Applying Logistic regression on Amazon fine food reviews dataset

1. Dataset:Amazon fine food reviews dataset.
2. Vectorizers used here are:-Bag of words,Tf-idf,Average Word 2 Vec and Tfidf weighted Word 2 vec.
3. Regularizers used here are:-"L1 and L2" regularizations.
4. Feature Importance Techniques:Recursive Feature Elimination (RFE) and Cross-validation (RFECV).
5. Metrics used here are:-Confusion metrics, Accuracy as a score metric is used here.

In [24]:
```
#Importing important libraries

%matplotlib inline

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.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score

from datetime import datetime
from scipy.stats import norm
from sklearn import metrics
from nltk.stem.porter import PorterStemmer
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
import warnings
warnings.filterwarnings(action='ignore')
from sklearn.model_selection import train_test_split
from sklearn.grid_search import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import RandomizedSearchCV
from prettytable import PrettyTable
```

Connecting to the preproccessed SQLite table

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]:
```
#Converting the Time column into standard Date-time standard

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

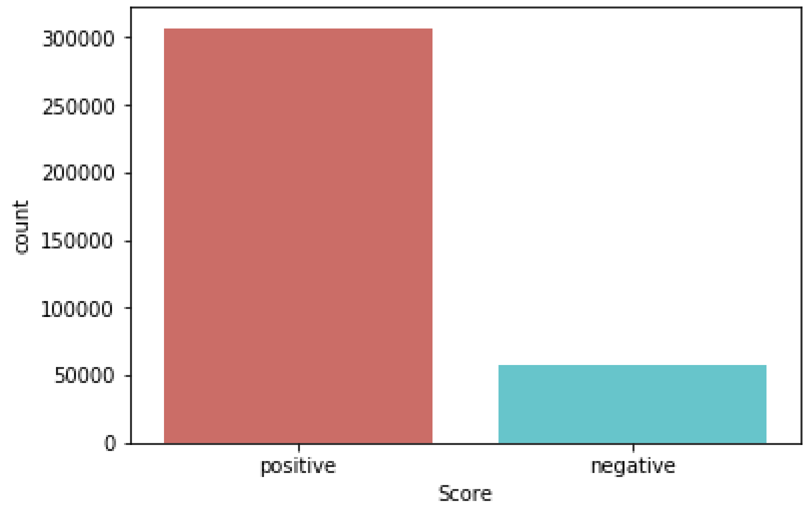
In [7]:
```
#Sampling the above data

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

Out[7]: (50000, 10)

In [8]:
```
#Sampling the above data for implementing the TF-idf technique

Samp_data=Sorted.sample(n=8000,replace='False')
TF_sort=Samp_data.sort_index()
TF_sort.shape
```

Out[8]: (8000, 10)

In [9]:
```
#Setting up the class label variables

Class=TF_sort["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 [ ]:

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

Out[10]: (8000, 9)

In [11]:
```
#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[11]: (50000, 9)

Observations

- Here after all the text-preprocesing and the data-cleaning only 364k datapoints remained.
- I have taken a sample size of 20k and 8k data out of the total population for the purpose of analyzing and studying the behaviour of the data by applying the Logistic regression 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 splitting up the datasets

In [12]:
```
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 [13]:
```
X=Sample_sort
Y=label

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: (24500, 9)
the shape of y_train is: (24500,)
the shape of x_cv is: (10500, 9)
the shape of y_cv is: (10500,)
the shape of x_test is: (15000, 9)
the shape of y_test is: (15000,)
```

Preparing the Train,CV and Test set for implementing the Tf-idf Vectorizer

In [14]:
```
TF_X=TF_sort
TF_Y=Class

TFX_tr,TFy_tr,TFX_cv,TFy_cv,TFX_test,TFy_test=data_split(TF_X,TF_Y)

print("The shape of x_train is:",TFX_tr.shape)
print("the shape of y_train is:",TFy_tr.shape)
print("the shape of x_cv is:",TFX_cv.shape)
print("the shape of y_cv is:",TFy_cv.shape)
print("the shape of x_test is:",TFX_test.shape)
print("the shape of y_test is:",TFy_test.shape)
```

```
The shape of x_train is: (3920, 9)
the shape of y_train is: (3920,)
the shape of x_cv is: (1680, 9)
the shape of y_cv is: (1680,)
the shape of x_test is: (2400, 9)
the shape of y_test is: (2400,)
```

Utility function for Training & Testing the models

In [15]:
```
def train(X_tr, y_tr,X_cv,y_cv,p="l2",C=float(1)):

    clf = LogisticRegression(penalty=p,class_weight="balanced",C=C,n_jobs=-1)
    model = clf.fit(X_tr, y_tr)

    print("The model score on train set is= ", model.score(X_tr,y_tr))

    pred=model.predict(X_cv)

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

    print('\nThe accuracy of Logistic Regression over cross-validation set is =  %d%% ' % ( acc))


    w = model.coef_

    print("The total number of non zero weights = ",np.count_nonzero(w))

    return pred,acc

#Hyperparameter tuning using GridSearchCV

def gridsearch(X_tr, y_tr,X_te, y_te,p="l2"):

    tuned_parameters = [{'C': [10 ** x for x in range(-6, 4)]}]

    model = GridSearchCV(LogisticRegression(penalty=p,class_weight="balanced",n_jobs=-1),tuned_paramet
ers,  scoring = 'accuracy', cv=10)
    model.fit(X_tr, y_tr)

    print(model.best_estimator_)
    print(model.score(X_te, y_te))
    return model.best_estimator_

#Hyperparameter tuning by using the Random search
def randomsearch(X_tr, y_tr,X_te, y_te,p="l2"):

    from scipy.stats import uniform
    from sklearn.model_selection import RandomizedSearchCV

# Create regularization hyperparameter distribution using uniform distribution
    C = uniform(loc=0, scale=3)

# Create hyperparameter options
    hyperparameters = dict(C=C)

    model1 =  RandomizedSearchCV(LogisticRegression(penalty=p,class_weight="balanced",n_jobs=-1),hyper
parameters, scoring = 'accuracy', cv=10)
    model1.fit(X_tr, y_tr)

    print(model1.best_estimator_)
    print(model1.score(X_te, y_te))
    return model1.best_estimator_

#Function for testing the models
def tuned_test(Best_param,X_tr,y_tr,X_test,y_test):

    New_clf=Best_param

    new_model=New_clf.fit(X_tr,y_tr)

    print("The model score on train set is= ", new_model.score(X_tr,y_tr))

    Y_pred=new_model.predict(X_test)

    new_acc = accuracy_score(y_test, Y_pred, normalize=True) * float(100)

    print('\nThe accuracy of Logistic Regression over Test set is =  %d%% ' % ( new_acc))


    W = new_model.coef_

    print("The total number of non zero weights = ",np.count_nonzero(W))
    return Y_pred,new_acc
```

Utility function for plotting the confusion matrix and the CV error plots

In [16]:
```
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 printing the Cross-validation errors

def cv_results(X_tr, y_tr):
    alpha = [10 ** x for x in range(-6, 4)]
    cv_erro_array = []
    for a in alpha:
        print("----------------------------------------------------------------------------------
-----------------")
        print("for alpha =", a)
        clf = LogisticRegression(C=a,class_weight='balanced')
        scores = cross_val_score(clf, X_tr, y_tr, cv=10,scoring='accuracy')
        cv_erro_array.append(scores.mean())

        mse=[1- x for x in cv_erro_array]
        # determining best alpha
        Best_alpha = alpha[mse.index(min(mse))]
        print("\nthe misclassification error for each alpha value is : ", np.round(mse,3))
```

```
    fig, ax = plt.subplots()
    ax.plot(alpha,mse,c='g')
    for i, txt in enumerate(np.round(mse,3)):
        ax.annotate((alpha[i],str(txt)), (alpha[i],mse[i]))
    plt.grid()
    plt.title("Cross Validation Error for each alpha")
    plt.xlabel("Alpha i's")
    plt.ylabel("Error measure")
    plt.show()

    Best_alpha = alpha[mse.index(min(mse))]
    print('\nThe optimal number of alpha value is %f%%.' % Best_alpha)
```

Utility function for vectorizing the data

In [17]:

```
#Code for standardizing the data
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler(with_mean=False)

#Function for vectorizing the train data
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)

#Standardizing the vectorized data
    standardized_data = scaler.fit_transform(BOW)
    standardized_data.shape
    return count_vect,standardized_data


#Function for vectorizing the CV data

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

    std_cv=scaler.transform(cv)
    std_cv.shape
    return std_cv


#Function for vectorizing the test data

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

    std_data=scaler.transform(test)
    std_data.shape
    return std_data

#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

#Function for displaying top frequent 50 tokens distributions
from yellowbrick.text import FreqDistVisualizer
from sklearn.feature_extraction.text import CountVectorizer
def display_token(Vect,data):

    vectorizer = Vect
    docs       = vectorizer.fit_transform(data)
    features   = vectorizer.get_feature_names()

    visualizer = FreqDistVisualizer(features=features)
    visualizer.fit(docs)
    visualizer.poof()
```

Vectorizing the inputs by using the Bag of words vectorization technique

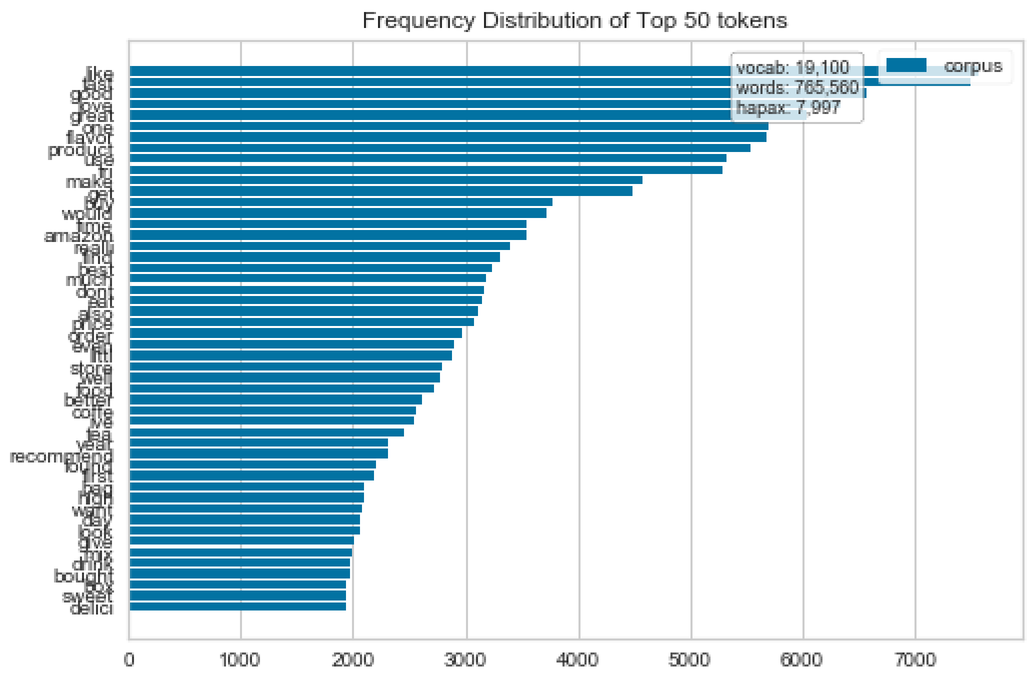
In [18]:
```
#Initializing the count vectorizer
Count_vect=CountVectorizer(binary=True)

#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:  (24500, 19273)
The shape of the X_cv is:  (10500, 19273)
The shape of the X_test is:  (15000, 19273)

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

Out[18]:

	feature	bow
0	maitland	110.684236
1	coaster	110.684236
2	danni	90.375145
3	demis	90.375145
4	elfman	90.375145
5	roller	78.268769
6	afterlif	78.268769
7	hilari	70.007144
8	adam	59.169251
9	journey	55.348896
10	burton	52.184505
11	beetlejuic	45.195875
12	tim	40.426896
13	til	35.923174
14	barbara	34.171150
15	score	28.594893
16	transport	27.265832
17	mysteri	26.862420
18	laugh	24.465540
19	cri	24.173023
20	pair	20.756370
21	vacat	20.402369
22	kill	17.865749
23	meet	16.715642
24	magic	16.006632

In [21]:
```
display_token(Count_vect,X_tr["CleanedText"])
```



Training the model over Cross_validation set by using the default parameters.

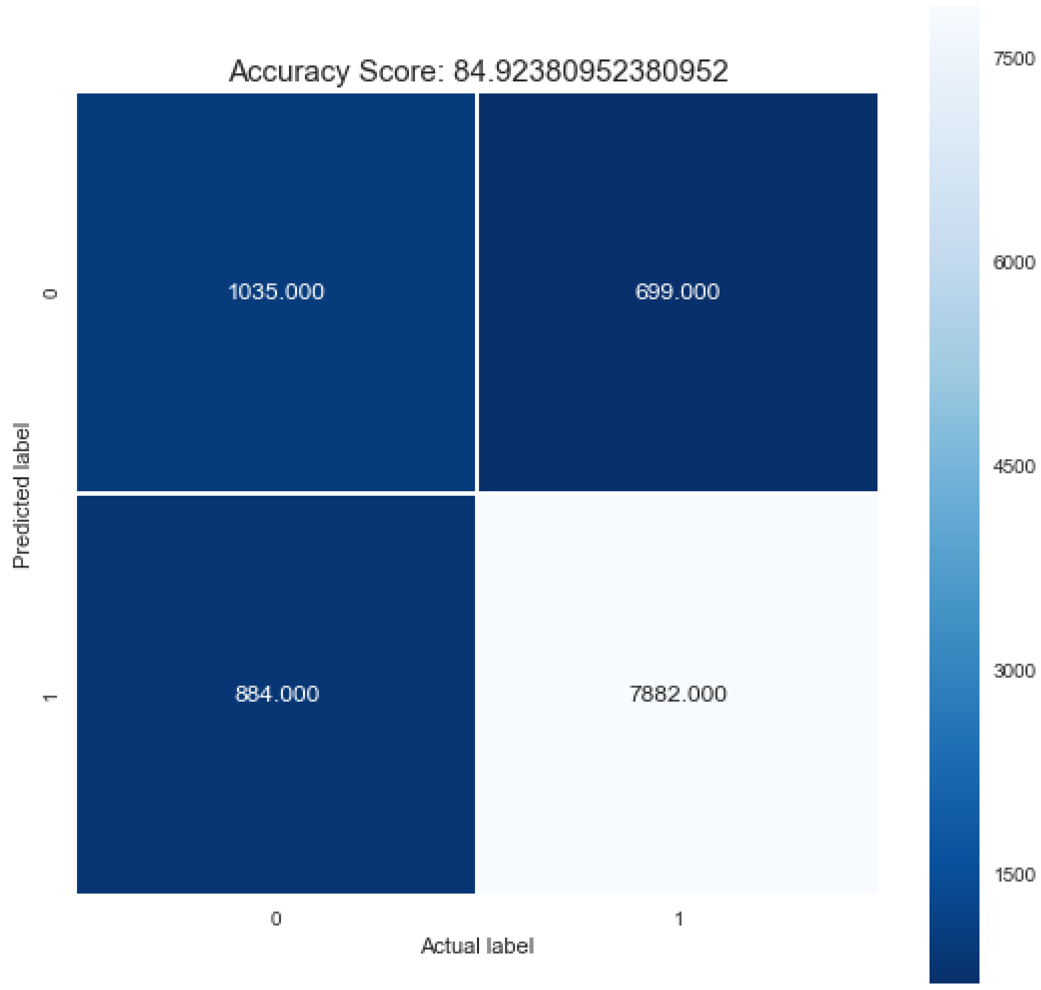
In [39]:
```
#Calling the train function and storing the prediction value and accuracy

Cpred,cacc=train(x_tr,y_tr,x_cv,y_cv)
```

```
The model score on train set is=  1.0

The accuracy of Logistic Regression over cross-validation set is =  84%
The total number of non zero weights =  18987
```

Confusion matrix of the above trained model

In [40]:
```
Confusion_metric(y_cv,Cpred,cacc)
```

```
[[1035  699]
 [ 884 7882]]
```



```
+-------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+---------------------------------+---------------------------+
|             Metrics             |           Scores          |
+---------------------------------+---------------------------+
|     Classification_accuracy     |     84.92380952380952     |
|       Classification_error      |     15.076190476190476    |
|          True positive          |            7882           |
|          False positive         |            699            |
|          True negative          |            1035           |
|          False negative         |            884            |
|        True positive rate       |     89.91558293406344     |
|       False negative rate       |     10.084417065936572    |
|        True negative rate       |     59.688581314878896    |
|       False positive rate       |     40.31141868512111     |
|         Precision value         |     91.85409625917725     |
|           Recall value          |     89.91558293406344     |
|          f1_score value         |      90.8745027958725     |
+---------------------------------+---------------------------+
```

Observation

- The above Logistic regression model was tested over the cross validation set and the train accuracy is about 85.03%.
- The Performance metrics of this model obtained after analyzing the confusion matrix is not that satisfactory due to the following reasons and they are as follows :

  1. The value of the diagonal elements of the matrix are not that much high infact the TP is 7837 and TN is 1092 which is far more less as compared to the TP value.
  2. The FNR value is 9.78% which is good because it is meant to be low but the TNR is 60.23% which is considerably not that high and the main reason of increase in the False positive rate (39.76).
  3. The Precision,Recall and the F1_Score values can't be trusted because of high TP value.
  4. So the model's performance can be improved by doing the hyperparameter tuning.

Hyperparameter Tuning by using Gridsearch and Random-search for finding the optimal value of alpha.

In [42]:
```
#Gridsearch implementation
best_param=gridsearch(x_tr,y_tr,x_cv,y_cv)
```

```
LogisticRegression(C=0.0001, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=-1, penalty='l2', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
0.8810476190476191
```

In [43]:
```
#Random-search Implementation
Best_par=randomsearch(x_tr, y_tr,x_cv, y_cv)
```

```
LogisticRegression(C=0.0843364870614276, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=-1, penalty='l2', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
0.8582857142857143
```

Testing the model over Test set by taking the optimal value of alpha

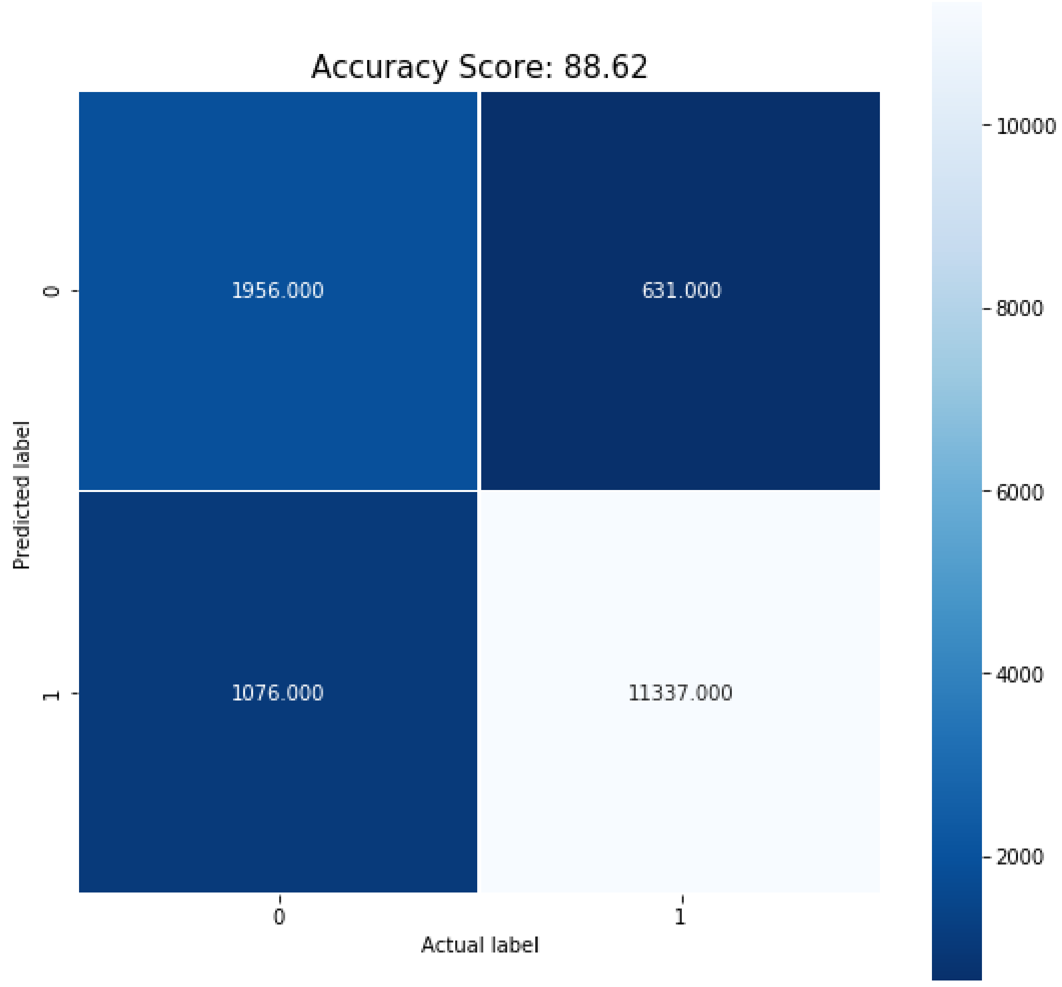
In [44]:
```
New_clf=best_param

y_pre,acc=tuned_test(New_clf,x_tr,y_tr,x_test,y_test)
```

```
The model score on train set is=  0.9617142857142857

The accuracy of Logistic Regression over Test set is =  88%
The total number of non zero weights =  18987
```

Confusion matrix of the above model

In [32]:
```
Confusion_metric(y_test,y_pre,acc)
```

```
[[ 1956   631]
 [ 1076 11337]]
```




```
+-------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+--------------------------------+----------------------------+
|            Metrics             |           Scores           |
+--------------------------------+----------------------------+
|    Classification_accuracy     |           88.62            |
|      Classification_error      |     11.379999999999999     |
|         True positive          |           11337            |
|         False positive         |            631             |
|         True negative          |            1956            |
|         False negative         |            1076            |
|       True positive rate       |     91.33166841214856      |
|      False negative rate       |     8.668331587851446      |
|       True negative rate       |     75.60881329725551      |
|      False positive rate       |     24.39118670274449      |
|        Precision value         |     94.72760695187165      |
|          Recall value          |     91.33166841214856      |
|         f1_score value         |     92.99864648701858      |
+--------------------------------+----------------------------+
```

Observations

- The test accuracy of the above model after taking the optimal alpha value is 88% which is quite good for a classification model.
- But still after doing hyperparameter tuning the model is still facing a little bias problem and the TP value still dominates.
- Since the above model has little bias problem but still it is a sensible and good model as the FNR & FPR have lower values as compared to other metrics which increases the TPR and TNR values.
- The model also has good Precision,Recall and F1_score values which is around (91% to 94%) which is very good for a classification model.
- Lets see by changing the regularization and alpha term how the model's performance changes and affects the logistic regression model

Applying the L1 regularization over the Existing the model

In [35]:

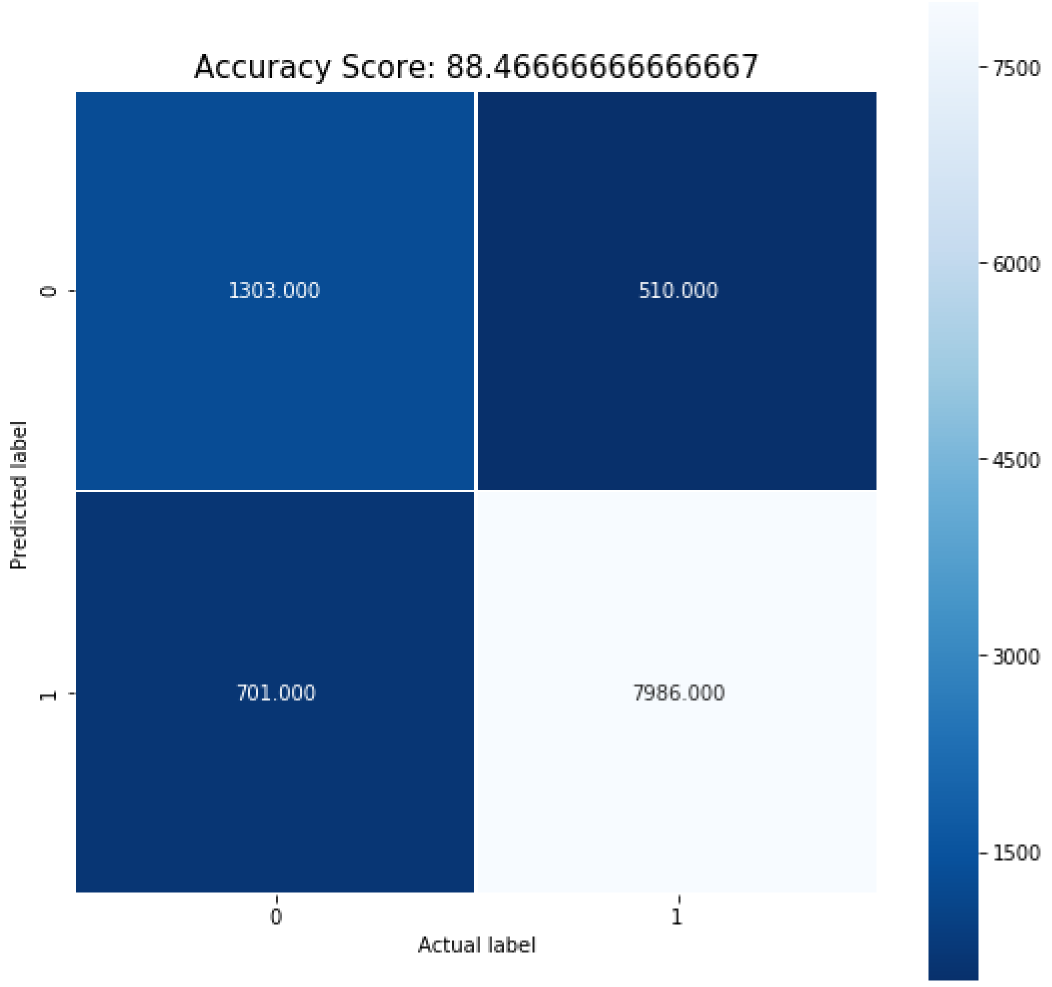
```
#Calling the train function and storing the prediction value and accuracy

l1pred,l1acc=train(x_tr,y_tr,x_cv,y_cv,p="l1",C=0.1)
```

```
The model score on train set is=  0.9884081632653061

The accuracy of Logistic Regression over cross-validation set is =  88%
The total number of non zero weights =  4830
```

In [36]:

```
Confusion_metric(y_cv,l1pred,l1acc)
```

```
[[1303  510]
 [ 701 7986]]
```



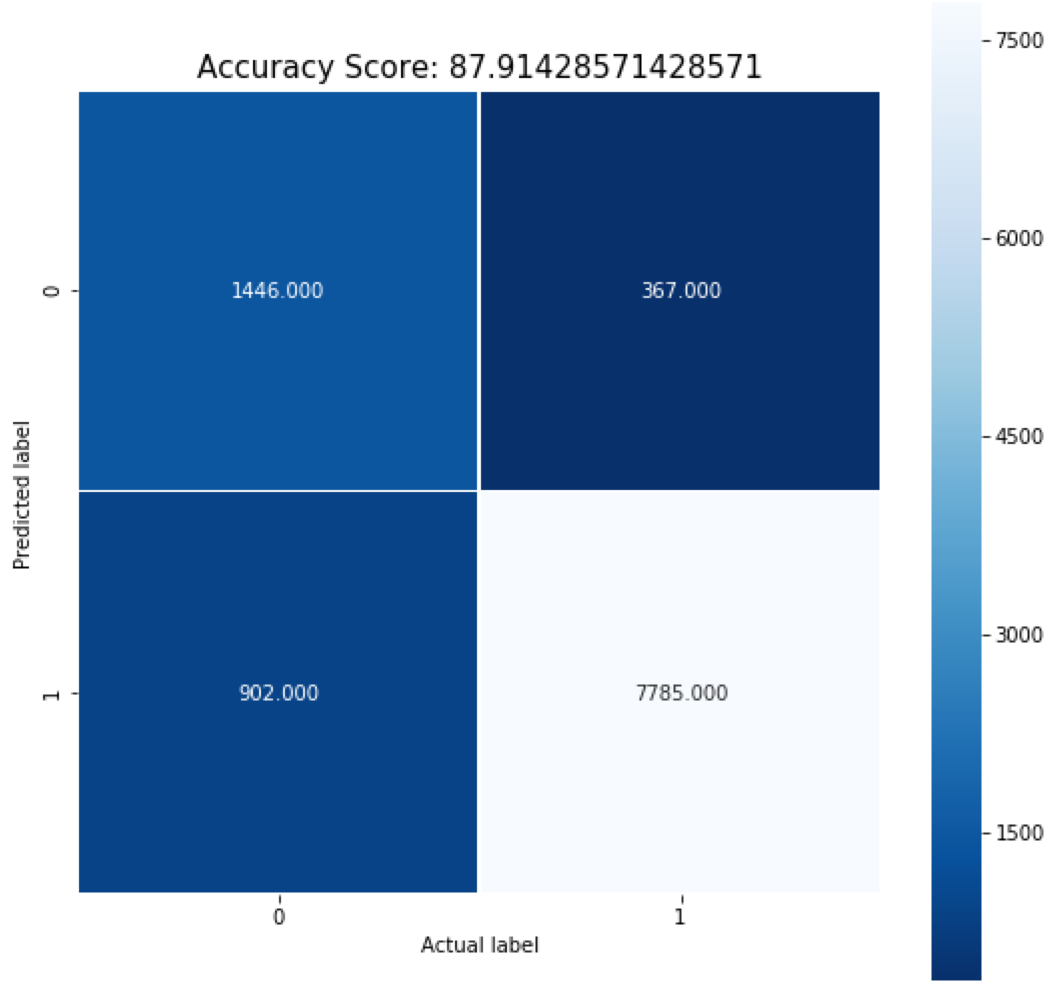

```
+-------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+----------------------------------+--------------------------+
|             Metrics              |          Scores          |
+----------------------------------+--------------------------+
|     Classification_accuracy      |    88.46666666666667     |
|       Classification_error       |    11.533333333333333    |
|          True positive           |           7986           |
|          False positive          |           510            |
|          True negative           |           1303           |
|          False negative          |           701            |
|        True positive rate        |    91.93047081846437     |
|       False negative rate        |    8.069529181535628     |
|        True negative rate        |    71.86982901268615     |
|       False positive rate        |    28.130170987313846    |
|         Precision value          |    93.99717514124293     |
|           Recall value           |    91.93047081846437     |
|          f1_score value          |    92.95233661176744     |
+----------------------------------+--------------------------+
```

In [37]:
```
#Calling the train function and storing the prediction value and accuracy

l1_pred,l1_acc=train(x_tr,y_tr,x_cv,y_cv,p="l1",C=0.01)
```

```
The model score on train set is=  0.9161632653061225

The accuracy of Logistic Regression over cross-validation set is =  87%
The total number of non zero weights =  1602
```

In [38]:
```
Confusion_metric(y_cv,l1_pred,l1_acc)
```

```
[[1446  367]
 [ 902 7785]]
```



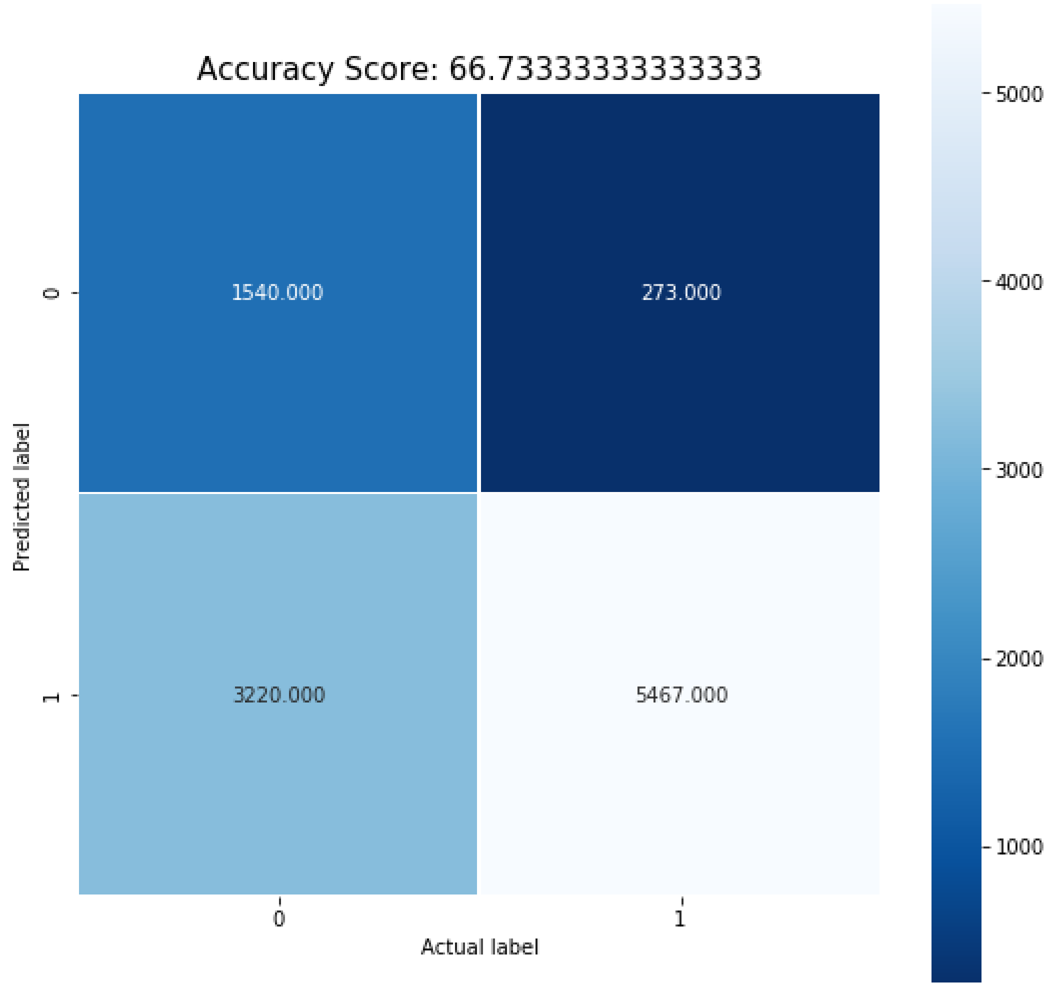

```
+-------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+----------------------------------+--------------------------+
|             Metrics              |          Scores          |
+----------------------------------+--------------------------+
|     Classification_accuracy      |    87.91428571428571     |
|       Classification_error       |    12.085714285714285    |
|          True positive           |           7785           |
|          False positive          |           367            |
|          True negative           |           1446           |
|          False negative          |           902            |
|        True positive rate        |    89.61666858524232     |
|       False negative rate        |    10.383331414757684    |
|        True negative rate        |     79.7573083287369     |
|       False positive rate        |     20.2426916712631     |
|         Precision value          |    95.49803729146223     |
|           Recall value           |    89.61666858524232     |
|          f1_score value          |    92.46392303580973     |
+----------------------------------+--------------------------+
```

In [39]:
```
#Calling the train function and storing the prediction value and accuracy

l1_Pred,l1_Acc=train(x_tr,y_tr,x_cv,y_cv,p="l1",C=0.001)
```

```
The model score on train set is=  0.6560408163265307

The accuracy of Logistic Regression over cross-validation set is =  66%
The total number of non zero weights =  42
```

In [40]:
```
Confusion_metric(y_cv,l1_Pred,l1_Acc)
```

```
[[1540  273]
 [3220 5467]]
```




```
+-------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+--------------------------------+----------------------------+
|            Metrics             |           Scores           |
+--------------------------------+----------------------------+
|     Classification_accuracy    |     66.73333333333333      |
|      Classification_error      |     33.266666666666666     |
|         True positive          |            5467            |
|         False positive         |            273             |
|         True negative          |            1540            |
|         False negative         |            3220            |
|       True positive rate       |     62.93311845286059      |
|      False negative rate       |      37.0668815471394      |
|       True negative rate       |     84.94208494208493      |
|      False positive rate       |     15.057915057915059     |
|        Precision value         |     95.24390243902438      |
|          Recall value          |     62.93311845286059      |
|         f1_score value         |     75.78845220766617      |
+--------------------------------+----------------------------+
```

Observations

- Since in the formulation of alpha in logistic regression it has a inverse relationship so here I had reduced the Lambda value by using the L1-regularisation and the results are as follows:
    1. By increasing the values of lambda the total number of non zero weights decreases sharply as the regularization term which is L1 dominates and create sparsity.
    2. The accuracy and the other performance metrics of the also detoriated consistently from (88.64% to 66.73%)
    3. As the lamda value increases the False negative and the False positive rates vary which decreases the performance of the model.
    4. So clearly by increasing the value of lambda with L1-regularization creates sparsity and reduces accuracy of the model.

