08 Amazon Fine Food Reviews Analysis_Decision Trees

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1 Amazon Fine Food Reviews Analysis

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

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

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

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

Attribute Information:

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

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

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

2 [1]. Reading Data

2.1 [1.1] Loading the data

The dataset is available in two forms 1. .csv file 2. SQLite Database

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

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

In [1]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
from bs4 import BeautifulSoup


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/
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.tree import DecisionTreeClassifier
from sklearn import tree
import pydotplus
from IPython.display import Image
from IPython.display import SVG
from graphviz import Source
import graphviz
import collections
from IPython.display import display
```

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import GridSearchCV

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 prettytable import PrettyTable
from sklearn.externals import joblib
from bs4 import BeautifulSoup
from graphviz import Source
```

```
C:\Users\hp\Anaconda3\lib\site-packages\sklearn\externals\joblib\__init__.py:15: DeprecationWa
  warnings.warn(msg, category=DeprecationWarning)
```

In [2]:
```
# using SQLite Table to read data.
con = sqlite3.connect('database.sqlite')

# filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
# SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000, will give top 500000 data point
# you can change the number to any other number based on your computing power

# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 1
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 1000

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

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

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

Out[2]:
```
   Id   ProductId          UserId                      ProfileName  \
0   1  B001E4KFG0  A3SGXH7AUHU8GW                       delmartian
```

```
1   2  B00813GRG4  A1D87F6ZCVE5NK                             dll pa
2   3  B000LQOCH0   ABXLMWJIXXAIN  Natalia Corres "Natalia Corres"

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

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

In [3]:
```python
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
LIMIT 100000
""", con)
```

In [4]:
```python
print(display.shape)
display.head(3)
```

```
(80668, 7)
```

Out[4]:
```
                UserId   ProductId             ProfileName        Time  Score  \
0  #oc-R115TNMSPFT9I7  B007Y59HVM                 Breyton  1331510400      2
1  #oc-R11D9D7SHXIJB9  B005HG9ET0  Louis E. Emory "hoppy"  1342396800      5
2  #oc-R11DNU2NBKQ23Z  B007Y59HVM        Kim Cieszykowski  1348531200      1

                                                Text  COUNT(*)
0  Overall its just OK when considering the price...         2
1  My wife has recurring extreme muscle spasms, u...         3
2  This coffee is horrible and unfortunately not ...         2
```

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

Out[5]:
```
              UserId   ProductId                       ProfileName        Time  \
80638  AZY10LLTJ71NX  B006P7E5ZI  undertheshrine "undertheshrine"  1334707200

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

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

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

3 [2] Exploratory Data Analysis

3.1 [2.1] Data Cleaning: Deduplication

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

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

```
Out[7]:        Id   ProductId         UserId      ProfileName  HelpfulnessNumerator  \
        0   78445  B000HDL1RQ  AR5J8UI46CURR  Geetha Krishnan                     2
        1  138317  B000HDOPYC  AR5J8UI46CURR  Geetha Krishnan                     2
        2  138277  B000HDOPYM  AR5J8UI46CURR  Geetha Krishnan                     2
        3   73791  B000HDOPZG  AR5J8UI46CURR  Geetha Krishnan                     2
        4  155049  B000PAQ75C  AR5J8UI46CURR  Geetha Krishnan                     2

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

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

                                                        Text
        0  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
        1  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
        2  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
        3  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
        4  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
```

As it can be seen above that same user has multiple reviews with same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8) ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

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

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

In [8]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fals
```

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

Out[9]:
```
(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  \
0  64422  B000MIDROQ  A161DK06JJMCYF  J. E. Stephens "Jeanne"
1  44737  B001EQ55RW  A2V0I904FH7ABY                      Ram

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

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

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

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

```
In [13]: #Before starting the next phase of preprocessing lets see the number of entries left
         print(final.shape)

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

```
(87773, 10)
```

```
Out[13]: 1    73592
         0    14181
         Name: Score, dtype: int64
```

4 [3] Preprocessing

4.1 [3.1]. Preprocessing Review Text

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

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

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

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

```
In [15]: # 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
==================================================
The Candy Blocks were a nice visual for the Lego Birthday party but the candy has little taste
==================================================
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 smell. So if you are afraid
==================================================
```

```
In [0]: # 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)
```

```
Why is this $[...] when the same product is available for $[...] here?<br /> /><br />The Victor
```

```
In [0]: # https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all-


        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)
```

```
Why is this $[...] when the same product is available for $[...] here? />The Victor M380 and M5
==================================================
I recently tried this flavor/brand and was surprised at how delicious these chips are.  The bes
==================================================
Wow.  So far, two two-star reviews.  One obviously had no idea what they were ordering; the oth
==================================================
```

```
love to order my coffee on amazon.  easy and shows up quickly.This k cup is great coffee.  dca
```

```
In [14]: # 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 [0]: sent_1500 = decontracted(sent_1500)
        print(sent_1500)
        print("="*50)
```

```
Wow.  So far, two two-star reviews.  One obviously had no idea what they were ordering; the otl
==================================================
```

```
In [0]: #remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
        sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
        print(sent_0)
```

```
Why is this $[...] when the same product is available for $[...] here?<br /> /><br />The Victo
```

```
In [0]: #remove spacial character: https://stackoverflow.com/a/5843547/4084039
        sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
        print(sent_1500)
```

```
Wow So far two two star reviews One obviously had no idea what they were ordering the other wa
```

```
In [15]: # https://gist.github.com/sebleier/554280
         # we are removing the words from the stop words list: 'no', 'nor', 'not'
         # <br /><br /> ==> after the above steps, we are getting "br br"
         # we are including them into stop words list
         # instead of <br /> if we have <br/> these tags would have revmoved in the 1st step
```

```
stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselve
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him'
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself',
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', '
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'a
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'throug
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', '
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'a
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'to
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", '
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mi
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't",
            'won', "won't", 'wouldn', "wouldn't"])
```

In [16]:
```
# Combining all the above stundents

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 stopwo
    preprocessed_reviews.append(sentance.strip())
```

```
100%|| 87773/87773 [00:35<00:00, 2460.75it/s]
```

In [17]:
```
preprocessed_reviews[1500]
```

Out[17]:
```
'way hot blood took bite jig lol'
```

5 [4] Featurization

Before we apply various featurizations to the data we need to split the data appropriately as train data, cross validation data and test data.

In [18]:
```
x = preprocessed_reviews
y = final["Score"].values
```

In [19]:
```
# splitting the data into 3 parts for furhter process,
# train data, cross validation data and test data
```

```
        x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.30)         # th
        x_train, x_cv, y_train, y_cv = train_test_split(x_train, y_train, test_size=0.30) # th
```

```
In [20]: # number of rows in earch data set, train, cross validation and test data respectively
         print(len(x_train))
         print(len(x_cv))
         print(len(x_test))
```

```
43008
18433
26332
```

5.1 [4.1] BAG OF WORDS

```
In [21]: #BoW
         count_vect = CountVectorizer(max_features=5000) #in scikit-learn
         count_vect.fit(x_train)
         print("some feature names ", count_vect.get_feature_names()[:10])
         print('='*50)

         x_train_bow = count_vect.transform(x_train)
         x_test_bow  = count_vect.transform(x_test)
         x_cv_bow    = count_vect.transform(x_cv)

         print(x_train_bow.shape, y_train.shape)
         print(x_cv_bow.shape, y_cv.shape)
         print(x_test_bow.shape, y_test.shape)
         print("="*50)
```

```
some feature names  ['ability', 'able', 'absolute', 'absolutely', 'absorb', 'absorbed', 'acai'
==================================================
(43008, 5000) (43008,)
(18433, 5000) (18433,)
(26332, 5000) (26332,)
==================================================
```

5.2 [4.2] TF-IDF

```
In [22]: # TFIDF using scikit-learn

         tf_idf = TfidfVectorizer(max_features=5000) #arguments: ngram_range=(1,2), min_df=10
         tf_idf.fit(x_train)

         print("some sample features",tf_idf.get_feature_names()[0:10])
         print('='*50)
```

```
# we use fit() method to learn the vocabulary from x_train
# and now transform text data to vectors using transform() method

x_train_tf = tf_idf.transform(x_train)
x_cv_tf    = tf_idf.transform(x_cv)
x_test_tf  = tf_idf.transform(x_test)

print("After featurization\n")

print(x_train_tf.shape, y_train.shape)
print(x_cv_tf.shape, y_cv.shape)
print(x_test_tf.shape, y_test.shape)
print("="*50)
```

```
some sample features ['ability', 'able', 'absolute', 'absolutely', 'absorb', 'absorbed', 'acai
==================================================
After featurization

(43008, 5000) (43008,)
(18433, 5000) (18433,)
(26332, 5000) (26332,)
==================================================
```

5.3 [4.3] Word2Vec

```
In [24]: # Train your own Word2Vec model using your own text corpus

         list_of_sentance_train =[]

         for sentance in x_train:
             list_of_sentance_train.append(sentance.split())
```

```
In [25]: # this line of code trains your w2v model on the give list of sentances
         w2v_model = Word2Vec(list_of_sentance_train, min_count=5, size=50, workers=-1)
```

```
In [26]: 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  9890
sample words  ['product', 'delivered', 'makes', 'good', 'sense', 'less', 'expensive', 'no', 'ne
```

5.4 [4.3.1] Converting text into vectors using Avg W2V, TFIDF-W2V

[4.3.1.1] Avg W2v Converting Train data

In [28]:
```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_train = []; # the avg-w2v for each sentence/review is stored in this lis
for sent in tqdm(list_of_sentance_train): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need t
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_train.append(sent_vec)
sent_vectors_train = np.array(sent_vectors_train)
print(sent_vectors_train.shape)
print(sent_vectors_train[0])
```

```
100%|| 26683/26683 [00:40<00:00, 663.60it/s]


(26683, 50)
[ 4.63802545e-04 -9.14620302e-05  8.39857914e-04 -2.11066650e-03
  1.01099800e-03 -6.99112447e-04  1.13057534e-04 -2.33749658e-03
  2.46977802e-04  2.16758822e-03 -9.14224789e-04  5.02322967e-05
 -1.28661920e-03 -1.52936805e-04 -5.33212005e-04 -1.95643255e-03
 -1.45448138e-03 -1.25641440e-03  3.01827744e-03 -3.62509658e-04
 -4.10847578e-04 -1.20700525e-03  5.90623898e-04 -3.58277544e-04
  1.13798814e-03  1.92258023e-04  1.75686782e-03 -2.34484246e-03
  7.88958533e-04 -2.46655214e-03  1.26468472e-03  3.14430194e-04
  8.09976467e-04 -3.97003982e-04  7.20299175e-05 -9.72705098e-04
  1.52828191e-03 -9.93454679e-05 -1.84080290e-03 -3.41153529e-04
 -8.03170251e-04 -2.46339480e-04  8.02687224e-04 -9.53865501e-06
  8.71069885e-05  2.27060837e-03 -1.60051999e-03  1.03006133e-03
 -5.10094745e-04  2.32021042e-03]
```

Converting cross validation data

In [29]:
```
list_of_sentance_cv=[]
for sentance in x_cv:
    list_of_sentance_cv.append(sentance.split())
```

In [30]:
```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_cv = []; # the avg-w2v for each sentence/review is stored in this list
for sent in tqdm(list_of_sentance_cv): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need t
    cnt_words =0; # num of words with a valid vector in the sentence/review
```

```
            for word in sent: # for each word in a review/sentence
                if word in w2v_words:
                    vec = w2v_model.wv[word]
                    sent_vec += vec
                    cnt_words += 1
            if cnt_words != 0:
                sent_vec /= cnt_words
            sent_vectors_cv.append(sent_vec)
        sent_vectors_cv = np.array(sent_vectors_cv)
        print(sent_vectors_cv.shape)
        print(sent_vectors_cv[0])
```

```
100%|| 11436/11436 [00:17<00:00, 636.61it/s]


(11436, 50)
[-1.03242384e-03  3.76358931e-03 -2.51476260e-03  7.22119235e-05
 -1.89193665e-03  2.32164932e-03  2.25421861e-03 -2.65163422e-04
 -5.86674522e-04  5.77809577e-04 -3.34824047e-03  1.01221524e-03
  9.17985861e-04  3.56046323e-05 -4.93111245e-04 -4.17788737e-04
  1.98521387e-04  1.21198383e-03  2.75606750e-03  1.86832314e-03
 -1.17973682e-03  2.38594148e-03 -4.30947689e-04 -2.88512610e-04
 -8.74792400e-05  1.19795708e-03  1.19823990e-03 -1.05462315e-04
  4.44062208e-04 -6.00271113e-04  2.80353440e-03  5.97353471e-04
  1.02167947e-03 -2.81745021e-03  2.24260753e-04 -6.99884621e-04
 -1.74778040e-03 -1.05528993e-04  1.47424738e-03  1.69324661e-03
 -9.36819235e-04 -3.83133185e-04 -6.45952218e-04  9.84170855e-04
  2.44978852e-03 -1.17407600e-03 -8.01381940e-04 -1.09122740e-03
 -1.41872834e-03 -5.21935188e-05]
```

Converting test data

```
In [31]: list_of_sentance_test=[]
         for sentance in x_test:
             list_of_sentance_test.append(sentance.split())
```

```
In [32]: # average Word2Vec
         # compute average word2vec for each review.
         sent_vectors_test = []; # the avg-w2v for each sentence/review is stored in this list
         for sent in tqdm(list_of_sentance_test): # for each review/sentence
             sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need t
             cnt_words =0; # num of words with a valid vector in the sentence/review
             for word in sent: # for each word in a review/sentence
                 if word in w2v_words:
                     vec = w2v_model.wv[word]
                     sent_vec += vec
                     cnt_words += 1
             if cnt_words != 0:
```

```
            sent_vec /= cnt_words
        sent_vectors_test.append(sent_vec)
    sent_vectors_test = np.array(sent_vectors_test)
    print(sent_vectors_test.shape)
    print(sent_vectors_test[0])
```

```
100%|| 16337/16337 [00:24<00:00, 653.73it/s]


(16337, 50)
[-3.29490924e-04  1.35128680e-03  1.91509802e-04 -1.07240085e-04
 -3.71133908e-05 -1.03080008e-03  1.06177745e-03 -4.98637289e-04
 -5.43941172e-04 -2.26938168e-04 -1.87221391e-04  2.15235642e-04
  3.61015919e-04 -1.41815911e-03 -7.01521644e-04 -5.20464557e-05
 -3.94306184e-04  6.87598424e-04  1.18277511e-03 -2.44187607e-06
 -1.03539405e-03 -4.20410591e-04 -7.47401327e-04  1.24861911e-04
  6.06622503e-04  1.66023103e-03  4.89868331e-04 -6.71348028e-04
  3.25429107e-05  7.30359683e-05  1.43803962e-03 -8.08677985e-04
 -6.92228650e-04  1.17659937e-03  1.39838197e-03  1.17497832e-03
  2.00884229e-03 -6.78563122e-04  1.09370656e-03  1.04497131e-04
 -1.42381500e-03 -2.09141948e-04 -6.80190001e-04  1.68796454e-03
  2.19503874e-04  1.42643027e-03  1.20387496e-03  7.92494045e-04
 -2.64997378e-04  3.88573043e-05]
```

[4.3.1.2] TFIDF weighted W2v

```
In [33]: # S = ["abc def pqr", "def def def abc", "pqr pqr def"]
         model = TfidfVectorizer()
         tf_idf_matrix_train = model.fit_transform(x_train)
         # 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_)))
```

converting train data

```
In [34]: # 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_train = []; # the tfidf-w2v for each sentence/review is stored in
         row=0;
         for sent in tqdm(list_of_sentance_train): # for each review/sentence
             sent_vec = np.zeros(50) # as word vectors are of zero length
             weight_sum =0; # num of words with a valid vector in the sentence/review
             for word in sent: # for each word in a review/sentence
                 if word in w2v_words and word in tfidf_feat:
                     vec = w2v_model.wv[word]
         #             tf_idf = 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_train.append(sent_vec)
        row += 1
```

```
100%|| 26683/26683 [07:38<00:00, 56.57it/s]
```

converting cross validation data

```
In [35]: # 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_cv = []; # the tfidf-w2v for each sentence/review is stored in thi
         row=0;
         for sent in tqdm(list_of_sentance_cv): # 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_cv.append(sent_vec)
             row += 1
```

```
100%|| 11436/11436 [03:18<00:00, 57.52it/s]
```

converting test data

```
In [36]: # 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_test = []; # the tfidf-w2v for each sentence/review is stored in th
```

```python
row=0;
for sent in tqdm(list_of_sentance_test): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
#             tf_idf = 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_test.append(sent_vec)
    row += 1
```

```
100%|| 16337/16337 [04:37<00:00, 58.96it/s]
```

6 [5] Assignment 8: Decision Trees

```
<li><strong>Apply Decision Trees on these feature sets</strong>
    <ul>
        <li><font color='red'>SET 1:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 2:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 3:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 4:</font>Review text, preprocessed one converted into vectors
    </ul>
</li>
<br>
<li><strong>The hyper paramter tuning (best `depth` in range [1, 5, 10, 50, 100, 500, 100], and
    <ul>
<li>Find the best hyper parameter which will give the maximum <a href='https://www.appliedaicou
<li>Find the best hyper paramter using k-fold cross validation or simple cross validation data
<li>Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this ta
    </ul>
</li>
<br>
<li><strong>Graphviz</strong>
    <ul>
<li>Visualize your decision tree with Graphviz. It helps you to understand how a decision is be
<li>Since feature names are not obtained from word2vec related models, visualize only BOW & TFI
<li>Make sure to print the words in each node of the decision tree instead of printing its inde
<li>Just for visualization purpose, limit max_depth to 2 or 3 and either embed the generated im
```

```
    </ul>
</li>
<br>
<li><strong>Feature importance</strong>
    <ul>
<li>Find the top 20 important features from both feature sets <font color='red'>Set 1</font> ar
    </ul>
</li>
<br>
<li><strong>Feature engineering</strong>
    <ul>
<li>To increase the performance of your model, you can also experiment with with feature engin
        <ul>
        <li>Taking length of reviews as another feature.</li>
        <li>Considering some features from review summary as well.</li>
    </ul>
    </ul>
</li>
<br>
<li><strong>Representation of results</strong>
    <ul>
<li>You need to plot the performance of model both on train data and cross validation data for
<img src='train_cv_auc.JPG' width=300px></li>
<li>Once after you found the best hyper parameter, you need to train your model with it, and fi
<img src='train_test_auc.JPG' width=300px></li>
<li>Along with plotting ROC curve, you need to print the <a href='https://www.appliedaicourse.c
<img src='confusion_matrix.png' width=300px></li>
    </ul>
</li>
<br>
<li><strong>Conclusion</strong>
    <ul>
<li>You need to summarize the results at the end of the notebook, summarize it in the table fo
    <img src='summary.JPG' width=400px>
</li>
    </ul>
```

Note: Data Leakage

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

6.1 Loading the Datasets using Joblib

```
In [3]: ##########################################    BoW   ####################################

        x_train_bow = joblib.load('x_tr_bow100k.pkl')
        x_test_bow  = joblib.load('x_te_bow100k.pkl')
        x_cv_bow    = joblib.load('x_cv_bow100k.pkl')

        y_train = joblib.load('y_train.pkl')
        y_test  = joblib.load('y_test.pkl')
        y_cv    = joblib.load('y_cv.pkl')

        ######################################## TF-IDF ######################################

        x_train_tf = joblib.load('x_tr_tfidf100k.pkl')
        x_test_tf  = joblib.load('x_te_tfidf100k.pkl')
        x_cv_tf    = joblib.load('x_cv_tfidf100k.pkl')

        ####################################### average w2v ##################################

        sent_vectors_train = joblib.load('sent_vectors_train_100k.pkl')
        sent_vectors_test  = joblib.load('sent_vectors_test_100k.pkl')
        sent_vectors_cv    = joblib.load('sent_vectors_cv_100k.pkl')

        ###################################### tfidf w2v  ####################################

        tfidf_sent_vectors_train = joblib.load('tfidf_sent_vectors_train_100k.pkl')
        tfidf_sent_vectors_test  = joblib.load('tfidf_sent_vectors_test_100k.pkl')
        tfidf_sent_vectors_cv    = joblib.load('tfidf_sent_vectors_cv_100k.pkl')
```

7 Applying Decision Trees

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

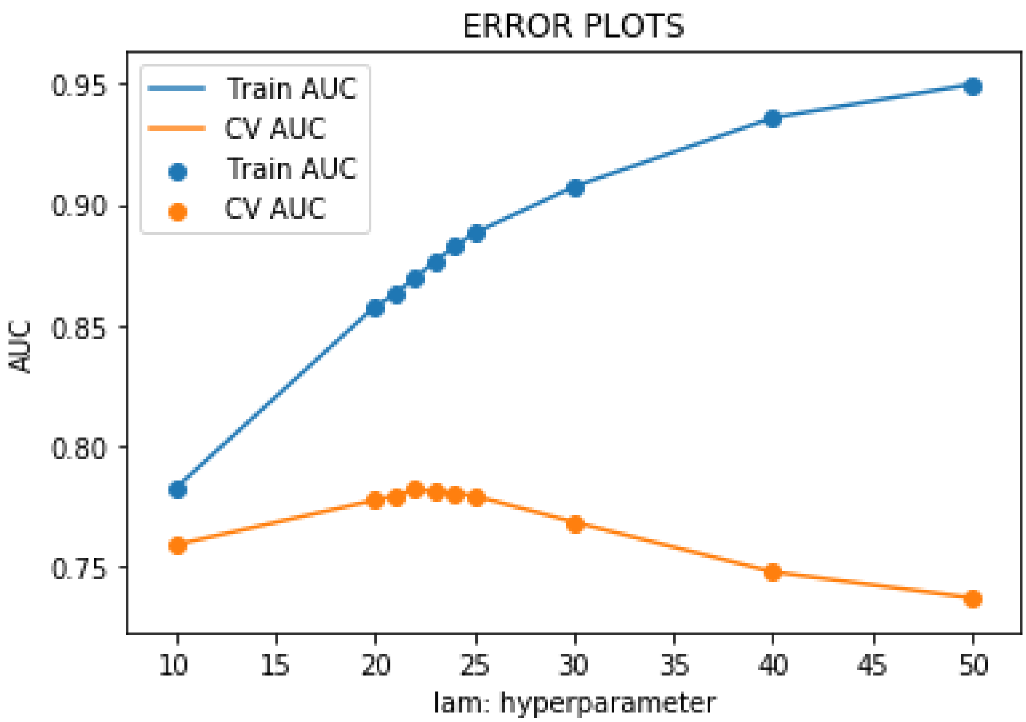
- Tuning Hyperparameter using gridsearch cross validation, tuning Depth(parameter) first.

```
In [23]: Depths = [10, 20, 21, 22, 23, 24, 25, 30, 40, 50]
         param_grid = {'max_depth':Depths} #, 'mimin_samples_split':min_sam
         clf = DecisionTreeClassifier(min_samples_split=50)

         grid = GridSearchCV(clf, param_grid ,cv= 3,n_jobs =-1, scoring='roc_auc', return_trai
         grid.fit(x_train_bow, y_train)

         print("Accuracy on train data = ", grid.best_score_*100)
         optimal_depth1 = grid.best_estimator_.max_depth
         print("The optimal number of depth is : ",optimal_depth1)
```

```
Accuracy on train data =  78.17628360772643
```

```
The optimal number of depth is :  22
```

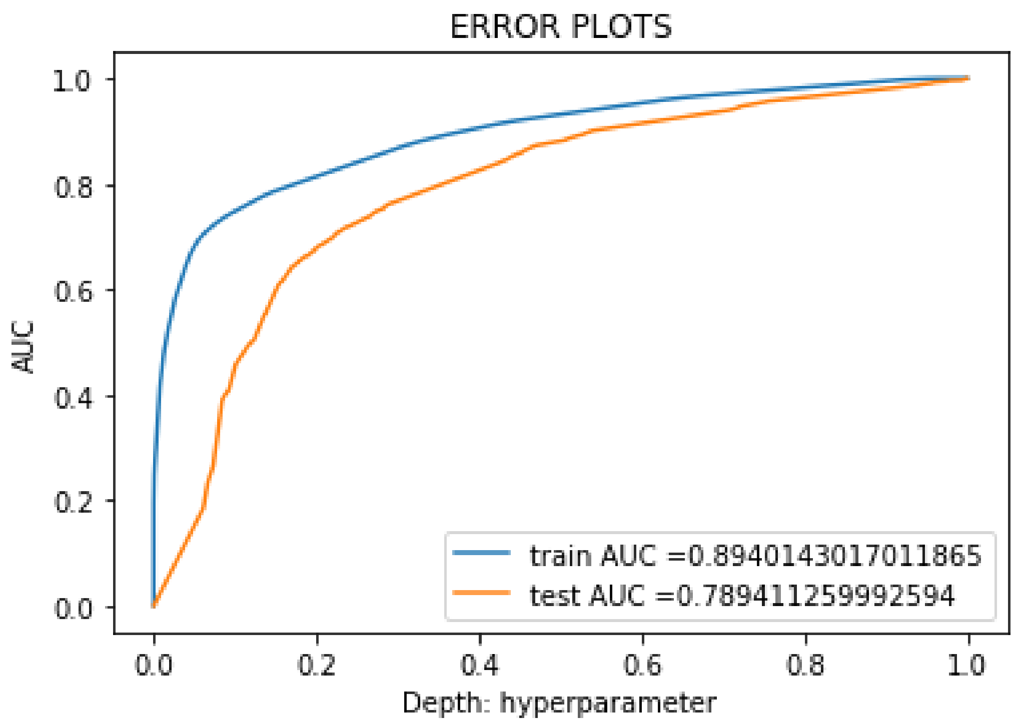
```
In [24]: bow_auc_train = grid.cv_results_['mean_train_score']
         bow_auc_cv    = grid.cv_results_['mean_test_score']

         plt.plot(Depths, bow_auc_train, label='Train AUC')
         plt.scatter(Depths, bow_auc_train, label='Train AUC')

         plt.plot(Depths, bow_auc_cv, label='CV AUC')
         plt.scatter(Depths, bow_auc_cv, label='CV AUC')

         plt.legend()
         plt.xlabel("lam: hyperparameter")
         plt.ylabel("AUC")
         plt.title("ERROR PLOTS")
         plt.show()
```



Testing with Test data

```
In [25]: clf = DecisionTreeClassifier(max_depth = optimal_depth1, class_weight ='balanced', mi
         clf.fit(x_train_bow, y_train)

         train_fpr_bow, train_tpr_bow, thresholds_bow = roc_curve(y_train, clf.predict_proba(x_
         test_fpr_bow, test_tpr_bow, thresholds_bow = roc_curve(y_test, clf.predict_proba(x_tes
```

```
plt.plot(train_fpr_bow, train_tpr_bow, label="train AUC ="+str(auc(train_fpr_bow, trai
plt.plot(test_fpr_bow, test_tpr_bow, label="test AUC ="+str(auc(test_fpr_bow, test_tp
plt.legend()
plt.xlabel("Depth: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



confusion matrix

```
In [7]: clf = DecisionTreeClassifier(max_depth = optimal_depth1, min_samples_split=150)
        clf.fit(x_train_bow,y_train)

        pred = clf.predict(x_test_bow)

        acc_1 = accuracy_score(y_test, pred) * 100
        pre_1 = precision_score(y_test, pred) * 100
        rec_1 = recall_score(y_test, pred) * 100
        f1_1  = f1_score(y_test, pred) * 100

        print('\nAccuracy = %f%%' % (acc_1))
        print('\nprecision= %f%%' % (pre_1))
        print('\nrecall    = %f%%' % (rec_1))
        print('\nF1-Score = %f%%' % (f1_1))
```

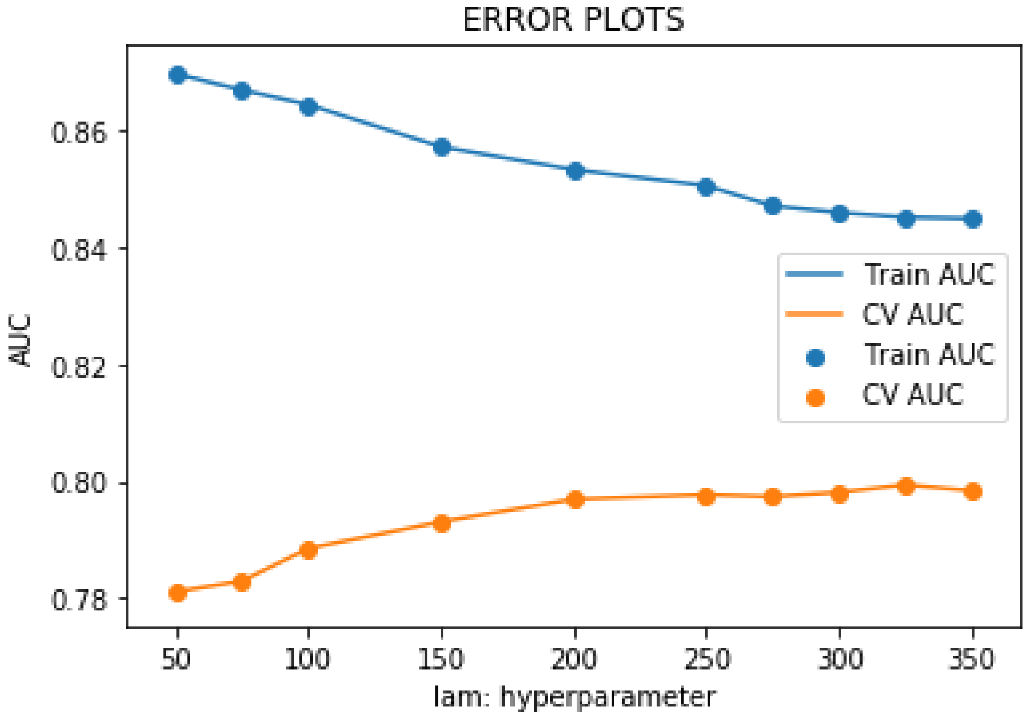
```
Accuracy = 85.557497%

precision= 88.899246%

recall    = 94.662757%

F1-Score = 91.690519%
```

- Hyperparamerter(min_split_size) tuning using GridSearchCV

```
In [8]: min_split = [50, 75, 100, 150, 200, 250, 275, 300, 325, 350]
        param_grid = {'min_samples_split': min_split}
        clf = DecisionTreeClassifier(max_depth=22)

        grid = GridSearchCV(clf, param_grid ,cv= 3,n_jobs =-1, scoring='roc_auc', return_train_
        grid.fit(x_train_bow, y_train)

        print("Accuracy on train data = ", grid.best_score_*100)
        optimal_split1 = grid.best_estimator_.min_samples_split
        print("The optimal number of depth is : ",optimal_split1)
```

```
Accuracy on train data =  79.9392966150601
The optimal number of depth is :  325
```

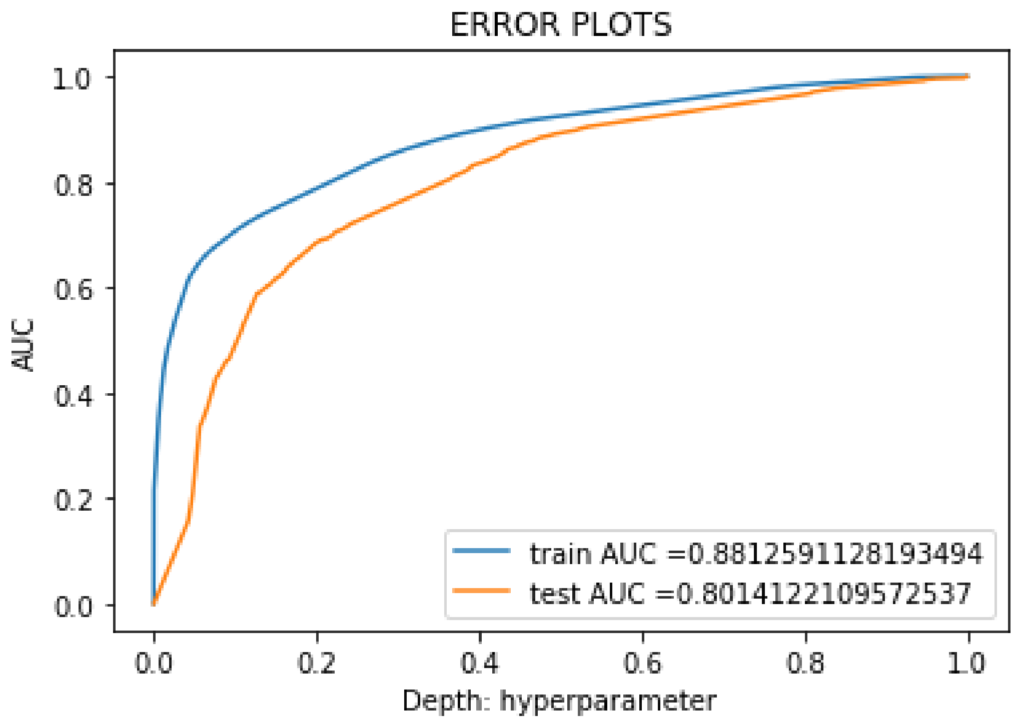
```
In [9]: bow_auc_train = grid.cv_results_['mean_train_score']
        bow_auc_cv    = grid.cv_results_['mean_test_score']

        plt.plot(min_split, bow_auc_train, label='Train AUC')
        plt.scatter(min_split, bow_auc_train, label='Train AUC')

        plt.plot(min_split, bow_auc_cv, label='CV AUC')
        plt.scatter(min_split, bow_auc_cv, label='CV AUC')

        plt.legend()
        plt.xlabel("lam: hyperparameter")
        plt.ylabel("AUC")
        plt.title("ERROR PLOTS")
        plt.show()
```



Testing with test data

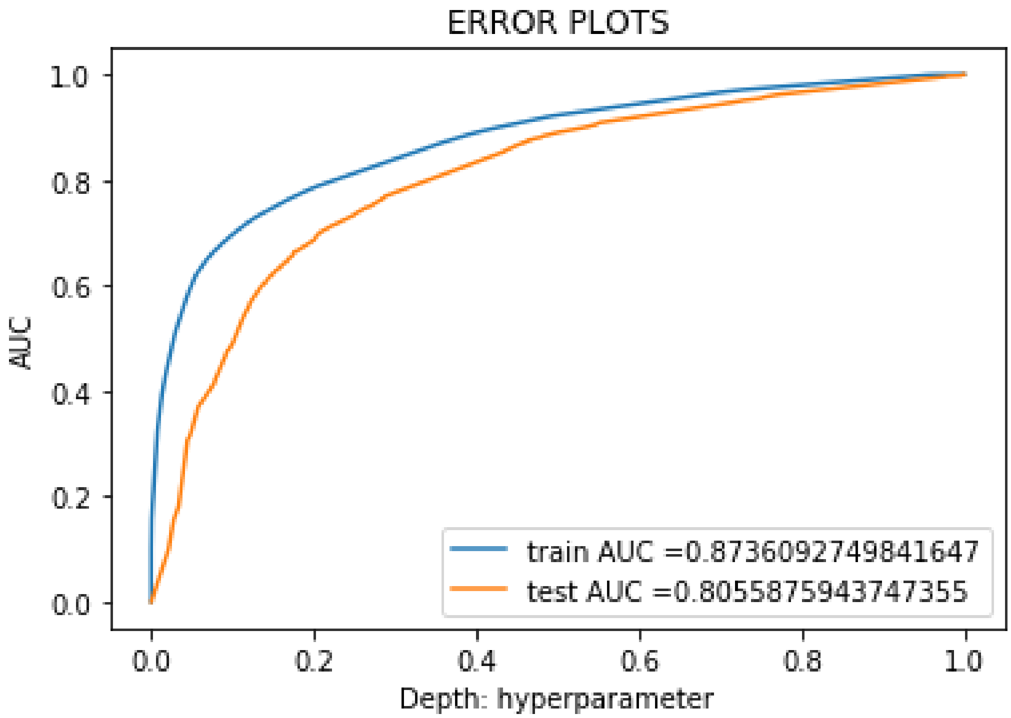
```
In [10]: optimal_split1 = 200
```

```
In [11]: clf = DecisionTreeClassifier(max_depth = optimal_depth1, class_weight ='balanced', min
         clf.fit(x_train_bow, y_train)

         train_fpr_bow, train_tpr_bow, thresholds_bow = roc_curve(y_train, clf.predict_proba(x_
         test_fpr_bow, test_tpr_bow, thresholds_bow = roc_curve(y_test, clf.predict_proba(x_tes

         plt.plot(train_fpr_bow, train_tpr_bow, label="train AUC ="+str(auc(train_fpr_bow, trai
         plt.plot(test_fpr_bow, test_tpr_bow, label="test AUC ="+str(auc(test_fpr_bow, test_tp

         plt.legend()
         plt.xlabel("Depth: hyperparameter")
         plt.ylabel("AUC")
         plt.title("ERROR PLOTS")
         plt.show()
```




```
In [118]: parameters = {'min_samples_split': min_split,'max_depth': Depths}
          grid = GridSearchCV(DecisionTreeClassifier(class_weight ='balanced'), parameters, cv=
          grid.fit(x_train_bow, y_train)

Out[118]: GridSearchCV(cv=3, error_score='raise-deprecating',
                 estimator=DecisionTreeClassifier(class_weight='balanced',
                                                  criterion='gini', max_depth=None,
                                                  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=None,
                                                  splitter='best'),
                 iid='warn', n_jobs=-1,
                 param_grid={'max_depth': [5, 6, 7, 8, 9, 10, 20, 30, 40, 50],
                             'min_samples_split': [10, 15, 25, 40, 50, 75, 100, 150,
                                                   200, 250]},
                 pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
                 scoring='roc_auc', verbose=0)

In [26]: optimal_depth1=22
         optimal_split1=300
```

```
clf = DecisionTreeClassifier(max_depth = optimal_depth1, class_weight ='balanced', mi
clf.fit(x_train_bow, y_train)

train_fpr_bow, train_tpr_bow, thresholds_bow = roc_curve(y_train, clf.predict_proba(x
test_fpr_bow, test_tpr_bow, thresholds_bow = roc_curve(y_test, clf.predict_proba(x_te

plt.plot(train_fpr_bow, train_tpr_bow, label="train AUC ="+str(auc(train_fpr_bow, tra
plt.plot(test_fpr_bow, test_tpr_bow, label="test AUC ="+str(auc(test_fpr_bow, test_tp

plt.legend()
plt.xlabel("Depth: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```




```
In [15]: clf = DecisionTreeClassifier(max_depth = optimal_depth1, min_samples_split=optimal_sp
         clf.fit(x_train_bow,y_train)

         pred = clf.predict(x_test_bow)

         acc_1 = accuracy_score(y_test, pred) * 100
         pre_1 = precision_score(y_test, pred) * 100
         rec_1 = recall_score(y_test, pred) * 100
         f1_1  = f1_score(y_test, pred) * 100
```

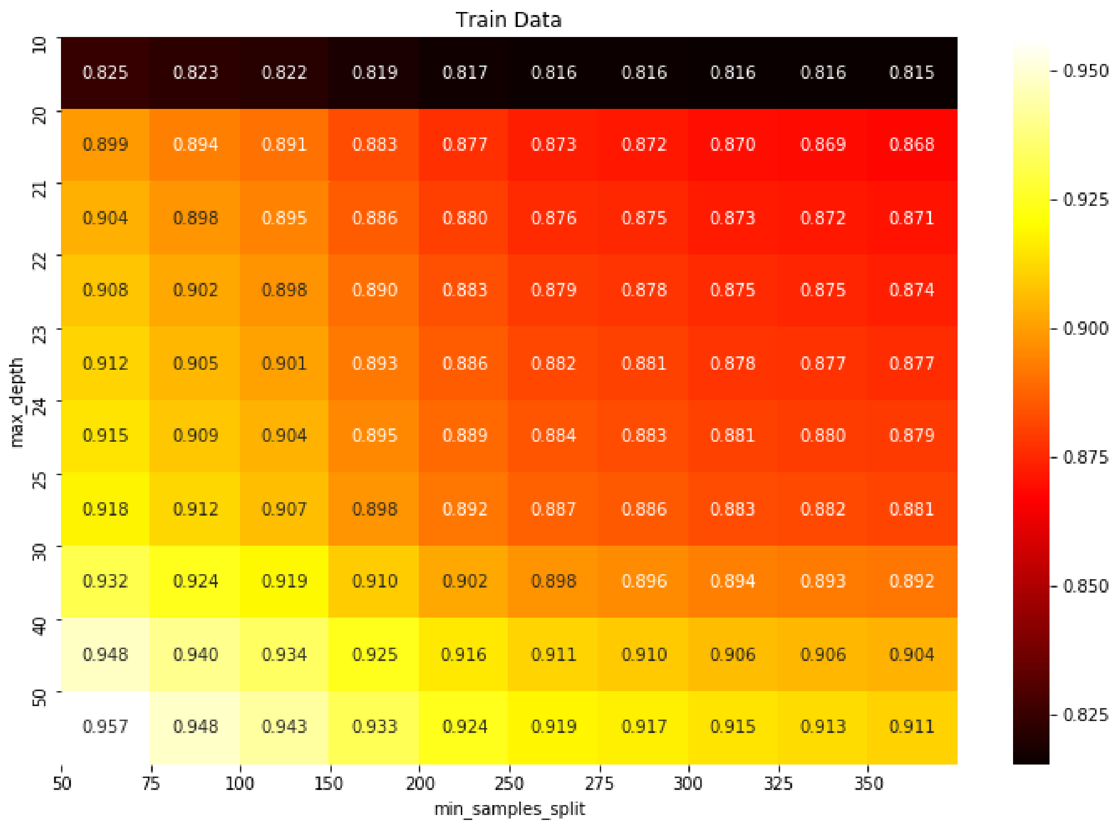
```
print('\nAccuracy = %f%%' % (acc_1))
print('\nprecision= %f%%' % (pre_1))
print('\nrecall    = %f%%' % (rec_1))
print('\nF1-Score = %f%%' % (f1_1))
```

```
Accuracy = 85.568890%

precision= 89.006414%

recall    = 94.531920%

F1-Score = 91.685993%
```

7.2 Heatmaps for train data and test data

For train data:

```
In [16]: heat_map1 = grid.cv_results_['mean_train_score'].reshape(len(min_split),len(Depths))
         plt.figure(figsize=(12,8))
         sns.heatmap(heat_map1, annot=True, cmap=plt.cm.hot, fmt=".3f", xticklabels=min_split,
         plt.xlabel('min_samples_split')
         plt.ylabel('max_depth')
         plt.xticks(np.arange(len(min_split)), min_split)
         plt.yticks(np.arange(len(Depths)), Depths)
         plt.title('Heatmap of Train Data')
         plt.show()
```



For test data:

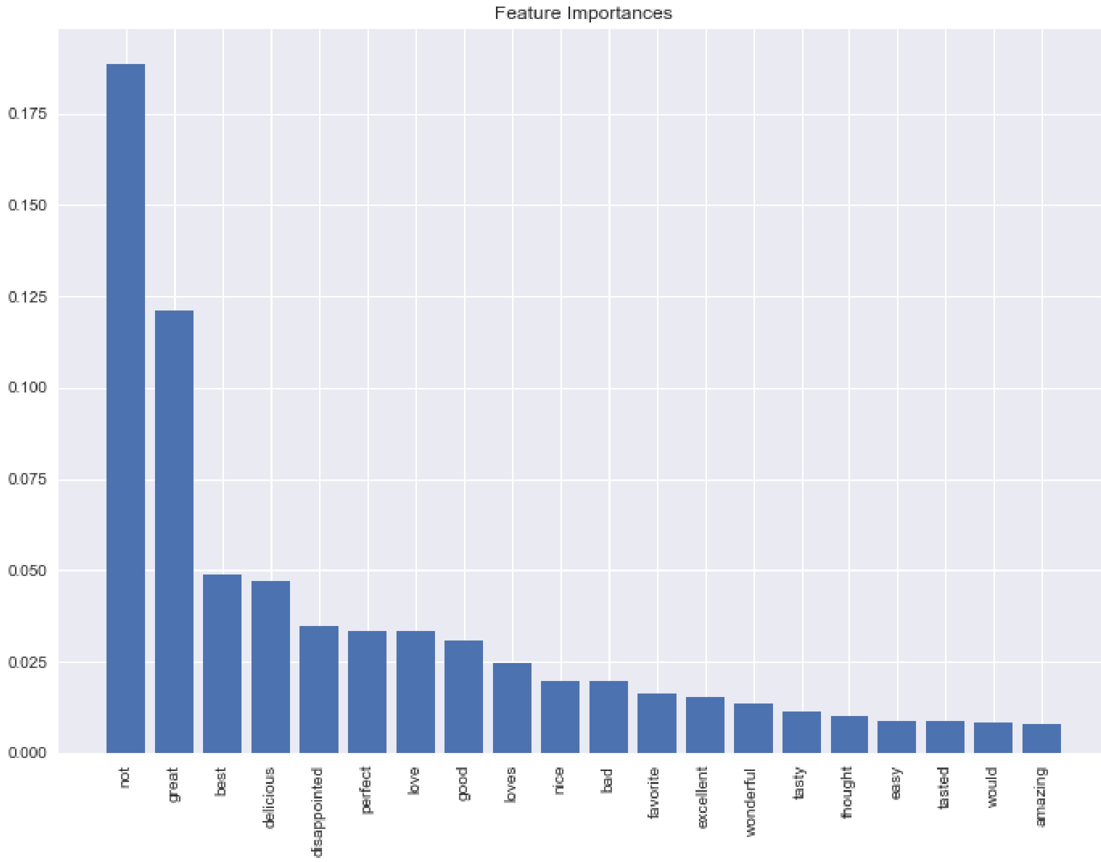
```
In [17]: heat_map1 = grid.cv_results_['mean_test_score'].reshape(len(min_split),len(Depths))
         plt.figure(figsize=(12,8))
         sns.heatmap(heat_map1, annot=True, cmap=plt.cm.hot, fmt=".3f", xticklabels=min_split,
         plt.xlabel('min_samples_split')
         plt.ylabel('max_depth')
         plt.xticks(np.arange(len(min_split)), min_split)
         plt.yticks(np.arange(len(Depths)), Depths)
         plt.title('Heatmap of Train Data')
         plt.show()
```

7.2.1 [5.1.1] Top 20 important features from SET 1

```
In [45]: # feature importance
         importances = clf.feature_importances_
         indices = list(np.argsort(importances)[::-1][:20])
         names = np.array(count_vect.get_feature_names())
         print(names[indices])
```

```
['not' 'great' 'best' 'delicious' 'disappointed' 'perfect' 'love' 'good'
 'loves' 'nice' 'bad' 'favorite' 'excellent' 'wonderful' 'tasty' 'thought'
 'easy' 'tasted' 'would' 'amazing']
```

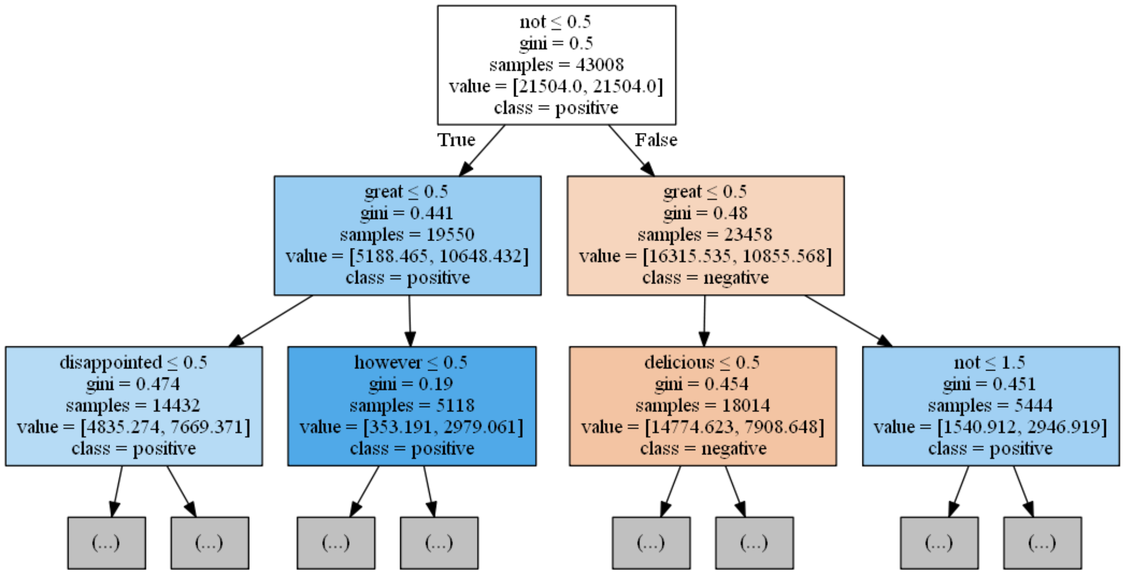
```
In [46]: plt.figure()
         plt.title("Feature Importances")
         plt.bar(range(20), importances[indices])
         plt.xticks(range(20), names[indices], rotation=90)
         plt.show()
```



7.2.2 [5.1.2] Graphviz visualization of Decision Tree on BOW, SET 1

In [52]:
```
target = ['negative','positive']
# Create DOT data ############ feature_names= names[indices],
data = tree.export_graphviz(clf, max_depth=2, feature_names= names ,out_file=None,clas

# Draw graph
graph = pydotplus.graph_from_dot_data(data)

# Show graph
Image(graph.create_png())
```

Out[52]:



7.3 [5.2] Applying Decision Trees on TFIDF, SET 2

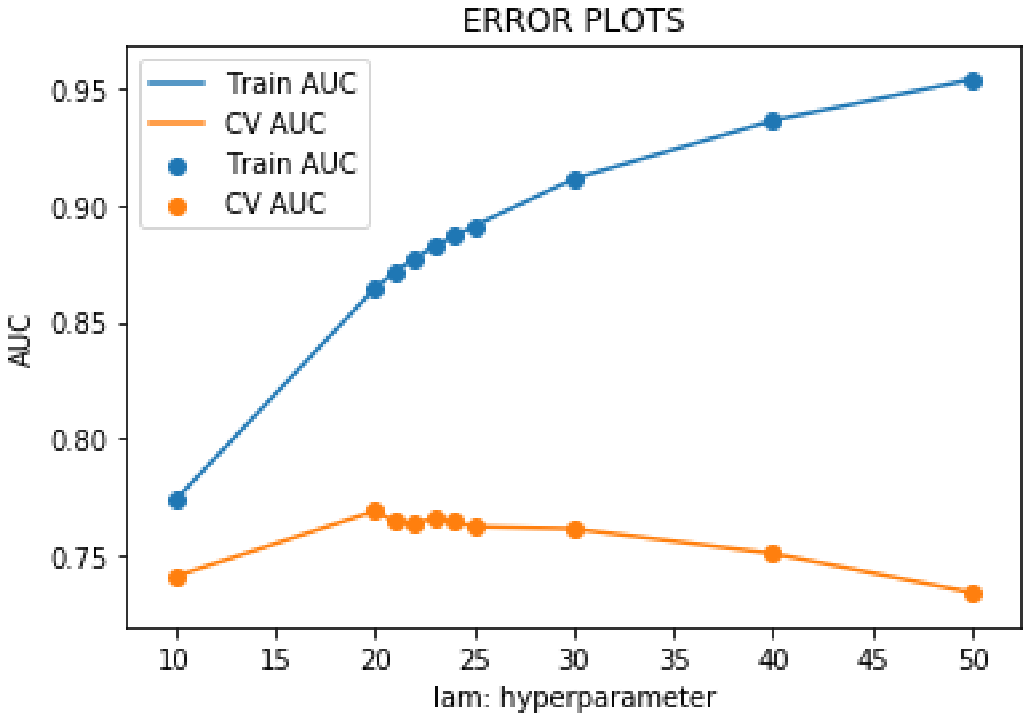
Hyperparameter tuning using grid serach cross validation for max_depth feature.

```
In [55]: Depths = [10, 20, 21, 22, 23, 24, 25, 30, 40, 50]
         param_grid = {'max_depth':Depths}
         clf = DecisionTreeClassifier(min_samples_split=50)

         grid = GridSearchCV(clf, param_grid ,cv= 3,n_jobs =-1, scoring='roc_auc', return_trai
         grid.fit(x_train_tf, y_train)

         print("Accuracy on train data = ", grid.best_score_*100)
         optimal_depth2 = grid.best_estimator_.max_depth
         print("The optimal number of depth is : ",optimal_depth2)
```

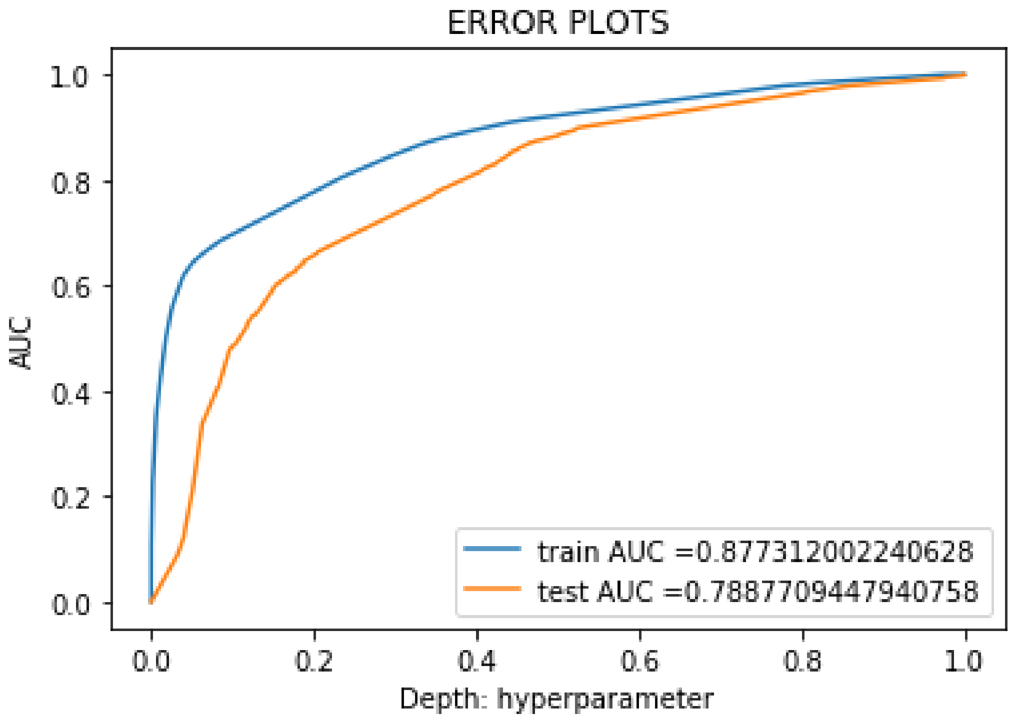
```
Accuracy on train data =  77.29089553475444
The optimal number of depth is :  24
```

```
In [24]: tf_auc_train = grid.cv_results_['mean_train_score']
         tf_auc_cv    = grid.cv_results_['mean_test_score']

         plt.plot(Depths, tf_auc_train, label='Train AUC')
         plt.scatter(Depths, tf_auc_train, label='Train AUC')

         plt.plot(Depths, tf_auc_cv, label='CV AUC')
         plt.scatter(Depths, tf_auc_cv, label='CV AUC')

         plt.legend()
```

```
plt.xlabel("lam: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```




```
In [27]: clf = DecisionTreeClassifier(max_depth = optimal_depth2, class_weight ='balanced', mi
         clf.fit(x_train_tf, y_train)

         train_fpr_tf, train_tpr_tf, thresholds_tf = roc_curve(y_train, clf.predict_proba(x_tr
         test_fpr_tf, test_tpr_tf, thresholds_tf = roc_curve(y_test, clf.predict_proba(x_test_

         plt.plot(train_fpr_tf, train_tpr_tf, label="train AUC ="+str(auc(train_fpr_tf, train_
         plt.plot(test_fpr_tf, test_tpr_tf, label="test AUC ="+str(auc(test_fpr_tf, test_tpr_t
         plt.legend()
         plt.xlabel("Depth: hyperparameter")
         plt.ylabel("AUC")
         plt.title("ERROR PLOTS")
         plt.show()
```

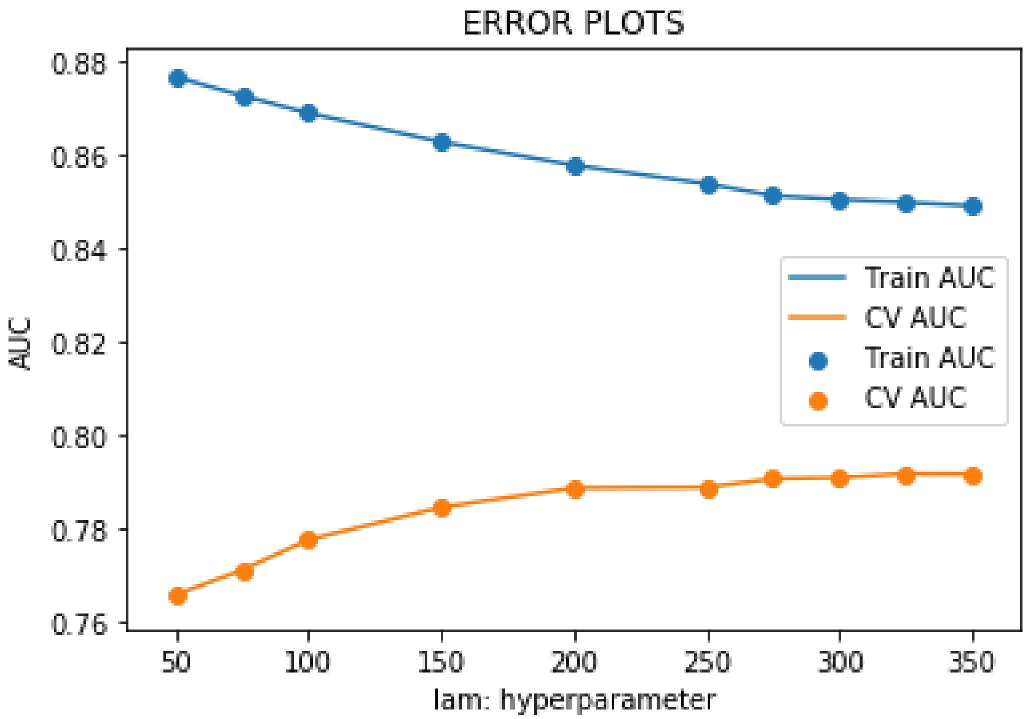



```
In [29]: min_split = [50, 75, 100, 150, 200, 250, 275, 300, 325, 350]
         param_grid = {'min_samples_split': min_split}
         clf = DecisionTreeClassifier(max_depth=22)

         grid = GridSearchCV(clf, param_grid ,cv= 3,n_jobs =-1, scoring='roc_auc', return_trai
         grid.fit(x_train_tf, y_train)

         print("Accuracy on train data = ", grid.best_score_*100)
         optimal_split2 = grid.best_estimator_.min_samples_split
         print("The optimal number of splits is : ",optimal_split2)
```

```
Accuracy on train data =  79.18876053017347
The optimal number of splits is :  325
```

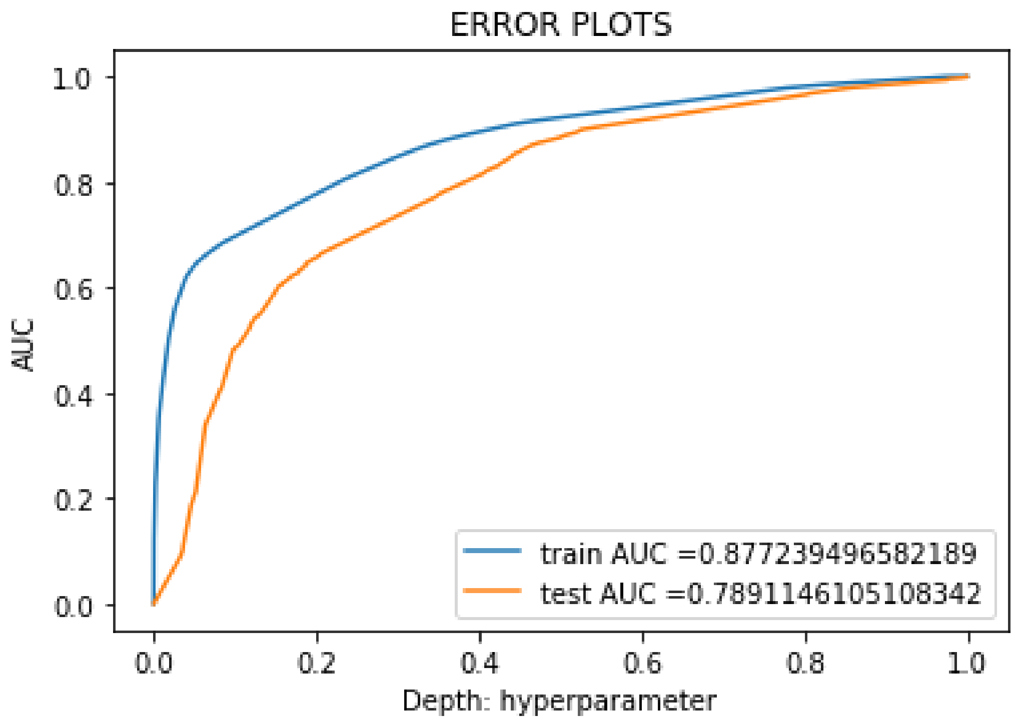
```
In [30]: tf_auc_train = grid.cv_results_['mean_train_score']
         tf_auc_cv    = grid.cv_results_['mean_test_score']

         plt.plot(min_split, tf_auc_train, label='Train AUC')
         plt.scatter(min_split, tf_auc_train, label='Train AUC')

         plt.plot(min_split, tf_auc_cv, label='CV AUC')
         plt.scatter(min_split, tf_auc_cv, label='CV AUC')
```

```
plt.legend()
plt.xlabel("lam: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [34]:
```
optimal_split2 = 300
```

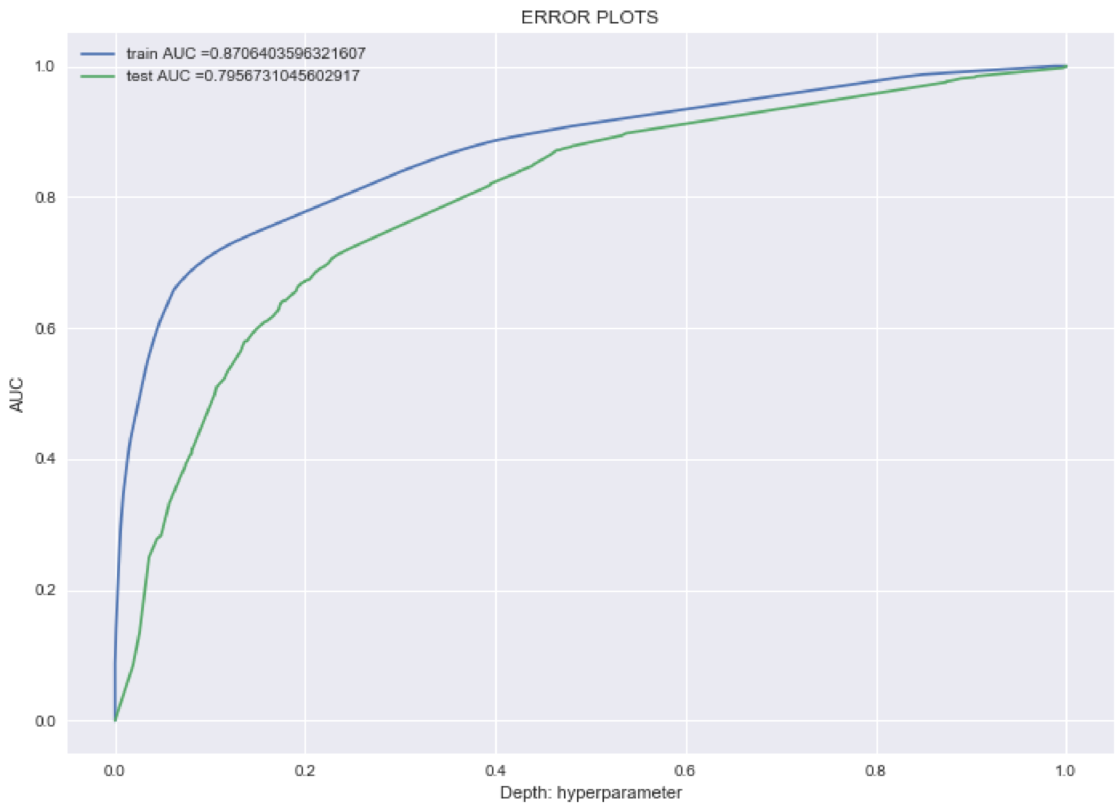
In [33]:
```
clf = DecisionTreeClassifier(max_depth = optimal_depth2, class_weight ='balanced', mi
clf.fit(x_train_tf, y_train)

train_fpr_tf, train_tpr_tf, thresholds_tf = roc_curve(y_train, clf.predict_proba(x_tr
test_fpr_tf, test_tpr_tf, thresholds_tf = roc_curve(y_test, clf.predict_proba(x_test_

plt.plot(train_fpr_tf, train_tpr_tf, label="train AUC ="+str(auc(train_fpr_tf, train_
plt.plot(test_fpr_tf, test_tpr_tf, label="test AUC ="+str(auc(test_fpr_tf, test_tpr_t
plt.legend()
plt.xlabel("Depth: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```




```
In [35]: parameters = {'min_samples_split': min_split,'max_depth': Depths}
         grid = GridSearchCV(DecisionTreeClassifier(class_weight ='balanced'), parameters, cv=3
         grid.fit(x_train_tf, y_train)

Out[35]: GridSearchCV(cv=3, error_score='raise-deprecating',
                      estimator=DecisionTreeClassifier(class_weight='balanced',
                                                        criterion='gini', max_depth=None,
                                                        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=None,
                                                        splitter='best'),
                      iid='warn', n_jobs=-1,
                      param_grid={'max_depth': [10, 20, 21, 22, 23, 24, 25, 30, 40, 50],
                                  'min_samples_split': [50, 75, 100, 150, 200, 250, 275,
                                                        300, 325, 350]},
                      pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
                      scoring='roc_auc', verbose=0)

In [36]: grid.best_params_
```

Out[36]: {'max_depth': 20, 'min_samples_split': 350}

In [57]:
```
optimal_depth2=20
optimal_split2=350
clf = DecisionTreeClassifier(max_depth = optimal_depth2, class_weight ='balanced', mi
clf.fit(x_train_tf, y_train)

train_fpr_tf, train_tpr_tf, thresholds_tf = roc_curve(y_train, clf.predict_proba(x_tr
test_fpr_tf, test_tpr_tf, thresholds_tf = roc_curve(y_test, clf.predict_proba(x_test_

plt.plot(train_fpr_tf, train_tpr_tf, label="train AUC ="+str(auc(train_fpr_tf, train_
plt.plot(test_fpr_tf, test_tpr_tf, label="test AUC ="+str(auc(test_fpr_tf, test_tpr_t

plt.legend()
plt.xlabel("Depth: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```

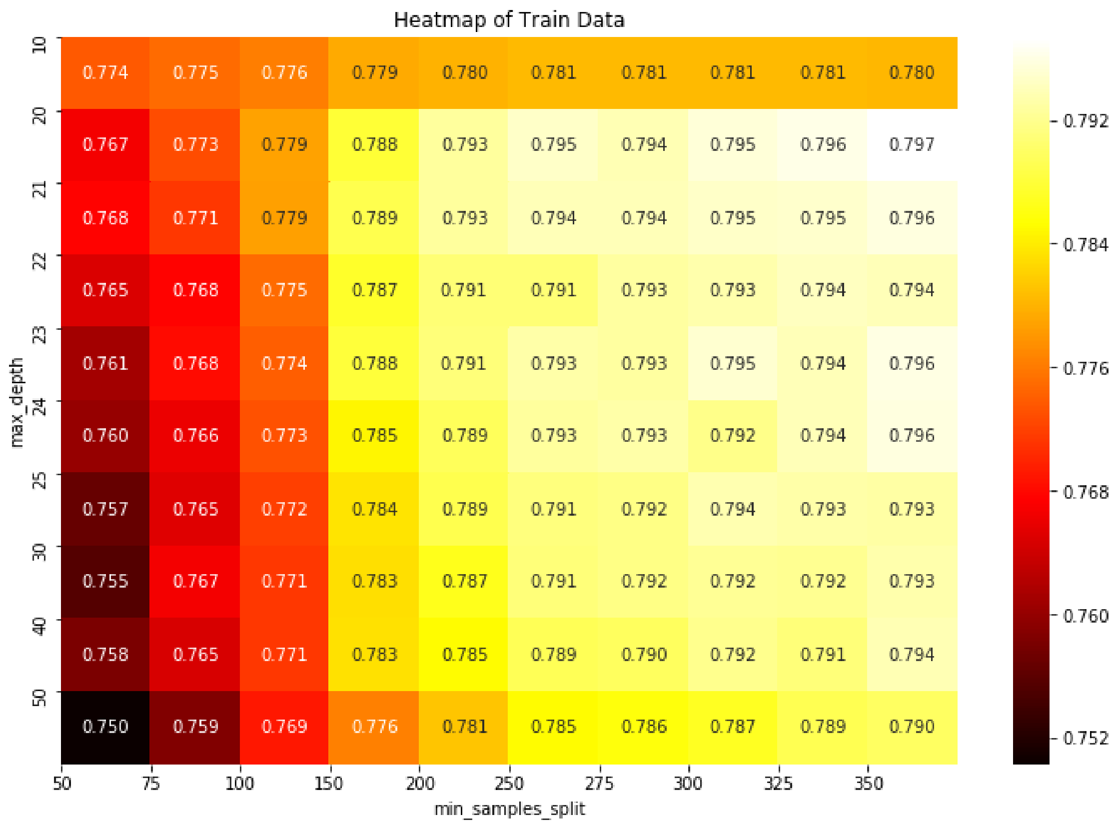


In [38]:
```
clf = DecisionTreeClassifier(max_depth = optimal_depth2, min_samples_split=optimal_sp
clf.fit(x_train_tf,y_train)
```

```
pred = clf.predict(x_test_tf)

acc_2 = accuracy_score(y_test, pred) * 100
pre_2 = precision_score(y_test, pred) * 100
rec_2 = recall_score(y_test, pred) * 100
f1_2  = f1_score(y_test, pred) * 100

print('\nAccuracy = %f%%' % (acc_2))
print('\nprecision= %f%%' % (pre_2))
print('\nrecall   = %f%%' % (rec_2))
print('\nF1-Score = %f%%' % (f1_2))
```

```
Accuracy = 85.773963%

precision= 89.068002%

recall   = 94.725919%

F1-Score = 91.809874%
```

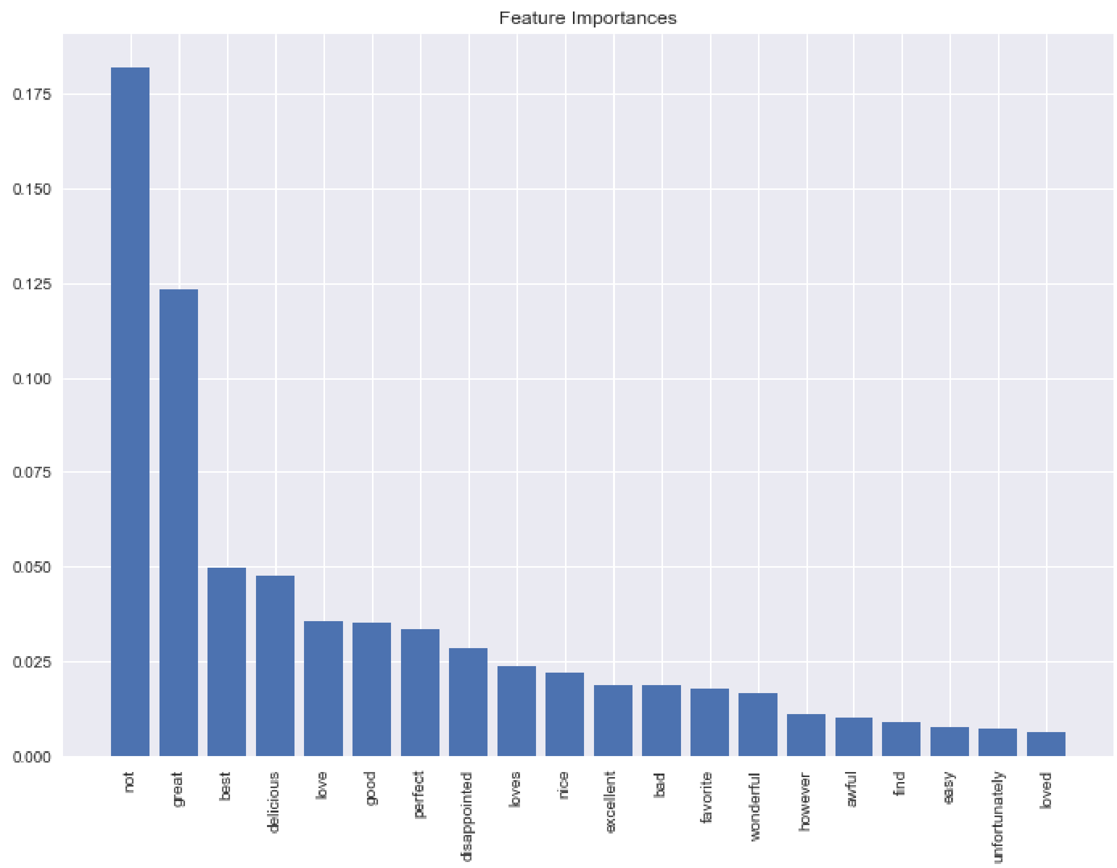
In [39]:
```
heat_map2 = grid.cv_results_['mean_test_score'].reshape(len(min_split),len(Depths))
plt.figure(figsize=(12,8))
sns.heatmap(heat_map2, annot=True, cmap=plt.cm.hot, fmt=".3f", xticklabels=min_split,
plt.xlabel('min_samples_split')
plt.ylabel('max_depth')
plt.xticks(np.arange(len(min_split)), min_split)
plt.yticks(np.arange(len(Depths)), Depths)
plt.title('Heatmap of Train Data')
plt.show()
```



7.3.1 [5.2.1] Top 20 important features from SET 2

```
In [58]: # feature importance
         importances = clf.feature_importances_
         indices = list(np.argsort(importances)[::-1][:20])
         names = np.array(tf_idf.get_feature_names())
         print(names[indices])

         # plotting feature importances as a simple bargraph
         plt.figure()
         plt.title("Feature Importances")
         plt.bar(range(20), importances[indices])
         plt.xticks(range(20), names[indices], rotation=90)
         plt.show()
```

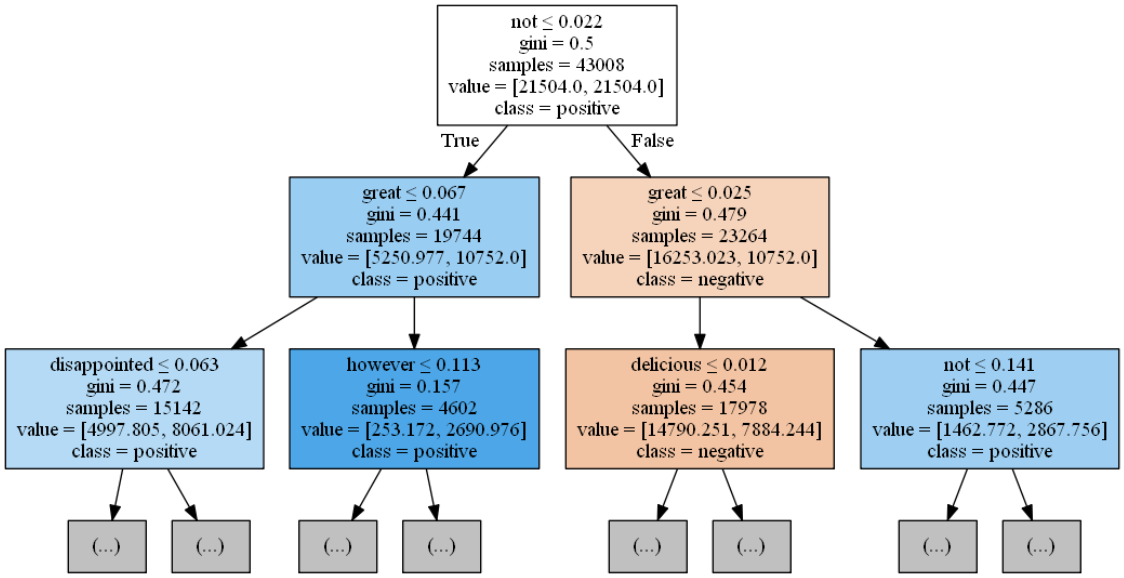
```
['not' 'great' 'best' 'delicious' 'love' 'good' 'perfect' 'disappointed'
 'loves' 'nice' 'excellent' 'bad' 'favorite' 'wonderful' 'however' 'awful'
 'find' 'easy' 'unfortunately' 'loved']
```



7.3.2 [5.2.2] Graphviz visualization of Decision Tree on TFIDF, SET 2

In [59]:
```
target = ['negative','positive']
# Create DOT data ############ feature_names= names[indices],
data = tree.export_graphviz(clf, max_depth=2, feature_names= names ,out_file=None,clas

# Draw graph
graph = pydotplus.graph_from_dot_data(data)

# Show graph
Image(graph.create_png())
```

Out[59]:



7.4 [5.3] Applying Decision Trees on AVG W2V, SET 3

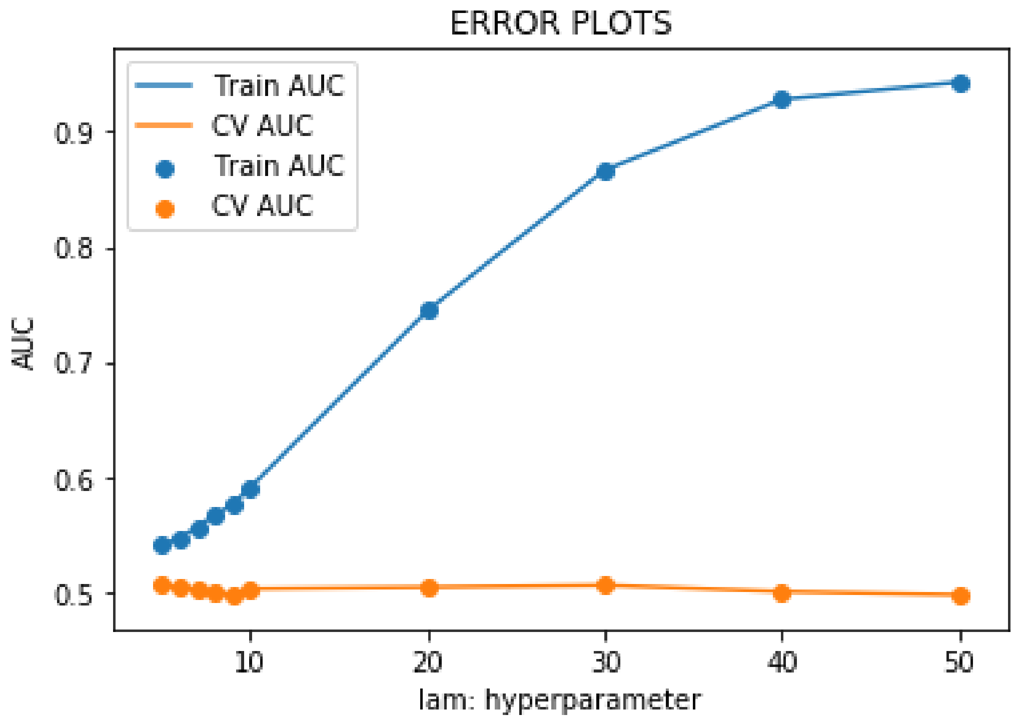
GridSearch CV implementation on Decision Trees

```
In [49]: Depths = [5, 6, 7, 8, 9, 10, 20, 30, 40, 50]
         param_grid = {'max_depth':Depths}
         clf = DecisionTreeClassifier(min_samples_split=50)

         grid = GridSearchCV(clf, param_grid ,cv= 3,n_jobs =-1, scoring='roc_auc', return_trai
         grid.fit(sent_vectors_train, y_train)

         print("Accuracy on train data = ", grid.best_score_*100)
         optimal_depth3 = grid.best_estimator_.max_depth
         print("The optimal number of depth is : ",optimal_depth3)
```

```
Accuracy on train data =  50.56925646421963
The optimal number of depth is :  30
```

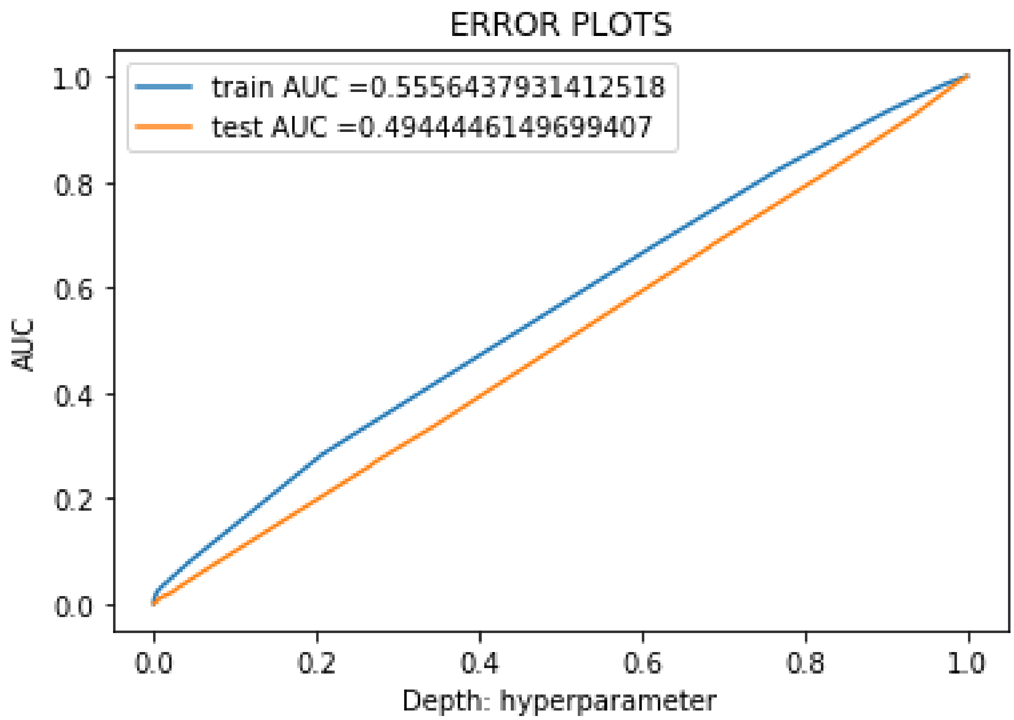
```
In [50]: aw2v_auc_train = grid.cv_results_['mean_train_score']
         aw2v_auc_cv    = grid.cv_results_['mean_test_score']

         plt.plot(Depths, aw2v_auc_train, label='Train AUC')
         plt.scatter(Depths, aw2v_auc_train, label='Train AUC')

         plt.plot(Depths, aw2v_auc_cv, label='CV AUC')
         plt.scatter(Depths, aw2v_auc_cv, label='CV AUC')
```

```
plt.legend()
plt.xlabel("lam: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



Testing with test data

```
In [51]: clf = DecisionTreeClassifier(max_depth = 5, class_weight ='balanced', min_samples_spli
         clf.fit(sent_vectors_train, y_train)

         train_fpr_aw2v, train_tpr_aw2v, thresholds_aw2v = roc_curve(y_train, clf.predict_proba
         test_fpr_aw2v, test_tpr_aw2v, thresholds_aw2v = roc_curve(y_test, clf.predict_proba(se

         plt.plot(train_fpr_aw2v, train_tpr_aw2v, label="train AUC ="+str(auc(train_fpr_aw2v, t
         plt.plot(test_fpr_aw2v, test_tpr_aw2v, label="test AUC ="+str(auc(test_fpr_aw2v, test_
         plt.legend()
         plt.xlabel("Depth: hyperparameter")
         plt.ylabel("AUC")
         plt.title("ERROR PLOTS")
         plt.show()
```



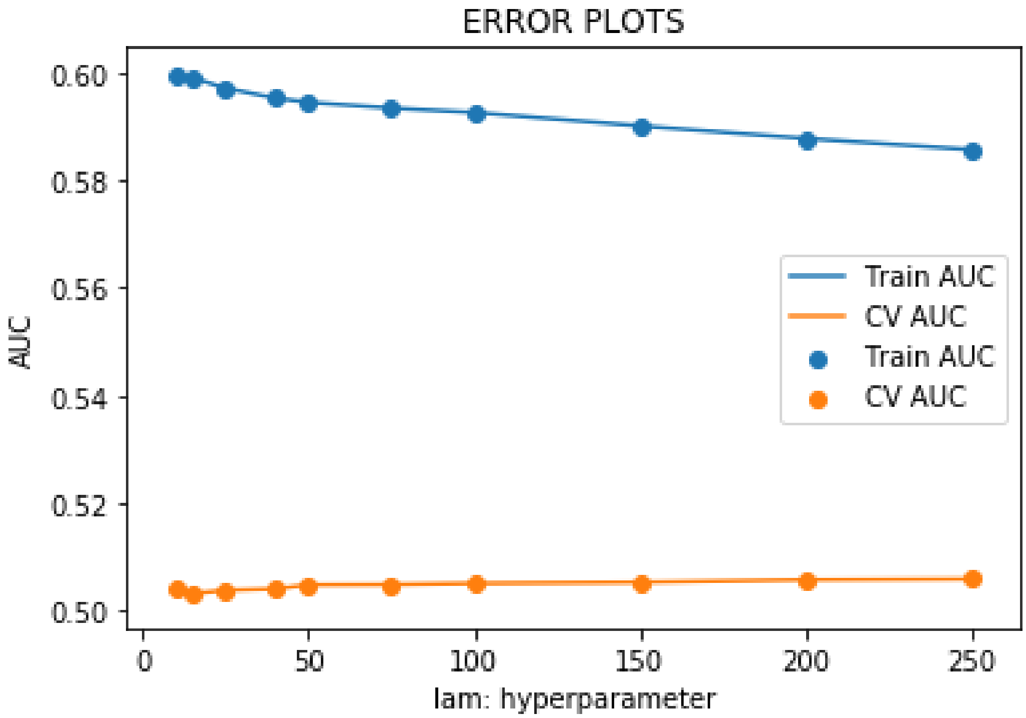
Hyperparameter tuning using grid serach cross validation(tuing min_sample_split feature)

```
In [52]: min_split = [10, 15, 25, 40, 50, 75, 100, 150, 200, 250]
         param_grid = {'min_samples_split': min_split}
         clf = DecisionTreeClassifier(max_depth=5)

         grid = GridSearchCV(clf, param_grid ,cv= 3,n_jobs =-1, scoring='roc_auc', return_trai
         grid.fit(sent_vectors_train, y_train)

         print("Accuracy on train data = ", grid.best_score_*100)
         optimal_split3 = grid.best_estimator_.min_samples_split
         print("The optimal number of splits is : ",optimal_split3)
```

```
Accuracy on train data =  50.59638832538694
The optimal number of splits is :  10
```

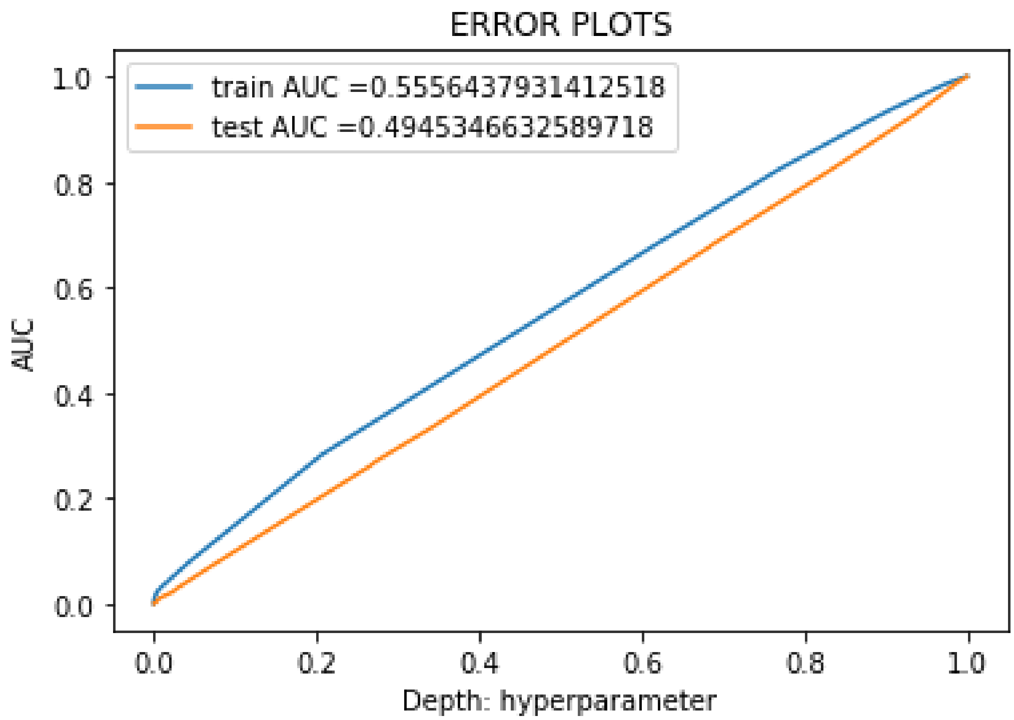
```
In [75]: aw2v_auc_train = grid.cv_results_['mean_train_score']
         aw2v_auc_cv    = grid.cv_results_['mean_test_score']

         plt.plot(min_split, aw2v_auc_train, label='Train AUC')
         plt.scatter(min_split, aw2v_auc_train, label='Train AUC')

         plt.plot(min_split, aw2v_auc_cv, label='CV AUC')
         plt.scatter(min_split, aw2v_auc_cv, label='CV AUC')
```

```
plt.legend()
plt.xlabel("lam: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



Testing with test data

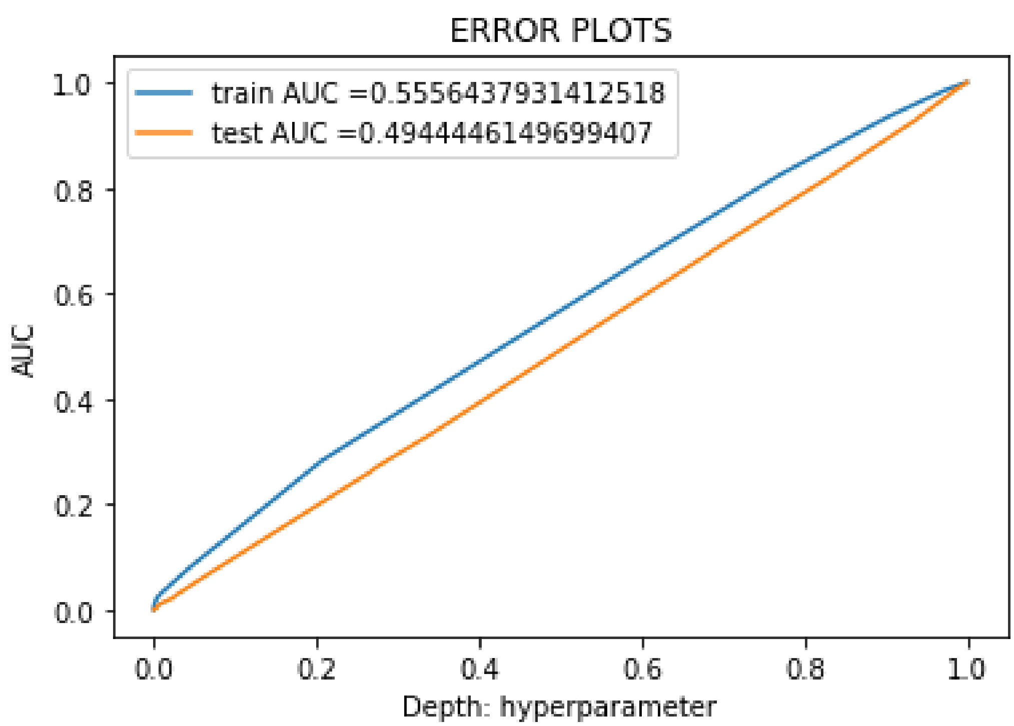
```
In [54]: clf = DecisionTreeClassifier(max_depth = 5, class_weight ='balanced', min_samples_spli
         clf.fit(sent_vectors_train, y_train)

         train_fpr_aw2v, train_tpr_aw2v, thresholds_aw2v = roc_curve(y_train, clf.predict_proba
         test_fpr_aw2v, test_tpr_aw2v, thresholds_aw2v = roc_curve(y_test, clf.predict_proba(se

         plt.plot(train_fpr_aw2v, train_tpr_aw2v, label="train AUC ="+str(auc(train_fpr_aw2v, t
         plt.plot(test_fpr_aw2v, test_tpr_aw2v, label="test AUC ="+str(auc(test_fpr_aw2v, test_
         plt.legend()
         plt.xlabel("Depth: hyperparameter")
         plt.ylabel("AUC")
         plt.title("ERROR PLOTS")
         plt.show()
```




```
In [55]: parameters = {'min_samples_split': min_split,'max_depth': Depths}
         grid = GridSearchCV(DecisionTreeClassifier(class_weight ='balanced'), parameters, cv=3
         grid.fit(sent_vectors_train, y_train)

Out[55]: GridSearchCV(cv=3, error_score='raise-deprecating',
                      estimator=DecisionTreeClassifier(class_weight='balanced',
                                                       criterion='gini', max_depth=None,
                                                       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=None,
                                                       splitter='best'),
                      iid='warn', n_jobs=-1,
                      param_grid={'max_depth': [5, 6, 7, 8, 9, 10, 20, 30, 40, 50],
                                  'min_samples_split': [10, 15, 25, 40, 50, 75, 100, 150,
                                                        200, 250]},
                      pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
                      scoring='roc_auc', verbose=0)

In [56]: grid.best_params_
```

Out[56]: {'max_depth': 5, 'min_samples_split': 10}

In [57]:
```
optimal_depth3=5
optimal_split3=10
clf = DecisionTreeClassifier(max_depth = 5, class_weight ='balanced', min_samples_spl
clf.fit(sent_vectors_train, y_train)

train_fpr_aw2v, train_tpr_aw2v, thresholds_aw2v = roc_curve(y_train, clf.predict_proba
test_fpr_aw2v, test_tpr_aw2v, thresholds_aw2v = roc_curve(y_test, clf.predict_proba(se

plt.plot(train_fpr_aw2v, train_tpr_aw2v, label="train AUC ="+str(auc(train_fpr_aw2v, t
plt.plot(test_fpr_aw2v, test_tpr_aw2v, label="test AUC ="+str(auc(test_fpr_aw2v, test_
plt.legend()
plt.xlabel("Depth: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```

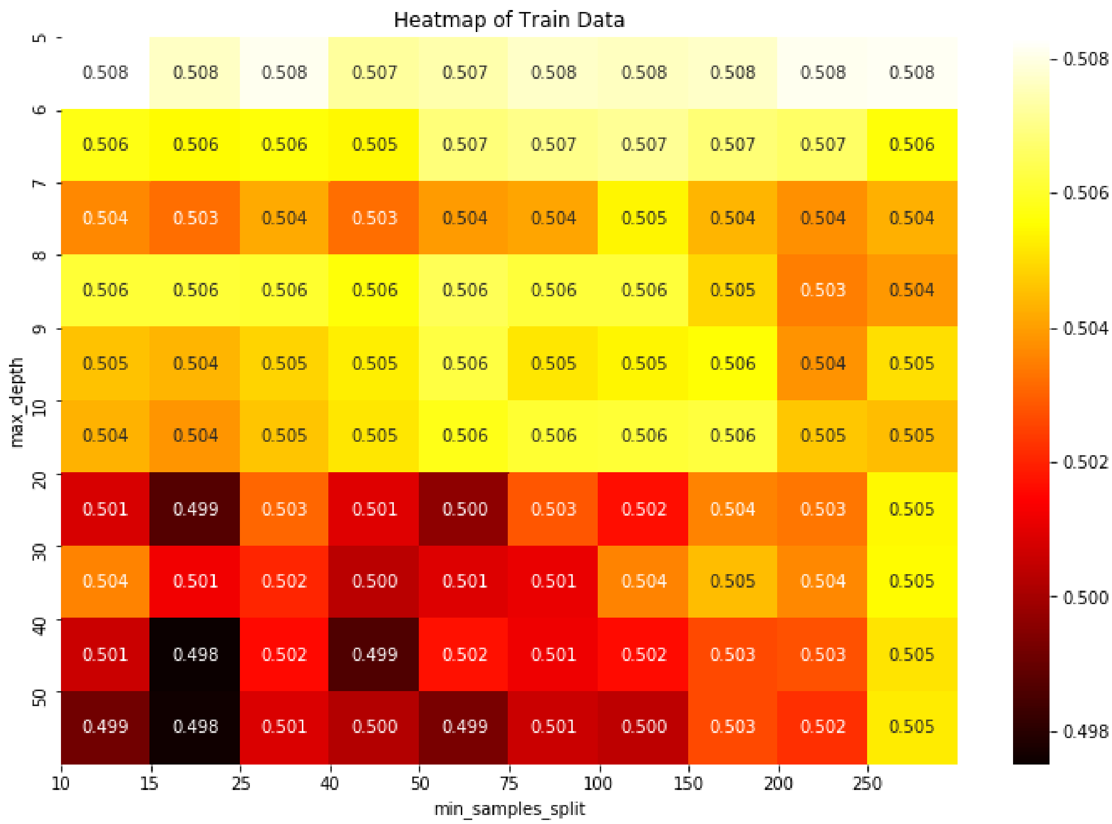


In [59]:
```
clf = DecisionTreeClassifier(max_depth = optimal_depth3, min_samples_split=optimal_spl
clf.fit(sent_vectors_train,y_train)

pred = clf.predict(sent_vectors_test)

acc_3 = accuracy_score(y_test, pred) * 100
```

```
pre_3 = precision_score(y_test, pred) * 100
rec_3 = recall_score(y_test, pred) * 100
f1_3  = f1_score(y_test, pred) * 100

print('\nAccuracy = %f%%' % (acc_3))
print('\nprecision= %f%%' % (pre_3))
print('\nrecall   = %f%%' % (rec_3))
print('\nF1-Score = %f%%' % (f1_3))
```

```
Accuracy = 84.076409%

precision= 84.177697%

recall   = 99.851117%

F1-Score = 91.346967%
```

```
In [61]: heat_map3 = grid.cv_results_['mean_test_score'].reshape(len(min_split),len(Depths))
         plt.figure(figsize=(12,8))
         sns.heatmap(heat_map3, annot=True, cmap=plt.cm.hot, fmt=".3f", xticklabels=min_split,
         plt.xlabel('min_samples_split')
         plt.ylabel('max_depth')
         plt.xticks(np.arange(len(min_split)), min_split)
         plt.yticks(np.arange(len(Depths)), Depths)
         plt.title('Heatmap of Train Data')
         plt.show()
```



7.5 [5.4] Applying Decision Trees on TFIDF W2V, SET 4

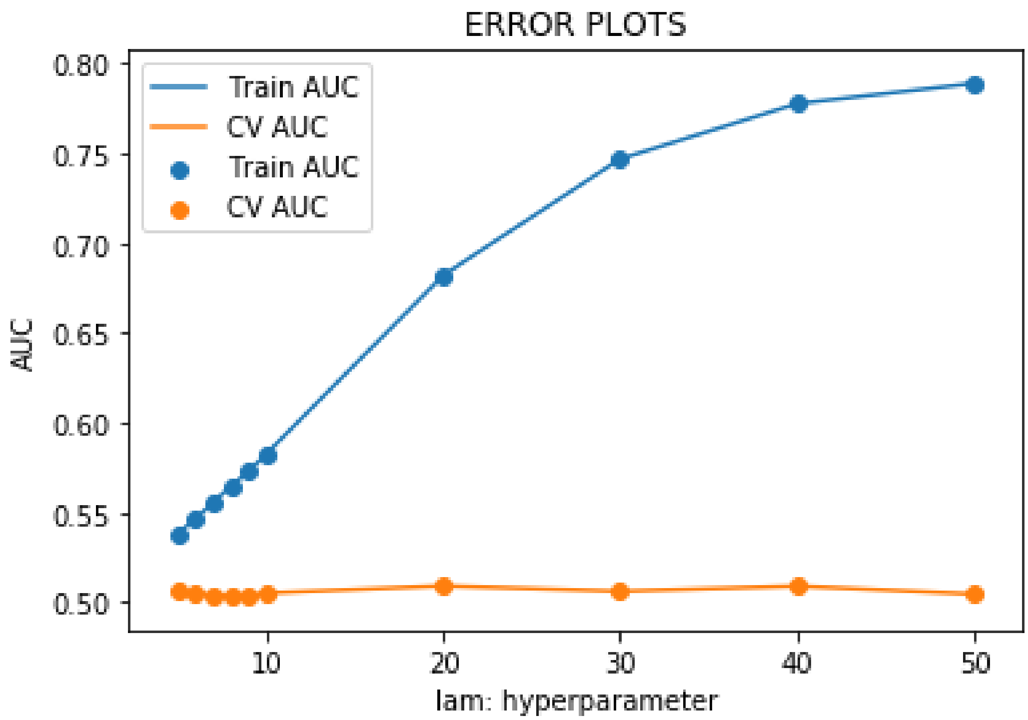
Hyperparameter tuning using grid serach cross validation for parameter max_depth

```
In [66]: Depths = [5, 6, 7, 8, 9, 10, 20, 30, 40, 50]
         param_grid = {'max_depth':Depths}
         clf = DecisionTreeClassifier(min_samples_split=300)

         grid = GridSearchCV(clf, param_grid ,cv= 3,n_jobs =-1, scoring='roc_auc', return_trai
         grid.fit(tfidf_sent_vectors_train, y_train)

         print("Accuracy on train data = ", grid.best_score_*100)
         optimal_depth4 = grid.best_estimator_.max_depth
         print("The optimal number of depth is : ",optimal_depth4)
```

```
Accuracy on train data =  50.91359419060575
The optimal number of depth is :  20
```

```
In [67]: tw2v_auc_train = grid.cv_results_['mean_train_score']
         tw2v_auc_cv    = grid.cv_results_['mean_test_score']
```

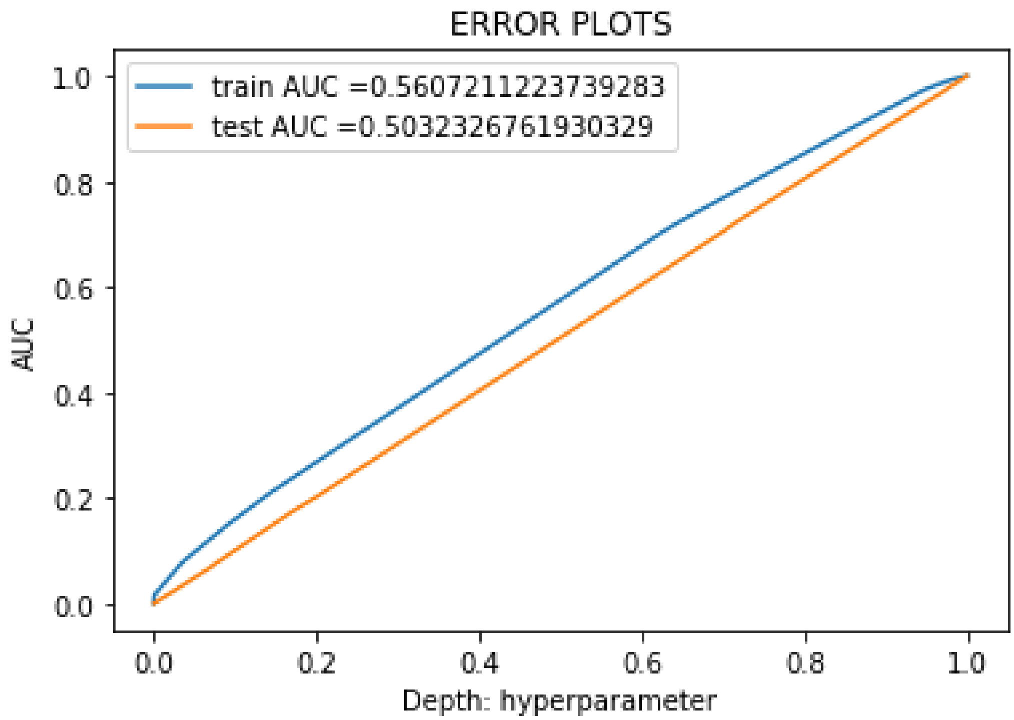
```
plt.plot(Depths, tw2v_auc_train, label='Train AUC')
plt.scatter(Depths, tw2v_auc_train, label='Train AUC')

plt.plot(Depths, tw2v_auc_cv, label='CV AUC')
plt.scatter(Depths, tw2v_auc_cv, label='CV AUC')

plt.legend()
plt.xlabel("lam: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



Testing with test data

```
In [70]: clf = DecisionTreeClassifier(max_depth = 5, class_weight ='balanced', min_samples_spli
         clf.fit(tfidf_sent_vectors_train, y_train)

         train_fpr_tw2v, train_tpr_tw2v, thresholds_tw2v = roc_curve(y_train, clf.predict_proba
         test_fpr_tw2v, test_tpr_tw2v, thresholds_tw2v = roc_curve(y_test, clf.predict_proba(t

         plt.plot(train_fpr_tw2v, train_tpr_tw2v, label="train AUC ="+str(auc(train_fpr_tw2v, 
         plt.plot(test_fpr_tw2v, test_tpr_tw2v, label="test AUC ="+str(auc(test_fpr_tw2v, test_
         plt.legend()
         plt.xlabel("Depth: hyperparameter")
         plt.ylabel("AUC")
```

```
plt.title("ERROR PLOTS")
plt.show()
```



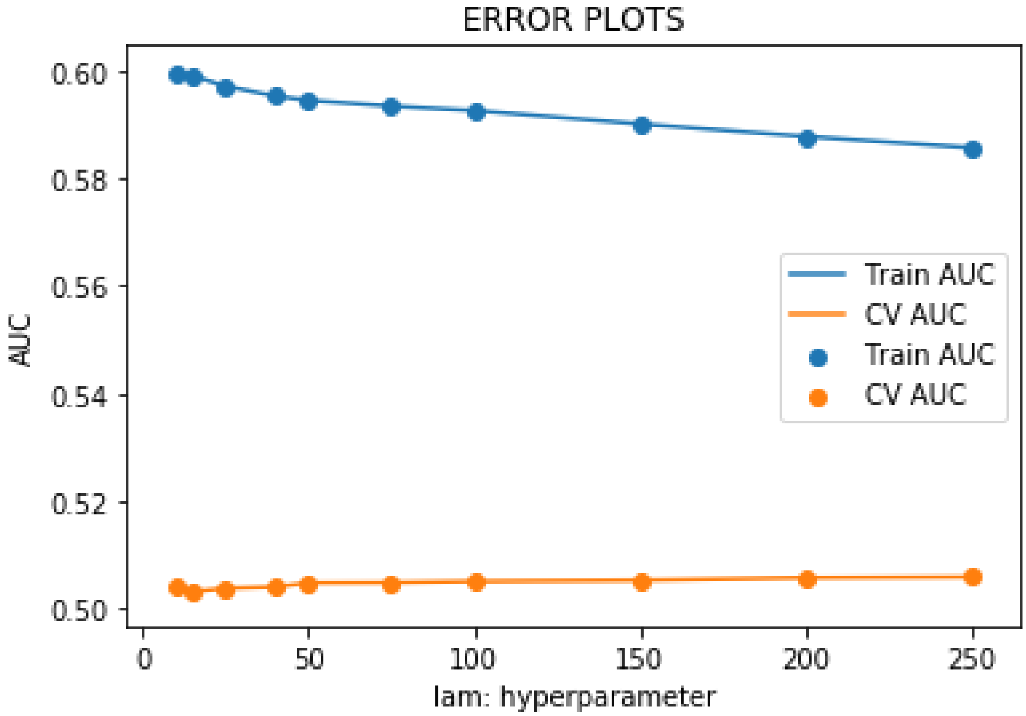
Hyperparameter tuning using grid search cross validation for paramaeter min_samples_split.

```
In [71]: min_split = [10, 15, 25, 40, 50, 75, 100, 150, 200, 250]
         param_grid = {'min_samples_split': min_split}
         clf = DecisionTreeClassifier(max_depth=10)

         grid = GridSearchCV(clf, param_grid ,cv= 3,n_jobs =-1, scoring='roc_auc', return_trai
         grid.fit(tfidf_sent_vectors_train, y_train)

         print("Accuracy on train data = ", grid.best_score_*100)
         optimal_split3 = grid.best_estimator_.min_samples_split
         print("The optimal number of splits is : ",optimal_split3)
```

```
Accuracy on train data =  50.58923114709584
The optimal number of splits is :  250
```

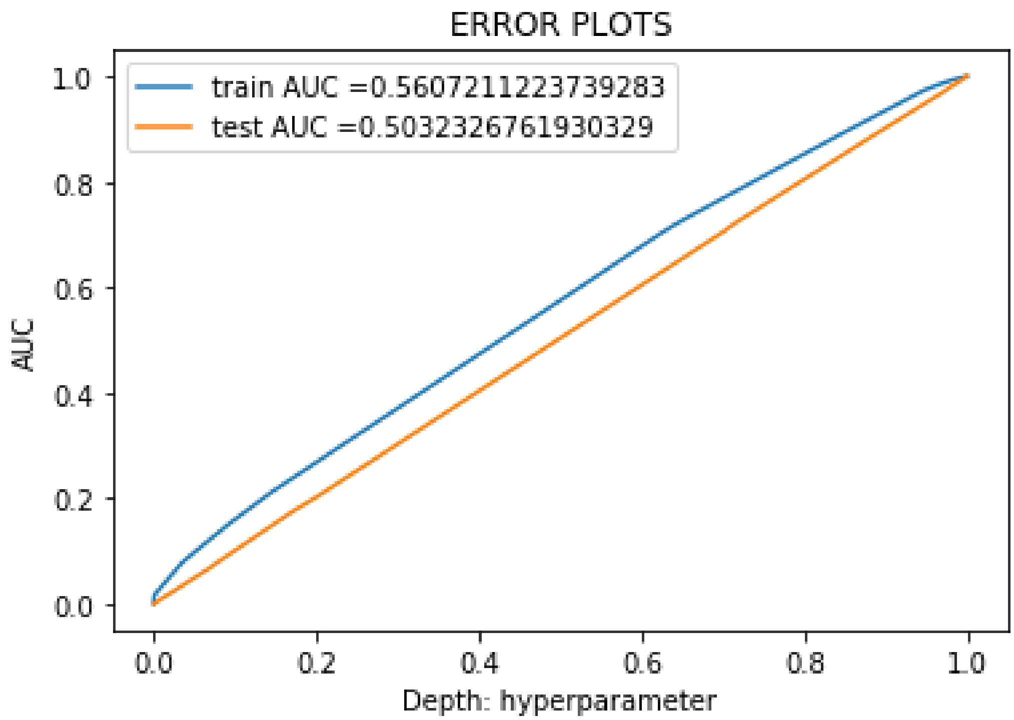
```
In [73]: tw2v_auc_train = grid.cv_results_['mean_train_score']
         tw2v_auc_cv    = grid.cv_results_['mean_test_score']

         plt.plot(min_split, tw2v_auc_train, label='Train AUC')
         plt.scatter(min_split, tw2v_auc_train, label='Train AUC')
```

```
plt.plot(min_split, tw2v_auc_cv, label='CV AUC')
plt.scatter(min_split, tw2v_auc_cv, label='CV AUC')

plt.legend()
plt.xlabel("lam: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



Testing with test data

```
In [76]: clf = DecisionTreeClassifier(max_depth = 5, class_weight ='balanced', min_samples_spli
         clf.fit(tfidf_sent_vectors_train, y_train)

         train_fpr_tw2v, train_tpr_tw2v, thresholds_tw2v = roc_curve(y_train, clf.predict_proba
         test_fpr_tw2v, test_tpr_tw2v, thresholds_tw2v = roc_curve(y_test, clf.predict_proba(t

         plt.plot(train_fpr_tw2v, train_tpr_tw2v, label="train AUC ="+str(auc(train_fpr_tw2v,
         plt.plot(test_fpr_tw2v, test_tpr_tw2v, label="test AUC ="+str(auc(test_fpr_tw2v, test_
         plt.legend()
         plt.xlabel("Depth: hyperparameter")
         plt.ylabel("AUC")
         plt.title("ERROR PLOTS")
         plt.show()
```



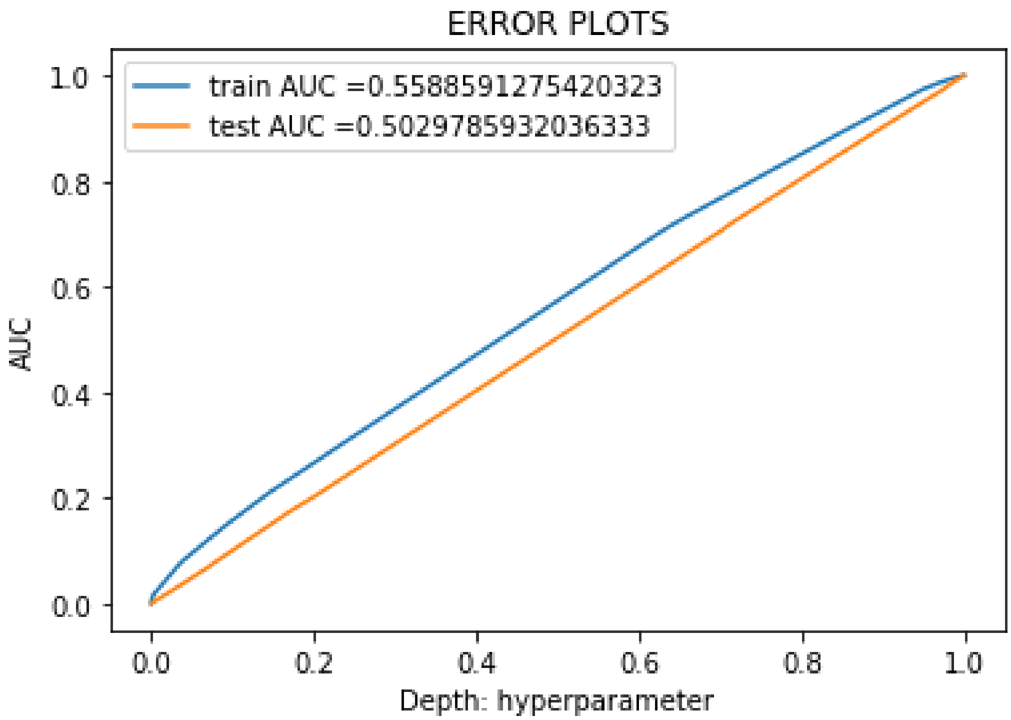
Tuning both parameters together.

```
In [77]: parameters = {'min_samples_split': min_split,'max_depth': Depths}
         grid = GridSearchCV(DecisionTreeClassifier(class_weight ='balanced'), parameters, cv=3
         grid.fit(tfidf_sent_vectors_train, y_train)

Out[77]: GridSearchCV(cv=3, error_score='raise-deprecating',
                      estimator=DecisionTreeClassifier(class_weight='balanced',
                                                       criterion='gini', max_depth=None,
                                                       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=None,
                                                       splitter='best'),
                      iid='warn', n_jobs=-1,
                      param_grid={'max_depth': [5, 6, 7, 8, 9, 10, 20, 30, 40, 50],
                                  'min_samples_split': [10, 15, 25, 40, 50, 75, 100, 150,
                                                        200, 250]},
                      pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
                      scoring='roc_auc', verbose=0)
```

```
In [78]: grid.best_params_
```

```
Out[78]: {'max_depth': 5, 'min_samples_split': 150}
```

```
In [80]: optimal_depth4=5
         optimal_split4=150
         clf = DecisionTreeClassifier(max_depth = 5, class_weight ='balanced', min_samples_spli
         clf.fit(tfidf_sent_vectors_train, y_train)

         train_fpr_tw2v, train_tpr_tw2v, thresholds_tw2v = roc_curve(y_train, clf.predict_proba
         test_fpr_tw2v, test_tpr_tw2v, thresholds_tw2v = roc_curve(y_test, clf.predict_proba(t

         plt.plot(train_fpr_tw2v, train_tpr_tw2v, label="train AUC ="+str(auc(train_fpr_tw2v, 
         plt.plot(test_fpr_tw2v, test_tpr_tw2v, label="test AUC ="+str(auc(test_fpr_tw2v, test_
         plt.legend()
         plt.xlabel("Depth: hyperparameter")
         plt.ylabel("AUC")
         plt.title("ERROR PLOTS")
         plt.show()
```

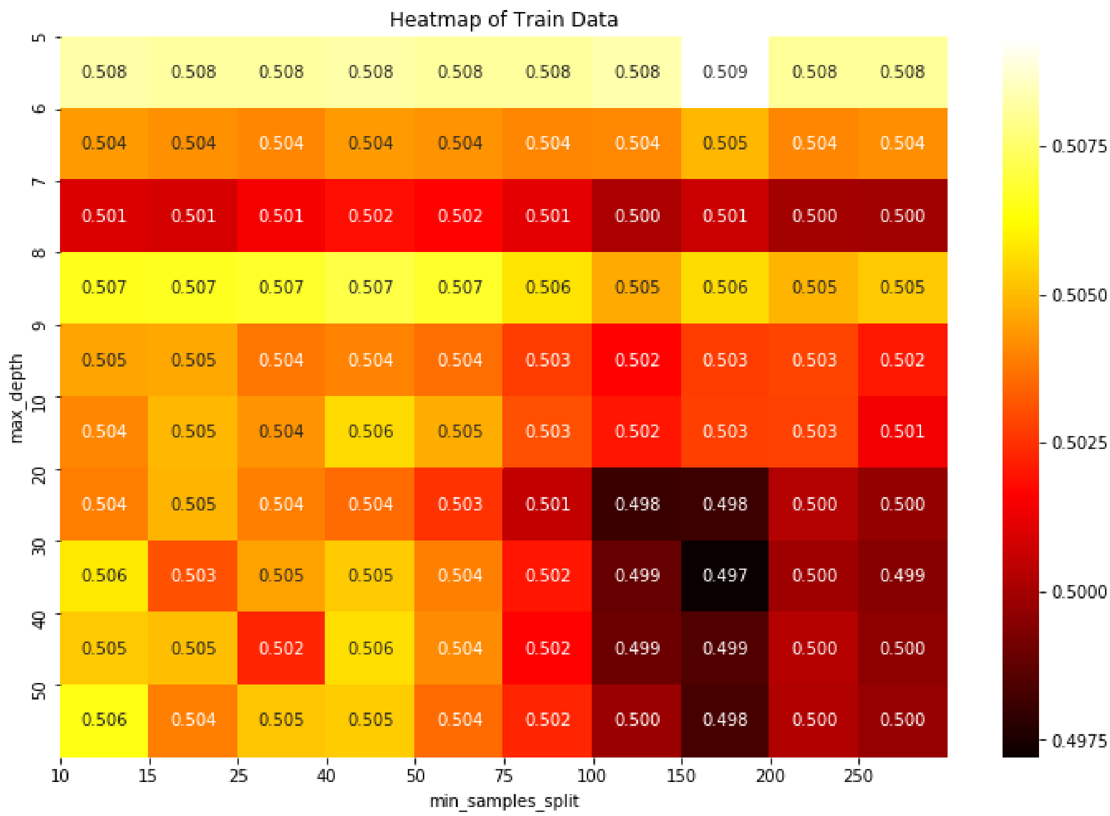



```
In [82]: clf = DecisionTreeClassifier(max_depth = optimal_depth4, min_samples_split=optimal_spl
         clf.fit(tfidf_sent_vectors_train,y_train)

         pred = clf.predict(tfidf_sent_vectors_test)
```

```
acc_4 = accuracy_score(y_test, pred) * 100
pre_4 = precision_score(y_test, pred) * 100
rec_4 = recall_score(y_test, pred) * 100
f1_4  = f1_score(y_test, pred) * 100

print('\nAccuracy = %f%%' % (acc_4))
print('\nprecision= %f%%' % (pre_4))
print('\nrecall    = %f%%' % (rec_4))
print('\nF1-Score = %f%%' % (f1_4))
```

```
Accuracy = 84.072611%

precision= 84.171896%

recall    = 99.855628%

F1-Score = 91.345440%
```

In [83]:
```
heat_map4 = grid.cv_results_['mean_test_score'].reshape(len(min_split),len(Depths))
plt.figure(figsize=(12,8))
sns.heatmap(heat_map4, annot=True, cmap=plt.cm.hot, fmt=".3f", xticklabels=min_split,
plt.xlabel('min_samples_split')
plt.ylabel('max_depth')
plt.xticks(np.arange(len(min_split)), min_split)
plt.yticks(np.arange(len(Depths)), Depths)
plt.title('Heatmap of Train Data')
plt.show()
```



8 [6] Conclusions

In [93]:
```
# Please compare all your models using Prettytable library
number    = [1,2,3,4]
name      = ["Bow", "Tfidf", "Avg W2v", "Tfidf W2v"]
op_depth  = [optimal_depth1, optimal_depth2, optimal_depth3, optimal_depth4]
op_splits= [optimal_split1, optimal_split2, optimal_split3, optimal_split4]

acc= [acc_1,acc_2,acc_3,acc_4]


#Initialize Prettytable
pt = PrettyTable()
pt.add_column("Index", number)
pt.add_column("Model", name)
pt.add_column("Optimal Depth", op_depth)
pt.add_column("Optimal Splits", op_splits)
pt.add_column("Accuracy%", acc)
print(pt)
```

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

Index	Model	Optimal Depth	Optimal Splits	Accuracy%
1	Bow	22	300	85.56888956402857
2	Tfidf	20	350	85.773963238645
3	Avg W2v	5	250	84.07640893209782
4	Tfidf W2v	5	150	84.0726112714568