Amazon Fine Food Reviews Analysis

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

EDA: https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/ (https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/)

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454
Number of users: 256,059
Number of products: 74,258
Timespan: Oct 1999 - Oct 2012
Number of Attributes/Columns in data: 10

Attribute Information:

1. Id
2. ProductId - unique identifier for the product
3. UserId - unqiue identifier for the user
4. ProfileName
5. HelpfulnessNumerator - number of users who found the review helpful
6. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
7. Score - rating between 1 and 5
8. Time - timestamp for the review
9. Summary - brief summary of the review
10. Text - text of the review

Objective:

Given a review, determine whether the review is positive (rating of 4 or 5) or negative (rating of 1 or 2).

[Q] How to determine if a review is positive or negative?

[Ans] We could use Score/Rating. A rating of 4 or 5 can be cosnidered as a positive review. A rating of 1 or 2 can be considered as negative one. A review of rating 3 is considered nuetral and such reviews are ignored from our analysis. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

[1]. Reading Data

[1.1] Loading the data

The dataset is available in two forms

1. .csv file
2. SQLite Database

In order to load the data, We have used the SQLITE dataset as it is easier to query the data and visualise the data efficiently.

Here as we only want to get the global sentiment of the recommendations (positive or negative), we will purposefully ignore all Scores equal to 3. If the score is above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

In [67]:

```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer

import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle
from sklearn.model_selection import train_test_split

from tqdm import tqdm
import os
```

In [7]:

```
# using SQLite Table to read data.
con = sqlite3.connect('database.sqlite')

# filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
# SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000, will give top 500000 data
 points
# you can change the number to any other number based on your computing power

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

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIM
IT 25000""", con)

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a n
egative rating(0).
def partition(x):
    if x < 3:
        return 0
    return 1

#changing reviews with score less than 3 to be positive and vice-versa
actualScore = filtered_data['Score']
positiveNegative = actualScore.map(partition)
filtered_data['Score'] = positiveNegative
print("Number of data points in our data", filtered_data.shape)
filtered_data.head(3)
```

```
Number of data points in our data (25000, 10)
```

Out[7]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDer
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	

In [8]:

```
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
""", con)
```

In [9]:

```
print(display.shape)
display.head()
```

```
(80668, 7)
```

Out[9]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUN
0	#oc-R115TNMSPFT9I7	B007Y59HVM	Breyton	1331510400	2	Overall its just OK when considering the price...	
1	#oc-R11D9D7SHXIJB9	B005HG9ET0	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	
2	#oc-R11DNU2NBKQ23Z	B007Y59HVM	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	
3	#oc-R11O5J5ZVQE25C	B005HG9ET0	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	
4	#oc-R12KPBODL2B5ZD	B007OSBE1U	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	

In [10]:

```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[10]:

	UserId	ProductId	ProfileName	Time	Score	Text	C
80638	AZY10LLTJ71NX	B006P7E5ZI	undertheshrine "undertheshrine"	1334707200	5	I was recommended to try green tea extract to ...	

In [11]:

```
display['COUNT(*)'].sum()
```

Out[11]:

```
393063
```

[2] Exploratory Data Analysis

[2.1] Data Cleaning: Deduplication

It is observed (as shown in the table below) that the reviews data had many duplicate entries. Hence it was necessary to remove duplicates in order to get unbiased results for the analysis of the data. Following is an example:

In [12]:

```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[12]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulnes
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	

As it can be seen above that same user has multiple reviews with same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that

ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8)

ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

It was inferred after analysis that reviews with same parameters other than ProductId belonged to the same product just having different flavour or quantity. Hence in order to reduce redundancy it was decided to eliminate the rows having same parameters.

The method used for the same was that we first sort the data according to ProductId and then just keep the first similar product review and delelte the others. for eg. in the above just the review for ProductId=B000HDL1RQ remains. This method ensures that there is only one representative for each product and deduplication without sorting would lead to possibility of different representatives still existing for the same product.

In [13]:

```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inpla
ce=False, kind='quicksort', na_position='last')
```

In [14]:

```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"},
 keep='first', inplace=False)
final.shape
```

Out[14]:

```
(23953, 10)
```

In [15]:

```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[15]:

```
95.812
```

Observation:- It was also seen that in two rows given below the value of HelpfulnessNumerator is greater than HelpfulnessDenominator which is not practically possible hence these two rows too are removed from calcualtions

In [16]:

```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[16]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessD
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	

In [17]:

```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [18]:

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

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

```
(23953, 10)
```

Out[18]:

```
1    20071
0     3882
Name: Score, dtype: int64
```

[3] Preprocessing

[3.1]. Preprocessing Review Text

Now that we have finished deduplication our data requires some preprocessing before we go on further with analysis and making the prediction model.

Hence in the Preprocessing phase we do the following in the order below:-

1. Begin by removing the html tags
2. Remove any punctuations or limited set of special characters like , or . or # etc.
3. Check if the word is made up of english letters and is not alpha-numeric
4. Check to see if the length of the word is greater than 2 (as it was researched that there is no adjective in 2-letters)
5. Convert the word to lowercase
6. Remove Stopwords
7. Finally Snowball Stemming the word (it was obsereved to be better than Porter Stemming)

After which we collect the words used to describe positive and negative reviews

In [19]:

```
# printing some random reviews
sent_0 = final['Text'].values[0]
print(sent_0)
print("="*50)

sent_1000 = final['Text'].values[1000]
print(sent_1000)
print("="*50)

sent_1500 = final['Text'].values[1500]
print(sent_1500)
print("="*50)

sent_4900 = final['Text'].values[4900]
print(sent_4900)
print("="*50)
```

```
My dogs loves this chicken but its a product from China, so we wont
be buying it anymore.  Its very hard to find any chicken products ma
de in the USA but they are out there, but this one isnt.  Its too ba
d too because its a good product but I wont take any chances till th
ey know what is going on with the china imports.
==================================================
I drink a lot of tea and this was a nice tea for a change. Lightly f
lavored and quite tasty.
==================================================
The bread has a good taste but does not rise properly and only makes
1/2 loaf.  I checked the temp of the water as suggested with bad res
ults.  After raising the temp to 100 degrees I got it to rise to 3/4
loaf.  Pretty expensive for the quality and I won't buy again.
==================================================
Dog broke the hard plastic the first day by slamming it around by th
e rope so we have to tape it up everytime we refill. Dog does enjoy,
carries it around wanting to play fetch but settles on tug a war. It
does keep him occupied trying to get the food out. Container needs t
o be made of different material to prevent breakage but still worth
the money for the enjoyment it has given him.
==================================================
```

In [20]:

```
# remove urls from text python: https://stackoverflow.com/a/40823105/4084039
sent_0 = re.sub(r"http\S+", "", sent_0)
sent_1000 = re.sub(r"http\S+", "", sent_1000)
sent_150 = re.sub(r"http\S+", "", sent_1500)
sent_4900 = re.sub(r"http\S+", "", sent_4900)

print(sent_0)
```

```
My dogs loves this chicken but its a product from China, so we wont
be buying it anymore.  Its very hard to find any chicken products ma
de in the USA but they are out there, but this one isnt.  Its too ba
d too because its a good product but I wont take any chances till th
ey know what is going on with the china imports.
```

In [21]:

```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remov
e-all-tags-from-an-element
from bs4 import BeautifulSoup

soup = BeautifulSoup(sent_0, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1000, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1500, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_4900, 'lxml')
text = soup.get_text()
print(text)
```

```
My dogs loves this chicken but its a product from China, so we wont
be buying it anymore.  Its very hard to find any chicken products ma
de in the USA but they are out there, but this one isnt.  Its too ba
d too because its a good product but I wont take any chances till th
ey know what is going on with the china imports.
==================================================
I drink a lot of tea and this was a nice tea for a change. Lightly f
lavored and quite tasty.
==================================================
The bread has a good taste but does not rise properly and only makes
1/2 loaf.  I checked the temp of the water as suggested with bad res
ults.  After raising the temp to 100 degrees I got it to rise to 3/4
loaf.  Pretty expensive for the quality and I won't buy again.
==================================================
Dog broke the hard plastic the first day by slamming it around by th
e rope so we have to tape it up everytime we refill. Dog does enjoy,
carries it around wanting to play fetch but settles on tug a war. It
does keep him occupied trying to get the food out. Container needs t
o be made of different material to prevent breakage but still worth
the money for the enjoyment it has given him.
```

In [22]:

```
# https://stackoverflow.com/a/47091490/4084039
import re

def decontracted(phrase):
    # specific
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)

    # general
    phrase = re.sub(r"n\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase
```

In [23]:

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

```
The bread has a good taste but does not rise properly and only makes
1/2 loaf.  I checked the temp of the water as suggested with bad res
ults.  After raising the temp to 100 degrees I got it to rise to 3/4
loaf.  Pretty expensive for the quality and I will not buy again.
==================================================
```

In [24]:

```
#remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
My dogs loves this chicken but its a product from China, so we wont
be buying it anymore.  Its very hard to find any chicken products ma
de in the USA but they are out there, but this one isnt.  Its too ba
d too because its a good product but I wont take any chances till th
ey know what is going on with the china imports.
```

In [25]:

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

```
The bread has a good taste but does not rise properly and only makes
1 2 loaf I checked the temp of the water as suggested with bad resul
ts After raising the temp to 100 degrees I got it to rise to 3 4 loa
f Pretty expensive for the quality and I will not buy again
```

In [26]:

```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
# <br /><br /> ==> after the above steps, we are getting "br br"
# we are including them into stop words list
# instead of <br /> if we have <br/> these tags would have revmoved in the 1st s
tep

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ou
rselves', 'you', "you're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he',
'him', 'his', 'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itse
lf', 'they', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'tha
t', "that'll", 'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'ha
s', 'had', 'having', 'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'becaus
e', 'as', 'until', 'while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 't
hrough', 'during', 'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'of
f', 'over', 'under', 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'al
l', 'any', 'both', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than'
, 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should'v
e", 'now', 'd', 'll', 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "d
idn't", 'doesn', "doesn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma'
, 'mightn', "mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "should
n't", 'wasn', "wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

In [27]:

```
# Combining all the above stundents
from tqdm import tqdm
preprocessed_reviews = []
# tqdm is for printing the status bar
for sentance in tqdm(final['Text'].values):
    sentance = re.sub(r"http\S+", "", sentance)
    sentance = BeautifulSoup(sentance, 'lxml').get_text()
    sentance = decontracted(sentance)
    sentance = re.sub("\S*\d\S*", "", sentance).strip()
    sentance = re.sub('[^A-Za-z]+', ' ', sentance)
    # https://gist.github.com/sebleier/554280
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in
stopwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|██████████| 23953/23953 [00:08<00:00, 2674.80it/s]
```

In [28]:

```
preprocessed_reviews[1500]
```

Out[28]:

```
'bread good taste not rise properly makes loaf checked temp water su
ggested bad results raising temp degrees got rise loaf pretty expens
ive quality not buy'
```

In [29]:

```
len(preprocessed_reviews)
```

Out[29]:

```
23953
```

In [30]:

```
final.shape
```

Out[30]:

```
(23953, 10)
```

In [31]:

```
final['Text'] = preprocessed_reviews
```

[3.2] Preprocessing Review Summary

In [32]:

```
## Similartly you can do preprocessing for review summary also.
```

In [33]:

```
#soring the values based on time stamp
final.sort_values('Time', axis=0, ascending=True, inplace=True, kind='quicksort'
, na_position='last')
final = final.drop(['ProductId','Id','UserId','ProfileName','HelpfulnessNumerato
r','HelpfulnessDenominator','Time','Summary'],axis=1)
```

In [34]:

```
final.columns
```

Out[34]:

```
Index(['Score', 'Text'], dtype='object')
```

In [35]:

```
y = final['Score']
text = final['Text']
```

In [ ]:

```
y = final['Score']
text = final['Text']
```

In [36]:

```
text.shape
```

Out[36]:

```
(23953,)
```

In [37]:

```
# X_train_1, test_df_1, y_train_1, y_test_1 = train_test_split(final, y, stratif
y=y, test_size=0.7)
# print(X_train_1.shape)
# print(y_train_1.shape)

X_train, test_df, y_train, y_test = train_test_split(text, y, stratify=y, test_s
ize=0.2)
train_df, cv_df, y, y_cv = train_test_split(X_train, y_train, stratify=y_train,
test_size=0.2)

print(train_df.shape)
print(y.shape)
print(cv_df.shape)
print(y_cv.shape)
```

```
(15329,)
(15329,)
(3833,)
(3833,)
```

In [38]:

```
y_train.shape
```

Out[38]:

```
(19162,)
```

In [39]:

```
print(np.unique(y_train))
print(np.unique(y_test))
print(np.unique(y_cv))
```

```
[0 1]
[0 1]
[0 1]
```

In [40]:

```
def do_pickling(filename,data):
    pickling_on= open(filename,"wb")
    pickle.dump(data,pickling_on)
```

In [243]:

```
do_pickling('y_trains.pickle',y)
do_pickling('y_tests.pickle',y_test)
do_pickling('y_cvs.pickle',y_cv)
```

In [41]:

```
do_pickling('y_train_rbf.pickle',y)
do_pickling('y_test_rbf.pickle',y_test)
do_pickling('y_cv_rbf.pickle',y_cv)
```

[4] Featurization

[4.1] BAG OF WORDS

In [72]:

```
#BoW
count_vect = CountVectorizer() #in scikit-learn
count_vect.fit(preprocessed_reviews)
print("some feature names ", count_vect.get_feature_names()[:10])
print('='*50)

final_counts = count_vect.transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_counts))
print("the shape of out text BOW vectorizer ",final_counts.get_shape())
print("the number of unique words ", final_counts.get_shape()[1])
```

```
some feature names  ['aa', 'aaa', 'aaaa', 'aaaaa', 'aaaaaaaaaaaa', 
'aaaaaaaaaaaaaaa', 'aaaaaaahhhhhh', 'aaaaaaarrrrrggghhh', 'aaaaaawww
wwwwwww', 'aaaaah']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (87773, 54904)
the number of unique words  54904
```

In [42]:

```
count_vect = CountVectorizer(ngram_range=(1,3),min_df=10)
bow_feature_train = count_vect.fit_transform(train_df)
bow_feature_test = count_vect.transform(test_df)
bow_feature_cv = count_vect.transform(cv_df)
```

In [43]:

```
bow_feature_train.shape
```

Out[43]:

```
(15329, 9749)
```

In [95]:

```
do_pickling('bow_trains.pickle',bow_feature_train)
do_pickling('bow_tests.pickle',bow_feature_test)
do_pickling('bow_cvs.pickle',bow_feature_cv)
do_pickling('count_vects.pickle',count_vect)
```

In [44]:

```
count_vect = CountVectorizer(ngram_range=(1,3),min_df=10,max_features=500)
bow_feature_train = count_vect.fit_transform(train_df)
bow_feature_test = count_vect.transform(test_df)
bow_feature_cv = count_vect.transform(cv_df)
```

In [45]:

```
do_pickling('bow_train_rbf.pickle',bow_feature_train)
do_pickling('bow_test_rbf.pickle',bow_feature_test)
do_pickling('bow_cv_rbf.pickle',bow_feature_cv)
do_pickling('count_vect_rbf.pickle',count_vect)
```

[4.2] Bi-Grams and n-Grams.

In [26]:

```
#bi-gram, tri-gram and n-gram

#removing stop words like "not" should be avoided before building n-grams
# count_vect = CountVectorizer(ngram_range=(1,2))
# please do read the CountVectorizer documentation http://scikit-learn.org/stabl
e/modules/generated/sklearn.feature_extraction.text.CountVectorizer.html

# you can choose these numebrs min_df=10, max_features=5000, of your choice
count_vect = CountVectorizer(ngram_range=(1,2), min_df=10, max_features=5000)
final_bigram_counts = count_vect.fit_transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_bigram_counts))
print("the shape of out text BOW vectorizer ",final_bigram_counts.get_shape())
print("the number of unique words including both unigrams and bigrams ", final_b
igram_counts.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (4986, 3144)
the number of unique words including both unigrams and bigrams  3144
```

[4.3] TF-IDF

In [111]:

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tf_idf_vect.fit(preprocessed_reviews)
print("some sample features(unique words in the corpus)",tf_idf_vect.get_feature
_names()[0:10])
print('='*50)

final_tf_idf = tf_idf_vect.transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_tf_idf))
print("the shape of out text TFIDF vectorizer ",final_tf_idf.get_shape())
print("the number of unique words including both unigrams and bigrams ", final_t
f_idf.get_shape()[1])
```

```
some sample features(unique words in the corpus) ['aa', 'aafco', 'ab
ack', 'abandon', 'abandoned', 'abdominal', 'ability', 'able', 'able
add', 'able brew']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (87773, 51709)
the number of unique words including both unigrams and bigrams  5170
9
```

In [112]:

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,3))
tf_idf_train = tf_idf_vect.fit_transform(train_df)
tf_idf_test = tf_idf_vect.transform(test_df)
tf_idf_cv = tf_idf_vect.transform(cv_df)
```

In [113]:

```
do_pickling('tfidf_train_li.pickle',tf_idf_train)
do_pickling('tfidf_test_li.pickle',tf_idf_test)
do_pickling('tfidf_cv_li.pickle',tf_idf_cv)
do_pickling('tf_idf_vect_li.pickle',tf_idf_vect)
```

In [46]:

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,3),min_df=10, max_features=500)
tf_idf_train = tf_idf_vect.fit_transform(train_df)
tf_idf_test = tf_idf_vect.transform(test_df)
tf_idf_cv = tf_idf_vect.transform(cv_df)
```

In [47]:

```
do_pickling('tfidf_train_rbf.pickle',tf_idf_train)
do_pickling('tfidf_test_rbf.pickle',tf_idf_test)
do_pickling('tfidf_cv_rbf.pickle',tf_idf_cv)
do_pickling('tf_idf_vect_rbf.pickle',tf_idf_vect)
```

[4.4] Word2Vec

In [48]:

```
# Train your own Word2Vec model using your own text corpus
i=0
list_of_sentance=[]
for sentance in preprocessed_reviews:
    list_of_sentance.append(sentance.split())
```

In [49]:

```
# Using Google News Word2Vectors

# in this project we are using a pretrained model by google
# its 3.3G file, once you load this into your memory
# it occupies ~9Gb, so please do this step only if you have >12G of ram
# we will provide a pickle file wich contains a dict ,
# and it contains all our courpus words as keys and  model[word] as values
# To use this code-snippet, download "GoogleNews-vectors-negative300.bin"
# from https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/edit
# it's 1.9GB in size.


# http://kavita-ganesan.com/gensim-word2vec-tutorial-starter-code/#.W17SRFAzZPY
# you can comment this whole cell
# or change these varible according to your need

is_your_ram_gt_16g=False
want_to_use_google_w2v = False
want_to_train_w2v = True

if want_to_train_w2v:
    # min_count = 5 considers only words that occured atleast 5 times
    w2v_model=Word2Vec(list_of_sentance,min_count=5,size=50, workers=4)
    print(w2v_model.wv.most_similar('great'))
    print('='*50)
    print(w2v_model.wv.most_similar('worst'))

elif want_to_use_google_w2v and is_your_ram_gt_16g:
    if os.path.isfile('GoogleNews-vectors-negative300.bin'):
        w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors-negative
300.bin', binary=True)
        print(w2v_model.wv.most_similar('great'))
        print(w2v_model.wv.most_similar('worst'))
    else:
        print("you don't have gogole's word2vec file, keep want_to_train_w2v = T
rue, to train your own w2v ")
```

```
WARNING:gensim.models.base_any2vec:consider setting layer size to a
multiple of 4 for greater performance

[('awesome', 0.8231269121170044), ('good', 0.8118637800216675), ('fa
ntastic', 0.7989206314086914), ('excellent', 0.7700639367103577),
('amazing', 0.7663317918777466), ('wonderful', 0.7623875141143799),
('perfect', 0.7306408286094666), ('decent', 0.694785475730896), ('te
rrific', 0.6767959594726562), ('delicious', 0.660306453704834)]
==================================================
[('closest', 0.7931296229362488), ('best', 0.7592700123786926), ('aw
ful', 0.7537202835083008), ('ever', 0.744742751121521), ('horrible',
0.7377067804336548), ('horrendous', 0.7309278845787048), ('persona
l', 0.7225382328033447), ('greatest', 0.7171108722686768), ('terribl
e', 0.7056512832641602), ('worse', 0.7049030065536499)]
```

In [50]:

```
w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])
```

```
number of words that occured minimum 5 times  9295
sample words  ['dogs', 'loves', 'chicken', 'product', 'china', 'won
t', 'buying', 'anymore', 'hard', 'find', 'products', 'made', 'usa',
'one', 'isnt', 'bad', 'good', 'take', 'chances', 'till', 'know', 'go
ing', 'imports', 'love', 'saw', 'pet', 'store', 'tag', 'attached',
'regarding', 'satisfied', 'safe', 'used', 'fly', 'bait', 'seasons',
'ca', 'not', 'beat', 'great', 'available', 'traps', 'unreal', 'cours
e', 'total', 'pretty', 'stinky', 'right', 'nearby', 'received']
```

[4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V

[4.4.1.1] Avg W2v

In [51]:

```
def getListOfSentences(values):
    list_of_sent=[]
    for sent in values:
        list_of_sent.append(sent.split())
    return list_of_sent
```

In [52]:

```
list_of_sent = getListOfSentences(train_df.values)
w2v_model=Word2Vec(list_of_sent,min_count=10,size=50, workers=4)
w2v_words = list(w2v_model.wv.vocab)
```

```
WARNING:gensim.models.base_any2vec:consider setting layer size to a
multiple of 4 for greater performance
```

In [53]:

```
def findAvgWord2Vec(list_of_sent):
    sent_vectors = []; # the avg-w2v for each sentence/review is stored in this
 list
    for sent in tqdm(list_of_sent): # for each review/sentence
        sent_vec = np.zeros(50) # as word vectors are of zero length
        cnt_words =0; # num of words with a valid vector in the sentence/review
        for word in sent: # for each word in a review/sentence
            if word in w2v_words:
                vec = w2v_model.wv[word]
                sent_vec += vec
                cnt_words += 1
        if cnt_words != 0:
            sent_vec /= cnt_words
        sent_vectors.append(sent_vec)
    return sent_vectors

sent_vectors = findAvgWord2Vec(list_of_sent)
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

```
100%|██████████| 15329/15329 [00:18<00:00, 817.01it/s]

15329
50
```

In [129]:

```
do_pickling('avg_w2v_train_li.pickle',sent_vectors)
```

In [54]:

```
do_pickling('avg_w2v_train_rbf.pickle',sent_vectors)
```

In [55]:

```
list_of_sent = getListOfSentences(test_df.values)
```

In [56]:

```
sent_vectors_test = findAvgWord2Vec(list_of_sent)
print(len(sent_vectors_test))
print(len(sent_vectors_test[0]))
```

```
100%|██████████| 4791/4791 [00:06<00:00, 778.02it/s]

4791
50
```

In [132]:

```
do_pickling('avg_w2v_test_li.pickle',sent_vectors_test)
```

In [57]:

```
do_pickling('avg_w2v_test_rbf.pickle',sent_vectors_test)
```

In [58]:

```
list_of_sent= getListOfSentences(cv_df.values)
sent_vectors_cv = findAvgWord2Vec(list_of_sent)
```

```
100%|██████████| 3833/3833 [00:05<00:00, 713.52it/s]
```

In [134]:

```
do_pickling('avg_w2v_cv_li.pickle',sent_vectors_cv)
```

In [59]:

```
do_pickling('avg_w2v_cv_rbf.pickle',sent_vectors_cv)
```

[4.4.1.2] TFIDF weighted W2v

In [60]:

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
tf_idf_matrix = model.fit_transform(train_df)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [61]:

```
list_of_sentance=[]
for sent in train_df.values:
    list_of_sentance.append(sent.split())
```

In [62]:

```
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val =
 tfidf

tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in t
his list
row=0;
for sent in tqdm(list_of_sentance): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors.append(sent_vec)
    row += 1
```

```
100%|██████████| 15329/15329 [03:05<00:00, 82.84it/s]
```

In [193]:

```
do_pickling('tfidf_w2v_train_li.pickle',tfidf_sent_vectors)
```

In [63]:

```
do_pickling('tfidf_w2v_train_rbf.pickle',tfidf_sent_vectors)
```

In [64]:

```
def findTfidfW2V(values):
    tf_idf_matrix = model.transform(values)
    # we are converting a dictionary with word as a key, and the idf as a value
    dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
    # TF-IDF weighted Word2Vec
    tfidf_feat = model.get_feature_names() # tfidf words/col-names
    # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_va
l = tfidf

    list_of_sent=[]
    for sent in values:
        list_of_sent.append(sent.split())

    tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored
 in this list
    row=0;
    for sent in tqdm(list_of_sent): # for each review/sentence
        sent_vec = np.zeros(50) # as word vectors are of zero length
        weight_sum =0; # num of words with a valid vector in the sentence/review
        for word in sent: # for each word in a review/sentence
            if word in w2v_words:
                if(len(word)!= 1):
                    vec = w2v_model.wv[word]
                    # tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
                    # to reduce the computation we are
                    # dictionary[word] = idf value of word in whole courpus
                    # sent.count(word) = tf valeus of word in this review
                    tf_idf = dictionary[word]*(sent.count(word)/len(sent))
                    sent_vec += (vec * tf_idf)
                    weight_sum += tf_idf
        if weight_sum != 0:
            sent_vec /= weight_sum
        tfidf_sent_vectors.append(sent_vec)
        row += 1
    return tfidf_sent_vectors
```

In [65]:

```
tfidf_sent_vectors_test = findTfidfW2V(test_df.values)
print(len(tfidf_sent_vectors_test))
```

```
100%|██████████| 4791/4791 [00:06<00:00, 758.39it/s]

4791
```

In [206]:

```
do_pickling('tfidf_w2v_test_li.pickle',tfidf_sent_vectors_test)
```

In [66]:

```
do_pickling('tfidf_w2v_test_rbf.pickle',tfidf_sent_vectors_test)
```

In [67]:

```
tfidf_sent_vectors_cv = findTfidfW2V(cv_df.values)
```

```
100%|██████████| 3833/3833 [00:06<00:00, 606.70it/s]
```

In [ ]:

```
do_pickling('tfidf_w2v_cv_li.pickle',tfidf_sent_vectors_cv)
```

In [68]:

```
do_pickling('tfidf_w2v_cv_rbf.pickle',tfidf_sent_vectors_cv)
```

[5] Assignment 7: SVM

1. **Apply SVM on these feature sets**

    - SET 1:Review text, preprocessed one converted into vectors using (BOW)
    - SET 2:Review text, preprocessed one converted into vectors using (TFIDF)
    - SET 3:Review text, preprocessed one converted into vectors using (AVG W2v)
    - SET 4:Review text, preprocessed one converted into vectors using (TFIDF W2v)

2. **Procedure**

    - You need to work with 2 versions of SVM
        - Linear kernel
        - RBF kernel
    - When you are working with linear kernel, use SGDClassifier' with hinge loss because it is computationally less expensive.
    - When you are working with 'SGDClassifier' with hinge loss and trying to find the AUC score, you would have to use CalibratedClassifierCV (https://scikit-learn.org/stable/modules/generated/sklearn.calibration.CalibratedClassifierCV.html)
    - Similarly, like kdtree of knn, when you are working with RBF kernel it's better to reduce the number of dimensions. You can put min_df = 10, max_features = 500 and consider a sample size of 40k points.

3. **Hyper paramter tuning (find best alpha in range [10^-4 to 10^4], and the best penalty among 'l1', 'l2')**

    - Find the best hyper parameter which will give the maximum AUC (https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/receiver-operating-characteristic-curve-roc-curve-and-auc-1/) value
    - Find the best hyper paramter using k-fold cross validation or simple cross validation data
    - Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this task of hyperparameter tuning

4. **Feature importance**

    - When you are working on the linear kernel with BOW or TFIDF please print the top 10 best features for each of the positive and negative classes.

5. **Feature engineering**

    - To increase the performance of your model, you can also experiment with with feature engineering like :
        - Taking length of reviews as another feature.
        - Considering some features from review summary as well.

6. **Representation of results**

    - You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure.
      Once after you found the best hyper parameter, you need to train your model with it, and find the AUC on test data and plot the ROC curve on both train and test.
      Along with plotting ROC curve, you need to print the confusion matrix (https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/confusion-matrix-tpr-fpr-fnr-tnr-1/) with predicted and original labels of test data points. Please visualize your confusion matrices using seaborn heatmaps.

(https://seaborn.pydata.org/generated/seaborn.heatmap.html)
(https://seaborn.pydata.org/generated/seaborn.heatmap.html)
(https://seaborn.pydata.org/generated/seaborn.heatmap.html)

(https://seaborn.pydata.org/generated/seaborn.heatmap.html)

7. **Conclusion** (https://seaborn.pydata.org/generated/seaborn.heatmap.html)

    (https://seaborn.pydata.org/generated/seaborn.heatmap.html)

    - You need to summarize the results at the end of the notebook, summarize it in the table format. To print out a table please refer to this prettytable library (https://seaborn.pydata.org/generated/seaborn.heatmap.html) link (http://zetcode.com/python/prettytable/)

Note: Data Leakage

1. There will be an issue of data-leakage if you vectorize the entire data and then split it into train/cv/test.
2. To avoid the issue of data-leakag, make sure to split your data first and then vectorize it.
3. While vectorizing your data, apply the method fit_transform() on you train data, and apply the method transform() on cv/test data.
4. For more details please go through this link. (https://soundcloud.com/applied-ai-course/leakage-bow-and-tfidf)

Applying SVM

In [13]:

```
import warnings
warnings.filterwarnings("ignore")
import sqlite3
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import pickle
import seaborn as sns

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import cross_val_score
from sklearn.preprocessing import label_binarize

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.metrics import roc_auc_score
from sklearn.linear_model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV
from sklearn.svm import SVC
from sklearn.decomposition import TruncatedSVD
```

In [ ]:

```
# function to load the pickle data
def loadPickleData(filename):
    with open(filename, "rb") as f:
        final = pickle.load(f)
    return final
```

In [ ]:

```
# load the y values because they are common across all feature engineering
y_train = loadPickleData('y_trains.pickle')
y_test = loadPickleData('y_tests.pickle')
y_cv = loadPickleData('y_cvs.pickle')
```

In [16]:

```
# encoded_column_vector = label_binarize(y_train, classes=['negative','positiv
e']) # ham will be 0 and spam will be 1
# y_train = np.ravel(encoded_column_vector)

# encoded_column_vector = label_binarize(y_test, classes=['negative','positiv
e']) # ham will be 0 and spam will be 1
# y_test = np.ravel(encoded_column_vector)

# encoded_column = label_binarize(y_cv, classes=['negative','positive']) # ham w
ill be 0 and spam will be 1
# y_cv = np.ravel(encoded_column)
```

In [17]:

```
# This function plots the confusion matrices given y_i, y_i_hat.
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)
    labels = [0,1]
    # representing A in heatmap format
    print("-"*20, "Confusion matrix", "-"*20)
    plt.figure(figsize=(20,7))
    sns.heatmap(C, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, yti
cklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
```

In [18]:

```
def drawplots(alpha,auc_array,auc_array_train):
    fig, ax = plt.subplots(2,1,figsize=(10,10))
    a = np.arange(len(alpha))
    l1 = [x for i,x in enumerate(auc_array) if i %2 ==0]
    l2 = [x for i,x in enumerate(auc_array) if i %2 !=0]
    l1_train = [x for i,x in enumerate(auc_array_train) if i %2 ==0]
    l2_train= [x for i,x in enumerate(auc_array) if i %2 !=0]

    ax[0].plot(a, l1,c='g',label="cv")
    for i, txt in enumerate(np.round(l1,3)):
        ax[0].annotate((a[i],str(txt)), (a[i],l1[i]))

    ax[0].plot(a, l1_train,c='r',label="train")
    for i, txt in enumerate(np.round(l1_train,3)):
        ax[0].annotate((a[i],str(txt)), (a[i],l1_train[i]),(a[i],l1_train[i]))

    ax[0].set_xticks(a)
    ax[0].set_xticklabels(alpha)
    plt.grid()
    ax[0].set_title("Cross Validation Error for each alpha - L1 ")
    ax[0].set_xlabel("Alpha i's")
    ax[0].set_ylabel("Error measure")

    ax[1].plot(a, l1,c='g',label="cv")
    for i, txt in enumerate(np.round(l1,3)):
        ax[1].annotate((a[i],str(txt)), (a[i],l1[i]))

    ax[1].plot(a, l1_train,c='r',label="train")
    for i, txt in enumerate(np.round(l1_train,3)):
        ax[1].annotate((a[i],str(txt)), (a[i],l1_train[i]),(a[i],l1_train[i]))

    ax[1].set_xticks(a)
    ax[1].set_xticklabels(alpha)
    plt.grid()
    ax[1].set_title("Cross Validation Error for each alpha - L2 ")
    ax[1].set_xlabel("Alpha i's")
    ax[1].set_ylabel("Error measure")

    plt.legend(loc='best')
    plt.show()
```

In [57]:

```
def plotAUC(train_fpr,train_tpr,test_fpr,test_tpr):
    fig, ax = plt.subplots(figsize=(10,10))
    ax.plot(train_fpr, train_tpr,c='g',label="cv")
    ax.plot(test_fpr, test_tpr,c='r',label="train")

    plt.grid()
    ax.set_title("ROC Curve")
    ax.set_xlabel("FPR")
    ax.set_ylabel("TPR")
```

In [20]:

```
def getImportantFeatures(indices,feature_names):
    words =[]
    for x in indices:
        words.append(feature_names[x])
    return words
```

[5.1] Linear SVM

In [80]:

```
def calculateMetricC(X,y,alpha,train,y_train):
    auc_array = []
    reg = ['l1','l2']
    for i in alpha:
        for r in reg:
            print("for alpha = {} and regularizer = {}".format(i,r))
            clf = SGDClassifier(class_weight='balanced', alpha=i, penalty=r, los
s='hinge', random_state=42)
            clf.fit(train, y_train)
            sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
            sig_clf.fit(train, y_train)
            pred = sig_clf.predict(X)
            area = roc_auc_score(y, pred)
            auc_array.append(area)
            print("Area:",area)
    return auc_array
```

In [81]:

```
def performHyperParameterTuningSGD(train,cv,test):
    alpha = [10 ** x for x in range(-4, 4)]
    reg =['l1','l2']
    auc_array = []
    auc_array = calculateMetricC(cv,y_cv,alpha,train,y_train)
    auc_array_train = calculateMetricC(train,y_train,alpha,train,y_train)
    drawplots(alpha,auc_array,auc_array_train)
    best_alpha = np.argmax(auc_array)
    best_a = alpha[int(best_alpha/2)]
    best_r = reg[int(best_alpha%2)]
    print("best alph = {} and regularizer = {}".format(best_a,best_r))
    return (best_a,best_r)
#     clf = SGDClassifier(class_weight='balanced', alpha=best_a, penalty=best_r,
 loss='hinge', random_state=42)
#     clf.fit(train, y_train)
#     sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
#     sig_clf.fit(train, y_train)

#     predict_y = sig_clf.predict(train)
#     plot_confusion_matrix(y_train,predict_y)
#     print('For values of best alpha = ', alpha[int(best_alpha/2)], "The AUC i
s:",roc_auc_score(y_train, predict_y))
#     predict_y = sig_clf.predict(cv)
#     print('For values of best alpha = ', alpha[int(best_alpha/2)], "The cross
 validation fpr is:",roc_auc_score(y_cv, predict_y))
#     predict_y = sig_clf.predict(test)
#     plot_confusion_matrix(y_test,predict_y)
#     print('For values of best alpha = ', alpha[int(best_alpha/2)], "The test f
pr is:",roc_auc_score(y_test, predict_y))
#     return clf,alpha[best_alpha]
```

In [82]:

```
def bestModel(train,cv,test,best_alpha,best_reg):
    clf = SGDClassifier(class_weight='balanced', alpha=best_alpha, penalty=best_
reg, loss='hinge', random_state=42)
    clf.fit(train, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(train, y_train)

    predict_y = sig_clf.predict(train)
    plot_confusion_matrix(y_train,predict_y)
    train_fpr,train_tpr , train_thresholds = roc_curve(y_train, predict_y)
    print('For values of best alpha = ',best_alpha, "The AUC is:",roc_auc_score(
y_train, predict_y))
    predict_y = sig_clf.predict(cv)
    print('For values of best alpha = ',best_alpha, "The AUC is:",roc_auc_score(
y_cv, predict_y))
    predict_y = sig_clf.predict(test)
    plot_confusion_matrix(y_test,predict_y)
    test_fpr,test_tpr ,train_thresholds = roc_curve(y_test, predict_y)
    print('For values of best alpha = ',best_alpha, "The AUC is:",roc_auc_score(
y_test, predict_y))
    plotAUC(train_fpr,train_tpr,test_fpr,test_tpr)
    return clf
```

[5.1.1] Applying Linear SVM on BOW, SET 1

In [96]:

```
count_vect = loadPickleData('count_vects.pickle')
train = loadPickleData("bow_trains.pickle")
test = loadPickleData('bow_tests.pickle')
cv = loadPickleData('bow_cvs.pickle')
```

In [97]:

```
train.shape
```

Out[97]:

```
(56174, 36451)
```

In [98]:

```
np.unique(y_train)
```

Out[98]:

```
array([0, 1])
```

In [108]:

```
y_train.shape
```

Out[108]:

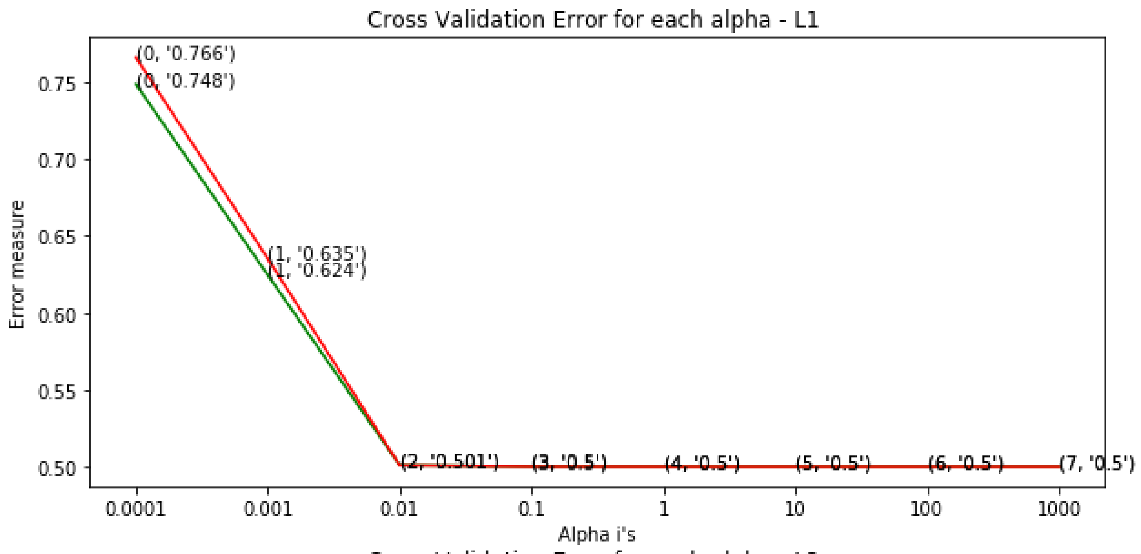
```
(56174,)
```

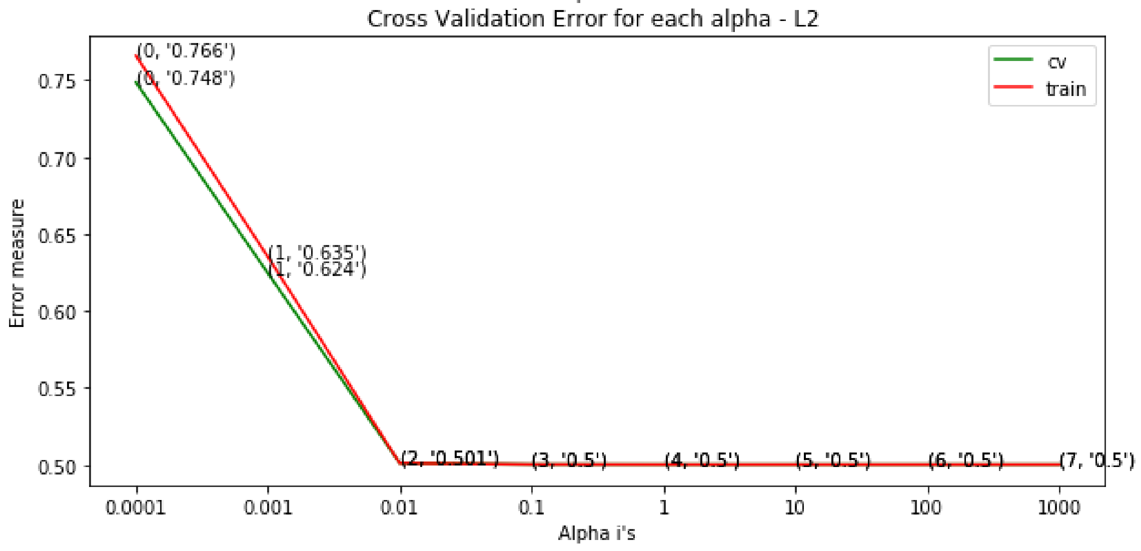
In [114]:

```
best_alpha,best_reg = performHyperParameterTuningSGD(train,cv,test)
```

```
for alpha = 0.0001 and regularizer = l1
Area: 0.7484121721831872
for alpha = 0.0001 and regularizer = l2
Area: 0.7916132793237385
for alpha = 0.001 and regularizer = l1
Area: 0.6244161733097907
for alpha = 0.001 and regularizer = l2
Area: 0.818126843947641
for alpha = 0.01 and regularizer = l1
Area: 0.500982465596019
for alpha = 0.01 and regularizer = l2
Area: 0.785371241107178
for alpha = 0.1 and regularizer = l1
Area: 0.5000585571802725
for alpha = 0.1 and regularizer = l2
Area: 0.6756612292142128
for alpha = 1 and regularizer = l1
Area: 0.5
for alpha = 1 and regularizer = l2
Area: 0.5562686780842875
for alpha = 10 and regularizer = l1
Area: 0.5
for alpha = 10 and regularizer = l2
Area: 0.5166733196157197
for alpha = 100 and regularizer = l1
Area: 0.5
for alpha = 100 and regularizer = l2
Area: 0.5166733196157197
for alpha = 1000 and regularizer = l1
Area: 0.5
for alpha = 1000 and regularizer = l2
Area: 0.5166733196157197
for alpha = 0.0001 and regularizer = l1
Area: 0.7657829554725131
for alpha = 0.0001 and regularizer = l2
Area: 0.8664085632349237
for alpha = 0.001 and regularizer = l1
Area: 0.6350520784274327
for alpha = 0.001 and regularizer = l2
Area: 0.8867097203114326
for alpha = 0.01 and regularizer = l1
Area: 0.5008874741845726
for alpha = 0.01 and regularizer = l2
Area: 0.8186299223877611
for alpha = 0.1 and regularizer = l1
Area: 0.5000757541999437
for alpha = 0.1 and regularizer = l2
Area: 0.6855931040592927
for alpha = 1 and regularizer = l1
Area: 0.5
for alpha = 1 and regularizer = l2
Area: 0.5500839621916033
for alpha = 10 and regularizer = l1
Area: 0.5
for alpha = 10 and regularizer = l2
Area: 0.516306029543979
for alpha = 100 and regularizer = l1
Area: 0.5
for alpha = 100 and regularizer = l2
Area: 0.51636111989215
for alpha = 1000 and regularizer = l1
```

```
Area: 0.5
for alpha = 1000 and regularizer = l2
Area: 0.51636111989215
```



