Amazon Fine Food Reviews Analysis

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

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

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

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

Attribute Information:

1. Id
2. ProductId - unique identifier for the product
3. UserId - unqiue identifier for the user
4. ProfileName
5. HelpfulnessNumerator - number of users who found the review helpful
6. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
7. Score - rating between 1 and 5
8. Time - timestamp for the review
9. Summary - brief summary of the review
10. Text - text of the review

Objective:

Given a review, determine whether the review is positive (rating of 4 or 5) or negative (rating of 1 or 2).

[Q] How to determine if a review is positive or negative?

[Ans] We could use Score/Rating. A rating of 4 or 5 can be cosnidered as a positive review. A rating of 1 or 2 can be considered as negative one. A review of rating 3 is considered nuetral and such reviews are ignored from our analysis. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

[1]. Reading Data

[1.1] Loading the data

The dataset is available in two forms

1. .csv file
2. SQLite Database

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

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

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

import sqlite3

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```python
import nltk
import string

from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from nltk.stem.porter import PorterStemmer

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

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

import pickle
from tqdm import tqdm
import os
from collections import Counter

# ============================== loading libraries ====================
=======================

from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_validate
from sklearn.model_selection import cross_val_score

from sklearn.preprocessing import StandardScaler

from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LogisticRegression

from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn import metrics
```

```
from sklearn.metrics import roc_curve, auc

from sklearn.feature_extraction.text import CountVectorizer

from prettytable import PrettyTable

from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

import itertools
from sklearn.linear_model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV
from sklearn.svm import SVC
```

```
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\gensim\utils.py:1197: UserWarning: detected Windows; aliasing chunkiz
e to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_seria
l")
```

Data Import and Preprocessing

Load preprocessed 'final' data for linear kernel

In [57]:
```
final = pickle.load(open('preprocessed_final_linear_kernel', 'rb'))
```

Checkpoint 2: Data is now sorted based on Time and preprocessed.

In [58]:
```
# Create X and Y variable
X = final['CleanedText'].values
y= final['Score'].values
```

In [59]:
```
type(X)
```

Out[59]: numpy.ndarray

In [60]:
```
type(y)
```
Out[60]:
```
numpy.ndarray
```

In [61]:
```
# ss
from sklearn.model_selection import train_test_split

# Splitting into train and test in the ratio 70:30
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3
0,shuffle=False, random_state=507)
#X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test
_size=0.30, shuffle=False, random_state=507)
```

In [62]:
```
print("Train Set:",X_train.shape, y_train.shape[0])
print("Test Set:",X_test.shape, y_test.shape[0])
```

```
Train Set: (61441,) 61441
Test Set: (26332,) 26332
```

Checkpoint 3: Data has been partioned into train, cv and test

Linear SVM

Defining functions that we will be using throughout the notebook for BoW, TFIDF, AvgW2V, TFIDF-WW2V

Finding the hyper parameter alpha (i.e. 1/C) using RandomSearchCV with cv = 5

In [63]:
```
def get_error_plot(X_train,penalty_l):

    """
    This funtion takes in the training data and runs CV with the penalt
y provided
    It returns the error plot
```

```
    """
    alpha = [10**-4, 10**-3,10**-2,10**-1, 10**0,10**1, 10**2,10**3, 10
**4]

    params_dict = {
                "alpha": [10**-4, 10**-3,10**-2,10**-1, 10**0,10**1, 10
**2,10**3, 10**4]

               }
    gs_obj = GridSearchCV(SGDClassifier(loss='hinge',penalty = penalty_
l), param_grid = params_dict, scoring = 'roc_auc', cv=5)

    gs_obj.fit(X_train, y_train)


    train_scores_mean= gs_obj.cv_results_['mean_train_score']
    train_scores_std= gs_obj.cv_results_['std_train_score']
    test_scores_mean = gs_obj.cv_results_['mean_test_score']
    test_scores_std= gs_obj.cv_results_['std_test_score']

    # draws the error plot

    plt.plot(alpha, train_scores_mean, label='Train AUC')
    # this code is copied from here: https://stackoverflow.com/a/488033
61/4084039
    #plt.gca().fill_between(alpha,train_auc - train_auc_std,train_auc +
 train_auc_std,alpha=0.2,color='darkblue')

    plt.plot(alpha, test_scores_mean, label='CV AUC')
    # this code is copied from here: https://stackoverflow.com/a/488033
61/4084039
    #plt.gca().fill_between(alpha,cv_auc - cv_auc_std,cv_auc + cv_auc_s
td,alpha=0.2,color='darkorange')
    plt.legend()
    plt.xlabel("log(alpha)- hyperparamter")
    plt.xscale('log')
    plt.ylabel("AUC")
    plt.title("ERROR PLOT")
    plt.show()
```

In [64]:

```
def get_best_hyperparameter_alpha(vectorizer, X_train, X_test, y_train,
 y_test):

    """
    This funtion takes in the vectorizer,  and performs SGDClassifier h
yperparameter tuning using GridSearchCV with 5 fold cv
    Returns the value of hyperparameter alpha and draws the error plot
 for various values of alpha

    Usage: get_best_hyperparameter_C(vectorizer, X_train, X_test, y_tra
in, y_test, penalty)
    """

    params_dict = {
                    "alpha": [10**-4, 10**-3,10**-2,10**-1, 10**0,10**1, 10
**2,10**3, 10**4],
                    "penalty": ['l1', 'l2']
                  }

    # Using GridSearchCVSearchCV with 5 fold cv
    #gs_obj = GridSearchCV(LogisticRegression(penalty= penalty_l), tune
d_parameters, scoring = 'roc_auc', cv=5)
    gs_obj = GridSearchCV(SGDClassifier(loss='hinge'), param_grid = par
ams_dict, scoring = 'roc_auc', cv=5)

    gs_obj.fit(X_train, y_train)


    # Code https://stackoverflow.com/questions/42793254/what-replaces-g
ridsearchcv-grid-scores-in-scikit#answer-42800056
    means = gs_obj.cv_results_['mean_test_score']
    stds = gs_obj.cv_results_['std_test_score']


    t1 = PrettyTable()
    t1.field_names = ['Mean CV Score', 'Std CV Score', 'Param']

    for mean, std, params in zip(means, stds, gs_obj.cv_results_['param
s']):
```

```
        t1.add_row([round(mean, 3), round(std * 2,5), params])

    print(t1)

    print("\nThe best estimator:{}".format(gs_obj.best_estimator_))
    print("\nThe best score is:{}".format(gs_obj.best_score_))
    print("The best value of C is:{}".format(gs_obj.best_params_))

    # Returns the mean accuracy on the given test data and labels.
    print("Mean Score: {}".format(gs_obj.score(X_test, y_test)))
    #print("penalty: {}".format(gs_obj.best_params_['penalty']))

    #draws error plot
    get_error_plot(X_train, gs_obj.best_params_['penalty'])
```

train and test AUC

In [65]:
```
def plot_auc_sgd(model, X_train, X_test):

    """
    This function will plot the AUC for the vectorized train and test d
ata.
    Returns the plot and also the values of auc for train and test

    Usage: auc_train, auc_test = plot_auc(model, X_train, X_test)
    """
    clf_sigmoid = CalibratedClassifierCV(model, cv=5, method='sigmoid')
    clf_sigmoid.fit(X_train, y_train)
    prob_pos_sigmoid = clf_sigmoid.predict_proba(X_test)[:, 1]

    train_fpr, train_tpr, thresholds = roc_curve(y_train, clf_sigmoid.p
redict_proba(X_train)[:, 1])
    test_fpr, test_tpr, thresholds = roc_curve(y_test, clf_sigmoid.pred
ict_proba(X_test)[:, 1])

    plt.plot([0,1],[0,1],'k--')
    plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fp
r, train_tpr)))
```

```
    plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, t
est_tpr)))
    plt.legend()
    plt.xlabel("fpr")
    plt.ylabel("tpr")
    plt.title("ROC Curve")
    plt.show()

    print("train AUC: {}".format(auc(train_fpr, train_tpr)))
    print("test AUC: {}".format(auc(test_fpr, test_tpr)))


    return auc(train_fpr, train_tpr), auc(test_fpr, test_tpr)
```

important features

In [66]:
```
# https://stackoverflow.com/questions/26976362/how-to-get-most-informat
ive-features-for-scikit-learn-classifier-for-different-c
def most_informative_feature_for_binary_classification(vectorizer, clas
sifier, n=10):

    """
     Takes in the vectorizer, classifier (model) and the number of impo
rtant features to return

     Usage: most_informative_feature_for_binary_classification(vectoriz
er, classifier, n=10)
    """
    class_labels = classifier.classes_
    feature_names = vectorizer.get_feature_names()
    topn_class_0 = sorted(zip(classifier.coef_[0], feature_names))[:n]
    topn_class_1 = sorted(zip(classifier.coef_[0], feature_names))[-n:]

    t1 = PrettyTable()
    t1.field_names = ['Class', 'Coefficient (Importance)', 'Feature Nam
e']
```

```
    for coef, feat in topn_class_0:
        t1.add_row([class_labels[0], abs(coef), feat])

    print(t1)

    print("*"*52)

    t2 = PrettyTable()
    t2.field_names = ['Class', 'Coefficient (Importance)', 'Feature Nam
e']

    for coef, feat in reversed(topn_class_1):
        t2.add_row([class_labels[1], abs(coef), feat])


    print(t2)

    #for coef, feat in topn_class1:
        #if coef < 0:
        #print(class_labels[0], abs(coef), feat)

    #print("*"*30)

    #for coef, feat in reversed(topn_class2):
        #if coef > 0:
     #   print(class_labels[1], abs(coef), feat)
```

print confustion matrix

In [67]:
```
def print_confusion_matrix(model, X_train, X_test):
    """
    Takes in the model, X_train, X_test and prints the confusion matrix
    Usage: print_confusion_matrix(model, X_train, X_test)
    """
    print("*****Train confusion matrix*****")
    print(confusion_matrix(y_train, model.predict(X_train)))
    print("\n*****Test confusion matrix*****")
    print(confusion_matrix(y_test, model.predict(X_test)))
```

heat map of confusion matrix

In [68]:
```
# Code modified from sklearn tutorial: https://scikit-learn.org/stable/
auto_examples/model_selection/plot_confusion_matrix.html

# Heat map of confusion matrix

def plot_confusion_matrix_heatmap(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    #if normalize:
     #   cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
     #   print("Normalized confusion matrix")
    #else:
      #  print('Confusion matrix')

    #print(cm)

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1
])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")
```

```
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.tight_layout()
```

[4.1] BAG OF WORDS

In [69]:

```
# ss
from sklearn.feature_extraction.text import CountVectorizer
bow_vectorizer= CountVectorizer(ngram_range=(1,2), min_df=10, max_features=10000)
bow_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 = bow_vectorizer.transform(X_train)
#X_cv_bow = vectorizer.transform(X_cv)
X_test_bow = bow_vectorizer.transform(X_test)

print("After vectorizations")
print(X_train_bow.shape, y_train.shape)
#print(X_cv_bow.shape, y_cv.shape)
print(X_test_bow.shape, y_test.shape)
print("="*100)
```

```
After vectorizations
(61441, 10000) (61441,)
(26332, 10000) (26332,)
=======================================================================
=============================
```

In [70]:

```
print("the type of count vectorizer ",type(X_train_bow))
print("the shape of cut text BOW vectorizer ",X_train_bow.get_shape())
print("the number of unique words: ", X_train_bow.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of cut text BOW vectorizer  (61441, 10000)
the number of unique words:  10000
```

Standardize the data

In [71]:
```
# We will set the attribute with_mean = False, as StandardScaler does n
ot work on sparse matrix
# when attempted on sparse matrices, because centering them entails bui
lding a dense matrix which in common use cases
# is likely to be too large to fit in memory.  ---> sklearn documentati
on

from sklearn.preprocessing import StandardScaler
X_train_bow=StandardScaler(with_mean=False).fit_transform(X_train_bow)
X_test_bow=StandardScaler(with_mean=False).fit_transform(X_test_bow)

print(X_train_bow.shape, y_train.shape)

print(X_test_bow.shape, y_test.shape)
```

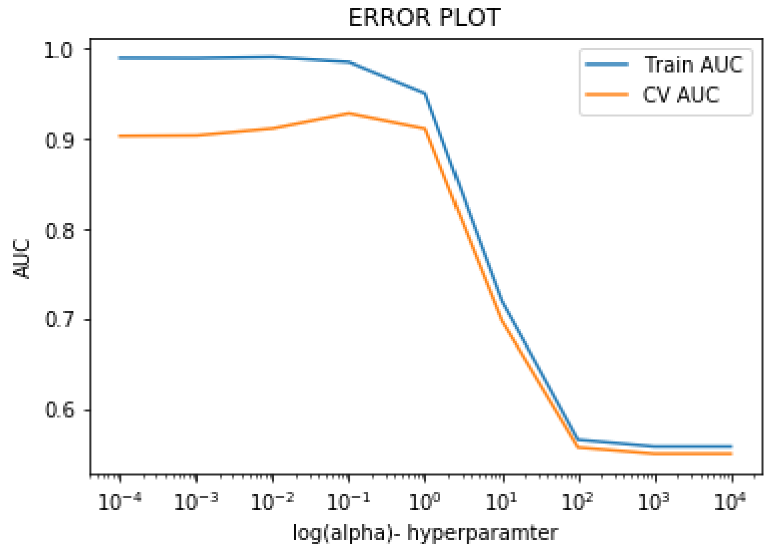
```
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\utils\validation.py:595: DataConversionWarning: Data with inp
ut dtype int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\utils\validation.py:595: DataConversionWarning: Data with inp
ut dtype int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\utils\validation.py:595: DataConversionWarning: Data with inp
ut dtype int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\utils\validation.py:595: DataConversionWarning: Data with inp
ut dtype int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
```

```
(61441, 10000) (61441,)
(26332, 10000) (26332,)
```

[5.1.1] Applying Linear SVM on BOW, SET 1

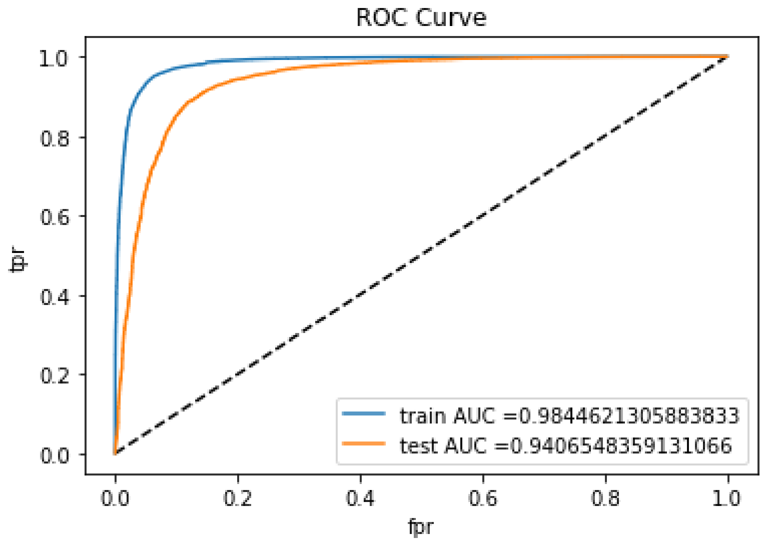
In [72]:
```
get_best_hyperparameter_alpha(bow_vectorizer, X_train_bow, X_test_bow,
y_train, y_test)
```

```
+---------------+-------------+-----------------------------------+
| Mean CV Score | Std CV Score |               Param              |
+---------------+-------------+-----------------------------------+
|     0.888     |   0.02585   | {'alpha': 0.0001, 'penalty': 'l1'} |
|     0.899     |   0.02626   | {'alpha': 0.0001, 'penalty': 'l2'} |
|     0.845     |   0.03581   | {'alpha': 0.001, 'penalty': 'l1'}  |
|     0.904     |   0.01819   | {'alpha': 0.001, 'penalty': 'l2'}  |
|     0.719     |   0.03024   |  {'alpha': 0.01, 'penalty': 'l1'}  |
|     0.912     |   0.01366   |  {'alpha': 0.01, 'penalty': 'l2'}  |
|     0.618     |    0.0509   |  {'alpha': 0.1, 'penalty': 'l1'}   |
|     0.928     |   0.01927   |  {'alpha': 0.1, 'penalty': 'l2'}   |
|      0.5      |    0.0184   |   {'alpha': 1, 'penalty': 'l1'}    |
|     0.912     |   0.02427   |   {'alpha': 1, 'penalty': 'l2'}    |
|      0.5      |   0.00111   |   {'alpha': 10, 'penalty': 'l1'}   |
|     0.698     |    0.0326   |   {'alpha': 10, 'penalty': 'l2'}   |
|      0.5      |     0.0     |  {'alpha': 100, 'penalty': 'l1'}   |
|     0.557     |    0.0272   |  {'alpha': 100, 'penalty': 'l2'}   |
|      0.5      |     0.0     |  {'alpha': 1000, 'penalty': 'l1'}  |
|      0.55     |   0.02709   |  {'alpha': 1000, 'penalty': 'l2'}  |
|      0.5      |     0.0     | {'alpha': 10000, 'penalty': 'l1'}  |
|      0.55     |   0.02709   | {'alpha': 10000, 'penalty': 'l2'}  |
+---------------+-------------+-----------------------------------+

The best estimator:SGDClassifier(alpha=0.1, average=False, class_weight
=None,
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=N
one,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)

The best score is:0.9275283273834641
The best value of C is:{'alpha': 0.1, 'penalty': 'l2'}
Mean Score: 0.93530213922538
```



In [98]:
```
model_bow_sgd = SGDClassifier(alpha= 0.1 ,penalty = 'l2')
model_bow_sgd.fit(X_train_bow,y_train)
y_pred = model_bow_sgd.predict(X_test_bow)
```

In [99]:
```
auc_train_bow_sgd, auc_test_bow_sgd = plot_auc_sgd(model_bow_sgd, X_tra
in_bow, X_test_bow)
```




```
train AUC: 0.9844621305883833
test AUC: 0.9406548359131066
```

https://answers.dataiku.com/2711/probability-calibration-in-dataiku

Most important features for BoW

In [100]:
```
most_informative_feature_for_binary_classification(bow_vectorizer, mode
l_bow_sgd)
```

```
+-------+-------------------------+--------------+
| Class | Coefficient (Importance) | Feature Name |
+-------+-------------------------+--------------+
|   0   |   0.09635004651467102   | disappointed |
|   0   |    0.0802213700099049   |    worst     |
|   0   |   0.07401661444290543   |  not worth   |
|   0   |   0.07161304594053323   |   not buy    |
|   0   |   0.07158800461883856   |   terrible   |
|   0   |   0.07084121621217061   |   not good   |
|   0   |   0.06940553529083396   | not recommend |
|   0   |   0.06360239115214682   | disappointing |
```

```
|   0   |    0.06306238333750386    |     awful     |
|   0   |    0.06061576273183535    |   two stars   |
+-------+-------------------------+---------------+
*****************************************************
+-------+-------------------------+--------------+
| Class | Coefficient (Importance) | Feature Name |
+-------+-------------------------+--------------+
|   1   |     0.1569419250296165    |    great     |
|   1   |    0.13017215299239665    |     good     |
|   1   |    0.12047203812380917    |     love     |
|   1   |    0.11848199616223926    |  delicious   |
|   1   |    0.11461126316072343    |     best     |
|   1   |    0.09088776179429825    |    loves     |
|   1   |    0.08395882323442243    |   perfect    |
|   1   |    0.07655350004722232    |    tasty     |
|   1   |    0.07584924118588247    |  excellent   |
|   1   |    0.07156665697203098    |  wonderful   |
+-------+-------------------------+--------------+
```

In [101]:

```
# Confusion Matrix
print_confusion_matrix(model_bow_sgd, X_train_bow, X_test_bow)
```

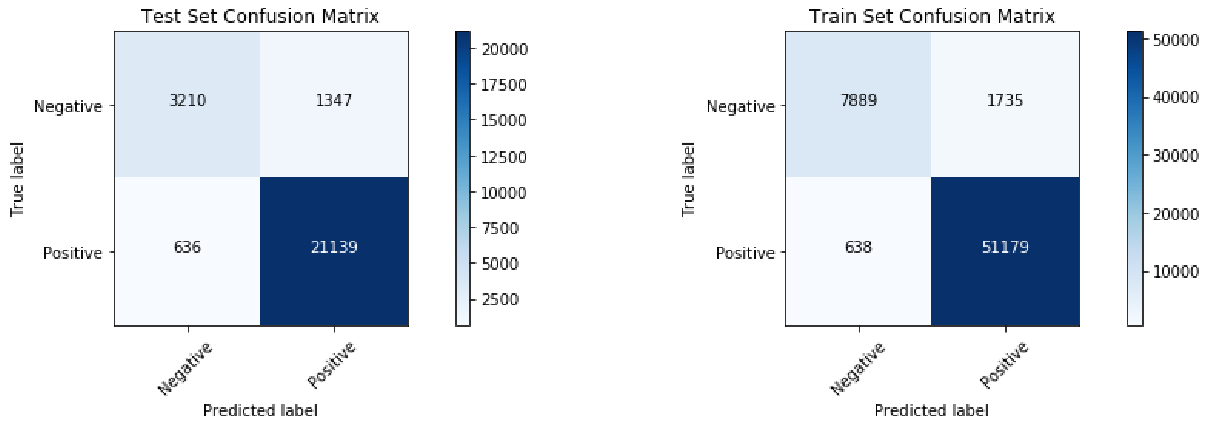
```
*****Train confusion matrix*****
[[ 7889  1735]
 [  638 51179]]

*****Test confusion matrix*****
[[ 3210  1347]
 [  636 21139]]
```

In [102]:

```
plt.figure(1)
plt.figure(figsize=(15, 4))


plt.subplot(121)  # Test confusion matrix
cnf_matrix = confusion_matrix(y_test, model_bow_sgd.predict(X_test_bow
))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
```

```
# Plot non-normalized confusion matrix
#plt.figure()
plot_confusion_matrix_heatmap(cnf_matrix, classes=class_names, title='Test Set Confusion Matrix');

plt.subplot(122) # Train Confusion matrix
cnf_matrix = confusion_matrix(y_train, model_bow_sgd.predict(X_train_bow))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
#plt.figure()
plot_confusion_matrix_heatmap(cnf_matrix, classes=class_names, title='Train Set Confusion Matrix');
```

```
<Figure size 432x288 with 0 Axes>
```



Observation

1. For the BoW vectorizer, we calculated alpha = 0.1 using GridSearchCV with cv = 5 and with penalty l2.
2. We got train AUC: 0.9844621305883833 and test AUC: 0.9406548359131066
3. Using the confusion matrix, we can say that our model correctly predicted 21139 positive reviews and 3210 negative reviews.
4. The model incorrectly classified 636 negative reviews and 1347 positive reviews.

Feature Engineering Let us perform FE to see if we can further improve the model. Here, we will append length of reviews as another feature.

In [73]:
```
def get_text_length(x):
    """
     This function takes in a array and returns the length of the elements in the array.
    """
    return np.array([len(t) for t in x]).reshape(-1, 1)
```

In [74]:
```
rev_len_X_train = get_text_length(X_train)
rev_len_X_test = get_text_length(X_test)
```

In [75]:
```
from sklearn.feature_extraction.text import CountVectorizer
bow_vectorizer_fe = CountVectorizer(ngram_range=(1,2), min_df=10, max_features=10000)
bow_vectorizer_fe.fit(X_train) # fit has to happen only on train data
```

Out[75]:
```
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=10000, min_df=10,
        ngram_range=(1, 2), preprocessor=None, stop_words=None,
        strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
        tokenizer=None, vocabulary=None)
```

In [76]:
```
# we use the fitted CountVectorizer to convert the text to vector
X_train_bow = bow_vectorizer_fe.transform(X_train)
X_test_bow = bow_vectorizer_fe.transform(X_test)

print("After vectorizations")
print(X_train_bow.shape, y_train.shape)
print(X_test_bow.shape, y_test.shape)
print("="*100)
```

```
After vectorizations
(61441, 10000) (61441,)
```

```
(26332, 10000) (26332,)
======================================================================
=============================
```

Standardize the data

In [77]:

```
# We will set the attribute with_mean = False, as StandardScaler does n
ot work on sparse matrix
# when attempted on sparse matrices, because centering them entails bui
lding a dense matrix which in common use cases
# is likely to be too large to fit in memory.  ---> sklearn documentati
on

from sklearn.preprocessing import StandardScaler
X_train_bow=StandardScaler(with_mean=False).fit_transform(X_train_bow)
X_test_bow=StandardScaler(with_mean=False).fit_transform(X_test_bow)

print(X_train_bow.shape, y_train.shape)

print(X_test_bow.shape, y_test.shape)
```

```
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\utils\validation.py:595: DataConversionWarning: Data with inp
ut dtype int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\utils\validation.py:595: DataConversionWarning: Data with inp
ut dtype int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\utils\validation.py:595: DataConversionWarning: Data with inp
ut dtype int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\utils\validation.py:595: DataConversionWarning: Data with inp
ut dtype int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
```

```
(61441, 10000) (61441,)
```

```
(26332, 10000) (26332,)
```

In [78]:
```python
type(rev_len_X_train)
```

Out[78]:
```
numpy.ndarray
```

In [79]:
```python
type(X_train_bow)
```

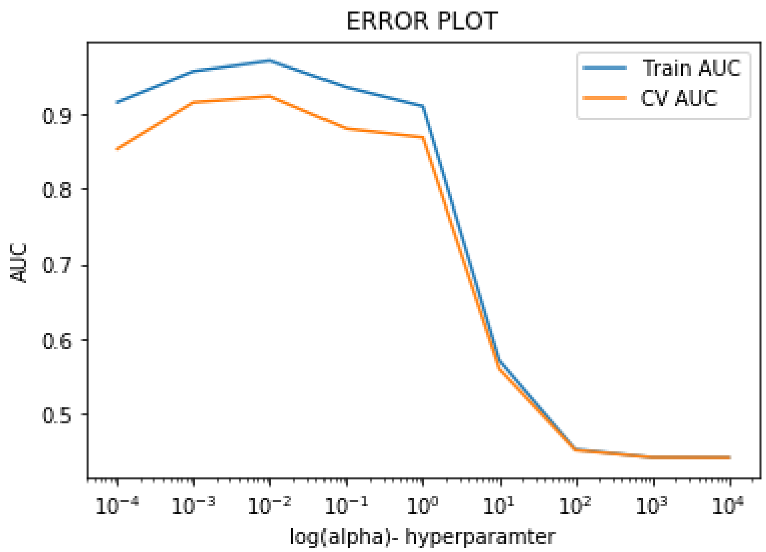
Out[79]:
```
scipy.sparse.csr.csr_matrix
```

In [80]:
```python
from scipy.sparse import hstack
# Here we append the sparse matrix and the dense array that contains th
e length of the text passed to it
X_train_bow_fe = hstack((X_train_bow, np.array(rev_len_X_train)))
X_test_bow_fe = hstack((X_test_bow, np.array(rev_len_X_test)))
```

In [81]:
```python
# Get the best hyperparameter using GridSearchCV with penalty l1 and cv
 = 5
get_best_hyperparameter_alpha(bow_vectorizer_fe, X_train_bow_fe, X_test
_bow_fe, y_train, y_test)
```

```
+---------------+-------------+-----------------------------------+
| Mean CV Score | Std CV Score |               Param               |
+---------------+-------------+-----------------------------------+
|     0.908     |    0.0301   | {'alpha': 0.0001, 'penalty': 'l1'} |
|     0.867     |   0.16914   | {'alpha': 0.0001, 'penalty': 'l2'} |
|     0.859     |   0.04961   | {'alpha': 0.001, 'penalty': 'l1'}  |
|      0.92     |   0.07292   | {'alpha': 0.001, 'penalty': 'l2'}  |
|     0.738     |   0.05858   |  {'alpha': 0.01, 'penalty': 'l1'}  |
|     0.937     |   0.01175   |  {'alpha': 0.01, 'penalty': 'l2'}  |
|     0.514     |   0.03485   |  {'alpha': 0.1, 'penalty': 'l1'}   |
|      0.93     |   0.03104   |  {'alpha': 0.1, 'penalty': 'l2'}   |
|     0.443     |   0.02479   |   {'alpha': 1, 'penalty': 'l1'}    |
|     0.901     |   0.04563   |   {'alpha': 1, 'penalty': 'l2'}    |
|     0.442     |   0.02502   |   {'alpha': 10, 'penalty': 'l1'}   |
|     0.557     |   0.04838   |   {'alpha': 10, 'penalty': 'l2'}   |
|     0.466     |   0.05638   |  {'alpha': 100, 'penalty': 'l1'}   |
|     0.451     |    0.0191   |  {'alpha': 100, 'penalty': 'l2'}   |
```

```
|      0.5      |     0.0      |  {'alpha': 1000, 'penalty': 'l1'}  |
|     0.441     |   0.01866    |  {'alpha': 1000, 'penalty': 'l2'}  |
|      0.5      |     0.0      | {'alpha': 10000, 'penalty': 'l1'}  |
|     0.441     |   0.01865    | {'alpha': 10000, 'penalty': 'l2'}  |
+---------------+--------------+-----------------------------------+

The best estimator:SGDClassifier(alpha=0.01, average=False, class_weigh
t=None,
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=N
one,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)

The best score is:0.936964376772133
The best value of C is:{'alpha': 0.01, 'penalty': 'l2'}
Mean Score: 0.9455859407575481
```

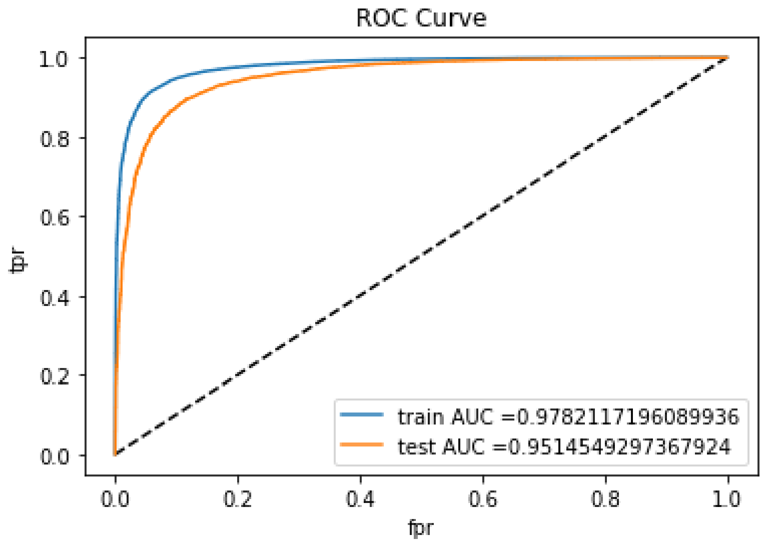


In [103]:

```
# Fitting the BoW vectorizer on LogisticRegression Model with penalty l
1 and C = 0.01
model_bow_fe_sgd = SGDClassifier(alpha = 0.01 ,penalty = 'l2')
```

```
model_bow_fe_sgd.fit(X_train_bow_fe,y_train)
y_pred = model_bow_fe_sgd.predict(X_test_bow_fe)
```

In [104]:
```
# AUC-ROC plot
auc_train_bow_fe_sgd, auc_test_bow_fe_sgd = plot_auc_sgd(model_bow_fe_s
gd, X_train_bow_fe, X_test_bow_fe)
```



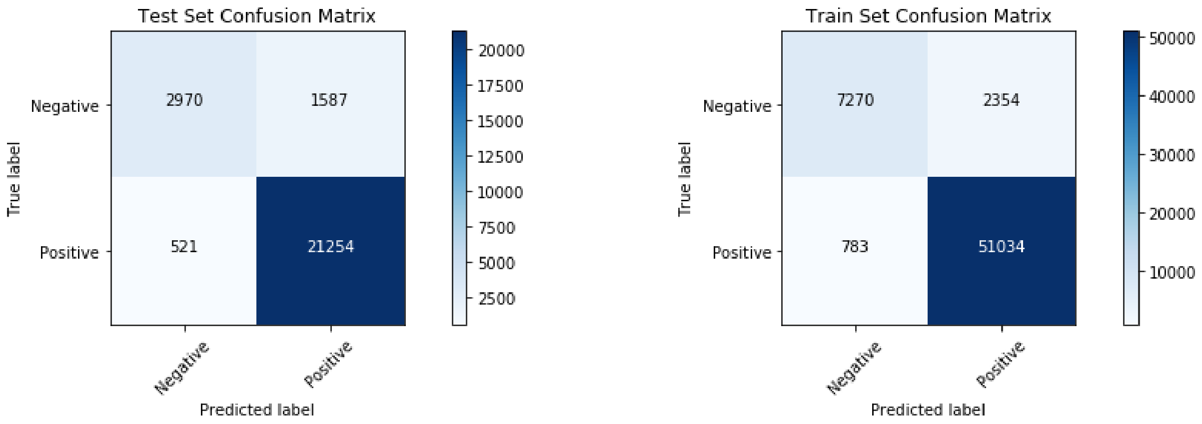

```
train AUC: 0.9782117196089936
test AUC: 0.9514549297367924
```

In [105]:
```
# Confusion Matrix
print_confusion_matrix(model_bow_fe_sgd, X_train_bow_fe, X_test_bow_fe)
```

```
*****Train confusion matrix*****
[[ 7270  2354]
 [  783 51034]]

*****Test confusion matrix*****
[[ 2970  1587]
 [  521 21254]]
```

In [106]:
```
# Confustion Matrix heatmap
plt.figure(1)
plt.figure(figsize=(15, 4))


plt.subplot(121)  # Test confusion matrix
cnf_matrix = confusion_matrix(y_test, model_bow_fe_sgd.predict(X_test_b
ow_fe))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
#plt.figure()
plot_confusion_matrix_heatmap(cnf_matrix, classes=class_names, title='T
est Set Confusion Matrix');

plt.subplot(122) # Train Confusion matrix
cnf_matrix = confusion_matrix(y_train, model_bow_fe_sgd.predict(X_train
_bow_fe))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
#plt.figure()
plot_confusion_matrix_heatmap(cnf_matrix, classes=class_names, title='T
rain Set Confusion Matrix');
```

```
<Figure size 432x288 with 0 Axes>
```



Observation

1. For the BoW vectorizer with Feature Engineering, we calculated C = 0.01 using GridSearchCV with cv = 5 and with penalty l2.
2. We got train AUC: 0.9782117196089936 and test AUC: 0.9514549297367924
3. Using the confusion matrix, we can say that our model correctly predicted 21245 positive reviews and 2970 negative reviews.
4. The model incorrectly classified 521 negative reviews and 1587 positive reviews.
5. **Doing Feature Engineering has made the model slightly perform better than the model without feature engineering.**

[4.2] Bi-Grams and n-Grams.

In [ ]:
```
#bi-gram, tri-gram and n-gram

#removing stop words like "not" should be avoided before building n-gra
ms
# count_vect = CountVectorizer(ngram_range=(1,2))
# please do read the CountVectorizer documentation http://scikit-learn.
org/stable/modules/generated/sklearn.feature_extraction.text.CountVecto
rizer.html

# you can choose these numebrs min_df=10, max_features=5000, of your ch
oice
#count_vect = CountVectorizer(ngram_range=(1,2), min_df=10, max_feature
s=5000)
#final_bigram_counts = count_vect.fit_transform(preprocessed_reviews)
#print("the type of count vectorizer ",type(final_bigram_counts))
#print("the shape of out text BOW vectorizer ",final_bigram_counts.get_
shape())
#print("the number of unique words including both unigrams and bigrams
 ", final_bigram_counts.get_shape()[1])
```

[4.3] TF-IDF

In [82]:
```
# ss
from sklearn.feature_extraction.text import TfidfVectorizer
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tf_idf_vect.fit(X_train) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_tfidf = tf_idf_vect.transform(X_train)
#X_cv_tfidf = tf_idf_vect.transform(X_cv)
X_test_tfidf = tf_idf_vect.transform(X_test)

print("After vectorizations")
print(X_train_tfidf.shape, y_train.shape)
#print(X_cv_tfidf.shape, y_cv.shape)
print(X_test_tfidf.shape, y_test.shape)
print("="*100)
```

```
After vectorizations
(61441, 36173) (61441,)
(26332, 36173) (26332,)
======================================================================
==============================
```

In [83]:
```
print("the type of count vectorizer ",type(X_train_tfidf))
print("the shape of cut text TFIDF vectorizer ",X_train_tfidf.get_shape
())
print("the number of unique words: ", X_train_tfidf.get_shape()[1])
```

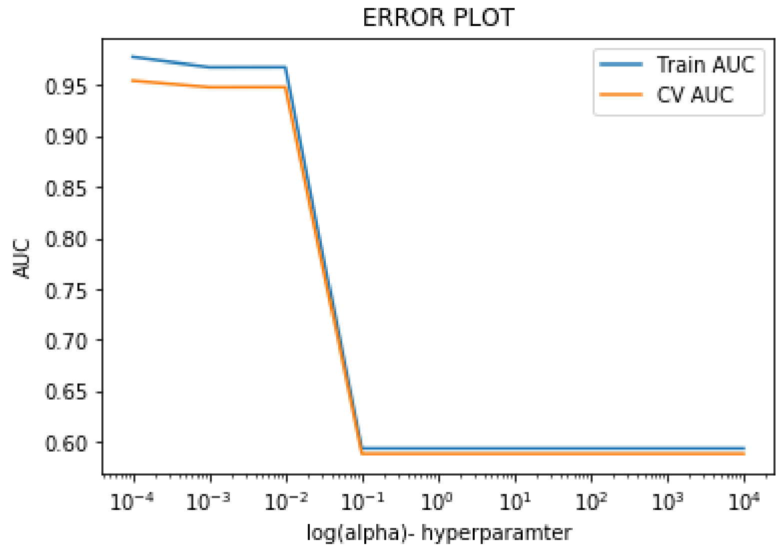
```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of cut text TFIDF vectorizer  (61441, 36173)
the number of unique words:  36173
```

[5.1.2] Applying Linear SVM on TFIDF, SET 2

In [84]:
```
# Get the best hyperparameter using GridSearchCV with penalty l1 and cv
 = 5
```

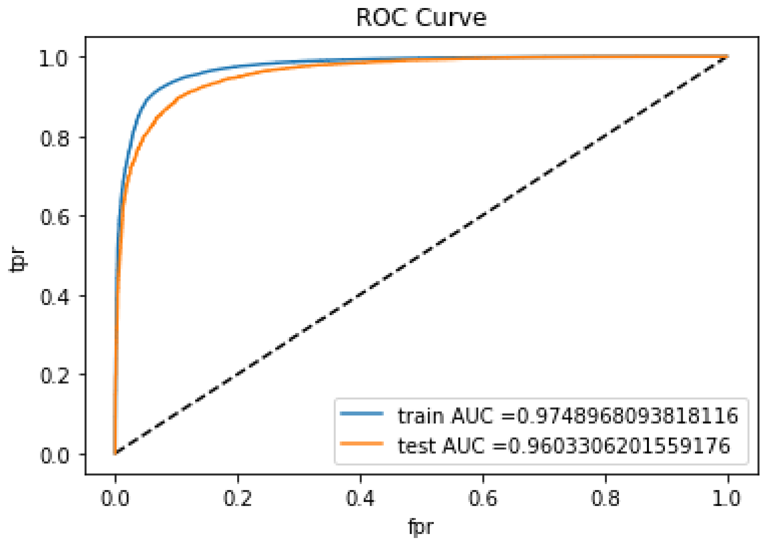
```
get_best_hyperparameter_alpha(tf_idf_vect, X_train_tfidf, X_test_tfidf,
 y_train, y_test)
```

```
+--------------+-------------+-----------------------------------+
| Mean CV Score | Std CV Score |               Param               |
+--------------+-------------+-----------------------------------+
|     0.93     |   0.01365   | {'alpha': 0.0001, 'penalty': 'l1'} |
|    0.955     |   0.01329   | {'alpha': 0.0001, 'penalty': 'l2'} |
|    0.678     |    0.0804   | {'alpha': 0.001, 'penalty': 'l1'}  |
|    0.948     |   0.01552   | {'alpha': 0.001, 'penalty': 'l2'}  |
|     0.5      |     0.0     |  {'alpha': 0.01, 'penalty': 'l1'}  |
|    0.948     |   0.01529   |  {'alpha': 0.01, 'penalty': 'l2'}  |
|     0.5      |     0.0     |  {'alpha': 0.1, 'penalty': 'l1'}   |
|    0.589     |   0.02017   |  {'alpha': 0.1, 'penalty': 'l2'}   |
|     0.5      |     0.0     |   {'alpha': 1, 'penalty': 'l1'}    |
|    0.589     |   0.02015   |   {'alpha': 1, 'penalty': 'l2'}    |
|     0.5      |     0.0     |   {'alpha': 10, 'penalty': 'l1'}   |
|    0.589     |   0.02015   |   {'alpha': 10, 'penalty': 'l2'}   |
|     0.5      |     0.0     |  {'alpha': 100, 'penalty': 'l1'}   |
|    0.589     |   0.02015   |  {'alpha': 100, 'penalty': 'l2'}   |
|     0.5      |     0.0     |  {'alpha': 1000, 'penalty': 'l1'}  |
|    0.589     |   0.02015   |  {'alpha': 1000, 'penalty': 'l2'}  |
|     0.5      |     0.0     | {'alpha': 10000, 'penalty': 'l1'}  |
|    0.589     |   0.02015   | {'alpha': 10000, 'penalty': 'l2'}  |
+--------------+-------------+-----------------------------------+

The best estimator:SGDClassifier(alpha=0.0001, average=False, class_wei
ght=None,
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=N
one,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)

The best score is:0.9545224952996035
The best value of C is:{'alpha': 0.0001, 'penalty': 'l2'}
Mean Score: 0.9600699999269364
```



In [107]:
```
# Fitting the model with the best hyperparameter
model_tfidf_sgd = SGDClassifier(alpha= 0.0001 ,penalty = 'l2')
model_tfidf_sgd.fit(X_train_tfidf,y_train)
y_pred = model_tfidf_sgd.predict(X_test_tfidf)
```

In [108]:
```
# AUC- ROC plot
auc_train_tfidf_sgd, auc_test_tfidf_sgd = plot_auc_sgd(model_tfidf_sgd,
 X_train_tfidf, X_test_tfidf)
```




```
train AUC: 0.9748968093818116
test AUC: 0.9603306201559176
```

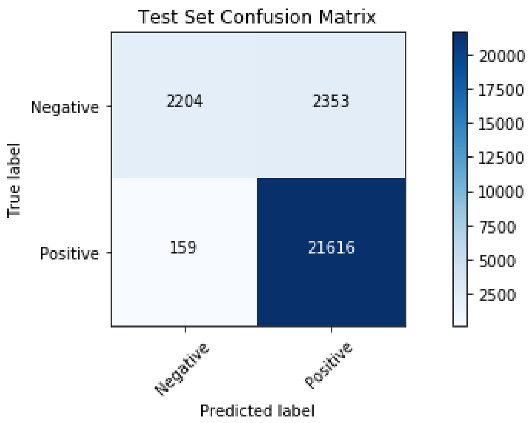
In [109]:
```
# Confusion Matrix
print_confusion_matrix(model_tfidf_sgd, X_train_tfidf, X_test_tfidf)
```

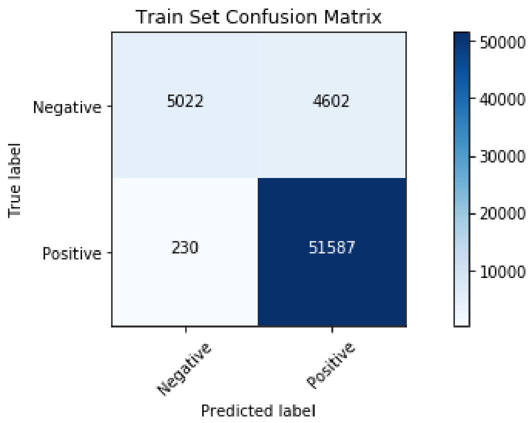
```
*****Train confusion matrix*****
[[ 5022  4602]
 [  230 51587]]

*****Test confusion matrix*****
[[ 2204  2353]
 [  159 21616]]
```

In [110]:
```
# Heatmap Confusion Matrix
plt.figure(1)
plt.figure(figsize=(15, 4))


plt.subplot(121)  # Test confusion matrix
cnf_matrix = confusion_matrix(y_test, model_tfidf_sgd.predict(X_test_tf
idf))
```

```
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
#plt.figure()
plot_confusion_matrix_heatmap(cnf_matrix, classes=class_names, title='T
est Set Confusion Matrix');

plt.subplot(122) # Train Confusion matrix
cnf_matrix = confusion_matrix(y_train, model_tfidf_sgd.predict(X_train_
tfidf))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
#plt.figure()
plot_confusion_matrix_heatmap(cnf_matrix, classes=class_names, title='T
rain Set Confusion Matrix');
```

```
<Figure size 432x288 with 0 Axes>
```





Observation

1. For the TFIDF vectorizer, we calculated C = 0.0001 using GridSearchCV with cv = 5 and with penalty l2.
2. We got train AUC: 0.9748968093818116 and test AUC: 0.9603306201559176

3. Using the confusion matrix, we can say that our model correctly predicted 21616 positive reviews and 2204 negative reviews.
4. The model incorrectly classified 159 negative reviews and 2353 positive reviews.

[4.4] Word2Vec

In [85]:
```
# Train your own Word2Vec model using your own text corpus
i=0
list_of_sentance_train=[]
for sentance in X_train:
    list_of_sentance_train.append(sentance.split())
```

In [86]:
```
print(list_of_sentance_train[0])
```

```
['bought', 'apartment', 'infested', 'fruit', 'flies', 'hours', 'trap',
'attracted', 'many', 'flies', 'within', 'days', 'practically', 'gone',
'may', 'not', 'long', 'term', 'solution', 'flies', 'driving', 'crazy',
'consider', 'buying', 'one', 'caution', 'surface', 'sticky', 'try', 'av
oid', 'touching']
```

In [87]:
```
is_your_ram_gt_16g=False
want_to_use_google_w2v = False
want_to_train_w2v = True

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

elif want_to_use_google_w2v and is_your_ram_gt_16g:
    if os.path.isfile('GoogleNews-vectors-negative300.bin'):
        w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors
-negative300.bin', binary=True)
```

```
        print(w2v_model.wv.most_similar('great'))
        print(w2v_model.wv.most_similar('worst'))
    else:
        print("you don't have gogole's word2vec file, keep want_to_trai
n_w2v = True, to train your own w2v ")
```

```
[('good', 0.821457028388977), ('terrific', 0.8163110613822937), ('fanta
stic', 0.8123440146446228), ('excellent', 0.8065283894538879), ('awesom
e', 0.8021259903907776), ('wonderful', 0.797581136226654), ('perfect',
0.7288220524787903), ('nice', 0.7148672938346863), ('fabulous', 0.70899
40309524536), ('decent', 0.695073127746582)]
==================================================
[('greatest', 0.7920302748680115), ('best', 0.7550718784332275), ('nast
iest', 0.7323176860809326), ('tastiest', 0.7221068143844604), ('closes
t', 0.6759981513023376), ('coolest', 0.662483274936676), ('disgusting',
0.6464158296585083), ('humble', 0.6225912570953369), ('softest', 0.5897
253751754761), ('smoothest', 0.5827312469482422)]
```

In [88]:

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

```
number of words that occured minimum 5 times  14799
sample words  ['bought', 'apartment', 'infested', 'fruit', 'flies', 'ho
urs', 'trap', 'attracted', 'many', 'within', 'days', 'practically', 'go
ne', 'may', 'not', 'long', 'term', 'solution', 'driving', 'crazy', 'con
sider', 'buying', 'one', 'caution', 'surface', 'sticky', 'try', 'avoi
d', 'touching', 'really', 'good', 'idea', 'final', 'product', 'outstand
ing', 'use', 'car', 'window', 'everybody', 'asks', 'made', 'two', 'thum
bs', 'received', 'shipment', 'could', 'hardly', 'wait', 'love', 'call']
```

Converting train text data

In [89]:

```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_train = []; # the avg-w2v for each sentence/review is stor
ed in this list
for sent in tqdm(list_of_sentance_train): # for each review/sentence
```

```
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, yo
u might need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/re
view
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_train.append(sent_vec)
sent_vectors_train = np.array(sent_vectors_train)
print(sent_vectors_train.shape)
print(sent_vectors_train[0])
```

```
100%|████████████████████████████████████████
██████████████████████████████████| 61441/61441
[01:52<00:00, 618.29it/s]
```

```
(61441, 50)
[ 0.5   0.28  0.01  0.78  0.19 -0.33 -0.03 -0.04 -0.18 -0.08  0.39  0.1
3
  0.2   0.1  -0.27 -0.62 -0.13 -0.44  0.11 -0.07 -0.22  0.14  0.17  0.2
7
  0.08  0.21  0.48  0.5   0.5   0.04  0.06 -0.39  0.38 -0.19 -0.28 -0.0
5
  1.   -0.05 -0.44 -0.11 -0.13 -0.32  0.11 -0.2   0.22  0.   -0.    0.4
2
  0.13 -0.12]
```

Converting test text data

In [90]:
```
i=0
list_of_sentance_test=[]
for sentance in X_test:
    list_of_sentance_test.append(sentance.split())
```

```
In [91]: # average Word2Vec
# compute average word2vec for each review.
sent_vectors_test = []; # the avg-w2v for each sentence/review is store
d in this list
for sent in tqdm(list_of_sentance_test): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, yo
u might need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/re
view
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_test.append(sent_vec)
sent_vectors_test = np.array(sent_vectors_test)

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

```
100%|██████████████████████████████████████████████████████████████████
█████████████████████████████████████████████████████████| 26332/26332
[00:44<00:00, 595.22it/s]
```

```
(26332, 50)
[-0.2   0.15  0.1  -0.8  -0.12  1.12 -0.45 -0.67 -0.05 -0.19  0.26 -0.8
1
 -0.47  1.24  0.33 -0.78  0.16  0.49  0.04 -0.53  0.3  -0.21  0.2   0.6
7
 -0.06 -0.68  0.22  0.41 -0.04 -0.09 -0.73  0.46  0.09 -0.74 -0.39 -1.0
4
  0.48  0.09 -0.01  0.49 -0.01 -0.5  -0.3  -0.27 -0.16  1.19 -0.3   0.3
6
  0.01  0.56]
```

hyperparameter tuning with cv = 5 using gridsearch

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

In [92]:

```
params_dict = {
                "alpha": [10**-4, 10**-3,10**-2,10**-1, 10**0,10**1, 10
**2,10**3, 10**4],
                "penalty": ['l1', 'l2']
               }

# Using GridSearchCVSearchCV with 5 fold cv
gs_obj = GridSearchCV(SGDClassifier(loss='hinge'), param_grid = params_
dict, scoring = 'roc_auc', cv=5)

gs_obj.fit(sent_vectors_train, y_train)

# Code https://stackoverflow.com/questions/42793254/what-replaces-grids
earchcv-grid-scores-in-scikit#answer-42800056
means = gs_obj.cv_results_['mean_test_score']
stds = gs_obj.cv_results_['std_test_score']


t1 = PrettyTable()
t1.field_names = ['Mean CV Score', 'Std CV Score', 'Param']

for mean, std, params in zip(means, stds, gs_obj.cv_results_['params'
]):
    t1.add_row([round(mean, 3), round(std * 2,5), params])

print(t1)

print("\nThe best estimator:{}".format(gs_obj.best_estimator_))
print("\nThe best score is:{}".format(gs_obj.best_score_))
print("The best value of C is:{}".format(gs_obj.best_params_))

# Returns the mean accuracy on the given test data and labels.
print("Mean Score: {}".format(gs_obj.score(sent_vectors_test, y_test)))

del t1
```

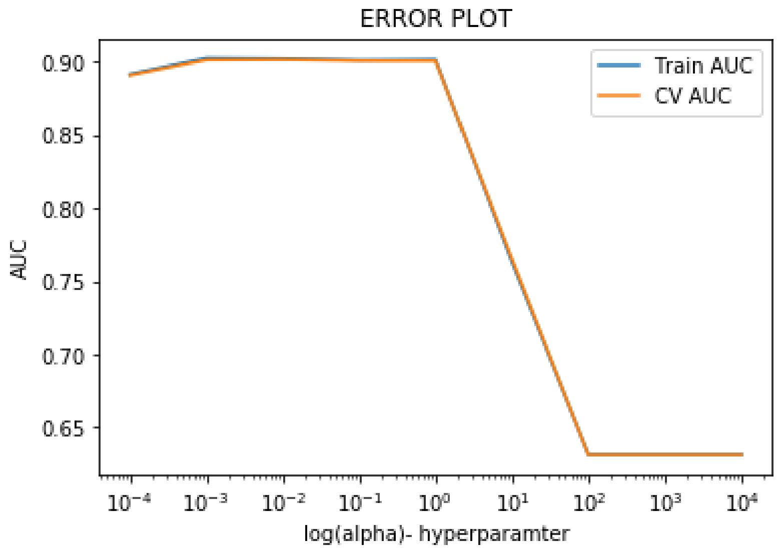
```
+--------------+-------------+----------------------------------+
```

```
| Mean CV Score | Std CV Score |                Param                |
+---------------+--------------+-------------------------------------+
|     0.894     |   0.01043    | {'alpha': 0.0001, 'penalty': 'l1'} |
|      0.89     |   0.01894    | {'alpha': 0.0001, 'penalty': 'l2'} |
|      0.9      |   0.01401    | {'alpha': 0.001, 'penalty': 'l1'}  |
|      0.9      |   0.01779    | {'alpha': 0.001, 'penalty': 'l2'}  |
|      0.86     |    0.0229    |  {'alpha': 0.01, 'penalty': 'l1'}  |
|     0.901     |   0.01561    |  {'alpha': 0.01, 'penalty': 'l2'}  |
|      0.5      |     0.0      |  {'alpha': 0.1, 'penalty': 'l1'}   |
|      0.9      |   0.01582    |  {'alpha': 0.1, 'penalty': 'l2'}   |
|      0.5      |     0.0      |   {'alpha': 1, 'penalty': 'l1'}    |
|     0.898     |   0.02486    |   {'alpha': 1, 'penalty': 'l2'}    |
|      0.5      |     0.0      |   {'alpha': 10, 'penalty': 'l1'}   |
|     0.798     |   0.02807    |   {'alpha': 10, 'penalty': 'l2'}   |
|      0.5      |     0.0      |  {'alpha': 100, 'penalty': 'l1'}   |
|     0.631     |   0.02232    |  {'alpha': 100, 'penalty': 'l2'}   |
|      0.5      |     0.0      |  {'alpha': 1000, 'penalty': 'l1'}  |
|     0.631     |   0.02232    |  {'alpha': 1000, 'penalty': 'l2'}  |
|      0.5      |     0.0      | {'alpha': 10000, 'penalty': 'l1'}  |
|     0.631     |   0.02232    | {'alpha': 10000, 'penalty': 'l2'}  |
+---------------+--------------+-------------------------------------+

The best estimator:SGDClassifier(alpha=0.01, average=False, class_weigh
t=None,
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=N
one,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)

The best score is:0.9014066804762465
The best value of C is:{'alpha': 0.01, 'penalty': 'l2'}
Mean Score: 0.9023320325500668
```

In [93]:

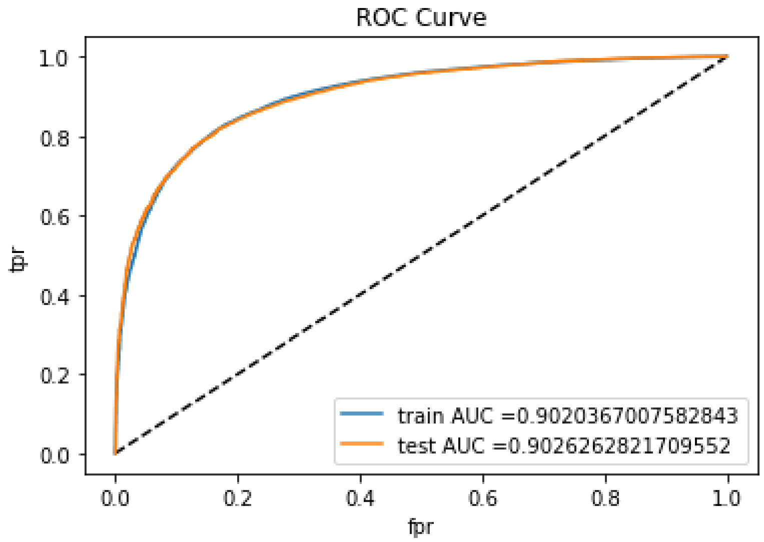
```
alpha = [10**-4, 10**-3,10**-2,10**-1, 10**0,10**1, 10**2,10**3, 10**4]

params_dict = {
                "alpha": [10**-4, 10**-3,10**-2,10**-1, 10**0,10**1, 10
```

```
**2,10**3, 10**4]

               }
gs_obj = GridSearchCV(SGDClassifier(loss='hinge',penalty = 'l2'), param
_grid = params_dict, scoring = 'roc_auc', cv=5)

gs_obj.fit(sent_vectors_train, y_train)


train_scores_mean= gs_obj.cv_results_['mean_train_score']
train_scores_std= gs_obj.cv_results_['std_train_score']
test_scores_mean = gs_obj.cv_results_['mean_test_score']
test_scores_std= gs_obj.cv_results_['std_test_score']

# draws the error plot

plt.plot(alpha, train_scores_mean, label='Train AUC')
    # this code is copied from here: https://stackoverflow.com/a/488033
61/4084039
    #plt.gca().fill_between(alpha,train_auc - train_auc_std,train_auc +
 train_auc_std,alpha=0.2,color='darkblue')

plt.plot(alpha, test_scores_mean, label='CV AUC')
    # this code is copied from here: https://stackoverflow.com/a/488033
61/4084039
    #plt.gca().fill_between(alpha,cv_auc - cv_auc_std,cv_auc + cv_auc_s
td,alpha=0.2,color='darkorange')
plt.legend()
plt.xlabel("log(alpha)- hyperparamter")
plt.xscale('log')
plt.ylabel("AUC")
plt.title("ERROR PLOT")
plt.show()
```



In [115]:
```
# Fitting the model with the best hyperparameter
model_avgw2v_sgd = SGDClassifier(alpha= 0.01 ,penalty = 'l2')
model_avgw2v_sgd.fit(sent_vectors_train,y_train)
y_pred = model_avgw2v_sgd.predict(sent_vectors_test)
```

In [116]:
```
# AUC - ROC plot
auc_train_avgw2v_l1, auc_test_avgw2v_l1 = plot_auc_sgd(model_avgw2v_sgd
, sent_vectors_train, sent_vectors_test)
```




```
train AUC: 0.9020367007582843
test AUC: 0.9026262821709552
```

In [117]:

```
# Confusion matrix
print_confusion_matrix(model_avgw2v_sgd, sent_vectors_train, sent_vecto
rs_test)
```

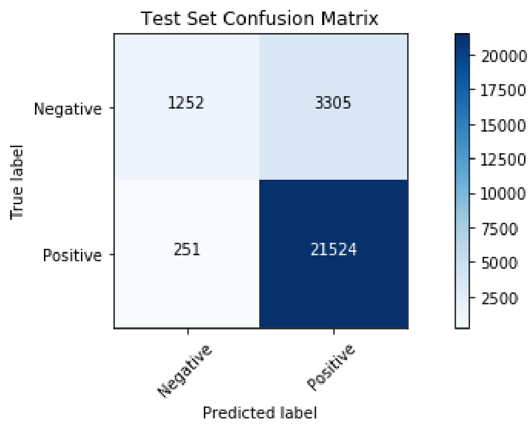
```
*****Train confusion matrix*****
[[ 2592  7032]
 [  627 51190]]

*****Test confusion matrix*****
[[ 1252  3305]
 [  251 21524]]
```

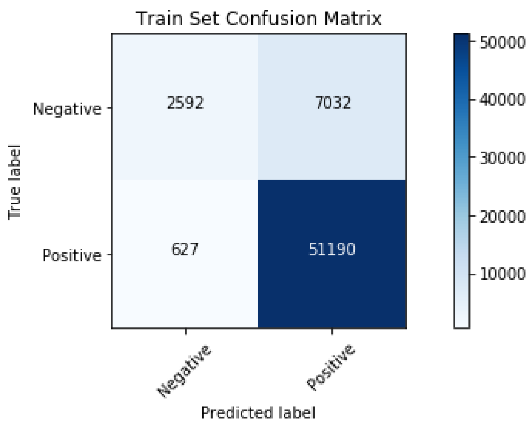
In [118]:

```
# Heatmap confusion matrix
plt.figure(1)
plt.figure(figsize=(15, 4))


plt.subplot(121)  # Test confusion matrix
cnf_matrix = confusion_matrix(y_test, model_avgw2v_sgd.predict(sent_vec
```

```
tors_test))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
#plt.figure()
plot_confusion_matrix_heatmap(cnf_matrix, classes=class_names, title='T
est Set Confusion Matrix');

plt.subplot(122) # Train Confusion matrix
cnf_matrix = confusion_matrix(y_train, model_avgw2v_sgd.predict(sent_ve
ctors_train))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
#plt.figure()
plot_confusion_matrix_heatmap(cnf_matrix, classes=class_names, title='T
rain Set Confusion Matrix');
```

```
<Figure size 432x288 with 0 Axes>
```





Observation

1. For the BoW vectorizer, we calculated C = 0.01 using GridSearchCV with cv = 5 and with penalty l2.
2. We got train AUC: 0.902424731877006 and test AUC: 0.9015779662481638

3. Using the confusion matrix, we can say that our model correctly predicted 20987 positive reviews and 2146 negative reviews.
4. The model incorrectly classified 788 negative reviews and 2411 positive reviews.

[4.4.1.2] TFIDF weighted W2v

In [94]:
```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
X_train_tf_idf_w2v = model.fit_transform(X_train)
X_test_tf_idf_w2v = model.transform(X_test)
# we are converting a dictionary with word as a key, and the idf as a v
alue
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [95]:
```
# TF-IDF weighted Word2Vec for sentences in X_train
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
ll_val = tfidf

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

```
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_train.append(sent_vec)
    row += 1
```

```
100%|██████████████████████████████████████████████████| 61441/61441 [24:44<00:00, 32.20it/s]
```

In [96]:

```
# TF-IDF weighted Word2Vec for sentences in X_test
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

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

    row += 1
```

```
100%|██████████████████████████████████████████████████| 26332/26332
```

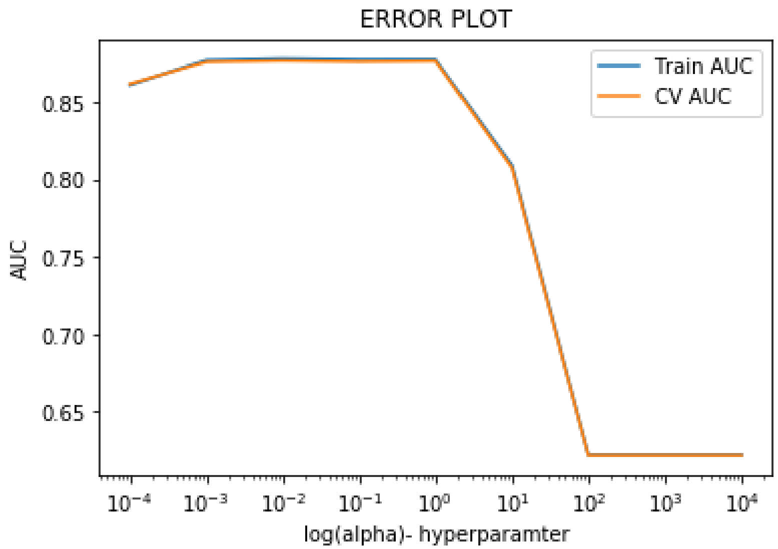
```
[11:18<00:00, 58.06it/s]
```

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

In [97]:
```
get_best_hyperparameter_alpha(model, tfidf_sent_vectors_train, tfidf_se
nt_vectors_test, y_train, y_test)
```

```
+---------------+--------------+-------------------------------------+
| Mean CV Score | Std CV Score |                Param                |
+---------------+--------------+-------------------------------------+
|     0.856     |    0.027     | {'alpha': 0.0001, 'penalty': 'l1'} |
|     0.858     |   0.02295    | {'alpha': 0.0001, 'penalty': 'l2'} |
|     0.877     |   0.01896    | {'alpha': 0.001, 'penalty': 'l1'}  |
|     0.876     |   0.02032    | {'alpha': 0.001, 'penalty': 'l2'}  |
|     0.819     |   0.04099    |  {'alpha': 0.01, 'penalty': 'l1'}  |
|     0.877     |   0.02028    |  {'alpha': 0.01, 'penalty': 'l2'}  |
|      0.5      |     0.0      |  {'alpha': 0.1, 'penalty': 'l1'}   |
|     0.876     |    0.0207    |  {'alpha': 0.1, 'penalty': 'l2'}   |
|      0.5      |     0.0      |   {'alpha': 1, 'penalty': 'l1'}    |
|     0.876     |   0.02009    |   {'alpha': 1, 'penalty': 'l2'}    |
|      0.5      |     0.0      |   {'alpha': 10, 'penalty': 'l1'}   |
|     0.756     |   0.14144    |   {'alpha': 10, 'penalty': 'l2'}   |
|      0.5      |     0.0      |  {'alpha': 100, 'penalty': 'l1'}   |
|     0.622     |    0.0264    |  {'alpha': 100, 'penalty': 'l2'}   |
|      0.5      |     0.0      |  {'alpha': 1000, 'penalty': 'l1'}  |
|     0.622     |    0.0264    |  {'alpha': 1000, 'penalty': 'l2'}  |
|      0.5      |     0.0      | {'alpha': 10000, 'penalty': 'l1'}  |
|     0.622     |    0.0264    | {'alpha': 10000, 'penalty': 'l2'}  |
+---------------+--------------+-------------------------------------+

The best estimator:SGDClassifier(alpha=0.01, average=False, class_weigh
t=None,
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=N
one,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

```
The best score is:0.8766964093747083
The best value of C is:{'alpha': 0.01, 'penalty': 'l2'}
Mean Score: 0.8748275435502894
```

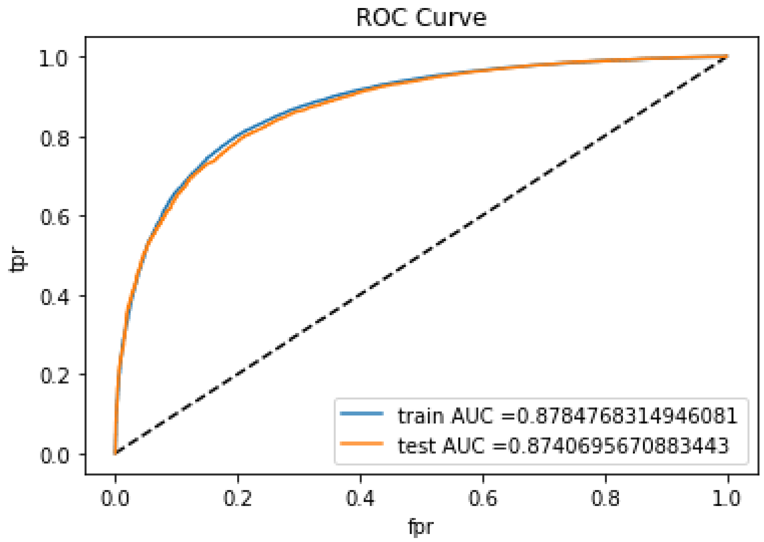


In [111]:

```
# Fitting the TFIDF - weighted W2V vectorizer on LogisticRegression Mod
el
model_tfidfw2v_sgd = SGDClassifier(alpha= 0.01 ,penalty = 'l2')
model_tfidfw2v_sgd.fit(tfidf_sent_vectors_train,y_train)
y_pred = model_tfidfw2v_sgd.predict(tfidf_sent_vectors_test)
```

In [112]:

```
# AUC- ROC plot
auc_train_tfidfw2v_sgd, auc_test_tfidfw2v_sgd = plot_auc_sgd(model_tfid
fw2v_sgd, tfidf_sent_vectors_train, tfidf_sent_vectors_test)
```




```
train AUC: 0.8784768314946081
test AUC: 0.8740695670883443
```

In [113]:

```
# Confusion Matrix
print_confusion_matrix(model_tfidfw2v_sgd, tfidf_sent_vectors_train, tf
idf_sent_vectors_test)
```

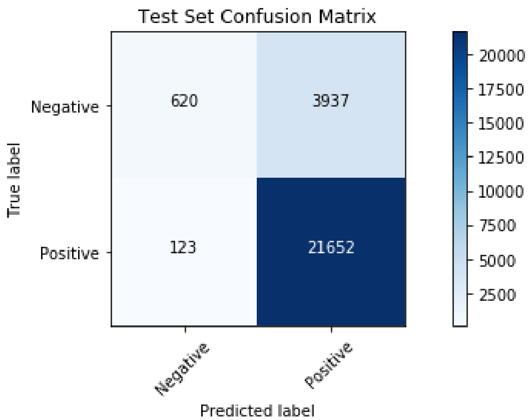
```
*****Train confusion matrix*****
[[ 1240  8384]
 [  292 51525]]

*****Test confusion matrix*****
[[  620  3937]
 [  123 21652]]
```

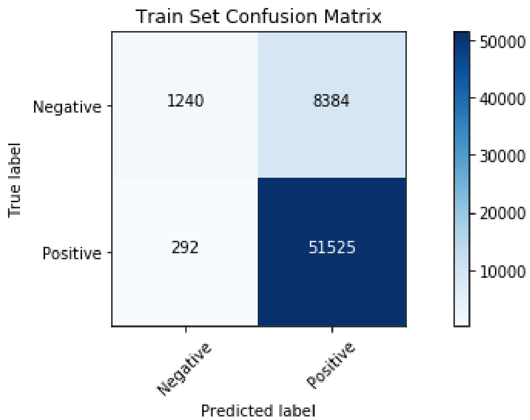
In [114]:

```
# Heatmap Confusion Matrix
plt.figure(1)
plt.figure(figsize=(15, 4))


plt.subplot(121)  # Test confusion matrix
cnf_matrix = confusion_matrix(y_test, model_tfidfw2v_sgd.predict(tfidf_
```

```
sent_vectors_test))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
#plt.figure()
plot_confusion_matrix_heatmap(cnf_matrix, classes=class_names, title='T
est Set Confusion Matrix');

plt.subplot(122) # Train Confusion matrix
cnf_matrix = confusion_matrix(y_train, model_tfidfw2v_sgd.predict(tfidf
_sent_vectors_train))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
#plt.figure()
plot_confusion_matrix_heatmap(cnf_matrix, classes=class_names, title='T
rain Set Confusion Matrix');
```

```
<Figure size 432x288 with 0 Axes>
```





Observation

1. For the BoW vectorizer, we calculated C = 0.01 using GridSearchCV with cv = 5 and with penalty l2.
2. We got train AUC: 0.8784768314946081 and test AUC: 0.8740695670883443

3. Using the confusion matrix, we can say that our model correctly predicted 21652 positive reviews and 620 negative reviews.
4. The model incorrectly classified 123 negative reviews and 3937 positive reviews.

In [121]:
```
#del final

#del X, y, X_train_tfidf, X_test, y_train, y_test, X_train_bow, X_test_bow,X_train_bow_fe, X_test_bow_fe
#del w2v_words, tfidf_feat, tfidf_sent_vectors_test, tfidf_sent_vectors_train, sent_vectors_test, sent_vectors_train, sent_vec
```

RBF SVM

In [2]:
```
final = pickle.load(open('preprocessed_final_rbf_kernel', 'rb'))
```

In [3]:
```
def get_best_hyperparameter_alpha_rbf(vectorizer, X_train, X_test, y_train, y_test):

    """
    This funtion takes in the vectorizer,  and performs LogissticRegression hyperparameter tuning using GridSearchCV with 5 fold cv
    Returns the value of hyperparameter C and draws the error plot for various values of C

    Usage: get_best_hyperparameter_C(vectorizer, X_train, X_test, y_train, y_test, penalty)
    """
    tuned_parameters = [{'C': [10**-4, 10**-3,10**-2,10**-1, 10**0,10**1, 10**2,10**3, 10**4]}]
    alpha = [10**-4, 10**-3,10**-2,10**-1, 10**0,10**1, 10**2,10**3, 10**4]  #k

    #tuned_parameters = [{'C': [10**-4, 10**-3,10**-2]}]
    #alpha = [10**-4, 10**-3,10**-2]
```

```
    # Using GridSearchCVSearchCV with 5 fold cv
    gs_obj = GridSearchCV(SVC(kernel='rbf'), tuned_parameters, scoring
= 'roc_auc', cv=3)

    gs_obj.fit(X_train, y_train)


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


    # draws the error plot

    plt.plot(alpha, train_auc, label='Train AUC')
    # this code is copied from here: https://stackoverflow.com/a/488033
61/4084039
    plt.gca().fill_between(alpha,train_auc - train_auc_std,train_auc +
train_auc_std,alpha=0.2,color='darkblue')

    plt.plot(alpha, cv_auc, label='CV AUC')
    # this code is copied from here: https://stackoverflow.com/a/488033
61/4084039
    plt.gca().fill_between(alpha,cv_auc - cv_auc_std,cv_auc + cv_auc_st
d,alpha=0.2,color='darkorange')
    plt.legend()
    plt.xlabel("log(C)- hyperparamter")
    plt.xscale('log')
    plt.ylabel("AUC")
    plt.title("ERROR PLOT")
    plt.show()


    # Results of the gs object


    # Code https://stackoverflow.com/questions/42793254/what-replaces-g
ridsearchcv-grid-scores-in-scikit#answer-42800056
```

```
    means = gs_obj.cv_results_['mean_test_score']
    stds = gs_obj.cv_results_['std_test_score']


    t1 = PrettyTable()
    t1.field_names = ['Mean CV Score', 'Std CV Score', 'Param']

    for mean, std, params in zip(means, stds, gs_obj.cv_results_['param
s']):
        t1.add_row([round(mean, 3), round(std * 2,5), params])

    print(t1)

    print("\nThe best estimator:{}".format(gs_obj.best_estimator_))
    print("\nThe best score is:{}".format(gs_obj.best_score_))
    print("The best value of C is:{}".format(gs_obj.best_params_))

    # Returns the mean accuracy on the given test data and labels.
    print("Mean Score: {}".format(gs_obj.score(X_test, y_test)))


    return gs_obj.best_params_
```

In [4]:

```
def plot_auc_rbf(model, X_train, X_test):

    """
    This function will plot the AUC for the vectorized train and test d
ata.
    Returns the plot and also the values of auc for train and test

    Usage: auc_train, auc_test = plot_auc(model, X_train, X_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_pr
oba(X_test)[:,1])

    plt.plot([0,1],[0,1],'k--')
```

```
    plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fp
r, train_tpr)))
    plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, t
est_tpr)))
    plt.legend()
    plt.xlabel("fpr")
    plt.ylabel("tpr")
    plt.title("ROC Curve")
    plt.show()

    print("train AUC: {}".format(auc(train_fpr, train_tpr)))
    print("test AUC: {}".format(auc(test_fpr, test_tpr)))


    return auc(train_fpr, train_tpr), auc(test_fpr, test_tpr)
```

Print Confusion Matrix

In [5]:
```
def print_confusion_matrix(model, X_train, X_test):
    """
    Takes in the model, X_train, X_test and prints the confusion matrix
    Usage: print_confusion_matrix(model, X_train, X_test)
    """
    print("*****Train confusion matrix*****")
    print(confusion_matrix(y_train, model.predict(X_train)))
    print("\n*****Test confusion matrix*****")
    print(confusion_matrix(y_test, model.predict(X_test)))
```

In [6]:
```
# Create X and Y variable
X = final['CleanedText'].values
y= final['Score'].values
```

In [7]:
```
from sklearn.model_selection import train_test_split

# Splitting into train and test in the ratio 70:30
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3
```

```
0,shuffle=False, random_state=507)
#X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test
_size=0.30, shuffle=False, random_state=507)
```

[5.2.1] Applying RBF SVM on BOW, SET 1

Bag Of Words

In [9]:
```
# ss
from sklearn.feature_extraction.text import CountVectorizer
bow_vectorizer_rbf= CountVectorizer(ngram_range=(1,2), min_df=10, max_f
eatures=500)
bow_vectorizer_rbf.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 = bow_vectorizer_rbf.transform(X_train)
#X_cv_bow = vectorizer.transform(X_cv)
X_test_bow = bow_vectorizer_rbf.transform(X_test)

print("After vectorizations")
print(X_train_bow.shape, y_train.shape)
#print(X_cv_bow.shape, y_cv.shape)
print(X_test_bow.shape, y_test.shape)
print("="*100)
```

```
After vectorizations
(26190, 500) (26190,)
(11225, 500) (11225,)
======================================================================
==============================
```

In [10]:
```
print("the type of count vectorizer ",type(X_train_bow))
print("the shape of cut text BOW vectorizer ",X_train_bow.get_shape())
print("the number of unique words: ", X_train_bow.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of cut text BOW vectorizer  (26190, 500)
```

```
the number of unique words:  500
```

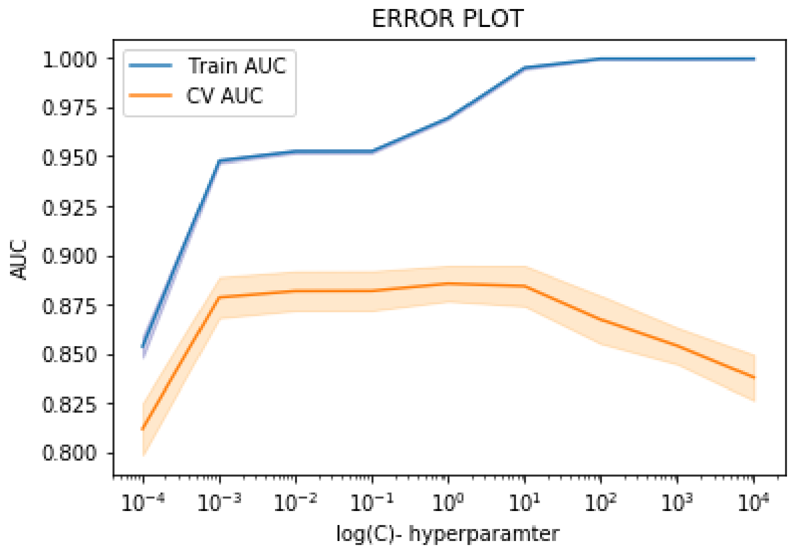
Standardize the data

In [11]:
```
# We will set the attribute with_mean = False, as StandardScaler does n
ot work on sparse matrix
# when attempted on sparse matrices, because centering them entails bui
lding a dense matrix which in common use cases
# is likely to be too large to fit in memory.  ---> sklearn documentati
on

from sklearn.preprocessing import StandardScaler
X_train_bow=StandardScaler(with_mean=False).fit_transform(X_train_bow)
X_test_bow=StandardScaler(with_mean=False).fit_transform(X_test_bow)

print(X_train_bow.shape, y_train.shape)

print(X_test_bow.shape, y_test.shape)
```

```
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\utils\validation.py:595: DataConversionWarning: Data with inp
ut dtype int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\utils\validation.py:595: DataConversionWarning: Data with inp
ut dtype int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\utils\validation.py:595: DataConversionWarning: Data with inp
ut dtype int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\utils\validation.py:595: DataConversionWarning: Data with inp
ut dtype int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
```

```
(26190, 500) (26190,)
(11225, 500) (11225,)
```

In [12]:
```
get_best_hyperparameter_alpha_rbf(bow_vectorizer_rbf, X_train_bow,X_tes
t_bow, y_train, y_test)
```



Mean CV Score	Std CV Score	Param
0.812	0.02647	{'C': 0.0001}
0.879	0.02059	{'C': 0.001}
0.882	0.01969	{'C': 0.01}
0.882	0.01978	{'C': 0.1}
0.886	0.01775	{'C': 1}
0.884	0.0203	{'C': 10}
0.867	0.02432	{'C': 100}
0.854	0.01855	{'C': 1000}
0.838	0.02302	{'C': 10000}

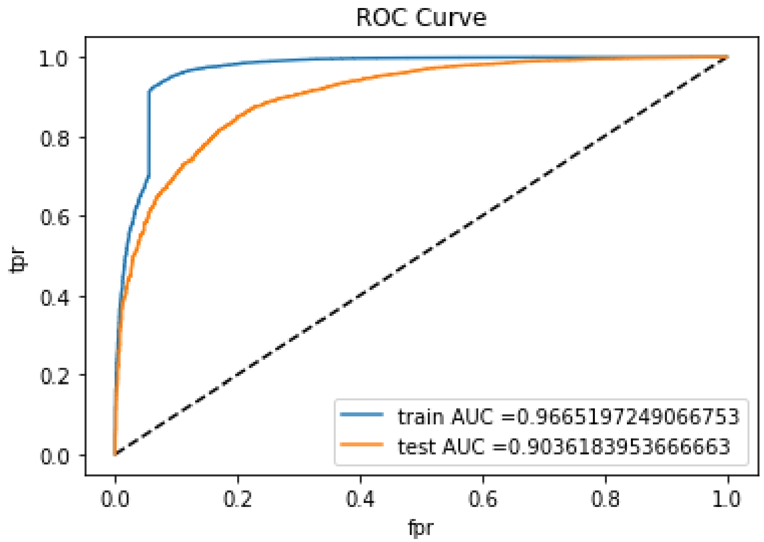
```
The best estimator:SVC(C=1, cache_size=200, class_weight=None, coef0=0.
0,
  decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
  kernel='rbf', max_iter=-1, probability=False, random_state=None,
  shrinking=True, tol=0.001, verbose=False)
```

```
The best score is:0.8855856974636146
The best value of C is:{'C': 1}
Mean Score: 0.9036181817268996
```

Out[12]:
```
{'C': 1}
```

In [31]:
```
#SVC(kernel='rbf')
model_bow_rbf = SVC(kernel='rbf', C= 1, probability=True)
model_bow_rbf.fit(X_train_bow,y_train)
y_pred = model_bow_rbf.predict(X_test_bow)
```

In [32]:
```
#train_auc, test_auc = plot_auc_rbf(bow_vectorizer_rbf, X_train_bow, X_
test_bow)
auc_train_bow_rbf, auc_test_bow_rbf = plot_auc_rbf(model_bow_rbf, X_tra
in_bow, X_test_bow)
```




```
train AUC: 0.9665197249066753
test AUC: 0.903618395366663
```

In [33]:
```
print_confusion_matrix(model_bow_rbf, X_train_bow, X_test_bow)
```

```
*****Train confusion matrix*****
[[ 2709  1344]
 [  109 22028]]

*****Test confusion matrix*****
[[ 742 1296]
 [ 142 9045]]
```

In [42]:
```
plt.figure(1)
plt.figure(figsize=(15, 4))


plt.subplot(121)  # Test confusion matrix
cnf_matrix = confusion_matrix(y_test, model_bow_rbf.predict(X_test_bow
))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
#plt.figure()
plot_confusion_matrix_heatmap(cnf_matrix, classes=class_names, title='T
est Set Confusion Matrix');

plt.subplot(122) # Train Confusion matrix
cnf_matrix = confusion_matrix(y_train, model_bow_rbf.predict(X_train_bo
w))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
#plt.figure()
plot_confusion_matrix_heatmap(cnf_matrix, classes=class_names, title='T
rain Set Confusion Matrix');
```

```
<Figure size 432x288 with 0 Axes>
```

Observation

1. For the BoW vectorizer, we used SVC classifier with RBF kernel and C = 1
2. We got train AUC: 0.9665197249066753 and test AUC: 0.9036183953666663
3. Using the confusion matrix, we can say that our model correctly predicted 9045 positive reviews and 742 negative reviews.
4. The model incorrectly classified 142 negative reviews and 1296 positive reviews.

[5.2.2] Applying RBF SVM on TFIDF, SET 2

TF-IDF

In [13]:
```
# ss
from sklearn.feature_extraction.text import TfidfVectorizer
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tf_idf_vect.fit(X_train) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_tfidf = tf_idf_vect.transform(X_train)
#X_cv_tfidf = tf_idf_vect.transform(X_cv)
X_test_tfidf = tf_idf_vect.transform(X_test)
```

```
print("After vectorizations")
print(X_train_tfidf.shape, y_train.shape)
#print(X_cv_tfidf.shape, y_cv.shape)
print(X_test_tfidf.shape, y_test.shape)
print("="*100)
```

```
After vectorizations
(26190, 15875) (26190,)
(11225, 15875) (11225,)
======================================================================
==============================
```

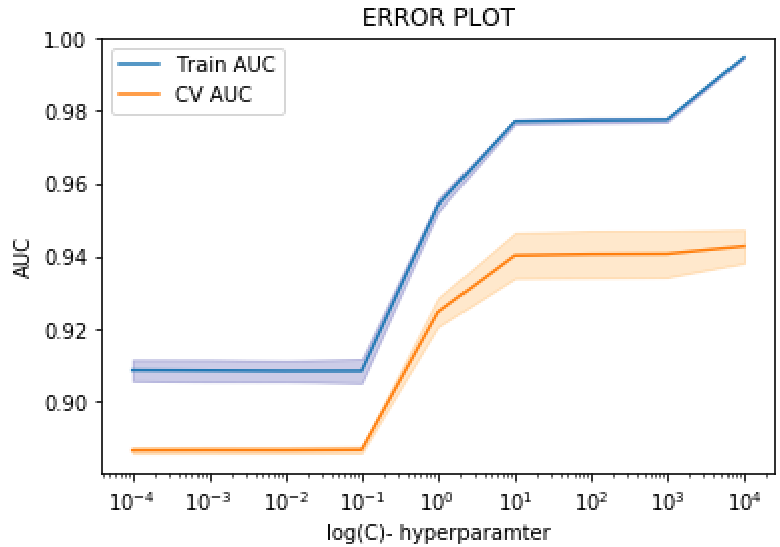
In [14]:

```
print("the type of count vectorizer ",type(X_train_tfidf))
print("the shape of cut text TFIDF vectorizer ",X_train_tfidf.get_shape
())
print("the number of unique words: ", X_train_tfidf.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of cut text TFIDF vectorizer  (26190, 15875)
the number of unique words:  15875
```

In [15]:

```
get_best_hyperparameter_alpha_rbf(tf_idf_vect, X_train_tfidf, X_test_tf
idf, y_train, y_test)
```



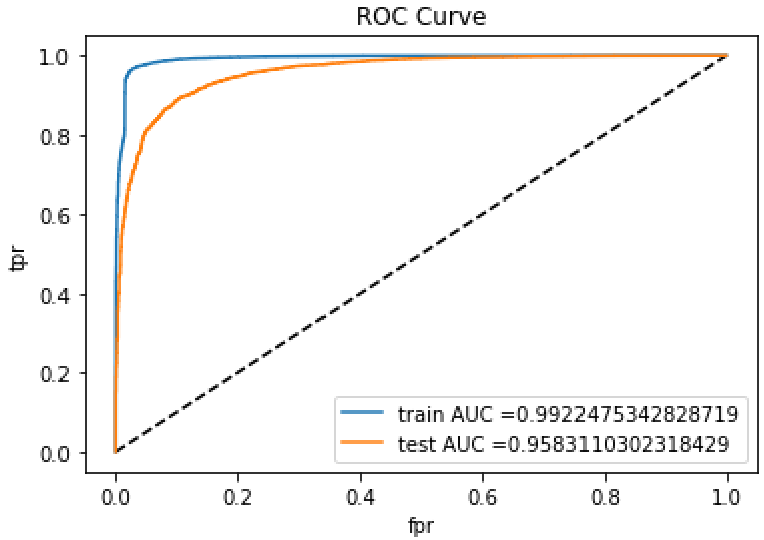
Mean CV Score	Std CV Score	Param
0.887	0.00168	{'C': 0.0001}
0.887	0.00175	{'C': 0.001}
0.887	0.00171	{'C': 0.01}
0.887	0.00185	{'C': 0.1}
0.925	0.00794	{'C': 1}
0.94	0.01257	{'C': 10}
0.941	0.01291	{'C': 100}
0.941	0.01278	{'C': 1000}
0.943	0.0093	{'C': 10000}

```
The best estimator:SVC(C=10000, cache_size=200, class_weight=None, coef
0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
  kernel='rbf', max_iter=-1, probability=False, random_state=None,
  shrinking=True, tol=0.001, verbose=False)

The best score is:0.9428445170872043
The best value of C is:{'C': 10000}
Mean Score: 0.9583121251356479
```

Out[15]: {'C': 10000}

In [43]:
```
# Fitting the model with the best hyperparameter
model_tfidf_rbf = SVC(kernel='rbf', C= 10000, probability=True)
model_tfidf_rbf.fit(X_train_tfidf,y_train)
y_pred = model_tfidf_rbf.predict(X_test_tfidf)
```

In [44]:
```
# AUC- ROC plot
auc_train_tfidf_rbf, auc_test_tfidf_rbf = plot_auc_rbf(model_tfidf_rbf,
 X_train_tfidf, X_test_tfidf)
```




```
train AUC: 0.9922475342828719
test AUC: 0.9583110302318429
```

In [45]:
```
# Confusion Matrix
print_confusion_matrix(model_tfidf_rbf, X_train_tfidf, X_test_tfidf)
```

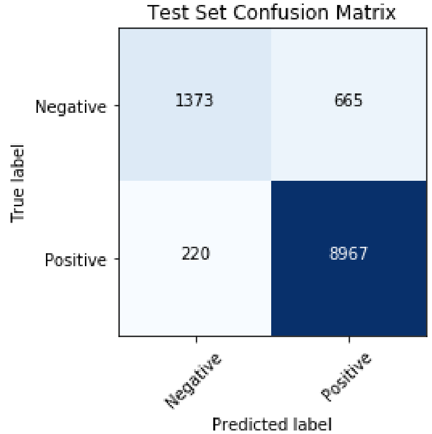
```
*****Train confusion matrix*****
[[ 3425   628]
```

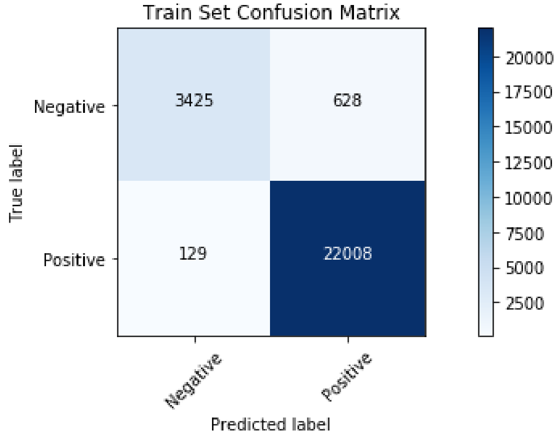
```
 [  129 22008]]

*****Test confusion matrix*****
[[1373  665]
 [ 220 8967]]
```

In [46]:

```
# Heatmap Confusion Matrix
plt.figure(1)
plt.figure(figsize=(15, 4))


plt.subplot(121)  # Test confusion matrix
cnf_matrix = confusion_matrix(y_test, model_tfidf_rbf.predict(X_test_tf
idf))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
#plt.figure()
plot_confusion_matrix_heatmap(cnf_matrix, classes=class_names, title='T
est Set Confusion Matrix');

plt.subplot(122) # Train Confusion matrix
cnf_matrix = confusion_matrix(y_train, model_tfidf_rbf.predict(X_train_
tfidf))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
#plt.figure()
plot_confusion_matrix_heatmap(cnf_matrix, classes=class_names, title='T
rain Set Confusion Matrix');
```

```
<Figure size 432x288 with 0 Axes>
```





Observation

1. For the TF-IDF vectorizer, we used SVC classifier with RBF kernel and C = 10000
2. We got train AUC: 0.9922475342828719 and test AUC: 0.9583110302318429
3. Using the confusion matrix, we can say that our model correctly predicted 8967 positive reviews and 1373 negative reviews.
4. The model incorrectly classified 220 negative reviews and 665 positive reviews.

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

Word2Vec

In [16]:
```
# Train your own Word2Vec model using your own text corpus
i=0
list_of_sentance_train=[]
for sentance in X_train:
    list_of_sentance_train.append(sentance.split())
```

In [17]:
```
print(list_of_sentance_train[0])
```

```
['really', 'good', 'idea', 'final', 'product', 'outstanding', 'use', 'd
```

ecals', 'car', 'window', 'everybody', 'asks', 'bought', 'decals', 'mad
e', 'two', 'thumbs']

In [18]:

```
is_your_ram_gt_16g=False
want_to_use_google_w2v = False
want_to_train_w2v = True

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

elif want_to_use_google_w2v and is_your_ram_gt_16g:
    if os.path.isfile('GoogleNews-vectors-negative300.bin'):
        w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors
-negative300.bin', binary=True)
        print(w2v_model.wv.most_similar('great'))
        print(w2v_model.wv.most_similar('worst'))
    else:
        print("you don't have gogole's word2vec file, keep want_to_trai
n_w2v = True, to train your own w2v ")
```

```
[('good', 0.8268220424652 1), ('fantastic', 0.7998963594436646), ('excel
lent', 0.7925567030906677), ('awesome', 0.7908499240875244), ('perfec
t', 0.7831145524978638), ('wonderful', 0.7818020582199097), ('decent',
0.7358627319335938), ('terrific', 0.7290688753128052), ('amazing', 0.72
86834716796875), ('nice', 0.6692759990692139)]
==================================================
[('ive', 0.7540286779403687), ('best', 0.7471846342086792), ('closest',
0.7454988956451416), ('greatest', 0.7454084157943726), ('ever', 0.71553
81441116333), ('tastiest', 0.714133620262146), ('coolest', 0.7013466358
184814), ('eaten', 0.6940063238143921), ('hottest', 0.681243419647216
8), ('hated', 0.6699789762496948)]
```

In [19]:

```
w2v_words = list(w2v_model.wv.vocab)
```

```
print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])
```

```
number of words that occured minimum 5 times  9806
sample words  ['really', 'good', 'idea', 'final', 'product', 'outstandi
ng', 'use', 'car', 'window', 'everybody', 'asks', 'bought', 'made', 'tw
o', 'thumbs', 'received', 'shipment', 'could', 'hardly', 'wait', 'try',
'love', 'call', 'instead', 'stickers', 'removed', 'easily', 'daughter',
'designed', 'signs', 'printed', 'reverse', 'windows', 'beautifully', 'p
rint', 'shop', 'program', 'going', 'lot', 'fun', 'everywhere', 'like',
'tv', 'screens', 'computer', 'stuff', 'sugar', 'free', 'not', 'rot']
```

Converting train text data

In [20]:

```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_train = []; # the avg-w2v for each sentence/review is stor
ed in this list
for sent in tqdm(list_of_sentance_train): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, yo
u might need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/re
view
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_train.append(sent_vec)
sent_vectors_train = np.array(sent_vectors_train)
print(sent_vectors_train.shape)
print(sent_vectors_train[0])
```

```
100%|██████████████████████████████████████████████████████████████████
████████████████████████████████████████████████████████| 26190/26190
[00:34<00:00, 756.52it/s]
```

```
(26190, 50)
[ 0.35539616  0.67507411  0.19811647 -0.04278817 -0.53013102 -0.7441445
5
  0.16542568 -0.0357427  -0.27203086 -0.29868526  0.18849524 -0.3464218
5
  0.08427245  0.02664626  0.22361641 -0.63246711 -0.1495512  -0.3398567
9
  0.24562876  0.14661298  0.30200606  0.31977542 -0.00309623  0.4416735
9
 -0.01330752  0.23788268  0.37888729  0.00837541  0.00578491 -0.1352378
9
  0.22031652  0.36268811  0.20990701 -0.23339066 -0.39685421  0.3277620
9
  0.36016558 -0.13402638 -0.03150598  0.59028035 -0.34930832 -0.1686932
9
 -0.26714816 -0.20518988  0.26488453  0.33967903 -0.2333802  -0.0152133
1
 -0.13767984  0.48225201]
```

Converting test text data

In [21]:

```
i=0
list_of_sentance_test=[]
for sentance in X_test:
    list_of_sentance_test.append(sentance.split())
```

In [22]:

```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_test = []; # the avg-w2v for each sentence/review is store
d in this list
for sent in tqdm(list_of_sentance_test): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, yo
u might need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/re
view
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
```

```
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_test.append(sent_vec)
sent_vectors_test = np.array(sent_vectors_test)

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

```
100%|████████████████████████████████████████████████████████████████
█████████████████████████████████████████████████████████| 11225/11225
[00:16<00:00, 683.93it/s]
```

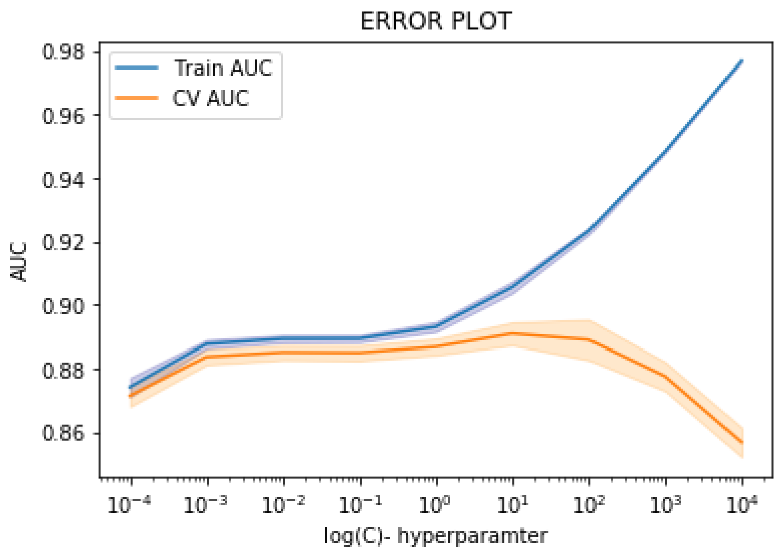
```
(11225, 50)
[ 0.39263485  0.19254257  0.28702555 -0.02937888 -0.43477099 -0.6266680
2
 -0.13603045 -0.46867406 -0.33439469 -0.62407038  0.19348719 -0.3411702
9
  0.06132343  0.00273981 -0.51565557 -0.27041241  0.00160172 -0.7450740
9
 -0.25218976 -0.27199106  0.84837491 -0.15923582 -0.32368128  0.7371478
9
 -0.60299446 -0.05784993  0.21502069 -0.06885471  0.13540346 -0.2446751
1
 -0.31086478  0.05702842  0.15125647 -0.07592223 -0.68130675  0.2081686
4
  0.61619861 -0.39252162  0.26105632  0.43081189 -0.29694408  0.0063386
 -0.04687208 -0.16527795  0.52037181  0.05131861 -0.39208821  0.0599849
8
 -0.01740427  0.39473478]
```

In [52]:

```
# Hyper parameter tuning and error plot
tuned_parameters = [{'C': [10**-4, 10**-3,10**-2,10**-1, 10**0,10**1, 1
0**2,10**3, 10**4]}]
alpha = [10**-4, 10**-3,10**-2,10**-1, 10**0,10**1, 10**2,10**3, 10**4]
  #k
```

```
# Using GridSearchCVSearchCV with 3 fold cv
gs_obj = GridSearchCV(SVC(kernel='rbf'), tuned_parameters, scoring = 'r
oc_auc', cv=3)
gs_obj.fit(sent_vectors_train, y_train)


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


# draws the error plot

plt.plot(alpha, train_auc, label='Train AUC')
    # this code is copied from here: https://stackoverflow.com/a/488033
61/4084039
plt.gca().fill_between(alpha,train_auc - train_auc_std,train_auc + trai
n_auc_std,alpha=0.2,color='darkblue')

plt.plot(alpha, cv_auc, label='CV AUC')
    # this code is copied from here: https://stackoverflow.com/a/488033
61/4084039
plt.gca().fill_between(alpha,cv_auc - cv_auc_std,cv_auc + cv_auc_std,al
pha=0.2,color='darkorange')
plt.legend()
plt.xlabel("log(C)- hyperparamter")
plt.xscale('log')
plt.ylabel("AUC")
plt.title("ERROR PLOT")
plt.show()


 # Results of the gs object


# Code https://stackoverflow.com/questions/42793254/what-replaces-grids
earchcv-grid-scores-in-scikit#answer-42800056
means = gs_obj.cv_results_['mean_test_score']
```

```
stds = gs_obj.cv_results_['std_test_score']


t1 = PrettyTable()
t1.field_names = ['Mean CV Score', 'Std CV Score', 'Param']

for mean, std, params in zip(means, stds, gs_obj.cv_results_['params'
]):
    t1.add_row([round(mean, 3), round(std * 2,5), params])

print(t1)

print("\nThe best estimator:{}".format(gs_obj.best_estimator_))
print("\nThe best score is:{}".format(gs_obj.best_score_))
print("The best value of C is:{}".format(gs_obj.best_params_))

# Returns the mean accuracy on the given test data and labels.
print("Mean Score: {}".format(gs_obj.score(sent_vectors_test, y_test)))

del t1
```




```
+--------------+-------------+--------------+
```

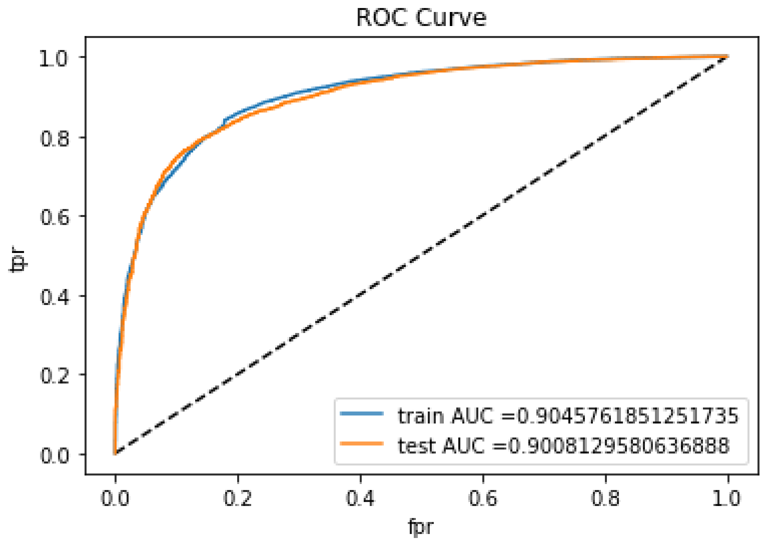
```
| Mean CV Score | Std CV Score |     Param     |
+---------------+--------------+---------------+
|     0.871     |   0.00665    | {'C': 0.0001} |
|     0.884     |   0.00481    |  {'C': 0.001} |
|     0.885     |   0.00469    |  {'C': 0.01}  |
|     0.885     |   0.00487    |   {'C': 0.1}  |
|     0.887     |   0.00526    |    {'C': 1}   |
|     0.891     |   0.00718    |   {'C': 10}   |
|     0.889     |   0.01278    |   {'C': 100}  |
|     0.878     |   0.00915    |  {'C': 1000}  |
|     0.857     |    0.0093    |  {'C': 10000} |
+---------------+--------------+---------------+

The best estimator:SVC(C=10, cache_size=200, class_weight=None, coef0=
0.0,
  decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
  kernel='rbf', max_iter=-1, probability=False, random_state=None,
  shrinking=True, tol=0.001, verbose=False)

The best score is:0.8909829967726378
The best value of C is:{'C': 10}
Mean Score: 0.9008120500946798
```

In [48]:

```
# Fitting the model with the best hyperparameter
model_avgw2v_rbf = SVC(kernel='rbf', C= 10,probability=True)
model_avgw2v_rbf.fit(sent_vectors_train,y_train)
y_pred = model_avgw2v_rbf.predict(sent_vectors_test)
```

In [49]:

```
# AUC - ROC plot
auc_train_avgw2v_rbf, auc_test_avgw2v_rbf = plot_auc_rbf(model_avgw2v_r
bf, sent_vectors_train, sent_vectors_test)
```




```
train AUC: 0.9045761851251735
test AUC: 0.9008129580636888
```

In [50]:

```
# Confusion matrix
print_confusion_matrix(model_avgw2v_rbf, sent_vectors_train, sent_vecto
rs_test)
```

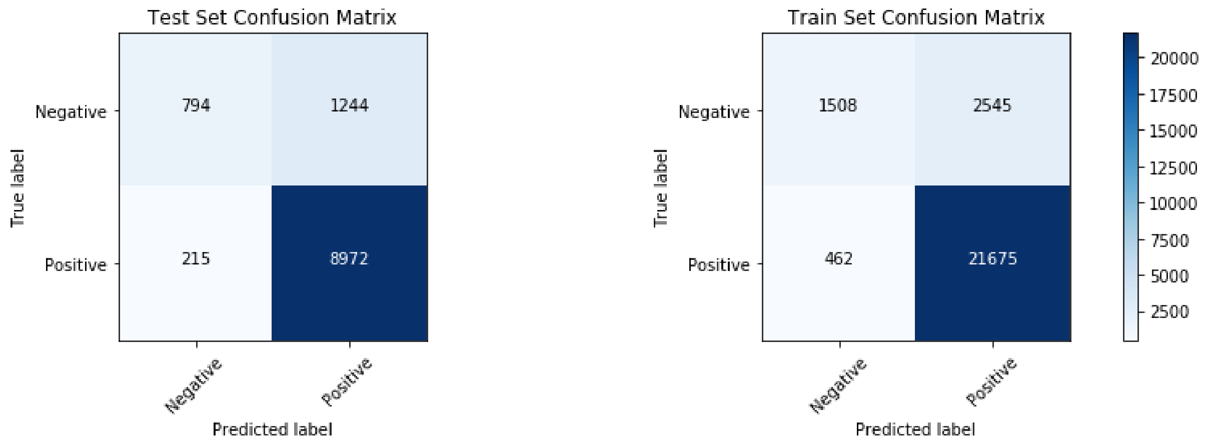
```
*****Train confusion matrix*****
[[ 1508  2545]
 [  462 21675]]

*****Test confusion matrix*****
[[ 794 1244]
 [ 215 8972]]
```

In [51]:

```
# Heatmap confusion matrix
plt.figure(1)
plt.figure(figsize=(15, 4))


plt.subplot(121)  # Test confusion matrix
cnf_matrix = confusion_matrix(y_test, model_avgw2v_rbf.predict(sent_vec
```

```
tors_test))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
#plt.figure()
plot_confusion_matrix_heatmap(cnf_matrix, classes=class_names, title='T
est Set Confusion Matrix');

plt.subplot(122) # Train Confusion matrix
cnf_matrix = confusion_matrix(y_train, model_avgw2v_rbf.predict(sent_ve
ctors_train))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
#plt.figure()
plot_confusion_matrix_heatmap(cnf_matrix, classes=class_names, title='T
rain Set Confusion Matrix');
```

```
<Figure size 432x288 with 0 Axes>
```



Observation

1. For the Avg. W2V vectorizer, we used SVC classifier with RBF kernel and C = 10
2. We got train AUC: 0.9045761851251735 and test AUC: 0.9008129580636888

3. Using the confusion matrix, we can say that our model correctly predicted 8972 positive reviews and 794 negative reviews.
4. The model incorrectly classified 215 negative reviews and 1244 positive reviews.

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

TFIDF-Weighted Word2Vec

In [23]:
```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
X_train_tf_idf_w2v = model.fit_transform(X_train)
X_test_tf_idf_w2v = model.transform(X_test)
# we are converting a dictionary with word as a key, and the idf as a v
alue
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [24]:
```
# TF-IDF weighted Word2Vec for sentences in X_train
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
ll_val = tfidf

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

```
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_train.append(sent_vec)
    row += 1
```

```
100%|██████████████████████████████████████████████████| 26190/26190
[05:59<00:00, 72.91it/s]
```

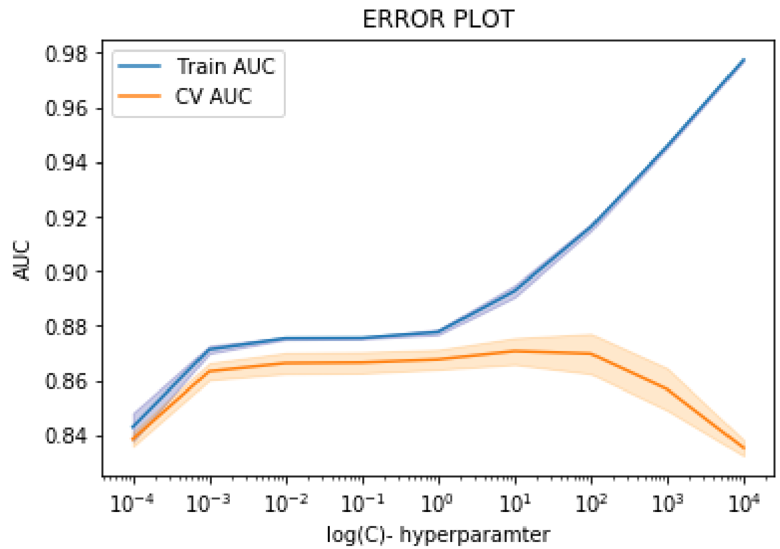
In [25]:

```
# TF-IDF weighted Word2Vec for sentences in X_test
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
ll_val = tfidf

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

    row += 1
```

```
100%|██████████████████████████████████████████████████████████████████████████████████████████████████████| 11225/11225 [02:33<00:00, 72.96it/s]
```

In [26]:

```
get_best_hyperparameter_alpha_rbf(model, tfidf_sent_vectors_train, tfidf_sent_vectors_test, y_train, y_test)
```




```
+---------------+--------------+---------------+
| Mean CV Score | Std CV Score |     Param     |
+---------------+--------------+---------------+
|     0.839     |   0.00531    | {'C': 0.0001} |
|     0.863     |    0.0062    |  {'C': 0.001} |
|     0.866     |   0.00765    |  {'C': 0.01}  |
|     0.867     |   0.00773    |   {'C': 0.1}  |
|     0.868     |   0.00725    |    {'C': 1}   |
|     0.871     |    0.0097    |   {'C': 10}   |
|      0.87     |   0.01467    |   {'C': 100}  |
|     0.857     |   0.01535    |  {'C': 1000}  |
|     0.835     |    0.0059    |  {'C': 10000} |
+---------------+--------------+---------------+
```

```
The best estimator:SVC(C=10, cache_size=200, class_weight=None, coef0=
```

```
0.0,
  decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
  kernel='rbf', max_iter=-1, probability=False, random_state=None,
  shrinking=True, tol=0.001, verbose=False)

The best score is:0.870704860021974
The best value of C is:{'C': 10}
Mean Score: 0.881100630418906
```

Out[26]:

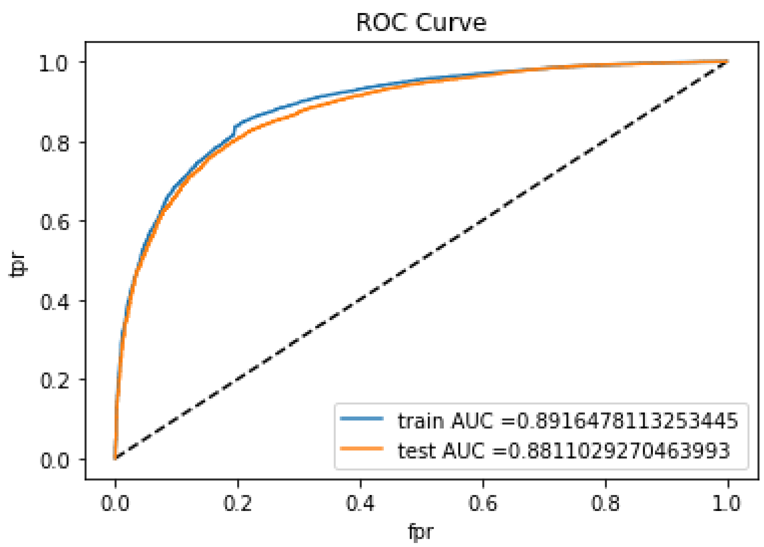
```
{'C': 10}
```

In [35]:

```
# Fitting the TFIDF - weighted W2V vectorizer on LogisticRegression Mod
el
model_tfidfw2v_rbf = SVC(kernel='rbf', C= 10, probability=True)
model_tfidfw2v_rbf.fit(tfidf_sent_vectors_train,y_train)
y_pred = model_tfidfw2v_rbf.predict(tfidf_sent_vectors_test)
```

In [36]:

```
# AUC- ROC plot
auc_train_tfidfw2v_rbf, auc_test_tfidfw2v_rbf = plot_auc_rbf(model_tfid
fw2v_rbf, tfidf_sent_vectors_train, tfidf_sent_vectors_test)
```




```
train AUC: 0.8916478113253445
```

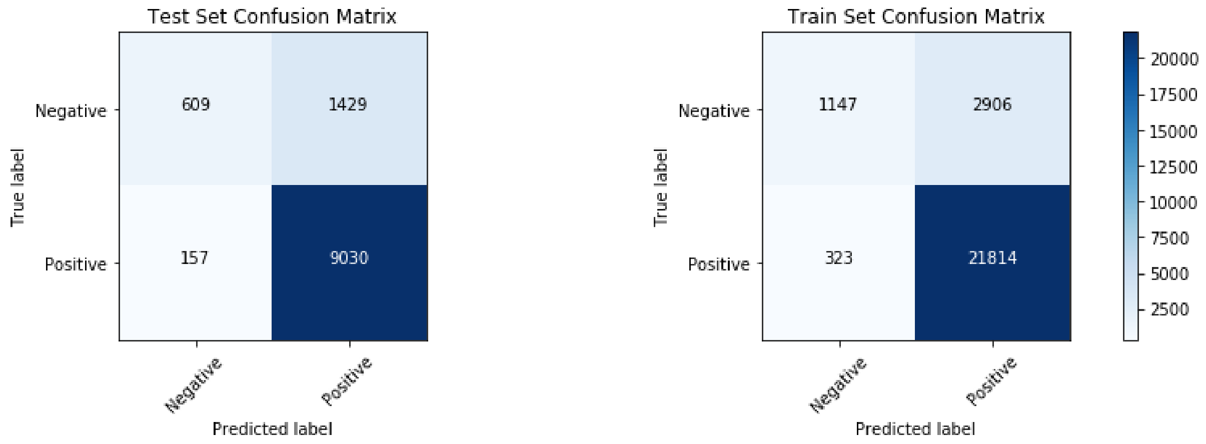
```
test AUC: 0.8811029270463993
```

In [37]:
```
# Confusion Matrix
print_confusion_matrix(model_tfidfw2v_rbf, tfidf_sent_vectors_train, tf
idf_sent_vectors_test)
```

```
*****Train confusion matrix*****
[[ 1147  2906]
 [  323 21814]]

*****Test confusion matrix*****
[[ 609 1429]
 [ 157 9030]]
```

In [41]:
```
# Heatmap Confusion Matrix
plt.figure(1)
plt.figure(figsize=(15, 4))


plt.subplot(121)  # Test confusion matrix
cnf_matrix = confusion_matrix(y_test, model_tfidfw2v_rbf.predict(tfidf_
sent_vectors_test))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
#plt.figure()
plot_confusion_matrix_heatmap(cnf_matrix, classes=class_names, title='T
est Set Confusion Matrix');

plt.subplot(122) # Train Confusion matrix
cnf_matrix = confusion_matrix(y_train, model_tfidfw2v_rbf.predict(tfidf
_sent_vectors_train))
np.set_printoptions(precision=2)
class_names = ['Negative', 'Positive']
# Plot non-normalized confusion matrix
#plt.figure()
plot_confusion_matrix_heatmap(cnf_matrix, classes=class_names, title='T
rain Set Confusion Matrix');
```

<Figure size 432x288 with 0 Axes>



Observation

1. For the TFIIDF-weightedW2V vectorizer, we used SVC classifier with RBF kernel and alpha = 10
2. We got train AUC: 0.8916478113253445 and test AUC: 0.8811029270463993
3. Using the confusion matrix, we can say that our model correctly predicted 9030 positive reviews and 609 negative reviews.
4. The model incorrectly classified 157 negative reviews and 1429 positive reviews.

[6] Conclusions

In [120]:

```
C = PrettyTable()

C.field_names = ['Sr. No', 'Vectorizer','Hyperparameter value','Penalt
y', 'Train AUC', 'Test AUC']
C.add_row([1, 'BoW', 'L2', 0.1, auc_train_bow_sgd, auc_train_bow_sgd])
C.add_row([2, 'BoW', 'L2', 1,auc_train_bow_rbf ,auc_test_bow_rbf])
C.add_row([3, 'TF_IDF', 'L2', 0.0001, auc_train_tfidf_sgd, auc_test_tfi
df_sgd])
```

```
C.add_row([4, 'TF_IDF', 'L2', 10000, auc_train_tfidf_rbf, auc_train_tfi
df_rbf])
C.add_row([5, 'Avg-W2V', 'L2', 0.01,auc_train_avgw2v_l1, auc_test_avgw2
v_l1])
C.add_row([6, 'Avg-W2V', 'L2', 10,auc_train_avgw2v_rbf ,auc_test_avgw2v
_rbf])
C.add_row([7, 'TFIDF-W2V', 'L2', 0.01,auc_train_tfidfw2v_sgd, auc_test_
tfidfw2v_sgd])
C.add_row([8, 'TFIDF-W2V', 'L2', 10, auc_train_tfidfw2v_rbf,auc_test_tf
idfw2v_rbf])


print(C)
del C
```

```
+--------+-----------+---------------------+---------+---------------
-----+--------------------+
| Sr. No | Vectorizer | Hyperparameter value | Penalty |     Train AUC
     |      Test AUC      |
+--------+-----------+---------------------+---------+---------------
-----+--------------------+
|   1    |    BoW     |          L2          |   0.1   | 0.984462130588
3833 | 0.9844621305883833 |
|   2    |    BoW     |          L2          |    1    | 0.966519724906
6753 | 0.9036183953666663 |
|   3    |   TF_IDF   |          L2          |  0.0001 | 0.974896809381
8116 | 0.9603306201559176 |
|   4    |   TF_IDF   |          L2          |  10000  | 0.992247534282
8719 | 0.9922475342828719 |
|   5    |  Avg-W2V   |          L2          |   0.01  | 0.902036700758
2843 | 0.9026262821709552 |
|   6    |  Avg-W2V   |          L2          |    10   | 0.904576185125
1735 | 0.9008129580636888 |
|   7    | TFIDF-W2V  |          L2          |   0.01  | 0.878476831494
6081 | 0.8740695670883443 |
|   8    | TFIDF-W2V  |          L2          |    10   | 0.891647811325
3445 | 0.8811029270463993 |
+--------+-----------+---------------------+---------+---------------
-----+--------------------+
```

Summary

1. We performed Support Vector Machine Classification on the Amazon fine food dataset using SGDClasssifier for the linear kernel and SVC for RBF kernel
2. Made use of GridSearchCV to find the best value of C , the hyperparameter. We also used CalibratedSearchCV when working with SGD classifier.
3. Performed Feature Engineering on the BoW model and found out the model slightly performed better.
4. Different vectors take on different hyperparameter values. We saw values being taken from 10**-4 to 10**4
5. We also found penalty L1 and L2 using hyperparameter tuning on BoW, TFIDF, Avg-W2V, TFIDF-WW2V on the Amazon Fine Food Reviews.
6. We also printed out feature importance for BoW vectorizer