Amazon Fine Food Reviews Analysis

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

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

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

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

Attribute Information:

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

Objective:

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

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

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

[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 wil be set to "positive". Otherwise, it will be set to "negative".

In [4]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
```

```python
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, roc_auc_score
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 numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
from collections import Counter
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_validate
```

In [5]:
```python
# using SQLite Table to read data.
con = sqlite3.connect('/Users/puravshah/Downloads/amazon-fine-food-revi
ews/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 50
0000 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 Sco
re != 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 40000""", con)

# Give reviews with Score>3 a positive rating(1), and reviews with a sc
ore<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 (40000, 10)
```

Out[5]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulnes
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulnes
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1

In [6]:

```
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
""", con)
```

In [7]:

```
print(display.shape)
display.head()
```

```
(80668, 7)
```

Out[7]:

	UserId	ProductId	ProfileName	Time	Score	Text	COU

	UserId	ProductId	ProfileName	Time	Score	Text	COU
0	#oc-R115TNMSPFT9I7	B007Y59HVM	Breyton	1331510400	2	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ET0	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B007Y59HVM	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ET0	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBE1U	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	2

In [8]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[8]:

	UserId	ProductId	ProfileName	Time	Score	Text

	UserId	ProductId	ProfileName	Time	Score	Text
80638	AZY10LLTJ71NX	B006P7E5ZI	undertheshrine "undertheshrine"	1334707200	5	I was recommended to try green tea extract to ...

In [9]:

```
display['COUNT(*)'].sum()
```

Out[9]: 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:

In [10]:

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

Out[10]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfuln

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfuln
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	2
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	2
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	2
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	2
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	2

As it can be seen above that same user has multiple reviews with same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that

ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8)

ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

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

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

In [11]:
```
#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 [12]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', inplace=False)
final.shape
```

Out[12]: (37415, 10)

In [13]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[13]: 93.5375

Observation:- It was also seen that in two rows given below the value of HelpfulnessNumerator is greater than HelpfulnessDenominator which is not practically possible hence these two rows too are removed from calcualtions

In [14]:

```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[14]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfuln
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2

In [15]:

```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [16]:

```
#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()
```

```
(37415, 10)
```

Out[16]:
```
1    31324
0     6091
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 obsereved to be better than Porter Stemming)

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

In [17]:
```
# 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)
```

```
Our dogs just love them.  I saw them in a pet store and a tag was attac
hed regarding them being made in China and it satisfied me that they we
re safe.
==================================================
It's Branston pickle, what is there to say. If you've never tried it yo
u most likely wont like it. If you grew up in the UK its a staple on ch
eese of cold meat sandwiches. It's on my lunch sandwich today! :)
==================================================
First Impression: The friendly folks over at "Exclusively Dog" heard ab
out my website and sent me 5 of their products to test.<br />Let me jus
t start off by saying that I Love how sweet all of these treats taste.
Dad was/is considering trying one because they look and smell so much l
ike human cookies. Plus the ingredients are very straight forward, they
are probably healthier than most the stuff Mom eats... But there in lie
s the problem. Dad thinks that they are too sweet for a puppy of any ag
e. The second ingredient in almost all of them is sugar. As we all know
puppies have a hard time processing sugar, and just like humans can dev
elop diabetes.<br /><br />Conclusion: Your puppy is nearly guaranteed t
o LOVE the taste. However these should only be used as an occasional tr
eat! If you were to feed your puppies these sugary sweet morsels every
day, they would soon plump up. If you puppy is already overweight or do
es not exercise regularly, you may want to think twice. On the PRO side
they are all natural, with no animal bi-products! 3 out of 4 paws, beca
use Dad made me! If we were judging on taste alone they would be a 4.
==================================================
It is hard to find candy that is overly sweet. My wife and Granddaughte
r both love Pink Grapefruit anyway and Pink Grapefruit candy has some o
```

```
f the tang of real grapefruit which cuts down on the sweetness a bit.<b
r />I did take away one star because I think they have a bit too much o
f sugar coating on the pieces but you can scrape some of it off to make
it less sweet.<br />My wife uses the pieces when she has a low sugar sp
ell since she is diabetic and sometimes when she has her insulin inject
ions and doesn't eat quickly enough after that her blood sugar drops to
o low. Since I bought this she hasn't had that problem, but has to guar
d her supply from my Granddaughter though.<br />I have bought a pack fo
r myself as well since I don't eat candy that often since I don't like
overly sweet candy. This candy tastes good to me. I want to try the fru
it salad next time just to have some change in taste. It has lime, grap
efruit, lemon, orange, cherry and passion fruit and I like all of those
flavors except cherry. But my wife likes cherry flavor so I can give th
ose to her. Wish they had watermelon instead of cherry in that mix but
its no big deal.
==================================================
```

In [18]:

```python
# remove urls from text python: https://stackoverflow.com/a/40823105/40
84039
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)
```

```
Our dogs just love them.  I saw them in a pet store and a tag was attac
hed regarding them being made in China and it satisfied me that they we
re safe.
```

In [19]:

```python
# 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)
```

```
Our dogs just love them.  I saw them in a pet store and a tag was attac
hed regarding them being made in China and it satisfied me that they we
re safe.
==================================================
It's Branston pickle, what is there to say. If you've never tried it yo
u most likely wont like it. If you grew up in the UK its a staple on ch
eese of cold meat sandwiches. It's on my lunch sandwich today! :)
==================================================
First Impression: The friendly folks over at "Exclusively Dog" heard ab
out my website and sent me 5 of their products to test.Let me just star
t off by saying that I Love how sweet all of these treats taste. Dad wa
s/is considering trying one because they look and smell so much like hu
man cookies. Plus the ingredients are very straight forward, they are p
robably healthier than most the stuff Mom eats... But there in lies the
problem. Dad thinks that they are too sweet for a puppy of any age. The
second ingredient in almost all of them is sugar. As we all know puppie
s have a hard time processing sugar, and just like humans can develop d
iabetes.Conclusion: Your puppy is nearly guaranteed to LOVE the taste.
However these should only be used as an occasional treat! If you were t
o feed your puppies these sugary sweet morsels every day, they would so
on plump up. If you puppy is already overweight or does not exercise re
gularly, you may want to think twice. On the PRO side they are all natu
ral, with no animal bi-products! 3 out of 4 paws, because Dad made me!
If we were judging on taste alone they would be a 4.
==================================================

It is hard to find candy that is overly sweet. My wife and Granddaughte
```

```
It is hard to find candy that is overly sweet. My wife and Granddaughte
r both love Pink Grapefruit anyway and Pink Grapefruit candy has some o
f the tang of real grapefruit which cuts down on the sweetness a bit.I
did take away one star because I think they have a bit too much of suga
r coating on the pieces but you can scrape some of it off to make it le
ss sweet.My wife uses the pieces when she has a low sugar spell since s
he is diabetic and sometimes when she has her insulin injections and do
esn't eat quickly enough after that her blood sugar drops too low. Sinc
e I bought this she hasn't had that problem, but has to guard her suppl
y from my Granddaughter though.I have bought a pack for myself as well
since I don't eat candy that often since I don't like overly sweet cand
y. This candy tastes good to me. I want to try the fruit salad next tim
e just to have some change in taste. It has lime, grapefruit, lemon, or
ange, cherry and passion fruit and I like all of those flavors except c
herry. But my wife likes cherry flavor so I can give those to her. Wish
they had watermelon instead of cherry in that mix but its no big deal.
```

In [20]:

```python
# 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 [21]:

```python
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
First Impression: The friendly folks over at "Exclusively Dog" heard ab
out my website and sent me 5 of their products to test.<br />Let me jus
t start off by saying that I Love how sweet all of these treats taste.
Dad was/is considering trying one because they look and smell so much l
ike human cookies. Plus the ingredients are very straight forward, they
are probably healthier than most the stuff Mom eats... But there in lie
s the problem. Dad thinks that they are too sweet for a puppy of any ag
e. The second ingredient in almost all of them is sugar. As we all know
puppies have a hard time processing sugar, and just like humans can dev
elop diabetes.<br /><br />Conclusion: Your puppy is nearly guaranteed t
o LOVE the taste. However these should only be used as an occasional tr
eat! If you were to feed your puppies these sugary sweet morsels every
day, they would soon plump up. If you puppy is already overweight or do
es not exercise regularly, you may want to think twice. On the PRO side
they are all natural, with no animal bi-products! 3 out of 4 paws, beca
use Dad made me! If we were judging on taste alone they would be a 4.
==================================================
```

In [22]:

```python
#remove words with numbers python: https://stackoverflow.com/a/1808237
0/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
Our dogs just love them.  I saw them in a pet store and a tag was attac
hed regarding them being made in China and it satisfied me that they we
re safe.
```

In [23]:

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

```
First Impression The friendly folks over at Exclusively Dog heard about
my website and sent me 5 of their products to test br Let me just start
off by saying that I Love how sweet all of these treats taste Dad was i
s considering trying one because they look and smell so much like human
cookies Plus the ingredients are very straight forward they are probabl
y healthier than most the stuff Mom eats But there in lies the problem
Dad thinks that they are too sweet for a puppy of any age The second in
gredient in almost all of them is sugar As we all know puppies have a h
```

```
ard time processing sugar and just like humans can develop diabetes br
br Conclusion Your puppy is nearly guaranteed to LOVE the taste However
these should only be used as an occasional treat If you were to feed yo
ur puppies these sugary sweet morsels every day they would soon plump u
p If you puppy is already overweight or does not exercise regularly you
may want to think twice On the PRO side they are all natural with no an
imal bi products 3 out of 4 paws because Dad made me If we were judging
on taste alone they would be a 4
```

In [24]:

```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'no
t'
# <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', 'o
urs', 'ourselves', 'you', "you're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselve
s', 'he', 'him', 'his', 'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'it
s', 'itself', 'they', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'th
is', 'that', "that'll", 'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'h
ave', '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', 'h
ow', 'all', 'any', 'both', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 's
o', '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', "is
n'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 [25]:

```
# 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%|██████████| 37415/37415 [00:11<00:00, 3267.77it/s]
```

In [26]:

```
preprocessed_reviews[1500]
```

Out[26]:

```
'first impression friendly folks exclusively dog heard website sent pro
ducts test let start saying love sweet treats taste dad considering try
ing one look smell much like human cookies plus ingredients straight fo
rward probably healthier stuff mom eats lies problem dad thinks sweet p
uppy age second ingredient almost sugar know puppies hard time processi
ng sugar like humans develop diabetes conclusion puppy nearly guarantee
d love taste however used occasional treat feed puppies sugary sweet mo
rsels every day would soon plump puppy already overweight not exercise
regularly may want think twice pro side natural no animal bi products p
aws dad made judging taste alone would'
```

[3.2] Preprocessing Review Summary

In [27]:
```
## Similartly you can do preprocessing for review summary also.
```

[4] Featurization

[4.1] BAG OF WORDS

In [28]:
```
#BoW
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler(with_mean=False)
X_1, X_test, y_1, y_test = train_test_split(preprocessed_reviews, final
['Score'], 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)
count_vect = CountVectorizer() #in scikit-learn
count_vect.fit(X_tr)

print("some feature names ", count_vect.get_feature_names()[:10])
print('='*50)

final_counts = count_vect.transform(X_tr)
final_counts=scaler.fit_transform(final_counts)
X_cv_bow=count_vect.transform(X_cv)
X_cv_bow=scaler.transform(X_cv_bow)
X_test_bow=count_vect.transform(X_test)
X_test_bow=scaler.transform(X_test_bow)
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(y_test.shape)
```

```
some feature names  ['aa', 'aaaa', 'aaaaa', 'aaaaaaaaaaaaaa', 'aache
n', 'aadp', 'aafco', 'aahs', 'aarthur', 'ab']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
```

```
the shape of out text BOW vectorizer  (18333, 25298)
the number of unique words  25298
(11225,)
```

[4.2] Bi-Grams and n-Grams.

In [29]:
```
#bi-gram, tri-gram and n-gram

#removing stop words like "not" should be avoided before building n-gra
ms
# count_vect = CountVectorizer(ngram_range=(1,2))
# please do read the CountVectorizer documentation http://scikit-learn.
org/stable/modules/generated/sklearn.feature_extraction.text.CountVecto
rizer.html

count_vect_gram = CountVectorizer(ngram_range=(1,2), min_df=10, max_fea
tures=5000)
count_vect_gram.fit(X_tr)
final_bigram_counts = count_vect_gram.transform(X_tr)
final_bigram_counts=scaler.fit_transform(final_bigram_counts)
X_cv_ngram = count_vect_gram.transform(X_cv)
X_cv_ngram=scaler.transform(X_cv_ngram)
X_test_ngram=count_vect_gram.transform(X_test)
X_test_ngram=scaler.transform(X_test_ngram)
print("the type of count vectorizer ",type(final_bigram_counts))
print("the shape of out text BOW vectorizer ",final_bigram_counts.get_s
hape())
print("the number of unique words including both unigrams and bigrams "
, final_bigram_counts.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (18333, 5000)
the number of unique words including both unigrams and bigrams  5000
```

[4.3] TF-IDF

In [30]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tf_idf_vect.fit(X_tr)

print("some sample features(unique words in the corpus)",tf_idf_vect.ge
t_feature_names()[0:10])
print('='*50)

final_tf_idf = tf_idf_vect.transform(X_tr)
final_tf_idf=scaler.fit_transform(final_tf_idf)
X_cv_tfidf=tf_idf_vect.transform(X_cv)
X_cv_tfidf=scaler.transform(X_cv_tfidf)
X_test_tfidf=tf_idf_vect.transform(X_test)
X_test_tfidf=scaler.transform(X_test_tfidf)
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])
```

```
some sample features(unique words in the corpus) ['ability', 'able', 'a
ble buy', 'able drink', 'able eat', 'able enjoy', 'able find', 'able ge
t', 'able give', 'able make']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (18333, 11013)
the number of unique words including both unigrams and bigrams  11013
```

[4.4] Word2Vec

In [31]:
```
i=0
list_of_sentance_train=[]
for sentance in X_tr:
    list_of_sentance_train.append(sentance.split())
```

In [32]:
```
i=0
list_of_sentance_cv=[]
```

```
for sentance in X_cv:
    list_of_sentance_cv.append(sentance.split())
```

In [33]:
```
i=0
list_of_sentance_test=[]
for sentance in X_test:
    list_of_sentance_test.append(sentance.split())
```

In [34]:
```
# 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 val
ues
# To use this code-snippet, download "GoogleNews-vectors-negative300.bi
n"
# from https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/edi
t
# it's 1.9GB in size.


# http://kavita-ganesan.com/gensim-word2vec-tutorial-starter-code/#.W17
SRFAzZPY
# 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_train=Word2Vec(list_of_sentance_train,min_count=5,size=50
, workers=4)
    print(w2v_model_train.wv.most_similar('great'))
    print('='*50)
```

```
    print(w2v_model_train.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_trai
n_w2v = True, to train your own w2v ")
```

```
[('awesome', 0.8241584897041321), ('good', 0.8196554780006409), ('excel
lent', 0.8115324378013611), ('fantastic', 0.8062401413917542), ('wonder
ful', 0.7809844613075256), ('amazing', 0.7776182293891907), ('perfect',
0.7070127129554749), ('decent', 0.6891011595726013), ('delicious', 0.68
66593360900879), ('love', 0.6519224643707275)]
==================================================
[('hooked', 0.8284764289855957), ('closest', 0.8278428912162781), ('hot
test', 0.8239474892616272), ('experienced', 0.818336009979248), ('ive',
0.8117782473564148), ('hated', 0.8094334602355957), ('kicking', 0.79508
04829597473), ('tastiest', 0.7943421006202698), ('hands', 0.79242128133
7738), ('nastiest', 0.7879497408866882)]
```

In [35]:

```
'''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_cv=Word2Vec(list_of_sentance_cv,min_count=5,size=50, work
ers=4)
    print(w2v_model_cv.wv.most_similar('great'))
    print('='*50)
    print(w2v_model_cv.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_trai
n_w2v = True, to train your own w2v ")'''
```

Out[35]:

```
'\'is_your_ram_gt_16g=False\nwant_to_use_google_w2v = False\nwant_to_tr
ain_w2v = True\n\nif want_to_train_w2v:\n    # min_count = 5 considers
only words that occured atleast 5 times\n    w2v_model_cv=Word2Vec(list
_of_sentance_cv,min_count=5,size=50, workers=4)\n    print(w2v_model_c
v.wv.most_similar(\'great\'))\n    print(\'=\'*50)\n    print(w2v_model
_cv.wv.most_similar(\'worst\'))\n    \nelif want_to_use_google_w2v and
is_your_ram_gt_16g:\n    if os.path.isfile(\'GoogleNews-vectors-negativ
e300.bin\'):\n        w2v_model=KeyedVectors.load_word2vec_format(\'Goo
gleNews-vectors-negative300.bin\', binary=True)\n        print(w2v_mode
l.wv.most_similar(\'great\'))\n        print(w2v_model.wv.most_similar
(\'worst\'))\n    else:\n        print("you don\'t have gogole\'s word2
vec file, keep want_to_train_w2v = True, to train your own w2v ")'
```

In [36]:

```
'''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_test=Word2Vec(list_of_sentance_test,min_count=5,size=50,
 workers=4)
    print(w2v_model_test.wv.most_similar('great'))
    print('='*50)
    print(w2v_model_test.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_trai
n_w2v = True, to train your own w2v ")'''
```

Out[36]:

```
'\'is_your_ram_gt_16g=False\nwant_to_use_google_w2v = False\nwant_to_tr
ain_w2v = True\n\nif want_to_train_w2v:\n    # min_count = 5 considers
only words that occured atleast 5 times\n    w2v_model_test=Word2Vec(li
st_of_sentance_test,min_count=5,size=50, workers=4)\n    print(w2v_mode
l_test.wv.most_similar(\'great\'))\n    print(\'=\'*50)\n    print(w2v_
model_test.wv.most_similar(\'worst\'))\n    \nelif want_to_use_google_w
2v and is_your_ram_gt_16g:\n    if os.path.isfile(\'GoogleNews-vectors-
negative300.bin\'):\n        w2v_model=KeyedVectors.load_word2vec_forma
t(\'GoogleNews-vectors-negative300.bin\', binary=True)\n        print(w
2v_model.wv.most_similar(\'great\'))\n        print(w2v_model.wv.most_s
imilar(\'worst\'))\n    else:\n        print("you don\'t have gogole\'s
word2vec file, keep want_to_train_w2v = True, to train your own w2v ")'
```

In [37]:

```
w2v_words_train = list(w2v_model_train.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words_tra
in))
print("sample words ", w2v_words_train[0:50])
```

```
number of words that occured minimum 5 times  8207
sample words  ['purchased', 'product', 'name', 'rumford', 'naturals',
'corn', 'starch', 'word', 'appears', 'large', 'clear', 'pictured', 'lab
el', 'also', 'amazon', 'description', 'said', 'made', 'non', 'genetical
ly', 'modified', 'actually', 'received', 'not', 'say', 'still', 'contai
ns', 'one', 'ingredient', 'ingredients', 'cornstarch', 'calcium', 'sugg
ested', 'servings', 'daily', 'value', 'makes', 'potentially', 'good',
'source', 'dietary', 'hand', 'persons', 'must', 'restrict', 'intake',
'example', 'kidney', 'stones', 'potential']
```

In [38]:

```
'''w2v_words_cv = list(w2v_model_cv.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words_c
v))
print("sample words ", w2v_words_cv[0:50])'''
```

Out[38]:

```
'\'w2v_words_cv = list(w2v_model_cv.wv.vocab)\nprint("number of words t
hat occured minimum 5 times ",len(w2v_words_cv))\nprint("sample words
", w2v_words_cv[0:50])'
```

In [39]:
```
''''w2v_words_test = list(w2v_model_test.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words_tes
t))
print("sample words ", w2v_words_test[0:50])'''
```

Out[39]:
```
'\'w2v_words_test = list(w2v_model_test.wv.vocab)\nprint("number of wor
ds that occured minimum 5 times ",len(w2v_words_test))\nprint("sample w
ords ", w2v_words_test[0:50])'
```

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

[4.4.1.1] Avg W2v

In [40]:
```
sent_vectors_train = []; # the avg-w2v for each sentence/review is stor
ed in this list
for sent in tqdm(list_of_sentance_train): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, yo
u 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/re
view
    for word in sent: # for each word in a review/sentence
        if word in w2v_words_train:
            vec = w2v_model_train.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_train.append(sent_vec)
print(len(sent_vectors_train))
print(len(sent_vectors_train[0]))
sent_vectors_train=scaler.fit_transform(sent_vectors_train)
```

```
100%|██████████| 18333/18333 [00:17<00:00, 1040.01it/s]
```

```
18333
50
```

In [41]:
```
sent_vectors_cv = []; # the avg-w2v for each sentence/review is stored
 in this list
for sent in tqdm(list_of_sentance_cv): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, yo
u 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/re
view
    for word in sent: # for each word in a review/sentence
        if word in w2v_words_train:
            vec = w2v_model_train.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_cv.append(sent_vec)
print(len(sent_vectors_cv))
print(len(sent_vectors_cv[0]))
sent_vectors_cv=scaler.transform(sent_vectors_cv)
```

```
100%|██████████| 7857/7857 [00:07<00:00, 1001.58it/s]
```

```
7857
50
```

In [42]:
```
sent_vectors_test = []; # the avg-w2v for each sentence/review is store
d 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, yo
u 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/re
view
    for word in sent: # for each word in a review/sentence
        if word in w2v_words_train:
            vec = w2v_model_train.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
```

```
    sent_vectors_test.append(sent_vec)
print(len(sent_vectors_test))
print(len(sent_vectors_test[0]))
sent_vectors_test=scaler.transform(sent_vectors_test)
```

```
100%|██████████| 11225/11225 [00:12<00:00, 903.31it/s]
```

```
11225
50
```

[4.4.1.2] TFIDF weighted W2v

In [43]:

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model_train= TfidfVectorizer()
tf_idf_matrix_train = model_train.fit_transform(X_tr)
# we are converting a dictionary with word as a key, and the idf as a v
alue
dictionary_train = dict(zip(model_train.get_feature_names(), list(model
_train.idf_)))
```

In [44]:

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
'''model_cv= TfidfVectorizer()
tf_idf_matrix_cv = model_cv.fit_transform(X_cv)
# we are converting a dictionary with word as a key, and the idf as a v
alue
dictionary_cv= dict(zip(model_cv.get_feature_names(), list(model_cv.idf
_)))'''
```

Out[44]:

```
"'model_cv= TfidfVectorizer()\ntf_idf_matrix_cv = model_cv.fit_transfor
m(X_cv)\n# we are converting a dictionary with word as a key, and the i
df as a value\ndictionary_cv= dict(zip(model_cv.get_feature_names(), li
st(model_cv.idf_)))"
```

In [45]:

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
'''model_test= TfidfVectorizer()
tf_idf_matrix_test = model_test.fit_transform(X_test)
# we are converting a dictionary with word as a key, and the idf as a v
```

```
alue
dictionary_test= dict(zip(model_test.get_feature_names(), list(model_te
st.idf_)))'''
```

Out[45]:

```
"'model_test= TfidfVectorizer()\ntf_idf_matrix_test = model_test.fit_tr
ansform(X_test)\n# we are converting a dictionary with word as a key, a
nd the idf as a value\ndictionary_test= dict(zip(model_test.get_feature
_names(), list(model_test.idf_)))"
```

In [46]:

```
# TF-IDF weighted Word2Vec
tfidf_feat_train = model_train.get_feature_names() # tfidf words/col-na
mes
# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
ll_val = tfidf

tfidf_sent_vectors_train = []; # the tfidf-w2v for each sentence/review
 is stored in this list
row=0;
for sent in tqdm(list_of_sentance_train): # for each review/sentence
    sent_vec_train = np.zeros(50) # as word vectors are of zero length
    weight_sum_train =0; # num of words with a valid vector in the sent
ence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words_train and word in tfidf_feat_train:
            vec_train = w2v_model_train.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_train[word]*(sent.count(word)/len(sent))
            sent_vec_train += (vec * tf_idf)
            weight_sum_train += tf_idf
    if weight_sum_train != 0:
        sent_vec_train /= weight_sum_train
    tfidf_sent_vectors_train.append(sent_vec_train)
    row += 1
tfidf_sent_vectors_train =scaler.fit_transform(tfidf_sent_vectors_train
)
```

```
100%|██████████| 18333/18333 [02:08<00:00, 142.64it/s]
```

In [47]:

```
tfidf_feat_cv = model_train.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
ll_val = tfidf

tfidf_sent_vectors_cv = []; # the tfidf-w2v for each sentence/review is
 stored in this list
row=0;
for sent in tqdm(list_of_sentance_cv): # for each review/sentence
    sent_vec_cv = np.zeros(50) # as word vectors are of zero length
    weight_sum_cv =0; # num of words with a valid vector in the sentenc
e/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words_train and word in tfidf_feat_cv:
            vec_cv = w2v_model_train.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_train[word]*(sent.count(word)/len(sent
))
            sent_vec_cv += (vec * tf_idf)
            weight_sum_cv += tf_idf
    if weight_sum_cv != 0:
        sent_vec_cv /= weight_sum_cv
    tfidf_sent_vectors_cv.append(sent_vec_cv)
    row += 1
tfidf_sent_vectors_cv =scaler.transform(tfidf_sent_vectors_cv)
```

```
100%|██████████| 7857/7857 [00:58<00:00, 135.46it/s]
```

In [48]:

```
tfidf_feat_test = model_train.get_feature_names() # tfidf words/col-nam
es
# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
ll_val = tfidf

tfidf_sent_vectors_test = []; # 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_test = np.zeros(50) # as word vectors are of zero length
    weight_sum_test =0; # num of words with a valid vector in the sente
nce/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words_train and word in tfidf_feat_test:
            vec_test = w2v_model_train.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_train[word]*(sent.count(word)/len(sent
))
            sent_vec_test += (vec * tf_idf)
            weight_sum_test += tf_idf
    if weight_sum_test != 0:
        sent_vec_test /= weight_sum_test
    tfidf_sent_vectors_test.append(sent_vec_test)
    row += 1
tfidf_sent_vectors_test =scaler.transform(tfidf_sent_vectors_test)
```

```
100%|██████████| 11225/11225 [01:22<00:00, 136.07it/s]
```

[5] Assignment 7: SVM

1. **Apply SVM 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. **Procedure**

    - You need to work with 2 versions of SVM

- Linear kernel
- RBF kernel

- When you are working with linear kernel, use SGDClassifier' with hinge loss because it is computationally less expensive.
- When you are working with 'SGDClassifier' with hinge loss and trying to find the AUC score, you would have to use CalibratedClassifierCV
- Similarly, like kdtree of knn, when you are working with RBF kernel it's better to reduce the number of dimensions. You can put min_df = 10, max_features = 500 and consider a sample size of 40k points.

3. **Hyper paramter tuning (find best alpha in range [10^-4 to 10^4], and the best penalty among 'l1', 'l2')**

- Find the best hyper parameter which will give the maximum AUC 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

4. **Feature importance**

- When you are working on the linear kernel with BOW or TFIDF please print the top 10 best features for each of the positive and negative classes.

5. **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.

6. **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 with predicted and original labels of test data points. Please visualize your confusion matrices using seaborn heatmaps.

7. **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

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.

Applying SVM

[5.1] Linear SVM

[5.1.1] Applying Linear SVM on BOW, SET 1

In [46]:
```
# Please write all the code with proper documentation
from sklearn.model_selection import GridSearchCV
```

```
from sklearn.linear_model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV
tuned_parameter=[{'alpha':[10**-4,10**-3,10**-2,10**-1,1,10,100,1000,10
000]}]
model=GridSearchCV(SGDClassifier(),tuned_parameter,scoring='roc_auc',cv
=10)
model.fit(final_counts,y_tr)
print(model.best_estimator_)
print(model.score(X_cv_bow,y_cv))
```

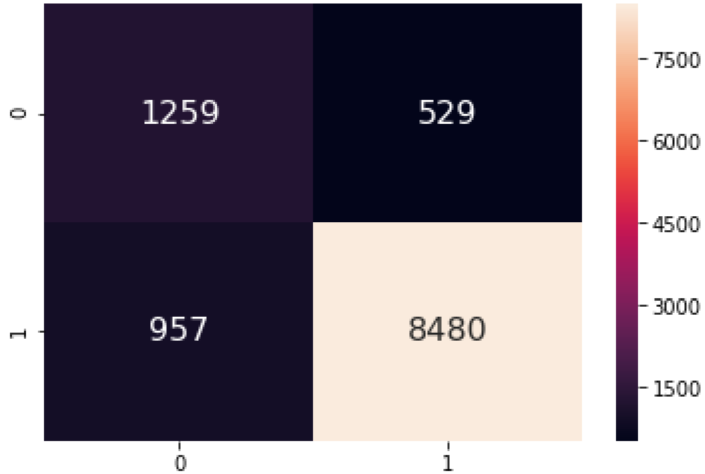
```
SGDClassifier(alpha=0.1, average=False, class_weight=None, early_stoppi
ng=False,
              epsilon=0.1, eta0=0.0, fit_intercept=True, l1_ratio=0.15,
              learning_rate='optimal', loss='hinge', max_iter=1000,
              n_iter_no_change=5, n_jobs=None, penalty='l2', power_t=0.
5,
              random_state=None, shuffle=True, tol=0.001,
              validation_fraction=0.1, verbose=0, warm_start=False)
0.8726887440708868
```

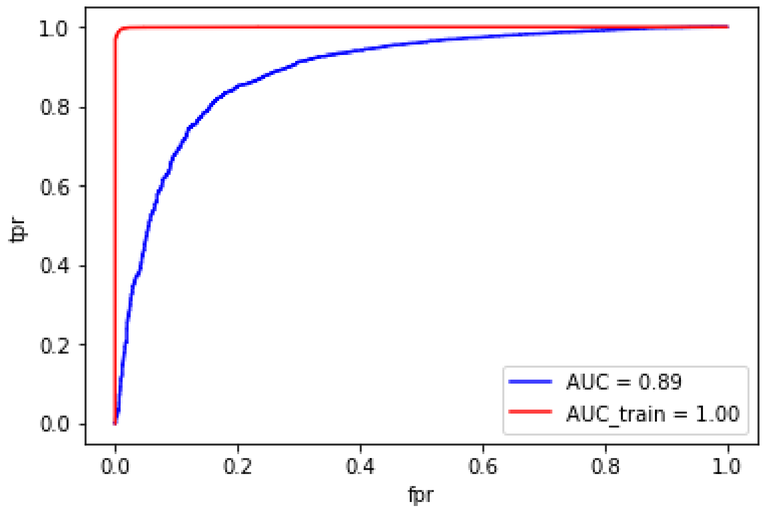
In [47]:

```
model_new=SGDClassifier(class_weight='balanced',loss='hinge',penalty='l
2',alpha=0.1)
model_new.fit(final_counts,y_tr)
pred=model_new.predict(X_test_bow)
acc=accuracy_score(y_test,pred,normalize=True)*float(100)
print("The accuracy of the model is =%d"%acc)
clf_sigmoid=CalibratedClassifierCV(model_new,cv=10,method='sigmoid')
clf_sigmoid.fit(final_counts,y_tr)
prob=clf_sigmoid.predict_proba(X_test_bow)[:,1]
fpr,tpr,thresholds=roc_curve(y_test,prob)
auc=roc_auc_score(y_test,prob)
prob1=clf_sigmoid.predict_proba(final_counts)[:,1]
fpr_train,tpr_train,thresholds=roc_curve(y_tr,prob1)
auc2=roc_auc_score(y_tr,prob1)
df_cm = pd.DataFrame(confusion_matrix(y_test, pred), range(2),range(2))
    #heatman for visualization of matrix
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
plt.show()
plt.plot(fpr,tpr,'b', label = 'AUC = %0.2f' %auc)
```

```python
plt.plot(fpr_train,tpr_train,'r', label = 'AUC_train = %0.2f' %auc2)
plt.legend(loc='lower right')
plt.xlabel('fpr')
plt.ylabel('tpr')
plt.show()
w=model_new.coef_
bow=count_vect.get_feature_names()
print(len(bow))
df=pd.DataFrame(w,columns=bow)
df=df.T
#df=df[0].sort_values(ascending=False)

#print(df.head(10))
print('The top ten positive features are-\n',df[0].sort_values(ascendin
g=False)[0:10])
print('The top ten negative features are-\n',df[0].sort_values(ascendin
g=True)[0:10])
```

```
The accuracy of the model is =86
```






```
25299
The top ten positive features are-
 great        0.178605
love          0.137985
best          0.124148
good          0.122803
loves         0.093239
delicious     0.091144
excellent     0.083276
favorite      0.082350
nice          0.079987
perfect       0.079251
Name: 0, dtype: float64
The top ten negative features are-
 not              -0.142656
disappointed     -0.101235
worst            -0.070600
terrible         -0.067936
thought          -0.067376
horrible         -0.067289
disappointing    -0.067145

ok               -0.062978
```

```
weak              -0.057784
unfortunately    -0.057647
Name: 0, dtype: float64
```

[5.1.2] Applying Linear SVM on TFIDF, SET 2

In [48]:

```
# Please write all the code with proper documentation
tuned_parameter=[{'alpha':[10**-4,10**-3,10**-2,10**-1,1,10,100,1000,10
000]}]
model=GridSearchCV(SGDClassifier(),tuned_parameter,scoring='roc_auc',cv
=10)
model.fit(final_tf_idf,y_tr)
print(model.best_estimator_)
print(model.score(X_cv_tfidf,y_cv))
```

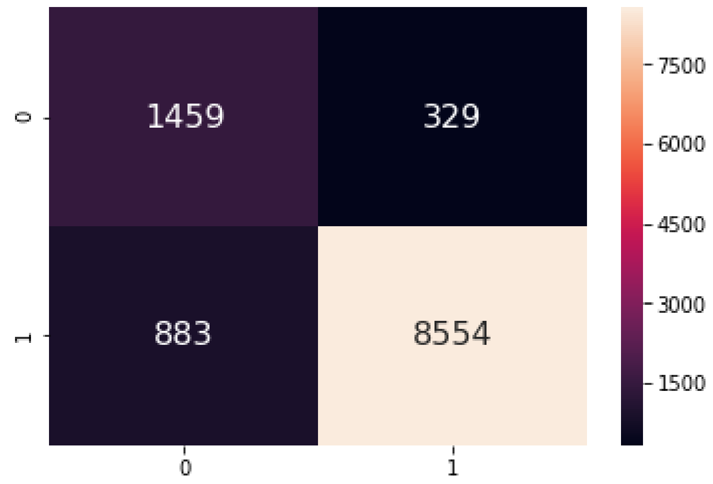
```
SGDClassifier(alpha=1, average=False, class_weight=None, early_stopping
=False,
              epsilon=0.1, eta0=0.0, fit_intercept=True, l1_ratio=0.15,
              learning_rate='optimal', loss='hinge', max_iter=1000,
              n_iter_no_change=5, n_jobs=None, penalty='l2', power_t=0.
5,
              random_state=None, shuffle=True, tol=0.001,
              validation_fraction=0.1, verbose=0, warm_start=False)
0.932930026616775
```

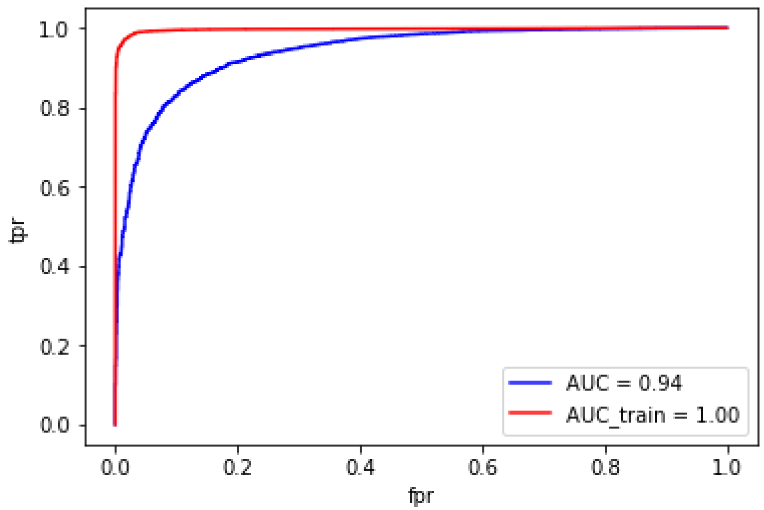
In [49]:

```
model_new=SGDClassifier(class_weight='balanced',loss='hinge',penalty='l
2',alpha=1)
model_new.fit(final_tf_idf,y_tr)
pred=model_new.predict(X_test_tfidf)
acc=accuracy_score(y_test,pred,normalize=True)*float(100)
print("The accuracy of the model is =%d"%acc)
clf_sigmoid=CalibratedClassifierCV(model_new,cv=10,method='sigmoid')
clf_sigmoid.fit(final_tf_idf,y_tr)
prob=clf_sigmoid.predict_proba(X_test_tfidf)[:,1]
fpr,tpr,thresholds=roc_curve(y_test,prob)
auc=roc_auc_score(y_test,prob)
```

```
prob1=clf_sigmoid.predict_proba(final_tf_idf)[:,1]
fpr_train,tpr_train,thresholds=roc_curve(y_tr,prob1)
auc2=roc_auc_score(y_tr,prob1)
df_cm = pd.DataFrame(confusion_matrix(y_test, pred), range(2),range(2))
    #heatman for visualization of matrix
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
plt.show()
plt.plot(fpr,tpr,'b', label = 'AUC = %0.2f' %auc)
plt.plot(fpr_train,tpr_train,'r', label = 'AUC_train = %0.2f' %auc2)
plt.legend(loc='lower right')
plt.xlabel('fpr')
plt.ylabel('tpr')
plt.show()
w=model_new.coef_
tfidf=tf_idf_vect.get_feature_names()
print(len(tfidf))
df=pd.DataFrame(w,columns=tfidf)
df=df.T
#df=df[0].sort_values(ascending=False)

#print(df.head(10))
print('The top ten positive features are-\n',df[0].sort_values(ascendin
g=False)[0:10])
print('The top ten negative features are-\n',df[0].sort_values(ascendin
g=True)[0:10])
```

```
The accuracy of the model is =89
```






```
10971
The top ten positive features are-
 great        0.057681
love         0.047789
good         0.045031
best         0.041013
delicious    0.036070
loves        0.032841
```

```
nice          0.028522
favorite      0.028435
perfect       0.027501
excellent     0.025684
Name: 0, dtype: float64
The top ten negative features are-
 disappointed    -0.039210
worst           -0.035148
not             -0.033992
not worth       -0.033030
disappointing   -0.032885
not recommend   -0.031896

terrible        -0.031041
not good        -0.030294
not purchase    -0.030123
horrible        -0.026707
Name: 0, dtype: float64
```

[5.1.3] Applying Linear SVM on AVG W2V, SET 3

In [50]:

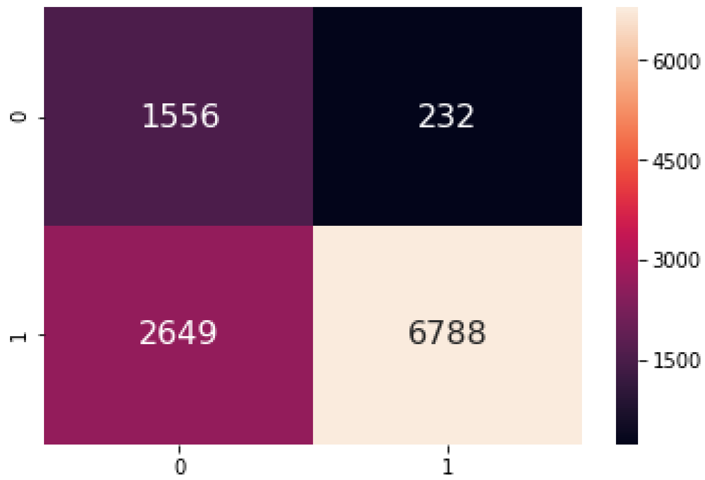
```
# Please write all the code with proper documentation
# Please write all the code with proper documentation
tuned_parameter=[{'alpha':[10**-4,10**-3,10**-2,10**-1,1,10,100,1000,10
000]}]
model=GridSearchCV(SGDClassifier(),tuned_parameter,scoring='roc_auc',cv
=10)
model.fit(sent_vectors_train,y_tr)
print(model.best_estimator_)
ideal_alpha=model.best_estimator_.alpha
print(model.score(sent_vectors_cv,y_cv))
```

```
SGDClassifier(alpha=0.01, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercep
t=True,
              l1_ratio=0.15, learning_rate='optimal', loss='hinge',
              max_iter=1000, n_iter_no_change=5, n_jobs=None, penalty
='l2',
              power_t=0.5, random_state=None, shuffle=True, tol=0.001,
```

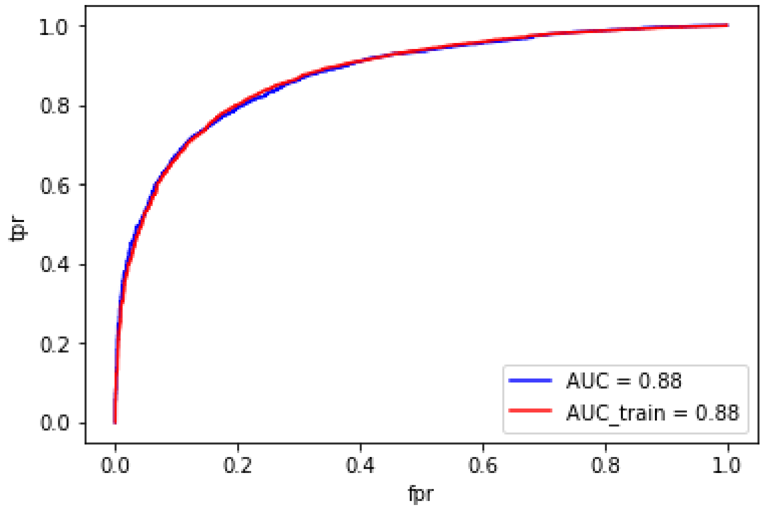
```
                 power_t=0.5, random_state=None, shuffle=True, tol=0.001,

                 validation_fraction=0.1, verbose=0, warm_start=False)
0.875623499296069
```

In [51]:
```
model_new=SGDClassifier(class_weight='balanced',loss='hinge',penalty='l
2',alpha=ideal_alpha)
model_new.fit(sent_vectors_train,y_tr)
pred=model_new.predict(sent_vectors_test)
acc=accuracy_score(y_test,pred,normalize=True)*float(100)
print("The accuracy of the model is =%d"%acc)
clf_sigmoid=CalibratedClassifierCV(model_new,cv=10,method='sigmoid')
clf_sigmoid.fit(sent_vectors_train,y_tr)
prob=clf_sigmoid.predict_proba(sent_vectors_test)[:,1]
fpr,tpr,thresholds=roc_curve(y_test,prob)
auc=roc_auc_score(y_test,prob)
prob1=clf_sigmoid.predict_proba(sent_vectors_train)[:,1]
fpr_train,tpr_train,thresholds=roc_curve(y_tr,prob1)
auc2=roc_auc_score(y_tr,prob1)
df_cm = pd.DataFrame(confusion_matrix(y_test, pred), range(2),range(2))
    #heatman for visualization of matrix
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
plt.show()
plt.plot(fpr,tpr,'b', label = 'AUC = %0.2f' %auc)
plt.plot(fpr_train,tpr_train,'r', label = 'AUC_train = %0.2f' %auc2)
plt.legend(loc='lower right')
plt.xlabel('fpr')
plt.ylabel('tpr')
```

```
The accuracy of the model is =74
```



Out[51]: Text(0,0.5,'tpr')



[5.1.4] Applying Linear SVM on TFIDF W2V, SET 4

In [52]:
```
# Please write all the code with proper documentation
tuned_parameter=[{'alpha':[10**-4,10**-3,10**-2,10**-1,1,10,100,1000,10
```

```
000]}]
model=GridSearchCV(SGDClassifier(),tuned_parameter,scoring='roc_auc',cv
=10)
model.fit(tfidf_sent_vectors_train,y_tr)
print(model.best_estimator_)
ideal_alpha=model.best_estimator_.alpha
print(model.score(tfidf_sent_vectors_cv,y_cv))
```

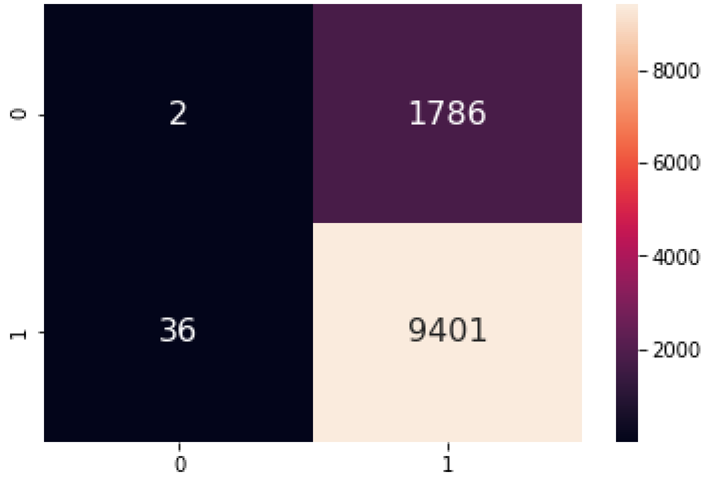
```
SGDClassifier(alpha=0.1, average=False, class_weight=None, early_stoppi
ng=False,
              epsilon=0.1, eta0=0.0, fit_intercept=True, l1_ratio=0.15,
              learning_rate='optimal', loss='hinge', max_iter=1000,
              n_iter_no_change=5, n_jobs=None, penalty='l2', power_t=0.
5,
              random_state=None, shuffle=True, tol=0.001,
              validation_fraction=0.1, verbose=0, warm_start=False)
0.5048129729336692
```

In [53]:

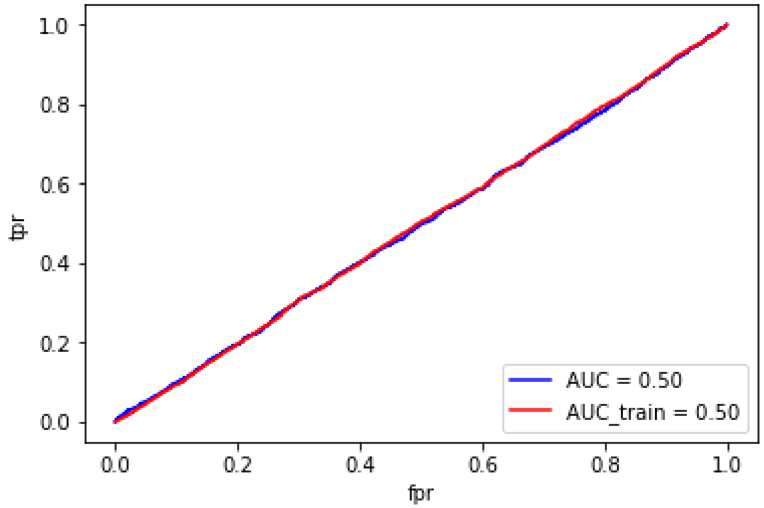
```
model_new=SGDClassifier(class_weight='balanced',loss='hinge',penalty='l
2',alpha=ideal_alpha)
model_new.fit(tfidf_sent_vectors_train,y_tr)
pred=model_new.predict(tfidf_sent_vectors_test)
acc=accuracy_score(y_test,pred,normalize=True)*float(100)
print("The accuracy of the model is =%d"%acc)
clf_sigmoid=CalibratedClassifierCV(model_new,cv=10,method='sigmoid')
clf_sigmoid.fit(tfidf_sent_vectors_train,y_tr)
prob=clf_sigmoid.predict_proba(tfidf_sent_vectors_test)[:,1]
fpr,tpr,thresholds=roc_curve(y_test,prob)
auc=roc_auc_score(y_test,prob)
prob1=clf_sigmoid.predict_proba(tfidf_sent_vectors_train)[:,1]
fpr_train,tpr_train,thresholds=roc_curve(y_tr,prob1)
auc2=roc_auc_score(y_tr,prob1)
df_cm = pd.DataFrame(confusion_matrix(y_test, pred), range(2),range(2))
    #heatman for visualization of matrix
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
plt.show()
plt.plot(fpr,tpr,'b', label = 'AUC = %0.2f' %auc)
plt.plot(fpr_train,tpr_train,'r', label = 'AUC_train = %0.2f' %auc2)
plt.legend(loc='lower right')
```

```python
plt.xlabel('fpr')
plt.ylabel('tpr')
```

```
The accuracy of the model is =83
```



Out[53]: Text(0,0.5,'tpr')



[5.2] RBF SVM

[5.2.1] Applying RBF SVM on BOW, SET 1

In [54]:
```
# Please write all the code with proper documentation
count_vect = CountVectorizer(min_df=10, max_features=50)
count_vect.fit(X_tr)

print("some feature names ", count_vect.get_feature_names()[:10])
print('='*50)

final_counts = count_vect.transform(X_tr)
final_counts=scaler.fit_transform(final_counts)
X_cv_bow=count_vect.transform(X_cv)
X_cv_bow=scaler.fit_transform(X_cv_bow)
X_test_bow=count_vect.transform(X_test)
X_test_bow=scaler.fit_transform(X_test_bow)
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(y_test.shape)
```

```
some feature names  ['also', 'amazon', 'bag', 'best', 'better', 'bough
t', 'buy', 'chocolate', 'coffee', 'could']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (18333, 50)
the number of unique words  50
(11225,)
```

In [55]:
```
from sklearn.svm import SVC
tuned_parameter=[{'C':[10**-4,10**-3,10**-2,10**-1,1,10,100,1000,10000
]}]
model=GridSearchCV(SVC(),tuned_parameter,scoring='roc_auc',cv=10)
model.fit(final_counts,y_tr)
print(model.best_estimator_)
```

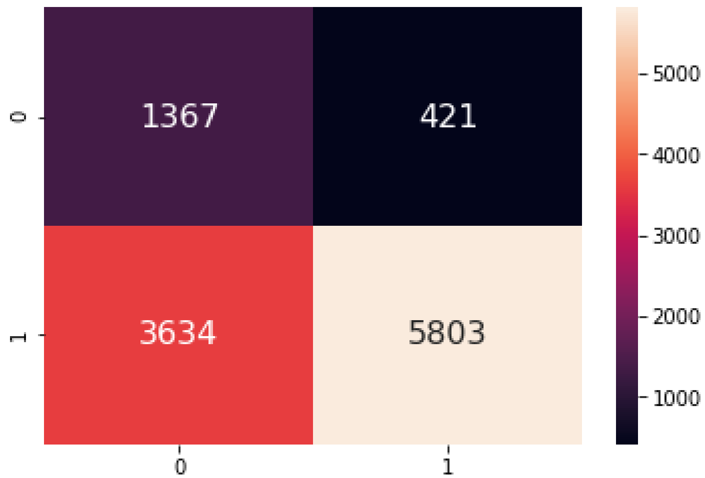
```
ideal_c=model.best_estimator_.C
print(model.score(X_cv_bow,y_cv))
```

```
SVC(C=0.1, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
    kernel='rbf', max_iter=-1, probability=False, random_state=None,
    shrinking=True, tol=0.001, verbose=False)
0.7434447947203654
```

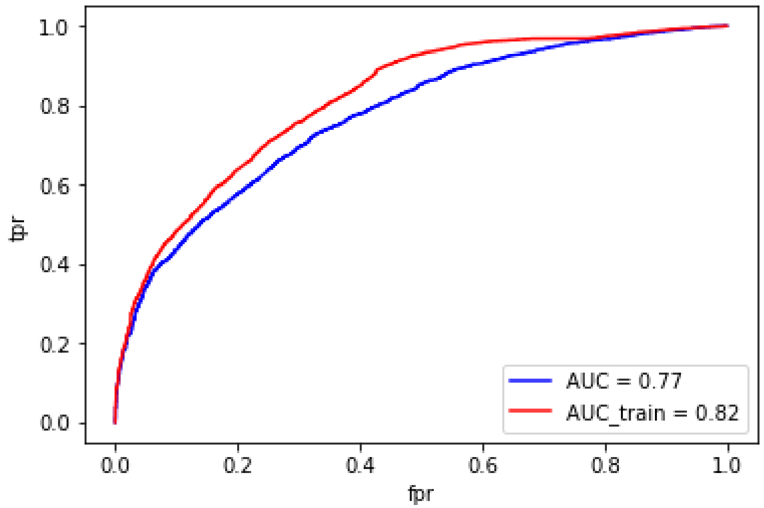
In [56]:

```
model_new=SVC(C=ideal_c,kernel='rbf',probability=True,class_weight='bal
anced')
model_new.fit(final_counts,y_tr)
pred=model_new.predict(X_test_bow)
acc=accuracy_score(y_test,pred,normalize=True)*float(100)
print("The accuracy of the model is =%d"%acc)
probab=model_new.predict_proba(X_test_bow)[:,1]
fpr,tpr,thresholds=roc_curve(y_test,probab)
auc=roc_auc_score(y_test,probab)
pred2=model_new.predict(final_counts)
probab2=model_new.predict_proba(final_counts)[:,1]
fpr_train,tpr_train,thresholds=roc_curve(y_tr,probab2)
auc2=roc_auc_score(y_tr,probab2)
df_cm = pd.DataFrame(confusion_matrix(y_test, pred), range(2),range(2))
    #heatman for visualization of matrix
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
plt.show()
plt.plot(fpr,tpr,'b', label = 'AUC = %0.2f' %auc)
plt.plot(fpr_train,tpr_train,'r', label = 'AUC_train = %0.2f' %auc2)
plt.legend(loc='lower right')
plt.xlabel('fpr')
plt.ylabel('tpr')
```

```
The accuracy of the model is =63
```



Out[56]: Text(0,0.5,'tpr')



[5.2.2] Applying RBF SVM on TFIDF, SET 2

In [57]:
```
# Please write all the code with proper documentation
```

```
# Please write all the code with proper documentation
count_vect_gram = CountVectorizer(ngram_range=(1,2), min_df=10, max_fea
tures=50)
count_vect_gram.fit(X_tr)
final_bigram_counts = count_vect_gram.transform(X_tr)
final_bigram_counts=scaler.fit_transform(final_bigram_counts)
X_cv_ngram = count_vect_gram.transform(X_cv)
X_cv_ngram=scaler.fit_transform(X_cv_ngram)
X_test_ngram=count_vect_gram.transform(X_test)
X_test_ngram=scaler.fit_transform(X_test_ngram)
print("the type of count vectorizer ",type(final_bigram_counts))
print("the shape of out text BOW vectorizer ",final_bigram_counts.get_s
hape())
print("the number of unique words including both unigrams and bigrams "
, final_bigram_counts.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (18333, 50)
the number of unique words including both unigrams and bigrams  50
```

In [58]:

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10,max_features
=500)
tf_idf_vect.fit(X_tr)

print("some sample features(unique words in the corpus)",tf_idf_vect.ge
t_feature_names()[0:10])
print('='*50)

final_tf_idf = tf_idf_vect.transform(X_tr)
final_tf_idf=scaler.fit_transform(final_tf_idf)
X_cv_tfidf=tf_idf_vect.transform(X_cv)
X_cv_tfidf=scaler.fit_transform(X_cv_tfidf)
X_test_tfidf=tf_idf_vect.transform(X_test)
X_test_tfidf=scaler.fit_transform(X_test_tfidf)
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])
```

```
some sample features(unique words in the corpus) ['able', 'absolutely',
'acid', 'actually', 'add', 'added', 'aftertaste', 'ago', 'almost', 'als
o']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (18333, 500)
the number of unique words including both unigrams and bigrams  500
```

In [59]:

```
tuned_parameter=[{'C':[10**-4,10**-3,10**-2,10**-1,1,10,100,1000,10000
]}]
model=GridSearchCV(SVC(),tuned_parameter,scoring='roc_auc',cv=10)
model.fit(final_tf_idf,y_tr)
print(model.best_estimator_)
ideal_c=model.best_estimator_.C
print(model.score(X_cv_tfidf,y_cv))
```

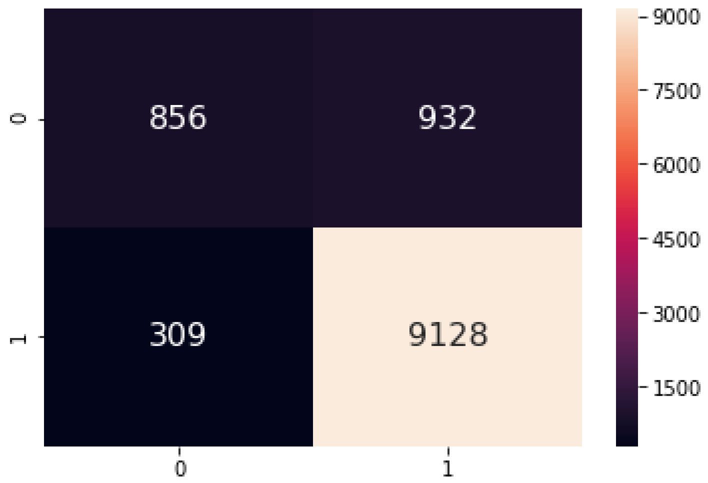
```
SVC(C=10, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
    kernel='rbf', max_iter=-1, probability=False, random_state=None,
    shrinking=True, tol=0.001, verbose=False)
0.9029224151652927
```

In [60]:

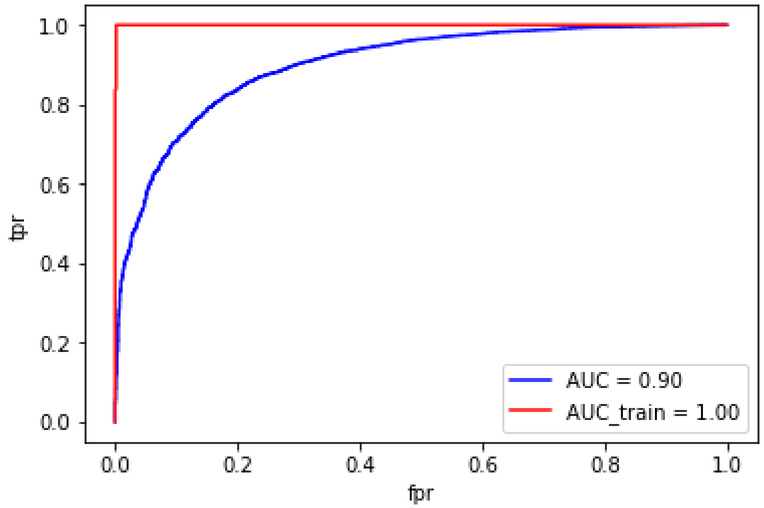
```
model_new=SVC(C=ideal_c,kernel='rbf',probability=True,class_weight='bal
anced')
model_new.fit(final_tf_idf,y_tr)
pred=model_new.predict(X_test_tfidf)
acc=accuracy_score(y_test,pred,normalize=True)*float(100)
print("The accuracy of the model is =%d"%acc)
probab=model_new.predict_proba(X_test_tfidf)[:,1]
fpr,tpr,thresholds=roc_curve(y_test,probab)
auc=roc_auc_score(y_test,probab)
pred2=model_new.predict(final_tf_idf)
probab2=model_new.predict_proba(final_tf_idf)[:,1]
fpr_train,tpr_train,thresholds=roc_curve(y_tr,probab2)
auc2=roc_auc_score(y_tr,probab2)
df_cm = pd.DataFrame(confusion_matrix(y_test, pred), range(2),range(2))
    #heatman for visualization of matrix
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
plt.show()
```

```
plt.plot(fpr,tpr,'b', label = 'AUC = %0.2f' %auc)
plt.plot(fpr_train,tpr_train,'r', label = 'AUC_train = %0.2f' %auc2)
plt.legend(loc='lower right')
plt.xlabel('fpr')
plt.ylabel('tpr')
```

```
The accuracy of the model is =88
```



Out[60]: Text(0,0.5,'tpr')



[5.2.3] Applying RBF SVM on AVG W2V, SET 3

In [50]:

```
# Please write all the code with proper documentation
from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC
tuned_parameter=[{'C':[10**-4,10**-3,10**-2,10**-1,1,10,100,1000,10000
]}]
model=GridSearchCV(SVC(),tuned_parameter,scoring='roc_auc',cv=10)
model.fit(sent_vectors_train,y_tr)
print(model.best_estimator_)
ideal_c=model.best_estimator_.C
print(model.score(sent_vectors_cv,y_cv))
```

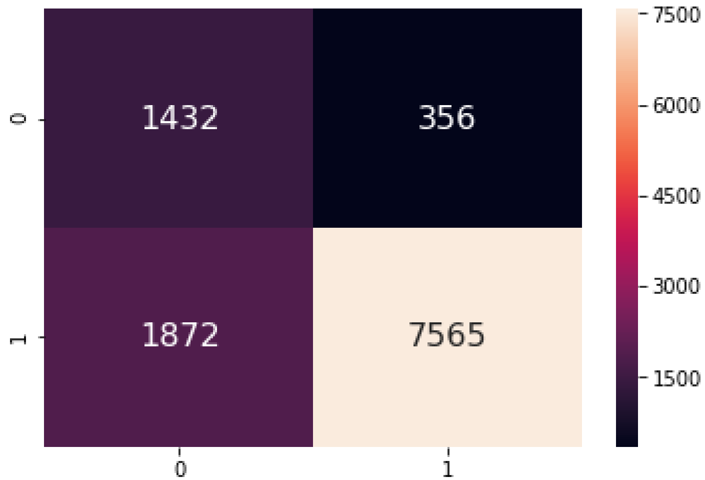
```
SVC(C=1, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
    kernel='rbf', max_iter=-1, probability=False, random_state=None,
    shrinking=True, tol=0.001, verbose=False)
0.8804138182789811
```

In [51]:

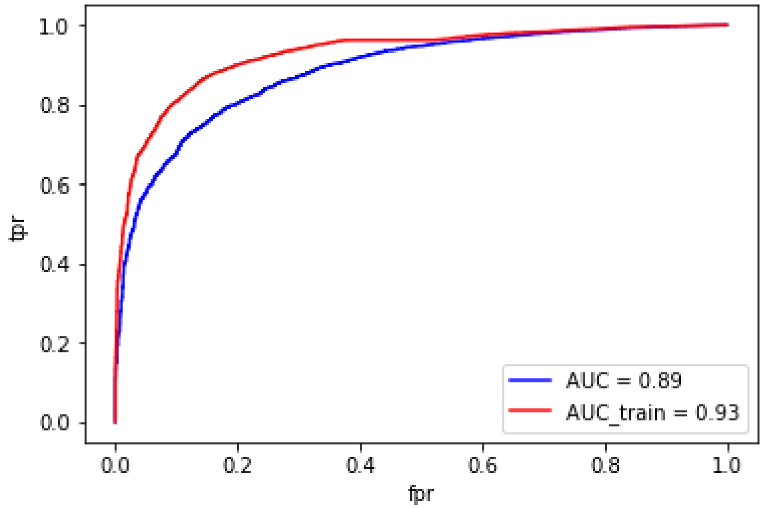
```
model_new=SVC(C=ideal_c,kernel='rbf',probability=True,class_weight='bal
anced')
model_new.fit(sent_vectors_train,y_tr)
pred=model_new.predict(sent_vectors_test)
acc=accuracy_score(y_test,pred,normalize=True)*float(100)
print("The accuracy of the model is =%d"%acc)
probab=model_new.predict_proba(sent_vectors_test)[:,1]
fpr,tpr,thresholds=roc_curve(y_test,probab)
auc=roc_auc_score(y_test,probab)
pred2=model_new.predict(sent_vectors_train)
probab2=model_new.predict_proba(sent_vectors_train)[:,1]
fpr_train,tpr_train,thresholds=roc_curve(y_tr,probab2)
auc2=roc_auc_score(y_tr,probab2)
df_cm = pd.DataFrame(confusion_matrix(y_test, pred), range(2),range(2))
    #heatman for visualization of matrix
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
plt.show()
```

```
plt.plot(fpr,tpr,'b', label = 'AUC = %0.2f' %auc)
plt.plot(fpr_train,tpr_train,'r', label = 'AUC_train = %0.2f' %auc2)
plt.legend(loc='lower right')
plt.xlabel('fpr')
plt.ylabel('tpr')
```

```
The accuracy of the model is =80
```



Out[51]: Text(0,0.5,'tpr')



[5.2.4] Applying RBF SVM on TFIDF W2V, SET 4

In [ ]:

```
'''# Please write all the code with proper documentation
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model_train= TfidfVectorizer(ngram_range=(1,2), min_df=10, max_features
=50)
tf_idf_matrix_train = model_train.fit_transform(X_tr)
# we are converting a dictionary with word as a key, and the idf as a v
alue
dictionary_train = dict(zip(model_train.get_feature_names(), list(model
_train.idf_)))'''
```

In [ ]:

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
''''model_cv= TfidfVectorizer(ngram_range=(1,2), min_df=10, max_feature
s=50)
tf_idf_matrix_cv = model_cv.fit_transform(X_cv)
# we are converting a dictionary with word as a key, and the idf as a v
alue
dictionary_cv= dict(zip(model_cv.get_feature_names(), list(model_cv.idf
_)))'''
```

In [ ]:
```
'''# TF-IDF weighted Word2Vec
tfidf_feat_train = model_train.get_feature_names() # tfidf words/col-na
mes
# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
ll_val = tfidf

tfidf_sent_vectors_train = []; # the tfidf-w2v for each sentence/review
 is stored in this list
row=0;
for sent in tqdm(list_of_sentance_train): # for each review/sentence
    sent_vec_train = np.zeros(50) # as word vectors are of zero length
    weight_sum_train =0; # num of words with a valid vector in the sent
ence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words_train and word in tfidf_feat_train:
            vec_train = w2v_model_train.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_train[word]*(sent.count(word)/len(sent))
            sent_vec_train += (vec * tf_idf)
            weight_sum_train += tf_idf
    if weight_sum_train != 0:
        sent_vec_train /= weight_sum_train
    tfidf_sent_vectors_train.append(sent_vec_train)
    row += 1
tfidf_sent_vectors_train =scaler.fit_transform(tfidf_sent_vectors_trai
n)'''
```

In [ ]:
```
'''tfidf_feat_cv = model_cv.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
ll_val = tfidf

tfidf_sent_vectors_cv = []; # the tfidf-w2v for each sentence/review is
 stored in this list
row=0;
for sent in tqdm(list_of_sentance_cv): # for each review/sentence
    sent_vec_cv = np.zeros(50) # as word vectors are of zero length
```

```
    weight_sum_cv =0; # num of words with a valid vector in the sentenc
e/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words_train and word in tfidf_feat_cv:
            vec_cv = w2v_model_train.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_train[word]*(sent.count(word)/len(sen
t))
            sent_vec_cv += (vec * tf_idf)
            weight_sum_cv += tf_idf
    if weight_sum_cv != 0:
        sent_vec_cv /= weight_sum_cv
    tfidf_sent_vectors_cv.append(sent_vec_cv)
    row += 1
tfidf_sent_vectors_cv =scaler.fit_transform(tfidf_sent_vectors_cv)'''
```

In [ ]:

```
'''tfidf_feat_test = model_test.get_feature_names() # tfidf words/col-n
ames
# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
ll_val = tfidf

tfidf_sent_vectors_test = []; # 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_test = np.zeros(50) # as word vectors are of zero length
    weight_sum_test =0; # num of words with a valid vector in the sente
nce/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words_train and word in tfidf_feat_test:
            vec_test = w2v_model_train.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_train[word]*(sent.count(word)/len(sen
```

```
t))
                sent_vec_test += (vec * tf_idf)
                weight_sum_test += tf_idf
    if weight_sum_test != 0:
        sent_vec_test /= weight_sum_test
    tfidf_sent_vectors_test.append(sent_vec_test)
    row += 1
tfidf_sent_vectors_test =scaler.fit_transform(tfidf_sent_vectors_tes
t)'''
```

In [52]:

```
# Please write all the code with proper documentation
tuned_parameter=[{'C':[10**-4,10**-3,10**-2,10**-1,1,10,100,1000,10000
]}]
model=GridSearchCV(SVC(),tuned_parameter,scoring='roc_auc',cv=10)
model.fit(tfidf_sent_vectors_train,y_tr)
print(model.best_estimator_)
ideal_c=model.best_estimator_.C
print(model.score(tfidf_sent_vectors_cv,y_cv))
```

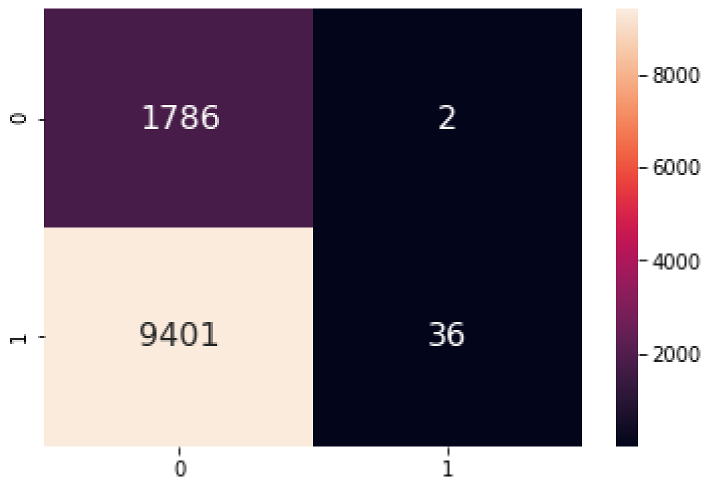
```
SVC(C=10, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
    kernel='rbf', max_iter=-1, probability=False, random_state=None,
    shrinking=True, tol=0.001, verbose=False)
0.500462363178603
```

In [53]:

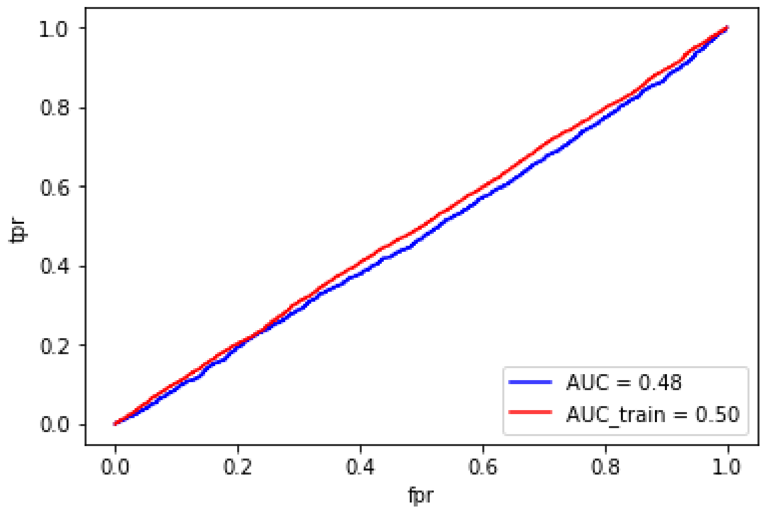
```
model_new=SVC(C=ideal_c,kernel='rbf',probability=True,class_weight='bal
anced')
model_new.fit(tfidf_sent_vectors_train,y_tr)
pred=model_new.predict(tfidf_sent_vectors_test)
acc=accuracy_score(y_test,pred,normalize=True)*float(100)
print("The accuracy of the model is =%d"%acc)
probab=model_new.predict_proba(tfidf_sent_vectors_test)[:,1]
fpr,tpr,thresholds=roc_curve(y_test,probab)
auc=roc_auc_score(y_test,probab)
pred2=model_new.predict(tfidf_sent_vectors_train)
probab2=model_new.predict_proba(tfidf_sent_vectors_train)[:,1]
fpr_train,tpr_train,thresholds=roc_curve(y_tr,probab2)
auc2=roc_auc_score(y_tr,probab2)
df_cm = pd.DataFrame(confusion_matrix(y_test, pred), range(2),range(2))
```

```
    #heatman for visualization of matrix
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
plt.show()
plt.plot(fpr,tpr,'b', label = 'AUC = %0.2f' %auc)
plt.plot(fpr_train,tpr_train,'r', label = 'AUC_train = %0.2f' %auc2)
plt.legend(loc='lower right')
plt.xlabel('fpr')
plt.ylabel('tpr')
```

```
The accuracy of the model is =16
```



Out[53]: `Text(0,0.5,'tpr')`



[6] Conclusions

In [54]:

```
# Please compare all your models using Prettytable library
from prettytable import PrettyTable
x=PrettyTable()
x.field_names=(['Vectorizer','Kernel','Hyperparameter-C','AUC'])
x.add_row(['BOW','Linear',0.1,0.90])
x.add_row(['TFIDF','linear',1,0.94])
x.add_row(['Avg W2V','Linear',0.01,0.88])
x.add_row(['Weighted TFIDF','Linear',0.01,0.49])
x.add_row(['BOW','RBF SVM',0.1,0.78])
x.add_row(['TFIDF','RBF SVM',0.1,0.39])
x.add_row(['Avg W2V','Linear',1,0.89])
x.add_row(['Weighted TFIDF','RBF SVM',10,0.48])
print(x)
```

```
+----------------+---------+------------------+------+
|   Vectorizer   |  Kernel | Hyperparameter-C | AUC  |
+----------------+---------+------------------+------+
|      BOW       |  Linear |       0.1        | 0.9  |
```

TFIDF	linear	1	0.94
Avg W2V	Linear	0.01	0.88
Weighted TFIDF	Linear	0.01	0.49
BOW	RBF SVM	0.1	0.78
TFIDF	RBF SVM	0.1	0.39
Avg W2V	Linear	1	0.89
Weighted TFIDF	RBF SVM	10	0.48