Amazon Fine Food Reviews Analysis

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

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

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

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

Attribute Information:

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

Objective:

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

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

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

[1]. Reading Data

[1.1] Loading the data

The dataset is available in two forms

1. .csv file
2. SQLite Database

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

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

In [1]:

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


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

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

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

from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle

from tqdm import tqdm
import os
from sklearn.model_selection import train_test_split
```

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
 points
# you can change the number to any other number based on your computing power

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

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIM
IT 125000""", con)

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

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

```
Number of data points in our data (125000, 10)
```

Out[2]:

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

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

In [5]:

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

Out[5]:

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

In [6]:

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

Out[6]:

```
393063
```

[2] Exploratory Data Analysis

[2.1] Data Cleaning: Deduplication

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

In [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	Helpfulnes
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	

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

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

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

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

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

In [8]:

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

In [9]:

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

Out[9]:

```
(107311, 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]:

```
85.8488
```

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

In [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	HelpfulnessNumerator	HelpfulnessD
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	

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()
```

```
(107309, 10)
```

Out[13]:

```
1    90143
0    17166
Name: Score, dtype: int64
```

[3] Preprocessing

[3.1]. Preprocessing Review Text

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

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

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

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

In [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)
```

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

In [15]:

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

print(sent_0)
```

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

In [16]:

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

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

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

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

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

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

In [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)
```

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

In [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)
```

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

In [20]:

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

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

In [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 s
tep

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

In [22]:

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

```
100%|██████████| 107309/107309 [00:39<00:00, 2714.14it/s]
```

In [65]:

```
preprocessed_reviews[100]
```

Out[65]:

```
'impression got buying dinos received one not good deal last time or
der rip'
```

In [66]:

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

In [67]:

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

In [68]:

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

In [69]:

```
text.shape
```

Out[69]:

```
(107309,)
```

In [ ]:

```

```

In [70]:

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

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

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

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

In [71]:

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

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

In [72]:

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

In [73]:

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

[3.2] Preprocessing Review Summary

In [139]:

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

[4] Featurization

[4.1] BAG OF WORDS

In [25]:

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

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

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

[4.2] Bi-Grams and n-Grams.

In [26]:

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

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

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

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

In [40]:

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

In [41]:

```
bow_feature_train.shape
```

Out[41]:

```
(68677, 114137)
```

In [42]:

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

[4.3] TF-IDF

In [27]:

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

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

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

In [46]:

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

In [47]:

```
tf_idf_train.shape
```

Out[47]:

```
(68677, 114137)
```

In [48]:

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

[4.4] Word2Vec

In [140]:

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

In [141]:

```
# Using Google News Word2Vectors

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


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

is_your_ram_gt_16g=False
want_to_use_google_w2v = False
want_to_train_w2v = True

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

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

```
[('fantastic', 0.8430249691009521), ('awesome', 0.8368998169898987),
('terrific', 0.828173041343689), ('good', 0.8232675790786743), ('exc
ellent', 0.8207688927650452), ('wonderful', 0.7675489783287048), ('p
erfect', 0.7497045397758484), ('nice', 0.7258481979370117), ('amazin
g', 0.7052987217903137), ('fabulous', 0.6872046589851379)]
==================================================
[('greatest', 0.8145409226417542), ('tastiest', 0.7404407858848572),
('best', 0.7321152091026306), ('nastiest', 0.7277255654335022), ('vi
le', 0.6806230545043945), ('disgusting', 0.6788105964660645), ('clos
est', 0.6277113556861877), ('terrible', 0.6277025938034058), ('horri
ble', 0.627235472202301), ('wins', 0.6269370913505554)]
```

In [142]:

```
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  19146
sample words  ['dogs', 'loves', 'chicken', 'product', 'china', 'won
t', 'buying', 'anymore', 'hard', 'find', 'products', 'made', 'usa',
'one', 'isnt', 'bad', 'good', 'take', 'chances', 'till', 'know', 'go
ing', 'imports', 'love', 'saw', 'pet', 'store', 'tag', 'attached',
'regarding', 'satisfied', 'safe', 'plant', 'work', 'well', 'decide
d', 'repot', 'larger', 'pot', 'must', 'gotten', 'funky', 'soil', 'so
on', 'repotted', 'large', 'colony', 'small', 'flies', 'getting']
```

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

[4.4.1.1] Avg W2v

In [74]:

```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors = []; # the avg-w2v for each sentence/review is stored in this list
for sent in tqdm(list_of_sentance): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might n
eed to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

```
---------------------------------------------------------------------
-------
NameError                                 Traceback (most recent cal
l last)
<ipython-input-74-82922ba63b7c> in <module>()
      2 # compute average word2vec for each review.
      3 sent_vectors = []; # the avg-w2v for each sentence/review is
 stored in this list
----> 4 for sent in tqdm(list_of_sentance): # for each review/senten
ce
      5     sent_vec = np.zeros(50) # as word vectors are of zero le
ngth 50, you might need to change this to 300 if you use google's w2
v
      6     cnt_words =0; # num of words with a valid vector in the
 sentence/review

NameError: name 'list_of_sentance' is not defined
```

In [76]:

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

In [77]:

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

In [78]:

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

In [79]:

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

```
100%|██████████| 68677/68677 [02:18<00:00, 497.54it/s]
```

In [80]:

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

In [81]:

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

In [82]:

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

```
100%|██████████| 21462/21462 [00:40<00:00, 533.41it/s]

21462
50
```

In [83]:

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

In [84]:

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

```
100%|██████████| 17170/17170 [00:35<00:00, 481.82it/s]
```

In [86]:

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

[4.4.1.2] TFIDF weighted W2v

In [160]:

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

In [41]:

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

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

```
100%|██████████████████████████████████████████████████████████████
██████████████| 4986/4986 [00:20<00:00, 245.63it/s]
```

In [89]:

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

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

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

In [90]:

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

```
100%|██████████| 68677/68677 [02:28<00:00, 461.96it/s]

68677
```

In [122]:

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

In [91]:

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

```
100%|██████████| 21462/21462 [00:44<00:00, 478.64it/s]

21462
```

In [92]:

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

In [93]:

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

```
100%|██████████| 17170/17170 [00:46<00:00, 366.59it/s]
```

In [127]:

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

[5] Assignment 8: Decision Trees

1. **Apply Decision Trees on these feature sets**

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

2. **The hyper paramter tuning (best `depth` in range [1, 5, 10, 50, 100, 500, 100], and the best `min_samples_split` in range [5, 10, 100, 500])**

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

3. **Graphviz**

   - Visualize your decision tree with Graphviz. It helps you to understand how a decision is being made, given a new vector.
   - Since feature names are not obtained from word2vec related models, visualize only BOW & TFIDF decision trees using Graphviz
   - Make sure to print the words in each node of the decision tree instead of printing its index.
   - Just for visualization purpose, limit max_depth to 2 or 3 and either embed the generated images of graphviz in your notebook, or directly upload them as .png files.

4. **Feature importance**

   - Find the top 10 features of positive class and top 10 features of negative class for both feature sets Set 1 and Set 2 using `feature_importances_` method of Decision Tree Classifier (https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html) and print their corresponding feature names

5. **Feature engineering**

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

6. **Representation of results**

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

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

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

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

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

Note: Data Leakage

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

Applying Decision Trees

In [99]:

```
import sqlite3
import pandas as pd
import numpy as np

import pickle
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import confusion_matrix

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

from sklearn.metrics import accuracy_score
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.preprocessing import label_binarize
from sklearn.metrics import roc_auc_score,roc_curve
from wordcloud import WordCloud
from sklearn import tree
from sklearn.metrics import f1_score
import graphviz
```

In [100]:

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

In [101]:

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

In [102]:

```
# # Encode labels

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

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

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

In [103]:

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

In [104]:

```
def drawplots(auc_array,auc_array_train):
    fig, ax = plt.subplots(4,1,figsize=(12,12))
    a = np.arange(len(depth))
    l5 = [x for i,x in enumerate(auc_array) if i %4 ==0]
    l10 = [x for i,x in enumerate(auc_array) if i %4 ==1]
    l100 = [x for i,x in enumerate(auc_array) if i %4 ==2]
    l500 = [x for i,x in enumerate(auc_array) if i %4 ==3]

    l5_train = [x for i,x in enumerate(auc_array_train) if i %4 ==0]
    l10_train= [x for i,x in enumerate(auc_array_train) if i %4 ==1]
    l100_train = [x for i,x in enumerate(auc_array_train) if i %4 ==2]
    l500_train = [x for i,x in enumerate(auc_array_train) if i %4 ==3]

    ax[0].plot(a, l5,c='g',label="cv")
    for i, txt in enumerate(np.round(l5,3)):
        ax[0].annotate((a[i],str(txt)), (a[i],l5[i]))

    ax[0].plot(a, l5_train,c='r',label="train")
    for i, txt in enumerate(np.round(l5_train,3)):
        ax[0].annotate((a[i],str(txt)), (a[i],l5_train[i]),(a[i],l5_train[i]))

    ax[0].set_xticks(a)
    ax[0].set_xticklabels(depth)
    plt.grid()
    ax[0].set_title("Cross Validation AUC for each depth ")
    ax[0].set_xlabel("depth i's")
    ax[0].set_ylabel("AUC")

    ax[1].plot(a, l10,c='g',label="cv")
    for i, txt in enumerate(np.round(l10,3)):
        ax[1].annotate((a[i],str(txt)), (a[i],l10[i]))

    ax[1].plot(a, l10_train,c='r',label="train")
    for i, txt in enumerate(np.round(l10_train,3)):
        ax[1].annotate((a[i],str(txt)), (a[i],l10_train[i]),(a[i],l10_train[i]))

    ax[1].set_xticks(a)
    ax[1].set_xticklabels(depth)
    plt.grid()
    ax[1].set_title("AUC ")
    ax[1].set_xlabel("depth i's")
    ax[1].set_ylabel("AUC")

    ax[2].plot(a, l100,c='g',label="cv")
    for i, txt in enumerate(np.round(l100,3)):
        ax[2].annotate((a[i],str(txt)), (a[i],l100[i]))

    ax[2].plot(a, l100_train,c='r',label="train")
    for i, txt in enumerate(np.round(l100_train,3)):
        ax[2].annotate((a[i],str(txt)), (a[i],l100_train[i]),(a[i],l100_train[i
]))

    ax[2].set_xticks(a)
    ax[2].set_xticklabels(depth)
    plt.grid()
    ax[2].set_title("AUC ")
    ax[2].set_xlabel("depth i's")
    ax[2].set_ylabel("AUC")
    ax[3].plot(a, l500,c='g',label="cv")
    for i, txt in enumerate(np.round(l5,3)):
        ax[3].annotate((a[i],str(txt)), (a[i],l5[i]))

    ax[3].plot(a, l500_train,c='r',label="train")
    for i, txt in enumerate(np.round(l500_train,3)):
        ax[3].annotate((a[i],str(txt)), (a[i],l500_train[i]),(a[i],l500_train[i
]))

    ax[3].set_xticks(a)
    ax[3].set_xticklabels(depth)
    plt.grid()
    ax[3].set_title("Cross Validation AUC for each depth ")
    ax[3].set_xlabel("depth i's")
    ax[3].set_ylabel("AUC")

    plt.legend(loc='best')
    plt.subplots_adjust(left=None, bottom=0.1, right=None, top=3, wspace=None, h
space=None)
    plt.show()
```

In [105]:

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

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

In [106]:

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

In [107]:

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

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

In [108]:

```
def drawTree(clf,featureNames=None,classNames=None):
    dot_data = tree.export_graphviz(clf, out_file=None,
                      feature_names=featureNames,
                      max_depth = 2,
                      class_names=classNames,
                      filled=True, rounded=True,
                      special_characters=True)
    graph = graphviz.Source(dot_data)
    return graph
```

In [109]:

```
# for cross validation
depth = [1, 5, 10, 50, 100, 500, 1000]
min_samples_split = [5, 10, 100, 500]
```

In [110]:

```
def calculateMetricC(X,y,train,y_train):
    auc_array = []
    for i in depth:
        for r in min_samples_split:
            print("for depth = {} and min_samples_split = {}".format(i,r))
            clf = tree.DecisionTreeClassifier(max_depth = i,min_samples_split =
r)
            clf.fit(train, y_train)
            pred = clf.predict(X)
            area = roc_auc_score(y, pred)
            auc_array.append(area)
            print("Area:",area)
    return auc_array
```

In [111]:

```
def performHyperParameterTuning(train,cv,test):
    auc_array = []
    auc_array = calculateMetricC(cv,y_cv,train,y_train)
    #print(auc_array)
    auc_array_train = calculateMetricC(train,y_train,train,y_train)
    #print(auc_array_train)
    return (auc_array,auc_array_train)
#     clf = SGDClassifier(class_weight='balanced', alpha=best_a, penalty=best_r,
 loss='hinge', random_state=42)
#     clf.fit(train, y_train)
#     sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
#     sig_clf.fit(train, y_train)

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

In [112]:

```
def draw(auc_array,auc_array_train):
    drawplots(auc_array,auc_array_train)
    best_alpha = np.argmax(auc_array)
    best_a = depth[int(best_alpha/4)]
    best_r = min_samples_split[int(best_alpha%4)]
    print("best depth = {} and min_samples_split = {}".format(best_a,best_r))
    return (best_a,best_r)
```

In [113]:

```
def bestModel(train,cv,test,best_depth,best_samples_split):
    clf = tree.DecisionTreeClassifier(max_depth = best_depth,min_samples_split =
 best_samples_split)
    clf.fit(train, y_train)

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

[5.1] Applying Decision Trees on BOW, SET 1

In [60]:

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

In [61]:

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

In [62]:

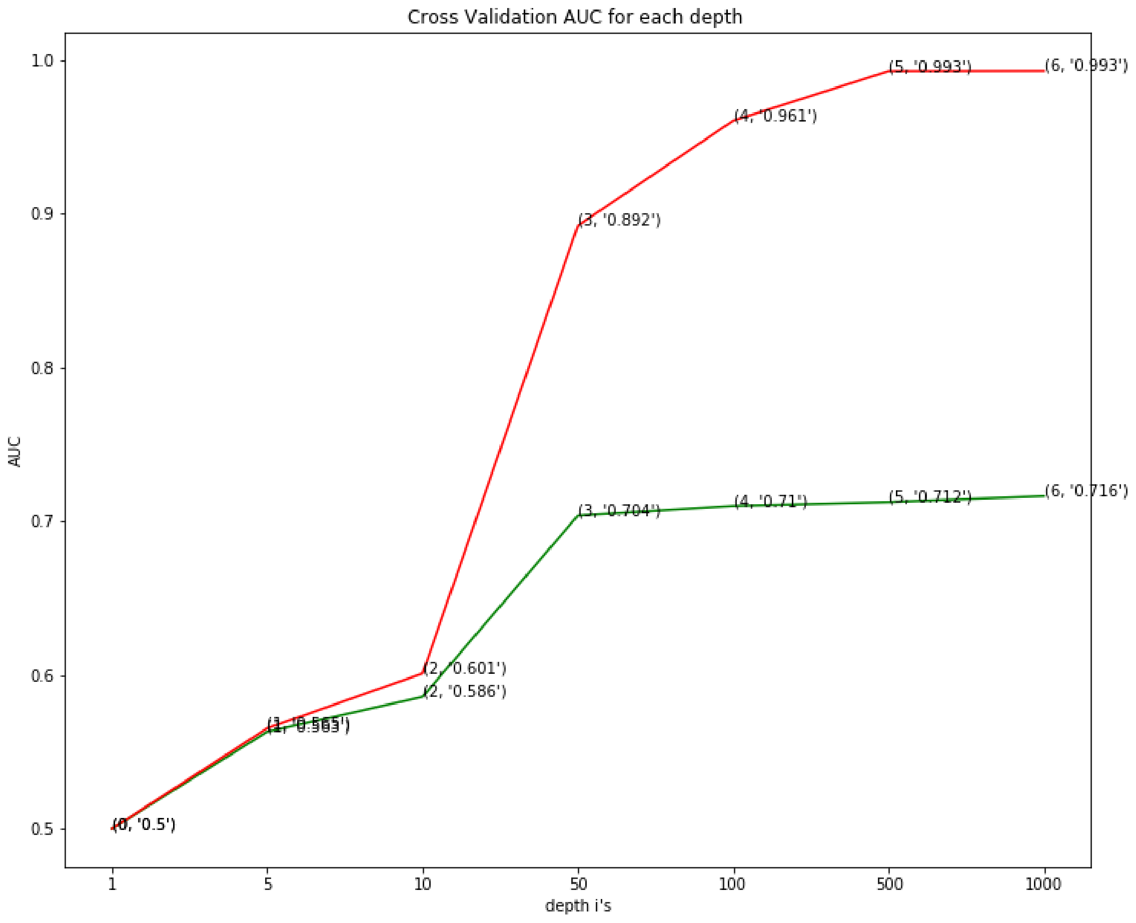
```
auc_array,auc_array_train = performHyperParameterTuning(train,cv,test)
```

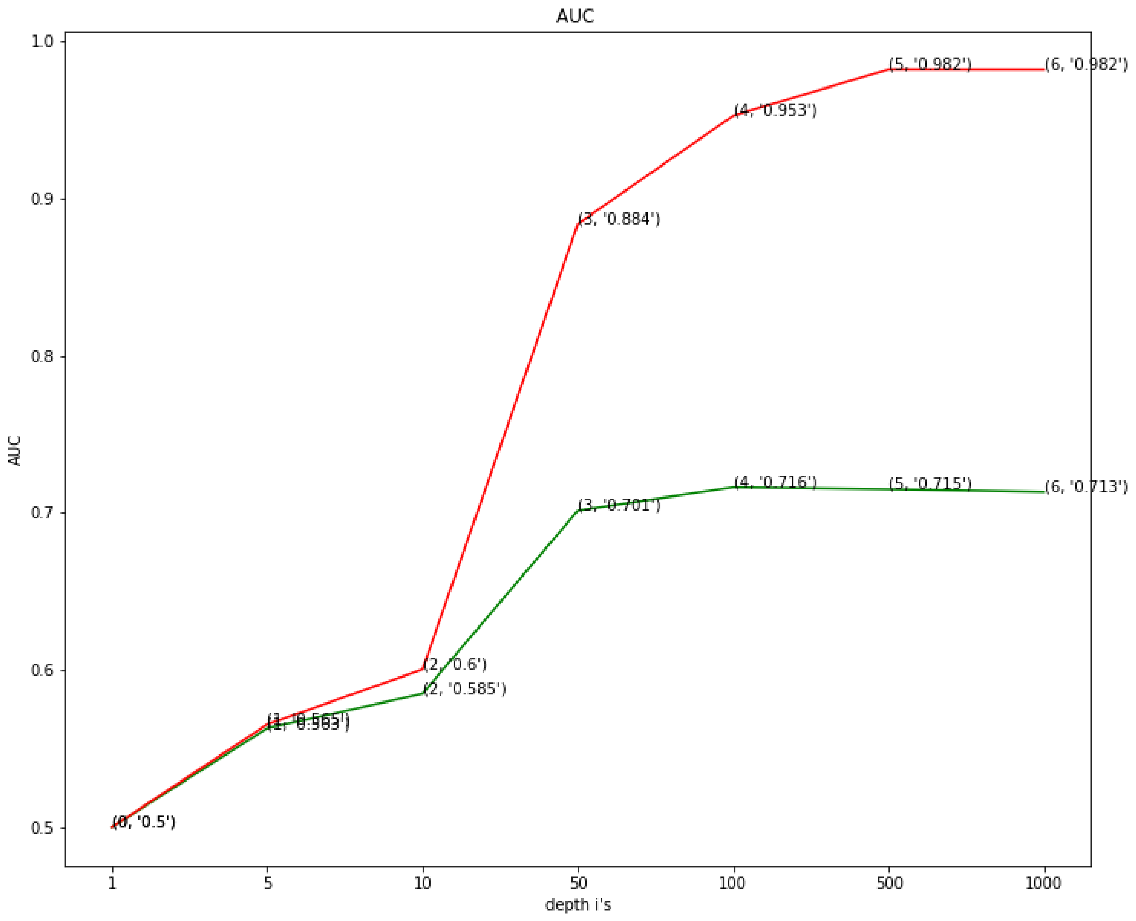
```
for depth = 1 and min_samples_split = 5
Area: 0.5
for depth = 1 and min_samples_split = 10
Area: 0.5
for depth = 1 and min_samples_split = 100
Area: 0.5
for depth = 1 and min_samples_split = 500
Area: 0.5
for depth = 5 and min_samples_split = 5
Area: 0.563125459348403
for depth = 5 and min_samples_split = 10
Area: 0.5629434426028624
for depth = 5 and min_samples_split = 100
Area: 0.5629434426028624
for depth = 5 and min_samples_split = 500
Area: 0.5660291078887696
for depth = 10 and min_samples_split = 5
Area: 0.5858343294006123
for depth = 10 and min_samples_split = 10
Area: 0.5849155631851515
for depth = 10 and min_samples_split = 100
Area: 0.5846815146125386
for depth = 10 and min_samples_split = 500
Area: 0.5903415248987626
for depth = 50 and min_samples_split = 5
Area: 0.7037573415292653
for depth = 50 and min_samples_split = 10
Area: 0.7014084257132784
for depth = 50 and min_samples_split = 100
Area: 0.704225438674491
for depth = 50 and min_samples_split = 500
Area: 0.7100325464567991
for depth = 100 and min_samples_split = 5
Area: 0.7099637806489609
for depth = 100 and min_samples_split = 10
Area: 0.7161785236595646
for depth = 100 and min_samples_split = 100
Area: 0.7136823210490686
for depth = 100 and min_samples_split = 500
Area: 0.7143495475174508
for depth = 500 and min_samples_split = 5
Area: 0.7124691074435398
for depth = 500 and min_samples_split = 10
Area: 0.7149047219381555
for depth = 500 and min_samples_split = 100
Area: 0.7137086209102422
for depth = 500 and min_samples_split = 500
Area: 0.7167681125339257
for depth = 1000 and min_samples_split = 5
Area: 0.7163781577785209
for depth = 1000 and min_samples_split = 10
Area: 0.7131713162608533
for depth = 1000 and min_samples_split = 100
Area: 0.7153815015711391
for depth = 1000 and min_samples_split = 500
Area: 0.7165514289368287
[0.5, 0.5, 0.5, 0.5, 0.563125459348403, 0.5629434426028624, 0.562943
4426028624, 0.5660291078887696, 0.5858343294006123, 0.58491556318515
15, 0.5846815146125386, 0.5903415248987626, 0.7037573415292653, 0.70
14084257132784, 0.704225438674491, 0.7100325464567991, 0.70996378064
89609, 0.7161785236595646, 0.7136823210490686, 0.7143495475174508,
0.7124691074435398, 0.7149047219381555, 0.7137086209102422, 0.716768
1125339257, 0.7163781577785209, 0.7131713162608533, 0.71538150157113
91, 0.7165514289368287]
for depth = 1 and min_samples_split = 5
Area: 0.5
for depth = 1 and min_samples_split = 10
Area: 0.5
for depth = 1 and min_samples_split = 100
Area: 0.5
for depth = 1 and min_samples_split = 500
Area: 0.5
for depth = 5 and min_samples_split = 5
Area: 0.5654261575483993
for depth = 5 and min_samples_split = 10
Area: 0.5654261575483993
for depth = 5 and min_samples_split = 100
Area: 0.5651747727618073
for depth = 5 and min_samples_split = 500
Area: 0.56615885065347
for depth = 10 and min_samples_split = 5
Area: 0.6010296580497599
for depth = 10 and min_samples_split = 10
Area: 0.6003621723211392
for depth = 10 and min_samples_split = 100
Area: 0.5949289918840199
for depth = 10 and min_samples_split = 500
Area: 0.5921556414432803
for depth = 50 and min_samples_split = 5
Area: 0.892300527317323
for depth = 50 and min_samples_split = 10
Area: 0.8837230876741672
for depth = 50 and min_samples_split = 100
Area: 0.8352595913892599
for depth = 50 and min_samples_split = 500
Area: 0.7833445787972844
for depth = 100 and min_samples_split = 5
Area: 0.9605325246040852
for depth = 100 and min_samples_split = 10
Area: 0.9525101302502512
for depth = 100 and min_samples_split = 100
Area: 0.8922546850864126
for depth = 100 and min_samples_split = 500
Area: 0.8284609177156277
for depth = 500 and min_samples_split = 5
Area: 0.9927122023686314
for depth = 500 and min_samples_split = 10
Area: 0.981930881045598
for depth = 500 and min_samples_split = 100
Area: 0.9227613379759697
for depth = 500 and min_samples_split = 500
Area: 0.8598452392034183
for depth = 1000 and min_samples_split = 5
Area: 0.9928703840595507
for depth = 1000 and min_samples_split = 10
Area: 0.9818507468789597
for depth = 1000 and min_samples_split = 100
Area: 0.9226963136244828
for depth = 1000 and min_samples_split = 500
Area: 0.8603220539434964
[0.5, 0.5, 0.5, 0.5, 0.5654261575483993, 0.5654261575483993, 0.56517
47727618073, 0.56615885065347, 0.6010296580497599, 0.600362172321139
```

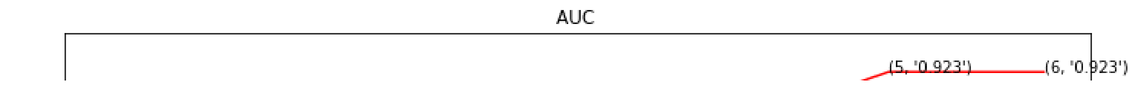
```
2, 0.5949289918840199, 0.5921556414432803, 0.892300527317323, 0.8837
230876741672, 0.8352595913892599, 0.7833445787972844, 0.960532524604
0852, 0.9525101302502512, 0.8922546850864126, 0.8284609177156277, 0.
9927122023686314, 0.981930881045598, 0.9227613379759697, 0.859845239
2034183, 0.9928703840595507, 0.9818507468789597, 0.9226963136244828,
0.8603220539434964]
```

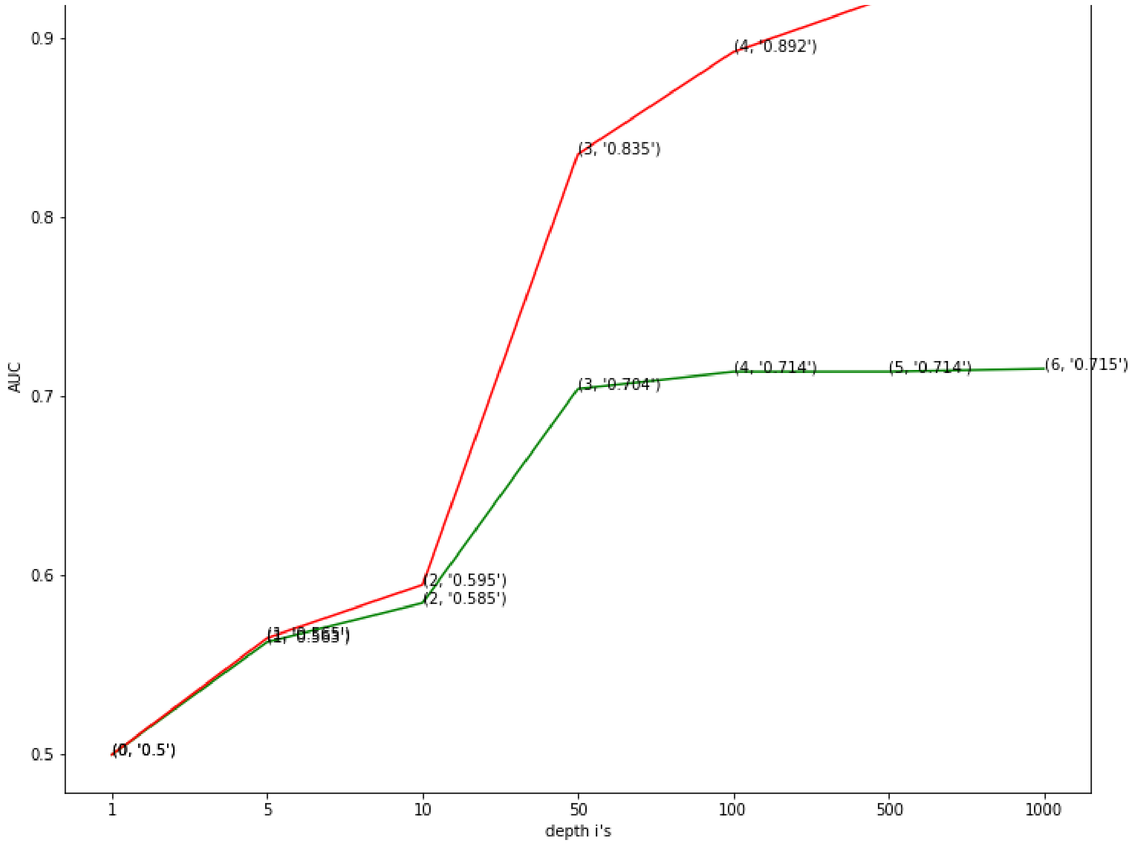
In [63]:

```
best_depth,best_samples_split = draw(auc_array,auc_array_train)
```

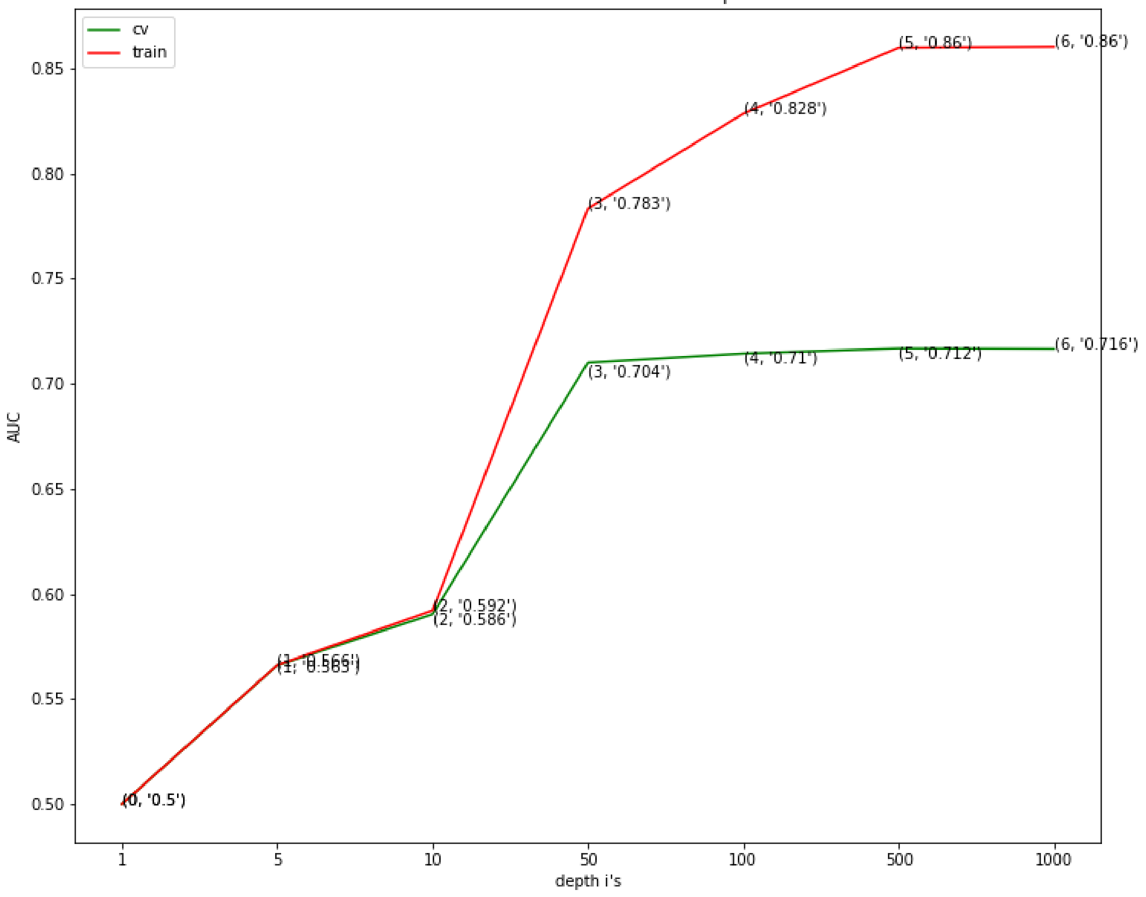

Cross Validation AUC for each depth
AUC
1.0
0.9
0.8
0.7
0.6
0.5
1
5
10
50
100
500
1000
depth i's
(0, '0.5')
(1, '0.565')
(1, '0.563')
(2, '0.601')
(2, '0.586')
(3, '0.892')
(3, '0.704')
(4, '0.961')
(4, '0.71')
(5, '0.993')
(5, '0.712')
(6, '0.993')
(6, '0.716')


AUC
AUC
1.0
0.9
0.8
0.7
0.6
0.5
1
5
10
50
100
500
1000
depth i's
(0, '0.5')
(1, '0.565')
(1, '0.563')
(2, '0.6')
(2, '0.585')
(3, '0.884')
(3, '0.701')
(4, '0.953')
(4, '0.716')
(5, '0.982')
(5, '0.715')
(6, '0.982')
(6, '0.713')


AUC
(5, '0.923')
(6, '0.923')



Cross Validation AUC for each depth

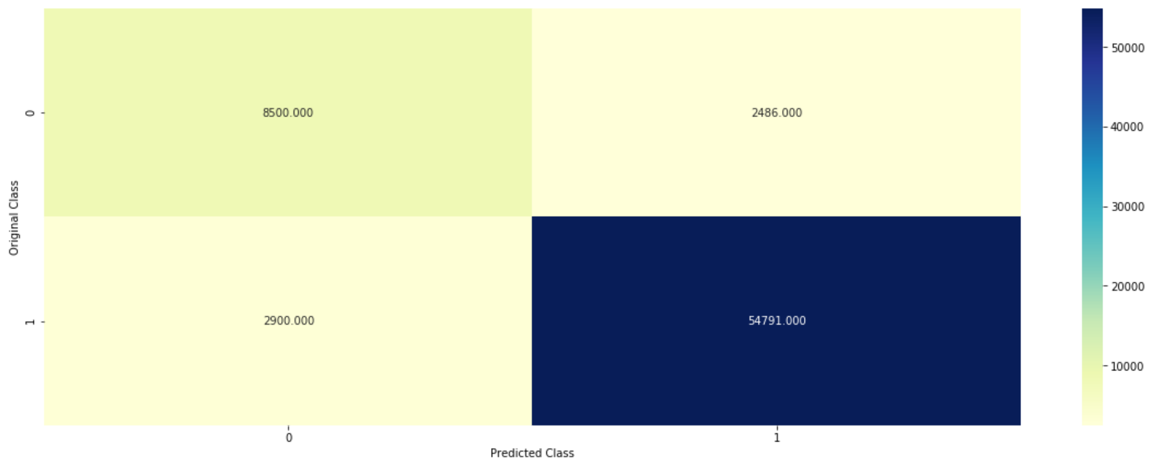


```
best depth = 500 and min_samples_split = 500
```

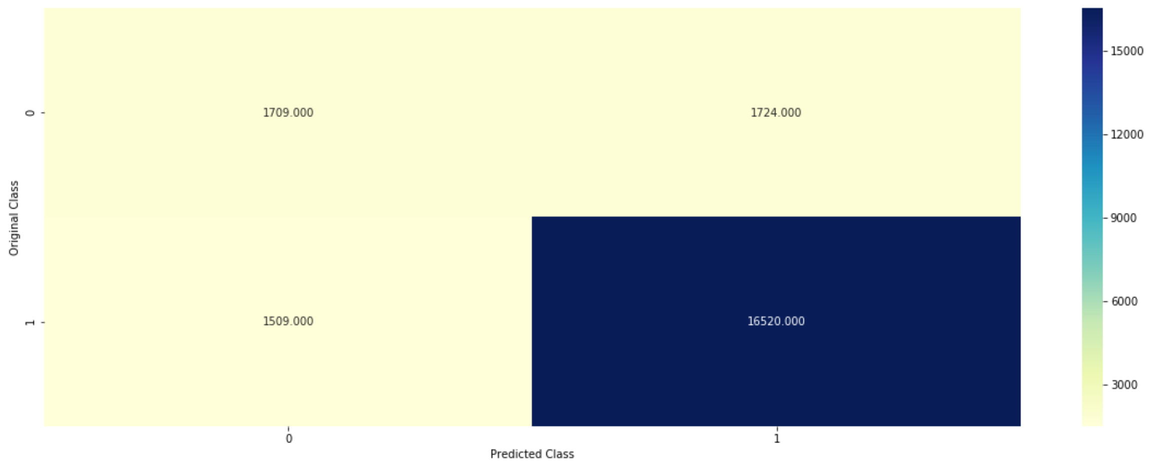
In [64]:

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

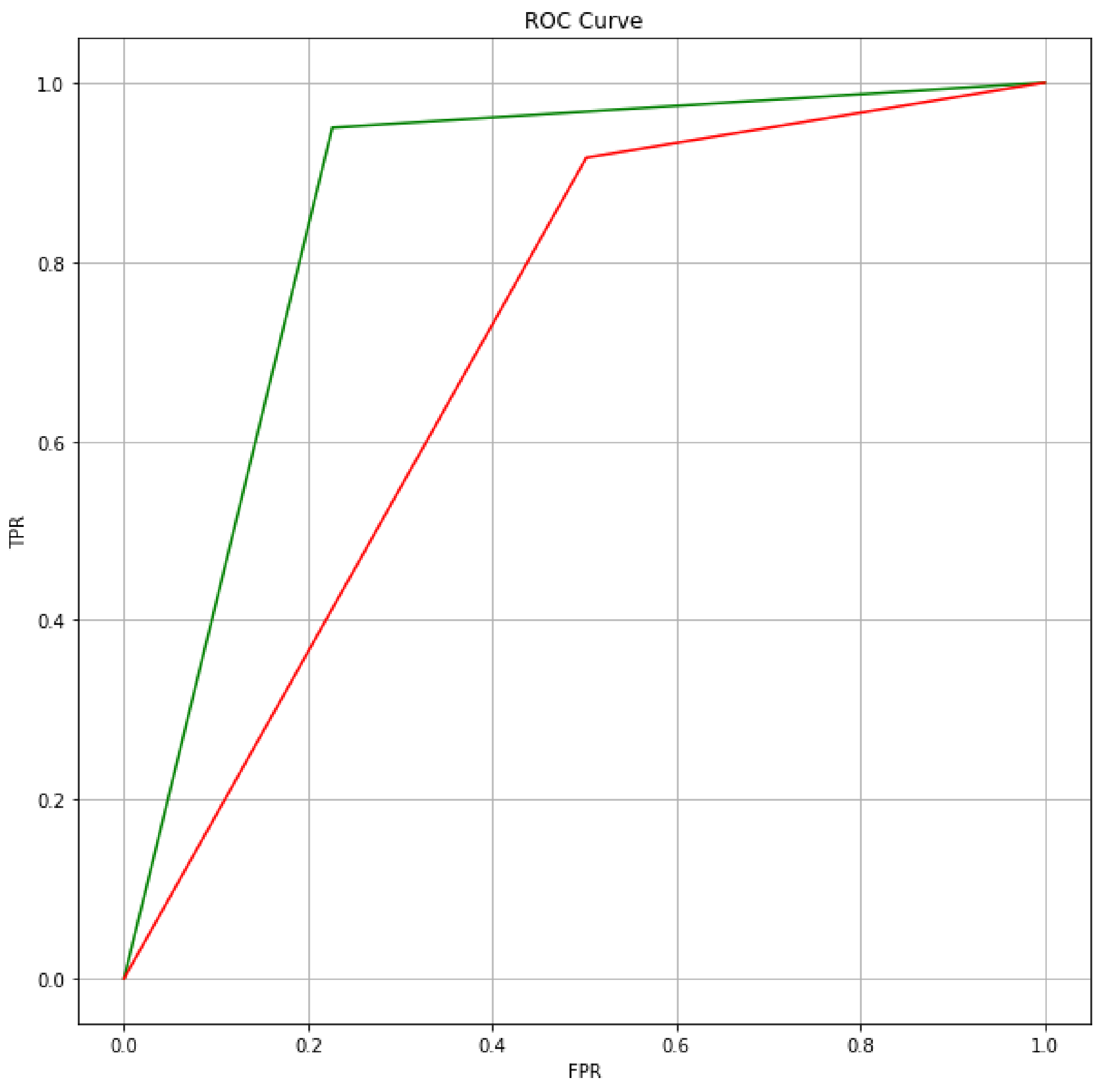
```
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  500 The AUC is: 0.8617220955084656
For values of best alpha =  500 The AUC is: 0.7164215071178354
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  500 The AUC is: 0.7070584180514944
```


ROC Curve
TPR
FPR
0.0
0.2
0.4
0.6
0.8
1.0

[5.1.1] Top 10 important features of positive class from SET 1

In [81]:

```
feature_names = count_vect.get_feature_names()
indices = np.argsort(-clf.feature_importances_)
word_indices = indices[-10:]
word_list = getImportantFeatures(word_indices,feature_names)
print(word_list)
```

```
['good could', 'good cookies', 'good cookie', 'good consistency', 'g
ood considering', 'good conscience', 'good condition the', 'good con
dition and', 'good customer service', 'zukes']
```

[5.1.2] Top 10 important features of negative class from SET 1

In [82]:

```
word_indices = indices[:10]
word_list = getImportantFeatures(word_indices,feature_names)
print(word_list)
```

```
['not', 'great', 'worst', 'disappointed', 'awful', 'not buy', 'very
disappointed', 'money', 'the best', 'threw']
```

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

In [83]:

```
n_nodes = clf.tree_.node_count
print(n_nodes)
```

```
3807
```

In [84]:

```
# words in each node of decision tree
feature = clf.tree_.feature
words = getImportantFeatures(feature,feature_names)
print(len(words))
```

```
3807
```

In [85]:

```
print(words[:20])
```

```
['not', 'worst', 'disappointed', 'awful', 'threw', 'horrible', 'grea
t', 'terrible', 'disappointing', 'bad', 'waste', 'disgusting', 'disa
ppointment', 'return', 'save your', 'love', 'the best', 'never buy',
'delicious', 'good']
```

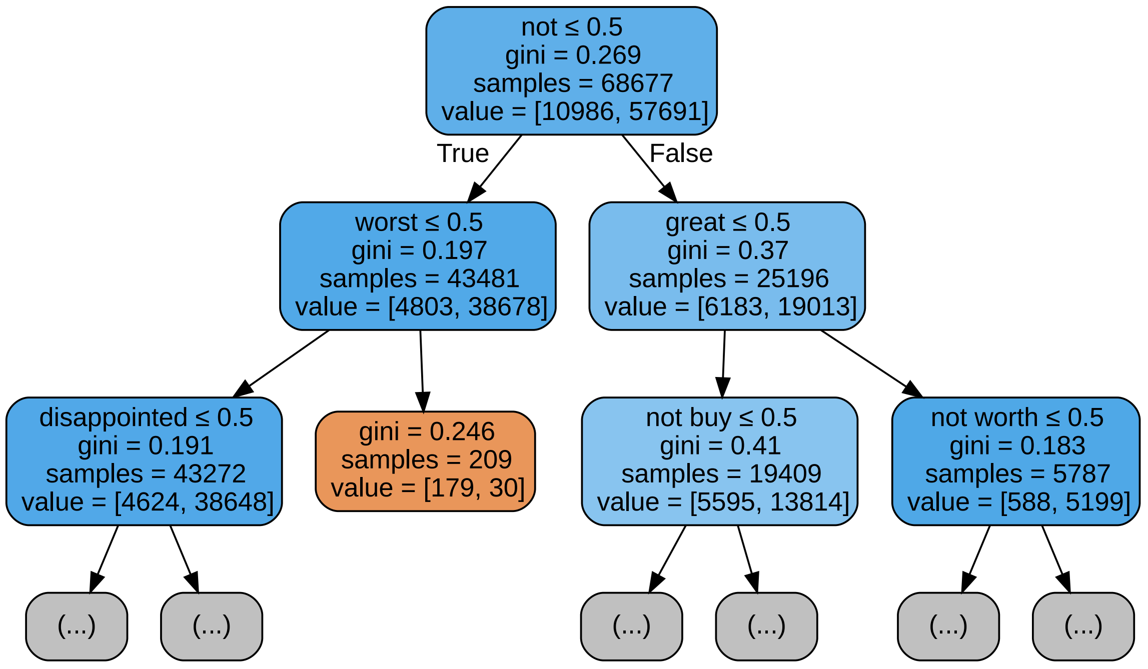
In [86]:

```
graph = drawTree(clf,feature_names)
```

In [87]:

```
graph
```

Out[87]:



[5.2] Applying Decision Trees on TFIDF, SET 2

In [88]:

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

In [89]:

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

In [90]:

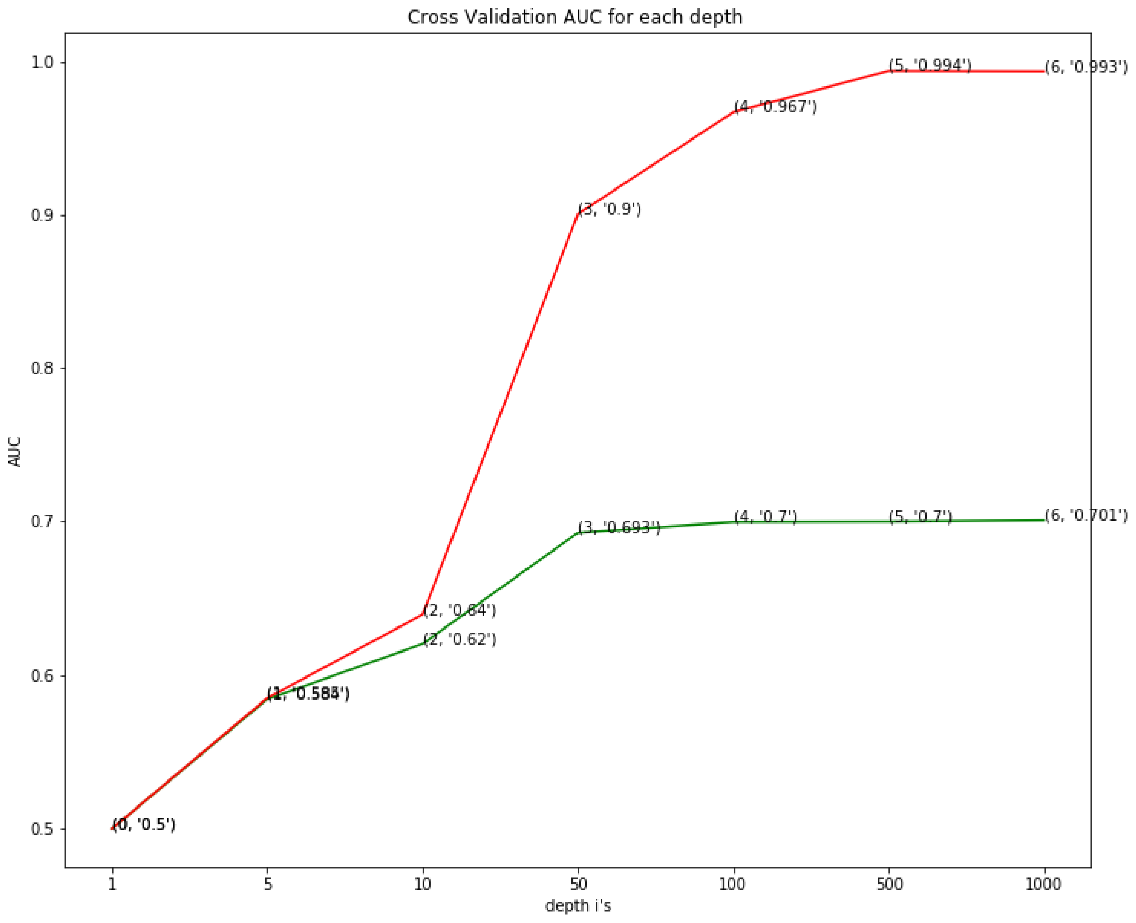
```
auc_array,auc_array_train = performHyperParameterTuning(train,cv,test)
```

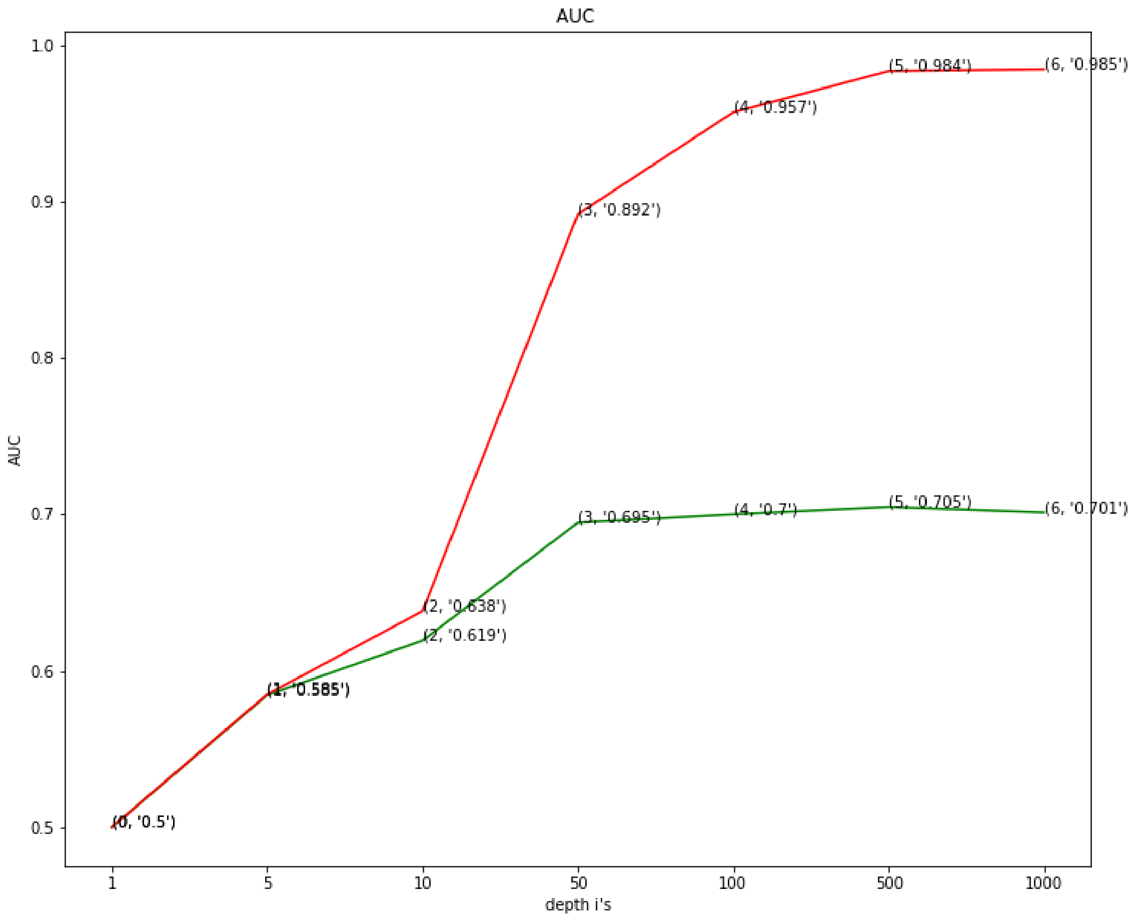
```
for depth = 1 and min_samples_split = 5
Area: 0.5
for depth = 1 and min_samples_split = 10
Area: 0.5
for depth = 1 and min_samples_split = 100
Area: 0.5
for depth = 1 and min_samples_split = 500
Area: 0.5
for depth = 5 and min_samples_split = 5
Area: 0.5843958759091783
for depth = 5 and min_samples_split = 10
Area: 0.5845778926547188
for depth = 5 and min_samples_split = 100
Area: 0.5841791923120812
for depth = 5 and min_samples_split = 500
Area: 0.5860167247430028
for depth = 10 and min_samples_split = 5
Area: 0.6204092702618913
for depth = 10 and min_samples_split = 10
Area: 0.619377821004003
for depth = 10 and min_samples_split = 100
Area: 0.6231395214450002
for depth = 10 and min_samples_split = 500
Area: 0.629189738884529
for depth = 50 and min_samples_split = 5
Area: 0.6928365260952549
for depth = 50 and min_samples_split = 10
Area: 0.6948820596355156
for depth = 50 and min_samples_split = 100
Area: 0.7031943680134527
for depth = 50 and min_samples_split = 500
Area: 0.7161437306090581
for depth = 100 and min_samples_split = 5
Area: 0.6997624759083049
for depth = 100 and min_samples_split = 10
Area: 0.7001526199621347
for depth = 100 and min_samples_split = 100
Area: 0.7107530667417534
for depth = 100 and min_samples_split = 500
Area: 0.7233729995983592
for depth = 500 and min_samples_split = 5
Area: 0.6999621731267363
for depth = 500 and min_samples_split = 10
Area: 0.7048507039920084
for depth = 500 and min_samples_split = 100
Area: 0.7109093515213952
for depth = 500 and min_samples_split = 500
Area: 0.7235206018902433
for depth = 1000 and min_samples_split = 5
Area: 0.7008289075151247
for depth = 1000 and min_samples_split = 10
Area: 0.7013836402395044
for depth = 1000 and min_samples_split = 100
Area: 0.7130848699801244
for depth = 1000 and min_samples_split = 500
Area: 0.7227492486682414
[0.5, 0.5, 0.5, 0.5, 0.5843958759091783, 0.5845778926547188, 0.58417
91923120812, 0.5860167247430028, 0.6204092702618913, 0.6193778210040
03, 0.6231395214450002, 0.629189738884529, 0.6928365260952549, 0.694
8820596355156, 0.7031943680134527, 0.7161437306090581, 0.69976247590
83049, 0.7001526199621347, 0.7107530667417534, 0.7233729995983592,
0.6999621731267363, 0.7048507039920084, 0.7109093515213952, 0.723520
6018902433, 0.7008289075151247, 0.7013836402395044, 0.71308486998012
44, 0.7227492486682414]
for depth = 1 and min_samples_split = 5
Area: 0.5
for depth = 1 and min_samples_split = 10
Area: 0.5
for depth = 1 and min_samples_split = 100
Area: 0.5
for depth = 1 and min_samples_split = 500
Area: 0.5
for depth = 5 and min_samples_split = 5
Area: 0.5851452291878505
for depth = 5 and min_samples_split = 10
Area: 0.5849718461692984
for depth = 5 and min_samples_split = 100
Area: 0.5849025112643739
for depth = 5 and min_samples_split = 500
Area: 0.5858627209652882
for depth = 10 and min_samples_split = 5
Area: 0.6395015880934032
for depth = 10 and min_samples_split = 10
Area: 0.6382423944931221
for depth = 10 and min_samples_split = 100
Area: 0.6329523774442523
for depth = 10 and min_samples_split = 500
Area: 0.6338942649263555
for depth = 50 and min_samples_split = 5
Area: 0.9004081900035659
for depth = 50 and min_samples_split = 10
Area: 0.8921558263616047
for depth = 50 and min_samples_split = 100
Area: 0.8498908301852329
for depth = 50 and min_samples_split = 500
Area: 0.8007942868429637
for depth = 100 and min_samples_split = 5
Area: 0.9666896855269189
for depth = 100 and min_samples_split = 10
Area: 0.9573712519655028
for depth = 100 and min_samples_split = 100
Area: 0.9069098835856154
for depth = 100 and min_samples_split = 500
Area: 0.8529499031045334
for depth = 500 and min_samples_split = 5
Area: 0.993572445728152
for depth = 500 and min_samples_split = 10
Area: 0.9836775513789491
for depth = 500 and min_samples_split = 100
Area: 0.9351385517745259
for depth = 500 and min_samples_split = 500
Area: 0.8788834358915292
for depth = 1000 and min_samples_split = 5
Area: 0.9932885716439369
for depth = 1000 and min_samples_split = 10
Area: 0.9847914949486231
for depth = 1000 and min_samples_split = 100
Area: 0.9326308265669556
for depth = 1000 and min_samples_split = 500
Area: 0.879767730466761
[0.5, 0.5, 0.5, 0.5, 0.5851452291878505, 0.5849718461692984, 0.58490
25112643739, 0.5858627209652882, 0.6395015880934032, 0.6382423944931
```

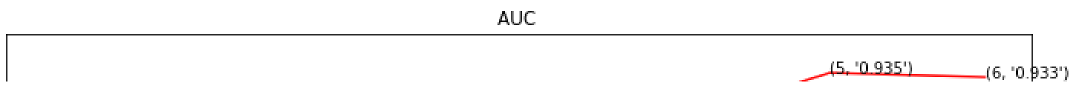
```
221, 0.6329523774442523, 0.6338942649263555, 0.9004081900035659, 0.8
921558263616047, 0.8498908301852329, 0.8007942868429637, 0.966689685
5269189, 0.9573712519655028, 0.9069098835856154, 0.8529499031045334,
0.993572445728152, 0.9836775513789491, 0.9351385517745259, 0.8788834
358915292, 0.9932885716439369, 0.9847914949486231, 0.932630826566955
6, 0.879767730466761]
```

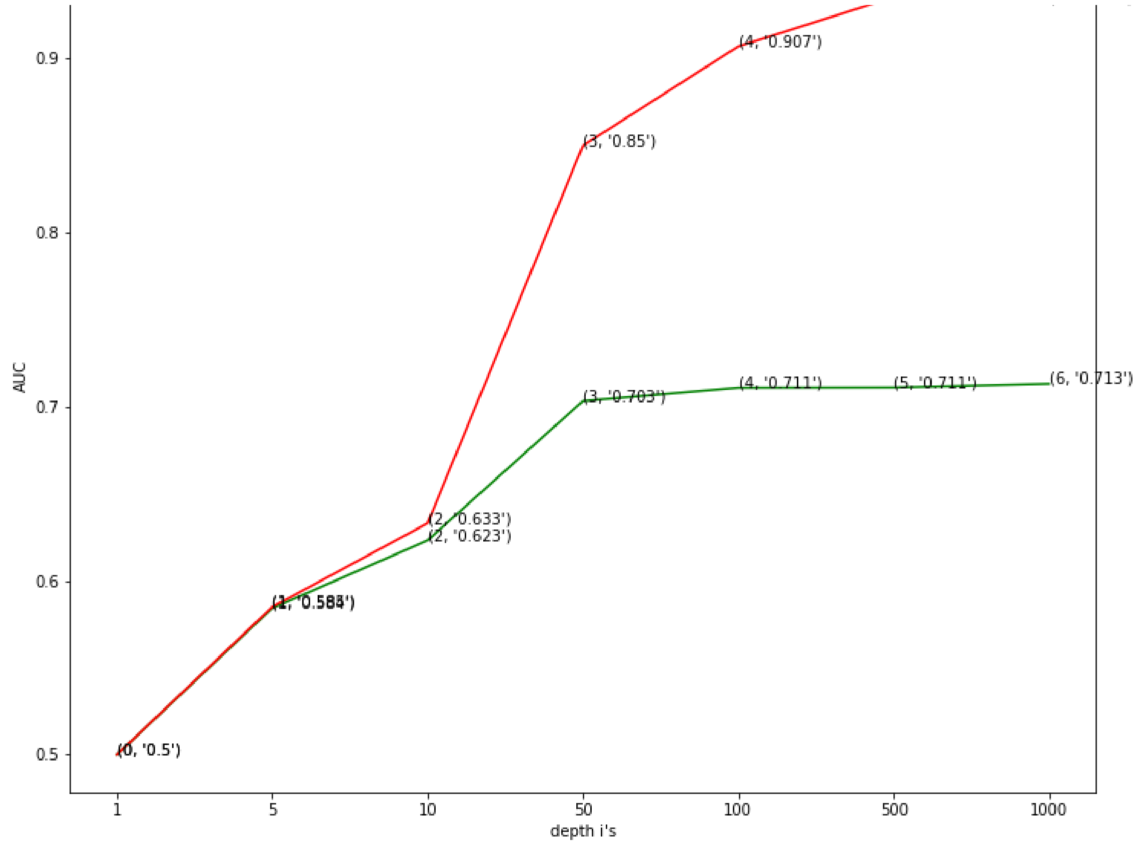
In [91]:

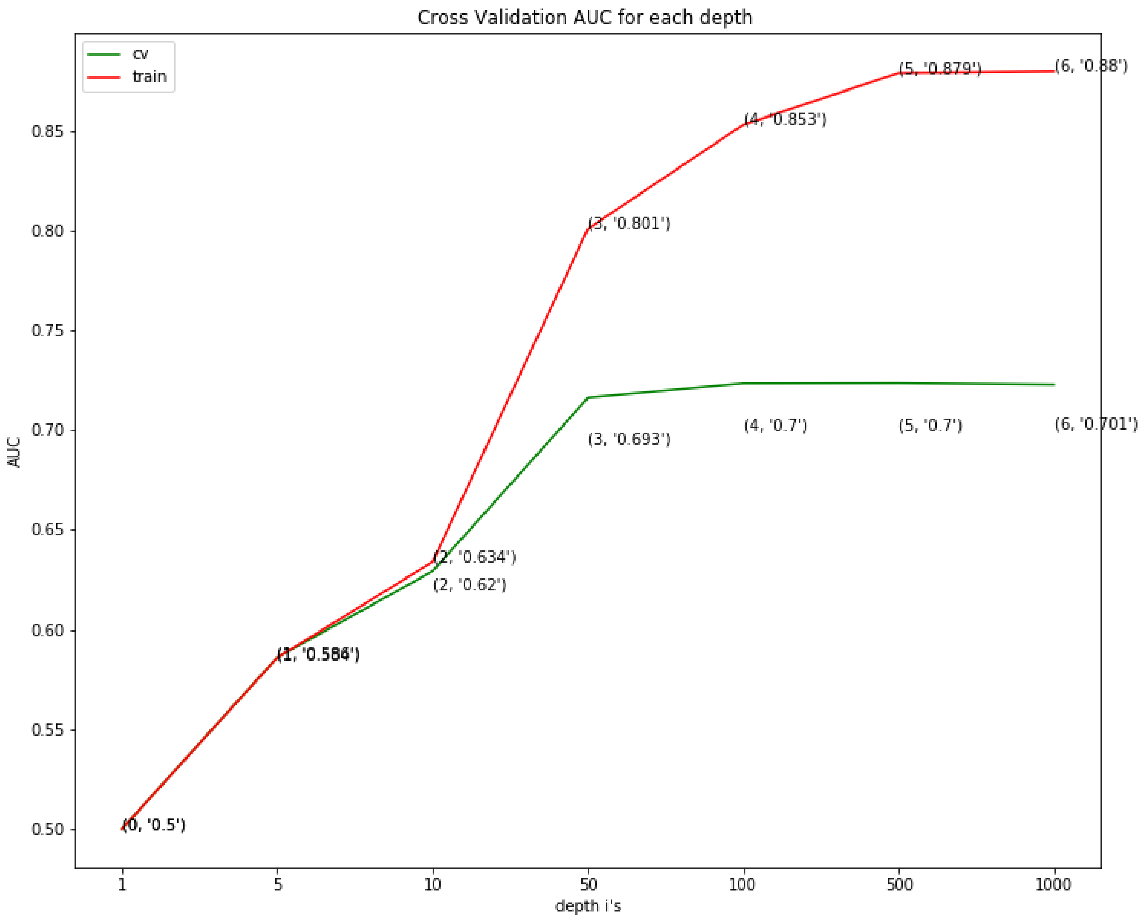
```
best_depth,best_samples_split = draw(auc_array,auc_array_train)
```


Cross Validation AUC for each depth
AUC
depth i's
1
5
10
50
100
500
1000
0.5
0.6
0.7
0.8
0.9
1.0
(0, '0.5')
(1, '0.584')
(2, '0.64')
(2, '0.62')
(3, '0.9')
(3, '0.693')
(4, '0.967')
(4, '0.7')
(5, '0.994')
(5, '0.7')
(6, '0.993')
(6, '0.701')


AUC
AUC
depth i's
1
5
10
50
100
500
1000
0.5
0.6
0.7
0.8
0.9
1.0
(0, '0.5')
(1, '0.585')
(2, '0.638')
(2, '0.619')
(3, '0.892')
(3, '0.695')
(4, '0.957')
(4, '0.7')
(5, '0.984')
(5, '0.705')
(6, '0.985')
(6, '0.701')


AUC
(5, '0.935')
(6, '0.933')



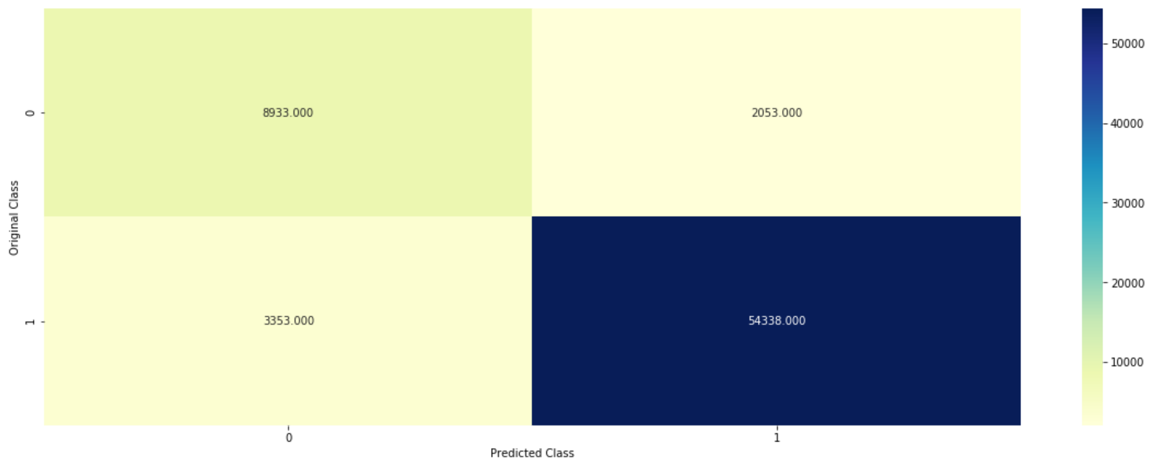


```
best depth = 500 and min_samples_split = 500
```

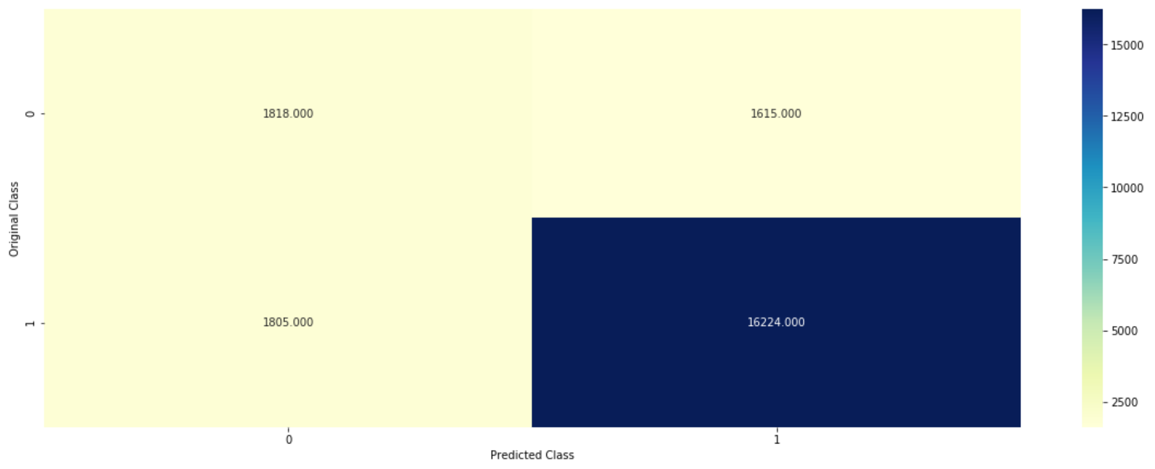
In [92]:

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

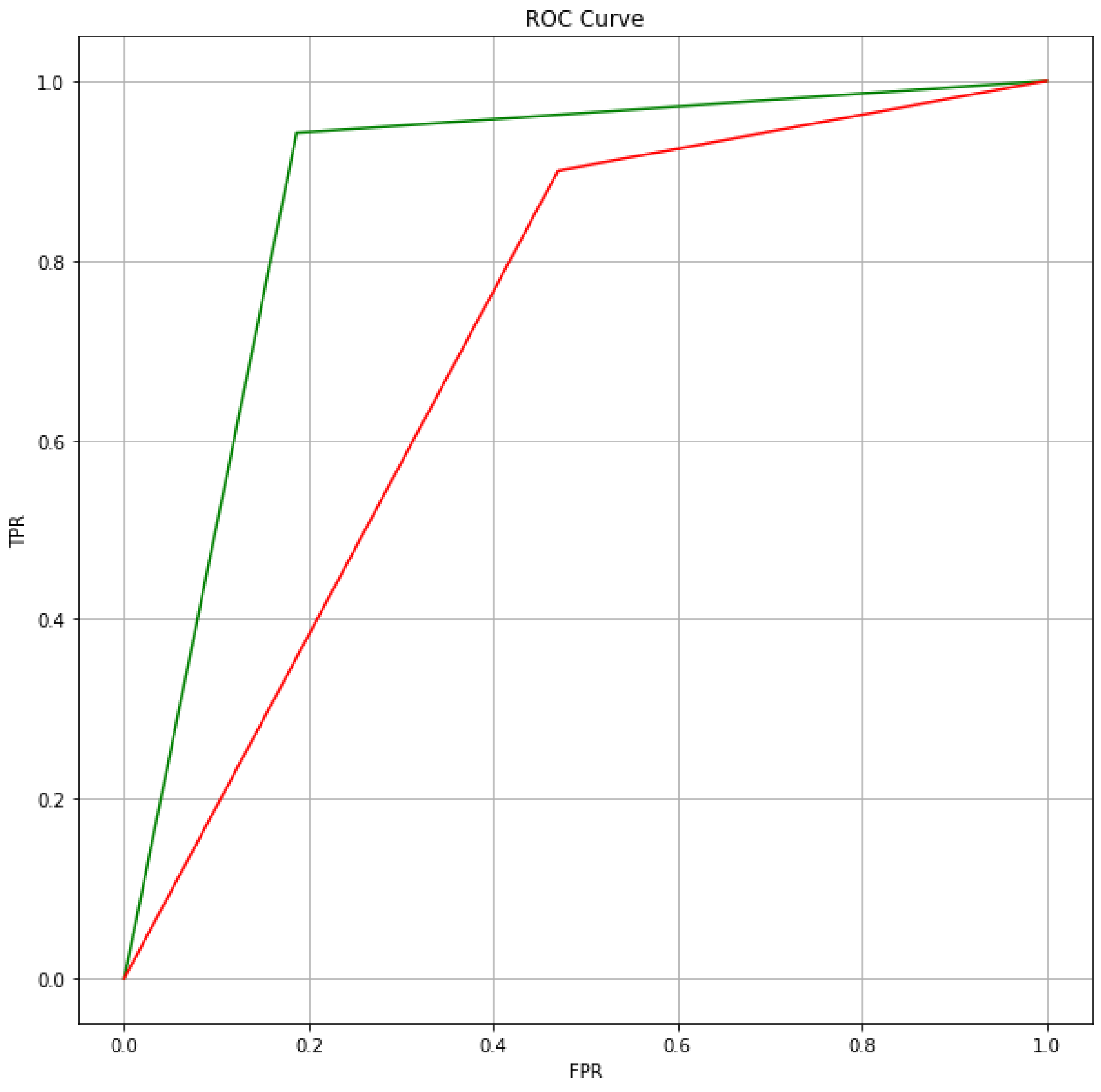
```
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  500 The AUC is: 0.8775029062076302
For values of best alpha =  500 The AUC is: 0.7239886990354689
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  500 The AUC is: 0.7147247491366508
```


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

[5.2.1] Top 10 important features of positive class from SET 2

In [94]:

```
feature_names = tf_idf_vect.get_feature_names()
indices = np.argsort(-clf.feature_importances_)
word_indices = indices[-10:]
word_list = getImportantFeatures(word_indices,feature_names)
print(word_list)
```

```
['good at', 'good as when', 'good as what', 'good as well', 'good as
this', 'good as they', 'good as the', 'good as starbucks', 'good bar
gain', 'zukes']
```

[5.2.2] Top 10 important features of negative class from SET 2

In [97]:

```
# Please write all the codeindices = np.argsort(-clf.feature_importances_)
word_indices = indices[:10]
word_list = getImportantFeatures(word_indices,feature_names)
print(word_list)
```

```
['not', 'great', 'worst', 'disappointed', 'awful', 'was', 'horribl
e', 'bad', 'threw', 'return']
```

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

In [100]:

```
# Please write all the code# words in each node of decision tree
feature = clf.tree_.feature
words = getImportantFeatures(feature,feature_names)
print(len(words))
```

```
3173
```

In [102]:

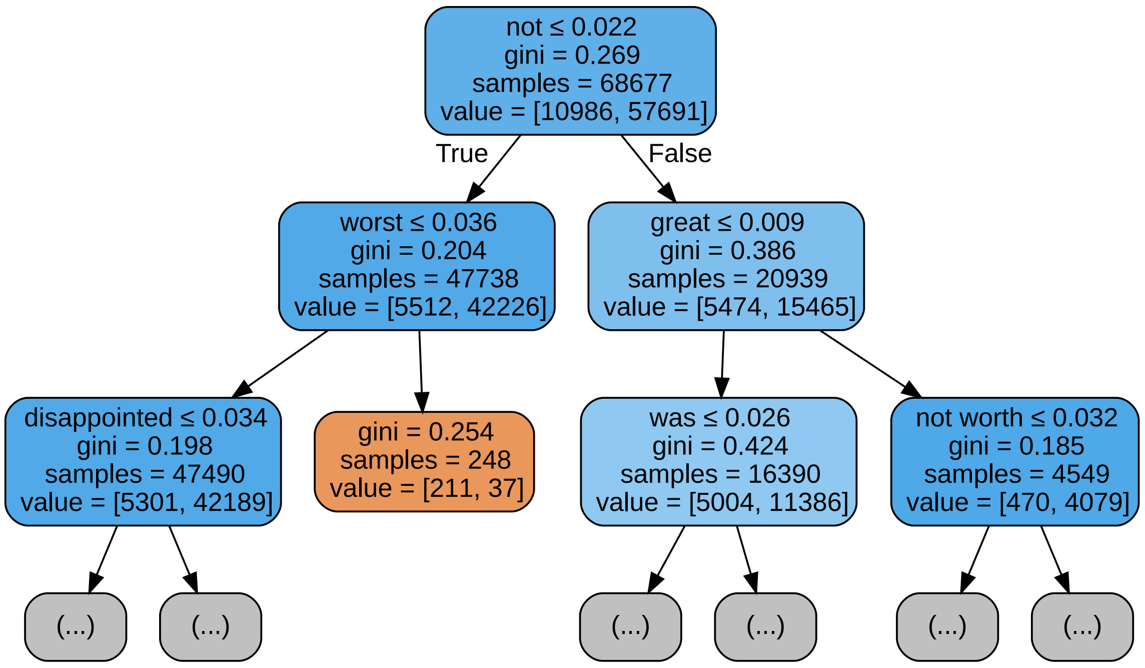
```
print(words[:20])
```

```
['not', 'worst', 'disappointed', 'awful', 'bad', 'threw', 'horribl
e', 'great', 'waste', 'terrible', 'disappointing', 'disappointment',
'return', 'disgusting', 'love', 'the best', 'never buy', 'deliciou
s', 'good', 'beware']
```

In [104]:

```
drawTree(clf,feature_names)
```

Out[104]:



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

In [114]:

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

In [117]:

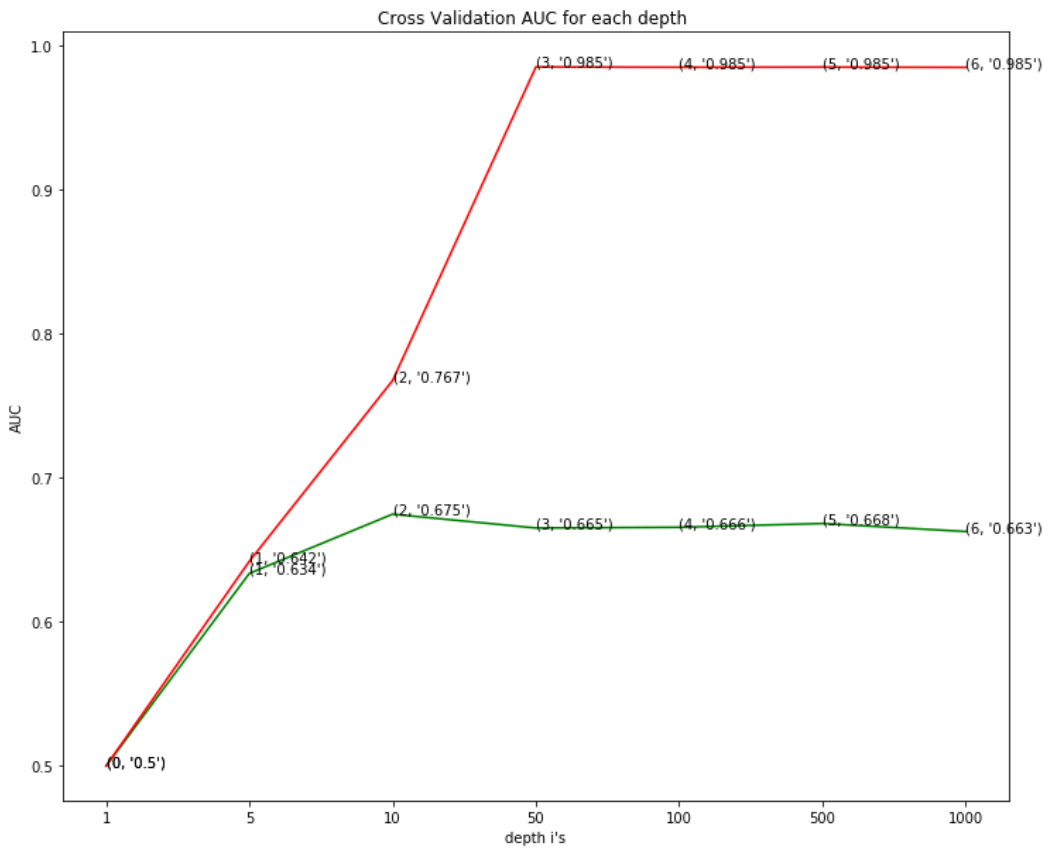
```
auc_array,auc_array_train = performHyperParameterTuning(train,cv,test)
```

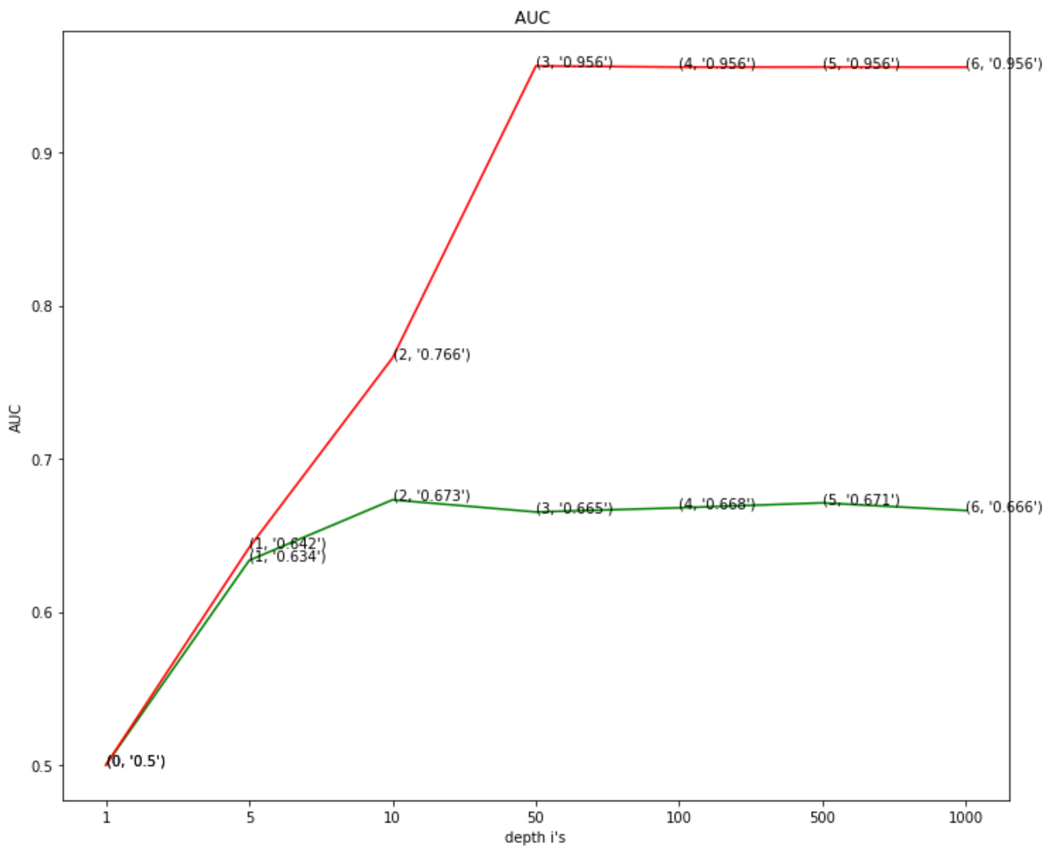
```
for depth = 1 and min_samples_split = 5
Area: 0.5
for depth = 1 and min_samples_split = 10
Area: 0.5
for depth = 1 and min_samples_split = 100
Area: 0.5
for depth = 1 and min_samples_split = 500
Area: 0.5
for depth = 5 and min_samples_split = 5
Area: 0.6336194860870832
for depth = 5 and min_samples_split = 10
Area: 0.6336194860870832
for depth = 5 and min_samples_split = 100
Area: 0.6336194860870832
for depth = 5 and min_samples_split = 500
Area: 0.6336194860870832
for depth = 10 and min_samples_split = 5
Area: 0.6747128046325918
for depth = 10 and min_samples_split = 10
Area: 0.6731526701135975
for depth = 10 and min_samples_split = 100
Area: 0.6674318193135933
for depth = 10 and min_samples_split = 500
Area: 0.6366875339995746
for depth = 50 and min_samples_split = 5
Area: 0.6651029817505466
for depth = 50 and min_samples_split = 10
Area: 0.6652067930067912
for depth = 50 and min_samples_split = 100
Area: 0.6708822752842813
for depth = 50 and min_samples_split = 500
Area: 0.6357775764708216
for depth = 100 and min_samples_split = 5
Area: 0.6656056195483788
for depth = 100 and min_samples_split = 10
Area: 0.6679369810904251
for depth = 100 and min_samples_split = 100
Area: 0.6704748924538859
for depth = 100 and min_samples_split = 500
Area: 0.6358815770254913
for depth = 500 and min_samples_split = 5
Area: 0.6682231245895852
for depth = 500 and min_samples_split = 10
Area: 0.6711526312948005
for depth = 500 and min_samples_split = 100
Area: 0.6705875754963133
for depth = 500 and min_samples_split = 500
Area: 0.6358469101739347
for depth = 1000 and min_samples_split = 5
Area: 0.6626761128431637
for depth = 1000 and min_samples_split = 10
Area: 0.6661863366365572
for depth = 1000 and min_samples_split = 100
Area: 0.6708822752842813
for depth = 1000 and min_samples_split = 500
Area: 0.6359162438770478
for depth = 1 and min_samples_split = 5
Area: 0.5
for depth = 1 and min_samples_split = 10
Area: 0.5
for depth = 1 and min_samples_split = 100
```

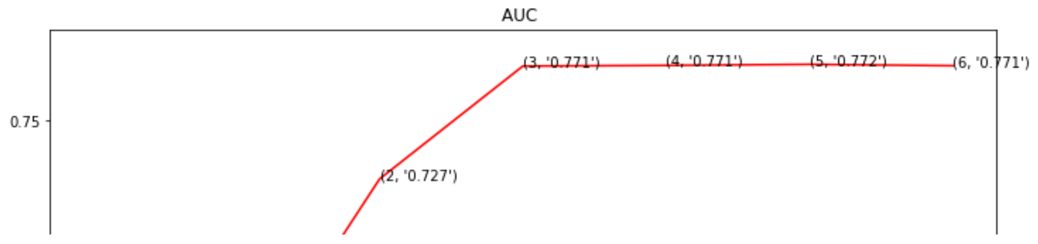
```
Area: 0.5
for depth = 1 and min_samples_split = 500
Area: 0.5
for depth = 5 and min_samples_split = 5
Area: 0.6420172843536696
for depth = 5 and min_samples_split = 10
Area: 0.6420172843536696
for depth = 5 and min_samples_split = 100
Area: 0.6420172843536696
for depth = 5 and min_samples_split = 500
Area: 0.6420172843536696
for depth = 10 and min_samples_split = 5
Area: 0.7674269103931838
for depth = 10 and min_samples_split = 10
Area: 0.7658882447746065
for depth = 10 and min_samples_split = 100
Area: 0.7271314063979272
for depth = 10 and min_samples_split = 500
Area: 0.6576526896087889
for depth = 50 and min_samples_split = 5
Area: 0.9849926449051943
for depth = 50 and min_samples_split = 10
Area: 0.9564401818898295
for depth = 50 and min_samples_split = 100
Area: 0.7709191710548243
for depth = 50 and min_samples_split = 500
Area: 0.6609599901340709
for depth = 100 and min_samples_split = 5
Area: 0.9847954394521347
for depth = 100 and min_samples_split = 10
Area: 0.9556838036189733
for depth = 100 and min_samples_split = 100
Area: 0.7711835790142101
for depth = 100 and min_samples_split = 500
Area: 0.6609599901340709
for depth = 500 and min_samples_split = 5
Area: 0.9848907749464059
for depth = 500 and min_samples_split = 10
Area: 0.9557314942442293
for depth = 500 and min_samples_split = 100
Area: 0.7715931912479621
for depth = 500 and min_samples_split = 500
Area: 0.6609599901340709
for depth = 1000 and min_samples_split = 5
Area: 0.9847130813744164
for depth = 1000 and min_samples_split = 10
Area: 0.9556491361665111
for depth = 1000 and min_samples_split = 100
Area: 0.7710665534840296
for depth = 1000 and min_samples_split = 500
Area: 0.6609599901340709
```

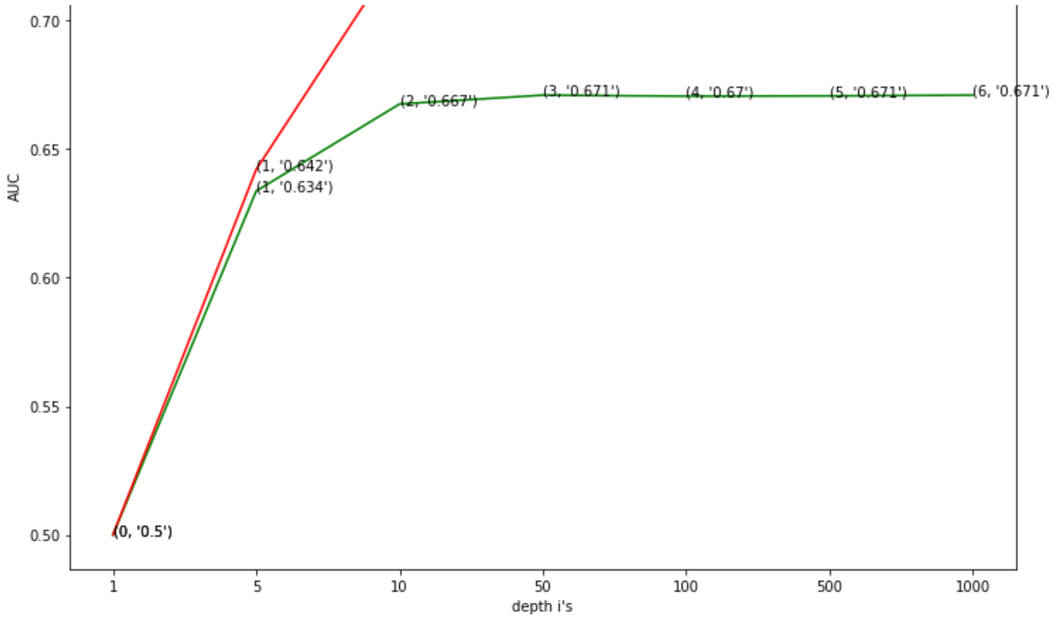
In [118]:

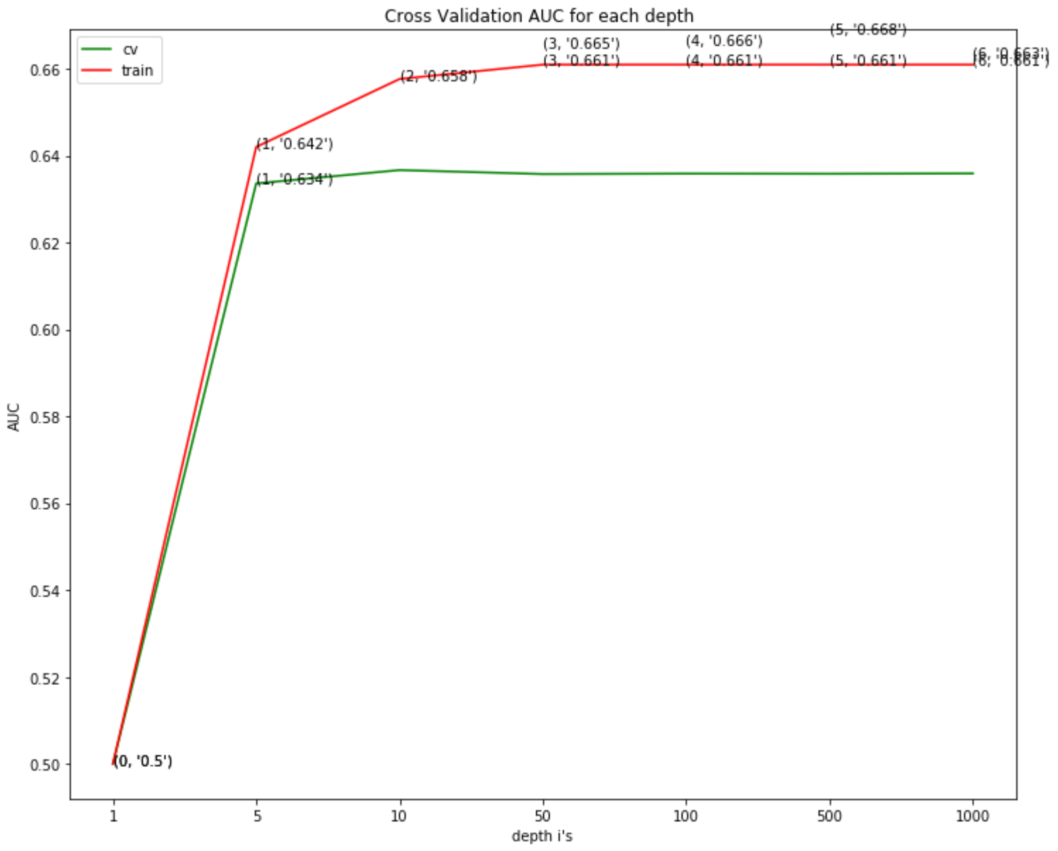
```
best_depth,best_samples_split = draw(auc_array,auc_array_train)
```


Cross Validation AUC for each depth
AUC
depth i's
1.0
0.9
0.8
0.7
0.6
0.5
1
5
10
50
100
500
1000
(0, '0.5')
(1, '0.642')
(1, '0.634')
(2, '0.767')
(2, '0.675')
(3, '0.985')
(3, '0.665')
(4, '0.985')
(4, '0.666')
(5, '0.985')
(5, '0.668')
(6, '0.985')
(6, '0.663')


AUC
AUC
depth i's
0.9
0.8
0.7
0.6
0.5
1
5
10
50
100
500
1000
(0, '0.5')
(1, '0.642')
(1, '0.634')
(2, '0.766')
(2, '0.673')
(3, '0.956')
(3, '0.665')
(4, '0.956')
(4, '0.668')
(5, '0.956')
(5, '0.671')
(6, '0.956')
(6, '0.666')


AUC
0.75
(2, '0.727')
(3, '0.771')
(4, '0.771')
(5, '0.772')
(6, '0.771')



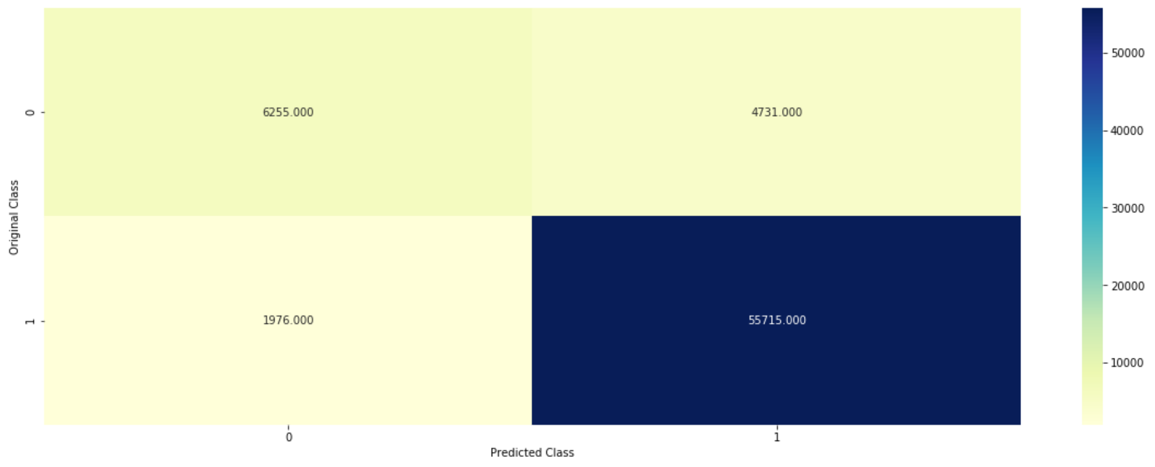


```
best depth = 10 and min_samples_split = 5
```

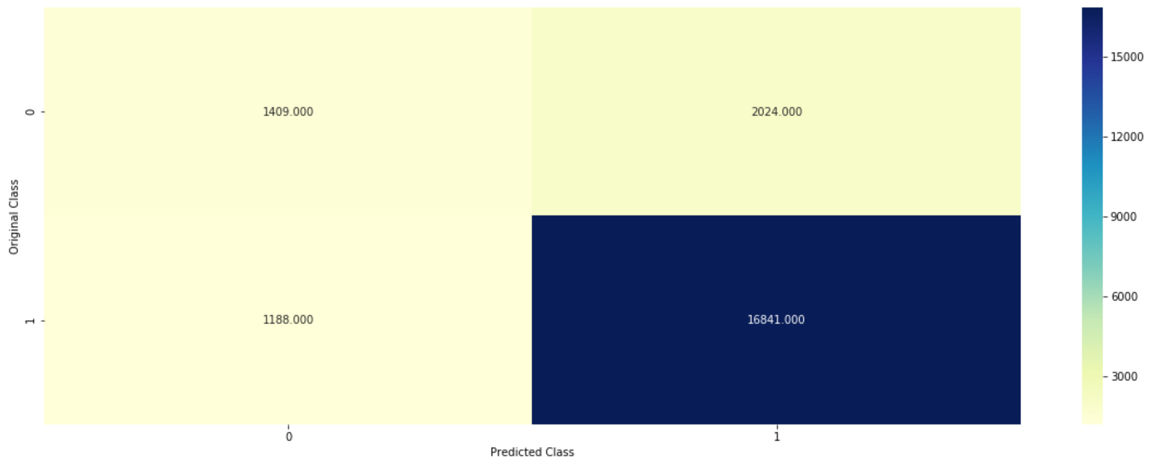
In [120]:

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

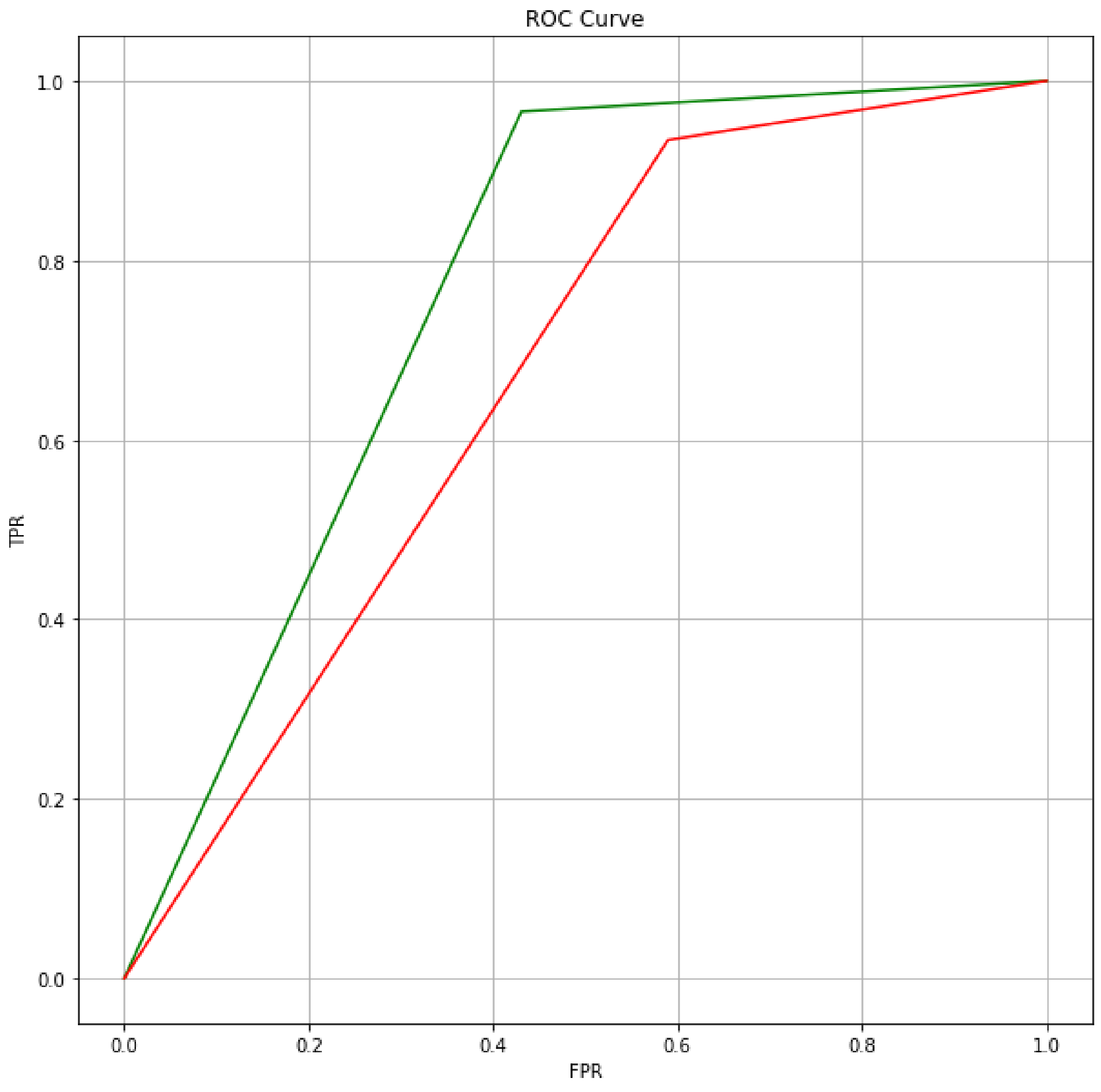
```
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  10 The AUC is: 0.767554780941319
For values of best alpha =  10 The AUC is: 0.675154854314544
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  10 The AUC is: 0.6722671796032016
```



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

In [128]:

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

In [130]:

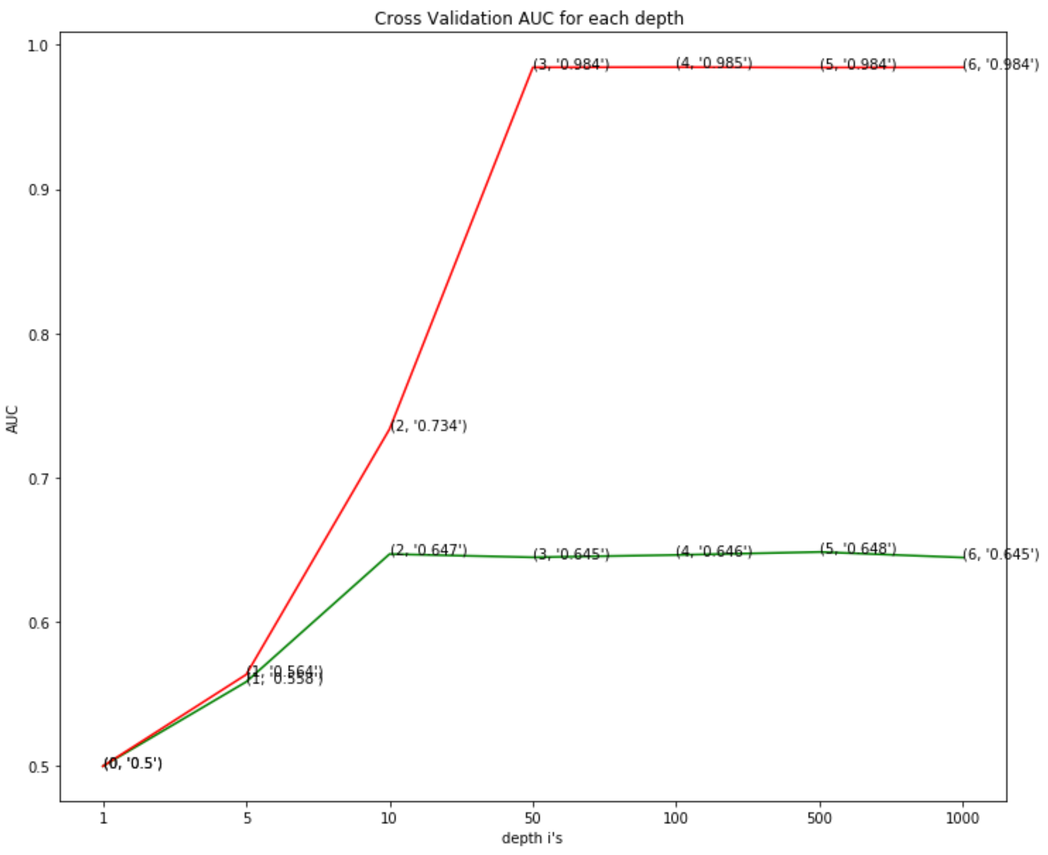
```
auc_array,auc_array_train = performHyperParameterTuning(train,cv,test)
```

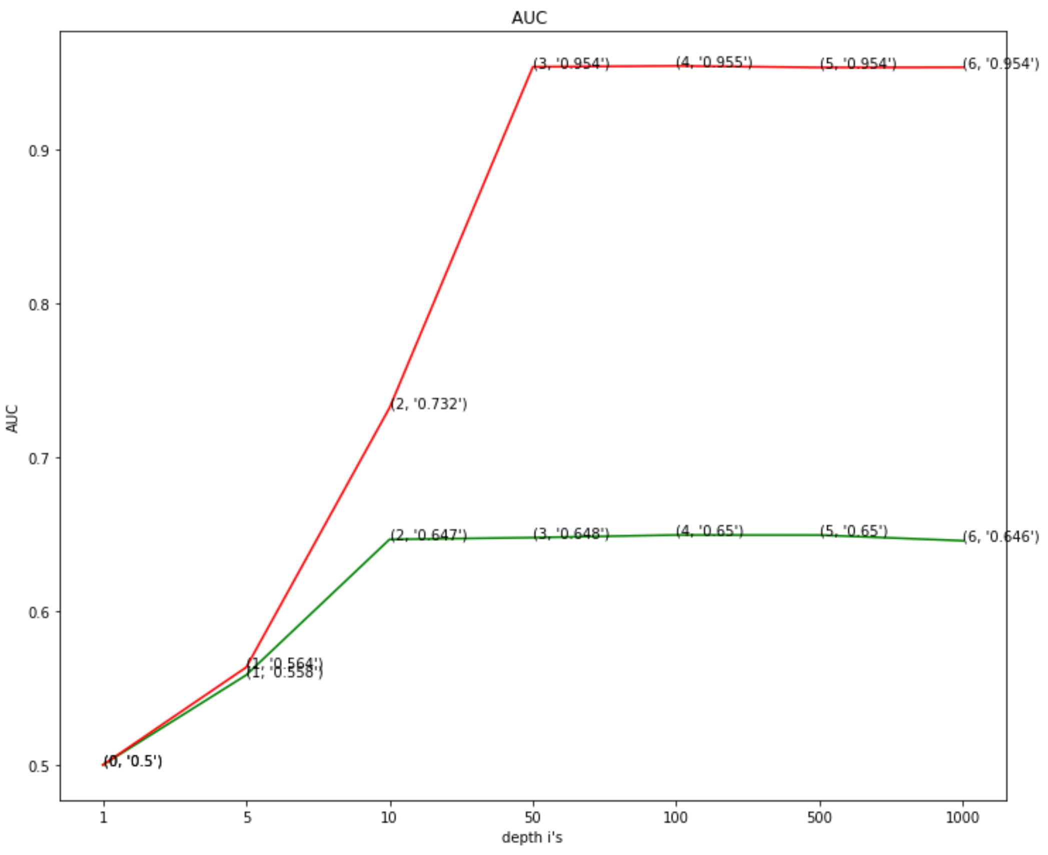
```
for depth = 1 and min_samples_split = 5
Area: 0.5
for depth = 1 and min_samples_split = 10
Area: 0.5
for depth = 1 and min_samples_split = 100
Area: 0.5
for depth = 1 and min_samples_split = 500
Area: 0.5
for depth = 5 and min_samples_split = 5
Area: 0.5584886575286343
for depth = 5 and min_samples_split = 10
Area: 0.5584886575286343
for depth = 5 and min_samples_split = 100
Area: 0.5584886575286343
for depth = 5 and min_samples_split = 500
Area: 0.5605949053837254
for depth = 10 and min_samples_split = 5
Area: 0.6470634349875131
for depth = 10 and min_samples_split = 10
Area: 0.6467601158112619
for depth = 10 and min_samples_split = 100
Area: 0.6430415123116793
for depth = 10 and min_samples_split = 500
Area: 0.613328676255549
for depth = 50 and min_samples_split = 5
Area: 0.6447780729627306
for depth = 50 and min_samples_split = 10
Area: 0.6479068982895271
for depth = 50 and min_samples_split = 100
Area: 0.6444464347421066
for depth = 50 and min_samples_split = 500
Area: 0.6131987544365556
for depth = 100 and min_samples_split = 5
Area: 0.6464248430608788
for depth = 100 and min_samples_split = 10
Area: 0.6496230651902635
for depth = 100 and min_samples_split = 100
Area: 0.6443684185512355
for depth = 100 and min_samples_split = 500
Area: 0.6131294207334426
for depth = 500 and min_samples_split = 5
Area: 0.6484790590888976
for depth = 500 and min_samples_split = 10
Area: 0.6495451120988674
for depth = 500 and min_samples_split = 100
Area: 0.6443597360634776
for depth = 500 and min_samples_split = 500
Area: 0.6133461043305397
for depth = 1000 and min_samples_split = 5
Area: 0.6446393424570294
for depth = 1000 and min_samples_split = 10
Area: 0.64588741221254
for depth = 1000 and min_samples_split = 100
Area: 0.6435276685266457
for depth = 1000 and min_samples_split = 500
Area: 0.6130167376910151
for depth = 1 and min_samples_split = 5
Area: 0.5
for depth = 1 and min_samples_split = 10
Area: 0.5
for depth = 1 and min_samples_split = 100
```

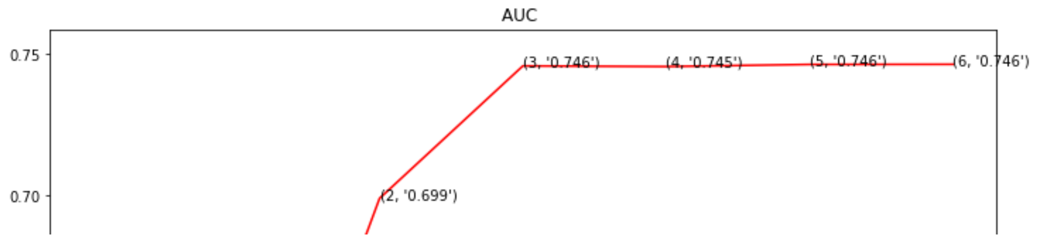
```
Area: 0.5
for depth = 1 and min_samples_split = 500
Area: 0.5
for depth = 5 and min_samples_split = 5
Area: 0.5635459973272108
for depth = 5 and min_samples_split = 10
Area: 0.5635459973272108
for depth = 5 and min_samples_split = 100
Area: 0.5635459973272108
for depth = 5 and min_samples_split = 500
Area: 0.5641789986283321
for depth = 10 and min_samples_split = 5
Area: 0.7337020783017839
for depth = 10 and min_samples_split = 10
Area: 0.7324170213808784
for depth = 10 and min_samples_split = 100
Area: 0.6990895562065291
for depth = 10 and min_samples_split = 500
Area: 0.6351954840559493
for depth = 50 and min_samples_split = 5
Area: 0.9844205861833264
for depth = 50 and min_samples_split = 10
Area: 0.9541995003588915
for depth = 50 and min_samples_split = 100
Area: 0.7456573430374052
for depth = 50 and min_samples_split = 500
Area: 0.6384030927772817
for depth = 100 and min_samples_split = 5
Area: 0.984554945439738
for depth = 100 and min_samples_split = 10
Area: 0.9547868061646329
for depth = 100 and min_samples_split = 100
Area: 0.7454298264415614
for depth = 100 and min_samples_split = 500
Area: 0.6383207346995635
for depth = 500 and min_samples_split = 5
Area: 0.9843122275162614
for depth = 500 and min_samples_split = 10
Area: 0.9537898881251395
for depth = 500 and min_samples_split = 100
Area: 0.746175359694463
for depth = 500 and min_samples_split = 500
Area: 0.6384030927772817
for depth = 1000 and min_samples_split = 5
Area: 0.9844205861833264
for depth = 1000 and min_samples_split = 10
Area: 0.9538787349111341
for depth = 1000 and min_samples_split = 100
Area: 0.7462208721648799
for depth = 1000 and min_samples_split = 500
Area: 0.6383662471699805
```

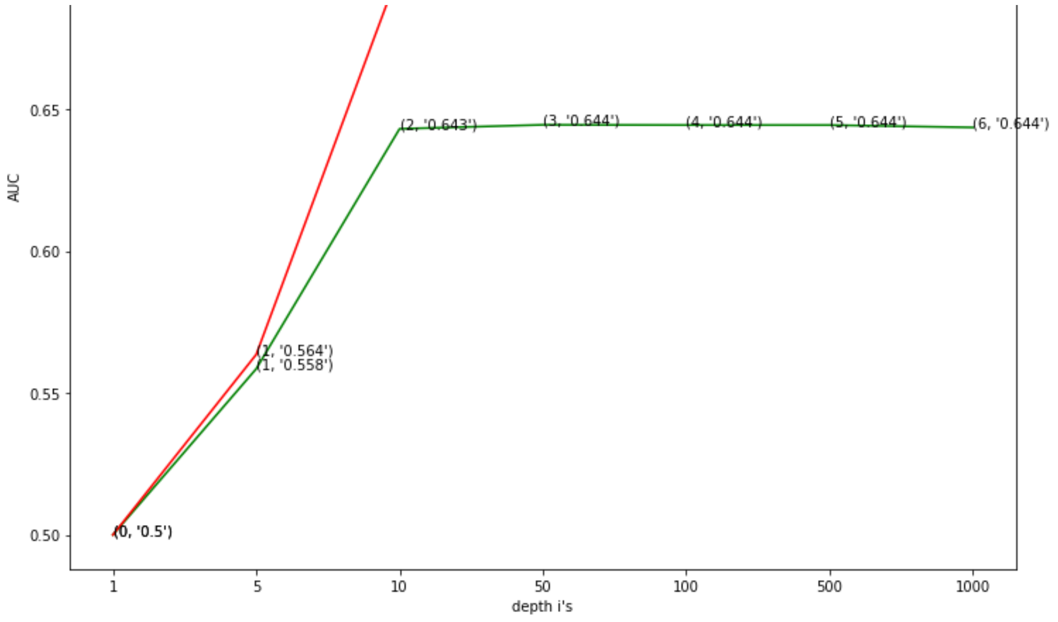
In [131]:

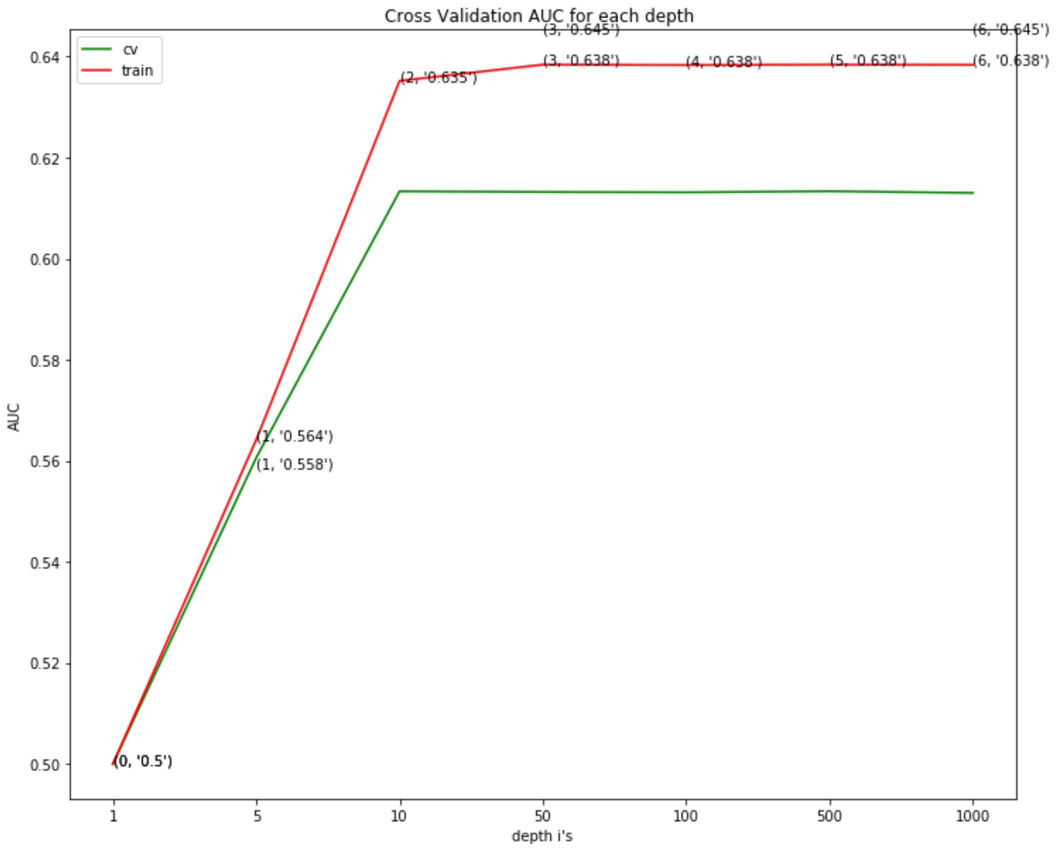
```
best_depth,best_samples_split = draw(auc_array,auc_array_train)
```


Cross Validation AUC for each depth
AUC
depth i's
1.0
0.9
0.8
0.7
0.6
0.5
1
5
10
50
100
500
1000
(0, '0.5')
(1, '0.564')
(1, '0.558')
(2, '0.734')
(2, '0.647')
(3, '0.984')
(3, '0.645')
(4, '0.985')
(4, '0.646')
(5, '0.984')
(5, '0.648')
(6, '0.984')
(6, '0.645')


AUC
AUC
depth i's
0.9
0.8
0.7
0.6
0.5
1
5
10
50
100
500
1000
(0, '0.5')
(1, '0.564')
(1, '0.558')
(2, '0.732')
(2, '0.647')
(3, '0.954')
(3, '0.648')
(4, '0.955')
(4, '0.65')
(5, '0.954')
(5, '0.65')
(6, '0.954')
(6, '0.646')


AUC
0.75
0.70
(2, '0.699')
(3, '0.746')
(4, '0.745')
(5, '0.746')
(6, '0.746')



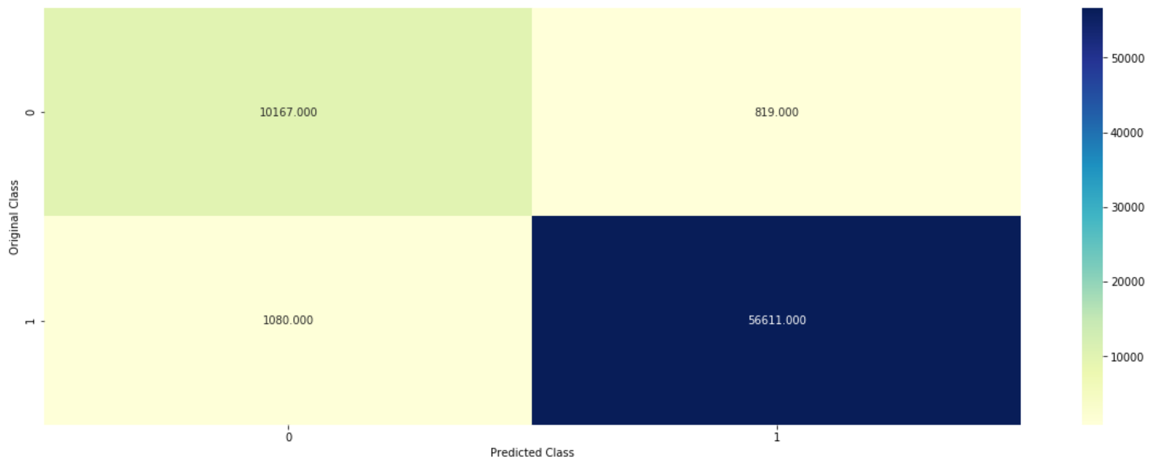


```
best depth = 100 and min_samples_split = 10
```

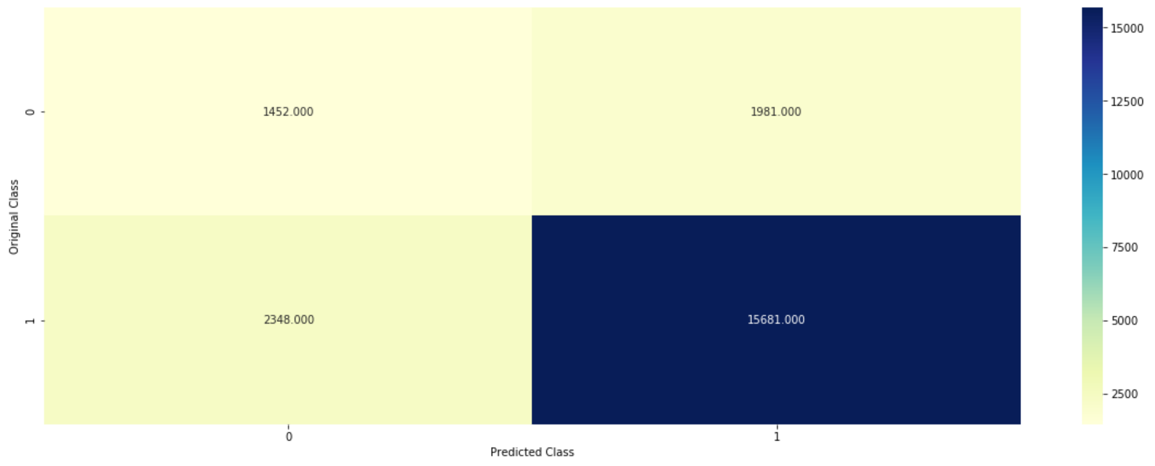
In [132]:

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

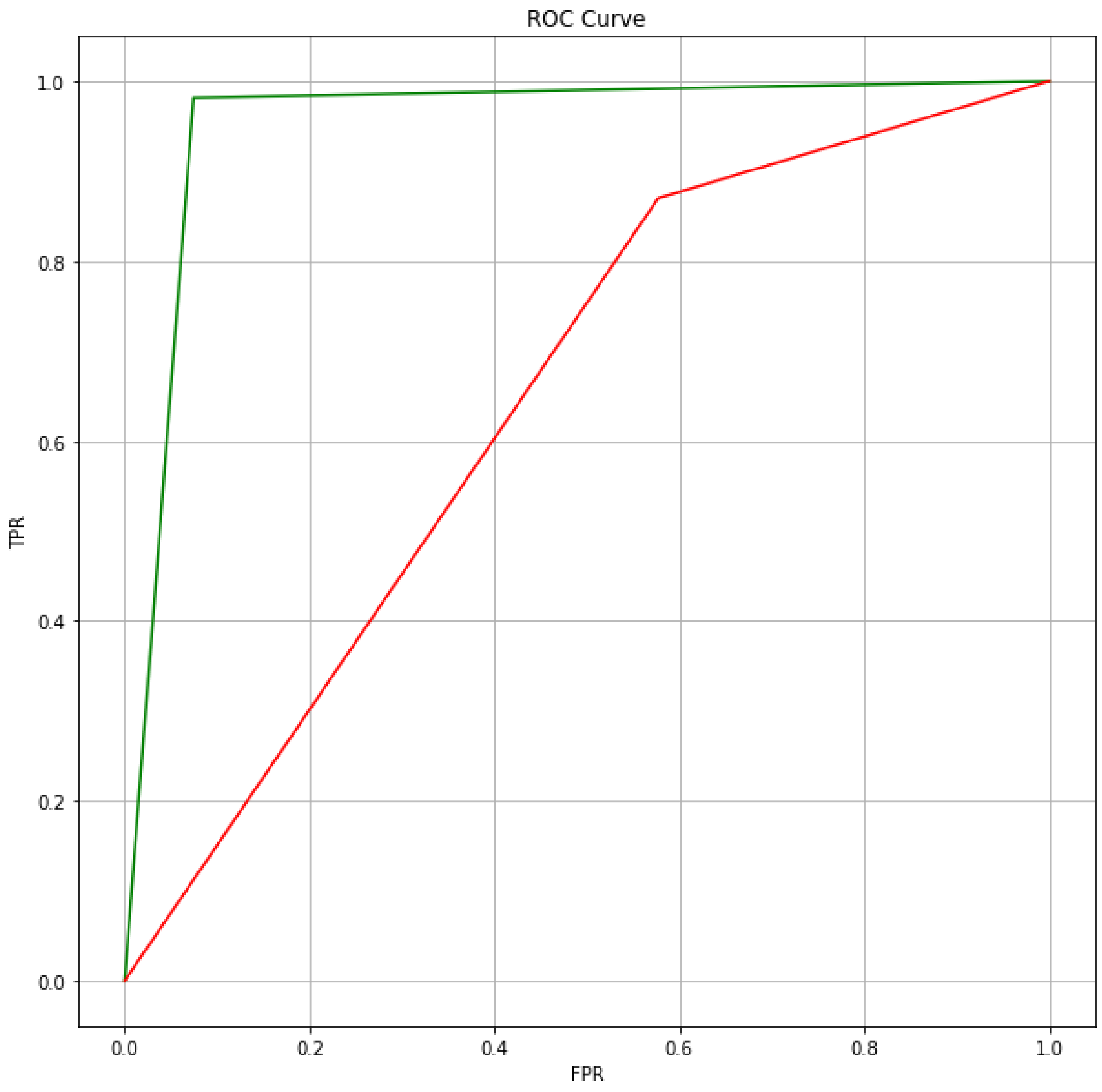
```
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  100 The AUC is: 0.9533650745637545
For values of best alpha =  100 The AUC is: 0.6471529731425161
-------------------- Confusion matrix --------------------
```



```
For values of best alpha =  100 The AUC is: 0.6463595314129384
```



[6] Conclusions

Vectorizer	Depth	min_samples_split	AUC
BOW	500	500	0.70
TFIDF	500	500	0.71
AvgW2V	10	5	0.67
TFIDFW2V	100	10	0.64

In [ ]:

```

```