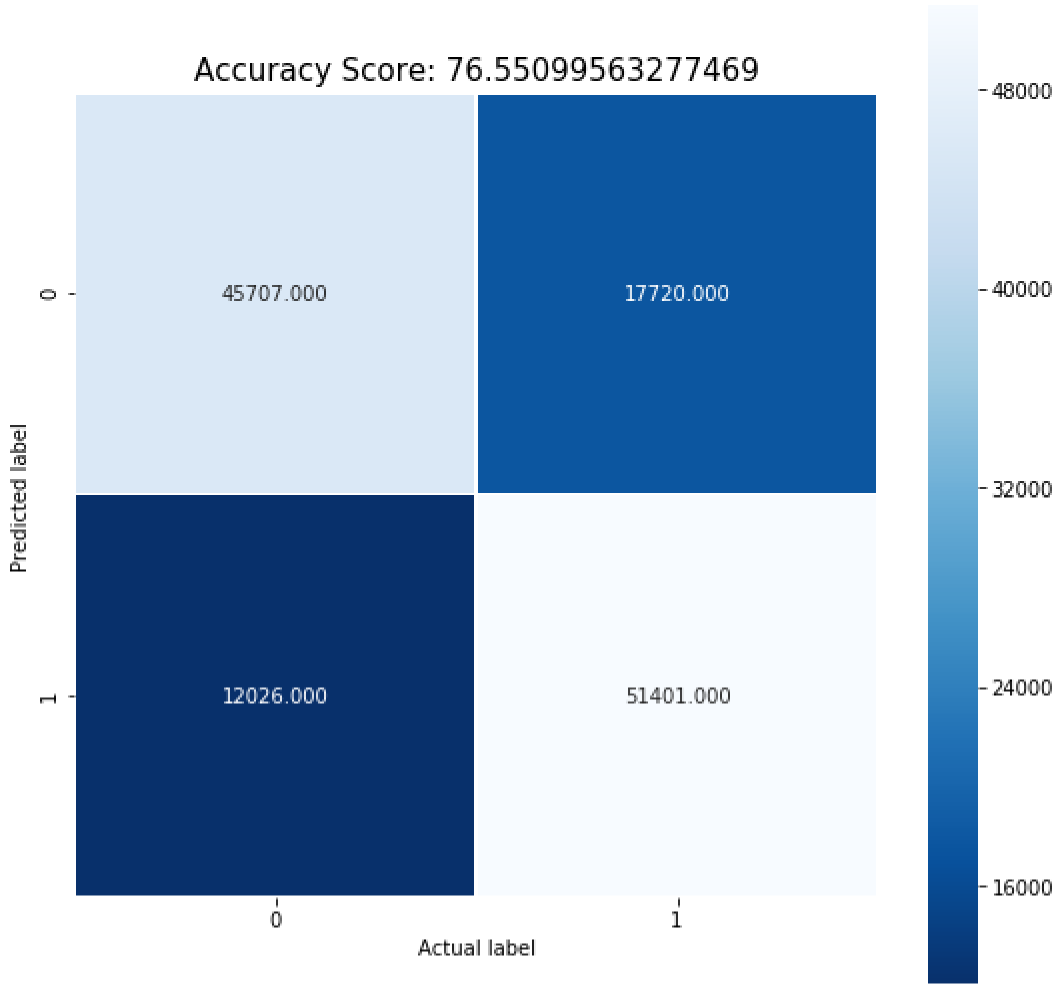
Training the SMOTE model

In [34]:
```
bal_xtr,bal_ytr,bal_xcv,bal_ycv,bal_xtes,bal_ytes,b_pre,b_acc=Bal_train(x_tr,y_tr,x_cv,y_cv,x_test,y_test)
```

```
 The TRAIN accuracy by using default alpha over CV set is =  76.550996%
```

In [35]:
```
Confusion_metric(bal_ycv,b_pre,b_acc)
```

```
[[45707 17720]
 [12026 51401]]
```




```
+--------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+---------------------------------+----------------------------+
|             Metrics             |           Scores           |
+---------------------------------+----------------------------+
|     Classification_accuracy     |     76.55099563277469      |
|      Classification_error       |     23.449004367225314     |
|          True positive          |           51401            |
|          False positive         |           17720            |
|          True negative          |           45707            |
|          False negative         |           12026            |
|        True positive rate       |     81.03962035095465      |
|       False negative rate       |     18.960379649045358     |
|        True negative rate       |     72.06237091459474      |
|       False positive rate       |     27.93762908540527      |
|         Precision value         |     74.36379682006915      |
|           Recall value          |     81.03962035095465      |
|          f1_score value         |      77.5583184959411      |
+---------------------------------+----------------------------+
```

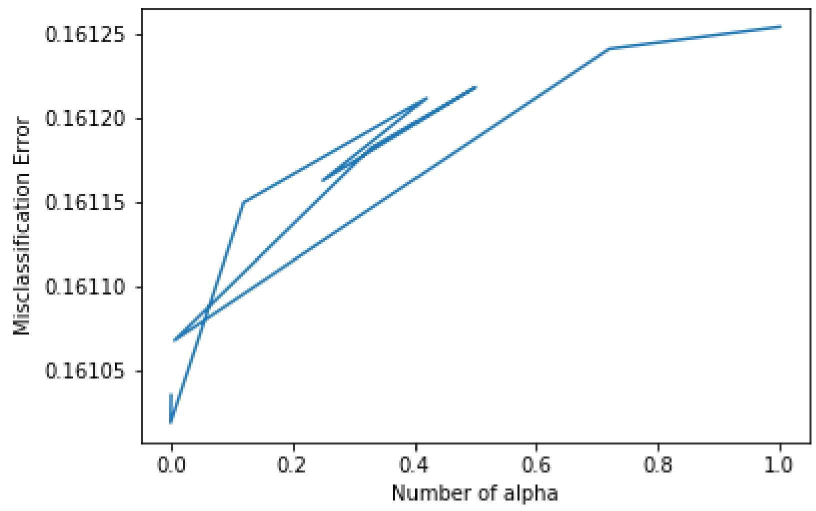
HYPERAMETER TUNING THE ALPHA FOR FINDING THE OPTIMAL ALPHA VALUE

In [36]:
```
BScore,Mutinom =cross_validation(bal_xtr,bal_ytr)
```

```
[0.83896452215018, 0.8389808128280135, 0.8388504880422468, 0.8387885845704425, 0.8388374561793419, 0.8
387820682143887, 0.8388179073234815, 0.8389319412191141, 0.8387592616051028, 0.8387462288929954]
```

In [37]:
```
Boptimal_a=MSE_plot(BScore,Mutinom) #CODE FOR PLOTTING THE ERROR PLOT
```

```
The optimal number of alpha value is 0.000100%.
```




```
the misclassification error for  alpha value is :  [0.161 0.161 0.161 0.161 0.161 0.161 0.161 0.161 0.
161 0.161]
```

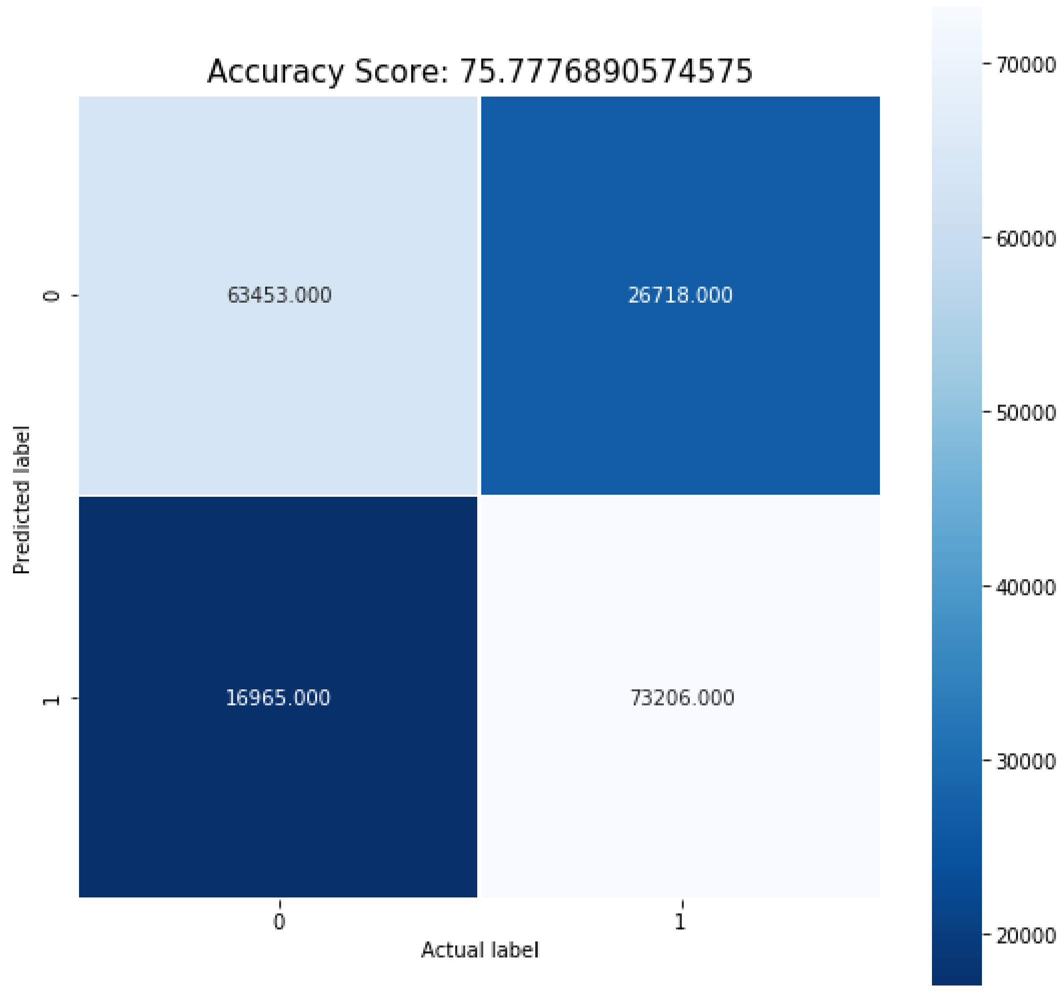
Testing the model by using the optimal alpha over the test set

