Amazon Fine Food Reviews Analysis

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

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

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

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

Attribute Information:

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

Objective:

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

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

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

[1]. Reading Data

[1.1] Loading the data

The dataset is available in two forms

1. .csv file
2. SQLite Database

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

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

In [1]:

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


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

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

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

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

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

from tqdm import tqdm
import os
```

```
C:\ProgramData\Anaconda3\lib\site-packages\gensim\utils.py:1209: UserWarning: detected Windows; al
iasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

In [2]:

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

Out[2]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	1	130386240(

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	1	134697600
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	1	121901760

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

In [5]:

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

Out[5]:

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

In [6]:

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

Out[6]:

```
393063
```

[2] Exploratory Data Analysis

[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	HelpfulnessDenominator	Score	Ti
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577(
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577(
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577(
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577(
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577(

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	HelpfulnessDenominator	Score	Ti
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1	5	1224892
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2	4	1212883

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 ver
y hard to find any chicken products made in the USA but they are out there, but this one isnt.  It
s too bad too because 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 were 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 smell. 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 these without
worrying about him over eating. Amazon's price was much more reasonable than any other retailer. Y
ou can buy a 1 pound bag on Amazon for almost the same price as a 6 ounce bag at other retailers.
It's definitely 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/40823105/4084039
```

```
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)
```

```
My dogs loves this chicken but its a product from China, so we wont be buying it anymore.  Its ver
y hard to find any chicken products made in the USA but they are out there, but this one isnt.  It
s too bad too because 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 ver
y hard to find any chicken products made in the USA but they are out there, but this one isnt.  It
s too bad too because 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 were 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 smell. 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 these without
worrying about him over eating. Amazon's price was much more reasonable than any other retailer. Y
ou can buy a 1 pound bag on Amazon for almost the same price as a 6 ounce bag at other retailers.
It's definitely worth it to buy a big bag if your dog eats them a lot.
```

In [17]:

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

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

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

```
    return phrase
```

In [18]:

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

```
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/18082370/4084039
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 ver
y hard to find any chicken products made in the USA but they are out there, but this one isnt.  It
s too bad too because 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', '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 [22]:

```
# Combining all the above stundents
```

```python
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
[00:39<00:00, 2243.20it/s]
```

In [23]:

```python
preprocessed_reviews[1500]
```

Out[23]:

```
'way hot blood took bite jig lol'
```

[3.2] Preprocessing Review Summary

In [24]:

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

[4] Featurization

Processing Texts from summary

In [25]:

```python
preprocessed_reviews_summary = []
# tqdm is for printing the status bar
for sentance in tqdm(final['Summary'].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_summary.append(sentance.strip())
```

```
 37%|██████████████████████████████                                                  | 32626/87773
[00:09<00:16, 3360.64it/s]C:\ProgramData\Anaconda3\lib\site-packages\bs4\__init__.py:219:
UserWarning: "b'...'" looks like a filename, not markup. You should probably open this file and pa
ss the filehandle into Beautiful Soup.
  ' Beautiful Soup.' % markup)
 70%|████████████████████████████████████████████████████████                        | 61151/87773
[00:18<00:07, 3353.85it/s]C:\ProgramData\Anaconda3\lib\site-packages\bs4\__init__.py:219:
UserWarning: "b'...'" looks like a filename, not markup. You should probably open this file and pa
ss the filehandle into Beautiful Soup.
  ' Beautiful Soup.' % markup)
 75%|████████████████████████████████████████████████████████████                    | 65519/87773 [00:19
<00:06, 3350.67it/s]C:\ProgramData\Anaconda3\lib\site-packages\bs4\__init__.py:219: UserWarning: "
b'...'" looks like a filename, not markup. You should probably open this file and pass the filehan
dle into Beautiful Soup.
  ' Beautiful Soup.' % markup)
 96%|█████████████████████████████████████████████████████████████████████████████   | 84251/87773
[00:25<00:01, 3402.73it/s]C:\ProgramData\Anaconda3\lib\site-packages\bs4\__init__.py:219:
UserWarning: "b'...'" looks like a filename, not markup. You should probably open this file and pa
ss the filehandle into Beautiful Soup.
  ' Beautiful Soup.' % markup)
```

```
100%|██████████████████████████████████████████████████████████████████████████| 87773/87773
[00:26<00:00, 3321.50it/s]
```

Including Texts from summary in the main text

In [26]:

```python
preprocessed_reviews_fe = []
for i in tqdm(range(0,len(preprocessed_reviews_summary))):
    preprocessed_reviews_fe.append(preprocessed_reviews_summary[i]+" "+ preprocessed_reviews[i])
```

```
100%|████████████████████████████████████████████████████████████████████████| 87773/87773
[00:00<00:00, 757548.59it/s]
```

Adding length of text as a feature

In [27]:

```python
preprocessed_reviews_fe_final = []
for i in tqdm(preprocessed_reviews_fe):
    count = 0;
    for j in i.split(" "):
        count += 1;
    i = i + " " + str(count);
    preprocessed_reviews_fe_final.append(i)
```

```
100%|████████████████████████████████████████████████████████████████████████| 87773/87773
[00:00<00:00, 119730.31it/s]
```

Test - Train Split

In [108]:

```python
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(preprocessed_reviews_fe_final, final['Score'],
test_size=0.33) # this is random splitting
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.33) # this is random
splitting
```

[4.1] BAG OF WORDS

In [109]:

```python
count_vect = CountVectorizer( min_df = 10) #in scikit-learn

X_train_vect = count_vect.fit_transform(X_train)
X_train_vect = X_train_vect.toarray()
X_cv_vect = count_vect.transform(X_cv)
X_cv_vect = X_cv_vect.toarray()
X_test_vect = count_vect.transform(X_test)
X_test_vect = X_test_vect.toarray()
```

[4.2] Bi-Grams and n-Grams.

[4.3] TF-IDF

In [110]:

```python
tf_idf = TfidfVectorizer(min_df = 10)
X_train_vect_tfidf = tf_idf.fit_transform(X_train)
```

```
X_train_vect_tfidf = tf_idf.fit_transform(X_train)
X_train_vect_tfidf = X_train_vect_tfidf.toarray()
X_test_vect_tfidf = tf_idf.transform(X_test)
X_test_vect_tfidf = X_test_vect_tfidf.toarray()
X_cv_vect_tfidf = tf_idf.transform(X_cv)
X_cv_vect_tfidf = X_cv_vect_tfidf.toarray()
```

[4.4] Word2Vec

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

[4.4.1.1] Avg W2v

In [31]:

```
# average Word2Vec
# compute average word2vec for each review.
i=0
list_of_sent=[]
X_train_list=[]
X_test_list=[]
X_cv_list=[]
for sent in X_train:
    X_train_list.append(sent.split())

for sent in X_cv:
    X_cv_list.append(sent.split())

for sent in X_test:
    X_test_list.append(sent.split())

w2v_model=Word2Vec(X_train_list,min_count=0,size=50, workers=4)
w2v_words = list(w2v_model.wv.vocab)

X_train_vectors = [];
for sent in tqdm(X_train_list):
    sent_vec = np.zeros(50)
    cnt_words =0;
    for word in sent:
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    X_train_vectors.append(sent_vec)


X_cv_vectors = []
for sent in tqdm(X_cv_list):
    sent_vec = np.zeros(50)
    cnt_words =0;
    for word in sent:
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    X_cv_vectors.append(sent_vec)

X_test_vectors = []
for sent in tqdm(X_test_list):
    sent_vec = np.zeros(50)
    cnt_words =0;
    for word in sent:
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
```

```
    X_test_vectors.append(sent_vec)
```

```
100%|██████████████████████████████████████████████████████████████████████████| 39400/39400 [01:
56<00:00, 339.06it/s]
100%|██████████████████████████████████████████████████████████████████████████| 19407/19407 [01:
09<00:00, 280.37it/s]
100%|██████████████████████████████████████████████████████████████████████████| 28966/28966 [01:
43<00:00, 279.84it/s]
```

[4.4.1.2] TFIDF weighted W2v

In [32]:

```
dictionary = dict(zip(tf_idf.get_feature_names(), list(tf_idf.idf_)))
tfidf_feat = tf_idf.get_feature_names()
tfidf_X_train_vectors = [];
tfidf_X_test_vectors = [];
tfidf_X_cv_vectors = [];

for sent in tqdm(X_train_list):
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in (w2v_words and tfidf_feat):
            vec = w2v_model.wv[word]
            tf_idf_count = dictionary[word]*sent.count(word)
            sent_vec += (vec * tf_idf_count)
            weight_sum += tf_idf_count
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_X_train_vectors.append(sent_vec)

for sent in tqdm(X_test_list):
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in (w2v_words and tfidf_feat):
            vec = w2v_model.wv[word]
            tf_idf_count = dictionary[word]*sent.count(word)
            sent_vec += (vec * tf_idf_count)
            weight_sum += tf_idf_count
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_X_test_vectors.append(sent_vec)

for sent in tqdm(X_cv_list):
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in (w2v_words and tfidf_feat):
            vec = w2v_model.wv[word]
            tf_idf_count = dictionary[word]*sent.count(word)
            sent_vec += (vec * tf_idf_count)
            weight_sum += tf_idf_count
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_X_cv_vectors.append(sent_vec)
```

```
100%|██████████████████████████████████████████████████████████████████████████| 39400/39400 [02:
48<00:00, 234.37it/s]
100%|██████████████████████████████████████████████████████████████████████████| 28966/28966 [01:
58<00:00, 244.23it/s]
100%|██████████████████████████████████████████████████████████████████████████| 19407/19407 [01:
18<00:00, 247.00it/s]
```

[5] Assignment 7: SVM

1. **Apply SVM 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. **Procedure**

   - You need to work with 2 versions of SVM
     - Linear kernel
     - RBF kernel
   - When you are working with linear kernel, use SGDClassifier' with hinge loss because it is computationally less expensive.
   - When you are working with 'SGDClassifier' with hinge loss and trying to find the AUC score, you would have to use CalibratedClassifierCV
   - Similarly, like kdtree of knn, when you are working with RBF kernel it's better to reduce the number of dimensions. You can put min_df = 10, max_features = 500 and consider a sample size of 40k points.

3. **Hyper paramter tuning (find best alpha in range [10^-4 to 10^4], and the best penalty among 'l1', 'l2')**

   - 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

4. **Feature importance**

   - When you are working on the linear kernel with BOW or TFIDF please print the top 10 best features for each of the positive and negative classes.

5. **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.

6. **Representation of results**

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

7. **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 SVM

[5.1] Linear SVM

[5.1.1] Applying Linear SVM on BOW, SET 1

Gridsearch CV

In [33]:

```
# Please write all the code with proper documentation
from sklearn.linear_model import SGDClassifier
from sklearn.grid_search import GridSearchCV
from sklearn.calibration import CalibratedClassifierCV

lnr_svm = SGDClassifier()
tuned_parameters = [{'alpha': [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]}]
alpha_list = [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]
#Using GridSearchCV
model = GridSearchCV(SGDClassifier(loss = 'hinge'), tuned_parameters, scoring = 'roc_auc')
model.fit(X_train_vect, y_train)

print(model.best_estimator_)
print(model.score(X_test_vect, y_test))
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\cross_validation.py:41: DeprecationWarning: Thi
s module was deprecated in version 0.18 in favor of the model_selection module into which all the
refactored classes and functions are moved. Also note that the interface of the new CV iterators a
re different from that of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\grid_search.py:42: DeprecationWarning: This mod
ule was deprecated in version 0.18 in favor of the model_selection module into which all the
refactored classes and functions are moved. This module will be removed in 0.20.
  DeprecationWarning)
```

```
SGDClassifier(alpha=0.01, average=False, class_weight=None, epsilon=0.1,
       eta0=0.0, fit_intercept=True, l1_ratio=0.15,
       learning_rate='optimal', loss='hinge', max_iter=None, n_iter=None,
       n_jobs=1, penalty='l2', power_t=0.5, random_state=None,
       shuffle=True, tol=None, verbose=0, warm_start=False)
0.9490865012742677
```

Simple CV

In [34]:

```
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_auc_score
alpha_list = [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]
ind = []
train_auc = []
cv_auc = []
for i in tqdm(alpha_list):
    lnr_svm = SGDClassifier(loss = 'hinge',alpha =i)
    cg_cv = CalibratedClassifierCV(base_estimator = lnr_svm)
    cg_cv.fit(X_train_vect, y_train)
    ind.append(i)
    y_train_pred =  cg_cv.predict_proba(X_train_vect)[:,1]
    y_cv_pred =  cg_cv.predict_proba(X_cv_vect)[:,1]
    train_auc.append(roc_auc_score(y_train,y_train_pred))
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
```

```
100%|██████████████████████████████████████████████████████████████████████████████████| 9/9 [04
:00<00:00, 27.35s/it]
```

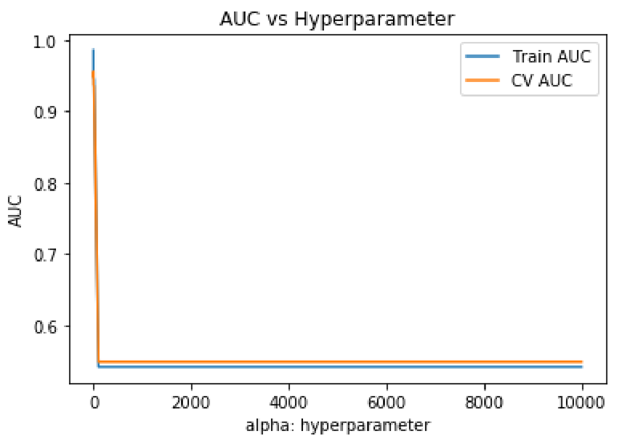
Plots

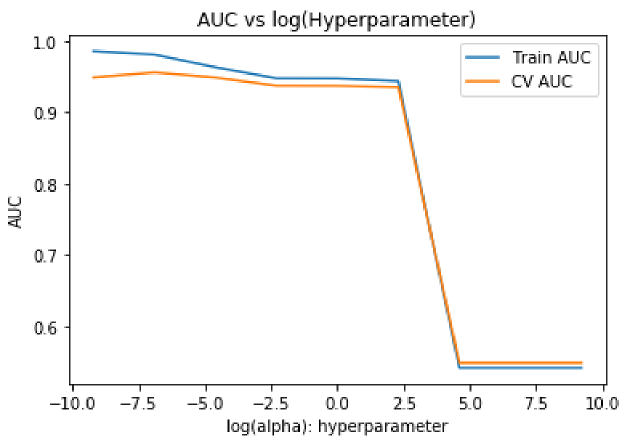
In [35]:

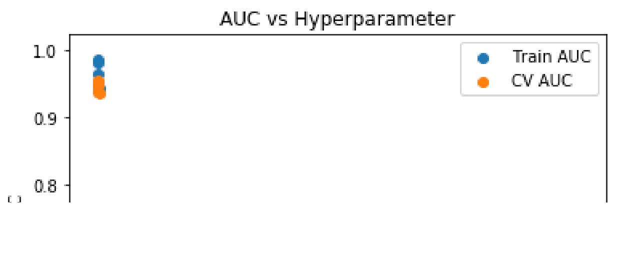
```
optimal_alpha_auc = ind[cv_auc.index(max(cv_auc))]
print('\nThe optimal alpha is (according to auc curve (max auc)): ' , optimal_alpha_auc)

plt.plot(alpha_list, train_auc, label='Train AUC')
plt.plot(alpha_list, cv_auc, label='CV AUC')
plt.legend()
```

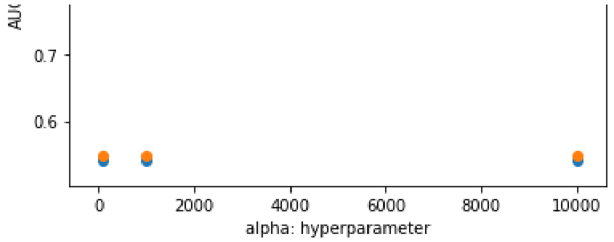
```
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs Hyperparameter")
plt.show()

plt.plot(np.log(alpha_list), train_auc, label='Train AUC')
plt.plot(np.log(alpha_list), cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("log(alpha): hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs log(Hyperparameter)")
plt.show()


plt.scatter(alpha_list, train_auc, label='Train AUC')
plt.scatter(alpha_list, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs Hyperparameter")
plt.show()

plt.scatter(np.log(alpha_list), train_auc, label='Train AUC')
plt.scatter(np.log(alpha_list), cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("log(alpha): hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs log(Hyperparameter)")
plt.show()
```

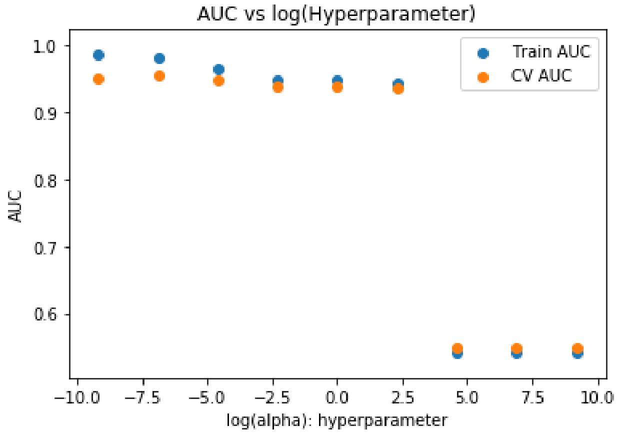
```
The optimal alpha is (according to auc curve (max auc)):  0.001
```







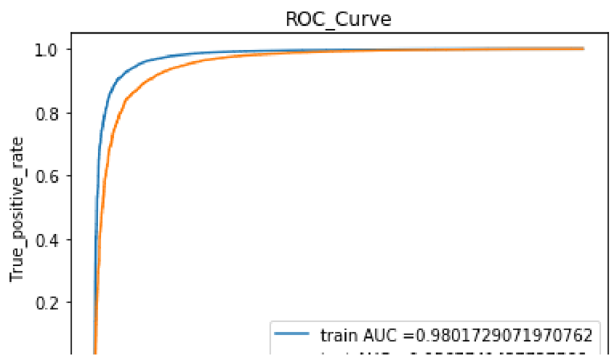


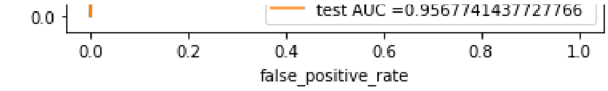


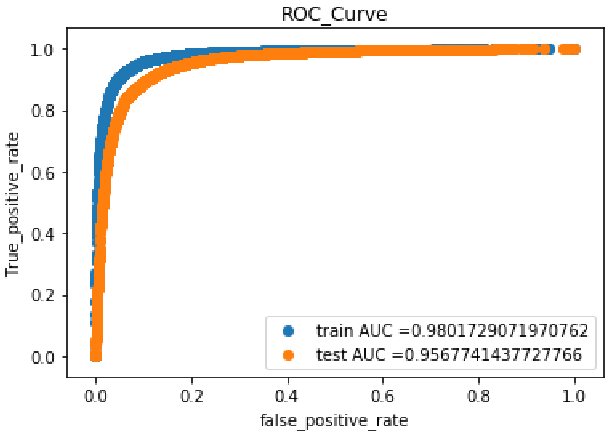
In [36]:

```
lnr_svm = SGDClassifier(loss = 'hinge',alpha =optimal_alpha_auc)
cg_cv = CalibratedClassifierCV(base_estimator = lnr_svm)
cg_cv.fit(X_train_vect, y_train)
pred = cg_cv.predict(X_test_vect)
acc = accuracy_score(y_test, pred, normalize=True) * float(100)
print('\n****Test accuracy for alpha = %f is %f%%' % (optimal_alpha_auc,acc))

train_fpr, train_tpr, thresholds = roc_curve(y_train, cg_cv.predict_proba(X_train_vect)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, cg_cv.predict_proba(X_test_vect)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("false_positive_rate")
plt.ylabel("True_positive_rate")
plt.title("ROC_Curve")
plt.show()



plt.scatter(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.scatter(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("false_positive_rate")
plt.ylabel("True_positive_rate")
plt.title("ROC_Curve")
plt.show()

print("="*100)
```

```
****Test accuracy for alpha = 0.001000 is 93.267969%
```








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

Confusion Matrix (Train)

In [37]:

```
from sklearn.metrics import confusion_matrix
print("Train confusion matrix\n")
print(confusion_matrix(y_train, cg_cv.predict(X_train_vect)))
```

```
Train confusion matrix

[[ 4890  1519]
 [  384 32607]]
```

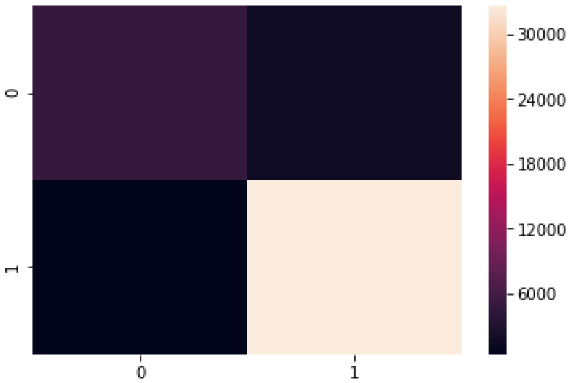
Heat Map (Train)

In [38]:

```
sns.heatmap(confusion_matrix(y_train, cg_cv.predict(X_train_vect)))
```

Out[38]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2030afc11d0>
```



Confusion Matrix (Test)

In [39]:

In [39]:

```
print("Test confusion matrix\n")
print(confusion_matrix(y_test, cg_cv.predict(X_test_vect)))
```

```
Test confusion matrix

[[ 3192  1455]
 [  495 23824]]
```

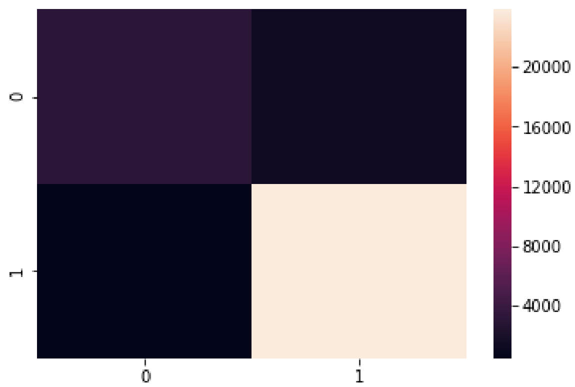
Heat Map (Test)

In [40]:

```
sns.heatmap(confusion_matrix(y_test, cg_cv.predict(X_test_vect)))
```

Out[40]:

<matplotlib.axes._subplots.AxesSubplot at 0x2030ae4cc88>



Top 10 important features of positive class

In [114]:

```
# Please write all the code with proper documentation
lnr_svm = SGDClassifier(loss = 'hinge',alpha =0.001)
lnr_svm.fit(X_train_vect, y_train)
vocab = list(count_vect.get_feature_names())
weights = list(lnr_svm.coef_[0])
dict_new = {'Words':vocab,'weights':weights}
df_new = pd.DataFrame(dict_new)
df_pos_sorted =df_new.sort_values('weights', axis=0, ascending=False, inplace=False, kind='quicksor
t', na_position='last')
df_neg_sorted =df_new.sort_values('weights', axis=0, ascending=True, inplace=False, kind='quicksort
', na_position='last')
print("The important features for predicting the positive class are the following:")
print(df_pos_sorted[0:10])
print("\n")
```

```
The important features for predicting the positive class are the following:
          Words   weights
1962  delicious  0.821598
2545  excellent  0.791168
361     amazing  0.730309
8084      yummy  0.664378
3206      great  0.618734
5173    perfect  0.613662
732        best  0.603519
575     awesome  0.593376
4757       nice  0.562946
7978  wonderful  0.562946
```

Top 10 important features of negative class

In [115]:

```
print("The important features for predicting the negative class are the following:")
print(df_neg_sorted[0:10])
```

```
The important features for predicting the negative class are the following:
               Words   weights
8011           worst -0.943316
2124    disappointing -0.923029
576            awful -0.826669
2123     disappointed -0.806383
7244         terrible -0.801311
2125   disappointment -0.770882
8073             yuck -0.745524
3472         horrible -0.735381
5346             poor -0.699879
6019              rip -0.623806
```

[5.1.2] Applying Linear SVM on TFIDF, SET 2

GridSearchCV

In [41]:

```
# Please write all the code with proper documentation
from sklearn.linear_model import SGDClassifier
from sklearn.grid_search import GridSearchCV
from sklearn.calibration import CalibratedClassifierCV

lnr_svm = SGDClassifier()
tuned_parameters = [{'alpha': [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]}]
alpha_list = [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]
#Using GridSearchCV
model = GridSearchCV(SGDClassifier(loss = 'hinge'), tuned_parameters, scoring = 'roc_auc')
model.fit(X_train_vect_tfidf, y_train)

print(model.best_estimator_)
print(model.score(X_test_vect_tfidf, y_test))
```

```
SGDClassifier(alpha=0.0001, average=False, class_weight=None, epsilon=0.1,
       eta0=0.0, fit_intercept=True, l1_ratio=0.15,
       learning_rate='optimal', loss='hinge', max_iter=None, n_iter=None,
       n_jobs=1, penalty='l2', power_t=0.5, random_state=None,
       shuffle=True, tol=None, verbose=0, warm_start=False)
0.9659765540325128
```

SimpleCV

In [42]:

```
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_auc_score
alpha_list = [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]
ind = []
train_auc = []
cv_auc = []
for i in tqdm(alpha_list):
    lnr_svm = SGDClassifier(loss = 'hinge',alpha =i)
    cg_cv = CalibratedClassifierCV(base_estimator = lnr_svm)
    cg_cv.fit(X_train_vect_tfidf, y_train)
    ind.append(i)
    y_train_pred =  cg_cv.predict_proba(X_train_vect_tfidf)[:,1]
    y_cv_pred =  cg_cv.predict_proba(X_cv_vect_tfidf)[:,1]
    train_auc.append(roc_auc_score(y_train,y_train_pred))
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
```

```
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
```

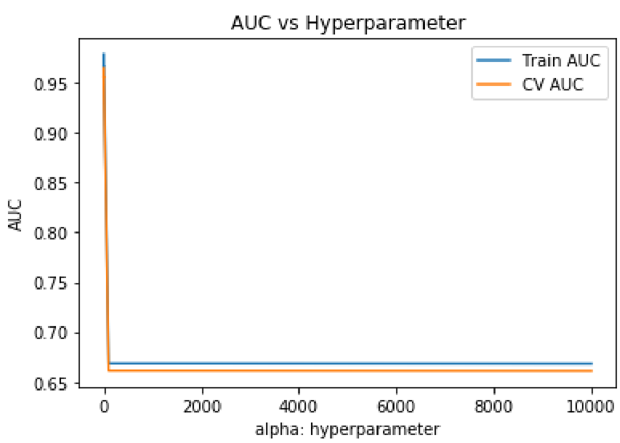
```
100%|██████████████████████████████████████████████████| 9/9 [02
:26<00:00, 16.99s/it]
```

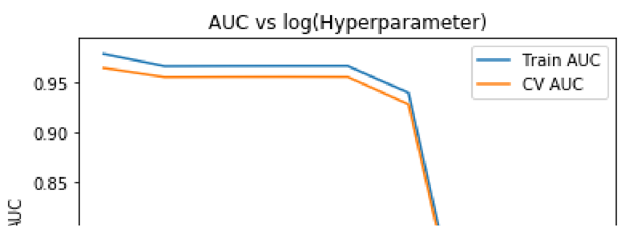
Plots

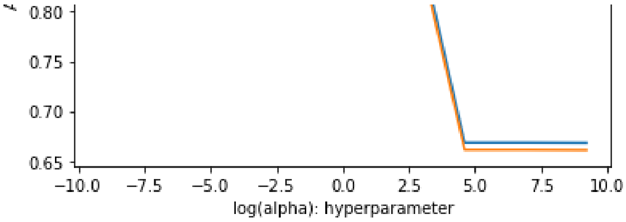
In [43]:

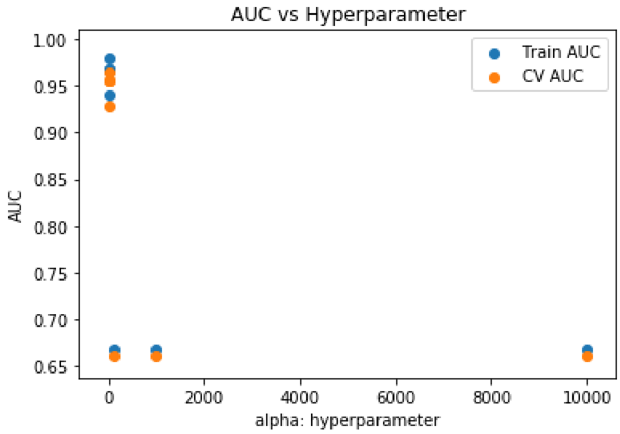
```
optimal_alpha_auc = ind[cv_auc.index(max(cv_auc))]
print('\nThe optimal alpha is (according to auc curve (max auc)): ' , optimal_alpha_auc)

plt.plot(alpha_list, train_auc, label='Train AUC')
plt.plot(alpha_list, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs Hyperparameter")
plt.show()

plt.plot(np.log(alpha_list), train_auc, label='Train AUC')
plt.plot(np.log(alpha_list), cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("log(alpha): hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs log(Hyperparameter)")
plt.show()


plt.scatter(alpha_list, train_auc, label='Train AUC')
plt.scatter(alpha_list, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs Hyperparameter")
plt.show()

plt.scatter(np.log(alpha_list), train_auc, label='Train AUC')
plt.scatter(np.log(alpha_list), cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("log(alpha): hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs log(Hyperparameter)")
plt.show()
```

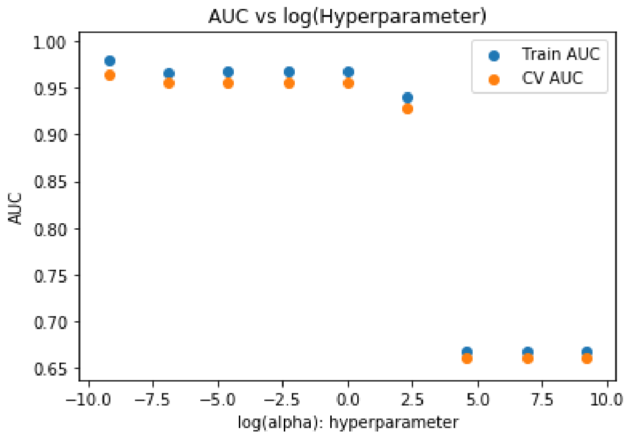
```
The optimal alpha is (according to auc curve (max auc)):  0.0001
```









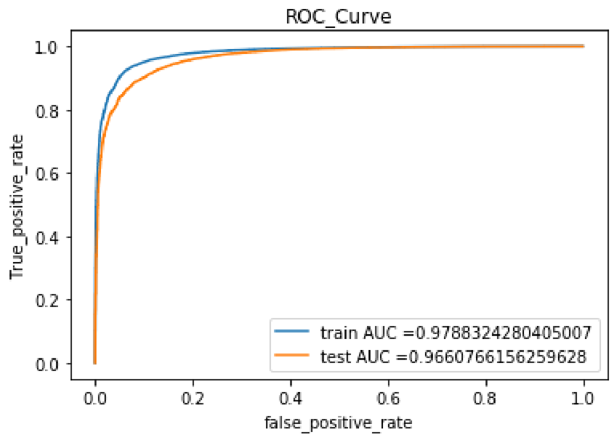


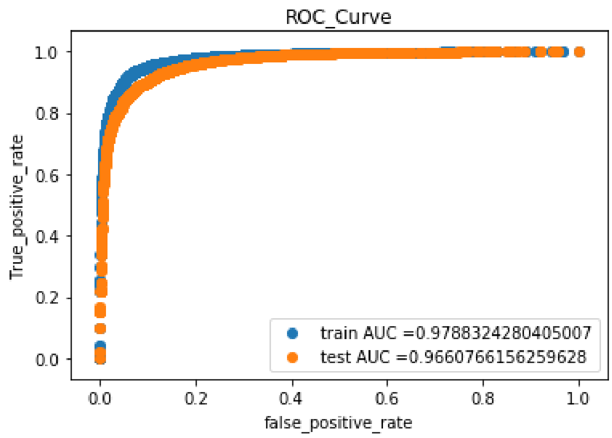
In [44]:

```
lnr_svm = SGDClassifier(loss = 'hinge',alpha =optimal_alpha_auc)
cg_cv = CalibratedClassifierCV(base_estimator = lnr_svm)
cg_cv.fit(X_train_vect_tfidf, y_train)
pred = cg_cv.predict(X_test_vect_tfidf)
acc = accuracy_score(y_test, pred, normalize=True) * float(100)
print('\n****Test accuracy for alpha = %f is %f%%' % (optimal_alpha_auc,acc))

train_fpr, train_tpr, thresholds = roc_curve(y_train, cg_cv.predict_proba(X_train_vect_tfidf)
[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, cg_cv.predict_proba(X_test_vect_tfidf)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("false_positive_rate")
plt.ylabel("True_positive_rate")
plt.title("ROC_Curve")
plt.show()



plt.scatter(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.scatter(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("false_positive_rate")
plt.ylabel("True_positive_rate")
plt.title("ROC_Curve")
plt.show()
```

```
print("="*100)
```

```
****Test accuracy for alpha = 0.000100 is 93.602845%
```






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

Confusion Matrix (Train)

In [45]:

```
from sklearn.metrics import confusion_matrix
print("Train confusion matrix\n")
print(confusion_matrix(y_train, cg_cv.predict(X_train_vect_tfidf)))
```

```
Train confusion matrix

[[ 4989  1420]
 [  598 32393]]
```

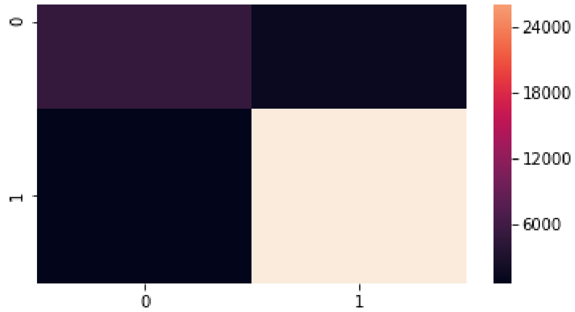
Heat Map (Train)

In [46]:

```
sns.heatmap(confusion_matrix(y_train, cg_cv.predict(X_train_vect_tfidf)))
```

Out[46]:

```
&lt;matplotlib.axes._subplots.AxesSubplot at 0x2030ad72908&gt;
```



Confusion Matrix (Train)

In [47]:

```
print("Test confusion matrix\n")
print(confusion_matrix(y_test, cg_cv.predict(X_test_vect_tfidf)))
```

```
Test confusion matrix

[[ 3397  1250]
 [  603 23716]]
```

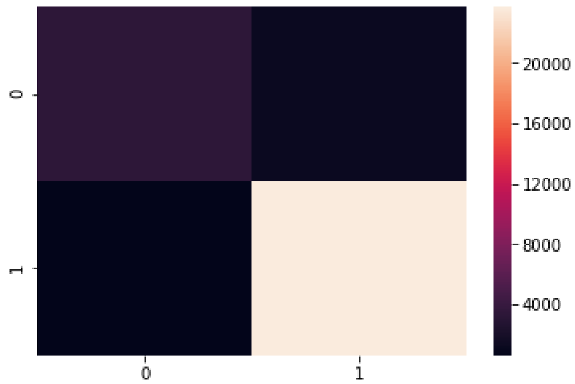
Heat Map (Train)

In [48]:

```
sns.heatmap(confusion_matrix(y_test, cg_cv.predict(X_test_vect_tfidf)))
```

Out[48]:

<matplotlib.axes._subplots.AxesSubplot at 0x20309949828>



Top 10 important features of positive class

In [116]:

```
# Please write all the code with proper documentation
lnr_svm = SGDClassifier(loss = 'hinge',alpha =0.0001)
lnr_svm.fit(X_train_vect_tfidf, y_train)
vocab = list(tf_idf.get_feature_names())
weights = list(lnr_svm.coef_[0])
dict_new = {'Words':vocab,'weights':weights}
df_new = pd.DataFrame(dict_new)
df_pos_sorted =df_new.sort_values('weights', axis=0, ascending=False, inplace=False, kind='quicksor
t', na_position='last')
df_neg_sorted =df_new.sort_values('weights', axis=0, ascending=True, inplace=False, kind='quicksort
', na_position='last')
print("The important features for predicting the positive class are the following:")
print(df_pos_sorted[0:10])
```

```
print("\n")
```

```
The important features for predicting the positive class are the following:
          Words   weights
3206      great  5.479673
732        best  3.935325
3143       good  3.877516
1962  delicious  3.691458
2545  excellent  3.088592
4757       nice  2.902722
4222       love  2.900174
5173    perfect  2.738491
4227      loves  2.630345
361     amazing  2.387689
```

Top 10 important features of negative class

In [117]:

```
print("The important features for predicting the negative class are the following:")
print(df_neg_sorted[0:10])
```

```
The important features for predicting the negative class are the following:
               Words   weights
4794             not -4.356391
2123    disappointed -3.866092
8011           worst -3.503328
7244        terrible -3.400240
576            awful -3.297672
2124   disappointing -3.281162
3472        horrible -3.216841
5346            poor -2.697623
8073            yuck -2.661658
2125  disappointment -2.638946
```

[5.1.3] Applying Linear SVM on AVG W2V, SET 3

GridSearch CV

In [49]:

```
from sklearn.linear_model import SGDClassifier
from sklearn.grid_search import GridSearchCV
from sklearn.calibration import CalibratedClassifierCV

lnr_svm = SGDClassifier()
tuned_parameters = [{'alpha': [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]}]
alpha_list = [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]
#Using GridSearchCV
model = GridSearchCV(SGDClassifier(loss = 'hinge'), tuned_parameters, scoring = 'roc_auc')
model.fit(X_train_vectors, y_train)

print(model.best_estimator_)
print(model.score(X_test_vectors, y_test))
```

```
SGDClassifier(alpha=0.001, average=False, class_weight=None, epsilon=0.1,
       eta0=0.0, fit_intercept=True, l1_ratio=0.15,
       learning_rate='optimal', loss='hinge', max_iter=None, n_iter=None,
       n_jobs=1, penalty='l2', power_t=0.5, random_state=None,
       shuffle=True, tol=None, verbose=0, warm_start=False)
0.9185655429054211
```

SimpleCV

In [50]:

```
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_auc_score
alpha_list = [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]
ind = []
train_auc = []
cv_auc = []
for i in tqdm(alpha_list):
    lnr_svm = SGDClassifier(loss = 'hinge',alpha =i)
    cg_cv = CalibratedClassifierCV(base_estimator = lnr_svm)
    cg_cv.fit(X_train_vectors, y_train)
    ind.append(i)
    y_train_pred =  cg_cv.predict_proba(X_train_vectors)[:,1]
    y_cv_pred =  cg_cv.predict_proba(X_cv_vectors)[:,1]
    train_auc.append(roc_auc_score(y_train,y_train_pred))
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
```

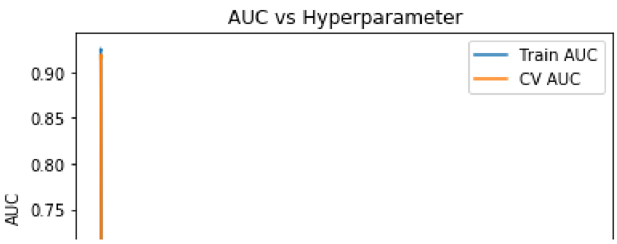
```
100%|██████████████████████████████████████████████████████████████████████████████████| 9/9 [00
:03<00:00,  2.52it/s]
```

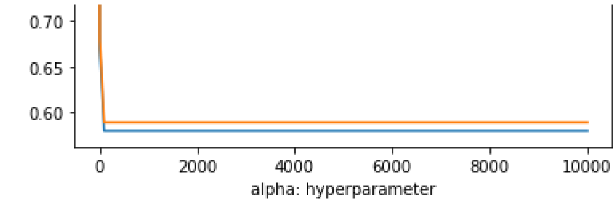
Plots

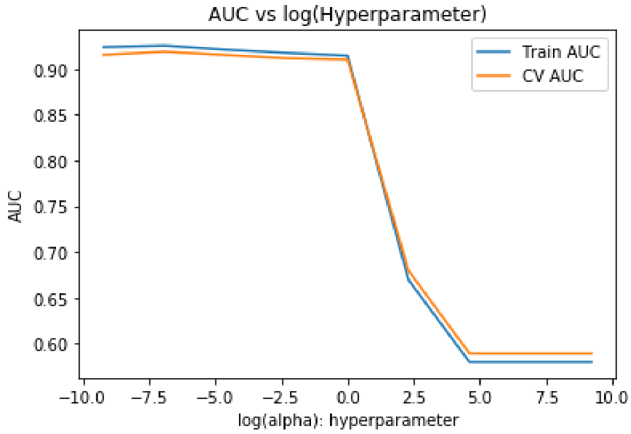
In [51]:

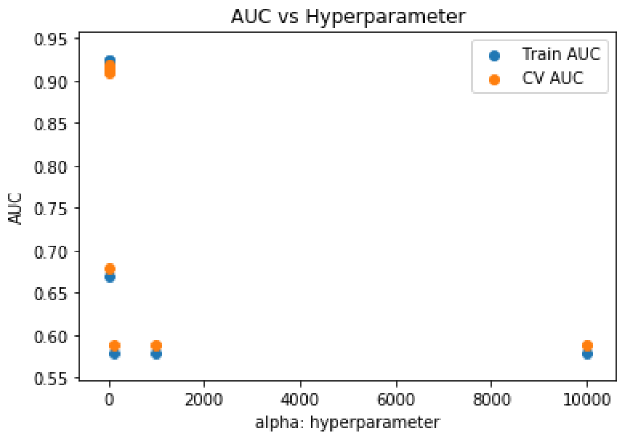
```
optimal_alpha_auc = ind[cv_auc.index(max(cv_auc))]
print('\nThe optimal alpha is (according to auc curve (max auc)): ' , optimal_alpha_auc)

plt.plot(alpha_list, train_auc, label='Train AUC')
plt.plot(alpha_list, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs Hyperparameter")
plt.show()

plt.plot(np.log(alpha_list), train_auc, label='Train AUC')
plt.plot(np.log(alpha_list), cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("log(alpha): hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs log(Hyperparameter)")
plt.show()


plt.scatter(alpha_list, train_auc, label='Train AUC')
plt.scatter(alpha_list, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs Hyperparameter")
plt.show()

plt.scatter(np.log(alpha_list), train_auc, label='Train AUC')
plt.scatter(np.log(alpha_list), cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("log(alpha): hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs log(Hyperparameter)")
plt.show()
```

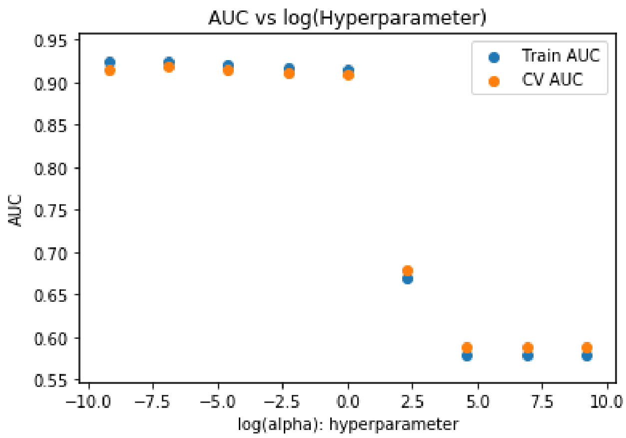
```
The optimal alpha is (according to auc curve (max auc)):  0.001
```









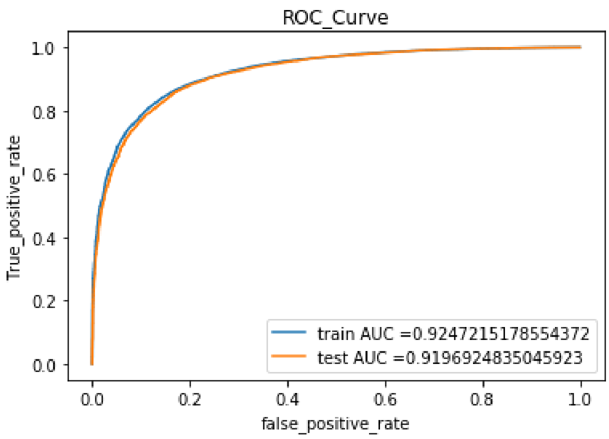


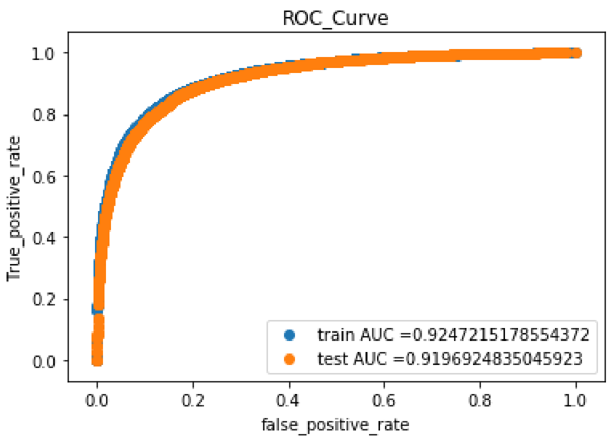
In [52]:

```
lnr_svm = SGDClassifier(loss = 'hinge',alpha =optimal_alpha_auc)
cg_cv = CalibratedClassifierCV(base_estimator = lnr_svm)
cg_cv.fit(X_train_vectors, y_train)
pred = cg_cv.predict(X_test_vectors)
acc = accuracy_score(y_test, pred, normalize=True) * float(100)
print('\n****Test accuracy for alpha = %f is %f%%' % (optimal_alpha_auc,acc))

train_fpr, train_tpr, thresholds = roc_curve(y_train, cg_cv.predict_proba(X_train_vectors)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, cg_cv.predict_proba(X_test_vectors)[:,1])

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

```
plt.legend()
plt.xlabel("false_positive_rate")
plt.ylabel("True_positive_rate")
plt.title("ROC_Curve")
plt.show()



plt.scatter(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.scatter(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("false_positive_rate")
plt.ylabel("True_positive_rate")
plt.title("ROC_Curve")
plt.show()

print("="*100)
```

```
****Test accuracy for alpha = 0.001000 is 89.798384%
```






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

Confusion Matrix(Test)

In [53]:

```
from sklearn.metrics import confusion_matrix
print("Train confusion matrix\n")
print(confusion_matrix(y_train, cg_cv.predict(X_train_vectors)))
```

```
Train confusion matrix

[[ 3536  2873]
 [ 1148 31843]]
```

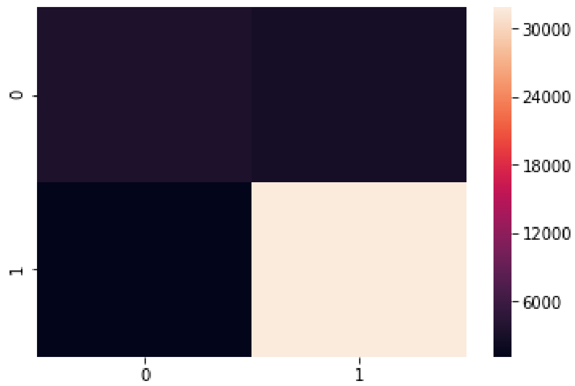
Heat Map (Test)

In [54]:

```
sns.heatmap(confusion_matrix(y_train, cg_cv.predict(X_train_vectors)))
```

Out[54]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20309c38048>
```



Confusion matrix (Test)

In [55]:

```
print("Test confusion matrix\n")
print(confusion_matrix(y_test, cg_cv.predict(X_test_vectors)))
```

```
Test confusion matrix

[[ 2540  2107]
 [  848 23471]]
```

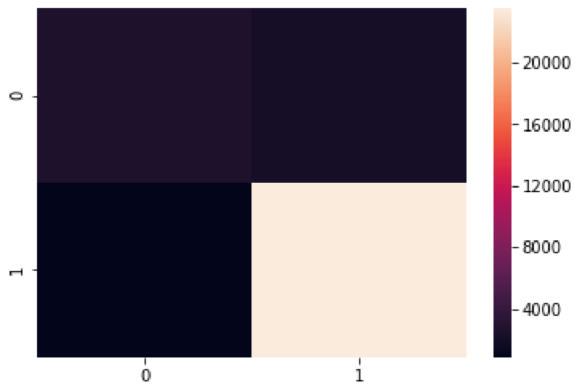
Heat Map (Test)

In [56]:

```
sns.heatmap(confusion_matrix(y_test, cg_cv.predict(X_test_vectors)))
```

Out[56]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2030b1535f8>
```



[5.1.4] Applying Linear SVM on TFIDF W2V, SET 4

GridSearch CV

In [57]:

```
# Please write all the code with proper documentation

from sklearn.linear_model import SGDClassifier
from sklearn.grid_search import GridSearchCV
from sklearn.calibration import CalibratedClassifierCV

lnr_svm = SGDClassifier()
tuned_parameters = [{'alpha': [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]}]
alpha_list = [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]
#Using GridSearchCV
model = GridSearchCV(SGDClassifier(loss = 'hinge'), tuned_parameters, scoring = 'roc_auc')
model.fit(tfidf_X_train_vectors, y_train)

print(model.best_estimator_)
print(model.score(tfidf_X_test_vectors, y_test))
```

```
SGDClassifier(alpha=0.001, average=False, class_weight=None, epsilon=0.1,
       eta0=0.0, fit_intercept=True, l1_ratio=0.15,
       learning_rate='optimal', loss='hinge', max_iter=None, n_iter=None,
       n_jobs=1, penalty='l2', power_t=0.5, random_state=None,
       shuffle=True, tol=None, verbose=0, warm_start=False)
0.8941577435271817
```

SimpleCV

In [58]:

```
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_auc_score
alpha_list = [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]
ind = []
train_auc = []
cv_auc = []
for i in tqdm(alpha_list):
    lnr_svm = SGDClassifier(loss = 'hinge',alpha =i)
    cg_cv = CalibratedClassifierCV(base_estimator = lnr_svm)
    cg_cv.fit(tfidf_X_train_vectors, y_train)
    ind.append(i)
    y_train_pred =  cg_cv.predict_proba(tfidf_X_train_vectors)[:,1]
    y_cv_pred =  cg_cv.predict_proba(tfidf_X_cv_vectors)[:,1]
    train_auc.append(roc_auc_score(y_train,y_train_pred))
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
```

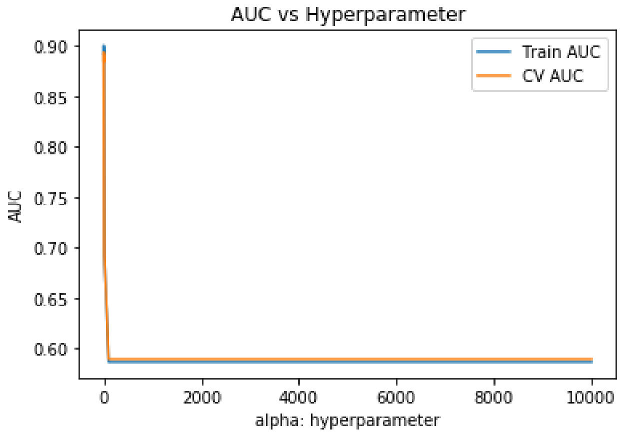
```
100%|██████████████████████████████████████████████████████████████████████████████████| 9/9 [00
:03<00:00,  2.63it/s]
```

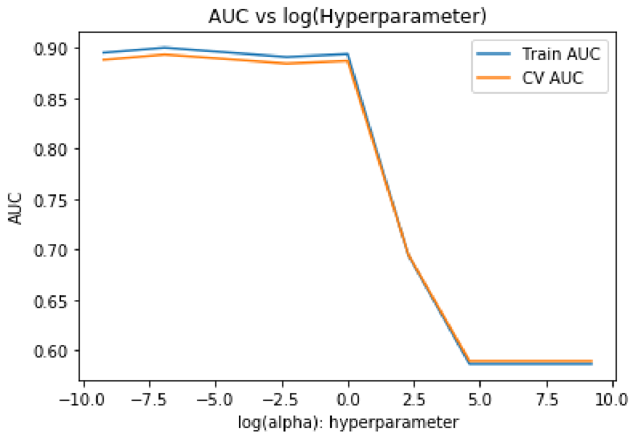
In [59]:

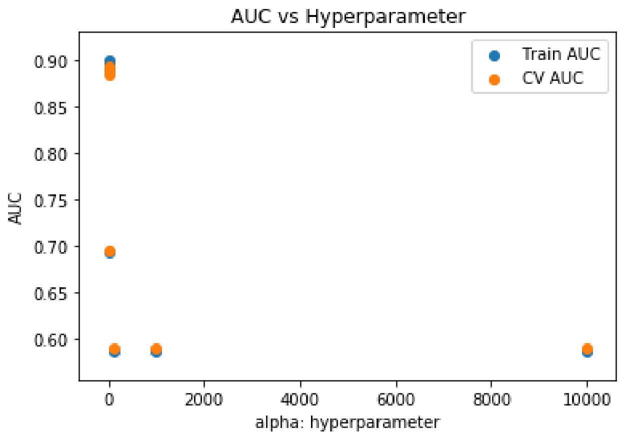
```
optimal_alpha_auc = ind[cv_auc.index(max(cv_auc))]
print('\nThe optimal alpha is (according to auc curve (max auc)): ' , optimal_alpha_auc)

plt.plot(alpha_list, train_auc, label='Train AUC')
plt.plot(alpha_list, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs Hyperparameter")
plt.show()

plt.plot(np.log(alpha_list), train_auc, label='Train AUC')
plt.plot(np.log(alpha_list), cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("log(alpha): hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs log(Hyperparameter)")
plt.show()
```

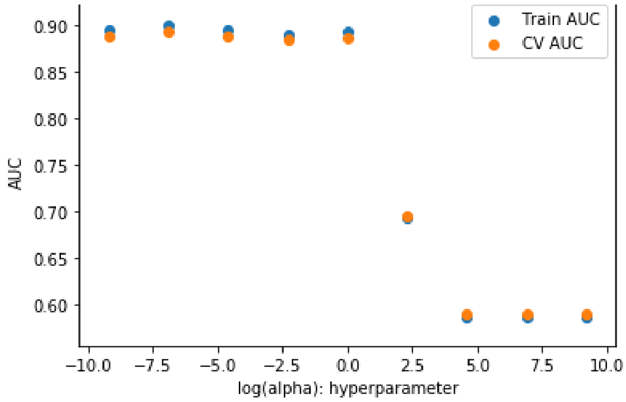
```
plt.show()


plt.scatter(alpha_list, train_auc, label='Train AUC')
plt.scatter(alpha_list, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs Hyperparameter")
plt.show()

plt.scatter(np.log(alpha_list), train_auc, label='Train AUC')
plt.scatter(np.log(alpha_list), cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("log(alpha): hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs log(Hyperparameter)")
plt.show()
```

```
The optimal alpha is (according to auc curve (max auc)):  0.001
```





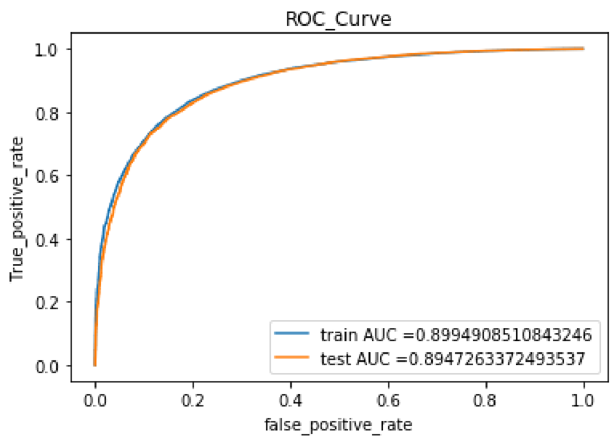


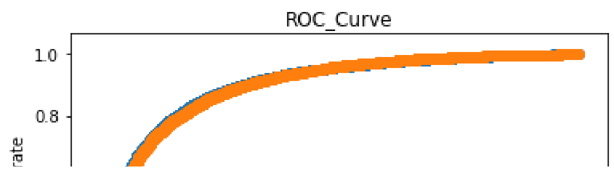


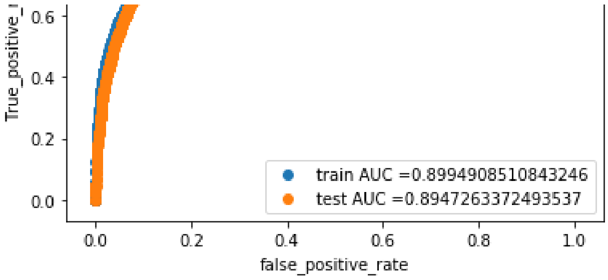
In [60]:

```
lnr_svm = SGDClassifier(loss = 'hinge',alpha =optimal_alpha_auc)
cg_cv = CalibratedClassifierCV(base_estimator = lnr_svm)
cg_cv.fit(tfidf_X_train_vectors, y_train)
pred = cg_cv.predict(tfidf_X_test_vectors)
acc = accuracy_score(y_test, pred, normalize=True) * float(100)
print('\n****Test accuracy for alpha = %f is %f%%' % (optimal_alpha_auc,acc))

train_fpr, train_tpr, thresholds = roc_curve(y_train, cg_cv.predict_proba(tfidf_X_train_vectors)
[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, cg_cv.predict_proba(tfidf_X_test_vectors)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("false_positive_rate")
plt.ylabel("True_positive_rate")
plt.title("ROC_Curve")
plt.show()



plt.scatter(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.scatter(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("false_positive_rate")
plt.ylabel("True_positive_rate")
plt.title("ROC_Curve")
plt.show()

print("="*100)
```

```
****Test accuracy for alpha = 0.001000 is 88.534834%
```







==

Confusion Matrix (Train)

In [61]:

```
from sklearn.metrics import confusion_matrix
print("Train confusion matrix\n")
print(confusion_matrix(y_train, cg_cv.predict(tfidf_X_train_vectors)))
```

```
Train confusion matrix

[[ 2881  3528]
 [ 1094 31897]]
```

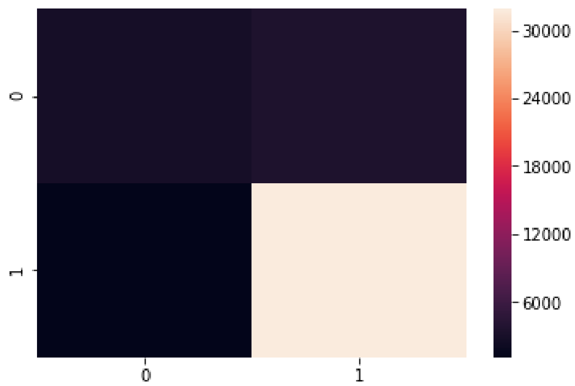
Heat Map (Train)

In [62]:

```
sns.heatmap(confusion_matrix(y_train, cg_cv.predict(tfidf_X_train_vectors)))
```

Out[62]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2030b1cc9b0>
```



Confusion Matrix (Test)

In [63]:

```
print("Test confusion matrix\n")
print(confusion_matrix(y_test, cg_cv.predict(tfidf_X_test_vectors)))
```

```
Test confusion matrix

[[ 2095  2552]
 [  769 23550]]
```

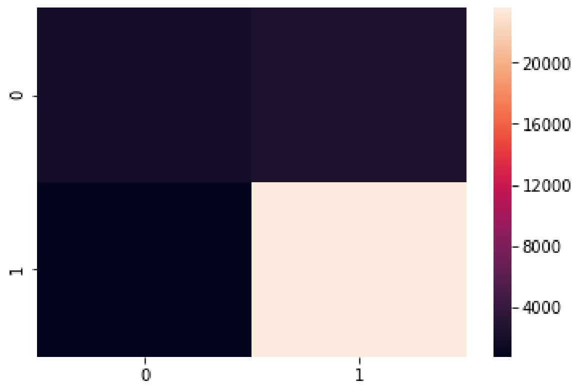
Heat Map (Test)

In [64]:

```
sns.heatmap(confusion_matrix(y_test, cg_cv.predict(tfidf_X_test_vectors)))
```

Out[64]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2030b27b358>
```



[5.2] RBF SVM

Test Train Split

- Considering 20k features for the RBF_SVM

In [65]:

```
X_train, X_test, y_train, y_test = train_test_split(preprocessed_reviews_fe_final[0:20000], final['
Score'][0:20000], test_size=0.33) # this is random splitting
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.33) # this is random
splitting
```

BOW for RBF SVC

In [66]:

```
count_vect = CountVectorizer(min_df=10, max_features=500) #in scikit-learn

X_train_vect = count_vect.fit_transform(X_train)
X_train_vect = X_train_vect.toarray()
X_cv_vect = count_vect.transform(X_cv)
X_cv_vect = X_cv_vect.toarray()
X_test_vect = count_vect.transform(X_test)
X_test_vect = X_test_vect.toarray()
```

TFIDF for RBF SVC

In [67]:

```
tf_idf = TfidfVectorizer(min_df=10, max_features=500)
X_train_vect_tfidf = tf_idf.fit_transform(X_train)
X_train_vect_tfidf = X_train_vect_tfidf.toarray()
X_test_vect_tfidf = tf_idf.transform(X_test)
X_test_vect_tfidf = X_test_vect_tfidf.toarray()
X_cv_vect_tfidf = tf_idf.transform(X_cv)
X_cv_vect_tfidf = X_cv_vect_tfidf.toarray()
```

Avg Word2Vec for RBF SVC

In [68]:

```
i=0
list_of_sent=[]
X_train_list=[]
X_test_list=[]
X_cv_list=[]
for sent in X_train:
    X_train_list.append(sent.split())

for sent in X_cv:
    X_cv_list.append(sent.split())

for sent in X_test:
    X_test_list.append(sent.split())

w2v_model=Word2Vec(X_train_list,min_count=0,size=50, workers=4)
w2v_words = list(w2v_model.wv.vocab)

X_train_vectors = [];
for sent in tqdm(X_train_list):
    sent_vec = np.zeros(50)
    cnt_words =0;
    for word in sent:
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    X_train_vectors.append(sent_vec)


X_cv_vectors = []
for sent in tqdm(X_cv_list):
    sent_vec = np.zeros(50)
    cnt_words =0;
    for word in sent:
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    X_cv_vectors.append(sent_vec)

X_test_vectors = []
for sent in tqdm(X_test_list):
    sent_vec = np.zeros(50)
    cnt_words =0;
    for word in sent:
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    X_test_vectors.append(sent_vec)
```

```
100%|██████████████████████████████████████████████████████████████████████████████| 8978/8978
[00:19<00:00, 456.84it/s]
100%|██████████████████████████████████████████████████████████████████████████████| 4422/4422
[00:11<00:00, 375.73it/s]
100%|██████████████████████████████████████████████████████████████████████████████| 6600/6600
[00:18<00:00, 353.19it/s]
```

Tfidf-Avg Word2Vec for RBF SVC

In [69]:

```
dictionary = dict(zip(tf_idf.get_feature_names(), list(tf_idf.idf_)))
tfidf_feat = tf_idf.get_feature_names()
tfidf_X_train_vectors = [];
tfidf_X_test_vectors = [];
tfidf_X_cv_vectors = [];

for sent in tqdm(X_train_list):
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in (w2v_words and tfidf_feat):
            vec = w2v_model.wv[word]
            tf_idf_count = dictionary[word]*sent.count(word)
            sent_vec += (vec * tf_idf_count)
            weight_sum += tf_idf_count
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_X_train_vectors.append(sent_vec)

for sent in tqdm(X_test_list):
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in (w2v_words and tfidf_feat):
            vec = w2v_model.wv[word]
            tf_idf_count = dictionary[word]*sent.count(word)
            sent_vec += (vec * tf_idf_count)
            weight_sum += tf_idf_count
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_X_test_vectors.append(sent_vec)

for sent in tqdm(X_cv_list):
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in (w2v_words and tfidf_feat):
            vec = w2v_model.wv[word]
            tf_idf_count = dictionary[word]*sent.count(word)
            sent_vec += (vec * tf_idf_count)
            weight_sum += tf_idf_count
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_X_cv_vectors.append(sent_vec)
```

```
100%|██████████████████████████████████████████████████████████████████████████| 8978/8978
[00:05<00:00, 1548.14it/s]
100%|██████████████████████████████████████████████████████████████████████████| 6600/6600
[00:04<00:00, 1593.53it/s]
100%|██████████████████████████████████████████████████████████████████████████| 4422/4422
[00:02<00:00, 1633.53it/s]
```

[5.2.1] Applying RBF SVM on BOW, SET 1

GridSearchCV

In [70]:

```
# Please write all the code with proper documentation
from sklearn.svm import SVC
tuned_parameters = [{'C': [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]}]
alpha_list = [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]
#Using GridSearchCV
model = GridSearchCV(SVC(), tuned_parameters, scoring = 'roc_auc')
model.fit(X_train_vect, y_train)

print(model.best_estimator_)
print(model.score(X_test_vect, y_test))
```

```
SVC(C=10, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
```

```
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
0.9230691854896195
```

SimpleCV

In [71]:

```python
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_auc_score
alpha_list = [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]
ind = []
train_auc = []
cv_auc = []
for i in tqdm(alpha_list):
    rbf_svm = SVC(C = i)
    cg_cv = CalibratedClassifierCV(base_estimator = rbf_svm)
    cg_cv.fit(X_train_vect, y_train)
    ind.append(i)
    y_train_pred =  cg_cv.predict_proba(X_train_vect)[:,1]
    y_cv_pred =  cg_cv.predict_proba(X_cv_vect)[:,1]
    train_auc.append(roc_auc_score(y_train,y_train_pred))
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
```

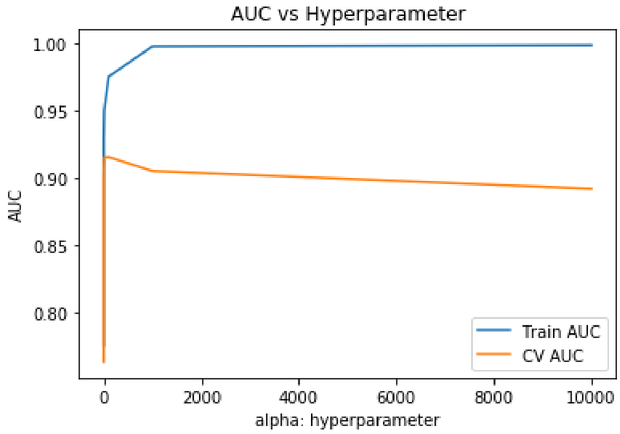
```
100%|██████████████████████████████████████████████████████████████████████████████| 9/9 [10
:59<00:00, 71.33s/it]
```

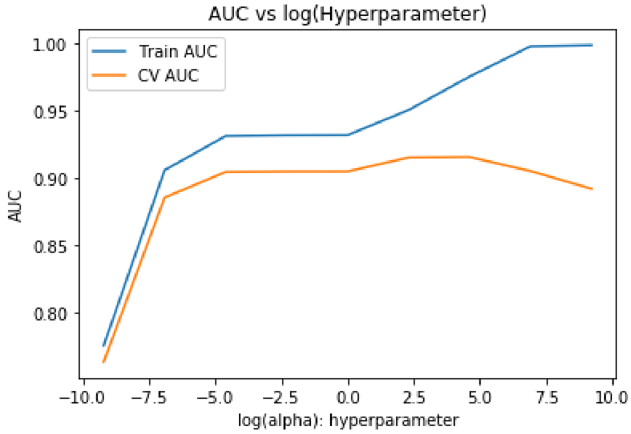
Plots

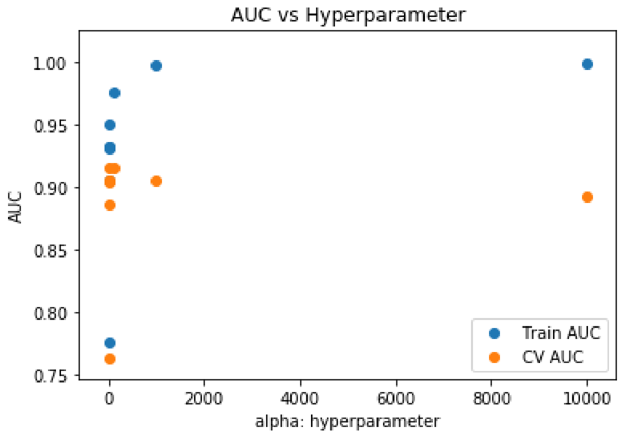
In [72]:

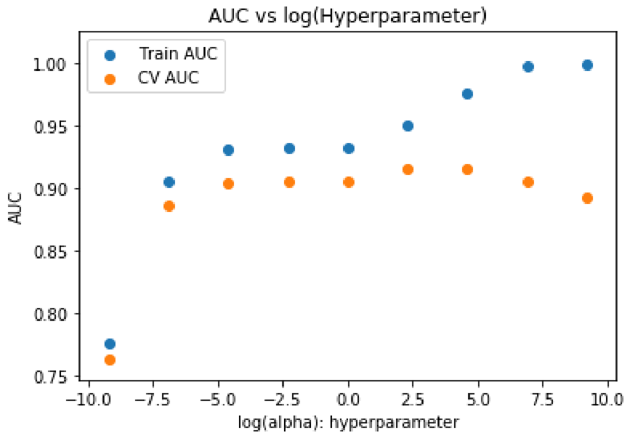
```python
optimal_alpha_auc = ind[cv_auc.index(max(cv_auc))]
print('\nThe optimal alpha is (according to auc curve (max auc)): ' , optimal_alpha_auc)

plt.plot(alpha_list, train_auc, label='Train AUC')
plt.plot(alpha_list, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs Hyperparameter")
plt.show()

plt.plot(np.log(alpha_list), train_auc, label='Train AUC')
plt.plot(np.log(alpha_list), cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("log(alpha): hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs log(Hyperparameter)")
plt.show()


plt.scatter(alpha_list, train_auc, label='Train AUC')
plt.scatter(alpha_list, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs Hyperparameter")
plt.show()

plt.scatter(np.log(alpha_list), train_auc, label='Train AUC')
plt.scatter(np.log(alpha_list), cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("log(alpha): hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs log(Hyperparameter)")
plt.show()
```

```
The optimal alpha is (according to auc curve (max auc)):  100
```







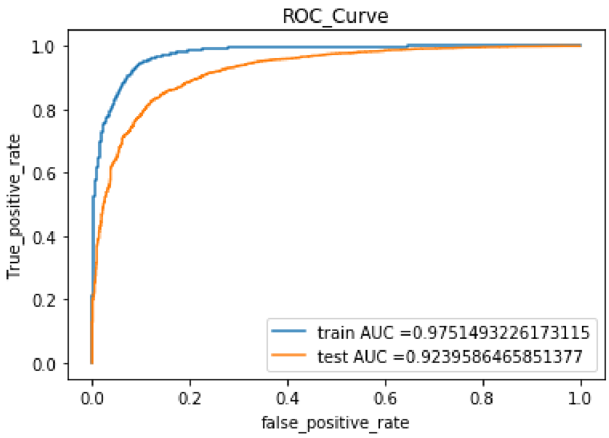


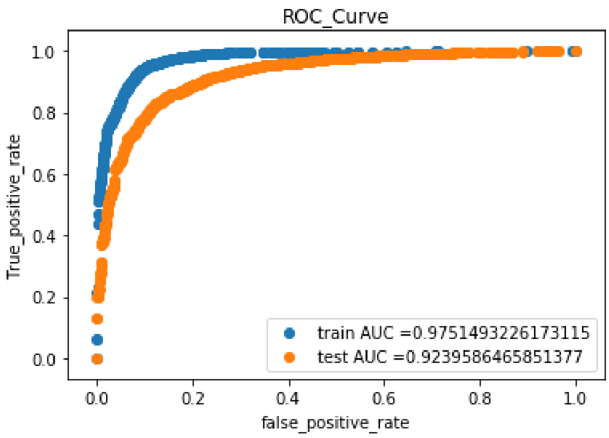
In [73]:

```
rbf_svm = SVC(C =optimal_alpha_auc)
cg_cv = CalibratedClassifierCV(base_estimator = rbf_svm)
cg_cv.fit(X_train_vect, y_train)
```

```
pred = cg_cv.predict(X_test_vect)
acc = accuracy_score(y_test, pred, normalize=True) * float(100)
print('\n****Test accuracy for alpha = %f is %f%%' % (optimal_alpha_auc,acc))

train_fpr, train_tpr, thresholds = roc_curve(y_train, cg_cv.predict_proba(X_train_vect)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, cg_cv.predict_proba(X_test_vect)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("false_positive_rate")
plt.ylabel("True_positive_rate")
plt.title("ROC_Curve")
plt.show()



plt.scatter(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.scatter(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("false_positive_rate")
plt.ylabel("True_positive_rate")
plt.title("ROC_Curve")
plt.show()

print("="*100)
```

```
****Test accuracy for alpha = 100.000000 is 89.803030%
```






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

Confusion Matrix (Train)

In [74]:

```
from sklearn.metrics import confusion_matrix
```

```
print("Train confusion matrix\n")
print(confusion_matrix(y_train, cg_cv.predict(X_train_vect)))
```

```
Train confusion matrix

[[ 881  462]
 [  36 7599]]
```

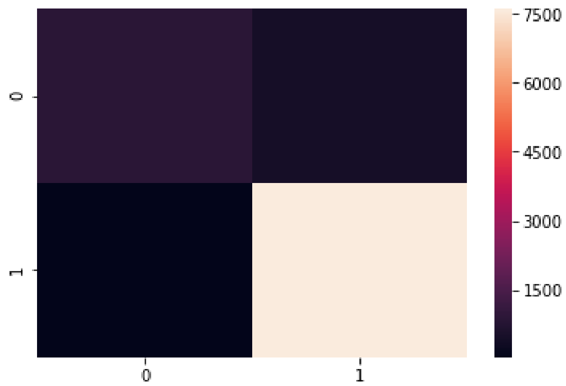
Heat Map (Train)

In [75]:

```
sns.heatmap(confusion_matrix(y_train, cg_cv.predict(X_train_vect)))
```

Out[75]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20349de9cf8>
```



Confusion Matrix (Test)

In [76]:

```
print("Test confusion matrix\n")
print(confusion_matrix(y_test, cg_cv.predict(X_test_vect)))
```

```
Test confusion matrix

[[ 484  548]
 [ 125 5443]]
```

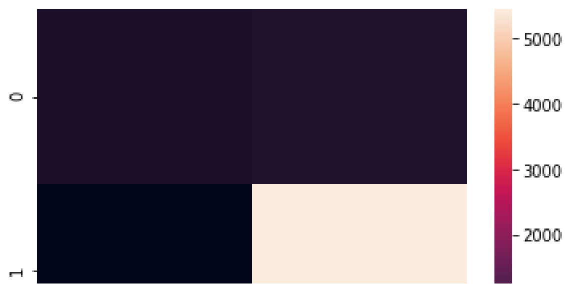
Heat Map (Test)

In [77]:

```
sns.heatmap(confusion_matrix(y_test, cg_cv.predict(X_test_vect)))
```

Out[77]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2034a060e10>
```



[5.2.2] Applying RBF SVM on TFIDF, SET 2

GridSearchCV

In [78]:

```
from sklearn.linear_model import SGDClassifier
from sklearn.grid_search import GridSearchCV
from sklearn.calibration import CalibratedClassifierCV

tuned_parameters = [{'C': [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]}]
alpha_list = [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]
#Using GridSearchCV
model = GridSearchCV(SVC(), tuned_parameters, scoring = 'roc_auc')
model.fit(X_train_vect_tfidf, y_train)

print(model.best_estimator_)
print(model.score(X_test_vect_tfidf, y_test))
```

```
SVC(C=100, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
0.9267042986500935
```

SimpleCV

In [79]:

```
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_auc_score
alpha_list = [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]
ind = []
train_auc = []
cv_auc = []
for i in tqdm(alpha_list):
    rbf_svm = SVC(C = i)
    cg_cv = CalibratedClassifierCV(base_estimator = rbf_svm)
    cg_cv.fit(X_train_vect_tfidf, y_train)
    ind.append(i)
    y_train_pred =  cg_cv.predict_proba(X_train_vect_tfidf)[:,1]
    y_cv_pred =  cg_cv.predict_proba(X_cv_vect_tfidf)[:,1]
    train_auc.append(roc_auc_score(y_train,y_train_pred))
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
```

```
100%|██████████████████████████████████████████████████████████████████████████████████| 9/9 [10
:30<00:00, 68.43s/it]
```

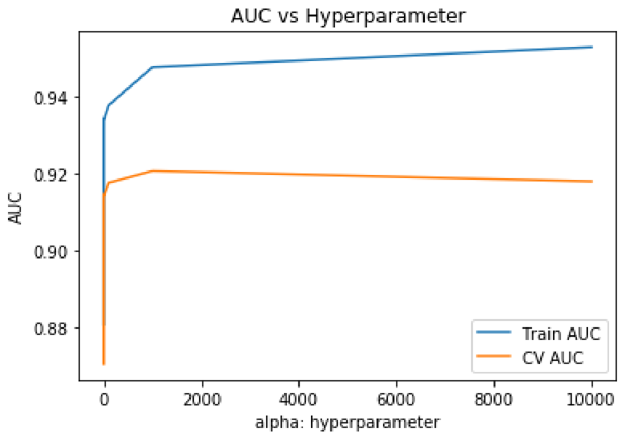
Plots

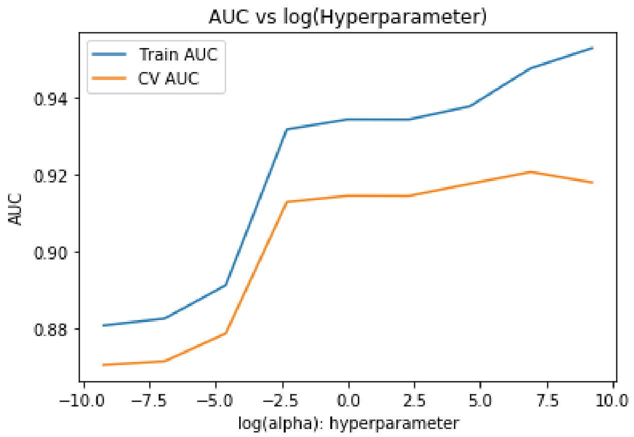
In [80]:

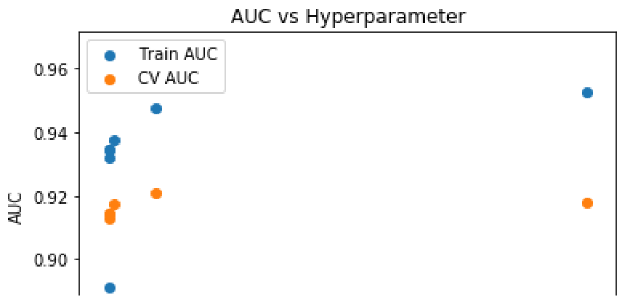
```
optimal_alpha_auc = ind[cv_auc.index(max(cv_auc))]
print('\nThe optimal alpha is (according to auc curve (max auc)): ' , optimal_alpha_auc)

plt.plot(alpha_list, train_auc, label='Train AUC')
plt.plot(alpha_list, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs Hyperparameter")
```

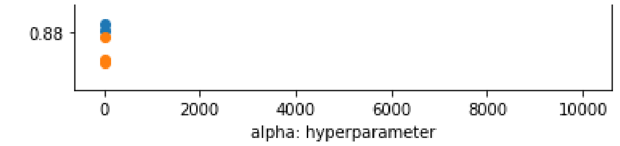
```
plt.show()

plt.plot(np.log(alpha_list), train_auc, label='Train AUC')
plt.plot(np.log(alpha_list), cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("log(alpha): hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs log(Hyperparameter)")
plt.show()


plt.scatter(alpha_list, train_auc, label='Train AUC')
plt.scatter(alpha_list, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs Hyperparameter")
plt.show()

plt.scatter(np.log(alpha_list), train_auc, label='Train AUC')
plt.scatter(np.log(alpha_list), cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("log(alpha): hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs log(Hyperparameter)")
plt.show()
```

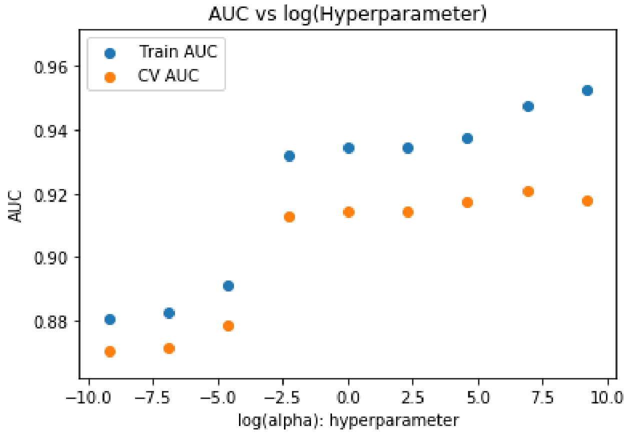
```
The optimal alpha is (according to auc curve (max auc)):  1000
```







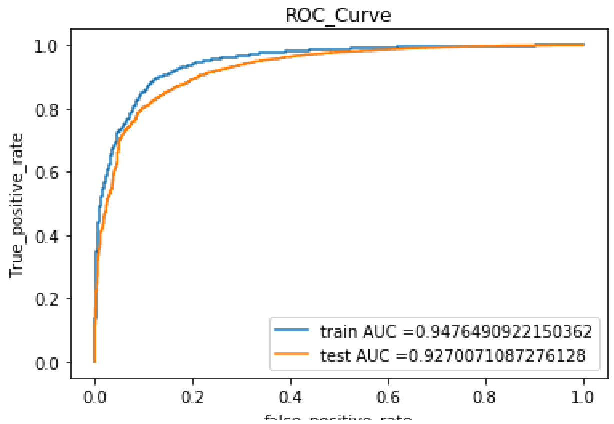




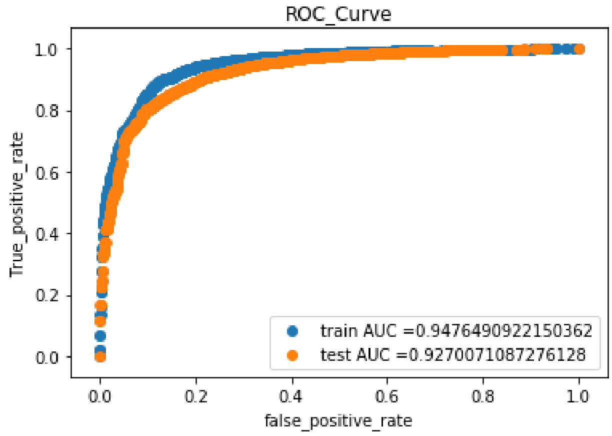
In [81]:

```
rbf_svm = SVC(C  =optimal_alpha_auc)
cg_cv = CalibratedClassifierCV(base_estimator = rbf_svm)
cg_cv.fit(X_train_vect_tfidf, y_train)
pred = cg_cv.predict(X_test_vect_tfidf)
acc = accuracy_score(y_test, pred, normalize=True) * float(100)
print('\n****Test accuracy for alpha = %f is %f%%' % (optimal_alpha_auc,acc))

train_fpr, train_tpr, thresholds = roc_curve(y_train, cg_cv.predict_proba(X_train_vect_tfidf)
[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, cg_cv.predict_proba(X_test_vect_tfidf)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("false_positive_rate")
plt.ylabel("True_positive_rate")
plt.title("ROC_Curve")
plt.show()



plt.scatter(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.scatter(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("false_positive_rate")
plt.ylabel("True_positive_rate")
plt.title("ROC_Curve")
plt.show()

print("="*100)
```

```
****Test accuracy for alpha = 1000.000000 is 90.257576%
```



false_positive_rate



==

Confusion Matrix(Train)

In [82]:

```
from sklearn.metrics import confusion_matrix
print("Train confusion matrix\n")
print(confusion_matrix(y_train, cg_cv.predict(X_train_vect_tfidf)))
```

```
Train confusion matrix

[[ 757  586]
 [ 124 7511]]
```

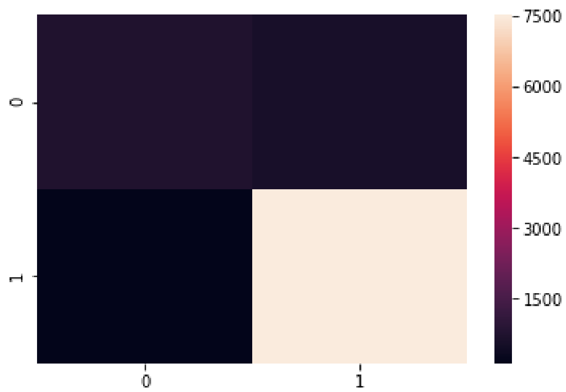
Heat map (Train)

In [83]:

```
sns.heatmap(confusion_matrix(y_train, cg_cv.predict(X_train_vect_tfidf)))
```

Out[83]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2034ad94198>
```



Confusion Matrix (Test)

In [84]:

```
print("Test confusion matrix\n")
```

```
print(confusion_matrix(y_test, cg_cv.predict(X_test_vect_tfidf)))
```

```
Test confusion matrix

[[ 511  521]
 [ 122 5446]]
```

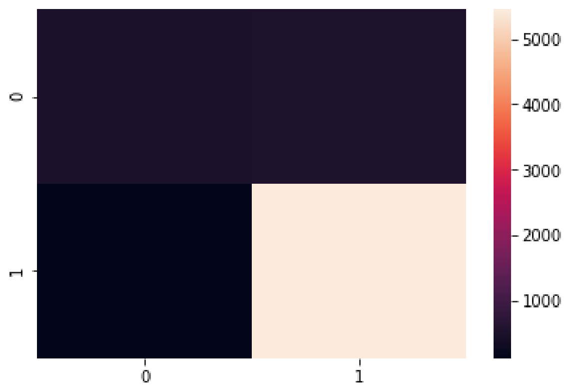
Heat Map (test)

In [85]:

```
sns.heatmap(confusion_matrix(y_test, cg_cv.predict(X_test_vect_tfidf)))
```

Out[85]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2034abecda0>
```



[5.2.3] Applying RBF SVM on AVG W2V, SET 3

GridSearch CV

In [86]:

```
# Please write all the code with proper documentation

from sklearn.linear_model import SGDClassifier
from sklearn.grid_search import GridSearchCV
from sklearn.calibration import CalibratedClassifierCV
tuned_parameters = [{'C': [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]}]
alpha_list = [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]
#Using GridSearchCV
model = GridSearchCV(SVC(), tuned_parameters, scoring = 'roc_auc')
model.fit(X_train_vectors, y_train)

print(model.best_estimator_)
print(model.score(X_test_vectors, y_test))
```

```
SVC(C=100, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
0.8928758882428941
```

SimpleCV

In [87]:

```
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_auc_score
alpha_list = [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]
```

```
ind = []
train_auc = []
cv_auc = []
for i in tqdm(alpha_list):
    rbf_svm = SVC(C = i)
    cg_cv = CalibratedClassifierCV(base_estimator = rbf_svm)
    cg_cv.fit(X_train_vectors, y_train)
    ind.append(i)
    y_train_pred =  cg_cv.predict_proba(X_train_vectors)[:,1]
    y_cv_pred =  cg_cv.predict_proba(X_cv_vectors)[:,1]
    train_auc.append(roc_auc_score(y_train,y_train_pred))
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
```

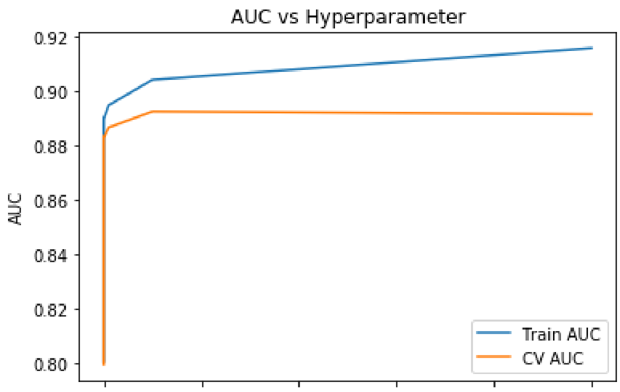
```
100%|██████████████████████████████████████████████████████████████████████████████████| 9/9 [01
:34<00:00, 13.90s/it]
```

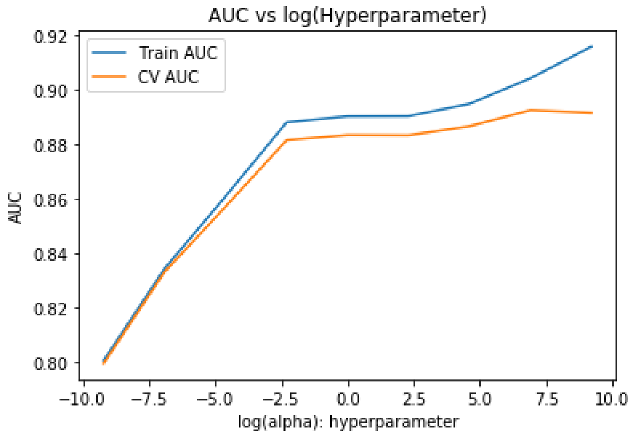
Plots

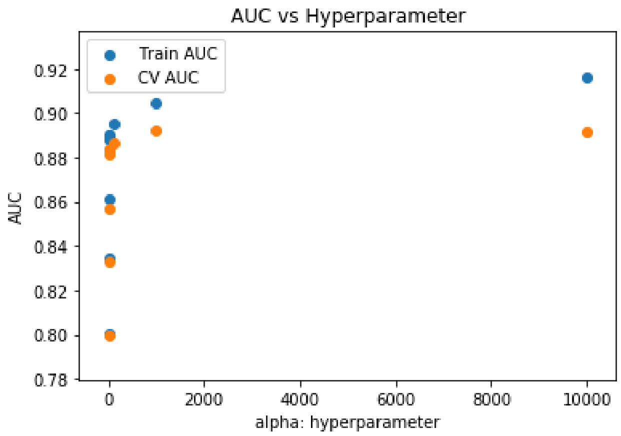
In [88]:

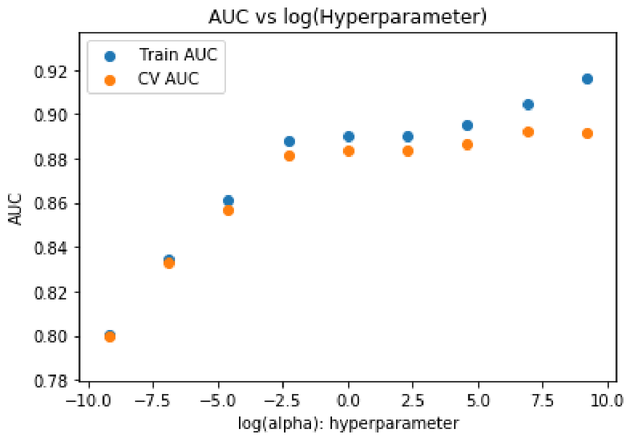
```
optimal_alpha_auc = ind[cv_auc.index(max(cv_auc))]
print('\nThe optimal alpha is (according to auc curve (max auc)): ' , optimal_alpha_auc)

plt.plot(alpha_list, train_auc, label='Train AUC')
plt.plot(alpha_list, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs Hyperparameter")
plt.show()

plt.plot(np.log(alpha_list), train_auc, label='Train AUC')
plt.plot(np.log(alpha_list), cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("log(alpha): hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs log(Hyperparameter)")
plt.show()


plt.scatter(alpha_list, train_auc, label='Train AUC')
plt.scatter(alpha_list, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs Hyperparameter")
plt.show()

plt.scatter(np.log(alpha_list), train_auc, label='Train AUC')
plt.scatter(np.log(alpha_list), cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("log(alpha): hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs log(Hyperparameter)")
plt.show()
```

```
The optimal alpha is (according to auc curve (max auc)):  1000
```







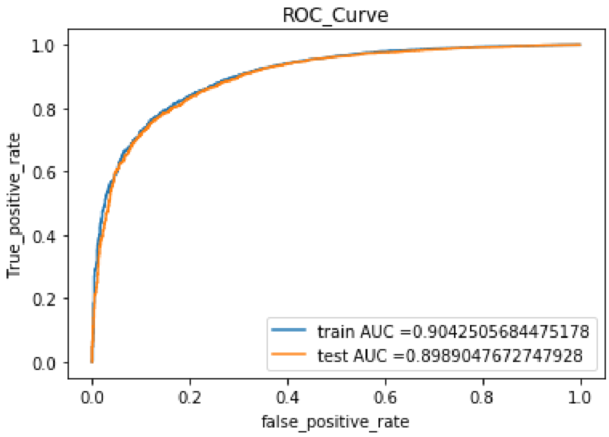


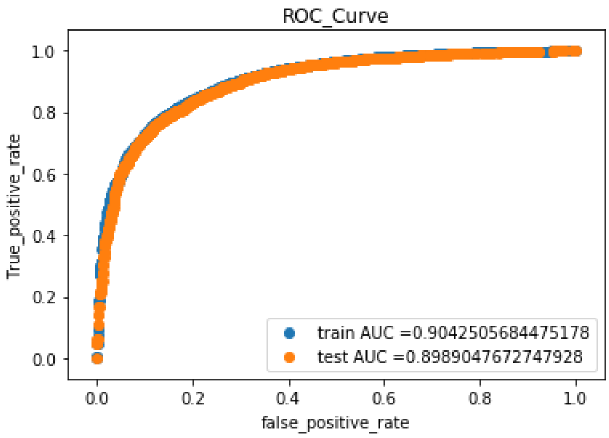
In [89]:

```
rbf_svm = SVC(C = optimal_alpha_auc)
cg_cv = CalibratedClassifierCV(base_estimator = rbf_svm)
cg_cv.fit(X_train_vectors, y_train)
pred = cg_cv.predict(X_test_vectors)
acc = accuracy_score(y_test, pred, normalize=True) * float(100)
print('\n****Test accuracy for alpha = %f is %f%%' % (optimal_alpha_auc,acc))

train_fpr, train_tpr, thresholds = roc_curve(y_train, cg_cv.predict_proba(X_train_vectors)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, cg_cv.predict_proba(X_test_vectors)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("false_positive_rate")
plt.ylabel("True_positive_rate")
plt.title("ROC_Curve")
plt.show()
```

```
plt.scatter(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.scatter(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("false_positive_rate")
plt.ylabel("True_positive_rate")
plt.title("ROC_Curve")
plt.show()

print("="*100)
```

```
****Test accuracy for alpha = 1000.000000 is 88.560606%
```






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

Confusion Matrix (Train)

In [90]:

```
from sklearn.metrics import confusion_matrix
print("Train confusion matrix\n")
print(confusion_matrix(y_train, cg_cv.predict(X_train_vectors)))
```

```
Train confusion matrix

[[ 556  787]
 [ 166 7469]]
```

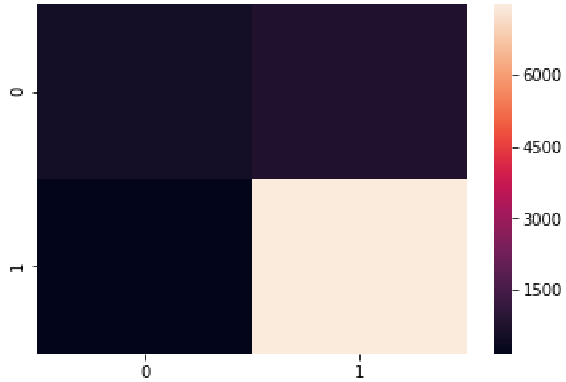
Heat map (Train)

In [91]:

```
sns.heatmap(confusion_matrix(y_train, cg_cv.predict(X_train_vectors)))
```

Out[91]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2034a379a20>
```



Confusion matrix (Test)

In [92]:

```
print("Test confusion matrix\n")
print(confusion_matrix(y_test, cg_cv.predict(X_test_vectors)))
```

```
Test confusion matrix

[[ 412  620]
 [ 135 5433]]
```

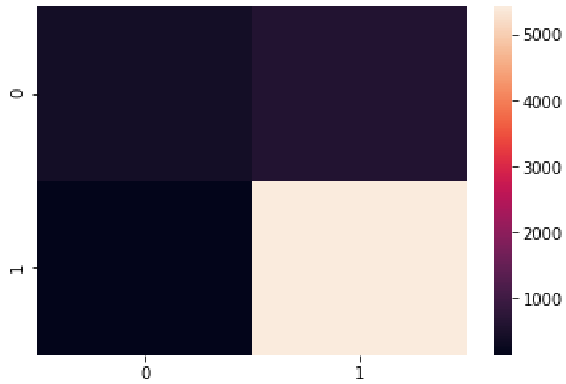
Heat map (test)

In [93]:

```
sns.heatmap(confusion_matrix(y_test, cg_cv.predict(X_test_vectors)))
```

Out[93]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2034a07a630>
```



[5.2.4] Applying RBF SVM on TFIDF W2V, SET 4

GridSearch CV

In [94]:

In [94]:

```
# Please write all the code with proper documentation

from sklearn.linear_model import SGDClassifier
from sklearn.grid_search import GridSearchCV
from sklearn.calibration import CalibratedClassifierCV

tuned_parameters = [{'C': [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]}]
alpha_list = [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]
#Using GridSearchCV
model = GridSearchCV(SVC(), tuned_parameters, scoring = 'roc_auc')
model.fit(tfidf_X_train_vectors, y_train)

print(model.best_estimator_)
print(model.score(tfidf_X_test_vectors, y_test))
```

```
SVC(C=100, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
0.8663084806312928
```

Simple CV

In [95]:

```
# Please write all the code with proper documentation
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_auc_score
alpha_list = [10**-4,10**-3,10**-2, 10**-1, 10**0, 10**1,10**2,10**3,10**4]
ind = []
train_auc = []
cv_auc = []
for i in tqdm(alpha_list):
    rbf_svm = SVC(C  =i)
    cg_cv = CalibratedClassifierCV(base_estimator = rbf_svm)
    cg_cv.fit(tfidf_X_train_vectors, y_train)
    ind.append(i)
    y_train_pred =  cg_cv.predict_proba(tfidf_X_train_vectors)[:,1]
    y_cv_pred =  cg_cv.predict_proba(tfidf_X_cv_vectors)[:,1]
    train_auc.append(roc_auc_score(y_train,y_train_pred))
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
```

```
100%|██████████████████████████████████████████████████| 9/9 [02:04<00:00, 22.16s/it]
```

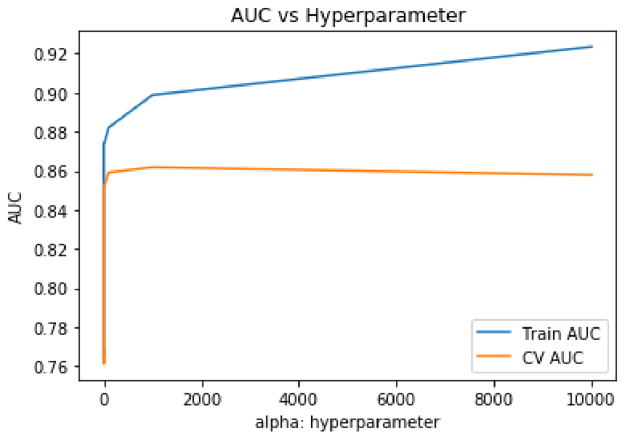
Plots

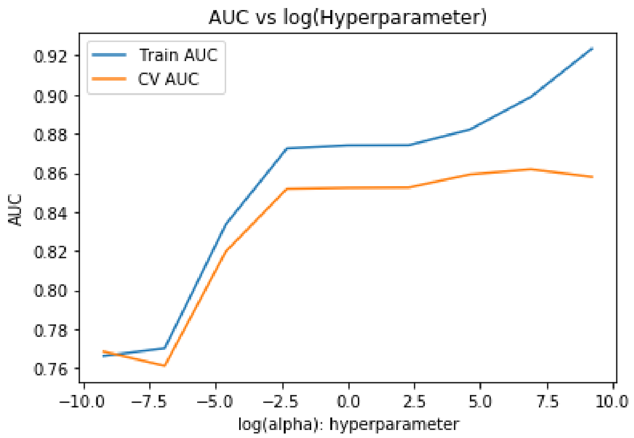
In [96]:

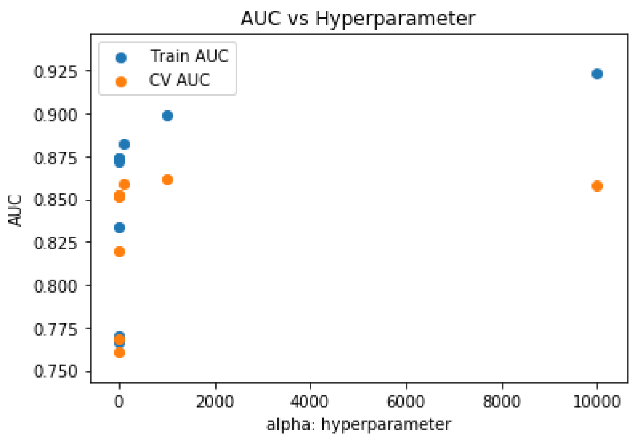
```
optimal_alpha_auc = ind[cv_auc.index(max(cv_auc))]
print('\nThe optimal alpha is (according to auc curve (max auc)): ' , optimal_alpha_auc)

plt.plot(alpha_list, train_auc, label='Train AUC')
plt.plot(alpha_list, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs Hyperparameter")
plt.show()

plt.plot(np.log(alpha_list), train_auc, label='Train AUC')
plt.plot(np.log(alpha_list), cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("log(alpha): hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs log(Hyperparameter)")
plt.show()
```

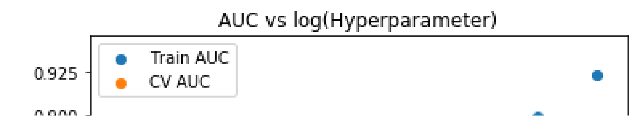
```
plt.scatter(alpha_list, train_auc, label='Train AUC')
plt.scatter(alpha_list, cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs Hyperparameter")
plt.show()

plt.scatter(np.log(alpha_list), train_auc, label='Train AUC')
plt.scatter(np.log(alpha_list), cv_auc, label='CV AUC')
plt.legend()
plt.xlabel("log(alpha): hyperparameter")
plt.ylabel("AUC")
plt.title("AUC vs log(Hyperparameter)")
plt.show()
```

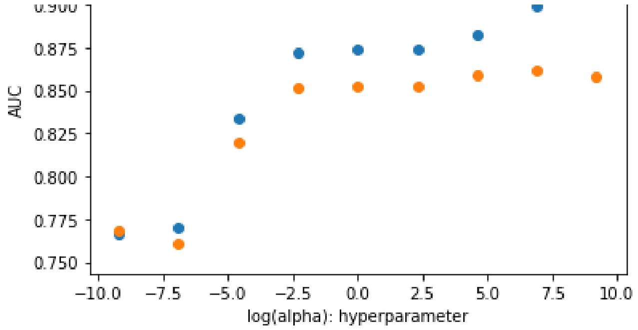
```
The optimal alpha is (according to auc curve (max auc)):  1000
```







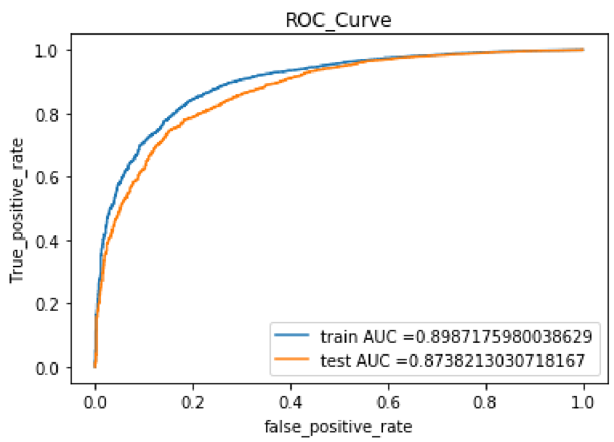


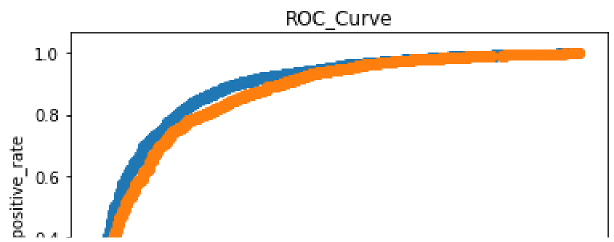


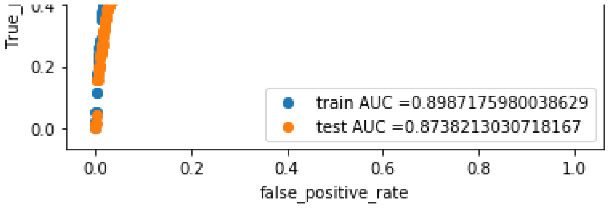
In [97]:

```
rbf_svm = SVC(C  =optimal_alpha_auc)
cg_cv = CalibratedClassifierCV(base_estimator = rbf_svm)
cg_cv.fit(tfidf_X_train_vectors, y_train)
pred = cg_cv.predict(tfidf_X_test_vectors)
acc = accuracy_score(y_test, pred, normalize=True) * float(100)
print('\n****Test accuracy for alpha = %f is %f%%' % (optimal_alpha_auc,acc))

train_fpr, train_tpr, thresholds = roc_curve(y_train, cg_cv.predict_proba(tfidf_X_train_vectors)
[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, cg_cv.predict_proba(tfidf_X_test_vectors)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("false_positive_rate")
plt.ylabel("True_positive_rate")
plt.title("ROC_Curve")
plt.show()



plt.scatter(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.scatter(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("false_positive_rate")
plt.ylabel("True_positive_rate")
plt.title("ROC_Curve")
plt.show()

print("="*100)
```

```
****Test accuracy for alpha = 1000.000000 is 87.636364%
```







===

Confusion Matrix (Train)

In [98]:

```
from sklearn.metrics import confusion_matrix
print("Train confusion matrix\n")
print(confusion_matrix(y_train, cg_cv.predict(tfidf_X_train_vectors)))
```

```
Train confusion matrix

[[ 432  911]
 [ 134 7501]]
```

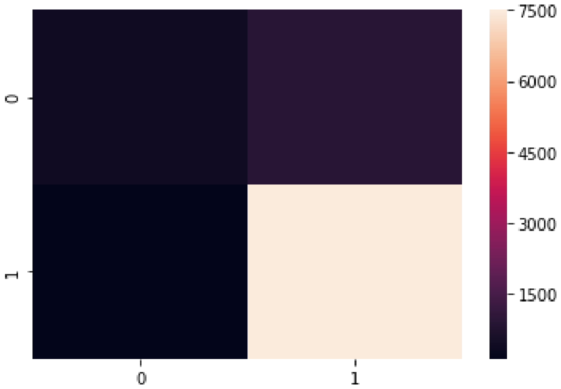
Heat Map (Train)

In [99]:

```
sns.heatmap(confusion_matrix(y_train, cg_cv.predict(tfidf_X_train_vectors)))
```

Out[99]:

```
&lt;matplotlib.axes._subplots.AxesSubplot at 0x2034a579358&gt;
```



Confusion Matrix (Test)

In [100]:

```
print("Test confusion matrix\n")
print(confusion_matrix(y_test, cg_cv.predict(tfidf_X_test_vectors)))
```

```
Test confusion matrix

[[ 315  717]
 [  99 5469]]
```

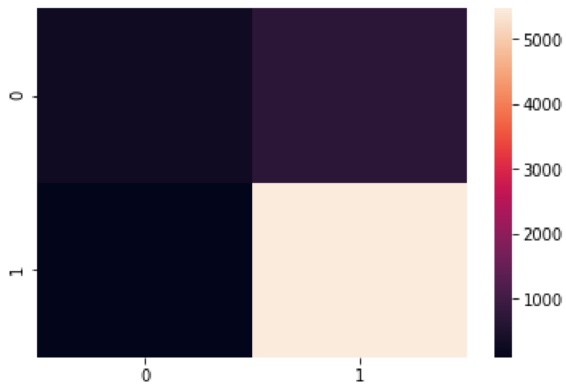
Heat Map (Test)

In [101]:

```
sns.heatmap(confusion_matrix(y_test, cg_cv.predict(tfidf_X_test_vectors)))
```

Out[101]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2034bf95e48>
```



[6] Conclusions

In [118]:

```
# Please compare all your models using Prettytable library
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["Vectorizer", "SVM_Type", "Hyperparameter", "AUC"]
x.add_row(["BOW", "Linear", 0.001, 0.9567])
x.add_row(["TFIDF", "Linear", 0.0001, 0.966])
x.add_row(["W2V", "Linear", 0.001, 0.9196])
x.add_row(["TFIDFW2V", "Linear", 0.001, 0.8947])
x.add_row(["BOW", "RBF", 100, 0.92395])
x.add_row(["TFIDF", "RBF", 1000, 0.927])
x.add_row(["W2V", "RBF", 1000, 0.8989])
x.add_row(["TFIDFW2V", "RBF", 1000, 0.8738])
print(x)
```

```
+------------+----------+----------------+---------+
| Vectorizer | SVM_Type | Hyperparameter |   AUC   |
+------------+----------+----------------+---------+
|    BOW     |  Linear  |     0.001      |  0.9567 |
|   TFIDF    |  Linear  |     0.0001     |  0.966  |
|    W2V     |  Linear  |     0.001      |  0.9196 |
|  TFIDFW2V  |  Linear  |     0.001      |  0.8947 |
|    BOW     |   RBF    |      100       | 0.92395 |
|   TFIDF    |   RBF    |      1000      |  0.927  |
|    W2V     |   RBF    |      1000      |  0.8989 |
|  TFIDFW2V  |   RBF    |      1000      |  0.8738 |
+------------+----------+----------------+---------+
```

- The best model of all is TFIDF with Linear SVM .
- Out of all the four models the SVM performs the worst in TFIDF-W2V (RBF)
- Feature Engineering by adding the no. of words in a review as a feature as well as considering the texts from summary tend to increase the performance
- Clearly by seeing the confusion matrix, it can be infered that the data set is imbalanced