08 Amazon Fine Food Reviews Analysis_Decision Trees

April 23, 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 [77]:
```
%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 IPython.display import Image
from sklearn.externals.six import StringIO
from sklearn.tree import export_graphviz
from sklearn.tree import DecisionTreeClassifier

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  B000LQOCHO   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-R1105J5ZVQE25C  B005HG9ESG           Penguin Chick  1346889600      5
        4  #oc-R12KPBODL2B5ZD  B0070SBEV0   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 [0]: display[display['UserId']=='AZY10LLTJ71NX']
```

```
Out[0]:               UserId   ProductId                      ProfileName        Time  \
        80638  AZY10LLTJ71NX  B006P7E5ZI  undertheshrine "undertheshrine"  1334707200

               Score                                               Text  COUNT(*)
        80638      5  I was recommended to try green tea extract to ...         5
```

```
In [5]: display['COUNT(*)'].sum()
```

```
Out[5]: 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 [6]: display= pd.read_sql_query("""
        SELECT *
        FROM Reviews
        WHERE Score != 3 AND UserId="AR5J8UI46CURR"
        ORDER BY ProductID
        """, con)
        display.head()
```

```
Out[6]:        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 [7]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fals
```

In [8]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep=
final.shape
```

Out[8]: (160178, 10)

In [9]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[9]: 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 [10]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[10]:
```
      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 [11]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [12]:
```
#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[12]:
```
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 [13]:
```
# 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 [14]:
```
# 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 [15]: # 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 "ch
==================================================
What can I say... If Douwe Egberts was good enough for my dutch grandmother, it's perfect for m
```

```
In [16]: # 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 [17]:
```
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 [18]:
```
#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 [19]:
```
#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 [20]:
```
# 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 [21]:
```
# 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 [01:14<00:00, 2139.28it/s]
```

In [22]:
```
prepr_rev[1500]
```

Out[22]:
```
'japanese version breadcrumb pan bread portuguese loan word ko child derived panko us
```

In [23]:
```
print(len(prepr_rev))
final.shape
```

```
160176
```

Out[23]:
```
(160176, 10)
```

[3.2] Preprocessing Review Summary

In [24]:
```
## 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%|    | 92533/160176 [00:27<00:19, 3466.71it/s]/Volumes/Saida/Applications/Anaconda/anaconda
  ' Beautiful Soup.' % markup)
100%|| 160176/160176 [00:47<00:00, 3382.00it/s]
```

```
In [25]: 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 katsudon
```

```
In [26]: final ['CleanText']= prepr_rev
         final.head(5)
```

```
Out[26]:             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...
```

5 [4] Featurization

5.1 [4.1] BAG OF WORDS

In [27]:
```
##Sorting data for Time Based Splitting
time_sorted_data = final.sort_values('Time', axis=0, ascending=True, inplace=False, ki


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

```
(100000, 11)
```

Out[27]:
```
            Id   ProductId          UserId        ProfileName  \
116456  126291  B000F8GWRM  A19QUHVT4ZQOFE         Cdutton626
61113    66407  B0039555VM  A2ZRQGSEYBE67J  Ronald I. Brigham
171281  185831  B000S6CCJ8  A1W1FJS9PMCN13      Jane Benedict
12209    13321  B004286RC6  A2NRNO4MDXRR3N         Tom Farrell
154359  167368  B007PE7ANY  A2DOO9CCQFMXTB              Gayle

        HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
116456                     0                       0      0  1339718400
61113                      0                       0      1  1293753600
171281                     2                       2      1  1254873600
12209                      0                       0      1  1333843200
154359                     0                       2      0  1346803200

                                            Summary  \
116456  DO NOT EAT WILL CAUSE YOU THE WORST GAS PAIN EVER
61113                                 My favorite coffee!
171281                                 Wisotsky Tea Chest
12209                                     Best Chocolate
154359                                              Salty

                                                   Text  \
116456  I love Twizlers so I thought I would try the s...
61113   I really like this coffee and have been buying...
171281  Great for personal use and for gifts. We've bo...
12209   See's, in my opinion, makes absolutely the bes...
154359  I tried this product, I didn't like it it was ...

                                               CleanText
116456  love twizlers thought would try sugar free ver...
61113   really like coffee buying several years howeve...
171281  great personal use gifts bought many people al...
12209   see opinion makes absolutely best chocolate un...
154359  tried product not like salty anyone high blood...
```

In [28]:
```
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 [31]:
```
#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 [34]:
```
#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 [35]:
```
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_name
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', 'ad
==================================================
```

5.4 [4.4] Word2Vec

In [36]:
```
# 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))
```

```
[('awesome', 0.8556177020072937), ('fantastic', 0.8334372043609619), ('terrific', 0.8264545202
==================================================
[('greatest', 0.7232632637023926), ('best', 0.7159654498100281), ('nastiest', 0.674301922321319
number of words that occured minimum 5 times  13343
```

In [37]:
```
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  13343
sample words  ['thick', 'utterly', 'delicious', 'balsamic', 'vinegar', 'no', 'caramel', 'colori
```

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

[4.4.1.1] Avg W2v

In [38]:
```
i=0
sent_of_test_cv=[]
for sentance in X_cv:
    sent_of_test_cv.append(sentance.split())
```

In [39]:
```
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 [01:12<00:00, 303.95it/s]

(22110, 50)
[ 2.10879025e-01 -3.48979588e-01 -2.82775587e-01  5.26032030e-01
  5.53550757e-03  2.10376255e-02  4.25016807e-01 -5.90636294e-01
 -2.70678211e-01  6.30688488e-02  7.79606439e-01  3.37669363e-01
 -5.56653980e-01  2.48347844e-04  3.28603715e-01  1.41075848e-01
  3.94519731e-01  4.10266740e-01 -8.83218416e-01  6.48740852e-02
 -8.42590893e-02  4.89774836e-01 -3.94979228e-01  2.32904077e-02
 -2.42288573e-01  1.95402906e-01  7.55785605e-01  6.08583945e-01
  4.63347926e-01  2.94547666e-01  7.61879325e-01 -1.81995569e-01
  6.91946273e-01  2.26891597e-01  6.94460502e-01 -5.22611486e-02
  7.77595306e-01  3.12045039e-02  4.23307268e-01  2.34798140e-01
  3.53932600e-01  5.94060239e-01 -3.31579724e-01 -4.59658874e-01
  1.62416048e-01  7.06878490e-01  6.94606354e-01 -3.08406014e-01
  4.56698843e-01 -7.25057525e-02]
```

```
In [40]: # 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 [01:55<00:00, 285.09it/s]
```

```
(33000, 50)
[-0.04484278 -0.98094821  0.06490975  0.77845469  0.06160066 -0.38127362
  0.12176091 -0.48559902  0.52513363 -0.54016219  0.1140505  -0.01575537
  0.16055723 -0.10981051 -0.24351136  0.26646428  0.15815589  0.07710142
  0.01434893 -0.36858722 -0.42938664 -0.11335435 -0.55403221  0.7508934
 -0.27931624 -0.32391615  0.21598508  0.05881603  0.5975235  -0.35665337
  0.41293948 -0.47716167  0.28751567 -0.0017753   1.29433724  0.01361005
  0.07377485 -0.17576912  0.48629449  0.24419177 -0.21880108  0.31494414
  0.56726783 -0.56366112  0.08059364  0.61108769  0.91993372 -0.61532114
  0.45034025 -0.11152897]
```

```
In [41]: # 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 [02:09<00:00, 347.64it/s]
```

```
(44890, 50)
[ 0.20589348 -0.46647361  0.30686487  0.67855221 -0.2245382  -0.14743991
  0.16249183 -0.56041429  0.0903703   0.19374888  0.41164201 -0.13900378
 -0.20276569  0.78398465 -0.07428925  0.74533296  0.20773133  0.29324919
 -0.22018799 -0.40283698 -0.50687322  0.86521718 -0.16656635  0.12893605
 -0.47053649 -0.14061254  0.27277417  0.00657488 -0.35115422  0.42768579
  0.56756557 -0.57841713 -0.24381239 -0.3229239   1.32751345  0.76809751
 -0.35866272  0.09910044  0.38541745 -0.03158472  0.16374991  0.6143065
  0.03423175 -0.24805431 -0.54617593  0.01464439  0.45464489  0.35100201
  0.13069364 -0.2408401 ]
```

[4.4.1.2] TFIDF weighted W2v

In [42]:
```
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 [23:11<00:00, 23.71it/s]

(33000, 50)
[-0.05867975 -0.81840016  0.01550789  0.76012586 -0.07593843 -0.25108136
  0.17660245 -0.29453132  0.4457865  -0.45814356  0.00955802  0.0207721
  0.16425236  0.05244858 -0.200853    0.15241338  0.21510971  0.10148712
  0.05810314 -0.30514034 -0.38030058 -0.07415261 -0.56575887  0.69470838
 -0.27209041 -0.1847674   0.27319222  0.10213101  0.53012813 -0.33384253
  0.38188978 -0.32749265  0.22372857 -0.13716998  1.12177612  0.10011898
  0.12335294 -0.11740182  0.38993361  0.23355767 -0.14113065  0.28826309
  0.48279012 -0.58987134  0.03591074  0.4788944   0.86686662 -0.58208808
  0.30676786 -0.22806437]
```

In [43]:
```
# TF-IDF weighted Word2Vec
# compute TFIDF Weighted Word2Vec for X_train .
```

```python
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 [32:24<00:00, 23.08it/s]
```

```
(44890, 50)
[ 0.23749914 -0.33554841  0.59981253  0.56687557 -0.41496096 -0.31974582
  0.21053894 -0.55191055 -0.00614808  0.06785204  0.2023     -0.46574261
  0.07462821  1.56342778  0.05565031  0.90016656  0.01315081  0.46672271
  0.11828226 -0.40188229 -0.50410301  0.90837816 -0.19803636  0.14962699
  0.12799858 -0.37108493  0.49690321 -0.19898207 -0.28724165  0.22887403
  0.27847209 -0.4231636  -0.38710967 -0.40896379  0.88220628  1.09786892
 -0.24679644  0.05527545  0.43963774 -0.19567637  0.42734269  0.88291983
 -0.03657182 -0.54552855 -0.61266246 -0.02088902  0.56070897  0.50443178
 -0.10266092 -0.37483865]
```

6 [5] Assignment 8: Decision Trees

```
<li><strong>Apply Decision Trees on these feature sets</strong>
    <ul>
        <li><font color='red'>SET 1:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 2:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 3:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 4:</font>Review text, preprocessed one converted into vectors
    </ul>
</li>
<br>
<li><strong>The hyper paramter tuning (best `depth` in range [1, 5, 10, 50, 100, 500, 100], and
```

```
    <ul>
<li>Find the best hyper parameter which will give the maximum <a href='https://www.appliedaicou
<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>Graphviz</strong>
    <ul>
<li>Visualize your decision tree with Graphviz. It helps you to understand how a decision is be
<li>Since feature names are not obtained from word2vec related models, visualize only BOW & TF
<li>Make sure to print the words in each node of the decision tree instead of printing its inde
<li>Just for visualization purpose, limit max_depth to 2 or 3 and either embed the generated in
    </ul>
</li>
<br>
<li><strong>Feature importance</strong>
    <ul>
<li>Find the top 20 important features from both feature sets <font color='red'>Set 1</font> an
    </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='train_cv_auc.JPG' width=300px></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.c
<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>
```


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.

7 Applying Decision Trees

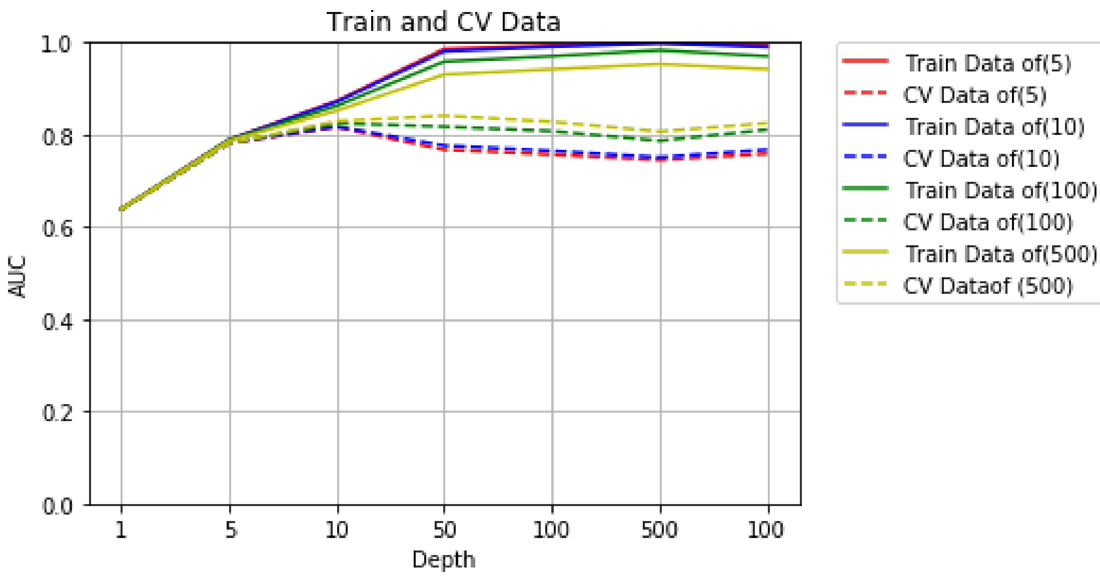
7.1 [5.1] Applying Decision Trees on BOW, SET 1

In [123]:
```
# Please write all the code with proper documentation
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
from sklearn.metrics import roc_auc_score, auc
from sklearn.model_selection import GridSearchCV

def all_dt(X_train,y_train,X_cv):
    depth = [1, 5, 10, 50, 100, 500, 100]
    min_sample_split = [5, 10, 100, 500]
    hyper_param = {'max_depth':depth, 'min_samples_split':min_sample_split}


    clf = DecisionTreeClassifier(class_weight='balanced')
    gsv = GridSearchCV(clf,hyper_param,scoring='roc_auc')
    gsv.fit(X_train_bow,y_train)
    opt_depth, opt_split  = gsv.best_params_.get('max_depth'), gsv.best_params_.get(


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


    x2 = np.arange(len(depth))
    plt.plot(x2,train_auc[::4],'r', label = 'Train Data of(5)')
    plt.plot(x2,cv_auc[::4],'r--', label = 'CV Data of(5)')

    plt.plot(x2,train_auc[1::4],'b', label = 'Train Data of(10)')
    plt.plot(x2,cv_auc[1::4],'b--', label = 'CV Data of(10)')

    plt.plot(x2,train_auc[2::4],'g', label = 'Train Data of(100)')
    plt.plot(x2,cv_auc[2::4],'g--', label = 'CV Data of(100)')
```

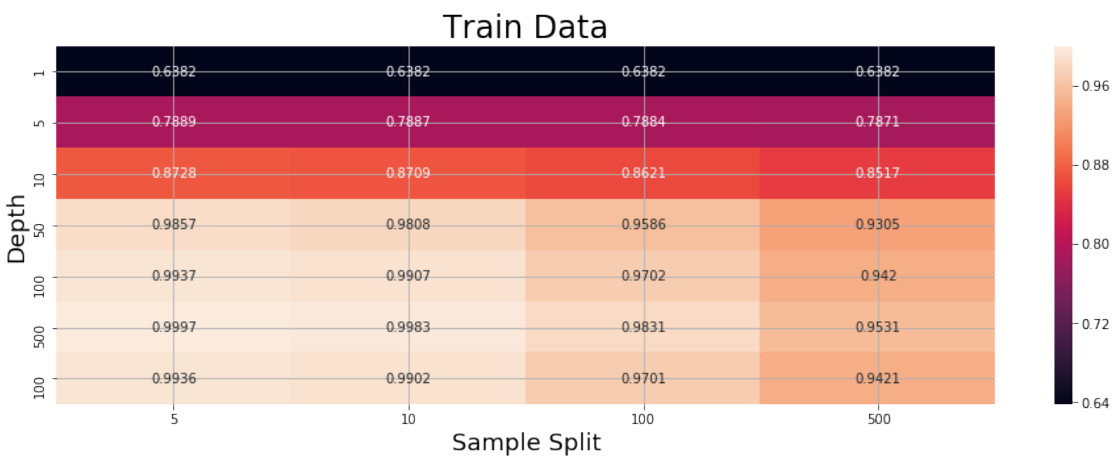
```
plt.plot(x2,train_auc[3::4],'y', label = 'Train Data of(500)')
plt.plot(x2,cv_auc[3::4],'y--', label = 'CV Dataof (500)')


plt.xticks(x2, depth)
plt.ylim(0,1)
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0.)
plt.grid(True)
plt.title("Train and CV Data")
plt.xlabel("Depth")
plt.ylabel("AUC")
plt.show()


df_heatmap = pd. DataFrame(train_auc. reshape(7, 4), index=depth, columns=min_sam
fig = plt. figure(figsize=(16,5))
heatmap = sns. heatmap(df_heatmap, annot=True, fmt='.4g')
plt.grid(True)
plt. ylabel('Depth', size=18)
plt. xlabel('Sample Split' , size=18)
plt. title("Train Data", size=24)
plt. show()

df_heatmap = pd. DataFrame(cv_auc . reshape(7, 4), index=depth, columns=min_sampl
fig = plt. figure(figsize=(16,5))
heatmap = sns. heatmap(df_heatmap, annot=True, fmt='.4g')
plt.grid(True)
plt. ylabel('Depth' , size=18)
plt. xlabel('Sample Split' , size=18)
plt. title("CV Data", size=24)
plt. show()

print("Optimal value of max_depth = ", opt_depth , " Optimal min_samples_split is

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

#test data

clf = DecisionTreeClassifier(max_depth=opt_depth, min_samples_split=opt_split,cla
clf.fit(X_train_bow,y_train)

train_fpr, train_tpr, thresholds = roc_curve(y_train, clf.predict_proba(X_train_b
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='rig
        heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='rig
        plt.ylabel('True label',size=18)
        plt.xlabel('Predict label',size=18)
        plt.title("Confusion Matrix\n",size=24)
        plt.show()
```

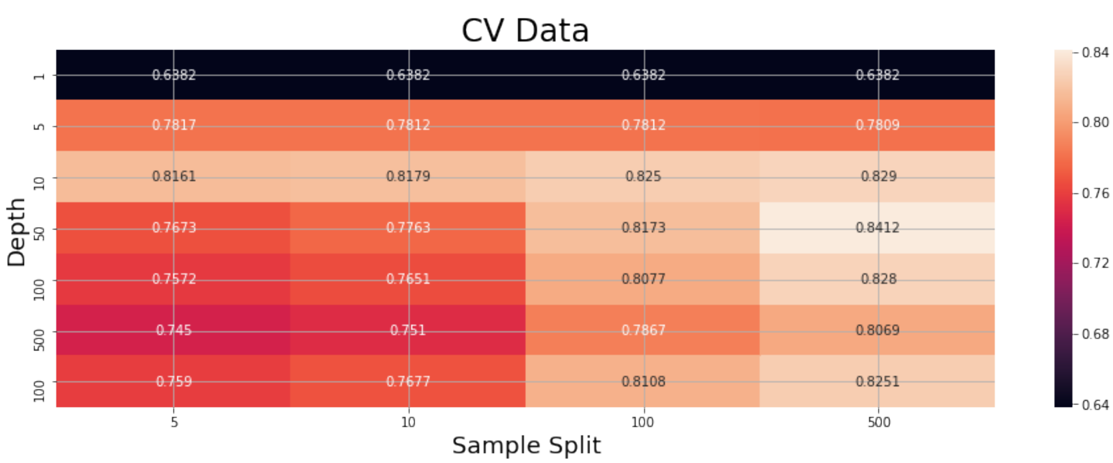
```
In [124]: all_dt(X_train_bow,y_train,X_cv_bow)
```



Train and CV Data
AUC
Depth
1.0
0.8
0.6
0.4
0.2
0.0
1
5
10
50
100
500
100
Train Data of(5)
CV Data of(5)
Train Data of(10)
CV Data of(10)
Train Data of(100)
CV Data of(100)
Train Data of(500)
CV Dataof (500)

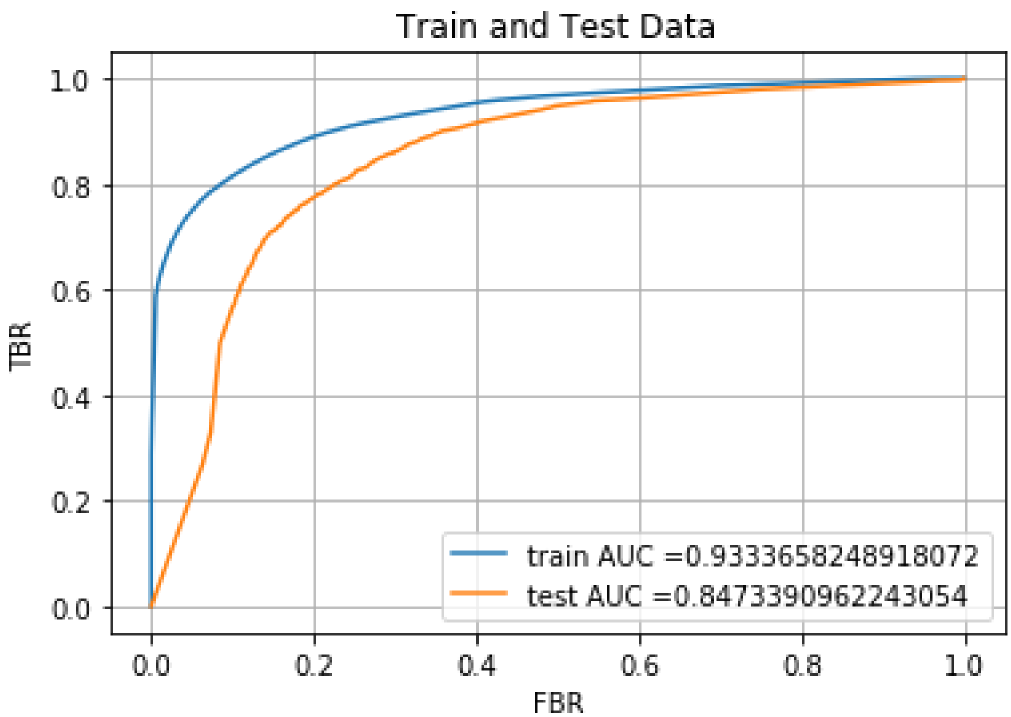


Train Data
Depth
Sample Split
1
5
10
50
100
500
100
0.6382 0.6382 0.6382 0.6382
0.7889 0.7887 0.7884 0.7871
0.8728 0.8709 0.8621 0.8517
0.9857 0.9808 0.9586 0.9305
0.9937 0.9907 0.9702 0.942
0.9997 0.9983 0.9831 0.9531
0.9936 0.9902 0.9701 0.9421
5
10
100
500
0.96
0.88
0.80
0.72
0.64

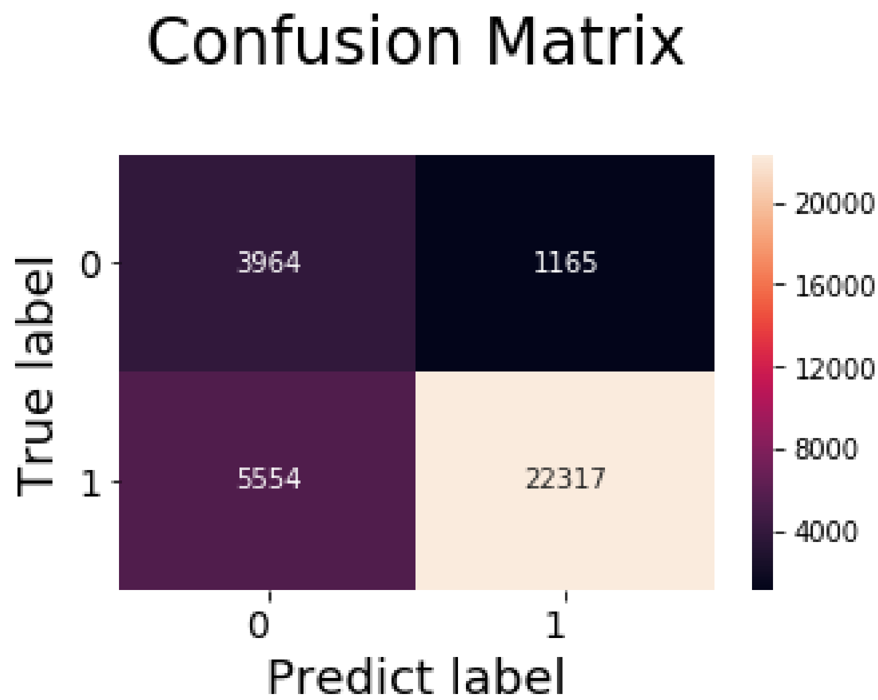


CV Data
Depth
Sample Split
1
5
10
50
100
500
100
0.6382 0.6382 0.6382 0.6382
0.7817 0.7812 0.7812 0.7809
0.8161 0.8179 0.825 0.829
0.7673 0.7763 0.8173 0.8412
0.7572 0.7651 0.8077 0.828
0.745 0.751 0.7867 0.8069
0.759 0.7677 0.8108 0.8251
5
10
100
500
0.84
0.80
0.76
0.72
0.68
0.64

```
Optimal value of max_depth =  50  Optimal min_samples_split is : 500
--------------------------
Cv auc scores
[0.63822825 0.63822825 0.63822825 0.63822825 0.78165477 0.78118162
 0.7811762  0.78089648 0.81610346 0.81785086 0.82497895 0.82901288
 0.76730866 0.77625887 0.8172913  0.84116786 0.75715314 0.7651314
 0.80773959 0.82803354 0.74499855 0.75098662 0.7867425  0.80687326
 0.75899993 0.7676521  0.8108232  0.82513108]
Maximun Auc value : 0.841167862983478
```




```
Train confusion matrix
[[ 6424   724]
 [ 6914 30828]]
Test confusion matrix
[[ 3964  1165]
 [ 5554 22317]]
```



7.1.1 [5.1.1] Top 20 important features from SET 1

```
In [125]: # Please write all the code with proper documentation
          clf = DecisionTreeClassifier(max_depth= 50, min_samples_split=500,class_weight= 'bala
          clf.fit(X_train_bow,y_train)
          feat = vectorizer.get_feature_names()
          n=20
          coefs = sorted(zip(clf.feature_importances_, feat))
          top = coefs[:-(n + 1):-1]

          print("Feature importances\tFeatures")
          for (coef1, feat1) in top:
              print("%.4f\t\t\t%-15s" % (coef1, feat1))
```

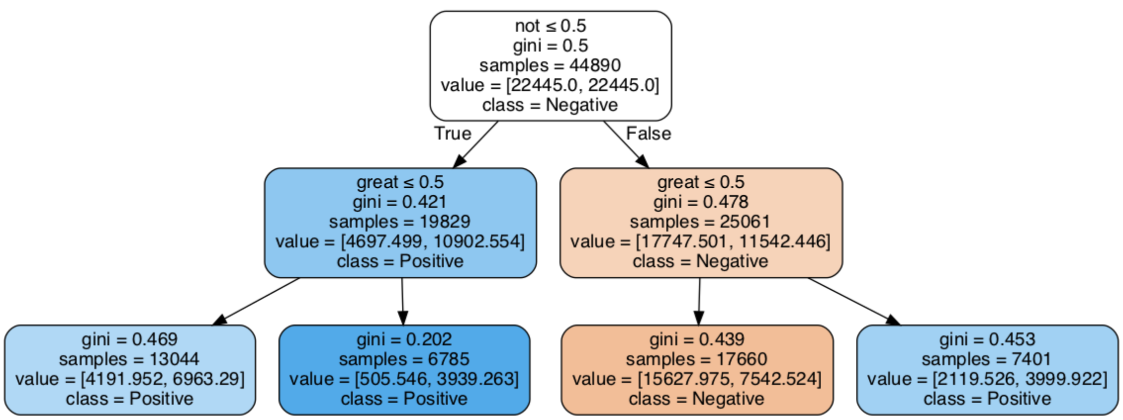
```
Feature importances        Features
0.1731                        not
0.1152                        great
0.0637                        best
0.0491                        delicious
0.0356                        good
0.0328                        love
0.0236                        excellent
0.0180                        perfect
0.0175                        loves
```

```
0.0175                          bad
0.0163                          disappointed
0.0159                          favorite
0.0135                          not good
0.0135                          not great
0.0122                          tasty
0.0094                          wonderful
0.0084                          nice
0.0076                          amazing
0.0073                          terrible
0.0068                          awesome
```

7.1.2 [5.1.2] Graphviz visualization of Decision Tree on BOW, SET 1

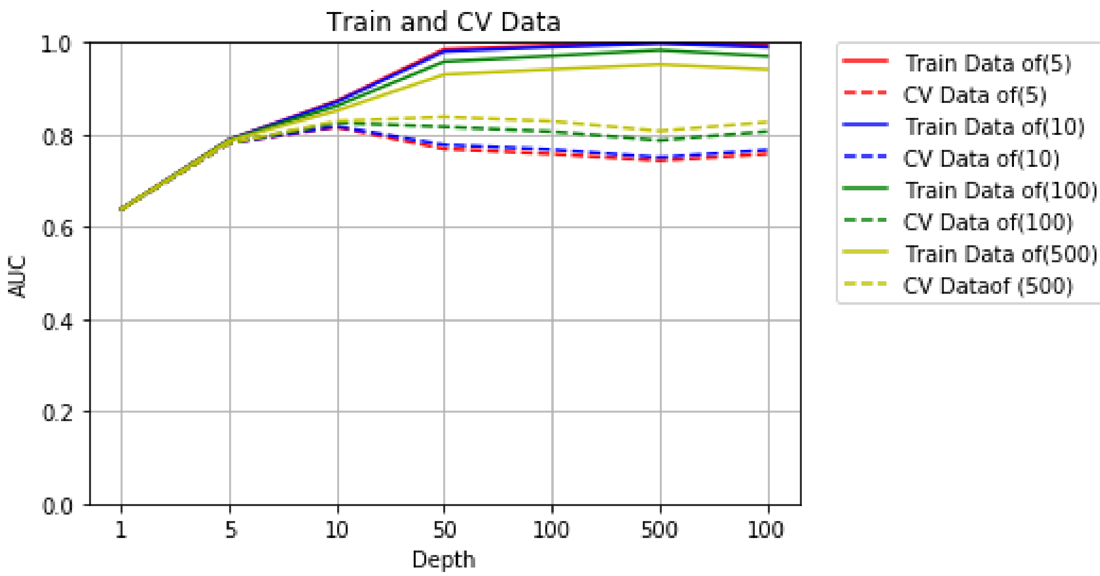
```
In [126]: # Please write all the code with proper documentation
          import pydot
          clf = DecisionTreeClassifier(max_depth= 2, min_samples_split=500,class_weight= 'balar
          clf.fit(X_train_bow,y_train)
          names=vectorizer.get_feature_names()
          dot_data = StringIO()
          tree.export_graphviz(clf, out_file=dot_data,feature_names=names,
                               class_names=['Negative','Positive'],
                               filled=True, rounded=True,
                               special_characters=True)
          graph = pydot.graph_from_dot_data(dot_data.getvalue())[0]
          Image(graph.create_png())
```

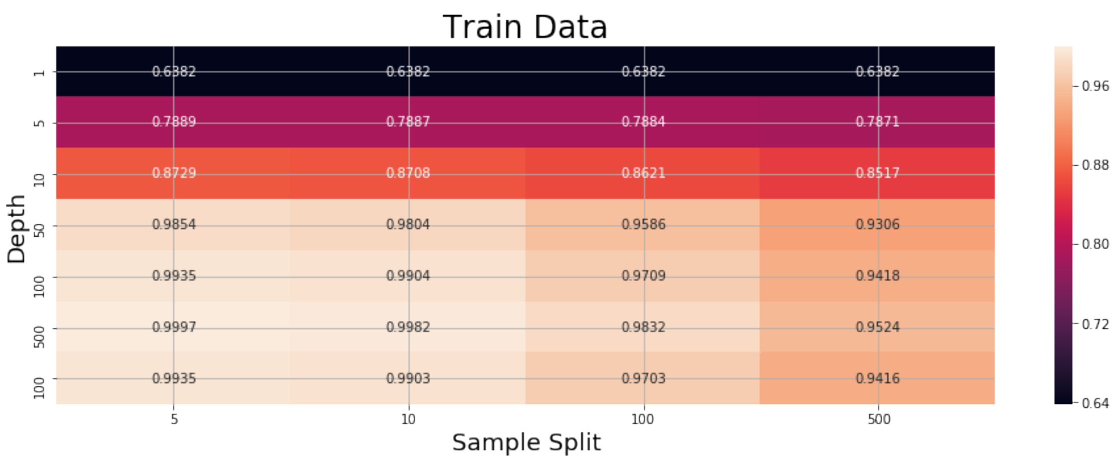
Out[126]:

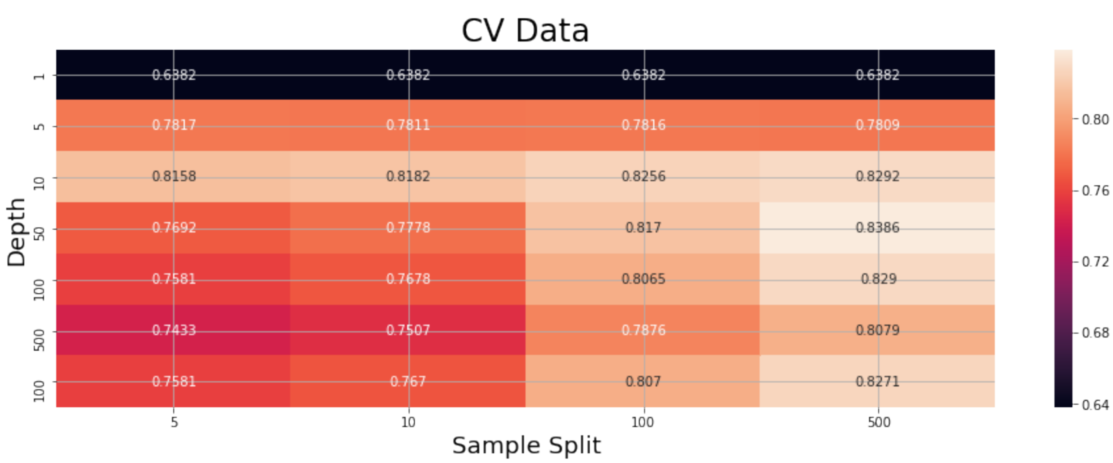


7.2 [5.2] Applying Decision Trees on TFIDF, SET 2

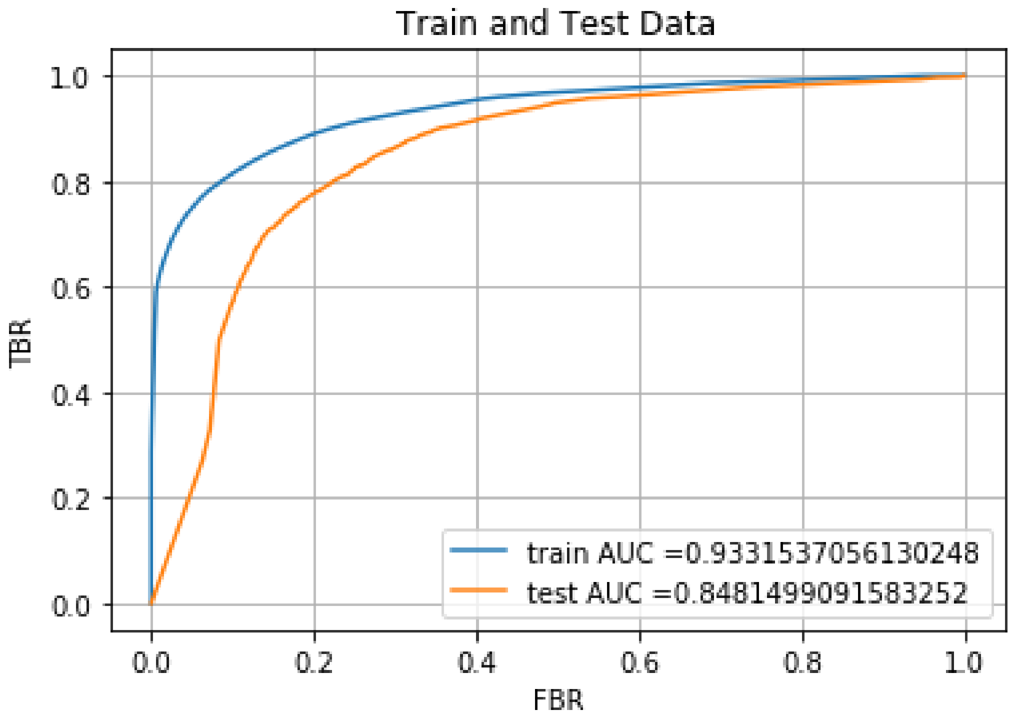
```
In [127]: # Please write all the code with proper documentation
          all_dt(X_train_tfidf,y_train,X_cv_tfidf)
```


Train and CV Data
AUC
Depth
1.0
0.8
0.6
0.4
0.2
0.0
1
5
10
50
100
500
100
Train Data of(5)
CV Data of(5)
Train Data of(10)
CV Data of(10)
Train Data of(100)
CV Data of(100)
Train Data of(500)
CV Dataof (500)

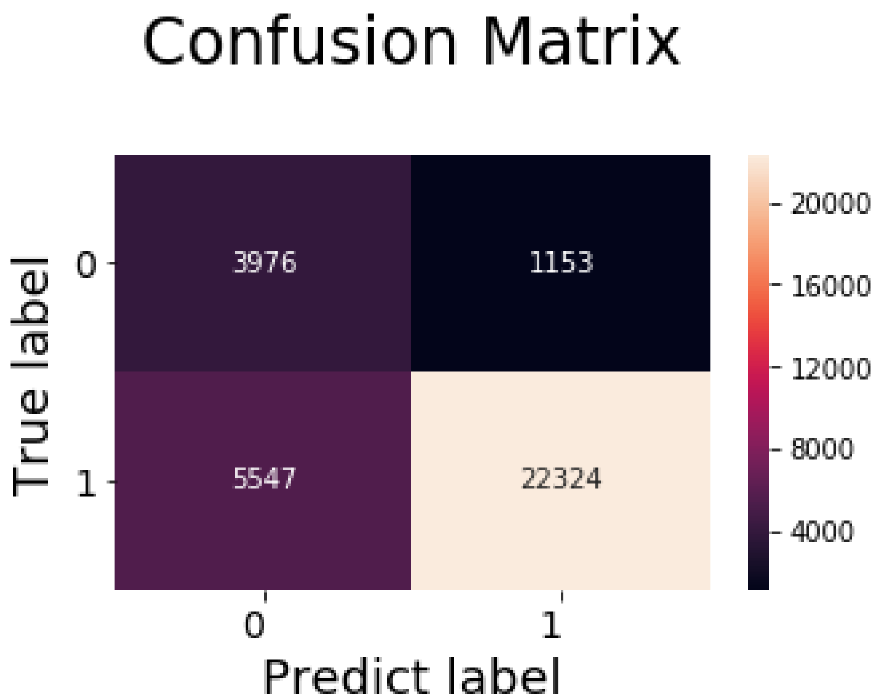

Train Data
Depth
Sample Split
1
5
10
50
100
500
100
0.6382 0.6382 0.6382 0.6382
0.7889 0.7887 0.7884 0.7871
0.8729 0.8708 0.8621 0.8517
0.9854 0.9804 0.9586 0.9306
0.9935 0.9904 0.9709 0.9418
0.9997 0.9982 0.9832 0.9524
0.9935 0.9903 0.9703 0.9416
5
10
100
500
0.96
0.88
0.80
0.72
0.64


CV Data
Depth
Sample Split
1
5
10
50
100
500
100
0.6382 0.6382 0.6382 0.6382
0.7817 0.7811 0.7816 0.7809
0.8158 0.8182 0.8256 0.8292
0.7692 0.7778 0.817 0.8386
0.7581 0.7678 0.8065 0.829
0.7433 0.7507 0.7876 0.8079
0.7581 0.767 0.807 0.8271
5
10
100
500
0.80
0.76
0.72
0.68
0.64

```
Optimal value of max_depth =  50  Optimal min_samples_split is : 500
--------------------------
Cv auc scores
[0.63822825 0.63822825 0.63822825 0.63822825 0.78170777 0.78107589
 0.78162128 0.78089648 0.81583388 0.81819682 0.8256137  0.82916547
 0.76923142 0.77782108 0.81700052 0.83855215 0.75807367 0.76777095
 0.80653847 0.82904648 0.74331187 0.7506596  0.78764356 0.807855
 0.75810284 0.76698066 0.80695758 0.82713734]
Maximun Auc value : 0.8385521546054655
```




```
Train confusion matrix
[[ 6423   725]
 [ 6937 30805]]
Test confusion matrix
[[ 3976  1153]
 [ 5547 22324]]
```



7.2.1 [5.2.1] Top 20 important features from SET 2

```
In [129]: # Please write all the code with proper documentation

          clf = DecisionTreeClassifier(max_depth= 50, min_samples_split=500,class_weight= 'bala
          clf.fit(X_train_tfidf,y_train)
          feat = tf_idf_vect.get_feature_names()
          n=20
          coefs = sorted(zip(clf.feature_importances_, feat))
          top = coefs[:-(n + 1):-1]

          print("Feature importances\tFeatures")
          for (coef1, feat1) in top:
              print("%.4f\t\t\t%-15s" % (coef1, feat1))
```

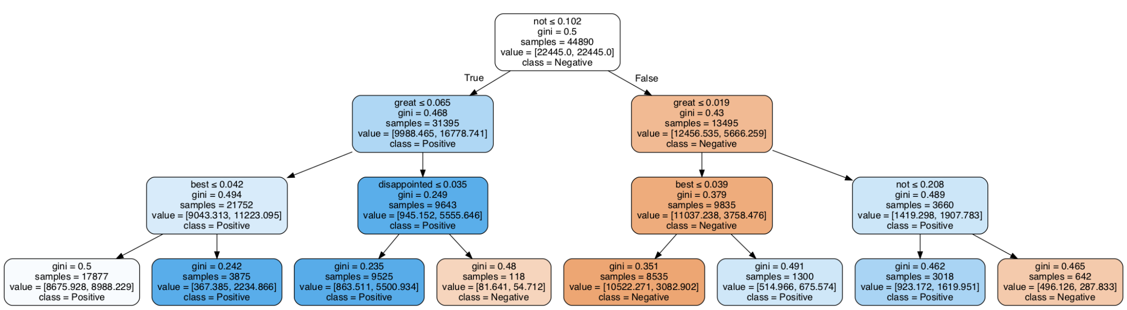
```
Feature importances        Features
0.1965                        not
0.1256                        great
0.0680                        best
0.0546                        delicious
0.0437                        love
0.0421                        good
0.0251                        disappointed
0.0240                        excellent
```

```
0.0214                        bad
0.0213                        perfect
0.0178                        favorite
0.0176                        loves
0.0123                        not good
0.0119                        wonderful
0.0116                        nice
0.0115                        easy
0.0098                        tasty
0.0092                        awesome
0.0081                        thought
0.0076                        works
```

7.2.2 [5.2.2] Graphviz visualization of Decision Tree on TFIDF, SET 2

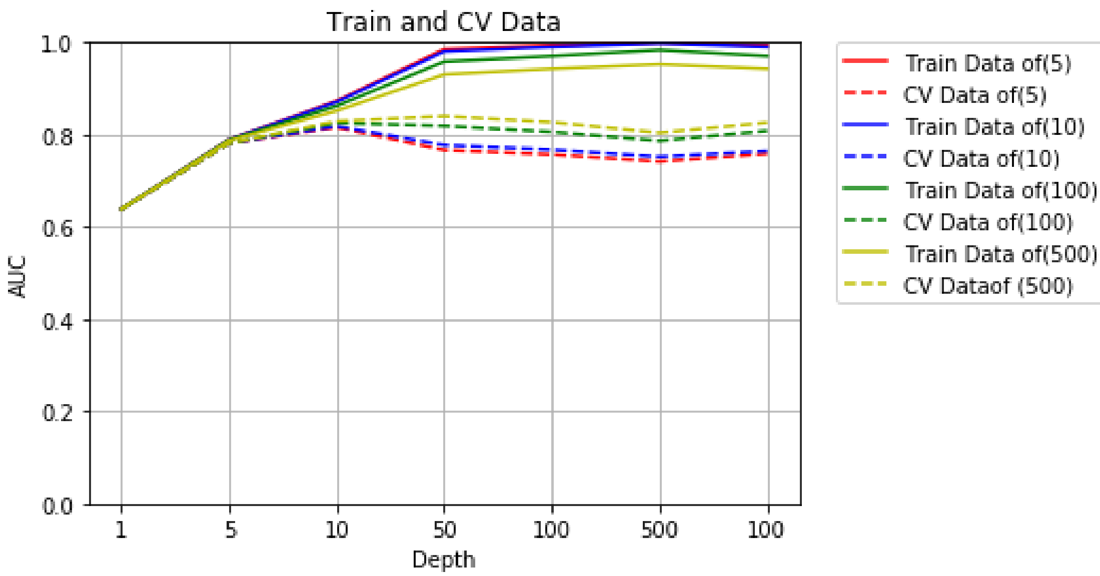
In [130]:
```
# Please write all the code with proper documentation
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10, max_features=500)
tf_idf_vect.fit(X_train)
clf = DecisionTreeClassifier(max_depth= 3, min_samples_split=500,class_weight= 'balan
clf.fit(X_train_tfidf,y_train)
names=tf_idf_vect.get_feature_names()
dot_data = StringIO()
tree.export_graphviz(clf, out_file=dot_data,feature_names=names,
                     class_names=['Negative','Positive'],
                     filled=True, rounded=True,
                     special_characters=True)
graph = pydot.graph_from_dot_data(dot_data.getvalue())[0]
Image(graph.create_png())
```

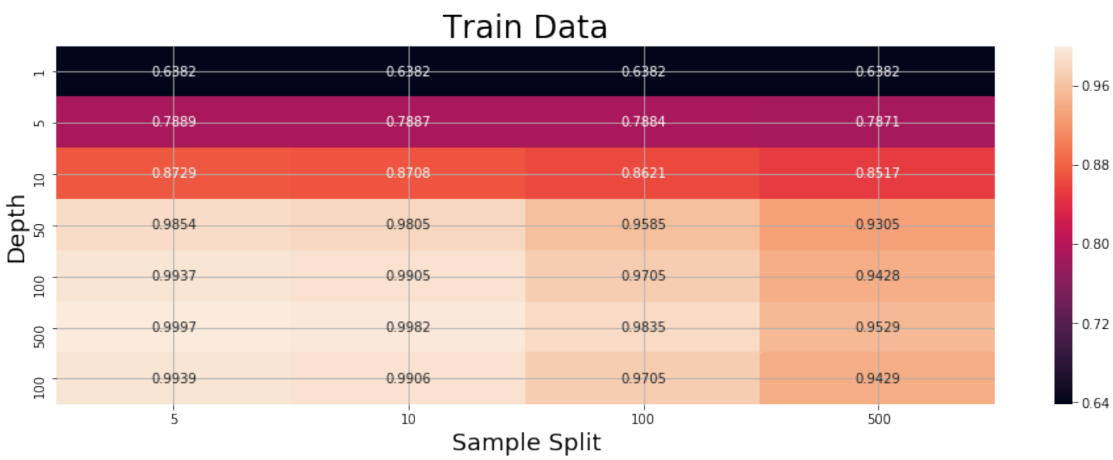
Out[130]:

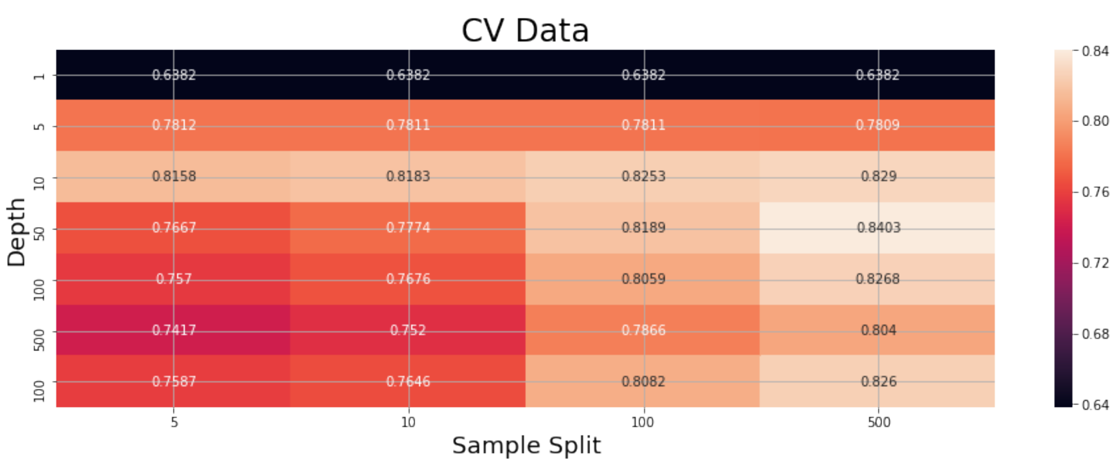


7.3 [5.3] Applying Decision Trees on AVG W2V, SET 3

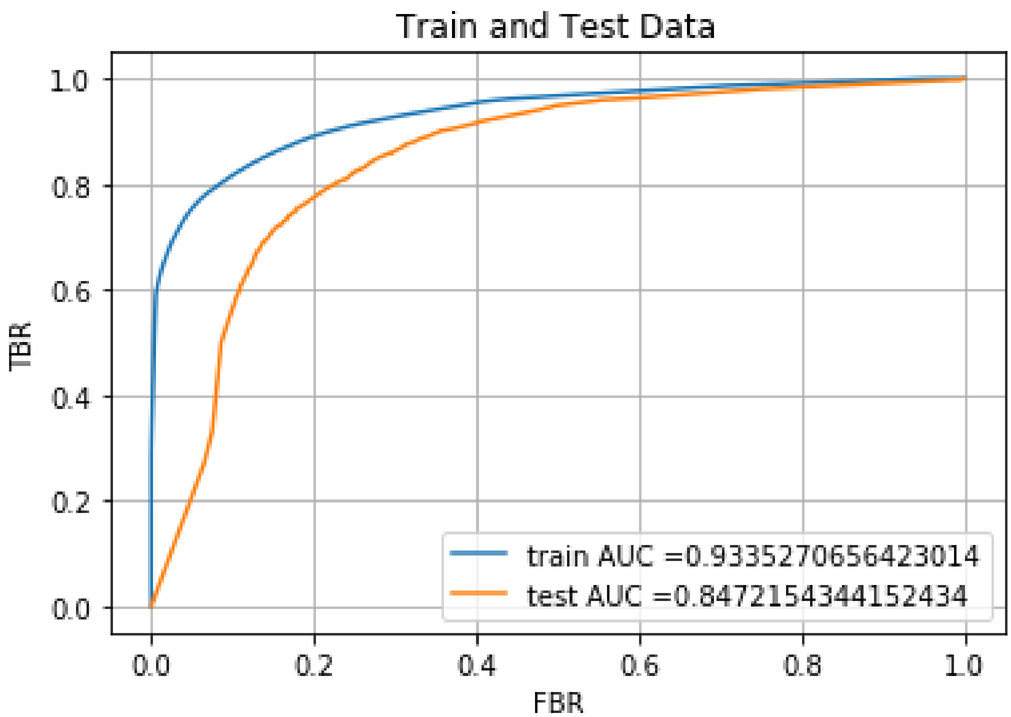
In [131]:
```
# Please write all the code with proper documentation
all_dt(train_vectors, y_train, X_cv)
```


Train and CV Data
AUC
1.0
0.8
0.6
0.4
0.2
0.0
1
5
10
50
100
500
100
Depth
Train Data of(5)
CV Data of(5)
Train Data of(10)
CV Data of(10)
Train Data of(100)
CV Data of(100)
Train Data of(500)
CV Dataof (500)

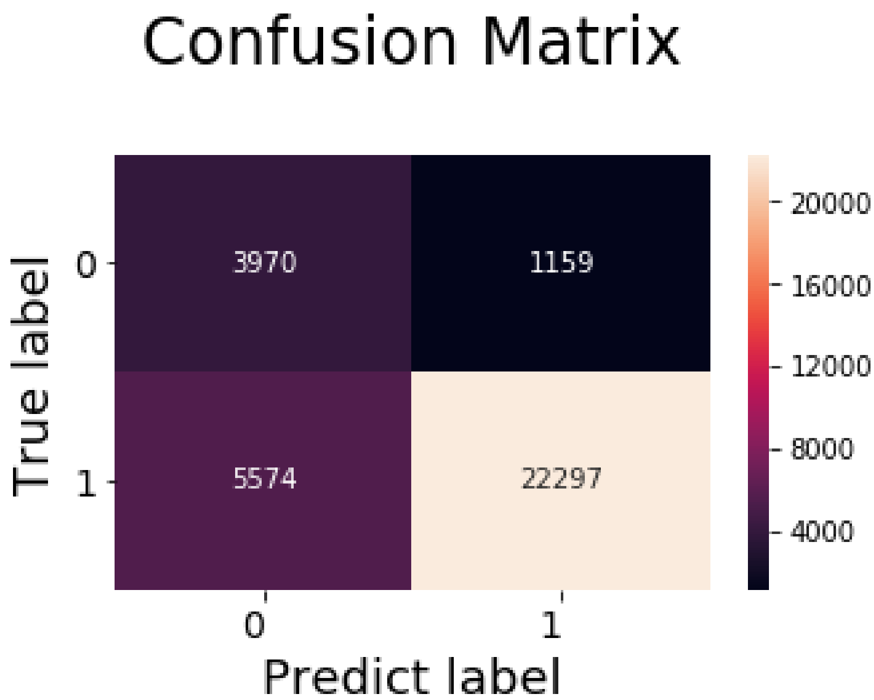

Train Data
Depth
1
0.6382 0.6382 0.6382 0.6382
5
0.7889 0.7887 0.7884 0.7871
10
0.8729 0.8708 0.8621 0.8517
50
0.9854 0.9805 0.9585 0.9305
100
0.9937 0.9905 0.9705 0.9428
500
0.9997 0.9982 0.9835 0.9529
100
0.9939 0.9906 0.9705 0.9429
5
10
100
500
Sample Split
0.96
0.88
0.80
0.72
0.64


CV Data
Depth
1
0.6382 0.6382 0.6382 0.6382
5
0.7812 0.7811 0.7811 0.7809
10
0.8158 0.8183 0.8253 0.829
50
0.7667 0.7774 0.8189 0.8403
100
0.757 0.7676 0.8059 0.8268
500
0.7417 0.752 0.7866 0.804
100
0.7587 0.7646 0.8082 0.826
5
10
100
500
Sample Split
0.84
0.80
0.76
0.72
0.68
0.64

```
Optimal value of max_depth =  50  Optimal min_samples_split is : 500
--------------------------
Cv auc scores
[0.63822825 0.63822825 0.63822825 0.63822825 0.78123644 0.78112886
 0.78114979 0.78092291 0.81576077 0.81828738 0.82528986 0.82901148
 0.76671242 0.77737196 0.81888577 0.84031347 0.75698099 0.76758686
 0.80590132 0.82684164 0.74174984 0.75201366 0.78657485 0.80401669
 0.75866764 0.76460384 0.80821069 0.82604573]
Maximun Auc value : 0.8403134699713916
```

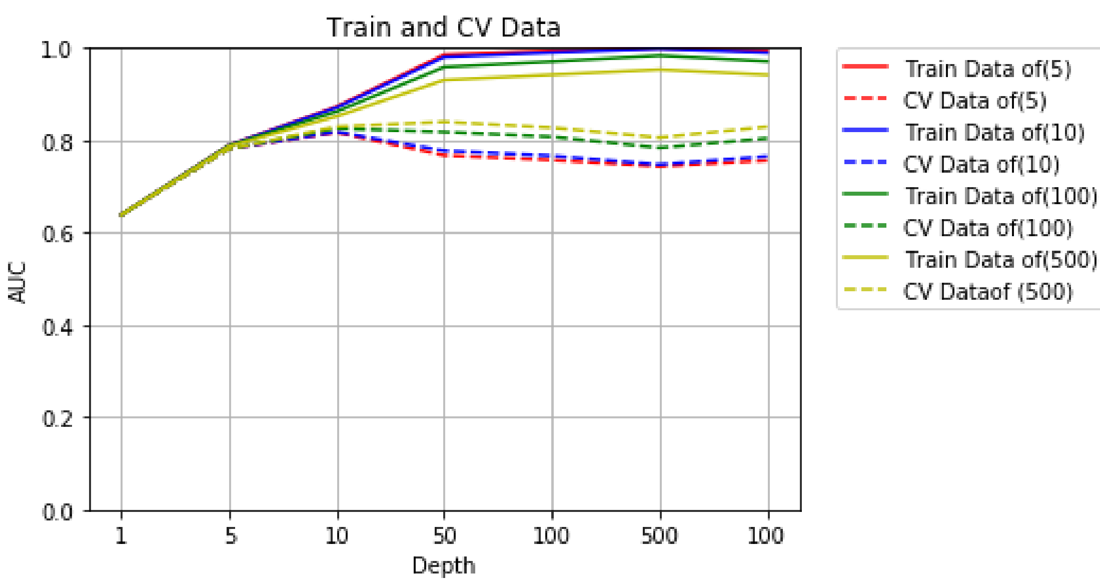


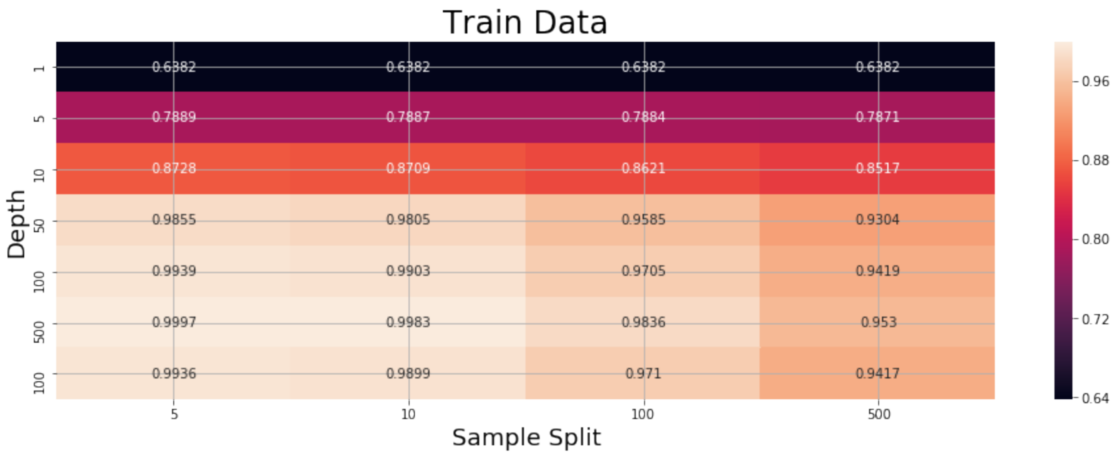

```
Train confusion matrix
[[ 6432   716]
 [ 6896 30846]]
Test confusion matrix
[[ 3970  1159]
 [ 5574 22297]]
```

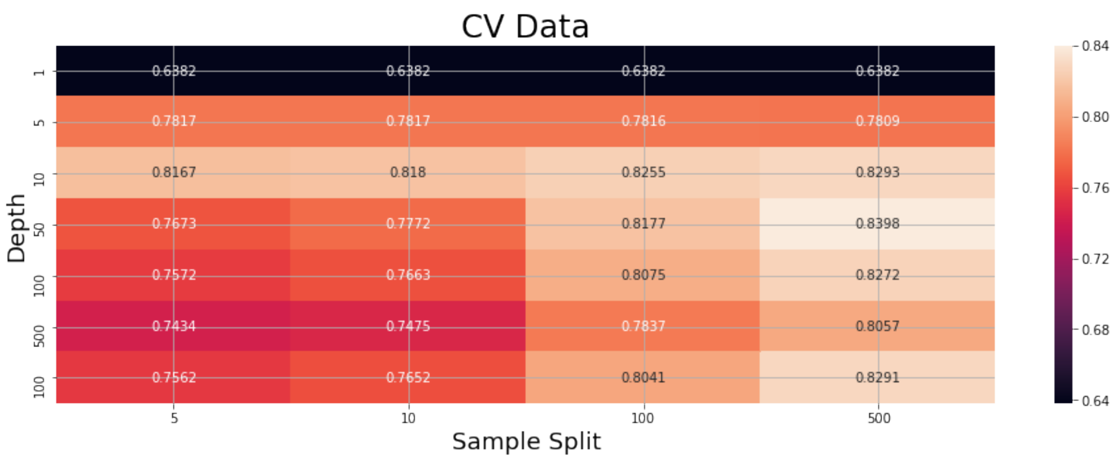


7.4 [5.4] Applying Decision Trees on TFIDF W2V, SET 4

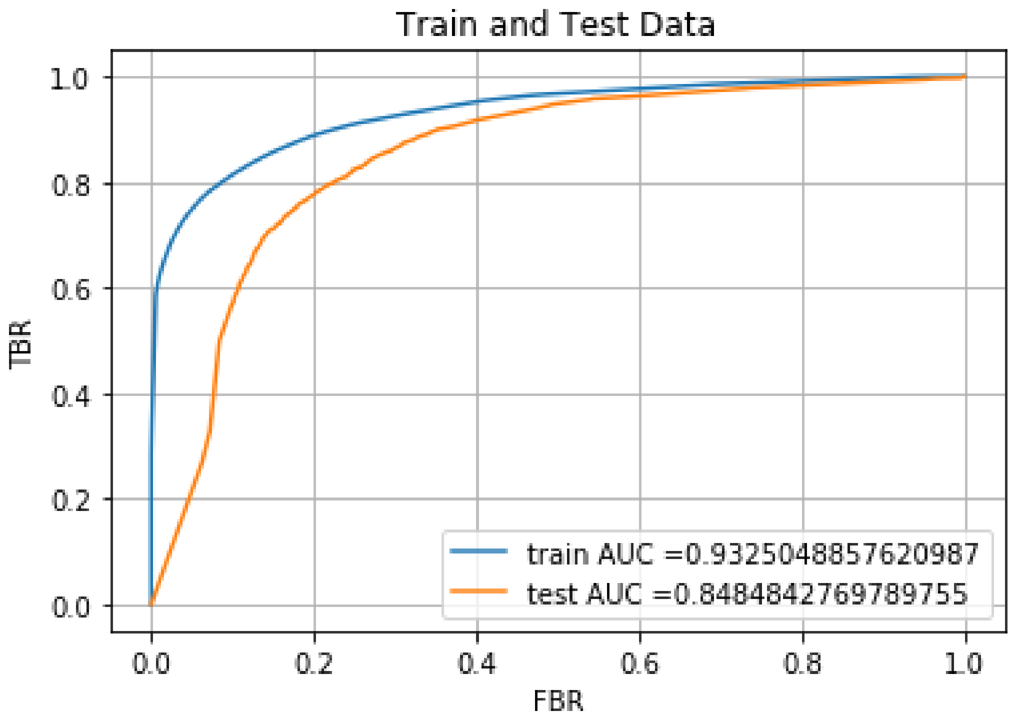
```
In [132]: # Please write all the code with proper documentation
          all_dt(tfidf_train_vectors,y_train,X_cv)
```



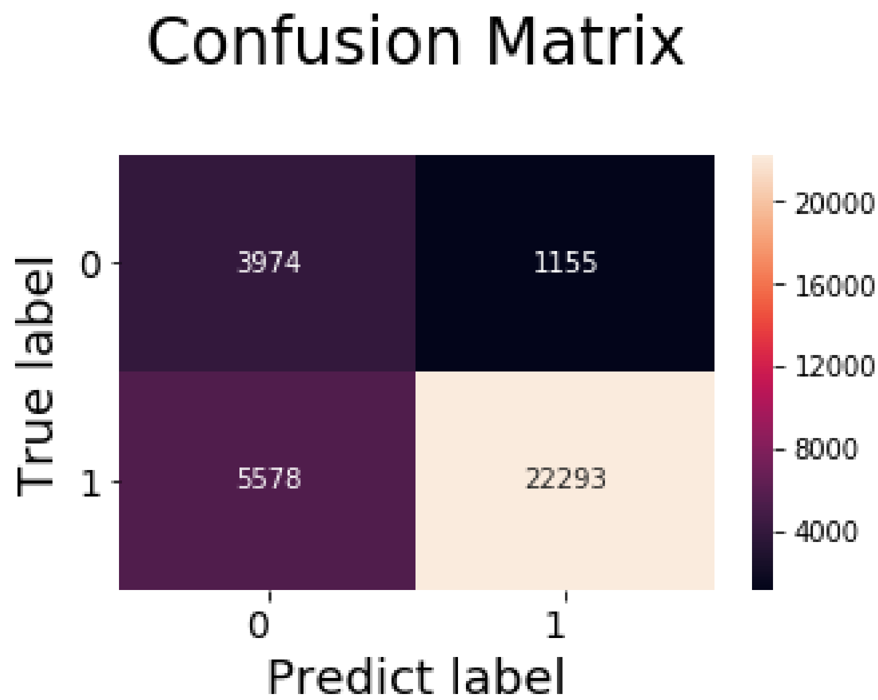





```
Optimal value of max_depth =  50  Optimal min_samples_split is : 500
--------------------------
Cv auc scores
[0.63822825 0.63822825 0.63822825 0.63822825 0.78165498 0.78165296
 0.78159487 0.78089648 0.81665358 0.81800719 0.82550669 0.82927569
 0.76734313 0.77720756 0.81772649 0.83975912 0.7572175  0.76630792
 0.80751379 0.82715567 0.74337999 0.74753721 0.78368366 0.80573015
 0.75618021 0.76524842 0.80408824 0.82906217]
Maximun Auc value : 0.8397591212163311
```




```
Train confusion matrix
[[ 6423   725]
 [ 6954 30788]]
Test confusion matrix
[[ 3974  1155]
 [ 5578 22293]]
```



8 [6] Conclusions

In [133]:
```
# Please compare all your models using Prettytable library

from prettytable import PrettyTable


Vectorizer = ['Bag of Words','TFIDF','AVG W2V','TFIDF W2V']

max_depth=[50, 50,50, 50]

sample_split =[500, 500,500, 500]

auc =[0.84,0.84,0.84,0.84]

numbering = [1,2,3,4]

# Initializing prettytable
ptable = PrettyTable()

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

```
ptable.add_column("Depth",max_depth)
ptable.add_column("Sample Split",sample_split)
ptable.add_column("AUC",auc)


print(ptable)
```

```
+--------+--------------+-------+--------------+------+
| S.NO.  |    MODEL     | Depth | Sample Split | AUC  |
+--------+--------------+-------+--------------+------+
|   1    | Bag of Words |   50  |     500      | 0.84 |
|   2    |    TFIDF     |   50  |     500      | 0.84 |
|   3    |   AVG W2V    |   50  |     500      | 0.84 |
|   4    |  TFIDF W2V   |   50  |     500      | 0.84 |
+--------+--------------+-------+--------------+------+
```

8.0.1 Conclussion

1: Decision Tree is faster.

2: BOW, TFIDF and Avg W2v featurisation gave 84% AUC value.

3:Some other previous models we applied had better results than this.

4: The data points is 100K maybe if we would have more than that with other features it could give us better insight.