In [38]:
```
#Testing the model with default value of alpha over the Test data
test(bal_xtr,bal_ytr,bal_xtes,bal_ytes)

print("*"*100)

#Testing the model with optimal alpha value over the test data
Y_pred,BalTest_acc,=optimal_test(Boptimal_a,bal_xtr,bal_ytr,bal_xcv,bal_ycv,bal_xtes,bal_ytes)
```

```
**** The Test accuracy by using default alpha is 76%
****************************************************************************************************

 The train accuracy of the NB classifier for the best alpha=0.000100% is 76.275876%
****************************************************************************************************

The Test accuracy of the NB classifier by using the best alpha = 0.000100% is 75.777689%
```

In [39]:
```
Confusion_metric(bal_ytes,Y_pred,BalTest_acc)
```

```
[[63453 26718]
 [16965 73206]]
```



```
+-----------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+--------------------------------+--------------------------+
|            Metrics             |          Scores          |
+--------------------------------+--------------------------+
|     Classification_accuracy    |     75.7776890574575     |
|       Classification_error     |    24.222310942542503    |
|          True positive         |          73206           |
|         False positive         |          26718           |
|          True negative         |          63453           |
|         False negative         |          16965           |
|        True positive rate      |    81.18574708054696     |
|       False negative rate      |    18.81425291945304     |
|        True negative rate      |    70.36963103436803     |
|       False positive rate      |    29.630368965631966    |
|         Precision value        |    73.26167887594572     |
|           Recall value         |    81.18574708054696     |
|          f1_score value        |    77.02043714984613     |
+--------------------------------+--------------------------+
```

OBSERVATION

- After oversampling the data the accuracy of the model reduced (from 81% to 75%) as compared to the previous model but the model is very stable and sensible because of high TP and TN values.
- There is a considerable increase in the TNR value (64%-70.36%)& considerable decrease in the FPR value(34% to 29.63%) which is a good sign for the improvement of the model.
- So the model is sensible and stable as compared to the previous model which is achieved by balanciing the data.
- The metric as accuracy is very misleading and can't be trusted in a imbalanced data.

Implemnting the Tf-idf vectorizeration technique

In [67]:

```
#Initializing the count vectorizer
TF_vect=TfidfVectorizer(ngram_range=(1,2),binary=True)

#vectorizing the X_train set
TF_count,X_tr=vec_train(TF_vect,X_tr["CleanedText"])

print("The shape of the X_train is: ",X_tr.shape)

#Vectgorizing the X_crossvalidation set
X_cv=vec_cv(TF_count,X_cv["CleanedText"])
print("The shape of the X_cv is: ",X_cv.shape)

#Vectorizing the X_test set
X_test=vec_test(TF_count,X_test["CleanedText"])
print("The shape of the X_test is: ",X_test.shape)


#Printing the total length of the features
print("\nTop 25 feaures acording to the Bow score are as follows")
Features = TF_vect.get_feature_names()
len(Features)


top_tfidf = top_tfidf_feats("tfidf",X_tr[1,:].toarray()[0],Features,25)
top_tfidf
```

```
The shape of the X_train is:  (178443, 1816552)
The shape of the X_cv is:  (76476, 1816552)
The shape of the X_test is:  (109252, 1816552)

Top 25 feaures acording to the Bow score are as follows
```

Out[67]:

	feature	tfidf
0	preschool turn	422.426325
1	teach preschool	422.426325
2	whole school	422.426325
3	school purchas	422.426325
4	sister later	422.426325
5	song student	422.426325
6	air televis	422.426325
7	child sister	422.426325
8	book song	422.426325
9	use seri	372.605606
10	seri book	366.076962
11	book children	358.410533
12	televis year	326.201503
13	day thirti	321.245669
14	thirti someth	310.170360
15	children tradit	308.586244
16	show air	297.616678
17	student teach	282.566459
18	ago child	246.284028
19	along book	203.244144
20	see show	196.984144
21	later bought	161.464536
22	tradit live	145.680425
23	turn whole	137.896025
24	rememb see	112.189152

Training the Tf-idf vectorized model over the CV set.

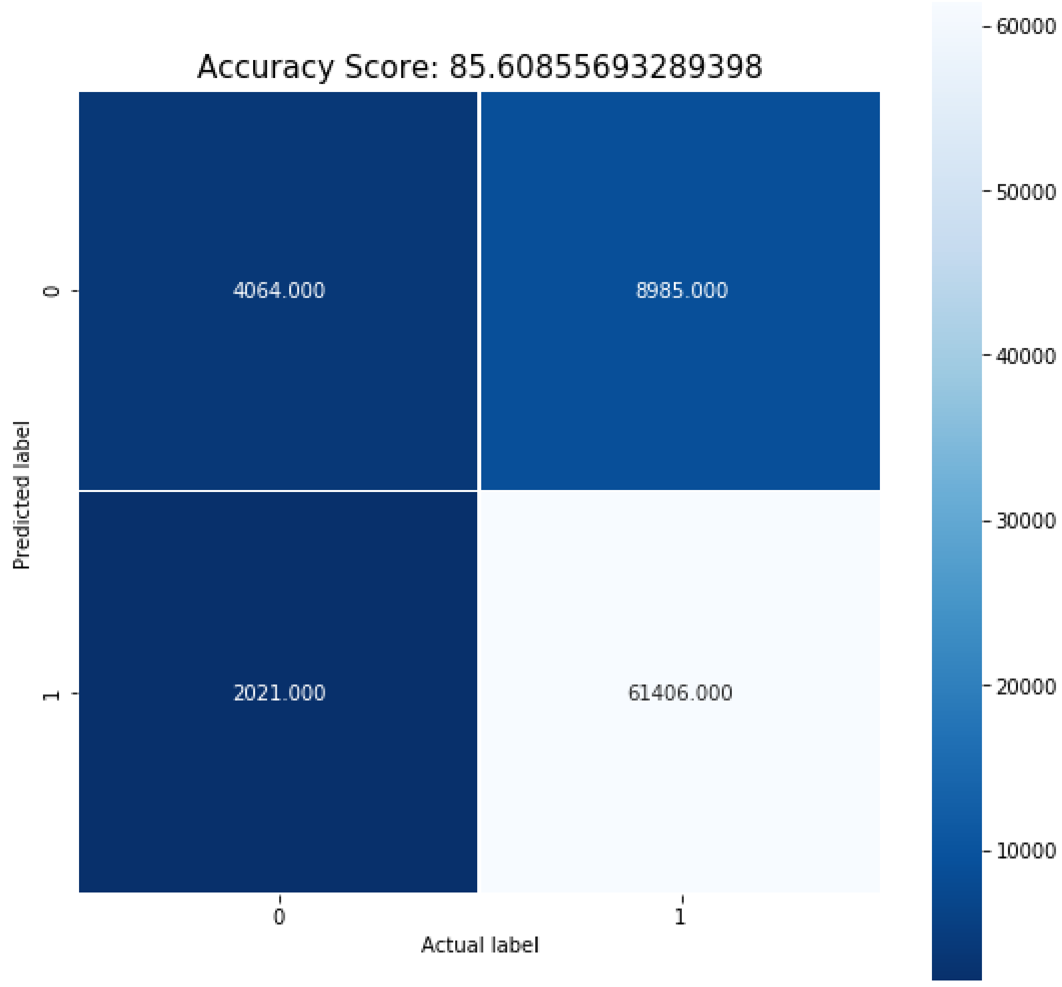
In [41]:
```
Predi,Acc=train(X_tr,y_tr,X_cv,y_cv)
```

```
 The train accuracy by using default alpha over cv set is =  85.608557%
```

Confusion metric of the above model.

In [42]:
```
Confusion_metric(y_cv,Predi,Acc)
```

```
[[ 4064  8985]
 [ 2021 61406]]
```




```
+-----------------------------------------------------------+
| The performance metrics of the above model are as follows: |
+--------------------------------+--------------------------+
|            Metrics             |          Scores          |
+--------------------------------+--------------------------+
|    Classification_accuracy     |    85.60855693289398     |
|      Classification_error      |    14.39144306710602     |
|         True positive          |          61406           |
|         False positive         |           8985           |
|         True negative          |           4064           |
|         False negative         |           2021           |
|       True positive rate       |    96.81365979787788     |
|      False negative rate       |    3.1863402021221248    |
|       True negative rate       |     31.1441489769331     |
|      False positive rate       |     68.8558510230669     |
|        Precision value         |    87.23558409455754     |
|          Recall value          |    96.81365979787788     |
|         f1_score value         |    91.77539643396254     |
+--------------------------------+--------------------------+
```

OBSERVATION

- The accuracy of the model by using the default alpha value is 85.60% which is good but the other metrics are very less and very alarming.
- In this model the TP value is very dominating which results in high TPR rate as compared to the other metrics which is not good as the model will become biased towards positive reviews.
- The TNR is very less and this model will fail to clasiffy the negative reviews properly.
- Let's see if the metrics become better after doing hyper-parameter tuning the alpha value.

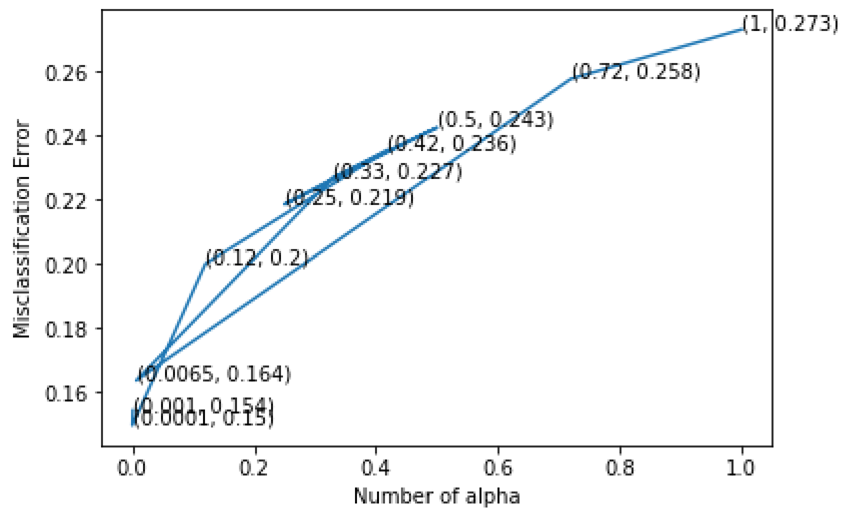
HYPERAMETER TUNING THE ALPHA FOR FINDING THE OPTIMAL ALPHA VALUE

In [43]:
```
CV_Score,Mutinomi =cross_validation(X_tr,y_tr)
```

```
[0.8456538275213425, 0.850350012363933, 0.7999472979891289, 0.7642888248070557, 0.781392345001281, 0.7573846559978202, 0.7729134422929673, 0.8363399278287986, 0.742136071851881, 0.7267473805074696]
```

In [44]:
```
Optimal_a=MSE_plot(CV_Score,Mutinomi) #CODE FOR PLOTTING THE ERROR PLOT
```

```
The optimal number of alpha value is 0.000100%.
```




```
the misclassification error for  alpha value is :  [0.154 0.15  0.2   0.236 0.219 0.243 0.227 0.164 0.
258 0.273]
```

Testing the model by using the optimal alpha over the test set

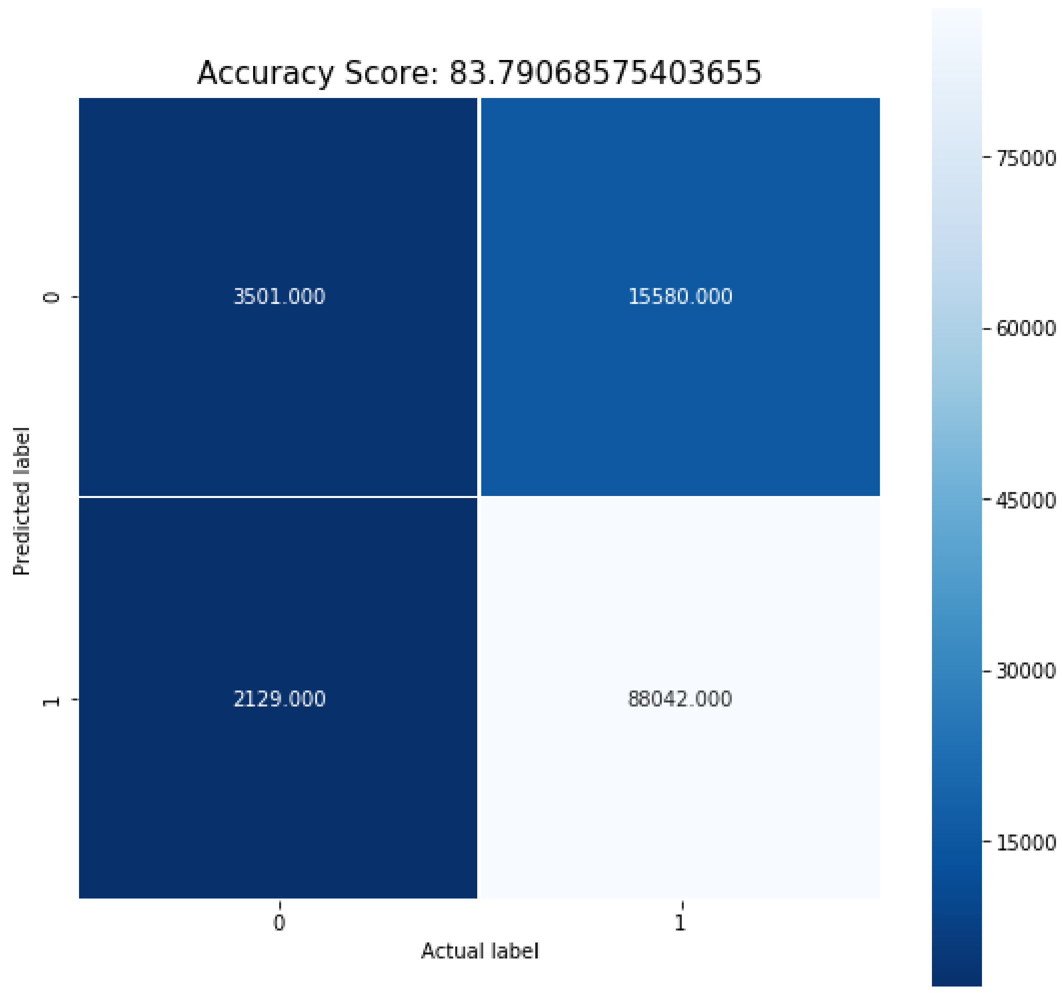
In [45]:
```
#Testing the model with default value of alpha over the Test data
test(X_tr,y_tr,X_test,y_test)

print("*"*100)

#Testing the model with optimal alpha value over the test data
Y_prediction,Test_accuracy=optimal_test(Optimal_a,X_tr,y_tr,X_cv,y_cv,X_test,y_test)
```

```
**** The Test accuracy by using default alpha is 84%
****************************************************************************************************

 The train accuracy of the NB classifier for the best alpha=0.000100% is 84.246038%
****************************************************************************************************

The Test accuracy of the NB classifier by using the best alpha = 0.000100% is 83.790686%
```

Confusion metric of the above model.

In [46]:
```
Confusion_metric(y_test,Y_prediction,Test_accuracy)
```

```
[[ 3501 15580]
 [ 2129 88042]]
```



```
+-------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+----------------------------------+--------------------------+
|              Metrics             |          Scores          |
+----------------------------------+--------------------------+
|     Classification_accuracy      |    83.79068575403655     |
|       Classification_error       |    16.209314245963462    |
|          True positive           |          88042           |
|          False positive          |          15580           |
|          True negative           |           3501           |
|          False negative          |           2129           |
|        True positive rate        |    97.63893047653902     |
|       False negative rate        |     2.36106952346098     |
|        True negative rate        |    18.348094963576333    |
|       False positive rate        |    81.65190503642367     |
|         Precision value          |    84.96458281060006     |
|           Recall value           |    97.63893047653902     |
|          f1_score value          |     90.8618990366009     |
+----------------------------------+--------------------------+
```

Observations

- The accuracy of the model has become low after tuning the alpha which is not good for a classification model.
- The main reason is because of the high FPR and low TNR which affects the model a lot.
- This model is also suffering from the heavy bias problem and may be solved by oversampling the datapoints.
- The high Precision,recall and f1_score value cannot be trusted because of high tpr as compared to other metrics.

Oversampling the data by using the SMOTE technique

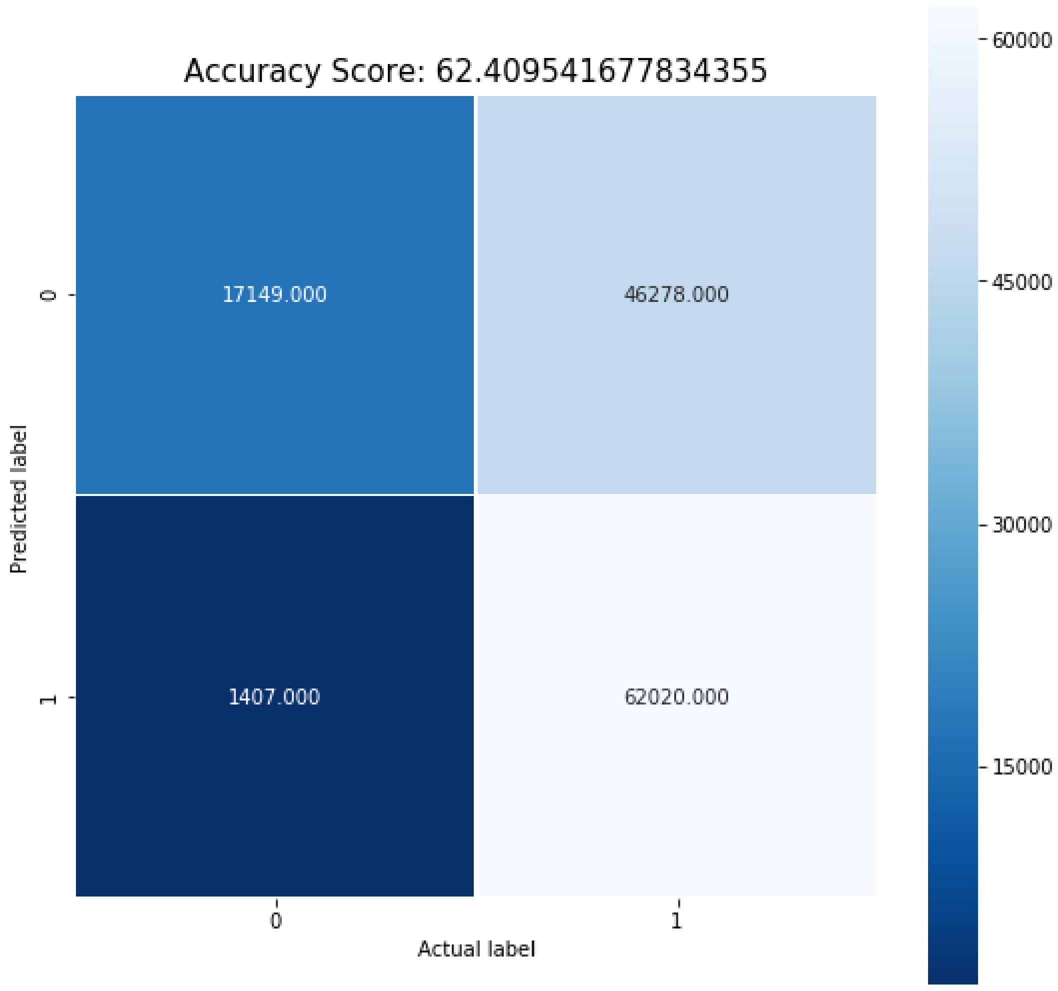
In [47]:
```
Bal_xtr,Bal_ytr,Bal_xcv,Bal_ycv,Bal_xtes,Bal_ytes,B_pre,B_acc=Bal_train(X_tr,y_tr,X_cv,y_cv,X_test,y_test)
```

```
 The TRAIN accuracy by using default alpha over CV set is =  62.409542%
```

Confusion metric of the above model.

In [48]:
```
Confusion_metric(Bal_ycv,B_pre,B_acc)
```

```
[[17149 46278]
 [ 1407 62020]]
```



The performance metrics of the above model are as follows:	
Metrics	**Scores**
Classification_accuracy	62.409541677834355
Classification_error	37.59045832216564
True positive	62020
False positive	46278
True negative	17149
False negative	1407
True positive rate	97.78170179891845
False negative rate	2.2182982010815584
True negative rate	27.03738155675028
False positive rate	72.96261844324971
Precision value	57.26790891798556
Recall value	97.78170179891845
f1_score value	72.23176590478964

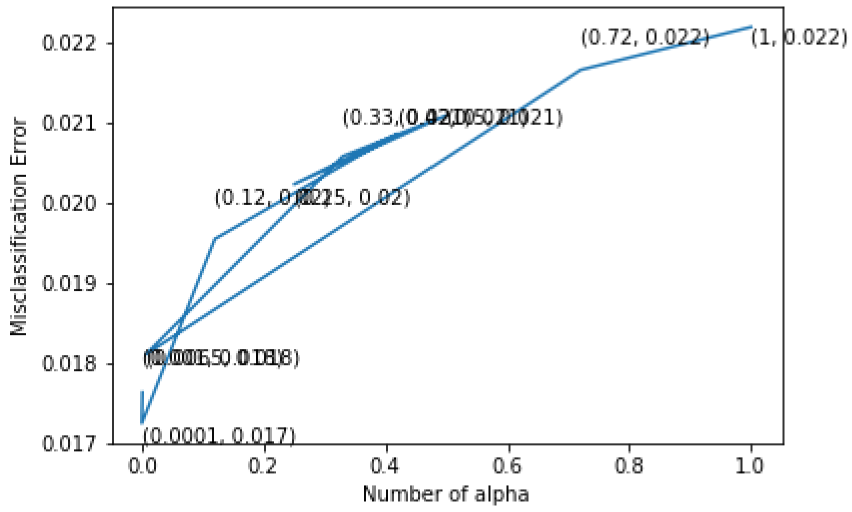
HYPERAMETER TUNING THE ALPHA FOR FINDING THE OPTIMAL ALPHA VALUE

In [49]:
```
BScoreS,Mutinomial =cross_validation(Bal_xtr,Bal_ytr)
```

```
[0.9823736553630698, 0.9827581127274145, 0.9804546256578697, 0.9791383491218069, 0.9797704214348719, 0.978907023152515, 0.9794218046657244, 0.9818979690139731, 0.9783401129138823, 0.977802524154485]
```

In [50]:
```
Bal_optimal_a=MSE_plot(BScoreS,Mutinomial) #CODE FOR PLOTTING THE ERROR PLOT
```

```
The optimal number of alpha value is 0.000100%.
```




```
the misclassification error for  alpha value is :  [0.018 0.017 0.02  0.021 0.02  0.021 0.021 0.018 0.022 0.022]
```

Testing the model by using the optimal alpha over the test set

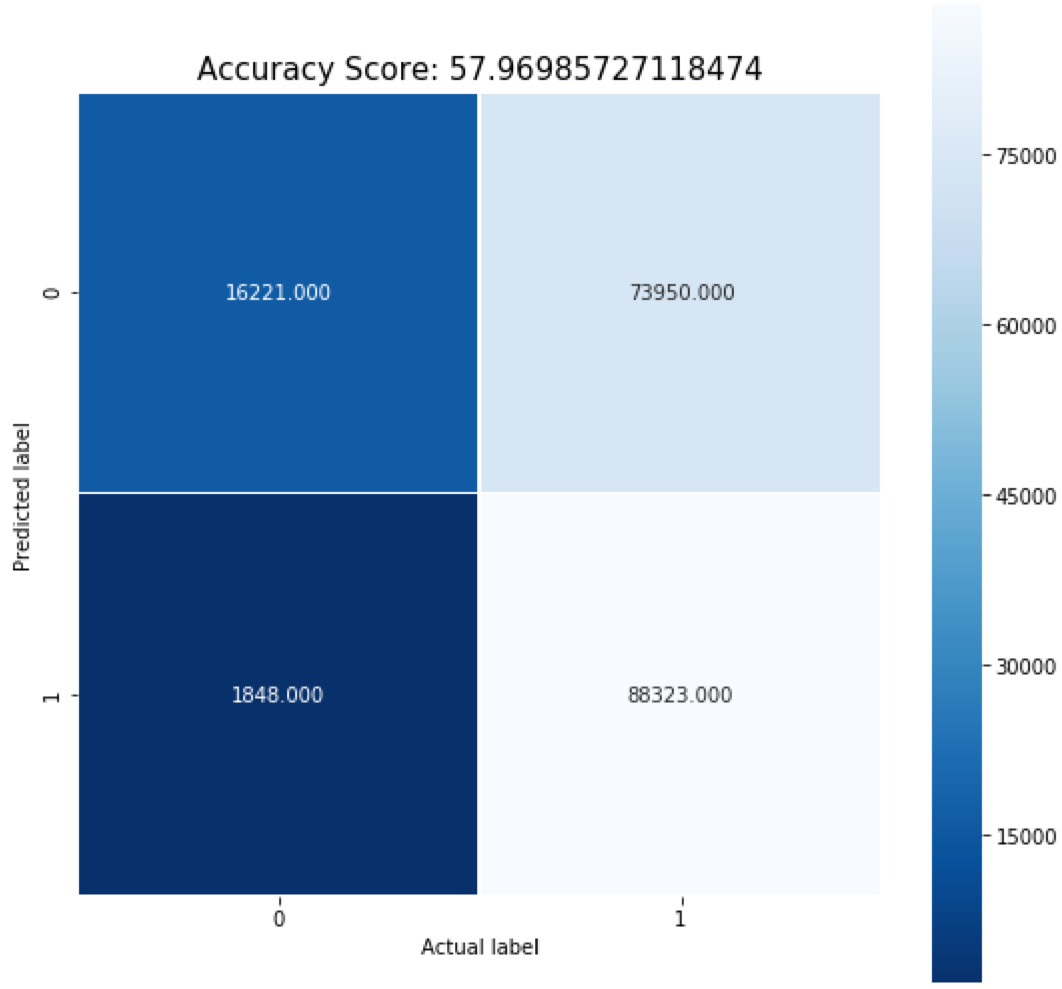
In [51]:
```
#Testing the model with default value of alpha over the Test data
test(Bal_xtr,Bal_ytr,Bal_xtes,Bal_ytes)

print("*"*100)

#Testing the model with optimal alpha value over the test data
Y_PRED,BalTest_Acc=optimal_test(Bal_optimal_a,Bal_xtr,Bal_ytr,Bal_xcv,Bal_ycv,Bal_xtes,Bal_ytes)
```

```
**** The Test accuracy by using default alpha is 61%
****************************************************************************************************

 The train accuracy of the NB classifier for the best alpha=0.000100% is 57.949296%
****************************************************************************************************

The Test accuracy of the NB classifier by using the best alpha = 0.000100% is 57.969857%
```

Confusion metric of the above model.

In [52]:
```
Confusion_metric(Bal_ytes,Y_PRED,BalTest_Acc)
```

```
[[16221 73950]
 [ 1848 88323]]
```




```
+-------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+------------------------------+------------------------------+
|            Metrics           |            Scores            |
+------------------------------+------------------------------+
|     Classification_accuracy  |     57.96985727118474        |
|     Classification_error     |     42.03014272881525        |
|          True positive       |           88323              |
|          False positive      |           73950              |
|          True negative       |           16221              |
|          False negative      |            1848              |
|        True positive rate    |     97.95056060152378        |
|       False negative rate    |     2.0494393984762285       |
|        True negative rate    |     17.989153940845725       |
|       False positive rate    |     82.01084605915428        |
|         Precision value      |     54.42864801907896        |
|          Recall value        |     97.95056060152378        |
|         f1_score value       |     69.97433094072348        |
+------------------------------+------------------------------+
```

Observations:

- Since after doing the data balancing technique the model score decreased very drastically due to poor performance metrics.
- I think the model is overfitting which leads to decrease in accuracy and other factor may be the high dimensions of the tf-idf vectorized data.
- In this model SMOTE didn't improved the model in terms of stability and accuracy.

In [ ]: