09 Amazon Fine Food Reviews Analysis_RF

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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 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.ensemble import RandomForestClassifier
        import xgboost as xgb
        from sklearn import tree
        import pydotplus
        from IPython.display import Image
        from IPython.display import SVG
        from graphviz import Source
        import graphviz
        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 wordcloud import WordCloud
        from sklearn.externals import joblib
        from datetime import datetime
        from xgboost import XGBClassifier
C:\Users\hp\Anaconda3\lib\site-packages\sklearn\externals\joblib\__init__.py:15: DeprecationWaternals
  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 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
                                                               ProfileName \
                                   UserId
           1 B001E4KFG0 A3SGXH7AUHU8GW
                                                                delmartian
```

```
2 B00813GRG4 A1D87F6ZCVE5NK
        1
                                                                     dll pa
            3 BOOOLQOCHO
                            ABXLMWJIXXAIN Natalia Corres "Natalia Corres"
           HelpfulnessNumerator
                                 HelpfulnessDenominator
                                                         Score
                                                                       Time
        0
                              1
                                                      1
                                                                1303862400
        1
                              0
                                                      0
                                                             0
                                                                1346976000
        2
                              1
                                                             1
                                                                1219017600
                         Summary
                                                                                Text
          Good Quality Dog Food I have bought several of the Vitality canned d...
               Not as Advertised Product arrived labeled as Jumbo Salted Peanut...
        1
           "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
                                                                                    2
        1 #oc-R11D9D7SHXIJB9 B005HG9ET0 Louis E. Emory "hoppy"
                                                                   1342396800
                                                                                    5
                                                 Kim Cieszykowski
        2 #oc-R11DNU2NBKQ23Z B007Y59HVM
                                                                   1348531200
                                                                                    1
        3 #oc-R1105J5ZVQE25C
                               B005HG9ET0
                                                    Penguin Chick
                                                                                    5
                                                                   1346889600
        4 #oc-R12KPBODL2B5ZD B0070SBE1U
                                            Christopher P. Presta
                                                                   1348617600
                                                                                    1
                                                              COUNT(*)
                                                        Text
        O 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
        4 I didnt like this coffee. Instead of telling y...
                                                                     2
In [5]: display[display['UserId'] == 'AZY10LLTJ71NX']
Out [5]:
                      UserId
                               ProductId
                                                              ProfileName
                                                                                  Time
        80638 AZY10LLTJ71NX B006P7E5ZI undertheshrine "undertheshrine"
                                                                            1334707200
                                                                   Text COUNT(*)
               Score
                    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]:
               Id
                    ProductId
                                      UserId
                                                   ProfileName
                                                                HelpfulnessNumerator
            78445
                   BOOOHDL1RQ
                               AR5J8UI46CURR Geetha Krishnan
        0
                                                                                   2
        1
           138317
                   BOOOHDOPYC
                               AR5J8UI46CURR Geetha Krishnan
                                                                                   2
          138277
                   BOOOHDOPYM AR5J8UI46CURR Geetha Krishnan
                                                                                   2
                   BOOOHDOPZG
        3
            73791
                              AR5J8UI46CURR Geetha Krishnan
                                                                                   2
           155049 B000PAQ75C AR5J8UI46CURR Geetha Krishnan
                                                                                   2
           HelpfulnessDenominator
                                   Score
                                                 Time
        0
                                          1199577600
                                       5
                                2
                                          1199577600
        1
                                       5
        2
                                2
                                          1199577600
                                       5
        3
                                2
                                          1199577600
        4
                                2
                                          1199577600
                                     Summary
           LOACKER QUADRATINI VANILLA WAFERS
        1
          LOACKER QUADRATINI VANILLA WAFERS
        2 LOACKER QUADRATINI VANILLA WAFERS
        3 LOACKER QUADRATINI VANILLA WAFERS
          LOACKER QUADRATINI VANILLA WAFERS
                                                         Text
          DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
          DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
         DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
          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.

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]:
               Ιd
                    ProductId
                                                           ProfileName
                                       UserId
        0 64422 B000MIDROQ A161DK06JJMCYF J. E. Stephens "Jeanne"
         1 44737
                  B001EQ55RW A2V0I904FH7ABY
                                                                   Ram
           HelpfulnessNumerator HelpfulnessDenominator Score
                                                                       Time
        0
                               3
                                                              5 1224892800
                                                       1
         1
                               3
                                                       2
                                                              4 1212883200
                                                 Summary
                       Bought This for My Son at College
           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...
```

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

Why is this \$[...] when the same product is available for \$[...] here?
http://www.amazon.

I recently tried this flavor/brand and was surprised at how delicious these chips are. The beautiful tried this flavor/brand and was surprised at how delicious these chips are.

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

Why is this [...] when the same product is available for [...] here?

'> /> (br /> The Victor)


```
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(text)
print("="*50)

soup = BeautifulSoup(sent_4900, 'lxml')
text = soup.get_text()
print("="*50)
```

I recently tried this flavor/brand and was surprised at how delicious these chips are. The beautiful tried this flavor/brand and was surprised at how delicious these chips are.

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

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 ot
_____
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 /> /><br/>The Victor
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 was
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', 'o
                     '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
         from tqdm import tqdm
         preprocessed_reviews = []
         # tqdm is for printing the status bar
         for sentance in tqdm(final['Text'].values):
             sentance = re.sub(r"http\S+", "", sentance)
             sentance = BeautifulSoup(sentance, 'lxml').get_text()
             sentance = decontracted(sentance)
             sentance = re.sub("\S*\d\S*", "", sentance).strip()
             sentance = re.sub('[^A-Za-z]+', ' ', sentance)
             # https://gist.github.com/sebleier/554280
             sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in stopwent
             preprocessed_reviews.append(sentance.strip())
100%|| 87773/87773 [00:34<00:00, 2517.72it/s]
In [221]: preprocessed_reviews[1500]
Out [221]: 'favorite stevia product subscribe save queried customer service nunaturals gmo use ;
```

[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

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.30)
                                                                                        # t
        x_train, x_cv, y_train, y_cv = train_test_split(x_train, y_train, test_size=0.30) # t
In [19]: # number of rows in earch data set, train, cross validation and test data respectivel
        print(len(x_train))
        print(len(x_cv))
        print(len(x_test))
43008
18433
26332
5.1 [4.1] BAG OF WORDS
In [20]: #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)
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, dtype=int) #arguments: ngram_range=(1,2),
        tf_idf.fit(x_train)
        print("some sample features",tf_idf.get_feature_names()[0:10])
        print('='*50)
        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)
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 [227]: # 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 [228]: # 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 [229]: 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 7075
sample words ['eating', 'fruit', 'years', 'recently', 'added', 'maltodextrin', 'check', 'new'
5.4 [4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V
[4.4.1.1] Avg W2v Converting Train data
In [230]: # average Word2Vec
          # compute average word2vec for each review.
          sent_vectors_train = []; # the avg-w2v for each sentence/review is stored in this li
          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
              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%|| 13755/13755 [00:17<00:00, 803.27it/s]
(13755, 50)
[ 2.08400891e-04 -9.54966694e-05 1.05930530e-03 -9.86759152e-04
  1.03871688e-03 -7.95648566e-04 -8.83831157e-04 1.80738693e-03
 -5.75234919e-04 -6.88477222e-04 -5.77197190e-04 5.88051477e-04
  1.85811609e-04 -1.05708501e-03 -1.87508407e-03 -1.14425059e-03
 4.71166263e-04 -1.84508484e-04 -1.86353642e-03 6.82333575e-05
 -5.87147159e-05 -4.54119609e-04 3.10231787e-04 -1.26688662e-03
  1.15916298e-03 -2.93292250e-04 -1.41279414e-03 -5.22746093e-04
 5.34880144e-04 -1.12079959e-03 -1.86780546e-04 1.06564831e-03
 -2.18338521e-04 1.25704851e-03 -2.04193813e-03 7.33595160e-04
 -2.25365151e-04 -2.60276241e-04 -1.69951864e-04 -8.34980092e-04
  2.92323443e-04 -1.46243181e-04 -8.50822371e-04 -1.98671771e-04
 -8.19005312e-04 6.45404169e-04 -1.70866120e-03 -1.76786259e-04
  4.06971635e-04 1.89786434e-03]
  Converting cross validation data
In [231]: list_of_sentance_cv=[]
          for sentance in x_cv:
              list_of_sentance_cv.append(sentance.split())
In [232]: # 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
              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%|| 5895/5895 [00:07<00:00, 799.38it/s]
(5895, 50)
[-6.17560340e-04 7.55331482e-06 1.52604801e-03 2.40280726e-04
 -1.42922778e-03 -1.54502122e-03 4.51177624e-04 1.19154557e-03
-1.10354970e-03 -2.68429812e-04 -1.13595537e-03 7.80510857e-05
  1.11606513e-03 -8.40682008e-04 -2.22607275e-04 -4.25091946e-04
 -2.58808414e-04 -1.01643840e-03 -1.29009563e-04 -1.67991852e-03
 7.73125610e-05 2.24201082e-04 3.51375646e-05 -1.27404562e-03
  1.43981027e-04 -4.53258076e-04 3.02517129e-04 -1.50014476e-03
 -7.89884356e-04 -9.79280966e-04 -1.49033784e-04 3.14250708e-04
  1.96919172e-04 -3.11776286e-04 6.92771680e-04 1.98478877e-03
 -4.84275350e-04 -3.95487196e-05 5.34298823e-04 1.56117009e-04
  6.55606185e-04 -4.20311362e-04 6.91347921e-05 -9.35181200e-04
 -5.39197399e-04 -2.93190391e-03 -1.53409674e-03 -6.43824854e-04
 -9.83724858e-05 1.59880866e-03]
  Converting test data
In [233]: list_of_sentance_test=[]
          for sentance in x_test:
              list_of_sentance_test.append(sentance.split())
In [234]: # average Word2Vec
          # compute average word2vec for each review.
          sent_vectors_test = []; # the avg-w2v for each sentence/review is stored in this lis
          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
              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%|| 8422/8422 [00:10<00:00, 822.97it/s]
```

```
(8422, 50)
[-1.56219284e-03 -1.73564562e-03 -1.00170932e-03 -5.73513190e-04
-2.28344657e-04 9.35348695e-05 -1.69841804e-03 -6.61160501e-04
 7.64101506e-04 5.97771903e-04 1.10285685e-03 4.80593677e-04
-1.45315857e-03 1.22763432e-03 7.32614992e-06 1.34973279e-03
  1.88991957e-04 -6.46397938e-04 -7.48702534e-04 -6.22506058e-04
 -1.04922720e-03 9.21336006e-04 1.67835982e-03 -1.53249911e-03
-9.46205665e-04 3.29417911e-05 -8.83911290e-04 -2.19926414e-05
 8.43897685e-04 -1.53225916e-03 2.04198787e-03 3.66656531e-04
  1.07966012e-03 -2.06591927e-03 8.75746773e-05 -2.57333644e-04
 -4.93653766e-04 -1.08368469e-03 -5.23676692e-04 5.19617067e-04
 7.22169644e-05 1.51460578e-03 -3.96378940e-04 -2.23183922e-03
  1.38375961e-03 1.05212250e-03 -8.95680219e-04 8.87400502e-04
 -2.79059866e-04 -8.46741223e-04]
[4.4.1.2] TFIDF weighted W2v
In [235]: \#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 using tf-idf w2v
In [236]: # 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 = tfid
          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%|| 13755/13755 [02:40<00:00, 85.76it/s]
In [331]: tfidf_sent_vectors_train = np.array(tfidf_sent_vectors_train)
  converting cross validation data
In [237]: \# 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 = tfid
          tfidf_sent_vectors_cv = []; # the tfidf-w2v for each sentence/review is stored in th
          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%|| 5895/5895 [01:07<00:00, 86.75it/s]
In [332]: tfidf_sent_vectors_cv = np.array(tfidf_sent_vectors_cv)
  Converting test data
In [238]: # 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 = tfid
          tfidf_sent_vectors_test = []; # the tfidf-w2v for each sentence/review is stored in
          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%|| 8422/8422 [01:36<00:00, 87.13it/s]
In [333]: tfidf_sent_vectors_test = np.array(tfidf_sent_vectors_test)
   [5] Assignment 9: Random Forests
<strong>Apply Random Forests & GBDT on these feature sets/strong>
   ul>
       <font color='red'>SET 1:</font>Review text, preprocessed one converted into vector
       <font color='red'>SET 2:</font>Review text, preprocessed one converted into vectors
       <font color='red'>SET 3:</font>Review text, preprocessed one converted into vector
       <font color='red'>SET 4:</font>Review text, preprocessed one converted into vector
   <strong>The hyper paramter tuning (Consider two hyperparameters: n_estimators & max_depth)
   <111>
Find the best hyper parameter which will give the maximum <a href='https://www.appliedaico</pre>
Find the best hyper paramter using k-fold cross validation or simple cross validation data
Vise gridsearch cv or randomsearch cv or you can also write your own for loops to do this to
   <strong>Feature importance</strong>
   ul>
Get top 20 important features and represent them in a word cloud. Do this for BOW & TFIDF.
<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>
   <u1>
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.

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

6.1 Loading featurized data using joblib

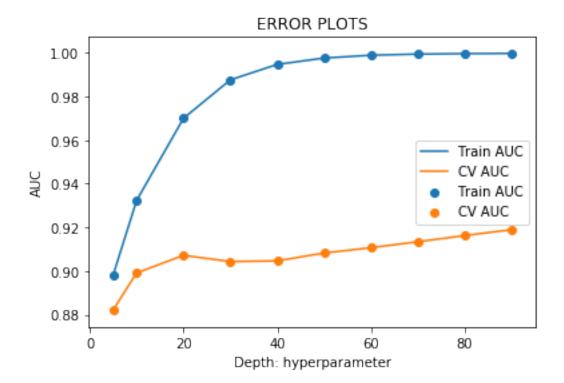
```
BoW
                                                ######################################
      x_train_bow = joblib.load('x_tr_bow100k.pkl')
      x_test_bow = joblib.load('x_te_bow100k.pkl')
              = joblib.load('x_cv_bow100k.pkl')
      y_train = joblib.load('y_train.pkl')
```

6.2 [5.1] Applying RF

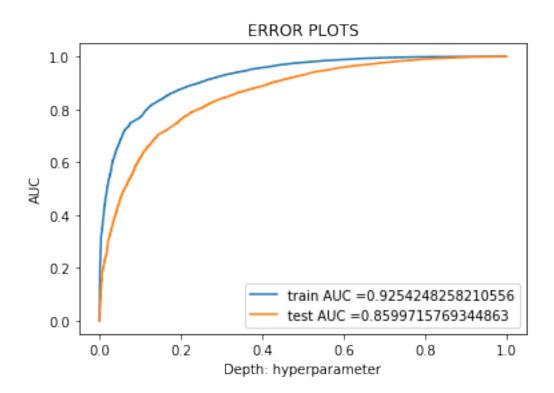
As here we have to tune two hyperparameter, so we'll use GridSearchCV for hyperparameter tuning.

```
In [24]: ######### tuning depth parameter first #########
         start = datetime.now()
        depth = [5,10,20,30,40,50,60,70,80,90]
        parameters = {'max_depth': depth}
         grid = GridSearchCV(RandomForestClassifier(class_weight = 'balanced',n_estimators = 10)
        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)
        print("Time taken: ", datetime.now() - start)
Accuracy on train data = 91.62604888002083
The optimal number of depth is: 90
Time taken: 0:04:21.318210
In [8]: 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()
```



Note: Here we can observe that after depth=20 model's performance is not increasing much. So we could take depth=20 and if we take depth= 90 then model may overfit.

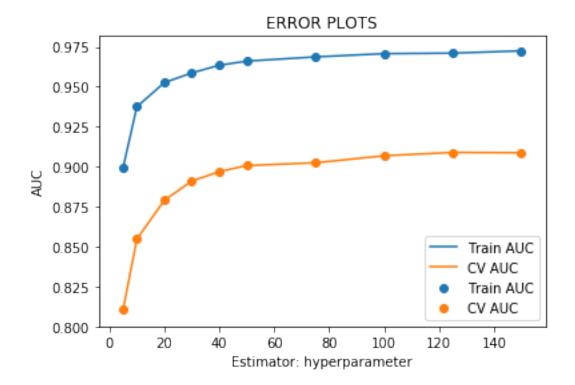


```
start = datetime.now()
        estimator = [5,10,20,30,40,50,75,100,125,150]
        parameters = {'n_estimators': estimator}
        grid = GridSearchCV(RandomForestClassifier(class_weight = 'balanced', max_depth = 20), ;
        grid.fit(x_train_bow, y_train)
        print("Accuracy on train data = ", grid.best_score_*100)
        optimal_est1 = grid.best_estimator_.n_estimators
        print("The optimal number of depth is : ",optimal_est1)
        print("Time taken: ", datetime.now() - start)
Accuracy on train data = 90.9036607195439
The optimal number of depth is: 125
Time taken: 0:00:57.372467
In [16]: 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()
```



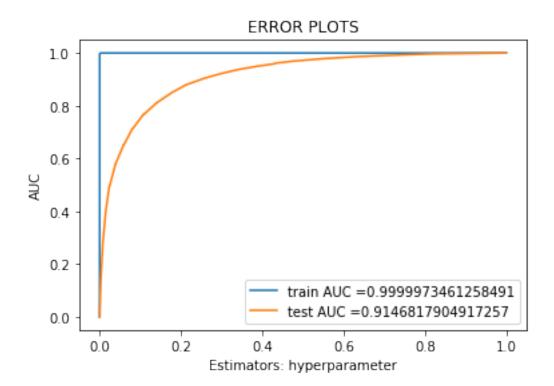
```
In [21]: start = datetime.now()
    clf = RandomForestClassifier(n_estimators = 40, class_weight = 'balanced')
    clf.fit(x_train_bow, y_train)

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_test_plot(train_fpr_bow, train_tpr_bow, label="train AUC ="+str(auc(train_fpr_bow, train_tpr_bow, tast_plt.plot(test_fpr_bow, test_tpr_bow, label="test AUC ="+str(auc(test_fpr_bow, test_tpr_bow, test_tpr_bow))

plt.legend()
    plt.xlabel("Estimators: hyperparameter")
    plt.ylabel("AUC")
```

plt.title("ERROR PLOTS")

```
plt.show()
print("Time taken: ", datetime.now() - start)
```



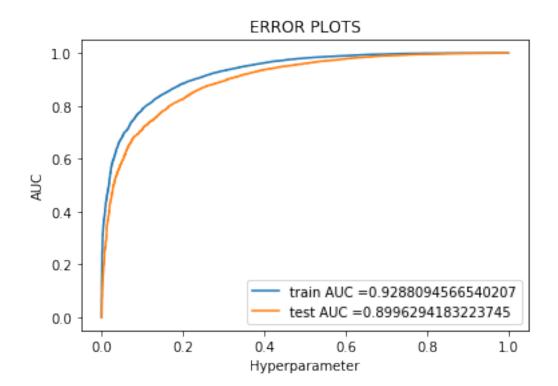
Out[23]: {'max_depth': 90, 'n_estimators': 125}

In [364]: optimal_depth1=20

optimal_est1 =40

```
In [29]: clf = RandomForestClassifier(max_depth = optimal_depth1, n_estimators= optimal_est1, 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_test_pr_bow), train_tpr_bow, label="train AUC ="+str(auc(train_fpr_bow, train_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()
```



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

Accuracy = 84.182743%

precision= 84.181542%

recall = 100.000000%

F1-Score = 91.411486%
```

6.2.1 [5.1.1] Applying Random Forests on BOW, SET 1

6.2.2 [5.1.2] Wordcloud of top 20 important features from SET 1

```
In [40]: # Calculate feature importances from decision trees
    importances = clf.feature_importances_
    indices = list(np.argsort(importances)[::-1][:20])
    names = np.array(count_vect.get_feature_names())
    print(names[indices],)

['not' 'great' 'love' 'favorite' 'disappointed' 'delicious' 'worst'
    'highly' 'bad' 'loves' 'waste' 'easy' 'money' 'wonderful' 'excellent'
    'nice' 'maybe' 'best' 'find' 'perfect']

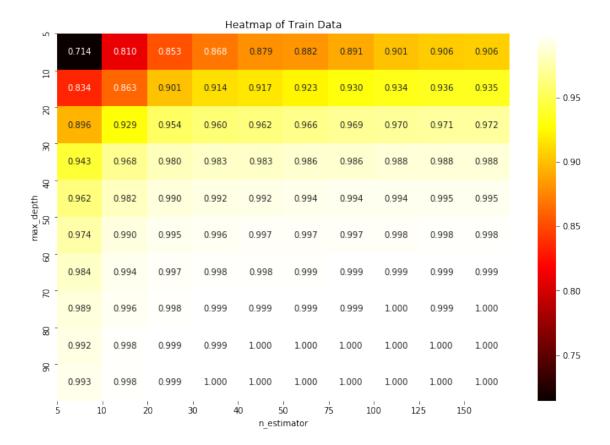
In [39]: text = str(names[indices])
    wordcloud = WordCloud(max_font_size=50, max_words=30, background_color="white").gener.

# Display the generated image:
    plt.imshow(wordcloud, interpolation="bilinear")
    plt.axis("off")
    plt.show()
```

```
money' waste' great highly!
disappointed' nice' bad'loves' highly!
worst' not wonderful'
easy'love delicious' find' love best' waste' great highly!

maybe favorite best' a
```

6.3 Heatmap for test data



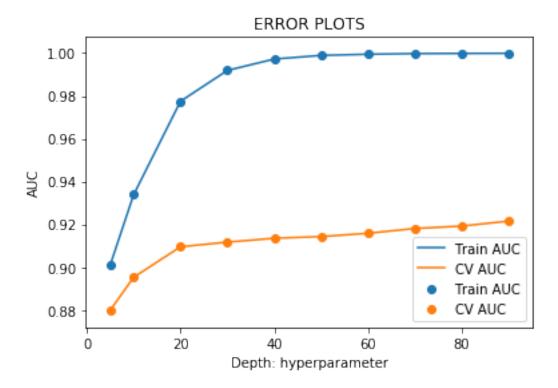
6.3.1 [5.1.3] Applying Random Forests on TFIDF, SET 2

cv_auc = grid.cv_results_['mean_test_score']

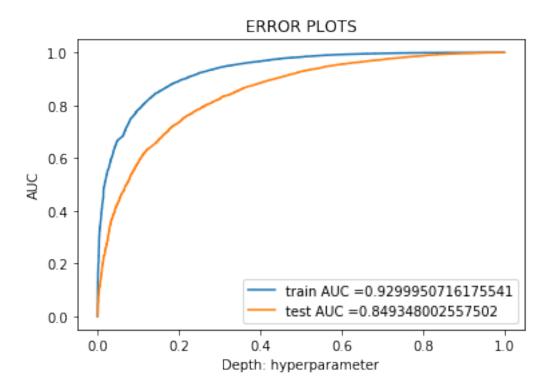
```
plt.plot(depth, train_auc, label='Train AUC')
plt.scatter(depth, train_auc, label='Train AUC')

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

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



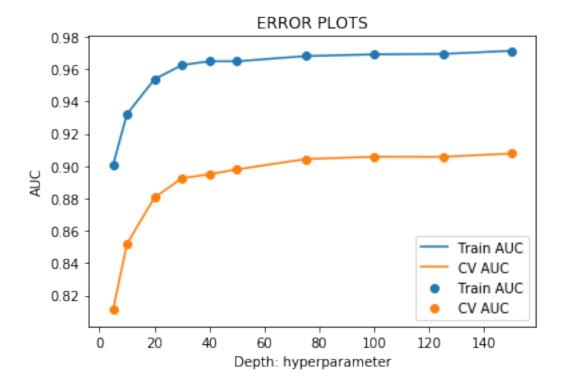
```
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



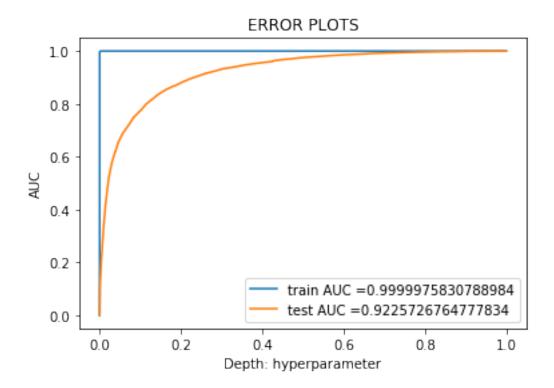
```
plt.plot(estimator, train_auc, label='Train AUC')
plt.scatter(estimator, train_auc, label='Train AUC')

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

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



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



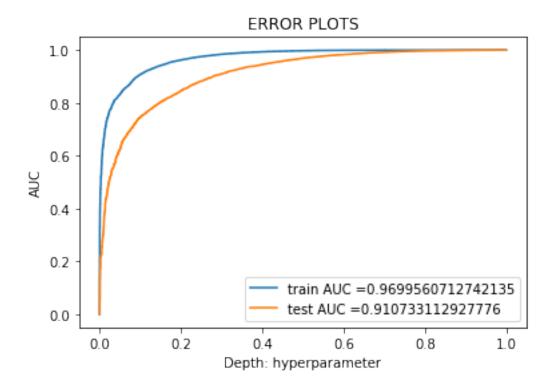
clf.fit(x_train_tf, y_train)

```
train_fpr, train_tpr, thresholds = roc_curve(y_train, clf.predict_proba(x_train_tf)[:
test_fpr, test_tpr, thresholds = roc_curve(y_test, clf.predict_proba(x_test_tf)[:,1]

plt.plot(train_fpr, train_tpr, label= "train AUC ="+str(auc(train_fpr, train_tpr)))

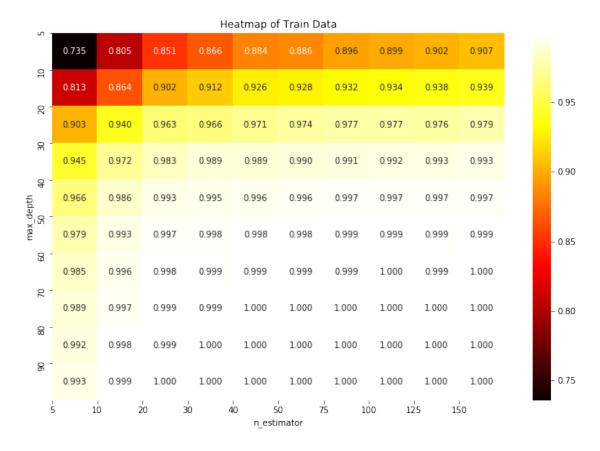
plt.plot(test_fpr, test_tpr, label= "test AUC ="+str(auc(test_fpr, test_tpr)))

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



```
print('\nrecall = %f\%' % (rec_2))
         print('\nF1-Score = %f%%' % (f1_2))
Accuracy = 84.649856%
precision= 84.579279%
recall
        = 99.995488%
F1-Score = 91.643581%
6.3.2 [5.1.4] Wordcloud of top 20 important features from SET 2
In [45]: # Calculate feature importances from decision trees
         importances = clf.feature_importances_
         indices = list(np.argsort(importances)[::-1][:20])
         names = np.array(tf_idf.get_feature_names())
         print(names[indices],)
['not' 'love' 'great' 'delicious' 'best' 'disappointed' 'highly' 'worst'
 'bad' 'money' 'maybe' 'good' 'find' 'product' 'unfortunately' 'loves'
 'would' 'disgusting' 'easy' 'away']
In [46]: text = str(names[indices])
         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()
```

6.4 Heatmap on test data



6.4.1 [5.1.5] Applying Random Forests on AVG W2V, SET 3

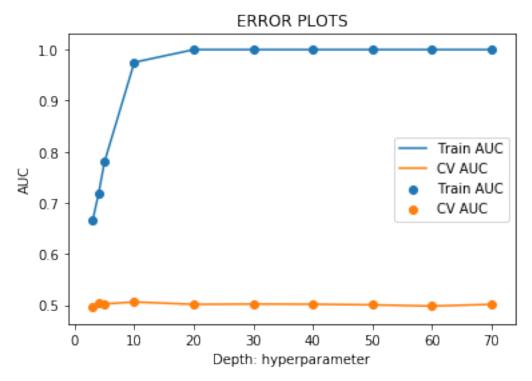
```
In [88]: ######### tuning depth parameter first #########

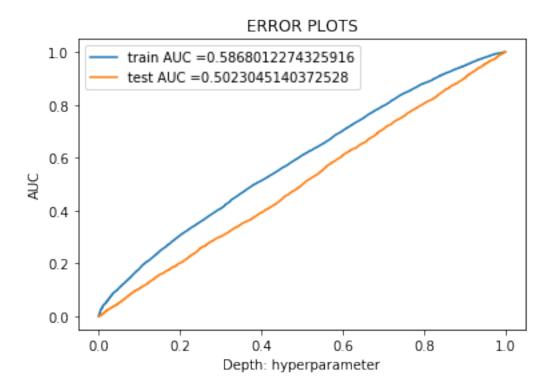
start = datetime.now()

depth = [3,4,5,10,20,30,40,50,60,70]

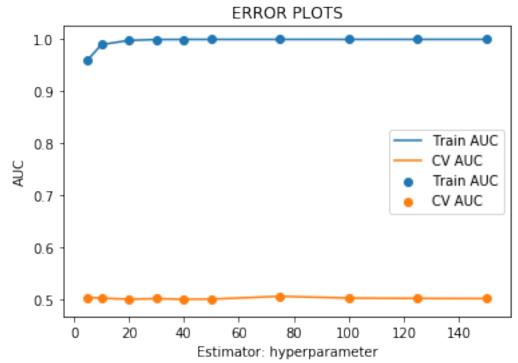
parameters = {'max_depth': depth}
```

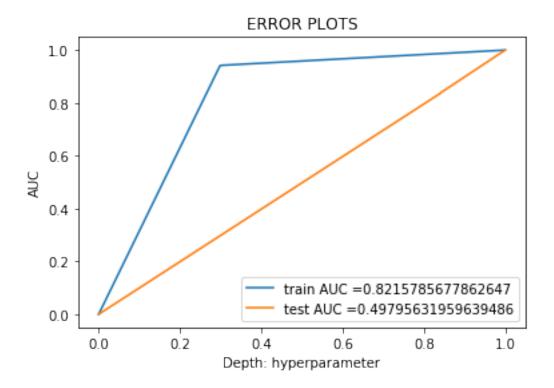
```
grid = GridSearchCV(RandomForestClassifier(class_weight = 'balanced',n_estimators = 10)
         grid.fit(sent_vectors_train, y_train)
         print("Accuracy on train data = ", grid.best_score_*100)
         optimal_depth3 = grid.best_estimator_.max_depth
         print("The optimal number of depth is : ",optimal_depth3)
         print("Time taken: ", datetime.now() - start)
Accuracy on train data = 50.60775812944234
The optimal number of depth is: 10
Time taken: 0:09:40.777559
In [89]: train_auc = grid.cv_results_['mean_train_score']
         cv_auc = grid.cv_results_['mean_test_score']
         plt.plot(depth, train_auc, label='Train AUC')
         plt.scatter(depth, train_auc, label='Train AUC')
         plt.plot(depth, cv_auc, label='CV AUC')
         plt.scatter(depth, cv_auc, label='CV AUC')
         plt.legend()
         plt.xlabel("Depth: hyperparameter")
         plt.ylabel("AUC")
         plt.title("ERROR PLOTS")
         plt.show()
```





```
grid.fit(sent_vectors_train, y_train)
        print("Accuracy on train data = ", grid.best_score_*100)
        optimal_est3 = grid.best_estimator_.n_estimators
        print("The optimal number of depth is : ",optimal_est3)
        print("Time taken: ", datetime.now() - start)
Accuracy on train data = 50.497741150059085
The optimal number of depth is: 75
Time taken: 0:07:44.084420
In [94]: train_auc = grid.cv_results_['mean_train_score']
         cv_auc = grid.cv_results_['mean_test_score']
        plt.plot(estimator, train_auc, label='Train AUC')
        plt.scatter(estimator, train_auc, label='Train AUC')
        plt.plot(estimator, cv_auc, label='CV AUC')
        plt.scatter(estimator, cv_auc, label='CV AUC')
        plt.legend()
        plt.xlabel("Estimator: hyperparameter")
        plt.ylabel("AUC")
        plt.title("ERROR PLOTS")
        plt.show()
```



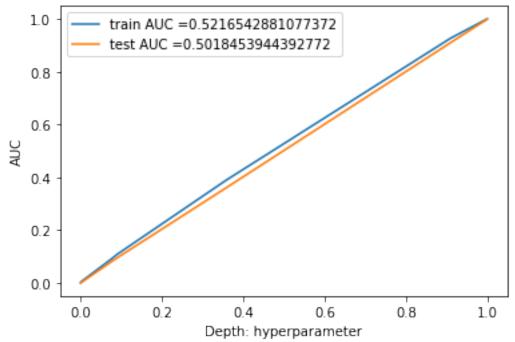


```
In [100]: start = datetime.now()
    depth = [3,4,5,10,20,30,40,50,60,70]
    estimator = [1,2,3,5, 10,20,30,40,50,75]

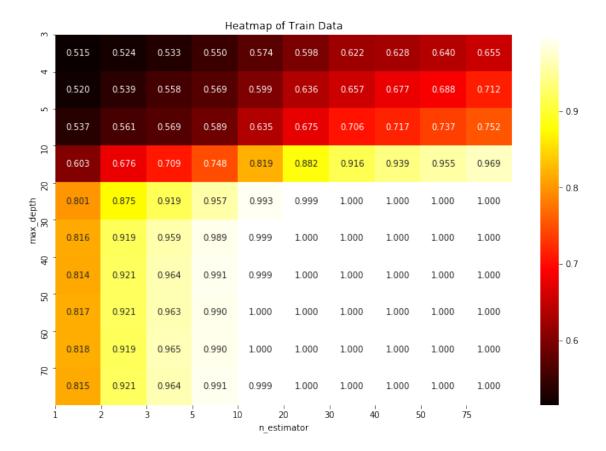
    parameters = {'n_estimators': estimator,'max_depth': depth}
    grid = GridSearchCV(RandomForestClassifier(class_weight ='balanced'), parameters, cv.
```

```
grid.fit(sent_vectors_train, y_train)
          print("Time taken: ", datetime.now() - start)
Time taken: 0:21:27.924150
In [101]: grid.best_params_
Out[101]: {'max_depth': 50, 'n_estimators': 20}
In [110]: optimal_depth3=3
          optimal_est3 =1
In [111]: clf = RandomForestClassifier(n_estimators= 1, max_depth= 3, class_weight ='balanced')
          clf.fit(sent_vectors_train, y_train)
          train_fpr, train_tpr, thresholds = roc_curve(y_train, clf.predict_proba(sent_vectors)
          test_fpr, test_tpr, thresholds = roc_curve(y_test, clf.predict_proba(sent_vectors_
          plt.plot(train_fpr, train_tpr, label= "train AUC ="+str(auc(train_fpr, train_tpr)))
          plt.plot(test_fpr, test_tpr, label= "test AUC ="+str(auc(test_fpr, test_tpr)))
          plt.legend()
          plt.xlabel("Depth: hyperparameter")
          plt.ylabel("AUC")
          plt.title("ERROR PLOTS")
          plt.show()
```

ERROR PLOTS



6.5 Heatmap for test data

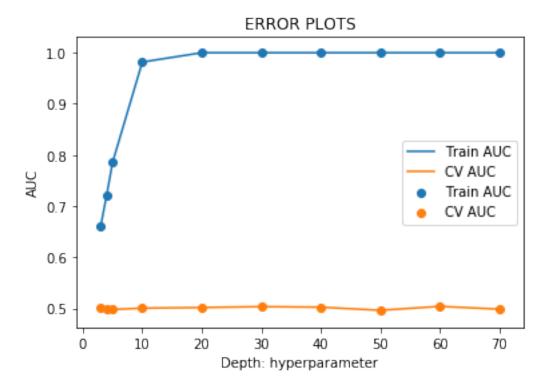


6.5.1 [5.1.6] Applying Random Forests on TFIDF W2V, SET 4

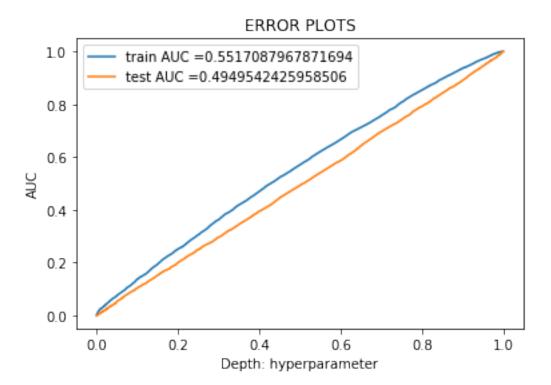
cv_auc = grid.cv_results_['mean_test_score']

```
plt.plot(depth, train_auc, label='Train AUC')
plt.scatter(depth, train_auc, label='Train AUC')
plt.plot(depth, cv_auc, label='CV AUC')
plt.scatter(depth, cv_auc, label='CV AUC')

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



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

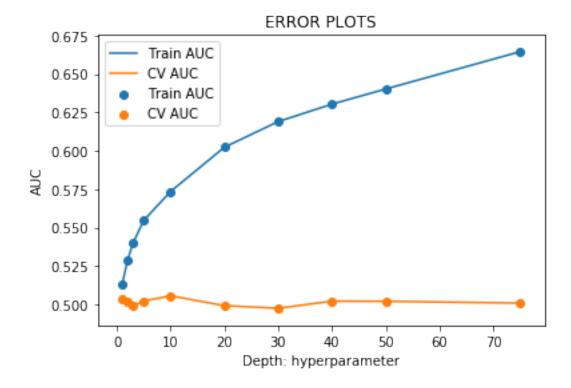


In [129]: train_auc = grid.cv_results_['mean_train_score']

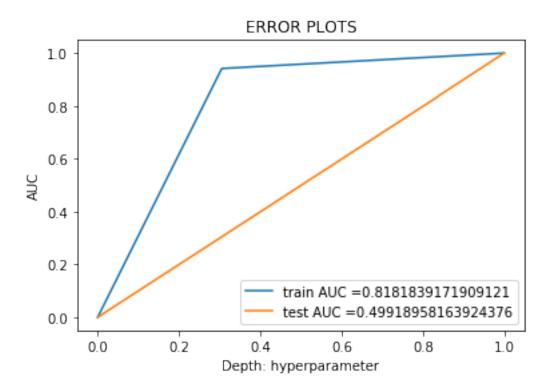
cv_auc = grid.cv_results_['mean_test_score']

```
plt.plot(estimator, train_auc, label='Train AUC')
plt.scatter(estimator, train_auc, label='Train AUC')
plt.plot(estimator, cv_auc, label='CV AUC')
plt.scatter(estimator, cv_auc, label='CV AUC')

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



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



```
In [135]: start = datetime.now()
    depth = [5,10,20,30,40,50,60,70, 80, 90 ]
        estimator = [5,10,20,30,40,50,75,100,125,150]

    parameters = {'n_estimators': estimator,'max_depth': depth}
        grid = GridSearchCV(RandomForestClassifier(class_weight ='balanced'), parameters, cv.
        grid.fit(tfidf_sent_vectors_train, y_train)
        print("Time taken: ", datetime.now() - start)

Time taken: 1:12:04.250837

In [136]: grid.best_params_
Out[136]: {'max_depth': 30, 'n_estimators': 100}

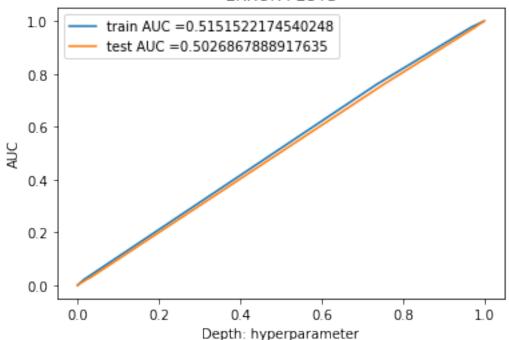
In [139]: optimal_depth4=3
        optimal_est4 =1

In [138]: clf = RandomForestClassifier(n_estimators= 1, max_depth=3, class_weight ='balanced')
        clf.fit(tfidf_sent_vectors_train, y_train)
```

```
train_fpr, train_tpr, thresholds = roc_curve(y_train, clf.predict_proba(tfidf_sent_vertest_fpr, test_tpr, thresholds = roc_curve(y_test, clf.predict_proba(tfidf_sent_vertest_fpr, train_tpr, label= "train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label= "test AUC ="+str(auc(test_fpr, test_tpr)))

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

ERROR PLOTS



print('\nprecision= %f\%' % (pre_4))

```
print('\nrecall = %f%%' % (rec_4))
print('\nF1-Score = %f%%' % (f1_4))

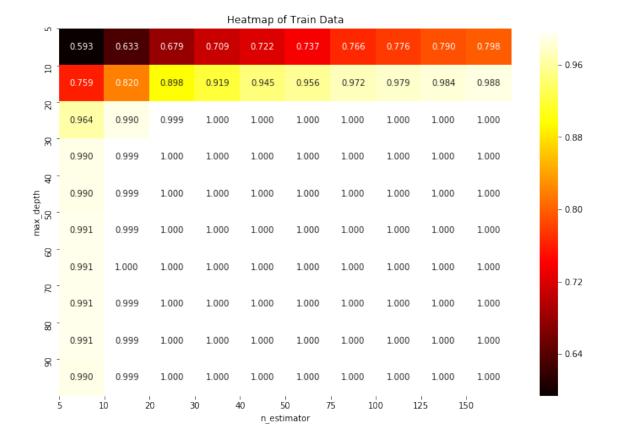
Accuracy = 75.436731%

precision= 84.030699%

recall = 87.435145%

F1-Score = 85.699124%
```

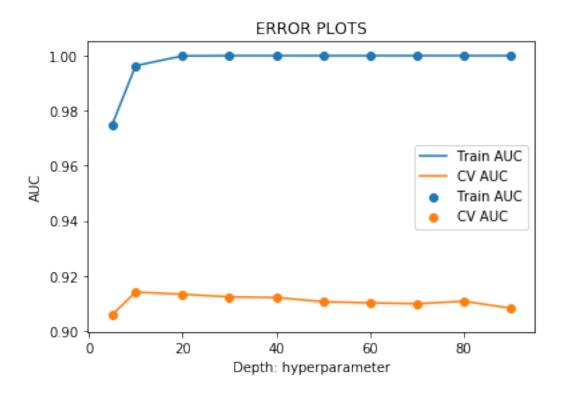
6.6 Heatmap for test data

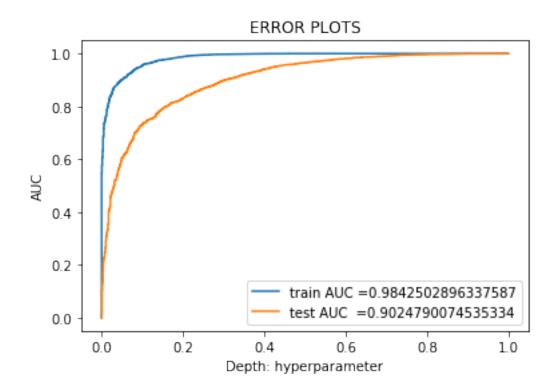


6.7 [5.2] Applying GBDT using XGBOOST

6.7.1 [5.2.1] Applying XGBOOST on BOW, SET 1

```
In [249]: ######### tuning depth parameter first #########
          start = datetime.now()
          depth = [5,10,20,30,40,50,60,70,80,90]
          parameters = {'max_depth': depth}
          grid = GridSearchCV(XGBClassifier(booster='gbtree',n_estimators=200), parameters, cv-
          grid.fit(x_train_bow, y_train)
          print("Accuracy on train data = ", grid.best_score_*100)
          optimal_depth5 = grid.best_estimator_.max_depth
          print("The optimal number of depth is : ",optimal_depth5)
          print("Time taken: ", datetime.now() - start)
Accuracy on train data = 91.41168382532123
The optimal number of depth is: 10
Time taken: 0:12:03.908564
In [250]: train_auc = grid.cv_results_['mean_train_score']
          cv_auc = grid.cv_results_['mean_test_score']
          plt.plot(depth, train_auc, label='Train AUC')
          plt.scatter(depth, train_auc, label='Train AUC')
          plt.plot(depth, cv_auc, label='CV AUC')
          plt.scatter(depth, cv_auc, label='CV AUC')
          plt.legend()
          plt.xlabel("Depth: hyperparameter")
          plt.ylabel("AUC")
          plt.title("ERROR PLOTS")
          plt.show()
```



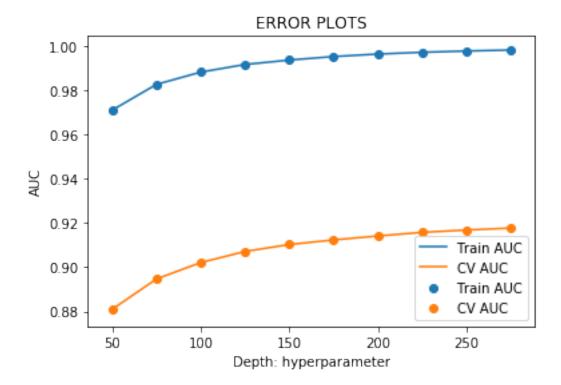


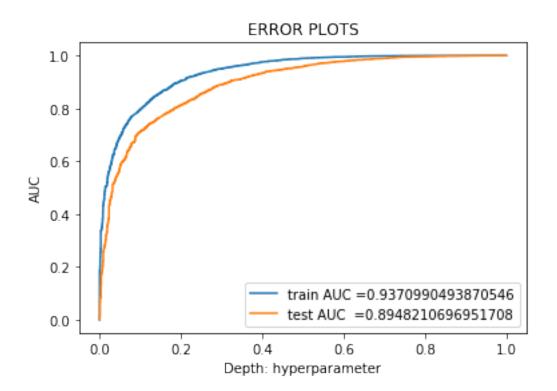
```
start = datetime.now()
        estimator = [50,75,100,125,150,175,200,225,250,275]
        parameters = {'n_estimators': estimator}
        grid = GridSearchCV(XGBClassifier(booster='gbtree', class_weight ='balanced',max_dep
        grid.fit(x_train_bow, y_train)
        print("Accuracy on train data = ", grid.best_score_*100)
        optimal_est5 = grid.best_estimator_.n_estimators
        print("The optimal number of depth is : ",optimal_est5)
        print("Time taken: ", datetime.now() - start)
Accuracy on train data = 91.76834436807442
The optimal number of depth is: 275
Time taken: 0:03:24.036335
In [265]: train_auc = grid.cv_results_['mean_train_score']
        cv_auc = grid.cv_results_['mean_test_score']
        plt.plot(estimator, train_auc, label='Train AUC')
```

plt.scatter(estimator, train_auc, label='Train AUC')

```
plt.plot(estimator, cv_auc, label='CV AUC')
plt.scatter(estimator, cv_auc, label='CV AUC')

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





= [5,10,20,30,40,50,60,70,80,90]

In [270]: start = datetime.now()

```
plt.plot(train_fpr, train_tpr, label= "train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label= "test AUC ="+str(auc(test_fpr, test_tpr)))

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

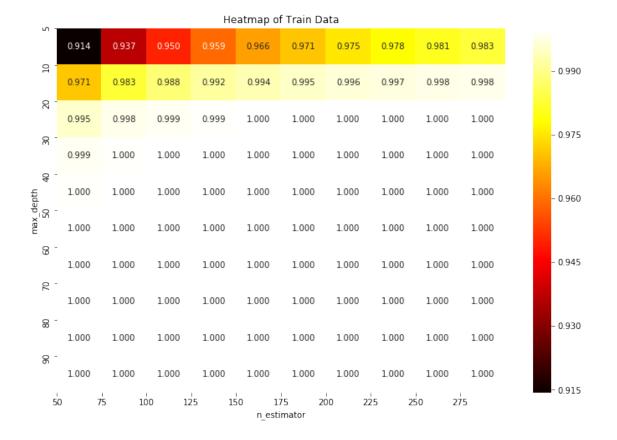
ERROR PLOTS 1.0 0.8 0.6 AUC 0.4 0.2 train AUC = 0.9941695160848906 test AUC = 0.9166443319498333 0.0 0.0 0.2 0.4 1.0 0.6 0.8 Depth: hyperparameter

```
Accuracy = 89.539302%

precision= 90.293160%

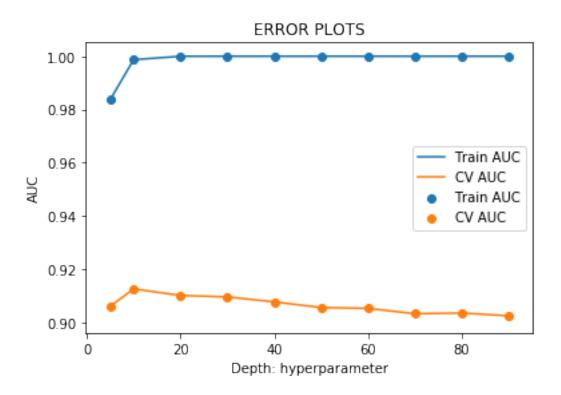
recall = 98.075290%

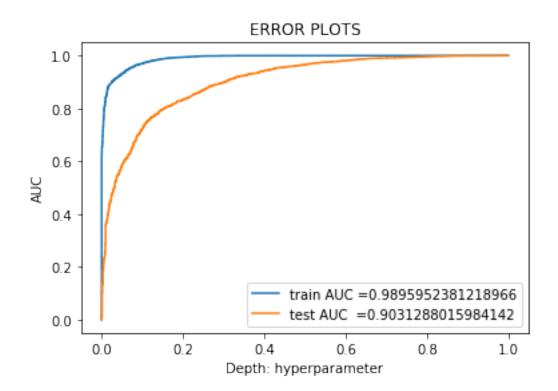
F1-Score = 94.023472%
```



6.7.2 [5.2.2] Applying XGBOOST on TFIDF, SET 2

```
In [276]: ######### tuning depth parameter first #########
          start = datetime.now()
          depth = [5,10,20,30,40,50,60,70,80,90]
          parameters = {'max_depth': depth}
          grid = GridSearchCV(XGBClassifier(booster='gbtree',n_estimators=200), parameters, cv
          grid.fit(x_train_tf, y_train)
          print("Accuracy on train data = ", grid.best_score_*100)
          optimal_depth6 = grid.best_estimator_.max_depth
          print("The optimal number of depth is : ",optimal_depth6)
          print("Time taken: ", datetime.now() - start)
Accuracy on train data = 91.26814329849708
The optimal number of depth is: 10
Time taken: 0:17:34.448552
In [277]: train_auc = grid.cv_results_['mean_train_score']
          cv_auc = grid.cv_results_['mean_test_score']
          plt.plot(depth, train_auc, label='Train AUC')
          plt.scatter(depth, train_auc, label='Train AUC')
          plt.plot(depth, cv_auc, label='CV AUC')
          plt.scatter(depth, cv_auc, label='CV AUC')
          plt.legend()
          plt.xlabel("Depth: hyperparameter")
          plt.ylabel("AUC")
          plt.title("ERROR PLOTS")
          plt.show()
```

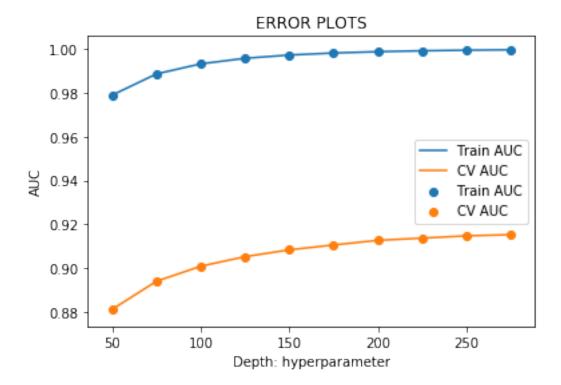


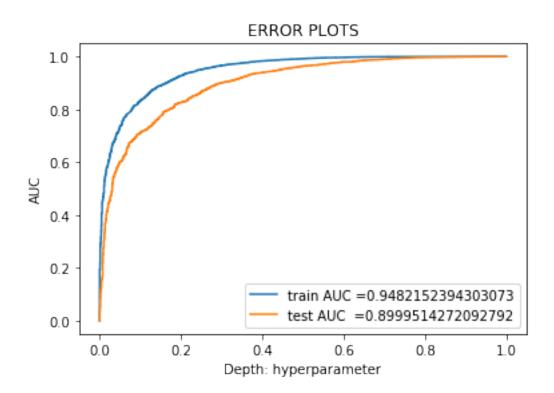


```
start = datetime.now()
        estimator = [50,75,100,125,150,175,200,225,250,275]
        parameters = {'n_estimators': estimator}
        grid = GridSearchCV(XGBClassifier(booster='gbtree', max_depth = 10), parameters, cv=3
        grid.fit(x_train_tf, y_train)
        print("Accuracy on train data = ", grid.best_score_*100)
        optimal_est6 = grid.best_estimator_.n_estimators
        print("The optimal number of depth is : ",optimal_est6)
        print("Time taken: ", datetime.now() - start)
Accuracy on train data = 91.52744093723638
The optimal number of depth is: 275
Time taken: 0:06:46.233185
In [281]: train_auc = grid.cv_results_['mean_train_score']
        cv_auc = grid.cv_results_['mean_test_score']
        plt.plot(estimator, train_auc, label='Train AUC')
```

plt.scatter(estimator, train_auc, label='Train AUC')

```
plt.plot(estimator, cv_auc, label='CV AUC')
plt.scatter(estimator, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("Depth: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```





```
In [285]: start = datetime.now()
                    = [5,10,20,30,40,50,60,70,80,90]
          estimator = [50,75,100,125,150,175,200,225,250,275]
          parameters = {'n_estimators': estimator, 'max_depth': depth}
          grid = GridSearchCV(XGBClassifier(booster='gbtree',class_weight = 'balanced'), parame
          grid.fit(x_train_tf, y_train)
          print("Time taken: ", datetime.now() - start)
Time taken: 2:16:10.437806
In [286]: grid.best_params_
Out[286]: {'max_depth': 10, 'n_estimators': 275}
In [287]: optimal_depth6 = 10
          optimal_est6
                         = 200
In [290]: clf = XGBClassifier(n_estimators= 200, max_depth=optimal_depth6, class_weight = bala
          clf.fit(x_train_tf, y_train)
          train_fpr, train_tpr, thresholds = roc_curve(y_train, clf.predict_proba(x_train_tf)[
          test_fpr, test_tpr, thresholds = roc_curve(y_test, clf.predict_proba(x_test_tf)[:,
```

```
plt.plot(train_fpr, train_tpr, label= "train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label= "test AUC ="+str(auc(test_fpr, test_tpr)))

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

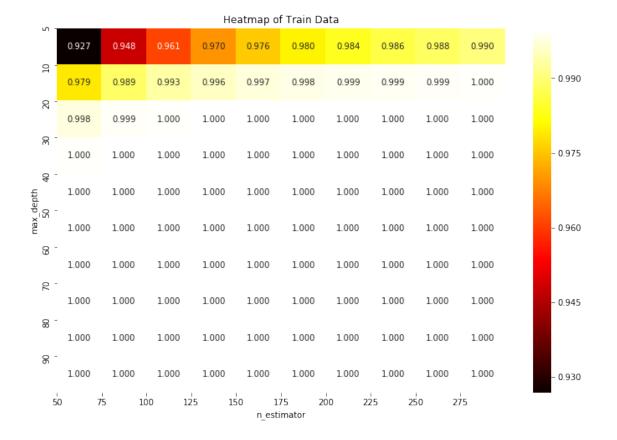
ERROR PLOTS 1.0 0.8 0.6 AUC 0.4 0.2 train AUC = 0.9972552372805474 test AUC = 0.9165291098592536 0.0 0.0 0.2 0.4 0.8 1.0 0.6 Depth: hyperparameter

```
Accuracy = 89.266208%

precision= 89.816490%

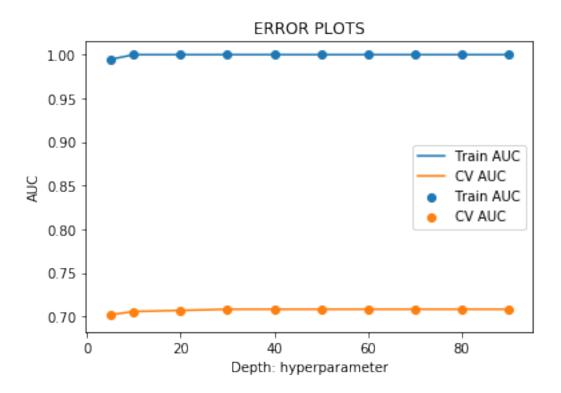
recall = 98.358336%

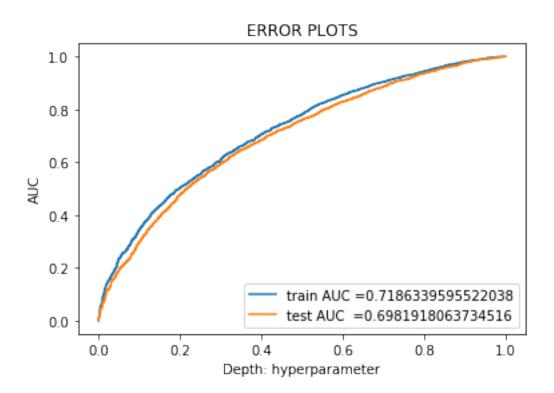
F1-Score = 93.893542%
```



6.7.3 [5.2.3] Applying XGBOOST on AVG W2V, SET 3

```
In [292]: ######### tuning depth parameter first #########
          start = datetime.now()
          depth = [5,10,20,30,40,50,60,70,80,90]
          parameters = {'max_depth': depth}
          grid = GridSearchCV(XGBClassifier(booster='gbtree',n_estimators=200), parameters, cv
          grid.fit(sent_vectors_train, y_train)
          print("Accuracy on train data = ", grid.best_score_*100)
          optimal_depth7 = grid.best_estimator_.max_depth
          print("The optimal number of depth is : ",optimal_depth7)
          print("Time taken: ", datetime.now() - start)
Accuracy on train data = 70.84431485262648
The optimal number of depth is: 30
Time taken: 0:08:12.008477
In [293]: train_auc = grid.cv_results_['mean_train_score']
          cv_auc = grid.cv_results_['mean_test_score']
          plt.plot(depth, train_auc, label='Train AUC')
          plt.scatter(depth, train_auc, label='Train AUC')
          plt.plot(depth, cv_auc, label='CV AUC')
          plt.scatter(depth, cv_auc, label='CV AUC')
          plt.legend()
         plt.xlabel("Depth: hyperparameter")
          plt.ylabel("AUC")
          plt.title("ERROR PLOTS")
          plt.show()
```



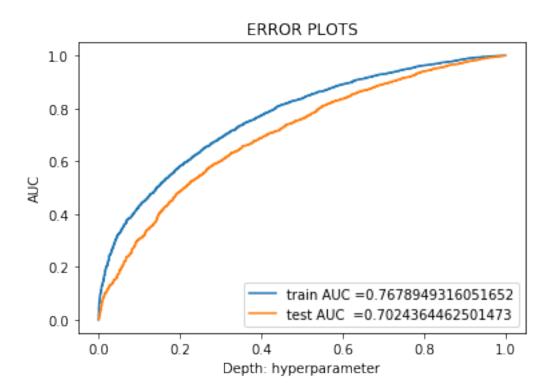


```
start = datetime.now()
        estimator = [50,75,100,125,150,175,200,225,250,275]
        parameters = {'n_estimators': estimator}
        grid = GridSearchCV(XGBClassifier(booster='gbtree', class_weight ='balanced',max_dep
        grid.fit(sent_vectors_train, y_train)
        print("Accuracy on train data = ", grid.best_score_*100)
        optimal_est7 = grid.best_estimator_.n_estimators
        print("The optimal number of depth is : ",optimal_est7)
        print("Time taken: ", datetime.now() - start)
Accuracy on train data = 70.52117119204024
The optimal number of depth is: 275
Time taken: 0:00:41.546684
In [300]: train_auc = grid.cv_results_['mean_train_score']
        cv_auc = grid.cv_results_['mean_test_score']
        plt.plot(estimator, train_auc, label='Train AUC')
```

plt.scatter(estimator, train_auc, label='Train AUC')

```
plt.plot(estimator, cv_auc, label='CV AUC')
plt.scatter(estimator, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("Depth: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```

ERROR PLOTS 0.76 Train AUC CV AUC Train AUC 0.74 CV AUC 0.72 0.70 0.68 50 100 150 200 250 Depth: hyperparameter



```
In [308]: start = datetime.now()
    depth = [5, 10,20,30,40, 50, 60, 70, 80, 90]
        estimator = [30,40,50,75,100,125,150,175,200,225]

    parameters = {'n_estimators': estimator,'max_depth': depth}
        grid = GridSearchCV(XGBClassifier(booster='gbtree',class_weight ='balanced'), parame
        grid.fit(sent_vectors_train, y_train)
        print("Time taken: ", datetime.now() - start)

Time taken: 0:45:41.868439

In [309]: grid.best_params_
Out[309]: {'max_depth': 30, 'n_estimators': 225}

In [324]: optimal_depth7= 3
        optimal_est7 = 40

In [325]: clf = XGBClassifier(n_estimators= optimal_est7, max_depth=optimal_depth7, class_weight = clf.fit(sent_vectors_train, y_train)
```

train_fpr, train_tpr, thresholds = roc_curve(y_train, clf.predict_proba(sent_vectors)
test_fpr, test_tpr, thresholds = roc_curve(y_test, clf.predict_proba(sent_vectors_))

```
plt.plot(train_fpr, train_tpr, label= "train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label= "test AUC ="+str(auc(test_fpr, test_tpr)))

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

ERROR PLOTS 1.0 0.8 0.6 AUC 0.4 0.2 train AUC = 0.7678949316051652 test AUC = 0.7024364462501473 0.0 0.0 0.2 0.4 1.0 0.6 0.8 Depth: hyperparameter

```
Accuracy = 83.899311%

precision= 83.899311%

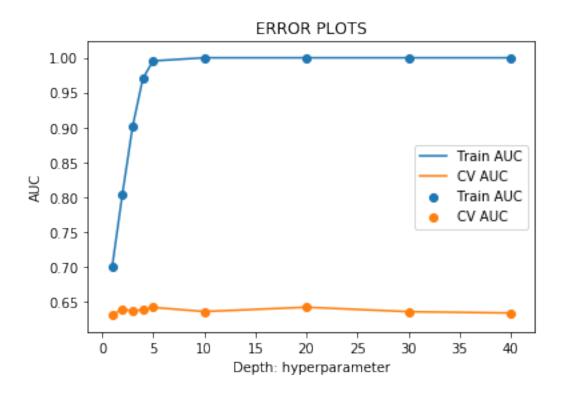
recall = 100.000000%

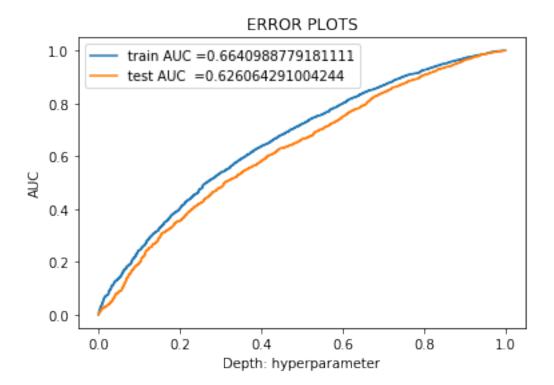
F1-Score = 91.244835%
```

Heatmap of Train Data												
	0.883	0.907	0.923	0.949	0.965	0.977	0.985	0.991	0.995	0.997		
10	0.999	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000		- 0.98
20	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000		
30	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000		- 0.96
max_depth 50 40	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000		
max o	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000		- 0.94
99 -	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000		- 0.92
70	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000		
8 -	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000		- 0.90
o6 ⁻	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000		
30) 4	40	50	75 10		25 15 mator	50 17	75 20	00 22	25	_	_

6.7.4 [5.2.4] Applying XGBOOST on TFIDF W2V, SET 4

```
In [334]: ######### tuning depth parameter first #########
          start = datetime.now()
          depth = [1,2,3,4,5,10,20,30,40,50]
          parameters = {'max_depth': depth}
          grid = GridSearchCV(XGBClassifier(booster='gbtree',n_estimators=200), parameters, cv
          grid.fit(tfidf_sent_vectors_train, y_train)
          print("Accuracy on train data = ", grid.best_score_*100)
          optimal_depth8 = grid.best_estimator_.max_depth
          print("The optimal number of depth is : ",optimal_depth8)
          print("Time taken: ", datetime.now() - start)
Accuracy on train data = 64.15613529318219
The optimal number of depth is: 20
Time taken: 0:05:08.582615
In [335]: train_auc = grid.cv_results_['mean_train_score']
          cv_auc = grid.cv_results_['mean_test_score']
          plt.plot(depth, train_auc, label='Train AUC')
          plt.scatter(depth, train_auc, label='Train AUC')
          plt.plot(depth, cv_auc, label='CV AUC')
          plt.scatter(depth, cv_auc, label='CV AUC')
          plt.legend()
          plt.xlabel("Depth: hyperparameter")
          plt.ylabel("AUC")
          plt.title("ERROR PLOTS")
          plt.show()
```



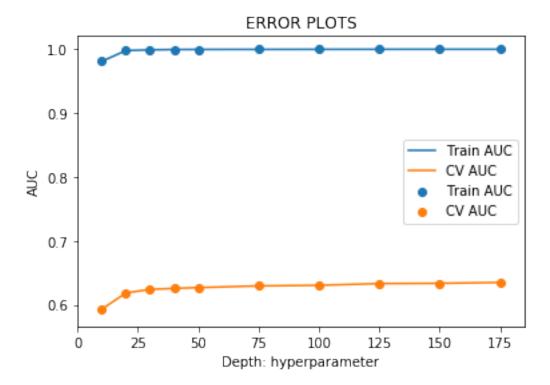


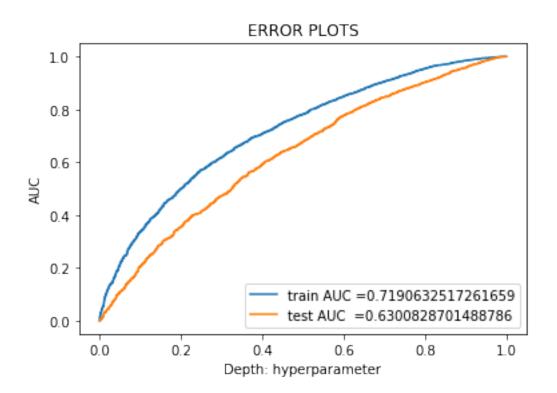
```
start = datetime.now()
        estimator = [10,20,30,40,50,75,100,125,150,175]
        parameters = {'n_estimators': estimator}
        grid = GridSearchCV(XGBClassifier(booster='gbtree', class_weight ='balanced',max_dep
        grid.fit(tfidf_sent_vectors_train, y_train)
        print("Accuracy on train data = ", grid.best_score_*100)
        optimal_est8 = grid.best_estimator_.n_estimators
        print("The optimal number of depth is : ",optimal_est)
        print("Time taken: ", datetime.now() - start)
Accuracy on train data = 63.488546299093926
The optimal number of depth is: 175
Time taken: 0:03:25.637023
In [346]: train_auc = grid.cv_results_['mean_train_score']
        cv_auc = grid.cv_results_['mean_test_score']
        plt.plot(estimator, train_auc, label='Train AUC')
```

plt.scatter(estimator, train_auc, label='Train AUC')

```
plt.plot(estimator, cv_auc, label='CV AUC')
plt.scatter(estimator, cv_auc, label='CV AUC')

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





train_fpr, train_tpr, thresholds = roc_curve(y_train, clf.predict_proba(tfidf_sent_vetest_fpr, test_tpr, thresholds = roc_curve(y_test, clf.predict_proba(tfidf_sent_vetest_tpr, test_tpr, thresholds = roc_curve(y_test, clf.predict_proba(tfidf_sent_vetest_tpr, test_tpr, thresholds = roc_curve(y_test, clf.predict_proba(tfidf_sent_vetest_tpr, test_tpr, thresholds = roc_curve(y_test_tpr, test_tpr, test_tpr,

clf.fit(tfidf_sent_vectors_train, y_train)

```
plt.plot(train_fpr, train_tpr, label= "train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label= "test AUC ="+str(auc(test_fpr, test_tpr)))

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

ERROR PLOTS 1.0 train AUC = 0.6261102694061815 test AUC = 0.6067567632444871 0.8 0.6 AUC 0.4 0.2 0.0 0.2 0.8 1.0 0.0 0.4 0.6

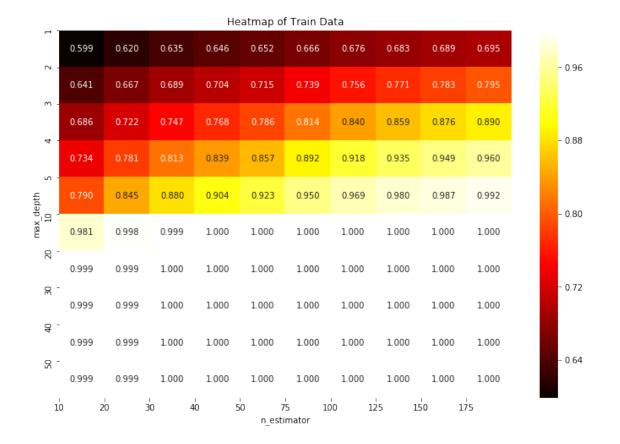
Depth: hyperparameter

```
Accuracy = 83.899311%

precision= 83.899311%

recall = 100.000000%

F1-Score = 91.244835%
```



7 [6] Conclusions

```
In [366]: number= [1,2,3,4,5,6,7,8]
                               feat = ["Bow", "Tfidf", "Avg W2v", "Tfidf W2v", "Bow", "Tfidf", "Avg W2v", "Tfidf W2v"]
                               model = ["Random Forest", "Random Forest", "Random Forest", "XGBoost",
                               depth = [optimal_depth1,optimal_depth2,optimal_depth3,optimal_depth4,optimal_depth5,optimal_depth4,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optimal_depth5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,optim5,op
                                                  = [optimal_est1,optimal_est2,optimal_est3,optimal_est4,optimal_est5,optimal_es
                                                  = [acc_1,acc_2,acc_3,acc_4,acc_5,acc_6,acc_7,acc_8]
                               acc
                                                  = [pre_1,pre_2,pre_3,pre_4,pre_5,pre_6,pre_7,pre_8]
                                                    = [rec_1, rec_2, rec_3, rec_4, rec_5, rec_6, rec_7, rec_8]
                                #f1
                                                     = [f1\_1, f1\_2, f1\_3, f1\_4, f1\_5, f1\_6, f1\_7, f1\_8]
                               #Initialize Prettytable
                               pt = PrettyTable()
                               pt.add_column("Sr.No.", number)
                               pt.add_column("Featurization", feat)
                               pt.add_column("Model", model)
                               pt.add_column("Optimal Depth", depth)
                               pt.add_column("Optimal Estimator", est)
                               pt.add_column("Accuracy%", acc)
                               pt.add_column("Precision%", pre)
                               #pt.add_column("Recall%", rec)
                               #pt.add_column("F1%", f1)
                               print(pt)
```

+		+		+		
İ	Sr.No.	Featurization	Model		Optimal Estimator	Accuracy%
1	1	Bow	Random Forest	20	40	84.18274343004
-	2	Tfidf	Random Forest	l 20	80	84.649855688895
-	3	Avg W2v	Random Forest	J 3	1	82.990277988758
1	4	Tfidf W2v	Random Forest	J 3	1	75.436730973720
1	5	Bow	XGBoost	10	200	89.53930182854
1	6	Tfidf	XGBoost	10	200	89.2662075516504
1	7	Avg W2v	XGBoost	J 3	40	83.899311327475
1	8	Tfidf W2v	XGBoost	1	30	83.899311327475
+		+		+	+	