Implementing SVM on Amazon fine food reviews dataset.

In [11]:
```
#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.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
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
import warnings
warnings.filterwarnings(action='ignore')
from sklearn.model_selection import train_test_split
from sklearn.grid_search import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.svm import SVC
from prettytable import PrettyTable
from sklearn.model_selection import TimeSeriesSplit
import datetime as dt
```

Connecting to the preprocessed SQLITE database table

In [5]:
```
#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

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

Processing the data for further use

In [12]:
```
#SETTING THE TIME COLUMN TO STANDARD DATE-TIME

Data['Time'] = Data[['Time']].applymap(lambda x: dt.datetime.fromtimestamp(x))

Data.head(5)
```

Out[12]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Su
0	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0	positive	1999-10-08 05:30:00	edu
1	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1	1	positive	2007-11-11 05:30:00	l bo
2	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1	1	positive	2007-10-04 05:30:00	s
3	150508	0006641040	AZGXZ2UUK6X	Catherine Hallberg " (Kate)"	1	1	positive	2004-02-06 05:30:00	rh
4	150509	0006641040	A3CMRKGE0P909G	Teresa	3	4	positive	2002-04-10 05:30:00	I

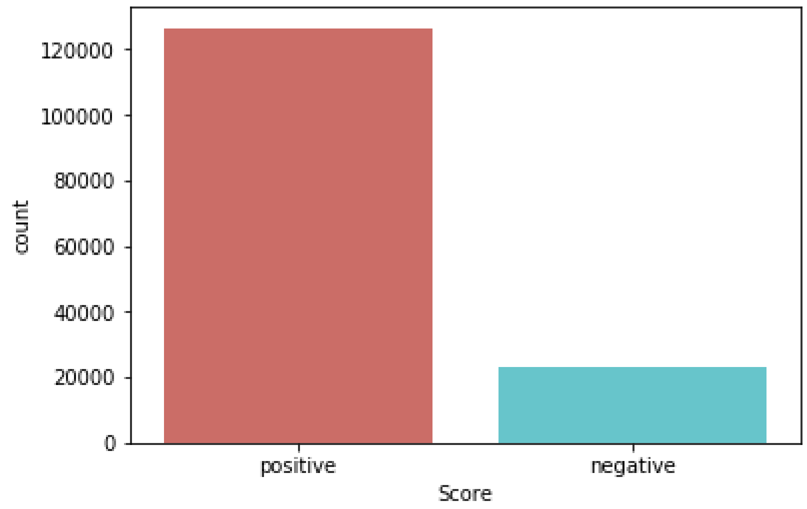
In [13]:
```
#Setting Time column as index of the dataframe
Data.set_index("Time",inplace=True)

#Sampling the above data

Sampled_data=Data.sample(n=30000,replace='False')
Sorted=Sampled_data.sort_index()
```

In [14]:
```
Sorted.head()
```

Out[14]:

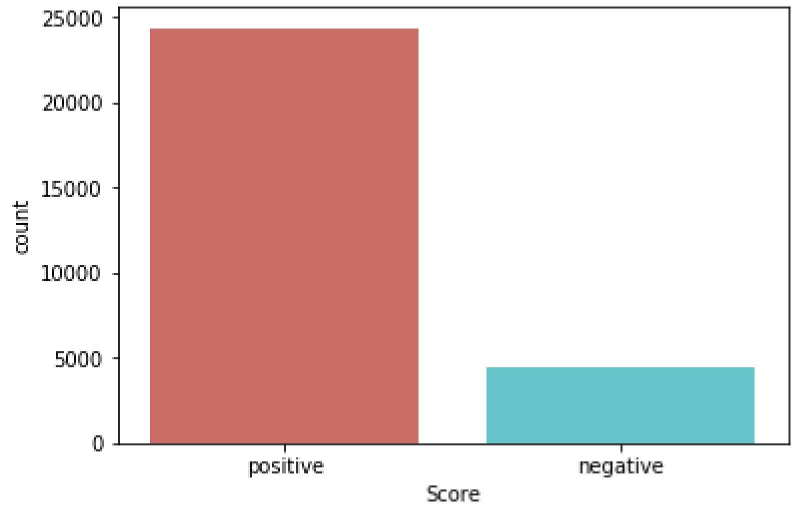
	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Sum
Time								
2000-06-03 05:30:00	374400	B00004CI84	A2DEE7F9XKP3ZR	jerome	0	3	positive	Resea Beatl v F ve
2000-12-19 05:30:00	374383	B00004CI84	A34NBH479RB0E	"dmab6395"	0	1	positive	FL
2001-06-11 05:30:00	451923	B00004CXX9	ANIMV3SPDD8SH	Guy De Federicis	1	12	negative	CAS IS GH WITH N
2002-01-06 05:30:00	361317	B00005IX96	A3ODTU118FKC5J	Rosemarie E Smith	5	7	positive	A pie he
2002-02-11 05:30:00	374420	B00004CI84	A1ZH086GZYL5MZ	Doug DeBolt	2	2	positive	A gross

```
In [15]: Sorted=Sorted.drop_duplicates(subset={"UserId","ProfileName","Summary","Text"}, keep='first', inplace=
False)

Full_data=Data.sample(n=150000,replace='False')
new_sample=Full_data.sort_index()

new_sample["Score"].value_counts()
#LABELS.value_counts()
LABELS=new_sample["Score"]
sns.countplot(x="Score",data=new_sample,palette="hls")
plt.show()
plt.savefig("count_plot")
```




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

```
In [16]: polarity=Sorted["Score"]
sns.countplot(x="Score",data=Sorted,palette="hls")
plt.show()
plt.savefig("count_plot")
```




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

Splitting the data into 70:30 partitions sets

```
In [17]: 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 the data for further use

```
In [18]: #PARTITIONING THE DATA FOR KERNEL SVMC
X=Sorted
Y=polarity

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_cval is:",X_cv.shape)
print("The shape of y_cval 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: (14110, 10)
the shape of y_train is: (14110,)
The shape of x_cval is: (6048, 10)
The shape of y_cval is: (6048,)
the shape of x_test is: (8640, 10)
the shape of y_test is: (8640,)
```

Partioining the data for the implementation of the Linear SVM

In [19]:

```
Linear_X=new_sample
Linear_Y=LABELS

li_xtr,li_ytr,li_xcv,li_ycv,li_xtest,li_ytest=data_split(Linear_X,Linear_Y)

print("The shape of x_train is:",li_xtr.shape)
print("the shape of y_train is:",li_ytr.shape)
print("The shape of x_cval is:",li_xcv.shape)
print("The shape of y_cval is:",li_ycv.shape)
print("the shape of x_test is:",li_xtest.shape)
print("the shape of y_test is:",li_ytest.shape)
```

```
The shape of x_train is: (73500, 10)
the shape of y_train is: (73500,)
The shape of x_cval is: (31500, 10)
The shape of y_cval is: (31500,)
the shape of x_test is: (45000, 10)
the shape of y_test is: (45000,)
```

Utility functions for training the models

In [20]:
```python
#Function for training the data
def train(X_tr, y_tr,X_cv,y_cv):
#Splitting the data into train and test set

    Model = SVC(class_weight="balanced") #Performing weight balancing technique due to class imbalance
    model = Model.fit(X_tr, y_tr)

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

    y_pred=model.predict(X_cv)

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

    print('\nThe accuracy of SVM over cross_val set is =  %d%% ' % ( acc))

    return y_pred,acc


#Hyper-parameter tuning of SVM using Gridsearch technique

def Grid_s(X_train, y_train,X_cv,y_cv):

    Cs = [ 10 ** x for x in range(-5, 3)]
    gammas = [10 ** x for x in range(-5, 3)]

    #cv = TimeSeriesSplit(max_train_size=None, n_splits=3)

    param_grid = {'C': Cs, 'gamma' : gammas}
    grid_search = GridSearchCV(SVC(class_weight= "balanced"), param_grid,scoring = 'accuracy', cv=3,n_
jobs=-1)
    grid_search.fit(X_train, y_train)

    print("The best model parameters for Gridsearch technique is ",grid_search.best_params_)
    print("The model score over the cv set is ",grid_search.score(X_cv,y_cv))
    return grid_search.best_params_

#Function for doing random search
def Random_s(X_train, y_train,X_cv,y_cv):

    from scipy.stats import uniform
    from sklearn.model_selection import RandomizedSearchCV
    cv = TimeSeriesSplit(max_train_size=None, n_splits=3)

    C = uniform(loc=0, scale=2)
    gammas=uniform(loc=0,scale=2)

    param_grid={"C":C,"gamma":gammas}

    model1 =  RandomizedSearchCV(SVC(class_weight="balanced"), param_grid,scoring = 'accuracy',n_jobs=
-1, cv=cv)
    model1.fit(X_train, y_train)

    print("The best model parameters for Randomsearch technique is ",model1.best_params_)
    print("The model score over the cv set is ",model1.score(X_cv, y_cv))
    return model1.best_params_


#Function for finding the test accuracy by using the default alpha
def tuned_test(X_tr,y_tr,X_test,y_test,c,gam):

    New_clf= SVC(C=c,gamma=gam,class_weight="balanced")

    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 svm over Test set is =  %d%% ' % ( new_acc))



    return Y_pred,new_acc
```

Common Utility functions for plotting the results

In [21]:
```
from sklearn.model_selection import learning_curve
def plot_learning_curve(estimator, title, X, y, ylim=None, cv=None,
                        n_jobs=None, train_sizes=np.linspace(.1, 1.0, 5)):
    """
    Generate a simple plot of the cv and training learning curve.

       """
    plt.figure()
    plt.title(title)
    if ylim is not None:
        plt.ylim(*ylim)
    plt.xlabel("Training examples")
    plt.ylabel("Score")
    train_sizes, train_scores, test_scores = learning_curve(
        estimator, X, y, cv=cv, n_jobs=n_jobs, train_sizes=train_sizes)
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    plt.grid()

    plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                     train_scores_mean + train_scores_std, alpha=0.1,
                     color="r")
    plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                     test_scores_mean + test_scores_std, alpha=0.1, color="g")
    plt.plot(train_sizes, train_scores_mean, 'o-', color="r",
             label="Training score")
    plt.plot(train_sizes, test_scores_mean, 'o-', color="g",
             label="Cross-validation score")

    plt.legend(loc="best")
    return plt
```

Utility functions for plotting the confusion matrix

```
In [22]: 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)
```

```
In [65]: def conclusion_table():
    print()
    ptable=PrettyTable()
    ptable.title="The comparisons of all the vectorizers are as follows: "
    ptable.field_names=["Vectorizer","Algorithm","Scores","Status"]
    ptable.add_row(["Bag-Of-Words","Kernel-SVM","86.6% ","Stable"])
    ptable.add_row(["Bag-Of-Words","Linear-SVM","92.87%" ,"Stable"])
    ptable.add_row(["Tf-IDF","Kernel-SVM","88.33%" ,"Stable"])
    ptable.add_row(["Tf-IDF","Linear-SVM","89.82%" ,"Unstable"])
    ptable.add_row(["Average-word2vec","Kernel-SVM","85.91%" ,"Unstable"])
    ptable.add_row(["Average-word2vec","Linear-SVM","88.05%" ,"Unstable"])
    ptable.add_row(["TF-IDF-Weighted-word2vec","Kernel-SVM","84.67%" ,"Unstable"])
    ptable.add_row(["TF-IDF-Weighted-word2vec","Linear-SVM", "85.94%","Unstable"])

    print(ptable)
```

Utilty functions for vectorizing the data

In [24]:
```
#Function for vectorizing the train data
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler(with_mean=False)


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()
```

Implementing the Bag of words vectorization technique

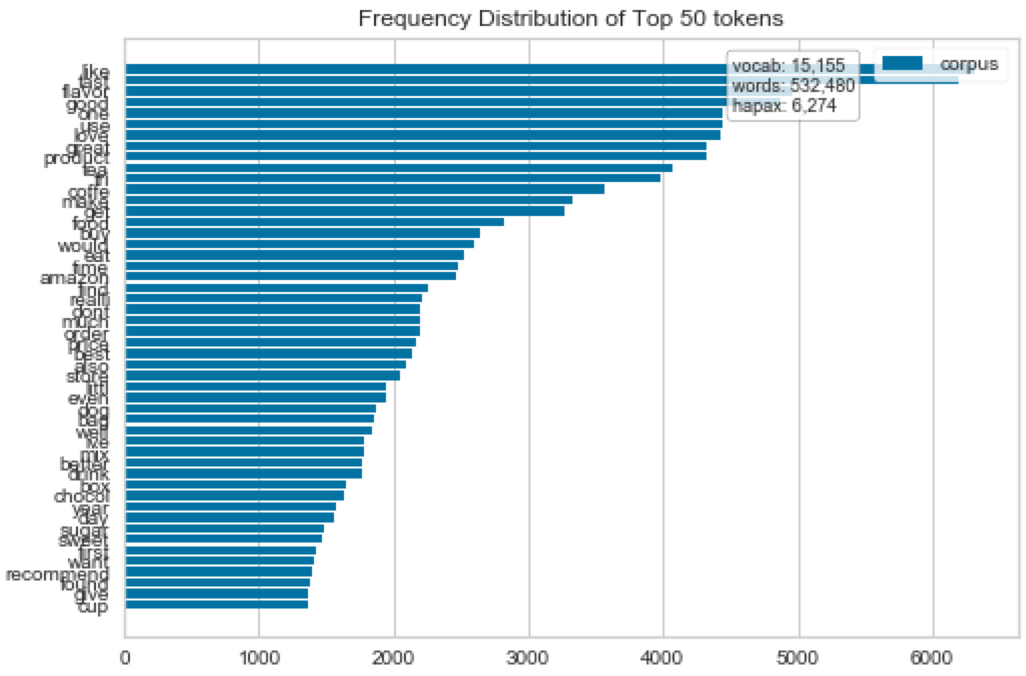
In [25]:
```python
#Initializing the count vectorizer
Count_vect=CountVectorizer()

#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:  (14110, 15155)
The shape of the X_cv is:  (6048, 15155)
The shape of the X_test is:  (8640, 15155)

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

Out[25]:

	feature	bow
0	geeki	118.789730
1	scenc	118.789730
2	priceless	68.588144
3	alec	53.131915
4	baldwin	48.504300
5	keaton	42.003722
6	michael	30.686605
7	beetlejuic	19.800394
8	funni	15.363626
9	play	11.058850
10	movi	8.427630
11	husband	5.510466
12	thought	4.598835
13	kid	4.230899
14	right	3.909289
15	enjoy	3.015589
16	realli	2.248107
17	love	1.652964
18	one	1.447356
19	folger	0.000000
20	fong	0.000000
21	fonder	0.000000
22	flipin	0.000000
23	fondant	0.000000
24	fond	0.000000

In [26]:
```python
display_token(Count_vect,X_tr["CleanedText"])
```



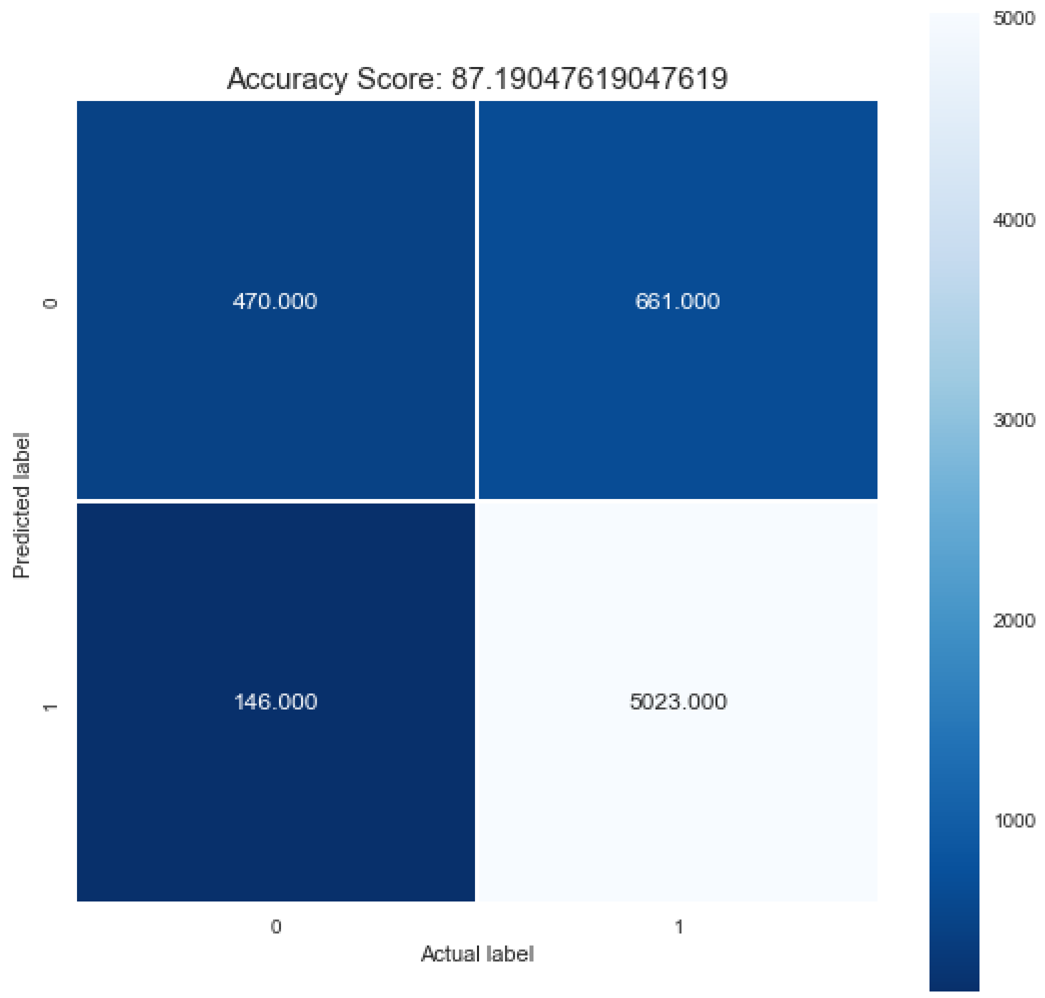
Training the model over the BOW vectorized data

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

```
The model score on train set is=  0.9806802721088436

The accuracy of SVM over cross_val set is =  87%
Wall time: 3min 21s
```

In [20]:
```
Confusion_metric(y_cv,pred,acc)
```

```
[[ 470  661]
 [ 146 5023]]
```



```
+----------------------------------------------------------+
| The performance metrics of the above model are as follows: |
+--------------------------------+-------------------------+
|            Metrics             |          Scores         |
+--------------------------------+-------------------------+
|    Classification_accuracy     |    87.19047619047619    |
|      Classification_error      |    12.80952380952381    |
|         True positive          |           5023          |
|         False positive         |           661           |
|         True negative          |           470           |
|         False negative         |           146           |
|       True positive rate       |     97.1754691429677    |
|      False negative rate       |    2.824530857032308    |
|       True negative rate       |    41.55614500442087    |
|      False positive rate       |    58.44385499557914    |
|        Precision value         |    88.37086558761436    |
|          Recall value          |     97.1754691429677    |
|         f1_score value         |     92.5642679443472    |
+--------------------------------+-------------------------+
```

Observation

- The train accuracy of the model over Bag-of-words vectorized data is 87.19% by using the default parameters.
- The performance metrics of the above model is not good as the True-positives rate are very high as compared to all other metrics so the model is not stable.
- The False positive rate is around 58.44% which is very high as compared to the False negative rate which is not good for a model.
- So the model has a bias problem which is affecting the model a lot and can be solved by tuning the hyperparameter.

Tuning the hyperparameters by performing the Gridsearch and Randomsearch technique.

In [21]:
```
%%time

#CODE FOR FINDING THE BEST HYPERPARAMETERS THROUGH GRIDSEARCH

Best_param=Grid_s(x_tr,y_tr,x_cv,y_cv)
```

```
The best model parameters for Gridsearch technique is  {'C': 10, 'gamma': 1e-05}
The model score over the cv set is  0.8846031746031746
Wall time: 41min 4s
```

Implementing the Randomsearch technique

In [22]:
```
%%time
#CODE FOR FINDING THE BEST HYPERPARAMETERS USING RANDOMSEARCH
Random_param=Random_s(x_tr,y_tr,x_cv,y_cv)
```

```
The best model parameters for Randomsearch technique is  {'C': 0.6591632021221285, 'gamma': 1.77122750
27341886}
The model score over the cv set is  0.8204761904761905
Wall time: 14min 24s
```

Testing the model over the test set using the optimal hyperparameters

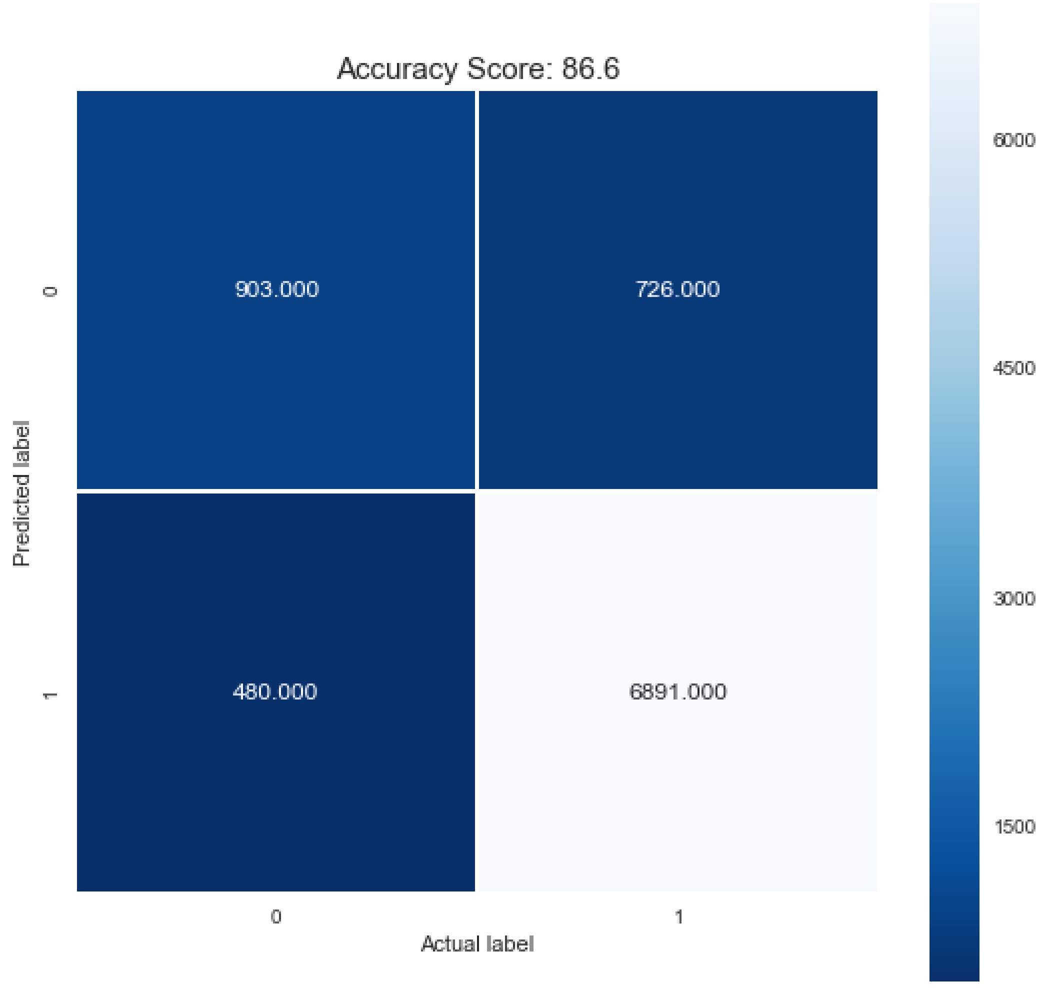
In [23]:
```
Y_pred,new_acc=tuned_test(x_tr,y_tr,x_test,y_test,c=10,gam=1e-05)
```

```
The model score on train set is=  0.9821768707482993

The accuracy of svm over Test set is =  86%
```

Confusion matrix of the above model

In [24]:
```
Confusion_metric(y_test,Y_pred,new_acc)
```

```
[[ 903  726]
 [ 480 6891]]
```




```
+-----------------------------------------------------------+
| The performance metrics of the above model are as follows: |
+--------------------------------+--------------------------+
|            Metrics             |          Scores          |
+--------------------------------+--------------------------+
|    Classification_accuracy     |           86.6           |
|      Classification_error      |           13.4           |
|         True positive          |           6891           |
|         False positive         |           726            |
|         True negative          |           903            |
|         False negative         |           480            |
|       True positive rate       |    93.48799348799349     |
|      False negative rate       |    6.512006512006511     |
|       True negative rate       |    55.432780847145494    |
|      False positive rate       |    44.56721915285451     |
|        Precision value         |    90.46868846002363     |
|          Recall value          |    93.48799348799349     |
|         f1_score value         |    91.95356285028022     |
+--------------------------------+--------------------------+
```

Observations

- After tuning the hyperparameters the test accuracy of the model is 86.6% which is quite good for a model.
- Here also the True positive rates are dominating and affecting the other parametrs a lot.
- The False positive rate is very high and alarming which is not good for a model.
- There is still bias problems in the model so the accuracy cannot be trusted blindly.

In [32]:
```
Count_vect=CountVectorizer()

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

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

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


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

```
The shape of the X_train is:  (73500, 29744)
The shape of the X_cv is:  (31500, 29744)
The shape of the X_test is:  (45000, 29744)
```

Implementing Linear SVM by using the SGD algorithm

In [60]:

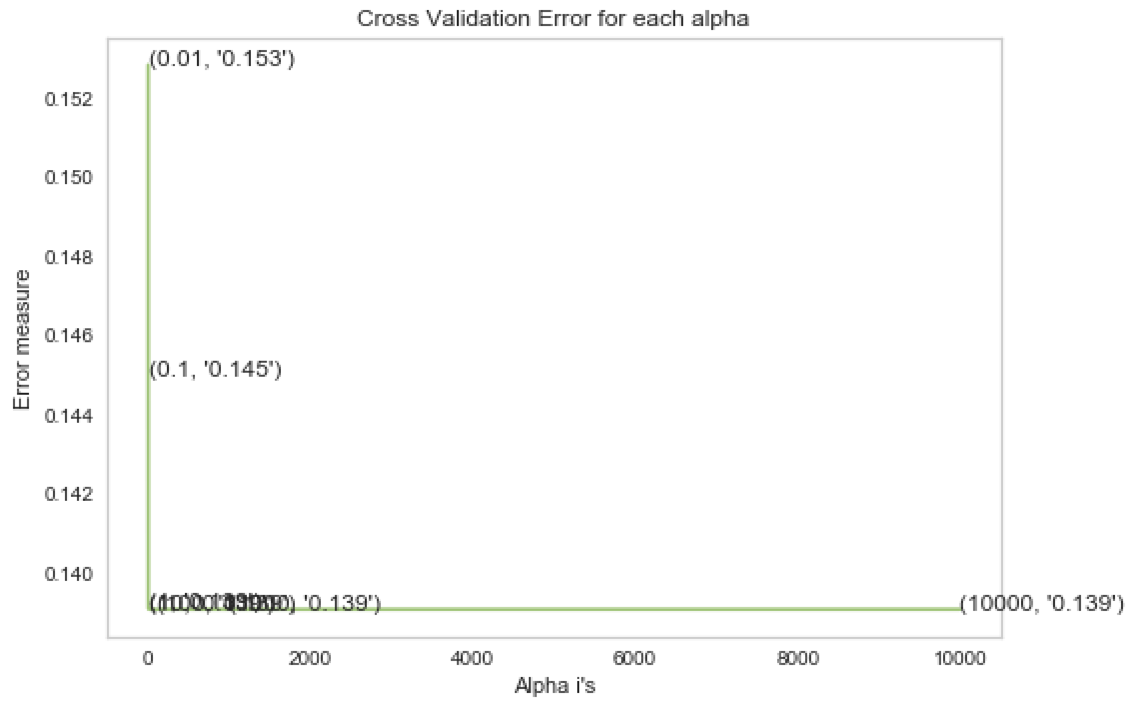
```
#FUNCTION FOR PERFORMING CROSS-VALIDATION

from sklearn import linear_model
from sklearn.linear_model import SGDClassifier
def Cv_results(X_cv, y_cv):
    cv_erro_array1 = []

    alpha = [10 ** x for x in range(-2, 5)]
    for a in alpha:
        print("------------------------------------------------------------------------------------
-----------------")
        print("for alpha =", a)
        clf = SGDClassifier(alpha=a, penalty='l1', loss='hinge', random_state=42)
        Scores = cross_val_score(clf, X_cv, y_cv, cv=10,scoring='accuracy')
        cv_erro_array1.append(Scores.mean())

        mse1=[1- x for x in cv_erro_array1]
        # determining best alpha
        #Best_alpha = alpha[mse.index(min(mse))]
        print("\nthe misclassification error for each alpha value is : ", np.round(mse1,3))
        #print("\nthe 10-fold CV_accuracy for each alpha is :",Scores)

    fig, ax = plt.subplots()
    ax.plot(alpha,mse1,c='g')
    for i, txt in enumerate(np.round(mse1,3)):
        ax.annotate((alpha[i],str(txt)), (alpha[i],mse1[i]))
    plt.grid()
    plt.title("Cross Validation Error for each alpha")
    plt.xlabel("Alpha i's")
    plt.ylabel("Error measure")
    plt.show()

    Best_alpha = np.round(alpha[mse1.index(min(mse1))])
```

Tuning the hyperaprametrs by doing the 10k-fold Crossvalidation technique

In [61]:

```
Cv_results(li_tr,li_ytr)
```

```
----------------------------------------------------------------------------------------------------
--
for alpha = 0.01

the misclassification error for each alpha value is :  [0.153]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.1

the misclassification error for each alpha value is :  [0.153 0.145]
----------------------------------------------------------------------------------------------------
--
for alpha = 1

the misclassification error for each alpha value is :  [0.153 0.145 0.139]
----------------------------------------------------------------------------------------------------
--
for alpha = 10

the misclassification error for each alpha value is :  [0.153 0.145 0.139 0.139]
----------------------------------------------------------------------------------------------------
--
for alpha = 100

the misclassification error for each alpha value is :  [0.153 0.145 0.139 0.139 0.139]
----------------------------------------------------------------------------------------------------
--
for alpha = 1000

the misclassification error for each alpha value is :  [0.153 0.145 0.139 0.139 0.139 0.139]
----------------------------------------------------------------------------------------------------
--
for alpha = 10000

the misclassification error for each alpha value is :  [0.153 0.145 0.139 0.139 0.139 0.139 0.139]
```



Utility function for training the Linear SVM

In [29]:
```
def linearsvm (x_test,y_test,a):

    clf = linear_model.SGDClassifier(loss="hinge",alpha=a,max_iter=1000)
    clf.fit(x_test,y_test)

    sgd_y=clf.predict(x_test)

    sgd_acc = accuracy_score(y_test, sgd_y, normalize=True) * float(100)

    print('\nThe accuracy of svm over Test set is =  %d%% ' % ( sgd_acc))
    return sgd_y,sgd_acc
```

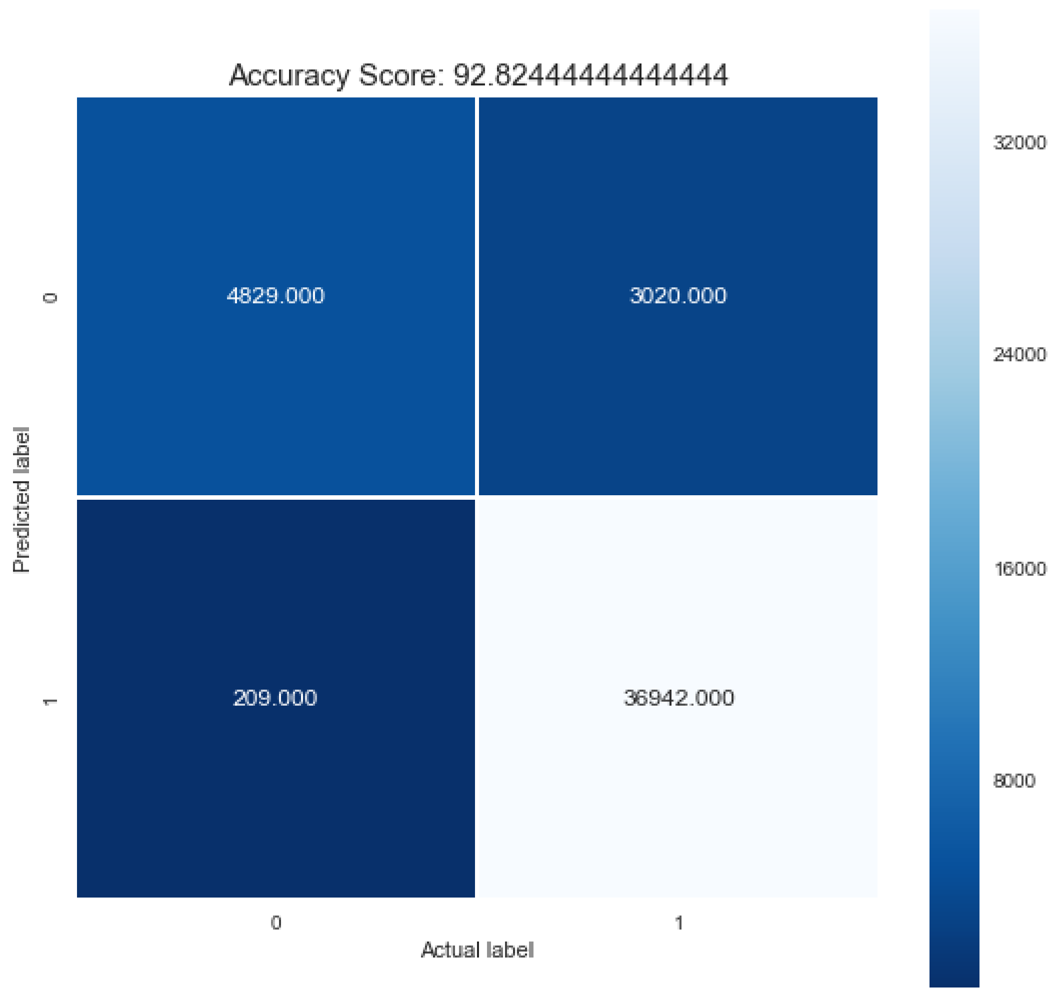
Testing the above model over the test set.

In [62]:
```
sgd_y,sgd_acc=linearsvm(li_test,li_ytest,1)
```

```
The accuracy of svm over Test set is =  92%
```

In [63]:
```
Confusion_metric(li_ytest,sgd_y,sgd_acc)
```

```
[[ 4829  3020]
 [  209 36942]]
```



```
+-----------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+--------------------------------+--------------------------+
|             Metrics            |          Scores          |
+--------------------------------+--------------------------+
|     Classification_accuracy    |     92.82444444444444    |
|       Classification_error     |     7.1755555555555555   |
|          True positive         |           36942          |
|          False positive        |           3020           |
|          True negative         |           4829           |
|          False negative        |            209           |
|        True positive rate      |      99.4374310247369    |
|        False negative rate     |     0.5625689752631154   |
|        True negative rate      |     61.52376098866098    |
|        False positive rate     |     38.476239011339025   |
|         Precision value        |     92.44282067964566    |
|           Recall value         |      99.4374310247369    |
|          f1_score value        |      95.8126385953082    |
+--------------------------------+--------------------------+
```

Observation

- The test accuracy of the linear model is 92.82% which is excellent for a classification model.
- The Diagonal elements of the confusion matrix are very high as compared to the non-diagonal ones so the model is doing a good job of classifying the positive and negative reviews.
- The False positive rate is significant around 38.47% which is quite alarming
- So linear SVM works well over the Bag-of-word vectorized text data.

Implementing the Tf-idf vectorization.

In [29]:

```
#Initializing the count vectorizer
TFIDF_vect=TfidfVectorizer(ngram_range=(1,2),min_df=5)

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

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

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

#Vectorizing the X_test set
tfx_test=vec_test(TF,X_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:  (14700, 19728)
The shape of the X_cv is:  (6300, 19728)
The shape of the X_test is:  (9000, 19728)

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

Out[29]:

	feature	TFIDF
0	know well	65.648498
1	fact like	61.357330
2	well known	59.406576
3	hey	51.134875
4	like see	46.112671
5	tri see	43.288227
6	danc	29.928701
7	film	27.479313
8	shown	23.619785
9	movi	20.884362
10	also tri	20.596561
11	funni	19.979427
12	big fan	17.236972
13	older	14.577870
14	apart	13.965427
15	known	13.251867
16	short	12.532525
17	like much	11.106913
18	see	10.286818
19	watch	8.661256
20	night	8.111786
21	wrong	7.562403
22	mayb	7.240360
23	fan	7.238508
24	decid	7.219122

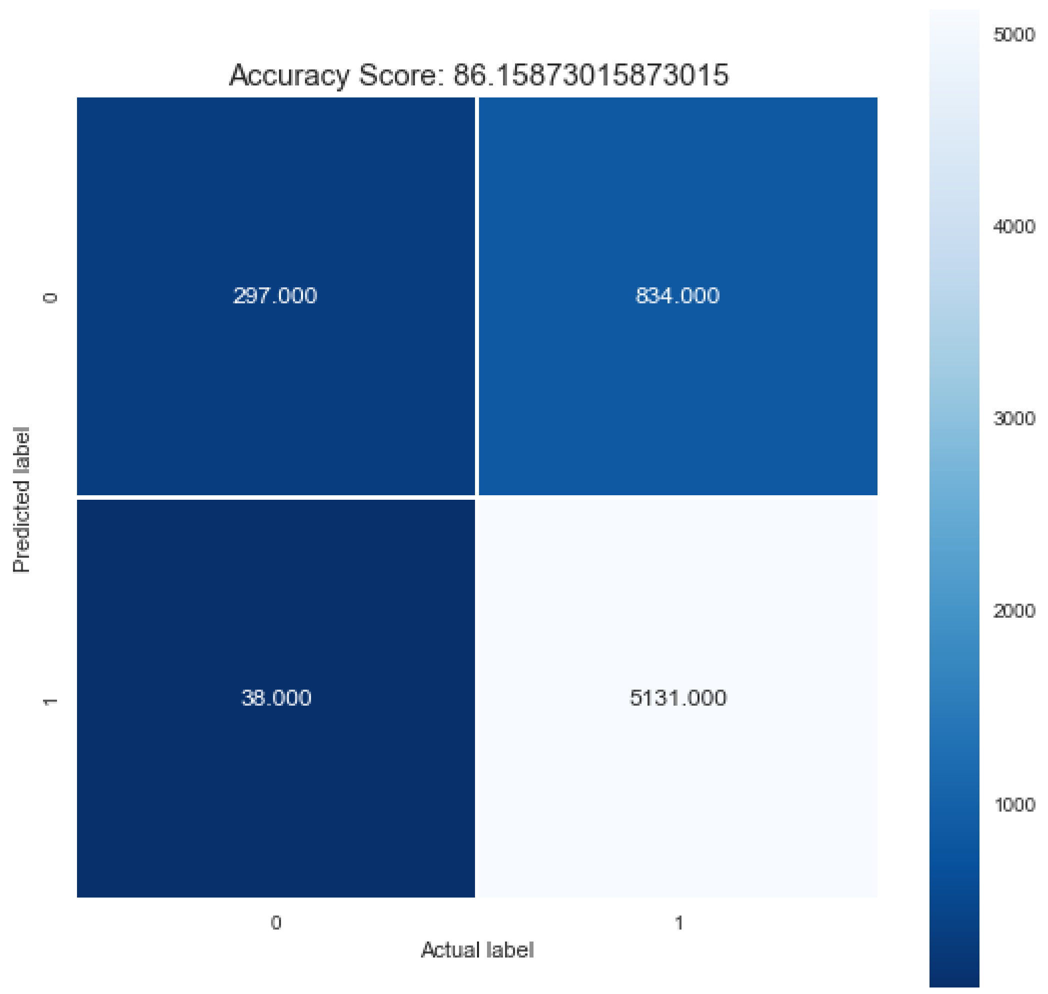
Training the model by using the default parameters.

In [30]:
```
Pred,Acc=train(tfx_tr,y_tr,tfx_cv,y_cv)
```

```
The model score on train set is=  0.9998639455782313

The accuracy of SVM over cross_val set is =  86%
```

In [31]:
```
Confusion_metric(y_cv,Pred,Acc)
```

```
[[ 297  834]
 [  38 5131]]
```



```
+-------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+--------------------------------+----------------------------+
|            Metrics             |           Scores           |
+--------------------------------+----------------------------+
|     Classification_accuracy    |      86.15873015873015     |
|      Classification_error      |      13.84126984126984     |
|         True positive          |            5131            |
|         False positive         |            834             |
|         True negative          |            297             |
|         False negative         |             38             |
|       True positive rate       |      99.26484813310118     |
|      False negative rate       |     0.7351518668988198     |
|       True negative rate       |      26.25994694960212     |
|      False positive rate       |      73.74005305039788     |
|        Precision value         |       86.0184409052808     |
|          Recall value          |      99.26484813310118     |
|         f1_score value         |      92.16813364469193     |
+--------------------------------+----------------------------+
```

Observations

- The performance metrics of the model is not that good which can be seen by the Confusion matrix scores.
- So the model's performance can be improved by tuning the hyperparameters.

Tuning the Hyperaparameters by using the GridSearchCV and RandomsearchCV techniques

In [32]:
```
%%time

#CODE FOR FINDING THE BEST HYPERPARAMETERS THROUGH GRIDSEARCH

Best_para=Grid_s(tfx_tr,y_tr,tfx_cv,y_cv)
```

```
The best model parameters for Gridsearch technique is  {'C': 1, 'gamma': 1e-05}
The model score over the cv set is  0.8917460317460317
Wall time: 50min 31s
```

Randomsearch techniques

In [33]:
```
%%time
#CODE FOR FINDING THE BEST HYPERPARAMETERS USING RANDOMSEARCH
Random_para=Random_s(tfx_tr,y_tr,tfx_cv,y_cv)
```

```
The best model parameters for Randomsearch technique is  {'C': 1.2897118382010795, 'gamma': 1.97646388
88738673}
The model score over the cv set is  0.8204761904761905
Wall time: 16min 6s
```

Testing the model by using the optimal hyperaprameters.

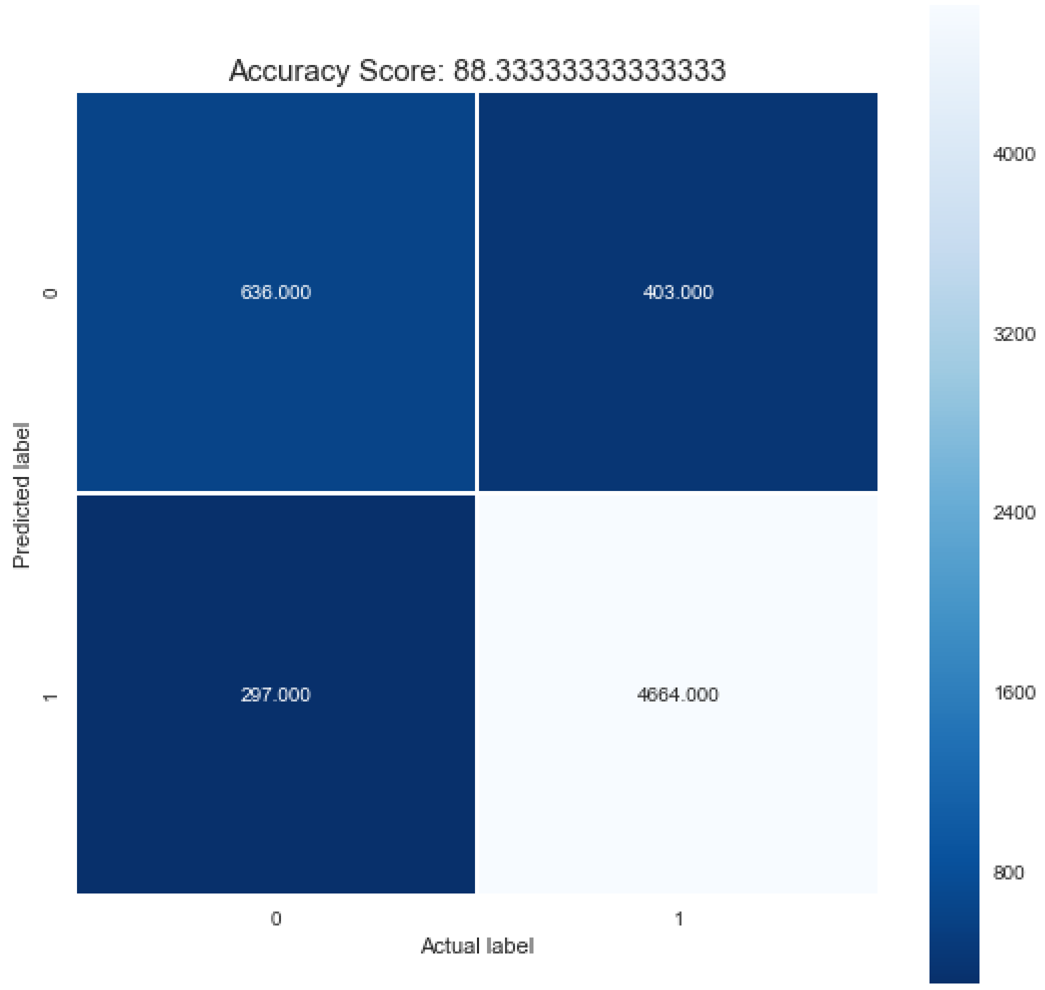
In [35]:
```
Y_Pred,new_accU=tuned_test(tfx_tr,y_tr,tfx_test,y_test,c=1,gam= 1e-05)
```

```
The model score on train set is=  0.9825850340136054

The accuracy of svm over Test set is =  88%
```

Confusion matrix of the above model.

In [35]:
```
Confusion_metric(y_test,Y_Pred,new_accU)
```

```
[[ 636  403]
 [ 297 4664]]
```



The performance metrics of the above model are as follows:	
Metrics	Scores
Classification_accuracy	88.33333333333333
Classification_error	11.666666666666666
True positive	4664
False positive	403
True negative	636
False negative	297
True positive rate	94.01330376940133
False negative rate	5.986696230598669
True negative rate	61.21270452358036
False positive rate	38.78729547641964
Precision value	92.04657588316559
Recall value	94.01330376940133
f1_score value	93.01954527323495

Observations

- The test accuracy of the model is 88.33% by using the optimal hyperparameters which is good for a model.
- The True-postive-rate and the True-Negative-rate are very good as compared to the metrics.
- The false rates are quite low and the model is sensible in classifying the reviews properly.

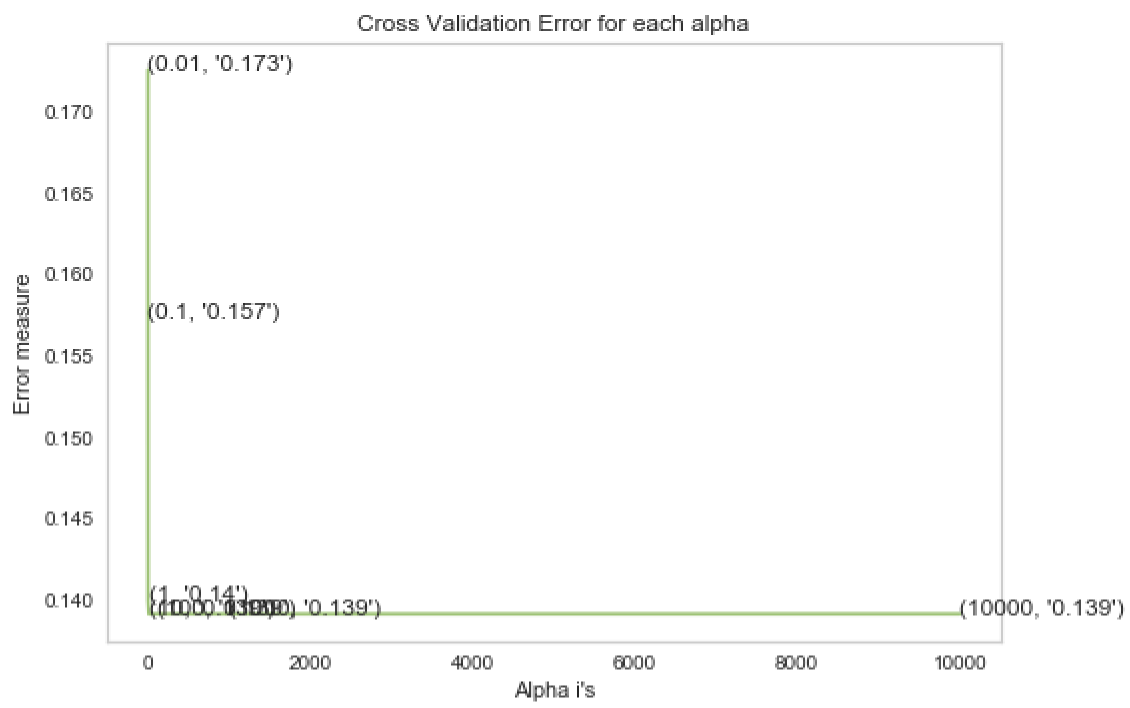
In [40]:
```
#Initializing the count vectorizer
TFIDF_vect=TfidfVectorizer(ngram_range=(1,2),min_df=5)

#vectorizing the X_train set
lin,lin_tr=vec_train(TFIDF_vect,li_xtr["CleanedText"])

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

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

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

```
The shape of the X_train is:  (73500, 102734)
The shape of the X_cv is:  (31500, 102734)
The shape of the X_test is:  (45000, 102734)
```

Implementing the Linear SVM model and performing 10k-Crossvalidation over it.

In [64]:
```
Cv_results(lin_tr,li_ytr)
```

```
----------------------------------------------------------------------------------------------------
--
for alpha = 0.01

the misclassification error for each alpha value is :  [0.173]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.1

the misclassification error for each alpha value is :  [0.173 0.157]
----------------------------------------------------------------------------------------------------
--
for alpha = 1

the misclassification error for each alpha value is :  [0.173 0.157 0.14 ]
----------------------------------------------------------------------------------------------------
--
for alpha = 10

the misclassification error for each alpha value is :  [0.173 0.157 0.14  0.139]
----------------------------------------------------------------------------------------------------
--
for alpha = 100

the misclassification error for each alpha value is :  [0.173 0.157 0.14  0.139 0.139]
----------------------------------------------------------------------------------------------------
--
for alpha = 1000

the misclassification error for each alpha value is :  [0.173 0.157 0.14  0.139 0.139 0.139]
----------------------------------------------------------------------------------------------------
--
for alpha = 10000

the misclassification error for each alpha value is :  [0.173 0.157 0.14  0.139 0.139 0.139 0.139]
```



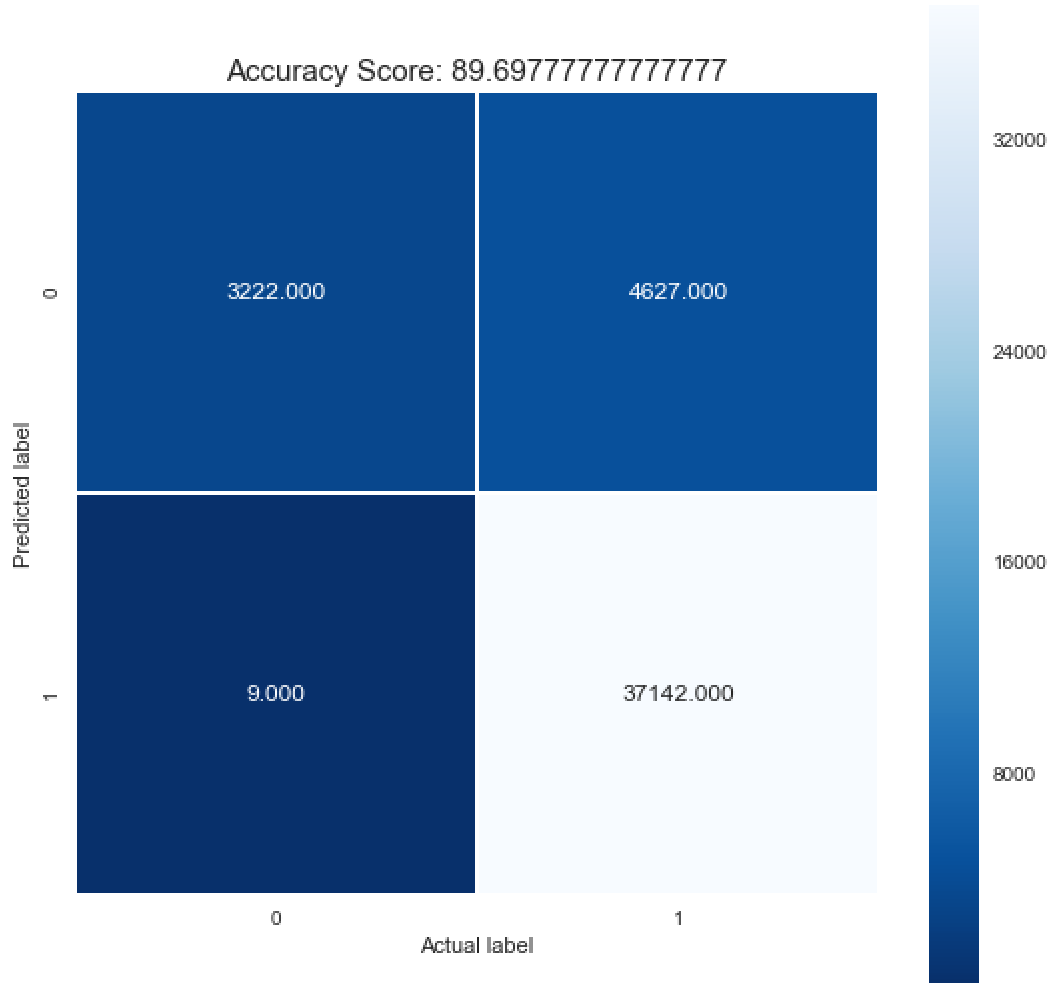
Testing the linear model over the test set

In [58]:
```
TF_sgd_y,TF_sgd_acc=linearsvm(lin_test,li_ytest,10)
```

```
The accuracy of svm over Test set is =  89%
```

In [59]:
```
Confusion_metric(li_ytest,TF_sgd_y,TF_sgd_acc)
```

```
[[ 3222  4627]
 [    9 37142]]
```



The performance metrics of the above model are as follows:

Metrics	Scores
Classification_accuracy	89.69777777777777
Classification_error	10.302222222222222
True positive	37142
False positive	4627
True negative	3222
False negative	9
True positive rate	99.97577454173509
False negative rate	0.024225458264918846
True negative rate	41.049815263090835
False positive rate	58.950184736909165
Precision value	88.9224065694654
Recall value	99.97577454173509
f1_score value	94.12569690826153

Implementing the Average-word2vec-Vectorization techniques.

In [100]:
```
#code for finding the average word2vec

#Utility function for implementing the Average-word2vec-vectorization techniques

import gensim
from gensim.models import word2vec
from gensim.models import KeyedVectors

def Average_word2Vec (X_tr,X_test):

# Train our own Word2Vec model using text corpus
    Train_sentence_list=[]
    for sentence in X_tr:
        Train_sentence_list.append(sentence.split())

    Test_sentence_list=[]
    for sentence in X_test:
        Test_sentence_list.append(sentence.split())

    print("length of train list set is as follows: ",len(Train_sentence_list))
    print("length of test list set is as follows : ",len(Test_sentence_list))
    print("*"*100)

# Generate model and train our model on train data
    w2v_model=w2v_model_train =gensim.models.Word2Vec(Train_sentence_list,min_count=5,size=50, workers
=6)

    # List of word in vocabulary
    w2v_words = list(w2v_model_train.wv.vocab)
    print("length of the W2v vocabulary is : ",len(w2v_words))

#Finding the average word2vec over the train set
    train_list = []
    for sentence in Train_sentence_list:
        word_2_vec = np.zeros(50)
        cnt_words = 0
        for word in sentence:
            if word in w2v_words:
                vec = w2v_model.wv[word]
                word_2_vec += vec
                cnt_words += 1
        if cnt_words != 0 :
            word_2_vec /= cnt_words
        train_list.append(word_2_vec)

 #Finding the average word2vec over the test set
    test_list = []
    for sentence in Test_sentence_list:
        word_2_vec = np.zeros(50)
        cnt_words = 0
        for word in sentence:
            if word in w2v_words:
                vec = w2v_model.wv[word]
                word_2_vec += vec
                cnt_words += 1
        if cnt_words != 0 :
            word_2_vec /= cnt_words
        test_list.append(word_2_vec)


    print("The size of the trained average word2vec is :",len(train_list))
    print("The dimensions of average word2vec is :",len(train_list[0]))
    print()
    print("The size of the test average word2vec is :",len(test_list))
    print("The dimensions of the test average word2vec is :",len(test_list[0]))

    return Train_sentence_list,Test_sentence_list,w2v_model,w2v_words,train_list,test_list
```

Preparing the data over the Average-word2vectorized data

In [101]:
```
Train=X_tr["CleanedText"]
Test=X_test["CleanedText"]

tr_list,tes_list,model,words,trw2v,testw2v=Average_word2Vec(Train,Test)
```

```
length of train list set is as follows:  14700
length of test list set is as follows :  9000
****************************************************************************************************
length of the W2v vocabulary is :  5446
The size of the trained average word2vec is : 14700
The dimensions of average word2vec is : 50

The size of the test average word2vec is : 9000
The dimensions of the test average word2vec is : 50
```

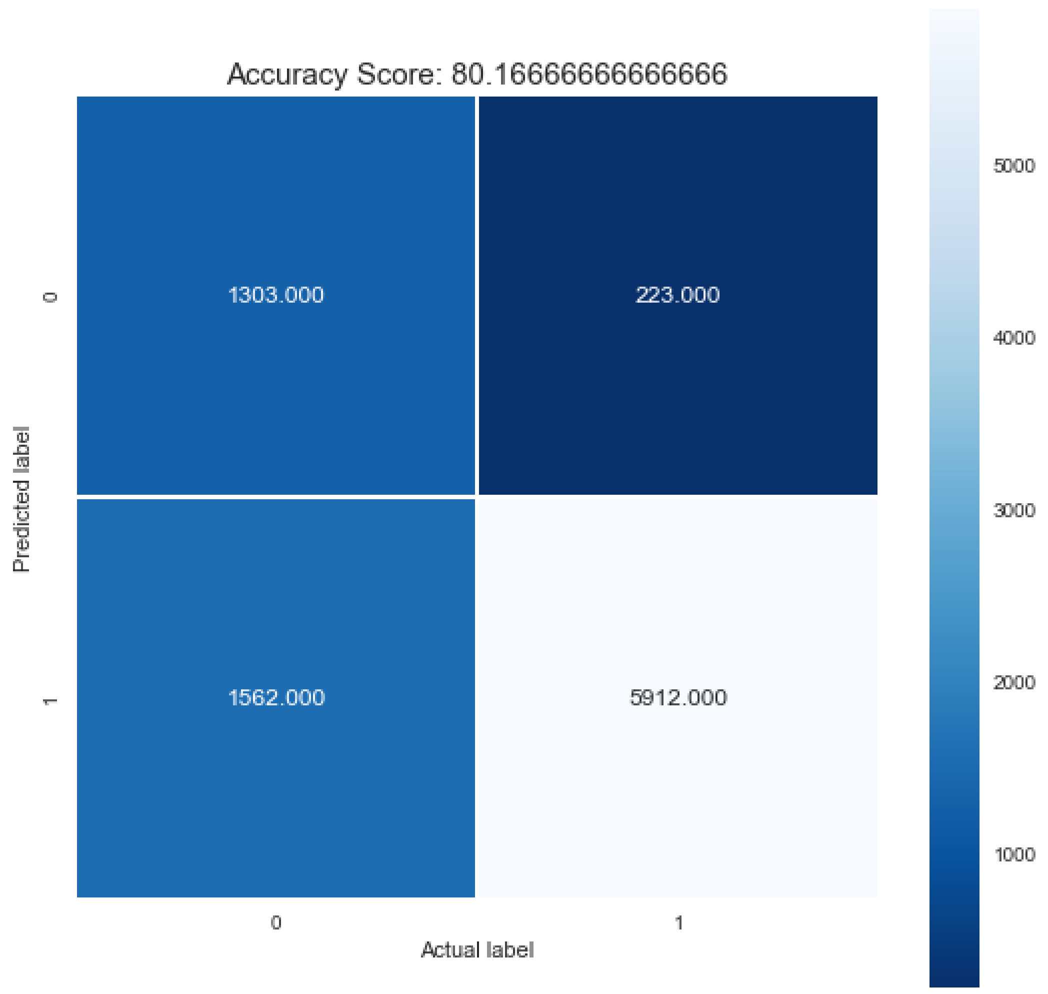
Training the model over the vectorized data by using default parameters

In [21]:
```
%%time
w2v_pred,w2v_acc=train(trw2v,y_tr,testw2v,y_test)
```

```
The model score on train set is=  0.8202721088435374

The accuracy of SVM over cross_val set is =  80%
Wall time: 17 s
```

In [23]:
```
Confusion_metric(y_test,w2v_pred,w2v_acc)
```

```
[[1303  223]
 [1562 5912]]
```




```
+-----------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+-------------------------------+---------------------------+
|            Metrics            |           Scores          |
+-------------------------------+---------------------------+
|    Classification_accuracy    |      80.16666666666666    |
|      Classification_error     |     19.833333333333332    |
|         True positive         |            5912           |
|         False positive        |            223            |
|         True negative         |            1303           |
|         False negative        |            1562           |
|       True positive rate      |      79.1008830612791     |
|      False negative rate      |     20.899116938720898    |
|       True negative rate      |      85.38663171690695    |
|      False positive rate      |     14.613368283093052    |
|        Precision value        |      96.36511817440912    |
|          Recall value         |      79.1008830612791     |
|         f1_score value        |      86.88367991770151    |
+-------------------------------+---------------------------+
```

