Assignment-5 - Apply-Logistic _Regression -On-Amazon-Review-Dataset

April 19, 2019

1 Assignment-5: Apply Logistic Regression On Amazon Fine Food Reviews DataSet

1.1 Introduction

(i).Logistic regression is used to describe data and to explain the relationship between one dependent binary variable and one or more nominal, ordinal, interval or ratio-level independent variables.

(ii).It's name is Regression but actually it is classification algorithm.

1.2 Objective

To Predict the Polarity of Amazon Fine Food Review Using Logistic Regression Algorithm.

1.3 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 LogisticRegression


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;
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

1.4 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 Logistic_Regression_Data 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    126413
        0     23587
        Name: Score, dtype: int64
```

1.5 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 o
        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:  150000

Number of Users:  115887

Number of Products:  42869

Shape of Data:  (150000, 13)

Column Name of DataSet :  Index(['level_0', 'index', 'Id', 'ProductId', 'UserId', 'ProfileName
       'HelpfulnessNumerator', 'HelpfulnessDenominator', 'Score', 'Time',
       'Summary', 'Text', 'CleanedText'],
      dtype='object')


Number of Attributes/Columns in data: 12

Number of Positive Reviews :  126413

Number of Negative Reviews :  23587
```

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

```
Number of Reviews:  150000
```

1.6 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]: Y = Data['Score'].values
        X = Data['CleanedText'].values
```

1.7 Splitting DataSet into Train and Test Data

```
In [8]: 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, shuffle=Fl
        X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.33,shuffle=False)

        print("Shape of Train and Test Dataset for 50k points")
        print(X_train.shape, Y_train.shape)
        print(X_test.shape, Y_test.shape)
```

```
Shape of Train and Test Dataset for 50k points
(100500,) (100500,)
(49500,) (49500,)
```

1.8 Defining Some Function

1.8.1 Train Data Confusion Matrix Plot

```
In [9]: 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()
```

1.8.2 Test Data Confusion Matrix Plot

```
In [10]: 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()
```

1.8.3 ROC-AUC Curve Plot

```
In [11]: 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)
             test_fpr, test_tpr, thresholds = roc_curve(y_test, model.predict_proba(X_test)[:,
```

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

1.8.4 Error Plot

```
In [12]: def plot(gsv):

             Res=gsv.cv_results_
             cv_auc=[(1-x) for x in Res['mean_test_score']]
             train_auc = [(1-x) for x in Res['mean_train_score']]

             x1=[10000,5000,1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001
             log_c= [math.log10(x) for x in x1]


             plt.xlabel("Hyperparameter (Log(C))",fontsize=15)
             plt.ylabel("Missclassification Error",fontsize=15)
             plt.title('Misclassification Error v/s C',fontsize=15)
             plt.plot(log_c,cv_auc,label="Cross-Validation")
             plt.plot(log_c,train_auc,label="Train")
             plt.legend()
             plt.show()
```

1.8.5 GridSearchCV

```
In [13]: def Grid_SearchCV(X_train,Y_train,regularisation_parameter):

             param_grid = {'C':[10000,5000,1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.00
                       'penalty':[regularisation_parameter]}
             tscv = TimeSeriesSplit(n_splits=10)
             LR = LogisticRegression(class_weight='balanced')

             gsv=GridSearchCV(LR,param_grid,cv=tscv,verbose=1,scoring='roc_auc')
             gsv.fit(X_train,Y_train)

             return gsv
```

1.8.6 30 Informative Feature

```
In [14]:  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
```

1.9 Bags of Words Vectorizer

```
In [15]: 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
(100500, 37994) (100500,)
```

```
(49500, 37994) (49500,)
```

1.10 Part 1 : Taking L1 as a Regularisation Parameter

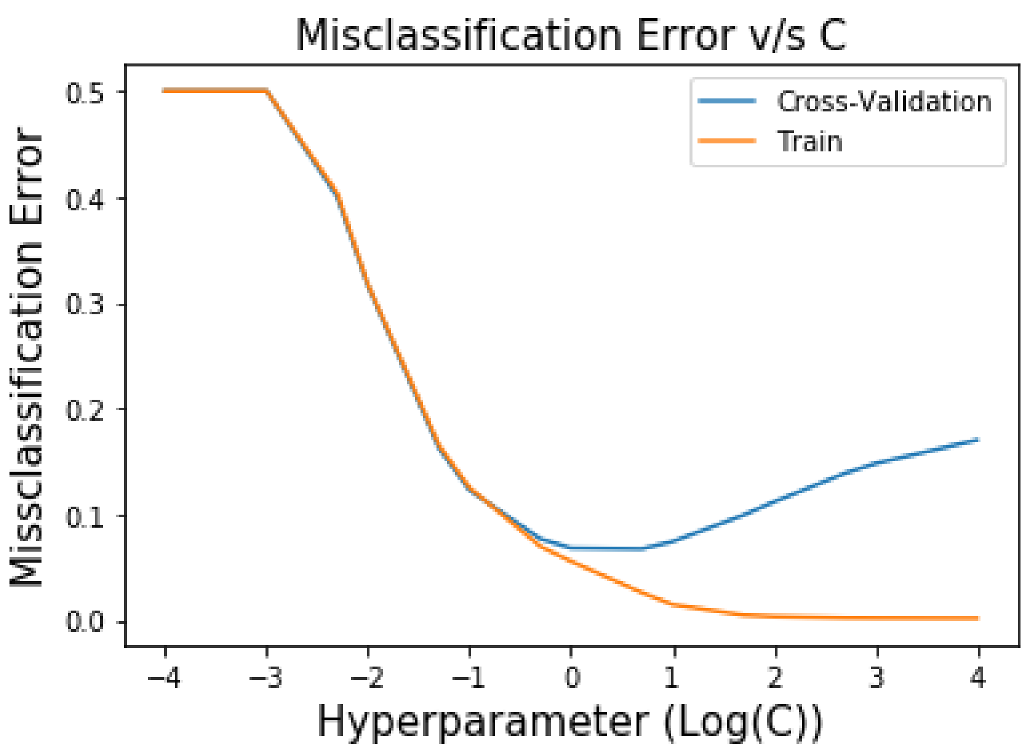
1.10.1 Finding the best value Of hyperparameter (C or 1/Lambda)

In [18]:
```
gsv=Grid_SearchCV(X_train_bow,Y_train,'l1')

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

```
Fitting 10 folds for each of 17 candidates, totalling 170 fits


[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 170 out of 170 | elapsed: 23.5min finished


Best HyperParameter:  {'C': 5, 'penalty': 'l1'}
Best Accuracy: 93.25%
```

1.10.2 Error-Plot

In [45]:
```
plot(gsv)
```



1.10.3 Training the model

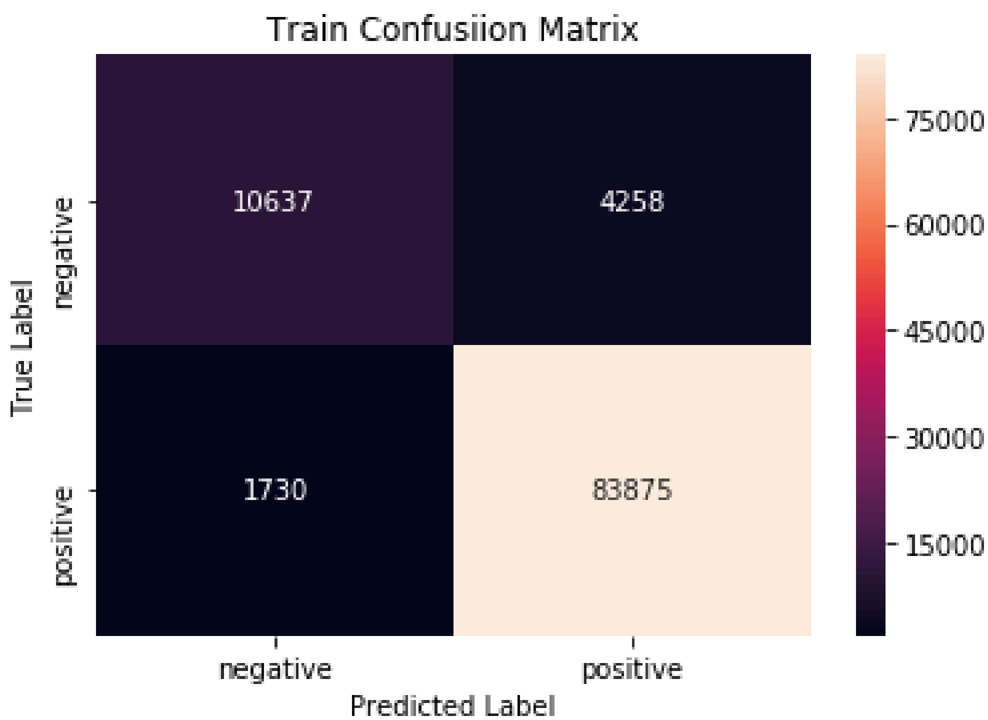
```
In [25]: Best_Param=gsv.best_params_
         C=Best_Param['C']
         Penalty = Best_Param['penalty']

         Model_Bow=LogisticRegression(C=C,penalty=Penalty,class_weight='balanced')
         Model_Bow.fit(X_train_bow,Y_train)
```

```
Out[25]: LogisticRegression(C=5, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, max_iter=100, multi_class='warn',
                   n_jobs=None, penalty='l1', random_state=None, solver='warn',
                   tol=0.0001, verbose=0, warm_start=False)
```

1.10.4 Evaluating the performance of model

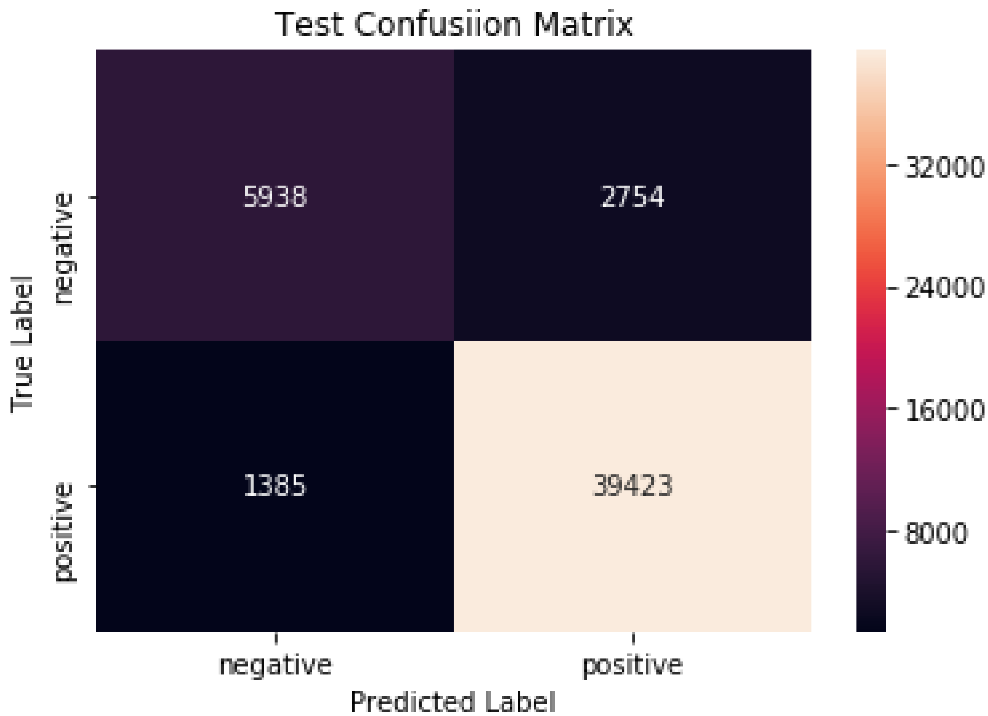
```
In [26]: trainconfusionmatrix(Model_Bow,X_train_bow,Y_train)
```

```
Confusion Matrix for Train set
```

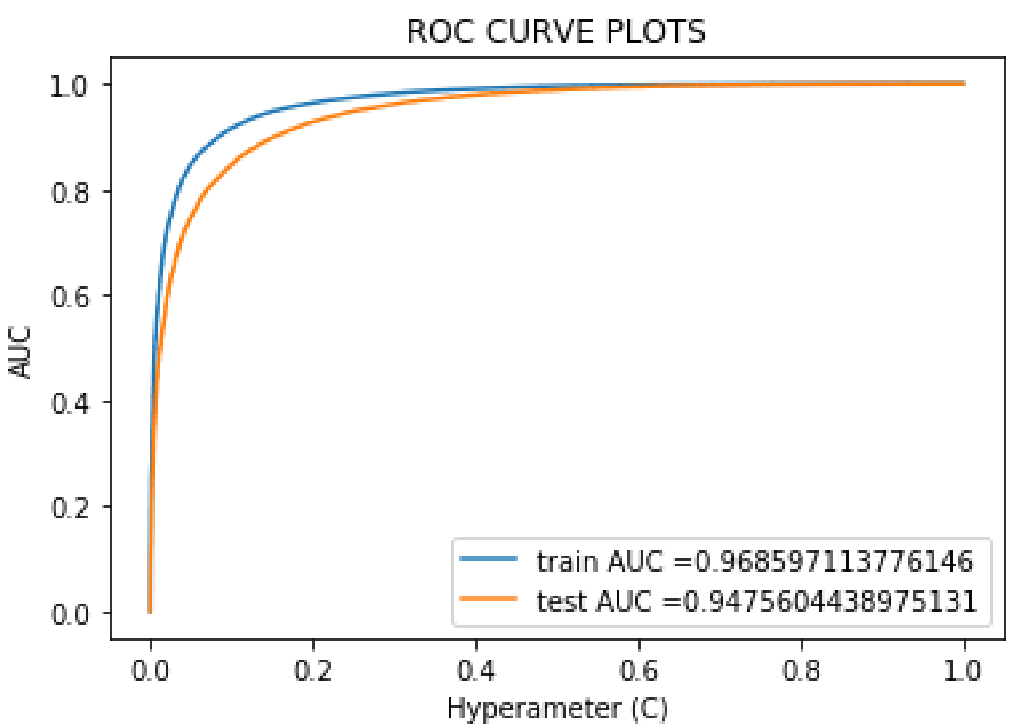



```
In [27]: testconfusionmatrix(Model_Bow,X_test_bow,Y_test)
```

```
Confusion Matrix for Test set
```



In [28]: `plot_auc_roc(Model_Bow,X_train_bow,X_test_bow,Y_train,Y_test)`



```
In [29]: 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       0.81      0.68      0.74      8692
           1       0.93      0.97      0.95     40808

   micro avg       0.92      0.92      0.92     49500
   macro avg       0.87      0.82      0.85     49500
weighted avg       0.91      0.92      0.91     49500
```

1.10.5 Displaying 30 most informative features

```
In [30]: show_30_informative_feature(vectorizer,Model_Bow)
```

```
S.N                   Positive                                                    Negative
------------------------------------------------------------------------------------------
1.                  10.751        addict                                        -15.221        as
2.                  14.850        bravo                                         -13.469        as
3.                  11.311        cujo                                          -12.922        aw
4.                  10.830        delici                                        -21.729        co
5.                  16.410        downsid                                       -15.091        de
6.                  12.746        fascin                                        -12.848        en
7.                  14.110        filbert                                       -13.724        ey
8.                  12.056        finest                                        -16.663        fe
9.                  12.521        goshoptnt                                     -13.234        he
10.                  14.539        gripe                                         -14.645        i
11.                  12.249        heal                                          -19.385        l
12.                  12.816        hook                                          -13.507        n
13.                  11.312        morsel                                        -12.876        r
14.                  13.046        narrow                                        -12.526        r
15.                  14.304        nevertheless                                  -17.224        o
16.                  11.407        penal                                         -12.653        p
17.                  12.362        rater                                         -12.851        o
18.                  10.762        reassur                                       -12.464        i
19.                  11.579        refresh                                       -12.738        i
20.                  14.879        skeptic                                       -12.960        t
21.                  10.681        solv                                          -20.452        t
22.                  11.757        sooth                                         -14.868        t
```

23.	14.262	spectacular	-12.400
24.	10.961	steal	-14.206
25.	11.518	stumbl	-13.515
26.	13.801	tastey	-13.100
27.	12.057	versatil	-19.808
28.	12.000	whim	-12.651
29.	11.250	yay	-17.415
30.	12.017	yum	-18.358

1.11 Part 2 : Taking L2 as a Regularisation Parameter

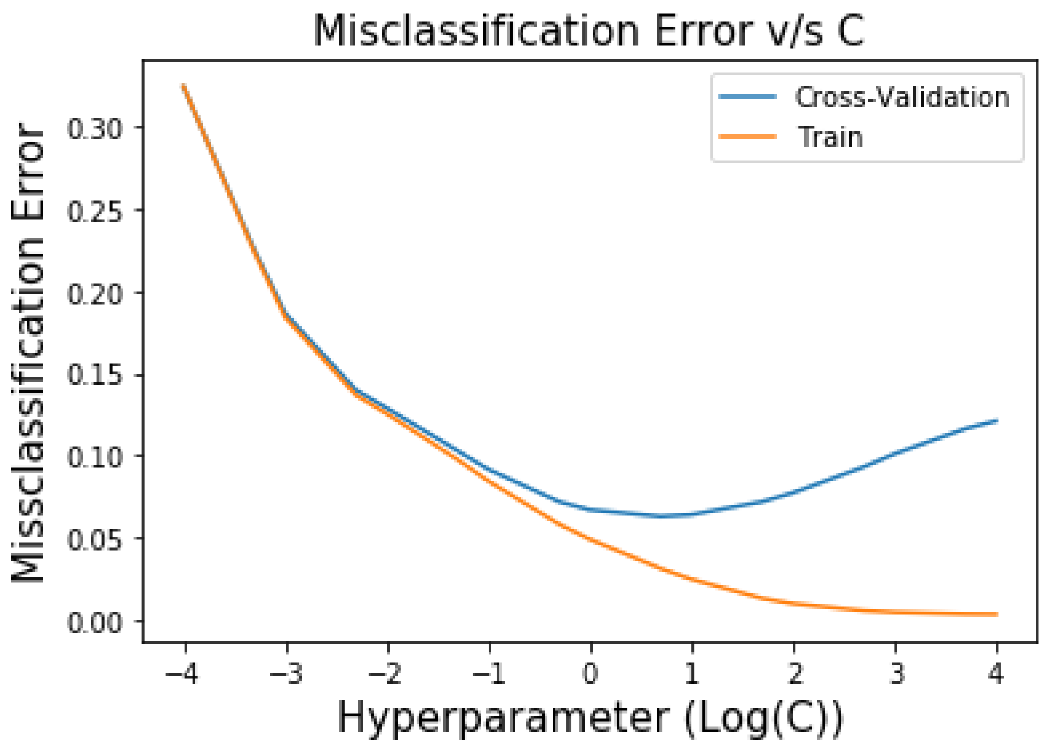
1.11.1 Finding the best value Of hyperparameter (C or 1/Lambda)

In [46]:
```
gsv=Grid_SearchCV(X_train_bow,Y_train,'l2')

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

```
Fitting 10 folds for each of 17 candidates, totalling 170 fits


[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 170 out of 170 | elapsed: 18.2min finished


Best HyperParameter:  {'C': 5, 'penalty': 'l2'}
Best Accuracy: 93.73%
```

1.11.2 Error Plot

In [47]:
```
plot(gsv)
```



1.11.3 Training the model

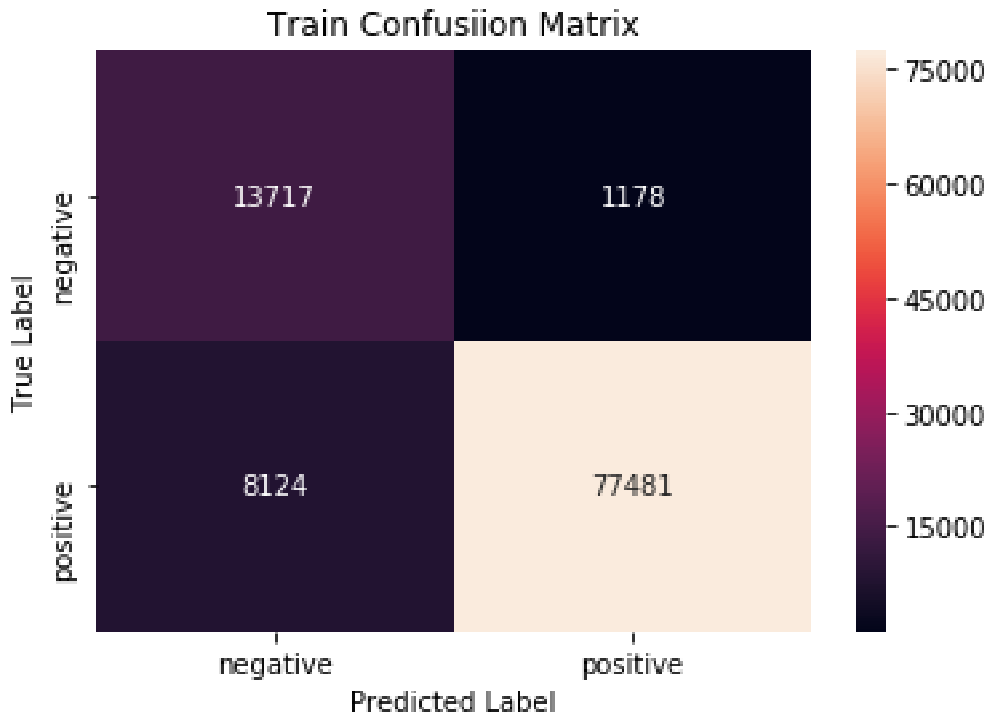
In [49]:
```
Best_Param=gsv.best_params_
C=Best_Param['C']
Penalty = Best_Param['penalty']

Model_Bow=LogisticRegression(C=C,penalty=Penalty,class_weight='balanced')
Model_Bow.fit(X_train_bow,Y_train)
```

Out[49]:
```
LogisticRegression(C=5, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='warn', n_jobs=None, penalty='l2', random_state=None,
          solver='warn', tol=0.0001, verbose=0, warm_start=False)
```

1.11.4 Evaluating the performance of model

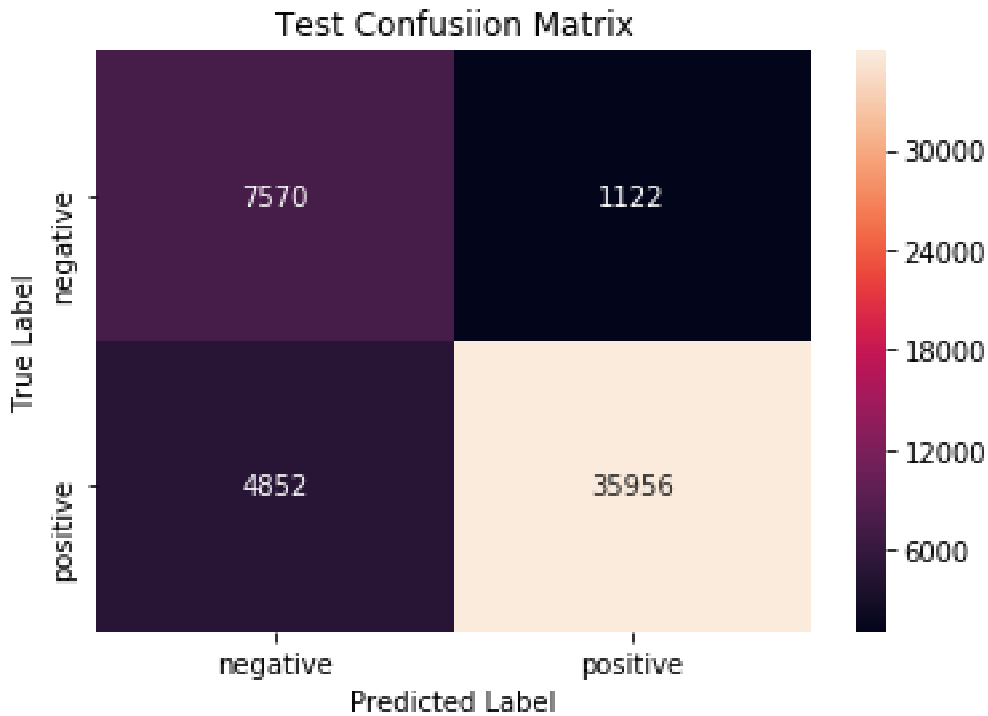
In [50]:
```
trainconfusionmatrix(Model_Bow,X_train_bow,Y_train)
```

```
Confusion Matrix for Train set
```

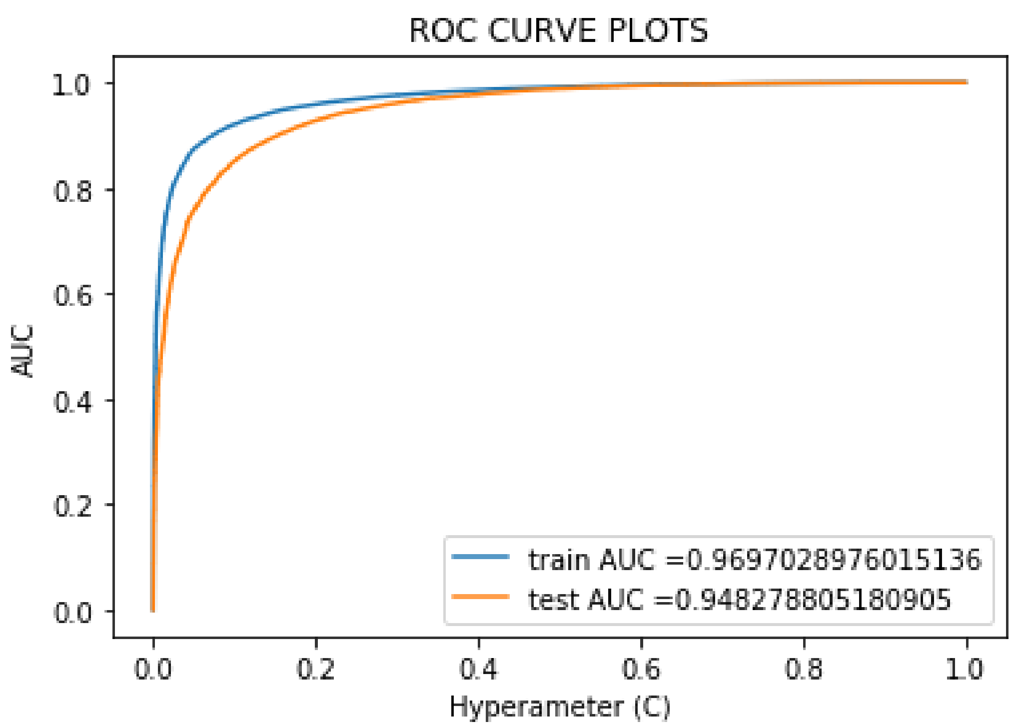



```
In [51]: testconfusionmatrix(Model_Bow,X_test_bow,Y_test)
```

```
Confusion Matrix for Test set
```




```
In [52]: plot_auc_roc(Model_Bow,X_train_bow,X_test_bow,Y_train,Y_test)
```



```
In [53]: 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       0.61      0.87      0.72      8692
           1       0.97      0.88      0.92     40808

   micro avg       0.88      0.88      0.88     49500
   macro avg       0.79      0.88      0.82     49500
weighted avg       0.91      0.88      0.89     49500
```

```
In [54]: show_30_informative_feature(vectorizer,Model_Bow)
```

```
S.N                 Positive                                                     Negative

------------------------------------------------------------------------------------------
1.                 9.411        addict                                    -11.813        aw
2.                 9.014        amaz                                      -8.823        bla
3.                 7.990        awesom                                    -8.392        can
4.                 8.843        beat                                      -8.716        con
5.                 6.319        beauti                                    -10.212        di
6.                 7.859        best                                      -9.389        dis
7.                 7.196        complaint                                 -6.951        ea
8.                 9.800        delici                                    -7.319        fai
9.                 7.950        downsid                                   -7.624        fla
10.                 5.720        drawback                                  -7.934        gr
11.                 8.252        excel                                     -9.971        ho
12.                 6.118        fabul                                     -7.615        in
13.                 7.002        fantast                                   -7.501        me
14.                 6.565        glad                                      -6.946        po
15.                 6.892        great                                     -7.751        re
16.                 5.885        habit                                     -8.956        re
17.                 6.093        happier                                   -8.352        ru
18.                 6.132        heaven                                    -7.053        sh
19.                 9.308        hook                                      -7.148        st
20.                 8.343        perfect                                   -9.299        ta
21.                 7.814        refresh                                   -11.563        t
22.                 7.599        satisfi                                   -9.097        th
23.                 8.586        skeptic                                   -7.799        un
24.                 6.738        smooth                                    -7.521        un
```

25.	6.210	sooth	-8.705	uni
26.	6.343	terrif	-9.674	unp
27.	6.375	uniqu	-7.638	wea
28.	7.160	worri	-8.367	wor
29.	8.218	yum	-15.006	wo
30.	8.129	yummi	-7.478	yuc

1.12 TF-IDF Vectorizer

```
In [30]: vectorizer_tfidf=TfidfVectorizer()
         vectorizer_tfidf.fit(X_train)
```

```
Out[30]: 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 [31]: 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 [32]: 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
(100500, 37994) (100500,)
(49500, 37994) (49500,)
```

1.13 Taking L1 as a Regularisation Parameter

1.13.1 Finding the best value Of hyperparameter (C or 1/Lambda)

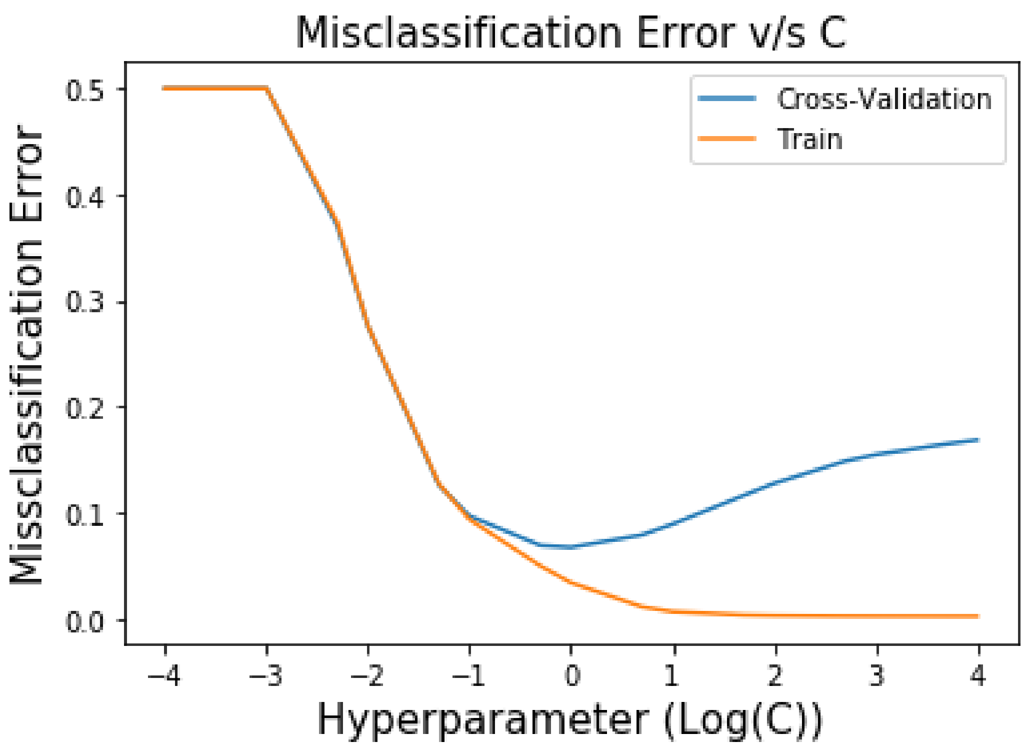
```
In [21]: gsv=Grid_SearchCV(X_Train_Tfidf,Y_train,'l1')

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

```
Fitting 10 folds for each of 17 candidates, totalling 170 fits


[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 170 out of 170 | elapsed: 163.2min finished
```

```
Best HyperParameter:  {'C': 1, 'penalty': 'l1'}
Best Accuracy: 93.30%
```

1.13.2 Error Plot

```
In [22]: plot(gsv)
```



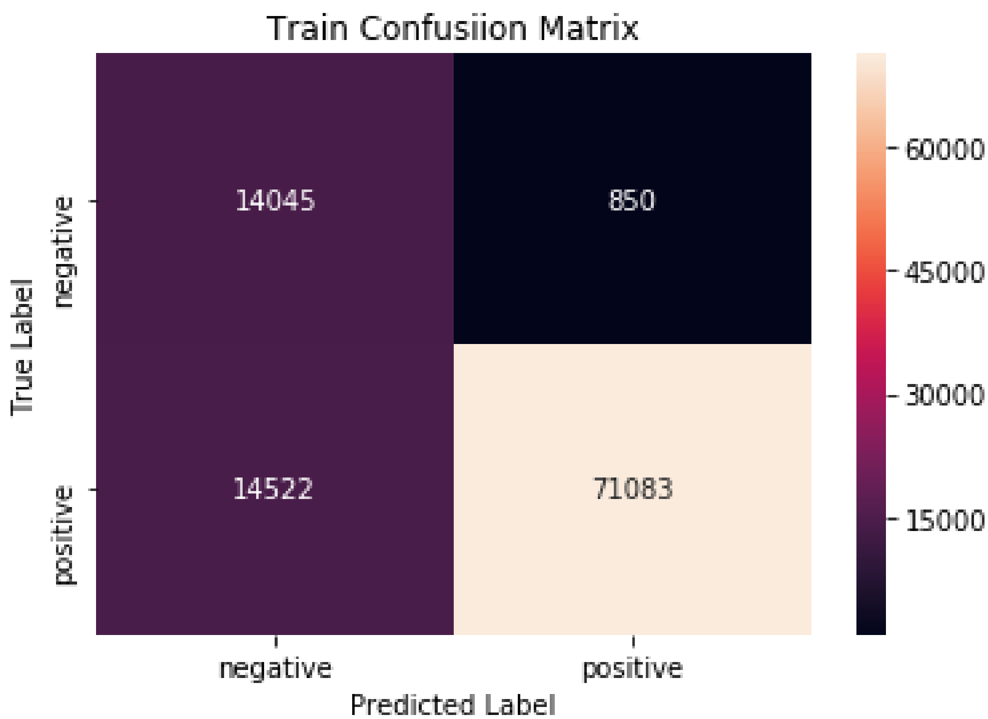
1.13.3 Training the model

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

         Model_Tfidf=LogisticRegression(C=C,penalty=Penalty,class_weight='balanced')
         Model_Tfidf.fit(X_train_bow,Y_train)

Out[23]: LogisticRegression(C=1, class_weight='balanced', dual=False,
                   fit_intercept=True, intercept_scaling=1, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l1', random_state=None,
                   solver='warn', tol=0.0001, verbose=0, warm_start=False)
```

1.13.4 Evaluating the performance of model

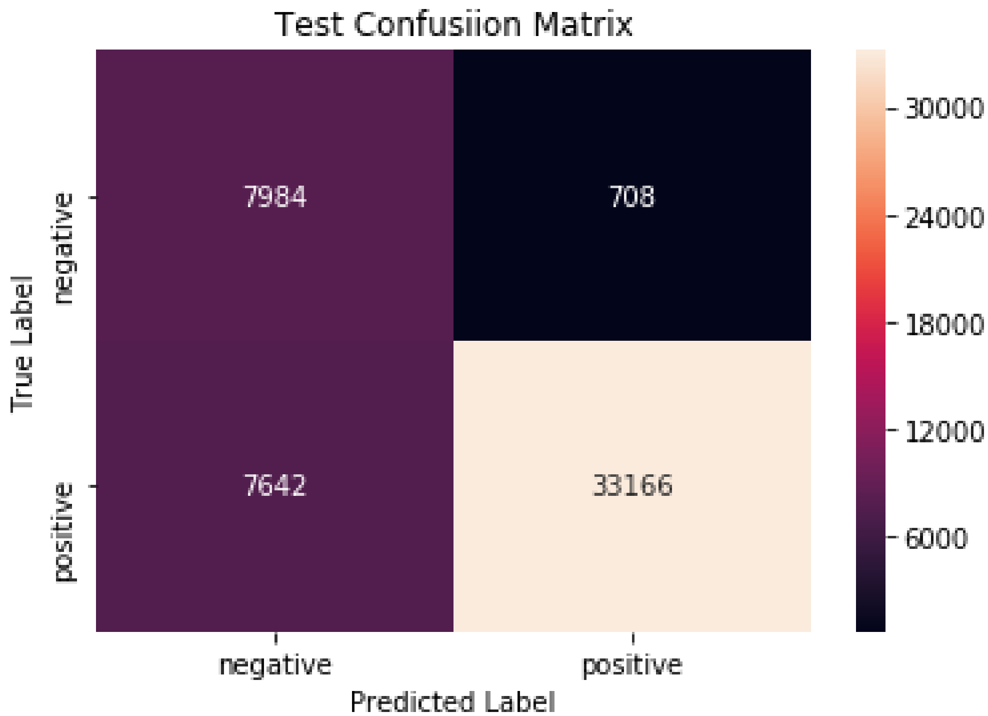
```
In [24]: trainconfusionmatrix(Model_Tfidf,X_Train_Tfidf,Y_train)
```

```
Confusion Matrix for Train set
```

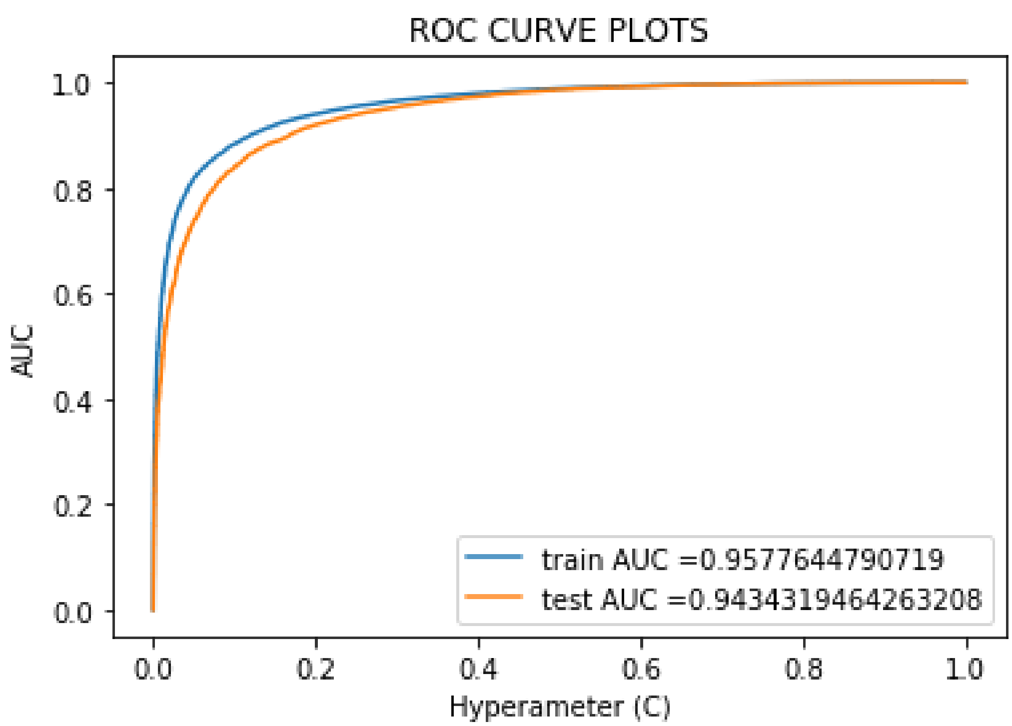



```
In [25]: testconfusionmatrix(Model_Tfidf,X_Test_Tfidf,Y_test)
```

```
Confusion Matrix for Test set
```




```
In [26]: plot_auc_roc(Model_Tfidf,X_Train_Tfidf,X_Test_Tfidf,Y_train,Y_test)
```



```
In [27]: 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       0.51      0.92      0.66      8692
           1       0.98      0.81      0.89     40808

   micro avg       0.83      0.83      0.83     49500
   macro avg       0.75      0.87      0.77     49500
weighted avg       0.90      0.83      0.85     49500
```

1.13.5 Displaying 30 most informative features

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

```
S.N                    Positive                                                       Negative
------------------------------------------------------------------------------------------
1.                  10.139        addict                                                 -13.064        a
2.                  9.406       amaz                                                   -9.133       bla
3.                  8.423       awesom                                                 -10.132        ca
4.                  10.021        beat                                                   -10.651        c
5.                  6.980       beauti                                                 -7.857       dec
6.                  7.909       best                                                   -9.879       dec
7.                  7.294       complaint                                              -10.159        di
8.                  9.996       delici                                                 -11.139       di
9.                  11.857        downsid                                                -7.996        dr
10.                  8.466        excel                                                  -8.134        fa
11.                  6.967        fabul                                                  -10.004        f
12.                  7.052        fantast                                                -8.553        gr
13.                  6.808        glad                                                   -10.879        h
14.                  6.894        great                                                  -10.254        i
15.                  7.186        habit                                                  -10.983        m
16.                  7.372        happier                                                -8.612        op
17.                  6.660        heaven                                                 -8.446        re
18.                  11.047         hook                                                   -9.221        r
19.                  8.251        perfect                                                -9.101        ru
20.                  8.721        refresh                                                -10.548        t
21.                  7.890        satisfi                                                -12.189        t
22.                  12.359         skeptic                                                -9.873        t
```

```
23.                6.920      smooth                                       -10.156       tl
24.                8.476      sooth                                        -9.988       una
25.                7.458      uniqu                                        -12.696       ur
26.                7.559      versatil                                     -9.074       uni
27.                7.442      whim                                         -11.399       ur
28.                7.932      worri                                        -9.091       wo
29.                9.618      yum                                          -17.436       wo
30.                8.364      yummi                                        -8.111       yu
```

1.14 Taking L2 as a Regularisation Parameter

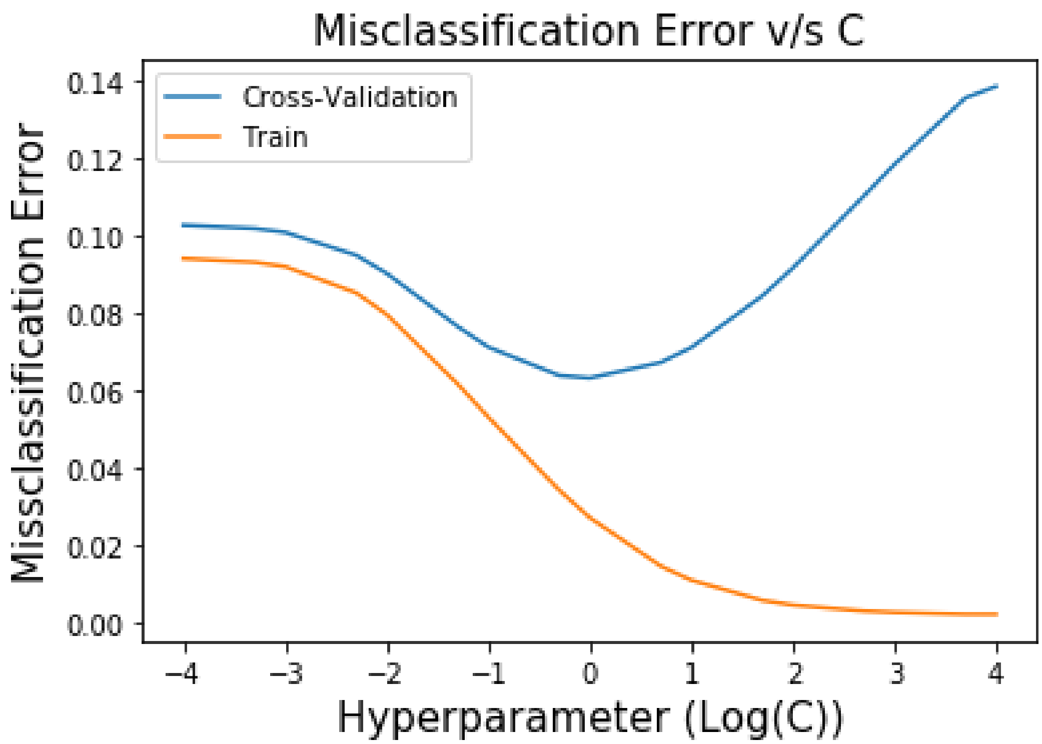
1.14.1 Finding the best value Of hyperparameter (C or 1/Lambda)

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))
```

```
Fitting 10 folds for each of 17 candidates, totalling 170 fits


[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 170 out of 170 | elapsed: 15.0min finished


Best HyperParameter:  {'C': 1, 'penalty': 'l2'}
Best Accuracy: 93.68%
```

1.14.2 Error Plot

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



1.14.3 Training the mode

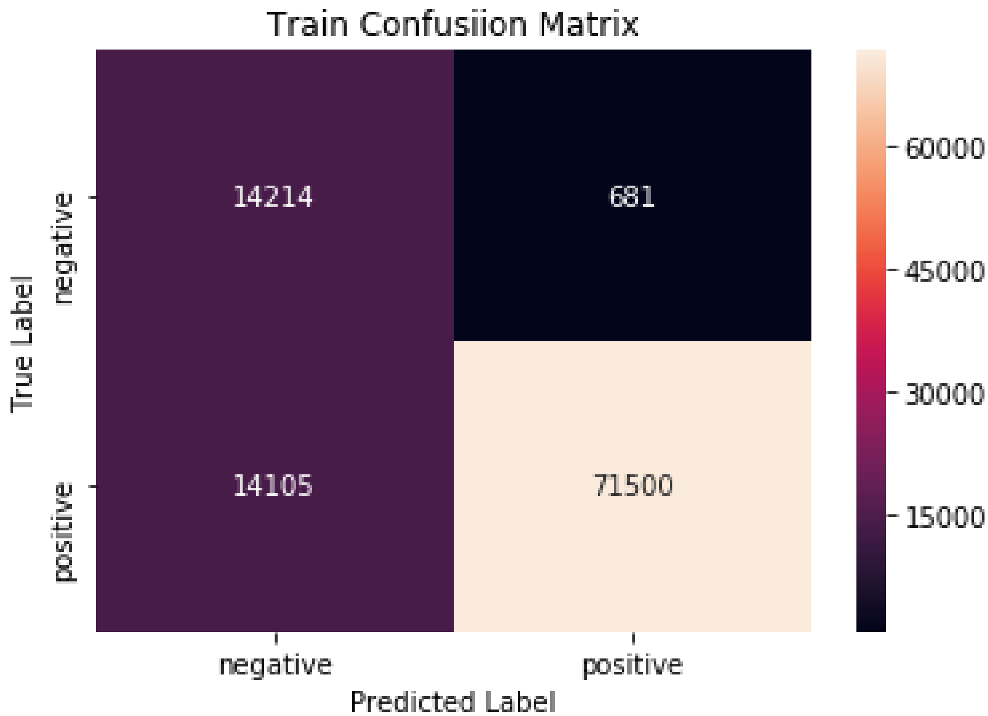
In [31]:
```
Best_Param=gsv.best_params_
C=Best_Param['C']
Penalty = Best_Param['penalty']

Model_Tfidf=LogisticRegression(C=C,penalty=Penalty,class_weight='balanced')
Model_Tfidf.fit(X_train_bow,Y_train)
```

Out[31]:
```
LogisticRegression(C=1, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='warn', n_jobs=None, penalty='l2', random_state=None,
          solver='warn', tol=0.0001, verbose=0, warm_start=False)
```

1.14.4 Evaluating the performance of model

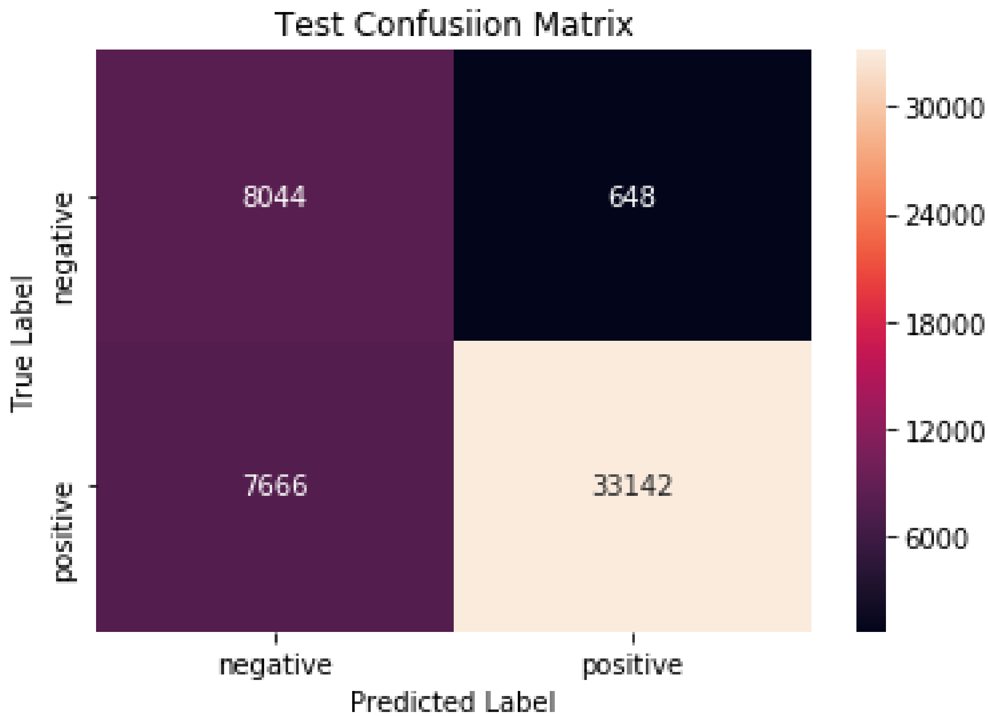
In [32]:
```
trainconfusionmatrix(Model_Tfidf,X_Train_Tfidf,Y_train)
```

```
Confusion Matrix for Train set
```

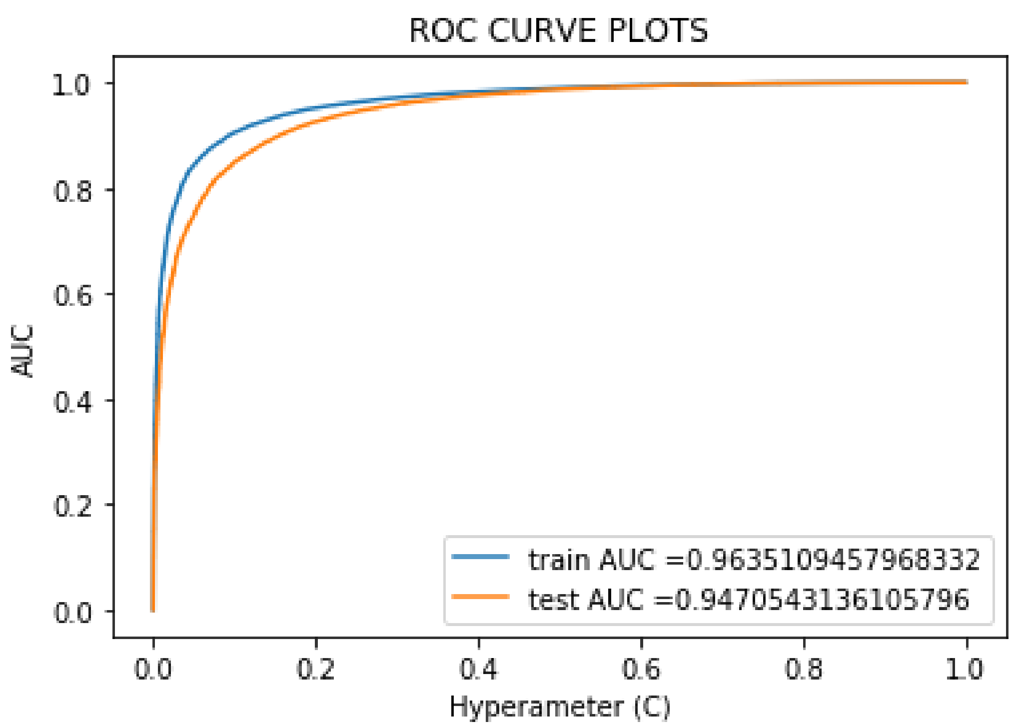



```
In [33]: testconfusionmatrix(Model_Tfidf,X_Test_Tfidf,Y_test)
```

```
Confusion Matrix for Test set
```




```
In [34]: plot_auc_roc(Model_Tfidf,X_Train_Tfidf,X_Test_Tfidf,Y_train,Y_test)
```



```
In [35]: 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       0.51      0.93      0.66      8692
           1       0.98      0.81      0.89     40808

   micro avg       0.83      0.83      0.83     49500
   macro avg       0.75      0.87      0.77     49500
weighted avg       0.90      0.83      0.85     49500
```

```
In [36]: show_30_informative_feature(vectorizer_tfidf,Model_Tfidf)
```

```
S.N                 Positive                                                      Negative
-----------------------------------------------------------------------------------------------
1.               6.398        addict                                              -8.666        aw
2.               7.030        amaz                                                -4.353        bar
3.               5.944        awesom                                              -4.465        bew
4.               5.792        beat                                                -6.507        bla
5.               4.120        beauti                                              -4.733        can
6.               7.024        best                                                -9.024        dis
7.               4.659        complaint                                           -6.022        dis
8.               8.489        delici                                              -4.433        ear
9.               4.560        easi                                                -5.182        gro
10.               7.182        excel                                               -7.371        ho
11.               5.105        fantast                                             -4.307        mo
12.               4.673        favorit                                             -5.133        po
13.               5.131        glad                                                -5.292        re
14.               6.400        great                                               -7.271        re
15.               4.215        happi                                               -5.036        ru
16.               5.426        hook                                                -4.640        sa
17.               4.936        love                                                -4.423        sh
18.               4.570        nice                                                -4.696        so
19.               7.153        perfect                                             -5.470        st
20.               4.929        refresh                                             -4.798        st
21.               5.876        satisfi                                             -5.644        ta
22.               5.373        smooth                                              -8.374        te
23.               4.051        tasti                                               -5.834        th
24.               4.327        thank                                               -7.005        un
```

```
25.                  3.958        uniqu                                           -5.636        unp
26.                  3.879        without                                         -4.787        was
27.                  4.456        wonder                                          -5.962        wea
28.                  4.659        worri                                           -5.332        wor
29.                  4.800        yum                                             -10.212        wo
30.                  6.071        yummi                                           -4.410        yuc
```

1.15 Word To Vector

In [15]:
```python
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 [16]:
```python
model=Word2Vec(list_of_Train_sent,min_count=5,size=50, workers=4)
```

1.16 Average Word To Vector

In [17]:
```python
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 [18]:
```python
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 [19]:
```
print("Shape of Test Vectors : ",Test_vectors.shape)
```

```
Shape of Test Vectors :  (49500, 50)
```

In [20]:
```
X_Train_Awv=Train_vectors
X_Test_Awv=Test_vectors
```

In [21]:
```
print(X_Train_Awv.shape, Y_train.shape)
print(X_Test_Awv.shape, Y_test.shape)
```

```
(100500, 50) (100500,)
(49500, 50) (49500,)
```

1.17 Taking L1 as a Regularisation Parameter

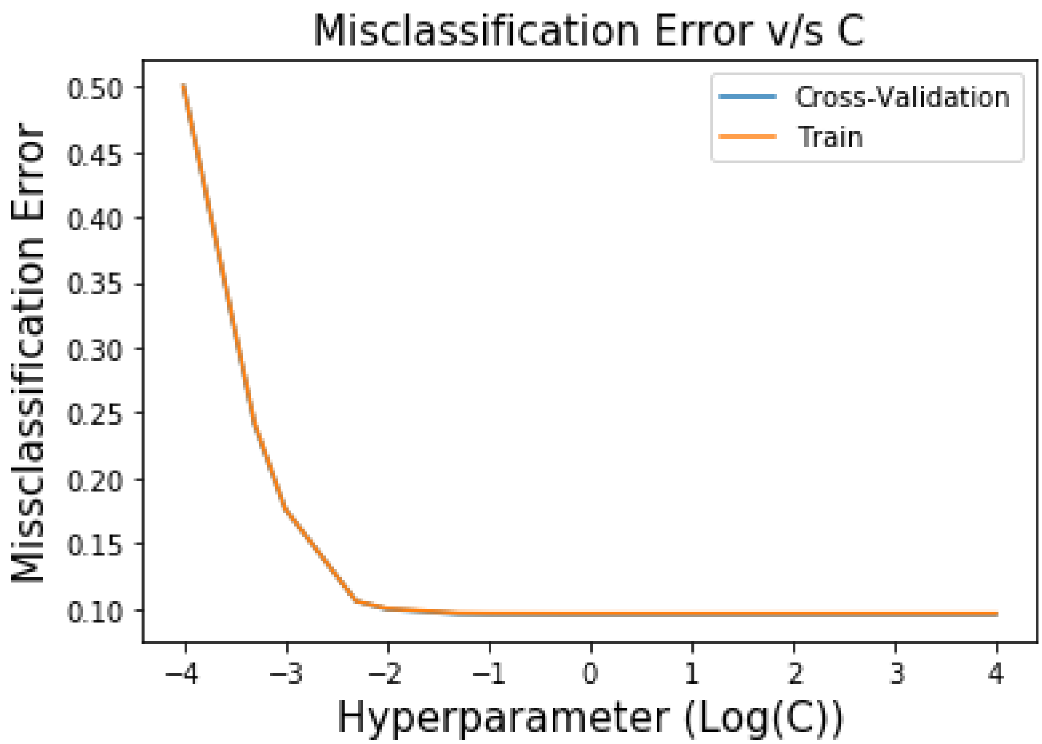
1.17.1 Finding the best value Of hyperparameter (C or 1/Lambda)

In [23]:
```
gsv=Grid_SearchCV(X_Train_Awv,Y_train,"l1")

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

```
Fitting 10 folds for each of 17 candidates, totalling 170 fits


[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 170 out of 170 | elapsed: 52.6min finished


Best HyperParameter:  {'C': 1, 'penalty': 'l1'}
Best Accuracy: 90.46%
```

1.17.2 Error Plot

In [24]:
```
plot(gsv)
```



1.17.3 Training Model

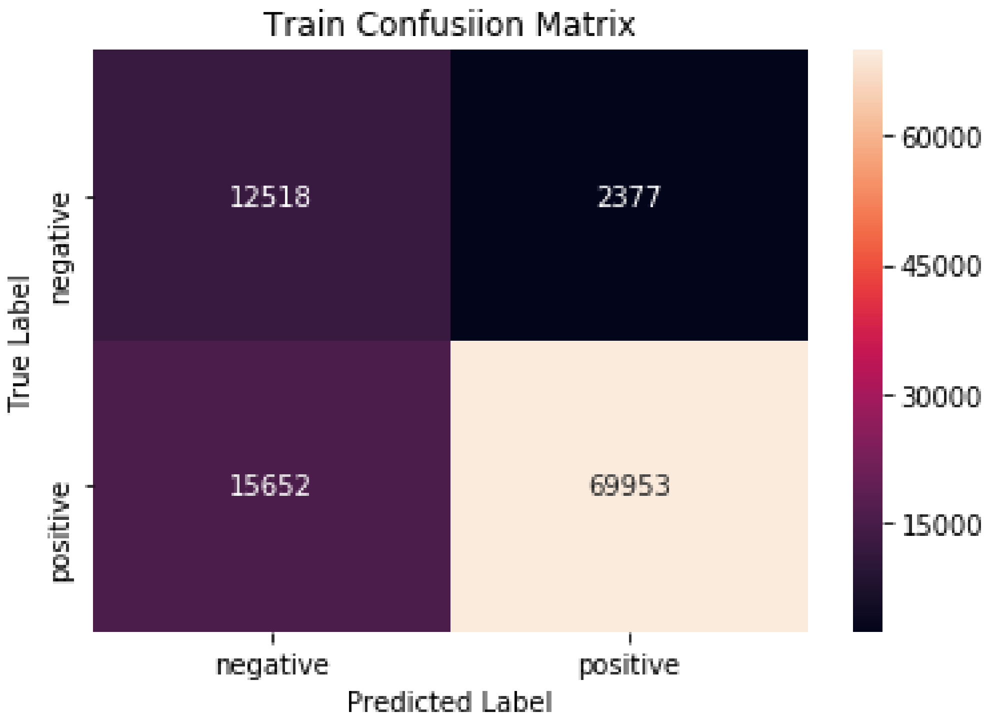
In [25]:
```
Best_Param=gsv.best_params_
C=Best_Param['C']
Penalty = Best_Param['penalty']

Model_Awv=LogisticRegression(C=C,penalty=Penalty,class_weight='balanced')
Model_Awv.fit(X_Train_Awv,Y_train)
```

Out[25]:
```
LogisticRegression(C=1, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='warn', n_jobs=None, penalty='l1', random_state=None,
          solver='warn', tol=0.0001, verbose=0, warm_start=False)
```

1.17.4 Evaluating the performance of model

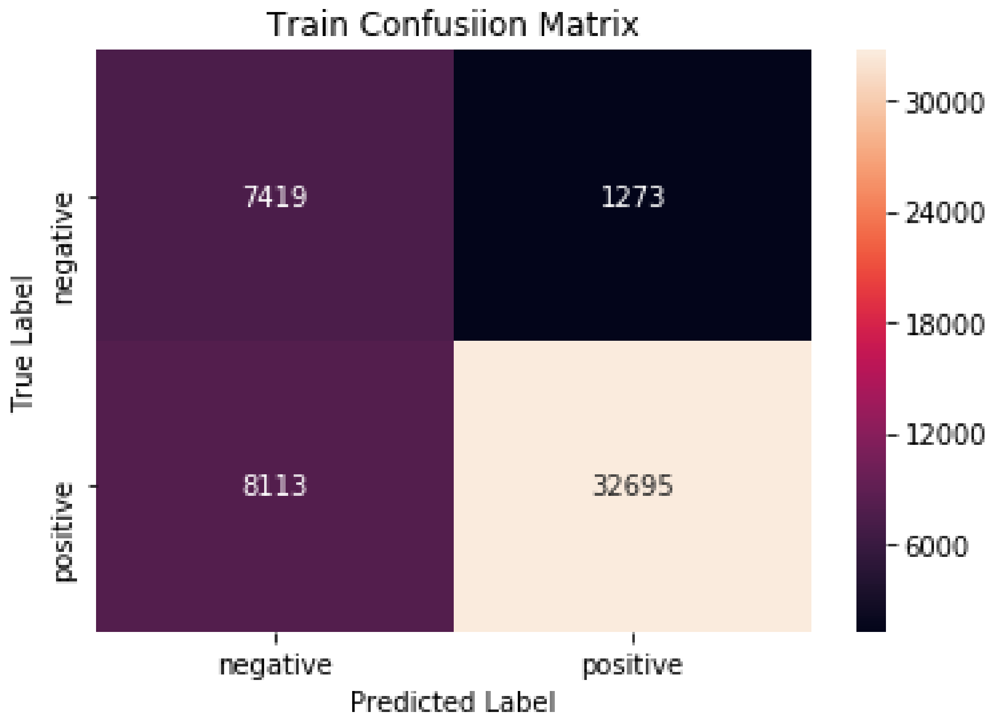
In [26]:
```
trainconfusionmatrix(Model_Awv,X_Train_Awv,Y_train)
```

```
Confusion Matrix for Train set
```

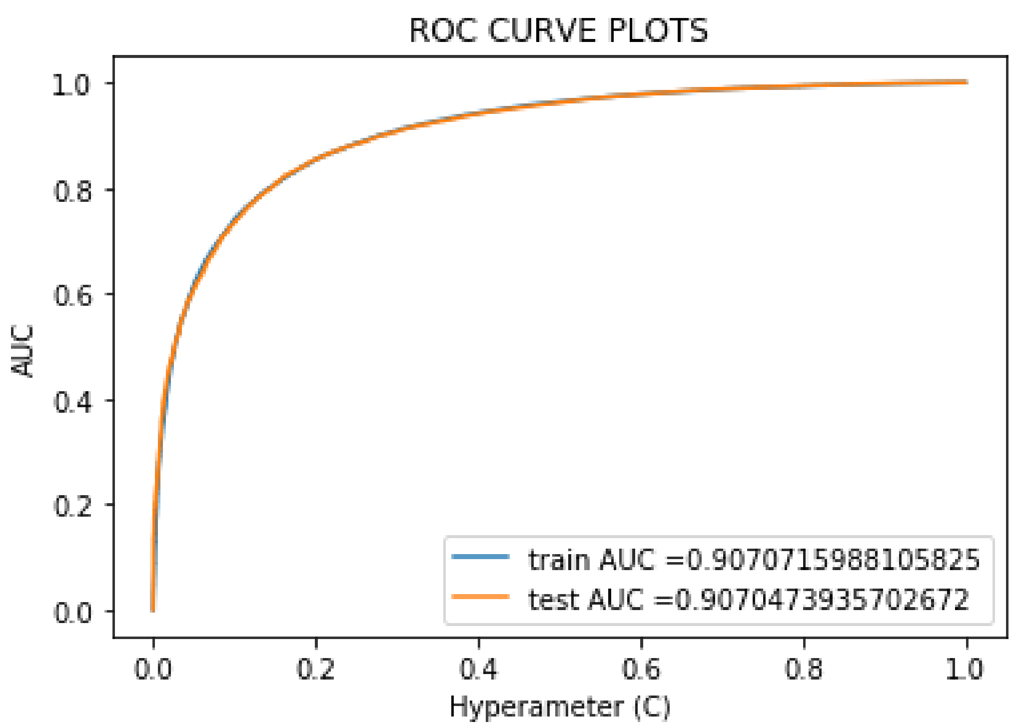



```
In [27]: trainconfusionmatrix(Model_Awv,X_Test_Awv,Y_test)
```

```
Confusion Matrix for Train set
```




```
In [28]: plot_auc_roc(Model_Awv,X_Train_Awv,X_Test_Awv,Y_train,Y_test)
```



```
In [29]: 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       0.48      0.85      0.61      8692
           1       0.96      0.80      0.87     40808

   micro avg       0.81      0.81      0.81     49500
   macro avg       0.72      0.83      0.74     49500
weighted avg       0.88      0.81      0.83     49500
```

1.18 Taking L2 as a Regularisation Parameter

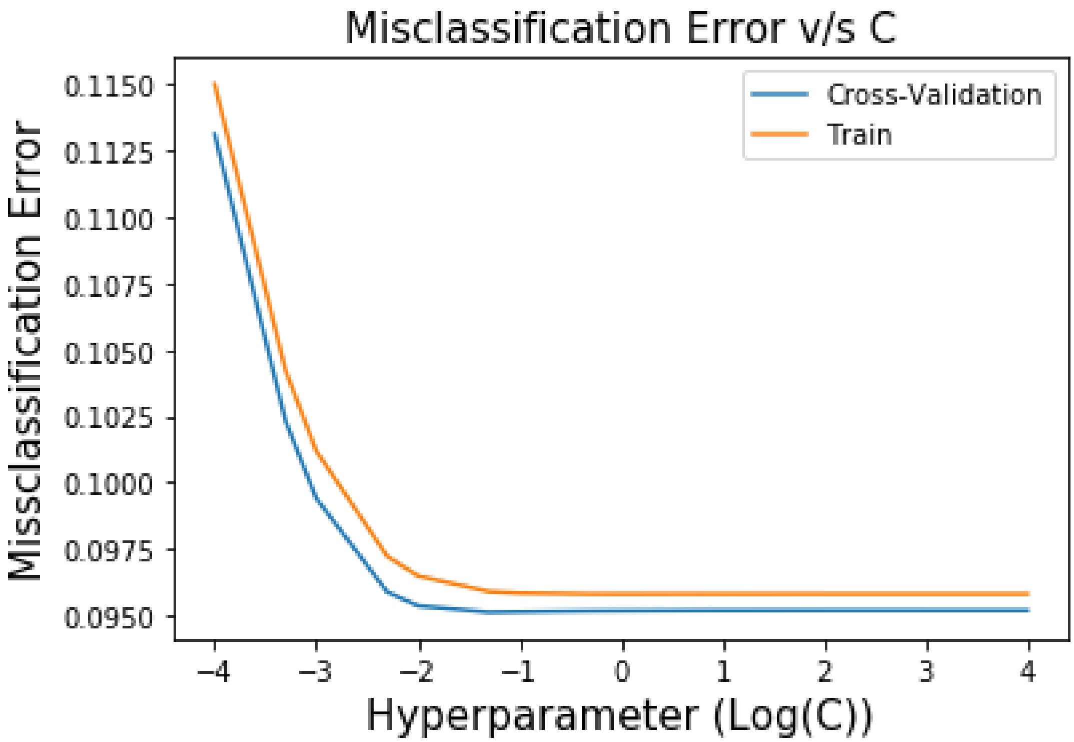
1.18.1 Finding the best value Of hyperparameter (C or 1/Lambda)

```
In [22]: gsv=Grid_SearchCV(X_Train_Awv,Y_train,"l2")

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

```
Fitting 10 folds for each of 17 candidates, totalling 170 fits


[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 170 out of 170 | elapsed:  3.2min finished


Best HyperParameter:  {'C': 0.05, 'penalty': 'l2'}
Best Accuracy: 90.49%
```

1.18.2 Error Plot

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



1.18.3 Training the model

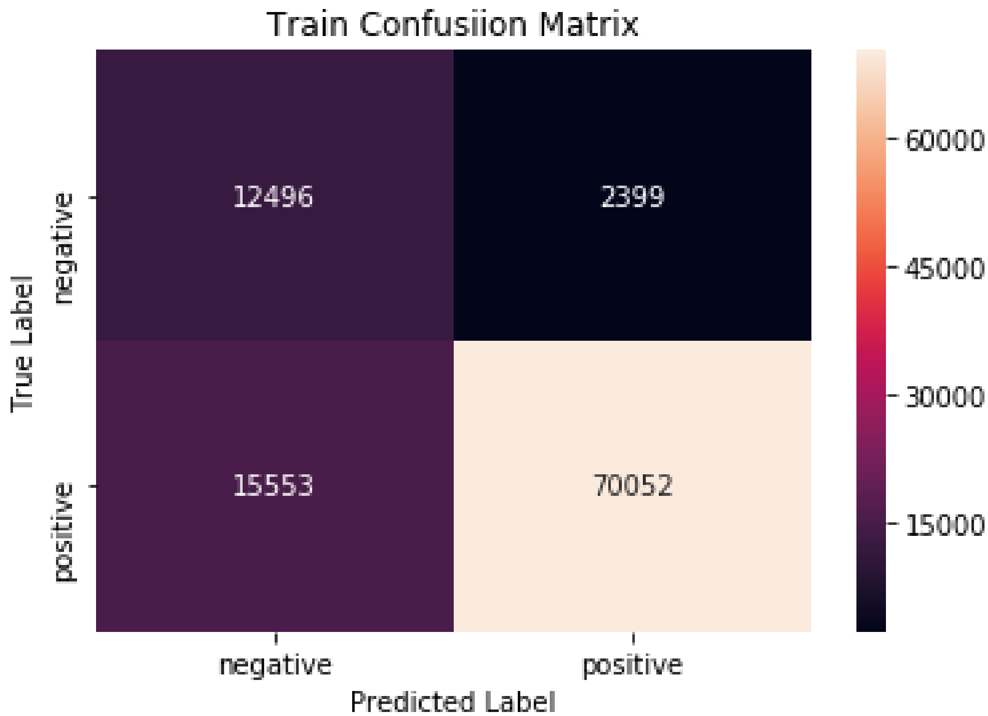
In [24]:
```
Best_Param=gsv.best_params_
C=Best_Param['C']
Penalty = Best_Param['penalty']

Model_Awv=LogisticRegression(C=C,penalty=Penalty,class_weight='balanced')
Model_Awv.fit(X_Train_Awv,Y_train)
```

Out[24]:
```
LogisticRegression(C=0.05, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='warn', n_jobs=None, penalty='l2', random_state=None,
          solver='warn', tol=0.0001, verbose=0, warm_start=False)
```

1.18.4 Evaluating the performance of model

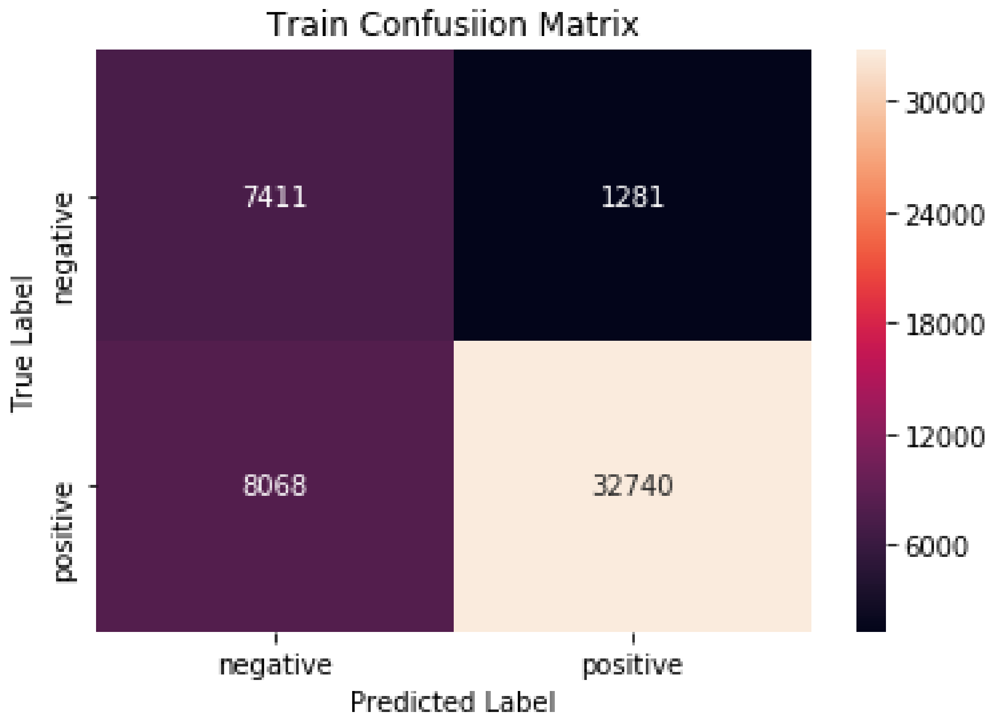
In [25]:
```
trainconfusionmatrix(Model_Awv,X_Train_Awv,Y_train)
```

```
Confusion Matrix for Train set
```

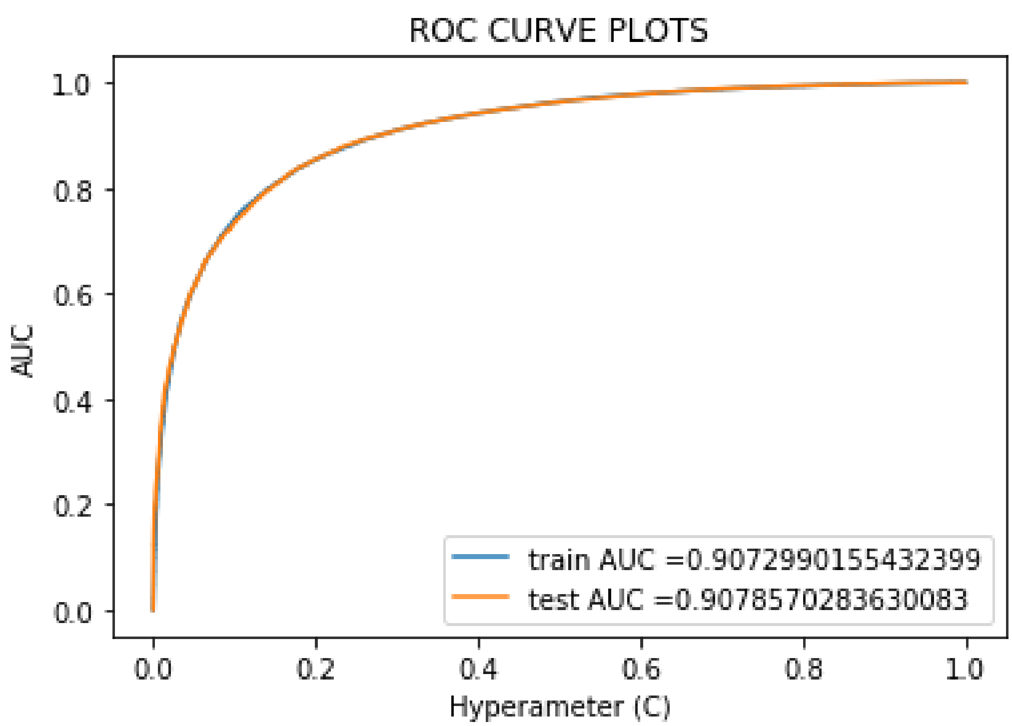



```
In [26]: trainconfusionmatrix(Model_Awv,X_Test_Awv,Y_test)
```

```
Confusion Matrix for Train set
```



In [27]: `plot_auc_roc(Model_Awv,X_Train_Awv,X_Test_Awv,Y_train,Y_test)`



```
In [28]: 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       0.48      0.85      0.61      8692
           1       0.96      0.80      0.88     40808

   micro avg       0.81      0.81      0.81     49500
   macro avg       0.72      0.83      0.74     49500
weighted avg       0.88      0.81      0.83     49500
```

1.19 TF-IDF Word To Vector

```
In [33]: TFIDF_Feature=vectorizer_tfidf.get_feature_names()
         print(len(TFIDF_Feature))
         print(TFIDF_Feature[0:20])
```

```
37994
['aaa', 'aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa', 'aaaaaaaaaaaaaaaaaaaaaargh', 'aaaaaaaaag
```

```
In [34]: 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%|| 100500/100500 [1:04:56<00:00, 25.79it/s]
```

```
In [35]: 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%|| 49500/49500 [24:01<00:00, 34.33it/s]
```

```
In [36]: 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 [37]: X_Train_TfidfW2v=Train_TFIDF_W2V_Vectors
         X_Test_TfidfW2v=Test_TFIDF_W2V_Vectors

In [38]: print(X_Train_TfidfW2v.shape, Y_train.shape)
         print(X_Test_TfidfW2v.shape, Y_test.shape)
```

```
(100500, 50) (100500,)
(49500, 50) (49500,)
```

1.20 Taking L1 as a Regularisation Parameter

1.20.1 Finding the best value Of hyperparameter (C or 1/Lambda)

```
In [39]: gsv=Grid_SearchCV(X_Train_TfidfW2v,Y_train,"l1")

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

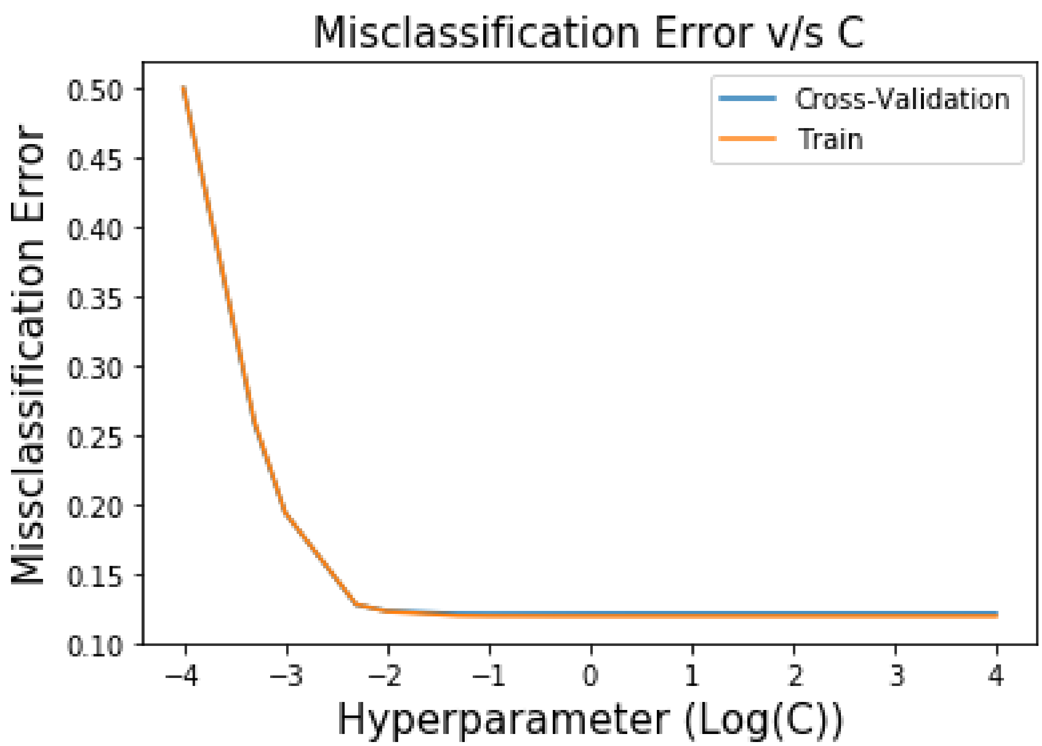
```
Fitting 10 folds for each of 17 candidates, totalling 170 fits
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 170 out of 170 | elapsed: 26.1min finished
```

```
Best HyperParameter:  {'C': 0.1, 'penalty': 'l1'}
Best Accuracy: 87.85%
```

1.20.2 Error Plot

```
In [40]: plot(gsv)
```



1.20.3 Training Model

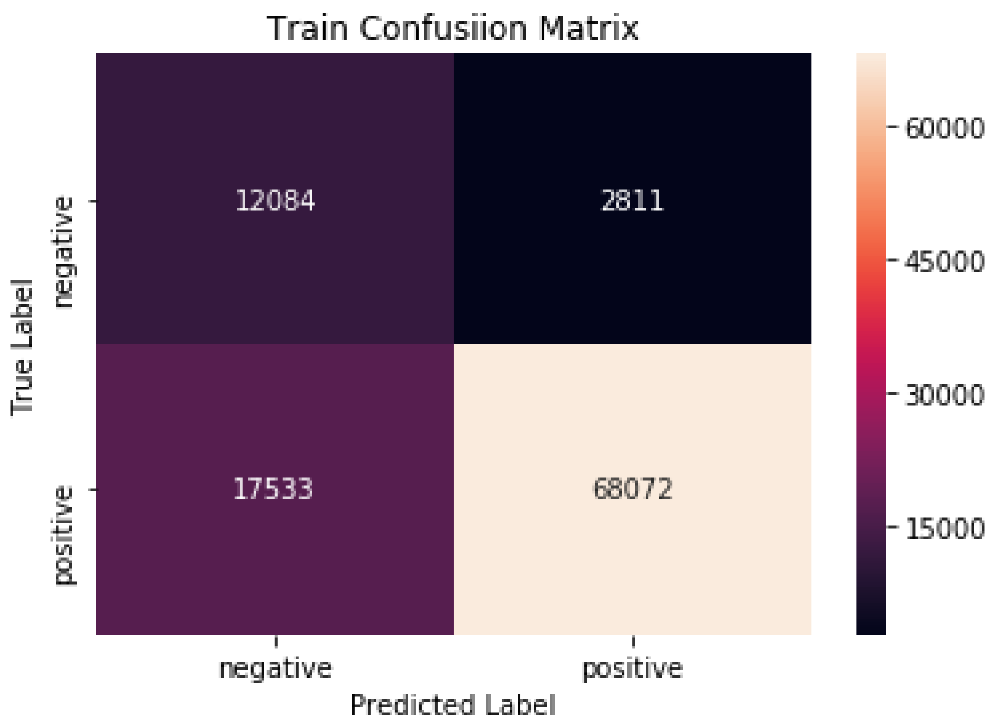
```
In [41]: Best_Param=gsv.best_params_
         C=Best_Param['C']
         Penalty = Best_Param['penalty']

         Model_TfidfW2v=LogisticRegression(C=C,penalty=Penalty,class_weight='balanced')
         Model_TfidfW2v.fit(X_Train_TfidfW2v,Y_train)
```

```
Out[41]: LogisticRegression(C=0.1, class_weight='balanced', dual=False,
                   fit_intercept=True, intercept_scaling=1, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l1', random_state=None,
                   solver='warn', tol=0.0001, verbose=0, warm_start=False)
```

1.20.4 Evaluating the performance of model

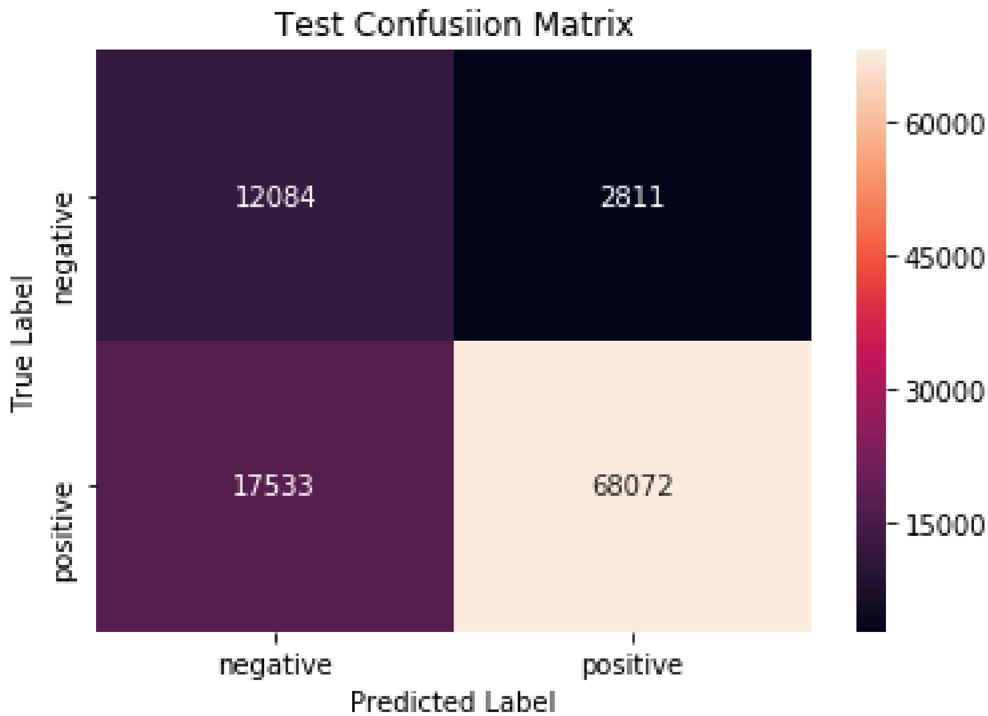
```
In [42]: trainconfusionmatrix(Model_TfidfW2v,X_Train_TfidfW2v,Y_train)
```

```
Confusion Matrix for Train set
```

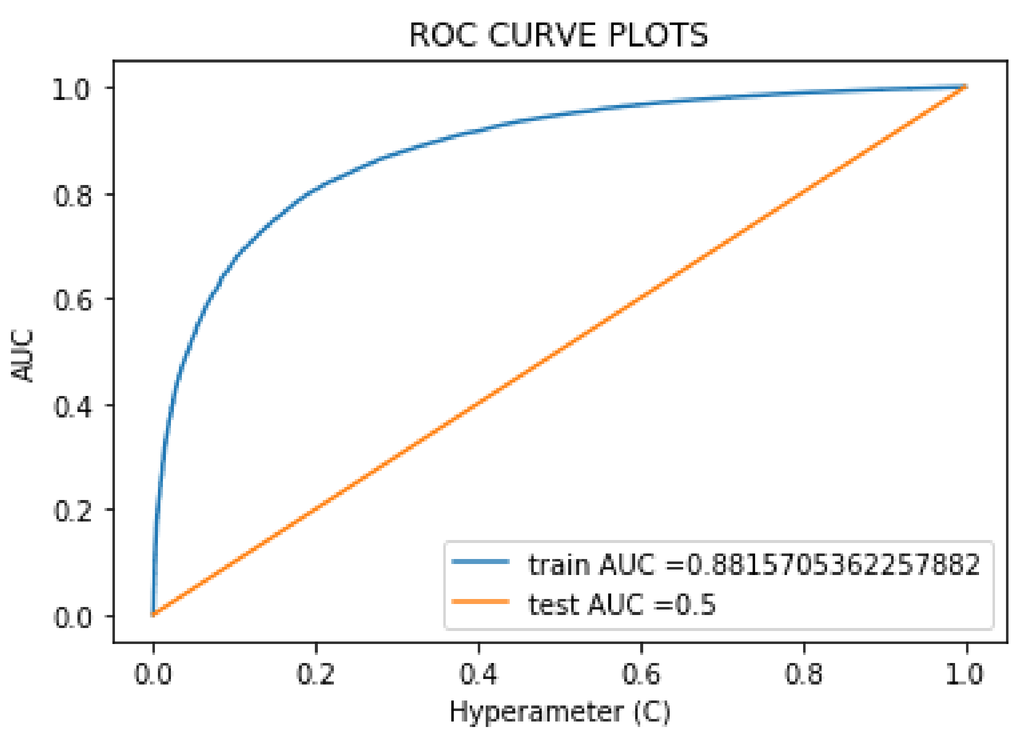



```
In [43]: testconfusionmatrix(Model_TfidfW2v,X_Train_TfidfW2v,Y_train)
```

```
Confusion Matrix for Test set
```



In [44]: `plot_auc_roc(Model_TfidfW2v,X_Train_TfidfW2v,X_Test_TfidfW2v,Y_train,Y_test)`



```
In [45]: 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       0.18      1.00      0.30      8692
           1       0.00      0.00      0.00     40808

   micro avg       0.18      0.18      0.18     49500
   macro avg       0.09      0.50      0.15     49500
weighted avg       0.03      0.18      0.05     49500
```

1.21 Taking L2 as a Regularisation Parameter

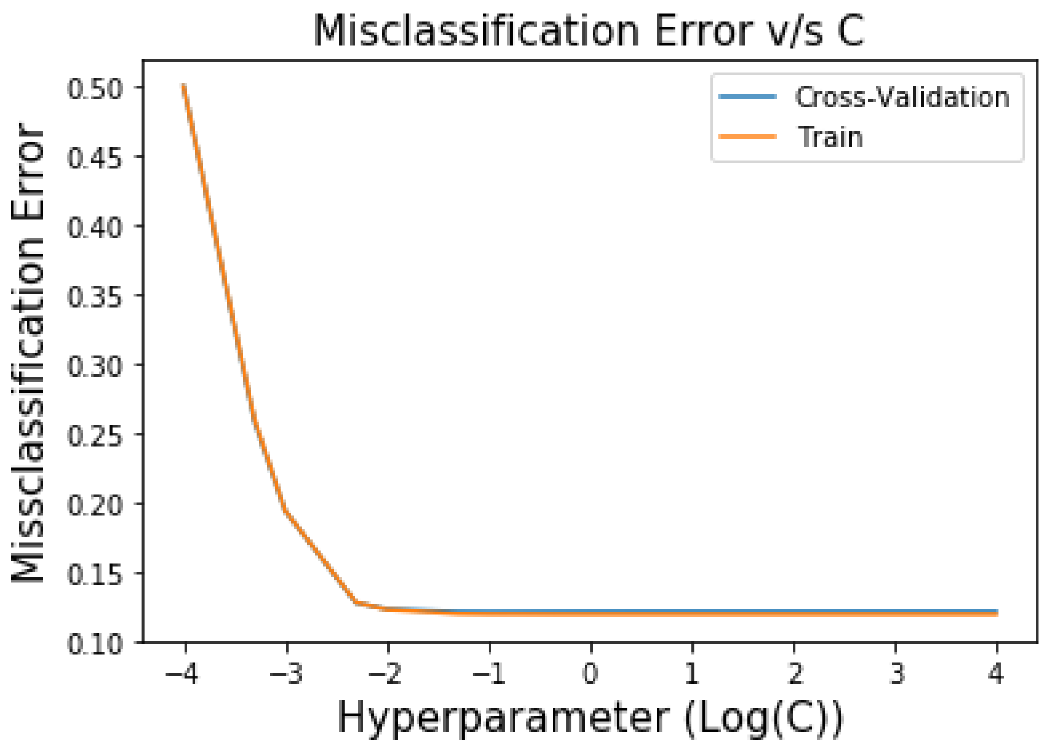
1.21.1 Finding the best value Of hyperparameter (C or 1/Lambda)

```
In [46]: gsv=Grid_SearchCV(X_Train_TfidfW2v,Y_train,"l1")

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

```
Fitting 10 folds for each of 17 candidates, totalling 170 fits


[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 170 out of 170 | elapsed: 27.0min finished


Best HyperParameter:  {'C': 0.1, 'penalty': 'l1'}
Best Accuracy: 87.85%
```

1.21.2 Error Plot

```
In [47]: plot(gsv)
```



1.21.3 Training the model

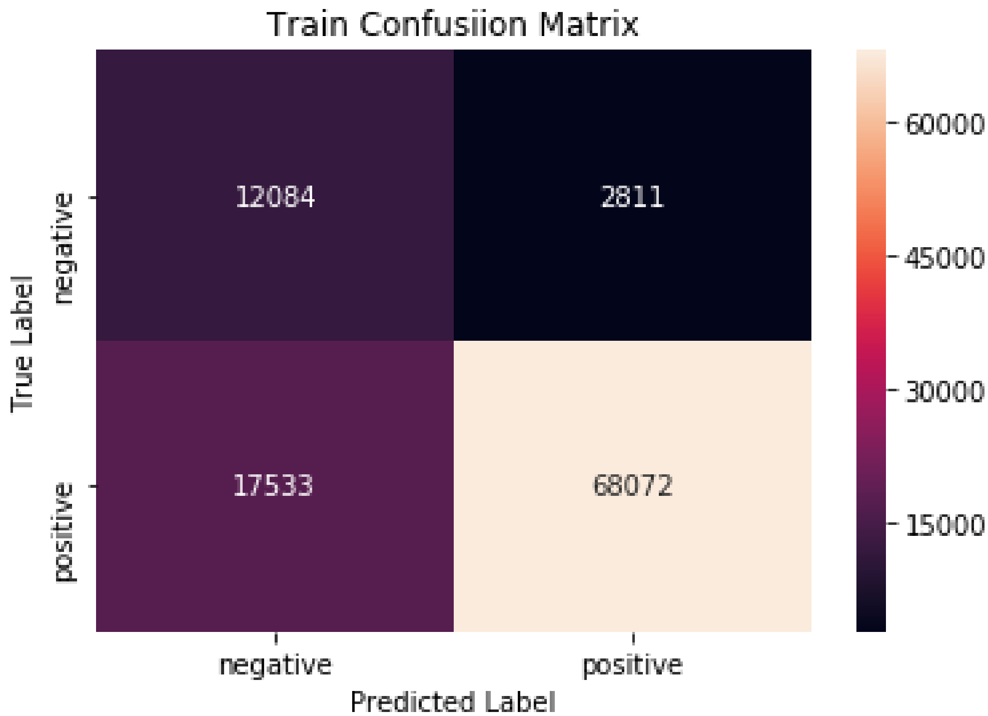
In [48]:
```
Best_Param=gsv.best_params_
C=Best_Param['C']
Penalty = Best_Param['penalty']

Model_TfidfW2v=LogisticRegression(C=C,penalty=Penalty,class_weight='balanced')
Model_TfidfW2v.fit(X_Train_TfidfW2v,Y_train)
```

Out[48]:
```
LogisticRegression(C=0.1, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='warn', n_jobs=None, penalty='l1', random_state=None,
          solver='warn', tol=0.0001, verbose=0, warm_start=False)
```

1.21.4 Evaluating the performance of model

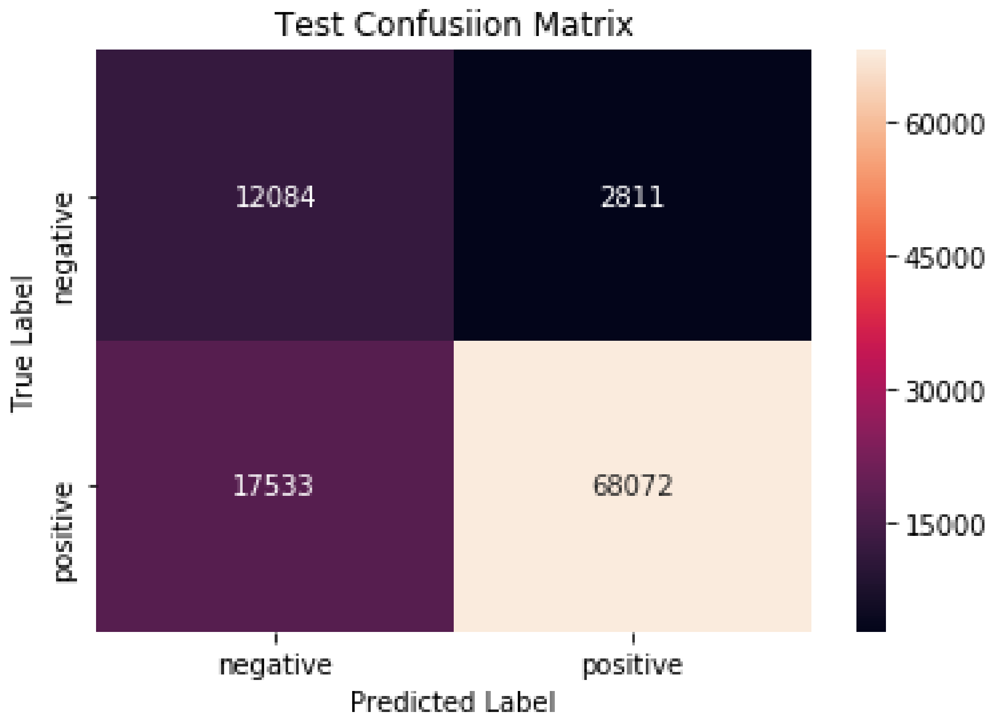
In [49]:
```
trainconfusionmatrix(Model_TfidfW2v,X_Train_TfidfW2v,Y_train)
```

```
Confusion Matrix for Train set
```

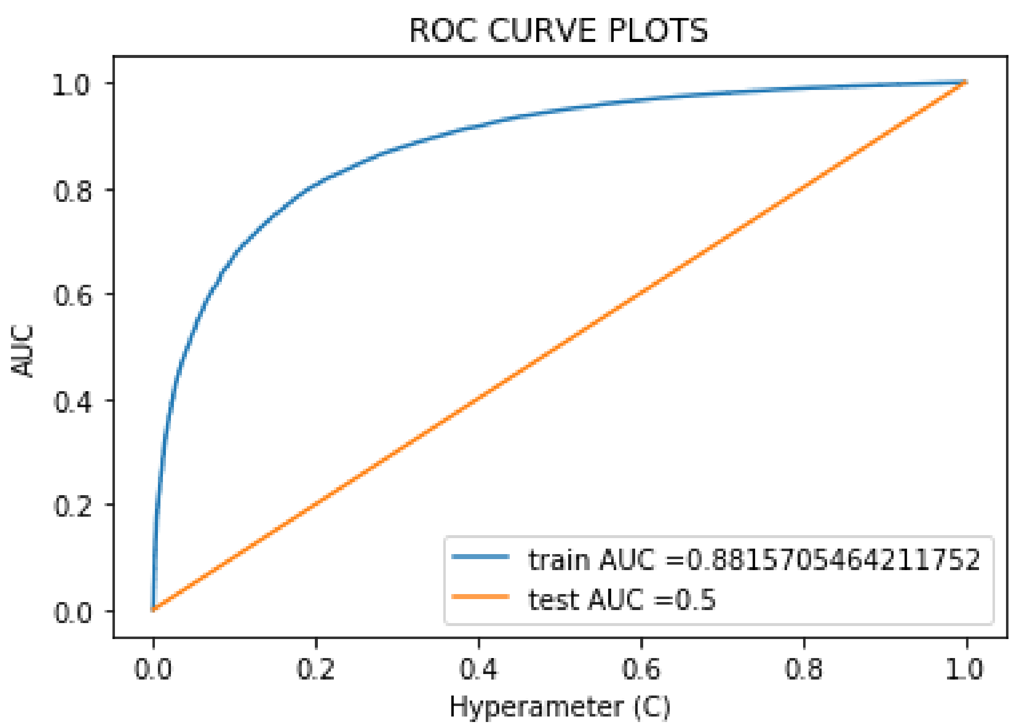



```
In [50]: testconfusionmatrix(Model_TfidfW2v,X_Train_TfidfW2v,Y_train)
```

```
Confusion Matrix for Test set
```



In [51]: `plot_auc_roc(Model_TfidfW2v,X_Train_TfidfW2v,X_Test_TfidfW2v,Y_train,Y_test)`



In [52]:
```
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       0.18      1.00      0.30      8692
           1       0.00      0.00      0.00     40808

   micro avg       0.18      0.18      0.18     49500
   macro avg       0.09      0.50      0.15     49500
weighted avg       0.03      0.18      0.05     49500
```

1.22 Pertubation Test On BOW Vectorizer and Regularisation Parameter L2

In [62]:
```
from scipy.sparse import find
#Weights before adding random noise
weights1 = find(Model_Bow.coef_[0])[2]
print(weights1[:50])
```

```
[ 1.13345591  0.02002588  0.00200432  0.03735237  0.00537296  0.00278505
 -0.05079941  0.00931602  0.00537296  0.13805403  0.03798705  0.0069488
  0.03927589  0.01479231  0.02671619  0.0565606  -0.40902605  0.03473881
  0.00330004  0.07520482 -0.05522391  0.06312428  0.02666827  0.032443
  0.04260278 -0.03394333  0.04648075  0.00561827  0.28007135  0.18782385
 -0.34749559  0.05698905  0.00788936 -1.170488    0.52939662  0.20041705
 -0.07370247 -0.23254724  0.23001907  0.09660233  0.3921331   0.35992047
 -0.27294236  0.17301799  0.80156947  0.07930274 -0.76391136  0.07604107
  0.0629005   0.02145765]
```

In [63]:
```
X_train_t = X_train_bow
#Random noise
epsilon = np.random.uniform(low=-0.0001, high=0.0001, size=(find(X_train_t)[0].size,))
#Getting the postions(row and column) and value of non-zero datapoints
a,b,c = find(X_train_t)

#Introducing random noise to non-zero datapoints
X_train_t[a,b] = epsilon + X_train_t[a,b]
```

In [64]:
```
Model_Pert= LogisticRegression(C=C, penalty= 'l2',class_weight='balanced')
Model_Pert.fit(X_train_t,Y_train)
```

```
y_pred = Model_Pert.predict(X_test_bow)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(Y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(Model_Pert.coef_))
```

```
Accuracy on test set: 87.933%
Non Zero weights: 37994
```

In [65]:
```
#Weights after adding random noise
weights2 = find(Model_Pert.coef_[0])[2]
print(weights2[:50])
```

```
[ 1.13328701  0.02007606  0.00200724  0.03734596  0.00538038  0.00278589
 -0.05092452  0.00931236  0.00538486  0.13790361  0.03810089  0.00694868
  0.03934439  0.0148218   0.02677143  0.0565591  -0.40895739  0.03471803
  0.00329922  0.07520774 -0.05585209  0.06320037  0.02665189  0.03241966
  0.04256979 -0.0338506   0.04647984  0.00561043  0.28022148  0.18792607
 -0.34781192  0.05681231  0.00787586 -1.17053264  0.52951101  0.20055738
 -0.07368803 -0.23281588  0.22997003  0.09659027  0.39222921  0.35980129
 -0.27276686  0.1729645   0.80172465  0.07946077 -0.76348883  0.07607611
  0.06293845  0.02146781]
```

In [66]:
```
weights_diff = (abs(weights1 - weights2)/weights1) * 100
```

In [67]:
```
print(weights_diff[np.where(weights_diff > 30)].size)
```

```
3
```

1.22.1 Showing How Sparsity increases as we decrease C or increase Lambada(1/C) When L1 Regularisation is used

In [55]:
```
Model_Sparse= LogisticRegression(C= 1000, penalty= 'l1',class_weight='balanced')
Model_Sparse.fit(X_train_bow,Y_train)
y_pred = Model_Sparse.predict(X_test_bow)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(Y_test, y_pred)*100))
print("F1-Score on test set: %0.3f"%(f1_score(Y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(Model_Sparse.coef_))
```

```
Accuracy on test set: 85.586%
F1-Score on test set: 0.910
Non Zero weights: 18732
```

In [56]:
```
Model_Sparse= LogisticRegression(C= 100, penalty= 'l1',class_weight='balanced')
Model_Sparse.fit(X_train_bow,Y_train)
y_pred = Model_Sparse.predict(X_test_bow)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(Y_test, y_pred)*100))
print("F1-Score on test set: %0.3f"%(f1_score(Y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(Model_Sparse.coef_))
```

```
Accuracy on test set: 86.901%
F1-Score on test set: 0.918
Non Zero weights: 14916
```

```
In [57]: Model_Sparse= LogisticRegression(C= 10, penalty= 'l1',class_weight='balanced')
         Model_Sparse.fit(X_train_bow,Y_train)
         y_pred = Model_Sparse.predict(X_test_bow)
         print("Accuracy on test set: %0.3f%%"%(accuracy_score(Y_test, y_pred)*100))
         print("F1-Score on test set: %0.3f"%(f1_score(Y_test, y_pred)))
         print("Non Zero weights:",np.count_nonzero(Model_Sparse.coef_))
```

```
Accuracy on test set: 88.222%
F1-Score on test set: 0.926
Non Zero weights: 7780
```

```
In [58]: Model_Sparse= LogisticRegression(C= 1, penalty= 'l1',class_weight='balanced')
         Model_Sparse.fit(X_train_bow,Y_train)
         y_pred = Model_Sparse.predict(X_test_bow)
         print("Accuracy on test set: %0.3f%%"%(accuracy_score(Y_test, y_pred)*100))
         print("F1-Score on test set: %0.3f"%(f1_score(Y_test, y_pred)))
         print("Non Zero weights:",np.count_nonzero(Model_Sparse.coef_))
```

```
Accuracy on test set: 87.299%
F1-Score on test set: 0.919
Non Zero weights: 1931
```

```
In [59]: Model_Sparse= LogisticRegression(C= 0.1, penalty= 'l1',class_weight='balanced')
         Model_Sparse.fit(X_train_bow,Y_train)
         y_pred = Model_Sparse.predict(X_test_bow)
         print("Accuracy on test set: %0.3f%%"%(accuracy_score(Y_test, y_pred)*100))
         print("F1-Score on test set: %0.3f"%(f1_score(Y_test, y_pred)))
         print("Non Zero weights:",np.count_nonzero(Model_Sparse.coef_))
```

```
Accuracy on test set: 83.978%
F1-Score on test set: 0.896
Non Zero weights: 409
```

```
In [60]: Model_Sparse= LogisticRegression(C= 0.01, penalty= 'l1')
         Model_Sparse.fit(X_train_bow,Y_train)
         y_pred = Model_Sparse.predict(X_test_bow)
         print("Accuracy on test set: %0.3f%%"%(accuracy_score(Y_test, y_pred)*100))
         print("F1-Score on test set: %0.3f"%(f1_score(Y_test, y_pred)))
         print("Non Zero weights:",np.count_nonzero(Model_Sparse.coef_))
```

```
Accuracy on test set: 82.828%
F1-Score on test set: 0.906
```

```
Non Zero weights: 21
```

```
In [61]: Model_Sparse= LogisticRegression(C= 0.001, penalty= 'l1',class_weight='balanced')
         Model_Sparse.fit(X_train_bow,Y_train)
         y_pred = Model_Sparse.predict(X_test_bow)
         print("Accuracy on test set: %0.3f%%"%(accuracy_score(Y_test, y_pred)*100))
         print("F1-Score on test set: %0.3f"%(f1_score(Y_test, y_pred)))
         print("Non Zero weights:",np.count_nonzero(Model_Sparse.coef_))
```

```
Accuracy on test set: 38.505%
F1-Score on test set: 0.423
Non Zero weights: 1
```

1. Decrease in value of C decrease the non of non zeros weight decrease , which means it is increasing the sparsity(No of Zeros)

1.22.2 Addition of another column length

```
In [18]: Train_len=[]
         Test_len=[]
         for i in X_train:
             Train_len.append(len(i))

         for i in X_test:
             Test_len.append(len(i))
```

```
In [19]: Train_len=np.array(Train_len)
         Test_len=np.array(Test_len)
```

```
In [20]: Train_len=Train_len[:,np.newaxis]
         Test_len=Test_len[:,np.newaxis]
```

Bag Of Word Vectorizer

```
In [21]: X_Train_BOW=X_train_bow.todense()
```

```
In [22]: X_Train_New=np.append(X_Train_BOW,Train_len,axis=1)
```

```
In [23]: from scipy.sparse import csr_matrix
         X_Train_New= csr_matrix(X_Train_New)
```

```
In [24]: print("Shape of Train Data Before Adding length column ")
         print(X_train_bow.shape)

         print("\nShape of Train Data After Adding length column ")
         print(X_Train_New.shape)
```

```
Shape of Train Data Before Adding length column
(100500, 37994)

Shape of Train Data After Adding length column
(100500, 37995)
```

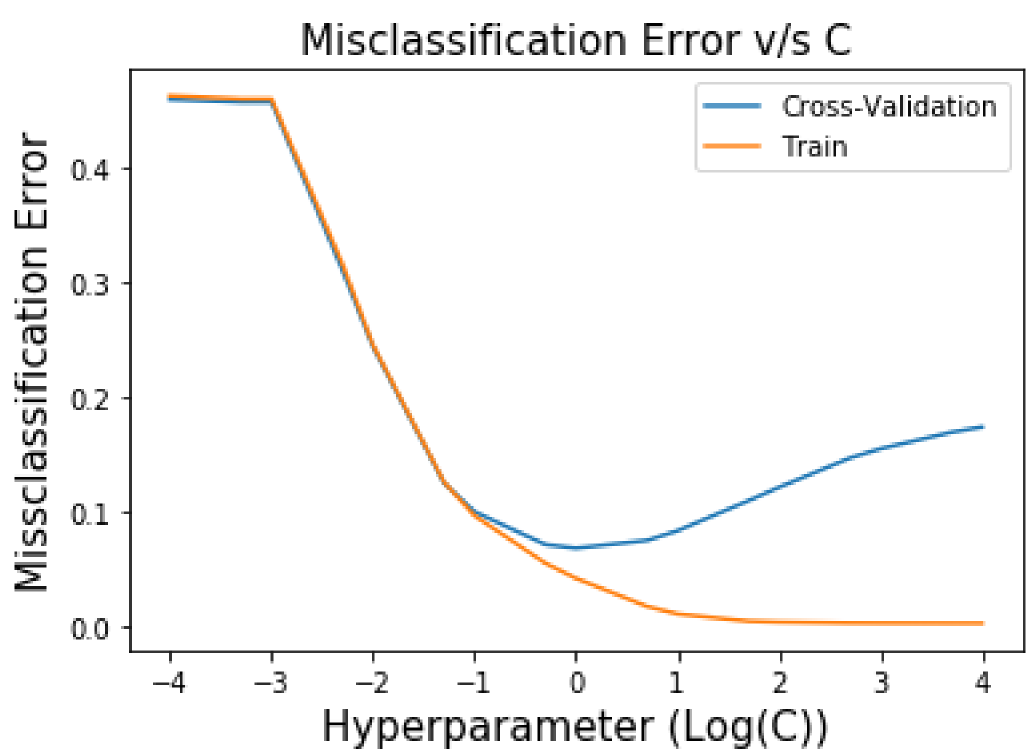
Finding the best value Of hyperparameter (C or 1/lambda)

```
In [29]: gsv=Grid_SearchCV(X_Train_New,Y_train,"l1")

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

```
Fitting 10 folds for each of 17 candidates, totalling 170 fits


[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 170 out of 170 | elapsed: 110.4min finished


Best HyperParameter:  {'C': 1, 'penalty': 'l1'}
Best Accuracy: 93.26%
```

Error Plot

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



Training the Model

```
In [25]: X_Test_Bow=X_test_bow.todense()
```

```
In [26]: X_Test_New=np.append(X_Test_Bow,Test_len,axis=1)
```

```
In [27]: from scipy.sparse import csr_matrix
         X_Test_New= csr_matrix(X_Test_New)
```

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

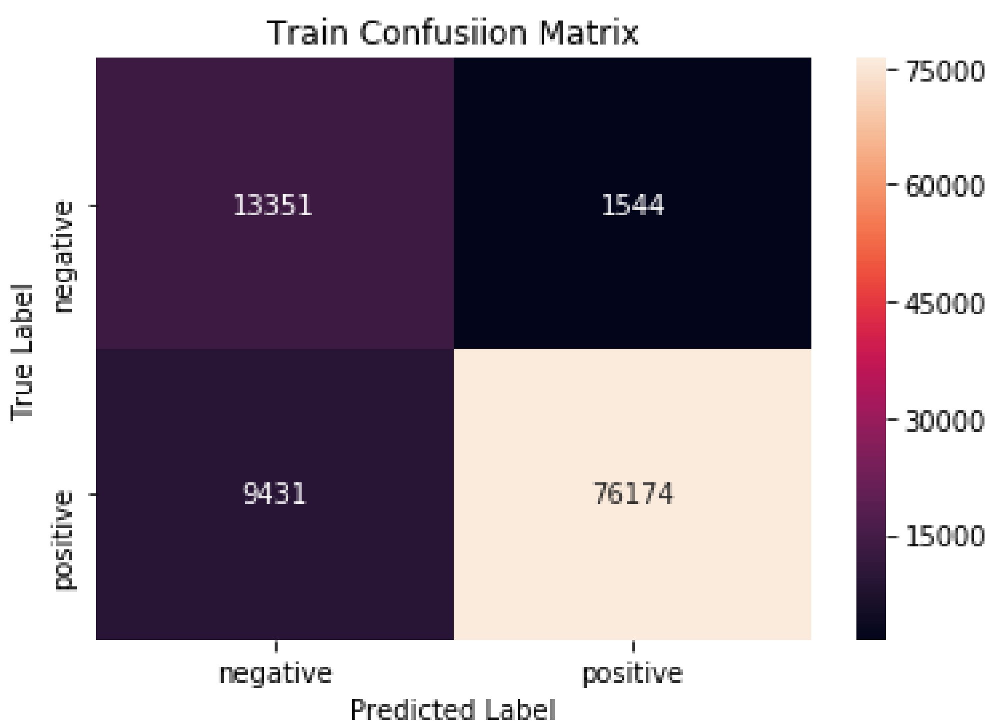
```
In [32]: Model_LBow = LogisticRegression(C=C,penalty = Penalty,class_weight='balanced')
         Model_LBow.fit(X_Train_New,Y_train)
```

```
Out[32]: LogisticRegression(C=1, class_weight='balanced', dual=False,
                   fit_intercept=True, intercept_scaling=1, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l1', random_state=None,
                   solver='warn', tol=0.0001, verbose=0, warm_start=False)
```

Evaluating the performance of the model

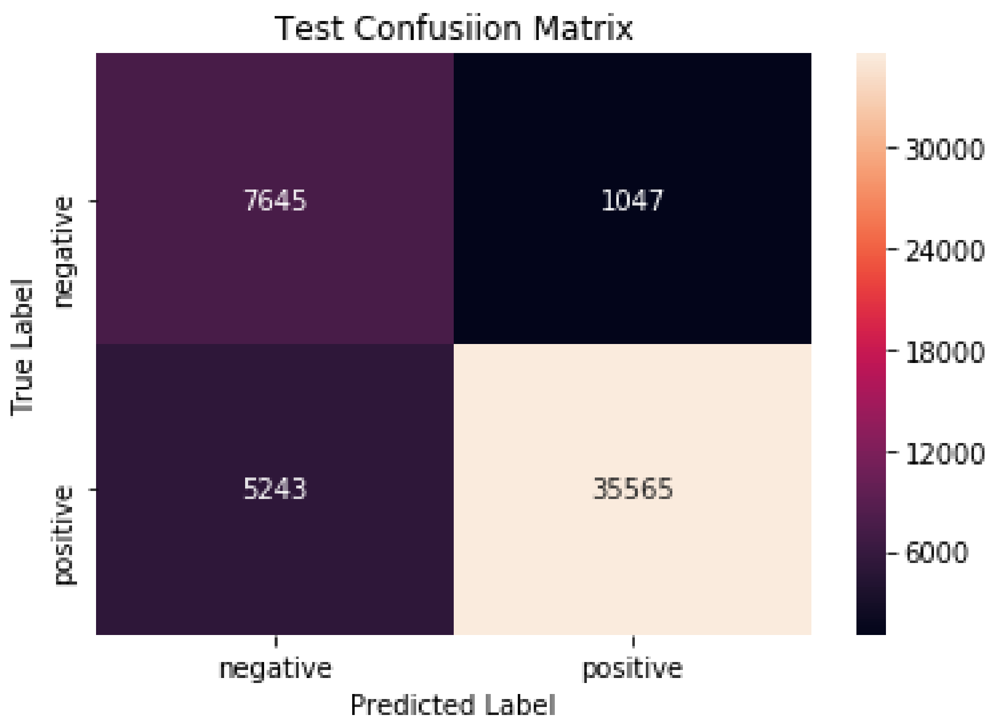
```
In [33]: trainconfusionmatrix(Model_LBow,X_Train_New,Y_train)
```

```
Confusion Matrix for Train set
```

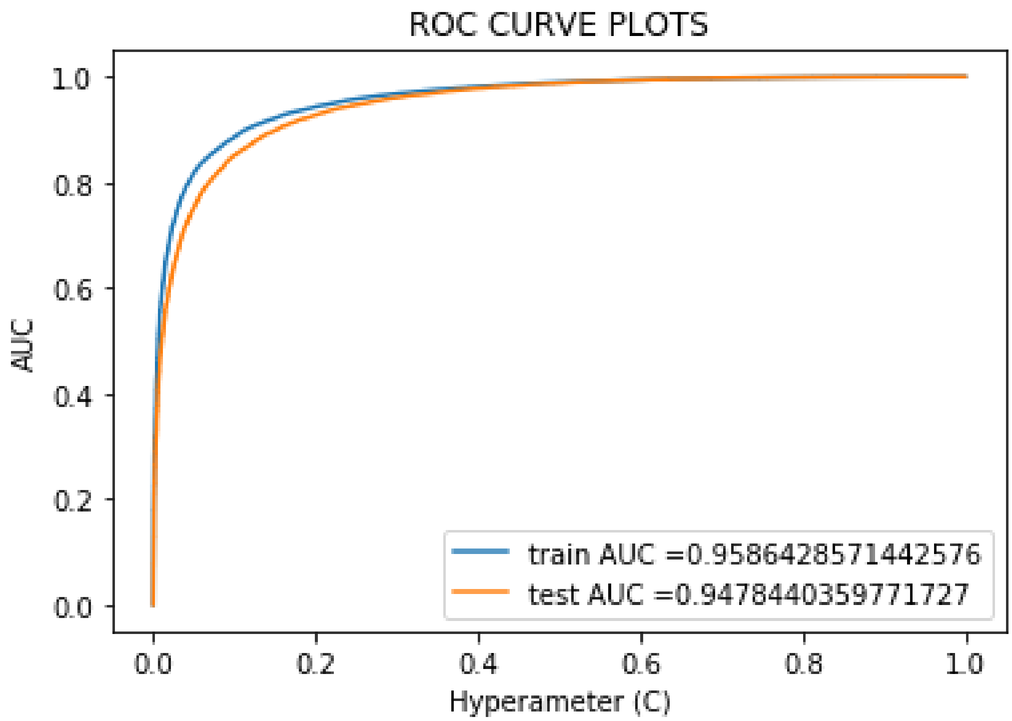


```
In [34]: testconfusionmatrix(Model_LBow,X_Test_New,Y_test)
```

```
Confusion Matrix for Test set
```




```
In [35]: plot_auc_roc(Model_LBow,X_Train_New,X_Test_New,Y_train,Y_test)
```




```
In [36]: print("Classification Report: \n")
         y_pred=Model_LBow.predict(X_Test_New)

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

```
Classification Report:

              precision    recall  f1-score   support

           0       0.59      0.88      0.71      8692
           1       0.97      0.87      0.92     40808

   micro avg       0.87      0.87      0.87     49500
   macro avg       0.78      0.88      0.81     49500
weighted avg       0.90      0.87      0.88     49500
```

1.22.3 Displaying 30 most informative features

```
In [37]: show_30_informative_feature(vectorizer,Model_LBow)
```

```
S.N                Positive                                                      Negative
------------------------------------------------------------------------------------------
```

```
1.                10.165       addict                                         -13.051       aw
2.                9.406       amaz                                          -9.123       blan
3.                8.438       awesom                                        -10.127       can
4.                10.038       beat                                          -10.607       co
5.                7.003       beauti                                        -7.860       dece
6.                7.925       best                                          -9.884       dece
7.                7.292       complaint                                     -10.151       dis
8.                10.010       delici                                        -11.124       di
9.                11.888       downsid                                       -7.976       dri
10.                8.479       excel                                         -8.112       fai
11.                6.976       fabul                                         -10.002       fl
12.                7.065       fantast                                       -8.534       gro
13.                6.811       glad                                          -10.867       ho
14.                6.903       great                                         -10.231       in
15.                7.235       habit                                         -10.951       me
16.                7.399       happier                                       -8.610       opp
17.                6.696       heaven                                        -8.455       ren
18.                11.030       hook                                          -9.208       re
19.                8.266       perfect                                       -9.089       run
20.                8.723       refresh                                       -10.560       ta
21.                7.902       satisfi                                       -12.177       te
22.                12.386       skeptic                                       -9.787       th
23.                6.934       smooth                                        -10.159       th
24.                8.470       sooth                                         -9.990       una
25.                7.506       uniqu                                         -12.711       un
26.                7.592       versatil                                      -9.064       uni
27.                7.450       whim                                          -11.392       un
28.                7.948       worri                                         -9.066       wor
29.                9.642       yum                                           -17.412       wo
30.                8.376       yummi                                         -8.098       yuc
```

1.Report On Different Vectorizer Method and Regularisation Parameter L1

```
In [1]: from prettytable import PrettyTable

        x = PrettyTable()

        x.field_names = ["Vectorizer", "Hyperparameter(C or 1/Lambda)","Train AUC","Test AUC","

        x.add_row(["BOW",5,0.96,0.94,0.91])
        x.add_row(["TF-IDF",1,0.95,0.94,0.85])
        x.add_row(["Avg W2V",1,0.90,0.90,0.83])
        x.add_row(["TF-IDF W2V",0.1,0.88,0.50,0.05])

        print(x)
```

```
+------------+-------------------------------+-----------+----------+----------+
| Vectorizer | Hyperparameter(C or 1/Lambda) | Train AUC | Test AUC | F1-Score |
```

```
+------------+------------------------------+-----------+----------+----------+
|    BOW     |              5               |    0.96   |   0.94   |   0.91   |
|   TF-IDF   |              1               |    0.95   |   0.94   |   0.85   |
|  Avg W2V   |              1               |    0.9    |   0.9    |   0.83   |
| TF-IDF W2V |             0.1              |    0.88   |   0.5    |   0.05   |
+------------+------------------------------+-----------+----------+----------+
```

2.Report On Different Vectorizer Method and Regularisation Parameter L2

```
In [2]: from prettytable import PrettyTable

        x = PrettyTable()

        x.field_names = ["Vectorizer", "Hyperparameter(C or 1/Lambda)","Train AUC","Test AUC","

        x.add_row(["BOW",5,0.96,0.94,0.89])
        x.add_row(["TF-IDF",1,0.96,0.94,0.85])
        x.add_row(["Avg W2V",0.05,0.90,0.90,0.83])
        x.add_row(["TF-IDF W2V",0.1,0.88,0.50,0.05])

        print(x)
```

```
+------------+------------------------------+-----------+----------+----------+
| Vectorizer | Hyperparameter(C or 1/Lambda) | Train AUC | Test AUC | F1-Score |
+------------+------------------------------+-----------+----------+----------+
|    BOW     |              5               |    0.96   |   0.94   |   0.89   |
|   TF-IDF   |              1               |    0.96   |   0.94   |   0.85   |
|  Avg W2V   |             0.05             |    0.9    |   0.9    |   0.83   |
| TF-IDF W2V |             0.1              |    0.88   |   0.5    |   0.05   |
+------------+------------------------------+-----------+----------+----------+
```

3.Report On Different Vectorizer Method After Addition Of Length as another Column

```
In [3]: from prettytable import PrettyTable

        x = PrettyTable()

        x.field_names = ["Vectorizer", "Hyperparameter(C or 1/Lambda)","Train AUC","Test AUC","

        x.add_row(["BOW",1,0.95,0.94,0.88])


        print(x)
```

```
+------------+------------------------------+-----------+----------+----------+
| Vectorizer | Hyperparameter(C or 1/Lambda) | Train AUC | Test AUC | F1-Score |
```

BOW	1	0.95	0.94	0.88

4. I have taken considerable amount of data but it did not take long time in execution .

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

6. After adding Length as another column , there is no any improvement.

7. TF-IDF W2V is not performing well .