07_Amazon_Fine_Food_Reviews_Analysis_Support_Vector_Machines

January 18, 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 [1]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

from sklearn.metrics import roc_auc_score
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.model_selection import KFold
from sklearn.metrics import roc_auc_score
from sklearn.calibration import CalibratedClassifierCV
from sklearn.linear_model import SGDClassifier
from sklearn.model_selection import ParameterGrid
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 sklearn.model_selection import cross_val_score
from sklearn.naive_bayes import MultinomialNB
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
!pip install -q scikit-plot
import scikitplot as skplt
from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle
#for finding nonzero elements in sparse matrix
from scipy.sparse import find
#for f1_Score
```

```
from sklearn.metrics import f1_score
#for roc curve
import numpy as np
import matplotlib.pyplot as plt
from itertools import cycle
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn import svm, datasets
from sklearn.metrics import roc_curve, auc
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import label_binarize
from sklearn.multiclass import OneVsRestClassifier
from scipy.sparse import coo_matrix, hstack
from scipy import interp
from sklearn.metrics import classification_report
from sklearn.model_selection import GridSearchCV
#for SGD
from sklearn.linear_model import LogisticRegression
#for SVC
from sklearn.svm import SVC
#for others
from tqdm import tqdm
import os
!apt-get install -y -qq software-properties-common python-software-properties module-i
!add-apt-repository -y ppa:alessandro-strada/ppa 2>&1 > /dev/null
!apt-get update -qq 2>&1 > /dev/null
!apt-get -y install -qq google-drive-ocamlfuse fuse
from google.colab import auth
auth.authenticate_user()
from oauth2client.client import GoogleCredentials
creds = GoogleCredentials.get_application_default()
import getpass
!google-drive-ocamlfuse -headless -id={creds.client_id} -secret={creds.client_secret} <
vcode = getpass.getpass()
!echo {vcode} | google-drive-ocamlfuse -headless -id={creds.client_id} -secret={creds.c
!mkdir drive
!google-drive-ocamlfuse drive
```

```
E: Package 'python-software-properties' has no installation candidate
Selecting previously unselected package google-drive-ocamlfuse.
(Reading database ... 110851 files and directories currently installed.)
Preparing to unpack .../google-drive-ocamlfuse_0.7.1-0ubuntu3~ubuntu18.04.1_amd64.deb ...
Unpacking google-drive-ocamlfuse (0.7.1-0ubuntu3~ubuntu18.04.1) ...
Setting up google-drive-ocamlfuse (0.7.1-0ubuntu3~ubuntu18.04.1) ...
Processing triggers for man-db (2.8.3-2ubuntu0.1) ...
Please, open the following URL in a web browser: https://accounts.google.com/o/oauth2/auth?cli
ůůůůůůůůůů
```

```
Please, open the following URL in a web browser: https://accounts.google.com/o/oauth2/auth?clie
Please enter the verification code: Access token retrieved correctly.
```

In [2]:
```python
# using SQLite Table to read data.
os.chdir("/content/drive/Colab Notebooks") #changing directory
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 5
# for tsne assignment you can take 5k data points

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

# 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 (525814, 10)
```

Out[2]:
```
   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 [0]: display = pd.read_sql_query("""
        SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
        FROM Reviews
        GROUP BY UserId
        HAVING COUNT(*)>1
        """, con)
```

```
In [4]: print(display.shape)
        display.head()
```

```
(80668, 7)
```

```
Out[4]:                UserId   ProductId             ProfileName        Time  Score  \
        0  #oc-R115TNMSPFT9I7  B007Y59HVM                 Breyton  1331510400      2
        1  #oc-R11D9D7SHXIJB9  B005HG9ET0  Louis E. Emory "hoppy"  1342396800      5
        2  #oc-R11DNU2NBKQ23Z  B007Y59HVM        Kim Cieszykowski  1348531200      1
        3  #oc-R11O5J5ZVQE25C  B005HG9ET0           Penguin Chick  1346889600      5
        4  #oc-R12KPBODL2B5ZD  B007OSBE1U   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 [5]: display[display['UserId']=='AZY10LLTJ71NX']
```

```
Out[5]:               UserId   ProductId                       ProfileName        Time  \
        80638  AZY10LLTJ71NX  B006P7E5ZI  undertheshrine "undertheshrine"  1334707200

               Score                                               Text  COUNT(*)
        80638      5  I was recommended to try green tea extract to ...         5
```

```
In [6]: display['COUNT(*)'].sum()
```

```
Out[6]: 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 [7]: display= pd.read_sql_query("""
        SELECT *
```

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

Out[7]:

```
       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 [0]:

```
#Sorting data according to ProductId in ascending order
```

```
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fal
```

```
In [9]: #Deduplication of entries
        final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep=
        final.shape
```

```
Out[9]: (364173, 10)
```

```
In [10]: #Checking to see how much % of data still remains
         (final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

```
Out[10]: 69.25890143662969
```

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

         display.head()
```

```
Out[11]:       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 [0]: final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

```
In [13]: #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()
```

```
(364171, 10)
```

```
Out[13]: 1    307061
         0     57110
         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

```
In [14]: # 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 witty little book makes my son laugh at loud. i recite it in the car as we're driving alo
==================================================
I was really looking forward to these pods based on the reviews.  Starbucks is good, but I pre
==================================================
Great ingredients although, chicken should have been 1st rather than chicken broth, the only t
==================================================
```

```
Can't do sugar.  Have tried scores of SF Syrups.  NONE of them can touch the excellence of thi
==================================================
```

```
In [15]: # 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 witty little book makes my son laugh at loud. i recite it in the car as we're driving alo
```

```
In [16]: # 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)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as we're driving alo
==================================================
I was really looking forward to these pods based on the reviews.  Starbucks is good, but I pre
==================================================
Great ingredients although, chicken should have been 1st rather than chicken broth, the only t
==================================================
Can't do sugar.  Have tried scores of SF Syrups.  NONE of them can touch the excellence of thi
```

```
In [0]: # https://stackoverflow.com/a/47091490/4084039
        import re
```

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

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

In [18]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
Great ingredients although, chicken should have been 1st rather than chicken broth, the only t
==================================================
```

In [19]:
```
#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 witty little book makes my son laugh at loud. i recite it in the car as we're driving alo
```

In [20]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
Great ingredients although chicken should have been 1st rather than chicken broth the only thi
```

In [0]:
```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
# <br /><br /> ==> after the above steps, we are getting "br br"
# we are including them into stop words list
# instead of <br /> if we have <br/> these tags would have revmoved in the 1st step

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', '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', "t
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'h
```

```
                  'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as
                  'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through
                  'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'o
                  'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any
                  'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too
                  's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'n
                  've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't"
                  "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mig
                  "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", '
                  'won', "won't", 'wouldn', "wouldn't"])
```

```
In [22]: # 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 stopw
             preprocessed_reviews.append(sentance.strip())
```

```
100%|| 364171/364171 [03:14<00:00, 1870.04it/s]
```

```
In [23]: preprocessed_reviews[1500]
```

```
Out[23]: 'great ingredients although chicken rather chicken broth thing not think belongs cano
```

5 [3.2] Splitting the data

```
In [24]: final['Text'] = preprocessed_reviews
         #sampling 100k point for linear SVM. Also balancing the data
         finalp = final[final.Score == 1].sample(50000,random_state =2)
         finaln = final[final.Score == 0].sample(50000,random_state =2)
         finalx = pd.concat([finalp,finaln],ignore_index=True)
         finalx = finalx.sort_values('Time')
         y = finalx.Score.values
         X = finalx.Text.values
         X_tr100, X_test100 , y_tr100, y_test100 = train_test_split(X,y,test_size=0.3)
         print(finalx.Score.value_counts())
         print(X_tr100.shape,X_test100.shape,y_tr100.shape,y_test100.shape)
         #Sampling 20k points for Kernel SVM. Also balancing the data
         finalp = final[final.Score == 1].sample(10000,random_state =2)
         finaln = final[final.Score == 0].sample(10000,random_state =2)
```

```
finalx = pd.concat([finalp,finaln],ignore_index=True)
finalx = finalx.sort_values('Time')
y = finalx.Score.values
X = finalx.Text.values
X_tr20, X_test20 , y_tr20, y_test20 = train_test_split(X,y,test_size=0.3)
print(final.Score.value_counts())
print(X_tr20.shape,X_test20.shape,y_tr20.shape,y_test20.shape)
```

```
1    50000
0    50000
Name: Score, dtype: int64
(70000,) (30000,) (70000,) (30000,)
1    307061
0     57110
Name: Score, dtype: int64
(14000,) (6000,) (14000,) (6000,)
```

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

6 [4] Featurization

6.1 [4.1] BAG OF WORDS

In [26]:
```
#BoW for linear SVM
count_vect1 = CountVectorizer(ngram_range=(1,2),min_df=10) #in scikit-learn
bow_vec_tr100 = count_vect1.fit_transform(X_tr100)
print("some feature names ", count_vect1.get_feature_names()[:10])
print('='*50)

bow_vec_test100 = count_vect1.transform(X_test100)
print("the type of count vectorizer ",type(bow_vec_tr100))
print("the shape of out text BOW vectorizer ",bow_vec_tr100.get_shape())
print("the number of unique words ", bow_vec_tr100.get_shape()[1])

#BoW for Kernel SVM
count_vect2 = CountVectorizer(ngram_range=(1,2),min_df=10,max_features = 5000) #in sc
bow_vec_tr20 = count_vect2.fit_transform(X_tr20)
print("some feature names ", count_vect2.get_feature_names()[:10])
print('='*50)

bow_vec_test20 = count_vect2.transform(X_test20)
print("the type of count vectorizer ",type(bow_vec_tr20))
print("the shape of out text BOW vectorizer ",bow_vec_tr20.get_shape())
print("the number of unique words ", bow_vec_tr20.get_shape()[1])
```

```
some feature names  ['aa', 'aafco', 'abandoned', 'abc', 'abdominal', 'abdominal pain', 'ability
==================================================
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (70000, 41647)
the number of unique words  41647
some feature names  ['ability', 'able', 'able buy', 'able find', 'able get', 'absolute', 'abso
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (14000, 5000)
the number of unique words  5000
```

6.2 [4.2] Bi-Grams and n-Grams.

Already using BoW with bigrams.

6.3 [4.3] TF-IDF

```
In [27]: #fidf for linear SVM
         tf_idf_vect1 = TfidfVectorizer(ngram_range=(1,2), min_df=10)
         tfidf_tr100 = tf_idf_vect1.fit_transform(X_tr100)
         print("some sample features(unique words in the corpus)",tf_idf_vect1.get_feature_name
         print('='*50)

         tfidf_test100 = tf_idf_vect1.transform(X_test100)
         print("the type of count vectorizer ",type(tfidf_tr100))
         print("the shape of out text TFIDF vectorizer ",tfidf_tr100.get_shape())
         print("the number of unique words including both unigrams and bigrams ", tfidf_tr100.g

         #tfidf for kernel SVM
         tf_idf_vect2 = TfidfVectorizer(ngram_range=(1,2), min_df=10,max_features=5000)
         tfidf_tr20 = tf_idf_vect2.fit_transform(X_tr20)
         print("some sample features(unique words in the corpus)",tf_idf_vect2.get_feature_name
         print('='*50)

         tfidf_test20 = tf_idf_vect2.transform(X_test20)
         print("the type of count vectorizer ",type(tfidf_tr20))
         print("the shape of out text TFIDF vectorizer ",tfidf_tr20.get_shape())
         print("the number of unique words including both unigrams and bigrams ", tfidf_tr20.g
```

```
some sample features(unique words in the corpus) ['aa', 'aafco', 'abandoned', 'abc', 'abdomina
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (70000, 41647)
the number of unique words including both unigrams and bigrams  41647
some sample features(unique words in the corpus) ['ability', 'able', 'able buy', 'able find',
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (14000, 5000)
the number of unique words including both unigrams and bigrams  5000
```

6.4 [4.4] Word2Vec

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

In [29]:
```
# Using Google News Word2Vectors

# in this project we are using a pretrained model by google
# its 3.3G file, once you load this into your memory
# it occupies ~9Gb, so please do this step only if you have >12G of ram
# we will provide a pickle file wich contains a dict ,
# and it contains all our courpus words as keys and  model[word] as values
# To use this code-snippet, download "GoogleNews-vectors-negative300.bin"
# from https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/edit
# it's 1.9GB in size.


# http://kavita-ganesan.com/gensim-word2vec-tutorial-starter-code/#.W17SRFAzZPY
# you can comment this whole cell
# or change these varible according to your need

is_your_ram_gt_16g=False
want_to_use_google_w2v = False
want_to_train_w2v = True

if want_to_train_w2v:
    # min_count = 5 considers only words that occured atleast 5 times
    w2v_model=Word2Vec(list_of_sentance,min_count=5,size=50, workers=4)
    print(w2v_model.wv.most_similar('great'))
    print('='*50)
    print(w2v_model.wv.most_similar('worst'))

elif want_to_use_google_w2v and is_your_ram_gt_16g:
    if os.path.isfile('GoogleNews-vectors-negative300.bin'):
        w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors-negative300.bi
        print(w2v_model.wv.most_similar('great'))
        print(w2v_model.wv.most_similar('worst'))
    else:
        print("you don't have gogole's word2vec file, keep want_to_train_w2v = True, t
```

```
[('fantastic', 0.8943659663200378), ('terrific', 0.8936077356338501), ('awesome', 0.87901580333
==================================================
[('nastiest', 0.8612643480300903), ('greatest', 0.7599353790283203), ('best', 0.74357473850250
```

In [30]:
```
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  33573
sample words  ['witty', 'little', 'book', 'makes', 'son', 'laugh', 'loud', 'recite', 'car', 'd
```

6.5 [4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V

[4.4.1.1] Avg W2v for linear SVM

In [31]:
```
# average Word2Vec for training data
i=0
list_of_sent_intr100=[]
for sent in X_tr100:
    list_of_sent_intr100.append(sent.split())

# compute average word2vec for each review.
sent_vectors_intr100 = []; # the avg-w2v for each sentence/review is stored in this l
for sent in tqdm(list_of_sent_intr100): # 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_intr100.append(sent_vec)
print(len(sent_vectors_intr100))
print(len(sent_vectors_intr100[0]))

# average Word2Vec for test data
i=0
list_of_sent_intest100=[]
for sent in X_test100:
    list_of_sent_intest100.append(sent.split())

# compute average word2vec for each review.
sent_vectors_intest100 = []; # the avg-w2v for each sentence/review is stored in this
for sent in tqdm(list_of_sent_intest100): # 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_intest100.append(sent_vec)
    print(len(sent_vectors_intest100))
    print(len(sent_vectors_intest100[0]))
```

```
100%|| 70000/70000 [04:06<00:00, 284.17it/s]
  0%|          | 0/30000 [00:00<?, ?it/s]

70000
50


100%|| 30000/30000 [01:44<00:00, 286.27it/s]

30000
50
```

[4.4.1.1.2] AVG W2V for Kernel SVM

```
In [32]: # average Word2Vec for training data
         i=0
         list_of_sent_intr20=[]
         for sent in X_tr20:
             list_of_sent_intr20.append(sent.split())

         # compute average word2vec for each review.
         sent_vectors_intr20 = []; # the avg-w2v for each sentence/review is stored in this li
         for sent in tqdm(list_of_sent_intr20): # 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_intr20.append(sent_vec)
         print(len(sent_vectors_intr20))
         print(len(sent_vectors_intr20[0]))

         # average Word2Vec for test data
         i=0
         list_of_sent_intest20=[]
```

```
        for sent in X_test20:
            list_of_sent_intest20.append(sent.split())

        # compute average word2vec for each review.
        sent_vectors_intest20 = []; # the avg-w2v for each sentence/review is stored in this
        for sent in tqdm(list_of_sent_intest20): # 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_intest20.append(sent_vec)
        print(len(sent_vectors_intest20))
        print(len(sent_vectors_intest20[0]))
```

```
100%|| 14000/14000 [00:49<00:00, 284.25it/s]
  1%|          | 31/6000 [00:00<00:20, 293.88it/s]

14000
50


100%|| 6000/6000 [00:21<00:00, 284.03it/s]


6000
50
```

[4.4.1.2] TFIDF weighted W2v for linear SVM

```
In [0]: # S = ["abc def pqr", "def def def abc", "pqr pqr def"]
        model = TfidfVectorizer(min_df=10)
        tf_idf_matrix = model.fit_transform(X_tr100)
        model.transform(X_test100)
        # we are converting a dictionary with word as a key, and the idf as a value
        dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

```
In [34]: # TF-IDF weighted Word2Vec
         tfidf_feat = model.get_feature_names() # tfidf words/col-names
         # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

         tfidf_sent_vectors_intr100 = []; # the tfidf-w2v for each sentence/review is stored i
         row=0;
         for sent in tqdm(list_of_sent_intr100): # for each review/sentence
```

```
        sent_vec = np.zeros(50) # as word vectors are of zero length
        weight_sum =0; # num of words with a valid vector in the sentence/review
        for word in sent: # for each word in a review/sentence
            if word in w2v_words and word in tfidf_feat:
                vec = w2v_model.wv[word]
#                   tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
                # to reduce the computation we are
                # dictionary[word] = idf value of word in whole courpus
                # sent.count(word) = tf valeus of word in this review
                tf_idf = dictionary[word]*(sent.count(word)/len(sent))
                sent_vec += (vec * tf_idf)
                weight_sum += tf_idf
        if weight_sum != 0:
            sent_vec /= weight_sum
        tfidf_sent_vectors_intr100.append(sent_vec)
        row += 1

    tfidf_sent_vectors_intest100 = []; # the tfidf-w2v for each sentence/review is stored
    row=0;
    for sent in tqdm(list_of_sent_intest100): # for each review/sentence
        sent_vec = np.zeros(50) # as word vectors are of zero length
        weight_sum =0; # num of words with a valid vector in the sentence/review
        for word in sent: # for each word in a review/sentence
            if word in w2v_words and word in tfidf_feat:
                vec = w2v_model.wv[word]
#                   tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
                # to reduce the computation we are
                # dictionary[word] = idf value of word in whole courpus
                # sent.count(word) = tf valeus of word in this review
                tf_idf = dictionary[word]*(sent.count(word)/len(sent))
                sent_vec += (vec * tf_idf)
                weight_sum += tf_idf
        if weight_sum != 0:
            sent_vec /= weight_sum
        tfidf_sent_vectors_intest100.append(sent_vec)
        row += 1
```

```
100%|| 70000/70000 [11:25<00:00, 102.07it/s]
100%|| 30000/30000 [04:49<00:00, 103.47it/s]
```

[4.4.1.2] TFIDF weighted W2v for kernel SVM

```
In [0]: # S = ["abc def pqr", "def def def abc", "pqr pqr def"]
        model = TfidfVectorizer(min_df=10,max_features=5000)
        tf_idf_matrix = model.fit_transform(X_tr20)
```

```
model.transform(X_test20)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [36]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

tfidf_sent_vectors_intr20 = []; # the tfidf-w2v for each sentence/review is stored in
row=0;
for sent in tqdm(list_of_sent_intr20): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_intr20.append(sent_vec)
    row += 1

tfidf_sent_vectors_intest20 = []; # the tfidf-w2v for each sentence/review is stored
row=0;
for sent in tqdm(list_of_sent_intest20): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_intest20.append(sent_vec)
    row += 1
```

```
100%|| 14000/14000 [01:38<00:00, 142.31it/s]
100%|| 6000/6000 [00:42<00:00, 140.44it/s]
```

7 [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 vectors
        <li><font color='red'>SET 2:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 3:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 4:</font>Review text, preprocessed one converted into vectors
    </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.

7.0.1 Functions

[5.0.1] Linear SVM

```
In [0]: def hypertuning(traindata):

            kf = KFold(n_splits=5,random_state=3, shuffle=True)
            cv = []
            train = []
            alphas = [0.0001,0.001,0.01,0.1,1,10,100,10000]
```

```
alphaslog = np.log(alphas)
alphaslog.reshape(1,8)
param_grid = {'alpha': [0.0001,0.001,0.01,0.1,1,10,100,10000], 'penalty': ['l1']}
hyper = (ParameterGrid(param_grid))
#finding best hyperparameter
for i in range(8):

  for train_index,test_index in kf.split(traindata):
    xxtrain, xxtest = traindata[train_index], traindata[test_index]
    yytrain, yytest = y_tr100[train_index], y_tr100[test_index]
    clf = SGDClassifier()
    clf.set_params = hyper[i]
    clf.fit(xxtrain,yytrain)
    model = CalibratedClassifierCV(clf,cv = 'prefit')
    model.fit(xxtrain,yytrain)
    trainscores = []
    cvscores = []
    trainvalues = model.predict_proba(xxtrain)

    trainscores.append(roc_auc_score(yytrain,trainvalues[:,1]))
    cvvalues =model.predict_proba(xxtest)
    cvscores.append(roc_auc_score(yytest,cvvalues[:,1]))

  train.append(np.mean(trainscores))
  cv.append(np.mean(cvscores))
  trainscores = []
  cvscores = []

for i in range(8):
  param_grid = {'alpha': [0.0001,0.001,0.01,0.1,1,10,100,10000], 'penalty': ['l2']}
  hyper = (ParameterGrid(param_grid))

  for train_index,test_index in kf.split(traindata):
    xxtrain, xxtest = traindata[train_index], traindata[test_index]
    yytrain, yytest = y_tr100[train_index], y_tr100[test_index]
    clf = SGDClassifier()
    clf.set_params = hyper[i]
    clf.fit(xxtrain,yytrain)
    model = CalibratedClassifierCV(clf,cv = 'prefit')
    model.fit(xxtrain,yytrain)
    trainscores = []
    cvscores = []
    trainvalues = model.predict_proba(xxtrain)

    trainscores.append(roc_auc_score(yytrain,trainvalues[:,1]))
    cvvalues =model.predict_proba(xxtest)
    cvscores.append(roc_auc_score(yytest,cvvalues[:,1]))
```

```
            train.append(np.mean(trainscores))
            cv.append(np.mean(cvscores))
            trainscores = []
            cvscores = []
          plt.figure()
          plt.plot(alphaslog,train[:8],'b',label='Train AUC with l1 reg')
          plt.plot(alphaslog,cv[:8],'r',label='CV AUC with l1 reg')
          plt.plot(alphaslog,train[8:16],'g',label='Train AUC with l2 reg')
          plt.plot(alphaslog,cv[8:16],'darkorange',label='CV AUC with l2 reg')
          plt.xlabel('alpha Value in natural log')
          plt.ylabel('Area Under ROC Curve')
          plt.gca().legend()
          plt.show()
           # determining alpha and reg by considering max cv
          cvl1 = np.mean(cv[0:8])
          cvl2 = np.mean(cv[8:16])
          if cvl1>cvl2:
            alphatrain = alphas[train[0:8].index(max(train[0:8]))]
            alphacv = alphas[cv[0:8].index(max(cv[0:8]))]
            reg = 'l1'
            optimal_alpha = np.median([alphacv,alphatrain])
          else:
            alphatrain = alphas[train[8:16].index(max(train[8:16]))]
            alphacv = alphas[cv[8:16].index(max(cv[8:16]))]
            reg = 'l2'
            optimal_alpha = np.median([alphacv,alphatrain])

          print('Optimal alpha is {} and reg is {}'.format(optimal_alpha,reg))

          return optimal_alpha,reg
```

In [0]:
```
#Applying SGD with optimal optimal alpha
def sgd_optimal(optimal_alpha,reg,Xtrain,Xtest):
  #training the data using optimal alpha and regularisation.
  model = SGDClassifier(alpha=optimal_alpha,penalty =reg)
  model.fit(Xtrain,y_tr100)
  p_train = model.predict(Xtrain)
  p_test = model.predict(Xtest)
  clf = CalibratedClassifierCV(model,cv = 2)
  clf.fit(Xtrain,y_tr100)
  pred_train = clf.predict_proba(Xtrain)
  pred_test = clf.predict_proba(Xtest)
  #Getting FPR AND TPR values for ROC Curve for train and test data
  fpr = dict()
  tpr = dict()
  roc_auc = dict()
  fpr,tpr,_ = roc_curve(y_tr100,pred_train[:,1])
  roc_auc_train = roc_auc_score(y_tr100,pred_train[:,1])
```

```
    fpr2 = dict()
    tpr2 = dict()
    roc_auc2 = dict()
    fpr2,tpr2,_ = roc_curve(y_test100,pred_test[:,1])
    roc_auc_test = roc_auc_score(y_test100,pred_test[:,1])

    plt.figure()
    plt.title(" ROC Curve")
    plt.plot(fpr,tpr,'b',label='ROC curve for train data(area = %0.2f)' % roc_auc_train)
    plt.plot(fpr2,tpr2,'r',label='ROC curve for test data(area = %0.2f)' % roc_auc_test)
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.legend(loc="lower right")
    plt.show()

    #for confusion matrix
    print("Confusion Matrix for Train data")
    skplt.metrics.plot_confusion_matrix(y_tr100,p_train)
    print(classification_report(y_tr100,p_train))
    print("="*50)
    print("Confusion matrix for Test data")
    skplt.metrics.plot_confusion_matrix(y_test100,p_test)
    print(classification_report(y_test100,p_test))
    #for sparcity check
    w = model.coef_

    return w
```

[5.0.2] RBF SVM

```
In [0]: #SVM with RBF Kernel
        def svmtuning(Xtrain):
        #Giving C parameters
          C_parameters = [{'C': [0.0001,0.001,0.01,0.1,1,10,100,10000]}]
          C_values = [0.0001,0.001,0.01,0.1,1,10,100,10000]

        #Using GridSearchCV
          validation_score = []
          train_score = []
          model = GridSearchCV(SVC(gamma="auto",probability=True), C_parameters, scoring = 'ro
          model.fit(Xtrain, y_tr20)
        #Train and test results are in model.cv_results_
          results = model.cv_results_
          validation_score = results['mean_test_score']
          train_score = results['mean_train_score']
        # Changing c values to log for plotting
          C_values_log = np.log(C_values)
```

```
        C_values_log.reshape(1,8)
      #Get best estimator according to Gridsearchcv
        print(model.best_estimator_)
      # Calculating best  c from train and test data by converting the array to list
        validation_score = validation_score.tolist()
        train_score = train_score.tolist()
        optimal_c_cv = C_values[validation_score.index(max(validation_score))]
        optimal_c_tr = C_values[train_score.index(max(train_score))]
        log_tr = np.log(optimal_c_tr)
        log_cv = np.log(optimal_c_cv)
        optimal_c = float(np.exp((log_tr+log_cv)/2))
      #plotting the curve
        plt.figure()
        plt.title("AUC vs C")
        plt.plot(C_values_log,train_score,'b',label='Train AUC')
        plt.plot(C_values_log,validation_score,'darkorange',label='Validation AUC')
        plt.xlabel('C Value in natural log')
        plt.ylabel('Area Under ROC Curve')
        plt.gca().legend()
        plt.show()
        print('\nThe optimal c for training data is %f and ROC is %f.' % (optimal_c_tr,max(t
        print('\nThe optimal c for validation data is %f and ROC is %f.' % (optimal_c_cv,max
        print('\nThe calculated optimal c for model is %f.' % optimal_c)

        return optimal_c
```

In [0]:
```
#Applying LR with optimal c
def svm_optimal(optimal_c,Xtrain,Xtest):
  #for ROC Curve on train data
  clf = SVC(C=optimal_c, gamma="auto",probability=True)
  clf.fit(Xtrain, y_tr20)
  pred_train = clf.predict_proba(Xtrain)
  #for ROC Curve on test data
  pred_test = clf.predict_proba(Xtest)
  #Getting FPR AND TPR values for ROC Curve for train and test data
  fpr = dict()
  tpr = dict()
  roc_auc = dict()
  fpr,tpr,_ = roc_curve(y_tr20,pred_train[:,1])
  roc_auc_train = roc_auc_score(y_tr20,pred_train[:,1])

  fpr2 = dict()
  tpr2 = dict()
  roc_auc2 = dict()
  fpr2,tpr2,_ = roc_curve(y_test20,pred_test[:,1])
  roc_auc_test = roc_auc_score(y_test20,pred_test[:,1])

  plt.figure()
```

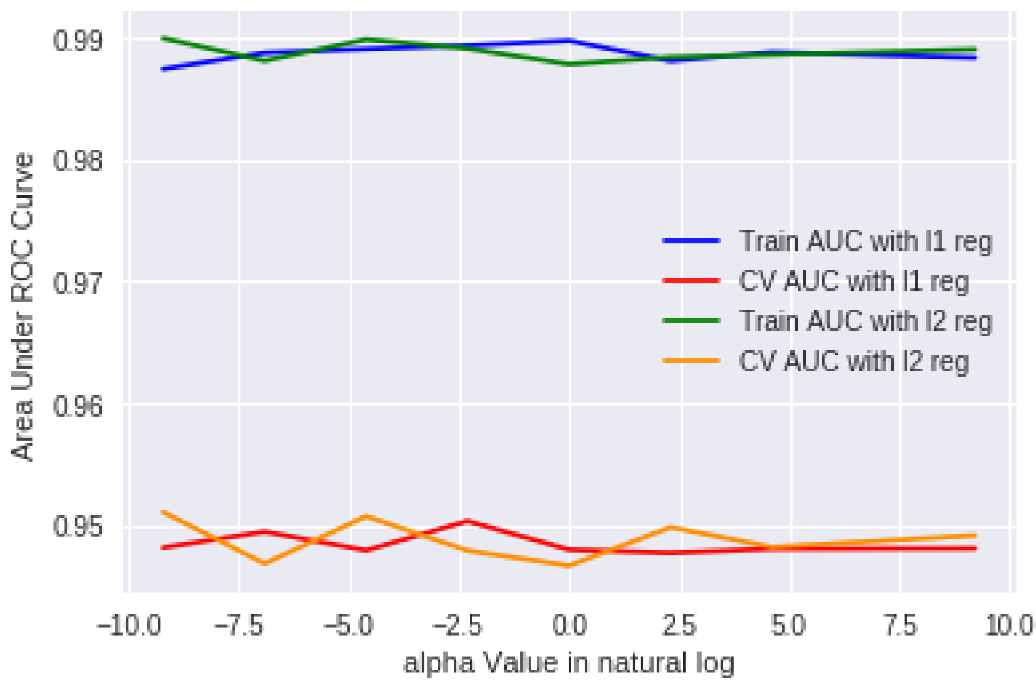
```
plt.title(" ROC Curve")
plt.plot(fpr,tpr,'b',label='ROC curve for train data(area = %0.2f)' % roc_auc_train)
plt.plot(fpr2,tpr2,'r',label='ROC curve for test data(area = %0.2f)' % roc_auc_test)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc="lower right")
plt.show()
#for confusion matrix
pred_train = clf.predict(Xtrain)
#for ROC Curve on test data
pred_test = clf.predict(Xtest)
print("Confusion Matrix for Train data")
skplt.metrics.plot_confusion_matrix(y_tr20,pred_train)
print(classification_report(y_tr20,pred_train))
print("="*50)
print("Confusion matrix for Test data")
skplt.metrics.plot_confusion_matrix(y_test20,pred_test)
print(classification_report(y_test20,pred_test))
```

8 Applying SVM

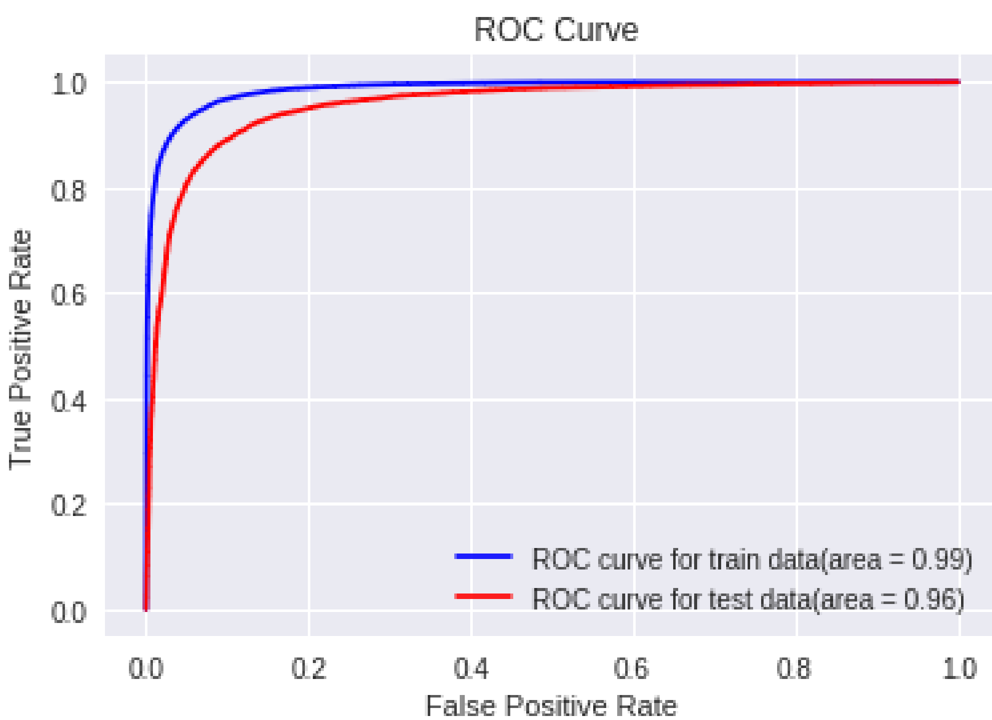
8.1 [5.1] Linear SVM

8.1.1 [5.1.1] Applying Linear SVM on BOW, SET 1

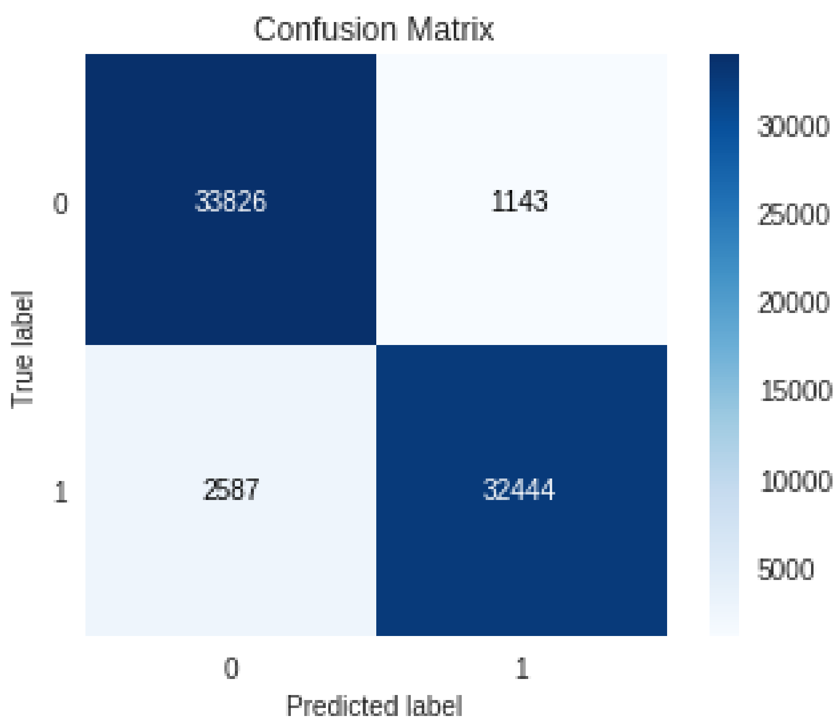
```
In [41]: #getting alpha and regularisation
         alpha,reg = hypertuning(bow_vec_tr100)
         #applying linear svm
         w = sgd_optimal(alpha,reg,bow_vec_tr100,bow_vec_test100)
```

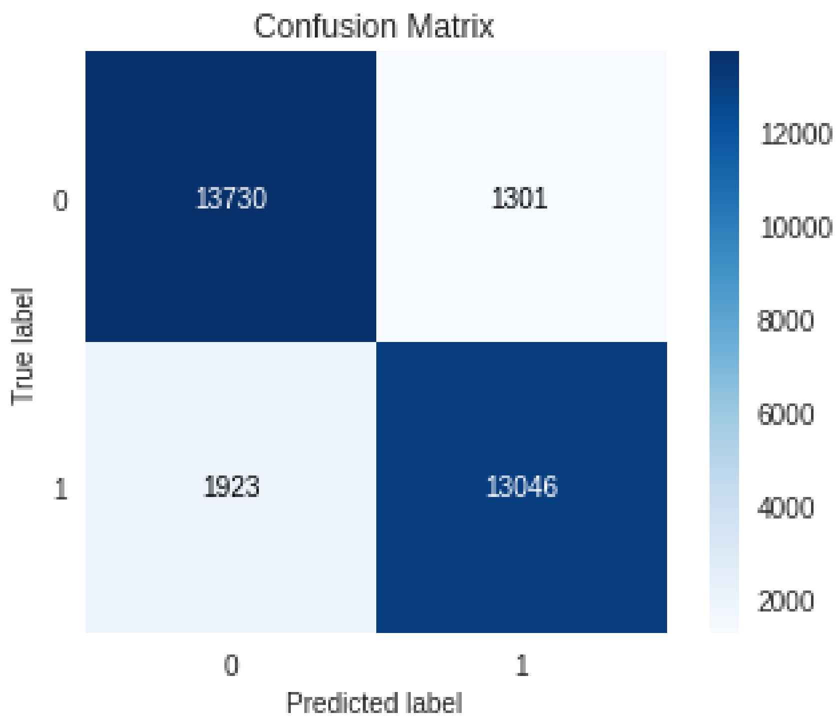



```
Optimal alpha is 0.0001 and reg is l2
```



```
Confusion Matrix for Train data
              precision    recall  f1-score   support

           0       0.93      0.97      0.95     34969
           1       0.97      0.93      0.95     35031

   micro avg       0.95      0.95      0.95     70000
   macro avg       0.95      0.95      0.95     70000
weighted avg       0.95      0.95      0.95     70000

==================================================
Confusion matrix for Test data
              precision    recall  f1-score   support

           0       0.88      0.91      0.89     15031
           1       0.91      0.87      0.89     14969

   micro avg       0.89      0.89      0.89     30000
   macro avg       0.89      0.89      0.89     30000
weighted avg       0.89      0.89      0.89     30000
```






```
In [42]: # Getting feature names from BoW vectorizer
         features_BoW = count_vect1.get_feature_names()

         #Merging them into a dataframe.
         top_features = pd.DataFrame(w,columns = features_BoW)
         top_features = top_features.T
         pos = top_features[top_features[0] > 0]
         neg = top_features[top_features[0] < 0]
         print(pos[0].sort_values(ascending=False)[0:10])
```

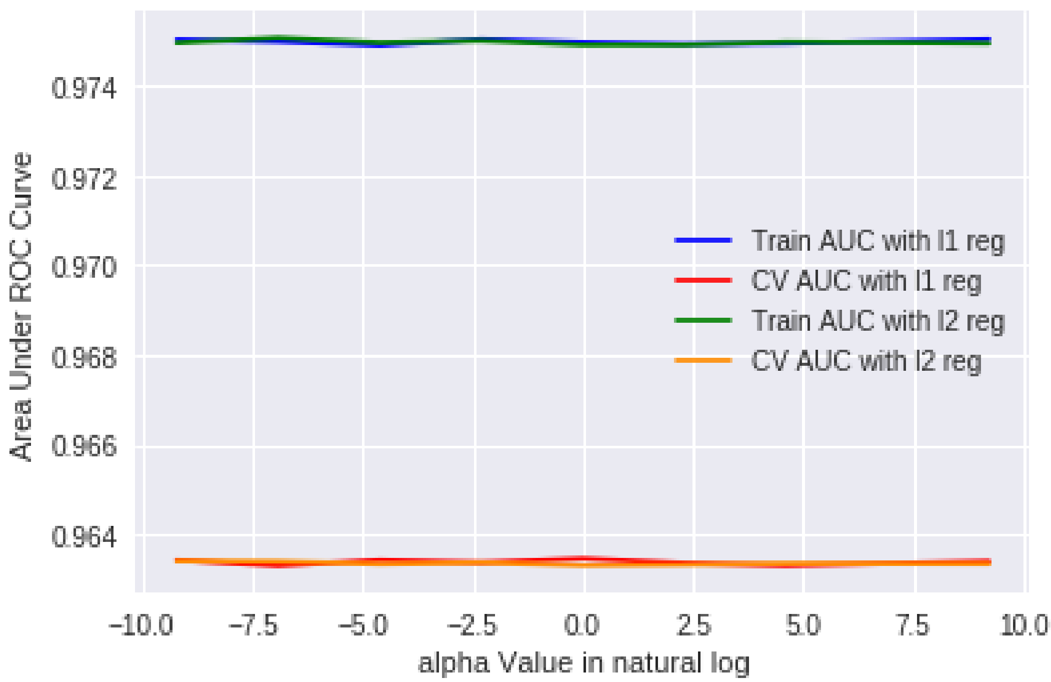
```
not disappointed    2.564110
skeptical           1.623936
go wrong            1.509976
four stars          1.481486
excellent           1.339035
not bitter          1.339035
addicting           1.310545
not overpowering    1.310545
delicious           1.310545
awesome             1.310545
Name: 0, dtype: float64
```

```
In [43]: print(neg[0].sort_values(ascending=False)[0:10])
```

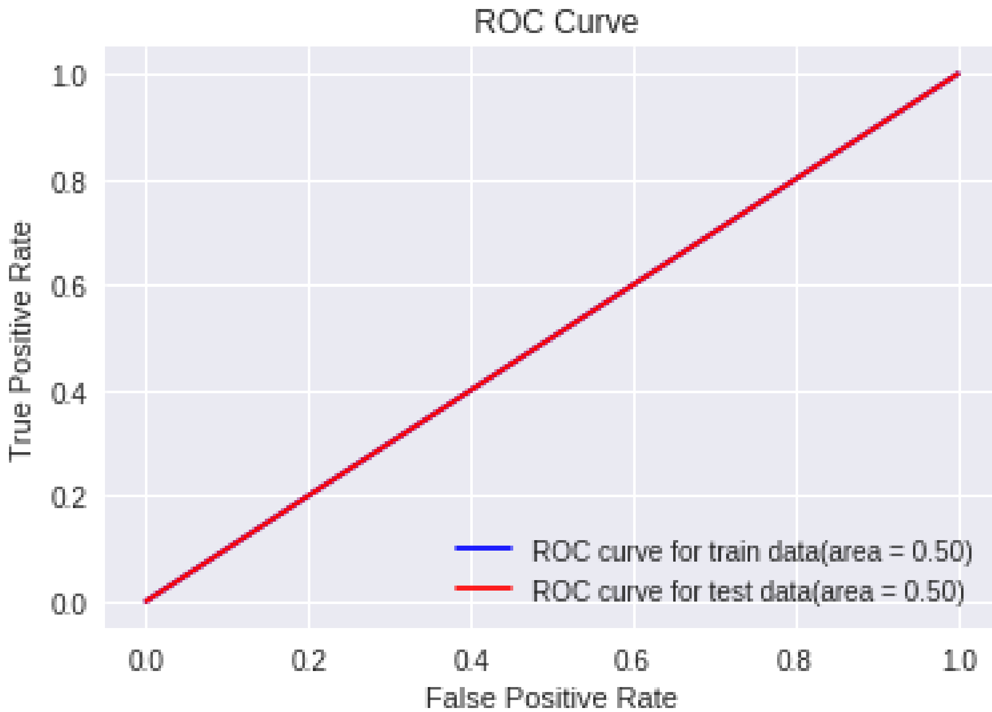
```
one opened            -5.055799e-18
hazelnut chocolate    -5.055799e-18
like straight         -1.011160e-17
quickly became        -1.011160e-17
repackaged            -1.011160e-17
know something        -1.011160e-17
makes question        -1.011160e-17
earth tea             -1.516740e-17
almost tasted         -1.516740e-17
made perfect          -1.516740e-17
Name: 0, dtype: float64
```

8.1.2 [5.1.2] Applying Linear SVM on TFIDF, SET 2

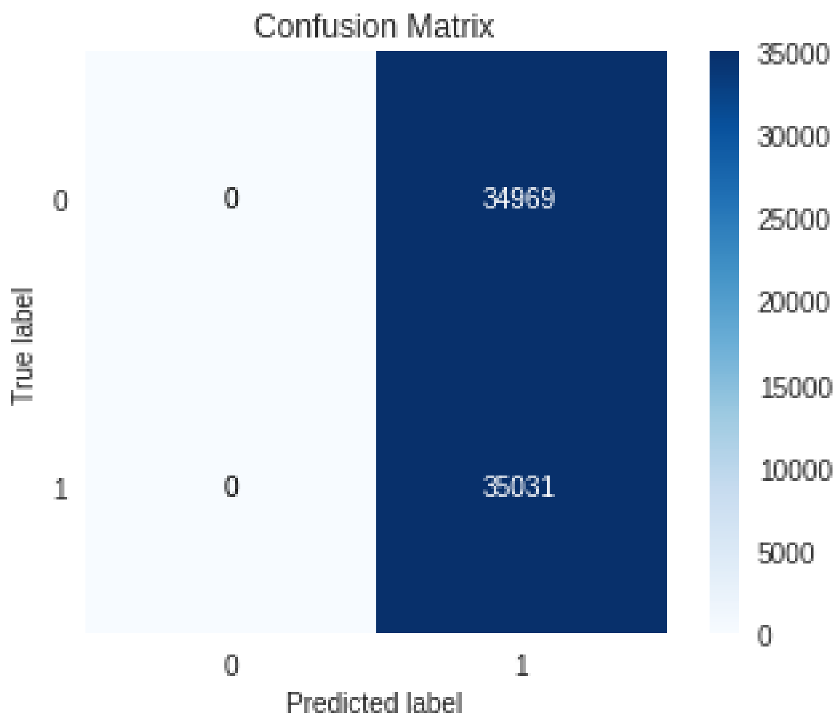
In [44]:
```
#getting alpha and regularisation
alpha,reg = hypertuning(tfidf_tr100)
#applying linear svm
w = sgd_optimal(alpha,reg,tfidf_tr100,tfidf_test100)
```

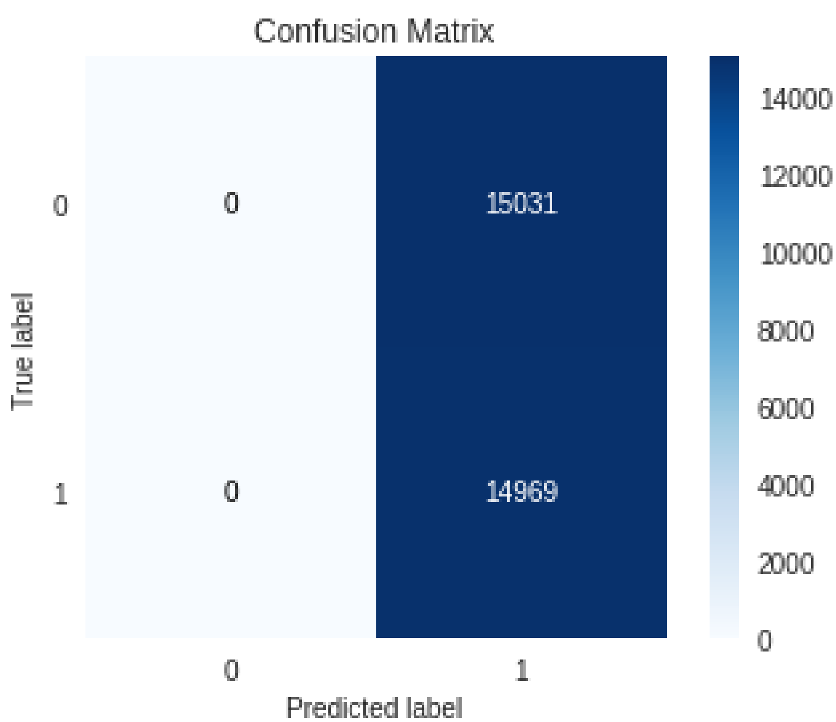



```
Optimal alpha is 0.55 and reg is l1
```

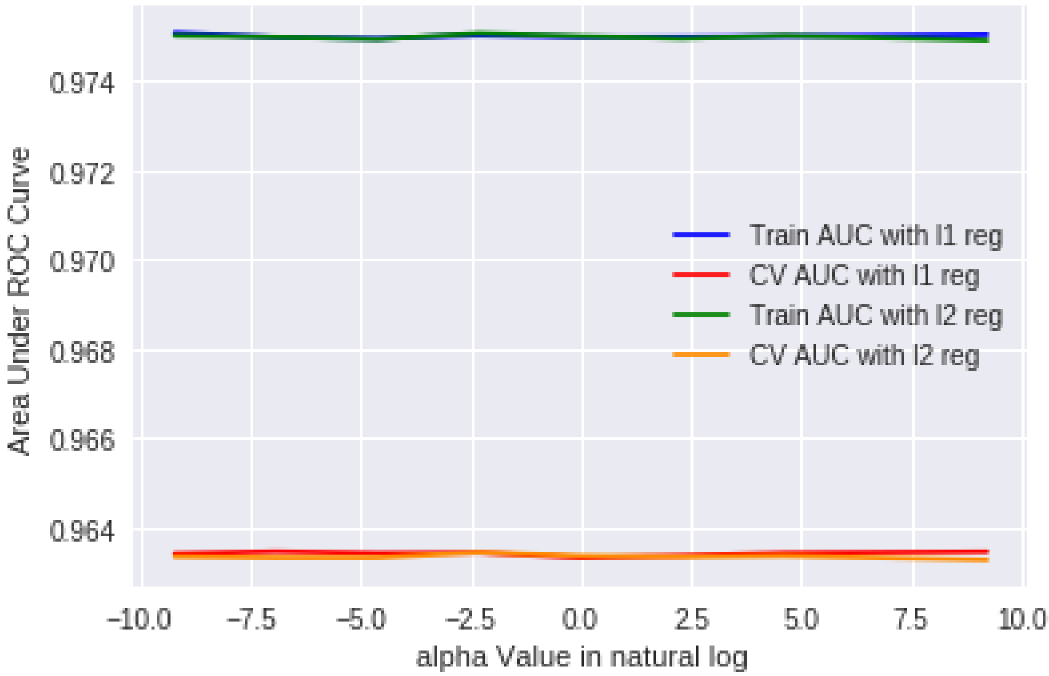



```
Confusion Matrix for Train data
              precision    recall  f1-score   support

           0       0.00      0.00      0.00     34969
           1       0.50      1.00      0.67     35031

   micro avg       0.50      0.50      0.50     70000
   macro avg       0.25      0.50      0.33     70000
weighted avg       0.25      0.50      0.33     70000

==================================================
Confusion matrix for Test data
              precision    recall  f1-score   support

           0       0.00      0.00      0.00     15031
           1       0.50      1.00      0.67     14969

   micro avg       0.50      0.50      0.50     30000
   macro avg       0.25      0.50      0.33     30000
weighted avg       0.25      0.50      0.33     30000
```

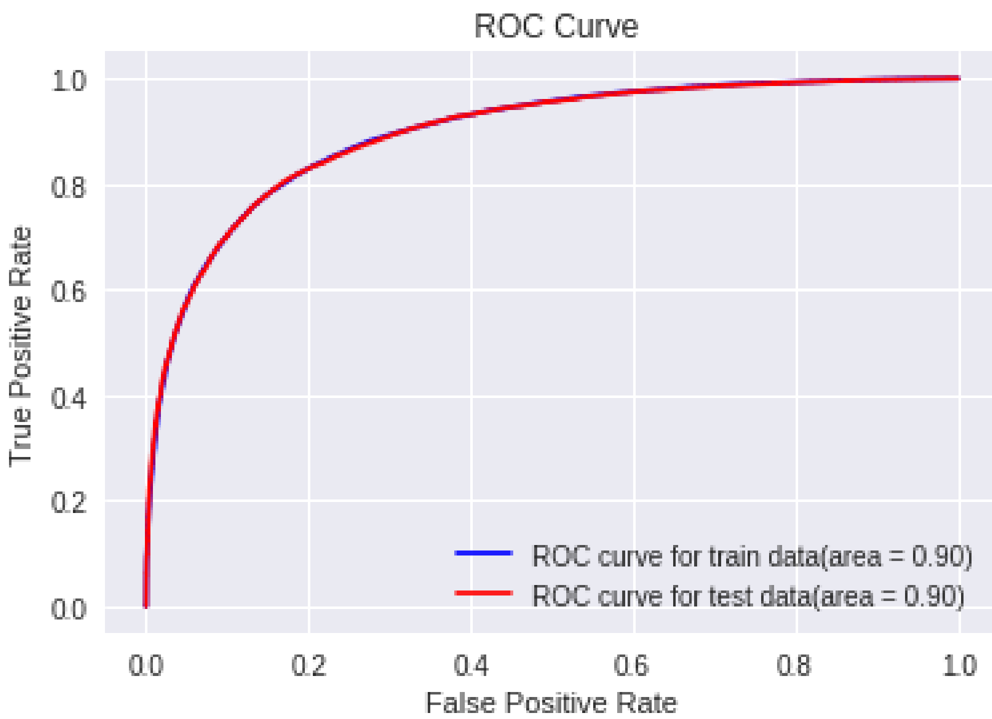

Confusion Matrix
0
34969
0
35031
0
1
True label
Predicted label
35000
30000
25000
20000
15000
10000
5000
0


Confusion Matrix
0
15031
0
14969
0
1
True label
Predicted label
14000
12000
10000
8000
6000
4000
2000
0

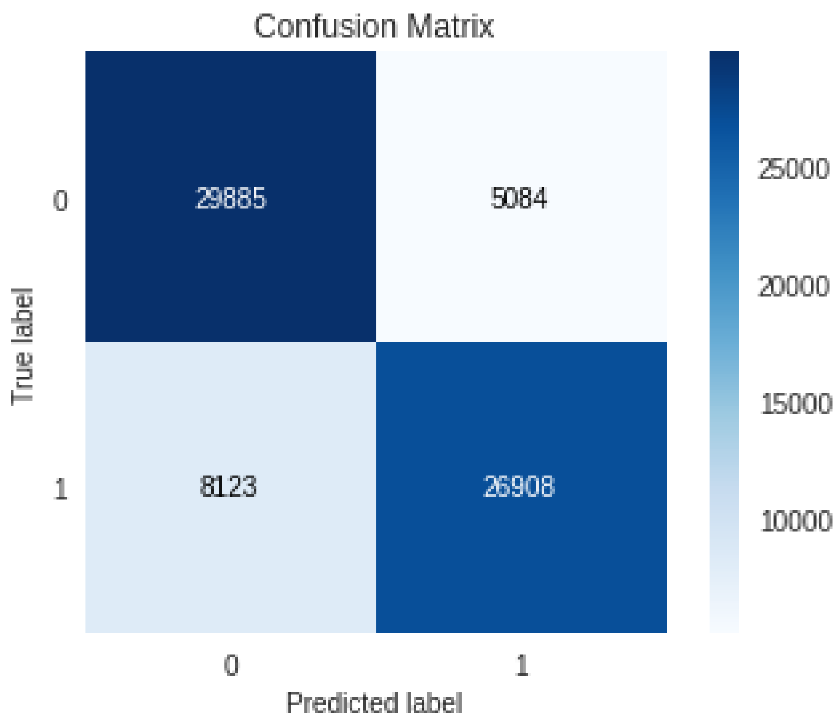
In [57]:
```
#trying again since we got a dumb model before
#getting alpha and regularisation
alpha,reg = hypertuning(tfidf_tr100)
#applying linear svm
w = sgd_optimal(alpha,reg,tfidf_tr100,tfidf_test100)
```

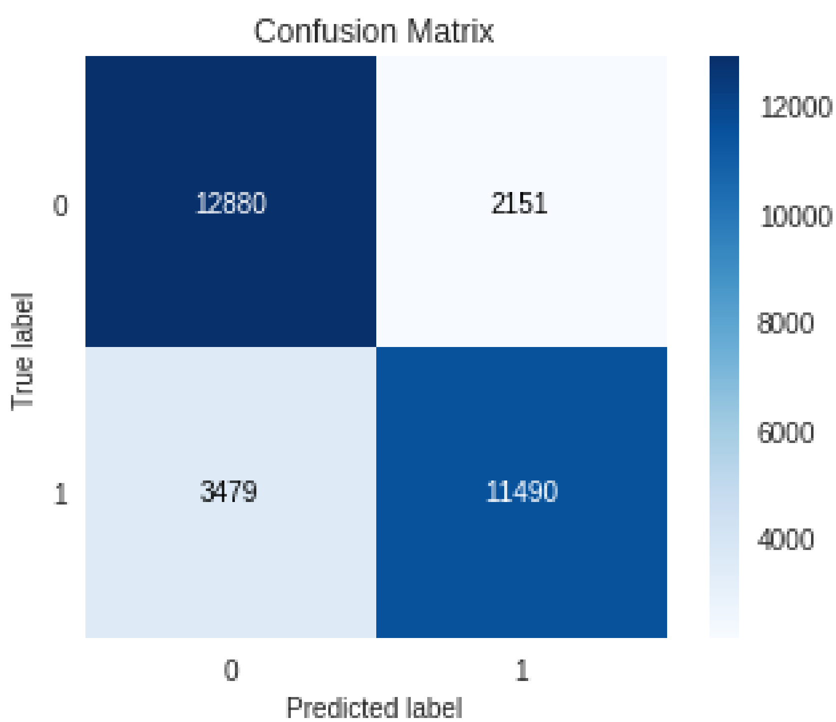



```
Optimal alpha is 0.00055 and reg is l1
```




```
Confusion Matrix for Train data
              precision    recall  f1-score   support

           0       0.79      0.85      0.82     34969
           1       0.84      0.77      0.80     35031

   micro avg       0.81      0.81      0.81     70000
   macro avg       0.81      0.81      0.81     70000
weighted avg       0.81      0.81      0.81     70000

==================================================
Confusion matrix for Test data
              precision    recall  f1-score   support

           0       0.79      0.86      0.82     15031
           1       0.84      0.77      0.80     14969

   micro avg       0.81      0.81      0.81     30000
   macro avg       0.81      0.81      0.81     30000
weighted avg       0.81      0.81      0.81     30000
```


Confusion Matrix
29885
5084
8123
26908
True label
Predicted label
0
1
0
1
25000
20000
15000
10000


Confusion Matrix
12880
2151
3479
11490
True label
Predicted label
0
1
0
1
12000
10000
8000
6000
4000

In [58]:
```
# Getting feature names from tfidf vectorizer
features_tfidf = tf_idf_vect1.get_feature_names()

#Merging them into a dataframe.
top_features = pd.DataFrame(w,columns = features_tfidf)
top_features = top_features.T
pos = top_features[top_features[0] > 0]
neg = top_features[top_features[0] < 0]
print(pos[0].sort_values(ascending=False)[0:10])
```

```
great        11.369413
best          8.665598
delicious     8.157048
good          7.148097
love          6.799800
perfect       6.142323
loves         5.900547
excellent     5.444510
favorite      5.420685
nice          4.652577
Name: 0, dtype: float64
```

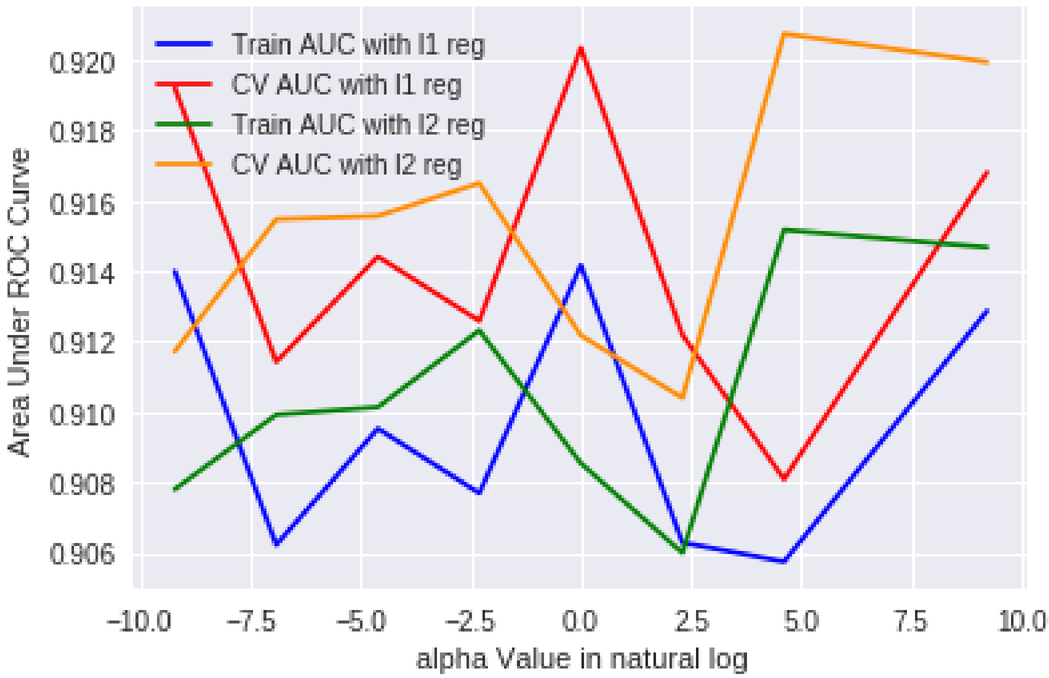
In [59]:
```
print(neg[0].sort_values(ascending=False)[0:10])
```

```
never        -0.139290
boxes        -0.153466
instead      -0.193632
pieces       -0.220026
even         -0.236083
disgusting   -0.254741
tasteless    -0.262613
package      -0.297609
would not    -0.355368
products     -0.410200
Name: 0, dtype: float64
```

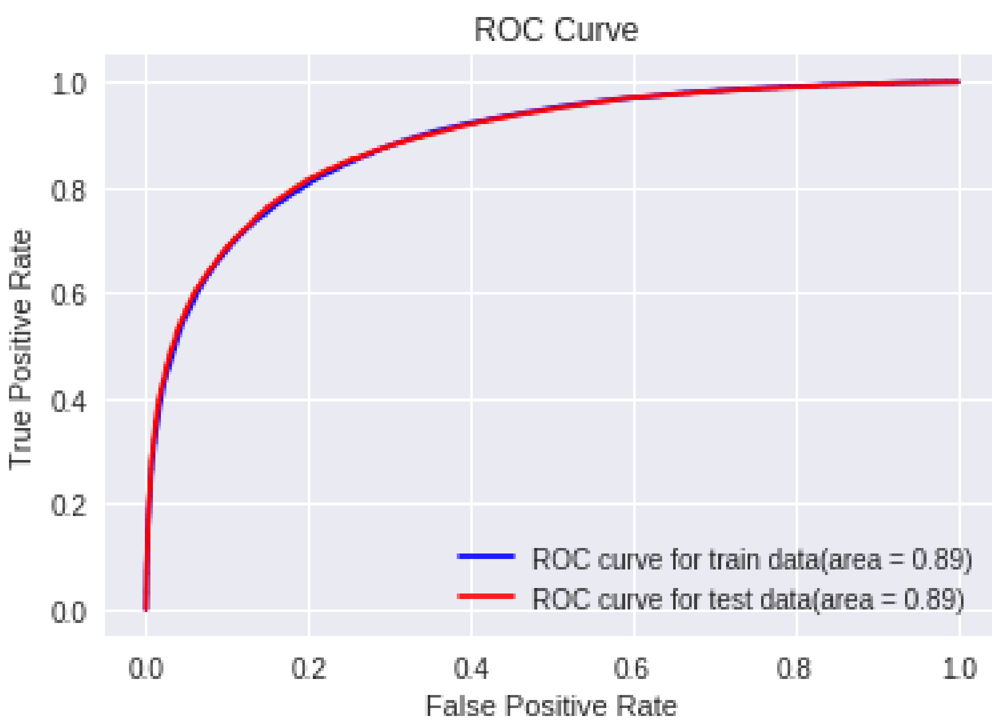
8.1.3 [5.1.3] Applying Linear SVM on AVG W2V, SET 3

In [0]:
```
sent_vectors_intr100 = np.asmatrix(sent_vectors_intr100)
sent_vectors_intest100 = np.asmatrix(sent_vectors_intest100)
```

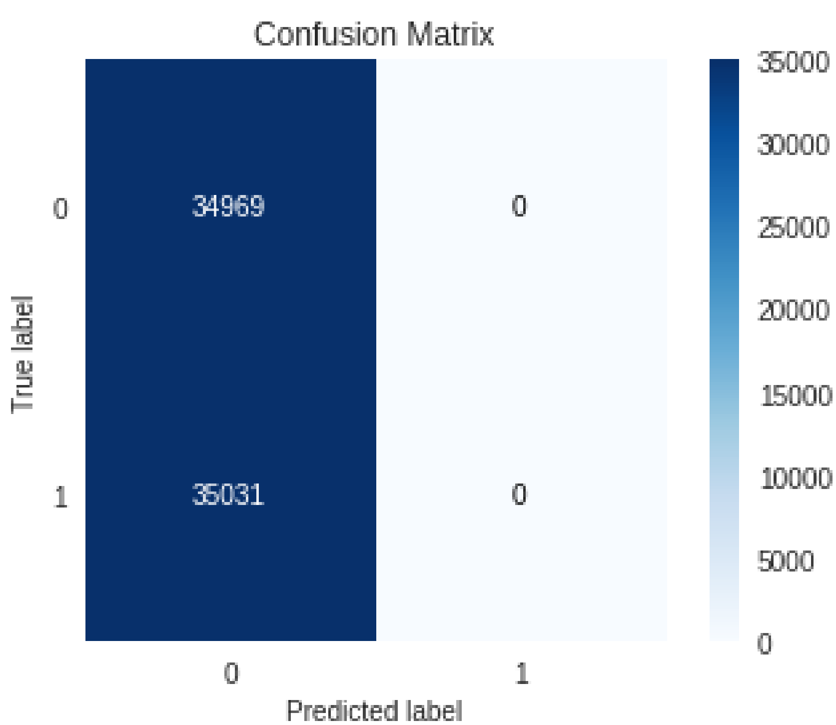
In [48]:
```
#getting alpha and regularisation
alpha,reg = hypertuning(sent_vectors_intr100)
#applying linear svm
w = sgd_optimal(alpha,reg,sent_vectors_intr100,sent_vectors_intest100)
```

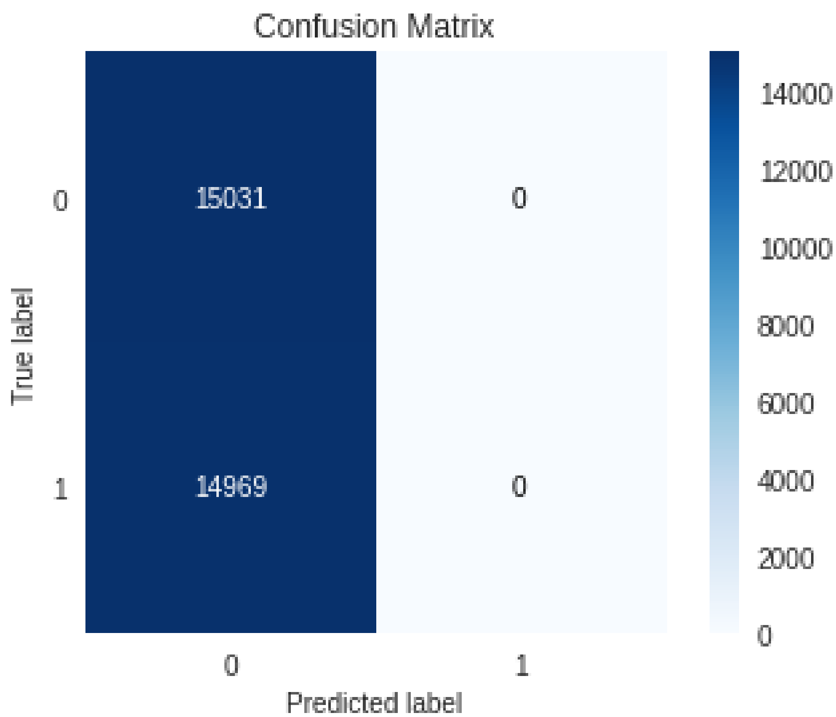



```
Optimal alpha is 100.0 and reg is l2
```

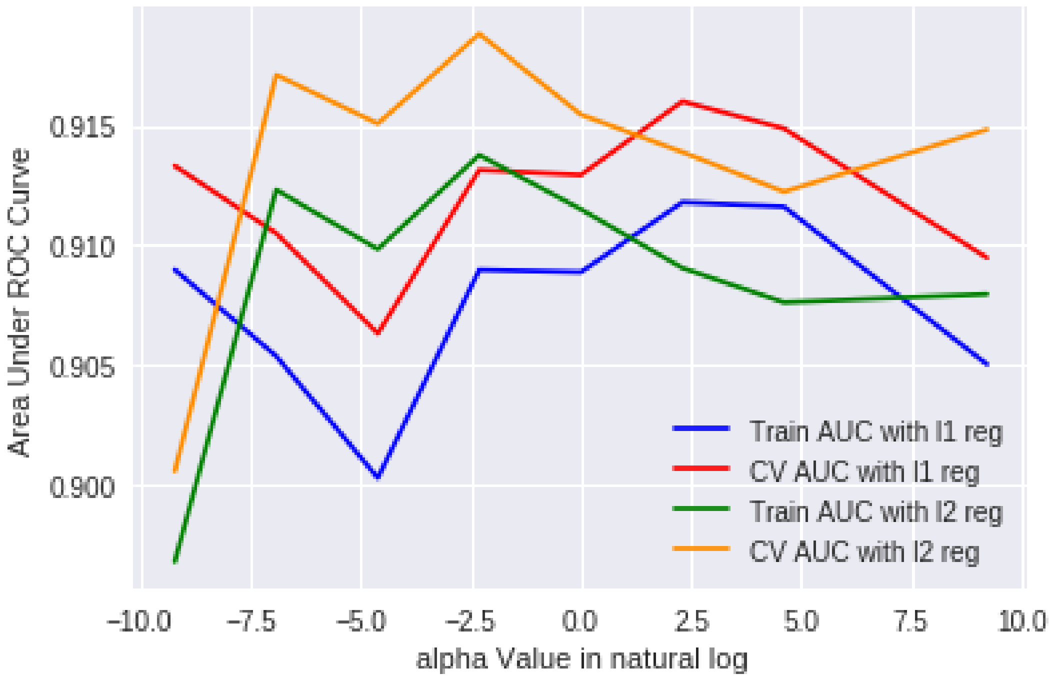


```
Confusion Matrix for Train data
              precision    recall  f1-score   support

           0       0.50      1.00      0.67     34969
           1       0.00      0.00      0.00     35031

   micro avg       0.50      0.50      0.50     70000
   macro avg       0.25      0.50      0.33     70000
weighted avg       0.25      0.50      0.33     70000

==================================================
Confusion matrix for Test data
              precision    recall  f1-score   support

           0       0.50      1.00      0.67     15031
           1       0.00      0.00      0.00     14969

   micro avg       0.50      0.50      0.50     30000
   macro avg       0.25      0.50      0.33     30000
weighted avg       0.25      0.50      0.33     30000
```

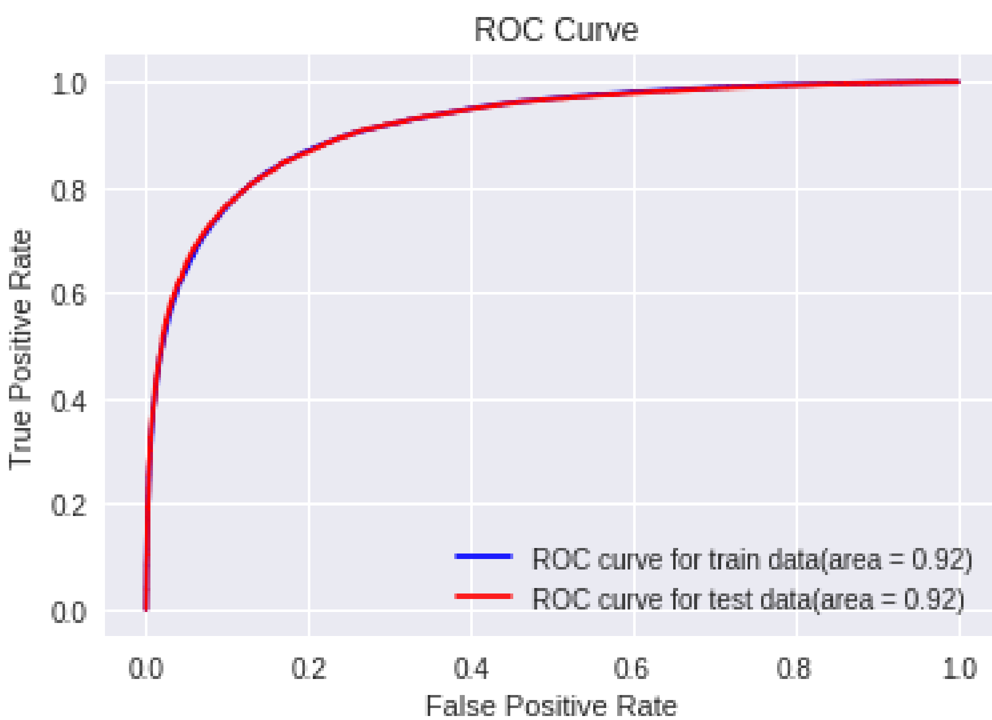




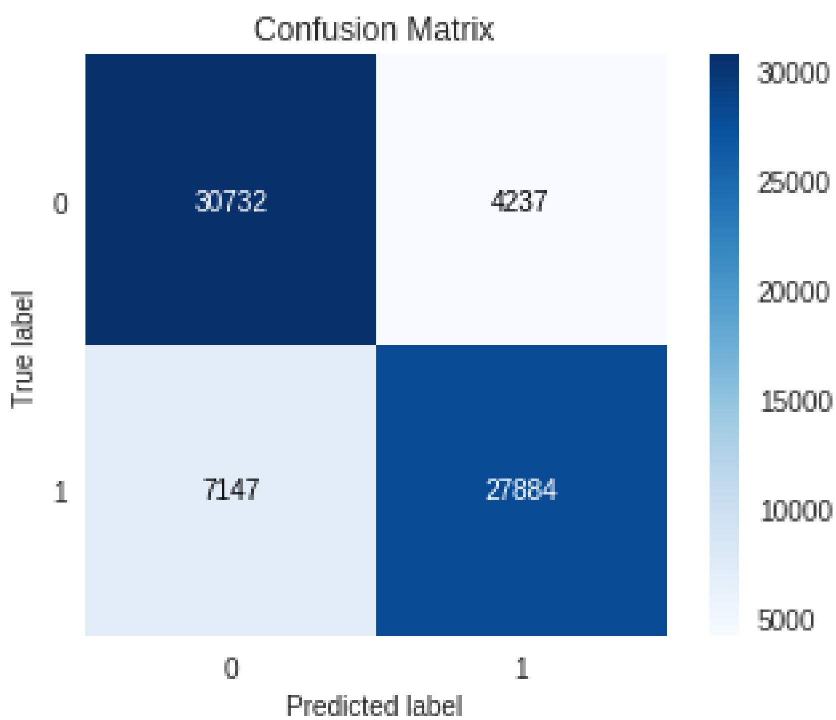
In [60]:
```
#trying again since we got a dumb model before
#getting alpha and regularisation
alpha,reg = hypertuning(sent_vectors_intr100)
#applying linear svm
w = sgd_optimal(alpha,reg,sent_vectors_intr100,sent_vectors_intest100)
```

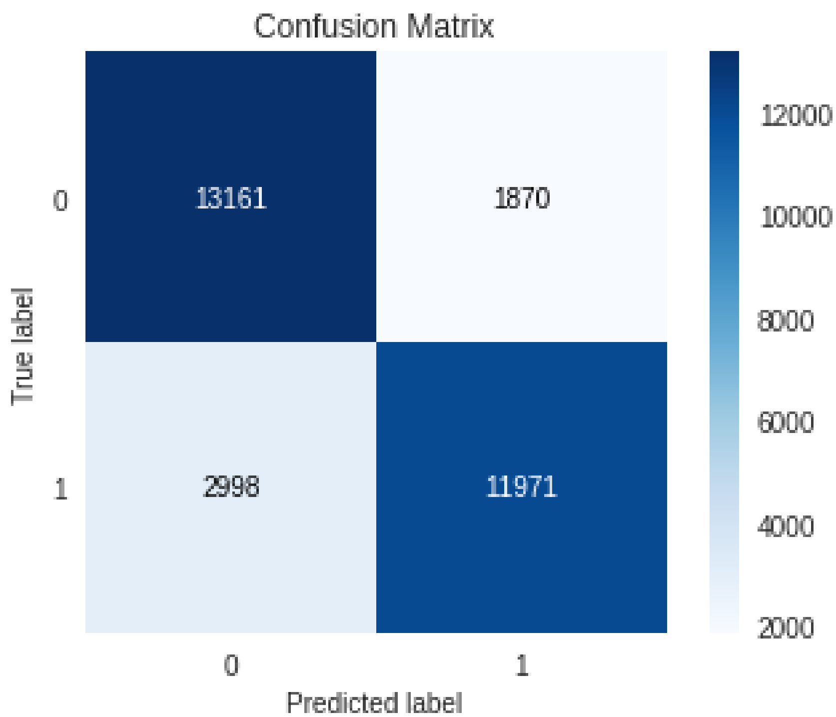



```
Optimal alpha is 0.1 and reg is l2
```



```
Confusion Matrix for Train data
              precision    recall  f1-score   support

           0       0.81      0.88      0.84     34969
           1       0.87      0.80      0.83     35031

   micro avg       0.84      0.84      0.84     70000
   macro avg       0.84      0.84      0.84     70000
weighted avg       0.84      0.84      0.84     70000

==================================================
Confusion matrix for Test data
              precision    recall  f1-score   support

           0       0.81      0.88      0.84     15031
           1       0.86      0.80      0.83     14969

   micro avg       0.84      0.84      0.84     30000
   macro avg       0.84      0.84      0.84     30000
weighted avg       0.84      0.84      0.84     30000
```

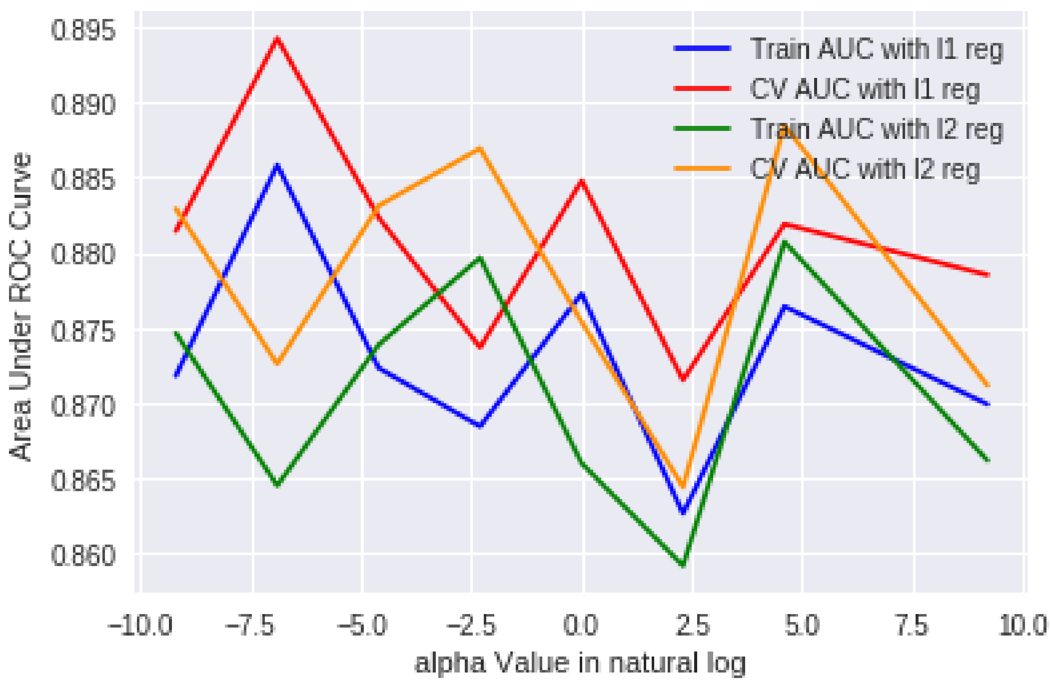




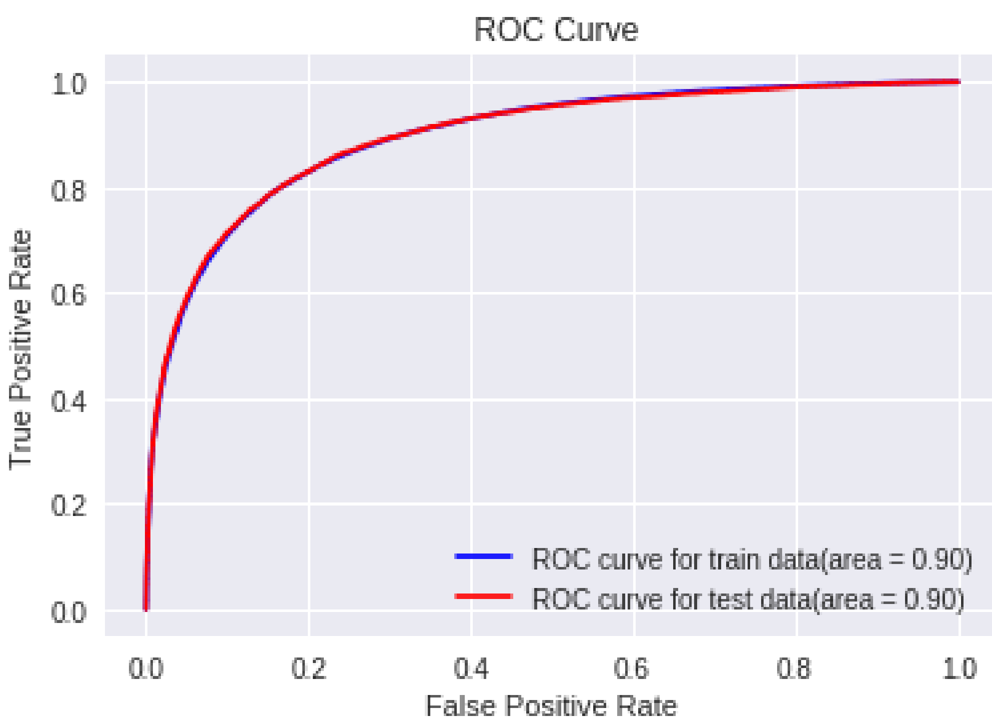
8.1.4 [5.1.4] Applying Linear SVM on TFIDF W2V, SET 4

```
In [0]: tfidf_sent_vectors_intr100 = np.asmatrix(tfidf_sent_vectors_intr100)
        tfidf_sent_vectors_intest100 = np.asmatrix(tfidf_sent_vectors_intest100)
```

```
In [50]: #getting alpha and regularisation
         alpha,reg = hypertuning(tfidf_sent_vectors_intr100)
         #applying linear svm
         w = sgd_optimal(alpha,reg,tfidf_sent_vectors_intr100,tfidf_sent_vectors_intest100)
```




```
Optimal alpha is 0.001 and reg is l1
```



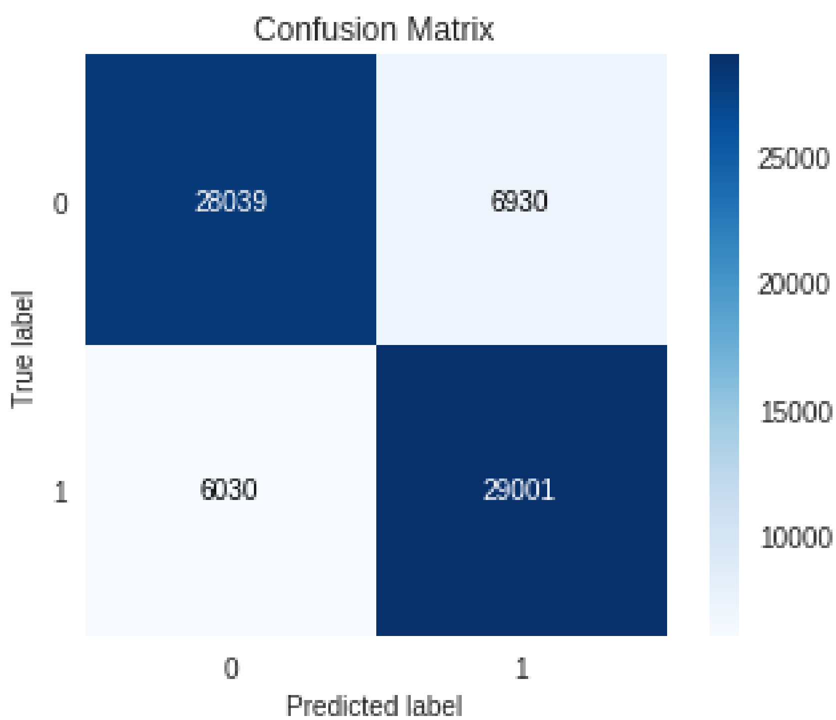
Confusion Matrix for Train data

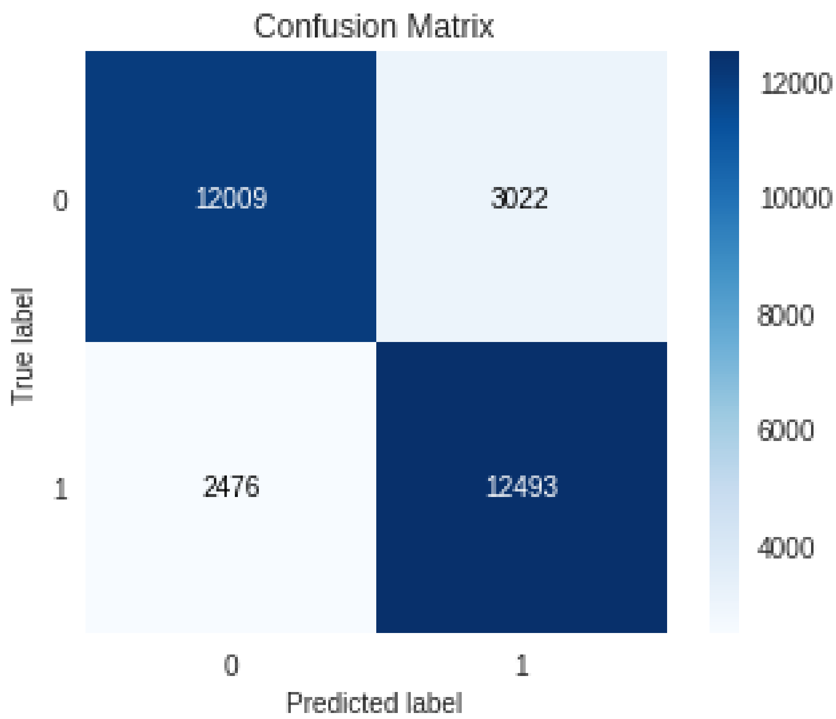
	precision	recall	f1-score	support
0	0.82	0.80	0.81	34969
1	0.81	0.83	0.82	35031
micro avg	0.81	0.81	0.81	70000
macro avg	0.82	0.81	0.81	70000
weighted avg	0.82	0.81	0.81	70000

==

Confusion matrix for Test data

	precision	recall	f1-score	support
0	0.83	0.80	0.81	15031
1	0.81	0.83	0.82	14969
micro avg	0.82	0.82	0.82	30000
macro avg	0.82	0.82	0.82	30000
weighted avg	0.82	0.82	0.82	30000



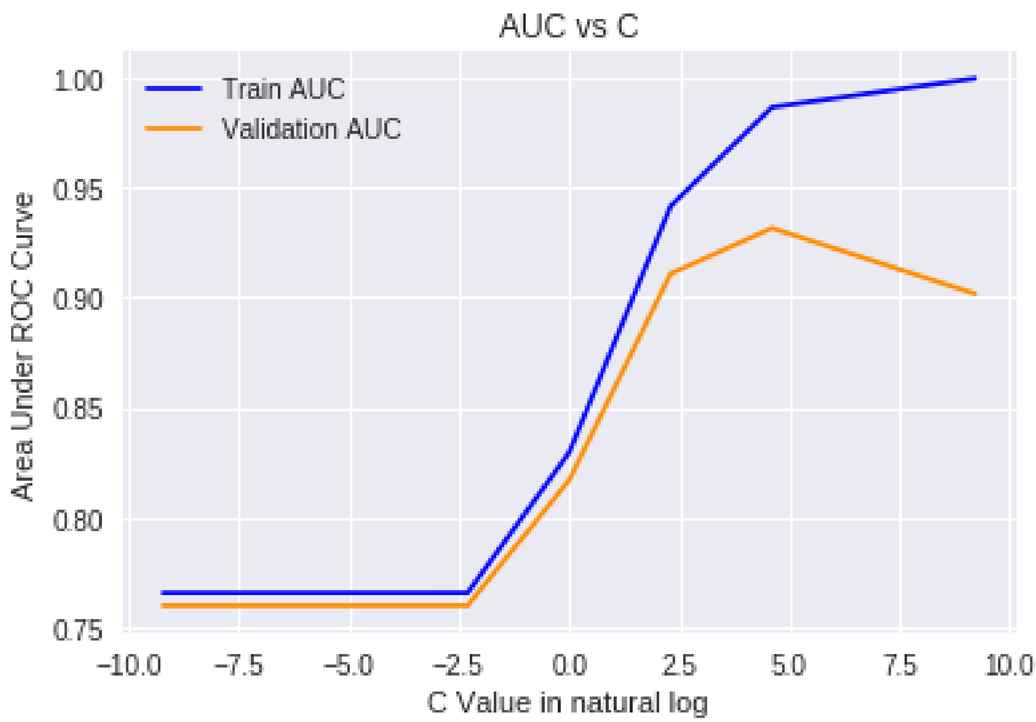


8.2 [5.2] RBF SVM

8.2.1 [5.2.1] Applying RBF SVM on BOW, SET 1

```
In [51]: #Get optimal c
         c = svmtuning(bow_vec_tr20)
         #Applying RBF SVM on data
         svm_optimal(c,bow_vec_tr20,bow_vec_test20)
```

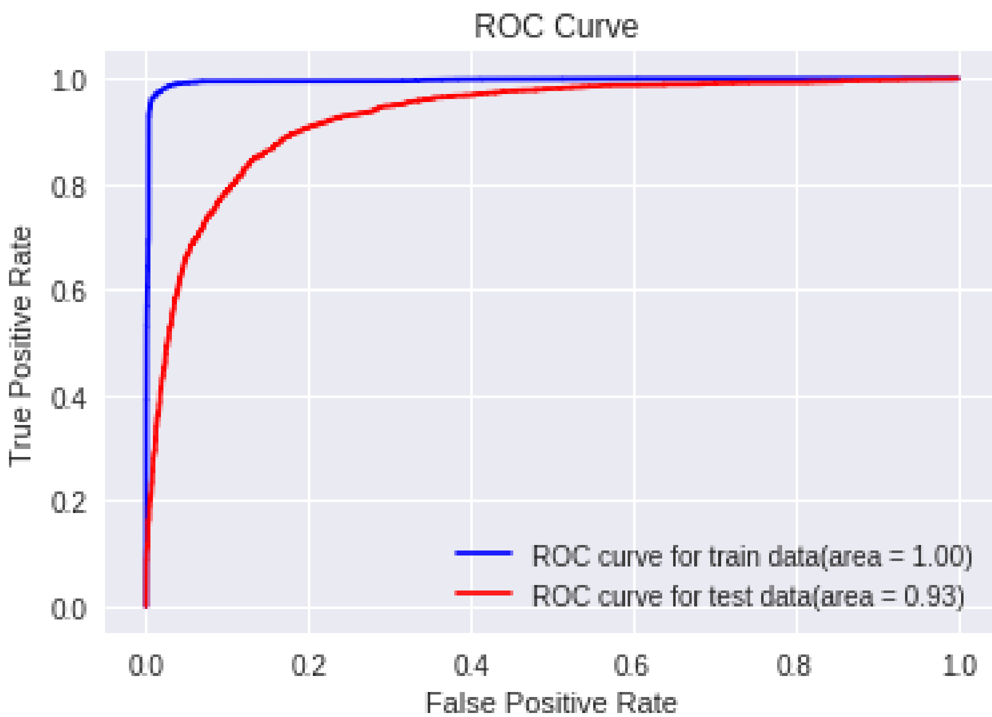
```
SVC(C=100, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
  max_iter=-1, probability=True, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```



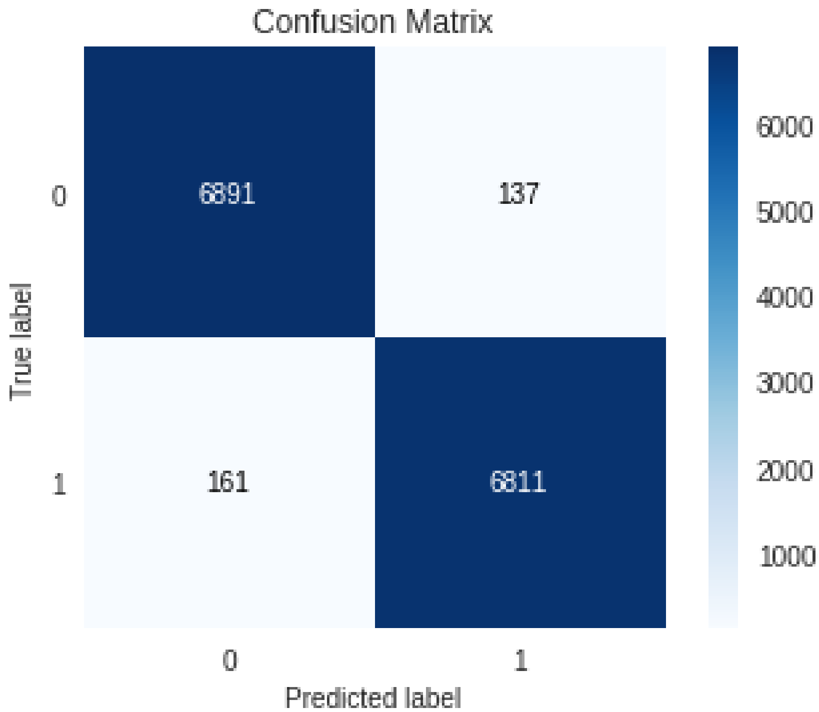
The optimal c for training data is 10000.000000 and ROC is 0.999996.

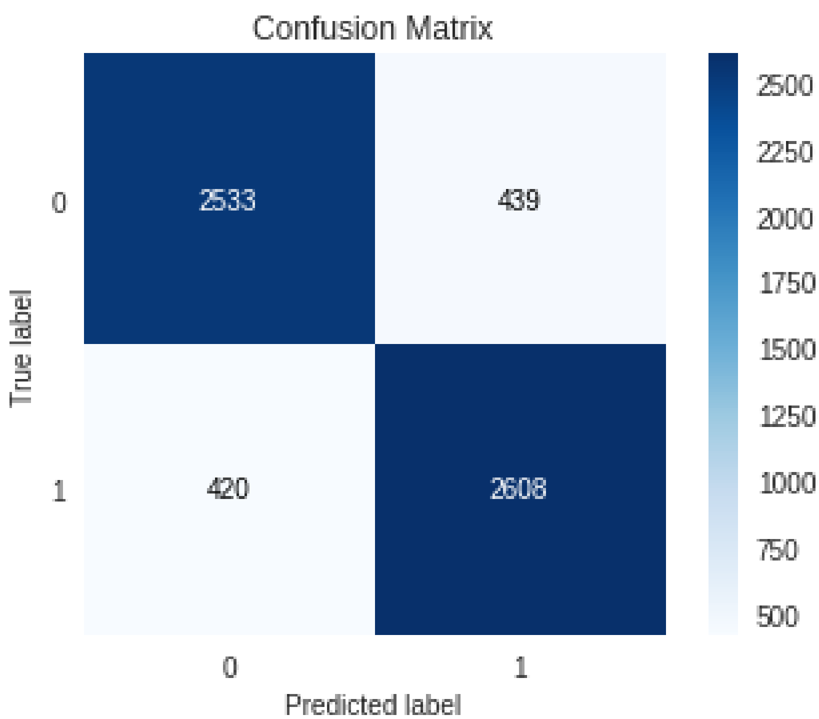
The optimal c for validation data is 100.000000 and ROC is 0.931740.

The calculated optimal c for model is 1000.000000.




```
Confusion Matrix for Train data
              precision    recall  f1-score   support

           0       0.98      0.98      0.98      7028
           1       0.98      0.98      0.98      6972

   micro avg       0.98      0.98      0.98     14000
   macro avg       0.98      0.98      0.98     14000
weighted avg       0.98      0.98      0.98     14000

==================================================
Confusion matrix for Test data
              precision    recall  f1-score   support

           0       0.86      0.85      0.86      2972
           1       0.86      0.86      0.86      3028

   micro avg       0.86      0.86      0.86      6000
   macro avg       0.86      0.86      0.86      6000
weighted avg       0.86      0.86      0.86      6000
```

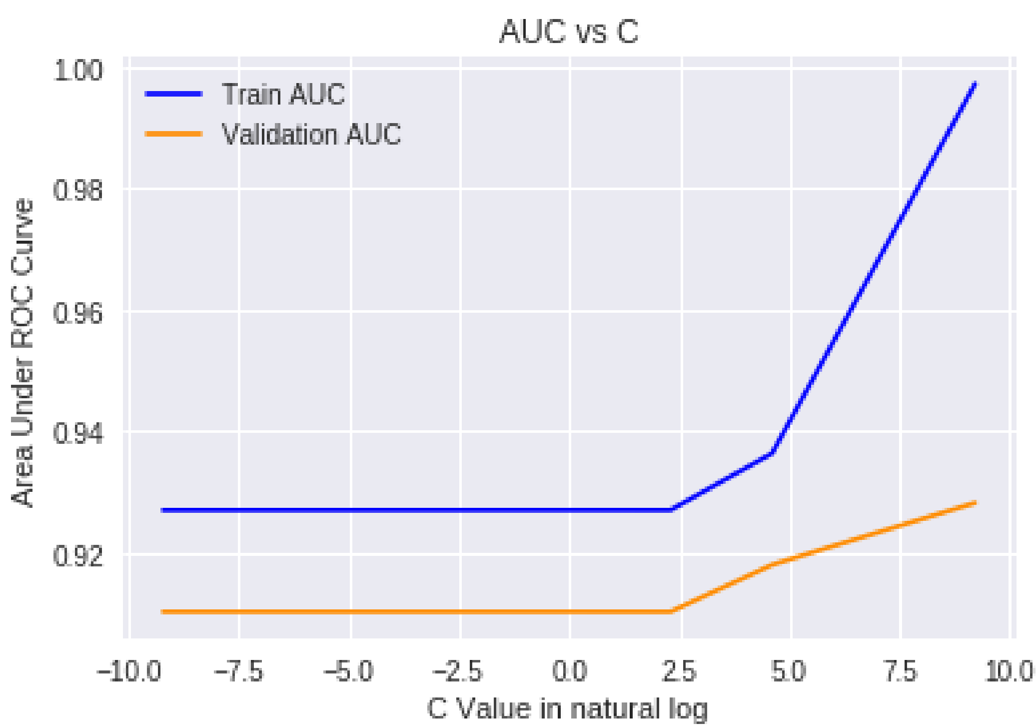

Confusion Matrix
True label
0
1
6891
137
161
6811
Predicted label
6000
5000
4000
3000
2000
1000


Confusion Matrix
True label
0
1
2533
439
420
2608
Predicted label
2500
2250
2000
1750
1500
1250
1000
750
500

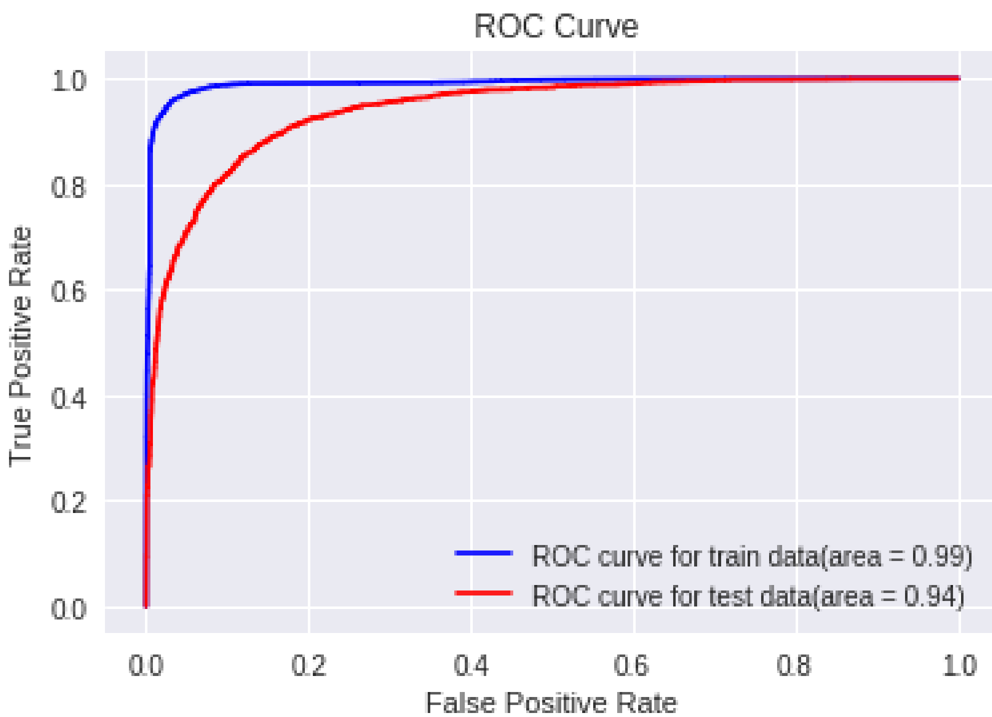
8.2.2 [5.2.2] Applying RBF SVM on TFIDF, SET 2

In [53]:
```
#Get optimal c
c = svmtuning(tfidf_tr20)
#Applying RBF SVM on data
svm_optimal(c,tfidf_tr20,tfidf_test20)
```

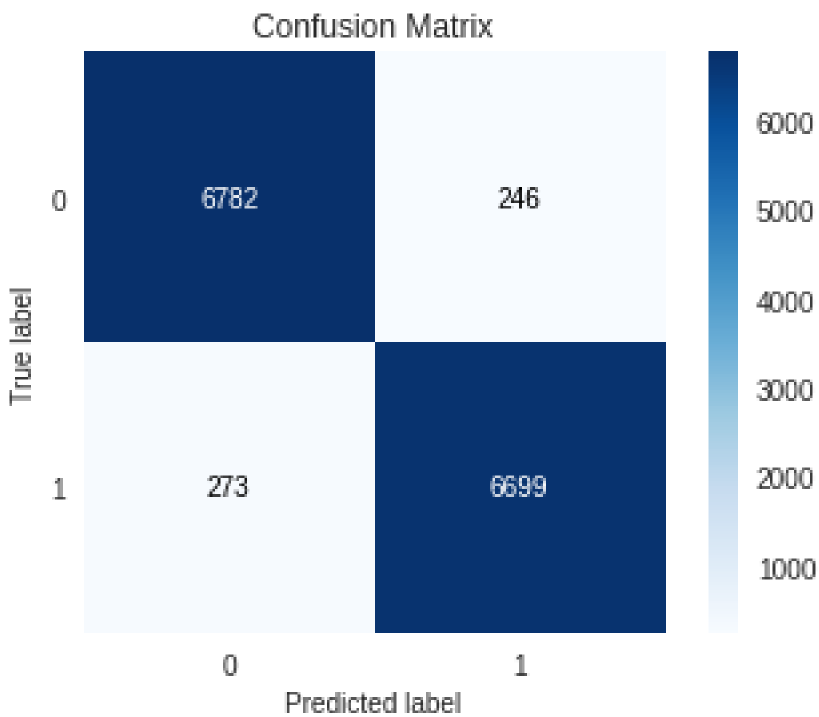
```
SVC(C=10000, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
  max_iter=-1, probability=True, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

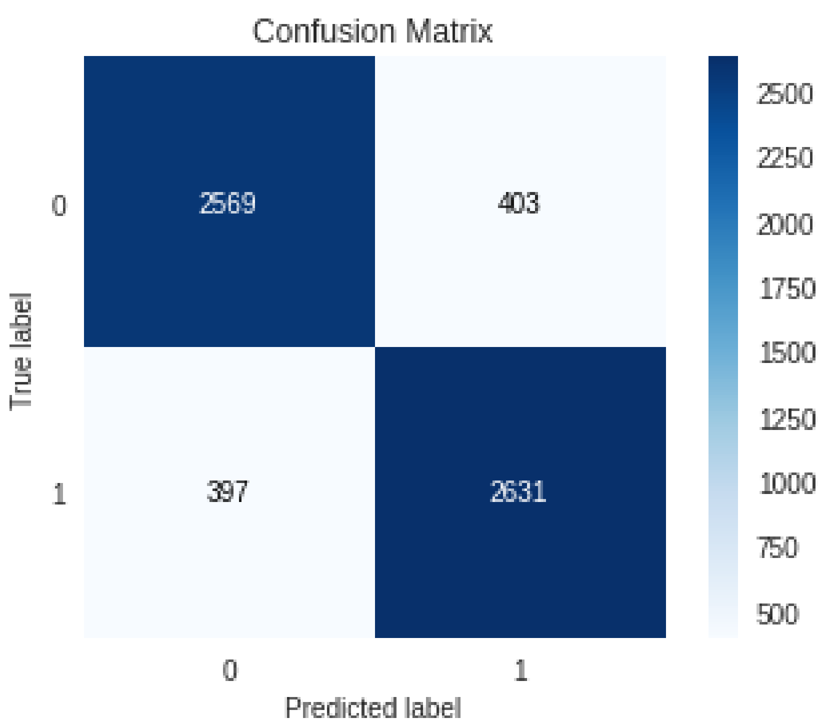



```
The optimal c for training data is 10000.000000 and ROC is 0.997122.

The optimal c for validation data is 10000.000000 and ROC is 0.928160.

The calculated optimal c for model is 10000.000000.
```




```
Confusion Matrix for Train data
              precision    recall  f1-score   support

           0       0.96      0.96      0.96      7028
           1       0.96      0.96      0.96      6972

   micro avg       0.96      0.96      0.96     14000
   macro avg       0.96      0.96      0.96     14000
weighted avg       0.96      0.96      0.96     14000

==================================================
Confusion matrix for Test data
              precision    recall  f1-score   support

           0       0.87      0.86      0.87      2972
           1       0.87      0.87      0.87      3028

   micro avg       0.87      0.87      0.87      6000
   macro avg       0.87      0.87      0.87      6000
weighted avg       0.87      0.87      0.87      6000
```

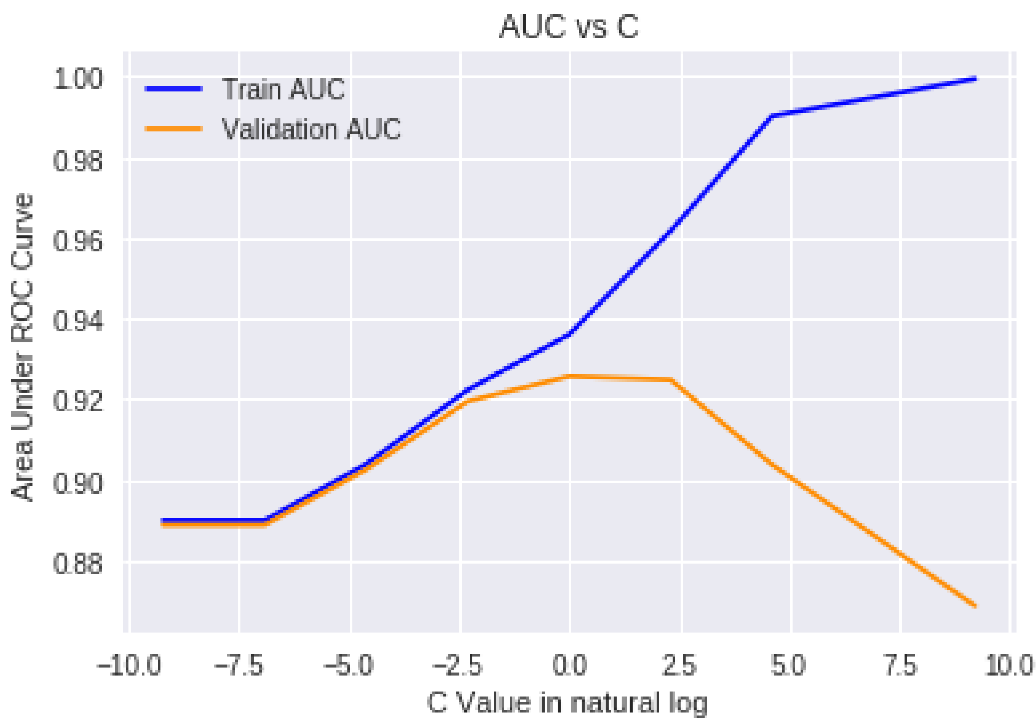

Confusion Matrix
0
1
True label
6782
246
273
6699
0
1
Predicted label
6000
5000
4000
3000
2000
1000


Confusion Matrix
0
1
True label
2569
403
397
2631
0
1
Predicted label
2500
2250
2000
1750
1500
1250
1000
750
500

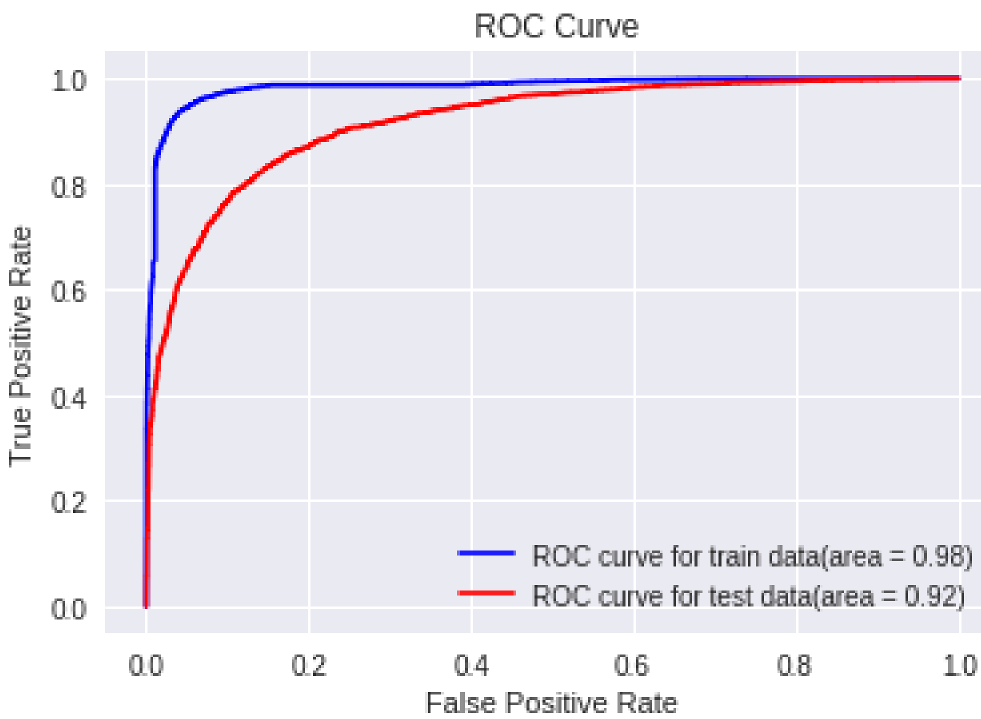
8.2.3 [5.2.3] Applying RBF SVM on AVG W2V, SET 3

```
In [54]: #Get optimal c
         c = svmtuning(sent_vectors_intr20)
         #Applying RBF SVM on data
         svm_optimal(c,sent_vectors_intr20,sent_vectors_intest20)
```

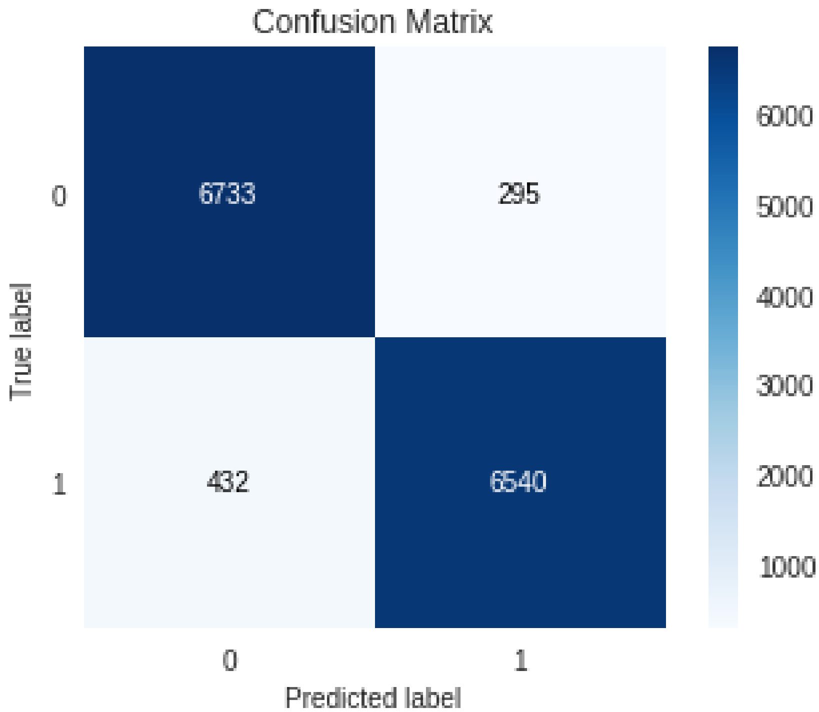
```
SVC(C=1, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
  max_iter=-1, probability=True, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

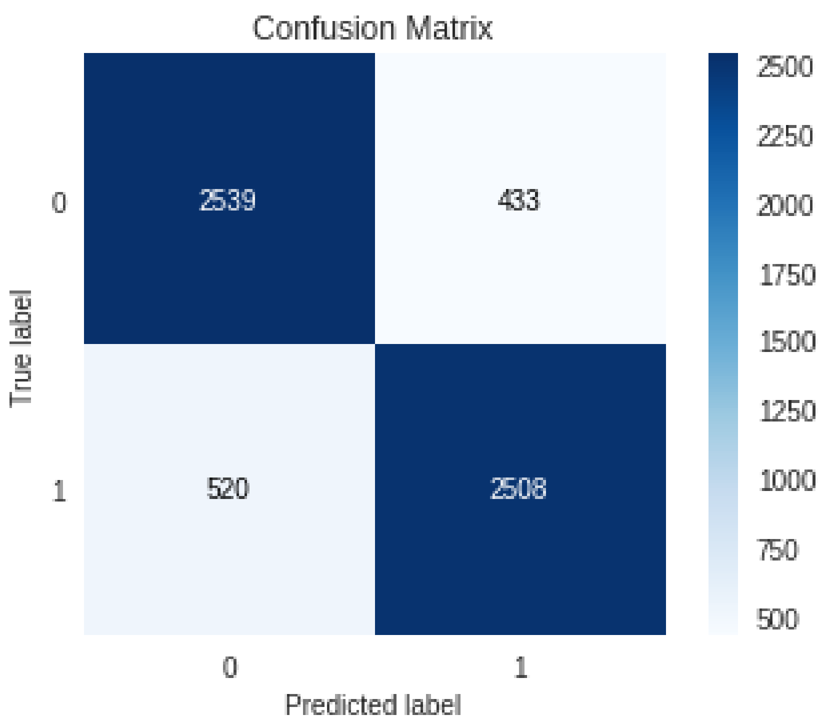



```
The optimal c for training data is 10000.000000 and ROC is 0.999496.

The optimal c for validation data is 1.000000 and ROC is 0.925695.

The calculated optimal c for model is 100.000000.
```




```
Confusion Matrix for Train data
              precision    recall  f1-score   support

           0       0.94      0.96      0.95      7028
           1       0.96      0.94      0.95      6972

   micro avg       0.95      0.95      0.95     14000
   macro avg       0.95      0.95      0.95     14000
weighted avg       0.95      0.95      0.95     14000

==================================================
Confusion matrix for Test data
              precision    recall  f1-score   support

           0       0.83      0.85      0.84      2972
           1       0.85      0.83      0.84      3028

   micro avg       0.84      0.84      0.84      6000
   macro avg       0.84      0.84      0.84      6000
weighted avg       0.84      0.84      0.84      6000
```

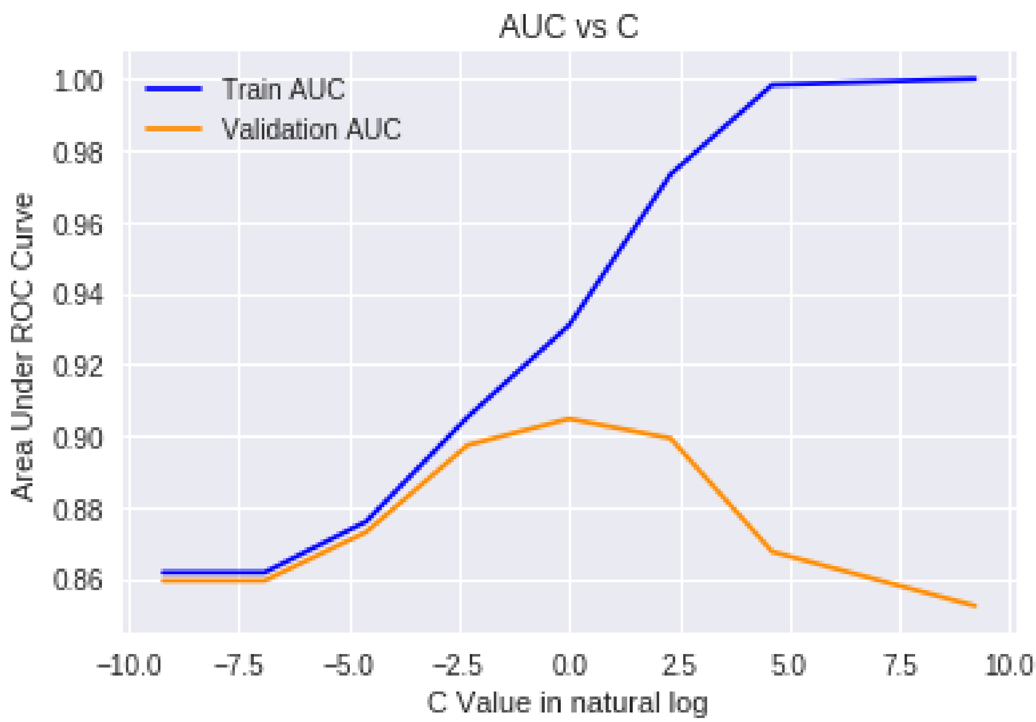

Confusion Matrix
6733
295
432
6540
True label
Predicted label
0
1
6000
5000
4000
3000
2000
1000


Confusion Matrix
2539
433
520
2508
True label
Predicted label
0
1
2500
2250
2000
1750
1500
1250
1000
750
500

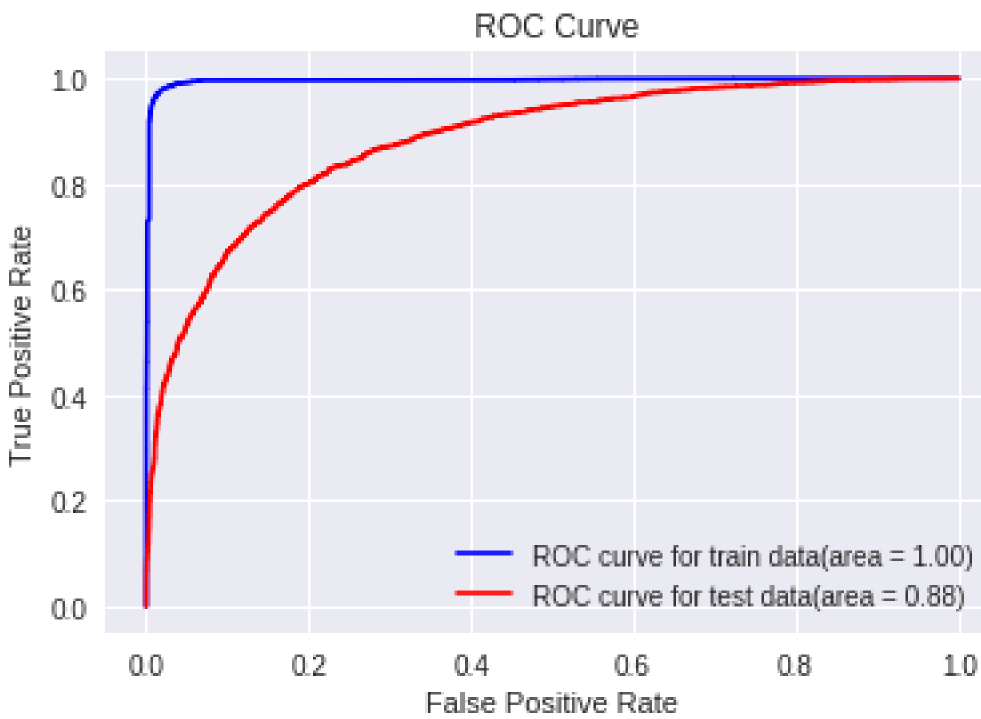
8.2.4 [5.2.4] Applying RBF SVM on TFIDF W2V, SET 4

In [55]:
```
#Get optimal c
c = svmtuning(tfidf_sent_vectors_intr20)
#Applying RBF SVM on data
svm_optimal(c,tfidf_sent_vectors_intr20,tfidf_sent_vectors_intest20)
```

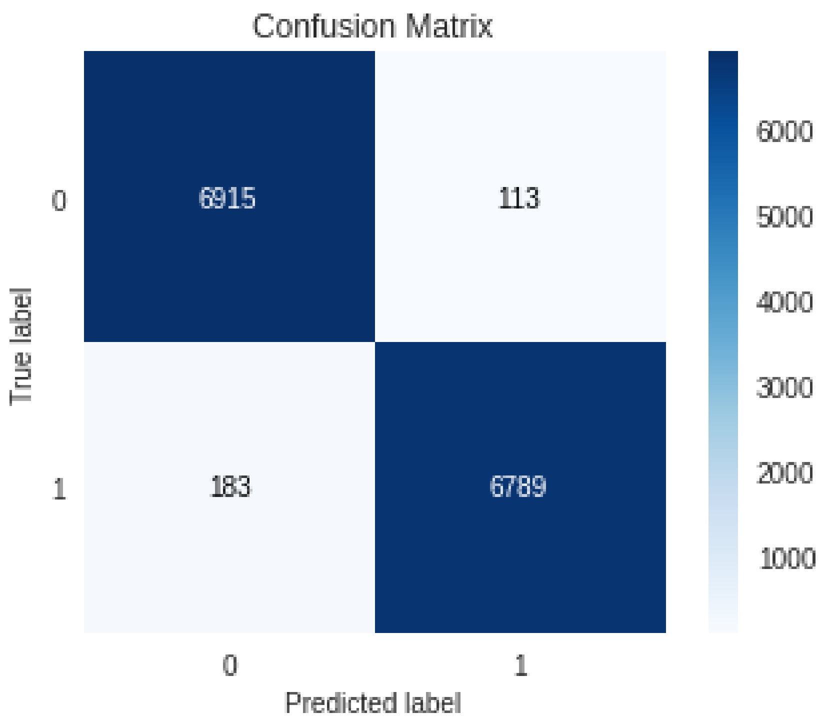
```
SVC(C=1, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
  max_iter=-1, probability=True, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

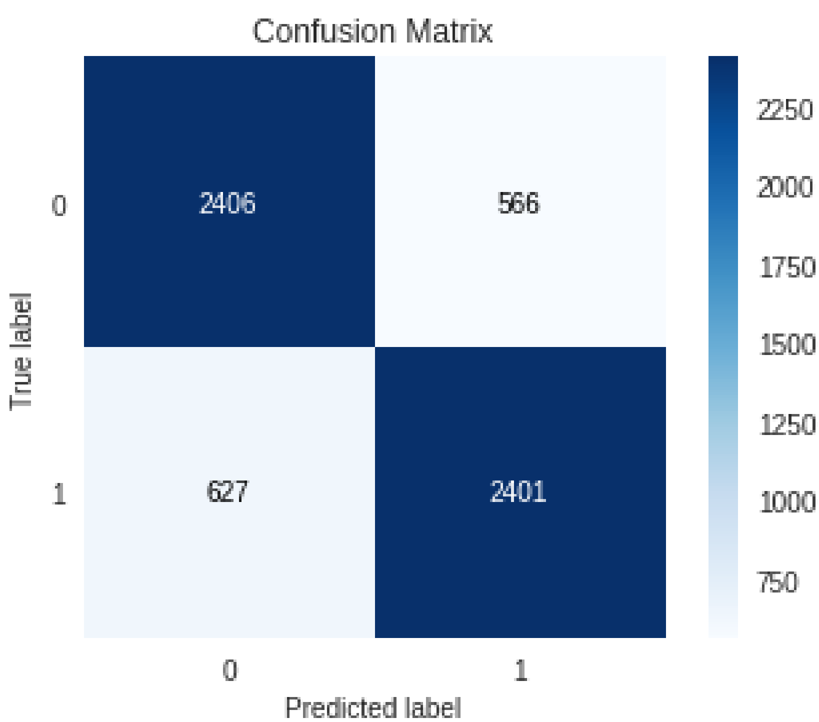



```
The optimal c for training data is 10000.000000 and ROC is 0.999921.

The optimal c for validation data is 1.000000 and ROC is 0.904731.

The calculated optimal c for model is 100.000000.
```




```
Confusion Matrix for Train data
              precision    recall  f1-score   support

           0       0.97      0.98      0.98      7028
           1       0.98      0.97      0.98      6972

   micro avg       0.98      0.98      0.98     14000
   macro avg       0.98      0.98      0.98     14000
weighted avg       0.98      0.98      0.98     14000

==================================================
Confusion matrix for Test data
              precision    recall  f1-score   support

           0       0.79      0.81      0.80      2972
           1       0.81      0.79      0.80      3028

   micro avg       0.80      0.80      0.80      6000
   macro avg       0.80      0.80      0.80      6000
weighted avg       0.80      0.80      0.80      6000
```


Confusion Matrix
True label
Predicted label
0
1
6915
113
183
6789
6000
5000
4000
3000
2000
1000


Confusion Matrix
True label
Predicted label
0
1
2406
566
627
2401
2250
2000
1750
1500
1250
1000
750

9 [6] Conclusions

```
In [61]: !pip install -q PTable
         from prettytable import PrettyTable
         z = PrettyTable()
         z.field_names = ["Vectorizer", "Model", "Regularisation","Hyperparameter[ in linear ar
         #Final summary
         z.add_row(["BoW", 'Linear SVM','l2',0.0001, '0.96'])
         z.add_row(["BoW", 'Kernel SVM', '-',1000, '0.93'])
         z.add_row(["TF_IDF",'Linear SVM','l1',0.00055, '0.90'])
         z.add_row(["TF_IDF", 'Kernel SVM','-', 10000, '0.94'])
         z.add_row(["Avg W2V", 'Linear SVM','l2', 0.1, '0.92'])
         z.add_row(["Avg W2V", 'Kernel SVM', '-',100, '0.92'])
         z.add_row(["TF_IDF weighted W2V",'Linear SVM','l1', 0.001, '0.90'])
         z.add_row(["TF_IDF weighted W2V", 'Kernel SVM','-', 100, '0.88'])
         print(z)
```

```
+---------------------+------------+----------------+----------------------------------------
|      Vectorizer     |   Model    | Regularisation | Hyperparameter[ in linear and c in RBF S
+---------------------+------------+----------------+----------------------------------------
|         BoW         | Linear SVM |       l2       |                  0.0001
|         BoW         | Kernel SVM |       -        |                   1000
|        TF_IDF       | Linear SVM |       l1       |                 0.00055
|        TF_IDF       | Kernel SVM |       -        |                  10000
|       Avg W2V       | Linear SVM |       l2       |                   0.1
|       Avg W2V       | Kernel SVM |       -        |                   100
| TF_IDF weighted W2V | Linear SVM |       l1       |                  0.001
| TF_IDF weighted W2V | Kernel SVM |       -        |                   100
+---------------------+------------+----------------+----------------------------------------
```

CONCLUSIONS:

1. Hyperparameters are to be chosen correctly. As can be observed in the above models in tfidf and avg w2v, the alpha chosen was different and gave dumb models. Sometimes we have to re run to get good results.
2. Here, standardising the data in some vectorizors also gave dumb models. It might be that the variance was lost due to standardisation.
3. Linear SVC was performed using SGDClasssifier using hinge loss(default).Since, it does not give probabiltiy estimates, calibratedclassifiercv was used, to get AUC.
4. In RBF SVM, the decision surface depends on hyperparameter c and gamma. Gamma was set to auto to get optimal gamma and GridSearch was done by setting SVC probability parameter as True.