Amazon Fine Food Reviews Analysis

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

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

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

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

Attribute Information:

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

Objective:

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

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

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

[1]. Reading Data

[1.1] Loading the data

The dataset is available in two forms

1. .csv file
2. SQLite Database

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

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

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

#import gensim
import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
```

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

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

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

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

from tqdm import tqdm
import os
```

In [3]:

```python
#from google.colab import drive

# This will prompt for authorization.
#drive.mount('/content/drive')
```

In [4]:

```python
# files will be present in "/content/drive/My Drive".
#!ls "/content/drive/My Drive/MachineLearning"
```

In [5]:

```python
# using the SQLite Table to read data.
#con = sqlite3.connect('/content/drive/My Drive/MachineLearning/databas
e.sqlite')
```

In [2]:

```python
# 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 100000""", 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 (100000, 10)
```

Out[2]:

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

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

In [3]:

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

In [4]:

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

```
(80668, 7)
```

Out[4]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
0	#oc-R115TNMSPFT9I7	B005ZBZLT4	Breyton	1331510400	2	Overall its just OK when considering the price...	2

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
1	#oc-R11D9D7SHXIJB9	B005HG9ESG	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B005ZBZLT4	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ESG	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBEV0	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	2

In [5]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[5]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
80638	AZY10LLTJ71NX	B001ATMQK2	undertheshrine "undertheshrine"	1296691200	5	I bought this 6 pack because for the price tha...	5

In [6]:
```
display['COUNT(*)'].sum()
```

Out[6]:
```
393063
```

[2] Exploratory Data Analysis

[2.1] Data Cleaning: Deduplication

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

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

Out[7]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenon
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenon
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 [8]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')
```

In [9]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time"
```

```
,"Text"}, keep='first', inplace=False)
final.shape
```

Out[9]: (87775, 10)

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

Out[10]: 87.775

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

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

display.head()
```

Out[11]:

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

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

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

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

```
(87773, 10)
```

Out[13]:
```
1    73592
0    14181
Name: Score, dtype: int64
```

[3] Preprocessing

[3.1]. Preprocessing Review Text

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

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

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

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

In [14]:

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

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)
```

```
My dogs loves this chicken but its a product from China, so we wont be
buying it anymore.  Its very hard to find any chicken products made in
the USA but they are out there, but this one isnt.  Its too bad too bec
ause its a good product but I wont take any chances till they know what
is going on with the china imports.
==================================================
The Candy Blocks were a nice visual for the Lego Birthday party but the
candy has little taste to it.  Very little of the 2 lbs that I bought w
ere eaten and I threw the rest away.  I would not buy the candy again.
==================================================
was way to hot for my blood, took a bite and did a jig  lol
==================================================
My dog LOVES these treats. They tend to have a very strong fish oil sme
ll. So if you are afraid of the fishy smell, don't get it. But I think
my dog likes it because of the smell. These treats are really small in
size. They are great for training. You can give your dog several of the
se without worrying about him over eating. Amazon's price was much more
reasonable than any other retailer. You can buy a 1 pound bag on Amazon
for almost the same price as a 6 ounce bag at other retailers. It's def
initely worth it to buy a big bag if your dog eats them a lot.
==================================================
```

In [15]:
```
# 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)
```

```
My dogs loves this chicken but its a product from China, so we wont be
buying it anymore.  Its very hard to find any chicken products made in
the USA but they are out there, but this one isnt.  Its too bad too bec
ause its a good product but I wont take any chances till they know what
is going on with the china imports.
```

In [16]:
```
# 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)
```

```
My dogs loves this chicken but its a product from China, so we wont be
```

```
buying it anymore.  Its very hard to find any chicken products made in
the USA but they are out there, but this one isnt.  Its too bad too bec
ause its a good product but I wont take any chances till they know what
is going on with the china imports.
==================================================
The Candy Blocks were a nice visual for the Lego Birthday party but the
candy has little taste to it.  Very little of the 2 lbs that I bought w
ere eaten and I threw the rest away.  I would not buy the candy again.
==================================================
was way to hot for my blood, took a bite and did a jig  lol
==================================================
My dog LOVES these treats. They tend to have a very strong fish oil sme
ll. So if you are afraid of the fishy smell, don't get it. But I think
my dog likes it because of the smell. These treats are really small in
size. They are great for training. You can give your dog several of the
se without worrying about him over eating. Amazon's price was much more
reasonable than any other retailer. You can buy a 1 pound bag on Amazon
for almost the same price as a 6 ounce bag at other retailers. It's def
initely worth it to buy a big bag if your dog eats them a lot.
```

In [17]:

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

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

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

In [18]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
was way to hot for my blood, took a bite and did a jig  lol
==================================================
```

In [19]:
```
#remove words with numbers python: https://stackoverflow.com/a/1808237
0/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
My dogs loves this chicken but its a product from China, so we wont be
buying it anymore.  Its very hard to find any chicken products made in
the USA but they are out there, but this one isnt.  Its too bad too bec
ause its a good product but I wont take any chances till they know what
is going on with the china imports.
```

In [20]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
was way to hot for my blood took a bite and did a jig lol
```

In [21]:
```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'no
t'
# <br /><br /> ==> after the above steps, we are getting "br br"
# we are including them into stop words list
# instead of <br /> if we have <br/> these tags would have revmoved in
 the 1st step

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'o
urs', 'ourselves', 'you', "you're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselve
s', 'he', 'him', 'his', 'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'it
s', 'itself', 'they', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'th
```

```
is', 'that', "that'll", 'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'h
ave', 'has', 'had', 'having', 'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or',
 'because', 'as', 'until', 'while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between',
'into', 'through', 'during', 'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out',
'on', 'off', 'over', 'under', 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'h
ow', 'all', 'any', 'both', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 's
o', 'than', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should',
"should've", 'now', 'd', 'll', 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't",
'didn', "didn't", 'doesn', "doesn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "is
n't", 'ma', 'mightn', "mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn',
 "shouldn't", 'wasn', "wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

In [22]:

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

```
100%|████████████████████████████████████████████████████
████████| 87773/87773 [00:27<00:00, 3205.75it/s]
```

| 87773/87773 [00:17<00:00, 5103.51it/s]

In [23]:
```
final['Cleaned Text'] = preprocessed_reviews
```

In [24]:
```
sample1 = pd.DataFrame()
```

In [25]:
```
sample1['Cleaned Text'] =preprocessed_reviews
```

In [26]:
```
sample1.tail(3)
```

Out[26]:

	Cleaned Text
87770	trader joe product good quality buy straight t...
87771	coffee supposedly premium tastes watery thin n...
87772	purchased product local store ny kids love qui...

In [27]:
```
k1 = []
```

In [28]:
```
sample1.shape
```

Out[28]:
```
(87773, 1)
```

In [29]:
```
for i in range(0,87773):
    k1.append(len(preprocessed_reviews[i]))
```

In [30]:
```
sample1['Length'] = k1
```

In [31]:
```
sample1.head(3)
```

Out[31]:

	Cleaned Text	Length
0	dogs loves chicken product china wont buying a...	162
1	dogs love saw pet store tag attached regarding...	72

	Cleaned Text	Length
2	infestation fruitflies literally everywhere fl...	406

[3.2] Preprocessing Review Summary

In [32]:
```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
```

Splitting the Data with feature engineering

In [33]:
```
X_train1, X_test1, y_train1, y_test1 = train_test_split(sample1,final[
'Score'].values,test_size=0.3,shuffle=False)
```

In [34]:
```
y_train1.shape
```

Out[34]: (61441,)

In [38]:
```
X_train1.shape
```

Out[38]: (61441, 2)

In [39]:
```
X_test1.shape
```

Out[39]: (26332, 2)

In [40]:
```
type(y_test1)
```

Out[40]: numpy.ndarray

In [41]:
```
type(X_test1)
```

Out[41]: pandas.core.frame.DataFrame

In [35]:
```
X_train1.head(3)
```

Out[35]:

	Cleaned Text	Length
0	dogs loves chicken product china wont buying a...	162
1	dogs love saw pet store tag attached regarding...	72
2	infestation fruitflies literally everywhere fl...	406

In [36]:
```
X_test1.head(3)
```

Out[36]:

	Cleaned Text	Length
61441	used treat training reward dog loves easy brea...	66
61442	much fun watching puppies asking chicken treat...	134
61443	little shih tzu absolutely loves cesar softies...	181

In [37]:
```
X_trainbow = pd.DataFrame()
```

In [38]:
```
X_trainbow['Cleaned Text'] = X_train1['Cleaned Text']
```

In [39]:
```
X_trainbow.head(3)
```

Out[39]:

	Cleaned Text
0	dogs loves chicken product china wont buying a...
1	dogs love saw pet store tag attached regarding...
2	infestation fruitflies literally everywhere fl...

In [40]:
```
X_testbow = pd.DataFrame()
```

In [41]:
```
X_testbow['Cleaned Text'] = X_test1['Cleaned Text']
```

In [42]:
```
X_testbow.head(3)
```
Out[42]:

	Cleaned Text
61441	used treat training reward dog loves easy brea...
61442	much fun watching puppies asking chicken treat...
61443	little shih tzu absolutely loves cesar softies...

BAG OF WORDS WITH FEATURE ENGINEERING

In [43]:
```
X_trainbow.shape
```
Out[43]:
```
(61441, 1)
```

In [44]:
```
X_testbow.shape
```
Out[44]:
```
(26332, 1)
```

In [45]:
```
count_vect = CountVectorizer()
a1 = count_vect.fit_transform(X_trainbow['Cleaned Text'].values)
b1 = count_vect.transform(X_testbow['Cleaned Text'])
```

In [46]:
```
print("the type of count vectorizer :",type(a1))
print("the shape of out text BOW vectorizer : ",a1.get_shape())
print("the number of unique words :", a1.get_shape()[1])
```
```
the type of count vectorizer : <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer :  (61441, 46008)
the number of unique words : 46008
```

ADDING LENGTH OF REVIEWS AS ONE FEATURE

In [47]:
```
from scipy import sparse
from scipy.sparse import csr_matrix
```

In [48]:
```
a1 = preprocessing.normalize(a1)
a2 = sparse.csr_matrix(X_train1['Length'].values)
a2 = preprocessing.normalize(a2)
a3 = sparse.hstack([a1, a2.T])
```

In [49]:
```
b1 = preprocessing.normalize(b1)
b2 = sparse.csr_matrix(X_test1['Length'].values)
b2 = preprocessing.normalize(b2)
b3 = sparse.hstack([b1, b2.T])
```

In [57]:
```
y_test1.shape
```

Out[57]:
```
(26332,)
```

In [58]:
```
y_train1.shape
```

Out[58]:
```
(61441,)
```

SVM FOR BOW with Feature Engineering

In [55]:
```
from sklearn.model_selection import train_test_split
#from sklearn.grid_search import GridSearchCV
from sklearn.model_selection import GridSearchCV
from sklearn.datasets import *
from sklearn.linear_model import LogisticRegression
```

In [54]:
```
from sklearn.model_selection  import train_test_split
from sklearn.metrics import accuracy_score
```

```python
from sklearn.model_selection  import cross_val_score
from collections import Counter
from sklearn.metrics import accuracy_score
from sklearn import model_selection
from sklearn.metrics import roc_auc_score
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.calibration import CalibratedClassifierCV
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.calibration import CalibratedClassifierCV
from sklearn.linear_model import SGDClassifier
```

Applying Linear SVM FOR bow

In [56]:

```python
alpha = [0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000,100000]
clf = SGDClassifier(loss='hinge',class_weight = 'balanced')
param_grid = {'alpha':alpha}
model_bow = GridSearchCV(estimator = clf,param_grid=param_grid ,scoring
 = 'roc_auc',cv = 10, return_train_score = True)
model_bow.fit(a3, y_train1)
print(model_bow.best_estimator_)
print(model_bow.score(b3, y_test1))
```

```
SGDClassifier(alpha=0.0001, average=False, class_weight='balanced',
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=N
one,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
0.9454290671371609
```

Observations:

1) We found that the optimal alpha = 0.0001 in Linear SVM and the AUC value is quite good.

In [50]:
```
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score,confusion_matrix,f1_score,pr
ecision_score,recall_score
```

Running the Model with Optimal HYPER PARAMETERS

In [51]:
```
from sklearn.metrics import roc_auc_score
```

In [57]:
```
train_auc1= model_bow.cv_results_['mean_train_score']
cv_auc1= model_bow.cv_results_['mean_test_score']
```

In [58]:
```
train_auc1
```

Out[58]:
```
array([0.97320285, 0.95855441, 0.91970162, 0.81935988, 0.78292612,
       0.78292612, 0.78292612, 0.78292612, 0.78292612, 0.78292612,
       0.78292612])
```

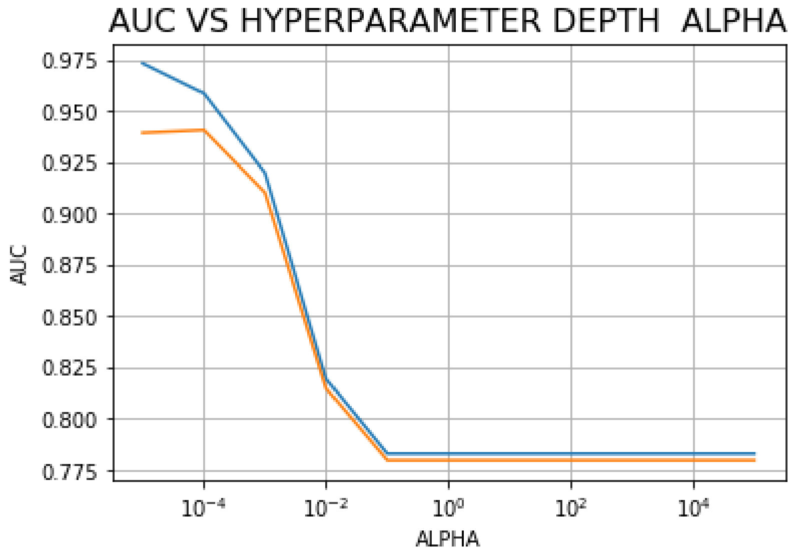
In [59]:
```
cv_auc1
```

Out[59]:
```
array([0.93924168, 0.94059129, 0.91008351, 0.81475138, 0.77966889,
       0.77966889, 0.77966889, 0.77966889, 0.77966889, 0.77966889,
       0.77966889])
```

In [60]:
```
import math
from math import log
```

In [61]:
```
# Firstly I am plotting depth vs AUC and then split vs AUC
plt.plot(alpha,train_auc1)
plt.plot(alpha,cv_auc1)
plt.xlabel('ALPHA',size=10)
plt.ylabel('AUC',size=10)
plt.title('AUC VS HYPERPARAMETER DEPTH  ALPHA',size=16)
```

```
plt.xscale('log')
plt.grid()
plt.show()
print("\n\n Alpha Values :\n", alpha)
print("\n Train AUC for each alpha value is :\n ", np.round(train_auc1,
5))
print("\n CV AUC for each alpha value is :\n ", np.round(cv_auc1,5))
```




```
 Alpha Values :
 [1e-05, 0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000, 100000]

 Train AUC for each alpha value is :
  [0.9732  0.95855 0.9197  0.81936 0.78293 0.78293 0.78293 0.78293 0.78
293
 0.78293 0.78293]

 CV AUC for each alpha value is :
  [0.93924 0.94059 0.91008 0.81475 0.77967 0.77967 0.77967 0.77967 0.77
967
 0.77967 0.77967]
```

In [62]:
```
max(cv_auc1)
```
Out[62]:
```
0.9405912899256196
```

Observations

1) We have found that the hyperparmeter ALPHA should be 0.0001 for having maximum AUC for CV

In [0]:
```
# after you found the best hyper parameter, you need to train your mode
l 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 confusi
on matrices using seaborn heatmaps.
```

Training the model with the best hyper parameter

In [63]:
```
om_bow = SGDClassifier(alpha=0.0001,class_weight = 'balanced') # Hinge
 loss is not used as probabilities I cannot get
om_bow = CalibratedClassifierCV(om_bow, cv= 5)
```

In [64]:
```
om_bow.fit(a3, y_train1)
ompredictions_bow  = om_bow.predict(b3)
```

In [0]:
```
# Probability Estimates are not there WHILE using hinge loss.
```

In [65]:
```
len(ompredictions_bow)
```
Out[65]:
```
26332
```

In [66]:
```
probs = om_bow.predict_proba(b3)
probs1 = om_bow.predict_proba(a3)
probs = probs[:, 1]
probs1 = probs1[:, -1]
```

FEATURE IMPORTANCE FOR BOW

In [0]:
```
# Again rerunning the model as I have to get feature importance
```

In [69]:
```
om_bowp = SGDClassifier(alpha=0.0001,class_weight = 'balanced')
```

In [70]:
```
om_bowp.fit(a3,y_train1)
```

Out[70]:
```
SGDClassifier(alpha=0.0001, average=False, class_weight='balanced',
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=N
one,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

In [71]:
```
om_bowp.get_params
```

Out[71]:
```
<bound method BaseEstimator.get_params of SGDClassifier(alpha=0.0001, a
verage=False, class_weight='balanced',
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=N
one,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)>
```

In [72]:
```
count_vect.get_params
```

Out[72]:

```
<bound method BaseEstimator.get_params of CountVectorizer(analyzer='wor
d', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), preprocessor=None, stop_words=None,
        strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
        tokenizer=None, vocabulary=None)>
```

In [73]:
```
features = count_vect.get_feature_names()
```

In [74]:
```
Coefficients = om_bowp.coef_
```

In [75]:
```
coef = Coefficients.reshape(46009,1)
```

In [76]:
```
coef.shape
```

Out[76]:
```
(46009, 1)
```

In [77]:
```
coef = coef.tolist()
```

In [78]:
```
type(coef)
```

Out[78]:
```
list
```

In [79]:
```
len(features)
features.append('zzzzzzzzzza')
```

In [80]:
```
len(features)
```

Out[80]:
```
46009
```

In [0]:
```
#features=np.argsort(features)[::-1]
```

In [81]:
```
cf = pd.DataFrame({'Word' : features, 'Coefficient' : coef})
cf_new = cf.sort_values("Coefficient", ascending = False)
```

```python
print('***** Top 10 IMPORTANT FEATURES FOR POSITIVE CLASS *****')
print('\n')
print(cf_new.head(10))
print('\n')
print('***** Top 10 IMPORTANT FEATURES FOR NEGATIVE CLASS *****')
print('\n')
print(cf_new.tail(10))
```

```
***** Top 10 IMPORTANT FEATURES FOR POSITIVE CLASS *****


            Word            Coefficient
10560  delicious   [4.455001909719882]
29622    perfect  [3.8362270713735867]
17569      great  [3.6708005160405612]
45177  wonderful   [3.561329279820464]
3744        best   [3.510946432908001]
13900  excellent  [3.4869254640950733]
23609      loves  [3.4791122711873963]
18895     highly   [3.174874780925968]
2762     awesome   [3.015127073025514]
1285     amazing  [3.0004170470635234]


***** Top 10 IMPORTANT FEATURES FOR NEGATIVE CLASS *****


                Word            Coefficient
38261          stale   [-2.662562682757956]
44424           weak  [-2.6853881669492004]
4105           bland  [-2.7377598318256386]
2768           awful  [-2.7519643992238314]
19249       horrible   [-2.757109149631728]
42813  unfortunately  [-3.1966425693619382]
40533       terrible   [-3.219130869703495]
11442  disappointing  [-3.7843594999913077]
45296          worst  [-3.9309858991070734]
11440   disappointed    [-4.00674289521191]
```

Observations :

1) We have found that not and great are the top 2 words are delicious and amazing that is impacting positive class.

2) Disappointing and the wrost are the top two words that are impacting the negative class the most.

PERFORMANCE MEASURMENTS FOR BOW (LINEAR SVM)

In [82]:
```
precision_bow = precision_score(y_test1, ompredictions_bow, pos_label = 1)
recall_bow = recall_score(y_test1, ompredictions_bow, pos_label = 1)
f1score_bow = f1_score(y_test1, ompredictions_bow, pos_label = 1)
```

In [83]:
```
print('\nThe Test Precision for optimal alpha for Linear SVM (BOW)   is %f' % (precision_bow))
print('\nThe Test Recall for optimal alpha for Linear SVM (BOW)  is %f' % (recall_bow))
print('\nThe Test F1-Score for optimal alpha for Linear SVM (BOW)  is %f' %  (f1score_bow))
```

```
The Test Precision for optimal alpha for Linear SVM (BOW)   is 0.933265

The Test Recall for optimal alpha for Linear SVM (BOW)  is 0.959503

The Test F1-Score for optimal alpha for Linear SVM (BOW)  is 0.946202
```

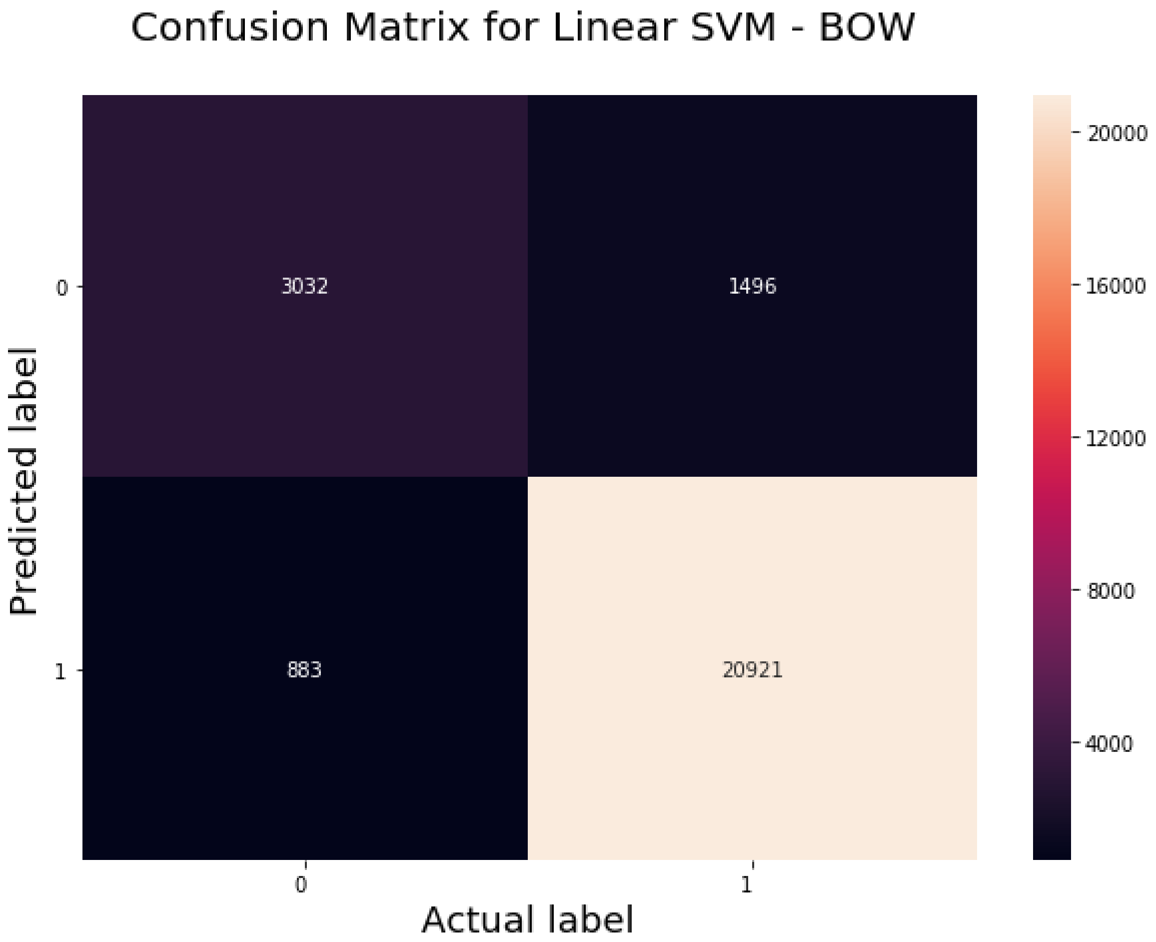
CONFUSION MATRIX

In [0]:
```
# Reference Links
```

```
# https://datatofish.com/confusion-matrix-python/
```

In [84]:

```
# Code for drawing seaborn heatmaps
class_names = [ 0,1]
df_heatmap = pd.DataFrame(confusion_matrix(y_test1, ompredictions_bow),
 index=class_names, columns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=10)#
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=10)
plt.ylabel('Predicted label',size=18)
plt.xlabel('Actual label',size=18)
plt.title("Confusion Matrix for Linear SVM - BOW \n",size=20)
plt.show()
```



In [85]:
```
TrueNeg,FalseNeg,FalsePos, TruePos = confusion_matrix(y_test1, ompredic
tions_bow).ravel()
TPR = TruePos/(FalseNeg + TruePos)
FPR = FalsePos/(TrueNeg + FalsePos)
TNR = TrueNeg/(TrueNeg + FalsePos)
FNR = FalseNeg/(FalseNeg + TruePos)
```

In [86]:
```
print("TPR of the Linear SVM  (BOW)   is :  %f" % (TPR))
print("FPR of the Linear SVM  (BOW)   is :  %f" % (FPR))
```

```
print("TNR of the Linear SVM (BOW)   is :  %f" % (TNR))
print("FNR of the Linear SVM  (BOW)  is :  %f" % (FNR))
```

```
TPR of the Linear SVM  (BOW)   is :  0.933265
FPR of the Linear SVM  (BOW)   is :  0.225543
TNR of the Linear SVM (BOW)   is :  0.774457
FNR of the Linear SVM  (BOW)  is :  0.066735
```

PLOTTING THE ROC CURVE (BOW) ---- > FOR BOTH TRAIN AND TEST DATA

In [91]:

```
len(y_train1)
```

Out[91]: 61441

In [0]:

```
len(probs1)
```

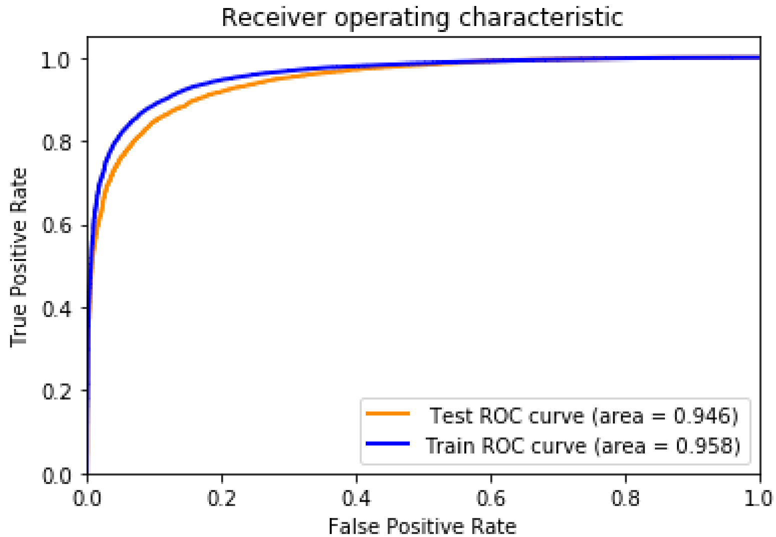
Out[0]: 61441

In [87]:

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc
fpr = dict()
tpr = dict()
roc_auc = dict()

fpr1 = dict()
tpr1 = dict()
roc_auc1 = dict()

#for i in range(26331):
for i in range(4):
    fpr[i], tpr[i], _ = roc_curve(y_test1,probs)
    roc_auc[i] = auc(fpr[i], tpr[i])

#for i in range(61441):
for i in range(4):
```

```
    fpr1[i], tpr1[i], _ = roc_curve(y_train1,probs1)
    roc_auc1[i] = auc(fpr1[i], tpr1[i])
```

In [88]:
```
#print(roc_auc_score(y_test1,ompredictions_bow))
plt.figure()
#plt.plot(fpr[1], tpr[1])
lw = 2
plt.plot(fpr[0], tpr[0], color='darkorange',lw=lw, label=' Test ROC cur
ve (area = %0.3f)' % roc_auc[0])
plt.plot(fpr1[0], tpr1[0], color='blue',lw=lw, label='Train ROC curve
 (area = %0.3f)' % roc_auc1[0])
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc="lower right")
plt.title('Receiver operating characteristic')
plt.show()
```



Observations

1) We observe that AUC for train data is 0.98 and the test data is 0.95 which implies that the model is reasonably good.

TFIDF WITH FEATURE ENGINEERING

In [89]:
```
tf_idf_vect = TfidfVectorizer(min_df=10)
c1 = tf_idf_vect.fit_transform(X_trainbow['Cleaned Text'].values)
d1 = tf_idf_vect.transform(X_testbow['Cleaned Text'])
print("the type of count vectorizer :",type(c1))
print("the shape of out text TFIDF vectorizer : ",c1.get_shape())
print("the number of unique words :", c1.get_shape()[1])
```

```
the type of count vectorizer : <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer :  (61441, 9723)
the number of unique words : 9723
```

In [90]:
```
c1 = preprocessing.normalize(c1)
c2 = sparse.csr_matrix(X_train1['Length'].values)
c2 = preprocessing.normalize(c2)
c3 = sparse.hstack([c1, c2.T])
```

In [91]:
```
d1 = preprocessing.normalize(d1)
d2 = sparse.csr_matrix(X_test1['Length'].values)
d2 = preprocessing.normalize(d2)
d3 = sparse.hstack([d1, d2.T])
```

Linear SVM - TFIDF

In [92]:
```
alpha = [0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000,100000]
clf = SGDClassifier(loss='hinge',class_weight = 'balanced')
param_grid = {'alpha':alpha}
model_tfidf = GridSearchCV(estimator = clf,param_grid=param_grid ,scori
ng = 'roc_auc',cv = 10, return_train_score = True, verbose = 3)
model_tfidf.fit(c3, y_train1)
```

```
print(model_tfidf.best_estimator_)
print(model_tfidf.score(d3, y_test1))
```

```
Fitting 10 folds for each of 11 candidates, totalling 110 fits
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent
workers.
```

```
[CV] alpha=1e-05 .....................................................
[CV] ........... alpha=1e-05, score=0.9259875344649139, total=   0.1s
```

```
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.1s remaining:
    0.0s
```

```
[CV] alpha=1e-05 .....................................................
[CV] ............ alpha=1e-05, score=0.946969905938819, total=   0.1s
```

```
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    0.3s remaining:
    0.0s
```

```
[CV] alpha=1e-05 .....................................................
[CV] ............ alpha=1e-05, score=0.949816646858211, total=   0.1s
[CV] alpha=1e-05 .....................................................
[CV] ........... alpha=1e-05, score=0.9367014257458628, total=   0.1s
[CV] alpha=1e-05 .....................................................
[CV] ........... alpha=1e-05, score=0.9460335531995994, total=   0.1s
[CV] alpha=1e-05 .....................................................
[CV] ............. alpha=1e-05, score=0.94110311971323, total=   0.1s
[CV] alpha=1e-05 .....................................................
[CV] ........... alpha=1e-05, score=0.9409478493757673, total=   0.1s
[CV] alpha=1e-05 .....................................................
[CV] ........... alpha=1e-05, score=0.9314015248907755, total=   0.1s
[CV] alpha=1e-05 .....................................................
[CV] ........... alpha=1e-05, score=0.9382002773791871, total=   0.1s
[CV] alpha=1e-05 .....................................................
[CV] ........... alpha=1e-05, score=0.9434428640902024, total=   0.1s
[CV] alpha=0.0001 ....................................................
[CV] .......... alpha=0.0001, score=0.9382723748599318, total=   0.1s
[CV] alpha=0.0001 ....................................................
[CV] .......... alpha=0.0001, score=0.9531219205447066, total=   0.1s
[CV] alpha=0.0001 ....................................................
```

```
[CV] ........... alpha=0.0001, score=0.9513445563925346, total=   0.1s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.9447902900013707, total=   0.1s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.9502588672668719, total=   0.1s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.9449486617437699, total=   0.1s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.9452397936265129, total=   0.1s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.9401432849080633, total=   0.1s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.9456468878895767, total=   0.1s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.9458458163973927, total=   0.1s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.9249119613089491, total=   0.1s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.9374922295286306, total=   0.1s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.9307781424985518, total=   0.1s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.9280761184816722, total=   0.1s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.9334092343831755, total=   0.2s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.9270767657748961, total=   0.1s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.929357198811O614, total=   0.1s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.9249684106900427, total=   0.1s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.9335764904128067, total=   0.1s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.9249533198446197, total=   0.1s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.8929465907269244, total=   0.1s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.9001505922348454, total=   0.1s
```

```
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.8958045251227585, total=   0.1s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.8922841046994288, total=   0.2s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.8972120370527848, total=   0.1s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.8887612088275989, total=   0.2s
[CV] alpha=0.01 ......................................................
[CV] .............. alpha=0.01, score=0.897994391459331, total=   0.1s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.8896556139931389, total=   0.1s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.9017223126139486, total=   0.1s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.8839290181457222, total=   0.1s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8929465907269245, total=   0.1s
[CV] alpha=0.1 .......................................................
[CV] ............... alpha=0.1, score=0.900120209941646, total=   0.1s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8956644067837265, total=   0.1s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8922831042462236, total=   0.1s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8974631508073158, total=   0.2s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8886361521769361, total=   0.1s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8977638870408293, total=   0.1s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8892770425002526, total=   0.1s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.9017069026591178, total=   0.1s
[CV] alpha=0.1 .......................................................
[CV] ............... alpha=0.1, score=0.883764511874671, total=   0.2s
[CV] alpha=1 .........................................................
[CV] ................ alpha=1, score=0.8929465907269245, total=   0.1s
[CV] alpha=1 .........................................................
```

```
[CV] ................. alpha=1, score=0.900120209941646, total=   0.1s
[CV] alpha=1 .........................................................
[CV] ................ alpha=1, score=0.8956644067837265, total=   0.1s
[CV] alpha=1 .........................................................
[CV] ................ alpha=1, score=0.8922831042462236, total=   0.1s
[CV] alpha=1 .........................................................
[CV] ................ alpha=1, score=0.8974631508073158, total=   0.1s
[CV] alpha=1 .........................................................
[CV] ................ alpha=1, score=0.8886361521769361, total=   0.1s
[CV] alpha=1 .........................................................
[CV] ................ alpha=1, score=0.8977638870408293, total=   0.1s
[CV] alpha=1 .........................................................
[CV] ................ alpha=1, score=0.8892770425002526, total=   0.1s
[CV] alpha=1 .........................................................
[CV] ................ alpha=1, score=0.9017069026591178, total=   0.2s
[CV] alpha=1 .........................................................
[CV] ................. alpha=1, score=0.883764511874671, total=   0.1s
[CV] alpha=10 ........................................................
[CV] ............... alpha=10, score=0.8929465907269245, total=   0.1s
[CV] alpha=10 ........................................................
[CV] ................ alpha=10, score=0.900120209941646, total=   0.2s
[CV] alpha=10 ........................................................
[CV] ............... alpha=10, score=0.8956644067837265, total=   0.1s
[CV] alpha=10 ........................................................
[CV] ............... alpha=10, score=0.8922831042462236, total=   0.1s
[CV] alpha=10 ........................................................
[CV] ............... alpha=10, score=0.8974631508073158, total=   0.1s
[CV] alpha=10 ........................................................
[CV] ............... alpha=10, score=0.8886361521769361, total=   0.1s
[CV] alpha=10 ........................................................
[CV] ............... alpha=10, score=0.8977638870408293, total=   0.1s
[CV] alpha=10 ........................................................
[CV] ............... alpha=10, score=0.8892770425002526, total=   0.1s
[CV] alpha=10 ........................................................
[CV] ............... alpha=10, score=0.9017069026591178, total=   0.1s
[CV] alpha=10 ........................................................
[CV] ................ alpha=10, score=0.883764511874671, total=   0.1s
[CV] alpha=100 .......................................................
[CV] .............. alpha=100, score=0.8929465907269245, total=   0.1s
```

```
[CV] alpha=100 .......................................................
[CV] ............... alpha=100, score=0.900120209941646, total=   0.1s
[CV] alpha=100 .......................................................
[CV] .............. alpha=100, score=0.8956644067837265, total=   0.1s
[CV] alpha=100 .......................................................
[CV] .............. alpha=100, score=0.8922831042462236, total=   0.1s
[CV] alpha=100 .......................................................
[CV] .............. alpha=100, score=0.8974631508073158, total=   0.0s
[CV] alpha=100 .......................................................
[CV] .............. alpha=100, score=0.8886361521769361, total=   0.1s
[CV] alpha=100 .......................................................
[CV] .............. alpha=100, score=0.8977638870408293, total=   0.1s
[CV] alpha=100 .......................................................
[CV] .............. alpha=100, score=0.8892770425002526, total=   0.1s
[CV] alpha=100 .......................................................
[CV] .............. alpha=100, score=0.9017069026591178, total=   0.1s
[CV] alpha=100 .......................................................
[CV] ............... alpha=100, score=0.883764511874671, total=   0.1s
[CV] alpha=1000 ......................................................
[CV] ............. alpha=1000, score=0.8929465907269245, total=   0.1s
[CV] alpha=1000 ......................................................
[CV] .............. alpha=1000, score=0.900120209941646, total=   0.1s
[CV] alpha=1000 ......................................................
[CV] ............. alpha=1000, score=0.8956644067837265, total=   0.1s
[CV] alpha=1000 ......................................................
[CV] ............. alpha=1000, score=0.8922831042462236, total=   0.0s
[CV] alpha=1000 ......................................................
[CV] ............. alpha=1000, score=0.8974631508073158, total=   0.1s
[CV] alpha=1000 ......................................................
[CV] ............. alpha=1000, score=0.8886361521769361, total=   0.1s
[CV] alpha=1000 ......................................................
[CV] ............. alpha=1000, score=0.8977638870408293, total=   0.0s
[CV] alpha=1000 ......................................................
[CV] ............. alpha=1000, score=0.8892770425002526, total=   0.1s
[CV] alpha=1000 ......................................................
[CV] ............. alpha=1000, score=0.9017069026591178, total=   0.1s
[CV] alpha=1000 ......................................................
[CV] .............. alpha=1000, score=0.883764511874671, total=   0.1s
[CV] alpha=10000 .....................................................
```

```
[CV] ............ alpha=10000, score=0.8929465907269245, total=   0.1s
[CV] alpha=10000 ....................................................
[CV] ............. alpha=10000, score=0.900120209941646, total=   0.0s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8956644067837265, total=   0.1s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8922831042462236, total=   0.1s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8974631508073158, total=   0.1s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8886361521769361, total=   0.1s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8977638870408293, total=   0.1s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8892770425002526, total=   0.1s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.9017069026591178, total=   0.1s
[CV] alpha=10000 ....................................................
[CV] ............. alpha=10000, score=0.883764511874671, total=   0.1s
[CV] alpha=100000 ...................................................
[CV] ........... alpha=100000, score=0.8929465907269245, total=   0.1s
[CV] alpha=100000 ...................................................
[CV] ............ alpha=100000, score=0.900120209941646, total=   0.1s
[CV] alpha=100000 ...................................................
[CV] ........... alpha=100000, score=0.8956644067837265, total=   0.1s
[CV] alpha=100000 ...................................................
[CV] ........... alpha=100000, score=0.8922831042462236, total=   0.1s
[CV] alpha=100000 ...................................................
[CV] ........... alpha=100000, score=0.8974631508073158, total=   0.1s
[CV] alpha=100000 ...................................................
[CV] ........... alpha=100000, score=0.8886361521769361, total=   0.1s
[CV] alpha=100000 ...................................................
[CV] ........... alpha=100000, score=0.8977638870408293, total=   0.1s
[CV] alpha=100000 ...................................................
[CV] ........... alpha=100000, score=0.8892770425002526, total=   0.1s
[CV] alpha=100000 ...................................................
[CV] ........... alpha=100000, score=0.9017069026591178, total=   0.1s
[CV] alpha=100000 ...................................................
[CV] ............ alpha=100000, score=0.883764511874671, total=   0.1s
```

```
[Parallel(n_jobs=1)]: Done 110 out of 110 | elapsed:   25.3s finished
```

```
SGDClassifier(alpha=0.0001, average=False, class_weight='balanced',
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=N
one,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
0.949641092534647
```

Observations :

1) We found that the accuracy has enhanced when we used all features . However computation time is more in this case.

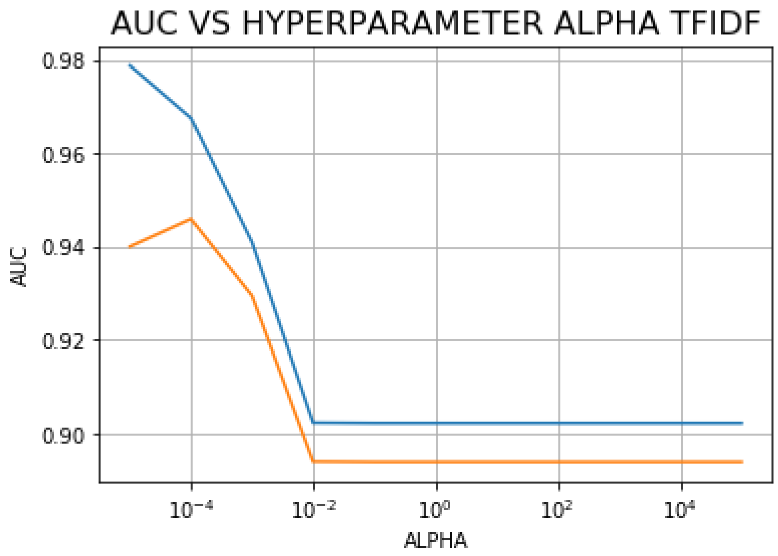
OPTIMAL ALPHA FOR TFIDF - THROUGH PLOTTING APPROACH

In [93]:

```
train_auc_tfidf = model_tfidf.cv_results_['mean_train_score']
cv_auc_tfidf = model_tfidf.cv_results_['mean_test_score']
```

In [94]:

```
plt.plot(alpha,train_auc_tfidf)
plt.plot(alpha,cv_auc_tfidf)
plt.xlabel('ALPHA',size=10)
plt.ylabel('AUC',size=10)
plt.title('AUC VS HYPERPARAMETER ALPHA TFIDF',size=16)
plt.xscale('log')
plt.grid()
plt.show()
print("\n\n Alpha Values :\n", alpha)
print("\n Train AUC for each  value is :\n ", np.round(train_auc_tfidf,
5))
print("\n CV AUC for each value is :\n ", np.round(cv_auc_tfidf,5))
```




```
 Alpha Values :
 [1e-05, 0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000, 100000]

 Train AUC for each  value is :
  [0.97879 0.96759 0.94096 0.90236 0.90228 0.90228 0.90228 0.90228 0.90
228
 0.90228 0.90228]

 CV AUC for each value is :
  [0.94006 0.94596 0.92946 0.89405 0.89396 0.89396 0.89396 0.89396 0.89
396
 0.89396 0.89396]
```

Observations :

1) We found that optimal value is 0.0001

Training the model with the best hyper parameter for TFIDF

In [95]:
```
om_tfidf = SGDClassifier(alpha=0.0001,class_weight = 'balanced') # Hing
e loss is not used as probabilities I cannot get
om_tfidf = CalibratedClassifierCV(om_tfidf, cv= 5)
```

In [96]:
```
om_tfidf.fit(c3, y_train1)
ompredictions_tfidf  = om_tfidf.predict(d3)
```

In [97]:
```
probs2 = om_tfidf.predict_proba(c3)
probs3 = om_tfidf.predict_proba(d3)
probs2= probs2[:, 1]
probs3 = probs3[:, 1]
```

Feature Importance for TFIDF (Linear SVM)

In [98]:
```
features_tfidf = tf_idf_vect.get_feature_names()
```

In [99]:
```
om_tfidfp = SGDClassifier(alpha=0.0001,class_weight = 'balanced')
om_tfidfp.fit(c3,y_train1)
```

Out[99]:
```
SGDClassifier(alpha=0.0001, average=False, class_weight='balanced',
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=N
one,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

In [100]:
```
len(features_tfidf)
```

Out[100]: 9723

In [101]:
```
features_tfidf.append('zzzzzzzzzzzzzzzaaaaa')
```

In [102]:
```
Coefficients.shape
```

Out[102]: (1, 46009)

In [103]:
```
Coefficients = om_tfidfp.coef_
coef = Coefficients.reshape(9724,1)
coef = coef.tolist()
```

In [104]:
```
len(coef)
```

Out[104]: 9724

In [105]:
```
type(coef)
```

Out[105]: list

In [106]:
```
len(features_tfidf), len(coef)
```

Out[106]: (9724, 9724)

In [107]:
```
cf = pd.DataFrame({'Word' : features_tfidf, 'Coefficient' : coef})
cf_new = cf.sort_values("Coefficient", ascending = False)
print('***** Top 10 IMPORTANT FEATURES FOR POSITIVE CLASS *****')
print('\n')
print(cf_new.head(10))
print('\n')
print('***** Top 10 IMPORTANT FEATURES FOR NEGATIVE CLASS *****')
print('\n')
print(cf_new.tail(10))
```

```
***** Top 10 IMPORTANT FEATURES FOR POSITIVE CLASS *****
```

```
             Word            Coefficient
3778        great  [5.8071582586193236]
2241    delicious   [4.836676910317802]
718          best   [4.539143206102038]
6176      perfect  [3.9417924070464587]
5008        loves  [3.8759689183827053]
2965    excellent   [3.566372697565489]
5003         love   [3.559462216077335]
9582    wonderful  [3.5026127258542696]
3698         good  [3.4185499916891304]
4045       highly   [3.197489635663025]


***** Top 10 IMPORTANT FEATURES FOR NEGATIVE CLASS *****


                  Word            Coefficient
2445  disappointment    [-2.58302096914942]
4116        horrible  [-2.6292981922236174]
8750         thought  [-2.6786562790627775]
788            bland    [-2.74841129339232]
9129   unfortunately   [-2.895517148378411]
8676        terrible  [-3.1642052667590126]
2444    disappointing   [-3.635976736334212]
9616           worst  [-3.7296610933116394]
2443     disappointed   [-3.869217530365912]
5710             not   [-4.804360175235075]
```

Observations :

1) We found that the top 2 most important features affecting positive class are great and delicious.

2) Top 2 most important features affecting negative class are not and disappointed

PERFORMANCE MEASURMENTS FOR TFIDF

```
In [108]: precision_tfidf = precision_score(y_test1, ompredictions_tfidf, pos_lab
el = 1)
recall_tfidf = recall_score(y_test1, ompredictions_tfidf, pos_label = 1
)
f1score_tfidf = f1_score(y_test1, ompredictions_tfidf, pos_label = 1)
```

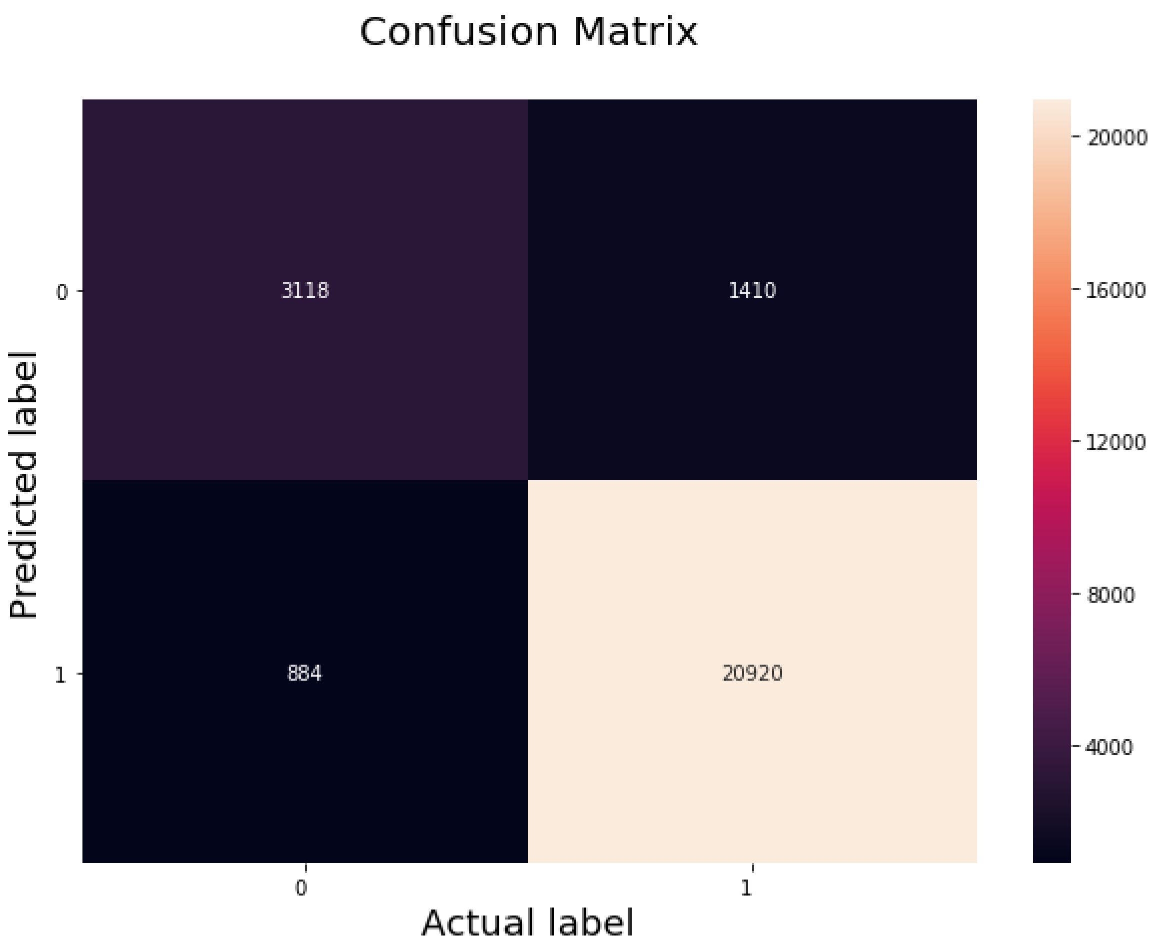
```
In [109]: print('\nThe Test Precision for optimal alpha for linear SVM  (TFIDF) i
s %f' % (precision_tfidf))
print('\nThe Test Recall for optimal alpha for linear SVM (TFIDF) is  %
f' % (recall_tfidf))
print('\nThe Test F1-Score for optimal alpha for linear SVM(TFIDF) is
%f' % (f1score_tfidf))
```

```
The Test Precision for optimal alpha for linear SVM  (TFIDF) is 0.93685
6

The Test Recall for optimal alpha for linear SVM (TFIDF) is  0.959457

The Test F1-Score for optimal alpha for linear SVM(TFIDF) is  0.948022
```

CONFUSION MATRIX (TFIDF)

```
In [110]: # Code for drawing seaborn heatmaps
class_names = [ 0,1]
df_heatmap = pd.DataFrame(confusion_matrix(y_test1, ompredictions_tfidf
), index=class_names, columns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=10)#
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=10)
plt.ylabel('Predicted label',size=18)
```

```
plt.xlabel('Actual label',size=18)
plt.title("Confusion Matrix\n",size=20)
plt.show()
```



In [111]:
```
TrueNeg,FalseNeg,FalsePos, TruePos = confusion_matrix(y_test1, ompredic
tions_tfidf).ravel()
TPR = TruePos/(FalseNeg + TruePos)
FPR = FalsePos/(TrueNeg + FalsePos)
TNR = TrueNeg/(TrueNeg + FalsePos)
FNR = FalseNeg/(FalseNeg + TruePos)
```

```
print("TPR of the Linear SVM  (TFIDF) for alpha  is :  %f" % (TPR))
print("FPR of the  Linear SVM  (TFIDF) for alpha  is :  %f" % (FPR))
print("TNR of the  Linear SVM  (TFIDF) for alpha  is :  %f" % (TNR))
print("FNR of the  Linear SVM  (TFIDF) for alpha  is :  %f" % (FNR))
```

```
TPR of the Linear SVM  (TFIDF) for alpha  is :  0.936856
FPR of the  Linear SVM  (TFIDF) for alpha  is :  0.220890
TNR of the  Linear SVM  (TFIDF) for alpha  is :  0.779110
FNR of the  Linear SVM  (TFIDF) for alpha  is :  0.063144
```

ROC CURVE FOR TFIDF

In [112]:

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc
fpr = dict()
tpr = dict()
roc_auc = dict()

fpr1 = dict()
tpr1 = dict()
roc_auc1 = dict()

for i in range(4):
    fpr[i], tpr[i], _ = roc_curve(y_test1,probs3)
    roc_auc[i] = auc(fpr[i], tpr[i])
```

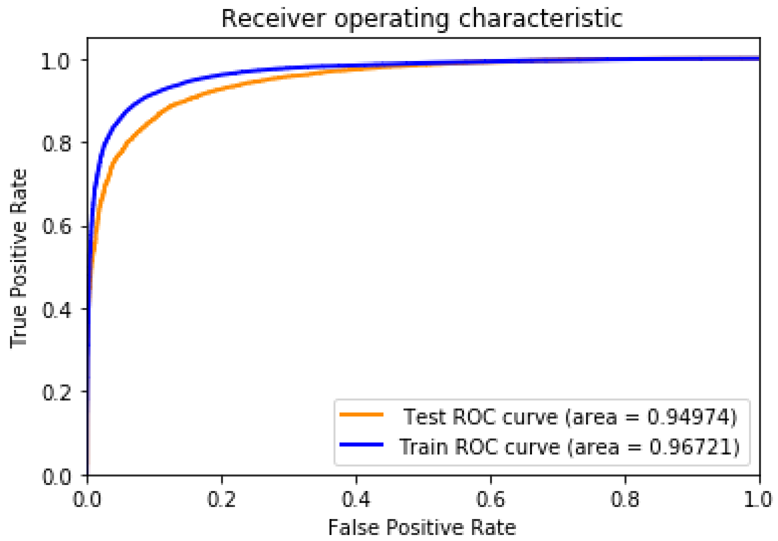
In [113]:

```
from tqdm import tqdm
for i in range(4):
    fpr1[i], tpr1[i], _ = roc_curve(y_train1,probs2)
    roc_auc1[i] = auc(fpr1[i], tpr1[i])
```

In [114]:

```
#print(roc_auc_score(y_test1,ompredictions_bow))
plt.figure()
#plt.plot(fpr[1], tpr[1])
lw = 2
plt.plot(fpr[2], tpr[2], color='darkorange',lw=lw, label=' Test ROC cur
```

```
ve (area = %0.5f)' % roc_auc[0])
plt.plot(fpr1[2], tpr1[2], color='blue',lw=lw, label='Train ROC curve
 (area = %0.5f)' % roc_auc1[0])
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc="lower right")
plt.title('Receiver operating characteristic')
plt.show()
```



Observations:

1) We found that the training score and the test score has been good. Hence the model is reasonably good

Word 2 Vector Data

Preparaing Training Data for Word to Vector

In [115]:
```
i=0
list_of_sentance=[]
for sentance in (X_trainbow['Cleaned Text'].values):
    list_of_sentance.append(sentance.split())
```

In [116]:
```
#WORD TO VECTOR

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])
```

```
[('awesome', 0.8387141227722168), ('fantastic', 0.825539231300354), ('t
errific', 0.80866539478302), ('good', 0.806596040725708), ('wonderful',
0.7872923612594604), ('amazing', 0.7825056314468384), ('excellent', 0.7
```

```
768963575363159), ('perfect', 0.7595521211624146), ('fabulous', 0.67638
99922370911), ('decent', 0.6671922206878662)]
==================================================
[('best', 0.723889172077179), ('tastiest', 0.7033755779266357), ('great
est', 0.6945815086364746), ('disgusting', 0.6411334872245789), ('awfu
l', 0.6349409818649292), ('coolest', 0.6270347237586975), ('closest',
0.6220861673355103), ('sweetest', 0.6094496846199036), ('smoothest', 0.
6014837026596069), ('experienced', 0.6008162498474121)]
number of words that occured minimum 5 times  14706
sample words  ['dogs', 'loves', 'chicken', 'product', 'china', 'wont',
'buying', 'anymore', 'hard', 'find', 'products', 'made', 'usa', 'one',
'isnt', 'bad', 'good', 'take', 'chances', 'till', 'know', 'going', 'imp
orts', 'love', 'saw', 'pet', 'store', 'tag', 'attached', 'regarding',
'satisfied', 'safe', 'infestation', 'literally', 'everywhere', 'flyin
g', 'around', 'kitchen', 'bought', 'hoping', 'least', 'get', 'rid', 'we
eks', 'fly', 'stuck', 'buggers', 'success', 'rate', 'day']
```

In [117]:

```python
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%|██████████████████████████████████████████████████████████████████
█████████| 61441/61441 [01:46<00:00, 576.72it/s]
```

```
61441
50
```

In [118]:
```
sent_vectors[1]
```

Out[118]:
```
array([-0.12912887, -0.76420906, -0.15761923,  0.40769311, -0.72918309,
        0.07135952, -0.16411569, -0.16107504, -0.59605415, -0.79738394,
       -0.26945326, -0.83281161,  0.17938109, -0.30916784, -0.33834869,
       -0.45378742,  0.5442509 ,  0.33933452,  0.48258768, -0.43977127,
       -0.25969976,  0.2234058 ,  0.84654541,  0.90660261,  0.47916459,
        0.74423378,  0.47660786, -0.3766901 ,  0.79599934, -0.10644283,
       -0.23197277, -0.16741426, -0.06251451, -0.635977  ,  0.52959876,
       -1.38729947, -0.60243387,  0.50411926,  0.39830671,  0.61259393,
        0.60565934,  0.22240643,  0.80609812,  0.08869576,  0.73663351,
       -0.26700896, -1.11758449,  0.61151643,  0.25568527, -0.3632660
9])
```

Preparing Test Data for Word to Vector

In [0]:
```
X_test1.head(4)
```

Out[0]:

	Cleaned Text	Length
61441	used treat training reward dog loves easy brea...	66
61442	much fun watching puppies asking chicken treat...	134
61443	little shih tzu absolutely loves cesar softies...	181
61444	westie like picture package loves treats perfe...	162

In [119]:
```
i=0
list_of_sentance1=[]
for sentance in (X_test1['Cleaned Text'].values):
    list_of_sentance1.append(sentance.split())
```

In [120]:
```
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_model1=Word2Vec(list_of_sentance1,min_count=5,size=50, workers=
4)
    print(w2v_model1.wv.most_similar('great'))
    print('='*50)
    print(w2v_model1.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_model1=KeyedVectors.load_word2vec_format('GoogleNews-vector
s-negative300.bin', binary=True)
        print(w2v_model1.wv.most_similar('great'))
        print(w2v_model1.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_words1 = list(w2v_model1.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words1))
print("sample words ", w2v_words1[0:50])
```

```
[('awesome', 0.848763108253479), ('excellent', 0.7997280955314636), ('f
antastic', 0.7893553972244263), ('good', 0.783993124961853), ('wonderfu
l', 0.7780619263648987), ('amazing', 0.7077950239181519), ('perfect',
0.6931569576263428), ('nice', 0.6887220740318298), ('decent', 0.6841213
10710907), ('delicious', 0.6560591459274292)]
==================================================
[('best', 0.757299542427063), ('greatest', 0.7377722263336182), ('eve
r', 0.7260575294494629), ('closest', 0.7169400453567505), ('nastiest',
0.7163026332855225), ('hottest', 0.7093741297721863), ('horrible', 0.69
63449716567993), ('superior', 0.6925037503242493), ('disgusting', 0.670
3665256500244), ('carob', 0.6548367738723755)]
number of words that occured minimum 5 times  9573
sample words  ['used', 'treat', 'training', 'reward', 'dog', 'loves',
'easy', 'break', 'smaller', 'pieces', 'buy', 'much', 'fun', 'watching',
'puppies', 'asking', 'chicken', 'treats', 'go', 'crazy', 'show', 'blu
e', 'package', 'small', 'eat', 'not', 'bad', 'smell', 'recommend', 'hap
```

```
py', 'little', 'shih', 'tzu', 'absolutely', 'tried', 'different', 'flav
ors', 'seems', 'enjoy', 'grilled', 'flavor', 'soft', 'enough', 'half',
'satisfy', 'westie', 'like', 'picture', 'perfect', 'size']
```

In [121]:

```
sent_vectors1 = []; # the avg-w2v for each sentence/review is stored in
 this list
for sent in tqdm(list_of_sentance1): # 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_words1:
            vec = w2v_model1.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors1.append(sent_vec)
print(len(sent_vectors1))
print(len(sent_vectors1[0]))
```

```
100%|██████████████████████████████████████████████████████████████████
█████████| 26332/26332 [00:30<00:00, 861.58it/s]
```

```
26332
50
```

In [122]:

```
e3 = sent_vectors
f3 = sent_vectors1
```

In [123]:

```
len(y_test1)
```

Out[123]:

```
26332
```

In [124]:

```
e3 = preprocessing.normalize(e3)
e4 = sparse.csr_matrix(X_train1['Length'].values)
```

```
e4 = preprocessing.normalize(e4)
e5 = sparse.hstack([e3, e4.T])
```

In [125]:
```
f3 = preprocessing.normalize(f3)
f4 = sparse.csr_matrix(X_test1['Length'].values)
f4 = preprocessing.normalize(f4)
f5 = sparse.hstack([f3, f4.T])
```

Applying SVM on Word to VECTOR

In [126]:
```
alpha = [0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000,100000]
clf = SGDClassifier(loss='hinge',class_weight = 'balanced')
param_grid = {'alpha':alpha}
model_w2v = GridSearchCV(estimator = clf,param_grid=param_grid ,scoring
 = 'roc_auc',cv = 10, return_train_score = True, verbose = 3)
model_w2v.fit(e5, y_train1)
print(model_w2v.best_estimator_)
print(model_w2v.score(f5, y_test1))
```

```
Fitting 10 folds for each of 11 candidates, totalling 110 fits
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent
workers.
```

```
[CV] alpha=1e-05 .....................................................
[CV] ............ alpha=1e-05, score=0.8922675864506165, total=   0.0s
```

```
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.1s remaining:
    0.0s
```

```
[CV] alpha=1e-05 .....................................................
[CV] ............ alpha=1e-05, score=0.9019527419419963, total=   0.0s
```

```
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    0.2s remaining:
    0.0s
```

```
[CV] alpha=1e-05 .....................................................
[CV] ............ alpha=1e-05, score=0.8879640945257105, total=   0.0s
[CV] alpha=1e-05 .....................................................
```

```
[CV] alpha=1e-05 .....................................................
[CV] ............ alpha=1e-05, score=0.9029029150205043, total=   0.0s
[CV] alpha=1e-05 .....................................................
[CV] ............ alpha=1e-05, score=0.8926499704366078, total=   0.0s
[CV] alpha=1e-05 .....................................................
[CV] .............. alpha=1e-05, score=0.87767378622516, total=   0.0s
[CV] alpha=1e-05 .....................................................
[CV] ............ alpha=1e-05, score=0.8953531949973337, total=   0.0s
[CV] alpha=1e-05 .....................................................
[CV] ............ alpha=1e-05, score=0.8785395784290284, total=   0.0s
[CV] alpha=1e-05 .....................................................
[CV] ............ alpha=1e-05, score=0.8976620897099528, total=   0.0s
[CV] alpha=1e-05 .....................................................
[CV] ............ alpha=1e-05, score=0.8745615667721349, total=   0.0s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.9033691164789162, total=   0.0s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.9107975871661995, total=   0.0s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.9067735323853259, total=   0.0s
[CV] alpha=0.0001 ....................................................
[CV] ............ alpha=0.0001, score=0.903461768180986, total=   0.0s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.9081247805255781, total=   0.0s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.8925209119731239, total=   0.0s
[CV] alpha=0.0001 ....................................................
[CV] ............ alpha=0.0001, score=0.900508530364255, total=   0.0s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.8915132555047437, total=   0.0s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.9074452096054051, total=   0.0s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.8849336671489783, total=   0.0s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.9068978599272344, total=   0.0s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.9092700773988919, total=   0.0s

[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.9055664358811685, total=   0.0s
```

```
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.8997955073648363, total=   0.0s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.9079535029368304, total=   0.0s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.8935463765085583, total=   0.0s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.9015558047795653, total=   0.0s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.8952467467762897, total=   0.0s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.9080065722456706, total=   0.0s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.8846136604246343, total=   0.0s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.9016117406775332, total=   0.0s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.9044596808979726, total=   0.1s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.9021660176449167, total=   0.0s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.8985085243615357, total=   0.0s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.9035929275962011, total=   0.0s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.8855549563952472, total=   0.0s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.8974271344919249, total=   0.0s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.8891041641863764, total=   0.0s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.9010134546917309, total=   0.0s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.8767719947085818, total=   0.0s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8819563958125204, total=   0.0s
[CV] alpha=0.1 .......................................................

[CV] ............... alpha=0.1, score=0.883673994795833, total=   0.0s
[CV] alpha=0.1 .......................................................
```

```
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8820783247523344, total=   0.0s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8873660768328052, total=   0.0s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8877265401226755, total=   0.0s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8603715483113851, total=   0.0s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8765526783632986, total=   0.0s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8561056158439773, total=   0.0s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8651644962645869, total=   0.0s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8553789748177322, total=   0.0s
[CV] alpha=1 .........................................................
[CV] .................. alpha=1, score=0.88194979965676, total=   0.1s
[CV] alpha=1 .........................................................
[CV] ................ alpha=1, score=0.8836775926989751, total=   0.0s
[CV] alpha=1 .........................................................
[CV] ................ alpha=1, score=0.8820719284800818, total=   0.0s
[CV] alpha=1 .........................................................
[CV] ................ alpha=1, score=0.8873670772860105, total=   0.0s
[CV] alpha=1 .........................................................
[CV] ................. alpha=1, score=0.887721537856649, total=   0.1s
[CV] alpha=1 .........................................................
[CV] ................ alpha=1, score=0.8603791517557453, total=   0.1s
[CV] alpha=1 .........................................................
[CV] ................ alpha=1, score=0.8765552795416325, total=   0.0s
[CV] alpha=1 .........................................................
[CV] ................. alpha=1, score=0.856124624454878, total=   0.1s
[CV] alpha=1 .........................................................
[CV] ................. alpha=1, score=0.865183108287954, total=   0.0s
[CV] alpha=1 .........................................................
[CV] ................ alpha=1, score=0.8553735713270773, total=   0.1s
[CV] alpha=10 ........................................................
[CV] ................. alpha=10, score=0.88194979965676, total=   0.1s

[CV] alpha=10 ........................................................
[CV] ............... alpha=10, score=0.8836775926989751, total=   0.1s
```

```
[CV] ............... alpha=10, score=0.8836775926989751, total=   0.1s
[CV] alpha=10 .........................................................
[CV] ............... alpha=10, score=0.8820719284800818, total=   0.1s
[CV] alpha=10 .........................................................
[CV] ............... alpha=10, score=0.8873670772860105, total=   0.1s
[CV] alpha=10 .........................................................
[CV] ................ alpha=10, score=0.887721537856649, total=   0.1s
[CV] alpha=10 .........................................................
[CV] ............... alpha=10, score=0.8603791517557453, total=   0.0s
[CV] alpha=10 .........................................................
[CV] ............... alpha=10, score=0.8765552795416325, total=   0.0s
[CV] alpha=10 .........................................................
[CV] ................ alpha=10, score=0.856124624454878, total=   0.0s
[CV] alpha=10 .........................................................
[CV] ................ alpha=10, score=0.865183108287954, total=   0.0s
[CV] alpha=10 .........................................................
[CV] ............... alpha=10, score=0.8553735713270773, total=   0.0s
[CV] alpha=100 ........................................................
[CV] ................ alpha=100, score=0.88194979965676, total=   0.0s
[CV] alpha=100 ........................................................
[CV] .............. alpha=100, score=0.8836775926989751, total=   0.0s
[CV] alpha=100 ........................................................
[CV] .............. alpha=100, score=0.8820719284800818, total=   0.0s
[CV] alpha=100 ........................................................
[CV] .............. alpha=100, score=0.8873670772860105, total=   0.0s
[CV] alpha=100 ........................................................
[CV] ............... alpha=100, score=0.887721537856649, total=   0.1s
[CV] alpha=100 ........................................................
[CV] .............. alpha=100, score=0.8603791517557453, total=   0.1s
[CV] alpha=100 ........................................................
[CV] .............. alpha=100, score=0.8765552795416325, total=   0.1s
[CV] alpha=100 ........................................................
[CV] ............... alpha=100, score=0.856124624454878, total=   0.1s
[CV] alpha=100 ........................................................
[CV] ............... alpha=100, score=0.865183108287954, total=   0.0s
[CV] alpha=100 ........................................................
[CV] .............. alpha=100, score=0.8553735713270773, total=   0.0s
[CV] alpha=1000 .......................................................

[CV] ............... alpha=1000, score=0.88194979965676, total=   0.0s
[CV] alpha=1000 .......................................................
```

```
[CV] alpha=1000 .....................................................
[CV] ............. alpha=1000, score=0.8836775926989751, total=   0.0s
[CV] alpha=1000 .....................................................
[CV] ............. alpha=1000, score=0.8820719284800818, total=   0.0s
[CV] alpha=1000 .....................................................
[CV] ............. alpha=1000, score=0.8873670772860105, total=   0.1s
[CV] alpha=1000 .....................................................
[CV] .............. alpha=1000, score=0.887721537856649, total=   0.0s
[CV] alpha=1000 .....................................................
[CV] ............. alpha=1000, score=0.8603791517557453, total=   0.0s
[CV] alpha=1000 .....................................................
[CV] ............. alpha=1000, score=0.8765552795416325, total=   0.0s
[CV] alpha=1000 .....................................................
[CV] .............. alpha=1000, score=0.856124624454878, total=   0.0s
[CV] alpha=1000 .....................................................
[CV] .............. alpha=1000, score=0.865183108287954, total=   0.0s
[CV] alpha=1000 .....................................................
[CV] ............. alpha=1000, score=0.8553735713270773, total=   0.0s
[CV] alpha=10000 ....................................................
[CV] .............. alpha=10000, score=0.88194979965676, total=   0.0s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8836775926989751, total=   0.1s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8820719284800818, total=   0.0s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8873670772860105, total=   0.0s
[CV] alpha=10000 ....................................................
[CV] ............. alpha=10000, score=0.887721537856649, total=   0.0s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8603791517557453, total=   0.0s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8765552795416325, total=   0.0s
[CV] alpha=10000 ....................................................
[CV] ............. alpha=10000, score=0.856124624454878, total=   0.0s
[CV] alpha=10000 ....................................................
[CV] ............. alpha=10000, score=0.865183108287954, total=   0.0s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8553735713270773, total=   0.0s

[CV] alpha=100000 ...................................................
[CV] ............. alpha=100000, score=0.88194979965676, total=   0.0s
```

```
[CV] alpha=100000 .....................................................
[CV] ........... alpha=100000, score=0.8836775926989751, total=   0.0s
[CV] alpha=100000 .....................................................
[CV] ........... alpha=100000, score=0.8820719284800818, total=   0.0s
[CV] alpha=100000 .....................................................
[CV] ........... alpha=100000, score=0.8873670772860105, total=   0.0s
[CV] alpha=100000 .....................................................
[CV] ............ alpha=100000, score=0.887721537856649, total=   0.0s
[CV] alpha=100000 .....................................................
[CV] ........... alpha=100000, score=0.8603791517557453, total=   0.0s
[CV] alpha=100000 .....................................................
[CV] ........... alpha=100000, score=0.8765552795416325, total=   0.0s
[CV] alpha=100000 .....................................................
[CV] ............ alpha=100000, score=0.856124624454878, total=   0.1s
[CV] alpha=100000 .....................................................
[CV] ............ alpha=100000, score=0.865183108287954, total=   0.0s
[CV] alpha=100000 .....................................................
[CV] ........... alpha=100000, score=0.8553735713270773, total=   0.0s
```

```
[Parallel(n_jobs=1)]: Done 110 out of 110 | elapsed:   18.8s finished
```

```
SGDClassifier(alpha=0.001, average=False, class_weight='balanced',
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=N
one,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
0.7358664637830256
```

Observations :

We observed that alpha = 0.001 . The AUC has been 0.735

In [127]:
```
train_auc_w2v = model_w2v.cv_results_['mean_train_score']
cv_auc_w2v = model_w2v.cv_results_['mean_test_score']
```

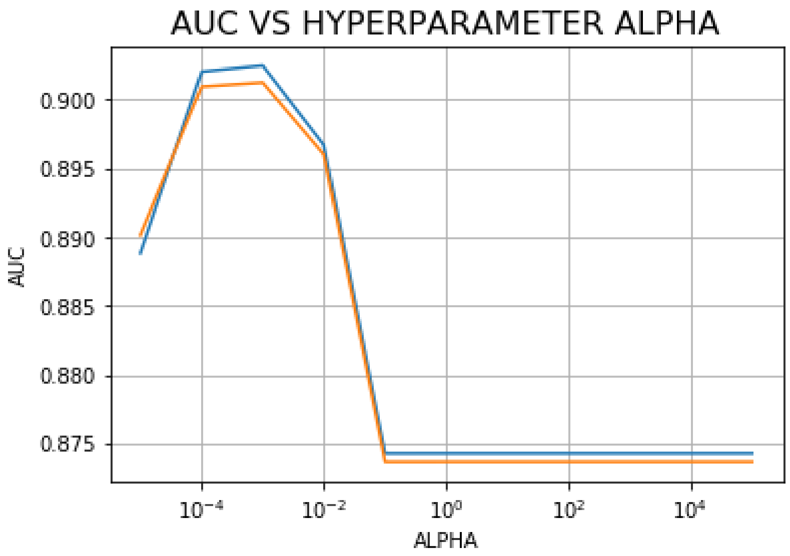
In [128]:
```
train_auc_w2v
```

Out[128]:
```
array([0.88883565, 0.9020286 , 0.9024773 , 0.89671323, 0.87425536,
       0.87425647, 0.87425647, 0.87425647, 0.87425647, 0.87425647,
       0.87425647])
```

In [129]:
```
cv_auc_w2v
```

Out[129]:
```
array([0.89015307, 0.90094529, 0.90124571, 0.89602162, 0.87363834,
       0.87364124, 0.87364124, 0.87364124, 0.87364124, 0.87364124,
       0.87364124])
```

In [130]:
```
plt.plot(alpha,train_auc_w2v)
plt.plot(alpha,cv_auc_w2v)
plt.xlabel('ALPHA',size=10)
plt.ylabel('AUC',size=10)
plt.title('AUC VS HYPERPARAMETER ALPHA',size=16)
plt.xscale('log')
plt.grid()
plt.show()
print("\n\n Alpha Values :\n", alpha)
print("\n Train AUC for each  value is :\n ", np.round(train_auc_w2v,5
))
print("\n CV AUC for each value is :\n ", np.round(cv_auc_w2v,5))
```




```
 Alpha Values :
 [1e-05, 0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000, 100000]

 Train AUC for each  value is :
  [0.88884 0.90203 0.90248 0.89671 0.87426 0.87426 0.87426 0.87426 0.87
426
 0.87426 0.87426]

 CV AUC for each value is :
  [0.89015 0.90095 0.90125 0.89602 0.87364 0.87364 0.87364 0.87364 0.87
364
 0.87364 0.87364]
```

In [131]:
```
max(cv_auc_w2v)
```

Out[131]: 0.901245708012137

Observations:

1) Optimal number of alpha= 0.001 as the cv_auc is high at that point

Running the model with the optimal hyperparameter

In [132]:
```
om_w2v = SGDClassifier(alpha=0.001,class_weight = 'balanced') # Hinge l
oss is not used as probabilities I cannot get
om_w2v = CalibratedClassifierCV(om_w2v, cv= 5)
```

In [133]:
```
om_w2v.fit(e5, y_train1)
ompredictions_w2v  = om_w2v.predict(f5)
probs4 = om_w2v.predict_proba(e5)
probs5 = om_w2v.predict_proba(f5)
probs4= probs4[:, 1]
probs5 = probs5[:, 1]
```

PERFORMANCE MEASURMENTS FOR w2v Decision Tree

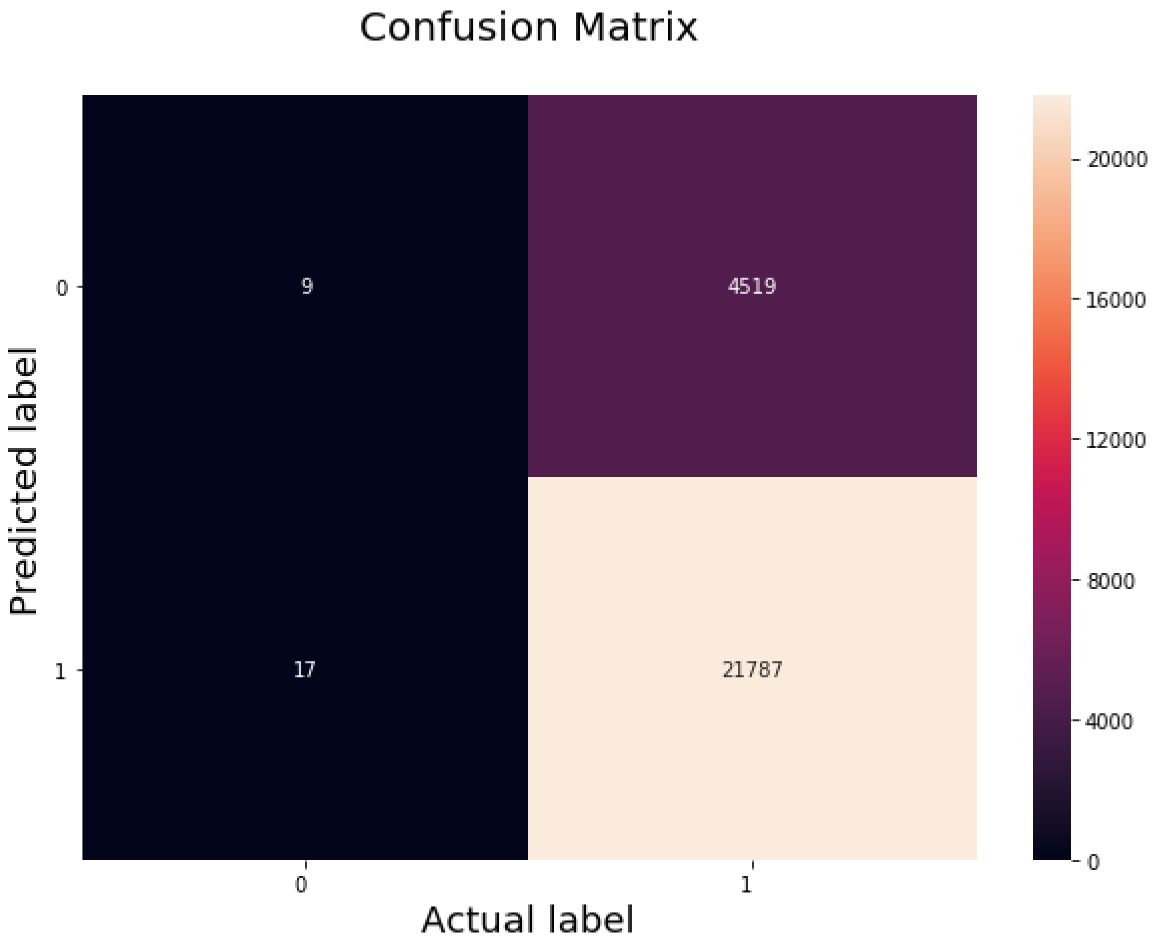
In [134]:
```
precision_w2v = precision_score(y_test1, ompredictions_w2v, pos_label =
 1)
recall_w2v = recall_score(y_test1, ompredictions_w2v, pos_label = 1)
f1score_w2v = f1_score(y_test1, ompredictions_w2v, pos_label = 1)

print('\nThe Test Precision for optimal alpha for Linear SVM (W2V) is %
f' % (precision_w2v))
print('\nThe Test Recall for optimal alpha for Linear SVM (W2V) is  %f'
 % (recall_w2v))
print('\nThe Test F1-Score for optimal alpha for Linear SVM (W2V) is  %
f' % (f1score_w2v))
```

```
The Test Precision for optimal alpha for Linear SVM (W2V) is 0.828214

The Test Recall for optimal alpha for Linear SVM (W2V) is  0.999220
```

```
The Test F1-Score for optimal alpha for Linear SVM (W2V) is  0.905716
```

In [135]:
```
class_names = [ 0,1]
df_heatmap = pd.DataFrame(confusion_matrix(y_test1, ompredictions_w2v),
 index=class_names, columns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=10)#
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=10)
plt.ylabel('Predicted label',size=18)
plt.xlabel('Actual label',size=18)
plt.title("Confusion Matrix\n",size=20)
```

Out[135]:
```
Text(0.5, 1.0, 'Confusion Matrix\n')
```



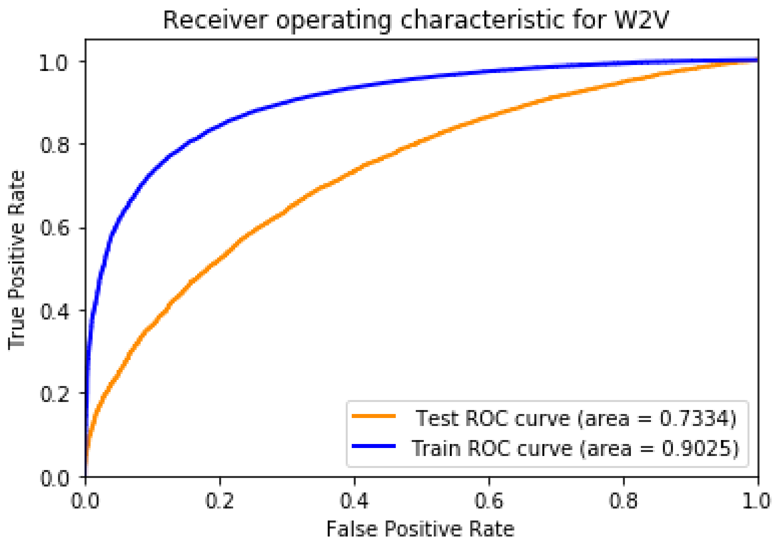
In [136]:
```
TrueNeg,FalseNeg,FalsePos, TruePos = confusion_matrix(y_test1, ompredic
tions_w2v).ravel()
TPR = TruePos/(FalseNeg + TruePos)
FPR = FalsePos/(TrueNeg + FalsePos)
TNR = TrueNeg/(TrueNeg + FalsePos)
FNR = FalseNeg/(FalseNeg + TruePos)
print("TPR of Linear SVM (W2V) for optimal alpha   is :  %f" % (TPR))
print("FPR of Linear SVM (W2V) for optimal  alpha  is :  %f" % (FPR))
print("TNR of Linear SVM (W2V) for optimal alpha  is :  %f" % (TNR))
print("FNR of Linear SVM (W2V)for optimal alpha  is :  %f" % (FNR))
```

```
TPR of Linear SVM (W2V) for optimal alpha   is :  0.828214
FPR of Linear SVM (W2V) for optimal  alpha  is :  0.653846
TNR of Linear SVM (W2V) for optimal alpha  is :  0.346154
FNR of Linear SVM (W2V)for optimal alpha  is :  0.171786
```

In [138]:

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc
fpr = dict()
tpr = dict()
roc_auc = dict()

fpr1 = dict()
tpr1 = dict()
roc_auc1 = dict()

for i in range(4):
    fpr[i], tpr[i], _ = roc_curve(y_test1,probs5)
    roc_auc[i] = auc(fpr[i], tpr[i])


from tqdm import tqdm
for i in range(4):
    fpr1[i], tpr1[i], _ = roc_curve(y_train1,probs4)
    roc_auc1[i] = auc(fpr1[i], tpr1[i])


#print(roc_auc_score(y_test1,ompredictions_bow))
plt.figure()
#plt.plot(fpr[1], tpr[1])
lw = 2
plt.plot(fpr[0], tpr[0], color='darkorange',lw=lw, label=' Test ROC cur
ve (area = %0.4f)' % roc_auc[0])
plt.plot(fpr1[0], tpr1[0], color='blue',lw=lw, label='Train ROC curve
 (area = %0.4f)' % roc_auc1[0])
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
```

```
plt.legend(loc="lower right")
plt.title('Receiver operating characteristic for W2V ')
plt.show()
```



Observations :

1) Word 2 Vector Vectorizer has not performed that efficiently when compared to BOW or TFIDF vectorizer.

2) Test Acuuracy is less when compared to train accuracy. Hence Overfitting would have been the issue here.

TFIDF AVERGE WORD TO VECTOR

Preparing Training Data for TFIDF-AVG W2V

```
In [139]: model = TfidfVectorizer()
          model.fit_transform(X_trainbow['Cleaned Text'].values)
          # 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 [141]: # 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%|████████████████████████████████████████████████████████████
████████| 61441/61441 [22:53<00:00, 44.73it/s]
```

Preparing Test Data for TFIDF- AVG W2V

In [140]:

```
# 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_vectors1 = []; # the tfidf-w2v for each sentence/review is s
tored in this list
row=0;
for sent in tqdm(list_of_sentance1): # 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_words1 and word in tfidf_feat:
            vec = w2v_model1.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_vectors1.append(sent_vec)
    row += 1
```

```
100%|██████████████████████████████████████████████████████████
█████████| 26332/26332 [09:12<00:00, 47.63it/s]
```

In [142]:

```
g3 = tfidf_sent_vectors
h3 = tfidf_sent_vectors1
```

In [143]:

```
g3 = preprocessing.normalize(g3)
h3 = preprocessing.normalize(h3)
```

In [ ]:

LINEAR SVM ON TFIDF - AVG W2V

In [144]:
```
alpha = [0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000,100000]
clf = SGDClassifier(loss='hinge',class_weight = 'balanced')
param_grid = {'alpha':alpha}
model_w2vtfidf = GridSearchCV(estimator = clf,param_grid=param_grid ,sc
oring = 'roc_auc',cv = 10, return_train_score = True,verbose = 3)
model_w2vtfidf.fit(g3, y_train1)
print(model_w2vtfidf.best_estimator_)
print(model_w2vtfidf.score(h3, y_test1))
```

```
Fitting 10 folds for each of 11 candidates, totalling 110 fits
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent
workers.
```

```
[CV] alpha=1e-05 .....................................................
[CV] ............ alpha=1e-05, score=0.8817886935493994, total=   0.1s
```

```
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.1s remaining:
    0.0s
```

```
[CV] alpha=1e-05 .....................................................
[CV] ............ alpha=1e-05, score=0.8592748146380289, total=   0.1s
```

```
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    0.3s remaining:
    0.0s
```

```
[CV] alpha=1e-05 .....................................................
[CV] ............. alpha=1e-05, score=0.858845065096062, total=   0.1s
[CV] alpha=1e-05 .....................................................
[CV] ............ alpha=1e-05, score=0.8694773732500823, total=   0.1s
[CV] alpha=1e-05 .....................................................
[CV] ............ alpha=1e-05, score=0.8681442693540173, total=   0.0s
[CV] alpha=1e-05 .....................................................
[CV] ............ alpha=1e-05, score=0.8561050155720541, total=   0.0s
[CV] alpha=1e-05 .....................................................
[CV] ............. alpha=1e-05, score=0.863829514770191, total=   0.1s
[CV] alpha=1e-05 .....................................................
```

```
[CV] ............ alpha=1e-05, score=0.8544730763035655, total=   0.1s
[CV] alpha=1e-05 .....................................................
[CV] ............ alpha=1e-05, score=0.8629394588904432, total=   0.1s
[CV] alpha=1e-05 .....................................................
[CV] ............ alpha=1e-05, score=0.8525633559279294, total=   0.1s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.8792283856968158, total=   0.1s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.8853334276783491, total=   0.1s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.8838468940301591, total=   0.1s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.8811466594367248, total=   0.1s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.8843217977743918, total=   0.1s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.8653808175103324, total=   0.1s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.8683115451299439, total=   0.0s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.8723291651117957, total=   0.1s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.8829774034025981, total=   0.1s
[CV] alpha=0.0001 ....................................................
[CV] ........... alpha=0.0001, score=0.8561654829019547, total=   0.1s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.8827189513951269, total=   0.1s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.8826517905364754, total=   0.1s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.8869262993527371, total=   0.1s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.8784196240897126, total=   0.0s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.8821021922931088, total=   0.1s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.8660579242396805, total=   0.1s
[CV] alpha=0.001 .....................................................
[CV] ............. alpha=0.001, score=0.870415498220694, total=   0.1s
```

```
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.8719341861863424, total=   0.0s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.8810045289256859, total=   0.0s
[CV] alpha=0.001 .....................................................
[CV] ............ alpha=0.001, score=0.8591462084506591, total=   0.1s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.8756294831372275, total=   0.0s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.8750076455441769, total=   0.1s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.8817447191776633, total=   0.0s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.8709286306696934, total=   0.1s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.8730975131734676, total=   0.1s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.8524467583815468, total=   0.1s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.8634527440930742, total=   0.1s
[CV] alpha=0.01 ......................................................
[CV] .............. alpha=0.01, score=0.862372054540707, total=   0.1s
[CV] alpha=0.01 ......................................................
[CV] .............. alpha=0.01, score=0.870585398167216, total=   0.1s
[CV] alpha=0.01 ......................................................
[CV] ............. alpha=0.01, score=0.8495808292156732, total=   0.1s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8566657352095199, total=   0.1s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8518873200698632, total=   0.0s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8582652030396685, total=   0.0s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8606063546786694, total=   0.1s
[CV] alpha=0.1 .......................................................
[CV] ............... alpha=0.1, score=0.855137377231886, total=   0.1s
[CV] alpha=0.1 .......................................................
[CV] .............. alpha=0.1, score=0.8268603677465892, total=   0.1s
[CV] alpha=0.1 .......................................................
```

```
[CV] .............. alpha=0.1, score=0.8416892852462166, total=   0.1s
[CV] alpha=0.1 .........................................................
[CV] .............. alpha=0.1, score=0.8259187411897589, total=   0.1s
[CV] alpha=0.1 .........................................................
[CV] .............. alpha=0.1, score=0.8328236040482151, total=   0.1s
[CV] alpha=0.1 .........................................................
[CV] .............. alpha=0.1, score=0.8255815256655801, total=   0.1s
[CV] alpha=1 ...........................................................
[CV] ................ alpha=1, score=0.8569503693247575, total=   0.1s
[CV] alpha=1 ...........................................................
[CV] ................. alpha=1, score=0.851530128241261, total=   0.1s
[CV] alpha=1 ...........................................................
[CV] ................ alpha=1, score=0.8581966429964616, total=   0.0s
[CV] alpha=1 ...........................................................
[CV] ................ alpha=1, score=0.8606529757980366, total=   0.1s
[CV] alpha=1 ...........................................................
[CV] ................ alpha=1, score=0.8548712566792758, total=   0.1s
[CV] alpha=1 ...........................................................
[CV] ................ alpha=1, score=0.8269029870531351, total=   0.1s
[CV] alpha=1 ...........................................................
[CV] ................ alpha=1, score=0.8416124504400494, total=   0.1s
[CV] alpha=1 ...........................................................
[CV] ................ alpha=1, score=0.8258655170792369, total=   0.0s
[CV] alpha=1 ...........................................................
[CV] ................ alpha=1, score=0.8322164118020241, total=   0.1s
[CV] alpha=1 ...........................................................
[CV] ................ alpha=1, score=0.8251524484817191, total=   0.1s
[CV] alpha=10 ..........................................................
[CV] ............... alpha=10, score=0.8563573149568431, total=   0.0s
[CV] alpha=10 ..........................................................
[CV] ............... alpha=10, score=0.8515235320855006, total=   0.1s
[CV] alpha=10 ..........................................................
[CV] ............... alpha=10, score=0.8581986418315406, total=   0.1s
[CV] alpha=10 ..........................................................
[CV] ............... alpha=10, score=0.8606165593013635, total=   0.1s
[CV] alpha=10 ..........................................................
[CV] ............... alpha=10, score=0.8548734576763274, total=   0.1s
[CV] alpha=10 ..........................................................
[CV] ............... alpha=10, score=0.8268897810708251, total=   0.1s
```

```
[CV] alpha=10 ........................................................
[CV] ............... alpha=10, score=0.8415922412853022, total=   0.1s
[CV] alpha=10 ........................................................
[CV] ............... alpha=10, score=0.8258703192546224, total=   0.0s
[CV] alpha=10 ........................................................
[CV] ............... alpha=10, score=0.8322018023643273, total=   0.0s
[CV] alpha=10 ........................................................
[CV] ............... alpha=10, score=0.8251302341312488, total=   0.0s
[CV] alpha=100 .......................................................
[CV] .............. alpha=100, score=0.8563573149568431, total=   0.1s
[CV] alpha=100 .......................................................
[CV] .............. alpha=100, score=0.8515235320855006, total=   0.0s
[CV] alpha=100 .......................................................
[CV] .............. alpha=100, score=0.8581986418315406, total=   0.1s
[CV] alpha=100 .......................................................
[CV] .............. alpha=100, score=0.8606165593013635, total=   0.1s
[CV] alpha=100 .......................................................
[CV] .............. alpha=100, score=0.8548734576763274, total=   0.1s
[CV] alpha=100 .......................................................
[CV] .............. alpha=100, score=0.8268897810708251, total=   0.0s
[CV] alpha=100 .......................................................
[CV] .............. alpha=100, score=0.8415922412853022, total=   0.0s
[CV] alpha=100 .......................................................
[CV] .............. alpha=100, score=0.8258703192546224, total=   0.1s
[CV] alpha=100 .......................................................
[CV] .............. alpha=100, score=0.8322018023643273, total=   0.0s
[CV] alpha=100 .......................................................
[CV] .............. alpha=100, score=0.8251238299941763, total=   0.1s
[CV] alpha=1000 ......................................................
[CV] ............. alpha=1000, score=0.8563573149568431, total=   0.0s
[CV] alpha=1000 ......................................................
[CV] ............. alpha=1000, score=0.8515235320855006, total=   0.1s
[CV] alpha=1000 ......................................................
[CV] ............. alpha=1000, score=0.8581986418315406, total=   0.0s
[CV] alpha=1000 ......................................................
[CV] ............. alpha=1000, score=0.8606165593013635, total=   0.1s
[CV] alpha=1000 ......................................................
[CV] ............. alpha=1000, score=0.8548734576763274, total=   0.1s
[CV] alpha=1000 ......................................................
```

```
[CV] ............. alpha=1000, score=0.8268897810708251, total=   0.0s
[CV] alpha=1000 .....................................................
[CV] ............. alpha=1000, score=0.8415922412853022, total=   0.0s
[CV] alpha=1000 .....................................................
[CV] ............. alpha=1000, score=0.8258703192546224, total=   0.1s
[CV] alpha=1000 .....................................................
[CV] ............. alpha=1000, score=0.8322018023643273, total=   0.1s
[CV] alpha=1000 .....................................................
[CV] ............. alpha=1000, score=0.8251302341312488, total=   0.1s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8563573149568431, total=   0.1s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8515235320855006, total=   0.1s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8581986418315406, total=   0.1s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8606165593013635, total=   0.1s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8548734576763274, total=   0.1s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8268897810708251, total=   0.1s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8415922412853022, total=   0.1s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8258703192546224, total=   0.1s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8322018023643273, total=   0.0s
[CV] alpha=10000 ....................................................
[CV] ............ alpha=10000, score=0.8251302341312488, total=   0.1s
[CV] alpha=100000 ...................................................
[CV] ........... alpha=100000, score=0.8563573149568431, total=   0.1s
[CV] alpha=100000 ...................................................
[CV] ........... alpha=100000, score=0.8515235320855006, total=   0.1s
[CV] alpha=100000 ...................................................
[CV] ........... alpha=100000, score=0.8581986418315406, total=   0.1s
[CV] alpha=100000 ...................................................
[CV] ........... alpha=100000, score=0.8606165593013635, total=   0.1s
[CV] alpha=100000 ...................................................
[CV] ........... alpha=100000, score=0.8548734576763274, total=   0.0s
```

```
[CV] alpha=100000 ....................................................
[CV] ........... alpha=100000, score=0.8268897810708251, total=   0.1s
[CV] alpha=100000 ....................................................
[CV] ........... alpha=100000, score=0.8415922412853022, total=   0.1s
[CV] alpha=100000 ....................................................
[CV] ........... alpha=100000, score=0.8258703192546224, total=   0.1s
[CV] alpha=100000 ....................................................
[CV] ........... alpha=100000, score=0.8322018023643273, total=   0.0s
[CV] alpha=100000 ....................................................
[CV] ........... alpha=100000, score=0.8251302341312488, total=   0.1s
```

```
[Parallel(n_jobs=1)]: Done 110 out of 110 | elapsed:   22.1s finished
```

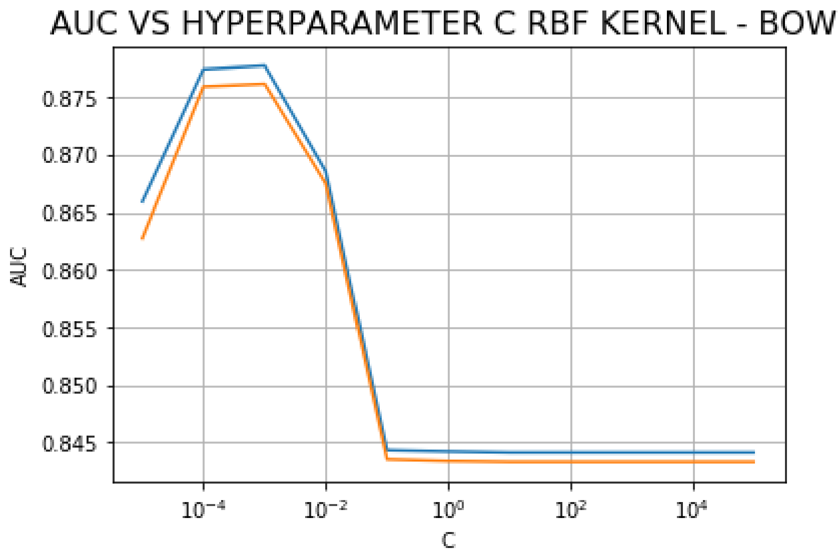
```
SGDClassifier(alpha=0.001, average=False, class_weight='balanced',
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=N
one,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
0.7001261499818816
```

In [153]:

```
train_auc1 = model_w2vtfidf.cv_results_['mean_train_score']
cv_auc1 = model_w2vtfidf.cv_results_['mean_test_score']
```

In [154]:

```
plt.plot(alpha,train_auc1)
plt.plot(alpha,cv_auc1)
plt.xlabel('C',size=10)
plt.ylabel('AUC',size=10)
plt.title('AUC VS HYPERPARAMETER C RBF KERNEL - BOW ',size=16)
plt.xscale('log')
plt.grid()
plt.show()
print("\n\n C Values :\n", alpha)
print("\n Train AUC for each c value is :\n ", np.round(train_auc1,5))
print("\n CV AUC for each c value is :\n ", np.round(cv_auc1,5))
```




```
 C Values :
 [1e-05, 0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000, 100000]

 Train AUC for each c value is :
  [0.86592 0.8774  0.87773 0.86855 0.84434 0.84423 0.84414 0.84414 0.84
414
 0.84414 0.84414]

 CV AUC for each c value is :
  [0.86274 0.8759  0.87614 0.86749 0.84354 0.8434  0.84333 0.84333 0.84
333
 0.84333 0.84333]
```

In [155]:
```
max(cv_auc1)
```

Out[155]: 0.8761383064366894

Running the model with the optimal Alpha for

TFIDF AVGW2V - Li SVM

In [156]:
```
om_w2vtfidf = SGDClassifier(alpha=0.001,class_weight = 'balanced') # Hi
nge loss is not used as probabilities I cannot get
om_w2vtfidf = CalibratedClassifierCV(om_w2vtfidf, cv= 5)
```

In [157]:
```
om_w2vtfidf.fit(g3, y_train1)
ompredictions_w2vtfidf  = om_w2vtfidf.predict(h3)
```

In [ ]:
```

```

In [158]:
```
probs6 = om_w2vtfidf.predict_proba(g3)
probs7 = om_w2vtfidf.predict_proba(h3)
probs6= probs6[:, 1]
probs7 = probs7[:, 1]
```

In [159]:
```
precision_w2vtfidf = precision_score(y_test1, ompredictions_w2vtfidf, p
os_label = 1)
recall_w2vtfidf = recall_score(y_test1, ompredictions_w2vtfidf, pos_lab
el = 1)
f1score_w2vtfidf = f1_score(y_test1, ompredictions_w2vtfidf, pos_label
= 1)
```

In [160]:
```
print('\nThe Test Precision FOR LINEAR SVM  (TFIDF AVGW2V) is %f' % (pr
ecision_w2vtfidf))
print('\nThe Test Recall FOR LINEAR SVM  (TFIDF AVGW2V) is  %f' % (reca
ll_w2vtfidf))
print('\nThe Test F1-Score FOR LINEAR SVM  (TFIDF AVGW2V) is  %f' % (f1
score_w2vtfidf))
```

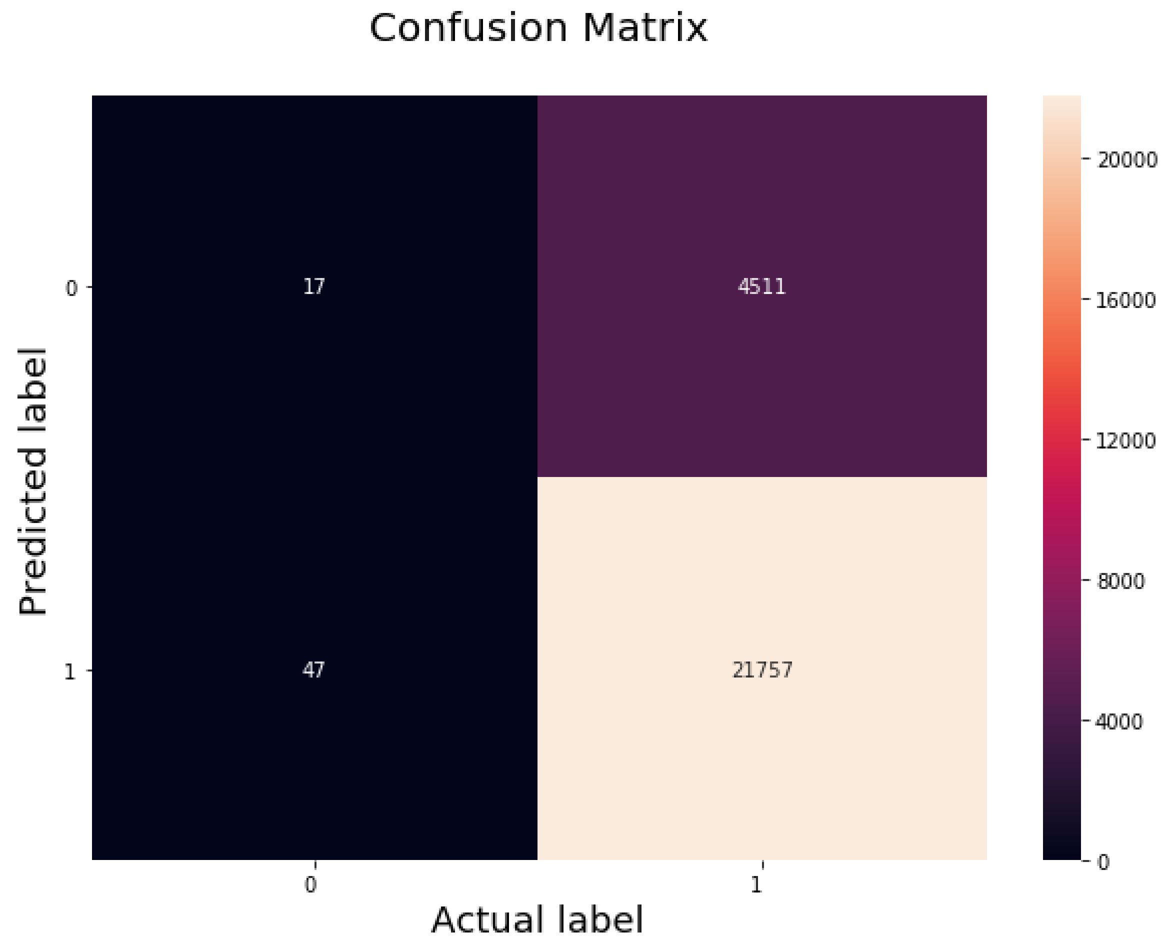
```
The Test Precision FOR LINEAR SVM  (TFIDF AVGW2V) is 0.828270

The Test Recall FOR LINEAR SVM  (TFIDF AVGW2V) is  0.997844

The Test F1-Score FOR LINEAR SVM  (TFIDF AVGW2V) is  0.905184
```

In [161]:

```
# Code for drawing seaborn heatmaps
class_names = [ 0,1]
df_heatmap = pd.DataFrame(confusion_matrix(y_test1, ompredictions_w2vtf
idf), index=class_names, columns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=10)#
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=10)
plt.ylabel('Predicted label',size=18)
plt.xlabel('Actual label',size=18)
plt.title("Confusion Matrix\n",size=20)
```

Out[161]:

```
Text(0.5, 1.0, 'Confusion Matrix\n')
```



In [162]:
```
TrueNeg,FalseNeg,FalsePos, TruePos = confusion_matrix(y_test1, ompredic
tions_w2vtfidf).ravel()
TPR = TruePos/(FalseNeg + TruePos)
FPR = FalsePos/(TrueNeg + FalsePos)
TNR = TrueNeg/(TrueNeg + FalsePos)
FNR = FalseNeg/(FalseNeg + TruePos)
print("TPR of the Linear SVM  (TFIDF AVG W2V) for alpha  is :  %f" % (T
PR))
print("FPR of the Linear SVM (TFIDF AVGW2V) for alpha  is :  %f" % (FPR
))
```

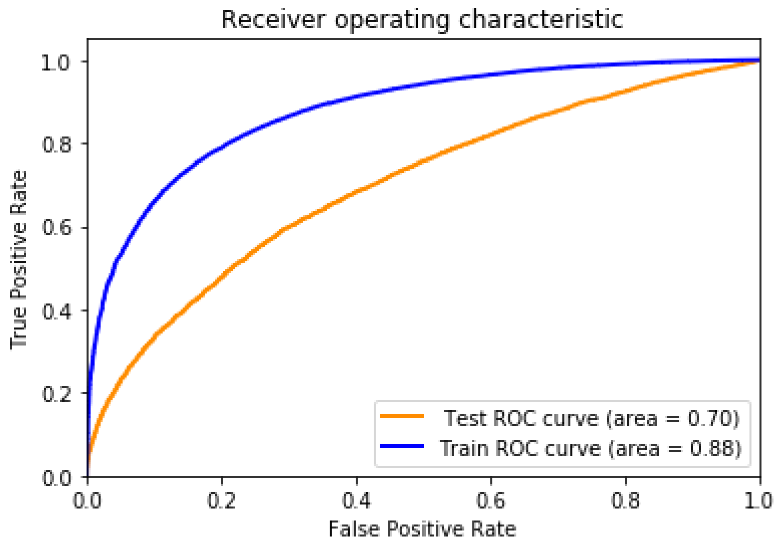
```
print("TNR of the Linear SVM (TFIDF AVGW2V) for alpha  is :  %f" % (TNR
))
print("FNR of the Linear SVM (TFIDF AVGW2V) for alpha  is :  %f" % (FNR
))
```

```
TPR of the Linear SVM  (TFIDF AVG W2V) for alpha  is :  0.828270
FPR of the Linear SVM (TFIDF AVGW2V) for alpha  is :  0.734375
TNR of the Linear SVM (TFIDF AVGW2V) for alpha  is :  0.265625
FNR of the Linear SVM (TFIDF AVGW2V) for alpha  is :  0.171730
```

In [163]:

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc
fpr = dict()
tpr = dict()
roc_auc = dict()

fpr1 = dict()
tpr1 = dict()
roc_auc1 = dict()

for i in range(4):
    fpr[i], tpr[i], _ = roc_curve(y_test1,probs7)
    roc_auc[i] = auc(fpr[i], tpr[i])


from tqdm import tqdm
for i in range(4):
    fpr1[i], tpr1[i], _ = roc_curve(y_train1,probs6)
    roc_auc1[i] = auc(fpr1[i], tpr1[i])


#print(roc_auc_score(y_test1,ompredictions_bow))
plt.figure()
#plt.plot(fpr[1], tpr[1])
lw = 2
plt.plot(fpr[0], tpr[0], color='darkorange',lw=lw, label=' Test ROC cur
ve (area = %0.2f)' % roc_auc[0])
plt.plot(fpr1[0], tpr1[0], color='blue',lw=lw, label='Train ROC curve
 (area = %0.2f)' % roc_auc1[0])
```

```
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc="lower right")
plt.title('Receiver operating characteristic')
plt.show()
```



Observations

1) Both Training Accuracy and Test acccuracy has been not that high in TFIDF- AVG W2V. The reason might be the case that I did not take feature engineering for this vectoriser and the model may be over fitted.

Preparing the Data for RBF Kernel

In [164]:
```
sample1.head(5)
```

Out[164]:

	Cleaned Text	Length
0	dogs loves chicken product china wont buying a...	162
1	dogs love saw pet store tag attached regarding...	72
2	infestation fruitflies literally everywhere fl...	406
3	worst product gotten long time would rate no s...	209
4	wish would read reviews making purchase basica...	277

In [165]:
```
X= sample1
y= np.array(final['Score'])
X= X[:20000]
y= y[:20000]
```

In [166]:
```
X_train2, X_test2, y_train2, y_test2 = train_test_split(X,y,test_size=
0.3,shuffle=False)
```

BOW DATA FOR RBF KERNEL

In [167]:
```
count_vect = CountVectorizer(min_df=10,max_features=500)
a1_rbf = count_vect.fit_transform(X_train2['Cleaned Text'].values)
b1_rbf = count_vect.transform(X_test2['Cleaned Text'])
```

In [168]:
```
a1_rbf = preprocessing.normalize(a1_rbf)
a2_rbf = sparse.csr_matrix(X_train2['Length'].values)
a2_rbf = preprocessing.normalize(a2_rbf)
a3_rbf = sparse.hstack([a1_rbf, a2_rbf.T])
```

In [169]:
```
b1_rbf = preprocessing.normalize(b1_rbf)
b2_rbf = sparse.csr_matrix(X_test2['Length'].values)
b2_rbf = preprocessing.normalize(b2_rbf)
b3_rbf = sparse.hstack([b1_rbf, b2_rbf.T])
```

Preparing TFIDF DATA FOR RBF KERNEL

In [170]:
```
tf_idf_vect = TfidfVectorizer(min_df=10,max_features=500)
c1_rbf = tf_idf_vect.fit_transform(X_train2['Cleaned Text'].values)
d1_rbf = tf_idf_vect.transform(X_test2['Cleaned Text'])
print("the type of count vectorizer :",type(c1_rbf))
print("the shape of out text TFIDF vectorizer : ",c1_rbf.get_shape())
print("the number of unique words :", c1_rbf.get_shape()[1])
```

```
the type of count vectorizer : <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer :  (14000, 500)
the number of unique words : 500
```

In [171]:
```
c1_rbf = preprocessing.normalize(c1_rbf)
c2_rbf = sparse.csr_matrix(X_train2['Length'].values)
c2_rbf = preprocessing.normalize(c2_rbf)
c3_rbf = sparse.hstack([c1_rbf, c2_rbf.T])
```

In [172]:
```
d1_rbf = preprocessing.normalize(d1_rbf)
d2_rbf = sparse.csr_matrix(X_test2['Length'].values)
d2_rbf = preprocessing.normalize(d2_rbf)
d3_rbf = sparse.hstack([d1_rbf, d2_rbf.T])
```

PREPARING W2V DATA FOR RBF KERNEL

Training Data

In [173]:
```
i=0
list_of_sentance=[]
for sentance in (X_train2['Cleaned Text'].values):
    list_of_sentance.append(sentance.split())
```

In [174]:
```
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])
```

```
[('good', 0.8201214671134949), ('excellent', 0.7648059725761414), ('per
fect', 0.7574174404144287), ('amazing', 0.7486943006515503), ('fantasti
c', 0.7406551241874695), ('wonderful', 0.7186780571937561), ('well', 0.
7147866487503052), ('love', 0.7107311487197876), ('delicious', 0.704160
5114936829), ('tasty', 0.6969573497772217)]
==================================================
[('leonidas', 0.9819067120552063), ('experienced', 0.9817522168159485),
('married', 0.9791007041931152), ('tipped', 0.9762768745422363), ('shar
ed', 0.9755205512046814), ('necco', 0.9727638959884644), ('belgium', 0.
9725375771522522), ('disgusting', 0.9715484380722046), ('addict', 0.971
3589549064636), ('introduce', 0.9708647131919861)]
number of words that occured minimum 5 times  7154
sample words  ['dogs', 'loves', 'chicken', 'product', 'china', 'wont',
'buying', 'anymore', 'hard', 'find', 'products', 'made', 'usa', 'one',
'isnt', 'bad', 'good', 'take', 'chances', 'till', 'know', 'going', 'imp
```

```
orts', 'love', 'saw', 'pet', 'store', 'tag', 'attached', 'regarding', 'satisfied', 'safe', 'infestation', 'literally', 'everywhere', 'flying', 'around', 'kitchen', 'bought', 'hoping', 'least', 'get', 'rid', 'weeks', 'fly', 'stuck', 'success', 'rate', 'day', 'clearly']
```

In [175]:
```
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, 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
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

```
100%|████████████████████████████████████████████████████████████| 14000/14000 [00:15<00:00, 896.49it/s]
```

```
14000
50
```

Test Data for RBF KERNEL

In [176]:
```
i=0
list_of_sentance1=[]
for sentance in (X_test2['Cleaned Text'].values):
    list_of_sentance1.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_model1=Word2Vec(list_of_sentance1,min_count=5,size=50, workers=
4)
    print(w2v_model1.wv.most_similar('great'))
    print('='*50)
    print(w2v_model1.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_model1=KeyedVectors.load_word2vec_format('GoogleNews-vector
s-negative300.bin', binary=True)
        print(w2v_model1.wv.most_similar('great'))
        print(w2v_model1.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_words1 = list(w2v_model1.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words1))
print("sample words ", w2v_words1[0:50])
```

```
[('good', 0.9847504496574402), ('pretty', 0.9795107245445251), ('stuf
f', 0.9754118323326111), ('greasy', 0.9752474427223206), ('salty', 0.97
49279022216797), ('crunchy', 0.9733189344406128), ('tasty', 0.972523808
4793091), ('chemical', 0.9713350534439087), ('chewy', 0.970232963562011
7), ('right', 0.9699370861053467)]
==================================================
[('bonus', 0.9979056119918823), ('kosher', 0.9974634647369385), ('certi
fied', 0.9974031448364258), ('kinds', 0.997395396232605), ('absolute',
0.9973660111427307), ('amy', 0.9973113536834717), ('hardly', 0.99718499
18365479), ('comment', 0.9970866441726685), ('tastiest', 0.997084736824
0356), ('non', 0.9970841407775879)]
number of words that occured minimum 5 times  3979
sample words  ['could', 'not', 'find', 'product', 'grocery', 'store',
'stores', 'shop', 'decided', 'check', 'amazon', 'husband', 'love', 'sea
```

```
soning', 'popcorn', 'really', 'good', 'speedy', 'delivery', 'thanks',

'cheaper', 'order', 'buy', 'thru', 'local', 'charges', 'bottle', 'usual
ly', 'weeks', 'time', 'one', 'bottles', 'broken', 'arrived', 'items',
'ordered', 'well', 'prevent', 'breakage', 'none', 'little', 'give', 'ex
tra', 'still', 'would', 'bought', 'recently', 'advertised', 'no', 'chee
sy']
```

In [177]:

```python
sent_vectors1 = []; # the avg-w2v for each sentence/review is stored in
 this list
for sent in tqdm(list_of_sentance1): # 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_words1:
            vec = w2v_model1.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors1.append(sent_vec)
print(len(sent_vectors1))
print(len(sent_vectors1[0]))
```

```
100%|████████████████████████████████████████████████████████████
██████████| 6000/6000 [00:04<00:00, 1465.97it/s]
```

```
6000
50
```

In [178]:

```python
e3 = sent_vectors
f3 = sent_vectors1
e3 = preprocessing.normalize(e3)
e4 = sparse.csr_matrix(X_train2['Length'].values)
e4 = preprocessing.normalize(e4)
e5_rbf = sparse.hstack([e3, e4.T])
f3 = preprocessing.normalize(f3)
```

```
f4 = sparse.csr_matrix(X_test2['Length'].values)
f4 = preprocessing.normalize(f4)
f5_rbf = sparse.hstack([f3, f4.T])
```

PREPARING TFIDF AVG W2V DATA FOR RBF KERNEL

In [179]:

```
model = TfidfVectorizer(min_df=10,max_features=500)
model.fit_transform(X_train2['Cleaned Text'].values)
# 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 [180]:

```
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%|██████████████████████████████████████████████████
████████| 14000/14000 [00:20<00:00, 679.28it/s]
```

In [181]:
```
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_vectors1 = []; # the tfidf-w2v for each sentence/review is s
tored in this list
row=0;
for sent in tqdm(list_of_sentance1): # 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_words1 and word in tfidf_feat:
            vec = w2v_model1.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_vectors1.append(sent_vec)
    row += 1
```

```
100%|██████████████████████████████████████████████████
█████████| 6000/6000 [00:05<00:00, 1125.55it/s]
```

In [182]:
```
g3 = tfidf_sent_vectors
h3 = tfidf_sent_vectors1
```

```
g3_rbf = preprocessing.normalize(g3)
h3_rbf = preprocessing.normalize(h3)
```

Grid Seach RBF KERNEL FOR ALL VECTORIZERS (BOW, TFIDF, AVGW2V, TFIDF-AVGW2V)

BOW

In [185]:
```
C = [0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000,100000]
clf = SVC()
param_grid = {'C': C}
model_bow = GridSearchCV(estimator = clf,param_grid=param_grid ,scoring
 = 'roc_auc',cv = 3, return_train_score = True, verbose = 3)
model_bow.fit(a3_rbf, y_train2)
print(model_bow.best_estimator_)
print(model_bow.score(b3_rbf, y_test2))
```

```
Fitting 3 folds for each of 11 candidates, totalling 33 fits
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent
workers.
```

```
[CV] C=1e-05 .........................................................
[CV] ................ C=1e-05, score=0.8032958073586891, total=   7.1s
```

```
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:   11.5s remaining:
    0.0s
```

```
[CV] C=1e-05 .........................................................
[CV] ................ C=1e-05, score=0.8021214759291662, total=   6.9s
```

```
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:   22.9s remaining:
    0.0s
```

```
[CV] C=1e-05 .........................................................
```

```
[CV] ................. C=1e-05, score=0.825800617236036, total=   7.2s
[CV] C=0.0001 ............................................................
[CV] ............... C=0.0001, score=0.8032958073586891, total=   8.3s
[CV] C=0.0001 ............................................................
[CV] ............... C=0.0001, score=0.8021214759291662, total=   7.6s
[CV] C=0.0001 ............................................................
[CV] ................ C=0.0001, score=0.825800617236036, total=   7.5s
[CV] C=0.001 .............................................................
[CV] ................ C=0.001, score=0.8032304969476353, total=   7.4s
[CV] C=0.001 .............................................................
[CV] ................. C=0.001, score=0.802892641167377, total=   7.6s
[CV] C=0.001 .............................................................
[CV] ................ C=0.001, score=0.8257916332462245, total=   7.7s
[CV] C=0.01 ..............................................................
[CV] ................. C=0.01, score=0.8264465538351564, total=   7.8s
[CV] C=0.01 ..............................................................
[CV] ................. C=0.01, score=0.8228729619204419, total=   7.2s
[CV] C=0.01 ..............................................................
[CV] ................. C=0.01, score=0.8389061022133676, total=   7.1s
[CV] C=0.1 ...............................................................
[CV] .................. C=0.1, score=0.8796271708534706, total=   7.9s
[CV] C=0.1 ...............................................................
[CV] ................... C=0.1, score=0.878449250939824, total=   8.1s
[CV] C=0.1 ...............................................................
[CV] .................. C=0.1, score=0.8895700549963921, total=   8.7s
[CV] C=1 .................................................................
[CV] .................... C=1, score=0.8810055076054332, total=   9.2s
[CV] C=1 .................................................................
[CV] .................... C=1, score=0.8838750389350527, total=   9.5s
[CV] C=1 .................................................................
[CV] .................... C=1, score=0.8872866841459173, total=  10.3s
[CV] C=10 ................................................................
[CV] ................... C=10, score=0.8809262021062966, total=   9.2s
[CV] C=10 ................................................................
[CV] ................... C=10, score=0.8837910684065551, total=   9.9s
[CV] C=10 ................................................................
[CV] ................... C=10, score=0.8874854100005463, total=   9.8s
[CV] C=100 ...............................................................
[CV] .................. C=100, score=0.8802382896997586, total=   8.4s
```

```
[CV] C=100 ............................................................
[CV] .................. C=100, score=0.8838244413089067, total=   8.9s
[CV] C=100 ............................................................
[CV] .................. C=100, score=0.8884768831161365, total=   8.6s
[CV] C=1000 ...........................................................
[CV] ................. C=1000, score=0.8744102326342488, total=   9.0s
[CV] C=1000 ...........................................................
[CV] .................. C=1000, score=0.885865212230128, total=   8.5s
[CV] C=1000 ...........................................................
[CV] ................. C=1000, score=0.8867307548563856, total=   8.1s
[CV] C=10000 ..........................................................
[CV] ................ C=10000, score=0.8729339302657056, total=  12.7s
[CV] C=10000 ..........................................................
[CV] ................ C=10000, score=0.8822440729007726, total=  13.3s
[CV] C=10000 ..........................................................
[CV] ................ C=10000, score=0.8626392877780366, total=  13.4s
[CV] C=100000 .........................................................
[CV] ................ C=100000, score=0.873130938044104, total=  40.6s
[CV] C=100000 .........................................................
[CV] ............... C=100000, score=0.8833561441307471, total=  38.6s
[CV] C=100000 .........................................................
[CV] ............... C=100000, score=0.8599803861534437, total=  39.0s
```

```
[Parallel(n_jobs=1)]: Done  33 out of  33 | elapsed:  8.9min finished
```

```
SVC(C=100, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
  kernel='rbf', max_iter=-1, probability=False, random_state=None,
  shrinking=True, tol=0.001, verbose=False)
0.8921129986638672
```

TFIDF

In [186]:

```
C = [0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000,100000]
clf = SVC()
param_grid = {'C': C}
model_tfidf = GridSearchCV(estimator = clf,param_grid=param_grid ,scori
```

```
ng = 'roc_auc',cv = 3, return_train_score = True, verbose = 3)
model_tfidf.fit(c3_rbf, y_train2)
```

```
Fitting 3 folds for each of 11 candidates, totalling 33 fits
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurre
nt workers.
[CV] C=1e-05
.........................................................
[CV] ................ C=1e-05, score=0.8388842398083463, total=   6.9
s
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:   11.9s remainin
g:    0.0s
[CV] C=1e-05
.........................................................
[CV] ................ C=1e-05, score=0.8374353893433505, total=   6.8
s
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:   23.1s remainin
g:    0.0s
[CV] C=1e-05
.........................................................
[CV] ................ C=1e-05, score=0.8301618052500999, total=   7.5
s
[CV] C=0.0001
........................................................
[CV] ............... C=0.0001, score=0.8388842398083463, total=   6.5
s
[CV] C=0.0001
........................................................
[CV] ............... C=0.0001, score=0.8374353893433505, total=   6.6
s
[CV] C=0.0001
........................................................
[CV] ............... C=0.0001, score=0.8301618052500999, total=   7.1
s
[CV] C=0.001
```

```
.........................................................
[CV] ................ C=0.001, score=0.8388842398083463, total=   7.5
s
[CV] C=0.001

.........................................................
[CV] ................ C=0.001, score=0.8374353893433505, total=   6.5
s
[CV] C=0.001
.........................................................
[CV] ................ C=0.001, score=0.8301618052500999, total=   6.7
s
[CV] C=0.01
..........................................................
[CV] ................. C=0.01, score=0.8545684273683636, total=   7.0
s
[CV] C=0.01
..........................................................
[CV] ................. C=0.01, score=0.8512973446652877, total=   6.8
s
[CV] C=0.01
..........................................................
[CV] ................. C=0.01, score=0.8500480463775116, total=   6.7
s
[CV] C=0.1
...........................................................
[CV] .................. C=0.1, score=0.8746298478626271, total=   8.0
s
[CV] C=0.1
...........................................................
[CV] .................. C=0.1, score=0.8764989098185232, total=   7.8
s
[CV] C=0.1
...........................................................
[CV] .................. C=0.1, score=0.8826678353040613, total=   7.9
s
[CV] C=1
.............................................................
[CV] .................... C=1, score=0.8766088968569185, total=   8.4
s
[CV] C=1
```

```
[CV] C=1
............................................................
[CV] .................... C=1, score=0.8815593901299461, total=   8.4
s

[CV] C=1
............................................................
[CV] .................... C=1, score=0.8853378770760204, total=   8.3
s
[CV] C=10
...........................................................
[CV] ................... C=10, score=0.8770029124137149, total=   8.0
s
[CV] C=10
...........................................................
[CV] ................... C=10, score=0.8823007709499291, total=   8.0
s
[CV] C=10
...........................................................
[CV] ................... C=10, score=0.8853960933299985, total=   8.2
s
[CV] C=100
..........................................................
[CV] .................. C=100, score=0.8762844978921245, total=   7.5
s
[CV] C=100
..........................................................
[CV] .................. C=100, score=0.8831871265285147, total=   7.4
s
[CV] C=100
..........................................................
[CV] .................. C=100, score=0.8872428422756374, total=   7.5
s
[CV] C=1000
.........................................................
[CV] ................. C=1000, score=0.8721563057560721, total=   7.1
s
[CV] C=1000
.........................................................
[CV] ................. C=1000, score=0.8821672793405227, total=   7.1
s
```

```
s
[CV] C=1000 ............................................................
[CV] ................. C=1000, score=0.8855649923384536, total=   7.3

s
[CV] C=10000 ...........................................................
[CV] ................ C=10000, score=0.8711953097077108, total=  11.7
s
[CV] C=10000 ...........................................................
[CV] ................ C=10000, score=0.8795501978690147, total=  11.7
s
[CV] C=10000 ...........................................................
[CV] ................. C=10000, score=0.860272904861704, total=  12.4
s
[CV] C=100000 ..........................................................
[CV] ............... C=100000, score=0.8738098792403323, total=  44.8
s
[CV] C=100000 ..........................................................
[CV] ............... C=100000, score=0.8842091268069812, total=  45.4
s
[CV] C=100000 ..........................................................
[CV] ................ C=100000, score=0.861565161956181, total=  48.5
s
```

```
[Parallel(n_jobs=1)]: Done  33 out of  33 | elapsed:  8.6min finished
```

Out[186]:

```
GridSearchCV(cv=3, error_score='raise-deprecating',
       estimator=SVC(C=1.0, cache_size=200, class_weight=None, coef0=
0.0,
  decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
  kernel='rbf', max_iter=-1, probability=False, random_state=None,
  shrinking=True, tol=0.001, verbose=False),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid={'C': [1e-05, 0.0001, 0.001, 0.01, 0.1, 1, 10, 100,
```

```
1000, 10000, 100000]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring='roc_auc', verbose=3)
```

In [187]:

```
print(model_tfidf.best_estimator_)
print(model_tfidf.score(d3_rbf, y_test2))
```

```
SVC(C=100, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
  kernel='rbf', max_iter=-1, probability=False, random_state=None,
  shrinking=True, tol=0.001, verbose=False)
0.8935110602108121
```

AVG W2V

In [189]:

```
C = [0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000,100000]
clf = SVC()
param_grid = {'C': C}
model_w2v = GridSearchCV(estimator = clf,param_grid=param_grid ,scoring
 = 'roc_auc',cv = 10, return_train_score = True, verbose = 3)
model_w2v.fit(e5_rbf, y_train2)
print(model_w2v.best_estimator_)
print(model_w2v.score(f5_rbf, y_test2))
```

```
Fitting 10 folds for each of 11 candidates, totalling 110 fits
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent
workers.
```

```
[CV] C=1e-05 ..........................................................
[CV] ................ C=1e-05, score=0.8280576685650564, total=   6.3s
```

```
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:   10.4s remaining:
    0.0s
```

```
[CV] C=1e-05 ..........................................................
[CV] ................ C=1e-05, score=0.8183400374367757, total=   6.7s
```

```
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:   21.0s remaining:
```

```
    0.0s
[CV] C=1e-05 .........................................................
[CV] .................. C=1e-05, score=0.796766568744295, total=   6.6s
[CV] C=1e-05 .........................................................
[CV] .................. C=1e-05, score=0.819941087137624, total=   6.3s
[CV] C=1e-05 .........................................................
[CV] .................. C=1e-05, score=0.818274945292352, total=   6.1s
[CV] C=1e-05 .........................................................
[CV] ................. C=1e-05, score=0.8406642245863545, total=   6.3s
[CV] C=1e-05 .........................................................
[CV] ................. C=1e-05, score=0.8499994021022086, total=   6.7s
[CV] C=1e-05 .........................................................
[CV] ................. C=1e-05, score=0.8414873305458008, total=   6.3s
[CV] C=1e-05 .........................................................
[CV] .................. C=1e-05, score=0.783964115503224, total=   6.2s
[CV] C=1e-05 .........................................................
[CV] ................. C=1e-05, score=0.8081941607593415, total=   6.2s
[CV] C=0.0001 ........................................................
[CV] ................ C=0.0001, score=0.8280576685650564, total=   6.3s
[CV] C=0.0001 ........................................................
[CV] ................ C=0.0001, score=0.8183400374367757, total=   6.8s
[CV] C=0.0001 ........................................................
[CV] ................. C=0.0001, score=0.796766568744295, total=   6.6s
[CV] C=0.0001 ........................................................
[CV] ................ C=0.0001, score=0.8194029791253952, total=   6.5s
[CV] C=0.0001 ........................................................
[CV] ................. C=0.0001, score=0.818274945292352, total=   6.6s
[CV] C=0.0001 ........................................................
[CV] ................ C=0.0001, score=0.8406642245863545, total=  21.2s
[CV] C=0.0001 ........................................................
[CV] ................ C=0.0001, score=0.8499994021022086, total=  23.9s
[CV] C=0.0001 ........................................................
[CV] ................ C=0.0001, score=0.8414873305458008, total=   7.5s
[CV] C=0.0001 ........................................................
[CV] ................. C=0.0001, score=0.783964115503224, total=   7.1s
[CV] C=0.0001 ........................................................
[CV] ................ C=0.0001, score=0.8081941607593415, total=   6.5s
[CV] C=0.001 .........................................................
[CV] ................. C=0.001, score=0.8296347923055478, total=   6.8s
```

```
[CV] C=0.001 .........................................................
[CV] ................ C=0.001, score=0.8197220120275599, total=   6.8s
[CV] C=0.001 .........................................................
[CV] ................ C=0.001, score=0.8002702498016973, total=   6.4s
[CV] C=0.001 .........................................................
[CV] ................ C=0.001, score=0.8199689890345546, total=   6.3s
[CV] C=0.001 .........................................................
[CV] ................ C=0.001, score=0.8196182223302868, total=   6.3s
[CV] C=0.001 .........................................................
[CV] ................ C=0.001, score=0.8430358858254376, total=   6.6s
[CV] C=0.001 .........................................................
[CV] ................ C=0.001, score=0.8517213477413415, total=   6.4s
[CV] C=0.001 .........................................................
[CV] ................ C=0.001, score=0.8468285508153333, total=   6.7s
[CV] C=0.001 .........................................................
[CV] ................. C=0.001, score=0.787760823421042, total=   6.3s
[CV] C=0.001 .........................................................
[CV] ................. C=0.001, score=0.809463735031439, total=   6.3s
[CV] C=0.01 ..........................................................
[CV] ................. C=0.01, score=0.8514118443585965, total=   7.5s
[CV] C=0.01 ..........................................................
[CV] ................. C=0.01, score=0.8634115257477398, total=   8.1s
[CV] C=0.01 ..........................................................
[CV] ................. C=0.01, score=0.8397474479729272, total=   8.2s
[CV] C=0.01 ..........................................................
[CV] ................. C=0.01, score=0.8360125797695304, total=   8.4s
[CV] C=0.01 ..........................................................
[CV] ................. C=0.01, score=0.8488235364458565, total=   7.6s
[CV] C=0.01 ..........................................................
[CV] ................. C=0.01, score=0.8644924445649098, total=   7.7s
[CV] C=0.01 ..........................................................
[CV] ................. C=0.01, score=0.8900984139764587, total=   7.7s
[CV] C=0.01 ..........................................................
[CV] ................. C=0.01, score=0.8786167833896021, total=   8.3s
[CV] C=0.01 ..........................................................
[CV] ................. C=0.01, score=0.8386238936280989, total=  19.2s
[CV] C=0.01 ..........................................................

[CV] ................. C=0.01, score=0.8086627417998318, total=  30.9s
[CV] C=0.1 ...........................................................
```

```
[CV] .................. C=0.1, score=0.8635110916404476, total=  10.8s
[CV] C=0.1 ...........................................................
[CV] ................... C=0.1, score=0.864383288860568, total=   8.7s
[CV] C=0.1 ...........................................................
[CV] .................. C=0.1, score=0.8501707994690668, total=   8.9s
[CV] C=0.1 ...........................................................
[CV] .................. C=0.1, score=0.8526421103400444, total=   8.6s
[CV] C=0.1 ...........................................................
[CV] .................. C=0.1, score=0.8633763686876941, total=   9.1s
[CV] C=0.1 ...........................................................
[CV] .................. C=0.1, score=0.8647555195931107, total=   8.2s
[CV] C=0.1 ...........................................................
[CV] .................. C=0.1, score=0.8901861056525256, total=   8.6s
[CV] C=0.1 ...........................................................
[CV] ................... C=0.1, score=0.880458308587008, total=  11.3s
[CV] C=0.1 ...........................................................
[CV] .................. C=0.1, score=0.8370779766910971, total=   9.2s
[CV] C=0.1 ...........................................................
[CV] .................. C=0.1, score=0.8188073210781368, total=   9.2s
[CV] C=1 .............................................................
[CV] ...................... C=1, score=0.85109721613764, total=   8.5s
[CV] C=1 .............................................................
[CV] .................... C=1, score=0.8713250229001552, total=   8.5s
[CV] C=1 .............................................................
[CV] .................... C=1, score=0.8633803546729698, total=   8.5s
[CV] C=1 .............................................................
[CV] .................... C=1, score=0.8531403584995157, total=   8.5s
[CV] C=1 .............................................................
[CV] ..................... C=1, score=0.857285783186317, total=  10.0s
[CV] C=1 .............................................................
[CV] .................... C=1, score=0.8780607384436322, total=   9.0s
[CV] C=1 .............................................................
[CV] .................... C=1, score=0.8993777876984523, total=   9.3s
[CV] C=1 .............................................................
[CV] .................... C=1, score=0.8970160914225584, total=  10.3s
[CV] C=1 .............................................................
[CV] .................... C=1, score=0.8399655572910408, total=   8.9s

[CV] C=1 .............................................................
[CV] ..................... C=1, score=0.830421722936441, total=   9.0s
```

```
[CV] C=10 ............................................................
[CV] .................... C=10, score=0.8547054840893704, total=   8.6s
[CV] C=10 ............................................................
[CV] .................... C=10, score=0.8703174160659524, total=   8.7s
[CV] C=10 ............................................................
[CV] .................... C=10, score=0.8642014676397786, total=   8.7s
[CV] C=10 ............................................................
[CV] .................... C=10, score=0.8520681284603335, total=   8.6s
[CV] C=10 ............................................................
[CV] .................... C=10, score=0.8578119332427185, total=   8.5s
[CV] C=10 ............................................................
[CV] .................... C=10, score=0.8778773831209468, total=   8.5s
[CV] C=10 ............................................................
[CV] .................... C=10, score=0.9010279856026212, total=   8.8s
[CV] C=10 ............................................................
[CV] .................... C=10, score=0.8988177567672064, total=   9.6s
[CV] C=10 ............................................................
[CV] .................... C=10, score=0.8406263767071167, total=   8.3s
[CV] C=10 ............................................................
[CV] .................... C=10, score=0.8316552525131162, total=   8.4s
[CV] C=100 ...........................................................
[CV] ................... C=100, score=0.8542315504400813, total=   8.0s
[CV] C=100 ...........................................................
[CV] ................... C=100, score=0.8703532597873274, total=   8.0s
[CV] C=100 ...........................................................
[CV] ................... C=100, score=0.8642174115808816, total=   8.5s
[CV] C=100 ...........................................................
[CV] ................... C=100, score=0.8520960303572639, total=   7.9s
[CV] C=100 ...........................................................
[CV] ................... C=100, score=0.8576126339789301, total=   8.0s
[CV] C=100 ...........................................................
[CV] ................... C=100, score=0.8780368225319776, total=   7.9s
[CV] C=100 ...........................................................
[CV] ................... C=100, score=0.9009004340737966, total=   8.4s
[CV] C=100 ...........................................................
[CV] .................... C=100, score=0.898738037061691, total=   8.8s
[CV] C=100 ...........................................................

[CV] ................... C=100, score=0.8405743121470624, total=   8.0s
[CV] C=100 ...........................................................
```

```
[CV] .................. C=100, score=0.8315951780207458, total=   7.9s
[CV] C=1000 ..........................................................
[CV] ................. C=1000, score=0.8504838902385599, total=   8.7s
[CV] C=1000 ..........................................................
[CV] ................. C=1000, score=0.8735911426181848, total=   9.2s
[CV] C=1000 ..........................................................
[CV] ................. C=1000, score=0.8664017315120037, total=   9.2s
[CV] C=1000 ..........................................................
[CV] ................. C=1000, score=0.8532878399547191, total=   8.5s
[CV] C=1000 ..........................................................
[CV] ................. C=1000, score=0.8560979595741374, total=   9.0s
[CV] C=1000 ..........................................................
[CV] ................. C=1000, score=0.8801932405661694, total=   8.3s
[CV] C=1000 ..........................................................
[CV] ................. C=1000, score=0.8996129608297229, total=   9.7s
[CV] C=1000 ..........................................................
[CV] ................. C=1000, score=0.8996229257929121, total=   8.7s
[CV] C=1000 ..........................................................
[CV] ................. C=1000, score=0.8355120349233048, total=   7.9s
[CV] C=1000 ..........................................................
[CV] ................. C=1000, score=0.8333333333333333, total=   8.1s
[CV] C=10000 .........................................................
[CV] ................. C=10000, score=0.848237683699072, total=  18.5s
[CV] C=10000 .........................................................
[CV] ................ C=10000, score=0.8778684933689116, total=  17.9s
[CV] C=10000 .........................................................
[CV] ................ C=10000, score=0.8602154823640081, total=  17.6s
[CV] C=10000 .........................................................
[CV] ................ C=10000, score=0.8496167475157346, total=  16.8s
[CV] C=10000 .........................................................
[CV] ................ C=10000, score=0.8561816652649284, total=  18.2s
[CV] C=10000 .........................................................
[CV] ................ C=10000, score=0.8724923170133809, total=  17.3s
[CV] C=10000 .........................................................
[CV] ................ C=10000, score=0.8931995105210082, total=  18.3s
[CV] C=10000 .........................................................
[CV] ................ C=10000, score=0.9005755762738212, total=  18.0s

[CV] C=10000 .........................................................
[CV] ................ C=10000, score=0.8238896231326844, total=  17.2s
```

```
[CV] C=10000 ...........................................................
[CV] ................ C=10000, score=0.8354840001601986, total=  16.9s
[CV] C=100000 ..........................................................
[CV] ............... C=100000, score=0.8524194511927994, total= 1.5min
[CV] C=100000 ..........................................................
[CV] ............... C=100000, score=0.8837269504958383, total= 1.7min
[CV] C=100000 ..........................................................
[CV] ............... C=100000, score=0.8594262572794057, total= 1.5min
[CV] C=100000 ..........................................................
[CV] ............... C=100000, score=0.8541807006564919, total= 1.4min
[CV] C=100000 ..........................................................
[CV] ............... C=100000, score=0.8640420282287478, total= 4.4min
[CV] C=100000 ..........................................................
[CV] ............... C=100000, score=0.8728032238648911, total= 1.7min
[CV] C=100000 ..........................................................
[CV] ............... C=100000, score=0.8929643373897376, total= 1.7min
[CV] C=100000 ..........................................................
[CV] ............... C=100000, score=0.8967171425268755, total= 2.3min
[CV] C=100000 ..........................................................
[CV] ............... C=100000, score=0.8244743481917578, total= 1.4min
[CV] C=100000 ..........................................................
[CV] ............... C=100000, score=0.8552765429132124, total= 1.4min
```

```
[Parallel(n_jobs=1)]: Done 110 out of 110 | elapsed: 43.5min finished
```

```
SVC(C=100000, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
  kernel='rbf', max_iter=-1, probability=False, random_state=None,
  shrinking=True, tol=0.001, verbose=False)
0.5392036224046151
```

TFIDF - AVGW2V

In [190]:

```
C = [0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000,100000]
clf = SVC()
```

```
param_grid = {'C': C}
model_w2vtfidf = GridSearchCV(estimator = clf,param_grid=param_grid ,sc
oring = 'roc_auc',cv = 3, return_train_score = True, verbose = 3)
model_w2vtfidf.fit(g3_rbf, y_train2)
print(model_w2vtfidf.best_estimator_)
print(model_w2vtfidf.score(h3_rbf, y_test2))
```

```
Fitting 3 folds for each of 11 candidates, totalling 33 fits
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent
workers.
```

```
[CV] C=1e-05 .........................................................
[CV] ................ C=1e-05, score=0.7526617580988499, total=   2.4s
```

```
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    3.8s remaining:
    0.0s
```

```
[CV] C=1e-05 .........................................................
[CV] ................ C=1e-05, score=0.7900130333743378, total=   2.3s
```

```
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    7.5s remaining:
    0.0s
```

```
[CV] C=1e-05 .........................................................
[CV] ................ C=1e-05, score=0.7627116268639982, total=   2.3s
[CV] C=0.0001 ........................................................
[CV] ............... C=0.0001, score=0.7526617580988499, total=   2.3s
[CV] C=0.0001 ........................................................
[CV] ............... C=0.0001, score=0.7900130333743378, total=   2.3s
[CV] C=0.0001 ........................................................
[CV] ............... C=0.0001, score=0.7627116268639982, total=   2.3s
[CV] C=0.001 .........................................................
[CV] ................ C=0.001, score=0.7565183019867284, total=   2.3s
[CV] C=0.001 .........................................................
[CV] ................ C=0.001, score=0.7927453051862208, total=   2.3s
[CV] C=0.001 .........................................................
[CV] ................ C=0.001, score=0.7657428250263769, total=   2.3s
[CV] C=0.01 ..........................................................
[CV] ................. C=0.01, score=0.7956266785134489, total=   2.4s
[CV] C=0.01 ..........................................................
[CV] ................. C=0.01, score=0.8118159452138951, total=   2.4s
```

```
[CV] .................. C=0.01, score=0.8118159452138951, total=   2.4s
[CV] C=0.01 ............................................................
[CV] .................. C=0.01, score=0.7973301738437965, total=   2.4s
[CV] C=0.1 .............................................................
[CV] ................... C=0.1, score=0.7984587101839745, total=   2.5s
[CV] C=0.1 .............................................................
[CV] ................... C=0.1, score=0.7998939244092996, total=   2.5s
[CV] C=0.1 .............................................................
[CV] ................... C=0.1, score=0.7809203774138185, total=   2.5s
[CV] C=1 ...............................................................
[CV] ..................... C=1, score=0.7661261093798668, total=   2.8s
[CV] C=1 ...............................................................
[CV] ..................... C=1, score=0.7697126198374273, total=   2.8s
[CV] C=1 ...............................................................
[CV] ..................... C=1, score=0.7872242633847074, total=   2.9s
[CV] C=10 ..............................................................
[CV] .................... C=10, score=0.8142907432898936, total=   3.6s
[CV] C=10 ..............................................................
[CV] .................... C=10, score=0.8124442887839776, total=   3.6s
[CV] C=10 ..............................................................
[CV] .................... C=10, score=0.8160337625524305, total=   3.6s
[CV] C=100 .............................................................
[CV] ................... C=100, score=0.8215265626771815, total=   4.0s
[CV] C=100 .............................................................
[CV] ................... C=100, score=0.8211879892000982, total=   4.2s
[CV] C=100 .............................................................
[CV] ................... C=100, score=0.8157901167487444, total=   4.0s
[CV] C=1000 ............................................................
[CV] .................. C=1000, score=0.8211730969909843, total=   4.4s
[CV] C=1000 ............................................................
[CV] .................. C=1000, score=0.8222989838848356, total=   4.6s
[CV] C=1000 ............................................................
[CV] .................. C=1000, score=0.8160466994977591, total=   4.3s
[CV] C=10000 ...........................................................
[CV] ................. C=10000, score=0.8213058709035659, total=   8.7s
[CV] C=10000 ...........................................................
[CV] ................. C=10000, score=0.8237803101311519, total=   9.3s
[CV] C=10000 ...........................................................
[CV] ................. C=10000, score=0.8201035099370115, total=   9.6s
[CV] C=100000 ..........................................................
```

```
[CV] ............... C=100000, score=0.8226289450000216, total=  43.5s
[CV] C=100000 .........................................................
[CV] ............... C=100000, score=0.8317341851916179, total=  41.4s
[CV] C=100000 .........................................................
[CV] ............... C=100000, score=0.8308724388441846, total=  47.1s
```

```
[Parallel(n_jobs=1)]: Done  33 out of  33 | elapsed:  4.8min finished
```

```
SVC(C=100000, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
  kernel='rbf', max_iter=-1, probability=False, random_state=None,
  shrinking=True, tol=0.001, verbose=False)
0.5555977603868423
```

Observations:

1) We observe that the optimal c is 100 for both BOW and TFIDF vectorizers.

2) However Optimal C is 100000 for W2V and 100000 for tfidf- avgw2v.

3) TFIDF performed slightly better when compared to BOW. However TFIDF AVGW2V efficiency was the least.

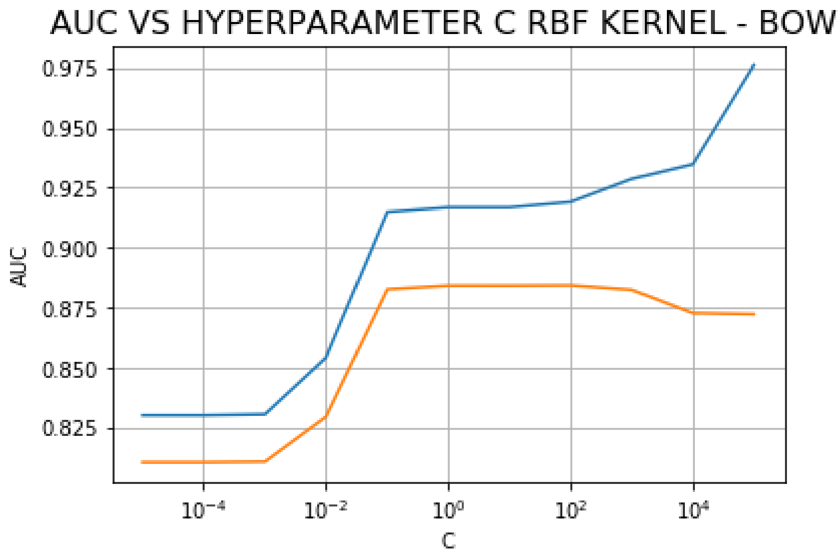
3) Now let us check whether these corresponding optimal hyperparameters are the actual ones by plotting grahs.

BOW

In [191]:
```
alpha = [0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000,100000]
```

In [192]:
```
train_auc1= model_bow.cv_results_['mean_train_score']
cv_auc1= model_bow.cv_results_['mean_test_score']
plt.plot(alpha,train_auc1)
plt.plot(alpha,cv_auc1)
```

```
plt.xlabel('C',size=10)
plt.ylabel('AUC',size=10)
plt.title('AUC VS HYPERPARAMETER C RBF KERNEL - BOW ',size=16)
plt.xscale('log')
plt.grid()
plt.show()
print("\n\n C Values :\n", alpha)
print("\n Train AUC for each c value is :\n ", np.round(train_auc1,5))
print("\n CV AUC for each c value is :\n ", np.round(cv_auc1,5))
```




```
 C Values :
 [1e-05, 0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000, 100000]

 Train AUC for each c value is :
  [0.83006 0.83006 0.83048 0.85409 0.91481 0.91677 0.91677 0.91903 0.92
857
 0.93465 0.97605]

 CV AUC for each c value is :
  [0.8104  0.8104  0.81064 0.82941 0.88255 0.88406 0.88407 0.88418 0.88
234
 0.87261 0.87216]
```

In [193]:
```
max(cv_auc1)
```
Out[193]:
```
0.8841795644455238
```

In [ ]:
```
# We found that the optimal C is 100
```

In [ ]:
```
# Running the model with optimal C
```

In [194]:
```
om_bow = SVC(C=100, probability = True)
om_bow.fit(a3_rbf, y_train2)
ompredictions_bow  = om_bow.predict(b3_rbf)
probs = om_bow.predict_proba(b3_rbf)
probs1 = om_bow.predict_proba(a3_rbf)
probs = probs[:, 1]
probs1 = probs1[:, -1]
```

PERFORMANCE METRICS - RBF KERNEL - BOW

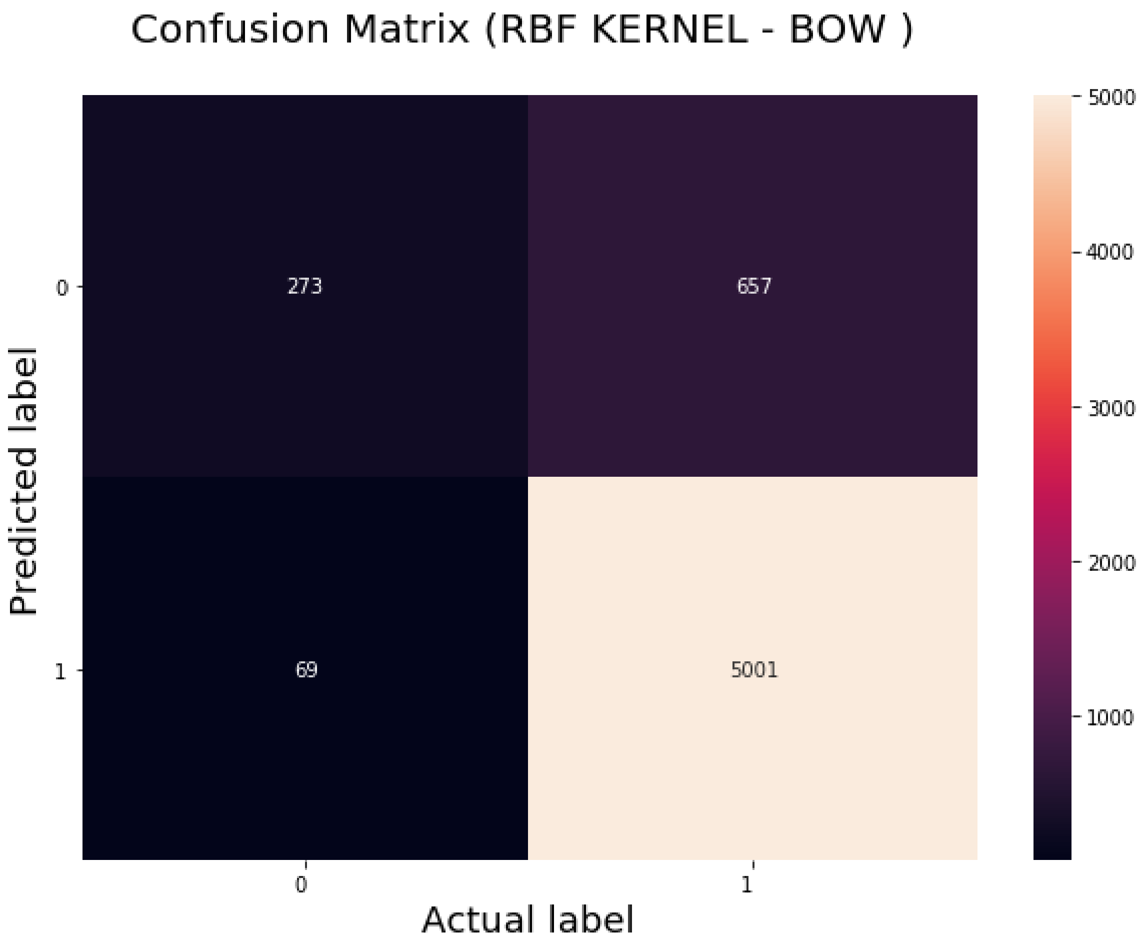
In [196]:
```
precision_bow = precision_score(y_test2, ompredictions_bow, pos_label = 1)
recall_bow = recall_score(y_test2, ompredictions_bow, pos_label = 1)
f1score_bow = f1_score(y_test2, ompredictions_bow, pos_label = 1)
print('\nThe Test Precision for OPTIMAL C for RBF KERNEL (BOW)   is %f' % (precision_bow))
print('\nThe Test Recall for  OPTIMAL C for RBF KERNEL (BOW)  is %f' % (recall_bow))
print('\nThe Test F1-Score for  OPTIMAL C for RBF KERNEL (BOW)  is %f' %  (f1score_bow))
```

```
The Test Precision for OPTIMAL C for RBF KERNEL (BOW)   is 0.883881

The Test Recall for  OPTIMAL C for RBF KERNEL (BOW)  is 0.986391

The Test F1-Score for  OPTIMAL C for RBF KERNEL (BOW)  is 0.932327
```

```
The Test F1-Score for  OPTIMAL C for RBF KERNEL (BOW)  is 0.932327
```

In [197]:

```
class_names = [ 0,1]
df_heatmap = pd.DataFrame(confusion_matrix(y_test2, ompredictions_bow),
 index=class_names, columns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=10)#
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=10)
plt.ylabel('Predicted label',size=18)
plt.xlabel('Actual label',size=18)
plt.title("Confusion Matrix (RBF KERNEL - BOW ) \n",size=20)
plt.show()
```



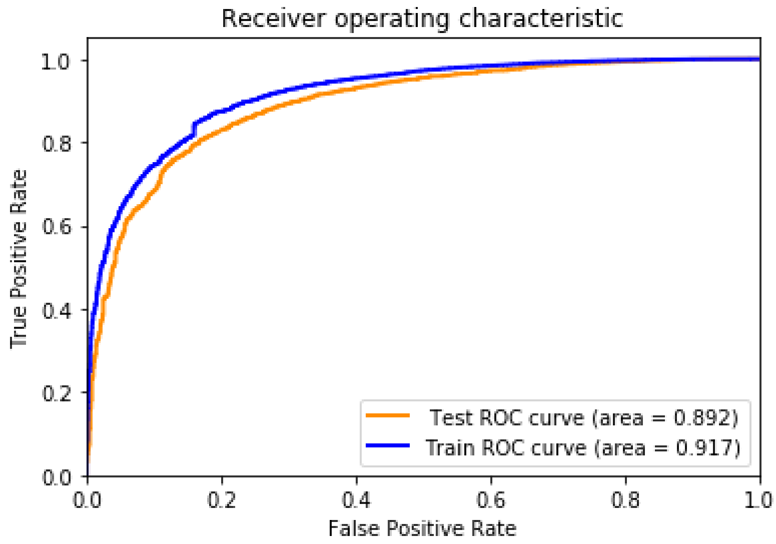
In [198]:
```
TrueNeg,FalseNeg,FalsePos, TruePos = confusion_matrix(y_test2, ompredic
tions_bow).ravel()
TPR = TruePos/(FalseNeg + TruePos)
FPR = FalsePos/(TrueNeg + FalsePos)
TNR = TrueNeg/(TrueNeg + FalsePos)
FNR = FalseNeg/(FalseNeg + TruePos)
print("TPR of the RBF KERNEL  (BOW)   is :  %f" % (TPR))
print("FPR of the RBF KERNEL (BOW)   is :  %f" % (FPR))
print("TNR of the RBF KERNEL (BOW)   is :  %f" % (TNR))
print("FNR of the RBF KERNEL (BOW)  is :  %f" % (FNR))
```

```
TPR of the RBF KERNEL  (BOW)   is :  0.883881
FPR of the RBF KERNEL (BOW)   is :  0.201754
TNR of the RBF KERNEL (BOW)   is :  0.798246
FNR of the RBF KERNEL (BOW)  is :  0.116119
```

In [199]:

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc
fpr = dict()
tpr = dict()
roc_auc = dict()

fpr1 = dict()
tpr1 = dict()
roc_auc1 = dict()

#for i in range(26331):
for i in range(4):
    fpr[i], tpr[i], _ = roc_curve(y_test2,probs)
    roc_auc[i] = auc(fpr[i], tpr[i])

#for i in range(61441):
for i in range(4):
    fpr1[i], tpr1[i], _ = roc_curve(y_train2,probs1)
    roc_auc1[i] = auc(fpr1[i], tpr1[i])

#print(roc_auc_score(y_test1,ompredictions_bow))
plt.figure()
#plt.plot(fpr[1], tpr[1])
lw = 2
plt.plot(fpr[0], tpr[0], color='darkorange',lw=lw, label=' Test ROC cur
ve (area = %0.3f)' % roc_auc[0])
plt.plot(fpr1[0], tpr1[0], color='blue',lw=lw, label='Train ROC curve
 (area = %0.3f)' % roc_auc1[0])
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc="lower right")
```

```
plt.title('Receiver operating characteristic')
plt.show()
```



Observations :

1) We found that the train score is 0.92 and the test score is 0.89 .

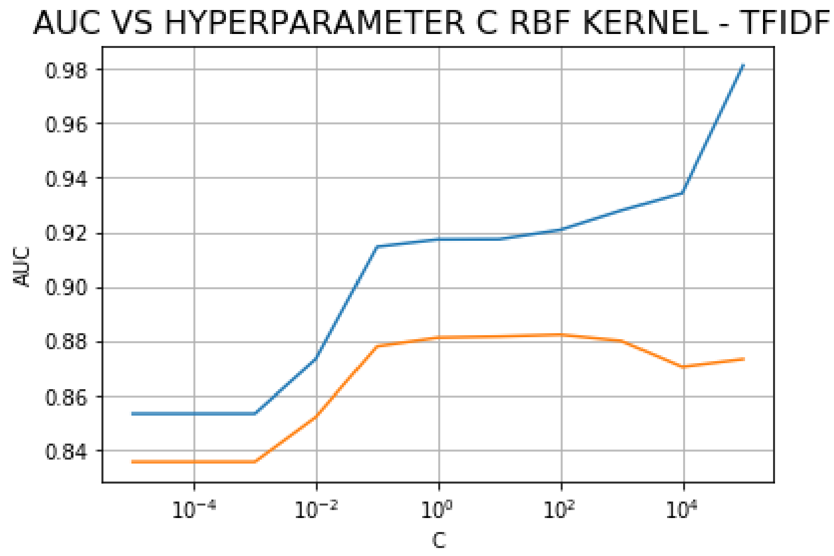
2) This implies that the model is reasonably good.

TFIDF

In [200]:

```
train_auc1= model_tfidf.cv_results_['mean_train_score']
cv_auc1= model_tfidf.cv_results_['mean_test_score']
plt.plot(alpha,train_auc1)
plt.plot(alpha,cv_auc1)
plt.xlabel('C',size=10)
plt.ylabel('AUC',size=10)
plt.title('AUC VS HYPERPARAMETER C RBF KERNEL - TFIDF ',size=16)
```

```python
plt.xscale('log')
plt.grid()
plt.show()
print("\n\n C Values :\n", alpha)
print("\n Train AUC for each c value is :\n ", np.round(train_auc1,5))
print("\n CV AUC for each c value is :\n ", np.round(cv_auc1,5))
```




```
 C Values :
 [1e-05, 0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000, 100000]

 Train AUC for each c value is :
  [0.85324 0.85324 0.85324 0.87326 0.91452 0.91721 0.91729 0.92072 0.92
789
 0.93426 0.98129]

 CV AUC for each c value is :
  [0.83549 0.83549 0.83549 0.85197 0.87793 0.88117 0.88157 0.88224 0.87
996
 0.87034 0.8732 ]
```

In [201]:

```python
max(cv_auc1)
```

Out[201]: 0.8822377980878033

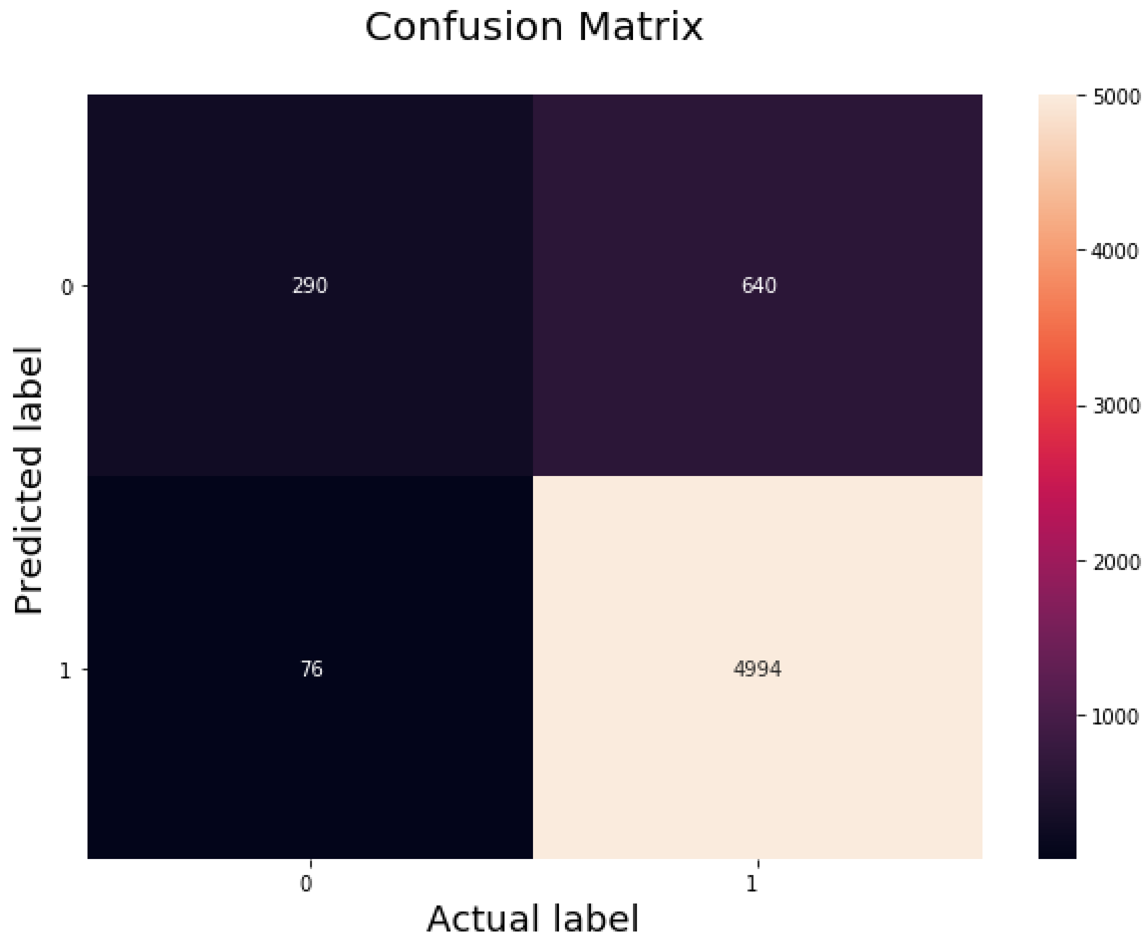
In [202]:
```
om_tfidf = SVC(C=100, probability = True)
om_tfidf.fit(c3_rbf, y_train2)
ompredictions_tfidf  = om_tfidf.predict(d3_rbf)
probs2 = om_tfidf.predict_proba(c3_rbf)
probs3 = om_tfidf.predict_proba(d3_rbf)
probs2= probs2[:, 1]
probs3 = probs3[:, 1]
```

In [203]:
```
precision_tfidf = precision_score(y_test2, ompredictions_tfidf, pos_lab
el = 1)
recall_tfidf = recall_score(y_test2, ompredictions_tfidf, pos_label = 1
)
f1score_tfidf = f1_score(y_test2, ompredictions_tfidf, pos_label = 1)
print('\nThe Test Precision for optimal C for RBF KERNEL (TFIDF)   is %
f' % (precision_bow))
print('\nThe Test Recall for optimal C for RBF KERNEL (TFIDF)  is %f' %
 (recall_bow))
print('\nThe Test F1-Score for optimal C for RBF KERNEL (TFIDF)  is %f'
 %  (f1score_bow))
```

```
The Test Precision for optimal C for RBF KERNEL (TFIDF)   is 0.883881

The Test Recall for optimal C for RBF KERNEL (TFIDF)  is 0.986391

The Test F1-Score for optimal C for RBF KERNEL (TFIDF)  is 0.932327
```

In [204]:
```
# Code for drawing seaborn heatmaps
class_names = [ 0,1]
df_heatmap = pd.DataFrame(confusion_matrix(y_test2, ompredictions_tfidf
), index=class_names, columns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=10)#
```

```
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=10)
plt.ylabel('Predicted label',size=18)
plt.xlabel('Actual label',size=18)
plt.title("Confusion Matrix\n",size=20)
plt.show()
```



In [205]:
```
TrueNeg,FalseNeg,FalsePos, TruePos = confusion_matrix(y_test2, ompredic
tions_tfidf).ravel()
TPR = TruePos/(FalseNeg + TruePos)
```

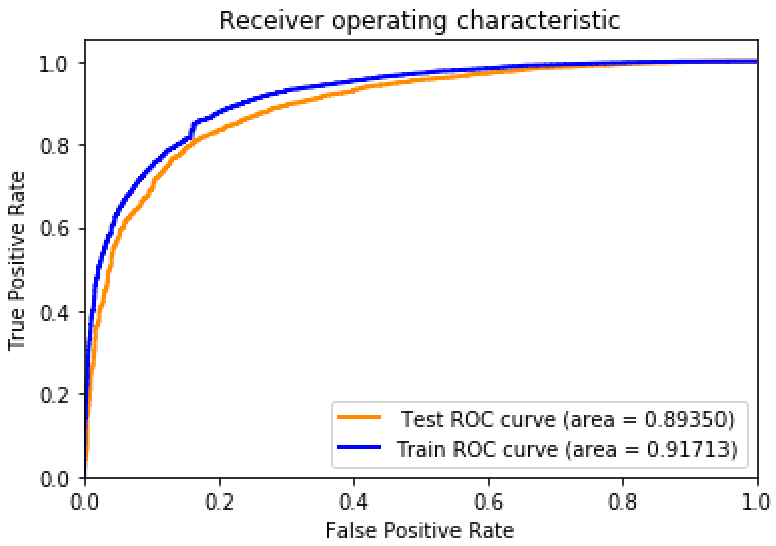
```
FPR = FalsePos/(TrueNeg + FalsePos)
TNR = TrueNeg/(TrueNeg + FalsePos)
FNR = FalseNeg/(FalseNeg + TruePos)
print("TPR of the SVM - RBF KERNEL (TFIDF) for OPTIMAL C   is :  %f" %
(TPR))
print("FPR of the SVM - RBF KERNEL (TFIDF) for OPTIMAL C:  %f" % (FPR))
print("TNR of the SVM - RBF KERNEL (TFIDF) for OPTIMAL C :  %f" % (TNR
))
print("FNR of the SVM - RBF KERNEL (TFIDF) for OPTIMAL C :  %f" % (FNR
))
```

```
TPR of the SVM - RBF KERNEL (TFIDF) for OPTIMAL C   is :  0.886404
FPR of the SVM - RBF KERNEL (TFIDF) for OPTIMAL C:  0.207650
TNR of the SVM - RBF KERNEL (TFIDF) for OPTIMAL C :  0.792350
FNR of the SVM - RBF KERNEL (TFIDF) for OPTIMAL C :  0.113596
```

In [206]:

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc
fpr = dict()
tpr = dict()
roc_auc = dict()

fpr1 = dict()
tpr1 = dict()
roc_auc1 = dict()

#for i in range(26331):
for i in range(4):
    fpr[i], tpr[i], _ = roc_curve(y_test2,probs3)
    roc_auc[i] = auc(fpr[i], tpr[i])

#for i in range(61441):
for i in range(4):
    fpr1[i], tpr1[i], _ = roc_curve(y_train2,probs2)
    roc_auc1[i] = auc(fpr1[i], tpr1[i])

#print(roc_auc_score(y_test1,ompredictions_bow))
plt.figure()
#plt.plot(fpr[1], tpr[1])
```

```
lw = 2
plt.plot(fpr[0], tpr[0], color='darkorange',lw=lw, label=' Test ROC cur
ve (area = %0.5f)' % roc_auc[0])
plt.plot(fpr1[0], tpr1[0], color='blue',lw=lw, label='Train ROC curve
 (area = %0.5f)' % roc_auc1[0])
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc="lower right")
plt.title('Receiver operating characteristic')
plt.show()
```

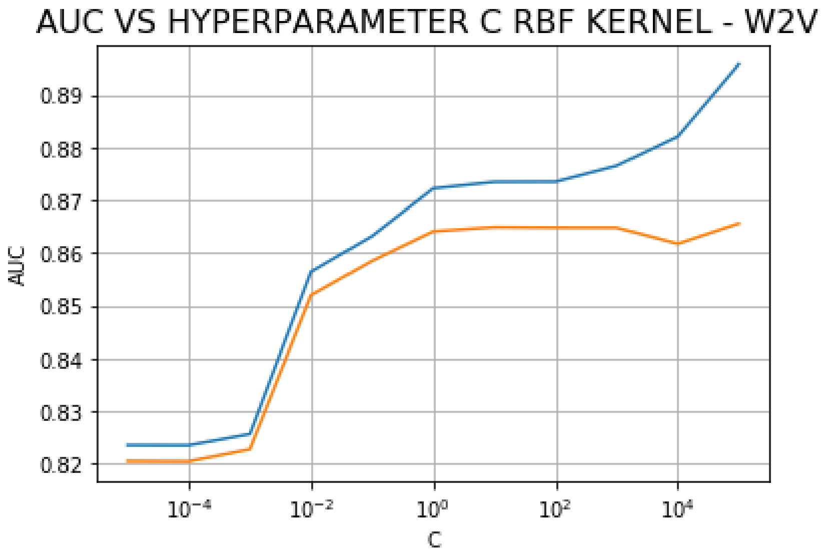


Observations :

1) We found that train auc is 0.91713 and test auc is 0.89350. This also imples that model is reasonably good.

W2V AVG

In [207]:
```
train_auc_w2v1= model_w2v.cv_results_['mean_train_score']
cv_auc_w2v1= model_w2v.cv_results_['mean_test_score']
plt.plot(alpha,train_auc_w2v1)
plt.plot(alpha,cv_auc_w2v1)
plt.xlabel('C',size=10)
plt.ylabel('AUC',size=10)
plt.title('AUC VS HYPERPARAMETER C RBF KERNEL - W2V ',size=16)
plt.xscale('log')
plt.grid()
plt.show()
print("\n\n C Values :\n", alpha)
print("\n Train AUC for each c value is :\n ", np.round(train_auc_w2v1,
5))
print("\n CV AUC for each c value is :\n ", np.round(cv_auc_w2v1,5))
```




```
 C Values :
 [1e-05, 0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000, 100000]

 Train AUC for each c value is :
  [0.82358 0.82356 0.82569 0.85645 0.86324 0.87227 0.8735  0.87353 0.87
655
```

```
655
 0.8821  0.89583]

 CV AUC for each c value is :
  [0.82057 0.82052 0.82281 0.85199 0.85854 0.86411 0.86491 0.86484 0.86
482
 0.86178 0.86561]
```

In [208]:
```
max(cv_auc_w2v1)
```

Out[208]:
```
0.8656071265247317
```

In [209]:
```
om_w2v = SVC(C=100000, probability = True)
om_w2v.fit(e5_rbf, y_train2)
ompredictions_w2v  = om_w2v.predict(f5_rbf)
probs4 = om_w2v.predict_proba(e5_rbf)
probs5 = om_w2v.predict_proba(f5_rbf)
probs4= probs4[:, 1]
probs5 = probs5[:, 1]
```

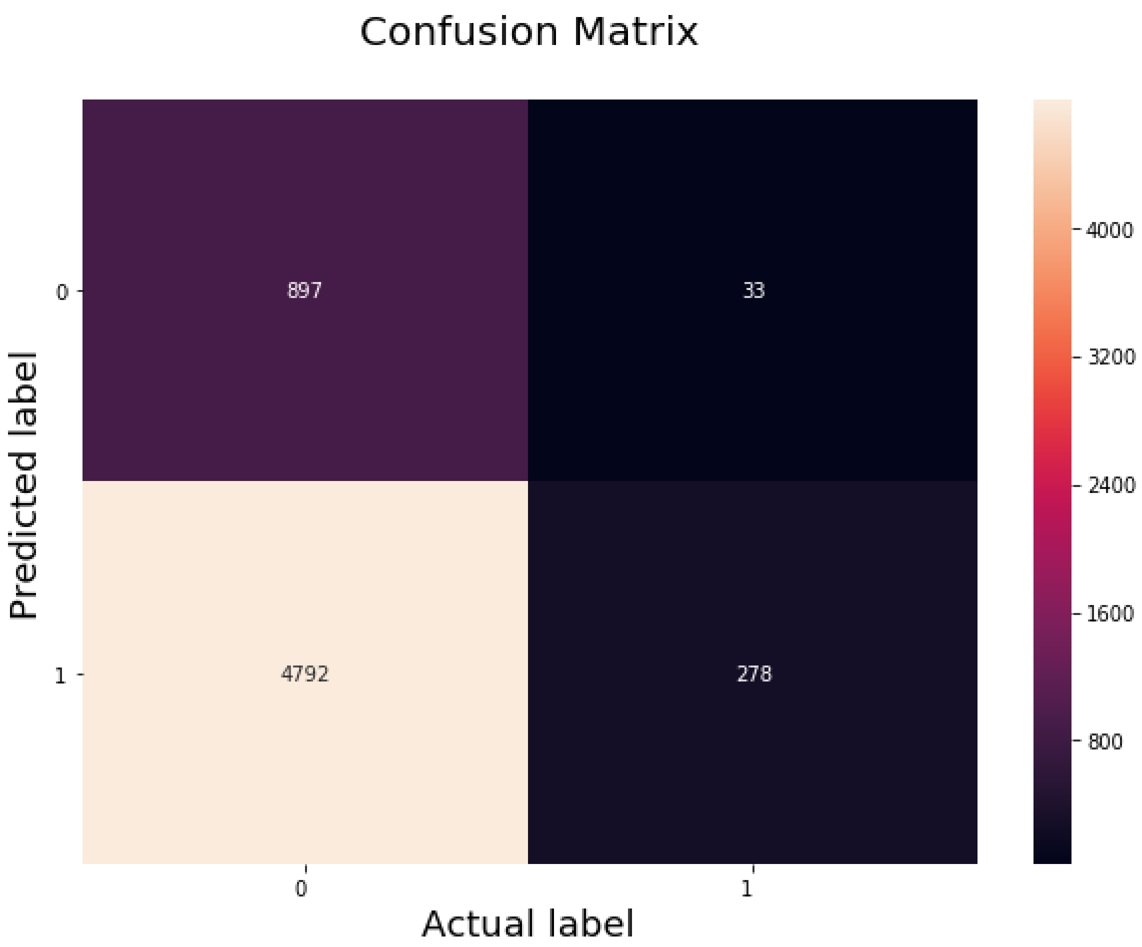
In [210]:
```
precision_w2v = precision_score(y_test2, ompredictions_w2v, pos_label =
 1)
recall_w2v = recall_score(y_test2, ompredictions_w2v, pos_label = 1)
f1score_w2v = f1_score(y_test2, ompredictions_w2v, pos_label = 1)

print('\nThe Test Precision for optimal c for RBF - KERNEL - SVM (W2V)
 is %f' % (precision_w2v))
print('\nThe Test Recall for optimal c for RBF - KERNEL - SVM (W2V) is
 %f' % (recall_w2v))
print('\nThe Test F1-Score for optimal c for RBF - KERNEL - SVM (W2V) i
s  %f' % (f1score_w2v))

class_names = [ 0,1]
df_heatmap = pd.DataFrame(confusion_matrix(y_test2, ompredictions_w2v),
 index=class_names, columns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")
```

```
# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=10)#
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=10)
plt.ylabel('Predicted label',size=18)
plt.xlabel('Actual label',size=18)
plt.title("Confusion Matrix\n",size=20)
```

```
The Test Precision for optimal c for RBF - KERNEL - SVM (W2V) is 0.8938
91

The Test Recall for optimal c for RBF - KERNEL - SVM (W2V) is  0.054832

The Test F1-Score for optimal c for RBF - KERNEL - SVM (W2V) is  0.1033
27
```

Out[210]:

```
Text(0.5, 1.0, 'Confusion Matrix\n')
```



In [211]:
```
TrueNeg,FalseNeg,FalsePos, TruePos = confusion_matrix(y_test2, ompredic
tions_w2v).ravel()
TPR = TruePos/(FalseNeg + TruePos)
FPR = FalsePos/(TrueNeg + FalsePos)
TNR = TrueNeg/(TrueNeg + FalsePos)
```

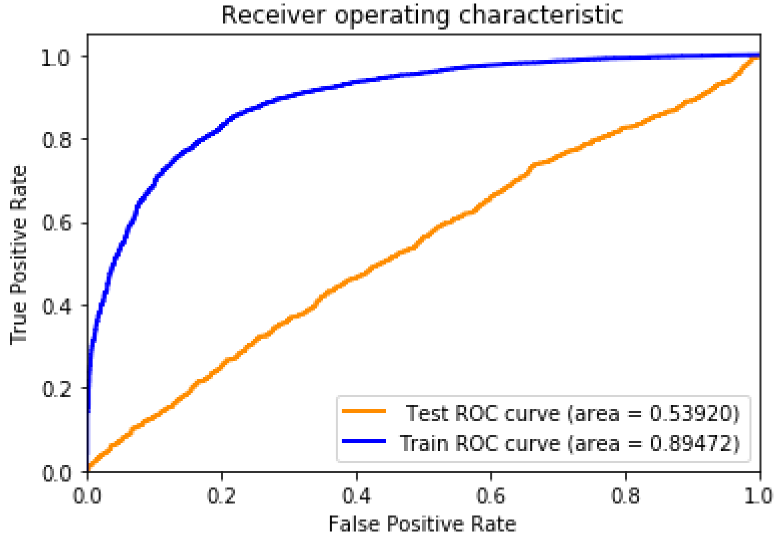
```
FNR = FalseNeg/(FalseNeg + TruePos)
print("TPR of the SVM - RBF KERNEL (W2V) for OPTIMAL C   is :  %f" % (T
PR))
print("FPR of the SVM - RBF KERNEL (W2V) for OPTIMAL C:  %f" % (FPR))
print("TNR of the SVM - RBF KERNEL (W2V) for OPTIMAL C :  %f" % (TNR))
print("FNR of the SVM - RBF KERNEL (W2V) for OPTIMAL C :  %f" % (FNR))
```

```
TPR of the SVM - RBF KERNEL (W2V) for OPTIMAL C   is :  0.893891
FPR of the SVM - RBF KERNEL (W2V) for OPTIMAL C:  0.842327
TNR of the SVM - RBF KERNEL (W2V) for OPTIMAL C :  0.157673
FNR of the SVM - RBF KERNEL (W2V) for OPTIMAL C :  0.106109
```

In [212]:

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc
fpr = dict()
tpr = dict()
roc_auc = dict()

fpr1 = dict()
tpr1 = dict()
roc_auc1 = dict()

#for i in range(26331):
for i in range(4):
    fpr[i], tpr[i], _ = roc_curve(y_test2,probs5)
    roc_auc[i] = auc(fpr[i], tpr[i])

#for i in range(61441):
for i in range(4):
    fpr1[i], tpr1[i], _ = roc_curve(y_train2,probs4)
    roc_auc1[i] = auc(fpr1[i], tpr1[i])

#print(roc_auc_score(y_test1,ompredictions_bow))
plt.figure()
#plt.plot(fpr[1], tpr[1])
lw = 2
plt.plot(fpr[0], tpr[0], color='darkorange',lw=lw, label=' Test ROC cur
ve (area = %0.5f)' % roc_auc[0])
plt.plot(fpr1[0], tpr1[0], color='blue',lw=lw, label='Train ROC curve
```

```
 (area = %0.5f)' % roc_auc1[0])
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc="lower right")
plt.title('Receiver operating characteristic')
plt.show()
```



Observations :

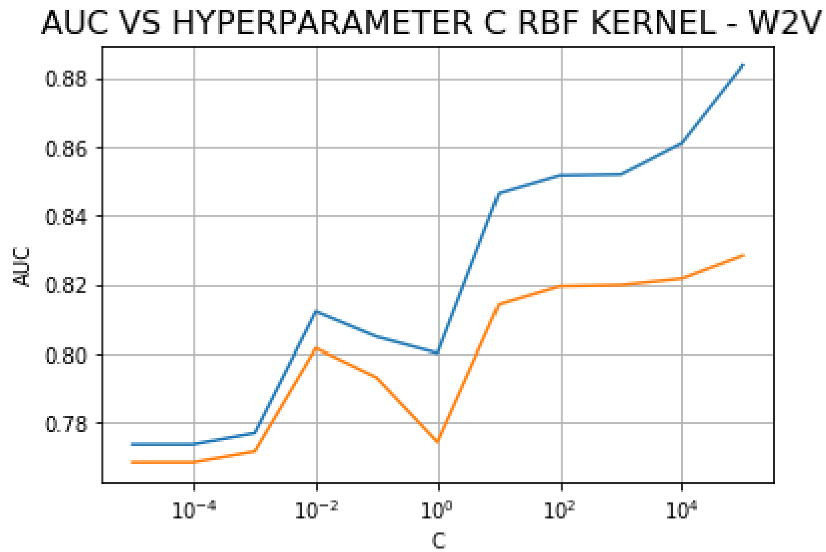
1) Even though the training score is high (0.8947) , the test score has been very less (0.5392)

2) This implies that the model has not been that efficient

TFIDF AVG W2V

In [213]:
```
train_auc_w2v1= model_w2vtfidf.cv_results_['mean_train_score']
```

```
cv_auc_w2v1=model_w2vtfidf.cv_results_['mean_test_score']
plt.plot(alpha,train_auc_w2v1)
plt.plot(alpha,cv_auc_w2v1)
plt.xlabel('C',size=10)
plt.ylabel('AUC',size=10)
plt.title('AUC VS HYPERPARAMETER C RBF KERNEL - W2V ',size=16)
plt.xscale('log')
plt.grid()
plt.show()
print("\n\n C Values :\n", alpha)
print("\n Train AUC for each c value is :\n ", np.round(train_auc_w2v1,
5))
print("\n CV AUC for each c value is :\n ", np.round(cv_auc_w2v1,5))
```




```
 C Values :
 [1e-05, 0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000, 100000]

 Train AUC for each c value is :
  [0.7737  0.7737  0.777   0.81216 0.80487 0.80015 0.84657 0.85173 0.85
202
 0.86113 0.88369]
```

```
CV AUC for each c value is :

 [0.76846 0.76846 0.77167 0.80159 0.79309 0.77435 0.81426 0.8195  0.81
984
 0.82173 0.82841]
```

In [214]:
```
max(cv_auc_w2v1) # Hence Optimal C = 100000
```

Out[214]:
```
0.828411680589382
```

In [215]:
```
om_w2vtfidf = SVC(C=100000, probability = True)
```

In [216]:
```
om_w2vtfidf.fit(g3_rbf, y_train2)
ompredictions_w2vtfidf  = om_w2vtfidf.predict(h3_rbf)
probs6 = om_w2vtfidf.predict_proba(g3_rbf)
probs7 = om_w2vtfidf.predict_proba(h3_rbf)
probs6= probs6[:, 1]
probs7 = probs7[:, 1]
precision_w2vtfidf = precision_score(y_test2, ompredictions_w2vtfidf, p
os_label = 1)
recall_w2vtfidf = recall_score(y_test2, ompredictions_w2vtfidf, pos_lab
el = 1)
f1score_w2vtfidf = f1_score(y_test2, ompredictions_w2vtfidf, pos_label
= 1)
print('\nThe Test Precision FOR RBF KERNEL SVM  (TFIDF AVGW2V) is %f' %
 (precision_w2vtfidf))
print('\nThe Test Recall FOR RBF KERNEL SVM  (TFIDF AVGW2V) is  %f' % (
recall_w2vtfidf))
print('\nThe Test F1-Score FOR RBF KERNEL SVM  (TFIDF AVGW2V) is  %f' %
 (f1score_w2vtfidf))
TrueNeg,FalseNeg,FalsePos, TruePos = confusion_matrix(y_test2, ompredic
tions_w2vtfidf).ravel()
TPR = TruePos/(FalseNeg + TruePos)
FPR = FalsePos/(TrueNeg + FalsePos)
TNR = TrueNeg/(TrueNeg + FalsePos)
FNR = FalseNeg/(FalseNeg + TruePos)
print("TPR of the RBF KERNEL SVM  (TFIDF AVG W2V) for alpha  is :  %f"
% (TPR))
```

```
print("FPR of the RBF KERNEL SVM (TFIDF AVGW2V) for alpha  is :  %f" %
(FPR))
print("TNR of the RBF KERNEL SVM (TFIDF AVGW2V) for alpha  is :  %f" %
(TNR))
print("FNR of the RBF KERNEL SVM (TFIDF AVGW2V) for alpha  is :  %f" %
(FNR))
```

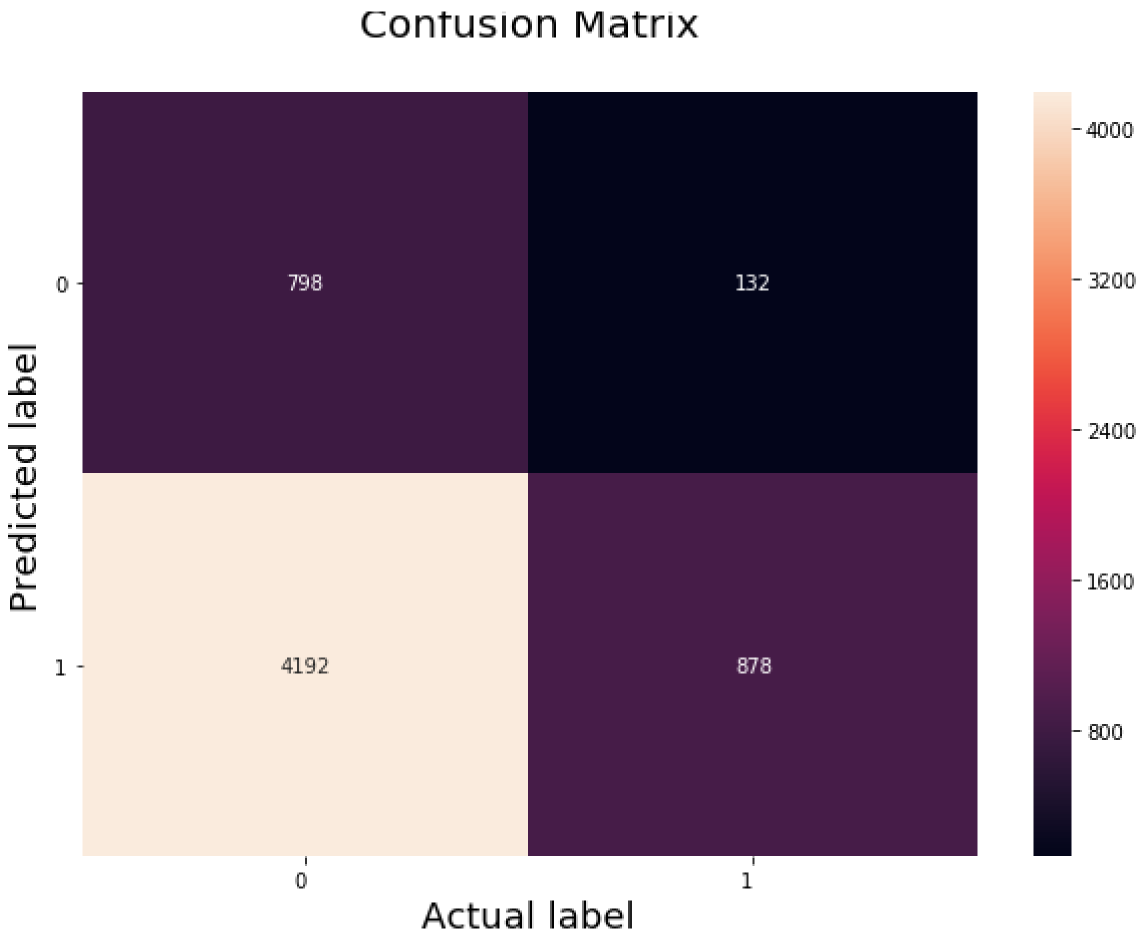
```
The Test Precision FOR RBF KERNEL SVM  (TFIDF AVGW2V) is 0.869307

The Test Recall FOR RBF KERNEL SVM  (TFIDF AVGW2V) is  0.173176


The Test F1-Score FOR RBF KERNEL SVM  (TFIDF AVGW2V) is  0.288816
TPR of the RBF KERNEL SVM  (TFIDF AVG W2V) for alpha  is :  0.869307
FPR of the RBF KERNEL SVM (TFIDF AVGW2V) for alpha  is :  0.840080
TNR of the RBF KERNEL SVM (TFIDF AVGW2V) for alpha  is :  0.159920
FNR of the RBF KERNEL SVM (TFIDF AVGW2V) for alpha  is :  0.130693
```

In [217]:

```
# Code for drawing seaborn heatmaps
class_names = [ 0,1]
df_heatmap = pd.DataFrame(confusion_matrix(y_test2, ompredictions_w2vtf
idf), index=class_names, columns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=10)#
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=10)
plt.ylabel('Predicted label',size=18)
plt.xlabel('Actual label',size=18)
plt.title("Confusion Matrix\n",size=20)
```

Out[217]:

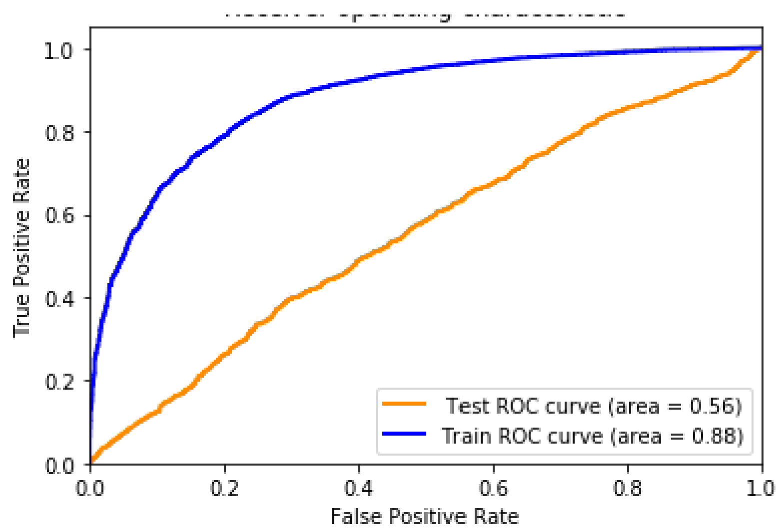
```
Text(0.5, 1.0, 'Confusion Matrix\n')
```



In [218]:
```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc
fpr = dict()
tpr = dict()
roc_auc = dict()

fpr1 = dict()
tpr1 = dict()
roc_auc1 = dict()

for i in range(4):
```

```
    fpr[i], tpr[i], _ = roc_curve(y_test2,probs7)
    roc_auc[i] = auc(fpr[i], tpr[i])


from tqdm import tqdm
for i in range(4):
    fpr1[i], tpr1[i], _ = roc_curve(y_train2,probs6)
    roc_auc1[i] = auc(fpr1[i], tpr1[i])


#print(roc_auc_score(y_test1,ompredictions_bow))
plt.figure()
#plt.plot(fpr[1], tpr[1])
lw = 2
plt.plot(fpr[0], tpr[0], color='darkorange',lw=lw, label=' Test ROC curve (area = %0.2f)' % roc_auc[0])
plt.plot(fpr1[0], tpr1[0], color='blue',lw=lw, label='Train ROC curve (area = %0.2f)' % roc_auc1[0])
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc="lower right")
plt.title('Receiver operating characteristic')
plt.show()
```

Receiver operating characteristic



Conclusions

In [225]:
```
res = pd.DataFrame()
```

In [226]:
```
model_names = ["Linear - KERNEL  SVM" , "Linear - KERNEL  SVM" ,"Linear - KERNEL  SVM" ,"Linear - KERNEL  SVM" ,"RBF - KERNEL SVM ","RBF - KERNEL SVM ","RBF - KERNEL SVM ","RBF - KERNEL SVM "]
vectorizer = ["BOW","TFIDF","AVG W2V","TFIDF AVGW2V"]*2
test_AUC = [0.946,0.9497,0.7334,0.70,0.892,0.8935,0.5392,0.56 ]
train_AUC = [0.958,0.9672,0.9025,0.88,0.917,0.917,0.8947, 0.88]
hyperparameter = ["alpha","alpha","alpha","alpha","C","C","C","C"]
Value = [0.0001,0.0001,0.001,0.001,100,100,100000,100000]
```

In [227]:
```
res['Vectorizer'] = vectorizer
res['Model '] = model_names
res['Hyperparameter'] = hyperparameter
res['Value'] = Value
res['Train_AUC'] = train_AUC
res['Test_AUC'] = test_AUC
```

In [228]:
```
res
```

Out[228]:

	Vectorizer	Model	Hyperparameter	Value	Train_AUC	Test_AUC
0	BOW	Linear - KERNEL SVM	alpha	0.0001	0.9580	0.9460
1	TFIDF	Linear - KERNEL SVM	alpha	0.0001	0.9672	0.9497
2	AVG W2V	Linear - KERNEL SVM	alpha	0.0010	0.9025	0.7334
3	TFIDF AVGW2V	Linear - KERNEL SVM	alpha	0.0010	0.8800	0.7000
4	BOW	RBF - KERNEL SVM	C	100.0000	0.9170	0.8920
5	TFIDF	RBF - KERNEL SVM	C	100.0000	0.9170	0.8935
6	AVG W2V	RBF - KERNEL SVM	C	100000.0000	0.8947	0.5392
7	TFIDF AVGW2V	RBF - KERNEL SVM	C	100000.0000	0.8800	0.5600

In [229]:
```
import tabulatehelper as th
```

DISPLAYING THE RESULTS IN TABULAR FORMAT

In [230]:
```
print(th.md_table(res, formats={-1: 'c'}))
```

```
| Vectorizer   | Model                | Hyperparameter   |       Value
|   Train_AUC |   Test_AUC |
|:-------------|:---------------------|:-----------------|------------:
|------------:|:----------:|
| BOW          | Linear - KERNEL  SVM | alpha            |      0.0001
|      0.958  |     0.946  |
| TFIDF        | Linear - KERNEL  SVM | alpha            |      0.0001
|      0.9672 |     0.9497 |
| AVG W2V      | Linear - KERNEL  SVM | alpha            |      0.001
|      0.9025 |     0.7334 |
| TFIDF AVGW2V | Linear - KERNEL  SVM | alpha            |      0.001
|      0.88   |     0.7    |
```

```
| BOW          | RBF - KERNEL SVM     | C                  |    100
|      0.917   |      0.892   |
| TFIDF        | RBF - KERNEL SVM     | C                  |    100
|      0.917   |      0.8935 |
| AVG W2V      | RBF - KERNEL SVM     | C                  | 100000
|      0.8947 |      0.5392 |
| TFIDF AVGW2V | RBF - KERNEL SVM     | C                  | 100000
|      0.88    |      0.56    |
```

Final Observations :

1) The best models have come through BOW and TFIDF. In TFIDF the test AUC has been slightly better when compared to BOW.

2) IN THE CASE OF Linear Kernel , among AVG W2V and TFIDF AVG W2V the AVG W2V has performed marginally better. However in the scenario of RBF- Kernel TFIDF AVG W2V has performed marginally better when compared to AVG W2V.

3) The important observation that has to be made is in the case of AVG W2V the test AUC has been 0.73 in Linear SVM. It has dropped to 0.54 in the case of RBF KERNEL SVM. The same is the case with TFIDF AVG W2V vectorizer too.

4) IN THE CASE OF TFIDF- AVG W2V, I HAVE NOT USED FEATURE ENGINEERING. Linear SVM performed better than the other one.

5) As suggested I have added length of preprocessed reviews as one more feature which has been contributed for more accuracy. However if i would have used more features like length of common words or something else, the results would have been different(my assumption)

6) In an overall perspective Linear Kernel performed better than RBF kernel in every vectoriser. However the point that needs to be noted is as I have taken few points for RBF kernel.

References

I have referred many links. However part of my code has been inspired from the following links

1) Applied AI Course

2) SKLEARN

3) STACK OVERFLOW - MANY