# 09 Amazon Fine Food Reviews Analysis_RF

April 28, 2019

# 1 Amazon Fine Food Reviews Analysis

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

EDA: 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.

# 2 [1]. Reading Data

## 2.1 [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

from sklearn.ensemble import RandomForestClassifier
from wordcloud import WordCloud, STOPWORDS
import xgboost as xgb

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
```

In [2]:
```
# 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 point
# 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 5
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 200

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a negativ
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 (200000, 10)
```

Out[2]:

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

   HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
0                     1                       1      1  1303862400
1                     0                       0      0  1346976000
2                     1                       1      1  1219017600

                 Summary                                               Text
0  Good Quality Dog Food  I have bought several of the Vitality canned d...
1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
2  "Delight" says it all  This is a confection that has been around a fe...
```

In [3]:

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

In [4]:

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

```
(80668, 7)
```

```
Out[4]:                 UserId   ProductId             ProfileName        Time  Score  \
        0  #oc-R115TNMSPFT9I7  B005ZBZLT4                  Breyton  1331510400      2
        1  #oc-R11D9D7SHXIJB9  B005HG9ESG  Louis E. Emory "hoppy"  1342396800      5
        2  #oc-R11DNU2NBKQ23Z  B005ZBZLT4        Kim Cieszykowski  1348531200      1
        3  #oc-R11O5J5ZVQE25C  B005HG9ESG            Penguin Chick  1346889600      5
        4  #oc-R12KPBODL2B5ZD  B007OSBEV0   Christopher P. Presta  1348617600      1

                                                        Text  COUNT(*)
        0  Overall its just OK when considering the price...         2
        1  My wife has recurring extreme muscle spasms, u...         3
        2  This coffee is horrible and unfortunately not ...         2
        3  This will be the bottle that you grab from the...         3
        4  I didnt like this coffee. Instead of telling y...         2
```

```
In [5]: display[display['UserId']=='AZY10LLTJ71NX']
```

```
Out[5]:               UserId   ProductId                          ProfileName        Time  \
        80638  AZY10LLTJ71NX  B001ATMQK2  undertheshrine "undertheshrine"  1296691200

               Score                                              Text  COUNT(*)
        80638      5  I bought this 6 pack because for the price tha...         5
```

```
In [6]: display['COUNT(*)'].sum()
```

```
Out[6]: 393063
```

# 3 [2] Exploratory Data Analysis

## 3.1 [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 [7]: display= pd.read_sql_query("""
        SELECT *
        FROM Reviews
        WHERE Score != 3 AND UserId="AR5J8UI46CURR"
        ORDER BY ProductID
        """, con)
        display.head()
```

```
Out[7]:        Id   ProductId         UserId      ProfileName  HelpfulnessNumerator  \
        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

   HelpfulnessDenominator  Score        Time  \
0                       2      5  1199577600
1                       2      5  1199577600
2                       2      5  1199577600
3                       2      5  1199577600
4                       2      5  1199577600

                             Summary  \
0  LOACKER QUADRATINI VANILLA WAFERS
1  LOACKER QUADRATINI VANILLA WAFERS
2  LOACKER QUADRATINI VANILLA WAFERS
3  LOACKER QUADRATINI VANILLA WAFERS
4  LOACKER QUADRATINI VANILLA WAFERS

                                              Text
0  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
1  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
2  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
3  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
4  DELICIOUS WAFERS. I FIND THAT EUROPEAN 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 [8]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fals
```

In [9]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep=
final.shape
```

Out[9]:
```
(160178, 10)
```

In [10]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[10]: 80.089

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 [11]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[11]:
```
      Id   ProductId          UserId              ProfileName  \
0  64422  B000MIDROQ  A161DK06JJMCYF  J. E. Stephens "Jeanne"
1  44737  B001EQ55RW  A2V0I904FH7ABY                      Ram

   HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
0                     3                       1      5  1224892800
1                     3                       2      4  1212883200

                                     Summary  \
0             Bought This for My Son at College
1  Pure cocoa taste with crunchy almonds inside

                                                Text
0  My son loves spaghetti so I didn't hesitate or...
1  It was almost a 'love at first bite' - the per...
```

In [12]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [13]:
```
#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()
```

```
(160176, 10)
```

Out[13]:
```
1    134799
0     25377
Name: Score, dtype: int64
```

# 4 [3] Preprocessing

## 4.1 [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 [14]:
```
# 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 remembered this book from my childhood and got it for my kids.  It's just as good as I rememb
==================================================
The qualitys not as good as the lamb and rice but it didn't seem to bother his stomach, you get
==================================================
This is the Japanese version of breadcrumb (pan=bread, a Portuguese loan-word, and&quot;ko-&quo
==================================================
What can I say... If Douwe Egberts was good enough for my dutch grandmother, it's perfect for m
==================================================
```

In [15]:
```
# 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 remembered this book from my childhood and got it for my kids.  It's just as good as I rememb
```

```
In [16]: # https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all
         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 remembered this book from my childhood and got it for my kids.  It's just as good as I rememb
==================================================
The qualitys not as good as the lamb and rice but it didn't seem to bother his stomach, you get
==================================================
This is the Japanese version of breadcrumb (pan=bread, a Portuguese loan-word, and"ko-"  is "cl
==================================================
What can I say... If Douwe Egberts was good enough for my dutch grandmother, it's perfect for m
```

```
In [17]: # 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 [18]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
This is the Japanese version of breadcrumb (pan=bread, a Portuguese loan-word, and&quot;ko-&quo
==================================================
```

In [19]:
```
#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 remembered this book from my childhood and got it for my kids.  It's just as good as I rememb
```

In [20]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
This is the Japanese version of breadcrumb pan bread a Portuguese loan word and quot ko quot is
```

In [21]:
```
# 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', 'ourselve
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him'
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself',
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'h
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'o
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'an
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'n
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't"
```

```
                    "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mi
                    "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't",
                    'won', "won't", 'wouldn', "wouldn't"])
```

```
In [22]: # Combining all the above stundents
         from tqdm import tqdm
         prepr_rev = []
         # 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 stopw
             prepr_rev.append(sentance.strip())
```

```
100%|| 160176/160176 [01:24<00:00, 1895.29it/s]
```

```
In [23]: prepr_rev[1500]
```

```
Out[23]: 'japanese version breadcrumb pan bread portuguese loan word ko child derived panko us
```

```
In [24]: print(len(prepr_rev))
         final.shape
```

```
160176
```

```
Out[24]: (160176, 10)
```

[3.2] Preprocessing Review Summary

```
In [25]: ## Similartly you can do preprocessing for review summary also.
         preprocessed_summary = []
         # tqdm is for printing the status bar
         for summary in tqdm(final['Summary'].values):
             summary = re.sub(r"http\S+", "", summary) # remove urls from text python: https:/
             summary = BeautifulSoup(summary, 'lxml').get_text() # https://stackoverflow.com/q
             summary = decontracted(summary)
             summary = re.sub("\S*\d\S*", "", summary).strip() #remove words with numbers pyth
             summary = re.sub('[^A-Za-z]+', ' ', summary) #remove spacial character: https://s
             # https://gist.github.com/sebleier/554280
             summary = ' '.join(e.lower() for e in summary.split() if e.lower() not in stopwor
             preprocessed_summary.append(summary.strip())
```

```
 58%|    | 92317/160176 [00:31<00:22, 2966.05it/s]/Volumes/Saida/Applications/Anaconda/anaconda
  ' Beautiful Soup.' % markup)
100%|| 160176/160176 [00:54<00:00, 2930.68it/s]
```

In [26]:
```python
prepr_rev = [i + ' ' + j for i, j in zip(prepr_rev,preprocessed_summary)]
print(prepr_rev[1500])
```

```
japanese version breadcrumb pan bread portuguese loan word ko child derived panko used katsudo
```

In [27]:
```python
final ['CleanText']= prepr_rev
final.head(5)
```

Out[27]:

| | Id | ProductId | UserId | ProfileName |
|---|---|---|---|---|
| 138695 | 150513 | 0006641040 | ASH0DZQQF6AIZ | tessarat |
| 138707 | 150525 | 0006641040 | A2QID6VCFTY51R | Rick |
| 138708 | 150526 | 0006641040 | A3E9QZFE9KXH8J | R. Mitchell |
| 138686 | 150504 | 0006641040 | AQEYF1AXARWJZ | Les Sinclair "book maven" |
| 138685 | 150503 | 0006641040 | A3R5XMPFU8YZ4D | Her Royal Motherliness "Nana" |

| | HelpfulnessNumerator | HelpfulnessDenominator | Score | Time |
|---|---|---|---|---|
| 138695 | 0 | 0 | 1 | 1325721600 |
| 138707 | 1 | 2 | 1 | 1025481600 |
| 138708 | 11 | 18 | 0 | 1129507200 |
| 138686 | 1 | 1 | 1 | 1212278400 |
| 138685 | 1 | 1 | 1 | 1233964800 |

| | Summary |
|---|---|
| 138695 | A classic |
| 138707 | In December it will be, my snowman's anniversa... |
| 138708 | awesome book poor size |
| 138686 | Chicken Soup with Rice |
| 138685 | so fun to read |

| | Text |
|---|---|
| 138695 | I remembered this book from my childhood and g... |
| 138707 | My daughter loves all the "Really Rosie" books... |
| 138708 | This is one of the best children's books ever ... |
| 138686 | A very entertaining rhyming story--cleaver and... |
| 138685 | This is my grand daughter's and my favorite bo... |

| | CleanText |
|---|---|
| 138695 | remembered book childhood got kids good rememb... |
| 138707 | daughter loves really rosie books introduced r... |
| 138708 | one best children books ever written mini vers... |
| 138686 | entertaining rhyming story cleaver catchy illu... |
| 138685 | grand daughter favorite book read loves rhythm... |

In [28]:
```
##Sorting data for Time Based Splitting
time_sorted_data = final.sort_values('Time', axis=0, ascending=True, inplace=False, k


final = time_sorted_data.take(np.random.permutation(len(final))[:100000])
print(final.shape)
final.head()
```

```
(100000, 11)
```

Out[28]:
```
            Id   ProductId          UserId             ProfileName  \
8906      9754  B000KFXEYE  A37HQ91X0DAEPT                   JGood
28063    30606  B004538TME  A18TD63LUDC3P2  R. Holland "Chatmandu"
5236      5676  B000H23YC2  A37H9RV4TNKLAH                    Bill
193647  209951  B001DDBL2Y  A2U8KKXRXZ2FVZ                 cathybb
27388    29870  B0045CTYNI   AM3VWXDW4YV96                     Ali

        HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
8906                       1                       1      1  1322611200
28063                      0                       0      1  1347148800
5236                       2                       2      1  1205798400
193647                     1                       1      1  1324080000
27388                      0                       0      1  1295913600

                       Summary  \
8906                  amazing!
28063         Best of the K-cups
5236                Great Deal
193647  Wonderful Truffle Flavor
27388               Delicious!

                                                     Text  \
8906    i found the packets at walmart for 57 cents i ...
28063   I find the Folgers Lively Colombian K-cup the ...
5236    Very good taste and a good price, no sales tax...
193647  I  had used this product before, mostly for sa...
27388   I first tried these at a friend's house, and f...

                                                CleanText
8906    found packets walmart cents believe went back ...
28063   find folgers lively colombian k cup best mediu...
5236    good taste good price no sales tax no shipping...
193647  used product mostly salad dressing unable get ...
27388   first tried friend house day forward hooked li...
```

# 5 [4] Featurization

## 5.1 [4.1] BAG OF WORDS

In [29]:
```
X = np.array(prepr_rev)
y = np.array(final['Score'])
```

In [30]:
```
from sklearn.model_selection import train_test_split
#splitting data into Train, C.V and Test
X_train, X_test, y_train, y_test = train_test_split(final ['CleanText'], final['Score
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.33)
print("Train:",X_train.shape,y_train.shape)
print("CV:",X_cv.shape,y_cv.shape)
print("Test:",X_test.shape,y_test.shape)
```

```
Train: (44890,) (44890,)
CV: (22110,) (22110,)
Test: (33000,) (33000,)
```

In [90]:
```
#BoW

vectorizer = CountVectorizer(min_df=10, max_features=500)
vectorizer.fit(X_train)
#vectorizer.fit(X_train) # fit has to happen only on train data
# we use the fitted CountVectorizer to convert the text to vector
X_train_bow = vectorizer.transform(X_train)
X_cv_bow = vectorizer.transform(X_cv)
X_test_bow = vectorizer.transform(X_test)
print("After vectorizations")
print(X_train_bow.shape, y_train.shape)
print(X_cv_bow.shape, y_cv.shape)
print(X_test_bow.shape, y_test.shape)
```

```
After vectorizations
(44890, 500) (44890,)
(22110, 500) (22110,)
(33000, 500) (33000,)
```

## 5.2 [4.2] Bi-Grams and n-Grams.

In [32]:
```
#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/stable/mod

# you can choose these numebrs min_df=10, max_features=5000, of your choice
```

```
vectorizer = CountVectorizer(ngram_range=(1,2), min_df=10, max_features=5000)
vectorizer.fit(X_train)
#vectorizer.fit(X_train) # fit has to happen only on train data
# we use the fitted CountVectorizer to convert the text to vector
X_train_bow = vectorizer.transform(X_train)
X_cv_bow = vectorizer.transform(X_cv)
X_test_bow = vectorizer.transform(X_test)
print("After vectorizations")
print(X_train_bow.shape, y_train.shape)
print(X_cv_bow.shape, y_cv.shape)
print(X_test_bow.shape, y_test.shape)

print("the number of unique words including both unigrams and bigrams ", X_train_bow.g
```

```
After vectorizations
(44890, 5000) (44890,)
(22110, 5000) (22110,)
(33000, 5000) (33000,)
the number of unique words including both unigrams and bigrams  5000
```

### 5.3 [4.3] TF-IDF

```
In [91]: tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10, max_features=500)
         tf_idf_vect.fit(X_train)
         # we use the fitted CountVectorizer to convert the text to vector
         X_train_tfidf = tf_idf_vect.transform(X_train)
         X_cv_tfidf = tf_idf_vect.transform(X_cv)
         X_test_tfidf = tf_idf_vect.transform(X_test)
         print("After vectorizations")
         print(X_train_tfidf.shape, y_train.shape)
         print(X_cv_tfidf.shape, y_cv.shape)
         print(X_test_tfidf.shape, y_test.shape)
         print("some sample features(unique words in the corpus)",tf_idf_vect.get_feature_names
         print('='*50)
```

```
After vectorizations
(44890, 500) (44890,)
(22110, 500) (22110,)
(33000, 500) (33000,)
some sample features(unique words in the corpus) ['able', 'absolutely', 'actually', 'add', 'add
==================================================
```

### 5.4 [4.4] Word2Vec

```
In [34]: # Train your own Word2Vec model using your own text corpus
         sent_of_train=[]
```

```
for sent in X_train:
    sent_of_train.append(sent.split())

# List of sentence in X_test text
sent_of_test=[]
for sent in X_test:
    sent_of_test.append(sent.split())

# Train your own Word2Vec model using your own train text corpus
# min_count = 5 considers only words that occured atleast 5 times
w2v_model=Word2Vec(sent_of_train,min_count=5,size=50, workers=4)
print(w2v_model.wv.most_similar('great'))
print('='*50)
print(w2v_model.wv.most_similar('worst'))

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

```
[('fantastic', 0.810080349445343), ('excellent', 0.809391975402832), ('good', 0.80701506137847
==================================================
[('greatest', 0.7800548672676086), ('best', 0.6784257888793945), ('coolest', 0.64886677265167
number of words that occured minimum 5 times  13466
```

```
In [35]: 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  13466
sample words  ['wondeful', 'product', 'shipping', 'fast', 'packing', 'perfect', 'love', 'matzo
```

### 5.5 [4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V

```
In [36]: i=0
         sent_of_test_cv=[]
         for sentance in X_cv:
             sent_of_test_cv.append(sentance.split())
```

```
In [37]: sent_vectors_cv = []; # the avg-w2v for each sentence/review is stored in this list
         for sent in tqdm(sent_of_test_cv): # for each review/sentence
             sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need t
             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_cv.append(sent_vec)
    sent_vectors_cv = np.array(sent_vectors_cv)
    print(sent_vectors_cv.shape)
    print(sent_vectors_cv[0])
```

```
100%|| 22110/22110 [01:13<00:00, 302.63it/s]

(22110, 50)
[ 0.06498721  0.79612739  0.26068903  0.20172371  0.37437537  0.04439201
  0.21733876 -0.54119455 -0.22884366  0.74916206 -0.06431492 -0.07987306
  1.11170487 -0.31706246 -0.13208098  1.00752133 -0.15806267 -0.23693262
  0.13166478  0.1162586  -1.00791549 -0.7041703  -0.33810824 -0.09102126
 -0.13344762  0.44736069  0.59063813 -0.32998469  0.15480058 -0.39336889
  0.03248305  0.02316775 -0.2707646  -1.34723554  0.15182858  0.15244402
 -0.41337191 -0.4309975  -0.09680952  0.07562984 -0.4351498  -0.1212412
  0.25109532 -1.22230623 -0.12066191  0.08960353  0.12554569  0.06179929
  0.20668169 -0.1875396 ]
```

#### [4.4.1.1] Avg W2v

In [38]:
```
# average Word2Vec
# compute average word2vec for each review.
# compute average word2vec for X_test .
test_vectors = [];
for sent in tqdm(sent_of_test):
    sent_vec = np.zeros(50)
    cnt_words =0;
    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_vectors.append(sent_vec)

test_vectors = np.array(test_vectors)

print(test_vectors.shape)
print(test_vectors[0])
```

```
100%|| 33000/33000 [01:50<00:00, 297.40it/s]
```

```
(33000, 50)
[-0.23268548  0.35172849  0.19188095 -0.08529245  0.40004842 -0.22606502
 -0.1418867  -0.70343915  0.06465353  0.21826539 -0.51531387 -0.18519199
  0.43089552  0.6235833  -0.02229553  0.35233837  0.00090884  0.24472451
  0.10192246  0.48772127  0.13919623 -0.3738773  -0.33740767 -0.04211258
  0.04843662 -0.56999221  0.08535804 -0.04759118  0.83089965 -0.38167918
 -0.56302446  0.1117191   0.26977195 -0.82601625  0.14647374  0.6241476
 -0.07788345  0.02959642 -0.45181998  0.25285222 -0.34787317 -0.00980091
 -0.24544531 -0.40470703 -0.09558729  0.61882325  0.3640449   0.71307979
  0.84713797 -0.46049427]
```

In [39]:
```python
# compute average word2vec for X_train .
train_vectors = [];
for sent in tqdm(sent_of_train):
    sent_vec = np.zeros(50)
    cnt_words =0;
    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_vectors.append(sent_vec)

train_vectors = np.array(train_vectors)

print(train_vectors.shape)
print(train_vectors[0])
```

```
100%|| 44890/44890 [02:29<00:00, 299.80it/s]

(44890, 50)
[-0.31910905  0.27935335  0.32598865  0.31491613  0.03758824 -0.50678713
 -0.08773003  0.05044405  0.473852    0.25108572 -0.59380067 -0.12560968
  0.11229882 -0.15477959 -0.32888119  0.28322356 -0.18378382  0.45001692
  0.02249543  0.09882321  0.14622723 -0.0857125  -0.33752663  0.0719414
  0.08242424 -0.6205999   0.18840833 -0.59825554  0.30026937 -0.56249011
 -0.16023349 -0.3777474  -0.1664964  -0.29557947 -0.09134184  0.35897609
 -0.10299782 -0.26266114 -0.1364854   0.12358404 -0.62402336 -0.02887721
 -0.19590467 -0.31029066  0.13540766  0.37399933  0.0732796   0.38830157
  0.68563001 -0.20348505]
```

**[4.4.1.2] TFIDF weighted W2v**

In [40]:
```
tf_idf_vect = TfidfVectorizer()

# final_tf_idf1 is the sparse matrix with row= sentence, col=word and cell_val = tfid
final_tf_idf1 = tf_idf_vect.fit_transform(X_train)
dictionary = dict(zip(tf_idf_vect.get_feature_names(), list(tf_idf_vect.idf_)))

# tfidf words/col-names
tfidf_feat = tf_idf_vect.get_feature_names()

# compute TFIDF Weighted Word2Vec for X_test .
tfidf_test_vectors = [];
row=0;
for sent in tqdm(sent_of_test):
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        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
    tfidf_test_vectors.append(sent_vec)

tfidf_test_vectors = np.array(tfidf_test_vectors)
print(tfidf_test_vectors.shape)
print(tfidf_test_vectors[0])
```

```
100%|| 33000/33000 [25:01<00:00, 15.81it/s]


(33000, 50)
[-0.20276099  0.30447506  0.17174864 -0.07191119  0.45382269 -0.23950305
 -0.05583434 -0.75551109 -0.06018428  0.29591458 -0.44489194 -0.20126017
  0.40175292  0.55755182  0.04899497  0.41795232  0.0594283   0.24494245
  0.18458354  0.42108216  0.19986278 -0.30134463 -0.2933384  -0.10489484
 -0.03140518 -0.50438341  0.11721851  0.012807    0.76551866 -0.34425957
 -0.50673818  0.24516161  0.23638625 -0.85461346  0.07109969  0.66123028
  0.03299534  0.06650675 -0.47469753  0.29820355 -0.35776846 -0.17524998
 -0.15472057 -0.18534192 -0.1779434   0.6307442   0.3993236   0.60414246
  0.89752377 -0.50729357]
```

In [41]:
```
# TF-IDF weighted Word2Vec
# compute TFIDF Weighted Word2Vec for X_train .
tfidf_train_vectors = [];
```

```
row=0;
for sent in tqdm(sent_of_train):
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        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
    tfidf_train_vectors.append(sent_vec)

tfidf_train_vectors = np.array(tfidf_train_vectors)
print(tfidf_train_vectors.shape)
print(tfidf_train_vectors[0])
```

```
100%|| 44890/44890 [32:10<00:00, 23.26it/s]


(44890, 50)
[-2.56802447e-01  3.14070048e-01  3.45627246e-01  3.68462719e-01
  2.25948723e-01 -3.56279106e-01 -2.48266758e-01  4.09600936e-02
  3.34919675e-01 -3.18066606e-04 -4.57560561e-01 -1.52397220e-01
  1.34887097e-01 -1.75561692e-01 -7.61514339e-03  6.08032479e-02
  1.09382645e-01  3.84822059e-01 -9.09374002e-02  4.70495199e-02
  2.06612782e-01 -4.69003473e-02 -1.49749163e-01  2.17264960e-02
  3.21512336e-02 -4.54173497e-01  2.87840300e-01 -3.65833184e-01
  1.92036222e-01 -6.48131327e-01 -1.28079410e-01 -3.66436702e-01
 -8.58847057e-02 -2.22805358e-01  7.90022147e-02  2.20167321e-01
 -2.76063352e-01 -2.74922634e-01 -8.23223315e-02  6.72367611e-03
 -4.66591485e-01 -2.47916430e-02 -2.21355611e-02 -1.00546210e-01
  5.43662395e-02  7.32211717e-02  5.50127946e-02  2.03007993e-01
  5.03268518e-01 -2.65069047e-01]
```

## 6 [5] Assignment 9: Random Forests

```
<li><strong>Apply Random Forests & GBDT on these feature sets</strong>
    <ul>
        <li><font color='red'>SET 1:</font>Review text, preprocessed one converted into vector
        <li><font color='red'>SET 2:</font>Review text, preprocessed one converted into vector
        <li><font color='red'>SET 3:</font>Review text, preprocessed one converted into vector
        <li><font color='red'>SET 4:</font>Review text, preprocessed one converted into vector
    </ul>
</li>
<br>
```

```
<li><strong>The hyper paramter tuning (Consider two hyperparameters: n_estimators & max_depth)
    <ul>
<li>Find the best hyper parameter which will give the maximum <a href='https://www.appliedaico
<li>Find the best hyper paramter using k-fold cross validation or simple cross validation data
<li>Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this ta
    </ul>
</li>
<br>
<li><strong>Feature importance</strong>
    <ul>
<li>Get top 20 important features and represent them in a word cloud. Do this for BOW & TFIDF.
    </ul>
</li>
<br>
<li><strong>Feature engineering</strong>
    <ul>
<li>To increase the performance of your model, you can also experiment with with feature engine
        <ul>
        <li>Taking length of reviews as another feature.</li>
        <li>Considering some features from review summary as well.</li>
    </ul>
    </ul>
</li>
<br>
<li><strong>Representation of results</strong>
    <ul>
<li>You need to plot the performance of model both on train data and cross validation data for
<img src='3d_plot.JPG' width=500px> with X-axis as <strong>n_estimators</strong>, Y-axis as <s
        <p style="text-align:center;font-size:30px;color:red;"><strong>(or)</strong></p> <br>
<li>You need to plot the performance of model both on train data and cross validation data for
<img src='heat_map.JPG' width=300px> <a href='https://seaborn.pydata.org/generated/seaborn.hea
<li>You choose either of the plotting techniques out of 3d plot or heat map</li>
<li>Once after you found the best hyper parameter, you need to train your model with it, and fi
<img src='train_test_auc.JPG' width=300px></li>
<li>Along with plotting ROC curve, you need to print the <a href='https://www.appliedaicourse.
<img src='confusion_matrix.png' width=300px></li>
    </ul>
</li>
<br>
<li><strong>Conclusion</strong>
    <ul>
<li>You need to summarize the results at the end of the notebook, summarize it in the table fo
    <img src='summary.JPG' width=400px>
</li>
    </ul>
```

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.

## 6.1 [5.1] Applying RF

### 6.1.1 [5.1.1] Applying Random Forests on BOW, SET 1

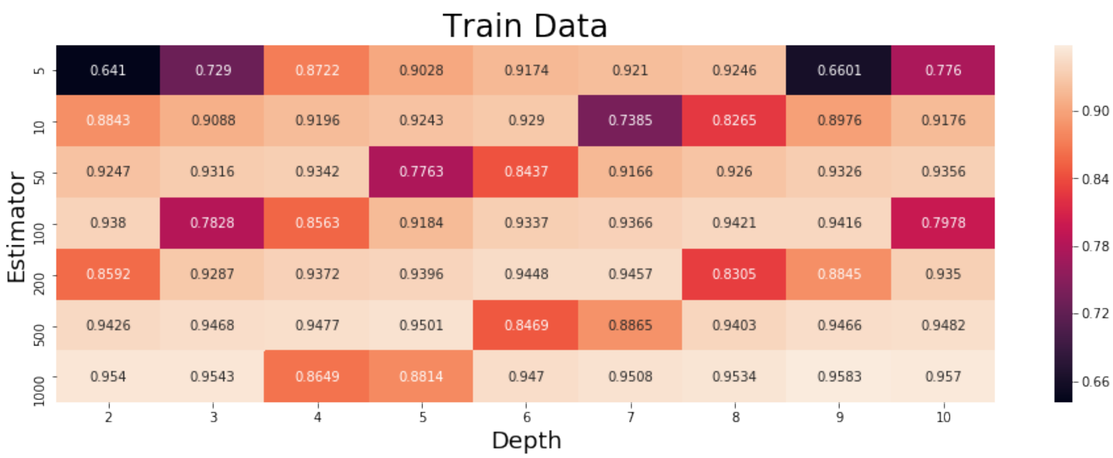
In [42]:
```
# Please write all the code with proper documentation
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_auc_score, auc
from sklearn.model_selection import GridSearchCV

def all_rf(X_train,y_train,X_cv):
    estimator = [5, 10, 50, 100, 200, 500, 1000]
    depth = [2, 3, 4, 5, 6, 7, 8, 9, 10]
    hyper_param = {'n_estimators':estimator, 'max_depth':depth}

    clf = GridSearchCV(RandomForestClassifier(class_weight = 'balanced'),hyper_param,
    clf.fit(X_train_bow,y_train)
    opt_estimator, opt_depth = clf.best_params_.get('n_estimators'), clf.best_params_

    train_auc= clf.cv_results_['mean_train_score']
    train_auc_std= clf.cv_results_['std_train_score']
    cv_auc = clf.cv_results_['mean_test_score']
    cv_auc_std= clf.cv_results_['std_test_score']

    df_heatmap = pd. DataFrame(train_auc.reshape(len(estimator), len(depth)), index=es
    fig = plt. figure(figsize=(16,5))
    heatmap = sns. heatmap(df_heatmap, annot=True, fmt='.4g')
    plt. title("Train Data", size=24)
    plt. xlabel('Depth' , size=18)
    plt. ylabel('Estimator' , size=18)
    plt. show()

    df_heatmap = pd. DataFrame(cv_auc.reshape(len(estimator), len(depth)), index=esti
    fig = plt. figure(figsize=(16,5))
    heatmap = sns. heatmap(df_heatmap, annot=True, fmt='.4g')
    plt. title("CV Data", size=24)
    plt. xlabel('Depth' , size=18)
    plt. ylabel('Estimator' , size=18)
    plt. show()


    print("Max depth is = ", opt_depth , " Optimal value of n_estimator :", opt_estima
```

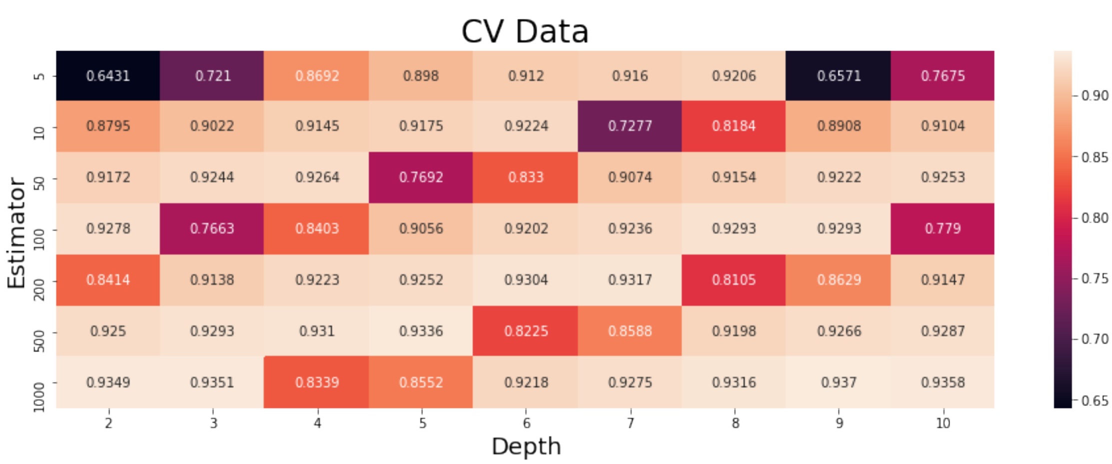
```
    #Cv auc scores
    print("--------------------------")
    print("Cv auc scores")
    print(cv_auc)
    print("Maximun Auc value :",max(cv_auc))

    #test data


    clf =RandomForestClassifier(max_depth=opt_depth, n_estimators=opt_estimator,class_
    clf.fit(X_train_bow,y_train)

    train_fpr, train_tpr, thresholds = roc_curve(y_train, clf.predict_proba(X_train_bo
    test_fpr, test_tpr, thresholds = roc_curve(y_test, clf.predict_proba(X_test_bow)[


    plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr))
    plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
    plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0.)
    plt.grid(True)
    plt.legend()
    plt.xlabel("FBR")
    plt.ylabel("TBR")
    plt.title("Train and Test Data")
    plt.show()


     #Confusion Matrix

    print("Train confusion matrix")
    print(confusion_matrix(y_train, clf.predict(X_train_bow)))
    print("Test confusion matrix")
    print(confusion_matrix(y_test, clf.predict(X_test_bow)))


    cm = confusion_matrix(y_train, clf.predict(X_train_bow))
    cm = confusion_matrix(y_test, clf.predict(X_test_bow))
    tn, fp, fn, tp = cm.ravel()
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix
# Code for drawing seaborn heatmaps
    class_names = ['0','1']
    df_heatmap = pd.DataFrame(cm, index=class_names, columns=class_names )
    fig = plt.figure(figsize=(5,3))
    heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
    heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='righ
    heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='righ
```

```
        plt.ylabel('True label',size=18)
        plt.xlabel('Predict label',size=18)
        plt.title("Confusion Matrix\n",size=24)
        plt.show()
```

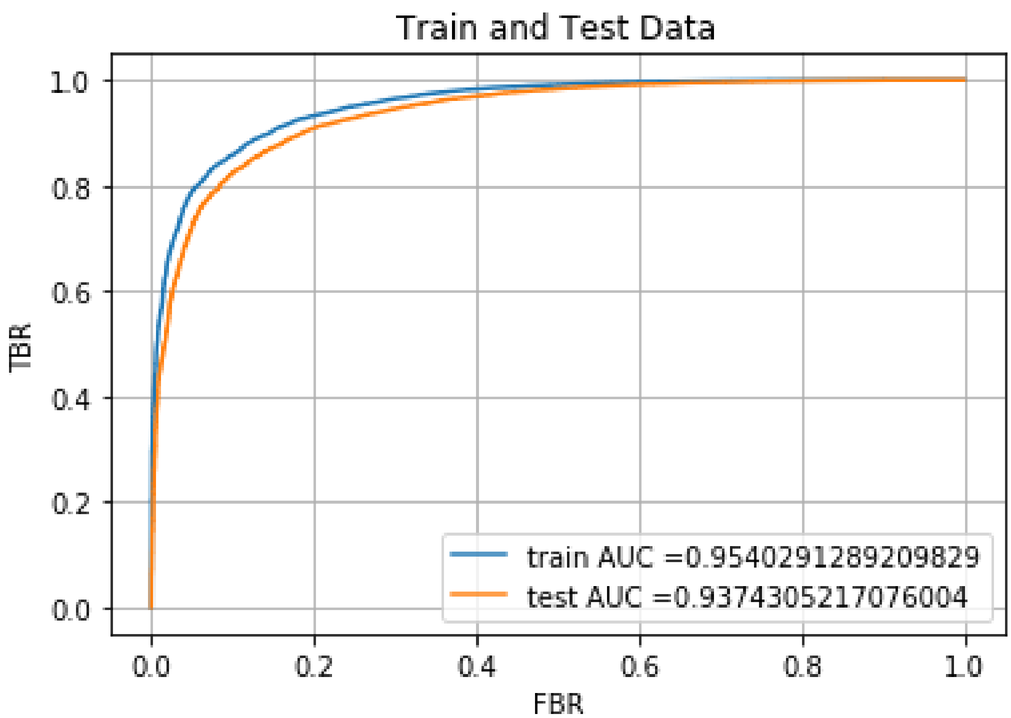
In [75]:
```
all_rf(X_train_bow,y_train,X_cv_bow)
```

```
Fitting 3 folds for each of 63 candidates, totalling 189 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  48 tasks      | elapsed:  1.9min
[Parallel(n_jobs=-1)]: Done 189 out of 189 | elapsed:  8.8min finished
```

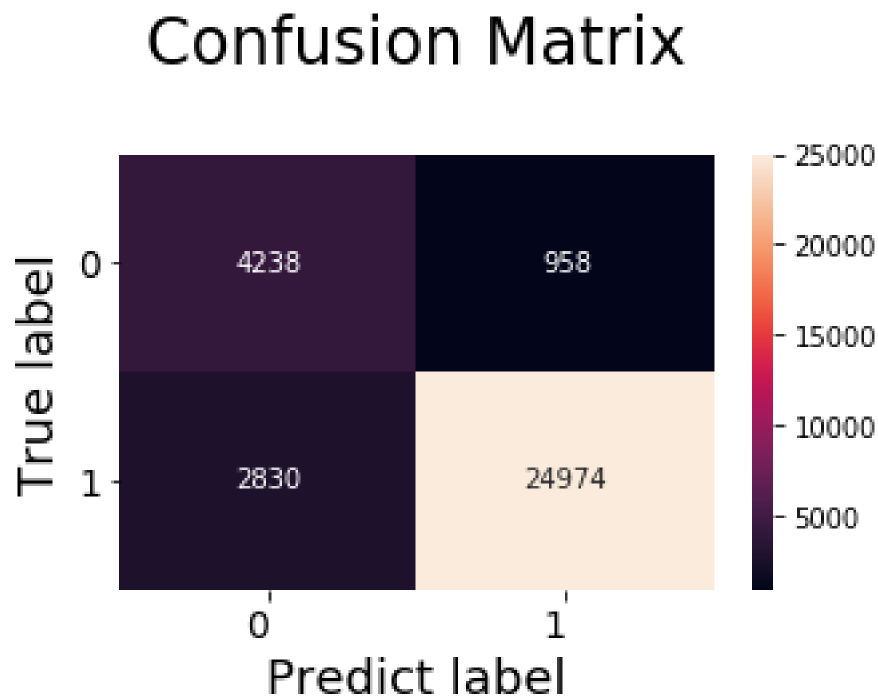


```
Max depth is =  10  Optimal value of n_estimator : 500
--------------------------
Cv auc scores
[0.64306296 0.72102825 0.86920008 0.89802974 0.9120104  0.91602503
 0.92063108 0.65714552 0.76750971 0.87950475 0.90215797 0.91453028
 0.91752454 0.9223938  0.72773727 0.81841925 0.89082506 0.91043621
 0.91717023 0.92437598 0.92642365 0.769206   0.83301082 0.90742643
 0.91544689 0.9222215  0.92528527 0.92780948 0.76631319 0.84030969
 0.90563715 0.92023849 0.92359432 0.92926564 0.92931172 0.77896497
 0.84138597 0.9137808  0.92225997 0.92519063 0.93043919 0.93167255
 0.8104872  0.8629247  0.91466523 0.92501138 0.92932048 0.93101859
 0.93364099 0.82246652 0.85878783 0.91982683 0.92659023 0.9286682
 0.93488273 0.93512712 0.83388712 0.85519033 0.92184951 0.92747775
 0.93160392 0.93700986 0.93575626]
Maximun Auc value : 0.9370098612086585
```




```
Train confusion matrix
[[ 6095  1101]
 [ 3505 34189]]
Test confusion matrix
[[ 4238   958]
 [ 2830 24974]]
```



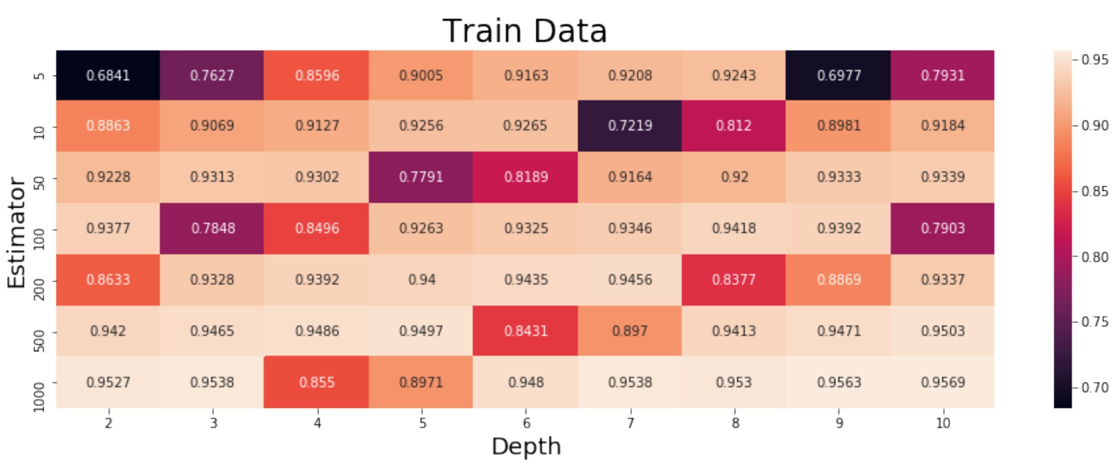

#### 6.1.2 [5.1.2] Wordcloud of top 20 important features from SET 1

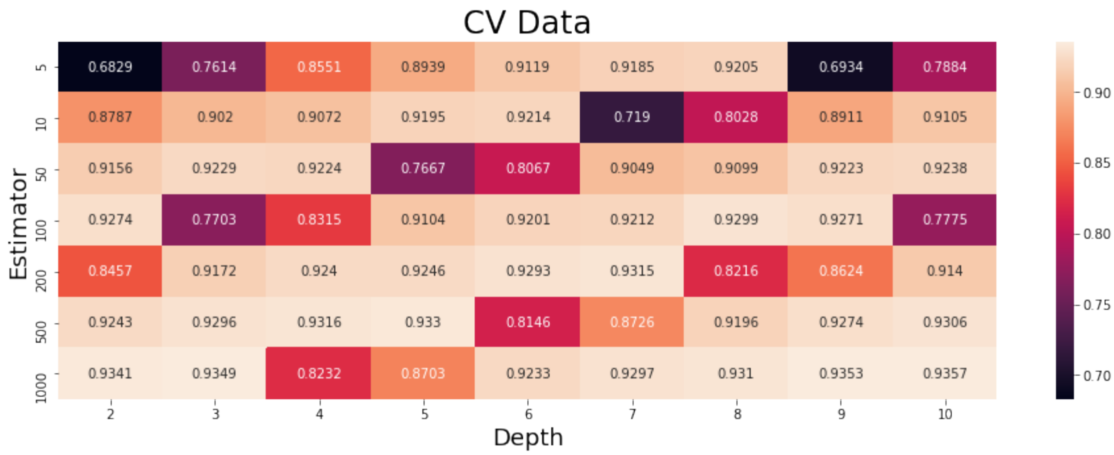
In [92]:
```
# Please write all the code with proper documentation
clf = RandomForestClassifier(max_depth= 10, n_estimators=500,class_weight='balanced')
clf.fit(X_train_bow,y_train)

feat = clf.feature_importances_
index=np.argsort(feat)
index_rev=index[::-1]
names=vectorizer.get_feature_names()
index_rev=index_rev[:30]

text=" "
for i in range(30):
    text = text + " " + names[index_rev[i]]
wordcloud = WordCloud(width=500, height=200, max_words=20).generate(text)

plt.figure(figsize=(12,12),facecolor='k' )
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.margins(x=0, y=0)
plt.show()
```


### 6.1.3 [5.1.3] Applying Random Forests on TFIDF, SET 2

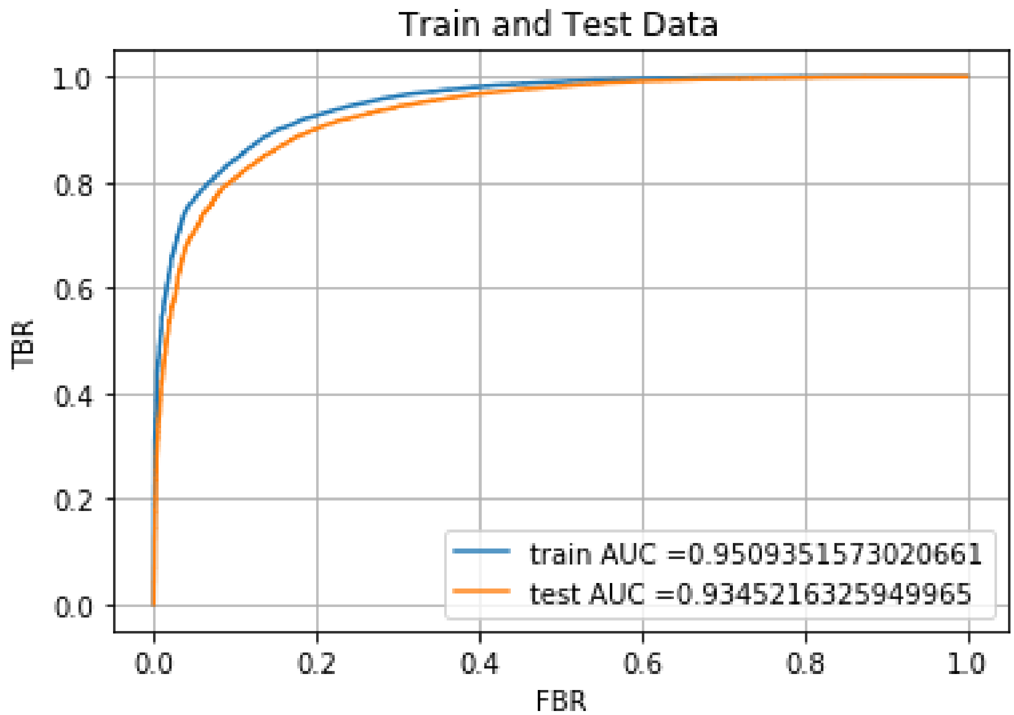
```
In [56]: # Please write all the code with proper documentation
         all_rf(X_train_tfidf,y_train,X_cv_tfidf)
```

```
Fitting 3 folds for each of 63 candidates, totalling 189 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  48 tasks      | elapsed:  1.7min
[Parallel(n_jobs=-1)]: Done 189 out of 189 | elapsed:  8.2min finished
```

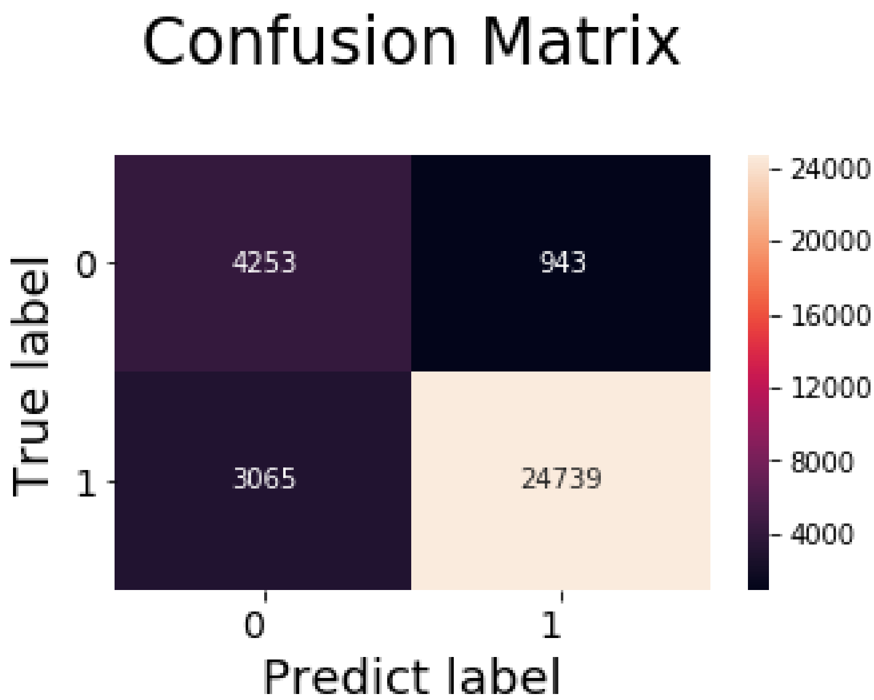





```
Max depth is =  10  Optimal value of n_estimator : 1000
--------------------------
Cv auc scores
[0.68286098 0.76142709 0.85507018 0.89394812 0.91190165 0.91851608
 0.92046121 0.6933842  0.78840661 0.87868933 0.90204536 0.90723438
 0.91946424 0.92141544 0.71899265 0.80277441 0.89111961 0.91050469
 0.91563363 0.92294541 0.92237332 0.7667209  0.80674262 0.90486909
 0.90992739 0.92232706 0.92381545 0.92744061 0.77026432 0.8315178
 0.9103639  0.92011372 0.92122408 0.9299138  0.92712863 0.77752776
 0.84567828 0.91723242 0.92398086 0.92462787 0.92933979 0.93153405
 0.82155301 0.86237955 0.91395101 0.92428194 0.92956058 0.93155128
 0.93303728 0.81462124 0.87256431 0.91960882 0.92735267 0.93056571
 0.93407258 0.93487938 0.82317334 0.87032882 0.9232574  0.92967838
 0.93098179 0.93528378 0.93574109]
Maximun Auc value : 0.9357410930140528
```

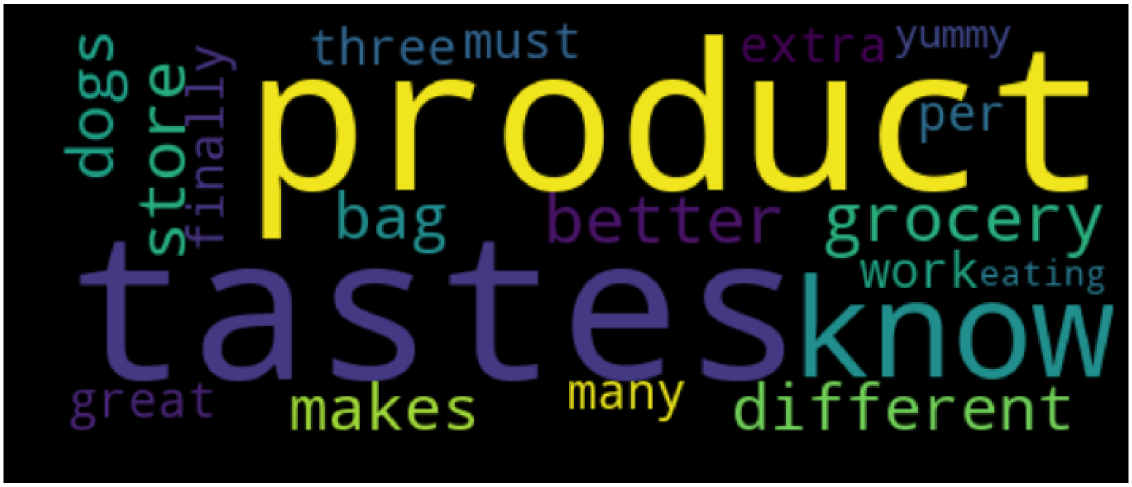



```
Train confusion matrix
[[ 6097  1099]
 [ 3781 33913]]
Test confusion matrix
[[ 4253   943]
 [ 3065 24739]]
```




#### 6.1.4 [5.1.4] Wordcloud of top 20 important features from SET 2

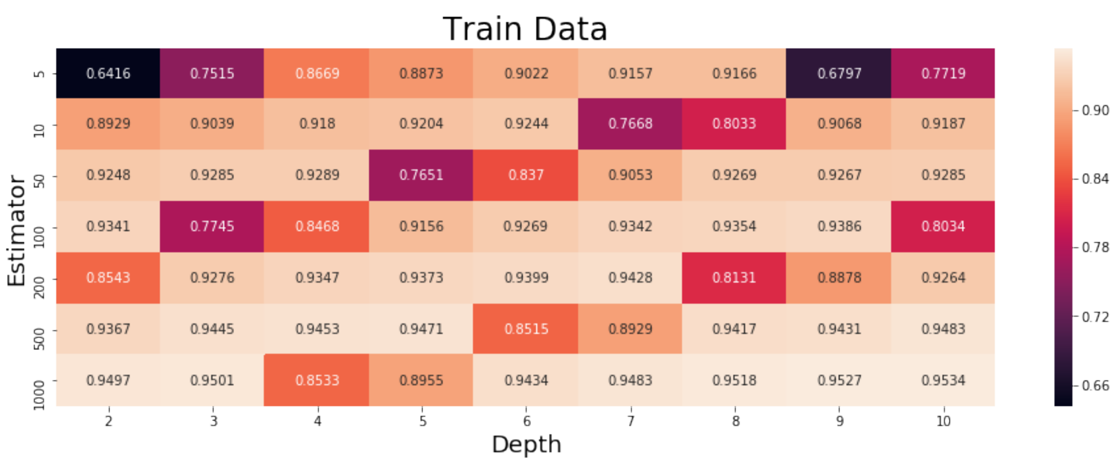
In [95]:
```
# Please write all the code with proper documentation
clf = RandomForestClassifier(max_depth= 10, n_estimators=1000,class_weight='balanced')
clf.fit(X_train_bow,y_train)

feat = clf.feature_importances_
index=np.argsort(feat)
index_rev=index[::-1]
names=tf_idf_vect.get_feature_names()
index_rev=index_rev[:30]

text=" "
for i in range(30):
    text = text + " " + names[index_rev[i]]
wordcloud = WordCloud(width=500, height=200, max_words=20).generate(text)

plt.figure(figsize=(12,12),facecolor='k' )
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.margins(x=0, y=0)
plt.show()
```

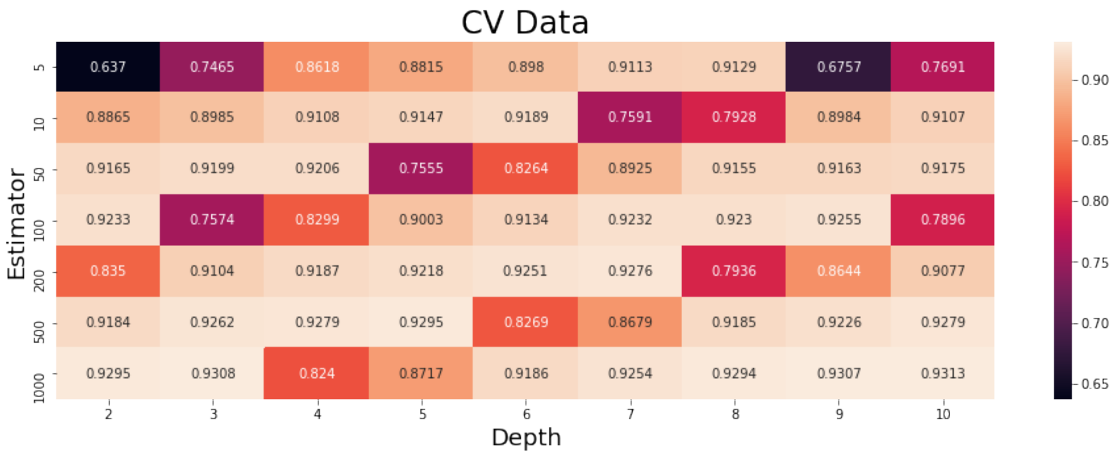



### 6.1.5 [5.1.5] Applying Random Forests on AVG W2V, SET 3

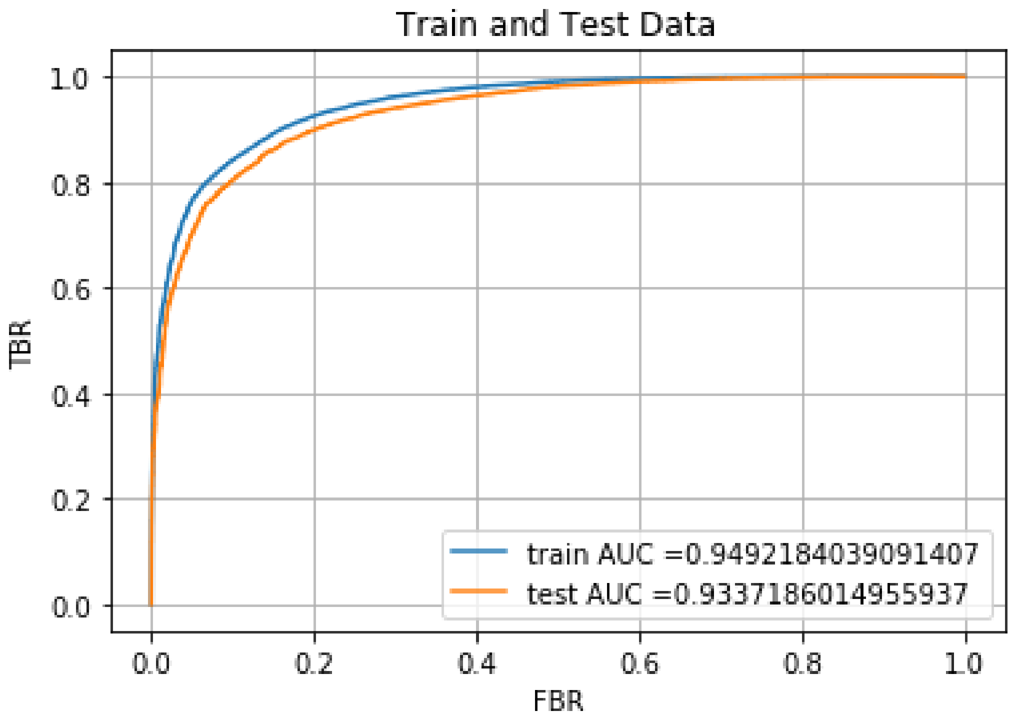
```
In [52]: # Please write all the code with proper documentation
         all_rf(train_vectors, y_train, X_cv)
```

```
Fitting 3 folds for each of 63 candidates, totalling 189 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  48 tasks      | elapsed:  1.6min
[Parallel(n_jobs=-1)]: Done 189 out of 189 | elapsed:  8.4min finished
```

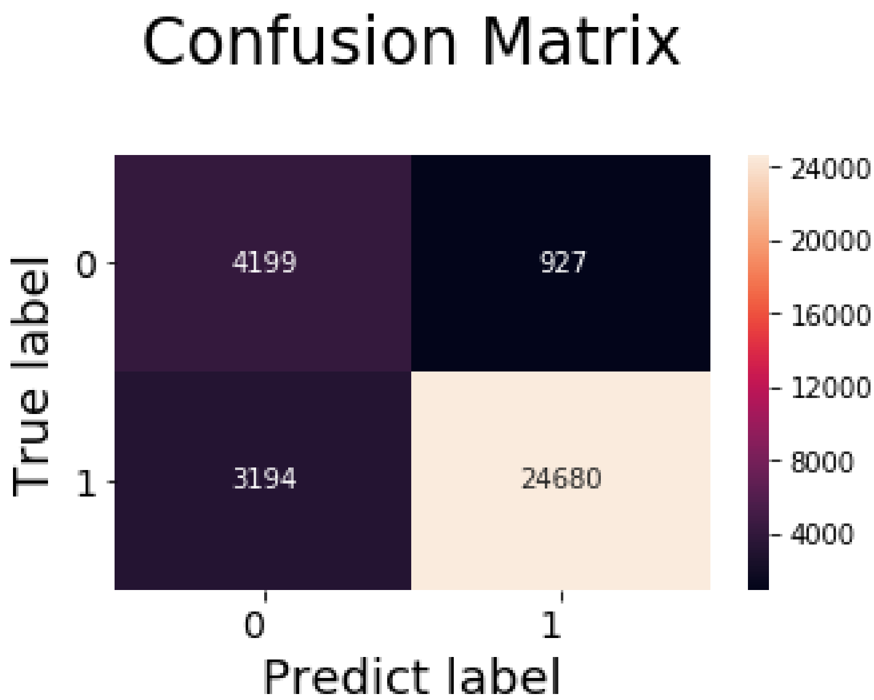





```
Max depth is =  10  Optimal value of n_estimator : 1000
--------------------------
Cv auc scores
[0.63703039 0.74651413 0.86179223 0.88154708 0.89798775 0.91127442
 0.91287378 0.67574295 0.7690975  0.88649984 0.89850633 0.91082222
 0.91473831 0.91894544 0.75908234 0.79277805 0.89843867 0.91069509
 0.91649076 0.91991837 0.92055706 0.75554251 0.82636891 0.89245141
 0.91545298 0.91628779 0.91748673 0.92325233 0.75737614 0.82990468
 0.90026087 0.91338176 0.92316353 0.92300582 0.92546764 0.78961935
 0.83504439 0.91041772 0.91866592 0.92181968 0.92510129 0.9276339
 0.79357003 0.86439589 0.90770235 0.91836227 0.92618697 0.92786057
 0.92946811 0.82691943 0.86789117 0.91852106 0.92263135 0.927867
 0.92951355 0.93078788 0.82398661 0.87171193 0.91857509 0.92535562
 0.92944238 0.93068038 0.93132632]
Maximun Auc value : 0.9313263198173527
```



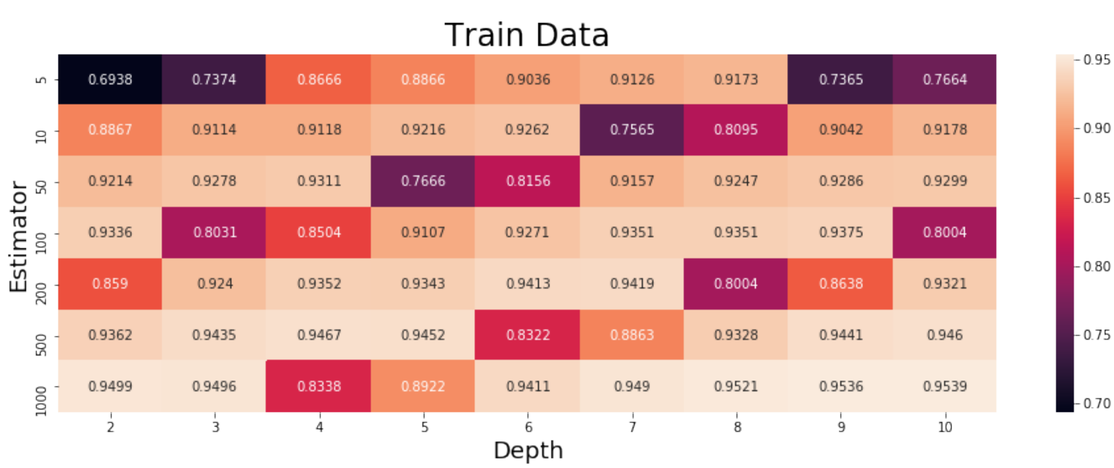

```
Train confusion matrix
[[ 6105  1138]
 [ 3841 33806]]
Test confusion matrix
[[ 4199   927]
 [ 3194 24680]]
```

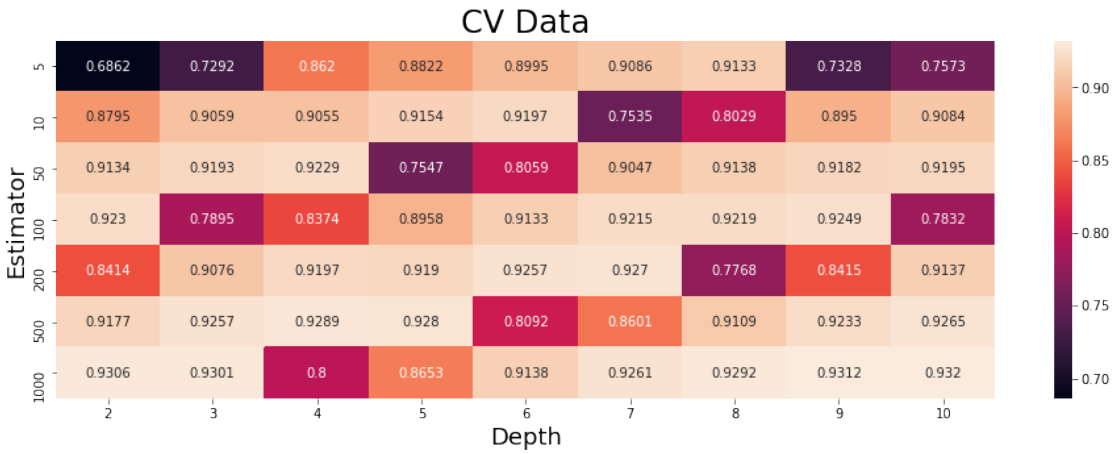



### 6.1.6 [5.1.6] Applying Random Forests on TFIDF W2V, SET 4

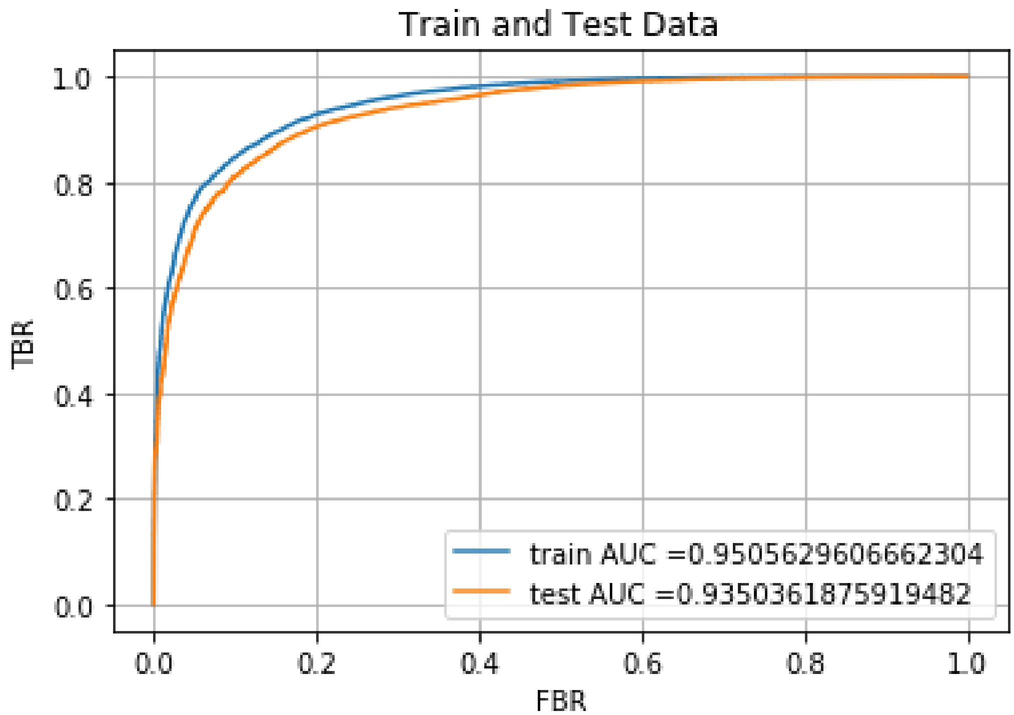
```
In [53]: # Please write all the code with proper documentation
         all_rf(tfidf_train_vectors,y_train,X_cv)
```

```
Fitting 3 folds for each of 63 candidates, totalling 189 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  48 tasks      | elapsed:  1.3min
[Parallel(n_jobs=-1)]: Done 189 out of 189 | elapsed:  7.6min finished
```

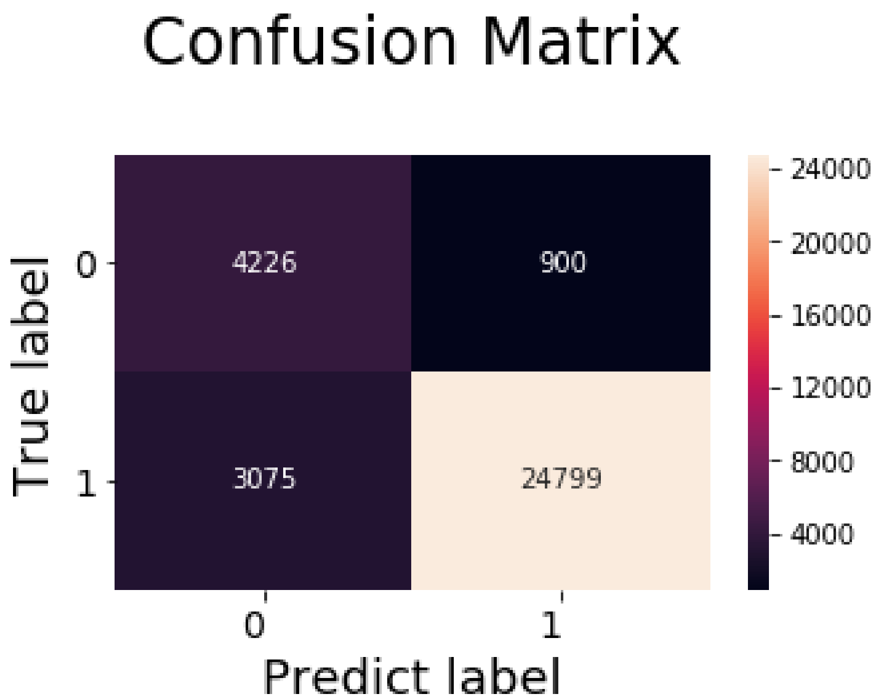





```
Max depth is =  10  Optimal value of n_estimator : 1000
--------------------------
Cv auc scores
[0.68620372 0.72915319 0.86195446 0.88215405 0.89946394 0.90860334
 0.91330617 0.73284026 0.75726952 0.8795419  0.90593102 0.90554532
 0.91540799 0.91972881 0.75351917 0.80290852 0.89500879 0.908375
 0.91335315 0.91928679 0.92286237 0.75470466 0.80590061 0.90471957
 0.91375045 0.91821072 0.91953689 0.92299218 0.78950238 0.83735446
 0.89582702 0.91326677 0.92148385 0.92191276 0.92489085 0.78316794
 0.8413537  0.90763394 0.91970834 0.91903725 0.92567512 0.92704196
 0.77677186 0.84151943 0.91369072 0.91774216 0.92573142 0.92890646
 0.92801267 0.80922807 0.86006371 0.91086335 0.92334284 0.92650346
 0.93058647 0.93007308 0.80001676 0.8653337  0.91384649 0.92606046
 0.92917037 0.93116979 0.93202383]
Maximun Auc value : 0.9320238272698838
```




```
Train confusion matrix
[[ 6096  1147]
 [ 3751 33896]]
Test confusion matrix
[[ 4226   900]
 [ 3075 24799]]
```




### 6.2 [5.2] Applying GBDT using XGBOOST

#### 6.2.1 [5.2.1] Applying XGBOOST on BOW, SET 1

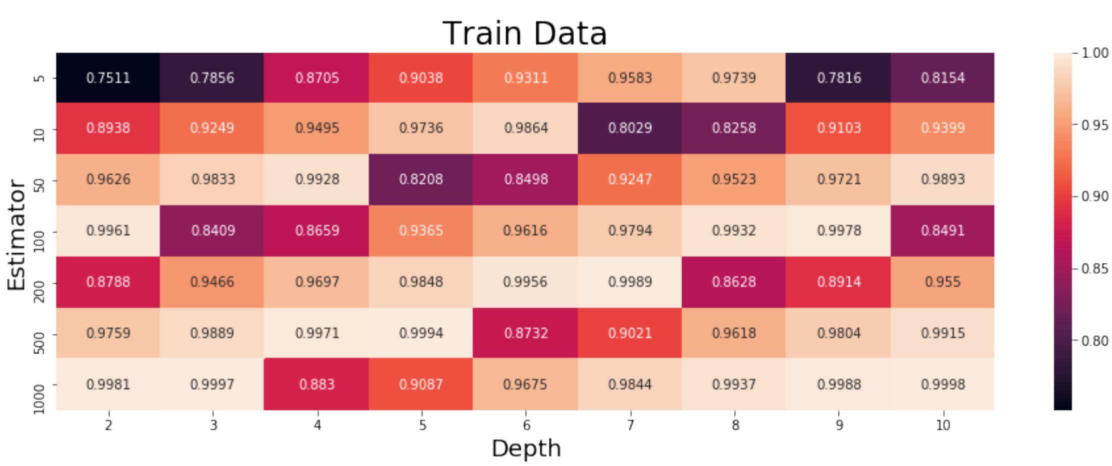
```
In [66]: # Please write all the code with proper documentation

         def all_xg(X_train,y_train,X_cv):

             estimator = [5, 10, 50, 100, 200, 500, 1000]
             depth = [2, 3, 4, 5, 6, 7, 8, 9, 10]
             param = {'n_estimators':estimator, 'max_depth':depth}

             clf = GridSearchCV(xgb.XGBClassifier(booster='gbtree',class_weight = 'balanced'),p
             clf.fit(X_train_bow,y_train)
             opt_estimator, opt_depth = clf.best_params_.get('n_estimators'), clf.best_params_

             train_auc= clf.cv_results_['mean_train_score']
             train_auc_std= clf.cv_results_['std_train_score']
             cv_auc = clf.cv_results_['mean_test_score']
             cv_auc_std= clf.cv_results_['std_test_score']

             df_heatmap = pd. DataFrame(train_auc.reshape(len(estimator), len(depth)), index=es
             fig = plt. figure(figsize=(16,5))
             heatmap = sns. heatmap(df_heatmap, annot=True, fmt='.4g')
```

```
plt. title("Train Data", size=24)
plt. xlabel('Depth' , size=18)
plt. ylabel('Estimator' , size=18)
plt. show()

df_heatmap = pd. DataFrame(cv_auc.reshape(len(estimator), len(depth)), index=estim
fig = plt. figure(figsize=(16,5))
heatmap = sns. heatmap(df_heatmap, annot=True, fmt='.4g')
plt. title("CV Data", size=24)
plt. xlabel('Depth' , size=18)
plt. ylabel('Estimator' , size=18)
plt. show()


print("Max depth is = ", opt_depth , " Optimal value of n_estimator :", opt_estima

#Cv auc scores
print("--------------------------")
print("Cv auc scores")
print(cv_auc)
print("Maximun Auc value :",max(cv_auc))

#test data

clf = xgb.XGBClassifier(max_depth=opt_depth, n_estimators=opt_estimator,random_sta
clf.fit(X_train_bow,y_train)

train_fpr, train_tpr, thresholds = roc_curve(y_train, clf.predict_proba(X_train_bo
test_fpr, test_tpr, thresholds = roc_curve(y_test, clf.predict_proba(X_test_bow)[


plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0.)
plt.grid(True)
plt.legend()
plt.xlabel("FBR")
plt.ylabel("TBR")
plt.title("Train and Test Data")
plt.show()


 #Confusion Matrix

print("Train confusion matrix")
print(confusion_matrix(y_train, clf.predict(X_train_bow)))
print("Test confusion matrix")
print(confusion_matrix(y_test, clf.predict(X_test_bow)))
```

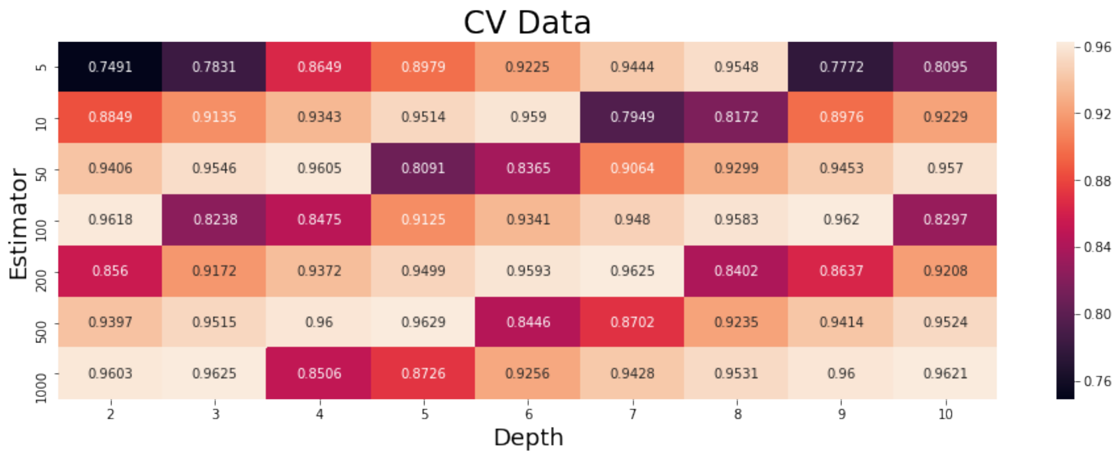
```
        cm = confusion_matrix(y_train, clf.predict(X_train_bow))
        cm = confusion_matrix(y_test, clf.predict(X_test_bow))
        tn, fp, fn, tp = cm.ravel()
    # https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix
    # Code for drawing seaborn heatmaps
        class_names = ['0','1']
        df_heatmap = pd.DataFrame(cm, index=class_names, columns=class_names )
        fig = plt.figure(figsize=(5,3))
        heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

    # Setting tick labels for heatmap
        heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='righ
        heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='righ
        plt.ylabel('True label',size=18)
        plt.xlabel('Predict label',size=18)
        plt.title("Confusion Matrix\n",size=24)
        plt.show()
```

```
In [57]: all_xg(X_train_bow,y_train,X_cv_bow)
```

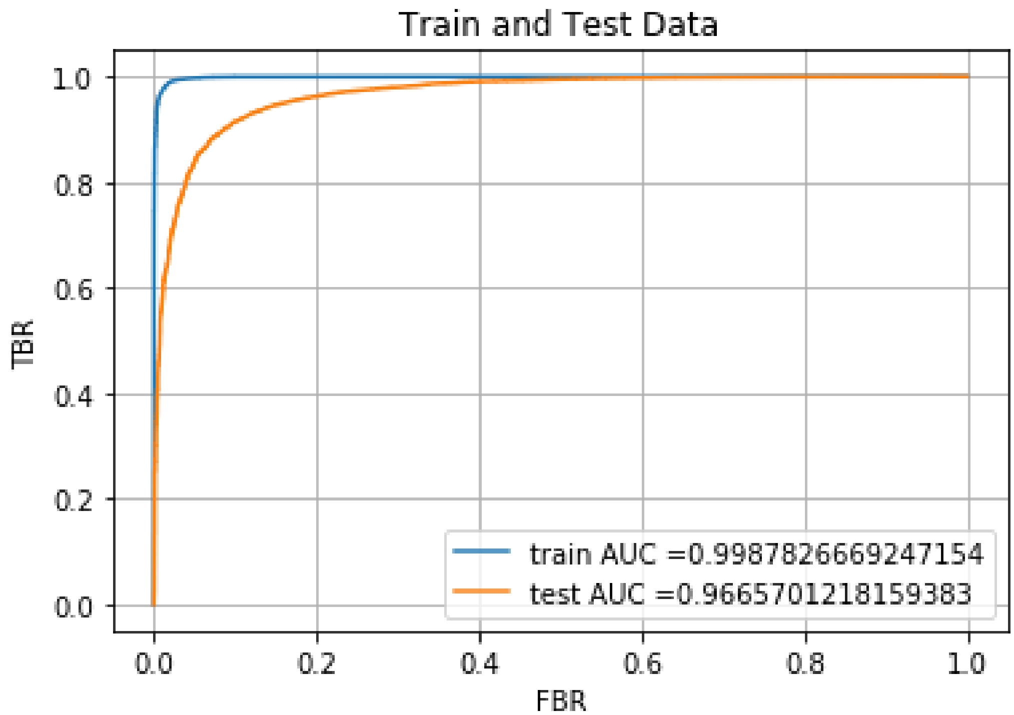
```
Fitting 3 folds for each of 63 candidates, totalling 189 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  48 tasks      | elapsed: 11.9min
[Parallel(n_jobs=-1)]: Done 189 out of 189 | elapsed: 98.7min finished
```



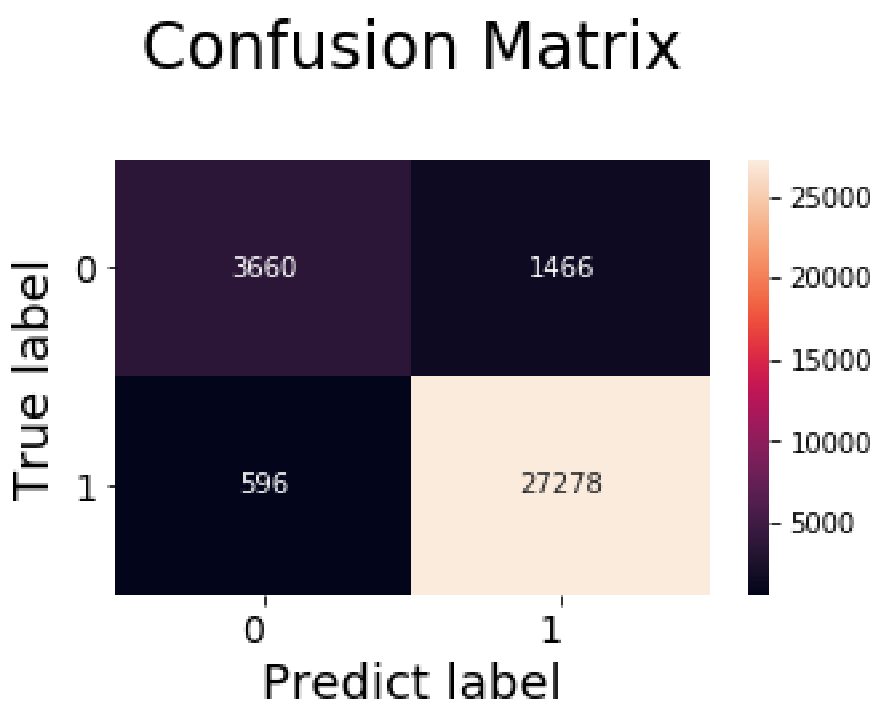

| Estimator \ Depth | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|
| 5 | 0.7511 | 0.7856 | 0.8705 | 0.9038 | 0.9311 | 0.9583 | 0.9739 | 0.7816 | 0.8154 |
| 10 | 0.8938 | 0.9249 | 0.9495 | 0.9736 | 0.9864 | 0.8029 | 0.8258 | 0.9103 | 0.9399 |
| 50 | 0.9626 | 0.9833 | 0.9928 | 0.8208 | 0.8498 | 0.9247 | 0.9523 | 0.9721 | 0.9893 |
| 100 | 0.9961 | 0.8409 | 0.8659 | 0.9365 | 0.9616 | 0.9794 | 0.9932 | 0.9978 | 0.8491 |
| 200 | 0.8788 | 0.9466 | 0.9697 | 0.9848 | 0.9956 | 0.9989 | 0.8628 | 0.8914 | 0.955 |
| 500 | 0.9759 | 0.9889 | 0.9971 | 0.9994 | 0.8732 | 0.9021 | 0.9618 | 0.9804 | 0.9915 |
| 1000 | 0.9981 | 0.9997 | 0.883 | 0.9087 | 0.9675 | 0.9844 | 0.9937 | 0.9988 | 0.9998 |




```
Max depth is =  8  Optimal value of n_estimator : 1000
--------------------------
Cv auc scores
[0.74914149 0.7830688  0.86485556 0.89790366 0.92252777 0.9443861
 0.95479245 0.77723378 0.80951478 0.884903   0.91350624 0.93426017
 0.9514343  0.95904899 0.79492082 0.81721252 0.89758297 0.92292511
 0.94056923 0.95460713 0.96048966 0.80908878 0.83646742 0.90638374
 0.92992244 0.94529508 0.95704848 0.96176269 0.82380639 0.84748675
 0.91246971 0.93405202 0.94799141 0.95831851 0.96204906 0.82973071
 0.85596184 0.91718078 0.93718239 0.94986793 0.95928038 0.96250128
 0.8401927  0.86367639 0.92079853 0.93971481 0.95149249 0.9600427
 0.96285202 0.84460868 0.8702411  0.92351061 0.94144369 0.95242703
 0.9603494  0.96253145 0.85058452 0.87259139 0.92563107 0.94281789
 0.95306491 0.95996007 0.96212908]
Maximun Auc value : 0.9628520199855344
```



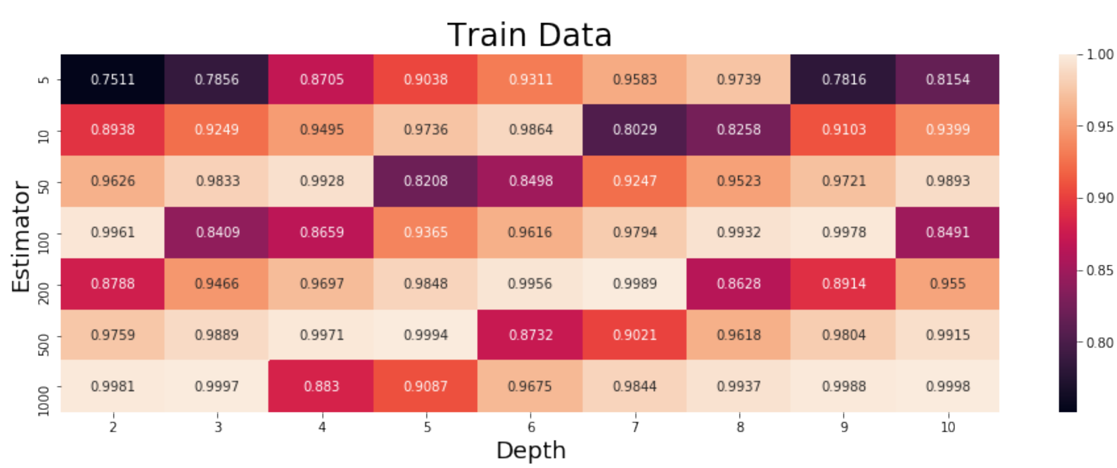

```
Train confusion matrix
[[ 6773   470]
 [   58 37589]]
Test confusion matrix
[[ 3660  1466]
 [  596 27278]]
```

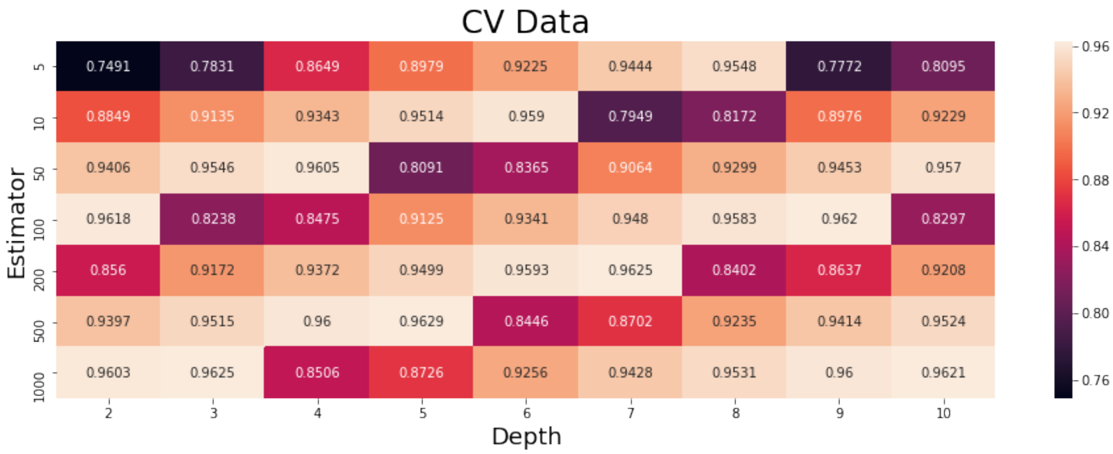



### 6.2.2 [5.2.2] Applying XGBOOST on TFIDF, SET 2

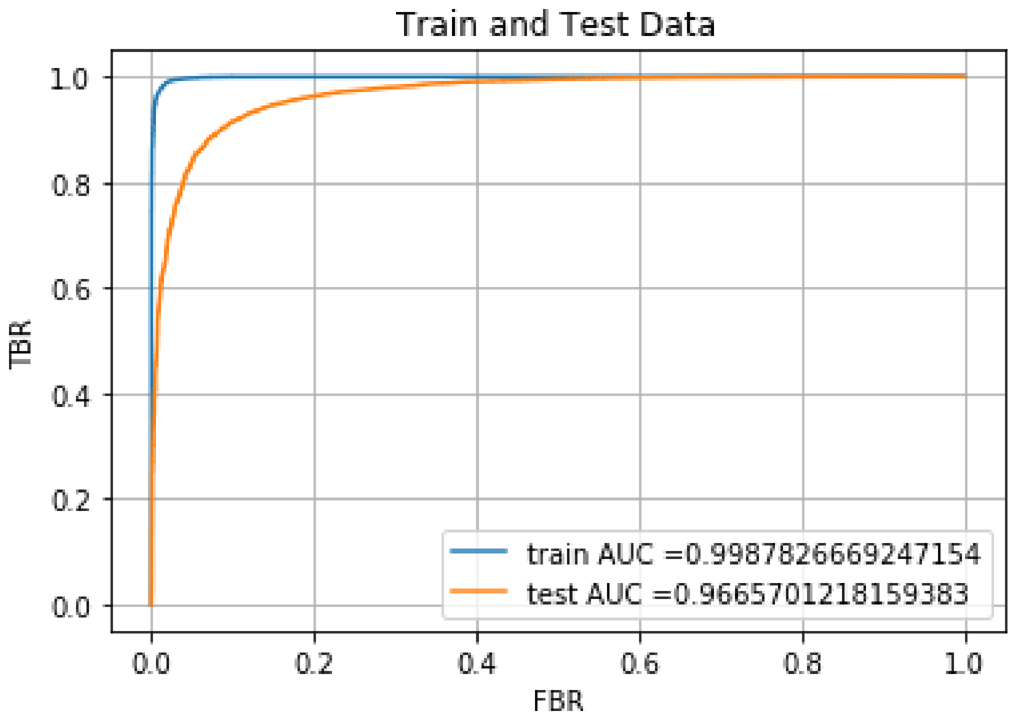
```
In [58]: # Please write all the code with proper documentation
         all_xg(X_train_tfidf,y_train,X_cv_tfidf)
```

```
Fitting 3 folds for each of 63 candidates, totalling 189 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  48 tasks      | elapsed: 10.8min
[Parallel(n_jobs=-1)]: Done 189 out of 189 | elapsed: 101.0min finished
```

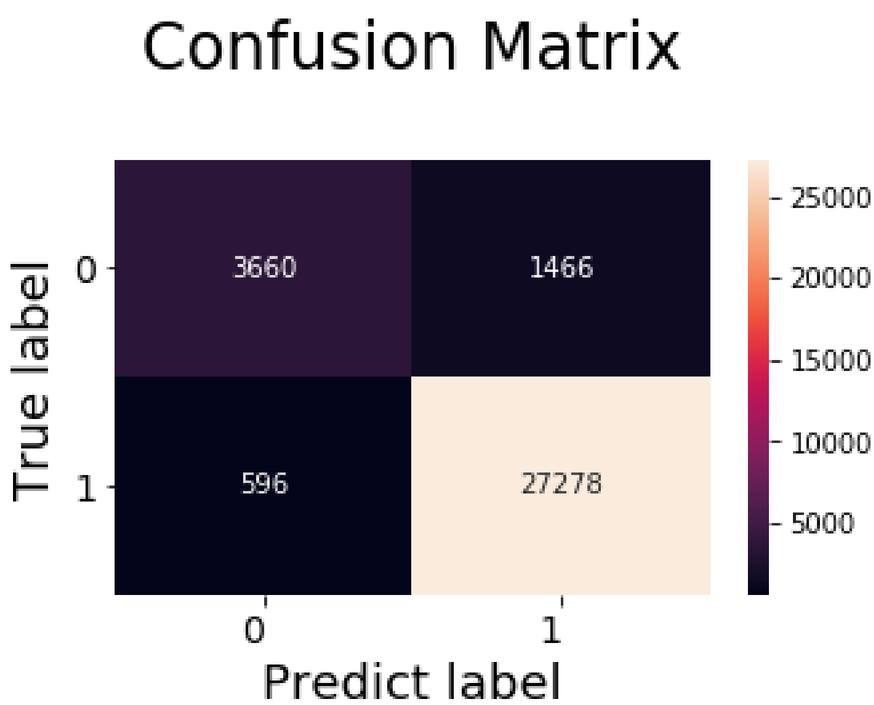





```
Max depth is =  8  Optimal value of n_estimator : 1000
--------------------------
Cv auc scores
[0.74914149 0.7830688  0.86485556 0.89790366 0.92252777 0.9443861
 0.95479245 0.77723378 0.80951478 0.884903   0.91350624 0.93426017
 0.9514343  0.95904899 0.79492082 0.81721252 0.89758297 0.92292511
 0.94056923 0.95460713 0.96048966 0.80908878 0.83646742 0.90638374
 0.92992244 0.94529508 0.95704848 0.96176269 0.82380639 0.84748675
 0.91246971 0.93405202 0.94799141 0.95831851 0.96204906 0.82973071
 0.85596184 0.91718078 0.93718239 0.94986793 0.95928038 0.96250128
 0.8401927  0.86367639 0.92079853 0.93971481 0.95149249 0.9600427
 0.96285202 0.84460868 0.8702411  0.92351061 0.94144369 0.95242703
 0.9603494  0.96253145 0.85058452 0.87259139 0.92563107 0.94281789
 0.95306491 0.95996007 0.96212908]
Maximun Auc value : 0.9628520199855344
```



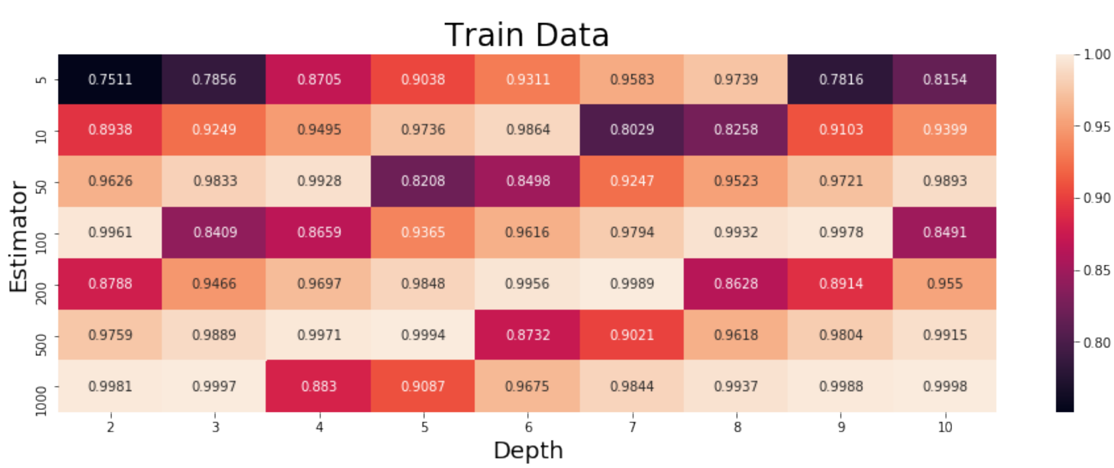

```
Train confusion matrix
[[ 6773   470]
 [   58 37589]]
Test confusion matrix
[[ 3660  1466]
 [  596 27278]]
```

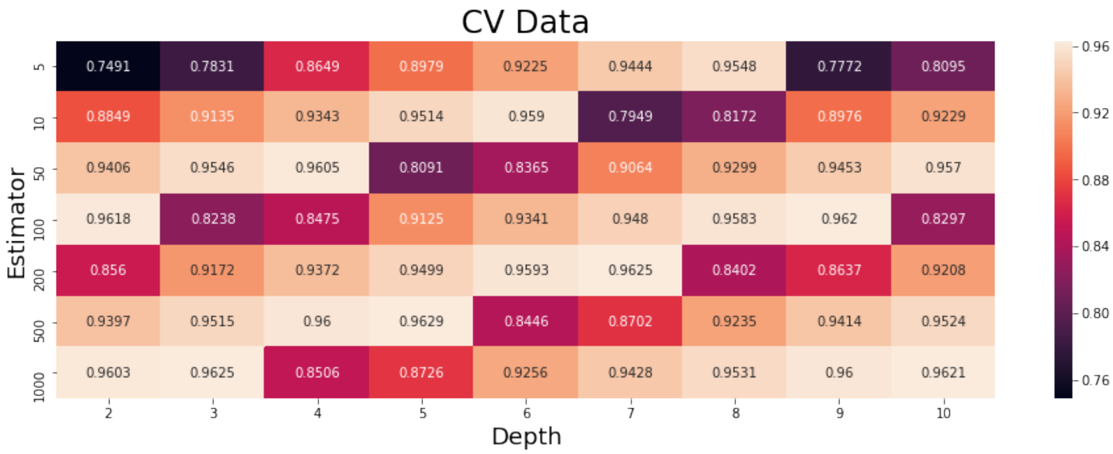



### 6.2.3 [5.2.3] Applying XGBOOST on AVG W2V, SET 3

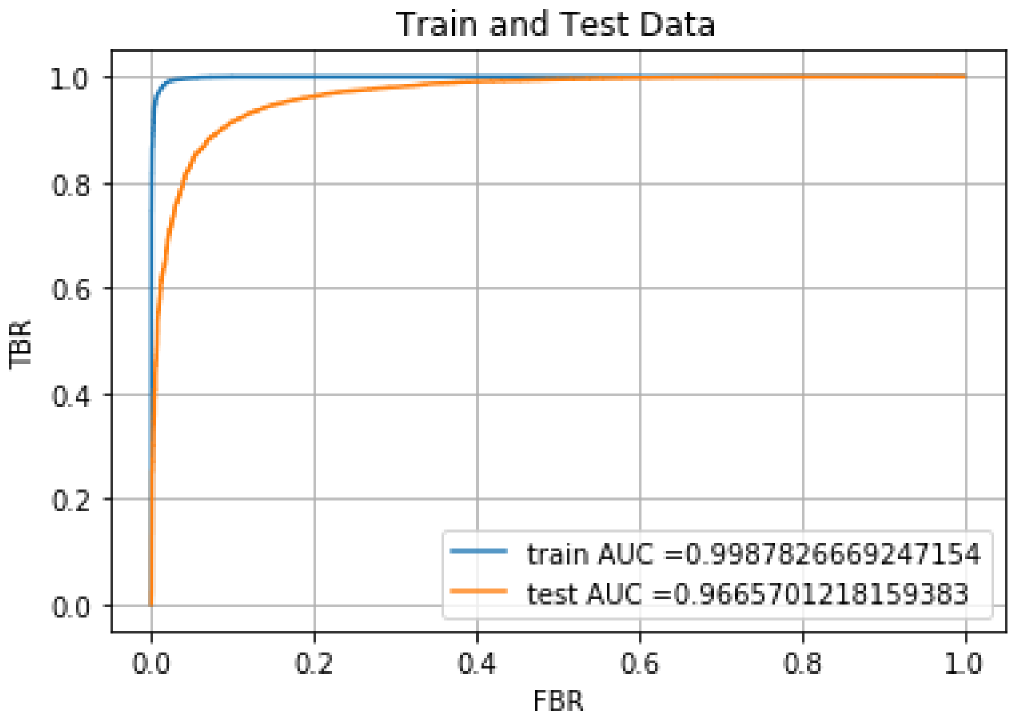
In [59]:
```
# Please write all the code with proper documentation
all_xg(train_vectors, y_train, X_cv)
```

```
Fitting 3 folds for each of 63 candidates, totalling 189 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  48 tasks      | elapsed: 10.6min
[Parallel(n_jobs=-1)]: Done 189 out of 189 | elapsed: 93.7min finished
```

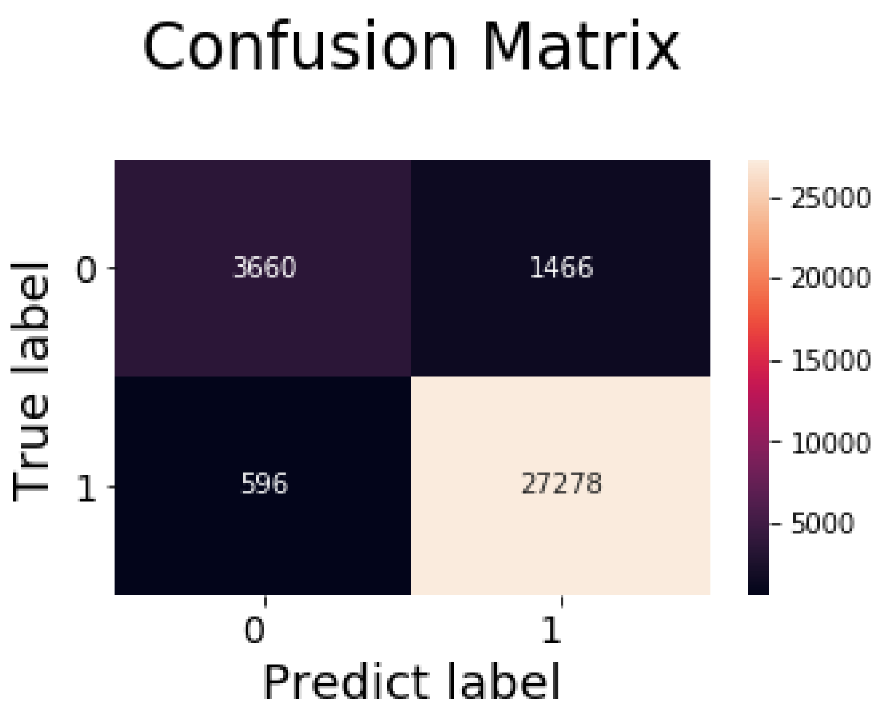





```
Max depth is =  8  Optimal value of n_estimator : 1000
--------------------------
Cv auc scores
[0.74914149 0.7830688  0.86485556 0.89790366 0.92252777 0.9443861
 0.95479245 0.77723378 0.80951478 0.884903   0.91350624 0.93426017
 0.9514343  0.95904899 0.79492082 0.81721252 0.89758297 0.92292511
 0.94056923 0.95460713 0.96048966 0.80908878 0.83646742 0.90638374
 0.92992244 0.94529508 0.95704848 0.96176269 0.82380639 0.84748675
 0.91246971 0.93405202 0.94799141 0.95831851 0.96204906 0.82973071
 0.85596184 0.91718078 0.93718239 0.94986793 0.95928038 0.96250128
 0.8401927  0.86367639 0.92079853 0.93971481 0.95149249 0.9600427
 0.96285202 0.84460868 0.8702411  0.92351061 0.94144369 0.95242703
 0.9603494  0.96253145 0.85058452 0.87259139 0.92563107 0.94281789
 0.95306491 0.95996007 0.96212908]
Maximun Auc value : 0.9628520199855344
```



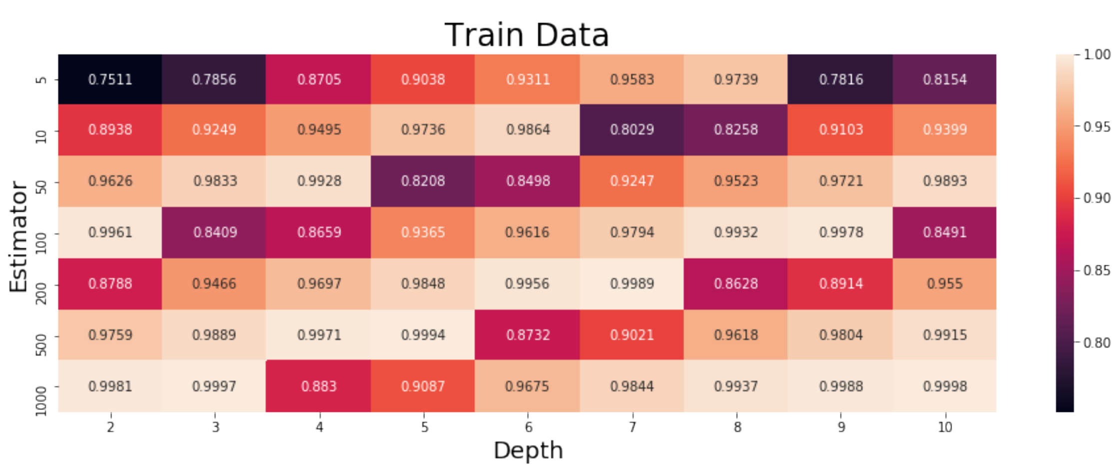

```
Train confusion matrix
[[ 6773   470]
 [   58 37589]]
Test confusion matrix
[[ 3660  1466]
 [  596 27278]]
```

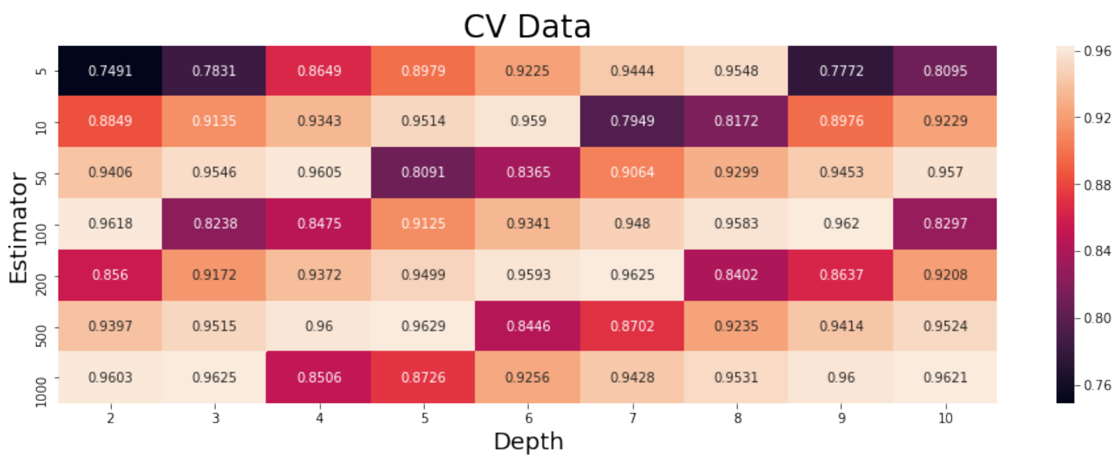



### 6.2.4 [5.2.4] Applying XGBOOST on TFIDF W2V, SET 4

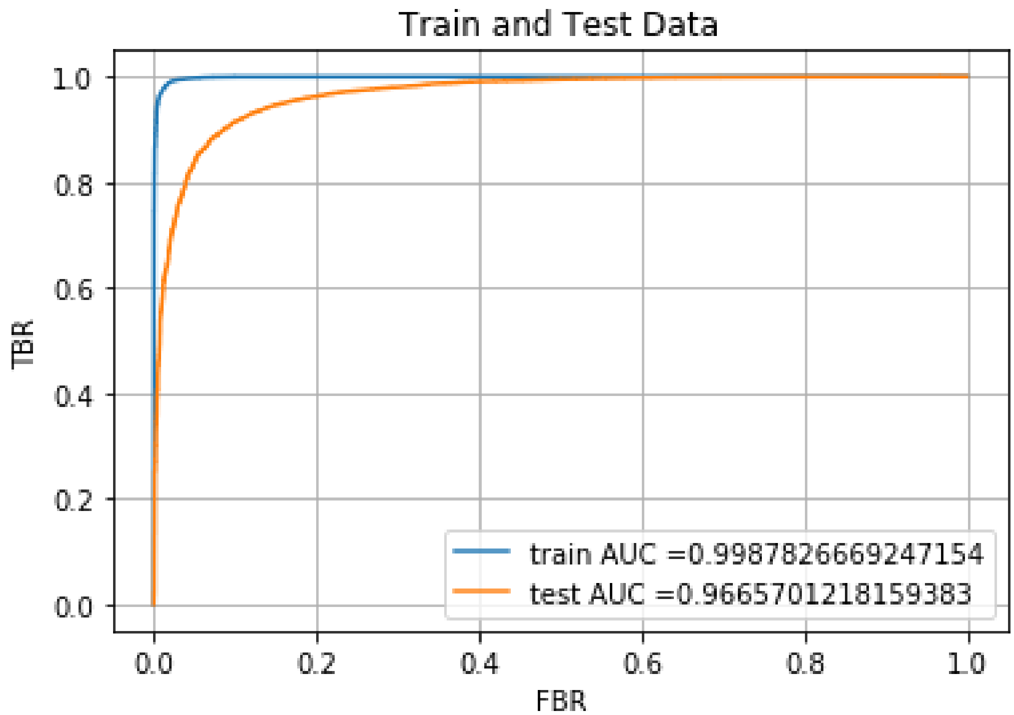
```
In [60]: # Please write all the code with proper documentation
         all_xg(tfidf_train_vectors,y_train,X_cv)
```

```
Fitting 3 folds for each of 63 candidates, totalling 189 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  48 tasks      | elapsed:  9.1min
[Parallel(n_jobs=-1)]: Done 189 out of 189 | elapsed: 85.9min finished
```

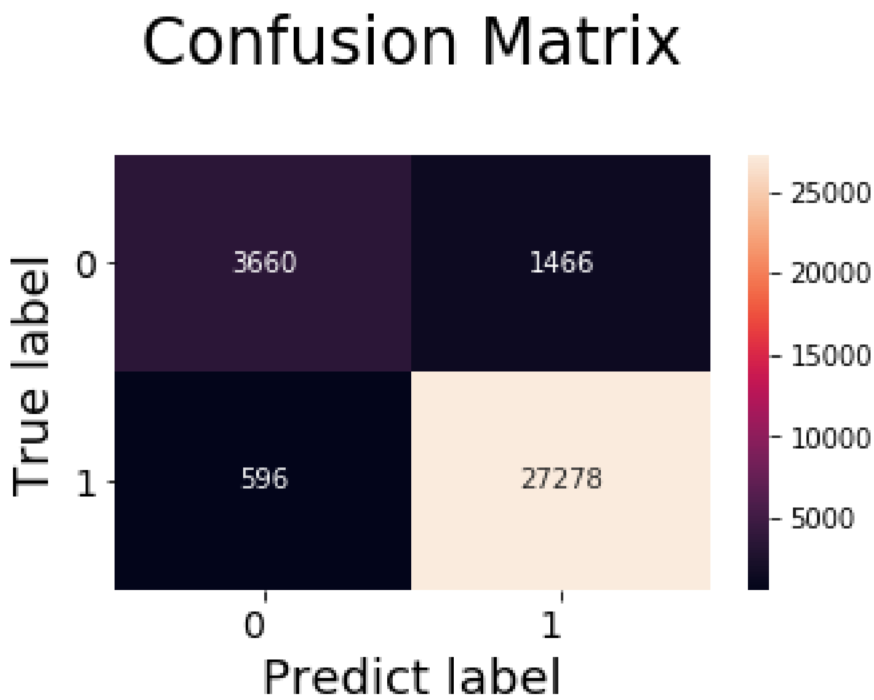





```
Max depth is =  8  Optimal value of n_estimator : 1000
--------------------------
Cv auc scores
[0.74914149 0.7830688  0.86485556 0.89790366 0.92252777 0.9443861
 0.95479245 0.77723378 0.80951478 0.884903   0.91350624 0.93426017
 0.9514343  0.95904899 0.79492082 0.81721252 0.89758297 0.92292511
 0.94056923 0.95460713 0.96048966 0.80908878 0.83646742 0.90638374
 0.92992244 0.94529508 0.95704848 0.96176269 0.82380639 0.84748675
 0.91246971 0.93405202 0.94799141 0.95831851 0.96204906 0.82973071
 0.85596184 0.91718078 0.93718239 0.94986793 0.95928038 0.96250128
 0.8401927  0.86367639 0.92079853 0.93971481 0.95149249 0.9600427
 0.96285202 0.84460868 0.8702411  0.92351061 0.94144369 0.95242703
 0.9603494  0.96253145 0.85058452 0.87259139 0.92563107 0.94281789
 0.95306491 0.95996007 0.96212908]
Maximun Auc value : 0.9628520199855344
```




```
Train confusion matrix
[[ 6773   470]
 [   58 37589]]
Test confusion matrix
[[ 3660  1466]
 [  596 27278]]
```




## 7 [6] Conclusions

```
In [96]: from prettytable import PrettyTable


         Vectorizer = ['Bag of Words','TFIDF','AVG W2V','TFIDF W2V','Bag of Words','TFIDF','AV
         Models = ['Random Forest','Random Forest','Random Forest','Random Forest','XGBOOST','X

         max_depth=[10, 10,10, 10,8, 8,8, 8]

         estimator =[500, 1000,1000, 1000,1000, 1000,1000, 1000]

         auc =[0.93,0.93,0.93,0.93,0.96,0.96,0.96,0.96]

         numbering = [1,2,3,4,5,6,7,8]

         # Initializing prettytable
         ptable = PrettyTable()

         # Adding columns
         ptable.add_column("S.NO.",numbering)
         ptable.add_column("Vectorizer",Vectorizer)
         ptable.add_column("Model",Models)
```

```
ptable.add_column("Max Depth",max_depth)
ptable.add_column("Estimator",estimator)
ptable.add_column("AUC",auc)


print(ptable)
```

```
+--------+--------------+---------------+-----------+-----------+------+
| S.NO.  |  Vectorizer  |     Model     | Max Depth | Estimator | AUC  |
+--------+--------------+---------------+-----------+-----------+------+
|   1    | Bag of Words | Random Forest |     10    |    500    | 0.93 |
|   2    |    TFIDF     | Random Forest |     10    |    1000   | 0.93 |
|   3    |   AVG W2V    | Random Forest |     10    |    1000   | 0.93 |
|   4    |  TFIDF W2V   | Random Forest |     10    |    1000   | 0.93 |
|   5    | Bag of Words |    XGBOOST    |     8     |    1000   | 0.96 |
|   6    |    TFIDF     |    XGBOOST    |     8     |    1000   | 0.96 |
|   7    |   AVG W2V    |    XGBOOST    |     8     |    1000   | 0.96 |
|   8    |  TFIDF W2V   |    XGBOOST    |     8     |    1000   | 0.96 |
+--------+--------------+---------------+-----------+-----------+------+
```

### 7.0.1 Observed:

-When Apply XGBOOST is not fast as some other models we have seen before or applied before in this same data set, it takes more run time.

-All 'Bow','TFIDF','AVG W2V','TFIDF W2V' for RF got 93% AUC values and XGBOOSTs 96%.