## **Amazon Fine Food Reviews Analysis**

Data Source: <a href="https://www.kaggle.com/snap/amazon-fine-food-reviews">https://www.kaggle.com/snap/amazon-fine-food-reviews</a>)

EDA: <a href="https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/">https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/</a> (<a href="https://nycdatascience.com/blog/student-works/">https://nycdatascience.com/blog/student-works/</a> (<a href="https://nycdatascien

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

#### Objective:

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

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

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

## [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".

```
In [0]: %matplotlib inline
        import warnings
        warnings.filterwarnings("ignore")
        import sqlite3
        import pandas as pd
        import numpy as np
        import nltk
        import string
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.model selection import train test split
        from sklearn.feature extraction.text import TfidfTransformer
        from sklearn.feature extraction.text import TfidfVectorizer
        from sklearn.feature extraction.text import CountVectorizer
        from sklearn.metrics import confusion matrix
        from sklearn import metrics
        from sklearn.metrics import roc curve, auc
        from nltk.stem.porter import PorterStemmer
        import re
        # Tutorial about Python regular expressions: https://pymotw.com/2/re/
        import string
        from nltk.corpus import stopwords
        from nltk.stem import PorterStemmer
        from nltk.stem.wordnet import WordNetLemmatizer
        from gensim.models import Word2Vec
        from gensim.models import KeyedVectors
        import pickle
        from tqdm import tqdm
        import os
        import prettytable
```

```
In [0]: #USER DEFINED FUNCTIONS

#changing reviews with score Less than 3 to be positive and vice-versa
def data_filter(filtered_data):
    actualScore = filtered_data['Score']
    positiveNegative = actualScore.map(partition)
    filtered_data['Score'] = positiveNegative
    return filtered_data["Score"]

# 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</pre>
```

```
In [0]: # Code to read csv file into colaboratory:
        !pip install -U -g PyDrive
        from pydrive.auth import GoogleAuth
        from pydrive.drive import GoogleDrive
        from google.colab import auth
        from oauth2client.client import GoogleCredentials
        # 1. Authenticate and create the PyDrive client.
        auth.authenticate user()
        gauth = GoogleAuth()
        gauth.credentials = GoogleCredentials.get_application_default()
        drive = GoogleDrive(gauth)
        #2. Get the file #Training Variants
        downloaded = drive.CreateFile({'id':'1PPCURbwWREuTo7ZgIt9MZv26tpsAp9Bs'}) # replace the id with id of file yo
        u want to access
        downloaded.GetContentFile('Reviews.csv')
        downloaded1 = drive.CreateFile({'id':'1PPC'}) # replace the id with id of file you want to access
        downloaded.GetContentFile('Reviews.csv')
        downloaded = drive.CreateFile({'id':'1PPCURbwWREuTo7ZgIt9MZv26tpsAp9Bs'}) # replace the id with id of file yo
        u want to access
        downloaded.GetContentFile('Reviews.csv')
        downloaded = drive.CreateFile({'id':'1PPCURbwWREuTo7ZgIt9MZv26tpsAp9Bs'}) # replace the id with id of file yo
        u want to access
        downloaded.GetContentFile('Reviews.csv')
        #3. Read file as panda dataframe
        import pandas as pd
        data = pd.read csv('Reviews.csv')
            100%
                                                    993kB 19.7MB/s
          Building wheel for PyDrive (setup.py) ... done
In [0]:
In [0]: data.head(20)
```

```
In [0]: #Converting from timestamp to datetime object.

from datetime import datetime
Time = []
for i in list(data["Time"]):
    Time.append(datetime.fromtimestamp(i).strftime('%d-%m-%Y'))

data["Time"] = pd.to_datetime(Time)
data = data.sort_values("Time")
```

In [0]: data.head(20)

#### Out[0]:

	ld	ProductId	Userld	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	
451855	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0	0	5	1999- 02-12	
230284	230285	B00004RYGX	A344SMIA5JECGM	Vincent P. Ross	1	2	5	1999- 06-12	
451877	451878	B00004CXX9	A344SMIA5JECGM	Vincent P. Ross	1	2	5	1999- 06-12	
374358	374359	B00004CI84	A344SMIA5JECGM	Vincent P. Ross	1	2	5	1999- 06-12	
150523	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0	5	1999- 08-10	
150500	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	2	5	1999- 10-25	This who
230268	230269	B00004RYGX	A1B2IZU1JLZA6	Wes	19	23	1	2000- 01-19	WARNII
374342	374343	B00004CI84	A1B2IZU1JLZA6	Wes	19	23	1	2000- 01-19	WARNII
451863	451864	B00004CXX9	A1B2IZU1JLZA6	Wes	19	23	1	2000- 01-19	WARNII

	ld	ProductId	Userld	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	
76881	76882	B00002N8SM	A32DW342WBJ6BX	Buttersugar	0	0	5	2000- 01-24	
451976	451977	B00004CXX9	ACJR7EQF9S6FP	Jeremy Robertson	2	3	4	2000- 02-26	Bettlejuice
374449	374450	B00004CI84	ACJR7EQF9S6FP	Jeremy Robertson	2	3	4	2000- 02-26	Bettlejuice
230375	230376	B00004RYGX	ACJR7EQF9S6FP	Jeremy Robertson	2	3	4	2000- 02-26	Bettlejuice
451854	451855	B00004CXX9	AJH6LUC1UT1ON	The Phantom of the Opera	0	0	5	2000- 03-01	
230325	230326	B00004RYGX	A2DEE7F9XKP3ZR	jerome	0	3	5	2000- 03-06	Resear
451902	451903	B00004CXX9	A2DEE7F9XKP3ZR	jerome	0	1	5	2000- 03-06	
374399	374400	B00004CI84	A2DEE7F9XKP3ZR	jerome	0	3	5	2000- 03-06	Resear

	ld	ProductId	Userld	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	
230333	230334	B00004RYGX	A1GB1Q193DNFGR	Bruce Lee Pullen	5	5	5	2000- 03-10	Fabulous
374407	374408	B00004CI84	A1GB1Q193DNFGR	Bruce Lee Pullen	5	5	5	2000- 03-10	Fabulous
451934	451935	B00004CXX9	A1GB1Q193DNFGR	Bruce Lee Pullen	5	5	5	2000- 03-10	Fabulous

```
In [0]: | # 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 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
        #Reading equal amount of positive and negative data.
        filtered data = data
        . . .
        filtered data 1 = data[data["Score"]>3][0:25000]
        filtered data 2 = data[data["Score"]<=2][0:25000]
        filtered data 1["Score"] = data filter(filtered data 1)
        filtered data 2["Score"] = data filter(filtered data 2)
        . . .
        # 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
        def data filter(filtered data):
            actualScore = filtered data['Score']
            positiveNegative = actualScore.map(partition)
            filtered data['Score'] = positiveNegative
            return filtered data["Score"]
        #print("Number of data points in our data", filtered data.shape)
        #filtered_data.head(3)
```

Out[0]: '\n# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a negative rating(0).\ndef pa rtition(x):\n if x < 3:\n return 0\n return 1\n\n#changing reviews with score less than 3 to be positive and vice-versa\n\ndef data\_filter(filtered\_data):\n actualScore = filtered\_data[\'Score\']\n p ositiveNegative = actualScore.map(partition) \n filtered\_data[\'Score\'] = positiveNegative\n return fi ltered\_data["Score"]\n\n#print("Number of data points in our data", filtered\_data.shape)\n#filtered\_data.he ad(3)\n'

```
In [0]:
In [0]:

"""

#Stacking both positive and negative data
filtered_data = filtered_data_1.append(filtered_data_2, ignore_index = True)

#Shuffling the data points to mix the data
from sklearn.utils import shuffle
filtered_data = shuffle(filtered_data)
"""
```

Out[0]: '\n#Stacking both positive and negative data\nfiltered\_data = filtered\_data\_1.append(filtered\_data\_2, ignore\_index = True)\n\n#Shuffling the data points to mix the data\nfrom sklearn.utils import shuffle\nfiltered\_data = shuffle(filtered\_data)\n'

```
In [0]: #Calling function partition
filtered_data["Score"] = filtered_data["Score"].map(partition)
```

In [0]: print("Number of data points in our data", filtered\_data.shape)
 filtered\_data.head()

Number of data points in our data (568454, 10)

#### Out[0]:

Summai	Time	Score	HelpfulnessDenominator	HelpfulnessNumerator	ProfileName	Userld	ProductId	ld	
Entertainin Funn	1999- 02-12	1	0	0	Elizabeth Medina	AIUWLEQ1ADEG5	B00004CXX9	451856	451855
A mode day fai ta	1999- 06-12	1	2	1	Vincent P. Ross	A344SMIA5JECGM	B00004RYGX	230285	230284
A mode day fai ta	1999- 06-12	1	2	1	Vincent P. Ross	A344SMIA5JECGM	B00004CXX9	451878	451877
A mode day fai ta	1999- 06-12	1	2	1	Vincent P. Ross	A344SMIA5JECGM	B00004CI84	374359	374358
EVER book education	1999- 08-10	1	0	0	shari zychinski	ACITT7DI6IDDL	0006641040	150524	150523

In [0]: | filtered\_data.reset\_index(drop = True)

#### Out[0]:

	ld	ProductId	Userld	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	
0	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0	0	1	1999- 02-12	
1	230285	B00004RYGX	A344SMIA5JECGM	Vincent P. Ross	1	2	1	1999- 06-12	
2	451878	B00004CXX9	A344SMIA5JECGM	Vincent P. Ross	1	2	1	1999- 06-12	
3	374359	B00004CI84	A344SMIA5JECGM	Vincent P. Ross	1	2	1	1999- 06-12	
4	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0	1	1999- 08-10	
5	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	2	1	1999- 10-25	This wh
6	3 230269	B00004RYGX	A1B2IZU1JLZA6	Wes	19	23	0	2000- 01-19	WARN
7	374343	B00004CI84	A1B2IZU1JLZA6	Wes	19	23	0	2000- 01-19	WARN
8	451864	B00004CXX9	A1B2IZU1JLZA6	Wes	19	23	0	2000- 01-19	WARN

	ld	ProductId	Userld	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	
9	76882	B00002N8SM	A32DW342WBJ6BX	Buttersugar	0	0	1	2000- 01-24	
10	451977	B00004CXX9	ACJR7EQF9S6FP	Jeremy Robertson	2	3	1	2000- 02-26	Bettlejuid
11	374450	B00004Cl84	ACJR7EQF9S6FP	Jeremy Robertson	2	3	1	2000- 02-26	Bettlejuic
12	230376	B00004RYGX	ACJR7EQF9S6FP	Jeremy Robertson	2	3	1	2000- 02-26	Bettlejuic
13	451855	B00004CXX9	AJH6LUC1UT1ON	The Phantom of the Opera	0	0	1	2000- 03-01	
14	230326	B00004RYGX	A2DEE7F9XKP3ZR	jerome	0	3	1	2000- 03-06	Resea
15	451903	B00004CXX9	A2DEE7F9XKP3ZR	jerome	0	1	1	2000- 03-06	
16	374400	B00004Cl84	A2DEE7F9XKP3ZR	jerome	0	3	1	2000- 03-06	Resea

	ld	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	
17	230334	B00004RYGX	A1GB1Q193DNFGR	Bruce Lee Pullen	5	5	1	2000- 03-10	Fabulo
18	374408	B00004CI84	A1GB1Q193DNFGR	Bruce Lee Pullen	5	5	1	2000- 03-10	Fabulo
19	451935	B00004CXX9	A1GB1Q193DNFGR	Bruce Lee Pullen	5	5	1	2000- 03-10	Fabulo
20	149768	B00004S1C5	A7P76IGRZZBFJ	E. Thompson "Soooooper Genius"	18	18	1	2000- 05-12	
21	1245	B00002Z754	A29Z5PI9BW2PU3	Robbie	7	7	1	2000- 06-23	
22	1244	B00002Z754	A3B8RCEI0FXFI6	B G Chase	10	10	1	2000- 06-29	١
23	131217	B00004RAMX	A5NQLNC6QPGSI	Kim Nason	7	8	1	2000- 07-31	
24	451948	B00004CXX9	A1FJOY14X3MUHE	Justin Howard	2	2	1	2000- 08-15	,
25	374421	B00004CI84	A1FJOY14X3MUHE	Justin Howard	2	2	1	2000- 08-15	1

	ld	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	
26	230347	B00004RYGX	A1FJOY14X3MUHE	Justin Howard	2	2	1	2000- 08-15	,
27	374422	B00004CI84	A1048CYU0OV4O8	Judy L. Eans	2	2	1	2000- 09-01	
28	230348	B00004RYGX	A1048CYU0OV4O8	Judy L. Eans	2	2	1	2000- 09-01	
29	451949	B00004CXX9	A1048CYU0OV4O8	Judy L. Eans	2	2	1	2000- 09-01	
568424	17883	B001EO653M	A3IGARBJ4SE9EQ	Arielle M.	0	0	1	2012- 12-10	C
568425	200504	B007PXI6CO	A1007OFJTJRYII	Jan	0	0	1	2012- 12-10	
568426	275087	B000FF3V06	A3EEJG97L9YIAB	Linda	0	0	1	2012- 12-10	
568427	566827	B001PQTYN2	AR4GVRPKO4MBL	ShahinX1	0	0	1	2012- 12-10	

	ld	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time
568428	201918	B009062AQW	ARUJ8B1HTISK0	Blondie	0	0	1	2012- 12-10
568429	201995	B000LQL9M6	AI2R6R7UP4NYB	Sparky	0	0	1	2012- 12-10
568430	549437	B004TGZRJA	A2GDTF5XZFVW2G	Kirk Henry "old school"	0	0	1	2012- 12-10
568431	513699	B000VK33C6	A3LRLNH9WJDQY6	Diane Milan	0	0	1	2012- 12-10
568432	203834	B000VK4CTO	A1V5J0VTEL8DS8	Peter	0	0	0	2012- 12-10
568433	377295	B004VLWASE	A36DVRTEHDJKNP	Steve	0	0	1	2012- 12-10
568434	330098	B001OHX1ZY	A88XJQH33JG01	maryann	0	0	1	2012- 12-10 b
568435	377319	B001IAQ8KC	AQO4BNFU7T4EH	Andrew P Freese	0	0	1	2012- 12-10
568436	203701	B004AW1Z94	A1D6FDBK9FJI8C	Jason Mark	0	0	0	2012- 12-10

	ld	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	
568437	432397	B003A199AI	A2VI7ZC4CWDUPW	Vanessa Close	2	2	1	2012- 12-10	
568438	432396	B003A199AI	A3F0WUGQIS488X	Daniel L	2	2	1	2012- 12-10	Perfe
568439	80520	B008ADQYYU	A2DKVL26ZX0WGS	Sil	0	0	1	2012- 12-10	
568440	50682	B007PQTIRI	A2XWFSMXJ1RR0R	Mel M.	0	0	1	2012- 12-10	
568441	398671	B001D09KAM	AUS545VE0P2J1	Paul	0	0	1	2012- 12-10	
568442	80622	B000WFKHN8	A29FD8FJONPAJ	Baxter "Uru"	0	0	1	2012- 12-10	
568443	254881	B007PA32L2	A2ZOKXJOQULWXS	marie johnston	0	0	1	2012- 12-10	
568444	398672	B001D09KAM	A2TKFP9YMPASAS	sammy3856	0	0	1	2012- 12-10	
568445	254880	B007PA32L2	A3JK142YXC2RGK	judaicagirl "Dalia L."	0	0	0	2012- 12-10	Tas

	ld	ProductId	Userld	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time
568446	254879	B007PA32L2	A2EJ1GFUFYUEBM	michael crow	0	0	0	2012- 12-10
568447	377320	B001IAQ8KC	A1JXRHA7PD04ZF	John	0	0	1	2012- 12-10
568448	274819	B005VOOOM0	AZS3RRB62EJVP	Dg7023	0	0	1	2012- 12-10
568449	305646	B001ELL4E0	AZ3EHLAKPMUU6	bigtiger	0	0	1	2012- 12-10
568450	202269	B000P0QHOI	AN4FZJKFHMAS0	Dawn E. Curran	0	0	1	2012- 12-10
568451	106712	B001HTG6E2	A29Y8V009MI4G5	Cate	0	0	1	2012- 12-10
568452	465911	B005OU6UD2	A2550XGZEFDH2Y	Melanie G. Nihart "Grammy"	0	0	0	2012- 12-10
568453	424141	B000EMK53G	A2B7BUH8834Y6M	Shelley Gammon "Geek"	0	0	1	2012- Shock 12-10

568454 rows × 10 columns

## [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:

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 Productld 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 delete the others. for eg. in the above just the review for ProductId=B000HDL1RQ remains. This method ensures that there is only one representative for each product and deduplication without sorting would lead to possibility of different representatives still existing for the same product.

```
In [0]: #Sorting data according to ProductId in ascending order
    sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='quicksort', n
    a_position='last')

In [0]: #Deduplication of entries
    final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', inplace=False)
    final.shape
Out[0]: (393933, 10)
```

**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

```
'''display= pd.read_sql_query("""
In [0]:
        SELECT *
        FROM Reviews
         WHERE Score != 3 AND Id=44737 OR Id=64422
         ORDER BY ProductID
        """, con)
        display.head()'''
Out[0]: 'display= pd.read_sql_query("""\nSELECT *\nFROM Reviews\nWHERE Score != 3 AND Id=44737 OR Id=64422\nORDER BY
        ProductID\n""", con)\n\ndisplay.head()'
In [0]: final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]</pre>
In [0]: #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()
        (393931, 10)
Out[0]: 1
             336824
              57107
        Name: Score, dtype: int64
In [0]: final.shape
Out[0]: (393931, 10)
```

## [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 observeed to be better than Porter Stemming)

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

```
In [0]: # printing some random reviews
    sent_0 = final['Text'].values[0]
    print(sent_0)
    print(sent_1000)
    print(sent_1000)
    print("="*50)

sent_1500 = final['Text'].values[1500]
    print(sent_1500)
    print(sent_1500)
    print("="*50)

sent_4900 = final['Text'].values[4300]
    print(sent_4900)
    print("="*50)
```

It's a great book with adorable illustrations. A true classic. Kids love the poem and there is music that goes with it, if you can find it. I think it's sung by Carol King.

\_\_\_\_\_

Well if you have had this product before you know it is amazing. I am not going to describe the taste but i will tell you the product was shipped neatly and fresh. Everything tasted great and the expiration date was much further into the future than this would have ever lasted. Top notch.

\_\_\_\_\_\_

Cat thought the bubbles were interesting, but didn't go crazy over them. They smell funny, leave a residue, a nd don't maintain form when they touch down as advertised. I'll go pick up a big bottle of regular bubbles fo r him to chase. Not worth the price.

The previous reviewer's experience is lamentable but after reading the reviews for other Brussel's Bonsai & a fter reception of my own tree it's clear that his experience was the exception, not the rule.<br/>
/>cbr />The tree arrived well-packaged, lush & green. The soil was moist & wrapped in plastic to ensure it remained that way. The tree is planted in a dark blue glazed ceramic pot. Included was a small pamphlet outlining the basic s of Indoor Bonsai care. Overall, quite nice & well done. I wouldn't hesitate to order another tree from Brus sel's. See my images above.<br/>
/>cbr />Cbr

\_\_\_\_\_\_

It's a great book with adorable illustrations. A true classic. Kids love the poem and there is music that g oes with it, if you can find it. I think it's sung by Carol King.

In [0]: | # 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)

It's a great book with adorable illustrations. A true classic. Kids love the poem and there is music that goes with it, if you can find it. I think it's sung by Carol King.

\_\_\_\_\_\_

Well if you have had this product before you know it is amazing. I am not going to describe the taste but i will tell you the product was shipped neatly and fresh. Everything tasted great and the expiration date was much further into the future than this would have ever lasted. Top notch.

\_\_\_\_\_\_

Cat thought the bubbles were interesting, but didn't go crazy over them. They smell funny, leave a residue, a nd don't maintain form when they touch down as advertised. I'll go pick up a big bottle of regular bubbles fo r him to chase. Not worth the price.

\_\_\_\_\_

The previous reviewer's experience is lamentable but after reading the reviews for other Brussel's Bonsai & a fter reception of my own tree it's clear that his experience was the exception, not the rule. The tree arrived well-packaged, lush & green. The soil was moist & wrapped in plastic to ensure it remained that way. The tree is planted in a dark blue glazed ceramic pot. Included was a small pamphlet outlining the basics of Indoor Bo nsai care. Overall, quite nice & well done. I wouldn't hesitate to order another tree from Brussel's. See my images above. UPDATE 08/11/2011:I ordered a second ficus from Brussel's & it arrived in the same excellent con dition as before & attractively trained. Very, very pleased.

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

Cat thought the bubbles were interesting, but did not go crazy over them. They smell funny, leave a residue, and do not maintain form when they touch down as advertised. I will go pick up a big bottle of regular bubble s for him to chase. Not worth the price.

\_\_\_\_\_

```
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)
```

It's a great book with adorable illustrations. A true classic. Kids love the poem and there is music that g oes with it, if you can find it. I think it's sung by Carol King.

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

Cat thought the bubbles were interesting but did not go crazy over them They smell funny leave a residue and do not maintain form when they touch down as advertised I will go pick up a big bottle of regular bubbles for him to chase Not worth the price

```
In [0]: # 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", "y
        ou'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', 'thos
        e', \
                    'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having', 'do', 'd
        oes', \
                    'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'until', 'while', 'o
        f', \
                    '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', 'fe
        w', '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',
                    '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", 'must
        n',\
                    "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn', "wasn't", 'were
        n', "weren't", \
                     'won', "won't", 'wouldn', "wouldn't"])
```

```
In [0]: # Combining all the above stundents
from tqdm import tqdm
preprocessed_reviews = []
# tqdm is for printing the status bar
for sentance in tqdm(final['Text'].values):
        sentance = re.sub(r"http\S+", "", sentance)
        sentance = BeautifulSoup(sentance, 'lxml').get_text()
        sentance = decontracted(sentance)
        sentance = re.sub("\S*\d\S*", "", sentance).strip()
        sentance = re.sub('[^A-Za-z]+', ' ', sentance)
# https://gist.github.com/sebleier/554280
sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in stopwords)
        preprocessed_reviews.append(sentance.strip())
```

100% | 393931/393931 [02:59<00:00, 2198.18it/s]

- In [0]: preprocessed\_reviews[1500]
- Out[0]: 'cat thought bubbles interesting not go crazy smell funny leave residue not maintain form touch advertised go pick big bottle regular bubbles chase not worth price'

```
In [0]: #Used when 50% of positive and 50% of negative reviews are needed.
'''
final["New_Text"] = preprocessed_reviews

a = final[final["Score"]==0][0:500]
b = final[final["Score"]==1][0:500]

#Stacking both positive and negative data
a = a.append(b, ignore_index = True)

#Shuffling the data points to mix the data
from sklearn.utils import shuffle
a = shuffle(a)'''
```

```
In [0]: #Train-Test Split

#X_train,X_test,y_train, y_test = train_test_split(preprocessed_reviews[0:len(preprocessed_reviews)], list(fi
nal["Score"][0:len(preprocessed_reviews)]), random_state = 42, test_size = 0.3, stratify = list(final["Score"][0:len(preprocessed_reviews)]))

X_train,X_test,y_train, y_test = train_test_split(preprocessed_reviews[0:50000], list(final["Score"][0:50000]))

In [0]:
In [0]:
```

### [3.2] Preprocessing Review Summary

```
In [0]: ## Similartly you can do preprocessing for review summary also.
```

# [4] Featurization

## [4.1] BAG OF WORDS

```
In [0]: | #BoW
        count vect = CountVectorizer(max features = 500) #in scikit-learn
        count vect.fit(X train)
        print("some feature names ", count vect.get feature names()[:10])
        print('='*50)
        final counts = count vect.transform(X train)
        final counts test = count vect.transform(X test)
        print("the type of count vectorizer ",type(final counts))
        print("the shape of out text BOW vectorizer ",final counts.get shape())
        print("the number of unique words ", final counts.get shape()[1])
        print("="*50)
        print("for test data")
        print("the type of count vectorizer ",type(final counts test))
        print("the shape of out text BOW vectorizer ",final counts test.get shape())
        print("the number of unique words ", final counts test.get shape()[1])
       some feature names ['able', 'absolutely', 'actually', 'add', 'added', 'adding', 'ago', 'almost', 'already',
        'also'l
        ______
       the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
       the shape of out text BOW vectorizer (35000, 500)
       the number of unique words 500
        _____
        for test data
       the type of count vectorizer <class 'scipy.sparse.csr.csr matrix'>
       the shape of out text BOW vectorizer (15000, 500)
       the number of unique words 500
```

#### [4.2] Bi-Grams and n-Grams.

```
In [0]: #bi-gram, tri-gram and n-gram
        #removing stop words like "not" should be avoided before building n-grams
        # count vect = CountVectorizer(ngram range=(1,2))
        # please do read the CountVectorizer documentation http://scikit-learn.org/stable/modules/generated/sklearn.f
        eature extraction.text.CountVectorizer.html
        # you can choose these numebrs min df=10, max features=5000, of your choice
        count vect = CountVectorizer(ngram range=(1,2), min df=10, max features=500)
        final bigram counts = count vect.fit transform(X train)
        final bigram counts test = count vect.transform(X test)
        print("the type of count vectorizer ",type(final bigram counts))
        print("the shape of out text BOW vectorizer ",final bigram counts.get shape())
        print("the number of unique words including both unigrams and bigrams ", final_bigram counts.get shape()[1])
        print("="*50)
        print("for test data")
        print("the type of count vectorizer ",type(final bigram counts test))
        print("the shape of out text BOW vectorizer ",final bigram counts test.get shape())
        print("the number of unique words including both unigrams and bigrams ", final bigram counts test.get shape()
        [1])
        the type of count vectorizer <class 'scipy.sparse.csr.csr matrix'>
        the shape of out text BOW vectorizer (35000, 500)
        the number of unique words including both unigrams and bigrams 500
        ______
        for test data
        the type of count vectorizer <class 'scipy.sparse.csr.csr matrix'>
        the shape of out text BOW vectorizer (15000, 500)
        the number of unique words including both unigrams and bigrams 500
```

### [4.3] TF-IDF

```
In [0]: tf idf vect = TfidfVectorizer(min df=10, max features = 500)
        tf idf vect.fit(X train)
        print("some sample features(unique words in the corpus)", tf idf vect.get feature names()[0:10])
        print('='*50)
        final tf idf = tf idf vect.transform(X train)
        final_tf_idf_test = tf_idf_vect.transform(X test)
        print("the type of count vectorizer ",type(final tf idf))
        print("the shape of out text TFIDF vectorizer ",final tf idf.get shape())
        print("the number of unique words including both unigrams and bigrams ", final tf idf.get shape()[1])
        print("="*50)
        print("for test data")
        print("the type of count vectorizer ",type(final tf idf test))
        print("the shape of out text TFIDF vectorizer ",final tf idf test.get shape())
        print("the number of unique words including both unigrams and bigrams ", final tf idf test.get shape()[1])
        some sample features(unique words in the corpus) ['able', 'absolutely', 'actually', 'add', 'added', 'adding',
        'ago', 'almost', 'already', 'also'l
        _____
       the type of count vectorizer <class 'scipy.sparse.csr.csr matrix'>
       the shape of out text TFIDF vectorizer (35000, 500)
       the number of unique words including both unigrams and bigrams 500
        for test data
       the type of count vectorizer <class 'scipy.sparse.csr.csr matrix'>
       the shape of out text TFIDF vectorizer (15000, 500)
       the number of unique words including both unigrams and bigrams 500
In [0]:
```

#### [4.4] Word2Vec

```
In [0]:
```

```
In [0]: # Train your own Word2Vec model using your own text corpus for train data
    i=0
    list_of_sentance=[]
    for sentance in X_train:
        list_of_sentance.append(sentance.split())

In [0]: # Train your own Word2Vec model using your own text corpus for test data
    i=0
    list_of_sentance_test=[]
    for sentance in X_test:
        list_of_sentance_test.append(sentance.split())
```

```
In [0]: # Using Google News Word2Vectors
        # in this project we are using a pretrained model by google
        # its 3.3G file, once you load this into your memory
        # it occupies ~9Gb, so please do this step only if you have >12G of ram
        # we will provide a pickle file wich contains a dict,
        # and it contains all our courpus words as keys and model[word] as values
        # To use this code-snippet, download "GoogleNews-vectors-negative300.bin"
        # from https://drive.google.com/file/d/0B7XkCwpI5KDYNLNUTTLSS21pOmM/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 occured atleast 5 times
            w2v model=Word2Vec(list of sentance,min count=5,size=50, workers=4)
            print(w2v model.wv.most similar('great'))
            print('='*50)
            print(w2v model.wv.most similar('worst'))
        elif want to use google w2v and is your ram gt 16g:
            if os.path.isfile('GoogleNews-vectors-negative300.bin'):
                w2v model=KeyedVectors.load word2vec format('GoogleNews-vectors-negative300.bin', binary=True)
                print(w2v model.wv.most similar('great'))
                print(w2v model.wv.most similar('worst'))
            else:
                print("you don't have gogole's word2vec file, keep want_to_train_w2v = True, to train your own w2v ")
```

```
[('fantastic', 0.8106623888015747), ('good', 0.8083468675613403), ('wonderful', 0.7978379726409912), ('excell
        ent', 0.7682069540023804), ('awesome', 0.748454213142395), ('amazing', 0.7277643084526062), ('perfect', 0.718
        1200981140137), ('terrific', 0.7043402194976807), ('decent', 0.6753935217857361), ('fabulous', 0.658634305000
        3052)1
        [('greatest', 0.8113981485366821), ('best', 0.7572190165519714), ('fowl', 0.7126210331916809), ('nastiest',
        0.6662765741348267), ('disgusting', 0.6581308245658875), ('closest', 0.6505348086357117), ('biggest', 0.64751
        17802619934), ('hottest', 0.6424438953399658), ('encountered', 0.6375048160552979), ('hated', 0.6318227052688
        599)]
In [0]: #Creating a word vocabulary based on training data.
        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 12177
        sample words ['grandmother', 'ever', 'told', 'swallow', 'gum', 'never', 'digested', 'stay', 'body', 'foreve
        r', 'wrong', 'least', 'comes', 'natural', 'nothing', 'artificial', 'feel', 'bad', 'top', 'really', 'tasty',
        'better', 'get', 'super', 'market', 'terms', 'flavor', 'consistency', 'favor', 'try', 'use', 'make', 'health
        y', 'curry', 'sauces', 'sometimes', 'add', 'dash', 'brown', 'rice', 'brings', 'new', 'life', 'love', 'long',
        'time', 'since', 'takes', 'little', 'bit']
In [0]:
```

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

[4.4.1.1] Avg W2v

```
In [0]: #Converting each word of a review from training data into vector of len 50, adding them up and the finding an
         average. Hence converting training data into vector form.
        # average Word2Vec
        # compute average word2vec for each review.
        sent vectors = []; # the avg-w2v for each sentence/review is stored in this list
        for sent in tqdm(list of sentance): # for each review/sentence
            sent vec = np.zeros(50) # as word vectors are of zero length 50, 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)
        print(len(sent vectors))
        print(len(sent vectors[0]))
```

100%| 35000/35000 [01:10<00:00, 496.58it/s] 35000 50

```
In [0]: #Resulting vector representation of Training data
X_tr_w2v = sent_vectors
```

```
In [0]: #Converting each word of a review from test data into vector of len 50, adding them up and the finding an ave
        rage. Hence converting test data into vector form.
        # average Word2Vec
        # compute average word2vec for each review.
        sent vectors = []; # the avg-w2v for each sentence/review is stored in this list
        for sent in tqdm(list of sentance test): # for each review/sentence
            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)
        print(len(sent vectors))
        print(len(sent vectors[0]))
        100%
               | 15000/15000 [00:32<00:00, 464.51it/s]
```

```
15000
50
```

```
In [0]: #Resulting vector representation of reviews of Test data
X_ts_w2v = sent_vectors
```

## [4.4.1.2] TFIDF weighted W2v

```
In [0]: #Training the TfidfVectorizer on Train data

# S = ["abc def pqr", "def def abc", "pqr pqr def"]
model = TfidfVectorizer()
tf_idf_matrix = model.fit_transform(X_train)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

```
In [0]: #Converting each word of a review from Train data into Tfidf W2v vector representation of len 50. Hence conve
        rting Train data into vector form.
        # TF-IDF weighted Word2Vec
        tfidf feat = model.get feature names() # tfidf words/col-names
        # final tf idf is the sparse matrix with row= sentence, col=word and cell val = tfidf
        tfidf sent vectors = []; # the tfidf-w2v for each sentence/review is stored in this list
        row=0;
        for sent in tqdm(list of sentance): # for each review/sentence
            sent vec = np.zeros(50) # as word vectors are of zero length
            weight_sum =0; # num of words with a valid vector in the sentence/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.append(sent vec)
            row += 1
```

## 100%| 35000/35000 [12:15<00:00, 47.61it/s]

```
In [0]: #Resulting vector representation of reviews of Train data
X_tr_tf = tfidf_sent_vectors
```

```
In [0]: #Converting each word of a review from Test data into Tfidf W2v vector representation of Len 50. Hence conver
        ting Test data into vector form.
        #Test data is converted to vectors using w2v model and TfidfVectorizer which were built on Training data.
        # TF-IDF weighted Word2Vec
        tfidf feat = model.get feature names() # tfidf words/col-names
        # final tf idf is the sparse matrix with row= sentence, col=word and cell val = tfidf
        tfidf sent vectors = []; # the tfidf-w2v for each sentence/review is stored in this list
        row=0;
        for sent in tqdm(list_of_sentance_test): # for each review/sentence
            sent vec = np.zeros(50) # as word vectors are of zero length
            weight sum =0; # num of words with a valid vector in the sentence/review
            for word in sent: # for each word in a review/sentence
                if word in w2v words and word in tfidf feat:
                    vec = w2v model.wv[word]
                      tf idf = tf idf matrix[row, tfidf feat.index(word)]
                    # to reduce the computation we are
                    # dictionary[word] = idf value of word in whole courpus
                    # sent.count(word) = tf valeus of word in this review
                    tf idf = dictionary[word]*(sent.count(word)/len(sent))
                    sent vec += (vec * tf idf)
                    weight sum += tf idf
            if weight sum != 0:
                sent vec /= weight sum
            tfidf sent vectors.append(sent vec)
            row += 1
                15000/15000 [04:46<00:00, 52.39it/s]
In [0]: #Resulting vector representation of reviews of Test data
        X ts tf = tfidf sent vectors
In [0]:
In [0]:
In [0]:
```

In [0]:	
In [0]:	
In [0]:	

# [5] Assignment 3: KNN

#### 1. Apply Knn(brute force version) 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. Apply Knn(kd tree version) on these feature sets

SET 5:Review text, preprocessed one converted into vectors using (BOW) but with restriction on maximum features generated.

```
count_vect = CountVectorizer(min_df=10, max_features=500)
count vect.fit(preprocessed reviews)
```

• SET 6:Review text, preprocessed one converted into vectors using (TFIDF) but with restriction on maximum features generated.

```
tf_idf_vect = TfidfVectorizer(min_df=10, max_features=500)
tf idf vect.fit(preprocessed reviews)
```

- SET 3:Review text, preprocessed one converted into vectors using (AVG W2v)
- SET 4:Review text, preprocessed one converted into vectors using (TFIDF W2v)

## 3. The hyper paramter tuning(find best K)

- Find the best hyper parameter which will give the maximum <u>AUC (https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/receiver-operating-characteristic-curve-roc-curve-and-auc-1/) value</u>
- 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

## 4. Representation of results

• You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure



• Once after you found the best hyper parameter, you need to train your model with it, and find the AUC on test data and plot the ROC curve on both train and test.

Along with plotting ROC curve, you need to print the confusion matrix

(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



#### 5. Conclusion

• You need to summarize the results at the end of the notebook, summarize it in the table format. To print out a table please refer to this prettytable library link (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 link. (https://soundcloud.com/applied-ai-course/leakage-bow-and-tfidf)

## [5.1] Applying KNN brute force

```
In [0]: # Common User defined function used.
        #Plots AUC Score vs Neighbors
        def plot best hyperparameter(gridcv):
            cv result = pd.DataFrame(gridcv.cv results ) #qridcv.cv results outputs dict object of cross valida
        tion score and train score.
            '''cv = {
            "neighbors" : cv result["param n neighbors"],
            "train score" : cv result["mean train score"],
            "validation score" : cv result["mean test score"]}'''
            #CV score = pd.DataFrame(cv)
            #Plot for Train data
            plt.figure()
            plt.title("Best hyperparameter for train data")
            plt.plot(cv result["param n neighbors"], cv result["mean train score"])
            plt.plot(cv result["param n neighbors"], cv result["mean test score"])
            plt.xticks(rotation=90)
            plt.xlabel("Neighbors/K")
            plt.ylabel("AUC Score")
            plt.legend()
            plt.show()
            '''Plot for Validation data
            plt.figure()
            plt.title("Best hyperparameter for validation data")
            plt.plot(cv result["param n neighbors"], cv result["mean test score"])
            plt.xticks(rotation=90)
            plt.xlabel("Neighbors")
            plt.ylabel("AUC Score")
            plt.show()'''
        def plot roc curve(test y, predict proba y): #Plots ROC Curve
            fpr, tpr, threshold = roc curve(test y, predict proba y)
            auc area = metrics.auc(fpr, tpr)
            plt.figure()
            plt.plot(fpr, tpr, color = 'darkorange', linewidth = 2,label = "AUC: %0.2f" %auc area)
            plt.plot([0,1],[0,1], linewidth = 2, linestyle="--")
```

```
plt.xlim([0,1])
plt.ylam([0,1])
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ROC Curve")
plt.legend(loc = "lower right")
plt.show()

def plot_confusion_mat(test_y, predict_proba_y): #PLots Confusion Matrix

    cnf_mat = confusion_matrix(test_y, predict_proba_y)
    cnf_df = pd.DataFrame(cnf_mat, index = ["Actual: 0", "Actual: 1"], columns = ["Predicted: 0", "Predicted: 1"], dtype= float)

plt.figure(figsize=(5,3))
plt.title("Confusion Matrix")
sns.heatmap(cnf_df, annot = True, fmt = "g")
```

In [0]:

## [5.1.1] Applying KNN brute force on BOW, SET 1

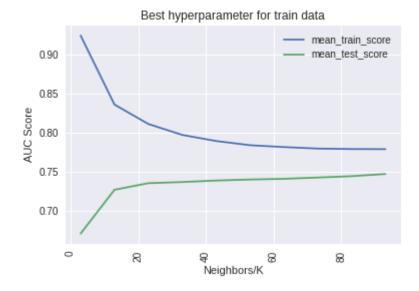
```
In [0]: # Please write all the code with proper documentation

from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier

#Parameters
params = {"n_neighbors":[3,13,23,33,43,53,63,73,83,93]}
knn_bow = KNeighborsClassifier(algorithm = "brute")
gridcv = GridSearchCV(knn_bow, params, scoring = 'roc_auc', cv = 5)
gridcv.fit(final_bigram_counts, y_train)
print(gridcv.best_params_)
bst_paramtr = gridcv.best_params_["n_neighbors"]

#Plots the graph for all parameters to find best hyperparameter.
plot_best_hyperparameter(gridcv)
```

## {'n\_neighbors': 93}



```
In [0]: from sklearn.metrics import roc_auc_score
    knn_bow_1 = KNeighborsClassifier(n_neighbors = bst_paramtr , algorithm = "brute")
    knn_bow_1.fit(final_bigram_counts, y_train)

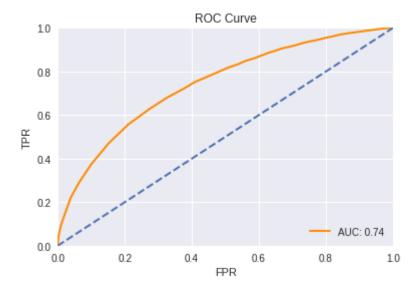
y_predict_proba_bow = knn_bow_1.predict_proba(final_bigram_counts_test)[:,1]
y_predict_bow = knn_bow_1.predict(final_bigram_counts_test)

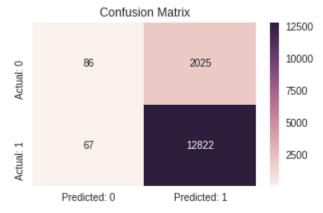
roc_auc = roc_auc_score(y_test, y_predict_proba_bow)
print("AUC for KNN with BOW for brute force method: ", roc_auc)

#Plots ROC curve
plot_roc_curve(y_test, y_predict_proba_bow)

#Plots Confusion matrix
plot_confusion_mat(y_test, y_predict_bow)
```

## AUC for KNN with BOW for brute force method: 0.7412674463174048

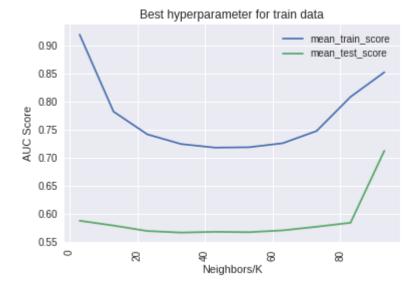




In [0]:

## [5.1.2] Applying KNN brute force on TFIDF, SET 2

## {'n\_neighbors': 93}



```
In [0]: knn_bow_1 = KNeighborsClassifier(n_neighbors = bst_paramtr ,algorithm = "brute")
knn_bow_1.fit(final_tf_idf, y_train)

y_predict_proba_tfidf = knn_bow_1.predict_proba(final_tf_idf_test)[:,1]
y_predict_tfidf = knn_bow_1.predict(final_tf_idf_test)

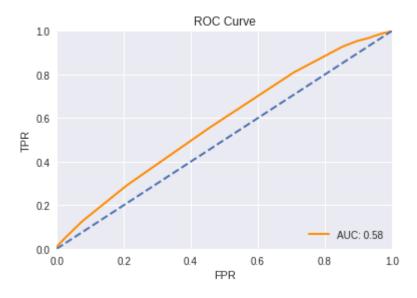
roc_auc = roc_auc_score(y_test, y_predict_proba_tfidf)

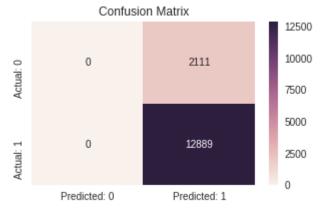
print("AUC for KNN with TFIDF for brute force method: ", roc_auc)

#Plots ROC curve
plot_roc_curve(y_test, y_predict_proba_tfidf)

#Plots Confusion matrix
plot_confusion_mat(y_test, y_predict_tfidf)
```

## AUC for KNN with TFIDF for brute force method: 0.5777730333765929





## [5.1.3] Applying KNN brute force on AVG W2V, SET 3

In [0]:

```
In [0]: # Please write all the code with proper documentation

#Parameters
params = {"n_neighbors":[3,13,23,33,43,53,63,73,83,93]}

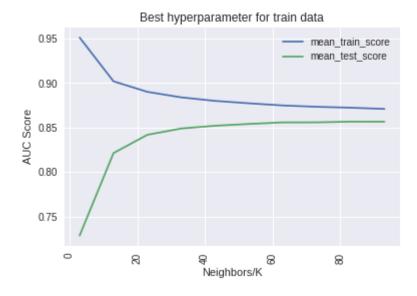
knn_bow = KNeighborsClassifier(algorithm = "brute")

gridcv = GridSearchCV(knn_bow, params, scoring = 'roc_auc', cv = 5)
gridcv.fit(X_tr_w2v, y_train)
print(gridcv.best_params_)

bst_paramtr = gridcv.best_params_["n_neighbors"]

#Plots the graph for all parameters to find best hyperparameter.
plot_best_hyperparameter(gridcv)
```

## {'n\_neighbors': 83}



```
In [0]: from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import roc_auc_score

knn_bow_1 = KNeighborsClassifier(n_neighbors = bst_paramtr , algorithm = "brute")
knn_bow_1.fit(X_tr_w2v, y_train)

y_predict_proba_w2v_kd = knn_bow_1.predict_proba(X_ts_w2v)[:,1]
y_predict_w2v_kd = knn_bow_1.predict(X_ts_w2v)

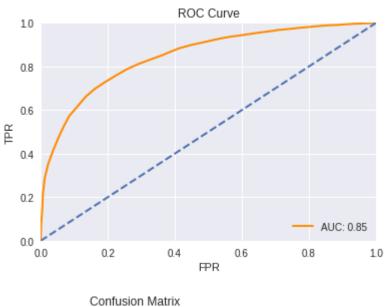
roc_auc = roc_auc_score(y_test, y_predict_proba_w2v_kd)

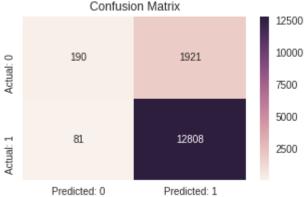
print("AUC for KNN with AVG W2V for KD Tree method: ", roc_auc)

#Plots ROC curve
plot_roc_curve(y_test, y_predict_proba_w2v_kd)

#Plots Confusion matrix
plot_confusion_mat(y_test, y_predict_w2v_kd)
```

## AUC for KNN with AVG W2V for KD Tree method: 0.8482575357664369





[5.2.4] Applying KNN kd-tree on TFIDF W2V, SET 4

```
In [0]: # Please write all the code with proper documentation

#Parameters
params = {"n_neighbors":[3,13,23,33,43,53,63,73,83,93]}

knn_bow = KNeighborsClassifier(algorithm = "brute")

gridcv = GridSearchCV(knn_bow, params, scoring = 'roc_auc', cv = 5)
 gridcv.fit(X_tr_tf, y_train)
 print(gridcv.best_params_)

bst_paramtr = gridcv.best_params_["n_neighbors"]

#Plots the graph for all parameters to find best hyperparameter.
plot_best_hyperparameter(gridcv)
```

## {'n\_neighbors': 83}



```
In [0]: knn_bow_1 = KNeighborsClassifier(n_neighbors = bst_paramtr , algorithm = "brute")
    knn_bow_1.fit(X_tr_tf, y_train)

y_predict_proba_tfidf_w2v_kd = knn_bow_1.predict_proba(X_ts_tf)[:,1]
y_predict_tfidf_w2v_kd = knn_bow_1.predict(X_ts_tf)

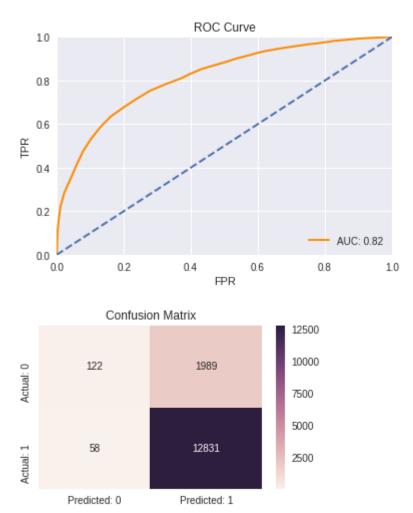
roc_auc = roc_auc_score(y_test, y_predict_proba_tfidf_w2v_kd)

print("AUC for KNN with TFIDF W2V for KD Tree method: ", roc_auc)

#Plots ROC curve
plot_roc_curve(y_test, y_predict_proba_tfidf_w2v_kd)

#Plots Confusion matrix
plot_confusion_mat(y_test, y_predict_tfidf_w2v_kd)
```

AUC for KNN with TFIDF W2V for KD Tree method: 0.815509768041293



Note: I ran the above models with KD Tree algorithm in next ipython notebook. Conclusions are also mentioned in that notebook.