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 [101]:

```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
```

```python
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 [102]:

```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 500000 data points
# you can change the number to any other number based on your computing power

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

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000""", con)

# Give reviews with Score>3 a positive rating(1), and reviews with a score<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 (500000, 10)
```

Out[102]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	1	1303862400	Good Quality Dog Food
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	0	1346976000	Not as Advertised
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia	1	1	1	1219017600	"Delight" says it all

Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary

In [103]:

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

In [104]:

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

```
(80668, 7)
```

Out[104]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
0	#oc-R115TNMSPFT9I7	B005ZBZLT4	Breyton	1331510400	2	Overall its just OK when considering the price...	2
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 [105]:

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

Out[105]:

	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 [106]:

```
display['COUNT(*)'].sum()
```

Out[106]:

```
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 [107]:

```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
```

```
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[107]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summ
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACK QUADRAT VANI WAFE
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACK QUADRAT VANI WAFE
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACK QUADRAT VANI WAFE
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACK QUADRAT VANI WAFE
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACK QUADRAT VANI WAFE

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 [108]:

```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='qui
cksort', na_position='last')
```

In [109]:

```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', inpl
ace=False)
final.shape
```

Out[109]:

```
(348262, 10)
```

In [110]:

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

Out[110]:

```
69.6524
```

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 [111]:

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

display.head()
```

Out[111]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1	5	1224892800	Bought This for My Son at College
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2	4	1212883200	Pure cocoa taste with crunchy almonds inside

In [112]:

```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [113]:

```
#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()
```

```
(348260, 10)
```

Out[113]:

```
1    293516
0     54744
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 [114]:

```
# 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)
```

```
This book was purchased as a birthday gift for a 4 year old boy. He squealed with delight and hugg
ed it when told it was his to keep and he did not have to return it to the library.
==================================================
I've purchased both the Espressione Espresso (classic) and the 100% Arabica.  My vote is definitel
y with the 100% Arabica.  The flavor has more bite and flavor (much more like European coffee than
American).
==================================================
This is a great product. It is very healthy for all of our dogs, and it is the first food that the
y all love to eat. It helped my older dog lose weight and my 10 year old lab gain the weight he ne
eded to be healthy.
==================================================
I find everything I need at Amazon so I always look there first. Chocolate tennis balls for a tenn
is party, perfect! They were the size of malted milk balls. Unfortunately, they arrived 3 days aft
er the party. The caveat here is, not everything from Amazon may arrive at an impressive 2 or 3 da
ys. This shipment took 8 days from the Candy/Cosmetic Depot back east to southern California.
==================================================
```

In [115]:

```
# remove urls from text python: https://stackoverflow.com/a/40823105/4084039
sent_0 = re.sub(r"http\S+", "", sent_0)
sent_1000 = re.sub(r"http\S+", "", sent_1000)
sent_150 = re.sub(r"http\S+", "", sent_1500)
sent_4900 = re.sub(r"http\S+", "", sent_4900)

print(sent_0)
```

```
This book was purchased as a birthday gift for a 4 year old boy. He squealed with delight and hugg
ed it when told it was his to keep and he did not have to return it to the library.
```

In [116]:

```
# 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)
```

```
This book was purchased as a birthday gift for a 4 year old boy. He squealed with delight and hugg
ed it when told it was his to keep and he did not have to return it to the library.
==================================================
I've purchased both the Espressione Espresso (classic) and the 100% Arabica.  My vote is definitel
y with the 100% Arabica.  The flavor has more bite and flavor (much more like European coffee than
American).
==================================================
This is a great product. It is very healthy for all of our dogs, and it is the first food that the
y all love to eat. It helped my older dog lose weight and my 10 year old lab gain the weight he ne
eded to be healthy.
==================================================
I find everything I need at Amazon so I always look there first. Chocolate tennis balls for a tenn
is party, perfect! They were the size of malted milk balls. Unfortunately, they arrived 3 days aft
er the party. The caveat here is, not everything from Amazon may arrive at an impressive 2 or 3 da
ys. This shipment took 8 days from the Candy/Cosmetic Depot back east to southern California.
```

In [117]:

```
# 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 [118]:

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

```
This is a great product. It is very healthy for all of our dogs, and it is the first food that the
y all love to eat. It helped my older dog lose weight and my 10 year old lab gain the weight he ne
eded to be healthy.
==================================================
```

In [119]:

```
#remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
This book was purchased as a birthday gift for a  year old boy. He squealed with delight and hugge
d it when told it was his to keep and he did not have to return it to the library.
```

In [120]:

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

```
This is a great product It is very healthy for all of our dogs and it is the first food that they
all love to eat It helped my older dog lose weight and my 10 year old lab gain the weight he neede
d to be healthy
```

In [121]:

```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
# <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', 'ours', 'ourselves', 'you', "y
ou're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his',
'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them',
'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll",
'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', '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', 'how', 'all', 'any', 'both', 'e
ach', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', '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', "do
esn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn'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 [122]:

```
# 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%|████████████████████████████████████████████████████████████████████████| 348260/348260
[02:50<00:00, 2039.05it/s]
```

In [123]:

```
preprocessed_reviews[1500]
```

Out[123]:

```
'great product healthy dogs first food love eat helped older dog lose weight year old lab gain wei
ght needed healthy'
```

In [124]:

```
final['Cleaned_Text'] = preprocessed_reviews
```

[3.2] Preprocessing Review Summary

In [26]:

```
## Similartly you can do preprocessing for review summary also.
```

[4] Featurization

[4.1] BAG OF WORDS

In [0]:

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

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

```
some feature names  ['aa', 'aahhhs', 'aback', 'abandon', 'abates', 'abbott', 'abby', 'abdominal', 'abiding', 'ability']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (4986, 12997)
the number of unique words  12997
```

[4.2] Bi-Grams and n-Grams.

In [0]:

```
#bi-gram, tri-gram and n-gram

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

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

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

[4.3] TF-IDF

In [0]:

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

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

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

[4.4] Word2Vec

In [0]:

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

In [0]:

```
# Using Google News Word2Vectors

# in this project we are using a pretrained model by google
# its 3.3G file, once you load this into your memory
# it occupies ~9Gb, so please do this step only if you have >12G of ram
# we will provide a pickle file wich contains a dict ,
# and it contains all our courpus words as keys and  model[word] as values
# To use this code-snippet, download "GoogleNews-vectors-negative300.bin"
# from https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/edit
# it's 1.9GB in size.


# http://kavita-ganesan.com/gensim-word2vec-tutorial-starter-code/#.W17SRFAzZPY
# you can comment this whole cell
# or change these varible according to your need

is_your_ram_gt_16g=False
want_to_use_google_w2v = False
want_to_train_w2v = True

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

elif want_to_use_google_w2v and is_your_ram_gt_16g:
    if os.path.isfile('GoogleNews-vectors-negative300.bin'):
        w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors-negative300.bin', binary=Tr
ue)
        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_train_w2v = True, to train your
own w2v ")
```

```
[('snack', 0.9951335191726685), ('calorie', 0.9946465492248535), ('wonderful',
0.9946032166481018), ('excellent', 0.9944332838058472), ('especially', 0.9941144585609436),
('baked', 0.9940600395202637), ('salted', 0.994047224521637), ('alternative', 0.9937226176261902),
('tasty', 0.9936816692352295), ('healthy', 0.9936649799346924)]
==================================================
[('varieties', 0.9994194507598877), ('become', 0.9992934465408325), ('popcorn',
0.9992750883102417), ('de', 0.9992610216140747), ('miss', 0.9992451071739197), ('melitta',
0.999218761920929), ('choice', 0.9992102384567261), ('american', 0.9991837739944458), ('beef',
0.9991780519485474), ('finish', 0.9991567134857178)]
```

In [0]:

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

```
number of words that occured minimum 5 times  3817
sample words  ['product', 'available', 'course', 'total', 'pretty', 'stinky', 'right', 'nearby', '
used', 'ca', 'not', 'beat', 'great', 'received', 'shipment', 'could', 'hardly', 'wait', 'try', 'lo
ve', 'call', 'instead', 'removed', 'easily', 'daughter', 'designed', 'printed', 'use', 'car', 'win
dows', 'beautifully', 'shop', 'program', 'going', 'lot', 'fun', 'everywhere', 'like', 'tv',
'computer', 'really', 'good', 'idea', 'final', 'outstanding', 'window', 'everybody', 'asks',
'bought', 'made']
```

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

[4.4.1.1] Avg W2v

In [0]:

```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors = []; # the avg-w2v for each sentence/review is stored in this list
for sent in tqdm(list_of_sentance): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, 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%|██████████████████████████████████████████████████████████████████████████████| 4986/4986
[00:03<00:00, 1330.47it/s]
```

```
4986
50
```

[4.4.1.2] TFIDF weighted W2v

In [0]:

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
tf_idf_matrix = model.fit_transform(preprocessed_reviews)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [0]:

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

tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored 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/review
    for word in sent: # for each word in a review/sentence
```

```
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
#               tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors.append(sent_vec)
    row += 1
```

```
100%|██████████████████████████████████████████████████████████████████████████████| 4986/4986
[00:20<00:00, 245.63it/s]
```

[5] Assignment 5: Apply Logistic Regression

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

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

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

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

3. **Pertubation Test**

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

4. **Sparsity**

   - Calculate sparsity on weight vector obtained after using L1 regularization

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

5. **Feature importance**

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

6. **Feature engineering**

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

7. **Representation of results**

   - You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure.
   - Once after you found the best hyper parameter, you need to train your model with it, and find the AUC on test data and plot

- Once after you found the best hyper parameter, you need to train your model with it, and find the AUC on test data and plot the ROC curve on both train and test.
- Along with plotting ROC curve, you need to print the [confusion matrix] with predicted and original labels of test data points. Please visualize your confusion matrices using [seaborn heatmaps.]

8. **Conclusion**

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

Note: Data Leakage

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

Applying Logistic Regression

[5.1] Logistic Regression on BOW, SET 1

In [202]:

```
lr_po = final[final["Score"]==1].sample(n=35000)
lr_na = final[final["Score"]==0].sample(n=35000)
tot_lr = pd.concat([lr_po,lr_na])
tot_lr.shape
tot_lr.head(4)
```

Out[202]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	S
252256	273483	B0015IMYIM	A2WG8RNVSRKBI9	Kathrine "Kat's Korner"	3	3	1	1320537600	
66936	72771	B001ET5Y52	A1ZIX3J7TUO8D	Abby Simons	3	3	1	1297728000	
119743	129844	B000E1BXGU	A30LN6RVEMZ0L4	Linda Powell "lover of torrone candy"	1	1	1	1170374400	
324931	351677	B000Q0WUNO	A22U6LSEI2SRZA	ELS	2	2	1	1227139200	

In [203]:

```
# Sorting data based on time
tot_lr["Time"] = pd.to_datetime(tot_lr["Time"],unit ="s")
tot_lr = tot_lr.sort_values(by = "Time")
tot_lr.head(5)
```

Out[203]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	
138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	2	1	1999-10-25	This is sp
346116	374422	B00004CI84	A1048CYU0OV4O8	Judy L. Eans	2	2	1	2000-01-09	
417883	451903	B00004CXX9	A2DEE7F9XKP3ZR	jerome	0	1	1	2000-06-03	
346113	374419	B00004CI84	ADIDQRLLR4KBQ	"paradise_found"	2	2	1	2002-03-08	Mi &quot
138691	150509	0006641040	A3CMRKGE0P909G	Teresa	3	4	1	2002-04-10	A lea

In [204]:

```
x = tot_lr['Cleaned_Text'].values
y = tot_lr['Score'].values
print(x.shape , y.shape)
```

```
(70000,) (70000,)
```

In [205]:

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.linear_model import LogisticRegression

import matplotlib.pyplot as plt
```

In [206]:

```
x_tr,x_te,y_tr,y_te = train_test_split(x,y,test_size=0.2,random_state=42,shuffle = False)
x_tr,x_cv,y_tr,y_cv = train_test_split(x,y,test_size=0.2,random_state=42,shuffle = False)
print('='*50)
print(x_tr.shape,y_tr.shape)
print(x_te.shape,y_te.shape)
print(x_cv.shape,y_cv.shape)
print('='*50)
```

```
==================================================
(56000,) (56000,)
(14000,) (14000,)
(14000,) (14000,)
==================================================
```

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

In [207]:

```
vect = CountVectorizer()
vect.fit(x_tr)
x_tr_bow = vect.transform(x_tr)
x_cv_bow = vect.transform(x_cv)
x_te_bow = vect.transform(x_te)
print('='*50)
print(x_tr_bow.shape,y_tr.shape)
print(x_cv_bow.shape,y_cv.shape)
print(x_te_bow.shape,y_te.shape)
print('='*50)
```

```
==================================================
(56000, 46322) (56000,)
(14000, 46322) (14000,)
(14000, 46322) (14000,)
==================================================
```

In [208]:

```
#Standardizing the data
from sklearn.preprocessing import StandardScaler
sca = StandardScaler(with_mean=False)
sca.fit(x_tr_bow)
x_tr_bow = sca.transform(x_tr_bow)
x_cv_bow = sca.transform(x_cv_bow)
x_te_bow = sca.transform(x_te_bow)
print('='*50)
print(x_tr_bow.shape,y_tr.shape)
print(x_cv_bow.shape,y_cv.shape)
print(x_te_bow.shape,y_te.shape)
print('='*50)
```

```
==================================================
(56000, 46322) (56000,)
(14000, 46322) (14000,)
(14000, 46322) (14000,)
==================================================
```

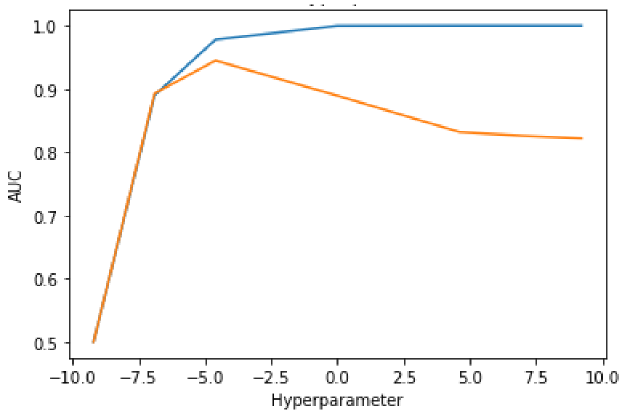
In [212]:

```
C = [10**-4,10**-3, 10**-2, 10**0, 10**2,10**3,10**4]
tr_auc = []
cv_auc = []
for c in tqdm(C):
    lr = LogisticRegression(penalty='l1',C=c,class_weight='balanced')
    lr.fit(x_tr_bow,y_tr)
    probtr = lr.predict_proba(x_tr_bow)[:,1]
    tr_auc.append(roc_auc_score(y_tr,probtr))
    probcv = lr.predict_proba(x_cv_bow)[:,1]
    cv_auc.append(roc_auc_score(y_cv,probcv))
optimal_c = C[cv_auc.index(max(cv_auc))]
C = [np.log(x) for x in C]
plt.plot(C,tr_auc,label="tr auc")
plt.plot(C,cv_auc,label="cv auc")
plt.title("AUC vs Hyperparameter")
plt.xlabel("Hyperparameter")
plt.ylabel("AUC")
print("optimal lambda : ",1//optimal_c)
```

```
100%|██████████████████████████████████████████████████| 7/7
[1:08:16<00:00, 916.73s/it]
```

```
optimal lambda :  99.0
```

AUC vs Hyperparameter



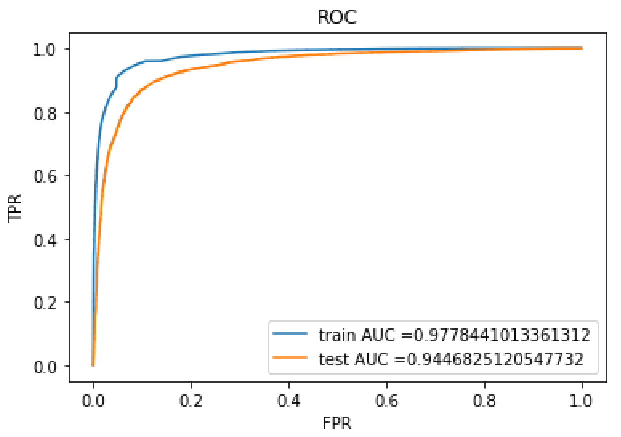
In [213]:

```
lr = LogisticRegression(penalty='l1',C=optimal_c,class_weight='balanced')
lr.fit(x_tr_bow,y_tr)
pred = lr.predict(x_te_bow)
# evaluate accuracy
acc = accuracy_score(y_te, pred) * 100
print('\nThe accuracy of the Logistic Regression C = %d is %f%%' % (1//optimal_c, acc))
```

```
The accuracy of the Logistic Regression C = 99 is 88.514286%
```

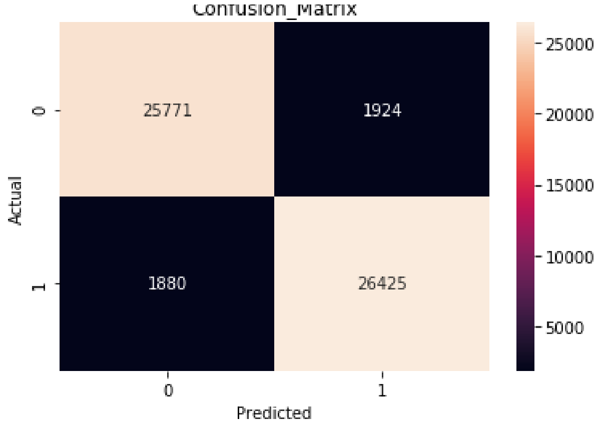
In [214]:

```
#plotting Auc
tr_fpr,tr_tpr,threshold = roc_curve(y_tr, lr.predict_proba(x_tr_bow)[:,1])
te_fpr,te_tpr,threshold = roc_curve(y_te, lr.predict_proba(x_te_bow)[:,1])
AUC = str(auc(te_fpr, te_tpr))
plt.plot(tr_fpr,tr_tpr,label="train AUC ="+str(auc(tr_fpr, tr_tpr)))
plt.plot(te_fpr,te_tpr,label="test AUC ="+str(auc(te_fpr, te_tpr)))
plt.legend()
plt.title("ROC")
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.show()
```



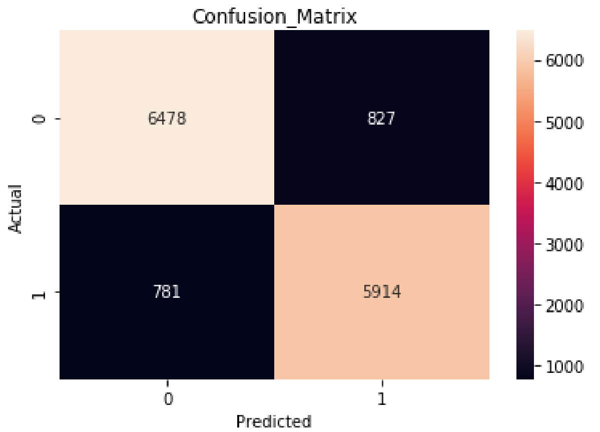
In [215]:

```
#Confusion Matrix for train
import seaborn as sb
con_matr = confusion_matrix(y_tr, lr.predict(x_tr_bow))
c_l = [0, 1] #Class Label
df_con_matr = pd.DataFrame(con_matr, index=c_l, columns=c_l)
sb.heatmap(df_con_matr, annot=True, fmt='d')
plt.title("Confusion_Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



In [216]:

```
#Confusion Matrix for test
import seaborn as sb
con_matr = confusion_matrix(y_te, lr.predict(x_te_bow))
c_l = [0, 1] #Class Label
df_con_matr = pd.DataFrame(con_matr, index=c_l, columns=c_l)
sb.heatmap(df_con_matr, annot=True, fmt='d')
plt.title("Confusion_Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



In [217]:

```
print('='*50)
print(classification_report(y_te, pred))
print('='*50)
```

```
==================================================
             precision    recall  f1-score   support

          0       0.89      0.89      0.89      7305
          1       0.88      0.88      0.88      6695

  micro avg       0.89      0.89      0.89     14000
  macro avg       0.88      0.89      0.88     14000
weighted avg      0.89      0.89      0.89     14000

==================================================
```

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

In [218]:

```
# Please write all the code with proper documentation
lr = LogisticRegression(penalty='l1',C=optimal_c,class_weight='balanced')
lr.fit(x_tr_bow,y_tr)
```

```
lr.fit(x_tr_bow,y_tr)
weight=lr.coef_
print('No of non zero element in weight vector ',np.count_nonzero(weight))
```

```
No of non zero element in weight vector  5684
```

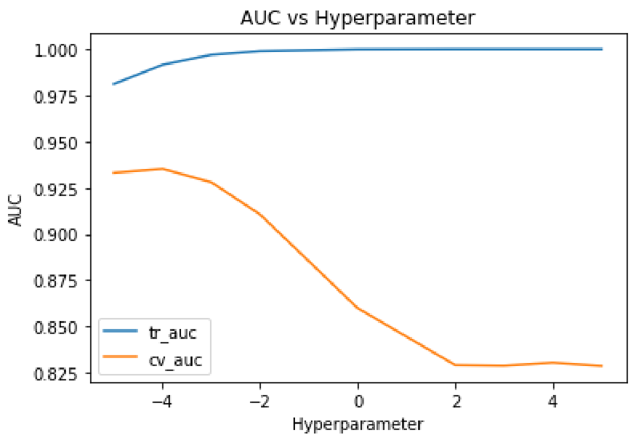
[5.1.2] Applying Logistic Regression with L2 regularization on BOW, SET 1

In [219]:

```
# Please write all the code with proper documentation
C = [10**-5,10**-4,10**-3, 10**-2, 10**0, 10**2,10**3,10**4,10**5]
tr_auc = []
cv_auc = []
for c in tqdm(C):
    lr = LogisticRegression(penalty='l2',C=c,class_weight='balanced')
    lr.fit(x_tr_bow,y_tr)
    probtr = lr.predict_proba(x_tr_bow)[:,1]
    tr_auc.append(roc_auc_score(y_tr,probtr))
    probcv = lr.predict_proba(x_cv_bow)[:,1]
    cv_auc.append(roc_auc_score(y_cv,probcv))
optimal_c1 = C[cv_auc.index(max(cv_auc))]
C = [np.log10(x) for x in C]
plt.plot(C,tr_auc,label="tr_auc")
plt.plot(C,cv_auc,label="cv_auc")
plt.legend()
plt.title("AUC vs Hyperparameter")
plt.xlabel("Hyperparameter")
plt.ylabel("AUC")
print("optimal lambda : ",1//optimal_c1)
```

```
100%|████████████████████████████████████████| 9/9 [04
:33<00:00, 43.38s/it]
```

```
optimal lambda :  9999.0
```



In [220]:

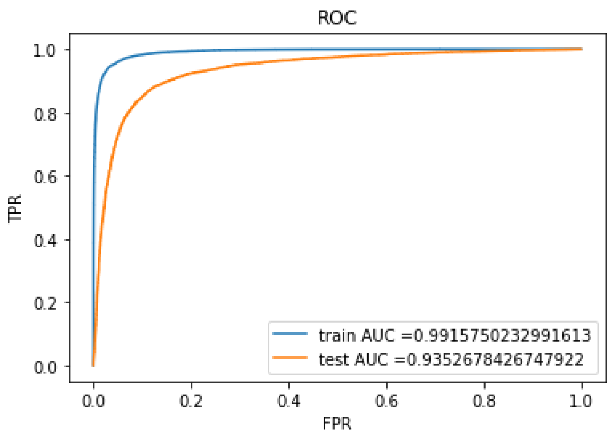
```
lr = LogisticRegression(penalty='l2',C=optimal_c1,class_weight='balanced')
lr.fit(x_tr_bow,y_tr)
pred1 = lr.predict(x_te_bow)
# evaluate accuracy
acc = accuracy_score(y_te, pred1) * 100
print('\nThe accuracy of the Logistic Regression C = %d is %f%%' % (1//optimal_c1, acc))
```

```
The accuracy of the Logistic Regression C = 9999 is 87.771429%
```

In [221]:

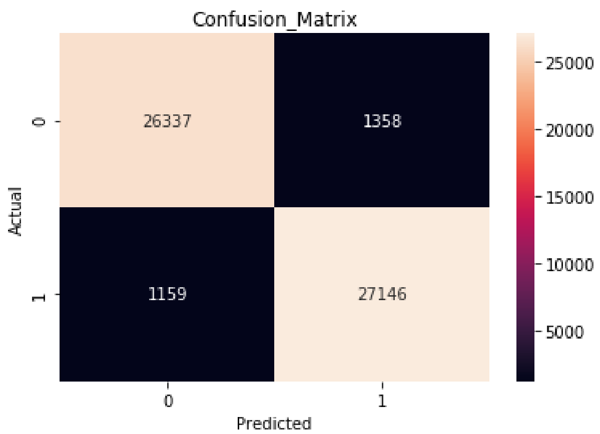
```
tr_fpr,tr_tpr,threshold = roc_curve(y_tr,lr.predict_proba(x_tr_bow)[:,1])
te_fpr,te_tpr,threshold = roc_curve(y_te,lr.predict_proba(x_te_bow)[:,1])
AUC1=str(auc(te_fpr, te_tpr))
plt.plot(tr_fpr,tr_tpr,label="train AUC ="+str(auc(tr_fpr, tr_tpr)))
```

```
plt.plot(te_fpr,te_tpr,label="test AUC ="+str(auc(te_fpr, te_tpr)))
plt.legend()
plt.title("ROC")
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.show()
```



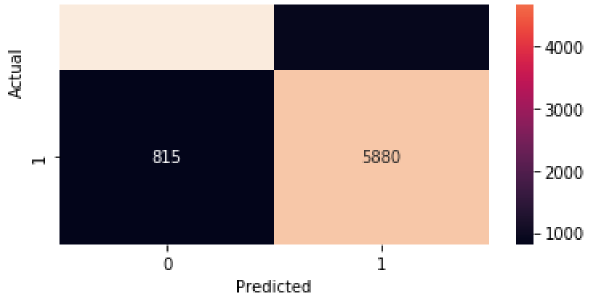
In [222]:

```
#Confusion Matrix for train
import seaborn as sb
con_matr = confusion_matrix(y_tr, lr.predict(x_tr_bow))
c_l = [0, 1] #Class Label
df_con_matr = pd.DataFrame(con_matr, index=c_l, columns=c_l)
sb.heatmap(df_con_matr, annot=True, fmt='d')
plt.title("Confusion_Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



In [223]:

```
#Confusion Matrix for test
import seaborn as sb
con_matr = confusion_matrix(y_te, lr.predict(x_te_bow))
c_l = [0, 1] #Class Label
df_con_matr = pd.DataFrame(con_matr, index=c_l, columns=c_l)
sb.heatmap(df_con_matr, annot=True, fmt='d')
plt.title("Confusion_Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



In [224]:

```
print('='*50)
print(classification_report(y_te, pred1))
print('='*50)
```

```
==================================================
              precision    recall  f1-score   support

           0       0.89      0.88      0.88      7305
           1       0.87      0.88      0.87      6695

   micro avg       0.88      0.88      0.88     14000
   macro avg       0.88      0.88      0.88     14000
weighted avg       0.88      0.88      0.88     14000

==================================================
```

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

In [225]:

```
# Please write all the code with proper documentation
We_be = lr.coef_
x_e = x_tr_bow
x_e.data = x_e.data+np.random.normal(0,0.001)
print(x_e.shape)
```

```
(56000, 46322)
```

In [226]:

```
#Training Lr
lr_e = LogisticRegression(penalty='l1',C=optimal_c,class_weight='balanced')
lr_e.fit(x_e,y_tr)
We_af = lr_e.coef_
#To eliminate divisible by zero error we will add 10^-6 to Weight_before and Weight_after
We_be += 10**-6
We_af += 10**-6

p_vec=[]
for i in range(len(We_be[0])):
    val = We_af[0][i]-We_be[0][i]
    val /= We_be[0][i]
    p_vec.append(val)

original_per_vec = np.absolute(p_vec)
p_vec=sorted(np.absolute(p_vec))[::-1]

#percentage change
p_vec[:10]
```

Out[226]:

```
[29.364702685432405,
 22.066013042518744,
 22.066013042518744,
 22.066013042518744,
 22.066013042518744,
```

```
 22.066013042518744,
 22.066013042518744,
 22.066013042518744,
 22.066013042518744,
 22.066013042518744]
```

In [227]:

```
#Percentiles from 0 to 100th
for s in range(0,11):
    print(str(s*10)+"th percentile = "+str(np.percentile(p_vec,s*10)))
```

```
0th percentile = 0.00028256006831533977
10th percentile = 0.9364269713213841
20th percentile = 0.9986728722891532
30th percentile = 0.9993818440897684
40th percentile = 0.9996255093844973
50th percentile = 0.999775303293422
60th percentile = 1.000248592578582
70th percentile = 1.0004128292189507
80th percentile = 1.0007182210827603
90th percentile = 1.0018071553663113
100th percentile = 29.364702685432405
```

In [228]:

```
#Percentile from 90 to 100
for s in range(90,101):
    print(str(s)+"th percentile = "+str(np.percentile(p_vec,s)))
```

```
90th percentile = 1.0018071553663113
91th percentile = 1.0021186455098101
92th percentile = 1.0025720619499299
93th percentile = 1.003254857445071
94th percentile = 1.0043982047783973
95th percentile = 1.006863088851542
96th percentile = 1.0132845970682403
97th percentile = 1.039137547973291
98th percentile = 1.1593004033838152
99th percentile = 1.6053075567334765
100th percentile = 29.364702685432405
```

In [229]:

```
#Percentile from 99 to 100
for s in range(1,11):
    print(str(99+(10**-1)*s)+"th percentile ="+str(np.percentile(p_vec,99+(10**-1)*s)))
```

```
99.1th percentile =1.7085578837845417
99.2th percentile =1.7930609590248925
99.3th percentile =1.8780741550542643
99.4th percentile =2.019763447602379
99.5th percentile =2.200622347947099
99.6th percentile =2.4083058751633537
99.7th percentile =2.7621027587201916
99.8th percentile =3.176125836958069
99.9th percentile =4.941550606497835
100.0th percentile =29.364702685432405
```

In [231]:

```
original_per_vec = original_per_vec.tolist()
a_f = vect.get_feature_names()
# for i in range(1,11):
#     indx=original_per_vec.index(np.percentile(p_vec,99.9+(10**-2)*i))
#     print(a_f[indx])
ind=original_per_vec.index(p_vec[0])
print(a_f[ind])
```

```
chipsoctober
```

[5.1.3] Feature Importance on BOW, SET 1

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

In [232]:

```
# Please write all the code with proper documentation
we = lr.coef_
p_index = np.argsort(we)[:,::-1]
for s in list(p_index[0][0:10]):
    print(a_f[s])
```

```
great
best
delicious
love
good
perfect
loves
excellent
highly
favorite
```

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

In [233]:

```
# Please write all the code with proper documentation
n_index = np.argsort(we)
for s in list(n_index[0][0:10]):
    print(a_f[s])
```

```
not
disappointed
worst
terrible
money
awful
bad
disappointing
horrible
waste
```

[5.2] Logistic Regression on TFIDF, SET 2

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

In [234]:

```
# Please write all the code with proper documentation
vect_tf = TfidfVectorizer(ngram_range=(1,2), min_df=10)
vect_tf.fit(x_tr)
x_tr_tfidf = vect_tf.transform(x_tr)
x_te_tfidf = vect_tf.transform(x_te)
x_cv_tfidf = vect_tf.transform(x_cv)
print(x_tr_tfidf.shape,y_tr.shape)
```

```
(56000, 33228) (56000,)
```

In [235]:

```
sca = StandardScaler(with_mean=False)
sca.fit(x_tr_tfidf)
x_tr_tfidf = sca.transform(x_tr_tfidf)
```

```
x_cv_tfidf = sca.transform(x_cv_tfidf)
x_te_tfidf = sca.transform(x_te_tfidf)
print('='*50)
print(x_tr_tfidf.shape,y_tr.shape)
print(x_cv_tfidf.shape,y_cv.shape)
print(x_te_tfidf.shape,y_te.shape)
print('='*50)
```

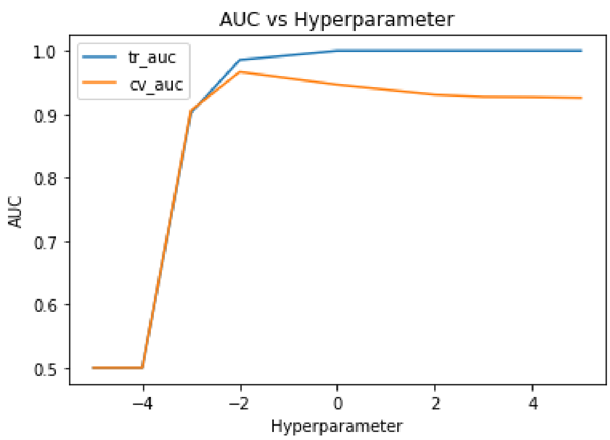
```
==================================================
(56000, 33228) (56000,)
(14000, 33228) (14000,)
(14000, 33228) (14000,)
==================================================
```

In [236]:

```
C = [10**-5,10**-4,10**-3, 10**-2, 10**0, 10**2,10**3,10**4,10**5]
tr_auc = []
cv_auc = []
for c in tqdm(C):
    lr = LogisticRegression(penalty='l1',C=c,class_weight='balanced')
    lr.fit(x_tr_tfidf,y_tr)
    probtr = lr.predict_proba(x_tr_tfidf)[:,1]
    tr_auc.append(roc_auc_score(y_tr,probtr))
    probcv = lr.predict_proba(x_cv_tfidf)[:,1]
    cv_auc.append(roc_auc_score(y_cv,probcv))
optimal_c2 = C[cv_auc.index(max(cv_auc))]
C = [np.log10(x) for x in C]
plt.plot(C,tr_auc,label="tr_auc")
plt.plot(C,cv_auc,label="cv_auc")
plt.legend()
plt.title("AUC vs Hyperparameter")
plt.xlabel("Hyperparameter")
plt.ylabel("AUC")
print("optimal lambda : ",1//optimal_c2)
```

```
100%|████████████████████████████████████████| 9/9 [00
:08<00:00,  1.07s/it]
```

```
optimal lambda :  99.0
```



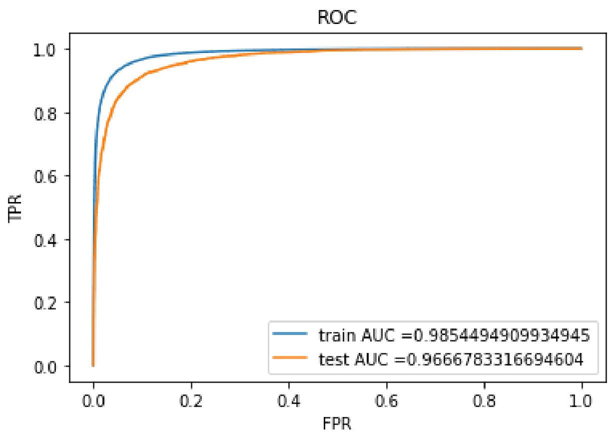
In [237]:

```
lr = LogisticRegression(penalty='l1',C=optimal_c2,class_weight='balanced')
lr.fit(x_tr_tfidf,y_tr)
pred2 = lr.predict(x_te_tfidf)
# evaluate accuracy
acc = accuracy_score(y_te, pred2) * 100
print('\nThe accuracy of the Logistic Regression C = %d is %f%%' % (1//optimal_c2, acc))
```

```
The accuracy of the Logistic Regression C = 99 is 90.592857%
```

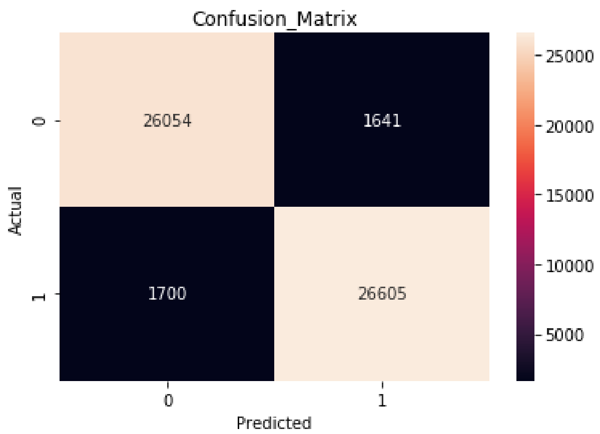
In [238]:

```
#plotting Auc
tr_fpr,tr_tpr,threshold = roc_curve(y_tr, lr.predict_proba(x_tr_tfidf)[:,1])
te_fpr,te_tpr,threshold = roc_curve(y_te, lr.predict_proba(x_te_tfidf)[:,1])
AUC2 = str(auc(te_fpr, te_tpr))
plt.plot(tr_fpr,tr_tpr,label="train AUC ="+str(auc(tr_fpr, tr_tpr)))
plt.plot(te_fpr,te_tpr,label="test AUC ="+str(auc(te_fpr, te_tpr)))
plt.legend()
plt.title("ROC")
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.show()
```



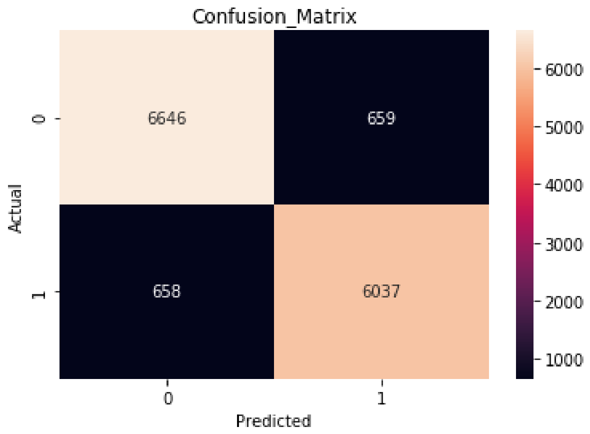
In [239]:

```
#Confusion Matrix for train
import seaborn as sb
con_matr = confusion_matrix(y_tr, lr.predict(x_tr_tfidf))
c_l = [0, 1] #Class Label
df_con_matr = pd.DataFrame(con_matr, index=c_l, columns=c_l)
sb.heatmap(df_con_matr, annot=True, fmt='d')
plt.title("Confusion_Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



In [240]:

```
#Confusion Matrix for test
import seaborn as sb
con_matr = confusion_matrix(y_te, lr.predict(x_te_tfidf))
c_l = [0, 1] #Class Label
df_con_matr = pd.DataFrame(con_matr, index=c_l, columns=c_l)
sb.heatmap(df_con_matr, annot=True, fmt='d')
plt.title("Confusion_Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



In [241]:

```
print('='*50)
print(classification_report(y_te, pred2))
print('='*50)
```

```
==================================================
              precision    recall  f1-score   support

           0       0.91      0.91      0.91      7305
           1       0.90      0.90      0.90      6695

   micro avg       0.91      0.91      0.91     14000
   macro avg       0.91      0.91      0.91     14000
weighted avg       0.91      0.91      0.91     14000

==================================================
```

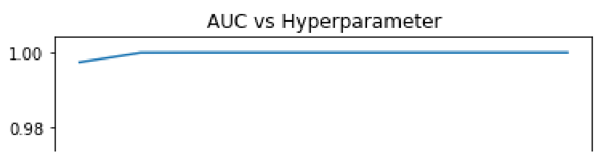
[5.2.2] Applying Logistic Regression with L2 regularization on TFIDF, SET 2

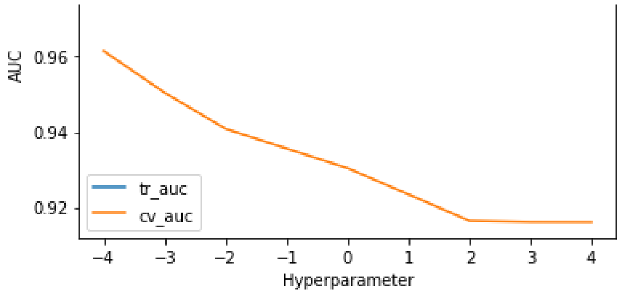
In [242]:

```
# Please write all the code with proper documentation
C = [10**-4,10**-3, 10**-2, 10**0, 10**2,10**3,10**4]
tr_auc = []
cv_auc = []
for c in tqdm(C):
    lr = LogisticRegression(penalty='l2',C=c,class_weight='balanced')
    lr.fit(x_tr_tfidf,y_tr)
    probtr = lr.predict_proba(x_tr_tfidf)[:,1]
    tr_auc.append(roc_auc_score(y_tr,probtr))
    probcv = lr.predict_proba(x_cv_tfidf)[:,1]
    cv_auc.append(roc_auc_score(y_cv,probcv))
optimal_c3 = C[cv_auc.index(max(cv_auc))]
C = [np.log10(x) for x in C]
plt.plot(C,tr_auc,label="tr_auc")
plt.plot(C,cv_auc,label="cv_auc")
plt.legend()
plt.title("AUC vs Hyperparameter")
plt.xlabel("Hyperparameter")
plt.ylabel("AUC")
print("optimal lambda : ",1//optimal_c3)
```

```
100%|████████████████████████████████████████████████████████████| 7/7 [00
:50<00:00,  8.37s/it]
```

```
optimal lambda :  9999.0
```





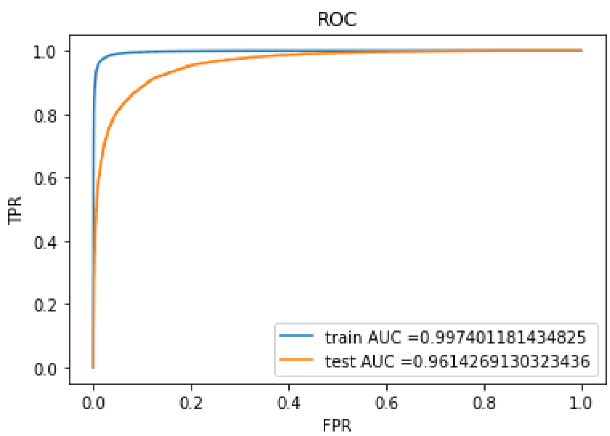
In [243]:

```
lr = LogisticRegression(penalty='l2',C=optimal_c3,class_weight='balanced')
lr.fit(x_tr_tfidf,y_tr)
pred3 = lr.predict(x_te_tfidf)
# evaluate accuracy
acc = accuracy_score(y_te, pred3) * 100
print('\nThe accuracy of the Logistic Regression C = %d is %f%%' % (1//optimal_c3, acc))
```

```
The accuracy of the Logistic Regression C = 9999 is 89.364286%
```

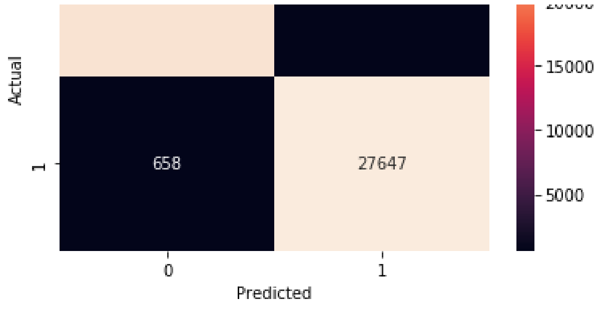
In [244]:

```
#plotting Auc
tr_fpr,tr_tpr,threshold = roc_curve(y_tr, lr.predict_proba(x_tr_tfidf)[:,1])
te_fpr,te_tpr,threshold = roc_curve(y_te, lr.predict_proba(x_te_tfidf)[:,1])
AUC3 = str(auc(te_fpr, te_tpr))
plt.plot(tr_fpr,tr_tpr,label="train AUC ="+str(auc(tr_fpr, tr_tpr)))
plt.plot(te_fpr,te_tpr,label="test AUC ="+str(auc(te_fpr, te_tpr)))
plt.legend()
plt.title("ROC")
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.show()
```



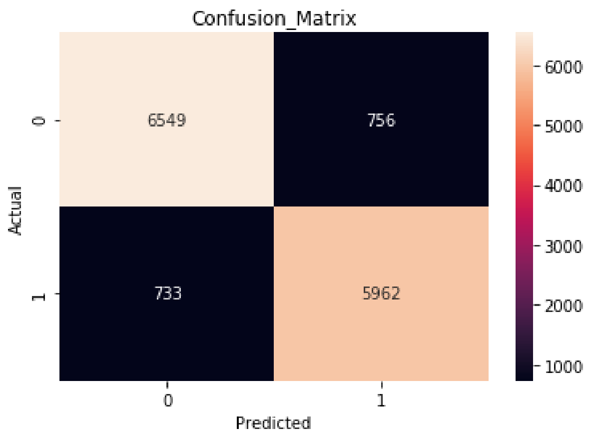
In [245]:

```
#Confusion Matrix for train
import seaborn as sb
con_matr = confusion_matrix(y_tr, lr.predict(x_tr_tfidf))
c_l = [0, 1] #Class Label
df_con_matr = pd.DataFrame(con_matr, index=c_l, columns=c_l)
sb.heatmap(df_con_matr, annot=True, fmt='d')
plt.title("Confusion_Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



In [246]:

```
#Confusion Matrix for test
import seaborn as sb
con_matr = confusion_matrix(y_te, lr.predict(x_te_tfidf))
c_l = [0, 1] #Class Label
df_con_matr = pd.DataFrame(con_matr, index=c_l, columns=c_l)
sb.heatmap(df_con_matr, annot=True, fmt='d')
plt.title("Confusion_Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



In [247]:

```
print('='*50)
print(classification_report(y_te,pred3))
print('='*50)
```

```
==================================================
              precision    recall  f1-score   support

           0       0.90      0.90      0.90      7305
           1       0.89      0.89      0.89      6695

   micro avg       0.89      0.89      0.89     14000
   macro avg       0.89      0.89      0.89     14000
weighted avg       0.89      0.89      0.89     14000

==================================================
```

[5.2.3] Feature Importance on TFIDF, SET 2

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

In [248]:

```
# Please write all the code with proper documentation
we = lr.coef_
p_index = np.argsort(we)[:,::-1]
for s in list(p_index[0][0:10]):
```

```
for s in list(p_index[0][0:10]):
    print(a_f[s])
```

```
earns
chihauhua
aspertame
gamja
dorothy
jolted
cornstarch
gene
radishy
crisis
```

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

In [249]:

```
# Please write all the code with proper documentation
n_index = np.argsort(we)
for s in list(n_index[0][0:10]):
    print(a_f[s])
```

```
homeowner
cited
huhm
hoped
rang
icebreakers
imparting
claim
parasites
reaffirmed
```

[5.3] Logistic Regression on AVG W2V, SET 3

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

In [250]:

```
# Please write all the code with proper documentation
i=0
list_of_sentance_tr=[]
for sentance in x_tr:
    list_of_sentance_tr.append(sentance.split())

# this line of code trains your w2v model on the give list of sentances
w2v_model=Word2Vec(list_of_sentance_tr,min_count=5,size=50, workers=4)

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

```
number of words that occured minimum 5 times  14919
sample words  ['remember', 'seeing', 'show', 'television', 'years', 'ago', 'child', 'sister',
'later', 'bought', 'day', 'thirty', 'something', 'used', 'series', 'books', 'student', 'teaching',
'turned', 'whole', 'school', 'purchasing', 'cd', 'along', 'children', 'tradition', 'lives', 'one',
'movie', 'collection', 'filled', 'comedy', 'action', 'whatever', 'else', 'want', 'call',
'getting', 'crazy', 'really', 'impossible', 'today', 'not', 'find', 'french', 'version', 'film', '
could', 'u', 'please']
```

In [251]:

```
##Train
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_tr = []; # the avg-w2v for each sentence/review is stored in this list
for sent in tqdm(list_of_sentance_tr): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need to change this
```

```
    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_tr.append(sent_vec)
print(len(sent_vectors_tr))
#print(sent_vectors_tr[0])

##CV
i=0
list_of_sentance_cv = []
for sentance in x_cv:
    list_of_sentance_cv.append(sentance.split())
sent_vectors_cv=[];# the avg-w2v for each sentence/review in CV is stored in this list
for sent in tqdm(list_of_sentance_cv): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, 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_cv.append(sent_vec)
print(len(sent_vectors_cv))
#print(sent_vectors_cv[0])

##Test
i=0
list_of_sentance_te = []
for sentance in x_te:
    list_of_sentance_te.append(sentance.split())
sent_vectors_te = []; # the avg-w2v for each sentence/review is stored in this list
for sent in tqdm(list_of_sentance_te): # 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_te.append(sent_vec)
print(len(sent_vectors_te))
#print(sent_vectors_te[0])
```

```
100%|██████████████████████████████████████████████████| 56000/56000 [02:
11<00:00, 425.27it/s]
```

```
56000
```

```
100%|██████████████████████████████████████████████████| 14000/14000 [00:
34<00:00, 403.09it/s]
```

```
14000
```

```
100%|██████████████████████████████████████████████████| 14000/14000 [00:
34<00:00, 402.54it/s]
```

```
14000
```

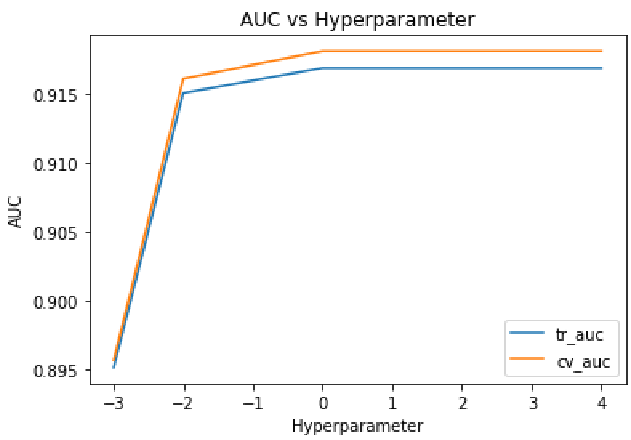
In [252]:

```python
# Please write all the code with proper documentation
x_tr_w2v = sent_vectors_tr
x_cv_w2v = sent_vectors_cv
x_te_w2v = sent_vectors_te

C = [10**-3, 10**-2, 10**0, 10**2,10**3,10**4]
tr_auc = []
cv_auc = []
for c in tqdm(C):
    lr = LogisticRegression(penalty='l1',C=c,class_weight='balanced')
    lr.fit(x_tr_w2v,y_tr)
    probtr = lr.predict_proba(x_tr_w2v)[:,1]
    tr_auc.append(roc_auc_score(y_tr,probtr))
    probcv = lr.predict_proba(x_cv_w2v)[:,1]
    cv_auc.append(roc_auc_score(y_cv,probcv))
optimal_c4 = C[cv_auc.index(max(cv_auc))]
C = [np.log10(x) for x in C]
plt.plot(C,tr_auc,label="tr_auc")
plt.plot(C,cv_auc,label="cv_auc")
plt.legend()
plt.title("AUC vs Hyperparameter")
plt.xlabel("Hyperparameter")
plt.ylabel("AUC")
print("optimal lambda : ",1//optimal_c4)
```

```
100%|██████████████████████████████████████████████████████████| 6/6 [00
:14<00:00,  2.65s/it]
```

```
optimal lambda :  0
```



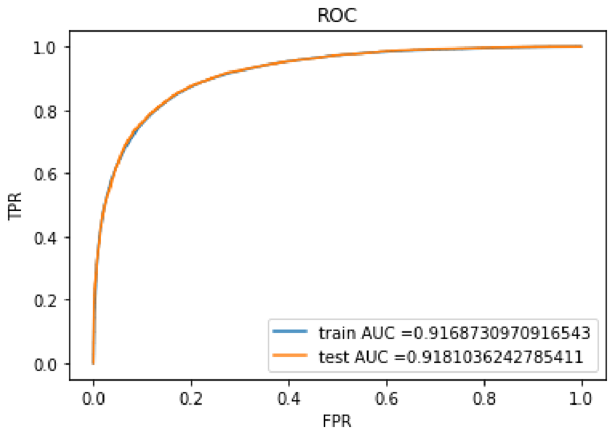
In [253]:

```python
lr = LogisticRegression(penalty='l1',C=optimal_c4,class_weight='balanced')
lr.fit(x_tr_w2v,y_tr)
pred4 = lr.predict(x_te_w2v)
# evaluate accuracy
acc = accuracy_score(y_te, pred4) * 100
print('\nThe accuracy of the Logistic Regression C = %d is %f%%' % (optimal_c4, acc))
```

```
The accuracy of the Logistic Regression C = 1000 is 83.950000%
```

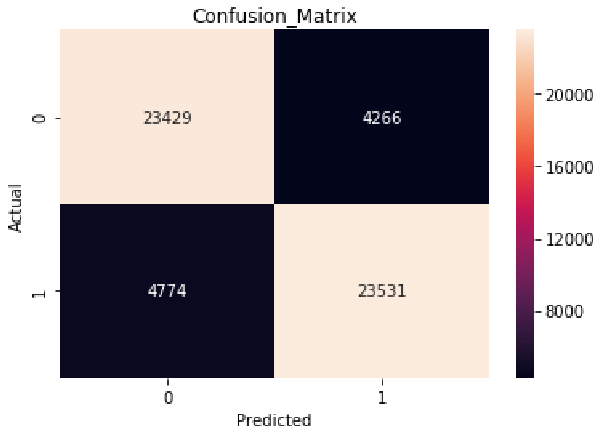
In [254]:

```python
#plotting Auc
tr_fpr,tr_tpr,threshold = roc_curve(y_tr, lr.predict_proba(x_tr_w2v)[:,1])
te_fpr,te_tpr,threshold =  roc_curve(y_te, lr.predict_proba(x_te_w2v)[:,1])
AUC4 = str(auc(te_fpr, te_tpr))
plt.plot(tr_fpr,tr_tpr,label="train AUC ="+str(auc(tr_fpr, tr_tpr)))
plt.plot(te_fpr,te_tpr,label="test AUC ="+str(auc(te_fpr, te_tpr)))
plt.legend()
plt.title("ROC")
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.show()
```



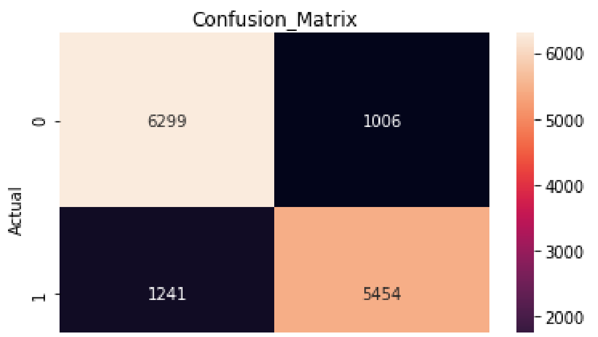
In [255]:

```
#Confusion Matrix for train
import seaborn as sb
con_matr = confusion_matrix(y_tr, lr.predict(x_tr_w2v))
c_l = [0, 1] #Class Label
df_con_matr = pd.DataFrame(con_matr, index=c_l, columns=c_l)
sb.heatmap(df_con_matr, annot=True, fmt='d')
plt.title("Confusion_Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



In [256]:

```
#Confusion Matrix for test
import seaborn as sb
con_matr = confusion_matrix(y_te, lr.predict(x_te_w2v))
c_l = [0, 1] #Class Label
df_con_matr = pd.DataFrame(con_matr, index=c_l, columns=c_l)
sb.heatmap(df_con_matr, annot=True, fmt='d')
plt.title("Confusion_Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



In [257]:

```
print('='*50)
print(classification_report(y_te, pred4))
print('='*50)
```

```
==================================================
              precision    recall  f1-score   support

           0       0.84      0.86      0.85      7305
           1       0.84      0.81      0.83      6695

   micro avg       0.84      0.84      0.84     14000
   macro avg       0.84      0.84      0.84     14000
weighted avg       0.84      0.84      0.84     14000

==================================================
```

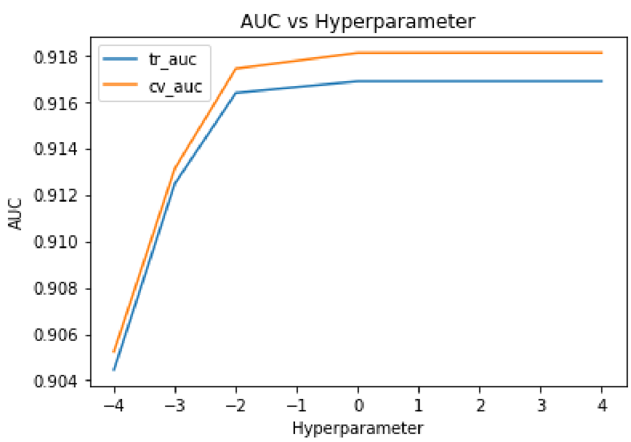
[5.3.2] Applying Logistic Regression with L2 regularization on AVG W2V, SET 3

In [258]:

```
# Please write all the code with proper documentation
C = [10**-4,10**-3, 10**-2, 10**0, 10**2,10**3,10**4]
tr_auc = []
cv_auc = []
for c in tqdm(C):
    lr = LogisticRegression(penalty='l2',C=c,class_weight='balanced')
    lr.fit(x_tr_w2v,y_tr)
    probtr = lr.predict_proba(x_tr_w2v)[:,1]
    tr_auc.append(roc_auc_score(y_tr,probtr))
    probcv = lr.predict_proba(x_cv_w2v)[:,1]
    cv_auc.append(roc_auc_score(y_cv,probcv))
optimal_c5 = C[cv_auc.index(max(cv_auc))]
C = [np.log10(x) for x in C]
plt.plot(C,tr_auc,label="tr_auc")
plt.plot(C,cv_auc,label="cv_auc")
plt.legend()
plt.title("AUC vs Hyperparameter")
plt.xlabel("Hyperparameter")
plt.ylabel("AUC")
print("optimal lambda : ",1//optimal_c5)
```

```
100%|████████████████████████████████████████████████████████████| 7/7 [00
:07<00:00,  1.23s/it]
```

```
optimal lambda :  0
```



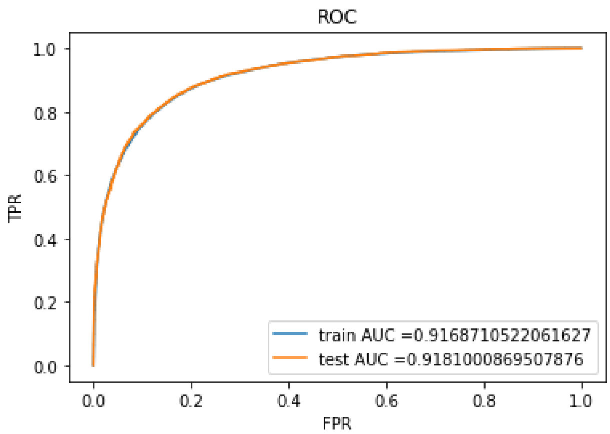
In [259]:

```
lr = LogisticRegression(penalty='l2',C=optimal_c5,class_weight='balanced')
lr.fit(x_tr_w2v,y_tr)
pred5 = lr.predict(x_te_w2v)
# evaluate accuracy
acc = accuracy_score(y_te, pred5) * 100
print('\nThe accuracy of the Logistic Regression C = %d is %f%%' % (optimal_c5, acc))
```

```
The accuracy of the Logistic Regression C = 100 is 83.942857%
```

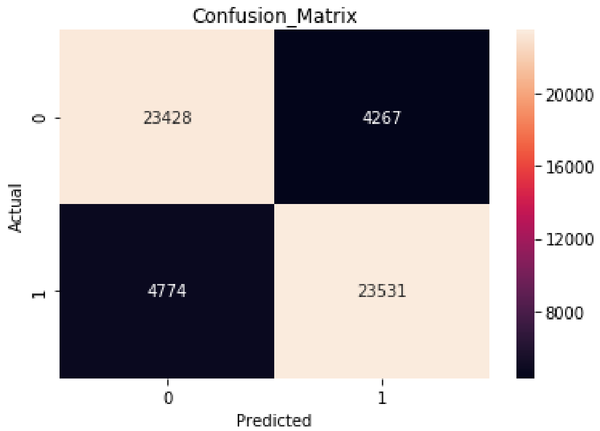
In [260]:

```
#plotting Auc
tr_fpr,tr_tpr,threshold = roc_curve(y_tr, lr.predict_proba(x_tr_w2v)[:,1])
te_fpr,te_tpr,threshold =  roc_curve(y_te, lr.predict_proba(x_te_w2v)[:,1])
AUC5 = str(auc(te_fpr, te_tpr))
plt.plot(tr_fpr,tr_tpr,label="train AUC ="+str(auc(tr_fpr, tr_tpr)))
plt.plot(te_fpr,te_tpr,label="test AUC ="+str(auc(te_fpr, te_tpr)))
plt.legend()
plt.title("ROC")
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.show()
```



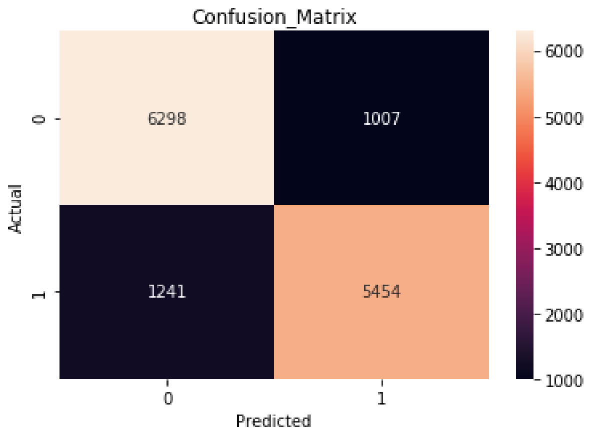
In [261]:

```
#Confusion Matrix for train
import seaborn as sb
con_matr = confusion_matrix(y_tr, lr.predict(x_tr_w2v))
c_l = [0, 1] #Class Label
df_con_matr = pd.DataFrame(con_matr, index=c_l, columns=c_l)
sb.heatmap(df_con_matr, annot=True, fmt='d')
plt.title("Confusion_Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



In [262]:

```
#Confusion Matrix for test
import seaborn as sb
con_matr = confusion_matrix(y_te, lr.predict(x_te_w2v))
c_l = [0, 1] #Class Label
df_con_matr = pd.DataFrame(con_matr, index=c_l, columns=c_l)
sb.heatmap(df_con_matr, annot=True, fmt='d')
plt.title("Confusion_Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



In [263]:

```
print('='*50)
print(classification_report(y_te, pred5))
print('='*50)
```

```
==================================================
              precision    recall  f1-score   support

           0       0.84      0.86      0.85      7305
           1       0.84      0.81      0.83      6695

   micro avg       0.84      0.84      0.84     14000
   macro avg       0.84      0.84      0.84     14000
weighted avg       0.84      0.84      0.84     14000

==================================================
```

[5.4] Logistic Regression on TFIDF W2V, SET 4

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

In [264]:

```
# Please write all the code with proper documentation
model = TfidfVectorizer()
tf_idf_matrix = model.fit_transform(x_tr)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [265]:

```
##train
i=0
list_of_sentance_tr=[]
for sentance in x_tr:
    list_of_sentance_tr.append(sentance.split())

# TF-IDF weighted Word2Vec
```

```
tfidf_feat = vect_tf.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

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

##cv
i=0
list_of_sentance_cv=[]
for sentance in x_cv:
    list_of_sentance_cv.append(sentance.split())

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

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

##test
i=0
list_of_sentance_te=[]
for sentance in x_te:
    list_of_sentance_te.append(sentance.split())

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

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

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

```
100%|████████████████████████████████████████████████████████████| 56000/56000 [24:55<00:00, 37.44it/s]
100%|████████████████████████████████████████████████████████████| 14000/14000 [06:14<00:00, 37.34it/s]
100%|████████████████████████████████████████████████████████████| 14000/14000 [06:14<00:00, 37.36it/s]
```

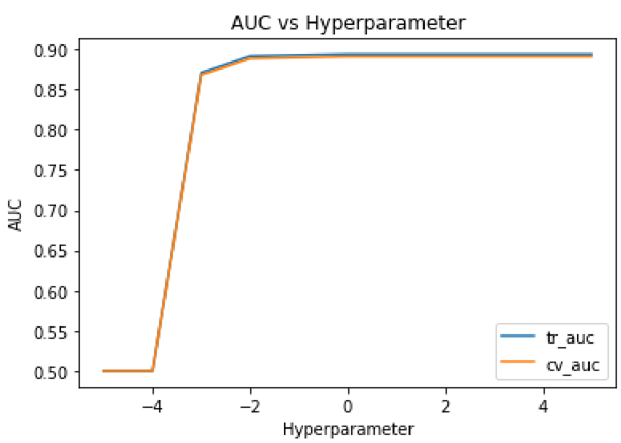
In [266]:

```
x_tr_tfw2v = tfidf_sent_vectors_tr
x_cv_tfw2v = tfidf_sent_vectors_cv
x_te_tfw2v = tfidf_sent_vectors_te

C = [10**-5,10**-4,10**-3, 10**-2, 10**0, 10**2,10**3,10**4,10**5]
tr_auc = []
cv_auc = []
for c in tqdm(C):
    lr = LogisticRegression(penalty='l1',C=c,class_weight='balanced')
    lr.fit(x_tr_tfw2v,y_tr)
    probtr = lr.predict_proba(x_tr_tfw2v)[:,1]
    tr_auc.append(roc_auc_score(y_tr,probtr))
    probcv = lr.predict_proba(x_cv_tfw2v)[:,1]
    cv_auc.append(roc_auc_score(y_cv,probcv))
optimal_c6 = C[cv_auc.index(max(cv_auc))]
C = [np.log10(x) for x in C]
plt.plot(C,tr_auc,label="tr_auc")
plt.plot(C,cv_auc,label="cv_auc")
plt.legend()
plt.title("AUC vs Hyperparameter")
plt.xlabel("Hyperparameter")
plt.ylabel("AUC")
print("optimal lambda : ",1//optimal_c6)
```

```
100%|██████████████████████████████████████████████████████████████████| 9/9 [00:18<00:00,  2.76s/it]
```

```
optimal lambda :  0
```



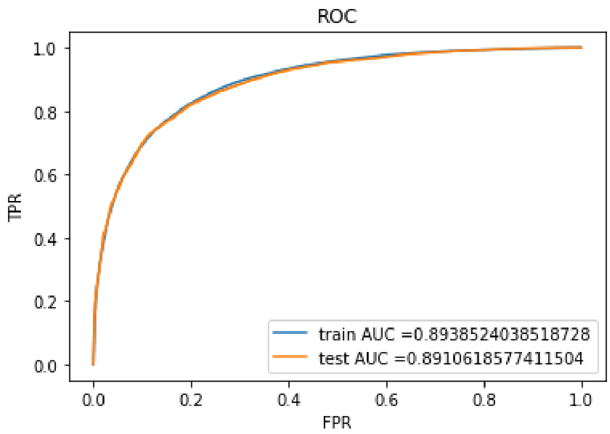
In [267]:

```
lr = LogisticRegression(penalty='l1',C=optimal_c6,class_weight='balanced')
lr.fit(x_tr_tfw2v,y_tr)
pred6 = lr.predict(x_te_tfw2v)
# evaluate accuracy
acc = accuracy_score(y_te, pred6) * 100
print('\nThe accuracy of the Logistic Regression C = %d is %f%%' % (optimal_c6, acc))
```

```
The accuracy of the Logistic Regression C = 1000 is 80.985714%
```

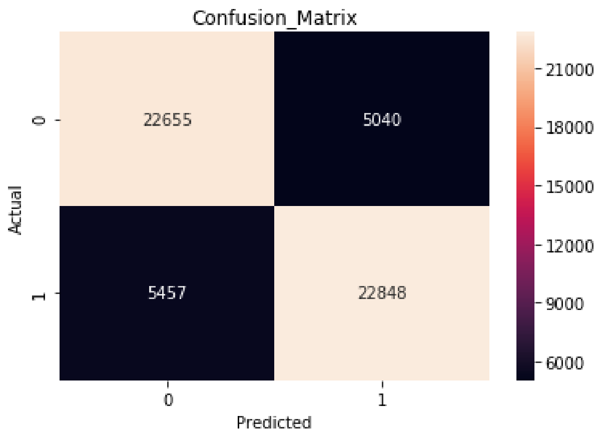
In [268]:

```
#plotting Auc
tr_fpr,tr_tpr,threshold = roc_curve(y_tr, lr.predict_proba(x_tr_tfw2v)[:,1])
te_fpr,te_tpr,threshold =  roc_curve(y_te, lr.predict_proba(x_te_tfw2v)[:,1])
AUC6 = str(auc(te_fpr, te_tpr))
plt.plot(tr_fpr,tr_tpr,label="train AUC ="+str(auc(tr_fpr, tr_tpr)))
plt.plot(te_fpr,te_tpr,label="test AUC ="+str(auc(te_fpr, te_tpr)))
plt.legend()
plt.title("ROC")
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.show()
```



In [269]:

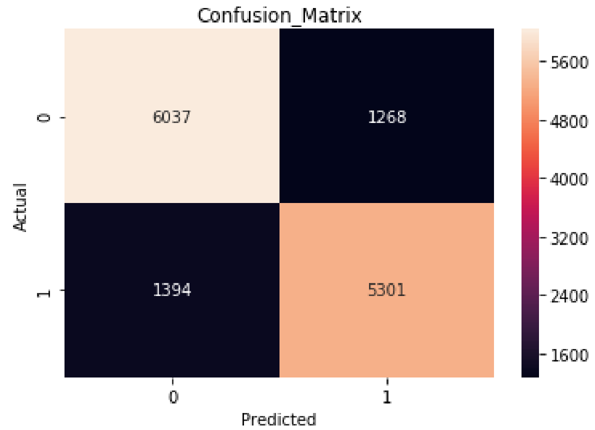
```
#Confusion Matrix for train
import seaborn as sb
con_matr = confusion_matrix(y_tr, lr.predict(x_tr_tfw2v))
c_l = [0, 1] #Class Label
df_con_matr = pd.DataFrame(con_matr, index=c_l, columns=c_l)
sb.heatmap(df_con_matr, annot=True, fmt='d')
plt.title("Confusion_Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



In [270]:

```
#Confusion Matrix for test
import seaborn as sb
con_matr = confusion_matrix(y_te, lr.predict(x_te_tfw2v))
c_l = [0, 1] #Class Label
df_con_matr = pd.DataFrame(con_matr, index=c_l, columns=c_l)
sb.heatmap(df_con_matr, annot=True, fmt='d')
plt.title("Confusion_Matrix")
plt.xlabel("Predicted")
```

```
plt.ylabel("Actual")
plt.show()
```



In [271]:

```
print('='*50)
print(classification_report(y_te, pred6))
print('='*50)
```

```
==================================================
              precision    recall  f1-score   support

           0       0.81      0.83      0.82      7305
           1       0.81      0.79      0.80      6695

   micro avg       0.81      0.81      0.81     14000
   macro avg       0.81      0.81      0.81     14000
weighted avg       0.81      0.81      0.81     14000

==================================================
```

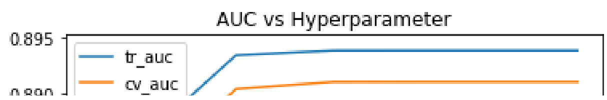
[5.4.2] Applying Logistic Regression with L2 regularization on TFIDF W2V, SET 4

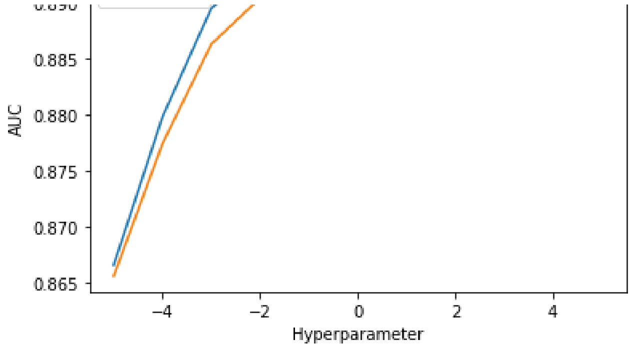
In [272]:

```
C = [10**-5,10**-4,10**-3, 10**-2, 10**0, 10**2,10**3,10**4,10**5]
tr_auc = []
cv_auc = []
for c in tqdm(C):
    lr = LogisticRegression(penalty='l2',C=c,class_weight='balanced')
    lr.fit(x_tr_tfw2v,y_tr)
    probtr = lr.predict_proba(x_tr_tfw2v)[:,1]
    tr_auc.append(roc_auc_score(y_tr,probtr))
    probcv = lr.predict_proba(x_cv_tfw2v)[:,1]
    cv_auc.append(roc_auc_score(y_cv,probcv))
optimal_c7 = C[cv_auc.index(max(cv_auc))]
C = [np.log10(x) for x in C]
plt.plot(C,tr_auc,label="tr_auc")
plt.plot(C,cv_auc,label="cv_auc")
plt.legend()
plt.title("AUC vs Hyperparameter")
plt.xlabel("Hyperparameter")
plt.ylabel("AUC")
print("optimal lambda : ",1//optimal_c7)
```

```
100%|████████████████████████████████████████████████████████████████████████████████| 9/9 [00
:10<00:00,  1.38s/it]
```

```
optimal lambda :  0
```





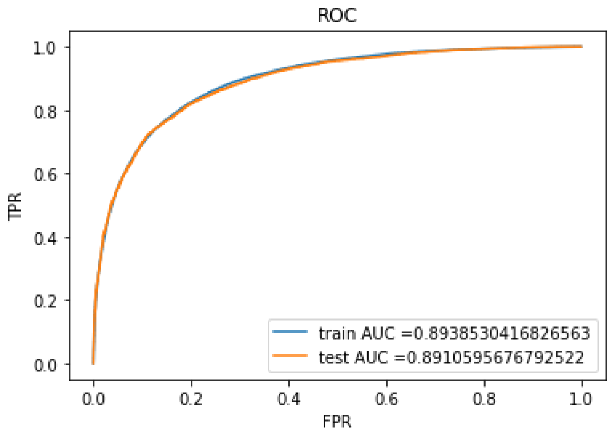
In [273]:

```
lr = LogisticRegression(penalty='l2',C=optimal_c7,class_weight='balanced')
lr.fit(x_tr_tfw2v,y_tr)
pred7 = lr.predict(x_te_tfw2v)
# evaluate accuracy
acc = accuracy_score(y_te, pred7) * 100
print('\nThe accuracy of the Logistic Regression C = %d is %f%%' % (1//optimal_c7, acc))
```

```
The accuracy of the Logistic Regression C = 0 is 80.992857%
```

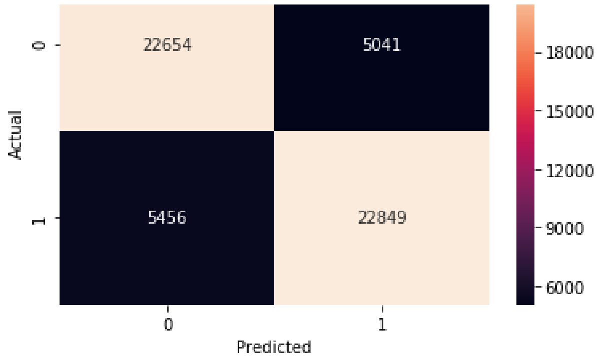
In [274]:

```
#plotting Auc
tr_fpr,tr_tpr,threshold = roc_curve(y_tr, lr.predict_proba(x_tr_tfw2v)[:,1])
te_fpr,te_tpr,threshold =  roc_curve(y_te, lr.predict_proba(x_te_tfw2v)[:,1])
AUC7 = str(auc(te_fpr, te_tpr))
plt.plot(tr_fpr,tr_tpr,label="train AUC ="+str(auc(tr_fpr, tr_tpr)))
plt.plot(te_fpr,te_tpr,label="test AUC ="+str(auc(te_fpr, te_tpr)))
plt.legend()
plt.title("ROC")
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.show()
```



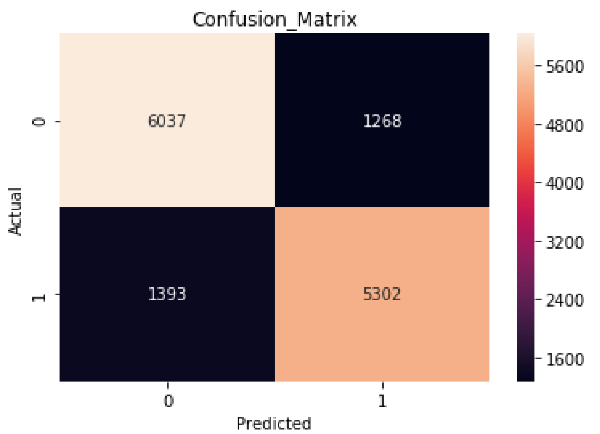
In [275]:

```
#Confusion Matrix for train
import seaborn as sb
con_matr = confusion_matrix(y_tr, lr.predict(x_tr_tfw2v))
c_l = [0, 1] #Class Label
df_con_matr = pd.DataFrame(con_matr, index=c_l, columns=c_l)
sb.heatmap(df_con_matr, annot=True, fmt='d')
plt.title("Confusion_Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



In [276]:

```
#Confusion Matrix for train
import seaborn as sb
con_matr = confusion_matrix(y_te, lr.predict(x_te_tfw2v))
c_l = [0, 1] #Class Label
df_con_matr = pd.DataFrame(con_matr, index=c_l, columns=c_l)
sb.heatmap(df_con_matr, annot=True, fmt='d')
plt.title("Confusion_Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



In [277]:

```
print('='*50)
print(classification_report(y_te, pred7))
print('='*50)
```

```
==================================================
              precision    recall  f1-score   support

           0       0.81      0.83      0.82      7305
           1       0.81      0.79      0.80      6695

   micro avg       0.81      0.81      0.81     14000
   macro avg       0.81      0.81      0.81     14000
weighted avg       0.81      0.81      0.81     14000

==================================================
```

[6] Conclusions

In [284]:

```
# Please compare all your models using Prettytable library
from prettytable import PrettyTable
comparison = PrettyTable()
comparison.field_names = ["Vectorizer", "Regularization", "Hyperparameter", "AUC"]
```

```
comparison.add_row(["BOW", 'L1', optimal_c, np.round(float(AUC),3)])
comparison.add_row(["TFIDF", 'L1', optimal_c2, np.round(float(AUC2),3)])
comparison.add_row(["AVG W2V", 'L1', 1/optimal_c4, np.round(float(AUC4),3)])
comparison.add_row(["Weighted W2V", 'L1', 1/optimal_c6,np.round(float(AUC6),3)])
comparison.add_row(["BOW", 'L2', optimal_c1, np.round(float(AUC1),3)])
comparison.add_row(["TFIDF", 'L2', optimal_c3, np.round(float(AUC3),3)])
comparison.add_row(["AVG W2V", 'L2', 1/optimal_c5, np.round(float(AUC5),3)])
comparison.add_row(["Weighted W2V", 'L2', 1/optimal_c7, np.round(float(AUC7),3)])
print(comparison)
```

```
+--------------+----------------+----------------+-------+
|  Vectorizer  | Regularization | Hyperparameter |  AUC  |
+--------------+----------------+----------------+-------+
|     BOW      |       L1       |      0.01      | 0.945 |
|    TFIDF     |       L1       |      0.01      | 0.967 |
|   AVG W2V    |       L1       |     0.001      | 0.918 |
| Weighted W2V |       L1       |     0.001      | 0.891 |
|     BOW      |       L2       |     0.0001     | 0.935 |
|    TFIDF     |       L2       |     0.0001     | 0.961 |
|   AVG W2V    |       L2       |      0.01      | 0.918 |
| Weighted W2V |       L2       |     0.0001     | 0.891 |
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