Assignment-5: Apply Support Vector Machine On Amazon Fine Food Reviews DataSet

Introduction

(i).“Support Vector Machine” (SVM) is a supervised machine learning algorithm which can be used for both classification or regression challenges. However, it is mostly used in classification problems.

(ii).The main goal of this algorithm is to find the optimal hyperplane.

Objective

To Predict the Polarity of Amazon Fine Food Review Using Support Vector Machine Algorithm.

Importing All Required Library

In [1]:
```
%matplotlib inline
import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
import math

from sklearn.model_selection import GridSearchCV
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.linear_model import SGDClassifier
from sklearn.svm import SVC
from sklearn.calibration import CalibratedClassifierCV


from sklearn.metrics import classification_report
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import TimeSeriesSplit

from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from sklearn.model_selection import cross_val_score
from sklearn import preprocessing
from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score

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


import pickle

from tqdm import tqdm
import os
import warnings
warnings.filterwarnings("ignore")
```

```
C:\Users\User\Anaconda3\lib\site-packages\gensim\utils.py:1197: UserWarning:
detected Windows; aliasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

Importing Amazon Fine Food Review Dataset

In [2]:
```
if os.path.isfile("final.sqlite"):
    conn=sqlite3.connect("final.sqlite")
    Data=pd.read_sql_query("select * from Reviews where Score!=3",conn)
    conn.close()
else :
    print("Error Importing the file")
```

In [3]:
```
# Printing some data of DataFrame

Data['Score'].value_counts()
```

Out[3]:
```
1    307061
0     57110
Name: Score, dtype: int64
```

Information About DataSet

In [4]:
```
print("\nNumber of Reviews: ",Data["Text"].count())
print("\nNumber of Users: ",len(Data["UserId"].unique())) # Unique returns 1-D array of unique values of DataFrame.
print("\nNumber of Products: ",len(Data["ProductId"].unique()))
print("\nShape of Data: ", Data.shape)
print("\nColumn Name of DataSet : ",Data.columns)
print("\n\nNumber of Attributes/Columns in data: 12")
print("\nNumber of Positive Reviews : ", Data['Score'].value_counts()[1])
print("\nNumber of Negative Reviews : ", Data['Score'].value_counts()[0])
```

```
Number of Reviews:  364171

Number of Users:  243414

Number of Products:  65442

Shape of Data:  (364171, 12)

Column Name of DataSet :  Index(['index', 'Id', 'ProductId', 'UserId', 'Profi
leName',
       'HelpfulnessNumerator', 'HelpfulnessDenominator', 'Score', 'Time',
       'Summary', 'Text', 'CleanedText'],
      dtype='object')


Number of Attributes/Columns in data: 12

Number of Positive Reviews :  307061

Number of Negative Reviews :  57110
```

In [5]:
```
print("\nNumber of Reviews: ",Data["Text"].count())
```

```
Number of Reviews:  364171
```

Attribute Information About DataSet

1.Id - A unique value starts from 1

2.ProductId - A unique identifier for the product

3.UserId - A unqiue identifier for the user

4.ProfileName - Name of user profile

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 0 or 1

8.Time - Timestamp for the review

9.Summary - Brief summary of the review

10.Text - Text of the review

11.Cleaned Text - Text that only alphabets

In [6]:
```
# Sorting on the basis of Time Parameter
Data.sort_values('Time',inplace=True)
```

In [7]:
```
Data=Data.head(100000)
```

In [8]:
```
Y = Data['Score']
X = Data['CleanedText']
```

Splitting DataSet into Train and Test Data

In [9]:
```
from sklearn.model_selection import train_test_split
# X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.33, sh
uffle=Flase): this is for time series split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.33,shuff
le=False) # this is random splitting

print("Shape of Train and Test Dataset for 100k points")
print(X_train.shape, Y_train.shape)
print(X_test.shape, Y_test.shape)
```

```
Shape of Train and Test Dataset for 100k points
(67000,) (67000,)
(33000,) (33000,)
```

Defining Some Function

Train Data Confusion Matrix Plot

In [10]:
```
def trainconfusionmatrix(model,X_train,y_train):
    print("Confusion Matrix for Train set")
    cm=confusion_matrix(y_train, model.predict(X_train))
    class_label = ["negative", "positive"]
    df_cm = pd.DataFrame(cm, index = class_label, columns = class_label)
    sns.heatmap(df_cm, annot = True, fmt = "d")
    plt.title("Train Confusiion Matrix")
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.show()
```

Test Data Confusion Matrix Plot

In [11]:
```
def testconfusionmatrix(model,X_test,y_test):
    print("Confusion Matrix for Test set")
    cm=confusion_matrix(y_test, model.predict(X_test))
    class_label = ["negative", "positive"]
    df_cm = pd.DataFrame(cm, index = class_label, columns = class_label)
    sns.heatmap(df_cm, annot = True, fmt = "d")
    plt.title("Test Confusiion Matrix")
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.show()
```

ROC-AUC Curve (RBF SVM)

In [12]:
```
def plot_auc_roc(model,X_train,X_test,y_train,y_test):
    train_fpr, train_tpr, thresholds = roc_curve(y_train,model.predict_proba(X
_train)[:,1])
    test_fpr, test_tpr, thresholds = roc_curve(y_test,model.predict_proba(X_te
st)[:,1])

    plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, trai
n_tpr)))
    plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr
)))
    plt.legend()
    plt.xlabel("Hyperameter (C)")
    plt.ylabel("AUC")
    plt.title("ROC CURVE PLOTS")
    plt.show()
```

Plot Linear

In [13]:
```
def plot_l(gsv):
    res=gsv.cv_results_
    cv_data=res['mean_test_score']
    train_data=res['mean_train_score']
    alpha=[0.0001,0.001,0.01,0.1,1,10,100,1000,10000]
    log_c= [math.log10(x) for x in alpha]


    plt.xlabel("Hyperparameter (Log(Alpha))",fontsize=15)
    plt.ylabel("Mean_Score",fontsize=15)
    plt.title('Mean Score v/s C',fontsize=15)
    plt.plot(log_c,cv_data,label="Cross-Validation")
    plt.plot(log_c,train_data,label="Train")
    plt.legend()
    plt.show()
```

Plot RBF

In [14]:
```
def plot_r(gsv):

    C=[0.0001,0.001,0.01,0.1,1,10,100,1000,10000]
    res=gsv.cv_results_
    cv_data=res['mean_test_score']
    train_data=res['mean_train_score']
    log_c= [math.log10(x) for x in C]


    plt.xlabel("Hyperparameter (Log(C))",fontsize=15)
    plt.ylabel("Mean_Score",fontsize=15)
    plt.title('Mean Score v/s C',fontsize=15)
    plt.plot(log_c,cv_data,label="Cross-Validation")
    plt.plot(log_c,train_data,label="Train")
    plt.legend()
    plt.show()
```

ROC-AUC Curve (Linear SVM)

In [15]:
```
def plot_auc_roc_L(model,X_train,X_test,y_train,y_test):

    Clf = CalibratedClassifierCV(model,cv='prefit')
    Clf.fit(X_train,y_train)
    train_fpr, train_tpr, thresholds = roc_curve(y_train,Clf.predict_proba(X_t
rain)[:,1])
    test_fpr, test_tpr, thresholds = roc_curve(y_test,Clf.predict_proba(X_test
)[:,1])

    plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, trai
n_tpr)))
    plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr
)))
    plt.legend()
    plt.xlabel("Hyperameter (C)")
    plt.ylabel("AUC")
    plt.title("ROC CURVE PLOTS")
    plt.show()
```

GridSearchCV Linear

In [16]:
```
def Grid_SearchCV(X_train,Y_train,regularisation_parameter):

    param_grid= {'alpha':[0.0001,0.001,0.01,0.1,1,10,100,1000,10000],
             'penalty':[regularisation_parameter]}
    tscv = TimeSeriesSplit(n_splits=10)

    gsv=GridSearchCV(SGDClassifier(shuffle=False,loss='hinge',class_weight="ba
lanced"), param_grid, scoring = 'roc_auc', cv=tscv,n_jobs = -1,pre_dispatch=2)
    gsv.fit(X_train,Y_train)

    return gsv
```

GridSearchCV RBF

In [17]:
```
def Grid_SearchCV_RBF(X_train,Y_train):

    param_grid = {'C':[0.0001,0.001,0.01,0.1,1,10,100,1000,10000]}
    tscv = TimeSeriesSplit(n_splits=5)

    gsv=GridSearchCV(SVC(class_weight="balanced"),param_grid,scoring="roc_auc"
,cv=tscv,verbose=1,n_jobs=-1)
    gsv.fit(X_train,Y_train)

    return gsv
```

30 Informative Feature

In [18]:
```
def show_30_informative_feature(vectorizer,model,n=30):


    Weights_Index = model.coef_[0].argsort()
    length = len(Weights_Index)
    # For Negative Class
    neg_class=Weights_Index[:30]

    neg_feat=[vectorizer.get_feature_names()[x] for x in neg_class]
    neg_prob=[model.coef_[0][x] for x in neg_class]

    neg_zip=list(zip(neg_feat,neg_prob))
    neg_zip.sort()

    # For Positive Class
    pos_class =  Weights_Index[-30:]

    pos_feat=[vectorizer.get_feature_names()[x] for x in pos_class]
    pos_prob=[model.coef_[0][x] for x in pos_class]
    pos_zip=list(zip(pos_feat,pos_prob))
    pos_zip.sort()

    top=zip(pos_zip,neg_zip)

    print("{0:20}{1:55}{2:20}".format("S.N","Positive","Negative"))
    print("_"*90)
    i=1
    for (fn_1,coef_1), (fn_2,coef_2) in top:
        print("%d.\t\t%.3f\t%-30s\t\t%.3f\t%s" % (i,coef_1, fn_1, coef_2, fn_2
))
        i+=1
```

Bags of Words Vectorizer

In [19]:
```
vectorizer = CountVectorizer()
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_train_bow=preprocessing.normalize(X_train_bow)

X_test_bow = vectorizer.transform(X_test)
X_test_bow=preprocessing.normalize(X_test_bow)

print("Shape of Train and Test Data After vectorizations")
print(X_train_bow.shape, Y_train.shape)
print(X_test_bow.shape, Y_test.shape)
```

```
Shape of Train and Test Data After vectorizations
(67000, 30737) (67000,)
(33000, 30737) (33000,)
```

Part 1 : Taking L1 as a Regularisation Parameter

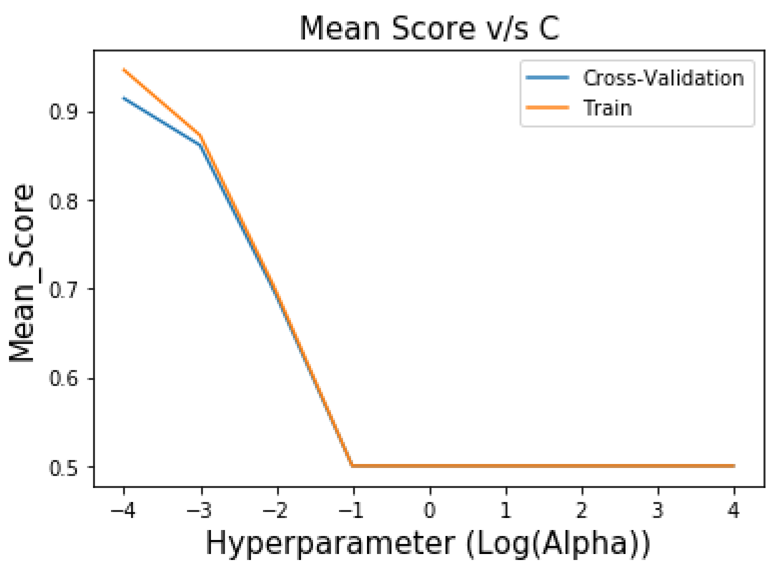
Finding the best value Of hyperparameter (Alpha)

In [20]:
```
gsv=Grid_SearchCV(X_train_bow,Y_train,'l1')

print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Best HyperParameter:  {'alpha': 0.0001, 'penalty': 'l1'}
Best Accuracy: 91.39%
```

Plot

In [21]:
```
plot_l(gsv)
```



Training the model

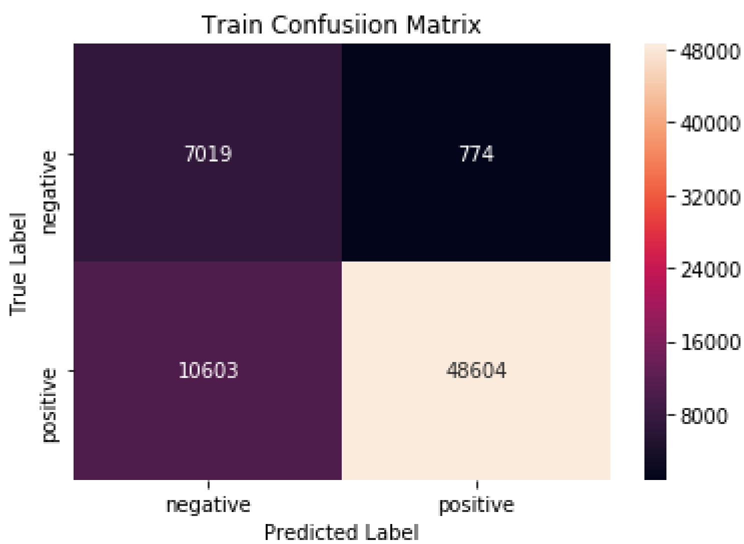
In [23]:
```
Best_Param=gsv.best_params_
C=Best_Param['alpha']
Penalty = Best_Param['penalty']

Model_Bow=SGDClassifier(alpha=C,penalty=Penalty,loss='hinge',shuffle=False,cla
ss_weight="balanced")
Model_Bow.fit(X_train_bow,Y_train)
```

Out[23]:
```
SGDClassifier(alpha=0.0001, average=False, class_weight='balanced',
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=None,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l1',
       power_t=0.5, random_state=None, shuffle=False, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

Evaluating the performance of model

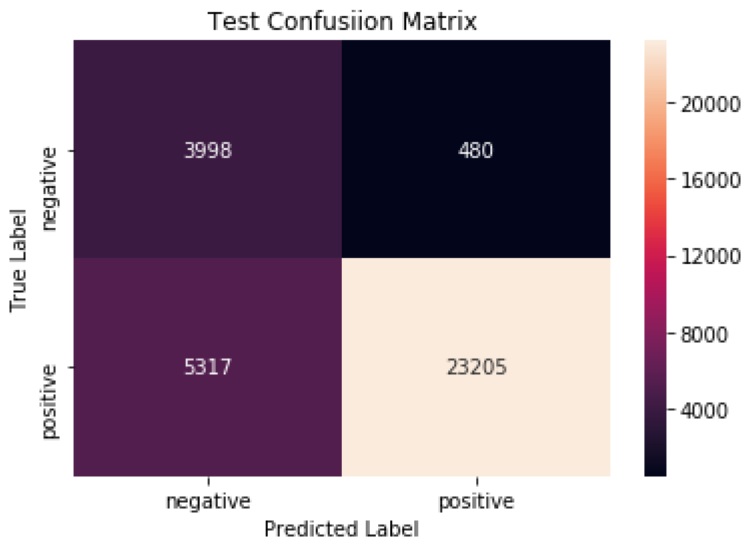
In [24]:
```
trainconfusionmatrix(Model_Bow,X_train_bow,Y_train)
```

```
Confusion Matrix for Train set
```

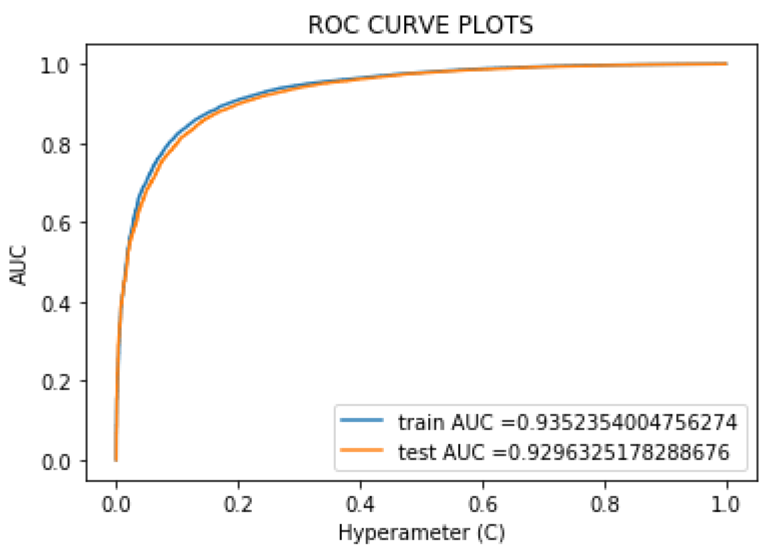


In [25]:
```
testconfusionmatrix(Model_Bow,X_test_bow,Y_test)
```

```
Confusion Matrix for Test set
```



In [26]:
```
plot_auc_roc_L(Model_Bow,X_train_bow,X_test_bow,Y_train,Y_test)
```



In [27]:
```
print("Classification Report: \n")
y_pred=Model_Bow.predict(X_test_bow)

print(classification_report(Y_test, y_pred))
```

```
Classification Report: 

              precision    recall  f1-score   support

           0       0.43      0.89      0.58      4478
           1       0.98      0.81      0.89     28522

   micro avg       0.82      0.82      0.82     33000
   macro avg       0.70      0.85      0.73     33000
weighted avg       0.91      0.82      0.85     33000
```

Displaying 30 most informative features

In [28]:
```
show_30_informative_feature(vectorizer,Model_Bow)
```

```
S.N                Positive                                             Ne
gative

____________________________________________________________________________

_____________
1.             6.557   addict                                   -5.486   ancho
vi
2.             3.099   alway                                    -5.576   aw
3.             5.918   amaz                                     -6.686   bland
4.             4.781   awesom                                   -4.886   brief
5.             3.891   beat                                     -7.289   clams
hel
6.             3.725   beauti                                   -5.133   conce
pt
7.             5.042   best                                     -7.386   credi
t
8.             3.831   burton                                   -5.385   dirt
9.             6.243   delici                                   -6.302   disap
point
10.            4.048   delight                                  -8.115   edit
11.            3.165   easi                                     -8.200   gophe
r
12.            6.141   excel                                    -6.973   horch
ata
13.            4.659   fantast                                  -10.263  horri
bl
14.            3.686   fast                                     -4.066   lack
15.            3.750   favorit                                  -4.140   leg
16.            4.033   glad                                     -8.273   poor
17.            4.977   great                                    -7.422   retur
n
18.            3.624   happi                                    -5.484   sept
19.            3.176   hook                                     -4.682   sorri
20.            3.119   keep                                     -5.333   stenc
h
21.            3.467   love                                     -6.720   sucra
los
22.            3.931   nice                                     -7.303   terri
bl
23.            7.188   perfect                                  -4.645   threw
24.            3.628   refresh                                  -4.404   throw
n
25.            3.335   rich                                     -5.133   trap
26.            4.295   satisfi                                  -6.764   twink
i
27.            4.254   smooth                                   -5.329   unfor
tun
28.            4.167   uniqu                                    -4.145   weak
29.            3.766   wonder                                   -7.557   wors
30.            5.052   yummi                                    -7.702   worst
```

Part 2 : Taking L2 as a Regularisation Parameter

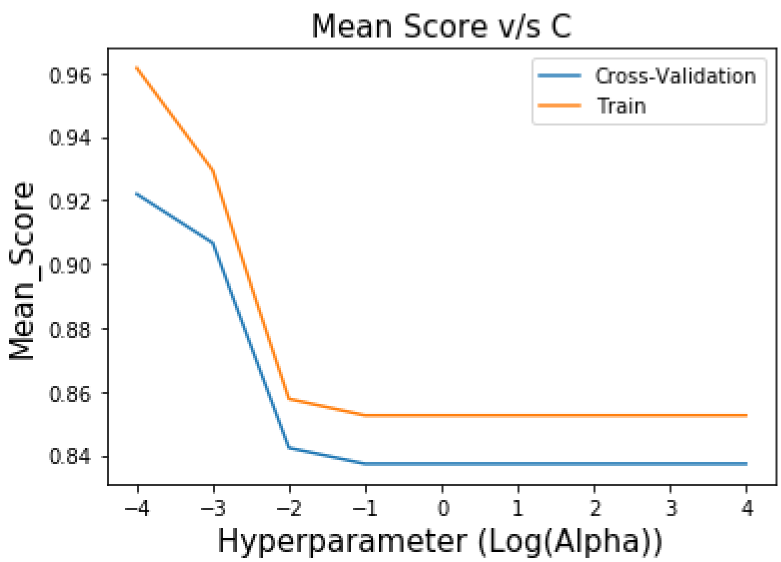
Finding the best value Of hyperparameter (Alpha)

In [22]:
```
gsv=Grid_SearchCV(X_train_bow,Y_train,'l2')

print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Best HyperParameter:  {'alpha': 0.0001, 'penalty': 'l2'}
Best Accuracy: 92.20%
```

Plot

In [23]:
```
plot_l(gsv)
```



Training the model

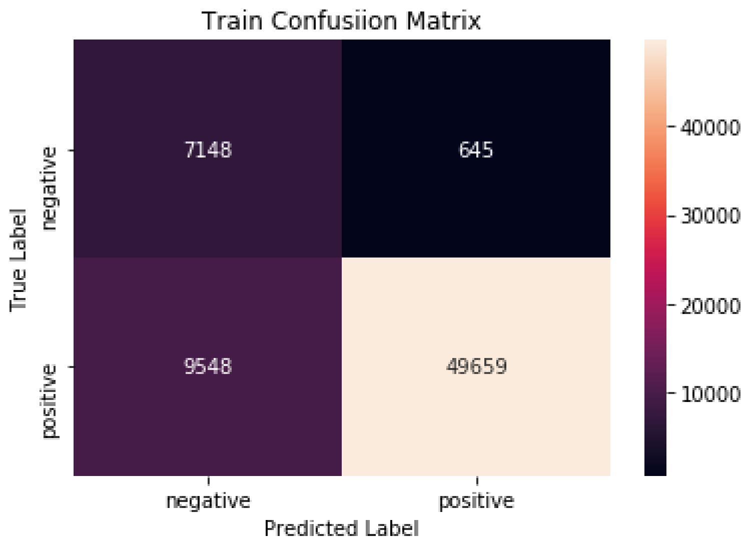
In [31]:
```
Best_Param=gsv.best_params_
C=Best_Param['alpha']
Penalty = Best_Param['penalty']

Model_Bow=SGDClassifier(alpha=C,penalty=Penalty,loss='hinge',shuffle=False,cla
ss_weight='balanced')
Model_Bow.fit(X_train_bow,Y_train)
```

Out[31]:
```
SGDClassifier(alpha=0.0001, average=False, class_weight='balanced',
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=None,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=False, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

Evaluating the performance of model

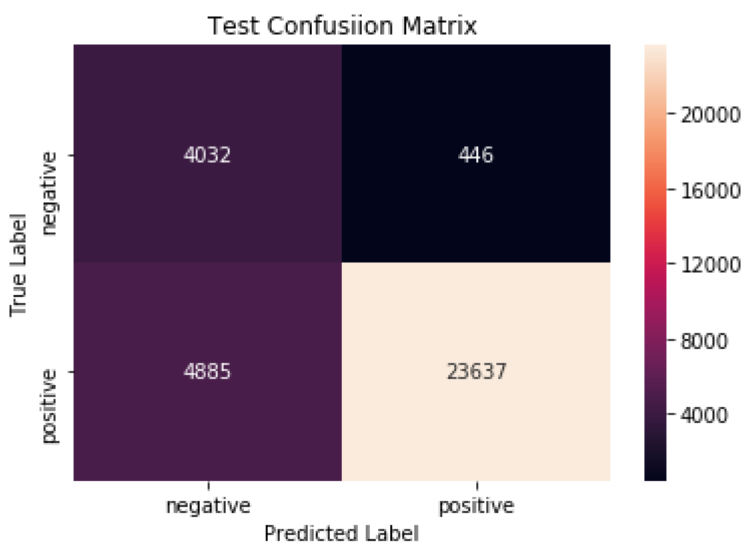
In [32]:
```
trainconfusionmatrix(Model_Bow,X_train_bow,Y_train)
```

```
Confusion Matrix for Train set
```

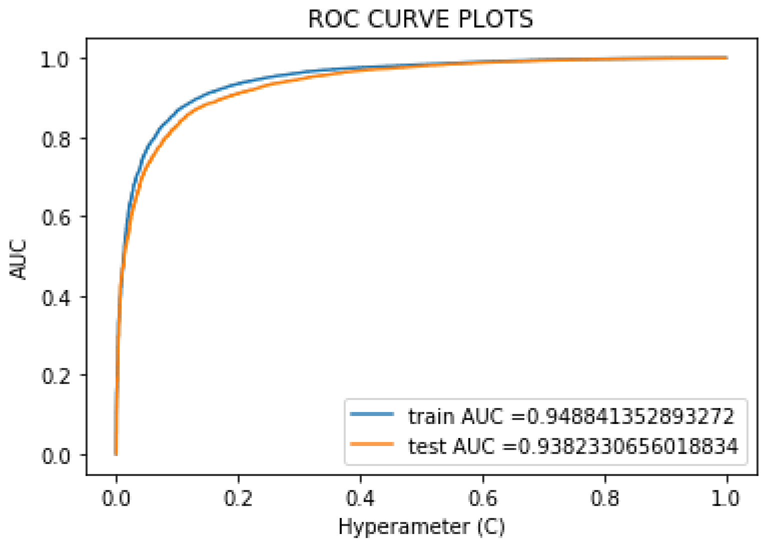


In [33]:
```
testconfusionmatrix(Model_Bow,X_test_bow,Y_test)
```

```
Confusion Matrix for Test set
```



In [34]:
```
plot_auc_roc_L(Model_Bow,X_train_bow,X_test_bow,Y_train,Y_test)
```



In [35]:
```
print("Classification Report: \n")
y_pred=Model_Bow.predict(X_test_bow)

print(classification_report(Y_test, y_pred))
```

```
Classification Report: 

              precision    recall  f1-score   support

           0       0.45      0.90      0.60      4478
           1       0.98      0.83      0.90     28522

   micro avg       0.84      0.84      0.84     33000
   macro avg       0.72      0.86      0.75     33000
weighted avg       0.91      0.84      0.86     33000
```

Displaying 30 most informative features

In [36]:
```
show_30_informative_feature(vectorizer,Model_Bow)
```

```
S.N                 Positive                                          Ne
gative

____________________________________________________________________________

_____________
1.              2.893   addict                                  -2.919  aw
2.              2.360   alway                                   -2.134  away
3.              3.197   amaz                                    -2.315  bad
4.              2.507   awesom                                  -3.416  bland
5.              1.977   beat                                    -2.024  didnt
6.              4.094   best                                    -4.536  disap
point
7.              4.449   delici                                  -1.933  disgu
st
8.              2.361   easi                                    -2.119  guess
9.              4.225   excel                                   -2.056  hope
10.             2.416   fantast                                 -2.413  horri
bl
11.             2.080   fast                                    -1.976  howev
12.             2.728   favorit                                 -2.306  lack
13.             2.383   glad                                    -2.317  mayb
14.             2.028   good                                    -2.377  money
15.             4.143   great                                   -2.103  perha
p
16.             2.732   happi                                   -2.069  refun
d
17.             2.326   keep                                    -2.037  retur
n
18.             2.859   love                                    -1.915  sad
19.             2.835   nice                                    -2.064  sorri
20.             4.463   perfect                                 -2.667  stale
21.             2.222   pleasant                                -2.100  stick
22.             1.984   quick                                   -1.929  stuck
23.             2.154   refresh                                 -2.467  taste
less
24.             2.323   rich                                    -3.430  terri
bl
25.             2.314   satisfi                                 -2.392  thoug
ht
26.             2.632   smooth                                  -2.086  threw
27.             2.330   tasti                                   -3.094  unfor
tun
28.             2.244   thank                                   -2.724  weak
29.             2.746   wonder                                  -2.064  wors
30.             2.673   yummi                                   -3.865  worst
```

TF-IDF Vectorizer

In [24]:
```
vectorizer_tfidf=TfidfVectorizer()
vectorizer_tfidf.fit(X_train)
```

Out[24]:
```
TfidfVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.float64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), norm='l2', preprocessor=None, smooth_idf=True,
        stop_words=None, strip_accents=None, sublinear_tf=False,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, use_idf=True,
        vocabulary=None)
```

In [25]:
```
X_Train_Tfidf=vectorizer_tfidf.transform(X_train)
X_Train_Tfidf=preprocessing.normalize(X_Train_Tfidf)

X_Test_Tfidf=vectorizer_tfidf.transform(X_test)
X_Test_Tfidf=preprocessing.normalize(X_Test_Tfidf)
```

In [26]:
```
print("Shape of Train and Test Data After vectorizations")
print(X_Train_Tfidf.shape, Y_train.shape)
print(X_Test_Tfidf.shape, Y_test.shape)
```

```
Shape of Train and Test Data After vectorizations
(67000, 30737) (67000,)
(33000, 30737) (33000,)
```

Taking L1 as a Regularisation Parameter

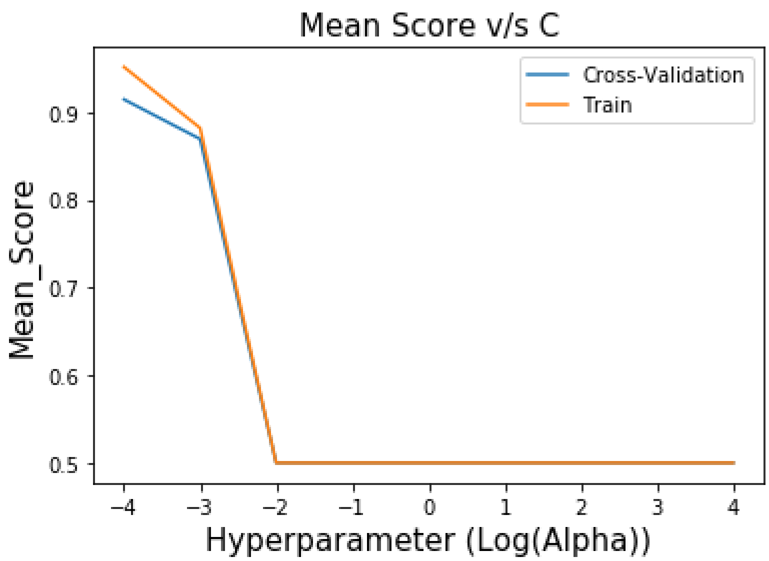
Finding the best value Of hyperparameter (Alpha)

In [27]:
```
gsv=Grid_SearchCV(X_Train_Tfidf,Y_train,'l1')

print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Best HyperParameter:  {'alpha': 0.0001, 'penalty': 'l1'}
Best Accuracy: 91.45%
```

Plot

In [28]:
```
plot_l(gsv)
```



Training the model

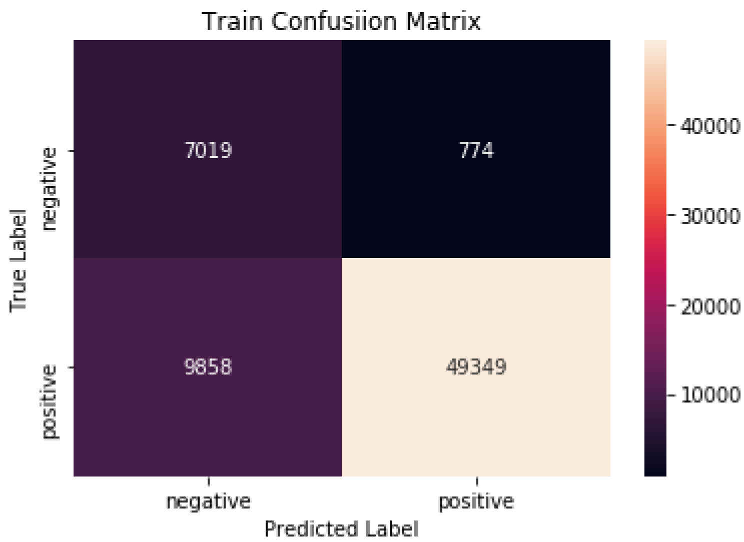
In [21]:
```
Best_Param=gsv.best_params_
C=Best_Param['alpha']
Penalty = Best_Param['penalty']

Model_Tfidf=SGDClassifier(alpha=C,penalty=Penalty,loss='hinge',shuffle=False,c
lass_weight='balanced')
Model_Tfidf.fit(X_Train_Tfidf,Y_train)
```

Out[21]:
```
SGDClassifier(alpha=0.0001, average=False, class_weight='balanced',
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=None,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l1',
       power_t=0.5, random_state=None, shuffle=False, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

Evaluating the performance of model

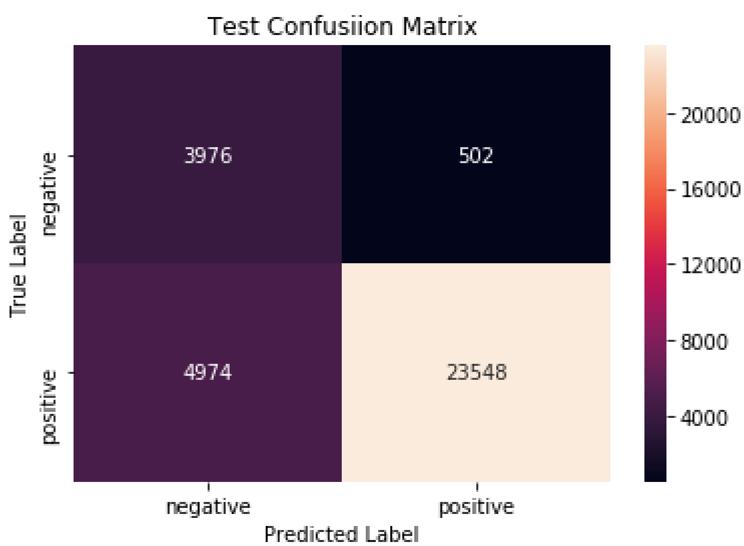
In [22]:
```
trainconfusionmatrix(Model_Tfidf,X_Train_Tfidf,Y_train)
```

Confusion Matrix for Train set

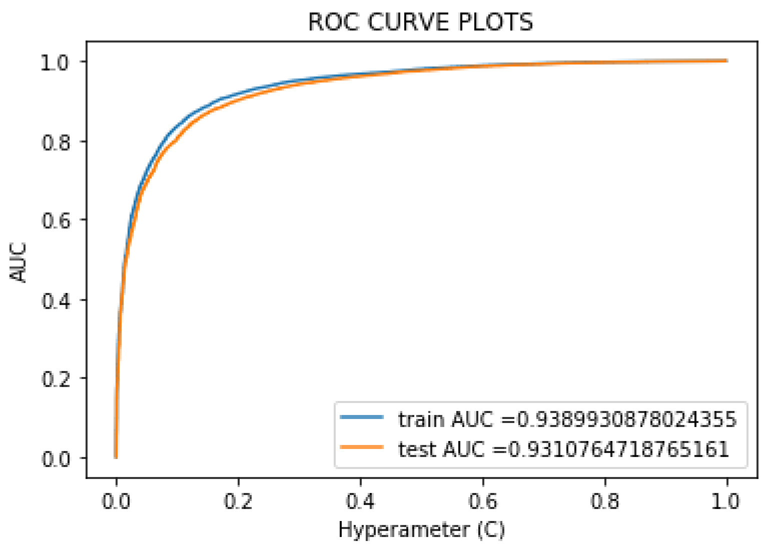


In [23]:
```
testconfusionmatrix(Model_Tfidf,X_Test_Tfidf,Y_test)
```

Confusion Matrix for Test set



In [24]:
```
plot_auc_roc_L(Model_Tfidf,X_Train_Tfidf,X_Test_Tfidf,Y_train,Y_test)
```



In [25]:
```
print("Classification Report: \n")
y_pred=Model_Tfidf.predict(X_Test_Tfidf)

print(classification_report(Y_test, y_pred))
```

```
Classification Report: 

              precision    recall  f1-score   support

           0       0.44      0.89      0.59      4478
           1       0.98      0.83      0.90     28522

   micro avg       0.83      0.83      0.83     33000
   macro avg       0.71      0.86      0.74     33000
weighted avg       0.91      0.83      0.85     33000
```

Displaying 30 most informative features

In [28]:
```
show_30_informative_feature(vectorizer_tfidf,Model_Tfidf)
```

```
S.N                 Positive                                                Ne
gative

_____________________________________________________________________________

_____________
1.              6.218   addict                                  -5.533  alvin
2.              3.493   alway                                   -5.740  billi
3.              6.243   amaz                                    -5.652  bland
4.              4.914   awesom                                  -8.018  brief
5.              3.631   beauti                                  -12.165 categ
or
6.              8.510   best                                    -7.380  cinem
atographi
7.              5.288   burton                                  -15.401 clams
hel
8.              8.874   delici                                  -8.837  credi
t
9.              4.007   delight                                 -6.060  debbi
10.             7.494   excel                                   -6.335  defic
it
11.             4.363   fantast                                 -7.808  dirt
12.             5.369   favorit                                 -6.838  disap
point
13.             3.787   find                                    -7.074  edit
14.             4.131   glad                                    -8.417  gazil
lion
15.             4.704   good                                    -6.761  ghoul
16.             9.627   great                                   -13.176 gophe
r
17.             4.196   happi                                   -8.771  horch
ata
18.             3.498   hotter                                  -8.035  horri
bl
19.             3.977   keep                                    -6.861  leg
20.             6.823   love                                    -6.551  misle
ad
21.             5.009   nice                                    -5.475  scrip
t
22.             3.390   often                                   -11.039 sept
23.             9.882   perfect                                 -8.171  spamm
er
24.             4.544   satisfi                                 -7.132  stenc
h
25.             4.150   smooth                                  -5.628  sucra
los
26.             3.599   tasti                                   -5.817  terri
bl
27.             3.788   tim                                     -6.206  titan
ium
28.             4.407   uniqu                                   -5.556  unfor
tun
29.             4.719   wonder                                  -7.890  wors
30.             5.013   yummi                                   -6.649  worst
```

Taking L2 as a Regularisation Parameter

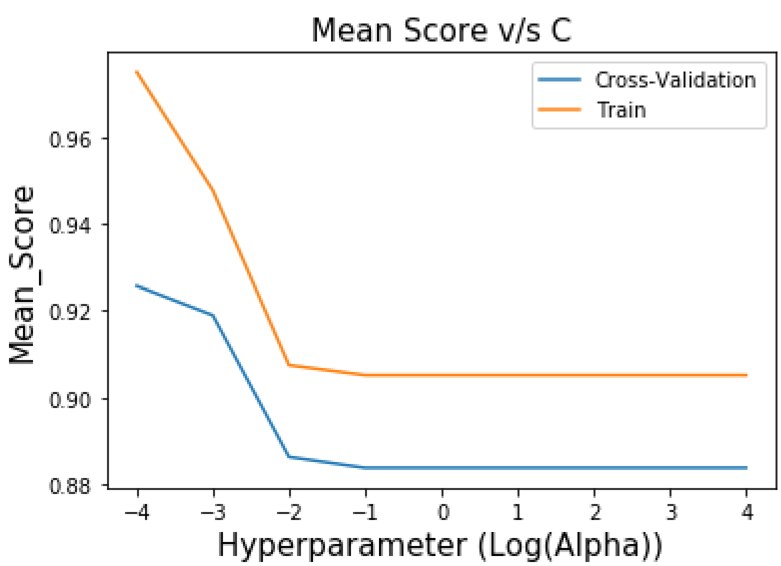
Finding the best value Of hyperparameter (Alpha)

In [29]:
```
gsv=Grid_SearchCV(X_Train_Tfidf,Y_train,'l2')

print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Best HyperParameter:  {'alpha': 0.0001, 'penalty': 'l2'}
Best Accuracy: 92.57%
```

Plot

In [30]:
```
plot_l(gsv)
```



Training the mode

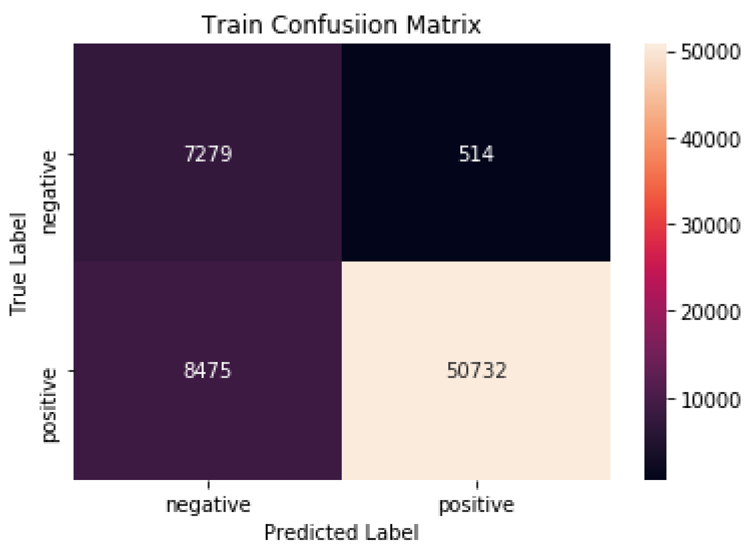
In [48]:
```
Best_Param=gsv.best_params_
C=Best_Param['alpha']
Penalty = Best_Param['penalty']

Model_Tfidf=SGDClassifier(alpha=C,penalty=Penalty,loss='hinge',shuffle=False,c
lass_weight='balanced')
Model_Tfidf.fit(X_Train_Tfidf,Y_train)
```

Out[48]:
```
SGDClassifier(alpha=0.0001, average=False, class_weight='balanced',
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=None,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=False, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

Evaluating the performance of model

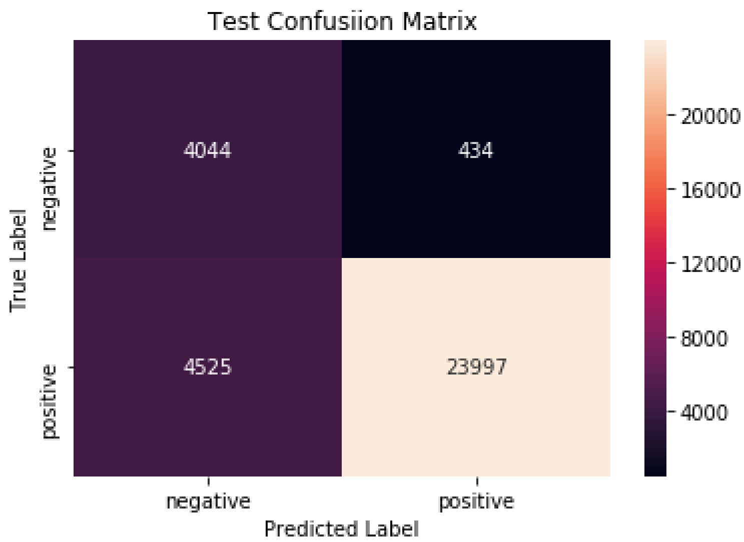
In [49]:
```
trainconfusionmatrix(Model_Tfidf,X_Train_Tfidf,Y_train)
```

```
Confusion Matrix for Train set
```

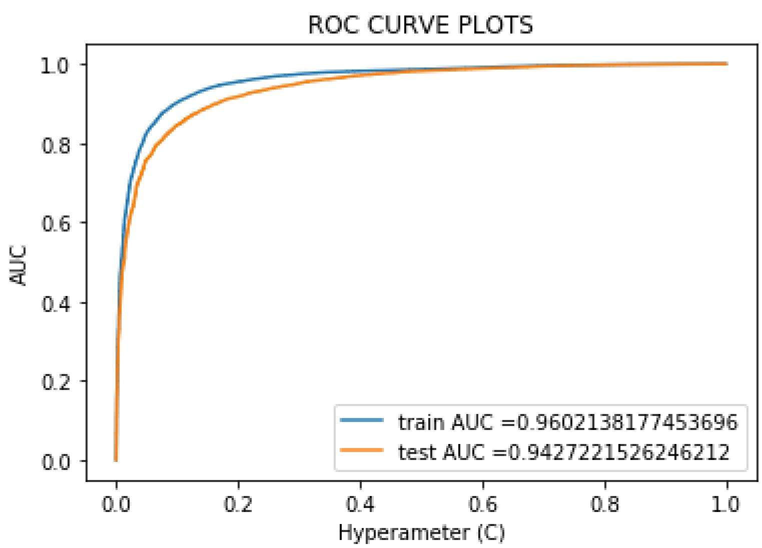


In [50]:
```
testconfusionmatrix(Model_Tfidf,X_Test_Tfidf,Y_test)
```

```
Confusion Matrix for Test set
```



In [51]:
```
plot_auc_roc_L(Model_Tfidf,X_Train_Tfidf,X_Test_Tfidf,Y_train,Y_test)
```



In [52]:
```
print("Classification Report: \n")
y_pred=Model_Tfidf.predict(X_Test_Tfidf)

print(classification_report(Y_test, y_pred))
```

```
Classification Report: 

              precision    recall  f1-score   support

           0       0.47      0.90      0.62      4478
           1       0.98      0.84      0.91     28522

   micro avg       0.85      0.85      0.85     33000
   macro avg       0.73      0.87      0.76     33000
weighted avg       0.91      0.85      0.87     33000
```

Displaying 30 most informative features

In [53]:
```
show_30_informative_feature(vectorizer_tfidf,Model_Tfidf)
```

```
S.N                 Positive                                                 Ne
gative

____________________________________________________________________________

_____________
1.              2.749   addict                                  -2.662   aw
2.              2.614   alway                                   -1.930   away
3.              2.992   amaz                                    -2.193   bad
4.              2.450   awesom                                  -3.264   bland
5.              2.087   beat                                    -2.160   didnt
6.              5.369   best                                    -4.585   disap
point
7.              4.792   delici                                  -1.957   disgu
st
8.              2.346   easi                                    -2.081   gross
9.              4.339   excel                                   -2.012   guess
10.             2.252   fantast                                 -2.115   hope
11.             2.046   fast                                    -2.416   horri
bl
12.             3.172   favorit                                 -2.484   lack
13.             2.483   find                                    -2.234   mayb
14.             2.164   glad                                    -2.366   money
15.             3.430   good                                    -1.959   perha
p
16.             6.535   great                                   -1.970   retur
n
17.             2.700   happi                                   -2.098   sorri
18.             2.560   keep                                    -2.445   stale
19.             4.743   love                                    -1.997   stick
20.             3.208   nice                                    -2.004   stuck
21.             4.640   perfect                                 -2.033   tast
22.             2.132   quick                                   -2.474   taste
less
23.             2.132   refresh                                 -3.163   terri
bl
24.             2.070   rich                                    -2.535   thoug
ht
25.             2.201   satisfi                                 -2.050   threw
26.             2.554   smooth                                  -2.916   unfor
tun
27.             2.429   tasti                                   -2.585   weak
28.             2.123   thank                                   -2.208   wors
29.             3.127   wonder                                  -3.548   worst
30.             2.548   yummi                                   -1.936   yuck
```

Word To Vector

In [31]:
```
list_of_Train_sent=[]
list_of_Test_sent=[]

for sent in X_train:
    list_of_Train_sent.append(sent.split())

for sent in X_test:
    list_of_Test_sent.append(sent.split())
```

In [32]:
```
model=Word2Vec(list_of_Train_sent,min_count=5,size=50, workers=4)
```

Average Word To Vector

In [33]:
```
import numpy as np

Train_vectors = []
for sent in list_of_Train_sent:
    sent_vec = np.zeros(50)
    cnt_words = 0
    for word in sent:
        try:
            vec = model.wv[word]
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    if cnt_words!=0:
        sent_vec /= cnt_words
    Train_vectors.append(sent_vec)
Train_vectors = np.nan_to_num(Train_vectors)
```

In [34]:
```
import numpy as np

Test_vectors=[]
for sent in list_of_Test_sent:
    sent_vec=np.zeros(50)
    cnt_words=0
    for word in sent:
        try:
            vec=model.wv[word]
            sent_vec+=vec
            cnt_words+=1
        except:
            pass
    if cnt_words!=0:
        sent_vec/=cnt_words
    Test_vectors.append(sent_vec)
Test_vectors=np.nan_to_num(Test_vectors)
```

In [35]:
```
print("Shape of Test Vectors : ",Test_vectors.shape)
```

```
Shape of Test Vectors :  (33000, 50)
```

In [36]:
```
X_Train_Awv=Train_vectors
X_Test_Awv=Test_vectors
```

In [37]:
```
print(X_Train_Awv.shape, Y_train.shape)
print(X_Test_Awv.shape, Y_test.shape)
```

```
(67000, 50) (67000,)
(33000, 50) (33000,)
```

Taking L1 as a Regularisation Parameter

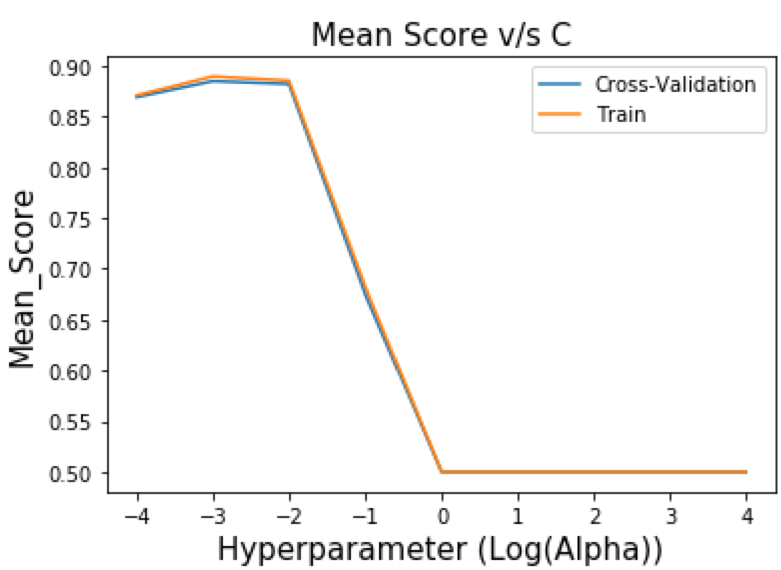
Finding the best value Of hyperparameter (Alpha)

In [38]:
```
gsv=Grid_SearchCV(X_Train_Awv,Y_train,"l1")

print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Best HyperParameter:  {'alpha': 0.001, 'penalty': 'l1'}
Best Accuracy: 88.50%
```

Plot

In [39]:
```
plot_l(gsv)
```



Training Model

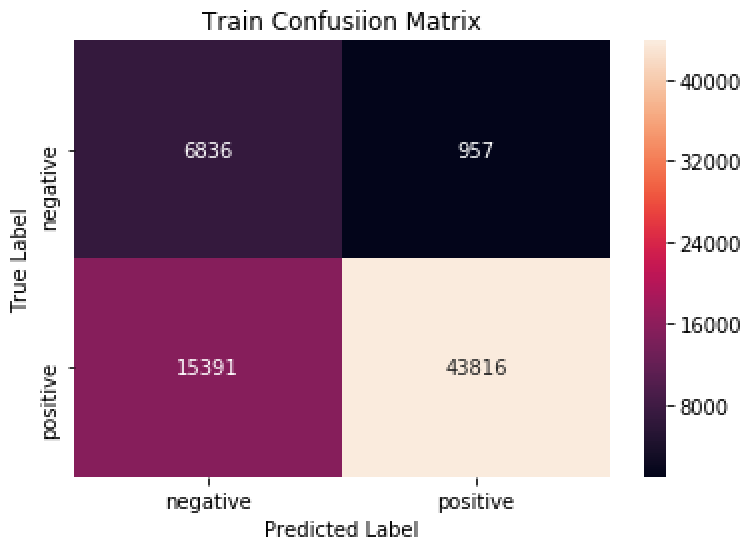
In [62]:
```
Best_Param=gsv.best_params_
C=Best_Param['alpha']
Penalty = Best_Param['penalty']

Model_Awv=SGDClassifier(alpha=C,penalty=Penalty,loss='hinge',shuffle=False,cla
ss_weight='balanced')
Model_Awv.fit(X_Train_Awv,Y_train)
```

Out[62]:
```
SGDClassifier(alpha=0.001, average=False, class_weight='balanced',
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=None,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l1',
       power_t=0.5, random_state=None, shuffle=False, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

Evaluating the performance of model

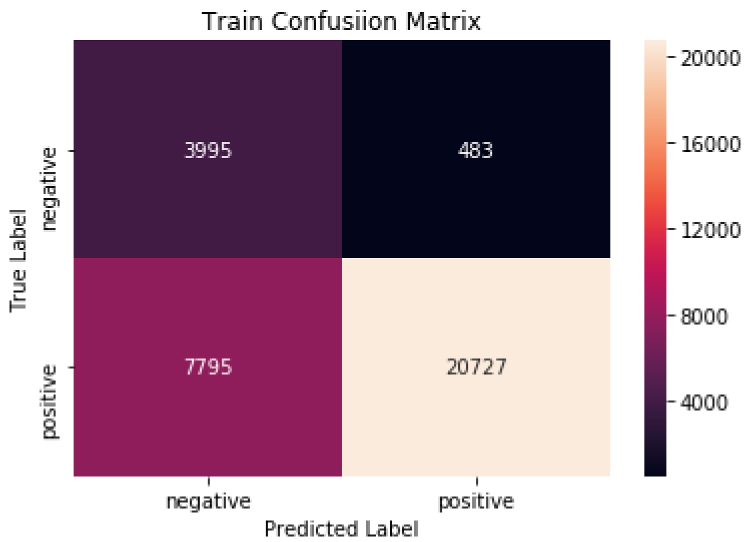
In [63]:
```
trainconfusionmatrix(Model_Awv,X_Train_Awv,Y_train)
```

```
Confusion Matrix for Train set
```

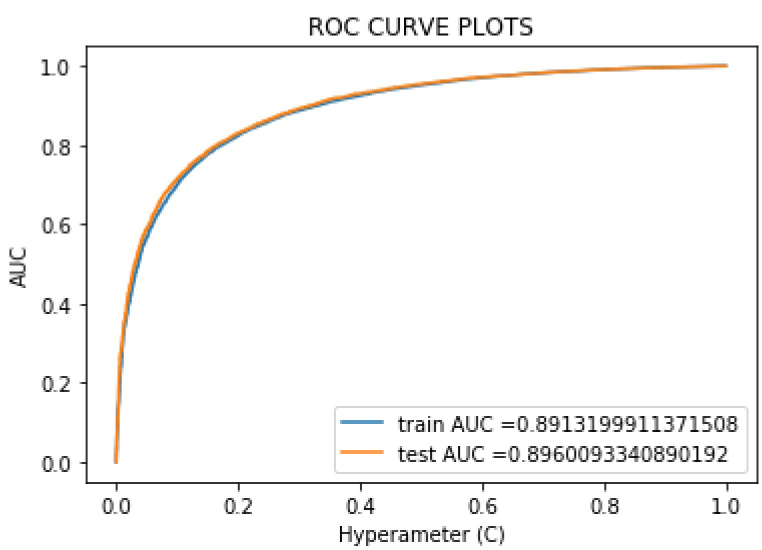


In [64]:
```
trainconfusionmatrix(Model_Awv,X_Test_Awv,Y_test)
```

```
Confusion Matrix for Train set
```



In [65]:
```
plot_auc_roc_L(Model_Awv,X_Train_Awv,X_Test_Awv,Y_train,Y_test)
```



In [66]:
```
print("Classification Report: \n")
y_pred=Model_Awv.predict(X_Test_Awv)

print(classification_report(Y_test, y_pred))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.34      0.89      0.49      4478
           1       0.98      0.73      0.83     28522

   micro avg       0.75      0.75      0.75     33000
   macro avg       0.66      0.81      0.66     33000
weighted avg       0.89      0.75      0.79     33000
```

Taking L2 as a Regularisation Parameter

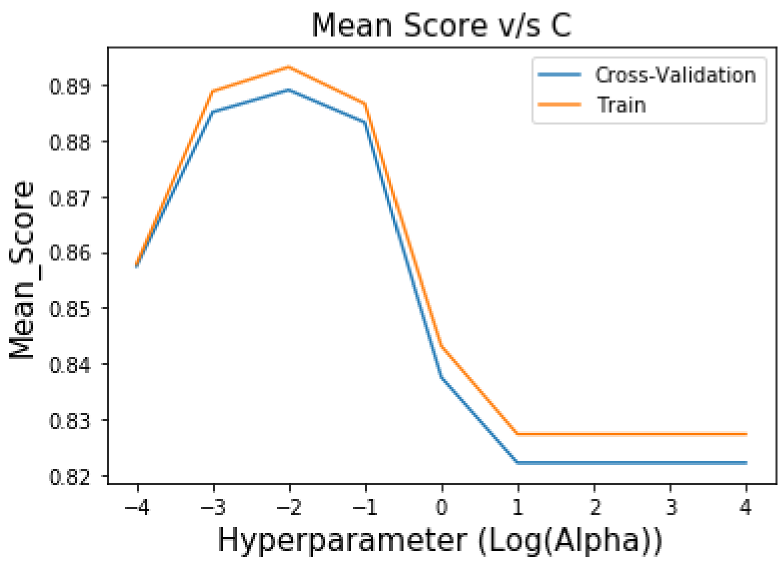
Finding the best value Of hyperparameter (Alpha)

In [40]:
```
gsv=Grid_SearchCV(X_Train_Awv,Y_train,"l2")

print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Best HyperParameter:  {'alpha': 0.01, 'penalty': 'l2'}
Best Accuracy: 88.90%
```

Plot

In [41]:
```
plot_l(gsv)
```



Training the model

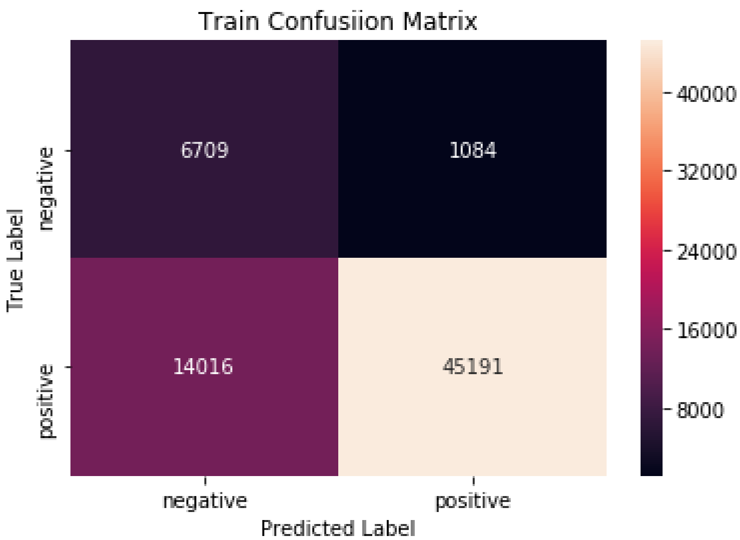
In [68]:
```
Best_Param=gsv.best_params_
C=Best_Param['alpha']
Penalty = Best_Param['penalty']

Model_Awv=SGDClassifier(alpha=C,penalty=Penalty,loss='hinge',shuffle=False,cla
ss_weight='balanced')
Model_Awv.fit(X_Train_Awv,Y_train)
```

Out[68]:
```
SGDClassifier(alpha=0.01, average=False, class_weight='balanced',
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=None,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=False, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

Evaluating the performance of model

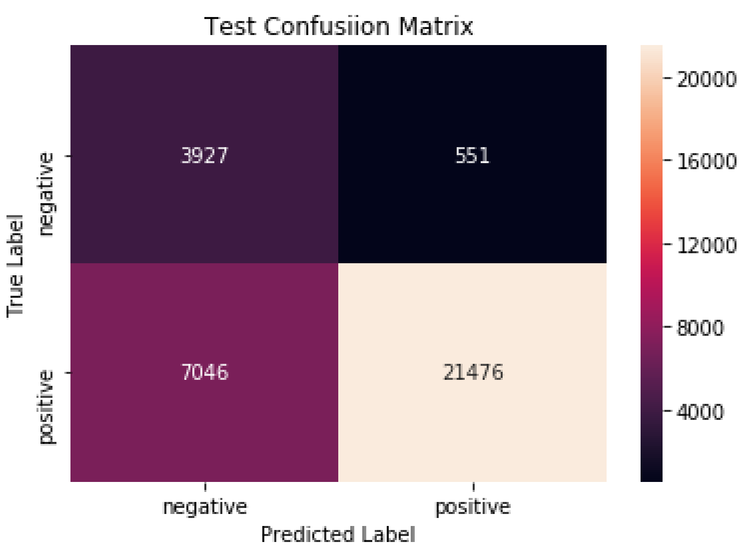
In [69]:
```
trainconfusionmatrix(Model_Awv,X_Train_Awv,Y_train)
```

```
Confusion Matrix for Train set
```

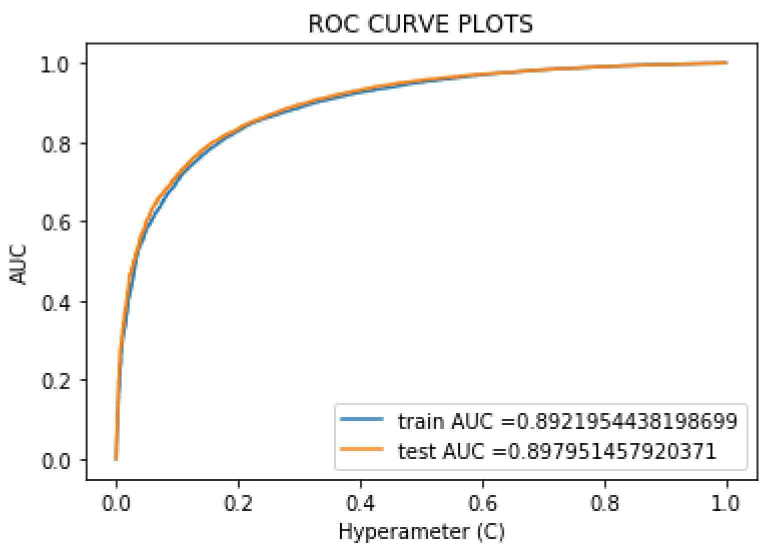


In [70]:
```
testconfusionmatrix(Model_Awv,X_Test_Awv,Y_test)
```

```
Confusion Matrix for Test set
```



In [71]:
```
plot_auc_roc_L(Model_Awv,X_Train_Awv,X_Test_Awv,Y_train,Y_test)
```



In [72]:
```
print("Classification Report: \n")
y_pred=Model_Awv.predict(X_Test_Awv)

print(classification_report(Y_test, y_pred))
```

```
Classification Report: 

              precision    recall  f1-score   support

           0       0.36      0.88      0.51      4478
           1       0.97      0.75      0.85     28522

   micro avg       0.77      0.77      0.77     33000
   macro avg       0.67      0.81      0.68     33000
weighted avg       0.89      0.77      0.80     33000
```

TF-IDF Word To Vector

In [42]:
```
TFIDF_Feature=vectorizer_tfidf.get_feature_names()
print(len(TFIDF_Feature))
print(TFIDF_Feature[0:20])
```

```
30737
['aaa', 'aaaaaaaaagghh', 'aaaaah', 'aaaaahhhhhhhhhhhhhhhh', 'aaaah', 'aaah',
'aachen', 'aad', 'aadp', 'aafco', 'aagh', 'aah', 'aahh', 'aand', 'aardvark',
'ab', 'aback', 'abandon', 'abaolut', 'abattoir']
```

In [43]:
```
from tqdm import tqdm
Train_TFIDF_W2V_Vectors=[]
row=0
for sent in tqdm(list_of_Train_sent):
    sent_vec=np.zeros(50)
    weight=0
    for word in sent:
        try :
            w2v_vec=model.wv[word]
            tfidf_vec=X_Train_Tfidf[row,TFIDF_Feature.index(word)]
            sent_vec+=(w2v_vec*tfidf_vec)
            weight+=tfidf_vec

        except :
            pass
    if weight!=0:
        sent_vec/=weight
    Train_TFIDF_W2V_Vectors.append(sent_vec)
    row+=1
```

```
100%|██████████| 67000/67000 [32:16<00:00, 34.60it/
s]
```

In [44]:
```
Test_TFIDF_W2V_Vectors=[]
row=0
for sent in tqdm(list_of_Test_sent):
    sent_vec=np.zeros(50)
    weight=0

    for word in sent:
        try:
            w2v_vec=model.wv[word]
            tfidf_vec=X_Test_Tfidf(row,TFIDF_Feature.index(word))
            sent_vec+=(w2v_vec*tfidf_vec)
            weight+=tfidf

        except :
            pass

    if weight!=0:
        sent_vec/=weight
    Test_TFIDF_W2V_Vectors.append(sent_vec)
    row+=1
```

```
100%|██████████| 33000/33000 [11:02<00:00, 49.84it/
s]
```

In [45]:
```
Train_TFIDF_W2V_Vectors = np.nan_to_num(Train_TFIDF_W2V_Vectors)
Test_TFIDF_W2V_Vectors = np.nan_to_num(Test_TFIDF_W2V_Vectors)
```

In [46]:
```
X_Train_TfidfW2v=Train_TFIDF_W2V_Vectors
X_Test_TfidfW2v=Test_TFIDF_W2V_Vectors
```

In [47]:
```
print(X_Train_TfidfW2v.shape, Y_train.shape)
print(X_Test_TfidfW2v.shape, Y_test.shape)
```

```
(67000, 50) (67000,)
(33000, 50) (33000,)
```

Taking L1 as a Regularisation Parameter

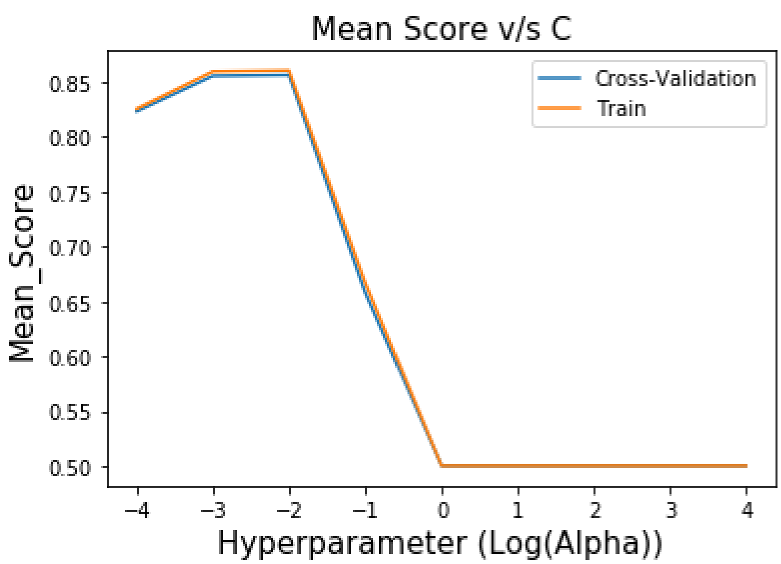
Finding the best value Of hyperparameter (Alpha)

In [48]:
```
gsv=Grid_SearchCV(X_Train_TfidfW2v,Y_train,"l1")

print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Best HyperParameter:  {'alpha': 0.01, 'penalty': 'l1'}
Best Accuracy: 85.66%
```

Plot

In [49]:
```
plot_l(gsv)
```



Training Model

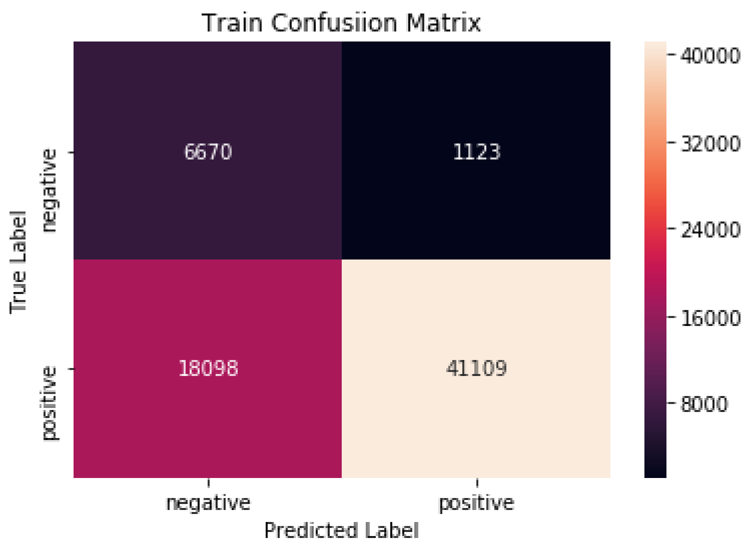
In [47]:
```
Best_Param=gsv.best_params_
C=Best_Param['alpha']
Penalty = Best_Param['penalty']

Model_TfidfW2v=SGDClassifier(alpha=C,penalty=Penalty,loss='hinge',shuffle=False,class_weight='balanced')
Model_TfidfW2v.fit(X_Train_TfidfW2v,Y_train)
```

Out[47]:
```
SGDClassifier(alpha=0.001, average=False, class_weight='balanced',
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=None,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l1',
       power_t=0.5, random_state=None, shuffle=False, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

Evaluating the performance of model

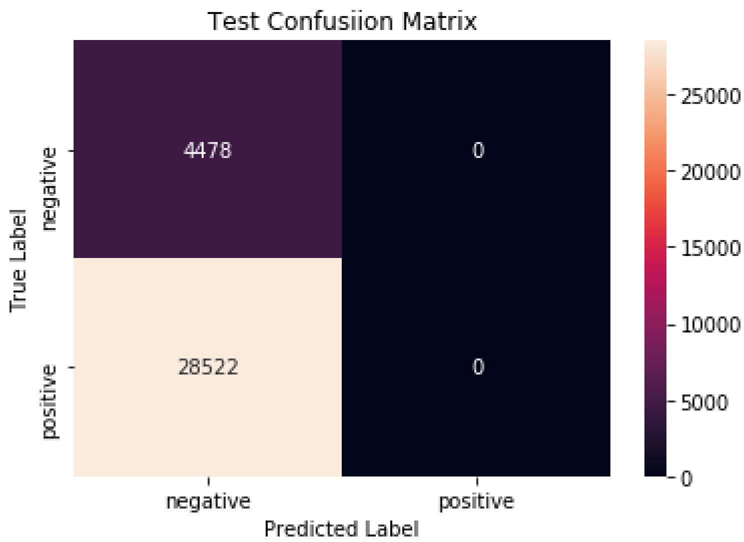
In [48]:
```
trainconfusionmatrix(Model_TfidfW2v,X_Train_TfidfW2v,Y_train)
```

```
Confusion Matrix for Train set
```

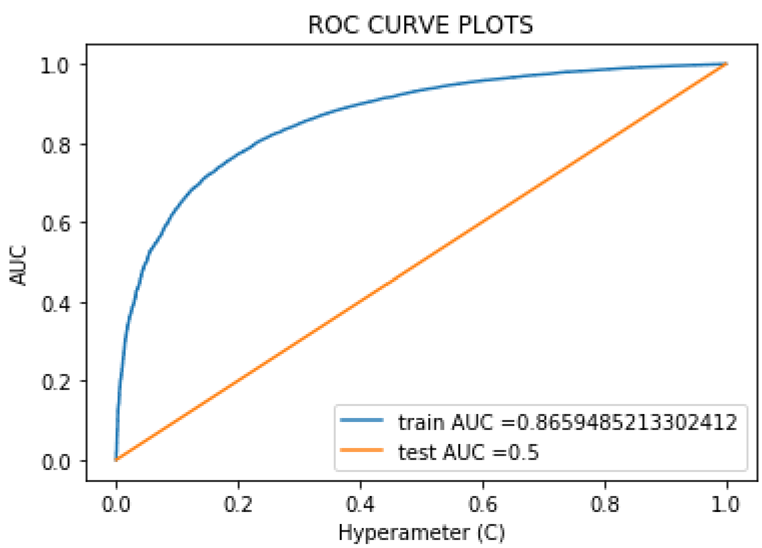


In [49]:
```
testconfusionmatrix(Model_TfidfW2v,X_Test_TfidfW2v,Y_test)
```

```
Confusion Matrix for Test set
```



In [86]:
```
plot_auc_roc_L(Model_TfidfW2v,X_Train_TfidfW2v,X_Test_TfidfW2v,Y_train,Y_test)
```



In [87]:
```
print("Classification Report: \n")
y_pred=Model_TfidfW2v.predict(X_Test_TfidfW2v)

print(classification_report(Y_test, y_pred))
```

```
Classification Report: 

              precision    recall  f1-score   support

           0       0.14      1.00      0.24      4478
           1       0.00      0.00      0.00     28522

   micro avg       0.14      0.14      0.14     33000
   macro avg       0.07      0.50      0.12     33000
weighted avg       0.02      0.14      0.03     33000
```

Taking L2 as a Regularisation Parameter

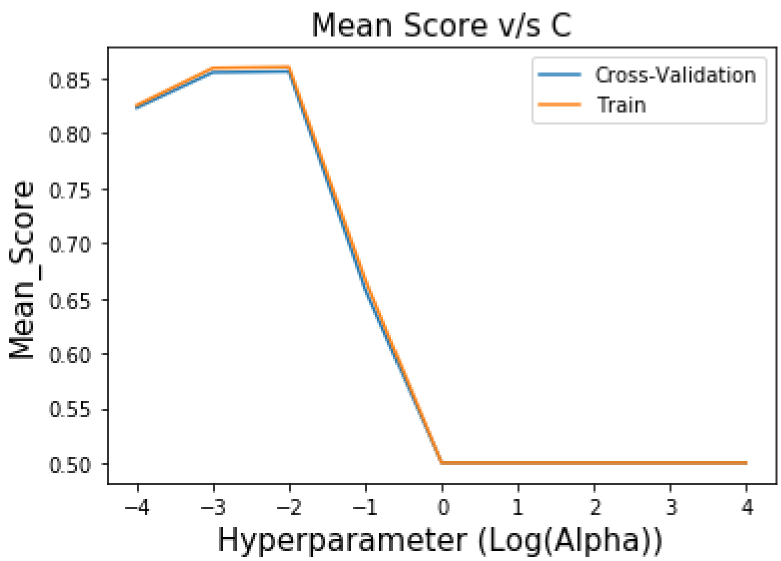
Finding the best value Of hyperparameter (Alpha)

In [50]:
```
gsv=Grid_SearchCV(X_Train_TfidfW2v,Y_train,"l1")

print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Best HyperParameter:  {'alpha': 0.01, 'penalty': 'l1'}
Best Accuracy: 85.66%
```

Plot

In [51]:
```
plot_l(gsv)
```



Training the model

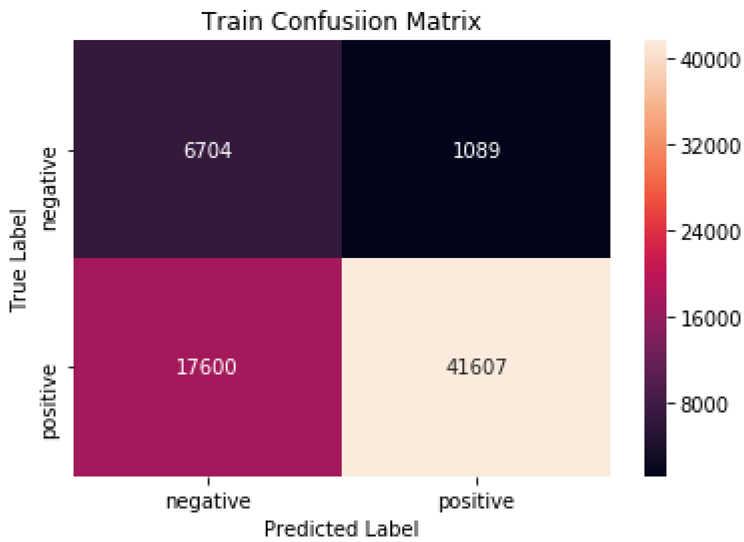
In [89]:
```
Best_Param=gsv.best_params_
C=Best_Param['alpha']
Penalty = Best_Param['penalty']

Model_TfidfW2v=SGDClassifier(alpha=C,penalty=Penalty,loss='hinge',shuffle=False,class_weight='balanced')
Model_TfidfW2v.fit(X_Train_TfidfW2v,Y_train)
```

Out[89]:
```
SGDClassifier(alpha=0.001, average=False, class_weight='balanced',
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=None,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l1',
       power_t=0.5, random_state=None, shuffle=False, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

Evaluating the performance of model

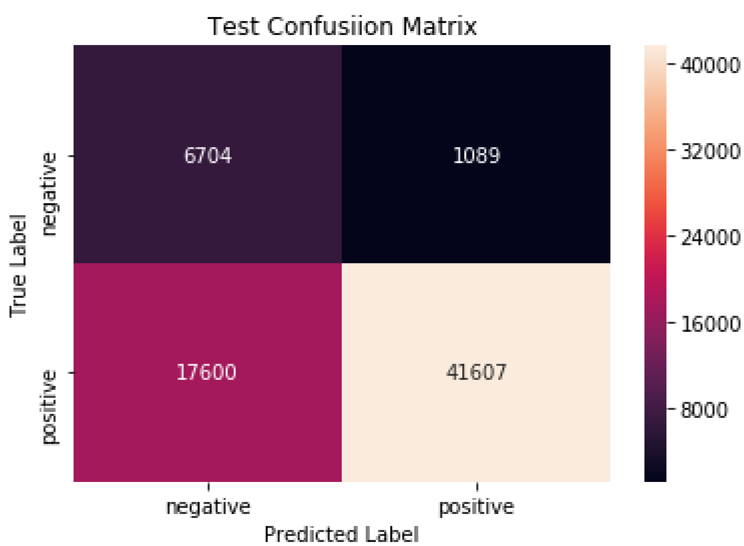
In [90]:
```
trainconfusionmatrix(Model_TfidfW2v,X_Train_TfidfW2v,Y_train)
```

```
Confusion Matrix for Train set
```

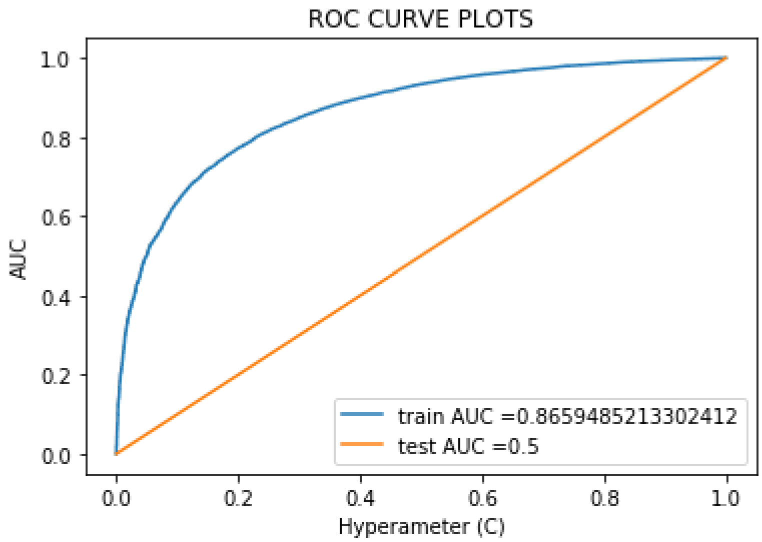


In [91]:
```
testconfusionmatrix(Model_TfidfW2v,X_Test_TfidfW2v,Y_train)
```

```
Confusion Matrix for Test set
```



In [92]:
```
plot_auc_roc_L(Model_TfidfW2v,X_Train_TfidfW2v,X_Test_TfidfW2v,Y_train,Y_test)
```



In [93]:
```
print("Classification Report: \n")
y_pred=Model_TfidfW2v.predict(X_Test_TfidfW2v)

print(classification_report(Y_test, y_pred))
```

```
Classification Report: 

              precision    recall  f1-score   support

           0       0.14      1.00      0.24      4478
           1       0.00      0.00      0.00     28522

   micro avg       0.14      0.14      0.14     33000
   macro avg       0.07      0.50      0.12     33000
weighted avg       0.02      0.14      0.03     33000
```

Using RBF Kernal

In [52]:
```
Data_RBF = Data.head(20000)
```

In [53]:
```
Y = Data_RBF['Score']
X = Data_RBF['CleanedText']
```

In [54]:
```
from sklearn.model_selection import train_test_split
# X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.33, sh
uffle=Flase): this is for time series split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.33,shuff
le=False) # this is random splitting

print("Shape of Train and Test Dataset for 100k points")
print(X_train.shape, Y_train.shape)
print(X_test.shape, Y_test.shape)
```

```
Shape of Train and Test Dataset for 100k points
(13400,) (13400,)
(6600,) (6600,)
```

Bag Of Words

In [55]:
```
vectorizer = CountVectorizer(max_features=500)
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_train_bow=preprocessing.normalize(X_train_bow)

X_test_bow = vectorizer.transform(X_test)
X_test_bow=preprocessing.normalize(X_test_bow)

print("Shape of Train and Test Data After vectorizations")
print(X_train_bow.shape, Y_train.shape)
print(X_test_bow.shape, Y_test.shape)
```

```
Shape of Train and Test Data After vectorizations
(13400, 500) (13400,)
(6600, 500) (6600,)
```

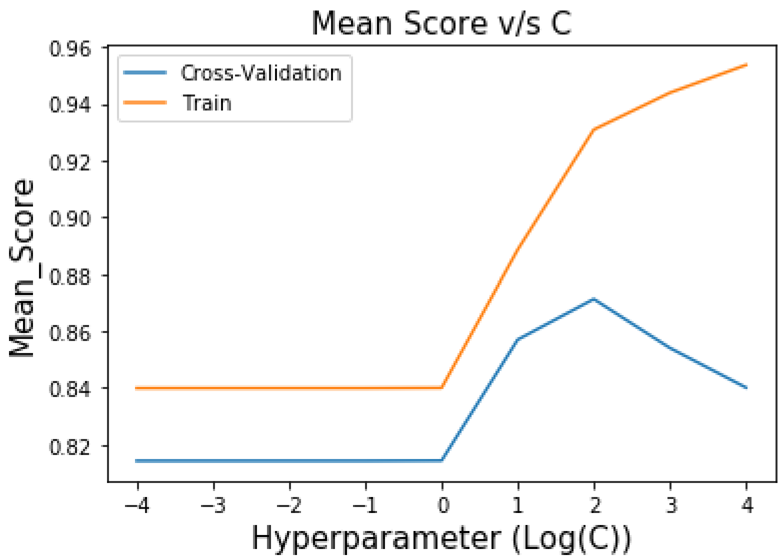
Finding the best value of hyperparameter Alpha

In [56]:
```
gsv=Grid_SearchCV_RBF(X_train_bow,Y_train)

print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Fitting 5 folds for each of 9 candidates, totalling 45 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  45 out of  45 | elapsed:  9.2min finished

Best HyperParameter:  {'C': 100}
Best Accuracy: 87.13%
```

Plot

In [57]:
```
plot_r(gsv)
```



Training the model

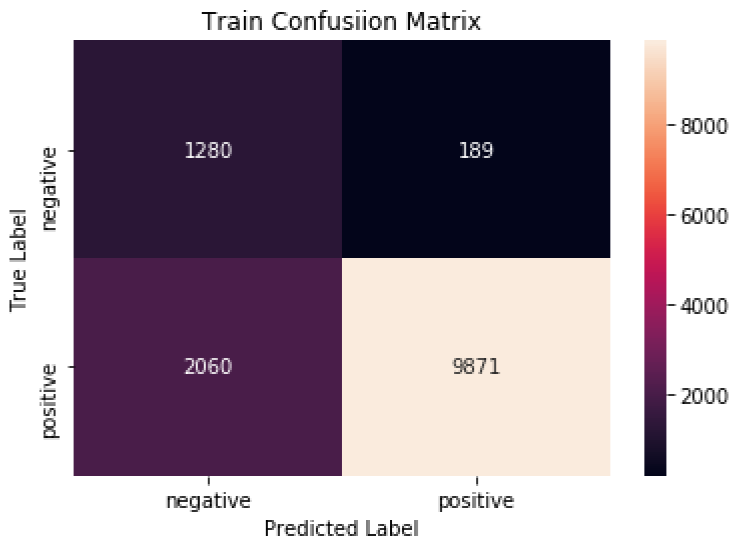
In [100]:
```
Best_Param=gsv.best_params_
C = Best_Param['C']

Model_Bow=SVC(C=C,probability=True,class_weight='balanced')
Model_Bow.fit(X_train_bow,Y_train)
```

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

Evaluating the performance of model

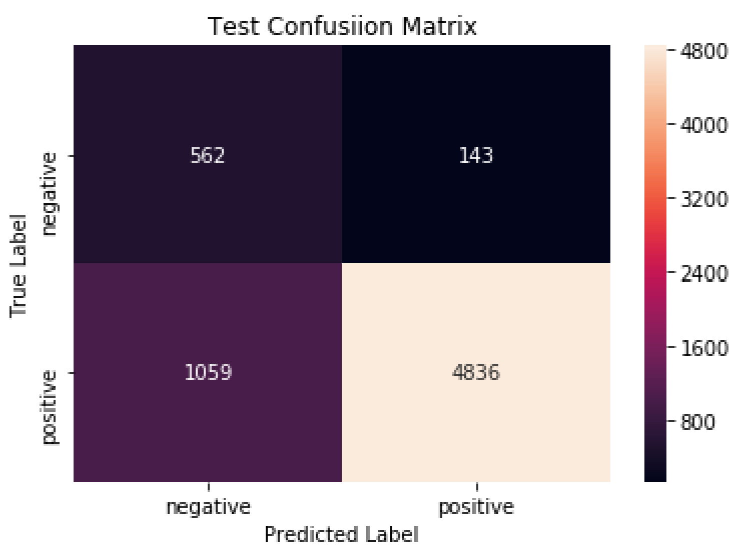
In [101]:
```
trainconfusionmatrix(Model_Bow,X_train_bow,Y_train)
```

Confusion Matrix for Train set

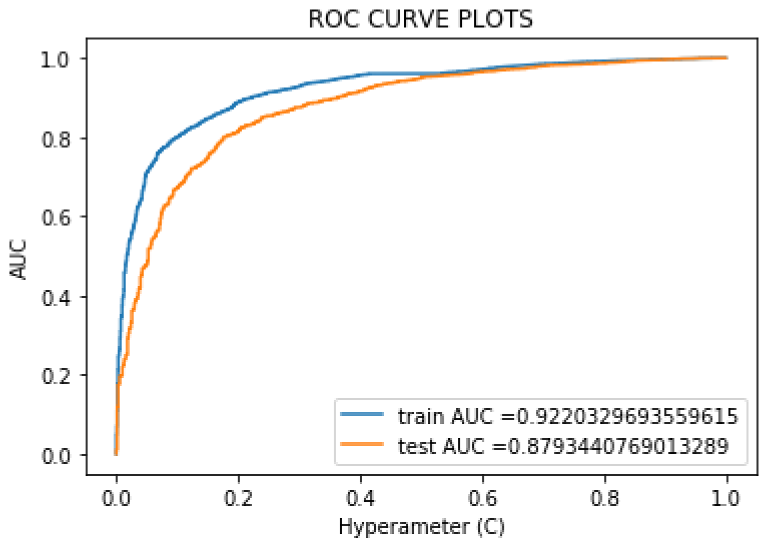


In [102]:
```
testconfusionmatrix(Model_Bow,X_test_bow,Y_test)
```

Confusion Matrix for Test set



In [103]:
```
plot_auc_roc(Model_Bow,X_train_bow,X_test_bow,Y_train,Y_test)
```



In [104]:
```
print("Classification Report: \n")
y_pred=Model_Bow.predict(X_test_bow)

print(classification_report(Y_test, y_pred))
```

```
Classification Report: 

              precision    recall  f1-score   support

           0       0.35      0.80      0.48       705
           1       0.97      0.82      0.89      5895

   micro avg       0.82      0.82      0.82      6600
   macro avg       0.66      0.81      0.69      6600
weighted avg       0.90      0.82      0.85      6600
```

TF-IDF Vectorizer

In [58]:
```
vectorizer_tfidf=TfidfVectorizer()
vectorizer_tfidf.fit(X_train)
```

Out[58]:
```
TfidfVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.float64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), norm='l2', preprocessor=None, smooth_idf=True,
        stop_words=None, strip_accents=None, sublinear_tf=False,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, use_idf=True,
        vocabulary=None)
```

In [59]:
```
X_Train_Tfidf=vectorizer_tfidf.transform(X_train)
X_Train_Tfidf=preprocessing.normalize(X_Train_Tfidf)

X_Test_Tfidf=vectorizer_tfidf.transform(X_test)
X_Test_Tfidf=preprocessing.normalize(X_Test_Tfidf)
```

In [60]:
```
print("Shape of Train and Test Data After vectorizations")
print(X_Train_Tfidf.shape, Y_train.shape)
print(X_Test_Tfidf.shape, Y_test.shape)
```

```
Shape of Train and Test Data After vectorizations
(13400, 15698) (13400,)
(6600, 15698) (6600,)
```

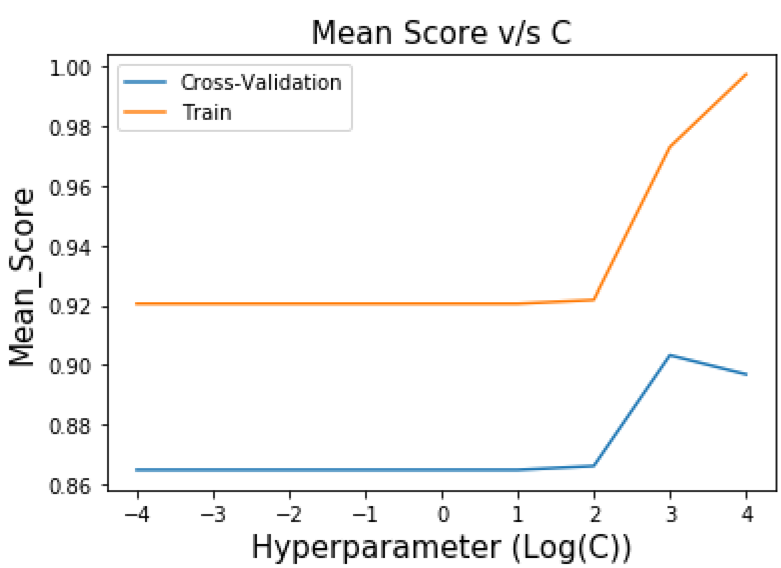
Finding the best value of hyperparameter Alpha

In [61]:
```
gsv=Grid_SearchCV_RBF(X_Train_Tfidf,Y_train)

print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Fitting 5 folds for each of 9 candidates, totalling 45 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  45 out of  45 | elapsed: 14.2min finished

Best HyperParameter:  {'C': 1000}
Best Accuracy: 90.33%
```

Plot

In [62]:
```
plot_r(gsv)
```



Training the model

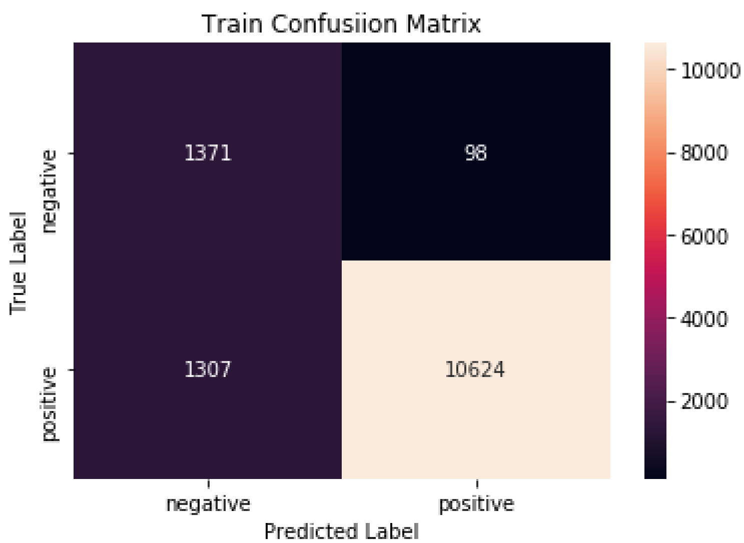
In [109]:
```
Best_Param=gsv.best_params_
C = Best_Param['C']

Model_Tfidf=SVC(C=C,probability=True,class_weight='balanced')
Model_Tfidf.fit(X_Train_Tfidf,Y_train)
```

Out[109]:
```
SVC(C=1000, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
  kernel='rbf', max_iter=-1, probability=True, random_state=None,
  shrinking=True, tol=0.001, verbose=False)
```

Evaluating the performance of model

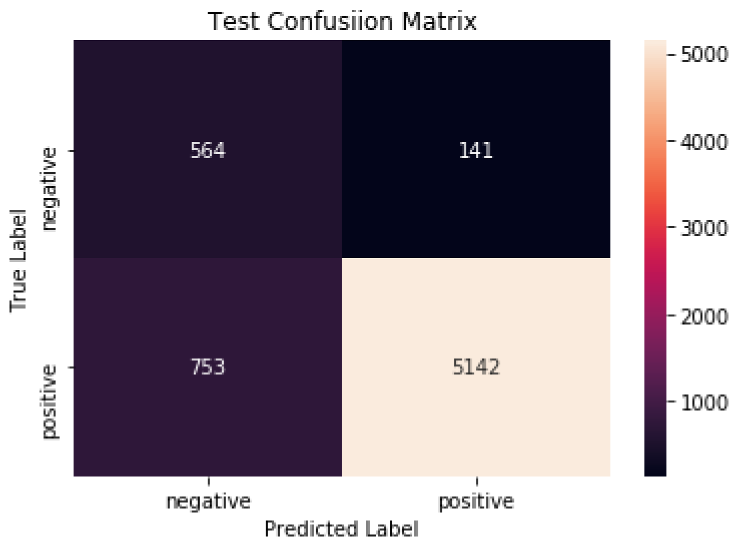
In [112]:
```
trainconfusionmatrix(Model_Tfidf,X_Train_Tfidf,Y_train)
```

```
Confusion Matrix for Train set
```

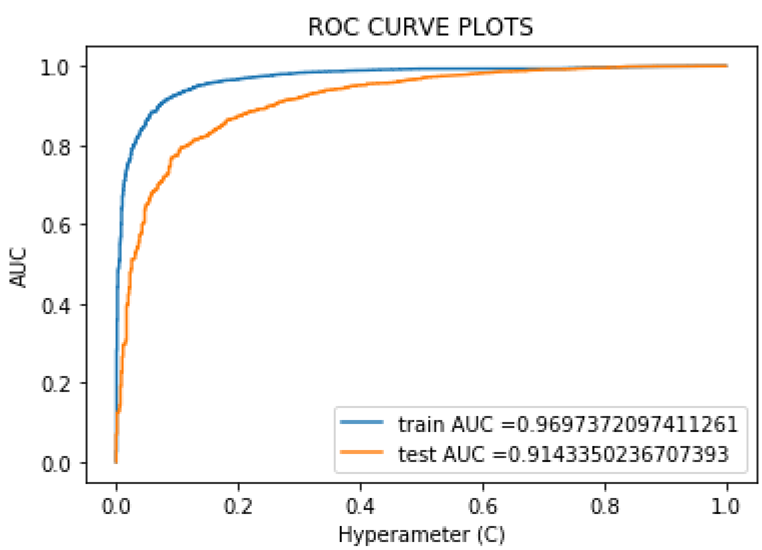


In [113]:
```
testconfusionmatrix(Model_Tfidf,X_Test_Tfidf,Y_test)
```

```
Confusion Matrix for Test set
```



In [114]:
```
plot_auc_roc(Model_Tfidf,X_Train_Tfidf,X_Test_Tfidf,Y_train,Y_test)
```



In [115]:
```
print("Classification Report: \n")
y_pred=Model_Tfidf.predict(X_Test_Tfidf)

print(classification_report(Y_test, y_pred))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.43      0.80      0.56       705
           1       0.97      0.87      0.92      5895

   micro avg       0.86      0.86      0.86      6600
   macro avg       0.70      0.84      0.74      6600
weighted avg       0.92      0.86      0.88      6600
```

Word To Vector

In [63]:
```
list_of_Train_sent=[]
list_of_Test_sent=[]

for sent in X_train:
    list_of_Train_sent.append(sent.split())

for sent in X_test:
    list_of_Test_sent.append(sent.split())
```

In [64]:
```
model=Word2Vec(list_of_Train_sent,min_count=5,size=50, workers=4)
```

In [65]:
```
import numpy as np

Train_vectors = []
for sent in list_of_Train_sent:
    sent_vec = np.zeros(50)
    cnt_words = 0
    for word in sent:
        try:
            vec = model.wv[word]
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    if cnt_words!=0:
        sent_vec /= cnt_words
    Train_vectors.append(sent_vec)
Train_vectors = np.nan_to_num(Train_vectors)
```

In [66]:
```
import numpy as np

Test_vectors=[]
for sent in list_of_Test_sent:
    sent_vec=np.zeros(50)
    cnt_words=0
    for word in sent:
        try:
            vec=model.wv[word]
            sent_vec+=vec
            cnt_words+=1
        except:
            pass
    if cnt_words!=0:
        sent_vec/=cnt_words
    Test_vectors.append(sent_vec)
Test_vectors=np.nan_to_num(Test_vectors)
```

In [67]:
```
print("Shape of Test Vectors : ",Test_vectors.shape)
```

```
Shape of Test Vectors :  (6600, 50)
```

In [68]:
```
X_Train_Awv=Train_vectors
X_Test_Awv=Test_vectors
```

In [69]:
```
print(X_Train_Awv.shape, Y_train.shape)
print(X_Test_Awv.shape, Y_test.shape)
```

```
(13400, 50) (13400,)
(6600, 50) (6600,)
```

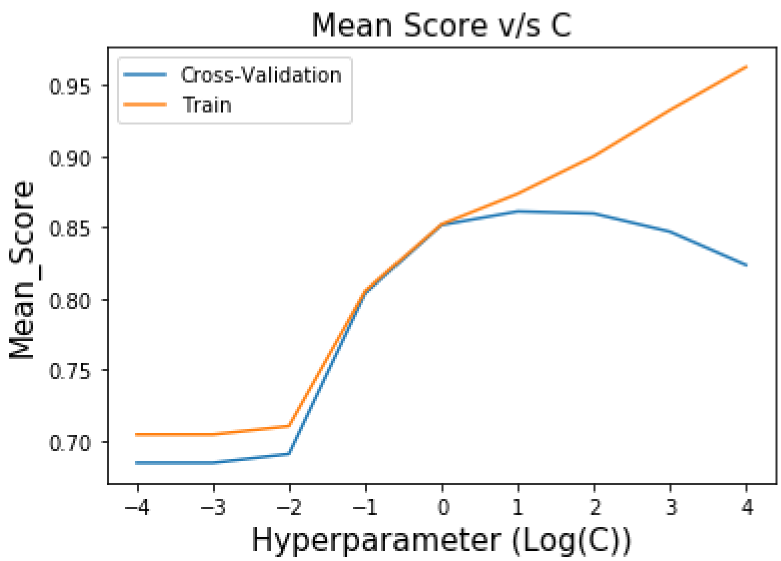
Finding the best hyperparameter (C)

In [70]:
```
gsv=Grid_SearchCV_RBF(X_Train_Awv,Y_train)

print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Fitting 5 folds for each of 9 candidates, totalling 45 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  45 out of  45 | elapsed:  5.5min finished

Best HyperParameter:  {'C': 10}
Best Accuracy: 86.11%
```

Plot

In [71]:
```
plot_r(gsv)
```



Training the model

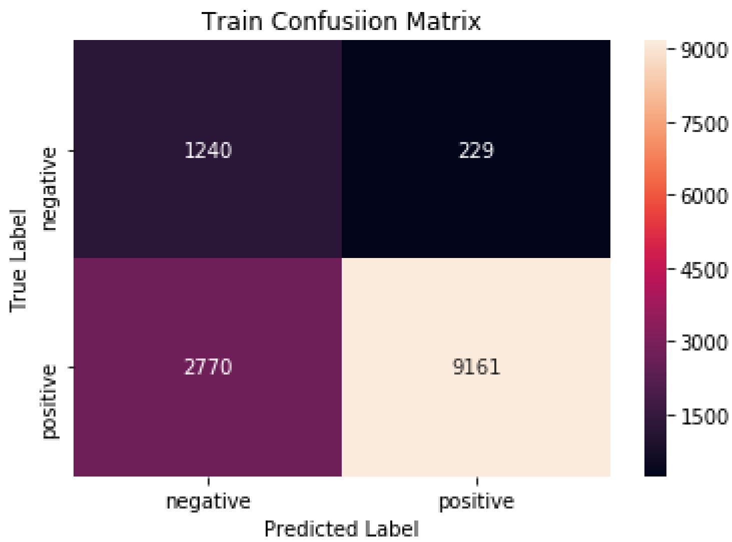
In [124]:
```
Best_Param=gsv.best_params_
C = Best_Param['C']

Model_Awv=SVC(C=C,probability=True,class_weight='balanced')
Model_Awv.fit(X_Train_Awv,Y_train)
```

Out[124]:
```
SVC(C=10, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
  kernel='rbf', max_iter=-1, probability=True, random_state=None,
  shrinking=True, tol=0.001, verbose=False)
```

Evaluating the performance of model

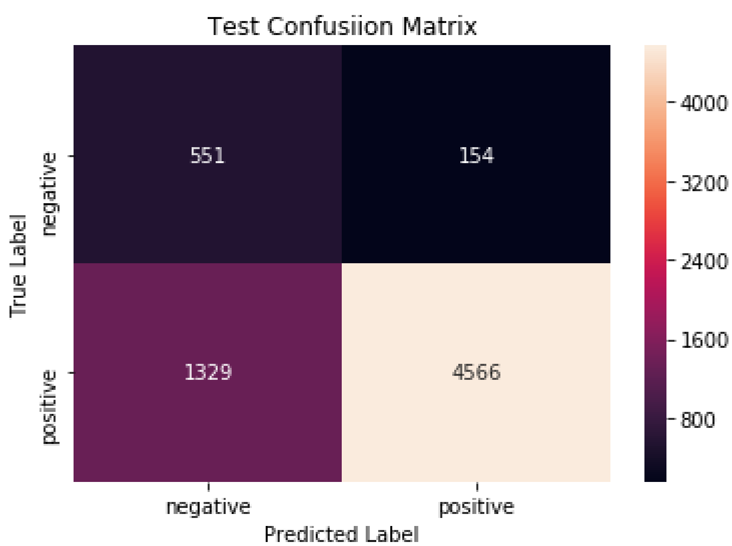
In [125]:
```
trainconfusionmatrix(Model_Awv,X_Train_Awv,Y_train)
```

```
Confusion Matrix for Train set
```

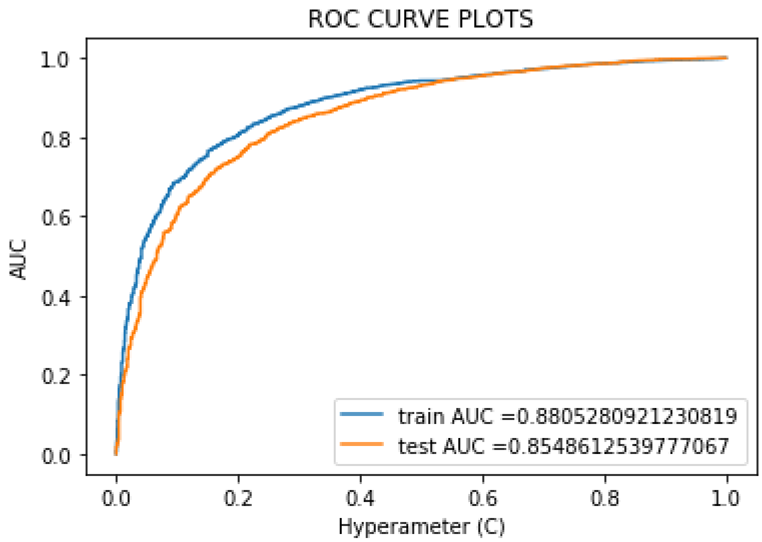


In [126]:
```
testconfusionmatrix(Model_Awv,X_Test_Awv,Y_test)
```

```
Confusion Matrix for Test set
```



In [127]:
```
plot_auc_roc(Model_Awv,X_Train_Awv,X_Test_Awv,Y_train,Y_test)
```



In [128]:
```
print("Classification Report: \n")
y_pred=Model_Awv.predict(X_Test_Awv)

print(classification_report(Y_test, y_pred))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.29      0.78      0.43       705
           1       0.97      0.77      0.86      5895

   micro avg       0.78      0.78      0.78      6600
   macro avg       0.63      0.78      0.64      6600
weighted avg       0.90      0.78      0.81      6600
```

Tf-IDF Word To Vector

In [72]:
```
TFIDF_Feature=vectorizer_tfidf.get_feature_names()
print(len(TFIDF_Feature))
print(TFIDF_Feature[0:20])
```

```
15698
['aaaaah', 'aafco', 'aagh', 'aah', 'ab', 'aback', 'abandon', 'abba', 'abc',
'abdomen', 'abdomin', 'abhor', 'abid', 'abil', 'abj', 'abl', 'abliti', 'abnor
m', 'aboard', 'abod']
```

In [73]:
```
from tqdm import tqdm
Train_TFIDF_W2V_Vectors=[]
row=0
for sent in tqdm(list_of_Train_sent):
    sent_vec=np.zeros(50)
    weight=0
    for word in sent:
        try :
            w2v_vec=model.wv[word]
            tfidf_vec=X_Train_Tfidf[row,TFIDF_Feature.index(word)]
            sent_vec+=(w2v_vec*tfidf_vec)
            weight+=tfidf_vec

        except :
            pass
    if weight!=0:
        sent_vec/=weight
    Train_TFIDF_W2V_Vectors.append(sent_vec)
    row+=1
```

```
100%|████████████████████████████████████| 13400/13400 [02:49<00:00, 79.23it/
s]
```

In [74]:
```
Test_TFIDF_W2V_Vectors=[]
row=0
for sent in tqdm(list_of_Test_sent):
    sent_vec=np.zeros(50)
    weight=0

    for word in sent:
        try:
            w2v_vec=model.wv[word]
            tfidf_vec=X_Test_Tfidf(row,TFIDF_Feature.index(word))
            sent_vec+=(w2v_vec*tfidf_vec)
            weight+=tfidf

        except :
            pass

    if weight!=0:
        sent_vec/=weight
    Test_TFIDF_W2V_Vectors.append(sent_vec)
    row+=1
```

```
100%|█████████████████████████████████████| 6600/6600 [00:56<00:00, 117.44it/
s]
```

In [75]:
```
Train_TFIDF_W2V_Vectors = np.nan_to_num(Train_TFIDF_W2V_Vectors)
Test_TFIDF_W2V_Vectors = np.nan_to_num(Test_TFIDF_W2V_Vectors)
```

In [76]:
```
X_Train_TfidfW2v=Train_TFIDF_W2V_Vectors
X_Test_TfidfW2v=Test_TFIDF_W2V_Vectors
```

In [77]:
```
print(X_Train_TfidfW2v.shape, Y_train.shape)
print(X_Test_TfidfW2v.shape, Y_test.shape)
```

```
(13400, 50) (13400,)
(6600, 50) (6600,)
```

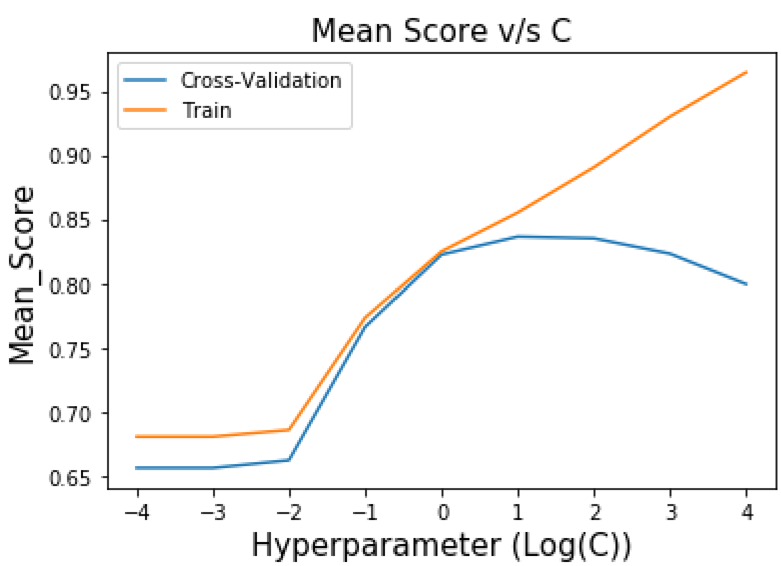
Finding the best hyperparameter (C)

In [78]:
```
gsv=Grid_SearchCV_RBF(X_Train_TfidfW2v,Y_train)

print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Fitting 5 folds for each of 9 candidates, totalling 45 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  45 out of  45 | elapsed:  5.8min finished

Best HyperParameter:  {'C': 10}
Best Accuracy: 83.63%
```

Plot

In [79]:
```
plot_r(gsv)
```



Training the model

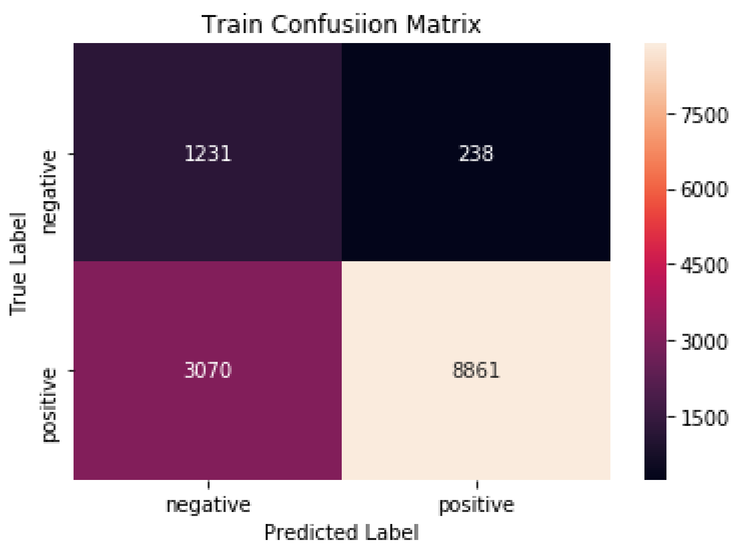
In [136]:
```
Best_Param=gsv.best_params_
C = Best_Param['C']

Model_TfidfW2v=SVC(C=C,probability=True,class_weight='balanced')
Model_TfidfW2v.fit(X_Train_TfidfW2v,Y_train)
```

Out[136]:
```
SVC(C=10, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
  kernel='rbf', max_iter=-1, probability=True, random_state=None,
  shrinking=True, tol=0.001, verbose=False)
```

Evaluating the performance of model

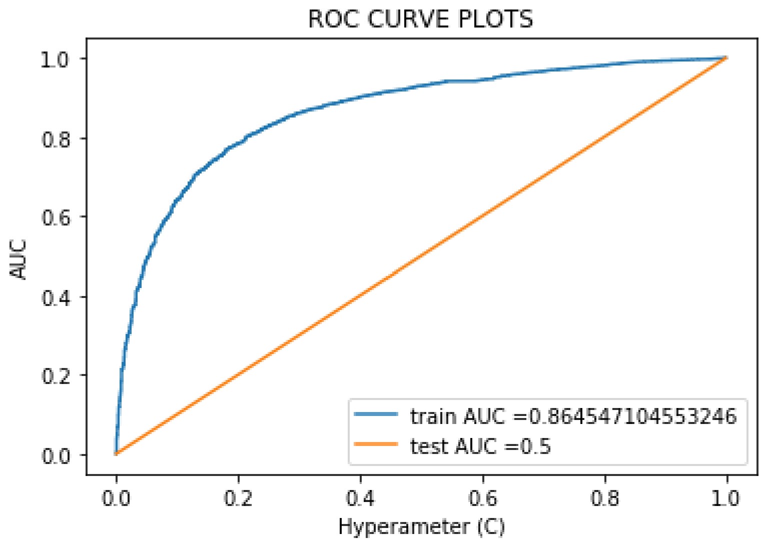
In [137]:
```
trainconfusionmatrix(Model_TfidfW2v,X_Train_TfidfW2v,Y_train)
```

```
Confusion Matrix for Train set
```



In [ ]:
```
testconfusionmatrix(Model_TfidfW2v,X_Test_TfidfW2v,Y_test)
```

In [139]:
```
plot_auc_roc(Model_TfidfW2v,X_Train_TfidfW2v,X_Test_TfidfW2v,Y_train,Y_test)
```



In [140]:
```
print("Classification Report: \n")
y_pred=Model_TfidfW2v.predict(X_Test_TfidfW2v)

print(classification_report(Y_test, y_pred))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.11      1.00      0.19       705
           1       0.00      0.00      0.00      5895

   micro avg       0.11      0.11      0.11      6600
   macro avg       0.05      0.50      0.10      6600
weighted avg       0.01      0.11      0.02      6600
```

1.Report On Different Vectorizer Method and RBF Kernel

In [75]:
```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["Vectorizer", "Hyperparameter(C)","Train AUC","Test AUC","F1-Score"]

x.add_row(["BOW",100,0.90,0.87,0.86])
x.add_row(["TF-IDF",1000,0.97,0.91,0.94])
x.add_row(["Avg W2V",100,0.88,0.84,0.85])
x.add_row(["TF-IDF W2V",1000,0.90,0.50,0.84])

print(x)
```

```
+------------+-------------------+-----------+----------+----------+
| Vectorizer | Hyperparameter(C) | Train AUC | Test AUC | F1-Score |
+------------+-------------------+-----------+----------+----------+
|    BOW     |        100        |    0.9    |   0.87   |   0.86   |
|   TF-IDF   |        1000       |    0.97   |   0.91   |   0.94   |
|  Avg W2V   |        100        |    0.88   |   0.84   |   0.85   |
| TF-IDF W2V |        1000       |    0.9    |   0.5    |   0.84   |
+------------+-------------------+-----------+----------+----------+
```

2.Report On Different Vectorizer Method and Linear Kernel (L1 Regularisation Parameter)

In [50]:
```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["Vectorizer", "Hyperparameter(Alpha)","Train AUC","Test AUC",
"F1-Score"]

x.add_row(["BOW",0.0001,0.93,0.92,0.87])
x.add_row(["TF-IDF",0.0001,0.93,0.93,0.87])
x.add_row(["Avg W2V",0.001,0.89,0.89,0.83])
x.add_row(["TF-IDF W2V",0.001,0.86,0.50,0.80])

print(x)
```

```
+------------+-----------------------+-----------+----------+----------+
| Vectorizer | Hyperparameter(Alpha) | Train AUC | Test AUC | F1-Score |
+------------+-----------------------+-----------+----------+----------+
|    BOW     |         0.0001        |    0.93   |   0.92   |   0.87   |
|   TF-IDF   |         0.0001        |    0.93   |   0.93   |   0.87   |
|  Avg W2V   |         0.001         |    0.89   |   0.89   |   0.83   |
| TF-IDF W2V |         0.001         |    0.86   |   0.5    |   0.8    |
+------------+-----------------------+-----------+----------+----------+
```

3.Report On Different Vectorizer Method and Linear Kernel (L2 Regularisation Parameter)

In [51]:
```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["Vectorizer", "Hyperparameter(Alpha)","Train AUC","Test AUC",
"F1-Score"]

x.add_row(["BOW",0.0001,0.94,0.93,0.88])
x.add_row(["TF-IDF",0.0001,0.96,0.94,0.88])
x.add_row(["Avg W2V",0.001,0.89,0.89,0.80])
x.add_row(["TF-IDF W2V",0.001,0.86,0.50,0.80])

print(x)
```

```
+------------+-----------------------+-----------+----------+----------+
| Vectorizer | Hyperparameter(Alpha) | Train AUC | Test AUC | F1-Score |
+------------+-----------------------+-----------+----------+----------+
|    BOW     |         0.0001        |    0.94   |   0.93   |   0.88   |
|   TF-IDF   |         0.0001        |    0.96   |   0.94   |   0.88   |
|  Avg W2V   |         0.001         |    0.89   |   0.89   |   0.8    |
| TF-IDF W2V |         0.001         |    0.86   |   0.5    |   0.8    |
+------------+-----------------------+-----------+----------+----------+
```

4. I have used SGDClassifier for Linear SVM on 100K DataSet and SVC for RBF SVM on 20K DataSet.

5. Since data is unbalanced , i did time based splitting and used roc_auc metric as scoring parameter in GridsearchCV .

6. In case of RBF SVM , TFIDF is performing better than other.

7. In Case of Linear SVM , TFIDF-W2V is overfitting.