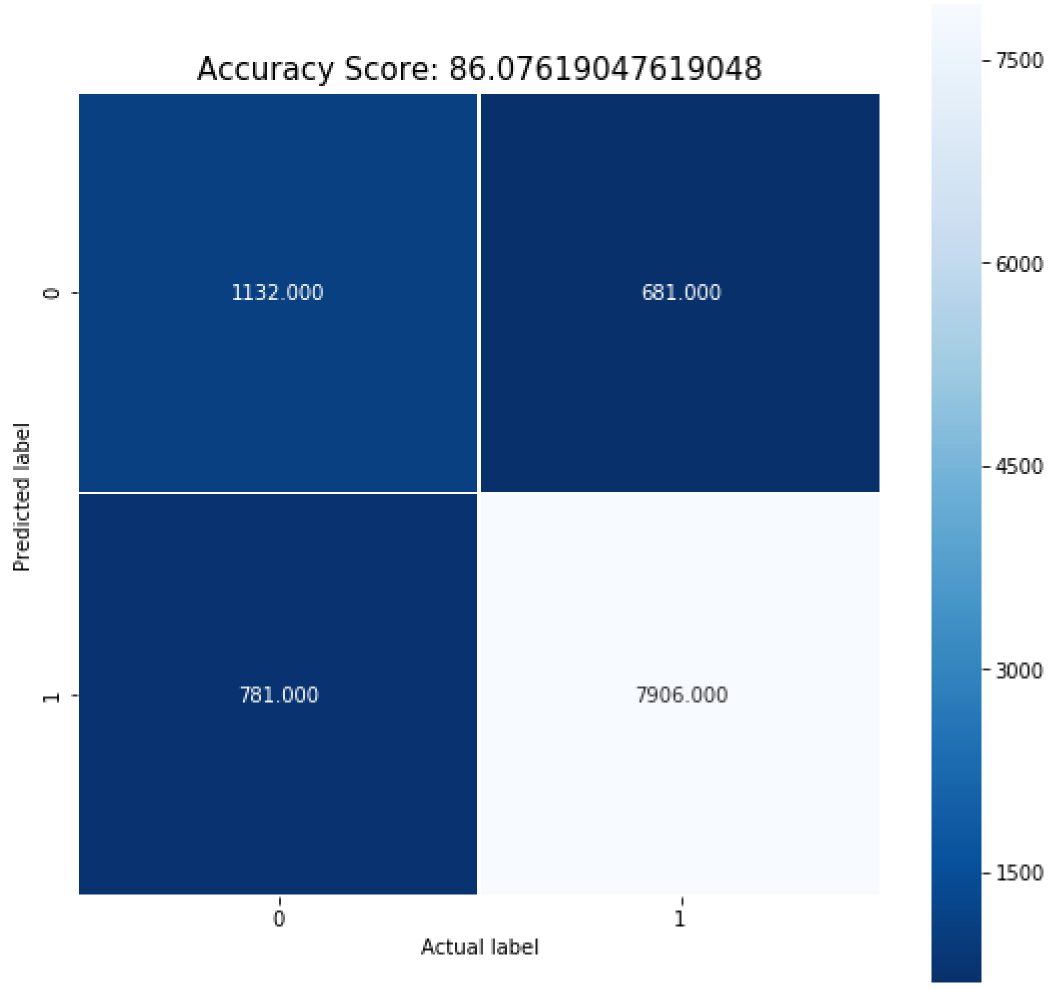
Decreasing the "LAMBDA" value with L1- Regularization

In [41]:
```
#Calling the train function and storing the prediction value and accuracy

L1pred,L1acc=train(x_tr,y_tr,x_cv,y_cv,p="l1",C=8)
```

```
The model score on train set is=  1.0

The accuracy of Logistic Regression over cross-validation set is =  86%
The total number of non zero weights =  5446
```

In [42]:
```
Confusion_metric(y_cv,L1pred,L1acc)
```

```
[[1132  681]
 [ 781 7906]]
```



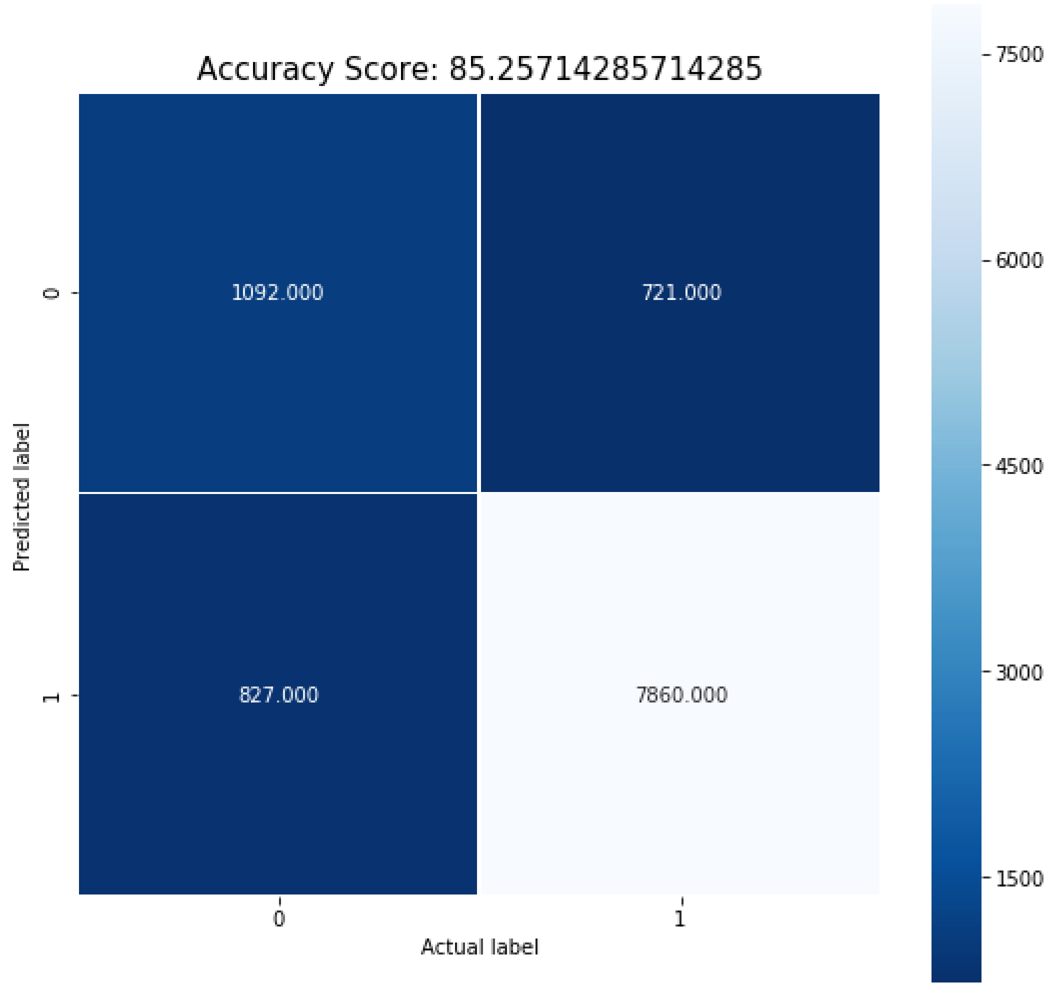

```
+--------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+----------------------------------+---------------------------+
|             Metrics              |           Scores          |
+----------------------------------+---------------------------+
|     Classification_accuracy      |     86.07619047619048     |
|       Classification_error       |     13.923809523809524    |
|          True positive           |            7906           |
|          False positive          |            681            |
|          True negative           |            1132           |
|          False negative          |            781            |
|        True positive rate        |      91.0095545067342     |
|       False negative rate        |     8.990445493265801     |
|        True negative rate        |     62.43794815223387     |
|       False positive rate        |     37.56205184776613     |
|         Precision value          |     92.06940724350763     |
|           Recall value           |      91.0095545067342     |
|          f1_score value          |     91.53641310640269     |
+----------------------------------+---------------------------+
```

In [43]:
```
L1_pred,L1_acc=train(x_tr,y_tr,x_cv,y_cv,p="l1",C=58)
```

```
The model score on train set is=  1.0

The accuracy of Logistic Regression over cross-validation set is =  85%
The total number of non zero weights =  6276
```

In [44]:
```
Confusion_metric(y_cv,L1_pred,L1_acc)
```

```
[[1092  721]
 [ 827 7860]]
```



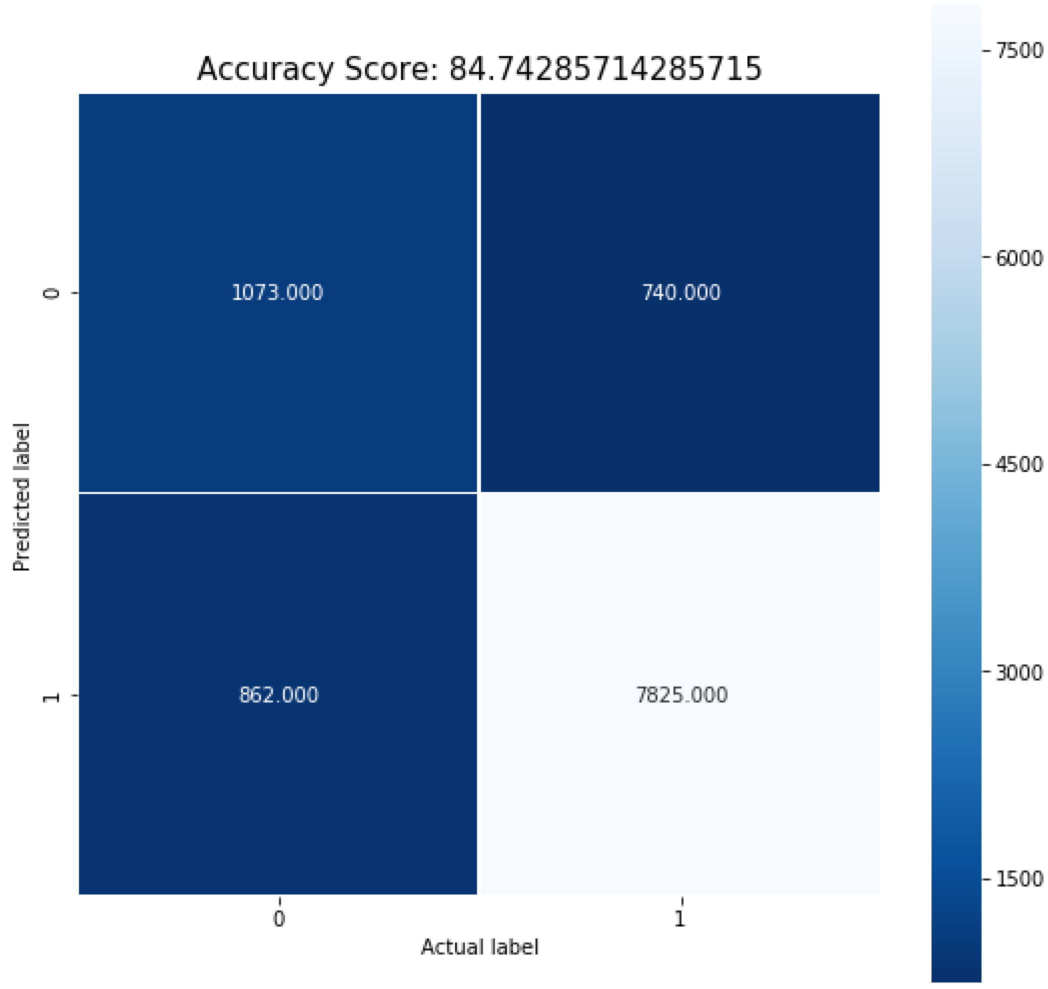

```
+-----------------------------------------------------------+
| The performance metrics of the above model are as follows: |
+----------------------------------+------------------------+
|              Metrics             |         Scores         |
+----------------------------------+------------------------+
|       Classification_accuracy    |    85.25714285714285   |
|         Classification_error     |    14.742857142857144  |
|            True positive         |          7860          |
|            False positive        |          721           |
|            True negative         |          1092          |
|            False negative        |          827           |
|          True positive rate      |    90.48002762748936   |
|         False negative rate      |    9.519972372510647   |
|          True negative rate      |    60.231660231660236  |
|         False positive rate      |    39.768339768339764  |
|           Precision value        |    91.59771588392961   |
|             Recall value         |    90.48002762748936   |
|            f1_score value        |    91.03544127866573   |
+----------------------------------+------------------------+
```

In [45]:
```
L1_Pred,L1_Acc=train(x_tr,y_tr,x_cv,y_cv,p="l1",C=100)
```

```
The model score on train set is=  1.0

The accuracy of Logistic Regression over cross-validation set is =  84%
The total number of non zero weights =  6863
```

In [46]:
```
Confusion_metric(y_cv,L1_Pred,L1_Acc)
```

```
[[1073  740]
 [ 862 7825]]
```




```
+-------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+----------------------------------+--------------------------+
|             Metrics              |          Scores          |
+----------------------------------+--------------------------+
|     Classification_accuracy      |    84.74285714285715     |
|       Classification_error       |    15.257142857142858    |
|          True positive           |           7825           |
|          False positive          |           740            |
|          True negative           |           1073           |
|          False negative          |           862            |
|        True positive rate        |     90.0771267411074     |
|       False negative rate        |    9.922873258892597     |
|        True negative rate        |    59.183673469387756    |
|       False positive rate        |    40.816326530612244    |
|         Precision value          |    91.36018680677175     |
|           Recall value           |     90.0771267411074     |
|          f1_score value          |    90.71412010201715     |
+----------------------------------+--------------------------+
```

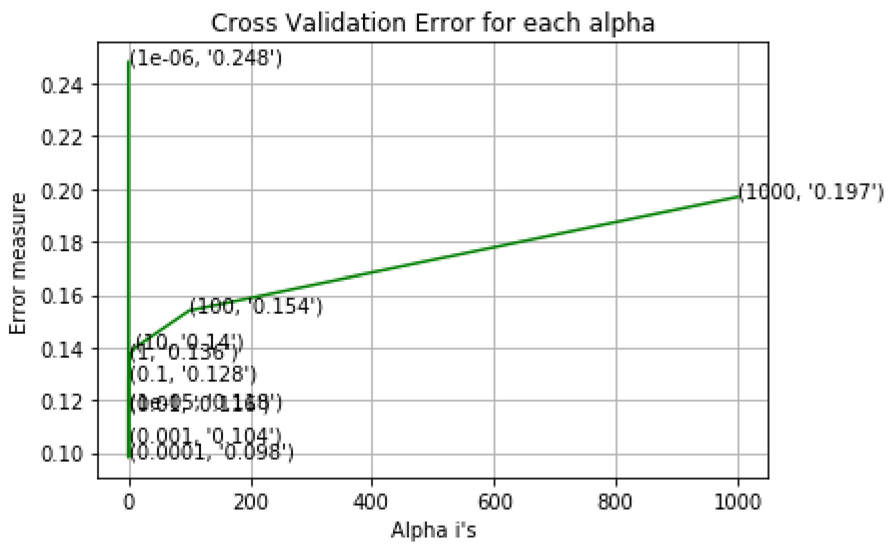
Observations

- Here there is a decrease in the total number of non zero weights but it becomes stable after a certain point and did not decreased further.
- The True negative rates are get affected most hence reducing the accuracy but it did not decrease beyond 84%.
- Since here sparsity is not seen very severe, that's why the accuracy did not drop sharply.

Plotting the cv error plot using 10K cross validation technique

In [47]:
```
cv_results(x_tr,y_tr)
```

```
----------------------------------------------------------------------------------------------------
--
for alpha = 1e-06

the misclassification error for each alpha value is :  [0.248]
----------------------------------------------------------------------------------------------------
--
for alpha = 1e-05

the misclassification error for each alpha value is :  [0.248 0.118]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.0001

the misclassification error for each alpha value is :  [0.248 0.118 0.098]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.001

the misclassification error for each alpha value is :  [0.248 0.118 0.098 0.104]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.01

the misclassification error for each alpha value is :  [0.248 0.118 0.098 0.104 0.116]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.1

the misclassification error for each alpha value is :  [0.248 0.118 0.098 0.104 0.116 0.128]
----------------------------------------------------------------------------------------------------
--
for alpha = 1

the misclassification error for each alpha value is :  [0.248 0.118 0.098 0.104 0.116 0.128 0.136]
----------------------------------------------------------------------------------------------------
--
for alpha = 10

the misclassification error for each alpha value is :  [0.248 0.118 0.098 0.104 0.116 0.128 0.136 0.14
]
----------------------------------------------------------------------------------------------------
--
for alpha = 100

the misclassification error for each alpha value is :  [0.248 0.118 0.098 0.104 0.116 0.128 0.136 0.14
  0.154]
----------------------------------------------------------------------------------------------------
--
for alpha = 1000

the misclassification error for each alpha value is :  [0.248 0.118 0.098 0.104 0.116 0.128 0.136 0.14
  0.154 0.197]
```




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

Testing the model over th test set using the optimal lamda value

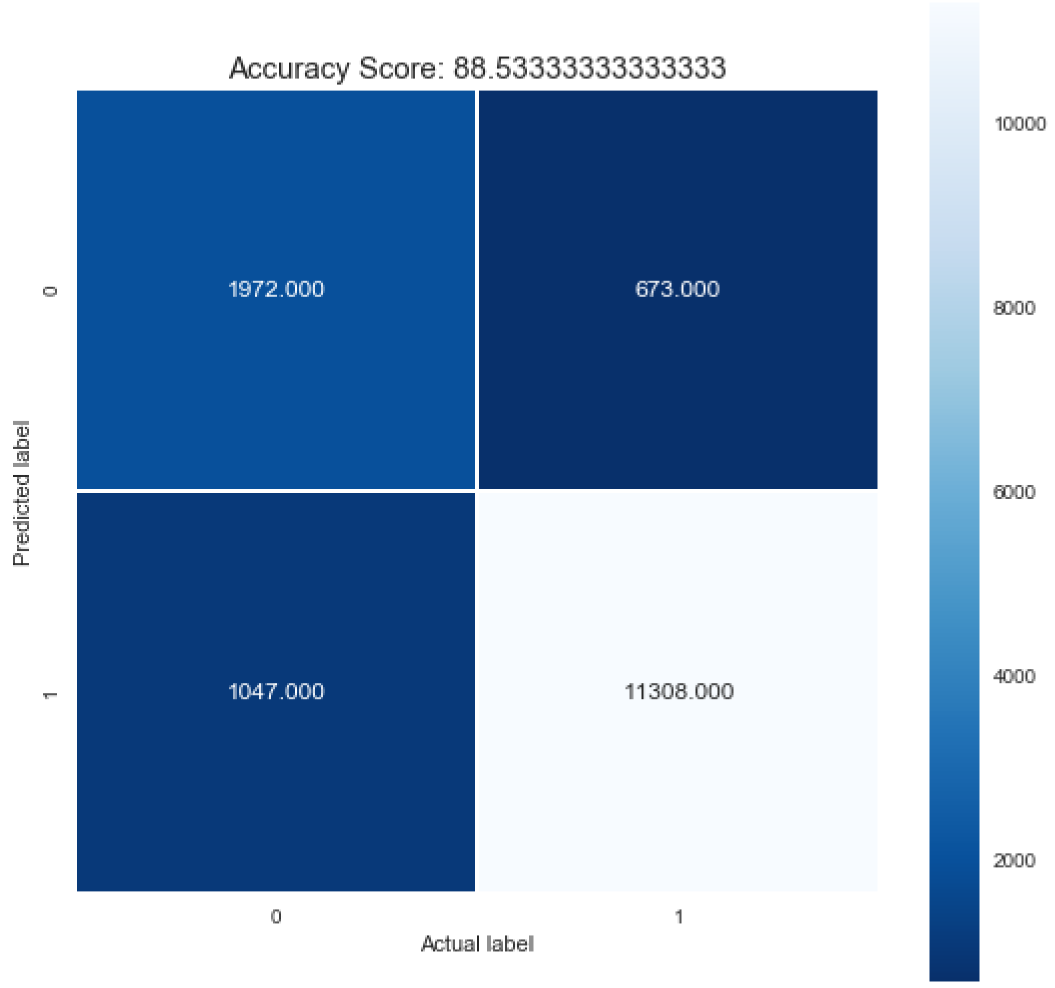
In [45]:
```
New_clf=best_param

y_pre,acc=tuned_test(New_clf,x_tr,y_tr,x_test,y_test)
```

```
The model score on train set is=  0.9617142857142857

The accuracy of Logistic Regression over Test set is =  88%
The total number of non zero weights =  18987
```

Confusion matrix of the above model

In [46]:
```
Confusion_metric(y_test,y_pre,acc)
```

```
[[ 1972   673]
 [ 1047 11308]]
```




```
+------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+----------------------------------+-------------------------+
|             Metrics              |          Scores         |
+----------------------------------+-------------------------+
|     Classification_accuracy      |    88.53333333333333    |
|      Classification_error        |    11.466666666666667   |
|          True positive           |          11308          |
|          False positive          |           673           |
|          True negative           |           1972          |
|          False negative          |           1047          |
|        True positive rate        |    91.52569809793606    |
|       False negative rate        |    8.474301902063942    |
|        True negative rate        |    74.55576559546314    |
|       False positive rate        |    25.444234404536864   |
|         Precision value          |    94.38277272347884    |
|           Recall value           |    91.52569809793606    |
|          f1_score value          |    92.93228139381985    |
+----------------------------------+-------------------------+
```

Observations

- The optimal number of lamda found after gridsearch and 10k crossvalidation is 0.0001 with a missclassification error of 11.46% and gave a test accuracy of 88.53% which is good for a classification model.
- The performance metrics of the logistic regression model over test set is good as compared with the earlier model.
- The model is sensible but still it is facing a slight bias problem as the True negative rate is low as compared to the True positive rates.
- Let's check the multicollinearity of features by using the pertubation test.

Implementing and checking the multicollinearity test.

Function for genarating and adding noise to the above model

In [19]:
```
import numpy as np
def Noise(x_tr,x_test):
    mu, sigma = 0, 0.01
# creating a noise with the same dimension as the dataset (2,2)
    Train_noise = np.random.normal(mu, sigma, x_tr.shape)
    print(Train_noise)

    Train_data=x_tr + Train_noise
    print("\nThe shape of the train data after adding noise is :",Train_data.shape)

    print("*"*100)


# creating a noise with the same dimension as the dataset (2,2)
    Test_noise = np.random.normal(mu, sigma, x_test.shape)
    print(Test_noise)

    Test_data= x_test + Test_noise
    print("\nThe shape of the test data after adding noise is :",Test_data.shape)

    return Train_data,Test_data
```

The shape of the noise added Train and Test set is as follows:

In [47]:
```
Train_nd,Test_nd=Noise(x_tr,x_test)
```

```
[[-0.00049436  0.00749982 -0.00832213 ... -0.0046638  -0.01298233
  -0.01178142]
 [-0.01473462 -0.01046555  0.00221836 ...  0.00110465  0.0056567
   0.00933101]
 [ 0.00018067 -0.01348652  0.00996227 ... -0.00863126 -0.00019525
   0.00274925]
 ...
 [ 0.00674569 -0.00579183 -0.01269166 ...  0.00068726  0.00528758
   0.00518848]
 [-0.00796659  0.01397421  0.00390764 ...  0.00125421 -0.00349247
   0.01187116]
 [-0.02003545  0.01269014 -0.00035191 ... -0.00517335  0.00957207
  -0.02423328]]

The shape of the train data after adding noise is : (24500, 18987)
****************************************************************************************************
[[-0.00706879 -0.00857271  0.00487714 ...  0.01416849  0.01692085
  -0.01188144]
 [-0.00354436 -0.0090666  -0.00869587 ...  0.00395706  0.00070504
   0.00319864]
 [ 0.00285856  0.01710856 -0.00473573 ... -0.00939172 -0.010282
   0.00178905]
 ...
 [-0.01442047  0.00400136  0.00775977 ...  0.00610265  0.0060188
   0.00499617]
 [-0.01823305  0.00324732 -0.010177   ...  0.00108983 -0.01260293
   0.0017822 ]
 [-0.01482802 -0.00073025 -0.01544105 ... -0.00028053  0.00448844
   0.00591461]]

The shape of the test data after adding noise is : (15000, 18987)
```

Testing the above model over the noise added Test set

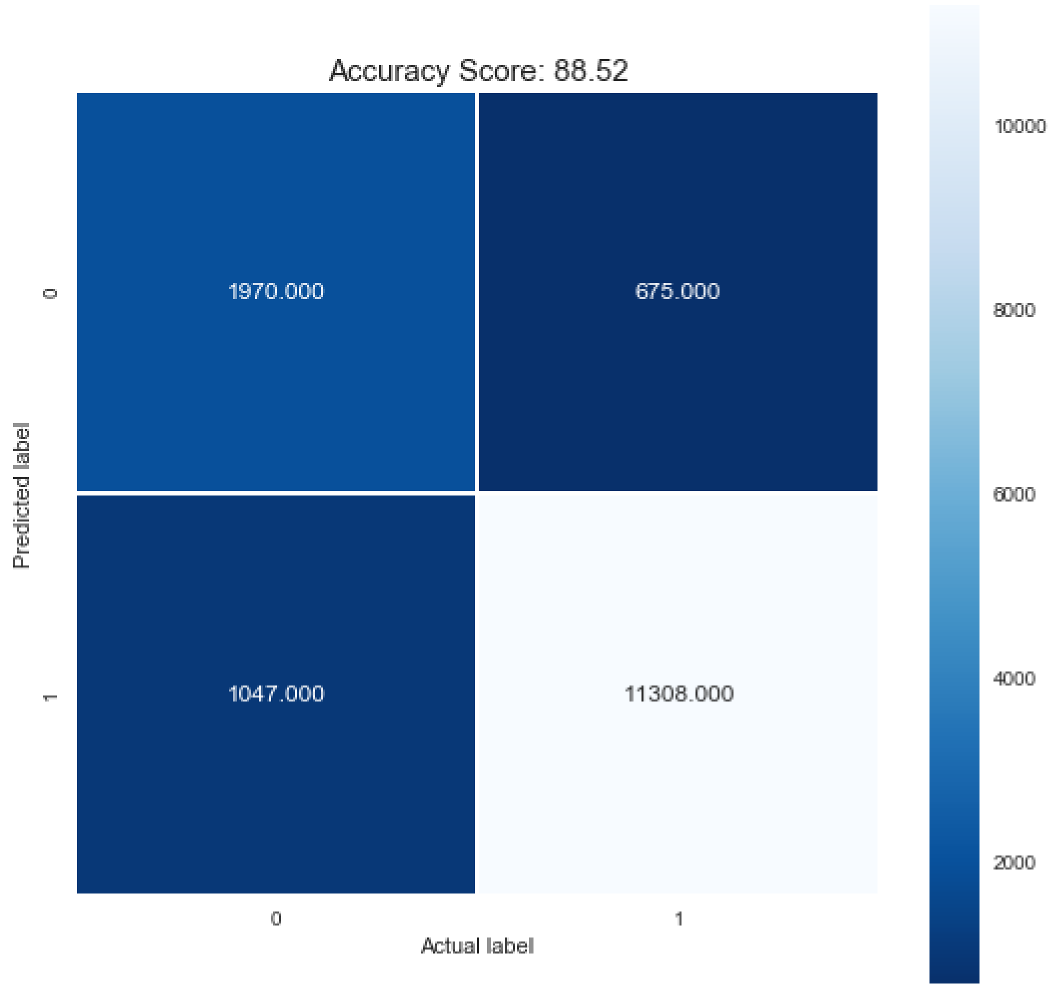
In [48]:
```
New_clf=best_param

Noise_pre,Noise_acc=tuned_test(New_clf,Train_nd,y_tr,Test_nd,y_test)
```

```
The model score on train set is=  0.9616326530612245

The accuracy of Logistic Regression over Test set is =  88%
The total number of non zero weights =  18987
```

Confusion matrix of the above model is as follows:

In [49]:
```
Confusion_metric(y_test,Noise_pre,Noise_acc)
```

```
[[ 1970   675]
 [ 1047 11308]]
```



The performance metrics of the above model are as follows:

Metrics	Scores
Classification_accuracy	88.52
Classification_error	11.48
True positive	11308
False positive	675
True negative	1970
False negative	1047
True positive rate	91.52569809793606
False negative rate	8.474301902063942
True negative rate	74.48015122873346
False positive rate	25.51984877126654
Precision value	94.36701994492196
Recall value	91.52569809793606
f1_score value	92.92464458870901

Observations

- Since the total number of non zero weights are same before and after adding the noise to the data so the features are not collinear with each other.
- The accuracy of the noise added model is slightly increased which is about 0.35% which is due to the small random noise introduced to the data.
- Since the features are not collinear we can find the feature importance by using the Recursive Feature Elimination technique.

Function for implementing the Recursive Feature Elimination Technique for finding the most important features present in the data

In [23]:
```
def feature_selection(best,tr_Noise, Train_y):
    from sklearn.feature_selection import RFECV
# Create the RFE object and compute a cross-validated score.
# The "accuracy" scoring is proportional to the number of correct classifications
    rfecv = RFECV(estimator=best, step=1, cv=3,scoring ='accuracy')
    rfecv.fit(tr_Noise, Train_y)

    print("Optimal number of features: %d" % rfecv.n_features_)
    print('Selected features: %s' % list(tr_Noise.columns[rfecv.support_]))

    NAMES=tr_Noise.columns
    print ("Features sorted by their rank:")
    print (sorted(zip(map(lambda x: round(x, 4), viz.ranking_), NAMES)))



# Plot number of features VS. cross-validation scores
    plt.figure(figsize=(10,6))
    plt.xlabel("Number of features selected")
    plt.ylabel("Cross validation score (nb of correct classifications)")
    plt.plot(range(1, len(rfecv.grid_scores_) + 1), rfecv.grid_scores_)
    plt.show()
```

In [ ]:
```
start = datetime.now()
best=best_param
feature_selection(best,Train_nd,y_tr)

print('Time taken :', datetime.now() - start)
```

Note

- The Recursive Feature elimination technique is used to find out the important features present in the dataset it is basically an Iterative feature selection approach.
- The goal of recursive feature elimination (RFE) is to select features by recursively considering smaller and smaller sets of features.
- First, the estimator is trained on the initial set of features and the importance of each feature is obtained either through a coef_ attribute or through a feature_importances_ attribute.
- The least important features are pruned from current set of features. That procedure is recursively repeated on the pruned set until the desired number of features to select is eventually reached.
- So the time complexity of this approach is very high. so I had implemented this technique in Avg W2V and Tf-idf weighted W2V where the dimensions of the data is reasonable and can be easily implemented.

Implementing the TF-IDF Vectorization technique over the given data.

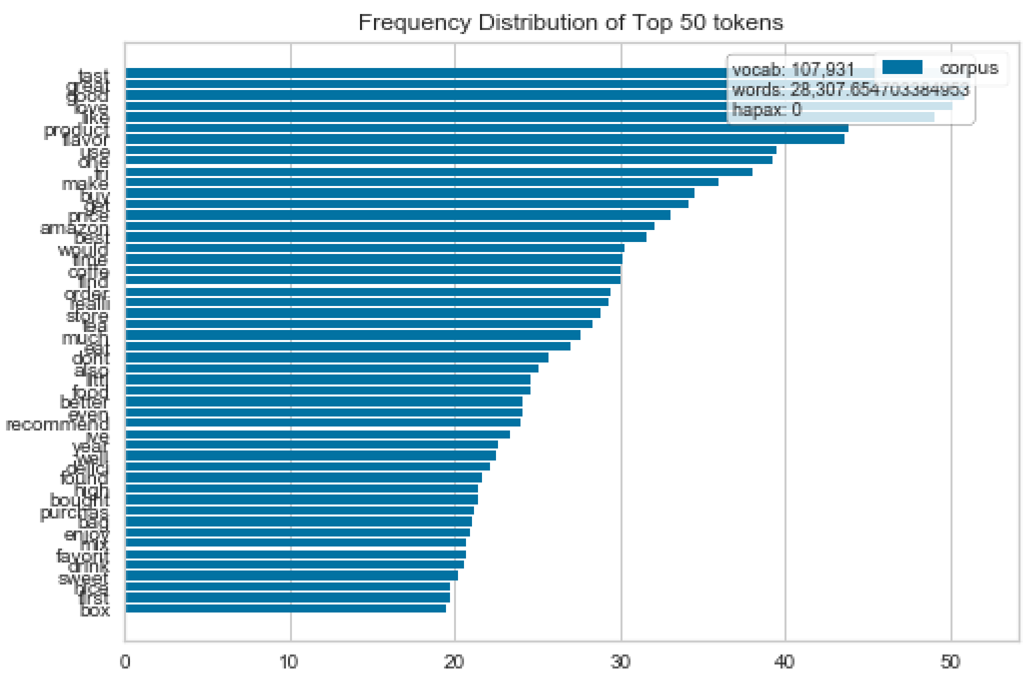
In [20]:
```
#Initializing the count vectorizer
TFIDF_vect=TfidfVectorizer(ngram_range=(1,2),binary=True)

#vectorizing the X_train set
TF,tfx_tr=vec_train(TFIDF_vect,TFX_tr["CleanedText"])

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

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

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


#Printing the total length of the features
print("\nTop 25 feaures acording to the TF-IDF score are as follows")
TF_features = TFIDF_vect.get_feature_names()
len(TF_features)


top_TFIDF = top_tfidf_feats("TFIDF",tfx_tr[1,:].toarray()[0],TF_features,25)
top_TFIDF
```

```
The shape of the X_train is:  (3920, 111810)
The shape of the X_cv is:  (1680, 111810)
The shape of the X_test is:  (2400, 111810)

Top 25 feaures acording to the TF-IDF score are as follows
```

Out[20]:

	feature	TFIDF
0	romanc	62.617891
1	world live	62.617891
2	break cover	62.617891
3	stori strang	62.617891
4	one funiest	62.617891
5	job see	62.617891
6	see movi	62.617891
7	deceas handbook	62.617891
8	haunt take	62.617891
9	romanc alec	62.617891
10	live dead	62.617891
11	wait hous	62.617891
12	recent deceas	62.617891
13	haunt peopl	62.617891
14	realiti stori	62.617891
15	cover stori	62.617891
16	strang world	62.617891
17	watch time	62.617891
18	deceas	62.617891
19	davi funni	62.617891
20	baldwin geena	62.617891
21	mix strang	62.617891
22	movi cant	62.617891
23	handbook wait	62.617891
24	movi ever	62.617891

In [23]:
```
display_token(TFIDF_vect,TFX_tr["CleanedText"])
```



Training the Tfidf Vectorized model over the cross-Validation set

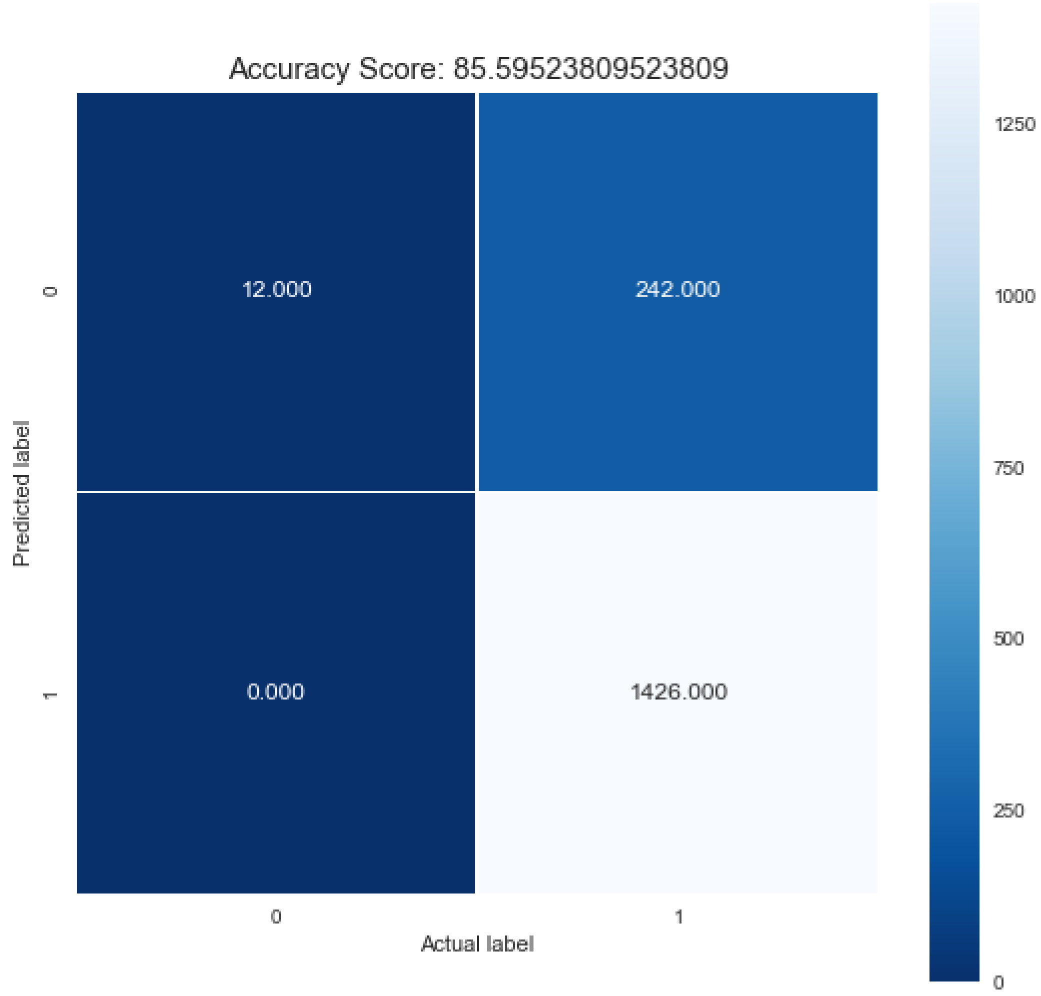
In [51]:
```
#Training the logistic regression model
tfy_pre,tfacc=train(tfx_tr,TFy_tr,tfx_cv,TFy_cv)
```

```
The model score on train set is=  1.0

The accuracy of Logistic Regression over cross-validation set is =  85%
The total number of non zero weights =  108306
```

Plotting the Confusion matrix of the above model

In [52]:
```
Confusion_metric(TFy_cv,tfy_pre,tfacc)
```

```
[[  12  242]
 [   0 1426]]
```




```
+------------------------------------------------------------+
| The performance metrics of the above model are as follows: |
+-------------------------------+----------------------------+
|            Metrics            |           Scores           |
+-------------------------------+----------------------------+
|    Classification_accuracy    |     85.59523809523809      |
|     Classification_error      |     14.404761904761903     |
|         True positive         |            1426            |
|         False positive        |            242             |
|         True negative         |             12             |
|         False negative        |             0              |
|       True positive rate      |           100.0            |
|      False negative rate      |            0.0             |
|       True negative rate      |     4.724409448818897      |
|      False positive rate      |      95.2755905511811      |
|        Precision value        |      85.4916067146283      |
|          Recall value         |           100.0            |
|         f1_score value        |     92.17840982546866      |
+-------------------------------+----------------------------+
```

Hyperparameter tuning the lamda value using the Gridsearch & randomsearch cross-validation technique.

In [21]:
```
#Gridsearch implementation
best_tfparam=gridsearch(tfx_tr,TFy_tr,tfx_cv,TFy_cv)
```

```
LogisticRegression(C=1e-05, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=-1, penalty='l2', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
0.8910714285714286
```

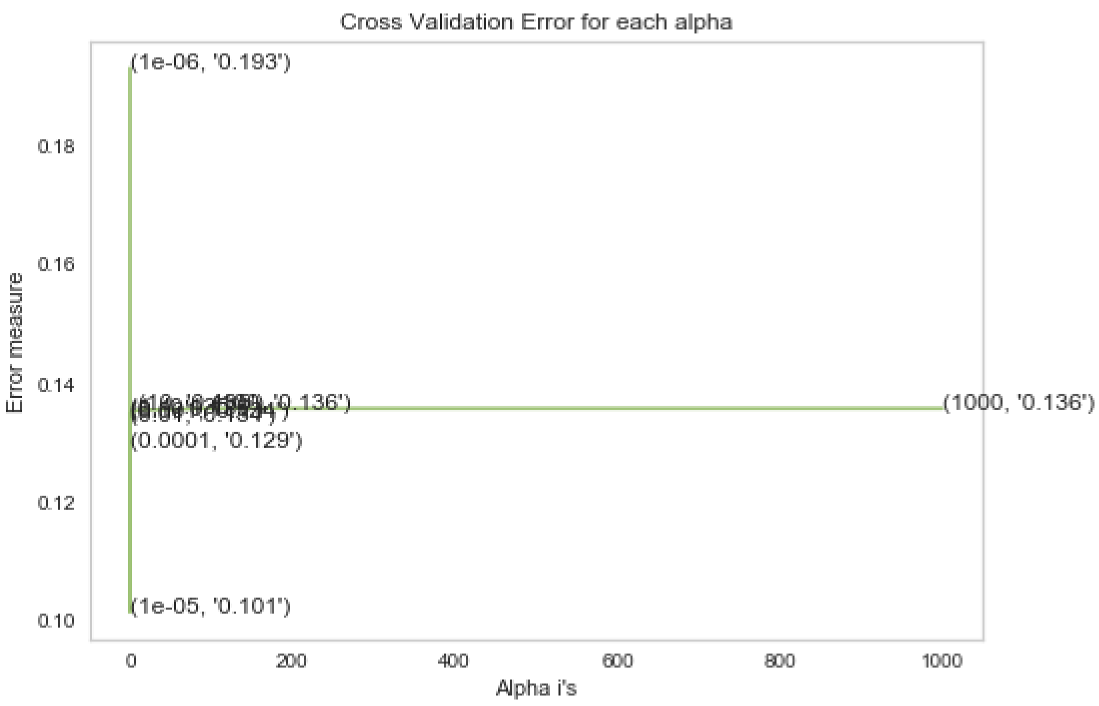
In [54]:
```
#Random-search Implementation
Best_randpar=randomsearch(tfx_tr, TFy_tr,tfx_cv, TFy_cv)
```

```
LogisticRegression(C=0.5131306580538797, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=-1, penalty='l2', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
0.856547619047619
```

Plotting the optimal lamda results using 10k crossvalidation technique.

In [55]:
```
cv_results(tfx_tr, TFy_tr)
```

```
------------------------------------------------------------------------------------------------------
--
for alpha = 1e-06

the misclassification error for each alpha value is :  [0.193]
------------------------------------------------------------------------------------------------------
--
for alpha = 1e-05

the misclassification error for each alpha value is :  [0.193 0.101]
------------------------------------------------------------------------------------------------------
--
for alpha = 0.0001

the misclassification error for each alpha value is :  [0.193 0.101 0.129]
------------------------------------------------------------------------------------------------------
--
for alpha = 0.001

the misclassification error for each alpha value is :  [0.193 0.101 0.129 0.134]
------------------------------------------------------------------------------------------------------
--
for alpha = 0.01

the misclassification error for each alpha value is :  [0.193 0.101 0.129 0.134 0.134]
------------------------------------------------------------------------------------------------------
--
for alpha = 0.1

the misclassification error for each alpha value is :  [0.193 0.101 0.129 0.134 0.134 0.135]
------------------------------------------------------------------------------------------------------
--
for alpha = 1

the misclassification error for each alpha value is :  [0.193 0.101 0.129 0.134 0.134 0.135 0.135]
------------------------------------------------------------------------------------------------------
--
for alpha = 10

the misclassification error for each alpha value is :  [0.193 0.101 0.129 0.134 0.134 0.135 0.135 0.13
5]
------------------------------------------------------------------------------------------------------
--
for alpha = 100

the misclassification error for each alpha value is :  [0.193 0.101 0.129 0.134 0.134 0.135 0.135 0.13
5 0.136]
------------------------------------------------------------------------------------------------------
--
for alpha = 1000

the misclassification error for each alpha value is :  [0.193 0.101 0.129 0.134 0.134 0.135 0.135 0.13
5 0.136 0.136]
```




```
The optimal number of alpha value is 0.000010%.
```

Testing the model over test set using optimal value of lamda

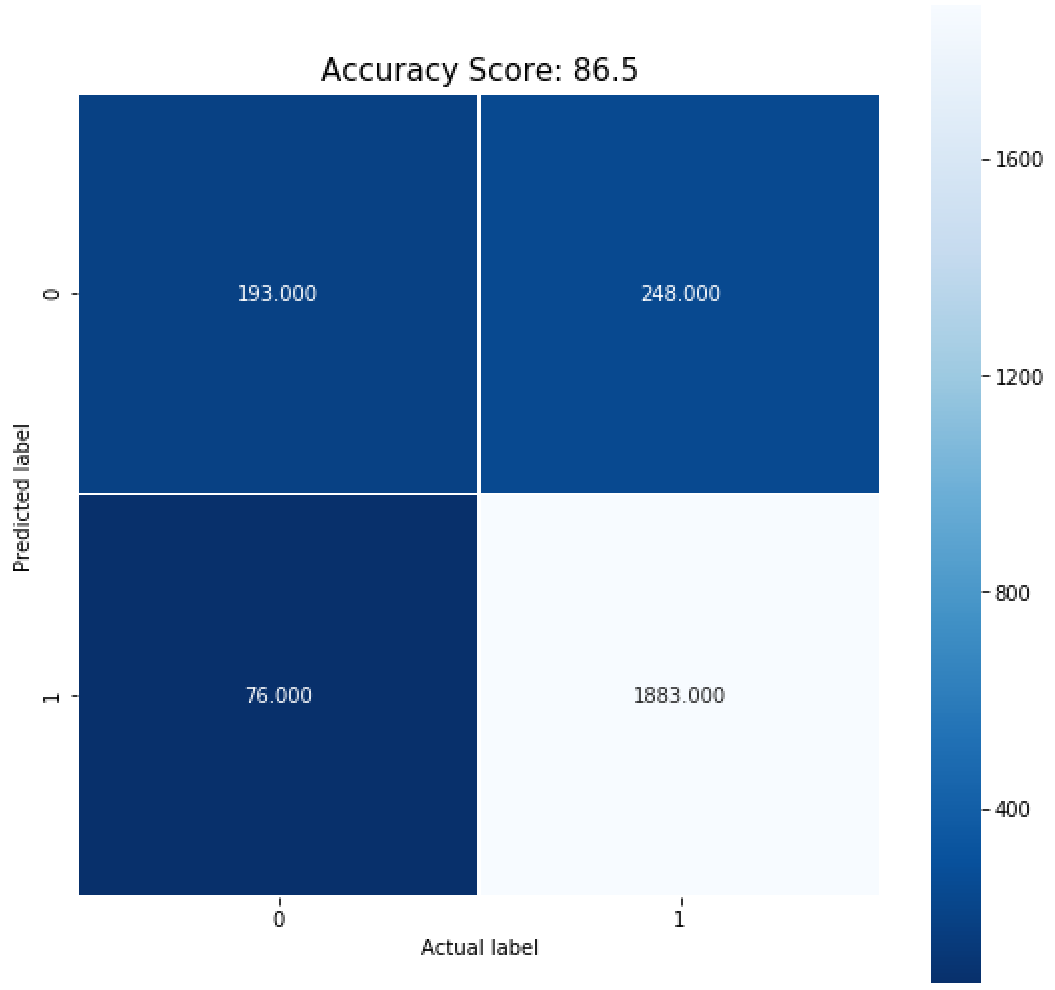
In [56]:
```
TF_clf=best_tfparam

TFy_pre,TF_acc=tuned_test(TF_clf,tfx_tr,TFy_tr,tfx_test,TFy_test)
```

```
The model score on train set is=  1.0

The accuracy of Logistic Regression over Test set is =  86%
The total number of non zero weights =  108306
```

Confusion matrix of the above model.

In [42]:
```
Confusion_metric(TFy_test,TFy_pre,TF_acc)
```

```
[[ 193  248]
 [  76 1883]]
```




```
+-----------------------------------------------------------+
| The performance metrics of the above model are as follows: |
+---------------------------------+-------------------------+
|             Metrics             |          Scores         |
+---------------------------------+-------------------------+
|     Classification_accuracy     |           86.5          |
|       Classification_error      |           13.5          |
|          True positive          |           1883          |
|          False positive         |           248           |
|          True negative          |           193           |
|          False negative         |            76           |
|        True positive rate       |    96.12046962736089    |
|       False negative rate       |    3.8795303726391013   |
|        True negative rate       |    43.76417233560091    |
|       False positive rate       |    56.235827664399096   |
|         Precision value         |    88.36227123416236    |
|           Recall value          |    96.12046962736089    |
|          f1_score value         |    92.07823960880195    |
+---------------------------------+-------------------------+
```

In [ ]:

Checking the Collinearity of features using the Pertubation test.

In [22]:
```
TrainTf_Noise,TestTF_Noise=Noise(tfx_tr,tfx_test)
```

```
[[-0.0293998   0.00574307 -0.01102008 ... -0.00566326 -0.00394131
   0.00733515]
 [ 0.0134632   0.00575275 -0.00194554 ... -0.01083167 -0.00697928
   0.01552455]
 [-0.01683894 -0.00300703  0.00960419 ...  0.00361058  0.01164493
  -0.00696104]
 ...
 [-0.0037834   0.0020388  -0.01235432 ... -0.00450846  0.01589632
   0.01166761]
 [-0.00076997  0.00264301 -0.0117148  ... -0.01369906 -0.00485977
  -0.00973072]
 [ 0.00940964  0.01028941 -0.00129644 ... -0.01832069 -0.00319472
   0.00191571]]

The shape of the train data after adding noise is : (3920, 111810)
****************************************************************************************************
[[-0.00417559 -0.00704755 -0.00141303 ...  0.01626558  0.00226082
  -0.01262548]
 [-0.0141736   0.00596285 -0.00596431 ...  0.00877768  0.00377179
  -0.01257661]
 [-0.0091882   0.00284102  0.00032274 ... -0.01078585  0.00518952
  -0.00123502]
 ...
 [ 0.00426562 -0.00367072  0.00452932 ...  0.00798885  0.01859829
   0.00881884]
 [-0.00904702 -0.00447615 -0.00053691 ... -0.00267147 -0.0101473
  -0.0028802 ]
 [-0.00040311 -0.00444414  0.02081097 ...  0.00818527 -0.00943785
   0.00025683]]

The shape of the test data after adding noise is : (2400, 111810)
```

Testing the above model over the noise added Test set

In [23]:

```
TF_clf=best_tfparam
Noise_tfpre,Noise_tfacc=tuned_test(TF_clf,TrainTf_Noise,TFy_tr,TestTF_Noise,TFy_test)
```

```
The model score on train set is=  1.0

The accuracy of Logistic Regression over Test set is =  87%
The total number of non zero weights =  111810
```

Observations

- Since the total number of non zero weights are same before and after adding the noise to the data so the features are not collinear with each other.
- The accuracy of the noise added model is slightly increased which is about 0.35% which is due to the small random noise introduced to the data.
- Since the features are not collinear we can find the feature importance by using the Recursive Feature Elimination technique.

Implementing the Avg Word to vectorization technique

In [20]:
```
start = datetime.now()
import gensim

# Train our own Word2Vec model using text corpus
list_of_sentence_vec=[]
for sentence in Sample_sort['CleanedText'].values:
    list_of_sentence_vec.append(sentence.split())
# Generate model.
w2v_Model = gensim.models.Word2Vec(list_of_sentence_vec,min_count=5,size=50, workers=6)

w2v_Words = list(w2v_Model.wv.vocab)
print("number of words that occured minimum 5 times is ",len(w2v_Words))


#code for finding the avg w2v
# average Word2Vec
# compute average word2vec for each review.
sent_vectors = []; # the avg-w2v for each sentence/review is stored in this list
for sent in list_of_sentence_vec: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_Model.wv[word]
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    sent_vec /= cnt_words
    #print(np.isnan(np.sum(sent_vec)))
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[0]))

print('Time taken :', datetime.now() - start)
```

```
number of words that occured minimum 5 times is  9352
50000
50
Time taken : 0:00:08.840139
```

Checking for the NAN Values in the dataset

In [21]:
```
np.argwhere(np.isnan(sent_vectors))#checking for nan values
```

Out[21]:
```
array([], shape=(0, 2), dtype=int64)
```

Preparing the data for the further implementations

In [22]:
```
X_w2v=sent_vectors
y_w2v=label

TrainX_w2v,Trainy_w2v,TrainX_w2vCV,Testy_w2vCV,TestX_w2v,Testy_data=data_split(X_w2v,y_w2v)
```

In [23]:
```
Train_df=pd.DataFrame(TrainX_w2v)
print(Train_df.shape)

Test_df=pd.DataFrame(TestX_w2v)
print(Test_df.shape)
```

```
(24500, 50)
(15000, 50)
```

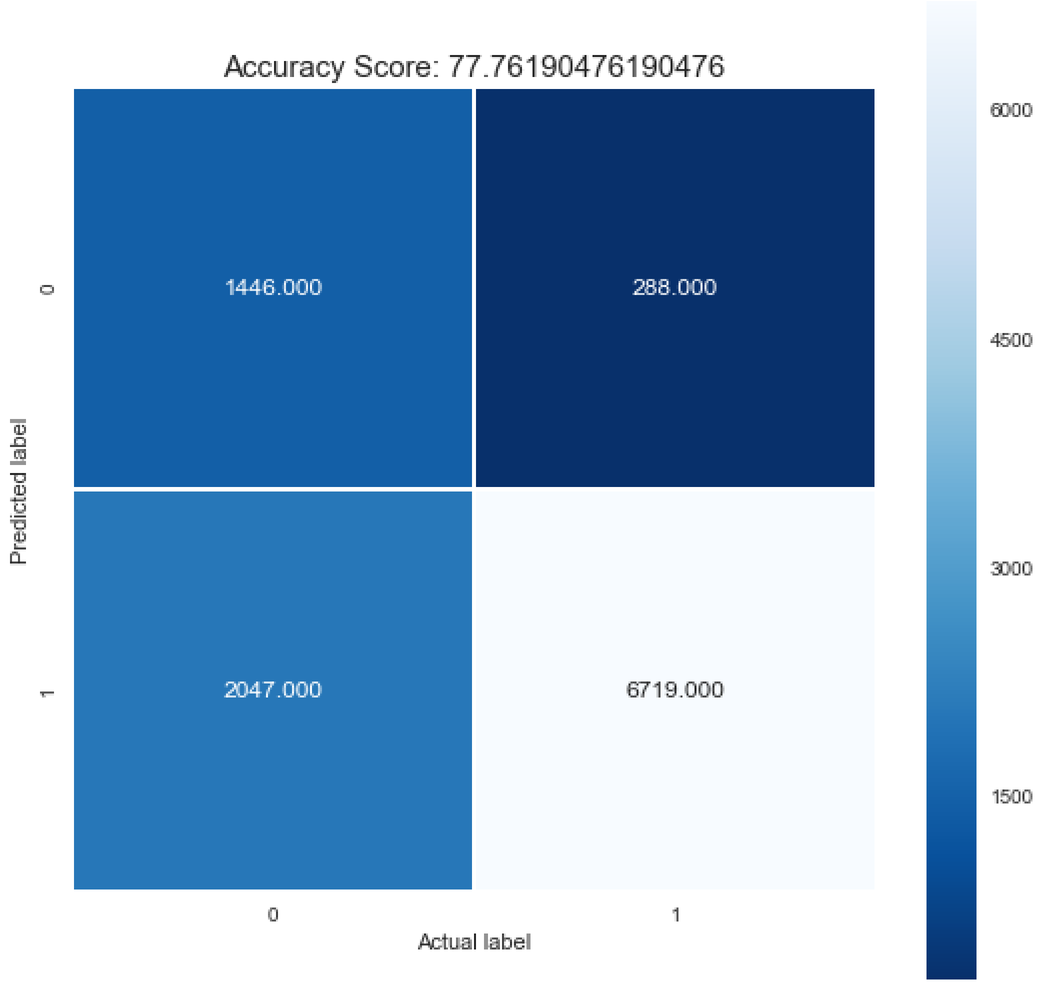
Training the model over the Avg word to vectorized data.

In [24]:
```
#Calling the train function and storing the prediction value and accuracy

W2V_pred,W2V_acc=train(TrainX_w2v,Trainy_w2v,TrainX_w2vCV,Testy_w2vCV)
```

```
The model score on train set is=  0.8046530612244898

The accuracy of Logistic Regression over cross-validation set is =  77%
The total number of non zero weights =  50
```

In [25]:
```
Confusion_metric(Testy_w2vCV,W2V_pred,W2V_acc)
```

```
[[1446  288]
 [2047 6719]]
```




```
+-------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+----------------------------------+--------------------------+
|             Metrics              |          Scores          |
+----------------------------------+--------------------------+
|     Classification_accuracy      |    77.76190476190476     |
|       Classification_error       |    22.238095238095237    |
|          True positive           |           6719           |
|          False positive          |           288            |
|          True negative           |           1446           |
|          False negative          |           2047           |
|        True positive rate        |    76.64841432808579     |
|       False negative rate        |    23.35158567191421     |
|        True negative rate        |    83.39100346020761     |
|       False positive rate        |    16.608996539792386    |
|         Precision value          |    95.88982446125304     |
|           Recall value           |    76.64841432808579     |
|          f1_score value          |     85.1962213909846     |
+----------------------------------+--------------------------+
```

Hyperparameter tuning for finding the optimal lambda using Gridsearch and Randomsearch technique

In [26]:
```
#Gridsearch implementation
best_W2Vparam=gridsearch(TrainX_w2v,Trainy_w2v,TrainX_w2vCV,Testy_w2vCV)
```

```
LogisticRegression(C=1e-06, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=-1, penalty='l2', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
0.784
```

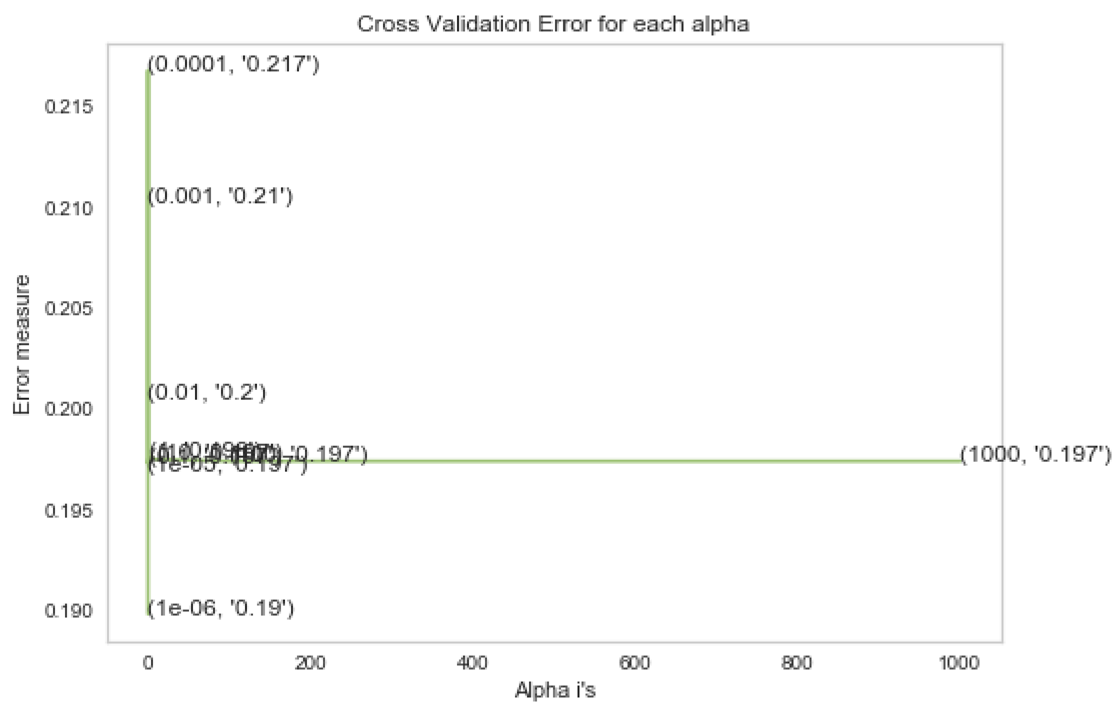
In [27]:
```
#Random-search Implementation
Best_W2Vpar=randomsearch(TrainX_w2v,Trainy_w2v,TrainX_w2vCV,Testy_w2vCV)
```

```
LogisticRegression(C=0.05288171502573946, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=-1, penalty='l2', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
0.7780952380952381
```

Implementing the 10K Cross-validation techniques for plotting the optimal K value

In [28]:
```
cv_results(TrainX_w2v,Trainy_w2v)
```

```
----------------------------------------------------------------------------------------------------
--
for alpha = 1e-06

the misclassification error for each alpha value is :  [0.19]
----------------------------------------------------------------------------------------------------
--
for alpha = 1e-05

the misclassification error for each alpha value is :  [0.19  0.197]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.0001

the misclassification error for each alpha value is :  [0.19  0.197 0.217]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.001

the misclassification error for each alpha value is :  [0.19  0.197 0.217 0.21 ]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.01

the misclassification error for each alpha value is :  [0.19  0.197 0.217 0.21  0.2  ]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.1

the misclassification error for each alpha value is :  [0.19  0.197 0.217 0.21  0.2   0.197]
----------------------------------------------------------------------------------------------------
--
for alpha = 1

the misclassification error for each alpha value is :  [0.19  0.197 0.217 0.21  0.2   0.197 0.198]
----------------------------------------------------------------------------------------------------
--
for alpha = 10

the misclassification error for each alpha value is :  [0.19  0.197 0.217 0.21  0.2   0.197 0.198 0.19
7]
----------------------------------------------------------------------------------------------------
--
for alpha = 100

the misclassification error for each alpha value is :  [0.19  0.197 0.217 0.21  0.2   0.197 0.198 0.19
7 0.197]
----------------------------------------------------------------------------------------------------
--
for alpha = 1000

the misclassification error for each alpha value is :  [0.19  0.197 0.217 0.21  0.2   0.197 0.198 0.19
7 0.197 0.197]
```




```
The optimal number of alpha value is 0.000001%.
```

Training the model over the cross-validation set.

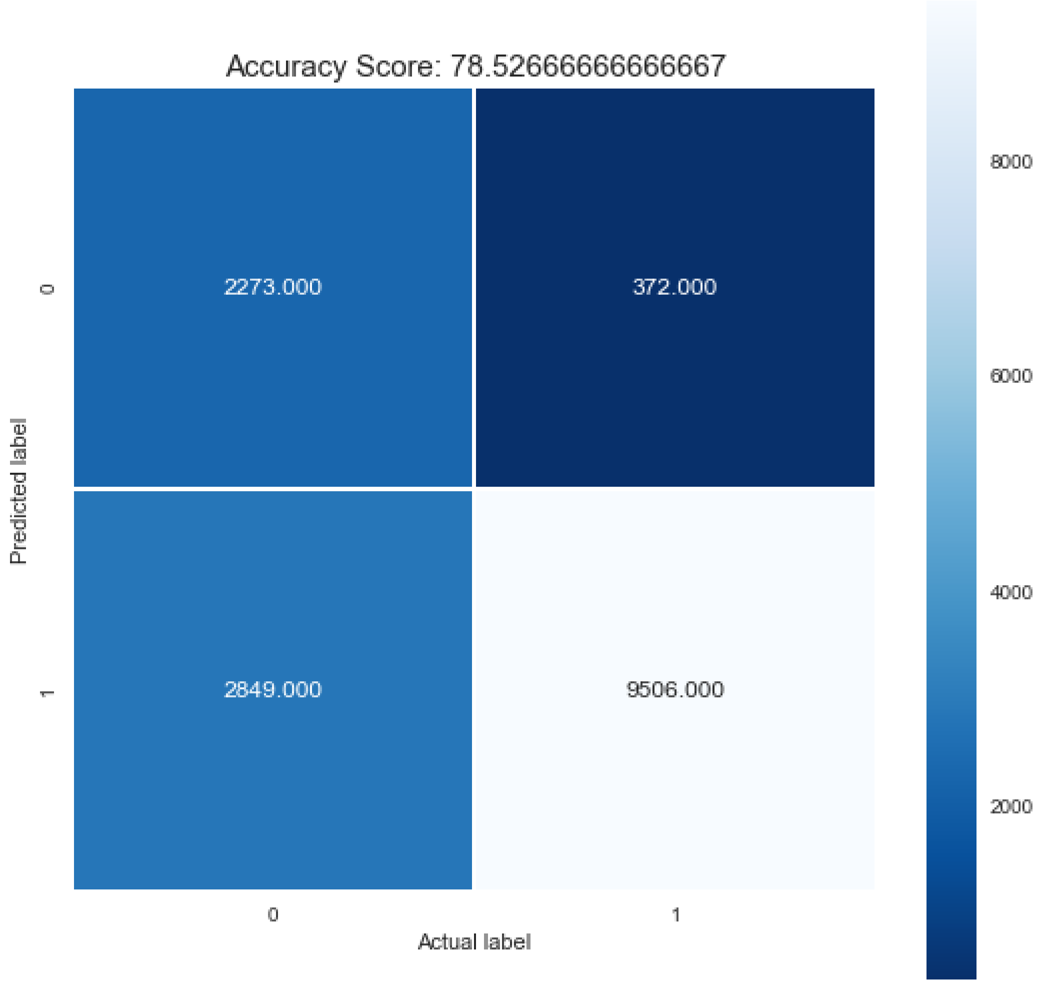
In [30]:
```
W2V_clf=Best_W2Vpar

TFy_pre,TF_acc=tuned_test(W2V_clf,TrainX_w2v,Trainy_w2v,TestX_w2v,Testy_data)
```

```
The model score on train set is=  0.8042448979591836

The accuracy of Logistic Regression over Test set is =  78%
The total number of non zero weights =  50
```

Confusion matrix of the above model

In [31]:
```
Confusion_metric(Testy_data,TFy_pre,TF_acc)
```

```
[[2273  372]
 [2849 9506]]
```




```
+-------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+---------------------------------+---------------------------+
|             Metrics             |           Scores          |
+---------------------------------+---------------------------+
|     Classification_accuracy     |     78.52666666666667     |
|       Classification_error      |     21.473333333333333    |
|          True positive          |            9506           |
|          False positive         |            372            |
|          True negative          |            2273           |
|          False negative         |            2849           |
|        True positive rate       |     76.94050991501416     |
|       False negative rate       |     23.059490084985836    |
|        True negative rate       |     85.93572778827976     |
|       False positive rate       |     14.064272211720228    |
|         Precision value         |     96.23405547681718     |
|           Recall value          |     76.94050991501416     |
|          f1_score value         |     85.51252642468404     |
+---------------------------------+---------------------------+
```

Implementing the pertubation test for checking the multicollinearity of features.

In [34]:
```
Trw2v_Noise,Tesw2v_Noise=Noise(Train_df,Test_df)
```

```
[[-3.02199141e-03 -6.40994457e-03  1.40113940e-02 ... -1.83079661e-02
   1.36145430e-02 -8.03450608e-03]
 [-6.80652054e-03  1.03672029e-02  9.71838403e-03 ... -1.35212441e-03
   2.17315200e-03  2.34714024e-05]
 [ 4.34024763e-03  6.21594492e-03 -1.43264778e-02 ...  2.98205029e-03
   3.14499459e-03  2.87263470e-03]
 ...
 [-1.75968199e-02  1.55204670e-02  3.35575260e-03 ... -4.42612518e-03
   1.93777972e-04  4.97164143e-03]
 [ 1.30101268e-02 -1.42451312e-02 -6.56538958e-03 ...  1.21692669e-03
  -3.02072584e-03  1.04822745e-02]
 [ 4.53560945e-04  1.59315463e-02 -7.14761609e-03 ... -8.17045105e-03
  -3.13140673e-03  1.22633742e-02]]

The shape of the train data after adding noise is : (24500, 50)
****************************************************************************************************
[[-1.68171043e-02  5.17149174e-03  1.70818856e-02 ... -1.47462812e-04
   1.88291463e-02 -1.23780137e-03]
 [-5.06956228e-03 -4.79932671e-03  2.07591027e-02 ...  2.62780661e-02
  -4.95871116e-03 -3.47703774e-04]
 [ 1.75299824e-03  6.77775224e-03  7.81561405e-03 ...  1.89639458e-03
   6.09511736e-05 -6.37163059e-03]
 ...
 [-7.30975822e-03 -1.20704029e-02 -1.38893907e-02 ...  1.06770342e-03
   1.71376229e-02 -2.10246406e-03]
 [ 1.51278074e-02 -7.93689043e-03  6.33493600e-03 ... -9.03321657e-03
   8.39426765e-03  7.41618894e-03]
 [-4.69488234e-03 -8.45927735e-04 -6.36421597e-03 ...  5.06711659e-03
   1.33999164e-02  1.61475279e-02]]

The shape of the test data after adding noise is : (15000, 50)
```

Testing the model over the noise added inputs

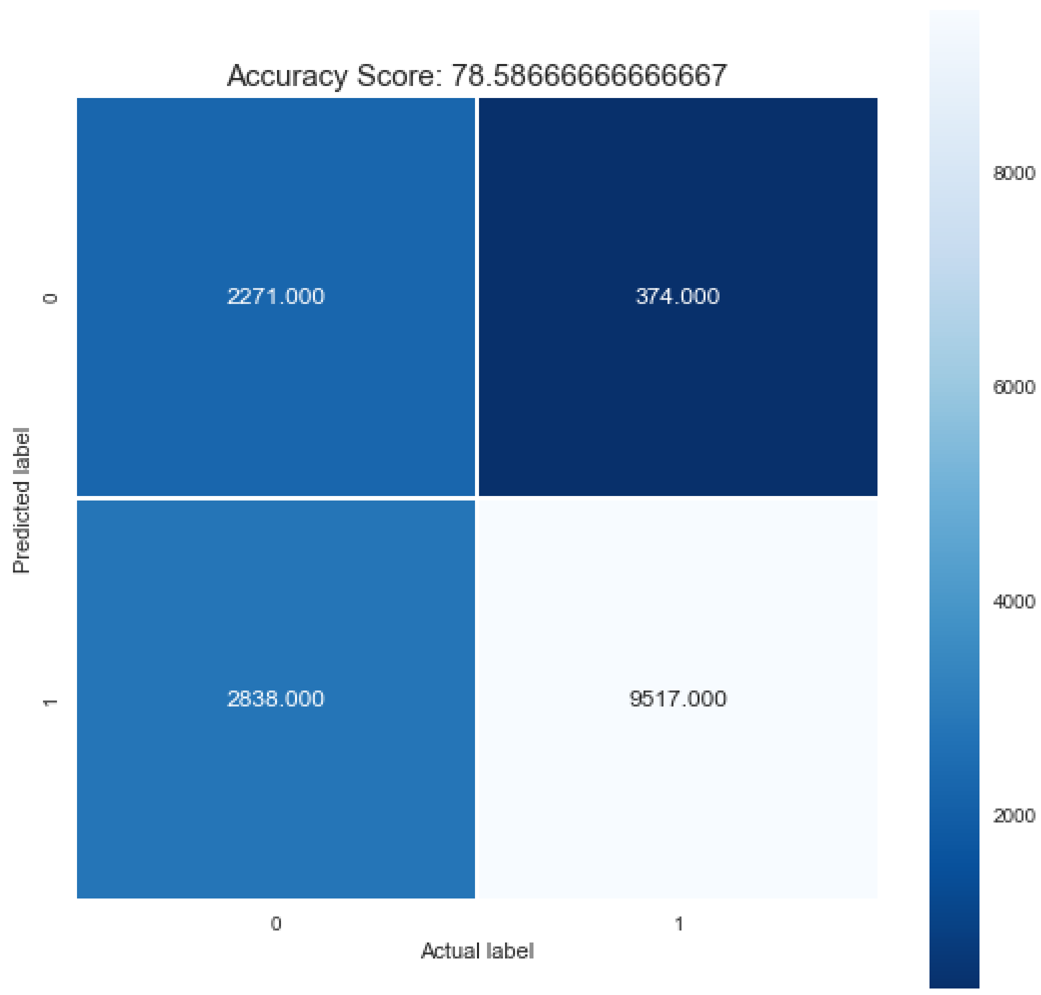
In [35]:
```
W2V_clf=Best_W2Vpar

w2v_Noise_pre,w2v_noise_acc=tuned_test(W2V_clf,Trw2v_Noise,Trainy_w2v,Tesw2v_Noise,Testy_data)
```

```
The model score on train set is=  0.804

The accuracy of Logistic Regression over Test set is =  78%
The total number of non zero weights =  50
```

Confusion matrix of the above model.

In [36]:
```
Confusion_metric(Testy_data,w2v_Noise_pre,w2v_noise_acc)
```

```
[[2271  374]
 [2838 9517]]
```



```
+-------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+--------------------------------+----------------------------+
|            Metrics             |          Scores            |
+--------------------------------+----------------------------+
|     Classification_accuracy    |     78.58666666666667      |
|       Classification_error     |     21.413333333333334     |
|          True positive         |           9517             |
|          False positive        |           374              |
|          True negative         |           2271             |
|          False negative        |           2838             |
|        True positive rate      |     77.02954269526508      |
|       False negative rate      |     22.970457304734925     |
|        True negative rate      |      85.8601134215501      |
|       False positive rate      |     14.139886578449905     |
|         Precision value        |      96.2187847538166      |
|           Recall value         |     77.02954269526508      |
|          f1_score value        |     85.56144924930327      |
+--------------------------------+----------------------------+
```

Observations

- After performing the pertubation test and testing the features over the test set the performance of the model did not changed that much.
- The total number of the non negative weights are same as compared to the previous model,So the features are not collinear which is good for the model.
- So I had implemented the feature importance by using the Recursive Feature elimination technique to find the most useful features which explain good amount of variance.

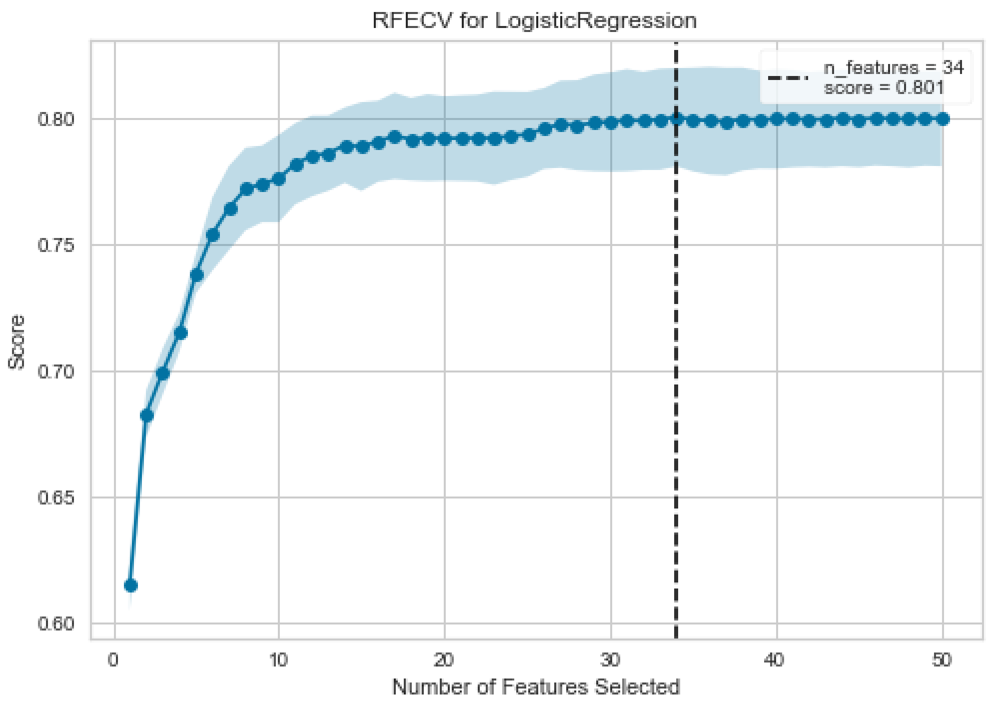
Function for performing Feature Importance using Recursive Feature elimination Cross-validation technique.

In [37]:
```
#Function for finding the Important features

from yellowbrick.features import RFECV
def Feature_imp(best,tr_Noise, Train_y):
    LOG= best
    viz = RFECV(LOG, cv=3, scoring='accuracy')
    viz.fit(tr_Noise, Train_y)

    print("Optimal number of features: %d" % viz.n_features_)
    print('Selected features: %s' % list(tr_Noise.columns[viz.support_]))

    NAMES=tr_Noise.columns
    print ("Features sorted by their rank:")
    print (sorted(zip(map(lambda x: round(x, 4), viz.ranking_), NAMES)))

    viz.poof()
```

Code for finding the calling the RFECV function and listing the important features by rank.

In [38]:
```
start = datetime.now()
best=Best_W2Vpar
Feature_imp(best,Trw2v_Noise,Trainy_w2v)

print('Time taken :', datetime.now() - start)
```

```
Optimal number of features: 34
Selected features: [0, 2, 3, 4, 6, 7, 8, 9, 12, 13, 15, 16, 17, 18, 21, 23, 24, 25, 26, 27, 28, 30, 3
2, 33, 34, 35, 36, 37, 38, 40, 41, 47, 48, 49]
Features sorted by their rank:
[(1, 0), (1, 2), (1, 3), (1, 4), (1, 6), (1, 7), (1, 8), (1, 9), (1, 12), (1, 13), (1, 15), (1, 16),
(1, 17), (1, 18), (1, 21), (1, 23), (1, 24), (1, 25), (1, 26), (1, 27), (1, 28), (1, 30), (1, 32), (1,
33), (1, 34), (1, 35), (1, 36), (1, 37), (1, 38), (1, 40), (1, 41), (1, 47), (1, 48), (1, 49), (2, 4
4), (3, 39), (4, 10), (5, 31), (6, 20), (7, 42), (8, 45), (9, 1), (10, 11), (11, 19), (12, 43), (13, 4
6), (14, 29), (15, 22), (16, 5), (17, 14)]
```




```
Time taken : 0:09:26.362678
```

Observation

1. Here after implementing the RFE technique the most important features present in the model is 34 which are displayed in the form of a list.
2. The Recursive feature elimination Cross validation (RFECV) is a feature selection method that fits a model and removes the weakest feature (or features) until the specified number of features is reached.
3. Features are ranked by the model's coef_ or feature_importances_ attributes, and by recursively eliminating a small number of features per loop, RFE attempts to eliminate dependencies and collinearity that may exist in the model.
4. Mostly the features which are having higher ranks are got selected and displayed above.
5. To find the optimal number of features cross-validation is used with RFE to score different feature subsets and select the best scoring collection of features.
6. The RFECV visualizer plots the number of features in the model along with their cross-validated test score and variability and visualizes the selected number of features quite properly.
7. This figure shows an ideal RFECV curve, the curve jumps to an excellent accuracy when the six informative features are captured, then gradually decreases in accuracy as the non informative features are added into the model.
8. The shaded area represents the variability of cross-validation, one standard deviation above and below the mean accuracy score drawn by the curve.
9. After selecting the optimum features the accuracy of the model increased by 2% which is very good.

Implementing TF-IDF Weighted Word to vectorization technique

In [52]:
```
start = datetime.now()

Tfidf_vector=TfidfVectorizer()
Tf_model=Tfidf_vector.fit_transform(Sample_sort["CleanedText"].values)

Dimension=Tfidf_vector.get_feature_names()

LIST_VECTOR=[]
row=0
for sentence in list_of_sentence_vec:
    word_2_vec=np.zeros(50)
    weight_tf_sum=0
    for word in sentence:
        try:
            vec=w2v_Model.wv[word]
            tfidf_value=Tf_model[row,Dimension.index(word)]
            word_2_vec += (vec* tfidf_value)
            weight_tf_sum += tfidf_value
        except:
            pass
    if weight_tf_sum !=0:
        word_2_vec /=weight_tf_sum
    LIST_VECTOR.append(word_2_vec)
    row += 1

print('Time taken :', datetime.now() - start)
```

```
Time taken : 0:07:25.215544
```

Preparing the data into train and test sets

In [53]:
```
X_tfw=LIST_VECTOR
y_tfw=label

TrainX_tfw,Trainy_tfw,TrainX_tfwCV,Testy_tfwCV,TestX_tfw,Testy_tfw=data_split(X_tfw,y_tfw)
```

Training the logistic regression model over the Cross-validation set.

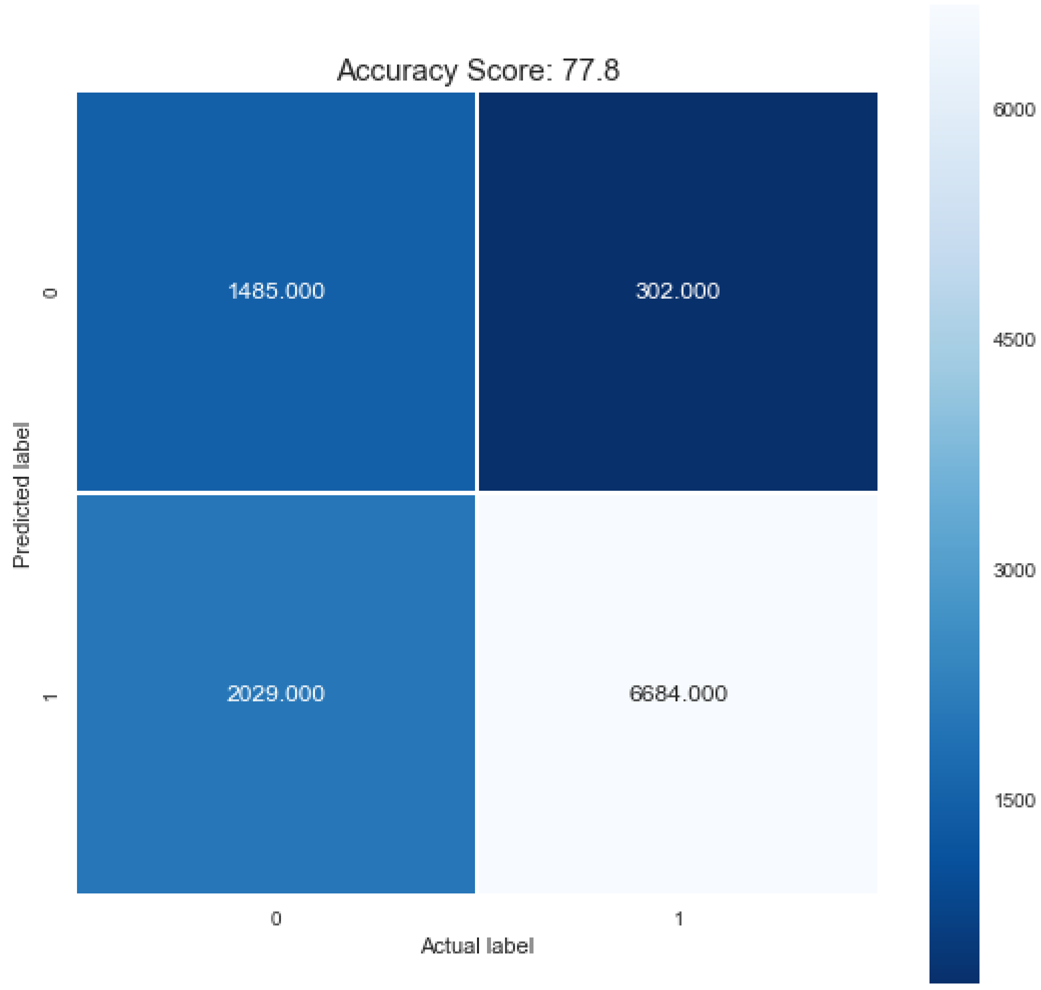
In [54]:
```
#Calling the train function and storing the prediction value and accuracy

TFW_pred,TFW_acc=train(TrainX_tfw,Trainy_tfw,TrainX_tfwCV,Testy_tfwCV)
```

```
The model score on train set is=  0.7897142857142857

The accuracy of Logistic Regression over cross-validation set is =  77%
The total number of non zero weights =  50
```

Plotting the confusion matrix of the above table

In [55]:
```
Confusion_metric(Testy_tfwCV,TFW_pred,TFW_acc)
```

```
[[1485  302]
 [2029 6684]]
```




```
+-----------------------------------------------------------+
| The performance metrics of the above model are as follows: |
+---------------------------------+-------------------------+
|             Metrics             |          Scores         |
+---------------------------------+-------------------------+
|     Classification_accuracy     |           77.8          |
|       Classification_error      |           22.2          |
|          True positive          |           6684          |
|          False positive         |           302           |
|          True negative          |           1485          |
|          False negative         |           2029          |
|        True positive rate       |    76.71295764948927    |
|       False negative rate       |    23.28704235051073    |
|        True negative rate       |    83.10016787912703    |
|       False positive rate       |    16.899832120872972   |
|         Precision value         |    95.67706842255942    |
|           Recall value          |    76.71295764948927    |
|          f1_score value         |    85.15192050449073    |
+---------------------------------+-------------------------+
```

Observations

- The train accuracy of the model is 77.8% which is quite low for a classification model.
- The true positive and true negative rates are good as compared to the other parameters of the model.
- Let's Hyperparameter tune the above model to find the optimum lamda and improve the model's performance further.

Hyperparameter tuning the lambda for optimal performance of the model

In [56]:
```
#Gridsearch implementation
best_TFWparam=gridsearch(TrainX_tfw,Trainy_tfw,TrainX_tfwCV,Testy_tfwCV)
```

```
LogisticRegression(C=10, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=-1, penalty='l2', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
0.7782857142857142
```

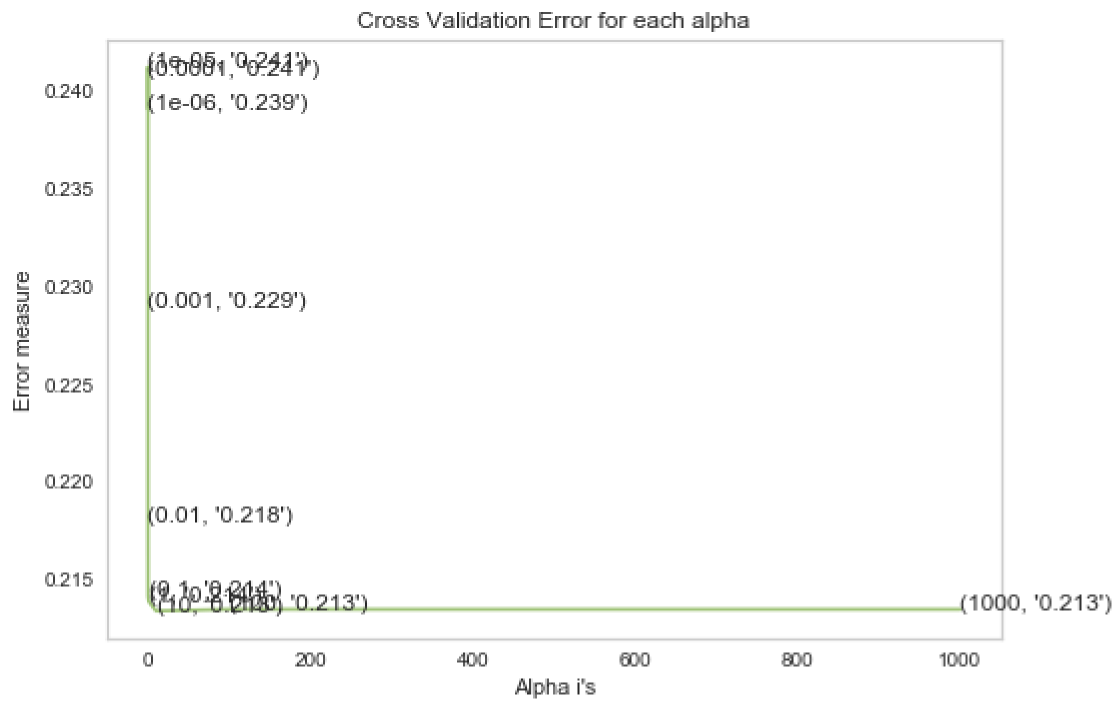
In [57]:
```
#Random-search Implementation
Best_TFWpar=randomsearch(TrainX_tfw,Trainy_tfw,TrainX_tfwCV,Testy_tfwCV)
```

```
LogisticRegression(C=0.17871030173670766, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=-1, penalty='l2', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
0.7780952380952381
```

Plotting the cross-validation error plots by using the 10k-fold Cross validation technique

In [58]:
```
cv_results(TrainX_tfw,Trainy_tfw)
```

```
----------------------------------------------------------------------------------------------------
--
for alpha = 1e-06

the misclassification error for each alpha value is :  [0.239]
----------------------------------------------------------------------------------------------------
--
for alpha = 1e-05

the misclassification error for each alpha value is :  [0.239 0.241]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.0001

the misclassification error for each alpha value is :  [0.239 0.241 0.241]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.001

the misclassification error for each alpha value is :  [0.239 0.241 0.241 0.229]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.01

the misclassification error for each alpha value is :  [0.239 0.241 0.241 0.229 0.218]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.1

the misclassification error for each alpha value is :  [0.239 0.241 0.241 0.229 0.218 0.214]
----------------------------------------------------------------------------------------------------
--
for alpha = 1

the misclassification error for each alpha value is :  [0.239 0.241 0.241 0.229 0.218 0.214 0.214]
----------------------------------------------------------------------------------------------------
--
for alpha = 10

the misclassification error for each alpha value is :  [0.239 0.241 0.241 0.229 0.218 0.214 0.214 0.21
3]
----------------------------------------------------------------------------------------------------
--
for alpha = 100

the misclassification error for each alpha value is :  [0.239 0.241 0.241 0.229 0.218 0.214 0.214 0.21
3 0.213]
----------------------------------------------------------------------------------------------------
--
for alpha = 1000

the misclassification error for each alpha value is :  [0.239 0.241 0.241 0.229 0.218 0.214 0.214 0.21
3 0.213 0.213]
```




```
The optimal number of alpha value is 10.000000%.
```

Testing the model over the test set

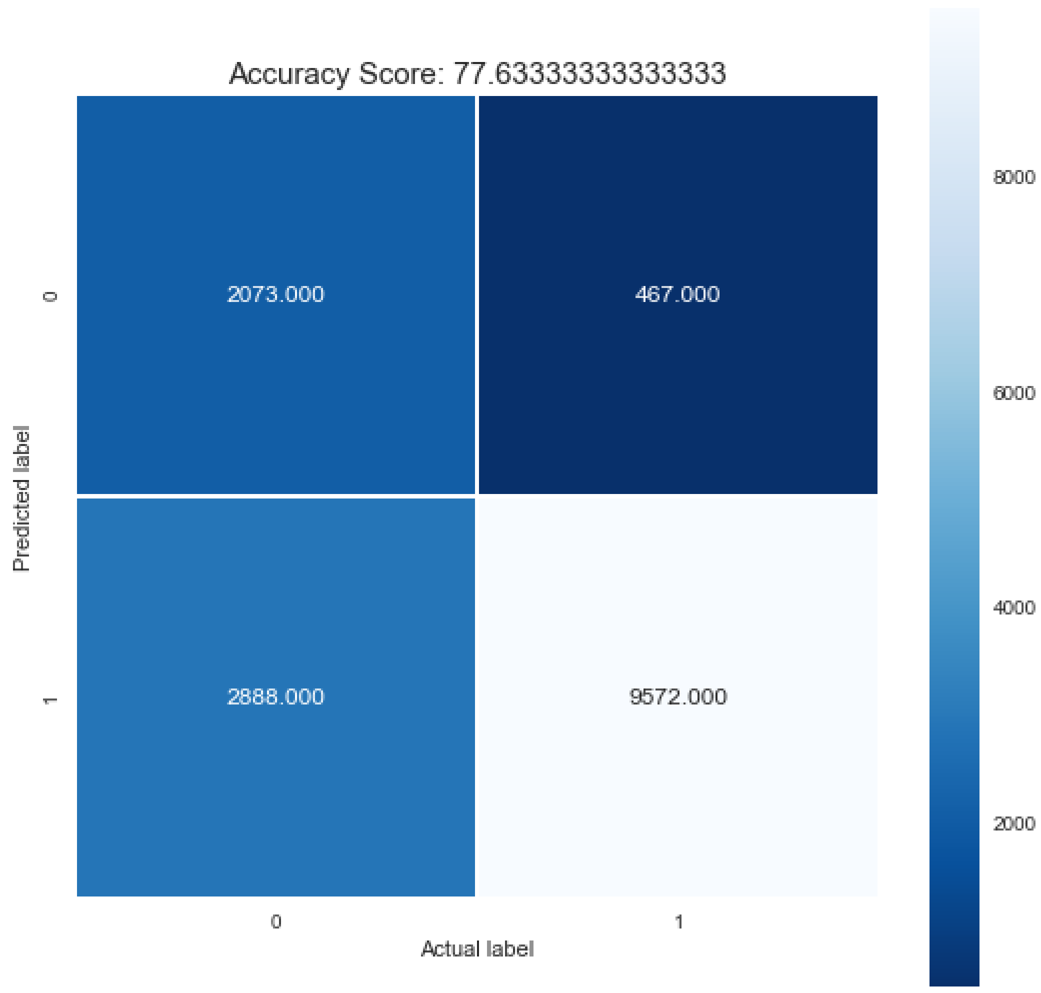
In [59]:
```
Tfw_clf=best_TFWparam


TFWordy_pre,TFWord_acc=tuned_test(Tfw_clf,TrainX_tfw,Trainy_tfw,TestX_tfw,Testy_tfw)
```

```
The model score on train set is=  0.7892653061224489

The accuracy of Logistic Regression over Test set is =  77%
The total number of non zero weights =  50
```

Confusion matrix of the above model

In [60]:
```
Confusion_metric(Testy_tfw,TFWordy_pre,TFWord_acc)
```

```
[[2073  467]
 [2888 9572]]
```



```
+-----------------------------------------------------------+
| The performance metrics of the above model are as follows: |
+-------------------------------+---------------------------+
|            Metrics            |           Scores          |
+-------------------------------+---------------------------+
|     Classification_accuracy   |     77.63333333333333     |
|      Classification_error     |     22.366666666666667    |
|         True positive         |            9572           |
|         False positive        |            467            |
|         True negative         |            2073           |
|         False negative        |            2888           |
|       True positive rate      |     76.82182985553771     |
|      False negative rate      |     23.17817014446228     |
|       True negative rate      |     81.61417322834646     |
|      False positive rate      |     18.385826771653544    |
|        Precision value        |     95.34814224524355     |
|          Recall value         |     76.82182985553771     |
|         f1_score value        |     85.08822614338416     |
+-------------------------------+---------------------------+
```

Observations

- The test accuracy of the model after using the optimal lamda value is around 77.63% which is somewhat not good for a model.
- Here the False negative value is high which is indeed decreasing the accuracy and alarming for a model but still it is manageable.
- The precision and the f1_score of the model is good but the recall score is low as compared to them.
- Let's check the multicollinearity of features by using the pertubation test.

Implementing the pertubation test for checking the multicollinearity of the features

In [61]:
```
Train_Df=pd.DataFrame(TrainX_tfw)
print(Train_Df.shape)

Test_Df=pd.DataFrame(TestX_tfw)
print(Test_Df.shape)
```

```
(24500, 50)
(15000, 50)
```

In [62]:
```
TF_tr_Noise,TF_test_Noise=Noise(Train_Df,Test_Df)
```

```
[[-0.0110854   0.01238318 -0.00895173 ... -0.00316227 -0.00861479
   0.0139621 ]
 [-0.00566234 -0.00611305 -0.0085816  ... -0.00280026  0.00415353
  -0.00246439]
 [-0.01033268  0.00701506 -0.00575518 ... -0.01006112 -0.00094393
  -0.0074085 ]
 ...
 [-0.00866337  0.0021541  -0.00639876 ... -0.00468766 -0.00124288
   0.00459445]
 [ 0.01035186  0.005232    0.00468396 ...  0.02468319 -0.00724922
   0.0073261 ]
 [-0.01189647  0.0116616  -0.00373697 ... -0.0099061   0.00913371
  -0.00532188]]

The shape of the train data after adding noise is : (24500, 50)
****************************************************************************************************
[[-0.00144414  0.01157601 -0.02103094 ... -0.00353485  0.014855
   0.00313991]
 [-0.0073264  -0.0089024  -0.00346809 ...  0.00692251  0.00852939
   0.01221543]
 [ 0.00329418 -0.0130511   0.0090682  ... -0.01372008  0.01148326
  -0.00046779]
 ...
 [-0.01784543 -0.01125     0.00703236 ...  0.00192382 -0.02163345
  -0.00499943]
 [ 0.01505103 -0.00621715  0.00963229 ...  0.02590472 -0.00056943
   0.01410102]
 [-0.01132558  0.00266143  0.01533239 ...  0.00679121  0.00795586
  -0.00483098]]

The shape of the test data after adding noise is : (15000, 50)
```

Testing the model over the noise added dataset

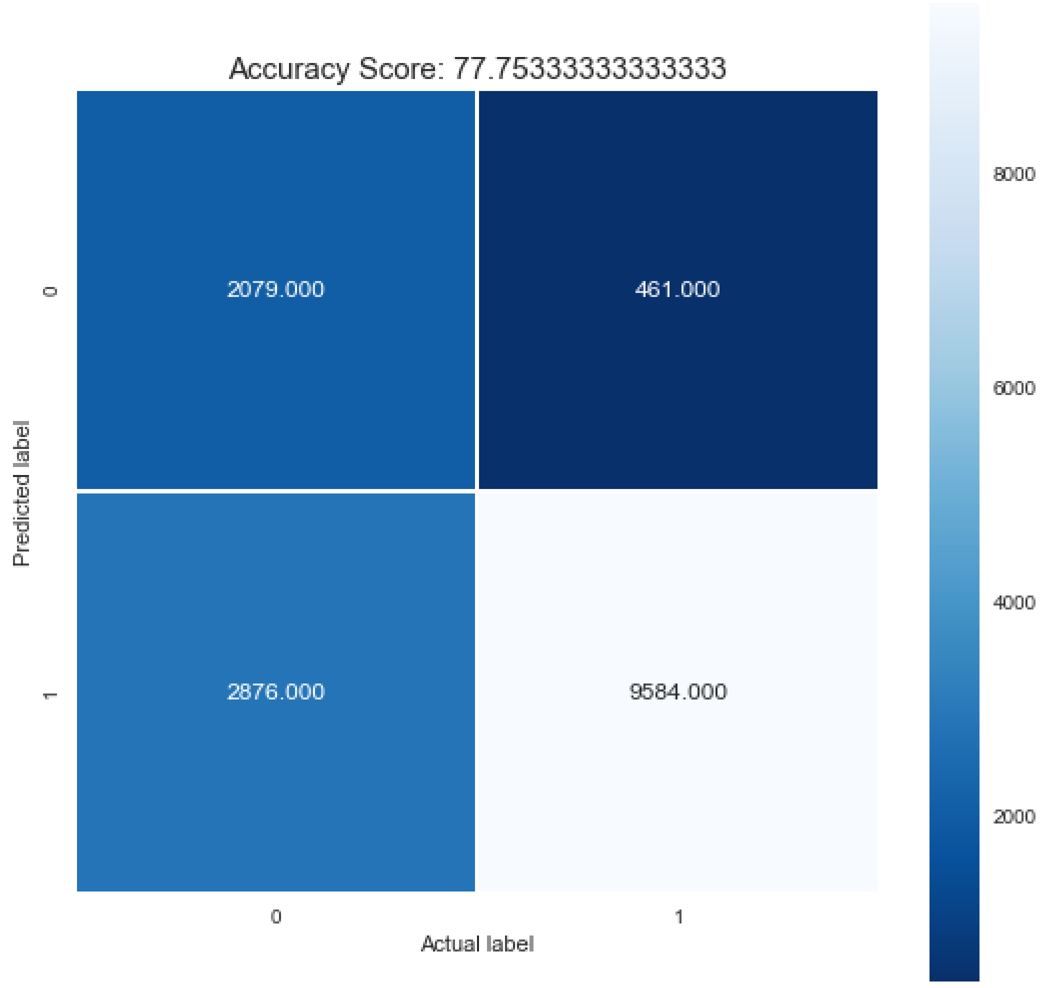
In [63]:
```
TFW2V_clf=best_TFWparam

TFw2v_Noise_pre,TFw2v_noise_acc=tuned_test(TFW2V_clf,TF_tr_Noise,Trainy_tfw,TF_test_Noise,Testy_tfw)
```

```
The model score on train set is=  0.7884081632653062

The accuracy of Logistic Regression over Test set is =  77%
The total number of non zero weights =  50
```

Confusion matrix of the above model.

In [64]:
```
Confusion_metric(Testy_tfw,TFw2v_Noise_pre,TFw2v_noise_acc)
```

```
[[2079  461]
 [2876 9584]]
```




```
+-----------------------------------------------------------+
| The performance metrics of the above model are as follows: |
+-------------------------------+---------------------------+
|            Metrics            |           Scores          |
+-------------------------------+---------------------------+
|    Classification_accuracy    |     77.75333333333333     |
|      Classification_error     |     22.246666666666666    |
|         True positive         |            9584           |
|         False positive        |            461            |
|         True negative         |            2079           |
|         False negative        |            2876           |
|       True positive rate      |     76.91813804173356     |
|      False negative rate      |     23.081861958266455    |
|       True negative rate      |     81.85039370078741     |
|      False positive rate      |     18.149606299212596    |
|        Precision value        |     95.41065206570433     |
|          Recall value         |     76.91813804173356     |
|         f1_score value        |     85.17218395912019     |
+-------------------------------+---------------------------+
```

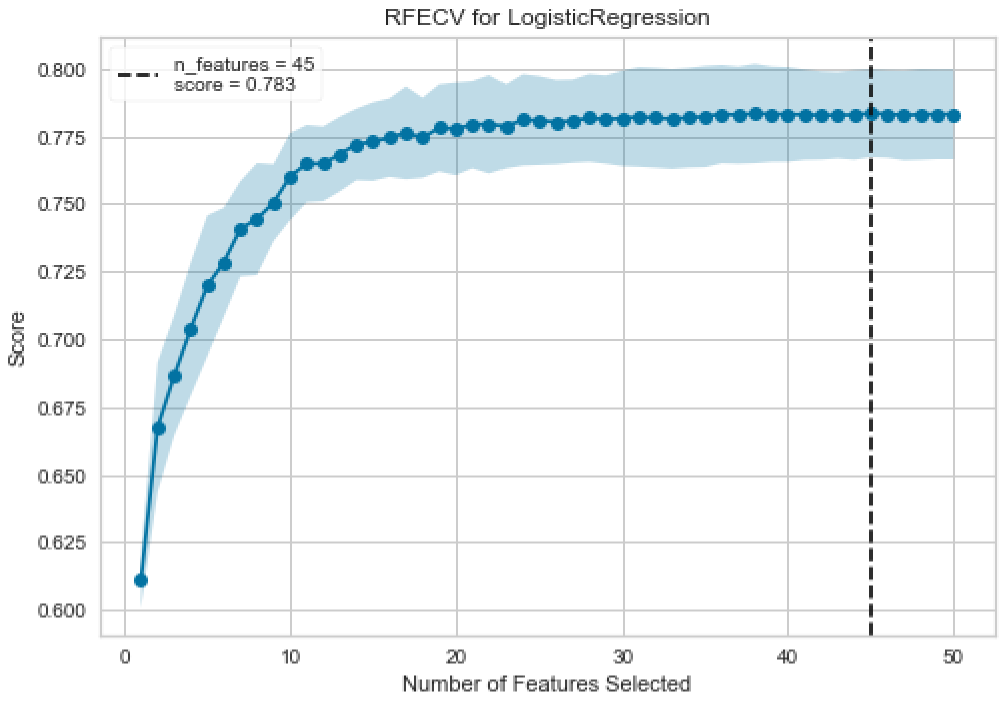
Observations

- There is a slight decrease in the accuracy in the model which is ithink due to the small random noise in the dataset
- All the performance metrics are same as compared to the previous model and the best part is that there is no change in the total number of the non negative weights presents in the model.
- So I can conclude that the features are not collinear and let's do some feature importance.

Finding & Ranking the total number of optimal features present in the model by using the RFECV technique.

In [70]:
```
start = datetime.now()
Best=best_TFWparam
Feature_imp(Best,TF_tr_Noise,Trainy_tfw)

print('Time taken :', datetime.now() - start)
```

```
Optimal number of features: 45
Selected features: [1, 2, 3, 5, 6, 7, 9, 10, 11, 12, 13, 14, 15, 17, 18, 19, 20, 21, 22, 23, 24, 25, 2
6, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 47, 48, 49]
Features sorted by their rank:
[(1, 1), (1, 2), (1, 3), (1, 5), (1, 6), (1, 7), (1, 9), (1, 10), (1, 11), (1, 12), (1, 13), (1, 14),
(1, 15), (1, 17), (1, 18), (1, 19), (1, 20), (1, 21), (1, 22), (1, 23), (1, 24), (1, 25), (1, 26), (1,
27), (1, 28), (1, 29), (1, 30), (1, 31), (1, 32), (1, 33), (1, 34), (1, 35), (1, 36), (1, 37), (1, 3
8), (1, 39), (1, 40), (1, 41), (1, 42), (1, 43), (1, 44), (1, 45), (1, 47), (1, 48), (1, 49), (2, 4),
(3, 0), (4, 46), (5, 16), (6, 8)]
```




```
Time taken : 0:13:12.753616
```

Observations

- After performing the RFECV technique the total number of the optimal features are 45 with an increase of 2.08% in the accuracy.
- The above RFECV plot shows that there is a spike in the accuracy the most important 3 features and the variance of the feature is increasing and maximum after the inclusion of the 45th feature in the list.
- So the above plot gives a very intutive and nice understanding of the nature of the features present in the model.

Conclusion

1. The Bag-of-words vectorizer technique yielded the best accuracy which is 88% after tuning the hyperaparameter as compared to the other vectorizers.
2. By changing the regularizers and lambda values from L2 to L1 severe effect of sparsity in the total number of non zero weights are seen and the accuracy of the model also dropped very sharply.
3. After performing the pertubation tests in all the vectorized models there is no sign of multicollinearity seen in the model as the total number of nonzero weights did not changed that much which is a good sign.
4. I have shown the feature importance in the Average and Tf-idf weighted word to vectorized models and not shown in the BOW and TF-IDF Vectorized models because the Recursive Feature elimination (RFE) takes a lot of time for the high dimensional data because it has very high time complexity and I was unable to do it because of compute and Time constraints.
5. So according to my observations and analysis I can conclude that the Logistic Regression model is very stable and good model as compared with the KNN algorithm.
6. Logistic regression model works fairly good with the text data and in this particular scenario it is doing a good job in classiffying the Positive and Negative reviews properly.

In [ ]:

In [ ]: