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 [0]:
```
%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.metrics import accuracy_score
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
```

In [3]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remoun
t, call drive.mount("/content/drive", force_remount=True).
```

In [0]:
```
!cp "/content/drive/My Drive/final.sqlite" "final.sqlite"
```

In [5]:
```
import os
if os.path.isfile('final.sqlite'):
    conn = sqlite3.connect('final.sqlite')
    final = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score !=
```

```
3 """, conn)
    conn.close()
else:
    print("Please the above cell")

print("Preprocessed Amzon fine food data columns  shape : ",final.shape
)
print("fPreprocessed Amzon fine food data columns       :",final.column
s.values)
```

```
Preprocessed Amzon fine food data columns  shape :  (364171, 12)
fPreprocessed Amzon fine food data columns       : ['index' 'Id' 'Produ
ctId' 'UserId' 'ProfileName' 'HelpfulnessNumerator'
 'HelpfulnessDenominator' 'Score' 'Time' 'Summary' 'Text' 'CleanedTex
t']
```

In [0]:

```
# 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

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score
 != 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 (5000, 10)
```

Out[0]:

	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 [0]:

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

In [0]:
```python
print(display.shape)
display.head()
```

(80668, 7)

Out[0]:

	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 [0]:
```python
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[0]:

	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 [0]:
```python
display['COUNT(*)'].sum()
```

Out[0]: 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 [0]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[0]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenon
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenon
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 [0]:

```
#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 [0]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time"
,"Text"}, keep='first', inplace=False)
final.shape
```

Out[0]: (4986, 10)

In [0]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[0]: 99.72

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 [0]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[0]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenom
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenom
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	

In [0]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [0]:
```
#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()
```

```
(4986, 10)
```

Out[0]:
```
1    4178
0     808
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 [0]:
```
# 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)
```

```
Why is this $[...] when the same product is available for $[...] here?<
br />http://www.amazon.com/VICTOR-FLY-MAGNET-BAIT-REFILL/dp/B00004RBDY<
br /><br />The Victor M380 and M502 traps are unreal, of course -- tota
l fly genocide. Pretty stinky, but only right nearby.
==================================================
I recently tried this flavor/brand and was surprised at how delicious t
hese chips are.  The best thing was that there were a lot of "brown" ch
ips in the bsg (my favorite), so I bought some more through amazon and
shared with family and friends.  I am a little disappointed that there
are not, so far, very many brown chips in these bags, but the flavor is
still very good.  I like them better than the yogurt and green onion fl
avor because they do not seem to be as salty, and the onion flavor is b
```

```
etter.  If you haven't eaten Kettle chips before, I recommend that you
try a bag before buying bulk.  They are thicker and crunchier than Lays
but just as fresh out of the bag.
==================================================
Wow.  So far, two two-star reviews.  One obviously had no idea what the
y were ordering; the other wants crispy cookies.  Hey, I'm sorry; but t
hese reviews do nobody any good beyond reminding us to look  before ord
ering.<br /><br />These are chocolate-oatmeal cookies.  If you don't li
ke that combination, don't order this type of cookie.  I find the combo
quite nice, really.  The oatmeal sort of "calms" the rich chocolate fla
vor and gives the cookie sort of a coconut-type consistency.  Now let's
also remember that tastes differ; so, I've given my opinion.<br /><br /
>Then, these are soft, chewy cookies -- as advertised.  They are not "c
rispy" cookies, or the blurb would say "crispy," rather than "chewy."
I happen to like raw cookie dough; however, I don't see where these tas
te like raw cookie dough.  Both are soft, however, so is this the confu
sion?  And, yes, they stick together.  Soft cookies tend to do that.  T
hey aren't individually wrapped, which would add to the cost.  Oh yeah,
chocolate chip cookies tend to be somewhat sweet.<br /><br />So, if you
want something hard and crisp, I suggest Nabiso's Ginger Snaps.  If you
want a cookie that's soft, chewy and tastes like a combination of choco
late and oatmeal, give these a try.  I'm here to place my second order.
==================================================
love to order my coffee on amazon.  easy and shows up quickly.<br />Thi
s k cup is great coffee.  dcaf is very good as well
==================================================
```

In [0]:

```
# 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)
```

```
Why is this $[...] when the same product is available for $[...] here?<
br /> /><br />The Victor M380 and M502 traps are unreal, of course -- t
otal fly genocide. Pretty stinky, but only right nearby.
```

In [0]:

```
# 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)
```

```
Why is this $[...] when the same product is available for $[...] here?
/>The Victor M380 and M502 traps are unreal, of course -- total fly gen
ocide. Pretty stinky, but only right nearby.
==================================================
I recently tried this flavor/brand and was surprised at how delicious t
hese chips are.  The best thing was that there were a lot of "brown" ch
ips in the bsg (my favorite), so I bought some more through amazon and
shared with family and friends.  I am a little disappointed that there
are not, so far, very many brown chips in these bags, but the flavor is
still very good.  I like them better than the yogurt and green onion fl
avor because they do not seem to be as salty, and the onion flavor is b
etter.  If you haven't eaten Kettle chips before, I recommend that you
try a bag before buying bulk.  They are thicker and crunchier than Lays
but just as fresh out of the bag.
==================================================
Wow.  So far, two two-star reviews.  One obviously had no idea what the
```

```
y were ordering; the other wants crispy cookies.  Hey, I'm sorry; but t
hese reviews do nobody any good beyond reminding us to look  before ord
ering.These are chocolate-oatmeal cookies.  If you don't like that comb
ination, don't order this type of cookie.  I find the combo quite nice,
really.  The oatmeal sort of "calms" the rich chocolate flavor and give
s the cookie sort of a coconut-type consistency.  Now let's also rememb
er that tastes differ; so, I've given my opinion.Then, these are soft,
chewy cookies -- as advertised.  They are not "crispy" cookies, or the
blurb would say "crispy," rather than "chewy."  I happen to like raw co
okie dough; however, I don't see where these taste like raw cookie doug
h.  Both are soft, however, so is this the confusion?  And, yes, they s
tick together.  Soft cookies tend to do that.  They aren't individually
wrapped, which would add to the cost.  Oh yeah, chocolate chip cookies
tend to be somewhat sweet.So, if you want something hard and crisp, I s
uggest Nabiso's Ginger Snaps.  If you want a cookie that's soft, chewy
and tastes like a combination of chocolate and oatmeal, give these a tr
y.  I'm here to place my second order.
==================================================
love to order my coffee on amazon.  easy and shows up quickly.This k cu
p is great coffee.  dcaf is very good as well
```

In [0]:

```
# 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 [0]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
Wow.  So far, two two-star reviews.  One obviously had no idea what the
y were ordering; the other wants crispy cookies.  Hey, I am sorry; but
these reviews do nobody any good beyond reminding us to look  before or
dering.<br /><br />These are chocolate-oatmeal cookies.  If you do not
like that combination, do not order this type of cookie.  I find the co
mbo quite nice, really.  The oatmeal sort of "calms" the rich chocolate
flavor and gives the cookie sort of a coconut-type consistency.  Now le
t is also remember that tastes differ; so, I have given my opinion.<br
/><br />Then, these are soft, chewy cookies -- as advertised.  They are
not "crispy" cookies, or the blurb would say "crispy," rather than "che
wy."  I happen to like raw cookie dough; however, I do not see where th
ese taste like raw cookie dough.  Both are soft, however, so is this th
e confusion?  And, yes, they stick together.  Soft cookies tend to do t
hat.  They are not individually wrapped, which would add to the cost.
Oh yeah, chocolate chip cookies tend to be somewhat sweet.<br /><br />S
o, if you want something hard and crisp, I suggest Nabiso is Ginger Sna
ps.  If you want a cookie that is soft, chewy and tastes like a combina
tion of chocolate and oatmeal, give these a try.  I am here to place my
second order.
==================================================
```

In [0]:
```
#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)
```

```
Why is this $[...] when the same product is available for $[...] here?<
br /> /><br />The Victor  and  traps are unreal, of course -- total fly
genocide. Pretty stinky, but only right nearby.
```

In [0]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
Wow So far two two star reviews One obviously had no idea what they wer
e ordering the other wants crispy cookies Hey I am sorry but these revi
ews do nobody any good beyond reminding us to look before ordering br b
r These are chocolate oatmeal cookies If you do not like that combinati
on do not order this type of cookie I find the combo quite nice really
The oatmeal sort of calms the rich chocolate flavor and gives the cooki
e sort of a coconut type consistency Now let is also remember that tast
es differ so I have given my opinion br br Then these are soft chewy co
okies as advertised They are not crispy cookies or the blurb would say
crispy rather than chewy I happen to like raw cookie dough however I do
not see where these taste like raw cookie dough Both are soft however s
o is this the confusion And yes they stick together Soft cookies tend t
o do that They are not individually wrapped which would add to the cost
Oh yeah chocolate chip cookies tend to be somewhat sweet br br So if yo
u want something hard and crisp I suggest Nabiso is Ginger Snaps If you
want a cookie that is soft chewy and tastes like a combination of choco
late and oatmeal give these a try I am here to place my second order
```

In [0]:

```
# 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 [0]:

```
# 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%|██████████████████████████████████████████████████████████████
██████████| 4986/4986 [00:01<00:00, 3137.37it/s]
```

In [0]:

```
preprocessed_reviews[1500]
```

Out[0]:

```
'wow far two two star reviews one obviously no idea ordering wants cris
py cookies hey sorry reviews nobody good beyond reminding us look order
```

```
ing chocolate oatmeal cookies not like combination not order type cooki
e find combo quite nice really oatmeal sort calms rich chocolate flavor
gives cookie sort coconut type consistency let also remember tastes dif
fer given opinion soft chewy cookies advertised not crispy cookies blur
b would say crispy rather chewy happen like raw cookie dough however no
t see taste like raw cookie dough soft however confusion yes stick toge
ther soft cookies tend not individually wrapped would add cost oh yeah
chocolate chip cookies tend somewhat sweet want something hard crisp su
ggest nabiso ginger snaps want cookie soft chewy tastes like combinatio
n chocolate oatmeal give try place second order'
```

[3.2] Preprocessing Review Summary

In [0]:
```
## Similartly you can do preprocessing for review summary also.
```

[4] Featurization

[4.1] BAG OF WORDS

In [0]:
```
#BoW
count_vect = CountVectorizer() #in scikit-learn
count_vect.fit(preprocessed_reviews)
print("some feature names ", count_vect.get_feature_names()[:10])
print('='*50)

final_counts = count_vect.transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_counts))
print("the shape of out text BOW vectorizer ",final_counts.get_shape())
print("the number of unique words ", final_counts.get_shape()[1])
```

```
some feature names  ['aa', 'aahhhs', 'aback', 'abandon', 'abates', 'abb
ott', 'abby', 'abdominal', 'abiding', 'ability']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
```

```
the shape of out text BOW vectorizer  (4986, 12997)
the number of unique words  12997
```

[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_features
=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_s
hape())
print("the number of unique words including both unigrams and bigrams "
, final_bigram_counts.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (4986, 3144)
the number of unique words including both unigrams and bigrams  3144
```

[4.3] TF-IDF

In [0]:

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tf_idf_vect.fit(preprocessed_reviews)
print("some sample features(unique words in the corpus)",tf_idf_vect.ge
t_feature_names()[0:10])
print('='*50)
```

```
final_tf_idf = tf_idf_vect.transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_tf_idf))
print("the shape of out text TFIDF vectorizer ",final_tf_idf.get_shape
())
print("the number of unique words including both unigrams and bigrams "
, final_tf_idf.get_shape()[1])
```

```
some sample features(unique words in the corpus) ['ability', 'able', 'a
ble find', 'able get', 'absolute', 'absolutely', 'absolutely deliciou
s', 'absolutely love', 'absolutely no', 'according']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (4986, 3144)
the number of unique words including both unigrams and bigrams  3144
```

[4.4] Word2Vec

In [0]:

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

In [0]:

```
# Using Google News Word2Vectors

# in this project we are using a pretrained model by google
# its 3.3G file, once you load this into your memory
# it occupies ~9Gb, so please do this step only if you have >12G of ram
# we will provide a pickle file wich contains a dict ,
# and it contains all our courpus words as keys and  model[word] as val
ues
# To use this code-snippet, download "GoogleNews-vectors-negative300.bi
n"
# from https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/edi
t
# it's 1.9GB in size.
```

```
# http://kavita-ganesan.com/gensim-word2vec-tutorial-starter-code/#.W17
SRFAzZPY
# you can comment this whole cell
# or change these varible according to your need

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,min_count=5,size=50, workers=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 ")
```

```
[('snack', 0.9951335191726685), ('calorie', 0.9946465492248535), ('wond
erful', 0.9946032166481018), ('excellent', 0.9944332838058472), ('espec
ially', 0.9941144585609436), ('baked', 0.9940600395202637), ('salted',
0.994047224521637), ('alternative', 0.9937226176261902), ('tasty', 0.99
36816692352295), ('healthy', 0.9936649799346924)]
==================================================
[('varieties', 0.9994194507598877), ('become', 0.9992934465408325), ('p
opcorn', 0.9992750883102417), ('de', 0.9992610216140747), ('miss', 0.99
92451071739197), ('melitta', 0.999218761920929), ('choice', 0.999210238
4567261), ('american', 0.9991837739944458), ('beef', 0.999178051948547
4), ('finish', 0.9991567134857178)]
```

In [0]:
```
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  3817
sample words  ['product', 'available', 'course', 'total', 'pretty', 'st
inky', 'right', 'nearby', 'used', 'ca', 'not', 'beat', 'great', 'receiv
ed', 'shipment', 'could', 'hardly', 'wait', 'try', 'love', 'call', 'ins
tead', 'removed', 'easily', 'daughter', 'designed', 'printed', 'use',
'car', 'windows', 'beautifully', 'shop', 'program', 'going', 'lot', 'fu
n', 'everywhere', 'like', 'tv', 'computer', 'really', 'good', 'idea',
'final', 'outstanding', 'window', 'everybody', 'asks', 'bought', 'mad
e']
```

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

[4.4.1.1] Avg W2v

In [0]:
```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors = []; # the avg-w2v for each sentence/review is stored in
 this list
for sent in tqdm(list_of_sentance): # 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.append(sent_vec)
```

```
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

```
100%|██████████████████████████████████████████████████
████████| 4986/4986 [00:03<00:00, 1330.47it/s]
```

```
4986
50
```

[4.4.1.2] TFIDF weighted W2v

In [0]:
```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
tf_idf_matrix = model.fit_transform(preprocessed_reviews)
# 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 [0]:
```
# TF-IDF weighted Word2Vec
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): # 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%|██████████████████████████████████████████████████████████████| 4986/4986 [00:20<00:00, 245.63it/s]
```

[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 i.e Train data.
    - 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 [0]:
```
final.columns
```

```
Out[0]: Index(['index', 'Id', 'ProductId', 'UserId', 'ProfileName',
               'HelpfulnessNumerator', 'HelpfulnessDenominator', 'Score', 'Tim
        e',
               'Summary', 'Text', 'CleanedText'],
              dtype='object')
```

In [0]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import TimeSeriesSplit
from sklearn.model_selection import train_test_split

preprocessed_reviews=final['CleanedText'][:100000]
score=final['Score'][:100000]
X_train, X_test, y_train, y_test = train_test_split(preprocessed_review
s, score, test_size=0.25,stratify=score, random_state=42)
```

In [8]:
```
#BoW
count_vect = CountVectorizer(max_df=0.95, min_df=2,stop_words='english'
,max_features=10000) #in scikit-learn
count_vect.fit(X_train)
print("some feature names ", count_vect.get_feature_names()[:10])
print('='*50)

X_train_bow = count_vect.transform(X_train)
print("the type of count vectorizer ",type(X_train_bow))
print("the shape of out text BOW vectorizer ",X_train_bow.get_shape())
print("the number of unique words ", X_train_bow.get_shape()[1])

X_test_bow = count_vect.transform(X_test)
print("the type of count vectorizer ",type(X_test_bow))
print("the shape of out text BOW vectorizer ",X_test_bow.get_shape())
print("the number of unique words ", X_test_bow.get_shape()[1])
```

```
some feature names  ['ab', 'aback', 'abandon', 'abbey', 'abc', 'abdomi
n', 'abil', 'abl', 'abnorm', 'abomin']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (75000, 10000)
the number of unique words  10000
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (25000, 10000)
the number of unique words  10000
```

In [0]:

```
#X_train_bow=X_train_bow.toarray()

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler(with_mean=False)
scaler.fit(X_train_bow)
X_train_bow=scaler.transform(X_train_bow)

X_test_bow=scaler.transform(X_test_bow)
```

In [0]:

```
from sklearn.linear_model import LogisticRegression

clf=LogisticRegression(penalty='l1')
param_grid={'C':[1000,100,10,1,0.1,0.001,0.0001]}
#timeseriessplit=TimeSeriesSplit(n_splits=10)
gcv=GridSearchCV(clf,param_grid,cv=5,scoring='roc_auc')
gcv.fit(X_train_bow,y_train)
print(gcv.best_params_)
print(gcv.best_score_)
```

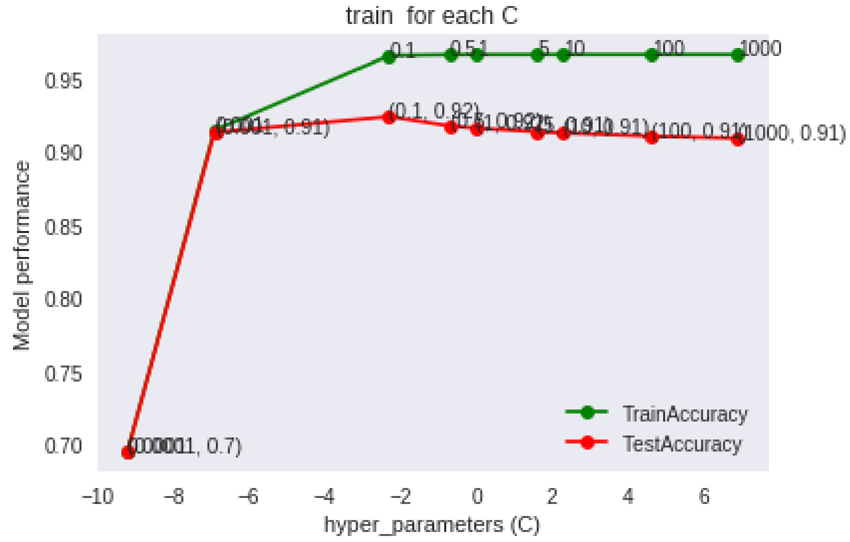
In [0]:

```
hyper_parameters=gcv.get_params()['param_grid']['C']
train_scores=gcv.cv_results_['mean_train_score'].tolist()
test_scores=gcv.cv_results_['mean_test_score'].tolist()

print(hyper_parameters)
print(test_scores)
print(train_scores)
```

```
[1000, 100, 10, 5, 1, 0.5, 0.1, 0.001, 0.0001]
[0.9088546452748788, 0.9103610412514892, 0.912518280012368, 0.913361678
1239468, 0.9157905093369368, 0.9173113487846236, 0.9236798904189109, 0.
9129397282067238, 0.6950984355652179]
[0.9659050271342888, 0.9659028612935927, 0.9658948545387306, 0.96588897
56573034, 0.9658521776960267, 0.9658079422705249, 0.965298273599571, 0.
914513249597746, 0.695107385548616]
```

In [7]:

```
import math
C =  [1000, 100, 10, 5, 1, 0.5, 0.1, 0.001, 0.0001]
C_log=[math.log(i) for i in C]

test_scores=[0.9088546452748788, 0.9103610412514892, 0.912518280012368,
 0.9133616781239468, 0.9157905093369368, 0.9173113487846236, 0.92367989
04189109, 0.9129397282067238, 0.6950984355652179]
train_scores=[0.9659050271342888, 0.9659028612935927, 0.965894854538730
6, 0.9658889756573034, 0.9658521776960267, 0.9658079422705249, 0.965298
273599571, 0.914513249597746, 0.695107385548616]


fig, ax = plt.subplots()
ax.plot(C_log, train_scores,c='g',marker='o',label="TrainAccuracy")

for i, txt in enumerate(C):
    ax.annotate(txt, (C_log[i], train_scores[i]))

ax.plot(C_log, test_scores ,c='r',marker='o',label="TestAccuracy")

for i, txt in enumerate(C):
    ax.annotate((txt,np.round(test_scores[i],2)) , (C_log[i], test_scor
es[i]))

plt.title("train  for each C")
plt.xlabel("hyper_parameters (C)")
plt.ylabel("Model performance")
plt.legend()
plt.grid()
plt.show()
```



In [0]:

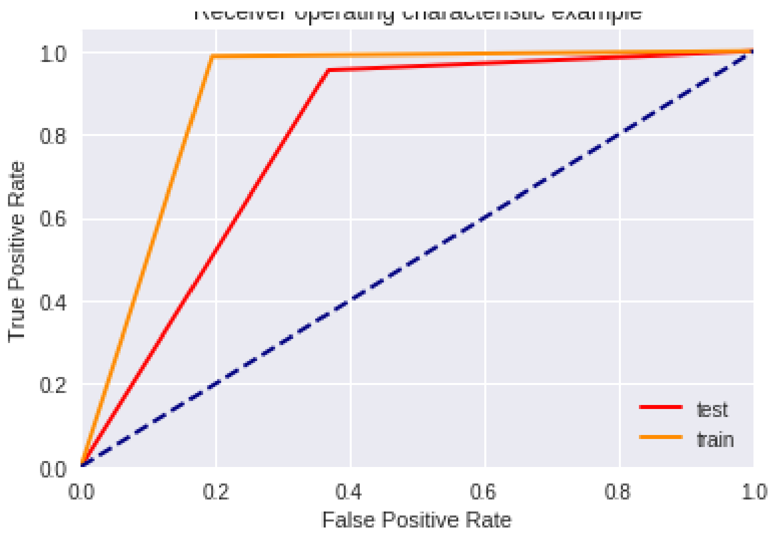
```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import auc
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score



clf1=LogisticRegression(C=0.1,penalty='l1')
clf1.fit(X_train_bow,y_train)
pred_train=clf1.predict(X_train_bow)
pred=clf1.predict(X_test_bow)

print("Accuracy Score : ",accuracy_score(y_test,pred)*100)
print("Precision Score : ",precision_score(y_test,pred)*100)
print("Recall Score : ",recall_score(y_test,pred)*100)
print("F1 Score : ",f1_score(y_test,pred)*100)

print("        ")
```

```
print("Classification Report")
print(classification_report(y_test,pred))
print("        ")

fpr_train,tpr_train,thresholds_train=roc_curve(y_train,pred_train)
print("AUC Score for train data :",metrics.auc(fpr_train,tpr_train))

fpr,tpr,thresholds=roc_curve(y_test,pred)
print("AUC Score for test data :",metrics.auc(fpr,tpr))

print("        ")

#y_true = # ground truth labels
#y_probas = # predicted probabilities generated by sklearn classifier
#skplt.metrics.plot_roc_curve(y_true, y_probas)
#plt.show()



plt.figure()
lw = 2
plt.plot(fpr, tpr, color='red',
         lw=lw,label='test')
plt.plot(fpr_train, tpr_train, color='darkorange',
         lw=lw,label='train')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()


print("       ")

tn, fp, fn, tp=confusion_matrix(y_test,pred).ravel()
print("""
```

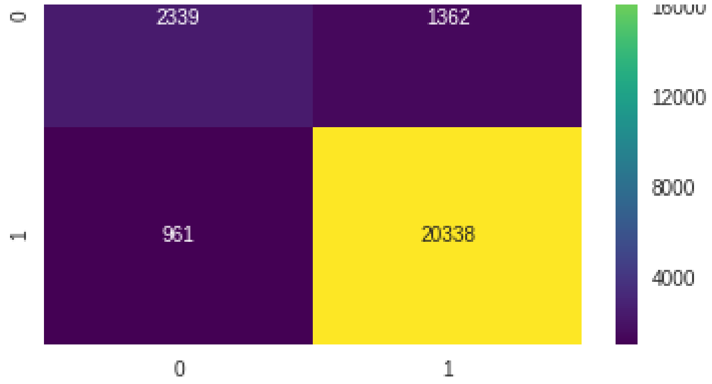
```
TrueNegative : {}
FalsePostive : {}
FalseNegative : {}
TruePostive  :  {}""".format(tn, fp, fn, tp))
print("        ")
print("        ")

confusionmatrix_DF=pd.DataFrame(confusion_matrix(y_test,pred),columns=[
'0','1'],index=['0','1'])
sns.heatmap(confusionmatrix_DF,annot=True,fmt='g',cmap='viridis')
plt.title("Confusion matrix ")
plt.show()
```

```
Accuracy Score :  90.708
Precision Score :  93.72350230414746
Recall Score :  95.48805108221043
F1 Score :  94.59754878020419

Classification Report
              precision    recall  f1-score   support

           0       0.71      0.63      0.67      3701
           1       0.94      0.95      0.95     21299

   micro avg       0.91      0.91      0.91     25000
   macro avg       0.82      0.79      0.81     25000
weighted avg       0.90      0.91      0.90     25000


AUC Score for train data : 0.8962604569087288
AUC Score for test data : 0.7934359322551484
```

Receiver operating characteristic example




```
TrueNegative : 2339
FalsePostive : 1362
FalseNegative : 961
TruePostive  :  20338
```



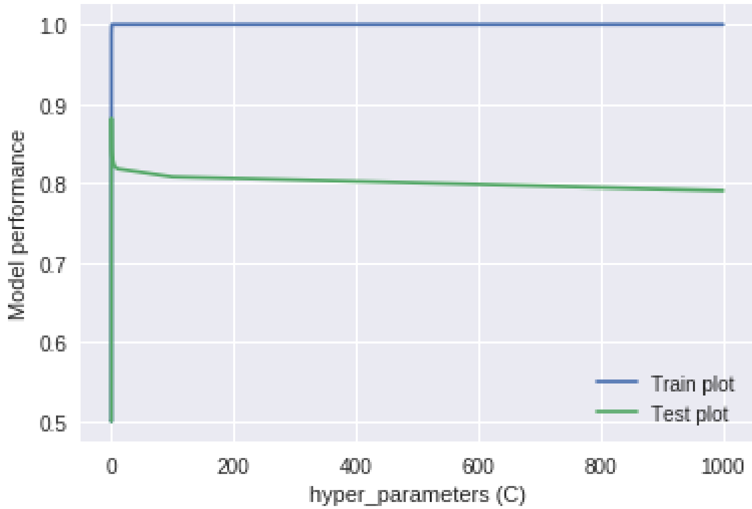
with PREROCESSED REVIEWS

In [0]:
```
hyper_parameters=gcv.get_params()['param_grid']['C']
train_scores=gcv.cv_results_['mean_train_score'].tolist()
test_scores=gcv.cv_results_['mean_test_score'].tolist()

print(hyper_parameters)
print(test_scores)
print(train_scores)
```

```
[1000, 100, 10, 5, 1, 0.5, 0.1, 0.001, 0.0001]
[0.7908377521433998, 0.8079856879597342, 0.8181680236380514, 0.82162558
65348513, 0.8335232007342616, 0.8431101705158265, 0.8819334254079269,
0.5, 0.5]
[1.0, 1.0, 1.0, 1.0, 0.9999706414160041, 0.9997050308702843, 0.98806266
76516027, 0.5, 0.5]
```

In [0]:
```
plt.plot( hyper_parameters ,train_scores , label='Train plot')
plt.plot( hyper_parameters ,test_scores ,  label='Test plot')
plt.xlabel("hyper_parameters (C)")
plt.ylabel("Model performance")

plt.legend()
```

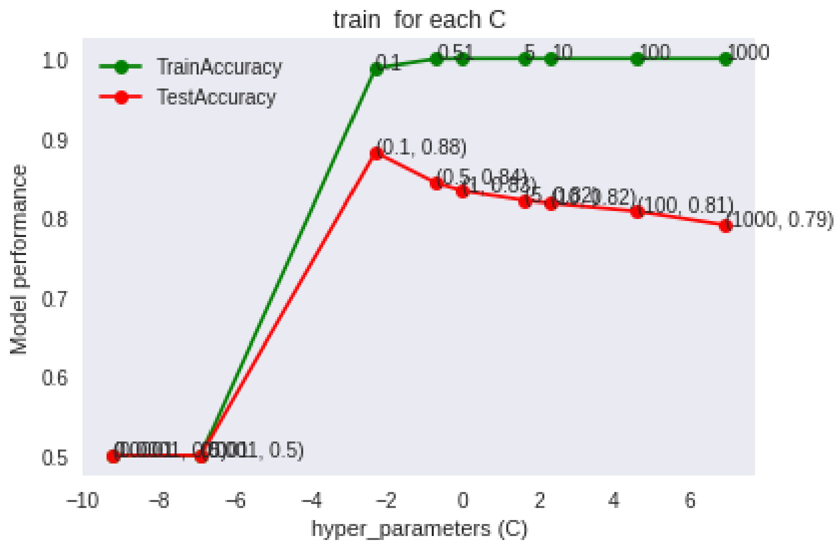
Out[0]:
```
<matplotlib.legend.Legend at 0x7ff8cc72bb00>
```



In [8]:

```
import math




C = [1000, 100, 10, 5, 1, 0.5, 0.1, 0.001, 0.0001]
C_log=[math.log(i) for i in C]
test_scores=[0.7908377521433998, 0.8079856879597342, 0.8181680236380514
, 0.8216255865348513, 0.8335232007342616, 0.8431101705158265, 0.8819334
254079269, 0.5, 0.5]
train_scores = [1.0, 1.0, 1.0, 1.0, 0.9999706414160041, 0.9997050308702
843, 0.9880626676516027, 0.5, 0.5]


fig, ax = plt.subplots()
ax.plot(C_log, train_scores,c='g',marker='o',label="TrainAccuracy")

for i, txt in enumerate(C):
    ax.annotate(txt, (C_log[i], train_scores[i]))

ax.plot(C_log, test_scores ,c='r',marker='o',label="TestAccuracy")

for i, txt in enumerate(C):
```

```
    ax.annotate((txt,np.round(test_scores[i],2)) , (C_log[i], test_scor
es[i]))

plt.title("train  for each C")
plt.xlabel("hyper_parameters (C)")
plt.ylabel("Model performance")
plt.legend()
plt.grid()
plt.show()
```



In [0]:

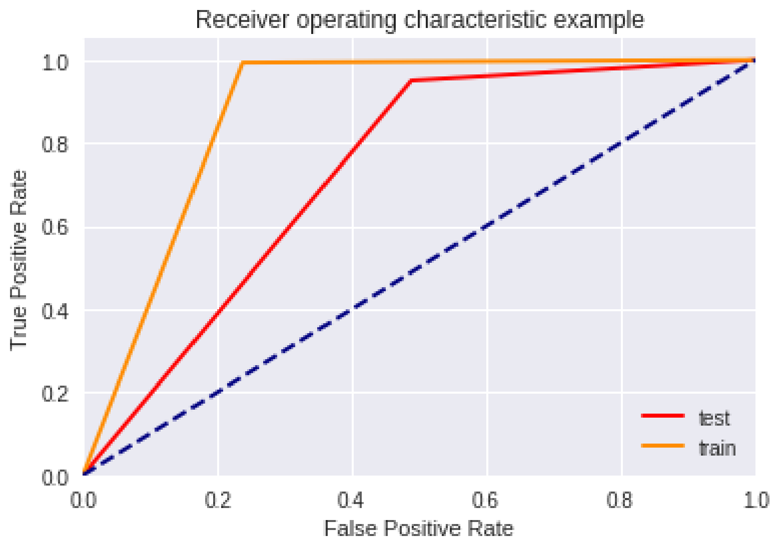
```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import auc
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score



clf1=LogisticRegression(C=0.1,penalty='l1')
```

```
clf1.fit(X_train_bow,y_train)
pred_train=clf1.predict(X_train_bow)
pred=clf1.predict(X_test_bow)

print("Accuracy Score : ",accuracy_score(y_test,pred)*100)
print("Precision Score : ",precision_score(y_test,pred)*100)
print("Recall Score : ",recall_score(y_test,pred)*100)
print("F1 Score : ",f1_score(y_test,pred)*100)

print("        ")
print("Classification Report")
print(classification_report(y_test,pred))
print("        ")

fpr_train,tpr_train,thresholds_train=roc_curve(y_train,pred_train)
print("AUC Score for train data :",metrics.auc(fpr_train,tpr_train))

fpr,tpr,thresholds=roc_curve(y_test,pred)
print("AUC Score for test data :",metrics.auc(fpr,tpr))

print("        ")

#y_true = # ground truth labels
#y_probas = # predicted probabilities generated by sklearn classifier
#skplt.metrics.plot_roc_curve(y_true, y_probas)
#plt.show()



plt.figure()
lw = 2
plt.plot(fpr, tpr, color='red',
         lw=lw,label='test')
plt.plot(fpr_train, tpr_train, color='darkorange',
         lw=lw,label='train')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
```

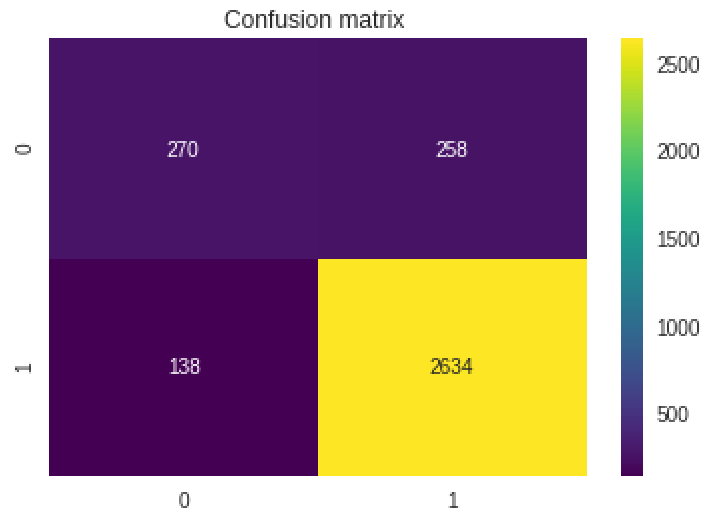
```
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()


print("       ")

tn, fp, fn, tp=confusion_matrix(y_test,pred).ravel()
print("""
TrueNegative : {}
FalsePostive : {}
FalseNegative : {}
TruePostive  :  {}""".format(tn, fp, fn, tp))
print("        ")
print("        ")

confusionmatrix_DF=pd.DataFrame(confusion_matrix(y_test,pred),columns=[
'0','1'],index=['0','1'])
sns.heatmap(confusionmatrix_DF,annot=True,fmt='g',cmap='viridis')
plt.title("Confusion matrix ")
plt.show()
```

```
Accuracy Score :  88.0
Precision Score :  91.07883817427386
Recall Score :  95.02164502164501
F1 Score :  93.00847457627118

Classification Report
              precision    recall  f1-score   support

           0       0.66      0.51      0.58       528
           1       0.91      0.95      0.93      2772

   micro avg       0.88      0.88      0.88      3300
   macro avg       0.79      0.73      0.75      3300
weighted avg       0.87      0.88      0.87      3300


AUC Score for train data : 0.8778612876448715
```

```
AUC Score for test data : 0.7307900432900433
```




```
TrueNegative : 270
FalsePostive : 258
FalseNegative : 138
TruePostive  :  2634
```



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

In [0]:
```
a=np.count_nonzero(clf1.coef_)
size=clf1.coef_.size
Sparsity=  (size - a)/size
```

In [0]:
```
hyper_parameters=gcv.get_params()['param_grid']['C']
train_scores=gcv.cv_results_['mean_train_score'].tolist()
test_scores=gcv.cv_results_['mean_test_score'].tolist()

print(hyper_parameters)
print(test_scores)
print(train_scores)
```

```
[1000, 100, 10, 5, 1, 0.5, 0.1, 0.001, 0.0001]
[0.9088546452748788, 0.9103610412514892, 0.912518280012368, 0.913361678
1239468, 0.9157905093369368, 0.9173113487846236, 0.9236798904189109, 0.
9129397282067238, 0.6950984355652179]
[0.9659050271342888, 0.9659028612935927, 0.9658948545387306, 0.96588897
```

56573034, 0.9658521776960267, 0.9658079422705249, 0.965298273599571, 0.914513249597746, 0.695107385548616]

In [0]:

```

```

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

In [0]:

```
from sklearn.linear_model import LogisticRegression

clf=LogisticRegression(penalty='l2')
param_grid={'C':[1000,100,10,1,0.1,0.001,0.0001]}
#timeseriessplit=TimeSeriesSplit(n_splits=10)
gcv=GridSearchCV(clf,param_grid,cv=5,scoring='roc_auc')
gcv.fit(X_train_bow,y_train)
print(gcv.best_params_)
print(gcv.best_score_)
```

{'C': 0.001}
0.9097617785177461

In [0]:

```
hyper_parameters=gcv.get_params()['param_grid']['C']
train_scores=gcv.cv_results_['mean_train_score'].tolist()
test_scores=gcv.cv_results_['mean_test_score'].tolist()

print(hyper_parameters)
print(test_scores)
print(train_scores)
```

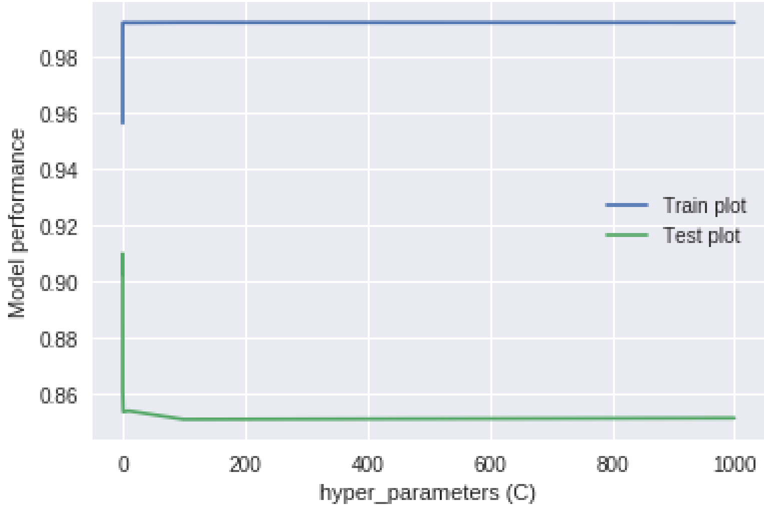
[1000, 100, 10, 1, 0.1, 0.001, 0.0001]
[0.8511000043019294, 0.8506357843347192, 0.8536634128701011, 0.8533230213012999, 0.8600912167589186, 0.9097617785177461, 0.90257602348846]
[0.9921086446080356, 0.992160164672204, 0.9920741278201515, 0.9921541963998797, 0.9918990281685094, 0.9822747157003355, 0.9562920434285788]

In [0]:

```
plt.plot( hyper_parameters ,train_scores , label='Train plot')
plt.plot( hyper_parameters ,test_scores ,  label='Test plot')
plt.xlabel("hyper_parameters (C)")
```

```
plt.ylabel("Model performance")

plt.legend()
```

Out[0]: <matplotlib.legend.Legend at 0x7fe9a9bc8438>

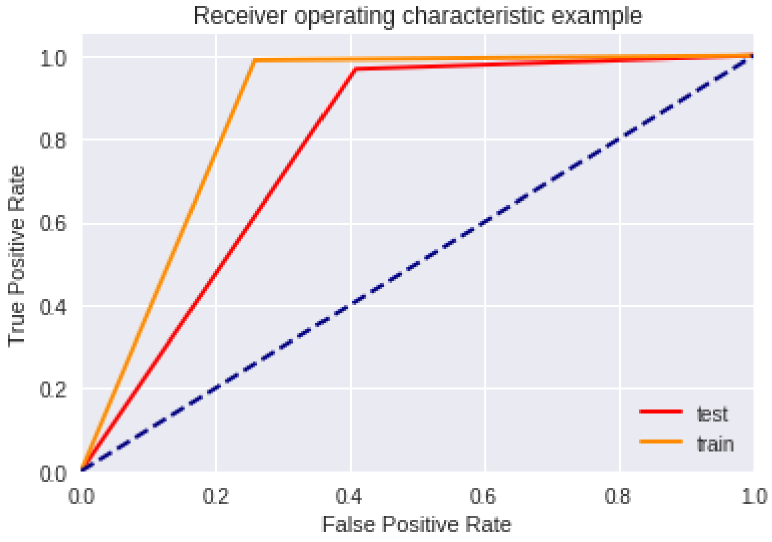


In [0]:
```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import auc
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score



clf1=LogisticRegression(C=0.001,penalty='l2')
clf1.fit(X_train_bow,y_train)
pred_train=clf1.predict(X_train_bow)
pred=clf1.predict(X_test_bow)

print("Accuracy Score : ",accuracy_score(y_test,pred)*100)
```

```
print("Precision Score : ",precision_score(y_test,pred)*100)
print("Recall Score : ",recall_score(y_test,pred)*100)
print("F1 Score : ",f1_score(y_test,pred)*100)

print("        ")
print("Classification Report")
print(classification_report(y_test,pred))
print("        ")

fpr_train,tpr_train,thresholds_train=roc_curve(y_train,pred_train)
print("AUC Score for train data :",metrics.auc(fpr_train,tpr_train))

fpr,tpr,thresholds=roc_curve(y_test,pred)
print("AUC Score for test data :",metrics.auc(fpr,tpr))

print("        ")

#y_true = # ground truth labels
#y_probas = # predicted probabilities generated by sklearn classifier
#skplt.metrics.plot_roc_curve(y_true, y_probas)
#plt.show()



plt.figure()
lw = 2
plt.plot(fpr, tpr, color='red',
         lw=lw,label='test')
plt.plot(fpr_train, tpr_train, color='darkorange',
         lw=lw,label='train')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
```

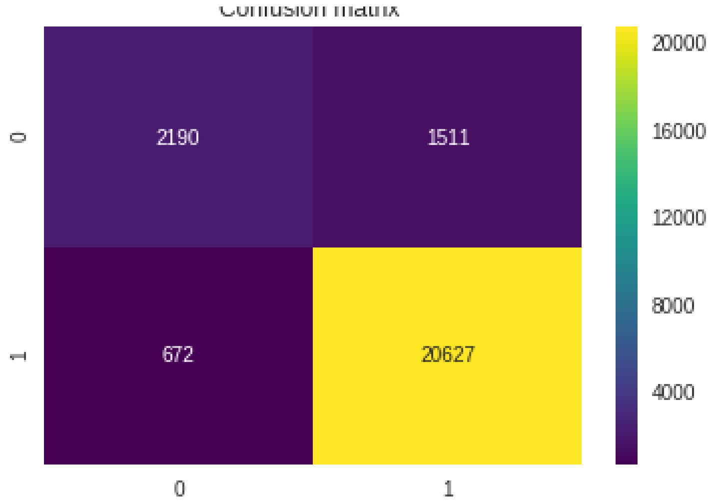
```
print("        ")

tn, fp, fn, tp=confusion_matrix(y_test,pred).ravel()
print("""
TrueNegative : {}
FalsePostive : {}
FalseNegative : {}
TruePostive  :  {}""".format(tn, fp, fn, tp))
print("         ")
print("         ")

confusionmatrix_DF=pd.DataFrame(confusion_matrix(y_test,pred),columns=[
'0','1'],index=['0','1'])
sns.heatmap(confusionmatrix_DF,annot=True,fmt='g',cmap='viridis')
plt.title("Confusion matrix ")
plt.show()
```

```
Accuracy Score :  91.268
Precision Score :  93.17463185472943
Recall Score :  96.84492229682145
F1 Score :  94.97433063977715

Classification Report
              precision    recall  f1-score   support

           0       0.77      0.59      0.67      3701
           1       0.93      0.97      0.95     21299

   micro avg       0.91      0.91      0.91     25000
   macro avg       0.85      0.78      0.81     25000
weighted avg       0.91      0.91      0.91     25000


AUC Score for train data : 0.8652155813496196
AUC Score for test data : 0.7800905936510891
```




```
TrueNegative : 2190
FalsePostive : 1511
FalseNegative : 672
TruePostive  :  20627
```

Confusion matrix



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

this nosie can also be used but this gives dense matrix

In [0]:
```
noise=0.000001
x_train_bow_noise=np.zeros(X_train_bow.shape)
for i in range(X_train_bow.shape[0]):
    x_train_bow_noise[i]=X_train_bow[i].toarray()+noise
```

In [12]:
```
#x_train_bow_noise
from sklearn.linear_model import LogisticRegression
clfNO=LogisticRegression(C=0.001,penalty='l2')
clfNO.fit(X_train_bow,y_train)
print("WEIGHTS with X_train_bow :", clfNO.coef_[0])
```

```
WEIGHTS with X_train_bow : [ 0.00019553 -0.00740731 -0.00017604 ...  0.
00757321  0.0008448
  0.00331951]
```

In [13]:
```
clfY=LogisticRegression(C=0.001,penalty='l2')
```

```
clfY.fit(x_train_noise1,y_train)
print("WEIGHTS with x_train_bow_noise  :",clfY.coef_[0])
```

```
WEIGHTS with x_train_bow_noise  : [ 0.00019553 -0.00740731 -0.00017604
...  0.00757321  0.0008448
  0.00331951]
```

I have used this noise

In [0]:

```
import copy
x_train_noise1=copy.deepcopy(X_train_bow)
#e=np.random.normal(0,0.01)
x_train_noise1.data += 0.00001
```

In [93]:

```
type(x_train_noise1)
```

Out[93]:

```
scipy.sparse.csr.csr_matrix
```

In [97]:

```
#weight without adding noise to data :::: so used X_train_bow
clfNO=LogisticRegression(C=0.001,penalty='l2')
clfNO.fit(X_train_bow,y_train)
print("weight without noise using X_train_bow : \n",clfNO.coef_[0])
print('\n')

#weight with adding noise to data :::: so used x_train_noise1
clfY=LogisticRegression(C=0.001,penalty='l2')
clfY.fit(x_train_noise1,y_train)
print("weight with noise using x_train_noise1 :\n ",clfY.coef_[0])
print('\n')

#Calculated WeightDifference
wgts_difference=(abs((clfNO.coef_[0]-clfY.coef_[0])/clfNO.coef_[0])*100
)
print("weight Difference between noise and not noise :\n ",wgts_differe
nce)
print('\n')
print("counting any weight difference greater than 0.5  : ",wgts_differ
```

```
ence[np.where(wgts_difference > 0.5)].size)
print('\n')
print("length of Weight difference is : ",len(wgts_difference))
print('\n')
print("Weight difference is : \n",wgts_difference)
```

```
weight without noise using X_train_bow :
 [ 0.00019553 -0.00740731 -0.00017604 ...  0.00757321  0.0008448
  0.00331951]


weight with noise using x_train_noise1 :
  [ 0.00019562 -0.00740731 -0.00017603 ...  0.00757322  0.00084479
  0.00331946]


weight Difference between noise and not noise :
  [4.87617935e-02 2.08552250e-05 4.87784215e-03 ... 1.49830512e-04
 1.28442956e-03 1.58088976e-03]


counting any weight difference greater than 0.5  :  15


length of Weight difference is :  10000


Weight difference is :
 [4.87617935e-02 2.08552250e-05 4.87784215e-03 ... 1.49830512e-04
 1.28442956e-03 1.58088976e-03]
```

In [98]:

```
from sklearn.linear_model import LogisticRegression

#weight without adding noise to data :::: so used x_train_noise1
clf1=LogisticRegression(C=0.001,penalty='l2')
clf1.fit(X_train_bow,y_train)
pred=clf1.predict(X_test_bow)
a=np.count_nonzero(clf1.coef_)
print("AccuracyScore : ",accuracy_score(y_test,pred))
```

```
print(a)

#After getting weights adding 10**-6 to weights
#adding  W=W+10^-6
print(clf1.coef_.shape)
wgts_without_noise=clf1.coef_[0]
print(wgts_without_noise)
wgts_without_noise=wgts_without_noise+0.000001
print(wgts_without_noise)


#x_train_noise1=copy.deepcopy(X_train_bow)
#x_train_noise1.data += 0.00001
#weight with adding noise to data :::: so used x_train_noise1
clf1_noise=LogisticRegression(C=0.001,penalty='l2')
clf1_noise.fit(x_train_noise1,y_train)
pred=clf1_noise.predict(X_test_bow)
a=np.count_nonzero(clf1_noise.coef_)
print("AccuracyScore : ",accuracy_score(y_test,pred))
print(a)

#After getting weights adding 10**-6 to weights
# adding W’ = W’+10^-6
print(clf1_noise.coef_.shape)
wgts_with_noise=clf1_noise.coef_[0]
print(wgts_with_noise)
wgts_with_noise=wgts_with_noise+0.000001
print(wgts_with_noise)


wgts_difference=(abs((wgts_without_noise-wgts_with_noise)/wgts_without_
noise)*100)
print(wgts_difference[np.where(wgts_difference > 0.5)].size)
print("Weight differeemce is : ",wgts_difference)



#Calculated WeightDifference
wgts_difference=(abs((wgts_without_noise-wgts_with_noise)/wgts_without_
```

```
noise)*100)
print("weight Difference between noise and not noise :\n ",wgts_differe
nce)
print('\n')
print("counting any weight difference greater than 0.5  : ",wgts_differ
ence[np.where(wgts_difference > 0.5)].size)
print('\n')
print("length of Weight difference is : ",len(wgts_difference))
print('\n')
print("Weight difference is : \n",wgts_difference)
```

```
AccuracyScore :  0.91268
10000
(1, 10000)
[ 0.00019553 -0.00740731 -0.00017604 ...  0.00757321  0.0008448
  0.00331951]
[ 0.00019653 -0.00740631 -0.00017504 ...  0.00757421  0.0008458
  0.00332051]
AccuracyScore :  0.91268
10000
(1, 10000)
[ 0.00019562 -0.00740731 -0.00017603 ...  0.00757322  0.00084479
  0.00331946]
[ 0.00019662 -0.00740631 -0.00017503 ...  0.00757422  0.00084579
  0.00332046]
7
Weight differeemce is :  [4.85136782e-02 2.08580409e-05 4.90570968e-03
... 1.49810731e-04
 1.28291097e-03 1.58041367e-03]
weight Difference between noise and not noise :
  [4.85136782e-02 2.08580409e-05 4.90570968e-03 ... 1.49810731e-04
 1.28291097e-03 1.58041367e-03]


counting any weight difference greater than 0.5  :  7


length of Weight difference is :  10000
```

```
Weight difference is :
 [4.85136782e-02 2.08580409e-05 4.90570968e-03 ... 1.49810731e-04
 1.28291097e-03 1.58041367e-03]
```

In [103]:

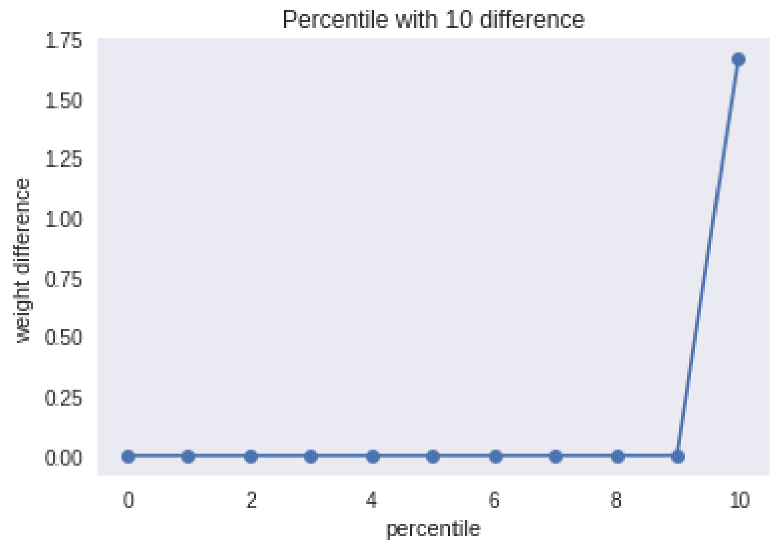
```
#tag_df_sorted = tag_df.sort_values(['Counts'], ascending=False)
#tag_counts = tag_df_sorted['Counts'].values

wgts_difference.sort()
print(wgts_difference)
```

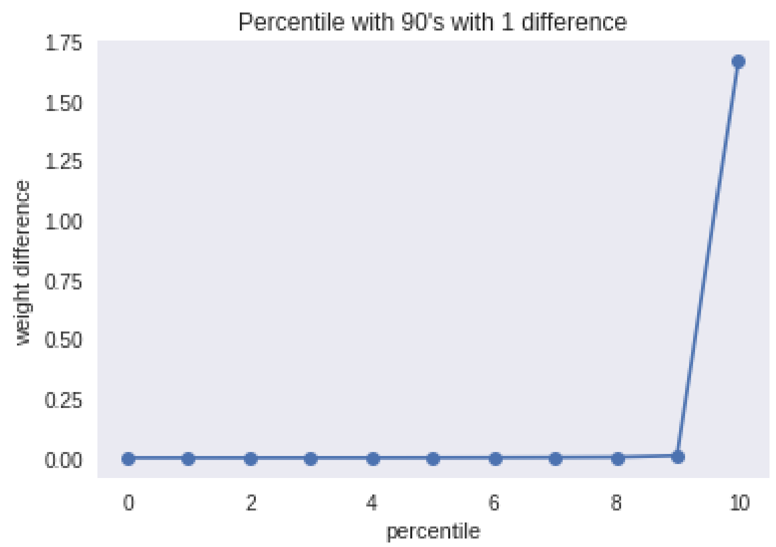
```
[2.95507520e-08 5.96602930e-08 7.91597000e-08 ... 9.64262480e-01
 1.43812690e+00 1.66461003e+00]
```

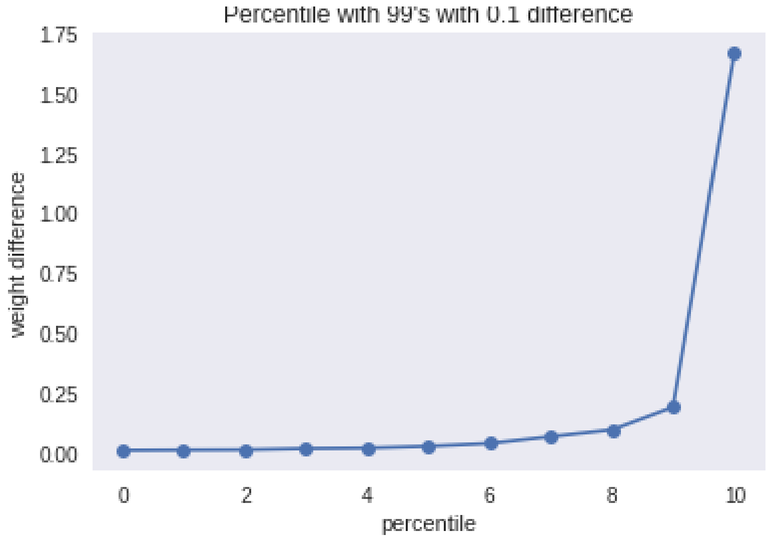
In [106]:

```
#wgts_difference
percentile10=np.percentile(wgts_difference, [0,10,20,30,40,50,60,70,80,
90,100])
plt.plot(percentile10,'-o')
plt.title("Percentile with 10 difference")
plt.grid()
plt.xlabel("percentile")
plt.ylabel("weight difference")
plt.show()


b=np.percentile(wgts_difference,[90,91,92,93,94,95,96,97,98,99,100])
plt.plot(b,'-o')
plt.title("Percentile with 90's with 1 difference")
plt.grid()
plt.xlabel("percentile")
plt.ylabel("weight difference")
plt.show()


a=np.percentile(wgts_difference,[99,99.1,99.2,99.3,99.4,99.5,99.6,99.7,
99.8,99.9,100])
plt.plot(a,'-o')
plt.title("Percentile with 99's with 0.1 difference")
plt.grid()
plt.xlabel("percentile")
```

```
plt.ylabel("weight difference")
plt.show()
```





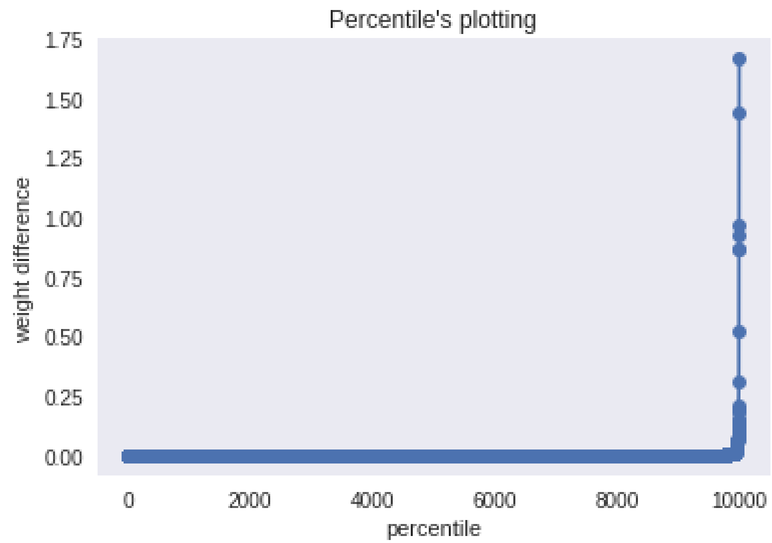


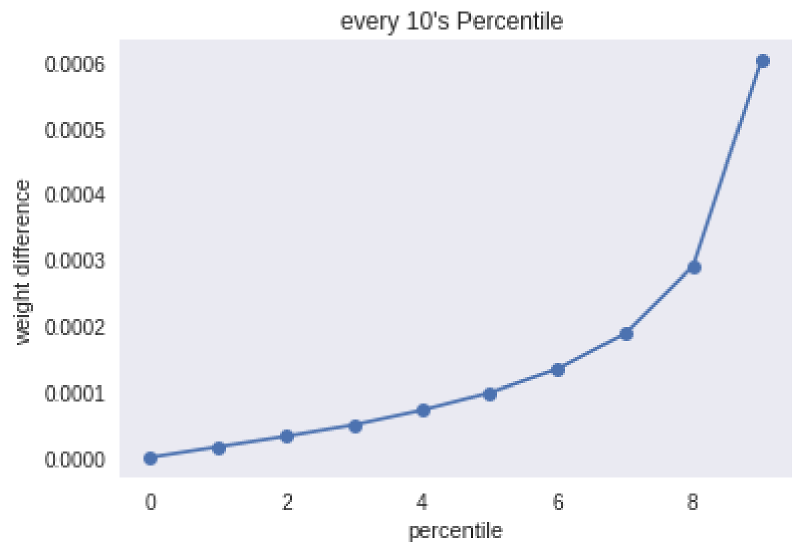
By the above graph sudden rise at 99.9 percentile

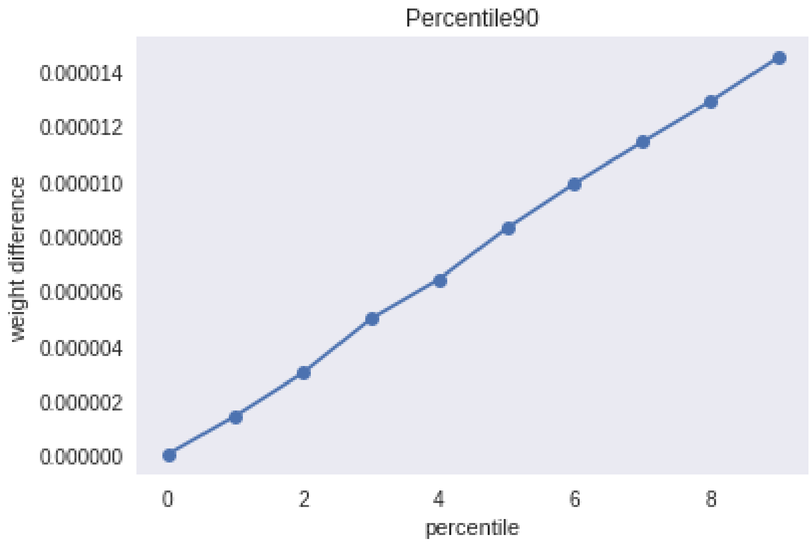
Another way of plotting percentiles

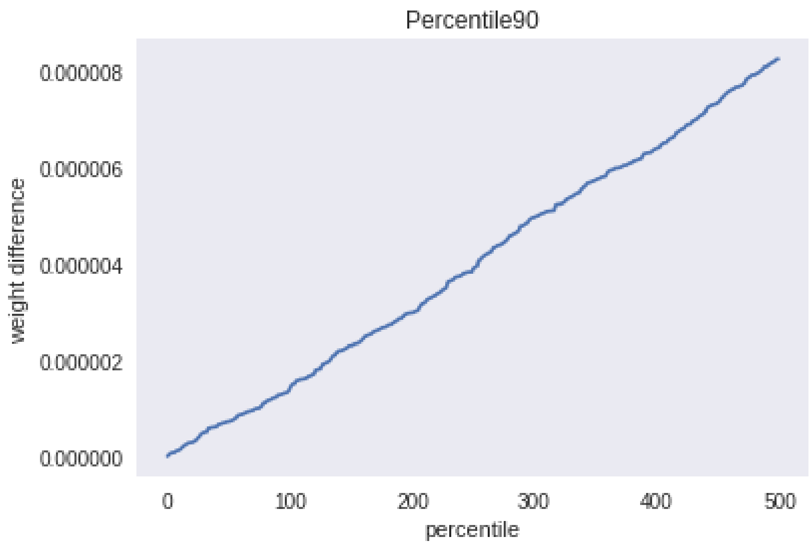
In [107]:
```
plt.plot(wgts_difference,'-o')
plt.title("Percentile's plotting")
plt.grid()
plt.xlabel("percentile")
plt.ylabel("weight difference")
plt.show()


plt.plot(wgts_difference[0:10000:1000],'-o')
plt.title("every 10's Percentile ")
plt.grid()
plt.xlabel("percentile")
plt.ylabel("weight difference")
plt.show()
```

```
plt.plot(wgts_difference[0:1000:100],'-o')
plt.title("Percentile90")
plt.grid()
plt.xlabel("percentile")
plt.ylabel("weight difference")
plt.show()


plt.plot(wgts_difference[0:500])
plt.title("Percentile90")
plt.grid()
plt.xlabel("percentile")
plt.ylabel("weight difference")
plt.show()



plt.plot(wgts_difference[0:10000], c='b')
plt.scatter(x=list(range(0,10000,2500)), y=wgts_difference[0:10000:2500
], c='red', label="quantiles with 0.25 intervals")
# quantiles with 0.25 difference
plt.scatter(x=list(range(0,10000,1000)), y=wgts_difference[0:10000:1000
], c='m', label = "quantiles with 0.05 intervals")
#for x,y in zip(list(range(0,100,25)), wgts_difference[0:100:25]):
#    plt.annotate(s="({} , {})".format(x,y), xy=(x,y))


plt.plot(wgts_difference[0:5000], c='b')
plt.scatter(x=list(range(0,5000,1250)), y=wgts_difference[0:5000:1250],
 c='red', label="quantiles with 0.25 intervals")
# quantiles with 0.25 difference
plt.scatter(x=list(range(0,5000,1250)), y=wgts_difference[0:5000:1250],
 c='m', label = "quantiles with 0.05 intervals")
#for x,y in zip(list(range(0,100,25)), wgts_difference[0:100:25]):
#    plt.annotate(s="({} , {})".format(x,y), xy=(x,y)
```


Percentile's plotting
weight difference
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
0
2000
4000
6000
8000
10000
percentile


every 10's Percentile
weight difference
0.0006
0.0005
0.0004
0.0003
0.0002
0.0001
0.0000
0
2
4
6
8
percentile





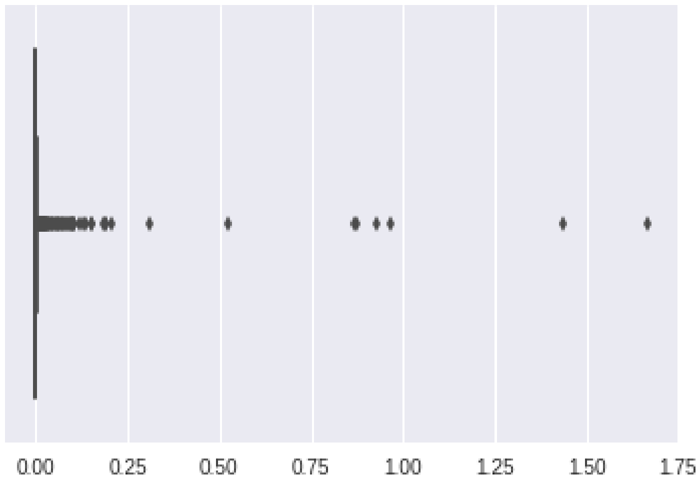
In [113]:
```
wgts_difference.sort()
wgts_difference[0:len(wgts_difference):1000]
```

Out[113]: array([2.95507520e-08, 1.61335340e-05, 3.20651557e-05, 4.95881036e-05,
       7.17487326e-05, 9.83537415e-05, 1.34006676e-04, 1.87983163e-04,
       2.90350526e-04, 6.02159641e-04])

In [114]:

```
print(type(wgts_difference))
sns.boxplot(wgts_difference)
plt.show()

from numpy import percentile
val= percentile(wgts_difference,[25,50,75])
val

np.sort(wgts_difference).size
```

<class 'numpy.ndarray'>



Out[114]: 10000

[5.1.3] Feature Importance on BOW, SET 1

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

In [115]:

```
feature_names=count_vect.get_feature_names()
coefs=sorted(zip(clf1.coef_[0],feature_names))

top20Negative=coefs[:20]
top20Postive=coefs[::-1][:20]

res_neg=pd.DataFrame(top20Negative,columns=['Features','Values'])
res_pos=pd.DataFrame(top20Postive,columns=['Features','Values'])
pd.concat([res_neg,res_pos],axis=1)
```

Out[115]:

	Features	Values	Features	Values
0	-0.261300	disappoint	0.497705	great
1	-0.182547	worst	0.425680	love
2	-0.163124	return	0.372925	best
3	-0.155267	terribl	0.295090	delici
4	-0.150823	thought	0.276514	good
5	-0.148989	aw	0.241148	excel
6	-0.148580	money	0.236529	perfect
7	-0.139838	horribl	0.220495	favorit
8	-0.136285	unfortun	0.214225	nice
9	-0.126837	threw	0.166982	wonder
10	-0.124238	stale	0.158020	amaz
11	-0.123137	bad	0.153355	easi
12	-0.122603	bland	0.151370	awesom
13	-0.121816	didnt	0.147459	use
14	-0.116762	wast	0.144988	glad
15	-0.107820	did	0.142276	addict
16	-0.106468	tast	0.139096	alway

	Features	Values	Features	Values
17	-0.099864	poor	0.137252	happi
18	-0.099568	hope	0.137182	tasti
19	-0.099322	refund	0.127082	thank

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

In [0]:
```
# Please write all the code with proper documentation
```

[5.2] Logistic Regression on TFIDF, SET 2

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

In [0]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10, max_df=0.95
,stop_words='english',max_features=50000 )
tf_idf_vect.fit(X_train)
print("some sample features(unique words in the corpus)",tf_idf_vect.ge
t_feature_names()[0:10])
print('='*50)

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

X_test_tfidf = tf_idf_vect.transform(X_test)
print("the type of count vectorizer ",type(X_test_tfidf))
print("the shape of out text TFIDF vectorizer ",X_test_tfidf.get_shape
())
print("the number of unique words ", X_test_tfidf.get_shape()[1])
```

```
some sample features(unique words in the corpus) ['aback', 'abandon', 'abc', 'abdomin', 'abil', 'abl', 'abl amazon', 'abl ani', 'abl anywhe
r', 'abl break']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (75000, 38379)
the number of unique words including both unigrams and bigrams  38379
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (25000, 38379)
the number of unique words  38379
```

In [0]:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler(with_mean=False)
scaler.fit(X_train_tfidf)
X_train_tfidf=scaler.transform(X_train_tfidf)

X_test_tfidf=scaler.transform(X_test_tfidf)
```

In [0]:

```
from sklearn.linear_model import LogisticRegression

clf=LogisticRegression(penalty='l1')
param_grid={'C':[1000,100,10,1,0.1,0.001,0.0001]}
#timeseriessplit=TimeSeriesSplit(n_splits=10)
gcv=GridSearchCV(clf,param_grid,cv=5,scoring='roc_auc')
gcv.fit(X_train_tfidf,y_train)
print(gcv.best_params_)
print(gcv.best_score_)
```

```
{'C': 0.1}
0.9292712996949454
```

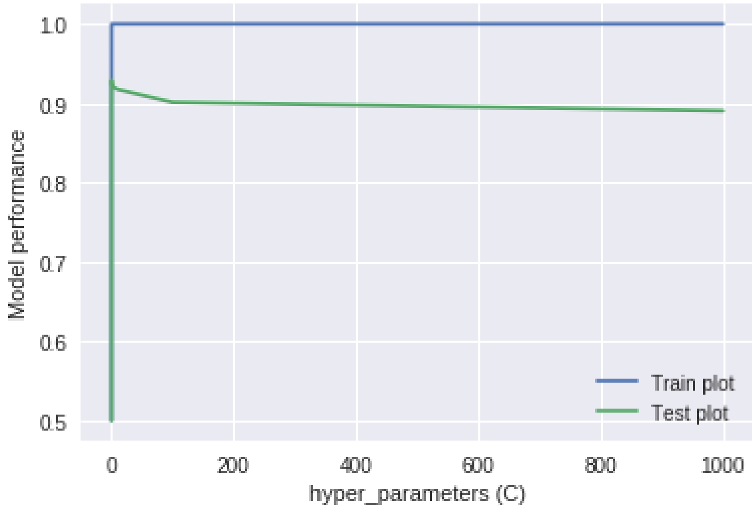
In [0]:

```
hyper_parameters=gcv.get_params()['param_grid']['C']
train_scores=gcv.cv_results_['mean_train_score'].tolist()
test_scores=gcv.cv_results_['mean_test_score'].tolist()

print(hyper_parameters)
print(test_scores)
print(train_scores)
```

```
plt.plot( hyper_parameters ,train_scores , label='Train plot')
plt.plot( hyper_parameters ,test_scores ,  label='Test plot')
plt.xlabel("hyper_parameters (C)")
plt.ylabel("Model performance")

plt.legend()
```

```
[1000, 100, 10, 1, 0.1, 0.001, 0.0001]
[0.8909053304983988, 0.9016360483725683, 0.9178976054051204, 0.9222105100849963, 0.9292712996949454, 0.8672104253999816, 0.5]
[1.0, 1.0, 1.0, 1.0, 0.999998432394815, 0.8695069653061985, 0.5]
```

Out[0]: <matplotlib.legend.Legend at 0x7fe9a597dc18>



In [0]:
```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import auc
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
```

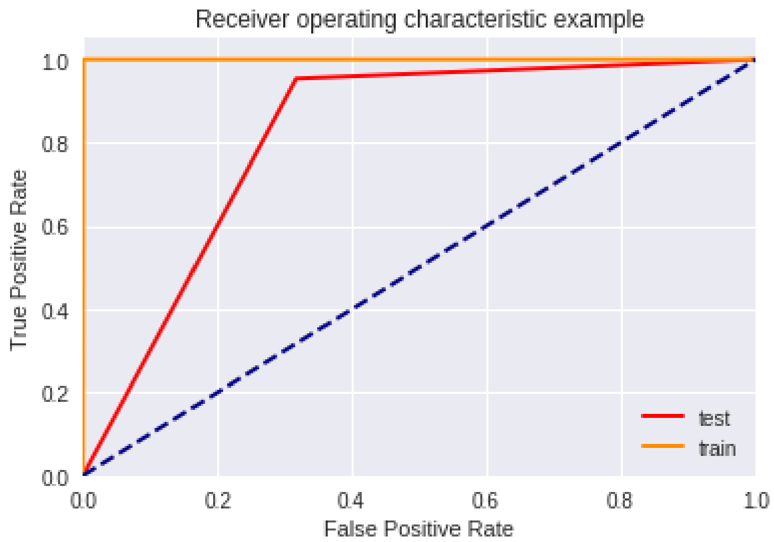
```
from sklearn.metrics import f1_score



clf1=LogisticRegression(C=0.1,penalty='l1')
clf1.fit(X_train_tfidf,y_train)
pred_train=clf1.predict(X_train_tfidf)
pred=clf1.predict(X_test_tfidf)

print("Accuracy Score : ",accuracy_score(y_test,pred)*100)
print("Precision Score : ",precision_score(y_test,pred)*100)
print("Recall Score : ",recall_score(y_test,pred)*100)
print("F1 Score : ",f1_score(y_test,pred)*100)

print("        ")
print("Classification Report")
print(classification_report(y_test,pred))
print("        ")

fpr_train,tpr_train,thresholds_train=roc_curve(y_train,pred_train)
print("AUC Score for train data :",metrics.auc(fpr_train,tpr_train))

fpr,tpr,thresholds=roc_curve(y_test,pred)
print("AUC Score for test data :",metrics.auc(fpr,tpr))

print("        ")

#y_true = # ground truth labels
#y_probas = # predicted probabilities generated by sklearn classifier
#skplt.metrics.plot_roc_curve(y_true, y_probas)
#plt.show()



plt.figure()
lw = 2
plt.plot(fpr, tpr, color='red',
         lw=lw,label='test')
plt.plot(fpr_train, tpr_train, color='darkorange',
```

```
        lw=lw,label='train')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()


print("       ")

tn, fp, fn, tp=confusion_matrix(y_test,pred).ravel()
print("""
TrueNegative : {}
FalsePostive : {}
FalseNegative : {}
TruePostive  :  {}""".format(tn, fp, fn, tp))
print("        ")
print("        ")

confusionmatrix_DF=pd.DataFrame(confusion_matrix(y_test,pred),columns=[
'0','1'],index=['0','1'])
sns.heatmap(confusionmatrix_DF,annot=True,fmt='g',cmap='viridis')
plt.title("Confusion matrix ")
plt.show()
```

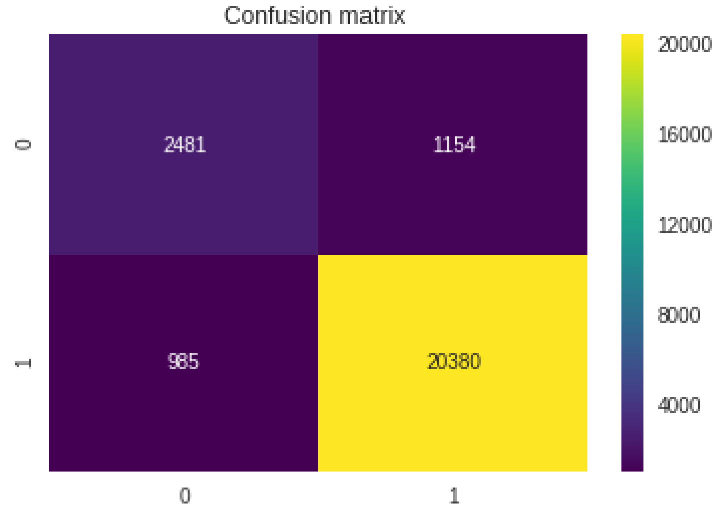
```
Accuracy Score :  91.444
Precision Score :  94.64103278536268
Recall Score :  95.38965597940557
F1 Score :  95.01386978717453

Classification Report
              precision    recall  f1-score   support

           0       0.72      0.68      0.70      3635
           1       0.95      0.95      0.95     21365

   micro avg       0.91      0.91      0.91     25000
```

```
   macro avg       0.83      0.82      0.82     25000
weighted avg       0.91      0.91      0.91     25000
```

```
AUC Score for train data : 0.9995970630372493
AUC Score for test data : 0.8182137544499852
```




```
TrueNegative : 2481
FalsePostive : 1154
FalseNegative : 985
TruePostive  :  20380
```



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

In [0]:
```
from sklearn.linear_model import LogisticRegression

clf=LogisticRegression(penalty='l2')
param_grid={'C':[1000,100,10,1,0.1,0.001,0.0001]}
#timeseriessplit=TimeSeriesSplit(n_splits=10)
gcv=GridSearchCV(clf,param_grid,cv=5,scoring='roc_auc')
gcv.fit(X_train_tfidf,y_train)
print(gcv.best_params_)
print(gcv.best_score_)
```

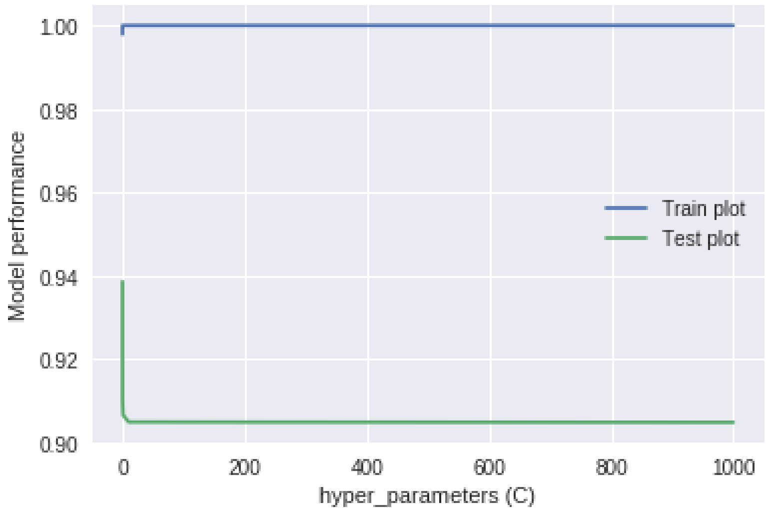
```
{'C': 0.0001}
0.9386103426546142
```

In [0]:
```
hyper_parameters=gcv.get_params()['param_grid']['C']
train_scores=gcv.cv_results_['mean_train_score'].tolist()
test_scores=gcv.cv_results_['mean_test_score'].tolist()

print(hyper_parameters)
```

```
print(test_scores)
print(train_scores)


plt.plot( hyper_parameters ,train_scores , label='Train plot')
plt.plot( hyper_parameters ,test_scores ,  label='Test plot')
plt.xlabel("hyper_parameters (C)")
plt.ylabel("Model performance")

plt.legend()
```

```
[1000, 100, 10, 1, 0.1, 0.001, 0.0001]
[0.9048738818353523, 0.9049524106876847, 0.904967451186365, 0.906631545
2519695, 0.9098220252645793, 0.926345752661734, 0.9386103426546142]
[1.0, 1.0, 1.0, 1.0, 1.0, 0.9999967420917926, 0.9978873148839904]
```

Out[0]: <matplotlib.legend.Legend at 0x7fe9af91ae48>



In [0]:
```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import auc
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
```

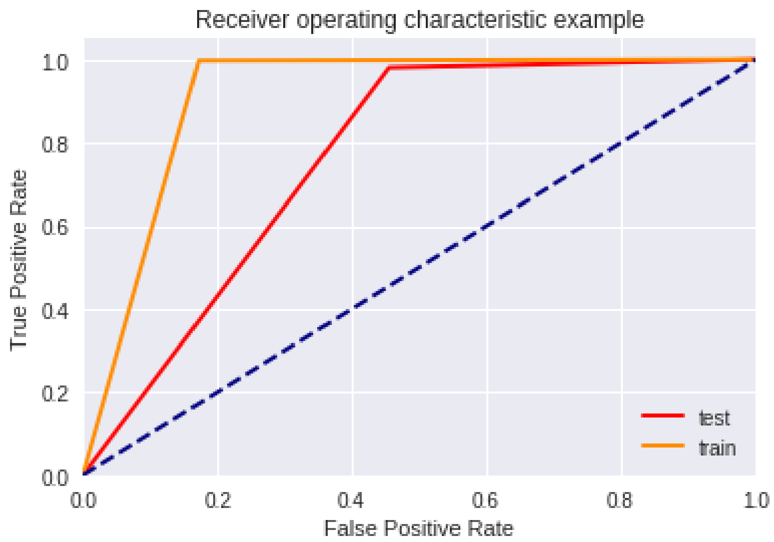
```python
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score



clf1=LogisticRegression(C=0.0001,penalty='l2')
clf1.fit(X_train_tfidf,y_train)
pred_train=clf1.predict(X_train_tfidf)
pred=clf1.predict(X_test_tfidf)

print("Accuracy Score : ",accuracy_score(y_test,pred)*100)
print("Precision Score : ",precision_score(y_test,pred)*100)
print("Recall Score : ",recall_score(y_test,pred)*100)
print("F1 Score : ",f1_score(y_test,pred)*100)

print("        ")
print("Classification Report")
print(classification_report(y_test,pred))
print("        ")

fpr_train,tpr_train,thresholds_train=roc_curve(y_train,pred_train)
print("AUC Score for train data :",metrics.auc(fpr_train,tpr_train))

fpr,tpr,thresholds=roc_curve(y_test,pred)
print("AUC Score for test data :",metrics.auc(fpr,tpr))

print("        ")

#y_true = # ground truth labels
#y_probas = # predicted probabilities generated by sklearn classifier
#skplt.metrics.plot_roc_curve(y_true, y_probas)
#plt.show()



plt.figure()
lw = 2
plt.plot(fpr, tpr, color='red',
```

```
         lw=lw,label='test')
plt.plot(fpr_train, tpr_train, color='darkorange',
         lw=lw,label='train')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()


print("       ")

tn, fp, fn, tp=confusion_matrix(y_test,pred).ravel()
print("""
TrueNegative : {}
FalsePostive : {}
FalseNegative : {}
TruePostive  :  {}""".format(tn, fp, fn, tp))
print("        ")
print("        ")

confusionmatrix_DF=pd.DataFrame(confusion_matrix(y_test,pred),columns=[
'0','1'],index=['0','1'])
sns.heatmap(confusionmatrix_DF,annot=True,fmt='g',cmap='viridis')
plt.title("Confusion matrix ")
plt.show()
```

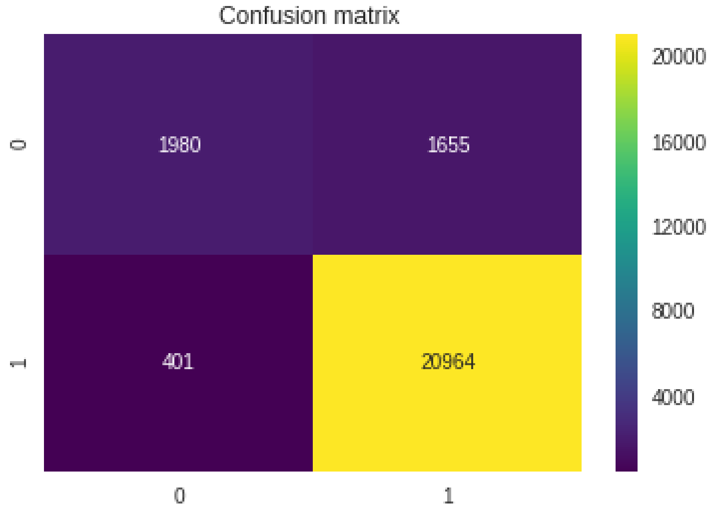
```
Accuracy Score :  91.776
Precision Score :  92.6831424908263
Recall Score :  98.12309852562603
F1 Score :  95.32557293561294

Classification Report
              precision    recall  f1-score   support

           0       0.83      0.54      0.66      3635
           1       0.93      0.98      0.95     21365
```

```
   micro avg       0.92      0.92      0.92     25000
   macro avg       0.88      0.76      0.81     25000
weighted avg       0.91      0.92      0.91     25000
```

```
AUC Score for train data : 0.9125294110148021
AUC Score for test data : 0.7629676246776487
```




```
TrueNegative : 1980
FalsePostive : 1655
FalseNegative : 401
TruePostive  :  20964
```



[5.2.3] Feature Importance on TFIDF, SET 2

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

In [0]:

```
feature_names=tf_idf_vect.get_feature_names()
coefs=sorted(zip(clf1.coef_[0],feature_names))

top20Negative=coefs[:20]
top20Postive=coefs[::-1][:20]

res_neg=pd.DataFrame(top20Negative,columns=['Features','Values'])
res_pos=pd.DataFrame(top20Postive,columns=['Features','Values'])
pd.concat([res_neg,res_pos],axis=1)
```

Out[0]:

	Features	Values	Features	Values
0	-0.071519	disappoint	0.122651	great
1	-0.067153	veri disappoint	0.121623	love

	Features	Values	Features	Values
2	-0.060787	worst	0.094357	best
3	-0.051640	terribl	0.080949	good
4	-0.050525	aw	0.075217	delici
5	-0.047269	return	0.059922	perfect
6	-0.045456	horribl	0.059878	excel
7	-0.042103	threw	0.058697	favorit
8	-0.041307	wors	0.052519	nice
9	-0.041176	wont buy	0.052321	use
10	-0.040446	wast money	0.051268	wonder
11	-0.040267	bland	0.048090	easi
12	-0.040092	wast	0.046017	high recommend
13	-0.039738	disgust	0.045918	make
14	-0.037786	money	0.042632	enjoy
15	-0.037536	tast like	0.041551	thank
16	-0.037288	stale	0.041076	alway
17	-0.037015	unfortun	0.040092	tasti
18	-0.036412	tasteless	0.039935	amaz
19	-0.033395	refund	0.039808	awesom

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

In [0]:
```
# Please write all the code with proper documentation
```

[5.3] Logistic Regression on AVG W2V, SET 3

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

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


#*************************************************************************
********************

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,min_count=5,size=50, workers=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 ")

#*************************************************************************
********************

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])

#************************************************************************
*********************



# average Word2Vec
# compute average word2vec for each review.
X_train_AvgW2V_100000 = []; # the avg-w2v for each sentence/review is s
tored in this list
for sent in tqdm(list_of_sentance): # 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
    X_train_AvgW2V_100000.append(sent_vec)
print(len(X_train_AvgW2V_100000))
print(len(X_train_AvgW2V_100000[0]))
```

```
  0%|          | 92/75000 [00:00<01:21, 915.01it/s]
```

```
[('terrif', 0.8637382388114929), ('awesom', 0.8417178392410278), ('exce
l', 0.8403081297874451), ('wonder', 0.8175906538963318), ('fantast', 0.
8126950263977051), ('good', 0.8095090389251709), ('perfect', 0.80067425
96626282), ('fabul', 0.7345156669616699), ('decent', 0.70958995819091
8), ('nice', 0.6975454688072205)]
==================================================
[('greatest', 0.7696366310119629), ('best', 0.7653523087501526), ('tast
iest', 0.6937639713287354), ('nicest', 0.6832467913627625), ('closest',
0.6737667918205261), ('disgust', 0.6405009627342224), ('nastiest', 0.63
55428695678711), ('hottest', 0.5996732115745544), ('finest', 0.58700078
72581482), ('horribl', 0.5557085275650024)]
number of words that occured minimum 5 times  11759
```

```
sample words  ['order', 'this', 'the', 'tastiest', 'oatmeal', 'have', 'ever', 'eaten', 'far', 'superior', 'organ', 'been', 'purchas', 'natur', 'section', 'local', 'groceri', 'store', 'better', 'flavor', 'and', 'textur', 'also', 'servic', 'was', 'great', 'summertim', 'has', 'gone', 'but', 'product', 'still', 'tast', 'hot', 'drink', 'for', 'summer', 'well', 'not', 'know', 'could', 'surviv', 'heat', 'without', 'cooler', 'ici', 'slush', 'unfortun', 'all', 'friend']
```

```
100%|██████████| 75000/75000 [02:07<00:00, 589.43it/s]
```

```
75000
50
```

In [0]:

```
import pickle
with open('X_train_AvgW2V.pkl', 'wb') as f:
  pickle.dump(X_train_AvgW2V, f)
```

In [0]:

```
import pickle
with open('X_train_AvgW2V_100000.pkl', 'wb') as f:
  pickle.dump(X_train_AvgW2V_100000, f)
```

In [0]:

```
#**********************************************************************
***********************


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

#**********************************************************************
*********************



# average Word2Vec
# compute average word2vec for each review.
X_test_AvgW2V_100000 = []; # the avg-w2v for each sentence/review is stored 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, you 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/review
    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
    X_test_AvgW2V_100000.append(sent_vec)
print(len(X_test_AvgW2V_100000))
print(len(X_test_AvgW2V_100000[0]))
```

```
100%|██████████| 25000/25000 [00:43<00:00, 579.18it/s]
```

```
25000
50
```

In [0]:

```
from google.colab import files
files.download('X_train_AvgW2V_100000.pkl')
```

In [0]:

```
import pickle
with open('X_test_AvgW2V_100000.pkl', 'wb') as f:
  pickle.dump(X_test_AvgW2V_100000, f)
```

In [0]:

```
from google.colab import files
files.download('X_test_AvgW2V_100000.pkl')
```

In [0]:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler(with_mean=False)
scaler.fit(X_train_AvgW2V_100000)
X_train_AvgW2V=scaler.transform(X_train_AvgW2V_100000)

X_test_AvgW2V=scaler.transform(X_test_AvgW2V_100000)
```

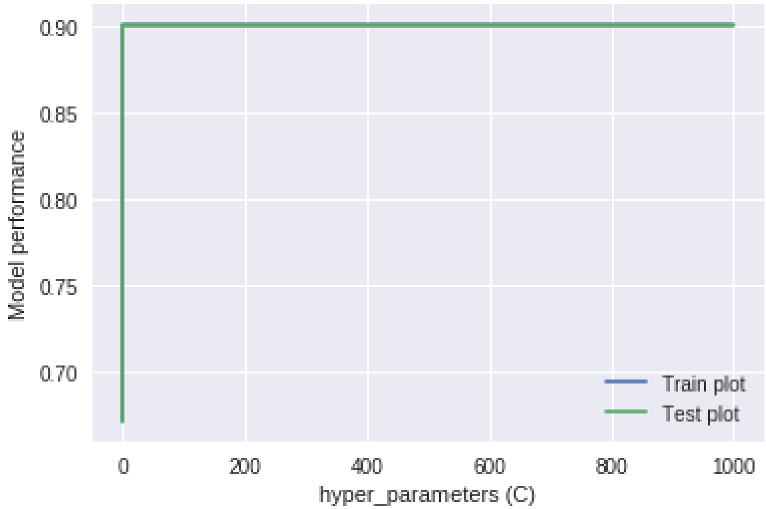
In [0]:
```
from sklearn.linear_model import LogisticRegression

clf=LogisticRegression(penalty='l1')
param_grid={'C':[1000,100,10,5,1,0.5,0.1,0.001,0.0001]}
#timeseriessplit=TimeSeriesSplit(n_splits=10)
gcv=GridSearchCV(clf,param_grid,cv=5,scoring='roc_auc')
gcv.fit(X_train_AvgW2V,y_train)
print(gcv.best_params_)
print(gcv.best_score_)
```

```
{'C': 0.1}
0.9007299333163759
```

In [0]:
```
hyper_parameters=gcv.get_params()['param_grid']['C']
train_scores=gcv.cv_results_['mean_train_score'].tolist()
test_scores=gcv.cv_results_['mean_test_score'].tolist()

print(hyper_parameters)
print(test_scores)
print(train_scores)


plt.plot( hyper_parameters ,train_scores , label='Train plot')
plt.plot( hyper_parameters ,test_scores ,  label='Test plot')
plt.xlabel("hyper_parameters (C)")
plt.ylabel("Model performance")

plt.legend()
```

```
[1000, 100, 10, 5, 1, 0.5, 0.1, 0.001, 0.0001]
[0.9007167027794262, 0.9007180144130086, 0.9007181265108707, 0.90071928
35458553, 0.9007202587848292, 0.9007170469938147, 0.9007299333163759,
0.8782740824196674, 0.6711832154829824]
[0.9014580585714148, 0.9014582111242412, 0.9014587867253511, 0.90145940
21766745, 0.9014579165038056, 0.9014517503699985, 0.901458403119588, 0.
8788911387273874, 0.6712408567467387]
```

Out[0]: <matplotlib.legend.Legend at 0x7fe9af3d6eb8>



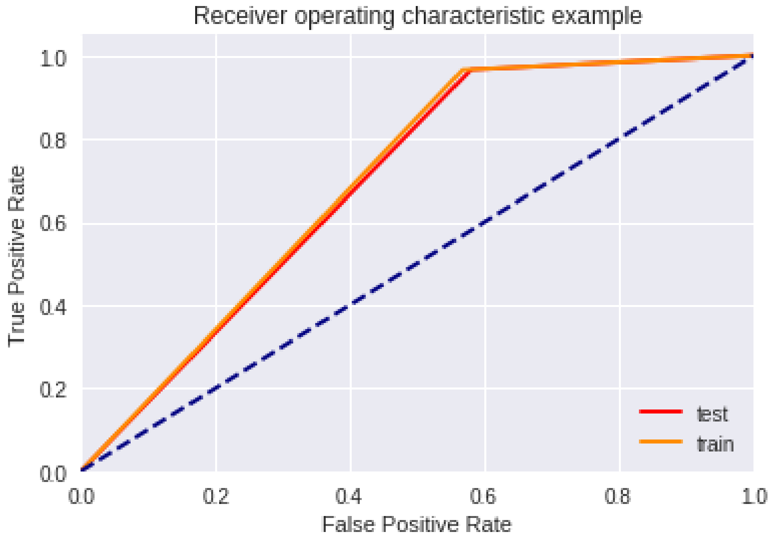
In [0]:

```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import auc
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score



clf1=LogisticRegression(C=0.1,penalty='l1')
clf1.fit(X_train_AvgW2V,y_train)
pred_train=clf1.predict(X_train_AvgW2V)
pred=clf1.predict(X_test_AvgW2V)

print("Accuracy Score : ",accuracy_score(y_test,pred)*100)
print("Precision Score : ",precision_score(y_test,pred)*100)
print("Recall Score : ",recall_score(y_test,pred)*100)
print("F1 Score : ",f1_score(y_test,pred)*100)

print("         ")
print("Classification Report")
```

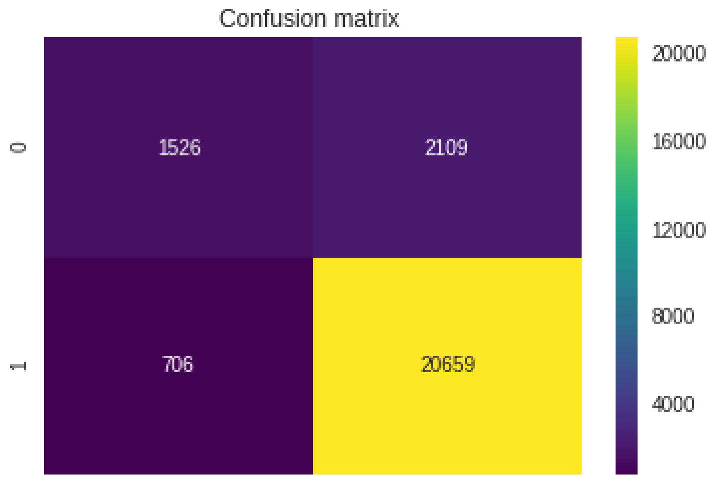
```
print(classification_report(y_test,pred))
print("         ")

fpr_train,tpr_train,thresholds_train=roc_curve(y_train,pred_train)
print("AUC Score for train data :",metrics.auc(fpr_train,tpr_train))

fpr,tpr,thresholds=roc_curve(y_test,pred)
print("AUC Score for test data :",metrics.auc(fpr,tpr))

print("         ")

#y_true = # ground truth labels
#y_probas = # predicted probabilities generated by sklearn classifier
#skplt.metrics.plot_roc_curve(y_true, y_probas)
#plt.show()



plt.figure()
lw = 2
plt.plot(fpr, tpr, color='red',
         lw=lw,label='test')
plt.plot(fpr_train, tpr_train, color='darkorange',
         lw=lw,label='train')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()


print("        ")

tn, fp, fn, tp=confusion_matrix(y_test,pred).ravel()
print("""
TrueNegative : {}
```

```
FalsePostive : {}
FalseNegative : {}
TruePostive  :  {}""".format(tn, fp, fn, tp))
print("        ")
print("        ")

confusionmatrix_DF=pd.DataFrame(confusion_matrix(y_test,pred),columns=[
'0','1'],index=['0','1'])
sns.heatmap(confusionmatrix_DF,annot=True,fmt='g',cmap='viridis')
plt.title("Confusion matrix ")
plt.show()
```

```
Accuracy Score :  88.74
Precision Score :  90.73699929725932
Recall Score :  96.69553007254856
F1 Score :  93.6215530328779

Classification Report
              precision    recall  f1-score   support

           0       0.68      0.42      0.52      3635
           1       0.91      0.97      0.94     21365

   micro avg       0.89      0.89      0.89     25000
   macro avg       0.80      0.69      0.73     25000
weighted avg       0.87      0.89      0.88     25000


AUC Score for train data : 0.6994174199573306
AUC Score for test data : 0.6933813642554526
```




```
TrueNegative : 1526
FalsePostive : 2109
FalseNegative : 706
TruePostive  :  20659
```



0 1

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

In [0]:

```
from sklearn.linear_model import LogisticRegression

clf=LogisticRegression(penalty='l2')
param_grid={'C':[1000,100,10,5,1,0.5,0.1,0.001,0.0001]}
#timeseriessplit=TimeSeriesSplit(n_splits=10)
gcv=GridSearchCV(clf,param_grid,cv=5,scoring='roc_auc')
gcv.fit(X_train_AvgW2V,y_train)
print(gcv.best_params_)
print(gcv.best_score_)
```

```
{'C': 0.1}
0.9007230793376875
```

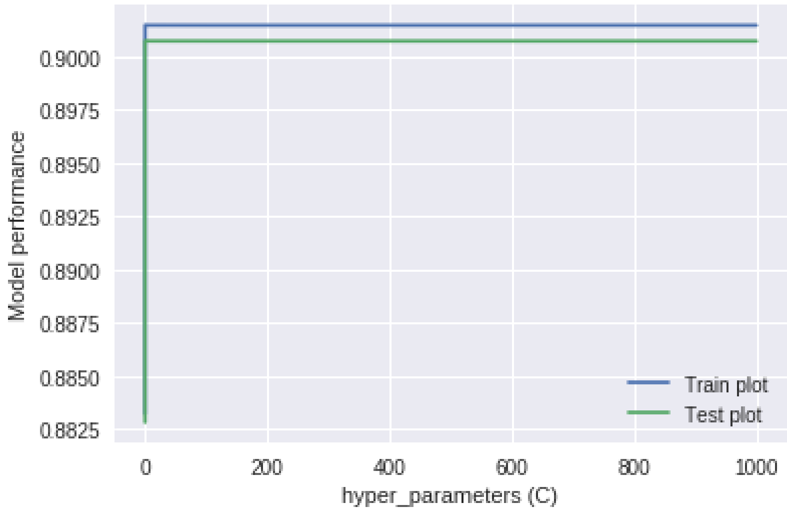
In [0]:

```
hyper_parameters=gcv.get_params()['param_grid']['C']
train_scores=gcv.cv_results_['mean_train_score'].tolist()
test_scores=gcv.cv_results_['mean_test_score'].tolist()

print(hyper_parameters)
print(test_scores)
print(train_scores)


plt.plot( hyper_parameters ,train_scores , label='Train plot')
plt.plot( hyper_parameters ,test_scores ,  label='Test plot')
plt.xlabel("hyper_parameters (C)")
plt.ylabel("Model performance")

plt.legend()
```

```
[1000, 100, 10, 5, 1, 0.5, 0.1, 0.001, 0.0001]
[0.9007046960046837, 0.9007049624469834, 0.9007073262931394, 0.90070835
69485211, 0.9007160648083817, 0.9007200974046736, 0.9007230793376875,
0.8988671134516509, 0.8828279813712571]
```

0.8988671134516509, 0.8828279813712571]
[0.9014466984609755, 0.9014467545675 38, 0.9014495941602446, 0.901449513
5941442, 0.9014572699788624, 0.9014608961262898, 0.9014580909601155, 0.
8994398345547424, 0.8832301217866835]

Out[0]: <matplotlib.legend.Legend at 0x7fe9aecddac8>

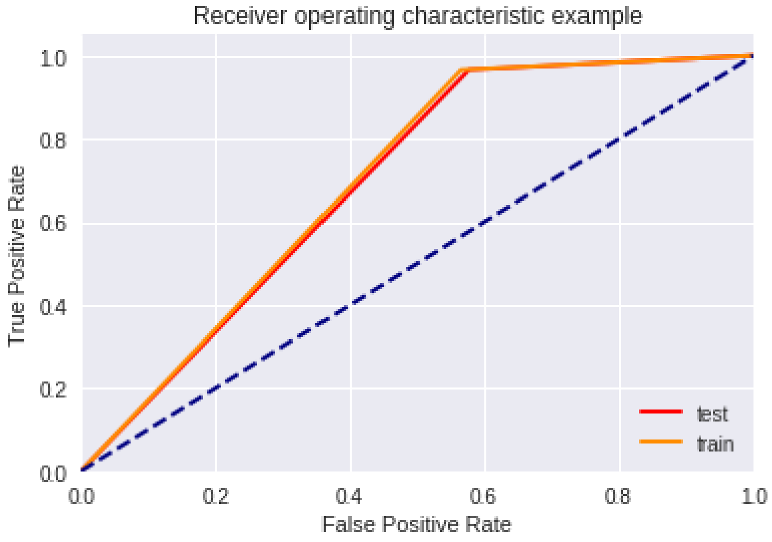


In [0]:
```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import auc
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score



clf1=LogisticRegression(C=0.1,penalty='l2')
clf1.fit(X_train_AvgW2V,y_train)
pred_train=clf1.predict(X_train_AvgW2V)
pred=clf1.predict(X_test_AvgW2V)
```

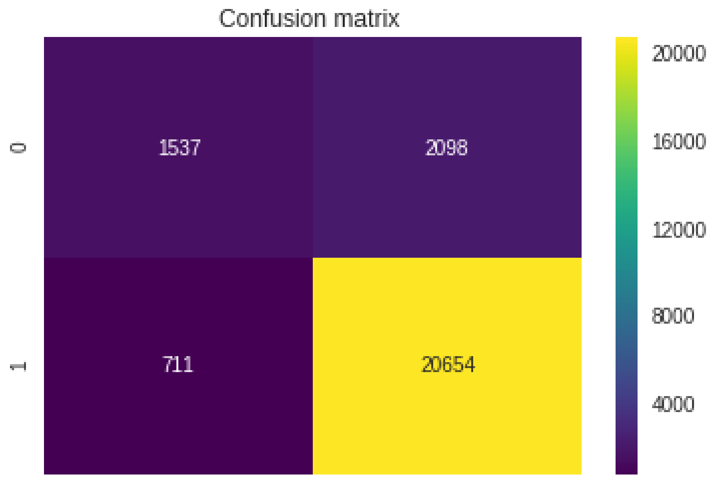
```
print("Accuracy Score : ",accuracy_score(y_test,pred)*100)
print("Precision Score : ",precision_score(y_test,pred)*100)
print("Recall Score : ",recall_score(y_test,pred)*100)
print("F1 Score : ",f1_score(y_test,pred)*100)

print("        ")
print("Classification Report")
print(classification_report(y_test,pred))
print("        ")

fpr_train,tpr_train,thresholds_train=roc_curve(y_train,pred_train)
print("AUC Score for train data :",metrics.auc(fpr_train,tpr_train))

fpr,tpr,thresholds=roc_curve(y_test,pred)
print("AUC Score for test data :",metrics.auc(fpr,tpr))

print("        ")

#y_true = # ground truth labels
#y_probas = # predicted probabilities generated by sklearn classifier
#skplt.metrics.plot_roc_curve(y_true, y_probas)
#plt.show()



plt.figure()
lw = 2
plt.plot(fpr, tpr, color='red',
         lw=lw,label='test')
plt.plot(fpr_train, tpr_train, color='darkorange',
         lw=lw,label='train')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
```

```
print("       ")

tn, fp, fn, tp=confusion_matrix(y_test,pred).ravel()
print("""
TrueNegative : {}
FalsePostive : {}
FalseNegative : {}
TruePostive  :  {}""".format(tn, fp, fn, tp))
print("        ")
print("        ")

confusionmatrix_DF=pd.DataFrame(confusion_matrix(y_test,pred),columns=[
'0','1'],index=['0','1'])
sns.heatmap(confusionmatrix_DF,annot=True,fmt='g',cmap='viridis')
plt.title("Confusion matrix ")
plt.show()
```

```
Accuracy Score :  88.764
Precision Score :  90.77883263009845
Recall Score :  96.6721273110227
F1 Score :  93.63283994831923

Classification Report
              precision    recall  f1-score   support

           0       0.68      0.42      0.52      3635
           1       0.91      0.97      0.94     21365

   micro avg       0.89      0.89      0.89     25000
   macro avg       0.80      0.69      0.73     25000
weighted avg       0.88      0.89      0.88     25000


AUC Score for train data : 0.7005523554218793
AUC Score for test data : 0.6947774178480983
```




```
TrueNegative : 1537
FalsePostive : 2098
FalseNegative : 711
TruePostive  :  20654
```



0 1

[5.4] Logistic Regression on TFIDF W2V, SET 4

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

In [0]:
```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer(ngram_range=(1,2), min_df=10, max_df=0.95,stop_
words='english',max_features=5000 )
tf_idf_matrix = model.fit_transform(X_train)
# 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_)))

#*********************************************************************
***********************


# TF-IDF weighted Word2Vec
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

X_train_Avgtfidf_100000 = []; # the tfidf-w2v for each sentence/review
 is stored in this list
row=0;
for sent in list_of_sentance: # 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
    X_train_Avgtfidf_100000.append(sent_vec)
    row += 1
```

In [0]:
```
#***********************************************************************
**********************

X_test_Avgtfidf_100000 = []; # the tfidf-w2v for each sentence/review i
s stored in this list
row=0;
for sent in 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
    X_test_Avgtfidf_100000.append(sent_vec)
    row += 1
```

```
  3%|▌          | 831/25000 [00:37<03:33, 113.03it/s]
```

In [0]:
```
import pickle
with open('X_train_Avgtfidf_100000.pkl', 'wb') as f:
```

```
  pickle.dump(X_train_Avgtfidf_100000, f)
```

In [0]:
```
import pickle
with open('X_test_Avgtfidf_100000.pkl', 'wb') as f:
  pickle.dump(X_test_Avgtfidf_100000, f)
```

In [0]:
```
from google.colab import files
files.download('X_train_Avgtfidf_100000.pkl')
```

In [0]:
```
from google.colab import files
files.download('X_test_Avgtfidf_100000.pkl')
```

In [0]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler(with_mean=False)
scaler.fit(X_train_Avgtfidf_100000)
X_train_Avgtfidf=scaler.transform(X_train_Avgtfidf_100000)

X_test_Avgtfidf=scaler.transform(X_test_Avgtfidf_100000)
```

In [0]:
```
print(X_train_Avgtfidf.shape,len(y_train),X_test_Avgtfidf.shape,len(y_t
est))
```

```
(75000, 50) 75000 (25000, 50) 25000
```

In [0]:
```
from sklearn.linear_model import LogisticRegression

clf=LogisticRegression(penalty='l1')
param_grid={'C':[1000,100,10,5,1,0.5,0.1,0.001,0.0001]}
#timeseriessplit=TimeSeriesSplit(n_splits=10)
gcv=GridSearchCV(clf,param_grid,cv=5,scoring='roc_auc')
gcv.fit(X_train_Avgtfidf,y_train)
print(gcv.best_params_)
print(gcv.best_score_)
```

```
{'C': 0.5}
0.8634936283951694
```

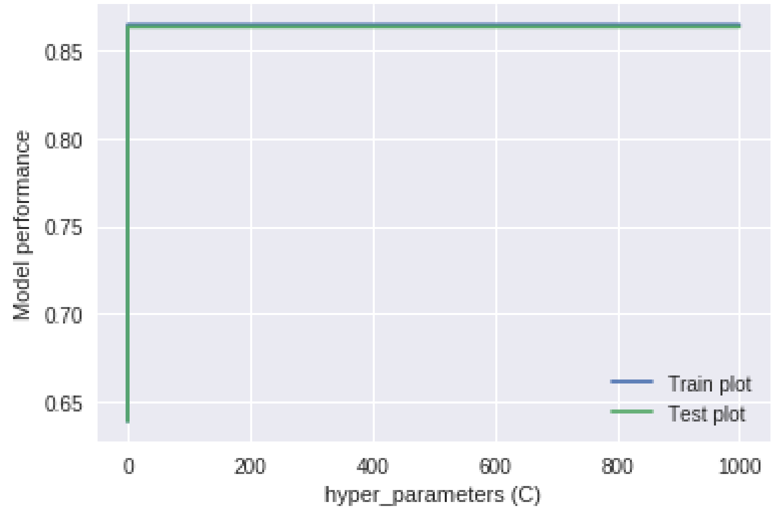
In [0]:

```
hyper_parameters=gcv.get_params()['param_grid']['C']
train_scores=gcv.cv_results_['mean_train_score'].tolist()
test_scores=gcv.cv_results_['mean_test_score'].tolist()

print(hyper_parameters)
print(test_scores)
print(train_scores)


plt.plot( hyper_parameters ,train_scores , label='Train plot')
plt.plot( hyper_parameters ,test_scores ,  label='Test plot')
plt.xlabel("hyper_parameters (C)")
plt.ylabel("Model performance")

plt.legend()
```

```
[1000, 100, 10, 5, 1, 0.5, 0.1, 0.001, 0.0001]
[0.8634130341529095, 0.8634134832056587, 0.8634180844298626, 0.86342183
02513165, 0.8634629300248184, 0.8634936283951694, 0.8634162350503543,
0.8152802608557099, 0.6386246100716295]
[0.8646048120674523, 0.8646051951826704, 0.8646106962769953, 0.86461335
87574667, 0.8646545997067424, 0.8646792115276515, 0.8645850224511005,
0.8160322620536167, 0.6386806669634713]
```

Out[0]:

```
<matplotlib.legend.Legend at 0x7fe9af210c88>
```

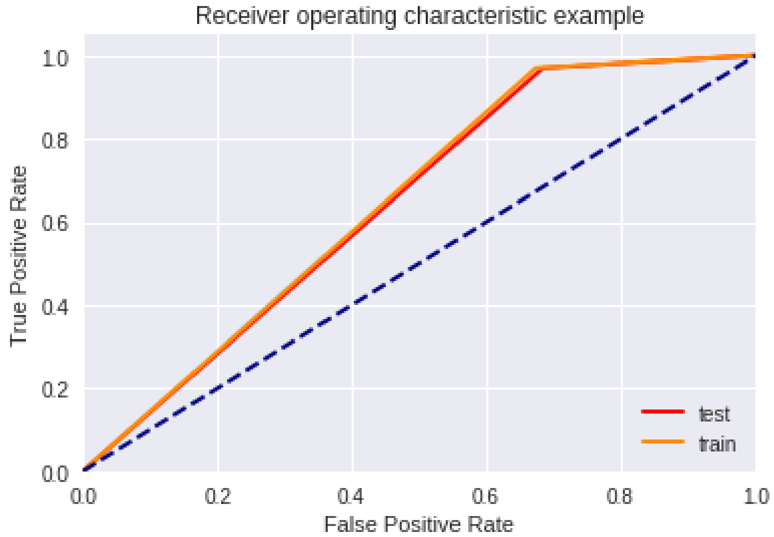


In [0]:
```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import auc
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score



clf1=LogisticRegression(C=0.5,penalty='l1')
clf1.fit(X_train_Avgtfidf,y_train)
pred_train=clf1.predict(X_train_Avgtfidf)
pred=clf1.predict(X_test_Avgtfidf)

print("Accuracy Score : ",accuracy_score(y_test,pred)*100)
print("Precision Score : ",precision_score(y_test,pred)*100)
print("Recall Score : ",recall_score(y_test,pred)*100)
print("F1 Score : ",f1_score(y_test,pred)*100)

print("        ")
print("Classification Report")
```

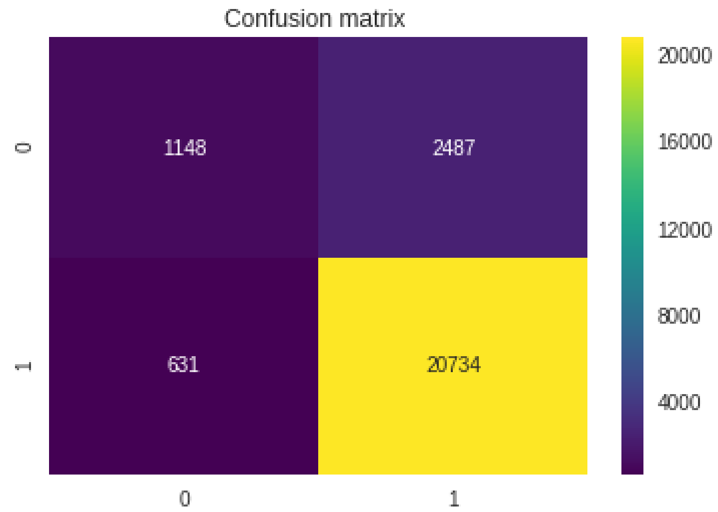
```
print(classification_report(y_test,pred))
print("        ")

fpr_train,tpr_train,thresholds_train=roc_curve(y_train,pred_train)
print("AUC Score for train data :",metrics.auc(fpr_train,tpr_train))

fpr,tpr,thresholds=roc_curve(y_test,pred)
print("AUC Score for test data :",metrics.auc(fpr,tpr))

print("        ")

#y_true = # ground truth labels
#y_probas = # predicted probabilities generated by sklearn classifier
#skplt.metrics.plot_roc_curve(y_true, y_probas)
#plt.show()



plt.figure()
lw = 2
plt.plot(fpr, tpr, color='red',
         lw=lw,label='test')
plt.plot(fpr_train, tpr_train, color='darkorange',
         lw=lw,label='train')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()


print("       ")

tn, fp, fn, tp=confusion_matrix(y_test,pred).ravel()
print("""
TrueNegative : {}
```

```
FalsePostive : {}
FalseNegative : {}
TruePostive  :  {}""".format(tn, fp, fn, tp))
print("        ")
print("        ")

confusionmatrix_DF=pd.DataFrame(confusion_matrix(y_test,pred),columns=[
'0','1'],index=['0','1'])
sns.heatmap(confusionmatrix_DF,annot=True,fmt='g',cmap='viridis')
plt.title("Confusion matrix ")
plt.show()
```

```
Accuracy Score :  87.52799999999999
Precision Score :  89.2898669307954
Recall Score :  97.04657149543647
F1 Score :  93.00677342663617

Classification Report
              precision    recall  f1-score   support

           0       0.65      0.32      0.42      3635
           1       0.89      0.97      0.93     21365

   micro avg       0.88      0.88      0.88     25000
   macro avg       0.77      0.64      0.68     25000
weighted avg       0.86      0.88      0.86     25000


AUC Score for train data : 0.6485271285189526
AUC Score for test data : 0.6431420734331659
```




```
TrueNegative : 1148
FalsePostive : 2487
FalseNegative : 631
TruePostive  :  20734
```



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

In [0]:
```
from sklearn.linear_model import LogisticRegression

clf=LogisticRegression(penalty='l2')
param_grid={'C':[1000,100,10,5,1,0.5,0.1,0.001,0.0001]}
#timeseriessplit=TimeSeriesSplit(n_splits=10)
gcv=GridSearchCV(clf,param_grid,cv=5,scoring='roc_auc')
gcv.fit(X_train_Avgtfidf,y_train)
print(gcv.best_params_)
print(gcv.best_score_)
```

```
{'C': 0.1}
0.8635213967923081
```

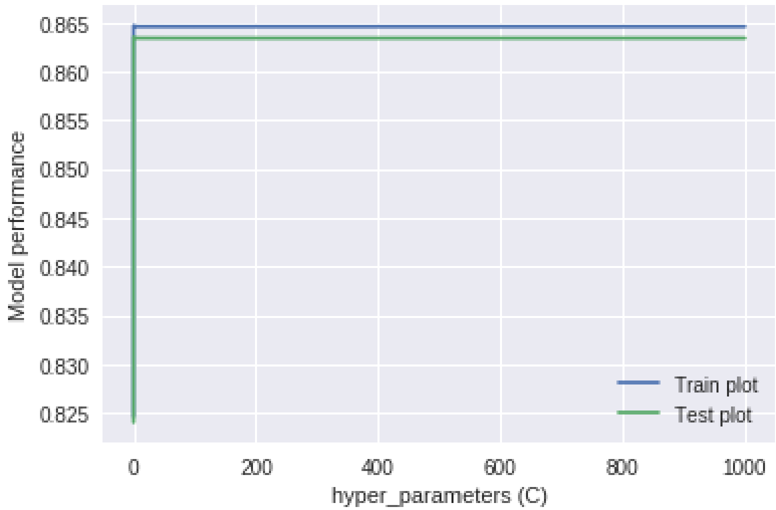
In [0]:
```
hyper_parameters=gcv.get_params()['param_grid']['C']
train_scores=gcv.cv_results_['mean_train_score'].tolist()
test_scores=gcv.cv_results_['mean_test_score'].tolist()
```

```
print(hyper_parameters)
print(test_scores)
print(train_scores)


plt.plot( hyper_parameters ,train_scores , label='Train plot')
plt.plot( hyper_parameters ,test_scores ,  label='Test plot')
plt.xlabel("hyper_parameters (C)")
plt.ylabel("Model performance")

plt.legend()
```

```
[1000, 100, 10, 5, 1, 0.5, 0.1, 0.001, 0.0001]
[0.8633956265099353, 0.8633952826912352, 0.8634009355048974, 0.86340985
6826655, 0.8634449191924536, 0.8634786199808072, 0.8635213967923081, 0.
8592823633143652, 0.8240068507338287]
[0.8645871843553113, 0.8645869507616778, 0.8645923646056921, 0.86459955
91362844, 0.8646347196807469, 0.8646650113597101, 0.8646980758164574,
0.8602040061553147, 0.8245984473005616]
```

Out[0]:

```
<matplotlib.legend.Legend at 0x7fe9a8f2c4a8>
```



In [0]:

```
from sklearn.metrics import roc_auc_score
```

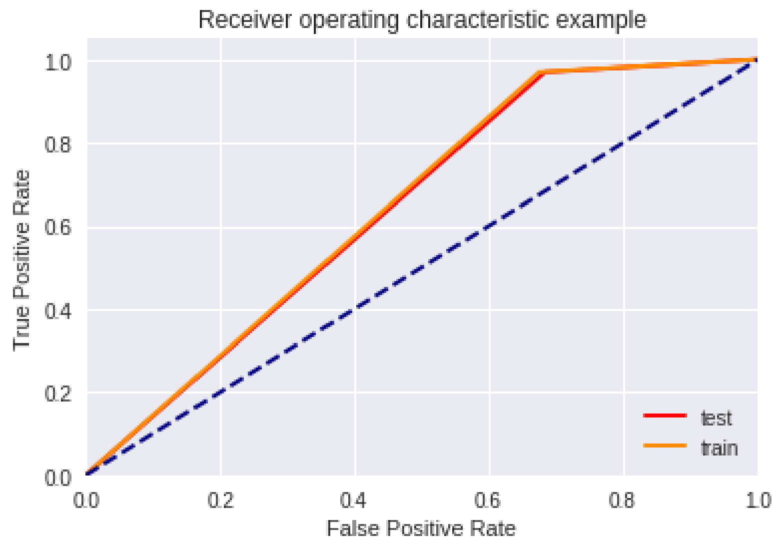
```python
from sklearn.metrics import auc
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score



clf1=LogisticRegression(C=0.1,penalty='l2')
clf1.fit(X_train_Avgtfidf,y_train)
pred_train=clf1.predict(X_train_Avgtfidf)
pred=clf1.predict(X_test_Avgtfidf)

print("Accuracy Score : ",accuracy_score(y_test,pred)*100)
print("Precision Score : ",precision_score(y_test,pred)*100)
print("Recall Score : ",recall_score(y_test,pred)*100)
print("F1 Score : ",f1_score(y_test,pred)*100)

print("        ")
print("Classification Report")
print(classification_report(y_test,pred))
print("        ")

fpr_train,tpr_train,thresholds_train=roc_curve(y_train,pred_train)
print("AUC Score for train data :",metrics.auc(fpr_train,tpr_train))

fpr,tpr,thresholds=roc_curve(y_test,pred)
print("AUC Score for test data :",metrics.auc(fpr,tpr))

print("        ")

#y_true = # ground truth labels
#y_probas = # predicted probabilities generated by sklearn classifier
#skplt.metrics.plot_roc_curve(y_true, y_probas)
#plt.show()
```

```python
plt.figure()
lw = 2
plt.plot(fpr, tpr, color='red',
         lw=lw,label='test')
plt.plot(fpr_train, tpr_train, color='darkorange',
         lw=lw,label='train')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()


print("       ")

tn, fp, fn, tp=confusion_matrix(y_test,pred).ravel()
print("""
TrueNegative : {}
FalsePostive : {}
FalseNegative : {}
TruePostive  :  {}""".format(tn, fp, fn, tp))
print("        ")
print("        ")

confusionmatrix_DF=pd.DataFrame(confusion_matrix(y_test,pred),columns=[
'0','1'],index=['0','1'])
sns.heatmap(confusionmatrix_DF,annot=True,fmt='g',cmap='viridis')
plt.title("Confusion matrix ")
plt.show()
```

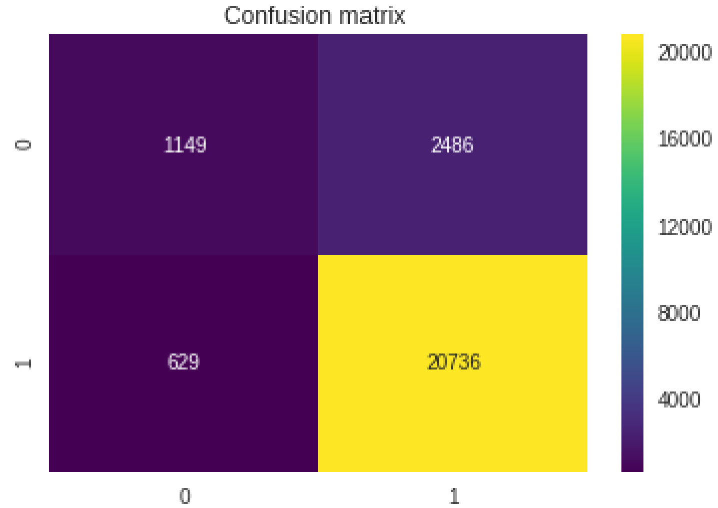
```
Accuracy Score :  87.53999999999999
Precision Score :  89.2946343984153
Recall Score :  97.0559326000468
F1 Score :  93.0136586897526

Classification Report
```

```
               precision    recall  f1-score   support

           0       0.65      0.32      0.42      3635
           1       0.89      0.97      0.93     21365

   micro avg       0.88      0.88      0.88     25000
   macro avg       0.77      0.64      0.68     25000
weighted avg       0.86      0.88      0.86     25000
```

```
AUC Score for train data : 0.6477156491287481
AUC Score for test data : 0.6433264305380608
```




```
TrueNegative : 1149
FalsePostive : 2486
FalseNegative : 629
TruePostive  :  20736
```



[6] Conclusions

In [0]:

```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["LogisticRegression with Different Vectorization","penalty" , "C-value" , 'Test_Accuracy','F1-Score','AUC_Score']


x.add_row([ "LR with BOW" , "l1" , 0.1  , 90.708  ,  94.59 ,79.34  ])
x.add_row([ "LR with BOW without Standardization" , "l1" , 0.1  , 88.0 ,  93.00 , 73.07 ])

x.add_row([ "LR with BOW" , "l2" , 0.001  , 91.268 ,94.974,  78.00 ])
x.add_row([ "LR with TFIDF" , "l1" ,0.1 , 91.444  ,  95.013 ,81.821 ])
x.add_row([ "LR with TFIDF" , "l2" , 0.0001  , 91.776  ,  95.322,76.296 ])

x.add_row([ "LR with AVG_W2V" , "l1" , 0.1, 88.74 ,  93.62 ,69.338  ])
x.add_row([ "LR with AVG_W2V" , "l2" , 0.1  , 88.764 ,  93.632,69.477])
```

```
x.add_row([ "LR with AVG_TFIDF" , "l1" , 0.5 , 87.527 , 93.000, 64.314
])
x.add_row([ "LR with AVG_TFIDF" , "l2" ,0.1, 87.539 ,  93.013 , 64.33
])



print(x)
```

```
+--------------------------------------------------+---------+---------+
---------------+----------+-----------+
| LogisticRegression with Different Vectorization | penalty | C-value |
Test_Accuracy | F1-Score | AUC_Score |
+--------------------------------------------------+---------+---------+
---------------+----------+-----------+
|                    LR with BOW                   |    l1   |   0.1   |
     90.708    |  94.59   |   79.34   |
|        LR with BOW without Standardization       |    l1   |   0.1   |
      88.0     |   93.0   |   73.07   |
|                    LR with BOW                   |    l2   |  0.001  |
     91.268    |  94.974  |    78.0   |
|                   LR with TFIDF                  |    l1   |   0.1   |
     91.444    |  95.013  |   81.821  |
|                   LR with TFIDF                  |    l2   |  0.0001 |
     91.776    |  95.322  |   76.296  |
|                  LR with AVG_W2V                 |    l1   |   0.1   |
     88.74     |  93.62   |   69.338  |
|                  LR with AVG_W2V                 |    l2   |   0.1   |
     88.764    |  93.632  |   69.477  |
|                 LR with AVG_TFIDF                |    l1   |   0.5   |
     87.527    |   93.0   |   64.314  |
|                 LR with AVG_TFIDF                |    l2   |   0.1   |
     87.539    |  93.013  |   64.33   |
+--------------------------------------------------+---------+---------+
---------------+----------+-----------+
```

Summy:

- Have Applied LR with All vectors and with voth penalty ie l1 and l2
- Among all vectorizatiob TFIDF with penalty l1 gives high accuracy
- Done LR with Standardization Data and without Standardization Data what i have observed is there is good amount of difference in both of the outputs
- StandardizationData output performs much better than not StandardizationData in LR
- Have Done Perbutation test on LR with BOW and observed 10's percentile on weight_difference
- TFIDF top 10Features :
  - top 10 negative features = [disappoint , veri disappoint , worst , terribl , return , horribl , th rew , wont buy , wast money]
  - top 10 Postive features = [great , love , best , good , delici , perfect , excel , favorit , nice , wonder]

In [0]:

```

```