Implementing the Decison-tree classiffier over the Amazon-fine food reviews dataset

In [2]:

```
#Importing all the relevant 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 prettytable import PrettyTable
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.grid_search import GridSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
from sklearn import metrics
from sklearn.model_selection import RandomizedSearchCV
from imblearn.over_sampling import SMOTE
```

Connecting to the pre-processed SQLite Table.

In [4]:

```
#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 the further use.

In [5]:

```
#SETTING THE TIME COLUMN TO STANDARD DATE-TIME

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

Out[5]:

	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

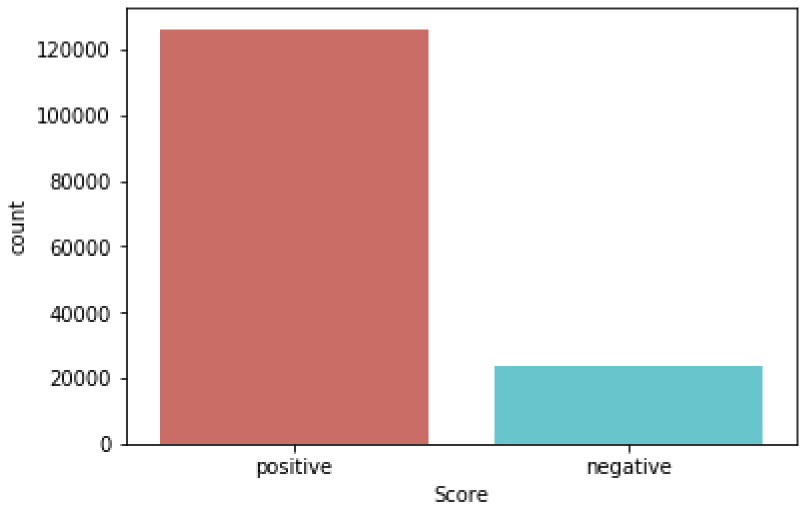
In [6]:

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

#Sampling the above data

Sampled_data=Data.sample(n=150000,replace='False')
Sorted=Sampled_data.sort_index()
Sorted.head()
```

Out[6]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Sc
Time							
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 00:00:00.947376000	374422	B00004CI84	A1048CYU0OV4O8	Judy L. Eans	2	2	posit
1970-01-01 00:00:00.951523200	374450	B00004CI84	ACJR7EQF9S6FP	Jeremy Robertson	2	3	posit
1970-01-01 00:00:00.959990400	451903	B00004CXX9	A2DEE7F9XKP3ZR	jerome	0	1	posit

In [7]:
```
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 80:20 partitions sets

In [8]:
```
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 [9]:
```
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_test is:",X_test.shape)
print("the shape of y_test is:",y_test.shape)
```

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

Utility functions for training & testing the data

In [21]:
```python
def train(X_tr, y_tr,X_cv,y_cv):

    clf = DecisionTreeClassifier(random_state=0,max_depth=None,class_weight="balanced")
    Model = clf.fit(X_tr, y_tr)

    print("\nThe model score on train set is= ", Model.score(X_tr,y_tr))

    Y_pred=Model.predict(X_cv)

    accuracy = accuracy_score(y_cv, Y_pred, normalize=True) * float(100)

    print('\nThe accuracy of Decision tree over cross_val set is =  %d%% ' % ( accuracy))
    return Y_pred,accuracy




def tuned_test(X_tr, y_tr,X_test,y_test,d):

    Best_clf= DecisionTreeClassifier(random_state=0,max_depth=d,class_weight="balanced")

    Best_Model = Best_clf.fit(X_tr, y_tr)

    print("\nThe model score on train set is= ", Best_Model.score(X_tr,y_tr))

    Y_pred=Best_Model.predict(X_test)

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

    print('\nThe accuracy of Decision tree over test set is =  %d%% ' % ( best_accuracy))
    return Y_pred,best_accuracy


def cv_results(X_cv, y_cv):
    cv_erro_array1 = []
    depth = [x for x in range(2, 10)]

    for d in depth:
        print("-------------------------------------------------------------------------------------
-----------------")
        print("for depth =", d)
        Clf = DecisionTreeClassifier(random_state=0,max_depth=(d),class_weight="balanced")
        Scores = cross_val_score(Clf, X_cv, y_cv, cv=10,scoring='accuracy',n_jobs=-1)
        cv_erro_array1.append(Scores.mean())

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

    #plt.subplot(1,2,1)

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

    Best_depth = np.round(depth[mse.index(min(mse))])
    print('\nThe optimal number of depth value is %d.' % Best_depth)
```

Utility function for plotting the confusion matrix.

In [11]:
```python
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 [51]:
```python
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","Decision-Tree-Classiffier",accuracy,"Overfitt"])
    ptable.add_row(["Tf-IDF","Decision-Tree-Classiffier",accur ,"Overfitt"])
    ptable.add_row(["Average-word2vec","Decision-Tree-Classiffier",accura ,"Overfitt"])
    ptable.add_row(["TF-IDF-Weighted-word2vec","Decision-Tree-Classiffier",tfaccura ,"Overfitt"])

    print(ptable)
```

Utility function for vectorizing the data

In [12]:
```python
#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 vectorizer

In [13]:
```
#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
```

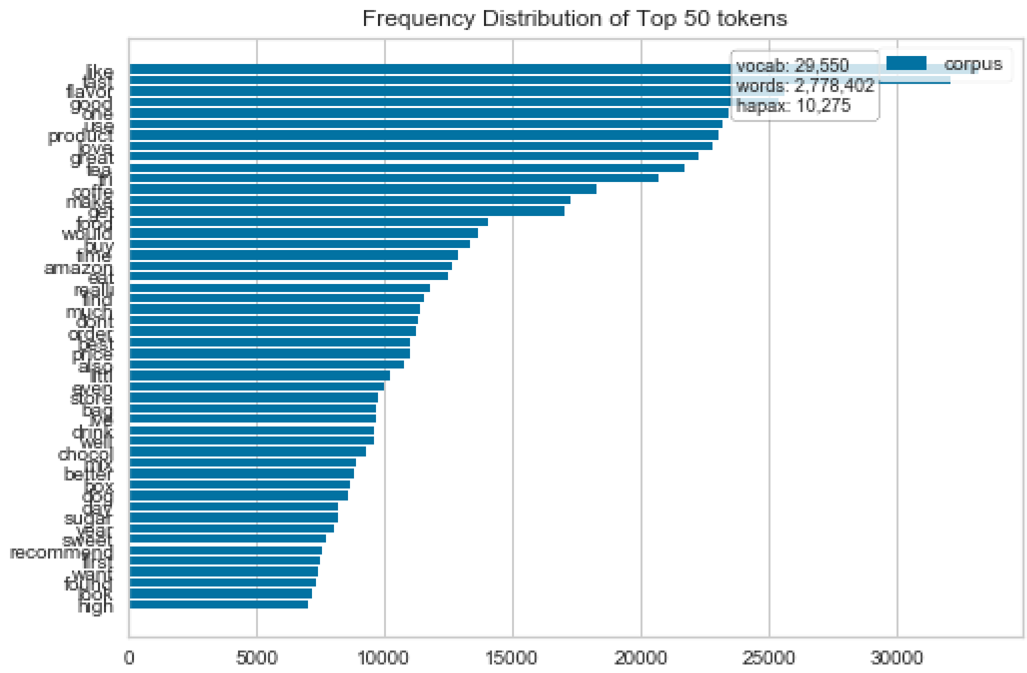
```
The shape of the X_train is:  (73500, 29756)
The shape of the X_cv is:  (31500, 29756)
The shape of the X_test is:  (45000, 29756)

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

Out[13]:

	feature	bow
0	televis	67.784587
1	preschool	52.183137
2	song	45.833249
3	thirti	35.308593
4	teach	34.166100
5	seri	32.651272
6	student	20.112397
7	book	18.799685
8	sister	11.680474
9	school	11.466476
10	child	11.147448
11	air	10.443262
12	show	9.254517
13	tradit	8.764491
14	children	8.457772
15	along	8.337187
16	later	8.281381
17	rememb	7.625671
18	ago	6.107664
19	turn	6.015751
20	live	5.432616
21	see	4.070845
22	someth	3.805621
23	whole	3.477331
24	bought	3.311197

Displaying the top frequency distribution of the top 50 tokens

In [13]:
```
display_token(Count_vect,X_tr["CleanedText"])
```



Training the Decision tree classifier model over the cross-validation set using default values

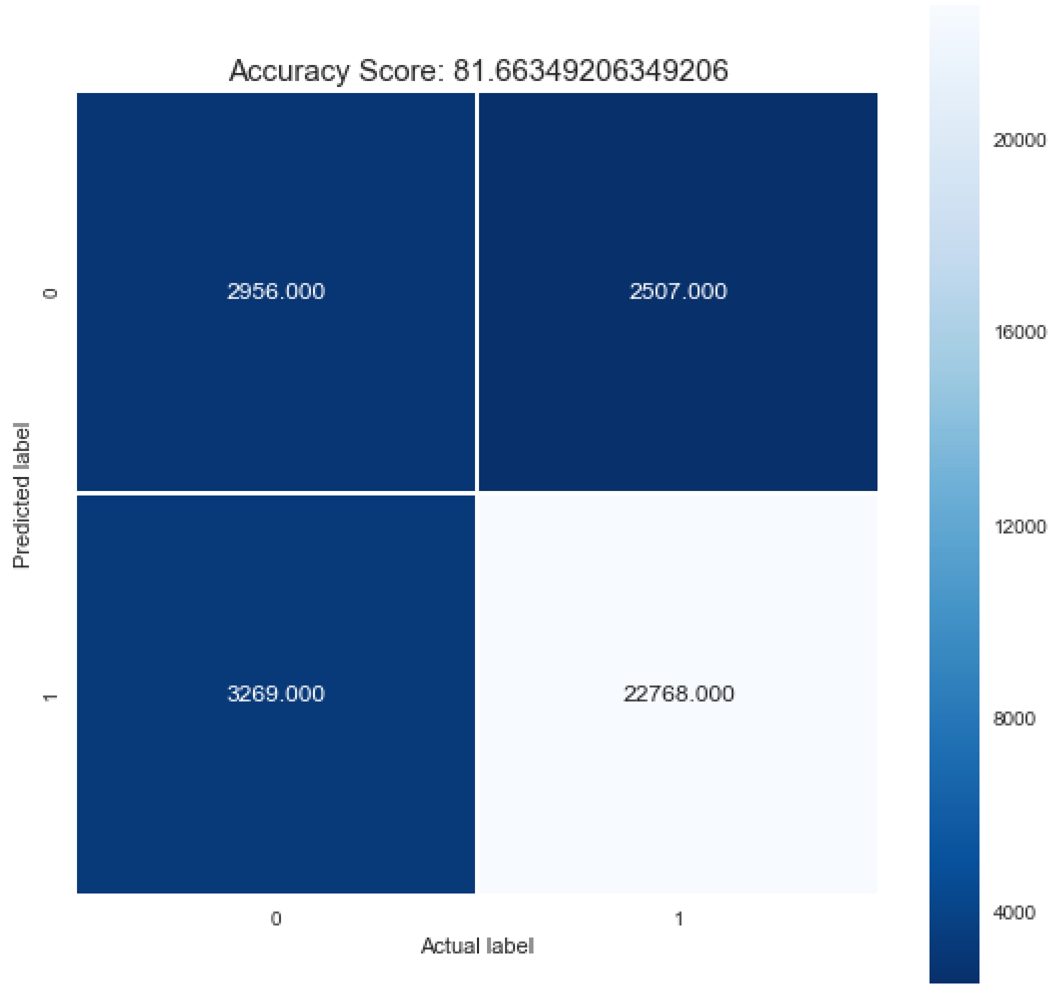
In [14]:
```
%%time

pred,acc=train(x_tr,y_tr,x_cv,y_cv)
```

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

The accuracy of Decision tree over cross_val set is =  81%
Wall time: 35.1 s
```

Confusion matrix of the model is as follows

In [46]:
```
Confusion_metric(y_cv,pred,acc)
```

```
[[ 2956  2507]
 [ 3269 22768]]
```



The performance metrics of the above model are as follows:	
Metrics	Scores
Classification_accuracy	81.66349206349206
Classification_error	18.336507936507935
True positive	22768
False positive	2507
True negative	2956
False negative	3269
True positive rate	87.44479010638706
False negative rate	12.555209893612934
True negative rate	54.10946366465312
False positive rate	45.89053633534688
Precision value	90.08110781404551
Recall value	87.44479010638706
f1_score value	88.74337386966012

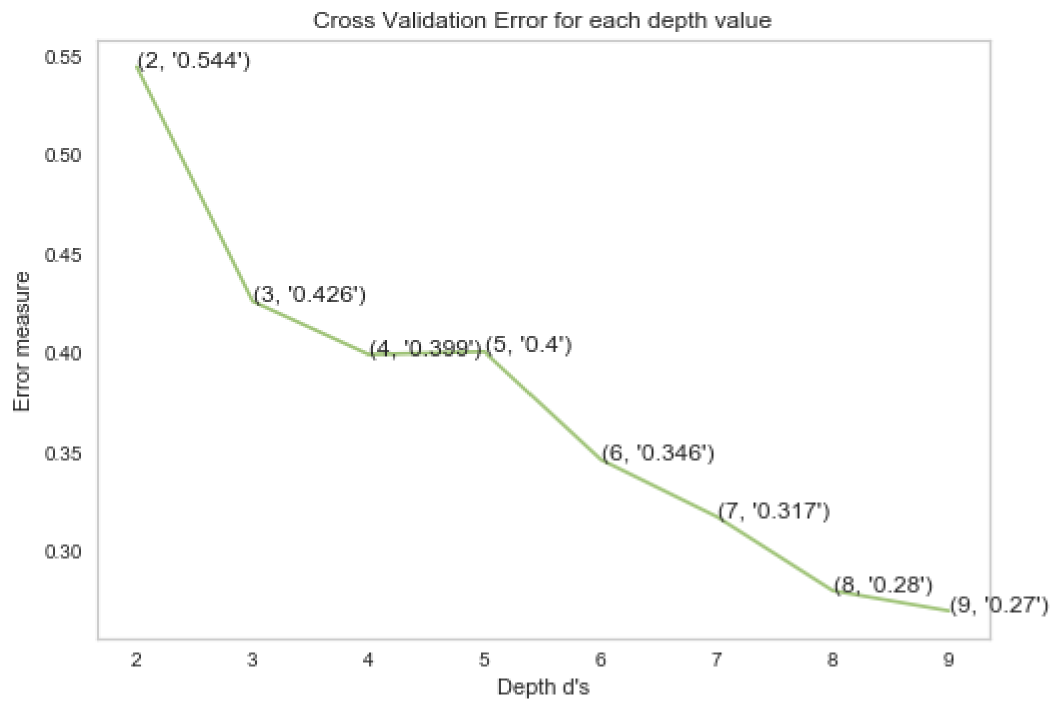
Observations

- The train accuracy of the above model is 81.422% but is quite misleading which can be observed by analyzing the performance metrics of the confusion matrix.
- The False positive rate and the false negative rate is quite high which is not good for an classification model.
- The True negative rate is quite low which is very bad as the negative reviews are not properly classified and the model is facing a bias problem which can be improved after tuning the hyperparameters.

Tuning the hyperparameters by performing 10k-fold Cross validation technique

In [16]:
```
cv_results(x_tr,y_tr)
```

```
----------------------------------------------------------------------------------------------------
--
for depth = 2

the misclassification error for each depth value is :  [0.544]
----------------------------------------------------------------------------------------------------
--
for depth = 3

the misclassification error for each depth value is :  [0.544 0.426]
----------------------------------------------------------------------------------------------------
--
for depth = 4

the misclassification error for each depth value is :  [0.544 0.426 0.399]
----------------------------------------------------------------------------------------------------
--
for depth = 5

the misclassification error for each depth value is :  [0.544 0.426 0.399 0.4  ]
----------------------------------------------------------------------------------------------------
--
for depth = 6

the misclassification error for each depth value is :  [0.544 0.426 0.399 0.4   0.346]
----------------------------------------------------------------------------------------------------
--
for depth = 7

the misclassification error for each depth value is :  [0.544 0.426 0.399 0.4   0.346 0.317]
----------------------------------------------------------------------------------------------------
--
for depth = 8

the misclassification error for each depth value is :  [0.544 0.426 0.399 0.4   0.346 0.317 0.28 ]
----------------------------------------------------------------------------------------------------
--
for depth = 9

the misclassification error for each depth value is :  [0.544 0.426 0.399 0.4   0.346 0.317 0.28  0.27
]
```




```
The optimal number of depth value is 9.
```

Testing the model with the optimal depth value over the Test set

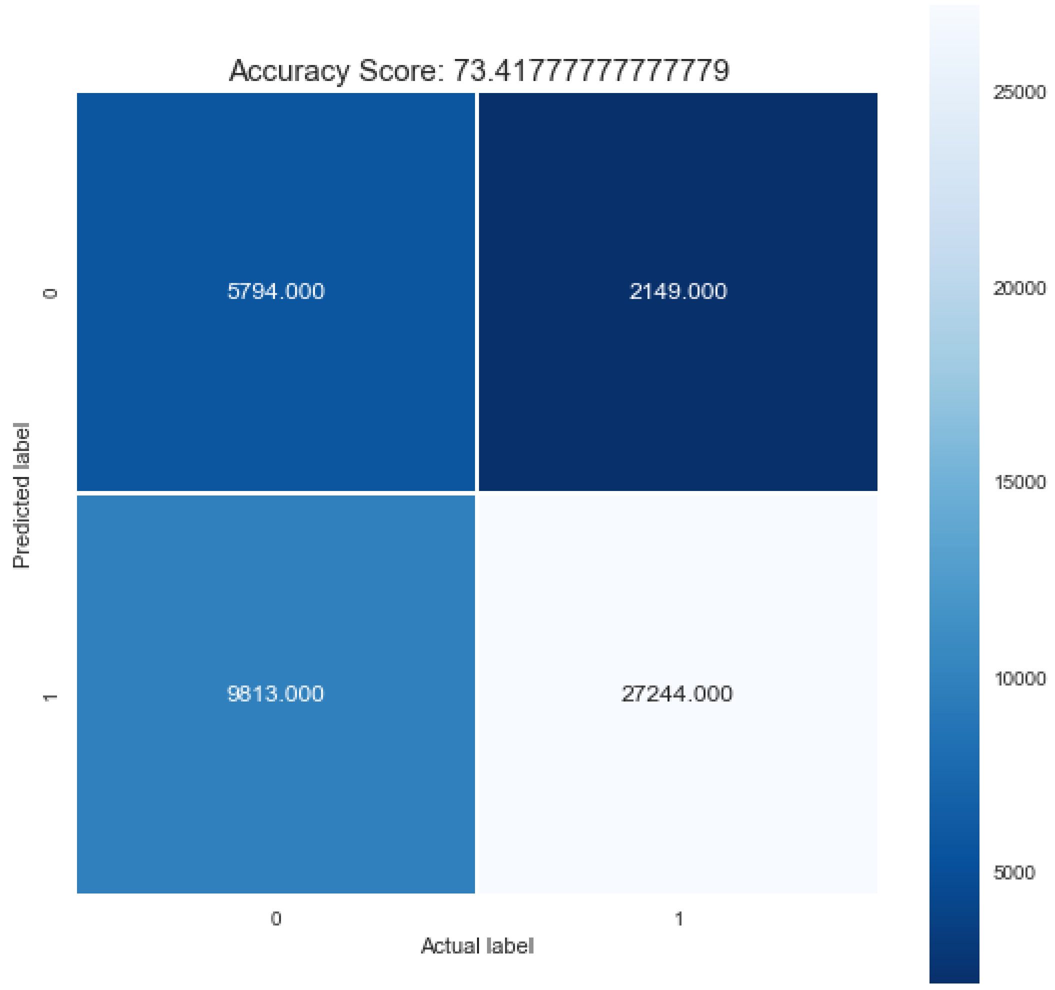
In [47]:
```
y_pred,accuracy=tuned_test(x_tr,y_tr,x_test,y_test,d=9)
```

```
The model score on train set is=  0.7459319727891156

The accuracy of Decision tree over test set is =  73%
```

Confusion matrix of the above model is as follows

In [48]:
```
Confusion_metric(y_test,y_pred,accuracy)
```

```
[[ 5794  2149]
 [ 9813 27244]]
```



```
+--------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+---------------------------------+----------------------------+
|             Metrics             |           Scores           |
+---------------------------------+----------------------------+
|     Classification_accuracy     |     73.41777777777779      |
|       Classification_error      |     26.582222222222224     |
|          True positive          |           27244            |
|          False positive         |            2149            |
|          True negative          |            5794            |
|          False negative         |            9813            |
|        True positive rate       |     73.51917316566372      |
|       False negative rate       |     26.48082683433629      |
|        True negative rate       |     72.94473120987033      |
|       False positive rate       |     27.055268790129674     |
|         Precision value         |     92.68873541319361      |
|           Recall value          |     73.51917316566372      |
|          f1_score value         |     81.99849510910461      |
+---------------------------------+----------------------------+
```

Observations

- The test accuracy with optimal depth is 73.41% which is quite low for a classification model.
- This drop in accuracy is due to increase in the false negative rates which is hampering the model's performance.
- But still the model is good and stable because of high True positive and negative rates as compared to the default model.
- The precision and the recall values are good but the recall value is very low which is quite alarming.
- Since descion trees tends to overfitt as the depth increases so this might be reason for low accuracy.

Implementing the TF-idf Vectorizeration technique

In [18]:

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

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

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


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


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


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


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

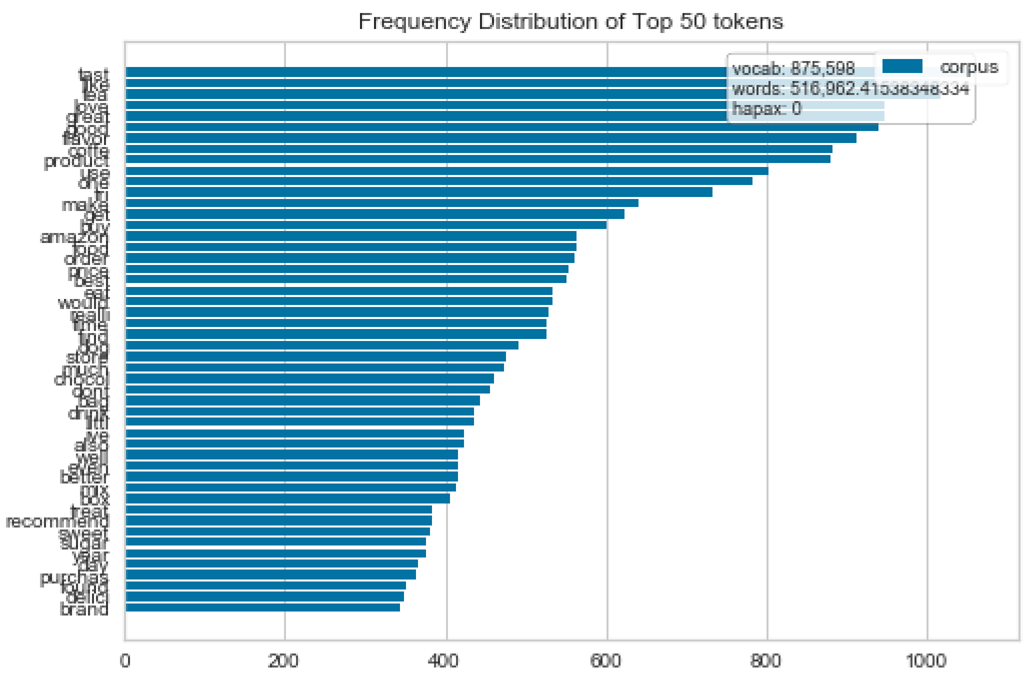
```
The shape of the X_train is:  (73500, 875598)
The shape of the X_cv is:  (31500, 875598)
The shape of the X_test is:  (45000, 875598)

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

Out[18]:

	feature	tfidf
0	book children	271.110679
1	day thirti	271.110679
2	song student	271.110679
3	children tradit	271.110679
4	air televis	271.110679
5	student teach	271.110679
6	child sister	271.110679
7	sister later	271.110679
8	thirti someth	271.110679
9	tradit live	271.110679
10	show air	271.110679
11	use seri	271.110679
12	preschool turn	271.110679
13	teach preschool	271.110679
14	whole school	271.110679
15	school purchas	271.110679
16	book song	271.110679
17	seri book	255.991893
18	ago child	224.977363
19	televis year	218.374631
20	turn whole	192.496849
21	later bought	160.642759
22	along book	144.295057
23	see show	126.218655
24	purchas along	111.273414

Displaying the frequency of the top 50 Tf-idf vectorized tokens

In [19]:
```
display_token(TF_vect,X_tr["CleanedText"])
```



Training the above model over the cross-validated data

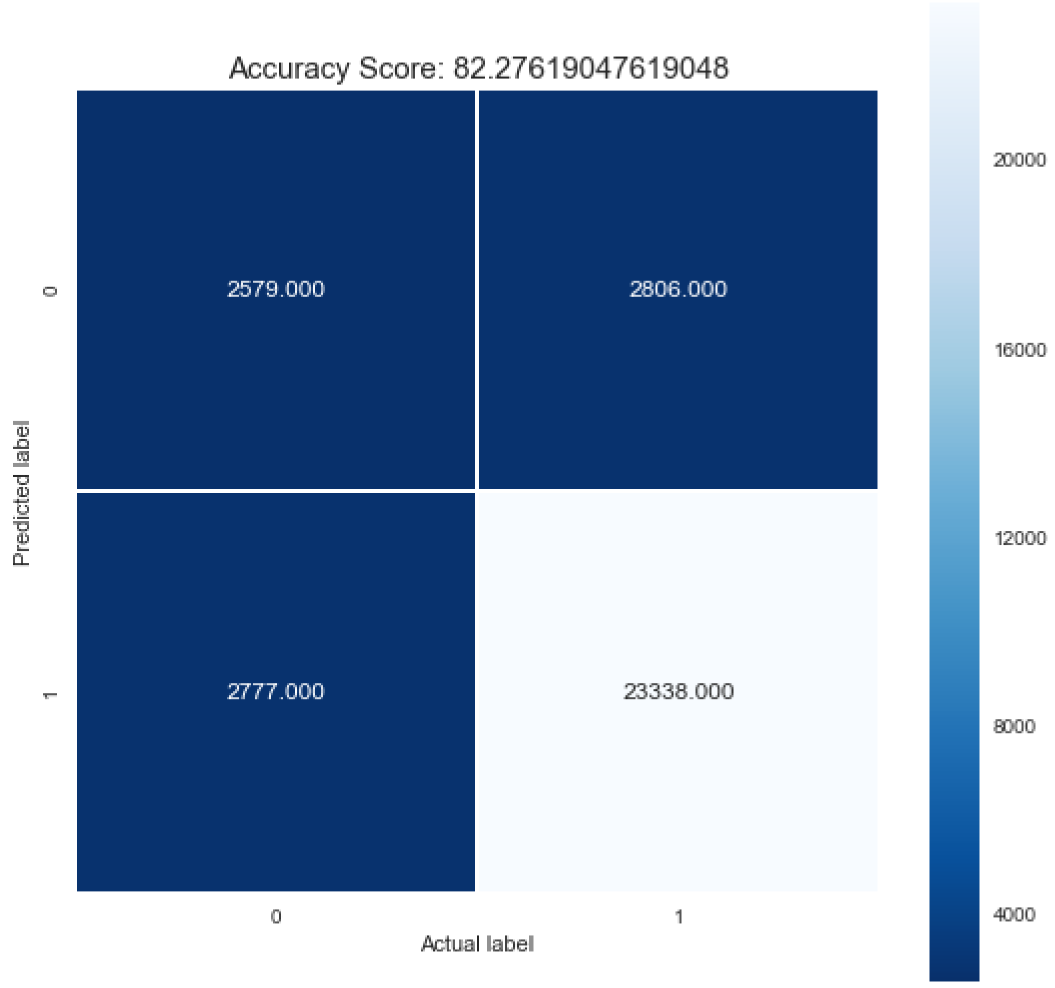
In [21]:
```
%%time

Pred,Acc=train(X_tra,y_tr,X_cv,y_cv)
```

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

The accuracy of Decision tree over cross_val set is =  82%
Wall time: 2min 41s
```

Confusion matrix of the above model is as follows

In [22]:
```
Confusion_metric(y_cv,Pred,Acc)
```

```
[[ 2579  2806]
 [ 2777 23338]]
```




```
+-------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+-------------------------------+-----------------------------+
|            Metrics            |            Scores           |
+-------------------------------+-----------------------------+
|    Classification_accuracy    |      82.27619047619048      |
|      Classification_error     |      17.723809523809525     |
|         True positive         |            23338            |
|         False positive        |             2806            |
|         True negative         |             2579            |
|         False negative        |             2777            |
|       True positive rate      |      89.36626459888953      |
|      False negative rate      |      10.633735401110473     |
|       True negative rate      |      47.89229340761374      |
|      False positive rate      |      52.10770659238626      |
|        Precision value        |       89.2671358629131      |
|          Recall value         |      89.36626459888953      |
|         f1_score value        |      89.31667272622896      |
+-------------------------------+-----------------------------+
```

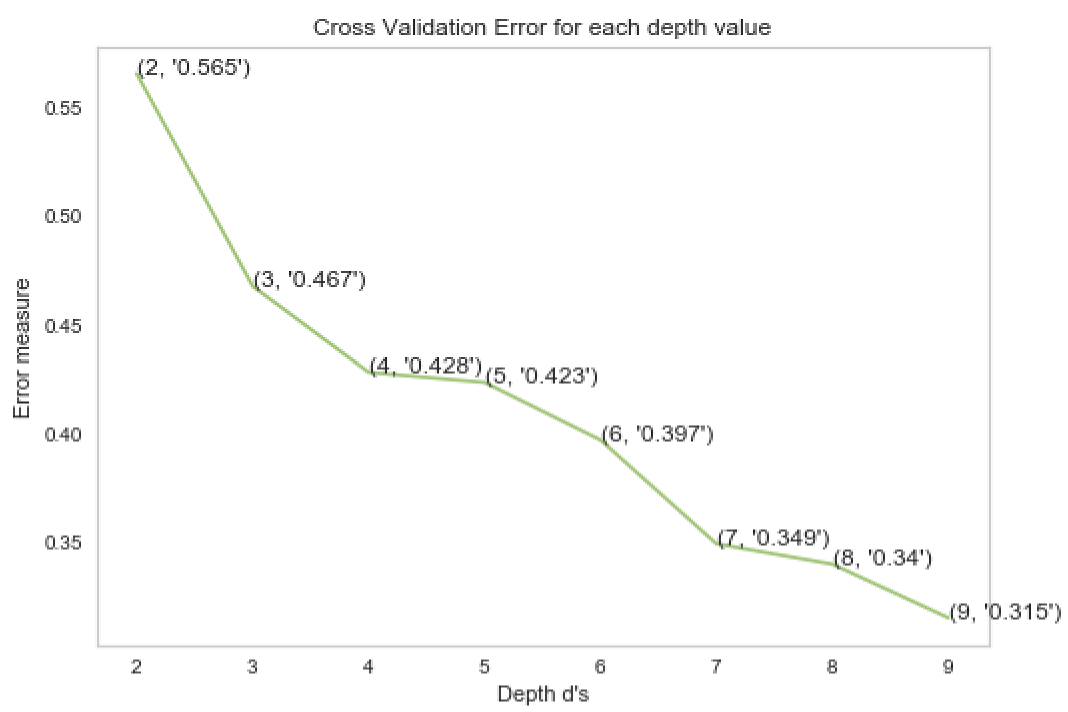
Observations

- The train accuracy of the above model is 82.276% but is quite misleading which can be observed by analyzing the performance metrics of the confusion matrix.
- The False positive rate and the false negative rate is quite high which is not good for an classification model.
- The True negative rate is quite low which is very bad as the negative reviews are not properly classified and the model is facing a bias problem which can be improved after tuning the hyperparameters.

Tuning the Hyper-parameters by using 10k-fold Cross validation technique

In [22]:
```
cv_results(X_tra,y_tr)
```

```
----------------------------------------------------------------------------------------------------
--
for depth = 2

the misclassification error for each depth value is :  [0.565]
----------------------------------------------------------------------------------------------------
--
for depth = 3

the misclassification error for each depth value is :  [0.565 0.467]
----------------------------------------------------------------------------------------------------
--
for depth = 4

the misclassification error for each depth value is :  [0.565 0.467 0.428]
----------------------------------------------------------------------------------------------------
--
for depth = 5

the misclassification error for each depth value is :  [0.565 0.467 0.428 0.423]
----------------------------------------------------------------------------------------------------
--
for depth = 6

the misclassification error for each depth value is :  [0.565 0.467 0.428 0.423 0.397]
----------------------------------------------------------------------------------------------------
--
for depth = 7

the misclassification error for each depth value is :  [0.565 0.467 0.428 0.423 0.397 0.349]
----------------------------------------------------------------------------------------------------
--
for depth = 8

the misclassification error for each depth value is :  [0.565 0.467 0.428 0.423 0.397 0.349 0.34 ]
----------------------------------------------------------------------------------------------------
--
for depth = 9

the misclassification error for each depth value is :  [0.565 0.467 0.428 0.423 0.397 0.349 0.34  0.31
5]
```




```
The optimal number of depth value is 9.
```

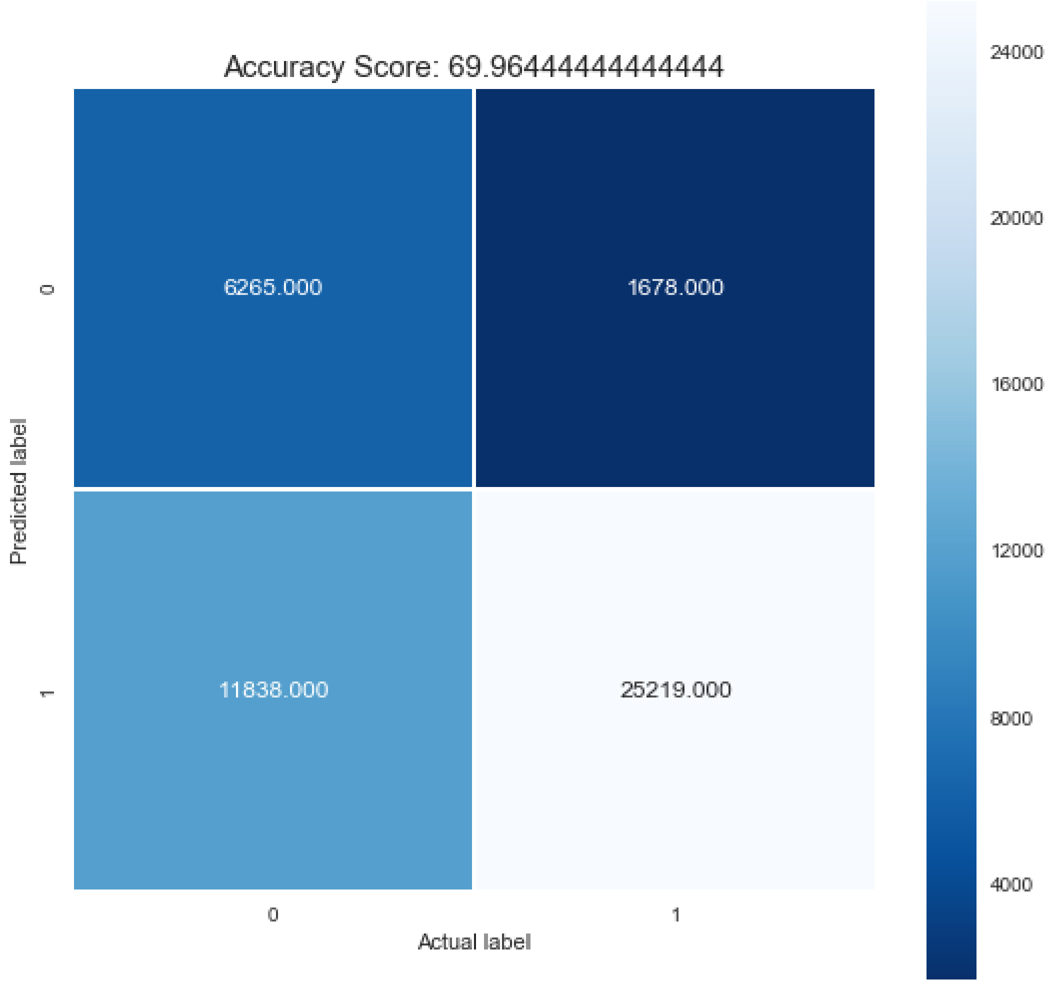
Training the Decision tree classiffier model with optimal depth value

In [23]:
```
y_Pred,accur=tuned_test(X_tra,y_tr,X_tes,y_test,9)
```

```
The model score on train set is=  0.6937687074829932

The accuracy of Decision tree over test set is =  69%
```

In [24]:
```
Confusion_metric(y_test,y_Pred,accur)
```

```
[[ 6265  1678]
 [11838 25219]]
```



The performance metrics of the above model are as follows:

Metrics	Scores
Classification_accuracy	69.96444444444444
Classification_error	30.035555555555554
True positive	25219
False positive	1678
True negative	6265
False negative	11838
True positive rate	68.05461856059584
False negative rate	31.945381439404162
True negative rate	78.87448067480801
False positive rate	21.125519325191995
Precision value	93.76138602818158
Recall value	68.05461856059584
f1_score value	78.86605998061107

Observations

- The test accuracy with optimal depth is 68.96% which is quite low for a classification model.
- This drop in accuracy is due to increase in the false negative rates and the False positive rates which is hampering the model's performance.
- But still the model is good and stable because of high True positive and negative rates as compared to the default model.
- The precision and the F1_scores values are good but the recall value is very low which is quite alarming.
- Since descion trees tends to overfitt as the depth increases so this might be reason for low accuracy because here after tuning the depth parameter the optimal value was 9.
- Let's see the performance of the model might increase after changing the vectorizers.

Implementing the Average word2vectorization technique

In [25]:
```
#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 Average word2vec data for further use

In [26]:
```
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:  73500
length of test list set is as follows :  45000
****************************************************************************************************
length of the W2v vocabulary is :  11158
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
```

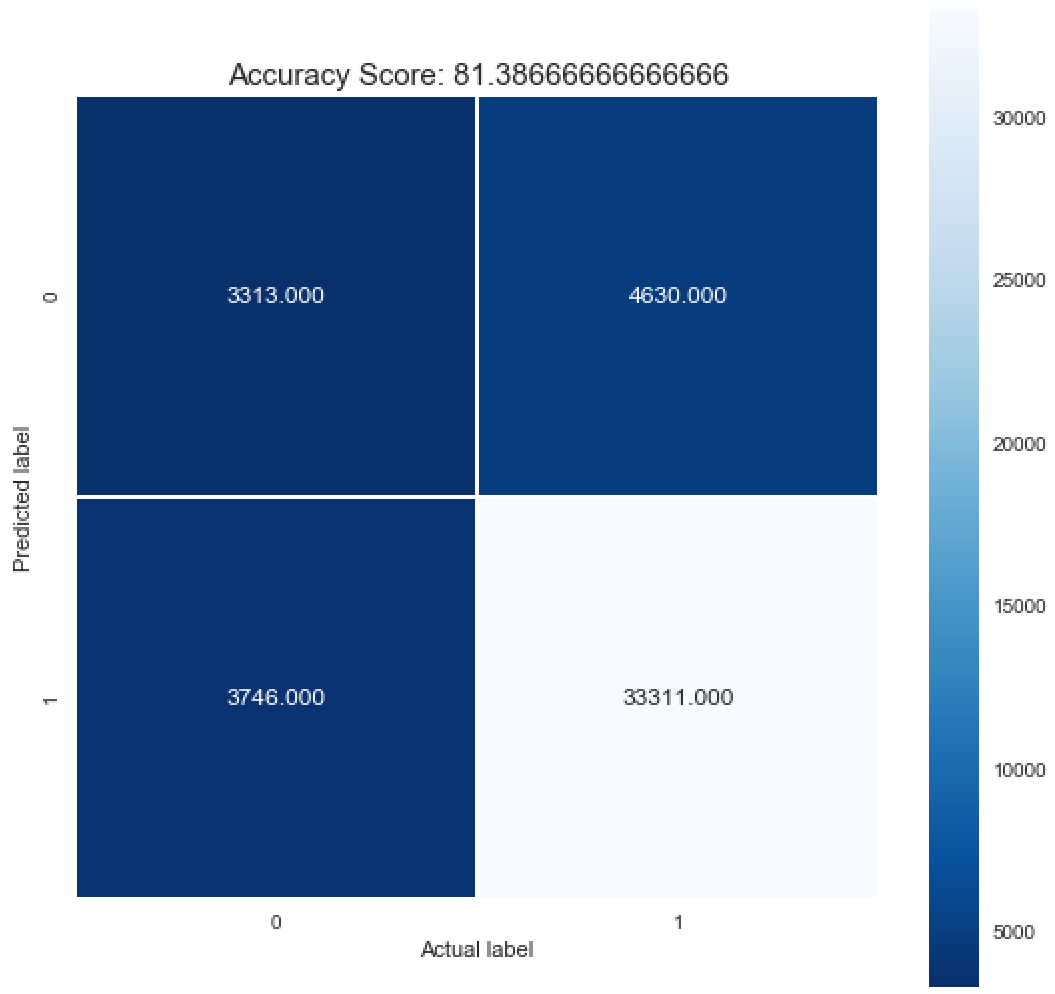
Training the Decision Tree classiffier with default hyperparameters

In [28]:
```
%%time
w2v_pred,w2v_acc=train(trw2v,y_tr,testw2v,y_test)
```

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

The accuracy of Decision tree over cross_val set is =  81%
Wall time: 5.1 s
```

In [29]:
```
Confusion_metric(y_test,w2v_pred,w2v_acc)
```

```
[[ 3313  4630]
 [ 3746 33311]]
```




```
+-----------------------------------------------------------+
| The performance metrics of the above model are as follows: |
+--------------------------------+--------------------------+
|             Metrics            |          Scores          |
+--------------------------------+--------------------------+
|     Classification_accuracy    |    81.38666666666666     |
|       Classification_error     |    18.613333333333333    |
|          True positive         |          33311           |
|          False positive        |           4630           |
|          True negative         |           3313           |
|          False negative        |           3746           |
|        True positive rate      |    89.89124861699544     |
|       False negative rate      |    10.108751383004561    |
|        True negative rate      |    41.70968148054891     |
|       False positive rate      |    58.29031851945109     |
|         Precision value        |    87.79684246593395     |
|           Recall value         |    89.89124861699544     |
|          f1_score value        |    88.83170217872477     |
+--------------------------------+--------------------------+
```

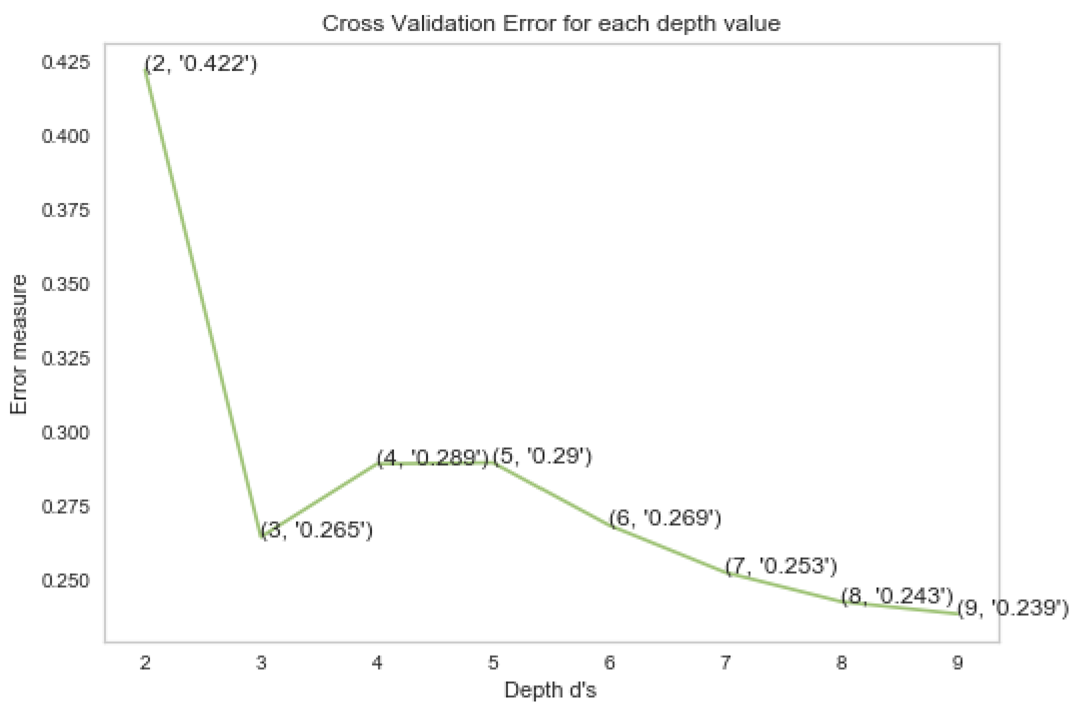
Observations

- The train accuracy of the above model is 81.36% but is quite misleading which can be observed by analyzing the performance metrics of the confusion matrix.
- The False positive rate and the false negative rate is quite high which is not good for an classification model.
- The True negative rate is quite low which is very bad as the negative reviews are not properly classified and the model is facing a bias problem which can be improved after tuning the hyperparameters.

Tuning the hyperparameters by using the 10k-fold cross validation technique

In [30]:
```
cv_results(trw2v,y_tr)
```

```
----------------------------------------------------------------------------------------------------
--
for depth = 2

the misclassification error for each depth value is :  [0.422]
----------------------------------------------------------------------------------------------------
--
for depth = 3

the misclassification error for each depth value is :  [0.422 0.265]
----------------------------------------------------------------------------------------------------
--
for depth = 4

the misclassification error for each depth value is :  [0.422 0.265 0.289]
----------------------------------------------------------------------------------------------------
--
for depth = 5

the misclassification error for each depth value is :  [0.422 0.265 0.289 0.29 ]
----------------------------------------------------------------------------------------------------
--
for depth = 6

the misclassification error for each depth value is :  [0.422 0.265 0.289 0.29  0.269]
----------------------------------------------------------------------------------------------------
--
for depth = 7

the misclassification error for each depth value is :  [0.422 0.265 0.289 0.29  0.269 0.253]
----------------------------------------------------------------------------------------------------
--
for depth = 8

the misclassification error for each depth value is :  [0.422 0.265 0.289 0.29  0.269 0.253 0.243]
----------------------------------------------------------------------------------------------------
--
for depth = 9

the misclassification error for each depth value is :  [0.422 0.265 0.289 0.29  0.269 0.253 0.243 0.23
9]
```




```
The optimal number of depth value is 9.
```

Testing the model over the Test set by using the optimal depth value

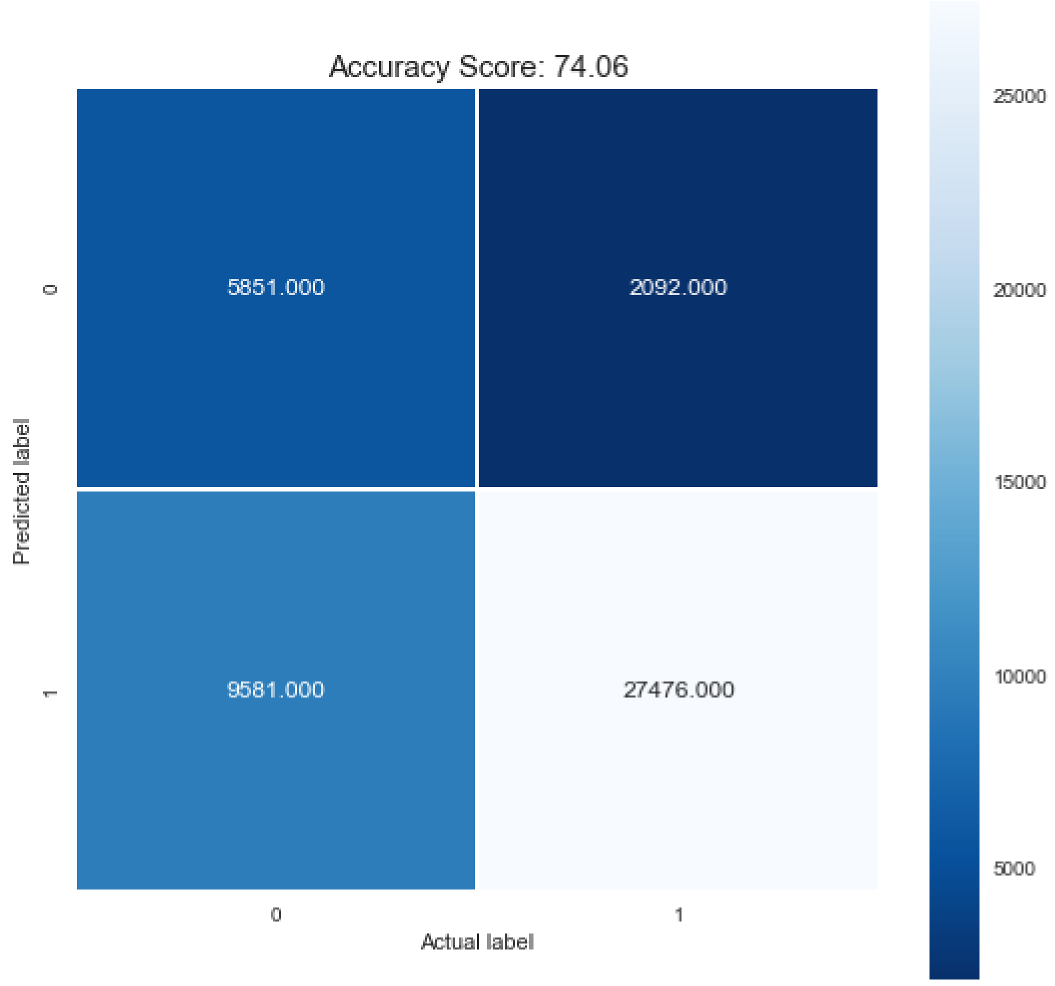
In [31]:
```
y_Predi,accura=tuned_test(trw2v,y_tr,testw2v,y_test,9)
```

```
The model score on train set is=  0.801795918367347

The accuracy of Decision tree over test set is =  74%
```

Confusion matrix of the above model is as follows

In [32]:
```
Confusion_metric(y_test,y_Predi,accura)
```

```
[[ 5851  2092]
 [ 9581 27476]]
```



The performance metrics of the above model are as follows:	
Metrics	Scores
Classification_accuracy	74.06
Classification_error	25.94
True positive	27476
False positive	2092
True negative	5851
False negative	9581
True positive rate	74.14523571794803
False negative rate	25.854764282051974
True negative rate	73.6623442024424
False positive rate	26.337655797557595
Precision value	92.92478354978356
Recall value	74.14523571794803
f1_score value	82.4795497185741

Observations

- The Test accuracy of the model is 74.06% which is low than default model but it is sensible as the diagonal element values are quite high as compared to other elements.
- The False positive and the negative rates are 25% and 26% which is considerable and the main reason of decreasing the accuracy so here the model is little overfitting.
- The model here is doing quite a good job in classiffying the model properly as compared to the previous vectorizers.
- So by Observing the the confusion matrix and the performance of the above model I can conclude that the model is quite stable and sensible in classifying the reviews properly.
- So let's try the Tf-idf weighted word2vec vectorization technique and hope for the best results.

Implementing the Tf-IDF Weighted word2vec Vectorization technique

In [33]:
```
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]))

#Code for preapring the test_list_vector
    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 TF-IDF weighted vectorized data for the further implementations

In [35]:
```
Xtrain=X_tr["CleanedText"]

tfidf_tr,tfidf_test=Tf_idf_vector(Xtrain,tr_list,tes_list,model,words)
```

```
73500
50
45000
50
```

Training the Decision tree classiffier model by using the default parameters

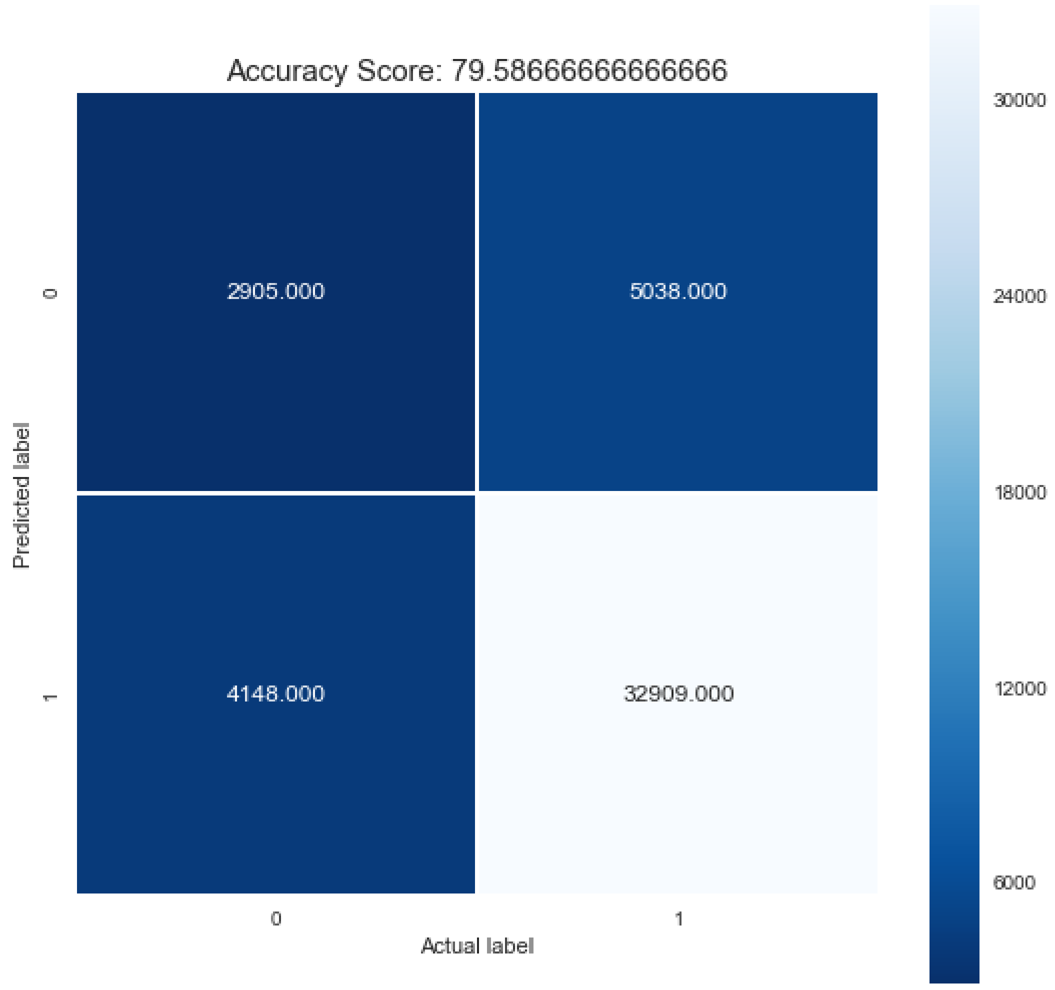
In [38]:
```
TF_pred,TF_acc=train(tfidf_tr,y_tr,tfidf_test,y_test)
```

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

The accuracy of Decision tree over cross_val set is =  79%
```

Confusion matrix of the above model is as follows

In [39]:
```
Confusion_metric(y_test,TF_pred,TF_acc)
```

```
[[ 2905  5038]
 [ 4148 32909]]
```

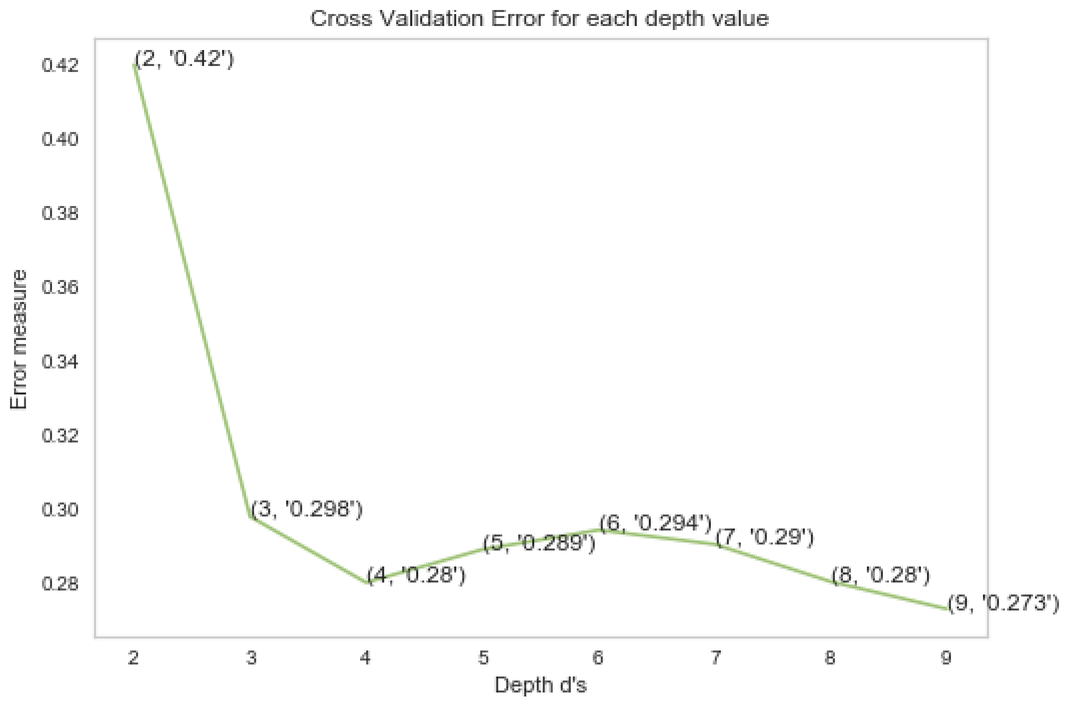



```
+-------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+--------------------------------+----------------------------+
|            Metrics             |           Scores           |
+--------------------------------+----------------------------+
|     Classification_accuracy    |     79.58666666666666      |
|      Classification_error      |     20.413333333333334     |
|          True positive         |           32909            |
|         False positive         |            5038            |
|          True negative         |            2905            |
|         False negative         |            4148            |
|       True positive rate       |     88.80643333243383      |
|      False negative rate       |     11.193566667566182     |
|       True negative rate       |     36.57308321792774      |
|      False positive rate       |     63.42691678207226      |
|        Precision value         |     86.72358816243708      |
|          Recall value          |     88.80643333243383      |
|         f1_score value         |     87.75265319182976      |
+--------------------------------+----------------------------+
```

Tuning the hyperaprameters by using 10k-fold Cross-validation technique

In [40]:
```
cv_results(tfidf_tr,y_tr)
```

```
----------------------------------------------------------------------------------------------------
--
for depth = 2

the misclassification error for each depth value is :  [0.42]
----------------------------------------------------------------------------------------------------
--
for depth = 3

the misclassification error for each depth value is :  [0.42  0.298]
----------------------------------------------------------------------------------------------------
--
for depth = 4

the misclassification error for each depth value is :  [0.42  0.298 0.28 ]
----------------------------------------------------------------------------------------------------
--
for depth = 5

the misclassification error for each depth value is :  [0.42  0.298 0.28  0.289]
----------------------------------------------------------------------------------------------------
--
for depth = 6

the misclassification error for each depth value is :  [0.42  0.298 0.28  0.289 0.294]
----------------------------------------------------------------------------------------------------
--
for depth = 7

the misclassification error for each depth value is :  [0.42  0.298 0.28  0.289 0.294 0.29 ]
----------------------------------------------------------------------------------------------------
--
for depth = 8

the misclassification error for each depth value is :  [0.42  0.298 0.28  0.289 0.294 0.29  0.28 ]
----------------------------------------------------------------------------------------------------
--
for depth = 9

the misclassification error for each depth value is :  [0.42  0.298 0.28  0.289 0.294 0.29  0.28  0.27
3]
```




```
The optimal number of depth value is 9.
```

Testing the Decision tree model with optimal hyperparmeters

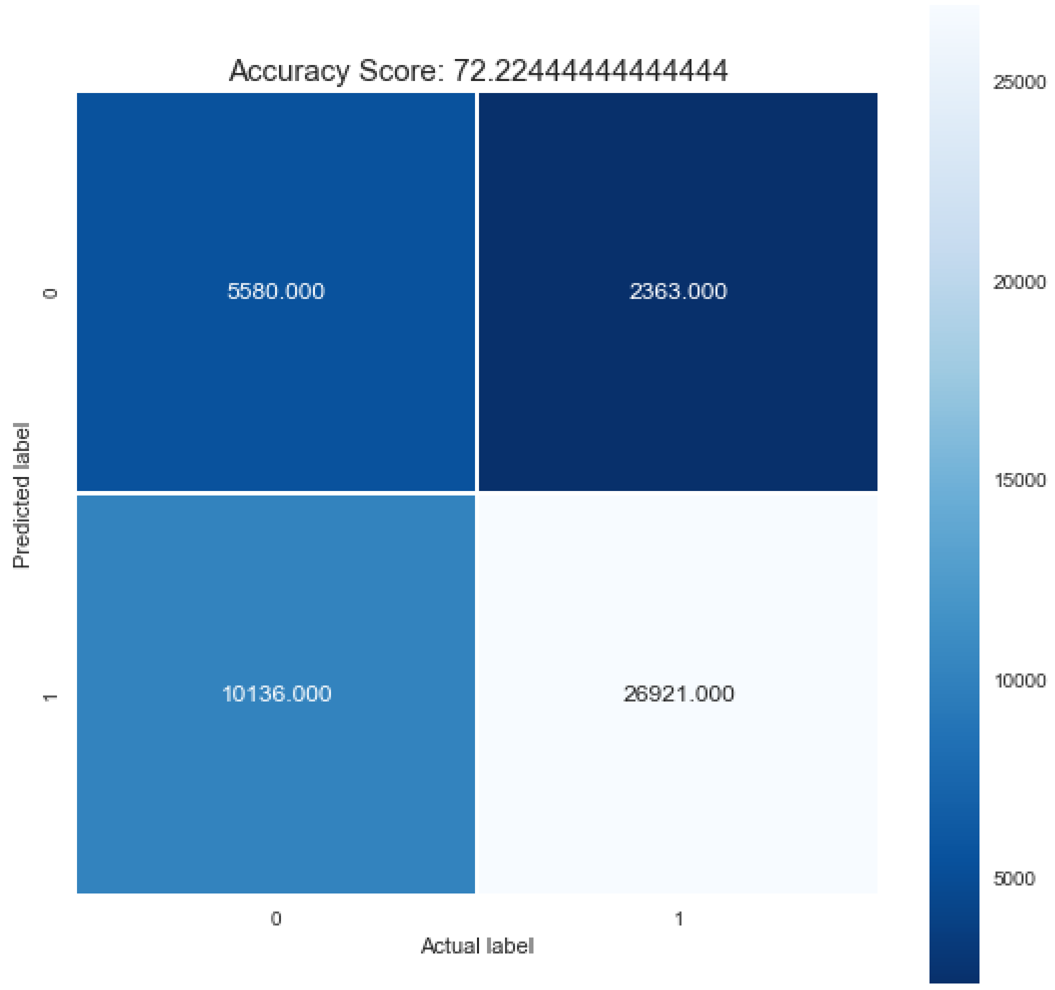
In [41]:
```
tfy_Predi,tfaccura=tuned_test(tfidf_tr,y_tr,tfidf_test,y_test,9)
```

```
The model score on train set is=  0.7780136054421769

The accuracy of Decision tree over test set is =  72%
```

Confusion matrix of the model

In [42]:
```
Confusion_metric(y_test,tfy_Predi,tfaccura)
```

```
[[ 5580  2363]
 [10136 26921]]
```



The performance metrics of the above model are as follows:	
Metrics	**Scores**
Classification_accuracy	72.22444444444444
Classification_error	27.775555555555552
True positive	26921
False positive	2363
True negative	5580
False negative	10136
True positive rate	72.64754297433683
False negative rate	27.352457025663167
True negative rate	70.25053506231902
False positive rate	29.749464937680976
Precision value	91.93074716568775
Recall value	72.64754297433683
f1_score value	81.15946398154986

Observations

- The Test accuracy of the model is 72.22% which is low than previous Avg-w2v-model but it is sensible as the diagonal element values are quite high as compared to other elements.
- The False positive and the negative rates are 29% and 27% which is considerable and the main reason of decreasing the accuracy so here the model is little overfitting.
- The model here is doing quite a good job in classiffying the model properly as compared to the previous vectorizers.
- So by Observing the the confusion matrix and the performance of the above model I can conclude that the model is quite stable and sensible in classifying the reviews properly.

Conclusion

In [52]:
```
conclusion_table()
```

The comparisons of all the vectorizers are as follows:			
Vectorizer	**Algorithm**	**Scores**	**Status**
Bag-Of-Words	Decision-Tree-Classiffier	73.41777777777779	Overfitt
Tf-IDF	Decision-Tree-Classiffier	69.96444444444444	Overfitt
Average-word2vec	Decision-Tree-Classiffier	74.06	Overfitt
TF-IDF-Weighted-word2vec	Decision-Tree-Classiffier	72.22444444444444	Overfitt

- From the above comparison table I can conclude that Decision tree Classiffier easily overfitts in text data because of increased depth value even after tuning the hyperparameters.

- The Average word2vec vectorizer gave the best accuracy as compared to the other vectorizers.
- Decsion tree classiffier is not the goto model if the data is text or a high dimensional data.

In [ ]:
```

```