Amazon Fine Food Reviews Analysis_Support Vector Machines

April 21, 2019

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".

In [4]:
```
%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 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 sklearn.linear_model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV
from sklearn.metrics import roc_auc_score, auc

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
```

In [5]:
```
# using SQLite Table to read data.
con = sqlite3.connect('database.sqlite')

# filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
# SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000, will give top 500000 data point
```

```
# you can change the number to any other number based on your computing power

# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 50
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 200

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

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

```
Number of data points in our data (200000, 10)
```

Out[5]:

```
   Id   ProductId          UserId                      ProfileName  \
0   1  B001E4KFG0  A3SGXH7AUHU8GW                       delmartian
1   2  B00813GRG4  A1D87F6ZCVE5NK                           dll pa
2   3  B000LQOCH0   ABXLMWJIXXAIN  Natalia Corres "Natalia Corres"

   HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
0                     1                       1      1  1303862400
1                     0                       0      0  1346976000
2                     1                       1      1  1219017600

                 Summary                                               Text
0  Good Quality Dog Food  I have bought several of the Vitality canned d...
1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
2  "Delight" says it all  This is a confection that has been around a fe...
```

In [6]:

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

In [7]:

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

```
(80668, 7)
```

```
Out[7]:                UserId   ProductId              ProfileName        Time  Score  \
        0  #oc-R115TNMSPFT9I7  B005ZBZLT4                  Breyton  1331510400      2
        1  #oc-R11D9D7SHXIJB9  B005HG9ESG  Louis E. Emory "hoppy"  1342396800      5
        2  #oc-R11DNU2NBKQ23Z  B005ZBZLT4         Kim Cieszykowski  1348531200      1
        3  #oc-R11O5J5ZVQE25C  B005HG9ESG            Penguin Chick  1346889600      5
        4  #oc-R12KPBODL2B5ZD  B007OSBEV0    Christopher P. Presta  1348617600      1

                                                Text  COUNT(*)
        0  Overall its just OK when considering the price...         2
        1  My wife has recurring extreme muscle spasms, u...         3
        2  This coffee is horrible and unfortunately not ...         2
        3  This will be the bottle that you grab from the...         3
        4  I didnt like this coffee. Instead of telling y...         2
```

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

```
Out[8]:               UserId   ProductId                       ProfileName        Time  \
        80638  AZY10LLTJ71NX  B001ATMQK2  undertheshrine "undertheshrine"  1296691200

               Score                                               Text  COUNT(*)
        80638      5  I bought this 6 pack because for the price tha...         5
```

```
In [9]: display['COUNT(*)'].sum()
```

```
Out[9]: 393063
```

3 [2] Exploratory Data Analysis

3.1 [2.1] Data Cleaning: Deduplication

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

```
In [10]: display= pd.read_sql_query("""
         SELECT *
         FROM Reviews
         WHERE Score != 3 AND UserId="AR5J8UI46CURR"
         ORDER BY ProductID
         """, con)
         display.head()
```

```
Out[10]:        Id   ProductId         UserId      ProfileName  HelpfulnessNumerator  \
         0   78445  B000HDL1RQ  AR5J8UI46CURR  Geetha Krishnan                     2
         1  138317  B000HDOPYC  AR5J8UI46CURR  Geetha Krishnan                     2
         2  138277  B000HDOPYM  AR5J8UI46CURR  Geetha Krishnan                     2
         3   73791  B000HDOPZG  AR5J8UI46CURR  Geetha Krishnan                     2
         4  155049  B000PAQ75C  AR5J8UI46CURR  Geetha Krishnan                     2
```

```
   HelpfulnessDenominator  Score        Time  \
0                       2      5  1199577600
1                       2      5  1199577600
2                       2      5  1199577600
3                       2      5  1199577600
4                       2      5  1199577600

                             Summary  \
0  LOACKER QUADRATINI VANILLA WAFERS
1  LOACKER QUADRATINI VANILLA WAFERS
2  LOACKER QUADRATINI VANILLA WAFERS
3  LOACKER QUADRATINI VANILLA WAFERS
4  LOACKER QUADRATINI VANILLA WAFERS

                                                Text
0  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
1  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
2  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
3  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
4  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
```

As it can be seen above that same user has multiple reviews with same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8) ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

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

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

In [11]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fal
```

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

Out[12]:
```
(160178, 10)
```

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

Out[13]:
```
80.089
```

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

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

display.head()
```

Out[14]:
```
      Id   ProductId          UserId              ProfileName  \
0  64422  B000MIDROQ  A161DK06JJMCYF  J. E. Stephens "Jeanne"
1  44737  B001EQ55RW  A2V0I904FH7ABY                      Ram

   HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
0                     3                       1      5  1224892800
1                     3                       2      4  1212883200

                                Summary  \
0            Bought This for My Son at College
1  Pure cocoa taste with crunchy almonds inside

                                                Text
0  My son loves spaghetti so I didn't hesitate or...
1  It was almost a 'love at first bite' - the per...
```

In [15]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [16]:
```
#Before starting the next phase of preprocessing lets see the number of entries left
print(final.shape)

#How many positive and negative reviews are present in our dataset?
final['Score'].value_counts()
```

```
(160176, 10)
```

Out[16]:
```
1    134799
0     25377
Name: Score, dtype: int64
```

In [17]:
```
##Sorting data for Time Based Splitting
time_sorted_data = final.sort_values('Time', axis=0, ascending=True, inplace=False, k


final = time_sorted_data.take(np.random.permutation(len(final))[:100000])
print(final.shape)
final.head()
```

```
(100000, 10)
```

```
Out[17]:             Id   ProductId          UserId      ProfileName  \
         153947  166923  B002GWMADK  A12UC87U5NUTOW   VoraciousBuyer
         138148  149929  B0028C44IM  A3SW8742TQAQH7  RalphT "RalphT"
         69745    75881  B002W1F6TK  A1OJZTRLA5K7FF      G. Wedgwood
         121516  131727  B004H4R27E  A2T6FXME2DBNFB            cw713
         7469      8158  B001IZA8S0  A3HX13IFJHOTMW         Bryan A.

                 HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
         153947                     0                       0      1  1348531200
         138148                     0                       0      1  1326153600
         69745                      1                       1      1  1301097600
         121516                     0                       0      1  1336608000
         7469                       1                       1      1  1323907200

                                          Summary  \
         153947  High-quality mild decaf green tea
         138148           Breath mints are perfect
         69745                  Healthy dog treats
         121516         Great for frying your catch!
         7469                 Relaxing and Delicious

                                                              Text
         153947  I like this green tea because it is:<br /><br ...
         138148  This was a re-order of this product for me.  T...
         69745   Excellent! Crunchy, 100% beef nuggets -- a hea...
         121516  This is a great tasting product.  The descript...
         7469    I have a lemongrass plant in my yard. I make t...
```

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

```
In [18]: # 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)
```

```
I like this green tea because it is:<br /><br />(1) The leaves look very quality and wholesome
==================================================
These are imported from the UK/EU and so the chocolate is much better than anything made in the
==================================================
the friends who introduced me to this don't even eat gluten-free but they use this as their cho
==================================================
So delicious, I did not know I loved licorice this much. I've been hunting across town trying t
==================================================
```

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

```
I like this green tea because it is:<br /><br />(1) The leaves look very quality and wholesome
```

```
In [20]: # https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all-
         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)
```

```
I like this green tea because it is:(1) The leaves look very quality and wholesome(2) It is org
==================================================
These are imported from the UK/EU and so the chocolate is much better than anything made in the
==================================================
the friends who introduced me to this don't even eat gluten-free but they use this as their cho
==================================================
So delicious, I did not know I loved licorice this much. I've been hunting across town trying t
```

In [21]:
```
# https://stackoverflow.com/a/47091490/4084039
import re

def decontracted(phrase):
    # specific
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)

    # general
    phrase = re.sub(r"n\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase
```

In [22]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
the friends who introduced me to this do not even eat gluten-free but they use this as their cl
==================================================
```

In [23]:
```
#remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
I like this green tea because it is:<br /><br  The leaves look very quality and wholesome<br  I
```

```
In [24]: #remove spacial character: https://stackoverflow.com/a/5843547/4084039
         sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
         print(sent_1500)
```

```
the friends who introduced me to this do not even eat gluten free but they use this as their cl
```

```
In [25]: # https://gist.github.com/sebleier/554280
         # we are removing the words from the stop words list: 'no', 'nor', 'not'
         # <br /><br /> ==> after the above steps, we are getting "br br"
         # we are including them into stop words list
         # instead of <br /> if we have <br/> these tags would have revmoved in the 1st step

         stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselve
                     "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him'
                     'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself',
                     'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "
                     'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', '
                     'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'a
                     'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'throug
                     'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', '
                     'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'a
                     'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'to
                     's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", '
                     've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't
                     "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mi
                     "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't",
                     'won', "won't", 'wouldn', "wouldn't"])
```

```
In [26]: # Combining all the above stundents
         from tqdm import tqdm
         prepr_rev = []
         # 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 stopw
             prepr_rev.append(sentance.strip())
```

```
100%|| 100000/100000 [00:50<00:00, 1998.23it/s]
```

In [27]:
```
print(len(prepr_rev))
final.shape
```

```
100000
```

Out[27]:
```
(100000, 10)
```

In [28]:
```
prepr_rev[1500]
```

Out[28]:
```
'friends introduced not even eat gluten free use chocolate chip cookie mix think best
```

In [29]:
```
final ['CleanedText']= prepr_rev
final.head(5)
```

Out[29]:
```
            Id   ProductId          UserId      ProfileName  \
153947  166923  B002GWMADK  A12UC87U5NUTOW   VoraciousBuyer
138148  149929  B0028C44IM  A3SW8742TQAQH7  RalphT "RalphT"
69745    75881  B002W1F6TK  A1OJZTRLA5K7FF      G. Wedgwood
121516  131727  B004H4R27E  A2T6FXME2DBNFB            cw713
7469      8158  B001IZA8SO  A3HX13IFJHOTMW         Bryan A.

        HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
153947                     0                       0      1  1348531200
138148                     0                       0      1  1326153600
69745                      1                       1      1  1301097600
121516                     0                       0      1  1336608000
7469                       1                       1      1  1323907200

                                  Summary  \
153947  High-quality mild decaf green tea
138148           Breath mints are perfect
69745                  Healthy dog treats
121516       Great for frying your catch!
7469              Relaxing and Delicious

                                                     Text  \
153947  I like this green tea because it is:<br /><br ...
138148  This was a re-order of this product for me.  T...
69745   Excellent! Crunchy, 100% beef nuggets -- a hea...
121516  This is a great tasting product.  The descript...
7469    I have a lemongrass plant in my yard. I make t...

                                              CleanedText
153947  like green tea leaves look quality organically...
138148   order product perfect breath mint come handy tin
69745   excellent crunchy beef nuggets healthy alterna...
121516  great tasting product description not correct ...
7469    lemongrass plant yard make tea wanted convenie...
```

[3.2] Preprocessing Review Summary

```
In [30]: ## Similartly you can do preprocessing for review summary also.
         preprocessed_summary = []
         # tqdm is for printing the status bar
         for summary in tqdm(final['Summary'].values):
             summary = re.sub(r"http\S+", "", summary) # remove urls from text python: https:/
             summary = BeautifulSoup(summary, 'lxml').get_text() # https://stackoverflow.com/q
             summary = decontracted(summary)
             summary = re.sub("\S*\d\S*", "", summary).strip() #remove words with numbers pytho
             summary = re.sub('[^A-Za-z]+', ' ', summary) #remove spacial character: https://s
             # https://gist.github.com/sebleier/554280
             summary = ' '.join(e.lower() for e in summary.split() if e.lower() not in stopword
             preprocessed_summary.append(summary.strip())
```

```
 56%|    | 56090/100000 [00:17<00:13, 3258.37it/s]/Volumes/Saida/Applications/Anaconda/anaconda
  ' Beautiful Soup.' % markup)
100%|| 100000/100000 [00:31<00:00, 3214.90it/s]
```

```
In [31]: prepr_rev = [i + ' ' + j for i, j in zip(prepr_rev,preprocessed_summary)]
         print(prepr_rev[1500])
```

```
friends introduced not even eat gluten free use chocolate chip cookie mix think best chocolate
```

5 [4] Featurization

5.1 [4.1] BAG OF WORDS

```
In [32]: X = np.array(final['CleanedText'])
         y = np.array(final['Score'])
```

```
In [33]: from sklearn.model_selection import train_test_split
         #splitting data into Train, C.V and Test
         X_train, X_test, y_train, y_test = train_test_split(final ['CleanedText'], final['Sco
         X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.33)
         print("Train:",X_train.shape,y_train.shape)
         print("CV:",X_cv.shape,y_cv.shape)
         print("Test:",X_test.shape,y_test.shape)
```

```
Train: (44890,) (44890,)
CV: (22110,) (22110,)
Test: (33000,) (33000,)
```

```
In [34]: #BoW
         vectorizer = CountVectorizer(min_df=10, max_features=500)
         vectorizer.fit(X_train)
```

```
#vectorizer.fit(X_train) # fit has to happen only on train data
# we use the fitted CountVectorizer to convert the text to vector
X_train_bow = vectorizer.transform(X_train)
X_cv_bow = vectorizer.transform(X_cv)
X_test_bow = vectorizer.transform(X_test)
print("After vectorizations")
print(X_train_bow.shape, y_train.shape)
print(X_cv_bow.shape, y_cv.shape)
print(X_test_bow.shape, y_test.shape)
```

```
After vectorizations
(44890, 500) (44890,)
(22110, 500) (22110,)
(33000, 500) (33000,)
```

5.2 [4.3] TF-IDF

```
In [35]: tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10, max_features=500)
         tf_idf_vect.fit(X_train)
         # we use the fitted CountVectorizer to convert the text to vector
         X_train_tfidf = tf_idf_vect.transform(X_train)
         X_cv_tfidf = tf_idf_vect.transform(X_cv)
         X_test_tfidf = tf_idf_vect.transform(X_test)
         print("After vectorizations")
         print(X_train_tfidf.shape, y_train.shape)
         print(X_cv_tfidf.shape, y_cv.shape)
         print(X_test_tfidf.shape, y_test.shape)
```

```
After vectorizations
(44890, 500) (44890,)
(22110, 500) (22110,)
(33000, 500) (33000,)
```

5.3 [4.4] Word2Vec

```
In [36]: # List of sentence in X_train text
         sent_of_train=[]
         for sent in X_train:
             sent_of_train.append(sent.split())

         # List of sentence in X_test text
         sent_of_test=[]
         for sent in X_test:
             sent_of_test.append(sent.split())

         # Train your own Word2Vec model using your own train text corpus
```

```
# min_count = 5 considers only words that occured atleast 5 times
w2v_model=Word2Vec(sent_of_train,min_count=5,size=50, workers=4)
print(w2v_model.wv.most_similar('great'))
print('='*50)
print(w2v_model.wv.most_similar('worst'))

w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
```

```
[('fantastic', 0.8507072925567627), ('awesome', 0.8395429849624634), ('good', 0.81946921348571
==================================================
[('tastiest', 0.7592607140541077), ('best', 0.7539705634117126), ('greatest', 0.74926435947418
number of words that occured minimum 5 times  12962
```

In [37]:
```
w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])
```

```
number of words that occured minimum 5 times  12962
sample words  ['labs', 'chicken', 'soup', 'dog', 'lovers', 'also', 'great', 'food', 'seemed',
```

5.4 [4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V

[4.4.1.1] Avg W2v

In [38]:
```
i=0
sent_of_test_cv=[]
for sentance in X_cv:
    sent_of_test_cv.append(sentance.split())
```

In [39]:
```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_cv = []; # the avg-w2v for each sentence/review is stored in this list
for sent in tqdm(sent_of_test_cv): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need t
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_cv.append(sent_vec)
sent_vectors_cv = np.array(sent_vectors_cv)
print(sent_vectors_cv.shape)
print(sent_vectors_cv[0])
```

```
100%|| 22110/22110 [00:59<00:00, 369.40it/s]

(22110, 50)
[ 6.46712401e-02 -3.52975899e-01  4.92302150e-01  9.09863875e-02
  1.00296698e+00 -2.60446464e-03 -2.07947951e-01 -7.80456103e-01
  5.23790111e-01 -1.38895452e-01  1.79256746e-01  6.26776293e-01
  6.24966438e-01  3.93841416e-04 -9.25423517e-02  7.04055431e-01
  2.99233822e-01  1.86208594e-02 -1.79614549e-01 -2.89561350e-01
 -1.44980738e-02 -5.29002039e-02  6.00518741e-02  4.14223386e-02
 -4.25162806e-01  6.10605976e-01 -6.25693725e-01  3.29619362e-01
 -2.21529338e-01  7.05666559e-02 -1.50315707e-01 -1.97038289e-01
 -3.24992413e-01 -1.14847526e-01  2.63256302e-01 -2.32312571e-02
  5.39948636e-01  1.03336458e+00 -8.13780364e-01  1.47670526e-01
 -2.97555103e-01  9.06608885e-02  2.06207365e-01 -1.01764707e-02
  3.60310878e-01  1.31050664e-01  6.12660272e-01  7.80724027e-01
 -2.42030407e-01 -2.09266569e-01]
```

In [40]:
```python
# compute average word2vec for X_test .
test_vectors = [];
for sent in tqdm(sent_of_test):
    sent_vec = np.zeros(50)
    cnt_words =0;
    for word in sent: #
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    test_vectors.append(sent_vec)

test_vectors = np.array(test_vectors)

print(test_vectors.shape)
print(test_vectors[0])
```

```
100%|| 33000/33000 [01:26<00:00, 380.43it/s]

(33000, 50)
[-1.01276283  0.14425641  0.68173014  0.70570306  0.23754832 -0.40908843
  0.19983431 -0.67782708  0.70915998 -0.24846734  0.16201461  0.42270878
  0.74599672  0.28481896 -0.51668128  0.31355953  0.20360958  0.71648194
 -0.31199088 -0.18056716  0.63985512  0.65358842 -0.10666942 -0.18445801
 -0.32821384  0.50565898 -0.31809535 -0.14268377  0.26001883  0.30798638
```

```
  0.01210203 -0.86323097 -0.48955397 -0.47556457 -0.2500978  -0.26662101
  0.15044521  0.95881502 -0.01814436 -0.19702292  0.05316422 -0.34803013
 -0.01712602 -0.04208278 -0.4975351  -0.14703294  1.04416858  0.24650076
 -0.12383749  0.07652589]
```

In [41]:
```
# compute average word2vec for X_train .
train_vectors = [];
for sent in tqdm(sent_of_train):
    sent_vec = np.zeros(50)
    cnt_words =0;
    for word in sent: #
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    train_vectors.append(sent_vec)

train_vectors = np.array(train_vectors)

print(train_vectors.shape)
print(train_vectors[0])
```

```
100%|| 44890/44890 [01:54<00:00, 393.64it/s]


(44890, 50)
[-0.40009983 -0.43564136  0.82301273 -0.10895452  0.21664387 -0.46494384
 -0.07864228  0.04020032  0.58628824 -0.27865495  0.23309086  0.19088887
  0.58127333  0.2966594  -0.26410347 -0.06450366 -0.29119727  0.22417836
 -0.49186427 -0.4475818   0.05089539  0.33734576 -0.13717777  0.30100819
 -0.54215029  0.1405718  -0.10719035  0.3024686   0.23967941 -0.4827349
 -0.7155806   0.14274824  0.55151182 -0.19837177  0.34081935 -0.58546564
  0.4500563   0.47166665 -0.35723679 -0.24917104 -0.36343603  0.23296906
 -0.94260318 -0.34233952 -0.3489895   0.23489252 -0.30933715  0.67176588
 -0.63670686  0.52221066]
```

[4.4.1.2] TFIDF weighted W2v

In [42]:
```
tf_idf_vect = TfidfVectorizer()

# final_tf_idf1 is the sparse matrix with row= sentence, col=word and cell_val = tfid
final_tf_idf1 = tf_idf_vect.fit_transform(X_train)
dictionary = dict(zip(tf_idf_vect.get_feature_names(), list(tf_idf_vect.idf_)))

# tfidf words/col-names
```

```
tfidf_feat = tf_idf_vect.get_feature_names()

# compute TFIDF Weighted Word2Vec for X_test .
tfidf_test_vectors = [];
row=0;
for sent in tqdm(sent_of_test):
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_test_vectors.append(sent_vec)

tfidf_test_vectors = np.array(tfidf_test_vectors)
print(tfidf_test_vectors.shape)
print(tfidf_test_vectors[0])
```

```
100%|| 33000/33000 [19:36<00:00, 28.05it/s]

(33000, 50)
[-0.90583639  0.18735425  0.54923324  0.67834463  0.18499273 -0.33317598
  0.23725528 -0.79149165  0.62644982 -0.23805753  0.11335978  0.44734548
  0.66796856  0.35269967 -0.45216802  0.214916    0.2174245   0.50478152
 -0.22982137 -0.15205063  0.51498101  0.54789954 -0.16259114 -0.04535524
 -0.42746938  0.39095321 -0.31773702 -0.13467749  0.27698708  0.35076738
 -0.12198095 -0.70004635 -0.2987131  -0.33743193 -0.2685451  -0.26766689
  0.15898748  0.95188318 -0.02797757 -0.39917058  0.07934803 -0.38129837
  0.05017205 -0.05356487 -0.47623262 -0.17533946  1.03841643  0.32985956
 -0.07308841  0.0735464 ]
```

In [43]:
```
# TF-IDF weighted Word2Vec.
tfidf_train_vectors = [];
row=0;
for sent in tqdm(sent_of_train):
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
```

```
                sent_vec += (vec * tf_idf)
                weight_sum += tf_idf
        if weight_sum != 0:
            sent_vec /= weight_sum
        tfidf_train_vectors.append(sent_vec)

    tfidf_train_vectors = np.array(tfidf_train_vectors)
    print(tfidf_train_vectors.shape)
    print(tfidf_train_vectors[0])
```

```
100%|| 44890/44890 [30:57<00:00, 24.16it/s]


(44890, 50)
[-0.18287831 -0.40228735  0.9256302  -0.17913426  0.09782794 -0.36189132
  0.0386502   0.2495045   0.50485755 -0.20739936  0.32368299  0.19608155
  0.55968764  0.4475972  -0.29176013 -0.13120472 -0.45375064  0.12317831
 -0.65697991 -0.45859406 -0.12515345  0.38660385 -0.18532818  0.38817971
 -0.51344629  0.01390275 -0.38785151  0.36350828  0.34795726 -0.46949204
 -0.92954534  0.18314032  0.58732073 -0.08698579  0.36775165 -0.57380523
  0.2962493   0.31183704 -0.39251479 -0.26711088 -0.44270847  0.25442182
 -0.98342732 -0.47646536 -0.38935788  0.34390487 -0.33726189  0.71749737
 -0.68967043  0.55585096]
```

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 c
<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/sk
<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 for
    <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

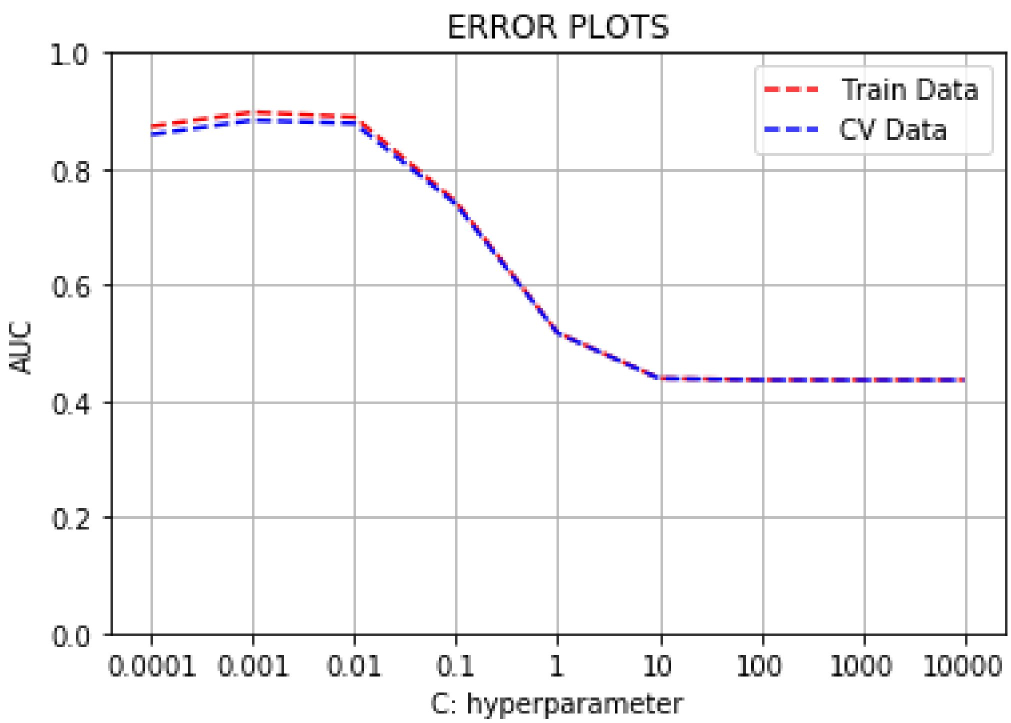
In [44]:
```
# Please write all the code with proper documentation

from sklearn.linear_model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV
from sklearn.metrics import roc_auc_score, auc
from sklearn.model_selection import GridSearchCV

def svm_all (X_train,y_train,X_cv):

    Alpha = [10**-4,10**-3,10**-2,10**-1,1,10,10**2,10**3,10**4]
    Penal = ['l1','l2']
    hyper_param = {'alpha':Alpha, 'penalty':Penal}

    clf = GridSearchCV(SGDClassifier(loss='hinge'),hyper_param,verbose=1,scoring='roc_
    clf.fit(X_train_bow,y_train)
    calbr = CalibratedClassifierCV(clf, method = "sigmoid")
    alpha_opt, penalty_opt = clf.best_params_.get('alpha'), clf.best_params_.get('pena


    train_auc = clf.cv_results_.get('mean_train_score')
    cv_auc = clf.cv_results_.get('mean_test_score')
    x2 = np.arange(len(Alpha))


    plt.plot(x2, train_auc[1::2],'r--', label = 'Train Data')
    plt.plot(x2,cv_auc[1::2],'b--', label = 'CV Data')
    plt.xticks(x2, Alpha)
    plt.ylim(0,1)
    plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0.)
    plt.grid(True)
    plt.legend()
    plt.xlabel("C: hyperparameter")
    plt.ylabel("AUC")
    plt.title("ERROR PLOTS")
    plt.show()
```

```
print("Optimal value of Alpha: ", alpha_opt , " and Penalty is : ", penalty_opt)
#Cv auc scores
print("---------------------------")
print("Cv auc scores")
print(cv_auc)
print("Maximun Auc value :",max(cv_auc))

#test data

sgd = SGDClassifier(penalty=penalty_opt,alpha=alpha_opt,class_weight='balanced')
sgd.fit(X_train_bow,y_train)

train_fpr, train_tpr, thresholds = roc_curve(y_train, sgd.decision_function(X_trai
test_fpr, test_tpr, thresholds = roc_curve(y_test, sgd.decision_function(X_test_bo


plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0.)
plt.grid(True)
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()


 #Confusion Matrix

print("Train confusion matrix")
print(confusion_matrix(y_train, sgd.predict(X_train_bow)))
print("Test confusion matrix")
print(confusion_matrix(y_test, sgd.predict(X_test_bow)))

cm = confusion_matrix(y_train, sgd.predict(X_train_bow))
cm = confusion_matrix(y_test, sgd.predict(X_test_bow))
tn, fp, fn, tp = cm.ravel()
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix
# Code for drawing seaborn heatmaps
class_names = ['0','1']
df_heatmap = pd.DataFrame(cm, index=class_names, columns=class_names )
fig = plt.figure(figsize=(5,3))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='righ
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='righ
plt.ylabel('True label',size=18)
```

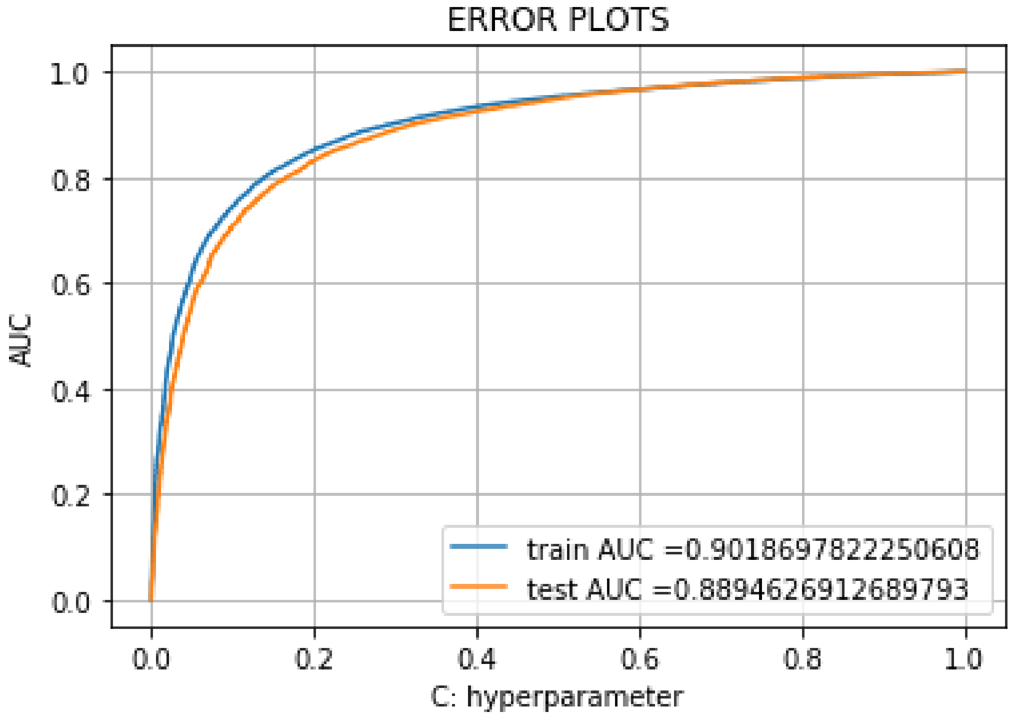
```
            plt.xlabel('Predict label',size=18)
            plt.title("Confusion Matrix\n",size=24)
            plt.show()
```

```
In [45]: svm_all(X_train_bow,y_train,X_cv_bow)
```

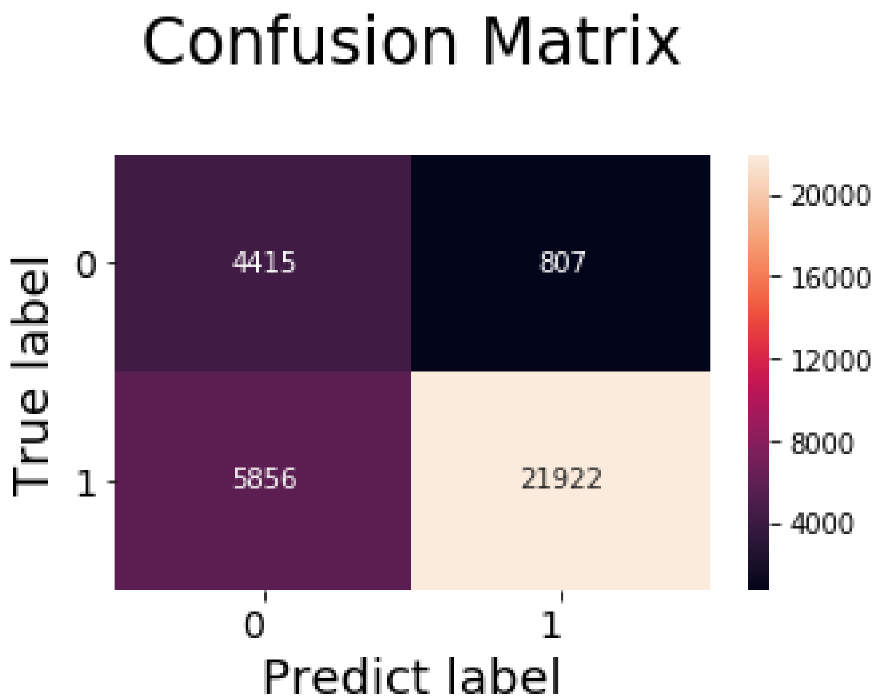
```
Fitting 3 folds for each of 18 candidates, totalling 54 fits


[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done  54 out of  54 | elapsed:    5.3s finished
```




```
Optimal value of Alpha:  0.001  and Penalty is :  l2
--------------------------
Cv auc scores
[0.84601524 0.85911213 0.86652901 0.88373628 0.68108755 0.8782753
 0.50679618 0.73890348 0.5        0.51672274 0.5        0.43868337
 0.5        0.43593929 0.5        0.4359367  0.5        0.43593667]
Maximun Auc value : 0.8837362776296454
```




```
Train confusion matrix
[[ 6137   919]
 [ 7969 29865]]
Test confusion matrix
[[ 4415   807]
 [ 5856 21922]]
```



In [46]:
```
# Please write all the code with proper documentation

sgd = SGDClassifier(penalty='l2',alpha=0.001)
sgd.fit(X_train_bow, y_train)
feat_log = sgd.coef_

vectorizer = CountVectorizer(min_df=10, max_features=500)
p = vectorizer.fit_transform(X_train)
p = pd.DataFrame(feat_log.T,columns=['+ve'])
p['feature'] = vectorizer.get_feature_names()

q = p.sort_values(by = '+ve',kind = 'quicksort',ascending= False)
print("Top 10 features positive class", np.array(q['feature'][:10]))
```

```
Top 10 features positive class ['delicious' 'best' 'perfect' 'excellent' 'fantastic' 'amazing'
 'loves' 'wonderful' 'yummy']
```

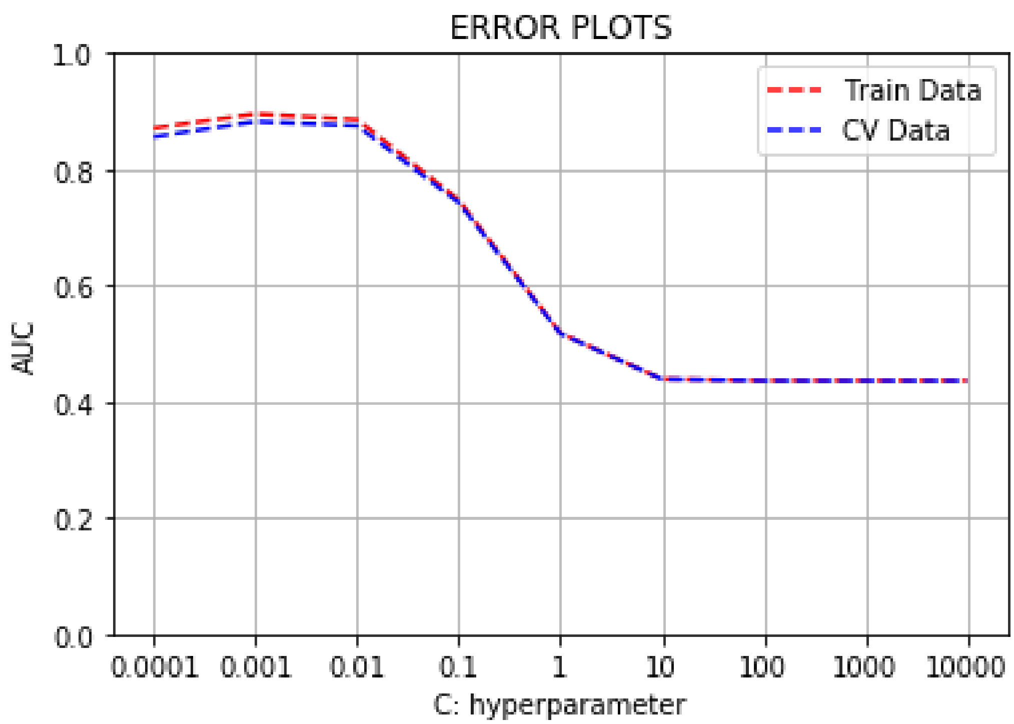
In [47]:
```
# Please write all the code with proper documentation
print("Top 10 features negative class",np.array(q.tail(10)['feature']))
```

```
Top 10 features negative class ['maybe' 'artificial' 'received' 'opened' 'thought' 'item' 'bad
 'money' 'disappointed']
```

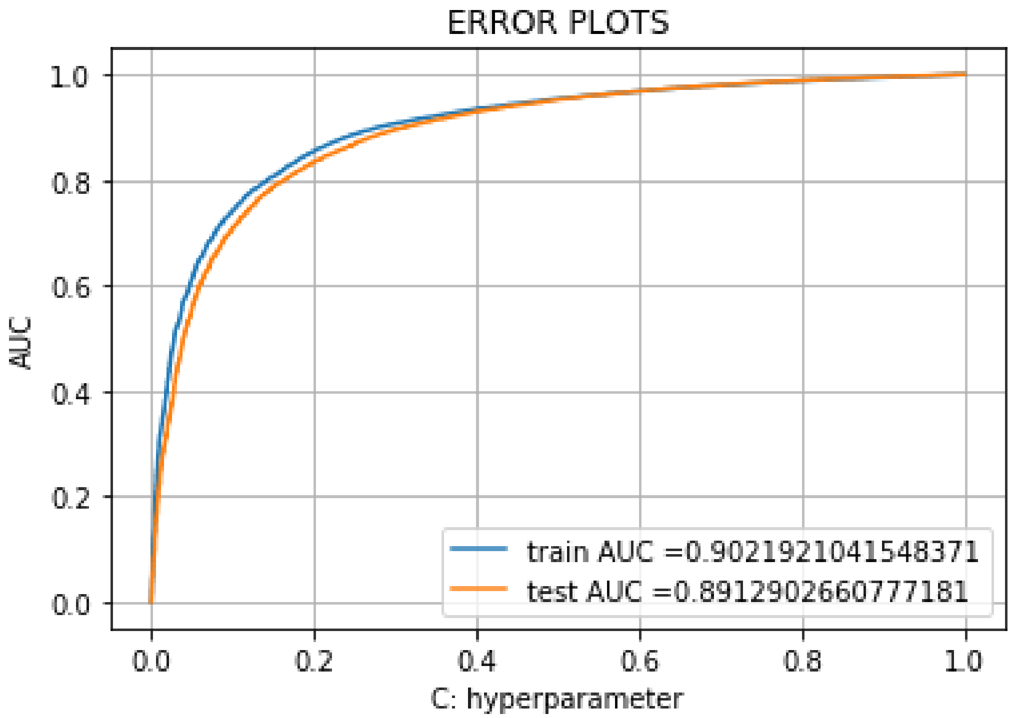
7.1.2 [5.1.2] Applying Linear SVM on TFIDF, SET 2

```
In [48]: # Please write all the code with proper documentation
         svm_all(X_train_tfidf,y_train,X_cv_tfidf)
```

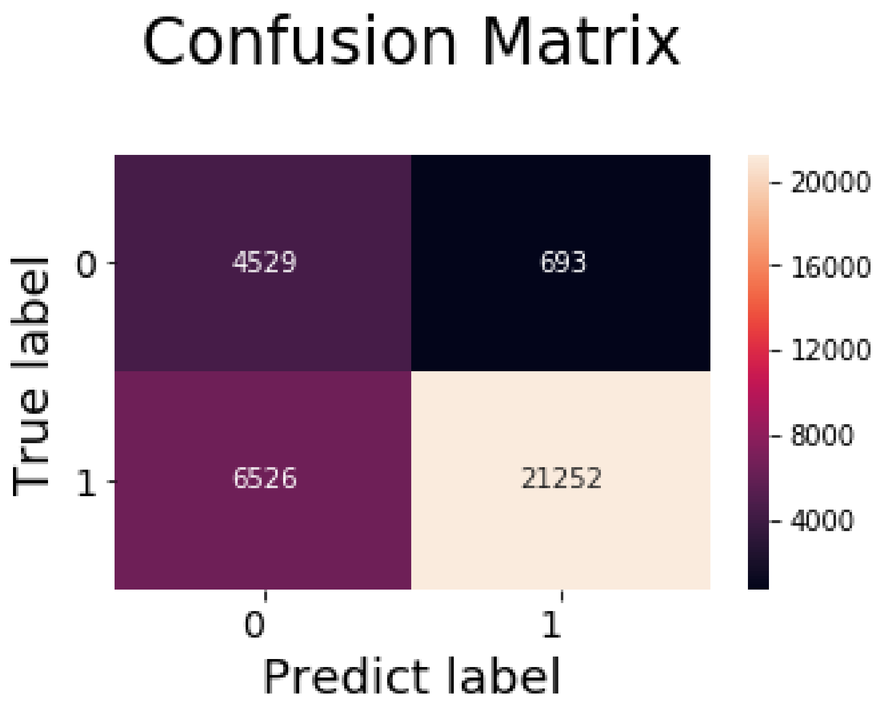
```
Fitting 3 folds for each of 18 candidates, totalling 54 fits


[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done  54 out of  54 | elapsed:    5.9s finished
```




```
Optimal value of Alpha:  0.001  and Penalty is :  l2
--------------------------
Cv auc scores
[0.85615156 0.85616223 0.86020422 0.88249536 0.63049843 0.87539981
 0.52293587 0.74278906 0.5        0.51720729 0.5        0.43870516
 0.5        0.43593924 0.5        0.43593751 0.5        0.43593667]
Maximun Auc value : 0.8824953566727332
```




```
Train confusion matrix
[[ 6233   823]
 [ 8713 29121]]
Test confusion matrix
[[ 4529   693]
 [ 6526 21252]]
```




```
In [49]: sgd = SGDClassifier(penalty='l2',alpha=0.001)
         sgd.fit(X_train_tfidf,y_train)
         feat_log = sgd.coef_

         tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10, max_features=500)
         p = tf_idf_vect.fit_transform(X_train)
         p = pd.DataFrame(feat_log.T,columns=['+ve'])
         p['feature'] = tf_idf_vect.get_feature_names()


         q = p.sort_values(by = '+ve',kind = 'quicksort',ascending= False)
         print("Top 10 features positive class", np.array(q['feature'][:10]))
```

```
Top 10 features positive class ['great' 'best' 'good' 'love' 'delicious' 'perfect' 'loves' 'exc
 'wonderful' 'amazing']
```

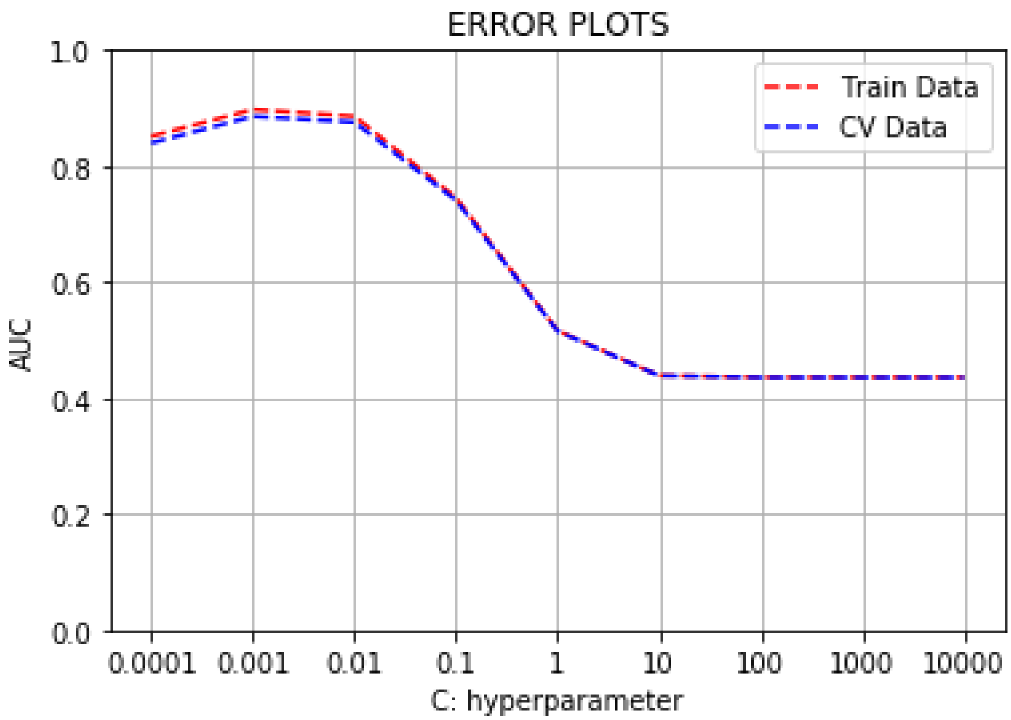
```
In [50]: # Please write all the code with proper documentation
         print("Top 10 features negative class",np.array(q.tail(10)['feature']))
```

```
Top 10 features negative class ['opened' 'thought' 'maybe' 'not even' 'away' 'bad' 'would not'
 'money' 'disappointed']
```

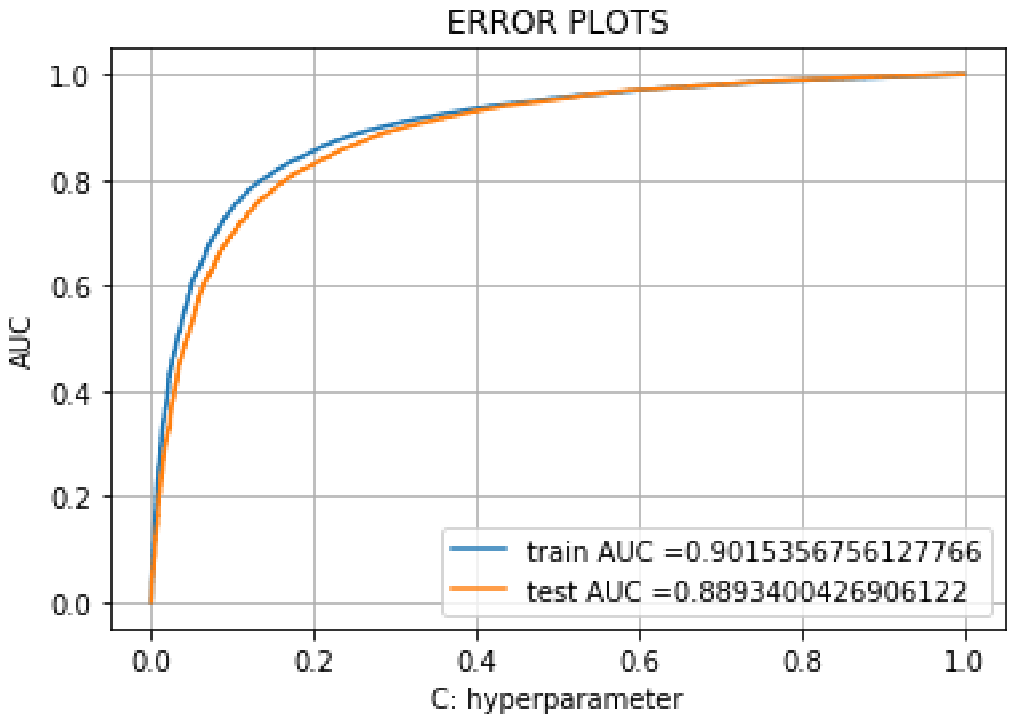
7.1.3 [5.1.3] Applying Linear SVM on AVG W2V, SET 3

```
In [51]: svm_all(train_vectors, y_train, X_cv)
```

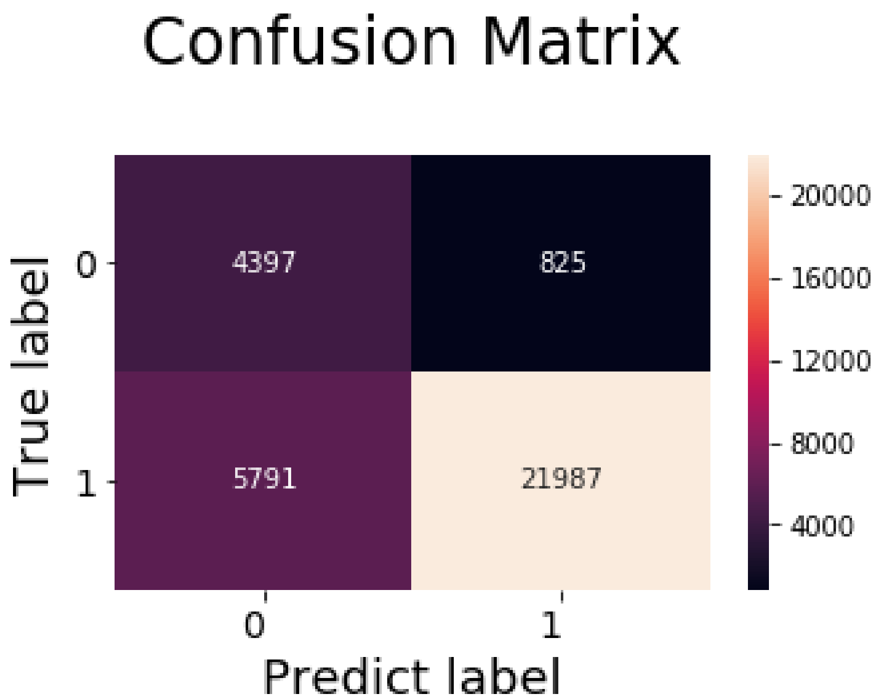
```
Fitting 3 folds for each of 18 candidates, totalling 54 fits


[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done  54 out of  54 | elapsed:    6.7s finished
```




```
Optimal value of Alpha:  0.001  and Penalty is :  l2
--------------------------
Cv auc scores
[0.84906137 0.83984384 0.85853664 0.88579769 0.70137577 0.87606268
 0.52096502 0.74089528 0.5        0.51577913 0.5        0.43873388
 0.5        0.43593935 0.5        0.43593673 0.5        0.43593712]
Maximun Auc value : 0.8857976924656128
```



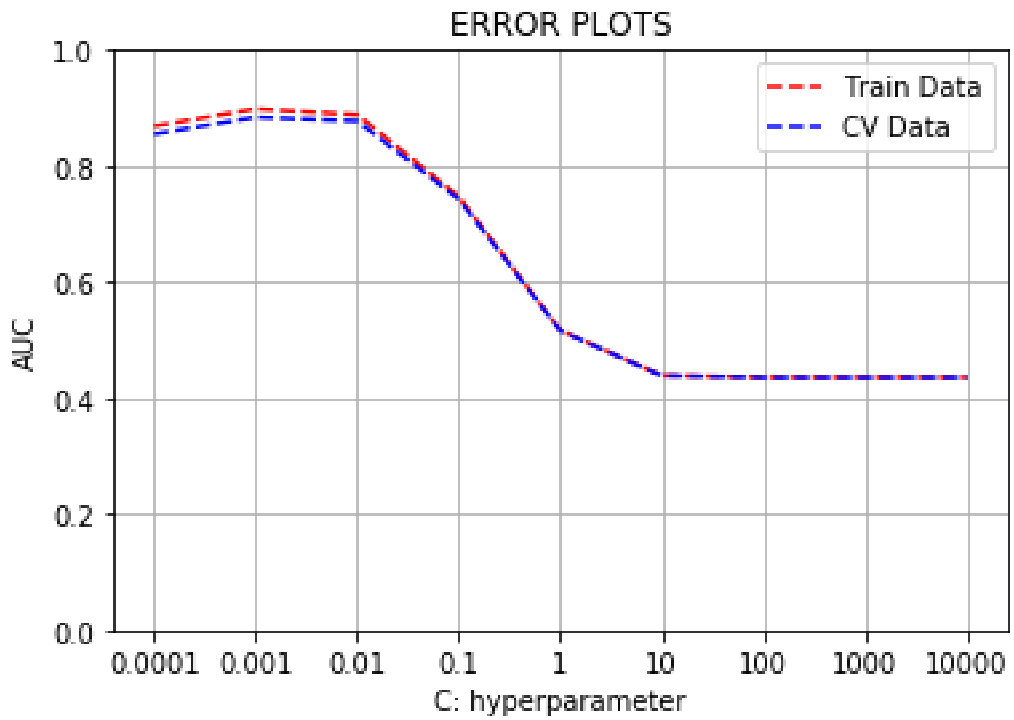

```
Train confusion matrix
[[ 6126   930]
 [ 7742 30092]]
Test confusion matrix
[[ 4397   825]
 [ 5791 21987]]
```



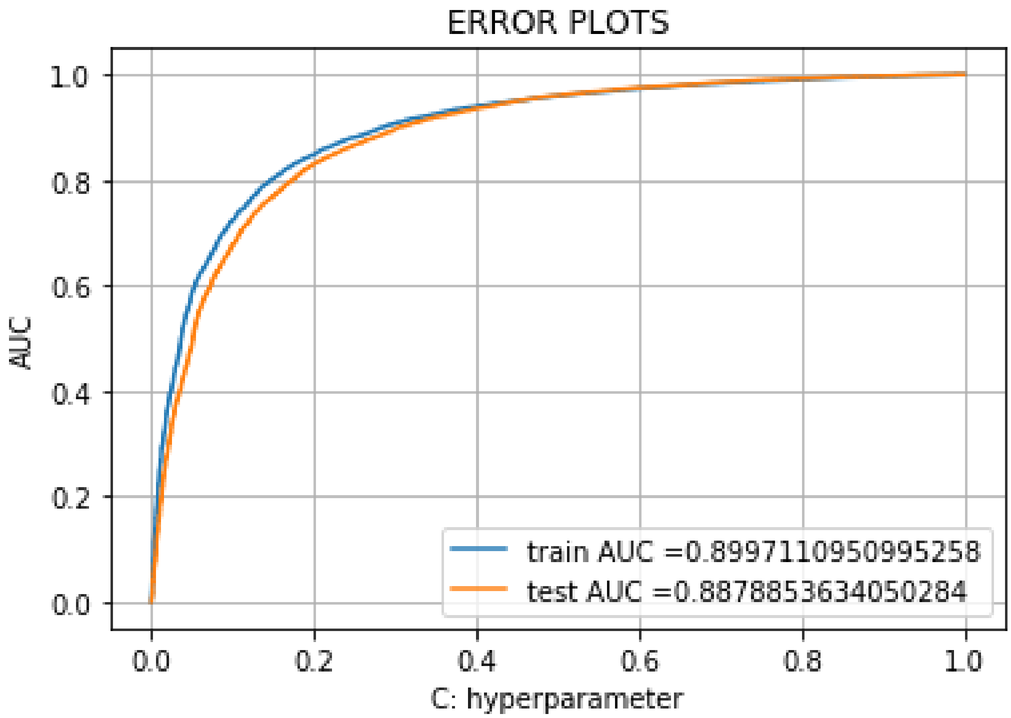
7.1.4 [5.1.4] Applying Linear SVM on TFIDF W2V, SET 4

```
In [52]: # Please write all the code with proper documentation
         svm_all(tfidf_train_vectors,y_train,X_cv)
```

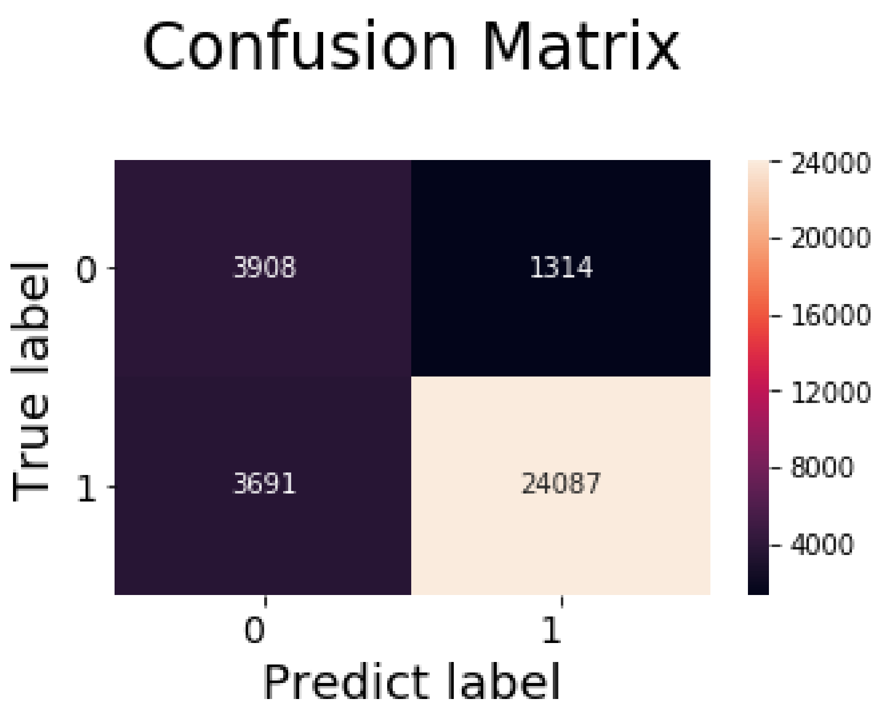
```
Fitting 3 folds for each of 18 candidates, totalling 54 fits


[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done  54 out of  54 | elapsed:    6.4s finished
```




```
Optimal value of Alpha:  0.001  and Penalty is :  l2
--------------------------
Cv auc scores
[0.85278642 0.85492238 0.86438725 0.88406984 0.64815774 0.87751864
 0.51634944 0.74259893 0.5        0.51645067 0.5        0.43873109
 0.5        0.43593981 0.5        0.43593671 0.5        0.43593669]
Maximun Auc value : 0.8840698421090125
```




```
Train confusion matrix
[[ 5455  1601]
 [ 4988 32846]]
Test confusion matrix
[[ 3908  1314]
 [ 3691 24087]]
```



7.2 [5.2] RBF SVM

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

In [53]:
```
##Sorting data for Time Based Splitting
from sklearn.model_selection import train_test_split

time_sorted_data = final.sort_values('Time', axis=0, ascending=True, inplace=False, ki


df_final = time_sorted_data.take(np.random.permutation(len(final))[:50000])
print(df_final.shape)
df_final.head()
```

```
(50000, 11)
```

Out[53]:

	Id	ProductId	UserId	ProfileName \
157508	170797	B001SB6CJ8	A3ICDLUQ3V2QY2	Kevin L. Nenstiel "omnivore"
59004	64098	B00007V3Q0	A3530DRMCQ2SQ4	C. McCashin "Gemini in Tennessee"
197832	214414	B0037N7GIQ	A3BTF24CZFBYUR	Judy
75370	82016	B003A8BE4U	AYLKRF0G2KIT5	Ed Johnston
22393	24508	B0016JJEFG	A3JZ5Q0VEWW2PY	Jessica Clifford

```
        HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
157508                     1                       2      0  1277683200
59004                      0                       0      1  1240531200
197832                     0                       1      1  1320796800
75370                      3                       3      1  1275696000
22393                      5                       5      1  1264982400

                         Summary  \
157508               Too Acidic
59004      IMHO, the best coffee
197832  Bran Flakes - No Raisins
75370               Great Garden
22393             Best tea by far

                                                     Text  \
157508  As I began eating, I thought this would be a p...
59004   This coffee along with the Tassimo coffee mach...
197832  The trouble with "Raisin Bran", where the rais...
75370   This is a great gift. I was looking for someth...
22393   I have been using Newman's products for 5 year...

                                              CleanedText
157508  began eating thought would pleasingly pungent ...
59004   coffee along tassimo coffee machine makes best...
197832  trouble raisin bran raisins already mixed rais...
75370   great gift looking something different wife mo...
22393   using newman products years recently bought bl...
```

In [54]:
```
X = df_final['CleanedText'].values
y = df_final['Score'].values

# split the data set into train and test
#X_rbf, X_test, y_rbf, y_test = train_test_split(X, y, test_size=0.3, random_state=0)

# split the train data set into cross validation train and cross validation test
#X_train, X_cv, y_train, y_cv = train_test_split(X_rbf, y_rbf, test_size=0.3,random_s
```

In [55]:
```
y_train=time_sorted_data['Score'][0:13000]
y_cv=time_sorted_data['Score'][13000:16000]
y_test=time_sorted_data['Score'][16000:20000]
```

In [56]:
```
X_train=time_sorted_data["CleanedText"][0:13000]
X_cv=time_sorted_data["CleanedText"][13000:16000]
X_test=time_sorted_data["CleanedText"][16000:20000]
```

In [57]:
```
print(X_train.shape, "   ", y_train.shape)
print(X_cv.shape, "   ", y_cv.shape)
print(X_test.shape, "   ", y_test.shape)
```

```
(13000,)     (13000,)
(3000,)     (3000,)
(4000,)     (4000,)
```

```
In [58]: from sklearn.preprocessing import StandardScaler
         vectorizer = CountVectorizer(ngram_range=(1,2), min_df=10, max_features=500)
         vectorizer.fit_transform(X_train)
         X_train_bow = vectorizer.transform(X_train)
         X_cv_bow  = vectorizer.transform(X_cv)
         X_test_bow = vectorizer.transform(X_test)
```

```
In [59]: print(X_train_bow.shape)
         print(X_cv_bow.shape)
         print(X_test_bow.shape)
```

```
(13000, 500)
(3000, 500)
(4000, 500)
```

```
In [60]: vect = TfidfVectorizer(ngram_range=(1,2), min_df=10, max_features=300)
         tf_idf_vect = vect.fit(X_train)


         X_train_tfidf = tf_idf_vect.transform(X_train)
         X_cv_tfidf = tf_idf_vect.transform(X_cv)
         X_test_tfidf = tf_idf_vect.transform(X_test)

         print(X_train_tfidf.shape)
         print(X_cv_tfidf.shape)
         print(X_test_tfidf.shape)
```

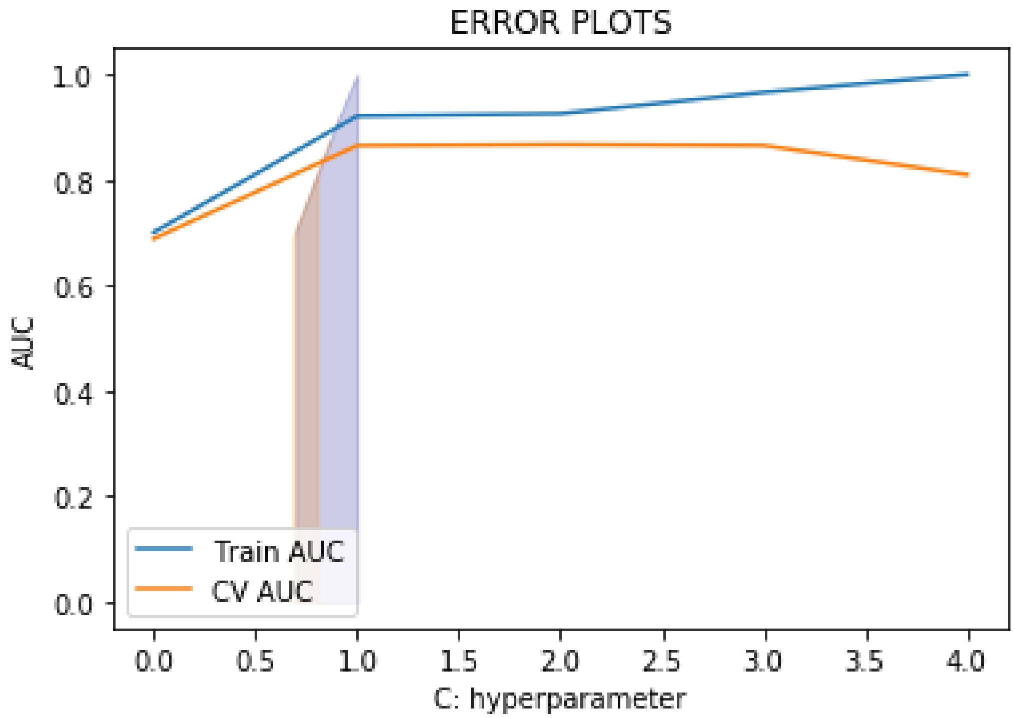
```
(13000, 300)
(3000, 300)
(4000, 300)
```

```
In [70]: from sklearn.svm import SVC
         def all_rbf(X_train, y_train,X_cv):
             C = [10**-4, 10**-2, 10**0, 10**2, 10**4]
             hyper_param  = [{'C':C}]


             clf = GridSearchCV(SVC(kernel = "rbf", probability=True), hyper_param, cv = 3, sco
             clf.fit(X_train_bow,y_train)
             alpha_opt = clf.best_params_.get("C")
```

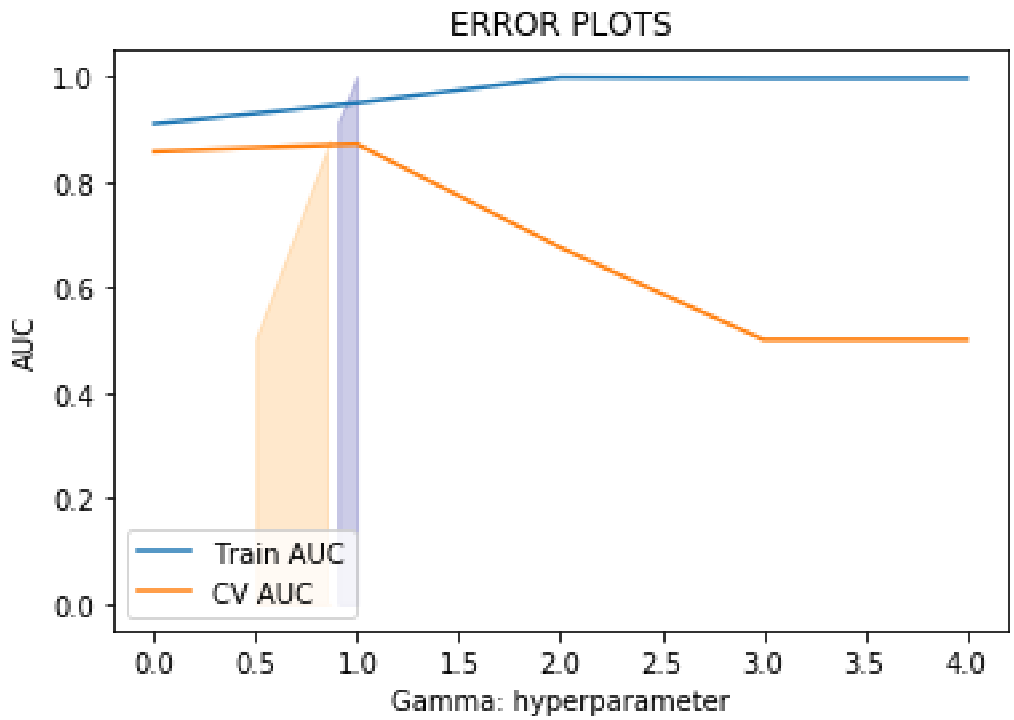
```
    train_auc= clf.cv_results_['mean_train_score']
    train_auc_std= clf.cv_results_['std_train_score']
    cv_auc = clf.cv_results_['mean_test_score']
    cv_auc_std= clf.cv_results_['std_test_score']

    plt.plot(train_auc, label='Train AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
    plt.gca().fill_between(train_auc - train_auc_std,train_auc + train_auc_std,alpha=

    plt.plot(cv_auc, label='CV AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
    plt.gca().fill_between(cv_auc - cv_auc_std,cv_auc + cv_auc_std,alpha=0.2,color='da
    plt.legend()
    plt.xlabel("C: hyperparameter")
    plt.ylabel("AUC")
    plt.title("ERROR PLOTS")
    plt.show()

    print("Optimal value of C: ", alpha_opt)

    #Cv auc scores
    print("---------------------------")
    print("Cv auc scores")
    print(cv_auc)
    print("Maximun Auc value :",max(cv_auc))


    gamma = [10**-4, 10**-2, 10**0, 10**2, 10**4]
    tunned_param  = [{'gamma':gamma}]
    clf = GridSearchCV(SVC(kernel = "rbf", probability=True), tunned_param, cv = 3, sc
    clf.fit(X_train_bow,y_train)
    gamma_opt = clf.best_params_.get("gamma")

    train_auc= clf.cv_results_['mean_train_score']
    train_auc_std= clf.cv_results_['std_train_score']
    cv_auc = clf.cv_results_['mean_test_score']
    cv_auc_std= clf.cv_results_['std_test_score']


    plt.plot(train_auc, label='Train AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
    plt.gca().fill_between(train_auc - train_auc_std,train_auc + train_auc_std,alpha=

    plt.plot(cv_auc, label='CV AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
    plt.gca().fill_between(cv_auc - cv_auc_std,cv_auc + cv_auc_std,alpha=0.2,color='da
    plt.legend()
    plt.xlabel("Gamma: hyperparameter")
```

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

    print("Optimal value of gamma: ", gamma_opt)


    model = SVC(C=alpha_opt, gamma = gamma_opt, kernel = "rbf",class_weight='balanced
    model.fit(X_train_bow,y_train)

    train_fpr, train_tpr, thresholds = roc_curve(y_train, model.predict_proba(X_train_
    test_fpr, test_tpr, thresholds = roc_curve(y_test, model.predict_proba(X_test_bow

    plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr))
    plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
    plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0.)
    plt.grid(True)
    plt.legend()
    plt.xlabel("hyperparameter")
    plt.ylabel("AUC")
    plt.title("ERROR PLOTS")
    plt.show()


     #Confusion Matrix

    print("Train confusion matrix")
    print(confusion_matrix(y_train, model.predict(X_train_bow)))
    print("Test confusion matrix")
    print(confusion_matrix(y_test, model.predict(X_test_bow)))

    cm = confusion_matrix(y_train, model.predict(X_train_bow))
    cm = confusion_matrix(y_test, model.predict(X_test_bow))
    tn, fp, fn, tp = cm.ravel()
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix
# Code for drawing seaborn heatmaps
    class_names = ['0','1']
    df_heatmap = pd.DataFrame(cm, index=class_names, columns=class_names )
    fig = plt.figure(figsize=(5,3))
    heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
    heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='righ
    heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='righ
    plt.ylabel('True label',size=18)
    plt.xlabel('Predict label',size=18)
    plt.title("Confusion Matrix\n",size=24)
    plt.show()
```

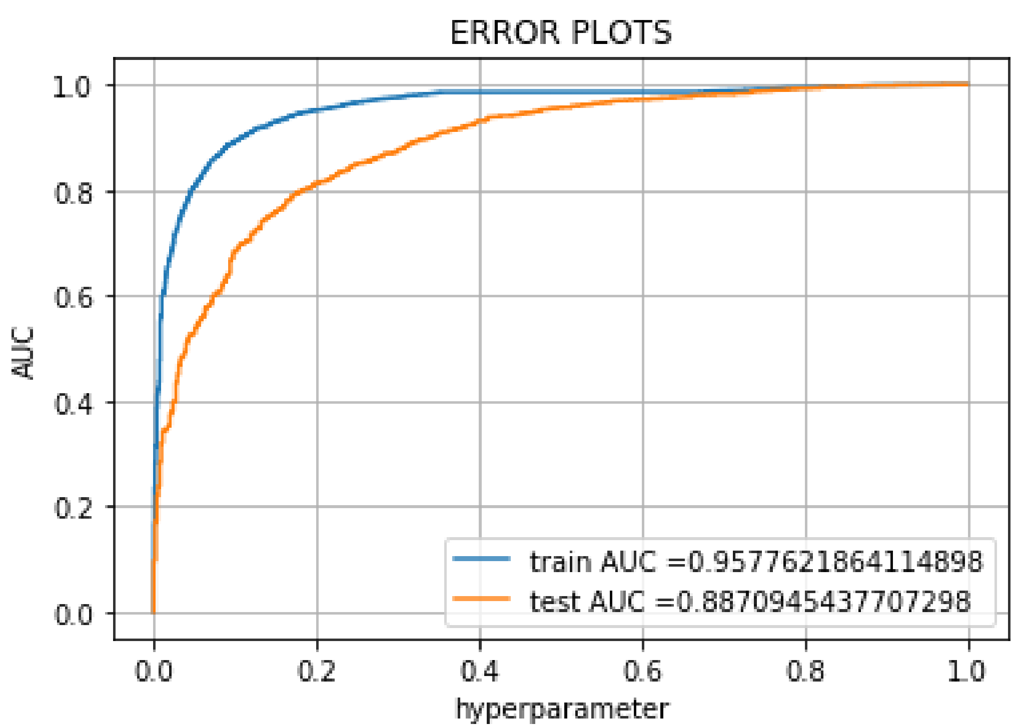
In [71]: all_rbf(X_train_bow,y_train,X_cv_bow)



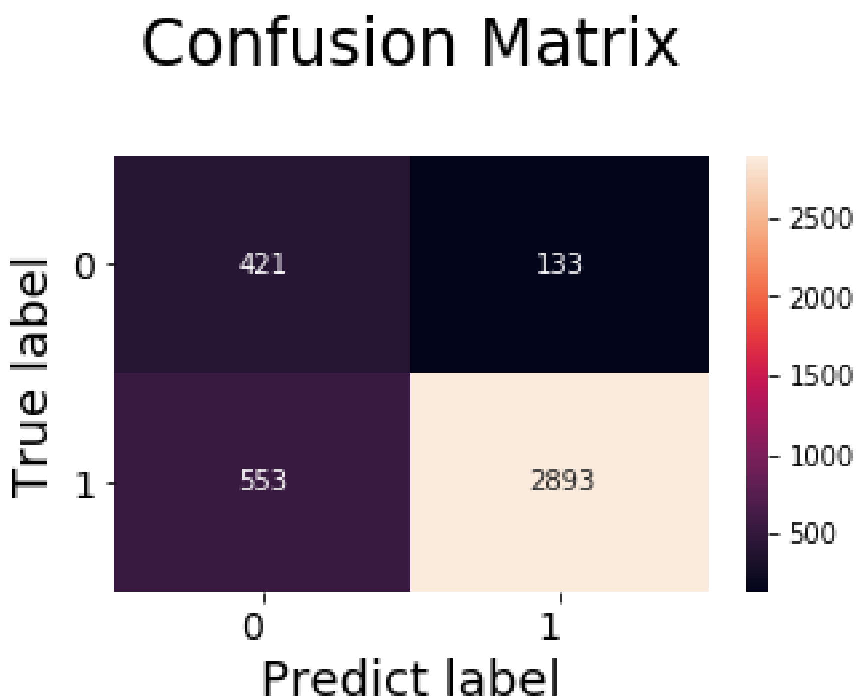

```
Optimal value of C:  1
--------------------------
Cv auc scores
[0.68799675 0.8645555  0.86665877 0.86491564 0.80950303]
Maximun Auc value : 0.8666587740126928
```




```
Optimal value of gamma:  0.01
```

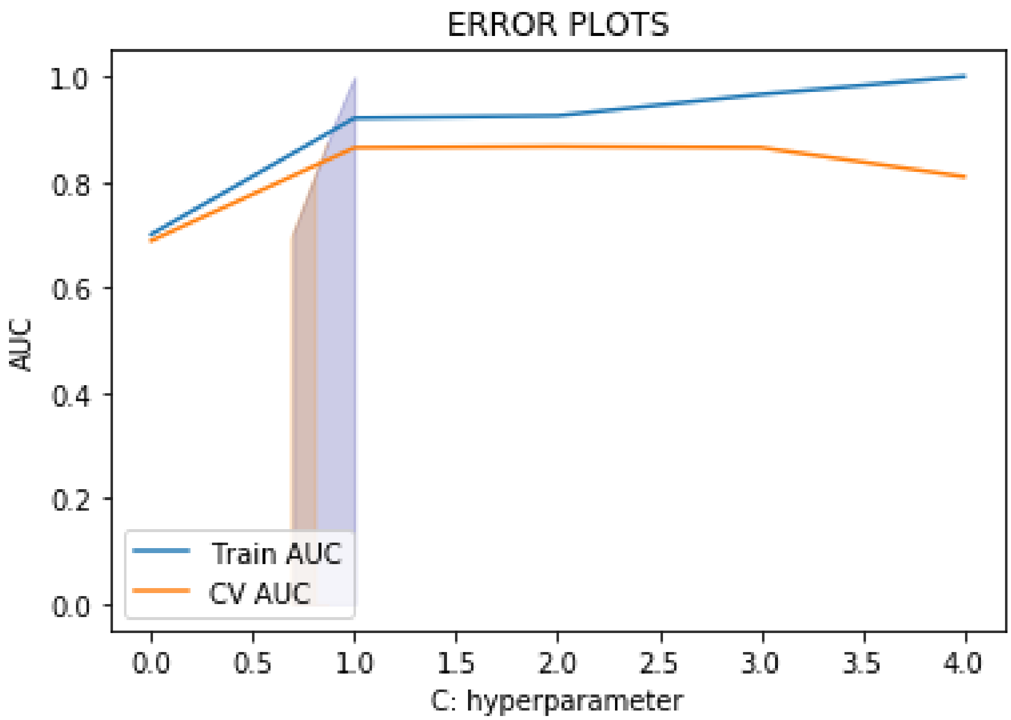


```
Train confusion matrix
[[ 1325   118]
 [ 1510 10047]]
Test confusion matrix
[[ 421  133]
 [ 553 2893]]
```

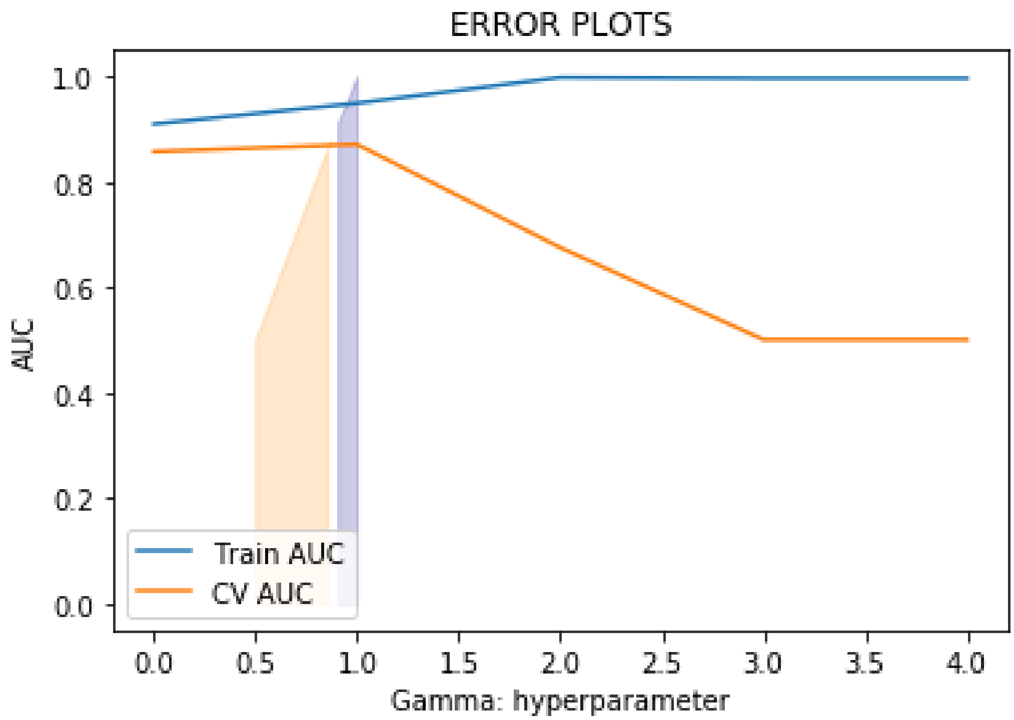


7.2.2 [5.2.2] Applying RBF SVM on TFIDF, SET 2

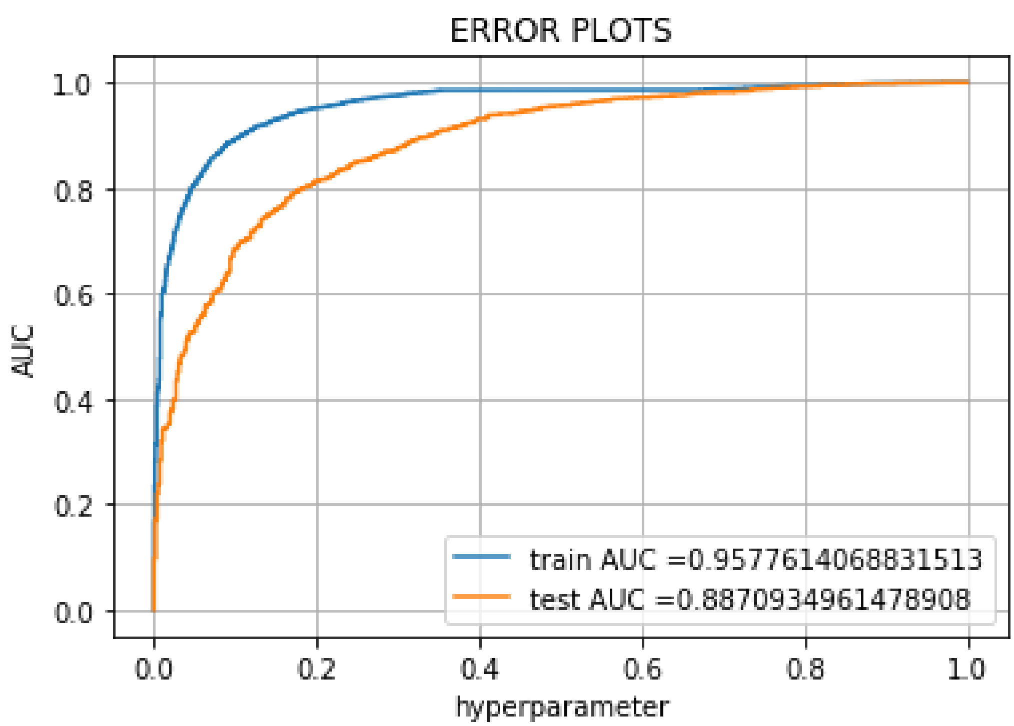
In [72]:
```
# Please write all the code with proper documentation
all_rbf(X_train_tfidf,y_train,X_cv_tfidf)
```



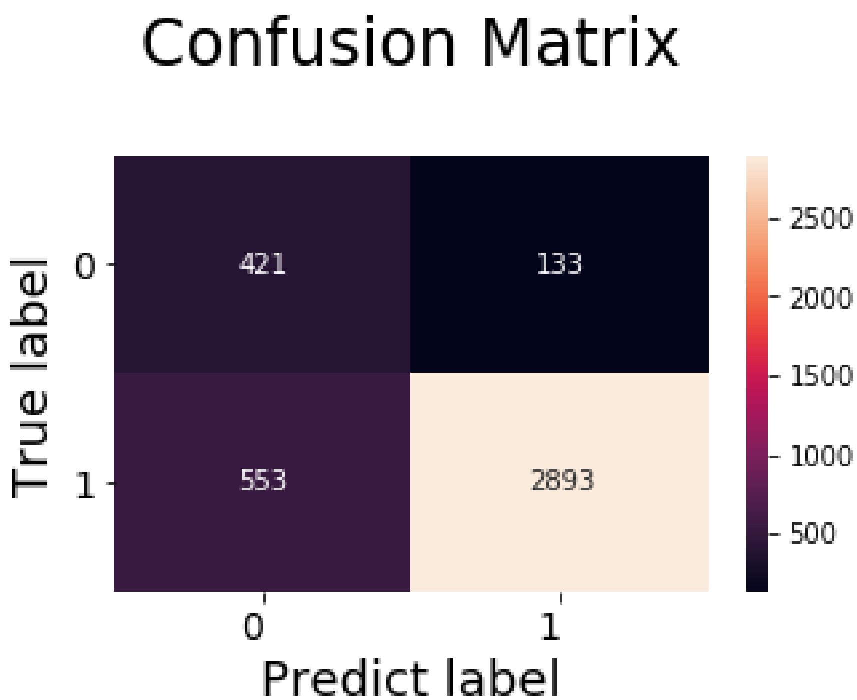

```
Optimal value of C:  1
--------------------------
Cv auc scores
[0.68799675 0.8645555  0.86665877 0.86491564 0.80950303]
Maximun Auc value : 0.8666587740126928
```




```
Optimal value of gamma:  0.01
```

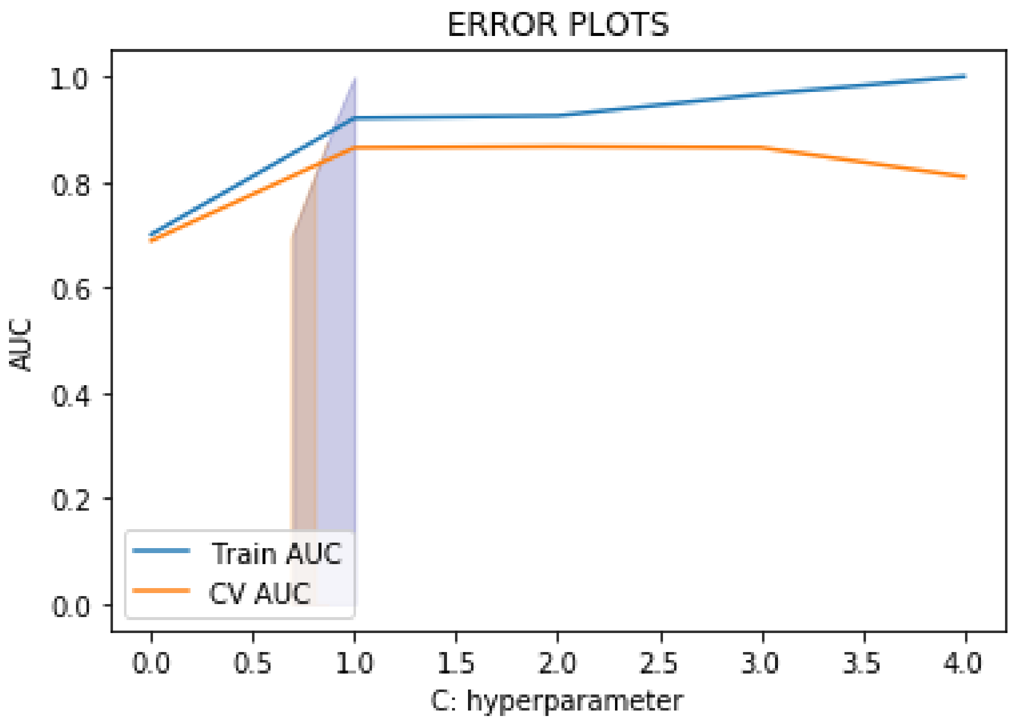


```
Train confusion matrix
[[ 1325   118]
 [ 1510 10047]]
Test confusion matrix
[[ 421  133]
 [ 553 2893]]
```

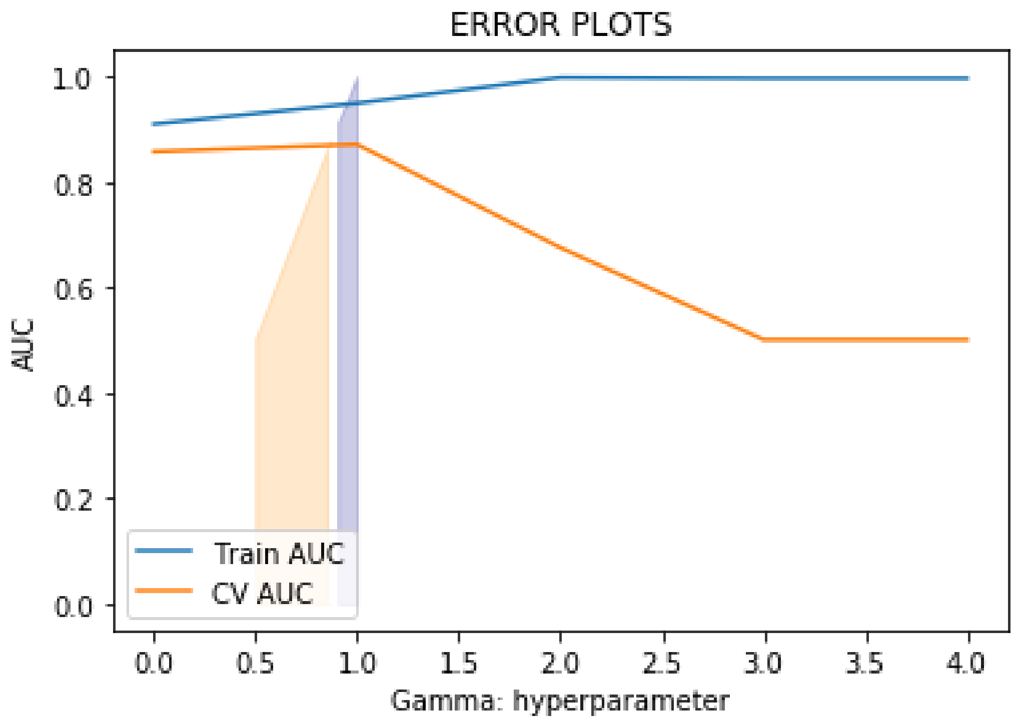


7.2.3 [5.2.3] Applying RBF SVM on AVG W2V, SET 3

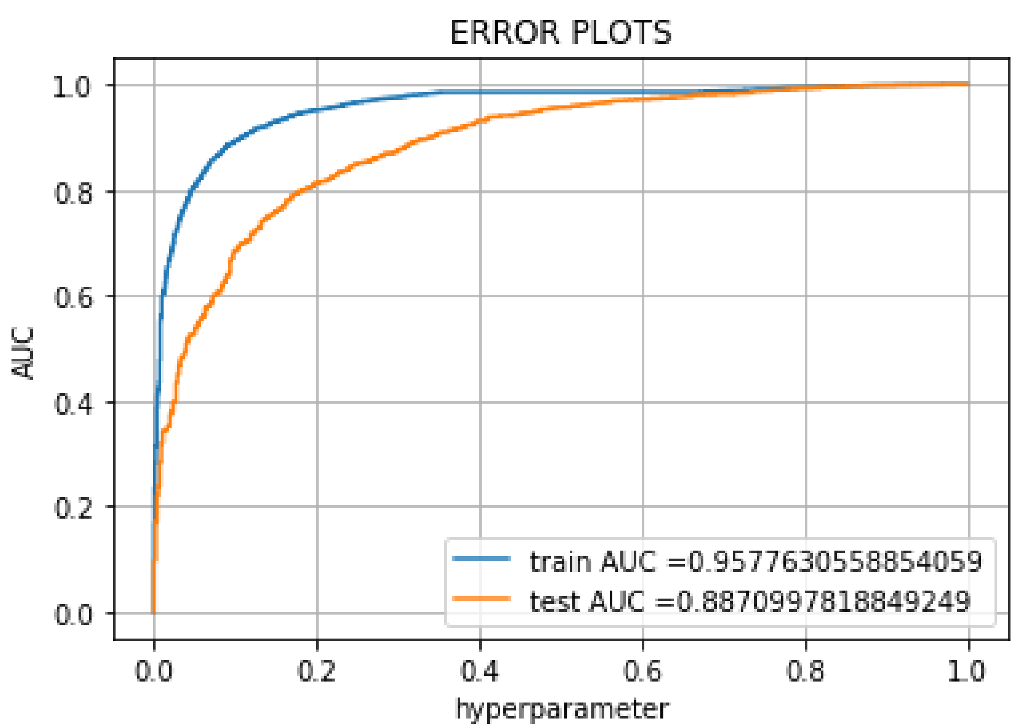
```
In [73]: all_rbf(train_vectors,y_train,X_cv)
```



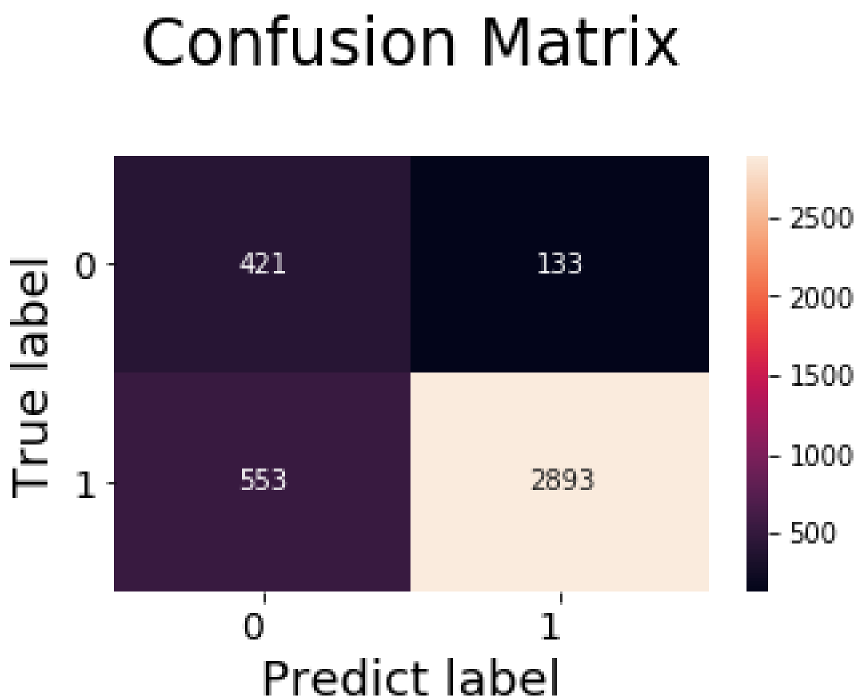

```
Optimal value of C:  1
--------------------------
Cv auc scores
[0.68799675 0.8645555  0.86665877 0.86491564 0.80950303]
Maximun Auc value : 0.8666587740126928
```




```
Optimal value of gamma:  0.01
```

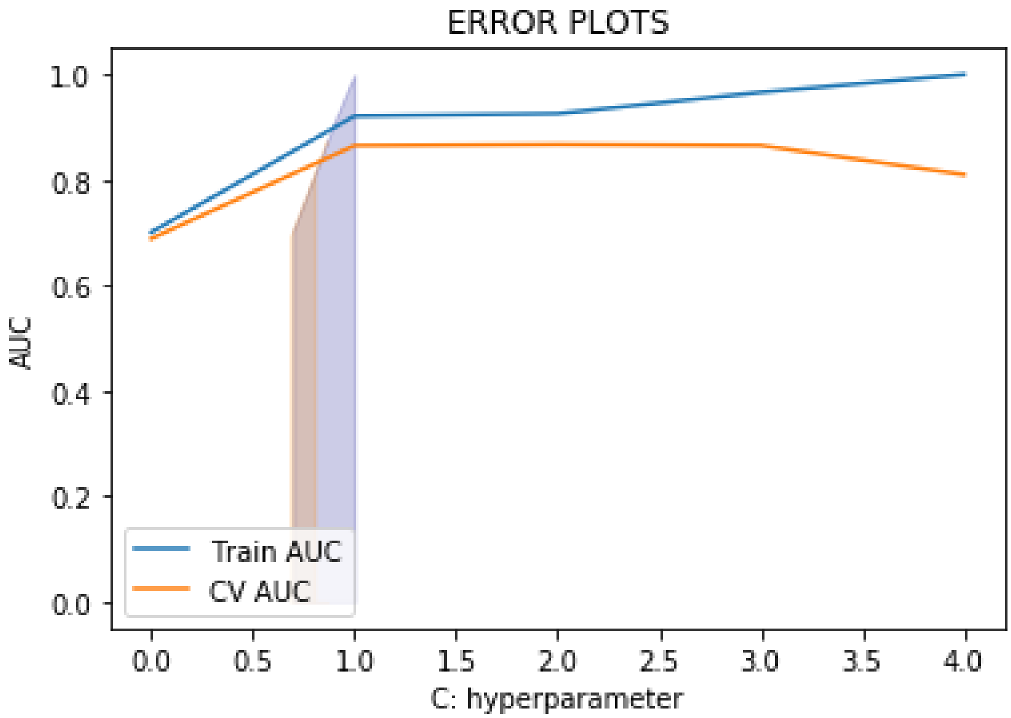


```
Train confusion matrix
[[ 1325   118]
 [ 1510 10047]]
Test confusion matrix
[[ 421  133]
 [ 553 2893]]
```

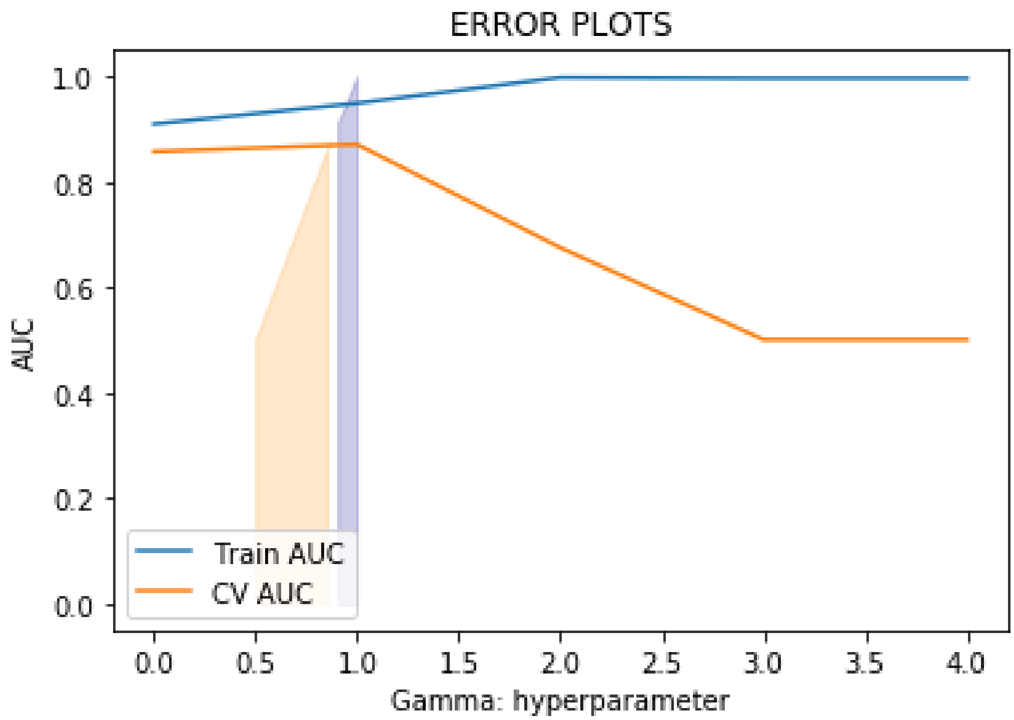


7.2.4 [5.2.4] Applying RBF SVM on TFIDF W2V, SET 4

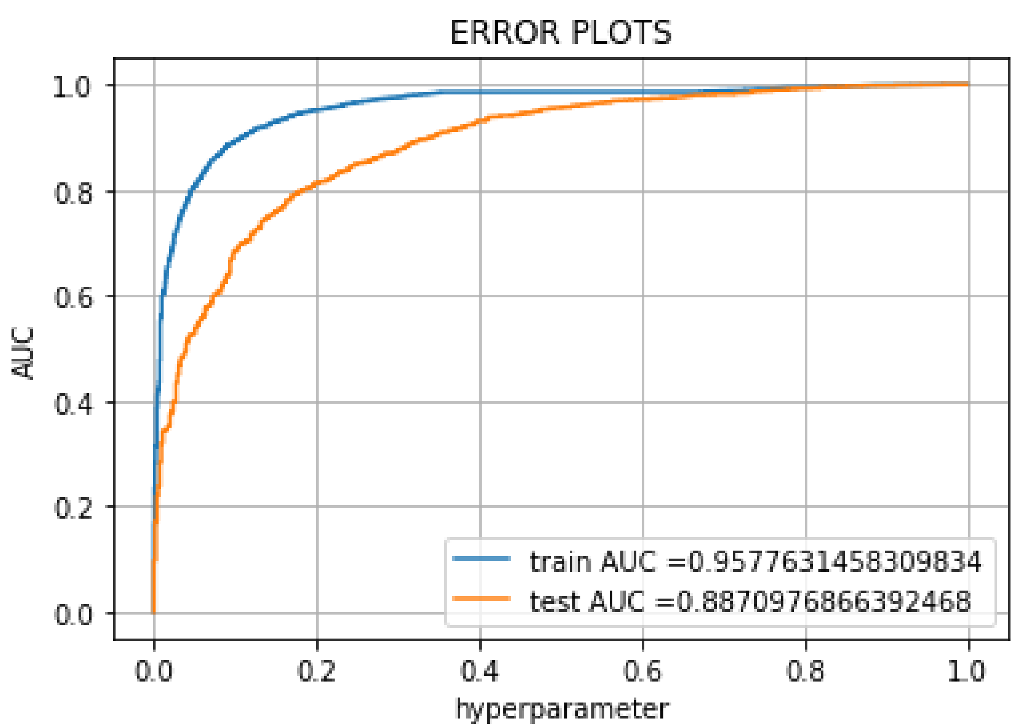
In [74]:
```
# Please write all the code with proper documentation

all_rbf(train_vectors,y_train,X_cv)
```



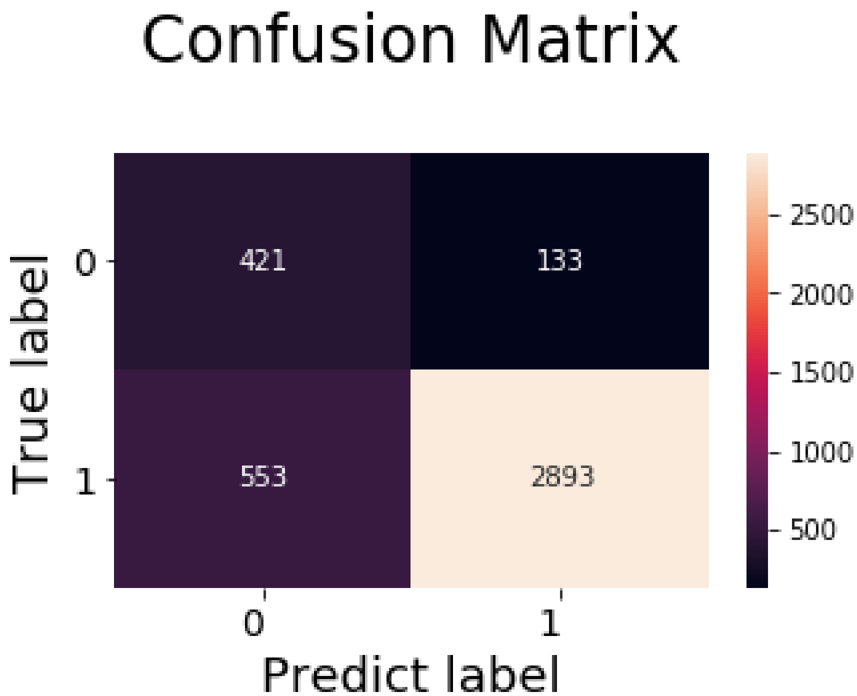

```
Optimal value of C:  1
--------------------------
Cv auc scores
[0.68799675 0.8645555  0.86665877 0.86491564 0.80950303]
Maximun Auc value : 0.8666587740126928
```




```
Optimal value of gamma:  0.01
```



```
Train confusion matrix
[[ 1325   118]
 [ 1510 10047]]
Test confusion matrix
[[ 421  133]
 [ 553 2893]]
```



8 [6] Conclusions

```
In [75]: # Please compare all your models using Prettytable library

         from prettytable import PrettyTable

         # Names of models
         Vectorizer = ['Bag of Words','TFIDF','AVG W2V','TFIDF W2V','Bag of Words', 'TFIDF', '


         hyper_Param=[0.001, 0.001,0.001,0.001,1, 1,1, 1]

         auc =[0.88,0.88,0.88,0.88,0.86,0.86,0.86,0.86]
```

```python
numbering = [1,2,3,4,5,6,7,8]

# Initializing prettytable
ptable = PrettyTable()

# Adding columns
ptable.add_column("S.NO.",numbering)
ptable.add_column("MODEL",Vectorizer)

ptable.add_column("Hyper Parameter",hyper_Param)
ptable.add_column("AUC",auc)


print(ptable)
```

```
+--------+--------------+-----------------+------+
| S.NO.  |    MODEL     | Hyper Parameter | AUC  |
+--------+--------------+-----------------+------+
|   1    | Bag of Words |      0.001      | 0.88 |
|   2    |    TFIDF     |      0.001      | 0.88 |
|   3    |   AVG W2V    |      0.001      | 0.88 |
|   4    |  TFIDF W2V   |      0.001      | 0.88 |
|   5    | Bag of Words |        1        | 0.86 |
|   6    |    TFIDF     |        1        | 0.86 |
|   7    |   AVG W2V    |        1        | 0.86 |
|   8    |  TFIDF W2V   |        1        | 0.86 |
+--------+--------------+-----------------+------+
```

8.1 conclusion

1. Linear kernel is faster than RBF Kernel.
2. BOW featurisation with Linear kernel and L2 regularization gave 88% AUC value.
3. Model can be improved by more data points although we notice that SVM doesnt perform well this dataset because the other model we have applied were better results than this.