Amazon Fine Food Reviews Analysis

Data Source: [https://www.kaggle.com/snap/amazon-fine-food-reviews (https://www.kaggle.com/snap/amazon-fine-food-reviews)](https://www.kaggle.com/snap/amazon-fine-food-reviews)

EDA: [https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/ (https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/)](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
```

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""", con)
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 50000""", 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 (50000, 10)
```

Out[2]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	Text
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	1	1303862400	Good Quality Dog Food	I have bought several of the Vitality canned d...
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	0	1346976000	Not as Advertised	Product arrived labeled as Jumbo Salted Peanut...
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	1	1219017600	"Delight" says it all	This is a confection that has been around a fe...

In [3]:

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

In [4]:
```
print(display.shape)
display.head()
```

(80668, 7)

Out[4]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
0	#oc-R115TNMSPFT9I7	B005ZBZLT4	Breyton	1331510400	2	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ESG	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B005ZBZLT4	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ESG	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBEV0	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	2

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

Out[5]:

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

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

Out[6]: 393063

[2] Exploratory Data Analysis

[2.1] Data Cleaning: Deduplication

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

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

Out[7]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACKER QUADRATINI VANILLA WAFERS	DELI WAF FIND EURC WAFI
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACKER QUADRATINI VANILLA WAFERS	DELI WAF FIND EURC WAFI
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACKER QUADRATINI VANILLA WAFERS	DELI WAF FIND EURC WAFI
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACKER QUADRATINI VANILLA WAFERS	DELI WAF FIND EURC WAFI
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	2	5	1199577600	LOACKER QUADRATINI VANILLA WAFERS	DELI WAF FIND EURC WAFI

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='quicksor
t', na_position='last')
```

In [9]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', inplace=Fa
lse)
final.shape
```

Out[9]:
```
(46072, 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]:
```
92.144
```

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	Time	Summary	Text
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1	5	1224892800	Bought This for My Son at College	My son loves spaghetti so I didn't hesitate or...
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2	4	1212883200	Pure cocoa taste with crunchy almonds inside	It was almost a 'love at first bite' - the per...

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()
```

```
(46071, 10)
```

Out[13]:
```
1    38479
0     7592
Name: Score, dtype: int64
```

[3] Preprocessing

[3.1]. Preprocessing Review Text

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

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

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

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

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

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

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

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

```
My dogs loves this chicken but its a product from China, so we wont be buying it anymore.  Its very hard t
o find any chicken products made in the USA but they are out there, but this one isnt.  Its too bad too be
cause its a good product but I wont take any chances till they know what is going on with the china import
s.
==================================================
this is yummy, easy and unusual. it makes a quick, delicous pie, crisp or cobbler. home made is better, bu
t a heck of a lot more work. this is great to have on hand for last minute dessert needs where you really
want to impress wih your creativity in cooking! recommended.
==================================================
Great flavor, low in calories, high in nutrients, high in protein! Usually protein powders are high priced
and high in calories, this one is a great bargain and tastes great, I highly recommend for the lady gym ra
ts, probably not "macho" enough for guys since it is soy based...
==================================================
For those of you wanting a high-quality, yet affordable green tea, you should definitely give this one a t
ry. Let me first start by saying that everyone is looking for something different for their ideal tea, and
I will attempt to briefly highlight what makes this tea attractive to a wide range of tea drinkers (whethe
r you are a beginner or long-time tea enthusiast).  I have gone through over 12 boxes of this tea myself,
and highly recommend it for the following reasons:<br /><br />-Quality:  First, this tea offers a smooth q
uality without any harsh or bitter after tones, which often turns people off from many green teas.  I've f
ound my ideal brewing time to be between 3-5 minutes, giving you a light but flavorful cup of tea.  Howeve
r, if you get distracted or forget about your tea and leave it brewing for 20+ minutes like I sometimes d
o, the quality of this tea is such that you still get a smooth but deeper flavor without the bad after tas
te.  The leaves themselves are whole leaves (not powdered stems, branches, etc commonly found in other bra
nds), and the high-quality nylon bags also include chunks of tropical fruit and other discernible ingredie
nts.  This isn't your standard cheap paper bag with a mix of unknown ingredients that have been ground dow
n to a fine powder, leaving you to wonder what it is you are actually drinking.<br /><br />-Taste:  This t
ea offers notes of real pineapple and other hints of tropical fruits, yet isn't sweet or artificially flav
ored.  You have the foundation of a high-quality young hyson green tea for those true "tea flavor" lovers,
yet the subtle hints of fruit make this a truly unique tea that I believe most will enjoy.  If you want it
sweet, you can add sugar, splenda, etc but this really is not necessary as this tea offers an inherent war
mth of flavor through it's ingredients.<br /><br />-Price:  This tea offers an excellent product at an exc
eptional price (especially when purchased at the prices Amazon offers).  Compared to other brands which I
believe to be of similar quality (Mighty Leaf, Rishi, Two Leaves, etc.), Revolution offers a superior prod
uct at an outstanding price.  I have been purchasing this through Amazon for less per box than I would be
paying at my local grocery store for Lipton, etc.<br /><br />Overall, this is a wonderful tea that is comp
arable, and even better than, other teas that are priced much higher.  It offers a well-balanced cup of gr
een tea that I believe many will enjoy.  In terms of taste, quality, and price, I would argue you won't fi
nd a better combination that that offered by Revolution's Tropical Green Tea.
==================================================
```

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 very hard t
o find any chicken products made in the USA but they are out there, but this one isnt.  Its too bad too be
cause its a good product but I wont take any chances till they know what is going on with the china import
s.
```

In [16]:
```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all-tags-from-an-elemen
t
from bs4 import BeautifulSoup

soup = BeautifulSoup(sent_0, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1000, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1500, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

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

```
My dogs loves this chicken but its a product from China, so we wont be buying it anymore.  Its very hard t
o find any chicken products made in the USA but they are out there, but this one isnt.  Its too bad too be
cause its a good product but I wont take any chances till they know what is going on with the china import
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this is yummy, easy and unusual. it makes a quick, delicous pie, crisp or cobbler. home made is better, bu
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Great flavor, low in calories, high in nutrients, high in protein! Usually protein powders are high priced
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ut any harsh or bitter after tones, which often turns people off from many green teas.  I've found my idea
l brewing time to be between 3-5 minutes, giving you a light but flavorful cup of tea.  However, if you ge
t distracted or forget about your tea and leave it brewing for 20+ minutes like I sometimes do, the qualit
y of this tea is such that you still get a smooth but deeper flavor without the bad after taste.  The leav
es themselves are whole leaves (not powdered stems, branches, etc commonly found in other brands), and the
high-quality nylon bags also include chunks of tropical fruit and other discernible ingredients.  This is
n't your standard cheap paper bag with a mix of unknown ingredients that have been ground down to a fine p
owder, leaving you to wonder what it is you are actually drinking.-Taste:  This tea offers notes of real p
ineapple and other hints of tropical fruits, yet isn't sweet or artificially flavored.  You have the found
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fruit make this a truly unique tea that I believe most will enjoy.  If you want it sweet, you can add suga
r, splenda, etc but this really is not necessary as this tea offers an inherent warmth of flavor through i
t's ingredients.-Price:  This tea offers an excellent product at an exceptional price (especially when pur
chased at the prices Amazon offers).  Compared to other brands which I believe to be of similar quality (M
ighty Leaf, Rishi, Two Leaves, etc.), Revolution offers a superior product at an outstanding price.  I hav
e been purchasing this through Amazon for less per box than I would be paying at my local grocery store fo
r Lipton, etc.Overall, this is a wonderful tea that is comparable, and even better than, other teas that a
re priced much higher.  It offers a well-balanced cup of green tea that I believe many will enjoy.  In ter
ms of taste, quality, and price, I would argue you won't find a better combination that that offered by Re
volution's Tropical Green Tea.
```

In [17]:
```
# https://stackoverflow.com/a/47091490/4084039
import re

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

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

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

```
Great flavor, low in calories, high in nutrients, high in protein! Usually protein powders are high priced
and high in calories, this one is a great bargain and tastes great, I highly recommend for the lady gym ra
ts, probably not "macho" enough for guys since it is soy based...
==================================================
```

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 very hard t
o find any chicken products made in the USA but they are out there, but this one isnt.  Its too bad too be
cause its a good product but I wont take any chances till they know what is going on with the china import
s.
```

In [20]:

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

```
Great flavor low in calories high in nutrients high in protein Usually protein powders are high priced and
high in calories this one is a great bargain and tastes great I highly recommend for the lady gym rats pro
bably not macho enough for guys since it is soy based
```

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', "you'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', 'the
ir',\
            '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', 'befor
e', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under', 'aga
in', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'each',
'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', "does
n'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", 'w
eren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

In [22]:
```
# Combining all the above stundents
from tqdm import tqdm
preprocessed_reviews = []
# tqdm is for printing the status bar
for sentance in tqdm(final['Text'].values):
    sentance = re.sub(r"http\S+", "", sentance)
    sentance = BeautifulSoup(sentance, 'lxml').get_text()
    sentance = decontracted(sentance)
    sentance = re.sub("\S*\d\S*", "", sentance).strip()
    sentance = re.sub('[^A-Za-z]+', ' ', sentance)
    # https://gist.github.com/sebleier/554280
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in stopwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|██████████| 46071/46071 [00:30<00:00, 1505.97it/s]
```

In [23]:
```
preprocessed_reviews[500]
```

Out[23]:
```
'good fruit slices flavor tart not sweet dusting sugar good left get little solid not gel like'
```

[3.2] Preprocessing Review Summary

In [24]:
```
## Similartly you can do preprocessing for review summary also.
from tqdm import tqdm
preprocessed_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_summary.append(sentance.strip())
```

```
100%|██████████| 46071/46071 [00:19<00:00, 2407.23it/s]
```

[4] Featurization

[4.1] BAG OF WORDS

In [25]:
```
#BoW
count_vect = CountVectorizer() #in scikit-learn
count_vect.fit(preprocessed_reviews)
print("some feature names ", count_vect.get_feature_names()[:10])
print('='*50)

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

```
some feature names  ['aa', 'aaa', 'aaaa', 'aaaaa', 'aaaaaaaaaaaa', 'aaaaaaaaaaaaaaa', 'aaaaaaahhhhhh', 'aa
aaaawwwwwwwwww', 'aaaaah', 'aaaand']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (46071, 39364)
the number of unique words  39364
```

[4.2] Bi-Grams and n-Grams.

In [26]:
```
#bi-gram, tri-gram and n-gram

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

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

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (46071, 5000)
the number of unique words including both unigrams and bigrams  5000
```

[4.3] TF-IDF

In [27]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tf_idf_vect.fit(preprocessed_reviews)
print("some sample features(unique words in the corpus)",tf_idf_vect.get_feature_names()[0:10])
print('='*50)

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

```
some sample features(unique words in the corpus) ['ability', 'able', 'able buy', 'able chew', 'able drin
k', 'able eat', 'able enjoy', 'able feed', 'able figure', 'able find']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (46071, 27311)
the number of unique words including both unigrams and bigrams  27311
```

[4.4] Word2Vec

In [28]:
```
# Train your own Word2Vec model using your own text corpus
i=0
list_of_sentance=[]
for sentance in preprocessed_reviews:
    list_of_sentance.append(sentance.split())
```

In [29]:
```
# Using Google News Word2Vectors

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


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

is_your_ram_gt_16g=False
want_to_use_google_w2v = False
want_to_train_w2v = True

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

elif want_to_use_google_w2v and is_your_ram_gt_16g:
    if os.path.isfile('GoogleNews-vectors-negative300.bin'):
        w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors-negative300.bin', binary=True)
        print(w2v_model.wv.most_similar('great'))
        print(w2v_model.wv.most_similar('worst'))
    else:
        print("you don't have gogole's word2vec file, keep want_to_train_w2v = True, to train your own w2
v ")
```

```
[('awesome', 0.8374980688095093), ('fantastic', 0.8105171918869019), ('good', 0.7832599878311157), ('terri
fic', 0.7737657427787781), ('excellent', 0.7583261728286743), ('wonderful', 0.7518240809440613), ('amazin
g', 0.7517659068107605), ('perfect', 0.7198998928070068), ('fabulous', 0.7060787081718445), ('decent', 0.6
77051842212677)]
==================================================
[('greatest', 0.7187121510505676), ('best', 0.7091323137283325), ('nastiest', 0.6895906329154968), ('tasti
est', 0.6627185344696045), ('honestly', 0.6524620056152344), ('eaten', 0.6507024765014648), ('experience
d', 0.6498685479164124), ('awful', 0.6451246738433838), ('closest', 0.6373002529144287), ('ive', 0.6348050
832748413)]
```

In [30]:
```
w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])
```

```
number of words that occured minimum 5 times  12798
sample words  ['dogs', 'loves', 'chicken', 'product', 'china', 'wont', 'buying', 'anymore', 'hard', 'fin
d', 'products', 'made', 'usa', 'one', 'isnt', 'bad', 'good', 'take', 'chances', 'till', 'know', 'going',
'imports', 'love', 'saw', 'pet', 'store', 'tag', 'attached', 'regarding', 'satisfied', 'safe', 'availabl
e', 'victor', 'traps', 'unreal', 'course', 'total', 'fly', 'pretty', 'stinky', 'right', 'nearby', 'used',
'bait', 'seasons', 'ca', 'not', 'beat', 'great']
```

[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.
sent_vectors = []; # the avg-w2v for each sentence/review is stored in this list
for sent in tqdm(list_of_sentance): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need to change this to 300
if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

```
100%|██████████| 46071/46071 [03:03<00:00, 250.42it/s]

46071
50
```

[4.4.1.2] TFIDF weighted W2v

In [32]:

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

In [33]:

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

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

