09affrrf

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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 unque 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 considered as a positive review. A rating of 1 or 2 can be considered as negative one. A review of rating 3 is considered nuetral and such reviews are ignored from our analysis. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

2 [1]. Reading Data

2.1 [1.1] Loading the data

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

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

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

```
In [1]: %matplotlib inline
        import warnings
        warnings.filterwarnings("ignore")
        import sqlite3
        import pandas as pd
        import numpy as np
        import nltk
        import string
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.feature_extraction.text import TfidfTransformer
        from sklearn.feature_extraction.text import TfidfVectorizer
        from sklearn.feature_extraction.text import CountVectorizer
        from sklearn.metrics import confusion_matrix
        from sklearn import metrics
        from sklearn.metrics import roc_curve, auc
        from nltk.stem.porter import PorterStemmer
        import re
        # Tutorial about Python regular expressions: https://pymotw.com/2/re/
        import string
        from nltk.corpus import stopwords
        from nltk.stem import PorterStemmer
        from nltk.stem.wordnet import WordNetLemmatizer
        from gensim.models import Word2Vec
        from gensim.models import KeyedVectors
        import pickle
        from tqdm import tqdm
        import os
        from sklearn.model_selection import train_test_split
        from sklearn.metrics import roc auc score
        from sklearn.model_selection import GridSearchCV
        from sklearn.metrics import roc_auc_score
        from sklearn.metrics import confusion_matrix
        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 xgboost import XGBClassifier
                 from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator
C:\Users\ACER\Anaconda3\lib\site-packages\gensim\utils.py:860: UserWarning: detected Windows;
    warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
C:\Users\ACER\Anaconda3\lib\site-packages\sklearn\ensemble\weight_boosting.py:29: DeprecationWater Deprecation Weight_boosting.py:29: Deprecation Weight_boosting.py:20: Deprecation Processed Proce
    from numpy.core.umath_tests import inner1d
In [2]: # using SQLite Table to read data.
                 con = sqlite3.connect('database.sqlite')
                 # filtering only positive and negative reviews i.e.
                 # not taking into consideration those reviews with Score=3
                 # SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000, will give top 500000 data point
                 # you can change the number to any other number based on your computing power
                 # filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 5
                 # for tsne assignment you can take 5k data points
                 filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 100
                 # 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
                         1 B001E4KFG0 A3SGXH7AUHU8GW
                                                                                                                                         delmartian
                         2 B00813GRG4 A1D87F6ZCVE5NK
                                                                                                                                                 dll pa
                 2
                                                           ABXLMWJIXXAIN Natalia Corres "Natalia Corres"
                         3 BOOOLQOCHO
                       HelpfulnessNumerator HelpfulnessDenominator Score
                                                                                                                                                     Time
                 0
                                                                                                                                  1 1303862400
                                                                1
                                                                                                                   1
                 1
                                                                0
                                                                                                                   0
                                                                                                                                  0 1346976000
                 2
                                                                1
                                                                                                                   1
                                                                                                                                       1219017600
                                                                                                                                  1
```

from sklearn.ensemble import RandomForestClassifier

```
Summary
                                                                                 Text
           Good Quality Dog Food
                                  I have bought several of the Vitality canned d...
        1
               Not as Advertised Product arrived labeled as Jumbo Salted Peanut...
           "Delight" says it all
                                  This is a confection that has been around a fe...
In [3]: display = pd.read_sql_query("""
        SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
        FROM Reviews
        GROUP BY UserId
        HAVING COUNT(*)>1
        """, con)
In [4]: print(display.shape)
        display.head()
(80668, 7)
Out [4]:
                       UserId
                                 ProductId
                                                       ProfileName
                                                                           Time
                                                                                 Score
           #oc-R115TNMSPFT9I7
                                B007Y59HVM
                                                           Brevton
                                                                     1331510400
          #oc-R11D9D7SHXIJB9
                                B005HG9ET0
                                            Louis E. Emory "hoppy"
                                                                     1342396800
                                                                                     5
        2 #oc-R11DNU2NBKQ23Z
                                                  Kim Cieszykowski
                                B007Y59HVM
                                                                     1348531200
                                                                                     1
        3 #oc-R1105J5ZVQE25C
                               B005HG9ET0
                                                     Penguin Chick
                                                                     1346889600
                                                                                     5
        4 #oc-R12KPBODL2B5ZD
                               B0070SBE1U
                                             Christopher P. Presta
                                                                     1348617600
                                                                                     1
                                                               COUNT(*)
                                                         Text
          Overall its just OK when considering the price...
        1 My wife has recurring extreme muscle spasms, u...
                                                                       3
        2 This coffee is horrible and unfortunately not ...
                                                                       2
        3 This will be the bottle that you grab from the...
                                                                       3
          I didnt like this coffee. Instead of telling y...
                                                                       2
In [5]: display[display['UserId'] == 'AZY10LLTJ71NX']
Out [5]:
                      UserId
                                ProductId
                                                               ProfileName
                                                                                   Time
               AZY10LLTJ71NX B006P7E5ZI
                                          undertheshrine "undertheshrine"
                                                                             1334707200
               Score
                                                                     Text
                                                                           COUNT(*)
                     I was recommended to try green tea extract to ...
        80638
                   5
In [6]: display['COUNT(*)'].sum()
Out[6]: 393063
```

3 [2] Exploratory Data Analysis

3.1 [2.1] Data Cleaning: Deduplication

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

```
In [7]: display= pd.read_sql_query("""
        SELECT *
        FROM Reviews
        WHERE Score != 3 AND UserId="AR5J8UI46CURR"
        ORDER BY ProductID
        """, con)
        display.head()
Out[7]:
                    ProductId
                                                                HelpfulnessNumerator
               Ιd
                                       UserId
                                                   ProfileName
                               AR5J8UI46CURR Geetha Krishnan
        0
            78445
                   B000HDL1RQ
                                                                                    2
                                                                                    2
        1
           138317
                   BOOOHDOPYC
                               AR5J8UI46CURR Geetha Krishnan
           138277
                   BOOOHDOPYM AR5J8UI46CURR Geetha Krishnan
                                                                                    2
        3
            73791
                   BOOOHDOPZG
                              AR5J8UI46CURR Geetha Krishnan
                                                                                    2
           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
                                          1199577600
                                      Summary
           LOACKER QUADRATINI VANILLA WAFERS
        0
          LOACKER QUADRATINI VANILLA WAFERS
          LOACKER QUADRATINI VANILLA WAFERS
          LOACKER QUADRATINI VANILLA WAFERS
           LOACKER QUADRATINI VANILLA WAFERS
                                                         Text
          DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
          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=Fal
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 HelpfulnessNumera-
tor 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]:
                                                            ProfileName \
               Ιd
                    ProductId
                                        UserId
         0 64422 B000MIDROQ A161DK06JJMCYF J. E. Stephens "Jeanne"
                   B001EQ55RW A2V0I904FH7ABY
            HelpfulnessNumerator HelpfulnessDenominator Score
                                                                         Time \
                                                                5 1224892800
         0
                                3
                                                        1
         1
                                3
                                                                4 1212883200
                                                  Summary \
                       Bought This for My Son at College
         1 Pure cocoa taste with crunchy almonds inside
         O 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]</pre>
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()
```

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 observed to be better than Porter Stemming)

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

My dogs loves this chicken but its a product from China, so we wont be buying it anymore. It

```
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 [15]: # remove urls from text python: https://stackoverflow.com/a/40823105/4084039
                      sent_0 = re.sub(r"http\S+", "", sent_0)
                      sent_1000 = re.sub(r"http\S+", "", sent_1000)
                      sent_150 = re.sub(r"http\S+", "", sent_1500)
                      sent_{4900} = re.sub(r"http\S+", "", sent_{4900})
                     print(sent_0)
My dogs loves this chicken but its a product from China, so we wont be buying it anymore.
 \label{localization} \textbf{In [16]:} \ \# \ https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-allowed and the property of the prop
                     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
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 [17]: # https://stackoverflow.com/a/47091490/4084039
```

import re

```
def decontracted(phrase):
            # specific
            phrase = re.sub(r"won't", "will not", phrase)
            phrase = re.sub(r"can\'t", "can not", phrase)
             # general
            phrase = re.sub(r"n\'t", " not", phrase)
            phrase = re.sub(r"\'re", " are", phrase)
            phrase = re.sub(r"\'s", " is", phrase)
            phrase = re.sub(r"\'d", " would", phrase)
            phrase = re.sub(r"\'ll", " will", phrase)
            phrase = re.sub(r"\'t", " not", phrase)
            phrase = re.sub(r"\'ve", " have", phrase)
            phrase = re.sub(r"\'m", " am", phrase)
            return phrase
In [18]: sent_1500 = decontracted(sent_1500)
        print(sent_1500)
        print("="*50)
was way to hot for my blood, took a bite and did a jig lol
______
In [19]: #remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
        sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
        print(sent_0)
My dogs loves this chicken but its a product from China, so we wont be buying it anymore.
                                                                                         Its
In [20]: #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 [21]: # https://gist.github.com/sebleier/554280
        # we are removing the words from the stop words list: 'no', 'nor', 'not'
        \# <br /><br /> ==> after the above steps, we are getting "br br"
        # we are including them into stop words list
        # instead of <br /> if we have <br/> these tags would have revmoved in the 1st step
        stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselve
                    "you'll", "you'd", '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', 'e
                     '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 [22]: # Combining all the above stundents
         from tqdm import tqdm
         preprocessed_reviews_rf = []
         # 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 stopwent
             preprocessed_reviews_rf.append(sentance.strip())
100%|| 87773/87773 [01:00<00:00, 1444.42it/s]
In [23]: preprocessed_reviews_rf[1500]
Out[23]: 'way hot blood took bite jig lol'
4.2 [4] Splitting the data
In [24]: X = preprocessed_reviews_rf
         Y = final['Score'].values
In [25]: # Here we are splitting the data(X, Y) into train and test data
         \# X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.33, shuffle=F)
         X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.30) # this is r
```

5 [4] Featurization

5.1 [4.1] BAG OF WORDS

```
In [26]: #BoW
    vectorizer = CountVectorizer(min_df = 10)
    vectorizer.fit(X_train) # fit has to happen only on train data
    print(vectorizer.get_feature_names()[:20])# printing some feature names
```

```
print("="*50)
        # we use the fitted CountVectorizer to convert the text to vector
        X_train_bow = vectorizer.transform(X_train)
        X_test_bow = vectorizer.transform(X_test)
        print("After vectorizations")
        print(X_train_bow.shape, Y_train.shape)
        print(X_test_bow.shape, Y_test.shape)
['aa', 'aafco', 'aback', 'abandoned', 'abdominal', 'ability', 'able', 'abroad', 'absence', 'ab
   _____
After vectorizations
(61441, 9727) (61441,)
(26332, 9727) (26332,)
5.2 [4.3] TF-IDF
In [27]: tfidf_vect = TfidfVectorizer(min_df=10)
        tfidf_vect.fit(X_train)
        print("some sample features ",tfidf_vect.get_feature_names()[0:10])
        print('='*50)
        # we use the fitted CountVectorizer to convert the text to vector
        X_train_tfidf = tfidf_vect.transform(X_train)
        X_test_tfidf = tfidf_vect.transform(X_test)
        print("After vectorizations")
        print(X_train_tfidf.shape, Y_train.shape)
        print(X_test_tfidf.shape, Y_test.shape)
some sample features ['aa', 'aafco', 'aback', 'abandoned', 'abdominal', 'ability', 'able', 'a
_____
After vectorizations
(61441, 9727) (61441,)
(26332, 9727) (26332,)
5.3 [4.4] Word2Vec
In [28]: # 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 [29]: # this line of code trains your w2v model on the give list of sentances, fitting the
        w2v_model=Word2Vec(list_of_sentance_train,min_count=5,size=50, workers=-1)
```

5.4 [4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V

[4.4.1.1] Avg W2v

5.4.1 Converting Train data set

```
In [31]: # 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%|| 61441/61441 [02:51<00:00, 358.64it/s]
(61441, 50)
[ 1.49530279e-03 1.74013253e-03 -3.35474421e-04 -1.79215600e-03
 -1.22944877e-03 6.37771201e-05 1.57838220e-03 1.83518851e-03
-2.46359594e-04 1.59830931e-03 -2.31750775e-04 -4.86755654e-05
 1.20638629e-03 2.72470262e-04 1.84368356e-03 1.17688291e-04
 -1.32211400e-04 4.92880523e-05 1.96743069e-04 9.99466279e-04
-2.17257638e-04 1.82484241e-03 1.28306261e-03 1.18840378e-03
  6.58293802e-04 1.55421265e-03 -2.73246577e-04 -1.88914748e-04
 2.19925632e-03 -1.72848888e-04 3.90295542e-04 -5.58386260e-05
 -6.23318934e-04 -1.24313771e-03 -5.19351171e-04 -2.93402546e-04
 -1.77312948e-03 1.65710942e-03 -5.65482641e-04 2.46362106e-03
 -2.24579809e-04 7.06118126e-04 -1.34266445e-03 5.98191188e-04
```

-7.05843118e-04 -9.57805030e-04 -1.14978465e-03 -6.45412965e-05

```
-5.61554718e-04 -1.21379622e-04]
In [32]: type(sent_vectors_train)
Out[32]: numpy.ndarray
5.4.2 Converting Test data set
In [33]: list_of_sentance_test=[]
        for sentance in X_test:
            list_of_sentance_test.append(sentance.split())
In [34]: # 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%|| 26332/26332 [01:13<00:00, 356.15it/s]
(26332, 50)
8.44555456e-04 1.32795192e-03 -8.84551686e-04 -1.13731602e-03
 -7.31953090e-04 -1.30945456e-03 -2.53102247e-04 -2.67113570e-04
 -2.64294749e-04 1.68484774e-03 1.14786019e-03 -6.89245567e-04
 -8.69215923e-05 -1.17180864e-03 -2.58920362e-03 -1.13680045e-03
 -4.75744506e-04 -6.86671648e-04 1.06466102e-03 -2.07969540e-04
  1.29443252e-03 2.73572570e-04 -1.47164530e-03 7.85484186e-04
 -1.95110830e-04 1.06518659e-03 -1.65947218e-03 5.17210330e-04
  2.34779015e-03 1.02078152e-03 1.28233555e-03 -4.07889093e-05
 8.94802575e-04 7.73024989e-05 -1.50300679e-04 -8.53352848e-04
  1.47817630e-03 -8.51270536e-04 -1.74862290e-04 -3.90027578e-04
 7.50398346e-04 -6.70166485e-04 -1.86333669e-03 5.60554299e-04
  1.90450745e-03 -5.34504875e-04]
```

[4.4.1.2] TFIDF weighted W2v

5.4.3 Converting Train data set

```
In [35]: \#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_)))
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_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%|| 61441/61441 [39:04<00:00, 26.21it/s]
In [37]: tfidf_sent_vectors_train1 = np.asarray(tfidf_sent_vectors_train)
         type(tfidf_sent_vectors_train1)
Out[37]: numpy.ndarray
In [39]: tfidf_sent_vectors_test1 = np.asarray(tfidf_sent_vectors_test)
         type(tfidf_sent_vectors_test1)
Out[39]: numpy.ndarray
```

5.4.4 Converting Test data set

```
In [38]: # 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 t
         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%|| 26332/26332 [07:50<00:00, 55.99it/s]
```

6 [5] Assignment 9: Random Forests


```
<strong>Feature importance</strong>
   <l
Get top 20 important features and represent them in a word cloud. Do this for BOW & TFIDF.
<br>
<strong>Feature engineering</strong>
To increase the performance of your model, you can also experiment with with feature engine
       Taking length of reviews as another feature.
       Considering some features from review summary as well.
   <br>
<strong>Representation of results</strong>
You need to plot the performance of model both on train data and cross validation data for
<img src='3d_plot.JPG' width=500px> with X-axis as <strong>n_estimators</strong>, Y-axis as <s:</pre>
       You need to plot the performance of model both on train data and cross validation data for
<img src='heat_map.JPG' width=300px> <a href='https://seaborn.pydata.org/generated/seaborn.hea</pre>
You choose either of the plotting techniques out of 3d plot or heat map
Once after you found the best hyper parameter, you need to train your model with it, and f
<img src='train_test_auc.JPG' width=300px>
Along with plotting ROC curve, you need to print the <a href='https://www.appliedaicourse.</pre>
<img src='confusion_matrix.png' width=300px>
   <br>
<strong>Conclusion</strong>
   ul>
You need to summarize the results at the end of the notebook, summarize it in the table for
   <img src='summary.JPG' width=400px>
```

Note: Data Leakage

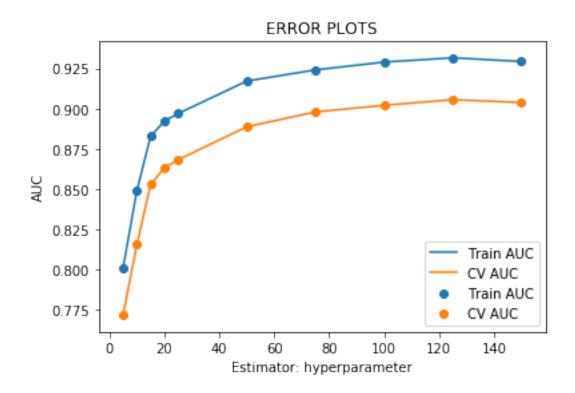
- 1. There will be an issue of data-leakage if you vectorize the entire data and then split it into train/cv/test.
- 2. To avoid the issue of data-leakag, make sure to split your data first and then vectorize it.
- 3. While vectorizing your data, apply the method fit_transform() on you train data, and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

6.1 [5.1] Applying RF

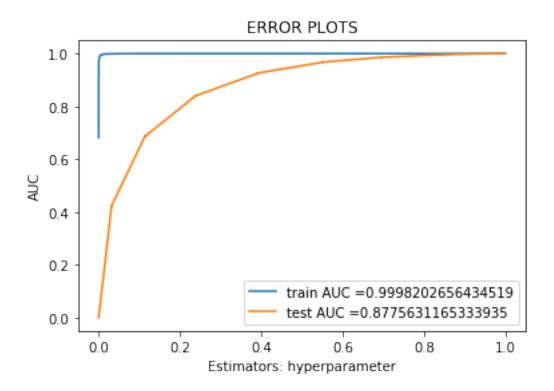
6.1.1 [5.1.1] Applying Random Forests on BOW, SET 1

6.1.2 Hyperparameter tuning using GridSearch

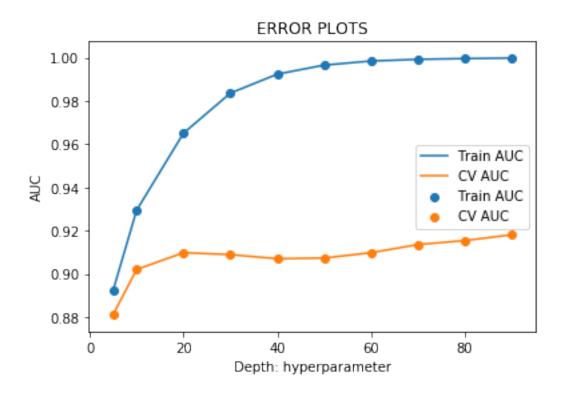
```
In [40]: #clf = RandomForestClassifier()
         # For Estimator
         estimator = [5,10,15,20,25,50,75,100,125,150]
         parameters = {'n_estimators': [5,10,15,20,25,50,75,100,125,150]}
         grid = GridSearchCV(RandomForestClassifier(class_weight = 'balanced', max_depth = 10), ]
         grid.fit(X_train_bow, Y_train)
         print("best estimator = ", grid.best_params_)
         train_auc_bow = grid.cv_results_['mean_train_score']
         cv_auc_bow = grid.cv_results_['mean_test_score']
         plt.plot(estimator, train_auc_bow, label='Train AUC')
         plt.scatter(estimator, train_auc_bow, label='Train AUC')
         plt.plot(estimator, cv_auc_bow, label='CV AUC')
         plt.scatter(estimator, cv_auc_bow, label='CV AUC')
         plt.legend()
         plt.xlabel("Estimator: hyperparameter")
         plt.ylabel("AUC")
         plt.title("ERROR PLOTS")
         plt.show()
best estimator = {'n_estimators': 125}
```



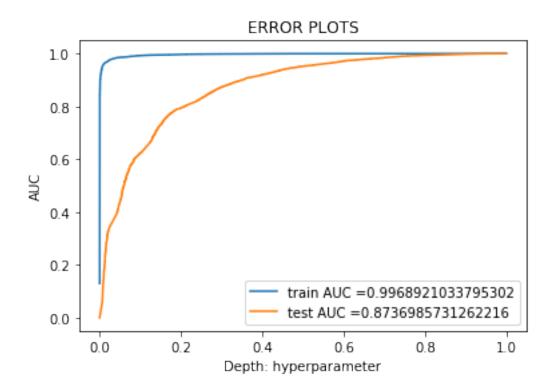
6.1.3 Testing with Test data



```
In [41]: #clf = RandomForestClassifier()
         # For Depth
         depth = [5,10,20,30,40,50,60,70,80,90]
         parameters = {'max_depth': [5,10,20,30,40,50,60,70,80,90]}
         grid = GridSearchCV(RandomForestClassifier(class_weight = 'balanced', n_estimators = 10
         grid.fit(X_train_bow, Y_train)
         print("best depth = ", grid.best_params_)
         train_auc_bow = grid.cv_results_['mean_train_score']
         cv_auc_bow = grid.cv_results_['mean_test_score']
         plt.plot(depth, train_auc_bow, label='Train AUC')
         plt.scatter(depth, train_auc_bow, label='Train AUC')
         plt.plot(depth, cv_auc_bow, label='CV AUC')
         plt.scatter(depth, cv_auc_bow, label='CV AUC')
         plt.legend()
         plt.xlabel("Depth: hyperparameter")
         plt.ylabel("AUC")
         plt.title("ERROR PLOTS")
        plt.show()
best depth = {'max_depth': 90}
```



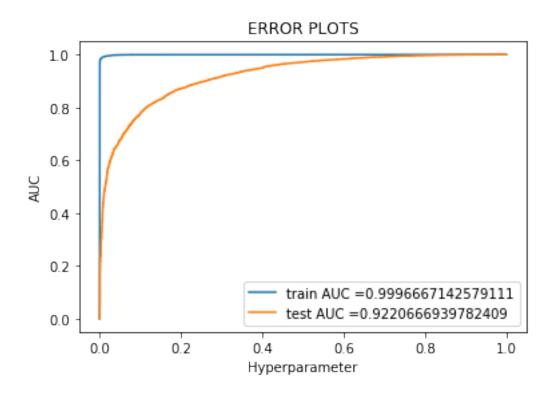
6.1.4 Testing with Test Data



- 1. Here best value for n_estimator = 100 because after 100, AUC value is not changing much.
- 2. Here best value for max_depth = 90 because after 90, AUC value is not changing much.

```
In [41]: # clf = RandomForestClassifier()
                             estimator = [5,10,15,20,25,50,75,100,125,150]
                             depth = [5,10,20,30,40,50,60,70,80,90]
                             parameters = {'n_estimators': estimator, 'max_depth': depth}
                             grid = GridSearchCV(RandomForestClassifier(class_weight = 'balanced', max_features='sqr'
                             grid.fit(X_train_bow, Y_train)
Out[41]: GridSearchCV(cv=3, error_score='raise',
                                                    {\tt estimator=RandomForestClassifier(bootstrap=True, class\_weight='balanced', class\_weight='bal
                                                                    criterion='gini', max_depth=None, max_features='sqrt',
                                                                    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,
                                                                    n_estimators=10, n_jobs=1, oob_score=False, random_state=None,
                                                                    verbose=0, warm_start=False),
                                                    fit_params=None, iid=True, n_jobs=-1,
                                                    param_grid={'n_estimators': [5, 10, 15, 20, 25, 50, 75, 100, 125, 150], 'max_d
                                                    pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                                                    scoring='roc_auc', verbose=0)
```

6.1.5 Testing with Test data



precision=86.861574%

recall=99.677668%

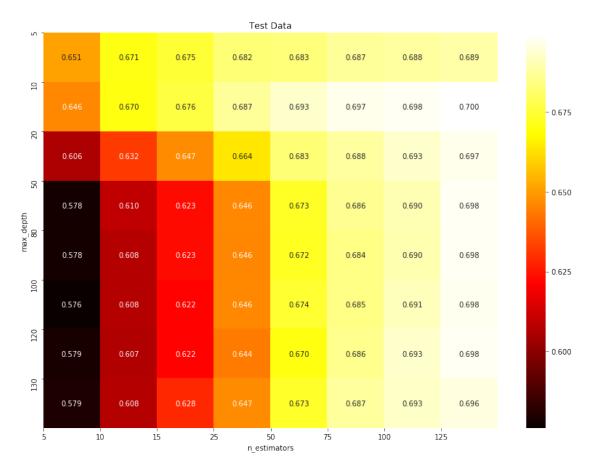
F1-Score=92.829359%

6.1.6 [5.1.2] Wordcloud of top 20 important features from SET 1

```
In [55]: # Calculate feature importances from decision trees
         importances = clf.feature_importances_
         # Sort feature importances in descending order
         indices = list(np.argsort(importances)[::-1][:20])
        print(indices)
[5693, 3770, 4992, 715, 3693, 4114, 9596, 2438, 6157, 6573, 4997, 548, 4048, 2241, 527, 8660,
In [56]: names = np.array(vectorizer.get_feature_names())
        print(names[indices])
['not' 'great' 'love' 'best' 'good' 'horrible' 'worst' 'disappointed'
 'perfect' 'product' 'loves' 'bad' 'highly' 'delicious' 'awful' 'terrible'
 'excellent' 'thought' 'money' 'favorite']
In [72]: text = str(names[indices])
         # Create and generate a word cloud image:
        wordcloud = WordCloud(max_font_size=50, max_words=30, background_color="white").general
         # Display the generated image:
        plt.imshow(wordcloud, interpolation="bilinear")
        plt.axis("off")
        plt.show()
              disappointed
```

6.1.7 [5.3.1] Heatmap on Test Data

```
In [95]: scores = grid.cv_results_['mean_test_score'].reshape(len(estimator),len(depth))
    plt.figure(figsize=(14,10))
    sns.heatmap(scores, annot=True, cmap=plt.cm.hot, fmt=".3f", xticklabels=estimator, yt
    plt.xlabel('n_estimators')
    plt.ylabel('max_depth')
    plt.xticks(np.arange(len(estimator)), estimator)
    plt.yticks(np.arange(len(depth)), depth)
    plt.title('Test_Data')
    plt.show()
```



6.1.8 [5.3.2] Heatmap on Train Data

```
plt.yticks(np.arange(len(depth)), depth)
plt.title('Train Data')
plt.show()
```



6.1.9 [5.1.3] Applying Random Forests on TFIDF, SET 2

6.1.10 Hyperparameter tuning using GridSearch

```
In [43]: # clf = RandomForestClassifier()
    # for Estimators in Random Forest
    estimator = [5,10,15,25,50,75,100,125]
    parameters = {'n_estimators':[5,10,15,25,50,75,100,125]}
    grid = GridSearchCV(RandomForestClassifier(class_weight ='balanced', max_depth=20), p.
    grid.fit(X_train_tfidf, Y_train)

    print("best estimator = ", grid.best_params_)

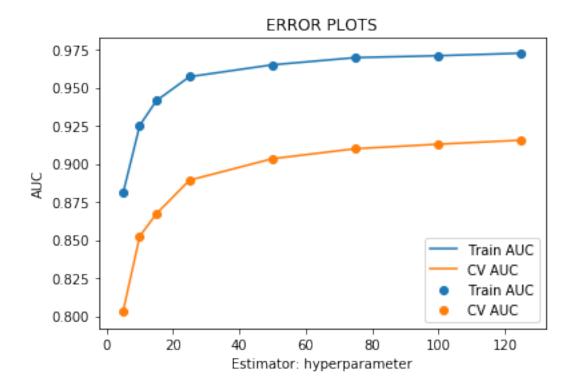
train_auc_tfidf = grid.cv_results_['mean_train_score']
```

cv_auc_tfidf = grid.cv_results_['mean_test_score']

```
plt.plot(estimator, train_auc_tfidf, label='Train AUC')
plt.scatter(estimator, train_auc_tfidf, label='Train AUC')
plt.plot(estimator, cv_auc_tfidf, label='CV AUC')
plt.scatter(estimator, cv_auc_tfidf, label='CV AUC')

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

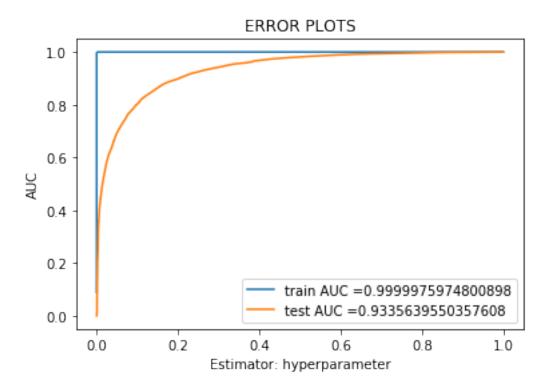
best estimator = {'n_estimators': 125}



6.1.11 Testing with Test Data

train_fpr_tfidf, train_tpr_tfidf, thresholds_tfidf = roc_curve(Y_train, clf.predict_predi

```
plt.plot(train_fpr_tfidf, train_tpr_tfidf, label="train AUC ="+str(auc(train_fpr_tfiden))
plt.plot(test_fpr_tfidf, test_tpr_tfidf, label="test AUC ="+str(auc(test_fpr_tfidf, test_legend()))
plt.slabel("Estimator: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



```
In [45]: # clf = RandomForestClassifier()
    # for Maximum Depth in Random Forest
    depth = [5,10,20,50,80,110,125,140]
    parameters = {'max_depth':[5,10,20,50,80,110,125,140]}
    grid = GridSearchCV(RandomForestClassifier(class_weight ='balanced', n_estimators=100
    grid.fit(X_train_tfidf, Y_train)

    print("best depth = ", grid.best_params_)

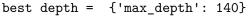
    train_auc_tfidf = grid.cv_results_['mean_train_score']
    cv_auc_tfidf = grid.cv_results_['mean_test_score']

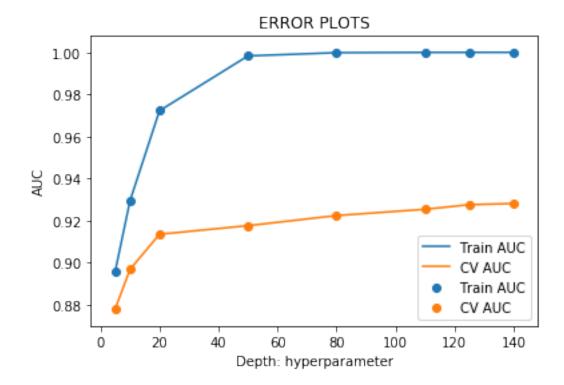
    plt.plot(depth, train_auc_tfidf, label='Train AUC')
    plt.scatter(depth, train_auc_tfidf, label='Train AUC')
```

plt.plot(depth, cv_auc_tfidf, label='CV AUC')

```
plt.scatter(depth, cv_auc_tfidf, label='CV AUC')

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



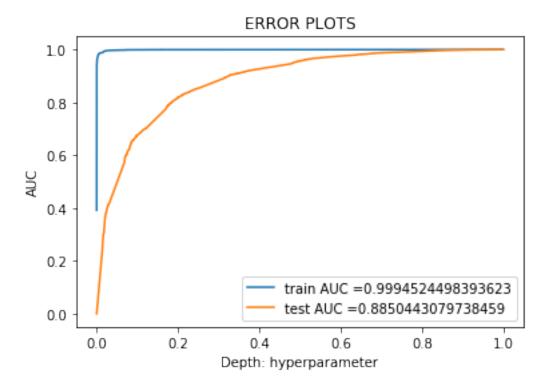


6.1.12 Testing with Test data

plt.plot(train_fpr_tfidf, train_tpr_tfidf, label="train AUC ="+str(auc(train_fpr_tfide))]
plt.plot(test_fpr_tfidf, test_tpr_tfidf, label="test AUC ="+str(auc(test_fpr_tfidf, test_tpr_tfidf))]

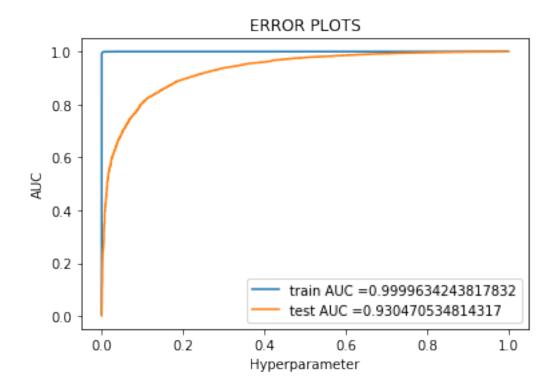
test_fpr_tfidf, test_tpr_tfidf, thresholds_tfidf = roc_curve(Y_test, clf.predict_prob

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



```
In [44]: # clf = RandomForestClassifier()
         estimator = [5,10,15,25,50,75,100,125]
         depth = [5,10,20,50,80,110,125,140]
         parameters = {'n_estimators': estimator, 'max_depth': depth}
         grid = GridSearchCV(RandomForestClassifier(class_weight = 'balanced', max_features='sqr'
         grid.fit(X_train_tfidf, Y_train)
Out[44]: GridSearchCV(cv=3, error_score='raise',
                estimator=RandomForestClassifier(bootstrap=True, class_weight='balanced',
                     criterion='gini', max_depth=None, max_features='sqrt',
                     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,
                     n_estimators=10, n_jobs=1, oob_score=False, random_state=None,
                     verbose=0, warm_start=False),
                fit_params=None, iid=True, n_jobs=-1,
                param_grid={'n_estimators': [5, 10, 15, 25, 50, 75, 100, 125], 'max_depth': [5
```

plt.show()



```
Accuracy=87.650008%

precision=87.381038%

recall=99.623190%

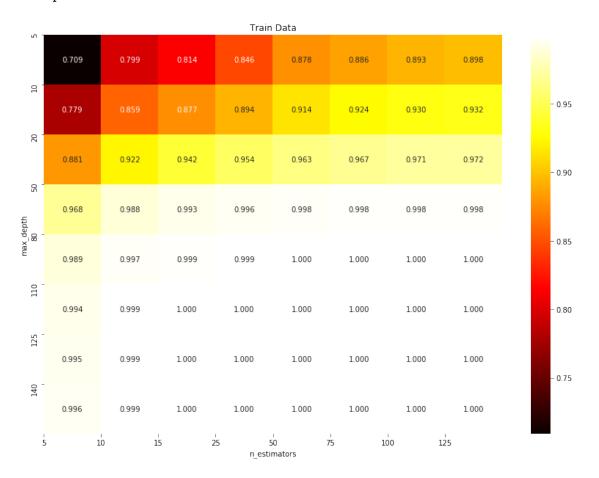
F1-Score=93.101400%
```

6.1.14 [5.1.4] Wordcloud of top 20 important features from SET 2

```
In [171]: # Calculate feature importances from decision trees
          importances = clf.feature_importances_
          # Sort feature importances in descending order
          indices = list(np.argsort(importances)[::-1][:20])
          print(indices)
[3770, 5693, 715, 2438, 3141, 9596, 7851, 5457, 2241, 523, 9389, 8660, 4997, 5200, 3693, 4114,
In [172]: names = np.array(vectorizer.get_feature_names())
          print(names[indices])
['great' 'not' 'best' 'disappointed' 'favorite' 'worst' 'snack' 'money'
 'delicious' 'away' 'waste' 'terrible' 'loves' 'maybe' 'good' 'horrible'
 'disappointing' 'tasted' 'reviews' 'thought']
In [173]: text = str(names[indices])
          # Create and generate a word cloud image:
          wordcloud = WordCloud(max_font_size=50, max_words=30, background_color="white").gene
          # Display the generated image:
          plt.imshow(wordcloud, interpolation="bilinear")
          plt.axis("off")
          plt.show()
```

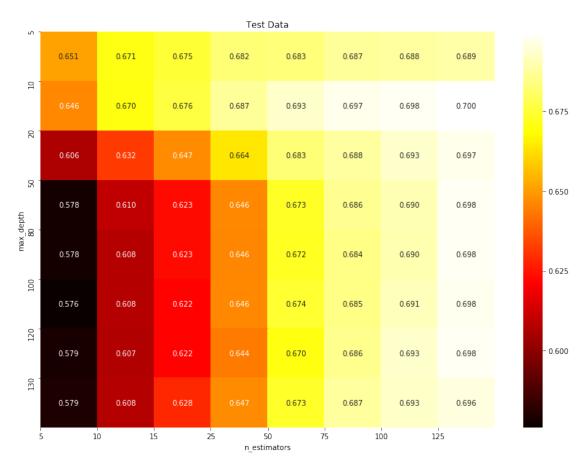
6.1.15 [5.4.1] Heatmap on Train Data

```
In [84]: scores = grid.cv_results_['mean_train_score'].reshape(len(estimator),len(depth))
    plt.figure(figsize=(14,10))
    sns.heatmap(scores, annot=True, cmap=plt.cm.hot, fmt=".3f", xticklabels=estimator, yt
    plt.xlabel('n_estimators')
    plt.ylabel('max_depth')
    plt.xticks(np.arange(len(estimator)), estimator)
    plt.yticks(np.arange(len(depth)), depth)
    plt.title('Train_Data')
    plt.show()
```



6.1.16 [5.4.2] Heatmap on Test Data

```
plt.yticks(np.arange(len(depth)), depth)
plt.title('Test Data')
plt.show()
```



6.1.17 [5.1.5] Applying Random Forests on AVG W2V, SET 3

6.1.18 Hyperparameter tuning using GridSearch

```
In [64]: # clf = RandomForestClassifier()
    # for Estimators in Random Forest
    estimator = [5,10,15,25,50,75,100,125]
    parameters = {'n_estimators':[5,10,15,25,50,75,100,125]}
    grid = GridSearchCV(RandomForestClassifier(class_weight ='balanced', max_depth=5), page    grid.fit(sent_vectors_train, Y_train)

    print("best estimator = ", grid.best_params_)

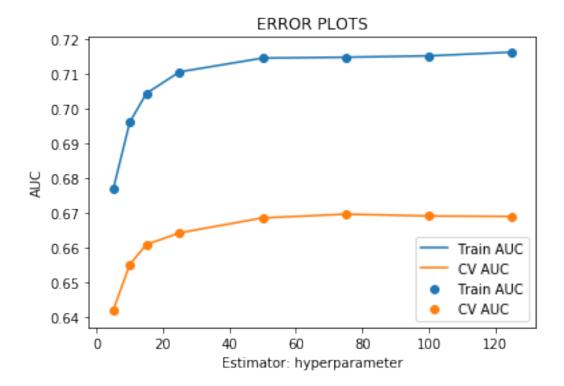
train_auc_aw2v = grid.cv_results_['mean_train_score']
```

cv_auc_aw2v = grid.cv_results_['mean_test_score']

```
plt.plot(estimator, train_auc_aw2v, label='Train AUC')
plt.scatter(estimator, train_auc_aw2v, label='Train AUC')
plt.plot(estimator, cv_auc_aw2v, label='CV AUC')
plt.scatter(estimator, cv_auc_aw2v, label='CV AUC')

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

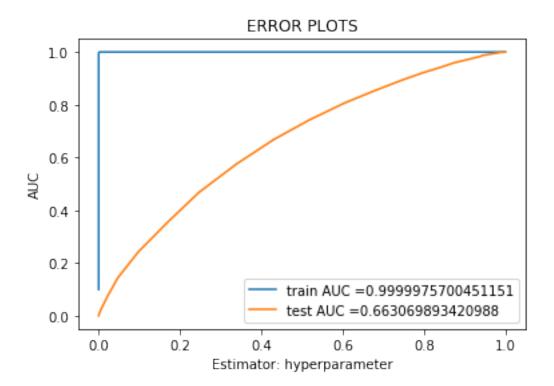
best estimator = {'n_estimators': 75}



6.1.19 Testing with Test data

train_fpr_aw2v, train_tpr_aw2v, thresholds_aw2v = roc_curve(Y_train, clf.predict_probetest_fpr_aw2v, test_tpr_aw2v, thresholds_aw2v = roc_curve(Y_test, clf.predict_proba(set_proba(s

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



```
In [69]: # clf = RandomForestClassifier()
    # for Maximum Depth in Random Forest
    depth = [5,10,20,50,80,100,120,130]
    parameters = {'max_depth':[5,10,20,50,80,100,120,130]}
    grid = GridSearchCV(RandomForestClassifier(class_weight ='balanced', n_estimators=80)
    grid.fit(sent_vectors_train, Y_train)

    print("best depth = ", grid.best_params_)

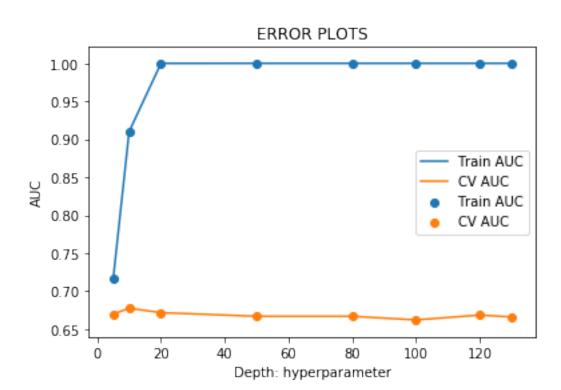
    train_auc_aw2v = grid.cv_results_['mean_train_score']
    cv_auc_aw2v = grid.cv_results_['mean_test_score']

    plt.plot(depth, train_auc_aw2v, label='Train AUC')
    plt.scatter(depth, train_auc_aw2v, label='Train AUC')
    plt.plot(depth, cv_auc_aw2v, label='CV AUC')
```

```
plt.scatter(depth, cv_auc_aw2v, label='CV AUC')

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

best depth = {'max_depth': 10}
```

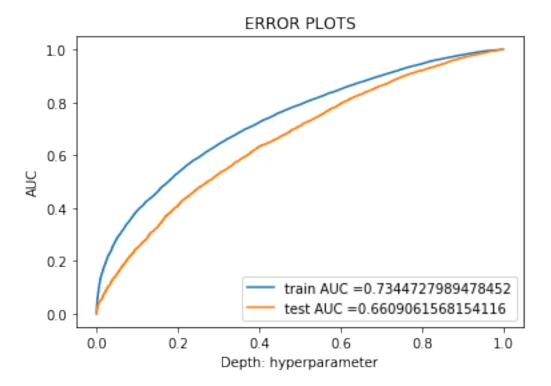


6.1.20 Testing with Test Data

plt.plot(train_fpr_aw2v, train_tpr_aw2v, label="train AUC ="+str(auc(train_fpr_aw2v, plt.plot(test_fpr_aw2v, test_tpr_aw2v, label="test AUC ="+str(auc(test_fpr_aw2v, test_tpr_aw2v, test_

test_fpr_aw2v, test_tpr_aw2v, thresholds_aw2v = roc_curve(Y_test, clf.predict_proba(set))

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



```
In [47]: # clf = RandomForestClassifier()
         estimator = [5,10,15,25,50,75,100,125]
         depth = [5,10,20,50,80,100,120,130]
         parameters = {'n_estimators': estimator, 'max_depth': depth}
         grid = GridSearchCV(RandomForestClassifier(class_weight = 'balanced', max_features='sqr'
         grid.fit(sent_vectors_train, Y_train)
Out[47]: GridSearchCV(cv=3, error_score='raise',
                estimator=RandomForestClassifier(bootstrap=True, class_weight='balanced',
                     criterion='gini', max_depth=None, max_features='sqrt',
                     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,
                     n_estimators=10, n_jobs=1, oob_score=False, random_state=None,
                     verbose=0, warm_start=False),
                fit_params=None, iid=True, n_jobs=-1,
                param_grid={'n_estimators': [5, 10, 15, 25, 50, 75, 100, 125], 'max_depth': [5
```

plt.legend()

plt.show()

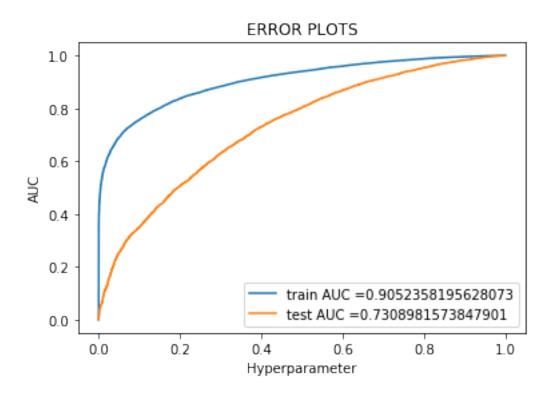
plt.ylabel("AUC")

plt.xlabel("Hyperparameter")

plt.title("ERROR PLOTS")

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, plt.plot(test_fpr_aw2v, test_tpr_aw2v, label="test AUC ="+str(auc(test_fpr_aw2v, test_tpr_aw2v, test_

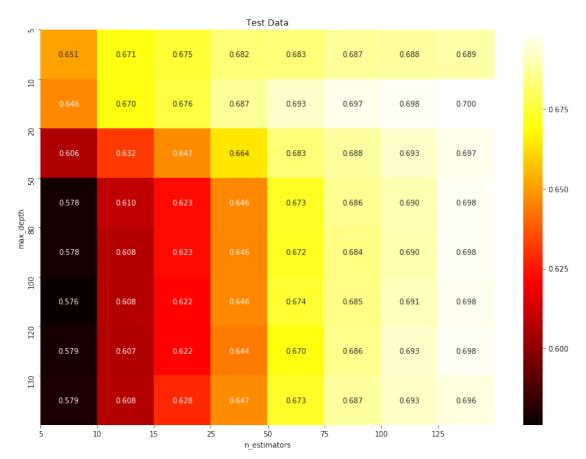


```
recall=100.000000%
F1-Score=91.101599%
```

Accuracy=83.658666%

precision=83.657425%

6.1.22 [5.5] Heatmap on Test Data



6.1.23 [5.1.6] Applying Random Forests on TFIDF W2V, SET 4

6.1.24 Hyperparameter tuning using GridSearch

```
grid.fit(tfidf_sent_vectors_train, Y_train)

print("best estimator = ", grid.best_params_)

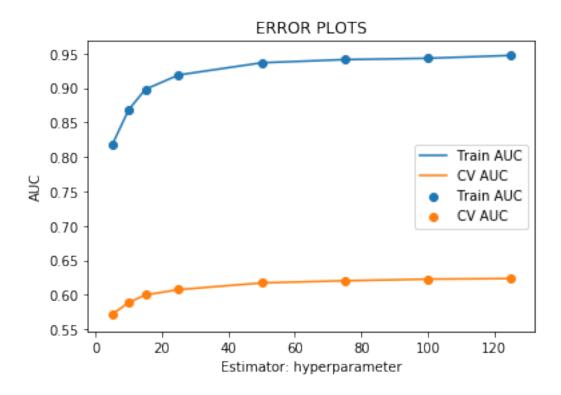
train_auc_tfw2v = grid.cv_results_['mean_train_score']
    cv_auc_tfw2v = grid.cv_results_['mean_test_score']

plt.plot(estimator, train_auc_tfw2v, label='Train AUC')
    plt.scatter(estimator, train_auc_tfw2v, label='Train AUC')
    plt.plot(estimator, cv_auc_tfw2v, label='CV AUC')
    plt.scatter(estimator, cv_auc_tfw2v, label='CV AUC')

plt.scatter(estimator, cv_auc_tfw2v, label='CV AUC')

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

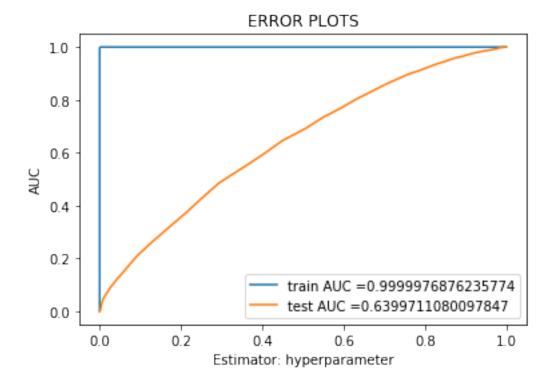
best estimator = {'n_estimators': 125}
```



6.1.25 Testing with Test data

```
\# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of \# not the predicted outputs
```

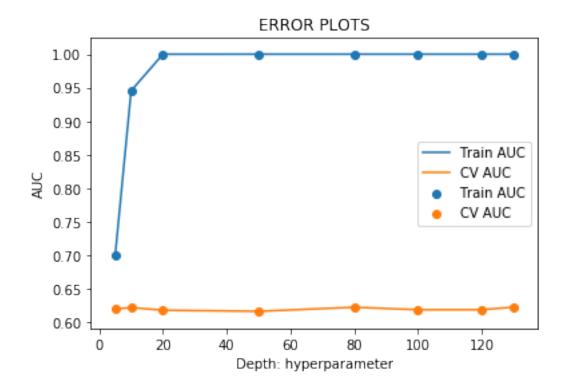
```
train_fpr_tfw2v, train_tpr_tfw2v, thresholds_tfw2v = roc_curve(Y_train, clf.predict_rotest_fpr_tfw2v, test_tpr_tfw2v, thresholds_tfw2v = roc_curve(Y_test, clf.predict_protest_fpr_tfw2v, train_tpr_tfw2v, label="train AUC ="+str(auc(train_fpr_tfw2v, plt.plot(test_fpr_tfw2v, test_tpr_tfw2v, label="test AUC ="+str(auc(test_fpr_tfw2v, plt.legend()))]
plt.xlabel("Estimator: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



```
train_auc_tfw2v = grid.cv_results_['mean_train_score']
    cv_auc_tfw2v = grid.cv_results_['mean_test_score']

plt.plot(depth, train_auc_tfw2v, label='Train AUC')
    plt.scatter(depth, train_auc_tfw2v, label='Train AUC')
    plt.plot(depth, cv_auc_tfw2v, label='CV AUC')
    plt.scatter(depth, cv_auc_tfw2v, label='CV AUC')

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

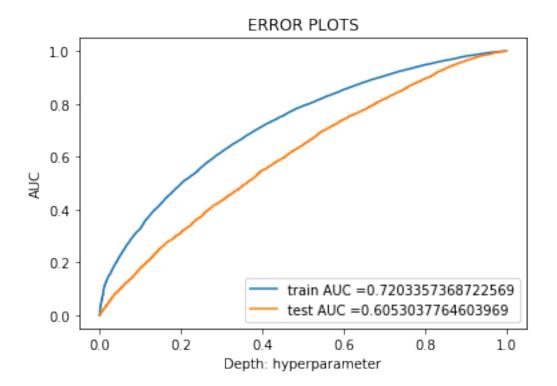


6.1.26 Testing with Test data

```
clf.fit(tfidf_sent_vectors_train, Y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of
# not the predicted outputs
```

In [89]: clf = RandomForestClassifier(max_depth = 7, class_weight = balanced)

```
train_fpr_tfw2v, train_tpr_tfw2v, thresholds_tfw2v = roc_curve(Y_train, clf.predict_probatest_fpr_tfw2v, test_tpr_tfw2v, thresholds_tfw2v = roc_curve(Y_test, clf.predict_probatest_fpr_tfw2v, train_tpr_tfw2v, label="train AUC ="+str(auc(train_fpr_tfw2v, plt.plot(test_fpr_tfw2v, test_tpr_tfw2v, label="test AUC ="+str(auc(test_fpr_tfw2v, test_legend()))))))
plt.slabel("Depth: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```

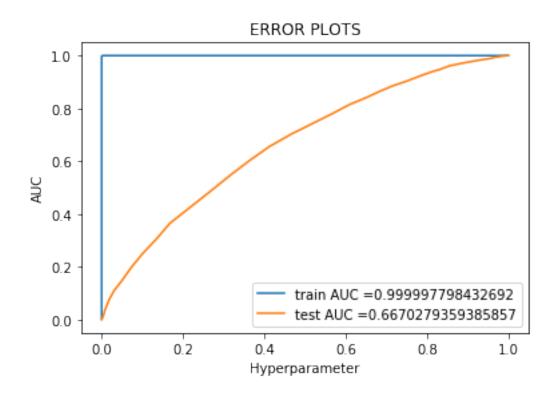


criterion='gini', max_depth=None, max_features='sqrt',

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,
                     n_estimators=10, n_jobs=1, oob_score=False, random_state=None,
                     verbose=0, warm_start=False),
                fit_params=None, iid=True, n_jobs=-1,
                param_grid={'n_estimators': [5, 10, 15, 25, 50, 75, 100, 125], 'max_depth': [5
                pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                scoring='roc_auc', verbose=0)
In [51]: optimal_estimator = grid.best_estimator_.n_estimators
         print("Value for optimal estimator : ",optimal_estimator)
         optimal_depth = grid.best_estimator_.max_depth
         print("Value for optimal depth : ",optimal_depth)
Value for optimal estimator: 125
Value for optimal depth: 100
6.1.27 Testing with Test data
```

```
In [52]: clf = RandomForestClassifier(max_depth = optimal_depth, n_estimators= optimal_estimate
                                                            clf.fit(tfidf_sent_vectors_train, Y_train)
                                                            # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of
                                                            # not the predicted outputs
                                                           train_fpr_tfw2v, train_tpr_tfw2v, thresholds_tfw2v = roc_curve(Y_train, clf.predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predict_predi
                                                           test_fpr_tfw2v, test_tpr_tfw2v, thresholds_tfw2v = roc_curve(Y_test, clf.predict_prob
                                                           plt.plot(train_fpr_tfw2v, train_tpr_tfw2v, label="train AUC ="+str(auc(train_fpr_tfw2)
                                                           plt.plot(test_fpr_tfw2v, test_tpr_tfw2v, label="test AUC ="+str(auc(test_fpr_tfw2v, test_tpr_tfw2v, test_tpr_t
                                                           plt.legend()
                                                           plt.xlabel("Hyperparameter")
                                                           plt.ylabel("AUC")
                                                           plt.title("ERROR PLOTS")
                                                           plt.show()
```

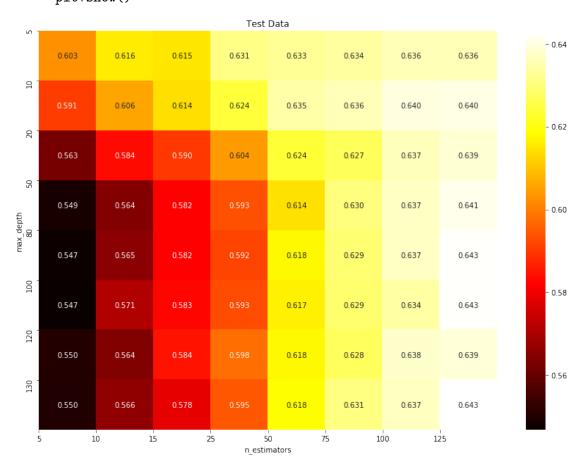


Here difference between Train AUC and Test AUC score is too much

recall=99.936442%

precision=83.763318%

6.1.28 [5.5] Heatmap on Test Data



NOTE:

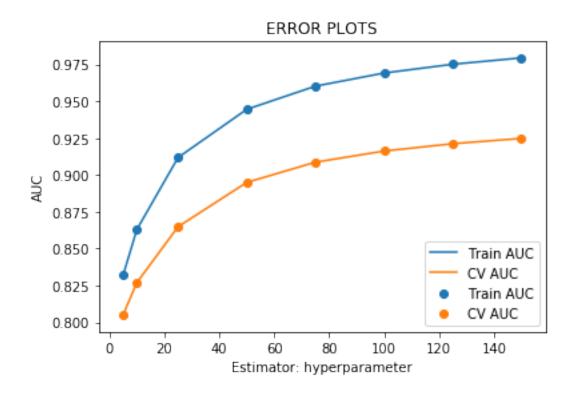
- 1. In Avg-W2V and Tfidf-W2V for n_estimators, difference between Train AUC and Test AUC score is too much. I have tried all the values(5,20,50,100,400,750,1000) for n_estimators while testing on test data. It does not change.
- 2. Similarly for max_depth, in Avg-W2v and Tfidf-W2v we should take value less than 10 to lower difference between Train AUC and Test AUC score.

6.2 [5.2] Applying GBDT using XGBOOST

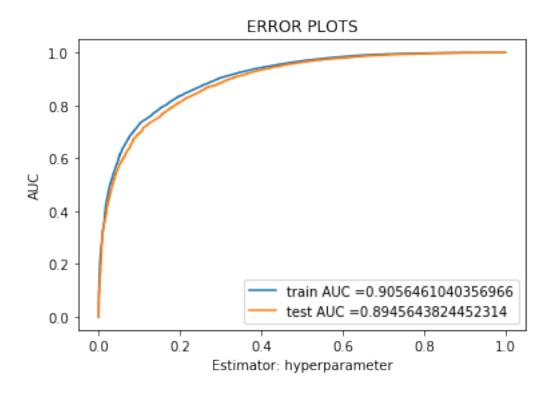
6.2.1 [5.2.1] Applying XGBOOST on BOW, SET 1

6.2.2 Hyperparameter tuning using GridSearch

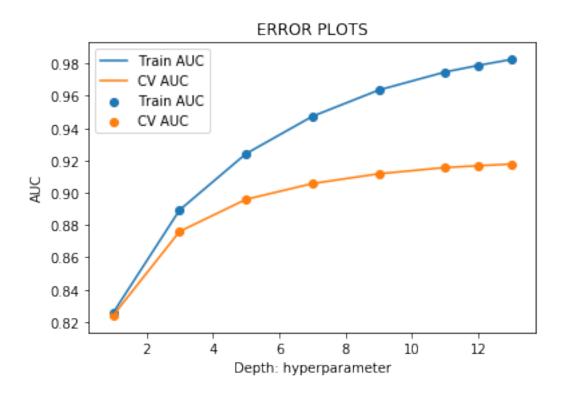
```
In [95]: #clf = XGBClassifier()
         # For Estimator
         estimator = [5,10,25,50,75,100,125,150]
         parameters = {'n_estimators': [5,10,25,50,75,100,125,150]}
         grid = GridSearchCV(XGBClassifier(booster='gbtree', max_depth = 10), parameters, cv=3,
         grid.fit(X_train_bow, Y_train)
         print("best estimator = ", grid.best_params_)
         train_auc_bow = grid.cv_results_['mean_train_score']
         cv_auc_bow = grid.cv_results_['mean_test_score']
         plt.plot(estimator, train_auc_bow, label='Train AUC')
         plt.scatter(estimator, train_auc_bow, label='Train AUC')
         plt.plot(estimator, cv_auc_bow, label='CV AUC')
         plt.scatter(estimator, cv_auc_bow, label='CV AUC')
        plt.legend()
         plt.xlabel("Estimator: hyperparameter")
         plt.ylabel("AUC")
         plt.title("ERROR PLOTS")
         plt.show()
best estimator = {'n_estimators': 150}
```



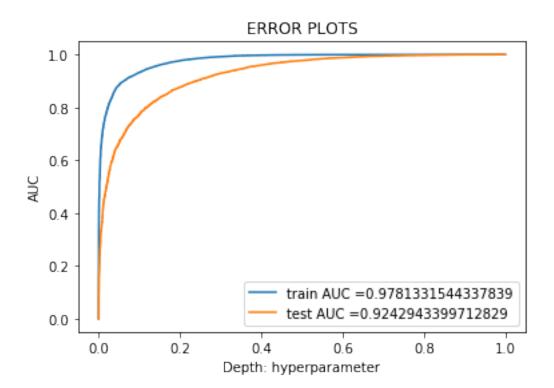
6.2.3 Testing with Test Data



```
In [113]: #clf = XGBClassifier()
          # For Depth
          depth = [1,3,5,7,9,11,12,13]
          parameters = {'max_depth':[1,3,5,7,9,11,12,13]}
          grid = GridSearchCV(XGBClassifier(booster='gbtree',n_estimators = 100), parameters,
          grid.fit(X_train_bow, Y_train)
          print("best depth = ", grid.best_params_)
          train_auc_bow = grid.cv_results_['mean_train_score']
          cv_auc_bow = grid.cv_results_['mean_test_score']
          plt.plot(depth, train_auc_bow, label='Train AUC')
          plt.scatter(depth, train_auc_bow, label='Train AUC')
          plt.plot(depth, cv_auc_bow, label='CV AUC')
          plt.scatter(depth, cv_auc_bow, label='CV AUC')
          plt.legend()
          plt.xlabel("Depth: hyperparameter")
          plt.ylabel("AUC")
          plt.title("ERROR PLOTS")
          plt.show()
best depth = {'max_depth': 13}
```



6.2.4 Testing with Test data



```
In [53]: # clf = RandomForestClassifier()
         estimator = [5,10,25,50,75,100,125,150]
         depth = [1,3,5,7,9,11,12,13]
         parameters = {'n_estimators': estimator, 'max_depth': depth}
         grid = GridSearchCV(XGBClassifier(max_features='sqrt'), parameters, cv=3, scoring='ro
         grid.fit(X_train_bow, Y_train)
Out[53]: GridSearchCV(cv=3, error_score='raise',
                estimator=XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                colsample_bynode=1, colsample_bytree=1, gamma=0, learning_rate=0.1,
                max_delta_step=0, max_depth=3, max_features='sqrt',
                min_child_weight=1, missing=None, n_estimators=100, n_jobs=1,
                nthread=None, objective='binary:logistic', random_state=0,
                reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
                silent=None, subsample=1, verbosity=1),
                fit_params=None, iid=True, n_jobs=-1,
                param_grid={'n_estimators': [5, 10, 25, 50, 75, 100, 125, 150], 'max_depth': [
                pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                scoring='roc_auc', verbose=0)
In [54]: optimal_estimator = grid.best_estimator_.n_estimators
```

print("Value for optimal estimator : ",optimal_estimator)

```
optimal_depth = grid.best_estimator_.max_depth
print("Value for optimal depth : ",optimal_depth)
```

Value for optimal estimator: 150 Value for optimal depth: 13

6.2.5 Testing with Test data

roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of # not the predicted outputs

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_test_fpr_bow))

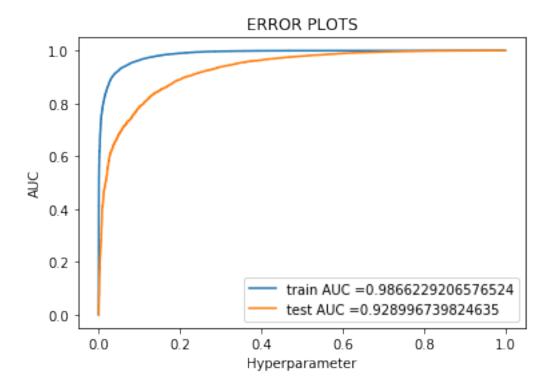
plt.plot(train_fpr_bow, train_tpr_bow, label="train AUC ="+str(auc(train_fpr_bow, tra
plt.plot(test_fpr_bow, test_tpr_bow, label="test AUC ="+str(auc(test_fpr_bow, test_tpr
plt.legend()

plt.xlabel("Hyperparameter")

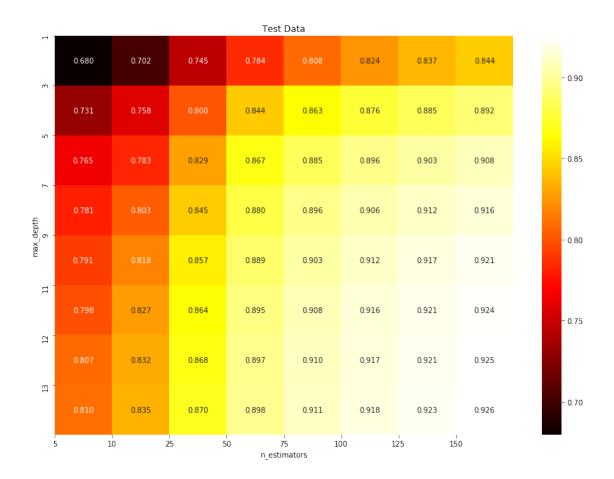
plt.ylabel("AUC")

plt.title("ERROR PLOTS")

plt.show()



6.2.6 Heatmap on Test data



6.2.7 [5.2.2] Applying XGBOOST on TFIDF, SET 2

6.2.8 Hyperparameter tuning using GridSearch

```
In [119]: #clf = XGBClassifier()
    # For Estimator
    estimator = [5,10,25,50,75,100,125,150]
    parameters = {'n_estimators':[5,10,25,50,75,100,125,150]}
    grid = GridSearchCV(XGBClassifier(booster='gbtree',max_depth = 5), parameters, cv=3,
    grid.fit(X_train_tfidf, Y_train)

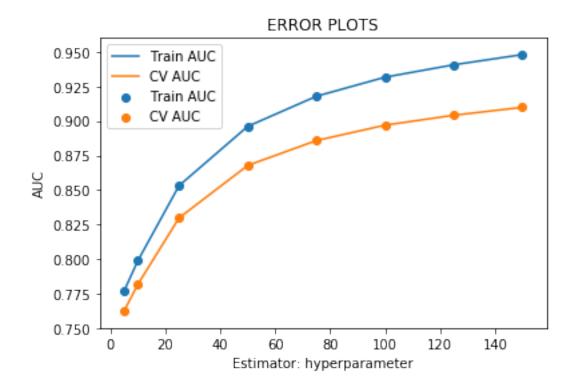
    print("best estimator = ", grid.best_params_)

    train_auc_tfidf = grid.cv_results_['mean_train_score']
    cv_auc_tfidf = grid.cv_results_['mean_test_score']

plt.plot(estimator, train_auc_tfidf, label='Train AUC')
    plt.scatter(estimator, cv_auc_tfidf, label='CV AUC')
    plt.scatter(estimator, cv_auc_tfidf, label='CV AUC')
    plt.scatter(estimator, cv_auc_tfidf, label='CV AUC')
```

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

best estimator = {'n_estimators': 150}

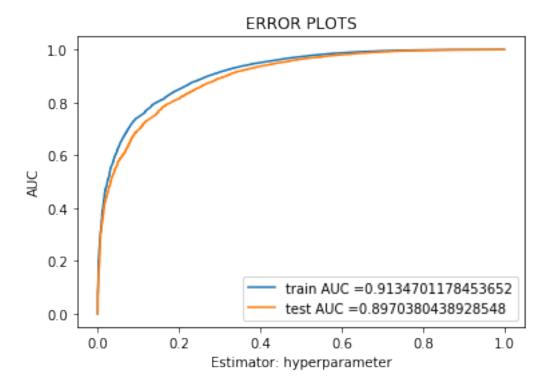


6.2.9 Testing with Test data

plt.legend()

plt.plot(train_fpr_tfidf, train_tpr_tfidf, label="train AUC ="+str(auc(train_fpr_tfide))
plt.plot(test_fpr_tfidf, test_tpr_tfidf, label="test AUC ="+str(auc(test_fpr_tfidf, test_tpr_tfidf))

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



```
In [120]: #clf = XGBClassifier()
    # For Depth
    depth = [1,3,5,7,9,11,12,13]
    parameters = {'max_depth':[1,3,5,7,9,11,12,13]}
    grid = GridSearchCV(XGBClassifier(booster='gbtree',n_estimators = 100), parameters, grid.fit(X_train_tfidf, Y_train)

print("best depth = ", grid.best_params_)

train_auc_tfidf = grid.cv_results_['mean_train_score']
    cv_auc_tfidf = grid.cv_results_['mean_test_score']

plt.plot(depth, train_auc_tfidf, label='Train AUC')
    plt.scatter(depth, train_auc_tfidf, label='Train AUC')
    plt.plot(depth, cv_auc_tfidf, label='CV AUC')

plt.scatter(depth, cv_auc_tfidf, label='CV AUC')

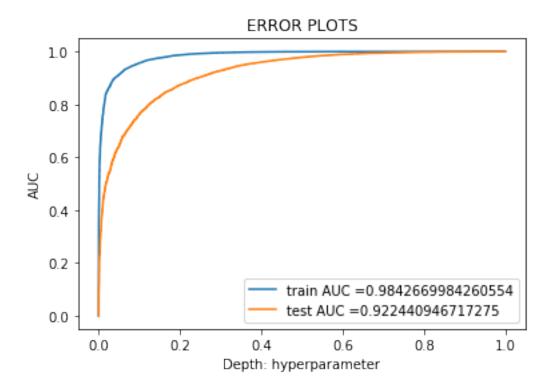
plt.legend()
    plt.xlabel("Depth: hyperparameter")
```

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

best depth = {'max_depth': 13}
```

Depth: hyperparameter

6.2.10 Testing with Test data



```
In [56]: # clf = XGBClassifier()
         estimator = [5,10,25,50,75,100,125,150]
         depth = [1,3,5,7,9,11,12,13]
         parameters = {'n_estimators': estimator, 'max_depth': depth}
         grid = GridSearchCV(XGBClassifier(max_features='sqrt'), parameters, cv=3, scoring='ro
         grid.fit(X_train_tfidf, Y_train)
Out[56]: GridSearchCV(cv=3, error_score='raise',
                estimator=XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                colsample_bynode=1, colsample_bytree=1, gamma=0, learning_rate=0.1,
                max_delta_step=0, max_depth=3, max_features='sqrt',
                min_child_weight=1, missing=None, n_estimators=100, n_jobs=1,
                nthread=None, objective='binary:logistic', random_state=0,
                reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
                silent=None, subsample=1, verbosity=1),
                fit_params=None, iid=True, n_jobs=-1,
                param_grid={'n_estimators': [5, 10, 25, 50, 75, 100, 125, 150], 'max_depth': [
                pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                scoring='roc_auc', verbose=0)
In [57]: optimal_estimator = grid.best_estimator_.n_estimators
         print("Value for optimal estimator : ",optimal_estimator)
```

```
optimal_depth = grid.best_estimator_.max_depth
print("Value for optimal depth : ",optimal_depth)
```

Value for optimal estimator: 150 Value for optimal depth: 13

6.2.11 Testing with Test data

roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of # not the predicted outputs

train_fpr_tfidf, train_tpr_tfidf, thresholds_tfidf = roc_curve(Y_train, clf.predict_predi

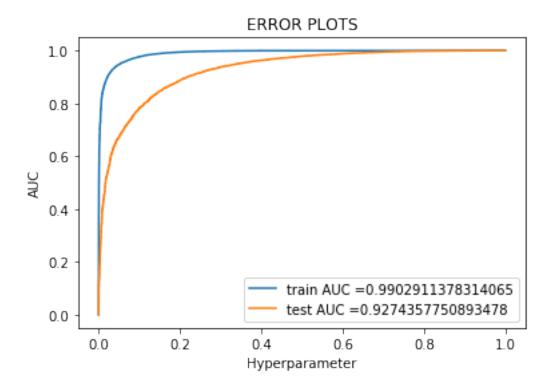
plt.plot(train_fpr_tfidf, train_tpr_tfidf, label="train AUC ="+str(auc(train_fpr_tfide))
plt.plot(test_fpr_tfidf, test_tpr_tfidf, label="test AUC ="+str(auc(test_fpr_tfidf, test_pr_tfidf)))

plt.xlabel("Hyperparameter")

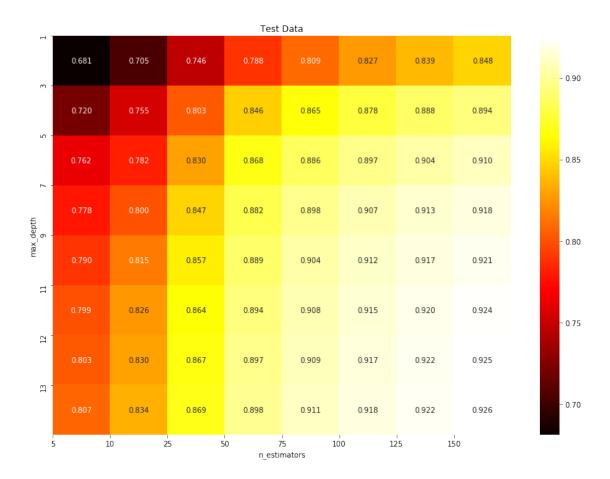
plt.ylabel("AUC")

plt.title("ERROR PLOTS")

plt.show()



6.2.12 Heatmap on Test data



6.2.13 [5.2.3] Applying XGBOOST on AVG W2V, SET 3

6.2.14 Hyperparameter tuning using GridSearch

```
In [128]: #clf = XGBClassifier()
    # For Estimator
    estimator = [5,10,25,50,75,100,125,150]
    parameters = {'n_estimators':[5,10,25,50,75,100,125,150]}
    grid = GridSearchCV(XGBClassifier(booster='gbtree',max_depth = 10), parameters, cv=3
    grid.fit(sent_vectors_train, Y_train)

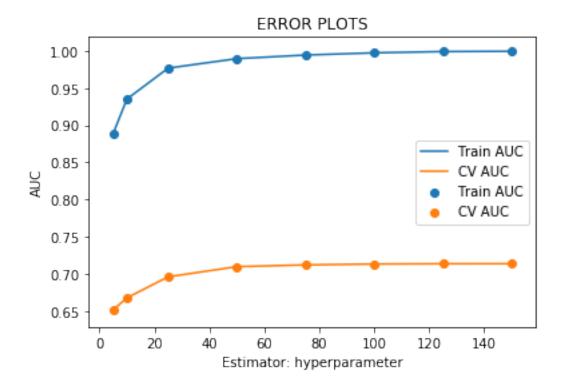
    print("best estimator = ", grid.best_params_)

    train_auc_aw2v = grid.cv_results_['mean_train_score']
    cv_auc_aw2v = grid.cv_results_['mean_test_score']

plt.plot(estimator, train_auc_aw2v, label='Train AUC')
    plt.scatter(estimator, cv_auc_aw2v, label='CV AUC')
    plt.scatter(estimator, cv_auc_aw2v, label='CV AUC')
    plt.scatter(estimator, cv_auc_aw2v, label='CV AUC')
```

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

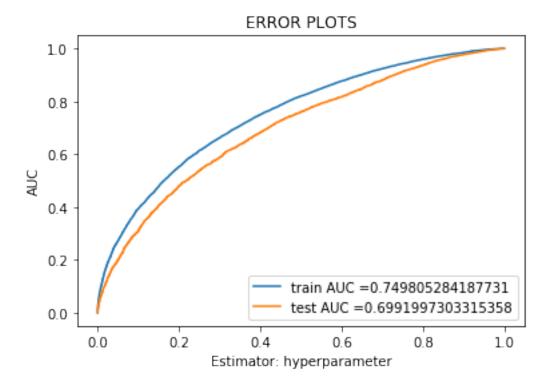
best estimator = {'n_estimators': 150}



6.2.15 Testing with Test data

plt.legend()

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



```
In [129]: #clf = XGBClassifier()
    # For Depth
    depth = [1,3,5,7,9,11,12,13]
    parameters = {'max_depth':[1,3,5,7,9,11,12,13]}
    grid = GridSearchCV(XGBClassifier(booster='gbtree',n_estimators = 70), parameters, credit grid.fit(sent_vectors_train, Y_train)

    print("best depth = ", grid.best_params_)

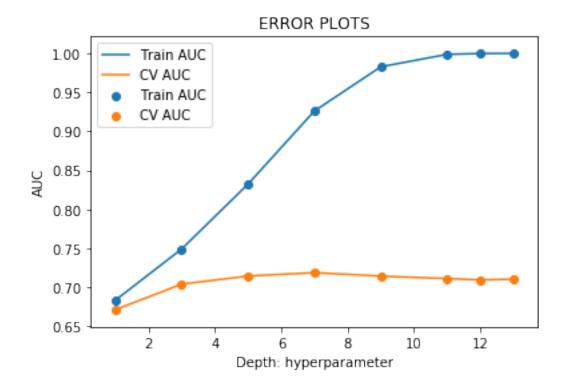
    train_auc_aw2v = grid.cv_results_['mean_train_score']
    cv_auc_aw2v = grid.cv_results_['mean_test_score']

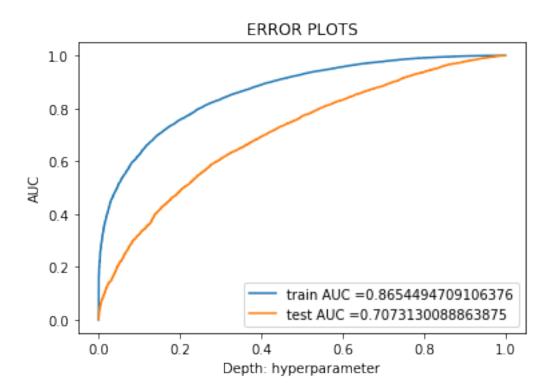
    plt.plot(depth, train_auc_aw2v, label='Train AUC')
    plt.scatter(depth, train_auc_aw2v, label='Train AUC')
    plt.plot(depth, cv_auc_aw2v, label='CV AUC')
    plt.scatter(depth, cv_auc_aw2v, label='CV AUC')
    plt.legend()
```

plt.xlabel("Depth: hyperparameter")

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

best depth = {'max_depth': 7}
```





```
In [59]: # clf = XGBClassifier()
         estimator = [5,10,25,50,75,100,125,150]
         depth = [1,3,5,7,9,11,12,13]
         parameters = {'n_estimators': estimator, 'max_depth': depth}
         grid = GridSearchCV(XGBClassifier(max_features='sqrt'), parameters, cv=3, scoring='ro
         grid.fit(sent_vectors_train, Y_train)
Out[59]: GridSearchCV(cv=3, error_score='raise',
                estimator=XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                colsample_bynode=1, colsample_bytree=1, gamma=0, learning_rate=0.1,
                max_delta_step=0, max_depth=3, max_features='sqrt',
                min_child_weight=1, missing=None, n_estimators=100, n_jobs=1,
                nthread=None, objective='binary:logistic', random_state=0,
                reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
                silent=None, subsample=1, verbosity=1),
                fit_params=None, iid=True, n_jobs=-1,
                param_grid={'n_estimators': [5, 10, 25, 50, 75, 100, 125, 150], 'max_depth': [
                pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                scoring='roc_auc', verbose=0)
In [60]: optimal_estimator = grid.best_estimator_.n_estimators
```

print("Value for optimal estimator : ",optimal_estimator)

```
optimal_depth = grid.best_estimator_.max_depth
print("Value for optimal depth : ",optimal_depth)
```

Value for optimal estimator: 150 Value for optimal depth: 5

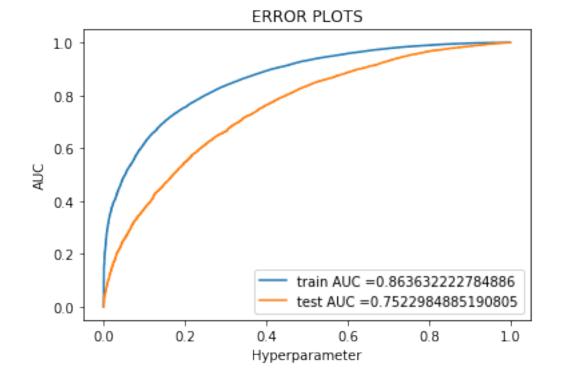
6.2.16 Testing with Test data

```
\# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of \# not the predicted outputs
```

train_fpr_aw2v, train_tpr_aw2v, thresholds_aw2v = roc_curve(Y_train, clf.predict_probetest_fpr_aw2v, test_tpr_aw2v, thresholds_aw2v = roc_curve(Y_test, clf.predict_proba(set_proba(s

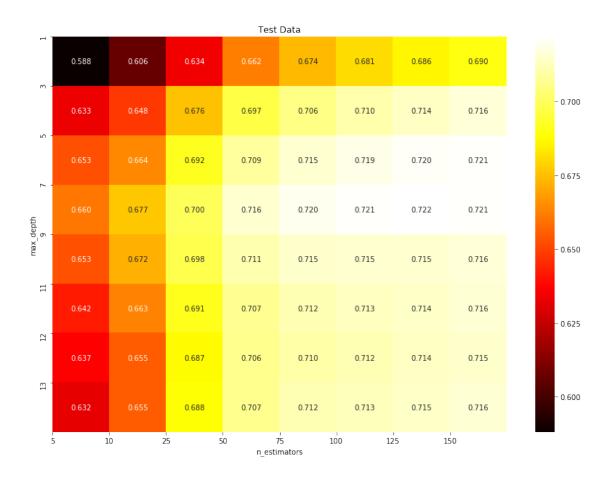
```
plt.plot(train_fpr_aw2v, train_tpr_aw2v, label="train AUC ="+str(auc(train_fpr_aw2v, plt.plot(test_fpr_aw2v, test_tpr_aw2v, label="test AUC ="+str(auc(test_fpr_aw2v, test_plt.legend())
plt.xlabel("Hyperparameter")
plt.ylabel("AUC")
```

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



6.2.17 Heatmap for Test Data

```
In [134]: scores = grid.cv_results_['mean_test_score'].reshape(len(estimator),len(depth))
    plt.figure(figsize=(14,10))
    sns.heatmap(scores, annot=True, cmap=plt.cm.hot, fmt=".3f", xticklabels=estimator, y
    plt.xlabel('n_estimators')
    plt.ylabel('max_depth')
    plt.xticks(np.arange(len(estimator)), estimator)
    plt.yticks(np.arange(len(depth)), depth)
    plt.title('Test_Data')
    plt.show()
```



6.2.18 [5.2.4] Applying XGBOOST on TFIDF W2V, SET 4

6.2.19 Hyperparamater tuning using GridSearch

```
In [157]: #clf = XGBClassifier()
    # For Estimator
    estimator = [5,10,25,50,75,100,125,150]
    parameters = {'n_estimators':[5,10,25,50,75,100,125,150]}
    grid = GridSearchCV(XGBClassifier(max_depth = 5), parameters, cv=3, scoring='roc_auc
    grid.fit(tfidf_sent_vectors_train1, Y_train)

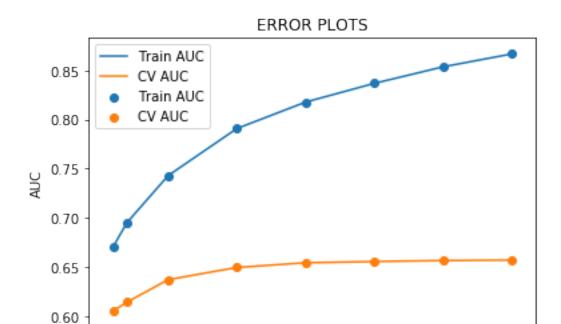
    print("best estimator = ", grid.best_params_)

    train_auc_tfw2v = grid.cv_results_['mean_train_score']
    cv_auc_tfw2v = grid.cv_results_['mean_test_score']

    plt.plot(estimator, train_auc_tfw2v, label='Train AUC')
    plt.scatter(estimator, cv_auc_tfw2v, label='CV AUC')
    plt.scatter(estimator, cv_auc_tfw2v, label='CV AUC')
    plt.scatter(estimator, cv_auc_tfw2v, label='CV AUC')
```

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

best estimator = {'n_estimators': 150}
```



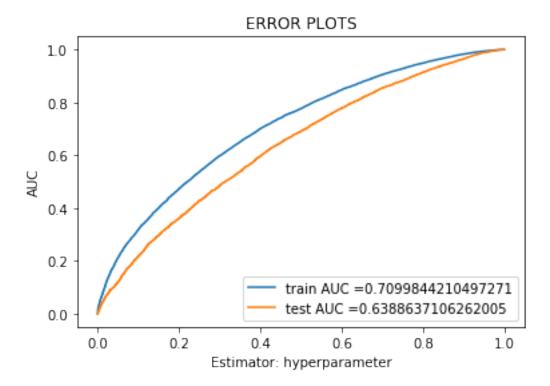
Estimator: hyperparameter

6.2.20 Testing with Test data

plt.legend()

plt.plot(test_fpr_tfw2v, test_tpr_tfw2v, label="test AUC ="+str(auc(test_fpr_tfw2v,

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



```
In [158]: #clf = XGBClassifier()
    # For Depth
    depth = [1,3,5,7,9,11,12,13]
    parameters = {'max_depth':[1,3,5,7,9,11,12,13]}
    grid = GridSearchCV(XGBClassifier(booster='gbtree',n_estimators = 80), parameters, credit (fitfidf_sent_vectors_train1, Y_train)

    print("best depth = ", grid.best_params_)

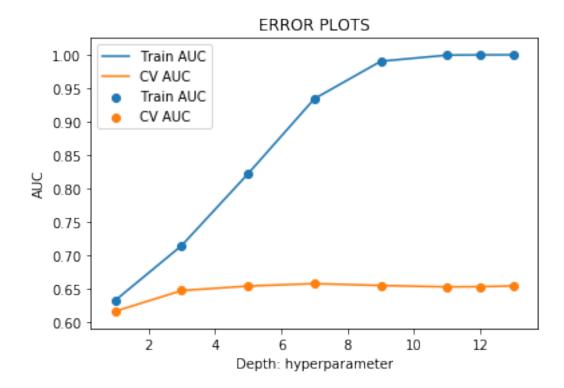
    train_auc_tfw2v = grid.cv_results_['mean_train_score']
    cv_auc_tfw2v = grid.cv_results_['mean_test_score']

    plt.plot(depth, train_auc_tfw2v, label='Train AUC')
    plt.scatter(depth, train_auc_tfw2v, label='Train AUC')
    plt.plot(depth, cv_auc_tfw2v, label='CV AUC')
    plt.scatter(depth, cv_auc_tfw2v, label='CV AUC')
    plt.legend()
```

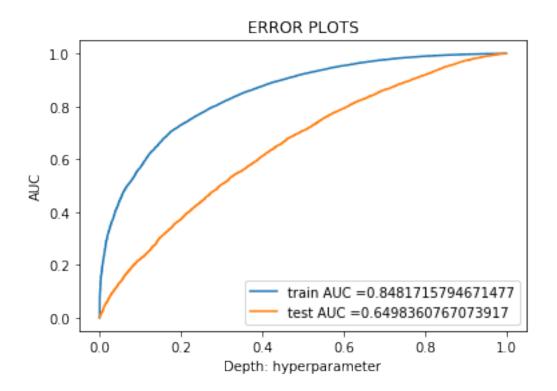
plt.xlabel("Depth: hyperparameter")

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

best depth = {'max_depth': 7}
```



6.2.21 Testing with Test Data



```
In [62]: # clf = XGBClassifier()
         estimator = [5,10,25,50,75,100,125,150]
         depth = [1,3,5,7,9,11,12,13]
         parameters = {'n_estimators': estimator, 'max_depth': depth}
         grid = GridSearchCV(XGBClassifier(max_features='sqrt'), parameters, cv=3, scoring='ro
         grid.fit(tfidf_sent_vectors_train1, Y_train)
Out[62]: GridSearchCV(cv=3, error_score='raise',
                estimator=XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                colsample_bynode=1, colsample_bytree=1, gamma=0, learning_rate=0.1,
                max_delta_step=0, max_depth=3, max_features='sqrt',
                min_child_weight=1, missing=None, n_estimators=100, n_jobs=1,
                nthread=None, objective='binary:logistic', random_state=0,
                reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
                silent=None, subsample=1, verbosity=1),
                fit_params=None, iid=True, n_jobs=-1,
                param_grid={'n_estimators': [5, 10, 25, 50, 75, 100, 125, 150], 'max_depth': [
                pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                scoring='roc_auc', verbose=0)
In [63]: optimal_estimator = grid.best_estimator_.n_estimators
```

print("Value for optimal estimator : ",optimal_estimator)

```
optimal_depth = grid.best_estimator_.max_depth
print("Value for optimal depth : ",optimal_depth)
```

Value for optimal estimator : 150 Value for optimal depth : 5

6.2.22 Testing with Test data

roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of # not the predicted outputs

train_fpr_tfw2v, train_tpr_tfw2v, thresholds_tfw2v = roc_curve(Y_train, clf.predict_predi

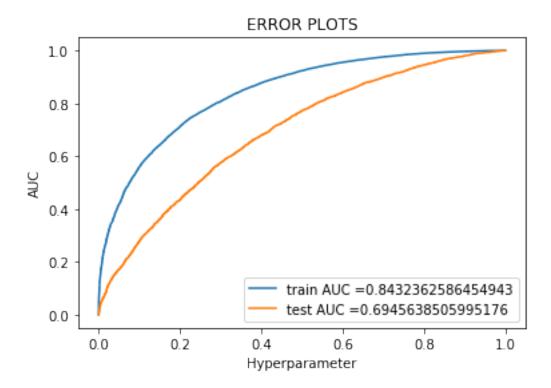
plt.plot(train_fpr_tfw2v, train_tpr_tfw2v, label="train AUC ="+str(auc(train_fpr_tfw2v)
plt.plot(test_fpr_tfw2v, test_tpr_tfw2v, label="test AUC ="+str(auc(test_fpr_tfw2v, test_tpr_tfw2v), test_tpr_tfw2v, test_tpr_tfw

plt.xlabel("Hyperparameter")

plt.ylabel("AUC")

plt.title("ERROR PLOTS")

plt.show()



```
In [163]: clf = XGBClassifier(n_estimators = optimal_estimator, max_depth = optimal_depth)
          clf.fit(tfidf_sent_vectors_train1, Y_train)
          predw1 = clf.predict(tfidf_sent_vectors_test1)
          accw1 = accuracy_score(Y_test, predw1) * 100
          prew1 = precision_score(Y_test, predw1) * 100
          recw1 = recall_score(Y_test, predw1) * 100
          f1w1 = f1_score(Y_test, predw1) * 100
          print('\nAccuracy=%f%%' % (accw1))
          print('\nprecision=%f%%' % (prew1))
          print('\nrecall=%f%%' % (recw1))
          print('\nF1-Score=%f%%' % (f1w1))
Accuracy=83.776394%
precision=83.928913%
recall=99.695828%
F1-Score=91.135458%
6.2.23 Heatmap for Test Data
In [164]: scores = grid.cv_results_['mean_test_score'].reshape(len(estimator),len(depth))
          plt.figure(figsize=(14,10))
          sns.heatmap(scores, annot=True, cmap=plt.cm.hot, fmt=".3f", xticklabels=estimator, y
          plt.xlabel('n_estimators')
```

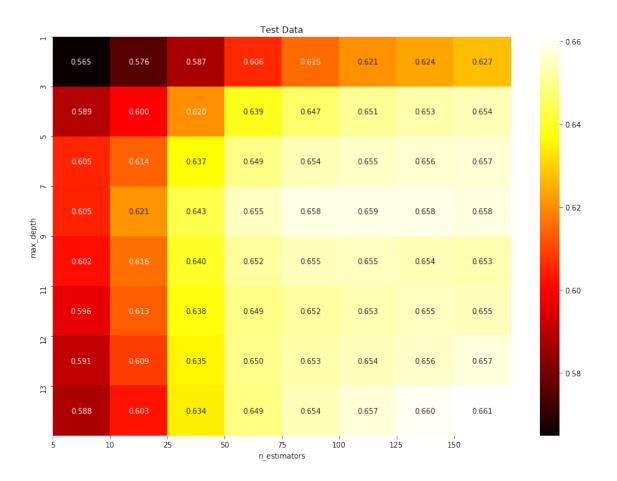
plt.ylabel('max_depth')

plt.title('Test Data')

plt.show()

plt.xticks(np.arange(len(estimator)), estimator)

plt.yticks(np.arange(len(depth)), depth)



7 [6] Conclusions

ptable.add_column("F1%", f1)
print(ptable)

_			L		+	
I	Index	Model	Ensemble Model	Accuracy%	Precision%	Recall%
+ 	1 2 3 4 5 6 7	Bow Tfidf Avg W2v Tfidf W2v Bow Tfidf Avg W2v	Random Forest Random Forest Random Forest Random Forest XGBoost XGBoost XGBoost	+	+	99.6776683161574 99.623189721705
+	8	Tfidf W2v	XGBoost	83.77639374145527 +	83.92891266959678 +	99.695827847641!

- 1. Both Bow and Tfidf have more accuracy than Avg W2v and Tfidf W2v in RF and XGBoost
- 2. Bow and Tfidf models of XGBoost have high accuracy.
- 3. Both parameters n_estimators and max_depth are used for hyperparameter tuning at same time.
- 4. Heatmap for Train and Test data are plotted for each model using n-estimator and max_depth.
- 5. For XGBoost we have taken smaller value of max_depth parameter.
- 6. On applying Random Forest on Avg-W2v and Tfidf-W2v, on plotting ROC curve we do not get good results.