# 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)

EDA: 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
```

```
E:\anaconda\lib\site-packages\gensim\utils.py:1197: UserWarning: detected Windo
ws; aliasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

In [2]:
```
#from google.colab import drive
#drive.mount('/content/gdrive')
```

In [3]:
```
# 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 p
# 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 LIM
# for tsne assignment you can take 5k data points

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

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a neg
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 (525814, 10)
```

Out[3]:

| | Id | ProductId | UserId | ProfileName | HelpfulnessNumerator | HelpfulnessDenominat |
|---|---|---|---|---|---|---|
| **0** | 1 | B001E4KFG0 | A3SGXH7AUHU8GW | delmartian | 1 | |
| **1** | 2 | B00813GRG4 | A1D87F6ZCVE5NK | dll pa | 0 | |
| **2** | 3 | B000LQOCH0 | ABXLMWJIXXAIN | Natalia Corres "Natalia Corres" | 1 | |

In [4]:
```
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
""", con)
```

In [5]:
```
print(display.shape)
display.head()
```

```
(80668, 7)
```

Out[5]:

| | UserId | ProductId | ProfileName | Time | Score | Text | COUNT(*) |
|---|---|---|---|---|---|---|---|
| **0** | #oc-R115TNMSPFT9I7 | B007Y59HVM | Breyton | 1331510400 | 2 | Overall its just OK when considering the price... | 2 |
| **1** | #oc-R11D9D7SHXIJB9 | B005HG9ET0 | Louis E. Emory "hoppy" | 1342396800 | 5 | My wife has recurring extreme muscle spasms, u... | 3 |
| **2** | #oc-R11DNU2NBKQ23Z | B007Y59HVM | Kim Cieszykowski | 1348531200 | 1 | This coffee is horrible and unfortunately not ... | 2 |
| **3** | #oc-R11O5J5ZVQE25C | B005HG9ET0 | Penguin Chick | 1346889600 | 5 | This will be the bottle that you grab from the... | 3 |
| **4** | #oc-R12KPBODL2B5ZD | B007OSBE1U | Christopher P. Presta | 1348617600 | 1 | I didnt like this coffee. Instead of telling y... | 2 |

In [6]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[6]:

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

In [7]:
```
display['COUNT(*)'].sum()
```

Out[7]:
```
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 [8]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[8]:

| | Id | ProductId | UserId | ProfileName | HelpfulnessNumerator | HelpfulnessDenomir |
|---|---|---|---|---|---|---|
| **0** | 78445 | B000HDL1RQ | AR5J8UI46CURR | Geetha Krishnan | 2 | |
| **1** | 138317 | B000HDOPYC | AR5J8UI46CURR | Geetha Krishnan | 2 | |
| **2** | 138277 | B000HDOPYM | AR5J8UI46CURR | Geetha Krishnan | 2 | |
| **3** | 73791 | B000HDOPZG | AR5J8UI46CURR | Geetha Krishnan | 2 | |
| **4** | 155049 | B000PAQ75C | AR5J8UI46CURR | Geetha Krishnan | 2 | |

As it can be seen above that same user has multiple reviews with same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that

ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8)

ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

It was inferred after analysis that reviews with same parameters other than ProductId belonged to the same product just having different flavour or quantity. Hence in order to reduce redundancy it was decided to eliminate the rows having same parameters.

The method used for the same was that we first sort the data according to ProductId and then just keep the first similar product review and delelte the others. for eg. in the above just the review for ProductId=B000HDL1RQ remains. This method ensures that there is only one representative for each product and deduplication without sorting would lead to possibility of different representatives still existing for the same product.

In [9]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplac
```

In [10]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"},
final.shape
```

Out[10]: (364173, 10)

In [11]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[11]: 69.25890143662969

**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 [12]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[12]:

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

In [13]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [14]:
```
#Before starting the next phase of preprocessing lets see the number of entries l
print(final.shape)
final = final.sample(100000)

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

```
(364171, 10)
```

Out[14]:
```
1    84199
0    15801
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 [15]:
```
# 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)
```

```
I have to be honest. I'm not entirely sure how water's PH impacts the body. I h
aven't really heard very much information on the subject. The Essentia Drinking
water tasted good - it has a nice smooth taste and I like that it has added ele
ctrolytes. I'm a long-distance runner and so I drank some of this water followi
ng a workout. I can't say that I noticed a huge difference between the water th
at I usually drink and this one, but it wasn't bad. Good taste and the electrol
ytes (and zero calories) made this a good post-workout drink.
==================================================
This reminds me of Mint chocolate chip ice cream without the calories. All thes
e flavors has help me drink more water to loose more weight. I love these in th
e morning to jump start the day or whenever I need a little perk up during the
day. They are a college student buddy during study time good as coffee but will
not give you the jitters.
==================================================
Previously I had been buying lunch meat and wrapping the pills in the meat. Tha
t got very expensive! This idea is genius! The dogs LOVE the taste. The pill fi
ts in perfectly! And it came the very next day! Awesome!
==================================================
I am very surprised that such a reasonably priced shampoo and conditioner work
so well...  I've always had problems finding mild enough products to clean and
leave the hair soft, but not "weighed down" with conditioners... or shampoo's t
hat don't dry the hair out<br /><br />I didn't expect much, even after reading
all the great reviews.  Since turning 50, my hair has thinned, is changing as i
t turns grey, and my scalp is so dry I have horrible itchy dandruf - which I've
never had to deal with in my life.  I've tried so many "all natural" dry scalp,
mild shampoo's over the past 2 years, and even the harsher "head and shoulder
s", "medicated" types, which are WAY too strong . . .<br /><br />This shampoo a
nd conditioner do the trick.  My hair feels so soft and is much more manageabl
e, and the itchy dry scalp seems to be much better after just 2 washes!!! I'm s
o happy.  It smells really pleasant too, kind of floral . . very fresh
==================================================
```

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

```
I have to be honest. I'm not entirely sure how water's PH impacts the body. I h
aven't really heard very much information on the subject. The Essentia Drinking
water tasted good - it has a nice smooth taste and I like that it has added ele
ctrolytes. I'm a long-distance runner and so I drank some of this water followi
ng a workout. I can't say that I noticed a huge difference between the water th
at I usually drink and this one, but it wasn't bad. Good taste and the electrol
ytes (and zero calories) made this a good post-workout drink.
```

In [17]:
```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove
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)
```

```
I have to be honest. I'm not entirely sure how water's PH impacts the body. I h
aven't really heard very much information on the subject. The Essentia Drinking
water tasted good - it has a nice smooth taste and I like that it has added ele
ctrolytes. I'm a long-distance runner and so I drank some of this water followi
ng a workout. I can't say that I noticed a huge difference between the water th
at I usually drink and this one, but it wasn't bad. Good taste and the electrol
ytes (and zero calories) made this a good post-workout drink.
==================================================
This reminds me of Mint chocolate chip ice cream without the calories. All thes
e flavors has help me drink more water to loose more weight. I love these in th
e morning to jump start the day or whenever I need a little perk up during the
day. They are a college student buddy during study time good as coffee but will
not give you the jitters.
==================================================
Previously I had been buying lunch meat and wrapping the pills in the meat. Tha
t got very expensive! This idea is genius! The dogs LOVE the taste. The pill fi
ts in perfectly! And it came the very next day! Awesome!
==================================================
I am very surprised that such a reasonably priced shampoo and conditioner work
so well...  I've always had problems finding mild enough products to clean and
leave the hair soft, but not "weighed down" with conditioners... or shampoo's t
hat don't dry the hair outI didn't expect much, even after reading all the grea
t reviews.  Since turning 50, my hair has thinned, is changing as it turns gre
y, and my scalp is so dry I have horrible itchy dandruf - which I've never had
to deal with in my life.  I've tried so many "all natural" dry scalp, mild sham
poo's over the past 2 years, and even the harsher "head and shoulders", "medica
ted" types, which are WAY too strong . . .This shampoo and conditioner do the t
rick.  My hair feels so soft and is much more manageable, and the itchy dry sca
lp seems to be much better after just 2 washes!!! I'm so happy.  It smells real
ly pleasant too, kind of floral . . very fresh
```

In [18]:
```
# 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 [19]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
Previously I had been buying lunch meat and wrapping the pills in the meat. Tha
t got very expensive! This idea is genius! The dogs LOVE the taste. The pill fi
ts in perfectly! And it came the very next day! Awesome!
==================================================
```

In [20]:
```
#remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
I have to be honest. I'm not entirely sure how water's PH impacts the body. I h
aven't really heard very much information on the subject. The Essentia Drinking
water tasted good - it has a nice smooth taste and I like that it has added ele
ctrolytes. I'm a long-distance runner and so I drank some of this water followi
ng a workout. I can't say that I noticed a huge difference between the water th
at I usually drink and this one, but it wasn't bad. Good taste and the electrol
ytes (and zero calories) made this a good post-workout drink.
```

In [21]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
Previously I had been buying lunch meat and wrapping the pills in the meat That
got very expensive This idea is genius The dogs LOVE the taste The pill fits in
perfectly And it came the very next day Awesome
```

In [22]:
```
# 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 st

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'our
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', '
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itsel
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because'
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'th
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all'
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than',
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "di
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma',
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn'
            'won', "won't", 'wouldn', "wouldn't"])
```

In [23]:
```
# 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 s
    preprocessed_reviews.append(sentance.strip())
```

```
100%|████████████████████████████████████████████████████████████████████████|
100000/100000 [00:44<00:00, 2258.23it/s]
```

In [24]:
```
preprocessed_reviews[1500]
```

Out[24]:
```
'previously buying lunch meat wrapping pills meat got expensive idea genius dog
s love taste pill fits perfectly came next day awesome'
```

In [25]:
```
del filtered_data
```

# Applying Logistic Regression

In [26]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
#here we are importing all the important libraries required for logistic regressi
```

## Splitting the data

In [27]:
```
X_train,X_test,Y_train,Y_test = train_test_split(preprocessed_reviews,final['Scor
#splitting the data into training and test in 7:3 ratio

print('size of training dataset is {} datapoints'.format(len(X_train)))
print('size of test dataset is {} datapoints'.format(len(X_test)))
```

```
size of training dataset is 70000 datapoints
size of test dataset is 30000 datapoints
```

# 1.Bag of Words

In [28]:
```

vect = CountVectorizer()#initiating the vectorizer

vect.fit(X_train)#fitting training data into vectorizer makes it learn all the vo

#transforming the data into training and test set
train_set = vect.transform(X_train)
test_set = vect.transform(X_test)

print('after vectoriztion')
print(train_set.shape)
print(test_set.shape)
```

```
after vectoriztion
(70000, 50636)
(30000, 50636)
```

In [29]:
```
print(train_set[10])#how the train dataset looks
```

```
  (0, 461)	1
  (0, 2167)	1
  (0, 3009)	1
  (0, 3117)	1
  (0, 3747)	1
  (0, 4106)	2
  (0, 4159)	1
  (0, 4407)	1
  (0, 4972)	1
  (0, 7211)	5
  (0, 7219)	1
  (0, 7281)	1
  (0, 8578)	2
  (0, 9055)	1
  (0, 12436)	2
  (0, 13256)	1
  (0, 13363)	1
  (0, 14807)	2
  (0, 15002)	2
  (0, 16274)	1
  (0, 16430)	1
  (0, 18267)	1
  (0, 18688)	1
  (0, 18793)	1
  (0, 18802)	1
  :	:
  (0, 33062)	1
  (0, 33330)	1
  (0, 34128)	1
  (0, 39390)	1
  (0, 39881)	1
  (0, 39923)	1
  (0, 40044)	1
  (0, 40546)	1
  (0, 41596)	1
  (0, 42110)	1
  (0, 42111)	1
  (0, 42178)	1
  (0, 42456)	1
  (0, 42671)	1
  (0, 42730)	1
  (0, 42902)	1
  (0, 43547)	2
  (0, 44084)	1
  (0, 45326)	1
  (0, 46286)	1
  (0, 46495)	1
  (0, 47080)	1
  (0, 47547)	1
  (0, 48924)	1
  (0, 49031)	1
```

# Standardizing the data

In [31]:
```
from sklearn.preprocessing import StandardScaler
warnings.filterwarnings('ignore')

train_std = StandardScaler(with_mean=False).fit_transform(train_set)
test_std = StandardScaler(with_mean=False).fit_transform(test_set)
# standardizing the data for applying logistic Regression
print('After Standardizing')
print(train_std.shape)
print(test_std.shape)
```

```
After Standardizing
(70000, 50636)
(30000, 50636)
```

# L2 Regularization and GridSearch cross validation

In [32]:
```
param = {'C': [10**i for i in range(-4,5)]}
model = GridSearchCV(LogisticRegression(penalty='l2'),param_grid = param,scoring
#using GridSearchCv
model.fit(train_std,Y_train)
```

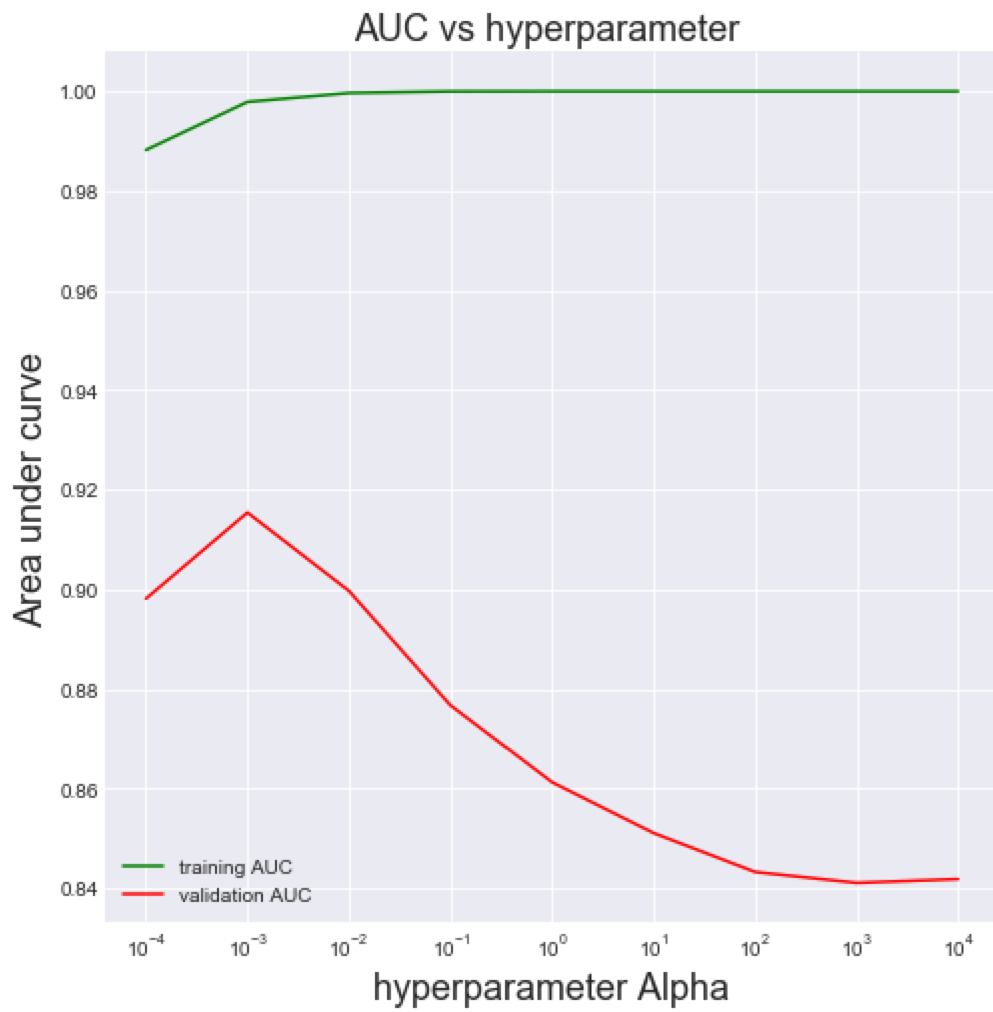
Out[32]:
```
GridSearchCV(cv='warn', error_score='raise-deprecating',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_i
ntercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid={'C': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='roc_auc', verbose=0)
```

In [33]:
```
best_C_l2_bow = model.best_params_['C']
print(best_C_l2_bow)
#this gives us the best hyperparameter found after gridsearch cross validation
```

```
0.001
```

In [34]:
```
train_auc = model.cv_results_['mean_train_score']#deriving the avg training score
cv_auc = model.cv_results_['mean_test_score']#deriving the average cross validati
```

In [35]:
```
def error(t_auc,c_auc):
    val = [10**i for i in range(-4,5)]
    sns.set_style('darkgrid')
    plt.figure(figsize=(8,8))
    plt.plot(val,t_auc,'g',label = 'training AUC')#t_auc refers to the auc on tra
    plt.plot(val,c_auc,'r',label='validation AUC')# c_auc refers to the auc on cr
#plotting the graph between AUC and hyperparameter for tuning

    plt.xscale('log')#taking log scale for x axis for better analysing the result
    plt.xlabel('hyperparameter Alpha',fontsize=18)
    plt.ylabel('Area under curve',fontsize=18)
    #plt.xticks([])
    #plt.yticks([])
    plt.legend(loc = 'best')
    plt.title('AUC vs hyperparameter ',fontsize=18)

error(train_auc,cv_auc)#plotting the curve for bag of vectors l2 regularization
```




.This graph of hperparameter vs area under the curve tells us how model is fitting the data which helps us in determining where the model is overfitting and where its undergitting .we can clearly see a tradeoff at C = 0.001 hence we choose this value for our model

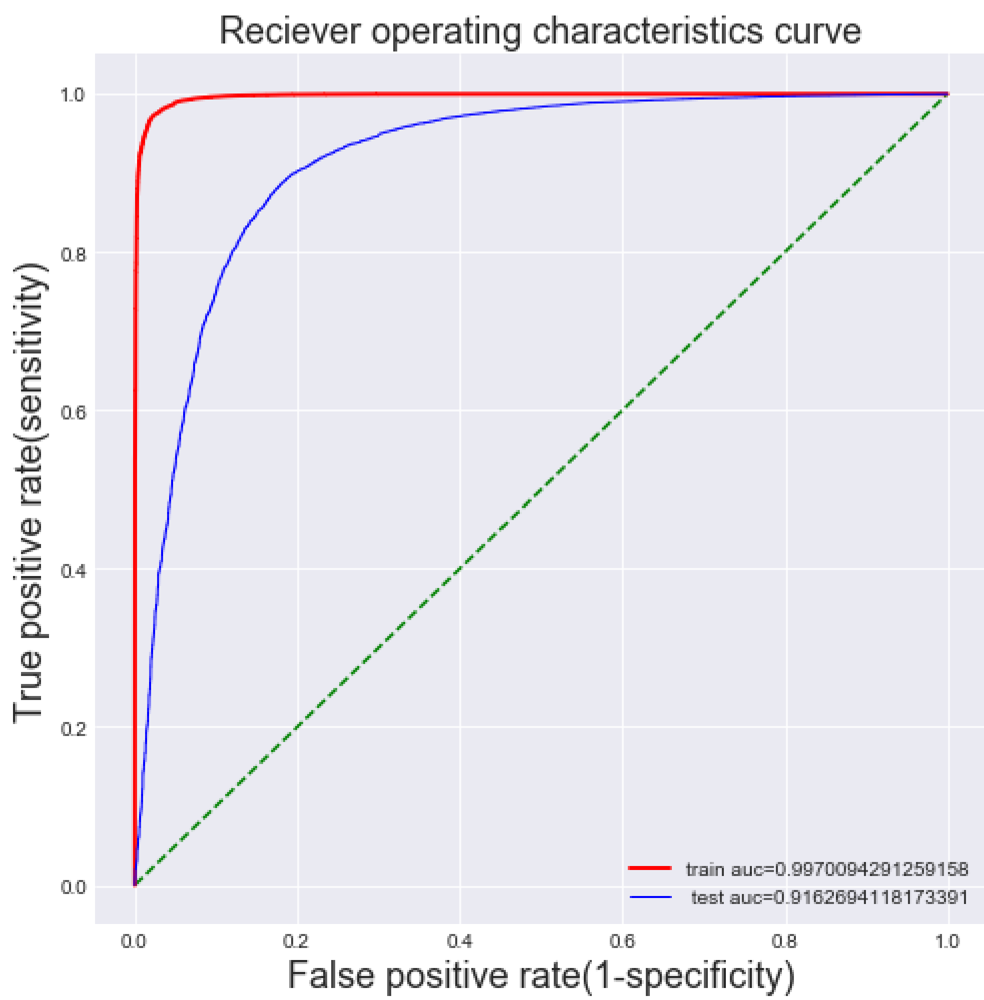
In [36]:
```
from sklearn.metrics import roc_auc_score
clf_optimal = LogisticRegression(C =0.001,penalty='l2')#fitting the best hyperpar
clf_optimal.fit(train_std,Y_train)
train_pred = clf_optimal.predict_proba(train_std)[:,1]
#predict_proba gives the probability of a data point belonging to a particular cl

test_pred = clf_optimal.predict_proba(test_std)[:,1]
#this predicts the probability of data pointsin test dataset belonging to class '

test_auc_bow_l2 = roc_auc_score(Y_test,test_pred)
#calculating the area under the curve for the roc curve that will be drawn on tes
```

In [37]:
```
print('AUC on test dataset is {}'.format(test_auc_bow_l2))
```

```
AUC on test dataset is 0.9162694118173391
```

## ROC Curve

In [38]:
```
from sklearn.metrics import roc_curve

fpr_tr, tpr_tr, _ = roc_curve(Y_train,train_pred)
fpr_test, tpr_test, _ = roc_curve(Y_test,test_pred)
#calculating the fpr,tpr and thresholds for each training and test dataset
auc_train = roc_auc_score(Y_train,train_pred)
auc_test = roc_auc_score(Y_test, test_pred)
sns.set_style('darkgrid')
plt.figure(figsize=(8,8))
plt.plot(np.linspace(0,1,100),np.linspace(0,1,100),"g--")#this plots the roc curve
plt.plot(fpr_tr,tpr_tr,'r',linewidth=2,label="train auc="+str(auc_train))
plt.plot(fpr_test,tpr_test,'b',linewidth=1,label=" test auc="+str(auc_test))
plt.xlabel('False positive rate(1-specificity)',fontsize=18)
plt.ylabel('True positive rate(sensitivity)',fontsize=18)
plt.title('Reciever operating characteristics curve',fontsize=18)
plt.legend(loc='best')
plt.show()
```




## F1 Score,Precision and Recall

In [39]:
```
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import confusion_matrix

pred = clf_optimal.predict(test_std)# predicting all the classes for test dataset
pred_tr = clf_optimal.predict(train_std)#predicting all the classes for train dat


# calculating the precison score
print('precison score is {}'.format(precision_score(Y_test,pred)))

#calculating the recall score
print('\nrecall_score is {}'.format(recall_score(Y_test,pred)))

#calculating the f1 score
print('\nf1 score is {}'.format(f1_score(Y_test,pred)))
```

```
precison score is 0.9285741293908572

recall_score is 0.9715551687304664

f1 score is 0.9495785322094192
```

## Confusion Matrix

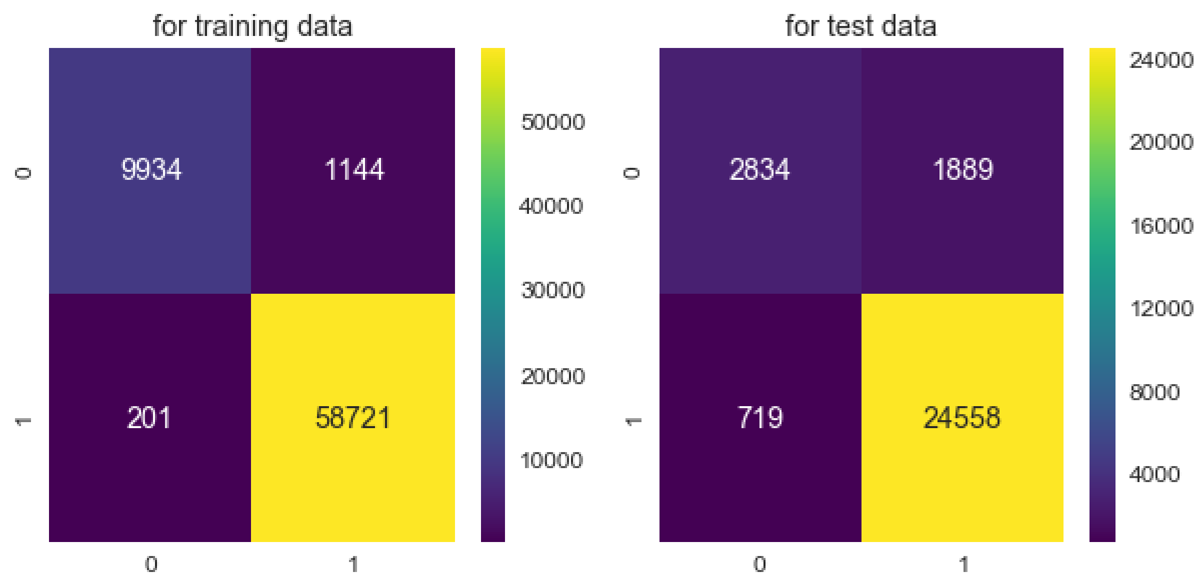
In [40]:
```
train_matrix = pd.DataFrame(confusion_matrix(Y_train,pred_tr),range(2),range(2))#
print('training data')
print(train_matrix.head())


print('******************************************')

print('test data')
test_matrix = pd.DataFrame(confusion_matrix(Y_test,pred),range(2),range(2))# svai
print(test_matrix.head())
```

```
training data
      0      1
0  9934   1144
1   201  58721
*****************************************
test data
      0      1
0  2834   1889
1   719  24558
```

so we need to visualize this dataframe in a heatmap for the Confusin Matrix

In [41]:
```
sns.set(font_scale = 1.2)
fig, ax = plt.subplots(figsize=(10,10))#setting the font size
plt.subplot(2,2,1)
plt.title('for training data')
sns.heatmap(train_matrix,annot = True,fmt = 'g',cmap = 'viridis')


#annot = True writes data values in each cell
# fmt is string formatting code which is to be used when adding annonations
# cmap is the mapping from data values to color space

plt.subplot(2,2,2)
plt.title('for test data')
sns.heatmap(test_matrix,annot = True,fmt = 'g',cmap = 'viridis')
```

Out[41]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1d0bca25da0>
```




## Most Important features

In [42]:
```
clf_optimal = LogisticRegression(C =best_C_l2_bow,penalty='l2')#fitting the best 
clf_optimal.fit(train_std,Y_train)
w = clf_optimal.coef_[0]#finding the coefficients of all features
print(w)
```

```
[0.00237672 0.00898837 0.00256652 ... 0.00145552 0.00557786 0.00255819]
```

In [43]:
```
features = vect.get_feature_names()#getting name of the features after fitting an
negative_indices = np.argsort(w)
positive_indices = np.argsort(w)[::-1]


print('TOP 20 important features for positive class and their coefficients in Bag
for i in (positive_indices[0:20]):
    print("%s\t --> \t%f"%(features[i],w[i]))
print("************************************************")

print('TOP 20 important features for negative class and their coefficients in Bag
for i in (negative_indices[0:20]):
    print("{} ---> {} ".format(features[i],w[i]))
```

```
TOP 20 important features for positive class and their coefficients in Bag of W
ords featurization using l2 regularization are:

great    -->    0.438527
love     -->    0.302308
best     -->    0.297170
good     -->    0.280709
delicious        -->    0.243617
excellent        -->    0.203756
perfect  -->    0.202239
loves    -->    0.196905
favorite         -->    0.180287
wonderful        -->    0.174039
nice     -->    0.173366
tasty    -->    0.146300
highly   -->    0.139235
easy     -->    0.138118
find     -->    0.136419
awesome  -->    0.127224
stores   -->    0.126735
pleased  -->    0.123507
amazing  -->    0.119508
smooth   -->    0.118069
************************************************
TOP 20 important features for negative class and their coefficients in Bag of W
ords featurization using l2 regularization are:

not ---> -0.31024603434674625
disappointed ---> -0.19121383030359548
worst ---> -0.17359327962272944
terrible ---> -0.1504054346167949
awful ---> -0.1494875515335521
horrible ---> -0.13865347871387815
disappointing ---> -0.13283802042188475
waste ---> -0.12942970564793033
money ---> -0.1261970346258956
stale ---> -0.12576132106762503
threw ---> -0.1240485684969925
unfortunately ---> -0.11493796718602955
sorry ---> -0.11314086564042185
```

```
weak ---> -0.11208089650599803
bad ---> -0.1108269357955348
disappointment ---> -0.10570703964639834
return ---> -0.10486225297366396
would ---> -0.10290311127013754
bland ---> -0.10063671149748286
thought ---> -0.09932685913813381
```

## Pertubation testing

In [44]:

```
#importing the scipy library
import scipy as sp

#weights before noise
W_before_noise = clf_optimal.coef_[0]
print(W_before_noise)

#taking a random small noise which follows the normal distribution
noise = sp.stats.distributions.norm.rvs(loc=0,scale=0.0001)
print(noise)

#here adding the noise to all the elements f sparse matrix
train_std.data = train_std.data + noise

#training the model with new sparse matrix which has added noise to every element
lr = LogisticRegression(C = best_C_l2_bow,penalty = 'l2' )
lr.fit(train_std,Y_train)
#weights after adding noise
W_after_noise = lr.coef_[0]
print(W_after_noise)

#adding epsilon to every element of vector w for avoiding division from zero
epsilon = 0.000001
W_before_noise = W_before_noise + epsilon
W_after_noise  = W_after_noise  + epsilon



#finding the percentage change in weights before and after
delta = ((abs((W_before_noise-W_after_noise)/W_before_noise))*100)
print(delta)

sorted_delta = np.sort(delta) #sorting the percentage change for plotting frequen
print(sorted_delta)
```

```
[0.00237672 0.00898837 0.00256652 ... 0.00145552 0.00557786 0.00255819]
-5.8824051715177196e-05
[0.00237793 0.00898788 0.0025667  ... 0.00145407 0.00557789 0.0025587 ]
[0.05083855 0.00546496 0.00710243 ... 0.09933708 0.00065248 0.02002303]
[8.43000604e-08 4.67146684e-07 9.30494403e-07 ... 1.60261676e+04
 1.74544314e+04 1.74544314e+04]
```

In [45]:
```
#elbow method
plt.figure(figsize = (15,10))
plt.plot(np.arange(0,len(delta)),sorted_delta,color = 'red',linestyle = '-',linew
plt.title('Percentage change in weights')
plt.ylabel('percentage change in weight vectors')
plt.show()


#plotting the percentiles
percentiles = []#list for storing the percentile values
for i in range(0,101,1):
    percentiles.append(np.percentile(sorted_delta,i))#calculating the percentile
plt.figure(figsize = (15,10))
plt.plot(np.arange(0,101),percentiles,color = 'red',linestyle = '-')
plt.title('Percentage change in weights')
plt.xlabel(' percentile')
plt.ylabel('percentage change in the weigh vectors')
plt.show()

print('we can see that there is a steep rise in perentage change vector values in


#plotting the percentiles from 90th to 100th
plt.figure(figsize=(15,10))
plt.plot(np.arange(90,101,1),percentiles[90:],color = 'red',linestyle = '-')
plt.title('90th to 100th percentile change in weights')
plt.xlabel('percentile')
plt.ylabel('percentage change in weight vectors')
plt.show()

print('we can see that there is an abrupt change or rise in pecentage change valu


#plotting percentiles from 99th to 100th
percentiles = []
for i in np.arange(99.0,100.1,0.1):
    percentiles.append(np.percentile(delta,i))
plt.figure(figsize=(15,10))
plt.plot(np.arange(99.0,100.1,0.1),percentiles)
plt.title('99th to 100th percentile')
plt.xlabel('')
plt.show()
print('from the graph it is clear that there is a very steep increase in vaue at
```


In [46]:
```
#calculating the threshold value at 99.8th percentile
threshold = np.percentile(sorted_delta,99.8)
print(threshold)

#storing the index of features whose pecentage change in weight vector is greater
indices = []
feat = [] #for storing the features
for i in delta:
  if i>threshold:
    indices.append(list(delta).index(i))

for i in indices:
    feat.append(features[i])

print('features for which change in weight vector is greater than the threshold a
print(feat)

print(len(feat)/len(delta))#percentage of features whose weight vector value has
print('AS number of features which have a considerable change in weight vectors a
```

```
903.565043269974
features for which change in weight vector is greater than the threshold are:
['abovementioned', 'acetaia', 'ackee', 'afra', 'abovementioned', 'artsy', 'abov
ementioned', 'backlog', 'beacon', 'acetaia', 'bries', 'cappichino', 'cataract',
'cheeese', 'chimichanga', 'codfish', 'coleslaw', 'collusion', 'cornbreads', 'cr
adle', 'critiques', 'dazzled', 'artsy', 'drycleaned', 'eatbaby', 'eatbaby', 'er
ythorbate', 'abovementioned', 'fal', 'floraly', 'fruitea', 'funkier', 'geeze',
'acetaia', 'grimy', 'grittyness', 'gruyere', 'gvn', 'halifax', 'drycleaned', 'h
armoniously', 'beacon', 'immobile', 'incubate', 'abovementioned', 'abovemention
ed', 'ladythis', 'linens', 'linstead', 'looose', 'beacon', 'lousinna', 'cappich
ino', 'acetaia', 'marriot', 'acetaia', 'acetaia', 'monrings', 'morel', 'mutatio
n', 'acetaia', 'cheeese', 'grittyness', 'organicsyrups', 'eatbaby', 'funkier',
'morel', 'pepperiness', 'pescatora', 'pheonix', 'cappichino', 'chimichanga', 'a
bovementioned', 'rejuvenating', 'drycleaned', 'siegelnew', 'srimp', 'sseriousl
y', 'bries', 'cappichino', 'szechwan', 'tangible', 'tasteresults', 'tasteresult
s', 'teenaged', 'tasteresults', 'afra', 'abovementioned', 'tournaments', 'looos
e', 'abovementioned', 'uncountable', 'harmoniously', 'volleyball', 'wart', 'wha
ler', 'critiques', 'beacon', 'yank', 'yonana']
0.001974879532348527
AS number of features which have a considerable change in weight vectors are ve
ry less around 0.1974879532348527%,so we can say that the features are not mult
icollinear and hence weight vectors can be used for feature importance
```

# l1 regularization

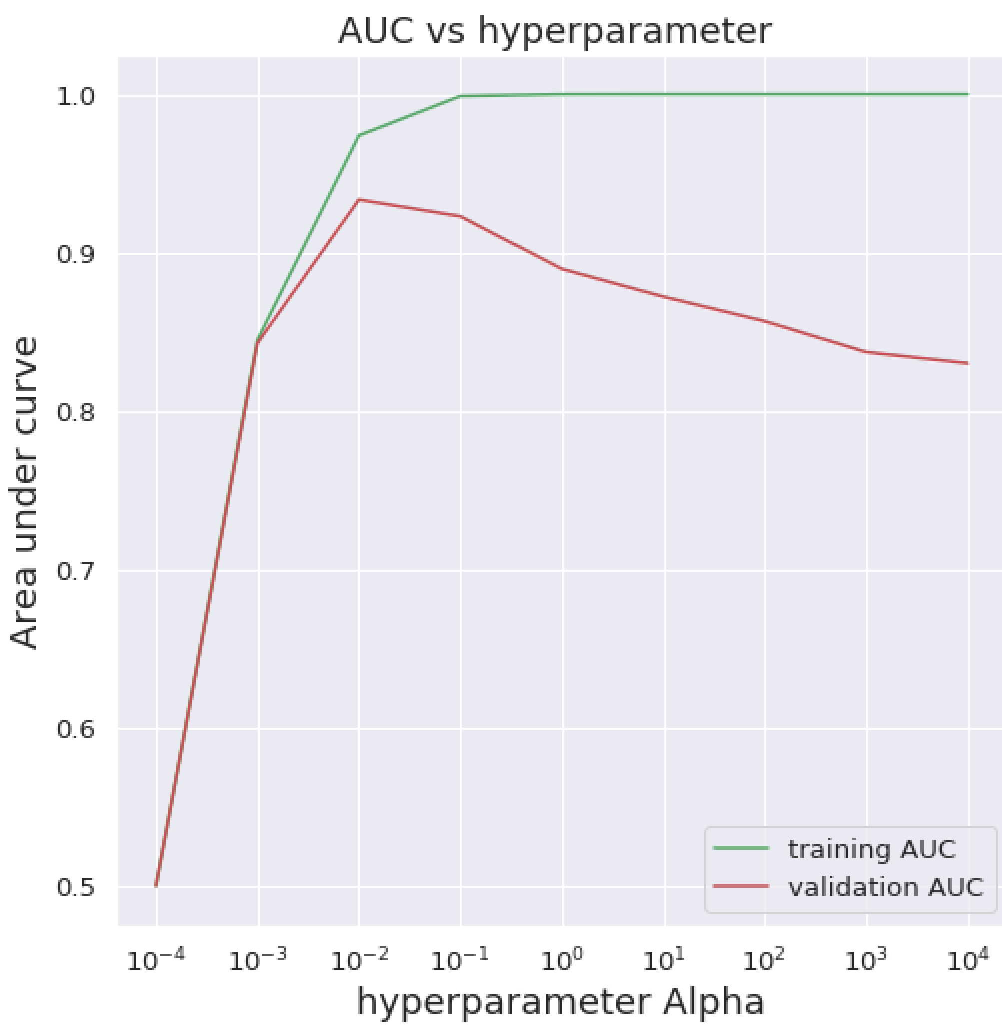
In [ ]:
```
param = {'C': [10**i for i in range(-4,5)]}
model = GridSearchCV(LogisticRegression(penalty='l1'),param_grid = param,scoring 
model.fit(train_std,Y_train)
```

In [0]:
```
best_C_l1_bow = model.best_params_['C']
print('best hyperparameter for l1 regularization in bag of words is:',best_C_l1_b
```

```
best hyperparameter for l1 regularization in bag of words is: 0.01
```

In [0]:
```
train_auc = model.cv_results_['mean_train_score']#deriving the avg training score
cv_auc = model.cv_results_['mean_test_score']#deriving the average cross validati
```