```
100%|██████████| 46071/46071 [36:08<00:00, 22.09it/s]
```

[5] Assignment 5: Apply Logistic Regression

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

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

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

 - Find the best hyper parameter which will give the maximum [AUC (https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/receiver-operating-characteristic-curve-roc-curve-and-auc-1/)](https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/receiver-operating-characteristic-curve-roc-curve-and-auc-1/) value
 - Find the best hyper paramter using k-fold cross validation or simple cross validation data
 - Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this task of hyperparameter tuning

3. **Pertubation Test**

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

4. **Sparsity**

 - Calculate sparsity on weight vector obtained after using L1 regularization

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

5. **Feature importance**

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

6. **Feature engineering**

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

7. **Representation of results**

- You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure.
- Once after you found the best hyper parameter, you need to train your model with it, and find the AUC on test data and plot the ROC curve on both train and test.
- Along with plotting ROC curve, you need to print the confusion matrix (https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/confusion-matrix-tpr-fpr-fnr-tnr-1/) with predicted and original labels of test data points. Please visualize your confusion matrices using seaborn heatmaps.

  (https://seaborn.pydata.org/generated/seaborn.heatmap.html)
  (https://seaborn.pydata.org/generated/seaborn.heatmap.html)
(https://seaborn.pydata.org/generated/seaborn.heatmap.html)

(https://seaborn.pydata.org/generated/seaborn.heatmap.html)

8. **Conclusion** (https://seaborn.pydata.org/generated/seaborn.heatmap.html)

  (https://seaborn.pydata.org/generated/seaborn.heatmap.html)
- 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 (https://seaborn.pydata.org/generated/seaborn.heatmap.html) link (http://zetcode.com/python/prettytable/)

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. (https://soundcloud.com/applied-ai-course/leakage-bow-and-tfidf)](https://soundcloud.com/applied-ai-course/leakage-bow-and-tfidf)

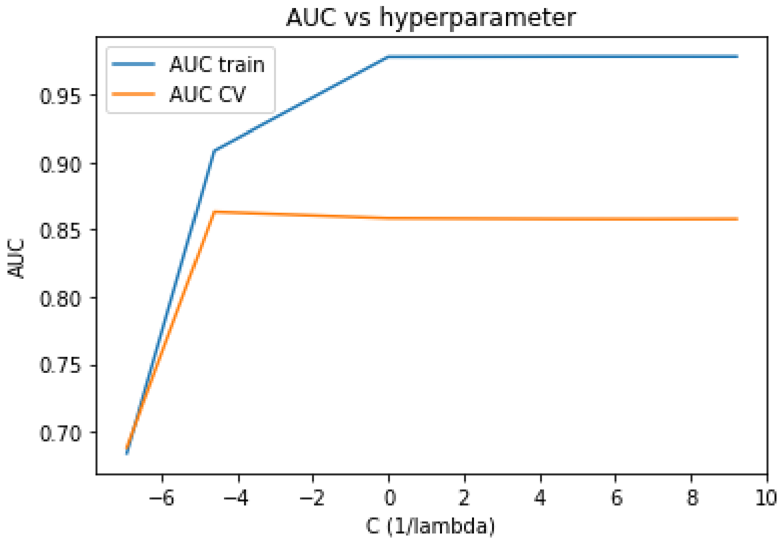
Applying Logistic Regression

[5.1] Logistic Regression on BOW, SET 1

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

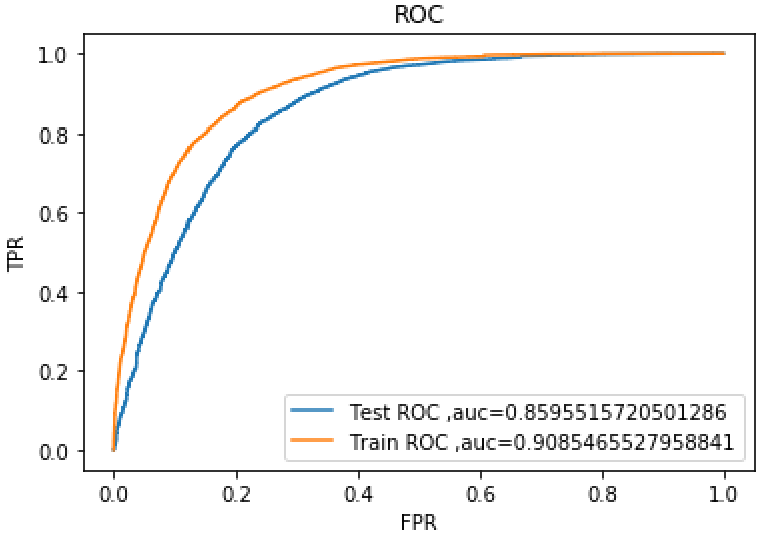
In [34]:
```
#Splitting preprocessed reviews into train,cross validation and test
import numpy as np
import pandas as pd
import math
import matplotlib.pyplot as plt
from sklearn.model_selection  import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.model_selection  import cross_val_score
from collections import Counter
from sklearn.metrics import accuracy_score
from sklearn import model_selection
from sklearn.metrics import roc_auc_score
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
X=preprocessed_reviews

y=np.array(final['Score'])
X_1, X_test, y_1, y_test = train_test_split(X, y, test_size=0.3, random_state=0)
X_train, X_cv, y_train, y_cv = train_test_split(X_1, y_1, test_size=0.3)
```

In [35]:
```
# Please write all the code with proper documentation
solver_list = ['liblinear', 'newton-cg', 'lbfgs', 'sag', 'saga']
params = dict(solver=solver_list)

count_vect = CountVectorizer()
X_train=count_vect.fit_transform(X_train)
X_cv=count_vect.transform(X_cv)
X_test=count_vect.transform(X_test)

scalar = StandardScaler(with_mean=False)
X_train = scalar.fit_transform(X_train)
X_test= scalar.transform(X_test)
X_cv=scalar.transform(X_cv)

C = [10**-3, 10**-2, 10**0, 10**2,10**3,10**4]#C=1/lambda
auc_train=[]
auc_cv=[]
for c in C:
    lr=LogisticRegression(penalty='l1',C=c,solver='saga')
    lr.fit(X_train,y_train)
    probcv=lr.predict_proba(X_cv)[:,1]
    auc_cv.append(roc_auc_score(y_cv,probcv))
    probtr=lr.predict_proba(X_train)[:,1]
    auc_train.append(roc_auc_score(y_train,probtr))
optimal_c= C[auc_cv.index(max(auc_cv))]
C=[math.log(x) for x in C]#converting values of C into logarithm
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(C, auc_train, label='AUC train')
ax.plot(C, auc_cv, label='AUC CV')
plt.title('AUC vs hyperparameter')
plt.xlabel('C (1/lambda)')
plt.ylabel('AUC')
ax.legend()
plt.show()
print('optimal lambda for which auc is maximum : ',1//optimal_c)
```

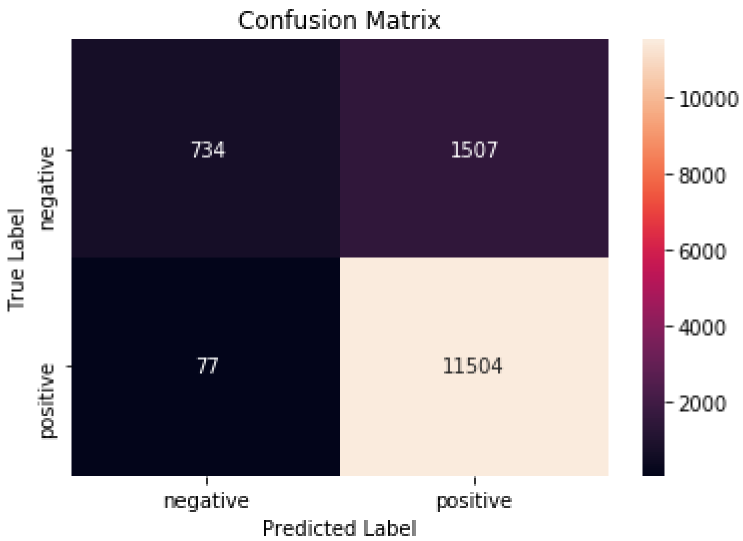



```
optimal lambda for which auc is maximum :  99.0
```

In [36]:
```
#ROC for lambda=99
lr=LogisticRegression(penalty='l1',C=optimal_c,  solver='saga')
lr.fit(X_train,y_train)
predi=lr.predict_proba(X_test)[:,1]
fpr1, tpr1, thresholds1 = metrics.roc_curve(y_test, predi)
pred=lr.predict_proba(X_train)[:,1]
fpr2,tpr2,thresholds2=metrics.roc_curve(y_train,pred)
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(fpr1, tpr1, label='Test ROC ,auc='+str(roc_auc_score(y_test,predi)))
ax.plot(fpr2, tpr2, label='Train ROC ,auc='+str(roc_auc_score(y_train,pred)))
plt.title('ROC')
plt.xlabel('FPR')
plt.ylabel('TPR')
ax.legend()
plt.show()
```



In [37]:
```
#Confusion matrix using heatmap for test data
from sklearn.metrics import confusion_matrix
lr=LogisticRegression(penalty='l1',C=optimal_c, solver='saga')
lr.fit(X_train,y_train)
predic=lr.predict(X_test)
import seaborn as sns
conf_mat = confusion_matrix(y_test, predic)
class_label = ["negative", "positive"]
df = pd.DataFrame(conf_mat, index = class_label, columns = class_label)
sns.heatmap(df, annot = True,fmt="d")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



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

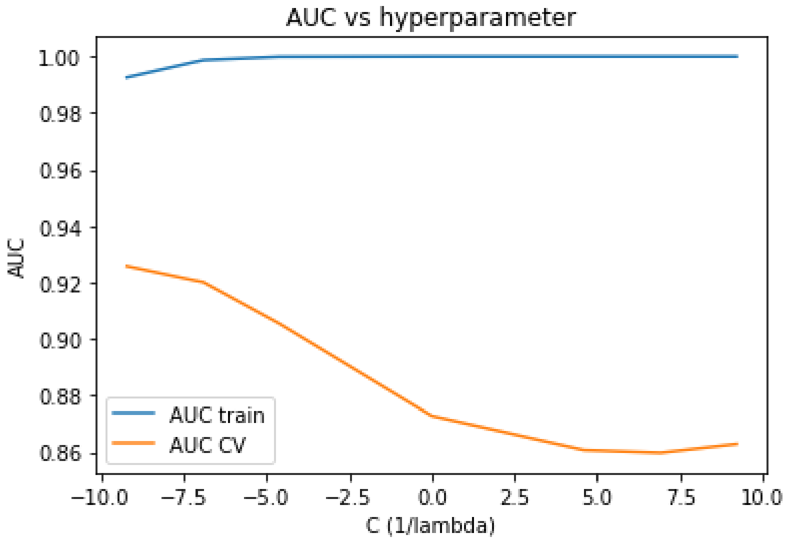
In [38]:
```
# Please write all the code with proper documentation
lr=LogisticRegression(penalty='l1',C=optimal_c, solver='saga')
lr.fit(X_train,y_train)
weight=lr.coef_
#Sparsity of vector weight=no of zero in weight vector
print('No of non zero element in weight vector ',np.count_nonzero(weight))
```

```
No of non zero element in weight vector  3880
```

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

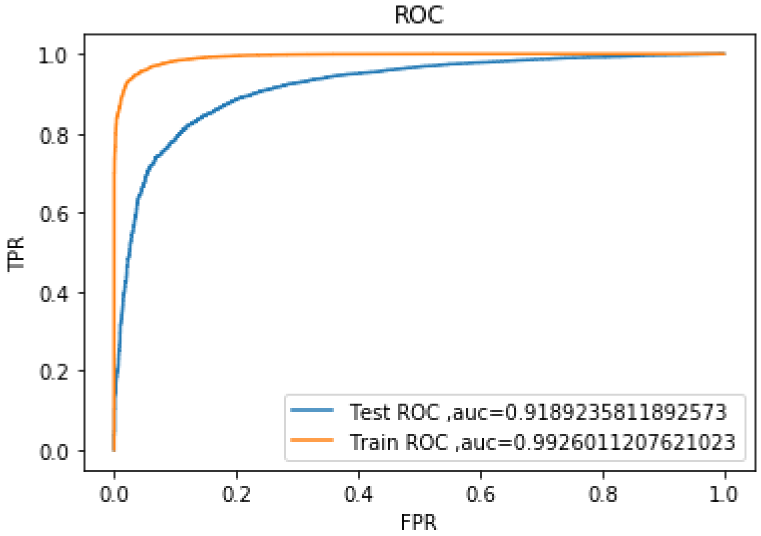
In [39]:
```
#Splitting preprocessed reviews into train,cross validation and test
import numpy as np
import pandas as pd
import math
import matplotlib.pyplot as plt
from sklearn.model_selection  import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.model_selection  import cross_val_score
from collections import Counter
from sklearn.metrics import accuracy_score
from sklearn import model_selection
from sklearn.metrics import roc_auc_score
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
X=preprocessed_reviews

y=np.array(final['Score'])
X_1, X_test, y_1, y_test = train_test_split(X, y, test_size=0.3, random_state=0)
X_train, X_cv, y_train, y_cv = train_test_split(X_1, y_1, test_size=0.3)
```

In [40]:
```
# Please write all the code with proper documentation
count_vect = CountVectorizer()
X_train=count_vect.fit_transform(X_train)
X_cv=count_vect.transform(X_cv)
X_test=count_vect.transform(X_test)

scalar = StandardScaler(with_mean=False)
X_train = scalar.fit_transform(X_train)
X_test= scalar.transform(X_test)
X_cv=scalar.transform(X_cv)
C = [10**-4,10**-3, 10**-2, 10**0, 10**2,10**3,10**4]#C=1/lambda
auc_train=[]
auc_cv=[]
for c in C:
    lr=LogisticRegression(penalty='l2',C=c)
    lr.fit(X_train,y_train)
    probcv=lr.predict_proba(X_cv)[:,1]
    auc_cv.append(roc_auc_score(y_cv,probcv))
    probtr=lr.predict_proba(X_train)[:,1]
    auc_train.append(roc_auc_score(y_train,probtr))
optimal_c= C[auc_cv.index(max(auc_cv))]
C=[math.log(x) for x in C]#converting values of C into logarithm
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(C, auc_train, label='AUC train')
ax.plot(C, auc_cv, label='AUC CV')
plt.title('AUC vs hyperparameter')
plt.xlabel('C (1/lambda)')
plt.ylabel('AUC')
ax.legend()
plt.show()
print('optimal lambda for which auc is maximum : ',1//optimal_c)
```

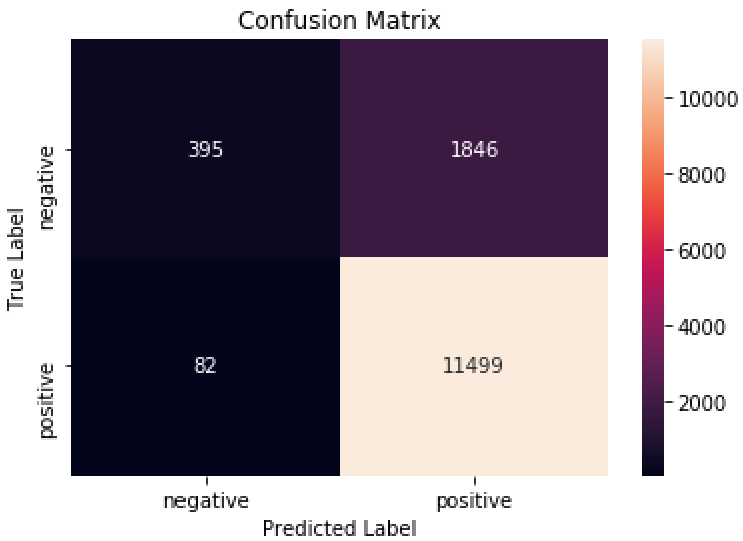



```
optimal lambda for which auc is maximum :  9999.0
```

In [41]:
```
#ROC for lambda=999
lr=LogisticRegression(penalty='l2',C=optimal_c)
lr.fit(X_train,y_train)
predi=lr.predict_proba(X_test)[:,1]
fpr1, tpr1, thresholds1 = metrics.roc_curve(y_test, predi)
pred=lr.predict_proba(X_train)[:,1]
fpr2,tpr2,thresholds2=metrics.roc_curve(y_train,pred)
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(fpr1, tpr1, label='Test ROC ,auc='+str(roc_auc_score(y_test,predi)))
ax.plot(fpr2, tpr2, label='Train ROC ,auc='+str(roc_auc_score(y_train,pred)))
plt.title('ROC')
plt.xlabel('FPR')
plt.ylabel('TPR')
ax.legend()
plt.show()
```



In [42]:
```
#Confusion matrix using heatmap for test data
from sklearn.metrics import confusion_matrix
lr=LogisticRegression(penalty='l2',C=optimal_c)
lr.fit(X_train,y_train)
predic=lr.predict(X_test)
import seaborn as sns
conf_mat = confusion_matrix(y_test, predic)
class_label = ["negative", "positive"]
df = pd.DataFrame(conf_mat, index = class_label, columns = class_label)
sns.heatmap(df, annot = True,fmt="d")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



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

In [43]:
```
# Please write all the code with proper documentation
#for checking multicollinearity we add e(small value) to train vector
W_before=lr.coef_

X_e=X_train

X_e.data=X_e.data+np.random.normal(loc=0,scale=0.0001,size=X_e.data.shape)

X_e.shape
```

Out[43]:
```
(22574, 28191)
```

In [44]:

```
#Training Logistic regression with X_e

lr_e=LogisticRegression(penalty='l2',C=optimal_c,)
lr_e.fit(X_e,y_train)
W_after=lr_e.coef_

#to eliminate divisible by zero error we will add 10^-6 to W_before and W_after
W_before+=10**-6
W_after+=10**-6

per_vector=[]

for i in range(len(W_before[0])):
    val=W_after[0][i]-W_before[0][i]
    val/=W_before[0][i]
    per_vector.append(val)

original_per_vect=np.array(per_vector)
per_vector=sorted(np.absolute(per_vector))[::-1]

#percentage change in vectors

per_vector[:10]
```

Out[44]:

```
[0.005821251304232240 5,
 0.004256509527186873,
 0.003321452198398827,
 0.003170515085906425,
 0.0024486427211313504,
 0.0023912540932288276,
 0.002163967299271423 8,
 0.0018428800788855835,
 0.0017105910044193705,
 0.0016820458819171314]
```

In [45]:
```
#calculating percentiles from 0 to 100

for i in range(11):
    print(str(i*10)+'th percentile = '+str(np.percentile(per_vector,i*10)))
```

```
0th percentile = 1.692792375440392e-10
10th percentile = 5.441477331964540e-07
20th percentile = 1.1225936273683284e-06
30th percentile = 1.7344459547769862e-06
40th percentile = 2.4377781227500157e-06
50th percentile = 3.2844433724190078e-06
60th percentile = 4.263898555575113e-06
70th percentile = 5.601630599564284e-06
80th percentile = 7.745741011962460e-06
90th percentile = 1.2352755291548988e-05
100th percentile = 0.0058212513042322405
```

In [46]:
```
#there is sudden rise in percentile from 90 to 100
#calculating percentile from 90 to 100
for i in range(90,101):
    print(str(i)+'th percentile ='+str(np.percentile(per_vector,i)))
```

```
90th percentile =1.2352755291548988e-05
91th percentile =1.3254701168600112e-05
92th percentile =1.437050953730924e-05
93th percentile =1.560522399402607e-05
94th percentile =1.7434392171033457e-05
95th percentile =1.9866679527883208e-05
96th percentile =2.3465761957805915e-05
97th percentile =3.0401248175227197e-05
98th percentile =4.4622245826159166e-05
99th percentile =8.636130231087683e-05
100th percentile =0.0058212513042322405
```

In [47]:
```
#from 99th percentile to 100 percentile sudden rise in the values from 0.498 to 10
#calculating percentile from 99.1 to 100
for i in range(1,11):
    print(str(99+(10**-1)*i)+'th percentile ='+str(np.percentile(per_vector,99+(10**-1)*i)))
```

```
99.1th percentile =9.566826248563016e-05
99.2th percentile =0.00010830924663230232
99.3th percentile =0.00012093231627411134
99.4th percentile =0.0001388623761200567
99.5th percentile =0.0001829118840918989
99.6th percentile =0.0002208229604009831
99.7th percentile =0.0003181661363822753
99.8th percentile =0.00046232893832290486
99.9th percentile =0.0007323814093129748
100.0th percentile =0.0058212513042322405
```

In [48]:
```
#100th percentile's percentage increment=48.327>2.5
#finding features from 99.9th percentile to 100th percentile
print('Features from 99.9th percentile to 100th percentile')
original_per_vect=original_per_vect.tolist()
all_features = count_vect.get_feature_names()

for i in range(1,11):
    print(str(99.9+(10**-2)*i)+'th percentile ='+str(np.percentile(per_vector,99.9+(10**-2)*i)))
```

```
Features from 99.9th percentile to 100th percentile
99.91000000000001th percentile =0.0007885862164132107
99.92th percentile =0.0008064210611374109
99.93th percentile =0.0009002757798394261
99.94000000000001th percentile =0.0011014605841574124
99.95th percentile =0.0011937303807324443
99.96000000000001th percentile =0.0014168490821754474
99.97th percentile =0.0016975458834358895
99.98th percentile =0.002246245118684229
99.99000000000001th percentile =0.0031978347032681734
100.0th percentile =0.0058212513042322405
```

[5.1.3] Feature Importance on BOW, SET 1

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

In [49]:
```
# Please write all the code with proper documentation

weight=lr.coef_
pos_indx=np.argsort(weight)[:,::-1]

neg_indx=np.argsort(weight)

print('Top 10 positive features :')
for i in list(pos_indx[0][0:10]):
    print(all_features[i])
```

```
Top 10 positive features :
great
best
love
delicious
good
perfect
loves
favorite
highly
excellent
```

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

In [50]:

```
# Please write all the code with proper documentation
print('Top 10 negative features :')
for i in list(neg_indx[0][:10]):
    print(all_features[i])
```

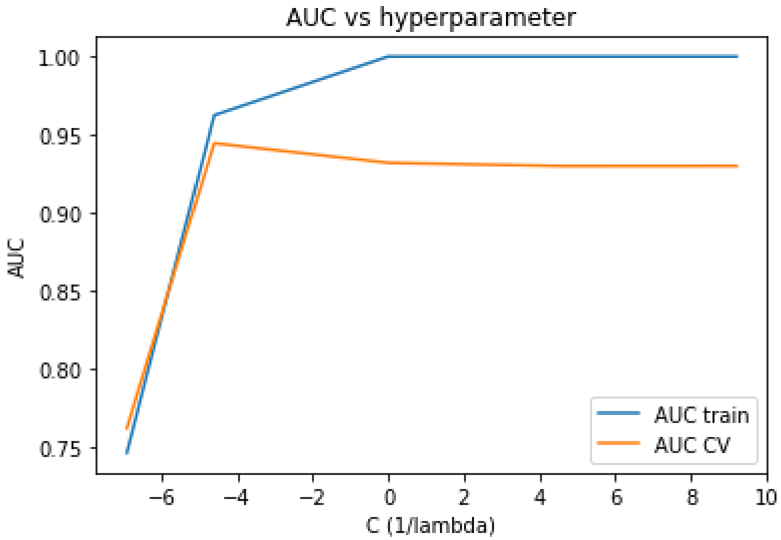
```
Top 10 negative features :
disappointed
not
worst
awful
horrible
bad
terrible
disappointing
money
waste
```

[5.2] Logistic Regression on TFIDF, SET 2

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

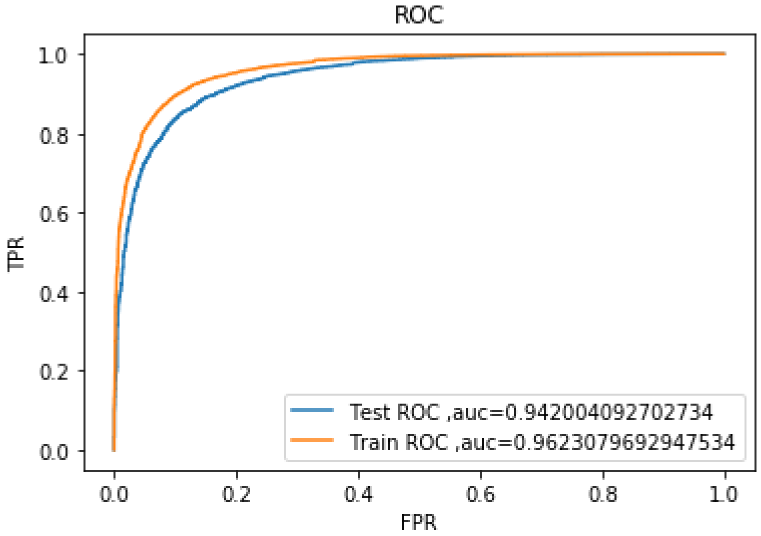
In [51]:
```
#Splitting preprocessed reviews into train,cross validation and test
import numpy as np
import pandas as pd
import math
import matplotlib.pyplot as plt
from sklearn.model_selection  import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.model_selection  import cross_val_score
from collections import Counter
from sklearn.metrics import accuracy_score
from sklearn import model_selection
from sklearn.metrics import roc_auc_score
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
X=preprocessed_reviews

y=np.array(final['Score'])
X_1, X_test, y_1, y_test = train_test_split(X, y, test_size=0.3, random_state=0)
X_train, X_cv, y_train, y_cv = train_test_split(X_1, y_1, test_size=0.3)
```

In [52]:
```
# Please write all the code with proper documentation
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
X_train_tf=tf_idf_vect.fit_transform(X_train)
X_cv_tf=tf_idf_vect.transform(X_cv)
X_test_tf=tf_idf_vect.transform(X_test)

scalar = StandardScaler(with_mean=False)
X_train_tf = scalar.fit_transform(X_train_tf)
X_test_tf= scalar.transform(X_test_tf)
X_cv_tf=scalar.transform(X_cv_tf)

C = [10**-3, 10**-2, 10**0, 10**2,10**3,10**4]#C=1/lambda
auc_train=[]
auc_cv=[]
for c in C:
    lr=LogisticRegression(penalty='l1',C=c,solver='saga')
    lr.fit(X_train_tf,y_train)
    probcv=lr.predict_proba(X_cv_tf)[:,1]
    auc_cv.append(roc_auc_score(y_cv,probcv))
    probtr=lr.predict_proba(X_train_tf)[:,1]
    auc_train.append(roc_auc_score(y_train,probtr))
optimal_c= C[auc_cv.index(max(auc_cv))]
C=[math.log(x) for x in C]#converting values of C into logarithm
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(C, auc_train, label='AUC train')
ax.plot(C, auc_cv, label='AUC CV')
plt.title('AUC vs hyperparameter')
plt.xlabel('C (1/lambda)')
plt.ylabel('AUC')
ax.legend()
plt.show()
print('optimal lambda for which auc is maximum : ',1//optimal_c)
```

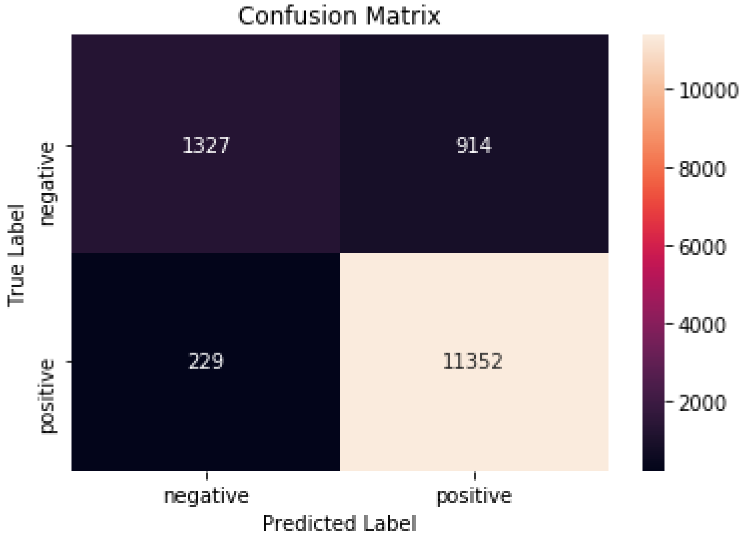



```
optimal lambda for which auc is maximum :  99.0
```

In [53]:
```
#ROC for lambda=99
lr=LogisticRegression(penalty='l1',C=optimal_c,solver='saga')
lr.fit(X_train_tf,y_train)
predi=lr.predict_proba(X_test_tf)[:,1]
fpr1, tpr1, thresholds1 = metrics.roc_curve(y_test, predi)
pred=lr.predict_proba(X_train_tf)[:,1]
fpr2,tpr2,thresholds2=metrics.roc_curve(y_train,pred)
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(fpr1, tpr1, label='Test ROC ,auc='+str(roc_auc_score(y_test,predi)))
ax.plot(fpr2, tpr2, label='Train ROC ,auc='+str(roc_auc_score(y_train,pred)))
plt.title('ROC')
plt.xlabel('FPR')
plt.ylabel('TPR')
ax.legend()
plt.show()
```

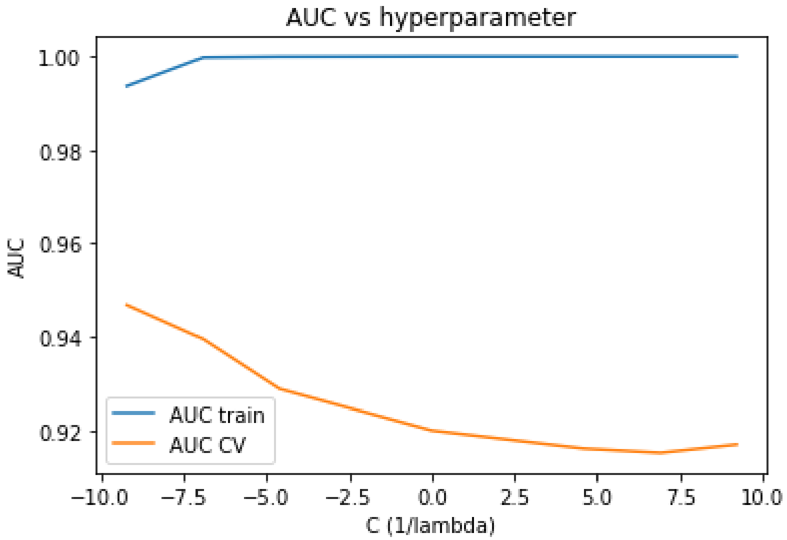


In [54]:
```
#Confusion matrix using heatmap for test data
from sklearn.metrics import confusion_matrix
lr=LogisticRegression(penalty='l1',C=optimal_c,solver='saga')
lr.fit(X_train_tf,y_train)
predic=lr.predict(X_test_tf)
import seaborn as sns
conf_mat = confusion_matrix(y_test, predic)
class_label = ["negative", "positive"]
df = pd.DataFrame(conf_mat, index = class_label, columns = class_label)
sns.heatmap(df, annot = True,fmt="d")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



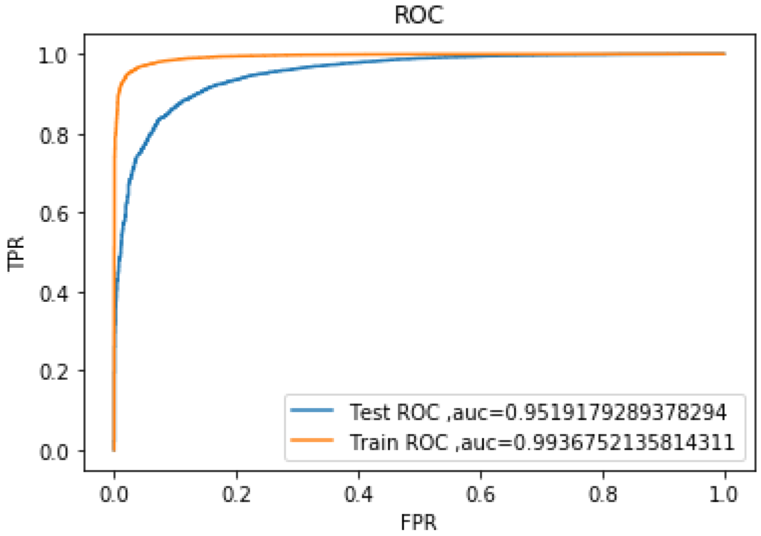
[5.2.2] Applying Logistic Regression with L2 regularization on TFIDF, SET 2

In [55]:
```
# Please write all the code with proper documentation
# Please write all the code with proper documentation
C = [10**-4,10**-3, 10**-2, 10**0, 10**2,10**3,10**4]#C=1/lambda
auc_train=[]
auc_cv=[]
for c in C:
    lr=LogisticRegression(penalty='l2',C=c)
    lr.fit(X_train_tf,y_train)
    probcv=lr.predict_proba(X_cv_tf)[:,1]
    auc_cv.append(roc_auc_score(y_cv,probcv))
    probtr=lr.predict_proba(X_train_tf)[:,1]
    auc_train.append(roc_auc_score(y_train,probtr))
optimal_c= C[auc_cv.index(max(auc_cv))]
C=[math.log(x) for x in C]#converting values of C into logarithm
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(C, auc_train, label='AUC train')
ax.plot(C, auc_cv, label='AUC CV')
plt.title('AUC vs hyperparameter')
plt.xlabel('C (1/lambda)')
plt.ylabel('AUC')
ax.legend()
plt.show()
print('optimal lambda for which auc is maximum : ',1//optimal_c)
```

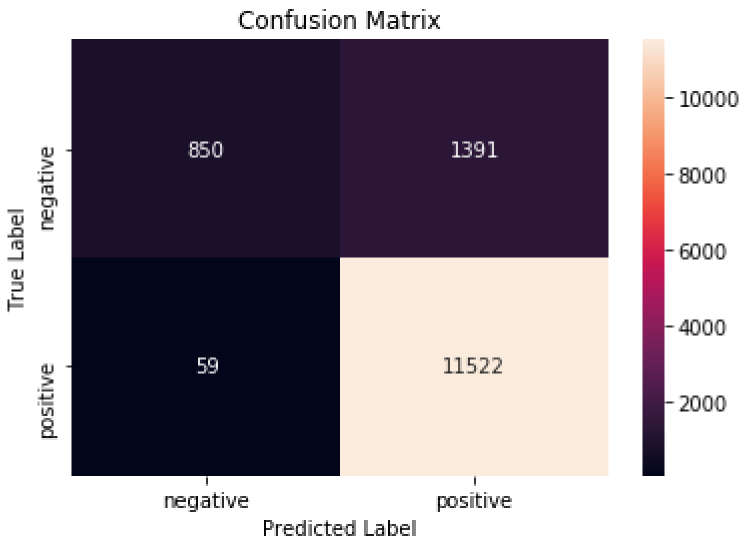



```
optimal lambda for which auc is maximum :  9999.0
```

In [56]:
```
#ROC for lambda=9999
lr=LogisticRegression(penalty='l2',C=optimal_c)
lr.fit(X_train_tf,y_train)
predi=lr.predict_proba(X_test_tf)[:,1]
fpr1, tpr1, thresholds1 = metrics.roc_curve(y_test, predi)
pred=lr.predict_proba(X_train_tf)[:,1]
fpr2,tpr2,thresholds2=metrics.roc_curve(y_train,pred)
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(fpr1, tpr1, label='Test ROC ,auc='+str(roc_auc_score(y_test,predi)))
ax.plot(fpr2, tpr2, label='Train ROC ,auc='+str(roc_auc_score(y_train,pred)))
plt.title('ROC')
plt.xlabel('FPR')
plt.ylabel('TPR')
ax.legend()
plt.show()
```



In [57]:
```
#Confusion matrix using heatmap for test data
from sklearn.metrics import confusion_matrix
lr=LogisticRegression(penalty='l2',C=optimal_c)
lr.fit(X_train_tf,y_train)
predic=lr.predict(X_test_tf)
import seaborn as sns
conf_mat = confusion_matrix(y_test, predic)
class_label = ["negative", "positive"]
df = pd.DataFrame(conf_mat, index = class_label, columns = class_label)
sns.heatmap(df, annot = True,fmt="d")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



[5.2.3] Feature Importance on TFIDF, SET 2

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

In [58]:
```
# Please write all the code with proper documentation
all_features = tf_idf_vect.get_feature_names()
weight=lr.coef_
pos_indx=np.argsort(weight)[:,::-1]

neg_indx=np.argsort(weight)

print('Top 10 positive features :')
for i in list(pos_indx[0][0:10]):
    print(all_features[i])
```

```
Top 10 positive features :
great
love
best
delicious
good
perfect
loves
nice
favorite
wonderful
```

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

In [59]:
```
# Please write all the code with proper documentation
print('Top 10 negative features :')
for i in list(neg_indx[0][:10]):
    print(all_features[i])
```

```
Top 10 negative features :
not
disappointed
worst
not buy
disappointing
not worth
awful
terrible
would not
bad
```

[5.3] Logistic Regression on AVG W2V, SET 3

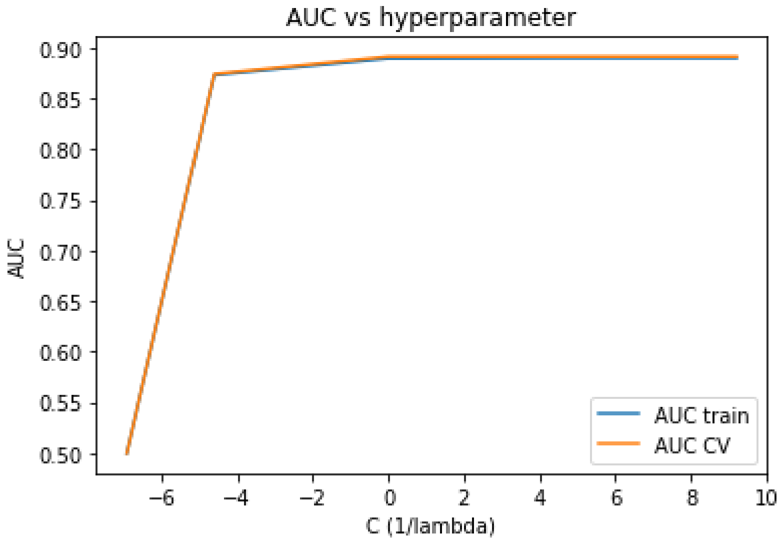
[5.3.1] Applying Logistic Regression with L1 regularization on AVG W2V SET 3

In [60]:
```
# Please write all the code with proper documentation
#word2vec for train
list_of_sentance_train=[]
for sentance in X_train:
    list_of_sentance_train.append(sentance.split())
w2v_model=Word2Vec(list_of_sentance_train,min_count=5,size=50, workers=4)
w2v_words = list(w2v_model.wv.vocab)
sent_vectors_train = [];
for sent in tqdm(list_of_sentance_train):
    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
    sent_vectors_train.append(sent_vec)
print(len(sent_vectors_train))
print(len(sent_vectors_train[0]))

#for cross validation we can use same w2v models and w2v words
list_of_sentance_cv=[]
for sentance in X_cv:
    list_of_sentance_cv.append(sentance.split())
sent_vectors_cv = [];
for sent in tqdm(list_of_sentance_cv):
    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
    sent_vectors_cv.append(sent_vec)
print(len(sent_vectors_cv))
print(len(sent_vectors_cv[0]))
```

```
#for test data
list_of_sentance_test=[]
for sentance in X_test:
    list_of_sentance_test.append(sentance.split())
sent_vectors_test = [];
for sent in tqdm(list_of_sentance_test):
    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
    sent_vectors_test.append(sent_vec)
print(len(sent_vectors_test))
print(len(sent_vectors_test[0]))
```

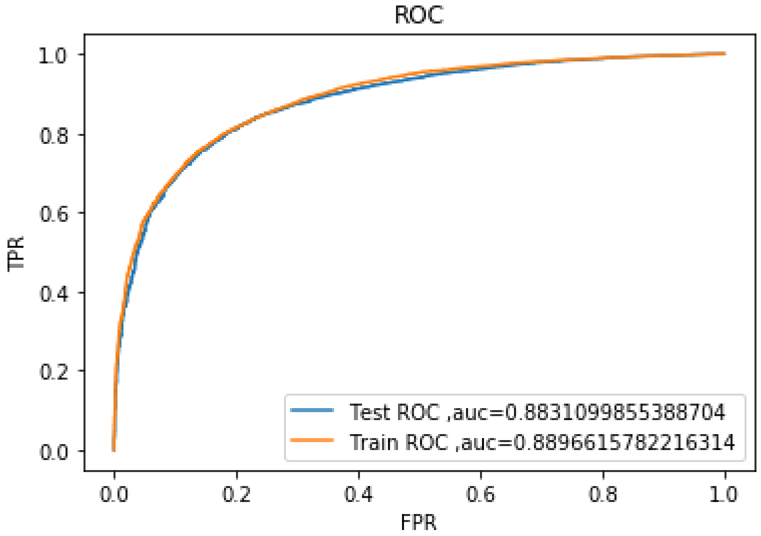
```
100%|██████████| 22574/22574 [01:05<00:00, 345.27it/s]

22574
50

100%|██████████| 9675/9675 [00:29<00:00, 328.10it/s]
  0%|          | 27/13822 [00:00<00:51, 268.87it/s]

9675
50

100%|██████████| 13822/13822 [00:41<00:00, 334.74it/s]

13822
50
```

In [61]:
```
X_train_w2v=sent_vectors_train
X_cv_w2v=sent_vectors_cv
X_test_w2v=sent_vectors_test

C = [10**-3, 10**-2, 10**0, 10**2,10**3,10**4]#C=1/lambda
auc_train=[]
auc_cv=[]
for c in C:
    lr=LogisticRegression(penalty='l1',C=c,solver='saga')
    lr.fit(X_train_w2v,y_train)
    probcv=lr.predict_proba(X_cv_w2v)[:,1]
    auc_cv.append(roc_auc_score(y_cv,probcv))
    probtr=lr.predict_proba(X_train_w2v)[:,1]
    auc_train.append(roc_auc_score(y_train,probtr))
optimal_c= C[auc_cv.index(max(auc_cv))]
C=[math.log(x) for x in C]#converting values of C into logarithm
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(C, auc_train, label='AUC train')
ax.plot(C, auc_cv, label='AUC CV')
plt.title('AUC vs hyperparameter')
plt.xlabel('C (1/lambda)')
plt.ylabel('AUC')
ax.legend()
plt.show()
print('optimal lambda for which auc is maximum : ',1//optimal_c)
```

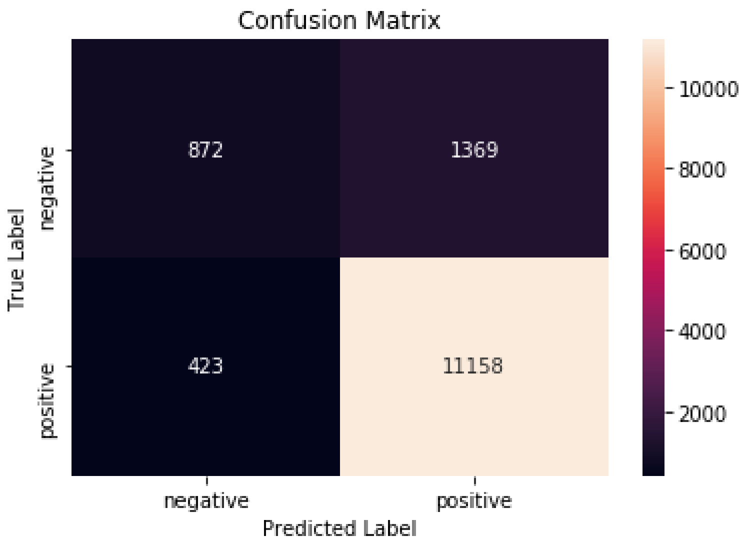



```
optimal lambda for which auc is maximum :  0
```

In [62]:
```
#ROC for lambda=1
lr=LogisticRegression(penalty='l1',C=optimal_c,solver='saga')
lr.fit(X_train_w2v,y_train)
predi=lr.predict_proba(X_test_w2v)[:,1]
fpr1, tpr1, thresholds1 = metrics.roc_curve(y_test, predi)
pred=lr.predict_proba(X_train_w2v)[:,1]
fpr2,tpr2,thresholds2=metrics.roc_curve(y_train,pred)
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(fpr1, tpr1, label='Test ROC ,auc='+str(roc_auc_score(y_test,predi)))
ax.plot(fpr2, tpr2, label='Train ROC ,auc='+str(roc_auc_score(y_train,pred)))
plt.title('ROC')
plt.xlabel('FPR')
plt.ylabel('TPR')
ax.legend()
plt.show()
```

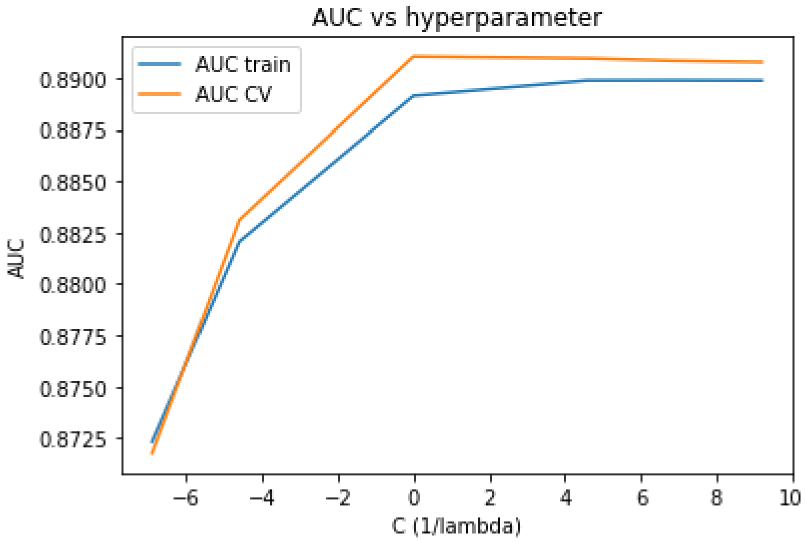


In [63]:
```
#Confusion matrix using heatmap for test data
from sklearn.metrics import confusion_matrix
lr=LogisticRegression(penalty='l1',C=optimal_c, solver='saga')
lr.fit(X_train_w2v,y_train)
predic=lr.predict(X_test_w2v)
import seaborn as sns
conf_mat = confusion_matrix(y_test, predic)
class_label = ["negative", "positive"]
df = pd.DataFrame(conf_mat, index = class_label, columns = class_label)
sns.heatmap(df, annot = True,fmt="d")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



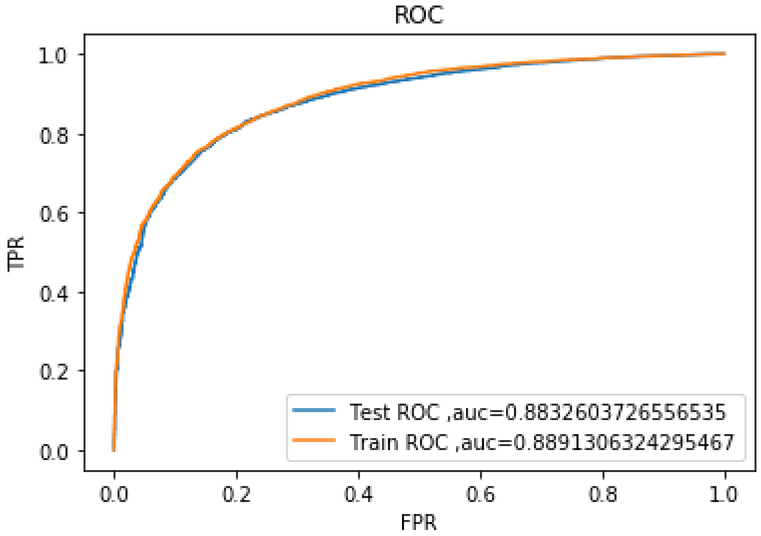
[5.3.2] Applying Logistic Regression with L2 regularization on AVG W2V, SET 3

In [64]:
```
# Please write all the code with proper documentation

C = [10**-3, 10**-2, 10**0, 10**2,10**3,10**4]#C=1/lambda
auc_train=[]
auc_cv=[]
for c in C:
    lr=LogisticRegression(penalty='l2',C=c)
    lr.fit(X_train_w2v,y_train)
    probcv=lr.predict_proba(X_cv_w2v)[:,1]
    auc_cv.append(roc_auc_score(y_cv,probcv))
    probtr=lr.predict_proba(X_train_w2v)[:,1]
    auc_train.append(roc_auc_score(y_train,probtr))
optimal_c= C[auc_cv.index(max(auc_cv))]
C=[math.log(x) for x in C]#converting values of C into logarithm
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(C, auc_train, label='AUC train')
ax.plot(C, auc_cv, label='AUC CV')
plt.title('AUC vs hyperparameter')
plt.xlabel('C (1/lambda)')
plt.ylabel('AUC')
ax.legend()
plt.show()
print('optimal lambda for which auc is maximum : ',1//optimal_c)
```

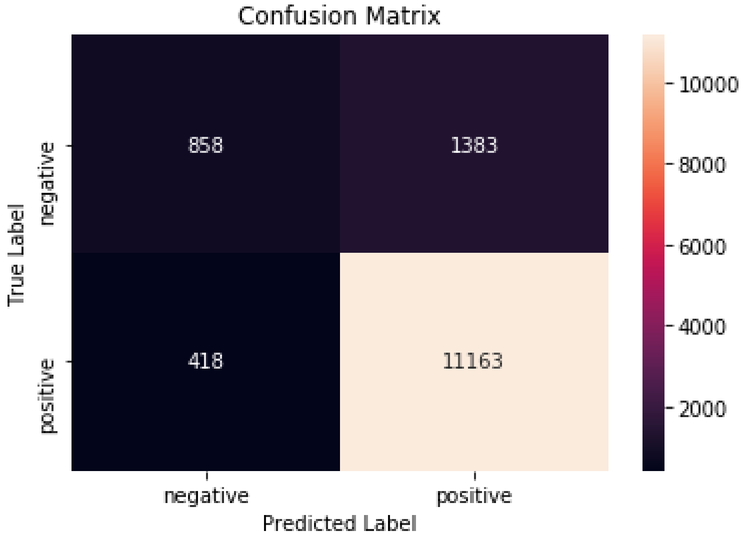



```
optimal lambda for which auc is maximum :  1
```

In [65]:
```
#ROC for lambda=1
lr=LogisticRegression(penalty='l2',C=optimal_c)
lr.fit(X_train_w2v,y_train)
predi=lr.predict_proba(X_test_w2v)[:,1]
fpr1, tpr1, thresholds1 = metrics.roc_curve(y_test, predi)
pred=lr.predict_proba(X_train_w2v)[:,1]
fpr2,tpr2,thresholds2=metrics.roc_curve(y_train,pred)
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(fpr1, tpr1, label='Test ROC ,auc='+str(roc_auc_score(y_test,predi)))
ax.plot(fpr2, tpr2, label='Train ROC ,auc='+str(roc_auc_score(y_train,pred)))
plt.title('ROC')
plt.xlabel('FPR')
plt.ylabel('TPR')
ax.legend()
plt.show()
```



In [66]:
```
#Confusion matrix using heatmap for test data
from sklearn.metrics import confusion_matrix
lr=LogisticRegression(penalty='l2',C=optimal_c)
lr.fit(X_train_w2v,y_train)
predic=lr.predict(X_test_w2v)
import seaborn as sns
conf_mat = confusion_matrix(y_test, predic)
class_label = ["negative", "positive"]
df = pd.DataFrame(conf_mat, index = class_label, columns = class_label)
sns.heatmap(df, annot = True,fmt="d")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



[5.4] Logistic Regression on TFIDF W2V, SET 4

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

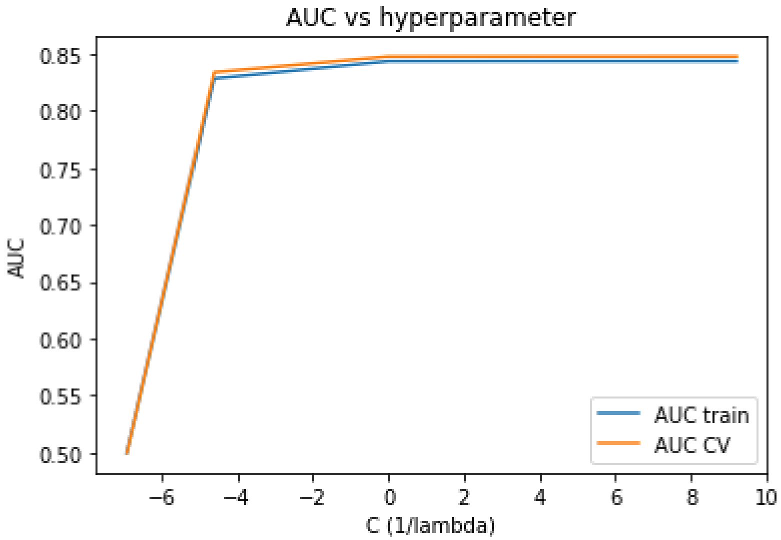
In [67]:

```
# Please write all the code with proper documentation
list_of_sentance_train=[]
for sentance in X_train:
    list_of_sentance_train.append(sentance.split())
w2v_model=Word2Vec(list_of_sentance_train,min_count=5,size=50, workers=4)
w2v_words = list(w2v_model.wv.vocab)
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2),min_df=10, max_features=500)

tf_idf_matrix=tf_idf_vect.fit_transform(X_train)


tfidf_feat = tf_idf_vect.get_feature_names()
dictionary = dict(zip(tf_idf_vect.get_feature_names(), list(tf_idf_vect.idf_)))

#for train data

tfidf_sent_vectors_train = [];
row=0;
for sent in tqdm(list_of_sentance_train):
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_train.append(sent_vec)
    row += 1

#for cross validation data and test we will use same words and models of train
list_of_sentance_cv=[]
for sentance in X_cv:
    list_of_sentance_cv.append(sentance.split())
tfidf_sent_vectors_cv = [];
row=0;
for sent in tqdm(list_of_sentance_cv):
    sent_vec = np.zeros(50)
    weight_sum =0;
```

```
    for word in sent:
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_cv.append(sent_vec)
    row += 1

#for test data
list_of_sentance_test=[]
for sentance in X_test:
    list_of_sentance_test.append(sentance.split())
tfidf_sent_vectors_test = [];
row=0;
for sent in tqdm(list_of_sentance_test):
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_test.append(sent_vec)
    row += 1
```

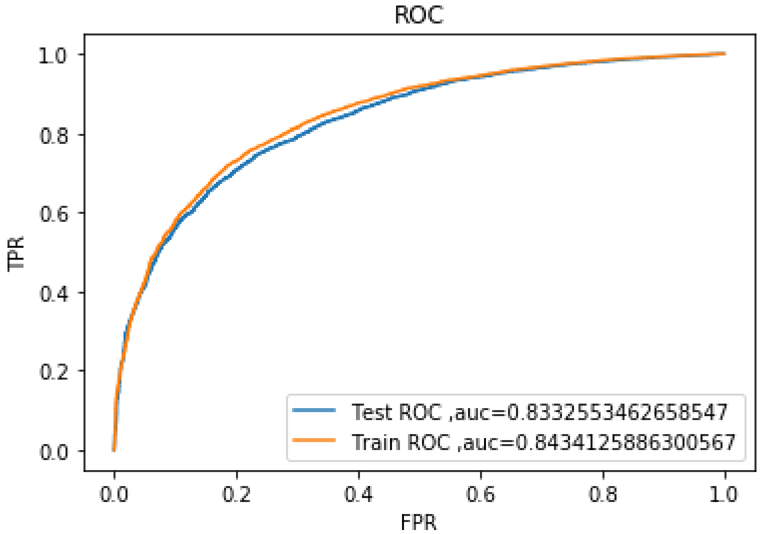
```
100%|██████████| 22574/22574 [01:21<00:00, 276.53it/s]
100%|██████████| 9675/9675 [00:35<00:00, 275.14it/s]
100%|██████████| 13822/13822 [00:49<00:00, 281.23it/s]
```

In [68]:
```
X_train_tfw2v=tfidf_sent_vectors_train
X_cv_tfw2v=tfidf_sent_vectors_cv
X_test_tfw2v=tfidf_sent_vectors_test

C = [10**-3, 10**-2, 10**0, 10**2,10**3,10**4]#C=1/lambda
auc_train=[]
auc_cv=[]
for c in C:
    lr=LogisticRegression(penalty='l1',C=c, solver='saga')
    lr.fit(X_train_tfw2v,y_train)
    probcv=lr.predict_proba(X_cv_tfw2v)[:,1]
    auc_cv.append(roc_auc_score(y_cv,probcv))
    probtr=lr.predict_proba(X_train_tfw2v)[:,1]
    auc_train.append(roc_auc_score(y_train,probtr))
optimal_c= C[auc_cv.index(max(auc_cv))]
C=[math.log(x) for x in C]#converting values of C into logarithm
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(C, auc_train, label='AUC train')
ax.plot(C, auc_cv, label='AUC CV')
plt.title('AUC vs hyperparameter')
plt.xlabel('C (1/lambda)')
plt.ylabel('AUC')
ax.legend()
plt.show()
print('optimal lambda for which auc is maximum : ',1//optimal_c)
```

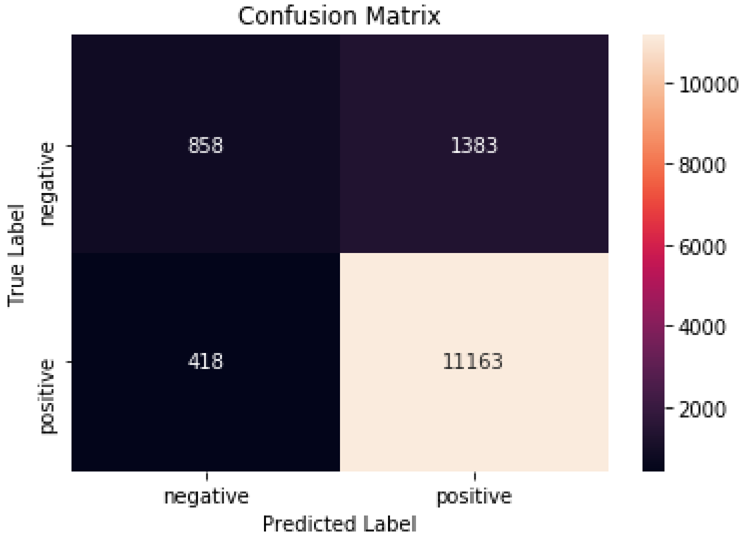



```
optimal lambda for which auc is maximum :  0
```

In [69]:
```
#ROC for lambda=1
lr=LogisticRegression(penalty='l1',C=optimal_c, solver='saga')
lr.fit(X_train_tfw2v,y_train)
predi=lr.predict_proba(X_test_tfw2v)[:,1]
fpr1, tpr1, thresholds1 = metrics.roc_curve(y_test, predi)
pred=lr.predict_proba(X_train_tfw2v)[:,1]
fpr2,tpr2,thresholds2=metrics.roc_curve(y_train,pred)
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(fpr1, tpr1, label='Test ROC ,auc='+str(roc_auc_score(y_test,predi)))
ax.plot(fpr2, tpr2, label='Train ROC ,auc='+str(roc_auc_score(y_train,pred)))
plt.title('ROC')
plt.xlabel('FPR')
plt.ylabel('TPR')
ax.legend()
plt.show()
```

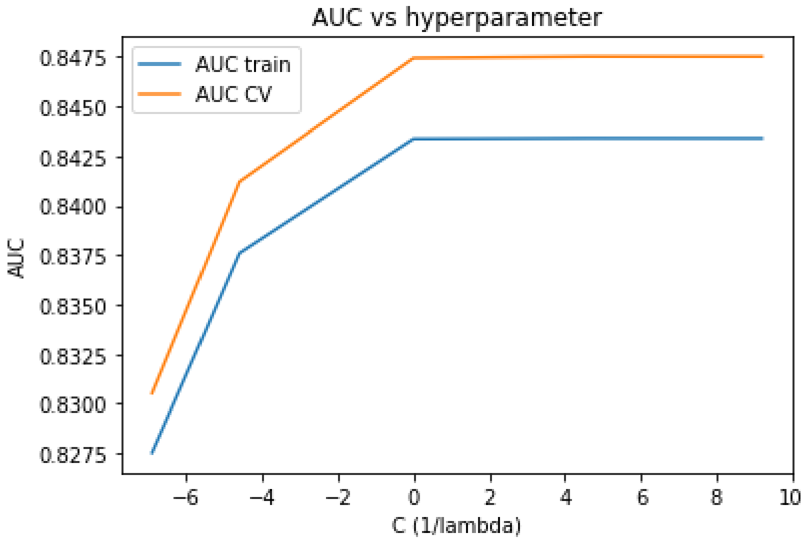


In [70]:
```
#Confusion matrix using heatmap for test data
from sklearn.metrics import confusion_matrix
import seaborn as sns
conf_mat = confusion_matrix(y_test, predic)
class_label = ["negative", "positive"]
df = pd.DataFrame(conf_mat, index = class_label, columns = class_label)
sns.heatmap(df, annot = True,fmt="d")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



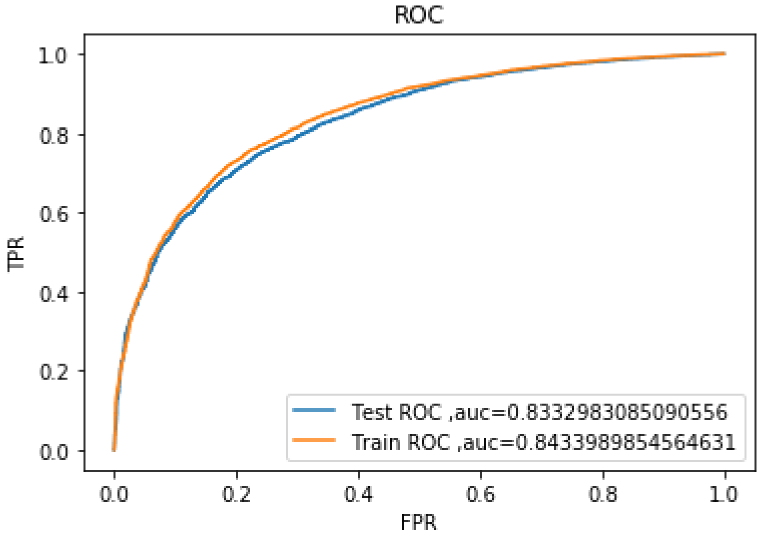
[5.4.2] Applying Logistic Regression with L2 regularization on TFIDF W2V, SET 4

In [71]:
```
# Please write all the code with proper documentation
C = [10**-3, 10**-2, 10**0, 10**2,10**3,10**4]#C=1/lambda
auc_train=[]
auc_cv=[]
for c in C:
    lr=LogisticRegression(penalty='l2',C=c)
    lr.fit(X_train_tfw2v,y_train)
    probcv=lr.predict_proba(X_cv_tfw2v)[:,1]
    auc_cv.append(roc_auc_score(y_cv,probcv))
    probtr=lr.predict_proba(X_train_tfw2v)[:,1]
    auc_train.append(roc_auc_score(y_train,probtr))
optimal_c= C[auc_cv.index(max(auc_cv))]
C=[math.log(x) for x in C]#converting values of C into logarithm
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(C, auc_train, label='AUC train')
ax.plot(C, auc_cv, label='AUC CV')
plt.title('AUC vs hyperparameter')
plt.xlabel('C (1/lambda)')
plt.ylabel('AUC')
ax.legend()
plt.show()
print('optimal lambda for which auc is maximum : ',1//optimal_c)
```

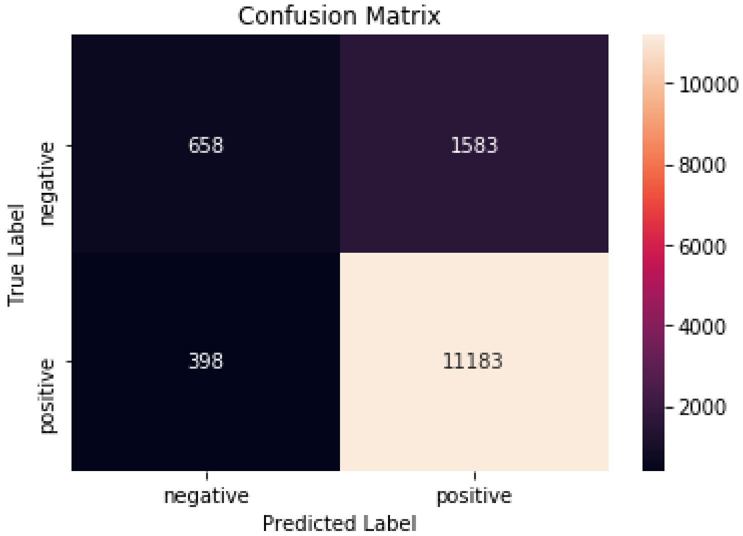



```
optimal lambda for which auc is maximum :  0
```

In [72]:
```
#ROC for lambda=1
lr=LogisticRegression(penalty='l2',C=optimal_c)
lr.fit(X_train_tfw2v,y_train)
predi=lr.predict_proba(X_test_tfw2v)[:,1]
fpr1, tpr1, thresholds1 = metrics.roc_curve(y_test, predi)
pred=lr.predict_proba(X_train_tfw2v)[:,1]
fpr2,tpr2,thresholds2=metrics.roc_curve(y_train,pred)
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(fpr1, tpr1, label='Test ROC ,auc='+str(roc_auc_score(y_test,predi)))
ax.plot(fpr2, tpr2, label='Train ROC ,auc='+str(roc_auc_score(y_train,pred)))
plt.title('ROC')
plt.xlabel('FPR')
plt.ylabel('TPR')
ax.legend()
plt.show()
```



In [73]:
```
#Confusion matrix using heatmap for test data
from sklearn.metrics import confusion_matrix
import seaborn as sns
predic=lr.predict(X_test_tfw2v)
conf_mat = confusion_matrix(y_test, predic)
class_label = ["negative", "positive"]
df = pd.DataFrame(conf_mat, index = class_label, columns = class_label)
sns.heatmap(df, annot = True,fmt="d")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

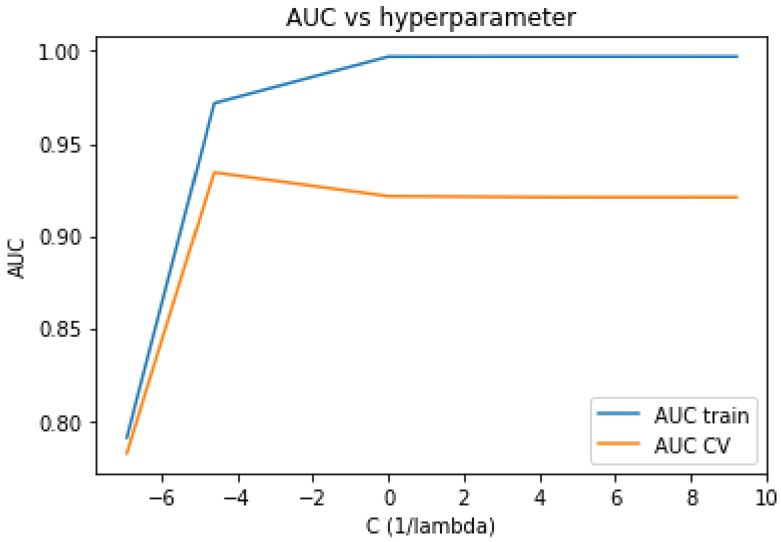


In [74]:
```
#Feature Engineering
#Adding preprocessed summary and review length to preprocessed summary
for i in range(len(preprocessed_reviews)):
    preprocessed_reviews[i]+=' '+preprocessed_summary[i]+' '+str(len(final.Text.iloc[i]))

preprocessed_reviews[500]
```

Out[74]:
```
'good fruit slices flavor tart not sweet dusting sugar good left get little solid not gel like great flavo
r 154'
```

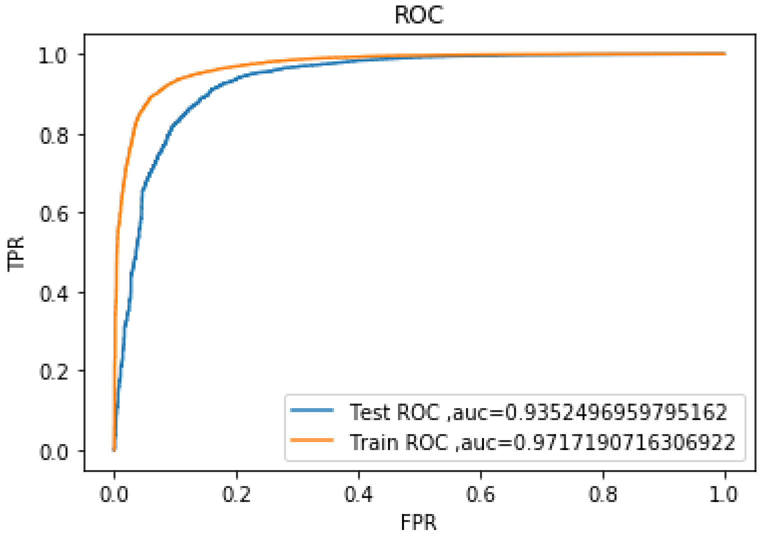
In [75]:
```
#Applying Logistic Regression on BoW
X=preprocessed_reviews

y=np.array(final['Score'])
X_1, X_test, y_1, y_test = train_test_split(X, y, test_size=0.3, random_state=0)
X_train, X_cv, y_train, y_cv = train_test_split(X_1, y_1, test_size=0.3)
```

In [76]:
```
count_vect = CountVectorizer()
X_train_bow=count_vect.fit_transform(X_train)
X_cv_bow=count_vect.transform(X_cv)
X_test_bow=count_vect.transform(X_test)

scalar = StandardScaler(with_mean=False)
X_train_bow = scalar.fit_transform(X_train_bow)
X_test_bow= scalar.transform(X_test_bow)
X_cv_bow=scalar.transform(X_cv_bow)

C = [10**-3, 10**-2, 10**0, 10**2,10**3,10**4]#C=1/lambda
auc_train=[]
auc_cv=[]
for c in C:
    lr=LogisticRegression(penalty='l1',C=c,solver='saga')
    lr.fit(X_train_bow,y_train)
    probcv=lr.predict_proba(X_cv_bow)[:,1]
    auc_cv.append(roc_auc_score(y_cv,probcv))
    probtr=lr.predict_proba(X_train_bow)[:,1]
    auc_train.append(roc_auc_score(y_train,probtr))
optimal_c= C[auc_cv.index(max(auc_cv))]
C=[math.log(x) for x in C]#converting values of C into logarithm
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(C, auc_train, label='AUC train')
ax.plot(C, auc_cv, label='AUC CV')
plt.title('AUC vs hyperparameter')
plt.xlabel('C (1/lambda)')
plt.ylabel('AUC')
ax.legend()
plt.show()
print('optimal lambda for which auc is maximum : ',1//optimal_c)
```

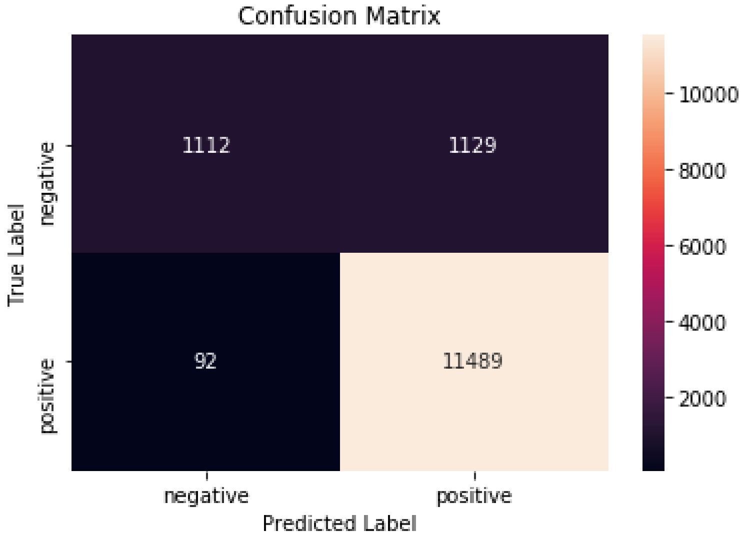



```
optimal lambda for which auc is maximum :  99.0
```

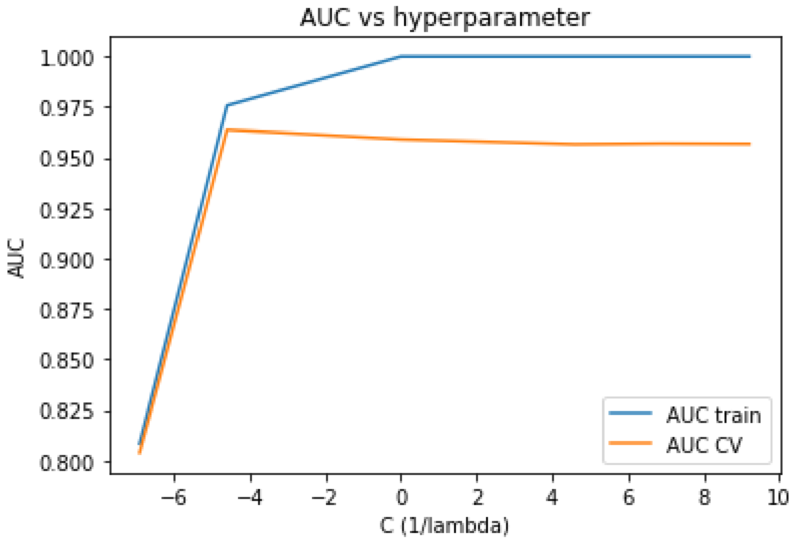
In [77]:
```
#ROC for lambda=99
lr=LogisticRegression(penalty='l1',C=optimal_c, solver='saga')
lr.fit(X_train_bow,y_train)
predi=lr.predict_proba(X_test_bow)[:,1]
fpr1, tpr1, thresholds1 = metrics.roc_curve(y_test, predi)
pred=lr.predict_proba(X_train_bow)[:,1]
fpr2,tpr2,thresholds2=metrics.roc_curve(y_train,pred)
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(fpr1, tpr1, label='Test ROC ,auc='+str(roc_auc_score(y_test,predi)))
ax.plot(fpr2, tpr2, label='Train ROC ,auc='+str(roc_auc_score(y_train,pred)))
plt.title('ROC')
plt.xlabel('FPR')
plt.ylabel('TPR')
ax.legend()
plt.show()
```



In [78]:
```
#Confusion matrix using heatmap for test data
from sklearn.metrics import confusion_matrix
import seaborn as sns
predic=lr.predict(X_test_bow)
conf_mat = confusion_matrix(y_test, predic)
class_label = ["negative", "positive"]
df = pd.DataFrame(conf_mat, index = class_label, columns = class_label)
sns.heatmap(df, annot = True,fmt="d")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

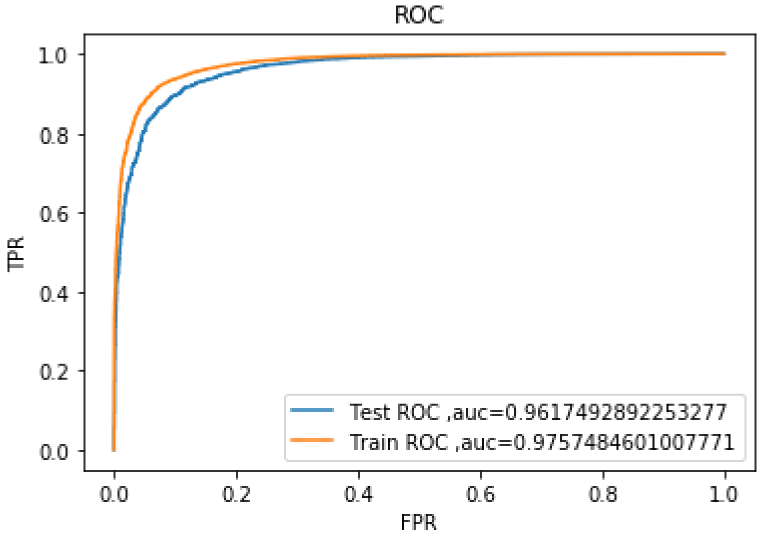


In [79]:
```
#Logistic Regression on TFIDF after feature engineering
# Please write all the code with proper documentation
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
X_train_tf=tf_idf_vect.fit_transform(X_train)
X_cv_tf=tf_idf_vect.transform(X_cv)
X_test_tf=tf_idf_vect.transform(X_test)

scalar = StandardScaler(with_mean=False)
X_train_tf = scalar.fit_transform(X_train_tf)
X_test_tf= scalar.transform(X_test_tf)
X_cv_tf=scalar.transform(X_cv_tf)

C = [10**-3, 10**-2, 10**0, 10**2,10**3,10**4]#C=1/lambda
auc_train=[]
auc_cv=[]
for c in C:
    lr=LogisticRegression(penalty='l1',C=c, solver='saga')
    lr.fit(X_train_tf,y_train)
    probcv=lr.predict_proba(X_cv_tf)[:,1]
    auc_cv.append(roc_auc_score(y_cv,probcv))
    probtr=lr.predict_proba(X_train_tf)[:,1]
    auc_train.append(roc_auc_score(y_train,probtr))
optimal_c= C[auc_cv.index(max(auc_cv))]
C=[math.log(x) for x in C]#converting values of C into logarithm
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(C, auc_train, label='AUC train')
ax.plot(C, auc_cv, label='AUC CV')
plt.title('AUC vs hyperparameter')
plt.xlabel('C (1/lambda)')
plt.ylabel('AUC')
ax.legend()
plt.show()
print('optimal lambda for which auc is maximum : ',1//optimal_c)
```

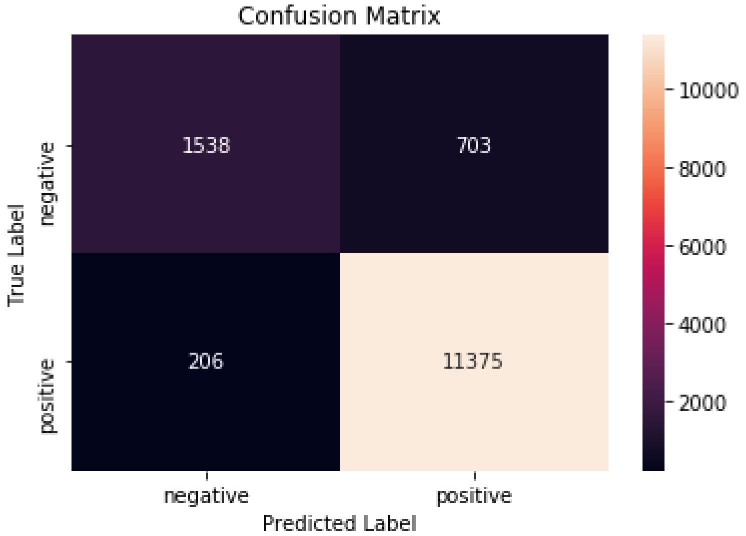



```
optimal lambda for which auc is maximum :  99.0
```

In [80]:
```
#ROC for lambda=99
lr=LogisticRegression(penalty='l1',C=optimal_c, solver='saga')
lr.fit(X_train_tf,y_train)
predi=lr.predict_proba(X_test_tf)[:,1]
fpr1, tpr1, thresholds1 = metrics.roc_curve(y_test, predi)
pred=lr.predict_proba(X_train_tf)[:,1]
fpr2,tpr2,thresholds2=metrics.roc_curve(y_train,pred)
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(fpr1, tpr1, label='Test ROC ,auc='+str(roc_auc_score(y_test,predi)))
ax.plot(fpr2, tpr2, label='Train ROC ,auc='+str(roc_auc_score(y_train,pred)))
plt.title('ROC')
plt.xlabel('FPR')
plt.ylabel('TPR')
ax.legend()
plt.show()
```



In [81]:
```
#Confusion matrix using heatmap for test data
from sklearn.metrics import confusion_matrix
import seaborn as sns
predic=lr.predict(X_test_tf)
conf_mat = confusion_matrix(y_test, predic)
class_label = ["negative", "positive"]
df = pd.DataFrame(conf_mat, index = class_label, columns = class_label)
sns.heatmap(df, annot = True,fmt="d")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

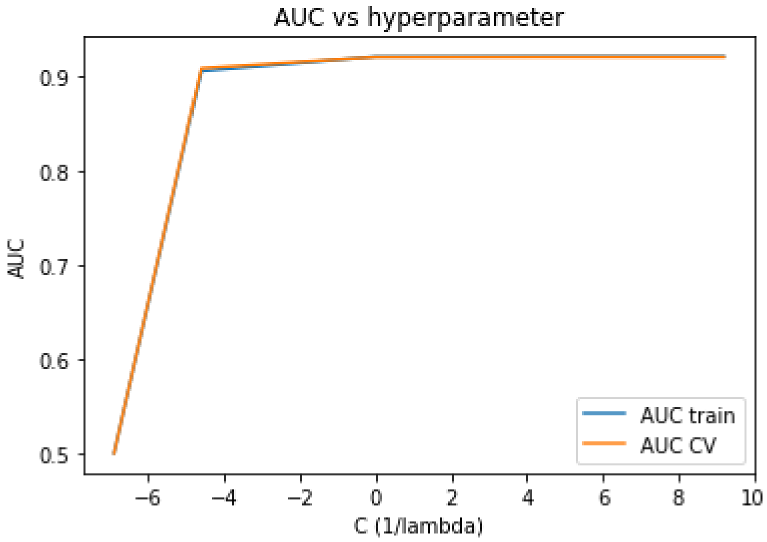


In [82]:
```
#Logistic regression on Word2vec after feature engineering
# Please write all the code with proper documentation
#word2vec for train
list_of_sentance_train=[]
for sentance in X_train:
    list_of_sentance_train.append(sentance.split())
w2v_model=Word2Vec(list_of_sentance_train,min_count=5,size=50, workers=4)
w2v_words = list(w2v_model.wv.vocab)
sent_vectors_train = [];
for sent in tqdm(list_of_sentance_train):
    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
    sent_vectors_train.append(sent_vec)
print(len(sent_vectors_train))
print(len(sent_vectors_train[0]))

#for cross validation we can use same w2v models and w2v words
list_of_sentance_cv=[]
for sentance in X_cv:
    list_of_sentance_cv.append(sentance.split())
sent_vectors_cv = [];
for sent in tqdm(list_of_sentance_cv):
    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
    sent_vectors_cv.append(sent_vec)
print(len(sent_vectors_cv))
print(len(sent_vectors_cv[0]))
```

```
#for test data
list_of_sentance_test=[]
for sentance in X_test:
    list_of_sentance_test.append(sentance.split())
sent_vectors_test = [];
for sent in tqdm(list_of_sentance_test):
    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
    sent_vectors_test.append(sent_vec)
print(len(sent_vectors_test))
print(len(sent_vectors_test[0]))
```

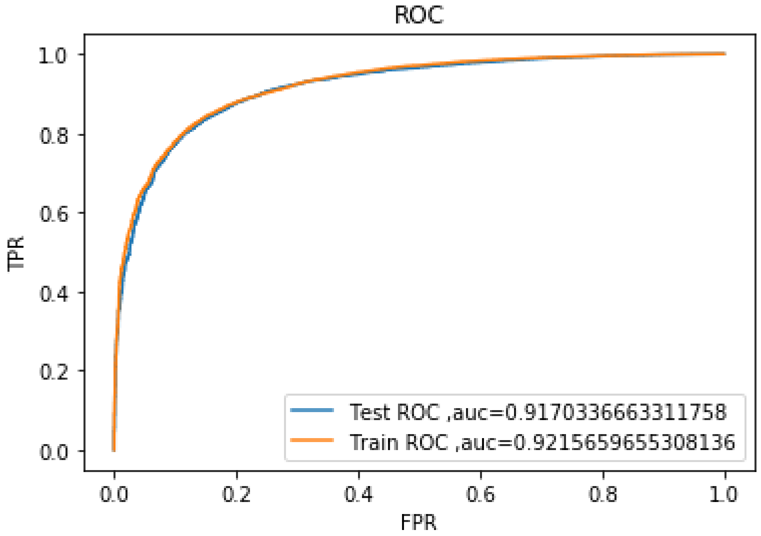
```
100%|██████████| 22574/22574 [01:21<00:00, 275.52it/s]
  0%|          | 31/9675 [00:00<00:31, 302.05it/s]

22574
50

100%|██████████| 9675/9675 [00:35<00:00, 269.05it/s]
  0%|          | 49/13822 [00:00<00:58, 233.77it/s]

9675
50

100%|██████████| 13822/13822 [00:51<00:00, 270.03it/s]

13822
50
```

In [83]:
```
X_train_w2v=sent_vectors_train
X_cv_w2v=sent_vectors_cv
X_test_w2v=sent_vectors_test

C = [10**-3, 10**-2, 10**0, 10**2,10**3,10**4]#C=1/lambda
auc_train=[]
auc_cv=[]
for c in C:
    lr=LogisticRegression(penalty='l1',C=c, solver='saga')
    lr.fit(X_train_w2v,y_train)
    probcv=lr.predict_proba(X_cv_w2v)[:,1]
    auc_cv.append(roc_auc_score(y_cv,probcv))
    probtr=lr.predict_proba(X_train_w2v)[:,1]
    auc_train.append(roc_auc_score(y_train,probtr))
optimal_c= C[auc_cv.index(max(auc_cv))]
C=[math.log(x) for x in C]#converting values of C into logarithm
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(C, auc_train, label='AUC train')
ax.plot(C, auc_cv, label='AUC CV')
plt.title('AUC vs hyperparameter')
plt.xlabel('C (1/lambda)')
plt.ylabel('AUC')
ax.legend()
plt.show()
print('optimal lambda for which auc is maximum : ',1//optimal_c)
```

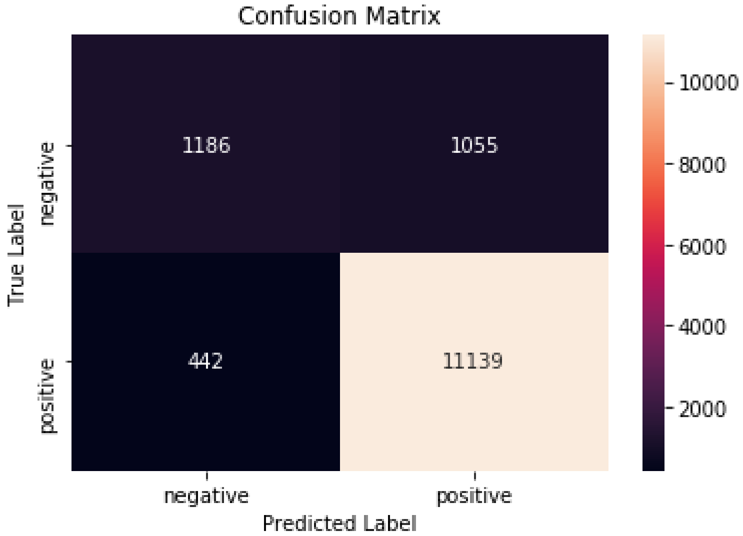



```
optimal lambda for which auc is maximum :  0
```

In [84]:
```
#ROC for lambda=1
lr=LogisticRegression(penalty='l1',C=optimal_c, solver='saga')
lr.fit(X_train_w2v,y_train)
predi=lr.predict_proba(X_test_w2v)[:,1]
fpr1, tpr1, thresholds1 = metrics.roc_curve(y_test, predi)
pred=lr.predict_proba(X_train_w2v)[:,1]
fpr2,tpr2,thresholds2=metrics.roc_curve(y_train,pred)
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(fpr1, tpr1, label='Test ROC ,auc='+str(roc_auc_score(y_test,predi)))
ax.plot(fpr2, tpr2, label='Train ROC ,auc='+str(roc_auc_score(y_train,pred)))
plt.title('ROC')
plt.xlabel('FPR')
plt.ylabel('TPR')
ax.legend()
plt.show()
```



In [85]:
```
#Confusion matrix using heatmap for test data
from sklearn.metrics import confusion_matrix
import seaborn as sns
predic=lr.predict(X_test_w2v)
conf_mat = confusion_matrix(y_test, predic)
class_label = ["negative", "positive"]
df = pd.DataFrame(conf_mat, index = class_label, columns = class_label)
sns.heatmap(df, annot = True,fmt="d")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

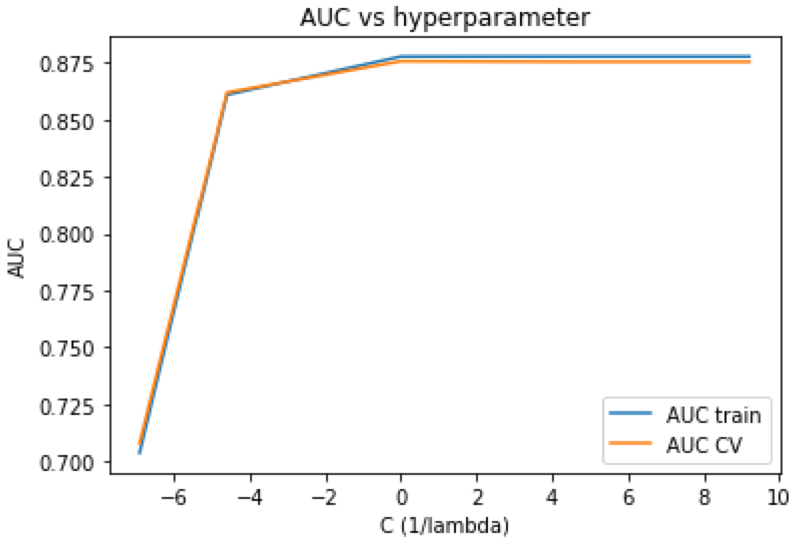


In [86]:
```
#Apllying Logistic Regression on Avg TFIDF W2vec after feature engineering
# Please write all the code with proper documentation
list_of_sentance_train=[]
for sentance in X_train:
    list_of_sentance_train.append(sentance.split())
w2v_model=Word2Vec(list_of_sentance_train,min_count=5,size=50, workers=4)
w2v_words = list(w2v_model.wv.vocab)
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2),min_df=10, max_features=500)

tf_idf_matrix=tf_idf_vect.fit_transform(X_train)


tfidf_feat = tf_idf_vect.get_feature_names()
dictionary = dict(zip(tf_idf_vect.get_feature_names(), list(tf_idf_vect.idf_)))

#for train data

tfidf_sent_vectors_train = [];
row=0;
for sent in tqdm(list_of_sentance_train):
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_train.append(sent_vec)
    row += 1

#for cross validation data and test we will use same words and models of train
list_of_sentance_cv=[]
for sentance in X_cv:
    list_of_sentance_cv.append(sentance.split())
tfidf_sent_vectors_cv = [];
row=0;
for sent in tqdm(list_of_sentance_cv):
    sent_vec = np.zeros(50)
```

```
    weight_sum =0;
    for word in sent:
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_cv.append(sent_vec)
    row += 1

#for test data
list_of_sentance_test=[]
for sentance in X_test:
    list_of_sentance_test.append(sentance.split())
tfidf_sent_vectors_test = [];
row=0;
for sent in tqdm(list_of_sentance_test):
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_test.append(sent_vec)
    row += 1
```

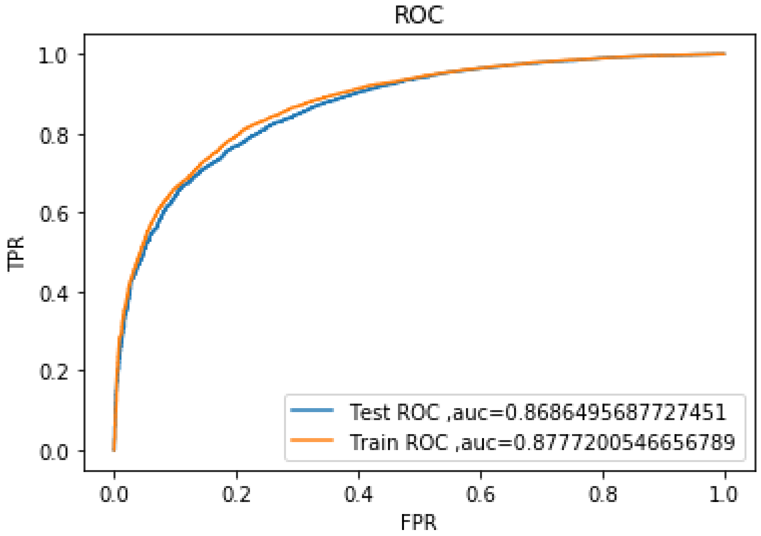
```
100%|██████████| 22574/22574 [01:42<00:00, 220.40it/s]
100%|██████████| 9675/9675 [00:44<00:00, 217.50it/s]
100%|██████████| 13822/13822 [01:03<00:00, 218.58it/s]
```

In [87]:
```
X_train_tfw2v=tfidf_sent_vectors_train
X_cv_tfw2v=tfidf_sent_vectors_cv
X_test_tfw2v=tfidf_sent_vectors_test

C = [10**-3, 10**-2, 10**0, 10**2,10**3,10**4]#C=1/lambda
auc_train=[]
auc_cv=[]
for c in C:
    lr=LogisticRegression(penalty='l1',C=c,solver='saga')
    lr.fit(X_train_tfw2v,y_train)
    probcv=lr.predict_proba(X_cv_tfw2v)[:,1]
    auc_cv.append(roc_auc_score(y_cv,probcv))
    probtr=lr.predict_proba(X_train_tfw2v)[:,1]
    auc_train.append(roc_auc_score(y_train,probtr))
optimal_c= C[auc_cv.index(max(auc_cv))]
C=[math.log(x) for x in C]#converting values of C into logarithm
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(C, auc_train, label='AUC train')
ax.plot(C, auc_cv, label='AUC CV')
plt.title('AUC vs hyperparameter')
plt.xlabel('C (1/lambda)')
plt.ylabel('AUC')
ax.legend()
plt.show()
print('optimal lambda for which auc is maximum : ',1//optimal_c)
```

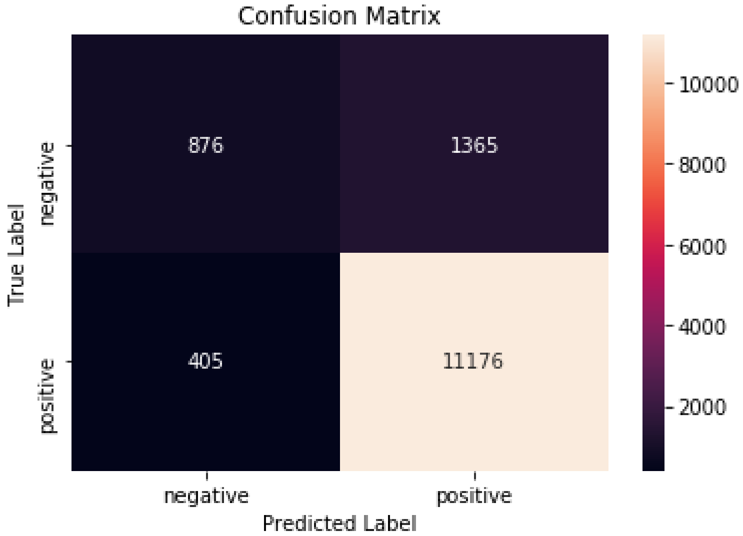



```
optimal lambda for which auc is maximum :  1
```

In [88]:
```
#ROC for lambda=0
lr=LogisticRegression(penalty='l1',C=optimal_c, solver='saga')
lr.fit(X_train_tfw2v,y_train)
predi=lr.predict_proba(X_test_tfw2v)[:,1]
fpr1, tpr1, thresholds1 = metrics.roc_curve(y_test, predi)
pred=lr.predict_proba(X_train_tfw2v)[:,1]
fpr2,tpr2,thresholds2=metrics.roc_curve(y_train,pred)
fig = plt.figure()
ax = plt.subplot(111)
ax.plot(fpr1, tpr1, label='Test ROC ,auc='+str(roc_auc_score(y_test,predi)))
ax.plot(fpr2, tpr2, label='Train ROC ,auc='+str(roc_auc_score(y_train,pred)))
plt.title('ROC')
plt.xlabel('FPR')
plt.ylabel('TPR')
ax.legend()
plt.show()
```



In [89]:
```
#Confusion matrix using heatmap for test data
from sklearn.metrics import confusion_matrix
import seaborn as sns
predic=lr.predict(X_test_tfw2v)
conf_mat = confusion_matrix(y_test, predic)
class_label = ["negative", "positive"]
df = pd.DataFrame(conf_mat, index = class_label, columns = class_label)
sns.heatmap(df, annot = True,fmt="d")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



[6] Conclusions

In [91]:

```
# Please compare all your models using Prettytable library
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["Vectorizer","Regularization", "Feature engineering", "Hyperameter(lambda)", "AUC"]
x.add_row(["BOW","l1","Not featured",99,0.859])
x.add_row(["BOW","l2","Not featured",9999,0.918])
x.add_row(["TFIDF","l1","Not featured",99,0.942])
x.add_row(["TFIDF","l2","Not featured",9999,0.951])
x.add_row(["Avg W2v","l1","Not featured",0,0.883])
x.add_row(["Avg W2v","l2","Not featured",1,0.883])
x.add_row(["TFIDF Avg W2v","l1","Not featured",0,0.833])
x.add_row(["TFIDF Avg W2v","l2","Not featured",0,0.833])
x.add_row(["BOW","l1","featured",99,0.935])
x.add_row(["TFIDF","l1","featured",99,0.961])
x.add_row(["Avg W2v","l1","featured",0,0.917])
x.add_row(["Avg W2v","l1","featured",1,0.868])
print(x)
```

```
+---------------+----------------+---------------------+---------------------+-------+
|   Vectorizer  | Regularization | Feature engineering | Hyperameter(lambda) |  AUC  |
+---------------+----------------+---------------------+---------------------+-------+
|      BOW      |       l1       |     Not featured    |          99         | 0.859 |
|      BOW      |       l2       |     Not featured    |         9999        | 0.918 |
|     TFIDF     |       l1       |     Not featured    |          99         | 0.942 |
|     TFIDF     |       l2       |     Not featured    |         9999        | 0.951 |
|    Avg W2v    |       l1       |     Not featured    |          0          | 0.883 |
|    Avg W2v    |       l2       |     Not featured    |          1          | 0.883 |
| TFIDF Avg W2v |       l1       |     Not featured    |          0          | 0.833 |
| TFIDF Avg W2v |       l2       |     Not featured    |          0          | 0.833 |
|      BOW      |       l1       |       featured      |          99         | 0.935 |
|     TFIDF     |       l1       |       featured      |          99         | 0.961 |
|    Avg W2v    |       l1       |       featured      |          0          | 0.917 |
|    Avg W2v    |       l1       |       featured      |          1          | 0.868 |
+---------------+----------------+---------------------+---------------------+-------+
```

1)First we split whole preprocessed review data to train ,cross validation and test 2)Then we applied logistic regression on Bag of Words vectoriser for both l1 regularisation and l2 regularisation then measured best hyperparameter and plotted ROC curve and heatmap on test data 3)After that we wrote down top 10 postive and negative features 4)Second we applied logistic regression on TFIDF vectoriser for both l1 and l2 regularisation ,then measured best lambda value and performed same process like Bag of words. 5)For Avg Word 2 vec we perform w2v on train data and used models and words of train data to cv and test data 6)Then after we applied logistic regression on Avg Word2vec for both l1 and l2 regularisation 7)Just like Avg word2vec we applied logistic regression on TFIDF avgW2vec 8)After that we performed feature engineering in this we added preprocessed summary and review length to preprocessed review and performed logistic regression on BoW,TFIDF,AvgW2vec and TFIDF AvgW2vec 9)Then we noticed that after performing feature engineering our performance of model increased.

In [ ]:

```

```