SVM

June 7, 2020

1 Amazon Fine Food Reviews Analysis

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

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

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

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

Attribute Information:

1. Id
2. ProductId - unique identifier for the product
3. UserId - 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.

2 [1]. Reading Data

2.1 [1.1] Loading the data

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

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

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

[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.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from numpy import random
from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler

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

from bs4 import BeautifulSoup


import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle

from tqdm import tqdm
import os

from sklearn.metrics import roc_curve,accuracy_score
from sklearn.metrics import precision_score, recall_score
from sklearn.metrics import f1_score, confusion_matrix
```

[3]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id
=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redire
ct_uri=urn%3aietf%3awg%3aoauth%3a2.0%3aoob&response_type=code&scope=email%20http
s%3a%2f%2fwww.googleapis.com%2fauth%2fdocs.test%20https%3a%2f%2fwww.googleapis.c
om%2fauth%2fdrive%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive.photos.reado
nly%20https%3a%2f%2fwww.googleapis.com%2fauth%2fpeopleapi.readonly

Enter your authorization code:
ůůůůůůůůůů
Mounted at /content/drive
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

[4]:
```
# using SQLite Table to read data.

con = sqlite3.connect('drive/My Drive/FFRDB/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

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3␣
↪LIMIT 50000""", con)

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a␣
↪negative rating(0).
def partition(x):
    if x < 3:
        return 0
    return 1

#changing reviews with score less than 3 to be positive and vice-versa
actualScore = filtered_data['Score']
positiveNegative = actualScore.map(partition)
filtered_data['Score'] = positiveNegative
print("Number of data points in our data", filtered_data.shape)
filtered_data.head(3)
```

```
Number of data points in our data (50000, 10)
```

[4]:
```
   Id  ...                                               Text
0   1  ...  I have bought several of the Vitality canned d...
1   2  ...  Product arrived labeled as Jumbo Salted Peanut...
2   3  ...  This is a confection that has been around a fe...

[3 rows x 10 columns]
```

[0]:
```
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
""", con)
```

[6]:
```
print(display.shape)
display.head()
```

```
(80668, 7)
```

[6]:
```
               UserId  ... COUNT(*)
0  #oc-R115TNMSPFT9I7  ...        2
1  #oc-R11D9D7SHXIJB9  ...        3
2  #oc-R11DNU2NBKQ23Z  ...        2
3  #oc-R11O5J5ZVQE25C  ...        3
4  #oc-R12KPBODL2B5ZD  ...        2

[5 rows x 7 columns]
```

[7]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

[7]:
```
              UserId  ... COUNT(*)
80638  AZY10LLTJ71NX  ...        5

[1 rows x 7 columns]
```

[8]:
```
display['COUNT(*)'].sum()
```

[8]:
```
393063
```

3 [2] Exploratory Data Analysis

3.1 [2.1] Data Cleaning: Deduplication

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

[9]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

[9]:
```
       Id  ...                                               Text
0   78445  ...  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
1  138317  ...  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
2  138277  ...  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
3   73791  ...  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
4  155049  ...  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...

[5 rows x 10 columns]
```

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.

[0]:
```
#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')
```

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

[11]:
```
(46072, 10)
```

[12]:
```
final.sort_values('Time',inplace=True)
print(final.head(5))
```

```
          Id  ...                                               Text
1146    1245  ...  This was a really good idea and the final prod...
1145    1244  ...  I just received my shipment and could hardly w...
28086  30629  ...  Nothing against the product, but it does bothe...
```

```
28087  30630  ...  I love this stuff. It is sugar-free so it does...
38740  42069  ...  Fresh limes are underappreciated, but a joy to...

[5 rows x 10 columns]
```

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

[13]:
```
92.144
```

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

[14]:
```python
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

[14]:
```
      Id  ...                                               Text
0  64422  ...  My son loves spaghetti so I didn't hesitate or...
1  44737  ...  It was almost a 'love at first bite' - the per...

[2 rows x 10 columns]
```

[0]:
```python
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

[16]:
```python
#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()
```

```
(46071, 10)
```

[16]:
```
1    38479
0     7592
Name: Score, dtype: int64
```

4 [3] Preprocessing

4.1 [3.1]. Preprocessing Review Text

Now that we have finished deduplication our data requires some preprocessing before we go on further with analysis and making the prediction model.

Hence in the Preprocessing phase we do the following in the order below:-

1. Begin by removing the html tags
2. Remove any punctuations or limited set of special characters like , or . or # etc.
3. Check if the word is made up of english letters and is not alpha-numeric
4. Check to see if the length of the word is greater than 2 (as it was researched that there is no adjective in 2-letters)
5. Convert the word to lowercase
6. Remove Stopwords
7. Finally Snowball Stemming the word (it was obsereved to be better than Porter Stemming)

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

[17]:
```python
# 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)
```

```
This was a really good idea and the final product is outstanding. I use the
decals on my car window and everybody asks where i bought the decals i made.
Two thumbs up!
==================================================
If your trying to do a low carb product.  This works out great.  There are
receipies on tova's website on how to make poundcake, pancakes, and a variety of
other items.  They turn out pretty great.<br /><br />Try it.  It's a great
product.<br /><br /> ~Donna
==================================================
The orange and lemon peels make this tea very hippy.  Despite  the initial
oohing and ahing over the pretty blue flowers, this is a regrettable purchase.
I was hoping for a stronger bergamot component than Twinings' Earl Grey but
instead I got something that seems very herbal.  Blech.  I disagree with the
positive reviews.
==================================================
I love these licorice.  Get licorice flavor--not just sugar with some flavor.
Very satisfying.
==================================================
```

[18]:
```
# remove urls from text python: https://stackoverflow.com/a/40823105/4084039
sent_0 = re.sub(r"http\S+", "", sent_0)
sent_1000 = re.sub(r"http\S+", "", sent_1000)
sent_150 = re.sub(r"http\S+", "", sent_1500)
sent_4900 = re.sub(r"http\S+", "", sent_4900)

print(sent_0)
```

```
This was a really good idea and the final product is outstanding. I use the
decals on my car window and everybody asks where i bought the decals i made.
Two thumbs up!
```

[19]:
```
# 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)
```

```
This was a really good idea and the final product is outstanding. I use the
decals on my car window and everybody asks where i bought the decals i made.
Two thumbs up!
==================================================
If your trying to do a low carb product.  This works out great.  There are
receipies on tova's website on how to make poundcake, pancakes, and a variety of
other items.  They turn out pretty great.Try it.  It's a great product. ~Donna
==================================================
The orange and lemon peels make this tea very hippy.  Despite  the initial
oohing and ahing over the pretty blue flowers, this is a regrettable purchase.
I was hoping for a stronger bergamot component than Twinings' Earl Grey but
instead I got something that seems very herbal.  Blech.  I disagree with the
```

```
positive reviews.
==================================================
I love these licorice.  Get licorice flavor--not just sugar with some flavor.
Very satisfying.
```

[0]:
```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
```

[21]:
```python
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
The orange and lemon peels make this tea very hippy.  Despite  the initial
oohing and ahing over the pretty blue flowers, this is a regrettable purchase.
I was hoping for a stronger bergamot component than Twinings' Earl Grey but
instead I got something that seems very herbal.  Blech.  I disagree with the
positive reviews.
==================================================
```

[22]:
```python
#remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
This was a really good idea and the final product is outstanding. I use the
decals on my car window and everybody asks where i bought the decals i made.
Two thumbs up!
```

[23]:
```python
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
The orange and lemon peels make this tea very hippy Despite the initial oohing
and ahing over the pretty blue flowers this is a regrettable purchase I was
hoping for a stronger bergamot component than Twinings Earl Grey but instead I
got something that seems very herbal Blech I disagree with the positive reviews
```

[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", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he',␣
 ↪'him', 'his', 'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its',␣
 ↪'itself', 'they', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this',␣
 ↪'that', "that'll", 'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have',␣
 ↪'has', 'had', 'having', 'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or',␣
 ↪'because', 'as', 'until', 'while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into',␣
 ↪'through', 'during', 'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on',␣
 ↪'off', 'over', 'under', 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how',␣
 ↪'all', 'any', 'both', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so',␣
 ↪'than', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should',␣
 ↪"should've", 'now', 'd', 'll', 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn',␣
 ↪"didn't", 'doesn', "doesn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't",␣
 ↪'ma', 'mightn', "mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn',␣
 ↪"shouldn't", 'wasn', "wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

[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%|| 46071/46071 [00:15<00:00, 2936.79it/s]
```

[26]:
```
preprocessed_reviews[1500]
```

[26]:
```
'orange lemon peels make tea hippy despite initial oohing ahing pretty blue
flowers regrettable purchase hoping stronger bergamot component twinings earl
grey instead got something seems herbal blech disagree positive reviews'
```

[3.2] Preprocessing Review Summary

5 [4] Featurization

5.0.1 Loading tfidf and avg W2V pickles of 50k points

[0]:
```
import pickle
import os

dbfile1 = open('/content/drive/My Drive/FFRDB/tfidf_50k.pkl', 'rb')
tfidf_sent_vectors = pickle.load(dbfile1)


dbfile2 = open('/content/drive/My Drive/FFRDB/sent_vectors_50k.pkl', 'rb')
sent_vectors= pickle.load(dbfile2)
```

6 [5] Assignment 7: SVM

```
<li><strong>Apply SVM on these feature sets</strong>
    <ul>
        <li><font color='red'>SET 1:</font>Review text, preprocessed one converted into vector
        <li><font color='red'>SET 2:</font>Review text, preprocessed one converted into vector
        <li><font color='red'>SET 3:</font>Review text, preprocessed one converted into vector
        <li><font color='red'>SET 4:</font>Review text, preprocessed one converted into vector
    </ul>
</li>
<br>
<li><strong>Procedure</strong>
    <ul>
```

```
<li>You need to work with 2 versions of SVM
    <ul><li>Linear kernel</li>
        <li>RBF kernel</li></ul>
<li>When you are working with linear kernel, use SGDClassifier with hinge loss because it is co
<li>When you are working with SGDClassifier with hinge loss and trying to find the AUC
    score, you would have to use <a href='https://scikit-learn.org/stable/modules/generated/skl
<li>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.

```
    </ul>
</li>
<br>
<li><strong>Hyper paramter tuning (find best alpha in range [10^-4 to 10^4], and the best penal
    <ul>
<li>Find the best hyper parameter which will give the maximum <a href='https://www.appliedaicou
<li>Find the best hyper paramter using k-fold cross validation or simple cross validation data
<li>Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this ta
    </ul>
</li>
<br>
<li><strong>Feature importance</strong>
    <ul>
<li>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.

```
    </ul>
</li>
<br>
<li><strong>Feature engineering</strong>
    <ul>
<li>To increase the performance of your model, you can also experiment with with feature engine
        <ul>
        <li>Taking length of reviews as another feature.</li>
        <li>Considering some features from review summary as well.</li>
    </ul>
    </ul>
</li>
<br>
<li><strong>Representation of results</strong>
    <ul>
<li>You need to plot the performance of model both on train data and cross validation data for
<img src='train_cv_auc.JPG' width=300px></li>
<li>Once after you found the best hyper parameter, you need to train your model with it, and fi
<img src='train_test_auc.JPG' width=300px></li>
<li>Along with plotting ROC curve, you need to print the <a href='https://www.appliedaicourse.c
<img src='confusion_matrix.png' width=300px></li>
```

```
    </ul>
</li>
<br>
<li><strong>Conclusion</strong>
    <ul>
<li>You need to summarize the results at the end of the notebook, summarize it in the table fo
    <img src='summary.JPG' width=400px>
</li>
    </ul>
```

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.

7 Applying SVM

7.1 [5.1] Linear SVM

7.1.1 [5.1.1] Applying Linear SVM on BOW, SET 1

7.1.2 L1 Reg

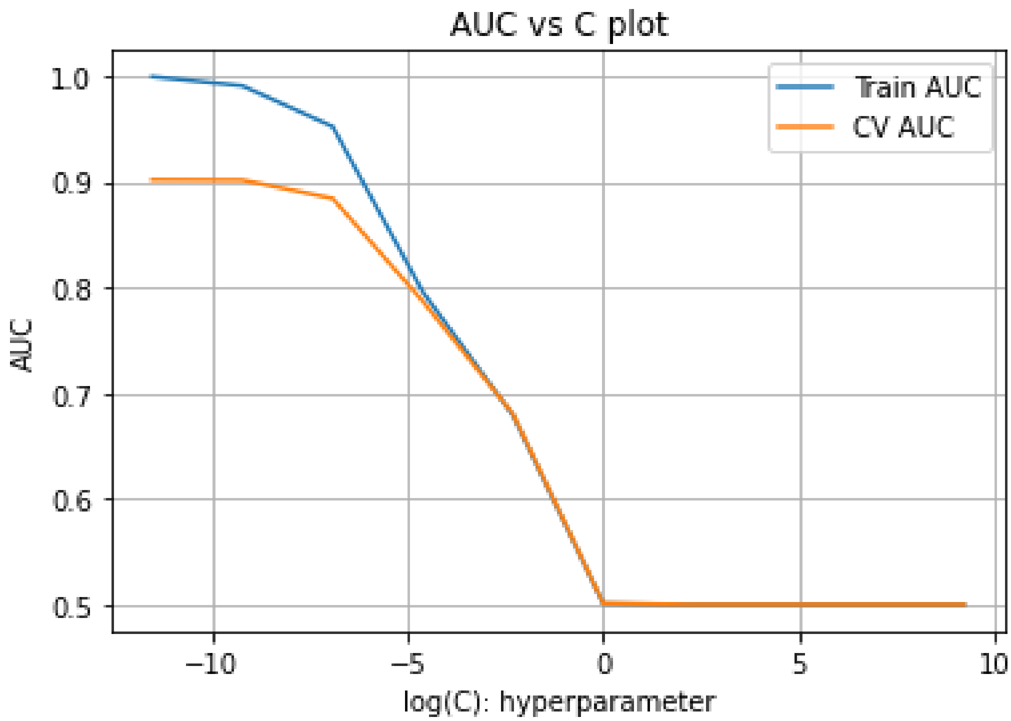
[0]:
```python
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

X_train, X_test, y_train, y_test = train_test_split(preprocessed_reviews,final['Score'].values,test_size=0.3,random_state=0)

vectorizer = CountVectorizer(ngram_range=(1,2), min_df=10, max_features= 5000)
vectorizer.fit(X_train)
X_train = vectorizer.transform(X_train)
X_test = vectorizer.transform(X_test)

ss = StandardScaler(with_mean = False)
X_train = ss.fit_transform(X_train)
X_test = ss.transform(X_test)

print(X_train.shape)
print(X_test.shape)
```

```
(32249, 5000)
(13822, 5000)
```

[0]:
```python
b=[10000,1000,100,10,1,0.1,0.01,0.001,0.0001,0.00001]

param = {'alpha':b}
print(param)

from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import SGDClassifier

L_SVM_L1=SGDClassifier(loss='hinge', penalty='l1', n_jobs=-1)
temp_gscv=␣
 ↪GridSearchCV(L_SVM_L1,param,cv=5,verbose=5,n_jobs=-1,scoring='roc_auc',return_train_score=T
temp_gscv.fit(X_train,y_train)
temp_gs = pd.DataFrame.from_dict(temp_gscv.cv_results_)
```

```
{'alpha': [10000, 1000, 100, 10, 1, 0.1, 0.01, 0.001, 0.0001, 1e-05]}
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  14 tasks      | elapsed:    2.0s
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:  3.9min finished
```

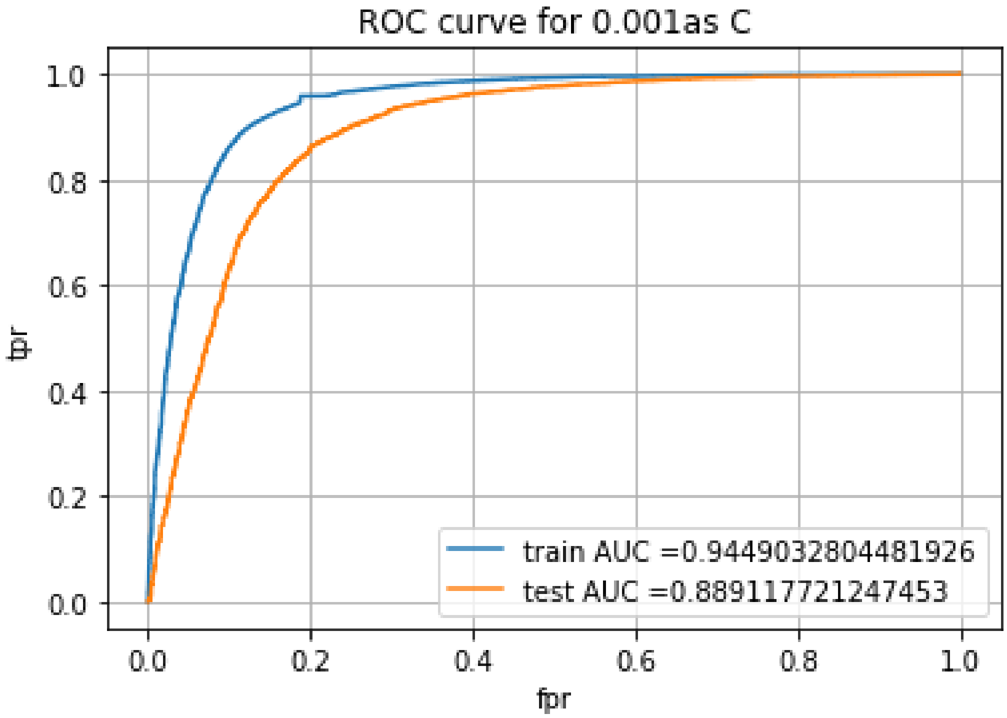
[0]:
```python
train_auc= temp_gs['mean_train_score']
cv_auc= temp_gs['mean_test_score']
plt.plot(np.log(b),train_auc,label='Train AUC')
plt.plot(np.log(b),cv_auc ,label='CV AUC')

# plt.scatter(param['n_neighbors'],train_auc,label='Train AUC')
# plt.scatter(param['n_neighbors'], cv_auc, label='cv AUC')
plt.grid()
plt.title('AUC vs C plot')
plt.xlabel("log(C): hyperparameter")
plt.ylabel("AUC")
plt.legend()
plt.show()
plt.clf()
plt.cla()
plt.close()
```



[0]:
```
'''from the above graph taking  alpha = 0.001'''


from sklearn.linear_model import SGDClassifier

from sklearn.metrics import␣
↪accuracy_score,confusion_matrix,f1_score,precision_score,recall_score,roc_curve,␣
↪auc

L_SVM_L1=SGDClassifier(loss='hinge', penalty='l1', alpha=0.001, n_jobs=-1)
L_SVM_L1.fit(X_train,y_train)
y_pred_tr = L_SVM_L1.decision_function(X_train)
y_pred_ts = L_SVM_L1.decision_function(X_test)
```

[0]:
```
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_pred_tr)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_pred_ts)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr,␣
↪train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.xlabel("fpr")
plt.ylabel("tpr")
plt.title('ROC curve for '+str (0.001)+'as C')
plt.legend()
```

```
plt.grid()
plt.show()
```



[0]:
```
# This section of code where ever implemented is taken from sample kNN python␣
↪notebook

def find_best_threshold(threshould, fpr, tpr):
    t = threshould[np.argmax(tpr*(1-fpr))]
    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very␣
↪high
    print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for␣
↪threshold", np.round(t,3))
    return t

def predict_with_best_t(proba, threshould):
    predictions = []
    for i in proba:
        if i>=threshould:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions
```

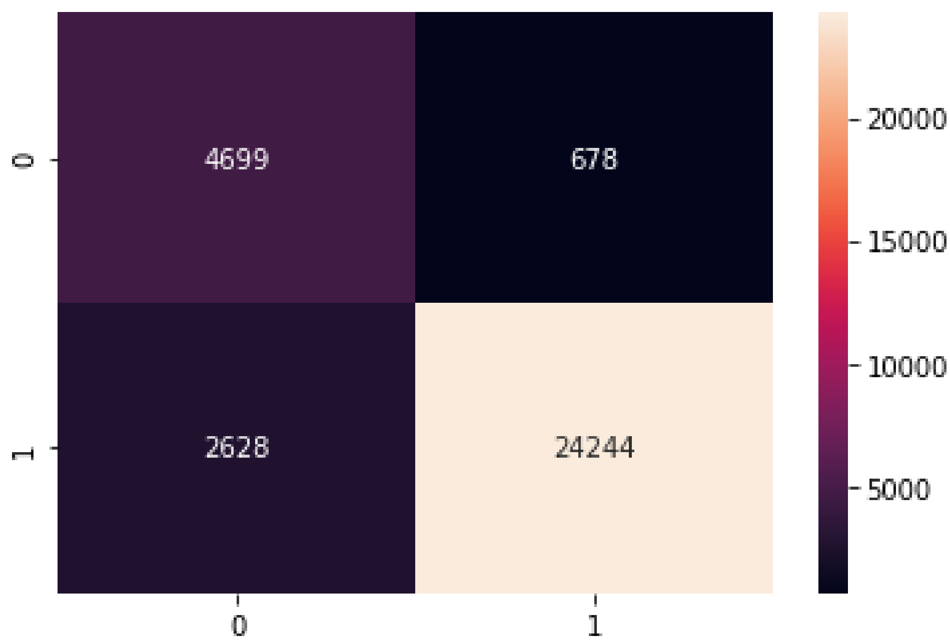
```
print('test')
best_ts_thres = find_best_threshold(te_thresholds, test_fpr, test_tpr)

print('train')
best_tr_thres = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
```

```
test
the maximum value of tpr*(1-fpr) 0.6890987204926737 for threshold 354.709
train
the maximum value of tpr*(1-fpr) 0.7884418949354984 for threshold 230.334
```

[0]:
```
print('train Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_train, predict_with_best_t(y_pred_tr,␣
↪best_tr_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
train Confusion Matrix
```

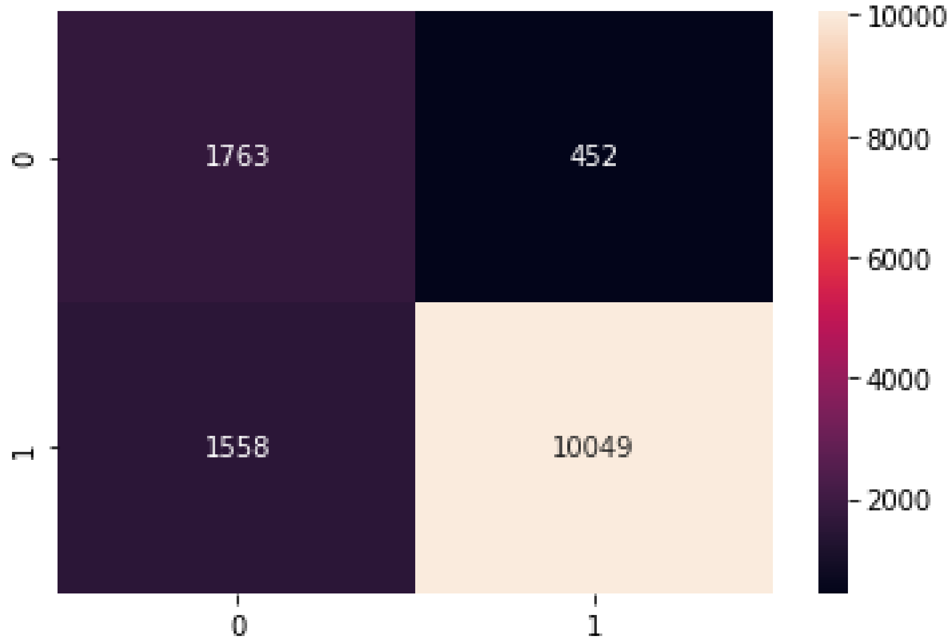
[0]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc30601fa90>
```



[0]:
```
print('Test Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_pred_ts,␣
↪best_ts_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
Test Confusion Matrix
```

[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc2ff112da0>



[0]:
```
acc=accuracy_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
ps=precision_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
rc=recall_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
f1=f1_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100

print("Accuracy on test set: %0.2f%%"%(acc))
print("Precision on test set: %0.2f%%"%(ps))
print("recall score on test set: %0.2f%%"%(rc))
print("f1 score on test set: %0.2f%%"%(f1))
```

```
Accuracy on test set: 85.46%
Precision on test set: 95.70%
recall score on test set: 86.58%
f1 score on test set: 90.91%
```

[0]:
```
count=0
value=[]
for i in L_SVM_L1.coef_.reshape(-1,1):
  count+=1
  value.extend(i)

x=vectorizer.get_feature_names()

features= pd.DataFrame({'feature_name':x,'value':value})
```

Top Most important features

[0]:
```
features.sort_values(by = ['value'], ascending=False).head(10)
```

[0]:
```
      feature_name       value
543          cakes  352.782905
3178         pasta  220.616778
4140      steeping  179.141488
24           acids  175.646968
1837         great  153.974761
327           best  131.198695
4331     taste tea  129.949369
1053     delicious  128.584951
3761     satisfies  126.039622
1667           gag  124.244681
```

Least Most important features

[0]:
```
features.sort_values(by = ['value'], ascending=True).head(10)
```

[0]:
```
       feature_name       value
545         calcium -149.392735
4526          toxic -135.018034
2738       naturals -133.388752
233        away not -109.130660
1125   disappointed  -98.842617
4901          worst  -93.419128
2242          label  -87.248897
2045       horrible  -84.721022
3657       returned  -83.308227
4645     unpleasant  -82.969421
```

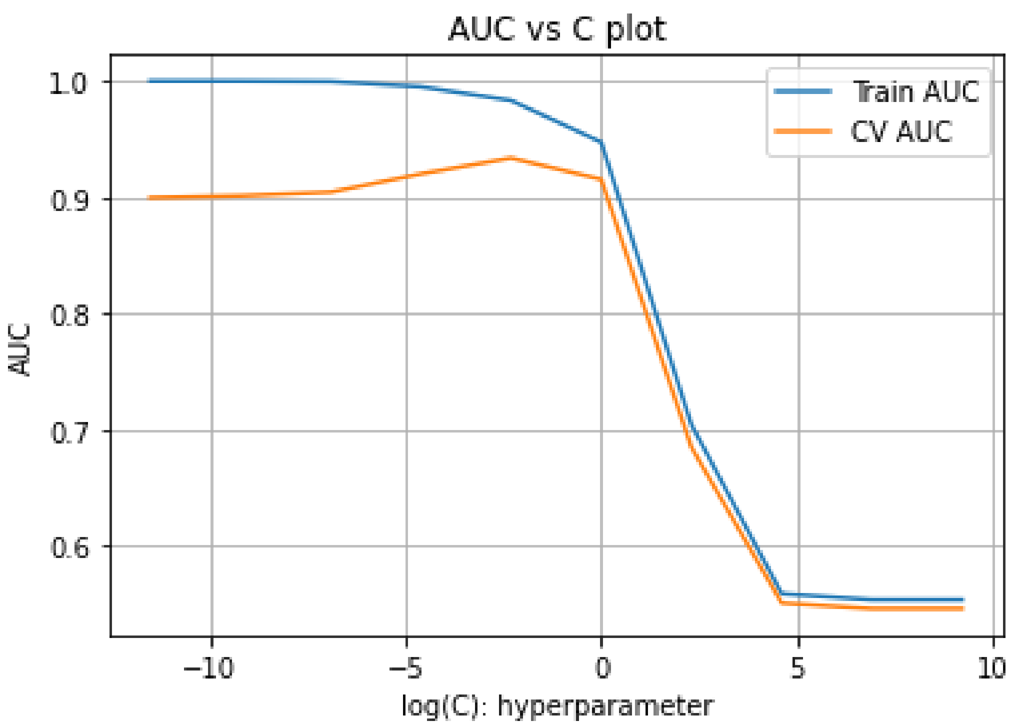
L2 Reg

[0]:
```
param = {'alpha':b}
print(param)

from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import SGDClassifier

L_SVM_L2=SGDClassifier(loss='hinge', penalty='l2', n_jobs=-1)
temp_gscv=␣
 ↪GridSearchCV(L_SVM_L2,param,cv=5,verbose=5,n_jobs=-1,scoring='roc_auc',return_train_score=T
temp_gscv.fit(X_train,y_train)
temp_gs = pd.DataFrame.from_dict(temp_gscv.cv_results_)
```

```
{'alpha': [10000, 1000, 100, 10, 1, 0.1, 0.01, 0.001, 0.0001, 1e-05]}
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  24 tasks      | elapsed:    1.7s
```

```
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:    7.1s finished
```

[0]:
```
train_auc= temp_gs['mean_train_score']
cv_auc= temp_gs['mean_test_score']
plt.plot(np.log(b),train_auc,label='Train AUC')
plt.plot(np.log(b),cv_auc ,label='CV AUC')

# plt.scatter(param['n_neighbors'],train_auc,label='Train AUC')
# plt.scatter(param['n_neighbors'], cv_auc, label='cv AUC')
plt.grid()
plt.title('AUC vs C plot')
plt.xlabel("log(C): hyperparameter")
plt.ylabel("AUC")
plt.legend()
plt.show()
plt.clf()
plt.cla()
plt.close()
```



[0]:
```
#finding the best CV score first then using the one which is least distant then␣
 ↪its AUC counter part to avoid using Dumb model.

from scipy.signal import argrelextrema
import numpy as np
```

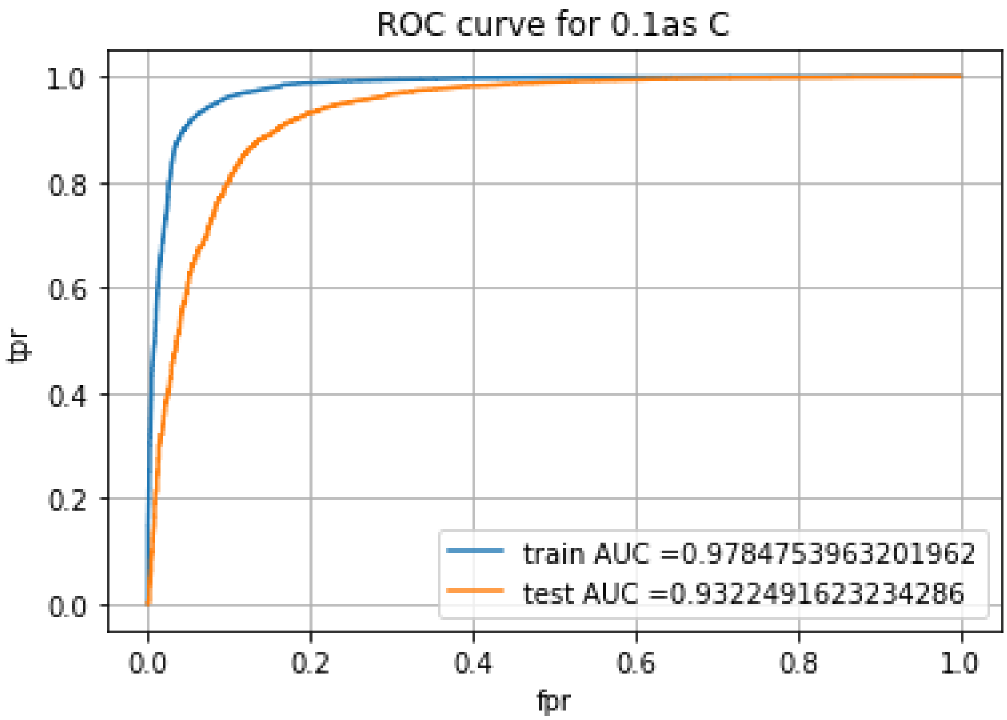
```
x = np.array(train_auc)
y = np.array(cv_auc)
c=b
local_max=()
#finding local maximas of CV
local_max_i=argrelextrema(y, np.greater)
l=list(i for i in np.nditer(local_max_i))


diff=x-y
# diff between CV and Test AUC at the local maxima
local_diff=list(diff[i] for i in l)
local_c=list(c[i] for i in l)
print(f'all local differences {local_diff}')
print(f'all local max C {local_c}')

for i in np.nditer(np.argmin(local_diff)):
  v=i
  break
print(f'best cv score to use = {y[l[v]]}')
best_c=c[l[v]]
print(f'best C to use = {c[l[v]]}')
```

```
all local differences [0.049599009378674445]
all local max C [0.1]
best cv score to use = 0.9335460417580169
best C to use = 0.1
```

[0]:
```
from sklearn.linear_model import SGDClassifier

from sklearn.metrics import␣
↪accuracy_score,confusion_matrix,f1_score,precision_score,recall_score,roc_curve,␣
↪auc

L_SVM_L2=SGDClassifier(loss='hinge', penalty='l2', alpha=best_c, n_jobs=-1)
L_SVM_L2.fit(X_train,y_train)
y_pred_tr = L_SVM_L2.decision_function(X_train)
y_pred_ts = L_SVM_L2.decision_function(X_test)
```

[0]:
```
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_pred_tr)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_pred_ts)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr,␣
↪train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.xlabel("fpr")
plt.ylabel("tpr")
plt.title('ROC curve for '+str (best_c)+'as C')
```

```
plt.legend()
plt.grid()
plt.show()
```



[0]:
```
# This section of code where ever implemented is taken from sample kNN python␣
↪notebook

def find_best_threshold(threshould, fpr, tpr):
    t = threshould[np.argmax(tpr*(1-fpr))]
    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very␣
↪high
    print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for␣
↪threshold", np.round(t,3))
    return t

def predict_with_best_t(proba, threshould):
    predictions = []
    for i in proba:
        if i>=threshould:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions
```

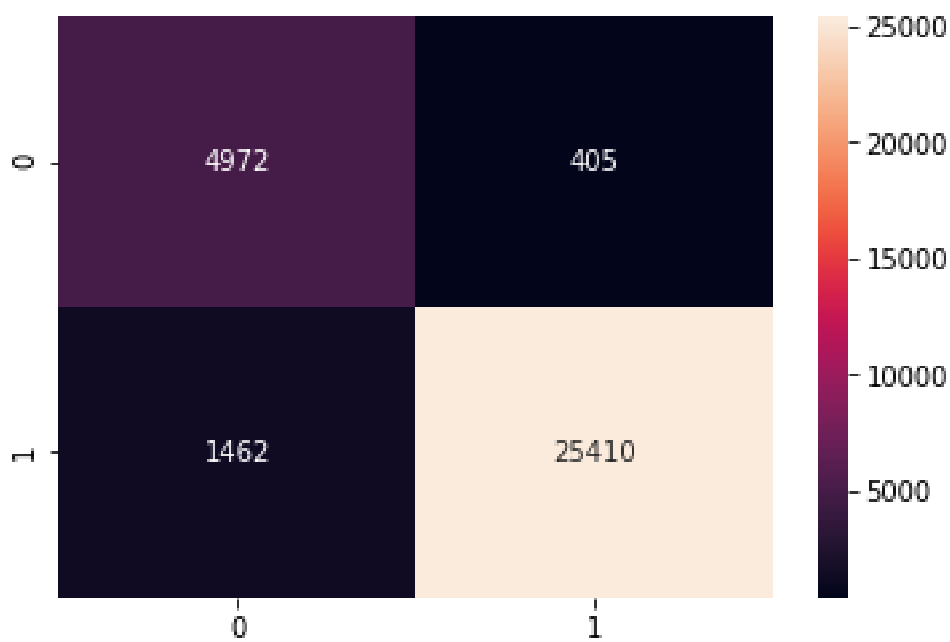
```python
print('test')
best_ts_thres = find_best_threshold(te_thresholds, test_fpr, test_tpr)

print('train')
best_tr_thres = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
```

```
test
the maximum value of tpr*(1-fpr) 0.7604253757511084 for threshold 0.594
train
the maximum value of tpr*(1-fpr) 0.8743710254547515 for threshold 0.539
```

[0]:
```python
print('train Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_train, predict_with_best_t(y_pred_tr,␣
↪best_tr_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
train Confusion Matrix
```

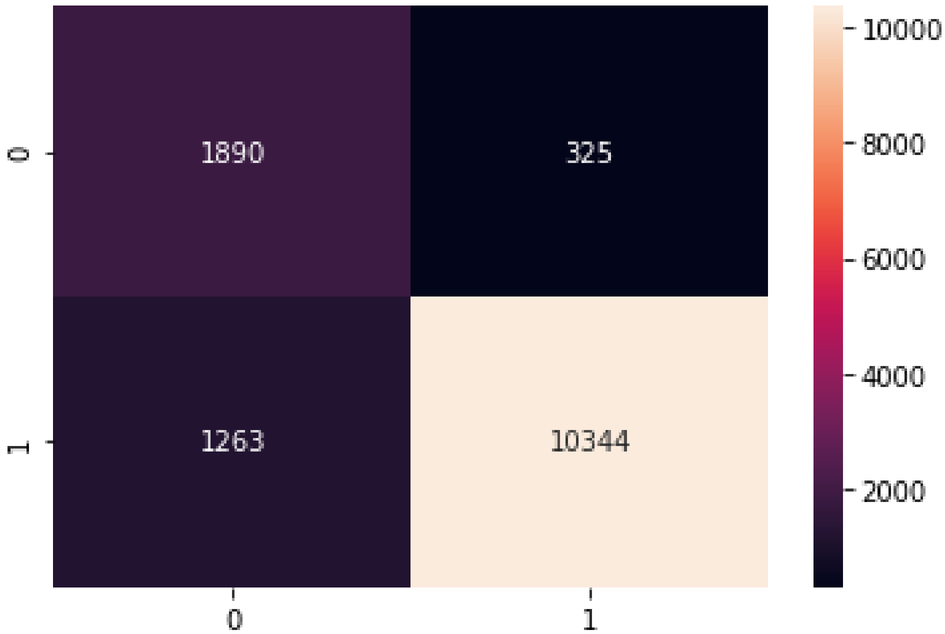
[0]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f494a412d68>
```



[0]:
```python
print('Test Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_pred_ts,␣
↪best_ts_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
Test Confusion Matrix
```

[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f494c7ec978>



[0]:
```
acc=accuracy_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
ps=precision_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
rc=recall_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
f1=f1_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100

print("Accuracy on test set: %0.2f%%"%(acc))
print("Precision on test set: %0.2f%%"%(ps))
print("recall score on test set: %0.2f%%"%(rc))
print("f1 score on test set: %0.2f%%"%(f1))
```

```
Accuracy on test set: 88.51%
Precision on test set: 96.95%
recall score on test set: 89.12%
f1 score on test set: 92.87%
```

[0]:
```
count=0
value=[]
for i in L_SVM_L1.coef_.reshape(-1,1):
  count+=1
  value.extend(i)

x=vectorizer.get_feature_names()
```

```
features= pd.DataFrame({'feature_name':x,'value':value})
```

Top Most important features

[0]:
```
features.sort_values(by = ['value'], ascending=False).head(10)
```

[0]:

	feature_name	value
1053	delicious	590.310095
1837	great	580.106146
1762	good	562.901375
1569	folgers	562.159305
327	best	548.516297
4695	vanilla chai	528.378712
1855	great quality	439.076255
2458	love	400.724393
1347	excellent	398.328007
2484	loves	384.671929

Least Most important features

[0]:
```
features.sort_values(by = ['value'], ascending=True).head(10)
```

[0]:

	feature_name	value
1125	disappointed	-444.489876
4622	two stars	-395.336432
4901	worst	-384.270760
2969	not worth	-341.783732
235	awful	-312.266706
4987	yuck	-303.490760
3878	shells	-299.503194
2825	not	-284.470606
4398	terrible	-277.302093
4824	wheatgrass	-276.907725

7.1.3 [5.1.2] Applying Linear SVM on TFIDF, SET 2

L1 Reg

[0]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

X_train, X_test, y_train, y_test =␣
 ↪train_test_split(preprocessed_reviews,final['Score'].values,test_size=0.
 ↪3,random_state=0)

vectorizer = TfidfVectorizer(ngram_range=(1,2), min_df=10, max_features=5000)
vectorizer.fit(X_train)
X_train = vectorizer.transform(X_train)
X_test = vectorizer.transform(X_test)
```

```
ss = StandardScaler(with_mean = False)
X_train = ss.fit_transform(X_train)
X_test = ss.transform(X_test)

print(X_train.shape)
print(X_test.shape)
```

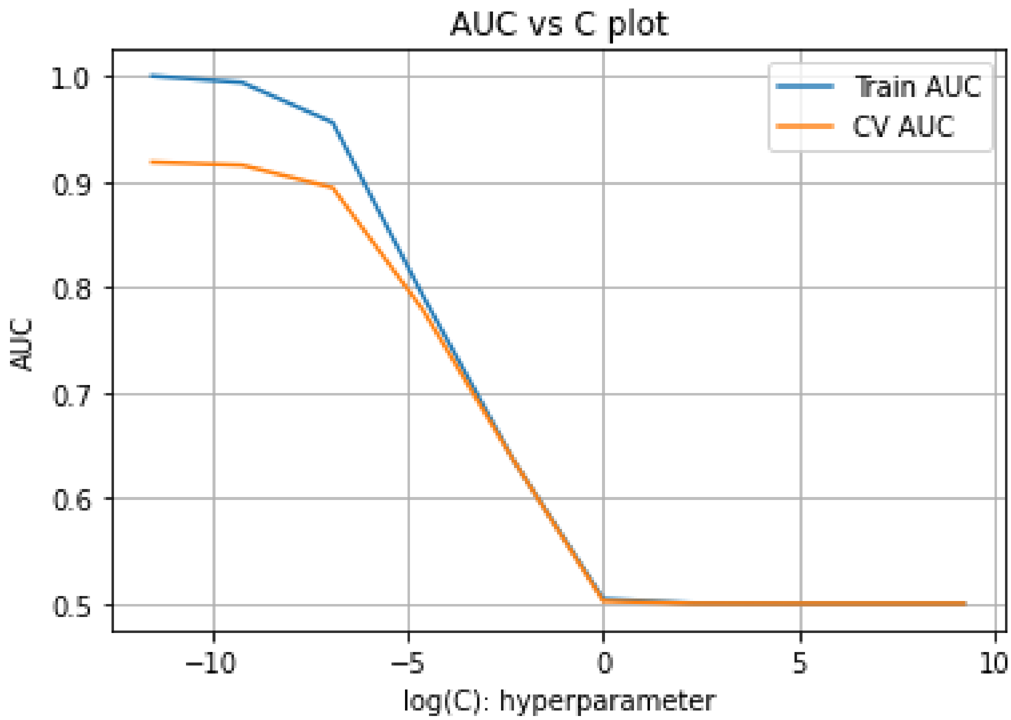
```
(32249, 5000)
(13822, 5000)
```

[0]:
```
b=[10000,1000,100,10,1,0.1,0.01,0.001,0.0001,0.00001]

param = {'alpha':b}
print(param)

from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import SGDClassifier

L_SVM_L1=SGDClassifier(loss='hinge', penalty='l1', n_jobs=-1)
temp_gscv=␣
 ↪GridSearchCV(L_SVM_L1,param,cv=5,verbose=5,n_jobs=-1,scoring='roc_auc',return_train_score=T
temp_gscv.fit(X_train,y_train)
temp_gs = pd.DataFrame.from_dict(temp_gscv.cv_results_)
```

```
{'alpha': [10000, 1000, 100, 10, 1, 0.1, 0.01, 0.001, 0.0001, 1e-05]}
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  24 tasks      | elapsed:    7.5s
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:  3.7min finished
```

[0]:
```
train_auc= temp_gs['mean_train_score']
cv_auc= temp_gs['mean_test_score']
plt.plot(np.log(b),train_auc,label='Train AUC')
plt.plot(np.log(b),cv_auc ,label='CV AUC')

# plt.scatter(param['n_neighbors'],train_auc,label='Train AUC')
# plt.scatter(param['n_neighbors'], cv_auc, label='cv AUC')
plt.grid()
plt.title('AUC vs C plot')
plt.xlabel("log(C): hyperparameter")
plt.ylabel("AUC")
plt.legend()
plt.show()
plt.clf()
plt.cla()
```

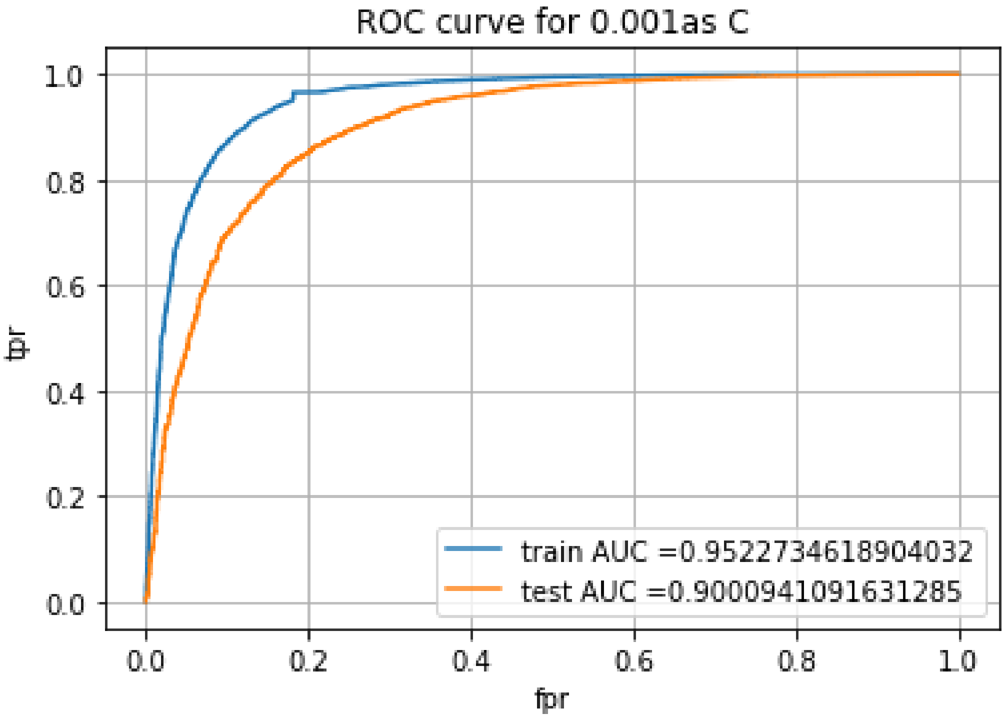
```
plt.close()
```



[0]:
```
'''from the above graph choosing value of alpha as  0.001'''
from sklearn.linear_model import SGDClassifier

from sklearn.metrics import␣
 ↪accuracy_score,confusion_matrix,f1_score,precision_score,recall_score,roc_curve,␣
 ↪auc

L_SVM_L1=SGDClassifier(loss='hinge', penalty='l1', alpha=0.001, n_jobs=-1)
L_SVM_L1.fit(X_train,y_train)
y_pred_tr = L_SVM_L1.decision_function(X_train)
y_pred_ts = L_SVM_L1.decision_function(X_test)
```

[0]:
```
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_pred_tr)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_pred_ts)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr,␣
 ↪train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.xlabel("fpr")
plt.ylabel("tpr")
plt.title('ROC curve for '+str (0.001)+'as C')
plt.legend()
```

```
plt.grid()
plt.show()
```



[0]:
```
# This section of code where ever implemented is taken from sample kNN python␣
↪notebook

def find_best_threshold(threshould, fpr, tpr):
    t = threshould[np.argmax(tpr*(1-fpr))]
    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very␣
↪high
    print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for␣
↪threshold", np.round(t,3))
    return t

def predict_with_best_t(proba, threshould):
    predictions = []
    for i in proba:
        if i>=threshould:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions
```

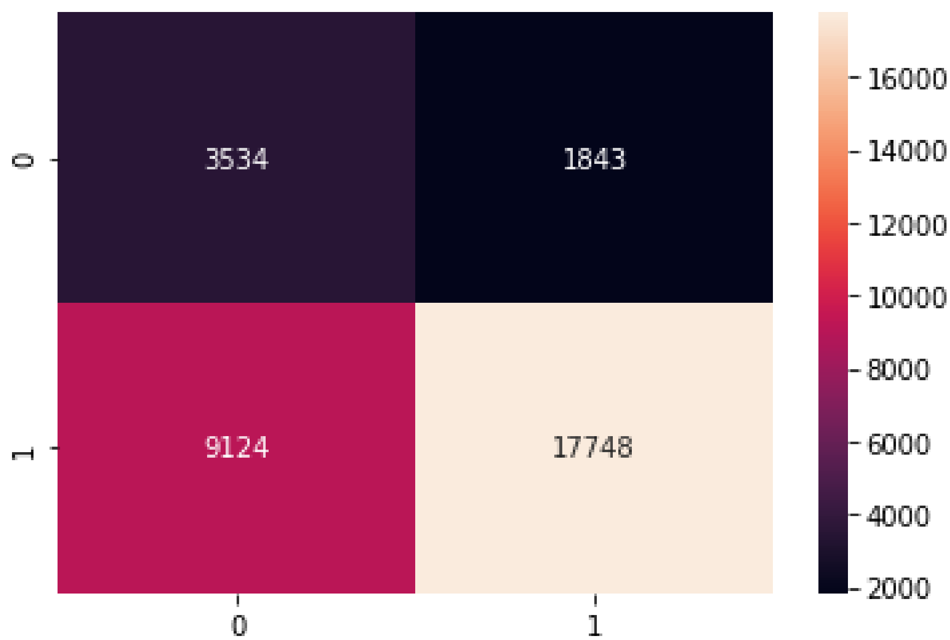
```
print('test')
best_ts_thres = find_best_threshold(te_thresholds, test_fpr, test_tpr)

print('train')
best_tr_thres = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
```

```
test
the maximum value of tpr*(1-fpr) 0.42535863681545016 for threshold 0.749
train
the maximum value of tpr*(1-fpr) 0.4340861584877714 for threshold 0.739
```

[0]:
```
print('train Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_train, predict_with_best_t(y_pred_tr,␣
↪best_tr_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
train Confusion Matrix
```

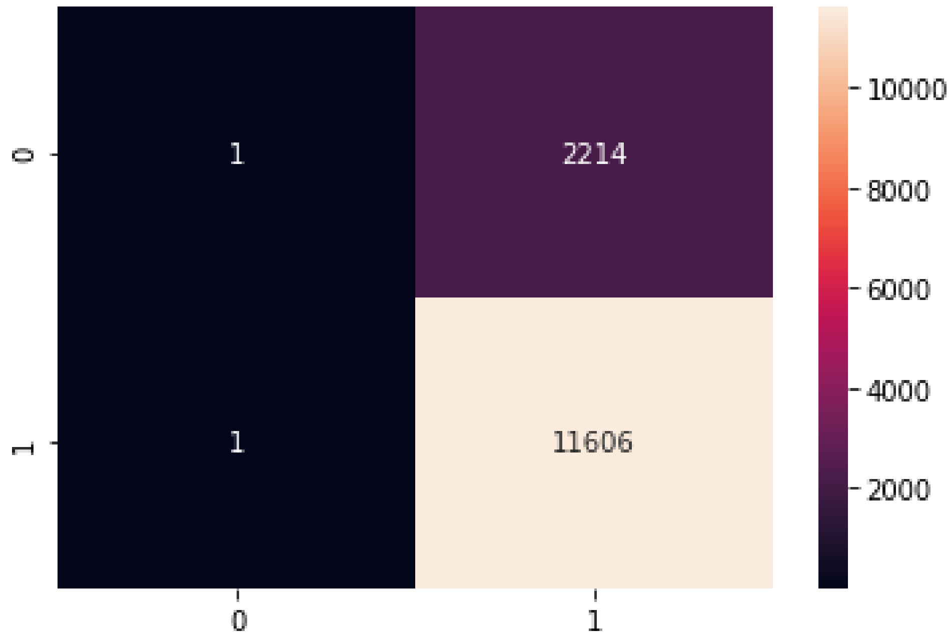
[0]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f494b129cf8>
```



[0]:
```
print('Test Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_pred_ts,␣
↪best_ts_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
Test Confusion Matrix
```

[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f494b7e1e10>



[0]:
```
acc=accuracy_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
ps=precision_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
rc=recall_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
f1=f1_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100

print("Accuracy on test set: %0.2f%%"%(acc))
print("Precision on test set: %0.2f%%"%(ps))
print("recall score on test set: %0.2f%%"%(rc))
print("f1 score on test set: %0.2f%%"%(f1))
```

```
Accuracy on test set: 83.97%
Precision on test set: 83.98%
recall score on test set: 99.99%
f1 score on test set: 91.29%
```

[0]:
```
count=0
value=[]
for i in L_SVM_L1.coef_.reshape(-1,1):
  count+=1
  value.extend(i)

x=vectorizer.get_feature_names()

features= pd.DataFrame({'feature_name':x,'value':value})
```

Top Most important features

[0]:
```
features.sort_values(by = ['value'], ascending=False).head(10)
```

[0]:
```
     feature_name  value
0         ability    0.0
3330         pots    0.0
3337       poured    0.0
3336         pour    0.0
3335       pounds    0.0
3334    pound bag    0.0
3333        pound    0.0
3332      pouches    0.0
3331        pouch    0.0
3329    potential    0.0
```

Least Most important features

[0]:
```
features.sort_values(by = ['value'], ascending=True).head(10)
```

[0]:
```
     feature_name     value
275          bark -2.258169
0         ability  0.000000
3336         pour  0.000000
3335       pounds  0.000000
3334    pound bag  0.000000
3333        pound  0.000000
3332      pouches  0.000000
3331        pouch  0.000000
3330         pots  0.000000
3329    potential  0.000000
```

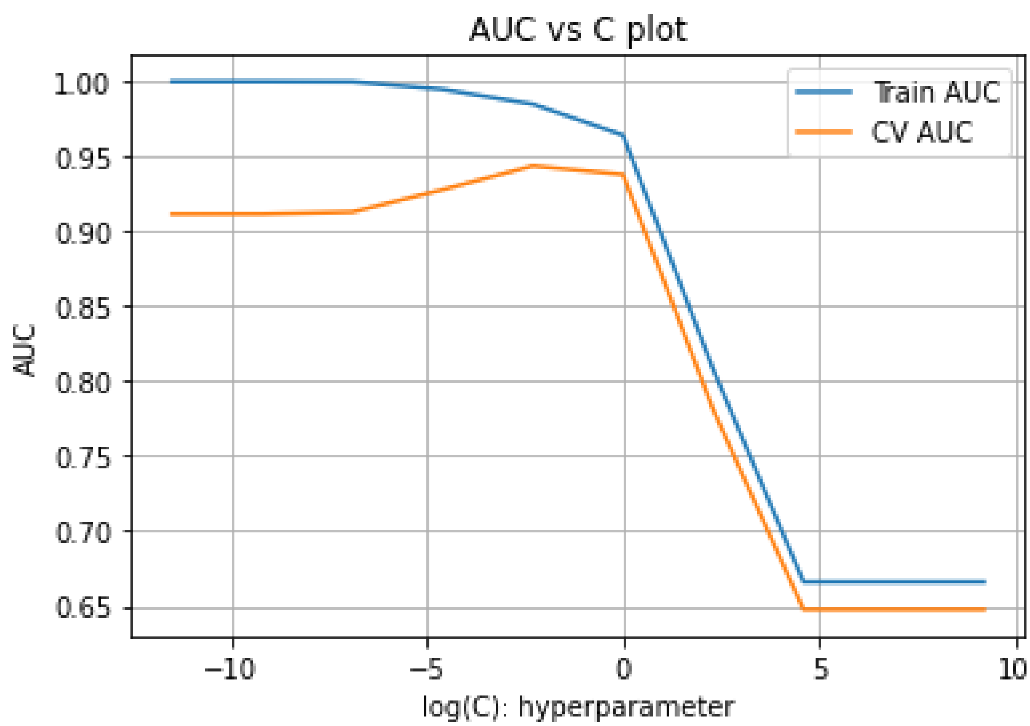
L2 Reg

[0]:
```
b=[10000,1000,100,10,1,0.1,0.01,0.001,0.0001,0.00001]

param = {'alpha':b}
print(param)

from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import SGDClassifier

L_SVM_L2=SGDClassifier(loss='hinge', penalty='l2', n_jobs=-1)
temp_gscv=␣
 ↪GridSearchCV(L_SVM_L2,param,cv=5,verbose=5,n_jobs=-1,scoring='roc_auc',return_train_score=T
temp_gscv.fit(X_train,y_train)
temp_gs = pd.DataFrame.from_dict(temp_gscv.cv_results_)
```

```
{'alpha': [10000, 1000, 100, 10, 1, 0.1, 0.01, 0.001, 0.0001, 1e-05]}
Fitting 5 folds for each of 10 candidates, totalling 50 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  24 tasks      | elapsed:    1.6s
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:    8.4s finished
```

[0]:
```
train_auc= temp_gs['mean_train_score']
cv_auc= temp_gs['mean_test_score']
plt.plot(np.log(b),train_auc,label='Train AUC')
plt.plot(np.log(b),cv_auc ,label='CV AUC')

# plt.scatter(param['n_neighbors'],train_auc,label='Train AUC')
# plt.scatter(param['n_neighbors'], cv_auc, label='cv AUC')
plt.grid()
plt.title('AUC vs C plot')
plt.xlabel("log(C): hyperparameter")
plt.ylabel("AUC")
plt.legend()
plt.show()
plt.clf()
plt.cla()
plt.close()
```



[0]:
```
#finding the best CV score first then using the one which is least distant then␣
↪its AUC counter part to avoid using Dumb model.
```

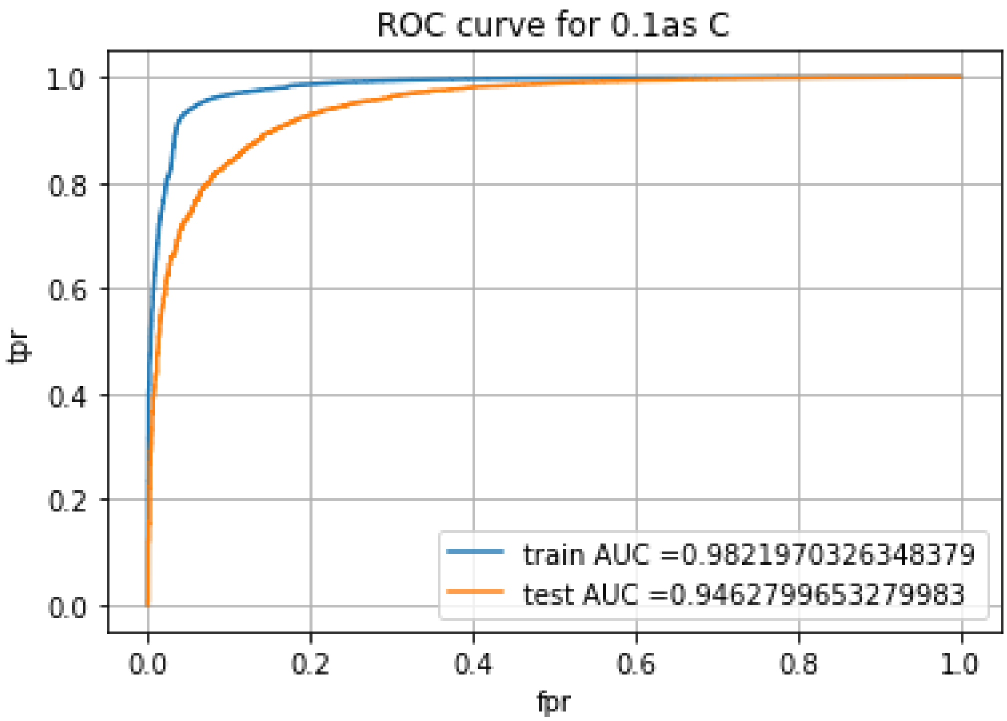
```
from scipy.signal import argrelextrema
import numpy as np
x = np.array(train_auc)
y = np.array(cv_auc)
c=b
local_max=()
#finding local maximas of CV
local_max_i=argrelextrema(y, np.greater)
l=list(i for i in np.nditer(local_max_i))


diff=x-y
# diff between CV and Test AUC at the local maxima
local_diff=list(diff[i] for i in l)
local_c=list(c[i] for i in l)
print(f'all local differences {local_diff}')
print(f'all local max C {local_c}')

for i in np.nditer(np.argmin(local_diff)):
  v=i
  break
print(f'best cv score to use = {y[l[v]]}')
best_c=c[l[v]]
print(f'best C to use = {c[l[v]]}')
```

```
all local differences [0.041260964409675416]
all local max C [0.1]
best cv score to use = 0.9437125827105811
best C to use = 0.1
```

[0]:
```
from sklearn.linear_model import SGDClassifier

from sklearn.metrics import␣
↪accuracy_score,confusion_matrix,f1_score,precision_score,recall_score,roc_curve,␣
↪auc

L_SVM_L2=SGDClassifier(loss='hinge', penalty='l2', alpha=beat_c, n_jobs=-1)
L_SVM_L2.fit(X_train,y_train)
y_pred_tr = L_SVM_L2.decision_function(X_train)
y_pred_ts = L_SVM_L2.decision_function(X_test)
```

[0]:
```
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_pred_tr)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_pred_ts)

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

```
plt.ylabel("tpr")
plt.title('ROC curve for '+str (best_c)+'as C')
plt.legend()
plt.grid()
plt.show()
```



[0]:

```
# This section of code where ever implemented is taken from sample kNN python␣
↪notebook

def find_best_threshold(threshould, fpr, tpr):
    t = threshould[np.argmax(tpr*(1-fpr))]
    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very␣
↪high
    print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for␣
↪threshold", np.round(t,3))
    return t

def predict_with_best_t(proba, threshould):
    predictions = []
    for i in proba:
        if i>=threshould:
            predictions.append(1)
        else:
            predictions.append(0)
```

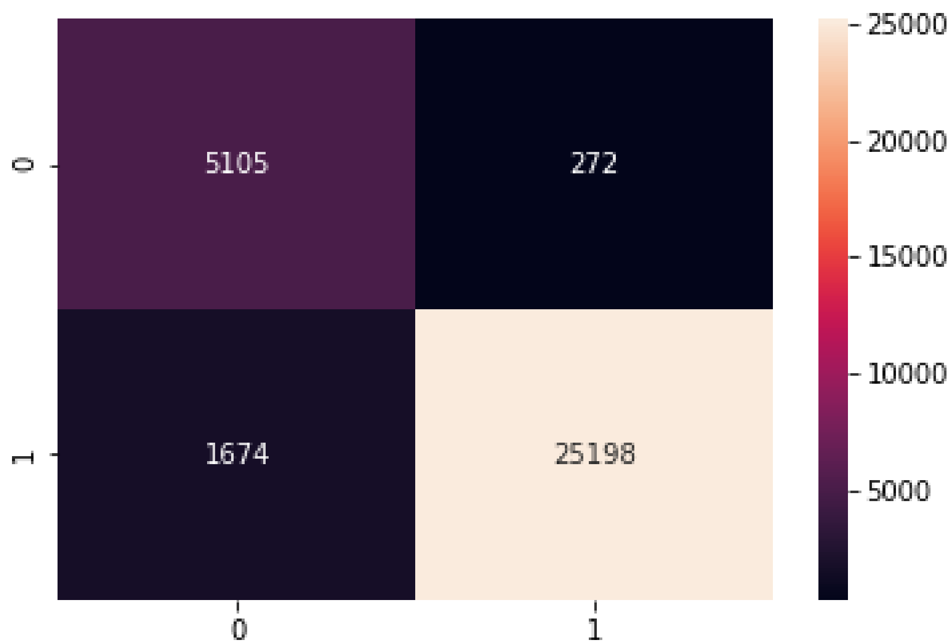
```
    return predictions


print('test')
best_ts_thres = find_best_threshold(te_thresholds, test_fpr, test_tpr)

print('train')
best_tr_thres = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
```

```
test
the maximum value of tpr*(1-fpr) 0.7642270825517644 for threshold 0.667
train
the maximum value of tpr*(1-fpr) 0.8902701061598797 for threshold 0.772
```

[0]:
```
print('train Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_train, predict_with_best_t(y_pred_tr,␣
↪best_tr_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
train Confusion Matrix
```

[0]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f494aa8f0f0>
```

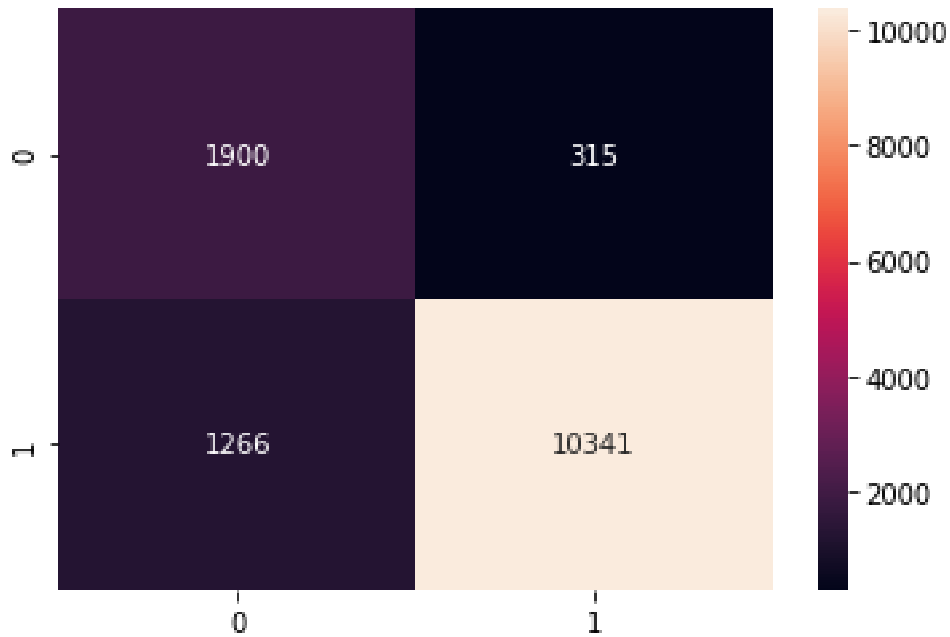


[0]:
```
print('Test Confusion Matrix')
```

```
cm2 = pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_pred_ts,␣
 ↪best_ts_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
Test Confusion Matrix
```

[0]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4947fafef0>
```



[0]:
```
acc=accuracy_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
ps=precision_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
rc=recall_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
f1=f1_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100

print("Accuracy on test set: %0.2f%%"%(acc))
print("Precision on test set: %0.2f%%"%(ps))
print("recall score on test set: %0.2f%%"%(rc))
print("f1 score on test set: %0.2f%%"%(f1))
```

```
Accuracy on test set: 88.56%
Precision on test set: 97.04%
recall score on test set: 89.09%
f1 score on test set: 92.90%
```

[0]:
```
count=0
value=[]
```

```
for i in L_SVM_L1.coef_.reshape(-1,1):
  count+=1
  value.extend(i)

x=vectorizer.get_feature_names()

features= pd.DataFrame({'feature_name':x,'value':value})
```

Top Most important features

[0]:
```
features.sort_values(by = ['value'], ascending=False).head(10)
```

[0]:

	feature_name	value
0	ability	0.0
3330	pots	0.0
3337	poured	0.0
3336	pour	0.0
3335	pounds	0.0
3334	pound bag	0.0
3333	pound	0.0
3332	pouches	0.0
3331	pouch	0.0
3329	potential	0.0

Least Most important features

[0]:
```
features.sort_values(by = ['value'], ascending=True).head(10)
```

[0]:

	feature_name	value
275	bark	-2.258169
0	ability	0.000000
3336	pour	0.000000
3335	pounds	0.000000
3334	pound bag	0.000000
3333	pound	0.000000
3332	pouches	0.000000
3331	pouch	0.000000
3330	pots	0.000000
3329	potential	0.000000

7.1.4 [5.1.3] Applying Linear SVM on AVG W2V, SET 3

L1 Reg

[0]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

X_train, X_test, y_train, y_test = train_test_split(sent_vectors,final['Score'].
 ↪values,test_size=0.3,random_state=0)
```

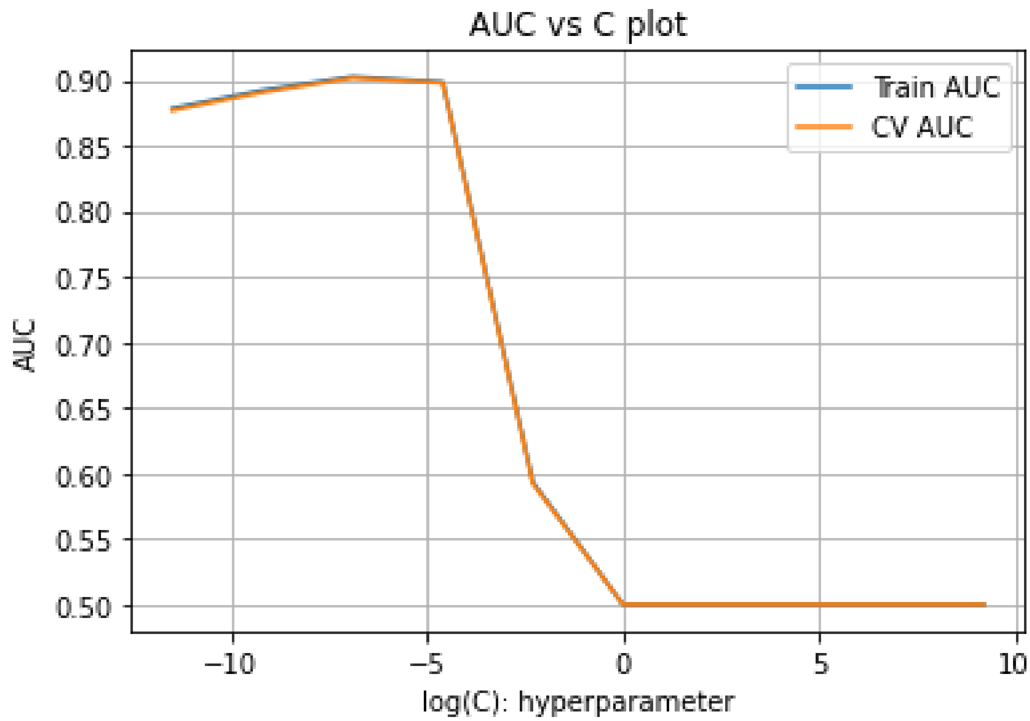
```
ss = StandardScaler(with_mean = False)
X_train = ss.fit_transform(X_train)
X_test = ss.transform(X_test)

print(X_train.shape)
print(X_test.shape)
```

```
(32249, 50)
(13822, 50)
```

[0]:
```
b=[10000,1000,100,10,1,0.1,0.01,0.001,0.0001,0.00001]

param = {'alpha':b}
print(param)

from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import SGDClassifier

L_SVM_L1=SGDClassifier(loss='hinge', penalty='l1', n_jobs=-1)
temp_gscv=␣
 ↪GridSearchCV(L_SVM_L1,param,cv=5,verbose=5,n_jobs=-1,scoring='roc_auc',return_train_score=T
temp_gscv.fit(X_train,y_train)
temp_gs = pd.DataFrame.from_dict(temp_gscv.cv_results_)
```

```
{'alpha': [10000, 1000, 100, 10, 1, 0.1, 0.01, 0.001, 0.0001, 1e-05]}
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  14 tasks      | elapsed:    1.9s
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:   13.1s finished
```

[0]:
```
train_auc= temp_gs['mean_train_score']
cv_auc= temp_gs['mean_test_score']
plt.plot(np.log(b),train_auc,label='Train AUC')
plt.plot(np.log(b),cv_auc ,label='CV AUC')

# plt.scatter(param['n_neighbors'],train_auc,label='Train AUC')
# plt.scatter(param['n_neighbors'], cv_auc, label='cv AUC')
plt.grid()
plt.title('AUC vs C plot')
plt.xlabel("log(C): hyperparameter")
plt.ylabel("AUC")
plt.legend()
plt.show()
plt.clf()
plt.cla()
plt.close()
```



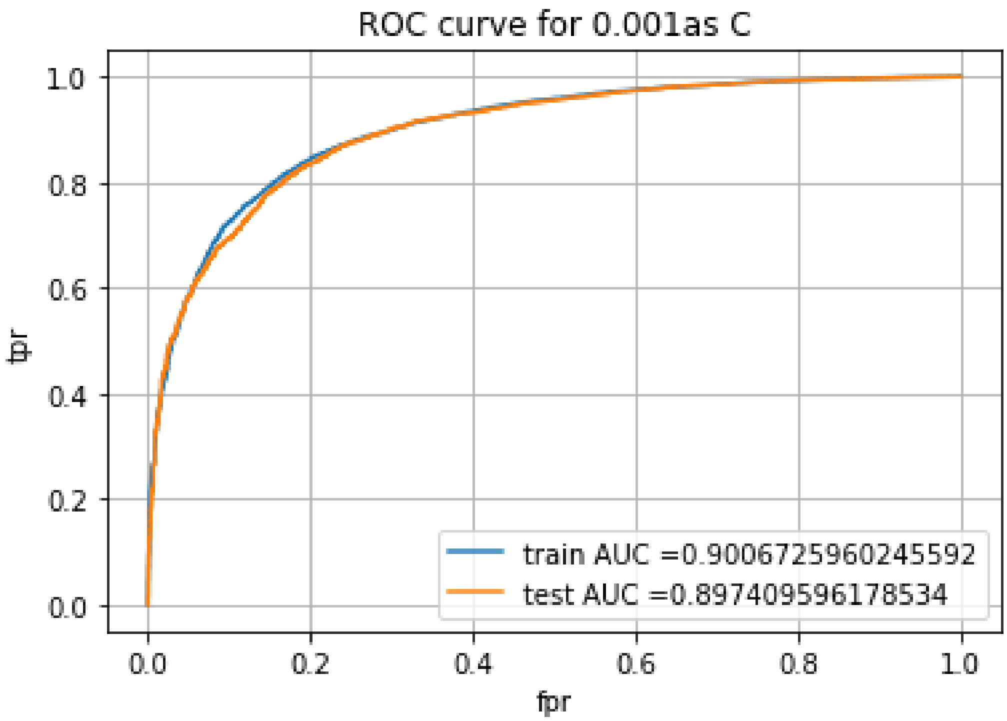
[0]:
```
#finding the best CV score first then using the one which is least distant then␣
↪its AUC counter part to avoid using Dumb model.

from scipy.signal import argrelextrema
import numpy as np
x = np.array(train_auc)
y = np.array(cv_auc)
c=b
local_max=()
#finding local maximas of CV
local_max_i=argrelextrema(y, np.greater)
l=list(i for i in np.nditer(local_max_i))


diff=x-y
# diff between CV and Test AUC at the local maxima
local_diff=list(diff[i] for i in l)
local_c=list(c[i] for i in l)
print(f'all local differences {local_diff}')
print(f'all local max C {local_c}')

for i in np.nditer(np.argmin(local_diff)):
  v=i
  break
```

```
print(f'best cv score to use = {y[l[v]]}')
best_c=c[l[v]]
print(f'best C to use = {c[l[v]]}')
```

```
all local differences [0.0010622737464192067]
all local max C [0.001]
best cv score to use = 0.9015297579354975
best C to use = 0.001
```

[0]:
```
from sklearn.linear_model import SGDClassifier

from sklearn.metrics import␣
↪accuracy_score,confusion_matrix,f1_score,precision_score,recall_score,roc_curve,␣
↪auc

L_SVM_L1=SGDClassifier(loss='hinge', penalty='l1', alpha=best_c, n_jobs=-1)
L_SVM_L1.fit(X_train,y_train)
y_pred_tr = L_SVM_L1.decision_function(X_train)
y_pred_ts = L_SVM_L1.decision_function(X_test)
```

[0]:
```
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_pred_tr)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_pred_ts)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr,␣
↪train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.xlabel("fpr")
plt.ylabel("tpr")
plt.title('ROC curve for '+str (best_c)+'as C')
plt.legend()
plt.grid()
plt.show()
```



[0]:
```
# This section of code where ever implemented is taken from sample kNN python␣
↪notebook

def find_best_threshold(threshould, fpr, tpr):
    t = threshould[np.argmax(tpr*(1-fpr))]
    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very␣
↪high
    print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for␣
↪threshold", np.round(t,3))
    return t

def predict_with_best_t(proba, threshould):
    predictions = []
    for i in proba:
        if i>=threshould:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions


print('test')
best_ts_thres = find_best_threshold(te_thresholds, test_fpr, test_tpr)
```

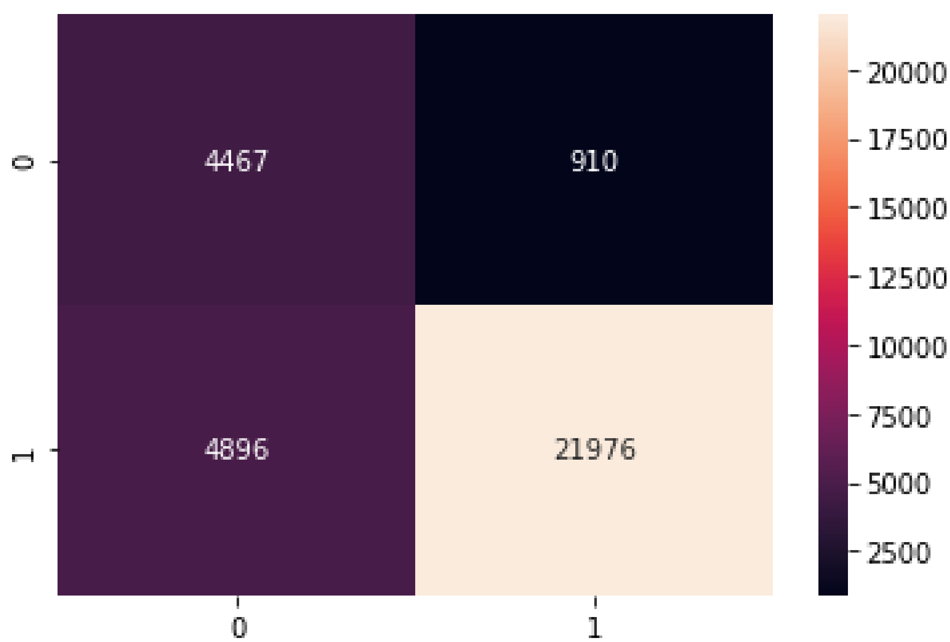
```
print('train')
best_tr_thres = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
```

```
test
the maximum value of tpr*(1-fpr) 0.6663495854937698 for threshold 0.98
train
the maximum value of tpr*(1-fpr) 0.6793984810542605 for threshold 1.053
```

[0]:
```
print('train Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_train, predict_with_best_t(y_pred_tr,␣
↪best_tr_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
train Confusion Matrix
```

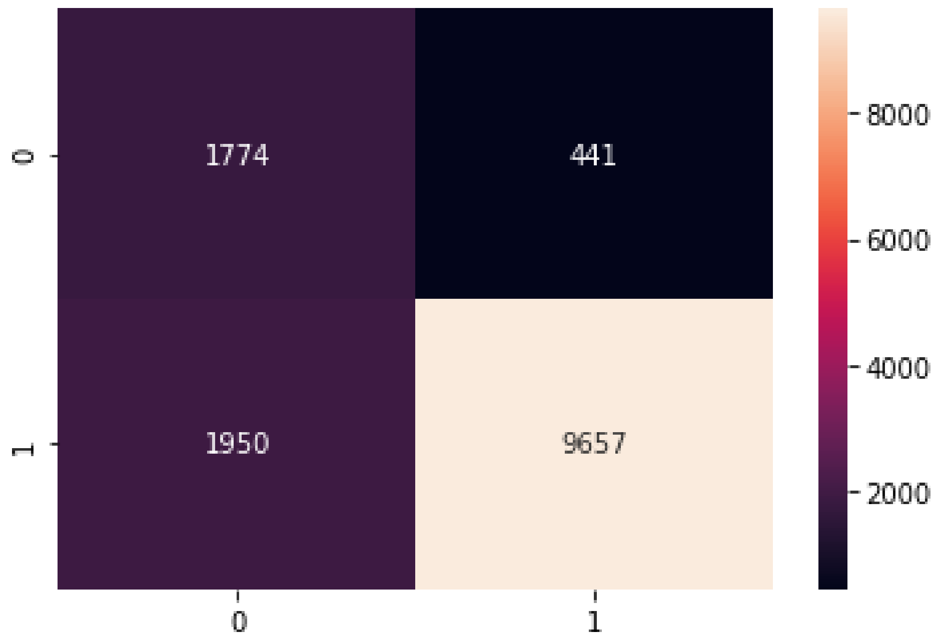
[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f49496fa6a0>



[0]:
```
print('Test Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_pred_ts,␣
↪best_ts_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
Test Confusion Matrix
```

[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f494a22c780>



[0]:
```
acc=accuracy_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
ps=precision_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
rc=recall_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
f1=f1_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100

print("Accuracy on test set: %0.2f%%"%(acc))
print("Precision on test set: %0.2f%%"%(ps))
print("recall score on test set: %0.2f%%"%(rc))
print("f1 score on test set: %0.2f%%"%(f1))
```

```
Accuracy on test set: 82.70%
Precision on test set: 95.63%
recall score on test set: 83.20%
f1 score on test set: 88.98%
```

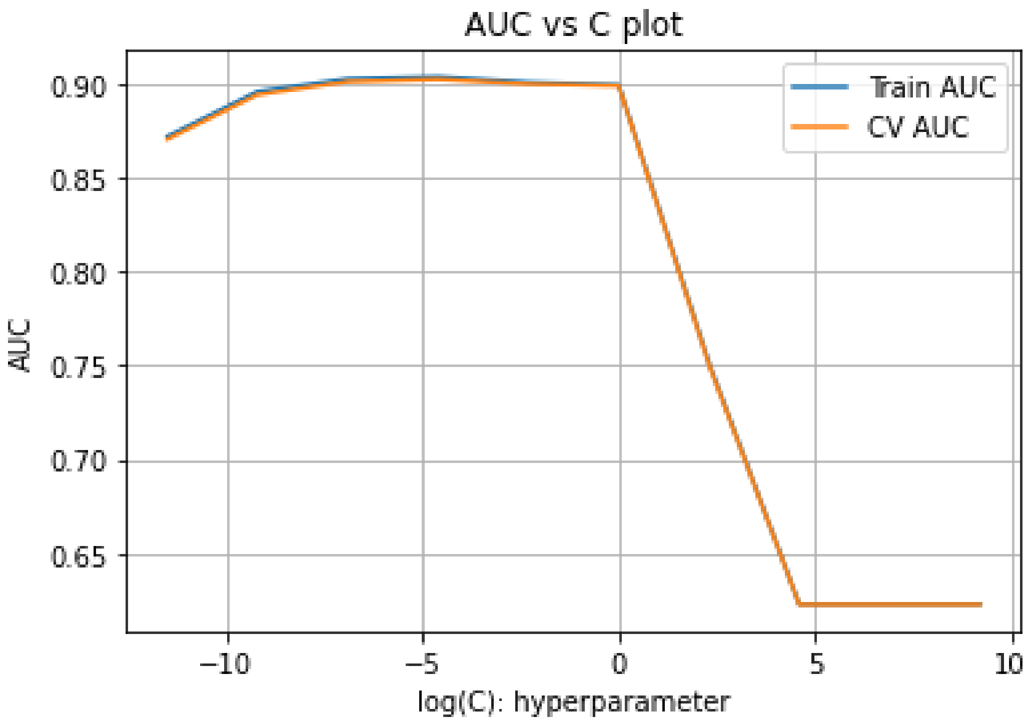
L2 Reg

[0]:
```
b=[10000,1000,100,10,1,0.1,0.01,0.001,0.0001,0.00001]

param = {'alpha':b}
print(param)

from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import SGDClassifier
```

```
L_SVM_L2=SGDClassifier(loss='hinge', penalty='l2', n_jobs=-1)
temp_gscv=␣
 ↪GridSearchCV(L_SVM_L2,param,cv=5,verbose=5,n_jobs=-1,scoring='roc_auc',return_train_score=Tr
temp_gscv.fit(X_train,y_train)
temp_gs = pd.DataFrame.from_dict(temp_gscv.cv_results_)
```

```
{'alpha': [10000, 1000, 100, 10, 1, 0.1, 0.01, 0.001, 0.0001, 1e-05]}
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  14 tasks      | elapsed:    3.8s
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:   11.3s finished
```

[0]:
```
train_auc= temp_gs['mean_train_score']
cv_auc= temp_gs['mean_test_score']
plt.plot(np.log(b),train_auc,label='Train AUC')
plt.plot(np.log(b),cv_auc ,label='CV AUC')

# plt.scatter(param['n_neighbors'],train_auc,label='Train AUC')
# plt.scatter(param['n_neighbors'], cv_auc, label='cv AUC')
plt.grid()
plt.title('AUC vs C plot')
plt.xlabel("log(C): hyperparameter")
plt.ylabel("AUC")
plt.legend()
plt.show()
plt.clf()
plt.cla()
plt.close()
```



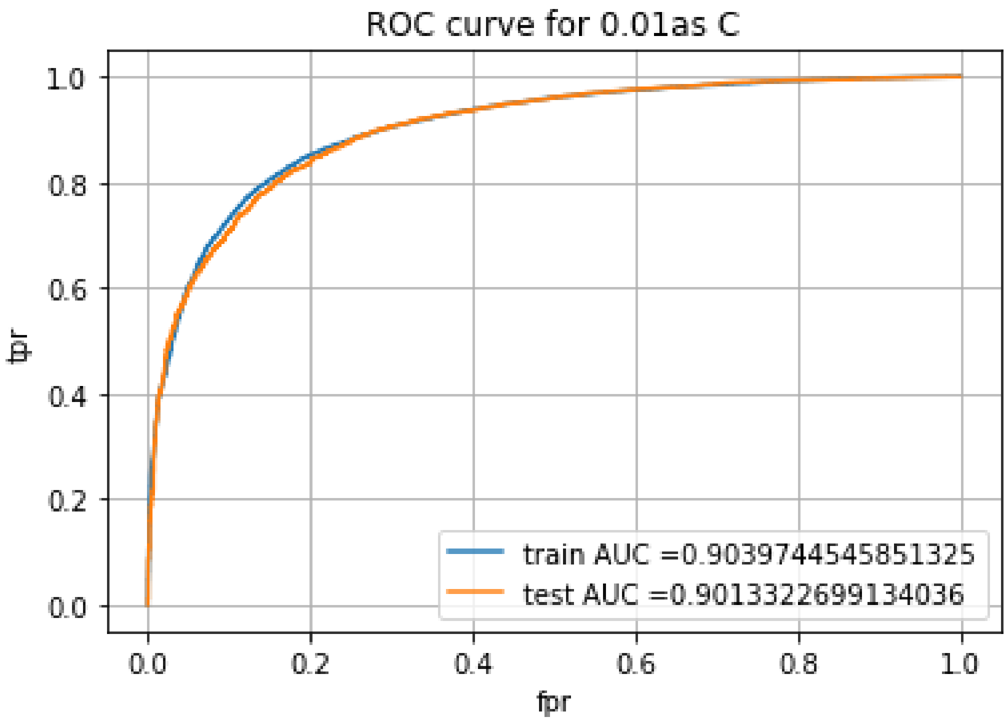
[0]:
```
#finding the best CV score first then using the one which is least distant then␣
↪its AUC counter part to avoid using Dumb model.

from scipy.signal import argrelextrema
import numpy as np
x = np.array(train_auc)
y = np.array(cv_auc)
c=b
local_max=()
#finding local maximas of CV
local_max_i=argrelextrema(y, np.greater)
l=list(i for i in np.nditer(local_max_i))


diff=x-y
# diff between CV and Test AUC at the local maxima
local_diff=list(diff[i] for i in l)
local_c=list(c[i] for i in l)
print(f'all local differences {local_diff}')
print(f'all local max C {local_c}')

for i in np.nditer(np.argmin(local_diff)):
  v=i
  break
```

```
print(f'best cv score to use = {y[l[v]]}')
best_c=c[l[v]]
print(f'best C to use = {c[l[v]]}')
```

```
all local differences [0.0013415658003620434]
all local max C [0.01]
best cv score to use = 0.902334007508338
best C to use = 0.01
```

[0]:
```
from sklearn.linear_model import SGDClassifier

from sklearn.metrics import␣
↪accuracy_score,confusion_matrix,f1_score,precision_score,recall_score,roc_curve,␣
↪auc

L_SVM_L2=SGDClassifier(loss='hinge', penalty='l2', alpha=best_c, n_jobs=-1)
L_SVM_L2.fit(X_train,y_train)
y_pred_tr = L_SVM_L2.decision_function(X_train)
y_pred_ts = L_SVM_L2.decision_function(X_test)
```

[0]:
```
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_pred_tr)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_pred_ts)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr,␣
↪train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.xlabel("fpr")
plt.ylabel("tpr")
plt.title('ROC curve for '+str (best_c)+'as C')
plt.legend()
plt.grid()
plt.show()
```



[0]:
```
# This section of code where ever implemented is taken from sample kNN python␣
↪notebook

def find_best_threshold(threshould, fpr, tpr):
    t = threshould[np.argmax(tpr*(1-fpr))]
    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very␣
↪high
    print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for␣
↪threshold", np.round(t,3))
    return t

def predict_with_best_t(proba, threshould):
    predictions = []
    for i in proba:
        if i>=threshould:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions


print('test')
best_ts_thres = find_best_threshold(te_thresholds, test_fpr, test_tpr)
```

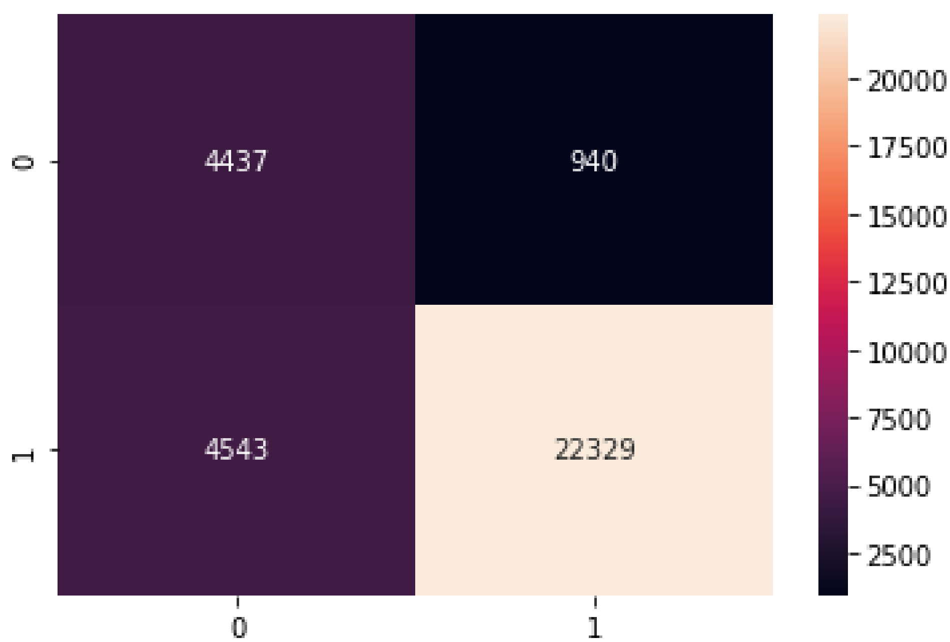
```
print('train')
best_tr_thres = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
```

```
test
the maximum value of tpr*(1-fpr) 0.676080033435105 for threshold 1.004
train
the maximum value of tpr*(1-fpr) 0.6856755682564691 for threshold 0.97
```

[0]:
```
print('train Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_train, predict_with_best_t(y_pred_tr,␣
↪best_tr_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
train Confusion Matrix
```

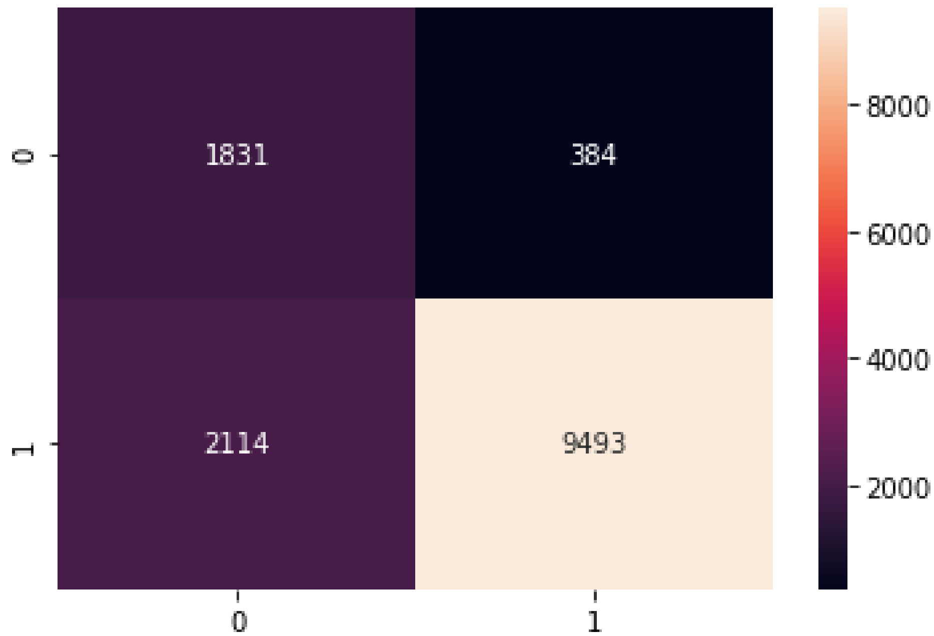
[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4947f91080>



[0]:
```
print('Test Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_pred_ts,␣
↪best_ts_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
Test Confusion Matrix
```

[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f494a75d390>




```
[0]: acc=accuracy_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
     ps=precision_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
     rc=recall_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
     f1=f1_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100

     print("Accuracy on test set: %0.2f%%"%(acc))
     print("Precision on test set: %0.2f%%"%(ps))
     print("recall score on test set: %0.2f%%"%(rc))
     print("f1 score on test set: %0.2f%%"%(f1))
```

```
Accuracy on test set: 81.93%
Precision on test set: 96.11%
recall score on test set: 81.79%
f1 score on test set: 88.37%
```

7.1.5 [5.1.4] Applying Linear SVM on TFIDF W2V, SET 4

L1 Reg

```
[0]: from sklearn.model_selection import train_test_split
     from sklearn.preprocessing import StandardScaler

     X_train, X_test, y_train, y_test =␣
      ↪train_test_split(tfidf_sent_vectors,final['Score'].values,test_size=0.
      ↪3,random_state=0)
```

```
ss = StandardScaler(with_mean = False)
X_train = ss.fit_transform(X_train)
X_test = ss.transform(X_test)

print(X_train.shape)
print(X_test.shape)
```

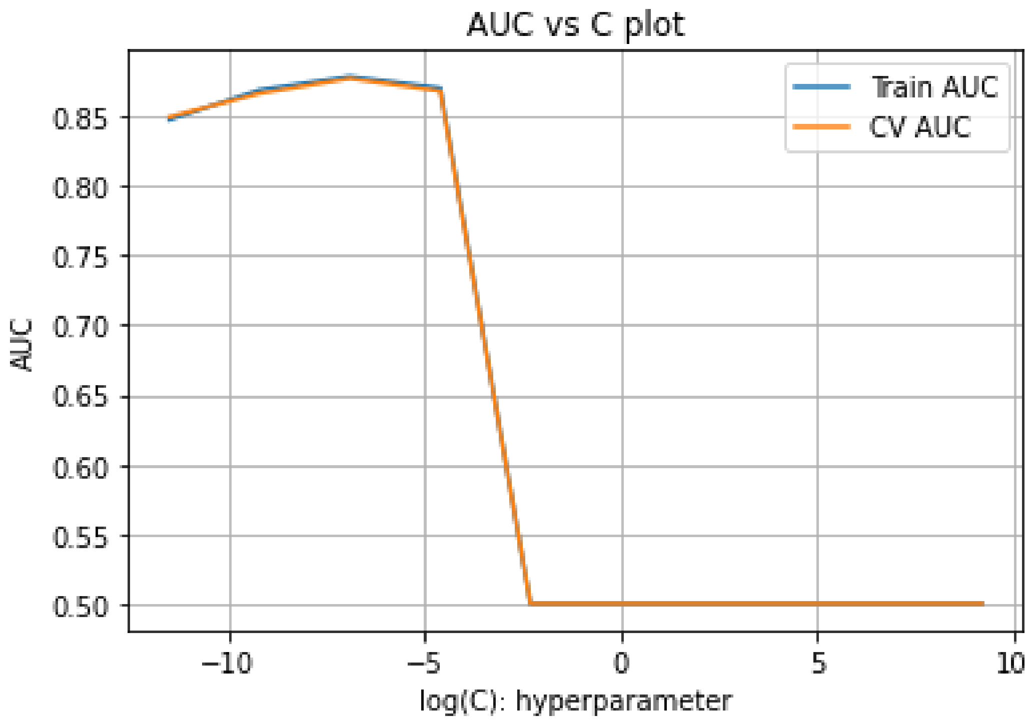
```
(32249, 50)
(13822, 50)
```

[0]:
```
b=[10000,1000,100,10,1,0.1,0.01,0.001,0.0001,0.00001]

param = {'alpha':b}
print(param)

from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import SGDClassifier

L_SVM_L1=SGDClassifier(loss='hinge', penalty='l1', n_jobs=-1)
temp_gscv=␣
 ↪GridSearchCV(L_SVM_L1,param,cv=5,verbose=5,n_jobs=-1,scoring='roc_auc',return_train_score=T
temp_gscv.fit(X_train,y_train)
temp_gs = pd.DataFrame.from_dict(temp_gscv.cv_results_)
```

```
{'alpha': [10000, 1000, 100, 10, 1, 0.1, 0.01, 0.001, 0.0001, 1e-05]}
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  14 tasks      | elapsed:    1.8s
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:   12.5s finished
```

[0]:
```
train_auc= temp_gs['mean_train_score']
cv_auc= temp_gs['mean_test_score']
plt.plot(np.log(b),train_auc,label='Train AUC')
plt.plot(np.log(b),cv_auc ,label='CV AUC')

# plt.scatter(param['n_neighbors'],train_auc,label='Train AUC')
# plt.scatter(param['n_neighbors'], cv_auc, label='cv AUC')
plt.grid()
plt.title('AUC vs C plot')
plt.xlabel("log(C): hyperparameter")
plt.ylabel("AUC")
plt.legend()
plt.show()
plt.clf()
```

```
plt.cla()
plt.close()
```



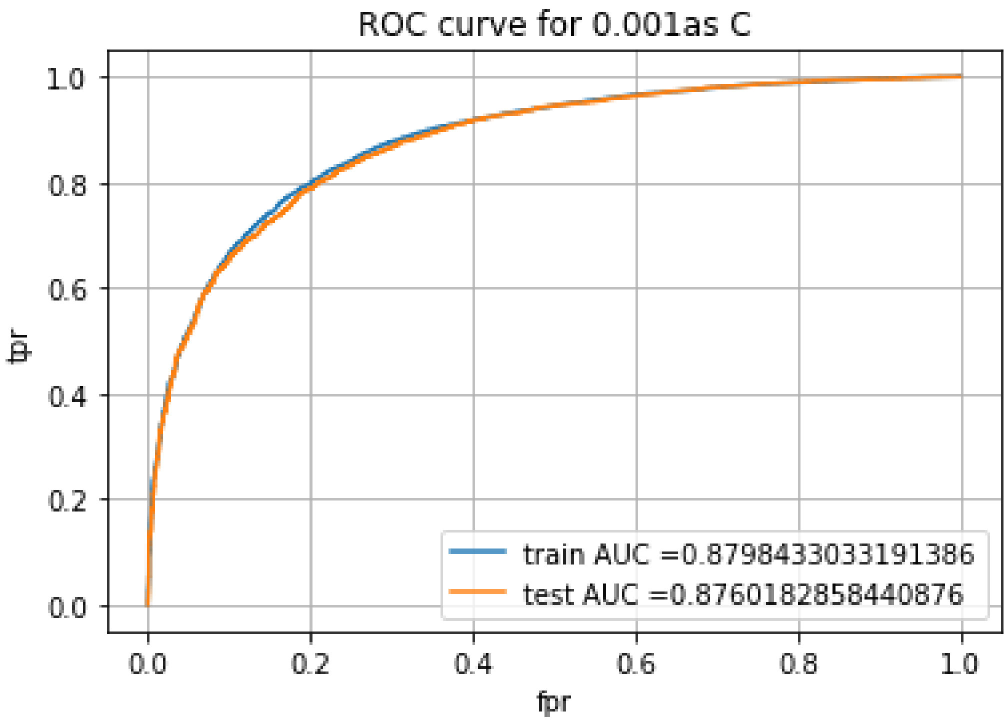
[0]:
```
#finding the best CV score first then using the one which is least distant then
↪its AUC counter part to avoid using Dumb model.

from scipy.signal import argrelextrema
import numpy as np
x = np.array(train_auc)
y = np.array(cv_auc)
c=b
local_max=()
#finding local maximas of CV
local_max_i=argrelextrema(y, np.greater)
l=list(i for i in np.nditer(local_max_i))


diff=x-y
# diff between CV and Test AUC at the local maxima
local_diff=list(diff[i] for i in l)
local_c=list(c[i] for i in l)
print(f'all local differences {local_diff}')
print(f'all local max C {local_c}')
```

```
for i in np.nditer(np.argmin(local_diff)):
  v=i
  break
print(f'best cv score to use = {y[l[v]]}')
best_c=c[l[v]]
print(f'best C to use = {c[l[v]]}')
```

```
all local differences [0.0014173315360446193]
all local max C [0.001]
best cv score to use = 0.876876553316813
best C to use = 0.001
```

[0]:
```
from sklearn.linear_model import SGDClassifier

from sklearn.metrics import␣
↪accuracy_score,confusion_matrix,f1_score,precision_score,recall_score,roc_curve,␣
↪auc

L_SVM_L1=SGDClassifier(loss='hinge', penalty='l1', alpha=best_c, n_jobs=-1)
L_SVM_L1.fit(X_train,y_train)
y_pred_tr = L_SVM_L1.decision_function(X_train)
y_pred_ts = L_SVM_L1.decision_function(X_test)
```

[0]:
```
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_pred_tr)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_pred_ts)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr,␣
↪train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.xlabel("fpr")
plt.ylabel("tpr")
plt.title('ROC curve for '+str (best_c)+'as C')
plt.legend()
plt.grid()
plt.show()
```



[0]:
```
# This section of code where ever implemented is taken from sample kNN python␣
↪notebook

def find_best_threshold(threshould, fpr, tpr):
    t = threshould[np.argmax(tpr*(1-fpr))]
    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very␣
↪high
    print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for␣
↪threshold", np.round(t,3))
    return t

def predict_with_best_t(proba, threshould):
    predictions = []
    for i in proba:
        if i>=threshould:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions


print('test')
best_ts_thres = find_best_threshold(te_thresholds, test_fpr, test_tpr)
```

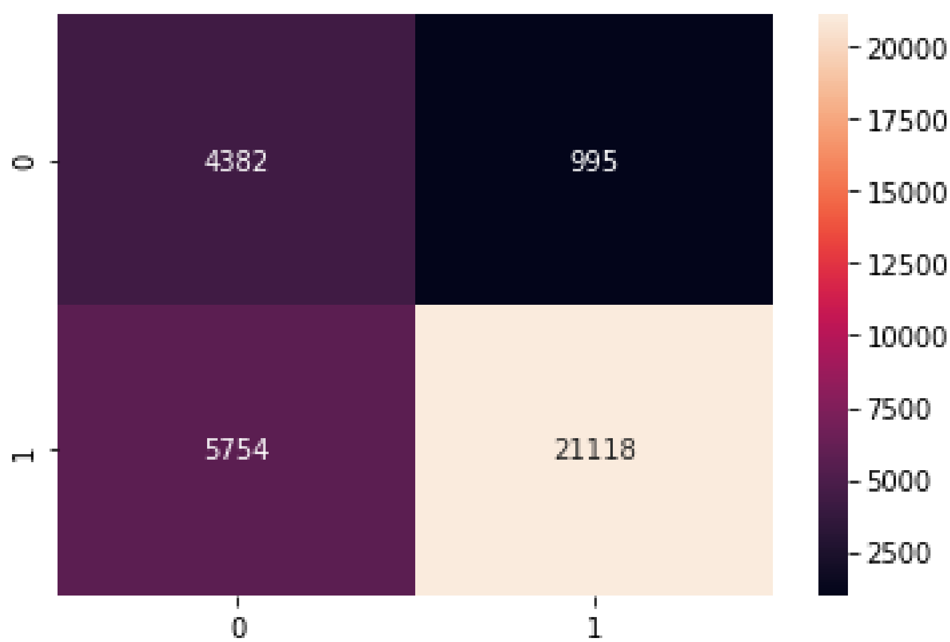
```
print('train')
best_tr_thres = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
```

```
test
the maximum value of tpr*(1-fpr) 0.6324649191028765 for threshold 1.043
train
the maximum value of tpr*(1-fpr) 0.640449854697959 for threshold 1.043
```

[0]:
```
print('train Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_train, predict_with_best_t(y_pred_tr,␣
↪best_tr_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
train Confusion Matrix
```

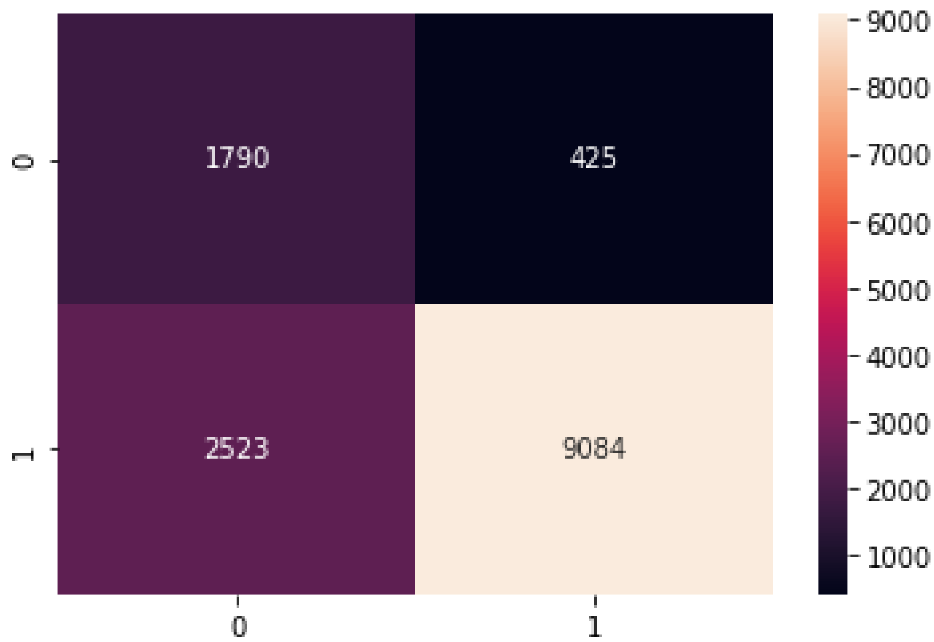
[0]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f494af2f390>
```



[0]:
```
print('Test Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_pred_ts,␣
↪best_ts_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
Test Confusion Matrix
```

[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f49495dc978>



[0]:
```
acc=accuracy_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
ps=precision_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
rc=recall_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
f1=f1_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100

print("Accuracy on test set: %0.2f%%"%(acc))
print("Precision on test set: %0.2f%%"%(ps))
print("recall score on test set: %0.2f%%"%(rc))
print("f1 score on test set: %0.2f%%"%(f1))
```

```
Accuracy on test set: 78.67%
Precision on test set: 95.53%
recall score on test set: 78.26%
f1 score on test set: 86.04%
```

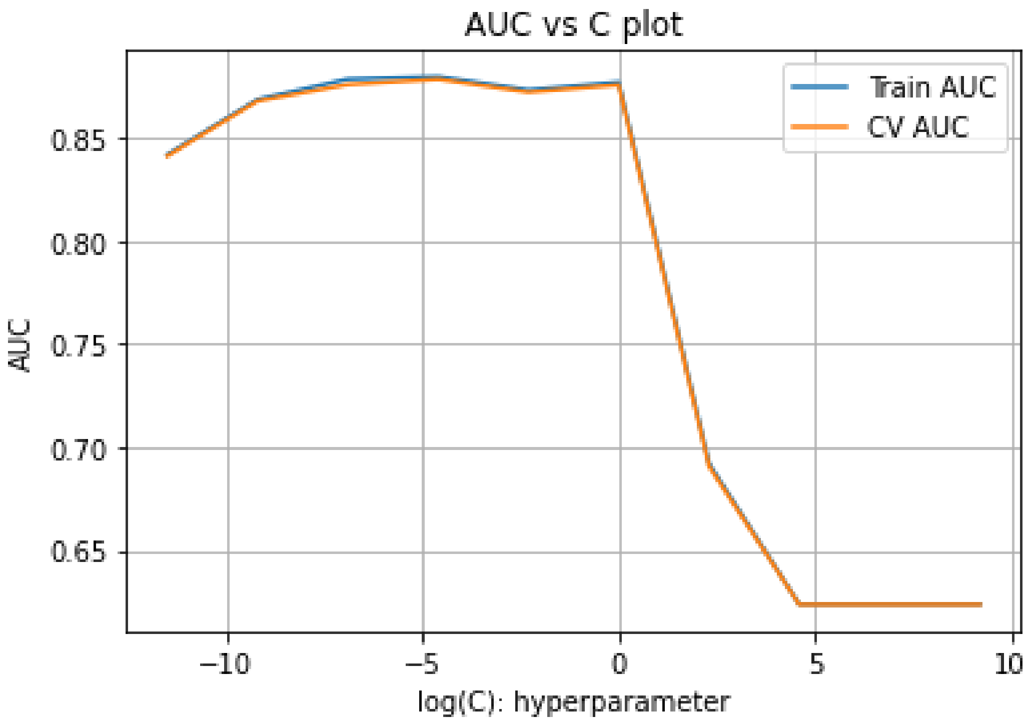
L2 Reg

[0]:
```
b=[10000,1000,100,10,1,0.1,0.01,0.001,0.0001,0.00001]

param = {'alpha':b}
print(param)

from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import SGDClassifier
```

```
L_SVM_L2=SGDClassifier(loss='hinge', penalty='l2', n_jobs=-1)
temp_gscv=␣
 ↪GridSearchCV(L_SVM_L2,param,cv=5,verbose=5,n_jobs=-1,scoring='roc_auc',return_train_score=Tr
temp_gscv.fit(X_train,y_train)
temp_gs = pd.DataFrame.from_dict(temp_gscv.cv_results_)
```

```
{'alpha': [10000, 1000, 100, 10, 1, 0.1, 0.01, 0.001, 0.0001, 1e-05]}
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  24 tasks      | elapsed:    1.7s
[Parallel(n_jobs=-1)]: Done  47 out of  50 | elapsed:    7.6s remaining:    0.5s
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:    8.8s finished
```

[0]:
```
train_auc= temp_gs['mean_train_score']
cv_auc= temp_gs['mean_test_score']
plt.plot(np.log(b),train_auc,label='Train AUC')
plt.plot(np.log(b),cv_auc ,label='CV AUC')

# plt.scatter(param['n_neighbors'],train_auc,label='Train AUC')
# plt.scatter(param['n_neighbors'], cv_auc, label='cv AUC')
plt.grid()
plt.title('AUC vs C plot')
plt.xlabel("log(C): hyperparameter")
plt.ylabel("AUC")
plt.legend()
plt.show()
plt.clf()
plt.cla()
plt.close()
```



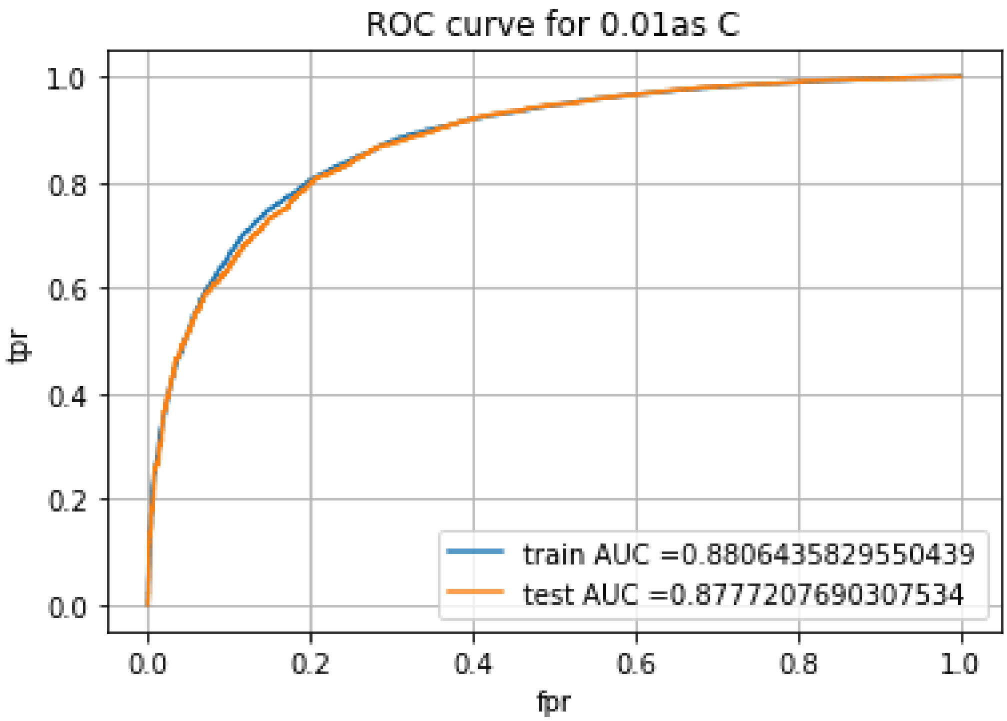
[0]:
```
#finding the best CV score first then using the one which is least distant then␣
↪its AUC counter part to avoid using Dumb model.

from scipy.signal import argrelextrema
import numpy as np
x = np.array(train_auc)
y = np.array(cv_auc)
c=b
local_max=()
#finding local maximas of CV
local_max_i=argrelextrema(y, np.greater)
l=list(i for i in np.nditer(local_max_i))


diff=x-y
# diff between CV and Test AUC at the local maxima
local_diff=list(diff[i] for i in l)
local_c=list(c[i] for i in l)
print(f'all local differences {local_diff}')
print(f'all local max C {local_c}')

for i in np.nditer(np.argmin(local_diff)):
  v=i
  break
```

```
print(f'best cv score to use = {y[l[v]]}')
best_c=c[l[v]]
print(f'best C to use = {c[l[v]]}')
```

```
all local differences [0.0013099793793687198, 0.0012198394920496236]
all local max C [1, 0.01]
best cv score to use = 0.87849406502283
best C to use = 0.01
```

[0]:
```
from sklearn.linear_model import SGDClassifier

from sklearn.metrics import␣
↪accuracy_score,confusion_matrix,f1_score,precision_score,recall_score,roc_curve,␣
↪auc

L_SVM_L2=SGDClassifier(loss='hinge', penalty='l2', alpha=best_c, n_jobs=-1)
L_SVM_L2.fit(X_train,y_train)
y_pred_tr = L_SVM_L2.decision_function(X_train)
y_pred_ts = L_SVM_L2.decision_function(X_test)
```

[0]:
```
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_pred_tr)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_pred_ts)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr,␣
↪train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.xlabel("fpr")
plt.ylabel("tpr")
plt.title('ROC curve for '+str (best_c)+'as C')
plt.legend()
plt.grid()
plt.show()
```



[0]:
```
# This section of code where ever implemented is taken from sample kNN python␣
↪notebook

def find_best_threshold(threshould, fpr, tpr):
    t = threshould[np.argmax(tpr*(1-fpr))]
    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very␣
↪high
    print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for␣
↪threshold", np.round(t,3))
    return t

def predict_with_best_t(proba, threshould):
    predictions = []
    for i in proba:
        if i>=threshould:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions


print('test')
best_ts_thres = find_best_threshold(te_thresholds, test_fpr, test_tpr)
```

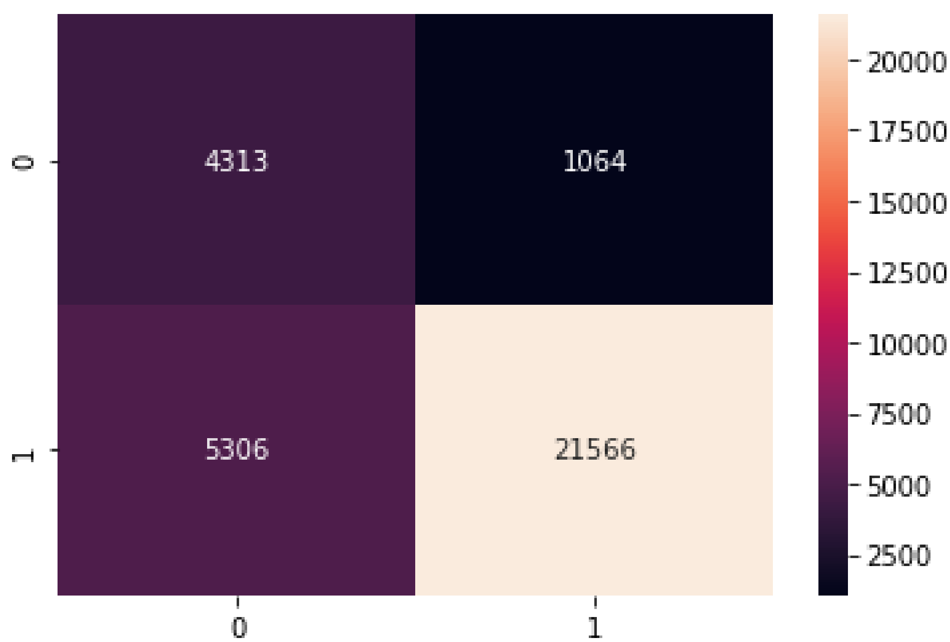
```
print('train')
best_tr_thres = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
```

```
test
the maximum value of tpr*(1-fpr) 0.6404870105433769 for threshold 0.965
train
the maximum value of tpr*(1-fpr) 0.643737830016295 for threshold 0.989
```

[0]:
```
print('train Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_train, predict_with_best_t(y_pred_tr,␣
↪best_tr_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
train Confusion Matrix
```

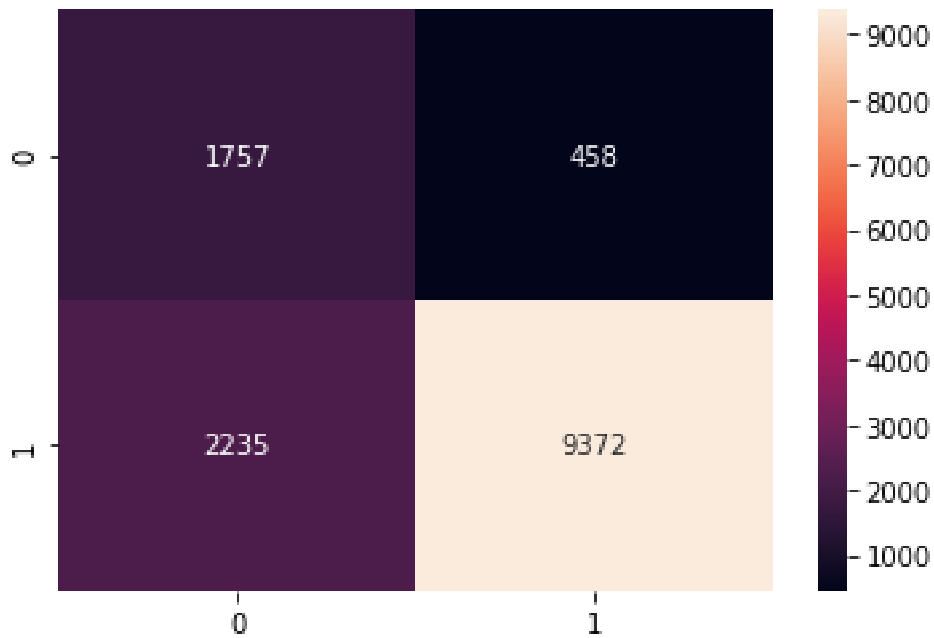
[0]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4947925e80>
```



[0]:
```
print('Test Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_pred_ts,␣
↪best_ts_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
Test Confusion Matrix
```

[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f494abecac8>



[0]:
```
acc=accuracy_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
ps=precision_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
rc=recall_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
f1=f1_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100

print("Accuracy on test set: %0.2f%%"%(acc))
print("Precision on test set: %0.2f%%"%(ps))
print("recall score on test set: %0.2f%%"%(rc))
print("f1 score on test set: %0.2f%%"%(f1))
```

```
Accuracy on test set: 80.52%
Precision on test set: 95.34%
recall score on test set: 80.74%
f1 score on test set: 87.44%
```

7.2 [5.2] RBF SVM

7.2.1 [5.2.1] Applying RBF SVM on BOW, SET 1

[0]:
```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

```
X_train, X_test, y_train, y_test = train_test_split(preprocessed_reviews[:
↪20000],final['Score'].values[:20000],test_size=0.3,random_state=0)

vectorizer = CountVectorizer(ngram_range=(1,2), min_df=10,max_features=500)
vectorizer.fit(X_train)
X_train = vectorizer.transform(X_train)
X_test = vectorizer.transform(X_test)

ss = StandardScaler(with_mean = False)
X_train = ss.fit_transform(X_train)
X_test = ss.transform(X_test)

print(X_train.shape)
print(X_test.shape)
```

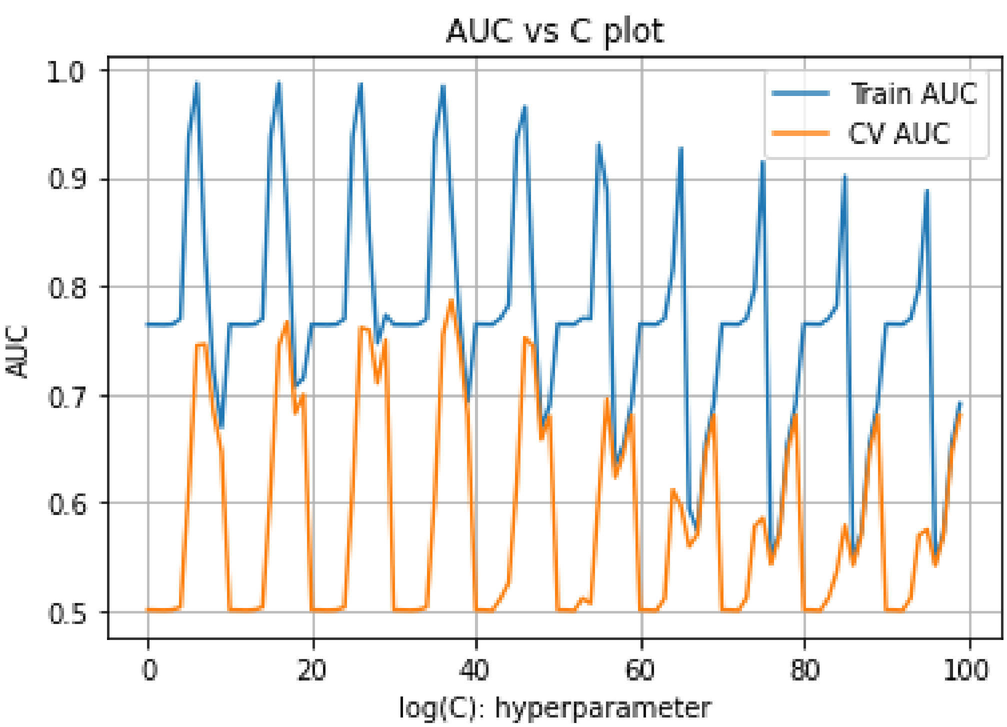
```
(14000, 500)
(6000, 500)
```

[0]:
```
b=[10000,1000,100,10,1,0.1,0.01,0.001,0.0001,0.00001]

param = {'C':b, 'gamma':b}
print(param)

from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC

RBF_SVM=SVC(kernel='rbf',max_iter=800)

temp_gscv=␣
↪GridSearchCV(RBF_SVM,param,cv=5,verbose=5,n_jobs=-1,scoring='roc_auc',return_train_score=Tr
temp_gscv.fit(X_train,y_train)
temp_gs = pd.DataFrame.from_dict(temp_gscv.cv_results_)
```

```
{'C': [10000, 1000, 100, 10, 1, 0.1, 0.01, 0.001, 0.0001, 1e-05], 'gamma':
[10000, 1000, 100, 10, 1, 0.1, 0.01, 0.001, 0.0001, 1e-05]}
Fitting 5 folds for each of 100 candidates, totalling 500 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  14 tasks      | elapsed:  1.5min
[Parallel(n_jobs=-1)]: Done  68 tasks      | elapsed:  6.8min
[Parallel(n_jobs=-1)]: Done 158 tasks      | elapsed: 15.7min
[Parallel(n_jobs=-1)]: Done 284 tasks      | elapsed: 28.4min
[Parallel(n_jobs=-1)]: Done 446 tasks      | elapsed: 44.1min
[Parallel(n_jobs=-1)]: Done 500 out of 500 | elapsed: 49.3min finished
```

[0]:

```
train_auc= temp_gs['mean_train_score']
cv_auc= temp_gs['mean_test_score']
plt.plot(range(100),train_auc,label='Train AUC')
plt.plot(range(100),cv_auc ,label='CV AUC')

# plt.scatter(param['n_neighbors'],train_auc,label='Train AUC')
# plt.scatter(param['n_neighbors'], cv_auc, label='cv AUC')
plt.grid()
plt.title('AUC vs C plot')
plt.xlabel("log(C): hyperparameter")
plt.ylabel("AUC")
plt.legend()
plt.show()
plt.clf()
plt.cla()
plt.close()
```



[0]:

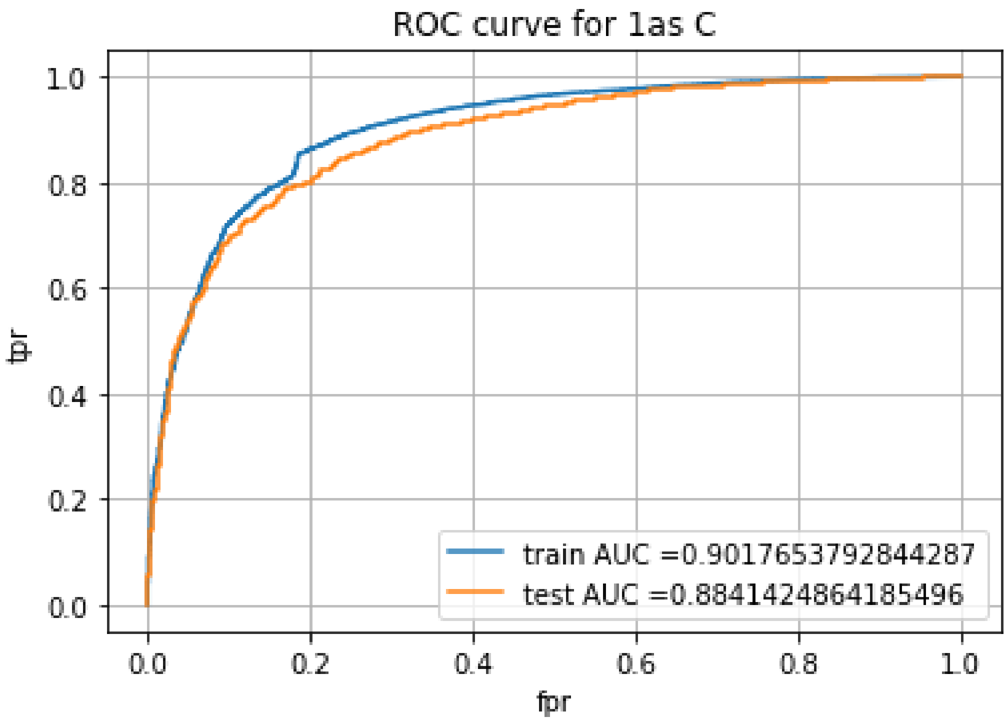
```
#finding the best CV scores that is maximas then using the one which is least␣
↪distant then its AUC counter part to derive
# C and gamma to avoid using Dumb model.

from scipy.signal import argrelextrema
import numpy as np
x = np.array(train_auc)
```

```
y = np.array(cv_auc)
c=b #using same range for gamma and C
local_max=()
diff=x-y

#finding index of maximas of CV scores
local_max_i=argrelextrema(y, np.greater)

#generating a list of indexs for maximas
l=list(i for i in local_max_i[0])

#generating list of indices in neighbor of maximas to check
k=[]
neighbor=0
for i in l:
  if i >neighbor and i<len(y):
    k.extend(range(i-neighbor,i+neighbor+1))
  elif i<neighbor and i < len(y):
    k.extend(range(i,i+neighbor+1))
  else:
    k.extend(range(i-neighbor,i+1))
l=k

# diff between CV and Test AUC at the local maximas
local_diff=list(diff[i] for i in l)
print(f'all local differences {local_diff}')

#fetching the index where local diff is min
for i in np.nditer(np.argmin(local_diff)):
  v=i
  break
print(f'best cv score to use = {y[l[v]]}')


best_index= l[v]

# as index are in range of 0 to hundread
# for differnt permutation of C and gamma
# fetching the C and Gamma index from them

best_c=c[int((best_index-(best_index%10))/10)]
print(f'best C to use = {best_c}')

best_gamma=c[best_index%10]
print('best gamma to use = {}'.format(best_gamma))

print('best index {}'.format(best_index))
```

```
all local differences [0.0834623601955713, 0.10006505771777519,
0.01539573816249773, 0.22435269068589936, 0.022905877932908325,
0.09145052288214106, 0.2129380824187166, 0.010095279105655552,
0.25819505010344845, 0.19102607837807672, 0.01029692736678156,
0.203281699021849, 0.010233541078124797, 0.3282732965647418,
0.010206030387288179, 0.3216317564551193, 0.010206030387288179,
0.31179566712224316]
best cv score to use = 0.6799018907274256
best C to use = 1
best gamma to use = 1e-05
best index 49
```

[0]:
```
from sklearn.metrics import␣
↪accuracy_score,confusion_matrix,f1_score,precision_score,recall_score,roc_curve,␣
↪auc
from sklearn.svm import SVC

RBF_SVM=SVC(kernel='rbf',C=best_c,gamma=best_gamma)

RBF_SVM.fit(X_train,y_train)
y_pred_tr = RBF_SVM.decision_function(X_train)
y_pred_ts = RBF_SVM.decision_function(X_test)
```

[0]:
```
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_pred_tr)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_pred_ts)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr,␣
↪train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.xlabel("fpr")
plt.ylabel("tpr")
plt.title('ROC curve for '+str (best_c)+'as C')
plt.legend()
plt.grid()
plt.show()
```



[0]:
```
# This section of code where ever implemented is taken from sample kNN python␣
↪notebook

def find_best_threshold(threshould, fpr, tpr):
    t = threshould[np.argmax(tpr*(1-fpr))]
    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very␣
↪high
    print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for␣
↪threshold", np.round(t,3))
    return t

def predict_with_best_t(proba, threshould):
    predictions = []
    for i in proba:
        if i>=threshould:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions


print('test')
best_ts_thres = find_best_threshold(te_thresholds, test_fpr, test_tpr)
```

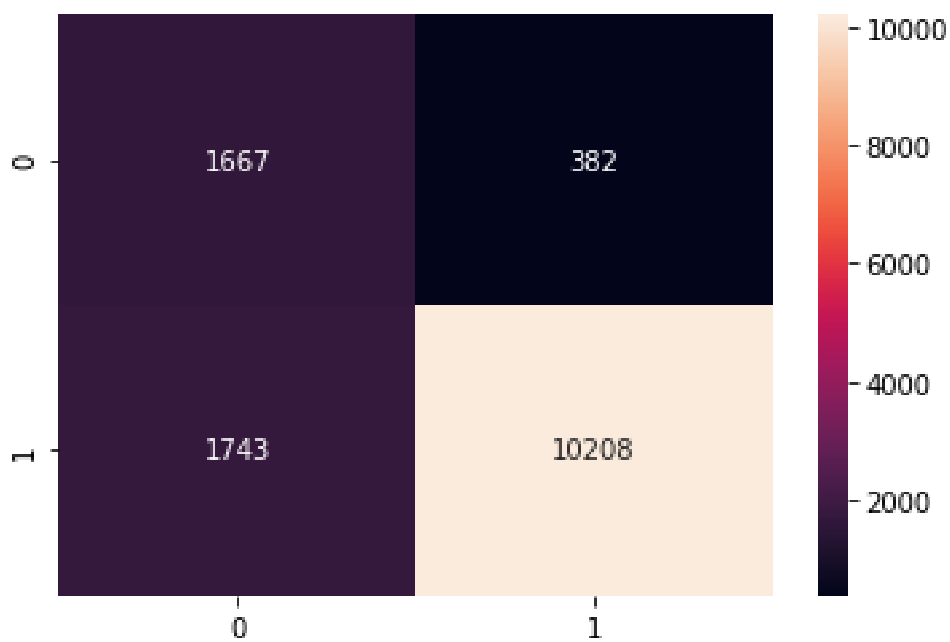
```
print('train')
best_tr_thres = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
```

```
test
the maximum value of tpr*(1-fpr) 0.6530735915784356 for threshold 1.002
train
the maximum value of tpr*(1-fpr) 0.6949123921867554 for threshold 1.0
```

[0]:
```
print('train Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_train, predict_with_best_t(y_pred_tr,␣
 ↪best_tr_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
train Confusion Matrix
```

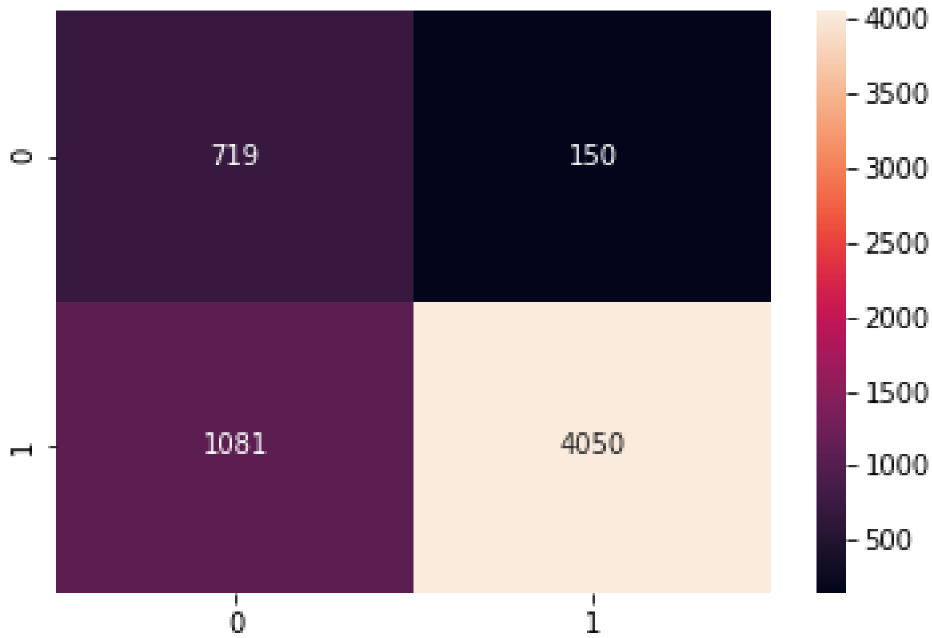
[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5c91327908>



[0]:
```
print('Test Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_pred_ts,␣
 ↪best_ts_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
Test Confusion Matrix
```

[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5c8e9096d8>



[0]:
```
acc=accuracy_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
ps=precision_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
rc=recall_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
f1=f1_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100

print("Accuracy on test set: %0.2f%%"%(acc))
print("Precision on test set: %0.2f%%"%(ps))
print("recall score on test set: %0.2f%%"%(rc))
print("f1 score on test set: %0.2f%%"%(f1))
```

```
Accuracy on test set: 79.48%
Precision on test set: 96.43%
recall score on test set: 78.93%
f1 score on test set: 86.81%
```

7.2.2 [5.2.2] Applying RBF SVM on TFIDF, SET 2

[36]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

X_train, X_test, y_train, y_test = train_test_split(preprocessed_reviews[:
↪20000],final['Score'].values[:20000],test_size=0.3,random_state=0)
```

```
vectorizer = TfidfVectorizer(ngram_range=(1,2), min_df=10,max_features=500)
vectorizer.fit(X_train)
X_train = vectorizer.transform(X_train)
X_test = vectorizer.transform(X_test)

ss = StandardScaler(with_mean = False)
X_train = ss.fit_transform(X_train)
X_test = ss.transform(X_test)

print(X_train.shape)
print(X_test.shape)
```

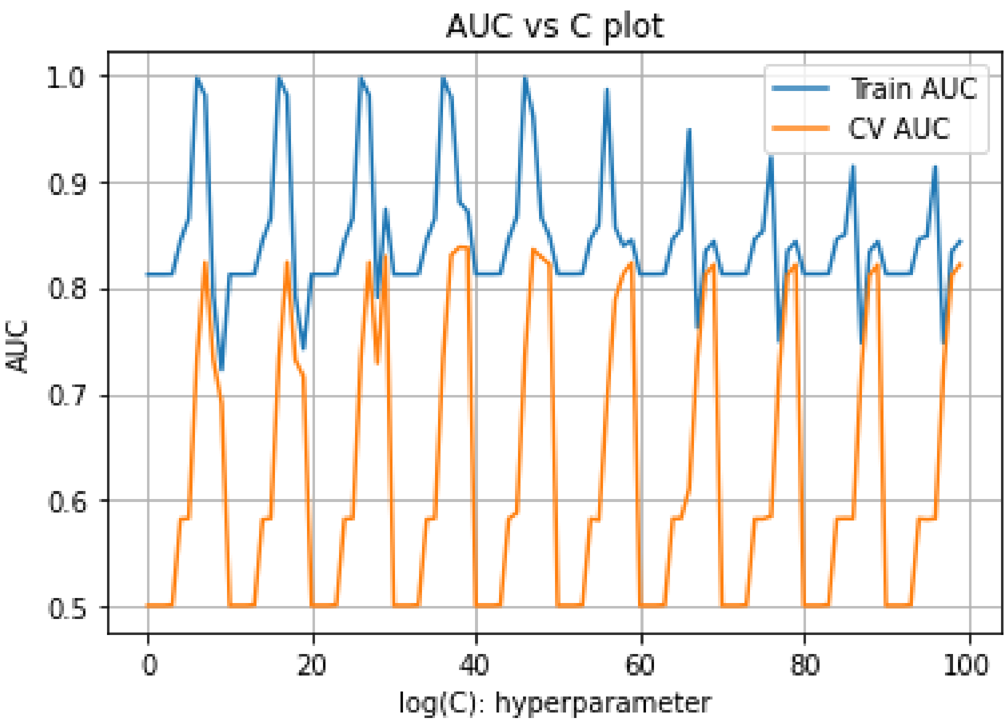
```
(14000, 500)
(6000, 500)
```

[37]:
```
b=[10000,1000,100,10,1,0.1,0.01,0.001,0.0001,0.00001]

param = {'C':b, 'gamma':b}
print(param)

from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC

RBF_SVM=SVC(kernel='rbf',max_iter=800)

temp_gscv=␣
 ↪GridSearchCV(RBF_SVM,param,cv=3,verbose=5,n_jobs=-1,scoring='roc_auc',return_train_score=Tr
temp_gscv.fit(X_train,y_train)
temp_gs = pd.DataFrame.from_dict(temp_gscv.cv_results_)
```

```
{'C': [10000, 1000, 100, 10, 1, 0.1, 0.01, 0.001, 0.0001, 1e-05], 'gamma':
[10000, 1000, 100, 10, 1, 0.1, 0.01, 0.001, 0.0001, 1e-05]}
Fitting 3 folds for each of 100 candidates, totalling 300 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  14 tasks      | elapsed:  1.5min
[Parallel(n_jobs=-1)]: Done  68 tasks      | elapsed:  6.7min
[Parallel(n_jobs=-1)]: Done 158 tasks      | elapsed: 16.0min
[Parallel(n_jobs=-1)]: Done 284 tasks      | elapsed: 28.8min
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed: 30.4min finished
```

[38]:
```
train_auc= temp_gs['mean_train_score']
cv_auc= temp_gs['mean_test_score']
plt.plot(range(100),train_auc,label='Train AUC')
plt.plot(range(100),cv_auc ,label='CV AUC')

# plt.scatter(param['n_neighbors'],train_auc,label='Train AUC')
```

```
# plt.scatter(param['n_neighbors'], cv_auc, label='cv AUC')
plt.grid()
plt.title('AUC vs C plot')
plt.xlabel("log(C): hyperparameter")
plt.ylabel("AUC")
plt.legend()
plt.show()
plt.clf()
plt.cla()
plt.close()
```



[39]:
```
#finding the best CV scores that is maximas then using the one which is least
 ↪distant then its AUC counter part to derive
# C and gamma to avoid using Dumb model.

from scipy.signal import argrelextrema
import numpy as np
x = np.array(train_auc)
y = np.array(cv_auc)
c=b #using same range for gamma and C
local_max=()
diff=x-y

#finding index of maximas of CV scores
```

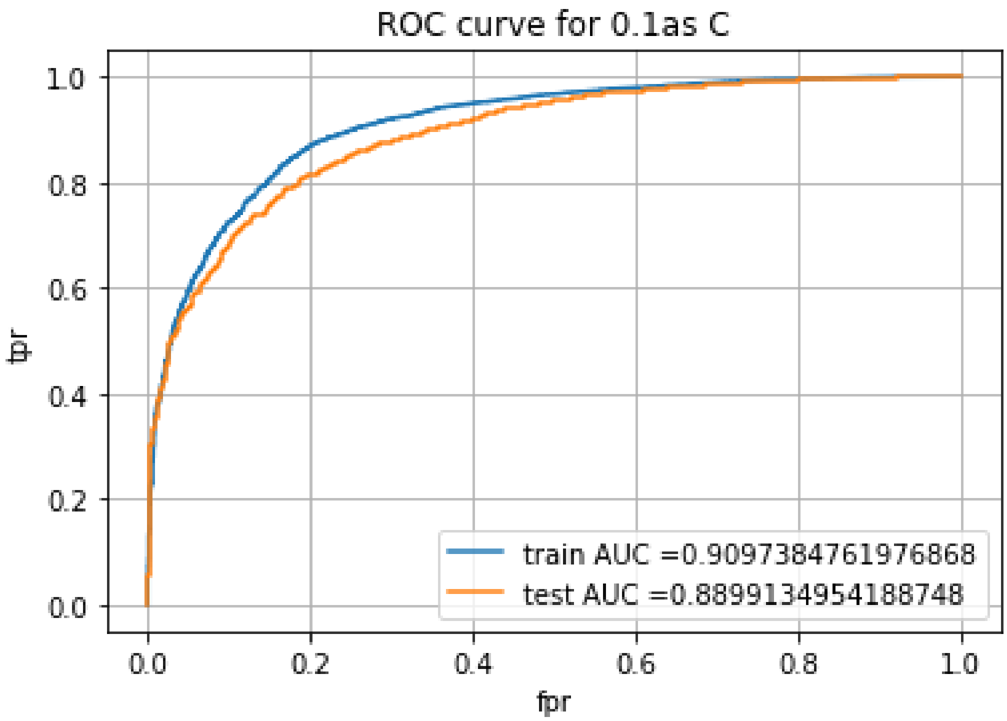
```
local_max_i=argrelextrema(y, np.greater)

#generating a list of indexs for maximas
l=list(i for i in local_max_i[0])

#generating list of indices in neighbor of maximas to check
k=[]
neighbor=1
for i in l:
  if i >neighbor and i<len(y):
    k.extend(range(i-neighbor,i+neighbor+1))
  elif i<neighbor and i < len(y):
    k.extend(range(i,i+neighbor+1))
  else:
    k.extend(range(i-neighbor,i+1))
dup_less=[]
[dup_less.append(x) for x in k if x not in dup_less]
l=dup_less

# diff between CV and Test AUC at the local maximas
local_diff=list(diff[i] for i in l)
print(f'all local differences {local_diff}')

#fetching the index where local diff is min
for i in np.nditer(np.argmin(local_diff)):
  v=i
  break
print(f'best cv score to use = {y[l[v]]}')


best_index= l[v]

# as index are in range of 0 to hundread
# for differnt permutation of C and gamma
# fetching the C and Gamma index from them

best_c=c[int((best_index-(best_index%10))/10)]
print(f'best C to use = {best_c}')

best_gamma=c[best_index%10]
print('best gamma to use = {}'.format(best_gamma))
```

```
all local differences [0.26296280773073133, 0.1566328908460144,
0.060229057767497984, 0.26296280773073133, 0.1566328908460144,
0.060229057767497984, 0.26296280773073133, 0.1566328908460144,
0.06190633158216985, 0.04426459917875758, 0.3109896414449488,
0.14761350387962924, 0.042444196436403514, 0.03422955383792914,
```

```
0.25892680242917754, 0.12470751026543281, 0.037300489567466566,
0.3111297271696932, 0.26238006181091333, 0.27686638753664206,
0.025718629060782927, 0.02138096244174803, 0.3112587787149147,
0.021650092023007828, 0.02188229819671461, 0.3113440499392851,
0.3110444559453227, 0.2625528727821933, 0.27010136515947136,
0.022261332959500946, 0.021678079084481272, 0.3114293211636554,
0.2624550966704735, 0.26646015872202466, 0.33062381211176384,
0.0222206219616341, 0.021678079084481272, 0.3114293211636554,
0.3111297271696932, 0.26241907494806327, 0.26578882573394724]
best cv score to use = 0.8228827904449189
best C to use = 0.1
best gamma to use = 1e-05
```

[0]:
```python
from sklearn.metrics import␣
↪accuracy_score,confusion_matrix,f1_score,precision_score,recall_score,roc_curve,␣
↪auc
from sklearn.svm import SVC

RBF_SVM=SVC(kernel='rbf',C=best_c,gamma=best_gamma)

RBF_SVM.fit(X_train,y_train)
y_pred_tr = RBF_SVM.decision_function(X_train)
y_pred_ts = RBF_SVM.decision_function(X_test)
```

[41]:
```python
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_pred_tr)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_pred_ts)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr,␣
↪train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.xlabel("fpr")
plt.ylabel("tpr")
plt.title('ROC curve for '+str (best_c)+'as C')
plt.legend()
plt.grid()
plt.show()
```



[42]:
```
# This section of code where ever implemented is taken from sample kNN python␣
↪notebook

def find_best_threshold(threshould, fpr, tpr):
    t = threshould[np.argmax(tpr*(1-fpr))]
    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very␣
↪high
    print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for␣
↪threshold", np.round(t,3))
    return t

def predict_with_best_t(proba, threshould):
    predictions = []
    for i in proba:
        if i>=threshould:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions


print('test')
best_ts_thres = find_best_threshold(te_thresholds, test_fpr, test_tpr)
```

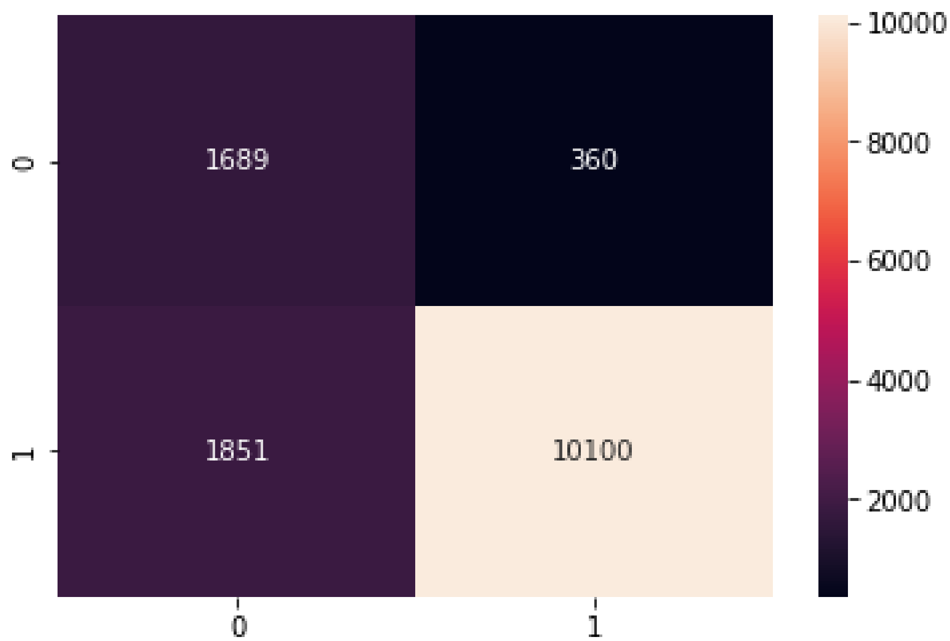
```
print('train')
best_tr_thres = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
```

```
test
the maximum value of tpr*(1-fpr) 0.6536589457479851 for threshold 1.0
train
the maximum value of tpr*(1-fpr) 0.6966342433163824 for threshold 1.0
```

[43]:
```
print('train Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_train, predict_with_best_t(y_pred_tr,␣
↪best_tr_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
train Confusion Matrix
```

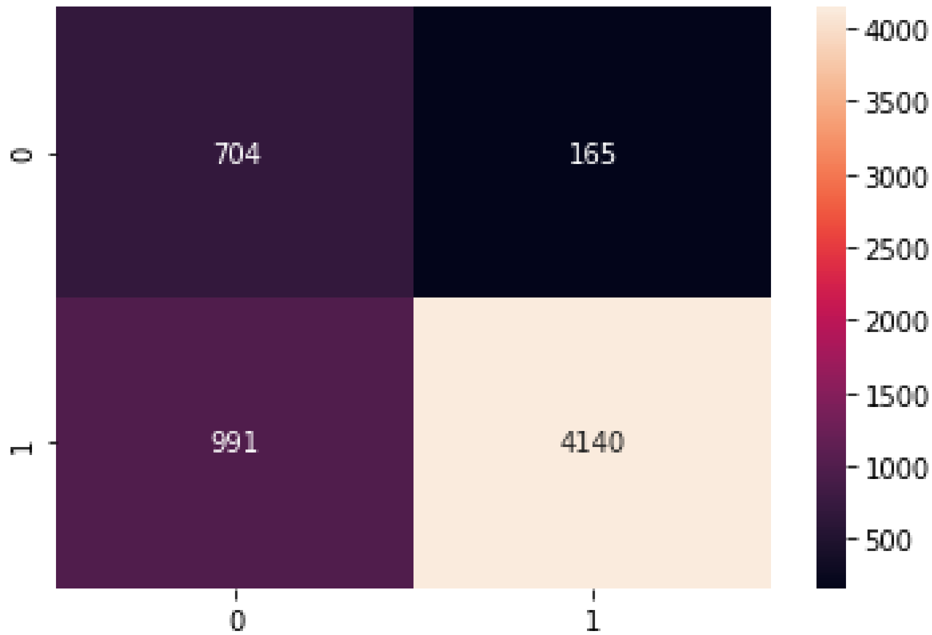
[43]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1e8aba28d0>
```



[44]:
```
print('Test Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_pred_ts,␣
↪best_ts_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
Test Confusion Matrix
```

[44]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1e8b9b6198>



[45]:
```
acc=accuracy_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
ps=precision_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
rc=recall_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
f1=f1_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100

print("Accuracy on test set: %0.2f%%"%(acc))
print("Precision on test set: %0.2f%%"%(ps))
print("recall score on test set: %0.2f%%"%(rc))
print("f1 score on test set: %0.2f%%"%(f1))
```

```
Accuracy on test set: 80.73%
Precision on test set: 96.17%
recall score on test set: 80.69%
f1 score on test set: 87.75%
```

7.2.3 [5.2.3] Applying RBF SVM on AVG W2V, SET 3

[46]:
```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

X_train, X_test, y_train, y_test = train_test_split(sent_vectors[:
↪20000],final['Score'].values[:20000],test_size=0.3,random_state=0)
```

```
ss = StandardScaler(with_mean = False)
X_train = ss.fit_transform(X_train)
X_test = ss.transform(X_test)

print(X_train.shape)
print(X_test.shape)
```

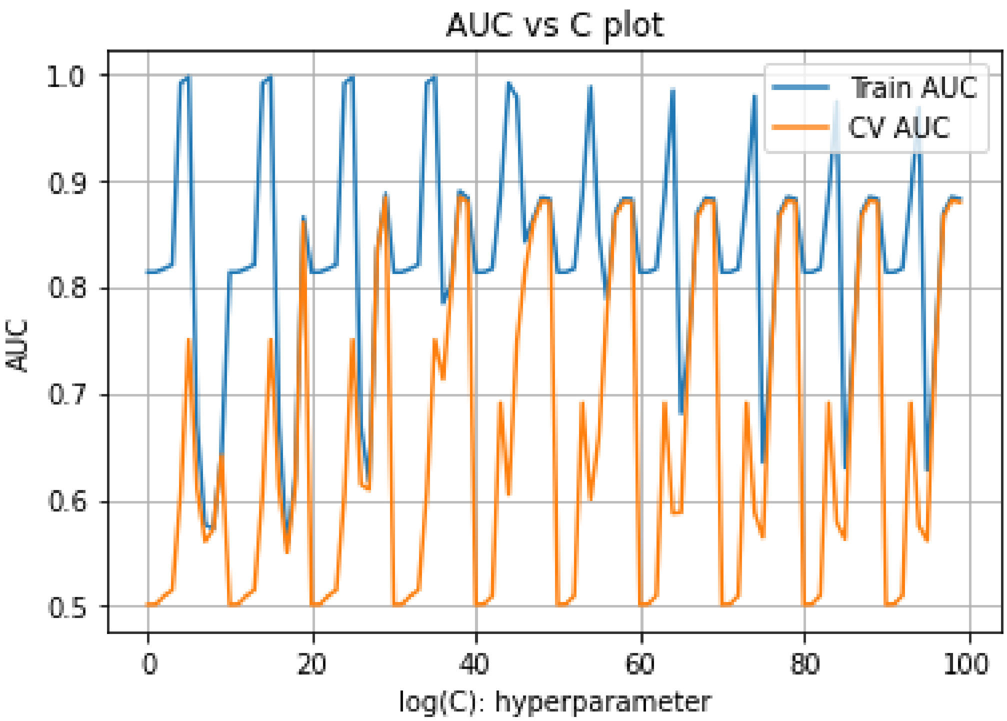
```
(14000, 50)
(6000, 50)
```

[47]:
```
b=[10000,1000,100,10,1,0.1,0.01,0.001,0.0001,0.00001]

param = {'C':b, 'gamma':b}
print(param)

from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC

RBF_SVM=SVC(kernel='rbf', max_iter=800)

temp_gscv=␣
 ↪GridSearchCV(RBF_SVM,param,cv=3,verbose=5,n_jobs=-1,scoring='roc_auc',return_train_score=Tr
temp_gscv.fit(X_train,y_train)
temp_gs = pd.DataFrame.from_dict(temp_gscv.cv_results_)
```

```
{'C': [10000, 1000, 100, 10, 1, 0.1, 0.01, 0.001, 0.0001, 1e-05], 'gamma':
[10000, 1000, 100, 10, 1, 0.1, 0.01, 0.001, 0.0001, 1e-05]}
Fitting 3 folds for each of 100 candidates, totalling 300 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  14 tasks      | elapsed:   33.0s
[Parallel(n_jobs=-1)]: Done  68 tasks      | elapsed:  2.4min
[Parallel(n_jobs=-1)]: Done 158 tasks      | elapsed:  5.8min
[Parallel(n_jobs=-1)]: Done 284 tasks      | elapsed: 10.8min
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed: 11.4min finished
```

[48]:
```
train_auc= temp_gs['mean_train_score']
cv_auc= temp_gs['mean_test_score']
plt.plot(range(100),train_auc,label='Train AUC')
plt.plot(range(100),cv_auc ,label='CV AUC')

# plt.scatter(param['n_neighbors'],train_auc,label='Train AUC')
# plt.scatter(param['n_neighbors'], cv_auc, label='cv AUC')
plt.grid()
plt.title('AUC vs C plot')
plt.xlabel("log(C): hyperparameter")
```

```
plt.ylabel("AUC")
plt.legend()
plt.show()
plt.clf()
plt.cla()
plt.close()
```



[49]:
```
#finding the best CV scores that is maximas then using the one which is least␣
↪distant then its AUC counter part to derive
# C and gamma to avoid using Dumb model.

from scipy.signal import argrelextrema
import numpy as np
x = np.array(train_auc)
y = np.array(cv_auc)
c=b #using same range for gamma and C
local_max=()
diff=x-y

#finding index of maximas of CV scores
local_max_i=argrelextrema(y, np.greater)

#generating a list of indexs for maximas
l=list(i for i in local_max_i[0])
```

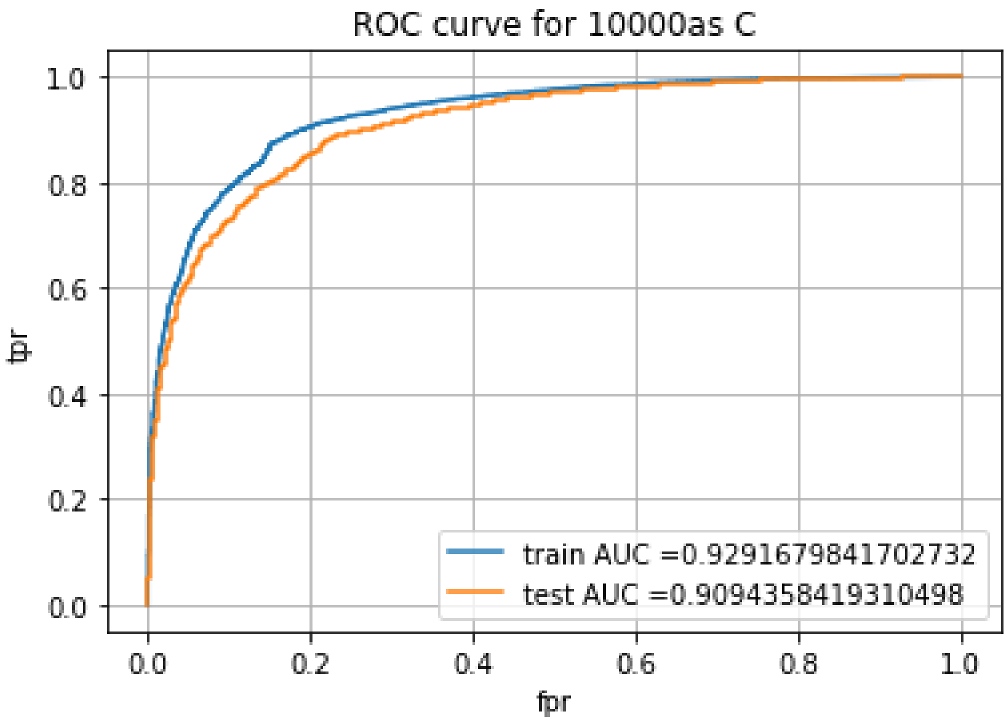
```
#generating list of indices in neighbor of maximas to check
k=[]
neighbor=1
for i in l:
  if i >neighbor and i<len(y):
    k.extend(range(i-neighbor,i+neighbor+1))
  elif i<neighbor and i < len(y):
    k.extend(range(i,i+neighbor+1))
  else:
    k.extend(range(i-neighbor,i+1))
dup_less=[]
[dup_less.append(x) for x in k if x not in dup_less]
l=dup_less

# diff between CV and Test AUC at the local maximas
local_diff=list(diff[i] for i in l)
print(f'all local differences {local_diff}')

#fetching the index where local diff is min
for i in np.nditer(np.argmin(local_diff)):
  v=i
  break
print(f'best cv score to use = {y[l[v]]}')


best_index= l[v]

# as index are in range of 0 to hundread
# for differnt permutation of C and gamma
# fetching the C and Gamma index from them

best_c=c[int((best_index-(best_index%10))/10)]
print(f'best C to use = {best_c}')

best_gamma=c[best_index%10]
print('best gamma to use = {}'.format(best_gamma))
```

```
all local differences [0.38542643977787083, 0.24636934992867143,
0.059422645172685695, -2.730328435152085e-05, 0.0011412068883860371,
0.3120450311756736, 0.38542643977787083, 0.24636934992867143,
0.059422645172685695, 0.007930452858324166, 0.005010827710314469,
0.3120450311756736, 0.38542643977787083, 0.24636934992867143,
0.05481535548856231, 4.2507799765334475e-05, 0.003358117440158903,
0.3120450311756736, 0.38542643977787083, 0.24636934992867143,
0.07176317892560657, 0.005452634895622088, 0.005212610586675215,
0.004092749233788773, 0.30711276610798244, 0.19445899945428735,
```

```
0.38560331478561827, 0.0042152124962759885, 0.0034365068080162153,
0.0033011323204528153, 0.3069312498985801, 0.19445899945428735,
0.3865876924342865, 0.003788197177292063, 0.003245905954156969,
0.003277232733068014, 0.30686545364589957, 0.1944588769458595,
0.39670806703903916, 0.004191477742078398, 0.003255299052406624,
0.003277232733068014, 0.306833165550924, 0.194459106602069, 0.3909884584273121,
0.004071367347006194, 0.0033453138332698584, 0.003277232733068014,
0.30663698486757296, 0.19445930566769332, 0.39469383857742135,
0.0038724399417048305, 0.0033453138332698584, 0.003277232733068014,
0.3067183457807856, 0.19445953533159044, 0.39246808311257386,
0.0038724399417048305, 0.0033453138332698584, 0.003277232733068014]
best cv score to use = 0.5723154312359955
best C to use = 10000
best gamma to use = 0.0001
```

[0]:
```python
from sklearn.metrics import␣
↪accuracy_score,confusion_matrix,f1_score,precision_score,recall_score,roc_curve,␣
↪auc
from sklearn.svm import SVC

RBF_SVM=SVC(kernel='rbf', C=best_c, gamma=best_gamma)

RBF_SVM.fit(X_train,y_train)
y_pred_tr = RBF_SVM.decision_function(X_train)
y_pred_ts = RBF_SVM.decision_function(X_test)
```

[51]:
```python
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_pred_tr)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_pred_ts)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr,␣
↪train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.xlabel("fpr")
plt.ylabel("tpr")
plt.title('ROC curve for '+str (best_c)+'as C')
plt.legend()
plt.grid()
plt.show()
```



[52]:
```
# This section of code where ever implemented is taken from sample kNN python␣
↪notebook

def find_best_threshold(threshould, fpr, tpr):
    t = threshould[np.argmax(tpr*(1-fpr))]
    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very␣
↪high
    print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for␣
↪threshold", np.round(t,3))
    return t

def predict_with_best_t(proba, threshould):
    predictions = []
    for i in proba:
        if i>=threshould:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions


print('test')
best_ts_thres = find_best_threshold(te_thresholds, test_fpr, test_tpr)
```

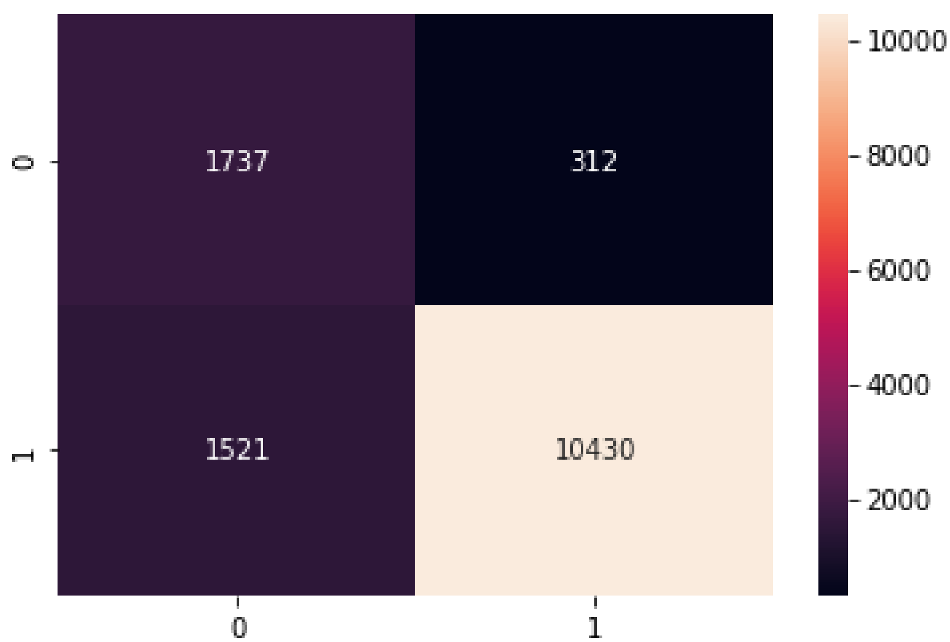
```
print('train')
best_tr_thres = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
```

```
test
the maximum value of tpr*(1-fpr) 0.6858771980777956 for threshold 0.868
train
the maximum value of tpr*(1-fpr) 0.7398401942142224 for threshold 0.981
```

[53]:
```
print('train Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_train, predict_with_best_t(y_pred_tr,
 ↪best_tr_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
train Confusion Matrix
```

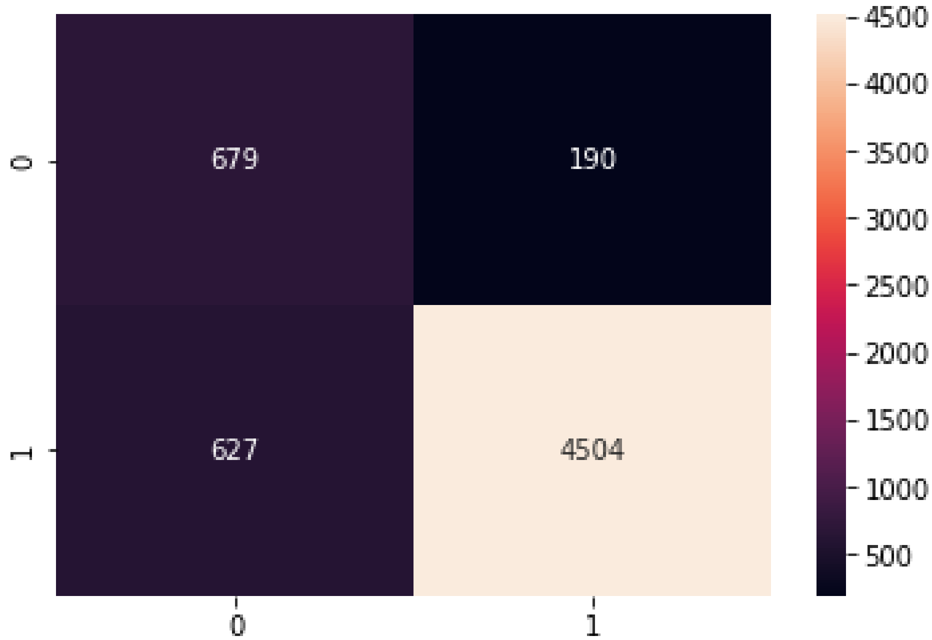
[53]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1e8eac1358>



[54]:
```
print('Test Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_pred_ts,
 ↪best_ts_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
Test Confusion Matrix
```

[54]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1e8b4864a8>



[55]:
```
acc=accuracy_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
ps=precision_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
rc=recall_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
f1=f1_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100

print("Accuracy on test set: %0.2f%%"%(acc))
print("Precision on test set: %0.2f%%"%(ps))
print("recall score on test set: %0.2f%%"%(rc))
print("f1 score on test set: %0.2f%%"%(f1))
```

```
Accuracy on test set: 86.38%
Precision on test set: 95.95%
recall score on test set: 87.78%
f1 score on test set: 91.68%
```

7.2.4 [5.2.4] Applying RBF SVM on TFIDF W2V, SET 4

[66]:
```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

X_train, X_test, y_train, y_test = train_test_split(tfidf_sent_vectors[:
↪20000],final['Score'].values[:20000],test_size=0.3,random_state=0)
```

```
ss = StandardScaler(with_mean = False)
X_train = ss.fit_transform(X_train)
X_test = ss.transform(X_test)

print(X_train.shape)
print(X_test.shape)
```

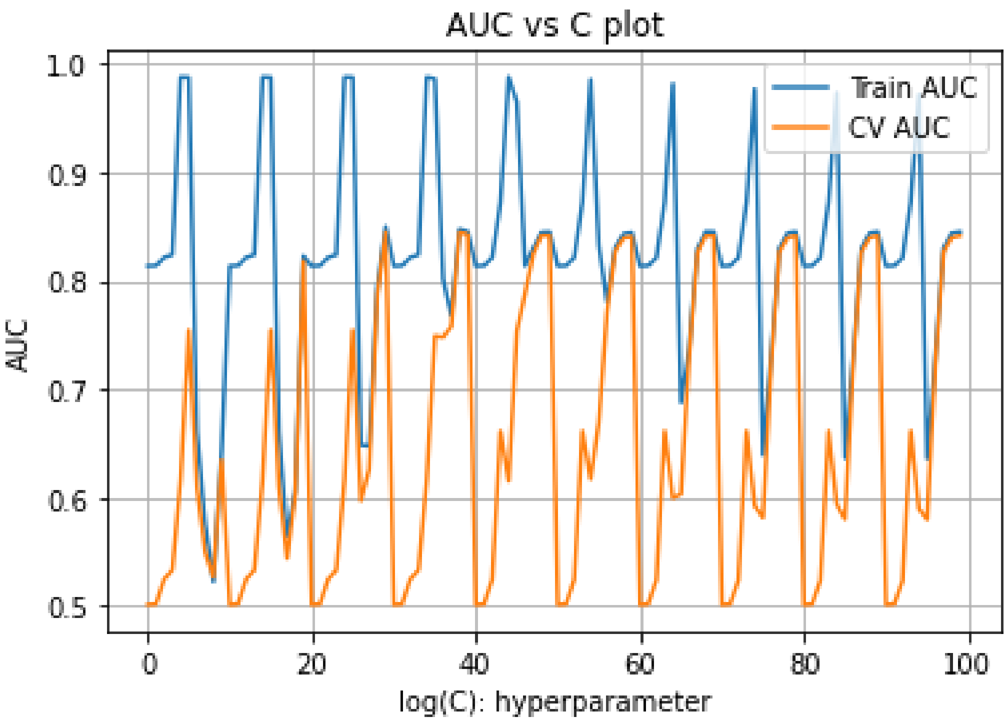
```
(14000, 50)
(6000, 50)
```

[67]:
```
b=[10000,1000,100,10,1,0.1,0.01,0.001,0.0001,0.00001]

param = {'C':b, 'gamma':b}
print(param)

from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC

RBF_SVM=SVC(kernel='rbf',max_iter=800)

temp_gscv=␣
 ↪GridSearchCV(RBF_SVM,param,cv=3,verbose=5,n_jobs=-1,scoring='roc_auc',return_train_score=Tr
temp_gscv.fit(X_train,y_train)
temp_gs = pd.DataFrame.from_dict(temp_gscv.cv_results_)
```

```
{'C': [10000, 1000, 100, 10, 1, 0.1, 0.01, 0.001, 0.0001, 1e-05], 'gamma':
[10000, 1000, 100, 10, 1, 0.1, 0.01, 0.001, 0.0001, 1e-05]}
Fitting 3 folds for each of 100 candidates, totalling 300 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  14 tasks      | elapsed:   37.4s
[Parallel(n_jobs=-1)]: Done  68 tasks      | elapsed:  2.5min
[Parallel(n_jobs=-1)]: Done 158 tasks      | elapsed:  5.9min
[Parallel(n_jobs=-1)]: Done 284 tasks      | elapsed: 10.8min
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed: 11.5min finished
```

[69]:
```
train_auc= temp_gs['mean_train_score']
cv_auc= temp_gs['mean_test_score']
plt.plot(range(100),train_auc,label='Train AUC')
plt.plot(range(100),cv_auc ,label='CV AUC')

# plt.scatter(param['n_neighbors'],train_auc,label='Train AUC')
# plt.scatter(param['n_neighbors'], cv_auc, label='cv AUC')
plt.grid()
plt.title('AUC vs C plot')
plt.xlabel("log(C): hyperparameter")
```

```
plt.ylabel("AUC")
plt.legend()
plt.show()
plt.clf()
plt.cla()
plt.close()
```



[70]:
```
#finding the best CV scores that is maximas then using the one which is least␣
↪distant then its AUC counter part to derive
# C and gamma to avoid using Dumb model.

from scipy.signal import argrelextrema
import numpy as np
x = np.array(train_auc)
y = np.array(cv_auc)
c=b #using same range for gamma and C
local_max=()
diff=x-y

#finding index of maximas of CV scores
local_max_i=argrelextrema(y, np.greater)

#generating a list of indexs for maximas
l=list(i for i in local_max_i[0])
```

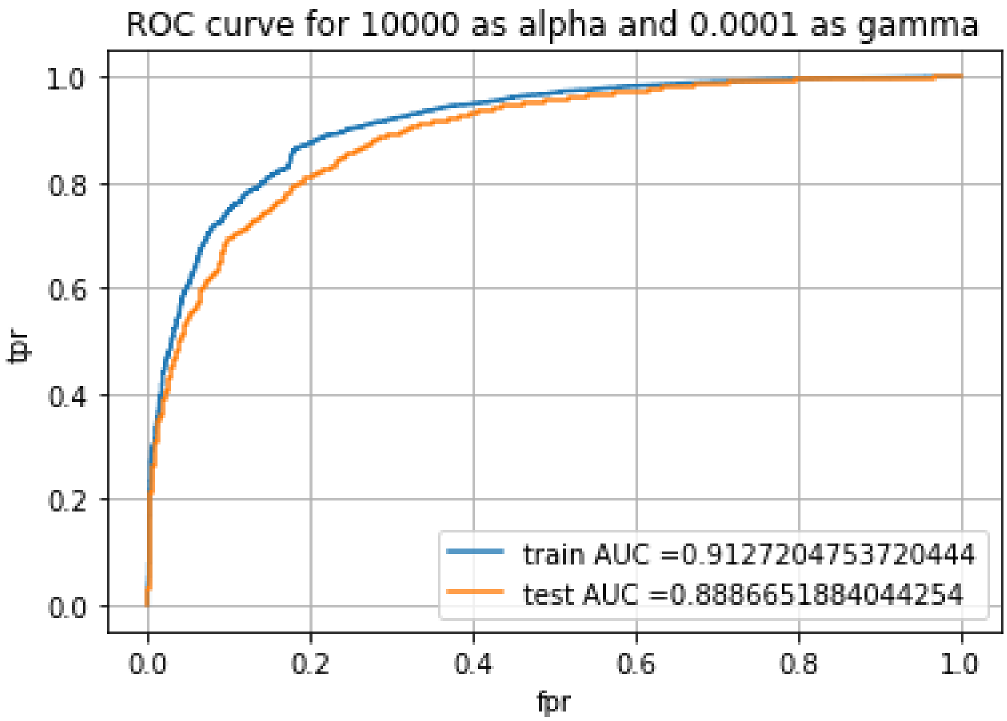
```
#generating list of indices in neighbor of maximas to check
k=[]
neighbor=1
for i in l:
  if i >neighbor and i<len(y):
    k.extend(range(i-neighbor,i+neighbor+1))
  elif i<neighbor and i < len(y):
    k.extend(range(i,i+neighbor+1))
  else:
    k.extend(range(i-neighbor,i+1))
dup_less=[]
[dup_less.append(x) for x in k if x not in dup_less]
l=dup_less

# diff between CV and Test AUC at the local maximas
local_diff=list(diff[i] for i in l)
print(f'all local differences {local_diff}')

#fetching the index where local diff is min
for i in np.nditer(np.argmin(local_diff)):
  v=i
  break
print(f'best cv score to use = {y[l[v]]}')


best_index= l[v]

# as index are in range of 0 to hundread
# for differnt permutation of C and gamma
# fetching the C and Gamma index from them

best_c=c[int((best_index-(best_index%10))/10)]
print(f'best C to use = {best_c}')

best_gamma=c[best_index%10]
print('best gamma to use = {}'.format(best_gamma))
```

```
all local differences [0.37137437939844153, 0.23275790771579996,
0.05114094070827524, -0.004152691125847374, 0.007386309472876773,
0.3120781512272939, 0.37137437939844153, 0.23275790771579996,
0.05114094070827524, 0.0028975196724085883, 0.004577958440894481,
0.3120781512272939, 0.37137437939844153, 0.23275790771579996,
0.05129694274818042, 0.006235896870168012, 0.005172455983185831,
0.3120781512272939, 0.37137437939844153, 0.23703939489642933,
0.053776981214547215, 0.009977141886247543, 0.003004623476214441,
0.0027314138854953596, 0.29645958393483807, 0.2110710693637179,
```

```
0.37224512473646, 0.005360878719183004, 0.002891717206916722,
0.003261978479454530З, 0.2967339490619092, 0.21110024568593944,
0.3684513778211208, 0.003769763885777988, 0.003633496969732808,
0.3120781512272939, 0.29696455845151903, 0.2111003069439975,
0.38152373293007646, 0.0038299715260168288, 0.0035176885516648992,
0.3120781512272939, 0.29719025452928216, 0.2111009808672244, 0.3843390384870443,
0.00411004221381539, 0.0035176885516648992, 0.3120781512272939,
0.2973560307457017, 0.21110091960916633, 0.3795586536416098,
0.00411004221381539, 0.0035176885516648992, 0.3120781512272939,
0.29763337599000383, 0.2111009502381953, 0.38187616937818236]
best cv score to use = 0.5266609078376829
best C to use = 10000
best gamma to use = 0.0001
```

[0]:
```
from sklearn.metrics import␣
↪accuracy_score,confusion_matrix,f1_score,precision_score,recall_score,roc_curve,␣
↪auc
from sklearn.svm import SVC

RBF_SVM=SVC(kernel='rbf',C=best_c,gamma=best_gamma)

RBF_SVM.fit(X_train,y_train)
y_pred_tr = RBF_SVM.decision_function(X_train)
y_pred_ts = RBF_SVM.decision_function(X_test)
```

[75]:
```
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_pred_tr)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_pred_ts)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr,␣
↪train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.xlabel("fpr")
plt.ylabel("tpr")
plt.title('ROC curve for '+str (best_c)+' as alpha and '+str (best_gamma)+' as␣
↪gamma')
plt.legend()
plt.grid()
plt.show()
```



[76]:
```
# This section of code where ever implemented is taken from sample kNN python␣
↪notebook

def find_best_threshold(threshould, fpr, tpr):
    t = threshould[np.argmax(tpr*(1-fpr))]
    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very␣
↪high
    print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for␣
↪threshold", np.round(t,3))
    return t

def predict_with_best_t(proba, threshould):
    predictions = []
    for i in proba:
        if i>=threshould:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions


print('test')
best_ts_thres = find_best_threshold(te_thresholds, test_fpr, test_tpr)
```

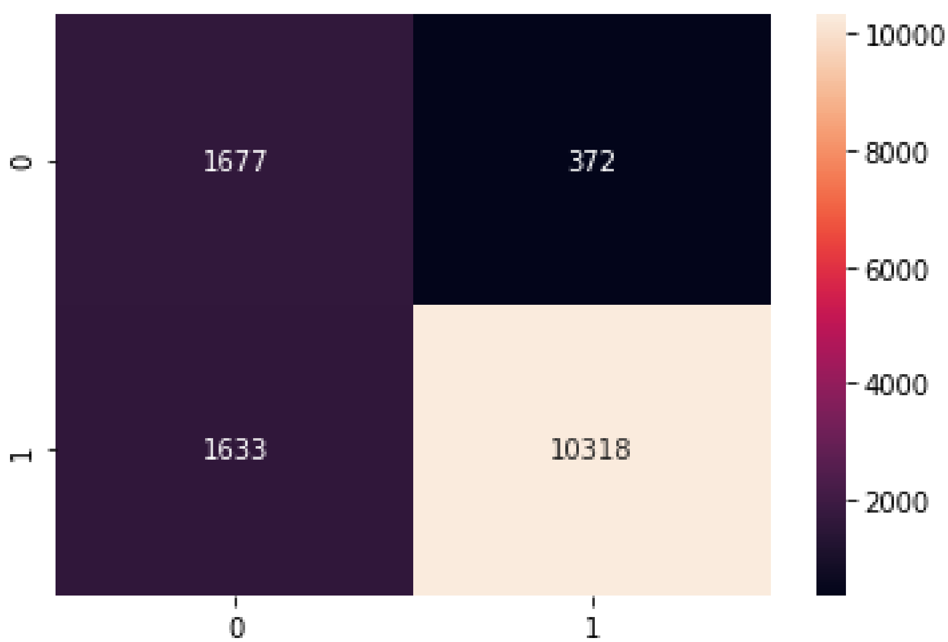
```
print('train')
best_tr_thres = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
```

```
test
the maximum value of tpr*(1-fpr) 0.6507299321639557 for threshold 1.093
train
the maximum value of tpr*(1-fpr) 0.7066142335963603 for threshold 0.981
```

[77]:
```
print('train Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_train, predict_with_best_t(y_pred_tr,␣
↪best_tr_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
train Confusion Matrix
```

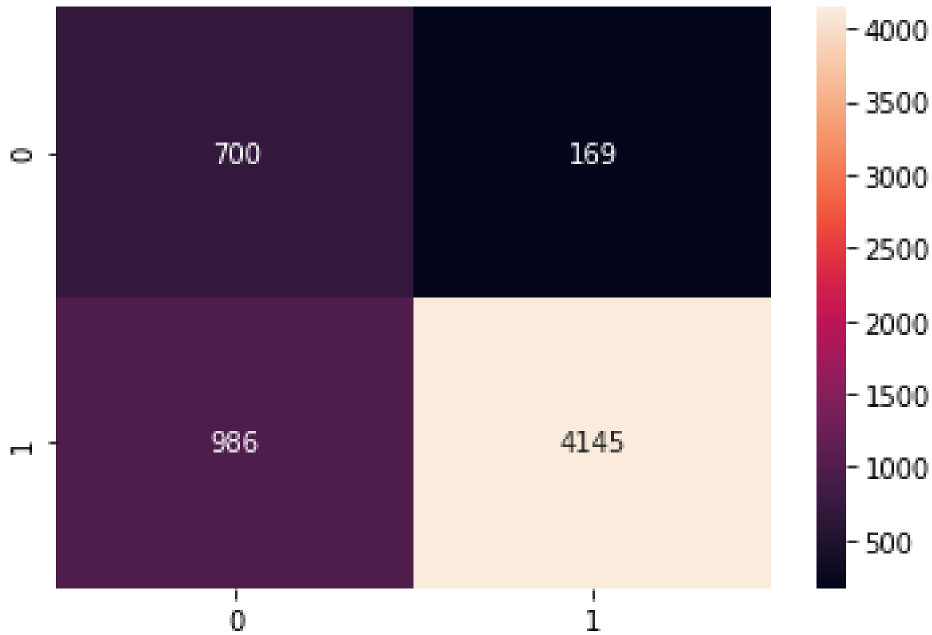
[77]: `<matplotlib.axes._subplots.AxesSubplot at 0x7f1e8b17eef0>`



[78]:
```
print('Test Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_pred_ts,␣
↪best_ts_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

```
Test Confusion Matrix
```

[78]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1e89a46518>



[79]:
```
acc=accuracy_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
ps=precision_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
rc=recall_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100
f1=f1_score(y_test, predict_with_best_t(y_pred_ts, best_ts_thres))*100

print("Accuracy on test set: %0.2f%%"%(acc))
print("Precision on test set: %0.2f%%"%(ps))
print("recall score on test set: %0.2f%%"%(rc))
print("f1 score on test set: %0.2f%%"%(f1))
```

```
Accuracy on test set: 80.75%
Precision on test set: 96.08%
recall score on test set: 80.78%
f1 score on test set: 87.77%
```

[84]:
```
print("Tabulation of results for LINEAR SVM")
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["S.NO.", "MODEL",  "alpha value", "Penalty","Test␣
↪AUC","Precision Score"]
x.add_row(["1", "BOW", "0.001", "L1","0.8991","95.70%"])
x.add_row(["", "", "0.1", "L2","0.9322","96.95%"])
x.add_row(["2", "TFIDF","0.001", "L1","0.9000","83.98%"])
x.add_row(["", "", "0.1", "L2","0.9462","97.04%"])
```

```
x.add_row(["3", "AVG W2V", "0.001", "L1","0.8974","95.63%"])
x.add_row(["", "", "0.01", "L2","0.9013","96.11%"])
x.add_row(["4", "TFIDF W2V", "0.001", "L1","0.8760","95.53%"])
x.add_row(["", "","0.01", "L2","0.8777","95.34%"])
print(x)
```

```
Tabulation of results for LINEAR SVM
+--------+-----------+-------------+---------+----------+-----------------+
| S.NO. |   MODEL    | alpha value | Penalty | Test AUC | Precision Score |
+--------+-----------+-------------+---------+----------+-----------------+
|   1    |    BOW    |    0.001    |    L1   |  0.8991  |      95.70%     |
|        |           |     0.1     |    L2   |  0.9322  |      96.95%     |
|   2    |   TFIDF   |    0.001    |    L1   |  0.9000  |      83.98%     |
|        |           |     0.1     |    L2   |  0.9462  |      97.04%     |
|   3    |  AVG W2V  |    0.001    |    L1   |  0.8974  |      95.63%     |
|        |           |     0.01    |    L2   |  0.9013  |      96.11%     |
|   4    | TFIDF W2V |    0.001    |    L1   |  0.8760  |      95.53%     |
|        |           |     0.01    |    L2   |  0.8777  |      95.34%     |
+--------+-----------+-------------+---------+----------+-----------------+
```

[85]:
```
print("Tabulation of results for RBF SVM")
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["S.NO.", "MODEL",  "alpha value", "gamma","Test␣
 ↪AUC","Precision Score"]
x.add_row(["1", "BOW", "0.001", "0.00001","0.8841","96.43%"])
x.add_row(["2", "TFIDF","0.1", "0.00001","0.8899","96.17%"])
x.add_row(["3", "AVG W2V", "10000", "0.0001","0.9094","95.95%"])
x.add_row(["4", "TFIDF W2V", "10000", "0.0001","0.8886","96.08%"])
print(x)
```

```
Tabulation of results for RBF SVM
+--------+-----------+-------------+---------+----------+-----------------+
| S.NO. |   MODEL    | alpha value |  gamma  | Test AUC | Precision Score |
+--------+-----------+-------------+---------+----------+-----------------+
|   1    |    BOW    |    0.001    | 0.00001 |  0.8841  |      96.43%     |
|   2    |   TFIDF   |     0.1     | 0.00001 |  0.8899  |      96.17%     |
|   3    |  AVG W2V  |    10000    |  0.0001 |  0.9094  |      95.95%     |
|   4    | TFIDF W2V |    10000    |  0.0001 |  0.8886  |      96.08%     |
+--------+-----------+-------------+---------+----------+-----------------+
```

[0]:
```
!sudo apt-get install pandoc texlive-xetex
!jupyter nbconvert --to pdf SVM.ipynb
```