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 [21]:

```
%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 tqdm import tqdm
import os
from sklearn.model_selection import train_test_split
from xgboost import XGBClassifier
```

In [8]:

```
# 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 125000""", 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 (125000, 10)
```

Out[8]:

	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 [9]:

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

In [10]:

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

(80668, 7)

Out[10]:

	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 [11]:

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

Out[11]:

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

In [12]:

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

Out[12]:

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 [13]:

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

Out[13]:

	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 [14]:

```
#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 [15]:

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

Out[15]:

```
(107311, 10)
```

In [16]:

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

Out[16]:

```
85.8488
```

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 [17]:

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

display.head()
```

Out[17]:

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

In [18]:

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

In [19]:

```
#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()
```

```
(107309, 10)
```

Out[19]:

```
1    90143
0    17166
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 [20]:

```
# 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.
==================================================
Back in March I ordered four dawn redwoods from a nursery on Ebay, a
ll about 2-3 feet tall.  They arrived bareroot and healthy.  The pla
n was to plant three in the ground to replace trees uprooted by Katr
ina.  The fourth was to go into a pot to be trained as bonsai.  All
four trees were thriving, but the one in the pot looked like a plant
that yearned to join the rest of its family out in the yard, rather
than being forested with my bonsai collection.  Clearly, it was goin
g to take time, patience, and training to get it to look like a bons
ai.  I decided to put it in the ground and order a Brussels Dawn Red
wood.<br /><br />And I'm glad I did.  The Brussels tree is a long wa
y from a specimen, but it already looks like a bonsai, a mature-look
ing but minature redwood with beatuiful tapered trunk and gorgeous l
ower branching, all of which was lacking in the nursery tree, which
had arrived pruned to favor topgrowth.  The Brussels Dawn redwood is
absolutely stunning, far superior to the tree pictured on Amazon.<br
/><br />Sure, the nursery tree would have acquired this look--eventu
ally, and after much training.  But it loves growing with its kinfol
k in the yard, and meanwhile I have this beautifully shaped little t
ree from Brussels to marvel at every time I sit outside with my bons
ai collection.  Frankly, I can't take my eyes off it.<br /><br />I'm
neither impatient by nature nor a champion of acting on impulse.  Bu
t there are times when instant gratification and acting on impulse h
as its rewards, and this was one of them.  The Brussels Dawn Redwood
looks like a tree, not a seedling.  It is nothing short of breathtak
ing.
==================================================
I first had this tea in a restaurant, immediately I tasted the natur
al sweetness of this tea. It was not a bitter tea,nor was it too swe
et. It was like the perfect cup of tea.
==================================================
If you grew up eating Guava Paste with cream cheese on galletas, the
n this will bring back memories.  Couldn't find this in any of our l
ocal grocery stores, but found it online.  Order arrived fast and I
shared some with my mother who used to give it to me on the weekends
as a special treat.  Just as great as it was back then.
==================================================
```

In [21]:

```python
# 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 [22]:

```
# 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.
==================================================
Back in March I ordered four dawn redwoods from a nursery on Ebay, a
ll about 2-3 feet tall.  They arrived bareroot and healthy.  The pla
n was to plant three in the ground to replace trees uprooted by Katr
ina.  The fourth was to go into a pot to be trained as bonsai.  All
four trees were thriving, but the one in the pot looked like a plant
that yearned to join the rest of its family out in the yard, rather
than being forested with my bonsai collection.  Clearly, it was goin
g to take time, patience, and training to get it to look like a bons
ai.  I decided to put it in the ground and order a Brussels Dawn Red
wood.And I'm glad I did.  The Brussels tree is a long way from a spe
cimen, but it already looks like a bonsai, a mature-looking but mina
ture redwood with beatuiful tapered trunk and gorgeous lower branchi
ng, all of which was lacking in the nursery tree, which had arrived
pruned to favor topgrowth.  The Brussels Dawn redwood is absolutely
stunning, far superior to the tree pictured on Amazon.Sure, the nurs
ery tree would have acquired this look--eventually, and after much t
raining.  But it loves growing with its kinfolk in the yard, and mea
nwhile I have this beautifully shaped little tree from Brussels to m
arvel at every time I sit outside with my bonsai collection.  Frankl
y, I can't take my eyes off it.I'm neither impatient by nature nor a
champion of acting on impulse.  But there are times when instant gra
tification and acting on impulse has its rewards, and this was one o
f them.  The Brussels Dawn Redwood looks like a tree, not a seedlin
g.  It is nothing short of breathtaking.
==================================================
I first had this tea in a restaurant, immediately I tasted the natur
al sweetness of this tea. It was not a bitter tea,nor was it too swe
et. It was like the perfect cup of tea.
==================================================
If you grew up eating Guava Paste with cream cheese on galletas, the
n this will bring back memories.  Couldn't find this in any of our l
ocal grocery stores, but found it online.  Order arrived fast and I
shared some with my mother who used to give it to me on the weekends
as a special treat.  Just as great as it was back then.
```

In [23]:

```
# 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 [24]:

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

```
I first had this tea in a restaurant, immediately I tasted the natur
al sweetness of this tea. It was not a bitter tea,nor was it too swe
et. It was like the perfect cup of tea.
==================================================
```

In [25]:

```
#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 [26]:

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

```
I first had this tea in a restaurant immediately I tasted the natura
l sweetness of this tea It was not a bitter tea nor was it too sweet
It was like the perfect cup of tea
```

In [27]:

```
# 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 [28]:

```
# 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%|██████████| 107309/107309 [00:38<00:00, 2774.42it/s]
```

In [29]:

```
preprocessed_reviews[1500]
```

Out[29]:

```
'first tea restaurant immediately tasted natural sweetness tea not b
itter tea nor sweet like perfect cup tea'
```

[3.2] Preprocessing Review Summary

In [30]:

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

In [31]:

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

In [32]:

```
#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 [33]:

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

In [34]:

```
# 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)
```

```
(68677,)
(68677,)
(17170,)
(17170,)
```

In [35]:

```
def do_pickling(filename,data):
    with open(filename, "wb") as f:
        pickle.dump(data,f)
```

In [36]:

```
do_pickling('y_train.pickle',y)
do_pickling('y_test.pickle',y_test)
do_pickling('y_cv.pickle',y_cv)
```

[4] Featurization

[4.1] BAG OF WORDS

In [25]:

```
#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', 'aahhhs', 'aback', 'abandon', 'abates',
'abbott', 'abby', 'abdominal', 'abiding', 'ability']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (4986, 12997)
the number of unique words  12997
```

[4.2] Bi-Grams and n-Grams.

In [37]:

```
#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  (107309, 5000)
the number of unique words including both unigrams and bigrams  5000
```

In [38]:

```
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 [39]:

```
do_pickling('bow_train.pickle',bow_feature_train)
do_pickling('bow_test.pickle',bow_feature_test)
do_pickling('bow_cv.pickle',bow_feature_cv)
do_pickling('count_vect.pickle',count_vect)
```

[4.3] TF-IDF

In [27]:

```
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) ['ability', 'able',
'able find', 'able get', 'absolute', 'absolutely', 'absolutely delic
ious', 'absolutely love', 'absolutely no', 'according']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (4986, 3144)
the number of unique words including both unigrams and bigrams  3144
```

In [40]:

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,3),min_df=10)
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 [41]:

```
do_pickling('tfidf_train.pickle',tf_idf_train)
do_pickling('tfidf_test.pickle',tf_idf_test)
do_pickling('tfidf_cv.pickle',tf_idf_cv)
do_pickling('tf_idf_vect.pickle',tf_idf_vect)
```

[4.4] Word2Vec

In [28]:

```
# 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 [42]:

```
# 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 ")
```

```
[('snack', 0.9951335191726685), ('calorie', 0.9946465492248535), ('w
onderful', 0.9946032166481018), ('excellent', 0.9944332838058472),
('especially', 0.9941144585609436), ('baked', 0.9940600395202637),
('salted', 0.994047224521637), ('alternative', 0.9937226176261902),
('tasty', 0.9936816692352295), ('healthy', 0.9936649799346924)]
==================================================
[('varieties', 0.9994194507598877), ('become', 0.9992934465408325),
('popcorn', 0.9992750883102417), ('de', 0.9992610216140747), ('mis
s', 0.9992451071739197), ('melitta', 0.999218761920929), ('choice',
0.9992102384567261), ('american', 0.9991837739944458), ('beef', 0.99
91780519485474), ('finish', 0.9991567134857178)]
```

In [36]:

```
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  3817
sample words  ['product', 'available', 'course', 'total', 'pretty',
'stinky', 'right', 'nearby', 'used', 'ca', 'not', 'beat', 'great',
'received', 'shipment', 'could', 'hardly', 'wait', 'try', 'love', 'c
all', 'instead', 'removed', 'easily', 'daughter', 'designed', 'print
ed', 'use', 'car', 'windows', 'beautifully', 'shop', 'program', 'goi
ng', 'lot', 'fun', 'everywhere', 'like', 'tv', 'computer', 'really',
'good', 'idea', 'final', 'outstanding', 'window', 'everybody', 'ask
s', 'bought', 'made']
```

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

[4.4.1.1] Avg W2v

In [43]:

```
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
```

In [44]:

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

In [45]:

```
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)
```

In [46]:

```
sent_vectors_train = findAvgWord2Vec(list_of_sent)
```

```
100%|██████████| 68677/68677 [02:01<00:00, 562.99it/s]
```

In [47]:

```
do_pickling('avg_w2v_train.pickle',sent_vectors_train)
```

In [48]:

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

In [49]:

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

```
100%|██████████| 21462/21462 [00:38<00:00, 557.97it/s]

21462
50
```

In [50]:

```
do_pickling('avg_w2v_test.pickle',sent_vectors_test)
```

In [51]:

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

```
100%|██████████| 17170/17170 [00:31<00:00, 546.21it/s]
```

In [60]:

```
do_pickling('avg_w2v_cv.pickle',sent_vectors_cv)
```

[4.4.1.2] TFIDF weighted W2v

In [39]:

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
tf_idf_matrix = model.fit_transform(preprocessed_reviews)
# 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 [41]:

```
# 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%|████████████████████████████████████████████████████████████████
██████████████| 4986/4986 [00:20<00:00, 245.63it/s]
```

In [53]:

```
def findTfidfW2V(values):
    model = TfidfVectorizer()
    tf_idf_matrix = model.fit_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 [54]:

```
tfidf_sent_vectors = findTfidfW2V(train_df)
print(len(tfidf_sent_vectors))
```

```
100%|██████████| 68677/68677 [02:20<00:00, 490.14it/s]

68677
```

In [55]:

```
do_pickling('tfidf_w2v_train.pickle',tfidf_sent_vectors)
```

In [56]:

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

```
100%|██████████| 21462/21462 [00:43<00:00, 491.38it/s]
```

```
21462
```

In [57]:

```
do_pickling('tfidf_w2v_test.pickle',tfidf_sent_vectors_test)
```

In [58]:

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

```
100%|██████████| 17170/17170 [00:35<00:00, 482.89it/s]
```

In [59]:

```
do_pickling('tfidf_w2v_cv.pickle',tfidf_sent_vectors_cv)
```

[5] Assignment 9: Random Forests

1. **Apply Random Forests & GBDT 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. **The hyper paramter tuning (Consider any two hyper parameters)**

    - 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

3. **Feature importance**

    - Get top 20 important features and represent them in a word cloud. Do this for BOW & TFIDF.

4. **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.

5. **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
      with X-axis as **n_estimators**, Y-axis as **max_depth**, and Z-axis as **AUC Score** , we have given the notebook which explains how to plot this 3d plot, you can find it in the same drive *3d_scatter_plot.ipynb*

(or)

- 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
  seaborn heat maps (https://seaborn.pydata.org/generated/seaborn.heatmap.html) with rows as **n_estimators**, columns as **max_depth**, and values inside the cell representing **AUC Score**
- You choose either of the plotting techniques out of 3d plot or heat map
- 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)
6. **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)

In [2]:

```
import warnings
warnings.filterwarnings("ignore")
import sqlite3
import pandas as pd
import numpy as np

import pickle
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV

from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV

from sklearn.metrics import accuracy_score
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.preprocessing import label_binarize
from sklearn.metrics.classification import log_loss
from wordcloud import WordCloud
from sklearn.ensemble import RandomForestClassifier
import seaborn as sns
from sklearn.metrics import roc_auc_score,roc_curve
```

In [3]:

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

In [4]:

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

In [5]:

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

In [6]:

```
def draw_wordcloud(train):
    wordcloud = WordCloud(    background_color='black',
                              width=1600,
                              height=800,
                         ).generate(train)

    fig = plt.figure(figsize=(30,20))
    plt.imshow(wordcloud)
    plt.axis('off')
    plt.tight_layout(pad=0)
    plt.show()
```

In [7]:

```
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 [8]:

```
estimators = [100,200,500,1000,2000]
depth = [1, 5, 10, 50, 100, 500]
```

In [9]:

```
# estimators = [100,200]
# depth = [1, 5, 10]
```

In [10]:

```
# 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 [11]:

```
def drawHeatMap(C,title):
    parameters = {'n_estimators' : estimators,
    'depth' : depth}
    labels_y = parameters['n_estimators']
    labels_x = parameters['depth']
    plt.figure(figsize=(20,7))
    sns.heatmap(C, annot=True, cmap="YlGnBu", fmt=".6f", xticklabels=labels_x, y
ticklabels=labels_y)
    plt.xlabel('Depth')
    plt.ylabel('No of estimators')
    plt.title(title)
    plt.show()
```

In [12]:

```
def calculateMetricC(X,y,train,y_train):
    auc_array = []
    C = np.zeros((len(estimators),len(depth)))
    for x,i in enumerate(estimators):
        for z,r in enumerate(depth):
            print("for estimator = {} and depth = {}".format(i,r))
            clf = RandomForestClassifier(n_estimators=i, criterion='gini', max_d
epth=r, random_state=42, n_jobs=-1)
            clf.fit(train, y_train)
            pred = clf.predict(X)
            area = roc_auc_score(y, pred)
            auc_array.append(area)
            print("Area:",area)
            C[x][z]= area
    return (auc_array,C)
```

In [13]:

```
def performHyperParameterTuning(train,cv,test):
    auc_array,C_cv = calculateMetricC(cv,y_cv,train,y_train)
    auc_array_train,C_train = calculateMetricC(train,y_train,train,y_train)
    drawHeatMap(C_cv,'Cross Validation')
    drawHeatMap(C_train,'Train')
    best_alpha = np.argmax(auc_array)
    best_a = estimators[int(best_alpha/6)]
    best_r = depth[int(best_alpha%6)]
    print("best estimators = {} and depth = {}".format(best_a,best_r))
    return (best_a,best_r)
```

In [14]:

```
def bestModel(train,cv,test,best_estimator,best_depth):
    clf = RandomForestClassifier(n_estimators=best_estimator, criterion='gini',
max_depth=best_depth, random_state=42, n_jobs=-1)
    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 estimator = ',best_estimator,'best depth = ' , bes
t_depth,"The AUC is:",roc_auc_score(y_train, predict_y))
    predict_y = clf.predict(cv)
    print('For values of best estimator = ',best_estimator,'best depth = ' , bes
t_depth, "The AUC is:",roc_auc_score(y_cv, predict_y))
    predict_y = 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 estimator = ',best_estimator,'best depth = ' , bes
t_depth, "The AUC is:",roc_auc_score(y_test, predict_y))
    plotAUC(train_fpr,train_tpr,test_fpr,test_tpr)
    return clf
```

[5.1] Applying RF

[5.1.1] Applying Random Forests on BOW, SET 1

In [74]:

```
np.unique(y_cv)
```

Out[74]:

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

In [75]:

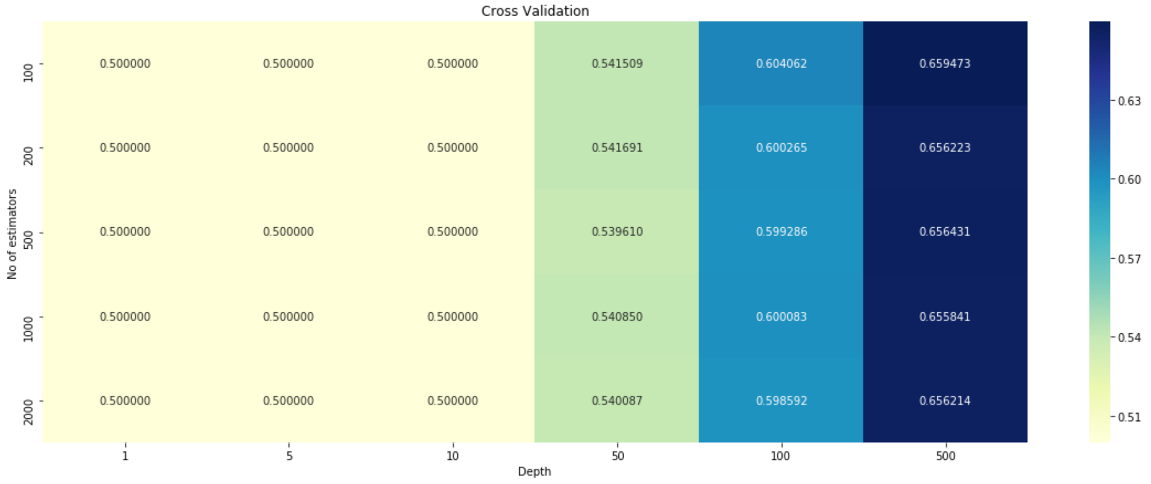
```
train = loadPickleData("bow_train.pickle")
test = loadPickleData('bow_test.pickle')
cv = loadPickleData('bow_cv.pickle')
```

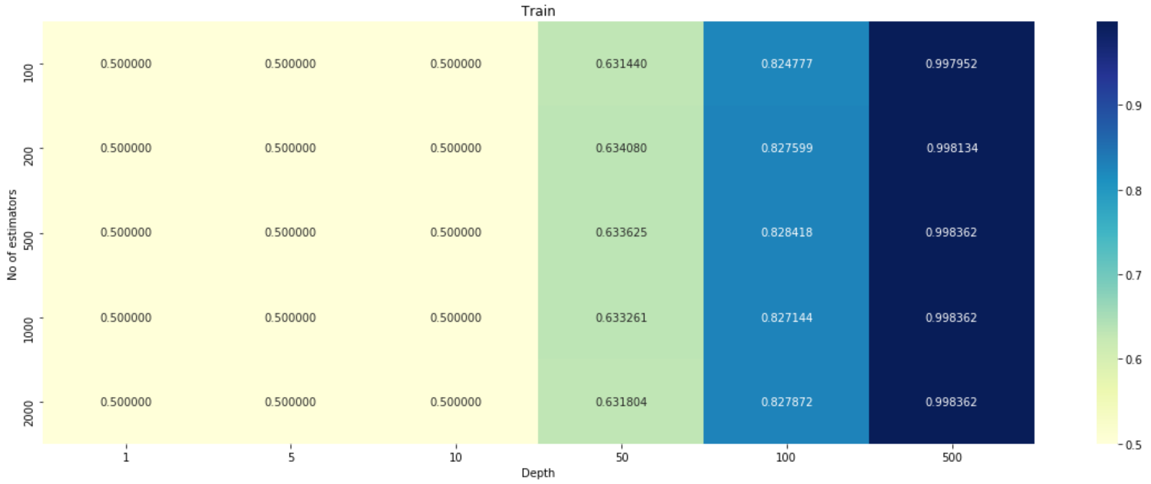
In [76]:

```
best_estimator,best_depth = performHyperParameterTuning(train,cv,test)
```

```
for estimator = 100 and depth = 1
Area: 0.5
for estimator = 100 and depth = 5
Area: 0.5
for estimator = 100 and depth = 10
Area: 0.5
for estimator = 100 and depth = 50
Area: 0.5415085004710124
for estimator = 100 and depth = 100
Area: 0.604061672821095
for estimator = 100 and depth = 500
Area: 0.6594729058552551
for estimator = 200 and depth = 1
Area: 0.5
for estimator = 200 and depth = 5
Area: 0.5
for estimator = 200 and depth = 10
Area: 0.5
for estimator = 200 and depth = 50
Area: 0.5416905172165529
for estimator = 200 and depth = 100
Area: 0.6002653055285413
for estimator = 200 and depth = 500
Area: 0.6562225887993233
for estimator = 500 and depth = 1
Area: 0.5
for estimator = 500 and depth = 5
Area: 0.5
for estimator = 500 and depth = 10
Area: 0.5
for estimator = 500 and depth = 50
Area: 0.5396103168247355
for estimator = 500 and depth = 100
Area: 0.5992858880977252
for estimator = 500 and depth = 500
Area: 0.6564305899086624
for estimator = 1000 and depth = 1
Area: 0.5
for estimator = 1000 and depth = 5
Area: 0.5
for estimator = 1000 and depth = 10
Area: 0.5
for estimator = 1000 and depth = 50
Area: 0.540849767191963
for estimator = 1000 and depth = 100
Area: 0.6000832887830008
for estimator = 1000 and depth = 500
Area: 0.6558411903327264
for estimator = 2000 and depth = 1
Area: 0.5
for estimator = 2000 and depth = 5
Area: 0.5
for estimator = 2000 and depth = 10
Area: 0.5
for estimator = 2000 and depth = 50
Area: 0.5400870333582442
for estimator = 2000 and depth = 100
Area: 0.5985924879671194
for estimator = 2000 and depth = 500
Area: 0.6562139063115653
for estimator = 100 and depth = 1
```

```
Area: 0.5
for estimator = 100 and depth = 5
Area: 0.5
for estimator = 100 and depth = 10
Area: 0.5
for estimator = 100 and depth = 50
Area: 0.6314400145639905
for estimator = 100 and depth = 100
Area: 0.8247769888949572
for estimator = 100 and depth = 500
Area: 0.9979519388312398
for estimator = 200 and depth = 1
Area: 0.5
for estimator = 200 and depth = 5
Area: 0.5
for estimator = 200 and depth = 10
Area: 0.5
for estimator = 200 and depth = 50
Area: 0.6340797378481704
for estimator = 200 and depth = 100
Area: 0.8275987620608046
for estimator = 200 and depth = 500
Area: 0.9981339887129073
for estimator = 500 and depth = 1
Area: 0.5
for estimator = 500 and depth = 5
Area: 0.5
for estimator = 500 and depth = 10
Area: 0.5
for estimator = 500 and depth = 50
Area: 0.6336246131440015
for estimator = 500 and depth = 100
Area: 0.8284179865283088
for estimator = 500 and depth = 500
Area: 0.9983615510649918
for estimator = 1000 and depth = 1
Area: 0.5
for estimator = 1000 and depth = 5
Area: 0.5
for estimator = 1000 and depth = 10
Area: 0.5
for estimator = 1000 and depth = 50
Area: 0.6332605133806664
for estimator = 1000 and depth = 100
Area: 0.8271436373566357
for estimator = 1000 and depth = 500
Area: 0.9983615510649918
for estimator = 2000 and depth = 1
Area: 0.5
for estimator = 2000 and depth = 5
Area: 0.5
for estimator = 2000 and depth = 10
Area: 0.5
for estimator = 2000 and depth = 50
Area: 0.6318041143273256
for estimator = 2000 and depth = 100
Area: 0.827871836883306
for estimator = 2000 and depth = 500
Area: 0.9983615510649918
```



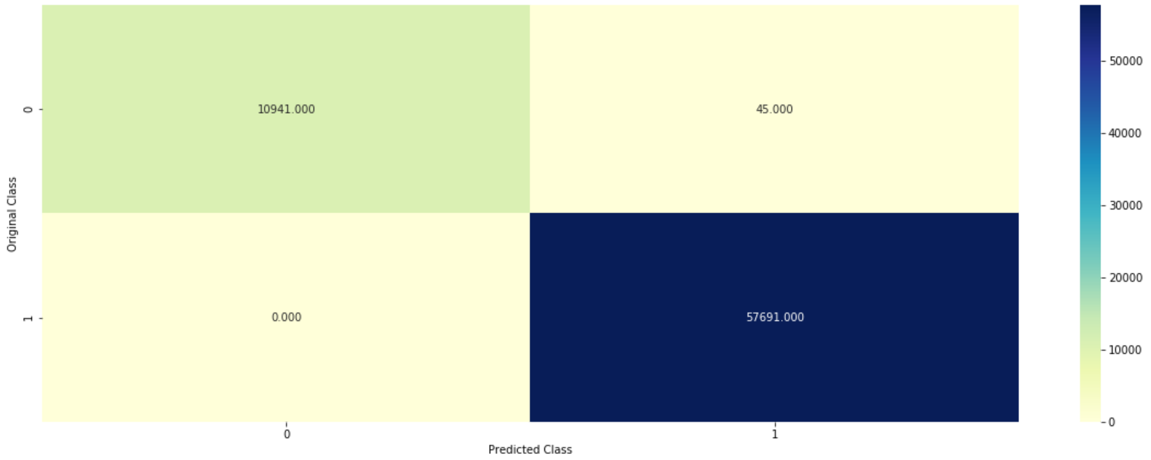



```
best estimators = 100 and depth = 500
```

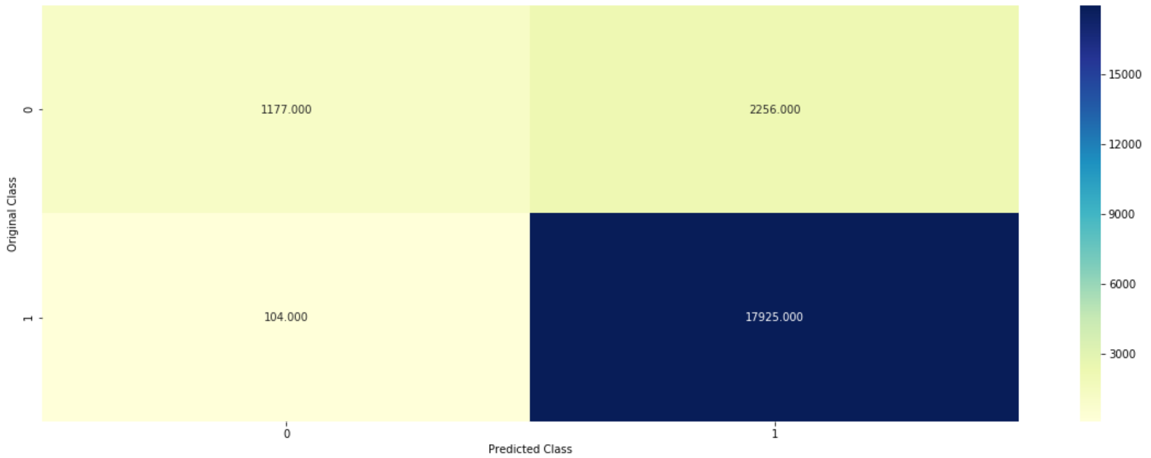
In [77]:

```
clf = bestModel(train,cv,test,best_estimator,best_depth)
```

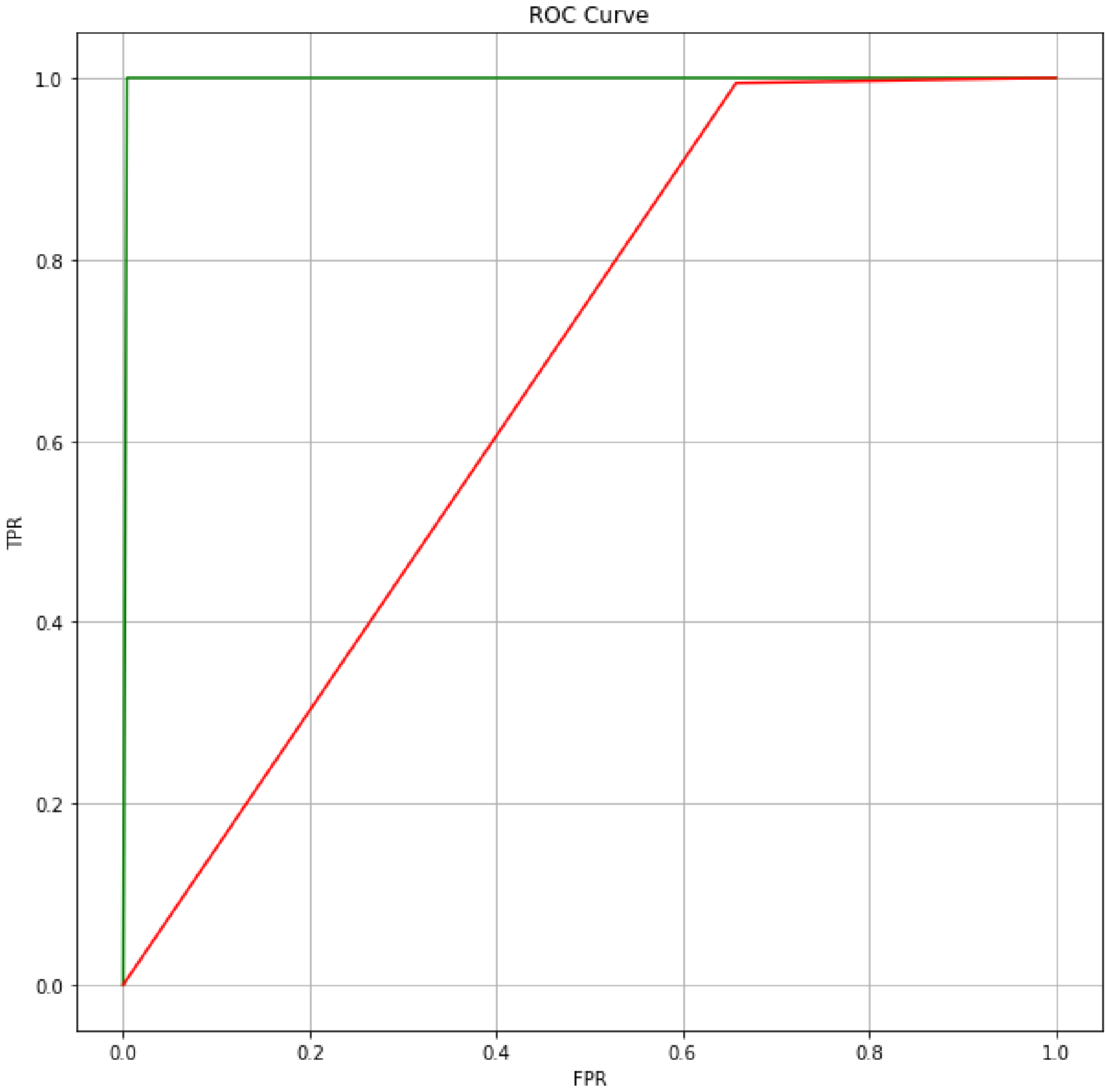
```
-------------------- Confusion matrix --------------------
```




```
For values of best estimator =  100 best depth =  500 The AUC is: 0.
9979519388312398
For values of best estimator =  100 best depth =  500 The AUC is: 0.
6594729058552551
-------------------- Confusion matrix --------------------
```




```
For values of best estimator =  100 best depth =  500 The AUC is: 0.
6685401680824388
```



[5.1.2] Wordcloud of top 20 important features from SET 1

In [78]:

```
indices = np.argsort(-clf.feature_importances_)
word_indices = indices[:20]
words = getImportantFeatures(word_indices,count_vect)
print(words)
```

```
['not', 'great', 'disappointed', 'not buy', 'horrible', 'worst', 'no
t worth', 'waste', 'awful', 'terrible', 'bad', 'return', 'love', 'no
t recommend', 'best', 'would not', 'threw', 'money', 'waste money',
'disappointing']
```

In [79]:

```
text = ''
for word in words:
    text = text+' '+word
```

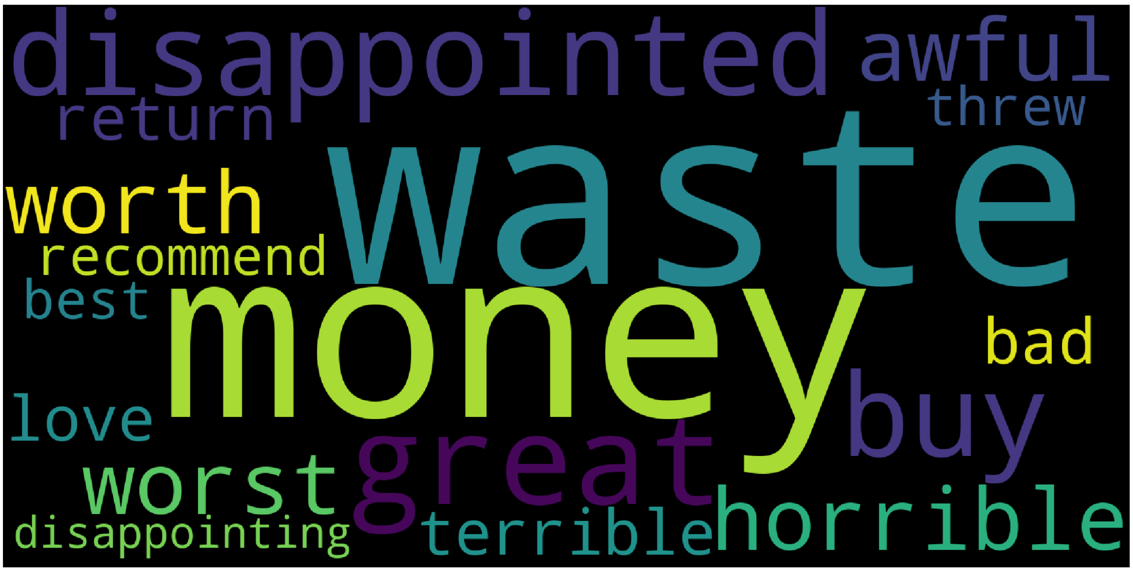
In [80]:

```
print(text)
```

```
 not great disappointed not buy horrible worst not worth waste awful
terrible bad return love not recommend best would not threw money wa
ste money disappointing
```

In [81]:

```
draw_wordcloud(text)
```



[5.1.3] Applying Random Forests on TFIDF, SET 2

In [82]:

```
train = loadPickleData("tfidf_train.pickle")
test = loadPickleData('tfidf_test.pickle')
cv = loadPickleData('tfidf_cv.pickle')
```

In [83]:

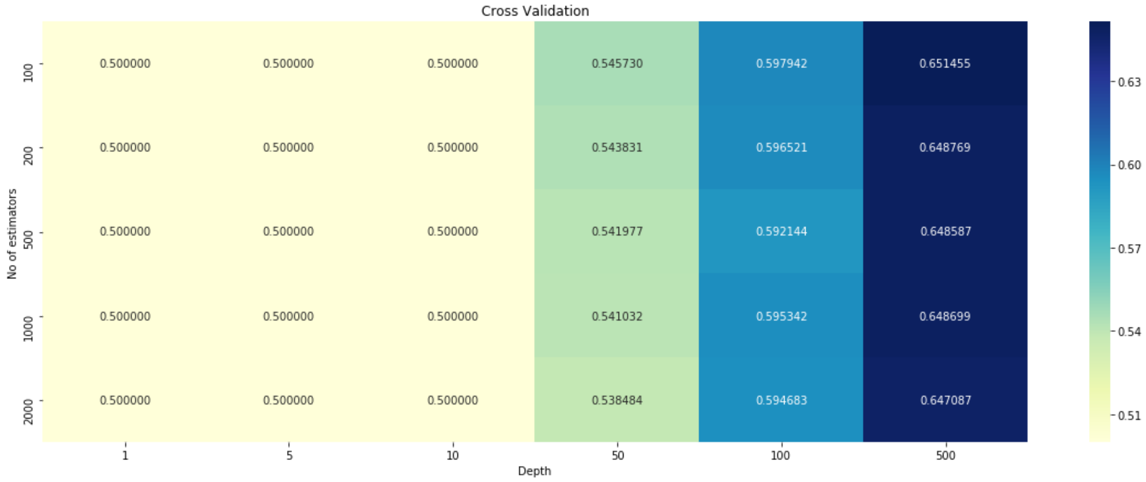
```
tf_idf_vect = loadPickleData('tf_idf_vect.pickle')
```

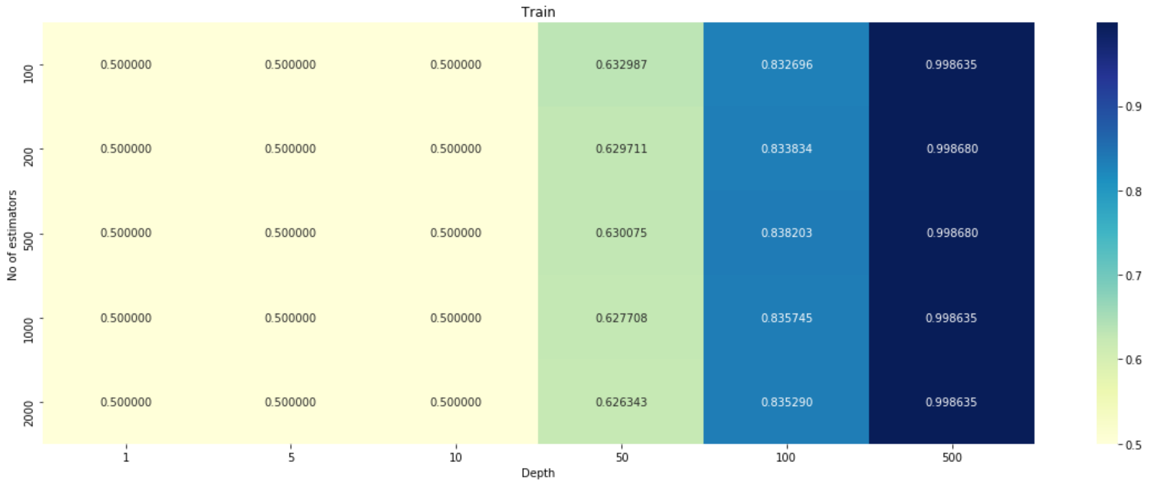
In [84]:

```
best_estimator,best_depth = performHyperParameterTuning(train,cv,test)
```

```
for estimator = 100 and depth = 1
Area: 0.5
for estimator = 100 and depth = 5
Area: 0.5
for estimator = 100 and depth = 10
Area: 0.5
for estimator = 100 and depth = 50
Area: 0.5457295524700024
for estimator = 100 and depth = 100
Area: 0.597942437175828
for estimator = 100 and depth = 500
Area: 0.6514554865637113
for estimator = 200 and depth = 1
Area: 0.5
for estimator = 200 and depth = 5
Area: 0.5
for estimator = 200 and depth = 10
Area: 0.5
for estimator = 200 and depth = 50
Area: 0.5438313688237255
for estimator = 200 and depth = 100
Area: 0.5965209700630598
for estimator = 200 and depth = 500
Area: 0.648768521620442
for estimator = 500 and depth = 1
Area: 0.5
for estimator = 500 and depth = 5
Area: 0.5
for estimator = 500 and depth = 10
Area: 0.5
for estimator = 500 and depth = 50
Area: 0.5419765345167632
for estimator = 500 and depth = 100
Area: 0.5921438856823278
for estimator = 500 and depth = 500
Area: 0.6485865048749013
for estimator = 1000 and depth = 1
Area: 0.5
for estimator = 1000 and depth = 5
Area: 0.5
for estimator = 1000 and depth = 10
Area: 0.5
for estimator = 1000 and depth = 50
Area: 0.5410317839375036
for estimator = 1000 and depth = 100
Area: 0.5953421709111875
for estimator = 1000 and depth = 500
Area: 0.648699187917329
for estimator = 2000 and depth = 1
Area: 0.5
for estimator = 2000 and depth = 5
Area: 0.5
for estimator = 2000 and depth = 10
Area: 0.5
for estimator = 2000 and depth = 50
Area: 0.5384835494999354
for estimator = 2000 and depth = 100
Area: 0.5946834376321382
for estimator = 2000 and depth = 500
Area: 0.6470870215712622
for estimator = 100 and depth = 1
```

```
Area: 0.5
for estimator = 100 and depth = 5
Area: 0.5
for estimator = 100 and depth = 10
Area: 0.5
for estimator = 100 and depth = 50
Area: 0.6329874385581649
for estimator = 100 and depth = 100
Area: 0.8326961587474968
for estimator = 100 and depth = 500
Area: 0.9986346258874932
for estimator = 200 and depth = 1
Area: 0.5
for estimator = 200 and depth = 5
Area: 0.5
for estimator = 200 and depth = 10
Area: 0.5
for estimator = 200 and depth = 50
Area: 0.6297105406881486
for estimator = 200 and depth = 100
Area: 0.8338339705079192
for estimator = 200 and depth = 500
Area: 0.9986801383579101
for estimator = 500 and depth = 1
Area: 0.5
for estimator = 500 and depth = 5
Area: 0.5
for estimator = 500 and depth = 10
Area: 0.5
for estimator = 500 and depth = 50
Area: 0.6300746404514836
for estimator = 500 and depth = 100
Area: 0.838203167667941
for estimator = 500 and depth = 500
Area: 0.9986801383579101
for estimator = 1000 and depth = 1
Area: 0.5
for estimator = 1000 and depth = 5
Area: 0.5
for estimator = 1000 and depth = 10
Area: 0.5
for estimator = 1000 and depth = 50
Area: 0.6277079919898052
for estimator = 1000 and depth = 100
Area: 0.8357454942654288
for estimator = 1000 and depth = 500
Area: 0.9986346258874932
for estimator = 2000 and depth = 1
Area: 0.5
for estimator = 2000 and depth = 5
Area: 0.5
for estimator = 2000 and depth = 10
Area: 0.5
for estimator = 2000 and depth = 50
Area: 0.6263426178772984
for estimator = 2000 and depth = 100
Area: 0.8352903695612598
for estimator = 2000 and depth = 500
Area: 0.9986346258874932
```



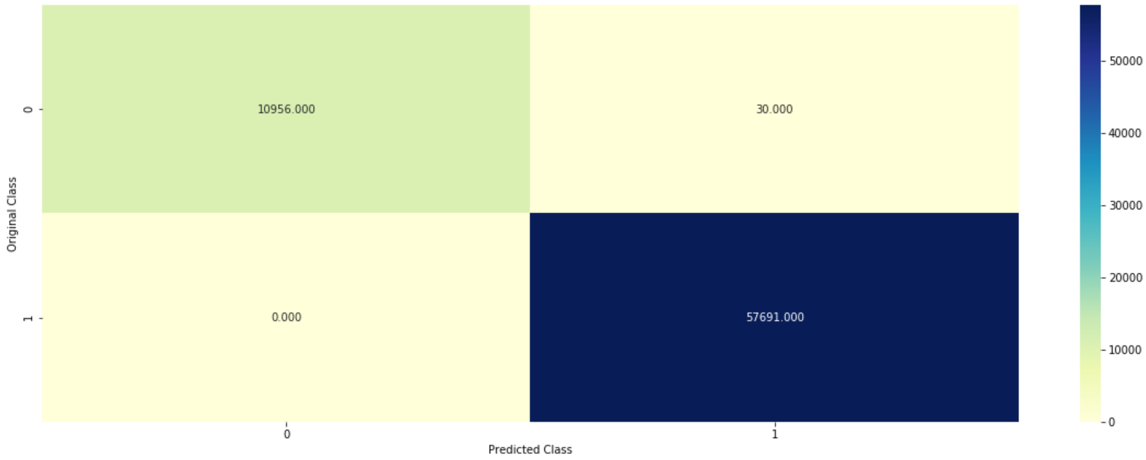



```
best estimators = 100 and depth = 500
```

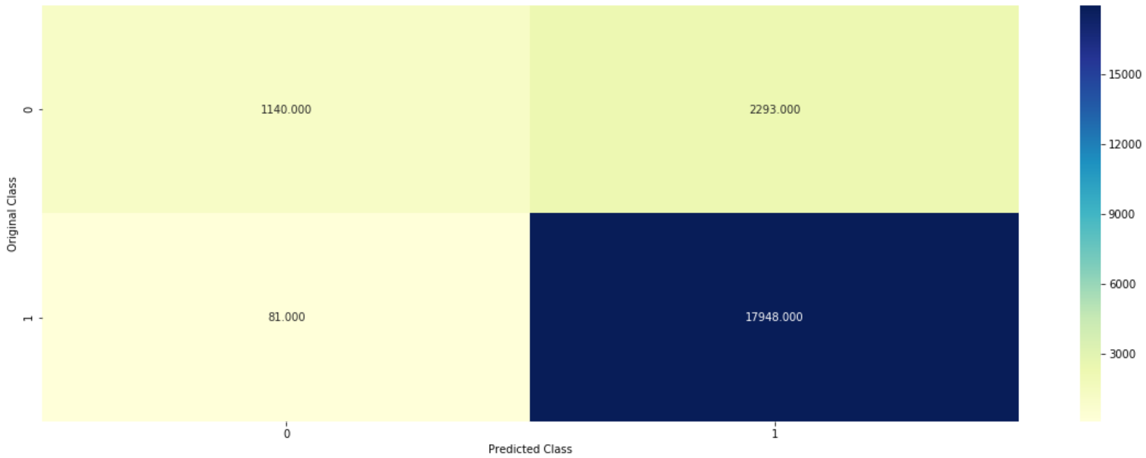
In [85]:

```
clf = bestModel(train,cv,test,best_estimator,best_depth)
```

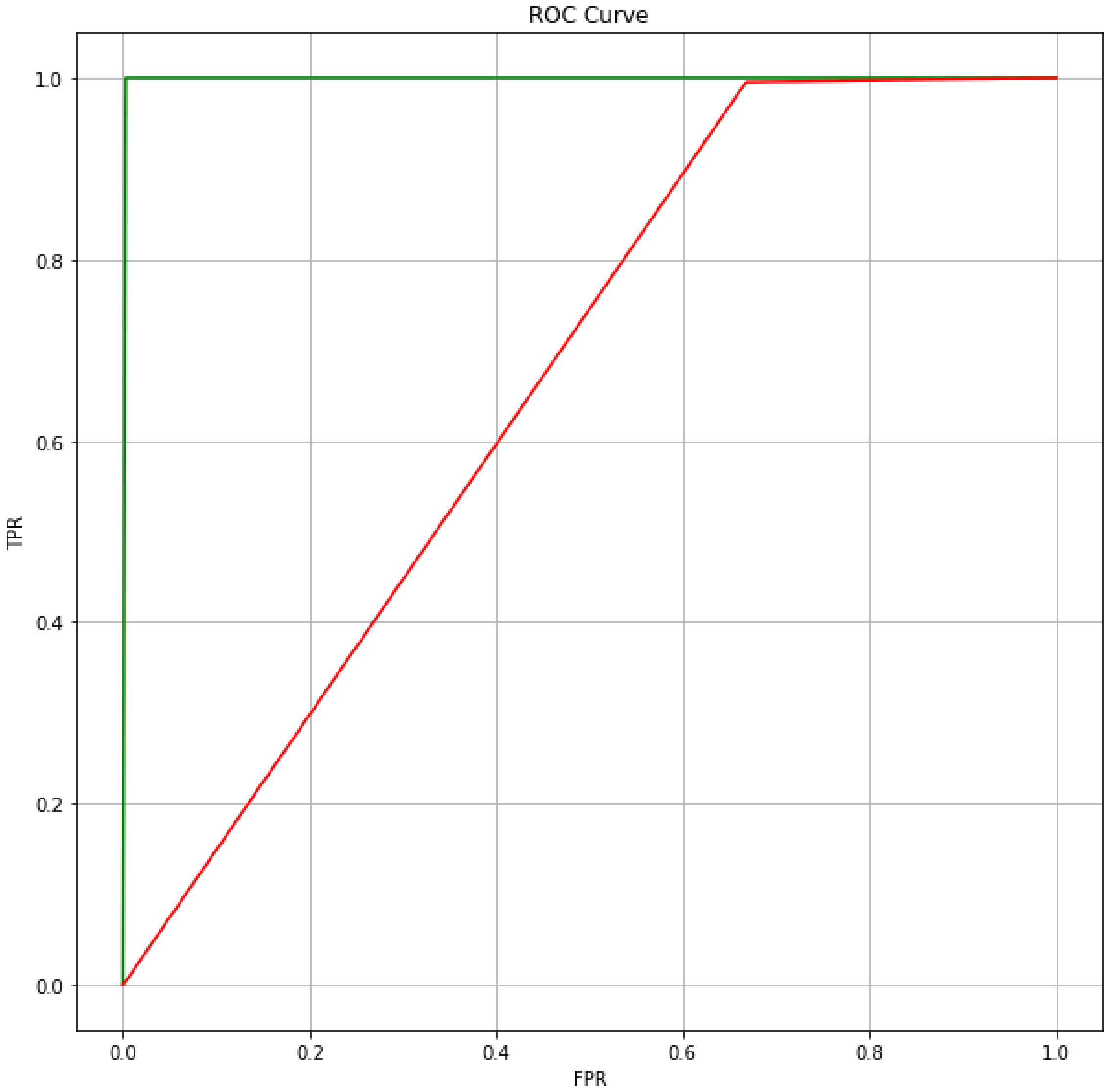
```
-------------------- Confusion matrix --------------------
```




```
For values of best estimator =  100 best depth =  500 The AUC is: 0.
9986346258874932
For values of best estimator =  100 best depth =  500 The AUC is: 0.
6514554865637113
-------------------- Confusion matrix --------------------
```




```
For values of best estimator =  100 best depth =  500 The AUC is: 0.
663789156599935
```



[5.1.4] Wordcloud of top 20 important features from SET 2

In [86]:

```
# Please write all the code with proper documenindices = np.argsort(-clf.feature
_importances_)
word_indices = indices[:20]
words = getImportantFeatures(word_indices,tf_idf_vect)
print(words)
```

```
['not', 'great', 'disappointed', 'not buy', 'horrible', 'worst', 'no
t worth', 'waste', 'awful', 'terrible', 'bad', 'return', 'love', 'no
t recommend', 'best', 'would not', 'threw', 'money', 'waste money',
'disappointing']
```

In [87]:

```
text = ''
for word in words:
    text = text+' '+word
```

In [88]:

```
draw_wordcloud(text)
```

[5.1.5] Applying Random Forests on AVG W2V, SET 3

In [89]:

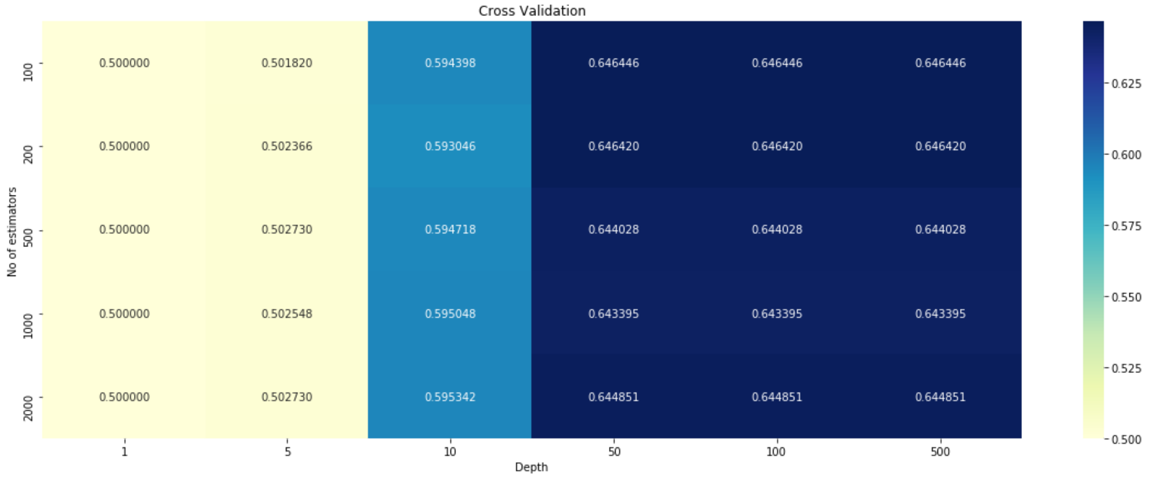
```
train = loadPickleData("avg_w2v_train.pickle")
test = loadPickleData('avg_w2v_test.pickle')
cv = loadPickleData('avg_w2v_cv.pickle')
```

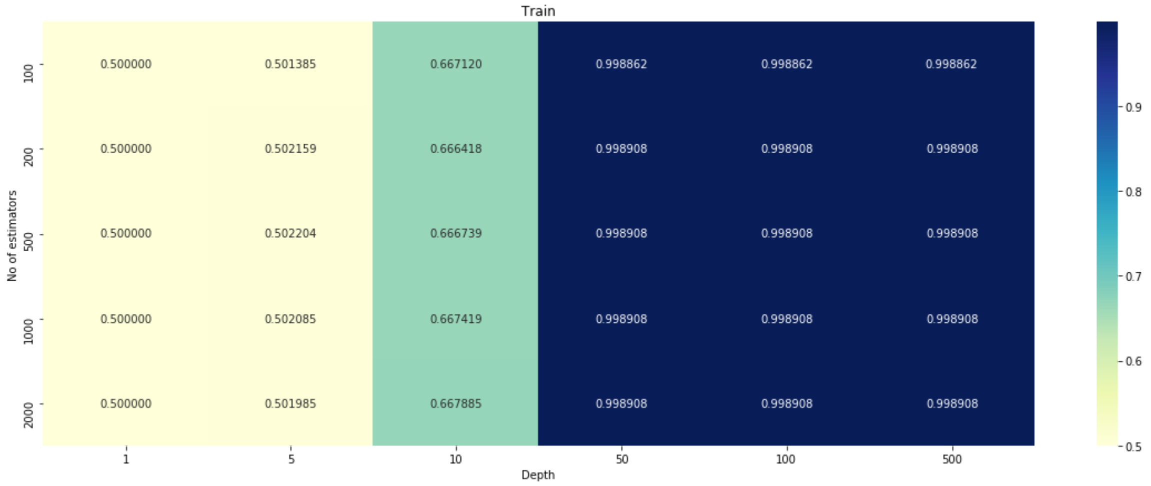
In [90]:

```
best_estimator,best_depth = performHyperParameterTuning(train,cv,test)
```

```
for estimator = 100 and depth = 1
Area: 0.5
for estimator = 100 and depth = 5
Area: 0.5018201674554059
for estimator = 100 and depth = 10
Area: 0.5943976727298279
for estimator = 100 and depth = 50
Area: 0.6464461580635286
for estimator = 100 and depth = 100
Area: 0.6464461580635286
for estimator = 100 and depth = 500
Area: 0.6464461580635286
for estimator = 200 and depth = 1
Area: 0.5
for estimator = 200 and depth = 5
Area: 0.5023662176920276
for estimator = 200 and depth = 10
Area: 0.5930455393201729
for estimator = 200 and depth = 50
Area: 0.646420110600255
for estimator = 200 and depth = 100
Area: 0.646420110600255
for estimator = 200 and depth = 500
Area: 0.646420110600255
for estimator = 500 and depth = 1
Area: 0.5
for estimator = 500 and depth = 5
Area: 0.5027302511831089
for estimator = 500 and depth = 10
Area: 0.5947183568815947
for estimator = 500 and depth = 50
Area: 0.6440278454449537
for estimator = 500 and depth = 100
Area: 0.6440278454449537
for estimator = 500 and depth = 500
Area: 0.6440278454449537
for estimator = 1000 and depth = 1
Area: 0.5
for estimator = 1000 and depth = 5
Area: 0.5025482344375682
for estimator = 1000 and depth = 10
Area: 0.5950477235211193
for estimator = 1000 and depth = 50
Area: 0.6433950965297031
for estimator = 1000 and depth = 100
Area: 0.6433950965297031
for estimator = 1000 and depth = 500
Area: 0.6433950965297031
for estimator = 2000 and depth = 1
Area: 0.5
for estimator = 2000 and depth = 5
Area: 0.5027302511831089
for estimator = 2000 and depth = 10
Area: 0.5953424233090874
for estimator = 2000 and depth = 50
Area: 0.6448512304940277
for estimator = 2000 and depth = 100
Area: 0.6448512304940277
for estimator = 2000 and depth = 500
Area: 0.6448512304940277
for estimator = 100 and depth = 1
```

```
Area: 0.5
for estimator = 100 and depth = 5
Area: 0.501384885993577
for estimator = 100 and depth = 10
Area: 0.6671201165346445
for estimator = 100 and depth = 50
Area: 0.9988621882395776
for estimator = 100 and depth = 100
Area: 0.9988621882395776
for estimator = 100 and depth = 500
Area: 0.9988621882395776
for estimator = 200 and depth = 1
Area: 0.5
for estimator = 200 and depth = 5
Area: 0.5021585979906642
for estimator = 200 and depth = 10
Area: 0.666417917597321
for estimator = 200 and depth = 50
Area: 0.9989077007099945
for estimator = 200 and depth = 100
Area: 0.9989077007099945
for estimator = 200 and depth = 500
Area: 0.9989077007099945
for estimator = 500 and depth = 1
Area: 0.5
for estimator = 500 and depth = 5
Area: 0.502204110461081
for estimator = 500 and depth = 10
Area: 0.6667386830450783
for estimator = 500 and depth = 50
Area: 0.9989077007099945
for estimator = 500 and depth = 100
Area: 0.9989077007099945
for estimator = 500 and depth = 500
Area: 0.9989077007099945
for estimator = 1000 and depth = 1
Area: 0.5
for estimator = 1000 and depth = 5
Area: 0.5020849067760615
for estimator = 1000 and depth = 10
Area: 0.6674191919464926
for estimator = 1000 and depth = 50
Area: 0.9989077007099945
for estimator = 1000 and depth = 100
Area: 0.9989077007099945
for estimator = 1000 and depth = 500
Area: 0.9989077007099945
for estimator = 2000 and depth = 1
Area: 0.5
for estimator = 2000 and depth = 5
Area: 0.5019852149721122
for estimator = 2000 and depth = 10
Area: 0.6678851616686163
for estimator = 2000 and depth = 50
Area: 0.9989077007099945
for estimator = 2000 and depth = 100
Area: 0.9989077007099945
for estimator = 2000 and depth = 500
Area: 0.9989077007099945
```



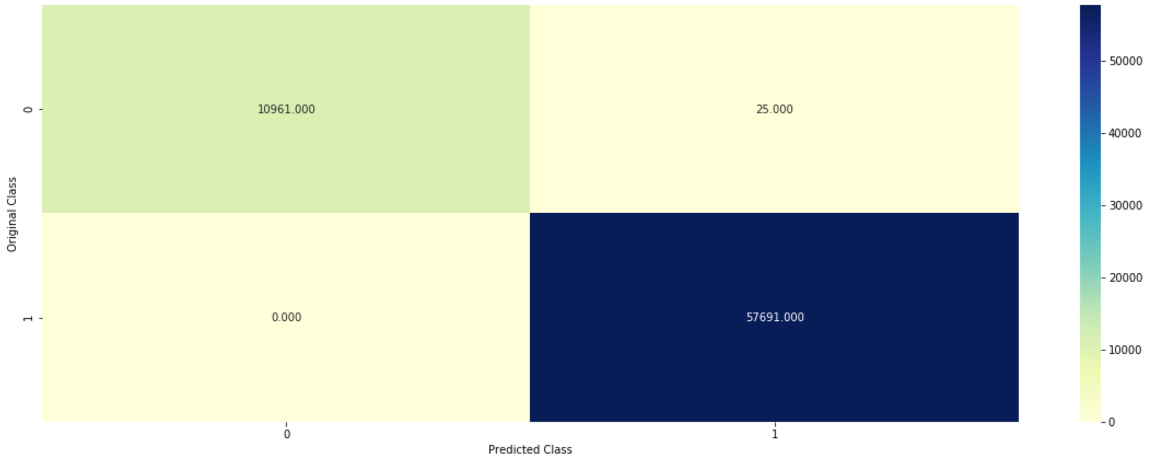



```
best estimators = 100 and depth = 50
```

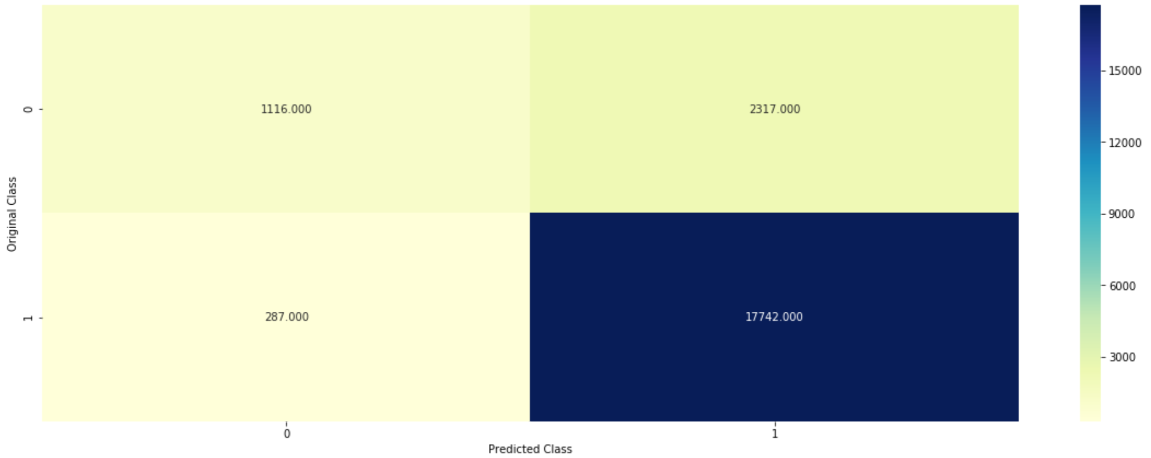
In [91]:

```
clf = bestModel(train,cv,test,best_estimator,best_depth)
```

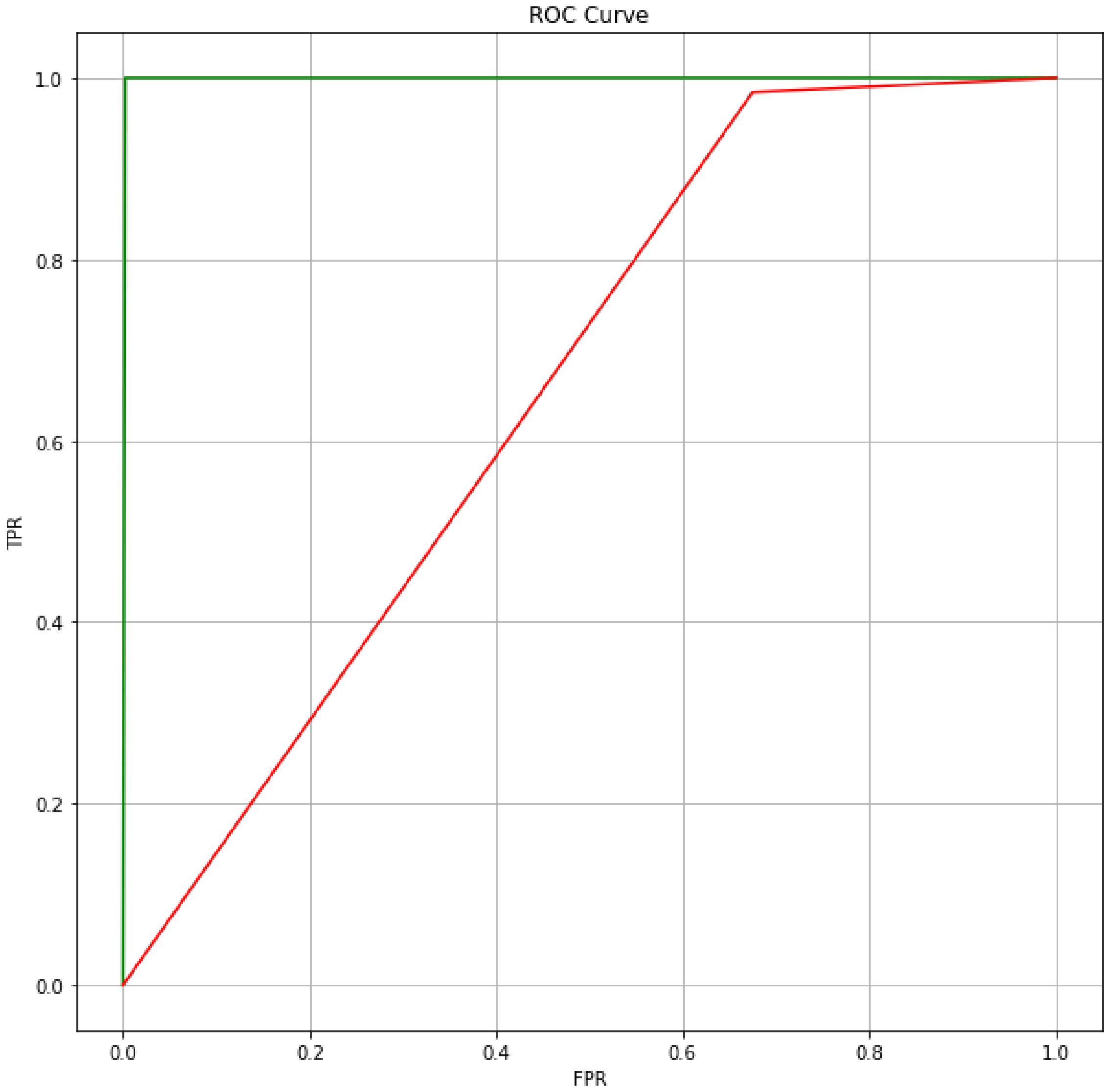
```
-------------------- Confusion matrix --------------------
```




```
For values of best estimator =  100 best depth =  50 The AUC is: 0.9
988621882395776
For values of best estimator =  100 best depth =  50 The AUC is: 0.6
464461580635286
-------------------- Confusion matrix --------------------
```




```
For values of best estimator =  100 best depth =  50 The AUC is: 0.6
54580653685811
```



[5.1.6] Applying Random Forests on TFIDF W2V, SET 4

In [92]:

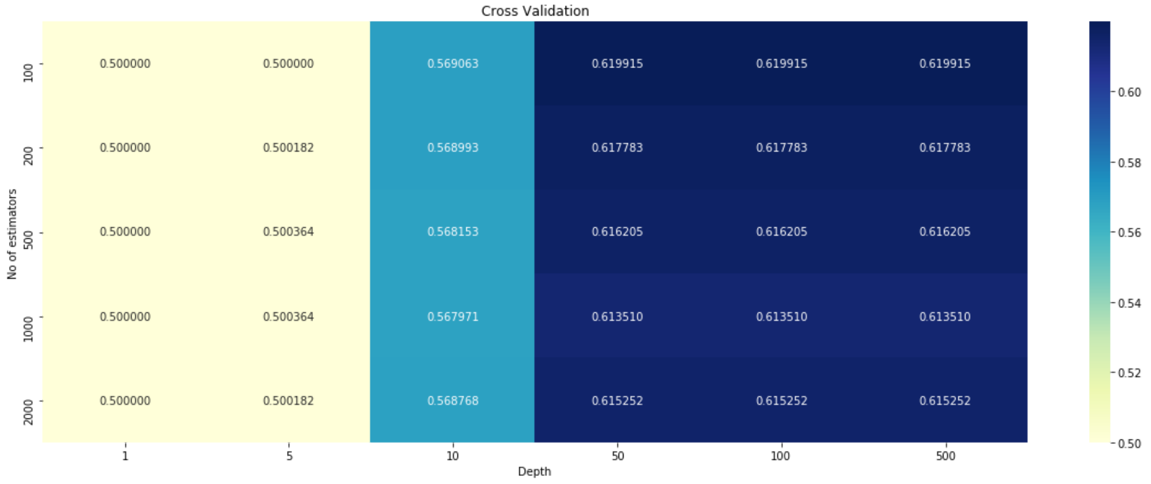
```
train = loadPickleData("tfidf_w2v_train.pickle")
test = loadPickleData('tfidf_w2v_test.pickle')
cv = loadPickleData('tfidf_w2v_cv.pickle')
```

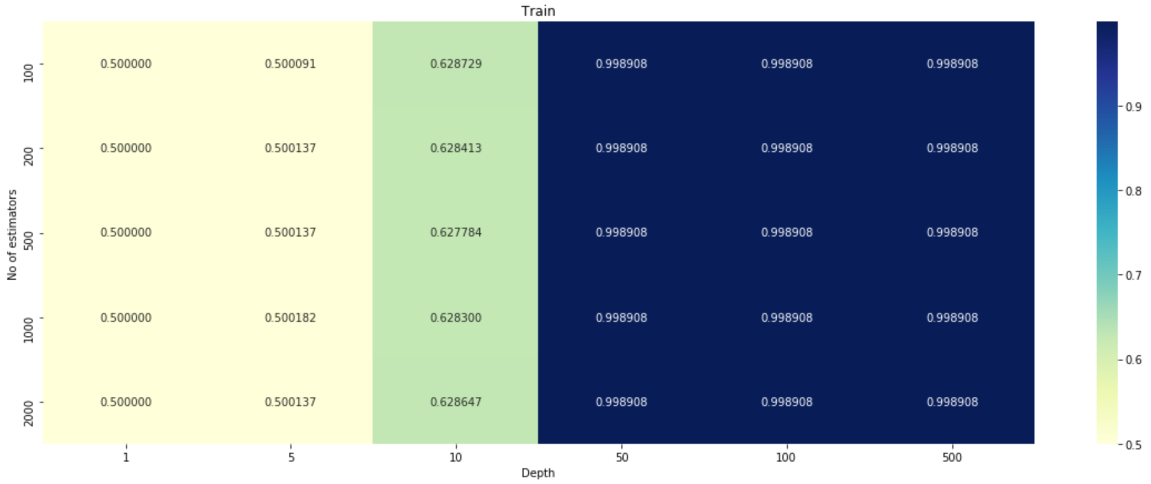
In [93]:

```
best_estimator,best_depth = performHyperParameterTuning(train,cv,test)
```

```
for estimator = 100 and depth = 1
Area: 0.5
for estimator = 100 and depth = 5
Area: 0.5
for estimator = 100 and depth = 10
Area: 0.5690626151486544
for estimator = 100 and depth = 50
Area: 0.619914936354967
for estimator = 100 and depth = 100
Area: 0.619914936354967
for estimator = 100 and depth = 500
Area: 0.619914936354967
for estimator = 200 and depth = 1
Area: 0.5
for estimator = 200 and depth = 5
Area: 0.5001820167455406
for estimator = 200 and depth = 10
Area: 0.5689932814455414
for estimator = 200 and depth = 50
Area: 0.6177827041360773
for estimator = 200 and depth = 100
Area: 0.6177827041360773
for estimator = 200 and depth = 500
Area: 0.6177827041360773
for estimator = 500 and depth = 1
Area: 0.5
for estimator = 500 and depth = 5
Area: 0.5003640334910812
for estimator = 500 and depth = 10
Area: 0.5681525314209515
for estimator = 500 and depth = 50
Area: 0.6162052046415671
for estimator = 500 and depth = 100
Area: 0.6162052046415671
for estimator = 500 and depth = 500
Area: 0.6162052046415671
for estimator = 1000 and depth = 1
Area: 0.5
for estimator = 1000 and depth = 5
Area: 0.5003640334910812
for estimator = 1000 and depth = 10
Area: 0.5679705146754108
for estimator = 1000 and depth = 50
Area: 0.6135096203100148
for estimator = 1000 and depth = 100
Area: 0.6135096203100148
for estimator = 1000 and depth = 500
Area: 0.6135096203100148
for estimator = 2000 and depth = 1
Area: 0.5
for estimator = 2000 and depth = 5
Area: 0.5001820167455406
for estimator = 2000 and depth = 10
Area: 0.5687679153606864
for estimator = 2000 and depth = 50
Area: 0.6152517715745497
for estimator = 2000 and depth = 100
Area: 0.6152517715745497
for estimator = 2000 and depth = 500
Area: 0.6152517715745497
for estimator = 100 and depth = 1
```

```
Area: 0.5
for estimator = 100 and depth = 5
Area: 0.5000910249408338
for estimator = 100 and depth = 10
Area: 0.6287290985137322
for estimator = 100 and depth = 50
Area: 0.9989077007099945
for estimator = 100 and depth = 100
Area: 0.9989077007099945
for estimator = 100 and depth = 500
Area: 0.9989077007099945
for estimator = 200 and depth = 1
Area: 0.5
for estimator = 200 and depth = 5
Area: 0.5001365374112507
for estimator = 200 and depth = 10
Area: 0.628412689375653
for estimator = 200 and depth = 50
Area: 0.9989077007099945
for estimator = 200 and depth = 100
Area: 0.9989077007099945
for estimator = 200 and depth = 500
Area: 0.9989077007099945
for estimator = 500 and depth = 1
Area: 0.5
for estimator = 500 and depth = 5
Area: 0.5001365374112507
for estimator = 500 and depth = 10
Area: 0.627784181652932
for estimator = 500 and depth = 50
Area: 0.9989077007099945
for estimator = 500 and depth = 100
Area: 0.9989077007099945
for estimator = 500 and depth = 500
Area: 0.9989077007099945
for estimator = 1000 and depth = 1
Area: 0.5
for estimator = 1000 and depth = 5
Area: 0.5001820498816676
for estimator = 1000 and depth = 10
Area: 0.6282999743989099
for estimator = 1000 and depth = 50
Area: 0.9989077007099945
for estimator = 1000 and depth = 100
Area: 0.9989077007099945
for estimator = 1000 and depth = 500
Area: 0.9989077007099945
for estimator = 2000 and depth = 1
Area: 0.5
for estimator = 2000 and depth = 5
Area: 0.5001365374112507
for estimator = 2000 and depth = 10
Area: 0.628646740436014
for estimator = 2000 and depth = 50
Area: 0.9989077007099945
for estimator = 2000 and depth = 100
Area: 0.9989077007099945
for estimator = 2000 and depth = 500
Area: 0.9989077007099945
```



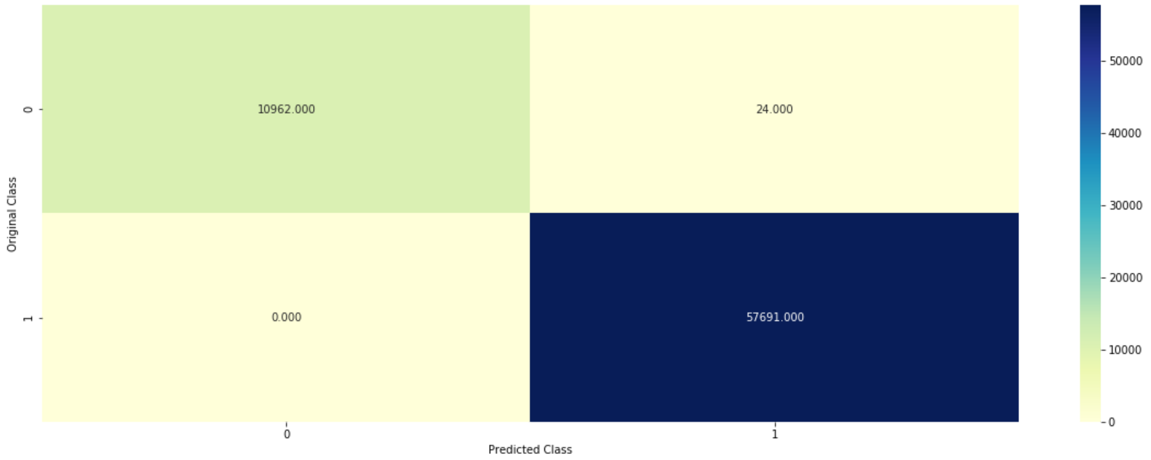



```
best estimators = 100 and depth = 50
```

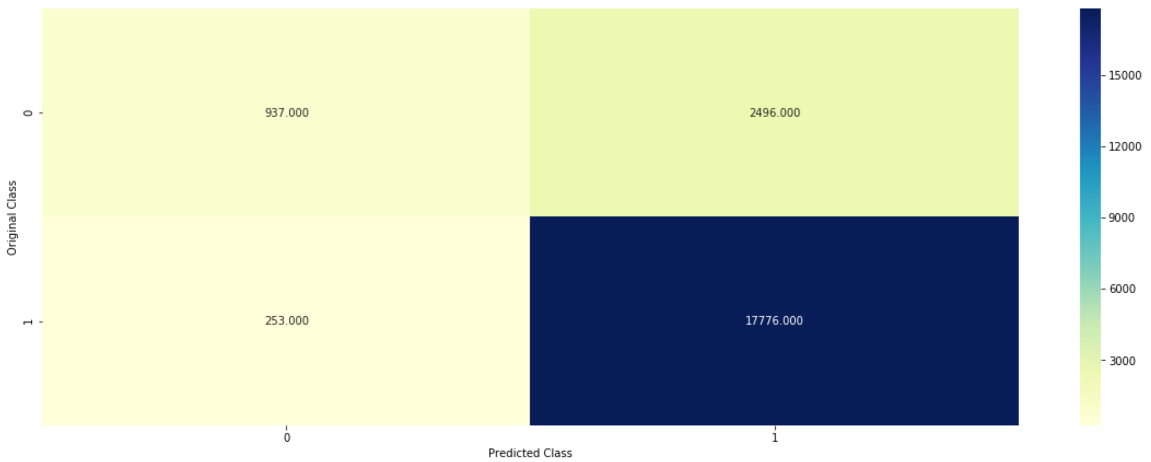
In [94]:

```
clf = bestModel(train,cv,test,best_estimator,best_depth)
```

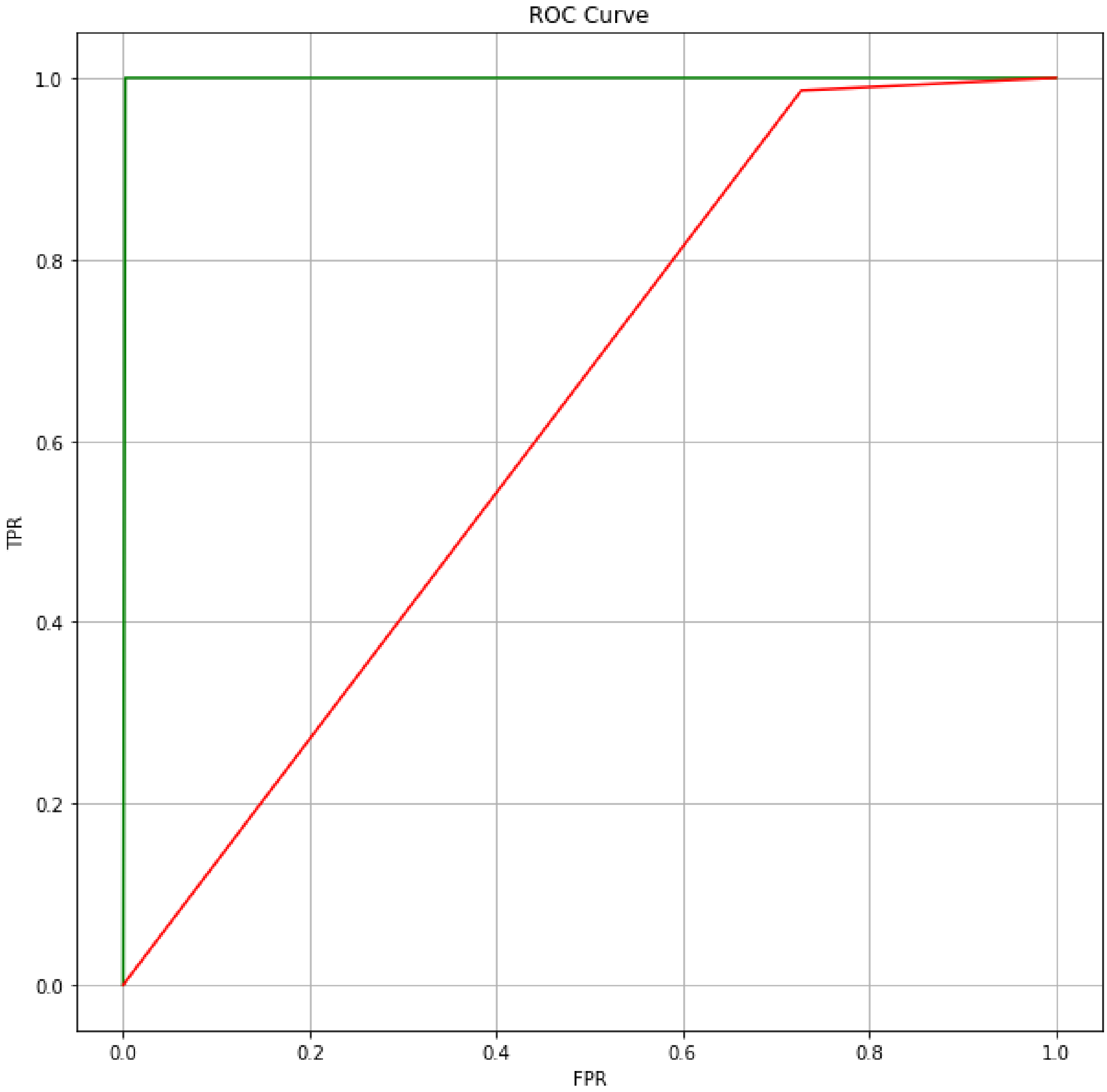
```
-------------------- Confusion matrix --------------------
```




```
For values of best estimator =  100 best depth =  50 The AUC is: 0.9
989077007099945
For values of best estimator =  100 best depth =  50 The AUC is: 0.6
19914936354967
-------------------- Confusion matrix --------------------
```




```
For values of best estimator =  100 best depth =  50 The AUC is: 0.6
294530866920445
```



[5.2] Applying GBDT using XGBOOST

In [15]:

```
def calculateMetricX(X,y,train,y_train):
    auc_array = []
    C = np.zeros((len(estimators),len(depth)))
    for x,i in enumerate(estimators):
        for z,r in enumerate(depth):
            print("for estimator = {} and depth = {}".format(i,r))
            clf =XGBClassifier(n_estimators=i,max_depth=r)
            clf.fit(train,y_train)
            pred = clf.predict(X)
            area = roc_auc_score(y, pred)
            auc_array.append(area)
            print("Area:",area)
            C[x][z]= area
    return (auc_array,C)
```

In [16]:

```
def bestModelX(train,cv,test,best_estimator,best_depth):
    clf =XGBClassifier(n_estimators=best_estimator,max_depth=best_depth)
    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 estimator = ',best_estimator,'best depth = ' , bes
t_depth,"The AUC is:",roc_auc_score(y_train, predict_y))
    predict_y = clf.predict(cv)
    print('For values of best estimator = ',best_estimator,'best depth = ' , bes
t_depth, "The AUC is:",roc_auc_score(y_cv, predict_y))
    predict_y = 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 estimator = ',best_estimator,'best depth = ' , bes
t_depth, "The AUC is:",roc_auc_score(y_test, predict_y))
    plotAUC(train_fpr,train_tpr,test_fpr,test_tpr)
    return clf
```

In [17]:

```
def performHyperParameterTuningX(train,cv,test):
    auc_array,C_cv = calculateMetricX(cv,y_cv,train,y_train)
    auc_array_train,C_train = calculateMetricX(train,y_train,train,y_train)
    drawHeatMap(C_cv,'Cross Validation')
    drawHeatMap(C_train,'Train')
    best_alpha = np.argmax(auc_array)
    best_a = estimators[int(best_alpha/5)]
    best_r = depth[int(best_alpha%5)]
    print("best estimators = {} and depth = {}".format(best_a,best_r))
    return (best_a,best_r)
```

In [18]:

```
# if estimator size is of 1000,2000 then the time taking is too long, so limited
 myself to it.
# TODO - train with 1000,2000 later with better machine
estimators = [100,200,500]
depth = [1, 5, 10, 50, 100]
```

[5.2.1] Applying XGBOOST on BOW, SET 1

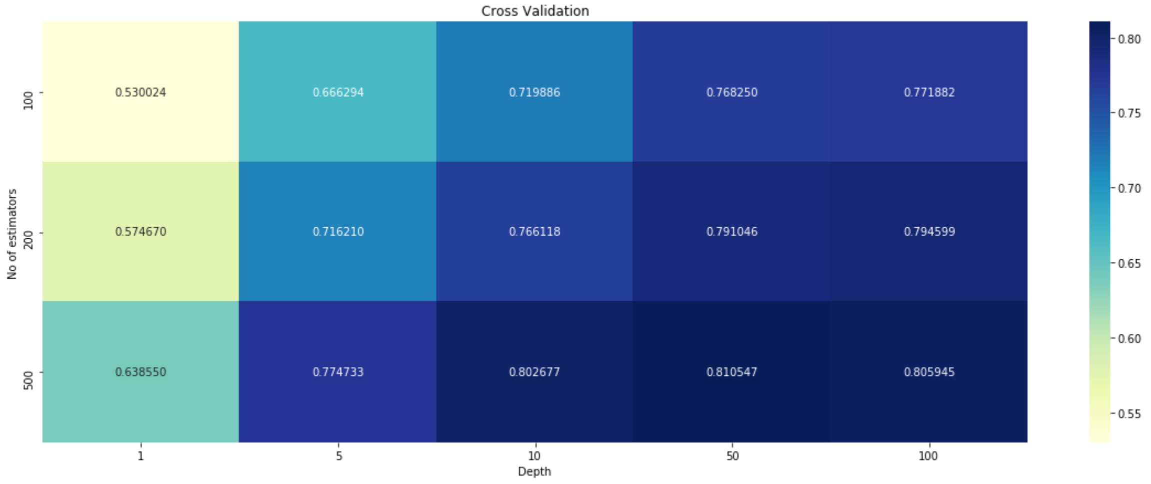
In [123]:

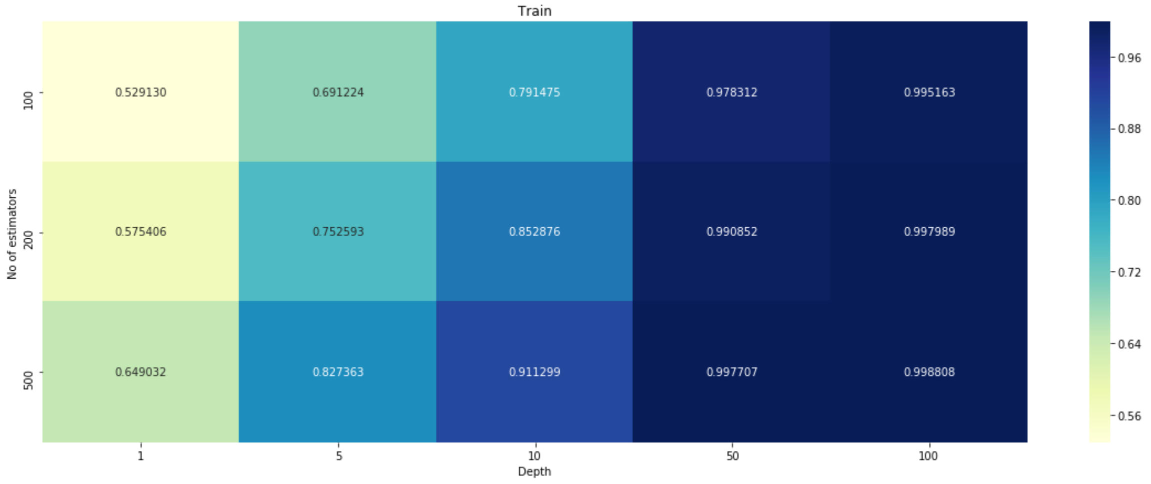
```
train = loadPickleData("bow_train.pickle")
test = loadPickleData('bow_test.pickle')
cv = loadPickleData('bow_cv.pickle')
```

In [124]:

```
best_estimator,best_depth = performHyperParameterTuningX(train,cv,test)
```

```
for estimator = 100 and depth = 1
Area: 0.5300241436259144
for estimator = 100 and depth = 5
Area: 0.6662943503178358
for estimator = 100 and depth = 10
Area: 0.7198855420955401
for estimator = 100 and depth = 50
Area: 0.7682502169801647
for estimator = 100 and depth = 100
Area: 0.7718819956021685
for estimator = 200 and depth = 1
Area: 0.5746703412099062
for estimator = 200 and depth = 5
Area: 0.7162104772336968
for estimator = 200 and depth = 10
Area: 0.7661179216617999
for estimator = 200 and depth = 50
Area: 0.7910456595120527
for estimator = 200 and depth = 100
Area: 0.7945994219431857
for estimator = 500 and depth = 1
Area: 0.6385497888047952
for estimator = 500 and depth = 5
Area: 0.7747333599175628
for estimator = 500 and depth = 10
Area: 0.8026773662511348
for estimator = 500 and depth = 50
Area: 0.8105474987481696
for estimator = 500 and depth = 100
Area: 0.8059451744815325
for estimator = 100 and depth = 1
Area: 0.5291302507341329
for estimator = 100 and depth = 5
Area: 0.6912244836418489
for estimator = 100 and depth = 10
Area: 0.7914753870412324
for estimator = 100 and depth = 50
Area: 0.9783123331595323
for estimator = 100 and depth = 100
Area: 0.9951627007192562
for estimator = 200 and depth = 1
Area: 0.5754058169113634
for estimator = 200 and depth = 5
Area: 0.752592856271257
for estimator = 200 and depth = 10
Area: 0.8528760201870602
for estimator = 200 and depth = 50
Area: 0.990852039202445
for estimator = 200 and depth = 100
Area: 0.9979887844385411
for estimator = 500 and depth = 1
Area: 0.6490324741917526
for estimator = 500 and depth = 5
Area: 0.8273634022141787
for estimator = 500 and depth = 10
Area: 0.911298739362238
for estimator = 500 and depth = 50
Area: 0.9977070427529242
for estimator = 500 and depth = 100
Area: 0.9988080089060452
```



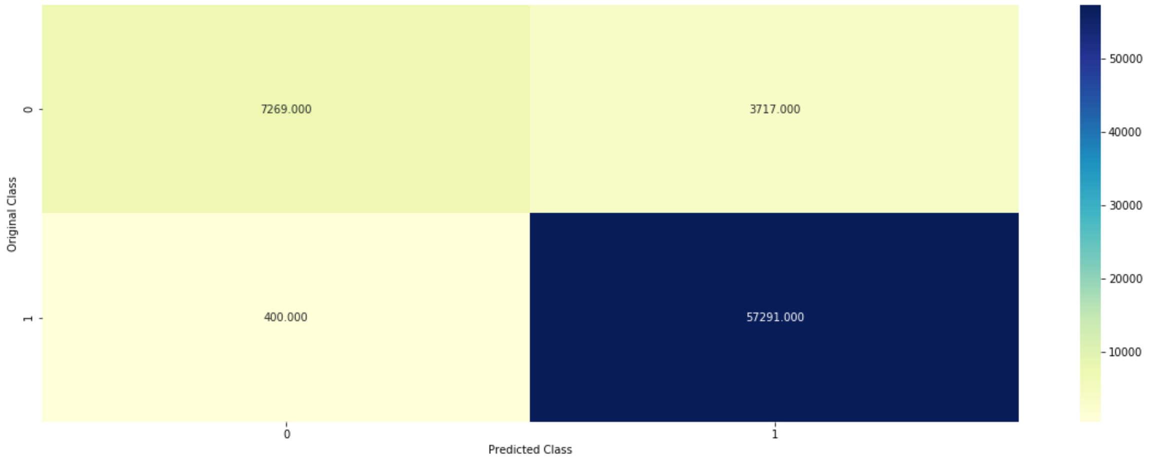



```
best estimators = 500 and depth = 5
```

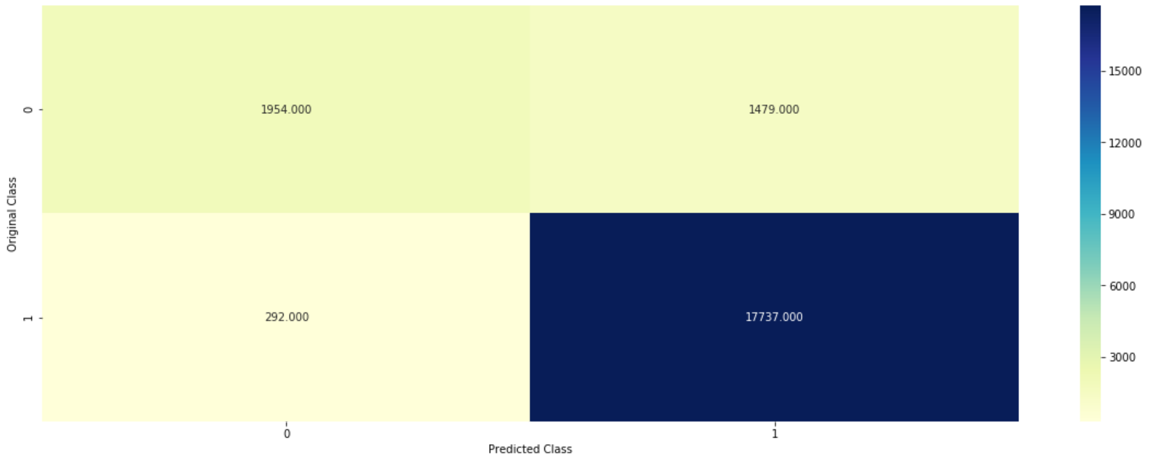
In [125]:

```
clf = bestModelX(train,cv,test,best_estimator,best_depth)
```

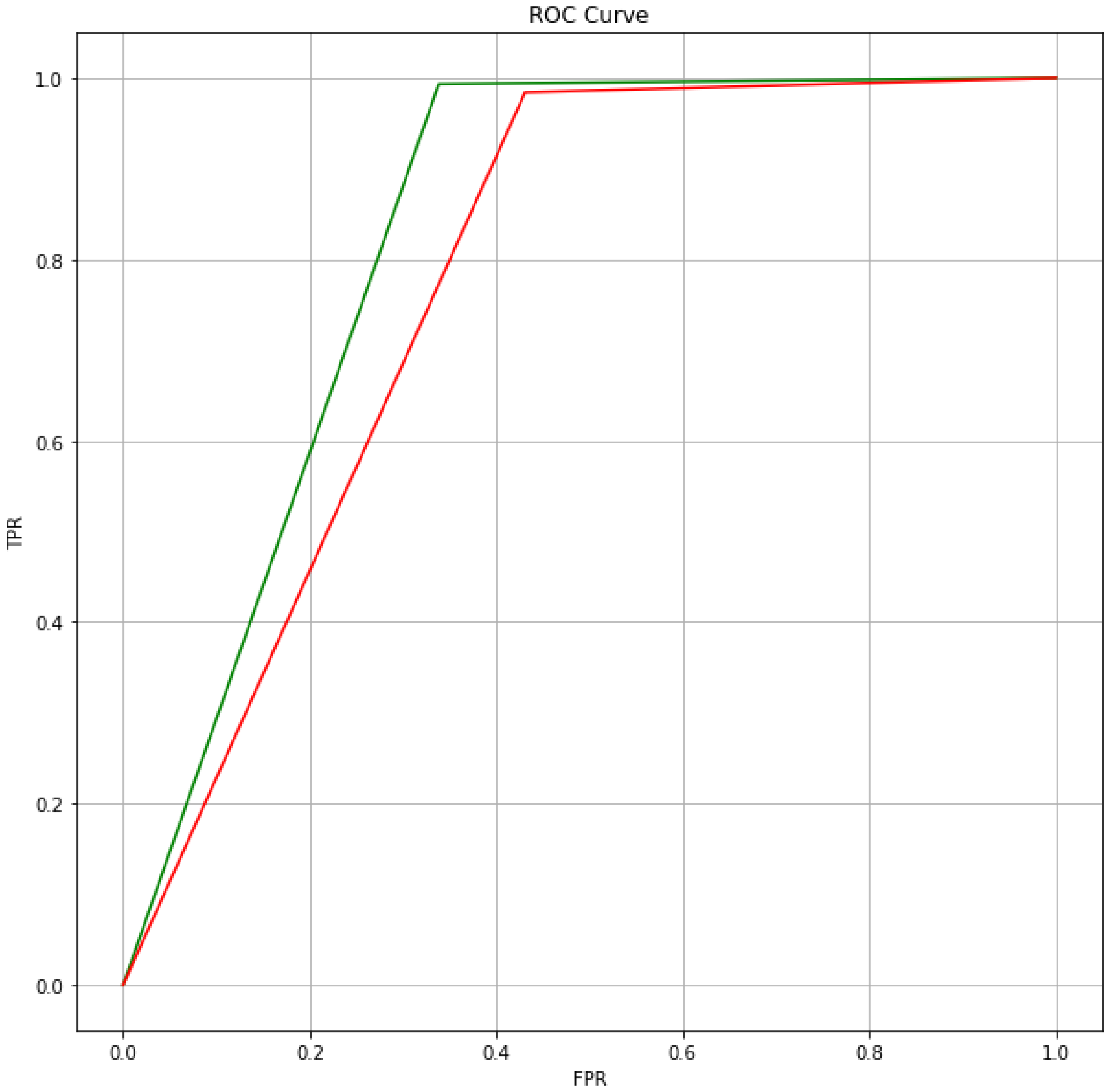
```
-------------------- Confusion matrix --------------------
```




```
For values of best estimator =  500 best depth =  5 The AUC is: 0.82
73634022141787
For values of best estimator =  500 best depth =  5 The AUC is: 0.77
47333599175628
-------------------- Confusion matrix --------------------
```




```
For values of best estimator =  500 best depth =  5 The AUC is: 0.77
6492672734902
```



[5.2.2] Applying XGBOOST on TFIDF, SET 2

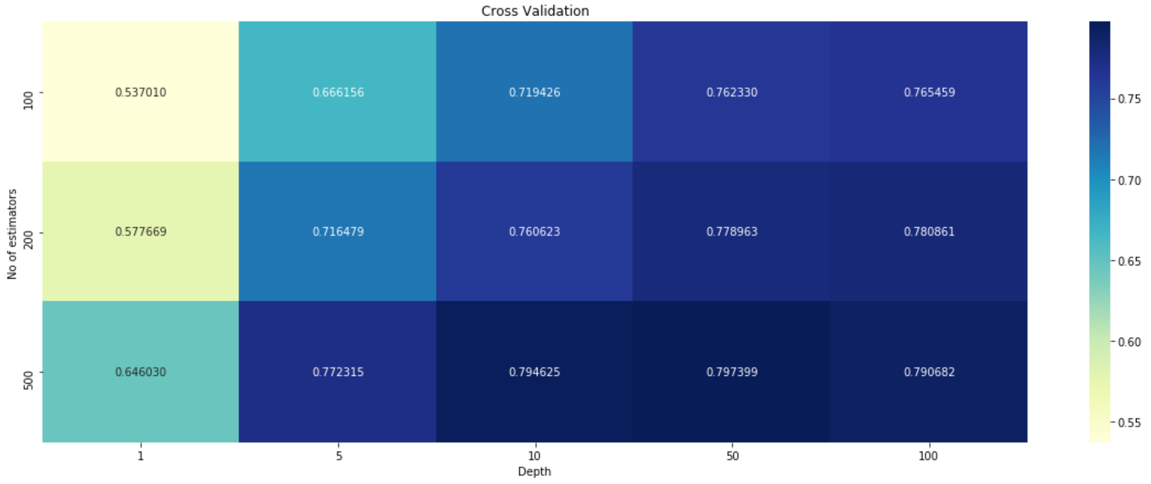
In [22]:

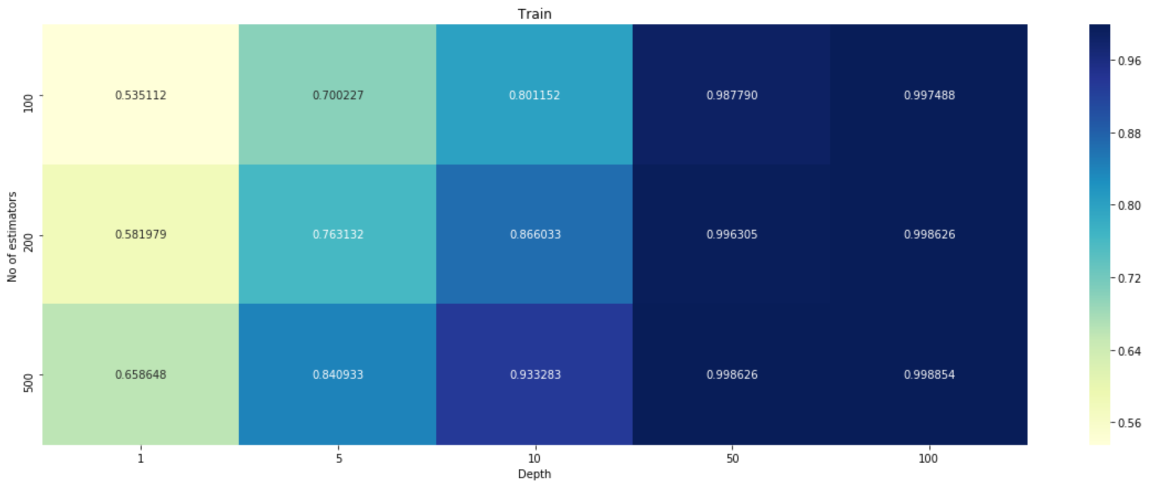
```
train = loadPickleData("tfidf_train.pickle")
test = loadPickleData('tfidf_test.pickle')
cv = loadPickleData('tfidf_cv.pickle')
```

In [23]:

```
best_estimator,best_depth = performHyperParameterTuningX(train,cv,test)
```

```
for estimator = 100 and depth = 1
Area: 0.53701011365957
for estimator = 100 and depth = 5
Area: 0.6661556829116096
for estimator = 100 and depth = 10
Area: 0.7194261274380722
for estimator = 100 and depth = 50
Area: 0.762330363055954
for estimator = 100 and depth = 100
Area: 0.7654593776811756
for estimator = 200 and depth = 1
Area: 0.5776693078171844
for estimator = 200 and depth = 5
Area: 0.7164791926578662
for estimator = 200 and depth = 10
Area: 0.7606227524440257
for estimator = 200 and depth = 50
Area: 0.7789632206032608
for estimator = 200 and depth = 100
Area: 0.7808614673490125
for estimator = 500 and depth = 1
Area: 0.6460297772480001
for estimator = 500 and depth = 5
Area: 0.7723151734979379
for estimator = 500 and depth = 10
Area: 0.7946252801080345
for estimator = 500 and depth = 50
Area: 0.7973989437299327
for estimator = 500 and depth = 100
Area: 0.7906817522199215
for estimator = 100 and depth = 1
Area: 0.5351118504835755
for estimator = 100 and depth = 5
Area: 0.7002272401650377
for estimator = 100 and depth = 10
Area: 0.8011521180013184
for estimator = 100 and depth = 50
Area: 0.9877896805117193
for estimator = 100 and depth = 100
Area: 0.9974881472639552
for estimator = 200 and depth = 1
Area: 0.5819790787762256
for estimator = 200 and depth = 5
Area: 0.7631321460144248
for estimator = 200 and depth = 10
Area: 0.8660333431784986
for estimator = 200 and depth = 50
Area: 0.996304823033116
for estimator = 200 and depth = 100
Area: 0.9986259590243777
for estimator = 500 and depth = 1
Area: 0.6586484455975481
for estimator = 500 and depth = 5
Area: 0.8409325155942081
for estimator = 500 and depth = 10
Area: 0.9332833034597149
for estimator = 500 and depth = 50
Area: 0.9986259590243777
for estimator = 500 and depth = 100
Area: 0.9988535213764619
```



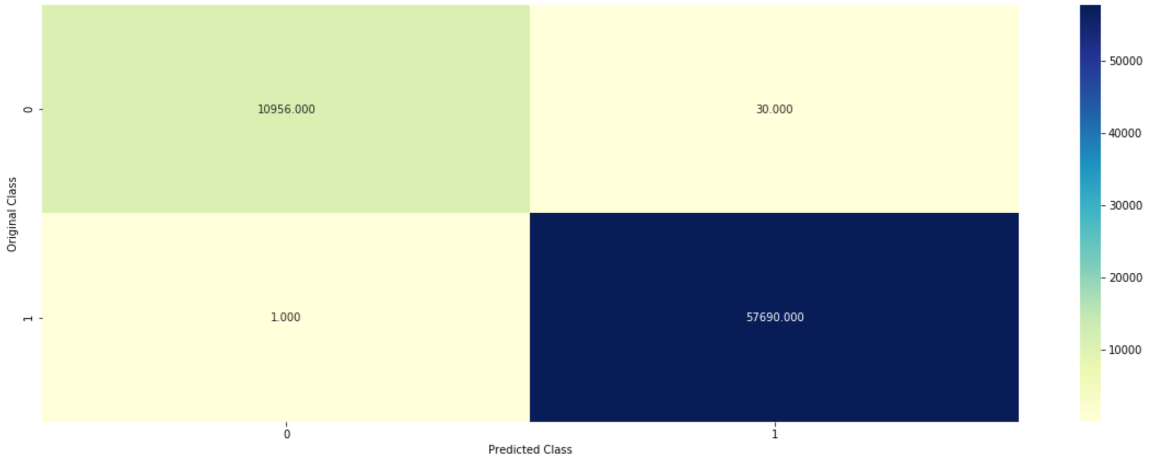



```
best estimators = 500 and depth = 50
```

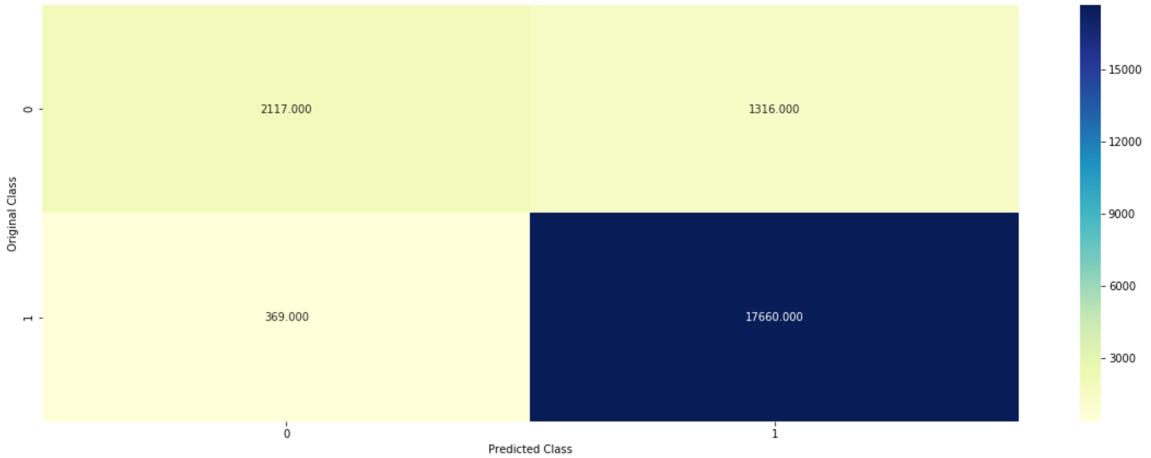
In [24]:

```
clf = bestModelX(train,cv,test,best_estimator,best_depth)
```

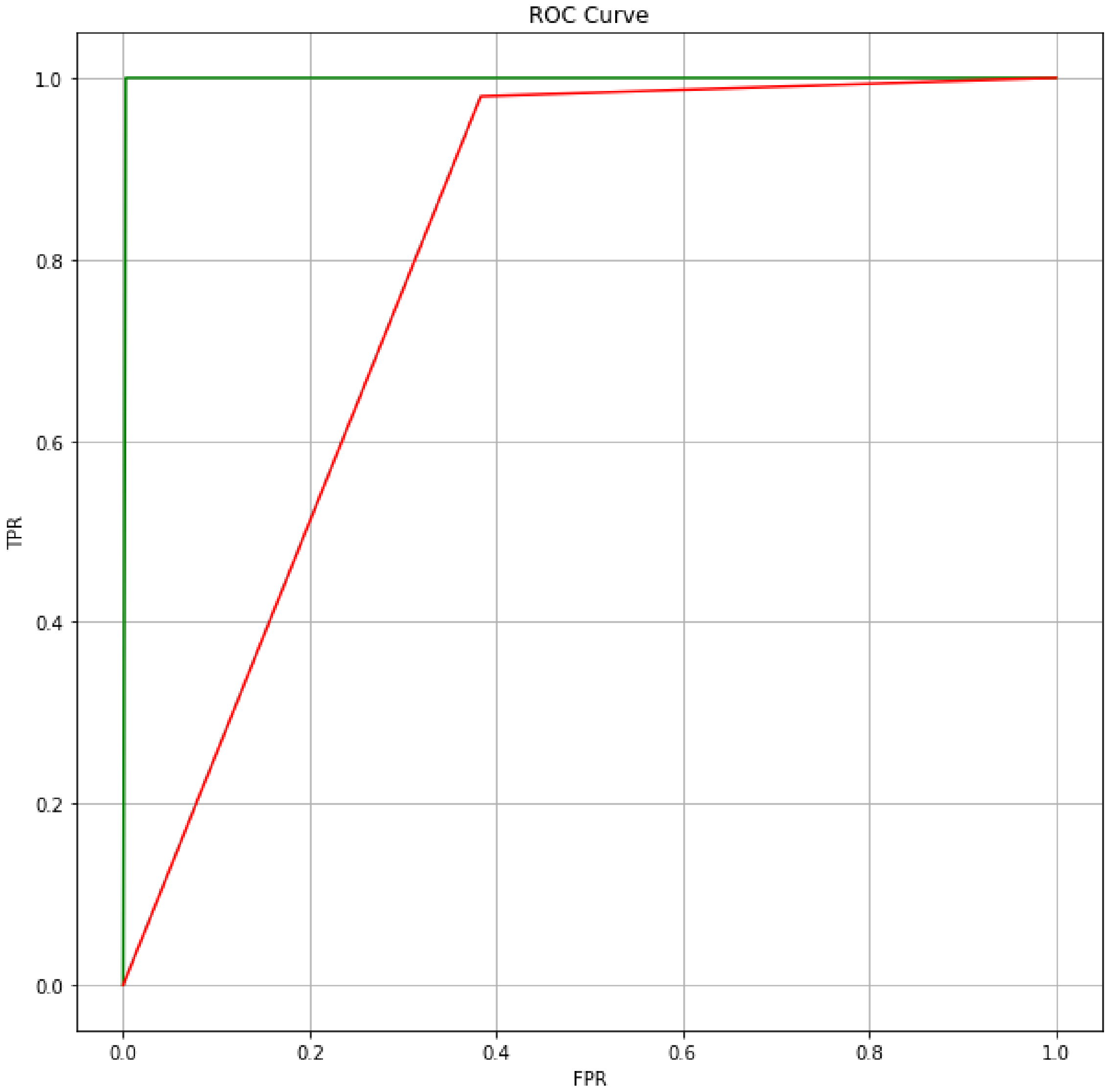
```
-------------------- Confusion matrix --------------------
```




```
For values of best estimator =  500 best depth =  50 The AUC is: 0.9
986259590243777
For values of best estimator =  500 best depth =  50 The AUC is: 0.7
973989437299327
-------------------- Confusion matrix --------------------
```




```
For values of best estimator =  500 best depth =  50 The AUC is: 0.7
980973932391703
```



[5.2.3] Applying XGBOOST on AVG W2V, SET 3

In [30]:

```
train = loadPickleData("avg_w2v_train.pickle")
test = loadPickleData('avg_w2v_test.pickle')
cv = loadPickleData('avg_w2v_cv.pickle')
```

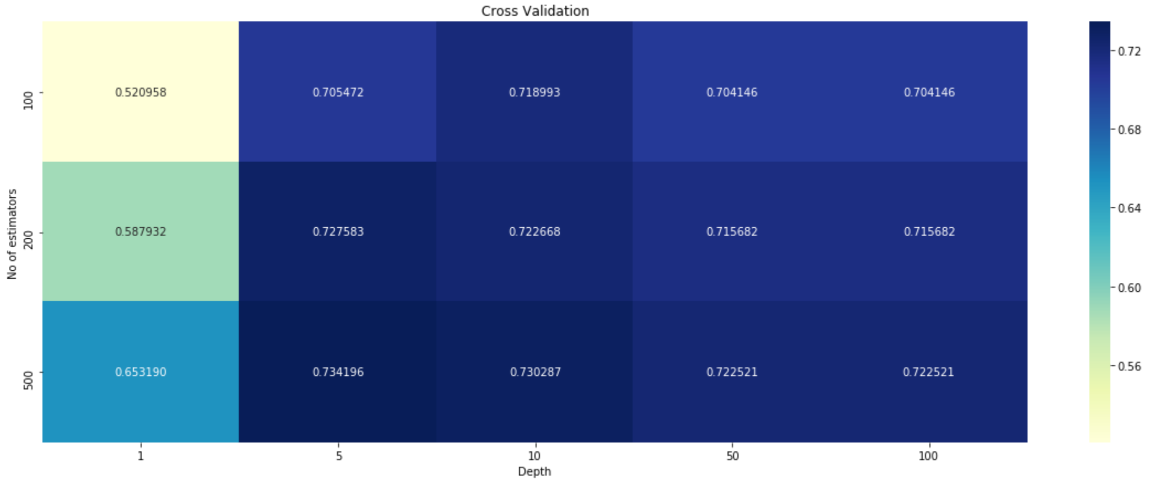
In [31]:

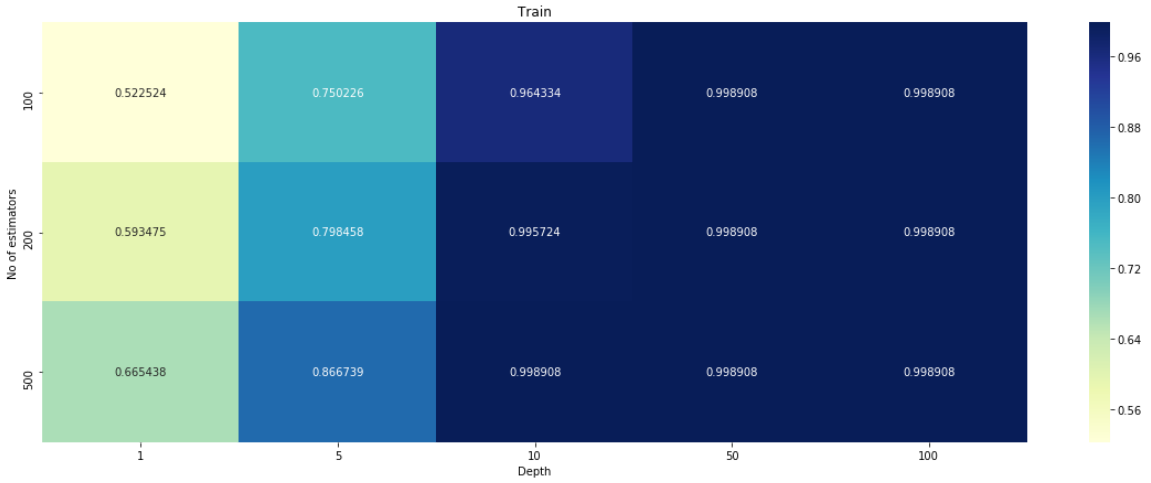
```
train = pd.DataFrame(train)
test = pd.DataFrame(test)
cv = pd.DataFrame(cv)
```

In [32]:

```
best_estimator,best_depth = performHyperParameterTuningX(train,cv,test)
```

```
for estimator = 100 and depth = 1
Area: 0.5209579732004415
for estimator = 100 and depth = 5
Area: 0.7054721202415518
for estimator = 100 and depth = 10
Area: 0.7189934543381027
for estimator = 100 and depth = 50
Area: 0.7041459080962205
for estimator = 100 and depth = 100
Area: 0.7041459080962205
for estimator = 200 and depth = 1
Area: 0.5879317685689955
for estimator = 200 and depth = 5
Area: 0.7275830344290171
for estimator = 200 and depth = 10
Area: 0.7226684561004711
for estimator = 200 and depth = 50
Area: 0.7156823598678657
for estimator = 200 and depth = 100
Area: 0.7156823598678657
for estimator = 500 and depth = 1
Area: 0.6531895863352383
for estimator = 500 and depth = 5
Area: 0.7341964146827834
for estimator = 500 and depth = 10
Area: 0.7302871750493772
for estimator = 500 and depth = 50
Area: 0.7225210431070122
for estimator = 500 and depth = 100
Area: 0.7225210431070122
for estimator = 100 and depth = 1
Area: 0.5225244995716474
for estimator = 100 and depth = 5
Area: 0.7502259056606095
for estimator = 100 and depth = 10
Area: 0.9643337448144728
for estimator = 100 and depth = 50
Area: 0.9989077007099945
for estimator = 100 and depth = 100
Area: 0.9989077007099945
for estimator = 200 and depth = 1
Area: 0.5934749082542407
for estimator = 200 and depth = 5
Area: 0.7984582335283221
for estimator = 200 and depth = 10
Area: 0.9957240059356509
for estimator = 200 and depth = 50
Area: 0.9989077007099945
for estimator = 200 and depth = 100
Area: 0.9989077007099945
for estimator = 500 and depth = 1
Area: 0.6654378481101266
for estimator = 500 and depth = 5
Area: 0.8667389556891612
for estimator = 500 and depth = 10
Area: 0.9989077007099945
for estimator = 500 and depth = 50
Area: 0.9989077007099945
for estimator = 500 and depth = 100
Area: 0.9989077007099945
```



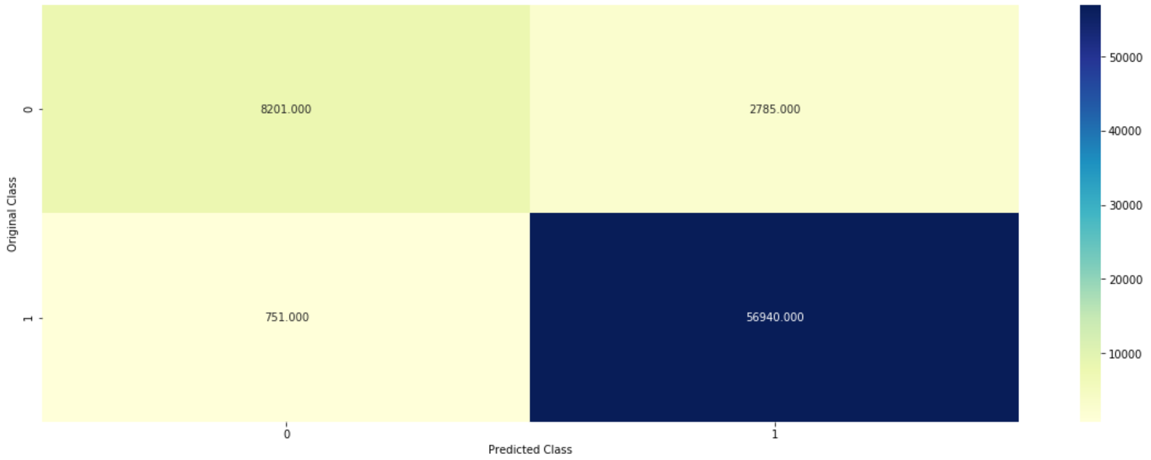



```
best estimators = 500 and depth = 5
```

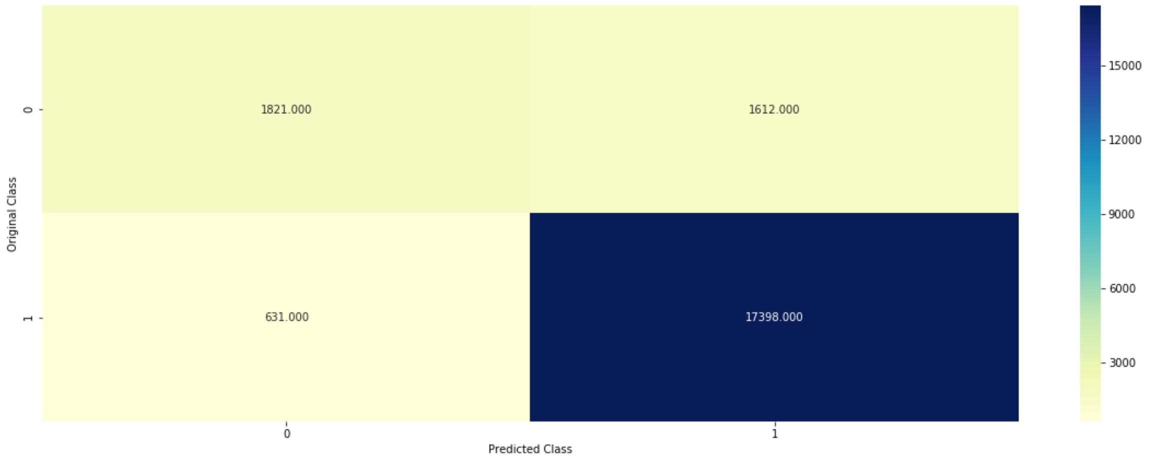
In [33]:

```
clf = bestModelX(train,cv,test,best_estimator,best_depth)
```

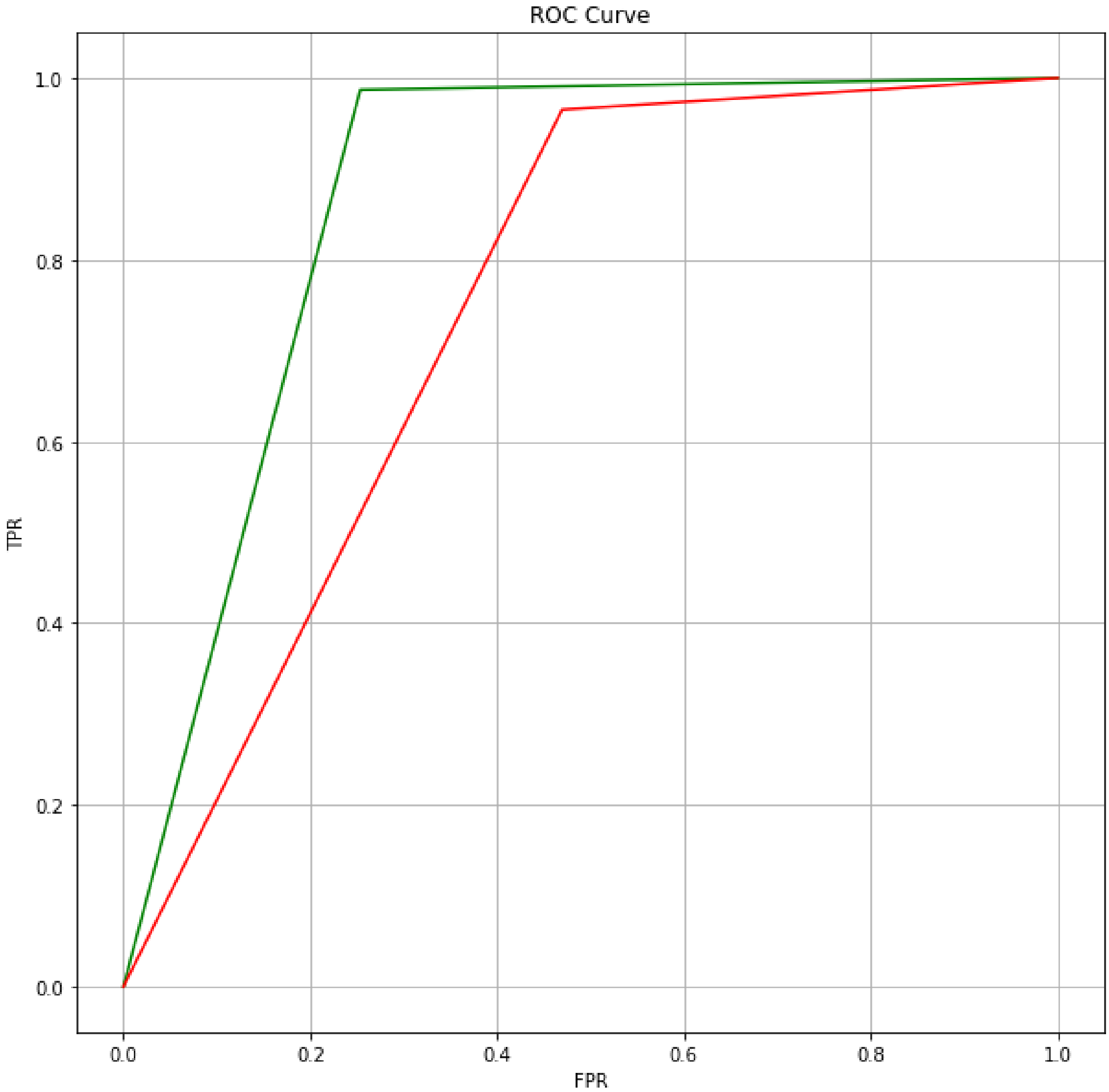
```
-------------------- Confusion matrix --------------------
```




```
For values of best estimator =  500 best depth =  5 The AUC is: 0.86
67389556891612
For values of best estimator =  500 best depth =  5 The AUC is: 0.73
41964146827834
-------------------- Confusion matrix --------------------
```




```
For values of best estimator =  500 best depth =  5 The AUC is: 0.74
77203402609419
```



[5.2.4] Applying XGBOOST on TFIDF W2V, SET 4

In [34]:

```
# Please write all the code with proper documentation
train = loadPickleData("tfidf_w2v_train.pickle")
test = loadPickleData('tfidf_w2v_test.pickle')
cv = loadPickleData('tfidf_w2v_cv.pickle')
```

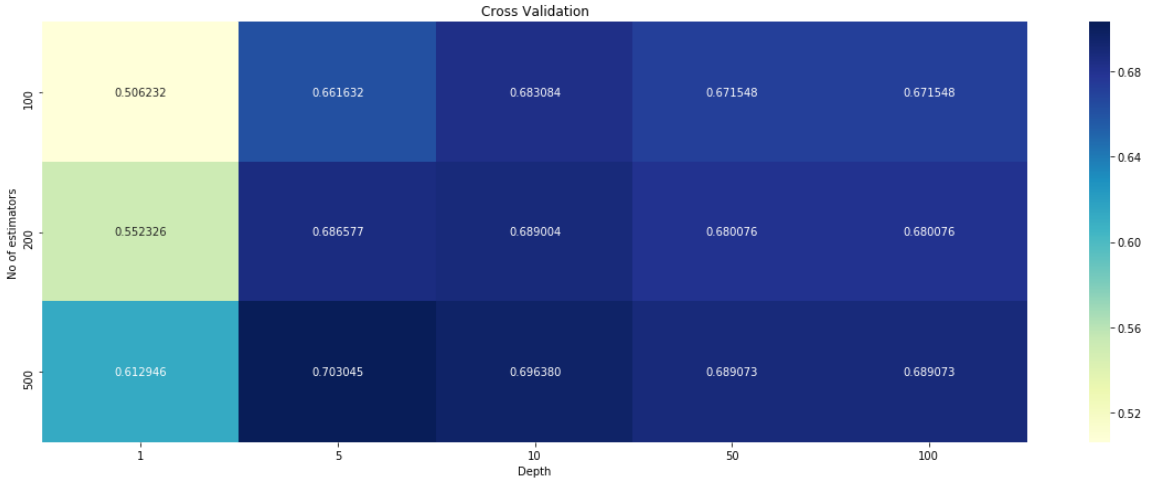
In [35]:

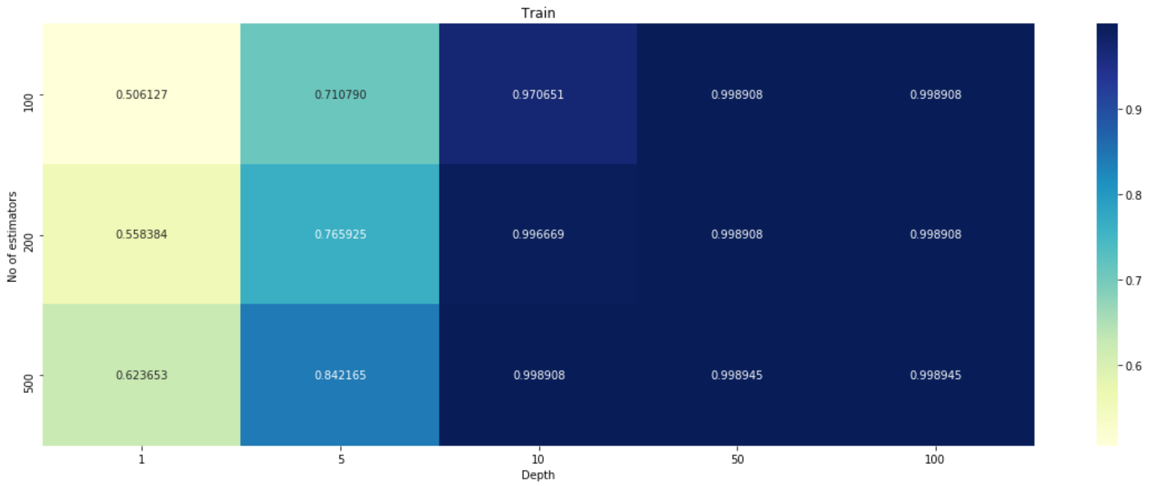
```
train = pd.DataFrame(train)
test = pd.DataFrame(test)
cv = pd.DataFrame(cv)
```

In [36]:

```
best_estimator,best_depth = performHyperParameterTuningX(train,cv,test)
```

```
for estimator = 100 and depth = 1
Area: 0.5062319186876945
for estimator = 100 and depth = 5
Area: 0.6616320058305933
for estimator = 100 and depth = 10
Area: 0.6830840605400593
for estimator = 100 and depth = 50
Area: 0.671547545668939
for estimator = 100 and depth = 100
Area: 0.671547545668939
for estimator = 200 and depth = 1
Area: 0.5523256939472031
for estimator = 200 and depth = 5
Area: 0.6865771717558371
for estimator = 200 and depth = 10
Area: 0.68900391446427
for estimator = 200 and depth = 50
Area: 0.6800763483455482
for estimator = 200 and depth = 100
Area: 0.6800763483455482
for estimator = 500 and depth = 1
Area: 0.6129463943963023
for estimator = 500 and depth = 5
Area: 0.7030454406325939
for estimator = 500 and depth = 10
Area: 0.6963799654522803
for estimator = 500 and depth = 50
Area: 0.689073185067908
for estimator = 500 and depth = 100
Area: 0.689073185067908
for estimator = 100 and depth = 1
Area: 0.5061268955362903
for estimator = 100 and depth = 5
Area: 0.7107901874624662
for estimator = 100 and depth = 10
Area: 0.9706512198268241
for estimator = 100 and depth = 50
Area: 0.9989077007099945
for estimator = 100 and depth = 100
Area: 0.9989077007099945
for estimator = 200 and depth = 1
Area: 0.5583843817566485
for estimator = 200 and depth = 5
Area: 0.7659253925308769
for estimator = 200 and depth = 10
Area: 0.9966689227964511
for estimator = 200 and depth = 50
Area: 0.9989077007099945
for estimator = 200 and depth = 100
Area: 0.9989077007099945
for estimator = 500 and depth = 1
Area: 0.623652632151573
for estimator = 500 and depth = 5
Area: 0.8421645828438401
for estimator = 500 and depth = 10
Area: 0.9989077007099945
for estimator = 500 and depth = 50
Area: 0.9989445463172958
for estimator = 500 and depth = 100
Area: 0.9989445463172958
```



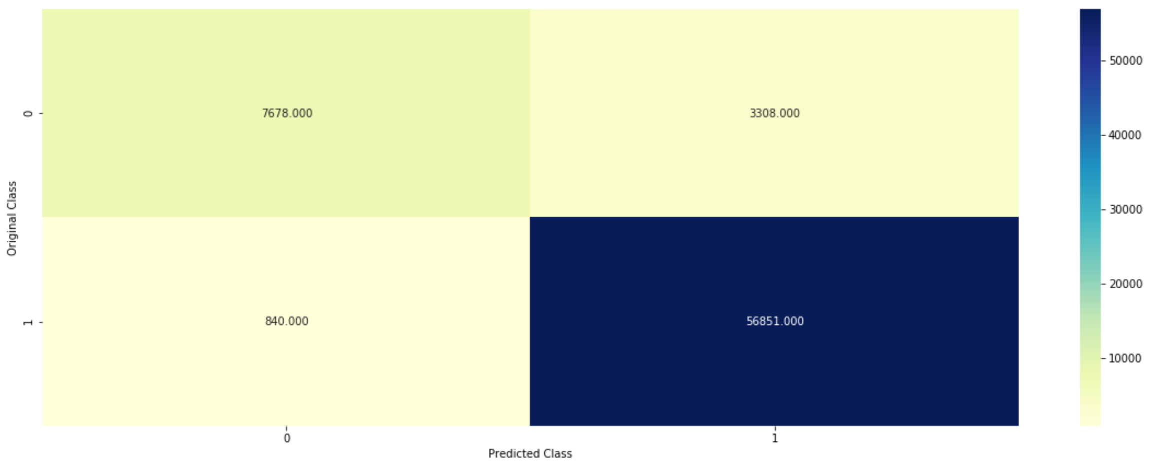



```
best estimators = 500 and depth = 5
```

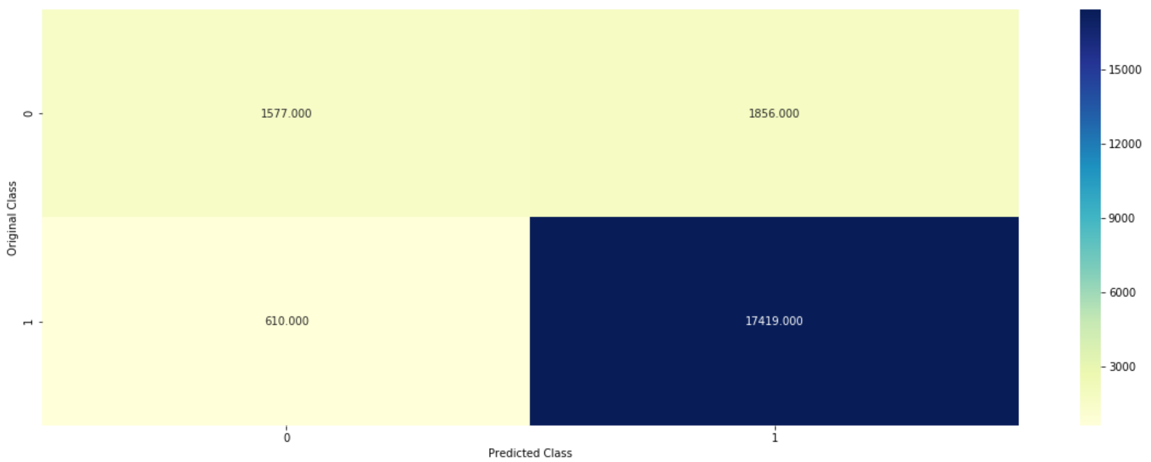
In [37]:

```
clf = bestModelX(train,cv,test,best_estimator,best_depth)
```

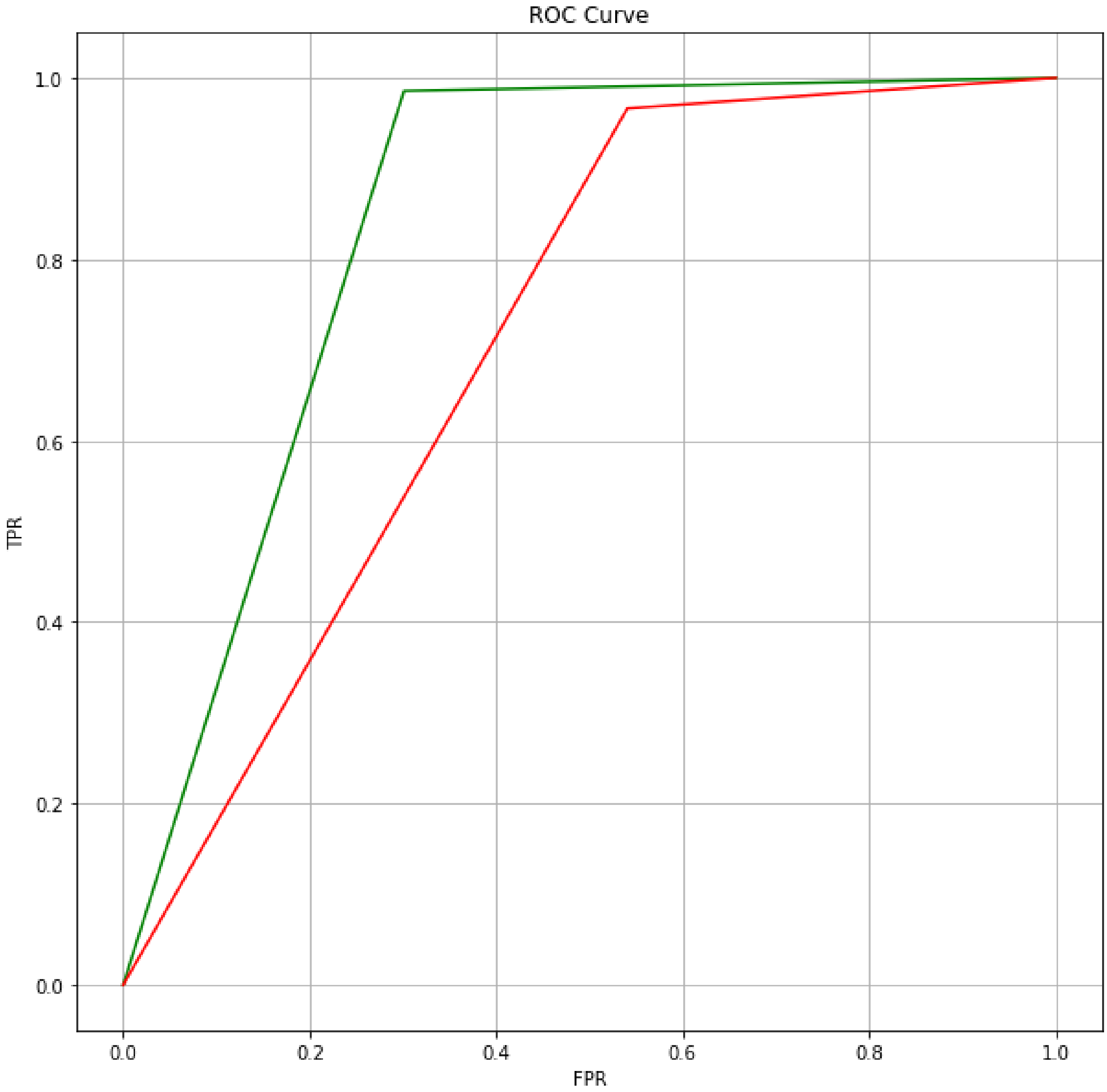
```
-------------------- Confusion matrix --------------------
```




```
For values of best estimator =  500 best depth =  5 The AUC is: 0.84
21645828438401
For values of best estimator =  500 best depth =  5 The AUC is: 0.70
30454406325939
-------------------- Confusion matrix --------------------
```




```
For values of best estimator =  500 best depth =  5 The AUC is: 0.71
27653044726449
```



[6] Conclusions

Vectorizer	Algorithm	Depth	min_samples_split	AUC
BOW	RF	100	500	0.65
TFIDF	RF	100	500	0.65
AvgW2V	RF	100	50	0.65
TFIDFW2V	RF	100	50	0.62
BOW	XgBoost	500	5	0.77
TFIDF	XgBoost	500	50	0.79
AvgW2V	XgBoost	500	5	0.74
TFIDFW2V	XgBoost	500	5	0.71

In [ ]: