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)](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/)](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 [1]:

```
%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
```

```
E:\anaconda\lib\site-packages\gensim\utils.py:1197: UserWarning: detected Windows; aliasing chunkize to chunkiz
e_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

In [2]:

```
#from google.colab import drive
#drive.mount('/content/gdrive')
```

In [3]:

```
# 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 LIMIT 500000""", con)


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

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a negative 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 (525814, 10)
```

Out[3]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	1	1303862400	Good Quality Dog Food	I sev c
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	0	1346976000	Not as Advertised	P a labe Pe

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	1	1219017600	"Delight" says it all	Th con th arc

In [4]:

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

In [5]:

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

```
(80668, 7)
```

Out[5]:

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

In [6]:

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

Out[6]:

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

In [7]:
```
display['COUNT(*)'].sum()
```

Out[7]:
```
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 [8]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[8]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACKER QUADRATINI VANILLA WAFERS
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACKER QUADRATINI VANILLA WAFERS
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACKER QUADRATINI VANILLA WAFERS
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACKER QUADRATINI VANILLA WAFERS
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACKER QUADRATINI VANILLA WAFERS

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 [9]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='quicksort',
```

In [10]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', inplace=False
final.shape
```

Out[10]:
```
(364173, 10)
```

In [11]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[11]:
```
69.25890143662969
```

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 [12]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[12]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1	5	1224892800	Bought This for My Son at College	sp h
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2	4	1212883200	Pure cocoa taste with crunchy almonds inside	a fi

In [13]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [14]:
```
#Before starting the next phase of preprocessing lets see the number of entries left
print(final.shape)
final = final.sample(100000
                    )

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

```
(364171, 10)
```

Out[14]:
```
1    84425
0    15575
Name: Score, dtype: int64
```

In [15]:
```
final = final.sort_values('Time',ascending = True)#sorting by time for time series cross validation
final.shape
```

Out[15]: (100000, 10)

In [16]:
```
final.head()
```

Out[16]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	
138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	2	1	940809600	This wh
417839	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0	0	1	944092800	
346055	374359	B00004CI84	A344SMIA5JECGM	Vincent P. Ross	1	2	1	944438400	
346116	374422	B00004CI84	A1048CYU0OV4O8	Judy L. Eans	2	2	1	947376000	
346141	374450	B00004CI84	ACJR7EQF9S6FP	Jeremy Robertson	2	3	1	951523200	Bettlejuic

[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 [17]:

```
# 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)
```

```
I can remember seeing the show when it aired on television years ago, when I was a child.  My sister later boug
ht me the LP (which I have to this day,  I'm thirty something).I used this series of books &amp; songs when I d
id my  student teaching for preschoolers &amp; turned the whole school on to it.  I am now purchasing it on CD,
along with the books for my children 5 &amp;  2.  The tradition lives on!
==================================================
Frank's Red Hot sauce is the best hot sauce there is.  It's good on just about anything - even Chinese food!<br
/><br />Seriously, try it on everything!  It gives anything a really great flavor & kick.
==================================================
I purchased these on the special Friday sale where they were $7.99 for 3 cans. At the store where I normally sh
op here one can is almost $5 so this was a fantastic deal. I liked how they were lightly salted and not as salt
y as alot of nuts are.<br /><br />I agree with the other review that they were mostly almonds. Id say 60% almon
ds, 30% cashews and 10% macadamias but they were still quite good.
==================================================
This is the second time that I have ordered Belly Flops.  They contain an excellent assortment of flavors.  The
odd shapes make them interesting, and the lack of the words "Jelly Belly" does not detract at all from the tast
e!
==================================================
```

In [18]:
```
# 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)
```

```
I can remember seeing the show when it aired on television years ago, when I was a child.  My sister later boug
ht me the LP (which I have to this day,  I'm thirty something).I used this series of books &amp; songs when I d
id my  student teaching for preschoolers &amp; turned the whole school on to it.  I am now purchasing it on CD,
along with the books for my children 5 &amp;  2.  The tradition lives on!
```

In [19]:

```python
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-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)
```

```
I can remember seeing the show when it aired on television years ago, when I was a child.  My sister later boug
ht me the LP (which I have to this day,  I'm thirty something).I used this series of books & songs when I did m
y  student teaching for preschoolers & turned the whole school on to it.  I am now purchasing it on CD, along w
ith the books for my children 5 &  2.  The tradition lives on!
==================================================
Frank's Red Hot sauce is the best hot sauce there is.  It's good on just about anything - even Chinese food!Ser
iously, try it on everything!  It gives anything a really great flavor & kick.
==================================================
I purchased these on the special Friday sale where they were $7.99 for 3 cans. At the store where I normally sh
op here one can is almost $5 so this was a fantastic deal. I liked how they were lightly salted and not as salt
y as alot of nuts are.I agree with the other review that they were mostly almonds. Id say 60% almonds, 30% cash
ews and 10% macadamias but they were still quite good.
==================================================
This is the second time that I have ordered Belly Flops.  They contain an excellent assortment of flavors.  The
odd shapes make them interesting, and the lack of the words "Jelly Belly" does not detract at all from the tast
e!
```

In [20]:

```
# 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 [21]:

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

```
I purchased these on the special Friday sale where they were $7.99 for 3 cans. At the store where I normally sh
op here one can is almost $5 so this was a fantastic deal. I liked how they were lightly salted and not as salt
y as alot of nuts are.<br /><br />I agree with the other review that they were mostly almonds. Id say 60% almon
ds, 30% cashews and 10% macadamias but they were still quite good.
==================================================
```

In [22]:

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

```
I can remember seeing the show when it aired on television years ago, when I was a child.  My sister later boug
ht me the LP (which I have to this day,  I'm thirty something).I used this series of books &amp; songs when I d
id my  student teaching for preschoolers &amp; turned the whole school on to it.  I am now purchasing it on CD,
along with the books for my children  &amp;    The tradition lives on!
```

In [23]:

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

```
I purchased these on the special Friday sale where they were 7 99 for 3 cans At the store where I normally shop
here one can is almost 5 so this was a fantastic deal I liked how they were lightly salted and not as salty as
alot of nuts are br br I agree with the other review that they were mostly almonds Id say 60 almonds 30 cashews
and 10 macadamias but they were still quite good
```

In [24]:

```
# 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 step

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

In [25]:
```
# 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%|██████████████████████████████████████████████████| 100000/100000 [00:42<00:00, 237
4.83it/s]
```

In [26]:
```
#Loading pickle for saving and retreiving files
import pickle
def savetofile(obj,filename):
    pickle.dump(obj,open(filename+".p","wb"))
def openfromfile(filename):
    temp = pickle.load(open(filename+".p","rb"))
    return temp
```

In [27]:
```
preprocessed_reviews[16]
```

Out[27]:
```
'spectra paste food colors simply fantastic provide depth clarity color impossible achieve liquid food colors h
ues beautiful distinctive black red two colors difficult get dying frostings etc especially nice probably best
manufacturer tried questions not certain sizes set mine bottles ounce might not seem like much need dot thick g
el paste end toothpick color large amounts material plenty coloring ability bottle many many times sized liquid
food color bottle highly recommended really good price time review'
```

Splitting the data

In [28]:
```
from sklearn.model_selection import train_test_split

X_train,X_test,Y_train,Y_test = train_test_split(preprocessed_reviews,final['Score'],test_size=0.3)
#splitting the dataset

print('Size of train dataset is:',len(X_train))#size of training dataset
print('Size of the test dataset is:',len(X_test))#size of test dataset
```

```
Size of train dataset is: 70000
Size of the test dataset is: 30000
```

In [29]:
```
from sklearn.model_selection import TimeSeriesSplit#importing for time series split
tscv = TimeSeriesSplit(n_splits=10)#time series split for the data
print(tscv)
```

```
TimeSeriesSplit(n_splits=10)
```

In [30]:
```
from sklearn.model_selection import TimeSeriesSplit
tscv = TimeSeriesSplit(n_splits=10)
for train, cv in tscv.split(X_train):
    print('train data shape:',train.shape,'test data shape',cv.shape)
```

```
train data shape: (6370,) test data shape (6363,)
train data shape: (12733,) test data shape (6363,)
train data shape: (19096,) test data shape (6363,)
train data shape: (25459,) test data shape (6363,)
train data shape: (31822,) test data shape (6363,)
train data shape: (38185,) test data shape (6363,)
train data shape: (44548,) test data shape (6363,)
train data shape: (50911,) test data shape (6363,)
train data shape: (57274,) test data shape (6363,)
train data shape: (63637,) test data shape (6363,)
```

[5] Applying Random forest

[5.1] Applying Random Forests on BOW with RandomizedSearch CROSS VALIDATION, SET 1

In [51]:

```
bow_vect = CountVectorizer()#initiating the vectorizer

bow_vect.fit(X_train)#fitting data into vectorizer makes it learn all the vocablury

#transforming the data into training and test dataset
train_set_bow = bow_vect.transform(X_train)
test_set_bow = bow_vect.transform(X_test)

print('AFTER VECTORIZATION:')
print(train_set_bow.shape)
print(test_set_bow.shape)
print('Some of the feature names are:',bow_vect.get_feature_names()[:10:-1])

```

```
AFTER VECTORIZATION:
(70000, 50810)
(30000, 50810)
```

In [52]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import RandomizedSearchCV

estimators = [10,50,100,250,450]#list of estimators that will be tuned
depths = [3,9,11,15,50]#tuning depth to avoid overfitting and underfitting

params = {'max_depth':depths,'n_estimators':estimators}#for passing as argument

tscv = TimeSeriesSplit(n_splits = 5)#initiating 5 time series splits for cross validation

model = RandomizedSearchCV(RandomForestClassifier(bootstrap = True,criterion = 'gini',max_features = 'auto')
                           return_train_score=True,n_jobs = -1)
#fitting the classifier
#fitting the parameter distribution


model.fit(train_set_bow,Y_train)


```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed: 10.4min
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed: 30.5min finished
```

Out[52]:
```
RandomizedSearchCV(cv=TimeSeriesSplit(n_splits=5), error_score='raise',
          estimator=RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_split=1e-07, min_samples_leaf=1,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            n_estimators=10, n_jobs=1, oob_score=False, random_state=None,
            verbose=0, warm_start=False),
          fit_params={}, iid=True, n_iter=10, n_jobs=-1,
          param_distributions={'max_depth': [3, 9, 11, 15, 50], 'n_estimators': [10, 50, 100, 250, 450]},
          pre_dispatch='2*n_jobs', random_state=None, refit=True,
          return_train_score=True, scoring='roc_auc', verbose=1)
```

In [53]:
```
savetofile(model,'model_bow_rf')#saving the model
```

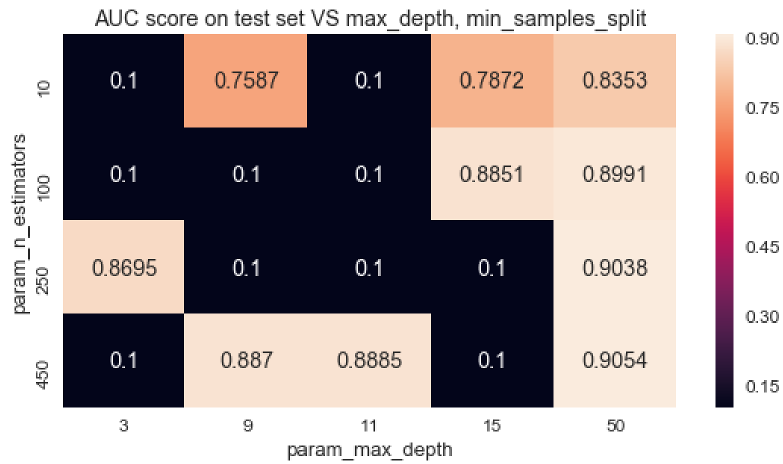
In [54]:
```
model_bow_rf = openfromfile('model_bow_rf')#retreiving the model
```

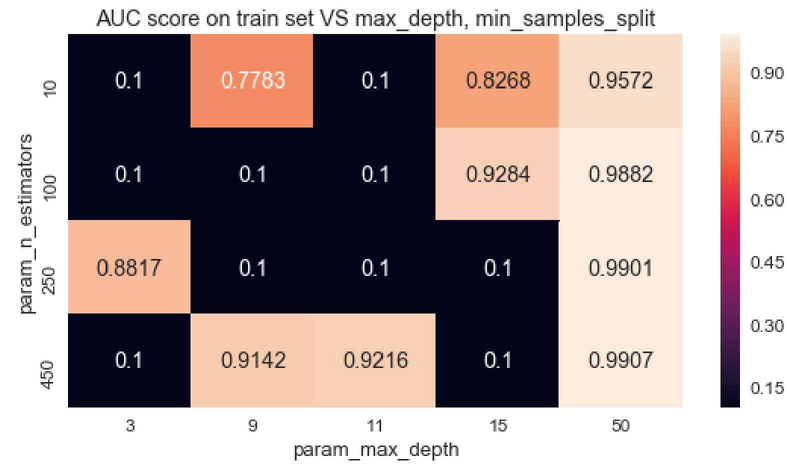
In [55]:

```
# as we have two hyperparameters to tune so we will plot heatmap and to show hyperparameters giving maximum
def plots(model):#function for plotting heatmaps

    print('Best Hyperparameters are:',model.best_params_)
    df = pd.DataFrame(model.cv_results_)#saving into the dataframe
    results = df.groupby(['param_n_estimators','param_max_depth']).min().unstack()[['mean_test_score',
                                                                                          'mean_train_sc
    #groupby by number of estimators and maximum depth and unstacking mean train and test score

    results = results.fillna(0.1)#imputing all null values by 0.1

    sns.set(font_scale = 1.2)
    fig, ax = plt.subplots(figsize=(20,10))#setting the font size
    plt.subplot(2,2,1)
    title_test = 'AUC score on test set VS max_depth, min_samples_split'
    fmt = 'png'
    sns.heatmap(results.mean_test_score, annot=True, fmt='.4g');#heatmap for test score
    plt.title(title_test);
    #plt.savefig('{title_test}.{fmt}', format=fmt, dpi=300);

    plt.subplot(2,2,2)
    title_train = 'AUC score on train set VS max_depth, min_samples_split'
    fmt = 'png'
    sns.heatmap(results.mean_train_score, annot=True, fmt='.4g');#heatmap for train score
    plt.title(title_train);
    #plt.savefig('{title_train}.{fmt}', format=fmt, dpi=300);
```

In [56]:
```
plots(model_bow_rf)
```

```
Best Hyperparameters are: {'n_estimators': 450, 'max_depth': 50}
```





In [64]:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
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 wordcloud import WordCloud
#from xgboost import XGBClassifier


#1.Function for calculating the test and train Area under curve after fitting with right hyperparameters
def auc(depth,estimator,train_set,test_set):
    tree_optimal = RandomForestClassifier(bootstrap = True,criterion = 'gini',max_depth = depth,n_estimators
    tree_optimal.fit(train_set,Y_train)
    pred_tr = tree_optimal.predict(train_set)# predicting all the classes for test dataset for confusion mat
    pred_test = tree_optimal.predict(test_set)#predicting all the classes for train dataset for confusin mat

    train_pred_proba = tree_optimal.predict_proba(train_set)[:,1]
    test_pred_proba = tree_optimal.predict_proba(test_set)[:,1]
    #predict_proba gives the probability of a particular data point belonging to the specified class

    train_auc = roc_auc_score(Y_train,train_pred_proba)
    test_auc = roc_auc_score(Y_test,test_pred_proba)
    print('AUC on train data is:',train_auc)
    print('AUC on test data is:',test_auc)
    print("*****************************************************\n")
    return train_auc,test_auc,train_pred_proba,test_pred_proba,pred_tr,pred_test


#**************************************************************************************************************

#2.Function for plotting the roc curve
def curve(train_pred,test_pred ):
    fpr_tr, tpr_tr, _ = roc_curve(Y_train,train_pred)
    fpr_test, tpr_test, _ = roc_curve(Y_test,test_pred)
#calculating the fpr,tpr and thresholds for each training and test dataset
    auc_train = roc_auc_score(Y_train,train_pred)
    auc_test = roc_auc_score(Y_test, test_pred)
    sns.set_style('darkgrid')
    plt.figure(figsize=(8,8))
    plt.plot(np.linspace(0,1,100),np.linspace(0,1,100),"g--")#this plots the roc curve for AUC = 0.5
```

```
    plt.plot(fpr_tr,tpr_tr,'r',linewidth=2,label="train auc="+str(auc_train))
    plt.plot(fpr_test,tpr_test,'b',linewidth=1,label=" test auc="+str(auc_test))
    plt.xlabel('False positive rate(1-specificity)',fontsize=18)
    plt.ylabel('True positive rate(sensitivity)',fontsize=18)
    plt.title('Reciever operating characteristics curve',fontsize=18)
    plt.legend(loc='best')
    plt.show()
    print('**************************************\n')

#**********************************************************************************************************

#3.Function for calculating F1,precision and recall
def metrics(pred):
    print('scores on test data are:\n')
    # calculating the precison score
    print('precison score is {}'.format(precision_score(Y_test,pred)))
    #calculating the recall score
    print('\nrecall_score is {}'.format(recall_score(Y_test,pred)))
    #calculating the f1 score
    print('\nf1 score is {}\n'.format(f1_score(Y_test,pred)))
    print("****************************************************************\n")

#**********************************************************************************************************

#4.Function for plotting the confusion matrix
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)

    A =(((C.T)/(C.sum(axis=1))).T)#for recall matrix

    B =(C/C.sum(axis=0))#for precision matrix
    plt.figure(figsize=(20,4))

    labels = [0,1]
    # representing A in heatmap format
    cmap=sns.light_palette("blue")
    plt.subplot(1, 3, 1)
    sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Confusion matrix")

    plt.subplot(1, 3, 2)
```

```
    sns.heatmap(B, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Precision matrix")

    plt.subplot(1, 3, 3)
    # representing B in heatmap format
    sns.heatmap(A, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Recall matrix")

    plt.show()
#**********************************************************************************************************
def features_and_wc(depth,estimator,train_set,vectorizer):
    text = "" #saving strings
    tree_optimal = RandomForestClassifier(criterion = 'gini',max_depth = depth,n_estimators = estimator)
    #tree_optimal = XGBClassifier(learning_rate = 0.1,booster = "gbtree",max_depth = depth,n_estimators = es
    tree_optimal.fit(train_set,Y_train)
    features = tree_optimal.feature_importances_
    indices = np.argsort(features)[::-1]
    feature_names = vectorizer.get_feature_names()
    print('TOP 20 important features which gives maximum information gain on splitting are:\n')
    for i in (indices[0:20]):
        text = text + " " + feature_names[i]
        print("%s\t -->\t%f  "%(feature_names[i],features[i]))

    wordcloud = WordCloud(width=1500, height=600,stopwords = stopwords).generate(text)
    # plot the WordCloud image
    plt.figure(figsize = (30,8))
    plt.imshow(wordcloud, interpolation="bilinear")
    plt.axis("off")
    plt.margins(x=0, y=0)
    plt.show()

```

Here 0.1 signifies that set of parameters from the list were not used for tuning in randomized serach cv

In [70]:

```
from IPython.core.display import display, HTML
display(HTML("<style>.container { width:100% !important; }</style>"))
```

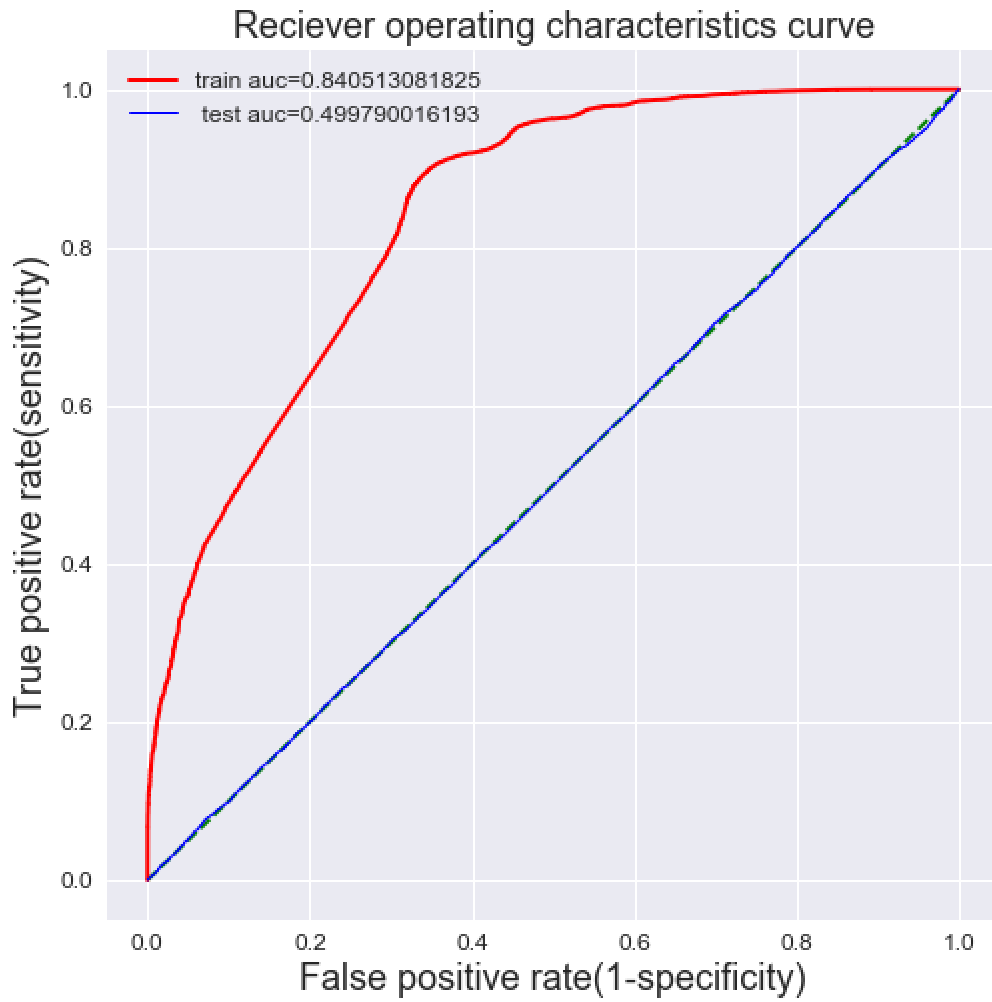
ROC and Confusion Matrix

In [65]:

```
best_depth_bow_rf = model_bow_rf.best_params_['max_depth']
best_n_bow_rf= model_bow_rf.best_params_['n_estimators']
```

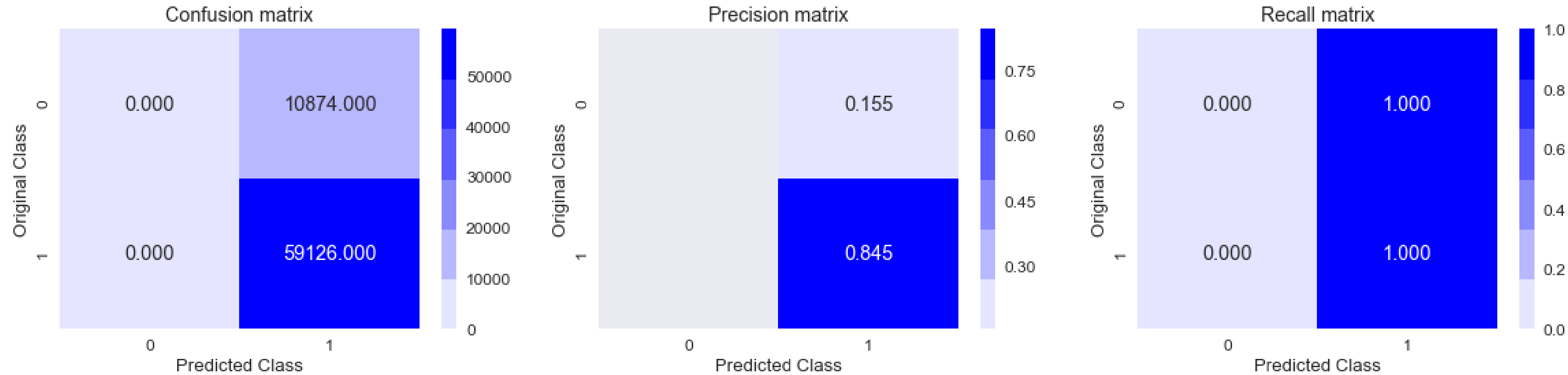
In [66]:
```
'''AUC ON TEST DATA'''
train_auc_BOW_rf,test_auc_BOW_rf,train_pred_proba,test_pred_proba,train_pred,test_pred = auc(best_depth_bow_

'''PLOTTING THE ROC CURVE'''
curve(train_pred_proba,test_pred_proba)

'''Precision,recall and f1 score'''
metrics(test_pred)



'''Plotting the confusion matrix'''
print('Confusin matrix on train data')
plot_confusion_matrix(Y_train,train_pred)
print('Confusion matrix for test data')
plot_confusion_matrix(Y_test,test_pred)
```

```
AUC on train data is: 0.840513081825
AUC on test data is: 0.499790016193
******************************************************
```

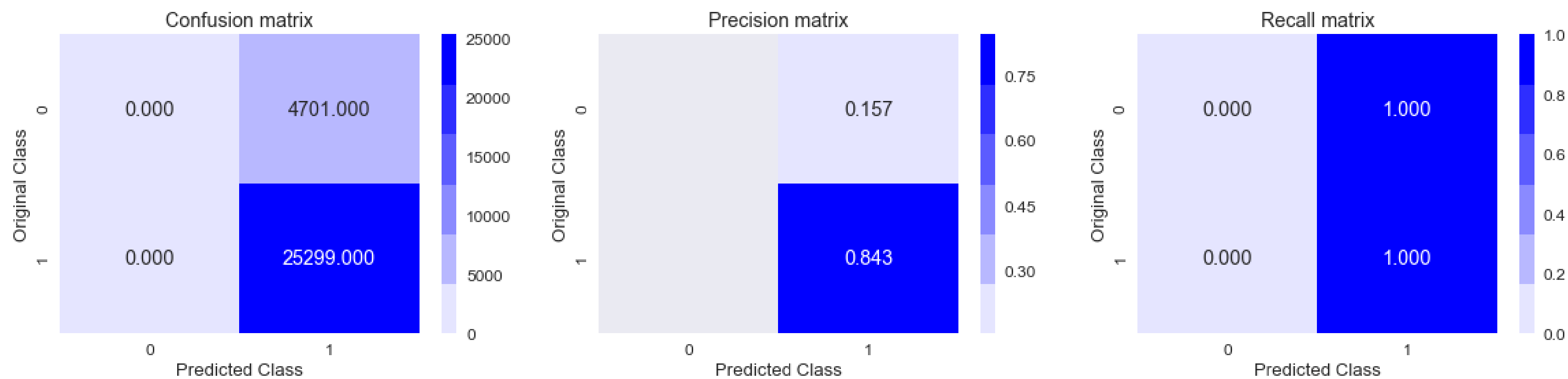



```
*************************************

scores on test data are:

precison score is 0.8433

recall_score is 1.0

f1 score is 0.9149894211468561

****************************************************************
```

```
Confusin matrix on train data
```




```
Confusion matrix for test data
```

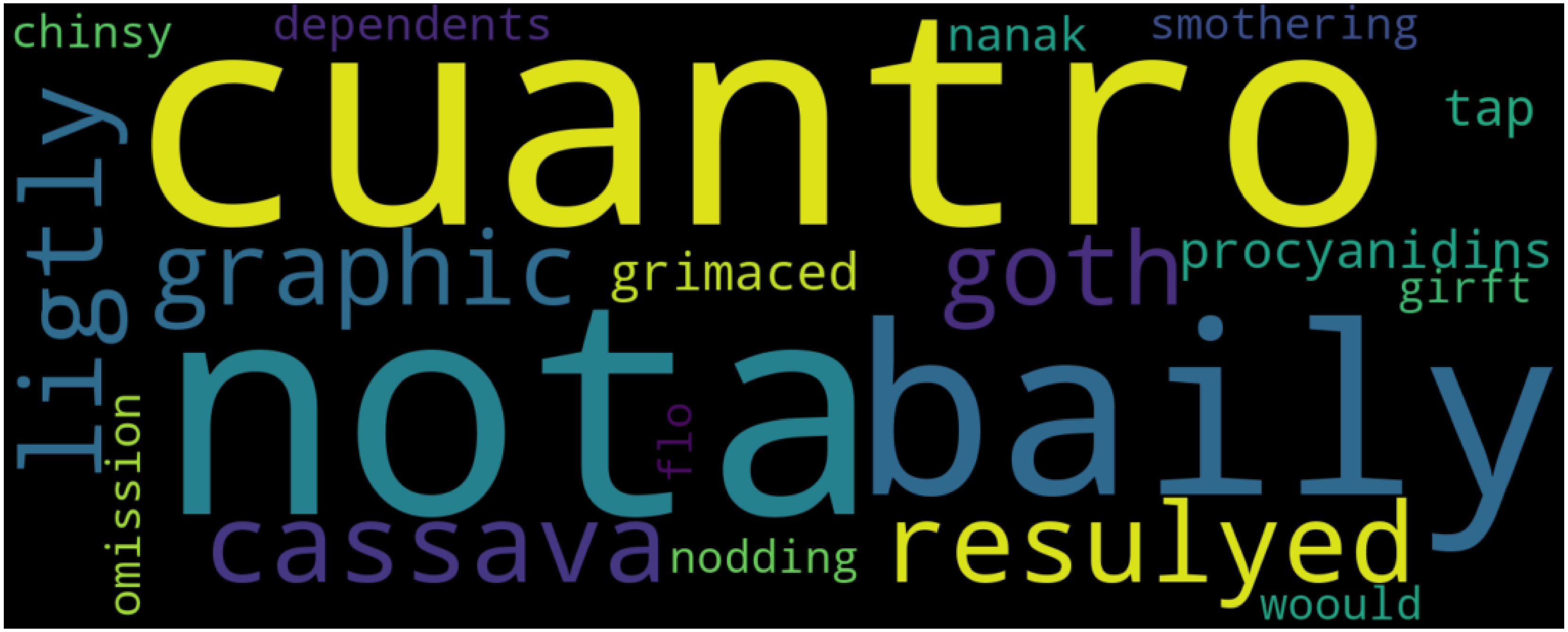


Feature Importance and WORDCLOUD

In [69]:

```
"""Most important features"""
features_and_wc(best_depth_bow_rf,best_n_bow_rf,train_bow,bow_vect)
```

```
TOP 20 important features which gives maximum information gain on splitting are:

nota     -->    0.002619
cuantro  -->    0.001636
baily    -->    0.001557
resulyed        -->    0.001541
ligtly   -->    0.001520
cassava  -->    0.001496
graphic  -->    0.001443
goth     -->    0.001434
procyanidins    -->    0.001418
grimaced        -->    0.001315
tap      -->    0.001277
dependents      -->    0.001249
nanak    -->    0.001243
omission        -->    0.001219
smothering      -->    0.001210
girft    -->    0.001183
flo      -->    0.001142
chinsy   -->    0.001134
woould   -->    0.001129
nodding  -->    0.001110
```



[5.2] Applying Random Forests on TFIDF, SET 2

In [0]:

```
# Please write all the code with proper documentation
tfidf_vect  = TfidfVectorizer(ngram_range = (1,2),min_df = 10)
#min_df signifies minimum number of times a word must occur in corpus for consideration
#ngram_range tells about the unigram and bigram
tfidf_vect.fit(X_train)
train_set = tfidf_vect.transform(X_train)
test_set = tfidf_vect.transform(X_test)

print('after vectorization training set:',train_set.shape)
print('after vectorization test set:',test_set.shape)

```

```
after vectorization training set: (70000, 40504)
after vectorization test set: (30000, 40504)
```

In [0]:
```
savetofile(train_set,'train_tfidf')#saving to file for future use
savetofile(test_set,'test_tfidf')
```

In [71]:
```
train_tfidf = openfromfile('computed/train_tfidf')
test_tfidf = openfromfile('computed/test_tfidf')
```

In [0]:
```

estimators = [10,50,100,250,450]#list of estimators that will be tuned
depths = [3,9,11,15,50]#tuning depth to avoid overfitting and underfitting

params = {'max_depth':depths,'n_estimators':estimators}#for passing as argument

tscv = TimeSeriesSplit(n_splits = 5)#initiating 5 time series splits for cross validation

model = RandomizedSearchCV(RandomForestClassifier(bootstrap = True,criterion = 'gini',max_features = 'auto')
                           return_train_score=True,n_jobs = -1)
#fitting the classifier
#fitting the parameter distribution


model.fit(train_tfidf,Y_train)


```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:  4.5min
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:  5.0min finished
```

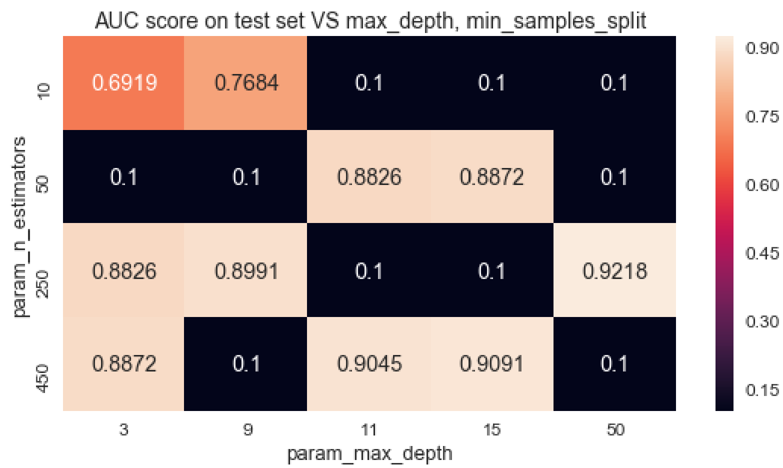
Out[50]:
```
RandomizedSearchCV(cv=TimeSeriesSplit(n_splits=5), error_score='raise',
          estimator=RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_split=1e-07, min_samples_leaf=1,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            n_estimators=10, n_jobs=1, oob_score=False, random_state=None,
            verbose=0, warm_start=False),
          fit_params={}, iid=True, n_iter=10, n_jobs=-1,
          param_distributions={'max_depth': [3, 9, 11, 15, 50], 'n_estimators': [10, 50, 100, 250, 450]},
          pre_dispatch='2*n_jobs', random_state=None, refit=True,
          return_train_score=True, scoring='roc_auc', verbose=1)
```

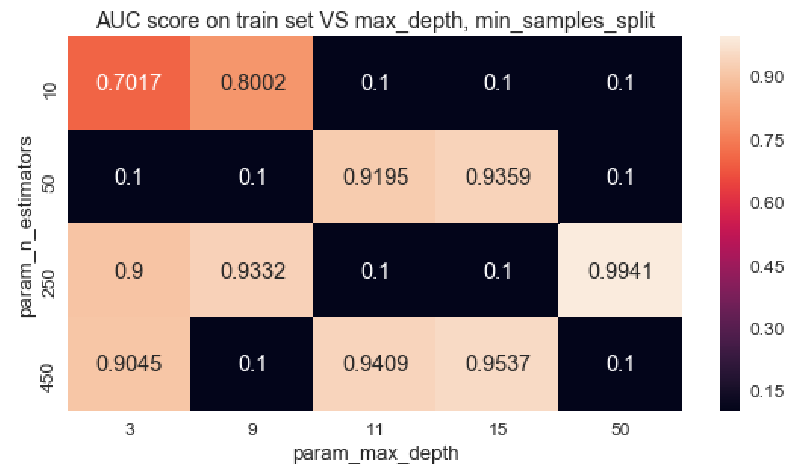
In [0]:
```
savetofile(model,'model_tfidf_rf')
```

In [72]:
```
model_tfidf_rf = openfromfile('model_tfidf_rf')
```

In [73]:
```
plots(model_tfidf_rf)
```

```
Best Hyperparameters are: {'n_estimators': 250, 'max_depth': 50}
```



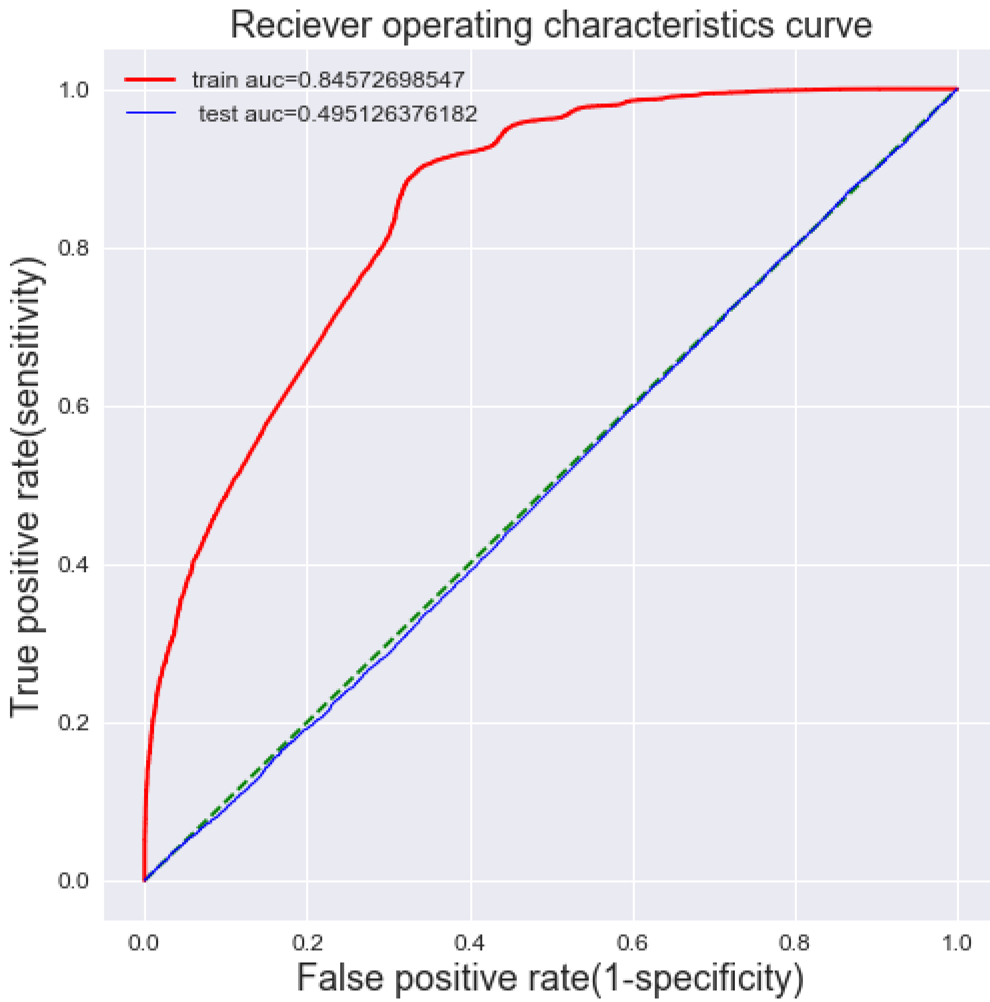


In [74]:
```
best_depth_tfidf_rf = model_tfidf_rf.best_params_['max_depth']#best depth of the decision trees
best_n_tfidf_rf = model_tfidf_rf.best_params_['n_estimators']#best number of decision tress
```

ROC and Confusion Matrix

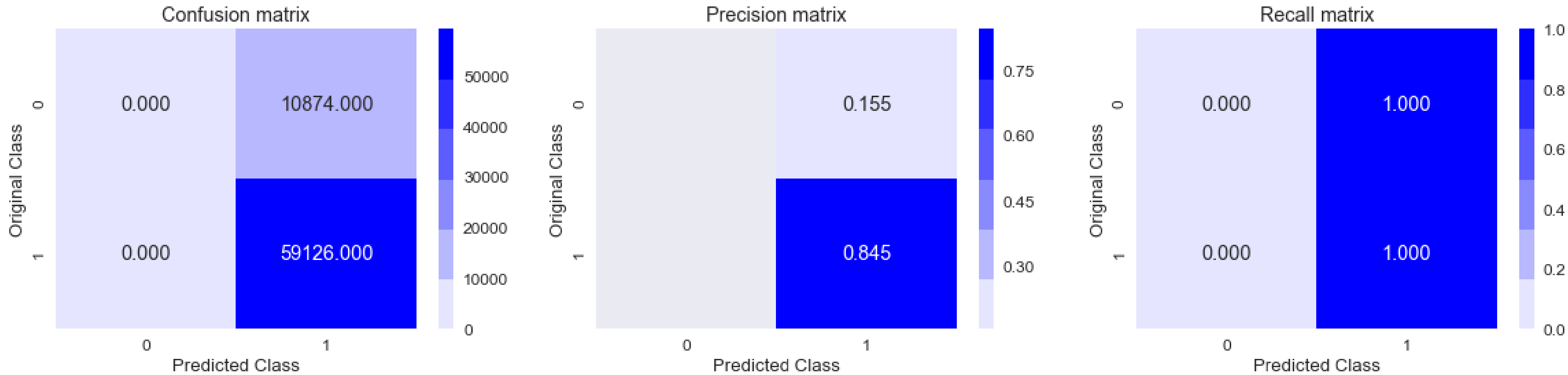
In [75]:
```
'''AUC ON TEST DATA'''
train_auc_tfidf_rf,test_auc_tfidf_rf,train_pred_proba,test_pred_proba,train_pred,test_pred = auc(best_depth_

'''PLOTTING THE ROC CURVE'''
curve(train_pred_proba,test_pred_proba)

'''Precision,recall and f1 score'''
metrics(test_pred)


'''Plotting the confusion matrix'''
print('Confusin matrix on train data')
plot_confusion_matrix(Y_train,train_pred)
print('Confusion matrix for test data')
plot_confusion_matrix(Y_test,test_pred)
```

```
AUC on train data is: 0.84572698547
AUC on test data is: 0.495126376182
******************************************************
```

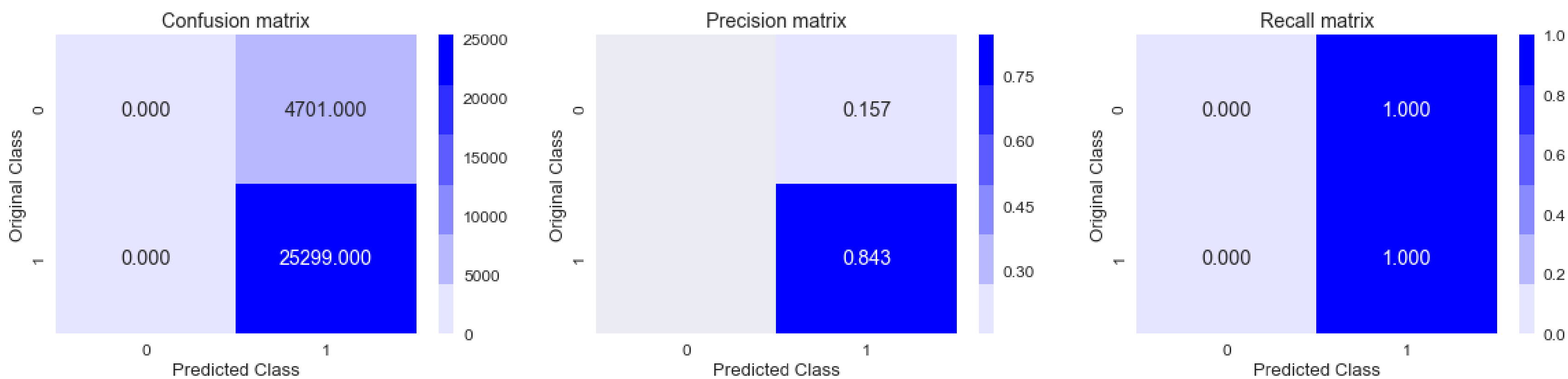



```
***************************************

scores on test data are:

precison score is 0.8433

recall_score is 1.0

f1 score is 0.9149894211468561

******************************************************************
```

```
Confusin matrix on train data
```




```
Confusion matrix for test data
```



Feature importance and WORDCLOUD

In [0]:

```
"""Most important features"""
features_and_wc(best_depth_tfidf_rf,best_n_tfidf_rf,train_tfidf,tfidf_vect)#for generating the wordcloud
```

```
TOP 20 important features which gives maximum information gain on splitting are:

not      -->    0.016877
great    -->    0.011052
disappointed     -->    0.010158
not buy  -->    0.009911
awful    -->    0.009760
worst    -->    0.009393
horrible         -->    0.008511
money    -->    0.008419
waste money      -->    0.008219
bad      -->    0.008164
waste    -->    0.007668
not recommend    -->    0.006845
disappointing    -->    0.006349
terrible         -->    0.006257
would not        -->    0.006193
best     -->    0.006062
threw    -->    0.005787
return   -->    0.005548
love     -->    0.005523
refund   -->    0.005472
```

[5.3] Applying Random Forests on AVG W2V and TFIDF W2V, SET 3

In [0]:

```
s_train = []
for sent in X_train:
    s_train.append(sent.split())
#preparing the training data for  word to vector vectorization

s_test = []
for sent in X_test:
    s_test.append(sent.split())
#preparing the test data for word to vector fatorization
```

In [0]:
```
# this line of code trains the w2v model on the give list of sentances

w2v_model=Word2Vec(s_train,min_count=5,size=50, workers=4)# min_count = 5 considers only words that occured

w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))

```

```
number of words that occured minimum 5 times  16003
```

In [0]:
```
print('sample words :',w2v_words[0:100])
```

```
sample words : ['four', 'cats', 'three', 'absolutely', 'love', 'treats', 'one', 'sometimes', 'accepts', 'howeve
r', 'ate', 'treat', 'would', 'not', 'touch', 'sniffed', 'walked', 'away', 'lovers', 'based', 'reaction', 'say',
'chance', 'cat', 'liking', 'pleased', 'delivery', 'product', 'expected', 'brach', 'mints', 'purchased', 'year
s', 'best', 'need', 'change', 'packaging', 'twist', 'ends', 'pressed', 'ease', 'taking', 'package', 'problem',
'made', 'mexico', 'usa', 'kraft', 'cheese', 'fill', 'blank', 'products', 'predictable', 'well', 'suited', 'youn
g', 'palates', 'followed', 'box', 'recipe', 'two', 'changes', 'instead', 'chicken', 'flaked', 'oz', 'leftover',
'salmon', 'also', 'melted', 'half', 'dozen', 'slices', 'american', 'stronger', 'flavor', 'kid', 'friendly', 'un
like', 'frozen', 'broccoli', 'prominent', 'florets', 'tiny', 'dehydrated', 'reconstitute', 'much', 'failed', 'c
ontribute', 'depending', 'eaters', 'may', 'consider', 'pro', 'con', 'hard', 'see', 'anybody', 'better', 'boxe
d']
```

[5.3.1] Average word to vector

In [0]:

```
#computing average word to vector for training data
train_set = [] # the avg-w2v for each sentence/review is stored in this list
for sent in tqdm(s_train):
    sent_vec = np.zeros(50)
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: #
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    train_set.append(sent_vec)

print(len(train_set))#number of data points
```

```
100%|██████████████████████████████████████████████████| 70000/70000 [02:23<00:00, 48
8.30it/s]

70000
```

In [0]:

```
#computing average word to vector for test data

test_set = [] # the avg-w2v for each sentence/review is stored in this list
for sent in tqdm(s_test):
    sent_vec = np.zeros(50)
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: #
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    test_set.append(sent_vec)

print(len(test_set))#number of datapoints in test set
```

```
100%|██████████████████████████████████████████████████| 30000/30000 [01:08<00:00, 44
0.16it/s]

30000
```

In [0]:

```
savetofile(train_set,'train_avgw2v')
savetofile(test_set,'test_avgw2v')
```

In [0]:

```
train_avgw2v = openfromfile('gdrive/My Drive/Colab Notebooks/computed/train_avgw2v')
test_avgw2v = openfromfile('gdrive/My Drive/Colab Notebooks/computed/test_avgw2v')

```

In [0]:

```
estimators = [10,50,100,250,450]#list of estimators that will be tuned
depths = [3,9,11,15,50]#tuning depth to avoid overfitting and underfitting
params = {'max_depth':depths,'n_estimators':estimators}#for passing as argument
tscv = TimeSeriesSplit(n_splits = 5)#initiating 5 time series splits for cross validation
model = RandomizedSearchCV(RandomForestClassifier(bootstrap = True,criterion = 'gini',max_features = 'auto')
                           return_train_score=True,n_jobs = -1)
#fitting the classifier
#fitting the parameter distribution
model.fit(train_avgw2v,Y_train)


```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:  7.4min
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed: 11.2min finished
```

Out[65]:

```
RandomizedSearchCV(cv=TimeSeriesSplit(n_splits=5), error_score='raise',
          estimator=RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_split=1e-07, min_samples_leaf=1,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            n_estimators=10, n_jobs=1, oob_score=False, random_state=None,
            verbose=0, warm_start=False),
          fit_params={}, iid=True, n_iter=10, n_jobs=-1,
          param_distributions={'max_depth': [3, 9, 11, 15, 50], 'n_estimators': [10, 50, 100, 250, 450]},
          pre_dispatch='2*n_jobs', random_state=None, refit=True,
          return_train_score=True, scoring='roc_auc', verbose=1)
```

In [0]:

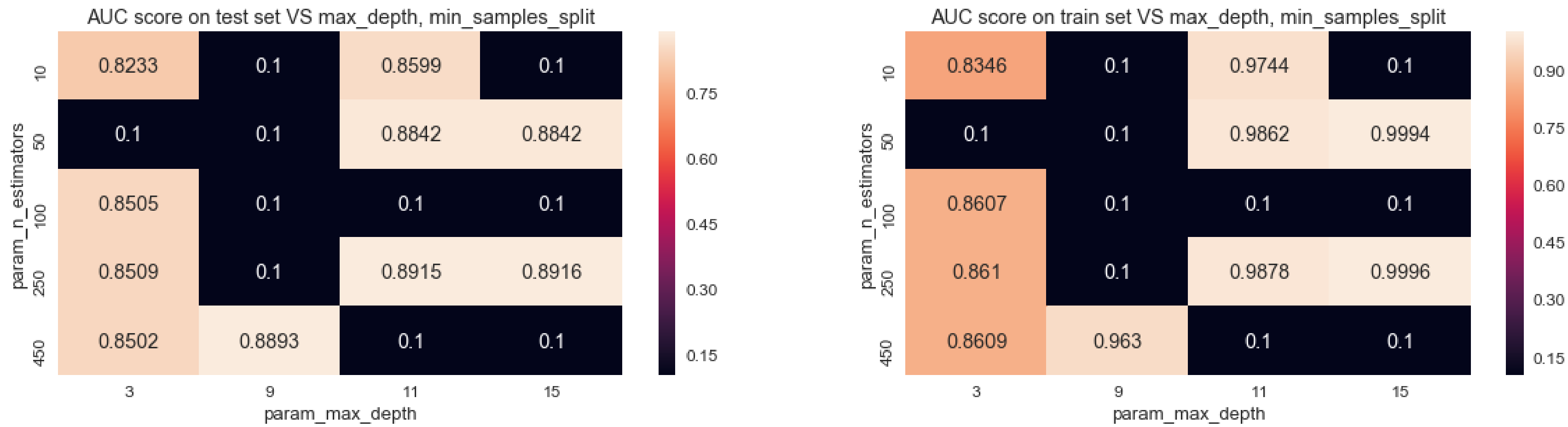
```
savetofile(model,'model_avgw2v_rf')
```

In [0]:

```
model_avgw2v_rf = openfromfile('model_avgw2v_rf')
```

In [0]:
```
plots(model_avgw2v_rf)
```

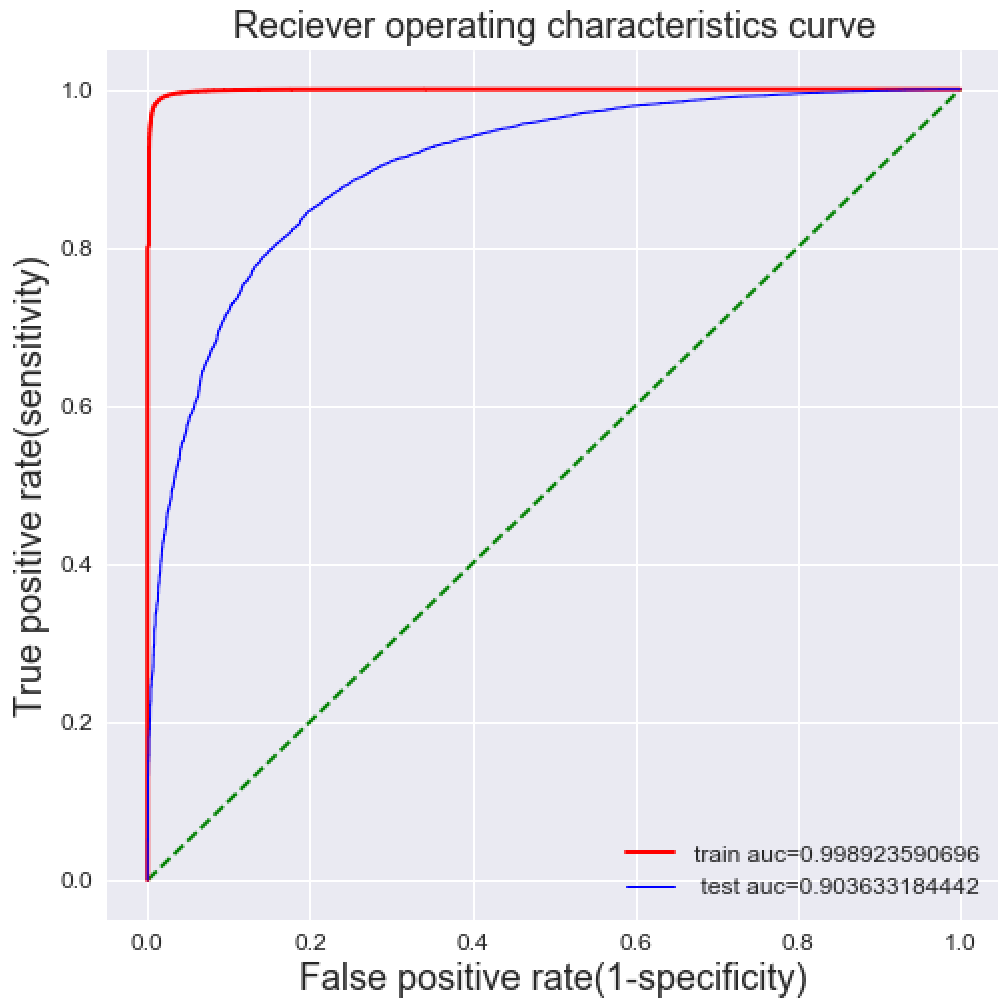
```
Best Hyperparameters are: {'n_estimators': 250, 'max_depth': 15}
```



ROC and Confusion Matrix

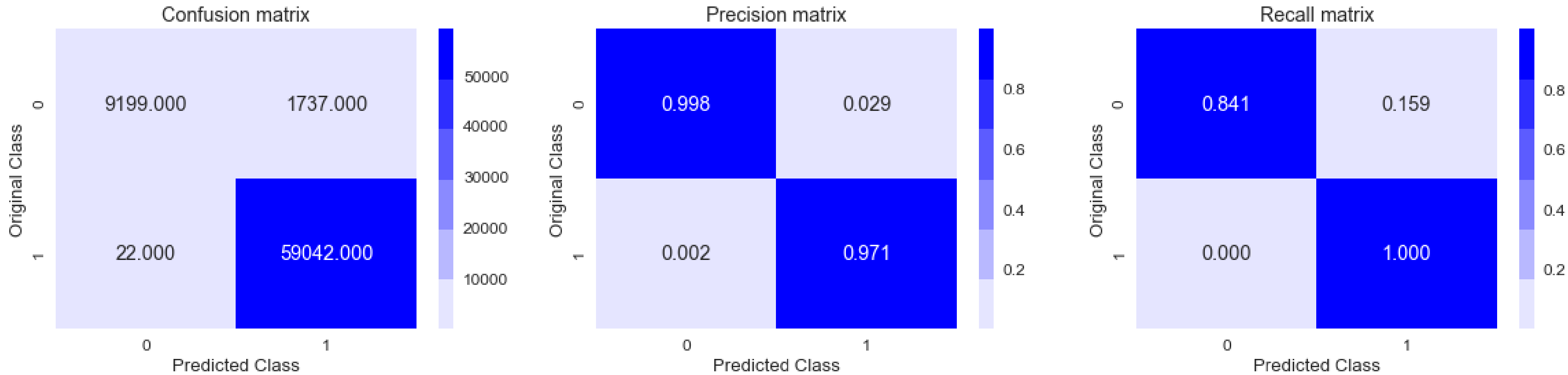
In [0]:
```
'''AUC ON TEST DATA'''
train_auc_avgw2v_rf,test_auc_avgw2v_rf,train_pred_proba,test_pred_proba,train_pred,test_pred = auc(best_dept

'''PLOTTING THE ROC CURVE'''
curve(train_pred_proba,test_pred_proba)

'''Precision,recall and f1 score'''
metrics(test_pred)


'''Plotting the confusion matrix'''
print('Confusin matrix on train data')
plot_confusion_matrix(Y_train,train_pred)
print('Confusion matrix for test data')
plot_confusion_matrix(Y_test,test_pred)
```

```
AUC on train data is: 0.998923590696
AUC on test data is: 0.903633184442
******************************************************
```

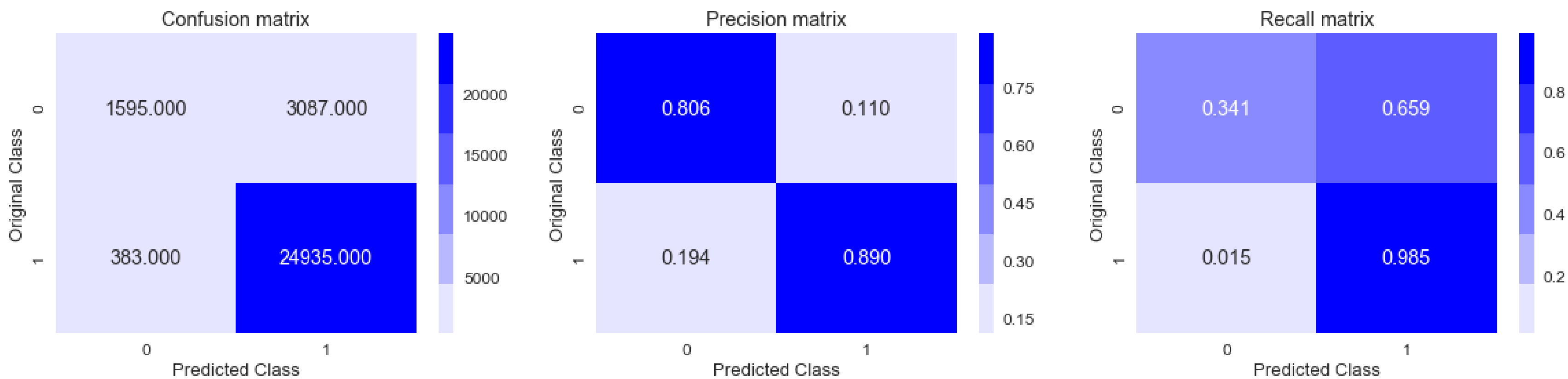



```
**************************************

scores on test data are:

precison score is 0.8898365569909357

recall_score is 0.9848724227822103

f1 score is 0.9349456317960255

****************************************************************
```

```
Confusin matrix on train data
```




```
Confusion matrix for test data
```



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

In [0]:

```python
vect_tfidfw2v = TfidfVectorizer()#initializing the tfidf vectorizer

tf_idf = vect_tfidfw2v.fit_transform(X_train)#fitting the training data
dictionary = dict(zip(vect_tfidfw2v.get_feature_names(), list(vect_tfidfw2v.idf_)))#zipping both of the feat
```

In [0]:

```
import itertools
dict(itertools.islice(dictionary.items(),20))
#printing first 20 elements of the dictionary
```

Out[73]:

```
{'aa': 9.5172074770284834,
 'aaa': 10.546826894209641,
 'aaaa': 11.463117626083797,
 'aaaaa': 11.463117626083797,
 'aaaaaa': 11.463117626083797,
 'aaaaaaaaaaaa': 11.463117626083797,
 'aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa': 11.463117626083797,
 'aaaaaahhhhhyaaaaaa': 11.463117626083797,
 'aaaaaand': 11.463117626083797,
 'aaaaah': 11.463117626083797,
 'aaaah': 11.057652517975633,
 'aaaand': 11.463117626083797,
 'aaaannnnddd': 11.463117626083797,
 'aaagh': 11.463117626083797,
 'aaah': 10.769970445523851,
 'aaahhh': 11.463117626083797,
 'aaahs': 11.463117626083797,
 'aadp': 11.463117626083797,
 'aafco': 10.076823264963906,
 'aafes': 10.769970445523851}
```

In [0]:

```
tfidf_feat = vect_tfidfw2v.get_feature_names() # tfidf words/col-names
print(tfidf_feat[:100])
```

```
['aa', 'aaa', 'aaaa', 'aaaaa', 'aaaaaa', 'aaaaaaaaaaaa', 'aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa', 'aaaaa
ahhhhhyaaaaaa', 'aaaaaand', 'aaaaah', 'aaaah', 'aaaand', 'aaaannnnddd', 'aaagh', 'aaah', 'aaahhh', 'aaahs', 'aa
dp', 'aafco', 'aafes', 'aafter', 'aah', 'aahhhs', 'aahing', 'aalouisiana', 'aanother', 'aap', 'aarrgh', 'aart
i', 'ab', 'aback', 'abandon', 'abandoned', 'abandoning', 'abbey', 'abbott', 'abby', 'abc', 'abd', 'abdomen', 'a
bdominal', 'abduct', 'aber', 'abhor', 'abhorrent', 'abide', 'abiding', 'abietate', 'abig', 'abigirl', 'abiiit
y', 'abilities', 'ability', 'abit', 'abj', 'abject', 'abjectly', 'ablation', 'ablaze', 'able', 'abletate', 'abl
eto', 'ablsolutely', 'ably', 'abmout', 'abnormal', 'abnormalities', 'abnormally', 'abnoxious', 'abominable', 'a
bominably', 'abomination', 'abondant', 'aboout', 'aboslutely', 'abosolutely', 'abot', 'abottle', 'abou', 'aboun
d', 'aboutamazon', 'abouthis', 'abouti', 'aboutits', 'aboutletting', 'aboutthis', 'aboutwhat', 'abouy', 'aboveo
ur', 'abover', 'abp', 'abra', 'abraham', 'abrasion', 'abrasions', 'abreakfast', 'abreast', 'abreviating', 'abri
dged', 'abroad']
```

In [0]:

```
train_set_tfidfw2v = []; # the tfidf-w2v for each sentence/review in training set is stored in this list
row=0;
for sent in tqdm(s_train): # 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 = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    train_set_tfidfw2v.append(sent_vec)
    row += 1
print(len(train_set_tfidfw2v))
```

```
100%|██████████| 70000/70000 [43:19<00:00, 2
3.53it/s]

70000
```

In [0]:

```
test_set_tfidfw2v = []; # the tfidf-w2v for each sentence/review in test set is stored in this list
row=0;
for sent in tqdm(s_test): # 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 = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    test_set_tfidfw2v.append(sent_vec)
    row += 1

print(len(test_set_tfidfw2v))

```

```
100%|██████████████████████████████████████████████████| 30000/30000 [18:22<00:00, 2
7.21it/s]

30000
```

In [0]:

```
train_tfidfw2v = openfromfile('gdrive/My Drive/Colab Notebooks/computed/train_tfidfw2v')
test_tfidfw2v = openfromfile('gdrive/My Drive/Colab Notebooks/computed/test_tfidfw2v')
```

In [0]:

```
estimators = [10,50,100,250,450]#list of estimators that will be tuned
depths = [3,9,11,15,50]#tuning depth to avoid overfitting and underfitting
params = {'max_depth':depths,'n_estimators':estimators}#for passing as argument
tscv = TimeSeriesSplit(n_splits = 5)#initiating 5 time series splits for cross validation
model = RandomizedSearchCV(RandomForestClassifier(bootstrap = True,criterion = 'gini',max_features = 'auto')
                           return_train_score=True,n_jobs = -1)
#fitting the classifier
#fitting the parameter distribution
model.fit(train_tfidfw2v,Y_train)


```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed: 11.0min
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed: 14.7min finished
```

Out[81]:

```
RandomizedSearchCV(cv=TimeSeriesSplit(n_splits=5), error_score='raise',
          estimator=RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_split=1e-07, min_samples_leaf=1,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            n_estimators=10, n_jobs=1, oob_score=False, random_state=None,
            verbose=0, warm_start=False),
          fit_params={}, iid=True, n_iter=10, n_jobs=-1,
          param_distributions={'max_depth': [3, 9, 11, 15, 50], 'n_estimators': [10, 50, 100, 250, 450]},
          pre_dispatch='2*n_jobs', random_state=None, refit=True,
          return_train_score=True, scoring='roc_auc', verbose=1)
```

In [0]:

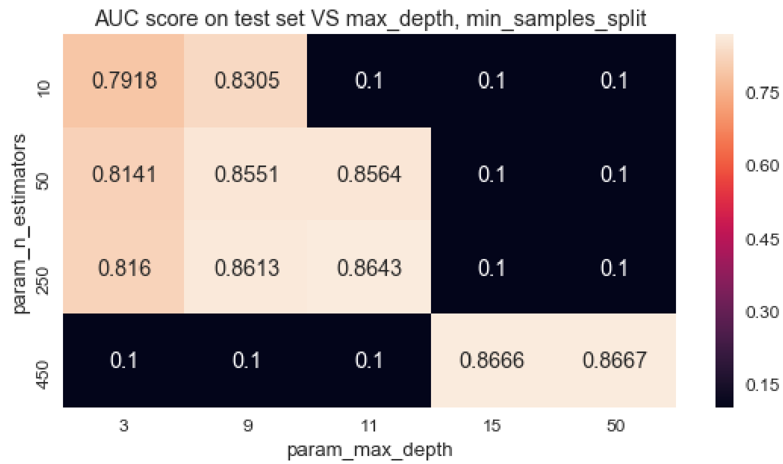
```
savetofile(model,'model_tfidfw2v_rf')
```

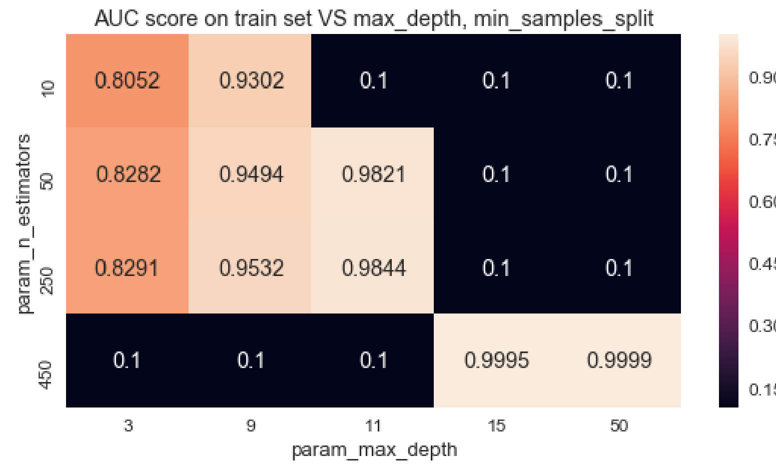
In [0]:

```
model_tfidfw2v_rf = openfromfile('model_tfidfw2v_rf')
```

In [0]:
```
plots(model_tfidfw2v_rf)
```

```
Best Hyperparameters are: {'n_estimators': 450, 'max_depth': 50}
```

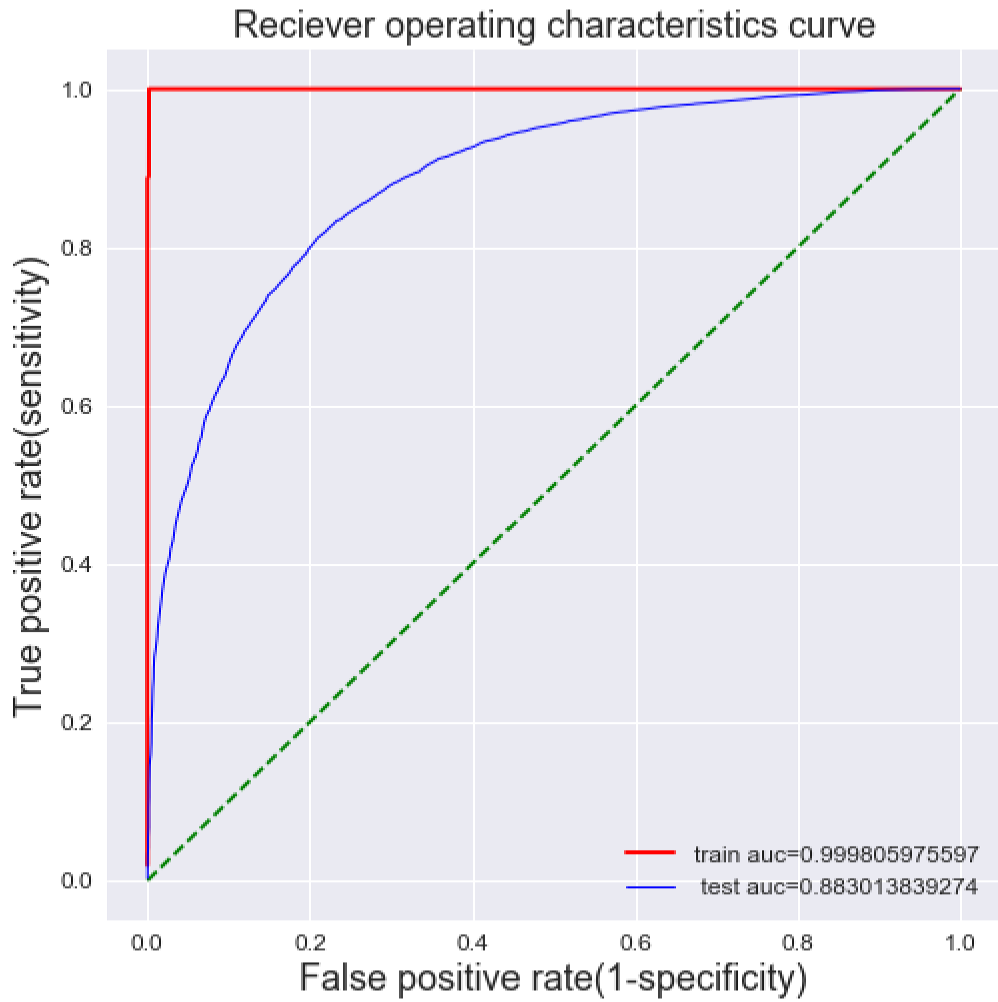




In [0]:
```
best_depth_tfidfw2v_rf = model_tfidfw2v_rf.best_params_['max_depth']
best_n_tfidfw2v_rf = model_tfidfw2v_rf.best_params_['n_estimators']
```

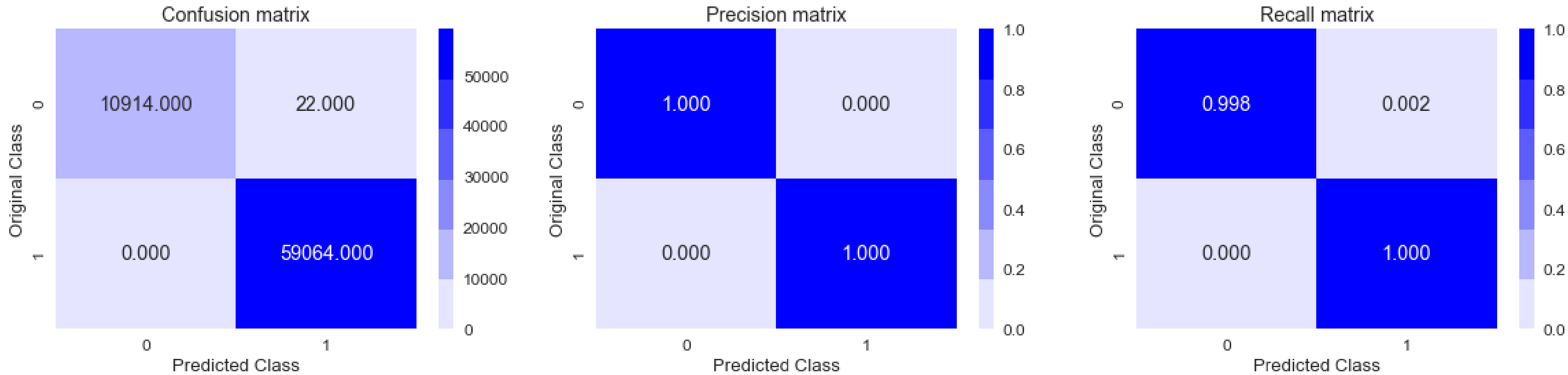
In [0]:
```
'''AUC ON TEST DATA'''
train_auc_tfidfw2v_rf,test_auc_tfidfw2v_rf,train_pred_proba,test_pred_proba,train_pred,test_pred = auc(best_

'''PLOTTING THE ROC CURVE'''
curve(train_pred_proba,test_pred_proba)

'''Precision,recall and f1 score'''
-metrics(test_pred)


'''Plotting the confusion matrix'''
print('Confusin matrix on train data')
plot_confusion_matrix(Y_train,train_pred)
print('Confusion matrix for test data')
plot_confusion_matrix(Y_test,test_pred)
```

```
AUC on train data is: 0.999805975597
AUC on test data is: 0.883013839274
******************************************************
```

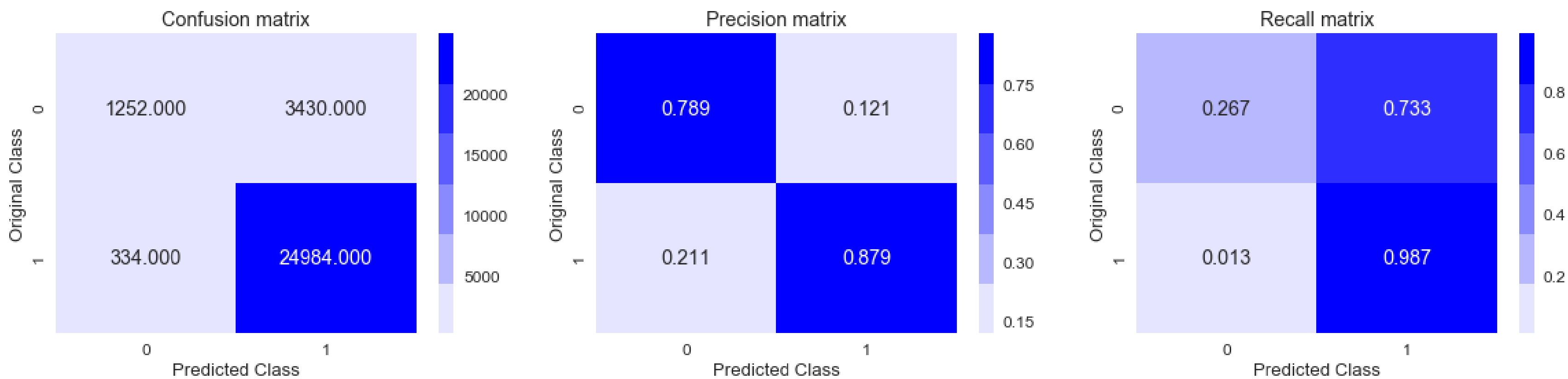



```
**************************************

scores on test data are:

precison score is 0.8792848595762652

recall_score is 0.9868078047239118

f1 score is 0.9299486339611404

*****************************************************************
```

```
Confusin matrix on train data
```




```
Confusion matrix for test data
```



[6] Applying GBDT using XGBOOST

[6.1] Applying XGBOOST on BOW, SET 1

In [0]:

```
from xgboost import XGBClassifier
from sklearn.model_selection import  RandomizedSearchCV
from sklearn.model_selection import TimeSeriesSplit



estimators = [10,50,100,200,450]#list of estimators that will be tuned
depths = [3,9,11,13,15]#tuning depth to avoid overfitting and underfitting
params = {'max_depth':depths,'n_estimators':estimators}#for passing as argument

tscv = TimeSeriesSplit(n_splits = 5)
model = RandomizedSearchCV(XGBClassifier(booster = 'gbtree',learning_rate = 0.1),param_distributions = param
model.fit(train_bow,Y_train)#fitting the model


```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done  50 out of  50 | elapsed: 73.7min finished
```

Out[60]:

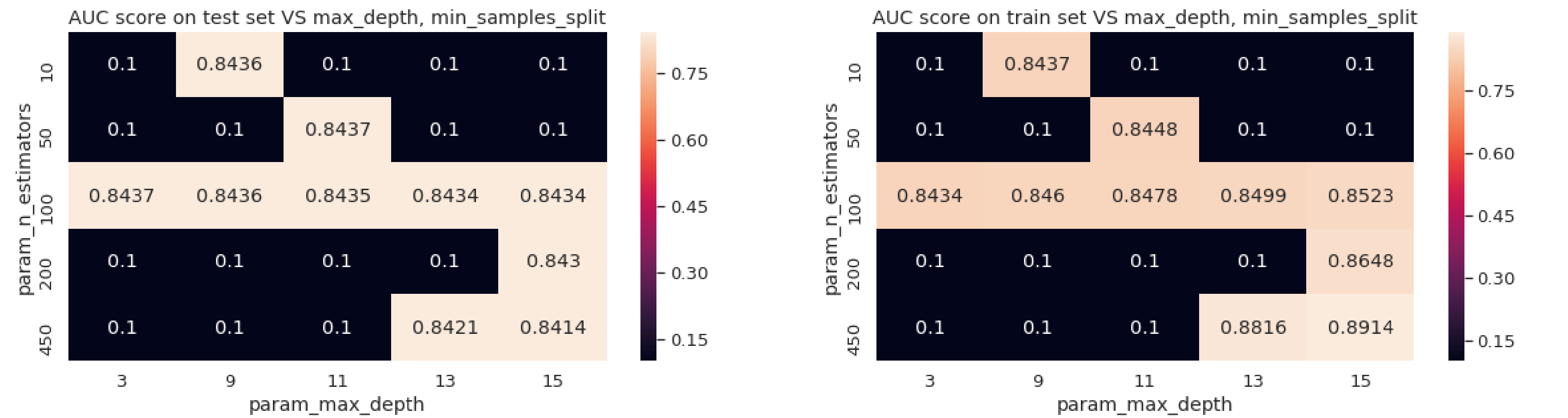
```
RandomizedSearchCV(cv=TimeSeriesSplit(max_train_size=None, n_splits=5),
                   error_score='raise-deprecating',
                   estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                           colsample_bylevel=1,
                                           colsample_bynode=1,
                                           colsample_bytree=1, gamma=0,
                                           learning_rate=0.1, max_delta_step=0,
                                           max_depth=3, min_child_weight=1,
                                           missing=None, n_estimators=100,
                                           n_jobs=1, nthread=None,
                                           objective='binary:logistic',
                                           random_state=0, reg_alpha=0,
                                           reg_lambda=1, scale_pos_weight=1,
                                           seed=None, silent=None, subsample=1,
                                           verbosity=1),
                   iid='warn', n_iter=10, n_jobs=None,
                   param_distributions={'max_depth': [3, 9, 11, 13, 15],
                                        'n_estimators': [10, 50, 100, 200,
                                                         450]},
                   pre_dispatch='2*n_jobs', random_state=None, refit=True,
                   return_train_score=True, scoring=None, verbose=1)
```

In [0]:
```
savetofile(model,'model_bow_gb')
```

In [0]:
```
model_bow_gb = openfromfile('model_bow_gb')
```

In [0]:
```
plots(model_bow_gb)
```

```
Best Hyperparameters are: {'n_estimators': 100, 'max_depth': 3}
```



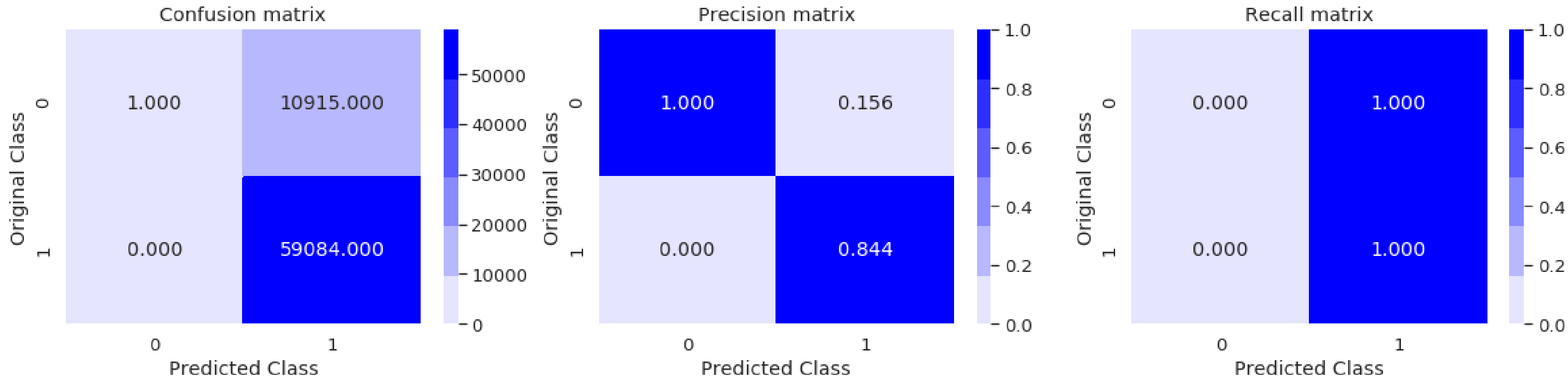
In [0]:
```
best_depth_bow_gb = model_bow_gb.best_params_['max_depth']
best_n_bow_gb = model_bow_gb.best_params_['n_estimators']
```

In [0]:
```
'''AUC ON TEST DATA'''
train_auc_bow_gb,test_auc_bow_gb,train_pred_proba,test_pred_proba,train_pred,test_pred = auc(best_depth_bow_

'''PLOTTING THE ROC CURVE'''
curve(train_pred_proba,test_pred_proba)

'''Precision,recall and f1 score'''
metrics(test_pred)


'''Plotting the confusion matrix'''
print('Confusin matrix on train data')
plot_confusion_matrix(Y_train,train_pred)
print('Confusion matrix for test data')
plot_confusion_matrix(Y_test,test_pred)
```

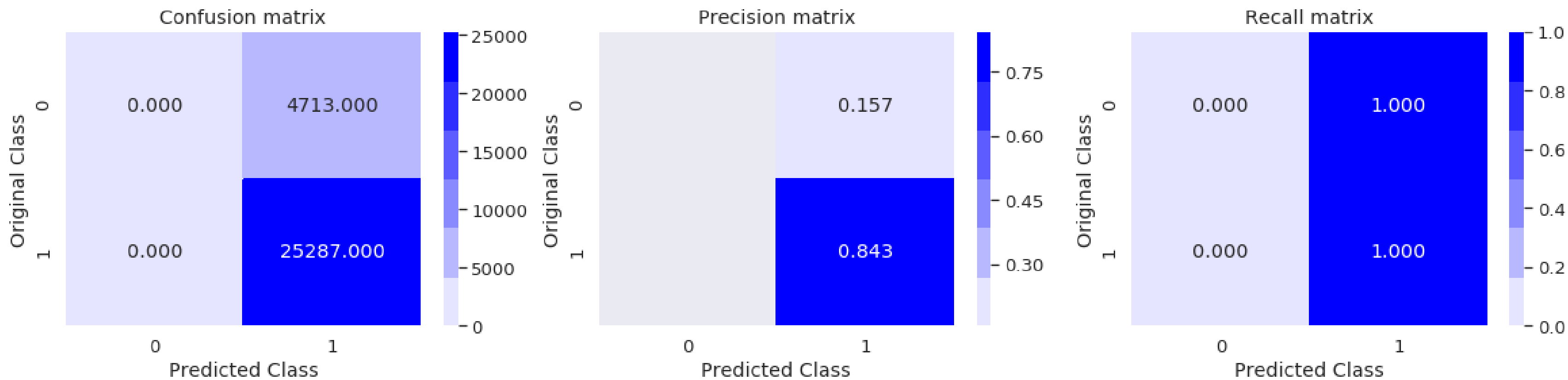
```
AUC on train data is: 0.589092490071771
AUC on test data is: 0.5008964517846474
******************************************************
```


```
**************************************

scores on test data are:

precison score is 0.8429

recall_score is 1.0

f1 score is 0.9147539204514623

****************************************************************
```

```
Confusin matrix on train data
```

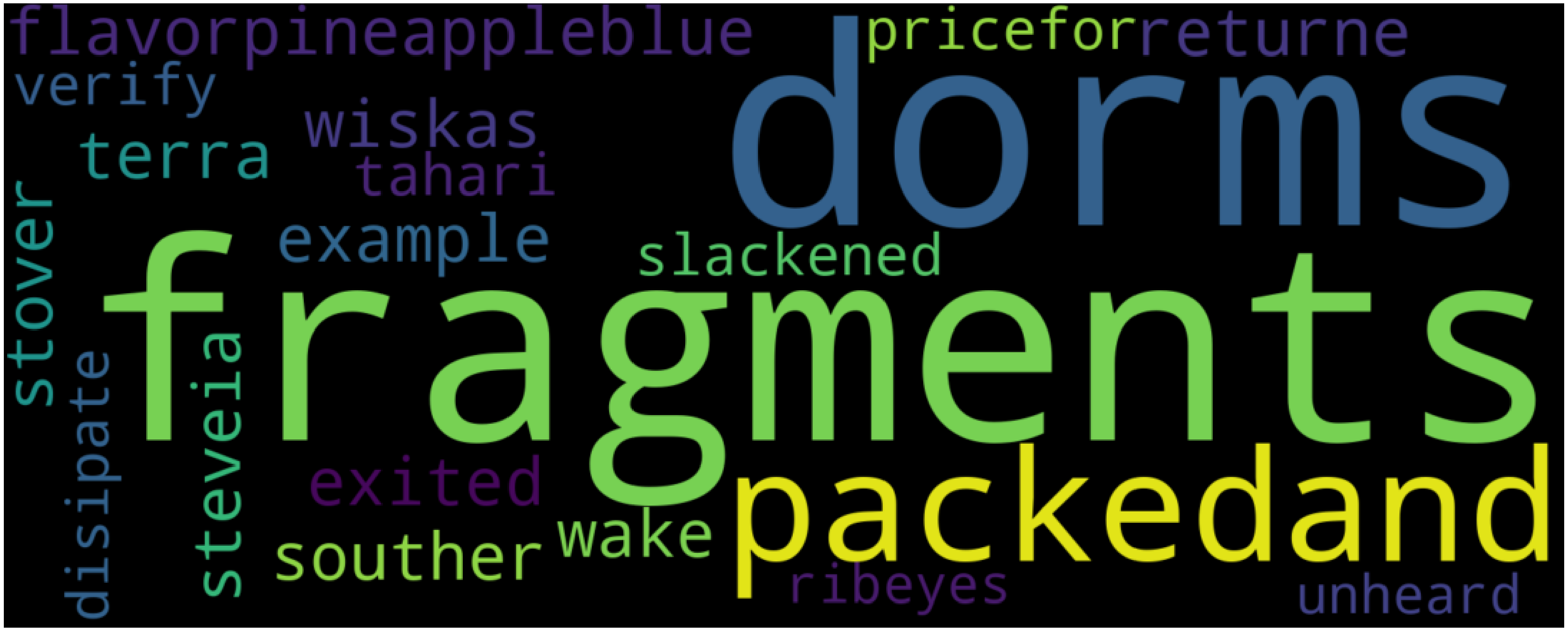



```
Confusion matrix for test data
```



In [0]:
```
"""Most important features"""
features_and_wc(best_depth_bow_gb,best_n_bow_gb,train_bow,bow_vect)#for generating the wordcloud
```

```
TOP 20 important features which gives maximum information gain on splitting are:

dorms    -->    0.007687
fragments        -->    0.007296
packedand        -->    0.007185
flavorpineappleblue      -->    0.007135
steveia  -->    0.006729
wake     -->    0.006622
terra    -->    0.006486
wiskas   -->    0.006415
exited   -->    0.006380
example  -->    0.006345
stover   -->    0.005949
souther  -->    0.005792
returne  -->    0.005623
pricefor         -->    0.005567
slackened        -->    0.005395
tahari   -->    0.005368
disipate         -->    0.005320
verify   -->    0.005293
ribeyes  -->    0.005286
unheard  -->    0.005201
```



[6.2] Applying XGBOOST on TFIDF, SET 2

In [0]:

```python

estimators = [10,50,100,200,450]#list of estimators that will be tuned
depths = [3,9,11,13,15]#tuning depth to avoid overfitting and underfitting
params = {'max_depth':depths,'n_estimators':estimators}#for passing as argument

tscv = TimeSeriesSplit(n_splits = 5)
model = RandomizedSearchCV(XGBClassifier(booster = 'gbtree',learning_rate = 0.1),param_distributions = param
model.fit(train_tfidf,Y_train)#fitting the model


```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done  50 out of  50 | elapsed: 96.0min finished
```

Out[76]:

```
RandomizedSearchCV(cv=TimeSeriesSplit(max_train_size=None, n_splits=5),
                   error_score='raise-deprecating',
                   estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                           colsample_bylevel=1,
                                           colsample_bynode=1,
                                           colsample_bytree=1, gamma=0,
                                           learning_rate=0.1, max_delta_step=0,
                                           max_depth=3, min_child_weight=1,
                                           missing=None, n_estimators=100,
                                           n_jobs=1, nthread=None,
                                           objective='binary:logistic',
                                           random_state=0, reg_alpha=0,
                                           reg_lambda=1, scale_pos_weight=1,
                                           seed=None, silent=None, subsample=1,
                                           verbosity=1),
                   iid='warn', n_iter=10, n_jobs=None,
                   param_distributions={'max_depth': [3, 9, 11, 13, 15],
                                        'n_estimators': [10, 50, 100, 200,
                                                         450]},
                   pre_dispatch='2*n_jobs', random_state=None, refit=True,
                   return_train_score=True, scoring=None, verbose=1)
```

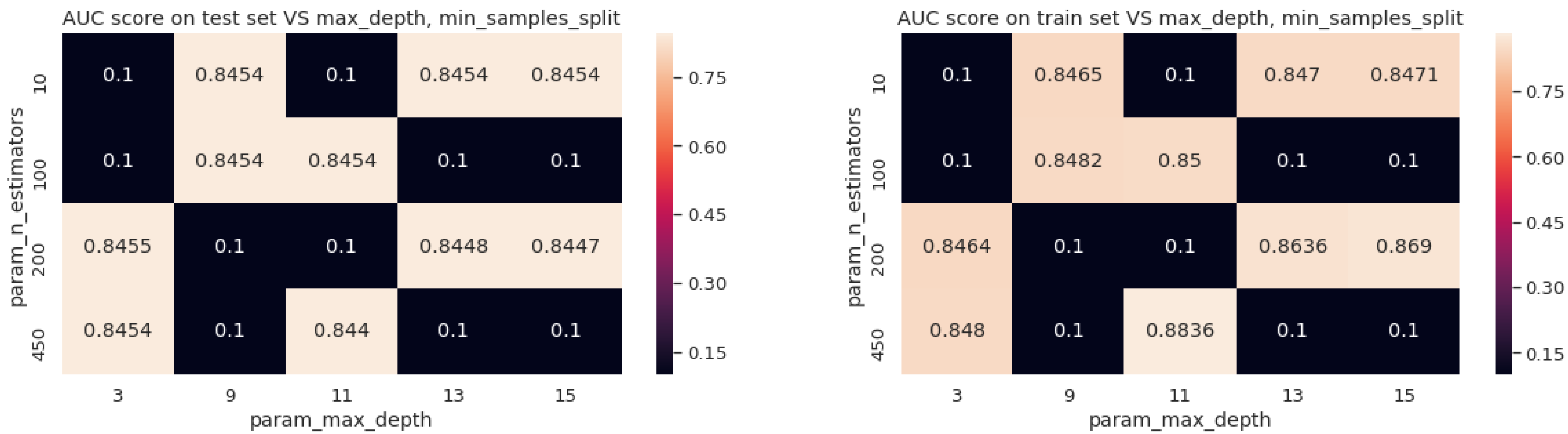
In [0]:

```python
savetofile(model,'model_tfidf_gb')
```

In [0]:
```
model_tfidf_gb = openfromfile('model_tfidf_gb')
```

In [0]:
```
plots(model_tfidf_gb)#plotting for the model
```

```
Best Hyperparameters are: {'n_estimators': 200, 'max_depth': 3}
```



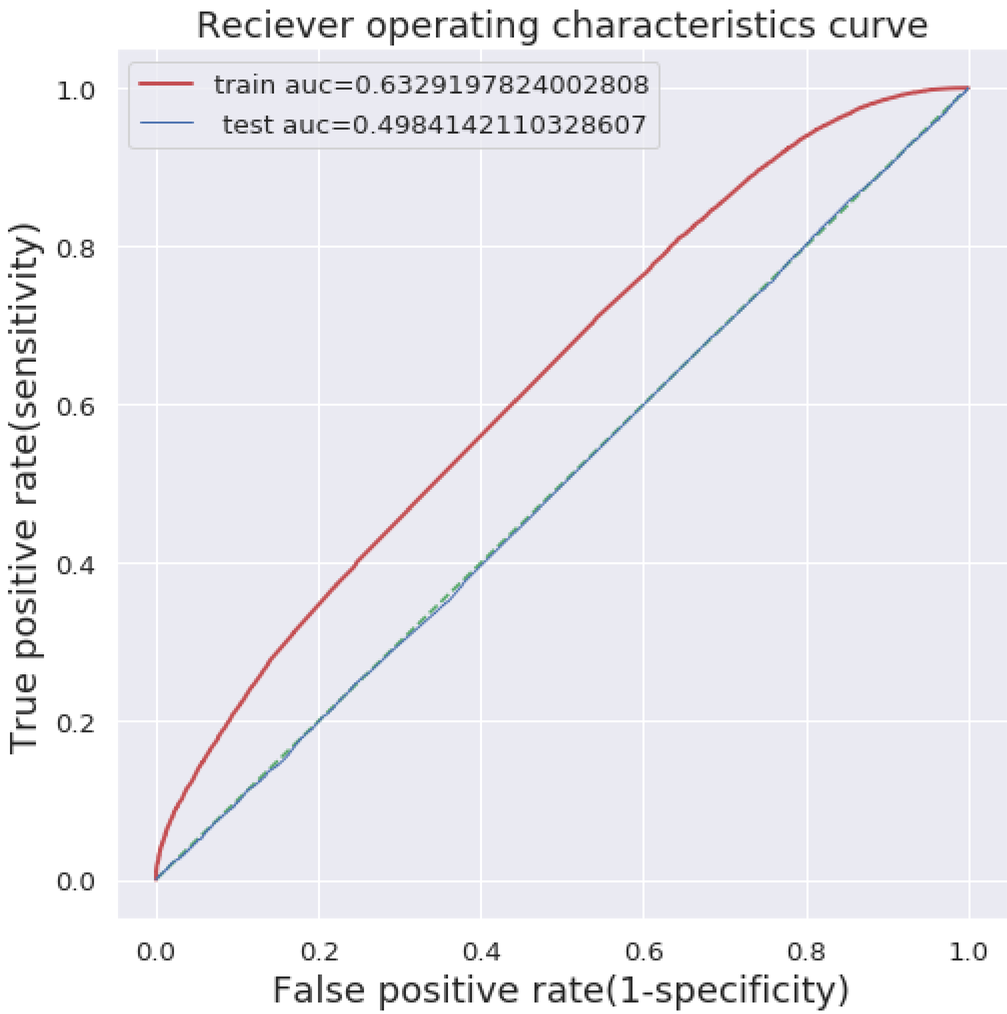
In [0]:
```

```

In [0]:
```
best_depth_tfidf_gb = model_tfidf_gb.best_params_['max_depth']
best_n_tfidf_gb = model_tfidf_gb.best_params_['n_estimators']
```

In [0]:

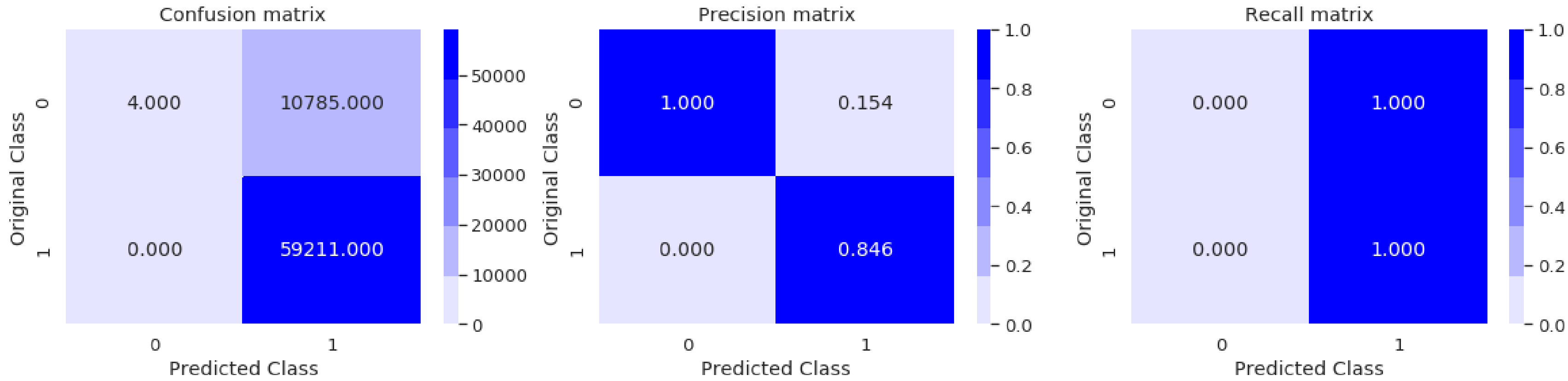
```
'''AUC ON TEST DATA'''
train_auc_tfidf_gb,test_auc_tfidf_gb,train_pred_proba,test_pred_proba,train_pred,test_pred = auc(best_depth_

'''PLOTTING THE ROC CURVE'''
curve(train_pred_proba,test_pred_proba)

'''Precision,recall and f1 score'''
metrics(test_pred)


'''Plotting the confusion matrix'''
print('Confusin matrix on train data')
plot_confusion_matrix(Y_train,train_pred)
print('Confusion matrix for test data')
plot_confusion_matrix(Y_test,test_pred)
```

```
AUC on train data is: 0.6329197824002808
AUC on test data is: 0.4984142110328607
******************************************************
```

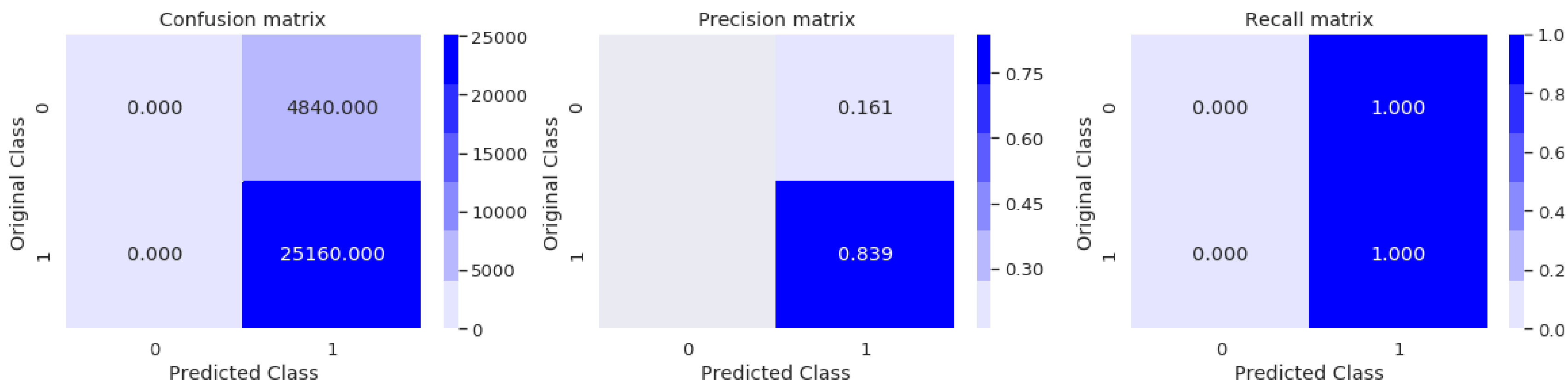



```
**************************************

scores on test data are:

precison score is 0.8386666666666667

recall_score is 1.0

f1 score is 0.9122552574329225

****************************************************************
```

```
Confusin matrix on train data
```




```
Confusion matrix for test data
```



[6.3] Applying XGBOOST on AVG W2V, SET 3

In [42]:

```
from sklearn.model_selection import RandomizedSearchCV
from xgboost import XGBClassifier
estimators = [10,50,100,200,450]#list of estimators that will be tuned
depths = [3,9,11,13,15]#tuning depth to avoid overfitting and underfitting
params = {'max_depth':depths,'n_estimators':estimators}#for passing as argument

tscv = TimeSeriesSplit(n_splits = 5)
model = RandomizedSearchCV(XGBClassifier(booster = 'gbtree',learning_rate = 0.1),param_distributions = param
model.fit(np.array(train_avgw2v),Y_train)#fitting the model

```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done  50 out of  50 | elapsed: 46.9min finished
```

Out[42]:

```
RandomizedSearchCV(cv=TimeSeriesSplit(max_train_size=None, n_splits=5),
                   error_score='raise-deprecating',
                   estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                           colsample_bylevel=1,
                                           colsample_bynode=1,
                                           colsample_bytree=1, gamma=0,
                                           learning_rate=0.1, max_delta_step=0,
                                           max_depth=3, min_child_weight=1,
                                           missing=None, n_estimators=100,
                                           n_jobs=1, nthread=None,
                                           objective='binary:logistic',
                                           random_state=0, reg_alpha=0,
                                           reg_lambda=1, scale_pos_weight=1,
                                           seed=None, silent=None, subsample=1,
                                           verbosity=1),
                   iid='warn', n_iter=10, n_jobs=None,
                   param_distributions={'max_depth': [3, 9, 11, 13, 15],
                                        'n_estimators': [10, 50, 100, 200,
                                                         450]},
                   pre_dispatch='2*n_jobs', random_state=None, refit=True,
                   return_train_score=True, scoring=None, verbose=1)
```

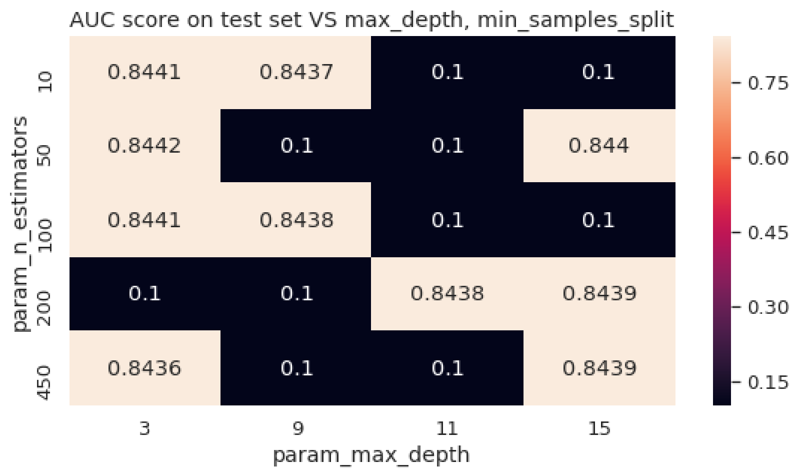
In [0]:

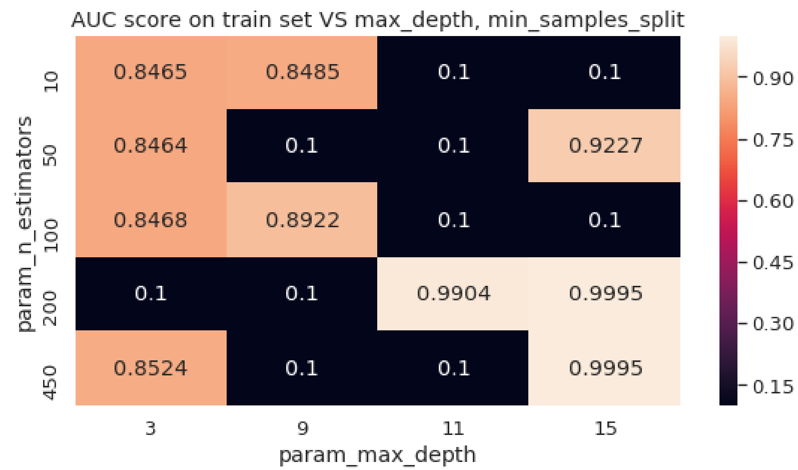
```
savetofile(model,'model_avgw2v_gb')
```

In [0]:
```
model_avgw2v_gb = openfromfile('model_avgw2v_gb')
```

In [45]:
```
plots(model_avgw2v_gb)
```

```
Best Hyperparameters are: {'n_estimators': 50, 'max_depth': 3}
```



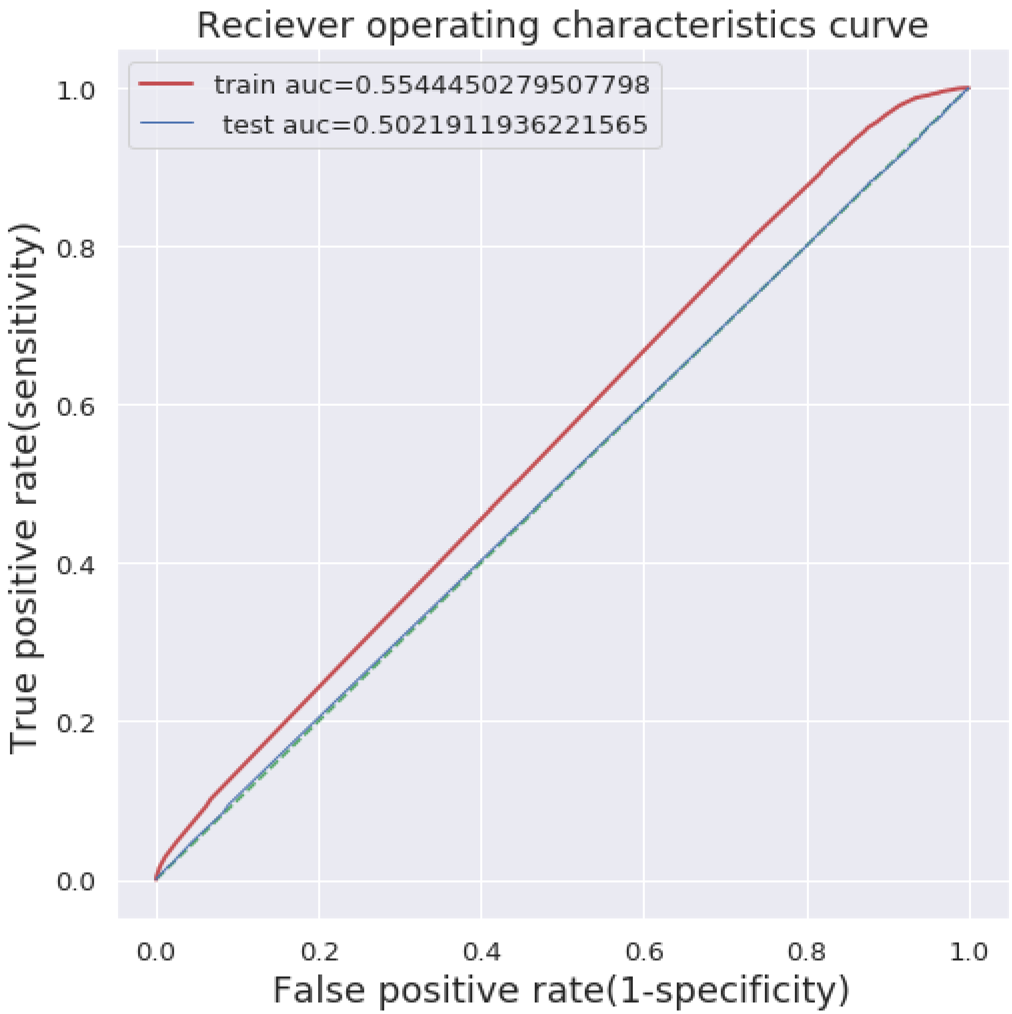


In [0]:
```
best_depth_avgw2v_gb = model_avgw2v_gb.best_params_['max_depth']
best_n_avgw2v_gb = model_avgw2v_gb.best_params_['n_estimators']
```

In [48]:

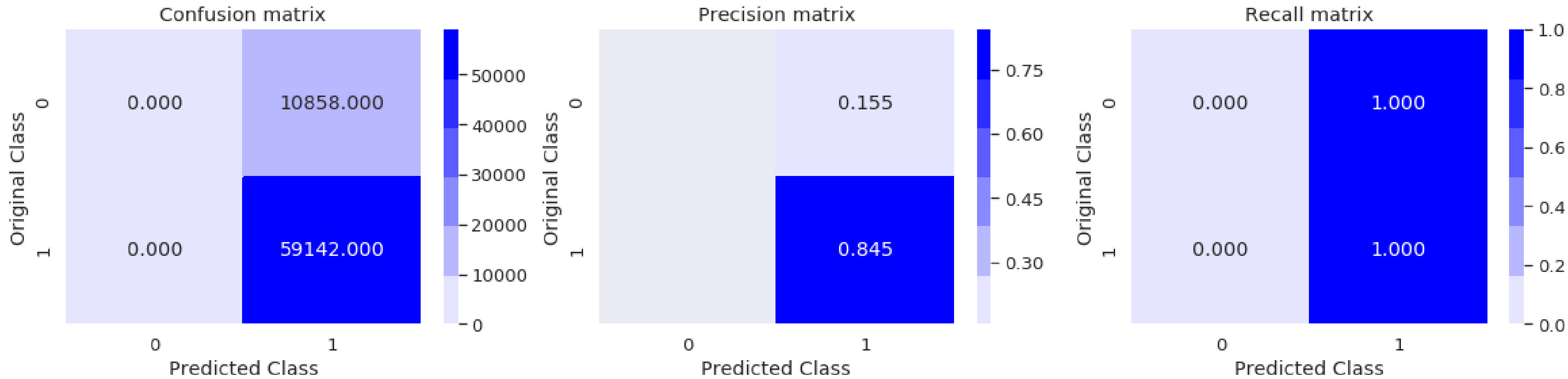
```
'''AUC ON TEST DATA'''
train_auc_avgw2v_gb,test_auc_avgw2v_gb,train_pred_proba,test_pred_proba,train_pred,test_pred = auc(best_dept

'''PLOTTING THE ROC CURVE'''
curve(train_pred_proba,test_pred_proba)

'''Precision,recall and f1 score'''
metrics(test_pred)


'''Plotting the confusion matrix'''
print('Confusin matrix on train data')
plot_confusion_matrix(Y_train,train_pred)
print('Confusion matrix for test data')
plot_confusion_matrix(Y_test,test_pred)
```

```
AUC on train data is: 0.5544450279507798
AUC on test data is: 0.5021911936221565
******************************************************
```

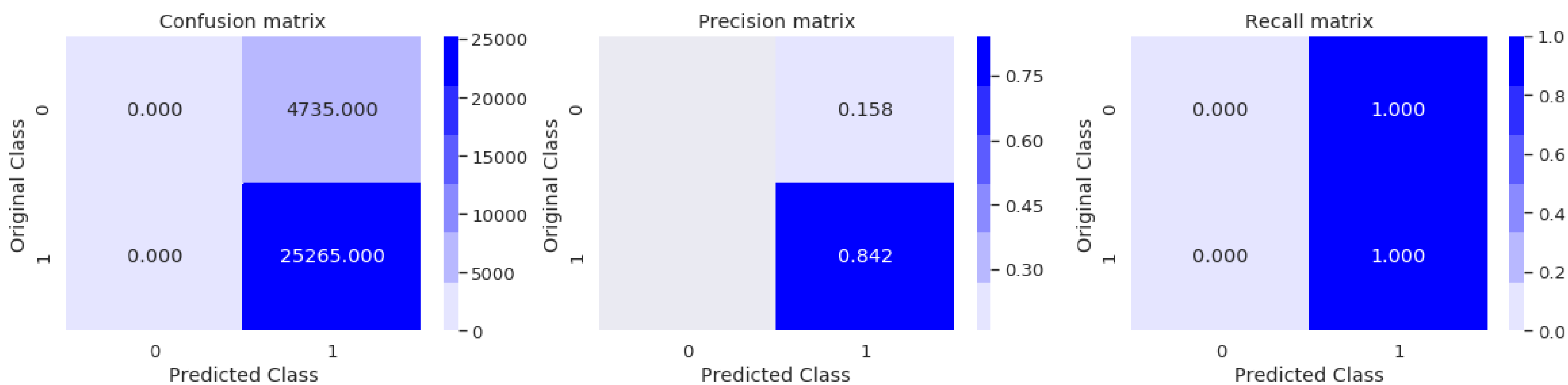



```
**************************************

scores on test data are:

precison score is 0.8421666666666666

recall_score is 1.0

f1 score is 0.9143219035555958

*****************************************************************
```

```
Confusin matrix on train data
```




```
Confusion matrix for test data
```



[6.4] Applying XGBOOST on TFIDF W2V, SET 4

In [32]:

```python
train_tfidfw2v = openfromfile('computed/train_tfidfw2v')
test_tfidfw2v = openfromfile('computed/test_tfidfw2v')
```

In [33]:
```
from sklearn.model_selection import RandomizedSearchCV
from xgboost import XGBClassifier

estimators = [10,50,100,200,450]#list of estimators that will be tuned
depths = [3,9,11,13,15]#tuning depth to avoid overfitting and underfitting
params = {'max_depth':depths,'n_estimators':estimators}#for passing as argument

tscv = TimeSeriesSplit(n_splits = 5)
model = RandomizedSearchCV(XGBClassifier(booster = 'gbtree',learning_rate = 0.1),param_distributions = param
model.fit(np.array(train_tfidfw2v),Y_train)#fitting the model
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=1)]: Done  50 out of  50 | elapsed: 128.9min finished
```

Out[33]:
```
RandomizedSearchCV(cv=TimeSeriesSplit(n_splits=5), error_score='raise',
          estimator=XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
       n_jobs=1, nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=1),
          fit_params={}, iid=True, n_iter=10, n_jobs=1,
          param_distributions={'max_depth': [3, 9, 11, 13, 15], 'n_estimators': [10, 50, 100, 200, 450]},
          pre_dispatch='2*n_jobs', random_state=None, refit=True,
          return_train_score=True, scoring=None, verbose=1)
```

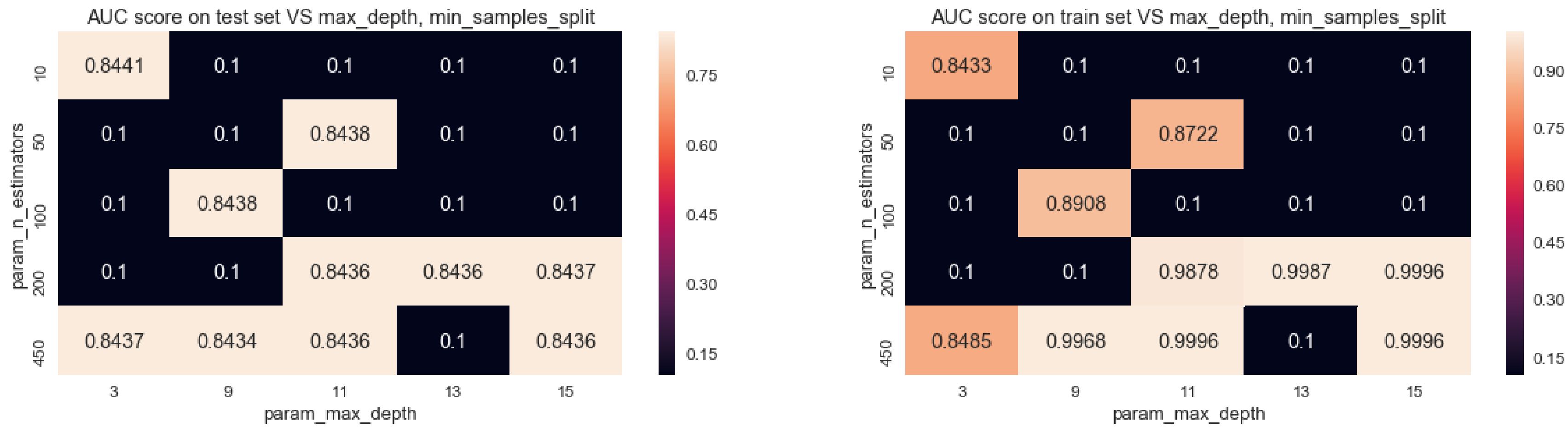
In [34]:
```
savetofile(model,'model_tfidfw2v_gb')
```

In [35]:
```
model_tfidfw2v_gb = openfromfile('model_tfidfw2v_gb')
```

In [39]:

```
plots(model_tfidfw2v_gb)
```

```
Best Hyperparameters are: {'n_estimators': 10, 'max_depth': 3}
```

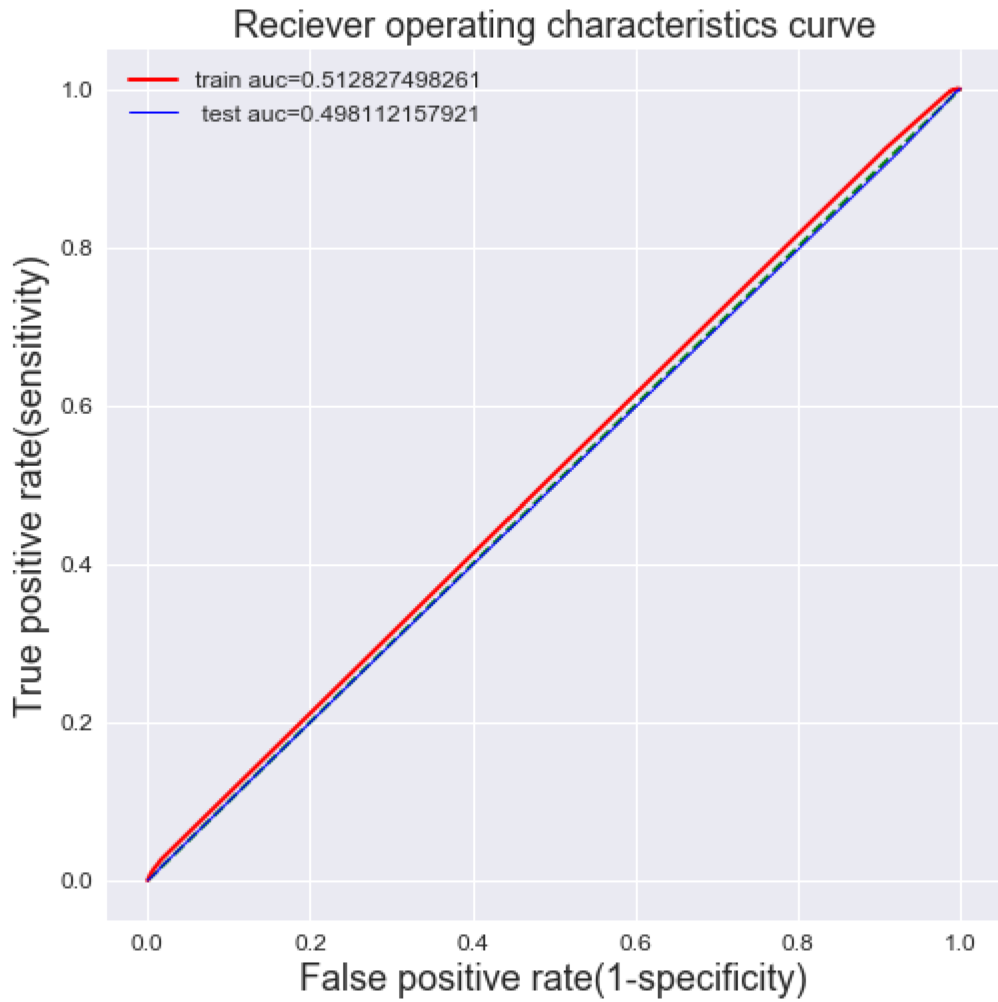


In [55]:

```
best_depth_tfidfw2v_gb = model_tfidfw2v_gb.best_params_['max_depth']
best_n_tfidfw2v_gb = model_tfidfw2v_gb.best_params_['n_estimators']
```

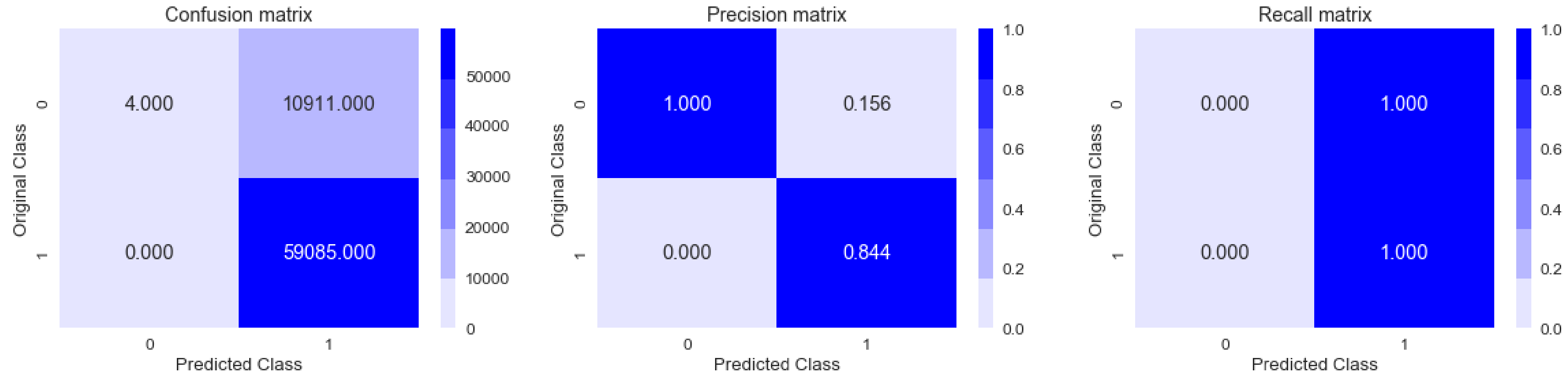
In [46]:
```
'''AUC ON TEST DATA'''
train_auc_tfidfw2v_gb,test_auc_tfidfw2v_gb,train_pred_proba,test_pred_proba,train_pred,test_pred = auc(best_
    best_n_tfidfw2v_gb,np.array(train_tfidfw2v),test_tfidfw2v)

'''PLOTTING THE ROC CURVE'''
curve(train_pred_proba,test_pred_proba)

'''Precision,recall and f1 score'''
metrics(test_pred)


'''Plotting the confusion matrix'''
print('Confusin matrix on train data')
plot_confusion_matrix(Y_train,train_pred)
print('Confusion matrix for test data')
plot_confusion_matrix(Y_test,test_pred)
```

```
AUC on train data is: 0.512827498261
AUC on test data is: 0.498112157921
******************************************************
```

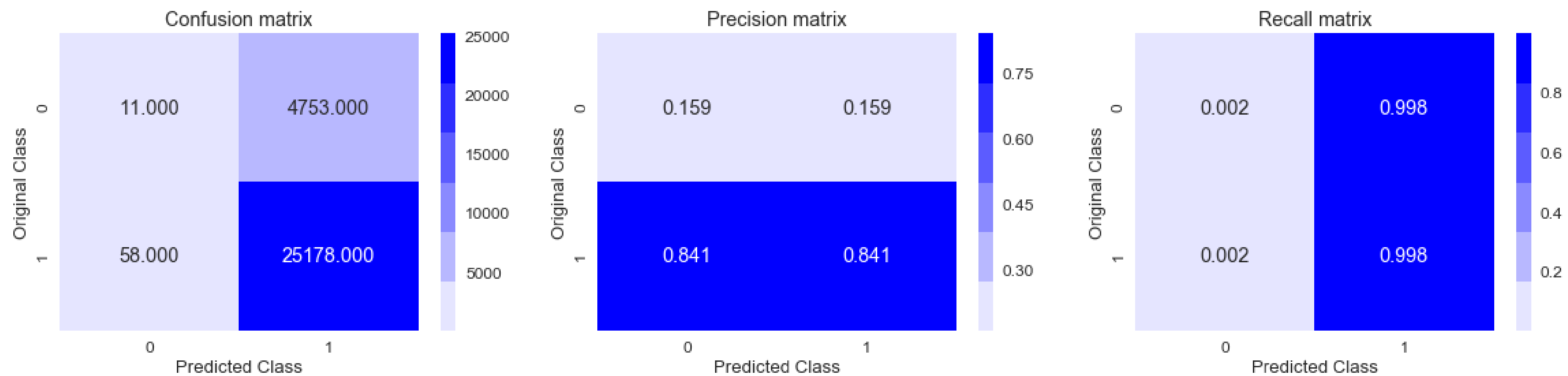



```
***************************************

scores on test data are:

precison score is 0.8412014299555645

recall_score is 0.9977016959898558

f1 score is 0.9127920677216452

******************************************************************
```

```
Confusin matrix on train data
```




```
Confusion matrix for test data
```



[7] Conclusions

In [85]:

```
#create table using prettytable
from prettytable import PrettyTable

#table for random forest
table_rf = PrettyTable()
no = [1,2,3,4]
vectorizers = ['Bag of vectors','TFIDF','Average Word 2 vector','TFIDF Word 2 vector']#all vectorizers
depths = ['50','50','15','50']#best parameters
estimators = ['450','250','250','450']
AUC = ['0.501','0.495','0.903','0.883']#their respective auc scores

table_rf.add_column("SNo",no)
table_rf.add_column('Vectorizers',vectorizers)
table_rf.add_column('max depth',depths)
table_rf.add_column('no. of estimators',estimators)
table_rf.add_column('AUC on test',AUC)
print('\t\t\t\t Table for Random Forest')
print(table_rf)
print('\n\n\n')


table_gb = PrettyTable()

no_gb = [1,2,3,4]
vectorizers_gb = ['Bag of vectors','TFIDF','Average Word 2 vector','TFIDF Word 2 vector']#all vectorizers
depths_gb = ['3','3','3','3']
estimators_gb = ['100','200','50','10']
AUC_gb = ['0.5008','0.4984','0.5021','0.4981']

table_gb.add_column("SNo",no_gb)
table_gb.add_column('Vectorizers',vectorizers_gb)
table_gb.add_column('max depth',depths_gb)
table_gb.add_column('no. of estimators',estimators_gb)
table_gb.add_column('AUC on test for GBDT',AUC_gb)
print('\t\t\t\t Table for GBDT using XGBoost')
print(table_gb)
```

```
                                 Table for Random Forest
+-----+-----------------------+-----------+-------------------+-------------+
```

SNo	Vectorizers	max depth	no. of estimators	AUC on test
1	Bag of vectors	50	450	0.501
2	TFIDF	50	250	0.495
3	Average Word 2 vector	15	250	0.903
4	TFIDF Word 2 vector	50	450	0.883

Table for GBDT using XGBoost

SNo	Vectorizers	max depth	no. of estimators	AUC on test for GBDT
1	Bag of vectors	3	100	0.5008
2	TFIDF	3	200	0.4984
3	Average Word 2 vector	3	50	0.5021
4	TFIDF Word 2 vector	3	10	0.4981

In [ ]: