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.

[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.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
from collections import Counter
from sklearn import model_selection
from sklearn.metrics import roc_auc_score
from sklearn.preprocessing import StandardScaler
from sklearn.calibration import CalibratedClassifierCV
from sklearn.tree import DecisionTreeClassifier, export_graphviz

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
```

```
C:\Anaconda\lib\site-packages\gensim\utils.py:1209: UserWarning: detect
ed Windows; aliasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_seria
l")
```

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 50
0000 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 Sco
re != 3 LIMIT 500000""", con)
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score
 != 3 LIMIT 100000""", con)

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

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

```
Number of data points in our data (100000, 10)
```

Out[2]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomin
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomin
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	COUNT(*)
0	#oc-R115TNMSPFT9I7	B007Y59HVM	Breyton	1331510400	2	Overall its just OK when considering the price...	2

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

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

Out[5]:

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

In [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	HelpfulnessDenon
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, inplace=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]:
```
(87775, 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]: 87.775

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	HelpfulnessDenom
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()
```

```
(87773, 10)
```

Out[13]:
```
1    73592
0    14181
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]:
```
from nltk.corpus import stopwords
stop = set(stopwords.words('english')) #set of stopwords
words_to_keep = set(('not'))
stop -= words_to_keep

sno = nltk.stem.SnowballStemmer('english')
```

```
def cleanhtml(sentence): #function to clean any HTML Tags
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext
def cleanpunc(sentence): #function to clean any word of punctuation or
 special character
    cleaned = re.sub(r'[?|!|\'|"|#]',r'', sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ', cleaned)
    return cleaned
```

In [15]:

```
#code for implementing step by step check mentioned in preprocessing ph
ase
#runtime wiil be high due to 500k sentences
i = 0
str1 = ' '
final_string = []
all_positive_words = []
all_negative_words = []
s=''
for sent in final['Text'].values:
    filtered_sentence=[]
    sent=cleanhtml(sent)
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                if(cleaned_words.lower() not in stop):
                    s=(sno.stem(cleaned_words.lower())).encode('utf8')
                    filtered_sentence.append(s)
                    if (final['Score'].values)[i] == 'positive':
                        all_positive_words.append(s)
                    if (final['Score'].values)[i] == 'negative':
                        all_negative_words.append(s)
                else:
                    continue
            else:
                continue
    str1 = b" ".join(filtered_sentence)
    final_string.append(str1)
    i+=1
```

In [16]:
```
final['cleanedText']=final_string #Adding a column of Cleanedtext which
 displays data after preprocesing.
final['cleanedText']=final['cleanedText'].str.decode("utf-8")
print('shape of final', final.shape)
final.head()
```

```
shape of final (87773, 11)
```

Out[16]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessD
22620	24750	2734888454	A13ISQV0U9GZIC	Sandikaye	1	
22621	24751	2734888454	A1C298ITT645B6	Hugh G. Pritchard	0	
70677	76870	B00002N8SM	A19Q006CSFT011	Arlielle	0	
70676	76869	B00002N8SM	A1FYH4S02BW7FN	wonderer	0	
70675	76868	B00002N8SM	AUE8TB5VHS6ZV	eyeofthestorm	0	

Time Based Splitting For As AFR is Time series Data

In [17]:
```
#sorting data according to time in ascending oreder for time based spli
tting
time_sorted_data = final.sort_values('Time', axis=0, ascending=True, in
place=False, kind='quicksort', na_position='last')
x = time_sorted_data['cleanedText'].values
y = time_sorted_data['Score']
#SPlit the dataset into Train and Test
X_train,X_test,Y_train,Y_test=train_test_split(x, y, test_size=0.3, ran
dom_state=0)
```

In [18]:
```
# 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 made in
the USA but they are out there, but this one isnt.  Its too bad too bec
ause its a good product but I wont take any chances till they know what
is going on with the china imports.
==================================================
The Candy Blocks were a nice visual for the Lego Birthday party but the
```

```
candy has little taste to it.  Very little of the 2 lbs that I bought w
ere eaten and I threw the rest away.  I would not buy the candy again.
==================================================
was way to hot for my blood, took a bite and did a jig  lol
==================================================
My dog LOVES these treats. They tend to have a very strong fish oil sme
ll. So if you are afraid of the fishy smell, don't get it. But I think
my dog likes it because of the smell. These treats are really small in
size. They are great for training. You can give your dog several of the
se without worrying about him over eating. Amazon's price was much more
reasonable than any other retailer. You can buy a 1 pound bag on Amazon
for almost the same price as a 6 ounce bag at other retailers. It's def
initely worth it to buy a big bag if your dog eats them a lot.
==================================================
```

In [19]:
```
# remove urls from text python: https://stackoverflow.com/a/40823105/40
84039
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 made in
the USA but they are out there, but this one isnt.  Its too bad too bec
ause its a good product but I wont take any chances till they know what
is going on with the china imports.
```

In [20]:
```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how
-to-remove-all-tags-from-an-element
from bs4 import BeautifulSoup

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

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

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

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

```
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 made in
the USA but they are out there, but this one isnt.  Its too bad too bec
ause its a good product but I wont take any chances till they know what
is going on with the china imports.
==================================================
The Candy Blocks were a nice visual for the Lego Birthday party but the
candy has little taste to it.  Very little of the 2 lbs that I bought w
ere eaten and I threw the rest away.  I would not buy the candy again.
==================================================
was way to hot for my blood, took a bite and did a jig  lol
==================================================
My dog LOVES these treats. They tend to have a very strong fish oil sme
ll. So if you are afraid of the fishy smell, don't get it. But I think
my dog likes it because of the smell. These treats are really small in
size. They are great for training. You can give your dog several of the
se without worrying about him over eating. Amazon's price was much more
reasonable than any other retailer. You can buy a 1 pound bag on Amazon
for almost the same price as a 6 ounce bag at other retailers. It's def
initely worth it to buy a big bag if your dog eats them a lot.
```

In [21]:
```
# 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 [22]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
was way to hot for my blood, took a bite and did a jig  lol
==================================================
```

In [23]:
```
#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 made in the USA but they are out there, but this one isnt.  Its too bad too because its a good product but I wont take any chances till they know what is going on with the china imports.
```

In [24]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
was way to hot for my blood took a bite and did a jig lol
```

In [25]:
```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'no
t'
# <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', 'o
urs', 'ourselves', 'you', "you're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselve
s', 'he', 'him', 'his', 'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'it
s', 'itself', 'they', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'th
is', 'that', "that'll", 'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'h
ave', 'has', 'had', 'having', 'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or',
 'because', 'as', 'until', 'while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between',
'into', 'through', 'during', 'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out',
'on', 'off', 'over', 'under', 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'h
ow', 'all', 'any', 'both', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 's
o', 'than', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should',
"should've", 'now', 'd', 'll', 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't",
'didn', "didn't", 'doesn', "doesn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "is
n't", 'ma', 'mightn', "mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn',
 "shouldn't", 'wasn', "wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

In [26]:
```
# 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%|████████████████████████████████████████████████████████████
████████| 87773/87773 [01:02<00:00, 1403.50it/s]
```

In [29]:
```
preprocessed_reviews[1500]
```

Out[29]:
```
'way hot blood took bite jig lol'
```

[3.2] Preprocessing Review Summary

In [29]:
```
## Similartly you can do preprocessing for review summary also.
# Combining all the above stundents
from tqdm import tqdm
preprocessed_summaries = []
# 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%|██████████| 87773/87773 [01:03<00:00, 1383.17it/s]
```

[4] Featurization

[4.1] BAG OF WORDS

In [0]:
```
#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', 'abb
ott', '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 [0]:
```
#bi-gram, tri-gram and n-gram

#removing stop words like "not" should be avoided before building n-gra
ms
```

```
# count_vect = CountVectorizer(ngram_range=(1,2))
# please do read the CountVectorizer documentation http://scikit-learn.org/stable/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_bigram_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
```

[4.3] TF-IDF

In [0]:

```
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_tf_idf.get_shape()[1])
```

```
some sample features(unique words in the corpus) ['ability', 'able', 'able find', 'able get', 'absolute', 'absolutely', 'absolutely delicious', '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
```

[4.4] Word2Vec

In [0]:
```
# 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 [0]:
```
# 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 val
ues
# To use this code-snippet, download "GoogleNews-vectors-negative300.bi
n"
# from https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/edi
t
# it's 1.9GB in size.


# http://kavita-ganesan.com/gensim-word2vec-tutorial-starter-code/#.W17
SRFAzZPY
# 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
-negative300.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_trai
n_w2v = True, to train your own w2v ")
```

```
[('snack', 0.9951335191726685), ('calorie', 0.9946465492248535), ('wond
erful', 0.9946032166481018), ('excellent', 0.9944332838058472), ('espec
ially', 0.9941144585609436), ('baked', 0.9940600395202637), ('salted',
0.994047224521637), ('alternative', 0.9937226176261902), ('tasty', 0.99
36816692352295), ('healthy', 0.9936649799346924)]
==================================================
[('varieties', 0.9994194507598877), ('become', 0.9992934465408325), ('p
opcorn', 0.9992750883102417), ('de', 0.9992610216140747), ('miss', 0.99
92451071739197), ('melitta', 0.999218761920929), ('choice', 0.999210238
4567261), ('american', 0.9991837739944458), ('beef', 0.999178051948547
4), ('finish', 0.9991567134857178)]
```

In [0]:
```
w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])
```

```
number of words that occured minimum 5 times  3817
sample words  ['product', 'available', 'course', 'total', 'pretty', 'st
inky', 'right', 'nearby', 'used', 'ca', 'not', 'beat', 'great', 'receiv
ed', 'shipment', 'could', 'hardly', 'wait', 'try', 'love', 'call', 'ins
tead', 'removed', 'easily', 'daughter', 'designed', 'printed', 'use',
'car', 'windows', 'beautifully', 'shop', 'program', 'going', 'lot', 'fu
```

```
n', 'everywhere', 'like', 'tv', 'computer', 'really', 'good', 'idea',
'final', 'outstanding', 'window', 'everybody', 'asks', 'bought', 'mad
e']
```

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

[4.4.1.1] Avg W2v

In [0]:
```
# 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, yo
u might need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/re
view
    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]))
```

```
100%|██████████| 4986/4986 [00:03<00:00, 1330.47it/s]
```

```
4986
50
```

[4.4.1.2] TFIDF weighted W2v

In [0]:
```
# 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 v
alue
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [0]:
```
# 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 ce
ll_val = tfidf

tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is st
ored in this 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/r
eview
    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]
```

[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 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 20 important features from both feature sets Set 1 and Set 2 using `feature_importances_` method of Decision Tree Classifier 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 with predicted and original labels of test data points. Please visualize your confusion matrices using seaborn heatmaps.
     

7. **Conclusion**

   - 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 link

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.

Applying Decision Trees

[5.1] Applying Decision Trees on BOW, SET 1

Randomly Sampling 40k Datapoints out of whole dataset

In [27]:
```
#randomly sampling 40k datapoints without repetition
my_final = time_sorted_data.take(np.random.permutation(len(final))[:400
00])
print(my_final.shape)

x = my_final['cleanedText'].values
y = my_final['Score']

#Split the dataset into train,test
X_train, X_test, Y_train, Y_test = train_test_split(x, y, test_size=0.3
, random_state=0)
```

```
(40000, 11)
```

In [28]:
```
# Please write all the code with proper documentation
#Bow
count_vect = CountVectorizer(min_df =50)
X_train_vec = count_vect.fit_transform(X_train)
X_test_vec = count_vect.transform(X_test)
print("the type of count vectorizer ",type(X_train_vec))
print("the shape of out text BOW vectorizer ",X_train_vec.get_shape())
print("the number of unique words including both unigrams and bigrams "
, X_train_vec.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (28000, 2002)
```

```
the number of unique words including both unigrams and bigrams  2002
```

In [29]:
```
#Standardizing
import warnings
warnings.filterwarnings("ignore")
sc = StandardScaler(with_mean=False)
X_train_vec_standardized = sc.fit_transform(X_train_vec)
X_test_vec_standardized = sc.transform(X_test_vec)
```

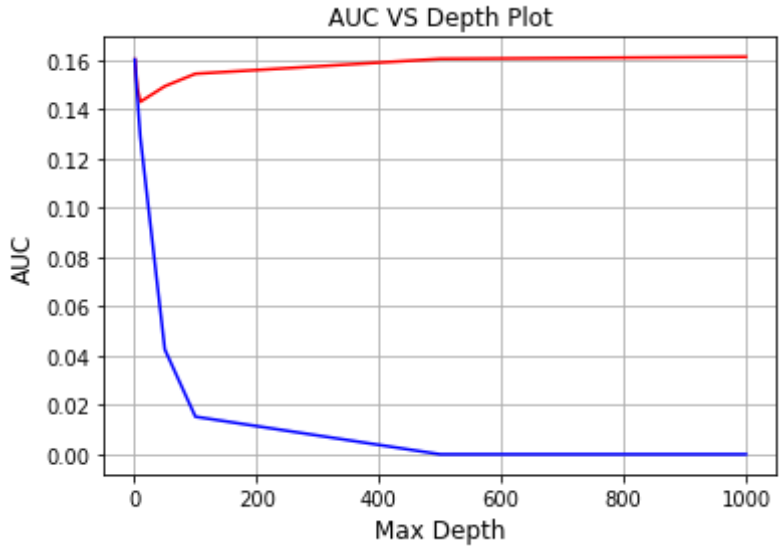
GridSearchCV (Decision Tree BOW)

In [43]:
```
import warnings
warnings.filterwarnings("ignore")
from sklearn.metrics import f1_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import f1_score
from sklearn.metrics import recall_score
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from scipy import *
from scipy.sparse import *
from scipy.stats import uniform
from prettytable import PrettyTable


Depths = [1,5,10,50,100,500,1000]
min_samples = [2,5,10,15,100,500]

param_grid = {'max_depth': Depths}
model = GridSearchCV(DecisionTreeClassifier(), param_grid, scoring = 'r
oc_auc', cv=3, n_jobs= -1, pre_dispatch=2)
model.fit(X_train_vec_standardized, Y_train)
print("Model with best parameters :\n", model.best_estimator_)
print("Accuracy of the model : ",model.score(X_test_vec_standardized, Y
_test))

#Cross-Validation Errors
```

```
cv_errors = [1-i for i in model.cv_results_['mean_test_score']]
training_scores = [1-i for i in model.cv_results_['mean_train_score']]

# Optimal value of depth
optimal_depth = model.best_estimator_.max_depth
print("The optimal value of depth is :",optimal_depth)

#DecisionTreeClaasifier with Optimal depth
dt = DecisionTreeClassifier(max_depth=optimal_depth)
dt.fit(X_train_vec_standardized, Y_train)
predict = dt.predict(X_test_vec_standardized)
pred_prob = dt.predict_proba(X_test_vec_standardized)[:,1]


#Variables will be used in conclusion part of prettytable
bow_depth = optimal_depth
bow_train_acc = model.score(X_train_vec_standardized, Y_train) * 100
bow_test_acc = accuracy_score(Y_test, predict) * 100
```

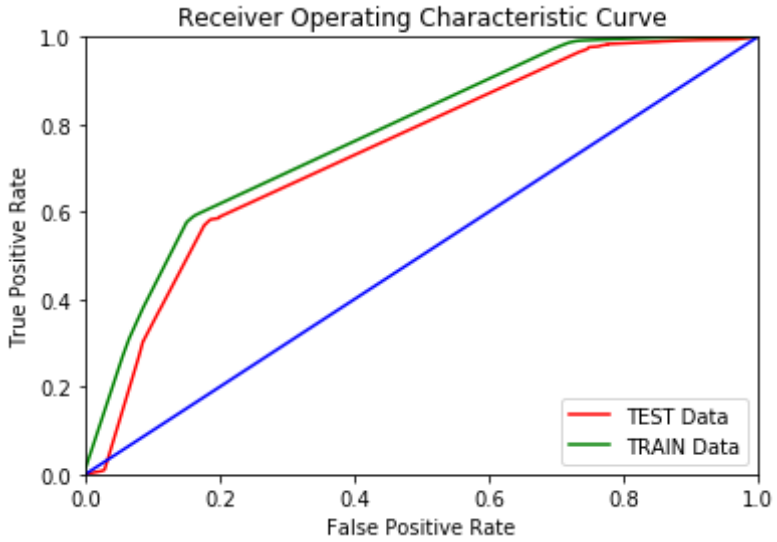
```
Model with best parameters :
 DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=
10,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=N
one,
            splitter='best')
Accuracy of the model :  0.741274377497
The optimal value of depth is : 10
```

In [34]:
```
#Plot for Cross-Validation Error Vs Depth Graph
plt.plot(Depths, cv_errors, 'r')
plt.plot(Depths, training_scores, 'b')
plt.xlabel('Max Depth', size=12)
plt.ylabel('AUC', size=12)
plt.title('AUC VS Depth Plot', size=12)
plt.grid()
plt.show()
```



In [46]:
```
from cycler import cycler
fpr, tpr, threshold = metrics.roc_curve(Y_test, dt.predict_proba(X_test
_vec_standardized)[:,1])
fpr2, tpr2, threshold2 = metrics.roc_curve(Y_train, dt.predict_proba(X_
train_vec_standardized)[:,1])

roc_auc = metrics.auc(fpr, tpr)
roc_auc2 = metrics.auc(fpr2, tpr2)

# method I: plt
import matplotlib.pyplot as plt
f, ax = plt.subplots()
plt.title('Receiver Operating Characteristic Curve')
cy = cycler('color', ['red', 'green', 'blue'])
ax.set_prop_cycle(cy)
ax.plot(fpr, tpr, label = 'AUC = %0.2f' % roc_auc)
ax.plot(fpr2, tpr2, label = 'AUC = %0.2f' % roc_auc2)
plt.legend(['TEST Data', 'TRAIN Data'],loc = 'lower right')

ax.plot([0, 1], [0, 1])
plt.xlim([0, 1])
```

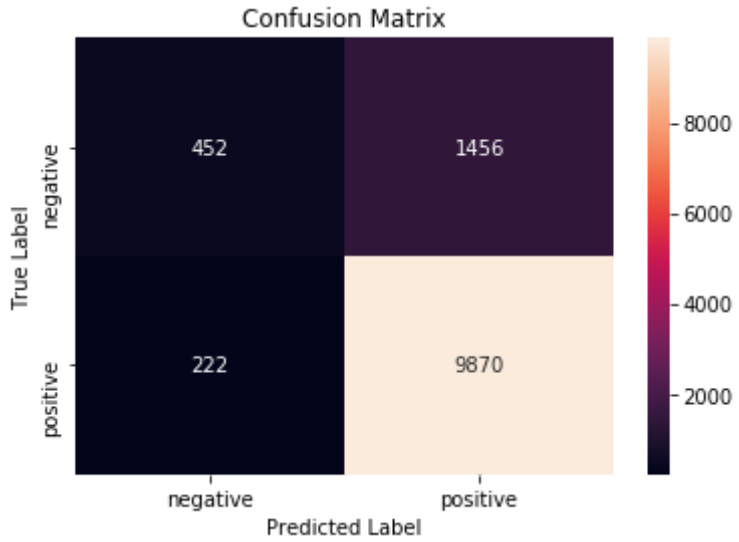
```
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



In [41]:
```
#Confusion Matrix
print("Train Confusion Matrix")
print(confusion_matrix(Y_train, dt.predict(X_train_vec_standardized)))
print("Test Confusion Matrix")
print(confusion_matrix(Y_test, dt.predict(X_test_vec_standardized)))
cm_test=confusion_matrix(Y_test, dt.predict(X_test_vec_standardized))
class_label = ["negative", "positive"]
df_cm = pd.DataFrame(cm_test, index=class_label, columns=class_label)
sns.heatmap(df_cm, annot = True, fmt = "d")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

```
Train Confusion Matrix
[[ 1338  3167]
 [  250 23245]]
```

```
Test Confusion Matrix
[[ 452 1456]
 [ 222 9870]]
```



[5.1.1] Top 20 important features from SET 1

In [35]:
```
# Please write all the code with proper documentation
all_features = count_vect.get_feature_names()

feat=dt.feature_importances_
features=np.argsort(feat)[::-1]
for i in features[0:20]:
    print(all_features[i])
```

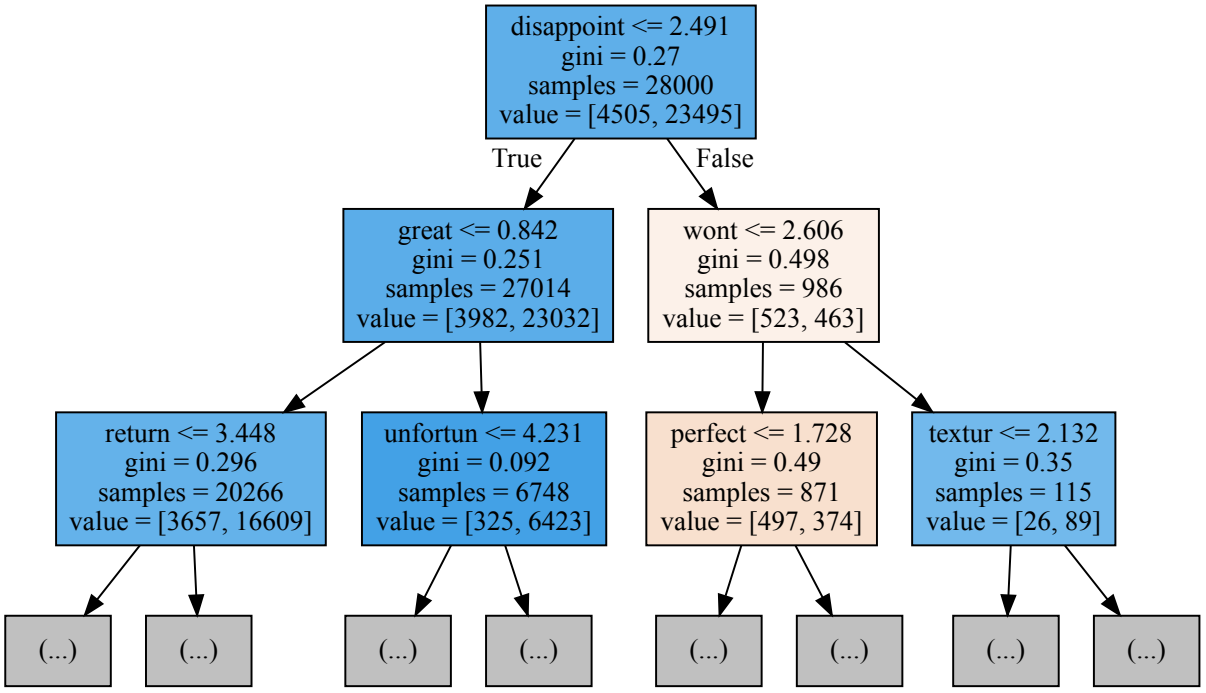
```
disappoint
great
return
wast
worst
love
threw
```

```
terribl
horribl
best
money
perfect
wont
delici
unfortun
bad
stale
aw
food
littl
```

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

In [39]:
```
from sklearn.tree import DecisionTreeClassifier, export_graphviz
import graphviz
export_graphviz(dt, out_file="mytree.dot", feature_names = count_vect.g
et_feature_names(), max_depth = 2, filled = True)
with open("mytree.dot") as f:
    dot_graph = f.read()
graphviz.Source(dot_graph)
```

Out[39]:



Observation:

- From the above plot of CV Error Vs Depth, we can infer that as depth increasing Erro is aslo increasing.
- AS we train our model on 40k datapoints , depth of tree is 10.
- Depth of tree is low means it is underfitting.
- Using Graphviz of sklearn library implemented visual Decision Tree of each Node, where interpretability is very high.

[5.2] Applying Decision Trees on TFIDF, SET 2

In [42]:
```
tf_idf_vect = TfidfVectorizer(min_df=50)
X_train_vec = tf_idf_vect.fit_transform(X_train)
```

```
X_test_vec = tf_idf_vect.transform(X_test)
print("the type of count vectorizer ",type(X_train_vec))
print("the shape of out text TFIDF vectorizer ",X_train_vec.get_shape
())
print("the number of unique words ", X_train_vec.get_shape()[1])

#Standardizing
sc = StandardScaler(with_mean=False)
X_train_vec_standardized = sc.fit_transform(X_train_vec)
X_test_vec_standardized = sc.transform(X_test_vec)
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (28000, 1994)
the number of unique words  1994
```

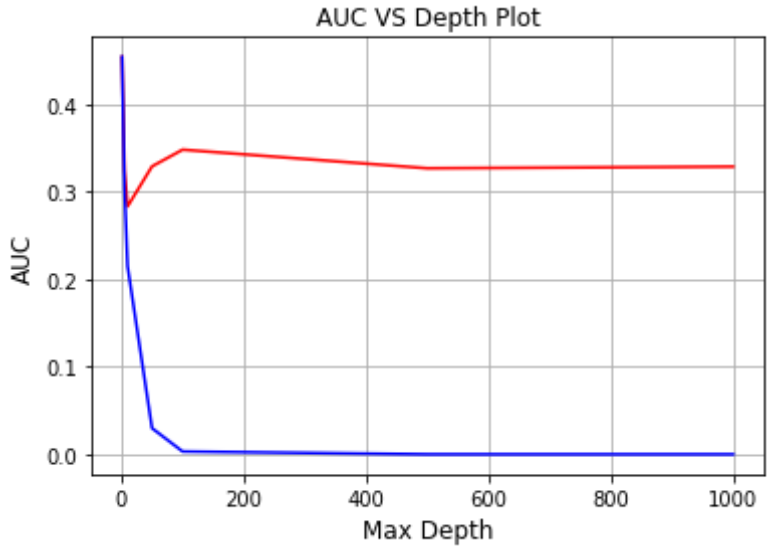
In [47]:

```
# Please write all the code with proper documentation
Depths = [1,5,10,50,100,500,1000]
min_samples = [2,5,10,15,100,500]

param_grid = {'max_depth': Depths}
model = GridSearchCV(DecisionTreeClassifier(), param_grid, scoring = 'r
oc_auc', cv=3, n_jobs= -1, pre_dispatch=2)
model.fit(X_train_vec_standardized, Y_train)
print("Model with best parameters :\n", model.best_estimator_)
print("Accuracy of the model : ",model.score(X_test_vec_standardized, Y
_test))

#Cross-Validation Errors
cv_errors = [1-i for i in model.cv_results_['mean_test_score']]
training_scores = [1-i for i in model.cv_results_['mean_train_score']]

# Optimal value of depth
optimal_depth = model.best_estimator_.max_depth
print("The optimal value of depth is :",optimal_depth)

#DecisionTreeClaasifier with Optimal depth
dt = DecisionTreeClassifier(max_depth=optimal_depth)
dt.fit(X_train_vec_standardized, Y_train)
predict = dt.predict(X_test_vec_standardized)
```

```
pred_prob = dt.predict_proba(X_test_vec_standardized)[:,1]

#Variables will be used in conclusion part of prettytable
tfidf_depth = optimal_depth
tfidf_train_acc = model.score(X_train_vec_standardized, Y_train) * 100
tfidf_test_acc = accuracy_score(Y_test, predict) * 100
```

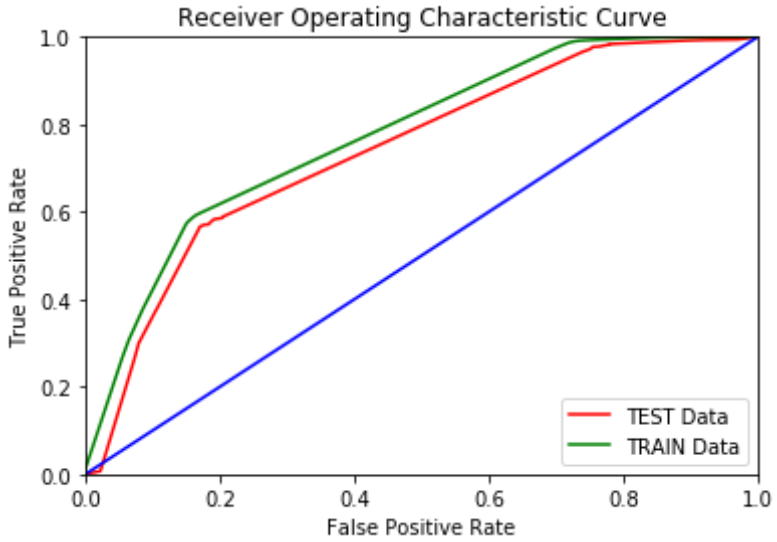
```
Model with best parameters :
 DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=
10,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=N
one,
            splitter='best')
Accuracy of the model :  0.736835900185
The optimal value of depth is : 10
```

In [48]:
```
#Plot for Cross-Validation Error Vs Depth Graph
plt.plot(Depths, cv_errors, 'r')
plt.plot(Depths, training_scores, 'b')
plt.xlabel('Max Depth', size=12)
plt.ylabel('AUC', size=12)
plt.title('AUC VS Depth Plot', size=12)
plt.grid()
plt.show()
```



In [49]:
```
from cycler import cycler
fpr, tpr, threshold = metrics.roc_curve(Y_test, dt.predict_proba(X_test
_vec_standardized)[:,1])
fpr2, tpr2, threshold2 = metrics.roc_curve(Y_train, dt.predict_proba(X_
train_vec_standardized)[:,1])

roc_auc = metrics.auc(fpr, tpr)
roc_auc2 = metrics.auc(fpr2, tpr2)

# method I: plt
import matplotlib.pyplot as plt
f, ax = plt.subplots()
plt.title('Receiver Operating Characteristic Curve')
cy = cycler('color', ['red', 'green', 'blue'])
ax.set_prop_cycle(cy)
ax.plot(fpr, tpr, label = 'AUC = %0.2f' % roc_auc)
ax.plot(fpr2, tpr2, label = 'AUC = %0.2f' % roc_auc2)
plt.legend(['TEST Data', 'TRAIN Data'],loc = 'lower right')

ax.plot([0, 1], [0, 1])
plt.xlim([0, 1])
```

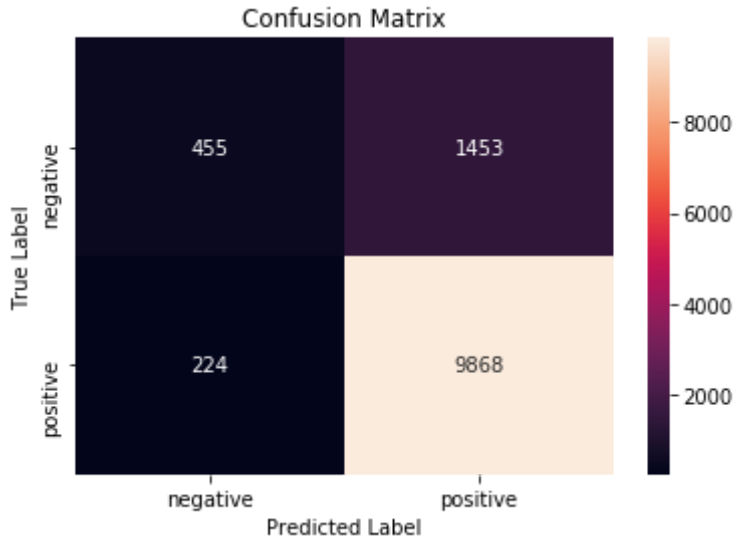
```
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



In [47]:
```
#Confusion Matrix
print("Train Confusion Matrix")
print(confusion_matrix(Y_train, dt.predict(X_train_vec_standardized)))
print("Test Confusion Matrix")
print(confusion_matrix(Y_test, dt.predict(X_test_vec_standardized)))
cm_test=confusion_matrix(Y_test, dt.predict(X_test_vec_standardized))
class_label = ["negative", "positive"]
df_cm = pd.DataFrame(cm_test, index=class_label, columns=class_label)
sns.heatmap(df_cm, annot = True, fmt = "d")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

```
Train Confusion Matrix
[[ 1298  3207]
 [  213 23282]]
```

```
Test Confusion Matrix
[[ 455 1453]
 [ 224 9868]]
```



[5.2.1] Top 20 important features from SET 2

In [44]:
```
# Please write all the code with proper documentation
# Please write all the code with proper documentation
all_features = tf_idf_vect.get_feature_names()

feat=dt.feature_importances_
features=np.argsort(feat)[::-1]
for i in features[0:20]:
    print(all_features[i])
```

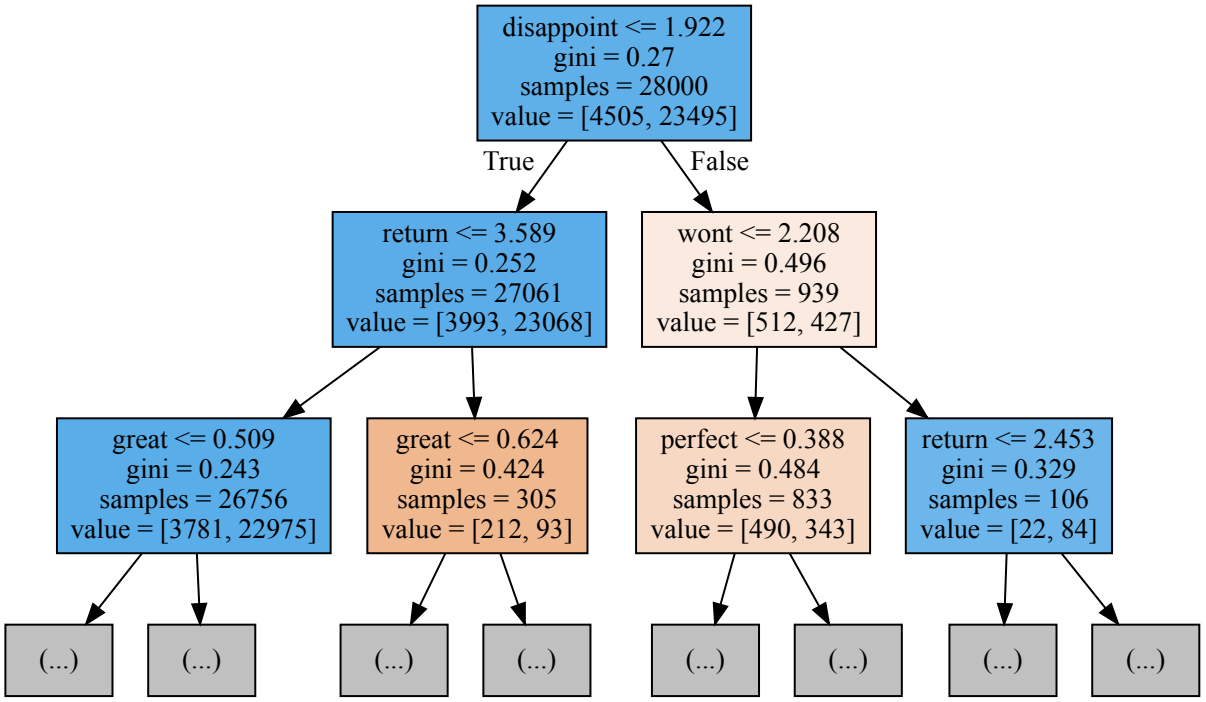
```
disappoint
great
return
wast
love
worst
```

```
horribl
terribl
bad
best
wont
perfect
money
stale
unfortun
delici
aw
thought
nice
bland
```

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

In [45]:
```
# Please write all the code with proper documentation
from sklearn.tree import DecisionTreeClassifier, export_graphviz
import graphviz
export_graphviz(dt, out_file="mytree_tfidf.dot", feature_names = count_
vect.get_feature_names(), max_depth = 2, filled = True)
with open("mytree_tfidf.dot") as f:
    dot_graph = f.read()
graphviz.Source(dot_graph)
```

Out[45]:



Observation:

- From the above plot of CV Error Vs Depth, we can infer that as depth increasing Erro is aslo increasing.
- AS we train our model on 40k datapoints , depth of tree is 10.
- Depth of tree is low means it is underfitting.
- Using Graphviz of sklearn library implemented visual Decision Tree of each Node, where interpretability is very high.

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

In [48]:
```
#List of sentance in X_train text
sent_of_train = []
```

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

#List of sentance in X_test text
sent_of_test = []
for sent in X_test:
    sent_of_test.append(sent.split())
#Train your own text corpus WOrd2Vec
w2v_model = Word2Vec(sent_of_train,min_count=5,size=50,workers=4)
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  7027
sample words  ['dog', 'crazi', 'treat', 'soon', 'open', 'bag', 'feet',
'wait', 'made', 'train', 'puppi', 'easi', 'caus', 'will', 'anyth', 'ge
t', 'first', 'want', 'say', 'love', 'bar', 'delici', 'way', 'uniqu', 'f
ill', 'eat', 'one', 'breakfast', 'hungri', 'hour', 'howev', 'expens',
'dont', 'mind', 'pay', 'given', 'weight', 'watcher', 'stumbl', 'onto',
'littl', 'gem', 'calori', 'per', 'like', 'find', 'dieter', 'miracl', 'p
rice', 'know']
```

In [49]:

```
#copute AvgWord2Vec for each review of X_train
train_vectors = [];
for sent in sent_of_train:
    sent_vec = np.zeros(50)
    cnt_words =0; # num of words with a valid vector in the sentence/re
view
    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
    train_vectors.append(sent_vec)

#compute AvgWord2Vec for each review of X_test
test_vectors = [];
```

```
for sent in sent_of_test:
    sent_vec = np.zeros(50)
    cnt_words =0; # num of words with a valid vector in the sentence/re
view
    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
    test_vectors.append(sent_vec)

#Standardizing
sc = StandardScaler()
X_train_vec_standardized = sc.fit_transform(train_vectors)
X_test_vec_standardized = sc.transform(test_vectors)
```

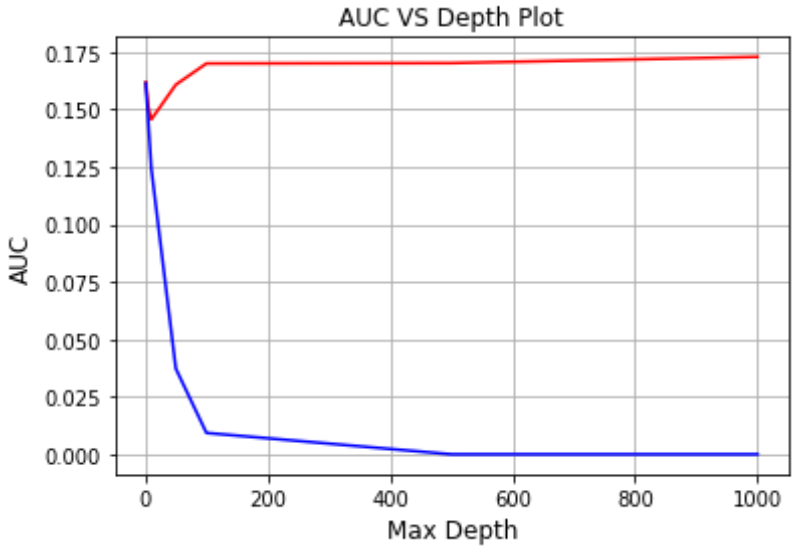
In [50]:

```
# Please write all the code with proper documentation
Depths = [1,5,10,50,100,500,1000]
min_samples = [2,5,10,15,100,500]

param_grid = {'max_depth': Depths}
model = GridSearchCV(DecisionTreeClassifier(), param_grid, scoring = 'r
oc_auc', cv=3, n_jobs= -1, pre_dispatch=2)
model.fit(X_train_vec_standardized, Y_train)
print("Model with best parameters :\n", model.best_estimator_)
print("Accuracy of the model : ",model.score(X_test_vec_standardized, Y
_test))

#Cross-Validation Errors
cv_errors = [1-i for i in model.cv_results_['mean_test_score']]
training_scores = [1-i for i in model.cv_results_['mean_train_score']]



# Optimal value of depth
optimal_depth = model.best_estimator_.max_depth
print("The optimal value of depth is :",optimal_depth)
```

```
#DecisionTreeClaasifier with Optimal depth
dt = DecisionTreeClassifier(max_depth=optimal_depth)
dt.fit(X_train_vec_standardized, Y_train)
predict = dt.predict(X_test_vec_standardized)
pred_prob = dt.predict_proba(X_test_vec_standardized)[:,1]

#Variables will be used in conclusion part of prettytable
AvgW2v_depth = optimal_depth
AvgW2v_train_acc = model.score(X_train_vec_standardized, Y_train) * 100
AvgW2v_test_acc = accuracy_score(Y_test, predict) * 100
```

```
Model with best parameters :
 DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=
10,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=N
one,
            splitter='best')
Accuracy of the model :  0.860166666667
The optimal value of depth is : 10
```

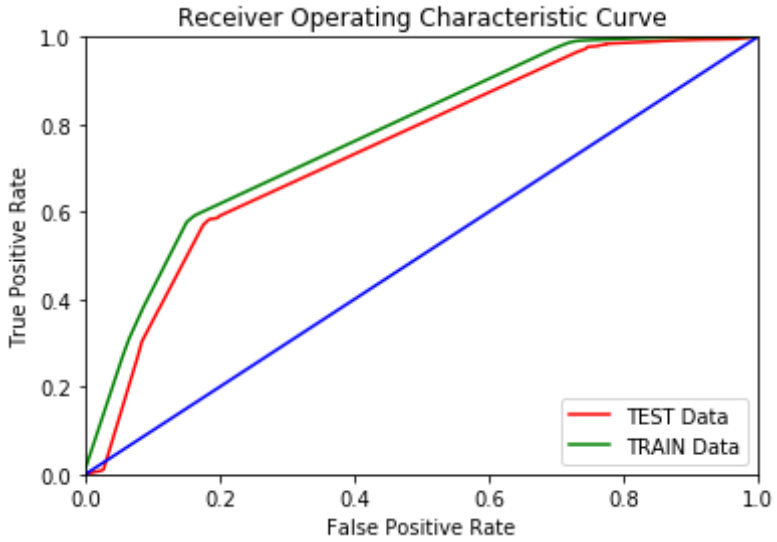
In [51]:
```
#Plot for Cross-Validation Error Vs Depth Graph
plt.plot(Depths, cv_errors, 'r')
plt.plot(Depths, training_scores, 'b')
plt.xlabel('Max Depth', size=12)
plt.ylabel('AUC', size=12)
plt.title('AUC VS Depth Plot', size=12)
plt.grid()
plt.show()
```



In [52]:

```
from cycler import cycler
fpr, tpr, threshold = metrics.roc_curve(Y_test, dt.predict_proba(X_test
_vec_standardized)[:,1])
fpr2, tpr2, threshold2 = metrics.roc_curve(Y_train, dt.predict_proba(X_
train_vec_standardized)[:,1])

roc_auc = metrics.auc(fpr, tpr)
roc_auc2 = metrics.auc(fpr2, tpr2)

# method I: plt
import matplotlib.pyplot as plt
f, ax = plt.subplots()
plt.title('Receiver Operating Characteristic Curve')
cy = cycler('color', ['red', 'green', 'blue'])
ax.set_prop_cycle(cy)
ax.plot(fpr, tpr, label = 'AUC = %0.2f' % roc_auc)
ax.plot(fpr2, tpr2, label = 'AUC = %0.2f' % roc_auc2)
plt.legend(['TEST Data', 'TRAIN Data'],loc = 'lower right')

ax.plot([0, 1], [0, 1])
plt.xlim([0, 1])
```

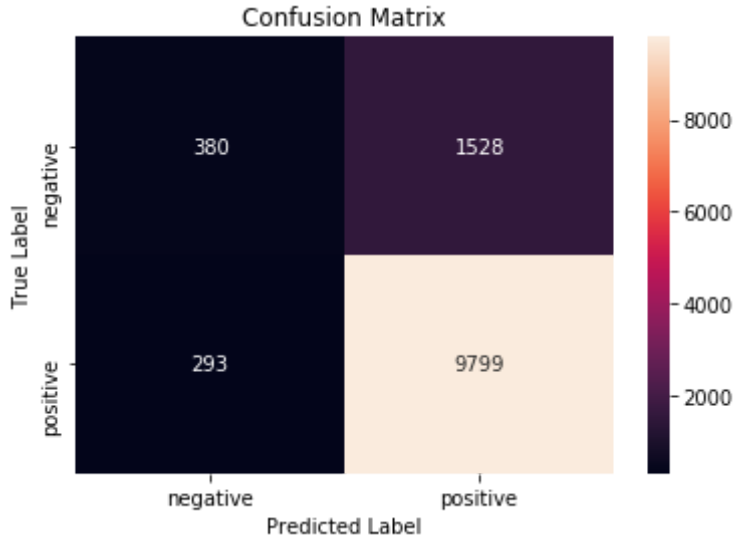
```
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



In [52]:
```
#Confusion Matrix
print("Train Confusion Matrix")
print(confusion_matrix(Y_train, dt.predict(X_train_vec_standardized)))
print("Test Confusion Matrix")
print(confusion_matrix(Y_test, dt.predict(X_test_vec_standardized)))
cm_test=confusion_matrix(Y_test, dt.predict(X_test_vec_standardized))
class_label = ["negative", "positive"]
df_cm = pd.DataFrame(cm_test, index=class_label, columns=class_label)
sns.heatmap(df_cm, annot = True, fmt = "d")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

```
Train Confusion Matrix
[[ 1009  3496]
 [  607 22888]]
```

```
Test Confusion Matrix
[[ 380 1528]
 [ 293 9799]]
```



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

In [53]:
```
# Please write all the code with proper documentation
# collect different 100k rows without repetition from time_sorted_data
 DataFrfame
my_final = time_sorted_data.take(np.random.permutation(len(final))[:100
000])
print(my_final.shape)

x = my_final['cleanedText'].values
y = my_final['Score']
#SPlit the dataset into Train and Test
X_train,X_test,Y_train,Y_test=train_test_split(x, y, test_size=0.3, ran
dom_state=0)

#List of sentance in X_train text
```

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

#List of sentance in X_test text
sent_of_test = []
for sent in X_test:
    sent_of_test.append(sent.split())
#Train your own text corpus WOrd2Vec
w2v_model = Word2Vec(sent_of_train,min_count=5,size=50,workers=4)
w2v_words = list(w2v_model.wv.vocab)
```

```
(87773, 11)
```

In [54]:
```
#TF-IDF weighted word2vec
tf_idf_vect = TfidfVectorizer()
final_tf_idf1 = tf_idf_vect.fit_transform(X_train)
tfidf_feat=tf_idf_vect.get_feature_names()
```

In [55]:
```
#compute TFIDF weighted word2vec of each review of X_train
#copute AvgWord2Vec for each review of X_train
tfidf_train_vectors = [];
row=0;
for sent in sent_of_train:
    sent_vec = np.zeros(50)
    weight_sum =0; # num of words with a valid vector in the sentence/r
eview
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            tf_idf = final_tf_idf1[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_train_vectors.append(sent_vec)
    row += 1
```

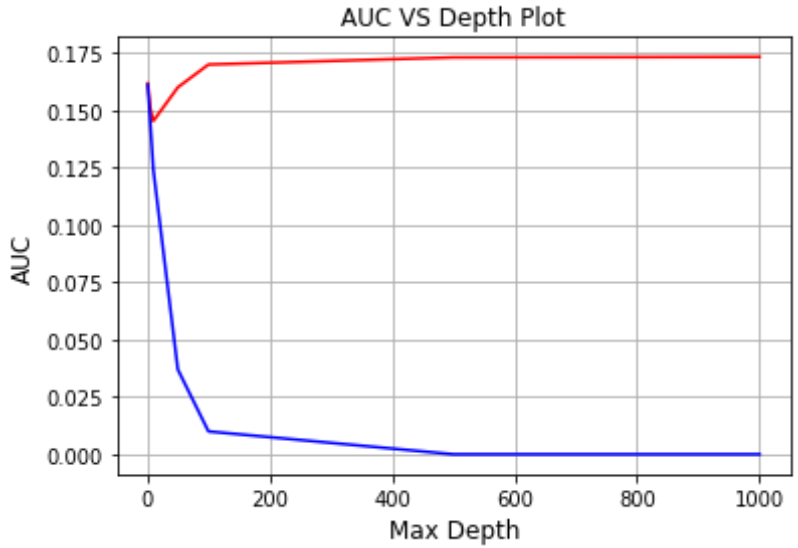
In [56]:
```
tfidf_test_vectors = [];
row=0;
for sent in sent_of_test:
    sent_vec = np.zeros(50)
    weight_sum =0; # num of words with a valid vector in the sentence/r
eview
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            tf_idf = final_tf_idf1[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_test_vectors.append(sent_vec)
    row += 1
#Standardizing
sc = StandardScaler()
X_train_vec_standardized = sc.fit_transform(tfidf_train_vectors)
X_test_vec_standardized = sc.transform(tfidf_test_vectors)
```

In [53]:
```
# Please write all the code with proper documentation
Depths = [1,5,10,50,100,500,1000]
min_samples = [2,5,10,15,100,500]

param_grid = {'max_depth': Depths}
model = GridSearchCV(DecisionTreeClassifier(), param_grid, scoring = 'r
oc_auc', cv=3, n_jobs= -1, pre_dispatch=2)
model.fit(X_train_vec_standardized, Y_train)
print("Model with best parameters :\n", model.best_estimator_)
print("Accuracy of the model : ",model.score(X_test_vec_standardized, Y
_test))

#Cross-Validation Errors
cv_errors = [1-i for i in model.cv_results_['mean_test_score']]
training_scores = [1-i for i in model.cv_results_['mean_train_score']]

# Optimal value of depth
optimal_depth = model.best_estimator_.max_depth
```

```
print("The optimal value of depth is :",optimal_depth)

#DecisionTreeClaasifier with Optimal depth
dt = DecisionTreeClassifier(max_depth=optimal_depth)
dt.fit(X_train_vec_standardized, Y_train)
predict = dt.predict(X_test_vec_standardized)
pred_prob = dt.predict_proba(X_test_vec_standardized)[:,1]

#Variables will be used in conclusion part of prettytable
AvgW2v_depth = optimal_depth
AvgW2v_train_acc = model.score(X_train_vec_standardized, Y_train) * 100
AvgW2v_test_acc = accuracy_score(Y_test, predict) * 100
```

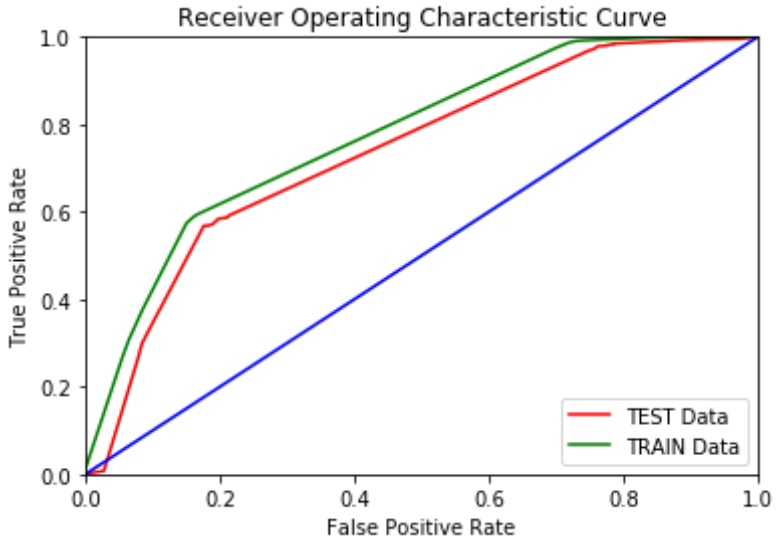
```
Model with best parameters :
 DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=
10,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=N
one,
            splitter='best')
Accuracy of the model :  0.860083333333
The optimal value of depth is : 10
```

In [54]:
```
#Plot for Cross-Validation Error Vs Depth Graph
plt.plot(Depths, cv_errors, 'r')
plt.plot(Depths, training_scores, 'b')
plt.xlabel('Max Depth', size=12)
plt.ylabel('AUC', size=12)
plt.title('AUC VS Depth Plot', size=12)
plt.grid()
plt.show()
```



In [55]:
```
from cycler import cycler
fpr, tpr, threshold = metrics.roc_curve(Y_test, dt.predict_proba(X_test
_vec_standardized)[:,1])
fpr2, tpr2, threshold2 = metrics.roc_curve(Y_train, dt.predict_proba(X_
train_vec_standardized)[:,1])

roc_auc = metrics.auc(fpr, tpr)
roc_auc2 = metrics.auc(fpr2, tpr2)

# method I: plt
import matplotlib.pyplot as plt
f, ax = plt.subplots()
plt.title('Receiver Operating Characteristic Curve')
cy = cycler('color', ['red', 'green', 'blue'])
ax.set_prop_cycle(cy)
ax.plot(fpr, tpr, label = 'AUC = %0.2f' % roc_auc)
ax.plot(fpr2, tpr2, label = 'AUC = %0.2f' % roc_auc2)
plt.legend(['TEST Data', 'TRAIN Data'],loc = 'lower right')

ax.plot([0, 1], [0, 1])
plt.xlim([0, 1])
```

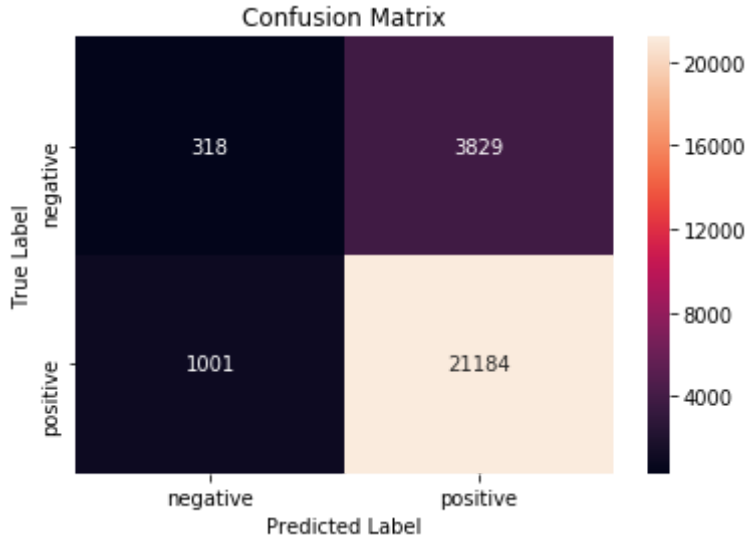
```
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



In [59]:
```
#Confusion Matrix
print("Train Confusion Matrix")
print(confusion_matrix(Y_train, dt.predict(X_train_vec_standardized)))
print("Test Confusion Matrix")
print(confusion_matrix(Y_test, dt.predict(X_test_vec_standardized)))
cm_test=confusion_matrix(Y_test, dt.predict(X_test_vec_standardized))
class_label = ["negative", "positive"]
df_cm = pd.DataFrame(cm_test, index=class_label, columns=class_label)
sns.heatmap(df_cm, annot = True, fmt = "d")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

```
Train Confusion Matrix
[[ 1588  8446]
 [  804 50603]]
```

```
Test Confusion Matrix
[[  318  3829]
 [ 1001 21184]]
```



[6] Conclusions

In [61]:
```
# Please compare all your models using Prettytable library
# Please compare all your models using Prettytable library
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["Vectorizer", "Feature Engineering", "Hyperparameter(O
ptimal_depth)", "AUC"]
x.add_row(["BOW", "GridSearchCV ", 10, 0.861])
x.add_row(["TFDIF", "GridSearchCV", 10, 0.860])
x.add_row(["AVG Word2Vec", "GridSearchCV", 5, 0.848])
x.add_row(["TFDIF Word2Vec", "GridSearchCV", 5, 0.816])

print(x)
```

```
+---------------+--------------------+------------------------------
```

```
+-------+
|   Vectorizer   | Feature Engineering | Hyperparameter(Optimal_depth)
|  AUC  |
+----------------+---------------------+------------------------------
+-------+
|      BOW       |    GridSearchCV     |               10
| 0.861 |
|     TFDIF      |     GridSearchCV    |               10
|  0.86 |
|  AVG Word2Vec  |     GridSearchCV    |               5
| 0.848 |
| TFDIF Word2Vec |     GridSearchCV    |               5
| 0.816 |
+----------------+---------------------+------------------------------
+-------+
```

- Using 40k Random Sample points, by using GridSearchCV obsreved an optimal depth of 10 with an AUC of 0.86
- Using Gini impurity is computational efficient and faster.
- Printed Decison Tree Nodes , for BOW and TFIDF through which we can interpret more.
- For every Decision we will get a hyperplane, interpretability is high.
- All of the Hyperpalnes are axis-parallel in a Decision tree.
- Depth of tree is small it could be underfitting.
- None of the models performing well on unseen data since depth of the tree is less comapritively than other vectorizers.