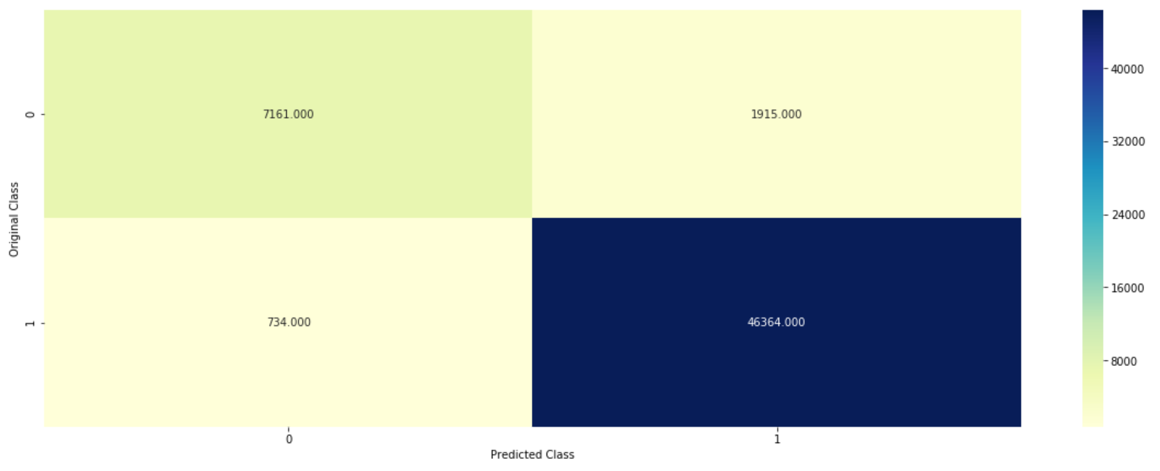


```
best alph = 0.001 and regularizer = l2
```

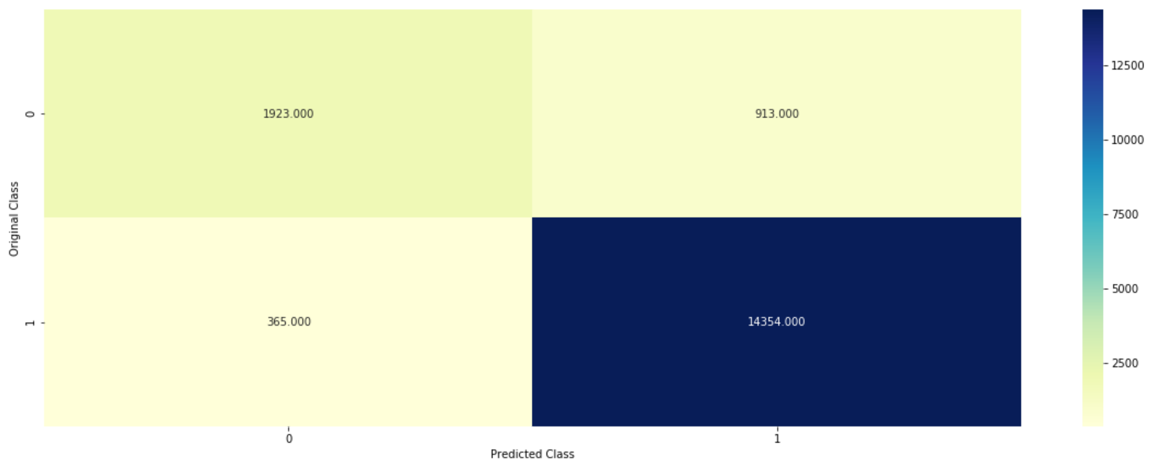
In [110]:

```
clf = bestModel(train,cv,test,best_alpha,best_reg)
```

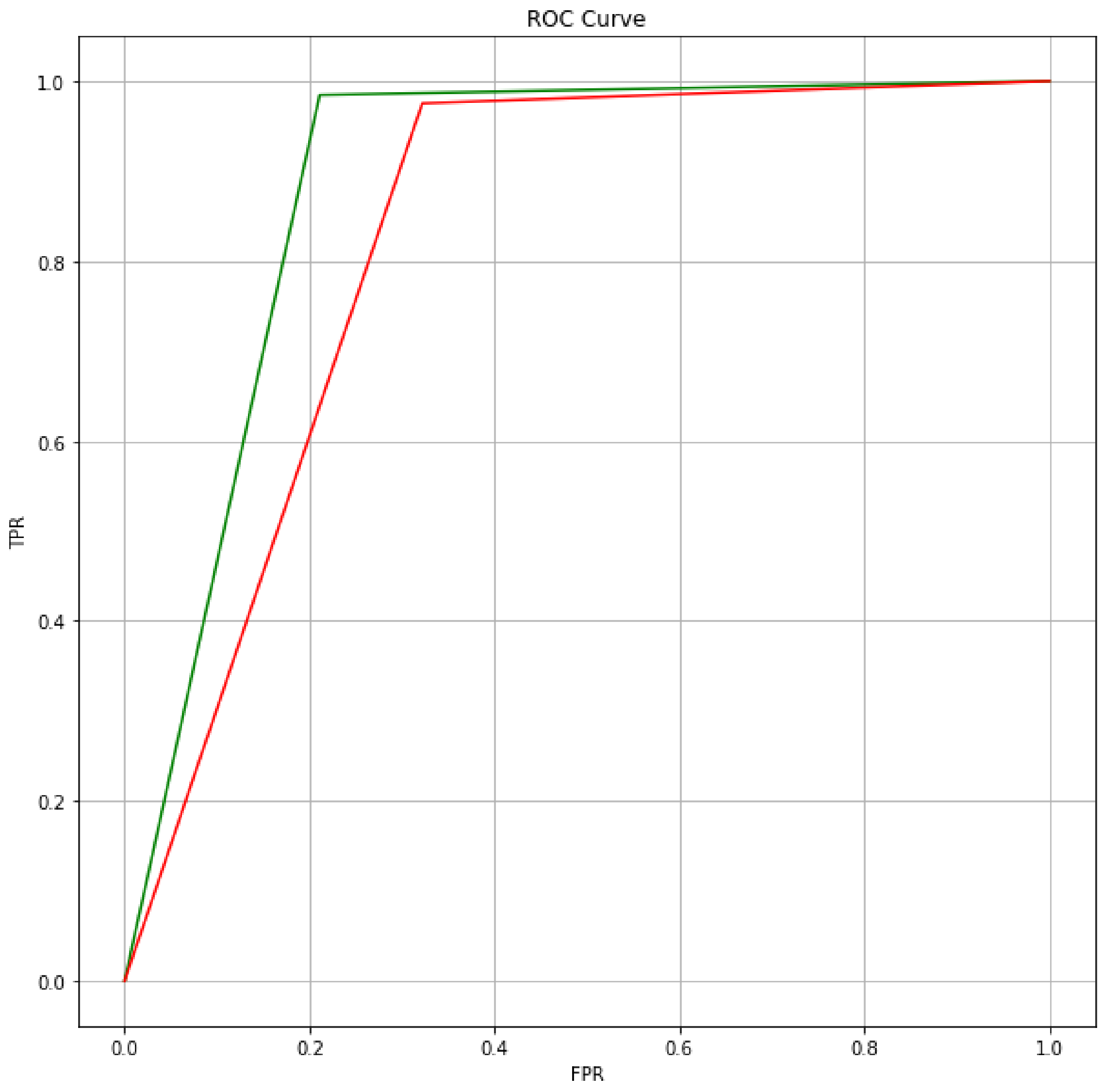
```
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  0.001 The AUC is: 0.8867097203114326
For values of best alpha =  0.001 The AUC is: 0.818126843947641
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  0.001 The AUC is: 0.8266349103482626
```


ROC Curve
TPR
FPR
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0

In [115]:

```
count_vect = loadPickleData('count_vects.pickle')
feature_names = count_vect.get_feature_names()
```

In [116]:

```
indices = np.argsort(-clf.coef_)[0][:]
negative_indices = indices[-10:]
words = getImportantFeatures(negative_indices,feature_names)
print(words)
```

```
['not great', 'disappointment', 'not good', 'not recommend', 'disapp
ointing', 'awful', 'terrible', 'disappointed', 'not worth', 'worst']
```

In [117]:

```
positive_indices = indices[:10]
words = getImportantFeatures(positive_indices,feature_names)
print(words)
```

```
['not disappointed', 'delicious', 'perfect', 'amazing', 'wonderful',
'best', 'yummy', 'loves', 'excellent', 'great']
```

[5.1.2] Applying Linear SVM on TFIDF, SET 2

In [115]:

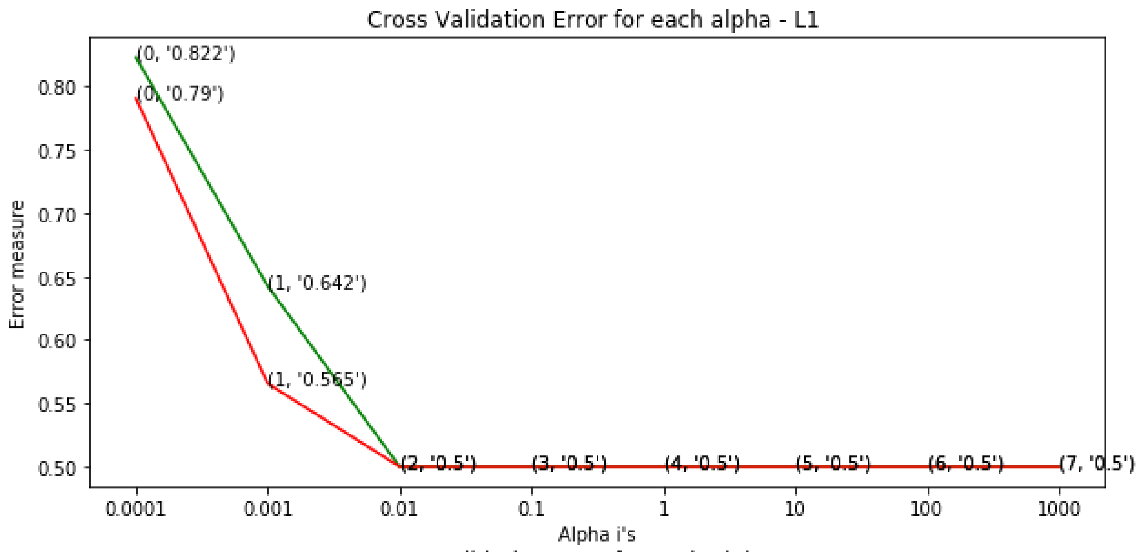
```
train = loadPickleData("tfidf_train_li.pickle")
test = loadPickleData('tfidf_test_li.pickle')
cv = loadPickleData('tfidf_cv_li.pickle')
```

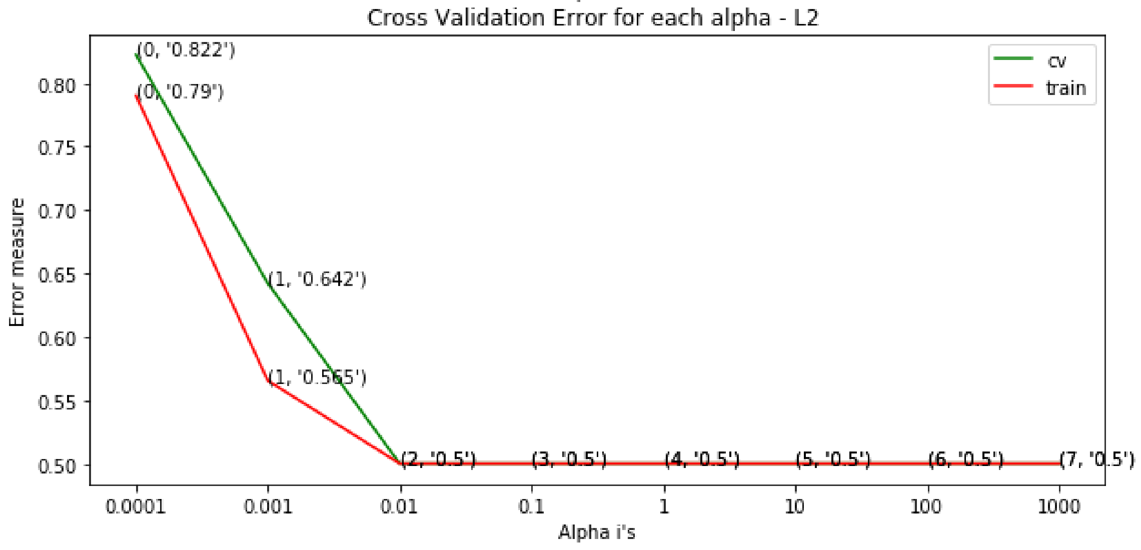
In [116]:

```
best_alpha,best_reg = performHyperParameterTuningSGD(train,cv,test)
```

```
for alpha = 0.0001 and regularizer = l1
Area: 0.8224443365250647
for alpha = 0.0001 and regularizer = l2
Area: 0.8573682767551948
for alpha = 0.001 and regularizer = l1
Area: 0.6420815215509699
for alpha = 0.001 and regularizer = l2
Area: 0.8011368963571596
for alpha = 0.01 and regularizer = l1
Area: 0.5
for alpha = 0.01 and regularizer = l2
Area: 0.799863011006841
for alpha = 0.1 and regularizer = l1
Area: 0.5
for alpha = 0.1 and regularizer = l2
Area: 0.799863011006841
for alpha = 1 and regularizer = l1
Area: 0.5
for alpha = 1 and regularizer = l2
Area: 0.799863011006841
for alpha = 10 and regularizer = l1
Area: 0.5
for alpha = 10 and regularizer = l2
Area: 0.799863011006841
for alpha = 100 and regularizer = l1
Area: 0.5
for alpha = 100 and regularizer = l2
Area: 0.799863011006841
for alpha = 1000 and regularizer = l1
Area: 0.5
for alpha = 1000 and regularizer = l2
Area: 0.799863011006841
for alpha = 0.0001 and regularizer = l1
Area: 0.7901993234253023
for alpha = 0.0001 and regularizer = l2
Area: 0.9616010892285192
for alpha = 0.001 and regularizer = l1
Area: 0.5654073814862481
for alpha = 0.001 and regularizer = l2
Area: 0.7700965421330813
for alpha = 0.01 and regularizer = l1
Area: 0.5
for alpha = 0.01 and regularizer = l2
Area: 0.7635554259386684
for alpha = 0.1 and regularizer = l1
Area: 0.5
for alpha = 0.1 and regularizer = l2
Area: 0.7635554259386684
for alpha = 1 and regularizer = l1
Area: 0.5
for alpha = 1 and regularizer = l2
Area: 0.7635554259386684
for alpha = 10 and regularizer = l1
Area: 0.5
for alpha = 10 and regularizer = l2
Area: 0.7635554259386684
for alpha = 100 and regularizer = l1
Area: 0.5
for alpha = 100 and regularizer = l2
Area: 0.7635554259386684
for alpha = 1000 and regularizer = l1
```

```
Area: 0.5
for alpha = 1000 and regularizer = l2
Area: 0.7635554259386684
```



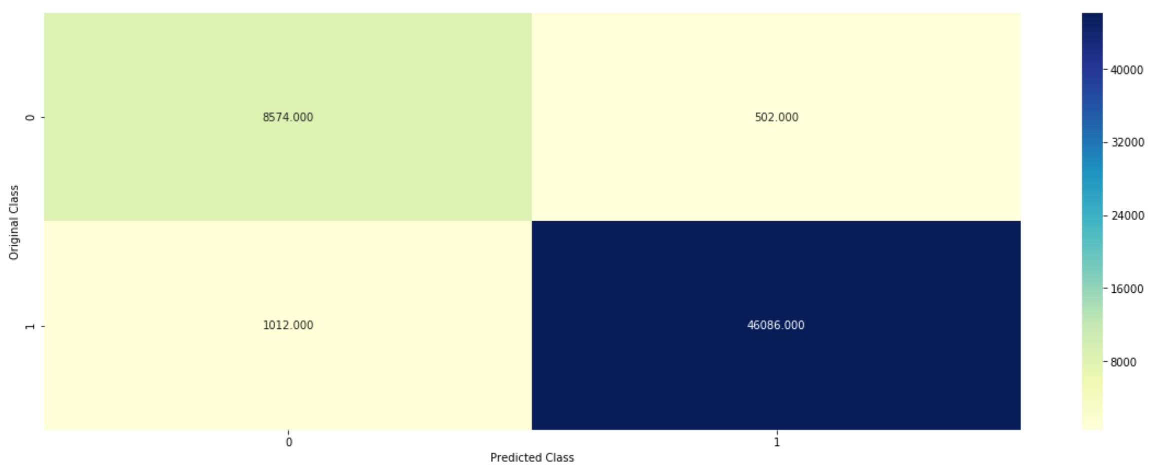


```
best alph = 0.0001 and regularizer = l2
```

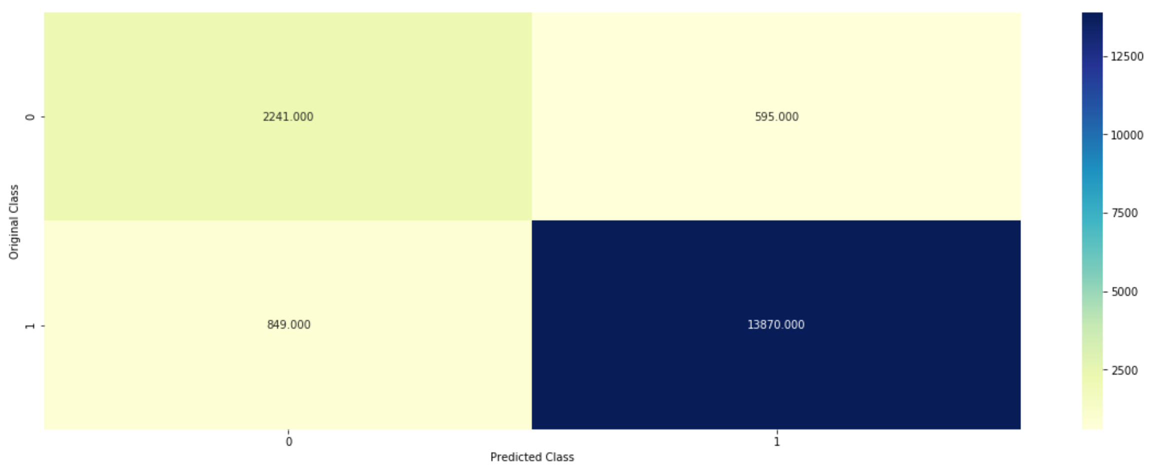
In [117]:

```
clf = bestModel(train,cv,test,best_alpha,best_reg)
```

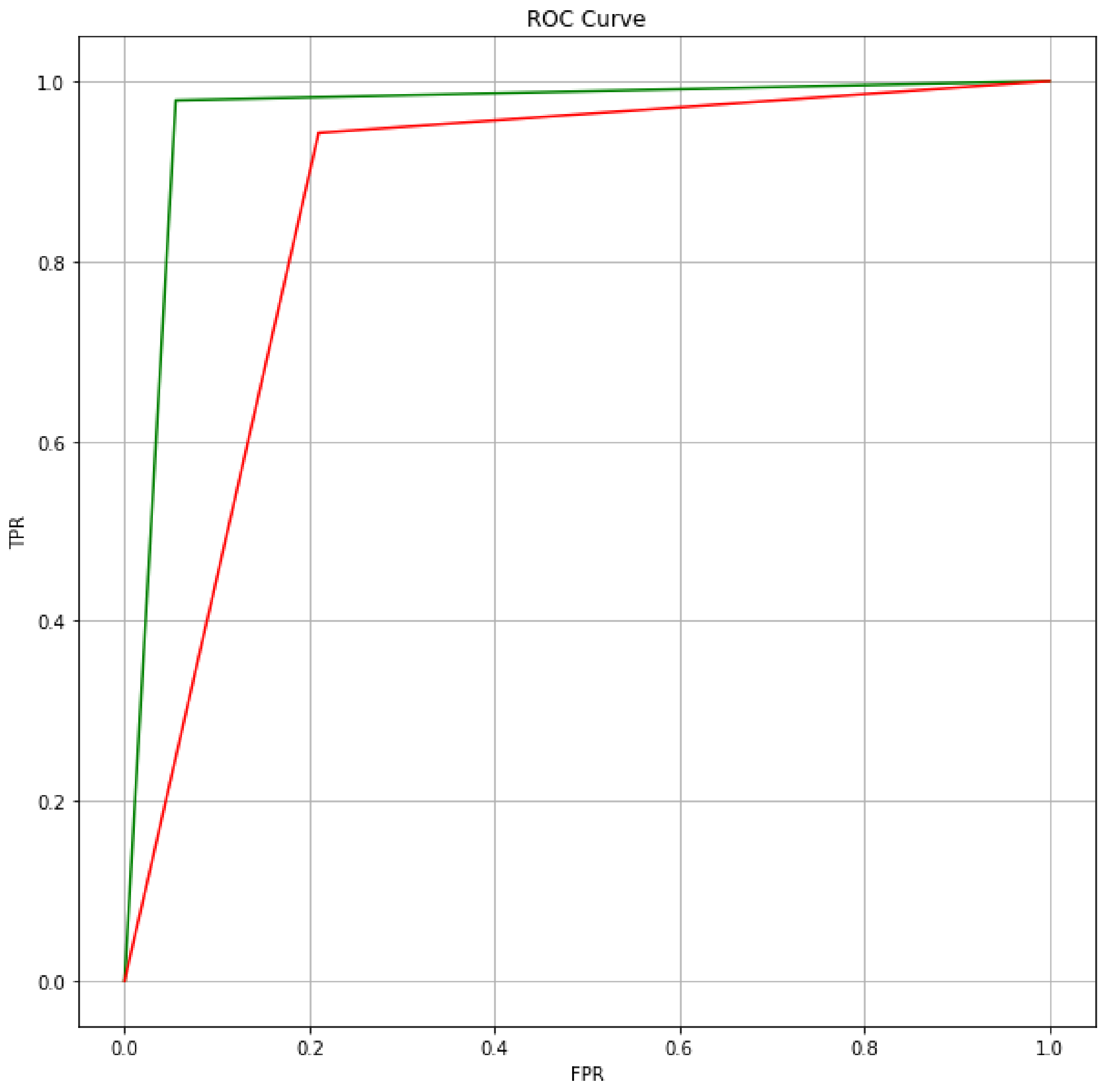
```
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  0.0001 The AUC is: 0.9616010892285192
For values of best alpha =  0.0001 The AUC is: 0.8573682767551948
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  0.0001 The AUC is: 0.86625845613132
```


ROC Curve
TPR
FPR
0.0
0.2
0.4
0.6
0.8
1.0

In [121]:

```
tf_idf_vect = loadPickleData('tf_idf_vect_li.pickle')
feature_names = tf_idf_vect.get_feature_names()
```

In [122]:

```
indices = np.argsort(-clf.coef_)[0][:]
negative_indices = indices[-10:]
words = getImportantFeatures(negative_indices,feature_names)
print(words)
```

```
['awful', 'unfortunately', 'terrible', 'horrible', 'thought', 'not g
ood', 'worst', 'bad', 'disappointed', 'not']
```

In [123]:

```
positive_indices = indices[:10]
words = getImportantFeatures(positive_indices,feature_names)
print(words)
```

```
['great', 'best', 'delicious', 'good', 'love', 'perfect', 'loves',
'nice', 'wonderful', 'excellent']
```

[5.1.3] Applying Linear SVM on AVG W2V, SET 3

In [215]:

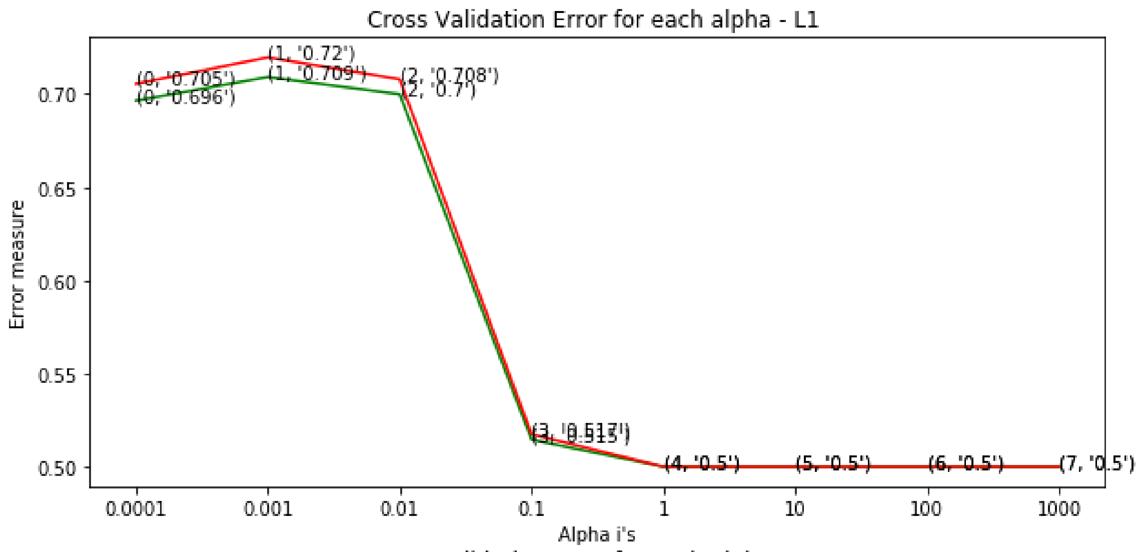
```
train = loadPickleData("avg_w2v_train_li.pickle")
test = loadPickleData('avg_w2v_test_li.pickle')
cv = loadPickleData('avg_w2v_cv_li.pickle')
```

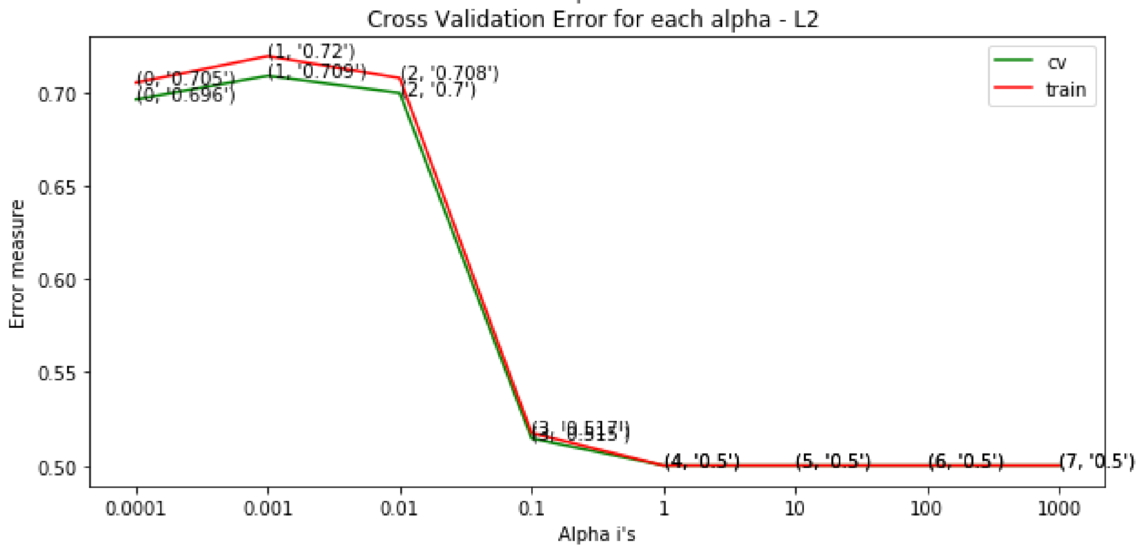
In [216]:

```
best_alpha,best_reg = performHyperParameterTuningSGD(train,cv,test)
```

```
for alpha = 0.0001 and regularizer = l1
Area: 0.6963407844491293
for alpha = 0.0001 and regularizer = l2
Area: 0.6961973015788355
for alpha = 0.001 and regularizer = l1
Area: 0.7089738083407957
for alpha = 0.001 and regularizer = l2
Area: 0.7095499668288265
for alpha = 0.01 and regularizer = l1
Area: 0.6997691398607091
for alpha = 0.01 and regularizer = l2
Area: 0.7081348256150704
for alpha = 0.1 and regularizer = l1
Area: 0.5145121685338903
for alpha = 0.1 and regularizer = l2
Area: 0.6989565256447325
for alpha = 1 and regularizer = l1
Area: 0.5
for alpha = 1 and regularizer = l2
Area: 0.6740762366204142
for alpha = 10 and regularizer = l1
Area: 0.5
for alpha = 10 and regularizer = l2
Area: 0.5275648615746811
for alpha = 100 and regularizer = l1
Area: 0.5
for alpha = 100 and regularizer = l2
Area: 0.6726266797292784
for alpha = 1000 and regularizer = l1
Area: 0.5
for alpha = 1000 and regularizer = l2
Area: 0.6726266797292784
for alpha = 0.0001 and regularizer = l1
Area: 0.7053151445835181
for alpha = 0.0001 and regularizer = l2
Area: 0.7059868449236152
for alpha = 0.001 and regularizer = l1
Area: 0.7195138589433684
for alpha = 0.001 and regularizer = l2
Area: 0.7196751109119903
for alpha = 0.01 and regularizer = l1
Area: 0.707796259558827
for alpha = 0.01 and regularizer = l2
Area: 0.7196573291914736
for alpha = 0.1 and regularizer = l1
Area: 0.5174190211417615
for alpha = 0.1 and regularizer = l2
Area: 0.7127265614839727
for alpha = 1 and regularizer = l1
Area: 0.5
for alpha = 1 and regularizer = l2
Area: 0.6834420024703607
for alpha = 10 and regularizer = l1
Area: 0.5
for alpha = 10 and regularizer = l2
Area: 0.5290455830767691
for alpha = 100 and regularizer = l1
Area: 0.5
for alpha = 100 and regularizer = l2
Area: 0.6813155838090924
for alpha = 1000 and regularizer = l1
```

```
Area: 0.5
for alpha = 1000 and regularizer = l2
Area: 0.6813155838090924
```



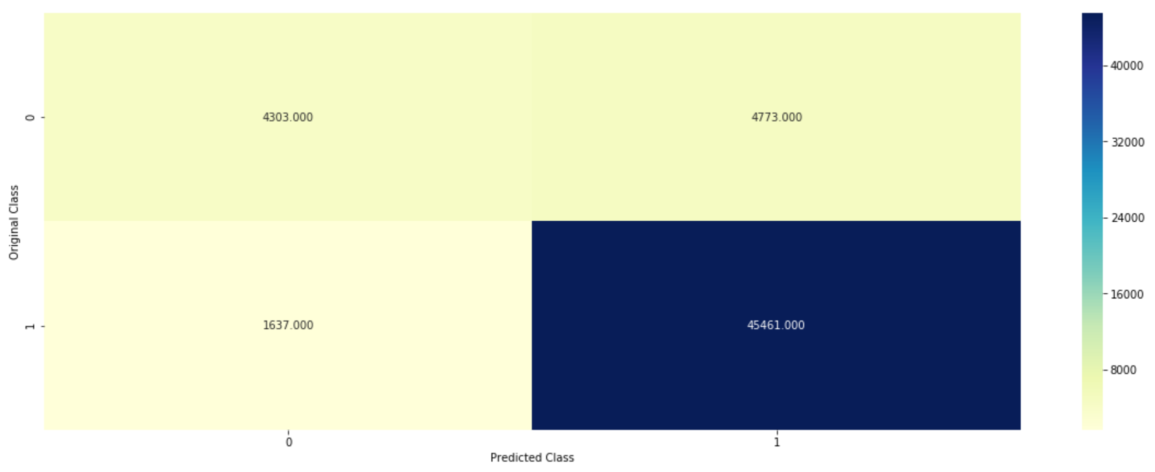


```
best alph = 0.001 and regularizer = l2
```

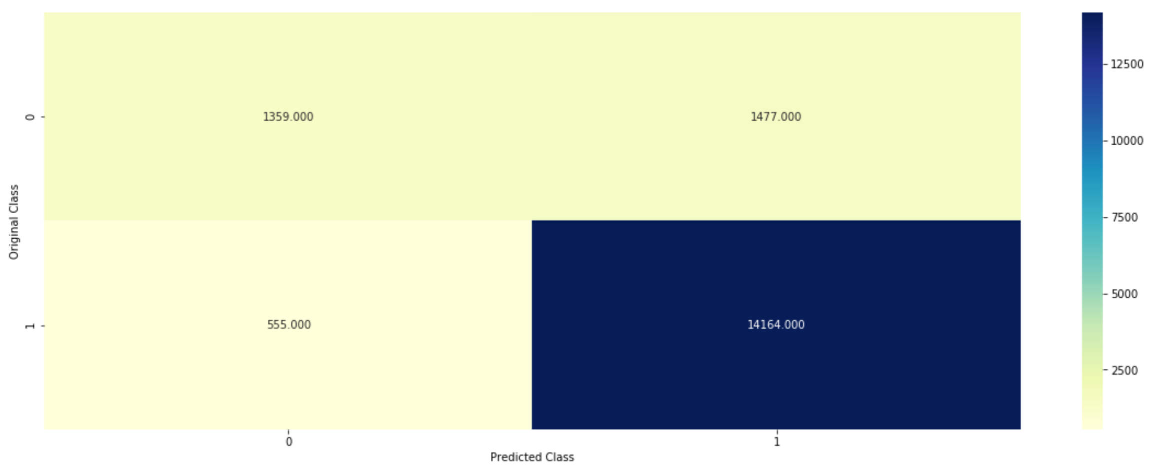
In [137]:

```
clf = bestModel(train,cv,test,best_alpha,best_reg)
```

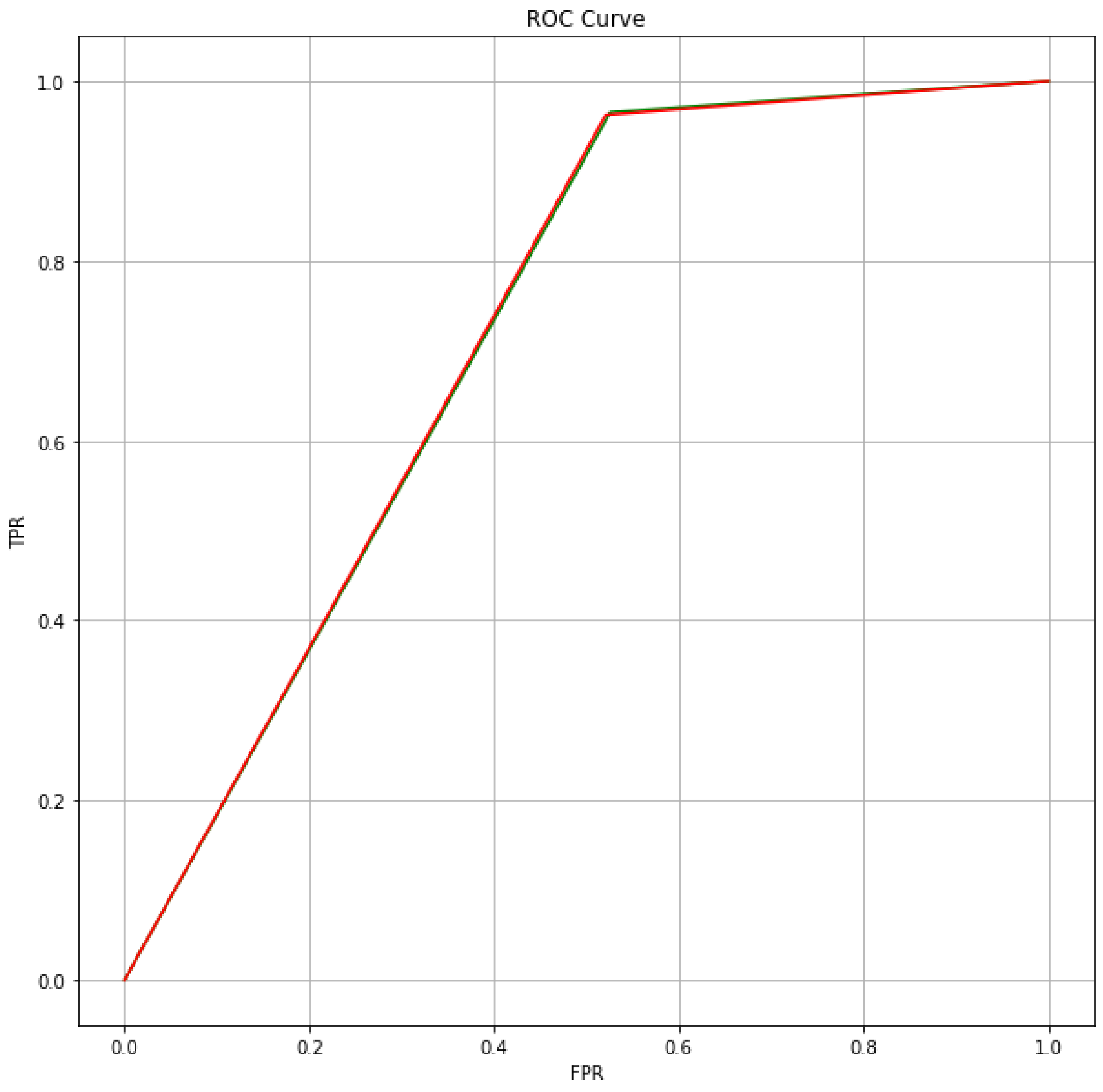
```
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  0.001 The AUC is: 0.7196751109119903
For values of best alpha =  0.001 The AUC is: 0.7095499668288265
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  0.001 The AUC is: 0.7207448424270713
```


ROC Curve
TPR
FPR
0.0
0.2
0.4
0.6
0.8
1.0

[5.1.4] Applying Linear SVM on TFIDF W2V, SET 4

In [14]:

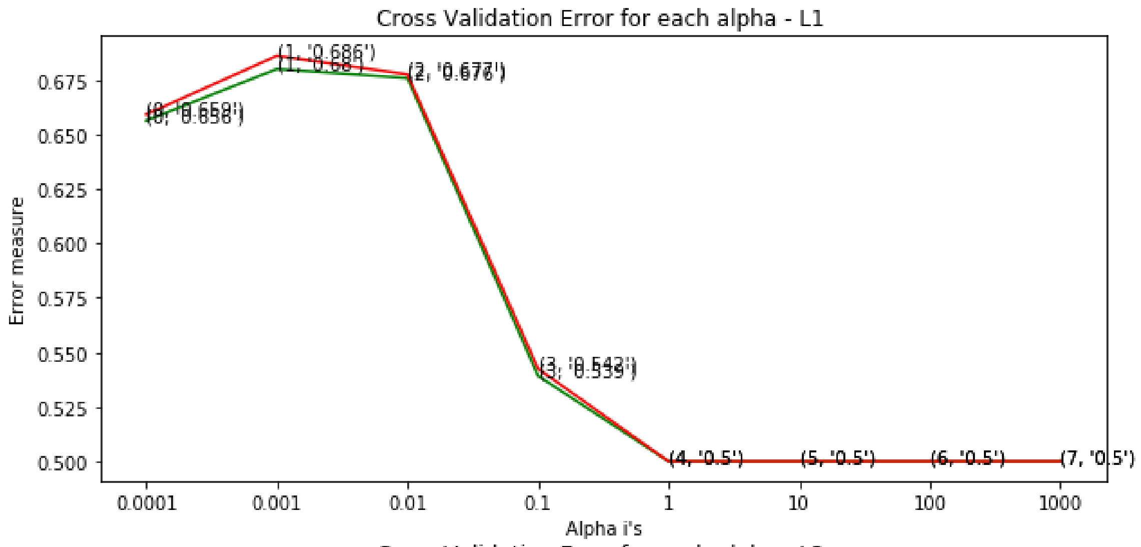
```
train = loadPickleData("tfidf_w2v_train_li.pickle")
test = loadPickleData('tfidf_w2v_test_li.pickle')
cv = loadPickleData('tfidf_w2v_cv_li.pickle')
```

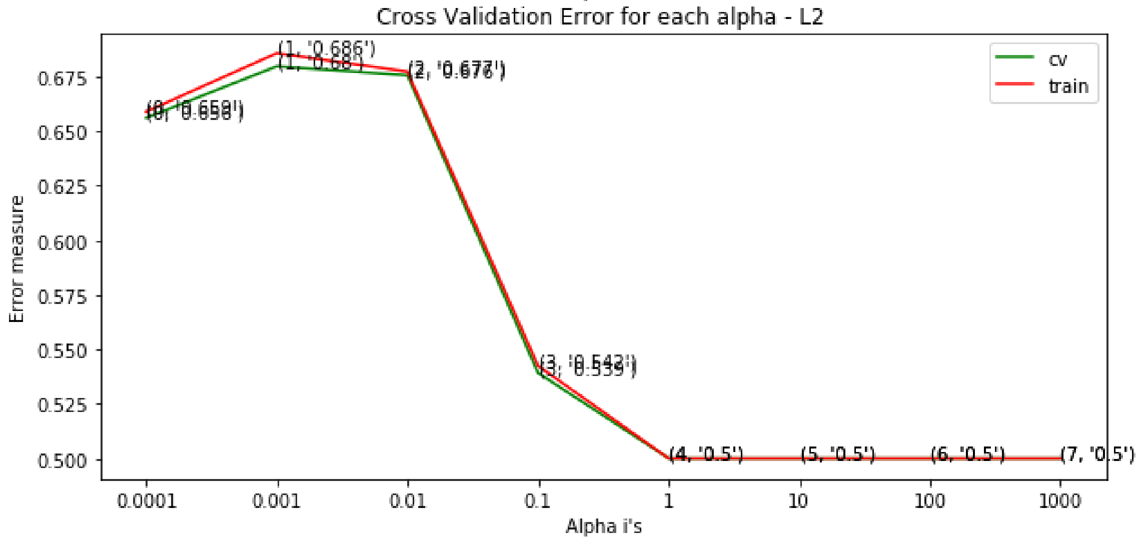
In [15]:

```
best_alpha,best_reg = performHyperParameterTuningSGD(train,cv,test)
```

```
for alpha = 0.0001 and regularizer = l1
Area: 0.6561567663111878
for alpha = 0.0001 and regularizer = l2
Area: 0.647633730358127
for alpha = 0.001 and regularizer = l1
Area: 0.6798078598370543
for alpha = 0.001 and regularizer = l2
Area: 0.6795633569414774
for alpha = 0.01 and regularizer = l1
Area: 0.6756773235494746
for alpha = 0.01 and regularizer = l2
Area: 0.6842128606838782
for alpha = 0.1 and regularizer = l1
Area: 0.5392145590105353
for alpha = 0.1 and regularizer = l2
Area: 0.6773391946656635
for alpha = 1 and regularizer = l1
Area: 0.5
for alpha = 1 and regularizer = l2
Area: 0.6485934205983163
for alpha = 10 and regularizer = l1
Area: 0.5
for alpha = 10 and regularizer = l2
Area: 0.6440427098743425
for alpha = 100 and regularizer = l1
Area: 0.5
for alpha = 100 and regularizer = l2
Area: 0.6440427098743425
for alpha = 1000 and regularizer = l1
Area: 0.5
for alpha = 1000 and regularizer = l2
Area: 0.6440427098743425
for alpha = 0.0001 and regularizer = l1
Area: 0.6590004626569271
for alpha = 0.0001 and regularizer = l2
Area: 0.6500422325804689
for alpha = 0.001 and regularizer = l1
Area: 0.6858404222689107
for alpha = 0.001 and regularizer = l2
Area: 0.6837495670486757
for alpha = 0.01 and regularizer = l1
Area: 0.6773800546336053
for alpha = 0.01 and regularizer = l2
Area: 0.6893366697246579
for alpha = 0.1 and regularizer = l1
Area: 0.5424940403046592
for alpha = 0.1 and regularizer = l2
Area: 0.6807572106479178
for alpha = 1 and regularizer = l1
Area: 0.5
for alpha = 1 and regularizer = l2
Area: 0.6515349075409486
for alpha = 10 and regularizer = l1
Area: 0.5
for alpha = 10 and regularizer = l2
Area: 0.6436676039145406
for alpha = 100 and regularizer = l1
Area: 0.5
for alpha = 100 and regularizer = l2
Area: 0.6436676039145406
for alpha = 1000 and regularizer = l1
```

```
Area: 0.5
for alpha = 1000 and regularizer = l2
Area: 0.6436676039145406
```



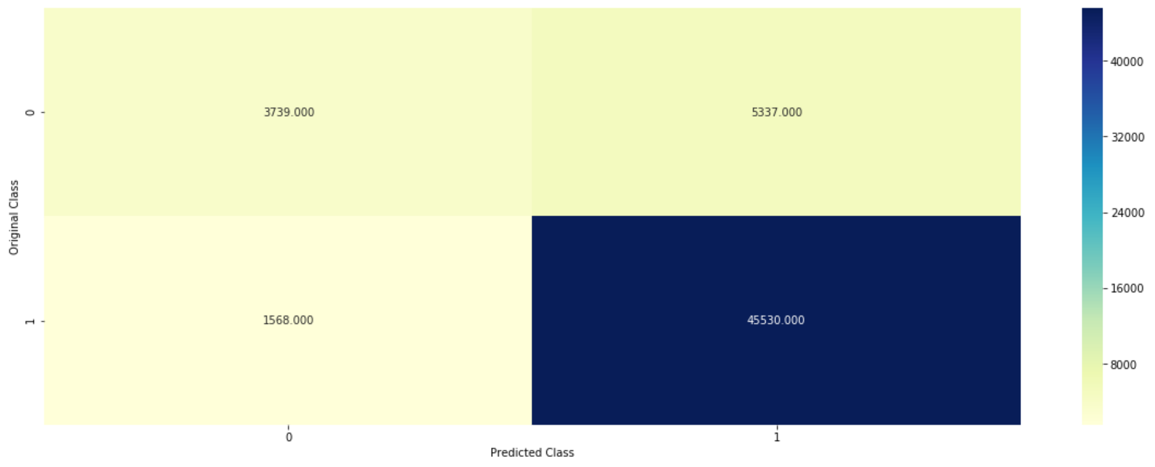


```
best alph = 0.01 and regularizer = l2
```

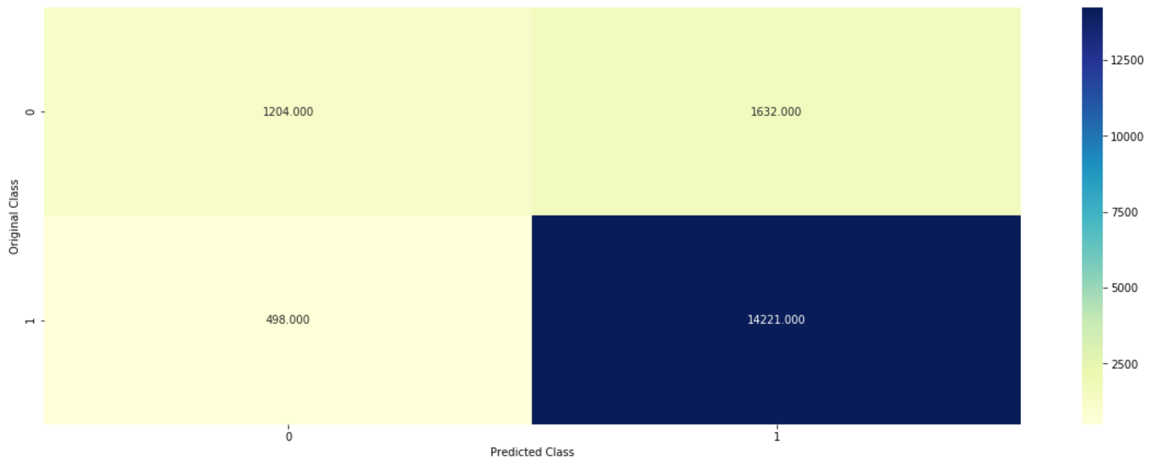
In [16]:

```
clf = bestModel(train,cv,test,best_alpha,best_reg)
```

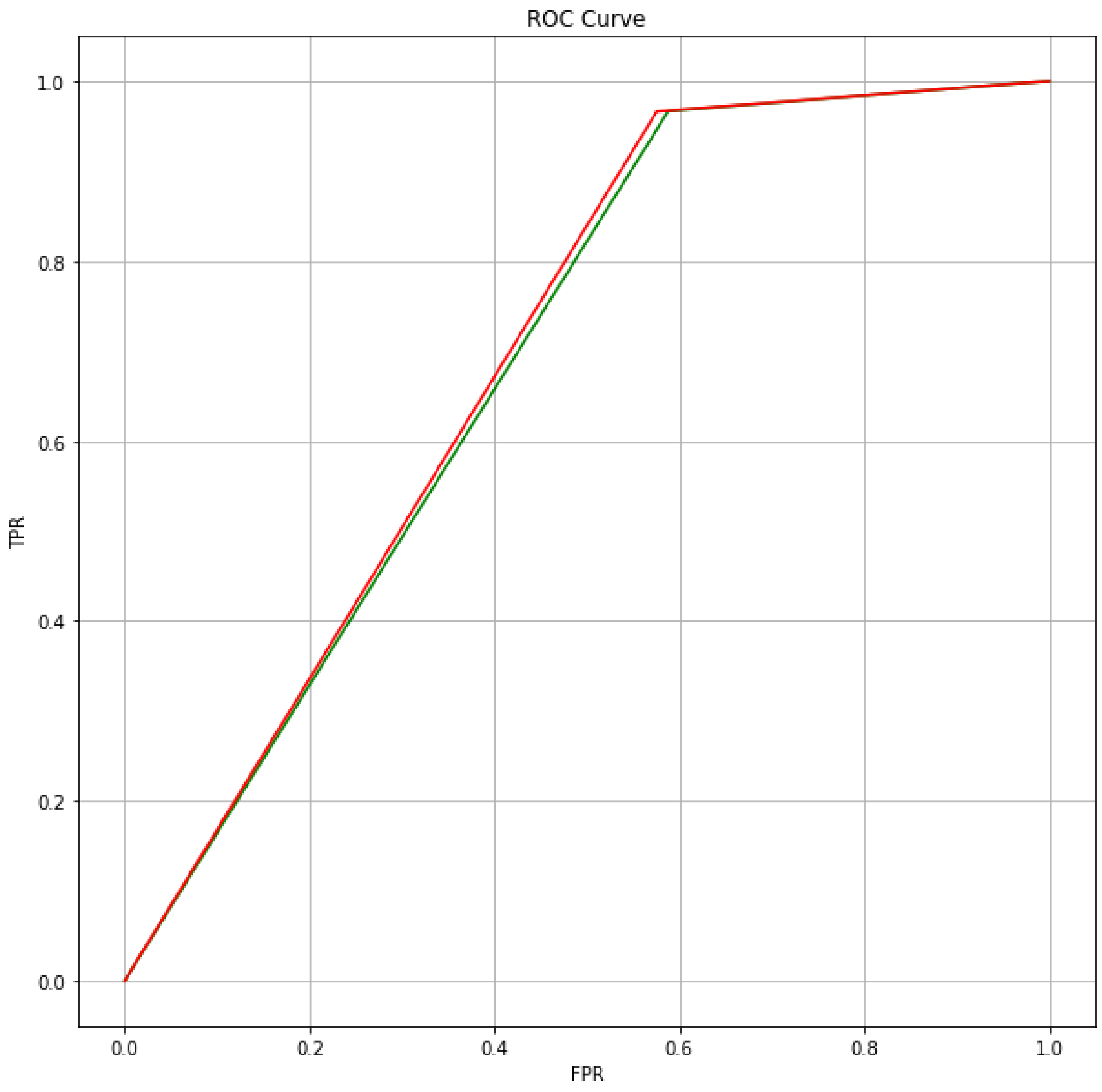
```
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  0.01 The AUC is: 0.6893366697246579
For values of best alpha =  0.01 The AUC is: 0.6842128606838782
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  0.01 The AUC is: 0.6953538938330479
```



[5.2] RBF SVM

In [ ]:

```
gamma = [10**x for x in range(-3,2)]
alpha = [10**x for x in range(-4,4)]
```

In [ ]:

```
def calculateMetric(X,y,train,y_train):
    auc_array = []
    C = np.zeros((len(gamma),len(alpha)))
    for row,i in enumerate(gamma):
        for col,g in enumerate(alpha):
            print("for alpha = {} and gamma = {} ".format(i,g))
            clf = SVC(C=g,kernel='rbf',gamma = i,probability=True, class_weight=
'balanced')
            clf.fit(train, y_train)
            pred = clf.predict(X)
            area = roc_auc_score(y, pred)
            auc_array.append(area)
            print("Area:",area)
            C[row][col] = area
    return (auc_array,C)
```

In [ ]:

```
def drawHeatMap(C,title):
    parameters = {'alpha' : alpha,
    'gamma' : gamma}
    labels_y = parameters['gamma']
    labels_x = parameters['alpha']
    plt.figure(figsize=(20,7))
    sns.heatmap(C, annot=True, cmap="YlGnBu", fmt=".6f", xticklabels=labels_x, y
ticklabels=labels_y)
    plt.xlabel('C values')
    plt.ylabel('Gamma values')
    plt.title(title)
    plt.show()
```

In [ ]:

```
def drawplots(auc_array,auc_array_train):
    fig, ax = plt.subplots(1,1,figsize=(10,10))
    a = np.arange(len(alpha))

    ax.plot(a, auc_array,c='g',label="cv")
    for i, txt in enumerate(np.round(auc_array,3)):
        ax.annotate((a[i],str(txt)), (a[i],auc_array[i]))

    ax.plot(a, auc_array_train,c='r',label="train")
    for i, txt in enumerate(np.round(auc_array_train,3)):
        ax.annotate((a[i],str(txt)), (a[i],auc_array_train[i]),(a[i],auc_array_t
rain[i]))

    ax.set_xticks(a)
    ax.set_xticklabels(alpha)
    plt.grid()
    ax.set_title("Cross Validation AUC for each alpha ")
    ax.set_xlabel("Alpha i's")
    ax.set_ylabel("AUC measure")

    plt.legend(loc='best')
    plt.show()
```

In [ ]:

```
def performHyperParameterTuningRBF(train,cv,test):
    auc_array = []
    auc_array,C_cv = calculateMetric(cv,y_cv,train,y_train)
    auc_array_train,C_train = calculateMetric(train,y_train,train,y_train)
    drawHeatMap(C_cv,'Cv Scores')
    drawHeatMap(C_train,'Train scores')
    best_ar = np.argmax(auc_array)
    print(best_ar)
    best_alpha = alpha[int(best_ar%8)]
    best_gamma = gamma[int(best_ar/8)]
    print("best alph = {} and gamma ={} ".format(best_alpha,best_gamma))
    clf = SVC(C=best_alpha,gamma = best_gamma,kernel='rbf',probability=True, cla
ss_weight='balanced')
    clf.fit(train, y_train)

    predict_y = clf.predict(train)
    plot_confusion_matrix(y_train,predict_y)
    train_fpr,train_tpr , train_thresholds = roc_curve(y_train, predict_y)

    print('For values of best alpha = ', best_alpha, "The AUC is:",roc_auc_score
(y_train, predict_y))
    predict_y = clf.predict(cv)
    print('For values of best alpha = ', best_alpha, "The cross validation AUC i
s:",roc_auc_score(y_cv, predict_y))
    predict_y = clf.predict(test)
    plot_confusion_matrix(y_test,predict_y)
    print('For values of best alpha = ', best_alpha, "The test AUC is:",roc_auc_
score(y_test, predict_y))
    test_fpr,test_tpr ,train_thresholds = roc_curve(y_test, predict_y)
    plotAUC(train_fpr,train_tpr,test_fpr,test_tpr)
    return clf,best_alpha
```

In [ ]:

```
# load the y values because they are common across all feature engineering
y_train = loadPickleData('y_train_rbf.pickle')
y_test = loadPickleData('y_test_rbf.pickle')
y_cv = loadPickleData('y_cv_rbf.pickle')
```

[5.2.1] Applying RBF SVM on BOW, SET 1

In [107]:

```
train = loadPickleData("bow_train_rbf.pickle")
test = loadPickleData('bow_test_rbf.pickle')
cv = loadPickleData('bow_cv_rbf.pickle')
```

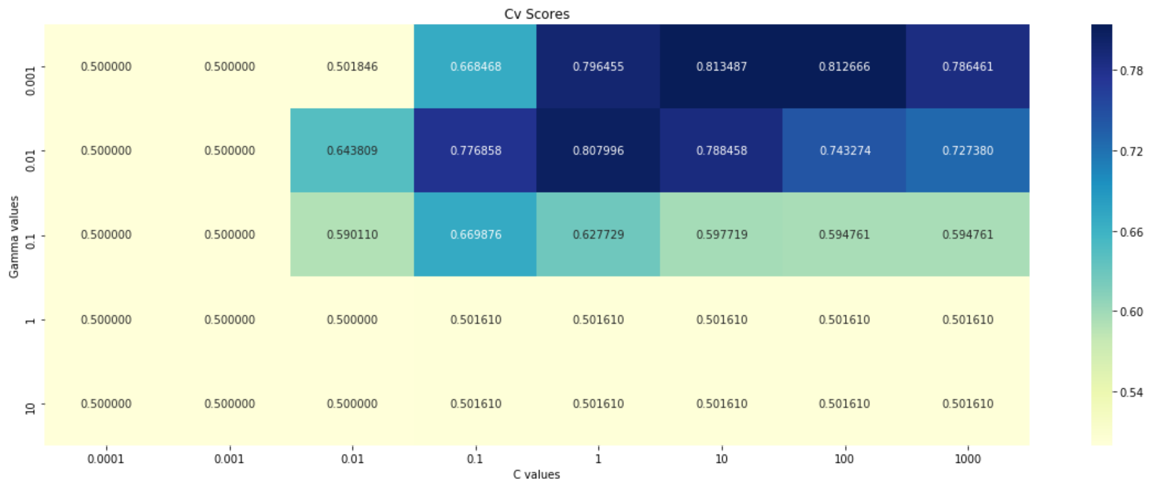
In [108]:

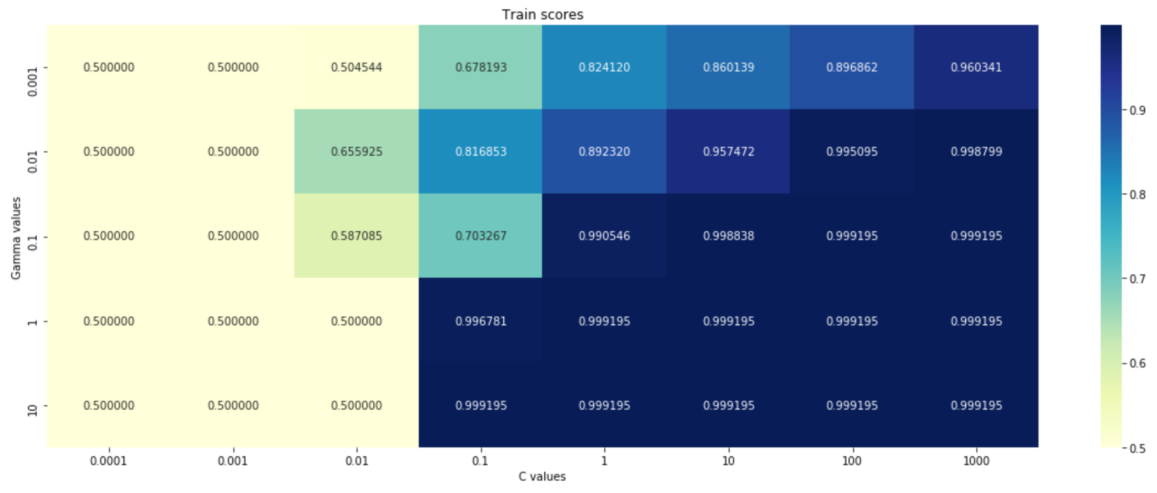
```
clf,alph = performHyperParameterTuningRBF(train,cv,test)
```

```
for alpha = 0.001 and gamma = 0.0001
Area: 0.5
for alpha = 0.001 and gamma = 0.001
Area: 0.5
for alpha = 0.001 and gamma = 0.01
Area: 0.5018464373735368
for alpha = 0.001 and gamma = 0.1
Area: 0.6684684847281631
for alpha = 0.001 and gamma = 1
Area: 0.7964552212616535
for alpha = 0.001 and gamma = 10
Area: 0.8134870142761745
for alpha = 0.001 and gamma = 100
Area: 0.8126660690686898
for alpha = 0.001 and gamma = 1000
Area: 0.7864614980457743
for alpha = 0.01 and gamma = 0.0001
Area: 0.5
for alpha = 0.01 and gamma = 0.001
Area: 0.5
for alpha = 0.01 and gamma = 0.01
Area: 0.6438085440467811
for alpha = 0.01 and gamma = 0.1
Area: 0.7768575671345177
for alpha = 0.01 and gamma = 1
Area: 0.8079960815219898
for alpha = 0.01 and gamma = 10
Area: 0.7884583375947283
for alpha = 0.01 and gamma = 100
Area: 0.7432735133747642
for alpha = 0.01 and gamma = 1000
Area: 0.7273797634875658
for alpha = 0.1 and gamma = 0.0001
Area: 0.5
for alpha = 0.1 and gamma = 0.001
Area: 0.5
for alpha = 0.1 and gamma = 0.01
Area: 0.5901102046873339
for alpha = 0.1 and gamma = 0.1
Area: 0.6698759984197744
for alpha = 0.1 and gamma = 1
Area: 0.6277290474729427
for alpha = 0.1 and gamma = 10
Area: 0.5977185494010986
for alpha = 0.1 and gamma = 100
Area: 0.5947608906215219
for alpha = 0.1 and gamma = 1000
Area: 0.5947608906215219
for alpha = 1 and gamma = 0.0001
Area: 0.5
for alpha = 1 and gamma = 0.001
Area: 0.5
for alpha = 1 and gamma = 0.01
Area: 0.5
for alpha = 1 and gamma = 0.1
Area: 0.501610305958132
for alpha = 1 and gamma = 1
Area: 0.501610305958132
for alpha = 1 and gamma = 10
Area: 0.501610305958132
for alpha = 1 and gamma = 100
```

```
Area: 0.501610305958132
for alpha = 1 and gamma = 1000
Area: 0.501610305958132
for alpha = 10 and gamma = 0.0001
Area: 0.5
for alpha = 10 and gamma = 0.001
Area: 0.5
for alpha = 10 and gamma = 0.01
Area: 0.5
for alpha = 10 and gamma = 0.1
Area: 0.501610305958132
for alpha = 10 and gamma = 1
Area: 0.501610305958132
for alpha = 10 and gamma = 10
Area: 0.501610305958132
for alpha = 10 and gamma = 100
Area: 0.501610305958132
for alpha = 10 and gamma = 1000
Area: 0.501610305958132
for alpha = 0.001 and gamma = 0.0001
Area: 0.5
for alpha = 0.001 and gamma = 0.001
Area: 0.5
for alpha = 0.001 and gamma = 0.01
Area: 0.5045442540011167
for alpha = 0.001 and gamma = 0.1
Area: 0.6781927629307455
for alpha = 0.001 and gamma = 1
Area: 0.8241198671317846
for alpha = 0.001 and gamma = 10
Area: 0.8601393474518867
for alpha = 0.001 and gamma = 100
Area: 0.8968624735018645
for alpha = 0.001 and gamma = 1000
Area: 0.960340711350006
for alpha = 0.01 and gamma = 0.0001
Area: 0.5
for alpha = 0.01 and gamma = 0.001
Area: 0.5
for alpha = 0.01 and gamma = 0.01
Area: 0.6559253528019566
for alpha = 0.01 and gamma = 0.1
Area: 0.8168533311359907
for alpha = 0.01 and gamma = 1
Area: 0.8923204909932971
for alpha = 0.01 and gamma = 10
Area: 0.9574722078970238
for alpha = 0.01 and gamma = 100
Area: 0.9950945316871646
for alpha = 0.01 and gamma = 1000
Area: 0.9987993203694293
for alpha = 0.1 and gamma = 0.0001
Area: 0.5
for alpha = 0.1 and gamma = 0.001
Area: 0.5
for alpha = 0.1 and gamma = 0.01
Area: 0.5870854369443067
for alpha = 0.1 and gamma = 0.1
Area: 0.7032667509259857
for alpha = 0.1 and gamma = 1
Area: 0.9905464396469129
```

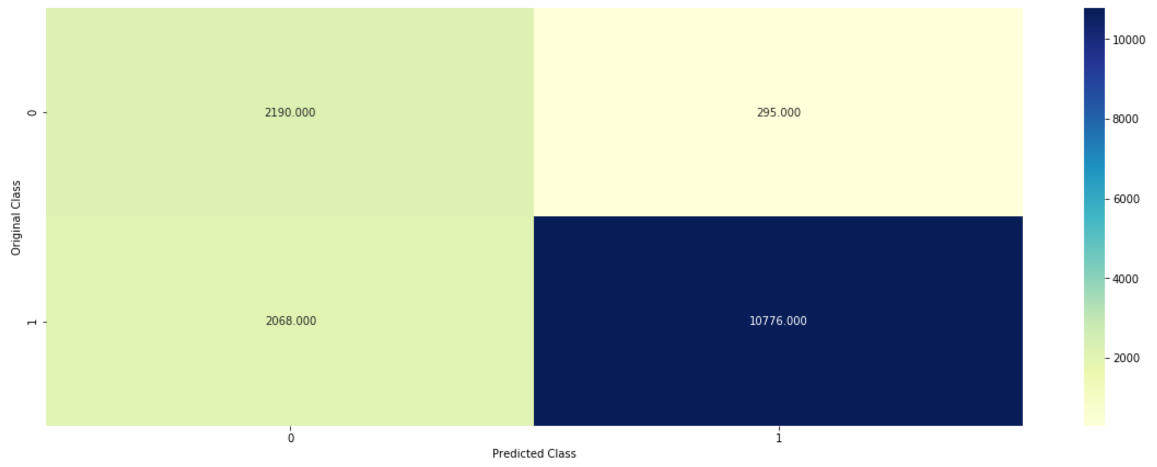
```
for alpha = 0.1 and gamma = 10
Area: 0.9988382490520827
for alpha = 0.1 and gamma = 100
Area: 0.999195171026157
for alpha = 0.1 and gamma = 1000
Area: 0.999195171026157
for alpha = 1 and gamma = 0.0001
Area: 0.5
for alpha = 1 and gamma = 0.001
Area: 0.5
for alpha = 1 and gamma = 0.01
Area: 0.5
for alpha = 1 and gamma = 0.1
Area: 0.9967806841046278
for alpha = 1 and gamma = 1
Area: 0.999195171026157
for alpha = 1 and gamma = 10
Area: 0.999195171026157
for alpha = 1 and gamma = 100
Area: 0.999195171026157
for alpha = 1 and gamma = 1000
Area: 0.999195171026157
for alpha = 10 and gamma = 0.0001
Area: 0.5
for alpha = 10 and gamma = 0.001
Area: 0.5
for alpha = 10 and gamma = 0.01
Area: 0.5
for alpha = 10 and gamma = 0.1
Area: 0.999195171026157
for alpha = 10 and gamma = 1
Area: 0.999195171026157
for alpha = 10 and gamma = 10
Area: 0.999195171026157
for alpha = 10 and gamma = 100
Area: 0.999195171026157
for alpha = 10 and gamma = 1000
Area: 0.999195171026157
```





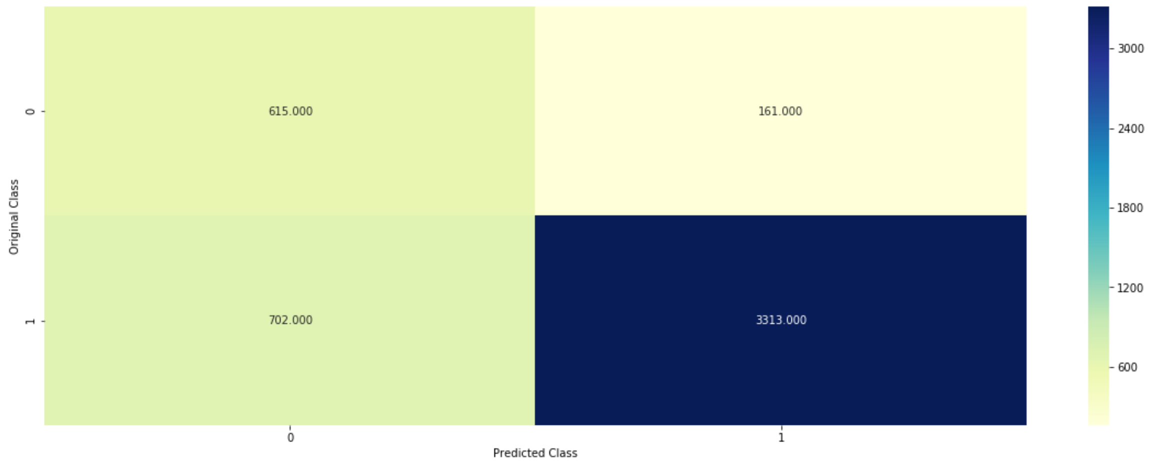
	0.0001	0.001	0.01	0.1	1	10	100	1000
0.001	0.500000	0.500000	0.504544	0.678193	0.824120	0.860139	0.896862	0.960341
0.01	0.500000	0.500000	0.655925	0.816853	0.892320	0.957472	0.995095	0.998799
0.1	0.500000	0.500000	0.587085	0.703267	0.990546	0.998838	0.999195	0.999195
1	0.500000	0.500000	0.500000	0.996781	0.999195	0.999195	0.999195	0.999195
10	0.500000	0.500000	0.500000	0.999195	0.999195	0.999195	0.999195	0.999195

```
5
best alph = 10 and gamma =0.001
-------------------- Confusion matrix --------------------
```

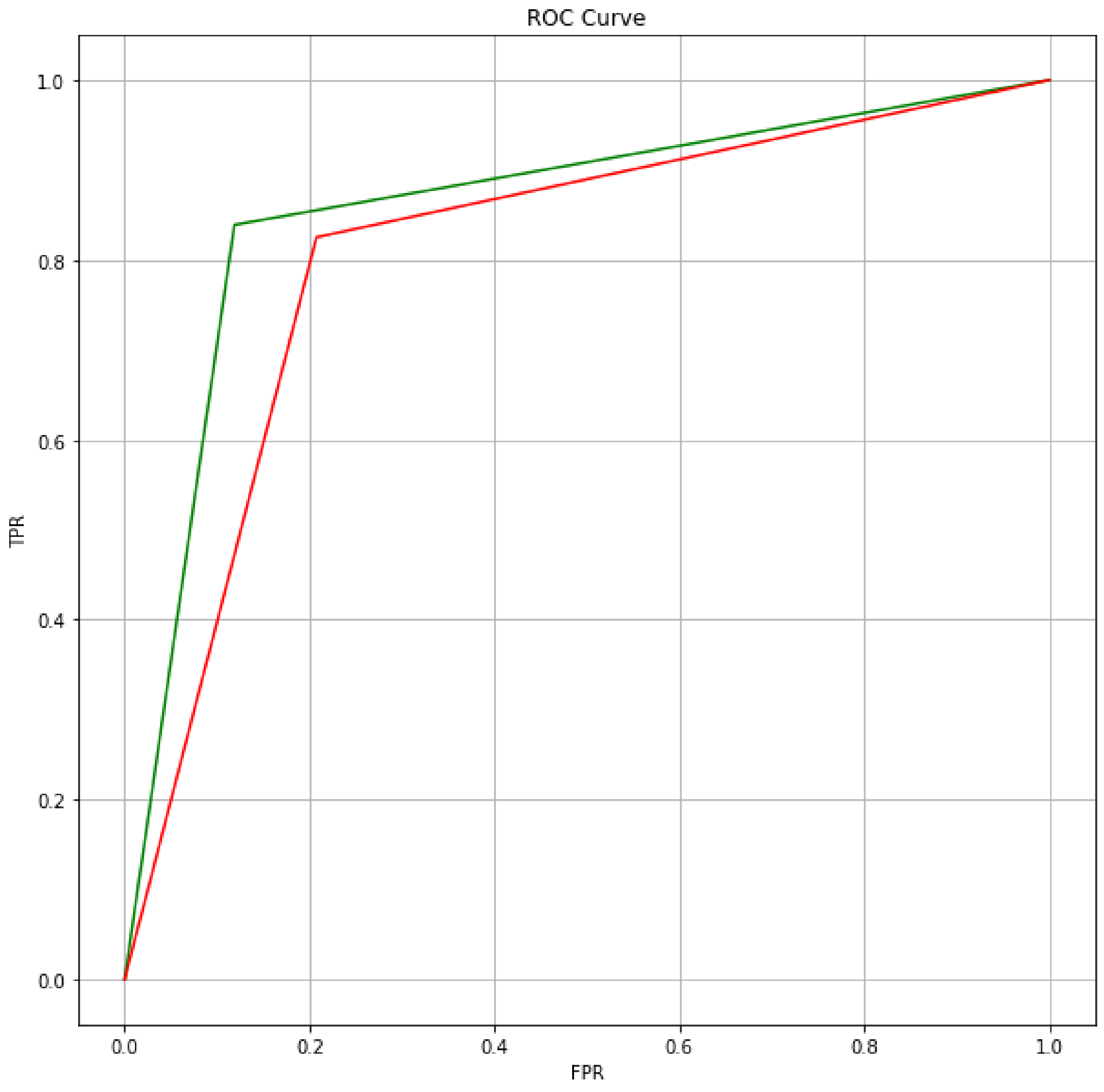


	0	1
0	2190.000	295.000
1	2068.000	10776.000

```
For values of best alpha =  10 The AUC is: 0.8601393474518867
For values of best alpha =  10 The cross validation AUC is: 0.813487
0142761745
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  10 The test AUC is: 0.8088407197237164
```



[5.2.2] Applying RBF SVM on TFIDF, SET 2

In [111]:

```
train = loadPickleData("tfidf_train_rbf.pickle")
test = loadPickleData('tfidf_test_rbf.pickle')
cv = loadPickleData('tfidf_cv_rbf.pickle')
```

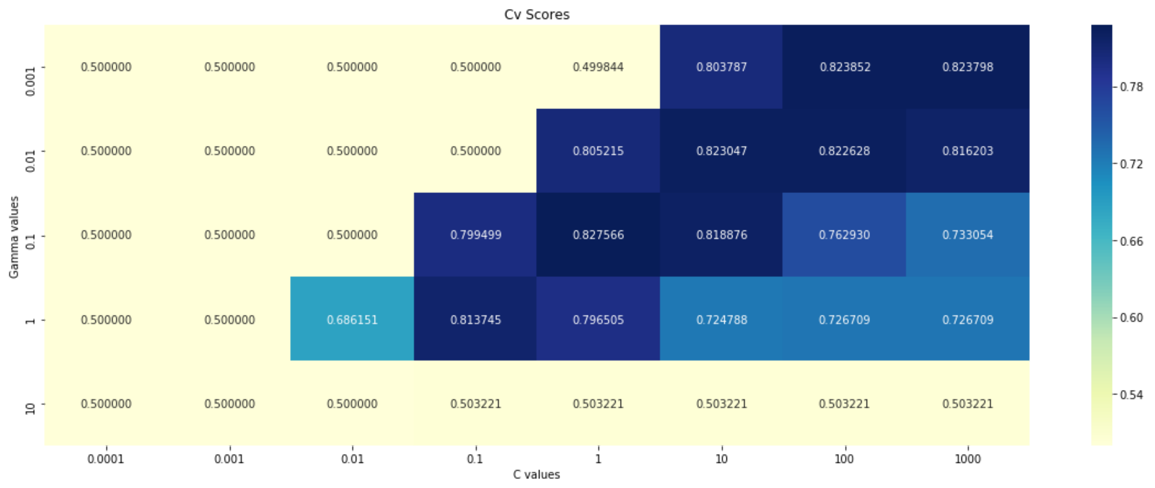
In [112]:

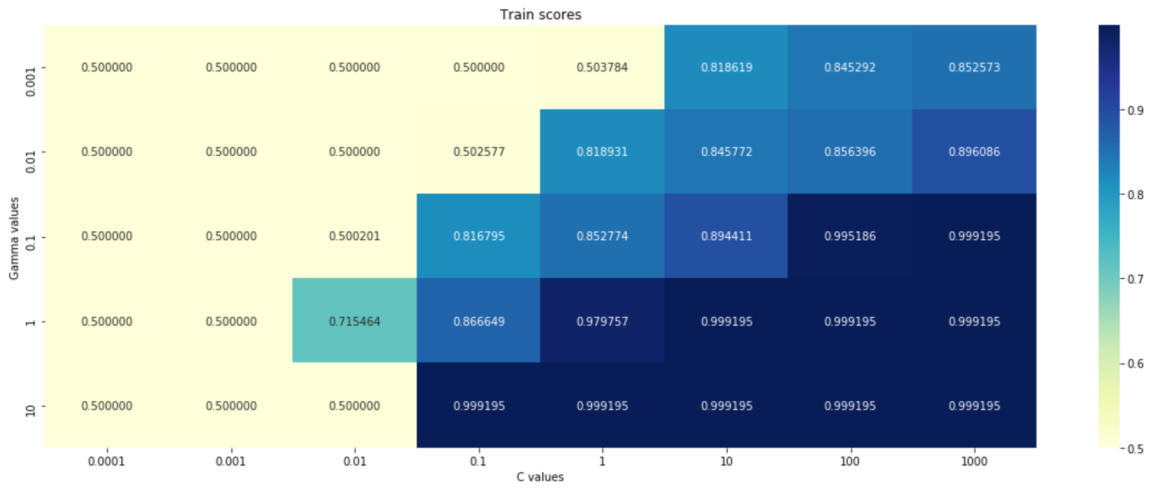
```
clf,alph = performHyperParameterTuningRBF(train,cv,test)
```

```
for alpha = 0.001 and gamma = 0.0001
Area: 0.5
for alpha = 0.001 and gamma = 0.001
Area: 0.5
for alpha = 0.001 and gamma = 0.01
Area: 0.5
for alpha = 0.001 and gamma = 0.1
Area: 0.5
for alpha = 0.001 and gamma = 1
Area: 0.49984433374844334
for alpha = 0.001 and gamma = 10
Area: 0.8037873273132357
for alpha = 0.001 and gamma = 100
Area: 0.8238519801950415
for alpha = 0.001 and gamma = 1000
Area: 0.823798336752476
for alpha = 0.01 and gamma = 0.0001
Area: 0.5
for alpha = 0.01 and gamma = 0.001
Area: 0.5
for alpha = 0.01 and gamma = 0.01
Area: 0.5
for alpha = 0.01 and gamma = 0.1
Area: 0.5
for alpha = 0.01 and gamma = 1
Area: 0.8052151452985282
for alpha = 0.01 and gamma = 10
Area: 0.8230468272159757
for alpha = 0.01 and gamma = 100
Area: 0.8226282078277314
for alpha = 0.01 and gamma = 1000
Area: 0.8162032775642067
for alpha = 0.1 and gamma = 0.0001
Area: 0.5
for alpha = 0.1 and gamma = 0.001
Area: 0.5
for alpha = 0.1 and gamma = 0.01
Area: 0.5
for alpha = 0.1 and gamma = 0.1
Area: 0.799498609281218
for alpha = 0.1 and gamma = 1
Area: 0.8275664125872583
for alpha = 0.1 and gamma = 10
Area: 0.8188764255619527
for alpha = 0.1 and gamma = 100
Area: 0.7629300750206051
for alpha = 0.1 and gamma = 1000
Area: 0.7330536855551746
for alpha = 1 and gamma = 0.0001
Area: 0.5
for alpha = 1 and gamma = 0.001
Area: 0.5
for alpha = 1 and gamma = 0.01
Area: 0.6861507671513627
for alpha = 1 and gamma = 0.1
Area: 0.8137447033367226
for alpha = 1 and gamma = 1
Area: 0.7965046033092489
for alpha = 1 and gamma = 10
Area: 0.7247875819942526
for alpha = 1 and gamma = 100
```

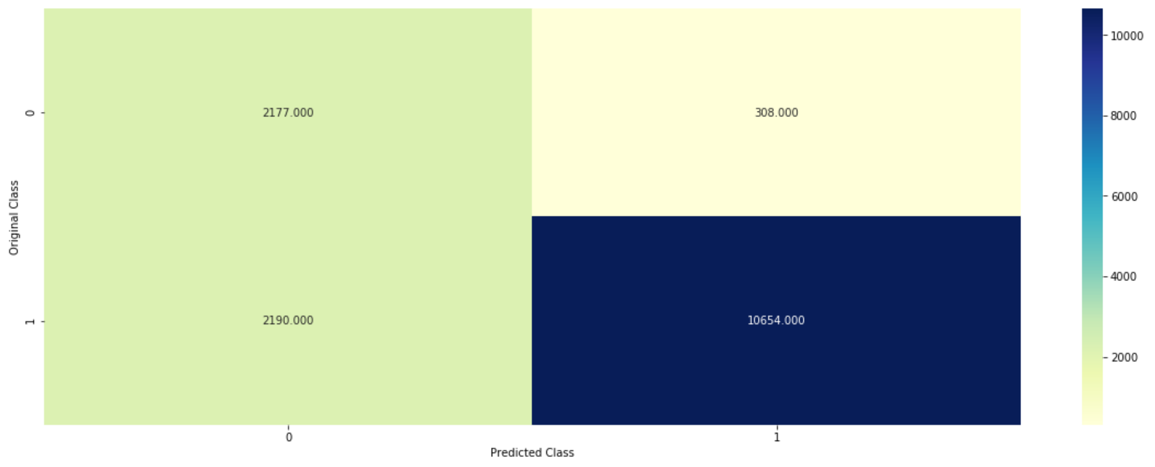
```
Area: 0.7267092204554979
for alpha = 1 and gamma = 1000
Area: 0.7267092204554979
for alpha = 10 and gamma = 0.0001
Area: 0.5
for alpha = 10 and gamma = 0.001
Area: 0.5
for alpha = 10 and gamma = 0.01
Area: 0.5
for alpha = 10 and gamma = 0.1
Area: 0.5032206119162641
for alpha = 10 and gamma = 1
Area: 0.5032206119162641
for alpha = 10 and gamma = 10
Area: 0.5032206119162641
for alpha = 10 and gamma = 100
Area: 0.5032206119162641
for alpha = 10 and gamma = 1000
Area: 0.5032206119162641
for alpha = 0.001 and gamma = 0.0001
Area: 0.5
for alpha = 0.001 and gamma = 0.001
Area: 0.5
for alpha = 0.001 and gamma = 0.01
Area: 0.5
for alpha = 0.001 and gamma = 0.1
Area: 0.5
for alpha = 0.001 and gamma = 1
Area: 0.5037840089431012
for alpha = 0.001 and gamma = 10
Area: 0.8186191581128002
for alpha = 0.001 and gamma = 100
Area: 0.8452916659095024
for alpha = 0.001 and gamma = 1000
Area: 0.8525731467597237
for alpha = 0.01 and gamma = 0.0001
Area: 0.5
for alpha = 0.01 and gamma = 0.001
Area: 0.5
for alpha = 0.01 and gamma = 0.01
Area: 0.5
for alpha = 0.01 and gamma = 0.1
Area: 0.5025767654823365
for alpha = 0.01 and gamma = 1
Area: 0.8189305875740271
for alpha = 0.01 and gamma = 10
Area: 0.8457719377617309
for alpha = 0.01 and gamma = 100
Area: 0.8563956300869684
for alpha = 0.01 and gamma = 1000
Area: 0.8960857170428362
for alpha = 0.1 and gamma = 0.0001
Area: 0.5
for alpha = 0.1 and gamma = 0.001
Area: 0.5
for alpha = 0.1 and gamma = 0.01
Area: 0.5002012072434607
for alpha = 0.1 and gamma = 0.1
Area: 0.8167947109627556
for alpha = 0.1 and gamma = 1
Area: 0.8527743540031845
```

```
for alpha = 0.1 and gamma = 10
Area: 0.8944113293902312
for alpha = 0.1 and gamma = 100
Area: 0.9951855167128589
for alpha = 0.1 and gamma = 1000
Area: 0.999195171026157
for alpha = 1 and gamma = 0.0001
Area: 0.5
for alpha = 1 and gamma = 0.001
Area: 0.5
for alpha = 1 and gamma = 0.01
Area: 0.7154640236310419
for alpha = 1 and gamma = 0.1
Area: 0.8666488184792341
for alpha = 1 and gamma = 1
Area: 0.9797566307217331
for alpha = 1 and gamma = 10
Area: 0.999195171026157
for alpha = 1 and gamma = 100
Area: 0.999195171026157
for alpha = 1 and gamma = 1000
Area: 0.999195171026157
for alpha = 10 and gamma = 0.0001
Area: 0.5
for alpha = 10 and gamma = 0.001
Area: 0.5
for alpha = 10 and gamma = 0.01
Area: 0.5
for alpha = 10 and gamma = 0.1
Area: 0.999195171026157
for alpha = 10 and gamma = 1
Area: 0.999195171026157
for alpha = 10 and gamma = 10
Area: 0.999195171026157
for alpha = 10 and gamma = 100
Area: 0.999195171026157
for alpha = 10 and gamma = 1000
Area: 0.999195171026157
```

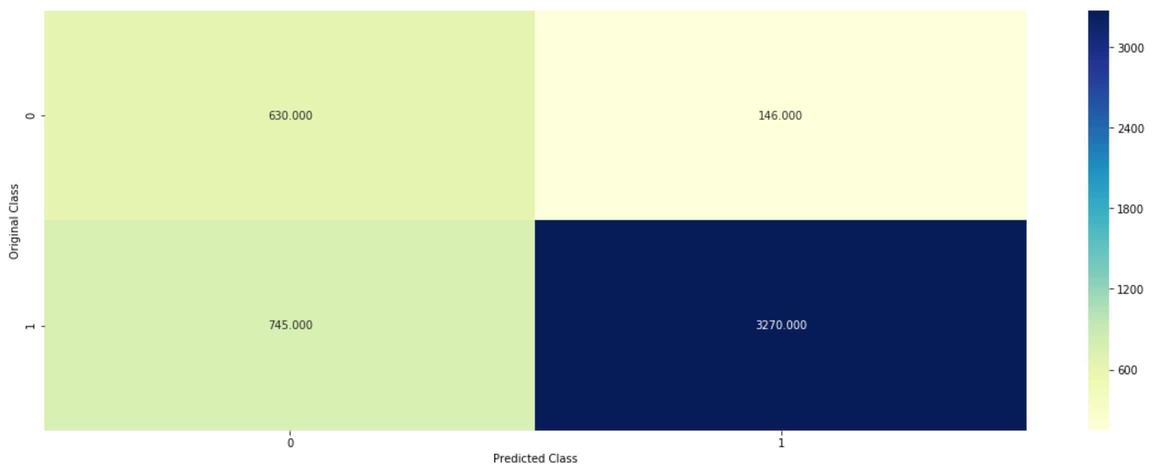




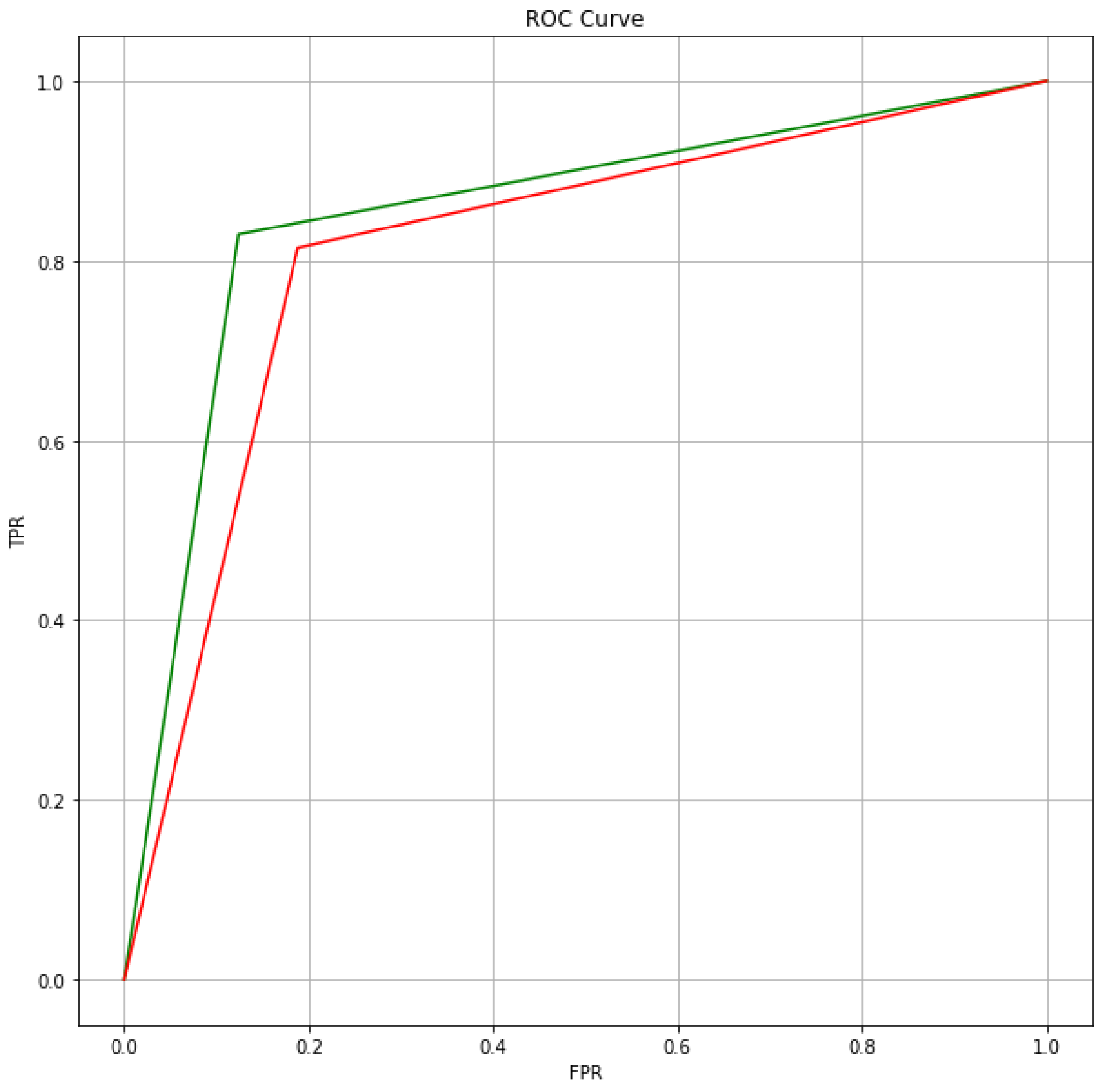
```
20
best alph = 1 and gamma =0.1
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  1 The AUC is: 0.8527743540031845
For values of best alpha =  1 The cross validation AUC is: 0.8275664
125872583
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  1 The test AUC is: 0.8131507491237756
```



[5.2.3] Applying RBF SVM on AVG W2V, SET 3

In [113]:

```
train = loadPickleData("avg_w2v_train_rbf.pickle")
test = loadPickleData('avg_w2v_test_rbf.pickle')
cv = loadPickleData('avg_w2v_cv_rbf.pickle')
```

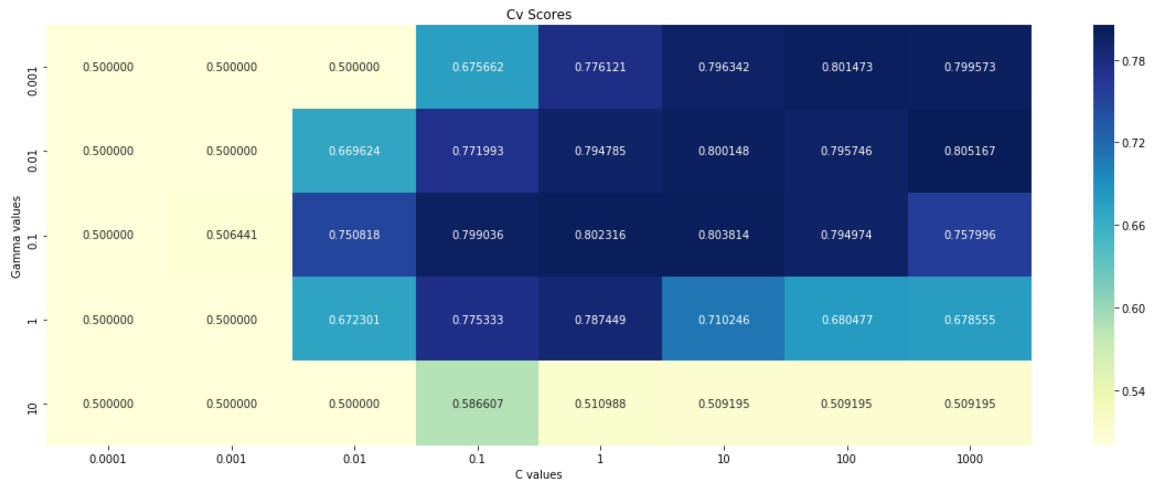
In [114]:

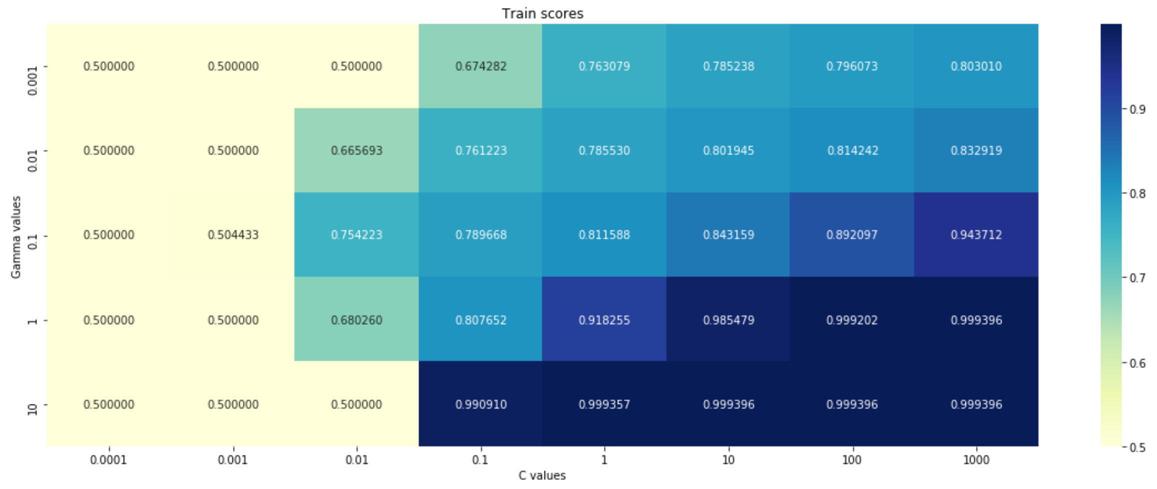
```
clf,alph = performHyperParameterTuningRBF(train,cv,test)
```

```
for alpha = 0.001 and gamma = 0.0001
Area: 0.5
for alpha = 0.001 and gamma = 0.001
Area: 0.5
for alpha = 0.001 and gamma = 0.01
Area: 0.5
for alpha = 0.001 and gamma = 0.1
Area: 0.6756624714486537
for alpha = 0.001 and gamma = 1
Area: 0.7761208471452663
for alpha = 0.001 and gamma = 10
Area: 0.7963416676192137
for alpha = 0.001 and gamma = 100
Area: 0.801473389844444
for alpha = 0.001 and gamma = 1000
Area: 0.7995733090283417
for alpha = 0.01 and gamma = 0.0001
Area: 0.5
for alpha = 0.01 and gamma = 0.001
Area: 0.5
for alpha = 0.01 and gamma = 0.01
Area: 0.6696235734353662
for alpha = 0.01 and gamma = 0.1
Area: 0.771993059440945
for alpha = 0.01 and gamma = 1
Area: 0.7947850051036472
for alpha = 0.01 and gamma = 10
Area: 0.8001475946681426
for alpha = 0.01 and gamma = 100
Area: 0.7957463256748546
for alpha = 0.01 and gamma = 1000
Area: 0.8051667659321025
for alpha = 0.1 and gamma = 0.0001
Area: 0.5
for alpha = 0.1 and gamma = 0.001
Area: 0.5064412238325282
for alpha = 0.1 and gamma = 0.01
Area: 0.7508176864936842
for alpha = 0.1 and gamma = 0.1
Area: 0.799036373262103
for alpha = 0.1 and gamma = 1
Area: 0.8023163940376566
for alpha = 0.1 and gamma = 10
Area: 0.8038141490345182
for alpha = 0.1 and gamma = 100
Area: 0.7949737598337957
for alpha = 0.1 and gamma = 1000
Area: 0.7579961316560483
for alpha = 1 and gamma = 0.0001
Area: 0.5
for alpha = 1 and gamma = 0.001
Area: 0.5
for alpha = 1 and gamma = 0.01
Area: 0.6723012334983747
for alpha = 1 and gamma = 0.1
Area: 0.7753334917569581
for alpha = 1 and gamma = 1
Area: 0.7874486376570949
for alpha = 1 and gamma = 10
Area: 0.7102459476640537
for alpha = 1 and gamma = 100
```

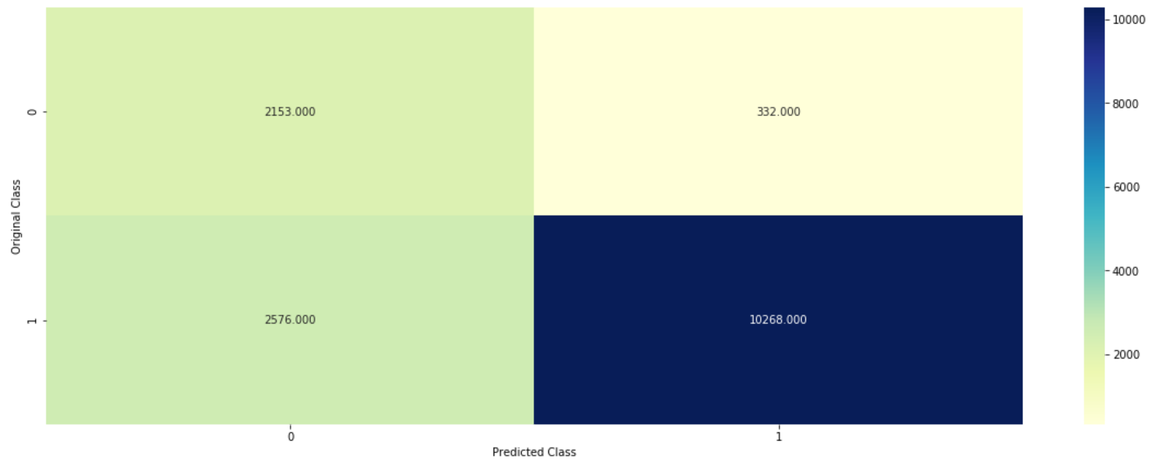
```
Area: 0.680476845083754
for alpha = 1 and gamma = 1000
Area: 0.6785552066225086
for alpha = 10 and gamma = 0.0001
Area: 0.5
for alpha = 10 and gamma = 0.001
Area: 0.5
for alpha = 10 and gamma = 0.01
Area: 0.5
for alpha = 10 and gamma = 0.1
Area: 0.5866068366812858
for alpha = 10 and gamma = 1
Area: 0.5109876309250937
for alpha = 10 and gamma = 10
Area: 0.5091948369941223
for alpha = 10 and gamma = 100
Area: 0.5091948369941223
for alpha = 10 and gamma = 1000
Area: 0.5091948369941223
for alpha = 0.001 and gamma = 0.0001
Area: 0.5
for alpha = 0.001 and gamma = 0.001
Area: 0.5
for alpha = 0.001 and gamma = 0.01
Area: 0.5
for alpha = 0.001 and gamma = 0.1
Area: 0.6742820516997969
for alpha = 0.001 and gamma = 1
Area: 0.7630790347817207
for alpha = 0.001 and gamma = 10
Area: 0.7852380398867826
for alpha = 0.001 and gamma = 100
Area: 0.7960728870262997
for alpha = 0.001 and gamma = 1000
Area: 0.8030096649658148
for alpha = 0.01 and gamma = 0.0001
Area: 0.5
for alpha = 0.01 and gamma = 0.001
Area: 0.5
for alpha = 0.01 and gamma = 0.01
Area: 0.6656933033893175
for alpha = 0.01 and gamma = 0.1
Area: 0.7612231313762361
for alpha = 0.01 and gamma = 1
Area: 0.7855302321559378
for alpha = 0.01 and gamma = 10
Area: 0.8019454628737859
for alpha = 0.01 and gamma = 100
Area: 0.814242179956099
for alpha = 0.01 and gamma = 1000
Area: 0.8329189086559219
for alpha = 0.1 and gamma = 0.0001
Area: 0.5
for alpha = 0.1 and gamma = 0.001
Area: 0.5044331231863306
for alpha = 0.1 and gamma = 0.01
Area: 0.7542231902783878
for alpha = 0.1 and gamma = 0.1
Area: 0.7896684372820543
for alpha = 0.1 and gamma = 1
Area: 0.8115880114069657
```

```
for alpha = 0.1 and gamma = 10
Area: 0.8431589693877998
for alpha = 0.1 and gamma = 100
Area: 0.8920966628171395
for alpha = 0.1 and gamma = 1000
Area: 0.9437116000268193
for alpha = 1 and gamma = 0.0001
Area: 0.5
for alpha = 1 and gamma = 0.001
Area: 0.5
for alpha = 1 and gamma = 0.01
Area: 0.6802598211505094
for alpha = 1 and gamma = 0.1
Area: 0.8076518751249321
for alpha = 1 and gamma = 1
Area: 0.9182547167151147
for alpha = 1 and gamma = 10
Area: 0.9854791470717799
for alpha = 1 and gamma = 100
Area: 0.9992017348563508
for alpha = 1 and gamma = 1000
Area: 0.9993963782696177
for alpha = 10 and gamma = 0.0001
Area: 0.5
for alpha = 10 and gamma = 0.001
Area: 0.5
for alpha = 10 and gamma = 0.01
Area: 0.5
for alpha = 10 and gamma = 0.1
Area: 0.9909099254511811
for alpha = 10 and gamma = 1
Area: 0.9993574495869643
for alpha = 10 and gamma = 10
Area: 0.9993963782696177
for alpha = 10 and gamma = 100
Area: 0.9993963782696177
for alpha = 10 and gamma = 1000
Area: 0.9993963782696177
```

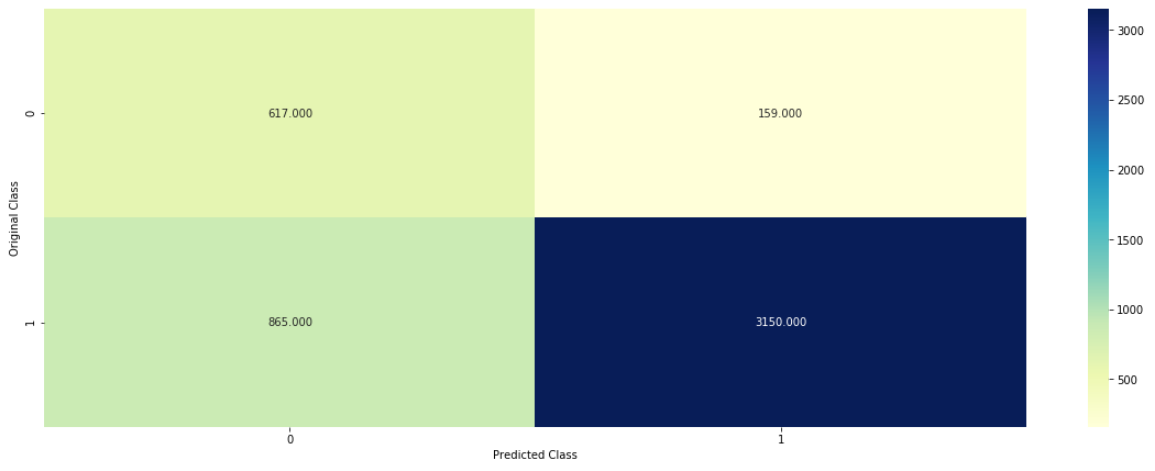




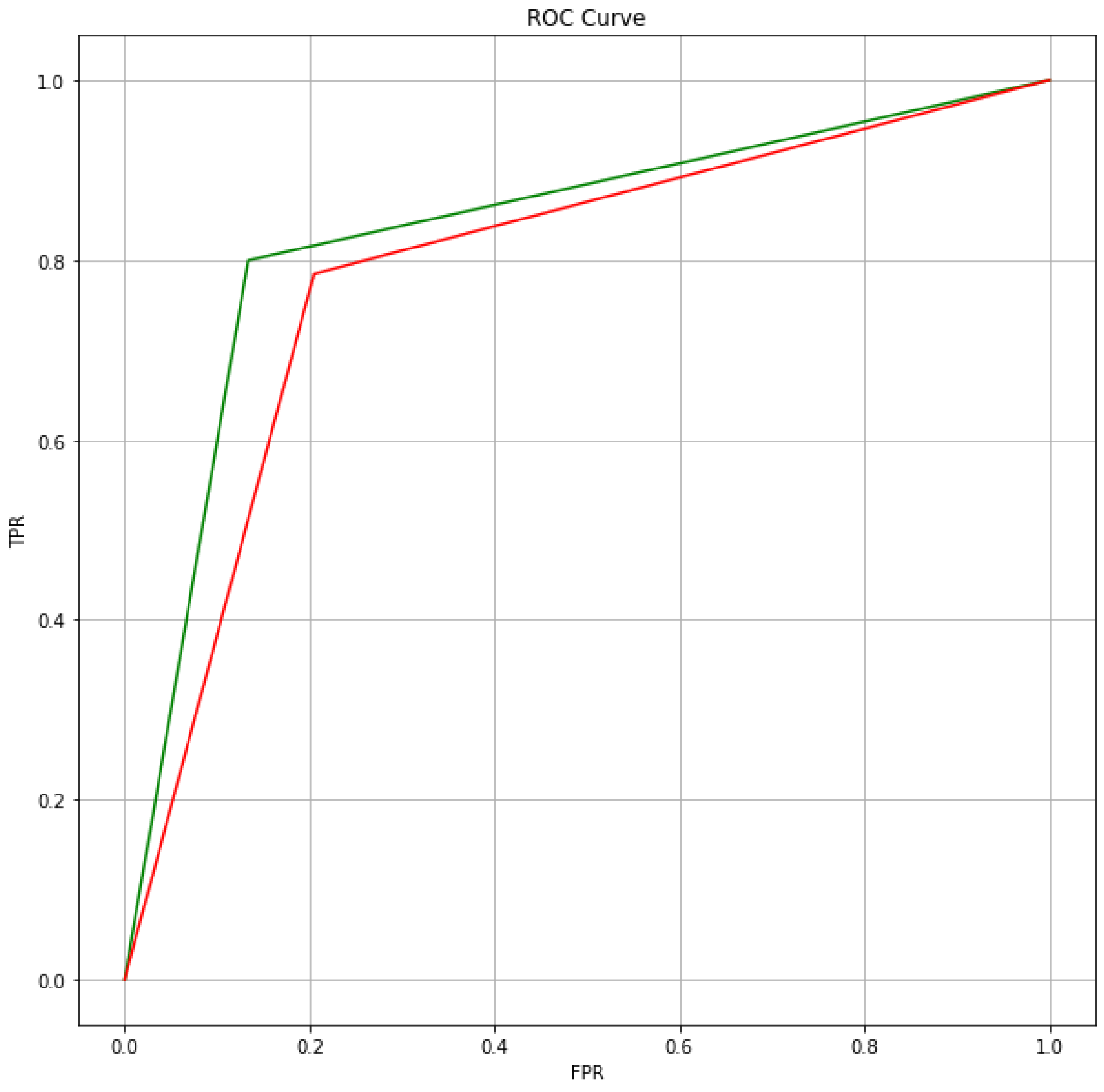
```
15
best alph = 1000 and gamma =0.01
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  1000 The AUC is: 0.8329189086559219
For values of best alpha =  1000 The cross validation AUC is: 0.8051
667659321025
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  1000 The test AUC is: 0.7898305003145423
```



[5.2.4] Applying RBF SVM on TFIDF W2V, SET 4

In [109]:

```
train = loadPickleData("tfidf_w2v_train_rbf.pickle")
test = loadPickleData('tfidf_w2v_test_rbf.pickle')
cv = loadPickleData('tfidf_w2v_cv_rbf.pickle')
```

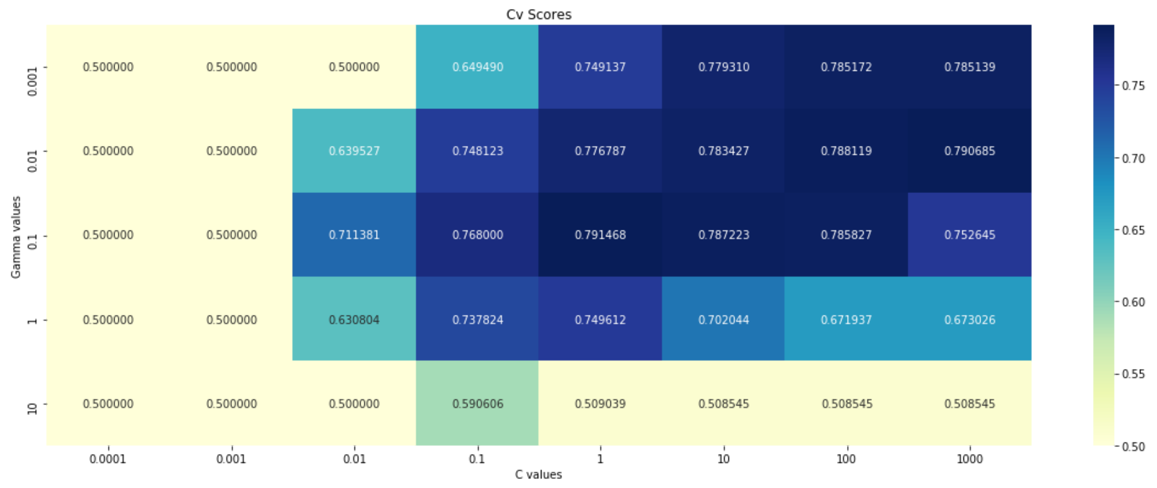
In [110]:

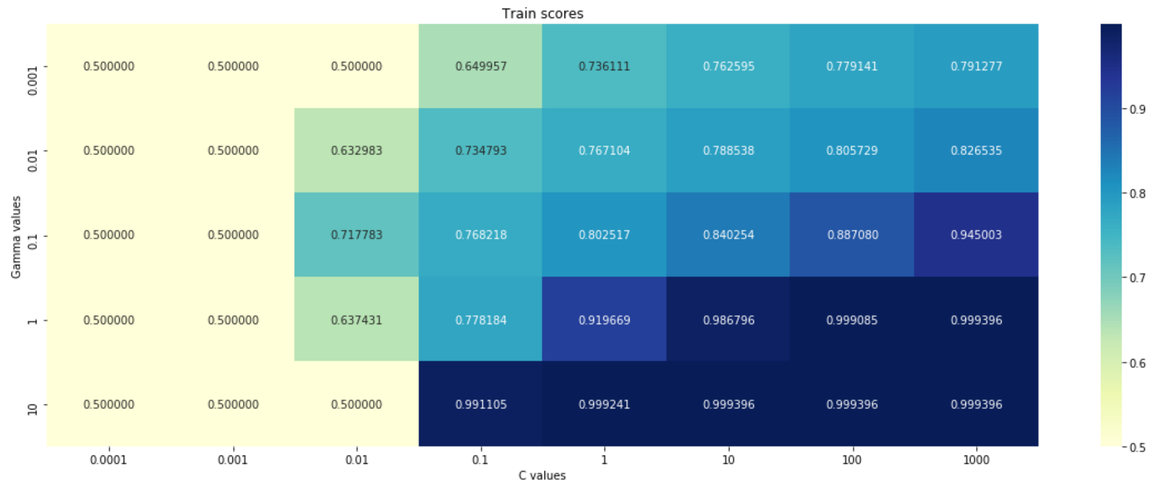
```
clf,alph = performHyperParameterTuningRBF(train,cv,test)
```

```
for alpha = 0.001 and gamma = 0.0001
Area: 0.5
for alpha = 0.001 and gamma = 0.001
Area: 0.5
for alpha = 0.001 and gamma = 0.01
Area: 0.5
for alpha = 0.001 and gamma = 0.1
Area: 0.6494899862231608
for alpha = 0.001 and gamma = 1
Area: 0.7491374435239831
for alpha = 0.001 and gamma = 10
Area: 0.7793098746046929
for alpha = 0.001 and gamma = 100
Area: 0.7851715487212807
for alpha = 0.001 and gamma = 1000
Area: 0.7851394629238584
for alpha = 0.01 and gamma = 0.0001
Area: 0.5
for alpha = 0.01 and gamma = 0.001
Area: 0.5
for alpha = 0.01 and gamma = 0.01
Area: 0.6395268447829496
for alpha = 0.01 and gamma = 0.1
Area: 0.748122980850795
for alpha = 0.01 and gamma = 1
Area: 0.7767871287823641
for alpha = 0.01 and gamma = 10
Area: 0.7834271341567351
for alpha = 0.01 and gamma = 100
Area: 0.788118679348578
for alpha = 0.01 and gamma = 1000
Area: 0.7906845404611933
for alpha = 0.1 and gamma = 0.0001
Area: 0.5
for alpha = 0.1 and gamma = 0.001
Area: 0.5
for alpha = 0.1 and gamma = 0.01
Area: 0.7113814840884525
for alpha = 0.1 and gamma = 0.1
Area: 0.7680003830242068
for alpha = 0.1 and gamma = 1
Area: 0.7914681357951161
for alpha = 0.1 and gamma = 10
Area: 0.7872225330533847
for alpha = 0.1 and gamma = 100
Area: 0.7858273022060992
for alpha = 0.1 and gamma = 1000
Area: 0.7526445715844168
for alpha = 1 and gamma = 0.0001
Area: 0.5
for alpha = 1 and gamma = 0.001
Area: 0.5
for alpha = 1 and gamma = 0.01
Area: 0.6308040199493445
for alpha = 1 and gamma = 0.1
Area: 0.7378241918891114
for alpha = 1 and gamma = 1
Area: 0.7496117117171317
for alpha = 1 and gamma = 10
Area: 0.7020440156979764
for alpha = 1 and gamma = 100
```

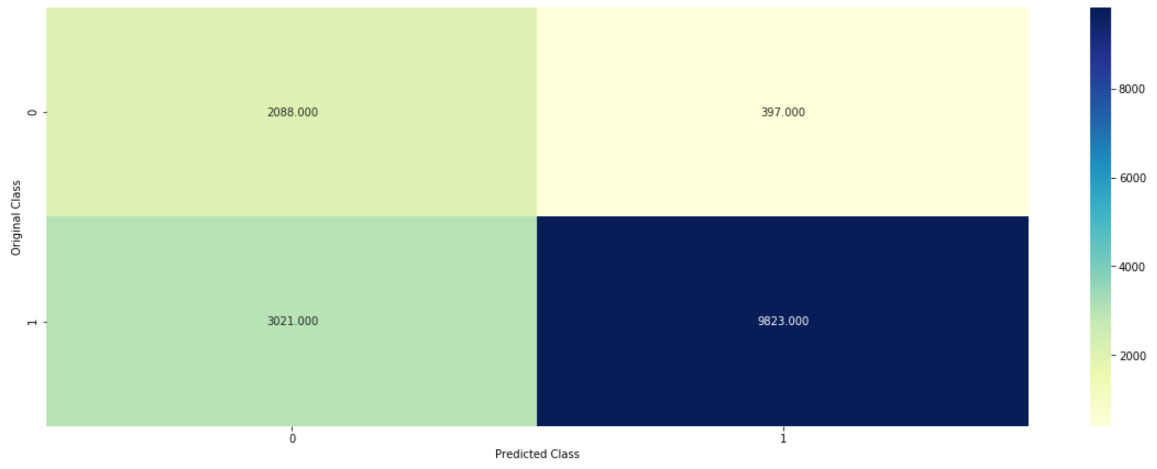
```
Area: 0.6719367588932806
for alpha = 1 and gamma = 1000
Area: 0.6730264226541773
for alpha = 10 and gamma = 0.0001
Area: 0.5
for alpha = 10 and gamma = 0.001
Area: 0.5
for alpha = 10 and gamma = 0.01
Area: 0.5
for alpha = 10 and gamma = 0.1
Area: 0.5906057798553332
for alpha = 10 and gamma = 1
Area: 0.5090391707425655
for alpha = 10 and gamma = 10
Area: 0.5085453502666129
for alpha = 10 and gamma = 100
Area: 0.5085453502666129
for alpha = 10 and gamma = 1000
Area: 0.5085453502666129
for alpha = 0.001 and gamma = 0.0001
Area: 0.5
for alpha = 0.001 and gamma = 0.001
Area: 0.5
for alpha = 0.001 and gamma = 0.01
Area: 0.5
for alpha = 0.001 and gamma = 0.1
Area: 0.6499567789797019
for alpha = 0.001 and gamma = 1
Area: 0.7361107003277841
for alpha = 0.001 and gamma = 10
Area: 0.76259487789396
for alpha = 0.001 and gamma = 100
Area: 0.7791413852156852
for alpha = 0.001 and gamma = 1000
Area: 0.7912767323342108
for alpha = 0.01 and gamma = 0.0001
Area: 0.5
for alpha = 0.01 and gamma = 0.001
Area: 0.5
for alpha = 0.01 and gamma = 0.01
Area: 0.6329827610947529
for alpha = 0.01 and gamma = 0.1
Area: 0.7347932346492533
for alpha = 0.01 and gamma = 1
Area: 0.7671044955500678
for alpha = 0.01 and gamma = 10
Area: 0.7885381425895768
for alpha = 0.01 and gamma = 100
Area: 0.805729471816887
for alpha = 0.01 and gamma = 1000
Area: 0.8265350589992775
for alpha = 0.1 and gamma = 0.0001
Area: 0.5
for alpha = 0.1 and gamma = 0.001
Area: 0.5
for alpha = 0.1 and gamma = 0.01
Area: 0.7177827162288587
for alpha = 0.1 and gamma = 0.1
Area: 0.7682180281940789
for alpha = 0.1 and gamma = 1
Area: 0.8025171740502185
```

```
for alpha = 0.1 and gamma = 10
Area: 0.8402538087447137
for alpha = 0.1 and gamma = 100
Area: 0.887080063689518
for alpha = 0.1 and gamma = 1000
Area: 0.9450028103845747
for alpha = 1 and gamma = 0.0001
Area: 0.5
for alpha = 1 and gamma = 0.001
Area: 0.5
for alpha = 1 and gamma = 0.01
Area: 0.6374309544592376
for alpha = 1 and gamma = 0.1
Area: 0.7781837239569462
for alpha = 1 and gamma = 1
Area: 0.9196692769510242
for alpha = 1 and gamma = 10
Area: 0.9867961584518008
for alpha = 1 and gamma = 100
Area: 0.9990849488083907
for alpha = 1 and gamma = 1000
Area: 0.9993963782696177
for alpha = 10 and gamma = 0.0001
Area: 0.5
for alpha = 10 and gamma = 0.001
Area: 0.5
for alpha = 10 and gamma = 0.01
Area: 0.5
for alpha = 10 and gamma = 0.1
Area: 0.991104568864448
for alpha = 10 and gamma = 1
Area: 0.9992406635390042
for alpha = 10 and gamma = 10
Area: 0.9993963782696177
for alpha = 10 and gamma = 100
Area: 0.9993963782696177
for alpha = 10 and gamma = 1000
Area: 0.9993963782696177
```

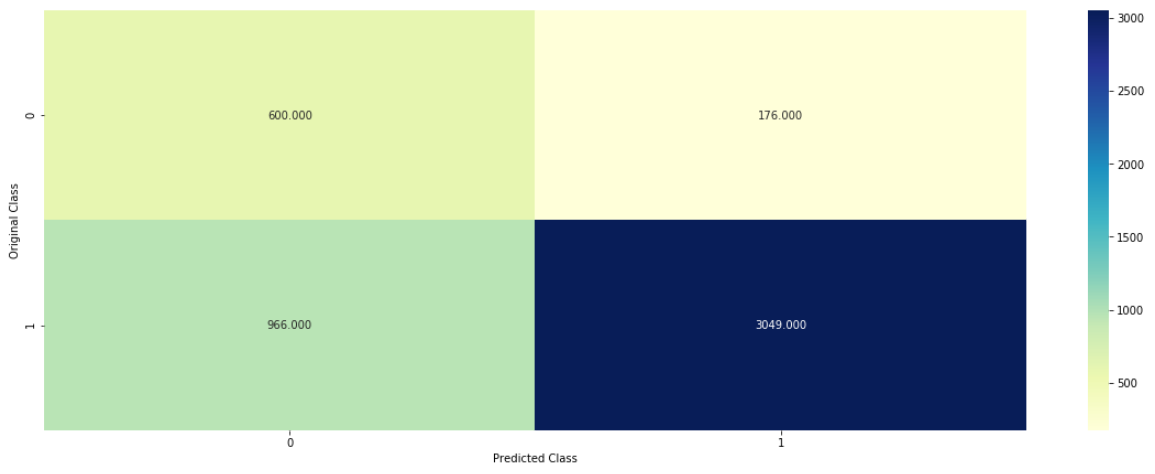




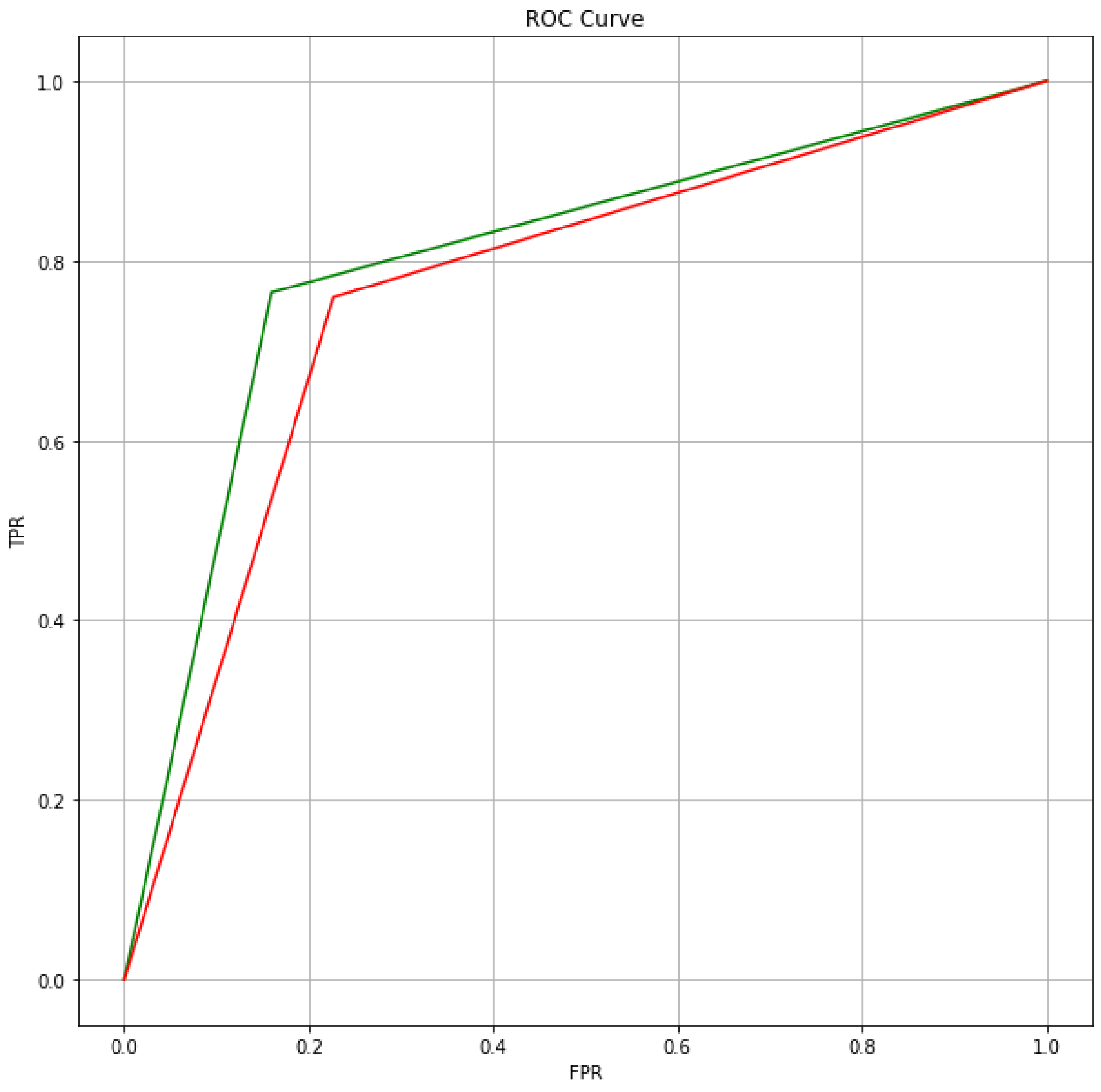
```
20
best alph = 1 and gamma =0.1
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  1 The AUC is: 0.8025171740502185
For values of best alpha =  1 The cross validation AUC is: 0.7914681
357951161
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  1 The test AUC is: 0.766299058941341
```



[6] Conclusions

Vectorizer	Alpha	Regularizer	Kernel	AUC
BOW	0.001	l2	Linear	0.82
TFIDF	0.0001	l2	Linear	0.86
AvgW2V	0.001	l2	Linear	0.72
TFIDFW2V	0.01	l2	Linear	0.69

Vectorizer	C	Gamma	Kernal	AUC
BOW	10	0.001	RBF	0.81
TFIDF	1	0.1	RBF	0.81
AvgW2V	1000	0.01	RBF	0.78
TFIDFW2V	1	0.1	RBF	0.76

In [ ]: