Amazon Fine Food Reviews Analysis

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

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

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. ld 2. ProductId - unique identifier for the product

3. UserId - unqiue identifier for the user 4. ProfileName

5. HelpfulnessNumerator - number of users who found the review helpful 6. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not 7. Score - rating between 1 and 5

8. Time - timestamp for the review 9. Summary - brief summary of the review 10. Text - text of the review

Objective:

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

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

[Ans] We could use Score/Rating. A rating of 4 or 5 can be cosnidered as a positive review. A rating of 1 or 2 can be considered 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.

Time

1346976000 Not as Advertised

1219017600 "Delight" says it all

Summary

1303862400 Good Quality Dog Food I have bought several of the Vitality canned d...

Product arrived labeled as Jumbo Salted Peanut.

This is a confection that has been around a fe...

Text

[1]. Reading Data

[1.1] Loading the data

The dataset is available in two forms

1. .csv file 2. SQLite Database

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

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

import warnings warnings.filterwarnings("ignore") import sqlite3 import pandas as pd import numpy as np import nltk import string import matplotlib.pyplot as plt

In [247]: **%matplotlib** inline

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.metrics import roc_curve, auc from nltk.stem.porter import PorterStemmer # 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

In [248]: # using SQLite Table to read data. con = sqlite3.connect('database.sqlite')

from sklearn import metrics

filtering only positive and negative reviews i.e. # not taking into consideration those reviews with Score=3 # SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000, will give top 500000 data points # you can change the number to any other number based on your computing power # filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000""", con) # for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 20000""", con) # Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a negative rating(0). def partition(x): if x < 3: return 0 return 1 #changing reviews with score less than 3 to be positive and vice-versa actualScore = filtered_data['Score']

positiveNegative = actualScore.map(partition) filtered_data['Score'] = positiveNegative print("Number of data points in our data", filtered_data.shape) filtered_data.head(3) Number of data points in our data (20000, 10)

ProfileName | HelpfulnessNumerator | HelpfulnessDenominator | Score | ProductId Userld B001E4KFG0 A3SGXH7AUHU8GW delmartian 1 2 B00813GRG4 A1D87F6ZCVE5NK 2 3 B000LQOCH0 ABXLMWJIXXAIN Natalia Corres "Natalia Corres" 1

In [249]: | display = pd.read_sql_query(""" SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*) FROM Reviews GROUP BY UserId HAVING COUNT(*)>1

In [250]: print(display.shape) display.head()

(80668, 7)

Out[248]:

Out[250]: **ProfileName** Time | Score Text | COUNT(*) Userld ProductId **0** #oc-R115TNMSPFT9I7 B007Y59HVM Breyton 1331510400 2 Overall its just OK when considering the price.. My wife has recurring extreme muscle spasms, u.. 2 #oc-R11DNU2NBKQ23Z B007Y59HVM Kim Cieszykowski 1348531200 This coffee is horrible and unfortunately not .. 3 #oc-R11O5J5ZVQE25C B005HG9ET0 Penguin Chick 1346889600 This will be the bottle that you grab from the... 4 #oc-R12KPBODL2B5ZD B007OSBE1U Christopher P. Presta

In [251]: display[display['UserId']=='AZY10LLTJ71NX']

Out[251]: Text | COUNT(*) UserId ProductId **ProfileName** Time Score 80638 AZY10LLTJ71NX B006P7E5ZI undertheshrine "undertheshrine" 1334707200 5 I was recommended to try green tea extract to .

1348617600

In [252]: display['COUNT(*)'].sum() Out[252]: 393063

[2] Exploratory Data Analysis

[2.1] Data Cleaning: Deduplication

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

I didnt like this coffee. Instead of telling y..

In [253]: display= pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 AND UserId="AR5J8UI46CURR" ORDER BY ProductID """, con)

display.head() Out[253]: ProductId Userld

ProfileName | HelpfulnessNumerator | HelpfulnessDenominator | Score Time Text Summary 0 78445 B000HDL1RQ AR5J8UI46CURR Geetha Krishnan 2 . i199577600 LOACKER QUADRATINI VANILLA WAFERS DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS 1 | 138317 | B000HDOPYC | AR5J8UI46CURR Geetha Krishnan 2 199577600 LOACKER QUADRATINI VANILLA WAFERS DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS . **2** | 138277 | B000HDOPYM | AR5J8UI46CURR | Geetha Krishnan | 2 . i199577600 LOACKER QUADRATINI VANILLA WAFERS DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS 3 73791 B000HDOPZG AR5J8UI46CURR Geetha Krishnan 2 . i199577600 LOACKER QUADRATINI VANILLA WAFERS DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS **4** 155049 B000PAQ75C AR5J8UI46CURR | Geetha Krishnan | 2 . i199577600 LOACKER QUADRATINI VANILLA 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=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 [254]: #Sorting data according to ProductId in ascending order sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=**True**, inplace=**False**, kind='quicksort', na_position='last')

In [255]: #Deduplication of entries final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', inplace=False)

Out[255]: (19354, 10) In [256]: #Checking to see how much % of data still remains

(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100 Out[256]: 96.77

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

SELECT * FROM Reviews WHERE Score != 3 AND Id=44737 OR Id=64422 ORDER BY ProductID """, con)

In [257]: display= pd.read_sql_query("""

display.head()

Out[257]: ProfileName | HelpfulnessNumerator | HelpfulnessDenominator | Score | Text ProductId Userld Time Summary 0 64422 B000MIDROQ A161DK06JJMCYF J. E. Stephens "Jeanne" 1224892800 Bought This for My Son at College My son loves spaghetti so I didn't hesitate or.. 1 44737 B001EQ55RW A2V0I904FH7ABY Ram 1212883200 Pure cocoa taste with crunchy almonds inside It was almost a 'love at first bite' - the per...

In [258]: final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]</pre>

```
In [259]: | #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()
           (19354, 10)
  Out[259]: 1 16339
           0 3015
           Name: Score, dtype: int64
[3] Preprocessing
[3.1]. Preprocessing Review Text
Now that we have finished deduplication our data requires some preprocessing before we go on further with analysis and making the prediction model.
Hence in the Preprocessing phase we do the following in the order below:-
 1. Begin by removing the html tags
 2. Remove any punctuations or limited set of special characters like , or . or # etc.
 3. Check if the word is made up of english letters and is not alpha-numeric
 4. Check to see if the length of the word is greater than 2 (as it was researched that there is no adjective in 2-letters)
 5. Convert the word to lowercase
 6. Remove Stopwords
 7. Finally Snowball Stemming the word (it was observed to be better than Porter Stemming)
After which we collect the words used to describe positive and negative reviews
  In [260]: # printing some random reviews
            sent_0 = final['Text'].values[0]
           print(sent_0)
           print("="*50)
           sent_1000 = final['Text'].values[1000]
           print(sent_1000)
           print("="*50)
           sent_1500 = final['Text'].values[1500]
           print(sent_1500)
           print("="*50)
           sent_4900 = final['Text'].values[4900]
           print(sent_4900)
           print("="*50)
           We have used the Victor fly bait for 3 seasons. Can't beat it. Great product!
           _____
           I received this box with great anticipation since they don't sell these on the west coast. I got the package, opened the box and was EXTREMELY disappointed. The cookies looked like a gorilla shook the box to death and left most of the box filled with crumbs. AND THERE WAS A RODENT SIZED HOLE ON THE SIDE OF THE BOX!!!!!!! So, needless to say I will not NOT be reordering these agai
           I have two cats. My big boy has eaten these and never had a problem...as a matter of fact he has never vomited or had a hair ball since I treat them equally these are no longer purchased. I hate to see my girl sick so I just recommend you watch your cats after you give them these trea
           ts. If not a problem...carry on.
           ______
           I was always a fan of Dave's, so I bought this at a local store to try Blair's and I'm glad I did. The jalepeno sause is very mild (for me) but one of the most delicious condiments I've ever tasted. The Afterdeath is a bit painful, but still very tasty on rice & beans, burritos, or any chicken dish I've tried it on. The Sudden Death kicked my ass when I underestimated it, but no
           w a few drops in a dish or pot are just right if I want heat without changing flavor much.
           _____
 In [261]: # 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)
           We have used the Victor fly bait for 3 seasons. Can't beat it. Great product!
 In [262]: | # https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all-tags-from-an-element
           from bs4 import BeautifulSoup
           soup = BeautifulSoup(sent_0, 'lxml')
           text = soup.get_text()
           print(text)
           print("="*50)
           soup = BeautifulSoup(sent_1000, 'lxml')
           text = soup.get_text()
           print(text)
           print("="*50)
           soup = BeautifulSoup(sent_1500, 'lxml')
           text = soup.get_text()
           print(text)
           print("="*50)
           soup = BeautifulSoup(sent_4900, 'lxml')
           text = soup.get_text()
           print(text)
           We have used the Victor fly bait for 3 seasons. Can't beat it. Great product!
           _____
           I received this box with great anticipation since they don't sell these on the west coast. I got the package, opened the box and was EXTREMELY disappointed. The cookies looked like a gorilla shook the box to death and left most of the box filled with crumbs. AND THERE WAS A RODENT SIZED HOLE ON THE SIDE OF THE BOX!!!!!!! So, needless to say I will not NOT be reordering these agai
           I have two cats. My big boy has eaten these and never had a problem...as a matter of fact he has never vomited or had a hair ball since I adopted him at 2 months. My girl sick so I just recommend you watch your cats after you give them these trea
           ts. If not a problem...carry on.
           I was always a fan of Dave's, so I bought this at a local store to try Blair's and I'm glad I did. The jalepeno sause is very mild (for me) but one of the most delicious condiments I've ever tasted. The Sudden Death kicked my ass when I underestimated it, but no
           w a few drops in a dish or pot are just right if I want heat without changing flavor much.
 In [263]: # https://stackoverflow.com/a/47091490/4084039
            import re
           def decontracted(phrase):
               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 [264]: sent_1500 = decontracted(sent_1500)
           print(sent_1500)
           print("="*50)
           I have two cats. My big boy has eaten these and never had a problem...as a matter of fact he has never vomited or had a hair ball since I adopted him at 2 months. My girl sick so I just recommend you watch your cats after you give them these trea
           ts. If not a problem...carry on.
           _____
  In [265]: #remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
            sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
           |print(sent_0)
           We have used the Victor fly bait for seasons. Can't beat it. Great product!
  In [266]: #remove spacial character: https://stackoverflow.com/a/5843547/4084039
            sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
           print(sent_1500)
           I have two cats My big boy has eaten these and never had a problem as a matter of fact he has never vomited or had a hair ball since I adopted him at 2 months My girl sick so I just recommend you watch your cats after you give them these treats If
           not a problem carry on
 In [267]: # 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', 'ourselves', 'you', "you're", "you've",
                       "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his', 'himself', \
                       'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them', 'their',\
                       'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll", 'these', 'those', \
                       'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having', 'do', 'does', \
                       'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'until', 'while', 'of', \
                       'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'during', 'before', 'after',\
                       'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under', 'again', 'further',\
                       'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'each', 'few', 'more',\
                       'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too', 'very', \
                       's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now', 'd', 'll', 'm', 'o', 're', \
                       've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't", 'doesn', "doesn't", 'hadn',
                       "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn', "mightn't", 'mustn',\
                       "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn', "wasn't", 'weren', "weren't", \
                       'won', "won't", 'wouldn', "wouldn't"])
  In [268]: # Combining all the above stundents
           from tqdm import tqdm
           preprocessed_reviews = []
           # tqdm is for printing the status bar
           for sentance in tqdm(final['Text'].values):
               sentance = re.sub(r"http\S+", "", sentance)
               sentance = BeautifulSoup(sentance, 'lxml').get_text()
               sentance = decontracted(sentance)
               sentance = re.sub("\S*\d\S*", "", sentance).strip()
               sentance = re.sub('[^A-Za-z]+', ' ', sentance)
               # https://gist.github.com/sebleier/554280
               sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in stopwords)
               preprocessed_reviews.append(sentance.strip())
                                                                                   | 19354/19354 [00:08<00:00, 2203.93it/s]
 In [269]: preprocessed_reviews[1500]
  Out[269]: 'two cats big boy eaten never problem matter fact never vomited hair ball since adopted months girl cat throws every time eats particular flavor since treat equally no longer purchased hate see girl sick recommend watch cats give treats not problem carry'
[3.2] Preprocessing Review Summary
 In [270]: X = preprocessed_reviews
           Y = final['Score']
 In [271]: from sklearn.cross_validation import train_test_split
           X_1 , X_test , Y_1 , Y_test = train_test_split(X,Y,test_size=0.3,random_state=0)
           X_tr , X_cv , Y_tr , Y_cv = train_test_split(X_1,Y_1,test_size=0.3,random_state=0)
 In [272]: | ## Similartly you can do preprocessing for review summary also.
[4] Featurization
[4.1] BAG OF WORDS
 In [273]: ##BoW
           count_vect = CountVectorizer( min_df=20, max_df=50) #in scikit-learn
           count_vect.fit(X_tr)
           print("some feature names ", count_vect.get_feature_names()[:10])
           print('='*50)
           X_Bow_Tr = count_vect.transform(X_tr)
           X_Bow_Cv = count_vect.transform(X_cv)
           X_Bow_Test = count_vect.transform(X_test)
           print("the type of count vectorizer ",type(X_Bow_Tr))
           print("the shape of out text BOW vectorizer ",X_Bow_Tr.get_shape())
           print("the number of unique words ", X_Bow_Tr.get_shape()[1])
           some feature names ['absolute', 'according', 'acidic', 'active', 'actual', 'addictive', 'additives', 'adult', 'adults', 'afford']
           the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
           the shape of out text BOW vectorizer (9482, 1119)
           the number of unique words 1119
  In [274]: Bow_Feature = count_vect.get_feature_names()
           X_Bow_Tr = X_Bow_Tr.toarray()
           X_Bow_Cv = X_Bow_Cv.toarray()
           X_Bow_Test = X_Bow_Test.toarray()
```

```
In [275]: tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=20, max_df=50)
               tf_idf_vect.fit(X_tr)
               print("some sample features(unique words in the corpus)",tf_idf_vect.get_feature_names()[0:10])
               X_Tfidf_Tr = tf_idf_vect.transform(X_tr)
               X_Tfidf_Cv = tf_idf_vect.transform(X_cv)
               X_Tfidf_Test = tf_idf_vect.transform(X_test)
               print("the type of count vectorizer ",type(X_Tfidf_Tr))
               print("the shape of out text TFIDF vectorizer ",X_Tfidf_Tr.get_shape())
               print("the number of unique words including both unigrams and bigrams ", X_Tfidf_Tr.get_shape()[1])
               some sample features(unique words in the corpus) ['able find', 'able get', 'absolute', 'absolutely delicious', 'absolutely loves', 'according', 'acidic', 'active', 'actual', 'add little']
               -----
               the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
               the shape of out text TFIDF vectorizer (9482, 1760)
               the number of unique words including both unigrams and bigrams 1760
  In [276]: X_Tfidf_Tr = X_Tfidf_Tr.toarray()
               X_Tfidf_Cv = X_Tfidf_Cv.toarray()
               X_Tfidf_Test = X_Tfidf_Test.toarray()
               tf_idf_feature = tf_idf_vect.get_feature_names()
[4.4] Word2Vec
  In [277]: # Train your own Word2Vec model using your own text corpus
               list_of_sentance=[]
               for sentance in preprocessed_reviews:
                   list_of_sentance.append(sentance.split())
  In [278]: # Using Google News Word2Vectors
               # in this project we are using a pretrained model by google
               # its 3.3G file, once you load this into your memory
               # it occupies ~9Gb, so please do this step only if you have >12G of ram
               # we will provide a pickle file wich contains a dict ,
               # and it contains all our courpus words as keys and model[word] as values
               # To use this code-snippet, download "GoogleNews-vectors-negative300.bin"
               # from https://drive.google.com/file/d/0B7XkCwpI5KDYNLNUTTLSS21pQmM/edit
               # it's 1.9GB in size.
               # http://kavita-ganesan.com/gensim-word2vec-tutorial-starter-code/#.W17SRFAzZPY
               # you can comment this whole cell
               # or change these varible according to your need
               is_your_ram_gt_16g=False
               want_to_use_google_w2v = False
               want_to_train_w2v = True
               if want_to_train_w2v:
                    # min_count = 5 considers only words that occurred atleast 5 times
                    w2v_model=Word2Vec(list_of_sentance,min_count=5,size=50, workers=4)
                    print(w2v_model.wv.most_similar('great'))
                    print('='*50)
                    print(w2v_model.wv.most_similar('worst'))
               elif want_to_use_google_w2v and is_your_ram_gt_16g:
                   if os.path.isfile('GoogleNews-vectors-negative300.bin'):
                         w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors-negative300.bin', binary=True)
                         print(w2v_model.wv.most_similar('great'))
                         print(w2v_model.wv.most_similar('worst'))
                         print("you don't have gogole's word2vec file, keep want_to_train_w2v = True, to train your own w2v ")
               [('awesome', 0.8423455953598022), ('good', 0.8371583223342896), ('fantastic', 0.8326070308685303), ('excellent', 0.7345545887947083), ('delicious', 0.7005295753479004), ('perfect', 0.694447934627533), ('especially', 0.6708776950836182)]
               [('closest', 0.8194966316223145), ('personal', 0.8029736280441284), ('disappointing', 0.7647767663002014)] ('closest', 0.8194966316223145), ('fav', 0.7664926052093506), ('bye', 0.7653446197509766), ('quenching', 0.7647767663002014)]
  In [279]: 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 8370
               sample words ['used', 'fly', 'bait', 'seasons', 'ca', 'not', 'beat', 'great', 'product', 'available', 'traps', 'course', 'total', 'made', 'two', 'thumbs', 'received', 'shipment', 'could', 'hardly', 'wait', 'try', 'love', 'call', 'instead',
               'stickers', 'removed', 'easily', 'daughter', 'designed', 'signs', 'printed', 'reverse', 'windows', 'beautifully']
[4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V
[4.4.1.1] Avg W2v
  In [353]: | # average Word2Vec
               # compute average word2vec for each review.
               def getAvgWordToVector(list_of_sentance):
                    sent_vectors = []; # the avg-w2v for each sentence/review is stored in this list
                    for sentence in list_of_sentance: # for each review/sentence
                        sent = sentence.split()
                         sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need to change this to 300 if you use google's w2v
                         cnt_words =0; # num of words with a valid vector in the sentence/review
                         for word in sent: # for each word in a review/sentence
                             if word in w2v_words:
                                  vec = w2v_model.wv[word]
                                  sent_vec += vec
                                  cnt_words += 1
                         if cnt_words != 0:
                              sent_vec /= cnt_words
                         sent_vectors.append(sent_vec)
                    return sent_vectors
  In [354]: | X_AvgW2V_Tr = getAvgWordToVector(X_tr)
               X_AvgW2V_Cv = getAvgWordToVector(X_cv)
               X_AvgW2V_Test = getAvgWordToVector(X_test)
  In [360]: X_AvgW2V_Tr = np.array(X_AvgW2V_Tr)
               X_AvgW2V_Cv = np.array(X_AvgW2V_Cv)
               X_AvgW2V_Test = np.array(X_AvgW2V_Test)
[4.4.1.2] TFIDF weighted W2v
  In [282]: # S = ["abc def pqr", "def def def abc", "pqr pqr def"]
                model = TfidfVectorizer()
               tf_idf_matrix = model.fit_transform(preprocessed_reviews)
               # we are converting a dictionary with word as a key, and the idf as a value
               dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
  In [283]: # 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
               def getAvgW2VtfIdfToVector(list_of_sentance):
                   tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this list
                    for sentence in list_of_sentance: # for each review/sentence
                         sent_vec = np.zeros(50) # as word vectors are of zero length
                         weight_sum =0; # num of words with a valid vector in the sentence/review
                         sent = sentence.split()
                         for word in sent: # for each word in a review/sentence3
                              if word in w2v_words and word in tfidf_feat:
                                  vec = w2v_model.wv[word]
                                  #tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
                                  # to reduce the computation we are
                                  # dictionary[word] = idf value of word in whole courpus
                                  # sent.count(word) = tf valeus of word in this review
                                  tf_idf = dictionary[word]*(sent.count(word)/len(sent))
                                  sent_vec += (vec * tf_idf)
                                  weight_sum += tf_idf
                        if weight_sum != 0:
                              sent vec /= weight sum
                         tfidf_sent_vectors.append(sent_vec)
                         row += 1
                    return tfidf_sent_vectors
  In [284]: X_AvgW2VtfIdf_Tr = getAvgW2VtfIdfToVector(X_tr)
               X_AvgW2VtfIdf_Cv = getAvgW2VtfIdfToVector(X_cv)
               X_AvgW2VtfIdf_Test = getAvgW2VtfIdfToVector(X_test)
  In [367]: X_AvgW2VtfIdf_Tr = np.array(X_AvgW2VtfIdf_Tr)
               X_AvgW2VtfIdf_Cv = np.array(X_AvgW2VtfIdf_Cv)
               X_AvgW2VtfIdf_Test = np.array(X_AvgW2VtfIdf_Test)
[5] Assignment 9: Random Forests
  1. Apply Random Forests & GBDT on these feature sets
      • SET 1:Review text, preprocessed one converted into vectors using (BOW)
      • SET 2:Review text, preprocessed one converted into vectors using (TFIDF)
      • SET 3:Review text, preprocessed one converted into vectors using (AVG W2v)
      • SET 4:Review text, preprocessed one converted into vectors using (TFIDF W2v)
  2. The hyper paramter tuning (Consider two hyperparameters: n_estimators & max_depth)
      • Find the best hyper parameter which will give the maximum AUC (https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/receiver-operating-characteristic-curve-roc-curve-and-auc-1/) value
      • Find the best hyper paramter using k-fold cross validation or simple cross validation data
      • Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this task of hyperparameter tuning
  3. Feature importance
      • Get top 20 important features and represent them in a word cloud. Do this for BOW & TFIDF.
  4. Feature engineering
      • To increase the performance of your model, you can also experiment with with feature engineering like :

    Taking length of reviews as another feature.

    Considering some features from review summary as well.

  5. Representation of results
      • You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure
        with X-axis as n_estimators, Y-axis as max_depth, and Z-axis as AUC Score, we have given the notebook which explains how to plot this 3d plot, you can find it in the same drive 3d_scatter_plot.ipynb
                                                                                                                                                                                                                                          (or)
      • You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure
        seaborn heat maps (https://seaborn.pydata.org/generated/seaborn.heatmap.html) with rows as n_estimators, columns as max_depth, and values inside the cell representing AUC Score

    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 find the AUC on test data and plot the ROC curve on both train and test.
                                                                                                                                                                                                                       Along with plotting ROC curve, you need to print the confusion matrix (https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/confusion-matrix-tpr-fpr-fnr-tnr-1/) with predicted and original labels of test data points. Please visualize your
        confusion matrices using seaborn heatmaps.
                                                                                                                                                                                                                       (https://seaborn.pydata.org/generated/seaborn.heatmap.html)
         (https://seaborn.pydata.org/generated/seaborn.heatmap.html)
     (https://seaborn.pydata.org/generated/seaborn.heatmap.html)
     (https://seaborn.pydata.org/generated/seaborn.heatmap.html)
  6. <u>Conclusion (https://seaborn.pydata.org/generated/seaborn.heatmap.html)</u>
        (https://seaborn.pydata.org/generated/seaborn.heatmap.html)
      • You need to summarize the results at the end of the notebook, summarize it in the table format. To print out a table please refer to this prettytable library (https://seaborn.pydata.org/generated/seaborn.heatmap.html) link (http://zetcode.com/python/prettytable/)
Note: Data Leakage
  1. There will be an issue of data-leakage if you vectorize the entire data and then split it into train/cv/test.
  2. To avoid the issue of data-leakag, make sure to split your data first and then vectorize it.
  3. While vectorizing your data, apply the method fit_transform() on you train data, and apply the method transform() on cv/test data.
  4. For more details please go through this <a href="mailto:link">link</a>. (<a href="https://soundcloud.com/applied-ai-course/leakage-bow-and-tfidf">link</a>. (<a href="https://soundcloud.com/applied-ai-course/leakage-bow-and-tfidf">https://soundcloud.com/applied-ai-course/leakage-bow-and-tfidf</a>. (<a href="https://soundcloud.com/applied-ai-course/leakage-bow-and-tfidf">https://soundcloud.com/applied-ai-course/leakage-bow-and-tfidf</a>. (<a href="https://soundcloud.com/applied-ai-course/leakage-bow-and-tfidf">https://soundcloud.com/applied-ai-course/leakage-bow-and-tfidf</a>. (<a href="https://soundcloud.com/applied-ai-course/leakage-bow-and-tfidf">https://soundcloud.com/applied-ai-course/le
[5.1] Applying RF
[5.1.1] Applying Random Forests on BOW, SET 1
  In [294]: from sklearn.ensemble import RandomForestClassifier
```

from sklearn.model selection import GridSearchCV

from sklearn.metrics import roc_curve, auc, roc_auc_score ,accuracy_score

from wordcloud import WordCloud

'n_estimators':[50,200,300,400], 'max_depth' : [3,5,7,10,12]

In [286]: params = {

```
In [287]: #https://www.datascience.com/resources/notebooks/random-forest-intro
            rf = RandomForestClassifier(criterion='gini', class_weight = "balanced")
           cv_rf = GridSearchCV(rf, cv = 10,param_grid=params,n_jobs = -1,scoring='roc_auc')
           cv_rf.fit(X_Bow_Cv, Y_cv)
           print('Best Parameters using grid search: \n',cv_rf.best_params_,"\n\n")
           Set1_Cv_Results = pd.DataFrame(cv_rf.cv_results_)[['mean_test_score', 'std_test_score', 'params']]
           print(Set1_Cv_Results)
           Best Parameters using grid search:
            {'max_depth': 10, 'n_estimators': 400}
               mean_test_score std_test_score
                                    0.025207 {'max_depth': 3, 'n_estimators': 50}
                      0.643441
                                    0.045558 {'max_depth': 3, 'n_estimators': 200}
                      0.695084
                                    0.039055 {'max_depth': 3, 'n_estimators': 300}
                     0.697472
                     0.697018
                                    0.044071 {'max_depth': 3, 'n_estimators': 400}
                     0.654929
                                    0.047565 {'max_depth': 5, 'n_estimators': 50}
                     0.696370
                                    0.034670 {'max_depth': 5, 'n_estimators': 200}
                     0.712885
                                    0.031875 {'max_depth': 5, 'n_estimators': 300}
                     0.715732
                                    0.027767 {'max_depth': 5, 'n_estimators': 400}
                     0.671349
                                    0.042850 {'max_depth': 7, 'n_estimators': 50}
                     0.701873
                                    0.037003 {'max_depth': 7, 'n_estimators': 200}
                                    0.047620 {'max_depth': 7, 'n_estimators': 300}
                     0.707175
                                    0.048585 {'max_depth': 7, 'n_estimators': 400}
                     0.707066
                     0.670914
                                    0.039886 {'max_depth': 10, 'n_estimators': 50}
                                    0.039936 {'max_depth': 10, 'n_estimators': 200}
                     0.716249
                     0.713800
                                    0.049178 {'max_depth': 10, 'n_estimators': 300}
                                    0.043703 {'max_depth': 10, 'n_estimators': 400}
                     0.717288
                                    0.039014 {'max_depth': 12, 'n_estimators': 50}
                                    0.038559 {'max_depth': 12, 'n_estimators': 200}
                     0.715042
                     0.712701
                                    0.040021 {'max_depth': 12, 'n_estimators': 300}
           19
                     0.717282
                                    0.031615 {'max_depth': 12, 'n_estimators': 400}
 In [288]: #examine the best model
           print("\t best_score_ :",cv_rf.best_score_)
           print("\t best_params_ :",cv_rf.best_params_)
           #print(" best_estimator_ :",cv_rf.best_estimator_)
           Set1_best = cv_rf.best_params_
           Set1_best_max_depth = cv_rf.best_params_['max_depth']
           Set1_best_estimator = cv_rf.best_params_['n_estimators']
           Set1_Cv_AUC = cv_rf.best_score_
                    best_score_ : 0.71728791847956
                    best_params_ : {'max_depth': 10, 'n_estimators': 400}
 In [289]: Set1_Weights = []
           rf = RandomForestClassifier(criterion='gini',max_depth = Set1_best_max_depth,n_estimators = Set1_best_estimator,class_weight = "balanced")
           rf.fit(X_Bow_Tr,Y_tr)
           Set1_Weights = rf.feature_importances_.tolist()
 In [290]: | #https://qiita.com/bmj0114/items/460424c110a8ce22d945
            Set1_Tr_prob = rf.predict_proba(X_Bow_Tr) # Probablity of TRAIN-Validation
           Set1_Tst_prob = rf.predict_proba(X_Bow_Test) # Probablity of Cross-Validation
           set1_tst_fpr, set1_tst_tpr, thresholds = roc_curve(Y_test,Set1_Tst_prob[:,1])
           set1_tst_roc_auc = auc(set1_tst_fpr, set1_tst_tpr)
           set1_train_fpr, set1_train_tpr, thresholds = roc_curve(Y_tr,Set1_Tr_prob[:,1])
           set1_train_roc_auc = auc(set1_train_fpr, set1_train_tpr)
           print(" Test Validaton AUC for the BEst Lamda is ", set1_tst_roc_auc)
           plt.figure()
           plt.plot(set1_tst_fpr, set1_tst_tpr, color='darkorange', lw=3, label='Test ROC curve (area = %0.2f)' % set1_tst_roc_auc)
           plt.plot(set1_train_fpr, set1_train_tpr, color='navy', lw=1, label='Train ROC curve (area = %0.2f)' % set1_train_roc_auc)
           plt.plot([0, 1], [0,1], color='red', lw=lw, linestyle='--')
           plt.xlim([0.0, 1.0])
           plt.ylim([0.0, 1.04])
           plt.xlabel('False Positive Rate')
           plt.ylabel('True Positive Rate')
           plt.title('ROC - Receiver operating characteristic')
           plt.legend(loc="lower right")
           plt.show()
            Train Data AUC for the Best Lamda is 0.834293209760876
            Test Validaton AUC for the BEst Lamda is 0.7409527746577063
                       ROC - Receiver operating characteristic
                                   Test ROC curve (area = 0.74)
                                   — Train ROC curve (area = 0.83)
                0.0
                                        0.6
                                                 0.8
                                False Positive Rate
[5.1.2] Wordcloud of top 20 important features from SET 1
 In [291]: # Top Important features
           set1_Imp_Features=pd.DataFrame([Bow_Feature,Set1_Weights],index=['feature','Decision_Imp']).T
           #set1_Imp_Features= set1_Imp_Features[(set1_Imp_Features['Decision_Imp']>0)]
           set1_Imp_Features_sortd = set1_Imp_Features.sort_values(by='Decision_Imp')[-20:][::-1]
  In [292]: | #wordcloud = WordCloud(width = 800, height = 800,background_color ='white',min_font_size = 10).generate(set1_Imp_Features_sortd)
            #text = .tolist()
            import matplotlib.pyplot as plt
           wordcloud = WordCloud(width = 2000, height = 800).generate(' '.join(set1_Imp_Features_sortd['feature']))
           #plot the WordCloud image figsize = (8,8), facecolor = None )
           plt.figure(figsize = (20, 5), facecolor = None)
           plt.imshow(wordcloud, interpolation='bilinear')
           plt.axis("off")
           plt.tight_layout(pad = 0)
           plt.show() # Please write all the code with proper documentation
                    poormistakedisappointing
 In [295]: set1_Tst_Pred = rf.predict(X_Bow_Test)
            set1_Tr_Pred = rf.predict(X_Bow_Tr)
           set1_Tr_Acc = accuracy_score(Y_tr,set1_Tr_Pred,normalize=True)
           set1_Tst_Acc = accuracy_score(Y_test,set1_Tst_Pred,normalize=True)
           print("\n\tAccuracy for Train Data : ",set1_Tr_Acc)
           print("\tAccuracy for Test Data : ",set1_Tst_Acc)
                   Accuracy for Train Data : 0.8830415524151023
                   Accuracy for Test Data : 0.8367487515068022
Train Confusion Matrix
 In [296]: print("\nTrain Accuracy ::",set1_Tr_Acc)
            Train_CM= confusion_matrix(Y_tr, set1_Tr_Pred, labels=None, sample_weight=None)
           print("Confusion Matrix::\n",Train_CM,"\n")
           plt.imshow(Train_CM, cmap='binary')
           sns.heatmap(Train_CM, cmap="YlGnBu", fmt="d" ,annot=True,annot_kws={"size": 17})
           plt.xlabel('Predicted label')
           plt.ylabel('True label')
           Train Accuracy :: 0.8830415524151023
           Confusion Matrix::
            [[ 666 827]
             [ 282 7707]]
 Out[296]: Text(83.4,0.5,'True label')
                                  827
                                               - 6000
                     282
                                               - 1500
                         Predicted label
Test Confusion Matrix
 In [297]: print("\nTest Accuracy ::",set1_Tst_Acc)
            Test_CM= confusion_matrix(Y_test, set1_Tst_Pred, labels=None, sample_weight=None)
           print("\n\nConfusion Matrix::\n",Test_CM,"\n")
           sns.heatmap(Test_CM, cmap="YlGnBu", fmt="d" ,annot=True,annot_kws={"size": 17})
           plt.xlabel('Predicted label')
           plt.ylabel('True label')
           Test Accuracy :: 0.8367487515068022
           Confusion Matrix::
             [ 379 4529]]
 Out[297]: Text(33,0.5,'True label')
                                       569
 In [299]: Total_AUC = {}
 In [301]: Total_AUC['set1']=[Set1_best , set1_tst_roc_auc , set1_Tst_Acc]
```

```
In [302]: # Please write all the code with proper documentation
            #https://www.datascience.com/resources/notebooks/random-forest-intro
            rf = RandomForestClassifier(criterion='gini', class_weight = "balanced")
            cv_rf = GridSearchCV(rf, cv = 10,param_grid=params,n_jobs = -1,scoring='roc_auc')
            cv_rf.fit(X_Tfidf_Cv, Y_cv)
            print('Best Parameters using grid search: \n',cv_rf.best_params_,"\n\n")
            set2_Cv_Results = pd.DataFrame(cv_rf.cv_results_)[['mean_test_score', 'std_test_score', 'params']]
            print(set2_Cv_Results)
            Best Parameters using grid search:
             {'max_depth': 7, 'n_estimators': 400}
                mean_test_score std_test_score
                      0.662213
                                     0.047307 {'max_depth': 3, 'n_estimators': 50}
                      0.735209
                                     0.045516 {'max_depth': 3, 'n_estimators': 200}
                      0.735797
                                    0.040532 {'max_depth': 3, 'n_estimators': 300}
                                    0.028849 {'max_depth': 3, 'n_estimators': 400}
                      0.744562
                      0.691272
                                    0.040558 {'max_depth': 5, 'n_estimators': 50}
                                    0.031082 {'max_depth': 5, 'n_estimators': 200}
                      0.748971
                      0.746537
                                    0.041614 {'max_depth': 5, 'n_estimators': 300}
                      0.753043
                                    0.043247 {'max_depth': 5, 'n_estimators': 400}
                      0.694922
                                    0.039421 {'max_depth': 7, 'n_estimators': 50}
                                    0.041287 {'max_depth': 7, 'n_estimators': 200}
                      0.744150
                      0.746680
                                    0.026723 {'max_depth': 7, 'n_estimators': 300}
                      0.757011
                                    0.036303 {'max_depth': 7, 'n_estimators': 400}
                      0.709144
                                    0.034387 {'max_depth': 10, 'n_estimators': 50}
                      0.736842
                                    0.029193 {'max_depth': 10, 'n_estimators': 200}
                      0.750815
                                    0.026400 {'max_depth': 10, 'n_estimators': 300}
                                    0.031484 {'max_depth': 10, 'n_estimators': 400}
                      0.754055
                      0.707134
                                     0.035376 {'max_depth': 12, 'n_estimators': 50}
                      0.750006
                                     0.037386 {'max_depth': 12, 'n_estimators': 200}
                      0.753781
                                     0.024363 {'max_depth': 12, 'n_estimators': 300}
            19
                      0.756736
                                     0.035124 {'max_depth': 12, 'n_estimators': 400}
  In [303]: #examine the best model
            print("\t best_score_ :",cv_rf.best_score_)
            print("\t best_params_ :",cv_rf.best_params_)
            #print(" best_estimator_ :",cv_rf.best_estimator_)
            set2_best = cv_rf.best_params_
            set2_best_max_depth = cv_rf.best_params_['max_depth']
            set2_best_estimator = cv_rf.best_params_['n_estimators']
            set2_Cv_AUC = cv_rf.best_score_
                     best_score_ : 0.7570108882707602
                    best_params_ : {'max_depth': 7, 'n_estimators': 400}
 In [304]: set2_Weights = []
            rf = RandomForestClassifier(criterion='gini',max_depth = set2_best_max_depth,n_estimators = set2_best_estimator,class_weight = "balanced")
            rf.fit(X_Tfidf_Tr,Y_tr)
            set2_Weights = rf.feature_importances_.tolist()
  In [305]: | #https://qiita.com/bmj0114/items/460424c110a8ce22d945
            set2_Tr_prob = rf.predict_proba(X_Tfidf_Tr) # Probablity of TRAIN-Validation
            set2_Tst_prob = rf.predict_proba(X_Tfidf_Test) # Probablity of Cross-Validation
            set2_tst_fpr, set2_tst_tpr, thresholds = roc_curve(Y_test,set2_Tst_prob[:,1])
            set2_tst_roc_auc = auc(set2_tst_fpr, set2_tst_tpr)
            set2_train_fpr, set2_train_tpr, thresholds = roc_curve(Y_tr,set2_Tr_prob[:,1])
            set2_train_roc_auc = auc(set2_train_fpr, set2_train_tpr)
            print(" Test Validaton AUC for the BEst Lamda is ", set2_tst_roc_auc)
            1w=1
            plt.figure()
            plt.plot(set2_tst_fpr, set2_tst_tpr, color='darkorange', lw=3, label='Test ROC curve (area = %0.2f)' % set2_tst_roc_auc)
            plt.plot(set2_train_fpr, set2_train_tpr, color='navy', lw=1, label='Train ROC curve (area = %0.2f)' % set2_train_roc_auc)
            plt.plot([0, 1], [0,1], color='red', lw=lw, linestyle='--')
            plt.xlim([0.0, 1.0])
            plt.ylim([0.0, 1.04])
            plt.xlabel('False Positive Rate')
            plt.ylabel('True Positive Rate')
            plt.title('ROC - Receiver operating characteristic')
            plt.legend(loc="lower right")
            plt.show()
             Train Data AUC for the Best Lamda is 0.8669396139718906
             Test Validaton AUC for the BEst Lamda is 0.7799772771158391
                       ROC - Receiver operating characteristic
                                   Test ROC curve (area = 0.78)
                                   --- Train ROC curve (area = 0.87)
                                                0.8
                         0.2
                                0.4 0.6
                0.0
                                False Positive Rate
[5.1.4] Wordcloud of top 20 important features from SET 2
 In [306]: # Top Important features
            set2_Imp_Features=pd.DataFrame([tf_idf_feature,set2_Weights],index=['feature','Decision_Imp']).T
            #set2_Imp_Features= set2_Imp_Features[(set2_Imp_Features['Decision_Imp']>0)]
            set2_Imp_Features_sortd = set2_Imp_Features.sort_values(by='Decision_Imp')[-20:][::-1]
            set2_Imp_Features_sortd
 Out[306]:
                        feature Decision_Imp
             1679 waste money
                              0.0428325
            398 disappointing
                               0.0319496
             1282 refund
                               0.0319321
                               0.0288037
             135 beware
             1566 threw
                               0.0287607
             1075 nothing like
                                0.024663
            403 disgusting
                                0.0189419
             1056 not purchase
                                .0187356
             367 definitely not
                                0.0180357
             1180 poor
                               0.0178736
             1069 not waste
                               0.0177539
             399 disappointment 0.0174419
             1658 vomiting
                               0.0164105
             990 never buy
                              0.0155283
             389 died
                               0.0141417
             892 made china
                               0.0136379
             1600 trash
                               0.0127151
             1185 positive
                               0.012324
             1324 sadly
                               0.0118478
             1461 stay away
                               0.0117262
 In [307]: | #wordcloud = WordCloud(width = 800, height = 800,background_color ='white',min_font_size = 10).generate(set2_Imp_Features_sortd)
            #text = .tolist()
            import matplotlib.pyplot as plt
            wordcloud = WordCloud(width = 2000, height = 800).generate(' '.join(set2_Imp_Features_sortd['feature']))
            #plot the WordCloud image figsize = (8,8), facecolor = None
            plt.figure(figsize = (20, 5), facecolor = None)
            plt.imshow(wordcloud, interpolation='bilinear')
            plt.axis("off")
            plt.tight_layout(pad = 0)
            plt.show() # Please write all the code with proper documentation
 In [308]: # Please write all the code with proper documentation
[5.1.5] Applying Random Forests on AVG W2V, SET 3
 In [309]: | #https://www.datascience.com/resources/notebooks/random-forest-intro
            rf = RandomForestClassifier(criterion='gini', class_weight = "balanced")
            cv_rf = GridSearchCV(rf, cv = 10,param_grid=params,n_jobs = -1,scoring='roc_auc')
            cv_rf.fit(X_AvgW2V_Cv, Y_cv)
            print('Best Parameters using grid search: \n',cv_rf.best_params_,"\n\n")
            set3_Cv_Results = pd.DataFrame(cv_rf.cv_results_)[['mean_test_score', 'std_test_score', 'params']]
            print(set3_Cv_Results)
            Best Parameters using grid search:
             {'max_depth': 12, 'n_estimators': 400}
                mean_test_score std_test_score
                      0.836160
                                     0.023008
                                                 {'max_depth': 3, 'n_estimators': 50}
                      0.840573
                                     0.023082
                                                {'max_depth': 3, 'n_estimators': 200}
                      0.841936
                                     0.023063
                                                {'max_depth': 3, 'n_estimators': 300}
```

0.840683

0.853525

0.852137

0.855531

0.855585 0.858596

0.858525

0.857500

0.851358

0.859845 0.860273

0.860595

0.853554

0.860726

0.860837

0.861734

set3_best = cv_rf.best_params_

set3_Cv_AUC = cv_rf.best_score_

rf.fit(X_AvgW2V_Tr,Y_tr)

print("\t best_score_ :",cv_rf.best_score_)
print("\t best_params_ :",cv_rf.best_params_)
#print(" best_estimator_ :",cv_rf.best_estimator_)

set3_best_max_depth = cv_rf.best_params_['max_depth']
set3_best_estimator = cv_rf.best_params_['n_estimators']

best_score_ : 0.861733977932179

set3_Weights = rf.feature_importances_.tolist()

best_params_ : {'max_depth': 12, 'n_estimators': 400}

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In [310]: #examine the best model

In [311]: set3_Weights = []

0.026147

{'max_depth': 3, 'n_estimators': 400}

0.025923 {'max_depth': 5, 'n_estimators': 50}

0.024603 {'max_depth': 5, 'n_estimators': 200}

0.025501 {'max_depth': 5, 'n_estimators': 300} 0.024954 {'max_depth': 5, 'n_estimators': 400}

0.025981 {'max_depth': 7, 'n_estimators': 50}

0.025968 {'max_depth': 7, 'n_estimators': 200}

0.024750 {'max_depth': 7, 'n_estimators': 300}

0.027270 {'max_depth': 7, 'n_estimators': 400}
0.024602 {'max_depth': 10, 'n_estimators': 50}

0.025576 {'max_depth': 10, 'n_estimators': 200}

0.026159 {'max_depth': 10, 'n_estimators': 300}

0.027224 {'max_depth': 10, 'n_estimators': 400}

0.025247 {'max_depth': 12, 'n_estimators': 50}

0.027989 {'max_depth': 12, 'n_estimators': 200}

0.027059 {'max_depth': 12, 'n_estimators': 300}

0.025802 {'max_depth': 12, 'n_estimators': 400}

rf = RandomForestClassifier(criterion='gini',max_depth = set3_best_max_depth,n_estimators = set3_best_estimator,class_weight = "balanced")

```
In [312]: #https://qiita.com/bmj0114/items/460424c110a8ce22d945
           set3_Tr_prob = rf.predict_proba(X_AvgW2V_Tr) # Probablity of TRAIN-Validation
           set3_Tst_prob = rf.predict_proba(X_AvgW2V_Test) # Probablity of Cross-Validation
           set3_tst_fpr, set3_tst_tpr, thresholds = roc_curve(Y_test,set3_Tst_prob[:,1])
           set3_tst_roc_auc = auc(set3_tst_fpr, set3_tst_tpr)
           set3_train_fpr, set3_train_tpr, thresholds = roc_curve(Y_tr,set3_Tr_prob[:,1])
           set3_train_roc_auc = auc(set3_train_fpr, set3_train_tpr)
           print(" Test Validaton AUC for the BEst Lamda is ", set3_tst_roc_auc)
           plt.figure()
           plt.plot(set3_tst_fpr, set3_tst_tpr, color='darkorange', lw=3, label='Test ROC curve (area = %0.2f)' % set3_tst_roc_auc)
           plt.plot(set3_train_fpr, set3_train_tpr, color='navy', lw=1, label='Train ROC curve (area = %0.2f)' % set3_train_roc_auc)
           plt.plot([0, 1], [0,1], color='red', lw=lw, linestyle='--')
           plt.xlim([0.0, 1.0])
           plt.ylim([0.0, 1.04])
           plt.xlabel('False Positive Rate')
           plt.ylabel('True Positive Rate')
           plt.title('ROC - Receiver operating characteristic')
           plt.legend(loc="lower right")
           plt.show()
            Train Data AUC for the Best Lamda is 0.9945529171599563
            Test Validaton AUC for the BEst Lamda is 0.8600261496745908
                      ROC - Receiver operating characteristic
                                  Test ROC curve (area = 0.86)
                                  Train ROC curve (area = 0.99)
                                               0.8
               0.0
                                       0.6
                               False Positive Rate
[5.1.6] Applying Random Forests on TFIDF W2V, SET 4
 In [313]: #https://www.datascience.com/resources/notebooks/random-forest-intro
           rf = RandomForestClassifier(criterion='gini', class_weight = "balanced")
           cv_rf = GridSearchCV(rf, cv = 10,param_grid=params,n_jobs = -1,scoring='roc_auc')
           cv_rf.fit(X_AvgW2VtfIdf_Cv, Y_cv)
           print('Best Parameters using grid search: \n',cv_rf.best_params_,"\n\n")
           set4_Cv_Results = pd.DataFrame(cv_rf.cv_results_)[['mean_test_score', 'std_test_score', 'params']]
           print(set4_Cv_Results)
           Best Parameters using grid search:
            {'max_depth': 12, 'n_estimators': 400}
               mean_test_score std_test_score
                                   0.022725 {'max_depth': 3, 'n_estimators': 50}
                     0.807602
                     0.813968
                                   0.024227 {'max_depth': 3, 'n_estimators': 200}
                     0.815410
                                   0.021999 {'max_depth': 3, 'n_estimators': 300}
                                   0.022441 {'max_depth': 3, 'n_estimators': 400}
                     0.814543
                     0.820643
                                   0.025053 {'max_depth': 5, 'n_estimators': 50}
                     0.826128
                                   0.024330 {'max_depth': 5, 'n_estimators': 200}
                                   0.022612 {'max_depth': 5, 'n_estimators': 300}
                     0.825642
                                   0.024993 {'max_depth': 5, 'n_estimators': 400}
                     0.825571
                     0.825886
                                   0.026777 {'max_depth': 7, 'n_estimators': 50}
                     0.830532
                                   0.024474 {'max_depth': 7, 'n_estimators': 200}
                                   0.024073 {'max_depth': 7, 'n_estimators': 300}
                     0.827999
                     0.829130
                                   0.025798 {'max_depth': 7, 'n_estimators': 400}
                                   0.025285 {'max_depth': 10, 'n_estimators': 50}
                     0.820379
                     0.827539
                                   0.024124 {'max_depth': 10, 'n_estimators': 200}
                     0.832652
                                   0.023917 {'max_depth': 10, 'n_estimators': 300}
                                   0.023785 {'max_depth': 10, 'n_estimators': 400}
                     0.831062
                     0.825817
                                   0.028909 {'max_depth': 12, 'n_estimators': 50}
                     0.829274
                                   0.025613 {'max_depth': 12, 'n_estimators': 200}
                     0.831568
                                   0.024501 {'max_depth': 12, 'n_estimators': 300}
                     0.833066
                                   0.024335 {'max_depth': 12, 'n_estimators': 400}
 In [314]: #examine the best model
           print("\t best_score_ :",cv_rf.best_score_)
           print("\t best_params_ :",cv_rf.best_params_)
           #print(" best_estimator_ :",cv_rf.best_estimator_)
           set4_best = cv_rf.best_params_
           set4_best_max_depth = cv_rf.best_params_['max_depth']
           set4_best_estimator = cv_rf.best_params_['n_estimators']
           set4_Cv_AUC = cv_rf.best_score_
                    best_score_ : 0.8330661854986233
                    best_params_ : {'max_depth': 12, 'n_estimators': 400}
 In [315]: set4_Weights = []
           rf = RandomForestClassifier(criterion='gini',max_depth = set4_best_max_depth,n_estimators = set4_best_estimator,class_weight = "balanced")
           rf.fit(X_AvgW2VtfIdf_Tr,Y_tr)
           set4_Weights = rf.feature_importances_.tolist()
 In [316]: #https://qiita.com/bmj0114/items/460424c110a8ce22d945
           set4_Tr_prob = rf.predict_proba(X_AvgW2VtfIdf_Tr) # Probablity of TRAIN-Validation
           set4_Tst_prob = rf.predict_proba(X_AvgW2VtfIdf_Test) # Probablity of Cross-Validation
           set4_tst_fpr, set4_tst_tpr, thresholds = roc_curve(Y_test,set4_Tst_prob[:,1])
           set4_tst_roc_auc = auc(set4_tst_fpr, set4_tst_tpr)
           set4_train_fpr, set4_train_tpr, thresholds = roc_curve(Y_tr,set4_Tr_prob[:,1])
           set4_train_roc_auc = auc(set4_train_fpr, set4_train_tpr)
           print(" Test Validaton AUC for the BEst Lamda is ", set4_tst_roc_auc)
           plt.figure()
           plt.plot(set4_tst_fpr, set4_tst_tpr, color='darkorange', lw=3, label='Test ROC curve (area = %0.2f)' % set4_tst_roc_auc)
           plt.plot(set4_train_fpr, set4_train_tpr, color='navy', lw=1, label='Train ROC curve (area = %0.2f)' % set4_train_roc_auc)
           plt.plot([0, 1], [0,1], color='red', lw=lw, linestyle='--')
           plt.xlim([0.0, 1.0])
           plt.ylim([0.0, 1.04])
           plt.xlabel('False Positive Rate')
           plt.ylabel('True Positive Rate')
           plt.title('ROC - Receiver operating characteristic')
           plt.legend(loc="lower right")
           plt.show()
```

Train Data AUC for the Best Lamda is 0.9967385245134028
Test Validaton AUC for the BEst Lamda is 0.8402028922836476

Test ROC curve (area = 0.84)
Train ROC curve (area = 1.00)

ROC - Receiver operating characteristic

False Positive Rate