Tuning the Hyper-parameters for finding the right alpha and gamma

In [24]:
```
%%time

#CODE FOR FINDING THE BEST HYPERPARAMETERS THROUGH GRIDSEARCH

w2v_para=Grid_s(trw2v,y_tr,testw2v,y_test)
```

```
The best model parameters for Gridsearch technique is  {'C': 1, 'gamma': 1}
The model score over the cv set is  0.8436666666666667
Wall time: 10min 27s
```

In [25]:
```
%%time
#CODE FOR FINDING THE BEST HYPERPARAMETERS USING RANDOMSEARCH
Randw2v_para=Random_s(trw2v,y_tr,testw2v,y_test)
```

```
The best model parameters for Randomsearch technique is  {'C': 1.1698528631164136, 'gamma': 0.60675144
52686538}
The model score over the cv set is  0.8591111111111112
Wall time: 2min 22s
```

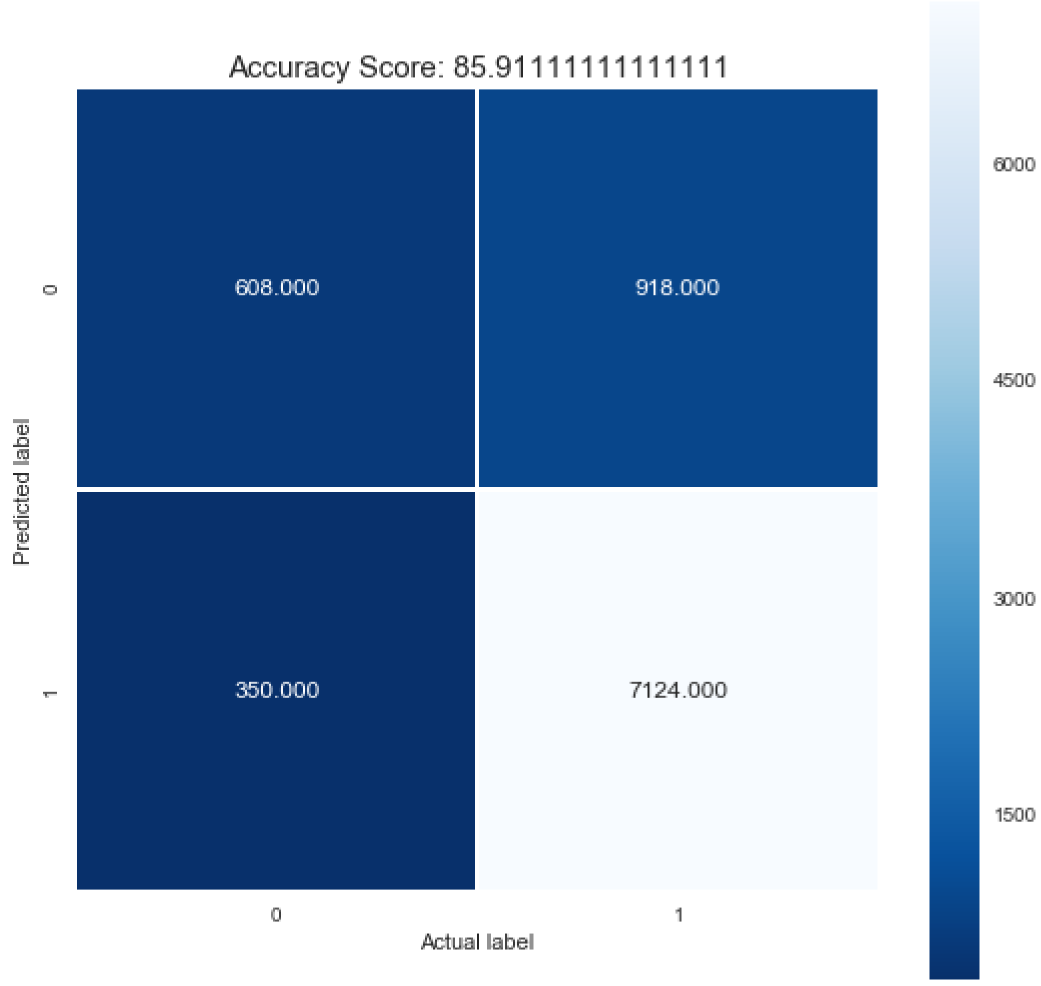
Testing the model over the test set using the optimal hyperaparameters

In [26]:
```
W2V_Pred,W2V_accu=tuned_test(trw2v,y_tr,testw2v,y_test,c=1.1698528631164136,gam= 0.60675144526865 38)
```

```
The model score on train set is=  0.9912244897959184

The accuracy of svm over Test set is =  85%
```

In [27]:
```
Confusion_metric(y_test,W2V_Pred,W2V_accu)
```

```
[[ 608  918]
 [ 350 7124]]
```




```
+-----------------------------------------------------------+
| The performance metrics of the above model are as follows: |
+-----------------------------------+-----------------------+
|              Metrics              |         Scores        |
+-----------------------------------+-----------------------+
|      Classification_accuracy      |   85.91111111111111   |
|        Classification_error       |   14.08888888888889   |
|           True positive           |          7124         |
|           False positive          |          918          |
|           True negative           |          608          |
|           False negative          |          350          |
|         True positive rate        |   95.31709927749532   |
|        False negative rate        |   4.682900722504683   |
|         True negative rate        |   39.84272608125819   |
|        False positive rate        |   60.15727391874181   |
|          Precision value          |   88.58492912210892   |
|            Recall value           |   95.31709927749532   |
|           f1_score value          |   91.82779066769784   |
+-----------------------------------+-----------------------+
```

Observations

- The test accuracy of the Kernel SVM model is 85.91% but it is miss-leading because after studying the confusion-matrix the model is not sensible.
- There is a serious bias problem as the majority points which are the positive reviews are dominating which leads to poor classiffication of the negative reviews.
- So here the Kernel SVM model fails to classify the reviews properly.
- Let's try the Linear SVM model for better accuracies.

Implementing the Average word-2-vec over the 150k datapoints

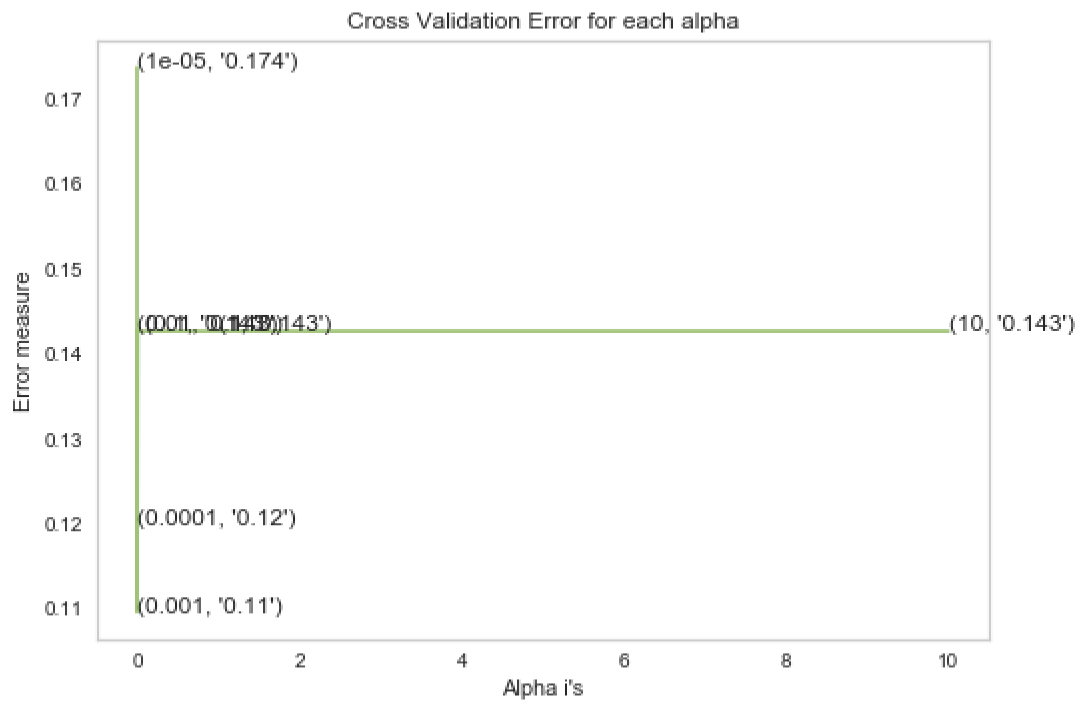
```
In [102]: Train_sgd=li_xtr["CleanedText"]
          Test_sgd=li_xtest["CleanedText"]

          Tr_list,Tes_list,Model,Words,Trw2v,Testw2v=Average_word2Vec(Train_sgd,Test_sgd)
```

```
length of train list set is as follows:  73500
length of test list set is as follows :  45000
****************************************************************************************************
length of the W2v vocabulary is :  11148
The size of the trained average word2vec is : 73500
The dimensions of average word2vec is : 50

The size of the test average word2vec is : 45000
The dimensions of the test average word2vec is : 50
```

Implementing the Linear SVM model and performing 10k-Crossvalidation over it.

```
In [103]: Cv_results(Trw2v,li_ytr)
```

```
----------------------------------------------------------------------------------------------------
--
for alpha = 1e-05

the misclassification error for each alpha value is :  [0.174]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.0001

the misclassification error for each alpha value is :  [0.174 0.12 ]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.001

the misclassification error for each alpha value is :  [0.174 0.12  0.11 ]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.01

the misclassification error for each alpha value is :  [0.174 0.12  0.11  0.143]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.1

the misclassification error for each alpha value is :  [0.174 0.12  0.11  0.143 0.143]
----------------------------------------------------------------------------------------------------
--
for alpha = 1

the misclassification error for each alpha value is :  [0.174 0.12  0.11  0.143 0.143 0.143]
----------------------------------------------------------------------------------------------------
--
for alpha = 10

the misclassification error for each alpha value is :  [0.174 0.12  0.11  0.143 0.143 0.143 0.143]
```



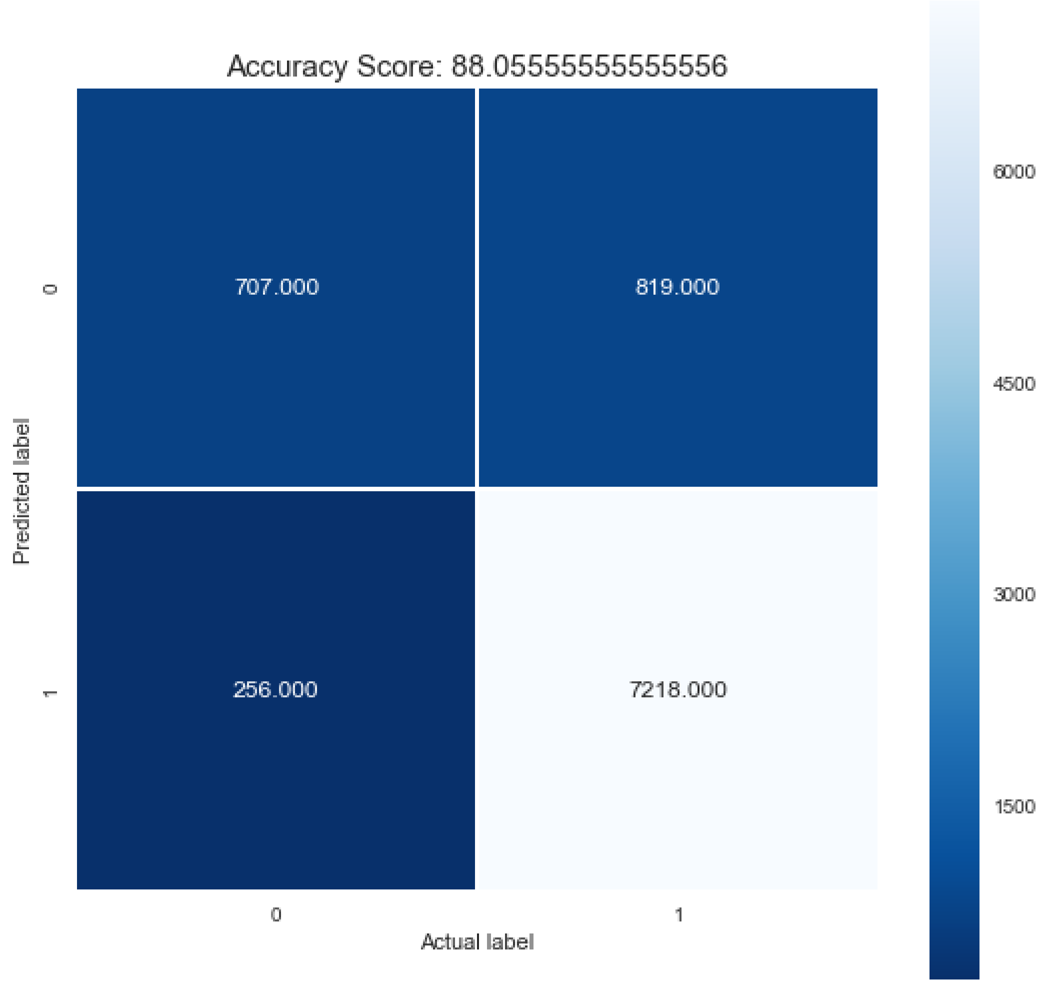
Testing the linear model over the test set

```
In [104]: w2v_sgd_y,w2v_sgd_acc=linearsvm(Testw2v,li_ytest,0.001)
```

```
The accuracy of svm over Test set is =  88%
```

In [34]:
```
Confusion_metric(y_test,w2v_sgd_y,w2v_sgd_acc)
```

```
[[ 707  819]
 [ 256 7218]]
```




```
+-----------------------------------------------------------+
| The performance metrics of the above model are as follows: |
+-----------------------------------+-----------------------+
|              Metrics              |         Scores        |
+-----------------------------------+-----------------------+
|      Classification_accuracy      |   88.05555555555556   |
|       Classification_error        |   11.944444444444445  |
|           True positive           |          7218         |
|           False positive          |          819          |
|           True negative           |          707          |
|           False negative          |          256          |
|         True positive rate        |   96.57479261439657   |
|        False negative rate        |   3.425207385603425   |
|         True negative rate        |   46.330275229357795  |
|        False positive rate        |   53.669724770642205  |
|          Precision value          |   89.80963045912654   |
|            Recall value           |   96.57479261439657   |
|           f1_score value          |   93.06943459480367   |
+-----------------------------------+-----------------------+
```

Observations

- The test accuracy of the linear SVM model is 88.05% but it is miss-leading because after studying the confusion-matrix the model is not sensible.
- There is a serious bias problem as the majority points which are the positive reviews are dominating which leads to poor classiffication of the negative reviews.
- So here the Linear SVM model also fails to classify the reviews properly.

Implementing the Tf-idf weighted-word2vectorization technique

In [109]:
```
def Tf_idf_vector( X_tr,train_list,test_list,model,words):

    Tfidf_vector=TfidfVectorizer()
    Tf_train=Tfidf_vector.fit_transform( X_tr)
    dictionary = dict(zip(Tfidf_vector.get_feature_names(), list(Tfidf_vector.idf_)))

    Train_sentence_list=train_list
    Test_sentence_list=test_list
    w2v_words=words
    w2v_model= model

    train_list_vector=[]
    row=0
    for sentence in  Train_sentence_list:
        word_2_vec=np.zeros(50)
        weight_tfidf_sum=0
        for word in sentence:
            if word in w2v_words:
                vec=w2v_model.wv[word]
            #tfidf_value=Tf_train[row,Dimension.index(word)]
                tf_idf = dictionary[word]*sentence.count(word)
                word_2_vec +=(vec *tf_idf)
                weight_tfidf_sum +=tf_idf
        if weight_tfidf_sum !=0:
            word_2_vec /=weight_tfidf_sum
        train_list_vector.append(word_2_vec)
        row +=1
    print(len(train_list_vector))
    print(len(train_list_vector[0]))


    TEST_LIST_VECTOR=[]
    Row=0
    for sentence in  Test_sentence_list:
        word_2_vec=np.zeros(50)
        weight_tf_sum=0
        for word in sentence:
            if word in w2v_words:
                vec=w2v_model.wv[word]
            #tfidf_value=Tf_test[Row,Dimension.index(word)]
                tf_idf = dictionary[word]*sentence.count(word)
                word_2_vec += (vec* tf_idf)
                weight_tf_sum += tf_idf
        if weight_tf_sum !=0:
            word_2_vec /=weight_tf_sum
        TEST_LIST_VECTOR.append(word_2_vec)
        row += 1
    print(len(TEST_LIST_VECTOR))
    print(len(TEST_LIST_VECTOR[0]))

    return train_list_vector,TEST_LIST_VECTOR
```

Preparing the data for the further use.

In [110]:
```
train_list=X_tr["CleanedText"]
test_list=X_test["CleanedText"]

tfidf_tr,tfidf_test=Tf_idf_vector(X_tr,train_list,test_list,model,words)
```

```
14700
50
9000
50
```

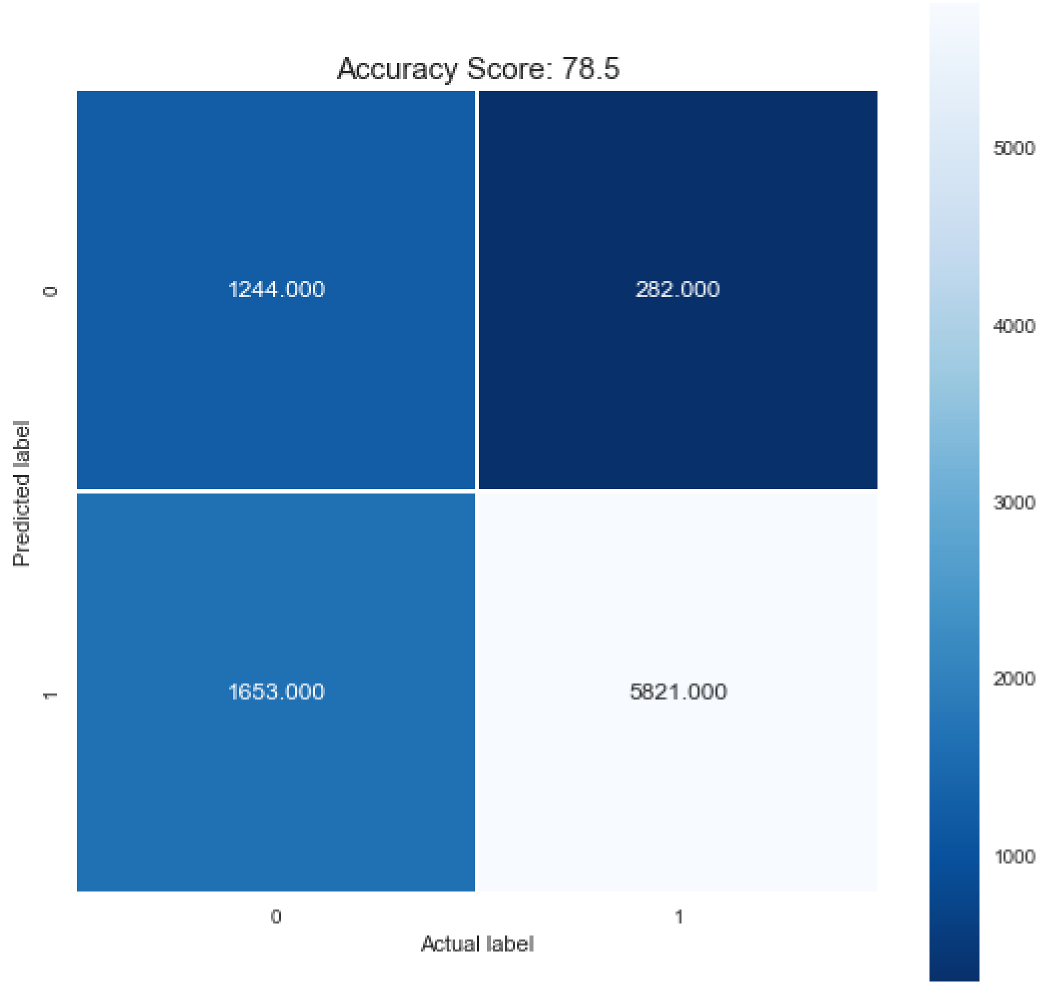
Training the Kernel-svm model over the TF-idf vectorized data.

In [73]:
```
TF_pred,TF_acc=train(train_list_vector,y_tr,TEST_LIST_VECTOR,y_test)
```

```
The model score on train set is=  0.8059863945578232

The accuracy of SVM over cross_val set is =  78%
```

In [75]:
```
Confusion_metric(y_test,TF_pred,TF_acc)
```

```
[[1244  282]
 [1653 5821]]
```




```
+-----------------------------------------------------------+
| The performance metrics of the above model are as follows: |
+-----------------------------------+-------------------------+
|              Metrics              |          Scores         |
+-----------------------------------+-------------------------+
|      Classification_accuracy      |           78.5          |
|        Classification_error       |           21.5          |
|           True positive           |           5821          |
|           False positive          |           282           |
|           True negative           |           1244          |
|           False negative          |           1653          |
|         True positive rate        |    77.88332887342789    |
|        False negative rate        |    22.116671126572115   |
|         True negative rate        |    81.52031454783749    |
|        False positive rate        |    18.479685452162517   |
|          Precision value          |    95.37932164509257    |
|            Recall value           |    77.88332887342789    |
|           f1_score value          |    85.74795610223173    |
+-----------------------------------+-------------------------+
```

Tuning the Hyper-parameters for finding the right alpha and gamma

In [76]:
```
%%time

#CODE FOR FINDING THE BEST HYPERPARAMETERS THROUGH GRIDSEARCH

TF_para=Grid_s(train_list_vector,y_tr,TEST_LIST_VECTOR,y_test)
```

```
The best model parameters for Gridsearch technique is  {'C': 1, 'gamma': 1}
The model score over the cv set is  0.8334444444444444
Wall time: 11min 59s
```

In [77]:
```
%%time
#CODE FOR FINDING THE BEST HYPERPARAMETERS USING RANDOMSEARCH
Rand_TF_para=Random_s(train_list_vector,y_tr,TEST_LIST_VECTOR,y_test)
```

```
The best model parameters for Randomsearch technique is  {'C': 0.8304998310063612, 'gamma': 0.41488323
755969314}
The model score over the cv set is  0.8467777777777777
Wall time: 2min 25s
```

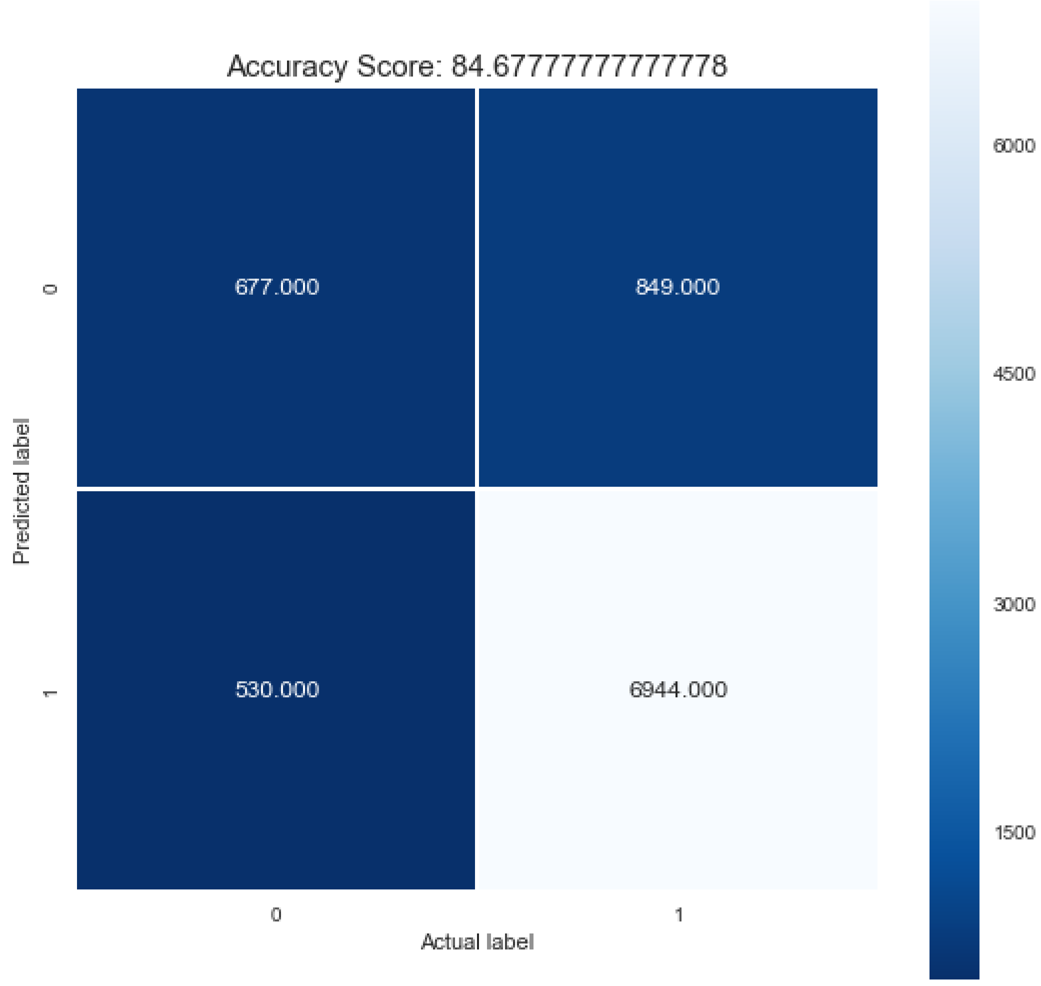
Testing the model over the test set using the optimal alpha and gamma.