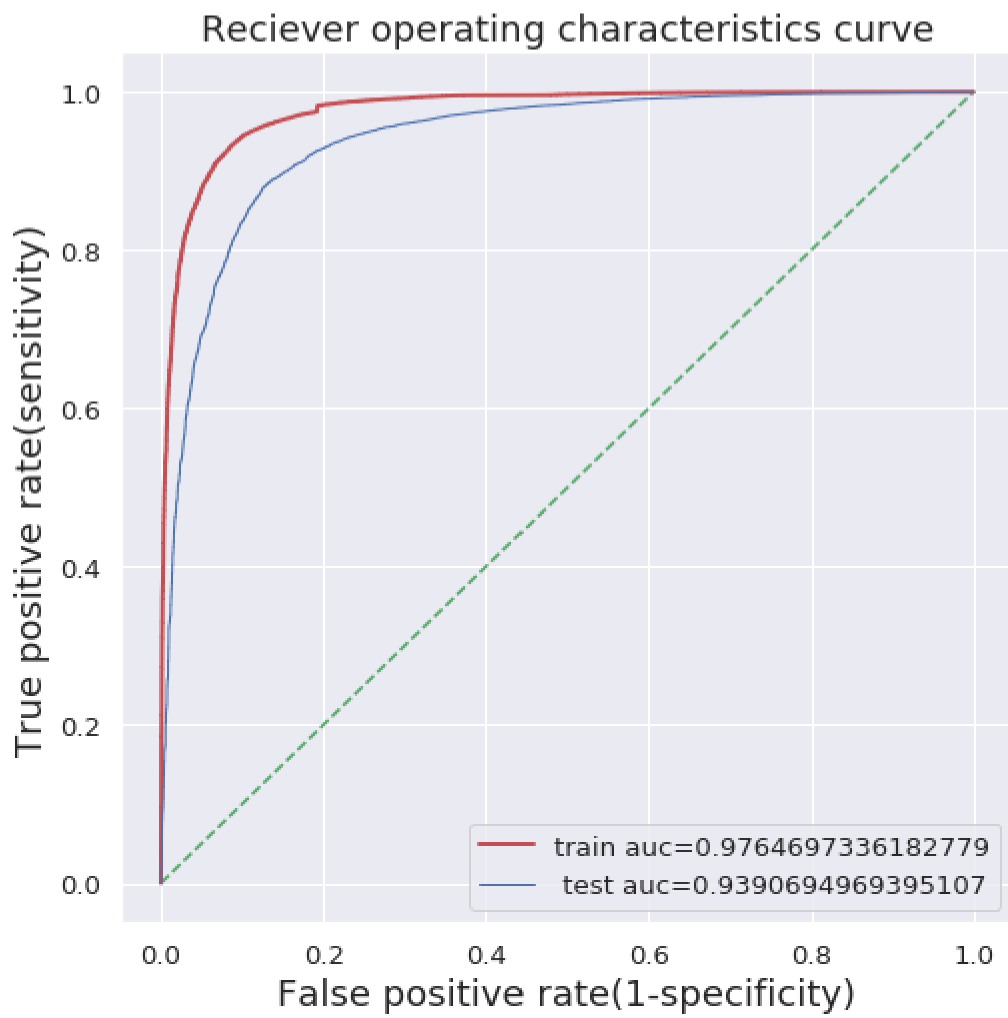
In [0]:
```
error(train_auc,cv_auc)#plotting the AUC vs Hyperparameter
```



In [0]:
```
from sklearn.metrics import roc_auc_score
clf_optimal = LogisticRegression(C =best_C_l1_bow,penalty='l1')#fitting the best 
clf_optimal.fit(train_std,Y_train)
train_pred = clf_optimal.predict_proba(train_std)[:,1]
#predict_proba gives the probability of a data point belonging to a particular cl

test_pred = clf_optimal.predict_proba(test_std)[:,1]
#this predicts the probability of data pointsin test dataset belonging to class '

test_auc_bow_l1 = roc_auc_score(Y_test,test_pred)
print('AUC on test dataset is{}'.format(test_auc_bow_l1))
#calculating the area under the curve for the roc curve that will be drawn on tes
```

```
AUC on test dataset is0.9390694969395107
```

In [0]:
```
from sklearn.metrics import roc_curve

fpr_tr, tpr_tr, _ = roc_curve(Y_train,train_pred)
fpr_test, tpr_test, _ = roc_curve(Y_test,test_pred)
#calculating the fpr,tpr and thresholds for each training and test dataset
auc_train = roc_auc_score(Y_train,train_pred)
auc_test = roc_auc_score(Y_test, test_pred)
sns.set_style('darkgrid')
plt.figure(figsize=(8,8))
plt.plot(np.linspace(0,1,100),np.linspace(0,1,100),"g--")
plt.plot(fpr_tr,tpr_tr,'r',linewidth=2,label="train auc="+str(auc_train))
plt.plot(fpr_test,tpr_test,'b',linewidth=1,label=" test auc="+str(auc_test))
plt.xlabel('False positive rate(1-specificity)',fontsize=18)
plt.ylabel('True positive rate(sensitivity)',fontsize=18)
plt.title('Reciever operating characteristics curve',fontsize=18)
plt.legend(loc='best')
plt.show()
```



In [0]:
```
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import confusion_matrix

pred = clf_optimal.predict(test_std)# predicting all the classes for test dataset
pred_tr = clf_optimal.predict(train_std)#predicting all the classes for train dat


# calculating the precison score
print('precison score is {}'.format(precision_score(Y_test,pred)))

#calculating the recall score
print('\nrecall_score is {}'.format(recall_score(Y_test,pred)))

#calculating the f1 score
print('\nf1 score is {}'.format(f1_score(Y_test,pred)))
```

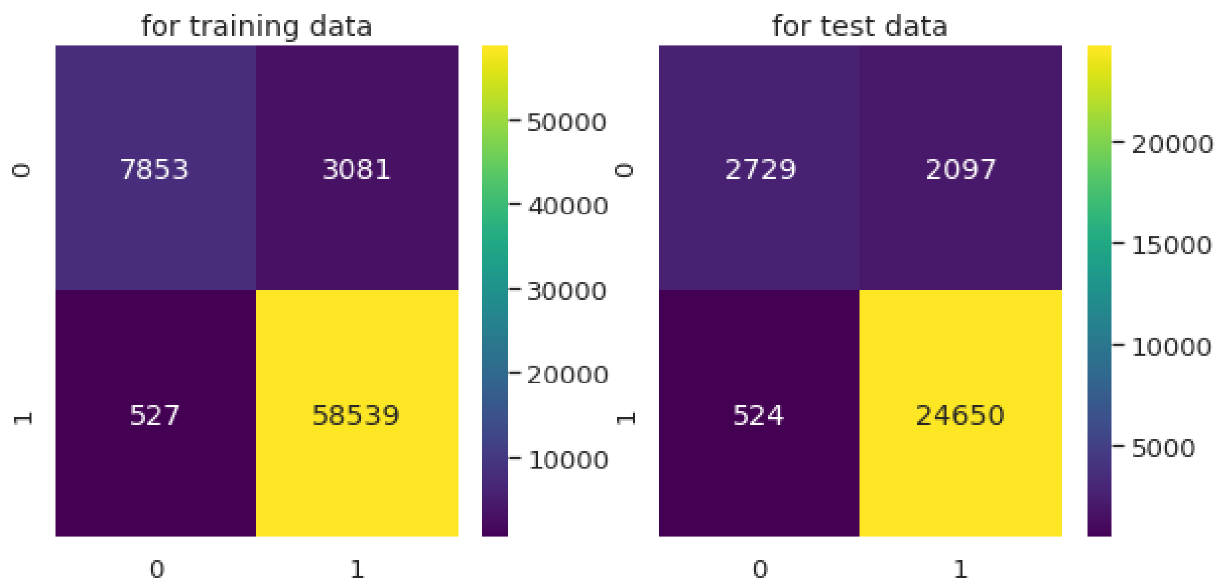
```
precison score is 0.9215986839645568

recall_score is 0.9791848732819576

f1 score is 0.9495194622599719
```

In [0]:
```
train_matrix = pd.DataFrame(confusion_matrix(Y_train,pred_tr),range(2),range(2))
print(train_matrix)

print('***********************************')

test_matrix = pd.DataFrame(confusion_matrix(Y_test,pred),range(2),range(2))# svai
print(test_matrix.head())
```

```
      0      1
0  7853   3081
1   527  58539
***********************************
      0      1
0  2729   2097
1   524  24650
```

In [0]:
```
sns.set(font_scale = 1.2)
fig, ax = plt.subplots(figsize=(10,10))#setting the font size
plt.subplot(2,2,1)
plt.title('for training data')
sns.heatmap(train_matrix,annot = True,fmt = 'g',cmap = 'viridis')


#annot = True writes data values in each cell
# fmt is string formatting code which is to be used when adding annonations
# cmap is the mapping from data values to color space

plt.subplot(2,2,2)
plt.title('for test data')
sns.heatmap(test_matrix,annot = True,fmt = 'g',cmap = 'viridis')
```

Out[71]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff7ca729eb8>
```




## Most important features

In [0]:
```
clf_optimal = LogisticRegression(C =best_C_l1_bow,penalty='l1')#fitting the best 
clf_optimal.fit(train_std,Y_train)
w = clf_optimal.coef_[0]#finding the coefficients of all features
print(w)
```

```
[ 0.          0.         -0.01062846 ...  0.          0.
  0.        ]
```

In [0]:
```
features = vect.get_feature_names()#getting name of the features after fitting and
negative_indices = np.argsort(w)
positive_indices = np.argsort(w)[::-1]


print('TOP 20 important features for positive class and their coefficients in Bag
for i in (positive_indices[0:20]):
    print("%s\t --> \t%f"%(features[i],w[i]))
print("**************************************************")

print('TOP 20 important features for negative class and their coefficients in Bag
for i in (negative_indices[0:20]):
    print("{} ---> {} ".format(features[i],w[i]))
```

```
TOP 20 important features for positive class and their coefficients in Bag of W
ords featurization using l2 regularization are:

great    -->    0.665626
best     -->    0.467307
delicious        -->    0.419023
love     -->    0.357422
good     -->    0.348398
perfect  -->    0.334929
loves    -->    0.274010
excellent        -->    0.261527
nice     -->    0.244055
highly   -->    0.230971
wonderful        -->    0.222770
amazing  -->    0.217440
favorite         -->    0.201767
happy    -->    0.195210
tasty    -->    0.181755
find     -->    0.169823
thank    -->    0.159034
yummy    -->    0.158329
awesome  -->    0.148319
works    -->    0.143094
**************************************************
TOP 20 important features for negative class and their coefficients in Bag of W
ords featurization using l2 regularization are:

not ---> -0.50361894119312
disappointed ---> -0.2403346898970079
worst ---> -0.20667290722671394
awful ---> -0.18977914885902306
terrible ---> -0.1835300525493563
disappointing ---> -0.16933446163413673
horrible ---> -0.1679227752774337
money ---> -0.1601981969170254
unfortunately ---> -0.15037341573923185
stale ---> -0.1453510553423234
disappointment ---> -0.13015007957833644
thought ---> -0.12763641137988116
taste ---> -0.12125278087674297
```

```
bland ---> -0.11946125879089595
return ---> -0.11884261054329673
threw ---> -0.11718600475810413
waste ---> -0.11443645668085377
bad ---> -0.10997067698643533
product ---> -0.10649160446881956
weak ---> -0.10648539244355062
```

# Sparsity after l1 regularization

This is being to done to see how l1 regularization creates sparsity and reducing feature importance also

**C = 0.01**

In [0]:
```
clf = LogisticRegression(C = 0.01,penalty = 'l1')#fitting the model with the best
clf.fit(train_std,Y_train)
w = clf.coef_
#this counts the number of non zero coefficients

print('After Regularization:')
print('\nnumber of non-zero elements in W are: {}'.format(np.count_nonzero(w)))
```

```
After Regularization:

number of non-zero elements in W are: 4885
```

**C = 0.1**

In [0]:
```
clf = LogisticRegression(C = 0.1,penalty = 'l1')#fitting the model with the best
clf.fit(train_std,Y_train)
w = clf.coef_
#this counts the number of non zero coefficients

print('After Regularization:')
print('\nnumber of non-zero elements in W are: {}'.format(np.count_nonzero(w)))
```

```
After Regularization:

number of non-zero elements in W are: 12799
```

**C = 1.0**

In [0]:
```
clf = LogisticRegression(C = 1,penalty = 'l1')#fitting the model with the best hy
clf.fit(train_std,Y_train)
w = clf.coef_
#this counts the number of non zero coefficients

print('After Regularization:')
print('\nnumber of non-zero elements in W are: {}'.format(np.count_nonzero(w)))
```

```
After Regularization:

number of non-zero elements in W are: 14826
```

**C = 10**

In [0]:
```
clf = LogisticRegression(C = 10,penalty = 'l1')#fitting the model with the best h
clf.fit(train_std,Y_train)
w = clf.coef_
#this counts the number of non zero coefficients

print('After Regularization:')
print('\nnumber of non-zero elements in W are: {}'.format(np.count_nonzero(w)))
```

```
After Regularization:

number of non-zero elements in W are: 15476
```

this shows that as we decrease 'C' which means increasing 'lambda' l1 regularization creates more and more sparsity which is making the coefficient of features zero and thus helping in determining the feature importance

# TFIDF

In [30]:
```
vect = TfidfVectorizer(ngram_range = (1,2),min_df = 10)#this ensures that  word w

vect.fit(X_train)#vectorizer reading and forming all the vocabalury from training

train_set = vect.transform(X_train)
test_set = vect.transform(X_test)
#transforming the data after learning the vocabalury this creates sparse matrices

print('After Vectorization:')
print('\nsize of training dataset is {}'.format(train_set.shape))
print("size of test dataset is {}".format(test_set.shape))
```

```
After Vectorization:

size of training dataset is (70000, 41055)
size of test dataset is (30000, 41055)
```

In [33]:
```
#Standardizing the data
from sklearn.preprocessing import StandardScaler
train_std = StandardScaler(with_mean = False).fit_transform(train_set)
test_std = StandardScaler(with_mean = False).fit_transform(test_set)
#with_mean cannot be True here because we are dealing with sparse matrices
print('after standardization: {}'.format(train_std.shape))
```

```
after standardization: (70000, 41055)
```

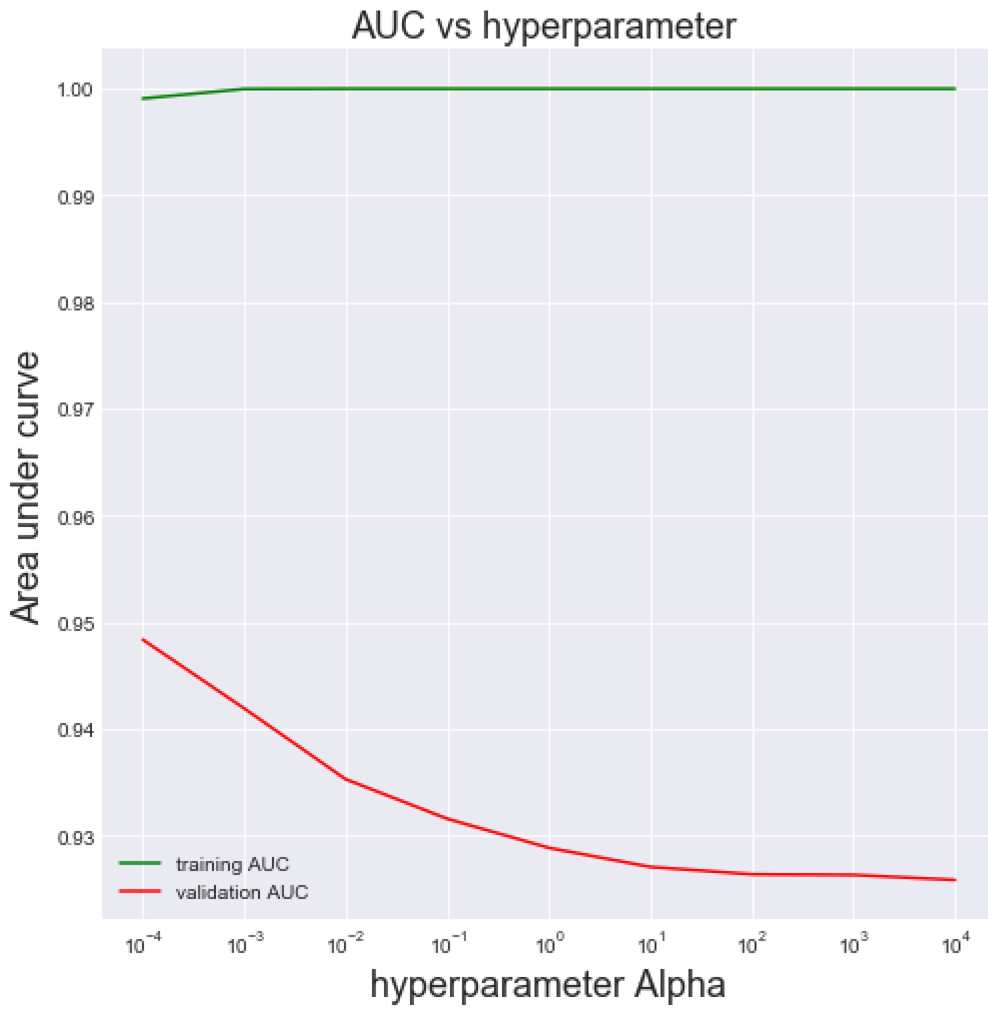
## L2 regularization

In [34]:
```
param = {'C': [10**i for i in range(-4,5)]}#fixing the size and range of paramete

model = GridSearchCV(LogisticRegression(penalty='l2'),param_grid = param,scoring 
model.fit(train_std,Y_train)
```

Out[34]:
```
GridSearchCV(cv='warn', error_score='raise-deprecating',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_i
ntercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid={'C': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='roc_auc', verbose=0)
```

In [39]:
```
train_auc = model.cv_results_['mean_train_score']# the avg training roc auc score
cv_auc = model.cv_results_['mean_test_score']# the average cross roc auc validati
```

In [40]:
```
error(train_auc,cv_auc)#plotting the auc vs hyperparameter curve
```




clearly we can see the Training AUC and cv AUC doing tradeoff at C = 0.0001

In [35]:
```
best_C_tfidf_l2 = model.best_params_['C']
print(best_C_tfidf_l2)
```

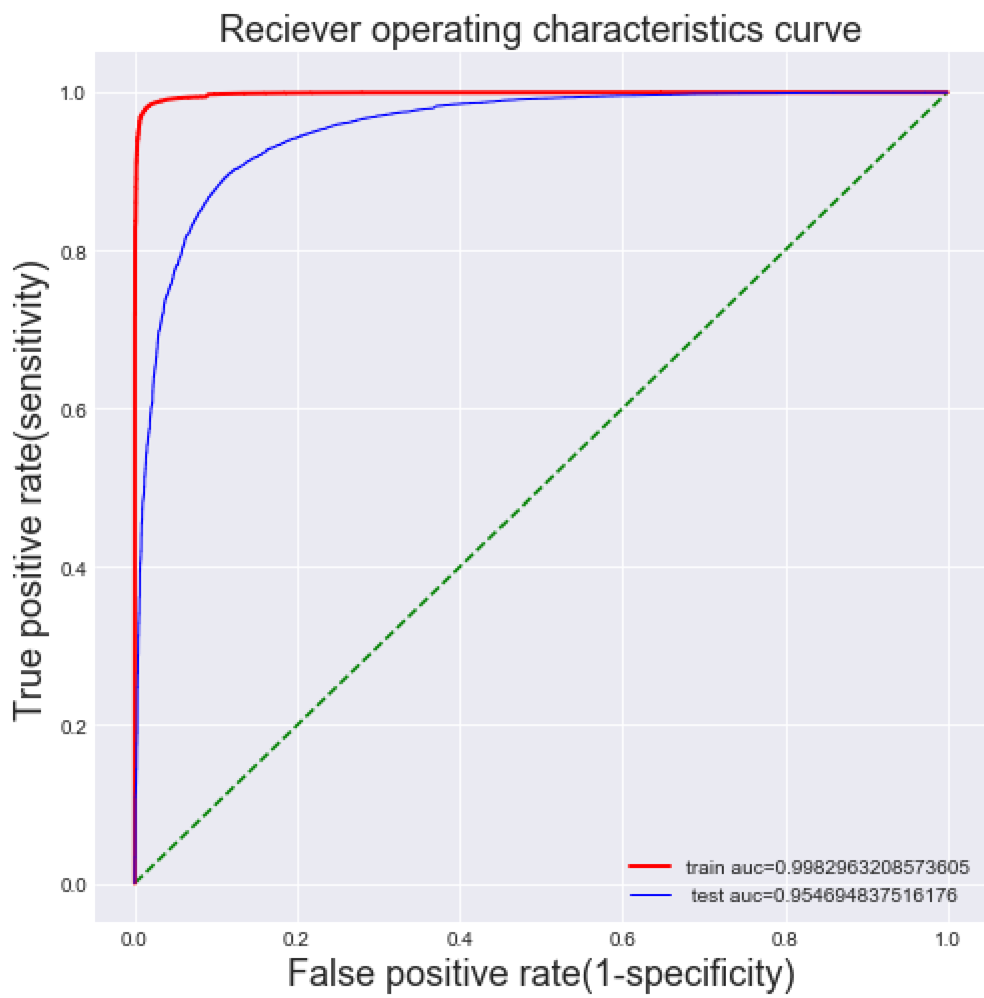
```
0.0001
```

thus we get best hyperparameter here as C = 0.0001

In [41]:
```
from sklearn.metrics import roc_auc_score
clf_optimal = LogisticRegression(C =0.0001,penalty='l2')#fitting the best hyperpa
clf_optimal.fit(train_std,Y_train)
train_pred = clf_optimal.predict_proba(train_std)[:,1]
#predict_proba gives the probability of a data point belonging to a particular cl

test_pred = clf_optimal.predict_proba(test_std)[:,1]
#this predicts the probability of data pointsin test dataset belonging to class '

test_auc_tfidf_l2 = roc_auc_score(Y_test,test_pred)
print('AUC on test dataset is{}'.format(test_auc_tfidf_l2))
#calculating the area under the curve for the roc curve that will be drawn on tes
```

```
AUC on test dataset is0.954694837516176
```

In [42]:
```
from sklearn.metrics import roc_curve

fpr_tr, tpr_tr, _ = roc_curve(Y_train,train_pred)
fpr_test, tpr_test, _ = roc_curve(Y_test,test_pred)
#calculating the fpr,tpr and thresholds for each training and test dataset
auc_train = roc_auc_score(Y_train,train_pred)
auc_test = roc_auc_score(Y_test, test_pred)
#calculating the area under the curve for both test and train auc after fitting th
sns.set_style('darkgrid')
plt.figure(figsize=(8,8))
plt.plot(np.linspace(0,1,100),np.linspace(0,1,100),"g--")
plt.plot(fpr_tr,tpr_tr,'r',linewidth=2,label="train auc="+str(auc_train))
plt.plot(fpr_test,tpr_test,'b',linewidth=1,label=" test auc="+str(auc_test))
plt.xlabel('False positive rate(1-specificity)',fontsize=18)
plt.ylabel('True positive rate(sensitivity)',fontsize=18)
plt.title('Reciever operating characteristics curve',fontsize=18)
plt.legend(loc='best')
plt.show()
```



In [45]:
```
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import confusion_matrix


pred = clf_optimal.predict(test_std)
pred_tr = clf_optimal.predict(train_std)


# predicting all the classes for test dataset for confusion matrix

# calculating the precison score
print('precison score is {}'.format(precision_score(Y_test,pred)))

#calculating the recall score
print('\nrecall_score is {}'.format(recall_score(Y_test,pred)))

#calculating the f1 score
print('\nf1 score is {}'.format(f1_score(Y_test,pred)))
```

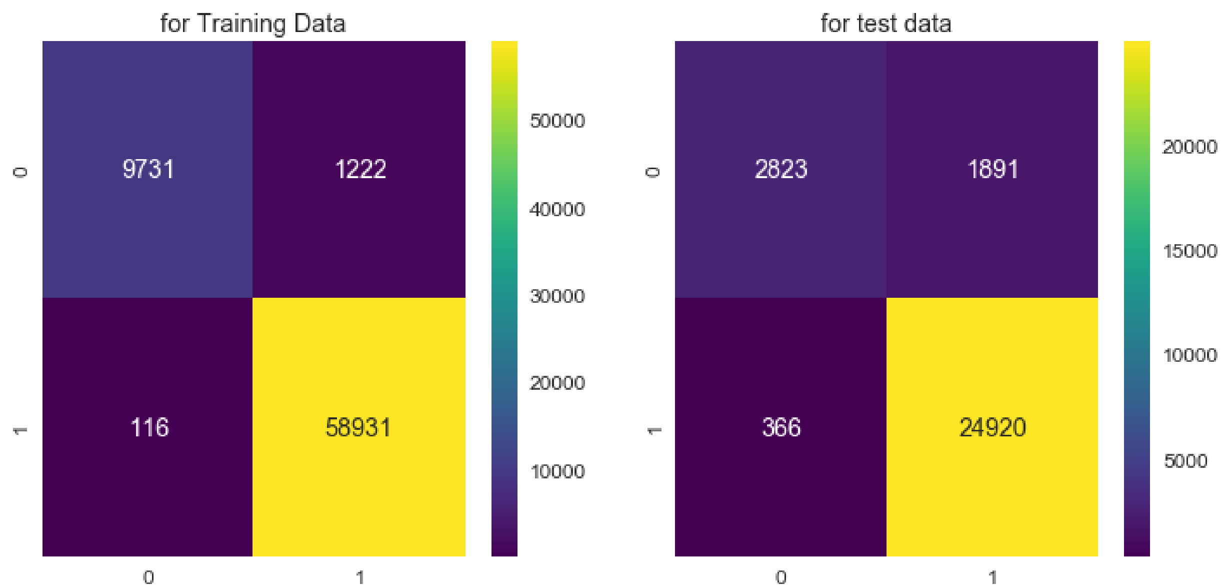
```
precison score is 0.9294692476968408

recall_score is 0.9855255872814996

f1 score is 0.9566769679636065
```

In [47]:
```
test_matrix = pd.DataFrame(confusion_matrix(Y_test,pred),range(2),range(2))# svai
print(test_matrix.head())

print("****************************************")

train_matrix = pd.DataFrame(confusion_matrix(Y_train,pred_tr),range(2),range(2))#
print(train_matrix.head())
```

```
      0      1
0  2823   1891
1   366  24920
****************************************
      0      1
0  9731   1222
1   116  58931
```

In [53]:
```
sns.set(font_scale = 1.2)
plt.figure(figsize = (12,12))#setting the font size
plt.subplot(2,2,1)
plt.title('for Training Data')
sns.heatmap(train_matrix,annot = True,fmt = 'g',cmap = 'viridis')#heatmap for tra

plt.subplot(2,2,2)
plt.title('for test data')
sns.heatmap(test_matrix,annot = True,fmt = 'g',cmap = 'viridis')
#annot = True writes data values in each cell
# fmt is string formatting code which is to be used when adding annonations
# cmap is the mapping from data values to color space
```

Out[53]: <matplotlib.axes._subplots.AxesSubplot at 0x2232a620b00>




## Most important Features

In [55]:
```
clf_optimal = LogisticRegression(C =best_C_tfidf_l2,penalty='l2')#fitting the bes
clf_optimal.fit(train_std,Y_train)
w = clf_optimal.coef_[0]#finding the coefficients of all features
print(w)
```

```
[ 0.00032754  0.00142451 -0.00222142 ...  0.00259823 -0.00295761
 -0.00301293]
```

In [56]:
```
features = vect.get_feature_names()#getting name of the features after fitting an

#sorting the indexes with respect to values
negative_indices = np.argsort(w)

#reversing the sorted indexes with respect to values for positive indexes
positive_indices = np.argsort(w)[::-1]


print('TOP 20 important features for positive class and their coefficients in Bag
for i in (positive_indices[0:20]):
    print("%s\t --> \t%f"%(features[i],w[i]))
print("************************************************")

print('TOP 20 important features for negative class and their coefficients in Bag
for i in (negative_indices[0:20]):
    print("{} ---> {} ".format(features[i],w[i]))
```

```
TOP 20 important features for positive class and their coefficients in Bag of W
ords featurization using l2 regularization are:

great    -->    0.113833
good     -->    0.085018
love     -->    0.083415
best     -->    0.080686
delicious        -->    0.071410
perfect  -->    0.056889
excellent        -->    0.055816
loves    -->    0.055595
favorite         -->    0.048871
tasty    -->    0.048011
nice     -->    0.047931
wonderful        -->    0.046754
happy    -->    0.045685
easy     -->    0.044156
highly   -->    0.042154
find     -->    0.041509
use      -->    0.041445
little   -->    0.040577
loved    -->    0.039478
awesome  -->    0.038515
************************************************
TOP 20 important features for negative class and their coefficients in Bag of W
ords featurization using l2 regularization are:

disappointed ---> -0.062242995887 20672
not buy ---> -0.05996253521825 1685
worst ---> -0.05695553218008697
not recommend ---> -0.055773149494665324
not worth ---> -0.05517043646370065
awful ---> -0.04973004114386868
disappointing ---> -0.049558474967031425
terrible ---> -0.04865020904046238
```

```
not good ---> -0.042293587842204494
threw ---> -0.04222980591182071
disappointment ---> -0.041368452684706215
would not ---> -0.04060437533605064
stale ---> -0.04037069873603459
two stars ---> -0.039409364910663144
horrible ---> -0.03870383634225348
disgusting ---> -0.038680694851069675
unfortunately ---> -0.03796956780651039
not ---> -0.03722775929441032
not purchase ---> -0.03636525903737527
waste money ---> -0.0363578922452465
```

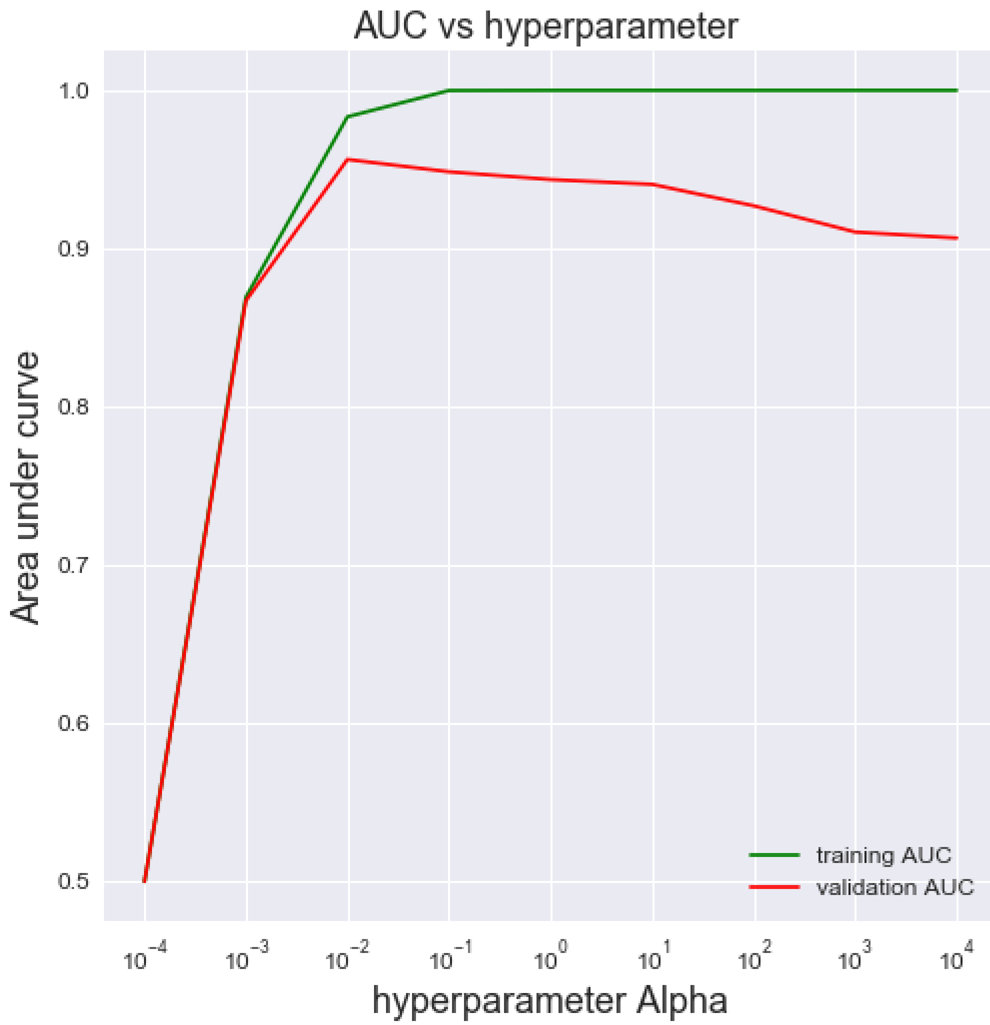
## L1 regularization

In [57]:
```
param = {'C': [10**i for i in range(-4,5)]}#fixing the size and range of paramete

model = GridSearchCV(LogisticRegression(penalty='l1'),param_grid = param,scoring 
model.fit(train_std,Y_train)
```

Out[57]:
```
GridSearchCV(cv='warn', error_score='raise-deprecating',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_i
ntercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l1', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid={'C': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='roc_auc', verbose=0)
```

In [100]:
```
train_auc = model.cv_results_['mean_train_score']#deriving the avg training score
cv_auc = model.cv_results_['mean_test_score']#deriving the average cross validati
```

In [59]:
```
error(train_auc,cv_auc)
```




After using l1 regularization we can clearly see the tradeoff between bias and variance happening at C = 0.01 from where we can definitely deduce that as l1 regularization creates sparsity thats why optimal value of hyperparameter 'lambda' decreases.

In [60]:
```
best_C_tfidf_l1 = model.best_params_["C"]
print(best_C_tfidf_l1)
```

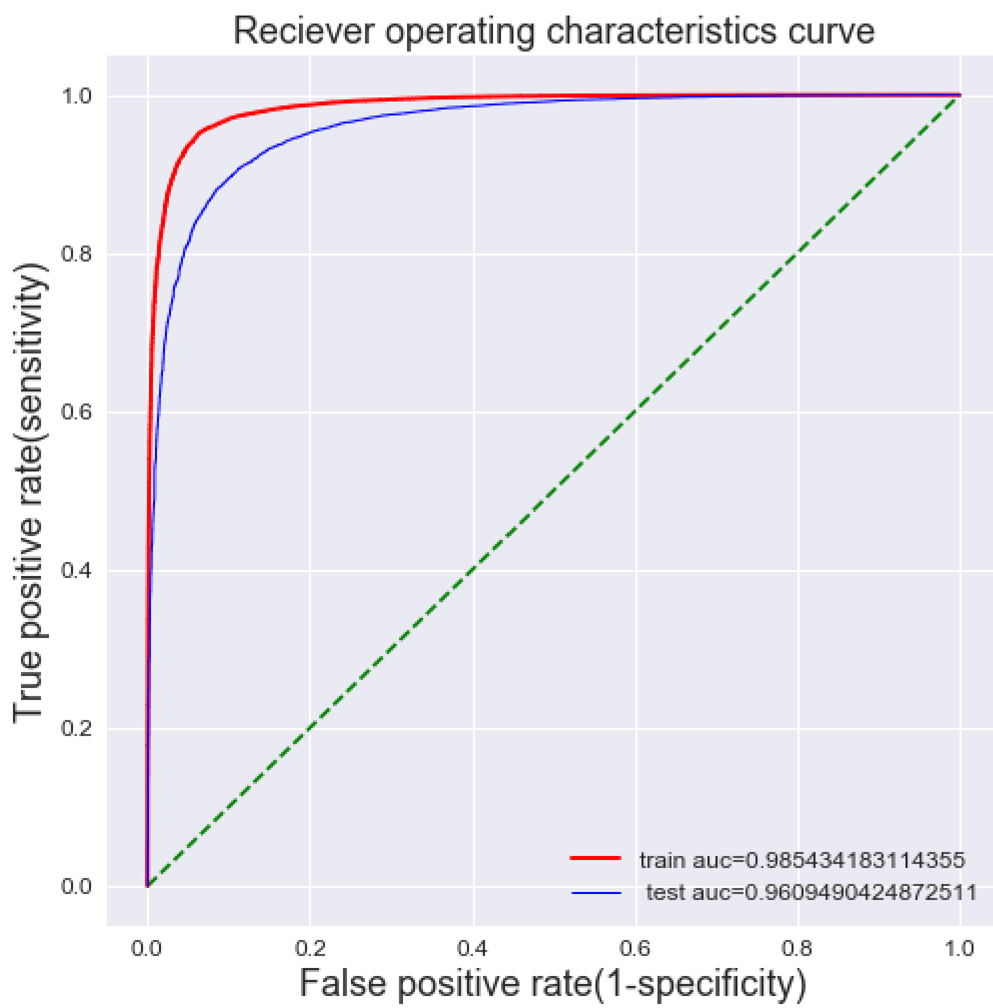
```
0.01
```

In [65]:

```
from sklearn.metrics import roc_auc_score
clf_optimal = LogisticRegression(C =best_C_tfidf_l1,penalty='l1')#fitting the bes
clf_optimal.fit(train_std,Y_train)
train_pred = clf_optimal.predict_proba(train_std)[:,1]
#predict_proba gives the probability of a data point belonging to a particular cl

test_pred = clf_optimal.predict_proba(test_std)[:,1]
#this predicts the probability of data pointsin test dataset belonging to class '

test_auc_tfidf_l1 = roc_auc_score(Y_test,test_pred)
print('AUC on test dataset is{}'.format(test_auc_tfidf_l1))
#calculating the area under the curve for the roc curve that will be drawn on tes
```

```
AUC on test dataset is0.9609490424872511
```

In [66]:
```
fpr_tr, tpr_tr, _ = roc_curve(Y_train,train_pred)
fpr_test, tpr_test, _ = roc_curve(Y_test,test_pred)
#calculating the fpr,tpr and thresholds for each training and test dataset
auc_train = roc_auc_score(Y_train,train_pred)
auc_test = roc_auc_score(Y_test, test_pred)
#calculating the area under the curve for both test and train auc after fitting t

sns.set_style('darkgrid')
plt.figure(figsize=(8,8))
plt.plot(np.linspace(0,1,100),np.linspace(0,1,100),"g--")
#This signifies the Area under curve = 0.5
plt.plot(fpr_tr,tpr_tr,'r',linewidth=2,label="train auc="+str(auc_train))
plt.plot(fpr_test,tpr_test,'b',linewidth=1,label=" test auc="+str(auc_test))
plt.xlabel('False positive rate(1-specificity)',fontsize=18)
plt.ylabel('True positive rate(sensitivity)',fontsize=18)
plt.title('Reciever operating characteristics curve',fontsize=18)
plt.legend(loc='best')
plt.show()
```



In [68]:
```
pred = clf_optimal.predict(test_std)
# predicting all the classes for test dataset for confusion matrix

#predicting all the values for class labels on training dataset
pred_tr = clf_optimal.predict(train_std)

# calculating the precison score
print('precison score is {}'.format(precision_score(Y_test,pred)))

#calculating the recall score
print('\nrecall_score is {}'.format(recall_score(Y_test,pred)))

#calculating the f1 score
print('\nf1 score is {}'.format(f1_score(Y_test,pred)))
```

```
precison score is 0.9384417354433255

recall_score is 0.9803053072846635

f1 score is 0.9589168278529981
```

In [69]:
```
test_matrix = pd.DataFrame(confusion_matrix(Y_test,pred),range(2),range(2))# svai
print(test_matrix.head())

print("****************************************")

train_matrix = pd.DataFrame(confusion_matrix(Y_train,pred_tr),range(2),range(2))#
print(train_matrix.head())
```

```
      0      1
0  3088   1626
1   498  24788
****************************************
      0      1
0  8374   2579
1   540  58507
```

In [70]:
```
sns.set(font_scale = 1.2)
plt.figure(figsize = (12,12))#setting the font size
plt.subplot(2,2,1)
plt.title('for Training Data')
sns.heatmap(train_matrix,annot = True,fmt = 'g',cmap = 'viridis')#heatmap for tra

plt.subplot(2,2,2)
plt.title('for test data')
sns.heatmap(test_matrix,annot = True,fmt = 'g',cmap = 'viridis')
#annot = True writes data values in each cell
# fmt is string formatting code which is to be used when adding annonations
# cmap is the mapping from data values to color space
```

Out[70]: <matplotlib.axes._subplots.AxesSubplot at 0x223098be668>


## Most Important Features

In [72]:
```
clf_optimal = LogisticRegression(C =best_C_tfidf_l1,penalty='l1')#fitting the bes
clf_optimal.fit(train_std,Y_train)
w = clf_optimal.coef_[0]#finding the coefficients of all features
print(w)



features = vect.get_feature_names()#getting name of the features after fitting an

#sorting the indexes with respect to values
negative_indices = np.argsort(w)

#reversing the sorted indexes with respect to values for positive indexes
positive_indices = np.argsort(w)[::-1]


print('TOP 20 important features for positive class and their coefficients in Bag
for i in (positive_indices[0:20]):
    print("%s\t --> \t%f"%(features[i],w[i]))
print("************************************************")

print('TOP 20 important features for negative class and their coefficients in Bag
for i in (negative_indices[0:20]):
    print("{} ---> {} ".format(features[i],w[i]))
```

```
[0. 0. 0. ... 0. 0. 0.]
TOP 20 important features for positive class and their coefficients in Bag of W
ords featurization using l1 regularization are:

great    -->    0.682281
best     -->    0.433707
good     -->    0.424674
delicious        -->    0.389063
perfect  -->    0.322125
love     -->    0.312741
excellent        -->    0.304821
loves    -->    0.263042
not disappointed         -->    0.248037
happy    -->    0.238137
favorite         -->    0.206476
tasty    -->    0.196615
wonderful        -->    0.193660
nice     -->    0.190582
definitely       -->    0.181934
awesome  -->    0.177287
easy     -->    0.168317
highly   -->    0.156395
pleased  -->    0.153040
yummy    -->    0.134047
************************************************
TOP 20 important features for negative class and their coefficients in Bag of W
ords featurization using l1 regularization are:
```

```
disappointed ---> -0.2981350031552851
not ---> -0.21638009311590178
worst ---> -0.19110919901648568
not worth ---> -0.17228516771546237
not recommend ---> -0.17075745761780933
awful ---> -0.16445842408829742
not good ---> -0.15870523420561203
not buy ---> -0.1560216493671657
terrible ---> -0.15263426089668153
disappointing ---> -0.1429993452024558
bad ---> -0.13870346003738562
stale ---> -0.1326055053624659
threw ---> -0.131327203017142
two stars ---> -0.12010781489888275
disappointment ---> -0.11797606071291529
horrible ---> -0.11084987893997335
return ---> -0.10849529672731895
disgusting ---> -0.1065695916301153
unfortunately ---> -0.09845199207569419
not happy ---> -0.09753165639613971
```

# WORD TO VEC

In [73]:
```
s_train = []
for sent in X_train:
    s_train.append(sent.split())
#preparing the training data for  word to vector vectorization

s_test = []
for sent in X_test:
    s_test.append(sent.split())
#preparing the test data for word to vector fatorization
```

In [74]:
```
# this line of code trains the w2v model on the give list of sentances

w2v_model=Word2Vec(s_train,min_count=5,size=50, workers=4)# min_count = 5 conside

w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
```

```
number of words that occured minimum 5 times  16065
```

In [75]:
```
print('sample words :',w2v_words[0:50])
```

```
sample words : ['received', 'sample', 'pack', 'raisin', 'variety', 'quaker', 's
oft', 'baked', 'oatmeal', 'cookies', 'influenster', 'test', 'family', 'month',
'old', 'son', 'loved', 'cookie', 'almost', 'ate', 'whole', 'thing', 'manage',
'couple', 'bites', 'love', 'chewy', 'ness', 'plus', 'provides', 'good', 'sourc
e', 'fiber', 'something', 'not', 'incorporate', 'enough', 'diets', 'sometimes',
'definitely', 'consider', 'purchasing', 'snack', 'big', 'bag', 'full', 'reall
y', 'individually', 'wrapped', 'keep']
```

# Average W2V

In [77]:
```
#computing average word to vector for training data

train_set = [] # the avg-w2v for each sentence/review is stored in this list
for sent in tqdm(s_train):
    sent_vec = np.zeros(50)
    cnt_words =0; # num of words with a valid vector in the sentence/review
    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
    train_set.append(sent_vec)

print(len(train_set))#number of datapoints in training set
```

```
100%|██████████████████████████████████████████████████████████████████████
█| 70000/70000 [02:47<00:00, 417.79it/s]

70000
```

In [78]:
```
#computing average word to vector for test data

test_set = [] # the avg-w2v for each sentence/review is stored in this list
for sent in s_test:
    sent_vec = np.zeros(50)
    cnt_words =0; # num of words with a valid vector in the sentence/review
    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
    test_set.append(sent_vec)

print(len(test_set))#number of datapoints in test set
```

```
30000
```

In [79]:
```
print(train_set[0])
```

```
[-0.01944027 -0.23175346 -0.07724504 -1.00644308 -0.96338314  0.45008989
 -0.23809615 -0.44930338 -0.94600899 -0.05514701  0.52156017 -0.10737156
 -0.59551718  0.48332506  0.30648719  0.28435665  0.00300338 -0.52443471
  0.42232519 -0.13700283  0.09899347 -0.10644326 -0.14390756 -0.89639726
  0.92507419 -0.08738389 -0.50632386  0.02995053  0.54368011 -0.45232807
 -1.19497342 -0.25348351 -0.4113364  -0.15183082  0.01128826  0.26426542
  0.120862    0.17180756 -0.41578801  0.79236498  0.48269884  0.85827908
 -0.14849857  0.24639349  0.45514648 -0.07611567 -0.12905833 -0.35698361
  0.31028208  1.07123898]
```

In [80]:
```
print(len(test_set[0]))
```

```
50
```

## Standardizing the data

In [81]:
```
#Standardizing the data
train_std = StandardScaler(with_mean = False).fit_transform(train_set)
test_std = StandardScaler(with_mean = False).fit_transform(test_set)
#with_mean cannot be True here because we are dealing with sparse matrices
print('after standardization: {}'.format(train_std.shape))
print("test data:",test_std.shape)
```

```
after standardization: (70000, 50)
test data: (30000, 50)
```

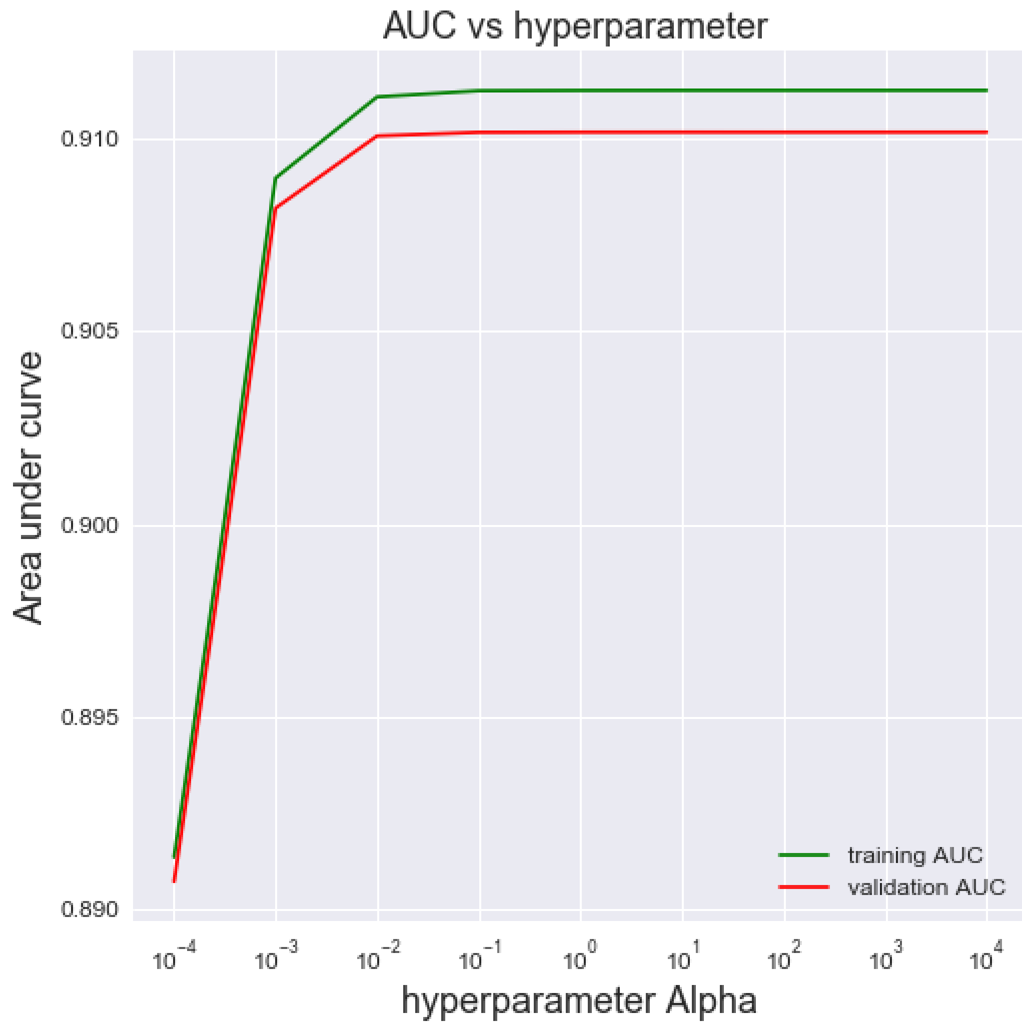
## L2 regularization and Grid Searchcv

In [86]:
```
param = {'C': [10**i for i in range(-4,5)]}#fixing the size and range of paramete

model = GridSearchCV(LogisticRegression(penalty='l2'),param_grid = param,scoring 
model.fit(train_std,Y_train)
```

Out[86]:
```
GridSearchCV(cv='warn', error_score='raise-deprecating',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_i
ntercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid={'C': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='roc_auc', verbose=0)
```

In [87]:
```
train_auc = model.cv_results_['mean_train_score']#deriving the avg training score
cv_auc = model.cv_results_['mean_test_score']#deriving the average cross validati
```

In [88]:
```
error(train_auc,cv_auc)#plotting the results
```




we see here best hyperparameter after tuning the model is c = 10

In [90]:
```
best_C_l2_aW2v = model.best_params_["C"]
print(best_C_l2_aW2v)
#this gives us the best hyperparameter found after gridsearch cross validation
```

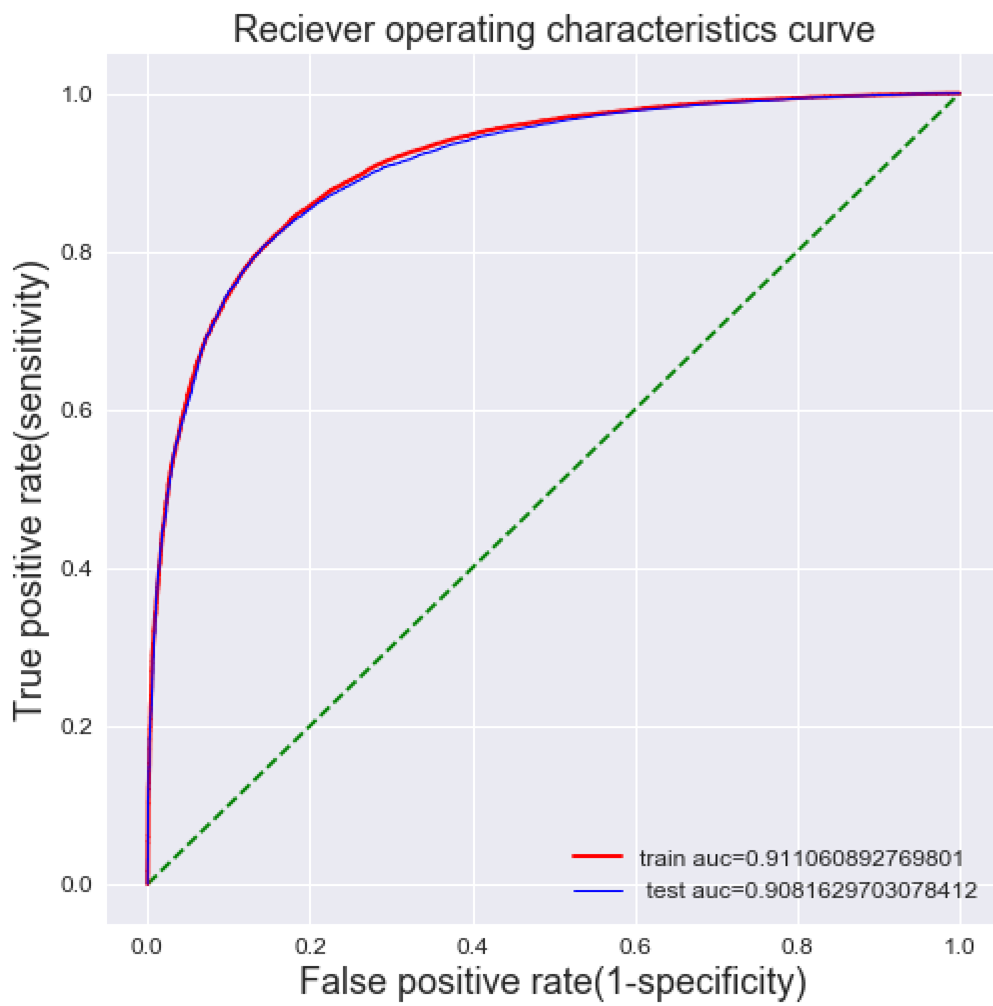
```
10
```

In [91]:
```
from sklearn.metrics import roc_auc_score
clf_optimal = LogisticRegression(C =best_C_l2_aW2v,penalty='l2')#fitting the best
clf_optimal.fit(train_std,Y_train)
train_pred = clf_optimal.predict_proba(train_std)[:,1]
#predict_proba gives the probability of a data point belonging to a particular cl

test_pred = clf_optimal.predict_proba(test_std)[:,1]
#this predicts the probability of data pointsin test dataset belonging to class '

test_auc_aW2v_l2 = roc_auc_score(Y_test,test_pred)
print('AUC on test dataset is {}'.format(test_auc_aW2v_l2))
#calculating the area under the curve for the roc curve that will be drawn on tes
```

```
AUC on test dataset is 0.9081629703078412
```

In [92]:

```
from sklearn.metrics import roc_curve

fpr_tr, tpr_tr, _ = roc_curve(Y_train,train_pred)
fpr_test, tpr_test, _ = roc_curve(Y_test,test_pred)
#calculating the fpr,tpr and thresholds for each training and test dataset
auc_train = roc_auc_score(Y_train,train_pred)
auc_test = roc_auc_score(Y_test, test_pred)
#calculating the area under the curve for both test and train auc after fitting th
sns.set_style('darkgrid')
plt.figure(figsize=(8,8))
plt.plot(np.linspace(0,1,100),np.linspace(0,1,100),"g--")
plt.plot(fpr_tr,tpr_tr,'r',linewidth=2,label="train auc="+str(auc_train))
plt.plot(fpr_test,tpr_test,'b',linewidth=1,label=" test auc="+str(auc_test))
plt.xlabel('False positive rate(1-specificity)',fontsize=18)
plt.ylabel('True positive rate(sensitivity)',fontsize=18)
plt.title('Reciever operating characteristics curve',fontsize=18)
plt.legend(loc='best')
plt.show()
```



In [94]:
```
pred = clf_optimal.predict(test_std)
# predicting all the classes for test dataset for confusion matrix

#predicting all the classes for training dataset for confusion matrix
pred_tr = clf_optimal.predict(train_std)

# calculating the precison score
print('precison score is {}'.format(precision_score(Y_test,pred)))

#calculating the recall score
print('\nrecall_score is {}'.format(recall_score(Y_test,pred)))

#calculating the f1 score
print('\nf1 score is {}'.format(f1_score(Y_test,pred)))
```

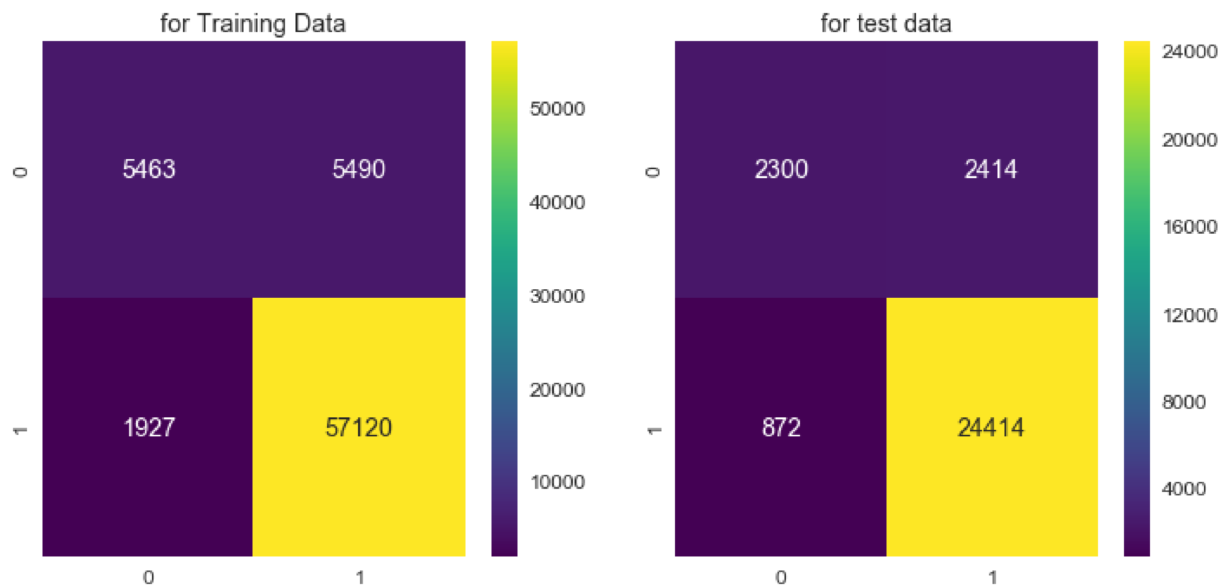
```
precison score is 0.9100193827344565

recall_score is 0.9655145139602942

f1 score is 0.9369459262386306
```

In [95]:
```
train_matrix = pd.DataFrame(confusion_matrix(Y_train,pred_tr),range(2),range(2))#
print(train_matrix.head())

print("******************************************")

test_matrix = pd.DataFrame(confusion_matrix(Y_test,pred),range(2),range(2))# savi
print(test_matrix.head())
```

```
      0      1
0  5463   5490
1  1927  57120
******************************************
      0      1
0  2300   2414
1   872  24414
```

In [97]:
```
sns.set(font_scale = 1.2)
plt.figure(figsize = (12,12))#setting the font size
plt.subplot(2,2,1)
plt.title('for Training Data')
sns.heatmap(train_matrix,annot = True,fmt = 'g',cmap = 'viridis')#heatmap for tra

plt.subplot(2,2,2)
plt.title('for test data')
sns.heatmap(test_matrix,annot = True,fmt = 'g',cmap = 'viridis')
#annot = True writes data values in each cell
# fmt is string formatting code which is to be used when adding annonations
# cmap is the mapping from data values to color space
```

Out[97]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2232f25a080>
```




In [0]:
```
print(w2v_words[:100])
```

```
['minute', 'web', 'search', 'ingredients', 'thai', 'pavilion', 'garlic', 'basi
l', 'stir', 'fry', 'rice', 'noodles', 'sauce', 'boxes', 'pack', 'noodle', 'flou
r', 'water', 'salt', 'fresh', 'green', 'chilies', 'soy', 'oil', 'oyster', 'can
e', 'sugar', 'extract', 'cornstarch', 'fish', 'anchovies', 'vinegar', 'soybean
s', 'tried', 'brand', 'europe', 'great', 'taste', 'fast', 'prep', 'see', 'amazo
n', 'com', 'like', 'dumplings', 'really', 'come', 'veg', 'biryani', 'think', 'b
est', 'gluten', 'free', 'enjoyed', 'shampoo', 'small', 'amount', 'needed', 'lat
er', 'entire', 'scalp', 'clean', 'scent', 'helps', 'control', 'dandruff', 'bu
y', 'product', 'highly', 'recommended', 'first', 'time', 'trying', 'good', 'eve
n', 'better', 'ca', 'not', 'wait', 'try', 'flavors', 'enjoy', 'cup', 'coffee',
'use', 'keurig', 'maker', 'want', 'timothys', 'extra', 'bold', 'rain', 'fores
t', 'blend', 'find', 'strong', 'satisfying', 'looking', 'box', 'raisins']
```

# Most important features

In [98]:
```
clf_optimal = LogisticRegression(C =best_C_tfidf_l1,penalty='l2')#fitting the bes
clf_optimal.fit(train_std,Y_train)
w = clf_optimal.coef_[0]#finding the coefficients of all features
print(w)



features = vect.get_feature_names()#getting name of the features after fitting an

#sorting the indexes with respect to values
negative_indices = np.argsort(w)

#reversing the sorted indexes with respect to values for positive indexes
positive_indices = np.argsort(w)[::-1]


print('TOP 20 important features for positive class and their coefficients in Ave
for i in (positive_indices[0:20]):
    print("%s\t --> \t%f"%(features[i],w[i]))
print("**********************************************")

print('TOP 20 important features for negative class and their coefficients in Ave
for i in (negative_indices[0:20]):
    print("{} ---> {} ".format(features[i],w[i]))
```

```
[ 0.33249754  0.22632542 -0.11215931 -0.14471572 -0.76657402  0.27410818
 -0.11775058  0.0120791   0.4687459  -0.52505134 -0.36869766  0.42565835
 -0.09548264  0.0258813   0.11040013  0.43214333  0.49404847  0.0463633
  0.39781691  0.29969006  0.07687872 -0.00619184  0.04651214  0.61701018
  0.24660535  0.08215599 -0.23136951 -0.23757829  0.42828935  0.20632952
 -0.18762274 -0.39311051 -0.06194791  0.04577286  0.09209197  0.02429106
 -0.3676515  -0.18372266 -0.10693906  0.27838581  0.14299725 -0.13471574
 -0.35477956 -0.1462672   0.25105813  0.11204479 -0.04418194 -0.07870766
 -0.29235997  0.26600071]
TOP 20 important features for positive class and their coefficients in Average
word to vector featurization using l2 regularization are:

able purchase    -->    0.617010
able give        -->    0.494048
able chew        -->    0.468746
able get         -->    0.432143
able stop        -->    0.428289
able enjoy       -->    0.425658
able keep        -->    0.397817
aa       -->    0.332498
able locate      -->    0.299690
absolute best    -->    0.278386
ability make     -->    0.274108
absolutely fantastic     -->    0.266001
absolutely awesome       -->    0.251058
able put         -->    0.246605
aback    -->    0.226325
able take        -->    0.206330
```

```
absolute favorite        -->    0.142997
absolutely awful         -->    0.112045
able finish      -->    0.110400
able use         -->    0.092092
************************************************
TOP 20 important features for negative class and their coefficients in Average
word to vector featurization using l2 regularization are:

ability ---> -0.7665740234090451
able drink ---> -0.5250513433437686
able tell ---> -0.3931105064646463
able eat ---> -0.36869765515614805
absence ---> -0.3676514966975827
absolutely adore ---> -0.3547795623438914
absolutely disgusting ---> -0.29235997154273147
able share ---> -0.23757828540059334
able see ---> -0.2313695116991936
able taste ---> -0.18762274373049387
absent ---> -0.1837226567982286
absolutely amazing ---> -0.1462671956253802
abdominal ---> -0.1447157155623541
absolutely ---> -0.13471574269068426
able ---> -0.11775057615955481
abandon ---> -0.11215931271669408
absolute ---> -0.1069390621208634
able feed ---> -0.09548263740965672
absolutely delicious ---> -0.0787076593553105
able tolerate ---> -0.061947914753729974
```

# L1 regularization

In [99]:

```python
param = {'C': [10**i for i in range(-4,5)]}#fixing the size and range of paramete

model = GridSearchCV(LogisticRegression(penalty='l1'),param_grid = param,scoring 
#using the grid search cross validation
model.fit(train_std,Y_train)
```

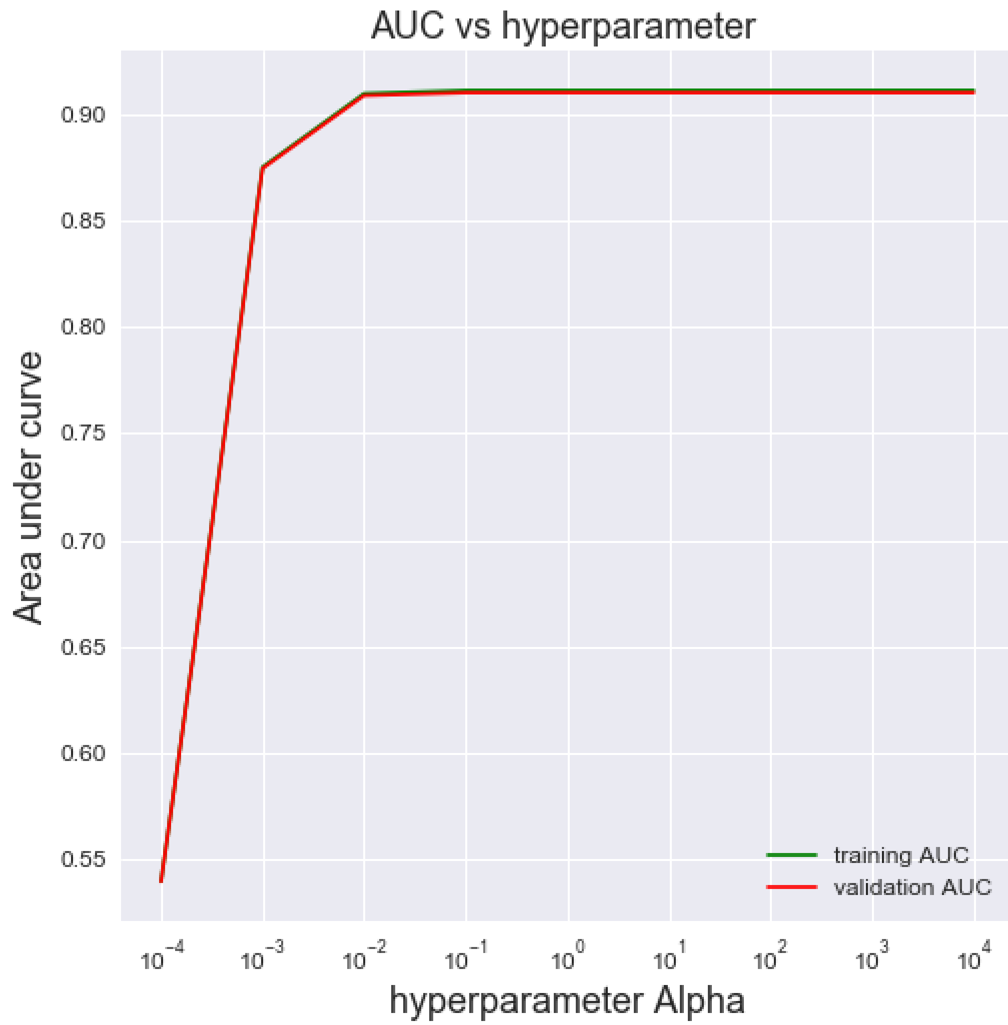
Out[99]:

```
GridSearchCV(cv='warn', error_score='raise-deprecating',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_i
ntercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l1', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid={'C': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='roc_auc', verbose=0)
```

In [104]:

```python
train_auc = model.cv_results_['mean_train_score']#deriving the avg training score
cv_auc = model.cv_results_['mean_test_score']#deriving the average cross validati
```

In [105]:
```
error(train_auc,cv_auc)
```




In [106]:
```
best_C_l1_aW2v = model.best_params_['C']
print(best_C_l1_aW2v)
#this gives us the best hyperparameter found after gridsearch cross validation
```

```
10000
```

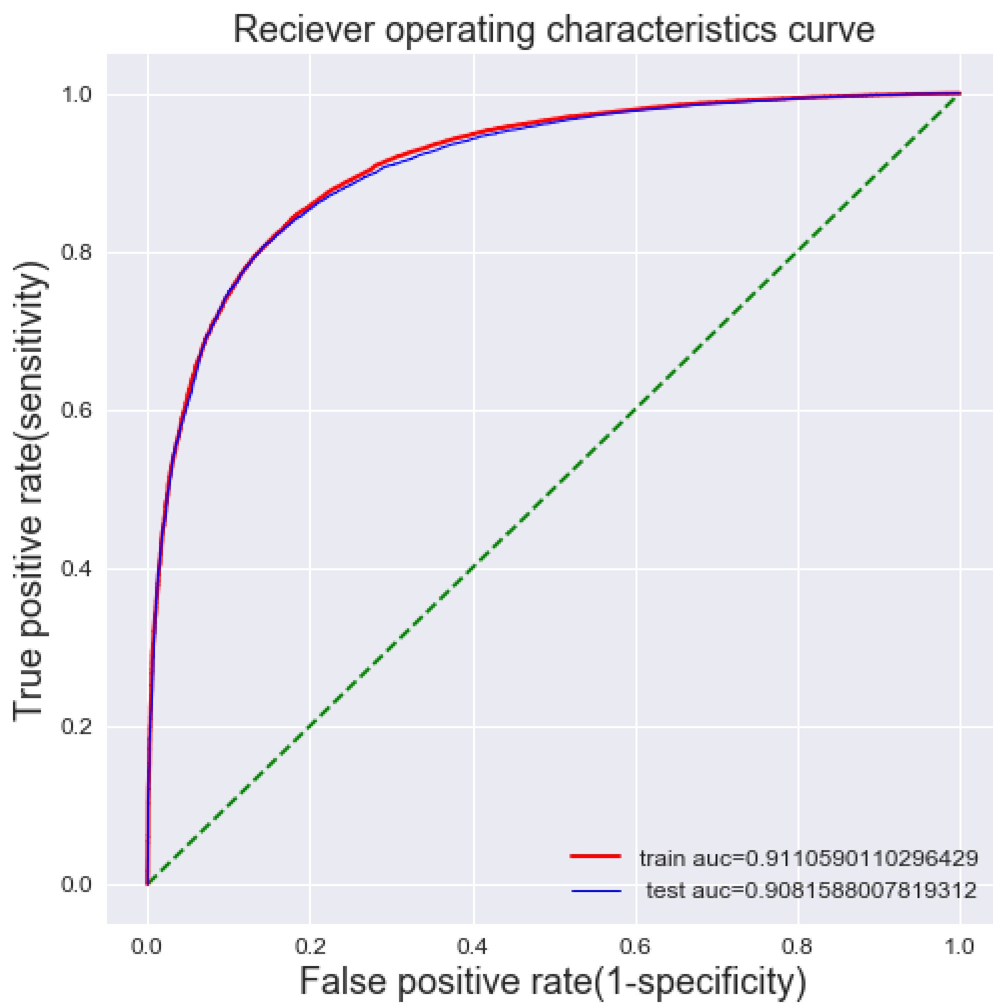
best value of hyperparameter in this case is C = 10000

In [107]:
```
from sklearn.metrics import roc_auc_score
clf_optimal = LogisticRegression(C =best_C_l1_aW2v,penalty='l1')#fitting the best
clf_optimal.fit(train_std,Y_train)
train_pred = clf_optimal.predict_proba(train_std)[:,1]
#predict_proba gives the probability of a data point belonging to a particular cla

test_pred = clf_optimal.predict_proba(test_std)[:,1]
#this predicts the probability of data pointsin test dataset belonging to class '

test_auc_aW2v_l1 = roc_auc_score(Y_test,test_pred)
print('AUC on test dataset is {}'.format(test_auc_aW2v_l1))
#calculating the area under the curve for the roc curve that will be drawn on tes
```

```
AUC on test dataset is 0.9081588007819312
```

In [108]:

```
from sklearn.metrics import roc_curve

fpr_tr, tpr_tr, _ = roc_curve(Y_train,train_pred)
fpr_test, tpr_test, _ = roc_curve(Y_test,test_pred)
#calculating the fpr,tpr and thresholds for each training and test dataset
auc_train = roc_auc_score(Y_train,train_pred)
auc_test = roc_auc_score(Y_test, test_pred)
#calculating the area under the curve for both test and train auc after fitting t
sns.set_style('darkgrid')
plt.figure(figsize=(8,8))
plt.plot(np.linspace(0,1,100),np.linspace(0,1,100),"g--")
plt.plot(fpr_tr,tpr_tr,'r',linewidth=2,label="train auc="+str(auc_train))
plt.plot(fpr_test,tpr_test,'b',linewidth=1,label=" test auc="+str(auc_test))
plt.xlabel('False positive rate(1-specificity)',fontsize=18)
plt.ylabel('True positive rate(sensitivity)',fontsize=18)
plt.title('Reciever operating characteristics curve',fontsize=18)
plt.legend(loc='best')
plt.show()
```



In [110]:

```
pred = clf_optimal.predict(test_std)
# predicting all the classes for test dataset for confusion matrix

#predicting all classes for training dataset for confusion matrix
pred_tr = clf_optimal.predict(train_std)

# calculating the precison score
print('precison score is {}'.format(precision_score(Y_test,pred)))

#calculating the recall score
print('\nrecall_score is {}'.format(recall_score(Y_test,pred)))

#calculating the f1 score
print('\nf1 score is {}'.format(f1_score(Y_test,pred)))
```

```
precison score is 0.909982108245117

recall_score is 0.9654749663845607

f1 score is 0.9369075488352459
```

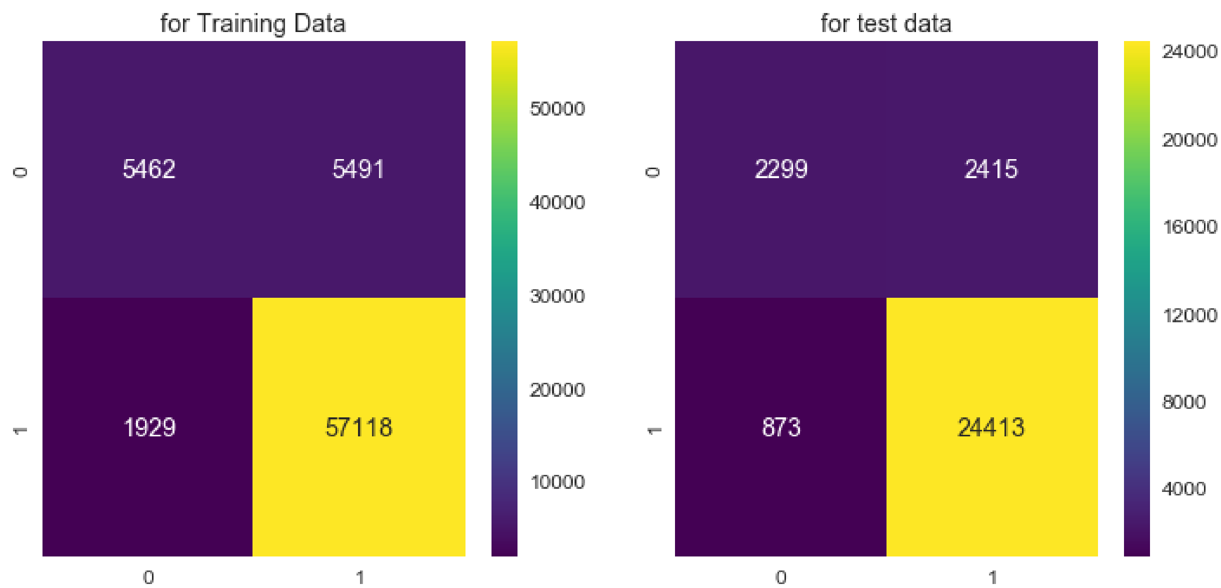
In [111]:

```
train_matrix = pd.DataFrame(confusion_matrix(Y_train,pred_tr),range(2),range(2))#
print(train_matrix.head())

test_matrix = pd.DataFrame(confusion_matrix(Y_test,pred),range(2),range(2))# svai
print(test_matrix.head())
```

```
      0      1
0  5462   5491
1  1929  57118
      0      1
0  2299   2415
1   873  24413
```

In [112]:
```
sns.set(font_scale = 1.2)
plt.figure(figsize = (12,12))#setting the font size
plt.subplot(2,2,1)
plt.title('for Training Data')
sns.heatmap(train_matrix,annot = True,fmt = 'g',cmap = 'viridis')#heatmap for tra

plt.subplot(2,2,2)
plt.title('for test data')
sns.heatmap(test_matrix,annot = True,fmt = 'g',cmap = 'viridis')
#annot = True writes data values in each cell
# fmt is string formatting code which is to be used when adding annonations
# cmap is the mapping from data values to color space
```

Out[112]: <matplotlib.axes._subplots.AxesSubplot at 0x223306ed128>




## Most important features

In [113]:

```
clf_optimal = LogisticRegression(C =best_C_tfidf_l1,penalty='l1')#fitting the bes
clf_optimal.fit(train_std,Y_train)
w = clf_optimal.coef_[0]#finding the coefficients of all features
print(w)



features = vect.get_feature_names()#getting name of the features after fitting an

#sorting the indexes with respect to values
negative_indices = np.argsort(w)

#reversing the sorted indexes with respect to values for positive indexes
positive_indices = np.argsort(w)[::-1]


print('TOP 20 important features for positive class and their coefficients in Ave
for i in (positive_indices[0:20]):
    print("%s\t --> \t%f"%(features[i],w[i]))
print("************************************************")

print('TOP 20 important features for negative class and their coefficients in Ave
for i in (negative_indices[0:20]):
    print("{} ---> {} ".format(features[i],w[i]))
```

```
[ 0.35382672  0.21826192 -0.09171839 -0.19006324 -0.78747075  0.24180057
 -0.11645953  0.          0.40906789 -0.50564411 -0.37807871  0.35613184
 -0.03502464  0.          0.07459885  0.37811542  0.51484649  0.00242207
  0.33168279  0.2266303   0.07158286  0.          0.00110876  0.56314176
  0.23915444  0.06431136 -0.23115775 -0.21874359  0.4279942   0.15725564
 -0.17880117 -0.43995641 -0.06908447  0.          0.08510936  0.03358359
 -0.35345095 -0.12748578 -0.09758805  0.14332622  0.07475794 -0.07254902
 -0.33960735 -0.10160292  0.25422559  0.09110122  0.         -0.05736251
 -0.20925416  0.24517293]
TOP 20 important features for positive class and their coefficients in Average
word to vector featurization using l1 regularization are:

able purchase    -->    0.563142
able give        -->    0.514846
able stop        -->    0.427994
able chew        -->    0.409068
able get         -->    0.378115
able enjoy       -->    0.356132
aa       -->    0.353827
able keep        -->    0.331683
absolutely awesome       -->    0.254226
absolutely fantastic     -->    0.245173
ability make     -->    0.241801
able put         -->    0.239154
able locate      -->    0.226630
aback    -->    0.218262
```

```
able take        -->    0.157256
absolute best    -->    0.143326
absolutely awful         -->    0.091101
able use         -->    0.085109
absolute favorite        -->    0.074758
able finish      -->    0.074599
************************************************
TOP 20 important features for negative class and their coefficients in Average
word to vector featurization using l1 regularization are:

ability ---> -0.7874707528362815
able drink ---> -0.5056441142548326
able tell ---> -0.43995640741537395
able eat ---> -0.3780787143511403
absence ---> -0.35345095446481894
absolutely adore ---> -0.3396073455065483
able see ---> -0.23115774883111612
able share ---> -0.21874359059789988
absolutely disgusting ---> -0.209254163665453
abdominal ---> -0.19006323597038455
able taste ---> -0.1788011707077563
absent ---> -0.12748577973528347
able ---> -0.11645952665013694
absolutely amazing ---> -0.1016029181634632
absolute ---> -0.09758805352238598
abandon ---> -0.09171838772356711
absolutely ---> -0.07254902252056716
able tolerate ---> -0.06908447147930724
absolutely delicious ---> -0.05736251025108829
able feed ---> -0.03502463606929593
```

## TFIDF weighted Word to vector

In [114]:
```
vect = TfidfVectorizer()#initializing the tfidf vectorizer

tf_idf = vect.fit_transform(X_train)#fitting the training data
dictionary = dict(zip(vect.get_feature_names(), list(vect.idf_)))#zipping both of
```

In [115]:
```
import itertools
dict(itertools.islice(dictionary.items(),20))
#printing first 20 elements of the dictionary
```

Out[115]:
```
{'aa': 9.758369533845372,
 'aaa': 10.210354657588429,
 'aaaaa': 11.057652517975633,
 'aaaaaaaaaaaaa': 11.463117626083797,
 'aaaaaaaaaaaaaaaaacccccccckkkkkk': 11.463117626083797,
 'aaaaaaahhhhhh': 11.463117626083797,
 'aaaaaah': 11.463117626083797,
 'aaaaaahhhhhyaaaaaa': 11.463117626083797,
 'aaaaaawwwwwwwwww': 11.463117626083797,
 'aaaah': 11.463117626083797,
 'aaaand': 11.463117626083797,
 'aaaannnnddd': 11.463117626083797,
 'aaaarrrrghh': 11.463117626083797,
 'aaah': 10.364505337415688,
 'aaahhh': 11.463117626083797,
 'aaahs': 11.463117626083797,
 'aabout': 11.463117626083797,
 'aabsolutely': 11.463117626083797,
 'aad': 11.463117626083797,
 'aadd': 11.463117626083797}
```

In [116]:
```
tfidf_feat = vect.get_feature_names() # tfidf words/col-names
print(tfidf_feat[:10])
```

```
['aa', 'aaa', 'aaaaa', 'aaaaaaaaaaaaa', 'aaaaaaaaaaaaaaaaacccccccckkkkkk', 'aaa
aaaahhhhhh', 'aaaaaah', 'aaaaaahhhhhyaaaaaa', 'aaaaaawwwwwwwwww', 'aaaah']
```

In [117]:
```
train_set = []; # the tfidf-w2v for each sentence/review in training set is store
row=0;
for sent in tqdm(s_train): # 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 = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    train_set.append(sent_vec)
    row += 1
print(len(train_set))
```

```
100%|
| 70000/70000 [1:03:47<00:00, 18.29it/s]

70000
```

In [118]:
```
test_set = []; # the tfidf-w2v for each sentence/review in test set is stored in
row=0;
for sent in s_test: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/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 = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    test_set.append(sent_vec)
    row += 1

print(len(test_set))
```

```
30000
```

In [119]:
```
#Standardizing the data
from sklearn.preprocessing import StandardScaler
train_std = StandardScaler(with_mean = False).fit_transform(train_set)
test_std = StandardScaler(with_mean = False).fit_transform(test_set)
#with_mean cannot be True here because we are dealing with sparse matrices
print('after standardization: {}'.format(train_std.shape))
print("test data:",test_std.shape)
```

```
after standardization: (70000, 50)
test data: (30000, 50)
```

## L2 regularization

In [120]:
```
param = {'C': [10**i for i in range(-4,5)]}#fixing the size and range of paramete

model = GridSearchCV(LogisticRegression(penalty='l2'),param_grid = param,scoring 
model.fit(train_std,Y_train)
```

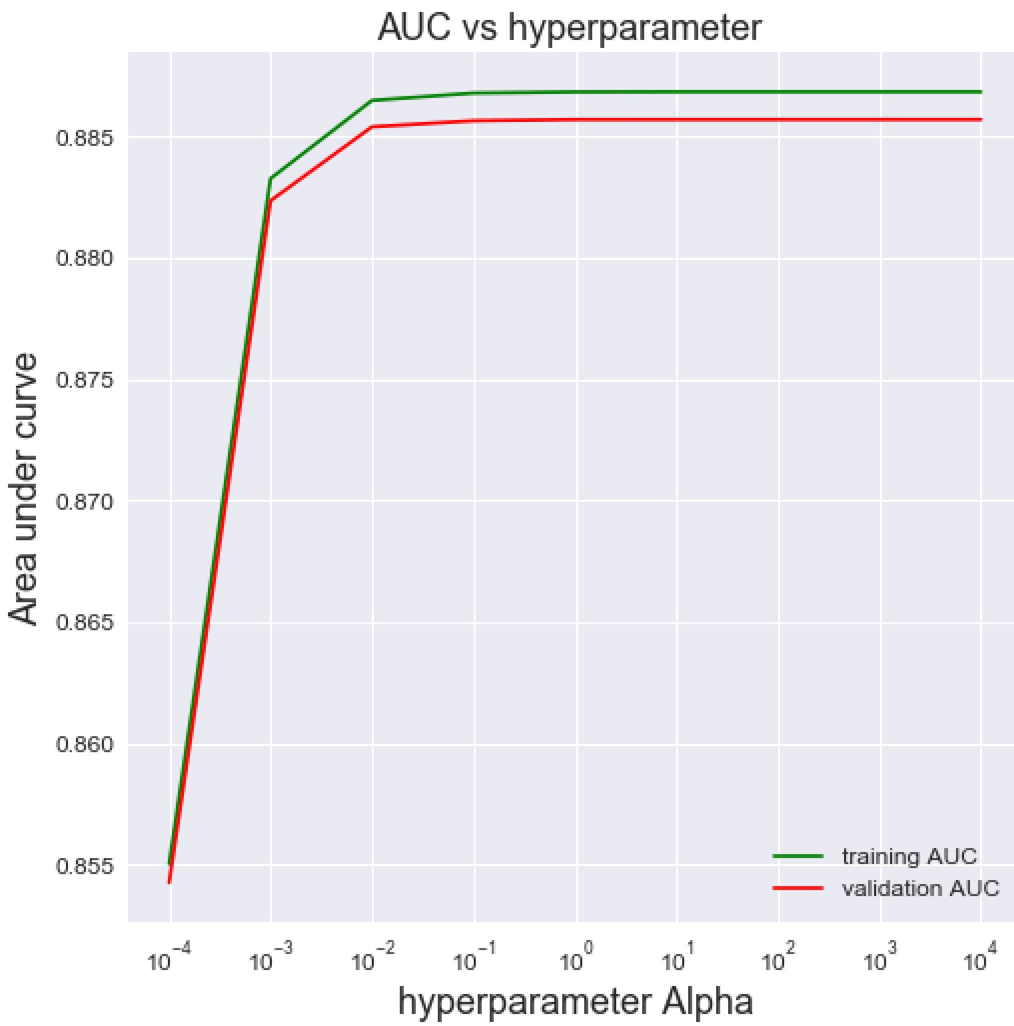
Out[120]:
```
GridSearchCV(cv='warn', error_score='raise-deprecating',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_i
ntercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid={'C': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='roc_auc', verbose=0)
```

In [121]:
```
best_C_l2_tiW2v = model.best_params_['C']
print(best_C_l2_tiW2v)
#this gives us the best hyperparameter found after gridsearch cross validation
```

```
10000
```

In [122]:
```
train_auc = model.cv_results_['mean_train_score']#deriving the avg training score
cv_auc = model.cv_results_['mean_test_score']#deriving the average cross validati
```

In [123]:
```
error(train_auc,cv_auc)
```

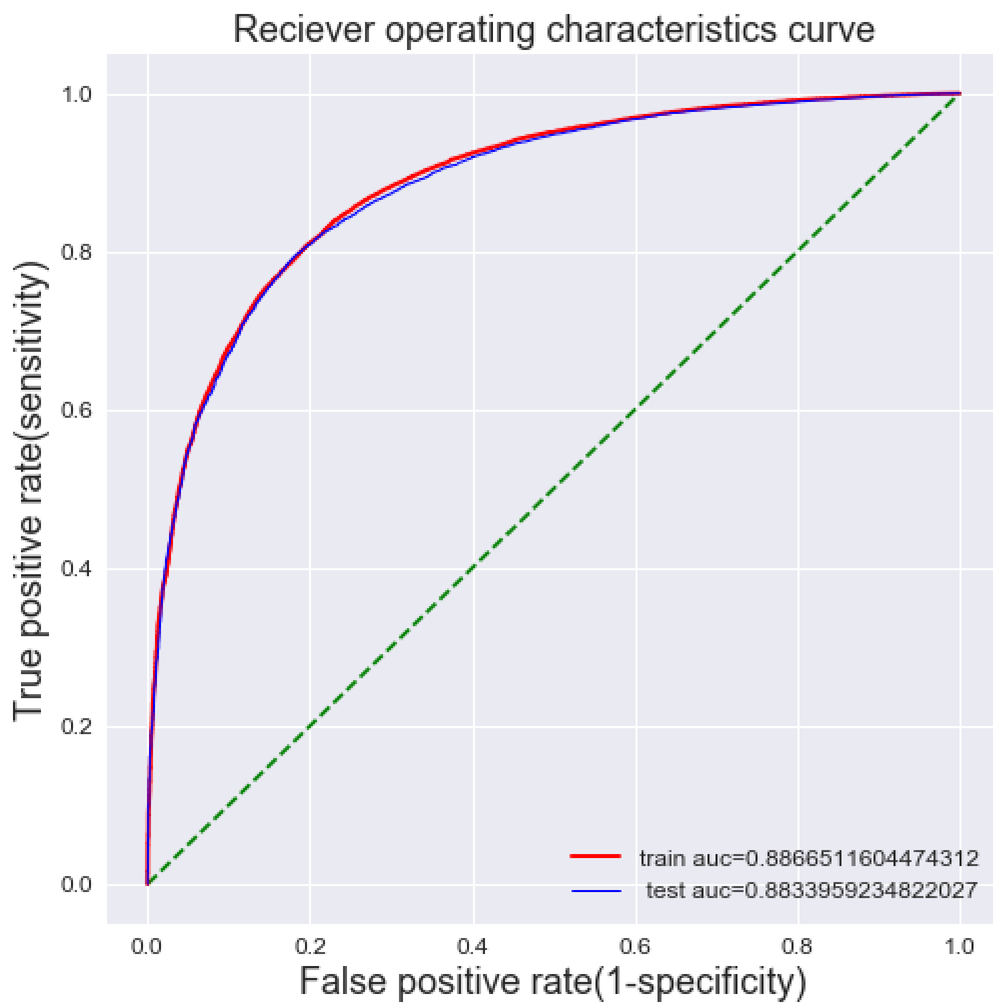



from AUC vs hyperparameter graph we can deduce that best C = 0.1

In [124]:
```
from sklearn.metrics import roc_auc_score
clf_optimal = LogisticRegression(C =0.1,penalty='l2')#fitting the best hyperparam
clf_optimal.fit(train_std,Y_train)
train_pred = clf_optimal.predict_proba(train_std)[:,1]
#predict_proba gives the probability of a data point belonging to a particular cl

test_pred = clf_optimal.predict_proba(test_std)[:,1]
#this predicts the probability of data pointsin test dataset belonging to class '

test_auc_tiW2v_l2 = roc_auc_score(Y_test,test_pred)
print('AUC on test dataset is {}'.format(test_auc_tiW2v_l2))
#calculating the area under the curve for the roc curve that will be drawn on tes
```

```
AUC on test dataset is 0.8833959234822027
```

In [125]:
```
from sklearn.metrics import roc_curve

fpr_tr, tpr_tr, _ = roc_curve(Y_train,train_pred)
fpr_test, tpr_test, _ = roc_curve(Y_test,test_pred)
#calculating the fpr,tpr and thresholds for each training and test dataset
auc_train = roc_auc_score(Y_train,train_pred)
auc_test = roc_auc_score(Y_test, test_pred)
#calculating the area under the curve for both test and train auc after fitting ti
sns.set_style('darkgrid')
plt.figure(figsize=(8,8))
plt.plot(np.linspace(0,1,100),np.linspace(0,1,100),"g--")
plt.plot(fpr_tr,tpr_tr,'r',linewidth=2,label="train auc="+str(auc_train))
plt.plot(fpr_test,tpr_test,'b',linewidth=1,label=" test auc="+str(auc_test))
plt.xlabel('False positive rate(1-specificity)',fontsize=18)
plt.ylabel('True positive rate(sensitivity)',fontsize=18)
plt.title('Reciever operating characteristics curve',fontsize=18)
plt.legend(loc='best')
plt.show()
```



In [126]:

```
pred = clf_optimal.predict(test_std)
# predicting all the classes for test dataset for confusion matrix

pred_tr = clf_optimal.predict(train_std)

# calculating the precison score
print('precison score is {}'.format(precision_score(Y_test,pred)))

#calculating the recall score
print('\nrecall_score is {}'.format(recall_score(Y_test,pred)))

#calculating the f1 score
print('\nf1 score is {}'.format(f1_score(Y_test,pred)))
```

```
precison score is 0.8960629921259843

recall_score is 0.9676105354741754

f1 score is 0.9304633872715864
```

In [128]:

```
train_matrix = pd.DataFrame(confusion_matrix(Y_train,pred_tr),range(2),range(2))#
print(train_matrix.head())

print("***********************************8")
test_matrix = pd.DataFrame(confusion_matrix(Y_test,pred),range(2),range(2))# svai
print(test_matrix.head())
```

```
      0      1
0  4453   6500
1  1883  57164
************************************8
      0      1
0  1876   2838
1   819  24467
```

In [129]:
```
sns.set(font_scale = 1.2)
plt.figure(figsize = (12,12))#setting the font size
plt.subplot(2,2,1)
plt.title('for Training Data')
sns.heatmap(train_matrix,annot = True,fmt = 'g',cmap = 'viridis')#heatmap for tra

plt.subplot(2,2,2)
plt.title('for test data')
sns.heatmap(test_matrix,annot = True,fmt = 'g',cmap = 'viridis')
#annot = True writes data values in each cell
# fmt is string formatting code which is to be used when adding annonations
# cmap is the mapping from data values to color space
```

Out[129]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2232ddd7e48>
```


## Most Important features

In [130]:
```
clf_optimal = LogisticRegression(C =best_C_tfidf_l1,penalty='l1')#fitting the bes
clf_optimal.fit(train_std,Y_train)
w = clf_optimal.coef_[0]#finding the coefficients of all features
print(w)



features = vect.get_feature_names()#getting name of the features after fitting an

#sorting the indexes with respect to values
negative_indices = np.argsort(w)

#reversing the sorted indexes with respect to values for positive indexes
positive_indices = np.argsort(w)[::-1]


print('TOP 20 important features for positive class and their coefficients in Ave
for i in (positive_indices[0:20]):
    print("%s\t --> \t%f"%(features[i],w[i]))
print("***********************************************")

print('TOP 20 important features for negative class and their coefficients in Ave
for i in (negative_indices[0:20]):
    print("{} ---> {} ".format(features[i],w[i]))
```

```
[ 0.36702762  0.21112755 -0.21402329 -0.16841412 -0.7900127   0.21776977
 -0.15435853  0.06156578  0.35105977 -0.55207297 -0.32306572  0.29290369
 -0.00326769  0.05898802  0.08320246  0.29528588  0.4923211   0.10028571
  0.32091022  0.26609583  0.04687623  0.          0.          0.57716042
  0.24803919  0.06642202 -0.10572838 -0.27510947  0.39632504  0.11925251
 -0.16300473 -0.54614754 -0.04805879 -0.03736122  0.08323652  0.10955805
 -0.39206037 -0.06273327 -0.13264115  0.19853702  0.08254298 -0.10456749
 -0.38018459 -0.02508837  0.23397396  0.02805636  0.0087161  -0.00979268
 -0.0912951   0.33869285]
TOP 20 important features for positive class and their coefficients in Average
word to vector featurization using l1 regularization are:

aafter   -->    0.577160
aabout   -->    0.492321
aaloo    -->    0.396325
aa       -->    0.367028
aaaaaawwwwwwwwwww        -->    0.351060
abd      -->    0.338693
aad      -->    0.320910
aaahs    -->    0.295286
aaaannnnddd      -->    0.292904
aadd     -->    0.266096
aahhed   -->    0.248039
abbey    -->    0.233974
aaaaaaahhhhhh    -->    0.217770
aaa      -->    0.211128
abandoned        -->    0.198537
```

```
aalouisiana      -->    0.119253
aauces   -->    0.109558
aabsolutely      -->    0.100286
aarthur  -->    0.083237
aaahhh   -->    0.083202
************************************************
TOP 20 important features for negative class and their coefficients in Average
word to vector featurization using l1 regularization are:

aaaaaaaaaaaaaaaaaccccccckkkkkk ---> -0.7900127035912485
aaaah ---> -0.5520729666893033
aand ---> -0.5461475423868151
ab ---> -0.3920603654123114
abattoir ---> -0.38018458693457796
aaaand ---> -0.32306571615074825
aalmost ---> -0.2751094691597204
aaaaa ---> -0.21402329380615145
aaaaaaaaaaaaa ---> -0.16841411739164036
aamazon ---> -0.16300473341228705
aaaaaah ---> -0.15435852542839978
abandon ---> -0.13264115206088054
aahs ---> -0.10572837654262779
abated ---> -0.10456749495056654
abc ---> -0.09129509610587135
aback ---> -0.06273327124331132
aare ---> -0.04805879384732754
aarrgghhhh ---> -0.03736121970746189
abb ---> -0.025088365420230928
abby ---> -0.009792684380209042
```

## L1 regularization

In [131]:

```python
param = {'C': [10**i for i in range(-4,5)]}#fixing the size and range of paramete

model = GridSearchCV(LogisticRegression(penalty='l1'),param_grid = param,scoring 
#and grid search cross validation
model.fit(train_std,Y_train)
```

Out[131]:

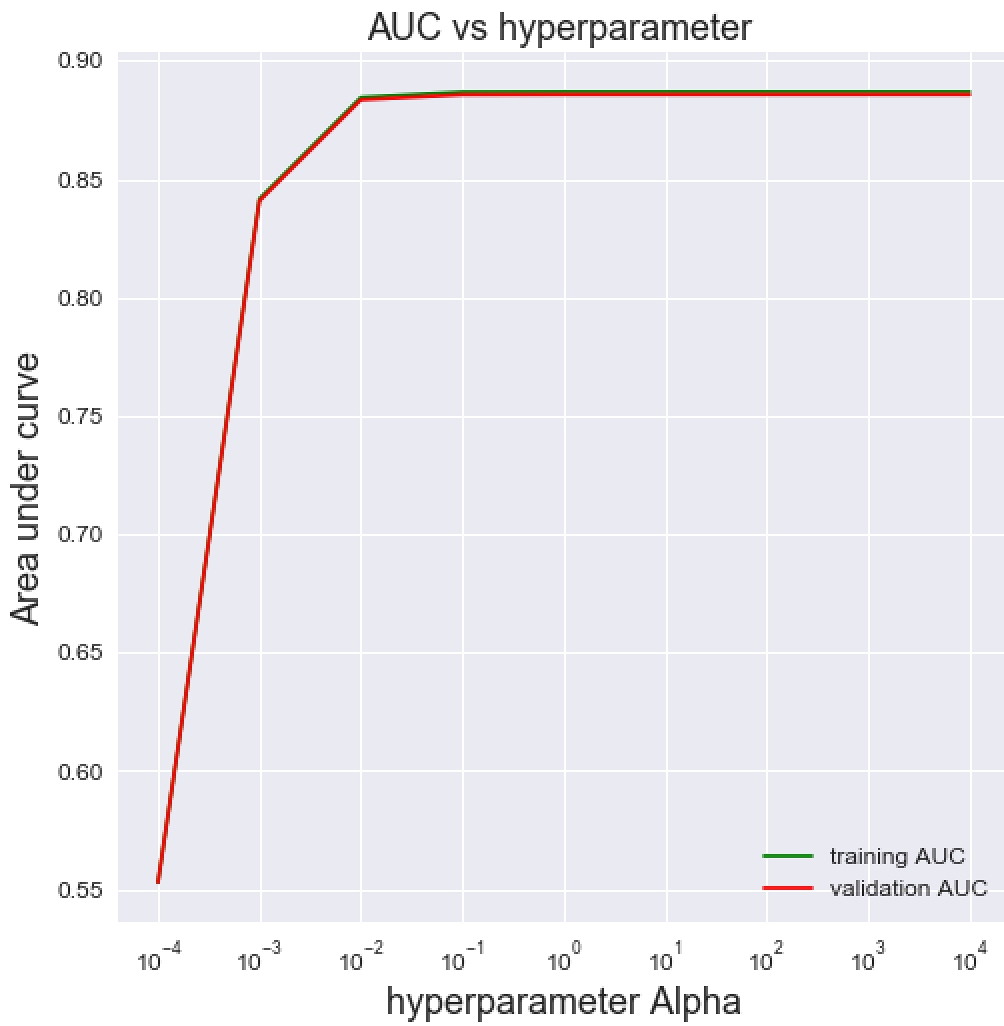
```
GridSearchCV(cv='warn', error_score='raise-deprecating',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_i
ntercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l1', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid={'C': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='roc_auc', verbose=0)
```

In [132]:
```
best_C_l1_tiW2v = model.best_params_['C']
print(best_C_l1_tiW2v)
#this gives us the best hyperparameter found after gridsearch cross validation
```

```
10000
```

In [133]:
```
train_auc = model.cv_results_['mean_train_score']#deriving the avg training score
cv_auc = model.cv_results_['mean_test_score']#deriving the average cross validati
```

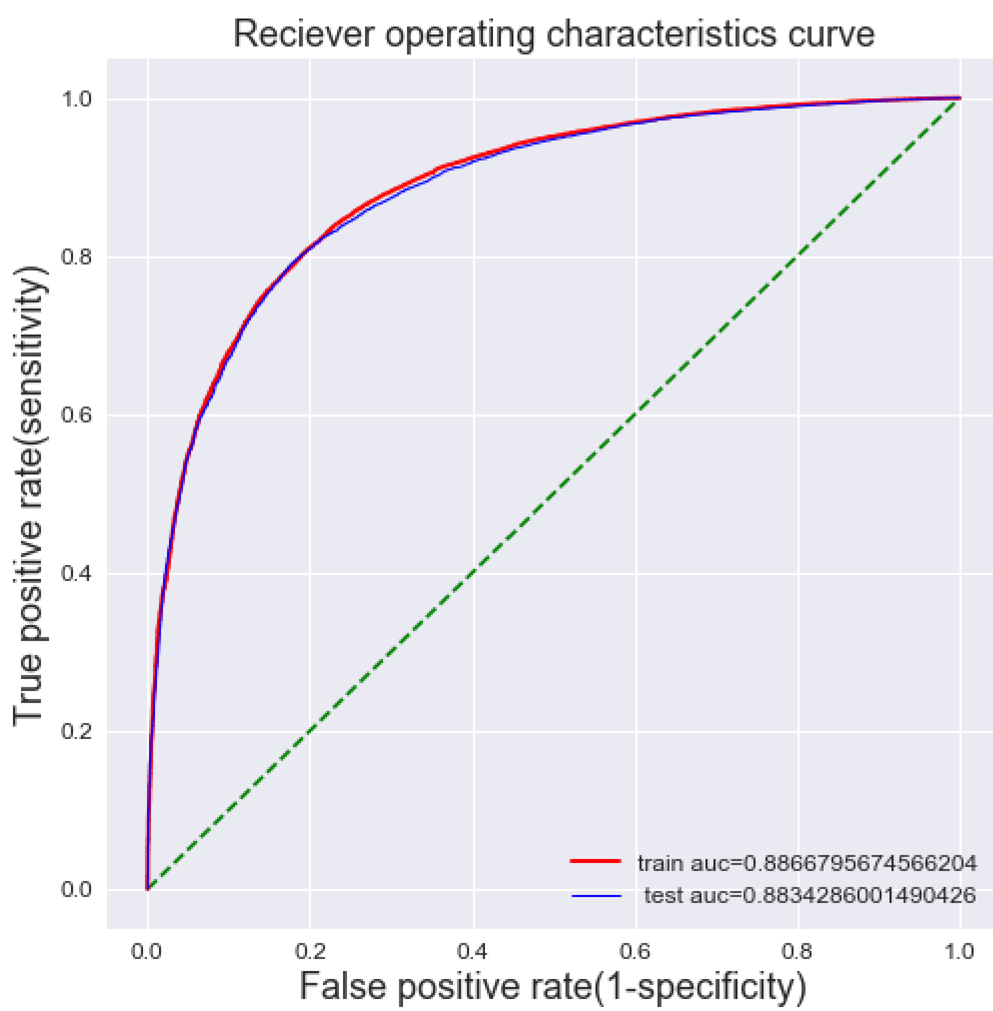
In [134]:
```
error(train_auc,cv_auc)
```



In [135]:
```
from sklearn.metrics import roc_auc_score
clf_optimal = LogisticRegression(C =10,penalty='l1')#fitting the best hyperparame
clf_optimal.fit(train_std,Y_train)
train_pred = clf_optimal.predict_proba(train_std)[:,1]
#predict_proba gives the probability of a data point belonging to a particular cl

test_pred = clf_optimal.predict_proba(test_std)[:,1]
#this predicts the probability of data pointsin test dataset belonging to class '

test_auc_tiW2v_l2 = roc_auc_score(Y_test,test_pred)
print('AUC on test dataset is {}'.format(test_auc_tiW2v_l2))
#calculating the area under the curve for the roc curve that will be drawn on tes
```

```
AUC on test dataset is 0.8834286001490426
```

In [136]:
```
from sklearn.metrics import roc_curve

fpr_tr, tpr_tr, _ = roc_curve(Y_train,train_pred)
fpr_test, tpr_test, _ = roc_curve(Y_test,test_pred)
#calculating the fpr,tpr and thresholds for each training and test dataset
auc_train = roc_auc_score(Y_train,train_pred)
auc_test = roc_auc_score(Y_test, test_pred)
#calculating the area under the curve for both test and train auc after fitting th
sns.set_style('darkgrid')
plt.figure(figsize=(8,8))
plt.plot(np.linspace(0,1,100),np.linspace(0,1,100),"g--")
plt.plot(fpr_tr,tpr_tr,'r',linewidth=2,label="train auc="+str(auc_train))
plt.plot(fpr_test,tpr_test,'b',linewidth=1,label=" test auc="+str(auc_test))
plt.xlabel('False positive rate(1-specificity)',fontsize=18)
plt.ylabel('True positive rate(sensitivity)',fontsize=18)
plt.title('Reciever operating characteristics curve',fontsize=18)
plt.legend(loc='best')
plt.show()
```



In [159]:
```
pred = clf_optimal.predict(test_std)
# predicting all the classes for test dataset for confusion matrix

pred_tr = clf_optimal.predict(train_std)
# calculating the precison score
print('precison score is {}'.format(precision_score(Y_test,pred)))

#calculating the recall score
print('\nrecall_score is {}'.format(recall_score(Y_test,pred)))

#calculating the f1 score
print('\nf1 score is {}'.format(f1_score(Y_test,pred)))
```

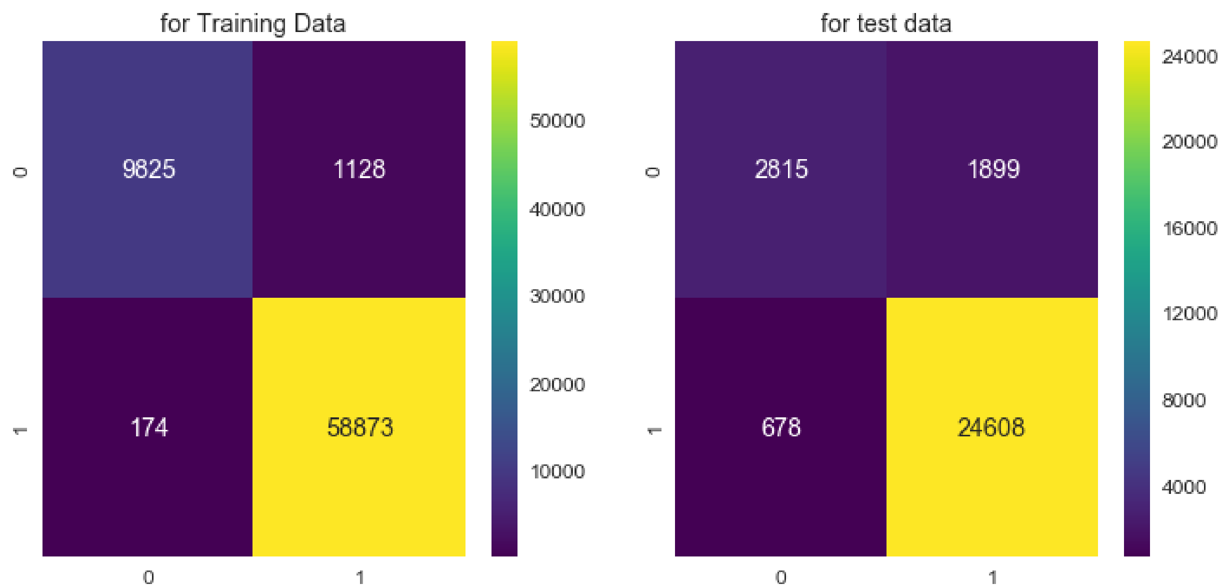
```
precison score is 0.9283585467989588

recall_score is 0.9731867436526142

f1 score is 0.9502442414998166
```

In [160]:
```
test_matrix = pd.DataFrame(confusion_matrix(Y_test,pred),range(2),range(2))# svai
print(test_matrix.head())

print("*************************************")

train_matrix = pd.DataFrame(confusion_matrix(Y_train,pred_tr),range(2),range(2))#
print(train_matrix.head())
```

```
      0      1
0  2815   1899
1   678  24608
*************************************
      0      1
0  9825   1128
1   174  58873
```

In [161]:
```
sns.set(font_scale = 1.2)
plt.figure(figsize = (12,12))#setting the font size
plt.subplot(2,2,1)
plt.title('for Training Data')
sns.heatmap(train_matrix,annot = True,fmt = 'g',cmap = 'viridis')#heatmap for tra

plt.subplot(2,2,2)
plt.title('for test data')
sns.heatmap(test_matrix,annot = True,fmt = 'g',cmap = 'viridis')
#annot = True writes data values in each cell
# fmt is string formatting code which is to be used when adding annonations
# cmap is the mapping from data values to color space
```

Out[161]: `<matplotlib.axes._subplots.AxesSubplot at 0x2231e708a58>`




## Most important features

In [162]:

```
clf_optimal = LogisticRegression(C =best_C_tfidf_l1,penalty='l1')#fitting the bes
clf_optimal.fit(train_std,Y_train)
w = clf_optimal.coef_[0]#finding the coefficients of all features
print(w)



features = vect.get_feature_names()#getting name of the features after fitting an

#sorting the indexes with respect to values
negative_indices = np.argsort(w)

#reversing the sorted indexes with respect to values for positive indexes
positive_indices = np.argsort(w)[::-1]


print('TOP 20 important features for positive class and their coefficients in Ave
for i in (positive_indices[0:20]):
    print("%s\t --> \t%f"%(features[i],w[i]))
print("***********************************************")

print('TOP 20 important features for negative class and their coefficients in Ave
for i in (negative_indices[0:20]):
    print("{} ---> {} ".format(features[i],w[i]))
```

```
[0. 0. 0. ... 0. 0. 0.]
TOP 20 important features for positive class and their coefficients in Average
word to vector featurization using l1 regularization are:

great    -->    0.664565
best     -->    0.478902
delicious        -->    0.407227
good     -->    0.390245
perfect  -->    0.353568
love     -->    0.338386
excellent        -->    0.324584
loves    -->    0.288892
highly   -->    0.257104
wonderful        -->    0.237511
nice     -->    0.225360
favorite         -->    0.215427
tasty    -->    0.207011
awesome  -->    0.201361
easy     -->    0.190536
happy    -->    0.184563
pleased  -->    0.165653
find     -->    0.156288
use      -->    0.149085
yummy    -->    0.146443
***********************************************
TOP 20 important features for negative class and their coefficients in Average
word to vector featurization using l1 regularization are:
```

```
not ---> -0.5192782548561297
disappointed ---> -0.2311863606830064
worst ---> -0.2093931061792437
awful ---> -0.18987746868348684
terrible ---> -0.16515559836251398
disappointing ---> -0.16159938206340538
money ---> -0.15282398939804986
threw ---> -0.14139000502264013
stale ---> -0.13682339655887904
unfortunately ---> -0.132886597310945
disappointment ---> -0.13104129081949806
would ---> -0.13012442942883967
horrible ---> -0.12932675806534397
thought ---> -0.1252883201873439
waste ---> -0.1217549483270329
bad ---> -0.12153865795489047
bland ---> -0.12109271011396236
product ---> -0.11526169456856768
disgusting ---> -0.11185302603664013
return ---> -0.11166872753141847
```

# Conclusion

In [163]:
```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ['featurization' , 'regularization' , 'best hyperparameter(C = 1/

#x.add_row(['Bag of words' , 'l2' ,best_C_l2_bow ,test_auc_bow_l2])
#x.add_row(['Bag of Words','l1',best_C_l1_bow,test_auc_bow_l1])
x.add_row(['TFIDF','l2',best_C_tfidf_l2,test_auc_tfidf_l2])
x.add_row(['TFIDF','l1',best_C_tfidf_l1,test_auc_tfidf_l1])
x.add_row(['Average W2V','l2',best_C_l2_aW2v,test_auc_aW2v_l2])
x.add_row(['Avergae W2V','l1',best_C_l1_aW2v,test_auc_aW2v_l1])
x.add_row(['tfidf W2V','l2',best_C_l2_tiW2v,test_auc_tiW2v_l2])
x.add_row(['tfidf W2V','l1',best_C_l1_tiW2v,test_auc_tiW2v_l2])





print(x)
```

```
+---------------+----------------+-----------------------------------+---------
-----------+
| featurization | regularization | best hyperparameter(C = 1/lambda) |  AUC on
Test data  |
+---------------+----------------+-----------------------------------+---------
-----------+
|     TFIDF     |       l2       |               0.0001              | 0.954694
837516176  |
|     TFIDF     |       l1       |                0.01               | 0.960949
0424872511 |
|  Average W2V  |       l2       |                 10                | 0.908162
9703078412 |
|  Avergae W2V  |       l1       |               10000               | 0.908158
8007819312 |
|   tfidf W2V   |       l2       |               10000               | 0.883428
6001490426 |
|   tfidf W2V   |       l1       |               10000               | 0.883428
6001490426 |
+---------------+----------------+-----------------------------------+---------
-----------+
```

1. We observe that best AUC score is given by TFIDF vectorizer using l1 regularization.
2. L1 regularization is computationally expensive due to the optimised solution creating sparsity
3. Using Pertubation Testing as a hack of checking multicollinearity,we obseved that due to very small percentage of features changing their weight vectors by huge margin

In [ ]:

In [ ]: