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
```

```
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")
```

In [2]:

```
import os
print(os.listdir("."))
```

```
['.ipynb_checkpoints', '04 Amazon Fine Food Reviews Analysis_NaiveBaye
s.ipynb', '05 Amazon Fine Food Reviews Analysis_Logistic Regression.ipy
nb', '05 Amazon Fine Food Reviews Analysis_Logistic Regression_origina
l.ipynb', 'Amazon Logistic Regression Submission.ipynb', 'Amazon_Logist
ic_Regression_Submission.ipynb', 'database.sqlite', 'Logistic Regressio
n in progress.ipynb', 'LogisticRegression.ipynb', 'LogisticRegression_c
opy.ipynb', 'Logistic_Regression_from_KNN_fun.ipynb', 'model_avgw2v_l1.
pkl', 'model_avgw2v_l2.pkl', 'preprocessed_final', 'sent_vectors_test.p
kl', 'sent_vectors_train.pkl', 'Some subtle python operations.ipynb']
```

In [3]:

```
# from google.colab import files
# files.upload()

# !pip install -q kaggle

# !mkdir -p ~/.kaggle
# !cp kaggle.json ~/.kaggle/

# !kaggle datasets download -d snap/amazon-fine-food-reviews
```

```
# !unzip amazon-fine-food-reviews.zip
```

Data Import and Preprocessing

In [0]:
```
# Google Drive
#final = pd.read_pickle('/content/drive/My Drive/Aaic/final_0317.pkl')
```

In [0]:
```
# Local
#final = final = pickle.load(open('preprocessed_final', 'rb'))
```

In [8]:
```
#!ls
```

```
amazon-fine-food-reviews.zip  hashes.txt   Reviews.csv
database.sqlite               kaggle.json  sample_data
```

In [4]:
```
# using SQLite Table to read data.
con = sqlite3.connect('database.sqlite')

# filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
# SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000, will give top 50
0000 data points
# you can change the number to any other number based on your computing
 power

# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Sco
re != 3 LIMIT 500000""", con)
# for tsne assignment you can take 5k data points
```

In [5]:
```
filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score
 != 3 LIMIT 100000""", con)
```

In [6]:
```
# Give reviews with Score>3 a positive rating(1), and reviews with a sc
ore<3 a negative rating(0).
```

```python
def partition(x):
    if x < 3:
        return 0
    return 1
```

In [7]:
```python
#changing reviews with score less than 3 to be positive and vice-versa
actualScore = filtered_data['Score']
positiveNegative = actualScore.map(partition)
filtered_data['Score'] = positiveNegative
print("Number of data points in our data", filtered_data.shape)
filtered_data.head(3)
```

```
Number of data points in our data (100000, 10)
```

Out[7]:

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

In [8]:
```python
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
```

```
GROUP BY UserId
HAVING COUNT(*)>1
""", con)
```

In [9]:
```
print(display.shape)
display.head()
```

(80668, 7)

Out[9]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
0	#oc-R115TNMSPFT9I7	B007Y59HVM	Breyton	1331510400	2	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ET0	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B007Y59HVM	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ET0	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBE1U	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	2

In [10]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[10]:

UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
80638	AZY10LLTJ71NX	B006P7E5ZI	undertheshrine "undertheshrine"	1334707200	5	I was recommended to try green tea extract to ...	5

In [11]:
```
display['COUNT(*)'].sum()
```

Out[11]:
```
393063
```

[2] Exploratory Data Analysis

[2.1] Data Cleaning: Deduplication

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

In [12]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[12]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenon
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenon
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	

As it can be seen above that same user has multiple reviews with same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that

ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8)

ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

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

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

In [13]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')
```

In [14]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', inplace=False)
final.shape
```

Out[14]: (87775, 10)

In [15]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[15]: 87.775

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

In [16]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[16]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenom
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	

In [17]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [18]:
```
final.head()
```

Out[18]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessI
22620	24750	2734888454	A13ISQV0U9GZIC	Sandikaye	1	
22621	24751	2734888454	A1C298ITT645B6	Hugh G. Pritchard	0	
70677	76870	B00002N8SM	A19Q006CSFT011	Arlielle	0	

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessI
70676	76869	B00002N8SM	A1FYH4S02BW7FN	wonderer	0	
70675	76868	B00002N8SM	AUE8TB5VHS6ZV	eyeofthestorm	0	

In [19]:
```
#Before starting the next phase of preprocessing lets see the number of
 entries left
print(final.shape)

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

```
(87773, 10)
```

Out[19]:
```
1    73592
0    14181
Name: Score, dtype: int64
```

Observation: This is an imbalance dataset. There are roughly 84% Positive review and 16% Negative reviews.

Checkpoint 1: Imported data and some basic eda

In [0]:
```
# Filtering 1 (positive) and 0 (negative) reviews
#pos_reviews = final[final['Score'] == 1].sample(n=10000, random_state=
507)
#neg_reviews = final[final['Score'] == 0].sample(n=10000, random_state=
507)
```

```
# Combining the above dataframes into one
#final = pd.concat([pos_reviews, neg_reviews])
```

In [20]:
```
# Converting Time to time format in seconds using a unix epoch time
# We will arrange the entire final dataframe in ascending order for tim
e based splitting

final["Time"] = pd.to_datetime(final["Time"], origin='unix', unit = "s"
)
final = final.sort_values(by = "Time")
```

In [21]:
```
final.size
```

Out[21]:
```
877730
```

[3] Preprocessing

[3.1]. Preprocessing Review Text

Now that we have finished deduplication our data requires some preprocessing before we go on further with analysis and making the prediction model.

Hence in the Preprocessing phase we do the following in the order below:-

1. Begin by removing the html tags
2. Remove any punctuations or limited set of special characters like , or . or # etc.
3. Check if the word is made up of english letters and is not alpha-numeric
4. Check to see if the length of the word is greater than 2 (as it was researched that there is no adjective in 2-letters)
5. Convert the word to lowercase
6. Remove Stopwords
7. Finally Snowball Stemming the word (it was obsereved to be better than Porter Stemming)

After which we collect the words used to describe positive and negative reviews

In [22]:

```
# printing some random reviews
sent_0 = final['Text'].values[0]
print(sent_0)
print("="*50)

sent_1000 = final['Text'].values[1000]
print(sent_1000)
print("="*50)

sent_1500 = final['Text'].values[1500]
print(sent_1500)
print("="*50)

sent_4900 = final['Text'].values[4900]
print(sent_4900)
print("="*50)
```

```
I bought a few of these after my apartment was infested with fruit flie
s. After only a few hours, the trap had &quot;attracted&quot; many flie
s and within a few days they were practically gone. This may not be a l
ong term  solution, but if flies are driving you crazy, consider buying
this. One  caution- the surface is very sticky, so try to avoid touchin
g it.
==================================================
I have made these brownies for family and for a den of cub scouts and n
o one would have known they were gluten free and everyone asked for sec
onds!  These brownies have a fudgy texture and have bits of chocolate c
hips in them which are delicious.  I would say the mix is very thick an
d a little difficult to work with.  The cooked brownies are slightly di
fficult to cut into very neat edges as the edges tend to crumble a litt
le and I would also say that they make a slightly thinner layer of brow
nies than most of the store brand gluten containing but they taste just
as good, if not better.  Highly recommended!<br /><br />(For those wond
ering, this mix requires 2 eggs OR 4 egg whites and 7 tbs melted butter
to prepare.  They do have suggestions for lactose free and low fat prep
arations)
==================================================
```

```
This gum is my absolute favorite. By purchasing on amazon I can get the
savings of large quanities at a very good price. I highly recommend to
all gum chewers. Plus as you enjoy the peppermint flavor and freshing o
f breath you are whitening your teeth all at the same time.
==================================================
This is an excellent product, both tastey and priced right. It's diffic
ult to find this product in regular local grocery stores, so I was thri
lled to find it.
==================================================
```

In [23]:

```
# remove urls from text python: https://stackoverflow.com/a/40823105/40
84039
sent_0 = re.sub(r"http\S+", "", sent_0)
sent_1000 = re.sub(r"http\S+", "", sent_1000)
sent_150 = re.sub(r"http\S+", "", sent_1500)
sent_4900 = re.sub(r"http\S+", "", sent_4900)

print(sent_0)
```

```
I bought a few of these after my apartment was infested with fruit flie
s. After only a few hours, the trap had &quot;attracted&quot; many flie
s and within a few days they were practically gone. This may not be a l
ong term  solution, but if flies are driving you crazy, consider buying
this. One  caution- the surface is very sticky, so try to avoid touchin
g it.
```

In [24]:

```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how
-to-remove-all-tags-from-an-element
from bs4 import BeautifulSoup

soup = BeautifulSoup(sent_0, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1000, 'lxml')
text = soup.get_text()
print(text)
print("="*50)
```

```
soup = BeautifulSoup(sent_1500, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_4900, 'lxml')
text = soup.get_text()
print(text)
```

```
I bought a few of these after my apartment was infested with fruit flie
s. After only a few hours, the trap had "attracted" many flies and with
in a few days they were practically gone. This may not be a long term
solution, but if flies are driving you crazy, consider buying this. One
  caution- the surface is very sticky, so try to avoid touching it.
==================================================
I have made these brownies for family and for a den of cub scouts and n
o one would have known they were gluten free and everyone asked for sec
onds!  These brownies have a fudgy texture and have bits of chocolate c
hips in them which are delicious.  I would say the mix is very thick an
d a little difficult to work with.  The cooked brownies are slightly di
fficult to cut into very neat edges as the edges tend to crumble a litt
le and I would also say that they make a slightly thinner layer of brow
nies than most of the store brand gluten containing but they taste just
as good, if not better.  Highly recommended!(For those wondering, this
mix requires 2 eggs OR 4 egg whites and 7 tbs melted butter to prepare.
  They do have suggestions for lactose free and low fat preparations)
==================================================
This gum is my absolute favorite. By purchasing on amazon I can get the
savings of large quanities at a very good price. I highly recommend to
all gum chewers. Plus as you enjoy the peppermint flavor and freshing o
f breath you are whitening your teeth all at the same time.
==================================================
This is an excellent product, both tastey and priced right. It's diffic
ult to find this product in regular local grocery stores, so I was thri
lled to find it.
```

In [25]:

```
# https://stackoverflow.com/a/47091490/4084039
import re
```

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

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

In [26]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
This gum is my absolute favorite. By purchasing on amazon I can get the
savings of large quanities at a very good price. I highly recommend to
all gum chewers. Plus as you enjoy the peppermint flavor and freshing o
f breath you are whitening your teeth all at the same time.
==================================================
```

In [27]:
```
#remove words with numbers python: https://stackoverflow.com/a/1808237
0/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
I bought a few of these after my apartment was infested with fruit flie
s. After only a few hours, the trap had &quot;attracted&quot; many flie
s and within a few days they were practically gone. This may not be a l
ong term  solution, but if flies are driving you crazy, consider buying
this. One  caution- the surface is very sticky, so try to avoid touchin
g it.
```

In [28]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
This gum is my absolute favorite By purchasing on amazon I can get the
savings of large quanities at a very good price I highly recommend to a
ll gum chewers Plus as you enjoy the peppermint flavor and freshing of
breath you are whitening your teeth all at the same time
```

In [29]:
```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'no
t'
# <br /><br /> ==> after the above steps, we are getting "br br"
# we are including them into stop words list
# instead of <br /> if we have <br/> these tags would have revmoved in
 the 1st step

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'o
urs', 'ourselves', 'you', "you're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselve
s', 'he', 'him', 'his', 'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'it
s', 'itself', 'they', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'th
is', 'that', "that'll", 'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'h
ave', 'has', 'had', 'having', 'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or',
 'because', 'as', 'until', 'while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between',
'into', 'through', 'during', 'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out',
'on', 'off', 'over', 'under', 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'h
ow', 'all', 'any', 'both', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 's
o', 'than', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should',
"should've", 'now', 'd', 'll', 'm', 'o', 're', \
```

```
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't",
'didn', "didn't", 'doesn', "doesn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "is
n't", 'ma', 'mightn', "mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn',
 "shouldn't", 'wasn', "wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

In [30]:
```
# Combining all the above stundents
from tqdm import tqdm
preprocessed_reviews = []
# tqdm is for printing the status bar
for sentance in tqdm(final['Text'].values):
    sentance = re.sub(r"http\S+", "", sentance)
    sentance = BeautifulSoup(sentance, 'lxml').get_text()
    sentance = decontracted(sentance)
    sentance = re.sub("\S*\d\S*", "", sentance).strip()
    sentance = re.sub('[^A-Za-z]+', ' ', sentance)
    # https://gist.github.com/sebleier/554280
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower
() not in stopwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|
| 87773/87773
[00:30<00:00, 2909.84it/s]
```

In [31]:
```
preprocessed_reviews[1500]
```

Out[31]:
```
'gum absolute favorite purchasing amazon get savings large quanities go
od price highly recommend gum chewers plus enjoy peppermint flavor fres
hing breath whitening teeth time'
```

[3.2] Preprocessing Review Summary

In [32]:
```
## Similartly you can do preprocessing for review summary also.
from tqdm import tqdm
```

```
preprocessed_summary = []
# tqdm is for printing the status bar
for sentence in tqdm(final['Summary'].values):
    sentence = re.sub(r"http\S+", "", sentence)
    sentence = BeautifulSoup(sentence, 'lxml').get_text()
    sentence = decontracted(sentence)
    sentence = re.sub("\S*\d\S*", "", sentence).strip()
    sentence = re.sub('[^A-Za-z]+', ' ', sentence)
    # https://gist.github.com/sebleier/554280
    sentence = ' '.join(e.lower() for e in sentence.split() if e.lower
() not in stopwords)
    preprocessed_summary.append(sentence.strip())
```

```
  2%|██
                                                              | 1694/87773
[00:00<00:32, 2682.41it/s]C:\Users\Nit-prj1010\AppData\Local\Continuum
\anaconda3\lib\site-packages\bs4\__init__.py:273: UserWarning: "b'...'"
looks like a filename, not markup. You should probably open this file a
nd pass the filehandle into Beautiful Soup.
  ' Beautiful Soup.' % markup)
 43%|████████████████████████████████████████████████████
                                                             | 37757/87773
[00:09<00:11, 4525.80it/s]C:\Users\Nit-prj1010\AppData\Local\Continuum
\anaconda3\lib\site-packages\bs4\__init__.py:273: UserWarning: "b'...'"
looks like a filename, not markup. You should probably open this file a
nd pass the filehandle into Beautiful Soup.
  ' Beautiful Soup.' % markup)
 56%|██████████████████████████████████████████████████████████████████
██                                                           | 48811/87773
[00:12<00:11, 3520.87it/s]C:\Users\Nit-prj1010\AppData\Local\Continuum
\anaconda3\lib\site-packages\bs4\__init__.py:273: UserWarning: "b'...'"
looks like a filename, not markup. You should probably open this file a
nd pass the filehandle into Beautiful Soup.
  ' Beautiful Soup.' % markup)
 82%|██████████████████████████████████████████████████████████████████
██████████████████████████████████                           | 72288/87773
[00:17<00:02, 5350.16it/s]C:\Users\Nit-prj1010\AppData\Local\Continuum
\anaconda3\lib\site-packages\bs4\__init__.py:273: UserWarning: "b'...'"
looks like a filename, not markup. You should probably open this file a
nd pass the filehandle into Beautiful Soup.
```

```
 ' Beautiful Soup.' % markup)
100%|██████████████████████████████████████████████████| 87773/87773
[00:20<00:00, 4329.33it/s]
```

In [33]:
```
final.head()
```

Out[33]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessD
70688	76882	B00002N8SM	A32DW342WBJ6BX	Buttersugar	0	
1146	1245	B00002Z754	A29Z5PI9BW2PU3	Robbie	7	
1145	1244	B00002Z754	A3B8RCEI0FXFI6	B G Chase	10	
28086	30629	B00008RCMI	A19E94CF5O1LY7	Andrew Arnold	0	
28087	30630	B00008RCMI	A284C7M23F0APC	A. Mendoza	0	

In [34]:
```python
final['CleanedText']= preprocessed_reviews
final['CleanedSummary']= preprocessed_summary
```

In [35]:
```python
final.CleanedText.isnull().sum()
```

Out[35]: 0

In [36]:
```python
final.head()
```

Out[36]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessD
70688	76882	B00002N8SM	A32DW342WBJ6BX	Buttersugar	0	
1146	1245	B00002Z754	A29Z5PI9BW2PU3	Robbie	7	
1145	1244	B00002Z754	A3B8RCEI0FXFI6	B G Chase	10	
28086	30629	B00008RCMI	A19E94CF5O1LY7	Andrew Arnold	0	

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessD
28087	30630	B00008RCMI	A284C7M23F0APC	A. Mendoza	0	

```
In [0]: # writing the preprocessed final dataframe to dist
#file_Name = "preprocessed_final"
# open the file for writing
#fileObject = open(file_Name,'wb')

# this writes the object a to the
# file named 'testfile'
#pickle.dump(final,fileObject)
```

Load saved final

```
In [0]: #final = pickle.load(open('preprocessed_final', 'rb'))
```

```
In [37]: final.columns
```

```
Out[37]: Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerato
r',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text',
       'CleanedText', 'CleanedSummary'],
      dtype='object')
```

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

```
In [38]: # Create X and Y variable
X = final['CleanedText'].values
y= final['Score'].values
```

```
In [39]: type(X)
```

Out[39]: numpy.ndarray

In [40]:
```
type(y)
```

Out[40]: numpy.ndarray

In [41]:
```
# 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 [42]:
```
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

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

1. **get_best_hyperparameter_C(vectorizer, X_train, X_test, y_train, y_test, penalty)** : This function will run GridSearchCV with cv = 5 and the penalty on the training and test set data specified by the user.
2. **plot_auc(model, X_train, X_test)**: This funtion will plot the AUC curve
3. **most_informative_feature_for_binary_classification(vectorizer, classifier, n=10)** : This function will return the most imporant features for the positive and the negative class
4. **print_confusion_matrix(model, X_train, X_test)**: Prints the confusion matrix for the train and test set data.

5. **plot_confusion_matrix_heatmap(cm, classes, normalize=False,title='Confusion matrix', cmap=plt.cm.Blues)** : Taken from the official sklearn website, this function will return heatmap representation of the confusion matrix
6. **plot_heatmap_confusion_matrix(model, X_test)**: Calculates the confusion matrix on the dataset provided and passes it to plot_confusion_matrix_heatmap() to print the heatmap

Finding the hyper parameter C (1/lambda) using RandomSearchCV with cv = 5

In [43]:
```
def get_best_hyperparameter_C(vectorizer, X_train, X_test, y_train, y_test, penalty_l):

    """
    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(LogisticRegression(penalty= penalty_l), tuned_parameters, scoring = 'roc_auc', cv=5)

    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_
```

train and test AUC

In [44]:
```
def plot_auc(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)
```

important features

In [45]:
```
# 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 [46]:
```
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 [47]:
```
# 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()
```

In [48]:
```
# def plot_heatmap_confusion_matrix(model, X_test):
#     cnf_matrix = confusion_matrix(y_test, model.predict(X_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, ti
tle='Test Set Confusion Matrix');
```

In [49]:
```
# def plot_heatmap_confusion_matrix_train(model, X_train):
#     cnf_matrix = confusion_matrix(y_train, model.predict(X_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, ti
tle='Train Set Confusion Matrix');
```

[4.1] BAG OF WORDS

In [50]:
```
# ss
from sklearn.feature_extraction.text import CountVectorizer
bow_vectorizer= CountVectorizer(ngram_range=(1,2), min_df=10, max_featu
res=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 [51]:
```
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 [52]:
```
# 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 Logistic Regression with L1 regularization on BOW, SET 1

In [107]:

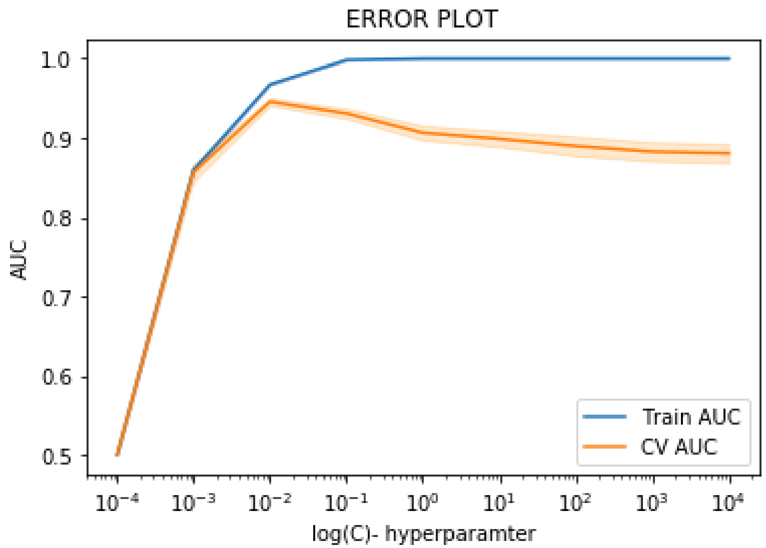
```
# Free up some space
del final,display, preprocessed_reviews, preprocessed_summary, X, y, so
rted_data, filtered_data, actualScore, sent_0, sent_1000, sent_150, sen
t_1500, sent_4900
#del sent_vectors_cv, sent_vectors_test, sent_vectors_train
#del tfidf_sent_vectors_train, tfidf_sent_vectors_cv, tfidf_sent_vector
s_test
#del list_of_sentance_cv, list_of_sentance_test, list_of_sentance_train
#del dictionary, stopwords, tfidf_feat, w2v_words
```

In [53]:

```
# Vectorizer = BoW, penalty = l1
best_estimator_bow_l1= get_best_hyperparameter_C(bow_vectorizer, X_trai
n_bow, X_test_bow, y_train, y_test, penalty_l = 'l1' )
```

```
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\svm\base.py:922: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)

C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
```

```
s\sklearn\svm\base.py:922: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
```



Mean CV Score	Std CV Score	Param
0.5	0.0	{'C': 0.0001}
0.857	0.02148	{'C': 0.001}
0.946	0.00967	{'C': 0.01}
0.931	0.01305	{'C': 0.1}
0.906	0.01855	{'C': 1}
0.899	0.01977	{'C': 10}
0.89	0.02458	{'C': 100}
0.883	0.02402	{'C': 1000}
0.88	0.02441	{'C': 10000}

```
The best estimator:LogisticRegression(C=0.01, class_weight=None, dual=F
alse, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l1', random_state=None, solver='warn',
```

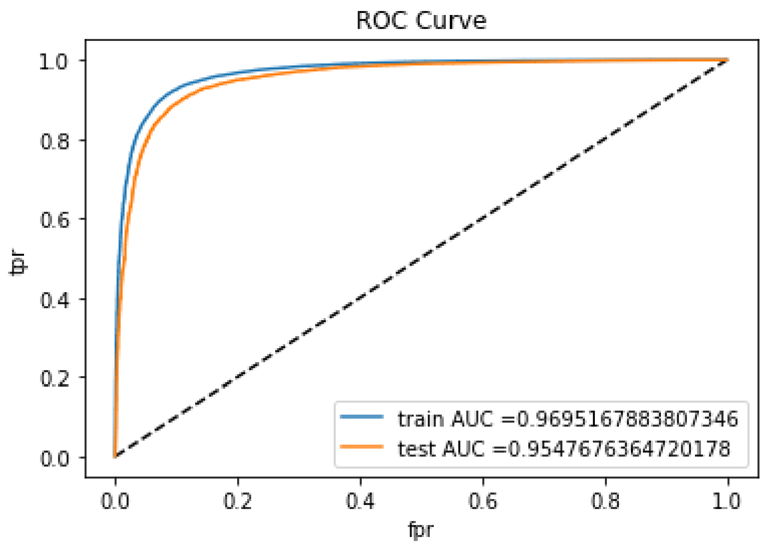
```
            tol=0.0001, verbose=0, warm_start=False)

The best score is:0.945815885045128
The best value of C is:{'C': 0.01}
Mean Score: 0.9547743986302348
```

In [66]:
```
# https://stackoverflow.com/questions/3097866/access-an-arbitrary-eleme
nt-in-a-dictionary-in-python
#list(my_dict.keys())[0]
list(best_estimator_bow_l1.values())[0]
```

Out[66]:
```
0.01
```

In [54]:
```
model_bow_l1 = LogisticRegression(C= list(best_estimator_bow_l1.values
())[0] ,penalty = 'l1')
model_bow_l1.fit(X_train_bow,y_train)
y_pred = model_bow_l1.predict(X_test_bow)
```

In [55]:
```
# AUC-ROC plot
auc_train_bow_l1, auc_test_bow_l1 = plot_auc(model_bow_l1, X_train_bow,
 X_test_bow)
```



```
train AUC: 0.9695167883807346
test AUC: 0.9547676364720178
```

In [56]:

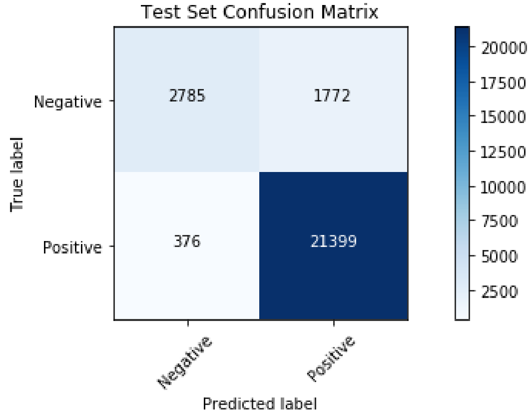
```
# Confusion Matrix
print_confusion_matrix(model_bow_l1, X_train_bow, X_test_bow)
```

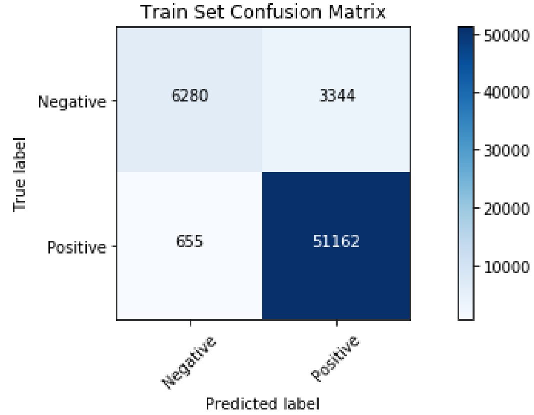
```
*****Train confusion matrix*****
[[ 6280  3344]
 [  655 51162]]

*****Test confusion matrix*****
[[ 2785  1772]
 [  376 21399]]
```

In [57]:

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


plt.subplot(121)  # Test confusion matrix
cnf_matrix = confusion_matrix(y_test, model_bow_l1.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_l1.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='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 l1.
2. We got train AUC: 0.9695167883807346 and test AUC: 0.9547676364720178
3. Using the confusion matrix, we can say that our model correctly predicted 21399 positive reviews and 2785 negative reviews.
4. The model incorrectly classified 376 negative reviews and 1772 positive reviews.
5. The True Postive Rate is 98.27 and the True Negative Rate is 61.11
6. The accuracy of the model is 91.84

In [58]:
```
# Confustion Matrix heatmap
#print("Train set")
#plot_heatmap_confusion_matrix(model_bow_l1, X_train_bow)
#plot_heatmap_confusion_matrix_train(model_bow_l1, X_train_bow)
#confusion_matrix(y_train, model_bow_l1.predict(X_train_bow))

# Confustion Matrix heatmap
#print("Train set")
#plot_heatmap_confusion_matrix(model_bow_l1, X_test_bow)
```

[5.1.1.1] Calculating sparsity on weight vector obtained using L1 regularization on BOW,

SET 1

In [59]:
```
# The model has already been fitted. Here we are just going to calculat
e the sparsity on weight vector
w = model_bow_l1.coef_
print("The sparsity (no. of non-zero elements) in weight vector is {}".
format(np.count_nonzero(w)))
```

```
The sparsity (no. of non-zero elements) in weight vector is 1910
```

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 [60]:
```
def get_text_length(x):
    """
     This function takes in a array and returns the length of the eleme
nts in the array.
    """
    return np.array([len(t) for t in x]).reshape(-1, 1)
```

In [61]:
```
rev_len_X_train = get_text_length(X_train)
rev_len_X_test = get_text_length(X_test)
```

In [62]:
```
from sklearn.feature_extraction.text import CountVectorizer
bow_vectorizer_fe = CountVectorizer(ngram_range=(1,2), min_df=10, max_f
eatures=10000)
bow_vectorizer_fe.fit(X_train) # fit has to happen only on train data
```

Out[62]:
```
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 [63]:
```
# 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 [64]:

```
# 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 [65]:
```python
type(rev_len_X_train)
```

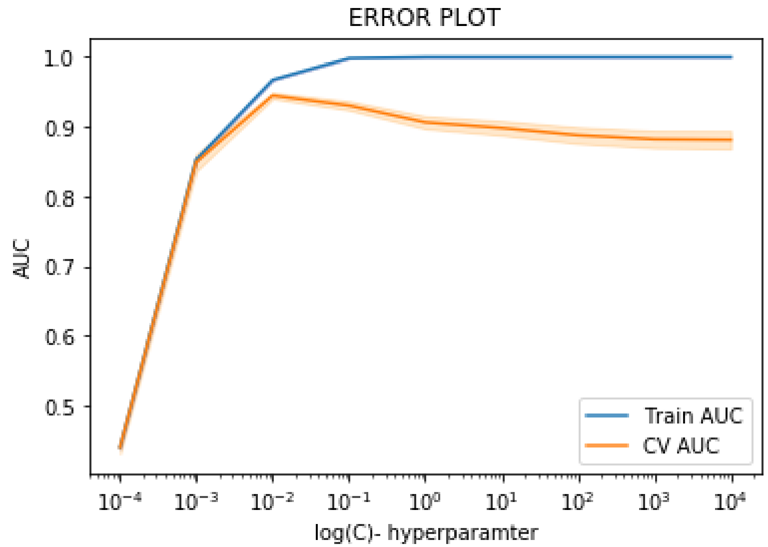
Out[65]:
```
numpy.ndarray
```

In [66]:
```python
type(X_train_bow)
```

Out[66]:
```
scipy.sparse.csr.csr_matrix
```

In [67]:
```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 [68]:
```python
# Get the best hyperparameter using GridSearchCV with penalty l1 and cv
 = 5
best_estimator_bow_l1_fe = get_best_hyperparameter_C(bow_vectorizer_fe,
 X_train_bow_fe, X_test_bow_fe, y_train, y_test, penalty_l = 'l1' )
```

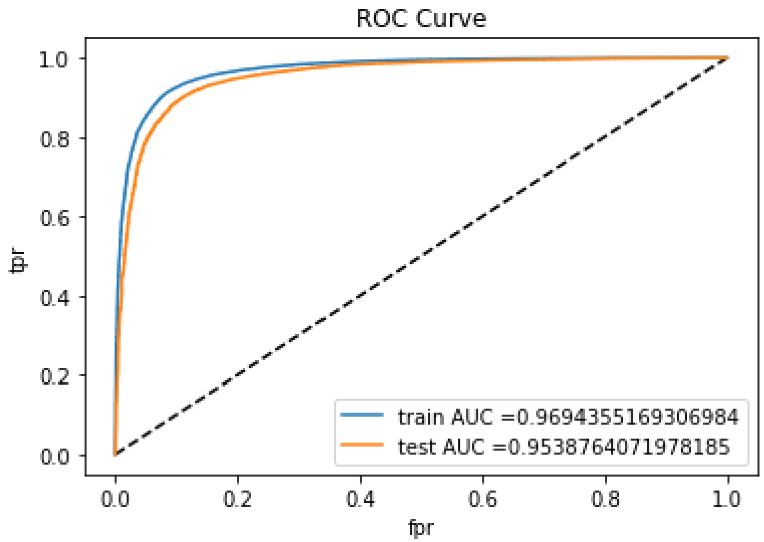


Mean CV Score	Std CV Score	Param
0.44	0.01866	{'C': 0.0001}
0.849	0.02492	{'C': 0.001}
0.945	0.00919	{'C': 0.01}
0.931	0.01316	{'C': 0.1}
0.906	0.01843	{'C': 1}
0.898	0.0208	{'C': 10}
0.888	0.02375	{'C': 100}
0.882	0.02482	{'C': 1000}
0.881	0.02594	{'C': 10000}

```
The best estimator:LogisticRegression(C=0.01, class_weight=None, dual=F
alse, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l1', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)

The best score is:0.9450663381665366
The best value of C is:{'C': 0.01}
Mean Score: 0.9538766994520484
```

In [69]:
```
# Fitting the BoW vectorizer on LogisticRegression Model with penalty l
1 and C = 0.01
model_bow_l1_fe = LogisticRegression(C= list(best_estimator_bow_l1_fe.v
alues())[0] ,penalty = 'l1')
model_bow_l1_fe.fit(X_train_bow_fe,y_train)
y_pred = model_bow_l1_fe.predict(X_test_bow_fe)
```

In [70]:
```
# AUC-ROC plot
auc_train_bow_l1_fe, auc_test_bow_l1_fe = plot_auc(model_bow_l1_fe, X_t
rain_bow_fe, X_test_bow_fe)
```




```
train AUC: 0.9694355169306984
test AUC: 0.9538764071978185
```

In [71]:
```
# Confusion Matrix
print_confusion_matrix(model_bow_l1_fe, X_train_bow_fe, X_test_bow_fe)
```

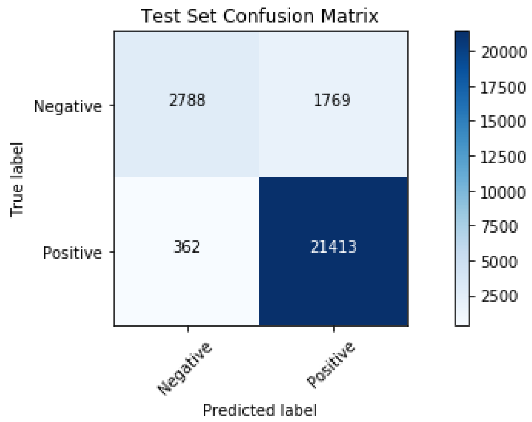
```
*****Train confusion matrix*****
[[ 6274  3350]
 [  652 51165]]
```

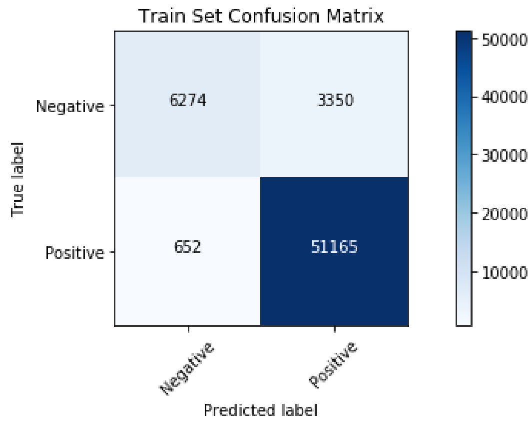
```
*****Test confusion matrix*****
[[ 2788  1769]
 [  362 21413]]
```

In [72]:

```
# 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_l1_fe.predict(X_test_bo
w_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_l1_fe.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 l1.
2. We got train AUC: 0.9694354808358998 and test AUC: 0.9538772738827763
3. Using the confusion matrix, we can say that our model correctly predicted 21413 positive reviews and 2788 negative reviews.
4. The model incorrectly classified 362 negative reviews and 1769 positive reviews.
5. The True Postive Rate is 98.33 and the True Negative Rate is 61.18
6. The overall accuracy of the model is 91.90
7. **Doing Feature Engineering has made the model slightly perform better than the model without feature engineering.**

Observation

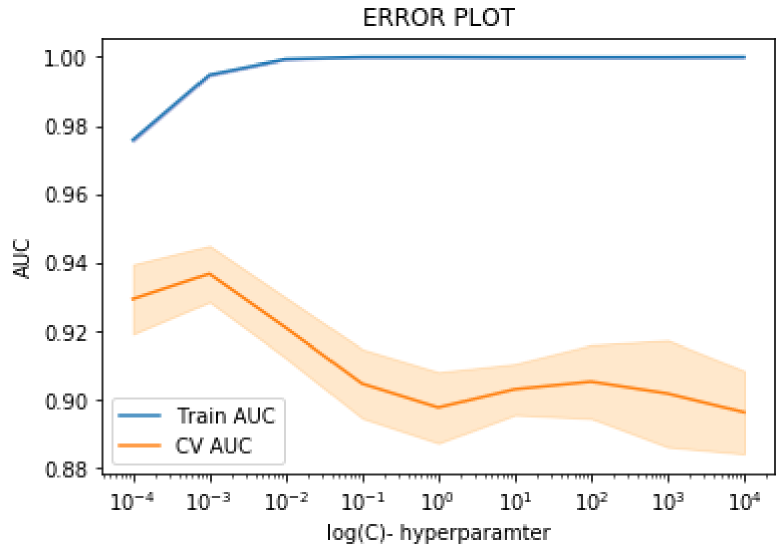
[5.1.2] Applying Logistic Regression with L2 regularization on BOW, SET 1

In [73]:
```
# Vectorizer = BoW, penalty = l2
best_estimator_bow_l2= get_best_hyperparameter_C(bow_vectorizer, X_trai
```

```
n_bow, X_test_bow, y_train, y_test, penalty_l = 'l2' )
```

```
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\svm\base.py:922: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\svm\base.py:922: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\svm\base.py:922: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\svm\base.py:922: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\svm\base.py:922: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\svm\base.py:922: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\svm\base.py:922: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\svm\base.py:922: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\svm\base.py:922: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\svm\base.py:922: ConvergenceWarning: Liblinear failed to conv
```

```
erge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\svm\base.py:922: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\svm\base.py:922: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\svm\base.py:922: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\svm\base.py:922: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\svm\base.py:922: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\svm\base.py:922: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Nit-prj1010\AppData\Local\Continuum\anaconda3\lib\site-package
s\sklearn\svm\base.py:922: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
```

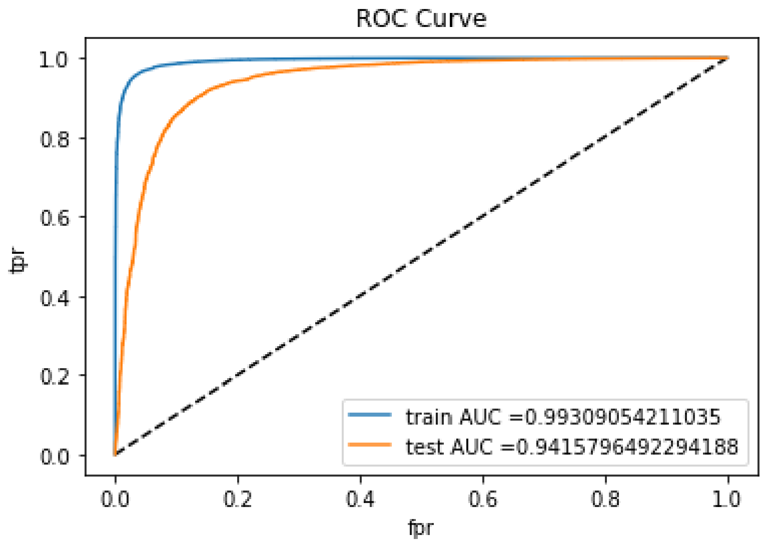



```
+---------------+--------------+---------------+
| Mean CV Score | Std CV Score |     Param     |
+---------------+--------------+---------------+
|     0.929     |   0.02038    | {'C': 0.0001} |
|     0.937     |   0.01645    |  {'C': 0.001} |
|     0.921     |   0.01764    |  {'C': 0.01}  |
|     0.905     |   0.02018    |   {'C': 0.1}  |
|     0.898     |   0.02079    |    {'C': 1}   |
|     0.903     |   0.01494    |   {'C': 10}   |
|     0.905     |   0.02151    |   {'C': 100}  |
|     0.902     |   0.03122    |  {'C': 1000}  |
|     0.896     |   0.02433    |  {'C': 10000} |
+---------------+--------------+---------------+

The best estimator:LogisticRegression(C=0.001, class_weight=None, dual=
False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)


The best score is:0.9367812057739767
The best value of C is:{'C': 0.001}
```

```
Mean Score: 0.9415796492294188
```

In [74]:
```python
# Fitting the model with the best hyperparameter
model_bow_l2 = LogisticRegression(C= list(best_estimator_bow_l2.values
())[0] ,penalty = 'l2')
model_bow_l2.fit(X_train_bow,y_train)
y_pred = model_bow_l2.predict(X_test_bow)
```

In [75]:
```python
# AUC- ROC plot
auc_train_bow_l2, auc_test_bow_l2 = plot_auc(model_bow_l2, X_train_bow,
 X_test_bow)
```




```
train AUC: 0.99309054211035
test AUC: 0.9415796492294188
```

In [76]:
```python
# Confusion Matrix
print_confusion_matrix(model_bow_l2, X_train_bow, X_test_bow)
```

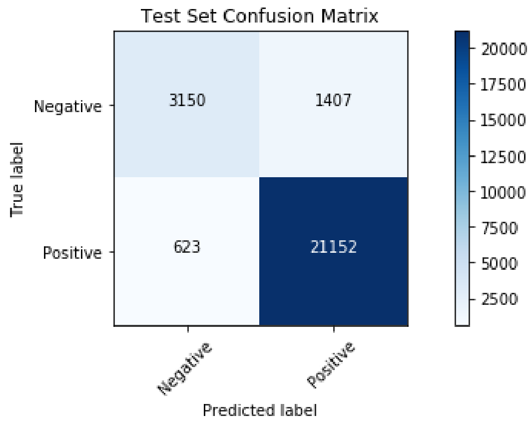
```
*****Train confusion matrix*****
[[ 8166  1458]
 [  412 51405]]
```

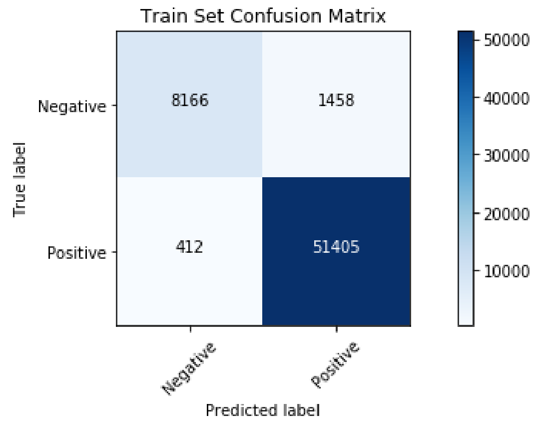
```
*****Test confusion matrix*****
[[ 3150  1407]
 [  623 21152]]
```

In [77]:

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


plt.subplot(121)  # Test confusion matrix
cnf_matrix = confusion_matrix(y_test, model_bow_l2.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_l2.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 C = 0.001 using GridSearchCV with cv = 5 and with penalty l2.
2. We got train AUC: 0.99309054211035 and test AUC: 0.9415796492294188
3. Using the confusion matrix, we can say that our model correctly predicted 21152 positive reviews and 3150 negative reviews.
4. The model incorrectly classified 623 negative reviews and 1407 positive reviews.
5. The True Postive Rate is 98.67 and the True Negative Rate is 60.03
6. The accuracy of the model is 91.98

In [0]:

```
import sys
def sizeof_fmt(num, suffix='B'):
    ''' By Fred Cirera, after https://stackoverflow.com/a/1094933/18702
54'''
    for unit in ['','Ki','Mi','Gi','Ti','Pi','Ei','Zi']:
        if abs(num) < 1024.0:
            return "%3.1f%s%s" % (num, unit, suffix)
        num /= 1024.0
    return "%.1f%s%s" % (num, 'Yi', suffix)

for name, size in sorted(((name, sys.getsizeof(value)) for name,value i
n locals().items()),
```

```
                          key= lambda x: -x[1])[:10]:
    print("{:>30}: {:>8}".format(name,sizeof_fmt(size)))
```

Pertubation Test

[5.1.2.1] Performing pertubation test (multicollinearity check) on BOW, SET 1

In [78]:
```
# Step 1: Get the weights W after fitting your model with the data X
W_vect = model_bow_l2.coef_
```

In [79]:
```
# Step 2: Add a noise to the X (X' = X+e) and get the new dataset X'

# We need to preserve our existing X and create a copy of it before we
 can add noise to it
# source: https://www.geeksforgeeks.org/copy-python-deep-copy-shallow-c
opy/
# deepcopy(): any changes made to a copy of object do not reflect in th
e original object.

import copy
X_train_bow_noisy = copy.deepcopy(X_train_bow) # copy of X_train_bow
uniform_noise = np.random.uniform(-0.0001,0.0001,1 ) # adding some rand
om uniform noise
```

In [80]:
```
type(X_train_bow)
```

Out[80]:
```
scipy.sparse.csr.csr_matrix
```

In [81]:
```
# Since X_train_bow is space matrix, we do X.data += e
X_train_bow_noisy.data += uniform_noise
print(X_train_bow_noisy.shape)
```

```
(61441, 10000)
```

In [82]:
```
# Step 3: We fit the model again on data X_train_bow_noisy and get the
 weights W'
```

```
# Fitting the BoW vectorizer on LogisticRegression Model
model_bow_l2_noisy = LogisticRegression(C= list(best_estimator_bow_l2.v
alues())[0],penalty = 'l2')
model_bow_l2_noisy.fit(X_train_bow_noisy,y_train)
y_pred = model_bow_l2_noisy.predict(X_test_bow)
```

In [83]:
```
# Get the weights W after fitting your model with the noisy data X'
W_vect_noisy = model_bow_l2_noisy.coef_
```

In [84]:
```
# Step 4: Add small epsilon value to eliminate the 'divisible by zero'
 error to W_vect and W_vect_noisy
esp = 10**-6
W_vect += esp
W_vect_noisy += esp
```

In [85]:
```
# Step 5: Find % change between W_vect and W_vect_noisy

W_percent_change_vector = abs((W_vect - W_vect_noisy) / W_vect) *100
```

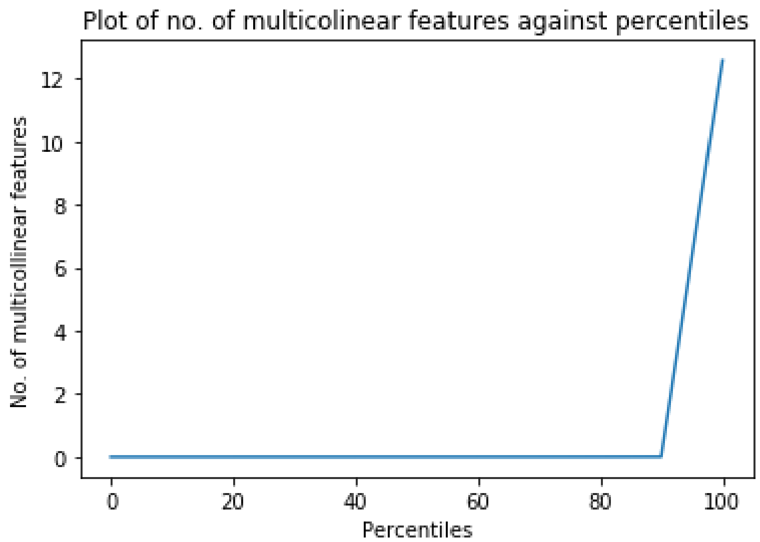
In [86]:
```
W_percent_change_vector
```

Out[86]:
```
array([[9.93e-04, 7.01e-06, 1.03e-02, ..., 2.59e-03, 5.13e-04, 6.51e-0
3]])
```

In [87]:
```
# Step 6: Calculate 0th, 10th, 20th ..100th Percentile
percentile_range= range(0,101,10)
tab = PrettyTable()
tab.field_names = ['Percentile ', 'Percentile Value']


for p in percentile_range:
    tab.add_row([p, np.percentile(W_percent_change_vector,p)])


plt.plot(percentile_range, np.percentile(W_percent_change_vector,percen
tile_range))
```

```
plt.xlabel('Percentiles')
plt.ylabel('No. of multicollinear features')
plt.title("Plot of no. of multicolinear features against percentiles")

print(tab)
del (tab)
```

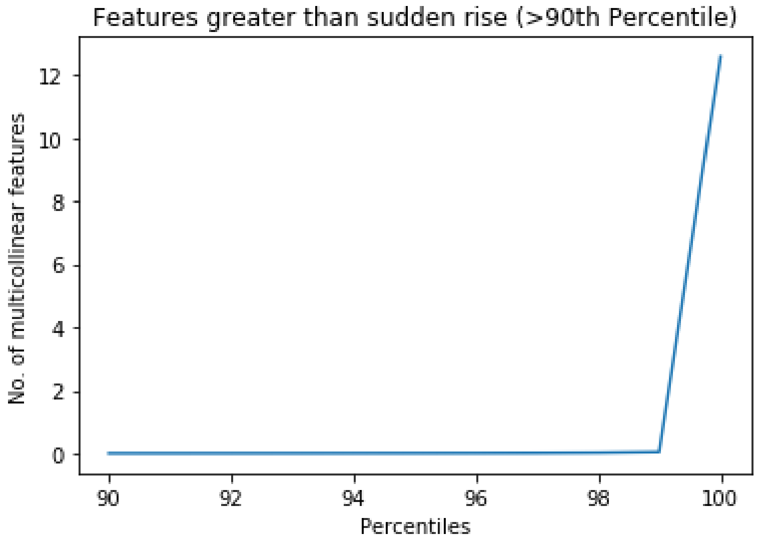
```
+-------------+-----------------------+
|  Percentile |    Percentile Value   |
+-------------+-----------------------+
|      0      |   2.1288236710142e-08  |
|      10     | 0.0001290710220424033 |
|      20     | 0.00026651132954525614 |
|      30     |  0.000404709561975814 |
|      40     |  0.000581215567616487 |
|      50     | 0.0007999871796000233 |
|      60     | 0.0010965094631658796 |
|      70     | 0.0015858030927552692 |
|      80     |  0.002512170755860659 |
|      90     |  0.005024878518104683 |
|     100     |   12.572261483067537  |
+-------------+-----------------------+
```



Observation: We see that there is a sudden rise in values after the 90th percentile value.

In [88]:
```
# Plot values after the sudden rise i.e. from the 90th percentile value
s

sudden_rise= range(90,101,1)
tab = PrettyTable()
tab.field_names = ['Percentile ', 'Percentile Value']

for i in sudden_rise:
    tab.add_row([i, np.percentile(W_percent_change_vector,i)])

print(tab)
plt.plot(sudden_rise,np.percentile(W_percent_change_vector,sudden_rise)
 );
plt.xlabel('Percentiles')
plt.ylabel('No. of multicollinear features')
plt.title("Features greater than sudden rise (>90th Percentile)")
del (tab)
```

```
+-------------+----------------------+
| Percentile  |   Percentile Value   |
+-------------+----------------------+
|      90     | 0.005024878518104683 |
|      91     | 0.005536440548611815 |
|      92     | 0.006223372849219215 |
|      93     | 0.007020458291498725 |
|      94     | 0.008347083172674468 |
|      95     | 0.00971386294287677  |
|      96     | 0.011739505021271607 |
|      97     | 0.016008687942597848 |
|      98     | 0.024976125423512584 |
|      99     | 0.047399636184165865 |
|     100     |  12.572261483067537  |
+-------------+----------------------+
```

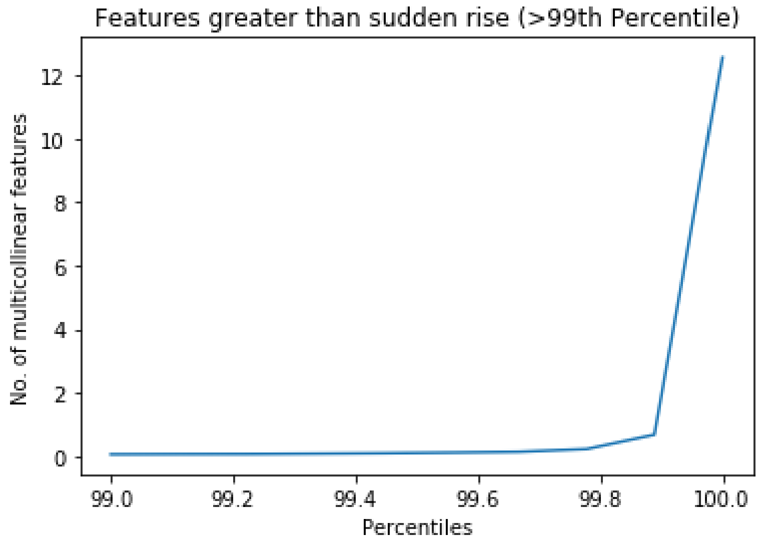


Observation: Here, after 99th percentile, we see there is sudden rise in values.

In [89]:
```
# Plot values after the sudden rise i.e. from the 90th percentile value
s

gt99= np.linspace(99,100,10)
tab = PrettyTable()
tab.field_names = ['Percentile ', 'Percentile Value']

for i in gt99:
    tab.add_row([i, np.percentile(W_percent_change_vector,i)])

print(tab)
plt.plot(gt99,np.percentile(W_percent_change_vector,gt99) );
plt.xlabel('Percentiles')
plt.ylabel('No. of multicollinear features')
plt.title("Features greater than sudden rise (>99th Percentile)")
del (tab)
```

```
+-------------------+---------------------+
|     Percentile    |   Percentile Value  |
```

```
+-------------------+----------------------+
|        99.0       | 0.047399636184165865 |
| 99.11111111111111 | 0.052915605599829704 |
| 99.22222222222223 | 0.05635737937635935  |
| 99.33333333333333 | 0.06811388084312188  |
| 99.44444444444444 | 0.08260693710378353  |
| 99.55555555555556 | 0.10265356775837843  |
| 99.66666666666667 | 0.12710099736555297  |
| 99.77777777777777 | 0.21553890490009822  |
| 99.88888888888889 |  0.6702054059627296  |
|       100.0       |  12.572261483067537  |
+-------------------+----------------------+
```



Observation: In this case the threshold value is the percentile **99.88**

In [90]:
```
# We will list down the features names which are greater than this inde
x value of threshold.
# We will print top 10 features by sorting values in descending values
 of the % changed vector
```

```
feature_names = bow_vectorizer.get_feature_names() # get feature names
weight_vector_values = model_bow_l2_noisy.coef_    # get weight values

# sorting change in percent weight vector in descending order i.e. feat
ures that have undergone maximum collinearity
# and selecting top 10 features out of it
mulc_features = np.argsort(W_percent_change_vector)[:,::-1][0,0:10]

# Top 10 features are
print("Printing 10 features:")

#tab = PrettyTable()
#tab.field_names = ['Feature name', 'Weight vector value']

for f in mulc_features:
    print(feature_names[f])
    #tab.add_row([feature_names[f], weight_vector_values[0,f]])


#print(tab)
#del(tab)
```

```
Printing 10 features:
minimal
free dairy
include
bowl
started using
quantity
good chocolate
not amazon
drink good
organic ingredients
```

Observation

1. We performed the perturbation test to find multicolinearity.
2. Here, we can see that very few features are collinear. Less than 0.02% features are multicolinear

3. We can conclude that this model is not affected by multicolinearity of features

feature importance

[5.1.3] Feature Importance on BOW, SET 1

In [91]:
```
model_bow_l2.classes_
```

Out[91]:
```
array([0, 1], dtype=int64)
```

[5.1.3.1] Top 10 important features of positive class from SET 1

[5.1.3.2] Top 10 important features of negative class from SET 1

In [92]:
```
most_informative_feature_for_binary_classification(bow_vectorizer, model_bow_l2)
```

```
+-------+------------------------+---------------+
| Class | Coefficient (Importance) |  Feature Name |
+-------+------------------------+---------------+
|   0   |    0.18118765370558954    |  disappointed |
|   0   |     0.1637476142766516    |     worst     |
|   0   |     0.1450317900116653    | not recommend |
|   0   |     0.1437890099604434    |    not good   |
|   0   |    0.14138196686305474    |   not worth   |
|   0   |     0.1394686428948509    |      not      |
|   0   |    0.13404722441563235    |    terrible   |
|   0   |    0.13008740467603347    |     awful     |
|   0   |    0.12911041632708453    |    not buy    |
|   0   |    0.12699445630766656    | disappointing |
+-------+------------------------+---------------+
****************************************************

+-------+------------------------+--------------+
| Class | Coefficient (Importance) | Feature Name |
```

```
+-------+--------------------------+-------------+
|   1   |    0.3205556750029913    |    great    |
|   1   |    0.2546191552577402    |     good    |
|   1   |   0.24534971037457565    |  delicious  |
|   1   |   0.22623311139831281    |     best    |
|   1   |   0.22139260541932348    |     love    |
|   1   |   0.18358386635904556    |    loves    |
|   1   |   0.17424257182496358    |   perfect   |
|   1   |   0.16690705041432588    |  excellent  |
|   1   |   0.14563081152530527    |  wonderful  |
|   1   |   0.14435945555081128    |    tasty    |
+-------+--------------------------+-------------+
```

[4.2] Bi-Grams and n-Grams.

In [0]:
```
#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 [93]:
```
# 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,)
========================================================================
=============================
```

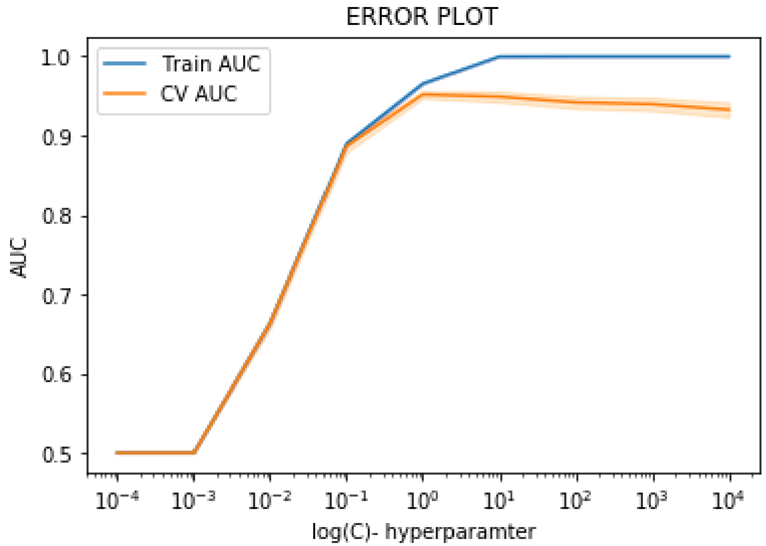
In [94]:
```
print("the type of count vectorizer ",type(X_train_tfidf))
print("the shape of cut text TFIDF vectorizer ",X_train_tfidf.get_shape
())
print("the number of unique words: ", X_train_tfidf.get_shape()[1])
```

```
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
```

[5.2.1] Applying Logistic Regression with L1 regularization on TFIDF, SET 2

In [95]:
```
# Get the best hyperparameter using GridSearchCV with penalty l1 and cv
 = 5
```

```
best_estimator_tfidf_l1 = get_best_hyperparameter_C(tf_idf_vect, X_trai
n_tfidf, X_test_tfidf, y_train, y_test, penalty_l = 'l1' )
```



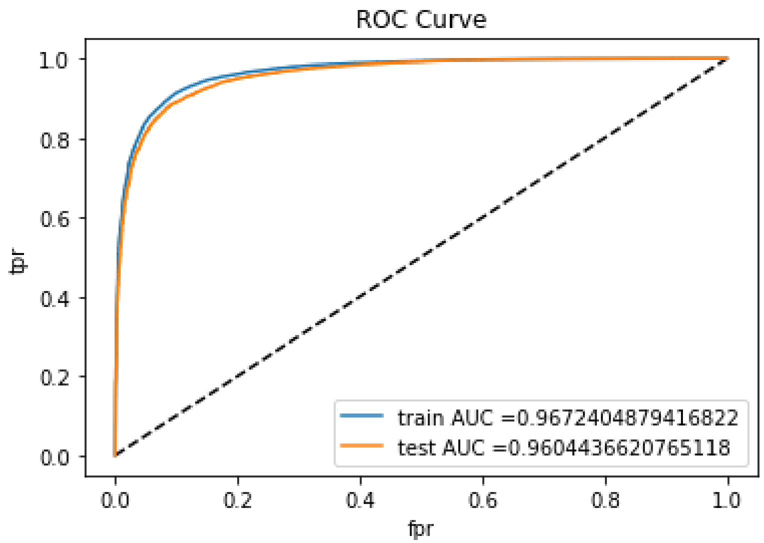
Mean CV Score	Std CV Score	Param
0.5	0.0	{'C': 0.0001}
0.5	0.0	{'C': 0.001}
0.664	0.01405	{'C': 0.01}
0.886	0.01464	{'C': 0.1}
0.952	0.00962	{'C': 1}
0.949	0.01358	{'C': 10}
0.942	0.01555	{'C': 100}
0.94	0.0167	{'C': 1000}
0.932	0.01891	{'C': 10000}

```
The best estimator:LogisticRegression(C=1, class_weight=None, dual=Fals
e, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l1', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)
```

```
The best score is:0.9516803305794055
The best value of C is:{'C': 1}
Mean Score: 0.9604442465849716
```

In [96]:
```
# Fitting the model with the best hyperparameter
model_tfidf_l1 = LogisticRegression(C= list(best_estimator_tfidf_l1.values())[0] ,penalty = 'l1')
model_tfidf_l1.fit(X_train_tfidf,y_train)
y_pred = model_tfidf_l1.predict(X_test_tfidf)
```

In [97]:
```
# AUC- ROC plot
auc_train_tfidf_l1, auc_test_tfidf_l1 = plot_auc(model_tfidf_l1, X_train_tfidf, X_test_tfidf)
```




```
train AUC: 0.9672404879416822
test AUC: 0.9604436620765118
```

In [98]:
```
# Confusion Matrix
print_confusion_matrix(model_tfidf_l1, X_train_tfidf, X_test_tfidf)
```

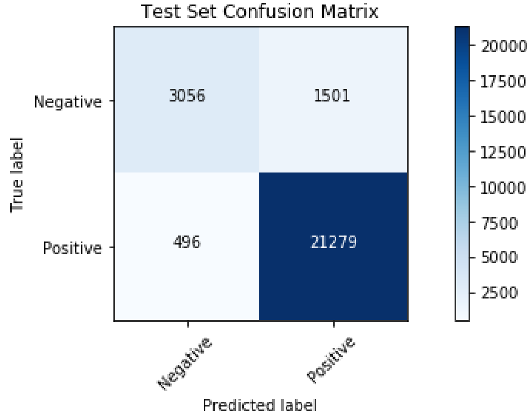
```
*****Train confusion matrix*****
```

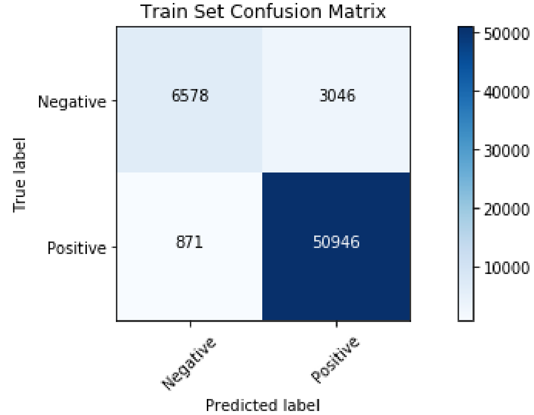
```
[[ 6578  3046]
 [  871 50946]]

*****Test confusion matrix*****
[[ 3056  1501]
 [  496 21279]]
```

In [99]:

```
# 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_l1.predict(X_test_tfi
df))
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_l1.predict(X_train_t
fidf))
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>
```



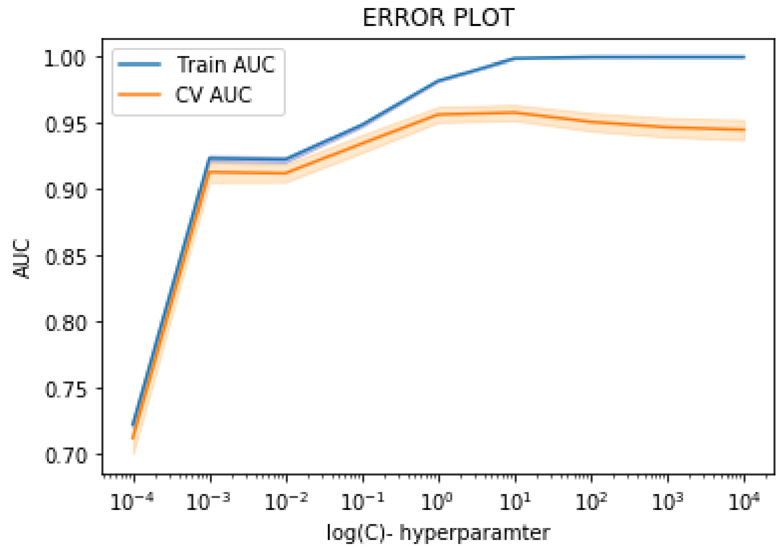


Observation

1. For the TFIDF vectorizer, we calculated C = 1 using GridSearchCV with cv = 5 and with penalty l1.
2. We got train AUC: 0.9672404879416822 and test AUC: 0.9604436620765118
3. Using the confusion matrix, we can say that our model correctly predicted 21279 positive reviews and 3055 negative reviews.
4. The model incorrectly classified 496 negative reviews and 1501 positive reviews.
5. The True Postive Rate is 97.84 and the True Negative Rate is 67.03
6. The accuracy of the model is 92.50

[5.2.2] Applying Logistic Regression with L2 regularization on TFIDF, SET 2

In [100]:
```
# Get the best hyperparameter
best_estimator_tfidf_l2 = get_best_hyperparameter_C(tf_idf_vect, X_trai
n_tfidf, X_test_tfidf, y_train, y_test, penalty_l = 'l2' )
```



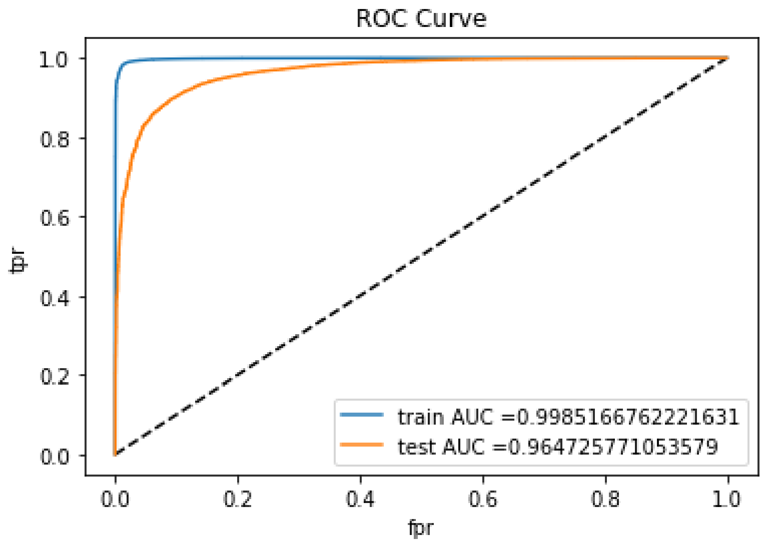
Mean CV Score	Std CV Score	Param
0.712	0.02389	{'C': 0.0001}
0.913	0.01532	{'C': 0.001}
0.912	0.01319	{'C': 0.01}
0.935	0.01353	{'C': 0.1}
0.957	0.01182	{'C': 1}
0.958	0.01198	{'C': 10}
0.951	0.01371	{'C': 100}
0.947	0.01465	{'C': 1000}
0.945	0.01516	{'C': 10000}

```
The best estimator:LogisticRegression(C=10, class_weight=None, dual=Fal
se, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)

The best score is:0.95818493762303
The best value of C is:{'C': 10}
Mean Score: 0.964725771053579
```

```
mean score: 0.964725771053579
```

In [101]:
```
# Fit the model with the best hyperparameter
model_tfidf_l2 = LogisticRegression(C= list(best_estimator_tfidf_l2.val
ues())[0], penalty = 'l2')
model_tfidf_l2.fit(X_train_tfidf,y_train)
y_pred = model_tfidf_l2.predict(X_test_tfidf)
```

In [102]:
```
# AUC- ROC plot
auc_train_tfidf_l2, auc_test_tfidf_l2 = plot_auc(model_tfidf_l2, X_trai
n_tfidf, X_test_tfidf)
```




```
train AUC: 0.9985166762221631
test AUC: 0.964725771053579
```

In [103]:
```
# Confusion matrix
print_confusion_matrix(model_tfidf_l2, X_train_tfidf, X_test_tfidf)
```

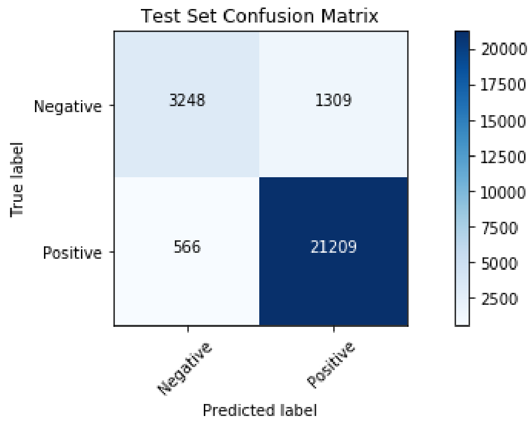
```
*****Train confusion matrix*****
[[ 8946   678]
 [  173 51644]]
```

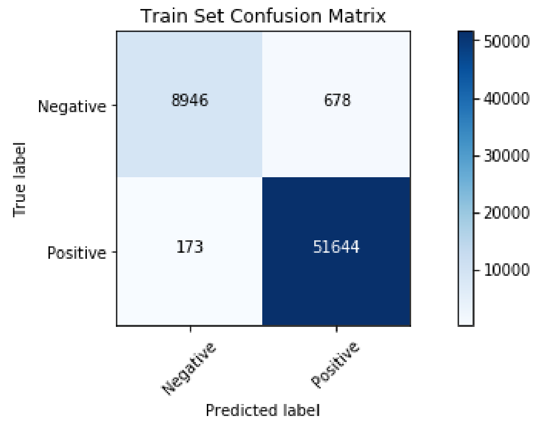
```
*****Test confusion matrix*****
[[ 3248  1309]
 [  566 21209]]
```

In [104]:

```
# 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_l2.predict(X_test_tfi
df))
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_l2.predict(X_train_t
fidf))
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 calculated C = 10 using GridSearchCV with cv = 5 and with penalty l2.
2. We got train AUC: 0.9985166762221631 and test AUC: 0.964725771053579
3. Using the confusion matrix, we can say that our model correctly predicted 21209 positive reviews and 3248 negative reviews.
4. The model incorrectly classified 566 negative reviews and 1309 positive reviews.
5. The True Postive Rate is 98.47 and the True Negative Rate is 60.21
6. The accuracy of the model is 91.85

[5.2.3] Feature Importance on TFIDF, SET 2

[5.2.3.1] Top 10 important features of positive class from SET 2

[5.2.3.2] Top 10 important features of negative class from SET 2

In [105]:
```
most_informative_feature_for_binary_classification(tf_idf_vect, model_tfidf_l2)
```

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

```
| Class | Coefficient (Importance) |  Feature Name  |
+-------+--------------------------+----------------+
|   0   |     14.05633689502798    |     worst      |
|   0   |     11.74311885235004    |   not worth    |
|   0   |     11.712297104959422   |  disappointed  |
|   0   |     11.553933190987355   |    terrible    |
|   0   |     11.31806567269511    |    not good    |
|   0   |     11.294343181493128   | not recommend  |
|   0   |     11.235079122127873   |   two stars    |
|   0   |     10.916559085516361   |     awful      |
|   0   |     10.615169158405667   | disappointing  |
|   0   |     9.237292164583296    | disappointment |
+-------+--------------------------+----------------+
****************************************************
+-------+--------------------------+------------------+
| Class | Coefficient (Importance) |   Feature Name   |
+-------+--------------------------+------------------+
|   1   |     16.229861601293226   |      great       |
|   1   |     14.71476530913575    |    delicious     |
|   1   |     12.67482046352735    | not disappointed |
|   1   |     12.54874612418282    |       good       |
|   1   |     12.181395785494692   |       best       |
|   1   |     11.90106615797133    |     perfect      |
|   1   |     11.111630609138262   |      loves       |
|   1   |     10.525449587060917   |    excellent     |
|   1   |     10.043258129638604   |     amazing      |
|   1   |     9.770806515013575    |    wonderful     |
+-------+--------------------------+------------------+
```

[4.4] Word2Vec

In [106]:

```
# 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 [108]:
```
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 [109]:
```
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 ")
```

```
[('fantastic', 0.8422129154205322), ('good', 0.8153432011604309), ('exc
ellent', 0.813062310218811), ('awesome', 0.8104643821716309), ('wonderf
ul', 0.8010066747665405), ('terrific', 0.7817002534866333), ('perfect',
0.767562747001648), ('amazing', 0.7452276945114136), ('fabulous', 0.719
0866470336914), ('decent', 0.7043147087097168)]
==================================================
[('greatest', 0.7702896595001221), ('best', 0.7596640586853027), ('tast
iest', 0.7124402523040771), ('nastiest', 0.6849291920661926), ('cooles
t', 0.6719734072685242), ('closest', 0.6640547513961792), ('toughest',
```

0.6579124927520752), ('disgusting', 0.6277365684509277), ('smoothest',
0.6193704605102539), ('ive', 0.6013782024383545)]

In [110]:

```
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 [111]:

```
# 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 [01:45<00:00, 582.36it/s]
```

```
(61441, 50)
[ 0.26 -0.27  0.11  0.07 -0.18  0.39 -0.26 -0.31  0.17 -0.01  0.11  0.4
5
  0.32  0.34 -0.19 -0.17  0.37  0.16 -0.03  0.3   0.21  0.57 -0.26 -0.3
  0.73  0.11 -0.03  0.08  0.11  0.47  0.11 -0.14 -0.19  0.14 -0.36 -0.3
8
 -0.04  0.02  0.57 -0.16  0.78  0.28 -0.42 -0.04  0.11 -0.41 -0.28 -0.2
1
 -0.74 -0.19]
```

Converting test text data

In [112]:

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

In [113]:

```
# 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
[00:48<00:00, 539.88it/s]
```

```
(26332, 50)
[-0.4  -0.13 -0.11 -0.54  0.27 -0.05  0.48 -0.41  1.71  0.11  0.21  0.1
7
  0.04  0.53 -0.26 -0.07  1.08  0.26  0.04 -0.26  0.4  -1.23 -0.03 -0.5
  0.68 -0.36 -0.38  0.14 -0.58  0.17  0.21 -0.55 -0.05  0.75 -0.48  0.1
3
 -0.84 -0.25 -0.57 -0.24 -0.56 -0.76  0.55  0.55 -0.16 -0.36  0.34  0.2
2
 -0.49 -0.27]
```

hyperparameter tuning with cv = 5 using gridsearch

In [139]:

```
# Get the best hyperparameter
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

# Using GridSearchCVSearchCV with 5 fold cv
gs_obj = GridSearchCV(LogisticRegression(penalty= 'l1'), tuned_paramete
rs, scoring = 'roc_auc', cv=5)

gs_obj.fit(sent_vectors_train, y_train)
```

Out[139]:

```
GridSearchCV(cv=5, error_score='raise-deprecating',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=Fals
e, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l1', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False),
```

```
             fit_params=None, iid='warn', n_jobs=None,
             param_grid=[{'C': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 1
0000]}],
             pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
             scoring='roc_auc', verbose=0)
```

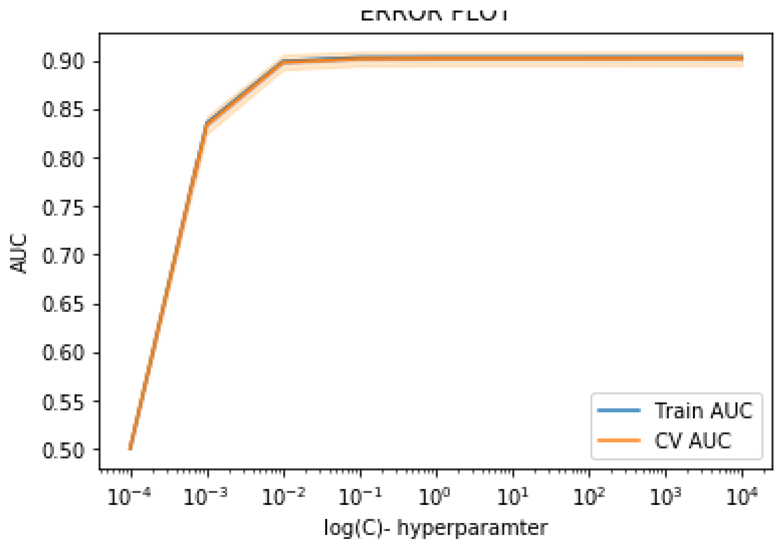
In [131]:
```
best_estimator_w2v_l1 = gs_obj.best_params_
```

In [132]:
```
list(best_estimator_w2v_l1.values())[0]
```

Out[132]:
```
100
```

In [140]:
```
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/48803361/4
084039
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/48803361/4
084039
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()
```

ERROR PLOT



In [141]:

```
# 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)))
```

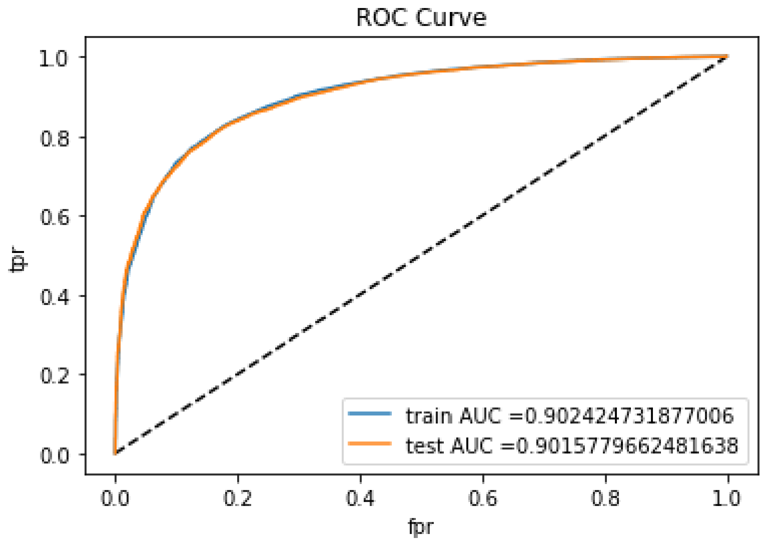
```
+---------------+--------------+---------------+
| Mean CV Score | Std CV Score |     Param     |
+---------------+--------------+---------------+
|      0.5      |     0.0      | {'C': 0.0001} |
|     0.833     |   0.01844    |  {'C': 0.001} |
|     0.898     |   0.01507    |  {'C': 0.01}  |
|     0.901     |    0.0144    |   {'C': 0.1}  |
|     0.901     |   0.01406    |    {'C': 1}   |
|     0.901     |   0.01405    |   {'C': 10}   |
|     0.901     |   0.01404    |   {'C': 100}  |
|     0.901     |   0.01399    |  {'C': 1000}  |
|     0.901     |   0.01404    |  {'C': 10000} |
+---------------+--------------+---------------+

The best estimator:LogisticRegression(C=1000, class_weight=None, dual=F
alse, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l1', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)

The best score is:0.901461054602771
The best value of C is:{'C': 1000}
Mean Score: 0.9015784802124991
```

In [142]:

```
# Fitting the model with the best hyperparameter
model_avgw2v_l1 = LogisticRegression(C= list(best_estimator_w2v_l1.valu
es())[0],penalty = 'l1')
model_avgw2v_l1.fit(sent_vectors_train,y_train)
y_pred = model_avgw2v_l1.predict(sent_vectors_test)
```

In [143]:

```
# AUC - ROC plot
auc_train_avgw2v_l1, auc_test_avgw2v_l1 = plot_auc(model_avgw2v_l1, sen
t_vectors_train, sent_vectors_test)
```




```
train AUC: 0.902424731877006
test AUC: 0.9015779662481638
```

In [144]:

```
# Confusion matrix
print_confusion_matrix(model_avgw2v_l1, sent_vectors_train, sent_vector
s_test)
```

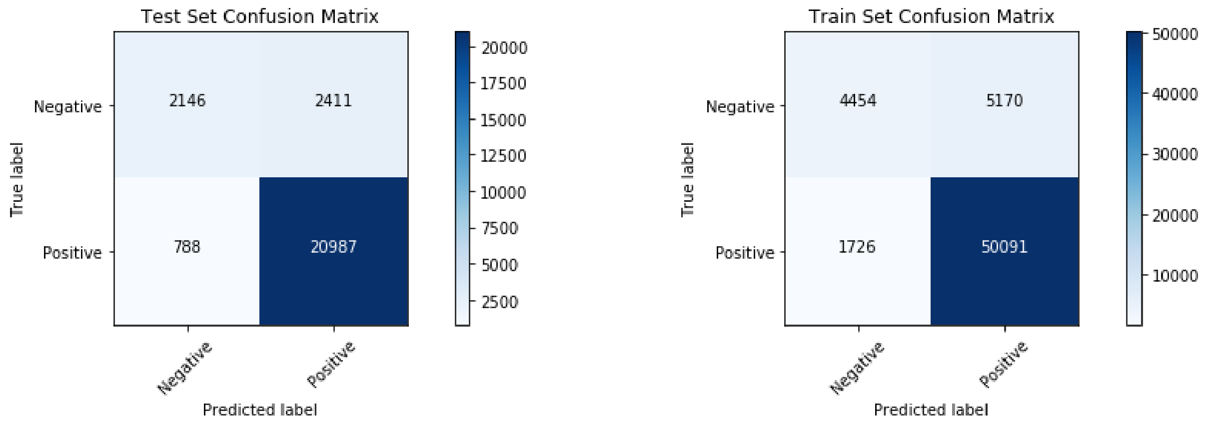
```
*****Train confusion matrix*****
[[ 4454  5170]
 [ 1726 50091]]

*****Test confusion matrix*****
[[ 2146  2411]
 [  788 20987]]
```

In [156]:

```
# 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_l1.predict(sent_vect
```

```
ors_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_l1.predict(sent_vec
tors_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 = 1000 using GridSearchCV with cv = 5 and with penalty l1.
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.
5. The True Postive Rate is 96.41 and the True Negative Rate is 47.65
6. The accuracy of the model is 87.97

[5.3.2] Applying Logistic Regression with L2 regularization on AVG W2V, SET 3

In [146]:

```
# Get the best hyperparameter
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

# Using GridSearchCVSearchCV with 5 fold cv
gs_obj = GridSearchCV(LogisticRegression(penalty= 'l2'), tuned_paramete
rs, scoring = 'roc_auc', cv=5)

gs_obj.fit(sent_vectors_train, y_train)
```

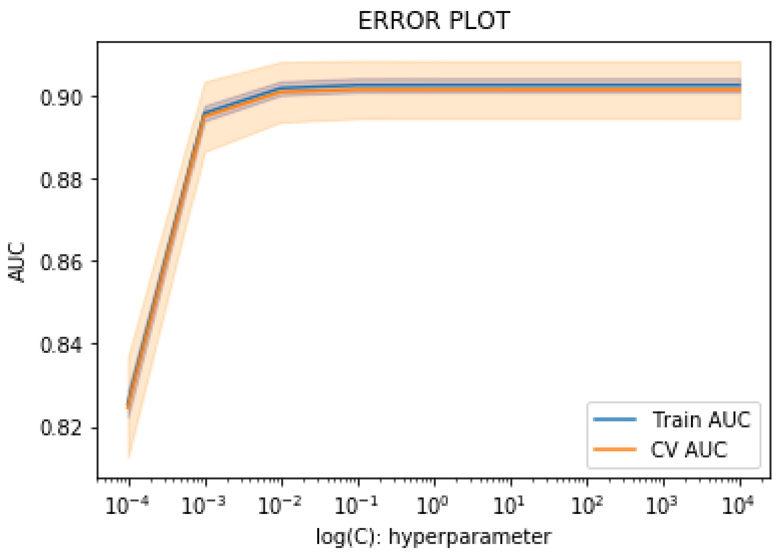
Out[146]:

```
GridSearchCV(cv=5, error_score='raise-deprecating',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=Fals
e, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid=[{'C': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 1
0000]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='roc_auc', verbose=0)
```

In [147]:

```
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/48803361/
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/48803361/4
084039
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): hyperparameter")
plt.xscale('log')
plt.ylabel("AUC")
plt.title("ERROR PLOT")
plt.show()
```



In [148]:
```
# 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']


t2 = PrettyTable()
t2.field_names = ['Mean CV Score', 'Std CV Score', 'Param']

for mean, std, params in zip(means, stds, gs_obj.cv_results_['params'
]):
    t2.add_row([round(mean, 3), round(std * 2,5), params])

print(t2)

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)))
```

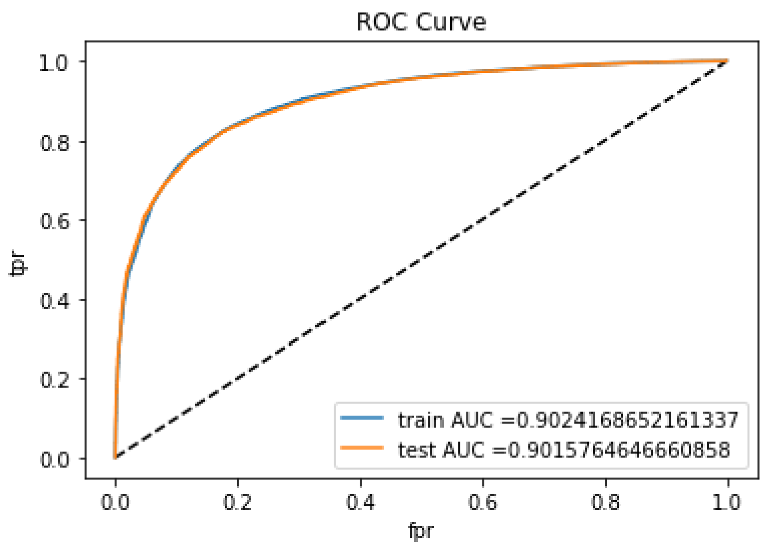
```
+---------------+--------------+---------------+
| Mean CV Score | Std CV Score |     Param     |
+---------------+--------------+---------------+
|     0.825     |   0.02433    | {'C': 0.0001} |
|     0.895     |   0.01698    |  {'C': 0.001} |
|     0.901     |   0.01463    |  {'C': 0.01}  |
|     0.901     |    0.0141    |   {'C': 0.1}  |
|     0.901     |   0.01402    |    {'C': 1}   |
|     0.901     |   0.01401    |   {'C': 10}   |
|     0.901     |   0.01401    |   {'C': 100}  |
|     0.901     |   0.01402    |  {'C': 1000}  |
|     0.901     |   0.01402    |  {'C': 10000} |
+---------------+--------------+---------------+

The best estimator:LogisticRegression(C=0.1, class_weight=None, dual=Fa
lse, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
```

```
             n_jobs=None, penalty='l2', random_state=None, solver='warn',
             tol=0.0001, verbose=0, warm_start=False)

The best score is:0.9014769955102173
The best value of C is:{'C': 0.1}
Mean Score: 0.9015764646660858
```

In [149]:
```
best_estimator_w2v_l2 = gs_obj.best_params_
```

In [150]:
```
# Fitting the Avg W2v vectorizer on LogisticRegression Model with  pena
lty = 'l2'
model_avgw2v_l2 = LogisticRegression(C= list(best_estimator_w2v_l2.valu
es())[0],penalty = 'l2')
model_avgw2v_l2.fit(sent_vectors_train,y_train)
y_pred = model_avgw2v_l2.predict(sent_vectors_test)
```

In [151]:
```
# AUC- ROC plot
auc_train_avgw2v_l2, auc_test_avgw2v_l2 = plot_auc(model_avgw2v_l2, sen
t_vectors_train, sent_vectors_test)
```




```
train AUC: 0.9024168652161337
```

```
test AUC: 0.9015764646660858
```

In [152]:

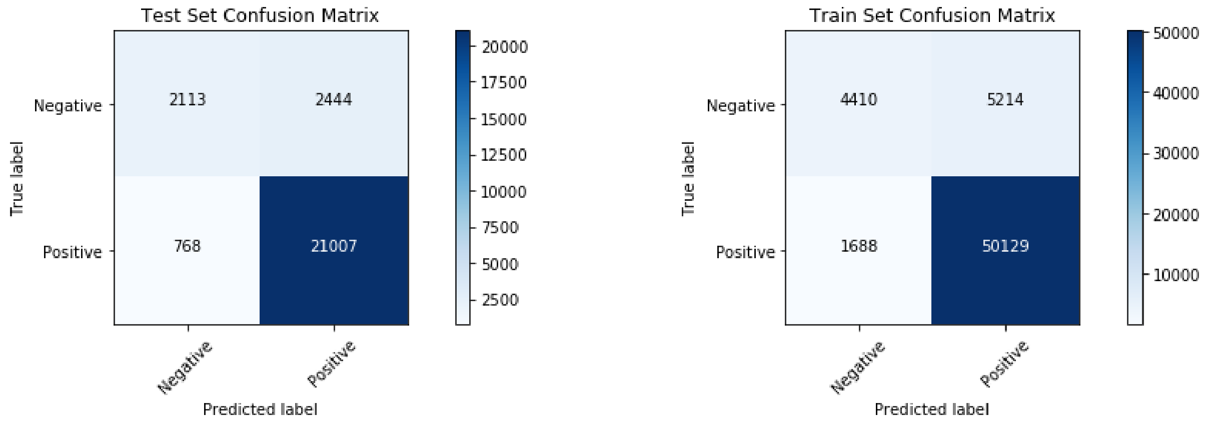
```
# Confusion Matrix
print_confusion_matrix(model_avgw2v_l2, sent_vectors_train, sent_vector
s_test)
```

```
*****Train confusion matrix*****
[[ 4410  5214]
 [ 1688 50129]]

*****Test confusion matrix*****
[[ 2113  2444]
 [  768 21007]]
```

In [155]:

```
# 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_l2.predict(sent_vect
ors_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_l2.predict(sent_vec
tors_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 = 0.1 using GridSearchCV with cv = 5 and with penalty l2.
2. We got train AUC: 0.9024168652161337 and test AUC: 0.9015764646660858
3. Using the confusion matrix, we can say that our model correctly predicted 21007 positive reviews and 2113 negative reviews.
4. The model incorrectly classified 768 negative reviews and 2444 positive reviews.
5. The True Postive Rate is 96.42 and the True Negative Rate is 47.59
6. The accuracy of the model is 87.97

[4.4.1.2] TFIDF weighted W2v

[5.4] Logistic Regression on TFIDF W2V, SET 4

In [114]:
```
# 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 [115]:

```
# 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
[27:08<00:00, 37.73it/s]
```

In [116]:

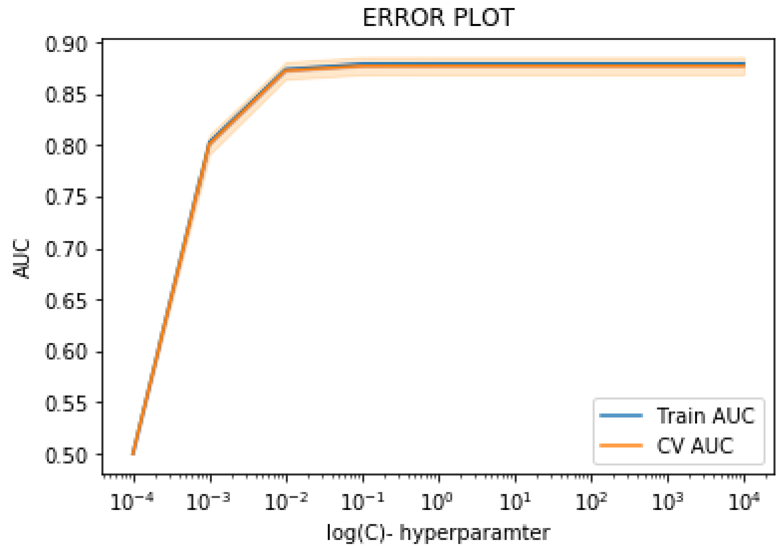
```
# TF-IDF weighted Word2Vec for sentences in X_test
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
```

```
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%|██████████████████████████████████████████████████████████████████| 26332/26332
[11:50<00:00, 37.08it/s]
```

[5.4.1] Applying Logistic Regression with L1 regularization on TFIDF W2V, SET 4

In [117]:
```
best_estimator_tfidfw2v_l1 = get_best_hyperparameter_C(model, tfidf_sen
t_vectors_train, tfidf_sent_vectors_test, y_train, y_test, penalty_l =
'l1' )
```

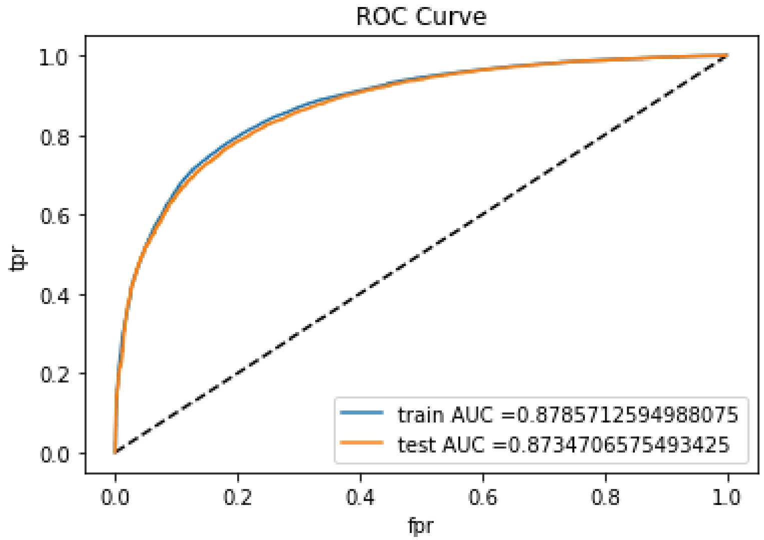



```
+---------------+-------------+---------------+
| Mean CV Score | Std CV Score |     Param     |
+---------------+-------------+---------------+
|      0.5      |     0.0     | {'C': 0.0001} |
|     0.801     |   0.01918   |  {'C': 0.001} |
|     0.872     |   0.01642   |  {'C': 0.01}  |
|     0.877     |   0.01663   |   {'C': 0.1}  |
|     0.877     |    0.0166   |    {'C': 1}   |
|     0.877     |   0.01661   |   {'C': 10}   |
|     0.877     |   0.01661   |   {'C': 100}  |
|     0.877     |   0.01661   |  {'C': 1000}  |
|     0.877     |   0.01661   |  {'C': 10000} |
+---------------+-------------+---------------+

The best estimator:LogisticRegression(C=1, class_weight=None, dual=Fals
e, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l1', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)

The best score is:0.8769711699379582
```

```
The best value of C is:{'C': 1}
Mean Score: 0.8734700629631506
```

In [118]:
```
# Fitting the TFIDF - weighted W2V vectorizer on LogisticRegression Mod
el
model_tfidfw2v_l1 = LogisticRegression(C= list(best_estimator_tfidfw2v_
l1.values())[0], penalty = 'l1')
model_tfidfw2v_l1.fit(tfidf_sent_vectors_train,y_train)
y_pred = model_tfidfw2v_l1.predict(tfidf_sent_vectors_test)
```

In [119]:
```
# AUC- ROC plot
auc_train_tfidfw2v_l1, auc_test_tfidfw2v_l1 = plot_auc(model_tfidfw2v_l
1, tfidf_sent_vectors_train, tfidf_sent_vectors_test)
```




```
train AUC: 0.8785712594988075
test AUC: 0.8734706575493425
```

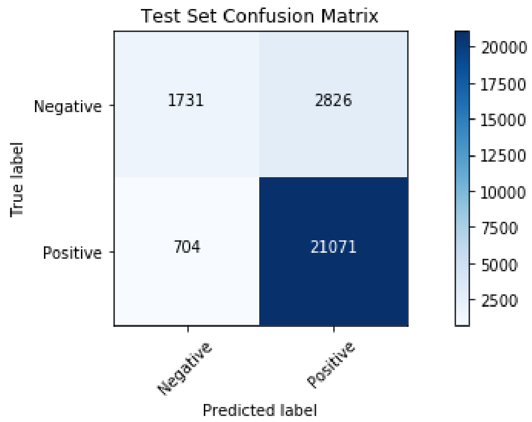
In [120]:
```
# Confusion Matrix
print_confusion_matrix(model_tfidfw2v_l1, tfidf_sent_vectors_train, tfi
df_sent_vectors_test)
```

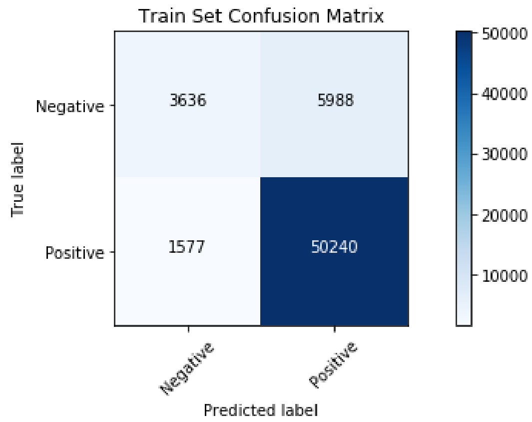
```
*****Train confusion matrix*****
[[ 3636  5988]
 [ 1577 50240]]

*****Test confusion matrix*****
[[ 1731  2826]
 [  704 21071]]
```

In [121]:

```
# 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_l1.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='Test Set Confusion Matrix');

plt.subplot(122) # Train Confusion matrix
cnf_matrix = confusion_matrix(y_train, model_tfidfw2v_l1.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='Train Set Confusion Matrix');
```

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



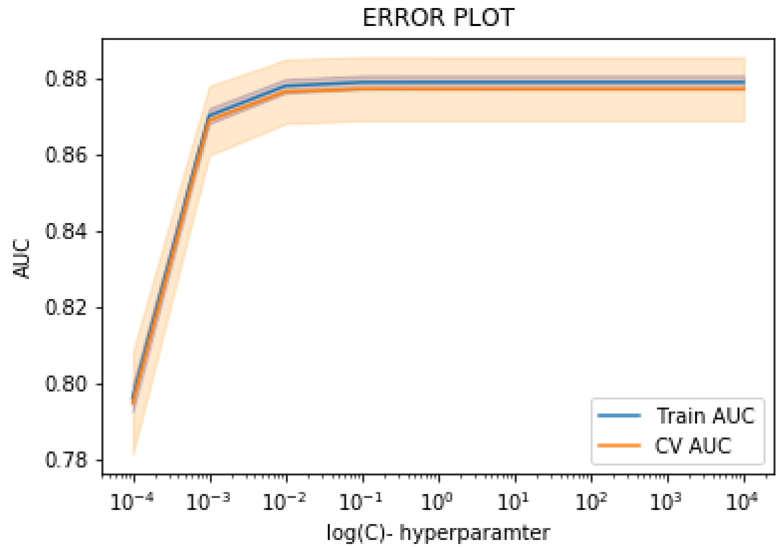


Observation

1. For the BoW vectorizer, we calculated C = 1 using GridSearchCV with cv = 5 and with penalty l1.
2. We got train AUC: 0.8785712594988075 and test AUC: 0.8734706575493425
3. Using the confusion matrix, we can say that our model correctly predicted 21071 positive reviews and 1731 negative reviews.
4. The model incorrectly classified 704 negative reviews and 2826 positive reviews.
5. The True Postive Rate is 96.60 and the True Negative Rate is 39.52
6. The accuracy of the model is 86.72

[5.4.2] Applying Logistic Regression with L2 regularization on TFIDF W2V, SET 4

In [122]:
```
best_estimator_tfidfw2v_l2 = get_best_hyperparameter_C(model, tfidf_sent_vectors_train, tfidf_sent_vectors_test, y_train, y_test, penalty_l = 'l2' )
```

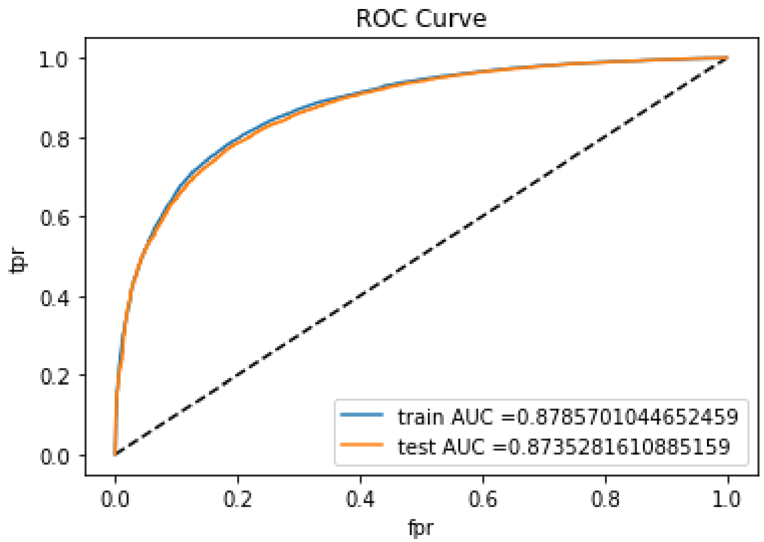



```
+---------------+--------------+---------------+
| Mean CV Score | Std CV Score |     Param     |
+---------------+--------------+---------------+
|     0.795     |   0.02675    | {'C': 0.0001} |
|     0.869     |   0.01828    |  {'C': 0.001} |
|     0.876     |   0.01677    |  {'C': 0.01}  |
|     0.877     |   0.01661    |   {'C': 0.1}  |
|     0.877     |   0.01662    |    {'C': 1}   |
|     0.877     |   0.01661    |   {'C': 10}   |
|     0.877     |   0.01661    |   {'C': 100}  |
|     0.877     |   0.01661    |  {'C': 1000}  |
|     0.877     |   0.01661    |  {'C': 10000} |
+---------------+--------------+---------------+

The best estimator:LogisticRegression(C=0.1, class_weight=None, dual=Fa
lse, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)

The best score is:0.8769926148015947
The best value of C is:{'C': 0.1}
Mean Score: 0.8735281610885159
```

```
Mean Score: 0.8735281610885159
```

In [123]:
```
# Fitting the TFIDF - weighted W2V vectorizer on LogisticRegression Mod
el with C =  and penalty = 'l2'
model_tfidfw2v_l2 = LogisticRegression(C= list(best_estimator_tfidfw2v_
l2.values())[0],penalty = 'l2')
model_tfidfw2v_l2.fit(tfidf_sent_vectors_train,y_train)
y_pred = model_tfidfw2v_l2.predict(tfidf_sent_vectors_test)
```

In [124]:
```
# AUC- ROC plot
auc_train_tfidfw2v_l2, auc_test_tfidfw2v_l2 = plot_auc(model_tfidfw2v_l
2, tfidf_sent_vectors_train, tfidf_sent_vectors_test)
```




```
train AUC: 0.8785701044652459
test AUC: 0.8735281610885159
```

In [125]:
```
# Confusion Matrix
print_confusion_matrix(model_tfidfw2v_l2, tfidf_sent_vectors_train, tfi
df_sent_vectors_test)
```

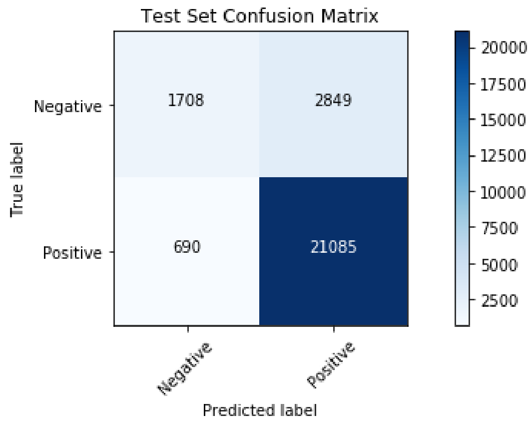
```
*****Train confusion matrix*****
[[ 3607  6017]
```

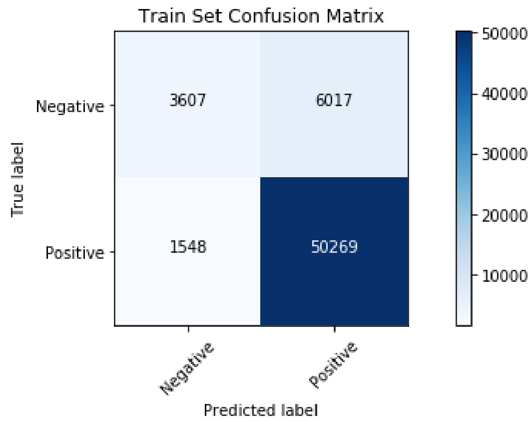
```
 [ 1548 50269]]

*****Test confusion matrix*****
[[ 1708  2849]
 [  690 21085]]
```

In [126]:

```
# 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_l2.predict(tfidf_s
ent_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_l2.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 TFIDF-W2V vectorizer, we calculated C = 0.1 using GridSearchCV with cv = 5 and with penalty l2.
2. We got train AUC: 0.8785701044652459 and test AUC: 0.8735281610885159
3. Using the confusion matrix, we can say that our model correctly predicted 21085 positive reviews and 1702 negative reviews.
4. The model incorrectly classified 690 negative reviews and 2849 positive reviews.
5. The True Postive Rate is 96.6 and the True Negative Rate is 39.54
6. The accuracy of the model is 86.73

Conclusions

In [157]:
```
C = PrettyTable()

C.field_names = ['Sr. No', 'Vectorizer','Norm','C', 'Train AUC', 'Test
 AUC']
C.add_row([1, 'BoW', 'L1', list(best_estimator_bow_l1.values())[0], auc
_train_bow_l1, auc_train_bow_l1])
C.add_row([1, 'BoW', 'L2',list(best_estimator_bow_l2.values())[0] ,auc_
train_bow_l2 ,auc_test_bow_l2])
```

```
C.add_row([1, 'TF_IDF', 'L1', list(best_estimator_tfidf_l1.values())[0
], auc_train_tfidf_l1, auc_test_tfidf_l1])
C.add_row([1, 'TF_IDF', 'L2',list(best_estimator_tfidf_l2.values())[0]
, auc_train_tfidf_l2, auc_train_tfidf_l2])
C.add_row([1, 'Avg-W2V', 'L1',list(best_estimator_w2v_l1.values())[0] ,
auc_train_avgw2v_l1 ,auc_test_avgw2v_l1])
C.add_row([1, 'Avg-W2V', 'L2', list(best_estimator_w2v_l2.values())[0],
auc_train_avgw2v_l2 ,auc_test_avgw2v_l2])
C.add_row([1, 'TFIDF-W2V', 'L1',list(best_estimator_tfidfw2v_l1.values
())[0] ,auc_train_tfidfw2v_l1, auc_test_tfidfw2v_l1])
C.add_row([1, 'TFIDF-W2V', 'L2', list(best_estimator_tfidfw2v_l2.values
())[0], auc_train_tfidfw2v_l2,auc_test_tfidfw2v_l2])


print(C)
del C
```

```
+--------+-----------+------+-------+--------------------+------------
--------+
| Sr. No | Vectorizer | Norm |   C   |     Train AUC      |      Test A
UC      |
+--------+-----------+------+-------+--------------------+------------
--------+
|   1    |    BoW     |  L1  |  0.01 | 0.9695167883807346 | 0.969516788
3807346 |
|   1    |    BoW     |  L2  | 0.001 |  0.99309054211035  | 0.941579649
2294188 |
|   1    |   TF_IDF   |  L1  |   1   | 0.9672404879416822 | 0.960443662
0765118 |
|   1    |   TF_IDF   |  L2  |   10  | 0.9985166762221631 | 0.998516676
2221631 |
|   1    |  Avg-W2V   |  L1  |  100  | 0.902424731877006  | 0.901577966
2481638 |
|   1    |  Avg-W2V   |  L2  |  0.1  | 0.9024168652161337 | 0.901576464
6660858 |
|   1    | TFIDF-W2V  |  L1  |   1   | 0.8785712594988075 | 0.873470657
5493425 |
|   1    | TFIDF-W2V  |  L2  |  0.1  | 0.8785701044652459 | 0.873528161
0885159 |
```

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

Summary

1. We performed Logistic Regression with L1 and L2 normalization on BoW, TFIDF, Avg-W2V, TFIDF-WW2V on the Amazon Fine Food Reviews.
2. Made use of GridSearchCV to find the best value of C, the hyperparameter in logistic regression.
3. Performed Feature Engineering on the BoW model and found out the model slightly performed better.
4. Different vectors take on different C values. We saw C values being taken from 10**-4 to 10**4
5. We obtained the colinear features using perturbation and found out that we have less than 0.02% of colinear features.
6. If dataset is balanced, we can get better TNR.