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 nltk
import string
```

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer

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

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

from tqdm import tqdm
import os
```

```
C:\Users\hemant\Anaconda\lib\site-packages\gensim\utils.py:1209: UserWa
rning: detected Windows; aliasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_seria
l")
```

In [2]:

```
# using SQLite Table to read data.
con = sqlite3.connect(r'G:\database_assignment\Logistic_regression\data
base5.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 Score
 != 3 """, con)
# for tsne assignment you can take 5k data points

#filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Scor
e != 3 LIMIT 5000""", con)

# Give reviews with Score>3 a positive rating(1), and reviews with a sc
ore<3 a negative rating(0).
def partition(x):
    if x < 3:
        return 0
    return 1

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

```
Number of data points in our data (525814, 10)
```

Out[2]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulnes
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulnes
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1

In [3]:

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

In [4]:

```
print(display.shape)
display.head()
```

```
(80668, 7)
```

Out[4]:

	UserId	ProductId	ProfileName	Time	Score	Text	COU

	UserId	ProductId	ProfileName	Time	Score	Text	COU
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 [5]:

```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[5]:

	UserId	ProductId	ProfileName	Time	Score	Text

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

In [6]:
```
display['COUNT(*)'].sum()
```
Out[6]: 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 [7]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```
Out[7]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfuln

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfuln
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	2
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	2
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	2
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	2
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	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 [8]:
```
#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 [9]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', inplace=False)
final.shape
```

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

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

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

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

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

display.head()
```

Out[11]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfuln
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2

In [12]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [13]:
```
#Before starting the next phase of preprocessing lets see the number of
 entries left
print(final.shape)
```

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

```
(364171, 10)
```

Out[13]:
```
1    307061
0     57110
Name: Score, dtype: int64
```

[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 [14]:
```
# printing some random reviews
sent_0 = final['Text'].values[0]
print(sent_0)
print("="*50)
```

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

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

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

```
this witty little book makes my son laugh at loud. i recite it in the c
ar as we're driving along and he always can sing the refrain. he's lear
ned about whales, India, drooping roses:  i love all the new words this
book  introduces and the silliness of it all.  this is a classic book i
am  willing to bet my son will STILL be able to recite from memory when
he is  in college
==================================================
I was really looking forward to these pods based on the reviews.  Starb
ucks is good, but I prefer bolder taste.... imagine my surprise when I
ordered 2 boxes - both were expired! One expired back in 2005 for gosh
sakes.  I admit that Amazon agreed to credit me for cost plus part of s
hipping, but geez, 2 years expired!!!  I'm hoping to find local San Die
go area shoppe that carries pods so that I can try something different
than starbucks.
==================================================
Great ingredients although, chicken should have been 1st rather than ch
icken broth, the only thing I do not think belongs in it is Canola oil.
Canola or rapeseed is not someting a dog would ever find in nature and
if it did find rapeseed in nature and eat it, it would poison them. Tod
ay's Food industries have convinced the masses that Canola oil is a saf
e and even better oil than olive or virgin coconut, facts though say ot
herwise. Until the late 70's it was poisonous until they figured out a
way to fix that. I still like it but it could be better.
==================================================
Can't do sugar.  Have tried scores of SF Syrups.  NONE of them can touc
h the excellence of this product.<br /><br />Thick, delicious.  Perfec
t.  3 ingredients: Water, Maltitol, Natural Maple Flavor.  PERIOD.  No

chemicals.  No garbage.<br /><br />Have numerous friends & family membe
```

```
chemicals.  No garbage.<br /><br />Have numerous friends & family membe
rs hooked on this stuff.  My husband & son, who do NOT like "sugar fre
e" prefer this over major label regular syrup.<br /><br />I use this as
my SWEETENER in baking: cheesecakes, white brownies, muffins, pumpkin p
ies, etc... Unbelievably delicious...<br /><br />Can you tell I like i
t? :)
==================================================
```

In [15]:

```python
# 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)
```

```
this witty little book makes my son laugh at loud. i recite it in the c
ar as we're driving along and he always can sing the refrain. he's lear
ned about whales, India, drooping roses:  i love all the new words this
book  introduces and the silliness of it all.  this is a classic book i
am  willing to bet my son will STILL be able to recite from memory when
he is  in college
```

In [16]:

```python
# 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')
```

```python
text = soup.get_text()
print(text)
print("="*50)

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

```
this witty little book makes my son laugh at loud. i recite it in the c
ar as we're driving along and he always can sing the refrain. he's lear
ned about whales, India, drooping roses:  i love all the new words this
book  introduces and the silliness of it all.  this is a classic book i
am  willing to bet my son will STILL be able to recite from memory when
he is  in college
==================================================
I was really looking forward to these pods based on the reviews.  Starb
ucks is good, but I prefer bolder taste.... imagine my surprise when I
ordered 2 boxes - both were expired! One expired back in 2005 for gosh
sakes.  I admit that Amazon agreed to credit me for cost plus part of s
hipping, but geez, 2 years expired!!!  I'm hoping to find local San Die
go area shoppe that carries pods so that I can try something different
than starbucks.
==================================================
Great ingredients although, chicken should have been 1st rather than ch
icken broth, the only thing I do not think belongs in it is Canola oil.
Canola or rapeseed is not someting a dog would ever find in nature and
if it did find rapeseed in nature and eat it, it would poison them. Tod
ay's Food industries have convinced the masses that Canola oil is a saf
e and even better oil than olive or virgin coconut, facts though say ot
herwise. Until the late 70's it was poisonous until they figured out a
way to fix that. I still like it but it could be better.
==================================================
Can't do sugar.  Have tried scores of SF Syrups.  NONE of them can touc
h the excellence of this product.Thick, delicious.  Perfect.  3 ingredi
ents: Water, Maltitol, Natural Maple Flavor.  PERIOD.  No chemicals.  N
o garbage.Have numerous friends & family members hooked on this stuff.
My husband & son, who do NOT like "sugar free" prefer this over major l
abel regular syrup.I use this as my SWEETENER in baking: cheesecakes, w

hite brownies, muffins, pumpkin pies, etc... Unbelievably delicious...C
```

an you tell I like it? :)

In [17]:

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

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

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

In [18]:

```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
Great ingredients although, chicken should have been 1st rather than ch
icken broth, the only thing I do not think belongs in it is Canola oil.
Canola or rapeseed is not someting a dog would ever find in nature and
if it did find rapeseed in nature and eat it, it would poison them. Tod
ay is Food industries have convinced the masses that Canola oil is a sa
fe and even better oil than olive or virgin coconut, facts though say o
therwise. Until the late 70 is it was poisonous until they figured out
a way to fix that. I still like it but it could be better.
==================================================
```

In [19]:

```
#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)
```

```
this witty little book makes my son laugh at loud. i recite it in the c
ar as we're driving along and he always can sing the refrain. he's lear
ned about whales, India, drooping roses:  i love all the new words this
book  introduces and the silliness of it all.  this is a classic book i
am  willing to bet my son will STILL be able to recite from memory when
he is  in college
```

In [20]:

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

```
Great ingredients although chicken should have been 1st rather than chi
cken broth the only thing I do not think belongs in it is Canola oil Ca
nola or rapeseed is not someting a dog would ever find in nature and if
it did find rapeseed in nature and eat it it would poison them Today is
Food industries have convinced the masses that Canola oil is a safe and
even better oil than olive or virgin coconut facts though say otherwise
Until the late 70 is it was poisonous until they figured out a way to f
ix that I still like it but it could be better
```

In [21]:

```
# 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 [22]:

```
# Combining all the above stundents
if not os.path.isfile('final.sqlite'):

    from tqdm import tqdm
    final_string=[]
    # 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.lo
wer() not in stopwords)
        final_string.append(sentance.strip())
```

```
        #############---- storing the data into .sqlite file ------###
#####################
    final['CleanedText']=final_string #adding a column of CleanedText w
hich displays the data after pre-processing of the review
    final['CleanedText']=final['CleanedText'].str.decode("utf-8")
        # store final table into an SQlLite table for future.
    conn = sqlite3.connect('final.sqlite')
    c=conn.cursor()
    conn.text_factory = str
    final05.to_sql('Reviews', conn,  schema=None, if_exists='replace',
 \
                 index=True, index_label=None, chunksize=None, dtype=No
ne)
    conn.close()
```

In [23]:

```
if os.path.isfile('final.sqlite'):
    conn = sqlite3.connect('final.sqlite')
    final1 = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score !=
 3 """, conn)
    conn.close()
else:
    print("Please the above cell")
```

In [24]:

```
final1.head(3)
final1['CleanedText'].head(5)
```

Out[24]:

```
0    witti littl book make son laugh loud recit car...
1    grew read sendak book watch realli rosi movi i...
2    fun way children learn month year learn poem t...
3    great littl book read nice rhythm well good re...
4    book poetri month year goe month cute littl po...
Name: CleanedText, dtype: object
```

In [25]:

```
sorted_sample = final1.sort_values('Time', axis=0, ascending=True, inpl
ace=False, kind='quicksort', na_position='last')
sample_60000 = sorted_sample.iloc[0:100000]
```

```
final.shape
y = sample_60000['Score']
```

In [26]:
```
sample_60000.shape
```

Out[26]: (100000, 12)

In [27]:
```
sample_60000["length"] = sample_60000['Text'].apply(len)
```

In [28]:
```
sample_60000.shape
```

Out[28]: (100000, 13)

In [29]:
```
y.shape
```

Out[29]: (100000,)

In [30]:
```
sample_60000.head(3)
```

Out[30]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerato
0	138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0
30	138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerato
424	417839	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0

In [31]:
```
sample_60000['Score'].value_counts()
```

Out[31]:
```
1    87729
0    12271
Name: Score, dtype: int64
```

In [32]:
```
from sklearn.model_selection import train_test_split

x_train, x_ts, y_train, y_ts = train_test_split(sample_60000, y, test_s
ize=0.33) # this is random splitting
```

In [33]:
```
x_train.shape
```

Out[33]:
```
(67000, 13)
```

In [34]:
```
y_train.shape
```

Out[34]:
```
(67000,)
```

In [35]:
```
x_ts.shape
```

Out[35]:
```
(33000, 13)
```

In [36]:
```
y_ts.shape
```

Out[36]:
```
(33000,)
```

[3.2] Preprocessing Review Summary

[4] Featurization

[4.1] BAG OF WORDS

[4.2] Bi-Grams and n-Grams.

In [37]:
```
#bi-gram, tri-gram and n-gram
from sklearn import preprocessing


#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) #in scikit-l
earn
x_tr_final_counts_bigram = count_vect.fit_transform(x_train['CleanedTex
t'].values)
#x_cv_final_counts_bigram = count_vect.transform(x_cv['CleanedText'].va
lues)
x_ts_final_counts_bigram = count_vect.transform(x_ts['CleanedText'].val
ues)


print("the type of count vectorizer ",type(x_tr_final_counts_bigram))
print("the shape of out text BOW vectorizer ",x_tr_final_counts_bigram.
get_shape())
```

```
print("the number of unique words ", x_tr_final_counts_bigram.get_shape
()[1])

#print("the type of count vectorizer ",type(x_cv_final_counts_bigram))
#print("the shape of out text BOW vectorizer ",x_cv_final_counts_bigra
m.get_shape())
#print("the number of unique words ", x_cv_final_counts_bigram.get_shap
e()[1])

print("the type of count vectorizer ",type(x_ts_final_counts_bigram))
print("the shape of out text BOW vectorizer ",x_ts_final_counts_bigram.
get_shape())
print("the number of unique words ", x_ts_final_counts_bigram.get_shape
()[1])


x_tr_final_counts_bigram = preprocessing.normalize(x_tr_final_counts_bi
gram)
#x_cv_final_counts_bigram = preprocessing.normalize(x_cv_final_counts_b
igram)
x_ts_final_counts_bigram = preprocessing.normalize(x_ts_final_counts_bi
gram)
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (67000, 38743)
the number of unique words  38743
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (33000, 38743)
the number of unique words  38743
```

[4.3] TF-IDF

In [38]:

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1, 2),min_df=10)
x_tr_final_counts_tfidf = tf_idf_vect.fit_transform(x_train['CleanedTex
t'].values)
#x_cv_final_counts_tfidf = tf_idf_vect.transform(x_cv['CleanedText'].va
lues)
x_ts_final_counts_tfidf = tf_idf_vect.transform(x_ts['CleanedText'].val
```

```
ues)


print("the type of count vectorizer ",type(x_tr_final_counts_tfidf))
print("the shape of out text TFIDF vectorizer ",x_tr_final_counts_tfidf
.get_shape())
print("the number of unique words including both unigrams and bigrams "
, x_tr_final_counts_tfidf.get_shape()[1])

#print("the type of count vectorizer ",type(x_cv_final_counts_tfidf))
#print("the shape of out text TFIDF vectorizer ",x_cv_final_counts_tfid
f.get_shape())
#print("the number of unique words including both unigrams and bigrams
 ", x_cv_final_counts_tfidf.get_shape()[1])

print("the type of count vectorizer ",type(x_ts_final_counts_tfidf))
print("the shape of out text TFIDF vectorizer ",x_ts_final_counts_tfidf
.get_shape())
print("the number of unique words including both unigrams and bigrams "
, x_ts_final_counts_tfidf.get_shape()[1])


x_tr_final_counts_tfidf = preprocessing.normalize(x_tr_final_counts_tfi
df)
#x_cv_final_counts_tfidf = preprocessing.normalize(x_cv_final_counts_tf
idf)
x_ts_final_counts_tfidf = preprocessing.normalize(x_ts_final_counts_tfi
df)
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (67000, 38743)
the number of unique words including both unigrams and bigrams  38743
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (33000, 38743)
the number of unique words including both unigrams and bigrams  38743
```

[4.4] Word2Vec Train Data

In [39]:
```
# Train your own Word2Vec model using your own text corpus
i=0
list_of_sentance_train=[]
for sentance in x_train['CleanedText'].values:
    list_of_sentance_train.append(sentance.split())
```

In [ ]:
```
# Train your own Word2Vec model using your own text corpus
#i=0
#list_of_sentance_cv=[]
#for sentance in x_cv['CleanedText'].values:
#    list_of_sentance_cv.append(sentance.split())
```

In [40]:
```
# Train your own Word2Vec model using your own text corpus
i=0
list_of_sentance_ts=[]
for sentance in x_ts['CleanedText'].values:
    list_of_sentance_ts.append(sentance.split())
```

In [41]:
```
print(len(list_of_sentance_train))
#print(len(list_of_sentance_cv))
print(len(list_of_sentance_ts))
```

```
67000
33000
```

In [42]:
```
def convertByteStringtoString(sentlist):
    for x in sentlist:
        for i in range(len(x)):
            x[i] = x[i]

    return sentlist
```

In [43]:
```
list_of_sentance_train = convertByteStringtoString(list_of_sentance_tra
in)
#list_of_sentance_cv = convertByteStringtoString(list_of_sentance_cv)
list_of_sentance_ts = convertByteStringtoString(list_of_sentance_ts)
```

In [44]:
```
# min_count = 5 considers only words that occured atleast 5 times
w2v_model=Word2Vec(list_of_sentance_train,min_count=5,size=50, workers=
4)
```

In [45]:
```
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  10576
sample words  ['high', 'recommend', 'gluten', 'free', 'diet', 'even',
'your', 'best', 'cooki', 'ive', 'ever', 'must', 'food', 'cabinet', 'exp
ect', 'stronger', 'lemon', 'flavor', 'use', 'lot', 'realli', 'tast', 't
erribl', 'pretti', 'mediocr', 'product', 'great', 'dog', 'keep', 'teet
h', 'clean', 'breath', 'fresh', 'tri', 'alway', 'packag', 'hand', 'fin
d', 'store', 'amazon', 'com', 'mix', 'make', 'good', 'oat', 'bran', 'mu
ffin', 'easi', 'like', 'throw']
```

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

[4.4.1.1] Avg W2v

In [46]:
```
# average Word2Vec
# compute average word2vec for each review.

train_avgw2v = []; # the avg-w2v for each sentence/review is stored 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
    train_avgw2v.append(sent_vec)
print(len(train_avgw2v))
print(len(train_avgw2v[0]))
```

```
100%|██████████████████████████████████████████████████| 67000/67000 [02:08<00:00, 52
2.05it/s]
```

```
67000
50
```

In [ ]:

```
"""
cv_avgw2v = []; # the avg-w2v for each sentence/review is stored in thi
s list
for sent in tqdm(list_of_sentance_cv): # 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
    cv_avgw2v.append(sent_vec)
print(len(cv_avgw2v))
print(len(cv_avgw2v[0]))
"""
```

In [47]:

```
test_avgw2v = []; # the avg-w2v for each sentence/review is stored in t
his list
for sent in tqdm(list_of_sentance_ts): # 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
    test_avgw2v.append(sent_vec)
print(len(test_avgw2v))
print(len(test_avgw2v[0]))
```

```
100%|██████████████████████████████████| 33000/33000 [01:05<00:00, 50
1.33it/s]
```

```
33000
50
```

In [48]:
```
train_avgw2v = preprocessing.normalize(train_avgw2v)
#cv_avgw2v = preprocessing.normalize(cv_avgw2v)
test_avgw2v = preprocessing.normalize(test_avgw2v)
```

In [49]:
```
train_avgw2v = np.array(train_avgw2v)
#cv_avgw2v = np.array(cv_avgw2v)
test_avgw2v = np.array(test_avgw2v)
```

In [50]:
```
np.isnan(train_avgw2v).any()
```

Out[50]:
```
False
```

In [ ]:
```
#np.isnan(cv_avgw2v).any()
```

In [51]:
```
np.isnan(test_avgw2v).any()
```

Out[51]:
```
False
```

[4.4.1.2] TFIDF weighted W2v

In [53]:
```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
x_tr_final_counts_TFIDF_w2v = model.fit_transform(x_train['CleanedText'
].values)
#x_cv_final_counts_TFIDF_w2v = model.transform(x_cv['CleanedText'].valu
es)
x_ts_final_counts_TFIDF_w2v = model.transform(x_ts['CleanedText'].value
s)

# 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 [54]:
```
# TF-IDF weighted Word2Vec Train Data
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 = []; # the tfidf-w2v for each sentence/review is st
ored 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.append(sent_vec)
    row += 1
```

```
100%|██████████| 67000/67000 [25:27<00:00, 5
7.95it/s]
```

In [ ]:
```
"""
# TF-IDF weighted Word2Vec cv Data
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_cv = []; # the tfidf-w2v for each sentence/review is
 stored in this list
row=0;
for sent in tqdm(list_of_sentance_cv): # 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_cv.append(sent_vec)
    row += 1
"""
```

In [55]:
```
# TF-IDF weighted Word2Vec test Data
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
```

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

```
100%|██████████████████████████████| 33000/33000 [13:29<00:00, 40.75it/s]
```

In [56]:
```python
tfidf_sent_vectors = preprocessing.normalize(tfidf_sent_vectors)
#tfidf_sent_vectors_cv = preprocessing.normalize(tfidf_sent_vectors_cv)
tfidf_sent_vectors_ts = preprocessing.normalize(tfidf_sent_vectors_ts)
```

In [57]:
```python
tfidf_sent_vectors = np.array(tfidf_sent_vectors)
#tfidf_sent_vectors_cv = np.array(tfidf_sent_vectors_cv)
tfidf_sent_vectors_ts = np.array(tfidf_sent_vectors_ts)
```

In [58]:
```python
np.isnan(tfidf_sent_vectors).any()
```

Out[58]:
```
False
```

In [ ]:
```
#np.isnan(tfidf_sent_vectors_cv).any()
```

In [59]:
```
np.isnan(tfidf_sent_vectors_ts).any()
```

Out[59]:
```
False
```

In [100]:
```
#To show how Time Series Split splits the data
from sklearn.model_selection import TimeSeriesSplit
tscv = TimeSeriesSplit(n_splits=10)
for train, cv in tscv.split(x_tr_final_counts_bigram):
    print("%s %s" % (train, cv))
#    print(x_tr_final_counts_bigram[train].shape,x_tr_final_counts_bigr
am[cv].shape)
```

```
[   0    1    2 ... 6097 6098 6099] [ 6100  6101  6102 ... 12187 12188
12189]
[    0     1     2 ... 12187 12188 12189] [12190 12191 12192 ... 18277
18278 18279]
[    0     1     2 ... 18277 18278 18279] [18280 18281 18282 ... 24367
24368 24369]
[    0     1     2 ... 24367 24368 24369] [24370 24371 24372 ... 30457
30458 30459]
[    0     1     2 ... 30457 30458 30459] [30460 30461 30462 ... 36547
36548 36549]
[    0     1     2 ... 36547 36548 36549] [36550 36551 36552 ... 42637
42638 42639]
[    0     1     2 ... 42637 42638 42639] [42640 42641 42642 ... 48727
48728 48729]
[    0     1     2 ... 48727 48728 48729] [48730 48731 48732 ... 54817
54818 54819]
[    0     1     2 ... 54817 54818 54819] [54820 54821 54822 ... 60907
60908 60909]
[    0     1     2 ... 60907 60908 60909] [60910 60911 60912 ... 66997
66998 66999]
```

[5] Assignment 5: Apply Logistic Regression

1. **Apply Logistic Regression on these feature sets**

    - SET 1:Review text, preprocessed one converted into vectors using (BOW)
    - SET 2:Review text, preprocessed one converted into vectors using (TFIDF)
    - SET 3:Review text, preprocessed one converted into vectors using (AVG W2v)
    - SET 4:Review text, preprocessed one converted into vectors using (TFIDF W2v)

2. **Hyper paramter tuning (find best hyper parameters corresponding the algorithm that you choose)**

    - Find the best hyper parameter which will give the maximum AUC value
    - Find the best hyper paramter using k-fold cross validation or simple cross validation data
    - Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this task of hyperparameter tuning

3. **Pertubation Test**

    - Get the weights W after fit your model with the data X.
    - Add a noise to the X (X' = X + e) and get the new data set X' (if X is a sparse matrix, X.data+=e)
    - Fit the model again on data X' and get the weights W'
    - Add a small eps value(to eliminate the divisible by zero error) to W and W' i.e W=W+10^-6 and W' = W'+10^-6
    - Now find the % change between W and W' (| (W-W') / (W) |)*100)
    - Calculate the 0th, 10th, 20th, 30th, ...100th percentiles, and observe any sudden rise in the values of percentage_change_vector
    - Ex: consider your 99th percentile is 1.3 and your 100th percentiles are 34.6, there is sudden rise from 1.3 to 34.6, now calculate the 99.1, 99.2, 99.3,..., 100th percentile values and get the proper value after which there is sudden rise the values, assume it is 2.5
    - Print the feature names whose % change is more than a threshold x(in our example it's 2.5)

4. **Sparsity**

- Calculate sparsity on weight vector obtained after using L1 regularization

NOTE: Do sparsity and multicollinearity for any one of the vectorizers. Bow or tf-idf is recommended.

5. **Feature importance**

- Get top 10 important features for both positive and negative classes separately.

6. **Feature engineering**

- To increase the performance of your model, you can also experiment with with feature engineering like :
  - Taking length of reviews as another feature.
  - Considering some features from review summary as well.

7. **Representation of results**

- You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure.
- Once after you found the best hyper parameter, you need to train your model with it, and find the AUC on test data and plot the ROC curve on both train and test.
- Along with plotting ROC curve, you need to print the confusion matrix with predicted and original labels of test data points. Please visualize your confusion matrices using seaborn heatmaps.

8. **Conclusion**

- You need to summarize the results at the end of the notebook, summarize it in the table format. To print out a table please refer to this prettytable library link

Note: Data Leakage

1. There will be an issue of data-leakage if you vectorize the entire data and then split it into train/cv/test.
2. To avoid the issue of data-leakag, make sure to split your data first and then vectorize it.
3. While vectorizing your data, apply the method fit_transform() on you train data, and apply the method transform() on cv/test data.
4. For more details please go through this link.

Applying Logistic Regression

[5.1] Logistic Regression on BOW, SET 1

[5.1.1] Applying Logistic Regression with L1 regularization on BOW, SET 1

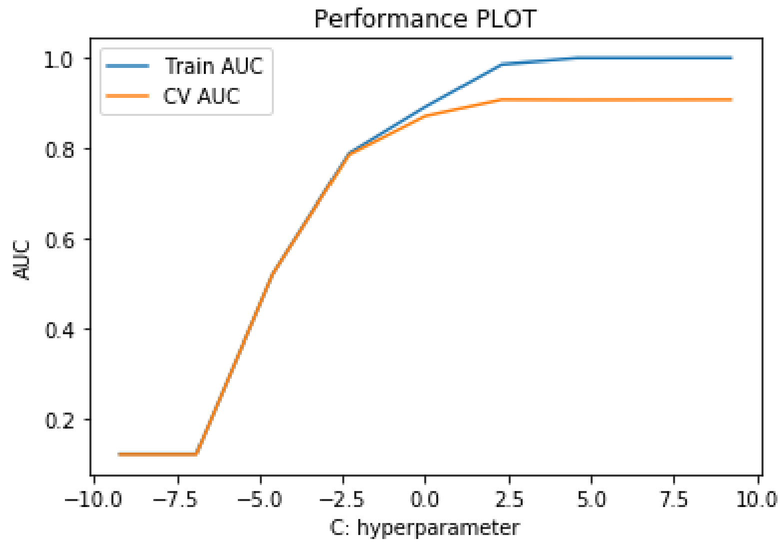
In [101]:
```
# Please write all the code with proper documentation
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score
from sklearn.metrics import roc_auc_score
from sklearn.metrics import accuracy_score
from math import log
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import GridSearchCV

alpha_values = np.arange(10)
C = np.array([0.0001,0.001,0.01,0.1,1,10,100,500,1000,10000])
cv_auc = []
train_auc = []
```

```
neigh = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[0.0001,0.001,0.01,0.1,1,10,100,500,1000,10000],
             'penalty':['l1'],'class_weight':['balanced']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
clf = RandomizedSearchCV(neigh,param_grid,cv=tscv,verbose=1)
clf.fit(x_tr_final_counts_bigram,y_train)


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




d = max(cv_auc)

i = np.where(cv_auc == d)

i = i[0][0]
best_alpha = float(C[i])
print("Best C is:-",best_alpha)


C = np.log(C)

plt.plot(C, train_auc, label='Train AUC')
plt.plot(C, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("Performance PLOT")
plt.show()
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
```

```
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  3.7min finished
```

```
Best C is:- 10.0
```

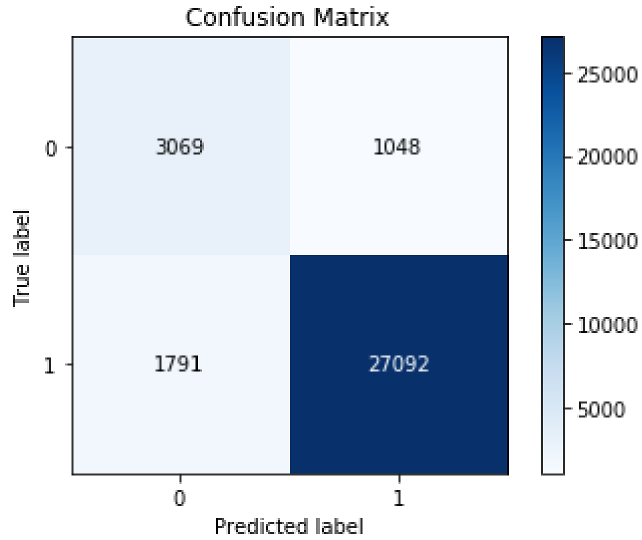


In [102]:
```
# LogisticRegression with best best "C" for l1 penalty of bow
model = LogisticRegression(penalty='l1',C = best_alpha,class_weight='ba
lanced')
model.fit(x_tr_final_counts_bigram,y_train)
#pred = model.predict_proba(x_ts_final_counts_bigram)
pred=model.predict(x_ts_final_counts_bigram)
    # evaluate CV AUC
auc_score_bowT_l1 = roc_auc_score(y_true=np.array(y_ts), y_score=model.
predict_proba(x_ts_final_counts_bigram)[:,1])*100
auc_score_bowT_lambda_l1 = best_alpha
print('\nThe AUC of the Logistic Regression classifier of best C = %f i
s %f%%' % (best_alpha, auc_score_bowT_l1))
```

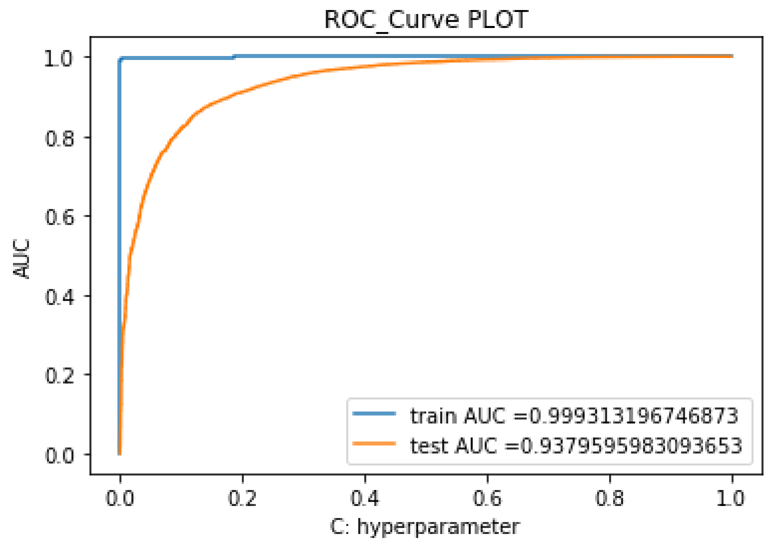
```
The AUC of the Logistic Regression classifier of best C = 10.000000 is
93.795960%
```

In [103]:
```
import scikitplot.metrics as skplt
skplt.plot_confusion_matrix(y_ts ,pred)
```

Out[103]: <matplotlib.axes._subplots.AxesSubplot at 0x6876864fd0>



In [104]:
```
from sklearn.metrics import roc_curve, auc

train_fpr, train_tpr, thresholds = roc_curve(y_train, model.predict_pro
ba(x_tr_final_counts_bigram)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_ts, model.predict_proba(x_
ts_final_counts_bigram)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
rain_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
tpr)))
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("ROC_Curve PLOT")
plt.show()
```



In [105]:
```
#classification report
from sklearn.metrics import classification_report
print(classification_report(y_ts, pred))
```

```
             precision    recall  f1-score   support

          0       0.63      0.75      0.68      4117
          1       0.96      0.94      0.95     28883

avg / total       0.92      0.91      0.92     33000
```

Terminology

true positives (TP): We predicted +ve review, and review is also +ve. true negatives (TN): We predicted -ve, and review is also -ve. false positives (FP): We predicted +ve, but the review is not actually +ve.(Also known as a "Type I error.") false negatives (FN): We predicted -ve, but the review is actually +ve.(Also known as a "Type II error.")

False Positive rate --> when it is actually -ve, how often does it predicted +ve = fp/actual-ve =

1048/4117 = .25

In [190]:
```
# FPR for bowt_l1
bowt_FPR_l1 = .25
```

[5.1.1.1] Calculating sparsity on weight vector obtained using L1 regularization on BOW, SET 1

In [107]:
```
# Please write all the code with proper documentation
import numpy as np

clf = LogisticRegression(C=10, penalty='l1');
clf.fit(x_tr_final_counts_bigram,y_train);
w = clf.coef_
print(np.count_nonzero(w))
```

```
7788
```

In [108]:
```
clf = LogisticRegression(C=5, penalty='l1');
clf.fit(x_tr_final_counts_bigram,y_train);
w = clf.coef_
print(np.count_nonzero(w))
```

```
4955
```

In [109]:
```
clf = LogisticRegression(C=1, penalty='l1');
clf.fit(x_tr_final_counts_bigram,y_train);
w = clf.coef_
print(np.count_nonzero(w))
```

```
1041
```

In [110]:
```
clf = LogisticRegression(C=.1, penalty='l1');
clf.fit(x_tr_final_counts_bigram,y_train);
w = clf.coef_
print(np.count_nonzero(w))
```

```
156
```

150

In [111]:
```
clf = LogisticRegression(C=.01, penalty='l1');
clf.fit(x_tr_final_counts_bigram,y_train);
w = clf.coef_
print(np.count_nonzero(w))
```

7

we can see how drastically the sparsity increases from 7788 non zero weights(@ c = 10) to only 7 non zero weights(@ c = .01) when we use L1 regulariazation

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

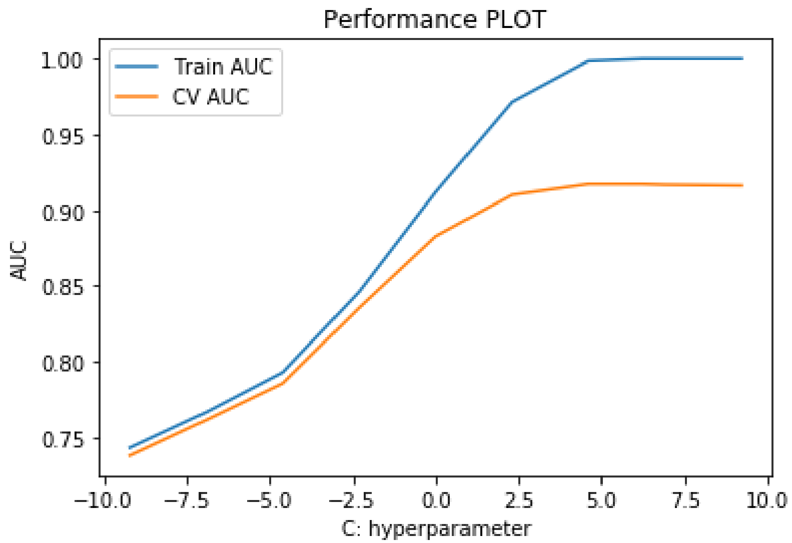
In [112]:
```
# Please write all the code with proper documentation
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score
from sklearn.metrics import roc_auc_score
from sklearn.metrics import accuracy_score
from math import log
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import GridSearchCV

alpha_values = np.arange(10)
C = np.array([0.0001,0.001,0.01,0.1,1,10,100,500,1000,10000])
cv_auc = []
train_auc = []


neigh = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[0.0001,0.001,0.01,0.1,1,10,100,500,1000,10000],
             'penalty':['l2'],'class_weight':['balanced']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
clf = RandomizedSearchCV(neigh,param_grid,cv=tscv,verbose=1)
clf.fit(x_tr_final_counts_bigram,y_train)
```

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



d = max(cv_auc)

i = np.where(cv_auc == d)

i = i[0][0]
best_alpha = float(C[i])
print("Best C is:-",best_alpha)


C = np.log(C)

plt.plot(C, train_auc, label='Train AUC')
plt.plot(C, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("Performance PLOT")
plt.show()
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
```

```
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  4.7min finished
```

```
Best C is:- 100.0
```



In [113]:

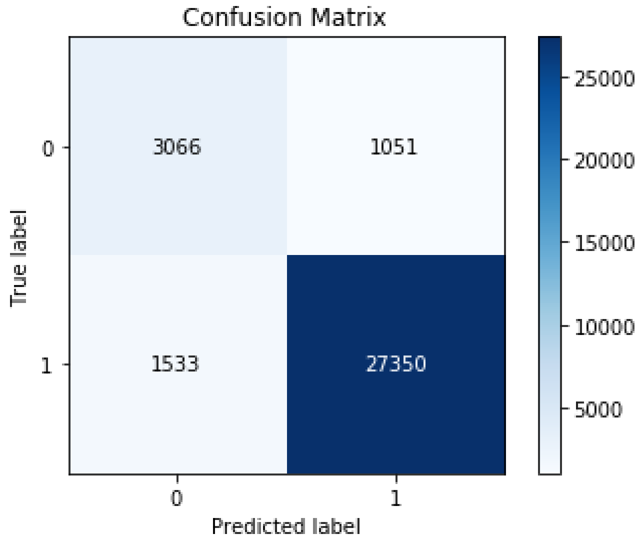
```
# LogisticRegression with best best "C" for l2 penalty of bow
model = LogisticRegression(penalty='l2',C = best_alpha,class_weight='ba
lanced')
model.fit(x_tr_final_counts_bigram,y_train)
#pred = model.predict_proba(x_ts_final_counts_bigram)
pred=model.predict(x_ts_final_counts_bigram)
    # evaluate CV AUC
auc_score_bowT_l2 = roc_auc_score(y_true=np.array(y_ts), y_score=model.
predict_proba(x_ts_final_counts_bigram)[:,1])*100
auc_score_bowT_lambda_l2 = best_alpha
print('\nThe AUC of the Logistic Regression classifier of best C = %f i
s %f%%' % (best_alpha, auc_score_bowT_l2))
```

```
The AUC of the Logistic Regression classifier of best C = 100.000000 is
94.313283%
```

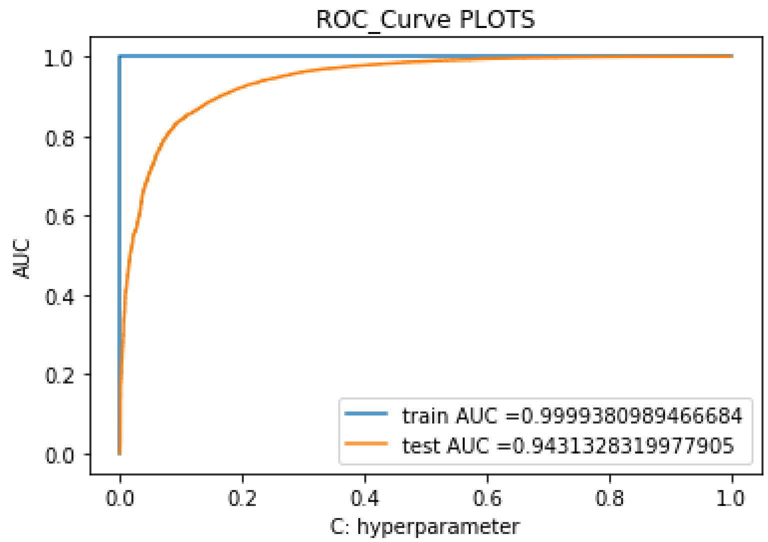
In [114]:

```
import scikitplot.metrics as skplt
skplt.plot_confusion_matrix(y_ts ,pred)
```

Out[114]: <matplotlib.axes._subplots.AxesSubplot at 0x687b089eb8>



In [115]:
```
from sklearn.metrics import roc_curve, auc

train_fpr, train_tpr, thresholds = roc_curve(y_train, model.predict_pro
ba(x_tr_final_counts_bigram)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_ts, model.predict_proba(x_
ts_final_counts_bigram)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
rain_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
tpr)))
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("ROC_Curve PLOTS")
plt.show()
```



In [116]:
```
#classification report
from sklearn.metrics import classification_report
print(classification_report(y_ts, pred))
```

```
             precision    recall  f1-score   support

          0       0.67      0.74      0.70      4117
          1       0.96      0.95      0.95     28883

avg / total       0.93      0.92      0.92     33000
```

False Positive rate --> when it is actually -ve, how often does it predicted +ve = fp/actual-ve = 1051/4117 = .25

In [191]:
```
# FPR for bowt_l2
bowt_FPR_l2 = .25
```

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

In [118]:
```
# Please write all the code with proper documentation
from scipy.sparse import find
#a.Get the (weights1)  after fit your model with the data X.
#weights before adding random noise
weights1 = find(model.coef_[0])[2]
print(weights1[:50])
```

```
[  1.18955656  -2.20009356   3.79440145  -0.07053348   0.45378631
   7.28808119  -0.57474561  -3.88172198   7.26022662  -4.26852288
   1.6210826    7.39560977  -0.48130551  -2.05348936  -2.50836553
  -0.60729209  -3.27374688   6.14993351  -3.0305784    6.59547615
   2.50748628  -1.2063141    0.76195719   1.30414638   8.28091731
  -1.861548    -2.34448654   0.19998559  -1.28097021   1.512335
  -0.03670947   0.57397928   0.13317334   0.37483528   2.94223169
   7.86971938   1.78820827   2.15211792   1.13798381   0.3512852
 -10.65293475   6.23239117   5.65749686  -3.40156139  -4.68244799
   3.47295991   0.36646869   1.25907923   1.66403164   3.12798741]
```

In [119]:
```
X_train_t = x_tr_final_counts_bigram
#Random noise
epsilon = np.random.uniform(low =-0.0001,high = 0.0001, size =(find(X_t
rain_t)[0].size,))
# getting position (row and column) and values of non-zero datapoints
a,b,c = find(X_train_t)
# b. Add a noise to the X (X' = X + e) and get the new data set X'
#introducing random noise to non-zero datapoints
X_train_t[a,b] = epsilon + X_train_t[a,b]
```

In [120]:
```
model = LogisticRegression(penalty='l2',C = best_alpha)
model.fit(X_train_t,y_train)
pred = model.predict(x_ts_final_counts_bigram)
#c. We fit the model again on data X' and get the weights W'
    # evaluate f1_score
f1_score_ = f1_score(y_ts, pred, average='macro') * float(100)
f1_score_alpha = best_alpha
print('\nThe f1_score of the Logistic Regression with L2 regularization
 of best_lambda = %f is %f%%' % (best_alpha, f1_score_))
```

```
The f1_score of the Logistic Regression with L2 regularization of best_
```

```
lambda = 100.000000 is 83.500513%
```

In [121]:

```python
from scipy.sparse import find
#weights after adding random noise
weights2 = find(model.coef_[0])[2]
print(weights2[:50])
```

```
[ 0.93317797 -1.79010104  3.32703816  0.18401846  0.47362836  6.5580111
8
 -0.44313874 -3.19677187  6.45494622 -3.97413723  1.2499949   6.5423339
9
 -0.48307918 -1.52078951 -2.16624668 -0.61889575 -2.98064684  5.4069558
2
 -2.63858047  5.80743914  2.18778822 -0.95079399  0.72049404  1.0148378
3
  7.38966994 -1.63500559 -2.06358399  0.11771985 -1.15712472  1.2526952
2
 -0.10998717  0.44947128  0.14932183  0.34794874  2.69192087  6.7940695
8
  1.39999254  1.98385728  0.95861264  0.34039663 -9.05332461  5.5642824
9
  5.02898985 -3.07588068 -4.13261745  3.27181846  0.3402462   1.1259495
1
  1.41227537  2.7238462 ]
```

In [122]:

```python
print(weights2.size)
```

```
38743
```

In [123]:

```python
# Finding percentage change :
# d.Adding a very small value to avoid divison by zero error
weights1 = weights1 + 0.000001
weights2 = weights2 + 0.000001
#0.000001
```

In [124]:

```python
# e. find the % change between W and W'
weights_dff = (abs(weights1 - weights2)/weights1)*100
```

In [125]:
```
print(weights_dff[np.where(weights_dff > 30)].size)
```

```
1863
```

14 features have weight changes greater than 30%.

In [126]:
```
# Printing Percentiles :
for i in range(0, 101, 10):
    print("{:3d}th Percentile value : {:.5f}".format(i, np.percentile(w
eights_dff, i)))
```

```
  0th Percentile value : -34578.20287
 10th Percentile value : -17.75843
 20th Percentile value : -13.65540
 30th Percentile value : -9.97454
 40th Percentile value : -0.91636
 50th Percentile value : 8.81428
 60th Percentile value : 11.92456
 70th Percentile value : 13.96748
 80th Percentile value : 16.19671
 90th Percentile value : 20.65157
100th Percentile value : 25857.83418
```

We see that there is a abrupt change when going from 90th percentile to 100th percentile.

In [127]:
```
# Printing close percentiles :
a = [99.1,99.2,99.3,99.4,99.5,99.6,99.7,99.8,99.9,100]
for i in a:
    print("{:3}th Percentile value : {:.5f}".format(i, np.percentile(we
ights_dff, i)))
```

```
99.1th Percentile value : 119.65333
99.2th Percentile value : 132.77663
99.3th Percentile value : 148.04562
99.4th Percentile value : 178.91649
99.5th Percentile value : 213.51310
99.6th Percentile value : 268.63673
99.7th Percentile value : 332.20748
```

```
99.8th Percentile value : 471.43184
99.9th Percentile value : 806.08585
100th Percentile value : 25857.83418
```

We see that there is an abrupt change from 99.9th percentile to 100th percentile. Let' see what these values are

In [128]:

```
# Creating dataframe of percentage change..
percendf = pd.DataFrame(weights_dff, index = count_vect.get_feature_nam
es(), columns=['%Change'])
percendf
```

Out[128]:

	%Change
abandon	21.552432
abc	-18.635240
abdomin	12.317178
abil	-360.900313
abl	4.372544
abl buy	10.017313
abl chew	-22.898322
abl continu	-17.645527
abl drink	11.091669
abl eat	-6.896665
abl enjoy	22.891337
abl find	11.537597
abl get	-0.368514
abl give	-25.941216

	%Change
abl keep	-13.639120
abl locat	-1.910723
abl make	-8.953048
abl order	12.081067
abl pick	-12.934761
abl purchas	11.948143
abl put	12.749738
abl see	-21.181906
abl stop	5.441658
abl tast	22.183731
abl tell	10.762663
abl toler	-12.169578
abl tri	-11.981415
abl use	41.135628
abroad	-9.668108
absenc	17.168128
...	...
zero	26.665782
zero calori	5.760524
zero carb	-39.746530
zero fat	38.955834
zero star	-9.885645

	%Change
zero tran	14.084263
zest	10.808479
zesti	44.543857
zevia	8.821251
zhena	17.385511
zico	10.276010
ziggi	-16.837728
zinc	16.057141
zing	12.563595
zinger	12.610179
zip	14.241086
zip lock	12.408905
ziploc	14.362585
ziploc bag	20.402852
ziplock	-16.771831
ziplock bag	-22.004978
zipper	8.002583
zippi	6.717518
ziti	15.342802
ziti meat	-15.331502
zoe	12.766728
zojirushi	-17.916614

	%Change
zone	-13.965685
zucchini	-54.070945
zuke	18.177085

38743 rows × 1 columns

[5.1.3] Feature Importance on BOW, SET 1

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

In [129]:
```
# Please write all the code with proper documentation
# To get all the features name
features = count_vect.get_feature_names()
print("some sample features(unique words in the corpus)",features[100:1
10])
```

```
some sample features(unique words in the corpus) ['acidi', 'acknowled
g', 'acn', 'acquaint', 'acquir', 'acquir tast', 'acr', 'acrid', 'acros
s', 'across brand']
```

In [130]:
```
#code references :- https://stackoverflow.com/questions/11116697/how-to
-get-most-informative-features-for-scikit-learn-classifiers
n = 10
coefs_with_fns = sorted(zip(model.coef_[0],features))
top = zip(coefs_with_fns[:n],coefs_with_fns[:-(n+1):-1])
```

In [131]:
```
print("\t\tNegative\t\t\tPositive")
print("_"*80)
for (coef_1, fn_1), (coef_2, fn_2) in top:
    print("\t%.4f\t%-15s\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, fn_2
))
```

```
                Negative                                Positive
```

```
            Negative                        Positive
______________________________________________________________________
_________
        -29.3667        two star                19.2539 never disappoin
t
        -24.6908        worst                   18.4156 high recommend
        -19.2238        way sweet               16.3254 yum
        -18.6567        candi delici            16.1402 four star
        -17.1764        terribl                 15.3324 skeptic
        -17.1590        threw                   15.0703 delici
        -16.4545        dont recommend          15.0096 uniqu
        -16.2274        great review            14.4001 wont disappoint
        -16.1725        dissapoint              14.2839 well worth
        -16.1598        disappoint              14.2629 fantast
```

[5.2] Logistic Regression on TFIDF, SET 2

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

In [132]:

```
#To show how Time Series Split splits the data
from sklearn.model_selection import TimeSeriesSplit
tscv1 = TimeSeriesSplit(n_splits=10)
for train, cv in tscv1.split(x_tr_final_counts_tfidf):
    print("%s %s" % (train, cv))
#    print(x_tr_final_counts_bigram[train].shape,x_tr_final_counts_bigr
am[cv].shape)
```

```
[   0    1    2 ... 6097 6098 6099] [ 6100  6101  6102 ... 12187 12188
12189]
[    0     1     2 ... 12187 12188 12189] [12190 12191 12192 ... 18277
18278 18279]
[    0     1     2 ... 18277 18278 18279] [18280 18281 18282 ... 24367
24368 24369]
[    0     1     2 ... 24367 24368 24369] [24370 24371 24372 ... 30457
30458 30459]
[    0     1     2 ... 30457 30458 30459] [30460 30461 30462 ... 36547
```

```
36548 36549]
[    0     1     2 ... 36547 36548 36549] [36550 36551 36552 ... 42637
42638 42639]
[    0     1     2 ... 42637 42638 42639] [42640 42641 42642 ... 48727
48728 48729]
[    0     1     2 ... 48727 48728 48729] [48730 48731 48732 ... 54817
54818 54819]
[    0     1     2 ... 54817 54818 54819] [54820 54821 54822 ... 60907
60908 60909]
[    0     1     2 ... 60907 60908 60909] [60910 60911 60912 ... 66997
66998 66999]
```

In [133]:

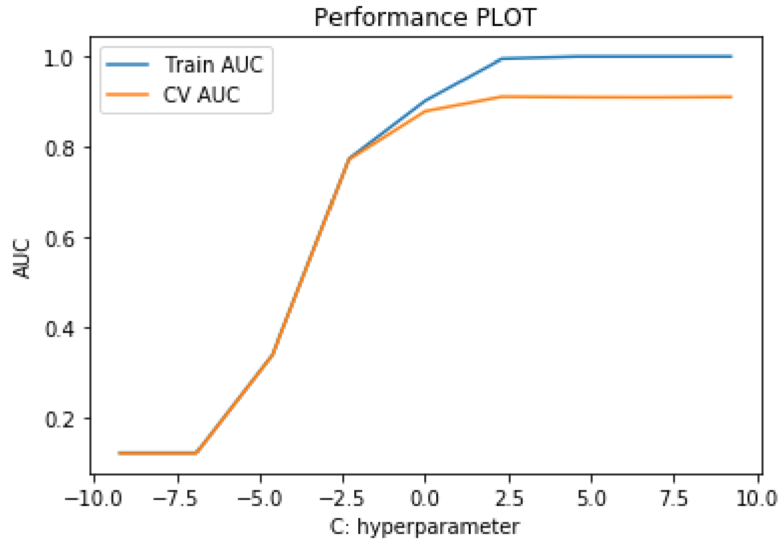
```
# Please write all the code with proper documentation
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score
from sklearn.metrics import roc_auc_score
from sklearn.metrics import accuracy_score
from math import log
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import GridSearchCV

alpha_values = np.arange(10)
C = np.array([0.0001,0.001,0.01,0.1,1,10,100,500,1000,10000])
cv_auc = []
train_auc = []


neigh = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[0.0001,0.001,0.01,0.1,1,10,100,500,1000,10000],
              'penalty':['l1'],'class_weight':['balanced']}
tscv1 = TimeSeriesSplit(n_splits=10) #For time based splitting
clf = RandomizedSearchCV(neigh,param_grid,cv=tscv1,verbose=1)
clf.fit(x_tr_final_counts_tfidf,y_train)


train_auc= clf.cv_results_['mean_train_score']
train_auc_std= clf.cv_results_['std_train_score']
cv_auc = clf.cv_results_['mean_test_score']
```

```python
cv_auc_std= clf.cv_results_['std_test_score']



d = max(cv_auc)

i = np.where(cv_auc == d)

i = i[0][0]
best_alpha = float(C[i])
print("Best C is:-",best_alpha)


C = np.log(C)

plt.plot(C, train_auc, label='Train AUC')
plt.plot(C, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("Performance PLOT")
plt.show()
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
```

```
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  3.0min finished
```

```
Best C is:- 10.0
```

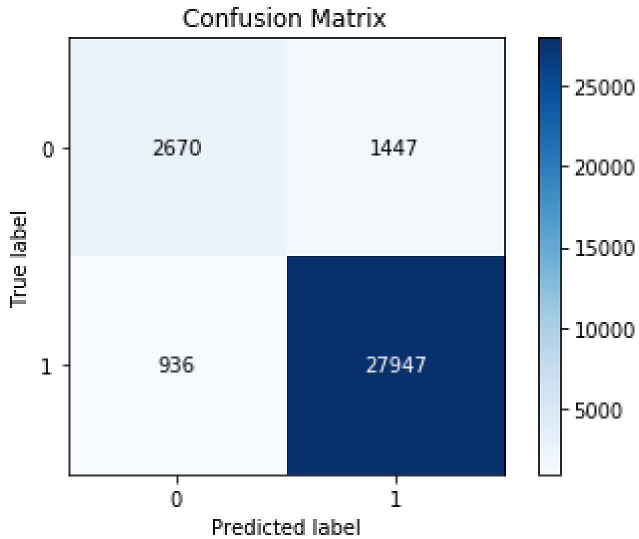


In [134]:
```
# LogisticRegression with best best "C" for l1 penalty of bow
model = LogisticRegression(penalty='l1',C = best_alpha)
model.fit(x_tr_final_counts_tfidf,y_train)
#pred = model.predict_proba(x_ts_final_counts_bigram)
pred=model.predict(x_ts_final_counts_tfidf)
    # evaluate CV AUC
auc_score_tfidf_l1 = roc_auc_score(y_true=np.array(y_ts), y_score=model
.predict_proba(x_ts_final_counts_tfidf)[:,1])*100
auc_score_tfidf_lambda_l1 = best_alpha
print('\nThe AUC of the Logistic Regression classifier of best C = %f i
s %f%%' % (best_alpha, auc_score_tfidf_l1))
```

```
The AUC of the Logistic Regression classifier of best C = 10.000000 is
93.826802%
```

In [135]:
```
import scikitplot.metrics as skplt
skplt.plot_confusion_matrix(y_ts,pred)
```

Out[135]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x687693e3c8>
```



In [136]:
```
print(classification_report(y_ts, pred))
```

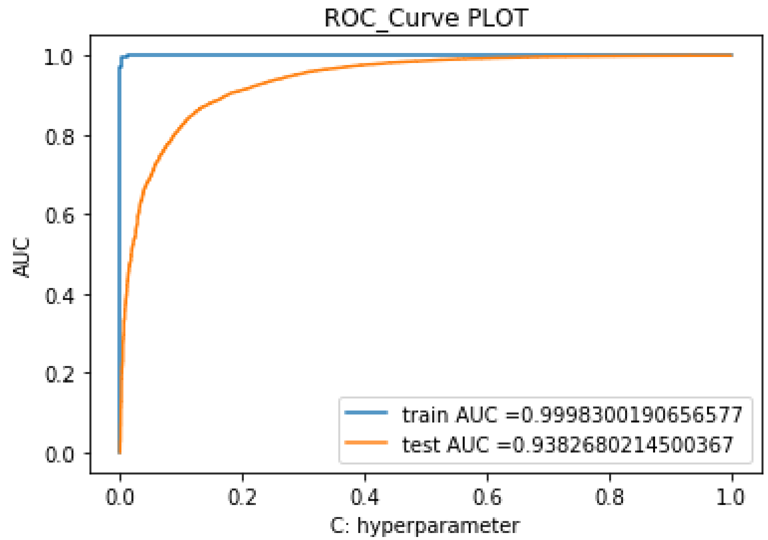
```
             precision    recall  f1-score   support

          0       0.74      0.65      0.69      4117
          1       0.95      0.97      0.96     28883

avg / total       0.92      0.93      0.93     33000
```

False Positive rate --> when it is actually -ve, how often does it predicted +ve = fp/actual-ve = 1447/4117 = .35

In [192]:
```
# FPR for tfidf_l1
tfidf_FPR_l1 = .35
```

In [138]:
```
from sklearn.metrics import roc_curve, auc

train_fpr, train_tpr, thresholds = roc_curve(y_train, model.predict_pro
ba(x_tr_final_counts_tfidf)[:,1])
```

```
test_fpr, test_tpr, thresholds = roc_curve(y_ts, model.predict_proba(x_
ts_final_counts_tfidf)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
rain_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
tpr)))
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("ROC_Curve PLOT")
plt.show()
```



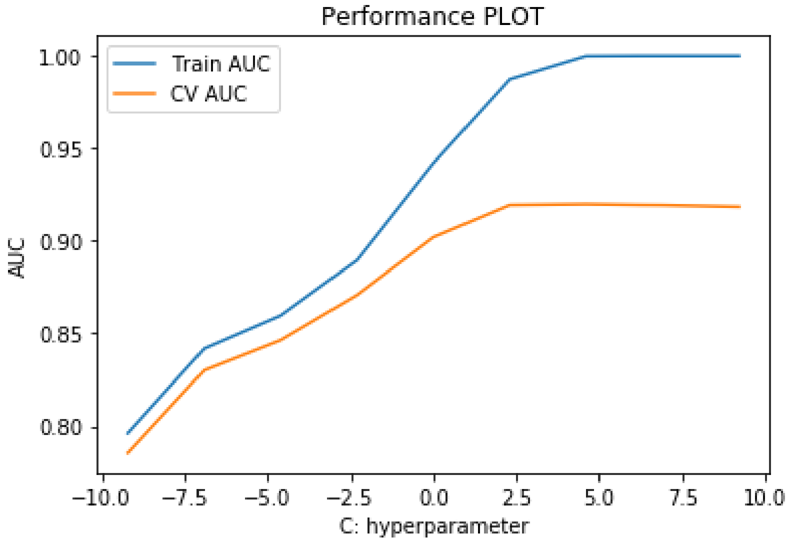
[5.2.2] Applying Logistic Regression with L2 regularization on TFIDF, SET 2

In [139]:
```
# Please write all the code with proper documentation
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score
from sklearn.metrics import roc_auc_score
```

```
from sklearn.metrics import accuracy_score
from math import log
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import GridSearchCV

alpha_values = np.arange(10)
C = np.array([0.0001,0.001,0.01,0.1,1,10,100,500,1000,10000])
cv_auc = []
train_auc = []


neigh = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[0.0001,0.001,0.01,0.1,1,10,100,500,1000,10000],
             'penalty':['l2'],'class_weight':['balanced']}
tscv1 = TimeSeriesSplit(n_splits=10) #For time based splitting
clf = RandomizedSearchCV(neigh,param_grid,cv=tscv1,verbose=1)
clf.fit(x_tr_final_counts_tfidf,y_train)


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



d = max(cv_auc)

i = np.where(cv_auc == d)

i = i[0][0]
best_alpha = float(C[i])
print("Best C is:-",best_alpha)


C = np.log(C)

plt.plot(C, train_auc, label='Train AUC')
```

```
plt.plot(C, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("Performance PLOT")
plt.show()
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  2.8min finished
Best C is:- 100.0
```



In [140]:

```
# LogisticRegression with best best "C" for l2 penalty of bow
model = LogisticRegression(penalty='l2',C = best_alpha)
model.fit(x_tr_final_counts_tfidf,y_train)
#pred = model.predict_proba(x_ts_final_counts_bigram)
pred=model.predict(x_ts_final_counts_tfidf)
    # evaluate CV AUC
auc_score_tfidf_l2 = roc_auc_score(y_true=np.array(y_ts), y_score=model
.predict_proba(x_ts_final_counts_tfidf)[:,1])*100
auc_score_tfidf_lambda_l2 = best_alpha
```

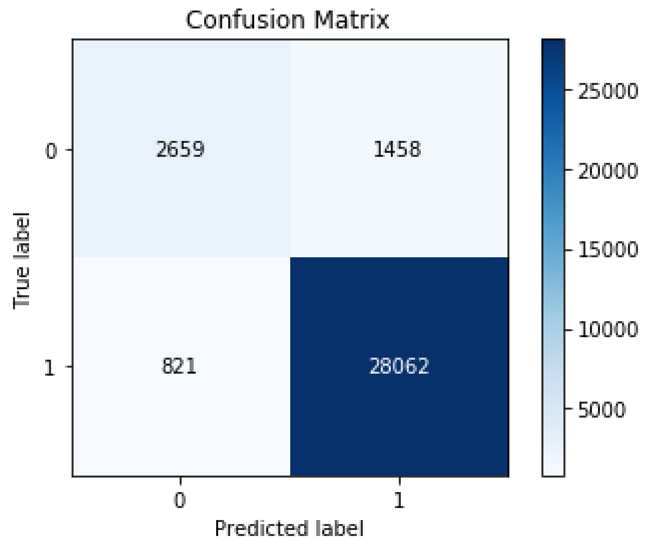
```
print('\nThe AUC of the Logistic Regression classifier of best C = %f i
s %f%%' % (best_alpha, auc_score_tfidf_l2))
```

```
The AUC of the Logistic Regression classifier of best C = 100.000000 is
94.203650%
```

In [141]:

```
import scikitplot.metrics as skplt
skplt.plot_confusion_matrix(y_ts ,pred)
```

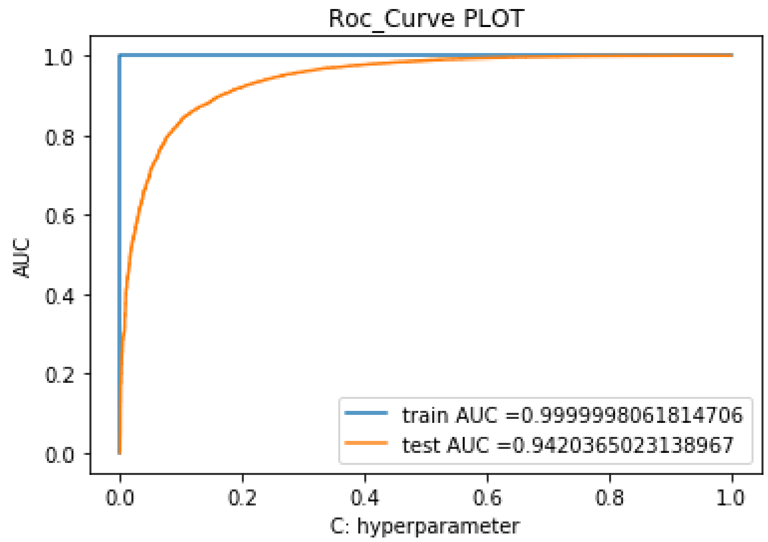
Out[141]: <matplotlib.axes._subplots.AxesSubplot at 0x6879eb1e48>



In [142]:

```
from sklearn.metrics import roc_curve, auc

train_fpr, train_tpr, thresholds = roc_curve(y_train, model.predict_pro
ba(x_tr_final_counts_tfidf)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_ts, model.predict_proba(x_
ts_final_counts_tfidf)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
rain_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
tpr)))
```

```
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("Roc_Curve PLOT")
plt.show()
```



In [143]:
```
print(classification_report(y_ts, pred))
```

```
             precision    recall  f1-score   support

          0       0.76      0.65      0.70      4117
          1       0.95      0.97      0.96     28883

avg / total       0.93      0.93      0.93     33000
```

False Positive rate --> when it is actually -ve, how often does it predicted +ve = fp/actual-ve = 1458/4117 = .35

In [193]:
```
# FPR for tfidf_l2
tfidf_FPR_l2 = .35
```

[5.2.3] Feature Importance on TFIDF, SET 2

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

In [145]:
```
# Please write all the code with proper documentation
# To get all the features name
features = tf_idf_vect.get_feature_names()
print("some sample features(unique words in the corpus)",features[100:1
10])
```

```
some sample features(unique words in the corpus) ['acidi', 'acknowled
g', 'acn', 'acquaint', 'acquir', 'acquir tast', 'acr', 'acrid', 'acros
s', 'across brand']
```

In [146]:
```
n = 10
coefs_with_fns = sorted(zip(model.coef_[0],features))
top = zip(coefs_with_fns[:n],coefs_with_fns[:-(n+1):-1])
```

In [147]:
```
print("\t\tNegative\t\t\tPositive")
print("_"*80)
for (coef_1, fn_1), (coef_2, fn_2) in top:
        print("\t%.4f\t%-15s\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, f
n_2))
```

```
                Negative                        Positive
________________________________________________________________________
__________
        -24.3494        two star                26.3311 great
        -23.5530        worst                   24.5588 delici
        -22.7272        disappoint              20.7322 best
        -17.7830        terribl                 20.5878 perfect
        -16.7495        candi delici            20.3138 high recommend
        -16.5353        horribl                 18.7786 love
        -16.4240        threw                   17.0516 excel
        -16.1894        aw                      17.0366 amaz
```

```
        -15.7759        way sweet                15.6025 never disappoin
t
        -14.8695        bland                    15.5662 fantast
```

[5.3] Logistic Regression on AVG W2V, SET 3

[5.3.1] Applying Logistic Regression with L1 regularization on AVG W2V SET 3

In [148]:

```
#To show how Time Series Split splits the data
from sklearn.model_selection import TimeSeriesSplit
tscv2 = TimeSeriesSplit(n_splits=10)
for train, cv in tscv1.split(train_avgw2v):
    print("%s %s" % (train, cv))
#    print(x_tr_final_counts_bigram[train].shape,x_tr_final_counts_bigr
am[cv].shape)
```

```
[   0    1    2 ... 6097 6098 6099] [ 6100  6101  6102 ... 12187 12188
12189]
[    0     1     2 ... 12187 12188 12189] [12190 12191 12192 ... 18277
18278 18279]
[    0     1     2 ... 18277 18278 18279] [18280 18281 18282 ... 24367
24368 24369]
[    0     1     2 ... 24367 24368 24369] [24370 24371 24372 ... 30457
30458 30459]
[    0     1     2 ... 30457 30458 30459] [30460 30461 30462 ... 36547
36548 36549]
[    0     1     2 ... 36547 36548 36549] [36550 36551 36552 ... 42637
42638 42639]
[    0     1     2 ... 42637 42638 42639] [42640 42641 42642 ... 48727
48728 48729]
[    0     1     2 ... 48727 48728 48729] [48730 48731 48732 ... 54817
54818 54819]
[    0     1     2 ... 54817 54818 54819] [54820 54821 54822 ... 60907
60908 60909]
```

```
[    0     1     2 ... 60907 60908 60909] [60910 60911 60912 ... 66997
66998 66999]
```

In [166]:

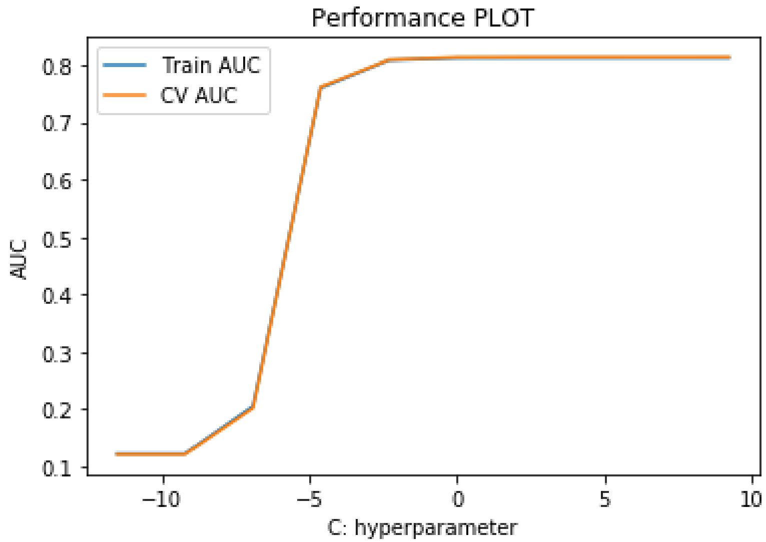
```
# Please write all the code with proper documentation
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score
from sklearn.metrics import roc_auc_score
from sklearn.metrics import accuracy_score
from math import log
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import GridSearchCV

alpha_values = np.arange(10)
C = np.array([0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000])
cv_auc = []
train_auc = []


neigh = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000],
             'penalty':['l1'],'class_weight':['balanced']}
tscv2 = TimeSeriesSplit(n_splits=10) #For time based splitting
clf = RandomizedSearchCV(neigh,param_grid,cv=tscv2,verbose=1)
clf.fit(train_avgw2v,y_train)


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



d = max(cv_auc)

i = np.where(cv_auc == d)

i = i[0][0]
```

```
best_alpha = float(C[i])
print("Best C is:-",best_alpha)


C = np.log(C)

plt.plot(C, train_auc, label='Train AUC')
plt.plot(C, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("Performance PLOT")
plt.show()
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
```

```
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  2.4min finished
```

```
Best C is:- 1000.0
```



In [167]:
```
# LogisticRegression with best best "C" for l1 penalty of bow
model = LogisticRegression(penalty='l1',C = best_alpha)
model.fit(train_avgw2v,y_train)
```

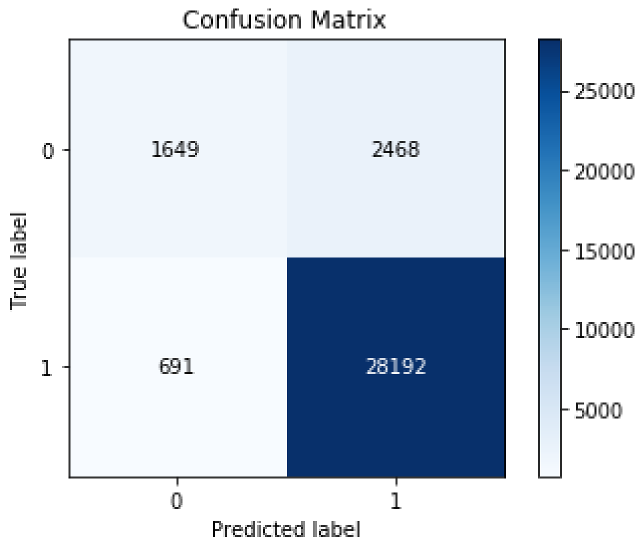
```
#pred = model.predict_proba(x_ts_final_counts_bigram)
pred=model.predict(test_avgw2v)
    # evaluate CV AUC
auc_score_word2vec_l1 = roc_auc_score(y_true=np.array(y_ts), y_score=mo
del.predict_proba(test_avgw2v)[:,1])*100
auc_score_word2vec_lambda_l1 = best_alpha
print('\nThe AUC of the Logistic Regression classifier of best C = %f i
s %f%%' % (best_alpha, auc_score_word2vec_l1))
```

```
The AUC of the Logistic Regression classifier of best C = 1000.000000 i
s 89.493334%
```

In [168]:

```
import scikitplot.metrics as skplt
skplt.plot_confusion_matrix(y_ts ,pred)
```

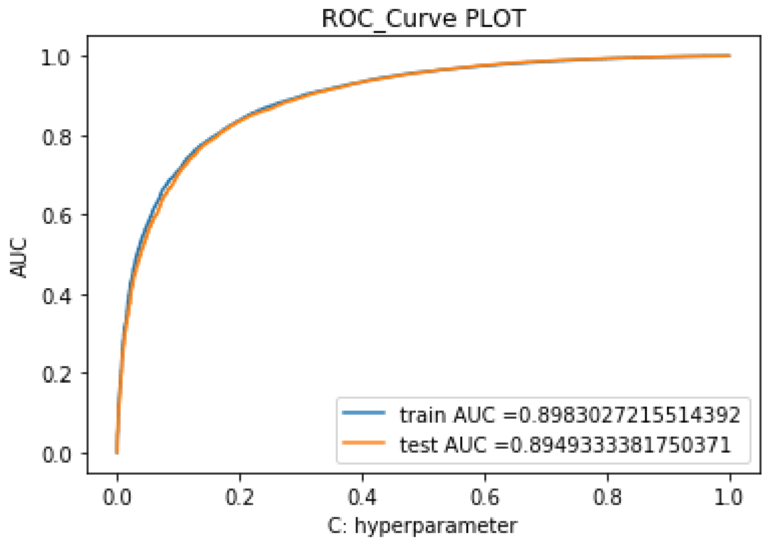
Out[168]: <matplotlib.axes._subplots.AxesSubplot at 0x687b095be0>



In [169]:

```
from sklearn.metrics import roc_curve, auc

train_fpr, train_tpr, thresholds = roc_curve(y_train, model.predict_pro
ba(train_avgw2v)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_ts, model.predict_proba(te
```

```
st_avgw2v)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
rain_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
tpr)))
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("ROC_Curve PLOT")
plt.show()
```



In [156]:
```
print(classification_report(y_ts, pred))
```

```
             precision    recall  f1-score   support

          0       0.70      0.40      0.51      4117
          1       0.92      0.98      0.95     28883

avg / total       0.89      0.90      0.89     33000
```

False Positive rate --> when it is actually -ve, how often does it predicted +ve = fp/actual-ve = 2468/4117 = .59

In [194]:
```
# FPR for avgw2vec_l1
avgw2vec_FPR_l1 = .59
```

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

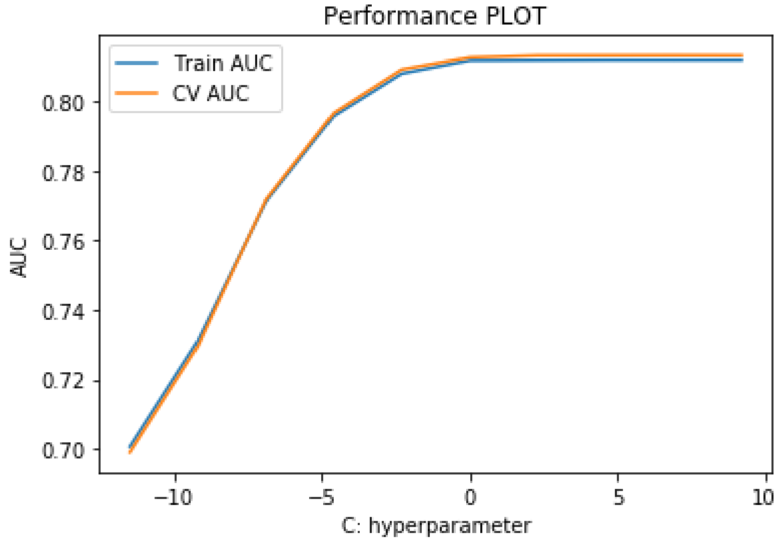
In [170]:
```
# Please write all the code with proper documentation
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score
from sklearn.metrics import roc_auc_score
from sklearn.metrics import accuracy_score
from math import log
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import GridSearchCV

alpha_values = np.arange(10)
C = np.array([0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000])
cv_auc = []
train_auc = []


neigh = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000],
              'penalty':['l2'],'class_weight':['balanced']}
tscv2 = TimeSeriesSplit(n_splits=10) #For time based splitting
clf = RandomizedSearchCV(neigh,param_grid,cv=tscv2,verbose=1)
clf.fit(train_avgw2v,y_train)


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

```
d = max(cv_auc)

i = np.where(cv_auc == d)

i = i[0][0]
best_alpha = float(C[i])
print("Best C is:-",best_alpha)


C = np.log(C)

plt.plot(C, train_auc, label='Train AUC')
plt.plot(C, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("Performance PLOT")
plt.show()
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
```

```
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:   44.4s finished
```

```
Best C is:- 1000.0
```

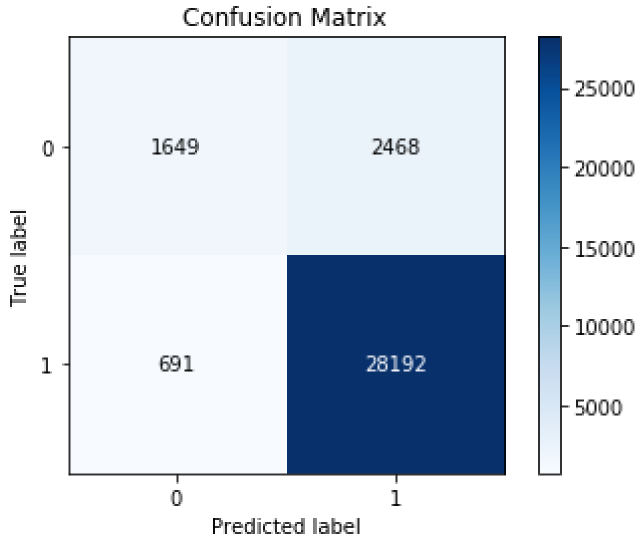


In [171]:
```
# LogisticRegression with best best "C" for l2 penalty of bow
model = LogisticRegression(penalty='l2',C = best_alpha)
model.fit(train_avgw2v,y_train)
#pred = model.predict_proba(x_ts_final_counts_bigram)
pred=model.predict(test_avgw2v)
    # evaluate CV AUC
auc_score_word2vec_l2 = roc_auc_score(y_true=np.array(y_ts), y_score=mo
del.predict_proba(test_avgw2v)[:,1])*100
auc_score_word2vec_lambda_l2 = best_alpha
print('\nThe AUC of the Logistic Regression classifier of best C = %f i
s %f%%' % (best_alpha, auc_score_word2vec_l2))
```

```
The AUC of the Logistic Regression classifier of best C = 1000.000000 i
s 89.493154%
```

In [172]:
```
import scikitplot.metrics as skplt
skplt.plot_confusion_matrix(y_ts ,pred)
```

Out[172]: <matplotlib.axes._subplots.AxesSubplot at 0x687c951d68>



In [173]:
```
print(classification_report(y_ts, pred))
```

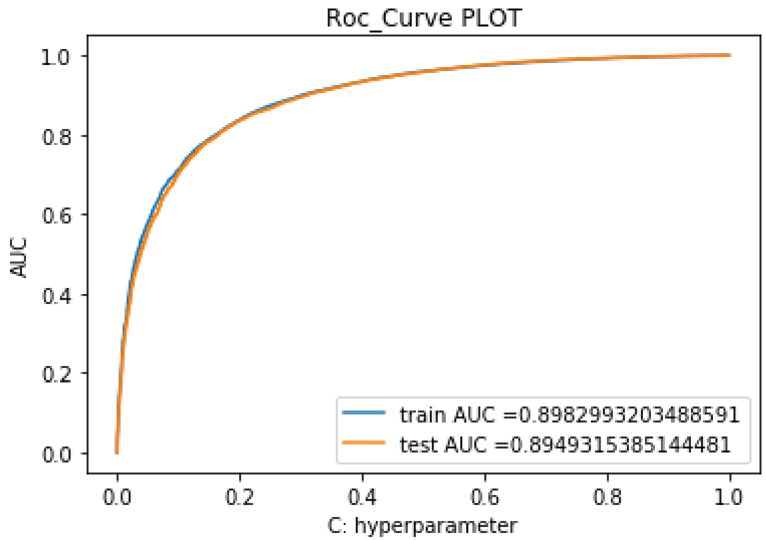
```
             precision    recall  f1-score   support

          0       0.70      0.40      0.51      4117
          1       0.92      0.98      0.95     28883

avg / total       0.89      0.90      0.89     33000
```

False Positive rate --> when it is actually -ve, how often does it predicted +ve = fp/actual-ve = 2468/4117 = .59

In [195]:
```
# FPR for avgw2vec_l2
avgw2vec_FPR_l2 = .59
```

In [175]:
```
from sklearn.metrics import roc_curve, auc

train_fpr, train_tpr, thresholds = roc_curve(y_train, model.predict_pro
ba(train_avgw2v)[:,1])
```

```
test_fpr, test_tpr, thresholds = roc_curve(y_ts, model.predict_proba(te
st_avgw2v)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
rain_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
tpr)))
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("Roc_Curve PLOT")
plt.show()
```



[5.4] Logistic Regression on TFIDF W2V, SET 4

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

In [176]:
```
#To show how Time Series Split splits the data
```

```python
from sklearn.model_selection import TimeSeriesSplit
tscv3 = TimeSeriesSplit(n_splits=10)
for train, cv in tscv1.split(train_avgw2v):
    print("%s %s" % (train, cv))
#    print(x_tr_final_counts_bigram[train].shape,x_tr_final_counts_bigr
am[cv].shape)
```

```
[   0    1    2 ... 6097 6098 6099] [ 6100  6101  6102 ... 12187 12188
12189]
[    0     1     2 ... 12187 12188 12189] [12190 12191 12192 ... 18277
18278 18279]
[    0     1     2 ... 18277 18278 18279] [18280 18281 18282 ... 24367
24368 24369]
[    0     1     2 ... 24367 24368 24369] [24370 24371 24372 ... 30457
30458 30459]
[    0     1     2 ... 30457 30458 30459] [30460 30461 30462 ... 36547
36548 36549]
[    0     1     2 ... 36547 36548 36549] [36550 36551 36552 ... 42637
42638 42639]
[    0     1     2 ... 42637 42638 42639] [42640 42641 42642 ... 48727
48728 48729]
[    0     1     2 ... 48727 48728 48729] [48730 48731 48732 ... 54817
54818 54819]
[    0     1     2 ... 54817 54818 54819] [54820 54821 54822 ... 60907
60908 60909]
[    0     1     2 ... 60907 60908 60909] [60910 60911 60912 ... 66997
66998 66999]
```

In [177]:

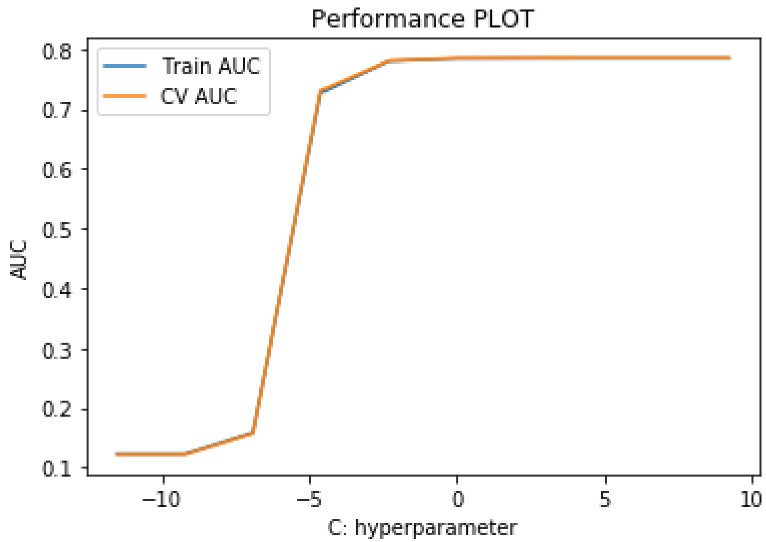
```python
# Please write all the code with proper documentation
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score
from sklearn.metrics import roc_auc_score
from sklearn.metrics import accuracy_score
from math import log
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import GridSearchCV

alpha_values = np.arange(10)
C = np.array([0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000])
```

```
cv_auc = []
train_auc = []


neigh = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000],
             'penalty':['l1'],'class_weight':['balanced']}
tscv3 = TimeSeriesSplit(n_splits=10) #For time based splitting
clf = RandomizedSearchCV(neigh,param_grid,cv=tscv3,verbose=1)
clf.fit(tfidf_sent_vectors,y_train)


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




d = max(cv_auc)

i = np.where(cv_auc == d)

i = i[0][0]
best_alpha = float(C[i])
print("Best C is:-",best_alpha)


C = np.log(C)

plt.plot(C, train_auc, label='Train AUC')
plt.plot(C, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("Performance PLOT")
plt.show()
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
```

```
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  1.6min finished
```

```
Best C is:- 100.0
```



In [178]:

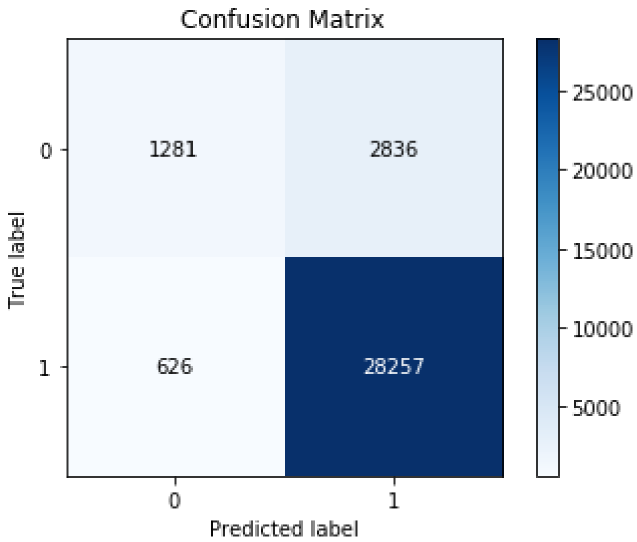
```
# LogisticRegression with best best "C" for l2 penalty of bow
model = LogisticRegression(penalty='l1',C = best_alpha)
model.fit(tfidf_sent_vectors,y_train)
#pred = model.predict_proba(x_ts_final_counts_bigram)
pred=model.predict(tfidf_sent_vectors_ts)
    # evaluate CV AUC
auc_score_tfidf_word2vec_l1 = roc_auc_score(y_true=np.array(y_ts), y_score=model.predict_proba(tfidf_sent_vectors_ts)[:,1])*100
auc_score_tfidf_word2vec_lambda_l1 = best_alpha
print('\nThe AUC of the Logistic Regression classifier of best C = %f is %f%%' % (best_alpha, auc_score_tfidf_word2vec_l1))
```

```
The AUC of the Logistic Regression classifier of best C = 100.000000 is
86.772829%
```

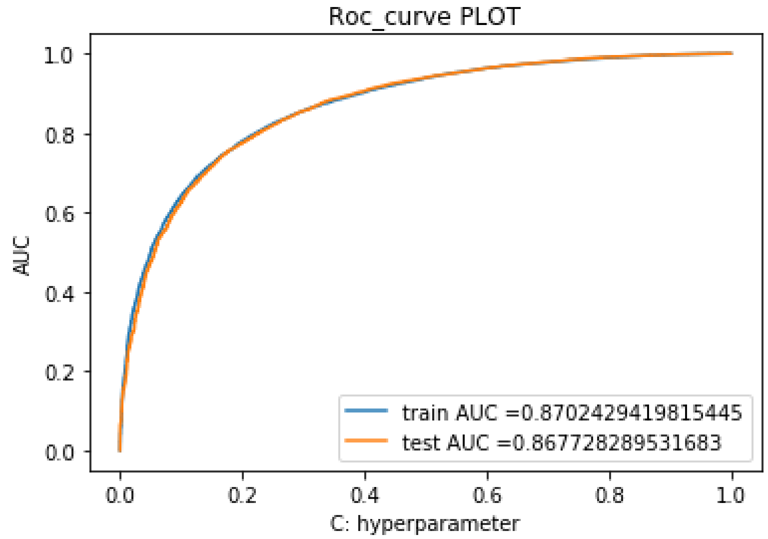
In [179]:

```
import scikitplot.metrics as skplt
skplt.plot_confusion_matrix(y_ts ,pred)
```

Out[179]: <matplotlib.axes._subplots.AxesSubplot at 0x687c4e81d0>



In [180]:
```
from sklearn.metrics import roc_curve, auc

train_fpr, train_tpr, thresholds = roc_curve(y_train, model.predict_pro
ba(tfidf_sent_vectors)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_ts, model.predict_proba(tf
idf_sent_vectors_ts)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
rain_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
tpr)))
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("Roc_curve PLOT")
plt.show()
```



In [181]:
```
print(classification_report(y_ts, pred))
```

```
             precision    recall  f1-score   support

          0       0.67      0.31      0.43      4117
          1       0.91      0.98      0.94     28883

avg / total       0.88      0.90      0.88     33000
```

False Positive rate --> when it is actually -ve, how often does it predicted +ve = fp/actual-ve = 2836/4117 = .68

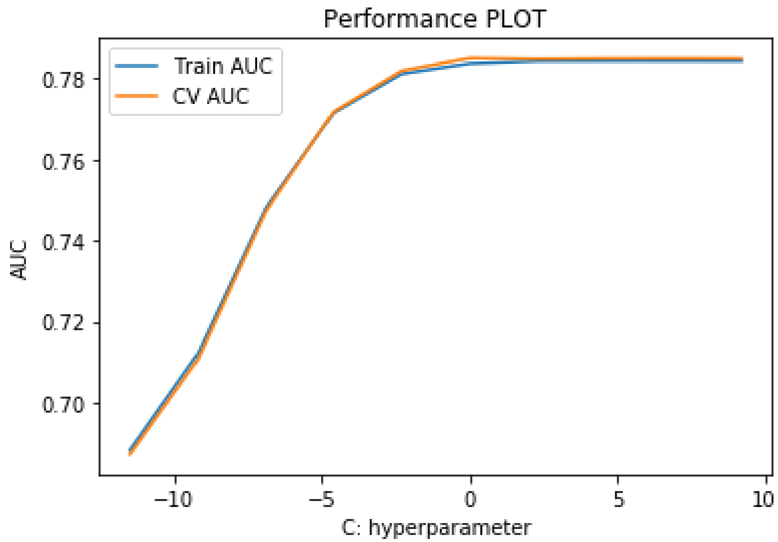
In [196]:
```
# FPR for tfidf_w2vec_l1
tfidf_w2vec_FPR_l1 = .68
```

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

In [183]:
```python
# Please write all the code with proper documentation
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score
from sklearn.metrics import roc_auc_score
from sklearn.metrics import accuracy_score
from math import log
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import GridSearchCV

alpha_values = np.arange(10)
C = np.array([0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000])
cv_auc = []
train_auc = []


neigh = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000],
             'penalty':['l2'],'class_weight':['balanced']}
tscv3 = TimeSeriesSplit(n_splits=10) #For time based splitting
clf = RandomizedSearchCV(neigh,param_grid,cv=tscv3,verbose=1)
clf.fit(tfidf_sent_vectors,y_train)


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



d = max(cv_auc)

i = np.where(cv_auc == d)

i = i[0][0]
best_alpha = float(C[i])
print("Best C is:-",best_alpha)
```

```
C = np.log(C)

plt.plot(C, train_auc, label='Train AUC')
plt.plot(C, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("Performance PLOT")
plt.show()
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:   47.8s finished
Best C is:- 1.0
```



In [184]:

```
# LogisticRegression with best best "C" for l2 penalty of bow
model = LogisticRegression(penalty='l2',C = best_alpha)
model.fit(tfidf_sent_vectors,y_train)
#pred = model.predict_proba(x_ts_final_counts_bigram)
pred=model.predict(tfidf_sent_vectors_ts)
    # evaluate CV AUC
```

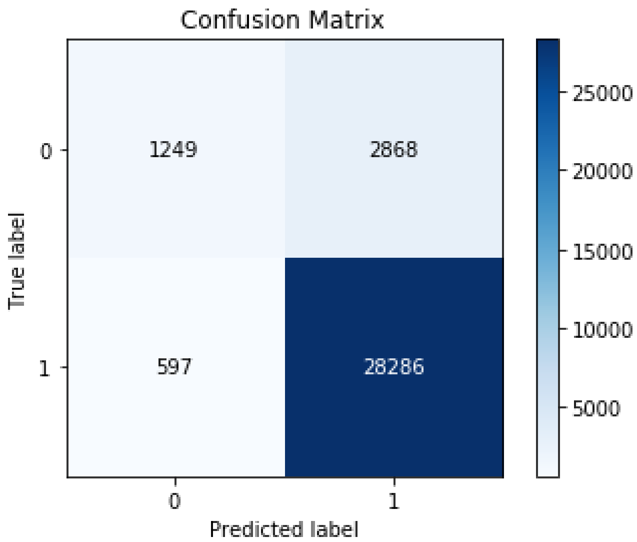
```
auc_score_tfidf_word2vec_l2 = roc_auc_score(y_true=np.array(y_ts), y_score=model.predict_proba(tfidf_sent_vectors_ts)[:,1])*100
auc_score_tfidf_word2vec_lambda_l2 = best_alpha
print('\nThe AUC of the Logistic Regression classifier of best C = %f is %f%%' % (best_alpha, auc_score_tfidf_word2vec_l2))
```

```
The AUC of the Logistic Regression classifier of best C = 1.000000 is 86.776556%
```

In [185]:

```
import scikitplot.metrics as skplt
skplt.plot_confusion_matrix(y_ts ,pred)
```

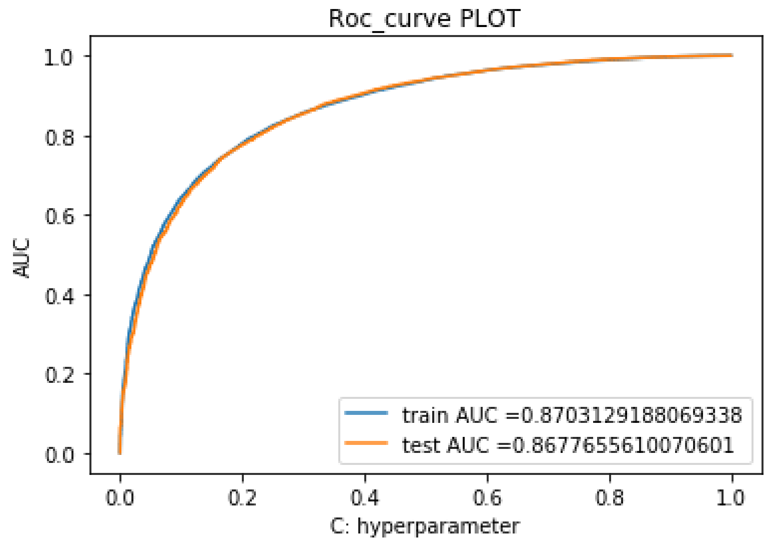
Out[185]: <matplotlib.axes._subplots.AxesSubplot at 0x687c572748>



In [186]:

```
from sklearn.metrics import roc_curve, auc

train_fpr, train_tpr, thresholds = roc_curve(y_train, model.predict_proba(tfidf_sent_vectors)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_ts, model.predict_proba(tfidf_sent_vectors_ts)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
```

```
rain_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
tpr)))
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("Roc_curve PLOT")
plt.show()
```



In [187]:
```
print(classification_report(y_ts, pred))
```

```
             precision    recall  f1-score   support

          0       0.68      0.30      0.42      4117
          1       0.91      0.98      0.94     28883

avg / total       0.88      0.90      0.88     33000
```

False Positive rate --> when it is actually -ve, how often does it predicted +ve = fp/actual-ve = 2868/4117 = .69

```
In [197]: # FPR for tfidf_w2vec_l2
tfidf_w2vec_FPR_l2 = .69
```

[6] Conclusions

```
In [198]: # Please compare all your models using Prettytable library
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["Vectorizer","penalty","hyperparameter(C)","roc_auc_score","FPR"]
x.add_row(["BOW","L1",auc_score_bowT_lambda_l1,auc_score_bowT_l1,bowt_FPR_l1])
x.add_row(["BOW","L2",auc_score_bowT_lambda_l2,auc_score_bowT_l2,bowt_FPR_l2])
x.add_row(["TF-IDF","L1",auc_score_tfidf_lambda_l1,auc_score_tfidf_l1,tfidf_FPR_l1])
x.add_row(["TF-IDF","L2",auc_score_tfidf_lambda_l2,auc_score_tfidf_l2,tfidf_FPR_l2])
x.add_row(["AVG -W2V","L1",auc_score_word2vec_lambda_l1,auc_score_word2vec_l1,avgw2vec_FPR_l1])
x.add_row(["AVG -W2V","L2",auc_score_word2vec_lambda_l2,auc_score_word2vec_l2,avgw2vec_FPR_l2])
x.add_row(["TFIDF-W2V","L1",auc_score_tfidf_word2vec_lambda_l1,auc_score_tfidf_word2vec_l1,tfidf_w2vec_FPR_l1])
x.add_row(["TFIDF-W2V","L2",auc_score_tfidf_word2vec_lambda_l2,auc_score_tfidf_word2vec_l2,tfidf_w2vec_FPR_l2])


print(x)
```

```
+------------+---------+-------------------+-------------------+------+
| Vectorizer | penalty | hyperparameter(C) |   roc_auc_score   | FPR  |
+------------+---------+-------------------+-------------------+------+
|    BOW     |    L1   |        10.0       | 93.79595983093652 | 0.25 |
|    BOW     |    L2   |       100.0       | 94.31328319977905 | 0.25 |
|   TF-IDF   |    L1   |        10.0       | 93.82680214500367 | 0.35 |
|   TF-IDF   |    L2   |       100.0       | 94.20365023138967 | 0.35 |
```

AVG -W2V	L1	1000.0	89.49333381750371	0.59
AVG -W2V	L2	1000.0	89.4931538514448	0.59
TFIDF-W2V	L1	100.0	86.7728289531683	0.68
TFIDF-W2V	L2	1.0	86.77655610070602	0.69

as per the table, we can consider BOW with L2 regularizor because it has less false positive rate and more roc_auc_score