In [79]:
```
tf_Pred,tf_accu=tuned_test(train_list_vector,y_tr,TEST_LIST_VECTOR,y_test,c=0.8304998310063612,gam= 0.
41488323755969314)
```

```
The model score on train set is=  0.9774149659863945

The accuracy of svm over Test set is =  84%
```

In [80]:
```
Confusion_metric(y_test,tf_Pred,tf_accu)
```

```
[[ 677  849]
 [ 530 6944]]
```




```
+--------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+--------------------------------+-----------------------------+
|            Metrics             |           Scores            |
+--------------------------------+-----------------------------+
|    Classification_accuracy     |    84.67777777777778        |
|      Classification_error      |    15.322222222222223       |
|         True positive          |           6944              |
|         False positive         |           849               |
|         True negative          |           677               |
|         False negative         |           530               |
|       True positive rate       |    92.90875033449291        |
|      False negative rate       |    7.091249665507091        |
|       True negative rate       |    44.36435124508519        |
|      False positive rate       |    55.63564875491481        |
|        Precision value         |    89.10560759656101        |
|          Recall value          |    92.90875033449291        |
|         f1_score value         |    90.96744612563043        |
+--------------------------------+-----------------------------+
```

Observations

- The test accuracy of the Kernel SVM model is 84.67% but it is miss-leading because after studying the confusion-matrix the model is not sensible.
- There is a serious bias problem as the majority points which are the positive reviews are dominating which leads to poor classiffication of the negative reviews.
- So here the Kernel SVM model fails to classify the reviews properly.
- Let's try the Linear SVM model for better accuracies.

Implementing the TF-idf weighted word-2-vec over the 150k datapoints

In [112]:

```
SGD_list=li_xtr["CleanedText"]
test_list=li_xtest["CleanedText"]

Tfidf_tr,Tfidf_test=Tf_idf_vector(SGD_list,Tr_list,Tes_list,Model,Words)
```

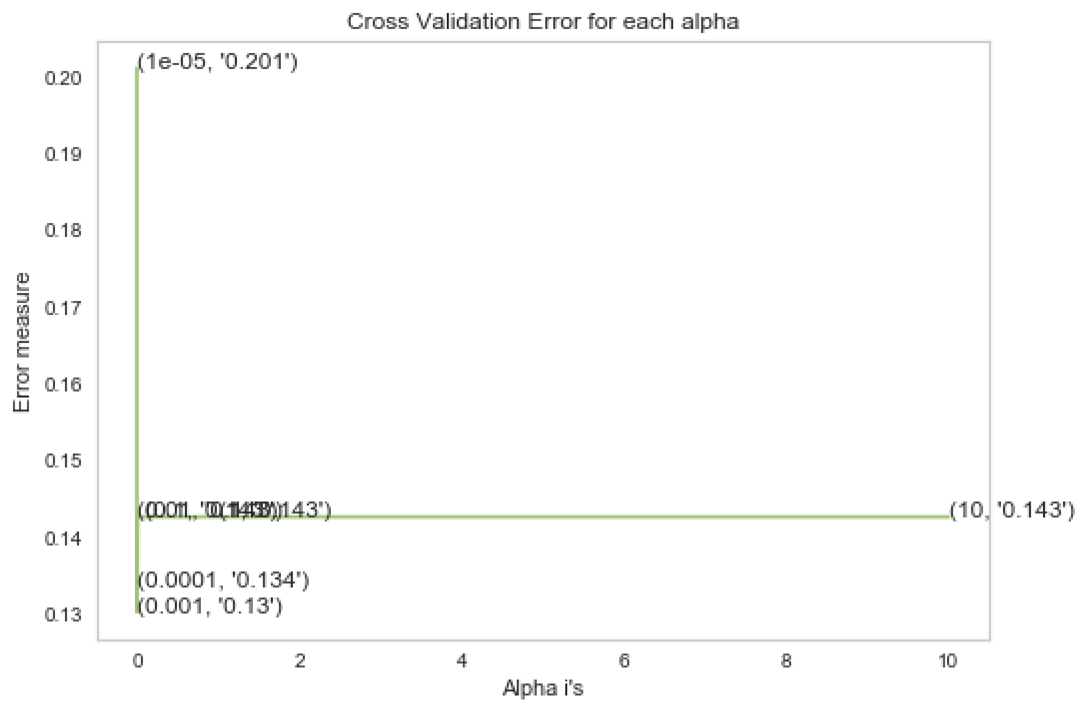
```
73500
50
45000
50
```

Implementing the Linear SVM model and performing 10k-Crossvalidation over it.

In [114]:

```
Cv_results(Tfidf_tr,li_ytr)
```

```
----------------------------------------------------------------------------------------------------
--
for alpha = 1e-05

the misclassification error for each alpha value is :  [0.201]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.0001

the misclassification error for each alpha value is :  [0.201 0.134]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.001

the misclassification error for each alpha value is :  [0.201 0.134 0.13 ]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.01

the misclassification error for each alpha value is :  [0.201 0.134 0.13  0.143]
----------------------------------------------------------------------------------------------------
--
for alpha = 0.1

the misclassification error for each alpha value is :  [0.201 0.134 0.13  0.143 0.143]
----------------------------------------------------------------------------------------------------
--
for alpha = 1

the misclassification error for each alpha value is :  [0.201 0.134 0.13  0.143 0.143 0.143]
----------------------------------------------------------------------------------------------------
--
for alpha = 10

the misclassification error for each alpha value is :  [0.201 0.134 0.13  0.143 0.143 0.143 0.143]
```



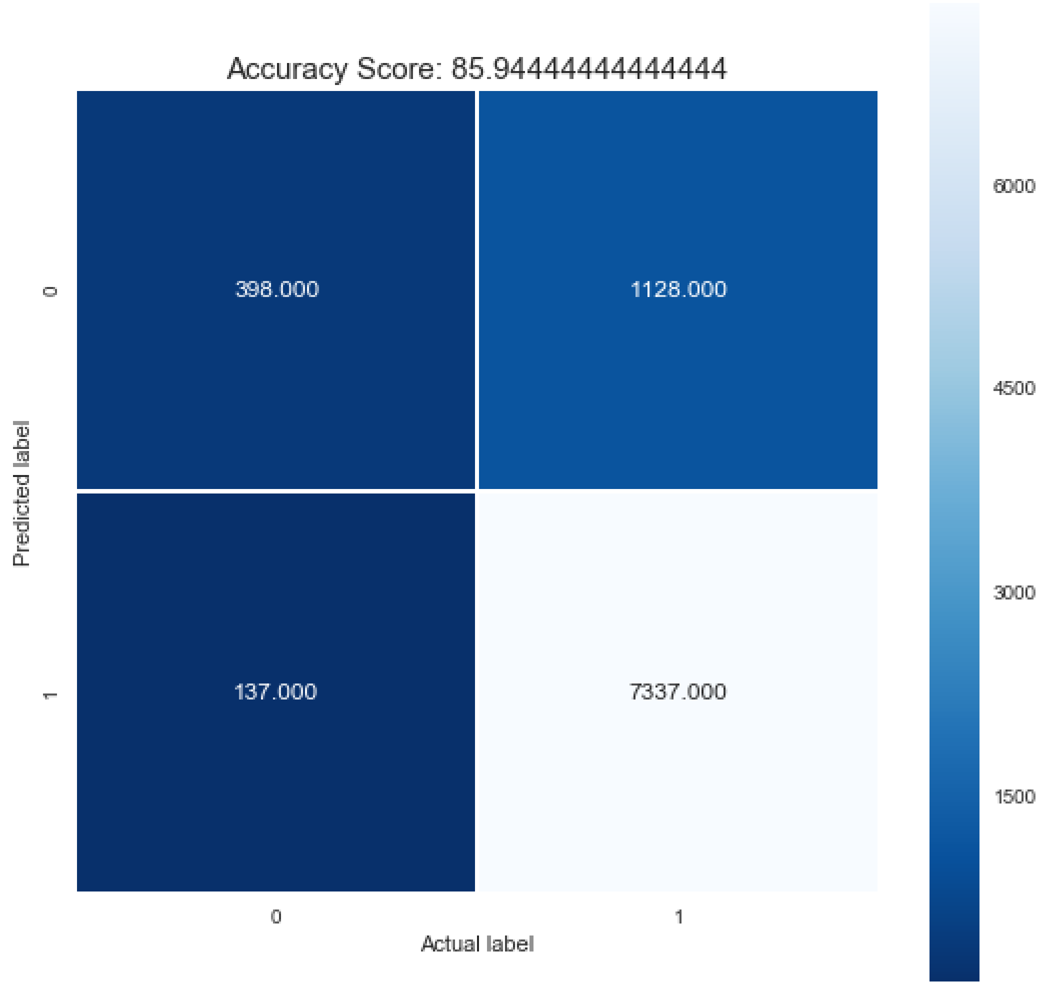
Testing the linear-SVM model over the test set by using the optimal alpha value.

In [115]:
```
tfw2v_sgd_y,tfw2v_sgd_acc=linearsvm(Tfidf_test,li_ytest,0.001)
```

```
The accuracy of svm over Test set is =  85%
```

In [83]:
```
Confusion_metric(y_test,tfw2v_sgd_y,tfw2v_sgd_acc)
```

```
[[ 398 1128]
 [ 137 7337]]
```



The performance metrics of the above model are as follows:	
Metrics	Scores
Classification_accuracy	85.94444444444444
Classification_error	14.055555555555554
True positive	7337
False positive	1128
True negative	398
False negative	137
True positive rate	98.16697886004818
False negative rate	1.833021139951833
True negative rate	26.08125819134993
False positive rate	73.91874180865007
Precision value	86.67454223272297
Recall value	98.16697886004818
f1_score value	92.06349206349208

Observations

- The test accuracy of the linear SVM model is 85.94% but it is miss-leading because after studying the confusion-matrix the model is not sensible.
- There is a serious bias problem as the majority points which are the positive reviews are dominating which leads to poor classiffication of the negative reviews.
- So here the Linear SVM model also fails to classify the reviews properly.

Conclusions

In [66]:
```
conclusion_table()
```

The comparisons of all the vectorizers are as follows:			
Vectorizer	Algorithm	Scores	Status
Bag-Of-Words	Kernel-SVM	86.6%	Stable
Bag-Of-Words	Linear-SVM	92.87%	Stable
Tf-IDF	Kernel-SVM	88.33%	Stable
Tf-IDF	Linear-SVM	89.82%	Unstable
Average-word2vec	Kernel-SVM	85.91%	Unstable
Average-word2vec	Linear-SVM	88.05%	Unstable
TF-IDF-Weighted-word2vec	Kernel-SVM	84.67%	Unstable
TF-IDF-Weighted-word2vec	Linear-SVM	85.94%	Unstable

1. From the above conclusion table the Linear SVM worked excellent with Bag-of-words & Tf-idf vectorizers and were also highly stable.

2. The Kernel-SVM was also stable with the BOW nad tf-idf but still they are facing Bias problems.
3. The gridearch and random search cross-validations are quite expensive interms of time and compute for larger datasets.
4. SGD with Linear-SVM was quite fast and have faster and good results.
5. The Average and Tf-idf weighted word2vec were unstable even after tuning the hyperparameters in both Kernel and Linear SVM'S because of bias problems.
6. So according to my observation I can Conclude that Linear model's are better in this case than Kernel-SVM's in case of BOW and Tf-idf vectorization techniques & Support Vector Machines are a good classification algorithm.

In [ ]: